Time after Time in Words: Chronology through Language Statistics

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Abstract

Previous research has shown that perceptual relations, social affiliations, and geographical locations can be predicted using distributional semantics. We investigated whether this extends to chronological relations. In several computational studies we demonstrated that the chronological order of days, months, years, and the chronological sequence of historical figures can be predicted using language statistics. In fact, both the leaders of the Soviet Union and the presidents of the United States can be ordered chronologically based on the co-occurrences of their names in language. An experiment also showed that the bigram frequency of US president names predicted the response time of participants in their evaluation of the chronology of these presidents. These findings are explained by the Symbol Interdependency Hypothesis which predicts that as a function of language use, language encodes relations in the world around us. Language users can then use language as a cognitive short-cut for mental representations.

Keywords: chronology; language statistics; distributional semantics; embodied cognition; symbol interdependency

Introduction

Veni, vidi, vici. Caesar's tricolon demonstrates that temporal relations can be extracted from language. It is because of the order of the verbs that chronology can be determined, which makes the tricolon *vidi, vici, veni* a common linguistic joke. The non-arbitrary order of event verbs presented in the Latin tricolon can also be found in modern languages. Even though one could say *after and before*, the past (e.g., *before*) typically precedes the presence or the future (e.g., *after*) (Benor & Levi, 2006; Cooper & Ross, 1975). Indeed, binomials such as *before and after*, in *the past and the future*, *long ago and recently*, perhaps in *2014 and 2015*, are more common than their achronological counterparts (e.g, *after and before*). This suggests that language encodes temporal relations, over and above the linguistic temporal markers that help to identify relations in time (Louwerse, 2001).

We have previously explained the presence of linguistic and perceptual effects in language processing in terms of the Symbol Interdependency Hypothesis (Louwerse & Benesh, 2012; Louwerse & Connell, 2011; Louwerse, 2007; 2008; 2011). For instance, when we encounter a word, a rough meaning is generated from its linguistic neighbors (e.g., *chair* would more often accompany *table* than *bird*, therefore chairs and tables can be assumed to have a closer relationship). However, if we need a more precise association, we then can perceptually simulate the features of that concept represented by the word. In short, we do not always rely on perceptual simulation, as in many cases we can process words by the presence of their word neighbors as well as the order in which they appear.

The goal of the present paper was to determine whether chronological information can be extracted through distributional semantics. In other words, we investigated whether the temporality of concepts could be retrieved from the way these concepts co-occur in language.

It is generally assumed that temporal relations and, more specifically, the temporal order of event concepts, is stored in memory along a temporal dimension. Crucially, this temporal dimension is considered directional (Freyd, 1992) in order to preserve the events' temporality. That is, chronological order is preferred upon recall and retrieval from memory (e.g., Raisig, Welke, Hagendorf, & van der Meer, 2010; Raisig, Hagendorf, & van der Meer, 2012). Freyd (1992) as well as Barsalou (2008) assume that this directionality is due to the perceptual and experiential input that is preserved in the conceptual representation: events are experienced and perceived chronologically, which is then stored in the conceptual representation. However, findings suggest that a chronological temporality may develop before the actual experience. Children as young as 3-8 years report events in their naturally occurring chronological order even when they have not yet experienced these events themselves (Nelson and Gruendel, 1986; Hudson & Nelson, 1986). This finding was supported by Raisig et al. (2009) who showed that students were able to report events in chronological order that belonged to an activity they had not experienced themselves (e.g., going scuba diving). The question that arises is how is temporality developed in these cases? One hypothesis is that language may play a role in this task (Louwerse, 2008; Louwerse & Zwaan, 2009).

Little is known about the nature of temporal representations. There appear to be some similarities between spatial and temporal representations (Friedman & Brudos, 1988). They both consist of elements that form relations with each other. Knowing from past research that spatial relations can be predicted from distributional semantics, the question can be raised whether language statistics also allows for temporal relations to be extracted.

In a series of studies, we have previously demonstrated that perceptual information can be extracted from language statistics. For instance, geographical locations can be predicted on the basis of co-occurrences of city names, following the idea that "cities that are located together, are mentioned together" (Louwerse & Zwaan, 2009). That is, *Pasadena* and *Los Angeles* are mentioned together more frequently than *Pasadena* and *Boston*, simply because their geographical locations are close. Conversely, the relative geographical locations from cities can be extracted on the basis of distributional semantics. Louwerse and Zwaan (2009) took the 50 largest cities of the United States and computed their co-occurrence frequencies in the English language. The frequency matrix was submitted to a multidimensional scaling algorithm. The loadings of the city names on a two-dimensional plane correlated with the longitude and latitude of the cities. Along the same line, Louwerse and Benesh (2012) showed that the same computational linguistic method applied to the city names in the Lord of the Rings trilogy allows for retrieving the longitude and latitude of cities in Middle Earth. Finally, Louwerse, Hutchinson, and Cai (2012) demonstrated that these findings are not confined to the English language, but can be replicated using Chinese and Arabic.

Given the similarities between spatial and temporal representations (Friedman & Brudos, 1988), the question can be raised whether the computational linguistic technique used to retrieve the geographical relations between cities can be used to estimate the temporal relations between concepts. We conducted a series of computational studies to determine whether distributional semantics can be used to predict chronological relations. These computational studies were followed by an experiment to determine whether language users might utilize these language statistical cues.

Computational studies

In the computational studies we used first-order and higher-order co-occurrences as dependent variables. For the first-order co-occurrence frequencies the *Web 1T 5-gram* corpus (Brants & Franz, 2006) was used. The corpus consists of unigrams, bigrams, trigrams, 4- and 5-grams of information from the Google database. It consists of 1 trillion word tokens (13,588,391 word types) from 95,119,665,584 sentences. The log frequency was computed for all combinations of words in a 5-gram window. That is, if the analysis was conducted for the days of the week, 7 x 7 first-order co-occurrence frequencies were computed for *Monday Friday*, *Monday* w1 *Friday*, *Monday* w1 w2 *Friday*, and *Monday* w1 w2 w3 Friday, whereby w1-w3 is any word in between the target words.

The higher-order co-occurrence frequencies were calculated using Latent Semantic Analysis (LSA) from the Touchstone Applied Science Associates (TASA) corpus. To begin we created a large term X document where if there were m terms in n paragraphs, a matrix of A = (f_{ij} x G(j) x L(i,j)) m x n was obtained. A function that represents the number of times a term *i* appears in document *j* is represented by f_{ij} and G(j) is the global weighting for the document *j*. L(i; j) is a local weighting of term of the word i appearing in document *j*. These weighting functions are used to reflect knowledge that is beyond the collection of the documents. As in most LSA studies (Landauer & Dumais, 1997; Martin & Berry, 2007), the natural log was used as the local weight and the log entropy was used as the global weight. We then used Singular Value Decomposition (SVD) to decompose the matrix A into three matrices A = UΣV', with one square term x term matrix represented by U, one square paragraph by paragraph matrix represented by V, and diagonal one term by paragraph with singular values on the diagonal being represented by Σ. Removing dimensions corresponding to smaller singular values and keeping the dimensions corresponding to larger singular values results in a low dimensional vector for each word. Although the new matrices for the words are no longer orthogonal, each word becomes a weighted vector on a standard 300 dimensions (Landauer & Dumais, 1997). The semantic relationship between words is then estimated by calculating the cosine between two vectors. With LSA the semantic relatedness is not only determined by the relation between words, but also by the words that accompany a word (Landauer & Dumais, 1997).

Time words

Days of the week The log frequency of the first-order co-occurrences of the seven days of the week were computed. The 7 x 7 log frequency matrix was submitted to a multidimensional scaling analysis. The multidimensional scaling (MDS) analysis was run using the ALSCAL algorithm (SPSS 15.0.1 MDS procedure). Default MDS criteria were used with an S-stress convergence of .001, a minimum stress value of .005, and a maximum of 30 iterations. The fitting on one dimension was moderate, Stress = .47, R^2 = .42. When the loadings of the days of the week on one dimension were compared with the actual ordering of the days of the week, a significant correlation was obtained, Spearman r = .96, p < .01. By comparison, a Monte Carlo simulation with 50 randomized orderings yielded an average correlation of r = .001, p > .05 (SD = .35), indicating that the results were not obtained by chance.

We also fitted the frequency matrix on a two-dimensional plane, unsurprisingly resulting in a better fitting, Stress = .09, R^2 = .98. The first dimension correlated with the order of the days of the week, r = .96, p < .01. The second dimension divided the days of the week into working days (Monday to Thursday) and (start of the) weekend days (Friday to Sunday).

The LSA cosine matrix yielded similar results. The fitting on one dimension was moderate, Stress = .41, R^2 = .79, with a significant correlation between the loadings of the days of the week on one dimension and the actual ordering of the days of the week, Spearman r = .89, p < .01. Fitting on a two-dimensional plane, Stress = .21, R^2 =.88, resulted in the first dimension correlating with order, Spearman r = .82, p =.02, with the second dimension again separating Monday to Thursday from Friday to Sunday.

Months of the year The same first-order co-occurence analysis was conducted for the 12 months of the year. The log frequencies of the 12 x 12 combinations of word pairs were computed and submitted to an MDS. The fitting of the data was moderate, Stress = .42, R^2 = .65. A correlation between the MDS loadings of the months and their rank ordering yielded a significant correlation, r = .92, p < .01. Again, a Monte Carlo simulation with 100 randomized orderings yielded an average correlation of r = .0002, p > .05 (SD = .28).

A fitting of the log frequency matrix on a two-dimensional plane explained almost all of the variance, Stress = .09, R^2 = .99. The first dimension correlated with the order, r = .90, p < .01. This was not the case for the second dimension, r = .04, p > .05. Instead, the second dimension distinguished the colder months of the year, October, November, December, January, February, and March, versus the warmer months of the year, April, May, June, July, August, and September. Note that the reverse could be argued for the southern hemisphere, but the lion's share of the corpus consists of American English.

The MDS fitting of the 12 x 12 LSA cosine matrix yielded similar results, Stress =.45, R^2 = .98, and a significant correlation with the actual order of the months, r = .67, p = .02. A two-dimensional fitting, Stress = .25, R^2 = .93, also yielded a correlation with the order of the months on the first dimension, r = 62, p = .03. Contrary to the first-order co-occurrence data, the second dimension separated May from the other months. The most likely explanation for this plotting lies in the ambiguity of the month's name, as a frequent modal verb.

Years This phenomenon of clustering days of the week and months of the year was extended to years. The frequencies of all combinations of 1901-2000 were computed, resulting in a 100 x 100 matrix of log frequencies, which was again submitted to an MDS algorithm. Fitting of the data on a one-dimensional scale was good, Stress = .38, R^2= .81. The loadings significantly correlated with the order, r = .99, p < .01. A Monte Carlo simulation with 1000 randomized ordering yielded an average r = .001, p > .05 (SD = .09).

As before, the LSA cosines for the years were also submitted to an MDS analysis. Three years, 1992, 1996, and 1998 were not present in the TASA corpus on which the LSA space was trained, leaving a 97 x 97 cosine matrix that resulted in a one dimensional loading of the 97 years with Stress = .41, R^2 = .67. Correlation with the actual years was high, r = .90, p < .01.

The correlation between the 'words' 1901-2000 and their chronology might however not indicate a chronology, but simply a numerical order (cf. Hutchinson & Louwerse, 2013). A two-dimensional MDS solution, however, showed that 1901-2000 should indeed be interpreted as years (Stress = .18, R^2 = .95). The first of the two-dimensional loadings correlated with the chronology (or order). The second dimension clustered the 100 years in what could be seen as historical periods: 1901-1945, 1946-1985 and 1986-2000, making these numerical data more likely to be years than numbers.

These findings show that both the order of time words in language (through first-order co-occurrences) as well as the semantic distribution of those words in language (higher-order co-occurrences) allow for extracting chronological information. The question, however, is whether these findings for temporal words can be extended to words that are non-temporal in meaning.

Leaders and presidents

In the first study, we investigated whether the order of the days of the week, the months of the year, and the years of a century can be retrieved using first-order and higher-order co-occurrences. In the second study, we investigated whether these findings from the first study could be extended to concepts that are not always temporally explicit, such as the names of presidents of the United States. Brown and Siegler (1991), for example, used US presidents to investigate their temporal organization in memory. They found that the 39 US presidents were subjectively organized into three categories: the Founding Fathers (Washington through John Quincy Adams), non-contemporary presidents (Jackson through Franklin D. Roosevelt), and post-WWII presidents (Truman through Reagan). To note, the names extracted from the large corpus are often not explicitly listed chronologically. The corpus used here spans a wide array of sources. These categories were accessed when making temporal judgments about which of two presented presidents was in office earlier. They concluded that there exists some sort of temporal classification in long-term memory which is accessed in order to make temporal judgments which also influences learning new president lists. The question we can try to answer is whether this temporal classification is encoded in language. We answer this question using the names of the leaders of the former Soviet Union, as well as the names of the presidents of the United States.

Soviet Union leaders The names of the eight leaders of the Soviet Union – Lenin, Stalin, Malenkov, Khrushchev, Brezhnev, Andropov, Chernenko, and Gorbachev – were compared using first-order and higher-order co-occurrences. The 8 x 8 matrix of log frequencies was submitted to an MDS analysis, using the same default criteria as in previous analyses. The fitting was good, Stress = .32, R^2 = .91. Loadings of the eight names correlated with their chronological order of being in power, r = .74, p = .04.

Next, the LSA cosines were computed for all 8 x 8 combinations. Again, the MDS fitting for these data was good, Stress =.25, R^2 = .94. The loadings of the names correlated with the chronological order of the Soviet Union leaders, r = .75, p = .04.

United States Presidents The names of all 44 presidents of the United States were considered. The current president, Obama, was not included in the analysis, as the corpus from which data were derived did not include the name. Moreover, there are a number of presidents with the same name: Adams, Bush, Harrison, Johnson, and Roosevelt. Duplicate names were removed by only using the name that occurred first in the list (e.g., Roosevelt was considered to be in the position of Theodore Roosevelt (26th actual presidency) rather than the position of Franklin D. Roosevelt (32nd presidency).

As before, we computed the log frequency of the combinations of president names and submitted this matrix to an MDS analysis. The fitting was good, Stress = .46 R^2 = .67. Loadings of the eight names moderately correlated with their chronological order, r = .37 p = .02. Next, we computed the LSA cosines of the 37 x 37 combination of president names. The MDS analysis showed a good fitting, Stress = .46, R^2 = .56. As with the previous analyses, the loadings of the names correlated with the chronological order of the presidents, r = .78, p < .001.

These findings demonstrate that both the names of Russian leaders as well as the names of United States presidents can be ordered chronologically, based on first- and higher-order co-occurrences. These findings replicate the findings for the time words (days of the week, months of the year, and years). However, even though these findings allow for the opportunity that language users utilize these cognitive shortcuts, they do not provide evidence that language users are sensitive to language statistics of names when they evaluate president names. This question was investigated next in a response time experiment.

Experiment

A response time experiment was conducted to determine whether participants were affected by the language statistics when presented with two names, including the names of US presidents in their chronological order or the reverse chronological order (e.g. *Jefferson – Reagan* vs. *Reagan – Jefferson*).

Methods

Participants Forty University of Memphis undergraduate students participated in this experiment for course credit. All were native English speakers.

1. Washington	15. Lincoln	29. Truman
2. Adams	16. Johnson	30. Eisenhower
3. Jefferson	17. Grant	31. Kennedy
4. Madison	18. Hayes	32. Nixon
5. Monroe	19. Garfield	33. Ford
6. Jackson	20. Arthur	34. Carter
7. Van Buren	21. Cleveland	35. Reagan
8. Harrison	22. McKinley	36. Bush
9. Tyler	23. Roosevelt	37. Clinton
10. Polk	24. Taft	
11. Taylor	25. Wilson	
12. Fillmore	26. Harding	
13. Pierce	27. Coolidge	
14. Buchanan	28. Hoover	

Table 1. Names of the presidents of the United with duplicates removed.

Materials and Design All 37 non-ambiguous names of presidents of the United States were used in the experiment. Each president name was combined with all of the other president names resulting in a complete paired comparison. Subjects were instructed to indicate as quickly and accurately as possible whether both were US presidents. In 50% of the trials this was the case which required a yes-response. In the remaining 50% of the trials one name of the pair was a well-known actor. Theses trials served as distracters that required a no-response. Hence, there was an even number of targets and distracters. Because of the large number of possible president-president combinations including the same amount of president-actor trials, 10 lists were created. Each list contained 198 different president-president combinations. No matter which critical item list a participant received, the distracters used were the same.

Each participant performed in two experiments. President-president and president-actor names were presented either horizontally (i.e., next to each other) or vertically (i.e., one above the other). In each experiment, the critical manipulation of the targets was the temporal order of the presidents. They were either presented in the correct temporal order, that is, in the order of their successive presidencies (chronological condition). Or they were presented in the reverse direction, where a later president was presented before/above an earlier president (reverse chronological condition).

Procedure Participants were seated in front of a computer screen and were asked to respond as quickly and as accurately as possible whether the two words were presidents or not. Names were presented in two configurations, either one above the other (vertical condition) or one next to each other (horizontal condition). The reason we opted for both configurations is to avoid that the effect of linguistic frequencies of names on response times could simply be explained by configuration (Louwerse, 2008). The order of the two configurations was counterbalanced between participants. Each participant randomly received one of the 10 lists. Targets and distracters were presented in a randomized order.

Results

The log frequency of the president names was computed using the first-order co-occurrence technique in the computational studies above.

Erroneous responses were identified as those responses where subjects answered having seen president names, while actor names were (also) included, or answered having not seen president names while those names were presented. These erroneous responses were excluded from the analyses of reaction times. Response times (RTs) that were greater than +2 SD or less than –2 SD from each participant's condition mean were considered outliers and were removed from the analysis.

A mixed effects model was used on the response times, with the log frequency of president name pairs as the fixed factor and subjects and items as random factor. Analyses were conducted for the two configurations (horizontal and vertical) separately.

As we have found in other studies (e.g., Hutchinson & Louwerse, 2014; Louwerse, 2008) log frequency of the two word combinations significantly predicted RTs in both the horizontal and vertical presentation of the president names, $F(1, 488.61) = 30.04$, $p < .001$ and $F(1, 528.72) = 26.94$, $p < .001$ respectively.

These findings indicate that in making judgments about individuals, linguistic frequency of the combinations of names affects those judgements. Moreover, given that the chronological order of presidents can be derived from linguistic frequencies, it is feasible that language users utilize these linguistic cues in their chronological estimates.

General Discussion

In this paper we have added to previous findings that support predictability based on linguistic frequency. Specifically, the findings presented here demonstrated that temporal relations are encoded in language. That is, on the basis of the language statistics the chronology of the days of the week, months of the year, years of a century, as well as the language statistics of names of country leaders can be extracted. Moreover, language users are sensitive to these linguistic frequencies, as we have shown in a response time experiments in which participants evaluated the names of presidents of the United States.

The fact that language encodes time is not surprising, as language contains many temporal markers that help us to order events (Louwerse, 2001). However, the fact that temporal relations can be extracted from distributional semantics (i.e., first- and higher-order co-occurrences) is less obvious. However, perhaps that finding is not very surprising either, given the evidence that geographical information, social relations, valence, modalities, and perceptual relations can be estimated using language statistics. Prelinguistic conceptual knowledge used when speakers formulate utterances gets translated into linguistic conceptualizations, so that as a function of language use, embodied relations are encoded in language (Louwerse, 2008).

It could be possible that the participants in the experiment knew the exact order of the U.S. presidents and that heavily influenced their responses. While unlikely, this is not necessarily the important factor as we have previously shown that people were more able to accurately locate cities in Middle Earth (in The *Lord of the Rings* Trilogy) when they read the text, rather than studied a map or watched the film (Louwerse & Benesh, 2012). More importantly, the results found were independent of whether or not the participant was familiar with the films.

This is the central idea behind the Symbol Interdependency Hypothesis (Louwerse, 2011): language encodes perceptual information, so that language users can utilize the language statistics cues in their cognitive processing. With very limited symbol grounding, meaning can thus be bootstrapped through distributional semantics. According to the Symbol Interdependency Hypothesis, whether language users rely more on language statistics or perceptual factors in conceptual processing, depends on a variety of factors, including the nature of the stimulus and the cognitive task, individual differences, and the time course of processing.

Language has evolved to become a communicative shortcut for language users, so that with limited grounding they can bootstrap meaning. The data presented here suggests that approximately 60% of the temporal relations could be retrieved through language statistics. Whether language users in fact rely on language statistics in making estimates about chronology may not yet be clear, however, the computational studies demonstrate they can, and the experiment reported here shows that they are at least sensitive to these patterns.

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