VERBS CHANGE MORE THAN NOUNS: A BOTTOM-UP COMPUTATIONAL APPROACH TO SEMANTIC CHANGE

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ABSTRACT: Linguists have identified a number of types of recurrent semantic change, and have proposed a number of explanations, usually based on specific lexical items. This paper takes a different approach, by using a distributional semantic model to identify and quantify semantic change across an entire lexicon in a completely bottom-up fashion, and by examining which distributional properties of words are causal factors in semantic change. Several independent contributing factors are identified. First, the degree of prototypicality of a word within its semantic cluster correlated inversely with its likelihood of change (the "Diachronic Prototypicality Effect"). Second, the word class assignment of a word correlates with its rate of change: verbs change more than nouns, and nouns change more than adjectives (the "Diachronic Word Class Effect"), which we propose may be the diachronic result of an independently established synchronic psycholinguistic effect (the "Verb Mutability Effect"). Third, we found that mere token frequency does not play a significant role in the likelihood of a word's meaning to change. A regression analysis shows that these effects complement each other, and together, cover a significant amount of the variance in the data.

KEYWORDS: semantic change, distributional semantics.

1. THE PROBLEM OF SEMANTIC CHANGE

Lexical semantic change - change in the meanings of words - is a basic fact of language change that can be observed over long periods of time. For example, the English word girl originally indicated a child of either sex, but in contemporary English, it refers only to a female child. Bybee shows the turning point was the fifteenth century, after the conventionalization of the word *boy* to refer to a male child, which "cut into the range of reference for girl" (Bybee 2015: 202). But semantic change is also "an undeniable and ubiquitous facet of our experience of language" (Newman 2015: 267), with words acquiring new senses, developing new polysemies, and entirely new meanings, in time-frames that can be observed even by casual observation by speakers. For example, recent changes in technology have led to novel meanings of words like *navigate*, *surf*, and *desktop* (Newman 2015: 266). Speakers and listeners may even be aware of "mini" semantic change in real time, when they experience an innovative use of an existing word.

Linguists have identified some recurring types of semantic change. Some of the major types include the textbook examples of change in scope, e.g., *widening* (Latin *caballus* 'nag, workhorse' > Spanish *caballo* 'horse') or narrowing (*hound* 'canine' > 'hunting dog'), or in connotation (*amelioration* or *pejoration*). However, the systematic search for an explanatory theory of semantic change was largely neglected until Geeraerts (1985, 1992) and Traugott & Dasher (2002), who both claimed that semantic change is overwhelmingly regular. Moreover, both Geeraerts and Traugott have claimed that semantic change – like language change in general – is rooted in and constrained by properties of human cognition and of language usage.

Contemporary research identifies different kinds of regularity in semantic change as *tendencies of change*, which are asymmetries with respect to the directions in which change is more likely to occur. For example, Traugott & Dasher (2002) propose that semantic change regularly follows the pathway: objective meaning > subjective meaning > intersubjective meaning. It has also been suggested that concrete meanings tend to develop into more abstract ones (Bloomfield 1933; Haspelmath 2004; Sweetser 1990). See the following examples:

(1) *see* 'visual perception' > 'understanding'

(2) *touch* 'tactile perception' > 'feel'

(3) *head* 'body part' > 'chief'

Another often-observed regularity is that semantic change overwhelmingly tends to entail polysemy, in which a word or expression acquire new senses that co-exist with the older conventionalized senses (e.g., a new sense for *surf* has emerged since the 1990s). These new senses can continue to co-exist stably with the older ones or to supplant earlier senses, thereby "taking over" the meaning of the word.

The existence of such regularities and asymmetries, or "unidirectional pathways of change", has been taken as evidence that language change is not random. Moreover, these asymmetries call for explanations that are plausible in terms of what we know about human cognition and communication. Numerous such explanations have been offered, from Traugott & Dasher's (2002) influential Neo-Gricean account to other pragmatically-based accounts (for an overview, see Grossman & Noveck 2015). However, while such accounts may offer potentially convincing explanations for observed changes, there is to date no empirically-grounded theory that can explain – or predict – which words are likely to undergo semantic change, and why this is so, across an entire lexicon.

This last point is the focus of the present article. While historical linguists have painstakingly accumulated much data about – and proposed explanations for – cross-linguistically recurrent pathways of semantic change (e.g., body-part term > spatial term), the data and explanations are usually specific to a particular group of words. For example, the explanations proposed for the development of body-part terms into spatial terms cannot necessarily be generalized to words of other semantic classes. In fact, the question posed in this article – what are the specific properties of words that make them more or less prone to semantic change? – has been almost entirely neglected in historical linguistic research. Furthermore, most studies of attested pathways of change tend to focus on their descriptive semantics, and have tended to ignore their distributional properties.

Nonetheless, some work in this direction can be found in earlier structuralist and cognitivist theories of semantic change, which emphasized the role of the structure of the lexicon in explaining semantic change. For example, it has often been assumed that changes in words' meanings are due to a tendency for languages to avoid ambiguous form-meaning pairings, such as homonymy, synonymy, and polysemy (Anttila 1989; Menner 1945). On the other hand, when related words are examined together, it has been observed that one word's change of meaning often "drags along" other words in the same semantic field, leading to parallel change (Lehrer 1985). These seemingly contradictory patterns of change lead to the conclusion that if ambiguity avoidance is indeed a reason of semantic change, its role is more complex than initially assumed.

However, what is common to both ideas – the putative tendency to avoid ambiguous form-meaning pairings and the equally putative tendency for words in the same semantic domain to change in similar ways – is the observation that changes in a word's meaning may result from – or cause – changes in the meaning of a semantically related word. The idea that words should be examined relative to each other, and that these relations play a causal role in semantic change is elaborated by Geeraerts (1985, 1992), who maps related words into clusters, and based on Rosch's prototype theory (1973), establishes which words are the prototypical or peripheral exemplars within each cluster. Geeraerts analyzes these clusters diachronically, finds characteristic patterns of change due to meaning overlap, and concludes that prototypical semantic areas are more stable diachronically than peripheral ones. While Geeraert's ideas are promising for studies of semantic change, they are based on case-studies hand-picked by the linguist, and are not based on large-scale corpora (Geeraerts 2010). This is a lacuna in the research field of semantic change, which we have addressed in a previous article (Dubossarsky et al. 2015) by articulating a method for identifying and quantifying semantic change across an entire lexicon, represented by a massive historical corpus.

Our aim in the present article is to evaluate whether other distributional properties of words are indeed implicated in semantic change. Specifically, we examine whether words of different parts-of-speech or word classes change at different rates. We assume that the null hypothesis is that there is no difference between word class assignment and rate of change. However, we predict that there will indeed be differences, based on the fact that different word classes prototypically encode cognitively different things: nouns prototypically encode entities, verbs prototypically encode events, and adjectives prototypically encode properties. Moreover, different word classes can have significantly different collocational properties, i.e., they occur in different types and ranges of contexts. Finally, Sagi et al. (2009), one of the only studies to tackle this question, found that in 19th century English, a small selection of verbs showed a higher rate of change than nouns.

It is important to stress that at no time do we, or any of the above works cited as far as we know, claim that semantic change is governed by a single factor. In fact, it is clear that previous work on semantic change is likely to be correct in supposing that social, historical, technological, cognitive, communicative, and other factors are implicated in semantic change. The question is how to tease them apart and understand their respective contributions. This paper demonstrates that an observable property of words, i.e., their part-of-speech or word class assignment, is indeed implicated in semantic change. Moreover, we demonstrate that this effect is in addition to another effect which we have argued for earlier, namely, that the position of a word within its semantic cluster – interpreted as its degree of prototypicality.

The structure of the paper is as follows: in Section 2, we sketch the methodology used, and in Section 3, we describe the experiment conducted. In Section 4 we discuss the results, and in Section 5 we analyze possible interactions with other factors. Section 6 is devoted to discussion on the results and their implications. Section 7 provides concluding remarks, focusing on directions for future research.

2. METHODOLOGY

2.1 The role of input frequency

There are numerous ways of representing lexical meaning. Computational models developed for representing meaning excel in what computational approaches do best and classical historical linguistics does poorly, namely, the large-scale analysis of language usage and the precise quantitative representation of meaning. At the heart of these models lies the “distributional hypothesis” (Firth 1957; Harris 1954), according to which the meaning of words can be deduced from the contexts in which they appear.

We employ a distributional semantic modeling (DSM) approach to represent word meanings. DSM collects distributional information on the co-occurrence profiles of words, essentially showing their collocates (Hilpert 2006; Stefanowitsch & Gries 2003), i.e., the other words with which they co-occur in specific contexts. Traditionally, this is done by representing each word in terms of its collocates across an entire lexicon. This type of model has the advantage of providing an explicit (or direct) quantitative measure of a word’s meaning, and is informative in that it tells us which words do or do not occur with a given word of interest. However, since most words occur with a limited range of collocates, most of the words in a lexicon will co-occur with most other words in the lexicon zero times. As such, these kinds of representations are sparse. This can be seen in the following illustrative example bellow, where only ten words collocate with the word *pan*, while the rest of the vocabulary (i.e., *surf, sky, dress, hat, call*, etc.) does not.

collocations	*pot*	*fry*	*cook*	*egg*	*bacon*	*cake*	*butter*	*oil*	*stir*	*stove*	*surf*	*sky*	*dress*	*hat*
#	87	69	61	55	51	49	23	19	17	9	0	0	0	0

TABLE 1. WORDS COLLOCATIONS STATISTICS FOR THE WORD *PAN* (ILLUSTRATIVE EXAMPLE)

This type of representation is usually further analyzed, e.g., by normalizing the word counts to frequencies, or with more sophisticated statistical methods, e.g., tf-idf or point mutual information. However, for our purposes, such models are inadequate, because in the end they tell us only whether a word co-occurs with another word or not. In order to understand the relationship of a word with the rest of the words in an entire lexicon, other types of models are necessary.

These models are the more recent ones that exploit machine-learning and neural network tools to learn the distributional properties of words automatically. Unlike traditional models, they do so by representing words in terms of the interaction of multiple properties. However, the specific contribution of each property, when taken on its own, is opaque; as such, the quantitative representation of a word's meaning is implicit. Of the available recent models of this type, we chose a recently developed skip-gram word2vec model (Mikolov et al. 2013c, 2013d). This word2vec model has been fruitfully applied to distributional semantic corpora research, and scores high in semantic evaluation tasks (Mikolov et al. 2013a). As we will show, proof-of-concept can also be found in our results.

The word2vec model captures the meaning of words through dense vectors in an n-dimensional space. Every time a word appears in the corpus, its corresponding vector is updated according to the collocational environment in which it is embedded, up to a fixed distance from that word. The update is carried out such that the probability in which these words predict their context is maximized (Figure 1a.). As a result, words that predict similar contexts would be represented with similar vectors. In fact, this is much like linguistic items in a classical structuralist paradigm, whose interchangeability at a given point or "slot" in the syntagmatic chain implies that they share certain aspects of function or meaning, i.e., the Saussurian notion of "value" (Figure 1b.). It is worth noticing that if taken individually, the vectors' dimensions are opaque; only when the full range of dimensions is taken together do they capture the meaning of a word in the semantic hyper-space they occupy.

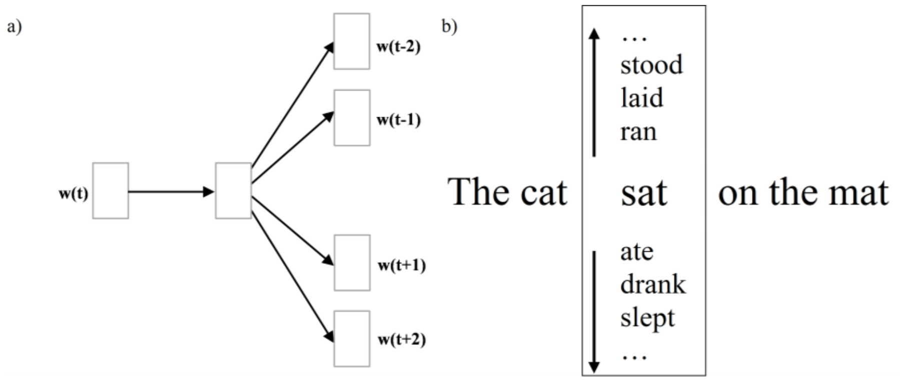

FIGURE 1. (A) WORD2VEC SKIP-GRAM ARCHITECTURE.
GIVEN A WORD, W(T), THE MODEL PREDICTS THE WORDS THAT PRECEDE AND PROCEED IT IN A WINDOW OF 4 WORDS, W(T-2),W(T-1),W(T+1),W(T+2) (MIKOLOV ET AL. 2013B).
(B) AN EXAMPLE OF THE CLASSICAL STRUCTURALIST PARADIGM.

While it may be surprising for linguists that one would choose to rely on a model whose individual dimensions are opaque, this is not a major concern, since it is well-established that words assigned similar vectors by the model are in fact semantically related in an intuitive way; for a recent demonstration, see Hilpert & Perek (2015), which looks at the collocates of a single construction in English. The similarity between vectors is evaluated quantitatively, and defined as the cosine distance between the vectors in the semantic hyperspace. Short distances are considered to reflect similarity in meaning: related words are closer to each other in the semantic space (Turney 2006; Mikolov et al. 2013d; Levy & Goldberg 2014). In fact, this is reflected in the words' nearest neighbors in the semantic space that often capture synonymic, antonymic or level-of-category relations.

Although the model uses the entire lexicon for training, the accuracy of the meaning representations that is captured in the corresponding vectors is expected to diminish for less frequent words. This is simply because these words do not appear frequently enough for the model to learn their corresponding contexts. Therefore, only the most frequent words in the corpus, excluding stop-words, are defined as words-of-interest and are further analyzed. These words represent the entire lexicon.

2.2 Corpus

A massive historical corpus is required to train distributional semantic models. This is because the words whose distributional properties we are interested in must appear frequently enough in each time period in order to collect enough statistical information about their properties. Clearly, the time resolution of any analysis on such models is limited by the nature of the historical corpus: the finer the tagging for time, the finer the analysis can be.

Google Ngrams is the best available historical corpus for our purposes, as it provides an unprecedented time resolution – year by year – on a massive scale; the second largest historical corpus is about 1000 times smaller. Tens of millions of books were scanned as part of the Google Books project, and aggregated counts of Ngrams on a yearly resolution from those books are provided.

We used a recently published syntactic-Ngram dataset (Goldberg & Orwant 2013), where the words[1] are analyzed syntactically using a dependency

[1] The present study deals with word forms rather than lexemes. While this is possibly a shortcoming, it is shared by most NLP studies of massive corpora. Furthermore, the issue is less likely to affect English, with its relatively poor morphology, than other languages. Nevertheless, one might speculate about the effects of this. For example, it might be that the meaning of a specific verb forms in the corpus will be narrower than that of specific noun forms, overall, in an analysis based on word forms than in one based on lexemes. While it would be of considerable interest to conduct an experiment to determine the effect of using word forms versus lexemes, the issue has never been dealt with explicitly in computational linguistics, as far as we know, and it is beyond the scope of the present paper. We thank an anonymous reviewer for bringing this issue to our attention.

parser in their original sentences. The dataset provides aggregated counts of syntactic Ngrams on a yearly resolution that includes their part-of-speech (POS)[2] assignments as well. The dataset distinguishes content words, which are meaning-bearing elements, from functional markers[3] that modify the content words. Therefore, a syntactic Ngram of order N includes exactly N content words and few optional function markers. We used syntactic Ngrams of 4 content words from the English fiction books,[4] and aggregated them over their dependency labels to provide POS Ngrams. The following is an example POS Ngram from the corpus.

(4) and_CC with_IN sanction_NN my_PR tears_NN gushed_VB out_RB

Verbs, nouns, and adjectives below a certain frequency threshold, and all the rest of the POS assignment, lose their tags. In this Ngram, only *tears* retains it.

The historical corpus is sorted diachronically, with 10 million POS Ngrams (about 50 million words) per year for the years 1850-2000. When the number of POS Ngrams in the corpus for a given year was bigger than that size, due to the increasing number of published and scanned books over time, a random subsampling process was conducted to keep a fixed corpus size per year. This resulted in a corpus size of about 7.5 billion words. Only the words-of-interest, the most frequent words in the corpus, retain their POS assignment, while the rest of the words reverted to their original word forms. All words were lowered case.

2.3 Diachronic Analysis

After initialization, the model is trained incrementally, one year after the other, for the entire historical corpus (POS-tagged and untagged words alike). In this way, the model's vectors at the end of one year's training are the starting point of the following year's training, which make them comparable diachronically. The model is saved after each year's training, so that the words' vectors could be later restored for synchronic and diachronic analyses.

The words vectors are compared diachronically in order to detect semantic change. Based on the affinity between similarity in meaning and similarity in vectors described in §2.1, semantic change is defined here as the difference between a word's two vectors at two time points. This allows us to quantify

[2] We use the term "part-of-speech" abbreviated POS, in the context of Natural Language Processing tagging, and the term "word class" otherwise.
[3] These include the following dependency labels: *det, poss, beg, aux, auxpass, ps, mark, complm* and *prt.*
[4] From the 2nd version of Google books.

semantic change in a straightforward fashion: the bigger the distance between the two vectors of a given word, the bigger the semantic change that this word underwent over that period of time. Specifically, the comparison is defined as the cosine distance between the word's two vectors according to equation 1, with 0 being identical vectors and 2 being maximally different. This is carried out for the entire lexicon.

$$(1) \qquad \Delta w^{t^0 \to t^1} = 1 - \frac{{v_w}^{t_0} \cdot {v_w}^{t_1}}{\|{v_w}^{t_0}\| \cdot \|{v_w}^{t_1}\|}$$

where ${v_w}^{t_0}$ and ${v_w}^{t_1}$ are the word's w vectors at two time points, t_0 and t_1, respectively.

In the following section, we present an experiment that investigates the relationship between word class assignments and likelihood of change.

3. EXPERIMENT

In this experiment, we evaluate the hypothesis that different parts of speech change at different rates. As noted above, we assume that the null hypothesis is that there is no difference between part of speech assignment and rate of change. However, we predict that there will indeed be differences, based on the fact that different parts of speech prototypically encode cognitively different things: nouns prototypically encode entities, verbs prototypically encode events, and adjectives prototypically encode properties. Moreover, different parts of speech can have significantly different collocational properties, i.e., they occur in different types and ranges of contexts. Finally, pilot studies of this question (Sagi et al. 2009) have indicated that some verbs show a higher rate of change than some nouns.

The word2vec model[5] was initialized with the length of vector set to 52, which means that the words' contexts are captured in a 52-dimension semantic hyper-space. The model was trained over the POS-tagged English fiction corpus (see §2.2), using the method described above (see §2.3). Words that appeared less than 10 times in the entire corpus were discarded from the lexicon and were ignored by the model.

The vectors of the 2000 most frequent verbs, nouns and adjectives (6000 in total) as they appear in the corpus were defined as the words-of-interest, and restored from the model at every decade from 1900 till 2000. For each word, the cosine distances between its vectors at every two consecutive decades were computed using equation (1). This resulted in 6000x10 semantic

[5] We used genism python library for its word2vec implementation (Řehůřek & Sojka 2010).

change scores that represent the degree of semantic change that each word underwent in every decade throughout the twentieth century (e.g., 1900-1910, 1910-1920, until 1990-2000). The average semantic change scores of each POS assignment were compared between groups.

4. RESULTS

Figure 2 shows the average semantic change for the different POS assignment groups at ten decades throughout the twentieth century. The results were submitted to a two-way ANOVA with POS *assignment* and *decade* as the independent variables. The first main effect, also clearly visible, is that the POS assignment groups differ in their rates of semantic change over all the decades ($F_{(2,59970)} = 6464$, $\eta = .177$, p-value <.001). The second main effect is that the semantic change rate appears to differ throughout different decades across all POS assignment groups ($F_{(9,59970)} = 576$, $\eta = .08$, p-value <.001). The interaction between the variables was found to be significant as well ($F_{(18,59970)} = 14.34$, $\eta = .004$, p-value <.001). This means that the rate of semantic change along the decades is not uniform across the POS assignment groups. However, the effect size of the first two variables reported above is robust, accounting for 17.7% and 8% of the overall variance in the words semantic change, respectively, which render these variables highly meaningful. In contrast, the effect size of the aforementioned interaction accounts for only 0.4% of the variance, which makes it unimportant, albeit statistically significant.

In order to evaluate the source of the first main effect – the difference in the rate of semantic change between the POS assignment, we conducted permutation tests as a post-hoc analysis on the pairs *verbs-nouns* and *nouns-adjectives*. The permutation tests created null hypotheses for each pair by assigning words to one of the two POS group randomly, then computing the differences between the averages of the two groups, and repeating the process 10,000 times for each decade. These distributions were later compared to the real differences in the average semantic change in each decade, so that their statistical significance could be evaluated. The permutation tests corroborate what is visibly clear from the descriptive pattern of the results (all p-values <.001), that *verbs* change more than *nouns*, and *nouns* change more than *adjectives*.

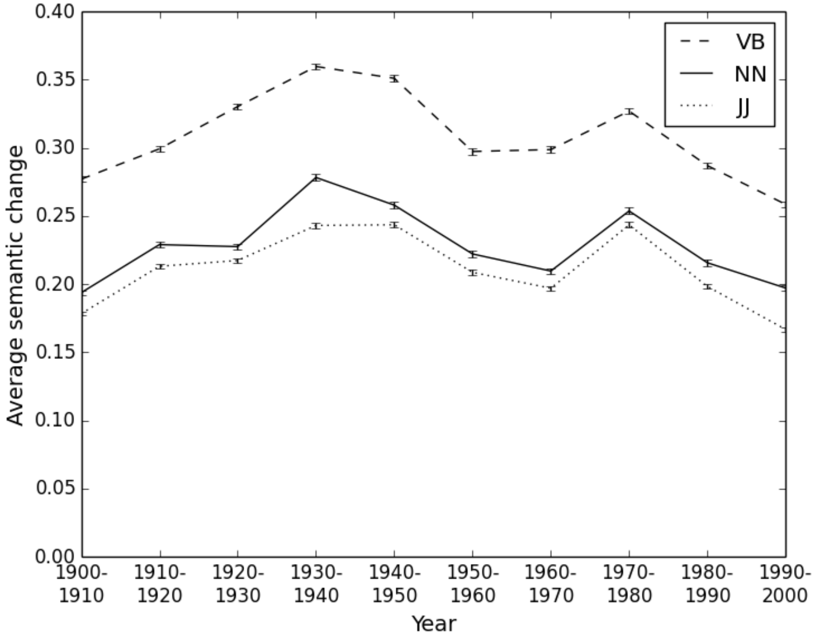

FIGURE 2. AVERAGE SEMANTIC CHANGE RATES THROUGHOUT THE DECADES IN THE TWENTIETH CENTURY FOR DIFFERENT POS ASSIGNMENT GROUPS. BARS REPRESENT STANDARD ERRORS.

5. INTERACTION WITH OTHER FACTORS: FREQUENCY AND PROTOTYPICALITY

In previous work, at least two observable properties of words have been argued to be causally implicated in semantic change, word frequency and prototypicality. We wanted to test their joint involvement in semantic change in light of the aforementioned findings.

5.1 Frequency

Frequency is often linked to language change, but its exact effects still remain to be worked out (Bybee 2006, 2010). While frequency clearly facilitates reductive formal change in grammaticalization and in sound change, it also protects morphological structures and syntactic constructions from analogy (e.g., irregular verbs forms are more frequent). Since no explicit hypothesis has been made regarding the role of frequency in semantic change per se, we set out to test the hypothesis that frequency plays some role in semantic change. The null hypothesis was that there is no correlation between words' frequencies and their degree of semantic change.

Token frequencies were extracted from the entire corpus (about 7.5 billion words) and served as the words frequencies. The degrees of semantic change were taken from the results reported in §4 above.

In general, frequency was not found to correlate with the degree of words' semantic change over the ten decades in the twentieth century. Only four decades (1900-1910; 1910-1920; 1950-1960; 1960-1970) showed significant (p-value $<.01$) correlations. However, such correlations are so small, with maximum correlation coefficient $<.07$, that in terms of their effect size they account for less than 0.5% of the variance in the semantic change scores. Similar results were obtained when the analysis was repeated for each POS assignment group separately. Most correlations were statistically insignificant, and the ones that were significant were very small. Overall these results suggest that frequency plays little or no role in semantic change. We think that this result is surprising, since frequency is often thought to correlate with the degree of entrenchment of linguistic items in the mental lexicon (Bybee 2010). As such, one might hypothesize that words with high token frequency might be "protected" from semantic change. However, this hypothesis is counter-indicated by the results of our experiment. It may be that token frequency is, in the end, mainly responsible for coding asymmetries (Haspelmath 2008) and does not contribute much to semantic change per se.

5.2 Prototypicality

One of the model's inherent properties is that similar words have similar vectors (see §2.1). This makes the vectors ideal for clustering, where each cluster captures the words' "semantic landscape," as Hilpert & Perek (2015) call it. Importantly, it turned out that these clusters exhibit an internal structure, with some words closer to the center and others further away. In Dubossarsky et al. (2015) we analyzed this structure, and interpreted the distance of a word from its cluster center to reflect its degree of prototypicality, which is the degree by which a word resembles its category prototype. Crucially, this prototypicality was found to play an important role in semantic change, as the further a word is from its category's prototype, the more likely it is to undergo change.

We employ the methodology described in Dubossarsky et al. (2015) to the current dataset. Specifically, for each decade we cluster the 6000 word vectors using 1500 clusters, and compute the words' distances from their cluster centroids. This resulted in ten "prototypicality scores" for each word.

In Table 2, we present two clusters as examples. In each cluster, the words are sorted in prototypicality order (distance from their cluster's center). As a result, said and chamber/room, appear at the tops of their lists, and constitute the most prototypical exemplars in their clusters, *verbs of utterance and enclosed habitats for humans* (see Dubossarsky et al. 2015 for further examples).

said_VB, 0.06 exclaimed_VB, 0.08 answered_VB, 0.08 added_VB, 0.11 whispered_VB, 0.13 cried_VB, 0.14 murmured_VB, 0.15 growled_VB, 0.16 repeated_VB, 0.2 muttered_VB, 0.25	chamber_NN, 0.04 room_NN, 0.04 drawing_NN, 0.05 bedroom_NN, 0.06 kitchen_NN, 0.07 apartment_NN, 0.1

TABLE 2. TWO WORD CLUSTERS, WITH POS TAGS AND DISTANCES FROM THEIR CENTROID, SORTED IN ASCENDING ORDER OF THE LATTER.

We used this approach to extend our previous finding that focused on semantic change in only one decade (1950-1960) to the entire twentieth century. Indeed, prototypicality at the beginning of each of the ten decades was related to the semantic change the words underwent by the end of that decade. Correlation coefficients ranged between r=.27 and r=.35, with average coefficient of r=.32 (all p-values <.001). This means that the farther a word is from the prototypical center of its category, the more likely it is to undergo semantic change, and attests to the meaning-conserving nature of prototypicality in semantic change. This could be called the “Diachronic Prototypicality Effect”.

5.3 Regression analysis

It is intuitively clear that semantic change is not induced solely by a single factor, and that different factors may also be involved. Therefore, we wanted to evaluate the interaction between the two factors that were proven to be involved in semantic change, word class assignment and prototypicality.

In order to discern the contribution of these two factors, whether they complement each other or are to a large extent redundant, they were submitted to a multiple linear regression analysis. Prototypicality, as distance from centroid, and POS assignment were the independent variables, and the semantic change scores was the dependent variable. Regression analyses were conducted for these variables at each of the ten decades, and also pulled over all the decades.

Table 3 shows the contribution of each of the two variables in accounting for the semantic change in each of the ten decades examined as well as overall the decades (all the results reported were statistically significant p-value <.01). The results show that the two variables account for a fair amount of the variance in semantic change, between 21%-29%. Although both variables account for a large part of semantic change when taken individually, POS plays a larger role. Prototypicality, despite playing a lesser role, accounts for a substantial amount of the variance in semantic change as well, which exactly reflects its correlation coefficients' values reported above.

Crucially, prototypicality's unique contribution to the variance in semantic change, over and above what is being explained by POS, is smaller than its individual contribution. This indicates that the two variables overlap to a certain degree, and are not fully independent. However, the fact that prototypicality adds a substantial and unique explanatory power to the regression model suggests that different independent causal elements are involved in semantic change. Our variables are unable to capture these elements in a fully independent form, but different choice of variables, at a different linguistic level, perhaps could. Nevertheless, the results support the hypothesis that the different factors involved in semantic change can be ultimately teased apart.

Decades / Variables	1	2	3	4	5	6	7	8	9	10	pulled
POS + Prototypicality	29	24	28	25	23	22	23	19	21	22	22
POS	24	17	23	19	19	16	20	12	14	17	17
Prototypicality	10	12	10	11	7	11	8	12	12	9	10
Δ Prototypicality	5	7	5	6	4	6	3	7	7	5	5

TABLE 3. PERCENTAGES OF THE EXPLAINED VARIANCE IN SEMANTIC CHANGE WITH DIFFERENT COMBINATIONS OF VARIABLES THROUGHOUT THE 10 DECADES, AND PULLED OVER THE DECADES.

6. DISCUSSION

In the above section, we have argued that the word class assignment of a word is a distinct and significant contributing factor to the likelihood for its meaning to change over time. While, as we have noted above, the null hypothesis is that part of speech assignment does not play a role in semantic change, it is nonetheless reasonable that verbs change at a faster rate than nouns, and that both change at a faster rate than adjectives.

For an explanation, we turn to psycholinguistic research that indicates that in particular contexts, verb meanings are more likely to be reinterpreted than noun meanings. In this section, we restrict ourselves to the noun-verb asymmetry, leaving adjectives for future research. Early work on this topic (Gentner 1981) identified a processing effect known as "verb mutability" which basically says that "the semantic structures conveyed by verbs and other predicate terms are more likely to be altered to fit the context than are the semantic structures conveyed by object-reference terms" (Gentner & France 1988: 343). Broadly speaking, this effect states that when language users are confronted with semantically implausible utterances, e.g., *the lizard worshipped*, they are more likely to reinterpret the verb's meaning than that of the collocate noun. While it would have been possible for lizard to be reinterpreted as meaning slimy man, in fact, experimental subjects preferentially reinterpreted the verb as meaning, e.g., look at the sun or some other action that lizards actually do.[6] Similarly, given the utterance *the flower kissed the rock*, English speakers did not reinterpret the meaning of the nouns, e.g., a flower-like and rock-like person kissing, but rather of the verb, interpreting *kissed* as describing an act of gentle contact (Gentner & France 1988: 345).

The verb mutability effect requires explanation. Several types of explanations have been proffered which mostly have to do with the inherent semantic and formal properties of nouns as opposed to verbs:

1. Nouns outnumber verbs in utterances (Gentner & France 1988).
2. Verbs are typically more polysemous than nouns (Gentner & France 1988).
3. Verbs are typically predicates, while nouns establish reference to objects (Gentner & France 1988).
4. Nouns concepts are more internally cohesive than verb representations (Gentner & France 1988).
5. Nouns are learned earlier than verbs, and presumably for this reason are more stable (Gentner & Boroditsky 2001).

However, all of these explanations have problems (Gentner & France 1988; Fausey et al. 2006; Ahrens 1999).

Our results do not allow us to take a position on the ultimate causal factors underlying the verb mutability effect, nor do we assume that it is universal.[7]

[6] Another line of research that may contribute to an explanation of this phenomenon is generally known as coercion, in which the meaning of a construction is "type-shifted" in appropriate contexts. For example, while the verb *know* in English has a stative default interpretation, when combined with an adverb like *suddenly*, e.g., *Suddenly, she knew it,* it takes on an inchoative meaning. Michaelis (2004) has provided a detailed theory of coercion in the framework of Construction Grammar, focusing on aspectual coercion. What we observe from the literature on coercion, although the point is not made explicitly therein, is that it is the event whose semantics is adjusted to fit the context, rather than the referring expressions.

[7] For example, Ahrens (1999) shows that the verb mutability effect observed in Mandarin is different from that observed in English, and Fausey et al. (2006) found that Japanese does not show a robust noun-verb asymmetry.

Rather, we opportunistically embrace the observation that in English, the language investigated here, this effect has been shown to be robust. Under the assumption that diachronic biases are ultimately rooted in synchronic "online" performance or usage, we expect that the tendency of verbs' meanings to be more frequently adapted to contexts of semantic strain than the meanings of their noun collocates should show up as a diachronic bias.

In fact, this is the leading hypothesis in most theories of semantic change: the interpretive strategies of language users, specifically listeners, are what lead to semantic reanalysis. For example, Bybee et al. (1994) propose that listeners' inferences cause some types of semantic change observed in grammaticalization. Traugott & Dasher (2002) make a similar argument, couching their theory in Neo-Gricean pragmatics. Detges & Waltereit (2002) propose a "Principle of Reference", according to which listeners interpret contextual meanings as coded meanings, and Heine (2002) talks about "context-induced reinterpretation". However, closest to the type of effect discussed here is Regina Eckardt (2009) principle of "Avoid Pragmatic Overload", which says that when listeners are confronted with utterances with implausible presuppositions, they may be coerced into a form-meaning remapping.[8]

Essentially, all of these theories argue that the ways in which listeners interpret semantically implausible utterances lead to biases in semantic change, and, ultimately, the appearance of "pathways" of semantic change. The verb mutability effect identified by Gentner (1981) may be one kind of synchronic interpretative bias implicated in the diachronic asymmetry observed in the present article: in terms of synchronic processing, verbs are more semantically mutable than nouns; correspondingly, in terms of diachronic change over time, verbs undergo more semantic change than nouns. However, the bridge between synchronic processing and diachronic change is not an obvious one. What does seem to be clear is that one would need an appropriate model of memory that would allow individual tokens of utterances, with their contextual meanings, to be stored as part of the representation of a word; for an example, see the exemplar-based model proposed in detail by Bybee (2010).

We would like to point out that we do not think that it is necessarily the word class as a structural label that is implicated in semantic change. Rather, we suspect, along with previous researchers, that this is but a proxy for another asymmetry: verbs, nouns, and adjectives prototypically encode different concepts, with verbs prototypically denoting events, nouns denoting entities, and adjectives denoting properties (Croft 1991, 2000, 2001). It is highly plausible

[8] Grossman et al. (2014) and Grossman & Polis (2014) have applied the latter to long-term diachronic changes in Ancient Egyptian, which provides some necessary comparative data from a language other than the well-studied western European languages.

that the diachronic asymmetry observed in this article is the result of the semantics of the concepts prototypically encoded by a word class rather than the formal appurtenance to a word class per se.

7. CONCLUSIONS

In this paper, we have proposed that a computational approach to the problem of semantic change can complement the toolbox of traditional historical linguistics, by detecting and quantifying semantic change over an entire lexicon using a completely bottom-up method. Using a word2vec model on a massive corpus of English, we characterized word meanings distributionally, and represented it as vectors. Defining the degree of semantic change as the cosine distance between two vectors of a single word at two points in time allowed us to characterize semantic change. While in earlier work (Dubossarsky et al. 2015), we argued that the degree of semantic change undergone by a word was found to correlate inversely with its degree of prototypicality, defined as its distance from its category's center, in the present article we argued that the degree of semantic change correlates with its word class assignment: robustly, verbs change more than nouns, and nouns change more than adjectives. A regression analysis showed that although these effects are not entirely independent from each other, they nevertheless complement each other to a large extent, and together account for about 25% of the variance found in the data. Interestingly, token frequency on its own did not play a role in semantic change.

These results are both reasonable and surprising. They are reasonable because part-of-speech assignment is probably a proxy for the prototypical meanings denoted by the different parts of speech. While verbs, nouns, and adjectives are formal categories of English ("descriptive categories," Haspelmath 2010), and as such, may encode non-prototypical meanings (e.g., the English word *flight* denotes an event rather than an entity), the majority of frequently encountered nouns are likely to denote entities, verbs to denote events, and adjectives to denote properties. Our results indicate that the inherent prototypical semantics of parts-of-speech does indeed influence the likelihood of word meanings to change, individually and aggregately across a lexicon.

We have addressed one part of the diachronic data observed, by relating the diachronic noun-verb asymmetry to the findings of experimental psychology: verbs not only change more than nouns over time, their meanings are also more likely to be changed in online synchronic usage, especially under conditions of "semantic strain," i.e., when language users are confronted with semantically implausible collocations. Under the assumption that semantic change over time is the result of "micro-changes" in synchronic usage, we think it is plausible that the "verb mutability effect" may be part of a real causal explanation for the diachronic noun-verb asymmetry. To the extent that this assumption is correct, it provides further evidence for the need for rich models of memory, possibly along the lines of Bybee's exemplar-based model.

Obviously, much remains for future research. The findings presented here are for a particular language over a particular time period. The most urgent desideratum, therefore, is cross-linguistic investigation. Since the computational tools used here require massive corpora, such cross-linguistic research would demand either larger corpora for more languages, or the development of computational tools that could deal adequately with smaller corpora. Another direction for future research is to continue to identify and tease apart the causal factors implicated in semantic change: while our findings account for a considerable amount of the variance found in the data, they hardly account for all of it. It is likely that further causal factors will be found both in purely distributional factors, the semantics of individual lexical items (given a finer-grained semantic tagging), and extra-linguistic factors. For example, our results show a lack of uniformity in the total amount of change across decades in the twentieth century, a finding that may be related to that of (Bochkarev et al. 2014), which showed that the total amount of change in the lexicons of European languages over the same time period correlated with actual historical events.

Despite the preliminary and language-specific nature of our results, we believe that this study makes a real contribution to the question of semantic change, by showing that a bottom-up analysis of an entire lexicon can identify and quantify semantic change, and that the interaction of the causal factors identified can be evaluated.

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