Sensing Sentiment in On-Line Recommendation Texts and Ratings

Author: James Cogley

B.A (Mod) Computer Science, Linguistics and French

Supervisor: Dr. Carl Vogel

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Declaration

I hereby declare that this thesis is entirely my own work and that it has not been submitted as an exercise for a degree at any other university.

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"Romance should never begin with sentiment.
It should begin with science and end with settlement"

Oscar Wilde

"Show me the business man or
institution not guided by sentiment and service"

Charles H. Spurgeon

Contents

1 Introduction **1**

2 Background **3**

2.1 Introduction 3

2.2 An overview of sentiment analysis 3

2.3 Existing Lexicons 5

2.3.1 SentiWordNet 5

2.3.2 General Inquirer 6

2.4 Motivation 9

2.5 What is meant by sentiment? 11

2.6 Outline of Project 12

2.7 Conclusion 13

3 Data **14**

3.1 Introduction 14

3.2 Acquiring Data 14

3.3 Data Representation 16

3.4 Conclusion 21

4 Outline of Approaches Used in Analyzing the Data **22**

4.1 Introduction 22

4.2 Working with Weka 22

4.2.1 Weka Data Formatting 23

4.2.2 How the data was formatted 26

4.2.3 Desired Output 26
4.3 Statistical Approach 27
4.3.1 Data Formatting 27
4.3.2 Tests Used 29
4.4 Conclusion 33

5 Discussion **34**
5.1 Introduction 34
5.2 Analysis of Machine Learning Approach 34
5.3 Analysis of Statistical Approach 36
5.4 Creating a Lexicon 45
5.5 Conclusion 48

6 Conclusions **49**

A Weka Command-Line Syntax **54**

B Generated Lexicon **56**

List of Figures

3.1 Sample robots.txt file showing structure 15

4.1 A sample .arff file 24
4.2 A sample sparse .arff file 25
4.3 Calculating the Variables 29
4.4 Formula to Calculate Pearson's Chi-Square 30
4.5 Calculating χ from variables A,B,C and D 30
4.6 Mutual Information 31
4.7 Mutual Information:Initial Implementation 32
4.8 Pointwise Mutual Information Formula 32

5.1 Weka Command Line 35

List of Tables

3.1 Reviews 18
3.2 Rating Specific Frequencies 20
3.3 Word Frequency Lexicon 20
3.4 Showing correspondence of ratings and sentiment 21

4.1 Chi-square contingency table 28

5.1 Sample Chi-Square Values 36
5.2 Top 11 words ordered by chi-values for each class 37
5.3 Sampling of Pointwise MI values 39
5.4 Top 10 words ordered by Pointwise MI for each class 40
5.5 Highlighting frequency differences 40
5.6 Recalculated Chi-Square 41
5.7 Recalculated Mutual Information 41
5.8 Top 10 words ordered by chi-square within each rating class . 42
5.9 Top 10 words ordered by pointwise mutual information within each rating class 43
5.10 Sample of Rankings 43
5.11 Top ranking words for each category according to pointwise mutual inforamtion on new dataset 44

Abstract

Current approaches to sentiment analysis utilise sentiment lexicons such as SentiWordNet or Harvard's General Inquirer. Sentiment lexicons are dictionaries which associate a word with its sentiment (positive, negative or neutral). There are, however, problems with existing sentiment lexicons; they can contain noisy and inconsistent data (SentiWordNet), they can be quite limited in coverage (General Inquirer) and they are not finely-tuned to particular text types or subject domains. This project's aim is to address such problems by developing a methodology which, given labeled data in a particular domain, will create a sentiment lexicon for that domain. The research in this project is concerned with user reviews taken from a database of labelled reviews from the website tripadvisor.ie, but will create a generalizable model which can be applied to any domain in creating sentiment lexicon.

Chapter 1

Introduction

Sentiment Analysis is a young and growing field of research which incorporates methods from computational linguistics, natural language processing and data mining in order to extract the sense or opinion behind a given text. One approach is to is to determine the polarity of lexical items. Once the polarity of a lexical item has been obtained, it may be combined with the polarity of other items in a given document, and combined in syntactic structures in order to obtain the polarity the document. Such methods rely on a sentiment lexicon such as SentiWordNet and General Inquirer, a dictionary of words and indicators of their polarities, as the items found in documents are checked off against the values in these lexicons. The indicators used may take many forms, for example, SentiWordNet uses numerical scoring on three possible categories (Objectivity, Positivity, Negativity) where there sum accounts to one. General Inquirer was multiple categories which a given token may or may not be denoted to be a member of. This project is concerned with the generation of such lexicons. This report will begin with a general description of sentiment analysis, underlining commonly used approaches, and looking at current work on developing sentiment lexicons such as SentiWordNet and the General Inquirer. From this a motivation for this project will be put forward. After this, an overview of the stages and aims of the project will be provided. We can then go in depth into these stages of de-

velopment, describing fully the reasoning behind each stage of the project and how it was implemented, looking first at machine-learning approaches and then statistical testing. Machine learning will treat a given review as a feature vector which is classified by the rating which accompanies it. The machine learning technique of feature selection will then be used to discover the terms with the strongest link to the given class. In the second approach, the statistical tests of chi-square and pointwise mutual information will be used to test how strong the link between a given word and a given class is. The next section will analyse the use of both approaches and evaluate both of these with respect to creating a sentiment lexicon. This chapter will also feature a discussion of the creation of a lexicon according to these methods. The final section will include conclusions that have been arrived at in the course of this research, highlighting its strengths and what can be carried forward into further research but also what did not go to plan, and possible solutions to eradicate such problems.

Chapter 2

Background

2.1 Introduction

This chapter commences with a discussion of what exactly is being investigated, a general overview of approaches to sentiment analysis, describing the most common approaches with examples. As this work is primarily concerned with the creation sentiment lexicons, two existing lexicons, *SentiWordNet* and *General Inquirer*, will be presented and examined. In analyzing these lexicons a motivation for the development of this project will be put forward. The chapter ends with an outline of general aims and stages in the project development and concluding remarks.

2.2 An overview of sentiment analysis

Sentiment analysis is a relatively new and fast-growing form of textual analysis[2]. The causes of the recent surge in research on the topic are outlined in pg. 4,5[2] as follows; "the rise of machine learning methods in natural language processing and information retrieval ... the availability of datasets for machine learning algorithms to be trained on, due to the blossoming of the World Wide Web and, specifically, the development of review-aggregation web-sites ... realization of the fascinating intellectual challenges and commercial and

intelligence applications that the area offers." This is all without saying what it actually does. In short, it is a process used to determine if a given document's sentiment toward some object. A good example of such a document would be a product review, where the writer expresses their sentiment towards the product.

At first glance, it doesn't seem necessary for an application to perform sentiment analysis, as we can ascertain the sentiment by simply reading the review. However, the problem arises when we are dealing with hundred's of thousands of documents as to evaluate all of the reviews by reading would be impractical and very time consuming. The perfect solution for this would be to get a machine to do all the dirty work given all these documents and outputting the overall sentiment towards the object in question [13] or a summary of the review [9].

Such software is already available[1] and has been implemented as Alex Wright reports an incident relating to the ticket vendor in relation to a rained out baseball game[21]:

> "Stadium officials mistakenly told hundreds of fans that the game had been cancelled, and StubHub denied fans requests for refunds, on the grounds that the game had actually been played. But after spotting trouble brewing online, the company offered discounts and credits to the affected fans. It is now re-evaluating its bad weather policy."

Such applications may take different approaches in determining the sentiment of a document. The first approach would take in documents which are annotated with some sort of polarity, then models can be generated using text categorisation methods. From this, the sentiment on a word level may

[1] http://www.scoutlabs.com/ - Last verified, February, 2009

be determined[16]. A second approach would begin at the word level, assigning each word a sentiment polarity which has been taken from a sentiment lexicon, and then building up to document level. Such an approach using compositional semantics has been outlined in [3] although in must be stated that approaches using this approach work on the basis that the semantics of a term is equal to its sentiment, thus applying a notion of "compositional sentiment". For the latter, sentiment lexicons are quite important as the overall sentiment of a document relies on the sentiment of all its components and how they interact.

1. There was a lot of noise in the morning

The above example shows the need for the correct assignment of sentiment polarity. In 1, the key word for defining the sentiment of the sentence is the term 'noise'. However, most approaches concern themselves with adjectives[6] or verbs[14], which would lead to an incorrect classification of 1 as 'noise' is a noun. This example can be generalized as a lot of nouns may contain sentiment[11]. Two sentiment lexicons, SentiWordNet and General Inquirer will be described in the next section.

2.3 Existing Lexicons

2.3.1 SentiWordNet

SentiWordnet[2] is a sentiment lexicon based upon WordNet[3] containing 147,278 synsets, which is free for use for academic research. Its approach took synsets from WordNet and then evaluated its polarity according to three numerical scores, *Obj*, *Pos* and *Neg*. These scores range between 0.0 and 1.0 and the sum for each synset is equal to 1.0. Although lexicons are more than often concerned with just words, a synset comprises of several words. With Senti-

[2]http://sentiwordnet.isti.cnr.it/ - Last verified, March , 2010
[3]http://wordnet.princeton.edu/ - Last verified, March, 2010

WordNet, there is no distinction between the senses of these words, therefore all are given the same score. A simple example of this is given in [5];

> "the synset [estimable(3)], corresponding to the sense may be computed or estimated of the adjective estimable, has an Obj score of 1.0 (and Pos and Neg scores of 0.0), while the synset [estimable(1)] corresponding to the sense deserving of respect or high regard has a Pos score of 0.75, a Neg score of 0.0, and an Obj score of 0.25."

The approach undertaken in the construction of SentiWordNet implements a ternary classifier. A classifier is an algorithm which may learn from data given to it in order to predict a class for other datasets. This classifier was semi-supervised, meaning that it was given some data which had already been labelled by humans. From this, the classifier classifies the synsets according to the three possible values. If the classifiers used in determining the scores classified it unanimously, it is then given the maximum score for that value in the synset. Otherwise, it is given a score proportional to the number of classifiers that assigned it[5]. The training data began as a set of 105 manually labelled positive, negative and objective synsets. The number of synsets was then incremented using classifiers.

Given its approach in working with synsets it has some clear advantages such as for word sense disambiguation. Synsets contain syntactic information also, the lexical items are accompanied by part-of-speech(POS) tags, something which it has in common with the General Inquirer which will be described in the next section.

2.3.2 General Inquirer

The General Inquirer[4] is a sentiment lexicon where words are tagged from four sources. These four sources are outlined below:

[4]http://www.wjh.harvard.edu/ inquirer/homecat.htm - Last verified, March, 2010

- the Harvard IV-4 dictionary
- the Lasswell value dictionary[5]
- several categories recently constructed
- marker categories

The Harvard IV-4 dictionary contains categories which apply the ideas of Charles Osgood regarding semantic differentials. These differentials describe the intensity of a term through combination. This is something implemented throughout the dictionary, in that the sentiment of each term is defined by the combination of categories. The Harvard IV-4 dictionary contains 14 other types of categories which are listed below;

- Words of pleasure, pain, virtue and vice
- Words indicating overstatement and understatement
- Words reflecting the language of a particular "institution"
- Words referring to roles, collectivities, rituals and forms of interpersonal relations
- Ascriptive social categories as well as general references to people and animals
- References to places, locations and routes between them
- References to objects
- Processes of communication
- Motivation-related words
- other process or change words

[5]http://www.wjh.harvard.edu/ inquirer/lasswell.htm - March, 2010

- cognitive orientation
- Pronouns and names
- Negation and interjections
- Verb types
- Adjective types

The second dictionary used is the Lasswell value dictionary. This dictionary is divided into four dereference domains: power, rectitude, respect and affiliation and four welfare domains: wealth, well-being, enlightenment and skill. These domains may be further divided into subcategories.

The marker categories described are much like part-of-speech tags, which are important in word sense disambiguation. The dictionary itself is available in a number of formats, as a spreadsheet, a Microsoft word file or web retrieval. Web retrieval methods have proven the most successful for automation although it is still possible using all formats. Like SentiWordNet it's freely open to those for research purposes, although its size is much smaller. With SentiWordNet accounting for 147,278 individual tokens,[6] as opposed to General Inquirer's 11789. This is due to the fact that work done in the creation of the General Inquirer was done manually, contributed to by volunteers and the addition of the already existing dictionaries.

Another key difference is the classification of words. As we saw for SentiWordNet, there are 3 possible categories and the words are scored numerically. General Inquirer's classifications differ in that there is no numerical score,(instead it is binary in that it subscribes to a category or does not) but the words are accompanied by tags indicating which categories they belong to, but also there is no limit to the number of categories a token may have.

[6]http://wordnet.princeton.edu/wordnet/man/wnstats.7WN.html#toc2 - Last verified, March, 2010

These categories may range from positive and negative, or it can include more precise measures such as strong, weak, passive and active. The fact that there is no limit on these categories invites people to contribute other categories to the lexicon to give a greater classification of sentiment to the tokens. However, this may work against the consistency of the General Inquirer as the only stipulation it has as regards creating categories is that it must have a unique name. Given the sentiment is such a subjective topic, and human evaluation is used, classifications may be rendered incompatible.

2.4 Motivation

Although the sentiment lexicons have their own advantages, there are disadvantages which do not just apply to those described above. Firstly, sentiment lexicons which are created manually are often limited in their coverage, as shown by the relatively few tokens accounted for by the General Inquirer lexicon. On the other side of things, large automatically constructed lexicons may contain a lot of noise and can be inaccurate in the sentiment analysis of several domains. This has been investigated in [4], where SentiWordNet was evaluated in classifying both news articles and user reviews, which gave some interesting points. As regards news articles, it was quite unsuccessful in determining their polarity, citing the neutral writing style of news articles. The overall accuracy of classifications stood at 40% on 535 news articles. The problem lies in the approach used. It was a rule based approach which denotes that all documents are to be considered negative if there is insufficient data to show it to be positive. The removal of such a rule, and instead treat the articles as "neutral" may have seen an improval in results. In the case of reviews, analysis was relatively successful. But it stipulates that "a classifier trained on documents of one domain is not transferable to other domains without a significant drop in accuracy" pg. 5[4]. Accuracy being the percentage of documents with correctly classified opinion (positivity Vs. negativity). Given this, it's clear that multi-domain sentiment analysis is

difficult using a "catch all" sentiment lexicon.

The difficulty in applying such lexicons is best described in the following example;

> "A quick search on Tweetfeel, for example, reveals that 77 percent of recent tweeters liked the movie 'Julie and Julia.' But the same search on Twitrratr reveals a few misfires. The site assigned a negative score to a tweet reading 'julie and julia was truly delightful!!' That same message ended with we all felt very hungry afterwards and the system took the word hungry to indicate a negative sentiment."[21]

Taking this example into account, it can be seen that sentiment analysis across multiple-domains is much more difficult than working in a single domain. But approaches taken, in particular, that of those creating General Inquirer, are time consuming, and limited in their coverage. Therefore, parts of both approaches may be implemented to attain the desired results. Firstly, as multi-domain analysis is particularly difficult, domains must be separated, thus there is a need for domain specific sentiment lexicons. However, doing this by hand would be very time consuming. Therefore the approach needs to be automated or semi-automated. This project will provide a basis in creating such an approach. Such a methodology would take in a set of labelled data, with the output being the sentiment associated with corresponding words. This kind of approach would eliminate problems such as that caused in the above example. As it's not often that the word hungry would be used in film reviews, and if it were it may be more often in a positive light; "it left me hungry for more" as opposed to the context of restaurant reviews. The next section will highlight the aims defined and stages undertaken in order to develop such a methodology.

2.5 What is meant by sentiment?

Sentiment analysis is a form of textual analysis used to determine the opinion a text contains which can be extended to subjectivity analysis whereby the level of subjectivity within a text is assessed. Opinion mining focuses on how a given object is perceived i.e. the opinion or sentiment expressed towards it. Subjectivity analysis analyzes the extent to which a given text is subjective/objective. An example application would be used in assessing in how impartial a news article referring to a political candidate is, to avoid bias. In the realm of opinion mining (sentiment analysis), the views towards the candidate is assessed.

One could argue that these opinions are the underlying semantics of the lexical forms. In this case, certain constituents would be more meaningful than others, for example, adjectives and adverbs[15] would indicate more than nouns. This is often true. If we were to try assess the "sentiment polarity" i.e the negativity or positivity given to a word, of the the adjective "great" and the noun "fish" in and of themselves, there is not much to talk about. The word great would more than likely be seen as a positive term whereas fish would be largely neutral. However, the importance of nouns is more clearly depicted in the use of "love" and "hate", as both words have inherent sentiment, but would be discarded if we were to treat only adjectives and adverbs as sentiment bearing words. To take another example sentence, in particular the noun "noise" it could be interpreted differently. In the context of a hotel review, it is clear that noise is something to be avoided as nobody wants to stay in a noisy hotel. So if we were to take nouns completely out of the picture the following sentence could give an incorrect assessment.

- There was noise all night at this hotel

If we were to discount the noun "noise", this sentence would be marked as objective, which is clearly not the case.

There can be the argument on the level of lexical semantics that such terms do not give much in the way of sentiment (like the interpretation of "fish"), so it may be possible to differentiate the two. The semantics of a word is vital in determining a sentiment loaded term, but it is not all that is needed. It may be argued that the sentiment or opinion loaded into a word is defined by association.

In light of the arguments that some text may be incorrectly classified if we were to discount nouns and that the semantics identified may not be in tune with sentiment classified, we must clarify the position on sentiment bearing tokens. A sentiment bearing item may be defined as any word which indicates an association with a particular sentiment polarity i.e. negativity, positivity, neutrality. In the case of this project, the association is manifested in the link of the word with a rating class. The idea of rating classes will be discussed in the next chapter. Such a definition allows things like subjectivity, or the use of uppercase letters as markers of sentiment.

In the next section, the approach used to apply this notion of sentiment is outlined.

2.6 Outline of Project

The overall aim of this project was to develop a methodology in creating domain specific sentiment lexicons from labelled texts. However, within this there are a number of subtasks and issues which need to be addressed. The first being to decide upon a data source. Web user reviews from the site *TripAdvisor* were chosen as the data source. Firstly, it deals with a very specific subject domain, that of hotels. Also, each review text is annotated or labeled with a set of ratings, giving not just an indication of positivity or negativity towards a given hotel but more fine grained sentiments such as value. Once this had been decided, it was then a question of how to gather the data and how best to store it. Finding the most suitable method

of storage would consist of weighting the methods of file systems against RBDMS.

Two approaches were investigated in order to find sentiment loaded words. The first approach consisted of using machine learning algorithms, known as classifiers in order to find which words predict the classification of a document. This in turn required more data formatting to make it readable by the machine learning software. The second approach implemented statistical tests based on the frequencies of words. For this, two tests were used, namely: Pearson's Chi-Square; Mutual Information. Again this required some new data formatting to make it readable for the programs performing the tests. After performing these tests, it was a question of what statistic provided the most useful information and also what approach best identified the sentiment loaded terms in order to create the lexicon.

2.7 Conclusion

This chapter introduced key concepts and approaches in sentiment analysis. The role of sentiment lexicons and how they are generated was then outlined in reference to the SentiWordNet and General Inquirer lexicon's. In examining these lexicons, it was found that there are problems in multi-domain analysis, and also size problems with manually created lexicons. This gives the motivation for the project, where a methodology is to be developed in generating subject-domain specific sentiment lexicons, thus eliminating the problems of other approaches. This is not to say that this approach is without its problems. In processing such a large amount of data, in particular as the data is unedited and may contain a lot of inconsistencies, there is a lot of noise. This along with other problems encountered will be discussed in chapter 5. Following the motivation for this project, an outline of the project was then given, highlighting the aims of the project and the course of action taken in its development.

Chapter 3

Data

3.1 Introduction

This chapter fleshes out the first part of the outline provided in the previous chapter. The primary concerns of this chapter is to highlight the importance of data in this project. Firstly, methods of retrieving data are discussed along with the ethical considerations for such accumulation. The second section will describe how the data was represented and why this form of representation was selected.

3.2 Acquiring Data

Before any analysis could be done, data first needed to be collected. As this project is founded on user reviews on the web, the most straightforward approach would have been to use a webcrawler. A webcrawler (or spider or robot) is a program which can be run on a local machine, from which it sends requests to a seed url. A webcrawler will crawl pages by parsing a given pages html source code, searching for links in it, adding them to the search frontier and the process is repeated. Typically these searches are performed in a depth-first fashion with which a depth bound is implemented, although other applications may utilise a breadth first approach. As is true

with search strategies in general, both approaches have their advantages and disadvantages. A depth first approach can prove troublesome in that it may reach a stage of infinite looping, whereas a breadth first can have problems due to the scope for links on-line as it has an exponential search space. My initial approach was using a data mining application named WebHarvest with an extension to become a webcrawling application.

For a website which provides a service, any information it contains is quite valuable and also bandwidth may be of huge importance. As webcrawling programs may download such information or also may send thousands of requests to a website which could possibly cause it to crash. For this reason, there is etiquette to be respected when it comes to trawling the web for information. This etiquette is known as the *Robots Exclusion Standard*. This standard comes in the form of a simple text document labeled *robots.txt*. This text file features instructions for web robots upon accessing the domain. If the owner of a website wishes to to this, the file must be located in the root of the web site hierarchy i.e. given 'www.123.com/' the file will be located at 'www.123.com/robots.txt'. This file is accessed before crawling commences and the instructions are parsed. Rules located in the file follow a rigid format, which was decided upon in 1994 by members of robots-request@nexor.co.uk. The format is as follows;

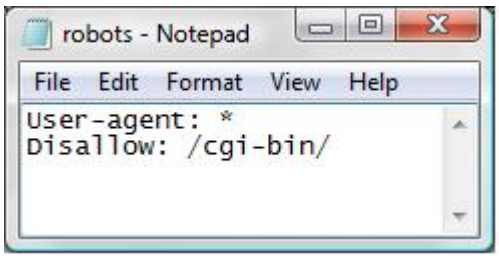

Figure 3.1: Sample robots.txt file showing structure

In figure 3.1, User-agent denotes the name of the robot ('*' represents all web crawlers) and Disallow will specify which directories of the web sites hierarchy may not be accessed by the given robot. This represents the stan-

dard format of the robots.txt file but there are also non-standard extensions. Such extended formats may specify what is allowed as well as what is disallowed, give the sitemap of the web site or directives of how many requests may be made to the site.

Web-sites also feature terms and conditions of usage as well as a robots.txt file. Many sites such as tripadvisor.com receive many hits and so bandwidth is imperative to them, so in their terms they outlined that the site may not be crawled without consent from tripadvisor. For this reason, a dialogue with tripadvisor was opened.

The program used to perform crawling was WebHarvest[1]. The initial idea was to pull down a set of webpages from TripAdvisor which contained reviews. Then a program developed for this project could parse through the HTML code and extract the review and other necessary information, such as the rating which accompanies the review. This parser was developed but was never fully used as the dialogue with TripAdvisor took time to develop, other resources were sought.

Fortunately, Carl Vogel had access to a previous database of reviews and ratings taken from TripadVisor.ie which was to be used in the analysis. As this data was accumulated with other work in mind, a bit of reworking with the data was needed and new tables were generated using this base representation in order to make it compatible with the work to be done. The next section will feature a discussion of how the data is stored and represented and also the processes undertaken in creating the representation.

3.3 Data Representation

This section will feature a description of how the dataset was stored, why this method of storage was used, and also how other data was accumulated

[1]http://web-harvest.sourceforge.net/ - Last Verified, October, 2010

from the dataset.

RDBMS & MySQL

Data used in this project was all stored on a local MySQL database. MySQL is an open-source relational database system developed by Sun Microsystems. There were several reasons as to why I picked a relational database and in particular, MySQL. Firstly, relational databases are a secure and persistent means of data storage. This does not particularly set it apart from file systems, their main advantage is in the speed of retrieval of data. For instance, using a file system for this task, the reviews would need to be organised with respect to each rating category. Other approaches within the file system would require extensive searching for elements, such as certain words, rating categories etc. With an RDBMS, the need for such searching is eliminated as data can be retrieved by simple SQL queries.

I chose MySQL in particular for a number of reasons. Firstly, it is open-source software, thus people who wish to use this methodology are not limited to using a proprietary product. It has been proven to be useful and provide enough functionality for companies such as Yahoo and Google.[2] Also it is not limited to one particular operating system, so the approach I have researched is not limited. It also has a lot of possibilities as regards coding. As a lot of API's are available for numerous programming languages, this approach can be modified to suit how comfortable one may be with a programming language.

Reviews & Ratings

Reviews on the TripAdvisor.ie website are accompanied by a lot of data other than the text itself. Such as the hotel being reviewed, along with various ratings for the given hotel. The initial dataset obtained contained fillers for this information and more, so for this reason a new data table was created in order to store data directly relevant to this exercise. The data

[2] www.mysql.com - Last verified, March, 2010

table contained the review text, and the eight possible ratings for a hotel which are {value, rooms, location, cleanliness, service, checkin, business, overallrating}. The names of these rating categories are self-explanatory in what aspect of the hotel to which they refer. The overallrating is not a composite score given all the other values but instead is an indication of the reviewer's overall assessment of the hotel in question. These ratings may have the values of 0,2,4,6,8,10 except for the OverallRating which cannot be zero due to a constraint by *TripAdvisor* on review submission.

The table also contains an id value, which is used by TripAdvisor itself in order to uniquely identify a given review. This attribute is important in that it uniquely identifies reviews as if only a subset of reviews is needed, they can easily be created and duplicates can be checked for. The resulting data table contained 43300 reviews and the structure of the table is described in table 3.1 below.

Attribute Name	TYPE	CONSTRAINT
Id	int	Primary Key
OverallRating	int	none
Value	int	none
Rooms	int	none
Location	int	none
Cleanliness	int	none
Service	int	none
Checkin	int	none
Business	int	none
Review	text	none

Table 3.1: Reviews

This data table allowed easy access to the reviews for analysis and provided the basis for all further data derived. Derived data came in the form of word frequency lexicons and also feature vectors which will be described

in the next section and section 4.2.2, respectively.

Word Frequency Lexicons

Word frequencies can be powerful in identifying words which have links to a given rating class. For example, if a token occurs more times in context A than in context B, the more likely it is tied to context A than context B. However, this is a brute force method and can be interpreted incorrectly. For instance, if we ask the question why is it more frequent in this context, we may look at the total number of tokens in this context and see that there are far more tokens in this context than in the others, which could render the difference in frequency of a token between contexts meaningless. Despite this, it is still useful in giving an indication as to what to expect. In initial stages of the project, work commenced with analysis of reviews ordered by their overallrating. That is to say, 5 rating classes were defined; r2, r4, r6, r8, r10. This allowed work for the polarity of words to be developed without having to contemplate specific issues as to whether it refers to a specific aspect of the hotel as with other ratings categories like service or value.

The above refers to the creation of word frequency lexicons specific to a given class; however, it was also important to create the frequencies for all words, irrespective of rating class or category type. This frequency lexicon is simply the sum of the frequencies taken from the rating class specific lexicons. There were two motivations for doing this. Firstly, it creates a reference point for frequencies generated for specific classes i.e. the specific frequency count for a word can be compared to that of the overall in order to inspect differences in distributions. The second reason was to create an indexing system, which would lend itself in data formatting for Weka which will be described in the next chapter. Thirdly, it allows singleton tokens to be identified, as they are largely insignificant, particularly for the task at hand. The structure for the rating specific frequency lexicons were all the same; however, the total frequency table was slightly different. The structure

of both tables are outlined in the tables below.

Attribute Name	TYPE	CONSTRAINT
word	VARCHAR(50)	Primary Key
freq	int	none

Table 3.2: Rating Specific Frequencies

Attribute Name	TYPE	CONSTRAINT
Id	int	Primary Key
word	VARCHAR(50)	unique
freq	int	none

Table 3.3: Word Frequency Lexicon

In counting the frequencies of tokens, all misspellings, words in uppercase/lowercase were treated as different words. The reason for this is that we are dealing with sentiment, in this case, how the reviewer felt at the time of writing. An example would be that someone who is angry about their experience may type quite quickly and be more error prone. Given this, the implemented algorithm was quite simple. The approach was to pull down all reviews, then go through a process of tokenizing the review, and simply counting the words. If the table already contained the given token, its count would be incremented, if it was not in the table, it was put in the table with a default frequency value of 1. Given the number of words (7,052,901) in the database, the same number of SQL statements needed to be executed which caused poor execution time for the program. To rectify this, the program was slightly altered. Instead of directly modifying the datatable, the tokens were placed in a hashtable, and all modifications were made to this hashtable. Once counting was completed, a simple flush, which consisted of inserting the elements into the database, was executed, drastically improving performance.

Investigated Rating Categories

At this point, it must be set out that categories other than overallrating were not investigated. This is due to what was outlined in section 3.3, where rating categories other than overallrating may have a value of zero. In analyzing the dataset, it was found that a lot of these other values were, in fact, zero. However, it was not clear as to whether these zero-values corresponded to a negative feeling towards one aspect of hotels or, seeing as it is not compulsory to fill out these values, people did not fill them out and so they were defaulted to zero. As a result, the only category which was clear in how it was marked was overallrating and thus was the only one investigated. The rating classes in the overall rating category can be classified as in table 3.4 to show how they will correspond to a sentiment value.

Rating	Sentiment
2	Very negative
4	Negative
6	Neutral
8	Positive
10	Very Positive

Table 3.4: Showing correspondence of ratings and sentiment

3.4 Conclusion

In this chapter, methods and restrictions on retrieval of information from the web was discussed. This was followed by a description of the best format for representing the data, why it was chosen and how it was implemented. In the next chapter, we will see how the analysis of this data was implemented.

Chapter 4

Outline of Approaches Used in Analyzing the Data

4.1 Introduction

This chapter features a discussion of the methods implemented to discover the sentiment loaded items in the reviews. The first approach described is using the machine learning toolkit Weka. In describing the approach used with Weka, the necessary formatting of data will also be outlined. The second section depicts a statistical approach posited to examine sentiment loaded terms in reviews. This approach incorporates further reformatting and also two statistical tests, namely: Chi-square and Pointwise Mutual Information. The theory behind these tests will feature as well as a discussion of their implementation.

4.2 Working with Weka

Weka is a machine learning toolkit developed in Java by The University of Waikato. [1] There were several reasons as to why this toolkit in particular was selected. Firstly, it is an open-source software, governed by the GNU

[1] http://www.cs.waikato.ac.nz/ml/weka/ - Last Verified, April, 2010

General Public License[2]. As this projects aim is to develop a general methodology, it was in the best interests of the project to stop it being restricted to proprietary software. All algorithms implemented in this toolkit are freely available subject to license and can therefore be implemented by anybody, if they do not wish to use just this one toolkit. Secondly, the code is all contained in a jar file, a file which contains compressed code of a given program, which can be utilised in a developer's own code. So all the ground work is given, and the developer does not have to spend hours developing a suitable algorithm. Instead, this package be taken and built upon, where only fine-tuning is needed not ground up development.

Machine learning tools are often used in document classification, however this was not the case for this project. This is not to say that it could not prove helpful. In the initial approach, the reviews were split into training and test datasets, the test sets were manipulated changing featured words to see could it change their classification. The second approach taken with Weka consisted of using its Attribute Selection algorithms. These algorithms function inversely to classification algorithms, in that they select the attributes which are seen in the most important in the classification process. The approach using Weka will be assessed in the final chapter.

4.2.1 Weka Data Formatting

The most common way in which data is input into weka is using the '.arff' (Attribute-Relation File Format) file format. This formatting, as seen below, outlines the name of the relation in question, what its attributes are, also what types these attributes are. This representations format is the standard method of representing datasets in which its instances are unordered and independent of one another. Attributes may be of four data types, numeric, string, nominal and date. Numeric attributes may be specified as real or integers, the string class is used for representing textual data, the nominal

[2]http://www.gnu.org/copyleft/gpl.html - Last Verified, April, 2010

class is used for representing the possibility for a number of values which are user-defined, for example, the declaration @attribute binary {true,false} denotes that the attribute binary may only have a value of 'true' or 'false'.[10]

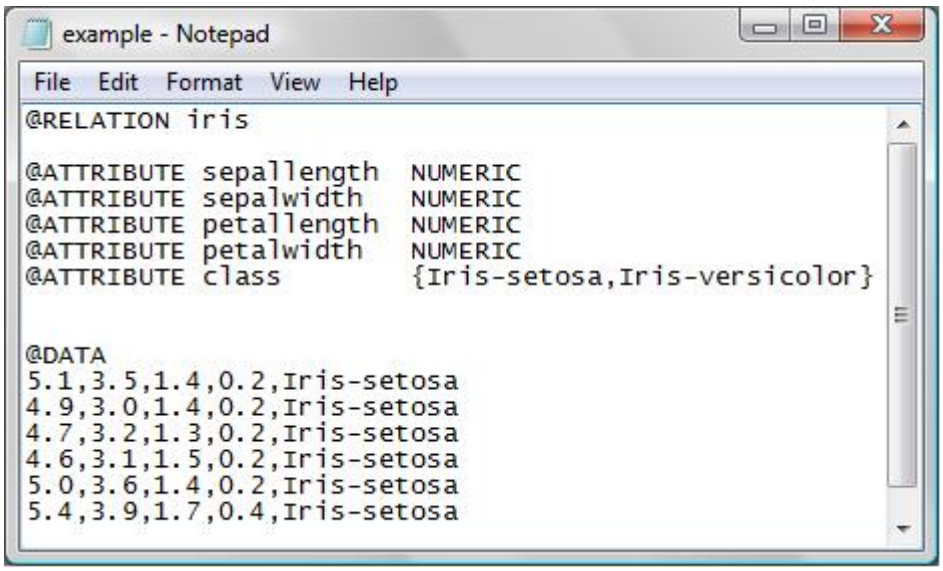

Figure 4.1: A sample .arff file

The standard ARFF format is quite useful; however, given the vastness of the feature space in question and also that all reviews cannot contain all the words in the frequency lexicon, it was adequate to represent the datasets in the sparse file format. The feature space in the case of ARFF files is represented in the data section. Whereas the attributes section corresponds to the features themselves. Each row in the data section is equivalent to a feature vector. The sparse format features the same header as a regular ARFF file, describing the relation and its attributes, the sole difference being the representation of the data itself. An example the layout of the data section of a sparse ARFF file can be seen below in figure 4.2. This example is based on figure 4.1, with one added attribute "emptyval" which is an empty value used to show how the sparse file format handles zero-valued features.

This form of representation removes the impracticality of explicitly ex-

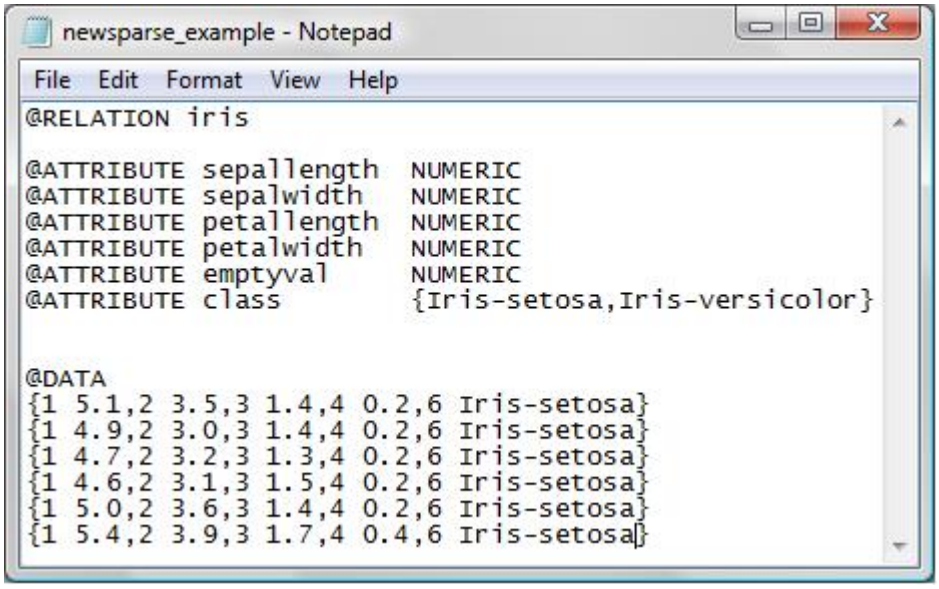

Figure 4.2: A sample sparse .arff file

pressing a sparse matrix by including all zero-valued attributes (in this case, zero-valued attributes are words which do not occur in a given review). This can be highlighted in particular by the example found in the dataset, a review containing 11 unique words. given that the whole lexicon consisted initially of 83631 words, that would mean including 83610 zero-valued attributes as opposed to the 11 meaningful attributes. The mean number of tokens contained in reviews comes to 183.2, with the longest review coming to 515 tokens and the shortest being 11 tokens. Even taking the longest review leaves 83116 zero-valued attributes. For this reason, the sparse file format proved to be quite useful, reducing the explicit vector space dramatically. As seen in the example, the data representation looks quite different to the standard format. Firstly, instances must be enclosed within curly braces. Also, due to the fact that many attributes may be missing in an instance, weka must have some way of knowing what attribute you are giving the value for. For this reason, each attribute in an instance is represented as ⟨INDEX⟩ ⟨VALUE⟩, where ⟨INDEX⟩ is the index of the attribute in the attribute block of the header and the ⟨VALUE⟩ corresponds to the value of the attribute.

Along with this, sparse datasets often include one 'class' attribute, that is an attribute which puts each instance into a specific class. This attribute is often a nominal attribute and is the last attribute defined in the attribute block. Given the large size of the data set, it would have taken a considerable amount of time to create these files. Thus programs were coded in Java to automate this process.

4.2.2 How the data was formatted

The input data for weka was a sparse .arff file featuring all reviews in the database. The relation for each file was the rating category to be analysed i.e. value, overallrating etc. were featured in different files. The attributes for each relation consisted of all words in the Word Frequency lexicon and the rating class for the relation. Each review was depicted by a feature vector, whereby the words were its features and it was classified by its rating class. Given the size of the dataset, it was decided that it would be better to represent the words as numbers rather than strings, as string processing could take longer. To do this, the Word Frequency Lexicon previously described was used, each word was identified in the vector by its corresponding index in the data table. In keeping with the format of sparse .arff files, these indices were also the indices needed to identify attributes in the vector, where its value could be 1, indicating the review contained the word. If the index did not occur in the vector then the corresponding word did not occur in the review.

4.2.3 Desired Output

This process had two desired outputs. Firstly, attribute selection selects the most relevant attributes. That is to say, attributes which have the greatest influence in defining the class attribute. This applies to the data above in that in selects the most important words in defining the rating class for a given review. The second output of this process is the cleansing of noisy

terms from the data. These would be words which are not good predictors of the rating class. Weka would output indicators of good indicators, then these results would be visualized to allow easier interpretation, given that the dataset would be so large. Moving away from using the toolkit Weka, the next section presents the statistical approach used in this project.

4.3 Statistical Approach

There is no clear line dividing line between machine learning and statistics, as it is often seen as a "continuum ... of data analysis techniques" pg. 29 [10]. At one end of this spectrum is the oversimplification of machine learning as "formulating the process of generalization as a search through possible hypotheses" pg. 29 [10]. At the other end of this continuum is the hypothesis testing found in statistical analysis. In this section, an approach founded in this statistical generalization will be discussed. With the implemented statistical approach, the data was gathered and analyzed using different statistical tests. These results could then be inspected to find any correlations in the data. For this approach, various algorithms were coded in Java, rather than using a statistical package. The reason for this being that the methods used featured the need for some specificity, as regards how it was calculated. Firstly, we will look at how the data was formatted in order for the statistics to be calculated, and then look at the tests used and how they were implemented.

4.3.1 Data Formatting

The data for the statistical tests was organised in spreadsheet format. This was used as all data could be easily viewed and manipulated at once. The frequency of the words was important in these tests, however it is not the only necessary information as shown by the table below.

	rc	¬ rc
t	A	B
¬ t	C	D

where rc is the rating class and t is the word

- A: The number of times term t occurs in rating class rc;
- B: The number of times term t occurs outside rating class rc;
- C: The number of times term ¬ t (i.e. every word other than t) occurs in rating class rc;
- D: The number of times term ¬ t occurs outside rating class rc

Table 4.1: Chi-square contingency table

The above table shows the necessary values in calculating statistics on the dataset. Some of these variables are difficult to implement, as its not clear how they can be calculated. To clarify this, their calculation is outlined in figure 4.3.

The data set was represented in a spreadsheet where each of these variables correspond to a column in the spreadsheet. Each spreadsheet represented the values for a particular rating, so overallrating or value. The spreadsheet contains all rating classes(2,4,6,8,10), for ease of comparison. Due to the size of the number of words, it was necessary to have it reduced into a more manageable space. To do this, words with a frequency higher than 300000 were removed as they were so common that they would be meaningless[20]. It was found that "the" was the only word which had and abnormally high value (it had a frequency of 472207 as opposed to the next highest frequency "and" which had 251546 occurences). Towards the lower end of the scale, singleton tokens were removed. These singleton tokens had a frequency so low (1) that it could not provide meaningful information using the statistical

A can be generated by calculating the frequency of the word in the rating class being tested

B can be calculated by subtracting A from the total frequency of the given word across ratings

C can be calculated by subtracting A from the total number of words in the rating class being tested

D can be calculated by getting the total number of words excluding the rating class being tested
and subtracting B from this total

Figure 4.3: Calculating the Variables

tests outlined. Upon testing, this was generalized to 5 for reasons discussed in 5.3.

4.3.2 Tests Used

The following sections will outline the statistical tests applied to the dataset, why they were used and also how they were implemented.

Pearson's Chi-Squared

Pearson's chi square is a statistical procedure whose results are evaluated by reference to the chi-square distribution first investigated by Karl Pearson. It has two purposes; either a goodness of fit test, where it checks if an observed frequency distribution differs to a theoretical distribution. But can also be used as a test of independence, where observations on two variables are assessed to determine as to whether they are independent of each other. For this project, the latter was implemented. The theory behind this is to "compare the observed frequencies in the table with the frequencies expected for independence".[12] The table to which it refers is a 2×2 contingency

$$\chi = \frac{(O-E)^2}{E}$$

Figure 4.4: Formula to Calculate Pearson's Chi-Square

table, such as that shown in table 4.1. The general formula for performing this test is outlined below where the chi-squared statistic is denoted as χ.

O represents the observed value and E denotes the expected value. The observed values are easily obtained due to the formatting data as described in the previous section. However, computation was needed in ascertaining the expected values. These values could be derived from the variables A, B, C, and D, as outlined in table 4.1 along with the total count N which is equal to A + B + C + D. The approach in calculating the statistic consisted of calculating the expected value for each cell in the contingency table, then applying the formula in 4.4 to the observed and expected values. Summing these values would then give the overall chi-square statistic as outlined in the formula below in figure 4.5. If the chi-square value is large then the null hypothesis of independence of rating class and the inspected term can be rejected.

$$\chi = \frac{(A-\frac{((A+C)*(A+B))}{N})^2}{\frac{((A+C)*(A+B))}{N}} + \frac{(B-\frac{((A+B)*(B+D))}{N})^2}{\frac{((A+B)*(B+D))}{N}} + \frac{(C-\frac{((A+C)*(C+D))}{N})^2}{\frac{((A+C)*(C+D))}{N}} + \frac{(D-\frac{((D+C)*(D+B))}{N})^2}{\frac{((D+C)*(D+B))}{N}}$$

Figure 4.5: Calculating χ from variables A,B,C and D

The formula in 4.5 was implemented in Java. The values needed were read in from the spreadsheet, described in the data formatting section, using Apache's POI API [3] and also to output corresponding results to the output spreadsheet. These calculations were performed over the overallrating category in all rating classes. Although the implemented method is often used

[3]http://poi.apache.org/ - February, 2010

to test independence of collocations, it has proven useful in this approach as will be discussed in chapter 6.

Mutual Information

A second statistical test used is that of Mutual Information. Mutual Information is a "symmetric, non-negative measure of the common information in the two variables."[12] Often the two variables being tested are two words in different languages e.g. "cow" in English and "vache" in French, to find the likelihood of a translation. In the case of this project, the two variables are the token in question and the rating class. It is often used as measure of independence as if the statistic measures to be 0, the two variables are deemed independent. The formula for calculating the mutual information between two variables is outlined in figure 4.6 below.

$$I(t; rc) = P(t, rc) \times log(\frac{P(t, rc)}{P(t) \times P(rc)})$$

where t is the token and rc is the rating class

Figure 4.6: Mutual Information

The method initially used in calculating the mutual information was a modified version from a formula in another final year project[7]. This formula is defined in figure 4.7.

Problems occurred with this approach in its initial phases. Firstly, values obtained were very small and close to zero, which makes it difficult to define words which are dependent on a class. Secondly, the general implementation mutual information is defined as a non-negative measure, however this was directly contradicted in a number of results returned. With this implementation, the value inside the logarithm very often came very close to zero. As log(0) is undefined, this returned a lot of error values. This led to a reformulation as to how mutual information would be calculated.

$$I(t;rc) = \frac{V}{Z} \times R \times log(\frac{VY}{ZW})$$

where

V = number of times t occurs in the current rating class
W = number of times t occurs outside of the current rating class
R = number of rating classes
Y = total number of words
Z = Total number of words in current rating class

Figure 4.7: Mutual Information:Initial Implementation

The new approach incorporated the idea of pointwise mutual information[12]. As this test is often used in examining the shared information between collocations, it was used in this case to calculate the shared information between a given token and rating class. The formula for calculating the statistic is given in figure 4.8

$$I(t';rc') = \log_2(\frac{P(t'rc')}{P(t')})$$

Figure 4.8: Pointwise Mutual Information Formula

In the application of this formula, t' is the word being investigated, where rc' is the rating class being examined. I(t';rc') denotes the pointwise mutual information between t' and rc'. P(t'rc') can be determined by dividing the number of times the term t occurs in the given class rc by the total number of tokens in rc. This test, like the original MI test used, is symmetric such that I(t';rc') = I(rc';t'). A key advantage of this test is that it allows negative values where the general test did not, with a higher number indicating a stronger tie between the variables. A reflection on the viability of this ap-

proach and how successful it was, is discussed further in the analysis section of this paper.

4.4 Conclusion

This chapter introduced the main ideas used in investigating the sentiment associated with certain terms and the necessary data formatting techniques used for each approach. The first section outlined how Weka works, the arff file format and how it is intended to be used. The second section described a statistical methodology using the chi-square and mutual information tests, highlighting shortcomings of the initial mutual information test and the need for the use of pointwise mutual information. Data formatting for this approach was also needed. In the next chapter, the effectiveness of each approach will be evaluated along with further investigation.

Chapter 5

Discussion

5.1 Introduction

This chapter discusses the approaches outlined in chapter 4. It comprises of an evaluation of both approaches and the results of the implementation. For the statistical approach, it will be further extended into seeing what statistical test has the best performance and a method for scoring these terms will be put forward. Approaches in creating such a lexicon will be put forward.

5.2 Analysis of Machine Learning Approach

This initial approach treated the reviews obtained as feature vectors, where each word corresponded to a feature. The class of this feature vector is defined by the rating which accompanies the each review. Using the machine learning toolkit Weka, feature selection would be performed on these reviews. Feature selection is a process which finds the most influential features in a vector which define its classification i.e. which words define the rating of the review. It was planned that from this feature selection positive and negative features could be derived.

However, the intended approach using Weka did not go as planned. Weka was developed in Java and thus has to deal with the constraints of the Java Virtual Machine(JVM). In this case, using Weka for the feature selection task resulted always in out of memory errors despite the allowed memory usage being set to the maximum. It was logical to think that the size of the dataset played a big role in these problems. However, on investigation, it was seen that reduction of the size of the dataset didn't seem to have the desired impact. It has been shown in several instances that Weka can be used on larger datasets, however, this work was constrained in its lack of access to 64-bit machines and also time constraints.

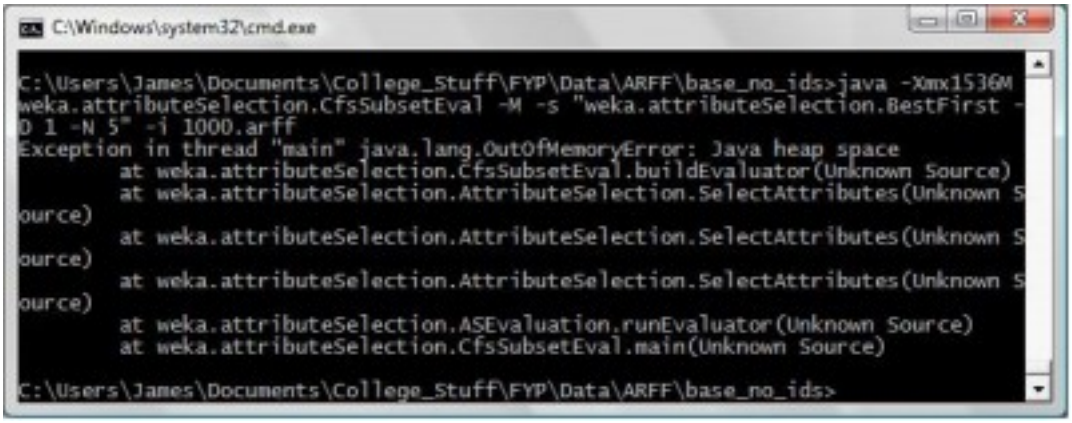

Figure 5.1: Weka Command Line

Figure 5.1 shows the command prompt window in an attempt to perform attribute selection on a test set of 1000 reviews, the input file is name 1000.arff. The command -Xmx1536M allocates the maximum amount of heap space to the program, but as the stacktrace following the initial command indicates, there is not adequate space for the program to perform the desired task. A fuller description of command line syntax for Weka is provided in the appendix. In spite of such problems in this project, Weka has proven more effective in other research[1] in determining the sentiment of words.

5.3 Analysis of Statistical Approach

The statistical approach in this project investigated how well two statistical tests performed in identifying sentiment loaded words in the reviews. The two tests used were: Pearson's Chi-Square, which investigates how independent two variables are of each other. In this case to see if the usage of a given word is independent of the class(es) in which it occurs; the second test used was Pointwise Mutual Information. This test is used to investigate whether or not two variables describe the same information. This type of test is particularly useful in testing translations, but was used in this context to decide which words conveyed the information contained in the rating best i.e. to find negative and positive items. The initial dataset contained of 38744 words after singleton values had been removed, as described in chapter 4. In this section, we will look at how successful each test was. First, an analysis of the output of Pearson's chi-square will be put forward.

Given the size of the dataset, there was a great disparity in the values obtained, in most cases the highest frequency terms (all around 200,000 in frequency), which had not been removed, having the highest values. As is shown in the table 5.1. The samples in this table are the highest frequency (and, a, to, was) and words which intuition would assess to be positive and negative, "great" and "smelly", respectively.

word	r2 chi	r4 chi	r6 chi	r8 chi	r10 chi
and	10.68	1.58	209269.16	5039.98	28840.86
a	0.95	175.01	154321.72	6471.77	10112.95
to	3233.26	1585.17	137619.56	767.96	6565.47
was	794	1340.51	122132.63	2639.99	4089.26
great	1674.19	749.18	17059.41	1465.81	7679.49
smelly	509.8	9.96	167.81	28.38	50.27

Table 5.1: Sample Chi-Square Values

From this table it is difficult to decide if a high chi-value determines high

dependence between word and class. If we were to interpret the results in this way; "a" would be seen to be a positive word and "great" could be shown to be overall a positive term, but is more likely to occur in a very negative context (r2) rather than a mildly positive one (r8), but is more suited to a middle of the road review (r6). It could also be said that "smelly" is a negative word, but outside of a very negative context, it is more likely to occur in a moderate to positive review than in a mildy negative review (r4). The most puzzling characteristic of these results is the high chi values in rating 6. It is not clear as to what caused these incorrect comparisons, however as will be shown later in this section, further reduction of the dataset by removing more infrequent values (with frequency 5 or less) had a positive impact. Such results are quite confusing in how they may be interpreted.

It's unclear as to whether results achieved in chi-square tests are an indicator of how tied a given class and word are in respect to the others. However, table 5.2 based on the chi-values calculated above, shows the differences in the usage of words more clearly.

rank	r2	r4	r6	r8	r10
1	to	not	and	a	and
2	told	to	a	and	a
3	dirty	told	to	good	in
4	not	that	was	very	great
5	that	was	in	is	to
6	worst	room	of	was	is
7	I	they	I	hotel	We
8	manager	poor	for	but	staff
9	rude	I	hotel	nice	of
10	great	we	we	for	with
11	they	asked	is	clean	excellent

Table 5.2: Top 11 words ordered by chi-values for each class

This shows the links between words and class more clearly than looking at the statistic across all rating classes. Although there is still confusion in the representation, where words such as “a”, “the” and “and” occupy the highest ranks, presumptions are reinforced. Negative terms such as “dirty” and “rude” are highly ranked in negative contexts where words such as “clean” and “great” are highly ranked in positive reviews. As well as these more obvious examples, it gave some more unexpected results. For example, “manager” has a higher ranking in negative contexts, but “staff” are more likely to be referred to in a positive context. But also the use of pronouns is more prominent in negative reviews. Aside from these, the results by in large, taking the classes on their own, were what was expected. Perhaps the best indicator is the number of function words that have the highest statistic in the middle class (r6).

The main advantage of chi-square is that it gives good indications of what words have the strongest tie with a given class, with larger chi-values indicating the strength of the link between word and class. Pointwise mutual information tests if a given word and class express the same information. Using this test gives a clearer picture of the use of words across the classes, something which could not be clearly read from chi-square testing. If we take a look at some of the sample values from the pointwise mutual information test in table 5.3, this is more apparent.

As this table shows, positive words show a stronger link to positive reviews and negative words showing a stronger link to negative reviews. Despite this strength in identifying sentiment loaded words across classes, its weakness lies in the strength of the chi-square test, in ranking the words within their respective categories. If the ranking approach taken in 5.2, we would end up with the table below.

It is clear from table 5.4 that pointwise mutual information is not without its problems, as a ranking according to the mutual information of words does not reveal much about the most important terms in the rating category.

word	r2	r4	r6	r8	r10
smelly	2.21	0.46	-0.57	-2.32	-2.9
terrible	1.74	0.96	-0.11	-1.34	-2.62
great	-2.3	-1.18	-0.56	0.32	0.57
friendly	-1.92	-0.98	-0.35	0.28	0.5
beautiful	-1.73	-1.23	-0.76	-0.3	0.83
I	0.31	0.14	0	-0.17	-0.08
clean	-1.22	-0.5	0.29	0.48	-0.02
dirty	2.02	0.92	-0.24	-2.4	-3.76

Table 5.3: Sampling of Pointwise MI values

These results posed a number of questions about the implemented tests. Firstly, as has already been posed, why were chi-values in r6 so high? As regards mutual information testing, it seems that it a lot of seemingly sentiment free words, or rather words which would not usually expected to be associated with a particular category. For the latter, it has been shown that mutual information may give high values to terms which occur a many times in a given category and there are very little (if any) occurences outside the document[7]. Given this information, a quick analysis of the frequencies of some of the most important terms according to mutual information took place. This can be seen in table 5.5 below, where words occuring a few times in one category as opposed to no occurences at all in the others correspond to high mutual information values.

In response to this, the tests were reimplemented on a smaller dataset. The dataset contained the same rating classes, and the same approach was used in both tests as in the initial stages. However, words with a frequency less than 6 were removed, these tokens accounting for 20,195 of the words, so the dataset was significantly reduced. This removal took place as "predictions should not be based on such rare observations"[8]pg.3. Both tests were then rerun on this new dataset. Chi-square was used again to see if these low frequency items accounted for the strange values obtained in the r6 class.

r2	r4	r6	r8	r10
cockroach	Ordinarily	door-slamming	towel-warmer	Marilyn
double-booking	2no	liveable	TCD	Cameron
bath\’	ACH	Istanbul	Raggy	Coopershill
\’Gala	unpeeled	363euro	scouring	Nuala
blarring	now’	sour-faced	***The	Convent
audacity	quaint’	weedy	poker	Tankardstown
Patric	backache	yield	Westlife	Cecelia
cc	venting	RIng	disruptions	Brid
discusted	boxer	Slobs	lobby’s	Rosney
Beauvet	ALREADY	nobbly	4S	Hughes
KNOCK	scribbled	mitres	octagon	Kileen

Table 5.4: Top 10 words ordered by Pointwise MI for each class

word	r2	r4	r6	r8	r10
Nuala	0	0	0	0	21
boxer	0	4	0	0	0
unpeeled	0	4	0	0	0
Westlife	0	0	0	6	0

Table 5.5: Highlighting frequency differences

Table 5.6 shows the new chi-statistic generated for the most frequent items. It can be noted that the values in r6 have significantly been reduced and seem more in keeping with the other values. Thus, it shows that large numbers of infrequent items may cause a skew in the generated statistic. Table 5.7 shows the calculated pointwise MI values for the three words in each category as a result of the changes to the dataset. These values correspond directly to those of the dataset which include infrequent items, indicating no change in that respect. The effects of ranking these terms according to chi-square and mutual information can be seen in tables 5.8 and 5.9, respectively.

word	r2	r4	r6	r8	r10
and	972.88	1052.54	468.76	1001.69	3063.72
a	545.35	212.72	54.02	113.21	3.78
to	1030.99	174.87	41.56	1792.07	73.51
was	30.55	118.9	164.55	448.93	499.9

Table 5.6: Recalculated Chi-Square

word	r2	r4	r6	r8	r10
smelly	2.21	0.46	-0.57	-2.32	-2.91
friendly	-1.91	-0.98	-0.35	0.28	0.5
great	-2.29	-1.18	-0.56	0.31	0.57

Table 5.7: Recalculated Mutual Information

From table 5.8, it shows that a lot of the function words are not as high ranking. Seeing in rating 2 that function words have a lesser importance and adjectives such as "dirty", as expected, are high ranking. However, as can be seen in table 5.9, there has not been the same effect on the mutual information results. This is due to the same reason as before. Despite words with a frequency lower than 6 being removed, there still remained words which had several occurrences in one category and none in two or more of the others. e.g. "Rain" occurred 6 times in r10 and had 0 occurrences elsewhere. The removal of words was done in accordance with the total frequencies of the words, their frequencies within the classes was not taken into account. If these values were instead removed, a more promising effect would have been acheived as other work has indicated that if these items are eliminated from the test, it will have a better correlation in judgement's with other tests, in this case the chi-square test[7].

The information which the statistics show is quite useful, however an amalgamation of the features of both would be the most informative. To do this, an average of rankings was calculated. This process is done in class by class

rank	r2	r4	r6	r8	r10
1	dirty	not	but	to	and
2	told	great	average	and	great
3	great	and	and	I	not
4	worst	told	fine	we	wonderful
5	very	excellent	ok	in	excellent
6	is	poor	wonderful	my	fantastic
7	manager	that	great	that	beautiful
8	rude	friendly	not	told	but
9	not	helpful	bit	our	highly
10	good	comfortable	We	this	amazing

Table 5.8: Top 10 words ordered by chi-square within each rating class

manner. That is to say all analysis was performed on each class, irrespective to the others. The first step in doing this is to gather the words, their chi-square values and their mutual information values. Rankings were then assigned to the words, first according to their chi values, and then by mutual information. A sample of these rankings is shown in table 5.10.

The second stage in this approach was to assign even rankings to tied values. As an example, the tokens A and B have rankings 1456 and 1457, respectively, both with a chi value of 20.4, having different rankings does not make sense. If two (or indeed any number of terms) have the same value, then they should have the same ranking. This was done by summing the rankings of terms with equal values, and then dividing this figure by the number of these terms with equal values. The returned value is the new ranking for the terms with equal values. In the above example, the new ranking for both A and B would be 1456.5. For the chi ranking, on average 9005 rankings were improved in the composite score but 9044 drop their ranking. For the pointwise mutual information rankings, on average 10189 moved up whereas 8359 moved down. A better correlation of pointwise mutual information and chi-square would cause a large drop in the number of changes.

rank	r2	r4	r6	r8	r10
1	discusted	unacceptably	kipper	***The	Eoin
2	Beauvet	ledges	Gordan	poker	Gracious
3	KNOCK	Flesk	VISA	Westlife	Marcus
4	audacity	rads	Weird	jetlag	Particular
5	Patric	Mattress	no-frills	peach	Z
6	cc	amend	\'upgraded\'	hydropool	Rain
7	RUDE	sixty	pppn	pressures	Helena
8	bedbug	17:00:00	henry	214	royality
9	DUMP	gutters	Sabine	nouvelle	proposal
10	liars	drone	goat\'s	firmer	sneem

Table 5.9: Top 10 words ordered by pointwise mutual information within each rating class

word	Chi-Value	MI Value	Chi Rank	MI Rank	Composite
wouldnt	32.45	1.1	1466	686	1076
Killarney	104.63	0.9	517	1652	1084.5
class	96.5	0.91	557	1647	1102

Table 5.10: Sample of Rankings

Once this had been completed the average ranking over chi-square and pointwise mutual information could be calulated. This was a simple task of taking the chi and mutual information rankings for each word and calculating the average ranking. Words were then ordered ascending according to this new ranking. The results of this new ranking were quite successful, as can be seen in table 5.11 where the top 10 words according to this new ranking are displayed.

At first glance, the high-ranking noise encountered in the mutual information test, such as place names and numbers are found in a few of these higher ranks. In fact a lot, if not all high-ranking terms in classes r4,r6 and r8 would not be defined as sentiment bearing terms. However, on the ex-

r2	r4	r6	r8	r10
filthy	bedsit	i-pod	Muskerry	highly
Avoid	litterally	yo	Downtown	amazing
AVOID	silky	childhood	weds	wonderful
enemy	buidling	IMMEDIATELY	Williams	moment
damp	henś	quad	emanating	loved
disgusted	cigerette	achieve	Contact	relaxed
worst	amateur	weed	downside	delicious
dirty	contempary	kiss	Taxiś	From
WORST	roll-away	lips	jaw	superb
refused	begged	77	reveiws	fantastic
Rude	skeleton	lifeless	Johnny	fabulous

Table 5.11: Top ranking words for each category according to pointwise mutual inforamtion on new dataset

tremities (r2 and r10), it appears to have been very successful. There are no function words contained in r2's top ranks, whereas just one occurs in r10. Of the top ranking r2 and r10 words, just one is a noun in each, "enemy" and "moment", respectively. These terms raise the question encountered in 2.3.1, as to whether or not nouns may contain sentiment. Certainly, adjectives and adverbs are the most prominent, in keeping with current research[6]. Nouns also feature, albeit not as frequently, but words like "enemy" would often have negative associations, so it is not uncommon for nouns to contain sentiment or subjectivity[11].Verbs also feature highly e.g. "Avoid", "refused", just by intuition, these terms would have more of an association with negative contexts, as the results show. This is not uncommon and further research[14] have indicated including verbs in sentiment analysis.

This new ranking was successful in that it identifies words which can be defined as having a negative sentiment and those which can be defined as having positive sentiment. The only problem with the rankings returned is

contained within the 3 classes r4,r6 and r8. The top-ranking words returned in these cases don't really subscribe to intuition. For example, can this misspelling "reveiws" really constitute a positive lexical item? Such problems remove the possibility of granularity of sentiment on a five point scale (in keeping with the review ratings), but allow further work in determining the sentiment of terms on a binary scale (positive vs negative). However, these problems could possibly be rectified with a further reduction of the dataset, by removing items such as those featured in table 5.5, thus improving the quality of the mutual information statistic.

5.4 Creating a Lexicon

In an ideal scenario, human judgement tests would be performed where a human subject would be asked if a given term is positive or negative in the sentiment it contains. However, there was not enough time remaining to properly design an experiment, have its ethical considerations reviewed and then run the experiment and interpret the results. Taking this into account, other approaches were sought. Two approaches were implemented and are described below. The first subscribes to the ideas found in the General Inquirer that a word may subscribe to different categories. The second approach gives the terms accompanied by two numbers, their ranking in r2 (negative) along with their ranking in r10 (positive).

To define words as positive or negative, the average rankings calculated were incorporated. This was done by implementing a program which compared the ranks of a word in r2 (negative class) and r10 (positive class). For example, the term "filthy" has rank 1 in the negative class but rank 10542 in the positive class. In comparing these values, the class which has the highest ranking (lowest number) for the term will be the assigned sentiment polarity of that class. So in this case, the term filthy would be assigned negative polarity. The process was implemented in a simple Java program which pulled

the word and its negative and positive rankings from the database, performed the comparison and stored the word in one of three polarity vectors (negative, positive, objective), and was in turn outputted according to this vector. Objectivity was introduced to deal with cases in which the rankings for negative and positive were equal.

This resulting lexicon approach was quite inconsistent. For the most part, the lexicon appealed to intuition in that words such as "friendly" and "clean" were classified as positive and words such as "smelly" and "rude" are classed as negative. However, words such as "noisy" are classed as positive. It must be reinforced that a lot this comes back to the initial calculations of mutual information which can be skewed if a word's occurences feature highly in one class and not at all in the others. The elimination of such noise would reduce the impact of vague mutual information results. As has been discussed, if the dataset has been necessarily reduced the results of mutual information should share a lot of its rankings with chi-square.

A second problem encountered with this lexicon is that of noisy data and non-words. For example, the lexicon contains dates, numbers, names, place names, unreadable characters and HTML tokens. Several things need to be done to rectify this. To avoid these kinds of problems, tokenizing the reviews needs to be improved. The first step would be to account for rarities in the reviews which were not anticipated, for instance the use of things like "f*!@"' for profanities but also less explicable things like "The***". In short, one must expect the unexpected. Secondly, tokenizing must disregard numbers and dates as such items are not relevant to the domain of sentiment analysis. The common use of names and place names could be rectified by the use of a named entity recognition system. Such a system would be implemented prior to tokenization, possibly adding tags to named entities for simple recognition for the tokenizer.

The resulting lexicon falls into a middle ground in describing how successful it is. Even without implementing the lexicon in some sort of sentiment analysis, it is clear that the presence of even a few incorrectly assigned terms such as "noise" show it is not totally reliable. However, the presence of a lot of correctly assigned terms shows promise in developing a fully reliable lexicon. Due to time constraints, it was not possible to exact the fine-tunings outlined above, but it has been shown that the methodology has a sound basis.

The second approach directly incorporated the composite rankings directly, no comparisons were needed between ranks as the word was accompanied by both ranks. The ranks range from 1 to 18536, with 1 being the best indicator for the class and 18536 being the worst. As each entry shows the word along with both ranks, it shows a degree of granularity. If both ranks are largely similar, little can be said about its sentiment, however, if there is a large difference between ranks, it can indicate the sentiment of the term. The rankings were initally put into a data table, however for the purpose of portability, they have been saved to a text file in the following format;

$$\langle \text{ WORD } \rangle \langle \text{ POSRANK } \rangle \langle \text{ NEGRANK } \rangle$$

This was done so words can be easily identified and extracted along with their ranks.

Not unlike the previous approach, this lexicon also features the noisy values, however, due to the inclusion of both rankings, more often than not they are identified by both low positive and negative ranks. Given this, this lexicon proves the most useful and has been included in the appendix. From looking at how the words are ranked, and are more than often correct, this approach seems quite viable. The process of building this lexicon could be further tested by exacting it in relation to another rating category, such as "rooms".

5.5 Conclusion

In this chapter, the approaches put forward in the previous chapter were evaluated. Beginning in a description of problems encountered with Weka, moving on to discuss problems with the statistical approach used and how these problems were rectified. Two approaches were then put forward in creating a sentiment lexicon, both based on rankings derived from statistical tests. The first attempts to classify words into a particular category, in this case, positive, negative or objective, based on rankings. The second attaches tags to a word, with these tags indicating the positive and negative rank of that word. Finally, it was decided that the latter was the best approach.

Chapter 6

Conclusions

Chapter 2 of this report began with a general introduction to the field of sentiment analysis, approaches used in performing the analysis while also highlighting the importance of sentiment lexicons in section 2.2. In section 2.3, two lexicons, SentiWordNet and General Inquirer were investigated, looking at the methods used to create each of them and discussing their advantages and disadvantages. The motivation for this project is anchored in these disadvantages of multi-domain analysis and the time needed to manually create such lexicons as was described in section 2.4. Section 2.5 then followed with a brief discussion by what is meant by the term "sentiment" and how it is applied in this work. In section 2.6, the goals and stages of this project were then outlined before delving into them in-depth in chapter 3. First describing methods of data accumulation and representation in sections 3.2 and 3.3, respectively. The means of analysis to be used on the dataset were then put forward in chapter 4. First looking at the machine learning toolkit Weka in section 4.2 and then the proposed statistical approach in section 4.3. Within the statistical approach, two tests were described in 4.3.2; Pearson's chi-square and mutual information. Here it was identified, that there were problems with the initial approach with mutual information and thus was replaced with pointwise mutual information. In chapter 5, these methods were evaluated. First highlighting problems with the initial machine learn-

ing approach in section 5.2. In section 5.3 the results of the statistical tests were evaluated and steps were outlined in optimizing their results, such as the elimination of nonlinguistic and infrequent data. A ranking system was then put forward based on the results of chi-square and pointwise mutual information in order to identify the best indicators of a rating class. In section 5.4, these rankings were applied in creating a sentiment lexicon. Two approaches were discussed; one where words were categorised into positive or negative according to their highest ranking with the second appending tags to the words indicating their rank in the positive and negative rankings. Chapter 5 ended on the idea of the latter being the most useful output.

Perhaps the most disappointing aspect of the project, was the failure to deploy the machine learning toolkit Weka. It is still not quite known why it could not perform the task but consistent failure point to the inadequacy of the hardware. Machine learning plays a pivotal role in text classification tasks shown in [19] and is also greatly useful in recognising patterns in text such as in [17] and Weka in particular has been shown to be successful in defining the sentiment of words as in [1]. Feature selection is a highly successful task and this project, and indeed the lexicon could be further augmented with the application of such a process as well as creating a quicker, more automated way of generating a lexicon.

The statistical approach proved quite successful in identifying sentiment laden terms, however the correlation between rankings could be improved with the tidying up of skewed frequencies which influence the mutual information statistic. To an extent, elimination of infrequent values took place and implementing such a process to a further degree would ensure noisy values would not have high rankings.

Preprocessing of the data is a must for optimization of results. Such preprocessing would include named entity recognition, better tokenizing and also to include some sort of parsing. Named entity recognition would remove the

possibility of names (John,Mary) and place names such as Dublin or Paris occuring in the output lexicon, which clearly can not bear any sentiment. Tokenizing could be improved to remove noisy expressions, such as numbers, dates and words with unreadable/special characters, taking the previously mentioned example of profanities marked with symbols. Parsing would allow the syntactic information of a word/phrase to be analyzed. This is particularly useful when dealing with things like "The food was not great". This could also be treated by dealing with bigrams. The approach used in this project was using a bag-of-words model, where words were treated as unigrams, that is to say, no information, such as the words around it were taken into account. If the analysis dealt with bigrams, features such as "not good" could be incorporated into the analysis and could explain things like "great" having a high chi value in negative reviews.

The output lexicon first described (where words are categorised) has its strengths and weaknesses. Its strengths lie in the fact that, for the most part, by intuition the terms are classified correctly i.e. terms perceived to be negative are classified as negative and terms perceived are classified as positive. Its main weakness is the amount of noisy data it contains, such as numbers, dates and names. Such problems could be avoided by having better tokenisation and reducing the data further for the statistical tests so that mutual information does not give a high ranking to rarer terms.

Despite the strengths of the aforementioned lexicon, the second lexicon outlined in chapter 5 proves the most powerful. The first lexicon more or less summarises the information in the lexicon where the word is accompanied by a positive and negative ranking. Although it is helpful to be able to identify positive and negative words, the method used in the first lexicon is quite simplified and may incorrectly categorise words. For example, classing a word as positive even though its positive rank may only be 1 point higher than its negative rating. A lexicon with these tags indicating positivity and negativity in terms of ranks, can easily show a positive word. To take an

extreme example, if a word has a positive rank of 1 and a negative rank of 18000, it is clearly visible that it is a word with positive sentiment. Given the large number of ranks, and the combination of two categories, it also gives the possibility of a finer granularity, something which is not seen in the binary classification of positive and negative. A snapshot of this lexicon is provided in the appendix of the printed version of this report, where the electronic copy features the full lexicon.

Given that the main goal of this project was to develop a general methodology for the creation of a sentiment lexicon, the following steps are provided as guidelines in creating a sentiment lexicon based on the ranks calculated.

1. Accumulate labelled data for subject-domain
2. Perform preprocessing (NER, Parsing, Tokenizing)
3. Calculate word frequencies
4. Reduce dataset for best performance of pointwise mutual information
5. Calculate contigency tables for each term according to table 4.1
6. Calculate chi-square and pointwise mutual information for each word
7. Create rankings for respective statistic
8. Calculate composite rankings
9. Append rankings to words in order to generate lexicon

Steps 4-8 could be bypassed by using a feature selection process in order to identify sentiment loaded words, however as this did not work in this project, its usage cannot be fully supported, but current research in the area shows that it should be seriously considered as a viable approach.

Although the resulting sentiment lexicon is not without its problems, it is perfectly viable that the outlined approach can work given the right resources. As has been shown, this approach has had a lot of success in identifying words which contain sentiment but also paves the way for further research on the topic.

Appendix A

Weka Command-Line Syntax

The aim of this appendix is to provide the reader with a general overview to the syntax of using Weka in its command-line form. For a more in depth synopsis of the command-line use of Weka, the reader is pointed to [18] pgs. 11 - 21. The issue of Weka's command line syntax first arose in figure 5.1, so in this chapter, this particular statement will be explained.

The first part of the statement in figure 5.1, "java -Xmx1536M", relates to how Java programs are run from the command-line. Weka was developped in Java and is contained in a .jre exexcutable. To execute a compiled Java program, the statement "java" must precede the program name. The part of command "-Xmx1536M" is an option for this Java command. It denotes the amount of memory from the Java virtual machine allocated to the program, in this case, it is the maximum amount permissible. The reason for such a large amount being allocated to Weka is the large size of the dataset on which Weka was exacted.

The second part of this command "weka.attributeSelection.CfsSubsetEval -M -s "weka.attributeSelection.BestFirst -D 1 -N 5" -i 1000.arff" denotes how Weka will perform the attribute selection."CfsSubsetEval" is the type of evaluation to be performed on the dataset and corresponds to the type of data being outputted. In this case the number of subsets evaluated would

be outputted. “weka.attributeSelection.BestFirst” determines what search algorithm will be used in selecting the attributes.

Things like “ -M -s ”’ are the options for the program. For example, “-M” means that missing values should be treated as separate values. “ -s ” sets the search method to be used for the subset evaluator. The final option of “-i” is used to mark the input dataset, this option is followed by the path to the file which contains the data. The input file is in the .arff format as was described in section 4.2.1.

Appendix B

Generated Lexicon

⟨-10⟩⟨12515⟩⟨16552⟩,⟨-2⟩⟨15535⟩⟨15513⟩
⟨00:00:00⟩⟨5456⟩⟨15599⟩,⟨0⟩⟨6045⟩⟨8358⟩
⟨01:00:00⟩⟨18143⟩⟨2751⟩,⟨02:00:00⟩⟨172⟩⟨7640⟩
⟨03:00:00⟩⟨3247⟩⟨7850⟩,⟨04:00:00⟩⟨557⟩⟨10025⟩
⟨05:00:00⟩⟨18494⟩⟨13231⟩,⟨25.00%⟩⟨17612⟩⟨17833⟩
⟨30.00%⟩⟨16823⟩⟨1616⟩,⟨09:00:00⟩⟨8036⟩⟨14260⟩
⟨10:00:00⟩⟨16106⟩⟨12550⟩,⟨50.00%⟩⟨1996⟩⟨1812⟩
⟨13:00:00⟩⟨8729⟩⟨14036⟩,⟨15:00:00⟩⟨523⟩⟨4372⟩
⟨70.00%⟩⟨16012⟩⟨11753⟩,⟨17:00:00⟩⟨15196⟩⟨16653⟩
⟨20:00:00⟩⟨4204⟩⟨11571⟩,⟨21:00:00⟩⟨1680⟩⟨9015⟩
⟨22:00:00⟩⟨10816⟩⟨4356⟩,⟨99.00%⟩⟨3443⟩⟨4667⟩
⟨40:00:00⟩⟨18463⟩⟨6011⟩,⟨42:00:00⟩⟨17407⟩⟨18293⟩
⟨50:00:00⟩⟨17039⟩⟨1610⟩,⟨57:00:00⟩⟨1277⟩⟨3007⟩
⟨3⟩⟨12522⟩⟨16562⟩,⟨4⟩⟨3956⟩⟨3479⟩
⟨5⟩⟨12405⟩⟨16485⟩,⟨6⟩⟨10510⟩⟨14560⟩
⟨8⟩⟨4416⟩⟨13184⟩,⟨9⟩⟨9659⟩⟨16453⟩
⟨13⟩⟨11066⟩⟨15917⟩,⟨15⟩⟨3541⟩⟨5418⟩
⟨19⟩⟨9115⟩⟨16733⟩,⟨20⟩⟨14108⟩⟨15161⟩
⟨24⟩⟨4548⟩⟨17048⟩,⟨26⟩⟨11281⟩⟨16637⟩
⟨30⟩⟨5316⟩⟨13240⟩,⟨31⟩⟨89⟩⟨3673⟩

⟨35⟩⟨9698⟩⟨8132⟩,⟨37⟩⟨14211⟩⟨16559⟩
⟨40⟩⟨16006⟩⟨11740⟩,⟨42⟩⟨12203⟩⟨8624⟩
⟨46⟩⟨15017⟩⟨8972⟩,⟨48⟩⟨2697⟩⟨1469⟩
⟨51⟩⟨17653⟩⟨17872⟩,⟨53⟩⟨5405⟩⟨3269⟩
⟨57⟩⟨8387⟩⟨15232⟩,⟨59⟩⟨10752⟩⟨13165⟩
⟨62⟩⟨7124⟩⟨5880⟩,⟨65⟩⟨10901⟩⟨15384⟩
⟨70⟩⟨7394⟩⟨14127⟩,⟨74⟩⟨6714⟩⟨5847⟩
⟨78⟩⟨14788⟩⟨12473⟩,⟨80⟩⟨6548⟩⟨13476⟩
⟨86⟩⟨13453⟩⟨16367⟩,⟨89⟩⟨7813⟩⟨10409⟩
⟨96⟩⟨15933⟩⟨9114⟩,⟨99⟩⟨3592⟩⟨8216⟩
⟨103⟩⟨9075⟩⟨14200⟩,⟨105⟩⟨4597⟩⟨5846⟩
⟨109⟩⟨4002⟩⟨2707⟩,⟨111⟩⟨13191⟩⟨16391⟩
⟨115⟩⟨12111⟩⟨8925⟩,⟨117⟩⟨6197⟩⟨12259⟩
⟨121⟩⟨6188⟩⟨12249⟩,⟨123⟩⟨15010⟩⟨7490⟩
⟨128⟩⟨12914⟩⟨15893⟩,⟨130⟩⟨8050⟩⟨9173⟩
⟨140⟩⟨1921⟩⟨8632⟩,⟨149⟩⟨9036⟩⟨7708⟩
⟨160⟩⟨11957⟩⟨14371⟩,⟨170⟩⟨13738⟩⟨17094⟩
⟨190⟩⟨16123⟩⟨17159⟩,⟨198⟩⟨12055⟩⟨8283⟩
⟨201⟩⟨10775⟩⟨11945⟩,⟨204⟩⟨16864⟩⟨15761⟩
⟨208⟩⟨16952⟩⟨7769⟩,⟨210⟩⟨7974⟩⟨5186⟩
⟨215⟩⟨16244⟩⟨15683⟩,⟨217⟩⟨15694⟩⟨9181⟩
⟨225⟩⟨13838⟩⟨17377⟩,⟨230⟩⟨9035⟩⟨4754⟩
⟨255⟩⟨17451⟩⟨18337⟩,⟨270⟩⟨15070⟩⟨10617⟩
⟨301⟩⟨6626⟩⟨12368⟩,⟨303⟩⟨12449⟩⟨15191⟩
⟨307⟩⟨14930⟩⟨17743⟩,⟨309⟩⟨15880⟩⟨12421⟩
⟨314⟩⟨13393⟩⟨11897⟩,⟨316⟩⟨8341⟩⟨10766⟩
⟨340⟩⟨17379⟩⟨18265⟩,⟨360⟩⟨5568⟩⟨8533⟩
⟨403⟩⟨16734⟩⟨15531⟩,⟨410⟩⟨7453⟩⟨4234⟩
⟨450⟩⟨10740⟩⟨8934⟩,⟨503⟩⟨18294⟩⟨688⟩
⟨700⟩⟨8492⟩⟨7638⟩,⟨730⟩⟨18500⟩⟨13239⟩
⟨800⟩⟨17306⟩⟨14440⟩,⟨1030⟩⟨17112⟩⟨16026⟩

⟨1916⟩⟨10630⟩⟨15400⟩,⟨1975⟩⟨18502⟩⟨13242⟩
⟨1999⟩⟨9062⟩⟨11035⟩,⟨2001⟩⟨8514⟩⟨14166⟩
⟨2005⟩⟨2140⟩⟨11540⟩,⟨2007⟩⟨1712⟩⟨13891⟩
⟨01/02/10⟩⟨14194⟩⟨14808⟩,⟨02/03/10⟩⟨7084⟩⟨11384⟩
⟨04/05/10⟩⟨13697⟩⟨8694⟩,⟨05/07/10⟩⟨5681⟩⟨7232⟩
⟨07/08/10⟩⟨14380⟩⟨15288⟩,⟨05/10/10⟩⟨1522⟩⟨6946⟩
⟨10/12/10⟩⟨7275⟩⟨12980⟩,⟨01/10/15⟩⟨1056⟩⟨7609⟩
⟨"–"⟩⟨1887⟩⟨13678⟩,⟨"—-"⟩⟨13988⟩⟨8891⟩
⟨"-but"⟩⟨13794⟩⟨14284⟩,⟨"-Excellent"⟩⟨15359⟩⟨16860⟩
⟨"-in"⟩⟨12950⟩⟨17221⟩,⟨"-no"⟩⟨16518⟩⟨17719⟩
⟨"-the"⟩⟨1959⟩⟨18530⟩,⟨"-There"⟩⟨17106⟩⟨16013⟩
⟨"-we"⟩⟨14824⟩⟨17106⟩,⟨"????"⟩⟨14553⟩⟨18106⟩
⟨"???????1"⟩⟨9484⟩⟨13578⟩,⟨"???????100"⟩⟨3485⟩⟨9426⟩
⟨"???????11"⟩⟨11287⟩⟨12155⟩,⟨"???????119"⟩⟨14353⟩⟨17297⟩
⟨"???????129"⟩⟨15556⟩⟨17100⟩,⟨"???????130"⟩⟨1362⟩⟨2250⟩
⟨"???????140"⟩⟨2652⟩⟨2032⟩,⟨"???????149"⟩⟨12782⟩⟨10514⟩
⟨"???????160"⟩⟨11252⟩⟨7861⟩,⟨"???????169"⟩⟨10234⟩⟨10038⟩
⟨"???????180"⟩⟨10366⟩⟨16275⟩,⟨"???????19"⟩⟨4761⟩⟨2434⟩
⟨"???????2"⟩⟨10710⟩⟨12701⟩,⟨"???????200"⟩⟨6391⟩⟨8043⟩
⟨"???????23"⟩⟨14871⟩⟨14655⟩,⟨"???????24"⟩⟨13087⟩⟨16986⟩
⟨"???????26"⟩⟨16510⟩⟨17710⟩,⟨"???????27"⟩⟨15944⟩⟨16407⟩
⟨"???????29"⟩⟨13609⟩⟨9122⟩,⟨"???????30"⟩⟨7902⟩⟨12934⟩
⟨"???????350"⟩⟨18121⟩⟨938⟩,⟨"???????39"⟩⟨16894⟩⟨18136⟩
⟨"???????42"⟩⟨17408⟩⟨18294⟩,⟨"???????48"⟩⟨12255⟩⟨10190⟩
⟨"???????500"⟩⟨9796⟩⟨5022⟩,⟨"???????58"⟩⟨15735⟩⟨13488⟩
⟨"???????62"⟩⟨15736⟩⟨13490⟩,⟨"???????69"⟩⟨7416⟩⟨12861⟩
⟨"???????78"⟩⟨15190⟩⟨16643⟩,⟨"???????8"⟩⟨8035⟩⟨7838⟩
⟨"???????89"⟩⟨4877⟩⟨11445⟩,⟨"???????90"⟩⟨12139⟩⟨14520⟩
⟨"???????Full"⟩⟨10196⟩⟨15898⟩,⟨"???????it"⟩⟨18335⟩⟨821⟩
⟨"???????the"⟩⟨15018⟩⟨8974⟩,⟨"????10"⟩⟨6818⟩⟨8526⟩
⟨"????15"⟩⟨9398⟩⟨14016⟩,⟨"????18"⟩⟨10280⟩⟨10106⟩

⟨”????25”⟩⟨11978⟩⟨11984⟩,⟨”????300”⟩⟨18195⟩⟨4570⟩
⟨”????45”⟩⟨6896⟩⟨13113⟩,⟨”????50”⟩⟨14461⟩⟨17070⟩
⟨”????70”⟩⟨13171⟩⟨16257⟩,⟨”????8”⟩⟨17354⟩⟨14997⟩
⟨”*”⟩⟨5371⟩⟨7103⟩,⟨”***”⟩⟨17739⟩⟨11677⟩
⟨””⟩⟨4802⟩⟨7352⟩,⟨”’06”⟩⟨14602⟩⟨11699⟩
⟨”’3”⟩⟨17880⟩⟨17971⟩,⟨”’A”⟩⟨17944⟩⟨18015⟩
⟨”’castle”’⟩⟨12385⟩⟨16474⟩,⟨”’country”⟩⟨12665⟩⟨10395⟩
⟨”’do”⟩⟨16762⟩⟨17763⟩,⟨”’double”’⟩⟨18135⟩⟨1179⟩
⟨”’executive”’⟩⟨13815⟩⟨14314⟩,⟨”’Family”⟩⟨18283⟩⟨15924⟩
⟨”’full”⟩⟨15130⟩⟨17815⟩,⟨”’get”⟩⟨9992⟩⟨5715⟩
⟨”’hot”’⟩⟨13371⟩⟨11875⟩,⟨”’hotel”’⟩⟨13268⟩⟨61⟩
⟨”’just”⟩⟨12295⟩⟨10264⟩,⟨”’luxury”⟩⟨18362⟩⟨624⟩
⟨”’nice”’⟩⟨18254⟩⟨2445⟩,⟨”’No”⟩⟨17727⟩⟨11660⟩
⟨”’ok”’⟩⟨16627⟩⟨17641⟩,⟨”’old”’⟩⟨9841⟩⟨4273⟩
⟨”’quiet”’⟩⟨17809⟩⟨17932⟩,⟨”’s”⟩⟨7973⟩⟨5184⟩
⟨”’standard”’⟩⟨14953⟩⟨10293⟩,⟨”’superior”’⟩⟨5638⟩⟨9027⟩
⟨”’til”⟩⟨9047⟩⟨11009⟩,⟨”’tired”’⟩⟨10647⟩⟨8921⟩
⟨”’well”⟩⟨17051⟩⟨6746⟩,⟨”’what”⟩⟨17562⟩⟨131⟩
⟨”&gt”⟩⟨6356⟩⟨11791⟩,⟨”&quot”⟩⟨3993⟩⟨844⟩
⟨”%”⟩⟨17839⟩⟨1680⟩,⟨”=”⟩⟨10680⟩⟨13779⟩
⟨”$$$”⟩⟨12813⟩⟨15780⟩,⟨”$10”⟩⟨13823⟩⟨14330⟩
⟨”$150”⟩⟨3927⟩⟨1585⟩,⟨”$20”⟩⟨15148⟩⟨12098⟩
⟨”$300”⟩⟨4295⟩⟨12531⟩,⟨”$350”⟩⟨17140⟩⟨18452⟩
⟨”$500”⟩⟨18150⟩⟨1197⟩,⟨”$60”⟩⟨18287⟩⟨586⟩
⟨”1&quot”⟩⟨17960⟩⟨18025⟩,⟨”10-15mins”⟩⟨12421⟩⟨12506⟩
⟨”100m”⟩⟨15102⟩⟨9571⟩,⟨”10Euro”⟩⟨10214⟩⟨10012⟩
⟨”10minute”⟩⟨16474⟩⟨10653⟩,⟨”10th”⟩⟨11510⟩⟨12718⟩
⟨”12euros”⟩⟨11088⟩⟨14849⟩,⟨”12th”⟩⟨7956⟩⟨3805⟩
⟨”15-20”⟩⟨6941⟩⟨1947⟩,⟨”15-minute”⟩⟨7296⟩⟨12993⟩
⟨”15min”⟩⟨7040⟩⟨6493⟩,⟨”15minutes”⟩⟨6540⟩⟨4052⟩
⟨”16A”⟩⟨7401⟩⟨10687⟩,⟨”17th”⟩⟨9703⟩⟨16899⟩

⟨"1950's"⟩⟨16591⟩⟨8956⟩,⟨"1960's"⟩⟨16390⟩⟨178⟩
⟨"1980's"⟩⟨1005⟩⟨2001⟩,⟨"1990s"⟩⟨13388⟩⟨11892⟩
⟨"1hr"⟩⟨2713⟩⟨8202⟩,⟨"1m"⟩⟨12412⟩⟨16489⟩
⟨"2-bedroom"⟩⟨7793⟩⟨11295⟩,⟨"2-night"⟩⟨13473⟩⟨11121⟩
⟨"2'"⟩⟨16005⟩⟨11738⟩,⟨"20-30"⟩⟨10689⟩⟨15567⟩
⟨"200m"⟩⟨15069⟩⟨10615⟩,⟨"20Euro"⟩⟨16732⟩⟨15529⟩
⟨"20mins"⟩⟨7387⟩⟨13890⟩,⟨"20minutes"⟩⟨16965⟩⟨7792⟩
⟨"21st"⟩⟨9510⟩⟨15497⟩,⟨"23rd"⟩⟨10442⟩⟨9166⟩
⟨"24hours"⟩⟨13660⟩⟨13407⟩,⟨"24hrs"⟩⟨8131⟩⟨3940⟩
⟨"25min"⟩⟨10556⟩⟨15319⟩,⟨"25th"⟩⟨11886⟩⟨12373⟩
⟨"29th"⟩⟨9567⟩⟨14470⟩,⟨"2BB"⟩⟨15358⟩⟨16859⟩
⟨"2m"⟩⟨12410⟩⟨16488⟩,⟨"2mins"⟩⟨7220⟩⟨10909⟩
⟨"2yr"⟩⟨9915⟩⟨1001⟩,⟨"3-day"⟩⟨10127⟩⟨14240⟩
⟨"3*"⟩⟨7922⟩⟨4162⟩,⟨"30-40"⟩⟨14589⟩⟨18213⟩
⟨"30euro"⟩⟨13781⟩⟨10582⟩,⟨"30ish"⟩⟨10220⟩⟨10018⟩
⟨"30p"⟩⟨15490⟩⟨9465⟩,⟨"30th"⟩⟨5341⟩⟨9468⟩
⟨"3km"⟩⟨14364⟩⟨15253⟩,⟨"3mins"⟩⟨15446⟩⟨9602⟩
⟨"3star"⟩⟨11101⟩⟨15095⟩,⟨"4-day"⟩⟨11462⟩⟨14323⟩
⟨"4-Star"⟩⟨15421⟩⟨9544⟩,⟨"4*"⟩⟨6639⟩⟨11485⟩
⟨"400m"⟩⟨15385⟩⟨16892⟩,⟨"40min"⟩⟨15404⟩⟨9516⟩
⟨"42&quot"⟩⟨10182⟩⟨6223⟩,⟨"45mins"⟩⟨8845⟩⟨12835⟩
⟨"4ft"⟩⟨3786⟩⟨1142⟩,⟨"4star"⟩⟨8706⟩⟨12523⟩
⟨"5-10mins"⟩⟨10553⟩⟨15316⟩,⟨"5-minute"⟩⟨3657⟩⟨4322⟩
⟨"5???????"⟩⟨15193⟩⟨16647⟩,⟨"50's"⟩⟨9419⟩⟨11956⟩
⟨"50mins"⟩⟨18345⟩⟨840⟩,⟨"5euro"⟩⟨15127⟩⟨16915⟩
⟨"5min"⟩⟨1679⟩⟨9878⟩,⟨"5minute"⟩⟨9973⟩⟨5684⟩
⟨"5yrs"⟩⟨9165⟩⟨4810⟩,⟨"60's"⟩⟨9489⟩⟨9428⟩
⟨"6euro"⟩⟨16228⟩⟨15965⟩,⟨"6ft"⟩⟨3874⟩⟨10155⟩
⟨"70s"⟩⟨4843⟩⟨4617⟩,⟨"75th"⟩⟨10264⟩⟨10082⟩
⟨"7th"⟩⟨10850⟩⟨17258⟩,⟨"80's"⟩⟨1588⟩⟨3956⟩
⟨"8euro"⟩⟨17125⟩⟨16052⟩,⟨"9-day"⟩⟨15625⟩⟨13467⟩

⟨"99euros"⟩⟨12335⟩⟨10342⟩,⟨"A"⟩⟨936⟩⟨3887⟩
⟨"A+++"⟩⟨10565⟩⟨15329⟩,⟨"A4"⟩⟨13878⟩⟨8271⟩
⟨"aback"⟩⟨5113⟩⟨9698⟩,⟨"abandon"⟩⟨16472⟩⟨10650⟩
⟨"abbey"⟩⟨9807⟩⟨9171⟩,⟨"abbeyglen"⟩⟨10397⟩⟨10148⟩
⟨"ability"⟩⟨12353⟩⟨15778⟩,⟨"able"⟩⟨1558⟩⟨4724⟩
⟨"About"⟩⟨6755⟩⟨16894⟩,⟨"Above"⟩⟨4323⟩⟨7420⟩
⟨"abruptly"⟩⟨14436⟩⟨3958⟩,⟨"absent"⟩⟨16260⟩⟨8434⟩
⟨"absolutely"⟩⟨129⟩⟨15488⟩,⟨"ABSOLUTELY"⟩⟨16617⟩⟨15488⟩
⟨"absoutely"⟩⟨17064⟩⟨10476⟩,⟨"abundance"⟩⟨8064⟩⟨15265⟩
⟨"abusive"⟩⟨7534⟩⟨6029⟩,⟨"AC"⟩⟨11621⟩⟨9991⟩
⟨"accents"⟩⟨14513⟩⟨13168⟩,⟨"acceptable"⟩⟨739⟩⟨1388⟩
⟨"accesible"⟩⟨7468⟩⟨6509⟩,⟨"Access"⟩⟨7919⟩⟨4647⟩
⟨"accessible"⟩⟨9725⟩⟨9416⟩,⟨"accessories"⟩⟨10912⟩⟨14347⟩
⟨"accolades"⟩⟨14769⟩⟨15655⟩,⟨"accomadate"⟩⟨10074⟩⟨12377⟩
⟨"accomdating"⟩⟨17461⟩⟨18347⟩,⟨"accommadation"⟩⟨16053⟩⟨12518⟩
⟨"accommodation"⟩⟨2154⟩⟨17825⟩,⟨"accommodations"⟩⟨3095⟩⟨8231⟩
⟨"accomodation"⟩⟨2525⟩⟨13054⟩,⟨"accomodations"⟩⟨3076⟩⟨8515⟩
⟨"accompanying"⟩⟨13905⟩⟨18202⟩,⟨"according"⟩⟨1422⟩⟨16846⟩
⟨"account"⟩⟨134⟩⟨3571⟩,⟨"accounts"⟩⟨11821⟩⟨9542⟩
⟨"accurately"⟩⟨14641⟩⟨15052⟩,⟨"accusing"⟩⟨17564⟩⟨93⟩
⟨"ache"⟩⟨13603⟩⟨7108⟩,⟨"achieve"⟩⟨13249⟩⟨14095⟩
⟨"Achill"⟩⟨4585⟩⟨2359⟩,⟨"acknowledge"⟩⟨1913⟩⟨7988⟩
⟨"acommodating"⟩⟨17885⟩⟨17976⟩,⟨"acquired"⟩⟨15041⟩⟨4456⟩
⟨"Across"⟩⟨8257⟩⟨5938⟩,⟨"actaully"⟩⟨16080⟩⟨14920⟩
⟨"actions"⟩⟨13859⟩⟨17399⟩,⟨"activated"⟩⟨12154⟩⟨7900⟩
⟨"activites"⟩⟨7829⟩⟨11342⟩,⟨"activity"⟩⟨3207⟩⟨8668⟩
⟨"acts"⟩⟨10116⟩⟨14224⟩,⟨"actually"⟩⟨3937⟩⟨15861⟩
⟨"Adam"⟩⟨8284⟩⟨14544⟩,⟨"Adams"⟩⟨10121⟩⟨14226⟩
⟨"adaptor"⟩⟨14560⟩⟨17619⟩,⟨"adaquate"⟩⟨6892⟩⟨13105⟩
⟨"add"⟩⟨2791⟩⟨8456⟩,⟨"Added"⟩⟨14687⟩⟨15572⟩
⟨"addition"⟩⟨9505⟩⟨12675⟩,⟨"Additional"⟩⟨15637⟩⟨17145⟩

⟨"additonal"⟩⟨17600⟩⟨13569⟩,⟨"addressed"⟩⟨11511⟩⟨9935⟩
⟨"adequate"⟩⟨6962⟩⟨17218⟩,⟨"adequately"⟩⟨11891⟩⟨17192⟩
⟨"Adjacent"⟩⟨12853⟩⟨15822⟩,⟨"adjoining"⟩⟨6130⟩⟨17193⟩
⟨"adjustable"⟩⟨14654⟩⟨17489⟩,⟨"adjusting"⟩⟨9743⟩⟨13846⟩
⟨"admired"⟩⟨17524⟩⟨18399⟩,⟨"admission"⟩⟨11230⟩⟨14399⟩
⟨"admittedly"⟩⟨13060⟩⟨16916⟩,⟨"adn"⟩⟨14570⟩⟨11656⟩
⟨"adore"⟩⟨8945⟩⟨10969⟩,⟨"adorned"⟩⟨8798⟩⟨4519⟩
⟨"adult"⟩⟨3459⟩⟨18146⟩,⟨"adults"⟩⟨2050⟩⟨9046⟩
⟨"advantage"⟩⟨918⟩⟨6146⟩,⟨"adventure"⟩⟨8988⟩⟨10422⟩
⟨"advert"⟩⟨13438⟩⟨16349⟩,⟨"advertised"⟩⟨3694⟩⟨9623⟩
⟨"advertises"⟩⟨772⟩⟨7368⟩,⟨"advertisment"⟩⟨16669⟩⟨154⟩
⟨"advisable"⟩⟨11730⟩⟨8669⟩,⟨"Advise"⟩⟨18256⟩⟨8561⟩
⟨"Adviser"⟩⟨8776⟩⟨6400⟩,⟨"advising"⟩⟨6074⟩⟨12236⟩
⟨"Aer"⟩⟨10904⟩⟨8075⟩,⟨"aerobics"⟩⟨9952⟩⟨5655⟩
⟨"afew"⟩⟨15083⟩⟨7699⟩,⟨"affair"⟩⟨11486⟩⟨14555⟩
⟨"affection"⟩⟨17872⟩⟨17963⟩,⟨"affiliated"⟩⟨9802⟩⟨7629⟩
⟨"afforded"⟩⟨7934⟩⟨8608⟩,⟨"afield"⟩⟨3724⟩⟨7020⟩
⟨"African"⟩⟨16478⟩⟨12908⟩,⟨"after"⟩⟨2582⟩⟨5513⟩
⟨"afternoon"⟩⟨685⟩⟨17480⟩,⟨"afternoons"⟩⟨8142⟩⟨6972⟩
⟨"afterwards"⟩⟨8455⟩⟨4950⟩,⟨"again"⟩⟨1284⟩⟨4176⟩
⟨"against"⟩⟨87⟩⟨3833⟩,⟨"aged"⟩⟨9251⟩⟨13331⟩
⟨"agenda"⟩⟨14677⟩⟨12203⟩,⟨"Agent"⟩⟨17425⟩⟨18311⟩
⟨"aggressive"⟩⟨797⟩⟨3934⟩,⟨"aghadoe"⟩⟨10941⟩⟨11630⟩
⟨"agitated"⟩⟨10525⟩⟨15285⟩,⟨"ago"⟩⟨19⟩⟨4965⟩
⟨"agree"⟩⟨3768⟩⟨12939⟩,⟨"agreeable"⟩⟨16431⟩⟨18097⟩
⟨"agus"⟩⟨10042⟩⟨5816⟩,⟨"ah"⟩⟨5429⟩⟨9151⟩
⟨"Ahernes"⟩⟨12461⟩⟨16508⟩,⟨"aid"⟩⟨9886⟩⟨11557⟩
⟨"Ailwee"⟩⟨8373⟩⟨10816⟩,⟨"aimed"⟩⟨5624⟩⟨12024⟩
⟨"Aine"⟩⟨15894⟩⟨16105⟩,⟨"aiport"⟩⟨9021⟩⟨16099⟩
⟨"AIR"⟩⟨13433⟩⟨16344⟩,⟨"air-condition"⟩⟨17785⟩⟨17908⟩
⟨"Airbus"⟩⟨11084⟩⟨14845⟩,⟨"aircoach"⟩⟨1998⟩⟨8083⟩

⟨"airconditioner"⟩⟨15616⟩⟨13451⟩,⟨"aircraft"⟩⟨8263⟩⟨7127⟩
⟨"airlines"⟩⟨13267⟩⟨7277⟩,⟨"airlink"⟩⟨5951⟩⟨11255⟩
⟨"airport"⟩⟨2078⟩⟨5086⟩,⟨"Airport&quot"⟩⟨10048⟩⟨10325⟩
⟨"airs"⟩⟨18003⟩⟨18057⟩,⟨"Aisling"⟩⟨11445⟩⟨14285⟩
⟨"akin"⟩⟨13242⟩⟨8621⟩,⟨"Al"⟩⟨7884⟩⟨13837⟩
⟨"alarm"⟩⟨9488⟩⟨338⟩,⟨"alarming"⟩⟨16215⟩⟨12661⟩
⟨"Albany"⟩⟨7170⟩⟨11469⟩,⟨"albums"⟩⟨7251⟩⟨10684⟩
⟨"alcove"⟩⟨13933⟩⟨14859⟩,⟨"Aldi"⟩⟨17166⟩⟨18478⟩
⟨"Alex"⟩⟨7095⟩⟨10838⟩,⟨"Alice"⟩⟨4082⟩⟨3357⟩
⟨"All"⟩⟨476⟩⟨7588⟩,⟨"ALL"⟩⟨2501⟩⟨7588⟩
⟨"All-Ireland"⟩⟨17966⟩⟨13673⟩,⟨"all-round"⟩⟨17922⟩⟨18001⟩
⟨"Allen"⟩⟨10683⟩⟨16788⟩,⟨"allergic"⟩⟨2654⟩⟨2540⟩
⟨"alley"⟩⟨7946⟩⟨13901⟩,⟨"alleyway"⟩⟨14468⟩⟨13913⟩
⟨"allocate"⟩⟨14242⟩⟨15105⟩,⟨"Allocated"⟩⟨17400⟩⟨18286⟩
⟨"allow"⟩⟨5428⟩⟨18344⟩,⟨"allowance"⟩⟨7201⟩⟨6297⟩
⟨"allways"⟩⟨8311⟩⟨10721⟩,⟨"almost"⟩⟨3327⟩⟨14153⟩
⟨"Along"⟩⟨11624⟩⟨11961⟩,⟨"aloof"⟩⟨12141⟩⟨17125⟩
⟨"Alot"⟩⟨14531⟩⟨17488⟩,⟨"alovely"⟩⟨10036⟩⟨5802⟩
⟨"also"⟩⟨892⟩⟨14959⟩,⟨"ALSO"⟩⟨17327⟩⟨14959⟩
⟨"alternative"⟩⟨2637⟩⟨5135⟩,⟨"alternatively"⟩⟨14747⟩⟨15557⟩
⟨"Although"⟩⟨4989⟩⟨5772⟩,⟨"altogether"⟩⟨5963⟩⟨15186⟩
⟨"always"⟩⟨182⟩⟨11000⟩,⟨"ALWAYS"⟩⟨8963⟩⟨11000⟩
⟨"Amanda"⟩⟨11337⟩⟨13774⟩,⟨"amateurish"⟩⟨17283⟩⟨9700⟩
⟨"amazement"⟩⟨5516⟩⟨11394⟩,⟨"amazing"⟩⟨2⟩⟨9655⟩
⟨"Amazingly"⟩⟨14854⟩⟨12780⟩,⟨"Amber"⟩⟨9465⟩⟨16863⟩
⟨"Ambience"⟩⟨17858⟩⟨3527⟩,⟨"ambitious"⟩⟨16870⟩⟨15770⟩
⟨"amend"⟩⟨10193⟩⟨6240⟩,⟨"ameneties"⟩⟨5133⟩⟨3454⟩
⟨"amenties"⟩⟨14934⟩⟨17457⟩,⟨"America"⟩⟨12125⟩⟨13823⟩
⟨"Americans"⟩⟨11127⟩⟨17416⟩,⟨"amid"⟩⟨11049⟩⟨14820⟩
⟨"amok"⟩⟨18144⟩⟨953⟩,⟨"Among"⟩⟨14303⟩⟨12297⟩
⟨"amounted"⟩⟨10413⟩⟨7514⟩,⟨"ample"⟩⟨458⟩⟨8310⟩

⟨"amuse"⟩⟨16623⟩⟨15495⟩,⟨"amusement"⟩⟨4578⟩⟨3912⟩
⟨"ancestors"⟩⟨5499⟩⟨4472⟩,⟨"ancient"⟩⟨2833⟩⟨6607⟩
⟨"Andrea"⟩⟨12827⟩⟨15795⟩,⟨"Andy"⟩⟨7455⟩⟨4236⟩
⟨"anger"⟩⟨14894⟩⟨374⟩,⟨"angles"⟩⟨9046⟩⟨13038⟩
⟨"animals"⟩⟨9515⟩⟨6290⟩,⟨"Ann"⟩⟨7609⟩⟨5524⟩
⟨"Anne"⟩⟨1934⟩⟨2146⟩,⟨"Anner"⟩⟨17031⟩⟨432⟩
⟨"anniversaries"⟩⟨9917⟩⟨5596⟩,⟨"Anniversary"⟩⟨5043⟩⟨7006⟩
⟨"annoyance"⟩⟨10092⟩⟨15547⟩,⟨"annoyed"⟩⟨858⟩⟨711⟩
⟨"annoys"⟩⟨10635⟩⟨15405⟩,⟨"annually"⟩⟨17876⟩⟨17967⟩
⟨"ans"⟩⟨10340⟩⟨9861⟩,⟨"answered"⟩⟨2211⟩⟨6284⟩
⟨"Anthony"⟩⟨16792⟩⟨17793⟩,⟨"anticipate"⟩⟨14936⟩⟨8352⟩
⟨"antics"⟩⟨16337⟩⟨18224⟩,⟨"antiquated"⟩⟨16347⟩⟨6566⟩
⟨"anxiously"⟩⟨18380⟩⟨2877⟩,⟨"any"⟩⟨2523⟩⟨17512⟩
⟨"anyday"⟩⟨18392⟩⟨2895⟩,⟨"anyhow"⟩⟨8847⟩⟨12844⟩
⟨"ANYONE"⟩⟨16682⟩⟨12815⟩,⟨"anyones"⟩⟨12007⟩⟨14456⟩
⟨"ANYTHING"⟩⟨18095⟩⟨7953⟩,⟨"Anytime"⟩⟨17487⟩⟨18370⟩
⟨"Anyways"⟩⟨10797⟩⟨17030⟩,⟨"ANYWHERE"⟩⟨13430⟩⟨16341⟩
⟨"apart"⟩⟨5949⟩⟨2964⟩,⟨"Apartment"⟩⟨13291⟩⟨14782⟩
⟨"apathy"⟩⟨17013⟩⟨85⟩,⟨"aplenty"⟩⟨8364⟩⟨10799⟩
⟨"apologise"⟩⟨131⟩⟨945⟩,⟨"apologising"⟩⟨1320⟩⟨7599⟩
⟨"apology"⟩⟨362⟩⟨3193⟩,⟨"apon"⟩⟨8789⟩⟨13464⟩
⟨"appallingly"⟩⟨17634⟩⟨98⟩,⟨"apparent"⟩⟨6940⟩⟨1921⟩
⟨"appartments"⟩⟨9546⟩⟨11441⟩,⟨"appauling"⟩⟨15022⟩⟨29⟩
⟨"appear"⟩⟨7982⟩⟨2719⟩,⟨"appearances"⟩⟨13788⟩⟨10588⟩
⟨"appears"⟩⟨7544⟩⟨12234⟩,⟨"apperance"⟩⟨12996⟩⟨523⟩
⟨"appetizer"⟩⟨3603⟩⟨2102⟩,⟨"appetizing"⟩⟨6509⟩⟨7253⟩
⟨"apples"⟩⟨9846⟩⟨7981⟩,⟨"appliances"⟩⟨7610⟩⟨10504⟩
⟨"apply"⟩⟨2887⟩⟨3050⟩,⟨"appointed"⟩⟨8164⟩⟨573⟩
⟨"appology"⟩⟨17014⟩⟨87⟩,⟨"appreciated"⟩⟨754⟩⟨6876⟩
⟨"apprehensive"⟩⟨2377⟩⟨6582⟩,⟨"approachable"⟩⟨7164⟩⟨3643⟩
⟨"appropriately"⟩⟨14040⟩⟨8609⟩,⟨"approved"⟩⟨6052⟩⟨279⟩

⟨"approximately"⟩⟨6900⟩⟨7376⟩,⟨"April"⟩⟨5090⟩⟨16690⟩
⟨"Apt"⟩⟨17011⟩⟨14150⟩,⟨"apts"⟩⟨12076⟩⟨14061⟩
⟨"aquarium"⟩⟨9765⟩⟨13871⟩,⟨"Aran"⟩⟨975⟩⟨543⟩
⟨"arbutus"⟩⟨11456⟩⟨14311⟩,⟨"arcade"⟩⟨12958⟩⟨17229⟩
⟨"archaic"⟩⟨17489⟩⟨18371⟩,⟨"arches"⟩⟨12832⟩⟨15799⟩
⟨"architecture"⟩⟨3583⟩⟨3015⟩,⟨"Ard"⟩⟨7331⟩⟨12455⟩
⟨"Ardmore"⟩⟨2635⟩⟨12462⟩,⟨"Ardsollus"⟩⟨6252⟩⟨2413⟩
⟨"Area"⟩⟨1402⟩⟨4098⟩,⟨"area-"⟩⟨17878⟩⟨17969⟩
⟨"areas"⟩⟨1962⟩⟨15313⟩,⟨"aren???????t"⟩⟨11955⟩⟨15179⟩
⟨"arent"⟩⟨14484⟩⟨17395⟩,⟨"argue"⟩⟨2378⟩⟨6092⟩
⟨"argument"⟩⟨1327⟩⟨1589⟩,⟨"arguments"⟩⟨17274⟩⟨5356⟩
⟨"Arklow"⟩⟨7952⟩⟨12557⟩,⟨"arlington"⟩⟨6221⟩⟨10925⟩
⟨"armchair"⟩⟨11393⟩⟨14178⟩,⟨"armed"⟩⟨14275⟩⟨12288⟩
⟨"arms"⟩⟨3374⟩⟨8257⟩,⟨"Army"⟩⟨18321⟩⟨834⟩
⟨"aroud"⟩⟨17599⟩⟨13568⟩,⟨"Around"⟩⟨8866⟩⟨11456⟩
⟨"arranged"⟩⟨3479⟩⟨2533⟩,⟨"arrangements"⟩⟨11201⟩⟨13900⟩
⟨"Arrival"⟩⟨6589⟩⟨4021⟩,⟨"arrive"⟩⟨4674⟩⟨3160⟩
⟨"arriving"⟩⟨3646⟩⟨14951⟩,⟨"arrogance"⟩⟨17067⟩⟨1109⟩
⟨"arrrived"⟩⟨14377⟩⟨15282⟩,⟨"Art"⟩⟨5174⟩⟨7544⟩
⟨"artificial"⟩⟨16640⟩⟨17657⟩,⟨"artistic"⟩⟨15755⟩⟨12293⟩
⟨"artwork"⟩⟨4783⟩⟨5582⟩,⟨"As"⟩⟨2096⟩⟨12741⟩
⟨"ASAP"⟩⟨11947⟩⟨13699⟩,⟨"ashamed"⟩⟨13511⟩⟨153⟩
⟨"Ashlee"⟩⟨7969⟩⟨13563⟩,⟨"Ashling"⟩⟨6039⟩⟨10146⟩
⟨"Asia"⟩⟨14704⟩⟨15527⟩,⟨"asian"⟩⟨8197⟩⟨9974⟩
⟨"ask"⟩⟨2828⟩⟨2457⟩,⟨"asked"⟩⟨5909⟩⟨5042⟩
⟨"asks"⟩⟨2542⟩⟨8145⟩,⟨"aslo"⟩⟨17798⟩⟨17921⟩
⟨"assault"⟩⟨14761⟩⟨3182⟩,⟨"assessment"⟩⟨10640⟩⟨15410⟩
⟨"assist"⟩⟨9548⟩⟨13889⟩,⟨"assistant"⟩⟨1316⟩⟨16678⟩
⟨"assisting"⟩⟨6091⟩⟨6975⟩,⟨"associated"⟩⟨3638⟩⟨5372⟩
⟨"assume"⟩⟨1435⟩⟨6569⟩,⟨"assuming"⟩⟨3453⟩⟨1120⟩
⟨"assure"⟩⟨8899⟩⟨4130⟩,⟨"assuring"⟩⟨17066⟩⟨1107⟩

⟨"astonished"⟩⟨3311⟩⟨4807⟩,⟨"astounded"⟩⟨11903⟩⟨6830⟩
⟨"aswel"⟩⟨17442⟩⟨18328⟩,⟨"asylum"⟩⟨17841⟩⟨1367⟩
⟨"Atalia"⟩⟨14336⟩⟨15214⟩,⟨"ate"⟩⟨367⟩⟨5492⟩
⟨"Athlone"⟩⟨6131⟩⟨12345⟩,⟨"athmosphere"⟩⟨7304⟩⟨10147⟩
⟨"atlantic"⟩⟨8825⟩⟨9675⟩,⟨"ATM's"⟩⟨17468⟩⟨18354⟩
⟨"atmostphere"⟩⟨16322⟩⟨17018⟩,⟨"atomsphere"⟩⟨15327⟩⟨16822⟩
⟨"atrocious"⟩⟨715⟩⟨4329⟩,⟨"Attached"⟩⟨12300⟩⟨13743⟩
⟨"attactions"⟩⟨11083⟩⟨14844⟩,⟨"attempt"⟩⟨229⟩⟨1481⟩
⟨"attend"⟩⟨2786⟩⟨5164⟩,⟨"attendant"⟩⟨4798⟩⟨1353⟩
⟨"attendees"⟩⟨14405⟩⟨17420⟩,⟨"attentative"⟩⟨4428⟩⟨1706⟩
⟨"attentive"⟩⟨68⟩⟨16084⟩,⟨"attentiveness"⟩⟨4087⟩⟨2499⟩
⟨"attitudes"⟩⟨3610⟩⟨9681⟩,⟨"attract"⟩⟨12146⟩⟨17259⟩
⟨"attractive"⟩⟨2221⟩⟨3159⟩,⟨"attracts"⟩⟨11307⟩⟨7242⟩
⟨"au"⟩⟨13951⟩⟨16155⟩,⟨"audacity"⟩⟨17248⟩⟨23⟩
⟨"Aug"⟩⟨11284⟩⟨17626⟩,⟨"Aughrim"⟩⟨16541⟩⟨2747⟩
⟨"aunt"⟩⟨12935⟩⟨15039⟩,⟨"aura"⟩⟨8324⟩⟨10742⟩
⟨"Australian"⟩⟨13378⟩⟨16253⟩,⟨"authentic"⟩⟨2956⟩⟨5548⟩
⟨"auto"⟩⟨14137⟩⟨17599⟩,⟨"automatic"⟩⟨6848⟩⟨7711⟩
⟨"avaiable"⟩⟨17917⟩⟨17998⟩,⟨"availability"⟩⟨5729⟩⟨9286⟩
⟨"availible"⟩⟨16055⟩⟨18432⟩,⟨"avaliable"⟩⟨10403⟩⟨16238⟩
⟨"avenue"⟩⟨7921⟩⟨5222⟩,⟨"Average"⟩⟨8889⟩⟨13049⟩
⟨"aviation"⟩⟨16049⟩⟨18429⟩,⟨"Avoca"⟩⟨13475⟩⟨13383⟩
⟨"AVOID"⟩⟨13727⟩⟨2391⟩,⟨"avoiding"⟩⟨3427⟩⟨2969⟩
⟨"awaiting"⟩⟨7519⟩⟨8104⟩,⟨"awake"⟩⟨804⟩⟨3011⟩
⟨"Award"⟩⟨17493⟩⟨15068⟩,⟨"awarded"⟩⟨11704⟩⟨17274⟩
⟨"awareness"⟩⟨13301⟩⟨7291⟩,⟨"away"⟩⟨990⟩⟨3905⟩
⟨"aways"⟩⟨5511⟩⟨7205⟩,⟨"aweful"⟩⟨18134⟩⟨1177⟩
⟨"Awful"⟩⟨14234⟩⟨5470⟩,⟨"awful-"⟩⟨17232⟩⟨3326⟩
⟨"awkward"⟩⟨6488⟩⟨3955⟩,⟨"awoke"⟩⟨889⟩⟨3183⟩
⟨"b"⟩⟨1377⟩⟨13964⟩,⟨"B???????s"⟩⟨5149⟩⟨3037⟩
⟨"b&"⟩⟨1624⟩⟨12897⟩,⟨"b+b"⟩⟨11735⟩⟨17026⟩

⟨"babies"⟩⟨9816⟩⟨16397⟩,⟨"Baby"⟩⟨11472⟩⟨10781⟩
⟨"babysitters"⟩⟨14169⟩⟨11828⟩,⟨"back"⟩⟨897⟩⟨10559⟩
⟨"backdrop"⟩⟨11305⟩⟨5180⟩,⟨"background"⟩⟨8891⟩⟨10071⟩
⟨"backpackers"⟩⟨3048⟩⟨7136⟩,⟨"backs"⟩⟨9275⟩⟨9486⟩
⟨"backyard"⟩⟨10702⟩⟨4675⟩,⟨"Bacon"⟩⟨14714⟩⟨12947⟩
⟨"bad"⟩⟨6042⟩⟨5576⟩,⟨"badly"⟩⟨2674⟩⟨831⟩
⟨"bag"⟩⟨3126⟩⟨10526⟩,⟨"bagels"⟩⟨14633⟩⟨13139⟩
⟨"Bags"⟩⟨6116⟩⟨11495⟩,⟨"Bailey's"⟩⟨7470⟩⟨6511⟩
⟨"baked"⟩⟨4778⟩⟨13716⟩,⟨"bakery"⟩⟨4954⟩⟨6731⟩
⟨"Balbriggan"⟩⟨7800⟩⟨11311⟩,⟨"balconies"⟩⟨2632⟩⟨4904⟩
⟨"bald"⟩⟨16028⟩⟨11761⟩,⟨"Ball"⟩⟨14981⟩⟨13993⟩
⟨"Ballinalacken"⟩⟨1156⟩⟨416⟩,⟨"balloons"⟩⟨5676⟩⟨7216⟩
⟨"Ballsbridge"⟩⟨2009⟩⟨17580⟩,⟨"Ballybofey"⟩⟨13768⟩⟨17808⟩
⟨"Ballygarry"⟩⟨7099⟩⟨13079⟩,⟨"Ballyliffin"⟩⟨14587⟩⟨17356⟩
⟨"ballymun"⟩⟨16218⟩⟨12664⟩,⟨"Ballyshannon"⟩⟨6259⟩⟨2804⟩
⟨"ban"⟩⟨1272⟩⟨8344⟩,⟨"bananas"⟩⟨11595⟩⟨9874⟩
⟨"bands"⟩⟨9900⟩⟨9109⟩,⟨"Bang"⟩⟨17190⟩⟨18502⟩
⟨"Banging"⟩⟨18045⟩⟨7080⟩,⟨"bangs"⟩⟨18067⟩⟨8981⟩
⟨"banking"⟩⟨18401⟩⟨2907⟩,⟨"banned"⟩⟨14782⟩⟨12465⟩
⟨"banqueting"⟩⟨13144⟩⟨18349⟩,⟨"banter"⟩⟨2012⟩⟨1733⟩
⟨"Bar"⟩⟨1895⟩⟨5489⟩,⟨"bar-"⟩⟨16491⟩⟨12926⟩
⟨"bar&quot"⟩⟨2999⟩⟨11334⟩,⟨"Barbara"⟩⟨13244⟩⟨15448⟩
⟨"barefoot"⟩⟨4466⟩⟨2231⟩,⟨"Barely"⟩⟨17909⟩⟨13605⟩
⟨"Bargain"⟩⟨11422⟩⟨14258⟩,⟨"Barge"⟩⟨7438⟩⟨14502⟩
⟨"barked"⟩⟨16461⟩⟨2678⟩,⟨"barley"⟩⟨5586⟩⟨16091⟩
⟨"barman"⟩⟨2302⟩⟨7351⟩,⟨"barmen"⟩⟨10648⟩⟨11280⟩
⟨"Barney"⟩⟨9779⟩⟨2780⟩,⟨"barrel"⟩⟨7668⟩⟨8802⟩
⟨"barriers"⟩⟨10802⟩⟨17034⟩,⟨"Barry"⟩⟨13904⟩⟨14001⟩
⟨"Bart"⟩⟨3663⟩⟨2042⟩,⟨"bartenders"⟩⟨2731⟩⟨1799⟩
⟨"Based"⟩⟨13005⟩⟨15709⟩,⟨"bases"⟩⟨15639⟩⟨17146⟩
⟨"basic&quot"⟩⟨9999⟩⟨5729⟩,⟨"Basically"⟩⟨2017⟩⟨5907⟩

⟨"basin"⟩⟨904⟩⟨2037⟩,⟨"basis"⟩⟨5089⟩⟨12511⟩
⟨"bass"⟩⟨1705⟩⟨4359⟩,⟨"bath"⟩⟨697⟩⟨16973⟩
⟨"bathrobe"⟩⟨11226⟩⟨15693⟩,⟨"Bathrobes"⟩⟨6283⟩⟨12344⟩
⟨"bathroom&quot"⟩⟨18235⟩⟨110⟩,⟨"Bathrooms"⟩⟨6334⟩⟨8824⟩
⟨"baths"⟩⟨2454⟩⟨9694⟩,⟨"bathtub"⟩⟨10428⟩⟨16191⟩
⟨"batteries"⟩⟨11266⟩⟨15657⟩,⟨"battle"⟩⟨2570⟩⟨9653⟩
⟨"Bayview"⟩⟨4407⟩⟨5610⟩,⟨"BB"⟩⟨13377⟩⟨16251⟩
⟨"bday"⟩⟨10552⟩⟨15314⟩,⟨"be"⟩⟨2723⟩⟨14156⟩
⟨"beaches"⟩⟨1253⟩⟨15839⟩,⟨"Beacon"⟩⟨13600⟩⟨16263⟩
⟨"Beag"⟩⟨15207⟩⟨16679⟩,⟨"beam"⟩⟨17597⟩⟨13564⟩
⟨"beans"⟩⟨6076⟩⟨16110⟩,⟨"bear"⟩⟨5995⟩⟨11388⟩
⟨"bearing"⟩⟨12584⟩⟨13379⟩,⟨"bearings"⟩⟨2969⟩⟨4412⟩
⟨"Beasley"⟩⟨5213⟩⟨12003⟩,⟨"beaten"⟩⟨3110⟩⟨3765⟩
⟨"beats"⟩⟨11351⟩⟨9551⟩,⟨"beauiful"⟩⟨15929⟩⟨16126⟩
⟨"beautician"⟩⟨13231⟩⟨9934⟩,⟨"beautiful"⟩⟨17⟩⟨14924⟩
⟨"beautifull"⟩⟨10861⟩⟨10854⟩,⟨"Beautifully"⟩⟨5903⟩⟨6749⟩
⟨"Beauvet"⟩⟨18029⟩⟨36⟩,⟨"becasue"⟩⟨4067⟩⟨5247⟩
⟨"becomes"⟩⟨10505⟩⟨12760⟩,⟨"becuase"⟩⟨13009⟩⟨15680⟩
⟨"bed-"⟩⟨10164⟩⟨6185⟩,⟨"bed's"⟩⟨16910⟩⟨18152⟩
⟨"bedclothes"⟩⟨2651⟩⟨2030⟩,⟨"bedcovers"⟩⟨18094⟩⟨4729⟩
⟨"bedlam"⟩⟨10472⟩⟨15238⟩,⟨"bedroom"⟩⟨1802⟩⟨14875⟩
⟨"Bedrooms"⟩⟨2391⟩⟨9478⟩,⟨"Beds"⟩⟨3404⟩⟨4020⟩
⟨"bedsit"⟩⟨17746⟩⟨1640⟩,⟨"bedspreads"⟩⟨611⟩⟨5016⟩
⟨"Beef"⟩⟨14929⟩⟨17742⟩,⟨"been"⟩⟨3242⟩⟨14656⟩
⟨"beer"⟩⟨4657⟩⟨12904⟩,⟨"beers"⟩⟨5608⟩⟨8020⟩
⟨"Before"⟩⟨2201⟩⟨12915⟩,⟨"BEFORE"⟩⟨16484⟩⟨12915⟩
⟨"beggars"⟩⟨14979⟩⟨13991⟩,⟨"begging"⟩⟨17311⟩⟨1715⟩
⟨"begins"⟩⟨3931⟩⟨3798⟩,⟨"behalf"⟩⟨12749⟩⟨9661⟩
⟨"behaviour"⟩⟨877⟩⟨5387⟩,⟨"Behind"⟩⟨5413⟩⟨4296⟩
⟨"being"⟩⟨3210⟩⟨16612⟩,⟨"beleive"⟩⟨14731⟩⟨16324⟩
⟨"Belgium"⟩⟨16342⟩⟨18229⟩,⟨"believe"⟩⟨2843⟩⟨12754⟩

⟨"belive"⟩⟨11258⟩⟨14397⟩,⟨"Bell"⟩⟨5870⟩⟨8030⟩
⟨"Bellinter"⟩⟨7563⟩⟨7925⟩,⟨"bellmen"⟩⟨18176⟩⟨4518⟩
⟨"Belmullet"⟩⟨9482⟩⟨13695⟩,⟨"belonged"⟩⟨5821⟩⟨1909⟩
⟨"beloved"⟩⟨15479⟩⟨8487⟩,⟨"Below"⟩⟨17292⟩⟨9734⟩
⟨"Ben"⟩⟨4089⟩⟨9303⟩,⟨"Benbulben"⟩⟨17457⟩⟨18343⟩
⟨"bend"⟩⟨13707⟩⟨15626⟩,⟨"bends"⟩⟨15323⟩⟨16817⟩
⟨"beneficial"⟩⟨17361⟩⟨15009⟩,⟨"benefited"⟩⟨18505⟩⟨13247⟩
⟨"Benners"⟩⟨8763⟩⟨4038⟩,⟨"bent"⟩⟨3482⟩⟨2069⟩
⟨"Berlin"⟩⟨10212⟩⟨10008⟩,⟨"Bernard"⟩⟨16953⟩⟨7773⟩
⟨"Bert"⟩⟨11025⟩⟨14792⟩,⟨"beside"⟩⟨600⟩⟨14297⟩
⟨"best"⟩⟨50⟩⟨7793⟩,⟨"BEST"⟩⟨3411⟩⟨7793⟩
⟨"Better"⟩⟨8882⟩⟨8171⟩,⟨"bettered"⟩⟨11381⟩⟨5560⟩
⟨"Between"⟩⟨8931⟩⟨6904⟩,⟨"beverage"⟩⟨10821⟩⟨9529⟩
⟨"Beware"⟩⟨10729⟩⟨17058⟩,⟨"bewleys"⟩⟨4285⟩⟨13045⟩
⟨"bf"⟩⟨5884⟩⟨7659⟩,⟨"Bianconi"⟩⟨15628⟩⟨13472⟩
⟨"bid"⟩⟨14882⟩⟨17010⟩,⟨"big"⟩⟨1257⟩⟨16163⟩
⟨"biggest"⟩⟨4703⟩⟨18076⟩,⟨"bike"⟩⟨2479⟩⟨8813⟩
⟨"Bill"⟩⟨14822⟩⟨17911⟩,⟨"billed"⟩⟨5713⟩⟨3738⟩
⟨"bin"⟩⟨512⟩⟨3191⟩,⟨"bins"⟩⟨755⟩⟨3827⟩
⟨"Birmingham"⟩⟨14360⟩⟨17304⟩,⟨"birth"⟩⟨16529⟩⟨17730⟩
⟨"biscuit"⟩⟨1383⟩⟨4879⟩,⟨"bisto"⟩⟨18260⟩⟨334⟩
⟨"Bit"⟩⟨2886⟩⟨10842⟩,⟨"bite"⟩⟨11277⟩⟨17187⟩
⟨"bitter"⟩⟨2571⟩⟨9656⟩,⟨"biz"⟩⟨10356⟩⟨10120⟩
⟨"bizzare"⟩⟨12504⟩⟨16537⟩,⟨"Black"⟩⟨5300⟩⟨2774⟩
⟨"Blacks"⟩⟨17126⟩⟨16054⟩,⟨"blah"⟩⟨14682⟩⟨13319⟩
⟨"blaming"⟩⟨17240⟩⟨9947⟩,⟨"bland"⟩⟨4602⟩⟨4695⟩
⟨"blankly"⟩⟨16967⟩⟨11221⟩,⟨"Blarney"⟩⟨469⟩⟨15941⟩
⟨"blasting"⟩⟨4250⟩⟨5287⟩,⟨"blatently"⟩⟨18337⟩⟨826⟩
⟨"Bleeding"⟩⟨7827⟩⟨18301⟩,⟨"blend"⟩⟨9729⟩⟨13947⟩
⟨"bless"⟩⟨16533⟩⟨17734⟩,⟨"blessing"⟩⟨6835⟩⟨3717⟩
⟨"blinds"⟩⟨2874⟩⟨3451⟩,⟨"blip"⟩⟨13280⟩⟨11522⟩

⟨"blissfully"⟩⟨5658⟩⟨4507⟩,⟨"blocked"⟩⟨2785⟩⟨2901⟩
⟨"blokes"⟩⟨5452⟩⟨13800⟩,⟨"blonde"⟩⟨11157⟩⟨10518⟩
⟨"bloom"⟩⟨10575⟩⟨15341⟩,⟨"blooming"⟩⟨15409⟩⟨9521⟩
⟨"blowing"⟩⟨2245⟩⟨713⟩,⟨"blows"⟩⟨13829⟩⟨14343⟩
⟨"blueberry"⟩⟨11417⟩⟨14252⟩,⟨"Blues"⟩⟨15534⟩⟨15512⟩
⟨"bnb"⟩⟨17155⟩⟨18467⟩,⟨"board"⟩⟨8161⟩⟨8040⟩
⟨"boardwalk"⟩⟨12860⟩⟨15829⟩,⟨"boasted"⟩⟨11259⟩⟨16136⟩
⟨"boating"⟩⟨12681⟩⟨10421⟩,⟨"Bob"⟩⟨10892⟩⟨6515⟩
⟨"bodied"⟩⟨17807⟩⟨17930⟩,⟨"bodily"⟩⟨18275⟩⟨249⟩
⟨"bog"⟩⟨13141⟩⟨18029⟩,⟨"bog-standard"⟩⟨16189⟩⟨12623⟩
⟨"boiler"⟩⟨4333⟩⟨2872⟩,⟨"boiling"⟩⟨2400⟩⟨1592⟩
⟨"bolognese"⟩⟨7686⟩⟨8819⟩,⟨"bolted"⟩⟨14036⟩⟨17364⟩
⟨"bones"⟩⟨11908⟩⟨8049⟩,⟨"Bono's"⟩⟨9098⟩⟨14244⟩
⟨"BOOK"⟩⟨16387⟩⟨12240⟩,⟨"Booked"⟩⟨1606⟩⟨6652⟩
⟨"booking"⟩⟨4319⟩⟨9924⟩,⟨"booklet"⟩⟨5099⟩⟨4324⟩
⟨"booster"⟩⟨7435⟩⟨4201⟩,⟨"booth"⟩⟨2893⟩⟨2425⟩
⟨"boozy"⟩⟨10804⟩⟨17036⟩,⟨"border"⟩⟨3053⟩⟨8758⟩
⟨"borders"⟩⟨16165⟩⟨18241⟩,⟨"bored"⟩⟨2539⟩⟨4342⟩
⟨"borrow"⟩⟨11076⟩⟨15122⟩,⟨"Bose"⟩⟨6807⟩⟨16873⟩
⟨"bot"⟩⟨17346⟩⟨14985⟩,⟨"both"⟩⟨470⟩⟨18026⟩
⟨"bother"⟩⟨5241⟩⟨11353⟩,⟨"bothering"⟩⟨11826⟩⟨17263⟩
⟨"bottled"⟩⟨5921⟩⟨17794⟩,⟨"bottles"⟩⟨1071⟩⟨5784⟩
⟨"bouche"⟩⟨10160⟩⟨6176⟩,⟨"bounce"⟩⟨13819⟩⟨14322⟩
⟨"bouncing"⟩⟨17195⟩⟨18507⟩,⟨"bound"⟩⟨13939⟩⟨16298⟩
⟨"bouquets"⟩⟨15225⟩⟨16704⟩,⟨"boutique"⟩⟨1083⟩⟨13559⟩
⟨"boutiques"⟩⟨7583⟩⟨12804⟩,⟨"bowl"⟩⟨2990⟩⟨363⟩
⟨"box"⟩⟨6058⟩⟨2651⟩,⟨"boxes"⟩⟨11214⟩⟨13580⟩
⟨"boy"⟩⟨6694⟩⟨13302⟩,⟨"Boyfriend"⟩⟨7949⟩⟨9156⟩
⟨"Boyle"⟩⟨17549⟩⟨18417⟩,⟨"boyne"⟩⟨17454⟩⟨18340⟩
⟨"bracket"⟩⟨14526⟩⟨17822⟩,⟨"brag"⟩⟨18413⟩⟨2924⟩
⟨"brand"⟩⟨6281⟩⟨11142⟩,⟨"branded"⟩⟨11896⟩⟨5519⟩

⟨"brandy"⟩⟨1908⟩⟨2224⟩,⟨"brass"⟩⟨13753⟩⟨16946⟩
⟨"braved"⟩⟨17154⟩⟨18466⟩,⟨"bray"⟩⟨16644⟩⟨17661⟩
⟨"Bread"⟩⟨6224⟩⟨10934⟩,⟨"breads"⟩⟨189⟩⟨1009⟩
⟨"break"⟩⟨353⟩⟨8032⟩,⟨"break'"⟩⟨17544⟩⟨18414⟩
⟨"breakdown"⟩⟨13123⟩⟨11703⟩,⟨"breakfast"⟩⟨1735⟩⟨15558⟩
⟨"breakfast'"⟩⟨14028⟩⟨15598⟩,⟨"breakfast&quot"⟩⟨7914⟩⟨17595⟩
⟨"Breakfasts"⟩⟨1048⟩⟨6860⟩,⟨"breakfest"⟩⟨17852⟩⟨3350⟩
⟨"breaks"⟩⟨3197⟩⟨13514⟩,⟨"breaksfast"⟩⟨11660⟩⟨14052⟩
⟨"breath-taking"⟩⟨8665⟩⟨13132⟩,⟨"breathing"⟩⟨14781⟩⟨12464⟩
⟨"breckfast"⟩⟨8902⟩⟨3669⟩,⟨"breeze"⟩⟨4481⟩⟨10591⟩
⟨"Brekfast"⟩⟨15503⟩⟨15636⟩,⟨"brekky"⟩⟨9079⟩⟨14205⟩
⟨"brewed"⟩⟨15133⟩⟨17818⟩,⟨"brewery"⟩⟨8885⟩⟨5223⟩
⟨"brick"⟩⟨3629⟩⟨8232⟩,⟨"Brid"⟩⟨7301⟩⟨12996⟩
⟨"Bride"⟩⟨7791⟩⟨11291⟩,⟨"bridesmaid"⟩⟨15969⟩⟨7439⟩
⟨"bridges"⟩⟨14690⟩⟨15575⟩,⟨"Bridie"⟩⟨10359⟩⟨10124⟩
⟨"brigade"⟩⟨14121⟩⟨17583⟩,⟨"Bright"⟩⟨9355⟩⟨11207⟩
⟨"briliant"⟩⟨5509⟩⟨7189⟩,⟨"Brill"⟩⟨12687⟩⟨10432⟩
⟨"brilliance"⟩⟨10163⟩⟨6182⟩,⟨"Brilliant"⟩⟨927⟩⟨10398⟩
⟨"Bring"⟩⟨2530⟩⟨11686⟩,⟨"bringing"⟩⟨8911⟩⟨16900⟩
⟨"Bristol"⟩⟨6118⟩⟨2598⟩,⟨"British"⟩⟨3319⟩⟨5687⟩
⟨"broadband"⟩⟨2333⟩⟨15632⟩,⟨"Broadhaven"⟩⟨13492⟩⟨9535⟩
⟨"brochures"⟩⟨11366⟩⟨14066⟩,⟨"brogue"⟩⟨17465⟩⟨18351⟩
⟨"Bronagh"⟩⟨15322⟩⟨16816⟩,⟨"brook"⟩⟨8114⟩⟨13618⟩
⟨"Brooklodge"⟩⟨9250⟩⟨15213⟩,⟨"Brooks"⟩⟨78⟩⟨14681⟩
⟨"brother"⟩⟨3014⟩⟨18494⟩,⟨"brother-in-law"⟩⟨6246⟩⟨6112⟩
⟨"brown"⟩⟨1899⟩⟨1336⟩,⟨"Brown's"⟩⟨3904⟩⟨5242⟩
⟨"brownies"⟩⟨4088⟩⟨3079⟩,⟨"browns"⟩⟨10503⟩⟨11975⟩
⟨"Bruce"⟩⟨14470⟩⟨16385⟩,⟨"brule"⟩⟨17142⟩⟨18454⟩
⟨"brushed"⟩⟨13205⟩⟨8081⟩,⟨"brushing"⟩⟨4709⟩⟨12168⟩
⟨"Bs"⟩⟨5887⟩⟨11940⟩,⟨"BTW"⟩⟨6601⟩⟨17023⟩
⟨"bubbles"⟩⟨5742⟩⟨10996⟩,⟨"bubbly"⟩⟨4949⟩⟨2638⟩

⟨"Buckley"⟩⟨6210⟩⟨12341⟩,⟨"Buckleys"⟩⟨8123⟩⟨13632⟩
⟨"buddy"⟩⟨7133⟩⟨5899⟩,⟨"budget"⟩⟨6952⟩⟨13839⟩
⟨"buffet"⟩⟨1855⟩⟨5206⟩,⟨"buffet-style"⟩⟨13014⟩⟨12817⟩
⟨"bug"⟩⟨2057⟩⟨2452⟩,⟨"bugged"⟩⟨13037⟩⟨17078⟩
⟨"buiding"⟩⟨17801⟩⟨17924⟩,⟨"build"⟩⟨11563⟩⟨15455⟩
⟨"building"⟩⟨4385⟩⟨17041⟩,⟨"buildings"⟩⟨1161⟩⟨8071⟩
⟨"bulb"⟩⟨1723⟩⟨1480⟩,⟨"bulk"⟩⟨15544⟩⟨9618⟩
⟨"bullet"⟩⟨17096⟩⟨15992⟩,⟨"bum"⟩⟨18125⟩⟨1163⟩
⟨"bumper"⟩⟨15310⟩⟨16803⟩,⟨"bumps"⟩⟨12960⟩⟨17231⟩
⟨"bunch"⟩⟨1698⟩⟨7488⟩,⟨"Buncrana"⟩⟨4076⟩⟨16591⟩
⟨"Bundoran"⟩⟨12130⟩⟨16177⟩,⟨"bunk"⟩⟨2849⟩⟨1674⟩
⟨"buns"⟩⟨10668⟩⟨9676⟩,⟨"bureau"⟩⟨16266⟩⟨17318⟩
⟨"Burke"⟩⟨10722⟩⟨15431⟩,⟨"Burlington"⟩⟨7894⟩⟨16161⟩
⟨"burns"⟩⟨13536⟩⟨740⟩,⟨"Burren"⟩⟨1288⟩⟨6640⟩
⟨"bus"⟩⟨1496⟩⟨18271⟩,⟨"BUS"⟩⟨17385⟩⟨18271⟩
⟨"Bush"⟩⟨6984⟩⟨3471⟩,⟨"busier"⟩⟨3147⟩⟨8129⟩
⟨"Business"⟩⟨6737⟩⟨5541⟩,⟨"businessman"⟩⟨18172⟩⟨3390⟩
⟨"busses"⟩⟨6228⟩⟨7630⟩,⟨"busstop"⟩⟨17817⟩⟨17940⟩
⟨"bustling"⟩⟨5053⟩⟨4852⟩,⟨"busy"⟩⟨2661⟩⟨10169⟩
⟨"But"⟩⟨4589⟩⟨8455⟩,⟨"Butler"⟩⟨3814⟩⟨6143⟩
⟨"Butlins"⟩⟨4316⟩⟨8454⟩,⟨"butt"⟩⟨16566⟩⟨7569⟩
⟨"Buttery"⟩⟨8960⟩⟨10994⟩,⟨"buttons"⟩⟨10287⟩⟨6039⟩
⟨"buying"⟩⟨8707⟩⟨14478⟩,⟨"buzzed"⟩⟨15657⟩⟨1850⟩
⟨"BW"⟩⟨12764⟩⟨10489⟩,⟨"By"⟩⟨6267⟩⟨8446⟩
⟨"Byrne"⟩⟨12321⟩⟨10311⟩,⟨"C"⟩⟨5302⟩⟨12362⟩
⟨"cab"⟩⟨2685⟩⟨9561⟩,⟨"cabaret"⟩⟨6303⟩⟨6764⟩
⟨"cabin"⟩⟨7175⟩⟨11476⟩,⟨"cabinets"⟩⟨12488⟩⟨15209⟩
⟨"Cabs"⟩⟨15779⟩⟨15993⟩,⟨"Caesar"⟩⟨4337⟩⟨10619⟩
⟨"Cafe"⟩⟨3303⟩⟨7325⟩,⟨"cafe's"⟩⟨7653⟩⟨3671⟩
⟨"cage"⟩⟨12695⟩⟨10442⟩,⟨"Cahernane"⟩⟨1995⟩⟨1303⟩
⟨"caked"⟩⟨17016⟩⟨90⟩,⟨"caliber"⟩⟨11503⟩⟨12807⟩

⟨"Call"⟩⟨14795⟩⟨13753⟩,⟨"Called"⟩⟨5370⟩⟨12260⟩
⟨"calm"⟩⟨2188⟩⟨6164⟩,⟨"calming"⟩⟨4952⟩⟨1601⟩
⟨"Camden"⟩⟨1616⟩⟨18185⟩,⟨"came"⟩⟨4008⟩⟨3225⟩
⟨"Cameron"⟩⟨3928⟩⟨10683⟩,⟨"Campbell"⟩⟨12686⟩⟨10431⟩
⟨"campus"⟩⟨6059⟩⟨12666⟩,⟨"Can"⟩⟨3088⟩⟨5331⟩
⟨"can't"⟩⟨445⟩⟨4624⟩,⟨"Canada"⟩⟨8172⟩⟨8435⟩
⟨"canapes"⟩⟨8978⟩⟨12999⟩,⟨"canceled"⟩⟨7363⟩⟨8447⟩
⟨"cancelled"⟩⟨439⟩⟨714⟩,⟨"cancer"⟩⟨17584⟩⟨13547⟩
⟨"candlelit"⟩⟨12934⟩⟨15038⟩,⟨"candy"⟩⟨14174⟩⟨9368⟩
⟨"CANNOT"⟩⟨9214⟩⟨6073⟩,⟨"cans"⟩⟨14453⟩⟨7187⟩
⟨"cap"⟩⟨5859⟩⟨5435⟩,⟨"capable"⟩⟨8491⟩⟨5851⟩
⟨"Capital"⟩⟨4511⟩⟨8506⟩,⟨"capitals"⟩⟨8283⟩⟨14543⟩
⟨"caps"⟩⟨1305⟩⟨1992⟩,⟨"captain"⟩⟨15927⟩⟨16775⟩
⟨"captured"⟩⟨17985⟩⟨18043⟩,⟨"Car"⟩⟨1867⟩⟨4856⟩
⟨"caravan"⟩⟨16253⟩⟨3974⟩,⟨"card"⟩⟨7059⟩⟨437⟩
⟨"cardio"⟩⟨6176⟩⟨7685⟩,⟨"care"⟩⟨1478⟩⟨7397⟩
⟨"careful"⟩⟨11117⟩⟨7827⟩,⟨"careless"⟩⟨4478⟩⟨7064⟩
⟨"Carlingford"⟩⟨8900⟩⟨4770⟩,⟨"Carlow"⟩⟨12098⟩⟨16950⟩
⟨"carlton"⟩⟨3871⟩⟨16205⟩,⟨"Carmen"⟩⟨15189⟩⟨16642⟩
⟨"Carol"⟩⟨6518⟩⟨11286⟩,⟨"carpark"⟩⟨5117⟩⟨17721⟩
⟨"carpet"⟩⟨1158⟩⟨8398⟩,⟨"carpeted"⟩⟨10879⟩⟨15614⟩
⟨"carriage"⟩⟨5957⟩⟨14972⟩,⟨"carriages"⟩⟨12812⟩⟨15779⟩
⟨"Carrickdale"⟩⟨12023⟩⟨9487⟩,⟨"carrier"⟩⟨16948⟩⟨3541⟩
⟨"carrot"⟩⟨4577⟩⟨3910⟩,⟨"carry"⟩⟨4459⟩⟨5009⟩
⟨"carte"⟩⟨3138⟩⟨7194⟩,⟨"carte'"⟩⟨18536⟩⟨6074⟩
⟨"carts"⟩⟨9684⟩⟨11602⟩,⟨"carvery"⟩⟨4902⟩⟨13996⟩
⟨"cases"⟩⟨5064⟩⟨8667⟩,⟨"Cashel"⟩⟨3041⟩⟨881⟩
⟨"Cassidy"⟩⟨15784⟩⟨16003⟩,⟨"Cassidys"⟩⟨2957⟩⟨15956⟩
⟨"Castle"⟩⟨225⟩⟨5982⟩,⟨"Castle&quot"⟩⟨17129⟩⟨16061⟩
⟨"castlecourt"⟩⟨6713⟩⟨5845⟩,⟨"Castlemartyr"⟩⟨12200⟩⟨7942⟩
⟨"Castlewood"⟩⟨1138⟩⟨8450⟩,⟨"Casual"⟩⟨12615⟩⟨16609⟩

⟨"catalogue"⟩⟨6142⟩⟨369⟩,⟨"Catch"⟩⟨16019⟩⟨11756⟩
⟨"cater"⟩⟨7381⟩⟨14698⟩,⟨"catering"⟩⟨3938⟩⟨12882⟩
⟨"cathedral"⟩⟨2136⟩⟨2299⟩,⟨"catherine"⟩⟨17823⟩⟨17946⟩
⟨"caught"⟩⟨5247⟩⟨16555⟩,⟨"cauliflower"⟩⟨11000⟩⟨14752⟩
⟨"causes"⟩⟨16964⟩⟨7791⟩,⟨"Causeway"⟩⟨15245⟩⟨16728⟩
⟨"Cavan"⟩⟨1726⟩⟨14749⟩,⟨"Cave"⟩⟨15241⟩⟨17200⟩
⟨"cavery"⟩⟨17572⟩⟨13519⟩,⟨"caves"⟩⟨15804⟩⟨16045⟩
⟨"cd"⟩⟨4620⟩⟨3441⟩,⟨"CD's"⟩⟨10058⟩⟨10347⟩
⟨"ceased"⟩⟨17684⟩⟨4380⟩,⟨"Cecilia"⟩⟨2609⟩⟨10440⟩
⟨"ceiling"⟩⟨6801⟩⟨460⟩,⟨"celebrate"⟩⟨1116⟩⟨1981⟩
⟨"celebrations"⟩⟨11635⟩⟨12749⟩,⟨"celebrity"⟩⟨11468⟩⟨14336⟩
⟨"Cellar"⟩⟨2608⟩⟨11878⟩,⟨"Celtic"⟩⟨10936⟩⟨14983⟩
⟨"cemetery"⟩⟨7093⟩⟨3971⟩,⟨"cental"⟩⟨8484⟩⟨4252⟩
⟨"centers"⟩⟨13950⟩⟨16154⟩,⟨"central"⟩⟨1101⟩⟨10533⟩
⟨"centrally-located"⟩⟨16155⟩⟨14946⟩,⟨"Centre"⟩⟨1406⟩⟨6084⟩
⟨"centres"⟩⟨3302⟩⟨7801⟩,⟨"century"⟩⟨11689⟩⟨17038⟩
⟨"cerals"⟩⟨5487⟩⟨3369⟩,⟨"cereal"⟩⟨6898⟩⟨16255⟩
⟨"ceremony"⟩⟨5725⟩⟨4593⟩,⟨"cerials"⟩⟨15084⟩⟨7702⟩
⟨"certainly"⟩⟨1165⟩⟨6616⟩,⟨"certaintly"⟩⟨17758⟩⟨1664⟩
⟨"chains"⟩⟨12000⟩⟨16447⟩,⟨"chairs"⟩⟨6619⟩⟨7308⟩
⟨"chalets"⟩⟨7456⟩⟨4238⟩,⟨"challenged"⟩⟨2670⟩⟨1380⟩
⟨"chambermaids"⟩⟨10759⟩⟨11937⟩,⟨"champagne"⟩⟨147⟩⟨11550⟩
⟨"championship"⟩⟨5668⟩⟨7198⟩,⟨"chance"⟩⟨815⟩⟨15586⟩
⟨"chandeliers"⟩⟨7984⟩⟨13975⟩,⟨"changed"⟩⟨3699⟩⟨18034⟩
⟨"Changing"⟩⟨4939⟩⟨15652⟩,⟨"Channel"⟩⟨14274⟩⟨12287⟩
⟨"chaotic"⟩⟨4665⟩⟨5494⟩,⟨"chapel"⟩⟨15145⟩⟨12093⟩
⟨"character"⟩⟨1846⟩⟨6338⟩,⟨"characteristic"⟩⟨12500⟩⟨16532⟩
⟨"charge"⟩⟨2932⟩⟨1768⟩,⟨"chargeable"⟩⟨8357⟩⟨10791⟩
⟨"chargers"⟩⟨7500⟩⟨8783⟩,⟨"charging"⟩⟨1014⟩⟨226⟩
⟨"Charleville"⟩⟨3299⟩⟨2617⟩,⟨"charm"⟩⟨299⟩⟨16116⟩
⟨"charming"⟩⟨71⟩⟨11670⟩,⟨"charmingly"⟩⟨16528⟩⟨17729⟩

⟨"chase"⟩⟨3192⟩⟨9082⟩,⟨"chasing"⟩⟨2712⟩⟨5978⟩
⟨"chatted"⟩⟨12124⟩⟨12425⟩,⟨"chatting"⟩⟨2811⟩⟨8633⟩
⟨"CHEAP"⟩⟨16812⟩⟨12962⟩,⟨"cheaper"⟩⟨793⟩⟨17828⟩
⟨"cheaply"⟩⟨2087⟩⟨9097⟩,⟨"cheapo"⟩⟨14806⟩⟨1215⟩
⟨"Check"⟩⟨3415⟩⟨16032⟩,⟨"check-"⟩⟨16242⟩⟨15970⟩
⟨"check-out"⟩⟨5577⟩⟨8470⟩,⟨"Checked"⟩⟨2966⟩⟨5940⟩
⟨"checkin"⟩⟨6537⟩⟨14179⟩,⟨"Checking"⟩⟨8716⟩⟨13176⟩
⟨"Checkout"⟩⟨12447⟩⟨16140⟩,⟨"checks"⟩⟨5967⟩⟨10570⟩
⟨"cheer"⟩⟨8762⟩⟨8448⟩,⟨"cheerful"⟩⟨2854⟩⟨7177⟩
⟨"Cheers"⟩⟨1554⟩⟨12787⟩,⟨"cheery"⟩⟨7485⟩⟨8932⟩
⟨"cheesecake"⟩⟨14504⟩⟨17256⟩,⟨"cheesy"⟩⟨4271⟩⟨11055⟩
⟨"chef&quot"⟩⟨16695⟩⟨6901⟩,⟨"Chefs"⟩⟨15922⟩⟨16117⟩
⟨"chemist"⟩⟨9368⟩⟨11231⟩,⟨"cheques"⟩⟨18425⟩⟨5941⟩
⟨"chestnut"⟩⟨8468⟩⟨14678⟩,⟨"chewing"⟩⟨14519⟩⟨206⟩
⟨"Chicago"⟩⟨5380⟩⟨10566⟩,⟨"chicken"⟩⟨8288⟩⟨9690⟩
⟨"chief"⟩⟨16395⟩⟨16648⟩,⟨"child"⟩⟨5401⟩⟨18177⟩
⟨"childern"⟩⟨10894⟩⟨8246⟩,⟨"Children"⟩⟨6377⟩⟨10852⟩
⟨"Children's"⟩⟨17364⟩⟨15015⟩,⟨"Childrens"⟩⟨8631⟩⟨11150⟩
⟨"chilled"⟩⟨597⟩⟨5374⟩,⟨"chilling"⟩⟨3515⟩⟨842⟩
⟨"china"⟩⟨5677⟩⟨8916⟩,⟨"Chinese"⟩⟨6964⟩⟨14131⟩
⟨"chip"⟩⟨3127⟩⟨9052⟩,⟨"chipper"⟩⟨13621⟩⟨9138⟩
⟨"chirpy"⟩⟨10554⟩⟨15317⟩,⟨"chlorinated"⟩⟨17656⟩⟨17875⟩
⟨"choclate"⟩⟨14837⟩⟨17309⟩,⟨"chocolate"⟩⟨139⟩⟨17469⟩
⟨"chocs"⟩⟨2602⟩⟨1167⟩,⟨"Choice"⟩⟨7620⟩⟨7295⟩
⟨"choked"⟩⟨4873⟩⟨1495⟩,⟨"Choose"⟩⟨5320⟩⟨5440⟩
⟨"chopped"⟩⟨13586⟩⟨5740⟩,⟨"chore"⟩⟨10665⟩⟨4367⟩
⟨"chosing"⟩⟨12885⟩⟨15856⟩,⟨"Chowder"⟩⟨17984⟩⟨18042⟩
⟨"ChristChurch"⟩⟨8777⟩⟨9369⟩,⟨"christening"⟩⟨14217⟩⟨12765⟩
⟨"Christine"⟩⟨3125⟩⟨1642⟩,⟨"Christmas"⟩⟨4468⟩⟨8128⟩
⟨"chucked"⟩⟨4283⟩⟨9902⟩,⟨"chunk"⟩⟨8705⟩⟨7550⟩
⟨"church"⟩⟨8894⟩⟨12626⟩,⟨"Churchtown"⟩⟨10568⟩⟨15332⟩

⟨"CIE"⟩⟨4683⟩⟨10745⟩,⟨"cigar"⟩⟨16412⟩⟨16686⟩
⟨"cigarrette"⟩⟨17044⟩⟨2844⟩,⟨"cinder"⟩⟨8461⟩⟨8964⟩
⟨"circa"⟩⟨1939⟩⟨7974⟩,⟨"circled"⟩⟨8497⟩⟨4268⟩
⟨"circulate"⟩⟨17846⟩⟨1689⟩,⟨"circulation"⟩⟨14035⟩⟨17363⟩
⟨"Cirk"⟩⟨10033⟩⟨5797⟩,⟨"Citi"⟩⟨9872⟩⟨13418⟩
⟨"Citron"⟩⟨7085⟩⟨10834⟩,⟨"city"⟩⟨1176⟩⟨6553⟩
⟨"Citywest"⟩⟨14052⟩⟨13129⟩,⟨"civilised"⟩⟨14041⟩⟨9283⟩
⟨"claiming"⟩⟨2320⟩⟨6482⟩,⟨"Claire"⟩⟨6635⟩⟨4321⟩
⟨"Clane"⟩⟨7237⟩⟨10677⟩,⟨"clanking"⟩⟨17321⟩⟨3559⟩
⟨"clare"⟩⟨11731⟩⟨11511⟩,⟨"Claremorris"⟩⟨12706⟩⟨10458⟩
⟨"clarion"⟩⟨12577⟩⟨17464⟩,⟨"clashing"⟩⟨18491⟩⟨13228⟩
⟨"classed"⟩⟨12972⟩⟨13018⟩,⟨"classic"⟩⟨3856⟩⟨9978⟩
⟨"classiest"⟩⟨10268⟩⟨10088⟩,⟨"classified"⟩⟨8239⟩⟨9305⟩
⟨"claustrophobic"⟩⟨14264⟩⟨18206⟩,⟨"claws"⟩⟨16071⟩⟨14915⟩
⟨"clean"⟩⟨1816⟩⟨7477⟩,⟨"clean-"⟩⟨15437⟩⟨9575⟩
⟨"cleaners"⟩⟨6731⟩⟨5137⟩,⟨"cleaniness"⟩⟨13151⟩⟨14617⟩
⟨"Cleanliness"⟩⟨13777⟩⟨17310⟩,⟨"clear"⟩⟨781⟩⟨5214⟩
⟨"clearly"⟩⟨1625⟩⟨7866⟩,⟨"Clerans"⟩⟨3428⟩⟨1482⟩
⟨"cleverly"⟩⟨10123⟩⟨14230⟩,⟨"clew"⟩⟨13554⟩⟨14861⟩
⟨"clientele"⟩⟨11121⟩⟨11389⟩,⟨"clients"⟩⟨6761⟩⟨14462⟩
⟨"Cliff"⟩⟨8725⟩⟨8079⟩,⟨"cliffs"⟩⟨4395⟩⟨7364⟩
⟨"climbed"⟩⟨2288⟩⟨4966⟩,⟨"clincher"⟩⟨18315⟩⟨779⟩
⟨"clip"⟩⟨17605⟩⟨17826⟩,⟨"clock"⟩⟨6097⟩⟨7865⟩
⟨"clogged"⟩⟨16300⟩⟨1492⟩,⟨"Clonakilty"⟩⟨9337⟩⟨15429⟩
⟨"clonmel"⟩⟨7029⟩⟨7983⟩,⟨"Clontarf"⟩⟨3290⟩⟨18048⟩
⟨"close-by"⟩⟨16017⟩⟨11755⟩,⟨"closed"⟩⟨6438⟩⟨1039⟩
⟨"closers"⟩⟨18459⟩⟨6004⟩,⟨"closest"⟩⟨9263⟩⟨15608⟩
⟨"closure"⟩⟨3788⟩⟨1340⟩,⟨"clothes"⟩⟨90⟩⟨4349⟩
⟨"clouds"⟩⟨5662⟩⟨10150⟩,⟨"cloudy"⟩⟨10329⟩⟨7473⟩
⟨"clubbing"⟩⟨14445⟩⟨11399⟩,⟨"Clubhouse"⟩⟨6915⟩⟨8658⟩
⟨"clueless"⟩⟨2047⟩⟨4613⟩,⟨"cluttered"⟩⟨11267⟩⟨17027⟩

⟨"co"⟩⟨12095⟩⟨10560⟩,⟨"co-ordinator"⟩⟨11851⟩⟨16307⟩
⟨"coaching"⟩⟨10139⟩⟨6137⟩,⟨"coarse"⟩⟨6099⟩⟨12894⟩
⟨"coastline"⟩⟨4540⟩⟨2573⟩,⟨"coated"⟩⟨4826⟩⟨11581⟩
⟨"Cobblestone"⟩⟨6314⟩⟨10503⟩,⟨"Cobh"⟩⟨7536⟩⟨11374⟩
⟨"Cocktail"⟩⟨10045⟩⟨13461⟩,⟨"Cocktails"⟩⟨6322⟩⟨6784⟩
⟨"cod"⟩⟨12582⟩⟨15563⟩,⟨"coded"⟩⟨13422⟩⟨16333⟩
⟨"coffe"⟩⟨12110⟩⟨16571⟩,⟨"coffee"⟩⟨1900⟩⟨9400⟩
⟨"Coffees"⟩⟨8298⟩⟨12282⟩,⟨"coffin"⟩⟨18112⟩⟨10868⟩
⟨"coincidence"⟩⟨5448⟩⟨13794⟩,⟨"coke"⟩⟨9606⟩⟨14713⟩
⟨"cold"⟩⟨6654⟩⟨3987⟩,⟨"cold&quot"⟩⟨17793⟩⟨17916⟩
⟨"coldness"⟩⟨5763⟩⟨3575⟩,⟨"collapse"⟩⟨12041⟩⟨7501⟩
⟨"colleagues"⟩⟨7234⟩⟨13161⟩,⟨"collected"⟩⟨8094⟩⟨11876⟩
⟨"College"⟩⟨3582⟩⟨17275⟩,⟨"collegue"⟩⟨10379⟩⟨16230⟩
⟨"color"⟩⟨13050⟩⟨16959⟩,⟨"colorful"⟩⟨9386⟩⟨11260⟩
⟨"coloured"⟩⟨10733⟩⟨11458⟩,⟨"colouring"⟩⟨10927⟩⟨16976⟩
⟨"combinations"⟩⟨5651⟩⟨4489⟩,⟨"combined"⟩⟨8206⟩⟨9674⟩
⟨"combo"⟩⟨13742⟩⟨17437⟩,⟨"Come"⟩⟨13695⟩⟨11593⟩
⟨"comfiest"⟩⟨4571⟩⟨11919⟩,⟨"comforatable"⟩⟨10620⟩⟨15389⟩
⟨"comfortable"⟩⟨318⟩⟨6897⟩,⟨"comfortably"⟩⟨5802⟩⟨8548⟩
⟨"comforts"⟩⟨3522⟩⟨3378⟩,⟨"comftable"⟩⟨10035⟩⟨5800⟩
⟨"coming"⟩⟨3321⟩⟨12153⟩,⟨"comings"⟩⟨16530⟩⟨17731⟩
⟨"commenced"⟩⟨7434⟩⟨4195⟩,⟨"commend"⟩⟨8155⟩⟨9038⟩
⟨"commentary"⟩⟨6839⟩⟨7096⟩,⟨"commenting"⟩⟨10765⟩⟨16167⟩
⟨"commission"⟩⟨14333⟩⟨17290⟩,⟨"commitments"⟩⟨11854⟩⟨8009⟩
⟨"Common"⟩⟨14073⟩⟨15140⟩,⟨"communal"⟩⟨3595⟩⟨9405⟩
⟨"communication"⟩⟨1706⟩⟨7112⟩,⟨"communion"⟩⟨16469⟩⟨10641⟩
⟨"commuting"⟩⟨4827⟩⟨11582⟩,⟨"comp"⟩⟨14437⟩⟨17560⟩
⟨"companies"⟩⟨10383⟩⟨14169⟩,⟨"companions"⟩⟨9855⟩⟨6820⟩
⟨"comparable"⟩⟨9633⟩⟨16127⟩,⟨"compare"⟩⟨2926⟩⟨3314⟩
⟨"comparing"⟩⟨13716⟩⟨16933⟩,⟨"comparison"⟩⟨7993⟩⟨10767⟩
⟨"compensated"⟩⟨12359⟩⟨14685⟩,⟨"compensation"⟩⟨151⟩⟨1251⟩

⟨"competetive"⟩⟨8279⟩⟨14536⟩,⟨"competition"⟩⟨5705⟩⟨7797⟩
⟨"competitors"⟩⟨11416⟩⟨14251⟩,⟨"complain"⟩⟨6976⟩⟨291⟩
⟨"complaining"⟩⟨2484⟩⟨3263⟩,⟨"complaint"⟩⟨4495⟩⟨5398⟩
⟨"complementary"⟩⟨5925⟩⟨14815⟩,⟨"complemented"⟩⟨4535⟩⟨2123⟩
⟨"completed"⟩⟨5319⟩⟨13739⟩,⟨"Completely"⟩⟨9041⟩⟨11171⟩
⟨"completly"⟩⟨1388⟩⟨498⟩,⟨"compliant"⟩⟨16958⟩⟨7781⟩
⟨"compliment"⟩⟨4929⟩⟨870⟩,⟨"Complimentary"⟩⟨1031⟩⟨5436⟩
⟨"Compliments"⟩⟨3217⟩⟨2117⟩,⟨"compote"⟩⟨9962⟩⟨5670⟩
⟨"comprehension"⟩⟨17718⟩⟨11644⟩,⟨"comprised"⟩⟨8252⟩⟨11684⟩
⟨"compromised"⟩⟨16197⟩⟨12637⟩,⟨"compulsory"⟩⟨11382⟩⟨5562⟩
⟨"comtemporary"⟩⟨6147⟩⟨3959⟩,⟨"con"⟩⟨10827⟩⟨13585⟩
⟨"conceivable"⟩⟨13445⟩⟨16356⟩,⟨"concentrated"⟩⟨9073⟩⟨14198⟩
⟨"concerning"⟩⟨10875⟩⟨13896⟩,⟨"Concert"⟩⟨5006⟩⟨6323⟩
⟨"Concierge"⟩⟨2738⟩⟨5640⟩,⟨"concierges"⟩⟨11346⟩⟨6983⟩
⟨"Conclusion"⟩⟨14132⟩⟨17594⟩,⟨"concrete"⟩⟨6418⟩⟨9386⟩
⟨"condescending"⟩⟨2915⟩⟨7858⟩,⟨"condition"⟩⟨4879⟩⟨2832⟩
⟨"conditioning"⟩⟨7312⟩⟨9469⟩,⟨"conditions"⟩⟨726⟩⟨3868⟩
⟨"conducive"⟩⟨7412⟩⟨8875⟩,⟨"conducted"⟩⟨17315⟩⟨2178⟩
⟨"conferencing"⟩⟨17789⟩⟨17912⟩,⟨"confidence"⟩⟨10493⟩⟨15915⟩
⟨"confined"⟩⟨12103⟩⟨16142⟩,⟨"confirmation"⟩⟨666⟩⟨705⟩
⟨"confrontation"⟩⟨17967⟩⟨13674⟩,⟨"confronted"⟩⟨14518⟩⟨1464⟩
⟨"confusion"⟩⟨10725⟩⟨11430⟩,⟨"congealed"⟩⟨15029⟩⟨7495⟩
⟨"congrats"⟩⟨17913⟩⟨17996⟩,⟨"congratulated"⟩⟨6033⟩⟨12453⟩
⟨"congregated"⟩⟨17081⟩⟨2949⟩,⟨"conjunction"⟩⟨11663⟩⟨14056⟩
⟨"connection"⟩⟨4222⟩⟨10901⟩,⟨"connectivity"⟩⟨6155⟩⟨3967⟩
⟨"Connell"⟩⟨7486⟩⟨10558⟩,⟨"Connemara"⟩⟨309⟩⟨18245⟩
⟨"Connolly"⟩⟨6753⟩⟨15359⟩,⟨"Connor"⟩⟨2092⟩⟨907⟩
⟨"Cons"⟩⟨7498⟩⟨16302⟩,⟨"conscience"⟩⟨9130⟩⟨13478⟩
⟨"consequence"⟩⟨11378⟩⟨5311⟩,⟨"Consequently"⟩⟨16216⟩⟨17614⟩
⟨"consider"⟩⟨4493⟩⟨14111⟩,⟨"considerable"⟩⟨8918⟩⟨14367⟩
⟨"considered"⟩⟨7978⟩⟨15627⟩,⟨"Considering"⟩⟨5816⟩⟨10605⟩

⟨"consistant"⟩⟨12287⟩⟨10251⟩,⟨"consisted"⟩⟨4656⟩⟨3763⟩
⟨"consisting"⟩⟨13694⟩⟨10967⟩,⟨"console"⟩⟨5698⟩⟨12893⟩
⟨"Constantly"⟩⟨16050⟩⟨18430⟩,⟨"constraints"⟩⟨9153⟩⟨4791⟩
⟨"constructive"⟩⟨14864⟩⟨14643⟩,⟨"consultation"⟩⟨13775⟩⟨10579⟩
⟨"consumer"⟩⟨17249⟩⟨7465⟩,⟨"consumption"⟩⟨17818⟩⟨17941⟩
⟨"Contacted"⟩⟨12998⟩⟨527⟩,⟨"contacts"⟩⟨18223⟩⟨8768⟩
⟨"containers"⟩⟨3057⟩⟨3152⟩,⟨"contains"⟩⟨12133⟩⟨14550⟩
⟨"contemporary"⟩⟨1789⟩⟨3400⟩,⟨"contempt"⟩⟨17022⟩⟨2096⟩
⟨"contention"⟩⟨18382⟩⟨2879⟩,⟨"contest"⟩⟨17330⟩⟨14963⟩
⟨"Continental"⟩⟨3301⟩⟨6245⟩,⟨"continous"⟩⟨8742⟩⟨6105⟩
⟨"continued"⟩⟨935⟩⟨4932⟩,⟨"continuing"⟩⟨8253⟩⟨12919⟩
⟨"contracted"⟩⟨5272⟩⟨4538⟩,⟨"contrary"⟩⟨12231⟩⟨15568⟩
⟨"contributed"⟩⟨6423⟩⟨8850⟩,⟨"contributors"⟩⟨10477⟩⟨15243⟩
⟨"controller"⟩⟨18473⟩⟨13202⟩,⟨"controls"⟩⟨11997⟩⟨10609⟩
⟨"convenient"⟩⟨2627⟩⟨6248⟩,⟨"Conveniently"⟩⟨7849⟩⟨11345⟩
⟨"conventional"⟩⟨7441⟩⟨4209⟩,⟨"conversations"⟩⟨3258⟩⟨4868⟩
⟨"convert"⟩⟨15126⟩⟨16914⟩,⟨"converter"⟩⟨11491⟩⟨8378⟩
⟨"conveyor"⟩⟨4559⟩⟨11568⟩,⟨"convienent"⟩⟨4103⟩⟨4149⟩
⟨"convince"⟩⟨9892⟩⟨13932⟩,⟨"convinient"⟩⟨7462⟩⟨6501⟩
⟨"Cooked"⟩⟨3725⟩⟨7022⟩,⟨"cookery"⟩⟨17890⟩⟨17981⟩
⟨"cooking"⟩⟨9678⟩⟨17273⟩,⟨"cool"⟩⟨1281⟩⟨15425⟩
⟨"cooler"⟩⟨12751⟩⟨17698⟩,⟨"cooling"⟩⟨13497⟩⟨12972⟩
⟨"coordinated"⟩⟨15477⟩⟨8483⟩,⟨"coordinator"⟩⟨4418⟩⟨9224⟩
⟨"coped"⟩⟨4537⟩⟨2126⟩,⟨"copies"⟩⟨8325⟩⟨10743⟩
⟨"copper"⟩⟨15867⟩⟨13638⟩,⟨"copy"⟩⟨787⟩⟨5502⟩
⟨"cordoned"⟩⟨10527⟩⟨15289⟩,⟨"Cork"⟩⟨465⟩⟨5668⟩
⟨"corkscrew"⟩⟨2930⟩⟨7859⟩,⟨"corn"⟩⟨17037⟩⟨868⟩
⟨"cornflakes"⟩⟨3036⟩⟨11565⟩,⟨"Corporate"⟩⟨15232⟩⟨16712⟩
⟨"correspondence"⟩⟨17751⟩⟨1652⟩,⟨"corrider"⟩⟨13315⟩⟨7300⟩
⟨"corridor"⟩⟨191⟩⟨6738⟩,⟨"Corridors"⟩⟨2909⟩⟨3026⟩
⟨"cosiness"⟩⟨9212⟩⟨6071⟩,⟨"cosmetics"⟩⟨15516⟩⟨12144⟩

⟨"Cosmos"⟩⟨10279⟩⟨10104⟩,⟨"Cost"⟩⟨5390⟩⟨14458⟩
⟨"costly"⟩⟨13077⟩⟨18536⟩,⟨"COSTS"⟩⟨18229⟩⟨1395⟩
⟨"cot"⟩⟨5983⟩⟨2363⟩,⟨"cottage"⟩⟨7512⟩⟨8742⟩
⟨"cotton"⟩⟨10468⟩⟨13078⟩,⟨"couches"⟩⟨3748⟩⟨9466⟩
⟨"could"⟩⟨2533⟩⟨16918⟩,⟨"COULD"⟩⟨11517⟩⟨16918⟩
⟨"couldn't"⟩⟨12401⟩⟨12496⟩,⟨"couldn????t"⟩⟨10355⟩⟨10118⟩
⟨"Couldnt"⟩⟨6446⟩⟨6959⟩,⟨"council"⟩⟨3957⟩⟨10532⟩
⟨"counter"⟩⟨1949⟩⟨1253⟩,⟨"counters"⟩⟨5639⟩⟨9028⟩
⟨"countless"⟩⟨9642⟩⟨12758⟩,⟨"country"⟩⟨213⟩⟨5559⟩
⟨"County"⟩⟨455⟩⟨7979⟩,⟨"countyside"⟩⟨9967⟩⟨5677⟩
⟨"coupled"⟩⟨10120⟩⟨13016⟩,⟨"couples"⟩⟨1477⟩⟨7448⟩
⟨"course"⟩⟨1084⟩⟨5149⟩,⟨"courses"⟩⟨753⟩⟨17542⟩
⟨"courteous"⟩⟨245⟩⟨6533⟩,⟨"courteousness"⟩⟨17449⟩⟨18335⟩
⟨"courtious"⟩⟨3499⟩⟨1643⟩,⟨"courts"⟩⟨2306⟩⟨10254⟩
⟨"Courtyard"⟩⟨2826⟩⟨7527⟩,⟨"cousin"⟩⟨7393⟩⟨13210⟩
⟨"Cove"⟩⟨6365⟩⟨13027⟩,⟨"cover"⟩⟨530⟩⟨1531⟩
⟨"coverings"⟩⟨16554⟩⟨3790⟩,⟨"covers"⟩⟨325⟩⟨733⟩
⟨"cows"⟩⟨4302⟩⟨1625⟩,⟨"cozy"⟩⟨1459⟩⟨14266⟩
⟨"Crabtree"⟩⟨12854⟩⟨15823⟩,⟨"cracked"⟩⟨255⟩⟨2512⟩
⟨"crackling"⟩⟨16987⟩⟨18188⟩,⟨"craft"⟩⟨8236⟩⟨7852⟩
⟨"craic&quot"⟩⟨10315⟩⟨13644⟩,⟨"cramped"⟩⟨1860⟩⟨4227⟩
⟨"cranky"⟩⟨5987⟩⟨12190⟩,⟨"crap"⟩⟨1788⟩⟨1718⟩
⟨"crashing"⟩⟨3264⟩⟨7975⟩,⟨"Crawl"⟩⟨12659⟩⟨10386⟩
⟨"craziness"⟩⟨10261⟩⟨10079⟩,⟨"Crazy"⟩⟨16212⟩⟨12657⟩
⟨"creaky"⟩⟨10811⟩⟨9351⟩,⟨"Cream"⟩⟨8813⟩⟨12789⟩
⟨"creased"⟩⟨18123⟩⟨940⟩,⟨"created"⟩⟨10508⟩⟨15024⟩
⟨"creativity"⟩⟨16620⟩⟨15492⟩,⟨"creche"⟩⟨8061⟩⟨6957⟩
⟨"credited"⟩⟨17561⟩⟨130⟩,⟨"creek"⟩⟨17439⟩⟨18325⟩
⟨"Cregg"⟩⟨2293⟩⟨5434⟩,⟨"creme"⟩⟨13303⟩⟨14619⟩
⟨"crew"⟩⟨8905⟩⟨7919⟩,⟨"cried"⟩⟨2248⟩⟨3636⟩
⟨"crisis"⟩⟨7473⟩⟨6516⟩,⟨"Crisp"⟩⟨15445⟩⟨9600⟩

⟨"critic"⟩⟨16023⟩⟨7458⟩,⟨"criticise"⟩⟨6171⟩⟨7676⟩
⟨"critics"⟩⟨9080⟩⟨14206⟩,⟨"critisism"⟩⟨11014⟩⟨14773⟩
⟨"croisants"⟩⟨15303⟩⟨16791⟩,⟨"croissants"⟩⟨2281⟩⟨14338⟩
⟨"Cromleach"⟩⟨3202⟩⟨6124⟩,⟨"cross"⟩⟨7924⟩⟨12676⟩
⟨"crossiants"⟩⟨12302⟩⟨10276⟩,⟨"crossings"⟩⟨15507⟩⟨12128⟩
⟨"crowding"⟩⟨13582⟩⟨5730⟩,⟨"crowed"⟩⟨9239⟩⟨6106⟩
⟨"crowne"⟩⟨10482⟩⟨15251⟩,⟨"cruise"⟩⟨2950⟩⟨15131⟩
⟨"crumbs"⟩⟨2313⟩⟨8759⟩,⟨"crunch"⟩⟨3909⟩⟨3842⟩
⟨"crusty"⟩⟨16992⟩⟨510⟩,⟨"crutches"⟩⟨17464⟩⟨18350⟩
⟨"Crystal"⟩⟨3876⟩⟨9152⟩,⟨"cubes"⟩⟨16398⟩⟨16656⟩
⟨"cucumber"⟩⟨17677⟩⟨216⟩,⟨"cue"⟩⟨17681⟩⟨220⟩
⟨"cultural"⟩⟨6096⟩⟨10569⟩,⟨"cumbersome"⟩⟨11649⟩⟨14033⟩
⟨"cupboards"⟩⟨15660⟩⟨4888⟩,⟨"cuppa"⟩⟨11608⟩⟨14375⟩
⟨"cured"⟩⟨17800⟩⟨17923⟩,⟨"curious"⟩⟨11541⟩⟨16128⟩
⟨"Curragh"⟩⟨12386⟩⟨9702⟩,⟨"currency"⟩⟨8934⟩⟨9502⟩
⟨"curry"⟩⟨6270⟩⟨13385⟩,⟨"cursing"⟩⟨18298⟩⟨601⟩
⟨"curtains"⟩⟨7976⟩⟨16233⟩,⟨"curteous"⟩⟨9708⟩⟨11271⟩
⟨"curve"⟩⟨17580⟩⟨13541⟩,⟨"cushion"⟩⟨12949⟩⟨17220⟩
⟨"custom"⟩⟨840⟩⟨11050⟩,⟨"Customer"⟩⟨1090⟩⟨1418⟩
⟨"Customs"⟩⟨9953⟩⟨5667⟩,⟨"cut"⟩⟨3015⟩⟨3106⟩
⟨"cutter"⟩⟨4848⟩⟨2469⟩,⟨"cycle"⟩⟨7971⟩⟨13567⟩
⟨"cynical"⟩⟨18001⟩⟨13707⟩,⟨"D"⟩⟨7958⟩⟨16194⟩
⟨"d'"⟩⟨12063⟩⟨7893⟩,⟨"d'Hote"⟩⟨7065⟩⟨6355⟩
⟨"dab"⟩⟨10522⟩⟨15278⟩,⟨"dad"⟩⟨12570⟩⟨17260⟩
⟨"Daily"⟩⟨8586⟩⟨11119⟩,⟨"dairy"⟩⟨6526⟩⟨11301⟩
⟨"Dame"⟩⟨4473⟩⟨10452⟩,⟨"Damian"⟩⟨15298⟩⟨16786⟩
⟨"dampen"⟩⟨7458⟩⟨4242⟩,⟨"dampner"⟩⟨13682⟩⟨17144⟩
⟨"dance"⟩⟨9596⟩⟨15145⟩,⟨"danced"⟩⟨5126⟩⟨3452⟩
⟨"dances"⟩⟨9178⟩⟨4817⟩,⟨"Dancing"⟩⟨9470⟩⟨11983⟩
⟨"Daniel"⟩⟨7619⟩⟨7293⟩,⟨"Danish"⟩⟨10481⟩⟨15248⟩
⟨"Dara"⟩⟨13043⟩⟨17086⟩,⟨"dare"⟩⟨1602⟩⟨7969⟩

⟨"dark"⟩⟨7082⟩⟨6915⟩,⟨"darker"⟩⟨16416⟩⟨18082⟩
⟨"darling"⟩⟨13562⟩⟨14871⟩,⟨"Darren"⟩⟨5666⟩⟨7196⟩
⟨"darts"⟩⟨8961⟩⟨10998⟩,⟨"dashed"⟩⟨17948⟩⟨18018⟩
⟨"Date"⟩⟨14566⟩⟨10470⟩,⟨"dates"⟩⟨7052⟩⟨11999⟩
⟨"Daughter"⟩⟨14867⟩⟨14647⟩,⟨"daughters"⟩⟨9458⟩⟨7948⟩
⟨"David"⟩⟨3075⟩⟨839⟩,⟨"Dawson"⟩⟨11919⟩⟨15500⟩
⟨"day???????s"⟩⟨16988⟩⟨18189⟩,⟨"Day's"⟩⟨11314⟩⟨8260⟩
⟨"Days"⟩⟨2528⟩⟨7258⟩,⟨"dazzling"⟩⟨17537⟩⟨18408⟩
⟨"De"⟩⟨5212⟩⟨12191⟩,⟨"de-stress"⟩⟨14171⟩⟨9358⟩
⟨"deaf"⟩⟨801⟩⟨1216⟩,⟨"deal"⟩⟨2208⟩⟨8761⟩
⟨"dealings"⟩⟨11930⟩⟨12534⟩,⟨"dealt"⟩⟨8445⟩⟨16920⟩
⟨"dearest"⟩⟨16730⟩⟨15526⟩,⟨"debacle"⟩⟨15058⟩⟨533⟩
⟨"Debbie"⟩⟨15366⟩⟨16871⟩,⟨"debit"⟩⟨13199⟩⟨16268⟩
⟨"dec"⟩⟨5746⟩⟨16214⟩,⟨"decade"⟩⟨11783⟩⟨7421⟩
⟨"decanter"⟩⟨4974⟩⟨2645⟩,⟨"deceived"⟩⟨17312⟩⟨1717⟩
⟨"decency"⟩⟨9256⟩⟨2555⟩,⟨"Decent"⟩⟨6960⟩⟨12218⟩
⟨"decide"⟩⟨6803⟩⟨6775⟩,⟨"Decided"⟩⟨4177⟩⟨8713⟩
⟨"decision"⟩⟨3471⟩⟨6734⟩,⟨"deck"⟩⟨7957⟩⟨11709⟩
⟨"Declan"⟩⟨3410⟩⟨10290⟩,⟨"decline"⟩⟨16303⟩⟨1925⟩
⟨"decor"⟩⟨1589⟩⟨8261⟩,⟨"decorate"⟩⟨14365⟩⟨15255⟩
⟨"decoration"⟩⟨9602⟩⟨16898⟩,⟨"decorative"⟩⟨13901⟩⟨13998⟩
⟨"decrepit"⟩⟨16607⟩⟨4640⟩,⟨"dedication"⟩⟨5498⟩⟨4471⟩
⟨"deep"⟩⟨2752⟩⟨11554⟩,⟨"deeply"⟩⟨3313⟩⟨7390⟩
⟨"Def"⟩⟨6578⟩⟨4936⟩,⟨"default"⟩⟨14249⟩⟨17242⟩
⟨"defects"⟩⟨12596⟩⟨16589⟩,⟨"defense"⟩⟨17419⟩⟨18305⟩
⟨"deffinetly"⟩⟨10631⟩⟨15401⟩,⟨"defiantely"⟩⟨10592⟩⟨15360⟩
⟨"Definately"⟩⟨6383⟩⟨9066⟩,⟨"Definatley"⟩⟨10254⟩⟨10068⟩
⟨"defines"⟩⟨9224⟩⟨6089⟩,⟨"definetley"⟩⟨9346⟩⟨11196⟩
⟨"definite"⟩⟨4648⟩⟨4626⟩,⟨"Definitely"⟩⟨1143⟩⟨8978⟩
⟨"definitley"⟩⟨3588⟩⟨1291⟩,⟨"Definitly"⟩⟨10579⟩⟨15345⟩
⟨"defo"⟩⟨5177⟩⟨18166⟩,⟨"defrosted"⟩⟨18052⟩⟨172⟩

⟨"dehydrated"⟩⟨18476⟩⟨13206⟩,⟨"Deirdre"⟩⟨6663⟩⟨11813⟩
⟨"delays"⟩⟨9313⟩⟨12480⟩,⟨"delegates"⟩⟨9777⟩⟨13884⟩
⟨"delicate"⟩⟨11525⟩⟨8221⟩,⟨"Delicious"⟩⟨2128⟩⟨14842⟩
⟨"delight"⟩⟨2948⟩⟨966⟩,⟨"Delighted"⟩⟨7226⟩⟨10671⟩
⟨"delights"⟩⟨7143⟩⟨10274⟩,⟨"deliver"⟩⟨7604⟩⟨11789⟩
⟨"delivers"⟩⟨8698⟩⟨8327⟩,⟨"delph"⟩⟨12327⟩⟨10323⟩
⟨"delux"⟩⟨3288⟩⟨14866⟩,⟨"deluxe"⟩⟨775⟩⟨6947⟩
⟨"demanded"⟩⟨370⟩⟨6577⟩,⟨"demands"⟩⟨14546⟩⟨16319⟩
⟨"demonstrated"⟩⟨12411⟩⟨12499⟩,⟨"Den"⟩⟨13395⟩⟨15200⟩
⟨"Denmark"⟩⟨5124⟩⟨3449⟩,⟨"dent"⟩⟨5442⟩⟨10603⟩
⟨"denying"⟩⟨15231⟩⟨16711⟩,⟨"departed"⟩⟨10762⟩⟨16273⟩
⟨"departs"⟩⟨10025⟩⟨5783⟩,⟨"departures"⟩⟨6403⟩⟨5347⟩
⟨"depends"⟩⟨4770⟩⟨1347⟩,⟨"deposit"⟩⟨9257⟩⟨42⟩
⟨"depressed"⟩⟨4296⟩⟨12533⟩,⟨"deprivation"⟩⟨18525⟩⟨13328⟩
⟨"depth"⟩⟨14825⟩⟨17108⟩,⟨"Deputy"⟩⟨14179⟩⟨17637⟩
⟨"Derek"⟩⟨6247⟩⟨4014⟩,⟨"Derg"⟩⟨8532⟩⟨6361⟩
⟨"Derrynane"⟩⟨6743⟩⟨6848⟩,⟨"descend"⟩⟨15954⟩⟨16413⟩
⟨"describe"⟩⟨1469⟩⟨1065⟩,⟨"describes"⟩⟨6787⟩⟨9060⟩
⟨"desert"⟩⟨5002⟩⟨11783⟩,⟨"deserts"⟩⟨9901⟩⟨16934⟩
⟨"deserves"⟩⟨4696⟩⟨8100⟩,⟨"design"⟩⟨1045⟩⟨6431⟩
⟨"designer"⟩⟨4745⟩⟨10419⟩,⟨"designs"⟩⟨14679⟩⟨13316⟩
⟨"desk"⟩⟨4145⟩⟨12363⟩,⟨"desks"⟩⟨7682⟩⟨9274⟩
⟨"desperation"⟩⟨12514⟩⟨16550⟩,⟨"Despite"⟩⟨9431⟩⟨14902⟩
⟨"Desserts"⟩⟨13079⟩⟨14706⟩,⟨"destination"⟩⟨5566⟩⟨2729⟩
⟨"detail"⟩⟨83⟩⟨5776⟩,⟨"detailing"⟩⟨16366⟩⟨472⟩
⟨"deter"⟩⟨7948⟩⟨8898⟩,⟨"deteriorated"⟩⟨16142⟩⟨6115⟩
⟨"detox"⟩⟨12878⟩⟨15848⟩,⟨"detracted"⟩⟨15982⟩⟨9738⟩
⟨"developed"⟩⟨11712⟩⟨13766⟩,⟨"developers"⟩⟨5764⟩⟨3576⟩
⟨"device"⟩⟨13207⟩⟨7415⟩,⟨"devine"⟩⟨1255⟩⟨941⟩
⟨"diabetic"⟩⟨18289⟩⟨589⟩,⟨"diagonally"⟩⟨15851⟩⟨10247⟩
⟨"Diane"⟩⟨11674⟩⟨14072⟩,⟨"diary"⟩⟨17900⟩⟨17989⟩

⟨"Did"⟩⟨5050⟩⟨14779⟩,⟨"didint"⟩⟨13596⟩⟨7104⟩
⟨"Didn???????t"⟩⟨15502⟩⟨9481⟩,⟨"didn'"⟩⟨13593⟩⟨7099⟩
⟨"didnt"⟩⟨4496⟩⟨17054⟩,⟨"didnt'"⟩⟨10240⟩⟨10046⟩
⟨"diesel"⟩⟨15948⟩⟨7401⟩,⟨"dietary"⟩⟨12144⟩⟨9318⟩
⟨"differant"⟩⟨6341⟩⟨6793⟩,⟨"difference"⟩⟨6041⟩⟨15691⟩
⟨"differently"⟩⟨13413⟩⟨17685⟩,⟨"difficult"⟩⟨4801⟩⟨18291⟩
⟨"dificult"⟩⟨15407⟩⟨9519⟩,⟨"digging"⟩⟨18411⟩⟨2922⟩
⟨"digusting"⟩⟨9135⟩⟨13491⟩,⟨"diluted"⟩⟨17602⟩⟨13572⟩
⟨"diminished"⟩⟨12384⟩⟨9699⟩,⟨"dimmed"⟩⟨10416⟩⟨8196⟩
⟨"Dined"⟩⟨9472⟩⟨13687⟩,⟨"Diner"⟩⟨10050⟩⟨10329⟩
⟨"dingle"⟩⟨6402⟩⟨6111⟩,⟨"dining"⟩⟨678⟩⟨14704⟩
⟨"diningroom"⟩⟨12054⟩⟨8281⟩,⟨"Dinner"⟩⟨1928⟩⟨8822⟩
⟨"Dinners"⟩⟨5025⟩⟨10739⟩,⟨"dinning"⟩⟨11565⟩⟨16907⟩
⟨"dips"⟩⟨10162⟩⟨6179⟩,⟨"direct"⟩⟨6132⟩⟨8361⟩
⟨"directions"⟩⟨1981⟩⟨17682⟩,⟨"directly"⟩⟨3226⟩⟨15609⟩
⟨"directors"⟩⟨17134⟩⟨16072⟩,⟨"dirt"⟩⟨307⟩⟨6612⟩
⟨"dirty"⟩⟨9269⟩⟨169⟩,⟨"DIRTY"⟩⟨16667⟩⟨169⟩
⟨"disadvantage"⟩⟨5948⟩⟨4381⟩,⟨"disagree"⟩⟨7378⟩⟨13268⟩
⟨"disapointing"⟩⟨5297⟩⟨8787⟩,⟨"disappear"⟩⟨16499⟩⟨15935⟩
⟨"disappoint"⟩⟨1987⟩⟨780⟩,⟨"Disappointed"⟩⟨11961⟩⟨17050⟩
⟨"disappointment"⟩⟨4646⟩⟨1725⟩,⟨"disappoints"⟩⟨12676⟩⟨10412⟩
⟨"disasterous"⟩⟨5268⟩⟨4524⟩,⟨"disastrous"⟩⟨2277⟩⟨357⟩
⟨"discerning"⟩⟨4379⟩⟨3121⟩,⟨"disco"⟩⟨4256⟩⟨5280⟩
⟨"disconcerting"⟩⟨11622⟩⟨8356⟩,⟨"discos"⟩⟨16957⟩⟨7779⟩
⟨"discourage"⟩⟨4874⟩⟨1496⟩,⟨"discourteous"⟩⟨15035⟩⟨200⟩
⟨"discovering"⟩⟨12134⟩⟨14551⟩,⟨"discreet"⟩⟨2292⟩⟨3448⟩
⟨"discretion"⟩⟨13417⟩⟨16331⟩,⟨"discuss"⟩⟨555⟩⟨3787⟩
⟨"discussions"⟩⟨13575⟩⟨5162⟩,⟨"discusting"⟩⟨16317⟩⟨3908⟩
⟨"disgraceful"⟩⟨13785⟩⟨4866⟩,⟨"disgruntled"⟩⟨3787⟩⟨1338⟩
⟨"disgusting"⟩⟨1184⟩⟨1876⟩,⟨"disgustingly"⟩⟨16140⟩⟨126⟩
⟨"dishevelled"⟩⟨17803⟩⟨17926⟩,⟨"disimproved"⟩⟨10198⟩⟨6250⟩

⟨"dislike"⟩⟨13376⟩⟨16250⟩,⟨"dislikes"⟩⟨5845⟩⟨7816⟩
⟨"dismissed"⟩⟨9836⟩⟨185⟩,⟨"Disney"⟩⟨5395⟩⟨2797⟩
⟨"dispelled"⟩⟨12323⟩⟨10314⟩,⟨"dispensed"⟩⟨17962⟩⟨18027⟩
⟨"dispersed"⟩⟨17912⟩⟨17995⟩,⟨"display"⟩⟨11072⟩⟨15578⟩
⟨"displeased"⟩⟨6545⟩⟨4058⟩,⟨"disposable"⟩⟨15546⟩⟨9620⟩
⟨"disregard"⟩⟨11989⟩⟨14442⟩,⟨"disrespect"⟩⟨12989⟩⟨222⟩
⟨"disruption"⟩⟨13740⟩⟨17433⟩,⟨"dissapoint"⟩⟨16656⟩⟨17673⟩
⟨"dissapointment"⟩⟨1650⟩⟨8544⟩,⟨"dissappointed"⟩⟨5295⟩⟨9273⟩
⟨"dissatisfied"⟩⟨16550⟩⟨2228⟩,⟨"distances"⟩⟨10080⟩⟨14217⟩
⟨"distinct"⟩⟨1020⟩⟨6033⟩,⟨"distinctly"⟩⟨13762⟩⟨18535⟩
⟨"distracting"⟩⟨16172⟩⟨12586⟩,⟨"distress"⟩⟨8456⟩⟨14668⟩
⟨"District"⟩⟨5344⟩⟨2398⟩,⟨"DISTURB"⟩⟨8412⟩⟨14621⟩
⟨"disturbance"⟩⟨11138⟩⟨14557⟩,⟨"disturbed"⟩⟨7660⟩⟨9228⟩
⟨"ditto"⟩⟨15774⟩⟨10208⟩,⟨"dive"⟩⟨1517⟩⟨876⟩
⟨"DIY"⟩⟨14226⟩⟨17702⟩,⟨"DJ"⟩⟨2223⟩⟨3646⟩
⟨"do"⟩⟨1917⟩⟨4323⟩,⟨"do'"⟩⟨12993⟩⟨522⟩
⟨"dock"⟩⟨7786⟩⟨8615⟩,⟨"docking"⟩⟨6407⟩⟨6932⟩
⟨"doctor"⟩⟨10431⟩⟨7913⟩,⟨"document"⟩⟨11569⟩⟨270⟩
⟨"dodgey"⟩⟨17931⟩⟨13646⟩,⟨"dodgy"⟩⟨2345⟩⟨8334⟩
⟨"doesn???????t"⟩⟨3834⟩⟨4972⟩,⟨"Doesn't"⟩⟨10077⟩⟨14210⟩
⟨"doing"⟩⟨3113⟩⟨2825⟩,⟨"dollars"⟩⟨3997⟩⟨2000⟩
⟨"dolphin"⟩⟨17853⟩⟨5760⟩,⟨"Dome"⟩⟨11067⟩⟨18193⟩
⟨"don"⟩⟨6405⟩⟨14878⟩,⟨"don‘t"⟩⟨3544⟩⟨1098⟩
⟨"DON'T"⟩⟨1545⟩⟨8098⟩,⟨"Don't"⟩⟨4414⟩⟨8098⟩
⟨"Done"⟩⟨14506⟩⟨18075⟩,⟨"done&quot"⟩⟨8743⟩⟨6108⟩
⟨"donkeys"⟩⟨16655⟩⟨17672⟩,⟨"Dont"⟩⟨195⟩⟨5709⟩
⟨"Dooley's"⟩⟨11734⟩⟨15502⟩,⟨"Doolin"⟩⟨432⟩⟨18093⟩
⟨"door"⟩⟨4906⟩⟨2822⟩,⟨"door's"⟩⟨13671⟩⟨17133⟩
⟨"doormen"⟩⟨12230⟩⟨12186⟩,⟨"Doors"⟩⟨4476⟩⟨7060⟩
⟨"doorway"⟩⟨5968⟩⟨10571⟩,⟨"dorm"⟩⟨11683⟩⟨17564⟩
⟨"dos"⟩⟨18012⟩⟨18063⟩,⟨"dosent"⟩⟨11812⟩⟨11800⟩

⟨"double"⟩⟨4013⟩⟨9523⟩,⟨"double-decker"⟩⟨16217⟩⟨12663⟩
⟨"doubles"⟩⟨4142⟩⟨3052⟩,⟨"doubtful"⟩⟨16891⟩⟨18133⟩
⟨"dour"⟩⟨4707⟩⟨12167⟩,⟨"dove"⟩⟨13626⟩⟨14007⟩
⟨"DOWN"⟩⟨17734⟩⟨11671⟩,⟨"down-to-earth"⟩⟨9941⟩⟨5635⟩
⟨"downfall"⟩⟨1861⟩⟨5132⟩,⟨"downgrade"⟩⟨17646⟩⟨17865⟩
⟨"Downings"⟩⟨6514⟩⟨11279⟩,⟨"downpour"⟩⟨13799⟩⟨14295⟩
⟨"Downside"⟩⟨9189⟩⟨15670⟩,⟨"Downsides"⟩⟨9392⟩⟨14008⟩
⟨"Downtown"⟩⟨9612⟩⟨6998⟩,⟨"downturn"⟩⟨7735⟩⟨14495⟩
⟨"dozens"⟩⟨6783⟩⟨3857⟩,⟨"drab"⟩⟨428⟩⟨1698⟩
⟨"dragged"⟩⟨2676⟩⟨3729⟩,⟨"dragon"⟩⟨12809⟩⟨10554⟩
⟨"draining"⟩⟨14135⟩⟨17597⟩,⟨"drama"⟩⟨14001⟩⟨11451⟩
⟨"drank"⟩⟨11546⟩⟨14357⟩,⟨"draperies"⟩⟨14381⟩⟨15290⟩
⟨"draughty"⟩⟨2419⟩⟨2265⟩,⟨"Draw"⟩⟨15594⟩⟨13660⟩
⟨"drawers"⟩⟨1989⟩⟨7018⟩,⟨"Drawing"⟩⟨4050⟩⟨1899⟩
⟨"dreaded"⟩⟨14448⟩⟨17623⟩,⟨"Dreadful"⟩⟨10511⟩⟨4850⟩
⟨"Dream"⟩⟨16488⟩⟨12923⟩,⟨"dreaming"⟩⟨9877⟩⟨14599⟩
⟨"drenched"⟩⟨13944⟩⟨13936⟩,⟨"dressed"⟩⟨3751⟩⟨6119⟩
⟨"dressing"⟩⟨7003⟩⟨18170⟩,⟨"drew"⟩⟨13751⟩⟨16187⟩
⟨"drift"⟩⟨10739⟩⟨8933⟩,⟨"drill"⟩⟨9616⟩⟨4174⟩
⟨"Drink"⟩⟨11861⟩⟨12220⟩,⟨"drinker"⟩⟨11369⟩⟨11381⟩
⟨"Drinks"⟩⟨11889⟩⟨16452⟩,⟨"dripped"⟩⟨14943⟩⟨9238⟩
⟨"driven"⟩⟨12210⟩⟨12918⟩,⟨"drivers"⟩⟨3398⟩⟨7735⟩
⟨"Driving"⟩⟨13730⟩⟨15888⟩,⟨"Dromhall"⟩⟨5990⟩⟨3186⟩
⟨"drop"⟩⟨4232⟩⟨9259⟩,⟨"dropped"⟩⟨5807⟩⟨14695⟩
⟨"drove"⟩⟨3474⟩⟨16038⟩,⟨"drown"⟩⟨5324⟩⟨4963⟩
⟨"Druids"⟩⟨3092⟩⟨5868⟩,⟨"Drumcondra"⟩⟨16908⟩⟨18150⟩
⟨"Drunken"⟩⟨18312⟩⟨4608⟩,⟨"Drury"⟩⟨11747⟩⟨17047⟩
⟨"dryers"⟩⟨12168⟩⟨11446⟩,⟨"du"⟩⟨16803⟩⟨17804⟩
⟨"Dubai"⟩⟨11489⟩⟨8376⟩,⟨"dubious"⟩⟨6682⟩⟨7506⟩
⟨"Dublin-"⟩⟨13443⟩⟨16354⟩,⟨"Dublin's"⟩⟨7788⟩⟨8096⟩
⟨"Dublinia"⟩⟨17650⟩⟨17869⟩,⟨"Duck"⟩⟨4051⟩⟨3146⟩

⟨"ducts"⟩⟨15756⟩⟨18114⟩,⟨"Due"⟩⟨7024⟩⟨4437⟩
⟨"Dull"⟩⟨17243⟩⟨9954⟩,⟨"dumb"⟩⟨6202⟩⟨2214⟩
⟨"dumped"⟩⟨1575⟩⟨6514⟩,⟨"dumpster"⟩⟨12015⟩⟨5066⟩
⟨"Dunboyne"⟩⟨1304⟩⟨4971⟩,⟨"Dundalk"⟩⟨5575⟩⟨11072⟩
⟨"Dunes"⟩⟨11192⟩⟨16092⟩,⟨"Dunfanaghy"⟩⟨17132⟩⟨16068⟩
⟨"Dungloe"⟩⟨17102⟩⟨16004⟩,⟨"Dunmore"⟩⟨5092⟩⟨8723⟩
⟨"duplex"⟩⟨14185⟩⟨7683⟩,⟨"during"⟩⟨1889⟩⟨14100⟩
⟨"durty"⟩⟨18527⟩⟨6046⟩,⟨"dust"⟩⟨34⟩⟨4314⟩
⟨"dusty"⟩⟨526⟩⟨4028⟩,⟨"Duty"⟩⟨644⟩⟨2361⟩
⟨"dvd"⟩⟨1236⟩⟨9185⟩,⟨"dvd's"⟩⟨11064⟩⟨15477⟩
⟨"dying"⟩⟨7421⟩⟨12870⟩,⟨"dylan"⟩⟨5361⟩⟨2837⟩
⟨"e-mail"⟩⟨5363⟩⟨18253⟩,⟨"e-mailed"⟩⟨12987⟩⟨16228⟩
⟨"e10"⟩⟨17774⟩⟨17897⟩,⟨"E15"⟩⟨16853⟩⟨15748⟩
⟨"E99"⟩⟨10245⟩⟨10056⟩,⟨"Each"⟩⟨5788⟩⟨4153⟩
⟨"eagerly"⟩⟨16844⟩⟨15739⟩,⟨"Eagles"⟩⟨7690⟩⟨8820⟩
⟨"ear"⟩⟨3705⟩⟨13205⟩,⟨"ear-plugs"⟩⟨14638⟩⟨13149⟩
⟨"earliest"⟩⟨3178⟩⟨6763⟩,⟨"early"⟩⟨2900⟩⟨16902⟩
⟨"earn"⟩⟨12062⟩⟨7573⟩,⟨"earplugs"⟩⟨10654⟩⟨5194⟩
⟨"earshot"⟩⟨15585⟩⟨13402⟩,⟨"earth"⟩⟨10799⟩⟨16239⟩
⟨"easier"⟩⟨5165⟩⟨11533⟩,⟨"easily"⟩⟨1385⟩⟨6562⟩
⟨"East"⟩⟨9264⟩⟨14583⟩,⟨"easter"⟩⟨4227⟩⟨7052⟩
⟨"easy"⟩⟨687⟩⟨6241⟩,⟨"Eat"⟩⟨12187⟩⟨16178⟩
⟨"eaters"⟩⟨8507⟩⟨5248⟩,⟨"eating"⟩⟨3087⟩⟨13873⟩
⟨"ebookers"⟩⟨8346⟩⟨10774⟩,⟨"Eccles"⟩⟨14079⟩⟨12970⟩
⟨"eclectic"⟩⟨6442⟩⟨5145⟩,⟨"economical"⟩⟨4737⟩⟨3036⟩
⟨"Eden"⟩⟨3222⟩⟨4678⟩,⟨"Edge"⟩⟨13787⟩⟨14765⟩
⟨"educated"⟩⟨18132⟩⟨1172⟩,⟨"Edward"⟩⟨4915⟩⟨5462⟩
⟨"effecient"⟩⟨5809⟩⟨8857⟩,⟨"effected"⟩⟨17748⟩⟨1647⟩
⟨"efficent"⟩⟨2264⟩⟨8709⟩,⟨"efficiant"⟩⟨15468⟩⟨7923⟩
⟨"efficiently"⟩⟨1330⟩⟨1565⟩,⟨"effort"⟩⟨3200⟩⟨9955⟩
⟨"eg"⟩⟨5611⟩⟨6902⟩,⟨"Egan's"⟩⟨4381⟩⟨3125⟩

⟨"eggs"⟩⟨3417⟩⟨13624⟩,⟨"ego"⟩⟨15249⟩⟨16734⟩
⟨"Eight"⟩⟨15453⟩⟨17749⟩,⟨"Eileen"⟩⟨6084⟩⟨2732⟩
⟨"either"⟩⟨5392⟩⟨9652⟩,⟨"elaborate"⟩⟨10913⟩⟨14349⟩
⟨"elderly"⟩⟨1488⟩⟨1200⟩,⟨"Eldons"⟩⟨4978⟩⟨2650⟩
⟨"electrical"⟩⟨2076⟩⟨9449⟩,⟨"electrics"⟩⟨14725⟩⟨13278⟩
⟨"elegant"⟩⟨9268⟩⟨13859⟩,⟨"elegantly"⟩⟨4586⟩⟨2360⟩
⟨"elemis"⟩⟨9085⟩⟨14216⟩,⟨"elephants"⟩⟨15588⟩⟨13409⟩
⟨"elevators"⟩⟨2718⟩⟨14969⟩,⟨"eleven"⟩⟨14544⟩⟨14592⟩
⟨"eliza"⟩⟨15806⟩⟨16049⟩,⟨"Elizalodge"⟩⟨15280⟩⟨16766⟩
⟨"elses"⟩⟨1868⟩⟨1989⟩,⟨"elswhere"⟩⟨13266⟩⟨5100⟩
⟨"em"⟩⟨13820⟩⟨14324⟩,⟨"Email"⟩⟨13261⟩⟨5092⟩
⟨"emanating"⟩⟨13784⟩⟨10586⟩,⟨"embarassing"⟩⟨14056⟩⟨11810⟩
⟨"embarrassed"⟩⟨620⟩⟨3148⟩,⟨"embarrassment"⟩⟨14758⟩⟨7771⟩
⟨"embassy"⟩⟨15766⟩⟨8579⟩,⟨"Emer"⟩⟨2091⟩⟨906⟩
⟨"emergency"⟩⟨875⟩⟨653⟩,⟨"emotional"⟩⟨9979⟩⟨5694⟩
⟨"emphasize"⟩⟨6243⟩⟨6100⟩,⟨"employed"⟩⟨12155⟩⟨8391⟩
⟨"employing"⟩⟨6492⟩⟨6567⟩,⟨"emptied"⟩⟨1511⟩⟨1082⟩
⟨"en"⟩⟨3007⟩⟨15073⟩,⟨"en-route"⟩⟨15239⟩⟨16721⟩
⟨"enable"⟩⟨14065⟩⟨15128⟩,⟨"enables"⟩⟨12317⟩⟨10304⟩
⟨"enclosed"⟩⟨12752⟩⟨16895⟩,⟨"Encore"⟩⟨13846⟩⟨17385⟩
⟨"encourage"⟩⟨4705⟩⟨4483⟩,⟨"encourages"⟩⟨16768⟩⟨17769⟩
⟨"end"⟩⟨2708⟩⟨15939⟩,⟨"end&quot"⟩⟨9137⟩⟨13493⟩
⟨"ending"⟩⟨9818⟩⟨13778⟩,⟨"endlessly"⟩⟨11477⟩⟨7038⟩
⟨"endured"⟩⟨14659⟩⟨2310⟩,⟨"energetic"⟩⟨3322⟩⟨9058⟩
⟨"enforced"⟩⟨14734⟩⟨18208⟩,⟨"engaged"⟩⟨4136⟩⟨1568⟩
⟨"engineer"⟩⟨15179⟩⟨332⟩,⟨"England"⟩⟨5186⟩⟨13101⟩
⟨"enhance"⟩⟨15111⟩⟨12069⟩,⟨"enjoy"⟩⟨405⟩⟨11243⟩
⟨"Enjoyable"⟩⟨11030⟩⟨14796⟩,⟨"Enjoyed"⟩⟨461⟩⟨7384⟩
⟨"Ennis"⟩⟨2623⟩⟨16416⟩,⟨"Enniscorthy"⟩⟨14502⟩⟨16660⟩
⟨"enormous"⟩⟨380⟩⟨660⟩,⟨"enough"⟩⟨652⟩⟨9881⟩
⟨"enquire"⟩⟨1732⟩⟨651⟩,⟨"enquiries"⟩⟨13890⟩⟨13156⟩

⟨"ensued"⟩⟨6231⟩⟨13805⟩,⟨"ensuite"⟩⟨6476⟩⟨18436⟩
⟨"ensured"⟩⟨4423⟩⟨1399⟩,⟨"ensuring"⟩⟨9598⟩⟨11372⟩
⟨"enterainment"⟩⟨13841⟩⟨17380⟩,⟨"entered"⟩⟨3509⟩⟨952⟩
⟨"entertaiment"⟩⟨8362⟩⟨10797⟩,⟨"entertained"⟩⟨6749⟩⟨2683⟩
⟨"Entertainment"⟩⟨5293⟩⟨9897⟩,⟨"enthusiastic"⟩⟨4682⟩⟨12075⟩
⟨"entire"⟩⟨807⟩⟨2259⟩,⟨"entitled"⟩⟨1315⟩⟨3977⟩
⟨"entrances"⟩⟨13035⟩⟨17076⟩,⟨"entrees"⟩⟨10670⟩⟨9679⟩
⟨"enveloped"⟩⟨17501⟩⟨18380⟩,⟨"environmental"⟩⟨12761⟩⟨10484⟩
⟨"epic"⟩⟨18079⟩⟨1885⟩,⟨"epitome"⟩⟨11389⟩⟨8372⟩
⟨"equestrian"⟩⟨11052⟩⟨14823⟩,⟨"equipment"⟩⟨9820⟩⟨11944⟩
⟨"equivalent"⟩⟨11831⟩⟨17565⟩,⟨"era"⟩⟨13500⟩⟨16962⟩
⟨"erratic"⟩⟨4028⟩⟨12166⟩,⟨"error"⟩⟨1252⟩⟨663⟩
⟨"escaped"⟩⟨14196⟩⟨9891⟩,⟨"escaping"⟩⟨13573⟩⟨5160⟩
⟨"esp"⟩⟨3883⟩⟨8604⟩,⟨"Espa"⟩⟨16219⟩⟨15891⟩
⟨"especialy"⟩⟨7580⟩⟨12800⟩,⟨"espically"⟩⟨9395⟩⟨14011⟩
⟨"essential"⟩⟨8454⟩⟨14433⟩,⟨"Essentially"⟩⟨13334⟩⟨9545⟩
⟨"establishment"⟩⟨3926⟩⟨2622⟩,⟨"estate"⟩⟨3504⟩⟨5505⟩
⟨"estimate"⟩⟨5445⟩⟨13790⟩,⟨"estimation"⟩⟨14183⟩⟨7297⟩
⟨"eternity"⟩⟨5757⟩⟨3568⟩,⟨"Ethna"⟩⟨10576⟩⟨15342⟩
⟨"EUR"⟩⟨7042⟩⟨12968⟩,⟨"euro"⟩⟨4216⟩⟨11623⟩
⟨"euro's"⟩⟨11233⟩⟨15883⟩,⟨"europe"⟩⟨13875⟩⟨16989⟩
⟨"Europeans"⟩⟨5169⟩⟨17371⟩,⟨"euros"⟩⟨1262⟩⟨14062⟩
⟨"evacuation"⟩⟨18225⟩⟨8772⟩,⟨"eve"⟩⟨7851⟩⟨13098⟩
⟨"even"⟩⟨1963⟩⟨7470⟩,⟨"evening"⟩⟨1301⟩⟨16536⟩
⟨"event"⟩⟨2061⟩⟨6559⟩,⟨"Eventhough"⟩⟨17499⟩⟨18378⟩
⟨"eventualy"⟩⟨18438⟩⟨5962⟩,⟨"EVER"⟩⟨762⟩⟨961⟩
⟨"Everthing"⟩⟨12714⟩⟨12822⟩,⟨"every"⟩⟨187⟩⟨8592⟩
⟨"Everybody"⟩⟨13983⟩⟨17510⟩,⟨"everynight"⟩⟨12733⟩⟨12594⟩
⟨"everyone's"⟩⟨4217⟩⟨6481⟩,⟨"Everything"⟩⟨47⟩⟨5210⟩
⟨"everytime"⟩⟨11264⟩⟨17053⟩,⟨"everyway"⟩⟨11340⟩⟨4998⟩
⟨"eveything"⟩⟨11063⟩⟨14836⟩,⟨"evidenced"⟩⟨18177⟩⟨4522⟩

⟨"Eviston"⟩⟨10751⟩⟨11930⟩,⟨"ex"⟩⟨8077⟩⟨11336⟩
⟨"Exactly"⟩⟨10057⟩⟨10345⟩,⟨"exaggerated"⟩⟨14044⟩⟨10202⟩
⟨"examination"⟩⟨18165⟩⟨3374⟩,⟨"examined"⟩⟨10210⟩⟨10004⟩
⟨"exams"⟩⟨15173⟩⟨15469⟩,⟨"excecutive"⟩⟨16169⟩⟨10642⟩
⟨"exceeds"⟩⟨8021⟩⟨12699⟩,⟨"excelent"⟩⟨4601⟩⟨8946⟩
⟨"excellence"⟩⟨11354⟩⟨9930⟩,⟨"excellent"⟩⟨69⟩⟨6925⟩
⟨"except"⟩⟨6213⟩⟨14697⟩,⟨"excepted"⟩⟨12338⟩⟨10348⟩
⟨"exceptionally"⟩⟨2494⟩⟨18098⟩,⟨"exceptions"⟩⟨11211⟩⟨16247⟩
⟨"excessive"⟩⟨12002⟩⟨9484⟩,⟨"exchange"⟩⟨3886⟩⟨8003⟩
⟨"excited"⟩⟨5700⟩⟨3712⟩,⟨"exciting"⟩⟨2102⟩⟨570⟩
⟨"exclusively"⟩⟨14011⟩⟨8001⟩,⟨"excrement"⟩⟨16806⟩⟨100⟩
⟨"excused"⟩⟨12776⟩⟨10507⟩,⟨"exec"⟩⟨6861⟩⟨7239⟩
⟨"execution"⟩⟨15211⟩⟨16687⟩,⟨"Executive"⟩⟨2587⟩⟨8917⟩
⟨"exemplary"⟩⟨1993⟩⟨1123⟩,⟨"exhaust"⟩⟨16706⟩⟨1787⟩
⟨"exhaustive"⟩⟨17945⟩⟨18016⟩,⟨"exhibition"⟩⟨12087⟩⟨6782⟩
⟨"existed"⟩⟨3086⟩⟨3952⟩,⟨"existent"⟩⟨2193⟩⟨2743⟩
⟨"exited"⟩⟨11376⟩⟨5156⟩,⟨"exits"⟩⟨16971⟩⟨11230⟩
⟨"expanded"⟩⟨14191⟩⟨14798⟩,⟨"expanse"⟩⟨8948⟩⟨10971⟩
⟨"expect"⟩⟨4883⟩⟨18249⟩,⟨"expectation"⟩⟨4619⟩⟨1387⟩
⟨"expecting"⟩⟨5752⟩⟨13241⟩,⟨"expects"⟩⟨9288⟩⟨7696⟩
⟨"expencive"⟩⟨15674⟩⟨17170⟩,⟨"expenses"⟩⟨16269⟩⟨17321⟩
⟨"expereince"⟩⟨16320⟩⟨17016⟩,⟨"experience"⟩⟨571⟩⟨13336⟩
⟨"experience'"⟩⟨13458⟩⟨16370⟩,⟨"experienced"⟩⟨9441⟩⟨6884⟩
⟨"expert"⟩⟨13919⟩⟨15437⟩,⟨"expertly"⟩⟨5017⟩⟨7074⟩
⟨"explain"⟩⟨1361⟩⟨5124⟩,⟨"explained"⟩⟨159⟩⟨2856⟩
⟨"explanations"⟩⟨17674⟩⟨8421⟩,⟨"explore"⟩⟨387⟩⟨7021⟩
⟨"Express"⟩⟨8528⟩⟨10002⟩,⟨"expressed"⟩⟨1566⟩⟨8591⟩
⟨"exquisit"⟩⟨15361⟩⟨16862⟩,⟨"exquisitely"⟩⟨5898⟩⟨11094⟩
⟨"extended"⟩⟨1926⟩⟨3071⟩,⟨"extends"⟩⟨8786⟩⟨6221⟩
⟨"Extensive"⟩⟨7228⟩⟨10672⟩,⟨"extent"⟩⟨6766⟩⟨3097⟩
⟨"extermely"⟩⟨18403⟩⟨2910⟩,⟨"externally"⟩⟨8338⟩⟨10760⟩

⟨"EXTRA"⟩⟨15549⟩⟨14164⟩,⟨"extract"⟩⟨8997⟩⟨3510⟩
⟨"extraordinary"⟩⟨3029⟩⟨3749⟩,⟨"extras&quot"⟩⟨11829⟩⟨11808⟩
⟨"extreme"⟩⟨3170⟩⟨7067⟩,⟨"extremelly"⟩⟨8588⟩⟨11124⟩
⟨"extrememly"⟩⟨7794⟩⟨11297⟩,⟨"extremly"⟩⟨8650⟩⟨16400⟩
⟨"Eye"⟩⟨17830⟩⟨17953⟩,⟨"eyed"⟩⟨5848⟩⟨7820⟩
⟨"Eyre"⟩⟨5530⟩⟨7535⟩,⟨"f"⟩⟨4024⟩⟨16556⟩
⟨"FAB"⟩⟨8984⟩⟨13005⟩,⟨"fabalous"⟩⟨11019⟩⟨14781⟩
⟨"fabrics"⟩⟨11247⟩⟨6529⟩,⟨"Fabulous"⟩⟨1376⟩⟨12572⟩
⟨"face"⟩⟨2560⟩⟨10192⟩,⟨"face'"⟩⟨7163⟩⟨6271⟩
⟨"facelift"⟩⟨6969⟩⟨13188⟩,⟨"facial"⟩⟨1484⟩⟨1213⟩
⟨"facilitating"⟩⟨17180⟩⟨18492⟩,⟨"facilities"⟩⟨1150⟩⟨11484⟩
⟨"facillities"⟩⟨13559⟩⟨14868⟩,⟨"facing"⟩⟨679⟩⟨2480⟩
⟨"factory"⟩⟨2435⟩⟨9129⟩,⟨"facts"⟩⟨14759⟩⟨3176⟩
⟨"Fahrenheit"⟩⟨4401⟩⟨3919⟩,⟨"failed"⟩⟨711⟩⟨1494⟩
⟨"Failte"⟩⟨14452⟩⟨544⟩,⟨"faint"⟩⟨4720⟩⟨9413⟩
⟨"Fairgreen"⟩⟨3723⟩⟨5046⟩,⟨"Fairly"⟩⟨14736⟩⟨18210⟩
⟨"fairy"⟩⟨3500⟩⟨1948⟩,⟨"faith"⟩⟨3285⟩⟨2408⟩
⟨"falcon"⟩⟨15301⟩⟨16789⟩,⟨"fallen"⟩⟨4219⟩⟨8370⟩
⟨"fame"⟩⟨17500⟩⟨18379⟩,⟨"familar"⟩⟨17712⟩⟨6446⟩
⟨"Families"⟩⟨8493⟩⟨7398⟩,⟨"family"⟩⟨204⟩⟨15660⟩
⟨"family-run"⟩⟨3432⟩⟨2128⟩,⟨"family&quot"⟩⟨15642⟩⟨17147⟩
⟨"famous"⟩⟨5868⟩⟨1703⟩,⟨"Fan"⟩⟨17273⟩⟨5355⟩
⟨"fancied"⟩⟨5620⟩⟨10041⟩,⟨"fancy"⟩⟨3132⟩⟨6195⟩
⟨"fantastic"⟩⟨10⟩⟨6345⟩,⟨"FANTASTIC"⟩⟨8247⟩⟨6345⟩
⟨"FAR"⟩⟨3446⟩⟨14389⟩,⟨"faraway"⟩⟨15217⟩⟨16696⟩
⟨"fared"⟩⟨7697⟩⟨8831⟩,⟨"fares"⟩⟨14262⟩⟨17412⟩
⟨"Farm"⟩⟨14717⟩⟨12214⟩,⟨"farmers"⟩⟨14843⟩⟨9401⟩
⟨"Farnham"⟩⟨2395⟩⟨3761⟩,⟨"fascilities"⟩⟨16999⟩⟨917⟩
⟨"fashioned"⟩⟨1733⟩⟨2950⟩,⟨"Fast"⟩⟨15080⟩⟨7691⟩
⟨"fat"⟩⟨1244⟩⟨4931⟩,⟨"father"⟩⟨9556⟩⟨17798⟩
⟨"fathers"⟩⟨14924⟩⟨17450⟩,⟨"faucet"⟩⟨1831⟩⟨2149⟩

⟨"faultless"⟩⟨515⟩⟨1089⟩,⟨"faulty"⟩⟨2014⟩⟨1458⟩
⟨"fave"⟩⟨9210⟩⟨6068⟩,⟨"favorable"⟩⟨14244⟩⟨15112⟩
⟨"favour"⟩⟨447⟩⟨3681⟩,⟨"favourably"⟩⟨11193⟩⟨12721⟩
⟨"favours"⟩⟨13837⟩⟨17376⟩,⟨"fawlty"⟩⟨13763⟩⟨5956⟩
⟨"Faythe"⟩⟨14155⟩⟨17605⟩,⟨"fear"⟩⟨491⟩⟨6996⟩
⟨"feast"⟩⟨1713⟩⟨1114⟩,⟨"feather"⟩⟨3394⟩⟨6441⟩
⟨"features"⟩⟨10815⟩⟨10891⟩,⟨"Feb"⟩⟨5892⟩⟨8076⟩
⟨"fed"⟩⟨7664⟩⟨14696⟩,⟨"feeble"⟩⟨8992⟩⟨2371⟩
⟨"feel"⟩⟨346⟩⟨7997⟩,⟨"feeling"⟩⟨1910⟩⟨12485⟩
⟨"fees"⟩⟨9120⟩⟨13971⟩,⟨"fell"⟩⟨4793⟩⟨594⟩
⟨"Fels"⟩⟨5031⟩⟨11744⟩,⟨"Felt"⟩⟨10439⟩⟨16200⟩
⟨"fenced"⟩⟨4830⟩⟨11584⟩,⟨"fencing"⟩⟨7499⟩⟨8782⟩
⟨"Fernhill"⟩⟨5419⟩⟨4300⟩,⟨"Ferry"⟩⟨7011⟩⟨12171⟩
⟨"ferryport"⟩⟨15622⟩⟨13463⟩,⟨"Festival"⟩⟨5830⟩⟨12353⟩
⟨"few"⟩⟨1674⟩⟨14575⟩,⟨"fewer"⟩⟨12398⟩⟨12492⟩
⟨"Fianc?????"⟩⟨18303⟩⟨10207⟩,⟨"fiance"⟩⟨10546⟩⟨17467⟩
⟨"Fiancee"⟩⟨15011⟩⟨7492⟩,⟨"fiddle"⟩⟨16615⟩⟨15485⟩
⟨"fields"⟩⟨2869⟩⟨3164⟩,⟨"fifteen"⟩⟨6075⟩⟨6870⟩
⟨"fight"⟩⟨1501⟩⟨6081⟩,⟨"fights"⟩⟨6759⟩⟨6719⟩
⟨"file"⟩⟨5237⟩⟨10987⟩,⟨"fill"⟩⟨2133⟩⟨4633⟩
⟨"Fillet"⟩⟨13863⟩⟨10665⟩,⟨"filling"⟩⟨7613⟩⟨8117⟩
⟨"filmed"⟩⟨14350⟩⟨17294⟩,⟨"filter"⟩⟨8222⟩⟨13736⟩
⟨"filthy"⟩⟨10542⟩⟨558⟩,⟨"Filthy"⟩⟨18241⟩⟨558⟩
⟨"finally"⟩⟨7898⟩⟨1015⟩,⟨"finals"⟩⟨16728⟩⟨15524⟩
⟨"find"⟩⟨2595⟩⟨4411⟩,⟨"finding"⟩⟨2416⟩⟨17044⟩
⟨"Fine"⟩⟨8708⟩⟨8810⟩,⟨"finer"⟩⟨3424⟩⟨1304⟩
⟨"fingers"⟩⟨1761⟩⟨5080⟩,⟨"finish"⟩⟨3255⟩⟨2687⟩
⟨"finishing"⟩⟨10425⟩⟨13914⟩,⟨"Finnstown"⟩⟨14147⟩⟨17615⟩
⟨"Fire"⟩⟨4844⟩⟨8896⟩,⟨"firendly"⟩⟨8637⟩⟨11156⟩
⟨"fireside"⟩⟨15930⟩⟨8785⟩,⟨"firm"⟩⟨6424⟩⟨3004⟩
⟨"First"⟩⟨5789⟩⟨7836⟩,⟨"first-class"⟩⟨11849⟩⟨16305⟩

⟨"fish"⟩⟨695⟩⟨11371⟩,⟨"Fishamble"⟩⟨12864⟩⟨15833⟩
⟨"Fishing"⟩⟨15354⟩⟨16855⟩,⟨"fishy"⟩⟨18025⟩⟨18072⟩
⟨"Fitness"⟩⟨8861⟩⟨6713⟩,⟨"fitted"⟩⟨8883⟩⟨17629⟩
⟨"Fitz's"⟩⟨12279⟩⟨10231⟩,⟨"Fitzgerald's"⟩⟨7167⟩⟨6280⟩
⟨"Fitzpatricks"⟩⟨13344⟩⟨11846⟩,⟨"Fitzsimons"⟩⟨5393⟩⟨2795⟩
⟨"fitzwilton"⟩⟨14123⟩⟨17585⟩,⟨"Five"⟩⟨8714⟩⟨15340⟩
⟨"fix"⟩⟨1891⟩⟨1572⟩,⟨"fixed"⟩⟨3472⟩⟨1633⟩
⟨"fixtures"⟩⟨6329⟩⟨16085⟩,⟨"flagging"⟩⟨10238⟩⟨10044⟩
⟨"flaking"⟩⟨16238⟩⟨404⟩,⟨"flannels"⟩⟨6128⟩⟨3233⟩
⟨"flashing"⟩⟨13330⟩⟨7321⟩,⟨"flask"⟩⟨4251⟩⟨8673⟩
⟨"flatly"⟩⟨18049⟩⟨171⟩,⟨"flatscreen"⟩⟨2167⟩⟨4102⟩
⟨"flavorful"⟩⟨8562⟩⟨6407⟩,⟨"flavoured"⟩⟨12825⟩⟨15793⟩
⟨"flawless"⟩⟨2485⟩⟨2781⟩,⟨"flaws"⟩⟨11715⟩⟨7904⟩
⟨"fleeced"⟩⟨18416⟩⟨2928⟩,⟨"fleet"⟩⟨8552⟩⟨6392⟩
⟨"flex"⟩⟨18204⟩⟨4582⟩,⟨"flexible"⟩⟨2478⟩⟨5159⟩
⟨"flies"⟩⟨250⟩⟨3222⟩,⟨"Flight"⟩⟨15515⟩⟨12142⟩
⟨"float"⟩⟨10736⟩⟨7551⟩,⟨"floating"⟩⟨917⟩⟨1836⟩
⟨"flooded"⟩⟨1755⟩⟨3710⟩,⟨"floodlight"⟩⟨15597⟩⟨13430⟩
⟨"Floor"⟩⟨11690⟩⟨16204⟩,⟨"floorboard"⟩⟨15591⟩⟨13420⟩
⟨"floors"⟩⟨5565⟩⟨6705⟩,⟨"flop"⟩⟨14120⟩⟨17582⟩
⟨"flotation"⟩⟨16869⟩⟨15768⟩,⟨"flowed"⟩⟨12744⟩⟨12627⟩
⟨"flowing"⟩⟨9809⟩⟨13254⟩,⟨"flows"⟩⟨12470⟩⟨15201⟩
⟨"fluffly"⟩⟨9157⟩⟨4797⟩,⟨"Fluffy"⟩⟨15281⟩⟨16768⟩
⟨"flushed"⟩⟨1034⟩⟨2567⟩,⟨"flushes"⟩⟨18097⟩⟨4733⟩
⟨"Fly"⟩⟨8310⟩⟨12101⟩,⟨"flyer"⟩⟨12915⟩⟨15894⟩
⟨"Flynns"⟩⟨10250⟩⟨10062⟩,⟨"foam"⟩⟨13698⟩⟨16244⟩
⟨"focal"⟩⟨11059⟩⟨14832⟩,⟨"focused"⟩⟨14550⟩⟨18103⟩
⟨"foie"⟩⟨7432⟩⟨3258⟩,⟨"foldaway"⟩⟨8472⟩⟨3770⟩
⟨"Foley's"⟩⟨9377⟩⟨11246⟩,⟨"Folk"⟩⟨13145⟩⟨15594⟩
⟨"follow-up"⟩⟨15251⟩⟨16736⟩,⟨"Following"⟩⟨2645⟩⟨2448⟩
⟨"fond"⟩⟨11396⟩⟨15897⟩,⟨"fondest"⟩⟨9918⟩⟨5598⟩

⟨"Food"⟩⟨1109⟩⟨14363⟩,⟨"food-"⟩⟨14351⟩⟨17295⟩
⟨"foodies"⟩⟨11671⟩⟨14069⟩,⟨"fool"⟩⟨14743⟩⟨3272⟩
⟨"fools"⟩⟨13324⟩⟨7313⟩,⟨"football"⟩⟨8951⟩⟨15138⟩
⟨"footpaths"⟩⟨15235⟩⟨16715⟩,⟨"for"⟩⟨1764⟩⟨15436⟩
⟨"for'"⟩⟨8401⟩⟨14610⟩,⟨"forbid"⟩⟨14233⟩⟨12777⟩
⟨"forcing"⟩⟨10965⟩⟨14728⟩,⟨"foreign"⟩⟨1283⟩⟨14527⟩
⟨"foremost"⟩⟨16410⟩⟨16682⟩,⟨"forest"⟩⟨5192⟩⟨8016⟩
⟨"forget"⟩⟨2415⟩⟨9162⟩,⟨"forgetful"⟩⟨12502⟩⟨16534⟩
⟨"forgive"⟩⟨13927⟩⟨11672⟩,⟨"forgiving"⟩⟨8751⟩⟨6141⟩
⟨"forgotton"⟩⟨14369⟩⟨15263⟩,⟨"forks"⟩⟨3538⟩⟨8703⟩
⟨"formed"⟩⟨13470⟩⟨9231⟩,⟨"formerly"⟩⟨3966⟩⟨4924⟩
⟨"formula"⟩⟨12735⟩⟨12602⟩,⟨"Forster"⟩⟨9717⟩⟨5902⟩
⟨"forthcoming"⟩⟨5799⟩⟨2284⟩,⟨"fortnight"⟩⟨17925⟩⟨18004⟩
⟨"fortune"⟩⟨7719⟩⟨16380⟩,⟨"Forum"⟩⟨6698⟩⟨17516⟩
⟨"forwards"⟩⟨5627⟩⟨9022⟩,⟨"fot"⟩⟨15504⟩⟨12125⟩
⟨"fought"⟩⟨4872⟩⟨1493⟩,⟨"Found"⟩⟨602⟩⟨8558⟩
⟨"fountains"⟩⟨11673⟩⟨14071⟩,⟨"four"⟩⟨2146⟩⟨13196⟩
⟨"fours"⟩⟨12736⟩⟨12606⟩,⟨"Fourth"⟩⟨8394⟩⟨14548⟩
⟨"foxford"⟩⟨15725⟩⟨15979⟩,⟨"Foyer"⟩⟨6882⟩⟨11077⟩
⟨"fraction"⟩⟨5235⟩⟨3931⟩,⟨"framed"⟩⟨14637⟩⟨13148⟩
⟨"france"⟩⟨11420⟩⟨14256⟩,⟨"franchise"⟩⟨17036⟩⟨679⟩
⟨"Frank"⟩⟨3615⟩⟨8181⟩,⟨"frankly"⟩⟨761⟩⟨8556⟩
⟨"frazzled"⟩⟨14655⟩⟨17490⟩,⟨"freaked"⟩⟨13773⟩⟨10577⟩
⟨"Fredericks"⟩⟨5485⟩⟨3365⟩,⟨"free"⟩⟨961⟩⟨6435⟩
⟨"freebie"⟩⟨16901⟩⟨18143⟩,⟨"freedom"⟩⟨5532⟩⟨11027⟩
⟨"freeze"⟩⟨3914⟩⟨3843⟩,⟨"FREEZING"⟩⟨7352⟩⟨5590⟩
⟨"freindly"⟩⟨3205⟩⟨1269⟩,⟨"French"⟩⟨1538⟩⟨16290⟩
⟨"frequent"⟩⟨9503⟩⟨4631⟩,⟨"frequenting"⟩⟨14809⟩⟨1219⟩
⟨"Fresh&quot"⟩⟨15795⟩⟨16027⟩,⟨"freshened"⟩⟨9361⟩⟨11217⟩
⟨"freshest"⟩⟨4373⟩⟨2143⟩,⟨"Freshly"⟩⟨8295⟩⟨10701⟩
⟨"fri"⟩⟨8458⟩⟨13763⟩,⟨"friday"⟩⟨10464⟩⟨15677⟩

⟨"fridges"⟩⟨14406⟩⟨17421⟩,⟨"Fried"⟩⟨12451⟩⟨15193⟩
⟨"friend's"⟩⟨9810⟩⟨17198⟩,⟨"friendliest"⟩⟨1270⟩⟨1524⟩
⟨"friendly-"⟩⟨15811⟩⟨16060⟩,⟨"friendly&quot"⟩⟨12794⟩⟨10535⟩
⟨"friends'"⟩⟨14649⟩⟨15062⟩,⟨"friendy"⟩⟨14771⟩⟨9982⟩
⟨"frightening"⟩⟨1559⟩⟨1730⟩,⟨"frinedly"⟩⟨9222⟩⟨6085⟩
⟨"From"⟩⟨8⟩⟨5035⟩,⟨"FROM"⟩⟨2512⟩⟨5035⟩
⟨"front-desk"⟩⟨16746⟩⟨15543⟩,⟨"frontage"⟩⟨4567⟩⟨11914⟩
⟨"fronts"⟩⟨12176⟩⟨8116⟩,⟨"frosted"⟩⟨8851⟩⟨3070⟩
⟨"fruit"⟩⟨871⟩⟨15700⟩,⟨"fruit&quot"⟩⟨17958⟩⟨13670⟩
⟨"frustrating"⟩⟨7329⟩⟨1760⟩,⟨"fry"⟩⟨5210⟩⟨12975⟩
⟨"frying"⟩⟨5761⟩⟨3573⟩,⟨"ft"⟩⟨10367⟩⟨7245⟩
⟨"fulfill"⟩⟨7218⟩⟨6309⟩,⟨"full"⟩⟨1838⟩⟨9769⟩
⟨"full-service"⟩⟨16069⟩⟨14912⟩,⟨"fully"⟩⟨2041⟩⟨16090⟩
⟨"fuming"⟩⟨17033⟩⟨434⟩,⟨"Fun"⟩⟨10019⟩⟨15981⟩
⟨"functional"⟩⟨4698⟩⟨2653⟩,⟨"functioning"⟩⟨12173⟩⟨17401⟩
⟨"funeral"⟩⟨2393⟩⟨8542⟩,⟨"fungus"⟩⟨18033⟩⟨67⟩
⟨"funniest"⟩⟨12803⟩⟨10549⟩,⟨"Funnily"⟩⟨16135⟩⟨12881⟩
⟨"furious"⟩⟨13883⟩⟨3051⟩,⟨"furnishing"⟩⟨6721⟩⟨5807⟩
⟨"furniture"⟩⟨5016⟩⟨10718⟩,⟨"Further"⟩⟨9863⟩⟨9425⟩
⟨"fuse"⟩⟨7641⟩⟨11635⟩,⟨"fusion"⟩⟨14312⟩⟨12298⟩
⟨"fusty"⟩⟨16452⟩⟨572⟩,⟨"future"⟩⟨2254⟩⟨424⟩
⟨"g"⟩⟨6047⟩⟨11743⟩,⟨"G&amp"⟩⟨15981⟩⟨9735⟩
⟨"Gaeity"⟩⟨15304⟩⟨16793⟩,⟨"Gaiety"⟩⟨3648⟩⟨1940⟩
⟨"gal"⟩⟨16593⟩⟨15470⟩,⟨"Gala"⟩⟨14925⟩⟨17451⟩
⟨"Gallaghers"⟩⟨5024⟩⟨10737⟩,⟨"Gallery"⟩⟨2827⟩⟨7353⟩
⟨"Galway"⟩⟨959⟩⟨13249⟩,⟨"Galway's"⟩⟨14076⟩⟨12272⟩
⟨"Gan"⟩⟨13553⟩⟨14860⟩,⟨"gangs"⟩⟨14698⟩⟨17365⟩
⟨"gap"⟩⟨4166⟩⟨8336⟩,⟨"garage"⟩⟨7523⟩⟨4650⟩
⟨"garda"⟩⟨14898⟩⟨3719⟩,⟨"gardai"⟩⟨18343⟩⟨2175⟩
⟨"Gardens"⟩⟨3478⟩⟨4122⟩,⟨"gargantuan"⟩⟨17943⟩⟨18014⟩
⟨"garnish"⟩⟨3754⟩⟨15323⟩,⟨"Garryvoe"⟩⟨4941⟩⟨2643⟩

⟨"Gasworks"⟩⟨4377⟩⟨2530⟩,⟨"gate"⟩⟨9668⟩⟨16943⟩
⟨"Gateway"⟩⟨6394⟩⟨11488⟩,⟨"gathered"⟩⟨1549⟩⟨4434⟩
⟨"gauge"⟩⟨13381⟩⟨11877⟩,⟨"Gave"⟩⟨16246⟩⟨15686⟩
⟨"gazebo"⟩⟨17543⟩⟨18413⟩,⟨"GB"⟩⟨13666⟩⟨13415⟩
⟨"geared"⟩⟨4661⟩⟨1183⟩,⟨"Geese"⟩⟨4933⟩⟨2049⟩
⟨"Gem"⟩⟨10695⟩⟨16764⟩,⟨"gems"⟩⟨5730⟩⟨5033⟩
⟨"Generally"⟩⟨9114⟩⟨14418⟩,⟨"generation"⟩⟨14087⟩⟨16941⟩
⟨"generic"⟩⟨13161⟩⟨17690⟩,⟨"generous"⟩⟨486⟩⟨4610⟩
⟨"gent"⟩⟨14586⟩⟨17355⟩,⟨"gentle"⟩⟨6799⟩⟨3781⟩
⟨"gently"⟩⟨7420⟩⟨12868⟩,⟨"Gents"⟩⟨12631⟩⟨16628⟩
⟨"George"⟩⟨9541⟩⟨17068⟩,⟨"georgeous"⟩⟨8666⟩⟨13135⟩
⟨"Georgina"⟩⟨7212⟩⟨6307⟩,⟨"Ger"⟩⟨16789⟩⟨17790⟩
⟨"Germans"⟩⟨16030⟩⟨16437⟩,⟨"Gerry"⟩⟨6216⟩⟨10903⟩
⟨"GET"⟩⟨16362⟩⟨17359⟩,⟨"get-together"⟩⟨16940⟩⟨965⟩
⟨"gettin"⟩⟨12286⟩⟨10248⟩,⟨"Getting"⟩⟨10727⟩⟨16584⟩
⟨"ghastly"⟩⟨13805⟩⟨4840⟩,⟨"ghetto"⟩⟨5587⟩⟨9020⟩
⟨"Gift"⟩⟨10159⟩⟨12162⟩,⟨"gig"⟩⟨12550⟩⟨17128⟩
⟨"Gilbert"⟩⟨17553⟩⟨18420⟩,⟨"Gill"⟩⟨15294⟩⟨16782⟩
⟨"gin"⟩⟨9623⟩⟨14479⟩,⟨"ginger"⟩⟨11855⟩⟨10373⟩
⟨"Girl"⟩⟨10292⟩⟨12237⟩,⟨"girlfriend"⟩⟨2222⟩⟨14584⟩
⟨"girlies"⟩⟨10151⟩⟨6159⟩,⟨"Girls"⟩⟨14916⟩⟨16850⟩
⟨"Given"⟩⟨2801⟩⟨1002⟩,⟨"gives"⟩⟨6852⟩⟨13925⟩
⟨"gladly"⟩⟨9116⟩⟨5977⟩,⟨"glamorous"⟩⟨8074⟩⟨11330⟩
⟨"glanced"⟩⟨15689⟩⟨17180⟩,⟨"Glanleam"⟩⟨17726⟩⟨11659⟩
⟨"glass"⟩⟨3449⟩⟨9088⟩,⟨"glassed-in"⟩⟨10265⟩⟨10084⟩
⟨"glasshouse"⟩⟨14103⟩⟨15156⟩,⟨"glassware"⟩⟨16009⟩⟨11748⟩
⟨"Gleeson"⟩⟨12648⟩⟨10361⟩,⟨"Gleesons"⟩⟨5424⟩⟨4301⟩
⟨"Glendalough"⟩⟨6827⟩⟨6864⟩,⟨"gleneagle"⟩⟨14219⟩⟨12768⟩
⟨"Glenmore"⟩⟨14906⟩⟨1731⟩,⟨"Glenview"⟩⟨9111⟩⟨5840⟩
⟨"glitz"⟩⟨10034⟩⟨5798⟩,⟨"global"⟩⟨16060⟩⟨18437⟩
⟨"gloomy"⟩⟨913⟩⟨1489⟩,⟨"glorious"⟩⟨4033⟩⟨7377⟩

⟨"gloves"⟩⟨17058⟩⟨10459⟩,⟨"glowing"⟩⟨5200⟩⟨1902⟩
⟨"GM"⟩⟨12175⟩⟨17403⟩,⟨"GO"⟩⟨1169⟩⟨13431⟩
⟨"goal"⟩⟨16604⟩⟨15482⟩,⟨"goats"⟩⟨13181⟩⟨9749⟩
⟨"God"⟩⟨565⟩⟨9071⟩,⟨"gods"⟩⟨13339⟩⟨7335⟩
⟨"Gogarty"⟩⟨15949⟩⟨7403⟩,⟨"goggles"⟩⟨18087⟩⟨4717⟩
⟨"goings"⟩⟨15123⟩⟨16911⟩,⟨"Gold"⟩⟨6453⟩⟨13655⟩
⟨"golf"⟩⟨86⟩⟨5758⟩,⟨"golfcourse"⟩⟨8610⟩⟨11134⟩
⟨"Golfers"⟩⟨13879⟩⟨12018⟩,⟨"Golfing"⟩⟨9201⟩⟨4838⟩
⟨"Good"⟩⟨132⟩⟨14354⟩,⟨"GOOD"⟩⟨13056⟩⟨14354⟩
⟨"goodbye"⟩⟨7277⟩⟨6840⟩,⟨"goodness"⟩⟨7722⟩⟨14395⟩
⟨"Google"⟩⟨16405⟩⟨16672⟩,⟨"Goose"⟩⟨17638⟩⟨17857⟩
⟨"gorg"⟩⟨12431⟩⟨16496⟩,⟨"Gorgeous"⟩⟨3746⟩⟨6664⟩
⟨"Gort"⟩⟨15019⟩⟨8976⟩,⟨"got"⟩⟨3155⟩⟨8225⟩
⟨"gotta"⟩⟨16046⟩⟨11776⟩,⟨"Gougane"⟩⟨13100⟩⟨16995⟩
⟨"Gourmet"⟩⟨8814⟩⟨6665⟩,⟨"gown"⟩⟨10991⟩⟨16212⟩
⟨"gr8"⟩⟨6502⟩⟨7233⟩,⟨"grabbed"⟩⟨11680⟩⟨13281⟩
⟨"graces"⟩⟨6927⟩⟨2223⟩,⟨"Gracious"⟩⟨15265⟩⟨16750⟩
⟨"graded"⟩⟨13973⟩⟨14388⟩,⟨"gradually"⟩⟨14112⟩⟨17574⟩
⟨"Graffton"⟩⟨9752⟩⟨16810⟩,⟨"Grafton"⟩⟨966⟩⟨8423⟩
⟨"Granby"⟩⟨4892⟩⟨8551⟩,⟨"grand"⟩⟨9662⟩⟨8492⟩
⟨"grande"⟩⟨10357⟩⟨10121⟩,⟨"grandmother"⟩⟨3649⟩⟨2757⟩
⟨"granite"⟩⟨4233⟩⟨3082⟩,⟨"granny"⟩⟨13857⟩⟨17397⟩
⟨"granted"⟩⟨11714⟩⟨17129⟩,⟨"grapefruit"⟩⟨2489⟩⟨8161⟩
⟨"grass"⟩⟨11335⟩⟨13310⟩,⟨"grat"⟩⟨15321⟩⟨16815⟩
⟨"gratefully"⟩⟨14847⟩⟨11504⟩,⟨"gratitude"⟩⟨8431⟩⟨14644⟩
⟨"graveyard"⟩⟨12226⟩⟨17481⟩,⟨"gravy"⟩⟨3990⟩⟨7932⟩
⟨"grease"⟩⟨634⟩⟨4190⟩,⟨"great"⟩⟨142⟩⟨6044⟩
⟨"greated"⟩⟨9848⟩⟨9092⟩,⟨"greatest"⟩⟨5701⟩⟨9475⟩
⟨"greedy"⟩⟨9039⟩⟨7718⟩,⟨"green"⟩⟨7750⟩⟨6744⟩
⟨"Greenes"⟩⟨7446⟩⟨4219⟩,⟨"greenhouse"⟩⟨13639⟩⟨13371⟩
⟨"Greeted"⟩⟨5672⟩⟨7206⟩,⟨"greeting"⟩⟨5336⟩⟨9541⟩

⟨"Gregory"⟩⟨11758⟩⟨14078⟩,⟨"Gresham"⟩⟨8044⟩⟨10657⟩
⟨"greyhound"⟩⟨7685⟩⟨8817⟩,⟨"Grianan"⟩⟨15344⟩⟨16839⟩
⟨"Grigio"⟩⟨12770⟩⟨10499⟩,⟨"grill"⟩⟨11408⟩⟨15901⟩
⟨"grimey"⟩⟨17550⟩⟨15136⟩,⟨"grin"⟩⟨16672⟩⟨4461⟩
⟨"grips"⟩⟨17822⟩⟨17945⟩,⟨"groans"⟩⟨16096⟩⟨14933⟩
⟨"Groom"⟩⟨7790⟩⟨11692⟩,⟨"grooms"⟩⟨16775⟩⟨17776⟩
⟨"grotty"⟩⟨544⟩⟨136⟩,⟨"ground"⟩⟨4492⟩⟨8943⟩
⟨"Group"⟩⟨6797⟩⟨9815⟩,⟨"groups"⟩⟨10415⟩⟨13729⟩
⟨"grow"⟩⟨10756⟩⟨11934⟩,⟨"grown"⟩⟨10466⟩⟨12308⟩
⟨"grubbiness"⟩⟨18266⟩⟨337⟩,⟨"gruby"⟩⟨18325⟩⟨809⟩
⟨"grumble"⟩⟨8927⟩⟨12855⟩,⟨"grumpy"⟩⟨1201⟩⟨5891⟩
⟨"guarantee"⟩⟨10916⟩⟨13338⟩,⟨"guarantees"⟩⟨12884⟩⟨15855⟩
⟨"guarentee"⟩⟨7689⟩⟨1042⟩,⟨"Guess"⟩⟨2943⟩⟨5321⟩
⟨"guest"⟩⟨2829⟩⟨6055⟩,⟨"guest's"⟩⟨7034⟩⟨12350⟩
⟨"guesthouses"⟩⟨12044⟩⟨8565⟩,⟨"guestrooms"⟩⟨14999⟩⟨17549⟩
⟨"guests'"⟩⟨4371⟩⟨11621⟩,⟨"guidance"⟩⟨14487⟩⟨15439⟩
⟨"guidebooks"⟩⟨10803⟩⟨17035⟩,⟨"guides"⟩⟨11124⟩⟨14741⟩
⟨"Guinea"⟩⟨15741⟩⟨13497⟩,⟨"guiness"⟩⟨7225⟩⟨8965⟩
⟨"Gulfstream"⟩⟨8350⟩⟨10779⟩,⟨"gum"⟩⟨14328⟩⟨47⟩
⟨"gushing"⟩⟨18179⟩⟨4529⟩,⟨"guts"⟩⟨18107⟩⟨10862⟩
⟨"guy"⟩⟨4685⟩⟨10353⟩,⟨"guys"⟩⟨9815⟩⟨13827⟩
⟨"Gym"⟩⟨2543⟩⟨2133⟩,⟨"gyms"⟩⟨8000⟩⟨12678⟩
⟨"ha"⟩⟨6032⟩⟨15468⟩,⟨"Ha'penny"⟩⟨9931⟩⟨15236⟩
⟨"hack"⟩⟨16817⟩⟨540⟩,⟨"had"⟩⟨2187⟩⟨16388⟩
⟨"hadn't"⟩⟨6577⟩⟨13458⟩,⟨"hadnt"⟩⟨582⟩⟨2612⟩
⟨"hair"⟩⟨994⟩⟨6831⟩,⟨"hair-dryer"⟩⟨12486⟩⟨15207⟩
⟨"hairdryer"⟩⟨4027⟩⟨7960⟩,⟨"hairdryers"⟩⟨6427⟩⟨11556⟩
⟨"hairy"⟩⟨4214⟩⟨4139⟩,⟨"Half"⟩⟨863⟩⟨3209⟩
⟨"Hall"⟩⟨3109⟩⟨8180⟩,⟨"Halloween"⟩⟨6809⟩⟨3828⟩
⟨"Halo"⟩⟨5993⟩⟨3836⟩,⟨"Halpins"⟩⟨17814⟩⟨17937⟩
⟨"Ham"⟩⟨17883⟩⟨17974⟩,⟨"hammer"⟩⟨4318⟩⟨8459⟩

⟨"Hampton"⟩⟨4911⟩⟨5455⟩,⟨"hand"⟩⟨6640⟩⟨5095⟩
⟨"Handel"⟩⟨16438⟩⟨515⟩,⟨"handheld"⟩⟨12634⟩⟨16632⟩
⟨"handily"⟩⟨12829⟩⟨15797⟩,⟨"handle"⟩⟨4458⟩⟨2377⟩
⟨"handmade"⟩⟨13046⟩⟨17089⟩,⟨"hands"⟩⟨2164⟩⟨5316⟩
⟨"handsomely"⟩⟨15543⟩⟨9616⟩,⟨"handwritten"⟩⟨11862⟩⟨10928⟩
⟨"hanger"⟩⟨6510⟩⟨11267⟩,⟨"hanging"⟩⟨910⟩⟨1436⟩
⟨"hangs"⟩⟨10519⟩⟨15272⟩,⟨"haphazard"⟩⟨11260⟩⟨16137⟩
⟨"happened"⟩⟨6860⟩⟨480⟩,⟨"happenings"⟩⟨9242⟩⟨6110⟩
⟨"happily"⟩⟨2482⟩⟨15978⟩,⟨"happiness"⟩⟨14357⟩⟨17301⟩
⟨"harassed"⟩⟨5430⟩⟨5830⟩,⟨"Harbor"⟩⟨6351⟩⟨6808⟩
⟨"harcourt"⟩⟨16507⟩⟨15955⟩,⟨"Hard"⟩⟨4792⟩⟨12734⟩
⟨"harding"⟩⟨13565⟩⟨14876⟩,⟨"Hardly"⟩⟨13197⟩⟨12548⟩
⟨"hardworking"⟩⟨8330⟩⟨10749⟩,⟨"Hardys"⟩⟨10192⟩⟨6238⟩
⟨"Harrington"⟩⟨4568⟩⟨11916⟩,⟨"Harry's"⟩⟨6871⟩⟨11063⟩
⟨"Harvey"⟩⟨16226⟩⟨15961⟩,⟨"Harveys"⟩⟨2118⟩⟨6080⟩
⟨"hash"⟩⟨6655⟩⟨4428⟩,⟨"hasn't"⟩⟨3097⟩⟨8359⟩
⟨"hassle-free"⟩⟨8938⟩⟨10958⟩,⟨"hassles"⟩⟨16109⟩⟨9494⟩
⟨"hasty"⟩⟨17703⟩⟨2669⟩,⟨"hate"⟩⟨6800⟩⟨6609⟩
⟨"hats"⟩⟨7819⟩⟨15211⟩,⟨"haul"⟩⟨12579⟩⟨14214⟩
⟨"haunted"⟩⟨12961⟩⟨17232⟩,⟨"haute"⟩⟨17647⟩⟨17866⟩
⟨"HAVE"⟩⟨1503⟩⟨8002⟩,⟨"haven"⟩⟨1736⟩⟨4152⟩
⟨"havent"⟩⟨2807⟩⟨9598⟩,⟨"Having"⟩⟨2350⟩⟨12753⟩
⟨"hay"⟩⟨10270⟩⟨10090⟩,⟨"hazard"⟩⟨1104⟩⟨7385⟩
⟨"He"⟩⟨340⟩⟨2492⟩,⟨"he'd"⟩⟨13710⟩⟨12437⟩
⟨"Head"⟩⟨1845⟩⟨2855⟩,⟨"headache"⟩⟨2334⟩⟨1705⟩
⟨"headed"⟩⟨1896⟩⟨8035⟩,⟨"heading"⟩⟨4612⟩⟨9619⟩
⟨"headquarters"⟩⟨8336⟩⟨10756⟩,⟨"healing"⟩⟨15244⟩⟨16727⟩
⟨"healthy"⟩⟨5367⟩⟨6331⟩,⟨"heaps"⟩⟨9104⟩⟨3549⟩
⟨"hearing"⟩⟨3740⟩⟨9272⟩,⟨"heart"⟩⟨578⟩⟨6311⟩
⟨"heartfelt"⟩⟨15372⟩⟨16877⟩,⟨"heartily"⟩⟨7150⟩⟨13192⟩
⟨"Heat"⟩⟨16995⟩⟨511⟩,⟨"Heated"⟩⟨14338⟩⟨15218⟩

⟨"Heather"⟩⟨11087⟩⟨14848⟩,⟨"heating"⟩⟨8088⟩⟨17691⟩
⟨"Heatons"⟩⟨1992⟩⟨708⟩,⟨"heaven"⟩⟨629⟩⟨3467⟩
⟨"heavens"⟩⟨17418⟩⟨18304⟩,⟨"heavily"⟩⟨4700⟩⟨10107⟩
⟨"hectic"⟩⟨3688⟩⟨9705⟩,⟨"heel"⟩⟨16681⟩⟨86⟩
⟨"heights"⟩⟨9301⟩⟨16446⟩,⟨"Heineken"⟩⟨4484⟩⟨17839⟩
⟨"Helen's"⟩⟨4091⟩⟨3085⟩,⟨"Helens"⟩⟨14230⟩⟨17706⟩
⟨"hell"⟩⟨305⟩⟨4798⟩,⟨"hello"⟩⟨9463⟩⟨17253⟩
⟨"helped"⟩⟨1299⟩⟨5836⟩,⟨"Helpful"⟩⟨5059⟩⟨11627⟩
⟨"helpfulness"⟩⟨2788⟩⟨1951⟩,⟨"helpings"⟩⟨4591⟩⟨10556⟩
⟨"Hen"⟩⟨11140⟩⟨17037⟩,⟨"hence"⟩⟨6324⟩⟨11610⟩
⟨"hens"⟩⟨5420⟩⟨1320⟩,⟨"heplful"⟩⟨8642⟩⟨11165⟩
⟨"herbal"⟩⟨4786⟩⟨5587⟩,⟨"herbs"⟩⟨14344⟩⟨15231⟩
⟨"Here"⟩⟨7663⟩⟨16164⟩,⟨"here's"⟩⟨5595⟩⟨16953⟩
⟨"heritage"⟩⟨8955⟩⟨8509⟩,⟨"herons"⟩⟨10583⟩⟨15349⟩
⟨"Hertz"⟩⟨14270⟩⟨12280⟩,⟨"hesitant"⟩⟨2295⟩⟨7200⟩
⟨"hesitations"⟩⟨9078⟩⟨14203⟩,⟨"Heuston"⟩⟨2062⟩⟨5446⟩
⟨"HHonors"⟩⟨6513⟩⟨11277⟩,⟨"Hi"⟩⟨8107⟩⟨15591⟩
⟨"hiccup"⟩⟨3815⟩⟨4401⟩,⟨"hid"⟩⟨17737⟩⟨11675⟩
⟨"hideaway"⟩⟨3623⟩⟨2153⟩,⟨"hideously"⟩⟨17794⟩⟨17917⟩
⟨"high-end"⟩⟨2919⟩⟨1293⟩,⟨"high-speed"⟩⟨5506⟩⟨4480⟩
⟨"higher"⟩⟨5751⟩⟨9203⟩,⟨"highlight"⟩⟨464⟩⟨14534⟩
⟨"highlights"⟩⟨2636⟩⟨6565⟩,⟨"highly"⟩⟨1⟩⟨6356⟩
⟨"highways"⟩⟨17633⟩⟨17854⟩,⟨"hike"⟩⟨4122⟩⟨10741⟩
⟨"hilarious"⟩⟨14162⟩⟨13732⟩,⟨"hill"⟩⟨4189⟩⟨11634⟩
⟨"hillside"⟩⟨7804⟩⟨11319⟩,⟨"hilton"⟩⟨13909⟩⟨16925⟩
⟨"himself"⟩⟨3507⟩⟨795⟩,⟨"hindsight"⟩⟨11935⟩⟨9829⟩
⟨"Hint"⟩⟨10142⟩⟨12123⟩,⟨"hip"⟩⟨3837⟩⟨3879⟩
⟨"his"⟩⟨1092⟩⟨3764⟩,⟨"historic"⟩⟨631⟩⟨7946⟩
⟨"hit"⟩⟨2006⟩⟨9373⟩,⟨"hits"⟩⟨9521⟩⟨7730⟩
⟨"hmmm"⟩⟨7738⟩⟨14500⟩,⟨"ho"⟩⟨16199⟩⟨12639⟩
⟨"Hodson"⟩⟨5706⟩⟨12874⟩,⟨"hoel"⟩⟨16843⟩⟨15738⟩

⟨"hold"⟩⟨4300⟩⟨4707⟩,⟨"holders"⟩⟨14109⟩⟨15162⟩
⟨"holed"⟩⟨17720⟩⟨11647⟩,⟨"holiday"⟩⟨8598⟩⟨15268⟩
⟨"holidays"⟩⟨4248⟩⟨14885⟩,⟨"Holland"⟩⟨12921⟩⟨12733⟩
⟨"hols"⟩⟨5750⟩⟨12567⟩,⟨"Holyhead"⟩⟨16933⟩⟨9235⟩
⟨"home-like"⟩⟨10610⟩⟨15378⟩,⟨"home'"⟩⟨15754⟩⟨12291⟩
⟨"homeliness"⟩⟨10381⟩⟨10139⟩,⟨"homemade"⟩⟨671⟩⟨5601⟩
⟨"Homes"⟩⟨13107⟩⟨16999⟩,⟨"homey"⟩⟨1531⟩⟨5963⟩
⟨"Honestly"⟩⟨10119⟩⟨5426⟩,⟨"Honey"⟩⟨9950⟩⟨13787⟩
⟨"honeymooners"⟩⟨7126⟩⟨5883⟩,⟨"honor"⟩⟨3213⟩⟨9304⟩
⟨"honoured"⟩⟨9038⟩⟨7715⟩,⟨"hooked"⟩⟨7582⟩⟨12803⟩
⟨"hoovered"⟩⟨821⟩⟨2481⟩,⟨"hop"⟩⟨80⟩⟨5522⟩
⟨"Hop-off"⟩⟨12517⟩⟨16558⟩,⟨"Hop-On"⟩⟨8564⟩⟨15821⟩
⟨"hope"⟩⟨2145⟩⟨6954⟩,⟨"hopeful"⟩⟨9004⟩⟨3518⟩
⟨"hopelessly"⟩⟨7753⟩⟨14511⟩,⟨"Hoping"⟩⟨8486⟩⟨8140⟩
⟨"hordes"⟩⟨16460⟩⟨2677⟩,⟨"horns"⟩⟨4931⟩⟨2812⟩
⟨"horrible"⟩⟨657⟩⟨9175⟩,⟨"HORRIBLE"⟩⟨16449⟩⟨9175⟩
⟨"horrified"⟩⟨834⟩⟨1776⟩,⟨"horrors"⟩⟨16824⟩⟨96⟩
⟨"horseback"⟩⟨4908⟩⟨2016⟩,⟨"horses"⟩⟨2210⟩⟨2431⟩
⟨"hospital"⟩⟨3735⟩⟨16283⟩,⟨"hospitality"⟩⟨49⟩⟨11837⟩
⟨"hosted"⟩⟨6649⟩⟨2883⟩,⟨"Hostel"⟩⟨3033⟩⟨11561⟩
⟨"hostile"⟩⟨1820⟩⟨219⟩,⟨"hosting"⟩⟨8623⟩⟨11449⟩
⟨"hot"⟩⟨3172⟩⟨12088⟩,⟨"hot-tub"⟩⟨4789⟩⟨10130⟩
⟨"HOTEL"⟩⟨121⟩⟨3718⟩,⟨"hotel"⟩⟨1493⟩⟨3718⟩
⟨"Hotel???????s"⟩⟨18222⟩⟨12461⟩,⟨"Hotel'"⟩⟨16616⟩⟨15487⟩
⟨"Hotel&quot"⟩⟨1199⟩⟨3601⟩,⟨"hoteliers"⟩⟨5218⟩⟨2416⟩
⟨"hotels'"⟩⟨8072⟩⟨11325⟩,⟨"hotle"⟩⟨14765⟩⟨17251⟩
⟨"hotspots"⟩⟨6608⟩⟨8008⟩,⟨"hottest"⟩⟨4946⟩⟨4485⟩
⟨"Hour"⟩⟨18414⟩⟨5932⟩,⟨"hour's"⟩⟨14569⟩⟨11654⟩
⟨"House"⟩⟨44⟩⟨15996⟩,⟨"HOUSE"⟩⟨17098⟩⟨15996⟩
⟨"House&quot"⟩⟨13804⟩⟨16284⟩,⟨"housed"⟩⟨14469⟩⟨16383⟩
⟨"housekeeping"⟩⟨5074⟩⟨11923⟩,⟨"houses"⟩⟨2792⟩⟨16448⟩

⟨"hovel"⟩⟨17557⟩⟨48⟩,⟨"hovered"⟩⟨16693⟩⟨6894⟩
⟨"HOW"⟩⟨18317⟩⟨1074⟩,⟨"However"⟩⟨5924⟩⟨11455⟩
⟨"Howver"⟩⟨12467⟩⟨16511⟩,⟨"hr"⟩⟨4615⟩⟨10271⟩
⟨"hub"⟩⟨2508⟩⟨2838⟩,⟨"hubbub"⟩⟨9357⟩⟨11210⟩
⟨"Hudson"⟩⟨16781⟩⟨17782⟩,⟨"huff"⟩⟨18269⟩⟨339⟩
⟨"HUGE"⟩⟨2325⟩⟨5510⟩,⟨"Hugh"⟩⟨3714⟩⟨12086⟩
⟨"human"⟩⟨1191⟩⟨8341⟩,⟨"humid"⟩⟨14621⟩⟨16971⟩
⟨"humour"⟩⟨6335⟩⟨4491⟩,⟨"hundred"⟩⟨6776⟩⟨16759⟩
⟨"hunger"⟩⟨3679⟩⟨8179⟩,⟨"hungry"⟩⟨5647⟩⟨9800⟩
⟨"Hunters"⟩⟨14308⟩⟨12532⟩,⟨"Hunting"⟩⟨9160⟩⟨13151⟩
⟨"hurried"⟩⟨11543⟩⟨16131⟩,⟨"hurt"⟩⟨2653⟩⟨9389⟩
⟨"husband's"⟩⟨3129⟩⟨11792⟩,⟨"hussle"⟩⟨4570⟩⟨11918⟩
⟨"HVAC"⟩⟨15983⟩⟨9739⟩,⟨"Hyde"⟩⟨13826⟩⟨14337⟩
⟨"Hydrotherapy"⟩⟨13557⟩⟨14865⟩,⟨"hygiene"⟩⟨438⟩⟨1045⟩
⟨"hype"⟩⟨10541⟩⟨6455⟩,⟨"i"⟩⟨1826⟩⟨1670⟩
⟨"I???????ll"⟩⟨2906⟩⟨9461⟩,⟨"I???????ve"⟩⟨9655⟩⟨14961⟩
⟨"i'd"⟩⟨4173⟩⟨5351⟩,⟨"i'll"⟩⟨11943⟩⟨16415⟩
⟨"i've"⟩⟨3838⟩⟨8929⟩,⟨"Ian"⟩⟨3613⟩⟨2191⟩
⟨"Ice"⟩⟨6323⟩⟨11157⟩,⟨"ice-cream"⟩⟨5021⟩⟨7075⟩
⟨"icy"⟩⟨13007⟩⟨2417⟩,⟨"ID"⟩⟨4205⟩⟨16917⟩
⟨"ideal"⟩⟨4383⟩⟨6599⟩,⟨"ideally"⟩⟨9404⟩⟨8990⟩
⟨"identified"⟩⟨15484⟩⟨9456⟩,⟨"identity"⟩⟨14777⟩⟨11628⟩
⟨"idyllic"⟩⟨2456⟩⟨3929⟩,⟨"IF"⟩⟨1524⟩⟨12267⟩
⟨"IFSC"⟩⟨3985⟩⟨10536⟩,⟨"ignorant"⟩⟨246⟩⟨2538⟩
⟨"ignoring"⟩⟨13767⟩⟨17807⟩,⟨"IKEA"⟩⟨15057⟩⟨9113⟩
⟨"Ill"⟩⟨14267⟩⟨9607⟩,⟨"illness"⟩⟨3314⟩⟨7391⟩
⟨"Im"⟩⟨7152⟩⟨5288⟩,⟨"image"⟩⟨5368⟩⟨3363⟩
⟨"imaginative"⟩⟨7910⟩⟨9980⟩,⟨"imagine"⟩⟨2682⟩⟨5484⟩
⟨"IMI"⟩⟨8625⟩⟨11453⟩,⟨"Immaculate"⟩⟨4971⟩⟨2337⟩
⟨"Immediately"⟩⟨5513⟩⟨10873⟩,⟨"immediatley"⟩⟨13472⟩⟨11117⟩
⟨"immigrants"⟩⟨15570⟩⟨9632⟩,⟨"IMO"⟩⟨15509⟩⟨12130⟩

⟨"impeccable"⟩⟨119⟩⟨1794⟩,⟨"impeccible"⟩⟨15820⟩⟨16076⟩
⟨"implied"⟩⟨13790⟩⟨10592⟩,⟨"imply"⟩⟨5270⟩⟨4532⟩
⟨"important"⟩⟨1455⟩⟨6239⟩,⟨"impose"⟩⟨12458⟩⟨16505⟩
⟨"impractical"⟩⟨7203⟩⟨6299⟩,⟨"impressed"⟩⟨215⟩⟨11213⟩
⟨"impressions"⟩⟨9832⟩⟨12916⟩,⟨"Impressive"⟩⟨15160⟩⟨12113⟩
⟨"improve"⟩⟨8824⟩⟨14248⟩,⟨"improvement"⟩⟨11203⟩⟨15642⟩
⟨"IN"⟩⟨806⟩⟨14911⟩,⟨"In"⟩⟨2878⟩⟨14911⟩
⟨"in-laws"⟩⟨10669⟩⟨9678⟩,⟨"in'"⟩⟨13432⟩⟨16343⟩
⟨"inability"⟩⟨3540⟩⟨10387⟩,⟨"inaccurate"⟩⟨13803⟩⟨4416⟩
⟨"inbetween"⟩⟨14642⟩⟨15053⟩,⟨"inc"⟩⟨2727⟩⟨9106⟩
⟨"incessant"⟩⟨13954⟩⟨17492⟩,⟨"inch"⟩⟨5386⟩⟨3648⟩
⟨"incident"⟩⟨1025⟩⟨3731⟩,⟨"incidentally"⟩⟨14636⟩⟨16195⟩
⟨"incl"⟩⟨2836⟩⟨1854⟩,⟨"inclination"⟩⟨17373⟩⟨18259⟩
⟨"Included"⟩⟨10082⟩⟨14222⟩,⟨"including"⟩⟨780⟩⟨4786⟩
⟨"incoming"⟩⟨17937⟩⟨13652⟩,⟨"incompetence"⟩⟨15023⟩⟨6525⟩
⟨"inconsistent"⟩⟨13308⟩⟨17811⟩,⟨"inconvenienced"⟩⟨14708⟩⟨9913⟩
⟨"incorporate"⟩⟨9968⟩⟨5678⟩,⟨"incorrect"⟩⟨2371⟩⟨3294⟩
⟨"increasing"⟩⟨5415⟩⟨4297⟩,⟨"incredible"⟩⟨35⟩⟨1658⟩
⟨"incur"⟩⟨17430⟩⟨18316⟩,⟨"indeed"⟩⟨2225⟩⟨13162⟩
⟨"independently"⟩⟨7463⟩⟨6502⟩,⟨"Indian"⟩⟨3995⟩⟨10904⟩
⟨"indicates"⟩⟨3899⟩⟨3274⟩,⟨"indication"⟩⟨1814⟩⟨7084⟩
⟨"indifferent"⟩⟨621⟩⟨2597⟩,⟨"indigo"⟩⟨12285⟩⟨11747⟩
⟨"individuals"⟩⟨7861⟩⟨9569⟩,⟨"indoors"⟩⟨9290⟩⟨11498⟩
⟨"indulgent"⟩⟨6565⟩⟨3688⟩,⟨"industrial"⟩⟨7151⟩⟨13566⟩
⟨"inebriated"⟩⟨17304⟩⟨801⟩,⟨"inedible"⟩⟨108⟩⟨4622⟩
⟨"inevitable"⟩⟨14042⟩⟨9285⟩,⟨"inexcusable"⟩⟨12748⟩⟨1906⟩
⟨"infact"⟩⟨7321⟩⟨15018⟩,⟨"infamous"⟩⟨10334⟩⟨9850⟩
⟨"infectious"⟩⟨15371⟩⟨16876⟩,⟨"infested"⟩⟨16934⟩⟨9236⟩
⟨"inflated"⟩⟨7101⟩⟨4973⟩,⟨"influence"⟩⟨14539⟩⟨13108⟩
⟨"Info"⟩⟨8543⟩⟨8677⟩,⟨"informal"⟩⟨5041⟩⟨2184⟩
⟨"informed"⟩⟨6973⟩⟨229⟩,⟨"informs"⟩⟨16785⟩⟨17786⟩

⟨"infuriating"⟩⟨8750⟩⟨6138⟩,⟨"ingredient"⟩⟨10375⟩⟨13540⟩
⟨"inhouse"⟩⟨11198⟩⟨12727⟩,⟨"Inishowen"⟩⟨14077⟩⟨12273⟩
⟨"Initial"⟩⟨13930⟩⟨12158⟩,⟨"Initially"⟩⟨13097⟩⟨16980⟩
⟨"inland"⟩⟨9150⟩⟨4422⟩,⟨"inlet"⟩⟨6709⟩⟨4097⟩
⟨"Inn&quot"⟩⟨9996⟩⟨5721⟩,⟨"innkeeper"⟩⟨17191⟩⟨18503⟩
⟨"inns"⟩⟨6340⟩⟨10845⟩,⟨"input"⟩⟨13824⟩⟨14332⟩
⟨"inquiring"⟩⟨8440⟩⟨8945⟩,⟨"inroom"⟩⟨17133⟩⟨16070⟩
⟨"insects"⟩⟨12100⟩⟨1312⟩,⟨"insert"⟩⟨16598⟩⟨15475⟩
⟨"Inside"⟩⟨12988⟩⟨15212⟩,⟨"insignificant"⟩⟨9774⟩⟨13881⟩
⟨"insisted"⟩⟨53⟩⟨7113⟩,⟨"insisting"⟩⟨13869⟩⟨7584⟩
⟨"inspecting"⟩⟨15573⟩⟨9638⟩,⟨"inspector"⟩⟨17317⟩⟨2180⟩
⟨"inspiring"⟩⟨7917⟩⟨1822⟩,⟨"installation"⟩⟨15976⟩⟨9724⟩
⟨"instances"⟩⟨17391⟩⟨18277⟩,⟨"instantly"⟩⟨4672⟩⟨3639⟩
⟨"instincts"⟩⟨16973⟩⟨11234⟩,⟨"institutional"⟩⟨15155⟩⟨12108⟩
⟨"instructor"⟩⟨6530⟩⟨11310⟩,⟨"insufficient"⟩⟨2908⟩⟨3024⟩
⟨"insulted"⟩⟨15087⟩⟨962⟩,⟨"insurance"⟩⟨14627⟩⟨17517⟩
⟨"integrated"⟩⟨8071⟩⟨11321⟩,⟨"intended"⟩⟨4182⟩⟨9339⟩
⟨"intention"⟩⟨1380⟩⟨7684⟩,⟨"inter-connecting"⟩⟨13323⟩⟨7311⟩
⟨"interactions"⟩⟨12911⟩⟨15889⟩,⟨"intercom"⟩⟨14148⟩⟨17616⟩
⟨"interested"⟩⟨5243⟩⟨901⟩,⟨"Interesting"⟩⟨6173⟩⟨12336⟩
⟨"interfere"⟩⟨4544⟩⟨4030⟩,⟨"interior"⟩⟨2739⟩⟨17757⟩
⟨"intermittently"⟩⟨14760⟩⟨3177⟩,⟨"internally"⟩⟨14095⟩⟨15148⟩
⟨"internet"⟩⟨2132⟩⟨13465⟩,⟨"INTERNET"⟩⟨15623⟩⟨13465⟩
⟨"interrupting"⟩⟨11574⟩⟨6047⟩,⟨"intersection"⟩⟨14319⟩⟨12311⟩
⟨"intervened"⟩⟨12217⟩⟨504⟩,⟨"interview"⟩⟨11004⟩⟨14758⟩
⟨"intimate"⟩⟨682⟩⟨2423⟩,⟨"intimidating"⟩⟨11289⟩⟨13220⟩
⟨"intoxicated"⟩⟨16997⟩⟨330⟩,⟨"intriguing"⟩⟨16765⟩⟨17766⟩
⟨"introduction"⟩⟨9445⟩⟨11285⟩,⟨"intrude"⟩⟨9345⟩⟨11194⟩
⟨"invaded"⟩⟨7730⟩⟨14493⟩,⟨"invaluable"⟩⟨15334⟩⟨16829⟩
⟨"invest"⟩⟨3952⟩⟨8013⟩,⟨"investigate"⟩⟨2662⟩⟨8451⟩
⟨"investing"⟩⟨16782⟩⟨17783⟩,⟨"invigorating"⟩⟨14424⟩⟨17443⟩

⟨"invited"⟩⟨5062⟩⟨3115⟩,⟨"invoice"⟩⟨3708⟩⟨9446⟩
⟨"involving"⟩⟨4753⟩⟨2362⟩,⟨"ipod"⟩⟨7940⟩⟨18248⟩
⟨"ireland"⟩⟨5956⟩⟨10480⟩,⟨"Ireland-"⟩⟨15740⟩⟨13496⟩
⟨"Ireland's"⟩⟨10514⟩⟨16919⟩,⟨"Irelands"⟩⟨9674⟩⟨7764⟩
⟨"irish"⟩⟨1049⟩⟨8576⟩,⟨"Irish???????"⟩⟨5397⟩⟨2799⟩
⟨"Irishman"⟩⟨10336⟩⟨9853⟩,⟨"Iron"⟩⟨9575⟩⟨13203⟩
⟨"ironically"⟩⟨17282⟩⟨10455⟩,⟨"Ironing"⟩⟨5899⟩⟨11096⟩
⟨"irritating"⟩⟨11966⟩⟨9377⟩,⟨"irritations"⟩⟨15109⟩⟨9593⟩
⟨"is'nt"⟩⟨18378⟩⟨2875⟩,⟨"Isaac's"⟩⟨6495⟩⟨7211⟩
⟨"Island"⟩⟨1844⟩⟨7737⟩,⟨"Islands"⟩⟨240⟩⟨9971⟩
⟨"isn't"⟩⟨3780⟩⟨16522⟩,⟨"isnt"⟩⟨9513⟩⟨12929⟩
⟨"Issue"⟩⟨12480⟩⟨16521⟩,⟨"issues"⟩⟨6491⟩⟨15164⟩
⟨"It"⟩⟨1512⟩⟨3421⟩,⟨"it‘s"⟩⟨8996⟩⟨2691⟩
⟨"it???????s"⟩⟨10539⟩⟨12194⟩,⟨"it'"⟩⟨3144⟩⟨321⟩
⟨"it's"⟩⟨2691⟩⟨4870⟩,⟨"Italian"⟩⟨5332⟩⟨15630⟩
⟨"itching"⟩⟨18042⟩⟨158⟩,⟨"item"⟩⟨7388⟩⟨11428⟩
⟨"Its"⟩⟨1485⟩⟨12255⟩,⟨"ITS"⟩⟨6194⟩⟨12255⟩
⟨"iv"⟩⟨8671⟩⟨4987⟩,⟨"Ive"⟩⟨10682⟩⟨14221⟩
⟨"J"⟩⟨8165⟩⟨6585⟩,⟨"jaccuzi"⟩⟨16297⟩⟨18548⟩
⟨"jacket"⟩⟨3181⟩⟨9149⟩,⟨"Jackie"⟩⟨16359⟩⟨14679⟩
⟨"Jacksons"⟩⟨7967⟩⟨5625⟩,⟨"jacquzzi"⟩⟨17471⟩⟨18357⟩
⟨"jacuzzi"⟩⟨9273⟩⟨5949⟩,⟨"jaded"⟩⟨10990⟩⟨16968⟩
⟨"James"⟩⟨10314⟩⟨2270⟩,⟨"Jameson"⟩⟨2250⟩⟨7453⟩
⟨"jams"⟩⟨3320⟩⟨973⟩,⟨"jan"⟩⟨14839⟩⟨17313⟩
⟨"january"⟩⟨13906⟩⟨16922⟩,⟨"jar"⟩⟨14240⟩⟨15099⟩
⟨"jaunt"⟩⟨11375⟩⟨5154⟩,⟨"Jaunting"⟩⟨12264⟩⟨10203⟩
⟨"jazuzzi"⟩⟨9155⟩⟨4793⟩,⟨"Jazz"⟩⟨13232⟩⟨9936⟩
⟨"jelly"⟩⟨6352⟩⟨6809⟩,⟨"Jenny"⟩⟨9005⟩⟨4440⟩
⟨"Jessica"⟩⟨9650⟩⟨5290⟩,⟨"jet-lagged"⟩⟨10975⟩⟨14739⟩
⟨"jetted"⟩⟨15724⟩⟨15977⟩,⟨"jewellery"⟩⟨16559⟩⟨7554⟩
⟨"JJ"⟩⟨17178⟩⟨18490⟩,⟨"Joan"⟩⟨14840⟩⟨17315⟩

⟨"jobs"⟩⟨8898⟩⟨15769⟩,⟨"Joe"⟩⟨5058⟩⟨7952⟩
⟨"John"⟩⟨1808⟩⟨13136⟩,⟨"John's"⟩⟨13068⟩⟨12851⟩
⟨"joined"⟩⟨7311⟩⟨5113⟩,⟨"joint"⟩⟨4611⟩⟨9211⟩
⟨"jokes"⟩⟨9635⟩⟨12751⟩,⟨"jolly"⟩⟨11399⟩⟨11532⟩
⟨"journey"⟩⟨880⟩⟨16216⟩,⟨"journeys"⟩⟨7881⟩⟨13834⟩
⟨"Joyce"⟩⟨14051⟩⟨11694⟩,⟨"jr"⟩⟨9977⟩⟨15444⟩
⟨"judgement"⟩⟨2619⟩⟨2765⟩,⟨"judging"⟩⟨7325⟩⟨10655⟩
⟨"jugs"⟩⟨11625⟩⟨11962⟩,⟨"Juice"⟩⟨12920⟩⟨12732⟩
⟨"jukebox"⟩⟨10175⟩⟨6205⟩,⟨"Julian"⟩⟨17251⟩⟨41⟩
⟨"july"⟩⟨11579⟩⟨14406⟩,⟨"jumped"⟩⟨4241⟩⟨3515⟩
⟨"June"⟩⟨1550⟩⟨14143⟩,⟨"junior"⟩⟨1289⟩⟨9852⟩
⟨"Jury"⟩⟨2703⟩⟨808⟩,⟨"Jury's"⟩⟨1438⟩⟨14229⟩
⟨"jus"⟩⟨14647⟩⟨15060⟩,⟨"just"⟩⟨1114⟩⟨12841⟩
⟨"justifies"⟩⟨18145⟩⟨955⟩,⟨"Justin"⟩⟨4841⟩⟨2314⟩
⟨"K's"⟩⟨6706⟩⟨4090⟩,⟨"Karen"⟩⟨2503⟩⟨1242⟩
⟨"Kathy"⟩⟨8583⟩⟨11111⟩,⟨"Katy"⟩⟨9756⟩⟨13860⟩
⟨"Keadeen"⟩⟨7792⟩⟨11293⟩,⟨"kebab"⟩⟨14420⟩⟨17439⟩
⟨"keep"⟩⟨3235⟩⟨17806⟩,⟨"KEEP"⟩⟨16805⟩⟨17806⟩
⟨"keeps"⟩⟨11322⟩⟨10565⟩,⟨"kegs"⟩⟨1823⟩⟨4230⟩
⟨"Kelly's"⟩⟨2367⟩⟨2636⟩,⟨"kellys"⟩⟨12817⟩⟨15785⟩
⟨"kenmare"⟩⟨14022⟩⟨13305⟩,⟨"kept"⟩⟨3877⟩⟨15933⟩
⟨"ketchup"⟩⟨4294⟩⟨12529⟩,⟨"Kettle"⟩⟨9649⟩⟨13511⟩
⟨"Key"⟩⟨9873⟩⟨13421⟩,⟨"keyboard"⟩⟨13741⟩⟨17435⟩
⟨"KFC"⟩⟨7451⟩⟨4232⟩,⟨"kicked"⟩⟨823⟩⟨2933⟩
⟨"kid"⟩⟨2799⟩⟨6301⟩,⟨"kiddie"⟩⟨8596⟩⟨11133⟩
⟨"kids"⟩⟨1490⟩⟨13264⟩,⟨"KIDS"⟩⟨18518⟩⟨13264⟩
⟨"Kilashee"⟩⟨18173⟩⟨3393⟩,⟨"Kildare"⟩⟨5862⟩⟨16833⟩
⟨"kilford"⟩⟨17644⟩⟨17863⟩,⟨"kilkenny"⟩⟨5916⟩⟨6651⟩
⟨"Killarney"⟩⟨22⟩⟨5750⟩,⟨"Killarney's"⟩⟨13569⟩⟨14881⟩
⟨"killed"⟩⟨2890⟩⟨3745⟩,⟨"Killenard"⟩⟨12823⟩⟨15791⟩
⟨"Killiane"⟩⟨8120⟩⟨13628⟩,⟨"killing"⟩⟨7714⟩⟨14482⟩

⟨"Kilmainham"⟩⟨1564⟩⟨3336⟩,⟨"Kilmurry"⟩⟨8620⟩⟨11145⟩
⟨"Kilronan"⟩⟨5609⟩⟨3561⟩,⟨"Kiltimagh"⟩⟨14990⟩⟨17540⟩
⟨"kinda"⟩⟨11944⟩⟨17830⟩,⟨"kindest"⟩⟨17994⟩⟨18050⟩
⟨"king"⟩⟨3220⟩⟨6495⟩,⟨"king-size"⟩⟨2425⟩⟨1841⟩
⟨"Kings"⟩⟨10639⟩⟨15409⟩,⟨"kingsize"⟩⟨4261⟩⟨11135⟩
⟨"Kingston"⟩⟨4386⟩⟨7945⟩,⟨"kinks"⟩⟨12778⟩⟨10509⟩
⟨"kip"⟩⟨14151⟩⟨1391⟩,⟨"kippers"⟩⟨3392⟩⟨5120⟩
⟨"kitchen"⟩⟨3157⟩⟨7333⟩,⟨"kitchenette"⟩⟨2390⟩⟨5000⟩
⟨"Kitty"⟩⟨11597⟩⟨9876⟩,⟨"KM"⟩⟨15879⟩⟨12418⟩
⟨"knew"⟩⟨1690⟩⟨15990⟩,⟨"knife"⟩⟨999⟩⟨6855⟩
⟨"Knightsbridge"⟩⟨6550⟩⟨4061⟩,⟨"knives"⟩⟨2180⟩⟨2075⟩
⟨"Knock"⟩⟨8761⟩⟨6026⟩,⟨"knocked"⟩⟨368⟩⟨6610⟩
⟨"knocks"⟩⟨8593⟩⟨11130⟩,⟨"Know"⟩⟨7494⟩⟨13448⟩
⟨"Knowing"⟩⟨14579⟩⟨14755⟩,⟨"knowledge"⟩⟨1407⟩⟨11823⟩
⟨"Knowth"⟩⟨15347⟩⟨16842⟩,⟨"KPH"⟩⟨15276⟩⟨16762⟩
⟨"l"⟩⟨10132⟩⟨15697⟩,⟨"L'Occitane"⟩⟨6261⟩⟨2807⟩
⟨"labeled"⟩⟨17591⟩⟨13555⟩,⟨"labels"⟩⟨12387⟩⟨16475⟩
⟨"lack"⟩⟨7831⟩⟨17813⟩,⟨"lacked"⟩⟨9614⟩⟨8190⟩
⟨"lacks"⟩⟨6909⟩⟨3408⟩,⟨"Ladder"⟩⟨15826⟩⟨16082⟩
⟨"Ladies"⟩⟨7041⟩⟨10542⟩,⟨"lady"⟩⟨3765⟩⟨12591⟩
⟨"lagged"⟩⟨16325⟩⟨17022⟩,⟨"laid"⟩⟨1396⟩⟨2633⟩
⟨"Lake"⟩⟨1298⟩⟨1939⟩,⟨"Lakes"⟩⟨5180⟩⟨1895⟩
⟨"lakeview"⟩⟨4102⟩⟨18052⟩,⟨"lamb"⟩⟨4704⟩⟨17693⟩
⟨"lamp"⟩⟨648⟩⟨1956⟩,⟨"lampshade"⟩⟨3338⟩⟨9347⟩
⟨"land"⟩⟨8863⟩⟨18362⟩,⟨"landed"⟩⟨3777⟩⟨3685⟩
⟨"landlord"⟩⟨17825⟩⟨17948⟩,⟨"Landmark"⟩⟨11610⟩⟨14377⟩
⟨"landscapes"⟩⟨10167⟩⟨6192⟩,⟨"Landsdown"⟩⟨18086⟩⟨4716⟩
⟨"lanes"⟩⟨13743⟩⟨14565⟩,⟨"Langton's"⟩⟨5345⟩⟨1663⟩
⟨"Lannagh"⟩⟨8119⟩⟨13626⟩,⟨"Lansdown"⟩⟨9934⟩⟨5624⟩
⟨"lap"⟩⟨4878⟩⟨12159⟩,⟨"laps"⟩⟨13182⟩⟨10899⟩
⟨"large"⟩⟨630⟩⟨5185⟩,⟨"largely"⟩⟨9315⟩⟨13740⟩

⟨"Las"⟩⟨16271⟩⟨17323⟩,⟨"laser"⟩⟨10833⟩⟨17878⟩
⟨"lashings"⟩⟨15928⟩⟨16125⟩,⟨"Last"⟩⟨9911⟩⟨14152⟩
⟨"Lastly"⟩⟨11150⟩⟨11413⟩,⟨"lastminute"⟩⟨8190⟩⟨16577⟩
⟨"latch"⟩⟨3549⟩⟨3136⟩,⟨"Late"⟩⟨12427⟩⟨11474⟩
⟨"later"⟩⟨4887⟩⟨8275⟩,⟨"laterooms"⟩⟨3849⟩⟨9884⟩
⟨"latter"⟩⟨4603⟩⟨6697⟩,⟨"laugh"⟩⟨5081⟩⟨3520⟩
⟨"laughs"⟩⟨4065⟩⟨5243⟩,⟨"launch"⟩⟨12252⟩⟨10183⟩
⟨"Laundry"⟩⟨17246⟩⟨14769⟩,⟨"laurels"⟩⟨16774⟩⟨17775⟩
⟨"lavish"⟩⟨11404⟩⟨11542⟩,⟨"law"⟩⟨2789⟩⟨10243⟩
⟨"lawn"⟩⟨4429⟩⟨12481⟩,⟨"laws"⟩⟨2481⟩⟨8634⟩
⟨"layers"⟩⟨12984⟩⟨9889⟩,⟨"layout"⟩⟨3460⟩⟨8354⟩
⟨"lazy"⟩⟨7317⟩⟨17166⟩,⟨"lcd"⟩⟨2757⟩⟨8482⟩
⟨"lead"⟩⟨2871⟩⟨5062⟩,⟨"leaders"⟩⟨16786⟩⟨17787⟩
⟨"leads"⟩⟨11892⟩⟨17339⟩,⟨"leaflet"⟩⟨6879⟩⟨11073⟩
⟨"league"⟩⟨13752⟩⟨16945⟩,⟨"leak"⟩⟨4010⟩⟨4985⟩
⟨"leaky"⟩⟨13840⟩⟨17379⟩,⟨"leaning"⟩⟨9878⟩⟨14600⟩
⟨"learnt"⟩⟨9493⟩⟨12960⟩,⟨"leasure"⟩⟨10956⟩⟨14720⟩
⟨"Leave"⟩⟨14978⟩⟨13990⟩,⟨"leaving"⟩⟨4663⟩⟨2755⟩
⟨"ledge"⟩⟨1420⟩⟨5220⟩,⟨"Lee"⟩⟨4157⟩⟨4569⟩
⟨"leery"⟩⟨17395⟩⟨18281⟩,⟨"Left"⟩⟨2011⟩⟨16662⟩
⟨"leftovers"⟩⟨10795⟩⟨17029⟩,⟨"legal"⟩⟨13000⟩⟨54⟩
⟨"Legends"⟩⟨12464⟩⟨15198⟩,⟨"legitimate"⟩⟨18468⟩⟨6021⟩
⟨"lein"⟩⟨15716⟩⟨15960⟩,⟨"leisure"⟩⟨1012⟩⟨7267⟩
⟨"leitrim"⟩⟨9154⟩⟨4792⟩,⟨"Lemon"⟩⟨4676⟩⟨12793⟩
⟨"lend"⟩⟨6825⟩⟨5263⟩,⟨"lenght"⟩⟨7698⟩⟨8832⟩
⟨"lengthy"⟩⟨9522⟩⟨11637⟩,⟨"Leo"⟩⟨12666⟩⟨10396⟩
⟨"leprechauns"⟩⟨12269⟩⟨10214⟩,⟨"Leslie"⟩⟨11463⟩⟨14325⟩
⟨"lesson"⟩⟨2751⟩⟨13520⟩,⟨"lessons"⟩⟨7916⟩⟨12222⟩
⟨"let-down"⟩⟨14329⟩⟨17286⟩,⟨"let's"⟩⟨13914⟩⟨17695⟩
⟨"letter"⟩⟨349⟩⟨60⟩,⟨"letterkenny"⟩⟨13112⟩⟨9160⟩
⟨"level"⟩⟨5322⟩⟨6275⟩,⟨"levels"⟩⟨6294⟩⟨15021⟩

⟨"liar"⟩⟨18043⟩⟨159⟩,⟨"library"⟩⟨2309⟩⟨8693⟩
⟨"lick"⟩⟨8734⟩⟨8572⟩,⟨"Lidl"⟩⟨17287⟩⟨9723⟩
⟨"lied"⟩⟨10903⟩⟨58⟩,⟨"life"⟩⟨1411⟩⟨5964⟩
⟨"lifeless"⟩⟨16420⟩⟨18086⟩,⟨"lifestyle"⟩⟨10426⟩⟨6849⟩
⟨"Liffy"⟩⟨9569⟩⟨13022⟩,⟨"lift"⟩⟨6163⟩⟨9360⟩
⟨"Lifts"⟩⟨12739⟩⟨14900⟩,⟨"Light"⟩⟨16335⟩⟨18222⟩
⟨"lighter"⟩⟨10806⟩⟨14506⟩,⟨"lighting"⟩⟨4846⟩⟨9047⟩
⟨"lights"⟩⟨4469⟩⟨9192⟩,⟨"liitle"⟩⟨15081⟩⟨7694⟩
⟨"Liked"⟩⟨3387⟩⟨6484⟩,⟨"likely"⟩⟨3154⟩⟨10469⟩
⟨"likewise"⟩⟨13477⟩⟨13391⟩,⟨"lillies"⟩⟨11042⟩⟨14813⟩
⟨"limerick"⟩⟨5975⟩⟨10141⟩,⟨"limescale"⟩⟨17254⟩⟨182⟩
⟨"limited"⟩⟨6603⟩⟨12406⟩,⟨"limiting"⟩⟨12469⟩⟨16512⟩
⟨"Linda"⟩⟨9709⟩⟨11272⟩,⟨"line"⟩⟨5013⟩⟨9748⟩
⟨"Linen"⟩⟨16158⟩⟨14949⟩,⟨"liner"⟩⟨17334⟩⟨14971⟩
⟨"lingering"⟩⟨9862⟩⟨9423⟩,⟨"lining"⟩⟨3152⟩⟨7574⟩
⟨"links"⟩⟨3916⟩⟨13629⟩,⟨"linnen"⟩⟨8790⟩⟨6229⟩
⟨"liqueur"⟩⟨15413⟩⟨9530⟩,⟨"liquor"⟩⟨14766⟩⟨17252⟩
⟨"Lisdonagh"⟩⟨8929⟩⟨3130⟩,⟨"Lisloughrey"⟩⟨10308⟩⟨11190⟩
⟨"listen"⟩⟨269⟩⟨1755⟩,⟨"listening"⟩⟨2289⟩⟨1300⟩
⟨"lit"⟩⟨10528⟩⟨9100⟩,⟨"literally"⟩⟨3524⟩⟨7628⟩
⟨"literature"⟩⟨8170⟩⟨12986⟩,⟨"litlle"⟩⟨9087⟩⟨14220⟩
⟨"litter"⟩⟨13196⟩⟨12546⟩,⟨"littered"⟩⟨1626⟩⟨4082⟩
⟨"Live"⟩⟨5054⟩⟨6293⟩,⟨"livelier"⟩⟨4979⟩⟨3470⟩
⟨"liver"⟩⟨10480⟩⟨15246⟩,⟨"lives"⟩⟨6950⟩⟨5478⟩
⟨"Liz"⟩⟨14359⟩⟨17303⟩,⟨"lo"⟩⟨10742⟩⟨8937⟩
⟨"loading"⟩⟨8872⟩⟨5675⟩,⟨"Loads"⟩⟨2747⟩⟨3230⟩
⟨"loaned"⟩⟨6708⟩⟨4095⟩,⟨"lobby"⟩⟨4814⟩⟨12766⟩
⟨"local"⟩⟨696⟩⟨12172⟩,⟨"local&quot"⟩⟨10594⟩⟨15362⟩
⟨"locals"⟩⟨1219⟩⟨14797⟩,⟨"locate"⟩⟨7895⟩⟨6867⟩
⟨"location"⟩⟨1675⟩⟨8158⟩,⟨"LOCATION"⟩⟨2297⟩⟨8158⟩
⟨"locations"⟩⟨5203⟩⟨9207⟩,⟨"Loch"⟩⟨1489⟩⟨410⟩

⟨"locker"⟩⟨2066⟩⟨4657⟩,⟨"locking"⟩⟨6019⟩⟨12442⟩
⟨"lodged"⟩⟨10405⟩⟨7500⟩,⟨"Lodges"⟩⟨12186⟩⟨14633⟩
⟨"log"⟩⟨1530⟩⟨6955⟩,⟨"logic"⟩⟨16567⟩⟨7571⟩
⟨"loin"⟩⟨12899⟩⟨15871⟩,⟨"loking"⟩⟨9184⟩⟨4823⟩
⟨"london"⟩⟨9107⟩⟨8324⟩,⟨"lonely"⟩⟨16440⟩⟨789⟩
⟨"Long"⟩⟨9813⟩⟨13796⟩,⟨"longer"⟩⟨499⟩⟨5806⟩
⟨"longing"⟩⟨10187⟩⟨6230⟩,⟨"longue"⟩⟨12613⟩⟨16607⟩
⟨"Look"⟩⟨8015⟩⟨9035⟩,⟨"Looked"⟩⟨10748⟩⟨12036⟩
⟨"looks"⟩⟨5365⟩⟨8318⟩,⟨"looming"⟩⟨15621⟩⟨13460⟩
⟨"Loose"⟩⟨17810⟩⟨17933⟩,⟨"loosing"⟩⟨3891⟩⟨1473⟩
⟨"Lorraine"⟩⟨9072⟩⟨14197⟩,⟨"lorry"⟩⟨16329⟩⟨18216⟩
⟨"losing"⟩⟨1326⟩⟨2613⟩,⟨"losses"⟩⟨17560⟩⟨7910⟩
⟨"LOT"⟩⟨9854⟩⟨7671⟩,⟨"lot's"⟩⟨12647⟩⟨10359⟩
⟨"lots"⟩⟨952⟩⟨10513⟩,⟨"LOTS"⟩⟨12781⟩⟨10513⟩
⟨"Loud"⟩⟨16232⟩⟨8419⟩,⟨"loudest"⟩⟨4427⟩⟨1971⟩
⟨"Loughrea"⟩⟨11953⟩⟨15176⟩,⟨"Louise"⟩⟨11253⟩⟨9376⟩
⟨"loungers"⟩⟨2093⟩⟨1155⟩,⟨"lounging"⟩⟨4308⟩⟨3392⟩
⟨"Love"⟩⟨4345⟩⟨17311⟩,⟨"loved"⟩⟨5⟩⟨6642⟩
⟨"loveliest"⟩⟨5510⟩⟨7203⟩,⟨"Lovely"⟩⟨320⟩⟨11182⟩
⟨"lovers"⟩⟨13932⟩⟨13306⟩,⟨"lovey"⟩⟨6829⟩⟨7089⟩
⟨"low"⟩⟨5461⟩⟨5308⟩,⟨"lower"⟩⟨7376⟩⟨12279⟩
⟨"loyal"⟩⟨13616⟩⟨9132⟩,⟨"lttle"⟩⟨10282⟩⟨10110⟩
⟨"Lucan"⟩⟨6497⟩⟨7217⟩,⟨"luck"⟩⟨5541⟩⟨18481⟩
⟨"Luckily"⟩⟨3467⟩⟨12321⟩,⟨"lucky"⟩⟨2089⟩⟨11924⟩
⟨"ludicrous"⟩⟨17701⟩⟨2667⟩,⟨"luggage"⟩⟨3114⟩⟨16224⟩
⟨"Luis"⟩⟨15042⟩⟨8657⟩,⟨"luke-warm"⟩⟨13269⟩⟨7278⟩
⟨"lumpy"⟩⟨393⟩⟨7017⟩,⟨"lunch"⟩⟨947⟩⟨9177⟩
⟨"lungs"⟩⟨13615⟩⟨9131⟩,⟨"lurking"⟩⟨14818⟩⟨6053⟩
⟨"luxe"⟩⟨14289⟩⟨15093⟩,⟨"luxuary"⟩⟨15632⟩⟨13479⟩
⟨"luxuriously"⟩⟨5131⟩⟨3453⟩,⟨"Luxury"⟩⟨12804⟩⟨16949⟩
⟨"Lynams"⟩⟨11951⟩⟨13706⟩,⟨"lynch"⟩⟨18072⟩⟨2424⟩

⟨"M"⟩⟨6672⟩⟨4107⟩,⟨"M&amp"⟩⟨5262⟩⟨10907⟩
⟨"Mac"⟩⟨7276⟩⟨12981⟩,⟨"MacCurtain"⟩⟨15797⟩⟨16031⟩
⟨"machines"⟩⟨5104⟩⟨14925⟩,⟨"Macroom"⟩⟨7290⟩⟨12982⟩
⟨"Maddens"⟩⟨10516⟩⟨15267⟩,⟨"made"⟩⟨519⟩⟨16983⟩
⟨"Madness"⟩⟨15447⟩⟨9604⟩,⟨"Maeve"⟩⟨17175⟩⟨18487⟩
⟨"magic"⟩⟨3316⟩⟨3544⟩,⟨"magical"⟩⟨1073⟩⟨1644⟩
⟨"magnificent"⟩⟨2694⟩⟨11239⟩,⟨"magnificently"⟩⟨15808⟩⟨16053⟩
⟨"magnolia"⟩⟨17375⟩⟨18261⟩,⟨"mahogany"⟩⟨13295⟩⟨14791⟩
⟨"Maids"⟩⟨10191⟩⟨9797⟩,⟨"mail"⟩⟨1510⟩⟨8073⟩
⟨"Main"⟩⟨6158⟩⟨13717⟩,⟨"mainland"⟩⟨17862⟩⟨3532⟩
⟨"maintain"⟩⟨9248⟩⟨13187⟩,⟨"maintainence"⟩⟨8083⟩⟨13586⟩
⟨"maintenance"⟩⟨510⟩⟨12396⟩,⟨"maintenence"⟩⟨11974⟩⟨11974⟩
⟨"majestic"⟩⟨6448⟩⟨15143⟩,⟨"major"⟩⟨5287⟩⟨11825⟩
⟨"majorly"⟩⟨10998⟩⟨14750⟩,⟨"make"⟩⟨1024⟩⟨14879⟩
⟨"makeover"⟩⟨348⟩⟨513⟩,⟨"Maker"⟩⟨13556⟩⟨14864⟩
⟨"makeshift"⟩⟨12389⟩⟨2828⟩,⟨"making"⟩⟨1208⟩⟨5922⟩
⟨"malahide"⟩⟨9766⟩⟨13872⟩,⟨"Maldron"⟩⟨2155⟩⟨10173⟩
⟨"Malin"⟩⟨8801⟩⟨4895⟩,⟨"Mall"⟩⟨4207⟩⟨8644⟩
⟨"Malone"⟩⟨6015⟩⟨10931⟩,⟨"Maltings"⟩⟨6981⟩⟨3172⟩
⟨"Man"⟩⟨13750⟩⟨16186⟩,⟨"manage"⟩⟨8011⟩⟨17269⟩
⟨"management"⟩⟨756⟩⟨3260⟩,⟨"managements"⟩⟨17241⟩⟨9949⟩
⟨"manager&quot"⟩⟨16388⟩⟨77⟩,⟨"manageress"⟩⟨6271⟩⟨11836⟩
⟨"manages"⟩⟨9895⟩⟨6536⟩,⟨"managing"⟩⟨13305⟩⟨14623⟩
⟨"manged"⟩⟨12627⟩⟨16622⟩,⟨"manger"⟩⟨932⟩⟨18369⟩
⟨"manic"⟩⟨16758⟩⟨17759⟩,⟨"manicured"⟩⟨2243⟩⟨1450⟩
⟨"manned"⟩⟨12590⟩⟨14563⟩,⟨"mannered"⟩⟨2056⟩⟨1427⟩
⟨"manning"⟩⟨14905⟩⟨5658⟩,⟨"Manor"⟩⟨29⟩⟨2604⟩
⟨"Mansion"⟩⟨9243⟩⟨6113⟩,⟨"manually"⟩⟨16829⟩⟨496⟩
⟨"Maol"⟩⟨8108⟩⟨13607⟩,⟨"Maple"⟩⟨2460⟩⟨2962⟩
⟨"Mar"⟩⟨17171⟩⟨18483⟩,⟨"Maranatha"⟩⟨7586⟩⟨12811⟩
⟨"Marble"⟩⟨11185⟩⟨9826⟩,⟨"March"⟩⟨3332⟩⟨3834⟩

⟨"margin"⟩⟨10001⟩⟨5733⟩,⟨"marginally"⟩⟨4693⟩⟨7966⟩
⟨"Marilyn"⟩⟨5534⟩⟨10572⟩,⟨"Marina"⟩⟨2213⟩⟨9309⟩
⟨"Mariott"⟩⟨10053⟩⟨10336⟩,⟨"Maritime"⟩⟨11685⟩⟨12195⟩
⟨"marker"⟩⟨8410⟩⟨8911⟩,⟨"market"⟩⟨4260⟩⟨8878⟩
⟨"markets"⟩⟨9610⟩⟨14586⟩,⟨"markings"⟩⟨18336⟩⟨825⟩
⟨"Marlfield"⟩⟨12591⟩⟨16442⟩,⟨"marquee"⟩⟨10385⟩⟨12115⟩
⟨"married"⟩⟨10507⟩⟨2163⟩,⟨"Marriot"⟩⟨13889⟩⟨12583⟩
⟨"marry"⟩⟨9065⟩⟨11040⟩,⟨"mart"⟩⟨15698⟩⟨9184⟩
⟨"martini"⟩⟨4945⟩⟨3297⟩,⟨"marvellous"⟩⟨6730⟩⟨16122⟩
⟨"mary"⟩⟨14478⟩⟨15187⟩,⟨"Maryborough"⟩⟨6463⟩⟨9777⟩
⟨"mask"⟩⟨14911⟩⟨1390⟩,⟨"masking"⟩⟨6107⟩⟨4602⟩
⟨"Massage"⟩⟨10684⟩⟨14160⟩,⟨"massaging"⟩⟨8489⟩⟨4259⟩
⟨"massive"⟩⟨273⟩⟨18176⟩,⟨"MASSIVE"⟩⟨16975⟩⟨18176⟩
⟨"masterpiece"⟩⟨10588⟩⟨15355⟩,⟨"match"⟩⟨4382⟩⟨13612⟩
⟨"mate"⟩⟨11079⟩⟨9573⟩,⟨"materialise"⟩⟨17699⟩⟨2664⟩
⟨"matress"⟩⟨668⟩⟨3656⟩,⟨"mats"⟩⟨5076⟩⟨161⟩
⟨"mattered"⟩⟨4528⟩⟨11520⟩,⟨"Matthew"⟩⟨16791⟩⟨17792⟩
⟨"mature"⟩⟨7306⟩⟨11933⟩,⟨"Maura"⟩⟨8022⟩⟨12700⟩
⟨"maximise"⟩⟨13352⟩⟨11850⟩,⟨"may"⟩⟨3706⟩⟨11607⟩
⟨"mayhem"⟩⟨14643⟩⟨15055⟩,⟨"Mayo"⟩⟨4369⟩⟨8474⟩
⟨"Mc"⟩⟨14543⟩⟨14591⟩,⟨"McCoys"⟩⟨16456⟩⟨1759⟩
⟨"McGann's"⟩⟨12810⟩⟨15696⟩,⟨"McWilliam"⟩⟨15723⟩⟨15975⟩
⟨"me&quot"⟩⟨13461⟩⟨16373⟩,⟨"meagre"⟩⟨5856⟩⟨7834⟩
⟨"Meals"⟩⟨3776⟩⟨5077⟩,⟨"mean"⟩⟨4687⟩⟨3525⟩
⟨"meant"⟩⟨5305⟩⟨1257⟩,⟨"meanwhile"⟩⟨5152⟩⟨17581⟩
⟨"measured"⟩⟨14844⟩⟨9402⟩,⟨"meat"⟩⟨6443⟩⟨7008⟩
⟨"mechanical"⟩⟨11797⟩⟨9316⟩,⟨"medal"⟩⟨12314⟩⟨10298⟩
⟨"medicine"⟩⟨18318⟩⟨608⟩,⟨"medieval"⟩⟨6055⟩⟨14335⟩
⟨"medium-sized"⟩⟨10267⟩⟨10086⟩,⟨"meeting"⟩⟨3605⟩⟨16913⟩
⟨"mega"⟩⟨14976⟩⟨13987⟩,⟨"melon"⟩⟨13213⟩⟨15424⟩
⟨"member"⟩⟨820⟩⟨17333⟩,⟨"member's"⟩⟨18376⟩⟨1998⟩

⟨"memeber"⟩⟨17705⟩⟨6436⟩,⟨"memorabilia"⟩⟨6520⟩⟨11288⟩
⟨"men"⟩⟨2837⟩⟨4534⟩,⟨"Menlo"⟩⟨6255⟩⟨2577⟩
⟨"mention"⟩⟨1213⟩⟨2466⟩,⟨"Mentioned"⟩⟨17231⟩⟨5443⟩
⟨"Menu"⟩⟨7087⟩⟨15249⟩,⟨"menu's"⟩⟨12115⟩⟨11440⟩
⟨"Mercedes"⟩⟨12678⟩⟨10414⟩,⟨"mere"⟩⟨10299⟩⟨12864⟩
⟨"Merlot"⟩⟨8230⟩⟨4908⟩,⟨"Merriman"⟩⟨13093⟩⟨17347⟩
⟨"merry"⟩⟨4275⟩⟨16851⟩,⟨"Mespil"⟩⟨1350⟩⟨15877⟩
⟨"messages"⟩⟨7624⟩⟨13941⟩,⟨"messing"⟩⟨3836⟩⟨3634⟩
⟨"metal"⟩⟨1382⟩⟨8587⟩,⟨"metered"⟩⟨15864⟩⟨12400⟩
⟨"meticulously"⟩⟨4760⟩⟨2430⟩,⟨"metres"⟩⟨4856⟩⟨11419⟩
⟨"metropole"⟩⟨18431⟩⟨14888⟩,⟨"Mews"⟩⟨11632⟩⟨16279⟩
⟨"Mezz"⟩⟨9241⟩⟨6109⟩,⟨"Mezzanine"⟩⟨13428⟩⟨16339⟩
⟨"Michael"⟩⟨45⟩⟨7613⟩,⟨"Michael's"⟩⟨15818⟩⟨16074⟩
⟨"michelin"⟩⟨5882⟩⟨7657⟩,⟨"Mick"⟩⟨15356⟩⟨16857⟩
⟨"Mid"⟩⟨15113⟩⟨12072⟩,⟨"mid-August"⟩⟨15431⟩⟨9559⟩
⟨"mid-morning"⟩⟨6251⟩⟨2383⟩,⟨"mid-week"⟩⟨5607⟩⟨8499⟩
⟨"middle-aged"⟩⟨17201⟩⟨18513⟩,⟨"middling"⟩⟨7191⟩⟨5918⟩
⟨"midnight"⟩⟨3828⟩⟨13372⟩,⟨"midst"⟩⟨8174⟩⟨9250⟩
⟨"Midweek"⟩⟨16926⟩⟨18168⟩,⟨"might"⟩⟨4980⟩⟨12059⟩
⟨"Milan"⟩⟨12240⟩⟨10167⟩,⟨"mild"⟩⟨5969⟩⟨11968⟩
⟨"mildly"⟩⟨1687⟩⟨468⟩,⟨"Mile"⟩⟨13721⟩⟨11391⟩
⟨"Milk"⟩⟨5274⟩⟨4545⟩,⟨"mill"⟩⟨5310⟩⟨13610⟩
⟨"millennium"⟩⟨14416⟩⟨17432⟩,⟨"Millers"⟩⟨12768⟩⟨10494⟩
⟨"Millrace"⟩⟨5026⟩⟨11735⟩,⟨"mills"⟩⟨16221⟩⟨15947⟩
⟨"mind"⟩⟨5038⟩⟨13083⟩,⟨"minded"⟩⟨12360⟩⟨15566⟩
⟨"mine"⟩⟨6943⟩⟨13828⟩,⟨"Minella"⟩⟨8840⟩⟨5251⟩
⟨"mini"⟩⟨1391⟩⟨16800⟩,⟨"mini-bar"⟩⟨5289⟩⟨3742⟩
⟨"miniature"⟩⟨13578⟩⟨5720⟩,⟨"Minibar"⟩⟨9998⟩⟨5727⟩
⟨"minimalist"⟩⟨2531⟩⟨6423⟩,⟨"minimise"⟩⟨16907⟩⟨18149⟩
⟨"Minnies"⟩⟨12828⟩⟨15796⟩,⟨"Minor"⟩⟨5313⟩⟨6706⟩
⟨"Mint"⟩⟨6691⟩⟨13701⟩,⟨"mintues"⟩⟨12182⟩⟨13662⟩

⟨"Minuses"⟩⟨16761⟩⟨17762⟩,⟨"Minute"⟩⟨6126⟩⟨5204⟩
⟨"minutes???????"⟩⟨17639⟩⟨17858⟩,⟨"minutes&quot"⟩⟨6205⟩⟨2217⟩
⟨"mirror"⟩⟨7297⟩⟨15646⟩,⟨"mirrors"⟩⟨2270⟩⟨3831⟩
⟨"miserably"⟩⟨15759⟩⟨12305⟩,⟨"misfortune"⟩⟨730⟩⟨156⟩
⟨"misinformed"⟩⟨12495⟩⟨16527⟩,⟨"misleading"⟩⟨1533⟩⟨755⟩
⟨"misplaced"⟩⟨14080⟩⟨12973⟩,⟨"miss"⟩⟨1822⟩⟨10664⟩
⟨"missing"⟩⟨7557⟩⟨6135⟩,⟨"mission"⟩⟨6288⟩⟨3593⟩
⟨"Mistake"⟩⟨16720⟩⟨3698⟩,⟨"mistaken"⟩⟨1504⟩⟨8006⟩
⟨"misunderstanding"⟩⟨10330⟩⟨7475⟩,⟨"mix"⟩⟨1076⟩⟨7019⟩
⟨"mixers"⟩⟨15786⟩⟨16007⟩,⟨"mixing"⟩⟨17440⟩⟨18326⟩
⟨"mmmm"⟩⟨7431⟩⟨15786⟩,⟨"moan"⟩⟨12573⟩⟨16277⟩
⟨"mobile"⟩⟨6770⟩⟨7015⟩,⟨"mobility"⟩⟨4987⟩⟨5793⟩
⟨"mode"⟩⟨11358⟩⟨9756⟩,⟨"moden"⟩⟨8312⟩⟨10722⟩
⟨"Modern"⟩⟨2375⟩⟨6412⟩,⟨"modernise"⟩⟨13341⟩⟨7338⟩
⟨"modernization"⟩⟨9937⟩⟨5630⟩,⟨"modernly"⟩⟨5885⟩⟨7662⟩
⟨"Moher"⟩⟨1392⟩⟨5420⟩,⟨"Mohr"⟩⟨6028⟩⟨12451⟩
⟨"mojito"⟩⟨7230⟩⟨10673⟩,⟨"mold"⟩⟨534⟩⟨2116⟩
⟨"Molloy's"⟩⟨8478⟩⟨4246⟩,⟨"Molten"⟩⟨8109⟩⟨13609⟩
⟨"mom"⟩⟨12428⟩⟨15581⟩,⟨"moment"⟩⟨4⟩⟨5305⟩
⟨"Mona"⟩⟨4937⟩⟨2055⟩,⟨"Monart"⟩⟨10543⟩⟨18095⟩
⟨"Monday"⟩⟨8604⟩⟨9278⟩,⟨"Money"⟩⟨2888⟩⟨2461⟩
⟨"Monica"⟩⟨10016⟩⟨5765⟩,⟨"monitor"⟩⟨13873⟩⟨16987⟩
⟨"Monkfish"⟩⟨16061⟩⟨12522⟩,⟨"monsoon"⟩⟨9048⟩⟨11011⟩
⟨"Montenotte"⟩⟨3004⟩⟨990⟩,⟨"monthly"⟩⟨16729⟩⟨15525⟩
⟨"mood"⟩⟨7080⟩⟨13730⟩,⟨"moon"⟩⟨3435⟩⟨2630⟩
⟨"mop"⟩⟨11964⟩⟨9357⟩,⟨"Mor"⟩⟨15533⟩⟨15511⟩
⟨"more"⟩⟨1439⟩⟨13926⟩,⟨"MORE"⟩⟨11898⟩⟨13926⟩
⟨"Morgan's"⟩⟨17573⟩⟨13522⟩,⟨"morn"⟩⟨4791⟩⟨7726⟩
⟨"morning&quot"⟩⟨17713⟩⟨6447⟩,⟨"Mornings"⟩⟨8755⟩⟨13390⟩
⟨"morrison"⟩⟨16846⟩⟨15741⟩,⟨"mortified"⟩⟨16671⟩⟨4459⟩
⟨"MOST"⟩⟨8425⟩⟨14638⟩,⟨"Mostly"⟩⟨14373⟩⟨15273⟩

⟨"mother"⟩⟨5321⟩⟨11092⟩,⟨"mother-in-law"⟩⟨6343⟩⟨6797⟩
⟨"Mothers"⟩⟨15497⟩⟨10668⟩,⟨"motivated"⟩⟨13677⟩⟨17139⟩
⟨"motorway"⟩⟨4128⟩⟨14766⟩,⟨"mould"⟩⟨1269⟩⟨886⟩
⟨"mound"⟩⟨17137⟩⟨18449⟩,⟨"mount"⟩⟨11497⟩⟨9786⟩
⟨"mountains"⟩⟨7853⟩⟨4144⟩,⟨"mouse"⟩⟨15658⟩⟨1851⟩
⟨"mouthful"⟩⟨14322⟩⟨12315⟩,⟨"mouthwatering"⟩⟨11766⟩⟨14083⟩
⟨"movement"⟩⟨4613⟩⟨10981⟩,⟨"movie"⟩⟨7567⟩⟨17095⟩
⟨"Moville"⟩⟨6613⟩⟨11008⟩,⟨"Moving"⟩⟨16986⟩⟨18187⟩
⟨"Mr"⟩⟨805⟩⟨13356⟩,⟨"Mrs"⟩⟨2767⟩⟨13477⟩
⟨"mth"⟩⟨18452⟩⟨5991⟩,⟨"much"⟩⟨1979⟩⟨13171⟩
⟨"muck"⟩⟨16379⟩⟨1545⟩,⟨"muckross"⟩⟨8423⟩⟨14636⟩
⟨"muesli"⟩⟨11603⟩⟨12845⟩,⟨"muffins"⟩⟨4526⟩⟨11053⟩
⟨"mugs"⟩⟨9861⟩⟨9422⟩,⟨"mulled"⟩⟨8018⟩⟨12693⟩
⟨"multi-channel"⟩⟨12340⟩⟨10352⟩,⟨"multi-story"⟩⟨11001⟩⟨14754⟩
⟨"multistory"⟩⟨12496⟩⟨16528⟩,⟨"Mum"⟩⟨4521⟩⟨14673⟩
⟨"mumbled"⟩⟨16032⟩⟨18425⟩,⟨"munchies"⟩⟨6301⟩⟨6759⟩
⟨"murder"⟩⟨16181⟩⟨18246⟩,⟨"Murphy"⟩⟨14563⟩⟨17622⟩
⟨"muscles"⟩⟨17850⟩⟨3346⟩,⟨"museum"⟩⟨4396⟩⟨8727⟩
⟨"mushroom"⟩⟨5234⟩⟨3606⟩,⟨"Mushrooms"⟩⟨15417⟩⟨14460⟩
⟨"music&quot"⟩⟨6185⟩⟨12245⟩,⟨"musician"⟩⟨4968⟩⟨2334⟩
⟨"mussels"⟩⟨6832⟩⟨17992⟩,⟨"must"⟩⟨1062⟩⟨12808⟩
⟨"mustard"⟩⟨14510⟩⟨17473⟩,⟨"mustn't"⟩⟨17782⟩⟨17905⟩
⟨"muttered"⟩⟨15529⟩⟨81⟩,⟨"MY"⟩⟨1544⟩⟨5221⟩
⟨"Myself"⟩⟨4348⟩⟨15129⟩,⟨"mysteriously"⟩⟨16415⟩⟨18081⟩
⟨"n"⟩⟨6064⟩⟨9963⟩,⟨"n't"⟩⟨14232⟩⟨12776⟩
⟨"N25"⟩⟨12772⟩⟨10501⟩,⟨"N4"⟩⟨14403⟩⟨17418⟩
⟨"Na"⟩⟨16355⟩⟨18235⟩,⟨"naas"⟩⟨17636⟩⟨17855⟩
⟨"nailed"⟩⟨14536⟩⟨722⟩,⟨"naked"⟩⟨9788⟩⟨3789⟩
⟨"names"⟩⟨6143⟩⟨13178⟩,⟨"Nancy"⟩⟨5580⟩⟨8816⟩
⟨"napkins"⟩⟨6536⟩⟨12119⟩,⟨"nappy"⟩⟨6200⟩⟨2212⟩
⟨"nasty"⟩⟨2917⟩⟨145⟩,⟨"National"⟩⟨230⟩⟨5479⟩

⟨"nationals"⟩⟨14606⟩⟨13183⟩,⟨"nations"⟩⟨14862⟩⟨17215⟩
⟨"Natural"⟩⟨10607⟩⟨15375⟩,⟨"naturally"⟩⟨12572⟩⟨16276⟩
⟨"nav"⟩⟨14650⟩⟨16498⟩,⟨"navigate"⟩⟨12042⟩⟨14391⟩
⟨"nd"⟩⟨2971⟩⟨4414⟩,⟨"near"⟩⟨2105⟩⟨9068⟩
⟨"nearer"⟩⟨6364⟩⟨4761⟩,⟨"nearing"⟩⟨18503⟩⟨13244⟩
⟨"neatly"⟩⟨16245⟩⟨15684⟩,⟨"necessary"⟩⟨9334⟩⟨15446⟩
⟨"Need"⟩⟨2905⟩⟨15650⟩,⟨"needed"⟩⟨1925⟩⟨12781⟩
⟨"needless"⟩⟨278⟩⟨3440⟩,⟨"needn't"⟩⟨10858⟩⟨6822⟩
⟨"negative"⟩⟨1651⟩⟨17265⟩,⟨"negatively"⟩⟨6995⟩⟨4045⟩
⟨"negativity"⟩⟨18191⟩⟨4564⟩,⟨"neglect"⟩⟨2644⟩⟨2459⟩
⟨"negotiating"⟩⟨13822⟩⟨14328⟩,⟨"neice"⟩⟨17079⟩⟨2945⟩
⟨"neighboring"⟩⟨14503⟩⟨16663⟩,⟨"neighbour"⟩⟨5732⟩⟨8108⟩
⟨"Neil"⟩⟨13724⟩⟨13731⟩,⟨"neither"⟩⟨6763⟩⟨2074⟩
⟨"Nenagh"⟩⟨18161⟩⟨2979⟩,⟨"nephew"⟩⟨10104⟩⟨8754⟩
⟨"Nesbitt"⟩⟨15021⟩⟨8980⟩,⟨"nest"⟩⟨18075⟩⟨1878⟩
⟨"Netherlands"⟩⟨9193⟩⟨4830⟩,⟨"network"⟩⟨7521⟩⟨8685⟩
⟨"Never"⟩⟨1215⟩⟨883⟩,⟨"Nevertheless"⟩⟨2069⟩⟨3195⟩
⟨"new&quot"⟩⟨7638⟩⟨9073⟩,⟨"Newcastle"⟩⟨11261⟩⟨16138⟩
⟨"newish"⟩⟨15564⟩⟨17109⟩,⟨"newly"⟩⟨1381⟩⟨16352⟩
⟨"newness"⟩⟨8541⟩⟨6371⟩,⟨"Newport"⟩⟨6789⟩⟨3094⟩
⟨"newsagents"⟩⟨11653⟩⟨14038⟩,⟨"Newspapers"⟩⟨4434⟩⟨2027⟩
⟨"NEXT"⟩⟨15540⟩⟨9612⟩,⟨"nextdoor"⟩⟨8634⟩⟨11153⟩
⟨"Niamh"⟩⟨11055⟩⟨14826⟩,⟨"nibbles"⟩⟨9686⟩⟨13150⟩
⟨"NICE"⟩⟨12724⟩⟨10454⟩,⟨"nice&quot"⟩⟨8223⟩⟨13737⟩
⟨"nicest"⟩⟨58⟩⟨1186⟩,⟨"nicley"⟩⟨12703⟩⟨10453⟩
⟨"niggle"⟩⟨2214⟩⟨5815⟩,⟨"niggling"⟩⟨10029⟩⟨5791⟩
⟨"NIGHT"⟩⟨2437⟩⟨5315⟩,⟨"Night"⟩⟨4853⟩⟨5315⟩
⟨"night-time"⟩⟨12052⟩⟨8279⟩,⟨"night'"⟩⟨13792⟩⟨10596⟩
⟨"nightcaps"⟩⟨15785⟩⟨16005⟩,⟨"Nightclub"⟩⟨1945⟩⟨1985⟩
⟨"Nightlife"⟩⟨12777⟩⟨10508⟩,⟨"nightmare"⟩⟨1929⟩⟨921⟩
⟨"Nights"⟩⟨13995⟩⟨11448⟩,⟨"nights'"⟩⟨11785⟩⟨7424⟩

⟨"nil"⟩⟨15073⟩⟨10624⟩,⟨"nip"⟩⟨5489⟩⟨3371⟩
⟨"niteclub"⟩⟨1462⟩⟨2342⟩,⟨"nitelife"⟩⟨8381⟩⟨15219⟩
⟨"no-one"⟩⟨226⟩⟨15175⟩,⟨"no-smoking"⟩⟨18206⟩⟨4584⟩
⟨"Nobody"⟩⟨1162⟩⟨4224⟩,⟨"Noel"⟩⟨1242⟩⟨8051⟩
⟨"NOISE"⟩⟨16939⟩⟨6919⟩,⟨"noiser"⟩⟨17086⟩⟨15972⟩
⟨"noisiest"⟩⟨2857⟩⟨6639⟩,⟨"Noisy"⟩⟨1035⟩⟨17417⟩
⟨"non"⟩⟨330⟩⟨12611⟩,⟨"NON"⟩⟨16185⟩⟨12611⟩
⟨"non-guests"⟩⟨17183⟩⟨18495⟩,⟨"non-Irish"⟩⟨10767⟩⟨8465⟩
⟨"non-smokers"⟩⟨12719⟩⟨8289⟩,⟨"non-stop"⟩⟨14918⟩⟨16854⟩
⟨"NONE"⟩⟨18342⟩⟨5825⟩,⟨"Nonetheless"⟩⟨14644⟩⟨15057⟩
⟨"nook"⟩⟨12400⟩⟨12494⟩,⟨"noon"⟩⟨6068⟩⟨8287⟩
⟨"Nor"⟩⟨2168⟩⟨8026⟩,⟨"Noreen"⟩⟨14989⟩⟨17539⟩
⟨"Normal"⟩⟨12766⟩⟨12712⟩,⟨"normally"⟩⟨5164⟩⟨15762⟩
⟨"North"⟩⟨8829⟩⟨12121⟩,⟨"northern"⟩⟨13690⟩⟨15174⟩
⟨"nose"⟩⟨1883⟩⟨7133⟩,⟨"nosey"⟩⟨18388⟩⟨2890⟩
⟨"NOT"⟩⟨3526⟩⟨2151⟩,⟨"Not"⟩⟨5866⟩⟨2151⟩
⟨"NOTE"⟩⟨3902⟩⟨7024⟩,⟨"Note"⟩⟨8792⟩⟨7024⟩
⟨"Nothing"⟩⟨718⟩⟨6813⟩,⟨"nothing"⟩⟨3367⟩⟨6813⟩
⟨"noticeably"⟩⟨16771⟩⟨17772⟩,⟨"Noticed"⟩⟨16386⟩⟨7578⟩
⟨"notified"⟩⟨1828⟩⟨7125⟩,⟨"notifying"⟩⟨17397⟩⟨18283⟩
⟨"notorious"⟩⟨17596⟩⟨13562⟩,⟨"Notwithstanding"⟩⟨16946⟩⟨18032⟩
⟨"nouvelle"⟩⟨15261⟩⟨16746⟩,⟨"nov"⟩⟨7444⟩⟨11605⟩
⟨"november"⟩⟨14464⟩⟨13160⟩,⟨"Novo"⟩⟨15803⟩⟨16043⟩
⟨"nowadays"⟩⟨9121⟩⟨12044⟩,⟨"Nowhere"⟩⟨12969⟩⟨7396⟩
⟨"nts"⟩⟨4763⟩⟨2436⟩,⟨"nugget"⟩⟨18192⟩⟨4565⟩
⟨"number"⟩⟨4125⟩⟨2579⟩,⟨"numbering"⟩⟨15551⟩⟨9627⟩
⟨"Nuns"⟩⟨15641⟩⟨15905⟩,⟨"nursing"⟩⟨2332⟩⟨518⟩
⟨"nxt"⟩⟨18060⟩⟨1137⟩,⟨"NYC"⟩⟨7681⟩⟨8746⟩
⟨"O"⟩⟨11324⟩⟨16166⟩,⟨"o???????clock"⟩⟨9406⟩⟨5534⟩
⟨"O'Brien"⟩⟨13993⟩⟨10661⟩,⟨"O'Callaghan"⟩⟨9555⟩⟨16396⟩
⟨"O'Connel"⟩⟨751⟩⟨4223⟩,⟨"O'Connell"⟩⟨1134⟩⟨8148⟩

⟨"O'Connells"⟩⟨16911⟩⟨18153⟩,⟨"O'Connor"⟩⟨6588⟩⟨12201⟩
⟨"O'Fabulous"⟩⟨7148⟩⟨3996⟩,⟨"O'Grady"⟩⟨15893⟩⟨16104⟩
⟨"O'Neill's"⟩⟨15254⟩⟨16739⟩,⟨"O'Neils"⟩⟨10595⟩⟨15363⟩
⟨"O'Sullivan"⟩⟨8595⟩⟨11132⟩,⟨"O2"⟩⟨4341⟩⟨4609⟩
⟨"Oakroom"⟩⟨15296⟩⟨16784⟩,⟨"oaks"⟩⟨9103⟩⟨13040⟩
⟨"oatmeal"⟩⟨7680⟩⟨8744⟩,⟨"objected"⟩⟨17993⟩⟨13690⟩
⟨"oblige"⟩⟨13128⟩⟨11401⟩,⟨"obliging"⟩⟨825⟩⟨910⟩
⟨"obscured"⟩⟨4554⟩⟨8469⟩,⟨"observant"⟩⟨10049⟩⟨10327⟩
⟨"observed"⟩⟨11301⟩⟨12204⟩,⟨"obstacle"⟩⟨5161⟩⟨5826⟩
⟨"obtrusive"⟩⟨7679⟩⟨8743⟩,⟨"obvious"⟩⟨6156⟩⟨1361⟩
⟨"ocassions"⟩⟨10638⟩⟨15408⟩,⟨"occasion"⟩⟨688⟩⟨11521⟩
⟨"occassion"⟩⟨11119⟩⟨16903⟩,⟨"occassionally"⟩⟨7154⟩⟨6260⟩
⟨"occupants"⟩⟨1636⟩⟨3588⟩,⟨"occupies"⟩⟨18120⟩⟨10882⟩
⟨"occurance"⟩⟨16376⟩⟨725⟩,⟨"occurence"⟩⟨11992⟩⟨14445⟩
⟨"Ocean"⟩⟨6953⟩⟨13084⟩,⟨"oconnell"⟩⟨6297⟩⟨15876⟩
⟨"oct"⟩⟨14222⟩⟨12771⟩,⟨"October"⟩⟨6638⟩⟨9222⟩
⟨"Odd"⟩⟨17376⟩⟨18262⟩,⟨"oddly"⟩⟨7627⟩⟨10256⟩
⟨"odors"⟩⟨7756⟩⟨14516⟩,⟨"OF"⟩⟨1460⟩⟨13594⟩
⟨"off"⟩⟨4127⟩⟨16162⟩,⟨"Off"⟩⟨8715⟩⟨16162⟩
⟨"off'"⟩⟨12721⟩⟨8299⟩,⟨"Offaly"⟩⟨15817⟩⟨16073⟩
⟨"offer"⟩⟨1980⟩⟨14903⟩,⟨"offered"⟩⟨2928⟩⟨1344⟩
⟨"offers"⟩⟨1054⟩⟨4047⟩,⟨"Office"⟩⟨3106⟩⟨11954⟩
⟨"official"⟩⟨2534⟩⟨360⟩,⟨"officious"⟩⟨12771⟩⟨10500⟩
⟨"Often"⟩⟨15478⟩⟨8486⟩,⟨"Oh"⟩⟨3969⟩⟨8284⟩
⟨"oil"⟩⟨1731⟩⟨1252⟩,⟨"oils"⟩⟨5841⟩⟨7808⟩
⟨"ok"⟩⟨8250⟩⟨13052⟩,⟨"ok&quot"⟩⟨4835⟩⟨17140⟩
⟨"Old"⟩⟨1671⟩⟨8954⟩,⟨"OLD"⟩⟨8452⟩⟨8954⟩
⟨"old&quot"⟩⟨8098⟩⟨13600⟩,⟨"Olde"⟩⟨12728⟩⟨15565⟩
⟨"olds"⟩⟨13528⟩⟨16942⟩,⟨"Olive"⟩⟨7219⟩⟨15830⟩
⟨"Olwen"⟩⟨11769⟩⟨14087⟩,⟨"omelet"⟩⟨6256⟩⟨2578⟩
⟨"OMG"⟩⟨3440⟩⟨2696⟩,⟨"omitted"⟩⟨4355⟩⟨9200⟩

⟨"ON"⟩⟨3081⟩⟨7106⟩,⟨"on-"⟩⟨16011⟩⟨11752⟩
⟨"on-site"⟩⟨8740⟩⟨9846⟩,⟨"on'"⟩⟨15871⟩⟨12409⟩
⟨"one"⟩⟨2496⟩⟨9330⟩,⟨"ONE"⟩⟨6308⟩⟨9330⟩
⟨"one-way"⟩⟨8888⟩⟨12514⟩,⟨"ones"⟩⟨3645⟩⟨2711⟩
⟨"onions"⟩⟨2120⟩⟨7622⟩,⟨"Only"⟩⟨2379⟩⟨9941⟩
⟨"only&quot"⟩⟨6211⟩⟨7693⟩,⟨"onto"⟩⟨4243⟩⟨12271⟩
⟨"oops"⟩⟨6541⟩⟨4053⟩,⟨"oozes"⟩⟨5805⟩⟨2471⟩
⟨"open-top"⟩⟨8575⟩⟨11095⟩,⟨"Opened"⟩⟨18307⟩⟨1268⟩
⟨"openly"⟩⟨15075⟩⟨10628⟩,⟨"opera"⟩⟨7188⟩⟨13599⟩
⟨"operates"⟩⟨9585⟩⟨5441⟩,⟨"operation"⟩⟨3359⟩⟨2871⟩
⟨"operator"⟩⟨8933⟩⟨9501⟩,⟨"opinion"⟩⟨6149⟩⟨9063⟩
⟨"opportunities"⟩⟨9682⟩⟨11599⟩,⟨"opposed"⟩⟨11126⟩⟨16120⟩
⟨"opt"⟩⟨2598⟩⟨4803⟩,⟨"optimistic"⟩⟨14950⟩⟨9251⟩
⟨"options"⟩⟨4867⟩⟨6136⟩,⟨"opulent"⟩⟨4623⟩⟨5429⟩
⟨"Or"⟩⟨3521⟩⟨9145⟩,⟨"Orange"⟩⟨14593⟩⟨7594⟩
⟨"Orbitz"⟩⟨13754⟩⟨16947⟩,⟨"Orchid"⟩⟨10593⟩⟨15361⟩
⟨"Order"⟩⟨13313⟩⟨7296⟩,⟨"orderd"⟩⟨17085⟩⟨2956⟩
⟨"Ordering"⟩⟨16890⟩⟨18132⟩,⟨"ordinarily"⟩⟨16143⟩⟨10633⟩
⟨"organisation"⟩⟨11566⟩⟨8497⟩,⟨"organised"⟩⟨767⟩⟨6929⟩
⟨"organization"⟩⟨17065⟩⟨1105⟩,⟨"organized"⟩⟨8990⟩⟨11535⟩
⟨"Orient"⟩⟨16849⟩⟨15744⟩,⟨"oriental"⟩⟨8862⟩⟨7468⟩
⟨"origin"⟩⟨10343⟩⟨13518⟩,⟨"originality"⟩⟨12249⟩⟨10178⟩
⟨"Orlando"⟩⟨15896⟩⟨16106⟩,⟨"Ormond"⟩⟨9964⟩⟨5673⟩
⟨"ornate"⟩⟨10122⟩⟨14228⟩,⟨"Oscars"⟩⟨13109⟩⟨17001⟩
⟨"ot"⟩⟨13499⟩⟨15669⟩,⟨"other"⟩⟨3259⟩⟨13261⟩
⟨"otherhand"⟩⟨18186⟩⟨4551⟩,⟨"Others"⟩⟨5259⟩⟨14004⟩
⟨"otherwise"⟩⟨9124⟩⟨8298⟩,⟨"Otters"⟩⟨11768⟩⟨14086⟩
⟨"Oughterard"⟩⟨11181⟩⟨9818⟩,⟨"Our"⟩⟨632⟩⟨4003⟩
⟨"Ours"⟩⟨12643⟩⟨17696⟩,⟨"ourselves"⟩⟨1371⟩⟨3436⟩
⟨"Out"⟩⟨12192⟩⟨15784⟩,⟨"out-"⟩⟨13636⟩⟨13366⟩
⟨"outage"⟩⟨8436⟩⟨14661⟩,⟨"outdated"⟩⟨329⟩⟨195⟩

⟨"outer"⟩⟨14495⟩⟨17352⟩,⟨"outgoing"⟩⟨12729⟩⟨9712⟩
⟨"Outlet"⟩⟨15776⟩⟨15987⟩,⟨"outlined"⟩⟨1621⟩⟨5175⟩
⟨"outrageous"⟩⟨1141⟩⟨1550⟩,⟨"outright"⟩⟨18246⟩⟨634⟩
⟨"Outside"⟩⟨7260⟩⟨12658⟩,⟨"outskirts"⟩⟨252⟩⟨4627⟩
⟨"outward"⟩⟨13356⟩⟨11856⟩,⟨"outweigh"⟩⟨13646⟩⟨13381⟩
⟨"OVER"⟩⟨5760⟩⟨16179⟩,⟨"over-all"⟩⟨17220⟩⟨3312⟩
⟨"over-rated"⟩⟨6597⟩⟨4404⟩,⟨"over-the-top"⟩⟨13012⟩⟨12814⟩
⟨"OVERALL"⟩⟨16514⟩⟨17714⟩,⟨"overbearing"⟩⟨2386⟩⟨1517⟩
⟨"overcast"⟩⟨12445⟩⟨16503⟩,⟨"overcharged"⟩⟨3494⟩⟨698⟩
⟨"overcrowded"⟩⟨9730⟩⟨4046⟩,⟨"overdone"⟩⟨8850⟩⟨2914⟩
⟨"overflowing"⟩⟨2910⟩⟨3758⟩,⟨"overhall"⟩⟨16969⟩⟨11225⟩
⟨"overheard"⟩⟨7939⟩⟨9970⟩,⟨"overjoyed"⟩⟨17131⟩⟨16065⟩
⟨"overlooking"⟩⟨453⟩⟨15222⟩,⟨"overlooks"⟩⟨5166⟩⟨9617⟩
⟨"overnighter"⟩⟨17414⟩⟨18300⟩,⟨"overpowering"⟩⟨1480⟩⟨5337⟩
⟨"overrun"⟩⟨7965⟩⟨14151⟩,⟨"overseas"⟩⟨2230⟩⟨8716⟩
⟨"oversight"⟩⟨6895⟩⟨13111⟩,⟨"overslept"⟩⟨15861⟩⟨12397⟩
⟨"overtly"⟩⟨18409⟩⟨2919⟩,⟨"overview"⟩⟨12734⟩⟨12600⟩
⟨"overworked"⟩⟨1151⟩⟨1054⟩,⟨"owed"⟩⟨1556⟩⟨5320⟩
⟨"owner"⟩⟨692⟩⟨4005⟩,⟨"owner's"⟩⟨4732⟩⟨2063⟩
⟨"owns"⟩⟨916⟩⟨8879⟩,⟨"Oyster"⟩⟨5735⟩⟨17547⟩
⟨"Oz"⟩⟨17211⟩⟨18523⟩,⟨"P"⟩⟨11764⟩⟨16176⟩
⟨"pack"⟩⟨1790⟩⟨2501⟩,⟨"Package"⟩⟨6609⟩⟨8010⟩
⟨"packed"⟩⟨5182⟩⟨12014⟩,⟨"packets"⟩⟨2500⟩⟨1813⟩
⟨"pad"⟩⟨12229⟩⟨11066⟩,⟨"paddling"⟩⟨8333⟩⟨10752⟩
⟨"Paddy's"⟩⟨8241⟩⟨9311⟩,⟨"padlock"⟩⟨15911⟩⟨15725⟩
⟨"pages"⟩⟨12140⟩⟨15764⟩,⟨"paid"⟩⟨5911⟩⟨9919⟩
⟨"painless"⟩⟨4618⟩⟨2302⟩,⟨"paint"⟩⟨6716⟩⟨7846⟩
⟨"painting"⟩⟨2586⟩⟨2165⟩,⟨"paintwork"⟩⟨2938⟩⟨2204⟩
⟨"pal"⟩⟨15465⟩⟨7651⟩,⟨"palace"⟩⟨9639⟩⟨12755⟩
⟨"palatial"⟩⟨7465⟩⟨6504⟩,⟨"pale"⟩⟨16433⟩⟨12071⟩
⟨"Palmerstown"⟩⟨10206⟩⟨6265⟩,⟨"paltry"⟩⟨17026⟩⟨426⟩

⟨"pan"⟩⟨11144⟩⟨15489⟩,⟨"pancakes"⟩⟨389⟩⟨2341⟩
⟨"paneling"⟩⟨15763⟩⟨8575⟩,⟨"panelling"⟩⟨7166⟩⟨11466⟩
⟨"panicked"⟩⟨9068⟩⟨14184⟩,⟨"paninis"⟩⟨5649⟩⟨4486⟩
⟨"pans"⟩⟨13019⟩⟨14873⟩,⟨"paper"⟩⟨2410⟩⟨9056⟩
⟨"Papers"⟩⟨12629⟩⟨16625⟩,⟨"par"⟩⟨9904⟩⟨17625⟩
⟨"Paradiso"⟩⟨17176⟩⟨18488⟩,⟨"Paramount"⟩⟨1666⟩⟨14162⟩
⟨"parents"⟩⟨6067⟩⟨15688⟩,⟨"parents'"⟩⟨13448⟩⟨16361⟩
⟨"park&quot"⟩⟨12294⟩⟨10263⟩,⟨"parking"⟩⟨1645⟩⟨17754⟩
⟨"parkland"⟩⟨8859⟩⟨5894⟩,⟨"parks"⟩⟨6392⟩⟨10287⟩
⟨"parlour"⟩⟨8111⟩⟨13613⟩,⟨"parma"⟩⟨12873⟩⟨15842⟩
⟨"parrot"⟩⟨7000⟩⟨4071⟩,⟨"part"⟩⟨2005⟩⟨15590⟩
⟨"partial"⟩⟨13802⟩⟨14767⟩,⟨"participants"⟩⟨16035⟩⟨11765⟩
⟨"particular"⟩⟨3987⟩⟨16752⟩,⟨"particularily"⟩⟨6806⟩⟨12570⟩
⟨"partied"⟩⟨8995⟩⟨2690⟩,⟨"parties"⟩⟨3637⟩⟨2581⟩
⟨"partly"⟩⟨13059⟩⟨12879⟩,⟨"Partner"⟩⟨8856⟩⟨14174⟩
⟨"parts"⟩⟨9447⟩⟨8582⟩,⟨"Party"⟩⟨11163⟩⟨15587⟩
⟨"partys"⟩⟨11798⟩⟨9320⟩,⟨"Pass"⟩⟨10932⟩⟨17462⟩
⟨"passed"⟩⟨3064⟩⟨7186⟩,⟨"passengers"⟩⟨4819⟩⟨1621⟩
⟨"passion"⟩⟨10888⟩⟨15624⟩,⟨"passports"⟩⟨14575⟩⟨12715⟩
⟨"Pasta"⟩⟨13021⟩⟨14883⟩,⟨"pasteries"⟩⟨5731⟩⟨8106⟩
⟨"pasture"⟩⟨8126⟩⟨13635⟩,⟨"Pat"⟩⟨1140⟩⟨10654⟩
⟨"patched"⟩⟨16237⟩⟨400⟩,⟨"patchy"⟩⟨8820⟩⟨7915⟩
⟨"pathetic"⟩⟨1168⟩⟨3507⟩,⟨"pathway"⟩⟨14391⟩⟨15310⟩
⟨"patiently"⟩⟨5325⟩⟨7344⟩,⟨"patios"⟩⟨17474⟩⟨18360⟩
⟨"Patrick???????s"⟩⟨9082⟩⟨14209⟩,⟨"Patricks"⟩⟨5047⟩⟨14291⟩
⟨"Patsy"⟩⟨10170⟩⟨6197⟩,⟨"patterned"⟩⟨12358⟩⟨7372⟩
⟨"Paula"⟩⟨15382⟩⟨16887⟩,⟨"paved"⟩⟨13638⟩⟨13369⟩
⟨"pavlova"⟩⟨9156⟩⟨4795⟩,⟨"pay"⟩⟨5914⟩⟨8384⟩
⟨"paying"⟩⟨7077⟩⟨1796⟩,⟨"payment"⟩⟨248⟩⟨5786⟩
⟨"PC"⟩⟨9173⟩⟨12759⟩,⟨"PCs"⟩⟨10166⟩⟨6191⟩
⟨"peaceful"⟩⟨689⟩⟨4156⟩,⟨"peacefully"⟩⟨12028⟩⟨9488⟩

⟨"peacocks"⟩⟨11086⟩⟨14847⟩,⟨"pealing"⟩⟨15554⟩⟨33⟩
⟨"Pearl"⟩⟨6504⟩⟨7240⟩,⟨"peas"⟩⟨11373⟩⟨5084⟩
⟨"pedestal"⟩⟨7890⟩⟨13843⟩,⟨"pedestrianised"⟩⟨12851⟩⟨15820⟩
⟨"pee"⟩⟨15045⟩⟨8663⟩,⟨"peeked"⟩⟨17849⟩⟨3345⟩
⟨"peep"⟩⟨8858⟩⟨5892⟩,⟨"peice"⟩⟨15213⟩⟨16692⟩
⟨"penalised"⟩⟨12337⟩⟨10346⟩,⟨"pencil"⟩⟨14964⟩⟨12039⟩
⟨"penne"⟩⟨14074⟩⟨15141⟩,⟨"penninsula"⟩⟨12616⟩⟨17152⟩
⟨"Penny"⟩⟨15783⟩⟨16001⟩,⟨"penthouse"⟩⟨2830⟩⟨11139⟩
⟨"people'"⟩⟨12491⟩⟨16526⟩,⟨"people&quot"⟩⟨17531⟩⟨18405⟩
⟨"peppercorn"⟩⟨14059⟩⟨11816⟩,⟨"Peppers"⟩⟨17177⟩⟨18489⟩
⟨"perched"⟩⟨14630⟩⟨17520⟩,⟨"Perfect"⟩⟨735⟩⟨8303⟩
⟨"perfectly"⟩⟨311⟩⟨7620⟩,⟨"perform"⟩⟨16590⟩⟨2094⟩
⟨"performers"⟩⟨16652⟩⟨17669⟩,⟨"perfume"⟩⟨16014⟩⟨7452⟩
⟨"peril"⟩⟨17255⟩⟨155⟩,⟨"period"⟩⟨2929⟩⟨8874⟩
⟨"perks"⟩⟨4913⟩⟨5460⟩,⟨"permanent"⟩⟨3309⟩⟨3249⟩
⟨"permit"⟩⟨12930⟩⟨15033⟩,⟨"permitted"⟩⟨11291⟩⟨9261⟩
⟨"Perrotts"⟩⟨9754⟩⟨13858⟩,⟨"persistent"⟩⟨17226⟩⟨3319⟩
⟨"Personal"⟩⟨6302⟩⟨6761⟩,⟨"personalised"⟩⟨13416⟩⟨17687⟩
⟨"personally"⟩⟨2095⟩⟨12095⟩,⟨"personel"⟩⟨15517⟩⟨12145⟩
⟨"persons"⟩⟨11509⟩⟨7810⟩,⟨"persuade"⟩⟨16492⟩⟨12927⟩
⟨"peruse"⟩⟨6507⟩⟨7249⟩,⟨"pesto"⟩⟨17725⟩⟨11657⟩
⟨"petit"⟩⟨4759⟩⟨2277⟩,⟨"pets"⟩⟨16062⟩⟨18438⟩
⟨"phenomenal"⟩⟨10661⟩⟨13757⟩,⟨"phew"⟩⟨12416⟩⟨16491⟩
⟨"philosophy"⟩⟨17268⟩⟨5346⟩,⟨"Phoenix"⟩⟨6846⟩⟨5782⟩
⟨"phonecalls"⟩⟨15185⟩⟨8374⟩,⟨"Phoned"⟩⟨16714⟩⟨5314⟩
⟨"photo's"⟩⟨8494⟩⟨6324⟩,⟨"photograph"⟩⟨10400⟩⟨16236⟩
⟨"photos"⟩⟨3641⟩⟨1898⟩,⟨"Phyllis"⟩⟨10611⟩⟨15379⟩
⟨"piano"⟩⟨2443⟩⟨13000⟩,⟨"pic"⟩⟨12903⟩⟨15875⟩
⟨"Picked"⟩⟨16622⟩⟨15494⟩,⟨"picks"⟩⟨3223⟩⟨6960⟩
⟨"pics"⟩⟨8189⟩⟨12027⟩,⟨"pictured"⟩⟨12520⟩⟨16627⟩
⟨"Pie"⟩⟨5394⟩⟨3824⟩,⟨"piece"⟩⟨3884⟩⟨7329⟩

⟨"pies"⟩⟨14991⟩⟨17541⟩,⟨"pigeon"⟩⟨11899⟩⟨6823⟩
⟨"piles"⟩⟨3546⟩⟨1525⟩,⟨"pillars"⟩⟨11657⟩⟨14045⟩
⟨"pillows"⟩⟨1811⟩⟨15496⟩,⟨"pin"⟩⟨2059⟩⟨6896⟩
⟨"pineapple"⟩⟨3598⟩⟨10810⟩,⟨"Pink"⟩⟨13027⟩⟨14894⟩
⟨"Pins"⟩⟨4995⟩⟨4688⟩,⟨"Pint"⟩⟨10938⟩⟨11169⟩
⟨"pipes"⟩⟨267⟩⟨5061⟩,⟨"pissed"⟩⟨5447⟩⟨13793⟩
⟨"pitched"⟩⟨9417⟩⟨11953⟩,⟨"pits"⟩⟨16389⟩⟨7796⟩
⟨"Pizza"⟩⟨5962⟩⟨10176⟩,⟨"pizzas"⟩⟨11113⟩⟨12346⟩
⟨"place"⟩⟨976⟩⟨15679⟩,⟨"PLACE"⟩⟨14740⟩⟨15679⟩
⟨"placement"⟩⟨15868⟩⟨12405⟩,⟨"Places"⟩⟨16929⟩⟨18171⟩
⟨"plain"⟩⟨5029⟩⟨2033⟩,⟨"plan"⟩⟨3305⟩⟨14760⟩
⟨"planet"⟩⟨1697⟩⟨8466⟩,⟨"planing"⟩⟨17854⟩⟨3353⟩
⟨"planning"⟩⟨317⟩⟨15374⟩,⟨"plans"⟩⟨9735⟩⟨12709⟩
⟨"plaque"⟩⟨14097⟩⟨15149⟩,⟨"Plasma"⟩⟨4643⟩⟨7354⟩
⟨"plasterwork"⟩⟨17396⟩⟨18282⟩,⟨"Plastic"⟩⟨18423⟩⟨5936⟩
⟨"Plates"⟩⟨10486⟩⟨15260⟩,⟨"Platinum"⟩⟨7789⟩⟨10699⟩
⟨"play"⟩⟨860⟩⟨15297⟩,⟨"played"⟩⟨4905⟩⟨3529⟩
⟨"players"⟩⟨12162⟩⟨17064⟩,⟨"playing"⟩⟨3844⟩⟨9794⟩
⟨"Plaza"⟩⟨264⟩⟨8540⟩,⟨"plazma"⟩⟨8943⟩⟨10966⟩
⟨"Pleasant"⟩⟨7348⟩⟨5122⟩,⟨"pleasantness"⟩⟨10573⟩⟨15338⟩
⟨"PLEASE"⟩⟨14532⟩⟨5085⟩,⟨"pleased"⟩⟨722⟩⟨1159⟩
⟨"pleasurable"⟩⟨6769⟩⟨2614⟩,⟨"pleasure&quot"⟩⟨18274⟩⟨344⟩
⟨"plentiful"⟩⟨659⟩⟨1117⟩,⟨"plently"⟩⟨8209⟩⟨14025⟩
⟨"plesant"⟩⟨3858⟩⟨9814⟩,⟨"plesent"⟩⟨11414⟩⟨11508⟩
⟨"plonked"⟩⟨2226⟩⟨3273⟩,⟨"ploy"⟩⟨7758⟩⟨14521⟩
⟨"plugs"⟩⟨8690⟩⟨5419⟩,⟨"plumbing"⟩⟨4652⟩⟨9391⟩
⟨"plunger"⟩⟨18360⟩⟨621⟩,⟨"plus"⟩⟨3261⟩⟨12862⟩
⟨"Pluses"⟩⟨17521⟩⟨18396⟩,⟨"plusses"⟩⟨10008⟩⟨5751⟩
⟨"poached"⟩⟨8627⟩⟨15775⟩,⟨"pockets"⟩⟨13902⟩⟨13999⟩
⟨"point"⟩⟨4884⟩⟨4204⟩,⟨"pointed"⟩⟨1804⟩⟨2115⟩
⟨"points"⟩⟨6387⟩⟨15782⟩,⟨"POINTS"⟩⟨12815⟩⟨15782⟩

⟨"pokey"⟩⟨521⟩⟨6836⟩,⟨"poky"⟩⟨4564⟩⟨11573⟩
⟨"police"⟩⟨263⟩⟨5514⟩,⟨"policies"⟩⟨16955⟩⟨7777⟩
⟨"polished"⟩⟨13778⟩⟨17312⟩,⟨"polite"⟩⟨985⟩⟨6370⟩
⟨"politicians"⟩⟨18221⟩⟨8766⟩,⟨"pollution"⟩⟨13589⟩⟨7090⟩
⟨"pong"⟩⟨7736⟩⟨14496⟩,⟨"Pontoon"⟩⟨6837⟩⟨5780⟩
⟨"Pool"⟩⟨9833⟩⟨5469⟩,⟨"poor"⟩⟨1627⟩⟨1694⟩
⟨"poorly"⟩⟨254⟩⟨217⟩,⟨"popcorn"⟩⟨14632⟩⟨18534⟩
⟨"popularity"⟩⟨14733⟩⟨17271⟩,⟨"population"⟩⟨10673⟩⟨9683⟩
⟨"porn"⟩⟨7677⟩⟨8812⟩,⟨"Porridge"⟩⟨8613⟩⟨11136⟩
⟨"porter"⟩⟨1325⟩⟨12380⟩,⟨"porterage"⟩⟨18196⟩⟨4572⟩
⟨"Porters"⟩⟨8679⟩⟨13554⟩,⟨"portions"⟩⟨1082⟩⟨15080⟩
⟨"Portmarnock"⟩⟨5524⟩⟨7405⟩,⟨"Portovino"⟩⟨11021⟩⟨14785⟩
⟨"Portumna"⟩⟨13903⟩⟨14000⟩,⟨"posed"⟩⟨8344⟩⟨10772⟩
⟨"positioned"⟩⟨6290⟩⟨1853⟩,⟨"positions"⟩⟨12694⟩⟨10441⟩
⟨"Positives"⟩⟨7278⟩⟨8206⟩,⟨"poss"⟩⟨12868⟩⟨15837⟩
⟨"possibility"⟩⟨7349⟩⟨4708⟩,⟨"possibly"⟩⟨1873⟩⟨11480⟩
⟨"postage"⟩⟨6286⟩⟨2291⟩,⟨"postcards"⟩⟨12740⟩⟨12617⟩
⟨"posters"⟩⟨11915⟩⟨16818⟩,⟨"postings"⟩⟨11969⟩⟨11959⟩
⟨"Pot"⟩⟨6525⟩⟨11299⟩,⟨"Potato"⟩⟨18159⟩⟨2975⟩
⟨"potentially"⟩⟨11679⟩⟨9034⟩,⟨"potions"⟩⟨12275⟩⟨10223⟩
⟨"Pound"⟩⟨8633⟩⟨11152⟩,⟨"pounding"⟩⟨1830⟩⟨6518⟩
⟨"pouring"⟩⟨11120⟩⟨14355⟩,⟨"powder"⟩⟨7630⟩⟨4615⟩
⟨"power-shower"⟩⟨12859⟩⟨15828⟩,⟨"powerful"⟩⟨1098⟩⟨16867⟩
⟨"powerless"⟩⟨16996⟩⟨329⟩,⟨"powerscourt"⟩⟨7880⟩⟨13833⟩
⟨"pppn"⟩⟨17365⟩⟨18251⟩,⟨"practical"⟩⟨6659⟩⟨2932⟩
⟨"practise"⟩⟨17730⟩⟨11663⟩,⟨"praise"⟩⟨995⟩⟨1051⟩
⟨"pram"⟩⟨3080⟩⟨4847⟩,⟨"prawn"⟩⟨2518⟩⟨3818⟩
⟨"Pre"⟩⟨13627⟩⟨13337⟩,⟨"pre-arranged"⟩⟨10531⟩⟨15295⟩
⟨"pre-booked"⟩⟨13708⟩⟨16937⟩,⟨"pre-dinner"⟩⟨4141⟩⟨5577⟩
⟨"prebooked"⟩⟨9893⟩⟨13935⟩,⟨"preceded"⟩⟨17838⟩⟨1679⟩
⟨"precise"⟩⟨6813⟩⟨6952⟩,⟨"precooked"⟩⟨4363⟩⟨12052⟩

⟨"predominantly"⟩⟨5492⟩⟨3379⟩,⟨"prefect"⟩⟨6253⟩⟨2414⟩
⟨"prefered"⟩⟨13723⟩⟨12438⟩,⟨"preferences"⟩⟨7139⟩⟨3985⟩
⟨"pregnancy"⟩⟨17763⟩⟨1669⟩,⟨"prehaps"⟩⟨18009⟩⟨18061⟩
⟨"premises"⟩⟨1670⟩⟨2109⟩,⟨"preoccupied"⟩⟨6542⟩⟨4055⟩
⟨"prepared"⟩⟨2538⟩⟨13885⟩,⟨"prepay"⟩⟨13847⟩⟨17386⟩
⟨"presentation"⟩⟨3345⟩⟨16684⟩,⟨"presented"⟩⟨391⟩⟨3587⟩
⟨"preserve"⟩⟨16004⟩⟨11736⟩,⟨"preserves"⟩⟨8149⟩⟨9093⟩
⟨"press"⟩⟨9110⟩⟨9520⟩,⟨"pressed"⟩⟨2902⟩⟨3203⟩
⟨"pressure"⟩⟨4421⟩⟨11377⟩,⟨"prestigious"⟩⟨16524⟩⟨17725⟩
⟨"presumed"⟩⟨3062⟩⟨7161⟩,⟨"pretend"⟩⟨11698⟩⟨9577⟩
⟨"pretensions"⟩⟨13657⟩⟨13400⟩,⟨"pretentious"⟩⟨3419⟩⟨5089⟩
⟨"prevailed"⟩⟨17157⟩⟨18469⟩,⟨"prevented"⟩⟨13211⟩⟨15418⟩
⟨"Previous"⟩⟨13488⟩⟨15701⟩,⟨"Previously"⟩⟨15645⟩⟨15906⟩
⟨"priceless"⟩⟨13286⟩⟨13036⟩,⟨"prices"⟩⟨3620⟩⟨10284⟩
⟨"pricier"⟩⟨7131⟩⟨5895⟩,⟨"pricy"⟩⟨2031⟩⟨8192⟩
⟨"primarily"⟩⟨6570⟩⟨13082⟩,⟨"prime"⟩⟨6786⟩⟨14572⟩
⟨"principal"⟩⟨14975⟩⟨18462⟩,⟨"principle"⟩⟨3452⟩⟨959⟩
⟨"printers"⟩⟨12260⟩⟨10197⟩,⟨"printout"⟩⟨7353⟩⟨5592⟩
⟨"priorities"⟩⟨17108⟩⟨16017⟩,⟨"Priority"⟩⟨14963⟩⟨15457⟩
⟨"private"⟩⟨5176⟩⟨7607⟩,⟨"privately"⟩⟨5747⟩⟨12564⟩
⟨"prize"⟩⟨11736⟩⟨14453⟩,⟨"pro"⟩⟨7168⟩⟨11468⟩
⟨"probably"⟩⟨4330⟩⟨6613⟩,⟨"probaly"⟩⟨5416⟩⟨4298⟩
⟨"problem'"⟩⟨18361⟩⟨862⟩,⟨"problematic"⟩⟨13092⟩⟨17345⟩
⟨"proceded"⟩⟨17161⟩⟨18473⟩,⟨"procedures"⟩⟨5275⟩⟨4548⟩
⟨"process"⟩⟨4247⟩⟨5158⟩,⟨"processing"⟩⟨17538⟩⟨18409⟩
⟨"producing"⟩⟨5692⟩⟨12887⟩,⟨"production"⟩⟨8447⟩⟨8948⟩
⟨"Professional"⟩⟨13135⟩⟨13065⟩,⟨"professionally"⟩⟨10446⟩⟨9668⟩
⟨"profile"⟩⟨15563⟩⟨17107⟩,⟨"profiteroles"⟩⟨8828⟩⟨5201⟩
⟨"program"⟩⟨5937⟩⟨12328⟩,⟨"programmed"⟩⟨15505⟩⟨12126⟩
⟨"progressed"⟩⟨16577⟩⟨1029⟩,⟨"prohibited"⟩⟨17658⟩⟨17877⟩
⟨"prom"⟩⟨8936⟩⟨10956⟩,⟨"prominent"⟩⟨17156⟩⟨18468⟩

⟨"promises"⟩⟨3061⟩⟨7160⟩,⟨"promote"⟩⟨14951⟩⟨10279⟩
⟨"promotional"⟩⟨9714⟩⟨13952⟩,⟨"prompt"⟩⟨452⟩⟨3080⟩
⟨"promtly"⟩⟨16007⟩⟨11742⟩,⟨"proof"⟩⟨4176⟩⟨4482⟩
⟨"proper"⟩⟨5020⟩⟨16444⟩,⟨"properly"⟩⟨202⟩⟨295⟩
⟨"proportion"⟩⟨17107⟩⟨16015⟩,⟨"proportions"⟩⟨17122⟩⟨16046⟩
⟨"propped"⟩⟨2099⟩⟨8025⟩,⟨"proprietors"⟩⟨5815⟩⟨1463⟩
⟨"Prosecco"⟩⟨18291⟩⟨591⟩,⟨"prospective"⟩⟨4264⟩⟨8681⟩
⟨"protector"⟩⟨18011⟩⟨18062⟩,⟨"protested"⟩⟨18211⟩⟨4596⟩
⟨"proudly"⟩⟨14639⟩⟨15050⟩,⟨"proved"⟩⟨9260⟩⟨13051⟩
⟨"provided"⟩⟨2965⟩⟨10308⟩,⟨"provider"⟩⟨15114⟩⟨12073⟩
⟨"provision"⟩⟨5593⟩⟨10763⟩,⟨"proximity"⟩⟨4338⟩⟨14139⟩
⟨"Ps"⟩⟨17861⟩⟨14568⟩,⟨"pub"⟩⟨8691⟩⟨7879⟩
⟨"pubic"⟩⟨14742⟩⟨1864⟩,⟨"Public"⟩⟨8878⟩⟨7486⟩
⟨"Pubs"⟩⟨7671⟩⟨10198⟩,⟨"pudding"⟩⟨5391⟩⟨11347⟩
⟨"puff"⟩⟨15959⟩⟨16418⟩,⟨"pull"⟩⟨1509⟩⟨712⟩
⟨"Pullman"⟩⟨6398⟩⟨4405⟩,⟨"pulls"⟩⟨16629⟩⟨17644⟩
⟨"pumps"⟩⟨7712⟩⟨14480⟩,⟨"Punch"⟩⟨12278⟩⟨15292⟩
⟨"Punches"⟩⟨11778⟩⟨14093⟩,⟨"Punchs"⟩⟨13031⟩⟨14898⟩
⟨"punter"⟩⟨18522⟩⟨13325⟩,⟨"puppy"⟩⟨12259⟩⟨10196⟩
⟨"purchasing"⟩⟨11481⟩⟨7044⟩,⟨"Pure"⟩⟨12150⟩⟨6937⟩
⟨"purpose"⟩⟨6604⟩⟨728⟩,⟨"purposely"⟩⟨16547⟩⟨1005⟩
⟨"pushchair"⟩⟨17104⟩⟨16009⟩,⟨"pushing"⟩⟨11806⟩⟨17262⟩
⟨"puts"⟩⟨9732⟩⟨12228⟩,⟨"putter"⟩⟨8574⟩⟨11093⟩
⟨"puzzling"⟩⟨18324⟩⟨807⟩,⟨"Q"⟩⟨7834⟩⟨13725⟩
⟨"qualified"⟩⟨6625⟩⟨12367⟩,⟨"qualify"⟩⟨14154⟩⟨17603⟩
⟨"qualms"⟩⟨5406⟩⟨3270⟩,⟨"quantity"⟩⟨8173⟩⟨13820⟩
⟨"Quay"⟩⟨2599⟩⟨9890⟩,⟨"quays"⟩⟨3323⟩⟨9059⟩
⟨"Queen"⟩⟨1915⟩⟨8123⟩,⟨"queen-sized"⟩⟨8303⟩⟨10712⟩
⟨"queried"⟩⟨1426⟩⟨4655⟩,⟨"query"⟩⟨9462⟩⟨14255⟩
⟨"questioned"⟩⟨920⟩⟨454⟩,⟨"questions"⟩⟨5414⟩⟨8130⟩
⟨"queueing"⟩⟨16417⟩⟨18083⟩,⟨"queuing"⟩⟨1654⟩⟨1562⟩

⟨"Quick"⟩⟨10822⟩⟨9534⟩,⟨"quickest"⟩⟨16418⟩⟨18084⟩
⟨"Quiet"⟩⟨3667⟩⟨8307⟩,⟨"quiet&quot"⟩⟨13089⟩⟨16990⟩
⟨"quietest"⟩⟨4637⟩⟨4386⟩,⟨"quietness"⟩⟨4406⟩⟨5608⟩
⟨"quirkiness"⟩⟨15124⟩⟨16912⟩,⟨"quirky"⟩⟨576⟩⟨10435⟩
⟨"Quite"⟩⟨11125⟩⟨14369⟩,⟨"quiz"⟩⟨16905⟩⟨18147⟩
⟨"quoting"⟩⟨13867⟩⟨6048⟩,⟨"r"⟩⟨5942⟩⟨12332⟩
⟨"RAC"⟩⟨18442⟩⟨5971⟩,⟨"Race"⟩⟨14562⟩⟨17621⟩
⟨"Races"⟩⟨10876⟩⟨13897⟩,⟨"Racing"⟩⟨8113⟩⟨17211⟩
⟨"racket"⟩⟨1954⟩⟨2985⟩,⟨"rad"⟩⟨17278⟩⟨5360⟩
⟨"radiator"⟩⟨1212⟩⟨17899⟩,⟨"radiators"⟩⟨583⟩⟨445⟩
⟨"radios"⟩⟨12688⟩⟨10433⟩,⟨"Radission"⟩⟨16056⟩⟨18433⟩
⟨"Radissons"⟩⟨14104⟩⟨15157⟩,⟨"rads"⟩⟨17554⟩⟨18421⟩
⟨"raging"⟩⟨5765⟩⟨3577⟩,⟨"Raheen"⟩⟨5215⟩⟨12006⟩
⟨"railings"⟩⟨16162⟩⟨14954⟩,⟨"rails"⟩⟨2783⟩⟨856⟩
⟨"Rain"⟩⟨15269⟩⟨16754⟩,⟨"rainfall"⟩⟨11658⟩⟨14047⟩
⟨"rainshower"⟩⟨10577⟩⟨15343⟩,⟨"raise"⟩⟨8806⟩⟨12042⟩
⟨"rally"⟩⟨14738⟩⟨18212⟩,⟨"Ramada"⟩⟨6850⟩⟨7863⟩
⟨"Rambler"⟩⟨8635⟩⟨11154⟩,⟨"rammed"⟩⟨18338⟩⟨827⟩
⟨"Ramsay"⟩⟨11294⟩⟨12561⟩,⟨"Ramsays"⟩⟨11672⟩⟨14070⟩
⟨"ran"⟩⟨5772⟩⟨420⟩,⟨"randles"⟩⟨10013⟩⟨5757⟩
⟨"rang"⟩⟨6653⟩⟨2207⟩,⟨"ranged"⟩⟨4047⟩⟨7967⟩
⟨"ranked"⟩⟨3820⟩⟨8706⟩,⟨"ranks"⟩⟨10820⟩⟨8638⟩
⟨"rapidly"⟩⟨12172⟩⟨16362⟩,⟨"rare"⟩⟨1099⟩⟨4689⟩
⟨"rash"⟩⟨18276⟩⟨250⟩,⟨"rashers"⟩⟨3372⟩⟨7849⟩
⟨"rate"⟩⟨2142⟩⟨13894⟩,⟨"rate&quot"⟩⟨6232⟩⟨13806⟩
⟨"Rathbaun"⟩⟨11065⟩⟨14838⟩,⟨"rather"⟩⟨5384⟩⟨5188⟩
⟨"rating"⟩⟨647⟩⟨2692⟩,⟨"ratio"⟩⟨7436⟩⟨4202⟩
⟨"rattling"⟩⟨16936⟩⟨557⟩,⟨"raucous"⟩⟨15580⟩⟨18194⟩
⟨"raving"⟩⟨4809⟩⟨8705⟩,⟨"raw"⟩⟨663⟩⟨1729⟩
⟨"Rd"⟩⟨10929⟩⟨15194⟩,⟨"RDS"⟩⟨3469⟩⟨5877⟩
⟨"re-book"⟩⟨16637⟩⟨17654⟩,⟨"re-done"⟩⟨17452⟩⟨18338⟩

⟨"re-opening"⟩⟨17848⟩⟨3262⟩,⟨"re-vamp"⟩⟨16445⟩⟨7043⟩
⟨"reached"⟩⟨7076⟩⟨14579⟩,⟨"reaching"⟩⟨2448⟩⟨1999⟩
⟨"Read"⟩⟨8855⟩⟨12137⟩,⟨"readers"⟩⟨5943⟩⟨12333⟩
⟨"reads"⟩⟨11628⟩⟨14574⟩,⟨"real"⟩⟨846⟩⟨13059⟩
⟨"realise"⟩⟨2158⟩⟨3706⟩,⟨"realising"⟩⟨3180⟩⟨9143⟩
⟨"realize"⟩⟨11095⟩⟨14499⟩,⟨"reall"⟩⟨17645⟩⟨17864⟩
⟨"REALLY"⟩⟨7672⟩⟨12644⟩,⟨"realy"⟩⟨6966⟩⟨2998⟩
⟨"Reason"⟩⟨17482⟩⟨15056⟩,⟨"Reasonable"⟩⟨8202⟩⟨13087⟩
⟨"reassurance"⟩⟨16725⟩⟨15521⟩,⟨"reassured"⟩⟨13159⟩⟨14437⟩
⟨"rebooked"⟩⟨4575⟩⟨3215⟩,⟨"rec"⟩⟨16826⟩⟨299⟩
⟨"reccomended"⟩⟨11234⟩⟨15634⟩,⟨"reccommend"⟩⟨6490⟩⟨9150⟩
⟨"receipt"⟩⟨3972⟩⟨8613⟩,⟨"receiptionist"⟩⟨18482⟩⟨13214⟩
⟨"Received"⟩⟨13382⟩⟨11879⟩,⟨"receiving"⟩⟨1019⟩⟨3073⟩
⟨"recepetion"⟩⟨17083⟩⟨2954⟩,⟨"recepionist"⟩⟨6543⟩⟨4056⟩
⟨"receptionest"⟩⟨14640⟩⟨15051⟩,⟨"receptionist"⟩⟨4965⟩⟨11587⟩
⟨"receptions"⟩⟨11545⟩⟨10391⟩,⟨"receptive"⟩⟨17729⟩⟨11662⟩
⟨"recharge"⟩⟨3651⟩⟨2762⟩,⟨"recieve"⟩⟨732⟩⟨3302⟩
⟨"reckon"⟩⟨13156⟩⟨16982⟩,⟨"recognise"⟩⟨13476⟩⟨13388⟩
⟨"recognized"⟩⟨8375⟩⟨10819⟩,⟨"recomendation"⟩⟨16229⟩⟨15967⟩
⟨"recommand"⟩⟨13830⟩⟨14344⟩,⟨"recommeded"⟩⟨6317⟩⟨6774⟩
⟨"recommendable"⟩⟨8670⟩⟨13144⟩,⟨"recommendations"⟩⟨601⟩⟨1554⟩
⟨"recommending"⟩⟨135⟩⟨2976⟩,⟨"recommened"⟩⟨11239⟩⟨17407⟩
⟨"reconsider"⟩⟨5433⟩⟨5833⟩,⟨"recorded"⟩⟨14998⟩⟨17548⟩
⟨"recovering"⟩⟨16490⟩⟨12925⟩,⟨"recpetion"⟩⟨13293⟩⟨14786⟩
⟨"rectify"⟩⟨2354⟩⟨9188⟩,⟨"recycling"⟩⟨16289⟩⟨18540⟩
⟨"red-eye"⟩⟨9945⟩⟨5642⟩,⟨"redcastle"⟩⟨15003⟩⟨17553⟩
⟨"redeem"⟩⟨17284⟩⟨9713⟩,⟨"redeeming"⟩⟨1160⟩⟨2665⟩
⟨"redirected"⟩⟨9134⟩⟨13489⟩,⟨"reds"⟩⟨16925⟩⟨18167⟩
⟨"reduction"⟩⟨625⟩⟨6832⟩,⟨"reeds"⟩⟨10157⟩⟨16348⟩
⟨"ref"⟩⟨17147⟩⟨18459⟩,⟨"refered"⟩⟨8416⟩⟨14628⟩
⟨"refers"⟩⟨17496⟩⟨18375⟩,⟨"refilled"⟩⟨10496⟩⟨7610⟩

⟨"refit"⟩⟨3757⟩⟨5276⟩,⟨"reflect"⟩⟨8907⟩⟨11457⟩
⟨"reflective"⟩⟨16842⟩⟨15737⟩,⟨"reflexology"⟩⟨9383⟩⟨11254⟩
⟨"refreshing"⟩⟨2271⟩⟨1477⟩,⟨"refreshment"⟩⟨6496⟩⟨7214⟩
⟨"refund"⟩⟨580⟩⟨5002⟩,⟨"refunded"⟩⟨386⟩⟨4930⟩
⟨"refurbish"⟩⟨6628⟩⟨13722⟩,⟨"refurbishing"⟩⟨13515⟩⟨18528⟩
⟨"refused"⟩⟨6746⟩⟨10⟩,⟨"refusing"⟩⟨6063⟩⟨5198⟩
⟨"regarded"⟩⟨12977⟩⟨7406⟩,⟨"Regarding"⟩⟨10766⟩⟨16240⟩
⟨"Regards"⟩⟨13527⟩⟨12235⟩,⟨"regency"⟩⟨14408⟩⟨17423⟩
⟨"Region"⟩⟨18371⟩⟨13951⟩,⟨"regions"⟩⟨16931⟩⟨18173⟩
⟨"registration"⟩⟨3085⟩⟨3951⟩,⟨"regrets"⟩⟨16972⟩⟨11232⟩
⟨"Regular"⟩⟨9394⟩⟨14010⟩,⟨"regulars"⟩⟨11407⟩⟨14474⟩
⟨"regulations"⟩⟨5643⟩⟨12883⟩,⟨"Reidh"⟩⟨8110⟩⟨13611⟩
⟨"reiterate"⟩⟨4782⟩⟨1488⟩,⟨"rejected"⟩⟨17021⟩⟨2095⟩
⟨"Relais"⟩⟨16176⟩⟨12601⟩,⟨"related"⟩⟨8185⟩⟨7191⟩
⟨"relations"⟩⟨2008⟩⟨1713⟩,⟨"relationship"⟩⟨14180⟩⟨12012⟩
⟨"relatives"⟩⟨10137⟩⟨9998⟩,⟨"relaxation"⟩⟨164⟩⟨6756⟩
⟨"relaxing"⟩⟨88⟩⟨7375⟩,⟨"relaxtion"⟩⟨12645⟩⟨10354⟩
⟨"relented"⟩⟨16443⟩⟨1230⟩,⟨"reliable"⟩⟨8852⟩⟨14115⟩
⟨"relies"⟩⟨17505⟩⟨18384⟩,⟨"relieving"⟩⟨15638⟩⟨15900⟩
⟨"relocate"⟩⟨15772⟩⟨9083⟩,⟨"reluctance"⟩⟨5148⟩⟨3035⟩
⟨"relying"⟩⟨15555⟩⟨17099⟩,⟨"remainder"⟩⟨5075⟩⟨9161⟩
⟨"remark"⟩⟨10320⟩⟨4311⟩,⟨"remarkably"⟩⟨3793⟩⟨2451⟩
⟨"remedied"⟩⟨13713⟩⟨16905⟩,⟨"remember"⟩⟨3519⟩⟨6308⟩
⟨"remembers"⟩⟨11757⟩⟨14077⟩,⟨"reminded"⟩⟨1746⟩⟨14486⟩
⟨"reminds"⟩⟨9496⟩⟨5416⟩,⟨"remnants"⟩⟨18026⟩⟨13720⟩
⟨"remote"⟩⟨3744⟩⟨12131⟩,⟨"remotely"⟩⟨7777⟩⟨11842⟩
⟨"removing"⟩⟨3491⟩⟨11907⟩,⟨"renamed"⟩⟨15550⟩⟨9626⟩
⟨"rennovation"⟩⟨17362⟩⟨15011⟩,⟨"renovate"⟩⟨14298⟩⟨17284⟩
⟨"renovations"⟩⟨6754⟩⟨9879⟩,⟨"rent"⟩⟨11570⟩⟨14690⟩
⟨"Renvyle"⟩⟨7539⟩⟨8700⟩,⟨"reopened"⟩⟨8267⟩⟨9455⟩
⟨"repair"⟩⟨2744⟩⟨947⟩,⟨"repairs"⟩⟨1331⟩⟨1765⟩

⟨"repeating"⟩⟨13908⟩⟨16924⟩,⟨"replace"⟩⟨4706⟩⟨1397⟩
⟨"replacing"⟩⟨7986⟩⟨4181⟩,⟨"replenished"⟩⟨2150⟩⟨7002⟩
⟨"replies"⟩⟨13572⟩⟨5097⟩,⟨"report"⟩⟨6741⟩⟨13789⟩
⟨"reports"⟩⟨1263⟩⟨8829⟩,⟨"representative"⟩⟨15174⟩⟨4116⟩
⟨"Republic"⟩⟨12184⟩⟨14975⟩,⟨"repulsive"⟩⟨15037⟩⟨670⟩
⟨"Request"⟩⟨14026⟩⟨15596⟩,⟨"Requested"⟩⟨6660⟩⟨5241⟩
⟨"required"⟩⟨4513⟩⟨10077⟩,⟨"requirements"⟩⟨6040⟩⟨11412⟩
⟨"resaurant"⟩⟨6234⟩⟨13809⟩,⟨"rescued"⟩⟨15525⟩⟨15503⟩
⟨"resemblance"⟩⟨16318⟩⟨3911⟩,⟨"resembled"⟩⟨842⟩⟨4954⟩
⟨"resented"⟩⟨8274⟩⟨14531⟩,⟨"Reservation"⟩⟨17938⟩⟨18011⟩
⟨"reserved"⟩⟨3857⟩⟨4917⟩,⟨"reset"⟩⟨13421⟩⟨12032⟩
⟨"resident"⟩⟨5528⟩⟨10136⟩,⟨"residential"⟩⟨1851⟩⟨4041⟩
⟨"residents&quot"⟩⟨17222⟩⟨3315⟩,⟨"resigned"⟩⟨17012⟩⟨7842⟩
⟨"resolution"⟩⟨14158⟩⟨17608⟩,⟨"resolved"⟩⟨9339⟩⟨12604⟩
⟨"Resort"⟩⟨5005⟩⟨14126⟩,⟨"resorted"⟩⟨4255⟩⟨8676⟩
⟨"respect"⟩⟨3691⟩⟨2569⟩,⟨"respected"⟩⟨13655⟩⟨13396⟩
⟨"respects"⟩⟨7368⟩⟨12943⟩,⟨"responce"⟩⟨17678⟩⟨218⟩
⟨"response"⟩⟨207⟩⟨607⟩,⟨"responsibility"⟩⟨1425⟩⟨5612⟩
⟨"Rest"⟩⟨8822⟩⟨9204⟩,⟨"restaraunt"⟩⟨6956⟩⟨10837⟩
⟨"restauant"⟩⟨12953⟩⟨17224⟩,⟨"restauarant"⟩⟨13290⟩⟨14780⟩
⟨"RESTAURANT"⟩⟨13464⟩⟨16376⟩,⟨"restaurant's"⟩⟨14277⟩⟨15076⟩
⟨"Restaurants"⟩⟨4195⟩⟨6421⟩,⟨"restauraunts"⟩⟨10158⟩⟨6174⟩
⟨"resterant"⟩⟨18081⟩⟨1887⟩,⟨"resteraunts"⟩⟨9773⟩⟨13880⟩
⟨"restock"⟩⟨16839⟩⟨15734⟩,⟨"restoration"⟩⟨11168⟩⟨6561⟩
⟨"restraunt"⟩⟨9336⟩⟨14282⟩,⟨"restraunts"⟩⟨6278⟩⟨10942⟩
⟨"restrictions"⟩⟨13016⟩⟨12819⟩,⟨"restroom"⟩⟨11987⟩⟨12002⟩
⟨"restuarant"⟩⟨6765⟩⟨1892⟩,⟨"resturant"⟩⟨1572⟩⟨14441⟩
⟨"result"⟩⟨2707⟩⟨15240⟩,⟨"resulted"⟩⟨725⟩⟨8414⟩
⟨"retail"⟩⟨6326⟩⟨4547⟩,⟨"retained"⟩⟨13917⟩⟨11261⟩
⟨"rethink"⟩⟨10734⟩⟨8650⟩,⟨"retired"⟩⟨7955⟩⟨14992⟩
⟨"Retreat"⟩⟨5748⟩⟨12565⟩,⟨"retreats"⟩⟨9940⟩⟨5634⟩

⟨"retrospect"⟩⟨13614⟩⟨9130⟩,⟨"return"⟩⟨149⟩⟨15416⟩
⟨"Returned"⟩⟨4370⟩⟨12165⟩,⟨"Returning"⟩⟨14228⟩⟨17704⟩
⟨"revamped"⟩⟨8254⟩⟨12922⟩,⟨"Revas"⟩⟨15381⟩⟨16886⟩
⟨"revelation"⟩⟨10586⟩⟨15353⟩,⟨"revellers"⟩⟨2176⟩⟨4436⟩
⟨"reverberated"⟩⟨17057⟩⟨10457⟩,⟨"reversed"⟩⟨13340⟩⟨7336⟩
⟨"reviewer"⟩⟨6617⟩⟨17677⟩,⟨"reviewer's"⟩⟨15847⟩⟨10236⟩
⟨"reviews"⟩⟨1807⟩⟨15772⟩,⟨"reviews-"⟩⟨12696⟩⟨10443⟩
⟨"revived"⟩⟨12609⟩⟨16603⟩,⟨"revolving"⟩⟨13256⟩⟨4339⟩
⟨"Rewards"⟩⟨15967⟩⟨17160⟩,⟨"Ri"⟩⟨7579⟩⟨12798⟩
⟨"rich"⟩⟨1964⟩⟨1583⟩,⟨"Richmond"⟩⟨8578⟩⟨11101⟩
⟨"ridden"⟩⟨17715⟩⟨6450⟩,⟨"rides"⟩⟨4788⟩⟨7543⟩
⟨"ridiculously"⟩⟨8462⟩⟨2627⟩,⟨"right"⟩⟨1335⟩⟨10273⟩
⟨"rightly"⟩⟨11678⟩⟨7570⟩,⟨"rigid"⟩⟨17747⟩⟨1357⟩
⟨"ringing"⟩⟨2162⟩⟨8640⟩,⟨"rink"⟩⟨7062⟩⟨6347⟩
⟨"riot"⟩⟨2356⟩⟨2293⟩,⟨"Rip"⟩⟨16078⟩⟨6872⟩
⟨"ripley"⟩⟨8434⟩⟨14659⟩,⟨"ripped"⟩⟨3009⟩⟨108⟩
⟨"risers"⟩⟨14658⟩⟨18532⟩,⟨"Rising"⟩⟨17326⟩⟨14958⟩
⟨"Rita"⟩⟨4994⟩⟨4687⟩,⟨"Ritz"⟩⟨2660⟩⟨13583⟩
⟨"rivals"⟩⟨11419⟩⟨14254⟩,⟨"river"⟩⟨645⟩⟨6999⟩
⟨"Riverfront"⟩⟨15697⟩⟨17197⟩,⟨"Riverside"⟩⟨2563⟩⟨7980⟩
⟨"Rm"⟩⟨12779⟩⟨15919⟩,⟨"road"⟩⟨2794⟩⟨8543⟩
⟨"roadway"⟩⟨15444⟩⟨9597⟩,⟨"roam"⟩⟨14542⟩⟨14589⟩
⟨"roast"⟩⟨4347⟩⟨11716⟩,⟨"roasted"⟩⟨12151⟩⟨7033⟩
⟨"Robbie"⟩⟨3804⟩⟨9223⟩,⟨"Robert"⟩⟨5559⟩⟨8529⟩
⟨"robot"⟩⟨18398⟩⟨2904⟩,⟨"Rocha"⟩⟨12887⟩⟨15858⟩
⟨"rocked"⟩⟨16413⟩⟨16688⟩,⟨"Rockets"⟩⟨4403⟩⟨3922⟩
⟨"Rococo"⟩⟨12662⟩⟨10390⟩,⟨"rod"⟩⟨14987⟩⟨17744⟩
⟨"role"⟩⟨10777⟩⟨14420⟩,⟨"Roll"⟩⟨12712⟩⟨10475⟩
⟨"roller"⟩⟨15875⟩⟨12413⟩,⟨"rolling"⟩⟨11074⟩⟨11143⟩
⟨"romance"⟩⟨7183⟩⟨12979⟩,⟨"Romantic"⟩⟨11012⟩⟨14768⟩
⟨"roms"⟩⟨15977⟩⟨9726⟩,⟨"Ronnie"⟩⟨11424⟩⟨14261⟩

⟨"rooftops"⟩⟨10473⟩⟨15239⟩,⟨"Room"⟩⟨1696⟩⟨4537⟩
⟨"room-service"⟩⟨14631⟩⟨18533⟩,⟨"room???????s"⟩⟨10022⟩⟨5777⟩
⟨"room&quot"⟩⟨1776⟩⟨12796⟩,⟨"roomed"⟩⟨17028⟩⟨428⟩
⟨"ROOMS"⟩⟨8925⟩⟨12063⟩,⟨"rooms'"⟩⟨8516⟩⟨5038⟩
⟨"roomy"⟩⟨247⟩⟨2548⟩,⟨"rooom"⟩⟨13463⟩⟨16375⟩
⟨"ropey"⟩⟨15744⟩⟨13503⟩,⟨"Rosann"⟩⟨15219⟩⟨16698⟩
⟨"Rose"⟩⟨9321⟩⟨7612⟩,⟨"rosette"⟩⟨14072⟩⟨15139⟩
⟨"Rosneys"⟩⟨15728⟩⟨15985⟩,⟨"ross"⟩⟨11809⟩⟨11797⟩
⟨"rosslare"⟩⟨15415⟩⟨12471⟩,⟨"rotten"⟩⟨463⟩⟨4166⟩
⟨"roughly"⟩⟨7718⟩⟨14148⟩,⟨"Round"⟩⟨12919⟩⟨12731⟩
⟨"rounds"⟩⟨10753⟩⟨14193⟩,⟨"roundtrip"⟩⟨7300⟩⟨12995⟩
⟨"router"⟩⟨12463⟩⟨16510⟩,⟨"routine"⟩⟨5966⟩⟨8734⟩
⟨"rowdy"⟩⟨5612⟩⟨6041⟩,⟨"rows"⟩⟨4419⟩⟨9225⟩
⟨"royality"⟩⟨15271⟩⟨16756⟩,⟨"royalty"⟩⟨4171⟩⟨1712⟩
⟨"rubbed"⟩⟨14801⟩⟨5538⟩,⟨"rubbery"⟩⟨2351⟩⟨1474⟩
⟨"rubish"⟩⟨18363⟩⟨863⟩,⟨"Rude"⟩⟨14554⟩⟨7257⟩
⟨"rudest"⟩⟨13693⟩⟨21⟩,⟨"rug"⟩⟨3784⟩⟨9512⟩
⟨"rugs"⟩⟨3310⟩⟨3252⟩,⟨"Ruin"⟩⟨17895⟩⟨17986⟩
⟨"rule"⟩⟨6384⟩⟨7847⟩,⟨"rum"⟩⟨18015⟩⟨13714⟩
⟨"Run"⟩⟨3890⟩⟨1560⟩,⟨"run-of-the-mill"⟩⟨16884⟩⟨18126⟩
⟨"runners"⟩⟨16454⟩⟨1048⟩,⟨"runny"⟩⟨11963⟩⟨17051⟩
⟨"rush"⟩⟨6923⟩⟨2602⟩,⟨"rushed"⟩⟨4654⟩⟨12064⟩
⟨"Russian"⟩⟨15488⟩⟨9462⟩,⟨"rusted"⟩⟨13936⟩⟨75⟩
⟨"rusty"⟩⟨2290⟩⟨8730⟩,⟨"Ryan's"⟩⟨5655⟩⟨4500⟩
⟨"Ryder"⟩⟨7035⟩⟨12351⟩,⟨"s"⟩⟨10671⟩⟨12009⟩
⟨"sack"⟩⟨13418⟩⟨16332⟩,⟨"sacrifice"⟩⟨14394⟩⟨17526⟩
⟨"saddle"⟩⟨4751⟩⟨12057⟩,⟨"sadly"⟩⟨6568⟩⟨11646⟩
⟨"safely"⟩⟨9476⟩⟨8164⟩,⟨"safes"⟩⟨14459⟩⟨17067⟩
⟨"saff"⟩⟨17916⟩⟨13623⟩,⟨"sagging"⟩⟨2621⟩⟨2768⟩
⟨"said&quot"⟩⟨17935⟩⟨13650⟩,⟨"sailing"⟩⟨11458⟩⟨14315⟩
⟨"salad"⟩⟨4773⟩⟨7057⟩,⟨"salami"⟩⟨12039⟩⟨7499⟩

⟨"Sales"⟩⟨9771⟩⟨13878⟩,⟨"salmon"⟩⟨2949⟩⟨11710⟩
⟨"salons"⟩⟨8305⟩⟨10714⟩,⟨"salt"⟩⟨1274⟩⟨12508⟩
⟨"salts"⟩⟨12963⟩⟨17234⟩,⟨"salubrious"⟩⟨13968⟩⟨17505⟩
⟨"SAMAS"⟩⟨10598⟩⟨15366⟩,⟨"same"⟩⟨4806⟩⟨18207⟩
⟨"sample"⟩⟨3438⟩⟨3697⟩,⟨"samples"⟩⟨14842⟩⟨8872⟩
⟨"Sand"⟩⟨7023⟩⟨13783⟩,⟨"Sandhouse"⟩⟨12924⟩⟨15027⟩
⟨"sandwhich"⟩⟨13253⟩⟨15451⟩,⟨"sandwich"⟩⟨839⟩⟨3533⟩
⟨"Sandwiches"⟩⟨14907⟩⟨4395⟩,⟨"Sandy"⟩⟨12272⟩⟨10217⟩
⟨"sanitary"⟩⟨13807⟩⟨8021⟩,⟨"sans"⟩⟨10145⟩⟨6145⟩
⟨"SAS"⟩⟨10983⟩⟨16441⟩,⟨"sash"⟩⟨10500⟩⟨14614⟩
⟨"Satellite"⟩⟨7239⟩⟨15210⟩,⟨"satff"⟩⟨14292⟩⟨15103⟩
⟨"satisfy"⟩⟨9679⟩⟨9439⟩,⟨"satisified"⟩⟨6192⟩⟨12253⟩
⟨"SATURDAY"⟩⟨18227⟩⟨14116⟩,⟨"saty"⟩⟨17207⟩⟨18519⟩
⟨"saucers"⟩⟨12980⟩⟨8388⟩,⟨"sauna"⟩⟨1050⟩⟨9871⟩
⟨"Sausage"⟩⟨15693⟩⟨15936⟩,⟨"Sausages"⟩⟨18495⟩⟨17081⟩
⟨"save"⟩⟨6372⟩⟨4253⟩,⟨"saver"⟩⟨5654⟩⟨4498⟩
⟨"savour"⟩⟨11771⟩⟨14089⟩,⟨"Savoy"⟩⟨8941⟩⟨10963⟩
⟨"sawdust"⟩⟨17318⟩⟨2181⟩,⟨"say"⟩⟨940⟩⟨10519⟩
⟨"Saying"⟩⟨6961⟩⟨12219⟩,⟨"Says"⟩⟨17811⟩⟨17934⟩
⟨"scalding"⟩⟨1433⟩⟨1414⟩,⟨"scales"⟩⟨17389⟩⟨18275⟩
⟨"scampi"⟩⟨11781⟩⟨6994⟩,⟨"Scandinavian"⟩⟨10153⟩⟨6161⟩
⟨"scary"⟩⟨4472⟩⟨10662⟩,⟨"scathing"⟩⟨17665⟩⟨17884⟩
⟨"scene"⟩⟨9456⟩⟨6997⟩,⟨"scenes"⟩⟨12715⟩⟨7164⟩
⟨"sceptical"⟩⟨7400⟩⟨8757⟩,⟨"schedule"⟩⟨6618⟩⟨12229⟩
⟨"schemes"⟩⟨15480⟩⟨8488⟩,⟨"School"⟩⟨5737⟩⟨11496⟩
⟨"schools"⟩⟨16001⟩⟨11731⟩,⟨"science"⟩⟨6191⟩⟨12252⟩
⟨"scoops"⟩⟨11980⟩⟨11987⟩,⟨"scored"⟩⟨14393⟩⟨17525⟩
⟨"Scott"⟩⟨12282⟩⟨10237⟩,⟨"Scottish"⟩⟨14915⟩⟨16848⟩
⟨"Scrambled"⟩⟨11388⟩⟨11730⟩,⟨"scrape"⟩⟨17497⟩⟨18376⟩
⟨"scraps"⟩⟨17690⟩⟨1619⟩,⟨"scratched"⟩⟨13146⟩⟨12619⟩
⟨"scream"⟩⟨3165⟩⟨753⟩,⟨"screaming"⟩⟨186⟩⟨2464⟩

⟨"Screen"⟩⟨10362⟩⟨10129⟩,⟨"screens"⟩⟨8713⟩⟨14687⟩
⟨"scrub"⟩⟨4576⟩⟨3907⟩,⟨"scruffy"⟩⟨1398⟩⟨5330⟩
⟨"scrupulously"⟩⟨15920⟩⟨16115⟩,⟨"scuffed"⟩⟨1932⟩⟨1847⟩
⟨"scum"⟩⟨14726⟩⟨261⟩,⟨"se"⟩⟨14128⟩⟨17590⟩
⟨"seabass"⟩⟨6560⟩⟨15333⟩,⟨"Seafield"⟩⟨9825⟩⟨7596⟩
⟨"seagulls"⟩⟨7165⟩⟨6276⟩,⟨"sealant"⟩⟨2361⟩⟨7524⟩
⟨"seam"⟩⟨11643⟩⟨14023⟩,⟨"seamlessly"⟩⟨10566⟩⟨15330⟩
⟨"search"⟩⟨3917⟩⟨4218⟩,⟨"searches"⟩⟨16848⟩⟨15743⟩
⟨"Season"⟩⟨11474⟩⟨6950⟩,⟨"seasoned"⟩⟨11299⟩⟨9710⟩
⟨"seated"⟩⟨5930⟩⟨2684⟩,⟨"seating"⟩⟨1475⟩⟨4677⟩
⟨"Seaview"⟩⟨13134⟩⟨13064⟩,⟨"seawater"⟩⟨18524⟩⟨13327⟩
⟨"second"⟩⟨1234⟩⟨14186⟩,⟨"secondary"⟩⟨3797⟩⟨2508⟩
⟨"secret"⟩⟨6010⟩⟨9538⟩,⟨"secretly"⟩⟨10176⟩⟨6207⟩
⟨"secure"⟩⟨3523⟩⟨12452⟩,⟨"secured"⟩⟨5127⟩⟨11128⟩
⟨"Security"⟩⟨11914⟩⟨8935⟩,⟨"see"⟩⟨1865⟩⟨10066⟩
⟨"seedy"⟩⟨9852⟩⟨15661⟩,⟨"Seeing"⟩⟨14683⟩⟨13320⟩
⟨"seemd"⟩⟨12050⟩⟨8276⟩,⟨"Seemed"⟩⟨10494⟩⟨5535⟩
⟨"seemless"⟩⟨15423⟩⟨9548⟩,⟨"Seems"⟩⟨12364⟩⟨15755⟩
⟨"Seine"⟩⟨16073⟩⟨14917⟩,⟨"select"⟩⟨13517⟩⟨15643⟩
⟨"Selection"⟩⟨9071⟩⟨14196⟩,⟨"self"⟩⟨1853⟩⟨13621⟩
⟨"self-serve"⟩⟨6865⟩⟨7250⟩,⟨"sell"⟩⟨1119⟩⟨683⟩
⟨"selves"⟩⟨1951⟩⟨442⟩,⟨"seminar"⟩⟨2438⟩⟨2521⟩
⟨"sends"⟩⟨17517⟩⟨18394⟩,⟨"Senior"⟩⟨10412⟩⟨7512⟩
⟨"sense"⟩⟨9272⟩⟨16381⟩,⟨"sensible"⟩⟨14479⟩⟨16468⟩
⟨"sent"⟩⟨5819⟩⟨283⟩,⟨"sentiment"⟩⟨15429⟩⟨9555⟩
⟨"Sep"⟩⟨15865⟩⟨12401⟩,⟨"Separate"⟩⟨6500⟩⟨7226⟩
⟨"seperate"⟩⟨409⟩⟨5368⟩,⟨"seperately"⟩⟨11348⟩⟨8039⟩
⟨"september"⟩⟨5953⟩⟨11822⟩,⟨"serene"⟩⟨4194⟩⟨1403⟩
⟨"Seriously"⟩⟨945⟩⟨4854⟩,⟨"serivce"⟩⟨15878⟩⟨12416⟩
⟨"server"⟩⟨5474⟩⟨14403⟩,⟨"servers"⟩⟨8685⟩⟨14465⟩
⟨"Service"⟩⟨1570⟩⟨7182⟩,⟨"service-"⟩⟨15603⟩⟨13432⟩

⟨"serviced"⟩⟨1652⟩⟨8138⟩,⟨"Services"⟩⟨14296⟩⟨15117⟩
⟨"Serving"⟩⟨8432⟩⟨14651⟩,⟨"session"⟩⟨7513⟩⟨4358⟩
⟨"set-up"⟩⟨10655⟩⟨12694⟩,⟨"setanta"⟩⟨13444⟩⟨16387⟩
⟨"setting"⟩⟨287⟩⟨8249⟩,⟨"settings"⟩⟨5724⟩⟨11263⟩
⟨"setup"⟩⟨11400⟩⟨11534⟩,⟨"seven"⟩⟨2185⟩⟨15678⟩
⟨"several"⟩⟨2276⟩⟨11427⟩,⟨"severe"⟩⟨2413⟩⟨7118⟩
⟨"sewage"⟩⟨14446⟩⟨4188⟩,⟨"sewerage"⟩⟨15659⟩⟨1852⟩
⟨"shabby"⟩⟨196⟩⟨8064⟩,⟨"shack"⟩⟨17269⟩⟨13258⟩
⟨"shadow"⟩⟨13925⟩⟨11667⟩,⟨"shady"⟩⟨7591⟩⟨2917⟩
⟨"shakes"⟩⟨16572⟩⟨9864⟩,⟨"shaky"⟩⟨12298⟩⟨10268⟩
⟨"shambolic"⟩⟨14723⟩⟨13274⟩,⟨"shame"⟩⟨6842⟩⟨3185⟩
⟨"shampoos"⟩⟨5422⟩⟨9451⟩,⟨"shamrock"⟩⟨14099⟩⟨15151⟩
⟨"Shannon"⟩⟨1613⟩⟨12469⟩,⟨"shape"⟩⟨5057⟩⟨5799⟩
⟨"shared"⟩⟨8892⟩⟨16318⟩,⟨"sharing"⟩⟨7382⟩⟨11994⟩
⟨"shave"⟩⟨1902⟩⟨5402⟩,⟨"shaving"⟩⟨12581⟩⟨17508⟩
⟨"she'd"⟩⟨2124⟩⟨7833⟩,⟨"Shearings"⟩⟨13434⟩⟨16345⟩
⟨"sheen"⟩⟨11605⟩⟨12849⟩,⟨"sheer"⟩⟨7932⟩⟨14234⟩
⟨"sheets"⟩⟨7350⟩⟨2551⟩,⟨"Shelbourne"⟩⟨7905⟩⟨1022⟩
⟨"shell"⟩⟨10105⟩⟨9707⟩,⟨"sheltered"⟩⟨16663⟩⟨17680⟩
⟨"sheraton"⟩⟨7145⟩⟨8120⟩,⟨"Shieling"⟩⟨12477⟩⟨16518⟩
⟨"shifts"⟩⟨11985⟩⟨12000⟩,⟨"shines"⟩⟨11589⟩⟨7188⟩
⟨"ship"⟩⟨7280⟩⟨9928⟩,⟨"ships"⟩⟨13067⟩⟨12850⟩
⟨"shirts"⟩⟨13155⟩⟨14435⟩,⟨"shock"⟩⟨338⟩⟨2752⟩
⟨"Shocking"⟩⟨10735⟩⟨8651⟩,⟨"shoddy"⟩⟨1041⟩⟨5383⟩
⟨"shoes"⟩⟨7529⟩⟨8958⟩,⟨"shook"⟩⟨1235⟩⟨1290⟩
⟨"Shop"⟩⟨4808⟩⟨11832⟩,⟨"shopped"⟩⟨5251⟩⟨8406⟩
⟨"shops"⟩⟨674⟩⟨8702⟩,⟨"shore"⟩⟨3640⟩⟨14821⟩
⟨"Short"⟩⟨7408⟩⟨8869⟩,⟨"shortbread"⟩⟨9707⟩⟨11270⟩
⟨"shortly"⟩⟨4367⟩⟨8599⟩,⟨"shorts"⟩⟨9414⟩⟨11949⟩
⟨"Should"⟩⟨3514⟩⟨8895⟩,⟨"SHOULD"⟩⟨11573⟩⟨8895⟩
⟨"shouldn't"⟩⟨7765⟩⟨7442⟩,⟨"shout"⟩⟨2228⟩⟨8715⟩

⟨"shoved"⟩⟨14622⟩⟨286⟩,⟨"Show"⟩⟨14442⟩⟨9898⟩
⟨"shower's"⟩⟨12619⟩⟨16614⟩,⟨"showergel"⟩⟨9063⟩⟨11037⟩
⟨"Showers"⟩⟨12938⟩⟨15043⟩,⟨"shown"⟩⟨1711⟩⟨1955⟩
⟨"shrine"⟩⟨12343⟩⟨15530⟩,⟨"shrivelled"⟩⟨18065⟩⟨3487⟩
⟨"shudder"⟩⟨17675⟩⟨8422⟩,⟨"shuts"⟩⟨10789⟩⟨14426⟩
⟨"Shuttle"⟩⟨4465⟩⟨5834⟩,⟨"shy"⟩⟨12108⟩⟨8924⟩
⟨"sickly"⟩⟨16265⟩⟨17317⟩,⟨"Side"⟩⟨12945⟩⟨17216⟩
⟨"sidewalks"⟩⟨12907⟩⟨15880⟩,⟨"Sidhe"⟩⟨10636⟩⟨15406⟩
⟨"sight"⟩⟨7200⟩⟨11497⟩,⟨"sighted"⟩⟨18474⟩⟨13204⟩
⟨"sign"⟩⟨5825⟩⟨819⟩,⟨"signal"⟩⟨12038⟩⟨12361⟩
⟨"significantly"⟩⟨13885⟩⟨17498⟩,⟨"signposted"⟩⟨5536⟩⟨7007⟩
⟨"silence"⟩⟨1022⟩⟨964⟩,⟨"silicone"⟩⟨15707⟩⟨9191⟩
⟨"sills"⟩⟨17676⟩⟨8425⟩,⟨"silver"⟩⟨9311⟩⟨13953⟩
⟨"similar"⟩⟨6160⟩⟨18428⟩,⟨"similarly"⟩⟨6353⟩⟨17620⟩
⟨"simple"⟩⟨3556⟩⟨15170⟩,⟨"simpler"⟩⟨7996⟩⟨11020⟩
⟨"sin"⟩⟨17570⟩⟨13515⟩,⟨"since"⟩⟨2796⟩⟨17237⟩
⟨"sincerely"⟩⟨11873⟩⟨10913⟩,⟨"Sinergie"⟩⟨8102⟩⟨13603⟩
⟨"Singapore"⟩⟨16112⟩⟨10602⟩,⟨"singers"⟩⟨6444⟩⟨5146⟩
⟨"singles"⟩⟨4710⟩⟨2429⟩,⟨"sink"⟩⟨7990⟩⟨4318⟩
⟨"sip"⟩⟨8026⟩⟨12705⟩,⟨"sipping"⟩⟨1749⟩⟨1475⟩
⟨"sirens"⟩⟨7859⟩⟨4935⟩,⟨"sister"⟩⟨2022⟩⟨15589⟩
⟨"sisters"⟩⟨5687⟩⟨7065⟩,⟨"Sit"⟩⟨17863⟩⟨15163⟩
⟨"sites"⟩⟨784⟩⟨6978⟩,⟨"Sitric"⟩⟨14184⟩⟨7299⟩
⟨"Sitting"⟩⟨8923⟩⟨12061⟩,⟨"situated"⟩⟨1129⟩⟨5375⟩
⟨"six"⟩⟨6048⟩⟨12951⟩,⟨"sixteen"⟩⟨9654⟩⟨8985⟩
⟨"sizable"⟩⟨16473⟩⟨10651⟩,⟨"Size"⟩⟨4590⟩⟨8861⟩
⟨"skating"⟩⟨7128⟩⟨5886⟩,⟨"Skeffington"⟩⟨6810⟩⟨4104⟩
⟨"skeptical"⟩⟨10061⟩⟨9319⟩,⟨"sketchy"⟩⟨10325⟩⟨5498⟩
⟨"skilled"⟩⟨14922⟩⟨17741⟩,⟨"skimmed"⟩⟨18210⟩⟨4594⟩
⟨"skinny"⟩⟨16897⟩⟨18139⟩,⟨"skip"⟩⟨5576⟩⟨4360⟩
⟨"skirts"⟩⟨15604⟩⟨13433⟩,⟨"sky"⟩⟨11838⟩⟨17460⟩

⟨"skyline"⟩⟨12048⟩⟨8273⟩,⟨"Skylon"⟩⟨950⟩⟨3883⟩
⟨"slam"⟩⟨13501⟩⟨18201⟩,⟨"slamming"⟩⟨6768⟩⟨11796⟩
⟨"slanted"⟩⟨14879⟩⟨17007⟩,⟨"slapped"⟩⟨5691⟩⟨12886⟩
⟨"sleek"⟩⟨5792⟩⟨3875⟩,⟨"Sleep"⟩⟨16316⟩⟨3906⟩
⟨"Sleeping"⟩⟨18243⟩⟨1732⟩,⟨"sleeps"⟩⟨13346⟩⟨14891⟩
⟨"SLH"⟩⟨18262⟩⟨243⟩,⟨"sliced"⟩⟨11872⟩⟨14970⟩
⟨"slide"⟩⟨6454⟩⟨12853⟩,⟨"sliding"⟩⟨11330⟩⟨14310⟩
⟨"Slight"⟩⟨11431⟩⟨14268⟩,⟨"slightly"⟩⟨1144⟩⟨13091⟩
⟨"sligo"⟩⟨9883⟩⟨16567⟩,⟨"slimy"⟩⟨17244⟩⟨9957⟩
⟨"slippers"⟩⟨190⟩⟨6833⟩,⟨"slippery"⟩⟨14599⟩⟨11695⟩
⟨"slop"⟩⟨15646⟩⟨395⟩,⟨"sloped"⟩⟨14407⟩⟨17422⟩
⟨"slot"⟩⟨10459⟩⟨14412⟩,⟨"slow"⟩⟨6331⟩⟨16616⟩
⟨"slowly"⟩⟨9432⟩⟨12429⟩,⟨"smacked"⟩⟨17565⟩⟨95⟩
⟨"small&quot"⟩⟨10535⟩⟨15303⟩,⟨"smallest"⟩⟨560⟩⟨5392⟩
⟨"smarten"⟩⟨16154⟩⟨14945⟩,⟨"smartly"⟩⟨16284⟩⟨17335⟩
⟨"smeared"⟩⟨18115⟩⟨10871⟩,⟨"Smell"⟩⟨18044⟩⟨160⟩
⟨"smelly"⟩⟨1107⟩⟨271⟩,⟨"Smerwick"⟩⟨18053⟩⟨325⟩
⟨"smiley"⟩⟨9898⟩⟨8058⟩,⟨"Smith"⟩⟨13078⟩⟨14705⟩
⟨"smoked"⟩⟨1245⟩⟨15091⟩,⟨"smoker"⟩⟨7051⟩⟨2621⟩
⟨"Smoking"⟩⟨7360⟩⟨8443⟩,⟨"SMOKING"⟩⟨18379⟩⟨8443⟩
⟨"smoothie"⟩⟨5674⟩⟨7210⟩,⟨"smoothly"⟩⟨6411⟩⟨10548⟩
⟨"snacks"⟩⟨5229⟩⟨16619⟩,⟨"snag"⟩⟨5491⟩⟨3375⟩
⟨"snapped"⟩⟨3894⟩⟨2782⟩,⟨"snatched"⟩⟨8385⟩⟨15227⟩
⟨"sneaky"⟩⟨6862⟩⟨7243⟩,⟨"sneem"⟩⟨15273⟩⟨16758⟩
⟨"snobbery"⟩⟨7061⟩⟨6344⟩,⟨"snobby"⟩⟨14460⟩⟨17069⟩
⟨"snored"⟩⟨17999⟩⟨18054⟩,⟨"snot"⟩⟨14892⟩⟨505⟩
⟨"snowing"⟩⟨9371⟩⟨11237⟩,⟨"snug"⟩⟨3816⟩⟨4403⟩
⟨"So"⟩⟨5460⟩⟨13850⟩,⟨"so-called"⟩⟨1444⟩⟨8420⟩
⟨"soaking"⟩⟨9658⟩⟨8402⟩,⟨"soap"⟩⟨1009⟩⟨13199⟩
⟨"sober"⟩⟨9424⟩⟨13770⟩,⟨"sociable"⟩⟨14285⟩⟨15086⟩
⟨"socialize"⟩⟨8358⟩⟨10792⟩,⟨"society"⟩⟨14142⟩⟨16430⟩

⟨"socks"⟩⟨1042⟩⟨4779⟩,⟨"sodas"⟩⟨6547⟩⟨4059⟩
⟨"sofas"⟩⟨2115⟩⟨7941⟩,⟨"Soft"⟩⟨9198⟩⟨4834⟩
⟨"softest"⟩⟨4962⟩⟨2082⟩,⟨"soggy"⟩⟨639⟩⟨622⟩
⟨"sold"⟩⟨1594⟩⟨8555⟩,⟨"Sole"⟩⟨18160⟩⟨9591⟩
⟨"Solis"⟩⟨5045⟩⟨3397⟩,⟨"solo"⟩⟨4114⟩⟨10382⟩
⟨"solved"⟩⟨9869⟩⟨14564⟩,⟨"Somebody"⟩⟨13874⟩⟨10670⟩
⟨"someone"⟩⟨7067⟩⟨2552⟩,⟨"someone's"⟩⟨7862⟩⟨9576⟩
⟨"Something"⟩⟨6689⟩⟨4764⟩,⟨"sometime"⟩⟨8809⟩⟨11588⟩
⟨"somewhat"⟩⟨2186⟩⟨4194⟩,⟨"Somewhere"⟩⟨12839⟩⟨15807⟩
⟨"son"⟩⟨942⟩⟨17320⟩,⟨"son-in-law"⟩⟨8942⟩⟨10965⟩
⟨"sons"⟩⟨4442⟩⟨3633⟩,⟨"soon"⟩⟨4009⟩⟨17424⟩
⟨"soooo"⟩⟨13103⟩⟨17563⟩,⟨"soooooo"⟩⟨11007⟩⟨14761⟩
⟨"sophistication"⟩⟨10419⟩⟨9631⟩,⟨"sore"⟩⟨10977⟩⟨13128⟩
⟨"sorry&quot"⟩⟨16351⟩⟨139⟩,⟨"sorted"⟩⟨2895⟩⟨13801⟩
⟨"soul"⟩⟨8895⟩⟨8500⟩,⟨"souless"⟩⟨13961⟩⟨17500⟩
⟨"sound-proof"⟩⟨17670⟩⟨17889⟩,⟨"sound-proofing"⟩⟨14002⟩⟨12241⟩
⟨"soundproof"⟩⟨7962⟩⟨11431⟩,⟨"soundproofing"⟩⟨5570⟩⟨18255⟩
⟨"Soup"⟩⟨3312⟩⟨7389⟩,⟨"soups"⟩⟨6000⟩⟨4574⟩
⟨"sources"⟩⟨10968⟩⟨14731⟩,⟨"south"⟩⟨2601⟩⟨5256⟩
⟨"Southern"⟩⟨7570⟩⟨11601⟩,⟨"southside"⟩⟨17124⟩⟨16050⟩
⟨"souvenir"⟩⟨7467⟩⟨6506⟩,⟨"soy"⟩⟨18014⟩⟨18065⟩
⟨"spa"⟩⟨360⟩⟨8507⟩,⟨"spa-"⟩⟨17345⟩⟨14984⟩
⟨"space"⟩⟨1428⟩⟨13676⟩,⟨"spaced"⟩⟨14231⟩⟨17707⟩
⟨"spacious"⟩⟨153⟩⟨6620⟩,⟨"spaciousness"⟩⟨5660⟩⟨4513⟩
⟨"Spain"⟩⟨5477⟩⟨18296⟩,⟨"spanish"⟩⟨7413⟩⟨8877⟩
⟨"Spar"⟩⟨7818⟩⟨9218⟩,⟨"spare"⟩⟨3764⟩⟨8234⟩
⟨"sparkly"⟩⟨8638⟩⟨11159⟩,⟨"sparsely"⟩⟨2702⟩⟨805⟩
⟨"Spas"⟩⟨15001⟩⟨17551⟩,⟨"speaker"⟩⟨13876⟩⟨16991⟩
⟨"speaks"⟩⟨9587⟩⟨8004⟩,⟨"special"⟩⟨208⟩⟨5114⟩
⟨"specially"⟩⟨3775⟩⟨4265⟩,⟨"specialty"⟩⟨10055⟩⟨10341⟩
⟨"specified"⟩⟨11794⟩⟨13656⟩,⟨"specious"⟩⟨12836⟩⟨15803⟩

⟨"spectacularly"⟩⟨9025⟩⟨12174⟩,⟨"speeches"⟩⟨14276⟩⟨12290⟩
⟨"speeds"⟩⟨15318⟩⟨16811⟩,⟨"spell"⟩⟨11726⟩⟨13284⟩
⟨"Spencers"⟩⟨11035⟩⟨14802⟩,⟨"spend"⟩⟨7979⟩⟨15649⟩
⟨"Spent"⟩⟨2844⟩⟨5296⟩,⟨"spicy"⟩⟨11814⟩⟨11802⟩
⟨"spill"⟩⟨4983⟩⟨4683⟩,⟨"spilling"⟩⟨13956⟩⟨17495⟩
⟨"Spinners"⟩⟨12301⟩⟨10275⟩,⟨"Spire"⟩⟨3324⟩⟨11478⟩
⟨"spirits"⟩⟨7047⟩⟨13343⟩,⟨"spite"⟩⟨3963⟩⟨2959⟩
⟨"splashes"⟩⟨16564⟩⟨7565⟩,⟨"splattered"⟩⟨17766⟩⟨1676⟩
⟨"splitting"⟩⟨17340⟩⟨14977⟩,⟨"splurged"⟩⟨8290⟩⟨10695⟩
⟨"spoils"⟩⟨15729⟩⟨12276⟩,⟨"spoke"⟩⟨5928⟩⟨12151⟩
⟨"spontaneous"⟩⟨15807⟩⟨16051⟩,⟨"spoon"⟩⟨11367⟩⟨14635⟩
⟨"Sport"⟩⟨18264⟩⟨16901⟩,⟨"Sports"⟩⟨1170⟩⟨17646⟩
⟨"spot-on"⟩⟨8565⟩⟨11048⟩,⟨"Spotless"⟩⟨6934⟩⟨2699⟩
⟨"spots"⟩⟨3782⟩⟨11355⟩,⟨"spotting"⟩⟨12402⟩⟨12497⟩
⟨"sprawling"⟩⟨8384⟩⟨15225⟩,⟨"sprayed"⟩⟨1546⟩⟨562⟩
⟨"spreading"⟩⟨10257⟩⟨10074⟩,⟨"spring"⟩⟨5083⟩⟨14382⟩
⟨"springs"⟩⟨426⟩⟨12205⟩,⟨"Springsteen"⟩⟨12593⟩⟨16445⟩
⟨"sprucing"⟩⟨11842⟩⟨16301⟩,⟨"spuds"⟩⟨11827⟩⟨11806⟩
⟨"Square"⟩⟨1922⟩⟨7742⟩,⟨"squares"⟩⟨17666⟩⟨17885⟩
⟨"squeaky"⟩⟨9292⟩⟨13968⟩,⟨"squeeze"⟩⟨7357⟩⟨13279⟩
⟨"squid"⟩⟨12805⟩⟨10550⟩,⟨"St"⟩⟨992⟩⟨6427⟩
⟨"Stables"⟩⟨12682⟩⟨10424⟩,⟨"stacked"⟩⟨9637⟩⟨12752⟩
⟨"staff"⟩⟨546⟩⟨5778⟩,⟨"STAFF"⟩⟨9176⟩⟨5778⟩
⟨"staffer"⟩⟨12390⟩⟨16476⟩,⟨"staffing"⟩⟨7560⟩⟨12670⟩
⟨"stage"⟩⟨2515⟩⟨1019⟩,⟨"stagger"⟩⟨12119⟩⟨14649⟩
⟨"staid"⟩⟨13101⟩⟨16996⟩,⟨"stained"⟩⟨9666⟩⟨221⟩
⟨"stains"⟩⟨773⟩⟨4929⟩,⟨"staion"⟩⟨12395⟩⟨16479⟩
⟨"stairs"⟩⟨500⟩⟨549⟩,⟨"stairways"⟩⟨14033⟩⟨17361⟩
⟨"stale"⟩⟨1467⟩⟨59⟩,⟨"stalls"⟩⟨10774⟩⟨11943⟩
⟨"stamps"⟩⟨16263⟩⟨15690⟩,⟨"stand"⟩⟨8132⟩⟨14247⟩
⟨"Standard"⟩⟨9566⟩⟨6765⟩,⟨"standards"⟩⟨3660⟩⟨3791⟩

⟨"standing"⟩⟨636⟩⟨1064⟩,⟨"stands"⟩⟨7524⟩⟨15005⟩
⟨"Star"⟩⟨7322⟩⟨15949⟩,⟨"star&quot"⟩⟨5515⟩⟨13413⟩
⟨"starched"⟩⟨7725⟩⟨14487⟩,⟨"stare"⟩⟨2197⟩⟨215⟩
⟨"starred"⟩⟨11840⟩⟨14242⟩,⟨"Stars"⟩⟨10835⟩⟨9647⟩
⟨"Started"⟩⟨8226⟩⟨15606⟩,⟨"Starter"⟩⟨17054⟩⟨6885⟩
⟨"Starting"⟩⟨13665⟩⟨13411⟩,⟨"starve"⟩⟨10942⟩⟨11178⟩
⟨"State"⟩⟨12656⟩⟨10381⟩,⟨"stated"⟩⟨6480⟩⟨709⟩
⟨"states"⟩⟨5863⟩⟨10011⟩,⟨"stating"⟩⟨5279⟩⟨8103⟩
⟨"statue"⟩⟨13044⟩⟨17087⟩,⟨"stature"⟩⟨17152⟩⟨18464⟩
⟨"STAY"⟩⟨474⟩⟨6674⟩,⟨"stay"⟩⟨849⟩⟨6674⟩
⟨"staydublin"⟩⟨15203⟩⟨16671⟩,⟨"Stayed"⟩⟨1813⟩⟨16436⟩
⟨"Staying"⟩⟨5466⟩⟨7962⟩,⟨"stays"⟩⟨524⟩⟨5057⟩
⟨"steak"⟩⟨3429⟩⟨9280⟩,⟨"Steakhouse"⟩⟨3431⟩⟨12376⟩
⟨"steam"⟩⟨2035⟩⟨16402⟩,⟨"steam-room"⟩⟨10178⟩⟨6212⟩
⟨"steamrooms"⟩⟨15825⟩⟨16081⟩,⟨"steel"⟩⟨5179⟩⟨8741⟩
⟨"Steer"⟩⟨18046⟩⟨2805⟩,⟨"steet"⟩⟨16721⟩⟨15517⟩
⟨"stench"⟩⟨13526⟩⟨133⟩,⟨"Stephane"⟩⟨17972⟩⟨18033⟩
⟨"Stephen's"⟩⟨765⟩⟨2700⟩,⟨"stephens"⟩⟨2593⟩⟨7128⟩
⟨"steps"⟩⟨5191⟩⟨3617⟩,⟨"sterile"⟩⟨12551⟩⟨17745⟩
⟨"stern"⟩⟨17869⟩⟨4048⟩,⟨"Steven"⟩⟨15722⟩⟨15973⟩
⟨"stew"⟩⟨4471⟩⟨11817⟩,⟨"steward"⟩⟨12857⟩⟨15826⟩
⟨"sticker"⟩⟨16511⟩⟨17711⟩,⟨"sticks"⟩⟨9891⟩⟨12933⟩
⟨"stiflingly"⟩⟨17920⟩⟨13631⟩,⟨"still"⟩⟨4474⟩⟨18008⟩
⟨"stingy"⟩⟨10890⟩⟨5787⟩,⟨"stinking"⟩⟨14889⟩⟨978⟩
⟨"stir"⟩⟨14517⟩⟨15673⟩,⟨"stock"⟩⟨6971⟩⟨11590⟩
⟨"stodgy"⟩⟨9425⟩⟨13771⟩,⟨"stolen"⟩⟨388⟩⟨2248⟩
⟨"stone"⟩⟨7568⟩⟨14608⟩,⟨"stone's"⟩⟨3331⟩⟨6977⟩
⟨"stools"⟩⟨14552⟩⟨18105⟩,⟨"Stop"⟩⟨7995⟩⟨11018⟩
⟨"stopped"⟩⟨4158⟩⟨9757⟩,⟨"stopper"⟩⟨3682⟩⟨10545⟩
⟨"store"⟩⟨5385⟩⟨12263⟩,⟨"stored"⟩⟨6382⟩⟨7049⟩
⟨"Stores"⟩⟨4404⟩⟨5371⟩,⟨"stories"⟩⟨10513⟩⟨11704⟩

⟨"stormy"⟩⟨12415⟩⟨12501⟩,⟨"stout"⟩⟨14177⟩⟨17635⟩
⟨"straightaway"⟩⟨14286⟩⟨15087⟩,⟨"straightforward"⟩⟨5590⟩⟨10759⟩
⟨"strains"⟩⟨9049⟩⟨11013⟩,⟨"strand"⟩⟨4529⟩⟨5073⟩
⟨"Strange"⟩⟨8255⟩⟨13919⟩,⟨"Strangely"⟩⟨11993⟩⟨17270⟩
⟨"strategically"⟩⟨13827⟩⟨14339⟩,⟨"straw"⟩⟨13057⟩⟨19⟩
⟨"strawberrys"⟩⟨9946⟩⟨5643⟩,⟨"stream"⟩⟨11834⟩⟨15907⟩
⟨"Street"⟩⟨1607⟩⟨6178⟩,⟨"streets"⟩⟨3439⟩⟨12956⟩
⟨"stress"⟩⟨7868⟩⟨12538⟩,⟨"stressed"⟩⟨1763⟩⟨7882⟩
⟨"stretched"⟩⟨10662⟩⟨13758⟩,⟨"stretching"⟩⟨4993⟩⟨10915⟩
⟨"stride"⟩⟨15485⟩⟨9458⟩,⟨"strikes"⟩⟨15962⟩⟨7427⟩
⟨"stripes"⟩⟨12422⟩⟨16493⟩,⟨"strips"⟩⟨15770⟩⟨9079⟩
⟨"strolled"⟩⟨13298⟩⟨13314⟩,⟨"strolls"⟩⟨9350⟩⟨11201⟩
⟨"strongly"⟩⟨1203⟩⟨13130⟩,⟨"struck"⟩⟨10436⟩⟨16935⟩
⟨"struggles"⟩⟨16192⟩⟨12630⟩,⟨"stuck"⟩⟨4650⟩⟨1073⟩
⟨"Student"⟩⟨18508⟩⟨13251⟩,⟨"studied"⟩⟨17601⟩⟨13571⟩
⟨"studying"⟩⟨16985⟩⟨18186⟩,⟨"Stuff"⟩⟨12705⟩⟨10867⟩
⟨"stuffy"⟩⟨6905⟩⟨13277⟩,⟨"stumbled"⟩⟨8919⟩⟨10858⟩
⟨"stunned"⟩⟨4304⟩⟨8373⟩,⟨"Stunning"⟩⟨9295⟩⟨6544⟩
⟨"sturdy"⟩⟨12630⟩⟨16626⟩,⟨"style"⟩⟨1065⟩⟨7619⟩
⟨"styles"⟩⟨7418⟩⟨12865⟩,⟨"stylish"⟩⟨289⟩⟨6767⟩
⟨"sub"⟩⟨13970⟩⟨1140⟩,⟨"sub-standard"⟩⟨14556⟩⟨3854⟩
⟨"subject"⟩⟨13725⟩⟨16245⟩,⟨"subjective"⟩⟨10352⟩⟨10114⟩
⟨"subsequent"⟩⟨4119⟩⟨4676⟩,⟨"Subsequently"⟩⟨15760⟩⟨12307⟩
⟨"substantially"⟩⟨16628⟩⟨17642⟩,⟨"subtle"⟩⟨10928⟩⟨16977⟩
⟨"suburbs"⟩⟨11272⟩⟨9043⟩,⟨"subway"⟩⟨16880⟩⟨18122⟩
⟨"successful"⟩⟨2459⟩⟨1855⟩,⟨"succulent"⟩⟨14422⟩⟨17441⟩
⟨"sucks"⟩⟨14810⟩⟨1220⟩,⟨"suddenly"⟩⟨1078⟩⟨1774⟩
⟨"suffering"⟩⟨2326⟩⟨2382⟩,⟨"suffice"⟩⟨6740⟩⟨16940⟩
⟨"sufficient"⟩⟨6358⟩⟨4867⟩,⟨"Suffolk"⟩⟨8657⟩⟨13121⟩
⟨"Suggest"⟩⟨4556⟩⟨9962⟩,⟨"suggested"⟩⟨141⟩⟨6922⟩
⟨"suggests"⟩⟨11093⟩⟨10806⟩,⟨"suit"⟩⟨1339⟩⟨8838⟩

⟨"suitcase"⟩⟨8482⟩⟨13002⟩,⟨"suite"⟩⟨451⟩⟨6342⟩
⟨"suite&quot"⟩⟨2873⟩⟨9837⟩,⟨"suited"⟩⟨384⟩⟨7036⟩
⟨"suits"⟩⟨8089⟩⟨11373⟩,⟨"sullen"⟩⟨1950⟩⟨7469⟩
⟨"summarize"⟩⟨18224⟩⟨8770⟩,⟨"Summary"⟩⟨9645⟩⟨14384⟩
⟨"summer's"⟩⟨18511⟩⟨13256⟩,⟨"summers"⟩⟨6240⟩⟨13818⟩
⟨"sumptuous"⟩⟨1136⟩⟨9036⟩,⟨"sun"⟩⟨596⟩⟨13294⟩
⟨"Sundays"⟩⟨12818⟩⟨17959⟩,⟨"sunk"⟩⟨13648⟩⟨13384⟩
⟨"sunrise"⟩⟨11173⟩⟨7341⟩,⟨"sunset"⟩⟨2993⟩⟨1754⟩
⟨"super"⟩⟨110⟩⟨17949⟩,⟨"SUPER"⟩⟨17826⟩⟨17949⟩
⟨"SUPERB"⟩⟨7247⟩⟨10945⟩,⟨"superficial"⟩⟨16631⟩⟨17648⟩
⟨"superior&quot"⟩⟨14707⟩⟨9912⟩,⟨"superlative"⟩⟨9965⟩⟨5674⟩
⟨"supermarkets"⟩⟨4321⟩⟨3860⟩,⟨"supervalu"⟩⟨9429⟩⟨13288⟩
⟨"supervise"⟩⟨17435⟩⟨18321⟩,⟨"supervision"⟩⟨14305⟩⟨17571⟩
⟨"supplements"⟩⟨13404⟩⟨16325⟩,⟨"supplier"⟩⟨13782⟩⟨10584⟩
⟨"supplying"⟩⟨11498⟩⟨9788⟩,⟨"supported"⟩⟨14977⟩⟨13989⟩
⟨"supposed"⟩⟨1532⟩⟨289⟩,⟨"Supposedly"⟩⟨18426⟩⟨6580⟩
⟨"suprise"⟩⟨11146⟩⟨8717⟩,⟨"suprising"⟩⟨16915⟩⟨18157⟩
⟨"surcharge"⟩⟨5945⟩⟨2674⟩,⟨"Sure"⟩⟨5073⟩⟨9159⟩
⟨"surface"⟩⟨550⟩⟨6708⟩,⟨"surfers"⟩⟨8939⟩⟨10960⟩
⟨"surname"⟩⟨11976⟩⟨11979⟩,⟨"surpassed"⟩⟨5012⟩⟨1332⟩
⟨"surprise"⟩⟨4272⟩⟨11718⟩,⟨"SURPRISE"⟩⟨18126⟩⟨11718⟩
⟨"surprising"⟩⟨6607⟩⟨8395⟩,⟨"Surprisingly"⟩⟨14210⟩⟨12763⟩
⟨"surrounded"⟩⟨8800⟩⟨16394⟩,⟨"Surrounding"⟩⟨6719⟩⟨5849⟩
⟨"surveyed"⟩⟨18228⟩⟨101⟩,⟨"survived"⟩⟨14789⟩⟨12474⟩
⟨"suspected"⟩⟨3758⟩⟨5277⟩,⟨"suspicion"⟩⟨18427⟩⟨5943⟩
⟨"swallow"⟩⟨17374⟩⟨18260⟩,⟨"swamp"⟩⟨15946⟩⟨7394⟩
⟨"Swanwick"⟩⟨10141⟩⟨6140⟩,⟨"swapped"⟩⟨16458⟩⟨1764⟩
⟨"swear"⟩⟨13967⟩⟨17503⟩,⟨"sweat"⟩⟨10717⟩⟨17120⟩
⟨"Swedish"⟩⟨6172⟩⟨13440⟩,⟨"sweep"⟩⟨18277⟩⟨346⟩
⟨"Sweet"⟩⟨12894⟩⟨15866⟩,⟨"sweltering"⟩⟨4357⟩⟨9202⟩
⟨"Swilly"⟩⟨4235⟩⟨4996⟩,⟨"swiming"⟩⟨6505⟩⟨7244⟩

⟨"Swimming"⟩⟨2547⟩⟨7531⟩,⟨"swims"⟩⟨12254⟩⟨10187⟩
⟨"swing"⟩⟨1173⟩⟨3044⟩,⟨"swings"⟩⟨17145⟩⟨18457⟩
⟨"swish"⟩⟨16666⟩⟨17683⟩,⟨"switch"⟩⟨1132⟩⟨5841⟩
⟨"swivel"⟩⟨10791⟩⟨14427⟩,⟨"Swords"⟩⟨10285⟩⟨16297⟩
⟨"swung"⟩⟨14706⟩⟨9907⟩,⟨"sympathetic"⟩⟨2422⟩⟨5579⟩
⟨"synthetic"⟩⟨16047⟩⟨11777⟩,⟨"system"⟩⟨5927⟩⟨3284⟩
⟨"t"⟩⟨7055⟩⟨14447⟩,⟨"t-shirts"⟩⟨12484⟩⟨16525⟩
⟨"tab"⟩⟨11401⟩⟨11536⟩,⟨"Table"⟩⟨10731⟩⟨15456⟩
⟨"Tables"⟩⟨3263⟩⟨7973⟩,⟨"tablet"⟩⟨18334⟩⟨820⟩
⟨"tacked"⟩⟨10213⟩⟨10010⟩,⟨"tacky"⟩⟨914⟩⟨4113⟩
⟨"tags"⟩⟨8331⟩⟨10750⟩,⟨"taht"⟩⟨17844⟩⟨1686⟩
⟨"take"⟩⟨2675⟩⟨14176⟩,⟨"TAKE"⟩⟨13328⟩⟨14176⟩
⟨"taken"⟩⟨3012⟩⟨1211⟩,⟨"Takes"⟩⟨6168⟩⟨4773⟩
⟨"Talbot"⟩⟨3365⟩⟨7767⟩,⟨"tale"⟩⟨16274⟩⟨17325⟩
⟨"talk"⟩⟨3163⟩⟨13772⟩,⟨"talkative"⟩⟨7474⟩⟨6517⟩
⟨"talks"⟩⟨12011⟩⟨5065⟩,⟨"Tallaght"⟩⟨4953⟩⟨4134⟩
⟨"tandem"⟩⟨15386⟩⟨8291⟩,⟨"Tankardstown"⟩⟨6021⟩⟨12444⟩
⟨"Tapas"⟩⟨16747⟩⟨15544⟩,⟨"taped"⟩⟨3599⟩⟨10812⟩
⟨"tara"⟩⟨15917⟩⟨16111⟩,⟨"tariff"⟩⟨14498⟩⟨14082⟩
⟨"Tarts"⟩⟨5652⟩⟨10363⟩,⟨"task"⟩⟨11933⟩⟨16056⟩
⟨"Taste"⟩⟨7870⟩⟨11454⟩,⟨"tasteful"⟩⟨253⟩⟨2355⟩
⟨"taster"⟩⟨11647⟩⟨14031⟩,⟨"tastey"⟩⟨11466⟩⟨14331⟩
⟨"tastless"⟩⟨14572⟩⟨12711⟩,⟨"Tasty"⟩⟨16850⟩⟨15745⟩
⟨"Tavern"⟩⟨15137⟩⟨14973⟩,⟨"tax"⟩⟨11319⟩⟨14109⟩
⟨"taxi's"⟩⟨2266⟩⟨12987⟩,⟨"taxied"⟩⟨12523⟩⟨16563⟩
⟨"te"⟩⟨7598⟩⟨5531⟩,⟨"Tea"⟩⟨1717⟩⟨9277⟩
⟨"teach"⟩⟨6395⟩⟨16697⟩,⟨"teacher"⟩⟨12850⟩⟨15819⟩
⟨"teams"⟩⟨9410⟩⟨8583⟩,⟨"teapots"⟩⟨13337⟩⟨7332⟩
⟨"teas"⟩⟨3693⟩⟨2171⟩,⟨"teaspoons"⟩⟨12375⟩⟨9692⟩
⟨"technician"⟩⟨8395⟩⟨14605⟩,⟨"Ted"⟩⟨7841⟩⟨4269⟩
⟨"teen"⟩⟨16136⟩⟨10629⟩,⟨"teenaged"⟩⟨10705⟩⟨15422⟩

⟨"teeny"⟩⟨4436⟩⟨2303⟩,⟨"teething"⟩⟨9113⟩⟨13888⟩
⟨"telephoned"⟩⟨799⟩⟨824⟩,⟨"teletext"⟩⟨10144⟩⟨6144⟩
⟨"televison"⟩⟨16020⟩⟨11758⟩,⟨"Tell"⟩⟨6342⟩⟨6796⟩
⟨"temp"⟩⟨11161⟩⟨10270⟩,⟨"temperamental"⟩⟨4317⟩⟨8457⟩
⟨"Temple"⟩⟨2381⟩⟨6886⟩,⟨"Templebar"⟩⟨11586⟩⟨12783⟩
⟨"temps"⟩⟨15998⟩⟨11727⟩,⟨"temptation"⟩⟨6932⟩⟨3170⟩
⟨"Ten"⟩⟨9590⟩⟨15165⟩,⟨"tend"⟩⟨2364⟩⟨8547⟩
⟨"tenders"⟩⟨16862⟩⟨15759⟩,⟨"tends"⟩⟨7920⟩⟨4007⟩
⟨"tense"⟩⟨17398⟩⟨18284⟩,⟨"tent"⟩⟨15650⟩⟨7704⟩
⟨"terminal"⟩⟨9293⟩⟨9053⟩,⟨"terminus"⟩⟨12247⟩⟨10174⟩
⟨"terraced"⟩⟨17743⟩⟨11681⟩,⟨"terrible"⟩⟨74⟩⟨6364⟩
⟨"terriffic"⟩⟨12796⟩⟨10538⟩,⟨"terrific"⟩⟨7324⟩⟨3246⟩
⟨"Tesco"⟩⟨2733⟩⟨14158⟩,⟨"Tesco's"⟩⟨9226⟩⟨6093⟩
⟨"tested"⟩⟨13131⟩⟨13061⟩,⟨"Texas"⟩⟨8137⟩⟨5424⟩
⟨"TGI"⟩⟨12837⟩⟨15804⟩,⟨"Th"⟩⟨14004⟩⟨8749⟩
⟨"Thailand"⟩⟨13877⟩⟨8270⟩,⟨"thank"⟩⟨97⟩⟨17445⟩
⟨"thankful"⟩⟨11804⟩⟨16226⟩,⟨"thankfully"⟩⟨3875⟩⟨7672⟩
⟨"Thanksgiving"⟩⟨9367⟩⟨11228⟩,⟨"Thankyou"⟩⟨8662⟩⟨13126⟩
⟨"that???????s"⟩⟨12436⟩⟨13608⟩,⟨"that's"⟩⟨4724⟩⟨13727⟩
⟨"thats"⟩⟨1230⟩⟨16542⟩,⟨"thay"⟩⟨3552⟩⟨3141⟩
⟨"theatre"⟩⟨8187⟩⟨11361⟩,⟨"thee"⟩⟨14316⟩⟨12304⟩
⟨"Their"⟩⟨9910⟩⟨13070⟩,⟨"them"⟩⟨3295⟩⟨1013⟩
⟨"themes"⟩⟨16664⟩⟨17681⟩,⟨"then"⟩⟨4133⟩⟨2177⟩
⟨"ther"⟩⟨4344⟩⟨9771⟩,⟨"therapies"⟩⟨9948⟩⟨5649⟩
⟨"THERE"⟩⟨1198⟩⟨14800⟩,⟨"there"⟩⟨2899⟩⟨14800⟩
⟨"there???????s"⟩⟨14472⟩⟨15616⟩,⟨"there's"⟩⟨3921⟩⟨3563⟩
⟨"thereby"⟩⟨13791⟩⟨10594⟩,⟨"Therefore"⟩⟨10492⟩⟨9183⟩
⟨"thermal"⟩⟨1250⟩⟨10100⟩,⟨"thermostat"⟩⟨12228⟩⟨10587⟩
⟨"THEY"⟩⟨3600⟩⟨16421⟩,⟨"THey"⟩⟨15974⟩⟨16421⟩
⟨"they're"⟩⟨9233⟩⟨17514⟩,⟨"they've"⟩⟨8728⟩⟨18006⟩
⟨"thieves"⟩⟨17950⟩⟨13665⟩,⟨"Thin"⟩⟨16819⟩⟨4632⟩

⟨"thingy"⟩⟨17856⟩⟨3358⟩,⟨"Think"⟩⟨6077⟩⟨12928⟩
⟨"thinks"⟩⟨2156⟩⟨7518⟩,⟨"third"⟩⟨4352⟩⟨10564⟩
⟨"thirsty"⟩⟨13493⟩⟨11767⟩,⟨"thirty"⟩⟨8169⟩⟨5297⟩
⟨"this&quot"⟩⟨18006⟩⟨13709⟩,⟨"tho'"⟩⟨14258⟩⟨9592⟩
⟨"thorough"⟩⟨8183⟩⟨9216⟩,⟨"thoroughfares"⟩⟨15836⟩⟨16095⟩
⟨"thou"⟩⟨3903⟩⟨5240⟩,⟨"though"⟩⟨4193⟩⟨9103⟩
⟨"thoughtful"⟩⟨1914⟩⟨1603⟩,⟨"thoughts"⟩⟨11535⟩⟨17178⟩
⟨"thr"⟩⟨12964⟩⟨17235⟩,⟨"threadbare"⟩⟨377⟩⟨2169⟩
⟨"three"⟩⟨1892⟩⟨14594⟩,⟨"THREE"⟩⟨16610⟩⟨14594⟩
⟨"three-star"⟩⟨11262⟩⟨16139⟩,⟨"threw"⟩⟨1195⟩⟨5848⟩
⟨"thro"⟩⟨17892⟩⟨17983⟩,⟨"throbbing"⟩⟨18323⟩⟨806⟩
⟨"throughly"⟩⟨7911⟩⟨16874⟩,⟨"throughout"⟩⟨441⟩⟨10496⟩
⟨"throw"⟩⟨10370⟩⟨13353⟩,⟨"throwing"⟩⟨2144⟩⟨3779⟩
⟨"ths"⟩⟨13072⟩⟨14701⟩,⟨"thugs"⟩⟨18279⟩⟨253⟩
⟨"thump"⟩⟨9914⟩⟨464⟩,⟨"thumping"⟩⟨2535⟩⟨423⟩
⟨"Thursday"⟩⟨6043⟩⟨17504⟩,⟨"Thus"⟩⟨3000⟩⟨5412⟩
⟨"ticked"⟩⟨7943⟩⟨14712⟩,⟨"tickets"⟩⟨2445⟩⟨8520⟩
⟨"tidy"⟩⟨898⟩⟨5442⟩,⟨"tie"⟩⟨10700⟩⟨4672⟩
⟨"Tiger"⟩⟨14485⟩⟨18546⟩,⟨"tight"⟩⟨6450⟩⟨10040⟩
⟨"tiled"⟩⟨9551⟩⟨11826⟩,⟨"Tiles"⟩⟨15062⟩⟨537⟩
⟨"Tim"⟩⟨6212⟩⟨12342⟩,⟨"time"⟩⟨909⟩⟨15514⟩
⟨"timed"⟩⟨11860⟩⟨10920⟩,⟨"timer"⟩⟨9289⟩⟨7703⟩
⟨"timetable"⟩⟨4688⟩⟨11489⟩,⟨"timing"⟩⟨8922⟩⟨10658⟩
⟨"tiniest"⟩⟨9043⟩⟨11175⟩,⟨"tinted"⟩⟨6179⟩⟨7837⟩
⟨"tip"⟩⟨1529⟩⟨11010⟩,⟨"TIP"⟩⟨6614⟩⟨11010⟩
⟨"tipping"⟩⟨13208⟩⟨7534⟩,⟨"tips"⟩⟨6464⟩⟨10719⟩
⟨"tire"⟩⟨3389⟩⟨7350⟩,⟨"Tired"⟩⟨15489⟩⟨9463⟩
⟨"tiring"⟩⟨7162⟩⟨8963⟩,⟨"tissue"⟩⟨1228⟩⟨1401⟩
⟨"Title"⟩⟨10637⟩⟨15407⟩,⟨"tlc"⟩⟨13033⟩⟨18099⟩
⟨"toast"⟩⟨5372⟩⟨9762⟩,⟨"toasted"⟩⟨6723⟩⟨17954⟩
⟨"toastie"⟩⟨15411⟩⟨9524⟩,⟨"toasts"⟩⟨9390⟩⟨14006⟩

⟨"Today"⟩⟨13314⟩⟨7911⟩,⟨"todays"⟩⟨10801⟩⟨17033⟩
⟨"toes"⟩⟨7361⟩⟨8444⟩,⟨"together"⟩⟨3577⟩⟨14828⟩
⟨"toilet"⟩⟨8831⟩⟨6213⟩,⟨"toiletries"⟩⟨1293⟩⟨11737⟩
⟨"toilettries"⟩⟨6894⟩⟨13109⟩,⟨"token"⟩⟨3948⟩⟨7059⟩
⟨"told"⟩⟨7776⟩⟨7001⟩,⟨"tolerant"⟩⟨8674⟩⟨6336⟩
⟨"tolietries"⟩⟨13257⟩⟨4340⟩,⟨"Tom"⟩⟨1574⟩⟨625⟩
⟨"tomatoes"⟩⟨7981⟩⟨12832⟩,⟨"Tommy"⟩⟨15340⟩⟨16835⟩
⟨"tones"⟩⟨6419⟩⟨2539⟩,⟨"tonic"⟩⟨11300⟩⟨10877⟩
⟨"Tony"⟩⟨2242⟩⟨1343⟩,⟨"TOO"⟩⟨7590⟩⟨11364⟩
⟨"Took"⟩⟨7608⟩⟨11187⟩,⟨"tools"⟩⟨14057⟩⟨11812⟩
⟨"toothpaste"⟩⟨2677⟩⟨9080⟩,⟨"Top"⟩⟨750⟩⟨10297⟩
⟨"topped"⟩⟨6412⟩⟨11544⟩,⟨"topping"⟩⟨3769⟩⟨5278⟩
⟨"torn"⟩⟨690⟩⟨3865⟩,⟨"torrential"⟩⟨13795⟩⟨14286⟩
⟨"total"⟩⟨3377⟩⟨9032⟩,⟨"totalling"⟩⟨16151⟩⟨14941⟩
⟨"touch"⟩⟨162⟩⟨5537⟩,⟨"touches"⟩⟨103⟩⟨3810⟩
⟨"tour"⟩⟨670⟩⟨9057⟩,⟨"tourbus"⟩⟨15316⟩⟨16809⟩
⟨"tourism"⟩⟨4331⟩⟨10825⟩,⟨"Tourist"⟩⟨5334⟩⟨11492⟩
⟨"touristy&quot"⟩⟨10353⟩⟨10115⟩,⟨"tours"⟩⟨1768⟩⟨12355⟩
⟨"toward"⟩⟨7554⟩⟨13917⟩,⟨"towel"⟩⟨4849⟩⟨393⟩
⟨"Towels"⟩⟨9552⟩⟨7886⟩,⟨"Tower"⟩⟨8179⟩⟨12735⟩
⟨"towles"⟩⟨5195⟩⟨4505⟩,⟨"Town"⟩⟨498⟩⟨7883⟩
⟨"Townhouse"⟩⟨2463⟩⟨8431⟩,⟨"townhouses"⟩⟨10750⟩⟨13164⟩
⟨"Trabolgan"⟩⟨2315⟩⟨9419⟩,⟨"trace"⟩⟨8673⟩⟨5488⟩
⟨"tracking"⟩⟨15150⟩⟨12102⟩,⟨"tracksuit"⟩⟨5434⟩⟨5835⟩
⟨"trade"⟩⟨4653⟩⟨10889⟩,⟨"trading"⟩⟨2648⟩⟨9104⟩
⟨"traditional&quot"⟩⟨12529⟩⟨16569⟩,⟨"traditions"⟩⟨17492⟩⟨18373⟩
⟨"Traffic"⟩⟨6016⟩⟨12436⟩,⟨"trailing"⟩⟨18400⟩⟨2906⟩
⟨"trained"⟩⟨2804⟩⟨8205⟩,⟨"trainees"⟩⟨8782⟩⟨6202⟩
⟨"trains"⟩⟨3854⟩⟨782⟩,⟨"traipsing"⟩⟨17923⟩⟨18002⟩
⟨"Tram"⟩⟨3225⟩⟨7977⟩,⟨"Tramore"⟩⟨843⟩⟨8178⟩
⟨"tranquil"⟩⟨1137⟩⟨418⟩,⟨"Tranquility"⟩⟨13225⟩⟨15447⟩

⟨"transaction"⟩⟨13099⟩⟨16994⟩,⟨"transfer"⟩⟨11937⟩⟨7707⟩
⟨"transformed"⟩⟨4225⟩⟨10820⟩,⟨"transition"⟩⟨8340⟩⟨10764⟩
⟨"Transport"⟩⟨7264⟩⟨11106⟩,⟨"transported"⟩⟨11257⟩⟨12878⟩
⟨"trappings"⟩⟨14379⟩⟨15286⟩,⟨"trash"⟩⟨1623⟩⟨9076⟩
⟨"traveler"⟩⟨10430⟩⟨17400⟩,⟨"travelers"⟩⟨6975⟩⟨15000⟩
⟨"Travelled"⟩⟨8175⟩⟨9252⟩,⟨"traveller"⟩⟨3241⟩⟨8581⟩
⟨"Travellers"⟩⟨12994⟩⟨17459⟩,⟨"Travelling"⟩⟨14619⟩⟨16970⟩
⟨"Travelodges"⟩⟨14334⟩⟨17291⟩,⟨"travels"⟩⟨6070⟩⟨6590⟩
⟨"tray"⟩⟨5998⟩⟨6788⟩,⟨"Treacy"⟩⟨15965⟩⟨7433⟩
⟨"treadmills"⟩⟨14577⟩⟨14040⟩,⟨"treasure"⟩⟨3101⟩⟨1366⟩
⟨"Treated"⟩⟨8208⟩⟨10693⟩,⟨"treatment"⟩⟨1424⟩⟨10941⟩
⟨"treats"⟩⟨3073⟩⟨8426⟩,⟨"tree"⟩⟨1660⟩⟨10321⟩
⟨"trek"⟩⟨2805⟩⟨10555⟩,⟨"tremendous"⟩⟨5107⟩⟨2685⟩
⟨"trepidation"⟩⟨4349⟩⟨3234⟩,⟨"triangular"⟩⟨17805⟩⟨17928⟩
⟨"trickle"⟩⟨1296⟩⟨241⟩,⟨"tricks"⟩⟨12313⟩⟨10296⟩
⟨"tried"⟩⟨6367⟩⟨7968⟩,⟨"trifle"⟩⟨17455⟩⟨18341⟩
⟨"Trinity"⟩⟨556⟩⟨16646⟩,⟨"Trinty"⟩⟨12834⟩⟨15801⟩
⟨"TRIP"⟩⟨12755⟩⟨16222⟩,⟨"Tripadvisor"⟩⟨1029⟩⟨16944⟩
⟨"Triple"⟩⟨13342⟩⟨7624⟩,⟨"tripped"⟩⟨16444⟩⟨3607⟩
⟨"triumph"⟩⟨9054⟩⟨11025⟩,⟨"trolley"⟩⟨12586⟩⟨9911⟩
⟨"trot"⟩⟨8477⟩⟨4244⟩,⟨"troubled"⟩⟨16243⟩⟨15682⟩
⟨"trouser"⟩⟨3573⟩⟨17952⟩,⟨"trousers"⟩⟨16210⟩⟨12654⟩
⟨"truely"⟩⟨4211⟩⟨14535⟩,⟨"truffles"⟩⟨14355⟩⟨17299⟩
⟨"trundle"⟩⟨16875⟩⟨18117⟩,⟨"trust"⟩⟨1243⟩⟨1289⟩
⟨"truth"⟩⟨931⟩⟨657⟩,⟨"truthfully"⟩⟨17308⟩⟨1711⟩
⟨"Trying"⟩⟨1557⟩⟨5322⟩,⟨"tthe"⟩⟨16195⟩⟨12635⟩
⟨"tube"⟩⟨13216⟩⟨16456⟩,⟨"tubs"⟩⟨9811⟩⟨9736⟩
⟨"Tues"⟩⟨6622⟩⟨5409⟩,⟨"tuesday"⟩⟨13916⟩⟨11420⟩
⟨"Tullow"⟩⟨6724⟩⟨5855⟩,⟨"tummy"⟩⟨18437⟩⟨5961⟩
⟨"tunes"⟩⟨12157⟩⟨11033⟩,⟨"tunnel"⟩⟨16099⟩⟨17149⟩
⟨"Turk"⟩⟨15805⟩⟨16047⟩,⟨"turkey"⟩⟨2312⟩⟨7483⟩

⟨"turn"⟩⟨4722⟩⟨13053⟩,⟨"turn-down"⟩⟨2475⟩⟨10410⟩
⟨"Turned"⟩⟨12104⟩⟨16143⟩,⟨"turning"⟩⟨1344⟩⟨13365⟩
⟨"Turns"⟩⟨14347⟩⟨15237⟩,⟨"tut"⟩⟨18073⟩⟨1154⟩
⟨"TV???????s"⟩⟨6868⟩⟨11058⟩,⟨"TV's"⟩⟨6684⟩⟨11500⟩
⟨"tweaking"⟩⟨12912⟩⟨15890⟩,⟨"Twelfth"⟩⟨12856⟩⟨15825⟩
⟨"twenty"⟩⟨2688⟩⟨18374⟩,⟨"twice"⟩⟨3190⟩⟨7525⟩
⟨"twin"⟩⟨3173⟩⟨14212⟩,⟨"twins"⟩⟨3910⟩⟨8087⟩
⟨"two"⟩⟨1862⟩⟨11787⟩,⟨"TWO"⟩⟨15030⟩⟨11787⟩
⟨"two-star"⟩⟨17616⟩⟨17837⟩,⟨"type"⟩⟨3518⟩⟨12880⟩
⟨"Typical"⟩⟨5989⟩⟨4726⟩,⟨"Typically"⟩⟨10015⟩⟨14596⟩
⟨"Tyrrelstown"⟩⟨13250⟩⟨15450⟩,⟨"U"⟩⟨5553⟩⟨9064⟩
⟨"ubiquitous"⟩⟨6866⟩⟨7252⟩,⟨"UCD"⟩⟨5988⟩⟨2587⟩
⟨"ugly"⟩⟨1112⟩⟨4721⟩,⟨"UHT"⟩⟨14749⟩⟨15559⟩
⟨"Ulster"⟩⟨6350⟩⟨6806⟩,⟨"Ultimately"⟩⟨7795⟩⟨16954⟩
⟨"umbrella"⟩⟨998⟩⟨1511⟩,⟨"un"⟩⟨1579⟩⟨356⟩
⟨"unacceptable"⟩⟨1458⟩⟨17904⟩,⟨"unacceptably"⟩⟨10524⟩⟨15283⟩
⟨"unappetising"⟩⟨2773⟩⟨10073⟩,⟨"unassuming"⟩⟨12253⟩⟨10185⟩
⟨"unaware"⟩⟨7684⟩⟨7279⟩,⟨"unbearably"⟩⟨1751⟩⟨3030⟩
⟨"unbelievably"⟩⟨2517⟩⟨6625⟩,⟨"unbelieveably"⟩⟨16057⟩⟨18434⟩
⟨"uncertain"⟩⟨11111⟩⟨8841⟩,⟨"uncle"⟩⟨16105⟩⟨18446⟩
⟨"uncleared"⟩⟨12020⟩⟨5074⟩,⟨"Uncomfortable"⟩⟨8774⟩⟨13428⟩
⟨"unconfortable"⟩⟨18251⟩⟨640⟩,⟨"uncooperative"⟩⟨18273⟩⟨343⟩
⟨"undercooked"⟩⟨1685⟩⟨1271⟩,⟨"undergoing"⟩⟨6328⟩⟨11191⟩
⟨"Underground"⟩⟨6175⟩⟨7682⟩,⟨"underneath"⟩⟨6643⟩⟨3416⟩
⟨"understand"⟩⟨3631⟩⟨1128⟩,⟨"understandably"⟩⟨14688⟩⟨15573⟩
⟨"understatement"⟩⟨2108⟩⟨181⟩,⟨"undertaken"⟩⟨17660⟩⟨17879⟩
⟨"underwhelmed"⟩⟨11958⟩⟨17049⟩,⟨"undesirable"⟩⟨16626⟩⟨17640⟩
⟨"undrinkable"⟩⟨17707⟩⟨6440⟩,⟨"uneaten"⟩⟨3339⟩⟨9348⟩
⟨"unexceptional"⟩⟨11642⟩⟨14021⟩,⟨"unexpected"⟩⟨4036⟩⟨9662⟩
⟨"unfamiliar"⟩⟨14529⟩⟨17486⟩,⟨"unfinished"⟩⟨9278⟩⟨17405⟩
⟨"unforgivable"⟩⟨18346⟩⟨841⟩,⟨"Unfortunately"⟩⟨137⟩⟨6199⟩

⟨"unfortunatly"⟩⟨14490⟩⟨17176⟩,⟨"unfortunetly"⟩⟨8785⟩⟨6218⟩
⟨"unfussy"⟩⟨9059⟩⟨11031⟩,⟨"unhappy"⟩⟨475⟩⟨4370⟩
⟨"Unhelpful"⟩⟨17010⟩⟨1095⟩,⟨"unhelpfulness"⟩⟨8788⟩⟨13462⟩
⟨"unidentifiable"⟩⟨8781⟩⟨6200⟩,⟨"uniformly"⟩⟨5256⟩⟨8411⟩
⟨"unimpressed"⟩⟨2380⟩⟨7523⟩,⟨"uninformed"⟩⟨8439⟩⟨8944⟩
⟨"uninteresting"⟩⟨14252⟩⟨17245⟩,⟨"unintrusive"⟩⟨8320⟩⟨10734⟩
⟨"Unique"⟩⟨15376⟩⟨16881⟩,⟨"uniqueness"⟩⟨15909⟩⟨15723⟩
⟨"units"⟩⟨6778⟩⟨10552⟩,⟨"universally"⟩⟨15835⟩⟨16094⟩
⟨"unkempt"⟩⟨14890⟩⟨6304⟩,⟨"unknown"⟩⟨2046⟩⟨4612⟩
⟨"unlike"⟩⟨4134⟩⟨11424⟩,⟨"unlimited"⟩⟨3108⟩⟨7378⟩
⟨"unlock"⟩⟨6816⟩⟨6958⟩,⟨"unlucky"⟩⟨8722⟩⟨3122⟩
⟨"unmissable"⟩⟨12261⟩⟨10199⟩,⟨"unnecessary"⟩⟨12027⟩⟨17566⟩
⟨"unobtrusively"⟩⟨10619⟩⟨15388⟩,⟨"unorganised"⟩⟨14753⟩⟨716⟩
⟨"unplanned"⟩⟨7439⟩⟨4206⟩,⟨"unpleasantness"⟩⟨18253⟩⟨2443⟩
⟨"unpolite"⟩⟨18245⟩⟨631⟩,⟨"unprepared"⟩⟨17686⟩⟨4384⟩
⟨"unreal"⟩⟨1276⟩⟨2197⟩,⟨"unreasonable"⟩⟨5478⟩⟨4179⟩
⟨"unremarkable"⟩⟨14548⟩⟨18101⟩,⟨"unresponsive"⟩⟨17277⟩⟨5359⟩
⟨"unsatisfactory"⟩⟨1120⟩⟨135⟩,⟨"unsavoury"⟩⟨4068⟩⟨5249⟩
⟨"unseen"⟩⟨17002⟩⟨920⟩,⟨"unsightly"⟩⟨4023⟩⟨7689⟩
⟨"unspoilt"⟩⟨9019⟩⟨7621⟩,⟨"unstuffy"⟩⟨15809⟩⟨16055⟩
⟨"unsupervised"⟩⟨4584⟩⟨11189⟩,⟨"unsurpassed"⟩⟨10562⟩⟨15326⟩
⟨"Until"⟩⟨1386⟩⟨7878⟩,⟨"untill"⟩⟨1275⟩⟨6856⟩
⟨"unusable"⟩⟨10322⟩⟨4788⟩,⟨"unused"⟩⟨16313⟩⟨1383⟩
⟨"unusually"⟩⟨6472⟩⟨7068⟩,⟨"unwashed"⟩⟨16446⟩⟨7046⟩
⟨"unwell"⟩⟨2234⟩⟨7745⟩,⟨"unwind"⟩⟨214⟩⟨2187⟩
⟨"UP"⟩⟨11166⟩⟨6555⟩,⟨"up-graded"⟩⟨12632⟩⟨16629⟩
⟨"upbeat"⟩⟨4735⟩⟨2370⟩,⟨"update"⟩⟨9333⟩⟨6037⟩
⟨"upfront"⟩⟨1710⟩⟨5366⟩,⟨"Upgrade"⟩⟨17417⟩⟨18303⟩
⟨"upgraded&quot"⟩⟨4836⟩⟨1806⟩,⟨"upgrading"⟩⟨10452⟩⟨6056⟩
⟨"upkeep"⟩⟨13495⟩⟨11772⟩,⟨"upload"⟩⟨8770⟩⟨13412⟩
⟨"Upon"⟩⟨4668⟩⟨2527⟩,⟨"Upper"⟩⟨8051⟩⟨13903⟩

⟨"upset"⟩⟨1113⟩⟨3108⟩,⟨"upside"⟩⟨4502⟩⟨8151⟩
⟨"upto"⟩⟨8928⟩⟨12857⟩,⟨"ur"⟩⟨12096⟩⟨12323⟩
⟨"urgency"⟩⟨17119⟩⟨16040⟩,⟨"urgently"⟩⟨16283⟩⟨17334⟩
⟨"US"⟩⟨3052⟩⟨17394⟩,⟨"us-"⟩⟨5348⟩⟨1857⟩
⟨"usage"⟩⟨14198⟩⟨14812⟩,⟨"use"⟩⟨2628⟩⟨12274⟩
⟨"Used"⟩⟨9112⟩⟨11711⟩,⟨"useless"⟩⟨887⟩⟨4186⟩
⟨"usher"⟩⟨7676⟩⟨17966⟩,⟨"ushered"⟩⟨7640⟩⟨9078⟩
⟨"Usual"⟩⟨6321⟩⟨6783⟩,⟨"Usually"⟩⟨11921⟩⟨13826⟩
⟨"utilise"⟩⟨17918⟩⟨13627⟩,⟨"utilitarian"⟩⟨14395⟩⟨17527⟩
⟨"utmost"⟩⟨12433⟩⟨12058⟩,⟨"utterly"⟩⟨1196⟩⟨1726⟩
⟨"vacancy"⟩⟨3461⟩⟨2186⟩,⟨"vacate"⟩⟨3709⟩⟨11368⟩
⟨"vacationers"⟩⟨8617⟩⟨11141⟩,⟨"Vacations"⟩⟨12245⟩⟨12595⟩
⟨"vacuum"⟩⟨3056⟩⟨9387⟩,⟨"vacuuming"⟩⟨17905⟩⟨13596⟩
⟨"Valentia"⟩⟨13446⟩⟨16357⟩,⟨"Valentine's"⟩⟨7058⟩⟨10803⟩
⟨"valet"⟩⟨785⟩⟨6847⟩,⟨"valid"⟩⟨6742⟩⟨12941⟩
⟨"Valley"⟩⟨3636⟩⟨8022⟩,⟨"Valu"⟩⟨9646⟩⟨14385⟩
⟨"value"⟩⟨833⟩⟨16057⟩,⟨"VALUE"⟩⟨17127⟩⟨16057⟩
⟨"values"⟩⟨5883⟩⟨7658⟩,⟨"vamp"⟩⟨12518⟩⟨16560⟩
⟨"vanity"⟩⟨9619⟩⟨16440⟩,⟨"variable"⟩⟨2541⟩⟨8142⟩
⟨"varieties"⟩⟨16327⟩⟨17024⟩,⟨"various"⟩⟨8916⟩⟨9796⟩
⟨"vase"⟩⟨13457⟩⟨16369⟩,⟨"vast"⟩⟨2246⟩⟨3927⟩
⟨"Vat"⟩⟨16981⟩⟨18182⟩,⟨"Vaughn"⟩⟨9197⟩⟨4833⟩
⟨"veal"⟩⟨8594⟩⟨11131⟩,⟨"Veg"⟩⟨8752⟩⟨13386⟩
⟨"vegetable"⟩⟨10760⟩⟨14394⟩,⟨"vegetarian"⟩⟨4697⟩⟨15698⟩
⟨"veggies"⟩⟨4077⟩⟨2706⟩,⟨"vehicles"⟩⟨5223⟩⟨8863⟩
⟨"velvet"⟩⟨13175⟩⟨16261⟩,⟨"veneer"⟩⟨15730⟩⟨18108⟩
⟨"ventilated"⟩⟨13460⟩⟨16372⟩,⟨"vents"⟩⟨2318⟩⟨448⟩
⟨"venue"⟩⟨9817⟩⟨2583⟩,⟨"ver"⟩⟨7874⟩⟨11351⟩
⟨"verdict"⟩⟨10328⟩⟨7472⟩,⟨"verging"⟩⟨16214⟩⟨12660⟩
⟨"versa"⟩⟨4981⟩⟨3474⟩,⟨"versions"⟩⟨17525⟩⟨18400⟩
⟨"Very"⟩⟨1251⟩⟨12502⟩,⟨"vey"⟩⟨6910⟩⟨5141⟩

⟨"vibes"⟩⟨16003⟩⟨11734⟩,⟨"vibrate"⟩⟨17275⟩⟨5357⟩
⟨"vibrations"⟩⟨2417⟩⟨707⟩,⟨"vice"⟩⟨5356⟩⟨2349⟩
⟨"victims"⟩⟨18367⟩⟨632⟩,⟨"Victoria"⟩⟨11356⟩⟨12669⟩
⟨"Vienna"⟩⟨4635⟩⟨2101⟩,⟨"View"⟩⟨4030⟩⟨14976⟩
⟨"viewable"⟩⟨17146⟩⟨18458⟩,⟨"viewing"⟩⟨11560⟩⟨12484⟩
⟨"vigilant"⟩⟨18175⟩⟨4515⟩,⟨"Viking"⟩⟨8699⟩⟨14213⟩
⟨"Villa"⟩⟨9724⟩⟨11375⟩,⟨"Village"⟩⟨5891⟩⟨10023⟩
⟨"Vincent"⟩⟨15798⟩⟨16033⟩,⟨"vino"⟩⟨11438⟩⟨14275⟩
⟨"VIP"⟩⟨12163⟩⟨17065⟩,⟨"Virginia"⟩⟨3078⟩⟨3123⟩
⟨"VISA"⟩⟨17959⟩⟨18024⟩,⟨"visible"⟩⟨1781⟩⟨6295⟩
⟨"Visit"⟩⟨6293⟩⟨4839⟩,⟨"Visited"⟩⟨5777⟩⟨6171⟩
⟨"visitor"⟩⟨5860⟩⟨13955⟩,⟨"Visitors"⟩⟨12368⟩⟨13368⟩
⟨"vista"⟩⟨11592⟩⟨9868⟩,⟨"visted"⟩⟨7805⟩⟨11322⟩
⟨"visually"⟩⟨11362⟩⟨9758⟩,⟨"Vitality"⟩⟨9163⟩⟨14358⟩
⟨"vodka"⟩⟨12521⟩⟨17123⟩,⟨"voiced"⟩⟨7937⟩⟨896⟩
⟨"voltage"⟩⟨16895⟩⟨18137⟩,⟨"volumes"⟩⟨12928⟩⟨15031⟩
⟨"vomit"⟩⟨684⟩⟨900⟩,⟨"vote"⟩⟨9626⟩⟨7078⟩
⟨"vouchers"⟩⟨11016⟩⟨4330⟩,⟨"vowing"⟩⟨15950⟩⟨7407⟩
⟨"W"⟩⟨11308⟩⟨15694⟩,⟨"wacky"⟩⟨9932⟩⟨5621⟩
⟨"waffles"⟩⟨2206⟩⟨2373⟩,⟨"wages"⟩⟨17313⟩⟨2174⟩
⟨"wait"⟩⟨1070⟩⟨13364⟩,⟨"Wait"⟩⟨13634⟩⟨13364⟩
⟨"waiter"⟩⟨6165⟩⟨11616⟩,⟨"waiteress"⟩⟨9211⟩⟨6070⟩
⟨"Waiting"⟩⟨6676⟩⟨8068⟩,⟨"waitress"⟩⟨495⟩⟨6597⟩
⟨"waitressing"⟩⟨15200⟩⟨16665⟩,⟨"waitstaff"⟩⟨3038⟩⟨1529⟩
⟨"wake"⟩⟨4713⟩⟨15776⟩,⟨"waken"⟩⟨16168⟩⟨10639⟩
⟨"waking"⟩⟨6374⟩⟨18156⟩,⟨"wales"⟩⟨6999⟩⟨16196⟩
⟨"walk-in"⟩⟨2856⟩⟨1632⟩,⟨"walkable"⟩⟨2054⟩⟨8733⟩
⟨"walker"⟩⟨4206⟩⟨10593⟩,⟨"walkers"⟩⟨10653⟩⟨12692⟩
⟨"walks"⟩⟨178⟩⟨2194⟩,⟨"walkways"⟩⟨14794⟩⟨13752⟩
⟨"walled"⟩⟨3102⟩⟨2300⟩,⟨"wallets"⟩⟨16072⟩⟨14916⟩
⟨"Walls"⟩⟨11576⟩⟨7450⟩,⟨"Walsh"⟩⟨14425⟩⟨17444⟩

⟨"wander"⟩⟨10925⟩⟨9835⟩,⟨"wandering"⟩⟨7233⟩⟨9447⟩
⟨"WANT"⟩⟨17050⟩⟨6743⟩,⟨"Wanted"⟩⟨11385⟩⟨6416⟩
⟨"ward"⟩⟨18124⟩⟨1162⟩,⟨"Wardrobe"⟩⟨13369⟩⟨11871⟩
⟨"warm"⟩⟨385⟩⟨4578⟩,⟨"WARM"⟩⟨18201⟩⟨4578⟩
⟨"warmest"⟩⟨7930⟩⟨7717⟩,⟨"warmly"⟩⟨2970⟩⟨823⟩
⟨"WARNED"⟩⟨16719⟩⟨720⟩,⟨"Warning"⟩⟨9412⟩⟨8585⟩
⟨"warped"⟩⟨8053⟩⟨461⟩,⟨"warranted"⟩⟨16464⟩⟨275⟩
⟨"was"⟩⟨2434⟩⟨11343⟩,⟨"WAS"⟩⟨6725⟩⟨11343⟩
⟨"washbasin"⟩⟨14047⟩⟨10210⟩,⟨"washcloth"⟩⟨12297⟩⟨10266⟩
⟨"Washer"⟩⟨17946⟩⟨18017⟩,⟨"Washington"⟩⟨14294⟩⟨15110⟩
⟨"wasn???????t"⟩⟨5753⟩⟨2589⟩,⟨"wasn'"⟩⟨12334⟩⟨10340⟩
⟨"wasps"⟩⟨14173⟩⟨9367⟩,⟨"wasted"⟩⟨1573⟩⟨6540⟩
⟨"watch"⟩⟨7655⟩⟨9208⟩,⟨"watching"⟩⟨2114⟩⟨16716⟩
⟨"Water"⟩⟨8103⟩⟨12051⟩,⟨"water's"⟩⟨10180⟩⟨6219⟩
⟨"Waterfall"⟩⟨5137⟩⟨8348⟩,⟨"Waterford"⟩⟨7657⟩⟨8325⟩
⟨"watering"⟩⟨2529⟩⟨3713⟩,⟨"waterside"⟩⟨8639⟩⟨11161⟩
⟨"Wave"⟩⟨10181⟩⟨16929⟩,⟨"waved"⟩⟨4297⟩⟨12535⟩
⟨"WAY"⟩⟨3060⟩⟨7615⟩,⟨"way'"⟩⟨18517⟩⟨13263⟩
⟨"WC"⟩⟨6103⟩⟨12899⟩,⟨"We"⟩⟨789⟩⟨3090⟩
⟨"We???????d"⟩⟨12293⟩⟨11685⟩,⟨"we???????re"⟩⟨6805⟩⟨18431⟩
⟨"we'd"⟩⟨3675⟩⟨13679⟩,⟨"We'll"⟩⟨1677⟩⟨1243⟩
⟨"We've"⟩⟨2203⟩⟨11566⟩,⟨"weak"⟩⟨5303⟩⟨13930⟩
⟨"wearing"⟩⟨3759⟩⟨8839⟩,⟨"weary"⟩⟨5591⟩⟨6648⟩
⟨"Web"⟩⟨13279⟩⟨9953⟩,⟨"webpage"⟩⟨16307⟩⟨6614⟩
⟨"website's"⟩⟨17548⟩⟨15132⟩,⟨"Wed"⟩⟨12566⟩⟨17151⟩
⟨"WEDDING"⟩⟨18005⟩⟨18059⟩,⟨"Weddings"⟩⟨13098⟩⟨16992⟩
⟨"wednesday"⟩⟨6017⟩⟨17052⟩,⟨"weds"⟩⟨17349⟩⟨14989⟩
⟨"weeds"⟩⟨17276⟩⟨5358⟩,⟨"Week"⟩⟨14032⟩⟨15603⟩
⟨"weekday"⟩⟨3823⟩⟨10830⟩,⟨"weeked"⟩⟨14102⟩⟨15155⟩
⟨"weekend-"⟩⟨15314⟩⟨16807⟩,⟨"weekend&quot"⟩⟨17706⟩⟨6437⟩
⟨"weeknights"⟩⟨17432⟩⟨18318⟩,⟨"Weeping"⟩⟨10172⟩⟨6201⟩

⟨"weights"⟩⟨6455⟩⟨3156⟩,⟨"Weird"⟩⟨12349⟩⟨16465⟩
⟨"Welcome"⟩⟨8188⟩⟨5476⟩,⟨"welcomed"⟩⟨222⟩⟨3605⟩
⟨"Well"⟩⟨259⟩⟨16434⟩,⟨"WELL"⟩⟨14145⟩⟨16434⟩
⟨"well-designed"⟩⟨7443⟩⟨4212⟩,⟨"well-furnished"⟩⟨4910⟩⟨5454⟩
⟨"well-located"⟩⟨6884⟩⟨11081⟩,⟨"well-managed"⟩⟨10351⟩⟨10113⟩
⟨"well-run"⟩⟨4085⟩⟨2497⟩,⟨"well-trained"⟩⟨16341⟩⟨18228⟩
⟨"wellies"⟩⟨4432⟩⟨2024⟩,⟨"welll"⟩⟨12345⟩⟨10364⟩
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⟨"zipped"⟩⟨7879⟩⟨13825⟩,⟨"zones"⟩⟨16075⟩⟨14918⟩

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P Poncelet. Sensing sentiment in on-line recommendation texts and ratings. B.A dissertation. J Cogley.Â A typical newsgroup posting consists of one or more quoted lines from another posting followed by the opinion of the author. This social behavior gives rise to a network in which the vertices are individuals and the links represent "responded-to" relationships. An interesting characteristic of many newsgroups is that people more frequently respond to a message when they disagree than when they agree. Sentiment analysis (also known as opinion mining or emotion AI) refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Sentiment analysis is widely applied to voice of the customer materials such as reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to