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Semantic Analysis suggests Dark Past & Bright Future

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Abstract

Based on the findings of the Ingroup Allocation Model (IAM), which suggests that people use evaluative communication to form and maintain groups and as a result increase the individuals' inclusive fitness, we present the Dark Past & Bright Future (DPBF) hypothesis. This framework suggests that people use positive evaluative statements to induce behaviors that are consistent with the speakers' goals. Negative evaluative statements, on the other hand, suggest correction of previous mistakes so that positive results can be obtained in the future. DPBF is compared to Construal Level Theory (CLT) which suggests that values diminish over time and favors symmetrical valence distributions. Data from text analysis suggest that DPBF's distribution is favored over CLT's.

Keywords: LSA, CLT, evaluative communication, semantic spaces, temporal markers

Introduction

A review of DPBF, IAM and CLT

The IAM (Gustavsson & Sikström, submitted) suggests that, evaluative communication in social groups has evolved so that the speaker is favored by inducing change in people’s behavior. We extend IAM to a new hypothesis, DPBF, which applies some of the findings on the future (events that can be influenced) and the past (events that cannot be influenced). This is then compared to CLT which postulates that values diminish with psychological distance, temporal or spatial alike. Gustavsson & Sikström (submitted) examined personal pronouns from a Reuter news corpus where they looked at associations between pronouns and words in the corpus. They argue that individuals that use this kind of evaluative communication are favored by natural selection. This is proven by a computer simulation. With this theory as a framework, this paper suggests that the future is valued higher, since it is not predetermined and can be influenced, while the past is valued lower because of the available feedback that exists. This works in concert with IAM´s prediction about positive and negative statements. However, CLT predicts that past and future events will be valued lower than the present, which contradict the assumption of the DPBF hypothesis.

This paper will cover all of the above theories and examine however the predictions of DPBF are more accurate than those of CLT.

Evaluative Evolution

The central theme of both IAM and DPBF is the theory of Evaluative Evolution (EE). As described above, Gustavsson & Sikström (submitted) showed that individuals who use evaluative communication are favored by natural selection by increasing their inclusive fitness. The increase in fitness is derived from the fact that individuals that use evaluative statement to strengthen their group and allocate resources to it, makes the group stronger and thus the individuals that belong to it. One can argue that evaluative statement are used as a recruiting tool, were groups are commercialized as attractive with the expectation that others may join. Groups are also continuously evaluated by their members (and by other outgroup). Gustavsson & Sikström (submitted) argue that this is made by using positive and negative valence signals, in their case the use of pronouns across contexts. Pronouns that are associated with positive words will have higher valence than those which are associated with negative words. This gives the speaker an evaluative tool to express what behaviors that are preferred (positive valence) and what behaviors that are not worth striving for (negative valence).

Ingroup Allocation Model

IAM suggests that evaluative statements are used to increase the ingroup value and hence the individuals inclusive fitness. It also suggests that individuals use evaluative statements as feedback when the group has performed poorly or need the change. This leads to a theory where groups are dynamic and focuses on how individuals influence group formation. Interested in semantic spaces, Sikström wrote a program (Semantic) that utilizes Latent Semantic Analysis (LSA) with which he has made various findings (Hall, Johannson, Lind, Sikström, & Tärning, 2006; Baath, Marklund, Nilsson, & Sikström, 2009.). In IAM, Gustavsson & Sikström (submitted) use language as a dependent variable for group formation and maintenance. By analyzing how personal pronouns (We, They, Them, etc) are associated across a corpus, valence can be extracted where positive valence suggests association with positive words (Sikström compares this to Barack Obama's famous election speech in which the sentence “Yes we can” is uttered. Here “We” is strongly associated with positive words: “Yes” and “Can”) and negative valence suggests association with negative words. They argue that with the use of positive valence the listener will hopefully see the group as attractive and join. IAM also argue that this kind of evaluative statements can be explicit or implicit. An example of explicit communication to weaken an outgroup could be the use of adjectives such as “They are terrorists”. This sentence also contains an implicit communication; “They” is closely associated with the low-valence word: “Terrorists”. Gustafsson and Sikström (submitted) also suggested that the use of personal pronouns to strengthen ingroups (or weaken outgroups) is favored by natural selection. A computer program was made to simulate the use of such pronouns in a world of fictitious inhabitants called “Sims”. They showed that a group that dominates its environment is better off in an evolutionary perspective when it comes to resource accumulation, influence and conflicts. Hence they have shown that pronouns become associated with patterns of valence, which affects group formation and, in turn, the reproductive success of the group.

DPBF

Gustavsson & Sikström (submitted) states that human cognition and interaction are reflected in language and hence choice of words. The use of words form patterns, a semantic/psychological model were we can trace interactions and extrapolate meanings from contexts. While IAM applies EE on social psychology, and especially on group formation, DPBF applies EE on how language is used to evaluate the past and influence the future. To measure this we examine how we value words and how abstract they appear to humans over time. DPBF suggests that evaluative statements regarding the future have evolved to create an incitement for other people to pursue goals consistent with the speaker's goals. According to this framework future evaluative statements should have a positive valence in order to create a strong incitement to following the speaker's goals. Consequently, a behavioral change will be induced to create a better environment for the speaker. In contrast, evaluative statements of the past are aimed to provide feedback so that repetitions of the same act can be modified to accomplish the goal more efficiently. Therefore, this framework predicts that past events are valued less than future event.

In concert, we also predict that past events will be rated as less abstract than future events. The point of this is that it will help in the formation of a better future, since recent events will have to be more up-to-date for an effective evaluation to occur. Future events, however, are predicted to be rated as more abstract since these events have not yet occurred.

Construal Level Theory

CLT is a theory that describes how temporal distance affect various psychological processes, such as morality (Eyal, Liberman & Trope, 2008), self control (Fujita, Trope, Liberman, Levin-Sagi, 2006; Fujita, Han 2009), social distance (Broemer, Diehl, Ermel, Gebauer, & Grabowski, 2008) and emotional intensity (Van Boven, Dale, Kan, & McGraw, 2010). This section elaborates how CLT treats temporal distance forward and back in time. The basic concept is that people tend to split perception about some subject into primary and secondary features, also called high- and low-level construals. The objects or events that are close in time (short temporal distance) are perceived as more concrete and contextualized; in addition participants tend to focus on peripheral features (low-level construal). In contrast, a long temporal distance can make that same object or event seem abstract and decontextualized, with focus on core features (Trope, Liberman & Wakslak, 2007). To exemplify this Trope & Liberman (2000) investigated how participants rated the purchase of a radio set given different conditions. They found that if the participants imagined that they would buy the radio set in the far future they focused more on peripheral features such as if the radio clock was accurate. The opposite relation was found when participants imagined buying the same radio set in the near future; the participants then focused on the core features such as the quality of the sound.

Other studies have looked at the implications of adopting a certain construal. Fujita & Han (2009) asked participants to specify a category of the words that were displayed on a screen.

To make the participants adopt a concrete construal they asked them to further specify an example of each category; for instance, “car” becomes “vehicle” becomes “Mercedes”. In this case, “Mercedes” is a concrete example and the participant has adopted a concrete construal. CLT also discuss value (valence) as a function of time. Chaiken, Eyal, Liberman, Sagristano, & Trope (2009) describe that values change over time given what level of construal that is the most appealing. They point out that it is a common assumption in the behavioral sciences that the value of something diminishes as perceived distance increases (Ainslie, 1975; O´Dononghue & Rabin, 2000). Trope et al. (2009), on the other hand, suggest that if the low-level construal (close in time) is favored over the high-level, intertemporal discounting will occur, making the outcome less attractive in the future. However, if the high-level outcome is favored over the low-level, the outcome should be more attractive in the future. To further support this, we go back to the study by Trope & Liberman (2000) with the radio set. There were two versions of the study: in one version, participants were led to believe that the sound quality of the radio was good, but that the built in clock was rather useless. In the other version, the opposite information was given; the clock was very accurate but the sound quality was bad. As predicted, when the participants imagined buying the radio set in the future, the value of the radio set was increased in the condition when the sound quality was good but the clock was not very accurate, and the opposite relation was found when the clock was accurate but the sound quality was poor. This implies, again, that long-term goals tend to focus on central features but only when those features are desirable and vice versa. The overall pattern we see when reviewing CLT is that temporal distance affect the values, features and contextualization we apply to an object or event.

Now that we are familiar with the basic concepts it is time to elaborate a formal definition of psychological distance. Van Boven, Dale, Kan, & McGraw (2010) stated that perceived past and future constitutes psychological reality. It was long operationalized by some kind of objective distance; days to exam, weeks until camping trip and so on (Van Boven et.al 2010). One problem with this, according to Van Boven et al. (2010) is that by operationalizing psychological distance with objective measures we can never ascertain whether it is the psychological or objective distance that effect human thoughts, feeling and perceptions. However, studies have recently differentiated and investigated the independent role of perceived psychological distance. For example; Kurtz (2008) showed that people are happier about momentary pleasures (in this case a graduation) when they are led to perceive a life transition as psychologically distant. This seems to clarify the independent contribution of psychological and objective distance.

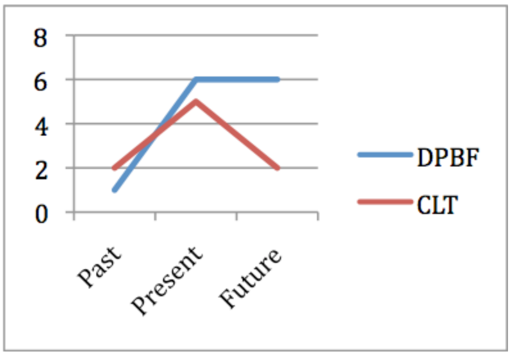
CLT versus DPBF

In this section we will clarify the similarities and differences between CLT and DPBF relevant to our thesis.

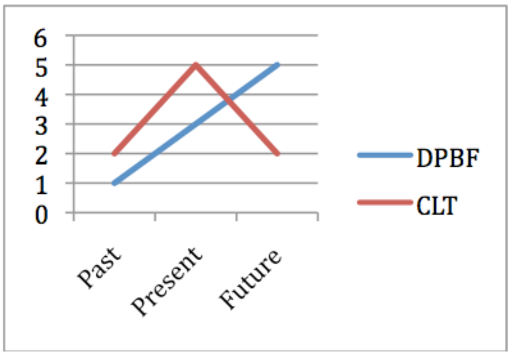
The scope of CLT is the adopting of construals given certain conditions. These construals affect the perception of an object or event. This is similar to DPBF, which states that perception of an event is changed based on semantic feedback from individuals. Therefore, the assumption that temporal distance somehow affects perception is common ground for both theories. Nevertheless, the basis of these assumptions is very different. CLT argues that people focus on different features depending on temporal distance; as this distance increases objects or event seem to be decontextualized where core features are emphasized. The opposite applies for short temporal distance. In contrast, DPBF focus on the induced behavioral changes that occur when temporal feedback is used. The concept of valence does also differ. Where CLT states that valence decrease as psychological distance increase, DPBF states that valence is used as an evaluative tool to create incitement for behavioral change. The most striking similarity is that valence prediction of the past and the present in both theories are roughly equal. DPBF predicts lower valence in the past while CLT predicts an overall decrease in valence relative to the past. Another similarity is the feeling of abstractness, which is predicted to be roughly the same for past events for both theories. However, while the values of these variables might be approximately the same for above conditions, the theoretical framework which explains these values is not. CLT argue that psychological distance diminishes symmetrically relative to the present, while DPBF propose an asymmetrical relation in both valence and abstractness prediction relative to the present. Hence, the above described relations might be equal, but for different reasons.

If we merge the findings and research on CLT we find three interesting aspects: 1. intertemporal discounting shifts values from low to high level construal and vice versa. 2. There is evidence that psychological distance (in any direction) seem to diminish the values of an item or event. 3. These should occur in everyday life and multiple times across a large sample, such as a text corpus. This produces a symmetrical graph where the valence and abstractness diminishes over time relative to the present. Based on the framework presented above, DPBF predicts significantly lower valence in the past compared to the present and future (Graph A). Furthermore, because the evaluative communication has evolved to improve the situation of the speaker, we suggest the valence to be higher or equal in the future compared to the past and present. These predictions are shown in graphs A1 and A2.

Graph A1. Valence prediction. Integers explain a relationship, not actual predictive value.



Graph A2. Abstractness prediction. Integers explain a relationship, not actual predictive value.



Method

Materials

The data extraction was performed on two different computers; one ASUS PRO50N (ASUS, submitted) Laptop (running windows Vista 32-bits, 2 GB RAM, AMD TK57 1.8 GHz processor) and one Desktop PC (running windows 7 64-bit, 2 GB RAM, Intel E6600 2.4 GHz processor). The Verb and Month analysis were performed on the Laptop while the Year analysis was performed on the Desktop PC. Matlab version R2008a was used on the Laptop while the PC was running version R2009b. The data was salvaged by the Matlab application LSALAB (Sikström, submitted), which were compatible with both versions of Matlab described above. During the course of data extraction, two minor changes were made to LSALAB. First, a bug was corrected so that words could be properly extracted from the news corpora. Secondly, the number of decimals obtained when using the "Summary Statistics" function was changed from two to four.

Statistical analysis of the data from LSALAB was conducted by Microsoft Excel 2007 and PASW SPSS v.18.

Latent Semantic Analysis, Semantic, and Semantic Spaces

In order for Semantic to be operational, and in order to analyze large text corpora, an algorithm is needed to construct a database that can be easily analyzed. In addition, this algorithm must also enable us analyze valence across such a corpora. Latent Semantic Analysis (LSA), patented in the US by Scott Deerwester, Susan Dumais, George Furnas, Richard Harshman, Thomas Landauer, Karen Lochbaum, and Lynn Streeter (US Patent, 1988), is such an algorithm. It is a method for calculating similarities between text corpora passages and words. It is able to analyze large amounts of text data and construct a matrix from which we can derive a relation of similarities that words have on a passage. Basically, this method gives us the best approximation of the effect on the meaning of the passage and vice versa.

To fully understand LSA, imagine that you have a large text corpus, in our case a Reuter news corpus. Each article in this corpus is considered to be a separate sample (later referred to as “documents”), and the whole corpus is considered a set. This set generates a matrix were every row is a single word that appears at least once in the set, and every column corresponds to one of the text samples in the set. Each element in this matrix is the frequency of a target word in a target sample. In our example the word “grateful” will have a frequency f_1 in a text sample about aiding children and a frequency f_2 in a sample about carwash accidents. This implies that every word is represented by *n* number of vectors were *n* is the number of times that a word occur at least once across text samples. Following the notion that words with similar meaning tend to occur in the same contexts implies that the vectors of these words should point in similar direction (Sun, 2008). To get a good estimate of any target word LSA uses some number of dimensions *k*. Dumais & Landauer (1997) exemplifies this by the “house/relation” situation. In short, the more dimensions you have generally give a better estimate of some function. There are of course an optimal number of dimensions and that number gives the best estimate of some function; in our case the best vector for any given word. This gives us a matrix that describes the semantic relatedness of words across contexts. This method has been proved to have a tremendous accuracy when comparing to human subjects, in other words; humans rated similarities between words approximately equally to the LSA algorithm (Landauer & Dumais, 1997, Landauer et. al. 1998, Howard & Kahana, 2002).

Valence is built on distance between words in contexts, but how can we be sure that this program rates language at least approximately as good as humans do? In his A NEW (Affective Norms for English Words) list, Bradley and Lang (1999) asked participants to rate about one thousand words on three dimensions; valence, arousal and dominance. This is where we get data for a comparison. To illustrate the rating process consider the words “Liberty” which had a valence score of 8.10 and “Lice” which had a valence score of 2.12 (Bradley et al. 1999). This implicates that we put more positive value in the word “Liberty” than the word “Lice”. To see if Semantic could predict valence across contexts, multiple linear analysis was performed between the ANEW list and the space produced by Semantic. Gustavsson & Sikström (submitted) showed that the validity of this method is roughly comparable to inter-rate agreement on classification of blogs (Semantic: r=0.621 vs. Classification of blogs: r=0.665). Furthermore, Semantic measures the valence in relation to contexts, not the valence of a single target word. The context is defined as the 15 words preceding or following each target word. This gives us a more reliable means of measuring; where every single context of a target word has an average predicted valence, rather than a predicted valence of just a target word.

Procedure

The temporal markers that are going to be used are presented below. This section will treat the selection, classification, and presentation of such markers.

In everyday life we use different tenses and modalities of language to emphasize what point in time we are referring to. Some of these are more easily analyzed, in our case months and years. Years, for instance, are very neat. By knowing when the articles were written (in year 1997) every occurrence of 1996, 1995, etc. denotes one year back in time relative to 1997. Of course the same logic applies to 1998, 1999, etc which denotes one year forward in time relative to 1997. The valence and abstractness extracted for these year gives us a solid timeline. Approximately the same applies to months: Every month is extracted from a corpus containing the correct date markers (12 months for articles written in August 1996; 12 months for articles in September 1996 etc), which generates valances and abstractness values in, again, solid timeline.

The verbs, however, work quite differently. We want to create a solid timeline using past, present and future tense. Since the English language lack proper future tense (Leech, 2003) and the fact that some conjugations can be used to describe past, present and/or future (ex. “Fall” can be used in multiple ways: I Fall [present] and I will Fall [future]), all of the ten verbs were controlled for multiple senses. This was made using Prismas Stora Engelska Lexicon. This method generated a complete list of 10 solid past conjugations and 8 present, shown in table 1. To analyze the future tense we rely on the fact that this is a modal construction which uses auxiliaries (Will or Shall) + infinitive (Leech, 2003). An example of this could be “I *will write* that tomorrow”, which describes our problem since *“write”* can occur in multiple tenses; such as “I *will write*” (future) and “I *write* like crazy” (implying present tense). Hence, only these two auxiliaries were analyzed to represent the future tense, with the assumption that these are mostly used to imply future tense. These auxiliaries are also shown in table 1.

Verbs and Years were extracted in the same way; words were selected and extracted from the Reuter news corpora (404Mb). A standard number of 2000 documents were chosen to scan each verb. Valence and abstractness were plotted for all words, which gave us a matrix for each word; their values were saved into .txt files. These files were then imported to SPSS or Excel where the statistical analysis took place.

Months were plotted approximately in this manner; the difference was that every month (January, February,…, December) was extracted from the files with the correct date markers. All month data were extracted using 5k documents and all year data was extracted using 10k documents. Year and Verb data was extracted, using LSALAB, from a Reuter news corpus (size 404Mb) which contained articles written in 1997. For Semantic to properly read the corpus the news articles are divided by certain markers. These are a “start” and “stop” sign. The space between each start and stop sign contains an article, or as we call it: a document (each document can be considered a participant). X number of documents was scanned (see above) for each condition. Verbs were chosen by extracting 300 of the most common verbs from McMillan’s essential dictionary. The verbs were then randomized and denoted an integer (from 1 to 300). Out of these 300 verbs, 10 were chosen at random to be analyzed. The words were randomized with the help of random.org, a site which can produce lists of true random integers.

Month data was extracted from thirteen separate files; this was due to an erroneous date marking in the original corpus. Each one of these files contains news articles ranging from August 1996 to August 1997. This gives us groups which are denoted numbers. Number 0 corresponds to the midpoint between August 19-96/-97, i.e. February 1997. Each extraction after Feb 1997 are denoted positive integers ranging from 1 to 6, whilst each extraction before is denoted negative integers, ranging from -1 to -6. This gives us a timeline where positive integers represents relative future and negative integers relative past.

Years are presented in the same manner, where 1997 is denoted as 0, while years before 1997 are represented by negative integers, ranging from -1 to -3, whilst years after 1997 is denoted with positive integers, ranging from 1 to 3.

Semantic uses the variable “concrete”, which is in dichotomy with abstractness. The concrete values are negative, which means that low concrete values mean high abstractness values and vice versa. Furthermore, “Valence” is displayed as “@_valence” and “Abstractness” as “@_concrete”.

Defining Past and Future

To analyze the data, we must properly define what we mean with future and past. As stated above we will divide groups using positive and negative integers. We hereby define positive integers as "Future" and negative integers as "Past". Temporal grouping of Verbs is already defined by their conjugations/auxiliaries.

Table 1. Verbs and auxiliaries analyzed.

Infinitive	Simple Past	Past Participle	Auxiliaries
Fall	Fell*	Fallen*	Will**
Go	Went*	Gone*	Shall**
Grow	Grew*	Grown*	
Speak	Spoke*	Spoken*	
Be	Was*	Been	
Write	Wrote*	Written*	
Eat	Ate*	Eaten*	
Drive	Drove*	Driven*	
Do	Did*	Done*	
Choose	Chose*	Chosen	

**= Verbs that were analyzed in this study; checked for unambiguousness. **= Auxiliaries*

Design

The analysis was carried out in the following manner:

A One-way Analysis of Variance (ANOVA) was computed for each variable. Means between groups was compared and Post-Hoc tests (Bonferroni) were conducted to distinguish significance (or non-significance) between each and every group. This procedure was used in each condition (Verbs, Months and Years).

Results

Verbs

A total of 18 verbs and 2 auxiliaries were analyzed generating a total of 15636 entries. Each group's means and standard deviations for valence can be found in Graph G1, and abstractness in Graph G2.

An ANOVA between the groups Past, Present and Future was conducted ($F(V)=283{,}359$, $df=2;15634$, $p<.0001$; $F(C)= 392{,}513$, $df=2;15634$, $p<.0001$). Multiple group comparisons (Bonferroni) for valence showed a significant difference between Past and Present for ($MD=-0{,}03886$, $p<.0001$), Past and Future ($MD=0{,}03856$, $p<.0001$), and for abstractness between Past and Present ($MD=0{,}0218$, $p<.0001$), Past and Future ($MD=0{,}6111$, $p<.0001$), Present and Future ($MD=0{,}0393$, $p<.0001$) and Future and Present ($MD=-0{,}0393$, $p<.0001$). Homogeneity of variances for both variables was significant at the 0.0001 level

(Levene(V)=17,625, df=2;15634, Levene(C)=15,619, df=2;15634). The table for multiple comparisons can be found in Appendix A1.

Months

A total of 12 month across 13 corpus files was analyzed generating a total of 26407 entries. Each group's means and standard deviations for valence can be found in Graph G3, and abstractness in Graph G4.

An ANOVA between the groups was conducted (F(V)=26,190, df=12;26406, p<.0001; F(C)=19,373, df=12;26406, p<.0001). For convenience we present the comparisons between group 0 and 4, -6 and 6, -5, -1 and 5 regarding valence; No significance was found between group 0 and 4 (MD=-0,00093, p=1,0), -6 and 6 (MD=-0,00487, p=1,0), 5 and -1 (MD=0,00578, p=1,0), 5 and -5 (MD=-0,00053, p=1,0). Abstractness comparisons concerned are between group -6 and -2, -6 and 2, -6 and 3, -6 and 6, -1 and 1, -1 and 4; No significances was found between group -6 and -2 (MD=0,00881, p=1,0), -6 and 2 (MD=-0,00280, p=1,0), -6 and 3 (MD=-0,00874, p=1,0), -6 and 6 (MD=0,00005, p=1,0), 1 and 0 (MD=-0,00721, p=1,0), 1 and 4 (MD=-0,00523, p=1,0).

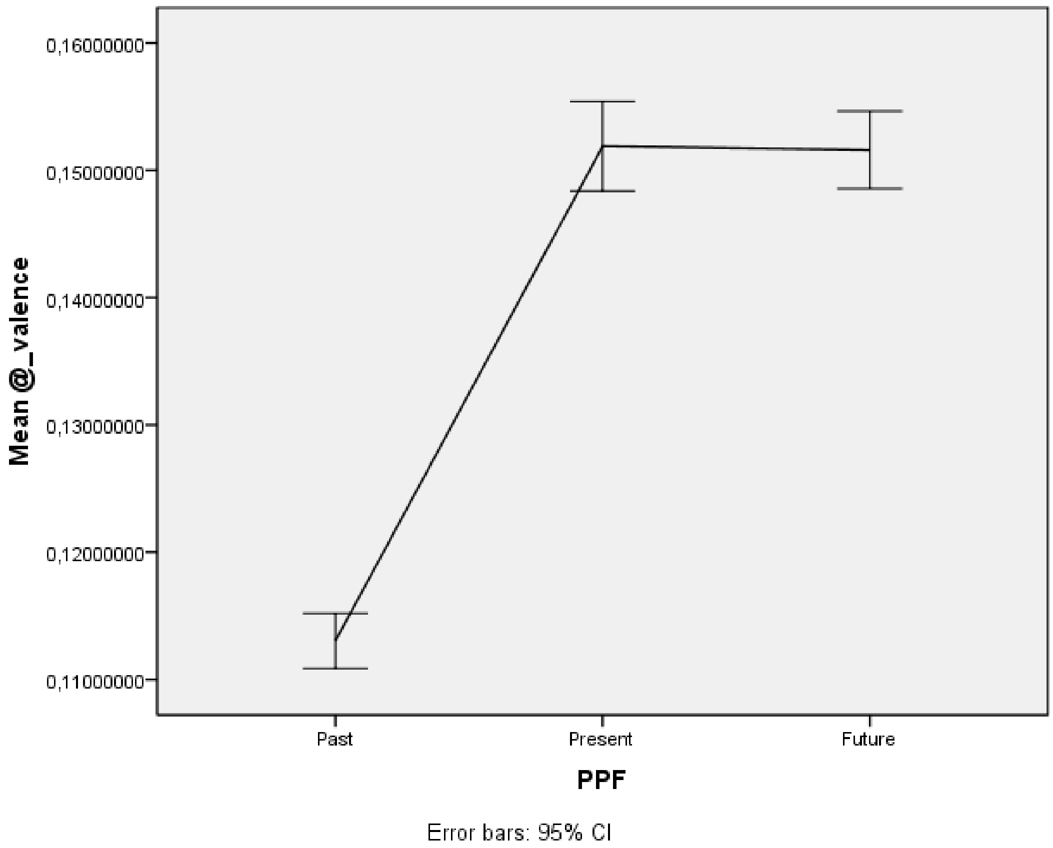
Homogeneity of variances for both variables were significant at the 0.0001 level (Levene(V)=10,317 df=12;26406, Levene(C)=4,026, df=12;26406). The table for multiple comparisons can be found in Appendix A2.

Years

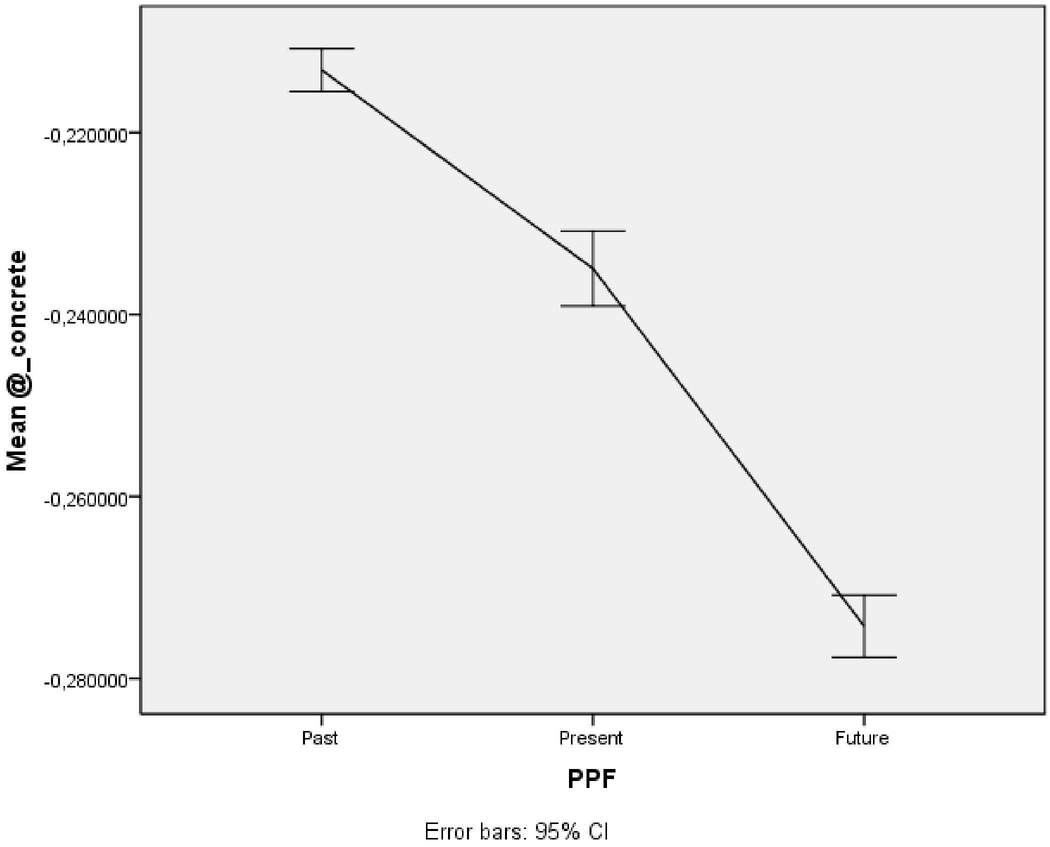
A total of 7 years were analyzed generating a total of 19515 entries. Each group's means and standard deviations for valence can be found in Graph G5, and abstractness in Graph G6.

An ANOVA between the groups was conducted (F(V)=94,012, df=6;19514, p<.0001; F(C)=42,954, df=6;19514, p<.0001).. For convenience we present the comparisons between group 0 and -1, 1 and 3 regarding valence; significance was found between 0 and -1 (MD=0,01185, p<.0001), 0 and 1 (MD=-0,01080, p<.001). No significance was found between 0 and 3(MD=0,00496, p>.05). For convenience we present the comparisons between group 0 and -1, 1 and 2 regarding abstractness; significance was found between 0 and -1 (MD=-0,03790, p<.0001) , 0 and 1(MD=-0,01734, p<.0001), 0 and 2 (MD=-0,01256, p<0,01).

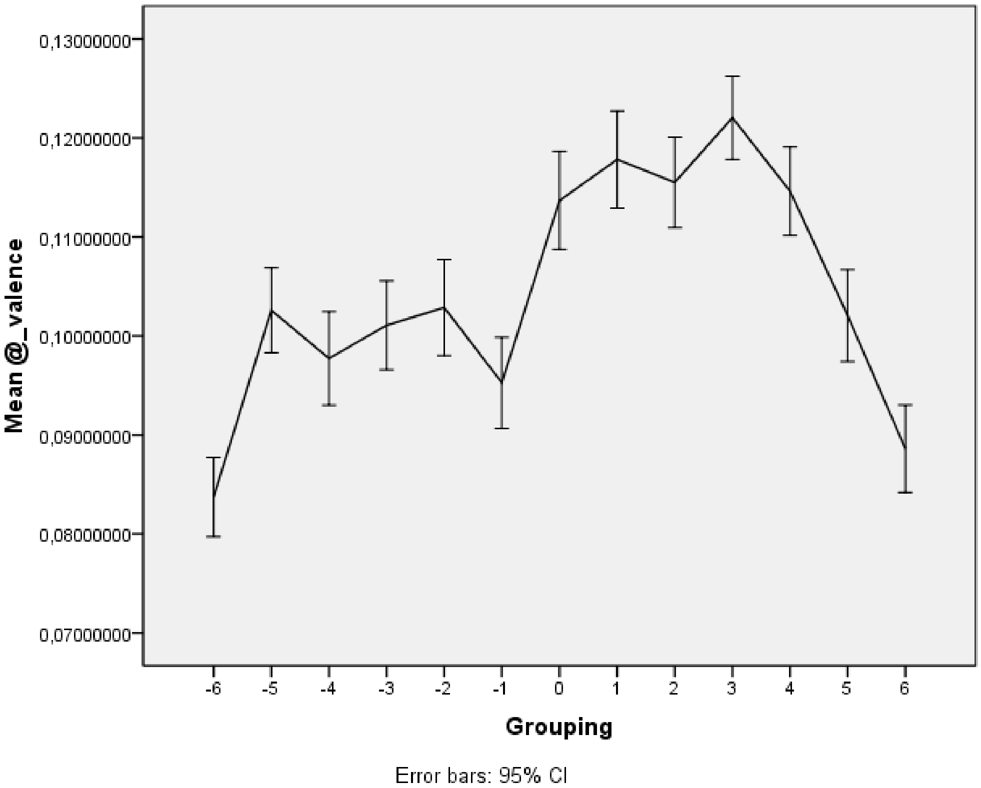
Homogeneity of variances for both variables were significant at the 0.0001 level (Levene(V)=11,710 df=6;19514, Levene(C)=87,683 df=6;19514). The table for multiple comparisons can be found in AppendixA3.



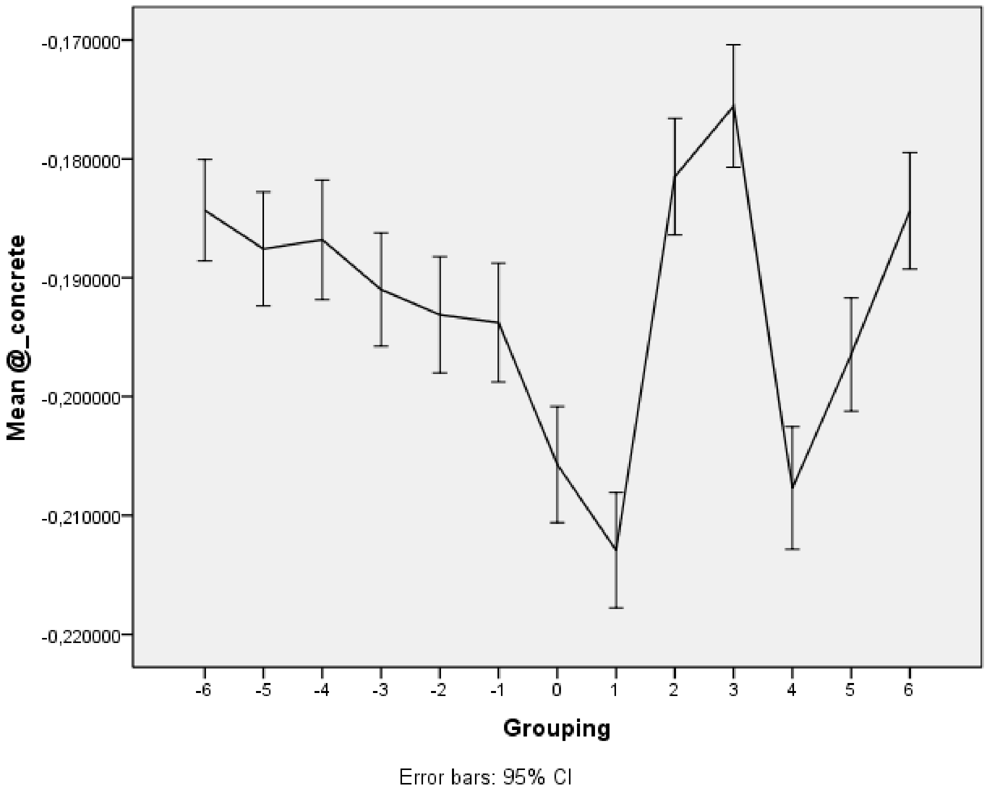
Graph G 1. Verb valence values and standard deviations for the groups Past, Present and Future



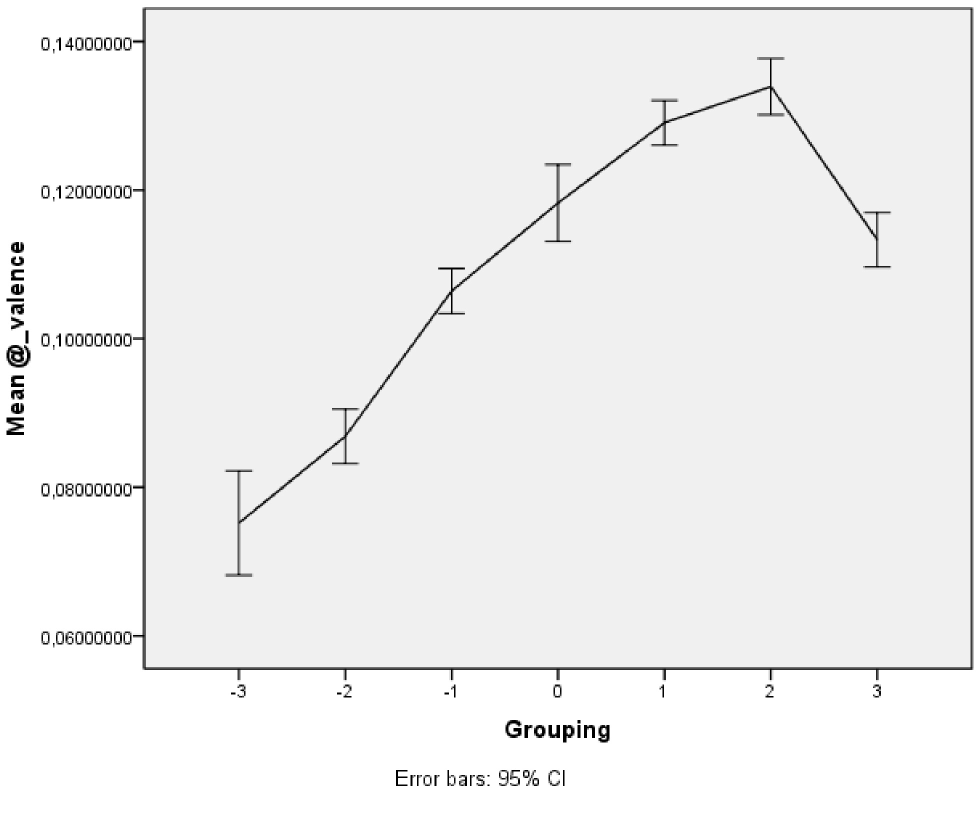
Graph G 2. Verb abstractness values and standard deviations for the groups Past, Present and Future.



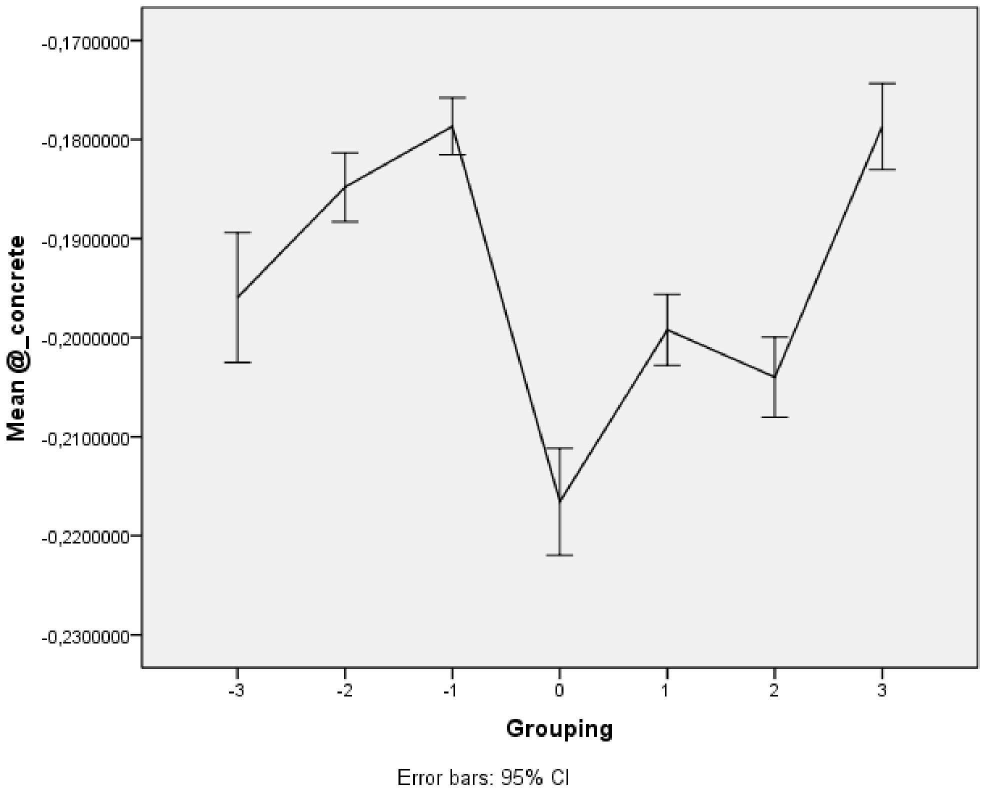
Graph G 3. Month valence values and standard deviations for the groups -6 to 6.



Graph G 4. Month abstractness values and standard deviations for the groups -6 to 6.



Graph G 5. Year valence values and standard deviations for the groups -3 to 3.



Graph G 6. Year abstractness values and standard deviations for the groups -3 to 3.

Discussion

Results

The start of this discussion will be reviewing the results and bring forth eventual issues.

Starting with the Verbs we see that these fit DPBF´s predictions almost perfectly. The valence in the past differs significantly from present and future while the abstractness is increasing significantly from past through present to future (Valence: Future ≥ Present > Past, Abstractness: Future > Present > Past). The Months on the other hand revealed a more complex pattern. According to DPBF valence in the future should be approximately equal to the present, so the fact that groups 1, 2, 3 and 4 is approximately equal is good news for DPBF. However, valence starts to decrease rapidly between group 4 and 5. Since the extraction compartment is cyclic, one can argue that group -6 and 6 are roughly the same (both represent the month August, one in 1996 the other in 1997, relative to February 1997). Furthermore, group -6 and 6 does not differ significantly from each other, making them approximately equal. This means that the term “Future” would somehow need to be more properly defined, and depending on where one draws the line the support for DPBF will change. The author argues that the line should be drawn at group 6 since, even due to its cyclic nature, represents the future relative to February 1997. The drop at group 5 and 6 could be due to several reasons, one of which could be that the limit for the term “Future” should be drawn earlier (more support for DPBF). Another reason could be that the assumption of DPBF does not apply in the extreme future. Taking a look at the overall results we see that Future > Present > Past, which supports DPBF.

Regarding the abstractness values, we see here a rather different pattern compared to the Verbs. Here the prediction that the values of “Present” should be between the Past and Future is challenged. Considering individual groups, group -2 and -1 is within DPBF´s predictions. This is however not enough since every other group (except perhaps group 4) is outside the predicted values. Group 2 and 3 are the most odd, since they score the lowest of all but should be equal or less to group 1 to 4. The standard deviations are low enough to indicate that the overall data are reliable, and because of this we must consider two things; 1: Can months be less adapt at measuring abstractness? And 2: Could the predictions of DPBF in this case be erroneous? It is the opinion of the author that the use of Months as a temporal marker, in this case, should not differ from the other markers used. Months are, as the other markers, treated in the same way, divided into a timeline as with Years and Verbs, the only difference being the extraction method. Verbs are extracted in a manner where the tenses (or auxiliaries) represent some time. Years are extracted and compared to the year that the corpus was written. Months, on the other hand, are extracted several times across the corpus and are then averaged. There is a possibility that this method is not reliable when extrapolating abstractness. There is also the possibility that DPBF´s prediction in this case simply does not apply.

Lastly we take a look at the Years. The results obtained are very similar to the Verbs. There is a minimum valence at group -3 with a steady increase up to group 2, making Present > Past. However we see a sudden drop of valence at group 3 which does not differ significantly compared to group 0. One can treat this in several ways. If we treat the results as three blocks where Past is constituted by group -3 to -1, Present is group 0 and Future is group 1 to 3, and summarize every subgroup within the blocks, we get Future > Present > Past as predicted. We could also “cut” groups -3 and 3 from the graph, which would also generate the predicted relation. The problem with this is that DPBF does not predict valence-drops in the Future. Once again, one could discuss where the future starts and where it transcends to “Far Future” It is the author’s opinion that we should treat this result with caution, mostly because of the different transformations that can be done in DPBF´s favor.

Once again, when looking at abstractness we see a most disturbing pattern. As with the Months, there is a huge spike at the midpoint, contradicting DPBF. The abstractness values for the past are acceptable, since they are higher than the future, but are at the same time questionable since they decrease as they come close to the present. The values for Future could be acceptable if it was not for group 3. In the discussion about the Month results, we examined the possibility that the method used in the extraction process could be responsible for these results. However, Years were extracted in such a way that this reasoning is not possible. In the next session we will discuss how these results relate to our thesis and give some alternative explanations for the deviant results discussed above.

Thesis versus Results

Starting by examining the results that fit the thesis, we find that both valence and abstractness scores in the Verb study proved to conform to the thesis very well, with strong significances and good quality data. However complications arise when examining the Month and Year results. The valence scores for “Past” in both cases are very good, starting out low and growing as they converge to the “Present”. The result for the midpoint which symbolizes the present is also within the thesis predictions: Present > Past. The issues begin when looking at the “Future” data. In both Month and Years there is a valence decline in this condition. It is already stated that this problem is of less concern in the Month condition due to its cyclic nature. This results in 3 valence drop points, one in the Year condition and two in the Month condition. The common nature of these drop points is that they represent the edge of the Future condition measured in this study. This could be due to several reasons: Firstly, the method used could be unreliable regarding far past/future data. Secondly, valence could be dependent on other variables such as anticipation (the year 2000 was a “doomsday” year). And thirdly, CLT could be applicable after a certain time. The last of these statements is the most interesting. Looking at the Month results one see a valence drop at group 5, which represents the end point of the Future condition. Looking at the values between Group 4 and 6 one can see a steady valence drop; the same applies between Group -5 and -6. CLT predicts that value diminishes over time, and this is what it shown here. If that is really the case then DPBF needs to be refined. However, this is not likely since this pattern do not occur in Verbs or Years.

Years show only a valence drop in the far future condition and verbs do not show such drops at all. On the other hand, Verbs lack the facets that Years and Months got, making changes in valence or abstractness over time easier to observe.

The abstractness values across the different conditions pose another challenge for DPBF, since the only results that support DPBF are found in the Verb condition. Again, this could be due to an erroneous prediction or a methodical problem. The next section will discuss the method's influence on the results reviewed above.

Method

Much of the reliability comes from the choice of words and analyzed context. Since the results differ greatly between different conditions, it can assume that the choice of words could have had some implications. It is already established that Verbs differ from Months and Years in regard to part of speech. They also differ in the manner of grouping, where Verbs are divided in three distinct categories while Months and Years are divided across an open timeline.

The nature of Verbs might have proven to be more useful when extrapolating the variables. Even though auxiliaries such as "Will" can have other meanings (example: "My father left me a *will* when he died"), it is still one of the most common auxiliaries to mark future events. Common for all verbs in this study is also that they are frequently used within their denoted tense. Considering this, verbs might be more adapt for the task, making them better predictors for the DPBF hypothesis. The use of months and years might be more irregular, with contextual inconsistencies~~;~~ such as different levels of anticipation or specific events. This could make them a less ideal temporal marker.

Strengths and limitations

The method used to obtain these results is a new emergence in the field of social psychology (Gustavsson & Sikström in press). Research made in accordance to this study is extremely limited. Because of this, the author cannot compare the findings to previous research.

The reliability of this study relies on the findings by Sikström et al. (2006, 2009, in press) regarding Semantic and comparisons between the LSA algorithm and human ratings (Landauer & Dumais, 1997, Landauer et. al. 1998, Howard & Kahana, 2002, Gustavsson & Sikström .in press). The tools provided are in other words extensively and repeatedly examined.

Quantifying language by extracting variables from contexts is extremely powerful, especially when the available data stretches to enormous proportions. Given that the use of a corpus is permitted, and the fact that programs such as Semantic are open source, gives anyone the opportunity to make strong, high quality research. This surely is a strong advantage.

In this article the author suggests a new hypothesis regarding how people relate to the past and the future; no studies are to be found that use the method described above to examine this phenomenon. The lack of comparisons makes the study weaker, since the questions that arise from our results cannot be crosschecked.

The choice of verbs/auxiliaries could certainly be improved if performed by a professional. Due to the English language lack of a proper future tense, linguistics may argue whether the verbs/auxiliaries chosen are valid temporal markers.

Further research

A variety of research could (and should) be done to sort out the questions that have arisen.

Firstly, the author suggests some effort to be put in sorting out reliable temporal markers. The choice of words in this study is mostly based on intuition as to what words are commonly used as a temporal marker in everyday language. Although supported by common use in language and literature, the markers need to be more closely examined.

Secondly, one could study how different contexts used in the extraction process affect the outcome of a hypothesis. One can wonder if the results would deviate if some other corpus was used. An area of study could be to examine literature, novels and short stories, to see if there is a consistency regarding language use through time, or any other question that relates to semantic spaces.

Others might be interested in how language changes or remains the same through time. Since variables can be easily extracted one could, for example, investigate frequencies of words, values of words, emergence and disappearance of words etc. across the 20th century.

Further studies regarding the presented hypothesis would also be desirable. As for now, one can consider this to be a pioneer study. Development on its different aspects is crucial to prove or disprove the assumptions made.

Conclusions

The DPBF theory proposed an asymmetrical distribution of both valence and abstractness values when comparing the past and future to the present. It has been shown to have strong support when it comes to the extrapolation of verbs through contexts. Less support for this distribution was found when months and years were used as temporal markers, where the valence values for years fit better to DPBF's assumption than months did. No or little support for abstractness values was found for these last mentioned conditions. It is the author's opinion that the DPBF hypothesis has come to a good start. Since it cannot be completely rejected, more studies are required to prove or disprove this hypothesis.

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Appendix

A1.

*Multiple group comparisons (Bonferroni) between Past, Present, and Future for Verbs regarding Valence and Abstractness. Significances (p<05) are flagged with *.*

Dependent Variable	(I) PPF	(J) PPF	Mean Difference (I-J)	Std. Error	Sig.
Valence	Past	Present	-,03886*	,00211	,000
		Future	-,03856*	,00195	,000
	Present	Past	,03886*	,00211	,000
		Future	,00029	,00244	1,000
	Future	Past	,03856*	,00195	,000
		Present	-,00029	,00244	1,000
Concrete	Past	Present	,02181*	,00236	,000
		Future	,06111*	,00218	,000
	Present	Past	-,02181*	,00236	,000
		Future	,03930*	,00273	,000
	Future	Past	-,06111*	,00218	,000
		Present	-,03930*	,00273	,000

A2

*Multiple group comparisons (Bonferroni) between Monthss regarding Valence and Abstractness. Significances (p<,05) are flagged with *.*

-6=August 1996; -5=September 1996; -4=October 1996; -3=November 1996; -2=December 1996; -1=January 1997; 0=February 1997; 1=March 1997; 2=April 1997; 3=May 1997; 4=June 1997; 5=July 1997; 6=August 1997

Dependent Variable	(I) Grouping	(J) Grouping	Mean Difference (I-J)	Std. Error	Sig.
Valence	-6	-5	-,01887760*	,00316701821	,000
		-4	-,01401391*	,00316186467	,001
		-3	-,01735895*	,00316015861	,000
		-2	-,01915359*	,00316701821	,000
		-1	-,01155713*	,00316701821	,021
		0	-,02996339*	,00316701821	,000
		1	-,03411100*	,00316658671	,000
		2	-,03180185*	,00316658671	,000
		3	-,03833296*	,00316701821	,000
		4	-,03089939*	,00316443478	,000
		5	-,01833836*	,00316701821	,000
		6	-,00487912	,00316658671	1,000
	-5	-6	,01887759913*	,00316701821	,000
		-4	,00486369321	,00330140028	1,000
		-3	,00151865045	,00329976636	1,000

		-2	-,00027599134	,00330633634	1,000
		-1	,00732046805	,00330633634	1,000
		0	-,01108579531	,00330633634	,062
		1	-,01523340486*	,00330592302	,000
		2	-,01292425166*	,00330592302	,007
		3	-,01945536280*	,00330633634	,000
		4	-,01202178865*	,00330386184	,021
		5	,00053924252	,00330633634	1,000
		6	,01399847639*	,00330592302	,002
	-4	-6	,01401390593*	,00316186467	,001
		-5	-,00486369321	,00330140028	1,000
		-3	-,00334504276	,00329482046	1,000
		-2	-,00513968454	,00330140028	1,000
		-1	,00245677484	,00330140028	1,000
		0	-,01594948852*	,00330140028	,000
		1	-,02009709807*	,00330098634	,000
		2	-,01778794487*	,00330098634	,000
		3	-,02431905601*	,00330140028	,000
		4	-,01688548185*	,00329892208	,000
		5	-,00432445069	,00330140028	1,000

		6	,00913478318	,00330098634	,441
	-3	-6	,01735894868*	,00316015861	,000
		-5	-,00151865045	,00329976636	1,000
		-4	,00334504276	,00329482046	1,000
		-2	-,00179464179	,00329976636	1,000
		-1	,00580181760	,00329976636	1,000
		0	-,01260444576*	,00329976636	,010
		1	-,01675205531*	,00329935222	,000
		2	-,01444290211*	,00329935222	,001
		3	-,02097401325*	,00329976636	,000
		4	-,01354043910*	,00329728694	,003
		5	-,00097940793	,00329976636	1,000
		6	,01247982594*	,00329935222	,012
	-2	-6	,01915359047*	,00316701821	,000
		-5	,00027599134	,00330633634	1,000
		-4	,00513968454	,00330140028	1,000
		-3	,00179464179	,00329976636	1,000
		-1	,00759645938	,00330633634	1,000
		0	-,01080980398	,00330633634	,084
		1	-,01495741352*	,00330592302	,000

		2	-,01264826033*	,00330592302	,010
		3	-,01917937147*	,00330633634	,000
		4	-,01174579731*	,00330386184	,030
		5	,00081523385	,00330633634	1,000
		6	,01427446772*	,00330592302	,001
	-1	-6	,01155713109*	,00316701821	,021
		-5	-,00732046805	,00330633634	1,000
		-4	-,00245677484	,00330140028	1,000
		-3	-,00580181760	,00329976636	1,000
		-2	-,00759645938	,00330633634	1,000
		0	-,01840626336*	,00330633634	,000
		1	-,02255387291*	,00330592302	,000
		2	-,02024471971*	,00330592302	,000
		3	-,02677583085*	,00330633634	,000
		4	-,01934225669*	,00330386184	,000
		5	-,00678122553	,00330633634	1,000
		6	,00667800834	,00330592302	1,000
	0	-6	,02996339445*	,00316701821	,000
		-5	,01108579531	,00330633634	,062
		-4	,01594948852*	,00330140028	,000

	-3	,01260444576*	,00329976636	,010
	-2	,01080980398	,00330633634	,084
	-1	,01840626336*	,00330633634	,000
	1	-,00414760955	,00330592302	1,000
	2	-,00183845635	,00330592302	1,000
	3	-,00836956749	,00330633634	,887
	4	-,00093599333	,00330386184	1,000
	5	,01162503783*	,00330633634	,034
	6	,02508427170*	,00330592302	,000
1	-6	,03411100399*	,00316658671	,000
	-5	,01523340486*	,00330592302	,000
	-4	,02009709807*	,00330098634	,000
	-3	,01675205531*	,00329935222	,000
	-2	,01495741352*	,00330592302	,000
	-1	,02255387291*	,00330592302	,000
	0	,00414760955	,00330592302	1,000
	2	,00230915320	,00330550965	1,000
	3	-,00422195794	,00330592302	1,000
	4	,00321161621	,00330344822	1,000
	5	,01577264737*	,00330592302	,000

		6	,02923188125*	,00330550965	,000
	2	-6	,03180185080*	,00316658671	,000
		-5	,01292425166*	,00330592302	,007
		-4	,01778794487*	,00330098634	,000
		-3	,01444290211*	,00329935222	,001
		-2	,01264826033*	,00330592302	,010
		-1	,02024471971*	,00330592302	,000
		0	,00183845635	,00330592302	1,000
		1	-,00230915320	,00330550965	1,000
		3	-,00653111114	,00330592302	1,000
		4	,00090246302	,00330344822	1,000
		5	,01346349418*	,00330592302	,004
		6	,02692272805*	,00330550965	,000
	3	-6	,03833296194*	,00316701821	,000
		-5	,01945536280*	,00330633634	,000
		-4	,02431905601*	,00330140028	,000
		-3	,02097401325*	,00329976636	,000
		-2	,01917937147*	,00330633634	,000
		-1	,02677583085*	,00330633634	,000
		0	,00836956749	,00330633634	,887

		1	,00422195794	,00330592302	1,000
		2	,00653111114	,00330592302	1,000
		4	,00743357416	,00330386184	1,000
		5	,01999460532*	,00330633634	,000
		6	,03345383919*	,00330592302	,000
	4	-6	,03089938778*	,00316443478	,000
		-5	,01202178865*	,00330386184	,021
		-4	,01688548185*	,00329892208	,000
		-3	,01354043910*	,00329728694	,003
		-2	,01174579731*	,00330386184	,030
		-1	,01934225669*	,00330386184	,000
		0	,00093599333	,00330386184	1,000
		1	-,00321161621	,00330344822	1,000
		2	-,00090246302	,00330344822	1,000
		3	-,00743357416	,00330386184	1,000
		5	,01256103116*	,00330386184	,011
		6	,02602026503*	,00330344822	,000
	5	-6	,01833835662*	,00316701821	,000
		-5	-,00053924252	,00330633634	1,000
		-4	,00432445069	,00330140028	1,000

		-3	,00097940793	,00329976636	1,000
		-2	-,00081523385	,00330633634	1,000
		-1	,00678122553	,00330633634	1,000
		0	-,01162503783*	,00330633634	,034
		1	-,01577264737*	,00330592302	,000
		2	-,01346349418*	,00330592302	,004
		3	-,01999460532*	,00330633634	,000
		4	-,01256103116*	,00330386184	,011
		6	,01345923387*	,00330592302	,004
	6	-6	,00487912275	,00316658671	1,000
		-5	-,01399847639*	,00330592302	,002
		-4	-,00913478318	,00330098634	,441
		-3	-,01247982594*	,00329935222	,012
		-2	-,01427446772*	,00330592302	,001
		-1	-,00667800834	,00330592302	1,000
		0	-,02508427170*	,00330592302	,000
		1	-,02923188125*	,00330550965	,000
		2	-,02692272805*	,00330550965	,000
		3	-,03345383919*	,00330592302	,000
		4	-,02602026503*	,00330344822	,000

		5	-,01345923387*	,00330592302	,004
Concrete	-6	-5	,003268511	,003388836	1,000
		-4	,002493301	,003383322	1,000
		-3	,006687989	,003381496	1,000
		-2	,008812236	,003388836	,727
		-1	,009472258	,003388836	,405
		0	,021413005*	,003388836	,000
		1	,028625061*	,003388374	,000
		2	-,002808933	,003388374	1,000
		3	-,008748855	,003388836	,767
		4	,023391880*	,003386072	,000
		5	,012163160*	,003388836	,026
		6	,000064420	,003388374	1,000
	-5	-6	-,003268511	,003388836	1,000
		-4	-,000775210	,003532630	1,000
		-3	,003419478	,003530882	1,000
		-2	,005543725	,003537912	1,000
		-1	,006203747	,003537912	1,000
		0	,018144494*	,003537912	,000
		1	,025356550*	,003537470	,000
		2	-,006077444	,003537470	1,000
		3	-,012017366	,003537912	,053
		4	,020123369*	,003535264	,000
		5	,008894649	,003537912	,931
		6	-,003204091	,003537470	1,000
	-4	-6	-,002493301	,003383322	1,000
		-5	,000775210	,003532630	1,000
		-3	,004194688	,003525590	1,000
		-2	,006318934	,003532630	1,000
		-1	,006978957	,003532630	1,000
		0	,018919703*	,003532630	,000
		1	,026131759*	,003532187	,000
		2	-,005302235	,003532187	1,000
		3	-,011242156	,003532630	,114
		4	,020898579*	,003529979	,000
		5	,009669859	,003532630	,484
		6	-,002428881	,003532187	1,000

	-3	-6	-,006687989	,003381496	1,000
		-5	-,003419478	,003530882	1,000
		-4	-,004194688	,003525590	1,000
		-2	,002124247	,003530882	1,000
		-1	,002784269	,003530882	1,000
		0	,014725016*	,003530882	,002
		1	,021937072*	,003530439	,000
		2	-,009496922	,003530439	,558
		3	-,015436844*	,003530882	,001
		4	,016703891*	,003528229	,000
		5	,005475171	,003530882	1,000
		6	-,006623569	,003530439	1,000
	-2	-6	-,008812236	,003388836	,727
		-5	-,005543725	,003537912	1,000
		-4	-,006318934	,003532630	1,000
		-3	-,002124247	,003530882	1,000
		-1	,000660023	,003537912	1,000
		0	,012600769*	,003537912	,029
		1	,019812825*	,003537470	,000
		2	-,011621169	,003537470	,080
		3	-,017561090*	,003537912	,000
		4	,014579645*	,003535264	,003
		5	,003350924	,003537912	1,000
		6	-,008747815	,003537470	1,000
	-1	-6	-,009472258	,003388836	,405
		-5	-,006203747	,003537912	1,000
		-4	-,006978957	,003532630	1,000
		-3	-,002784269	,003530882	1,000
		-2	-,000660023	,003537912	1,000
		0	,011940746	,003537912	,058
		1	,019152802*	,003537470	,000
		2	-,012281192*	,003537470	,040
		3	-,018221113*	,003537912	,000
		4	,013919622*	,003535264	,006
		5	,002690902	,003537912	1,000
		6	-,009407838	,003537470	,611
	0	-6	-,021413005*	,003388836	,000
		-5	-,018144494*	,003537912	,000

		-4	-,018919703*	,003532630	,000
		-3	-,014725016*	,003530882	,002
		-2	-,012600769*	,003537912	,029
		-1	-,011940746	,003537912	,058
		1	,007212056	,003537470	1,000
		2	-,024221938*	,003537470	,000
		3	-,030161859*	,003537912	,000
		4	,001978876	,003535264	1,000
		5	-,009249845	,003537912	,697
		6	-,021348584*	,003537470	,000
	1	-6	-,028625061*	,003388374	,000
		-5	-,025356550*	,003537470	,000
		-4	-,026131759*	,003532187	,000
		-3	-,021937072*	,003530439	,000
		-2	-,019812825*	,003537470	,000
		-1	-,019152802*	,003537470	,000
		0	-,007212056	,003537470	1,000
		2	-,031433994*	,003537028	,000
		3	-,037373915*	,003537470	,000
		4	-,005233180	,003534822	1,000
		5	-,016461901*	,003537470	,000
		6	-,028560640*	,003537028	,000
	2	-6	,002808933	,003388374	1,000
		-5	,006077444	,003537470	1,000
		-4	,005302235	,003532187	1,000
		-3	,009496922	,003530439	,558
		-2	,011621169	,003537470	,080
		-1	,012281192*	,003537470	,040
		0	,024221938*	,003537470	,000
		1	,031433994*	,003537028	,000
		3	-,005939921	,003537470	1,000
		4	,026200814*	,003534822	,000
		5	,014972093*	,003537470	,002
		6	,002873354	,003537028	1,000
	3	-6	,008748855	,003388836	,767
		-5	,012017366	,003537912	,053
		-4	,011242156	,003532630	,114
		-3	,015436844*	,003530882	,001

	-2	,017561090*	,003537912	,000
	-1	,018221113*	,003537912	,000
	0	,030161859*	,003537912	,000
	1	,037373915*	,003537470	,000
	2	,005939921	,003537470	1,000
	4	,032140735*	,003535264	,000
	5	,020912015*	,003537912	,000
	6	,008813275	,003537470	,993
4	-6	-,023391880*	,003386072	,000
	-5	-,020123369*	,003535264	,000
	-4	-,020898579*	,003529979	,000
	-3	-,016703891*	,003528229	,000
	-2	-,014579645*	,003535264	,003
	-1	-,013919622*	,003535264	,006
	0	-,001978876	,003535264	1,000
	1	,005233180	,003534822	1,000
	2	-,026200814*	,003534822	,000
	3	-,032140735*	,003535264	,000
	5	-,011228720	,003535264	,117
	6	-,023327460*	,003534822	,000
5	-6	-,012163160*	,003388836	,026
	-5	-,008894649	,003537912	,931
	-4	-,009669859	,003532630	,484
	-3	-,005475171	,003530882	1,000
	-2	-,003350924	,003537912	1,000
	-1	-,002690902	,003537912	1,000
	0	,009249845	,003537912	,697
	1	,016461901*	,003537470	,000
	2	-,014972093*	,003537470	,002
	3	-,020912015*	,003537912	,000
	4	,011228720	,003535264	,117
	6	-,012098740*	,003537470	,049
6	-6	-,000064420	,003388374	1,000
	-5	,003204091	,003537470	1,000
	-4	,002428881	,003532187	1,000
	-3	,006623569	,003530439	1,000
	-2	,008747815	,003537470	1,000
	-1	,009407838	,003537470	,611

		0	,021348584*	,003537470	,000
		1	,028560640*	,003537028	,000
		2	-,002873354	,003537028	1,000
		3	-,008813275	,003537470	,993
		4	,023327460*	,003534822	,000
		5	,012098740*	,003537470	,049

A3
*Multiple group comparisons (Bonferroni) between Years regarding Valence and Abstractness. Significances (p<,05) are flagged with *.*

-3=1994; -2=1995; -1=1996; 0=1997; 1=1998; 2=1999; 3=2000

Dependent Variable	(I) Grouping	(J) Grouping	Mean Difference (I-J)	Std. Error	Sig.
Valence	-3	-2	-,01166463531*	,00381960411	,048
		-1	-,03124061241*	,00366960913	,000
		0	-,04309643508*	,00419173163	,000
		1	-,05389783246*	,00368312384	,000
		2	-,05875801103*	,00381681551	,000
		3	-,03812964182*	,00377952587	,000
	-2	-3	,01166463531*	,00381960411	,048
		-1	-,01957597710*	,00246716002	,000
		0	-,03143179977*	,00319240684	,000
		1	-,04223319715*	,00248721704	,000
		2	-,04709337572*	,00268121764	,000
		3	-,02646500651*	,00262786285	,000
	-1	-3	,03124061241*	,00366960913	,000
		-2	,01957597710*	,00246716002	,000
		0	-,01185582267*	,00301133143	,002
		1	-,02265722005*	,00225008982	,000
		2	-,02751739862*	,00246284056	,000
		3	-,00688902941	,00240464524	,088
	0	-3	,04309643508*	,00419173163	,000
		-2	,03143179977*	,00319240684	,000
		-1	,01185582267*	,00301133143	,002
		1	-,01080139738*	,00302778583	,008
		2	-,01566157595*	,00318906984	,000
		3	,00496679326	,00314434438	1,000
	1	-3	,05389783246*	,00368312384	,000

		-2	,04223319715*	,00248721704	,000
		-1	,02265722005*	,00225008982	,000
		0	,01080139738*	,00302778583	,008
		2	-,00486017857	,00248293247	1,000
		3	,01576819064*	,00242521933	,000
	2	-3	,05875801103*	,00381681551	,000
		-2	,04709337572*	,00268121764	,000
		-1	,02751739862*	,00246284056	,000
		0	,01566157595*	,00318906984	,000
		1	,00486017857	,00248293247	1,000
		3	,02062836921*	,00262380796	,000
	3	-3	,03812964182*	,00377952587	,000
		-2	,02646500651*	,00262786285	,000
		-1	,00688902941	,00240464524	,088
		0	-,00496679326	,00314434438	1,000
		1	-,01576819064*	,00242521933	,000
		2	-,02062836921*	,00262380796	,000
Concrete	-3	-2	-,0111371826	,0040683453	,130
		-1	-,0172809901*	,0039085823	,000
		0	,0206215110*	,0044647065	,000
		1	,0032754393	,0039229771	1,000
		2	,0080527078	,0040653750	1,000
		3	-,0172560373*	,0040256570	,000
	-2	-3	,0111371826	,0040683453	,130
		-1	-,0061438075	,0026278270	,407
		0	,0317586936*	,0034003035	,000
		1	,0144126220*	,0026491902	,000
		2	,0191898904*	,0028558245	,000
		3	-,0061188547	,0027989951	,605
	-1	-3	,0172809901*	,0039085823	,000
		-2	,0061438075	,0026278270	,407
		0	,0379025011*	,0032074361	,000
		1	,0205564294*	,0023966207	,000
		2	,0253336979*	,0026232262	,000
		3	,0000249528	,0025612411	1,000
	0	-3	-,0206215110*	,0044647065	,000
		-2	-,0317586936*	,0034003035	,000
		-1	-,0379025011*	,0032074361	,000

		1	-,0173460716*	,0032249620	,000
		2	-,0125688032*	,0033967492	,005
		3	-,0378775483*	,0033491111	,000
	1	-3	-,0032754393	,0039229771	1,000
		-2	-,0144126220*	,0026491902	,000
		-1	-,0205564294*	,0023966207	,000
		0	,0173460716*	,0032249620	,000
		2	,0047772684	,0026446266	1,000
		3	-,0205314767*	,0025831550	,000
	2	-3	-,0080527078	,0040653750	1,000
		-2	-,0191898904*	,0028558245	,000
		-1	-,0253336979*	,0026232262	,000
		0	,0125688032*	,0033967492	,005
		1	-,0047772684	,0026446266	1,000
		3	-,0253087451*	,0027946762	,000
	3	-3	,0172560373*	,0040256570	,000
		-2	,0061188547	,0027989951	,605
		-1	-,0000249528	,0025612411	1,000
		0	,0378775483*	,0033491111	,000
		1	,0205314767*	,0025831550	,000
		2	,0253087451*	,0027946762	,000