LScDC - NEW LARGE SCIENTIFIC DICTIONARY

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ABSTRACT. In this paper, we present a scientific corpus of abstracts of academic papers in English – Leicester Scientific Corpus (LSC). The LSC contains 1,673,824 abstracts of research articles and proceeding papers indexed by Web of Science (WoS) in which publication year is 2014. Each abstract is assigned to at least one of 252 subject categories. Paper metadata include these categories and the number of citations. We then develop scientific dictionaries named Leicester Scientific Dictionary (LScD) and Leicester Scientific Dictionary-Core (LScDC), where words are extracted from the LSC. The LScD is a list of 974,238 unique words (lemmas). The LScDC is a core list (sub-list) of the LScD with 104,223 lemmas. It was created by removing LScD words appearing in not greater than 10 texts in the LSC. LScD and LScDC are available online. Both the corpus and dictionaries are developed to be later used for quantification of meaning in academic texts.

Finally, the core list LScDC was analysed by comparing its words and word frequencies with a classic academic word list 'New Academic Word List (NAWL)' containing 963 word families, which is also sampled from an academic corpus. The major sources of the corpus where NAWL is extracted are Cambridge English Corpus (CEC), oral sources and textbooks. We investigate whether two dictionaries are similar in terms of common words and ranking of words. Our comparison leads us to main conclusion: most of words of NAWL (99.6%) are present in the LScDC but two lists differ in word ranking. This difference is measured.

Keywords: Natural Language Processing, Text Mining, Information Extraction, Scientific Corpus, Scientific Dictionary, Text Data, Quantification of Meaning, Meaning of Research Texts, R Programming

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1. Introduction

1.1. Quantification of Meaning in Academic Texts

The interest of adaptation the modern technologies to text mining is growing fast, along with the awareness of the importance of textual data in almost all industries. The increase in the number of users of the internet and social media platforms makes a huge amount of textual data available that play a crucial role on research and marketing strategies.

The storage of almost all types of data in electronic platforms and the spread of the social networking sites for scientists open up opportunities for researchers to share scientific researches and to access a wide range of publication repositories freely and effectively. According to [1, 2], the largest academic social network ResearchGate has 15+ million researchers registered, with a huge number of publications in multidisciplinary journals. The problem of searching for relevant papers

out of an enormous number of publications and extraction the information from texts gradually becomes crucial. Therefore, automated procedure of text processing and extracting the meaning of a text have become important issues.

In Natural Language Processing (NLP) and computational linguistics, formal identifying 'which meaning a text includes is still an open problem. Although in standard text mining applications one may relate the problem to topic identification or determining the class of text, we consider this problem more widely. Our goal is not only determining which class (classes) a text belongs to or the topic (content) of a text, but also numerical representing the meaning of the text.

This task is different from quantification in classification applications. Quantification (or text quantification) in classification is defined as the activity of estimating the prevalence (relative frequency) of each class in a set of unlabelled items [3]. The aim here is, given a training set with class labels, to induce a quantifier that takes unlabelled test set, and then accurately estimate the number of cases in each class. Rather than estimating the prevalence of classes (or different meanings) in the corpus or determining the topic of the paper, we intend to represent the meaning in a research text numerically so-called quantification of meaning in research texts. Our assumption is that words and texts have meaning priors and meaning of a text can be extracted, at least, partially, from the information of words for subject categories distributed over the corpus. Given such information, these priors can be exploited firstly for each word and then each research text which is a collection of words. In other words, meaning of a research text is generated when different bits of information are associated with subject categories [4].

This approach follows the classical psycholinguistic ideas of measurement of meaning [5] but instead of psychologically important sentiments the research categories are used. Each word is represented as a vector of information scores for various categories, and the meaning of the whole text is formalised as a cloud of these vectors for words from the text. For larger texts this approach can take into account correlations between words (co-occurrence of words and combinations of words).

Quantities of meanings of texts can be later used in a number of applications involving categorisation of texts to pre-existing categories, creation of 'natural' categories or more precisely, clustering of similar texts in such a way that texts in the same group have same/similar meanings. The solution to the problem of quantification of meanings in text also impacts on other issues such as prediction of success of a scientific paper.

Let us consider, for instance, grouping texts based on their contents. Bringing related research texts together gives the community a convenient and easily accessible location where a deep digging becomes possible inside. This provides users many benefits such as learning the hottest topics, the most significant researches and the latest developments in a specific field. Such automated mechanisms have also benefit for editors to help them in associating researches, for instance in the step of evaluating a new submission to determine whether it fits to the journal and standards in the field in terms of content, and more importantly to initiate the peer review process by selecting experts in the field.

In practice, searching and preliminary express understanding of a paper's content is generally done by reading title and abstract rather than reading full-text of the paper. Therefore, it is reasonable to search for relevant papers by searching of relevant abstracts. Natural questions needed to be answered here are: how to automatically process the abstracts, extract the meaning from such relatively short texts and represent the meaning in a text numerically to make them usable for text mining algorithms. These questions are some of our focuses to be answered through our research.

This work is the first stage in the project outlined. In this paper, we consider the creation of an academic corpus and scientific dictionaries where words are extracted from the corpus. All steps in the creation process will be presented in details. The corpus and dictionaries will be used for quantification of meaning in academic texts in later stages of our research.

1.2. Building a Scientific Corpus: Leicester Scientific Corpus (LSC)

One of the key issues in the analysis of meaning of texts is to use a corpus that is built in accordance with the scope of the study. Quantification of meaning of research texts, extracting information of words for subject categories and later prediction of success of the paper using quantity of texts naturally require well-organised, up-to-date and annotated corpus by subject categories and the information of citations along with the abstracts. For this purpose, we developed a scientific corpus where texts are abstracts of research papers or proceeding papers, followed by creation of scientific dictionaries where words are extracted from the corpus. In this paper, we focus on building of a scientific corpus and dictionary to be used in future work on the quantification of the meaning of research texts. All steps of creation the corpus and the dictionary are presented in the later sections of the paper.

The Leicester Scientific Corpus (LSC) is a collection of 1,673,824 English written abstracts of research articles and proceeding papers indexed by Web of Science (WoS) [6], selected so as to represent the largest variety of abstracts of scientific works published in 2014 [7]. Texts within the corpus are distributed across 252 subject categories – with over 298 million words including stop words. No consideration is given to the selection of categories, we extracted all texts regardless of how many texts are included in an individual category. Each document in the corpus includes the text of abstract and the following metadata: title, list of subject categories, list of research areas, and times cited [8, 9, 10]. Documents also have the list of authors with the exception of 119 documents, we did not exclude these documents. We collected documents in July 2018; therefore, the number of citations is from the publication date to July 2018.

Given the LSC, we also intend to create scientific dictionary where words are extracted from the texts of abstracts in LSC to be used on measuring the information of words for subject categories in the process of quantification of meaning of texts. To better represent scientific fields, the variety of disciplines and corpus size are very important criteria in dictionary creation. The more disciplines where texts are collected from, the bigger and comprehensive dictionary can be created. Similarly, the more articles are collected, the more representative set of words for specific fields can be gathered. As we did not exclude any category from the corpus of 1,673,824 texts distibuted over 252 categories, we expect a reasonable representativeness of words. In addition, the dynamic nature of languages and changes of words with new discoveries – due to fast changes in science and technology – lead to a need for an up-to-date scientific dictionary. Thus, we created two scientific dictionaries

based on a large, multidisciplinary corpus of academic English: Leicester Scientific Dictionary (LScD) and Leicester Scientific Dictionary-Core (LScDC) [11, 12].

1.3. Building Scientific Dictionaries: Leicester Scientific Dictionary (LScD) and Leicester Scientific Dictionary-Core (LScDC)

LScD is a list of words extracted from the texts of abstracts in the LSC. The words in the LScD is sorted by the number of documents containing the word in descending order. There are 974,238 unique words (lemmas) in the dictionary. All words in the LScD are in stemmed form and stop words are excluded. The dictionary also contains the number of documents containing each word and the number of appearance of the word in entire corpus. All steps to process the LSC, build LScD and the basic statistics with characteristics of words in the LScD are presented in the later sections of this paper.

LScDC is a core list (sub-list) of the LScD. The dictionary contains of 104,223 unique words (lemmas). The following decision is taken in the creation of the LScDC: words (in LScD) that appearing in not greater than 10 documents (≤ 10) are removed under the assumption that too rare words are not informative for text categorisation and gives almost zero scores in the calculation of information score as they appear in less than 0.01\% of documents. 60\% of words in LScD appear in only one document. Our casual observation of words indicates that many of such words are non-words or not in an appropriate format to use (e.g. misspelling); therefore, they are likely to be non-informative signals (noise) for algorithms. More information and examples can be found in Section 5 and Section 6. Removal of such words results in reducing the number of words in applications of text mining algorithms. When the threshold 10 is decided, we consider a cut which is not too small or high to be able to keep a reasonable number of words for analysis, but we paid attention to have a noticeable impact on size of dictionary and results. We did not remove any frequent words in this stage as stop words are already removed in pre-processing steps. The core dictionary is also ordered by the number of documents containing the words and includes the information of the number of appearance of the word in entire corpus.

1.4. A Comparison of the LScDC and the New Academic Word List (NAWL)

This study also compares the LScDC and the New Academic Word List (NAWL) [13]. The procedure used to compare involves looking at a classic academic list of words NAWL and investigating whether two lists contain the same words, the number of common words, possible reason of mismatches and whether ratings of matched words are actually the same/similar in two dictionaries. Overall, we intend to see whether there is similarity between two lists.

The reason why we consider the NAWL for comparison lies in two facts. The major reason lies in the way the sampling of the vocabulary, which is similar to ours in terms of being from a general and academic corpus. The second reason is that the AWL and NAWL are classics and landmarks as academic lists in vocabulary and corpus-based lexical studies. Our aim is not to replace the AWL and NAWL, but create a large corpus and scientific dictionary representing research papers from

various subject fields without any limitation in disciplines for our goal of discovering and quantifying the meaning of research texts.

The NAWL consists of 963 word families based on a academic corpus of 288 million running words (all words in text without tables' captions, titles and references) [13]. The major categories of the corpus where words are extracted are: the Cambridge English Corpus (CEC), oral sources and textbooks. The largest proportion of tokens came from the CEC, about 86% (over 248 million words). The oral part was taken from the Michigan Corpus of Academic Spoken (MICASE) and the British Academic Spoken English (BASE) corpus. The oral corpora and the corpus of textsbooks are divided into four categories: Arts and Humanities, Life and Medical Sciences, Physical Sciences, and Social Sciences. The NAWL covers 92% of its corpus when combined with the New General Service List (NGSL) [14]. In the list, words are listed by headwords of word families where various inflected forms are contained in. However, we observed that some of headwords in the NAWL indicate the same stemmed word in the LScDC. For instance, two distinct headwords 'accumulate' and 'accumulation' in the NAWL matched with 'accumul' in the LScDC. To avoid the effect of this difference on our analysis, we applied stemming on words of the NAWL. We used average statistics of different forms as the final statistics for stemmed word. After stemming, the number unique words (lemmas) decreased to 895 in the NAWL, we take these words into account in the comparison study.

The NAWL hovewer does not contain much specialised technical terms such as chemical terms and species in biology. To illustrate this, let us explain more details. The Coxheads Academic Word List (AWL) created in 2000 - inspried to create NAWL -, includes 570 word families (from a corpus of 3.5 million words) [15]. According to Coxhead, academic words are supportive of academic text but not central to the topics of the text. The list of AWL contains words that account for approximately 10% of the total words in the collection of academic texts. The AWL and GSL (General Service List) covers approximately 86% of total words in academic corpus. Coverage refers to the number of words (tokens, i.e. all forms of words) in texts which are covered by the list of words. By updating this list with an expended and carefully selected corpus of 288 million words (corpus where NAWL is designed), the coverage was improved to 92% of new corpus when combined with NGSL, with approximately 5% improvement [13, 14]. Not all words extracted from the corpus is included in the list. In the creation of list, a measure considering the distribution of words over disciplines (Dispersion) was taken into account as well as the frequency (Standard Frequency Index). In LScDC, we include all of words appearing in not less than 10 texts in the corpus – distributed over 252 subject categories –, we did not apply any procedure to exclude any other words. This explains the difference between the number of lemmas in two lists – with 895 lemmas of NAWL and 104,223 lemmas in the LScDC.

The NAWL and the LScDC were actually developed from different corpora and the number of words are quite different, but overall the LScDC contains the much lemmas of NAWL (except only 4 words). In this stage, we did not include the New General Service List (NGSL) as our aim is to evaluate only academic words. In comparison, it must be stressed that there is 103,328 more lemmas in LScDC than the NAWL. Adding the NGSL could result in an increase in the number of the same words in the LScDC and NAWL plus NGSL.

In the comparison study, we initially investigate dictionaries to see the coverage of NAWL words by LScDC. We will see that there are 891 words that occur in both the LScDC and the NAWL, which means that the overlap between the LScDC and the NAWL is 99.6%. Four words appearing only in the NAWL are: "ex", "pi", "pardon" and "applaus". This seems to be the result of differences in types and processing of texts in corpora. It is worth to note that corpus of NAWL includes full texts from academic domain, while the LSC includes abstracts of academic texts. This, for instance, may be the reason why "pi" does not appear in LSC as it is commonly used by the symbol π (pi) in math world and not many articles include formulas in abstract. The other two words "pardon" and "applaus" are contained in LScD with low frequencies (5 and 9 respectively); therefore, they are removed in the step of LScDC creation. However, these two words have low rank in the NAWL as well: rank 924 and 956 in the list). Finally, the word "ex" does not occur in the LScDC due to pre-processing steps applied in the creation of the dictionary. We united some prefixes including "ex" with the following words (e.g. ex-president is converted to expresident).

We also present different approaches for comparison to understand what fragment of LScDC contains the NAWL. This is performed by repeatedly searching NAWL words in various subsets of LScDC. Our second focus in dictionary comparison will be the comparison of ranks of words in two dictionaries. In this study, only common words (891 words) are taken into account. Several different methods to compare ranks are considered such as direct comparison of ranks, pairwise comparison of partitions in dictionaries (lists are divided into sub-lists and overlapping words are count in each sub-list), comparison of the top n words, and the comparison of the bottom n words. We will also test similarity of ranks by statistical tests. It is expected to observe that words in two lists are not distributed in the same way as the statistics to order lists are not calculated in the same way. The NAWL considers the dispersion of words over categories, while we simple take the number of documents containing words in the LScDC. All approaches and results are presented in the section of comparison in detail.

In this study, we also consider the reproducibility of dictionaries from the LSC and list of texts from other sources to be used by researchers in many other text mining applications. For this purpose, we made R codes for producing the LScD and the LScDC, and instructions for usage of the code available in [16].

1.5. The Structure of This Paper

The paper is organised as follows. Section 2 contains the principles in corpus and dictionary design as well as the text and word representation approaches. In Section 3, we describe some of widely used and well-known analogue corpora and dictionaries. Section 4 sets out all pre-processing steps in creation process and the structure of LSC. Similarly, Section 5 and Section 6 present pre-processing steps to build the LScD and the LScDC respectively, and the organisation of dictionaries. In Section 7, a study of comparison of the LScDC and the NAWL with several approaches is contained. Finally, Section 8 concludes the paper.

2. Methodology

2.1. Fundementals of Corpus Design

In linguistics, a text corpus is defined as a large collection of text and they are used by linguists, lexicographers, experts in NLP (Natural Language Processing) and in many other disciplines in order to generate language databases, study general linguistic features, do statistical analysis or learn linguistic rules.

Types of corpora vary depending on how they are sampled and designed for specific research goals. Texts in a corpus are assembled to ensure maximum representativeness of a particular language or language variety. Representativeness refers a sample that includes the complete range of texts in a target population [17]. Target population is closely related to the scope of the research and respectively sampling. Any selection of text is described as a sample; however, representativeness for a sample depends on the definition of the population that sample is intended to represent and methods of selection of the sample from that population. To define the population, the most important two considerations are: boundary of the population (what texts are included) and the range of genres (what text categories are included) within the population. For instance, Lancaster-Oslo/Bergen Corpus (LOB) is defined as the collection of British English texts that all are published in 1961 in the British National Bibliography Cumulated Subject Index 1960-1964 for books and all 1961 publications in Willing's Press Guide 1961 for periodicals and newspapers; distributed across 15 text categories (such as general fiction, romance-love story etc.) [18, 19]. The target population for the LOB was written British English texts that all are published in 1961 in United Kingdom (boundary)—distributed across 15 text categories (genres).

The goal of corpus construction is very important for corpus design as it determines the target population. For instance, if the goal of the research is to investigate learners' English, it is reasonable to collect essay of students learning English. However, one who wants to capture the complete range of varieties of English will attempt to collect contemporary British English written texts from a wide variety of different domains. With a given research purpose, a simple broad distinction on corpus types can be done: general corpus and specialised corpus. The criteria for representativeness for these corpora differ from each other by sampling principles. A general corpus contains a broad range of genres with a balance of texts from a wide variety of the language in different domains, while a specialised corpus contains texts from a particular genre or a specific time. For instance, a corpus can be representative for general English language which is an example for general corpus; fiction books or researches in medicine which are examples for specialised corpus.

Some other considerations in sampling decision are the kinds of texts, the number of texts and the length of text samples as well as sampling techniques. Sampling techniques rely on random selection. Basically, selection can be done by a simple random sampling or stratified random sampling. In basic random sampling, texts having equal chance to be selected in a population are randomly selected. In stratified random sampling, the whole population is divided into smaller groups (e.g. genres) and then each subset is sampled using random selection techniques (with proportionality to the subgroups)[20]. In the LOB corpus, for example, the population was first divided into 15 categories; and samples were drawn from each category.

2.2. Representation of Texts and Words

In order for an effective text processing to be accomplished, one of the most fundamental tasks is to select the most appropriate text representation technique for a particular application of NLP. The quality of any text mining and NLP techniques is strongly dependent on the text representation. It aims to represent texts to enable them to be used in mathematical computations by the machine.

In general, the most common text representation model in text mining is the Vector Space Model (VSM) [21, 22]. In this model, each text is represented by a numerical vector where its components are taken from the content of the text. Components of the vector denote the features that characterise the text such as words, phrases, paragraphs or a single character etc (tokens). Therefore, each text is represented by a collection of words (or words' combinations) and the corpus can be represented by the union of such collections. The most common and simplest way to transform a text into a vector space is to represent them by words from the vocabulary of the text collection. Each text in the collection is thus a feature vector in the vector space. In that case, the dimensions of the vector space is equal to the vocabulary size, and the order of the words in each text is ignored.

Having the texts represented by vector of words, list of words can be extracted with various statistics such as weight of words for a given text. This representation of the text by a bunch of words is called Bag of Words (BoW) [23]. In BoW, different word weighting schemes can be used. One simple count for each feature's value (word weight) might be Boolean model. In Boolean model, 1 indicates that the word appears in the text and 0 indicates the word does not appear in the text. This scheme holds only the information about presence or absence of a given word in texts. As an extension of the Boolean model, TF (term frequency) shows how many times a word appears in the text [24]. In this scheme, the distribution of the word across the collection is not taken into account. However, some words can be more significance than others in the corpus. In that case, TF can be multiplied by IDF (inverse document frequency), which is defined as the logarithm of the division of the corpus size by the number of documents containing the word. This scheme is called TF-IDF [25]. In addition, another scheme is to count the number of appearance of a word in the entire corpus when the corpus is considered as one large document.

Designing the texts by words can be performed in different ways depending on the query. One may want to represent text by all inflected forms of words or stop words. For instance, in the creation of the list of the most widely used conjunctions in a language, removing stop words leads to unreliable results. Therefore, the objection in text representation should be to turn each text into a set of words that supply the task with necessary inputs.

2.3. Building a Dictionary from Text Collection

In this study, a dictionary is defined as the set of unique words (*lemmas*) extracted from texts in a corpus. In other words, a dictionary is produced based on corpus data. In corpus linguistics, every dictionary is compiled from a particular corpus and the way to establish of a word list must be defined individually for a given purpose.

Dictionaries differ from one another by the words selected. Several distinctions can be done based on their scopes and purposes. From the overview, the simplest distinction can be observed between general and specialised dictionaries (also refereed as technical dictionaries). In specialised dictionaries, words are extracted from a corpus in a single (or multi) specific field(s) and indicate the concepts of the field(s) while general dictionaries contain a complete range of words. Words in specialised dictionaries are called terms or topic-specific words. In the contrast to terms, a word that has a little lexical meaning is called function word in linguistics. Some examples of function words are prepositions, pronouns, determiners etc. In English semantic, non-function words (content words) are words that indicate the content or the meaning of the texts such as nouns, verbs and adjectives. In addition, Coxhead used the notion *supportive* for academic words in AWL [15]. She stated that academic words in AWL are supportive of the academic texts. As supportive, she meant words which are not central to the topic of the text. One would consider words that do not indicate any terminology or specialised technical terms in the subject field. 'establish' and 'inherent', for example, are two of supportive words according to Coxhead. These are words which authors from most or all academic disciplines tend to use them; the majority of them are also used in general English. She excluded all terminologies such as marine species in Oceanography and function names in Mathematics (e.g. Gaussian).

To define words and dictionaries, several other distinctions are applied by lexicographers and experts such as prescriptive or descriptive, dictionaries by language, dictionaries by size, Language-for-Specific-Purposes dictionary (LSP such as medical dictionaries) etc [26]. In this study, rather than consider such distinctions, we focus on building a corpus-based dictionary from scientific abstracts written in English. Such dictionary may be considered as *scientific dictionary* giving the guidance to scientific writers on such matters as up-to-date, topic-specific and supportive words of academic texts.

In the creation of a scientific dictionary from academic texts, two important criteria are: corpus size and the variety of disciplines where texts are categorised into. The more texts are collected, the more representative set of words for specific fields can be gathered. Similarly, the more disciplines where collected texts belong to, the bigger and more comprehensive dictionary can be created. A large and multidisciplinary dictionary with all supportive and topic-specific words of academic texts can also cover to other corpora and be used for any text analysis tasks on them.

3. Related Works

3.1. Corpora of English

There are several freely available corpora for NLP tasks. In this section, we begin by listing some of those well-known corpora developed for English. The earliest corpus in electronic form was developed in 1964 at Brown University, which contains written American English published in 1961 [27, 28]. Brown corpus includes 500 samples of American English text of published works in the United States in 1961. Each text consists of over 2,000 words sampled from 15 text categories, with totally over one million running words. Although today the size of corpus is considered

small when comparing recent corpora, it is still widely seen as a landmark publication as a computer readable and general corpus among linguistic researchers. The corpus is similarly designed as LOB which followed the design and sampling practice of the Brown corpus in order to match the Brown corpus for British English [18, 19]. These two corpus became a model for other national corpora, so-called 'Brown Family' [29]. In selecting texts for inclusion in the Brown corpus and the LSC, different considerations applied based on the aim of the design of corpora as well as the differences in size of corpora. Brown corpus is sampled from a wide variety of different types of sources such as novels, news, editorials, reviews and many more; while the LSC is sampled from scientific abstracts and proceeding papers.

British National Corpus (BNC) is a monolingual, general corpus of over 4,000 samples of modern spoken and written British English covering English of the later part of 20th century (from 1960 onwards) [30, 31, 32]. The latest edition of the BNC is published in 2007. In general, it covers many different styles and varieties of text from various subject fields and genres. The written part of the corpus contains samples from a wide source of text such as: regional and national newspapers, journals, academic books, fiction, letters, school and university essays, other literary text. The spoken component of the corpus is made up of informal conversations recorded by volunteers who were selected from different age, social class and gender, and task-oriented spoken language ranging from formal meetings to radio shows and lectures. The corpus was designed to identify social and generic uses of contemporary British English with 100 million words [28]. The major differences between the BNC and the LSC lie in the size of the corpus, in the aim of design (being to capture the full range of varieties of contemporary language use versus to extract scientific ones), in the definition of the populations and in the sampling of corpora in terms of being mixed corpus (spoken and written English) versus written English.

One other well-known corpus is Oxford English Corpus (OEC) which is also used by Oxford lexicographers to construct Oxford English Dictionary (OED), supplied by Oxford University Press [33]. The corpus contains of over 10 billion words of 20th and 21st century English from English-speaking countries: the UK, USA, Ireland, Australia, New Zealand, the Caribbean, Canada, India, Singapore and South Africa. It is one of the largest corpus in the world [33]. The corpus is mainly drawn from the web with all types of English such as academic journals, literary novels, newspapers, magazines, language of blogs, emails and social media [35]. Another Oxford University Press corpus is Oxford Corpus of Academic English (OCAE) contains academic journals and textbooks from four main disciplines: physical sciences, life sciences, social sciences, and humanities with 85 million words included [36].

The *SciCorp* is a corpus of 14 English scientific articles sampled from two disciplines: genetics and computational linguistic, released in 2016 [34]. The corpus includes 61,045 tokens. The population of the corpus being compiled from scientific text is similar to the LSC. However, sampling of SciCorp differs from the LSC as being restricted to two disciplines. Apart from sampling principals and the size of corpus, one other difference of SciCorp from the LSC lies in the type of texts: full-text in SciCorp and abstracts of scientific papers in LSC.

The Reuters-21578 corpus (Reuters-21578 Text Categorization Collection) is a collection of 21,578 news documents used for text categorisation [37]. It contains

news appeared in 1987 with categories. The main differences between the Reuters corpus and the LSC is genre of texts: Reuters corpus contains texts of news while LSC contains abstracts of scientific publications. The LSC is more than 70 times as large as the Reuters corpus.

The *GENIA corpus* is similar to the LSC in terms of the content of texts, both contain the abstracts of scientific papers [38]. The GENIA corpus is built by annotating abstracts with keywords (MeSH terms) Human, Blood Cells and Transcription Factors. 2,000 abstracts are selected for a research objective in Biological and Clinical domains. LSC was created without research area restriction and contains 700 times more abstracts from different research areas.

The *DBpedia abstract corpus* contains 4,415,993 texts of the introductory section of Wikipedia articles, these sections may not necessarily be scientific writing [39]. As introductory section of Wikipedia articles are not actual abstracts of papers, the average length of documents are different than average length of abstracts: 178 words for the LSC and approximately 524 words for the DBpedia.

3.2. English Dictionaries

One question that can not be easily answered in dictionary design is whether there is an exact count of the number of English words. The major reason for this issue lies in the dynamic nature of languages. It is comonly accepted that languages change rapidly with cultural and technological evalution, and adoption from other languages [40]. For instance, the Oxford English Dictionary has recently added 'satoshi' (the smallest unit of a bitcoin), 'yeesh' (expressing exasperation, annoyance, disapproval) and 'simit' (a type of ring-shaped bread roll originating in Turkey) to its database in 2019 [41, 42, 43]. Another consideration on counting the number of words is that what words a dictionary includes. For example, a dictionary would include all technical terms, scientific entries or slang; all of the inflected form of a word (e.g. listen, listening etc.); plurals of words as separate word; or compounds which is made up two words. Therefore, the simple question 'what exactly is a word?' turns out to be surprisingly complicated. Some dictionarymakers agree that different versions of words should be counted only once, while some others consider each form as a separate word [44]. This means that there may be unlimited number of words in writing and spoken English, which do not appear in any dictionary.

Although it is not possible to know exact number of words in English, the estimate has been given roughly one million words (ranging from half a million to over two million) – including names of chemicals and scientific terms– in vocabulary [45, 46]. Many of these words are too rarely used, so it is expected that they do not appear in any English dictionary. One of the most well-known and commonly used dictionary Oxford English Dictionary (OED) includes over 600,000 words recorded in 20-volumes [47]. The dictionary provides both present days meaning of the words and the history of words from the across of English speaking countries. In addition to the print edition, the dictionary is available online [48]. Similar to the OED, the Webster's Third New International Dictionary contains over 470,000 entries [45, 49]. Another Oxford dictionary so-called New Oxford Dictionary for Writers and Editors is built to guide writers, editors, journalists and everyone who works with words [50]. It includes 25,000 words and phrases with providing advice

on spelling, capitalisation, specialist words and cultural context such as names, mathematical symbols, chemical elements. The Oxford Learners's Dictionary of Academic English (OLDAE) is also supplied by Oxford University Press with over 22,000 words based on the OCAE [51]. The aim of the dictionary is to help students particularly in academic English writing. As an example of specialised dictionary, Stedman's Medical Dictionary contains more than 107,000 terms with images (including abbreviations and measurements) in medical references in its 28th edition [52, 53]. It is designed to provide language of medicine, nursing and health profession to medical students, researchers, physicians and many more medical language users. Finally, we paid attention to the work of AWL and NAWL as they are classics as academic word list [15, 14]. The AWL includes 570 word families from the collection of written academic texts distributed across the four main disciplines: arts, commerce, law and science. It covers 86% of the total words in the corpus when combining with GSL. Similarly, NAWL contains 963 word families based on an up-to-date corpus of academic texts. NAWL-NGSL covers 87% of new corpus. The more detailed explanation is given in the Section 7.

Although the estimation of number of words in a language is not a easy task and numbers of words in dictionaries vary differently depending on the content of the dictionary, a corpus-based analysis may give a sight to understand the average number of words for a vocabulary. Let us consider Oxford English Corpus and Oxford English Dictionary with base forms of words (lemmas). It is stated in [54] that 25% of all words used in OED is one of lemmas: the, be, to, of, and, a, in, that, have and I. These are the most common 10 lemmas in English. In similar way, the most common 100 and 1,000 lemmas account for 50% and respectively 75% of all words used in OEC. To cover 90% of the corpus, one needs 7,000 lemmas. 95% of the corpus includes approximately 50,000 lemmas which words in between occur very rarely (e.g. only once every several million words). To cover 99% of the corpus, we need a vocabulary of over 1 million lemmas. In that case, many words may appear only once or twice in entire corpus (e.g. specialised technical terms), but lemmas will be representative of the whole corpus. To represent notable part of English, 90-95% of the corpus may be taken as a reasonable number.

4. Leicester Scientific Corpus (LSC)

Leicester Scientific Corpus (LSC) is a collection of abstracts of articles and proceeding papers published in 2014 and indexed by the Web of Science (WoS) database [6]. Each document contains the text of abstract and the following metadata: title, list of authors, list of categories, list of research areas, and times cited [8, 9, 10]. The corpus comprises only documents in English. The LSC was collected in July 2018 and contains the number of citations from publication date to July 2018.

We describe a *document* as the text of abstract with metadata listed above. The total number of documents in LSC is **1,673,824** [7]. All documents in LSC have non-empty abstract, title, categories, research areas and times cited in WoS databases. There are 119 documents with empty authors list, we did not exclude these documents.

4.1. Corpus Construction

This section describes all steps in order for the LSC to be collected, cleaned and made available to researchers. Data processing consists of four main steps:

- 4.1.1. Step 1: Collecting the Data. The dataset is downloaded online by exporting documents as tab-delimited files, so all documents are available online. The data are extracted from Web of Science [6]. You may not copy or distribute the data in whole or in part without the written consent of Clarivate Analytics¹
- 4.1.2. Step 2: Cleaning the Data from Documents with Empty Abstract or without Category. Not all papers have abstract and categories in the collection. As our research is based on the analysis of abstracts and categories, preliminary detecting and removing inaccurate documents were performed. All documents with empty abstracts and documents without categories are removed.
- 4.1.3. Step 3: Identification and Correction of Concatenated Words in **Abstracts.** Traditionally, abstracts are written in a format of executive summary with one paragraph of continuous writing, which is known as unstructured abstract. However, especially medicine-related publications use structured abstracts. Such type of abstracts are divided into sections with distinct headings such as introduction, aim, objective, method, result, conclusion etc.

Used tool for extracting documents leads to concatenated words of section headings with the first word of the section in abstracts. As a result, some of structured abstracts in the LSC require additional process of correction to split such concatenated words. For instance, we observe words such as ConclusionHigher and ConclusionsRT etc. in the corpus. The detection and identification of concatenated words cannot be totally automated. Human intervention is needed in the identification of possible headings of sections. We note that we only consider concatenated words captured in headings of sections in medicine-related papers as it is not possible to detect all concatenated words without deep knowledge of research areas. Identification of such words is done by sampling of medicine-related publications. The section headings in such abstracts are listed in Table A.1.

In headings of a section, the words usually start with a capital letter and end with a colon, unless there is typographical error in an electronic material. The words following a heading word (or a colon) also start with a capital letter in structured abstracts. We take these properties into consideration while detecting concatenated words.

All words including headings in the Table A.1 are detected in the entire corpus, and then words are split into two words. For instance, the word ConclusionHigher is split into Conclusion and Higher.

4.1.4. Step 4: Extracting (Sub-setting) the Data Based on Lengths of Abstracts. After correction of concatenate words is completed, the lengths of abstracts are calculated. Length refers the total number of words in the text, calculated by the same rule as for Microsoft Word word count [55]. An abstract is a short text that is written to capture the interest of a reader of the paper. Thus, abstracts briefly describe and summarise the work and the findings usually in one paragraph of words, but very rarely more than a page.

According to APA style manual [56], an abstract should contain between 150 to 250 words. However, word limits vary from journal to journal. For instance, Journal of Vascular Surgery recommends that Clinical and basic research studies must include a structured abstract of 400 words or less [57].

 $^{^{1}}$ Use of the LSC is subject to acceptance of request of the link by email. To access the LSC for research purposes, please email to ${\tt ns4330le.ac.uk}$ or ${\tt suzenneslihan@hotmail.com}.$

In LSC, the length of abstracts varies from 1 to 3,805. We decided to limit length of abstracts from 30 to 500 words in order to study documents with abstracts of typical length ranges and to avoid the effect of the length to the analysis. Documents containing less than 30 and more than 500 words in abstracts are removed. Figure 1 shows the distribution of lengths over documents of LSC before and after removing documents containing less than 30 and more than 500 words.

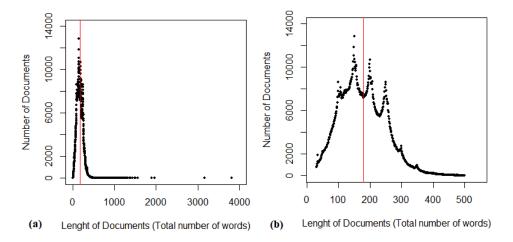


FIGURE 1. Length distribution of documents (a) before and (b) after removing documents containing less than 30 and more than 500 words (maximum length was 3,805 before removing). The vertical line shows the average length.

Four main peaks observed on the length graph: at 100 words, 150 words, 200 words and 250 words. The second peak shows the maximum number of documents, where those observed when the number of words in an abstract is 150. This result is expected as typically word limits range from 150 to 250 words for an abstract.

After the process of correction and cleaning, the database contains of raw texts of abstracts with title, list of authors, list of categories, list of research areas, and times cited. The total number of documents is 1,673,824 in LSC (see Table 4.1).

Table 4.1. Number of documents before and after cleaning documents with empty abstracts or without category, and after removing too short and too long abstracts.

# of Do	ocuments
Original data	1,727,464
After cleaning documents with empty abstracts or without category	1,681,469
After removing too short and too long abstracts	1,673,824

4.2. Organisation of the LSC

In LSC, the information is organised with one record on each line and parts of List of Authors, Title, Abstract, Categories, Research Areas, Total Times cited, and Times cited in Core Collection is recorded in separated fields [7]. Table B.1 demonstrates the structure of a document in LSC.

The Categories field contains the list of the subject categories where the document is assigned to [8]. Each document in LSC is assigned to at least 1 and at most 6 categories. There are totally 252 categories in the corpus. The full list of categories are presented in Table C.1 and [7].

The Research Areas field consists of the list of research areas described as a subject categorisation scheme in WoS database [9]. Each category is mapped to one research area in the WoS collection. There are totally 151 research areas in the corpus. The full list of research areas is presented in Table D.1 and [7].

Total Times Cited consists the number of times the paper was cited by other items from all databases within Web of Science platform. A paper can appear in multiple databases indexed in Web of Science collection. The citation indexes in WoS are: Web of Science Core Collection, BIOSIS Citation index, Chinese Science Citation Database, Data Citation Index, Russian Science Citation Index and Sci-ELO Citation Index. Duplicate documents across multiple databases is counted only once [10].

Times Cited in Core Collection is the total number of times the paper cited by other papers within the WoS Core Collection. The citation indexes in Core Collection are: Science Citation Index Expanded, Social Sciences Citation Index, Arts and Humanities Citation Index, Conference Proceedings Citation IndexScience, Conference Proceedings Citation IndexSocial Sciences and Humanities, Book Citation IndexScience, Book Citation IndexSocial Sciences and Humanities, Emerging Sources Citation Index [10].

5. Leicester Scientific Dictionary (LScD)

This section presents the pre-processing steps for creating an ordered list of words from the LSC [7] and the description of *Leicester Scientific Dictionary (LScD)*.

LScD is an ordered list of words from texts of abstracts in LSC [11]. The dictionary is sorted by the number of documents containing the word in descending order. The dictionary stores 974,238 unique words, where abbreviations of terminologies and words with number are contained in. All words in the dictionary are in stemmed form of words. The LScD contains the following information: unique words in abstracts in the LSC, number of documents containing each word and number of appearance of each word in the entire corpus.

The number of documents containing a word is the number of the documents with the corresponding word. A word that appears multiple times in a document is counted once (binary representation for existence). Number of appearance of a word in the entire corpus is defined to be the total number of occurrences of a word in the LSC when the corpus is considered as one large document.

All words obtained after pre-processing steps are included in the LScD. The most frequent 20 words (frequency is calculated by the number of documents containing a word) are presented in Table 5.1.

Table 5.1. The most frequent 20 words in the LScD.

Word	Number of documents containing the word	Word	Number of documents containing the word
use	902,033	also	400,642
result	812,154	present	389,735
studi	723,827	increas	383,676
show	498,705	two	375,586
method	491,586	model	372,911
effect	476,757	signific	370,435
base	446,436	compar	355,381
differ	445,739	paper	346,514
can	441,512	time	344,817
high	402,737	perform	341,547

5.1. Processing the LSC and Building the LScD

The main challenge of using text data is that it is mess and not concretely structured. This means that a number of steps is needed to be taken to form the LScD. The initial step of building the dictionary is to convert unstructured text (raw corpus) into structured data. Structured data means highly organised and formatted in a way so the information contained can be easily used by data mining algorithms, mostly numerical data in relational databases [58]. There are different ways to pre-process text data and pre-processing steps should be described for each corpus individually. Decision taken and steps of processing for creation of LScD are described below. All steps can be applied for arbitrary list of texts from any source with changes of parameters and also to LSC to reproduce the dictionary.

5.1.1. Step 1: Text Pre-processing Steps on the Collection of Abstracts. Text pre-processing means to bring the text into a form of analysable for the task. This step is highly important for transferring text from human language to machine analysable format by data mining algorithms. As each task requires different procedures to process the text based on aim of the study, ideal pre-processing procedure of each task should be developed individually. We used standard pre-processing methods in text processing studies such as tokenization, stop word removal, removal of punctuations and special characters, lowercasing, removal of numbers and stemming as well as two non-standard pre-processing steps: uniting prefixes of words and substitution of words. In this section, we present our approaches to pre-process abstracts of the LSC.

(1) Removing punctuations and special characters: This is the process of substitution of all non-alphanumeric characters by space. We did not substitute the character - in this step, because we need to keep words like z-score, non-payment and pre-processing in order not to lose the actual

- meaning of such words. A processing of uniting prefixes with words are performed later.
- (2) Lowercasing the text data: Lowercasing is one of the most effective pre-processing step in text mining problems to avoid considering the same words like Corpus, corpus and CORPUS differently. Entire collection of texts are converted to lowercase.
- (3) Uniting prefixes of words: Prefixes are letters placed before a word to create a new word with different meaning. Words containing prefixes joined with character are united as a word. The list of prefixes united for this research are listed in Table E.1. The most of prefixes are extracted from [59]. We also added commonly used prefixes: e, extra, per, self and ultra.
- (4) **Substitution of words:** Some of words joined with in the abstracts of the LSC require an additional process of substitution to avoid losing the meaning of the word before removing the character -. Some examples of such words are z-test, well-known and chi-square. These words have been substituted to ztest, wellknown and chi-square. Identification of such words is done by sampling of abstracts from LSC. The full list of such words and decision taken for substitution are presented in Table E.2.
- (5) Removing the character -: All remaining character are replaced by space.
- (6) **Removing numbers:** All digits which are not included in a word are replaced by space. All words that contain digits and letters are kept for this study because alphanumeric characters such as chemical formula might be important for our analysis. Some examples of words with digits are co2, h2o, 1990s, zn2 and 21st.
- (7) **Stemming:** Stemming is the process of converting inflected words into their word stem. In this process, multiple forms of a specific word are eliminated and words that have the same base in different grammatical forms are mapped to the same stem. As stemming removes suffixes and reduces the number of words in corpus, this step results in uniting several forms of words with similar meaning into one form and also saving memory space and time [60]. For instance, the word listen is the word stem for listens, listened, and listening. All words in the LScD are stemmed to their word stem by R package [61].
- (8) **Stop words removal:** In natural language processing, stop words (including function words) are defined as words that are extreme common but provide little value in a language. Some common stop words in English are I, the, a etc. Such words appear to be of little informative in documents matching as all documents are likely to include them. There is no universal list of stop words. Stop words must be chosen for a given purpose. In our research, we used tm package in R to remove stop words [62]. There are 174 English stop words listed in the package. Full list of stop words in tm package can be found in Table F.1.
- 5.1.2. Step 2: Extracting Words from Abstracts. After pre-processing the abstracts of LSC, there are 1,673,824 processed plain texts for further analysis. All unique words in the processed texts are extracted and listed in the LScD.

5.2. Organisation of the LScD

The total number of words in LScD is 974,238. Unique words, the number of documents containing the word and the number of appearance of the word in the entire corpus are recorded on each line in separated fields.

The Word field contains unique words from the corpus. All words are in lowercase and their stem form. The list of words is sorted by the number of documents that contain words in descending order.

Number of documents containing the word is the number of documents containing the corresponding word in Word field. In this content, binary calculation is used: if a word exists in an abstract then there is a count of 1. If the word appears more than once in a document, the count is still 1. Total number of document containing the word is counted as the sum of 1s in the entire corpus.

A word can appear many times in the same document. Number of appearance of a word in the entire corpus is computed as the sum of appearance of the word in each document. The field contains how many times a word occurs in the corpus when the corpus is considered as one large document.

5.3. Basic Statistics in the LScD

Before moving on creation of a core dictionary LScDC from LScD, we investigated basic statistics of LScD. The Table 5.2 shows the number of the rarest words over documents, where words appear in at most 20 documents. For instance, there are 592,161 words contained in only 1 document in the corpus. This distribution is also presented for all words in the Figure 2. As expected, very few words occur very often, there is a larger number of mid-frequency words and very many words occur very rare in the collection. This is a typical property of text data and the distribution of words in texts [63].

5.4. Decision Taken for Rare and Frequent Words

5.4.1. Traditional Approaches to Rare and Frequent Words

In most studies on text classification and information extraction, it is common to discard rare words in order to improve the performance of methods. The idea of the usability of rare and frequent words for discriminating texts dates back to Luhns idea [64]. He proposed a model to automatically generate the abstract by extracting the most representative sentences among all the sentences in an article. To select those sentences, a measure of information based on an analysis of words in sentences is used. It is assumed that the word occurrence in an article can be used to compile a set of significant word, and the frequency of such significant words within sentence reflects the significance of sentence in the text. According to Luhn, rare and frequent words in a text do not contribute much to the content of the text. Luhn stated that only words between two cut-offs, middle frequency words, can be determined as significant words for the text.

Besides extraction of significant words in an article, such an analysis can be also applied to the collection of documents to extract the most significant words to discriminate articles across the collection. In other words, significant words can be extracted on a corpus basis rather than a per-document basis. Luhns original

Table 5.2. The number of documents and the number of words contained in the corresponding number of documents only for those words appearing in at most 20 documents.

Number of Documents	Number of Words Contained in the Corresponding Number of Documents Only	Number of Documents	Number of Words Contained in the Corresponding Number of Documents Only
1	592,161	11	5,605
2	118,989	12	4,912
3	54,193	13	4,268
4	32,032	14	3,689
5	21,624	15	3,385
6	15,554	16	2,971
7	11,877	17	2,752
8	9,384	18	2,522
9	7,709	19	2,253
10	6,492	20	2,161

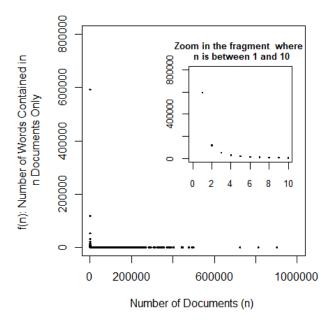


FIGURE 2. The number of documents (n) versus the number of words contained in n documents only.

idea of counting frequencies can be used to provide weighting to words in order to discriminate documents in a collection. Following to this, it is showed that words appearing in low number of documents and words appearing in high number of documents are not good discriminators across the collection in [65]. They verified Luhns conclusion that words with middle frequency are the best discriminator, and words occurring in between 1% and 90% of texts have the highest discriminatory power across the collection. Pruning rare and frequent words is followed by many researchers in text categorisation tasks as it is a common belief that they are not good discriminators of classes [66].

However, as noted in [67] common words (or frequent words) contribute to the text categorisation contrary to a common belief that the removal of frequent words improves the performance of information retrieval methods. In their study, stop words are discarded before evaluation of the performances. They also examined another common assumption that rare words are informative and should not be removed; and concluded that words appearing in less than some pre-determined number of documents (up to 90% or more unique words) can be removed with either an improvement or no loss in the accuracy of text categorisation models. Similar conclusion is obtained for clustering in [68]. They investigate the side effect of vocabulary size to clustering algorithms. The results show that keeping frequent words leads to an improvement on the performance of models in general, while rare words can be removed without loss on the performance. It is also worth to mention that the score that is used to evaluate mutual information is almost 0 when using only words with 1 occurrences in the corpus. Similar results are observed in [69] for their scoring measure where rare words skew the distribution of score defined. A minimum threshold of 10 is used in our study to mitigate this issue.

In information retrieval systems, a common belief among researchers is that both frequent and rare words can be important for a specific field. However, the extraction of words from these two classes should be done by using two criteria not one as their distributions are different in specific areas [70]. Rare words can be topic-specific words and extracted by analysing their co-occurrence in the academic domain. It is stated that a rare word will be a topic-specific word if it is related to a huge number of other possible topic-specific words or words that are considered as informative with a large weight defined [71]. In [72], it is reported that most of rare words that are generally discarded in standard information extraction tasks can be topic-specific words in medical abstracts. They stated that even the frequency of 5 is too high for extraction of informative words in medical abstracts but words appearing only once is needed to be removed in information based statistical models [70, 71, 72].

5.4.2. Characteristics of Words in the LScD and the Decision Taken

In practice, word selection strategy is fundamentally important for different text processing tasks since it determines the space of words that can be obtained from the texts and be effectively used for a specific task. Differences in types of corpora must also be considered as a complementary effect in the selection of words. In order for the differences between rare/frequent words importance in two corpora to be explainable, corpora should be comparable by sampling in the same way. For example, it is natural to expect that frequent words of a topic-specialised corpus are different from frequent words appearing in a general corpus where its texts are from a wide variety of different domains. For information extraction problems, frequent words in a topic-specialised corpus are likely to be extracted as content words while such words can be assessed as non-informative in a general corpus. As mentioned

before, 5 occurrences of a word in a topic specific corpus (e.g. medical abstracts) may be too high when compared with a general corpus of the same size. However, one can find that words with 5 occurrences are useless for text categorisation tasks due to its score in probabilistic models (e.g. entropy).

Essentially, rare words fall into two classes: those which are rarely used in the corpus and those which are misspelling. There are several reasons for the first class. It may be because it is used very uniquely like names referring people, places, brands or products. Rare words may also refer infrequent usage or synonyms of words. Similarly, shorten version and abbreviations of words can cause a huge number of rare words. Particularly, those who use corpus containing texts from medical or chemistry domains will tend to see huge number of shorten words, abbreviations and also chemical formulas. The second class of rare words involves words that are misspelled in the writing. Especially, such words is one of the main factor contributing the number of words occurring once in large corpora. As one would expect, a list with all correctly spelled words would not be realistic, especially for a large corpus. In [73], it is predicted that 38% of 42,340 words, from a collection of life science abstracts, are misspellings. For both classes of rare words, one needs to be careful about removing them. The decision of cut-off for rare words should be determined individually for each corpus depending on the characteristic of the corpus such as type and size.

Therefore, a natural question arises: what is the optimal cut for rare words in LSC? A simple initial characterisation is taken into account. As mentioned before, LSC is a collection which texts are from 252 different categories. Two expected consequences of this fact are: the identification of informative rare words for text categorisation by using their co-occurrences with other words of the corpus is not reasonable for our case; and it is very likely to observe words occurring only once in the corpus. The first consequence is caused by the fact that two rare words that used in texts from two well-separated categories will tend to be associated with each other due to co-occurrence of these words with the same subset of other words. In the case that the subset of related words has a large weight in terms of containing informative words but one of rare words is actually not informative, the selection of this rare word will be biased on the other one. When considering the large size of LSC, having a large number of categories has also a side effect: many misspellings and unique names. In fact, approximately 60% of words appear in only 1 document in LSC (Table 5.2). Casual observation of words showed that many of them are non-words or not in an appropriate format to use (e.g. misspellings); therefore, they are likely to be non-informative signals (or noise) for algorithms. Some examples of such cases in LSC for randomly selected rare words are presented in Table 5.3. Our basic assumption is that too rare words are not informative for text categorisation, or not effective in the performance of methods.

In order to mitigate this issue, we set a minimum cut (10) so that words appearing in less than the cut-off will not be included in further analysis. There is no trivial way to decide the optimal cut. We took decision that the threshold which is not too low or high to be able to keep a reasonable number of words for analysis under the assumption that rare words can be relatively informative and they should not be removed aggressively [67]. The criteria, removing rare words to improve the performance of information-based text categorisation methods, is taken into

Table 5.3. Some of rare words in LScD with the number of documents containing them. The last column shows the description of the word provided by checking the papers containing the word in WoS database, and possible reason why it is rare.

Word	Number of documents containing the word	Description of the word and possible reason why it is rare	
luhman	4	An author name	
lazerian	5	An author name	
goodluck	2	A name (President Goodluck Jonathan)	
hansel	5	A name (a name in fairy tale Hansel and Gretel and an authors name)	
masculina	8	A marine specie: Appendix Masculina (Latin name)	
heterocop	1	A freshwater specie: Heterocope Borealis (Latin name)	
lunac18(2)	1	A term in Chemistry	
wr3	3	A term in Agriculture (a water regime)	
gausian	3	Misspelling- Gaussian	
antilmog	1	Misspelling in the database: AntiLMOG (correct writing in the paper is anti-MOG.	
acetosa	10	A plant specie Rumex Acetosa (another usage is sorreal appearing in 13 documents)	
ansdic	1	An abbreviation for Ammonium Nitrate and Sodium Salt of Dichloroisocyanuric	
18cm	10	Non-word	
000009sl	1	Non-word (from the expression DW=0.000009SL(3.047))	
limite	8	French word	
resultan	1	1 French word	
resultadoscon	1	Spanish word with error: ResultadosCon (resultado means result in English and appears 90 times in the LSC)	

account with an attention to have a noticeable impact on size of dictionary and results.

The Figure 3 shows the number of words contained in the corresponding or less number of documents. To explore the fragment where words are very rare, we generate an enlarged view on a fragment in the Figure 4. For instance, there are 592,161 words containing in only 1 document and 711,150 words containing in 2 or

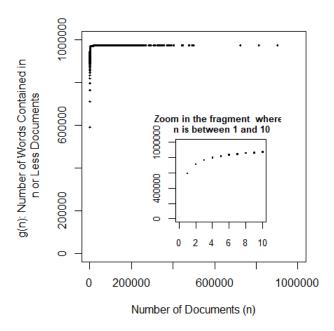


FIGURE 3. The number of documents (n) versus the number of LScD words contained in n or less documents in the LSC.

1 documents. We can conclude from the figures and Table 5.2 that 870,015 words out of 974,238 words in LScD are contained in 10 or less than 10 documents, thus, it is reasonable to consider such words as non-informative signals in the corpus of 1,673,824 documents and can be removed from the dictionary for further analysis. If such words are removed from the dictionary, the number of words becomes significantly reduced from 974,238 to 104,223. Note that we did not exclude any frequent words in this stage as stop words are already removed in pre-processing steps.

Figure 5 and 6 present the normalised number of words contained in the corresponding (n) or less number of documents. The data are normalised using (maximum-number of words) on y-axis. This means that the plot shows the number of words appearing in more than n documents against these numbers of documents. We observe more or less a negative relationship on a logarithmic scale. However, a remarkable pattern emerges: the plot does not follow a single straight line which fits the data. Instead, the plot starts with a linear behaviour, and a curve is observable in the right tail of the distribution, which follows a Pareto distribution behaviour. Pareto originally purposed that the number of people with incomes higher than a certain limit follows a power law [74, 75, 76, 77, 78]. The Pareto principle is also known as 80-20 rule. The rule states that 80% of people's income is held by the top 20% of income recipients in the society. Such characteristic of the distribution is also very typical property for the distribution of words over documents in text data. Under Pareto principle, the number of words appearing in more than n documents can be modelled as a power law:

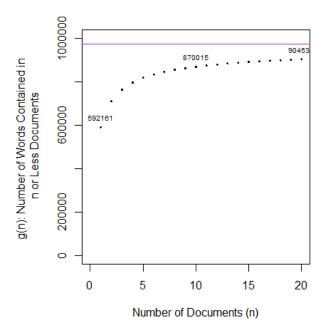


FIGURE 4. The number of documents (n) versus the number of LScD words contained in n or less documents in the LSC for those words appearing in at most 20 documents. The horizontal line indicates the number of words in the dictionary (974,238).

$$N_x = \frac{\beta}{x^{\alpha}} \tag{1}$$

where N_x is the number of words, x is a certain documents limit and α and β are constants.

A more general description of the Pareto principle is stated by Pareto distribution. Pareto distribution is a two parameter distribution to fit the trend that a large portion of data is held by a small fraction in the tails of distribution (heavy-tailed distribution) [79]. The distribution is characterised by a shape parameter α and a location (scale) parameter x_m . The tail function and the cumulative distribution function of a Pareto random variable X are given by [80, 81]:

$$P(X > x) = \begin{cases} (\frac{x_m}{x})^{\alpha} & x \ge x_m \\ 1 & x < x_m \end{cases}$$

and

$$F(X) = \begin{cases} 1 - (\frac{x_m}{x})^{\alpha} & x \ge x_m \\ 0 & x < x_m \end{cases}$$

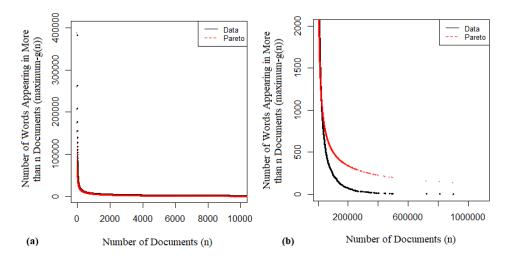


FIGURE 5. The number of documents (n) versus the number of LScD words appearing in more than n documents in the LSC for (a) n < 10,000 and (b) $n \ge 10,000$. The y-axis is calculated by normalising g(n) to the maximum (maximum-g(n)), where g(n) is the number of words contained in n or less documents. The black points are the data; the red points are the fitted Pareto distribution.

where x_m is the (necessarily positive) minimum value of X (the lower bound of the data). The density function is defined as

$$f_X(x) = \begin{cases} \frac{\alpha x_m^{\alpha}}{x^{\alpha+1}} & x \ge x_m \\ 0 & x < x_m \end{cases}$$

For $0<\alpha\leq 1,$ the distribution is heavy-tailed and the right tail becomes heavier as α decreases .

In Figure 6, power-law behaviour in the upper tail is well documented. The Pareto distribution (Equation 1) is fitted to the data and resulting graphs are also shown in Figure 5. Table 5.4 presents the estimated parameters and the mean squared error (MSE).

Table 5.4. Estimated parameters of Pareto distribution and the Mean Squared Error (MSE) for LScD.

α	β	MSE
0.5752	388,756	25188

If the logarithm of the number of words appearing in more than a certain number of documents is plotted against the logarithm of these numbers of documents, a straight line (see Figure 6 (b)), where the slope is α , is obtained. α is also known as *Pareto index*.

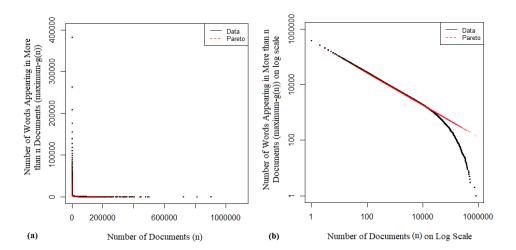


FIGURE 6. (a) The number of documents (n) versus the number of LScD words appearing in more than n documents in the LSC for whole data (b) The same plot on logarithmic scales. The y-axis is calculated by normalising g(n) to the maximum (maximum-g(n)), where g(n) is the number of words contained in n or less documents. The black points are the data; the red points are the fitted Pareto distribution. In (b), the slope of the line is -0.5752.

Due to the characteristic of the data, the log-log plot presents a noisy and diffused behaviour in the upper tail. This is actually because 81 observations fall in the interval 1-100 on y-axis, while there are 5,453 observations lying in the interval 10,000-1,000,000. However, on the logarithmic scale, the size of intervals 1-100 and 10,000-1,000,000 are the same, this leads to a diffusion in the tail. From a heuristic point of view, the plot suggests that there are three subset of words in the collection: too rare words, mid-frequent words and frequent words. A straight down-sloping line covers words the largest part of the list, in which words are not too rare and frequent. It is not actually surprising as words occurring in a few or almost all documents tend to be more evenly diffused across the corpus.

6. Leicester Scientific Dictionary-Core (LScDC)

Leicester Scientific Dictionary-Core (LScDC) is an ordered sub-list from existing LScD [12]. There are 104,223 unique words (lemmas) in the LScDC. To build the LScDC, we decided the following process on LScD: removing words that appear in not greater than 10 documents (\leq 10). As mentioned before, such words do not contribute much to discrimination of texts as they appear in less than 0.01% of documents. Ignoring these words has the advantages on the reducing the size of words for applications of text mining algorithms. The core dictionary is also sorted by the number of documents as in LScD.

Table 6.1 summarizes the number of words before and after removal. 870,015 words are removed from the LScD, that is, around 89% of words are removed. After removing such words, we also re-check the number of words in each document to affirm that all abstracts have at least 3 words. We note that in this stage the

TABLE 6.1. Number of words before and after removing words appearing in not greater than 10 documents in the LSC.

	Number of Words
LScD	974,238
LScDC	104,223

number of words in an abstract does not indicate the length of the abstract but the number of unique content words from the LScDC. After removing 870,015 words from the pre-processed abstracts, all documents have at least 3 unique words. None of documents are removed in this stage.

6.1. Organisation of the LScDC

In the LScDC, unique stemmed words, the number of documents containing the word and the number of appearance of the word in the entire corpus are recorded on each line in separated fields in the same way as for the LScD [11, 12].

6.2. Chracteristics of Words in the LScDC

After cleaning words appearing in not greater than 10 documents, the distribution of words over documents is presented in Figure 7. As one can expect, we observe the same behaviour here that very few words occur very often, very many words occur very rare in the collection.

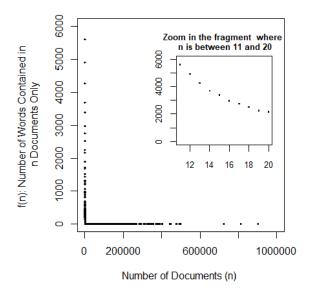


FIGURE 7. The number of documents (n) versus the number of LScDC words contained in n documents only after cleaning words appearing in not greater than 10 (\leq 10) documents.

The Figure 8 and Figure 9 show the number of words contained in the corresponding or less number of documents with and without rescaling the x-axis. We can conclude that approximately half of words occur in less than 30 documents.

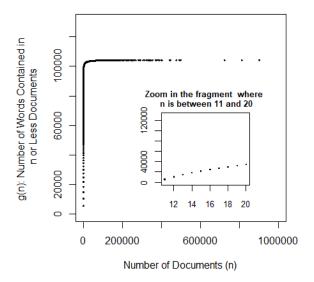


FIGURE 8. The number of documents (n) versus the number of LScDC words contained in n or less documents in the LSC after cleaning words appearing in not greater than 10 (< 10) documents.

Figure 10 demonstrates the normalised number of words contained in the corresponding or less number of documents after removing words appearing in not greater than 10 documents. The data are normalised using (maximum-number of words) on y-axis as in Figure 6. As expected, noisy behaviour in the lower tail is avoided. A downward linear trend is observable at the beginning and a curve is present in the upper tail. From a heuristic point of view, words can be group into two subsets: mid-frequent words and frequent words.

The plots in Figure 10 reveals power-law behaviour (Pareto distribution) in upper tail of documents distribution, but apparently not for the lower tail as expected. The estimated parameters by fitting the power-law (Equation 1) to the data is presented in Table 6.2.

Table 6.2. Estimated parameters of Pareto distribution and the Mean Squared Error (MSE) for LScDC.

α	β	MSE
0.5796	397,707	10737

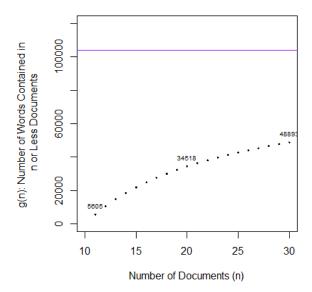


FIGURE 9. The number of documents (n) versus the number of LScDC words contained in n or less documents in the LSC (for those words appearing in at most 30 documents) after cleaning words appearing in not greater than $10 (\leq 10)$ documents. The horizontal line indicates the total number of words in the dictionary (104,223).

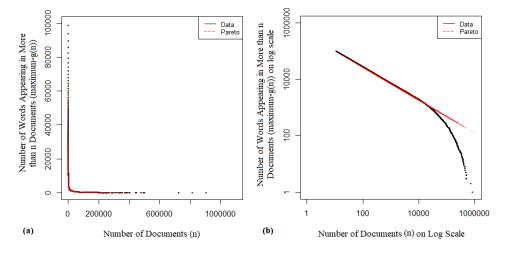


FIGURE 10. (a) The number of documents (n) versus the number of LScDC words appearing in more than n documents in the LSC for whole data (b) The same plot on logarithmic scales. The y-axis is calculated by normalising g(n) to the maximum (maximum-g(n)), where g(n) is the number of words contained in n or less documents. The black points are the data; the red points are the fitted Pareto distribution. In (b), the slope of the line is -0.5797.

7. A COMPARISON OF LScDC AND NAWL

This section provides a comprehensive study of comparison of the NAWL and the LScDC. Several different approaches are taken into account based on direct comparison of words and comparison of ranks of words in two dictionaries.

7.1. Academic Word List (AWL) and New Academic Word List (NAWL)

Academic word list (AWL) is developed from a written academic corpus with 3.5 million running words [15]. The corpus is gathered from four discipline specific sub-corpora: arts, commerce, law and science with a seven sub-disciplines for each (see Table 7.1). Each sub-corpora has approximately 875,000 running words. The list of words is collected from a total of 414 academic texts in the form of textbooks, articles, book chapters, and laboratory manuals.

Discipline Law Science Arts Commerce Education Accounting Constitutional Biology History **Economics** Criminal Chemistry Linguistics Finance Family and medicolegal Computer science Philosophy International Industrial relations Geography Politics Geology Management Pure commercial Psychology Mathematics Marketing Quasi-commercial Sociology Public policy Rights and remedies Physics 122 texts 107 texts72 texts 113 texts 883,214 words 879,547 words 874,723 words 875,846 words

Table 7.1. Corpus structure of the AWL.

A word family is defined as the collection of words that appears in various form of the same word (e.g. indicate and indication are in the same family). To select words, three rules are taken into account:

- Specialised occurrence: Academic list does not contain the General Service List (GSL) published by West [82], defined as the first 2,000 frequent words of English.
- Range: The number of appearance of a family member has to be at least 10 in each of main discipline, and 15 or more in 28 sub-disciplines.
- Frequency: The number of appearance of a family member has to be at least 100 in the academic corpus. Frequency is the secondary criteria for range.

AWL includes 570 word families. It covers 10% of the total words in academic texts. In addition, words in Wests GSL and words in AWL together (GSL/AWL) cover approximately 86% of total words in academic corpus. In Coxhead words, Academic words (e.g. substitute, underline, establish, inherent) are not highly

salient in academic texts, as they are supportive of but not central to the topics of the texts in which they occur.

The New Academic Word List (NAWL) is then created by [14] based on an updated and expanded academic corpus of 288 million words with modified lexemes. The corpus, which NAWL is created from, includes Cambridge English Corpus (CEC), oral academic discourse (Michigan Corpus of Academic Spoken MICASE and British Academic Spoken English BASE), and textbooks (Corpus of 100s topselling academic textbooks). From CEC, the frequency generated word list is used as one group. This made up the largest proportion of total tokens, about 86% (over 248 million words). The oral corpora and the corpus of textbooks are divided into four main categories: Arts and Humanities (AH), Life and Medical Sciences (LS), Physical Sciences (PS), and Social Sciences (SS). The number of tokens for each group in the corpus is presented in Table 7.2. The list is developed by the conjunction with New General Service List (NGSL) as in Coxheads GSL-AWL. NGSL is also created by [14], which is based on 273 million words from CEC academic.

Source		# of tokens
Cambridge English	Corpus (CEC)	248,666,554
	Arts and Humanities	803,113
Oral Discourse	Life and Medical Sciences	749,610
	Physical Sciences	686,926
	Social Sciences	852,990
	Arts and Humanities	6,082,267
Textbooks	Life and Medical Sciences	16,822,357
	Physical Sciences	4,467,629
	Social Sciences	9,044,779

Table 7.2. Corpus Structure of the NAWL.

NAWL contains of 963 word families. While combined GSL/AWL covers approximately 87% of the new corpus, the NAWL covers 92% of the corpus when combined with NGSL. Therefore, NAWL gives an improvement in coverage, with about 5% more coverage [13].

In the published list of academic words (NAWL), the authors computed the statistics SFI (Standard Frequency Index), U (Estimated Word Frequency per Million) and D (Dispersion) to describe the number of occurrence of the words and the distribution of words in their corpus. To illustrate the information given in the list, we present Table 7.3 that shows 10 words with statistics in the NAWL, ordered by SFI values [83, 84, 85].

D shows the uniformity of frequency of the word in subject categories of NAWL in a 0-1 scale: 0 means that the a word (all forms) appears in a single category, 1 means that frequencies are distributed over all categories proportianally to the total number of words (all inflected forms of words) in a category. U is the estimated frequency per million. It is derived form the frequency of the word in the corpus with an adjustment for D. SFI indicates frequency derived from U in a 0-100 scale. Higher scores of SFI show greater frequency [86]. A word family with SFI=90 occurs once in every 10 tokens (all words with different inflected forms in the corpus); a word with SFI=80 occurs once in every 100 tokens [83, 84].

Table 7.3. Sample words with highest SFIs from NAWL.

Word	SFI	U	D
repertoire	72.452	1759	0.5923
obtain	66.519	449	0.7531
distribution	65.665	369	0.6863
parameter	64.369	273	0.6943
aspect	64.190	262	0.9385
dynamic	63.506	224	0.8548
impact	63.491	223	0.9426
domain	63.467	222	0.8276
publish	62.897	195	0.9039
denote	62.571	181	0.7035

7.2. Difference Between the Principles in Preparetion of the LScDC and the NAWL

Both the NAWL and the LScDC are actually made up of academic texts distributed over multiple categories for building academic lists of words. In this manner, two lists seem similar. However, more detailed analysis shows that they differ one another in many respects such as types of texts where words are extracted (e.g. full-text or a part of the text), kind of words included, dictionary size and the statistics used to extract words.

Let us begin with corpora where two dictionaries are created. An obvious difference of corpora lies in the types of texts. As types of texts, we meant the NAWL having extracted from full-texts from academic domains and the LScDC having extracted from abstracts of articles. This is actually an important difference as there is side effect of word limit for an abstract such as the frequency of a word and the vocabulary used. In this case, it is likely to observe changes in the statistics calculated for each word and respectively the ranks of words. The change in statistics may lead to select different words as word selection in NAWL is based on frequency and range. One other difference between two corpora is that NAWL contains oral academic discourse as well as written texts while LSC includes only written academic English. This may have influence on the words listed as spoken and written English are often different in terms of vocabulary used.

It is worth to stress that the calculation of statistics for words in the NAWL and the LScDC are different. In the NAWL, words are selected based on SFI derived from frequency. The dispersion (D) of words over categories is calculated to adjust frequency in SFI calculation. However, in LScDC words are simply sorted by the number of documents containing words. The dispersion of words and SFI are both taken into account to select words in NAWL, not all words appearing in the corpus are included in the NAWL. This difference leads to firstly difference in ranking of common words in both dictionaries, secondly kinds of words and words selected and respectively the size of the dictionaries.

One of the major differences lies in the kind of words. According to the Coxhead, words in AWL are supportive of the academic text but not central to the topics of the text [15]. Words in AWL account for approximately 10% of the total words in the collection of academic texts. The AWL and GSL (general service list) together cover approximately 86% of total words in academic corpus. By updating this list with an expended corpus of 288 million words (NAWL), the coverage was improved to 92% of new corpus when combined with NGSL (New General Service Words), with approximately 5% improvement. By a casual observation of the NAWL, one can see the same property for words in the NAWL. Words in NAWL are not much specialised technical terms such as names of chemicals or names. In contrary, LScDC contains both supportive and topic-specific words such as mathematical terms, chemical elements, names, biological species and many more. As or aim is to quantifying meaning of research texts, we kept such words in LScDC.

Such differences in word selection also effected the size of dictionaries. As expected, the LScDC is much more larger than the NAWL, namely 963 word families in the NAWL and 104,223 lemmas in the LScDC.

7.3. Comparison of the LScDC and the NAWL

This section describes a study of comparison of the LScDC [12] and the NAWL. Our primary focus is on obtaining the coverage of NAWL by LScDC, and on analysing how the rank of words in both dictionary are related.

7.3.1. Coverage of the NAWL by the LScDC

One feature of NAWL is that words are listed by headwords of word families from combination of their derived forms. When comparing with LScDC, headwords with different inflected forms indicate the same stemmed word in LScDC (see Table 7.4). In order to examine the agreement between NAWL and LScDC, we processed stemming to headwords in NAWL. This process returns various forms of each headword into a common root as in LScDC. After stemming, words in NAWL are eliminated, with a decrease number from 963 to 895. Note that as SFIs of two headwords, having actually the same root, are different, we used the average of SFIs for unique stemmed words.

TABLE 7.4. Headwords and inflected forms in the NAWL, and stems of the headwords in the LScDC.

Headword in NAWL	Inflected Forms in NAWL	Stemmed Headword in LScDC
accumulate	accumulates, accumulated, accumulating, accumulatings	accumul
accumulation	accumulations	accumul
acid	acids	acid
acidic	acidics	acid

For purpose of comparison of dictionaries, stemmed words are used. Table 7.5 illustrates the comparison of dictionaries by showing the coverage of the NAWL words by the LScDC. The overlap between the LScDC and the NAWL is 99.6%, with 891 word occurring in both. This means 4 words occurring only in NAWL: ex, pi, pardon and applaus. The lower coverage of the dictionary seems to be the result of differences in types and processing of texts in corpora. The corpus of NAWL includes full texts from academic domain [15], while LSC is made up abstracts of texts in LSC.

Table 7.5. Coverage of the NAWL by the LScDC.

Number of Words in NAWL		Number of Words in NAWL (after stemming)	Coverage of NAWL by LScDC (#)	Coverage of NAWL by LScDC (%)
	963	895	891	99.6%

The reason why pi does not occur in LScDC lies in the nature of abstracts and also in the usage of this word in articles. It is commonly used by the symbol π (pi) in the math world, and not many articles include formulas in abstracts. Uniting prefixes with the following words is the reason that the word ex does not occur in LScDC. For instance, words such as ex-president and ex-wife are converted to expresident and exwife in pre-processing step. The other two words pardon and applaus are not included in LScDC. However, they occurred in LScD before removing words that appear in not greater than 10 documents, with very low occurrences in documents (5 and 9 respectively). Similarly, these two words have low ranks on the NAWL: rank 924 and rank 956 in the list.

We also evaluated different comparison scheme that is focused on a subtly different goal: to give an understanding about what fragment of LScDC contains the NAWL. This analysis performs a search of NAWL words over a specific subset of our rank ordered dictionary, repeatedly searching NAWL words in various subsets of the dictionary. Table 7.6 and Figure 11 show the coverage of NAWL in particular fragments of LScDC. From this perspective, we see that NAWL is covered in the first 89,351 (85.7% of all words) words of LScDC, where the frequency of 89,351th word is 14. Observe that when doubling the number of words from 40,000 to 80,000 there are only 8 more words found in LScDC. This means the majority of NAWL is contained in the first 38.4% of LScDC. The number of documents containing 40,000th and 80,000th words are 16 and 53 in the LSC. It is remarkable that in 10,000 words, the coverage of the NAWL is 90.9%, with a frequency of 572 in LSC. This may be considered that the NAWL is representative of our 10,000 words (9.6%) of LScDC). This partly supports that wide range of LScDC is constructed by more specific terminologies of academic disciplines. This is explainable given the variety of texts categories in corpus, differences in selection methods of words and the fact that abstracts have slightly different writing structure and words.

An alternative view of fragment comparison is to evaluate the last position of the words of a specific fragment of the NAWL in LScDC. Table 7.7 shows the fragment of NAWL and positions in LScDC. Both dictionaries are ranked by their frequencies: SFI for NAWL and the number of documents containing the word for the LScDC. We see that the first half of NAWL words is in approximately the first

TABLE 7.6. Coverage of the NAWL by the fragments of LScDC. The last column presents words of NAWL which are found between two fragments in LScDC.

Fragment of LScDC		Coveraş NAWI LScD	by	Words added between two fragment
#	%	#	%	Words
1,000	1.0%	231	25.8%	
5,000	4.8%	678	75.8%	
10,000	9.6%	814	90.9%	
15,000	14.4%	845	94.4%	
20,000	19.2%	860	96.1%	
25,000	24.0%	877	98.0%	
30,000	28.8%	879	98.2%	bizarr, terribl
35,000	33.6%	882	98.5%	comma,sneez,jazz
40,000	38.4%	882	98.5%	
45,000	43.2%	884	98.8%	sniff, handout
50,000	48.0%	888	99.2%	unintellig, cheer, footnot, ridicul
55,000	52.8%	888	99.2%	
60,000	57.6%	888	99.2%	
75,000	72.0%	889	99.3%	nasti
80,000	76.8%	890	99.4%	parenthesi
89,351	85.7%	891	99.6%	whoever

14% of LScDC. When the fragment of words in NAWL doubles, the position became around 5 times far from the first word in LScD. We see that there are 300 words lies between 10,967th and 14,017th words in LScDC (100-400), with an interval of approximately 4,000 words. This interval is around 9,000 for the next 200 words, and followed by an interval of 55,000 for the third 200 words. Thus, we conclude that there are dense regions of LScDC in terms of the coverage of NAWL.

7.3.2. Comparison of Ranks of Words in Two Dictionaries

Our second approach to compare two lists is based on the order of words. The goal is to examine whether the ranking of words (frequency-based sorting) in dictionaries are actually similar. Note that only common words in both dictionaries (891 words) are taken into account. Words in both lists are descending ordered by their ranks in corpora, which are the number of documents containing the word in LScDC and SFI in NAWL. Table 7.8 shows stemmed versions of top 10 words with corresponding statistics in two lists.

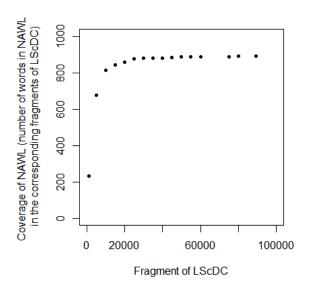


FIGURE 11. Coverage of the NAWL by the fragments of LScDC.

TABLE 7.7. Last position of the words of a specific fragment of the NAWL in LScDC. Both dictionaries are sorted by their frequencies defined.

Fragment of NAWL	Last position of words of NAWL in LScDC	Fragment of LScD (%)
100	10,967	10.5%
200	10,967	10.5%
300	10,967	10.5%
400	14,017	13.4%
500	17,212	16.5%
600	23,188	22.2%
700	78,492	75.3%
800	78,492	75.3%
891	89,351	85.7%

From an inspection of order of words, 7 words in the lists is in the same order in both dictionaries when LScDC is restricted by NAWL words. Such words are listed in the Table 7.9. Thus, the direct comparison of order cannot be used.

A new evaluation method is offered that focuses on pairwise comparison of partitions in dictionaries. The word lists are divided into smaller sub-lists, with the same number of intervals. We introduce an analysis that is focused on the overlapping words in intervals by counting the number of words in common. Within intervals, the common words are counted, and then the percentage of pairwise intersection of

Table 7.8. The top 10 words in stemmed form with corresponding statistics in lists. Blue coloured words are matches in the top 10 of two dictionaries.

Word in NAWL	SFI in NAWL	Word in LScDC	The number of documents containing the word in LScDC
repertoir	72.45	effect	476,757
obtain	66.52	compar	355,381
distribut	65.67	activ	255,630
paramet	64.37	observ	249,965
aspect	64.19	found	234,720
dynam	63.51	import	233,138
impact	63.49	indic	229,775
domain	63.47	demonstr	218,861
publish	62.89	obtain	218,578
denot	62.57	condit	205,643

TABLE 7.9. Words in the same order in both dictionaries. The LScDC is restricted by NAWL words, we ignore other words to compare raking of words in dictionaries.

Word	Order of word in the lists	Number of documents containing the word in LScDC	SFI in NAWL
acut	182	30,876	57.72
decay	368	12,761	55.66
horizon	543	4,897	53.83
portfolio	656	2,299	52.13
kilomet	778	872	49.14
cheat	844	310	46.02
handout	883	51	42.85

parts (total overlap) are considered to be the agreement of rating between LScDC and NAWL. As would expected, the larger width of intervals (small number of splits) yields the highest agreement of rating. The highest possible width is 891 (only 1 split) as there are 891 words in lists. To find the percentage of total overlap within intervals, the following statistical computation is done:

$$\frac{\sum_{i} n_i}{N_t}$$

where n_i is the size of intersection in ith interval, and N_t is the total number of words (891). We repeated the same calculation for different widths of intervals, with an increasing sequence 5, 10, 15, 890, 891. For instance, when the width is 5 the lists are divided into 179 intervals: 178 complete interval with 5 words, 1 shorter interval with 1 word. Figure 12 shows the fraction of the intersection in intervals with specified width. Observe that not in all cases lists are divided into equal intervals. For instance, the width 890 of interval means that there are two partitions with 890 and 1 words and so the comparison is not much meaningful in these cases. To avoid unbalanced classes, we consider only those number of intervals where partitions have almost equal widths. Figure 13 and Table 7.10 show the number of intervals selected and the width of intervals for these intervals. When the lists are divided into two intervals, the fraction of overlap is 0.73. Hence, 27% of words of a list do not lie within the same half of the other list. In addition, almost half of words are in different intervals when splitting the lists into 3 intervals, with approximately 300 words in each interval (300 words in two intervals and 291 words in one interval). Our findings raise the possibility that two lists are slightly different in terms of ranking words within lists.

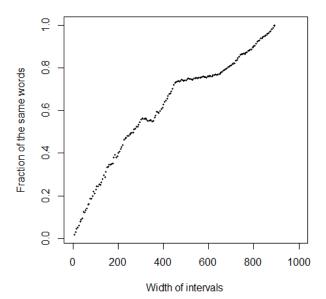


FIGURE 12. The fraction of the intersection of words in intervals with specified width.

7.3.3. Testing Similarity of Ranks in Two Dictionaries

The scatter plot suggests a positive correlation between frequencies in the LScDC and SFI values in the NAWL (see Figure 14). In order to test whether there is any

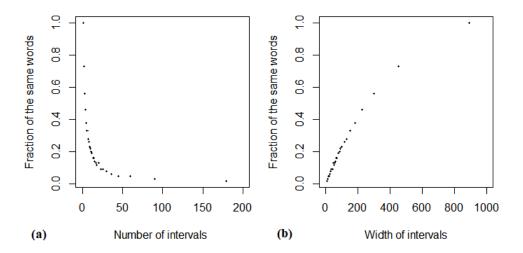


FIGURE 13. The fraction of the intersection of words in intervals with number of intervals and specified width. Figures present only those number of intervals and widths where partitions have almost equal widths (e.g. 2 intervals with approximately 450 words in each, 450 in one of intervals and 441 in the other interval).

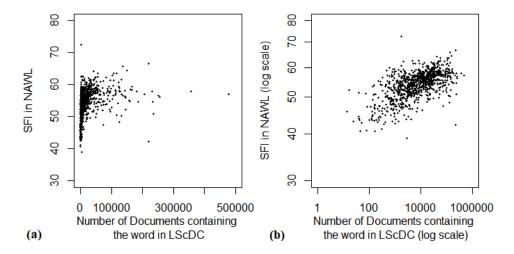


FIGURE 14. Relationship between the number of documents containing the word in LScD and SFIs in NAWL. The figure on the right hand side is on logarithmic scale.

or no evidence to suggest that linear correlation of ranks is present in two dictionaries, the Spearmans Rank Correlation (SRC) is used. Spearmans correlation coefficient is a statistical measure of the strength and direction of a monotonic association between two ranked variables. It is actually equal to Pearsons Correlation Coefficient (PCC) between two variables with ranked-values [87].

TABLE 7.10. The percentage of the overlapping of words in intervals with number of intervals and width of intervals.

Number of interval	Width of interval	Percentage of overlap- ping	Number of interval	Width of interval	Percentage of overlap- ping
179	5	1.8%	13	70	16.2%
90	10	2.9%	12	75	18.5%
60	15	4.5%	11	85	20.0%
45	20	5.1%	10	90	21.9%
36	257	6.2%	9	100	22.9%
30	30	8.0%	8	115	25.5%
26	35	8.6%	7	130	27.9%
23	40	9.3%	6	150	33.2%
20	45	12.6%	5	180	37.9%
18	50	12.2%	4	225	46.4%
17	55	13.2%	3	300	55.7%
15	60	14.1%	2	450	72.8%
14	65	15.8%	1	891	100.0%

For a sample size n, the Spearmans coefficient R_s is computed as:

$$R_s = \frac{1 - 6(\sum d_i^2)}{n^3 - n}$$

where d_i is the difference in the ranks of each variable pair [88].

In this study, the Spearmans correlation is calculated by assigning a rank of 1 to the highest value within each list, 2 to the next highest and so on. Figure 15 presents the relationship between ranks of words in lists. The correlation between words in two lists will be high when words have a similar rank within lists. The calculation of Spearman correlation for this study gives a value of 0.58 which confirms what was found in the comparison of ranks and what was apparent from the graph. There is indeed a moderate positive correlation between two lists, which are monotonically related. We also calculated the Pearsons correlation coefficient with frequencies and logarithmic scaled-frequencies, found 0.30 and 0.61 respectively (see Table 7.11). This is expected results because we did not observe a linear relationship of frequencies, but monotonic in Figure 14. However, the logarithmic scaled-frequencies show a linear relation.

7.3.4. An Alternative Comparison of Ranks of Words in Two Dictionaries

Finally, we perform another analysis that is focused on ranks of words, similar to the comparison of ranks by partitioning intervals. Here, common words in both dictionaries (891 words) are used for analysis as in the previous comparison of

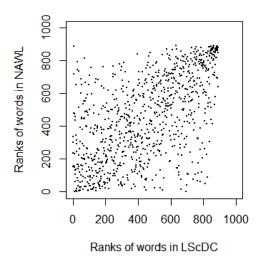


FIGURE 15. Relationship between ranks of words in lists (LScDC and NAWL).

TABLE 7.11. Correlation coefficients that measure the relationship between ranks of words in NAWL and LScDC: Pearsons Correlation Coefficient (PCC), Spearmans Rank Correlation (SRC) and PCC for logarithmic scaled frequencies.

Test	Test Statistics
PCC	0.30
SRC	0.58
PCC-log	0.61

ranks. The difference in this approach is the creation of intervals. Rather than dividing the whole lists into intervals, we consider the top n words by frequencies presented in dictionaries, where n=5,10,15,890,891. For instance, if n=5 we compare the first 5 words in dictionaries, where words are ordered by the number of documents containing the word for LScDC and SFI for NAWL. Figure 16 shows the number of overlapping of words in top words for specified top n words. Note that in the figures, words are in descending order by their frequencies in both dictionary. We see that there are only 2 common words in the first frequent 20 words of lists. In the top 100 words, this number is 25, which means 25% of words are common. This shows that the widely used words in corpora are slightly different. This may be result of the differences in calculations of statistics for words (the number of documents containing the word and SFI).

We repeated this analysis for ascending order of frequencies. In this case, we consider the bottom n words, where n=5,10,15,,890,891. Figure 17 shows the number of overlapping of words for specified bottom n words. We can see that the number of overlapped words for bottom is much more when comparing top words. There are 7 common words in the least frequent 20 words of lists and 50

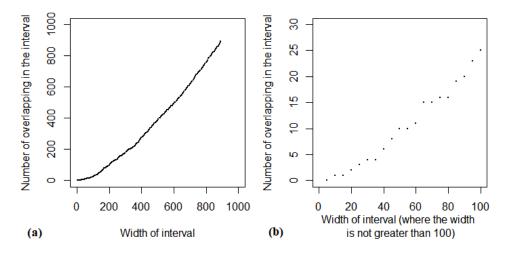


FIGURE 16. The number of overlapping of words in the top n words of the lists (width of interval) where n=5,10,15,,890,891. Lists are in descending order by their statistics provided (the number of documents containing the word and SFI). The figure on right hand side presents widths until n=100.

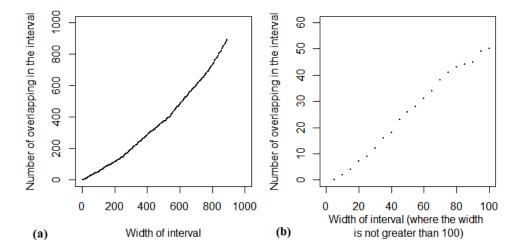


FIGURE 17. The number of overlapping of words in the bottom n words of the lists (width of interval) where n=5,10,15,,890,891. Lists are in ascending order by their statistics provided (the number of documents containing the word and SFI). The figure on right hand side presents widths until n=100.

common words in the bottom 100 words (50% of words). This means that there is an improvement in common words for the least frequent words. Dictionaries are more similar for bottom words.

8. Conclusion and Discussion

In this work, we presented Leicester Scietific Corpus (LSC), Leicester Scientific Dictionary (LScD) and Leicester Scientific Dictionary-Core (LScDC) with a description of the methodology and all steps in construction processes. Both the corpus and the dictionaries set out with the aim of quantifying the meaning in research texts in our future work.

LSC is a corpus of abstracts of academic articles and proceeding papers, where all papers are indexed by WoS and published in 2014 in English. It consists of 1,673,824 abstracts with the metadata: title, list of authors, list of subject categories, list of research areas, times cited. In 119 documents, list of authors are not present; however, we did not exclude them. The average length of abstract is 178 words (all words including stop words and different forms of words) with a minimum 30 and a maximum 500 words. Each paper in WoS is assigned to at least one of subject categories and research areas. The number of subject categories that a paper is assigned to vary from 1 to 6 in the LSC.

We then developed the LScD by extracting unique words (excluding stop words and various inflected forms of words) from the LSC. LScD is a scientific dictionary where all words are in stemmed form. It consists of 974,238 words; the number of documents containing each word and the number of appearance of each word in entire corpus are presented with the dictionary. Approximately 60% of words appear in only one document, followed by 72% for one or two documents. We observed that very few words occur very often, large number of mid-frequency words and very many words occur very rare (see Figure 2). This indicates the Pareto's distribution behaviour. Pareto's law originally stated that 'number of people with incomes higher than a certain limit follows a power law'. We can reword the law as 'number of words appearing in more than a certain limit of document (n) follows a power law' (heavy-tailed distribution). The Pareto distribution is fitted the data with the Pareto index 0.5752 (see Figure 5).

LScDC is a core dictionary built by sub-setting the LScD. We decided to remove too rare words under the assumption that they do not contribute to the text categorisation and are likely to have noisy behaviour in the algorithms. Such words also have impact on measuring of meaning in texts by using the probabilistic approaches such as information gain. They are given almost zero score in such approaches. Therefore, we set a cut-off (10) to remove all words (in LScD) appearing in not greater than 10 documents in LSc. After removal of words, we obtained the LScDC containing 104,223 unique words. Words in LScDC, similar to the LScD, are associated with the number of documents containing the word and appearance of the word in entire corpus.

Finally, we present a comprehensive analysis of LScDC by comparing with the NAWL. The NAWL is a list of academic words containing 973 word families. Our aim is to investigate how similar two lists are in terms of mainly matched words and the ranking of words. We applied many approaches based on both direct comparison of words and pairwise comparison of partitions of dictionaries in smaller subsets.

Identification of the NAWL words in LScDC shows that out of the 895 word families (after applying stemming to the NAWL words) in NAWL, 891 were found to be included in LScDC, indicating that the LScDC represents almost complete NAWL words. Four words which appear in only NAWL are "pi", "ex", "applaus" and

"pardon". These words did not appear in LScDC but in NAWL due to differences in pre-processing and types of texts in corpora.

The ranking positions of many words of NAWL words found in LScDC are slightly different from those in the NAWL itself. We hypothesize that this is due to the difference in calculation of statistics used to order words in lists. In NAWL, the ordering of words is based on both the frequency and the dispersion of words over categories (SFI), while LScDC words are ordered by the number of documents containing the word only. From the plot of frequencies of matched words (SFI against the number of documents containing the word), we observed a monotonic relationship of frequencies (see Figure 14). However, the log-log plot of matched words' statistics suggests a positive correlation between statistics (linear relationship). We tested this similarity of rankings by Spearsman's Rank Correlation (SRC), Pearson's Correlation Coefficient (PCC) with statistics given and PCC with logarithmic scaled-statistics. We found correlation coefficients of 0.58, 0.30 and 0.61 respectively. This was indeed an expected result as it is the same what we observed from plots.

We then perform an analysis on ranking positions of words by checking the overlap the top n words in the LScDC and the NAWL successively where n=5,10,15,...,890,891. We report that there are only 2 common words in the top 20 words of dictionaries, followed by 25 in the top 100 words. The same analysis was repeated for the bottom n words and found that there are 7 common words in the least frequent 20 words, followed by 50 common words in the bottom 100 words. From these findings, we conclude that the LScDC and the NAWL are more similar for least frequent words.

LSC is a multidisciplinary academic corpus of abstracts where the subject categories and citations are known. The dictionaries LScD and LScDC are scientific dictionaries where words are extracted from the LSC. This corpus and dictionaries will be used in a comprehensive research in quantification of meaning of research texts. The meaning of each word will be represented by an analysis of information on categories and areas of research that can be extracted from the appearance of this word in the text. Therefore, the next step will be measuring meaning in LSC texts and then using such measures in several data mining applications including prediction of success of the paper, categorisation of texts to pre-existing categories and clustering of texts into 'natural categories'.

LSC, LScD and LScDC are available online in [7, 11, 12].

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APPENDICES

APPENDIX A. TABLE OF HEADINGS OF SECTIONS IN MEDICAL ABSTRACTS

Table A.1. Headings of sections identified in structured abstracts.

	Headings of Sections				
Abstract Aim(s) Approach		Background	Conclusion(s)	Design	
Discussion	Finding(s)	Hypothesis	Introduction	Limitation(s)	Location
Material(s)	Measure(s)	Measurement(s)	Method(s)	Methodology	Objective(s)
Patient(s)	Population	Procedure(s)	Process	Purpose(s)	Rationale(s)
Result(s) Setting(s) Subject(s)		Theoretical			
Implication(Implication(s) for health and nursing policy				

APPENDIX B. AN EXAMPLE OF DOCUMENT STRUCTURE IN THE LSC.

Total Times Times Cited Cited in CC	24		
Total Times Cited	24		
Research Areas	Science & Technology - Other Topics		
Categories	Multidisci- plinary Sciences		
Abstract	Objective: Because reduction of the microtubule-associated protein Tau has beneficial effects in mouse models of Alzheimer's disease and epilepsy, we wanted to determine whether this strategy can also improve the outcome of mild traumatic brain injury (TBI). (truncated)		
Title	Tau Reduction Diminishes Spatial Learning and Memory Deficits after Mild Repetitive Traumatic Brain Injury in Mice		
Authors	Cheng, JS; Craft, R; Yu, GQ; Ho, K; Wang, X; Mohan, G; Mangnitsky, S; Ponnusamy, R; Mucke, L		

Table B.1. Structure of a document in the LSC.

APPENDIX C. LIST OF CATEGORIES.

Table C.1. The list of categories with the number of documents assigned to the corresponding category. There are 252 categories in the LSC.

No.	Category	Number of
110.		Documents
1	Engineering, Electrical & Electronic	174,305
2	Materials Science, Multidisciplinary	112,920
3	Physics, Applied	78,824
4	Chemistry, Physical	58,070
5	Chemistry, Multidisciplinary	55,919
6	Computer Science, Theory & Methods	55,596
7	Multidisciplinary Sciences	53,140
8	Engineering, Mechanical	50,972
9	Optics	47,776
10	Biochemistry & Molecular Biology	47,491
11	Computer Science, Information Systems	45,867
12	Energy & Fuels	44,202
13	Environmental Sciences	42,083
14	Computer Science, Artificial Intelligence	41,210
15	Telecommunications	40,550
16	Nanoscience & Nanotechnology	35,052
17	Oncology	34,340
18	Mechanics	33,550
19	Neurosciences	32,974
20	Surgery	30,818
21	Pharmacology & Pharmacy	30,714
22	Automation & Control Systems	29,429
23	Engineering, Chemical	29,172
24	Computer Science, Interdisciplinary Applications	29,156
25	Mathematics, Applied	28,105
26	Physics, Condensed Matter	27,316
27	Biotechnology & Applied Microbiology	26,286
28	Mathematics	25,615
29	Public, Environmental & Occupational Health	25,494
30	Geosciences, Multidisciplinary	24,644
31	Cell Biology	23,108
32	Physics, Multidisciplinary	22,932
33	Astronomy & Astrophysics	22,833
34	Economics	22,343
35	Clinical Neurology	22,131
36	Engineering, Civil	22,127
37	Chemistry, Analytical	21,491
38	Plant Sciences	21,322

Table C.1. The list of categories with the number of documents assigned to the corresponding category. There are 252 categories in the LSC.

No.	Category	Number of Documents
39	Engineering, Multidisciplinary	21,146
40	Radiology, Nuclear Medicine & Medical Imaging	21,140
41	Food Science & Technology	20,414
42	Education & Educational Research	20,088
43	Medicine, Research & Experimental	19,744
44	Genetics & Heredity	19,512
45	Computer Science, Hardware & Architecture	18,489
46	Immunology	18,270
47	Chemistry, Organic	18,038
48	Polymer Science	18,017
49	Engineering, Biomedical	17,786
50	Microbiology	17,750
51	Computer Science, Software Engineering	17,104
52	Instruments & Instrumentation	17,104
53	Physics, Atomic, Molecular & Chemical	17,090
54		16,899
55	Metallurgy & Metallurgical Engineering	16,760
56	Ecology Cardiac & Cardiovascular Systems	16,760
57	Medicine, General & Internal	16,179
58	Psychiatry	16,056
59		15,664
60	Electrochemistry Biochemical Research Methods	15,051
61		· ·
62	Endocrinology & Metabolism	14,622
63	Engineering, Environmental	14,615
	Management	14,339
65	Chemistry, Applied	14,060
66	Water Resources	13,997
	Thermodynamics Pediatrics	13,852
67		13,370
68	Physics, Particles & Fields	13,208
69	Engineering, Manufacturing	13,102
70	Biophysics	12,630
71	Chemistry, Inorganic & Nuclear	12,604
72	Infectious Diseases	12,524
73	Chemistry, Medicinal	12,463
74	Meteorology & Atmospheric Sciences	12,319
75	Construction & Building Technology	12,078
76	Operations Research & Management Science	11,882
77	Veterinary Sciences	11,502
78	Remote Sensing	11,388

Table C.1. The list of categories with the number of documents assigned to the corresponding category. There are 252 categories in the LSC.

No.	Category	Number of
		Documents
79	Nuclear Science & Technology	11,360
80	Zoology	11,218
81	Social Sciences, Interdisciplinary	11,035
82	Gastroenterology & Hepatology	10,943
83	Orthopedics	10,539
84	Physics, Mathematical	10,441
85	Engineering, Industrial	10,362
86	Marine & Freshwater Biology	10,124
87	Mathematics, Interdisciplinary Applications	10,077
88	Geochemistry & Geophysics	10,024
89	Biology	9,917
90	Obstetrics & Gynecology	9,885
91	Physics, Fluids & Plasmas	9,708
92	Toxicology	9,613
93	Statistics & Probability	9,551
94	Nutrition & Dietetics	9,416
95	Business	9,394
96	Imaging Science & Photographic Technology	9,354
97	Hematology	9,096
98	Physiology	9,009
99	Peripheral Vascular Disease	8,700
100	Agronomy	8,651
101	Dentistry, Oral Surgery & Medicine	8,504
102	Robotics	8,491
103	Transportation Science & Technology	8,412
104	Sport Sciences	8,368
105	Psychology, Multidisciplinary	8,333
106	Urology & Nephrology	8,264
107	Materials Science, Biomaterials	8,040
108	Mathematical & Computational Biology	8,015
109	Health Care Sciences & Services	8,000
110	Physics, Nuclear	7,886
111	Ophthalmology	7,832
112	Environmental Studies	7,811
113	Rehabilitation	7,791
114	Respiratory System	7,669
115	Oceanography	7,417
116	Spectroscopy	7,389
117	Materials Science, Coatings & Films	7,226
118	Pathology	7,217
110	1 401101083	1,211

Table C.1. The list of categories with the number of documents assigned to the corresponding category. There are 252 categories in the LSC.

No.	Category	Number of
119	Business, Finance	Documents 7,214
120	Psychology	6,989
120	Acoustics	6,935
122	Crystallography	6,935
123	Psychology, Clinical	6,860
123	Geography, Physical	6,806
124	Psychology, Experimental	6,784
126	Nursing Nursing	6,637
127	Green & Sustainable Science & Technology	
		6,412
128	Agriculture, Multidisciplinary	6,406
129	Education, Scientific Disciplines	6,309
130	Virology	6,270
131	Materials Science, Ceramics	6,222
132	Agriculture, Dairy & Animal Science	6,163
133	Behavioral Sciences	5,922
134	Linguistics	5,921
135	Dermatology	5,793
136	Evolutionary Biology	5,742
137	Entomology	5,705
138	Parasitology	5,683
139	Horticulture	5,338
140	Health Policy & Services	5,318
141	Language & Linguistics	5,174
142	Political Science	5,106
143	Soil Science	4,800
144	Otorhinolaryngology	4,797
145	Geriatrics & Gerontology	4,743
146	Sociology	4,726
147	Biodiversity Conservation	4,705
148	Fisheries	4,702
149	Engineering, Geological	4,573
150	Information Science & Library Science	4,566
151	Forestry	4,472
152	Engineering, Aerospace	4,435
153	Psychology, Developmental	4,390
154	Materials Science, Composites	4,277
155	Planning & Development	4,115
156	Transplantation	4,105
157	Transportation	4,036
158	Medical Informatics	3,992

Table C.1. The list of categories with the number of documents assigned to the corresponding category. There are 252 categories in the LSC.

No. Category		Number of
110.	Category	Documents
159	Reproductive Biology	3,986
160	Critical Care Medicine	3,982
161	Rheumatology	3,942
162	Geography	3,908
163	Materials Science, Characterization & Testing	3,878
164	Agricultural Engineering	3,727
165	Tropical Medicine	3,696
166	Philosophy	3,657
167	Computer Science, Cybernetics	3,652
168	Developmental Biology	3,594
169	Law	3,574
170	Psychology, Social	3,549
171	Psychology, Applied	3,523
172	Social Sciences, Mathematical Methods	3,497
173	History	3,487
174	Integrative & Complementary Medicine	3,453
175	Substance Abuse	3,433
176	Communication	3,200
177	Anthropology	3,150
178	Social Sciences, Biomedical	3,003
179	Hospitality, Leisure, Sport & Tourism	2,998
180	Anesthesiology	2,943
181	International Relations	2,941
182	Neuroimaging	2,702
183	Mining & Mineral Processing	2,687
184	Emergency Medicine	2,627
185	Medical Laboratory Technology	2,598
186	Humanities, Multidisciplinary	2,559
187	Mineralogy	2,550
188	Materials Science, Textiles	2,548
189	Gerontology	2,531
190	Paleontology	2,503
191	Cell & Tissue Engineering	2,455
192	Engineering, Ocean	2,352
193	Religion	2,335
194	Urban Studies	2,309
195	Family Studies	2,229
196	Public Administration	2,204
197	History & Philosophy Of Science	2,199
198	Geology	2,153

Table C.1. The list of categories with the number of documents assigned to the corresponding category. There are 252 categories in the LSC.

No.	Cotomore	Number of
NO.	Category	Documents
199	Archaeology	2,118
200	Social Work	2,114
201	Psychology, Educational	2,112
202	Engineering, Marine	2,110
203	Audiology & Speech-Language Pathology	2,052
204	Area Studies	2,046
205	Criminology & Penology	2,015
206	Materials Science, Paper & Wood	1,963
207	Limnology	1,941
208	Engineering, Petroleum	1,930
209	Ethics	1,928
210	Anatomy & Morphology	1,890
211	Mycology	1,829
212	Logic	1,791
213	Allergy	1,765
214	Medicine, Legal	1,712
215	Education, Special	1,666
216	Literature	1,608
217	Psychology, Biological	1,527
218	Ergonomics	1,431
219	Architecture	1,376
220	Women's Studies	1,341
221	Microscopy	1,319
222	Social Issues	1,296
223	Primary Health Care	1,269
224	Ornithology	1,008
225	Cultural Studies	948
226	Demography	948
227	Music	888
228	Agricultural Economics & Policy	880
229	History Of Social Sciences	879
230	Industrial Relations & Labor	879
231	Asian Studies	877
232	Art	725
233	Ethnic Studies	675
234	Medical Ethics	674
235	Psychology, Mathematical	538
236	Literary Theory & Criticism	498
237	Medieval & Renaissance Studies	485
238	Film, Radio, Television	398

Table C.1. The list of categories with the number of documents assigned to the corresponding category. There are 252 categories in the LSC.

No.	Category	Number of Documents
239	Andrology	391
240	Psychology, Psychoanalysis	345
241	Classics	325
242	Theater	300
243	Literature, Romance	269
244	Literature, British Isles	220
245	Folklore	134
246	Literature, German, Dutch, Scandinavian	128
247	Literature, American	75
248	Dance	74
249	Literature, African, Australian, Canadian	59
250	Poetry	42
251	Literary Reviews	35
252	Literature, Slavic	35

APPENDIX D. LIST OF RESEARCH AREAS.

TABLE D.1. The list of research areas with the number of documents assigned to the corresponding research area. There are 151 research areas in the LSC.

No.	Research Area	Number of			
INO.	Research Area	Documents			
1	Engineering	328,173			
2	Chemistry	163,052			
3	Physics	158,496			
4	Computer Science	142,642			
5	Materials Science	141,762			
6	Science & Technology - Other Topics	96,395			
7	Environmental Sciences & Ecology	60,658			
8	Biochemistry & Molecular Biology	60,029			
9	Mathematics	59,757			
10	Neurosciences & Neurology	48,684			
11	Optics	47,776			
12	Energy & Fuels	44,202			
13	Business & Economics	40,748			
14	Telecommunications	40,550			
15	Pharmacology & Pharmacy	38,844			
16	Psychology	36,284			
17	Oncology	34,340			
18	Mechanics	33,550			

TABLE D.1. The list of research areas with the number of documents assigned to the corresponding research area. There are 151 research areas in the LSC.

No.	Research Area	Number of		
10	A:	Documents		
19 20	Agriculture	31,191		
20	Surgery Automation & Control Systems	30,818		
21	Automation & Control Systems	29,429		
23	Geology Biotrophysical Microbiology	26,632		
23	Biotechnology & Applied Microbiology Education & Educational Research	26,286		
25	Public, Environmental & Occupational Health	25,926		
26	Cell Biology	25,494		
27	Cardiovascular System & Cardiology	$\begin{array}{r} 24,145 \\ \hline 23,402 \end{array}$		
28				
	Astronomy & Astrophysics Plant Sciences	22,833		
29 30		21,322		
31	Radiology, Nuclear Medicine & Medical Imaging	21,015		
	Food Science & Technology	20,414		
32	General & Internal Medicine	20,409		
33	Research & Experimental Medicine	19,744		
34	Genetics & Heredity	19,512		
35	Immunology	18,270		
36	Polymer Science	18,017		
37	Microbiology	17,252		
38	Instruments & Instrumentation	17,090		
39	Metallurgy & Metallurgical Engineering	16,899		
40	Social Sciences - Other Topics	16,666		
41	Psychiatry	16,056		
42	Electrochemistry	15,664		
43	Endocrinology & Metabolism	15,013		
44	Water Resources	13,997		
45	Thermodynamics	13,852		
46	Pediatrics	13,370		
47	Biophysics	12,630		
48	Infectious Diseases	12,524		
49	Meteorology & Atmospheric Sciences	12,319		
50	Zoology	12,200		
51	Construction & Building Technology	12,078		
52	Operations Research & Management Science	11,882		
53	Marine & Freshwater Biology	11,562		
54	Veterinary Sciences	11,502		
55	Remote Sensing	11,388		
56	Nuclear Science & Technology	11,360		
57	Gastroenterology & Hepatology	10,943		
58	Orthopedics	10,539		

TABLE D.1. The list of research areas with the number of documents assigned to the corresponding research area. There are 151 research areas in the LSC.

No.	Research Area	Number of		
110.	Itesearch Area	Documents		
59	Transportation	10,281		
60	Health Care Sciences & Services	10,244		
61	Geochemistry & Geophysics	10,024		
62	Life Sciences & Biomedicine - Other Topics	9,917		
63	Obstetrics & Gynecology	9,885		
64	Toxicology	9,613		
65	Nutrition & Dietetics	9,416		
66	Imaging Science & Photographic Technology	9,354		
67	Hematology	9,096		
68	Physiology	9,009		
69	Dentistry, Oral Surgery & Medicine	8,504		
70	Government & Law	8,492		
71	Robotics	8,491		
72	Sport Sciences	8,368		
73	Urology & Nephrology	8,264		
74	Mathematical & Computational Biology	8,015		
75	Ophthalmology	7,832		
76	Rehabilitation	7,791		
77	Respiratory System	7,669		
78	Oceanography	7,417		
79	Spectroscopy	7,389		
80	Pathology	7,217		
81	Linguistics	7,077		
82	Acoustics	6,935		
83	Crystallography	6,935		
84	Physical Geography	6,806		
85	Nursing	6,637		
86	Virology	6,270		
87	Public Administration	6,120		
88	Behavioral Sciences	5,922		
89	Dermatology	5,793		
90	Evolutionary Biology	5,742		
91	Entomology	5,705		
92	Parasitology	5,683		
93	Geriatrics & Gerontology	5,506		
94	Otorhinolaryngology	4,797		
95	Sociology	4,726		
96	Biodiversity & Conservation	4,705		
97	Fisheries	4,702		
98	Information Science & Library Science	4,566		

TABLE D.1. The list of research areas with the number of documents assigned to the corresponding research area. There are 151 research areas in the LSC.

No.	Research Area	Number of		
		Documents		
99	Forestry	4,472		
100	Transplantation	4,105		
101	Medical Informatics	3,992		
102	Reproductive Biology	3,986		
103	Rheumatology	3,942		
104	Geography	3,908		
105	Tropical Medicine	3,696		
106	Philosophy	3,657		
107	Developmental Biology	3,594		
108	Mathematical Methods In Social Sciences	3,497		
109	History	3,487		
110	Integrative & Complementary Medicine	3,453		
111	Substance Abuse	3,433		
112	Communication	3,200		
113	Arts & Humanities - Other Topics	3,178		
114	Anthropology	3,150		
115	Biomedical Social Sciences	3,003		
116	Anesthesiology	2,943		
117	International Relations	2,941		
118	Literature	2,735		
119	Mining & Mineral Processing	2,687		
120	Emergency Medicine	2,627		
121	Medical Laboratory Technology	2,598		
122	Mineralogy	2,550		
123	Paleontology	2,503		
124	Religion	2,335		
125	Urban Studies	2,309		
126	Family Studies	2,229		
127	History & Philosophy Of Science	2,199		
128	Archaeology	2,118		
129	Social Work	2,114		
130	Audiology & Speech-Language Pathology	2,052		
131	Area Studies	2,046		
132	Criminology & Penology	2,015		
133	Anatomy & Morphology	1,890		
134	Mycology Mycology	1,829		
135	Allergy	1,765		
136	Legal Medicine	1,712		
137	Architecture	1,376		
138	Women's Studies	1,341		

TABLE D.1. The list of research areas with the number of documents assigned to the corresponding research area. There are 151 research areas in the LSC.

No.	Research Area	Number of Documents
139	Microscopy	1,319
140	Social Issues	1,296
141	Cultural Studies	948
142	Demography	948
143	Music	888
144	Asian Studies	877
145	Art	725
146	Ethnic Studies	675
147	Medical Ethics	674
148	Film, Radio, Television	398
149	Classics	325
150	Theater	300
151	Dance	74

APPENDIX E. LISTS OF PREFIXES AND SUBSTITUTES.

Table E.1. The List of Prefixes.

Prefixes							
anti-	nti- ante- auto- co- de-		de-	deca- di-			
dia-	dis-	e-	ex-	extra-	fore-	hemi-	
hexa-	hepta-	homo-	hyper-	in-	inter-	im-	
ir-	kilo-	micro-	mid-	milli-	mis-	mono-	
multi-	non-	octo-	over-	para-	penta-	per-	
poly-	post-	pre-	pro-	quadri-	re-	retro-	
self-	semi-	sub-	super-	tele-	tetra-	therm-	
trans-	tri-	ultra-	un-	under-	uni-		

Table E.2. The List of Substitution.

Word	Substitute
well-known	wellknown
z-test	ztest
z-testing	ztest
z-tests	ztest
z-score	zscore
z-scored	zscored
z-scores	zscore
p-value	pvalue
p-values	pvalue
p-valued	pvalue
p-valuesof	pvalue
chi-square	chisquare
chi-squares	chisquare
chi-squared	chisquared
chi2-test	chisquared

APPENDIX F. LIST OF STOP WORDS IN TM PACKAGE (R PACKAGE).

TABLE F.1. The List of Stop Words.

Stop Words in tm Package							
i	me	my	myself	we	our	ours	ourselves
yours	yourself	yourselves	he	him	his	himself	she
herself	it	its	itself	they	them	their	theirs
which	who	whom	this	that	these	those	am
was	were	be	been	being	have	has	had
does	did	doing	would	should	could	ought	i'm
she's	it's	we're	they're	i've	you've	we've	they've
he'd	she'd	we'd	they'd	i'll	you'll	he'll	she'll
isn't	aren't	wasn't	weren't	hasn't	haven't	hadn't	doesn't
won't	wouldn't	shan't	shouldn't	can't	cannot	couldn't	mustn't
who's	what's	here's	there's	when's	where's	why's	how's
the	and	but	if	or	because	as	until
at	by	for	with	about	against	between	into
before	after	above	below	to	from	up	down
on	off	over	under	again	further	then	once
when	where	why	how	all	any	both	each
most	other	some	such	no	nor	not	only
you	your	her	hers	themselves	what	is	are
having	do	you're	he's	i'd	you'd	we'll	they'll
don't	didn't	let's	that's	a	an	while	of
through	during	in	out	here	there	few	more
so	than	too	very	own	same		