The Evolutionary Pattern of Language in English Fiction over the Last Two Centuries: Insights from Linguistic Concreteness and Imageability

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Abstract:

Fiction has come to play an essential part in human culture and life in recent centuries. Because of its importance, the language or discourse of fiction has been widely studied. Discerning the evolutionary pattern of language in fiction is greatly helpful in understanding the changes in human culture and society. However, most previous studies on literary language that made use of quantitative or computational methods restricted themselves to a few authors or groups and only took into account a relative short span of time. Furthermore, most of the quantitative analysis therein was based on a primary and rather primitive algorithm that summarizes the frequencies of linguistic units in corpora. To overcome these limitations, this study uses semantic similarity as computed by semi-supervised methods to examine diachronic changes. In this study, the three large-scale corpora representing the English language and English fiction were used to investigate the evolutionary patterns concerning diachronic concreteness/imageability. The data from the two measures are well mapped and shown to support the argument that English fiction, as a special genre, exhibits an evolutionary tendency towards increasing concreteness/imageability. This indicates that modern fiction may have become increasingly important in human society, but easier to read and process in words than 19th century English fiction. This study proposed that learnability, genre difference, the changes of population size, and the other factors might have caused the systemic change. The current study is thus an important contribution to understanding the evolutionary trend of language in fiction as well as understanding the development of the English language as a whole. This study creates a novel quantitative methodology and applies this to the examination of diachronic changes of language in literary works.

Key words: *semantic similarity, concreteness, semi-supervision, diachronic changes, evolutionary pattern*

1. Introduction

Discerning the patterns of cultural evolution is obviously crucial to gaining a better understanding of both human nature and how the world has been formed and has changed (Shennan, 2009). The evolution of specific cultural phenomena has been investigated quantitatively with the development of computational technology and the increasing amount of digitalized materials available (Carr et al., 2017; Hughes et al., 202; Hutchison et al., 2018; Hills, et al., 2019; Sun et al. 2021). Such studies have helped to establish a quantitative science of cultural change and have also provided insights into the evolutionary patterns in human culture.

Languages clearly do evolve over time (Labov, 2011, Lieberman et al., 2007). The importance of diachronic studies of evolving language semantics and related social change is hard to over-estimate. The knowledge of language changes probably helps in gaining significant insights into the origins of present-day culture and society. And such knowledge is also helpful in understanding how human communication and their communicative tools have evolved (Sneffjella et al., 2019). And it is clear that discerning the evolutionary pattern of language in fiction also yields insights into changes in human language, culture and society. Past studies of such changes in language have often taken a number of linguistic features and have measured and examined the changes these linguistic features have undergone. However, because of the availability of massive digitized texts and recent progress of computational technologies, today we can obtain high-quality corpora, and more importantly, effective algorithms from computational linguistics that can be adopted to measure linguistic changes. This has important practical and research implications. It means that we need no longer be confined to small corpora and to a single algorithm (such as word frequency) in investigating the evolutionary patterns in the language over history.

As we know, fiction has become an essential part of human culture and life in recent centuries (Daly, 2000; Davies, 1997). Reading fiction can provide many surprising benefits, such as better understanding of our world and allowing us to be more productive (Zunshine, 2006; Kidd & Castano, 2013). Because of the cultural and social significance of fiction, its language or discourse has been the subject of much academic research (Fludernik, 2003). Understanding the evolutionary patterns of language in fiction is essential to understanding the changes in human culture and society. The application of quantitative analysis to the language in fiction or literature has grown significantly in recent years. One example of this is *stylometry*, which is the application of the study of linguistic style, usually to written language, and often with a view to assigning authorship to anonymous or disputed documents by using quantitative or computational methods (Kenny, 2013; Grieve, 2007; Eder et al. 2016). Most studies concerning language in literature use quantitative or computational methods focused on the synchronic perspectives. Although there have been a very limited number of diachronic studies, the majority of these studies confined themselves to a few authors or groups over a short period of time (Peng & Hengartner, 2002; Mahlberg, 2013; Morin & Acerbi, 2017). However, the absence of diachronic studies that use quantitative analysis to explore language in fiction has hitherto prevented us from gaining insight into the developmental patterns of language in fiction. In addition, most quantitative analysis is based on a primary and rather primitive algorithm that summarizes the frequencies of words (or grammatical units) in fiction corpora. However, with recent developments in computational models and computational linguistics, we now have multiple effective and sophisticated algorithms at our disposal that can be employed in quantitative analysis.

A frequent complaint about 19th century English fiction (e.g. Victorian novels) is that it is hard to read (Biber and Conrad, 2019: 155). One of the reasons for this difficulty is that the vocabulary is somewhat archaic. On the other hand, with the development of society and science, the English

language has been widely perceived as having become more varied and abstract as a whole. Our question is whether the words used in English fiction have become more abstract or more concrete since the 19th century. A number of studies have already examined this topic. [Biber and Finegan \(1989\)](#) and [Biber and Conrad \(2019:155\)](#) held that English fiction from the 18th century has been becoming less abstract, that is to say, more concrete in its style. In other words, the linguistic concreteness in English fiction has decreased since 18th century. These studies supported this conclusion with statistics concerning frequency from a number of English fictional works taken from different periods. However, a broader question can be raised here: is it possible to detect lexical developments in large-scale fiction corpora over centuries using the algorithm that is not limited to merely detecting the frequencies of words?

One of convenient and credible ways to discerning the evolutionary patterns in the language of literary works is to examine diachronic linguistic changes. Linguistic concreteness has proved to be an efficient means of detecting the semantic changes of words ([Hamilton et al, 2016b](#); [Hills & Adelman, 2015](#); [Iliev et al., 2011](#)). Concreteness has an extensive literature supporting its relevance to memory, learning, and word recognition, and this dimension has been investigated extensively in historical studies recently. Concreteness in a corpus (or text or document) can be estimated by semi-supervised methods, which could be also appropriate for application to documents (texts, corpora) ([Hamilton et al., 2016a](#); [Hamilton et al., 2016b](#)). To date, however, there has been limited evidence for diachronic changes in abstractness in a naturally occurring language. The challenge in documenting such changes rests in identifying a clear linguistic marker of concreteness and tracking this marker in relation to diachronic corpora over a sufficient time scale and in a language environment likely to be under the influence of selective forces that are sufficient to produce linguistic change.

Everyday language has various genres. The language in these texts covers too broad a range and it is influenced by numerous multifaceted, unknown and uncontrolled factors. To date, several corpora on English language texts have been created that contain a balance of different genres. Previous studies of historical records have focused on language use as indicative of larger shifts in style, grammar and usage. However, by focusing on a single genre, we can make comparisons with the English language as a whole. The specific concern of the present study, however, is to investigate whether English fiction has evolved towards increasing abstraction or not. Although past work has found a pattern of rising concreteness in American English ([Hills & Adelman, 2015](#), [Sneffjella et al., 2019](#)), we would like to know whether this pattern is followed in other Englishes (i.e., British English) as well.

In order to address this concern, we adopt a new methodology that allows us to quantitatively investigate how language in English fiction evolved over the last two centuries. The following methods from computational linguistics have recently been extensively used to detect linguistic changes and other related phenomena: linguistic concreteness. These methods are based on semi-supervised methods and are used to estimate the degree concreteness in a corpus (text or document). Linguistic concreteness is closely associated with imageability ([Scott et al, 2019](#)). The dimension of imageability will be used for comparison and to evaluate the validity of the concreteness detected. This study will use concreteness and imageability based on word embeddings for the purposes of cross-verification, thus creating a novel methodology for examining evolutionary patterns in the language of fiction. In order to better understand how language in English fiction developed, we still need to examine whether the evolution of the British English followed the general evolutionary trend towards abstractness. This study will address the two questions:

- 1) How did language in English fiction evolve with respect to its concreteness and imageability over the course of the last two centuries?

2) How did the evolutionary pattern of language in English fiction differ from that of the English language (American vs. British English) generally?

2. Background

In recent years, more and more large collections of text data (corpus) have become available in digital form, thus boosting computational approaches. Computational linguistics uses various machine learning models, text mining techniques and visualization algorithms to enable an understanding of language and to build artifacts that process and produce language. Text (or language) being the most natural way of encoding human knowledge, these computational approaches and techniques could then be extensively employed to study many areas in social science and the humanities (Clark et al., 2013). The computational methods paradigm that is used to analyze large text data has unprecedented advantages over traditional methods in the relevant fields. The tremendous influence of computational approaches is widespread and rapidly increasing. The quick growth and development of digital humanities reflects how computational approaches have influenced the humanities (Berry, 2011). We can take two examples to illustrate this. The first example is *culturomics*. This uses computational lexicology to study human behavior and cultural trends through the quantitative analysis of digitized texts (Michel et al., 2011). Researchers can mine large digital archives to investigate cultural phenomena as reflected in language and word usage. The other example is *sentiment analysis* which is a promising field of research in text mining that computes opinions, sentiments and emotion. Opinions and sentiment are central to almost all human activities and behaviors. It is for this reason that humans often seek out the opinions of others when they make a decision. Sentiment analysis systems are applied in almost every business, social domain and in academics (Liu, 2012). The approaches used in Culturomics and Sentiment Analysis are closely related to the present study. The following will provide the background to the two types of measures and discuss how they were computed.

2.1 Concreteness and Imageability

Words can roughly be classified into two groups: concrete and abstract. Concrete words usually denote relatively concrete entities, events, or actions. In contrast, abstract words denote feelings, ideas, social concepts, and introspective states. Generally, concreteness evaluates the degree to which the concept denoted by a word refers to a perceptible entity. Numerous studies have tried to examine the effect of concreteness and abstractness on psycholinguistics and cognitive studies, including cognitive processing, effects in working memory, storage and retrieval (Kounios & Holcomb, 1994; Kousta et al., 2011; Brysbaert et al., 2014; Buccino et al. 2019). Concreteness and abstractness have been successfully used to detect linguistic diachronic changes (Hills & Adelman, 2015; Snefjella et al., 2019). Changes of concreteness will be helpful in understanding a tendency toward becoming more abstract/concrete in words of English fiction. Such changes, or the lack therefore, can also show whether words in English fiction became more concrete and imageable or not. There are a number of factors that influence changes in linguistic concreteness. One example is word learnability. Numerous accounts of language evolution have suggested that language should evolve so as to be learnable (Christiansen & Chater, 2008; Smith & Kirby, 2008). Hills and Adelman (2015) demonstrated the diachronic evolution of a property associated with learnability in a natural language. Specifically, changes of concreteness are associated with word learnability. That is to say, people could use more

concrete words in order to facilitate word learning. [Hills and Adelman \(2015\)](#) associated with learnability driving by the language market.

Furthermore, although concreteness is the main measure, we will also measure another dimension, that of “imageability”, so as to allow comparison with the first measure and thus to test its validity. “Imageability” represents the degree of effort involved in generating a mental image of something (imageable, unimageable). Many studies have examined the effect of imageability on psycholinguistics and cognitive studies ([McMullen & Bryden, 1987](#); [Strain & Herdman, 1999](#)). The core textual items are likely to be made up of highly imageable words. Although imageability is strongly correlated with concreteness ([Paivio et al., 1968](#); [Richardson, 1975](#)), the two have seldom been used to capture distinct semantic aspects of a word ([Scott et al., 2019](#)). In a similar vein, changes of imageability also reflect a tendency towards increasing imageability in language over the course of the last two centuries. When the degree of imageability is lower, this means that more difficult and less imageable words are being used. Changes in both concreteness and imageability can thus show whether English fiction has become increasingly concrete and imageable or not.

Although often correlated with concreteness, imageability is not a redundant property. Most abstract things are hard to visualize; however, some still can easily evoke images. For instance, *pain* summons up an emotional and even visual image. However, there are also concrete things that are difficult to visualize, for example, *monastery* is harder to visualize than *monkey*. In this sense, concreteness and imageability overlap but they are not synonymous constructs ([Soares et al., 2017](#); [Connell & Lynott, 2012](#)). A likely reason for their overlap lies in the fact that one of the criteria for concreteness is whether a word describes an object that exists in real life, which criteria is naturally connected with whether the word can arouse a visual image. This criterion therefore overlaps with the criterion for imageability and explains their shared variance. [Connell & Lynott \(2012\)](#) suggest that a contributing factor to the concreteness rating of a word is the degree to which it is a typical exemplar of a concrete category (objects, materials, etc.). For these reasons, imageability can be used to cross-verify the reliability of changes in concreteness. That is to say, when concreteness and imageability have similar diachronic change trends, this could well indicate that such trends are reliable. In such a case, imageability can be treated as the baseline.

Quantitative use relies on the concreteness and imageability norms. The recent collection of large-scale concreteness norms has been provided by online participants who ranked concreteness ([Brysbaert et al., 2014](#)). The concreteness ratings in the database of [Brysbaert et al. \(2014\)](#) were obtained from over 4,000 participants by collecting information on subjective norms. The information used in this database was collected by the Amazon Mechanical Turk. All participants were self-identified native speakers of American English residing in the U.S. Each participant was given one or more lists of words and asked to rate each word using a 5-point rating scale going from the most abstract to the most concrete. The database on imageability ([Scott et al., 2019](#)) gathered its data online via an in-house experimental platform. The participants were English speakers from the University of Glasgow.

2.2 Computational Methods

The method for assessing the concreteness of an individual word is quite distinct from the method for evaluating the degree of concreteness of a corpus. There have been three main methods used hitherto to assess the degree of concreteness of a corpus. The first method proposed searching for the words (*lemmatized tokens*) in a corpus and then retrieving the rating norms for these words in the concreteness database and finally calculating the mean of all rating norms of these words in this corpus ([Graesser et al., 2004](#)). The second method was proposed by [Hills & Adelman \(2015\)](#). It estimates the

concreteness of a word according to a word's concreteness ratings as weighted by the word's frequency of occurrence in a corpus. The third method that was proposed by [Hamilton et al. \(2016b\)](#) and [Snefjella et al. \(2019\)](#) used semantic similarity as derived from the word embeddings (that are themselves obtained by transforming the corpus) in order to calculate the degree of concreteness of each word in a corpus. This was done by measuring the semantic similarity between "seed words" and all words in this corpus. The following discussion compares the three methods.

The Coh-Metrix ([Graesser et al., 2004](#)) tool was created using the first method to calculate the degree of word concreteness (and the other word properties) for the content words in a corpus. Another tool, the Automatic Analysis of Lexical Sophistication (TAALES) ([Kyle et al., 2018](#)), was used to compute lexical features related to word concreteness. This tool employed an algorithm similar to the Coh-Metrix. However, there is a potential problem with the mean obtained here: the degree of concreteness for this corpus is not equal to the mean of the summation of the scores of all (unique) content words in this corpus. The first possible deficiency concerns the frequency with which a word is considered in this algorithm. The description of word frequency cannot be found in the relevant literature on the two tools, which strongly suggests that word frequency was not considered in this algorithm. Secondly, even if all the content words were included, the final score is still potentially problematic. This is because the status of the remaining words in this corpus is unknown. The degree of concreteness in a corpus must consider all the words in this corpus, including function words. For example, [Brysbaert et al. \(2014\)](#) provided the database of concreteness norms for function words such as numbers, pronouns, determiners, propositions and the other types of function words. However, despite the fact that all the words were considered, this method of summation is still problematic because the summing up of the scores of all the words totally ignores the frequency of words, the usage of a lemma and its context. The problem with ignoring word frequency was discussed in the preceding. In the following, we want to illustrate the problem that arises from ignoring word usage and context. For instance, "taking" has the lemma "take" just as "took" has the lemma "taken". However, "taking" can be also used as a noun. If we calculate the degree of concreteness of "taking"(noun), should we also treat "taking"(noun) in the same way as "take"(verb)? It is clear that we should not assign the same score in an absolute fashion to various word forms with the same lemma. This means that this algorithm is incapable of precisely measuring the concreteness of a corpus.

The assumption that a word is perceived to have the same degree of concreteness/imageability for English users over all decades or used with the same degree of concreteness/imageability across may be problematic and the static approach falls short of capturing such potentially different perceptions and usages. As discussed in the 2.1, numerous studies have explored the semantic changes words have undergone in history ([Hamilton et al., 2016 a, b](#); [Garg et al., 2018](#); [Kozłowski et al., 2019](#)). It is also possible that the same word has a different degree of concreteness/imageability for English users in different genres. For example, "chaos" may be an abstract word in fiction, but a concrete word in a scientific text. In the light of such cases, we believe that concreteness/imageability changes over time in different genres. That is to say, the trends in changes of concreteness/imageability in English fiction might differ from those in the English language generally.

The second method discussed by [Hills & Adelman \(2015\)](#) and [Hills, Adelman & Noguchi \(2016\)](#) assessed the linguistic concreteness of historical changes in a corpus according to a word's concreteness ratings as weighted by the word's frequency of occurrence in a corpus. The algorithm is potentially better than the first method for summing up the concreteness scores of words in a corpus. The reason for this is that the algorithm in [Hills & Adelman \(2015\)](#) solved the problem of neglecting words that occur twice or more.

However, the effective calculation of linguistic concreteness can be carried out based on word embeddings (mainly computed by word2vec, GloVe or FastText). Before reviewing the third method,

we need to introduce one crucial concept. The meanings of words can be represented using vectors as part of a high-dimensional “semantic space”. These vectors are called “word embeddings”. Word embeddings are numbers which are converted from texts (or corpus). Word embeddings can represent the co-occurrences of words in a corpus and each vector represents the typical context for one word. In this sense, word embeddings contain the semantic information on word meanings, word frequency, and context etc. In addition to this, word embeddings have been widely applied in natural language processing, cognitive sciences and language studies (ref. [Bakarov, 2018](#)). Word embeddings are also widely used to explore diachronic changes in language and culture ([Hamilton et al., 2016 b](#); [Garg et al., 2018](#)). However, these studies are based on word association or semantic similarity. A key problem that must be considered in the current context is that of ascertaining which words are crucial in sciences that have a variety of subfields. It is obviously very hard to ascertain what the crucial words are when, as in this study, a wide variety of different kinds of fiction spanning two centuries are the object of study. However, instead of using word association, we can examine changes in word concreteness. Concreteness is a specific psychological construct with a rich theoretical literature, and a reliable means of detecting linguistic changes.

[Hamilton et al. \(2016, b\)](#) subsequently proposed a new algorithm for quantifying semantic change by evaluating the word embeddings. [Sneffjella et al. \(2019\)](#) borrowed the algorithm of [Hamilton et al. \(2016, b\)](#) to measure the changes of diachronic concreteness. If the algorithm of [Hills & Adelman \(2015\)](#) is “static”, the method of [Hamilton et al. \(2016, b\)](#) is “dynamic”. We will not use the static approach to evaluate historical changes ([Hills & Adelman, 2015](#)) where the sum of a word's concreteness ratings is weighted by the word's frequency of occurrence in a given decade. The use of contemporary norms would not be able to account for an abrupt change in the meanings of many words or a periodic fluctuation in meanings of many words over time.

Further evidence for the great advantages of our algorithm in measuring the degree of concreteness in a corpus as compared to other methods can be found in the recent overview of the measurement of sentiment in natural language processing. [Jurafsky and Martin \(2019, <https://web.stanford.edu/~jurafsky/slp3/21.pdf>\)](#) provide a comprehensive overview of the measurement of sentiment, affect and connotation in documents (i.e. a text or a corpus, not an individual word or entity in a text). Semi-supervised methods require only minimal human supervision (in the form of seed words). [Jurafsky and Martin \(2019\)](#) introduce several semi-supervised algorithms which share great similarities: “seed words” and semantic similarity based on word embeddings. The core of semi-supervised algorithms is the metric for measuring the similarity to the seed words. [Hamilton et al. \(2016a\)](#) have developed the *SentProp* (Sentiment Propagation) tool to carry out this task. Further, [Hamilton et al. \(2016 b\)](#) have applied the algorithm of [Hamilton et al. \(2016 b\)](#) to measure historical changes in concreteness. [Sneffjella et al. \(2019\)](#) subsequently elaborated the algorithm used by [Hamilton et al. \(2016 a\)](#) and [Hamilton et al. \(2016 b\)](#) to measure the concreteness of corpora. The primary advantage of *SentProp* is that it is quite simply impossible to allow for dynamic changes in word meaning in any other way. This is why this semantic similarity algorithm was selected to measure the concreteness and imageability of a corpus.

A few remarks suffice to illustrate how this “dynamic” algorithm works. We want to calculate the concreteness of a given text. Using this “dynamic” algorithm, the first step is training the text into a database of word embeddings and thereby building a weighted lexical graph by connecting each word. Second, we choose the positive and negative “seed words” that must occur in this text. After that, random walks from the seed words are run and polarity scores (shown in Figure 1 as colors green or red) are then assigned based on the frequency of random walk visits. Finally, we walk from both the positive and negative seed sets, resulting in positive (score + (w_i)) and negative (score – (w_i)) label scores. These values can be combined into a positive-polarity score and the mean of all such scores can

be obtained. The mean is this text’s degree of concreteness. For further details about this, see the section on Methods.

Figure 1: Visual summary of the *dynamic* algorithm of semantic similarity (Hamilton et al. 2016 a). In this graph, “love” and “hate” are “seed words” representing positive and negative dimensions. Based on the semantic similarity between the other words and “seed words”, the other words obtain their positive or negative scores.

3. Materials and Methods

3.1 Materials

The current study will use the three different types of corpora in order to make comparisons. Two of the corpora are comprehensive and contain various genres. The third one is the corpus of English fiction from the Google Books corpus.

COHA is a good balanced historical corpus; however, it only goes back to 1800s. To our knowledge, there are no large and balanced historical corpora currently available. The Corpus of Late Modern English (CLMET) can work as an alternative if comparisons are also made with other genres. The two corpora can thus represent the English language as a whole. Snejfjella et al. (2019) once trained the COHA into the twenty sub-corpora of FastText-style word embeddings according to one decade (<http://kupermanreadlab.mcmaster.ca/kupermanreadlab/downloads/embeddings.zip>).

The Corpus of Late Modern English Texts is a corpus of roughly 35 million words of British English from 1710–1920 (De Smet, 2005; Driller, et al., 2011). As we know, COHA is balanced for different genres in each decade. By contrast, CLMET is not balanced, because there is a relatively significant portion of literary works. The annotation is XML style and similar methods to those used in RSC were employed to extract text and yield word embeddings. Comparing three corpora with different genres yields new findings. Google Books Corpus contains different genres of books. The current study makes use of the selection of English fiction. The word embeddings in the selection were trained by Hamilton et al. (2016 b) (<https://nlp.stanford.edu/projects/histwords/>). This corpus represents

the fiction genre and includes complete literary works. Table 1 provides the basic information on the four corpora used in the current study, including their duration, size, material genres.

Table 1: The three corpora used in the present study

Corpora	Years	Genre(s)	Tokens
English Fiction of Google Books (EngFic)	1820s-1990s	fiction	32,851 million
CLMET	1740s-1920s	literary works (50%) + treatises + non-fiction(?treaties)	34 million
COHA	1800s-2000s	four genres: fiction (50%) + magazines + newspaper + non-fiction	400 million

The Google Fiction word embeddings are assigned a greater importance than the others in the present study. The dimension of word embeddings for each decade is 300. The calculation method used in the present study needs to find the “seed words” among the shared words for the sub-corpora that we want to process. If we include all twenty sub-corpora, it would mean that the shared word number is the minimum of all (686 words). Further, we need to choose “seed words” from the 686 words. When the shared word number is small, it will have a negative influence on the selection of “seed words”. The number of word embeddings in 1800s and 1810s is too small, so these were not included. In order to verify our methods, we formed two groups: the first starting from 1820 and the second starting from 1850. The first group has the 1,750 shared words and the second group has 4499 shared words. Each group will have different “seed words” due to the different shared words. Further details can be found in the following section.¹ Here the division between fiction and non-fiction (Table 1) is possible in COHA and CLMET, but such a temporary division is not necessarily clear-cut. This is because one of the two points of focus in the present study is the examination of language changes in fiction. The other genres can be taken as non-fiction so as to enable comparison.

3.2 Methods

a) Dynamic algorithm

The “dynamic” algorithm of (Sneffjella et al. 2019) is potentially better than the “static” one. The “dynamic” algorithm, derived from Hamilton et al. (2016, b), can measure the historical concreteness of English words. The “dynamic” algorithm applies semantic similarity using word embeddings, as repeatedly mentioned above. We will now provide a brief introduction to this algorithm.

First, the preparation work consists in dividing a corpus into several small sub-corpora according to their historical time span and the transformation of each sub-corpus into a database of word embeddings by FastText (Bojanowski et al., 2017). Here we used dimension 300 with subword information ranging from character bigrams up to character 6-grams in order to maintain consistency with Sneffjella et al. (2019). The database of word embeddings for this sub-corpus contains the vectors

1 The size of word embeddings for the three corpora and “seed words” of concreteness and imageability can be seen in section 1 of the **supplementary material (abbreviated as: SM)**.

of all the words occurring in this corpus. The word embeddings of this sub-corpus actually contain the information on the frequency of each word in this sub-corpus. All target words we examined for concreteness/imageability are a set of words that occurred in each sub-corpus (words with frequency ≤ 2 were excluded). We then selected a small set of seed words (the number of seed words can be reset according to the corpus size) using the criteria of concreteness and abstractness and chosen by considering the factors that are discussed below.

An essential component here is called “SentProp” in the SocialSent package (Hamilton et al., 2016, a). SentProp is used to produce two random walks over a graph of semantic similarities between each word (i.e., word tokens) in this sub-corpus (the database of word embeddings of this corpus) and the “seed words”. In this graph, the nodes are words and edges **which** are constructed by connecting each word to its twenty-five nearest semantic neighbors as based on the *cosine distance*. SentProp is thus able to estimate a semantic dimension (e.g. concreteness) for the words. The SentProp package then randomly samples subsets of seed words for each sub-corpus and uses word embeddings to calculate the scores with sampled seed words. After the graph has been built, the semantic similarities are transformed into probabilities. We therefore obtain a transition matrix. This matrix provides information on the probability of randomly moving from a word to one of its semantic neighbors (More details can be seen in Hamilton et al. (2016, b)). Two polarity scores are computed in each word and a random subset of seeds: abstraction (a) and concreteness(c). The final score is $c/(c+a)$. The final score is between 0 and 1. When the score of a word approaches 1, this means that the concreteness of this word is high and vice versa. We can obtain the mean concreteness score for each sub-corpus if the sum of the scores of all the words in each sub-corpus is divided by the number of words in this sub-corpus. The mean concreteness score is treated as the degree of concreteness. When the mean concreteness score approaches 0, this means that the concreteness degree is low and vice versa. The great advantage of the algorithm is that it produces a concreteness value that reflects the usage within a specific corpus, i.e. the historical period of use or genre.

With regard to the setup of “SentProp”, we basically followed the settings of Sneffjella et al. (2019) in processing the word embeddings. However, as the number of “seed words” (20 positive and 20 negative) was a little larger than that in Sneffjella et al. (2019) (15 positive and 15 negative), we made small changes to the setups in the SentProp, namely, the 30 nearest neighbors, $\beta = 0.9$, a tolerance of $1-e8$, and 100 bootstrap iterations using 15 random seed words out of the 20 at each pole of the concreteness continuum to process CLMET and EngFic respectively. Note that Sneffjella et al. (2019) used 10 random seed words out of the 15 at each pole of the concreteness continuum (some details can be seen in the subsection of “seed words”). In spite of this, the setup difference does not make a great difference in detecting diachronic changes in the CLMET and EngFic. To make convenient comparisons, we used the same settings as Sneffjella et al. (2019) in processing the imageability in COHA with 15 positive and 15 negative words.

The core of this algorithm lies in the use of semantic similarity derived from word embeddings in order to calculate the approximate concreteness score of each word according to the “seed words” of concreteness. Word embeddings can represent co-occurrences of each word with other words in a corpus such that each vector describes the typical context of one word. The following factors, which have been neglected or unsolved in the first and second algorithms, need to be fully considered: word frequency, word meaning and word context. Because it includes these factors, this computational algorithm is able to precisely estimate the concreteness degree of a corpus. For this reason, this algorithm is better than the first two algorithms for estimating the concreteness of a corpus. A number of “seed words” that should have a high frequency in each corpus represent the highest and lowest score of concreteness in the corpora that are to be compared here. We use the database of Brysbaert et al. (2014) (40,000 English word lemmas) to obtain the concreteness scores of “seed words” used in our

algorithm. The largest database of imageability subjective norms is the Glasgow database, which contains 5,500 words (Scott et al., 2019). Similarly, we use this database of "imageability" to obtain the imageability scores for "seed words". In the following, we will discuss how to choose "seed words" for these psycholinguistic properties.

b) "Seed words"

Snefjella et al. (2019) took fifteen concrete and abstract words as "seed words". They chose seed words that (i) occurred with high frequency in each decade between 1850 and 2000 and were associated with (ii) extreme concrete or abstract ratings. Similarly, we applied such criteria in choosing seed words. We set up the word frequency (> 200 occurrences) in each decade between 1665 and 1869 and chose words with high concreteness or abstractness ratings. In addition to this, we used the topic modeling (Hornik & Grün, 2011) to train in this corpus in order to obtain "topics". Topic modeling concerns the finding of essential words/terms in a collection of documents that best represents the collection. After that, we obtained a collection of 500 topics (words) which are essential in each corpus. Moreover, we considered some other factors, namely that i) these seed words should be covered in a multiple of disciplines, ii) the concrete "seed words" we obtained must be found in the collection of topics; otherwise, they will be removed and iii) the fact that those words have undergone few changes in meaning. In this sense, these seed words are optimally selected and representative of concreteness, topics and terminologies in diversified disciplines.

The "seed words" should be the same in each sub-corpus that is to be investigated. That is to say, the same "seed words" depend on the given number of sub-corpora examined. We then searched for the twenty words with highest concreteness scores and for the twenty words with lowest concreteness scores according to the database of concreteness. Meanwhile, the frequency (>10) and "topics" were then considered so as to remove these unqualified words. The process continued until forty words with high and low concreteness scores are yielded. The "seed words" of imageability are selected using the same method.² In contrast to Snefjella et al. (2019), we used 40 'seed words' (20 positive and 20 negative) to process CLMET and EngFic. Snefjella et al. (2019) only used 30 "seed words" (15 positive and 15 negative) to compute concreteness in COHA. However, we believe that an appropriate increase in the number of "seed words" contributes to the validity of computed scores and robustness of the calculation. Despite this, our new setup and the original setup in Snefjella et al. (2019) yielded the same trend in detecting diachronic changes. The "seed words" can be seen in section 2 of the SM.

4. Results

4.1 Validity of the Computed Scores

2 The choice of seed words can influence the performance of some data. However, the general trend of diachronic changes will not be influenced by a change of seed words. We have tested this with different groups of seed words, but the general trends remain the same. The "seed words" can be seen in Table 2 of SM.

Figure 2: the correlations between human ratings and computed scores for the three corpora

First, we need to test the reliability and validity of the computed concreteness and imageability in the three corpora. Figure 2 compares human concreteness and imageability ratings to the computed scores of concreteness and imageability aggregated across all the decades for the three corpora. The aggregated data is the mean of the same set of words across all the decades in one corpus. It turned out that all correlations were strong and significant.

Specifically, with regard to CLMET, our unsupervised model’s concreteness scores correlate with Brysbaert et al. (2014) at $\rho = .56$ ($p < .001$) and imageability scores correlate with Scott et al. (2019) at $\rho = .53$ ($p < .001$). As for EngFic, our unsupervised model’s concreteness scores correlate with Brysbaert et al. (2014) at $\rho = .63$ ($p < .001$) and the imageability scores correlate with Scott et al. (2019) at $\rho = .68$ ($p < .001$). Snefjella et al. (2019) have computed concreteness in COHA with $\rho = .70$ ($p < .001$). Our model’s imageability in COHA correlates with Scott et al. (2014) at $\rho = .66$. The p value in all correlations is smaller than 0.001. Note that the correlation coefficients ($\rho = 0.66, 0.56, 0.53, 0.63, 0.68$) would be described as “strong” positive associations because all ρ values are greater than 0.5 (Cohen, 1992). The associations are clearly statistically significant ($p < 0.001$). This strongly suggests our computed scores are reliable and valid.

4.2 The Historical Changes in Concreteness/ Imageability in the Three Corpora

COHA was used to estimate the diachronic change of concreteness and imageability for the English language, as is shown in Figure 3. When linear regression analysis is performed, different regression lines can be compared to see if their constants and slope coefficients are different. The dotted lines located in the center of a see-saw line are linear regression ones. The parameters of linear regression are displayed at the right-top. The negative value of slope coefficient indicates a decline trend, or vice versa. If the p value is smaller than 0.001, it will be followed by three stars, i.e. it has a strong statistical significance. If the p value is between 0.001 and 0.01, it will be followed by two stars, i.e. its statistical significance is not stronger than three stars. When the p value is greater than 0.05, there will be no stars, i.e. there is no statistical significance.

We found the concreteness in the COHA rose slightly since 1850s. By contrast, imageability shows a clear decline in the same time frame. The absolute value of the change in the slope coefficients of imageability (linear regression) is much larger than that of the change of concreteness. We can find that the imageability data does not converge with that of concreteness.

Figure 3: The diachronic change of linguistic concreteness and imageability in COHA (1850-2000)

The data on concreteness and imageability from the CLMET does converge: both have negative slopes coefficients for linear regression, as shown in Figure 4. The p value in either concreteness or imageability is of significance here. It suggests that both concreteness and imageability in this corpus have markedly declined in the period from 1740 to 1920. They are both taken to be representative of the English language, yet both of these corpora exhibit contrary trends.

The CLMET exhibits an opposite trend with respect to linguistic concreteness. It indicates that the English language in this corpus has become more abstract during the period under consideration. However, the trends concerning changes in imageability from these two corpora are consistent with one another.

Figure 4: The diachronic change of linguistic concreteness and imageability in CLMET (1740-1920).

Figure 5 shows that concreteness and imageability in the Google Books Corpus of English Fiction increased from 1820 to 1990. The p value in both measures is very significant here. More important still, the two types of data converge. This indicates that English fiction has become increasingly concrete and imageable.

Figure 5: Google Books Corpus of English Fiction (1820-1990)

5. Discussion

5.1 Comparison of the Developmental Trends

We thus obtained the data concerning the slopes coefficient of linear regression of the data on concreteness/imageability and the p-values in each corpus. The value of slope coefficient and p-value potentially reflects the direction and degree of changes. The relevant data is summarized in Table 2.

Table 2: Comparison between the development of concreteness/imageability in the three corpora

Corpora	Slope coefficients of linear regression of the data on diachronic concreteness	Slope coefficients of linear regression of the data on diachronic imageability
Fiction in Google Books (1820-1990)	0.0002956 (p-value <0.001 ***)	0.0003047 (p-value<0.001 ***)
CLMET (1740-1920) [literary works (50%) + treatises +non-fiction(? treatises)]	-0.002734 (p-value<0.001 ***)	-0.001814 (p-value <0.01 **)
COHA (1850-2000)[four genres: fiction (50%)+ magazines + newspaper + non-fictions]	0.0006 (p-value <0.01 **)	-0.003715 (p-value <0.001 ***)

As we know, CLMET and COHA are comprehensive corpora that contain texts from multiple genres. What also must be considered here is that there is one negative slope coefficient for the two corpora, in other words, the positive slope coefficient of concreteness is in the minority. This means we found that concreteness has opposed trends in the two corpora. By contrast, the data on imageability in the two corpora converge. However, this does not indicate that English as a whole has become less imageable over the period of 250 years. The dimension of imageability has been not extensively explored, so the database size of its state-of-art rating norm is small (5500 words, Scott et al., 2019). The seed words of imageability selected from this database seems not to be comprehensive. The imageability seed words are useful to detect changes in small-scale corpora like CLMET and EnglishFiction. However, detecting the changes in so large COHA may not work very well given we use these imageability seed words. We choose to believe that the decline of imageability is not realistic (i.e.,imageability should have increased). The problem cannot be solved well until another larger database of imageability will become available. This is the limit of the dynamic algorithm, that is, the success of this algorithm depends on the quality of seed words to some degree. The selection of seed words correspondingly depends on the large-scale database of rating norm (more details can be seen in Section 4 of **SM**).

Additionally, [Hills and Adelman \(2015\)](#) showed using multiple corpora (Google ngrams, COHA, and presidential speeches) that concreteness has risen in American English over the last two hundred

years. The findings of [Hills and Adelman \(2015\)](#) are basically consistent with our findings. The discrepancy in concreteness between COHA and CLMET could be mainly due to the different backgrounds of the two corpora. The CLMET is made up of British English but the COHA represents American English. It is not difficult to conceive that British and American English could well have undergone different diachronic changes. We want to further analyze what caused such changes in the English language and in English fiction.

Whether a word is acquired or processed with ease or with difficulty depends on a number of factors such as pronounceability, orthography, length, morphology, grammar, and various semantic features ([Schmitt and MacCarthy, 1997:143-153](#)). All these factors can be defined as “word learnability”. The semantic properties, including abstractness, idiomaticity and multiple meanings, may interfere with the learning process. It is generally assumed that abstract nouns are more difficult to learn than concrete nouns due to the more complex nature of the former. As discussed in the subsection 2.1, the concreteness changes trend could tally with the direction of the evolution of learnability. In order to learn language more easily and quickly, language users are likely to use more concrete words as time goes by. However, this general trend could vary in different genres or styles. We found that American English (COHA) may have become more concrete, but British English (CLMET) does not seem to follow this trend. There is a clear trend towards concreteness in English fiction. These findings are partly consistent with the ones of [Hills and Adelman \(2015\)](#). All of this potentially supports the hypotheses that language adapts to the cognitive demands of its users. However, we believe that language changes must intersect with more complex factors such as genre differences as well as social and cultural factors. Every genre has been created to serve a particular group of readers. In this sense, learnability in English fiction may be a little different from the English language as a whole.

The hypothesis in [Sneffjella et al \(2019\)](#) could provide a better interpretation of the discrepancy in concreteness between COHA and CLMET. [Sneffjella et al \(2019\)](#) hold that there are languages where the population of its speakers (or of non-native learners of that language) did not grow over time or where the language marketplace became less crowded.” This argument should be inspired by the language market hypothesis proposed by [Hills et al. \(2017\)](#). Later, [Hills et al \(2019\)](#) extend this hypothesis further by arguing that cognitive biases drive information evolution in crowded information environments, which are both producer and consumer effects. The potential for demographic factors has extensively been investigated to influence language evolution ([Bromham et al., 2015](#)). For example, language may become simpler at the structural level as the size of population has been increasing and our world becomes increasingly interconnected ([Reali et al. 2018](#)). Given the CLMET represents British English, its changes in concreteness/imageability could reflect the changes in the population of its speakers, particularly in the late 19th century with decline of the British empire. By contrast, the increasing population in and national power of the US from mid-19th century parallels the increase of concreteness in American English (COHA) (more details can be found in section 5 in **SM**). Although in theory the English language should increase its degree of concreteness, following the demands of language learnability, historical developments and population are also important factors that impact the evolution of concreteness. We can predict the increase of concreteness as a general (universal) phenomenon but this general phenomenon could be justified under some conditions because the change of concreteness in the CLMET does not support this general phenomenon. Specially, we believe that the increase of concreteness might have happened when the size of population speaking this language has been increasing.

Both concreteness and imageability in English fiction have positive slopes. The data on the two measures converges. This strongly suggests that English fiction has become more concrete (that is less abstract) and more imageable. It is for this reason that we assume that English fiction has become increasingly easy to read. It could also indicate that 19th century fiction is more difficult to read than

modern fiction. The impact of changes in population can also explain such changes. With the rise of the English language on a world scale, English fiction also acquired a wider market. That means that English novelists would be likely to consider concrete and imageable words as a means for attracting more readers. The concreteness and imageability changes in English fiction are consistent with the past studies (Biber and Finegan, 1989; Biber and Conrad, 2019). These studies used frequency evidence from a number of English fiction texts taken from different periods in order to observe the patterns in its development. They found that English fiction from 18th century onwards became less abstract and more concrete in its style.

Contrary to this trend in English fiction, imageability in the English language has decreased. This suggests that at the least the English language has become less imageable over the last two centuries. More discussions on this can be found in section 3 of **SM**. In contrast to this, English fiction has become more imageable. They thus exhibit two opposed trends as regards in imageability. We can also note that concreteness/imageability is likely to be subject to different changes over time in different genres. As mentioned in 2.2, the same word can be perceived by English language users as having a different degree of concreteness/imageability in different genres. English fiction, as a distinct genre to the English language itself, may have followed a different diachronic law because it has been influenced by very unique factors which will be discussed in the following subsection.

5. 2 Other Causes of the Changes in English Fiction

In 5.1, we have discussed how learnability, genre difference and the changes of population size influenced the changes of concreteness/imageability. The following section analyzes what other factors could have caused the increase of concreteness/imageability in English fiction over the last two centuries. As discussed in the Introduction, fiction as a special style of writing plays a crucial role in human society. As an essential part of human culture, the language of fiction must also have been greatly impacted by social and cultural changes.

In the 1800s, people had no television, radio, movies or internet to distract them and they spent their leisure time on books and theater. In view of this situation, writers of fiction tended to engage in a lot of scene setting in their works much as one would in a play. For instance, they would typically give their readers a great deal of background on the characters, often add a bit of general history and were likely to tell their readers about the weather too. These descriptions were used to make readers feel as though they were watching a play. However, for modern readers, such scene-setting could seem rather unnecessary, redundant and tedious because such readers have more channels for the receipt of visual information due to the influence of movies, TV, color books etc. Consequently, the words used the 19th century authors seem unfamiliar to modern readers. For example, the pastures were not “green”; they were instead “verdant”, a term that describes the lushness of thick new grass. Such terms are clearly likely to confuse modern readers. Another factor here is that much that was familiar to the readers in Victorian era is not familiar to modern readers. The words used in Victorian era had specific connotations. However, these words have undergone drastic changes in their meaning or have been abandoned or used less frequently. Modern readers feel uncomfortable in reading such unfamiliar words. All these factors could make the words used in the 19th century fiction seem more abstract and difficult than the words employed in 20th century works.

Not only do the words in English fiction themselves change over time, but also the styles of writing do as well. For instance, Charles Dickens wrote in a style that was very popular among English authors in the 19th century. This style is very flowery, descriptive, and ornate, with a great deal of what modern critics often deride as “purple prose”. This style is the exact opposite of what most readers

today look for in their novels. Modern readers' expectations for novels have been heavily shaped by the styles of early twentieth-century modernist writers such as Ernest Hemingway and John Steinbeck. The thesis that style in fiction has undergone linguistic changes over time has been much discussed (Leech & Short, 2007: 298-303). Although the aforementioned writers' respective styles were in many respects different, all wrote in a style that is deliberately much simpler, plainer, and less elaborate than the styles of Dickens and his contemporaries in the 19th century. This could be a second reason why the 19th century fiction seems less concrete and imageable than that of the 20th century.

A final factor that needs to be considered here is the influence of social changes with respect to the readers' background and the impact of this on the diachronic changes in the language of English fiction. As mentioned in 5.1, Biber and Finegan (1989) and Biber and Conrad (2019) concluded that language in English fiction from the 18th century onwards down to the present has become increasingly concrete. They also provide some reasons for this in their analysis of these trends. As Biber and Conrad (2019:156) pointed out:

"One major change that might have had an influence is the target audience. At the beginning of the eighteenth century, relatively few adults could read and write, [and these who could were] mostly restricted to members of the upper class or aristocracy... With the rise of mass schooling in the nineteenth century, these literacy skills were extended to the majority of the population. Because of these demographic changes, novels came to be written for a much wider reading public in the nineteenth and twentieth centuries than in earlier periods."

According to Biber and Conrad (2019:156), the increase in literacy brought about a rise in demand for fiction that was simpler and easier to read. This could provide a reason why the language used in fiction became easier to read, namely such language encourages a larger readership and this in turn has commercial benefits. Fiction seems to have become an essential component of mass (popular) culture, although this thesis is controversial (Fluck, 1988). The evidence for this is that children's fiction, science fiction, fantasy were all created in 19th century (or earlier) but became popular in the 20th century (McCracken, 1998; Leavis, 2011). These diversified fictional genres were written in plain language in order to attract more readers.

Therefore, Biber and Conrad (2019: 155) concluded: "18th century novels used an elaborated linguistic style, with long sentences and complex noun phrases, while twentieth-century novels have changed so that they typically rely on a simpler style with more verbs, short clauses, and adverbials. The linguistic changes between eighteenth- and twentieth-century novels reflect these changing attitudes about language. Thus, there is a fairly steady progression towards simpler, more colloquial styles in novels across these periods."

Based on an analysis of population increase and changes in concreteness, we see that when the population of speakers of a given language did in fact grow or the language marketplace became crowded, the concreteness of this language is likely to diachronically increase. The increase in concreteness in English fiction indicates that the number of readers of English fiction has increased. This supports our argument that fiction plays a crucial role in human society. In comparison to fiction, the English language overall became more complicated in this period. We have already mentioned that the two main factors (word learnability and the rate of increase in population) potentially had a great impact on diachronic changes in concreteness/imageability. However, other factors could also have influenced such changes. For example, numerous scientific writings were published as modern science developed. The greater numbers of people in higher education encouraged the creation of a more complicated language overall. By contrast, several social and cultural reasons probably lay behind the trend towards concreteness in fiction, but these certainly did not impact in the entire English language, which was itself influenced by other unknown factors.

6. Conclusion

This study used a semi-supervised computational method to detect the evolutionary patterns in linguistic concreteness and imageability in the three corpora. Linguistic concreteness and imageability based on word embeddings were used to quantify the diachronic changes in word concreteness and imageability over a number of decades using the data contained in three corpora. We found that the COHA representing American English exhibited a marked increase in concreteness. By contrast, the CLMET representing British English exhibited a clear downward trend in both concreteness and imageability in this same period. The overall trends in diachronic concreteness and imageability in English fiction show a little difference from that of the British English as a whole. From the perspective of concreteness and imageability, English fiction has become more concrete and imageable over the last two centuries. This also indicates that English fiction has taken on an increasingly prominent role in human society. Moreover, the current study put forward what caused the systemic change of concreteness/imageability in English language and English fiction, for instance cognitive factors, genre difference, the changes of population size, social and cultural factors etc. Our findings, which are based on ‘big-data’ analysis, are confirmed by previous studies. Overall, this study clearly demonstrates how language in English fiction followed a general evolutionary pattern. The current study revealed how the evolutionary pattern of language in English fiction differed from that of the English language generally. This study created a novel methodology for examining evolutionary patterns in literary works and thus provided a new outlook on the cultural changes, which was described using a qualitative historical analysis.

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The Supplementary Material (SM) of “*The Evolutionary Pattern of Language in English Fiction over the Last Two Centuries: Insights from Linguistic Concreteness and Imageability*”

1. Three Corpora Information

Table 1: The size of tokens and word embeddings by decade for the three corpora

COHA (from Snefjella et al., 2019)			CLMET			Google Books Corpus of EngFic (from https://nlp.stanford.edu/projects/histwords)		
<i>decade</i>	<i>tokens</i>	<i>embed.</i>		<i>tokens</i>	<i>embed.</i>		<i>tokens</i>	<i>embed.</i>
1850	16.2M	44138	1740	10.6M	11906	1820	104.3M	1750
1860	16.7M	48973	1750	12. 9M	11705	1830	144.3M	2665
1870	18.2M	48377	1760	9.2M	13744	1840	212.3M	3355
1880	19.8M	52036	1770	12.7M	18006	1850	300M	4499
1890	20.1M	53934	1780	4M	8922	1860	294.4M	4385
1900	21.5M	57824	1790	5.5M	10243	1870	348.9M	4742
1910	22.1M	57217	1800	1.5M	4583	1880	527.9M	6184
1920	24.9M	57217	1810	5.1M	10982	1890	892M	8898
1930	23.8M	64789	1820	8.8M	15592	1900	1110M	9719
1940	23.6M	65822	1830	10. 4M	17966	1910	926M	7735
1950	23.7M	69399	1840	19.1M	23930	1920	1141.2M	10225
1960	23.2M	68927	1850	8.3M	16114	1930	1086.8M	9163
1970	23.0M	70250	1860	7.9M	14369	1940	1035.6M	8657
1980	24.3M	77667	1870	6.2M	13294	1950	1637M	11682
1990	26.9M	82203	1880	8.2M	15268	1960	2267.8M	13755
2000	28.4M	86527	1890	13.5M	19905	1970	3135.9M	13521
			1900	9. 6M	16079	1980	6369.4M	19353
			1910	6.5M	12731	1990	11317.9M	24049
			1920	0. 8M	3091			

(embed.= word embeddings)

2. “Seed Words”

Table 2: “Seed words” used to measure concreteness/imageability for each corpus

	<i>Concreteness</i>		<i>Imageability</i>	
	The most concrete (20 words)	The most abstract (20 words)	The most imageable (20 words)	The least imageable (20 words)
COHA	See Snefjella et al. (2019) , 15 words railroad, tree, bed, bird, neck, ball, baby, water, sand, cotton, knife, horse, clay, moon, student	See Snefjella et al. (2019) , 15 words belief, existence, principle, responsibility, extent, justice, theory, purpose, courage, wisdom, chance, imagination, fate, glory, curiosity	bee, pencil, hand, apple, bullet, piano, dog, frog, lion, water, cow, strawberry, sheep, violin, elephant (15 words)	aspect, aptitude, dogma, instance, economy, disparity, personality, philosophy, notion, paradox, disposition, irony, virtue, omission, phenomenon (15 words)
CLMET	ball, bed, bird, cup, ear, finger, horse, house, neck, tree, water, bridge, coat, hair, arm, gate, human, boat, dress, grass	courage, purpose, motive, probable, naturally now, unknown, really, belong, ago, injustice, principles ,anything, suppose, could, enough, therefore, possibility, hope, because,	hand, dog, water, ear, horse, rose, boat, coat, bread, eye, table, hat, moon, bird, grass, finger, king, dress, foot, sea	instance, notion, least, mind, opinion, language, fact, value, circumstances, wish, chance, moment, truth, necessity, advantage, doubt, knowledge, rate, situation, method
EngFic	bed, cup, ear, finger, horse, house, neck, tree, water bridge, coat hair rain bell castle gate island mountain, teeth human	hope, purpose, fate, courage, extent, existence, spirit, mercy, curiosity, idea, moment, peace , value, virtue, manner, faith, risk, patience, pride, probability, pride, probability	hand, dog , water, ear, mountain, horse, nose, rose, boat, coat, bread, eye, table, hat, sky, moon, finger, snow, circle, king	instance, disposition, believe, least, virtue, fate, tone, fault, perceive, opinion , conclusion, language, fault, fact, value, circumstances, wish, chance, necessity, advantage

3. Changes of Concreteness/Imageability in the Static Approach

Figure 1: Concreteness/imageability changes in the CLMET using the static method (Hills & Adelman, 2015) considering all words in the corpora. The results show that there is no significant increase or decline in either concreteness or imageability (p -value > 0.05).

Figure 2: Concreteness/imageability changes in the CLMET using the static method (Hills & Adelman, 2015) but considering the 25% most stable words in the corpora. The method of choosing stable words can be seen in Hills et al. (2019). The results show that both concreteness and imageability in the CLMET decreased significantly (p value < 0.001). In this sense, Figure 2 here is consistent with Figure 3 in the main text. It indicates that the result yielded by the static approach using the 25% most stable words is consistent with the result yielded by our dynamic approach. By contrast, the result from the static approach using all words does not yield any significant results.

4. The Validity of Computed Scores Using the Other Human Databases and the Limitation of Our Algorithm

The most unbelievable thing is that concreteness and imageability show an opposing trend in COHA. Following the validity methods of Snefjella et al. (2019), we used the other two human rating databases (Paivio et al. 1968; MRC (Coltheart, 1981; Wilson, 1987)) on concreteness and imageability. The two sets of human databases on concreteness and imageability were collected in 1960 and 1980 respectively. We will use both aggregated and decade-specific computational score to correlate with the human scores. The imageability validity results of COHA is shown in Figure 3.

Figure 3: The correlations between human ratings in the other two databases and imageability computed scores for COHA

Our unsupervised model’s imageability scores (aggregated) correlate with [Paivio et al. \(1968\)](#) at $\rho = .65 (p < .001)$ and imageability scores (aggregated) correlate with [MRC \(1981, 1987\)](#) at $\rho = .62 (p < .001)$. Our unsupervised model’s imageability score in 1960s correlates with [Paivio et al. \(1968\)](#) at $\rho = .7 (p < .001)$ and imageability score in 1980s correlates with [MRC \(1981, 1987\)](#) at $\rho = .60 (p < .001)$. All of this shows that our unsupervised model’s imageability scores are valid, This also support s that the decrease of imageability in COHA is reliable.

Meanwhile, we also used the same method (aggregated vs. specific-decade) to check with the correlations of our computed scores regarding concreteness and imageability in CLMET and EngFic with the two databases ([Paivio et al. 1968](#); [MRC](#)). In all cases, the values of ρ are between 0.58 and 0.71 ($p < .001$). These correlation values indicate that our computed scores are strongly valid, and these guarantee the reliability of our results. Due to the space limit, we do not provide these details and plots here.

In the following, we provide another perspective to explain why imageability has an opposite trend with concreteness, and we also want to extend the limitation of our dynamic algorithm which has been mentioned in the body text.

Figure 4: Imageability changes in the COHA using the dynamic approach with new seed words adopted from Snefjella et al. (2019). Figure 3 in the main text shows that the decline of imageability using the dynamic approach is significant.

As shown in Table 1 in the **SM**, we find that the “seed words” in the COHA for concreteness and imageability are distinct. The criteria for choosing candidate “seed words” was clearly explained in the section of Methods. The selection of concrete “seed words” is based on the concreteness ratings in the database of Brysbaert et al. (2014) which is the largest of the concreteness databases currently available. By contrast, the selection of imageable “seed words” is based on the database on imageability (Scott et al., 2019), which is also the largest of the imageability databases. However, the size of the Brysbaert et al. (2014) database is larger than that of Scott et al. (2019). This is the main reason why “seed words” for concreteness and imageability are different when we process the large-scale COHA.

We used most of “seed words” for concreteness in Snefjella et al. (2019) because quite a few “seed words” in Snefjella et al. (2019) are absent in the database of Scott et al. (2019). The result is shown in Figure 3 here. These new “seed words” are as follows:

The most imageable words: *baby, ball, bed, bird, cotton, horse, knife, moon, neck, railroad, student, tree, water, bee, hand.*

The least imageable words: *belief, chance, courage, existence, fate, glory, imagination, justice, responsibility, theory, wisdom, aspect, instance, economy, personality.*

In the group of the most imageable words, “bee” and “hand” are not included in the “seed words” of Snefjella et al. (2019). In the group of the most concrete words, “aspect”, “instance”, “economy”, “personality” are not included in the “seed words” of Snefjella et al. (2019). In comparison with our original imageability “seed words”, most of these new “seed words” are not more imageable or less imageable although these new words are good candidates. For example,

Figure 4 shows the results when these new “seed words” are used in our dynamic approach. The result indicates that the change of imageability in the COHA is **not** significant (the p value = 0.448 > 0.05). However, the computed imageability scores using these new seed words are still valid, shown in Figure 4 here.

Figure 5: The validity of computed imageability using new seed words in Figure 3 of SM. The correlation percentage is 62% between computed imageability and human ratings.

Figure 5 here indicates that using new “seed words” to compute imageability in Figure 3 is highly valid. However, all of this does not support the claim that imageability has significantly increased. As discussed above, the possible reason for the discrepancy between the change of concreteness and imageability is that the size of imageability norms (Scott et al., 2019) is relatively small in comparison with that of the concreteness norms (Brysbaert et al., 2014). The imageability seed words which are not so comprehensive are useful to detect changes in small-scale corpora (i.e., CLMET and EnglishFiction). However, it will be problematic to detect changes in so large-scale COHA given we use these imageability seed words. In this sense, we believe that the result of imageability in COHA is *temporary*. It is possible that the imageability change trend could show a different picture (i.e., imageability should have increased in COHA) when a new large-scale database of imageability norm will become available.

5. The Growth Rate of Population of UK and the other English-speaking Countries.

Figure 6: the population growth between 1800 and 2019. The data comes from <https://ourworldindata.org/world-population-growth>

The relative change of population between 1800 and 2019 for UK is 448%. In contrast, it is 4738% for US. For Brazil, Nigeria and Australia, it is 5699%, 1561%, and 7,080% respectively. However, Japan has a change of 319%. Other English-speaking countries also exhibit a higher rate of increase than UK. For example, Canada has an increase of 5695%; New Zealand has an increase of 4683%; Ireland has an increase of 3550%. Clearly, UK has a lowest rate of increase in population in comparison with these English-speaking countries (The data comes from <https://ourworldindata.org/grapher/population?tab=table>). It thus makes sense that British English has undergone a decrease of concreteness/imageability due to the slow rate of increase of population of language users.

Such data can support our analysis on the possible effect on the discrepancy of diachronic change between COHA and CLMET. The population increase in UK is clearly much slower than US. In comparison with the other English-speaking countries, its rate of increase is also slow. When the increase of population slows down, this means that the language users become less active in using this language. It also renders the language less concrete.