The Promotion of a Bright Future and the Prevention of a Dark Future: Time Anchored Incitements in News Articles and Facebook’s Status Updates

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Background: Research suggests that humans have the tendency to increase the valence of events when these are imagined to happen in the future, but to decrease the valence when the same events are imagined to happen in the past. This line of research, however, has mostly been conducted by asking participants to value imagined, yet probable, events. Our aim was to re-examine this time-valence asymmetry using real-life data: a Reuters news and a Facebook status updates corpus.

Method: We organized the Reuters news (120,000,000 words) and the Facebook status updates data (41,056,346 words) into contexts grouped in chronological order (i.e., past, present, and future) using verbs and years as time markers. These contexts were used to estimate the valence of each article and status update, respectively, in relation to the time markers using natural language processing tools (i.e., the Latent Semantic Analysis algorithm).

Results: Our results using verbs, in both text corpus, showed that valence for the future was significantly higher compared to the past (future > past). Similarly, in the Reuters year condition, valence increased approximately linear from 1994 to 1999 for texts written 1996–1997. In the Facebook year condition, the valence of the future was also significantly higher than past valence.

Conclusion: Generally, the analyses of the Reuters data indicated that the past is devaluated relative to both the present and the future, while the analyses of the Facebook data indicated that both the past and the present are devaluated against the future. On this basis, we suggest that people strive to communicate the promotion of a bright future and the prevention of a dark future, which in turn leads to a temporal-valence asymmetrical phenomenon (valence = past < present < future).

Keywords: future, latent semantic analysis, past, present, prevention focus, promotion focus, time-anchored incitements
“I have a dream that one day this nation will rise up and live out the true meaning of its creed: “We hold these truths to be self-evident, that all men are created equal.”

“I have a dream that one day on the red hills of Georgia, the sons of former slaves and the sons of former slave owners will be able to sit down together at the table of brotherhood.

“I have a dream that one day even the state of Mississippi, a state sweltering with the heat of injustice, sweltering with the heat of oppression, will be transformed into an oasis of freedom and justice.

“I have a dream that my four little children will one day live in a nation where they will not be judged by the color of their skin but by the content of their character.

“I have a dream today!”

Martin Luther King, Jr., 28th of August 1963, at the Lincoln Memorial, Washington, DC, United States

INTRODUCTION

A myriad of theories and empirical studies illuminate our understanding of how we evaluate the past, the present, and the future (e.g., Higgins, 1997; Trope and Liberman, 2000; Caruso et al., 2008; Kurtz, 2008). This line of research has mostly been conducted by asking participants, in experimental conditions, to value imagined positive and/or negative events as occurring either back or forward in time (for some exceptions see: Wilson et al., 2012). At a general level, people usually assign higher values to future events compared to past events (e.g., Trope and Liberman, 2000; D’Argembeau and Van der Linden, 2004; Van Boven and Ashworth, 2007; Caruso, 2010). In the present study, we use data from a Reuter’s news corpus and Facebook status updates or “real-life data” (i.e., peoples’ actual narratives about past, present, and future events). These real-life data contain statements of both positive and negative events with frequencies that more closely reflect their occurrence in peoples’ life, in contrast to controlled experiments with either positive or negative events in equal numbers. We measured the valence of the statements using a semantic statistical method, namely, the Latent Semantic Analysis (LSA; Landauer et al., 1998) algorithm. Thus, the present study makes an important addition to the existing literature because it is based on ecological data from multiple events over time, that we organized in statements of events remembered or imagined to happen in the past, the present, and the future. In sum, we use a larger sample, actual behavior, and data with natural validity that circumvent the limitations of self-reports.

Most experiments on how humans evaluate events in different temporal dimensions ask participants to imagine fictional, yet probable, scenarios. For example, participants are asked to imagine performing a mundane task (e.g., entering data into a computer) and then to rate, at random, the amount of money they would like to get paid if they will perform the task in the future versus if they had already performed the task in the past. Intuitively, one might suspect small differences, however, participants who imagine doing a mundane 5-h task one month in the future demand twice as much more money compared to participants who imagine having completed the same task one month ago (Caruso et al., 2008). This temporal asymmetry is stable across various types of judgments, such as, monetary gain, generosity, and pleasure (e.g., Caruso et al., 2008). In addition, moral transgressions are judged more negatively and deserving more punishment if people imagine them to happen in the future rather than if these transgressions already have happened in the past (Caruso, 2010). In other words, this line of research suggests that when we create a representation of an event happening in the future, both positive and negative events seem to increase in their evaluative magnitude, but to decrease when we imagine that the same events have already happened in the past. One possible reason for this is that people see the future as more exciting and interesting, thus, future events evoke more emotions and curiosity which lead us to make more extreme predictions of the valence of future events (i.e., future heuristic; see Van Boven and Ashworth, 2007; Herbert, 2010). In addition, people in general have a sense of being able to influence the future; therefore, most of us use narratives of the future to promote behavior that is beneficial for ourselves or our group. For example, the Martin Luther King Jr. I have a dream” speech communicates a positively framed future with desirable values, such as, tolerance and justice. Importantly, the research reviewed here, suggest that the same should hold for negative events, that is, if we are imagining or speak about a negative event that might happen in the future, we value it more negatively than if we imagine or speak about the same event as if it already have happened in the past (e.g., Caruso, 2010). However, we argue that this temporal asymmetry (i.e., future > past, or past < future, for both positive and negative events) needs to be tested using real life data (cf. Hsee et al., 2014), because in contrast to experimental designs, people typically talk, or write, about different topics and events when making statements about the past, the present, and the future. In other words, the occurrence of positive versus negative past/present/future events in everyday narratives differs from that of experimental controlled designs, which, for good reasons, always present and equal amount of positive and negative events.

These everyday life narratives of past, present, and future events are possible thanks to human beings’ unique ability to mental time travel (Suddendorf and Corballis, 1997). These narratives of positive and negative statements of future and past events might influence how humans perceive and recall emotional events. In this context, the ability to react fast to dangerous or negative stimuli is considered essential for an organism to ensure its survival. For example, in a series of experiments (Dijksterhuis and Aarts, 2003), participants detected negatively loaded words more accurately than positive ones, and this was true even when the words were presented subliminally, that is, so fast that the meaning of the words could not be explicitly understood. In other words, suggesting negative valence, rather than positive, as the most common state of being when humans imagine the past and the future. Indeed, a vast amount of research supports the notion that “bad is stronger than good” (Baumeister et al., 2001, p. 323). This includes findings showing that negative emotions, negative feedback, and negative major life events have greater impact in our physical, psychological and social health than positive
ones. This underlying precedence of negativity is also reflected in our language: negative emotions have been shown to be overrepresented in the English language by approximately a 3/5 ratio and this ratio is even stronger (3/4) regarding words describing personality traits (for a review see Baumeister et al., 2001). On this basis, we could expect that an “I have a nightmare” speech would be the most common scenario when people imagine the future.

However, other empirical evidence emphasizes the importance and prevalence of positivity. For example, the analysis of the 5,000 most frequently used words in Twitter, lyrics, books, and the New York Times, suggested an overrepresentation of positive words (Dodds et al., 2011; Kloumann et al., 2012; see also Kramer et al., 2014 for research on emotional contagion in social networks). Moreover, when people imagine a future or past event, positive information is accessed more easily making it more central to the construction of the imagined event (D’Argembeau and Van der Linden, 2004). Perhaps because positive information is more contextual, leading to the construction of more positive and richer imagined future and past events. For instance, despite our tendency to detect negative stimuli faster, negative stimuli are more difficult to remember after longer delays compared to neutral and positive stimuli (Szpunar et al., 2012). That is, showing that humans have a fallacy for a “rosy simulated future” (Szpunar, 2010; Szpunar et al., 2012; see also research on self-enhancement and positivity bias; D’Argembeau and Van der Linden, 2004).

This fallacy of a “rosy simulated future,” however, might as well be part of what makes people healthy. As the matter of fact, the apprehension of events is also related to peoples’ self-regulation (Higgins, 1997; see also Garcia et al., 2010). The “I have a dream” speech is a good example of promotion focused regulation, because it is based on envisioning a successful and bright future (cf. Higgins, 1997). In contrast, people might have a prevention focus when constructing and communicating future events; for example, by envisioning failure and being more vigilant about forthcoming events, in order to avoid or prevent such a dark future (cf. Higgins, 1997). Thus, promotion and prevention focus are important motivators of behavior and even mental health2 (Higgins, 1997; Amato et al., 2017; Garcia et al., 2017; Amato and Garcia, 2018; see also Walker et al., 2003; D’Argembeau and Van der Linden, 2004). From this perspective, speeches or narratives that envision the promotion of a brighter future or preventing a dark future; both communicate a pleasant or desired state because the individual either envisions a happy and pleasant future or the pleasant relief by avoiding dark or bad outcomes (cf. Higgins, 1997). People, for instance, strive to create legacies that will survive beyond their own existence (Wade-Benzonzi and Tost, 2009). Accordingly, having the belief that one has made a difference and will leave the world a better place (cf. promotion focus) leads to the sense of purpose and meaning in life (Wade-Benzoii and Tost, 2003; de St Aubin et al., 2004; Grant and Wade-Benzoii, 2009). The motivation to not leave a negative legacy behind (cf.

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2Even if both types of regulatory focus motivate individuals toward attention to future states (i.e., a brighter future and a less dark future), people’s behavior (e.g., action, inaction, counteraction) might differ depending on which type of future is being envisioned.

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MATERIALS AND METHODS

Ethics Statement

This research protocol was approved by the Ethics Committee of Lund University.

Participants

The first data set comprised news stories from Reuters during 1997. We chose this corpus because it was one of the few large news corpus that were public available at the time when the research was conducted. In addition, a few thousand Facebook
users also provided us with 1,183,180 status updates (see the myPersonality project*). The Facebook data was collected during 2009 through 2011.

Statistical Method and Procedure

We quantified the valence of temporal markers (i.e., words representing the past, the present, and the future, respectively) using the LSA algorithm. The analyses were conducted in a web-based automated program for analyses of quantitative semantics called semanticexcel, which was developed by one of the authors of this paper. Technical details of how this software generates a semantic representation and predict numbers (valence) from a text based on this representation can be found elsewhere (see Roll et al., 2012, for predicting abstractness; Garcia and Sikström, 2013b, for predicting affectivity scores; and Garcia and Sikström, 2014; Garcia et al., 2015 for predicting personality scores; see also Kjell et al., 2018). Here we just present a brief overview.

Semanticexcel contains semantic representations of several languages, including English. The representation of English used here was generated for the 1997 Reuter news corpus. First, a matrix is generated where rows correspond to unique single words and each column corresponds to contexts within the words in the corpus. The rows consisted of the 120,000 most frequent words in corpora, whereas the columns consisted of the contexts of the 10,000 most common words. The contexts of the words were generated from the fifteen words preceding and fifteen words following, the word in each column. Thus, cells in this matrix represent the frequency of occurrence of a word (rows) within a context of a word (columns). For example, the word “grateful” may have a frequency $f_1$ in the context “aiding” and a frequency $f_2$ in the context “accidents.” In this way, every word is represented by an array of frequencies of occurrence in each related context to a word.

A basic assumption is that words with similar meaning tend to occur in the same contexts. This implies that the vectors representing similar words should point in similar directions (Sun, 2008). However, to get a good semantic representation this word-by-context sample matrix needs to be compressed to a smaller word-by-semantic dimension matrix, where this smaller matrix tends to create a more generalized semantic representation. We conducted this data compression using Singular Value Decomposition (Strang, 1998), a widespread dimensionality-reduction technique similar to Principal Component Analysis. The resulting matrix is called a semantic space, which describes the semantic relatedness between words. This method has a high level of accuracy, comparable to human performance in different tasks, such as, rating grades (e.g., Landauer and Dumais, 1997, Landauer et al., 1998, Howard and Kahana, 2002). In our analysis, the resulting semantic representation consisted of 120,000 words, where each word is represented in a vector consisting of 100 dimensions.

These representations were used to predict/estimate the valence of each article/status update, respectively, in relation to the time markers (years and verbs were selected as time markers).

In the present study, we first identified words related to the past, the present, and the future (i.e., target words). Then we evaluate, using LSA, whether the contexts (the context is defined as the 15 words preceding or following each target word) these words were written in consist of positive or negative words (i.e., the valence). For the sake of clarity, we first briefly describe the rationale behind the chosen time markers, then how we computed valence and then how we did the statistical analyses for testing our hypotheses.

Year-data were divided into categories relative to the publication date. In the Reuter news corpus, the year condition of groups was arranged around the year 1997. By comparing the year that the articles were written, which in the Reuter data was 1997, we identified 1994–1996, as markers of the past, whereas 1998 and 1999, as makers for the future. In the Facebook corpus, this was based on the context content in relation to when the users’ status was published. For target words in both Reuter and Facebook data, the verbs were chosen by randomly selecting verbs from McMillan’s essential dictionary (Rundell and Fox, 2003). Random selection was used to minimize author bias. This method generated a list of 10 solid past conjugations (see Table 1). The English language lack unambiguous usage of the future tense; auxiliary verbs (i.e., verbs that add functional or grammatical meaning and usually accompany a main verb in infinitive) are often needed to imply future tense (Leech, 2004). Some conjugations can be used to describe past, present and/or future (e.g., “Fall” can be used in multiple ways: I Fall [present] and I will Fall [future]). To analyze the future tense, we therefore relied on the fact that this is a modal construction which uses auxiliaries (will or shall) + infinitive (Leech, 2004). Hence, only these two auxiliaries (“will” and “shall”) without the infinitive were analyzed to represent the future tense, with the assumption that these are the most frequently used auxiliaries to imply future tense. It should be noted that these auxiliaries can refer to events in the near or far away future, which implies that our data is likely to contain referrals to both near and far away future events. These auxiliaries are shown in Table 1.

The method used for predicting the valence of words was multiple-linear regression ($y = c + x$), where the semantic

| TABLE 1 | Verbs and auxiliaries analyzed. |
|----------------|-----------------|-----------------|----------------|
| Infinitive | Simple Past (Past) | Past Participle (Present) | Auxiliaries (Future) |
| 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* | |

* = Words analyzed in the “Verb” condition.
representations \((x)\) is used as predictors, which are trained on a limited number of words ranked by valence \((y)\). The ANEW (Affective Norms for English Words) wordlist, (Bradley and Lang, 1999) was used to identify one thousand words ranked on valence. Multiple-linear regression was performed between the ANEW list and the semantic space. The resulting regression coefficients \((c)\) can then be used to predict the valence of all words represented in the semantic space. The validity of this method was estimated with a leave-one-out procedure so that the tested word was removed from the training set, showing a high correlation between predicted and rated scores \((r = 0.62)\). Thus, the LSA algorithm generalizes from the evaluation of a small set of ANEW words, to all words in the semantic representation, and thus allows estimation of the valence of a larger number of words, compared to simply counting and affective score based on their ANEW values. We calculated the average valence for words in contexts for target words. This provides a more reliable means of measuring valance; where every single context of a target word has an average predicted valence, rather than the estimated valence of just a target word. In both corpora, 10,000 articles were scanned to obtain the valence of the contexts.

A One-way Analysis of Variance (ANOVA) was computed for each variable in both corpora. In each analysis three conditions were created (Past, Present, and Future). The verbs were assigned into the Past condition if it was written in Simple Past and the Present condition if it was written in Past Participle. Auxiliaries were assigned into the Future condition. Years were assigned to the Past condition if written earlier than the publication date(s), to the Present condition if they were the publication date(s), and the Past condition if written later than the publication date(s). In both corpora, post-hoc two-tailed independent \(t\)-tests were conducted to examine the difference in valence between the Past and the Present, and the Present and the Future.

**RESULTS**

**Verbs (Reuters)**

Ten verbs and two auxiliaries from 10,000 documents produced 14,165 contexts, where some documents produced more than one context. The mean and standard deviation for the valence associated to each group is presented in Figure 1A. The frequency

![Figure 1A](https://www.frontiersin.org)
of occurrence of each verb and condition can be found in Table 2A. We conducted an ANOVA to investigate if the valence of the contexts differed between the three conditions: Past, Present and Future \(F = 164.0, df = 2, 14162, p < 0.001, \eta^2 = 0.023, 95\% CI(0.018, 0.027)\). Homogeneity of variances was significant at the 0.001 level \((\text{Levene} = 13.17, df = 2, 14162)\). A two-tailed independent sample t-test showed that there was a significant difference between Past and Present \(t(11181) = -7.95, p < 0.001, d = -0.162, 95\% CI(-0.201, -121))\) and between Present and Future \(t(6504) = -8.98, p < 0.001, d = 0.223, 95\% CI(-0.272, -0.174))\). In other words, the Present had higher valence than the Past, while the Future had higher valence than the Present. The effects sizes were, however, weak.

**Years (Reuters)**

Data from six years was analyzed, generating a total of 16,396 contexts.

The mean and standard deviation of the valence for each group can be found in Figure 1B. The frequency of occurrence of each year and condition can be found in Table 2B. An ANOVA revealed a significant difference in valence between the groups \(F = 114.22, df = 5, 16390, p < 0.001, \eta^2 = 0.038, 90\% CI(0.029, 0.039)\). Homogeneity of variances was significant at the 0.001 level \((\text{Levene} = 13.238, df = 5, 16390)\). A two-tailed independent sample t-test showed that there was a significant difference in valence between Past and Present \(t(9520) = -7.99, p < 0.001, d = -0.221, 95\% CI(-0.275, -0.166))\) and between Present and Future \(t(68438) = -4.55, p < 0.001, d = -0.130, 95\% CI(-0.182, -0.072))\). In other words, as for the verbs, the Present had higher valence than the Past, while the Future had higher valence than the Present. The effects sizes were, however, weak.

**Verbs (Facebook)**

Ten verbs and two auxiliaries from 10,000 documents produced 860,127 contexts, where some documents produced more than one context. The mean and standard deviation for the valence associated to each group is presented in Figure 2B. The frequency of occurrence of each verb and condition can be found in Table 3A. An ANOVA revealed a significant difference in valence between the groups \(F = 16717, df = 2, 858668, p < 0.001, \eta^2 = 0.038, 90\% CI(0.037, 0.038)\). Homogeneity of variances was significant at the 0.001 level \((\text{Levene} = 371.55, df = 2, 858668)\). A two-tailed independent sample t-test showed that there was a significant difference in valence between Past and Present \(t(716660) = 18.98, p < 0.001, d = -0.45, 95\% CI(-0.50, -0.041))\) and between Present and Future \(t(458000) = -172.71, p < 0.001, d = 0.55, 95\% CI(0.546, 0.558))\). In other words, conversely to findings in the Reuters data, the Present had lower valence than the Past, while the Future had higher valence than the Present. The effects sizes were weak or close to moderate.

**Years (Facebook)**

Data from eleven years were analyzed generating a total of 64,009 contexts. The mean and standard deviation of the valence for each group can be found in Figure 2B. The frequency of occurrence of each verb and condition can be found in Table 3B. An ANOVA revealed a significant difference between the groups \(F = 182.2, df = 10, 63513, p < 0.001, \eta^2 = 0.028, 90\% CI(0.026, 0.030)\). Homogeneity of variances was significant at the 0.001 level \((\text{Levene} = 96.09, df = 2, 63521)\). A two-tailed independent sample t-test showed that there was a significant difference in valence between Past and Present \(t(585751) = -27.86, p < 0.001, d = 0.48, 95\% CI(0.446, 0.513))\) and between Present and Future \(t(59925) = 29.05, p < 0.001, d = 0.10, 95\% CI(0.06, 0.146)\). In other words, as for the Reuters’ findings, Present had higher valence than the Past, while the Future had higher valence than the Present. The effects sizes were, however, weak.

**TABLE 2A** | Verb frequency, proportions of verbs and proportions of conditions in the Reuters corpus.

| Condition | Verb | Frequency | Verb proportions relative to corpus size | Condition proportions relative to corpus size |
|-----------|------|-----------|----------------------------------------|---------------------------------------------|
| Future    | Shall| 992       | 7.00%                                  | 21.05%                                      |
| Future    | Will | 1990      | 14.05%                                 |                                              |
| Past      | Ate  | 222       | 1.57%                                  |                                              |
| Past      | Chose| 495       | 3.49%                                  |                                              |
| Past      | Did  | 930       | 6.57%                                  |                                              |
| Past      | Drove| 446       | 3.15%                                  |                                              |
| Past      | Fell | 1240      | 8.75%                                  |                                              |
| Past      | Grew | 824       | 5.82%                                  |                                              |
| Past      | Spoke| 980       | 6.92%                                  |                                              |
| Past      | Was  | 1080      | 7.62%                                  |                                              |
| Past      | Went | 482       | 3.40%                                  |                                              |
| Past      | Wrote| 720       | 5.08%                                  | 52.38%                                      |
| Present   | Been| 278       | 1.96%                                  |                                              |
| Present   | Chosen| 743      | 5.25%                                  |                                              |
| Present   | Done | 240       | 1.69%                                  |                                              |
| Present   | Driven| 595      | 4.20%                                  |                                              |
| Present   | Eaten| 169       | 1.19%                                  |                                              |
| Present   | Fallen| 124      | 0.88%                                  |                                              |
| Present   | Gone | 194       | 1.37%                                  |                                              |
| Present   | Crown| 334       | 2.36%                                  |                                              |
| Present   | Spoken| 317     | 2.24%                                  |                                              |
| Present   | Written| 770    | 5.44%                                  | 26.57%                                      |
| Total     |      | 14165     | 100.00%                                | 100.00%                                      |

**TABLE 2B** | Year frequency, proportions of years and proportions of conditions in the Reuters corpus.

| Condition | Year | Frequency | Year proportions relative to corpus size | Condition proportions relative to corpus size |
|-----------|------|-----------|----------------------------------------|---------------------------------------------|
| Future    | 1998| 3996      | 24.37%                                 | 41.92%                                      |
| Future    | 1999| 2878      | 17.55%                                 |                                              |
| Past      | 1996| 4156      | 25.35%                                 |                                              |
| Past      | 1995| 2861      | 17.45%                                 |                                              |
| Past      | 1994| 939       | 5.73%                                  | 48.52%                                      |
| Present   | 1997| 1566      | 9.55%                                  | 9.55%                                       |
| Total     |      | 16396     | 100.00%                                | 100.00%                                      |
DISCUSSION

We investigated the temporal valence asymmetry of events using real-life data (i.e., two large text corpora from online newspapers and Facebook status updates) by applying language processing methods and tools. We identified specific words or target words in the narratives at hand in relations to time markers of the past, the present and the future. We then measured the valence of the contexts (the context is defined as the 15 words preceding or following each target word) in which these target words appeared. Our results using verbs as temporal markers showed, in both the Reuter and Facebook corpus, that valence for the future was significantly higher (i.e., more positive) compared to the past (future > past). Similarly, in the Reuter year condition, valence increased approximately linear from 1994 to 1999. In the Facebook year condition, it is also evident that the valence of the future is significantly higher (i.e., more positive) than past valence. However, for the Facebook data, 2012 did not differ significantly in valence compared to 2007. Nevertheless, the analyses of the Reuters data indicated that the past is devaluated against both the present and the future, while the analyses of the Facebook data indicated that both the past and the present are devaluated against the future. That is, by either devaluing the past against the future or by devaluing the present against the future, both people who engage in the “I have a dream” speech or the “I have a nightmare” speech try always to reach a more pleasant state (cf. Higgins, 1997).

In the present study, the future seems to be valued positively higher than the past, even though current research suggest that evaluations of the future should be more extreme both when it comes to negative and positive events (Caruso et al., 2008; Caruso, 2010). This is even more accentuated in the Reuters data set, which is striking, considering that there was a high likelihood that the sample would include an overrepresentation of lower valence contexts. For instance, news stories that have a more negative valence are twice as likely to be featured in print (Soroka, 2012; see also Trussler and Soroka, 2014). According to the future heuristic, the future is more exciting and interesting, thus, evoking more emotions and curiosity (Herbert, 2010). However, this heuristic only explains that more emotions, both positive and negative, should be associated to texts found in the context of future time-markers. That is, the future heuristic only explains the temporal asymmetry (i.e., past vs. future), not the valence asymmetry found in the present study. Our results, however, might mirror our increased excitement about the future compared to the past (i.e., the future heuristic) in conjunction with our tendency to favor positive information when imagining future events (i.e., positivity bias). This positive excitement about the future is probably based on a solid foundation derived from our concrete perception and physical interaction with the world (i.e., cognitive scaffolding; Herbert, 2010). We humans move forward, and not backward, which in turn might explain why concepts like “progress” and “advancement” are generally associated to something good, while “backward thinking” is
TABLE 3A | Verb frequency, proportions of verbs and proportions of conditions in the Facebook corpus.

| Condition | Verb | Frequency | Verb proportions relative to corpus size | Condition proportions relative to corpus size |
|-----------|------|-----------|------------------------------------------|-----------------------------------------------|
| Future    | Shall| 42011     | 4.88%                                    |                                               |
| Future    | Will | 100000    | 11.63%                                   | 16.51%                                        |
| Past      | Ate  | 28653     | 3.33%                                    |                                               |
| Past      | Chose| 6440      | 0.75%                                    |                                               |
| Past      | Did  | 100000    | 11.63%                                   |                                               |
| Past      | Drove| 10421     | 1.21%                                    |                                               |
| Past      | Fell | 30519     | 3.55%                                    |                                               |
| Past      | Grew | 6656      | 0.77%                                    |                                               |
| Past      | Spoke| 6423      | 0.75%                                    |                                               |
| Past      | Was  | 100000    | 11.63%                                   |                                               |
| Past      | Went | 100000    | 11.63%                                   |                                               |
| Past      | Wrote| 13014     | 1.51%                                    |                                               |
| Present   | Been| 100000    | 11.63%                                   |                                               |
| Present   | Chosen| 3639     | 0.42%                                    |                                               |
| Present   | Done | 100000    | 11.63%                                   |                                               |
| Present   | Driven| 2500     | 0.29%                                    |                                               |
| Present   | Eaten| 8919      | 1.04%                                    |                                               |
| Present   | Fallen| 8875     | 1.03%                                    |                                               |
| Present   | Gone | 66040     | 7.68%                                    |                                               |
| Present   | Grown| 12203     | 1.42%                                    |                                               |
| Present   | Spoken| 3150    | 0.37%                                    |                                               |
| Present   | Written| 10664  | 1.24%                                    |                                               |
| Total     |      | 860127    | 100.00%                                  |                                               |

TABLE 3B | Year frequency, proportions of years and proportions of conditions in the Facebook corpus.

| Condition | Year | Frequency | Year proportions relative to corpus size | Condition proportions relative to corpus size |
|-----------|------|-----------|------------------------------------------|-----------------------------------------------|
| Future    | 2012 | 3753      | 5.86%                                    |                                               |
| Future    | 2013 | 324       | 0.51%                                    |                                               |
| Future    | 2014 | 327       | 0.51%                                    |                                               |
| Future    | 2015 | 398       | 0.62%                                    |                                               |
| Past      | 2005 | 645       | 1.01%                                    |                                               |
| Past      | 2006 | 1016      | 1.59%                                    |                                               |
| Past      | 2007 | 951       | 1.49%                                    |                                               |
| Past      | 2008 | 1069      | 1.67%                                    |                                               |
| Present   | 2009 | 4759      | 7.43%                                    |                                               |
| Present   | 2010 | 28515     | 44.55%                                   |                                               |
| Present   | 2011 | 22252     | 34.76%                                   |                                               |
| Total     |      | 64009     | 100.00%                                  |                                               |

often regarded as bad (see Herbert, 2010, for more examples such as “up vs. down”). Indeed, people seek to make a positive impression upon the world by leaving a legacy that will transcend themselves into future generations (e.g., Wade-Benzoni, 2003; de St Aubin et al., 2004; Grant and Wade-Benzoni, 2009; Wade-Benzoni et al., 2010).

Strengths and Limitations

The quantification of language by extracting words from contexts is a powerful research tool when a large amount of data is available (Landauer and Dumais, 1997; Landauer et al., 1998; Howard and Kahana, 2002; Arvidsson et al., 2011). That being said, research using similar methods in social psychology is limited, making it difficult to compare our findings with previous research. To the best of our knowledge, no previous studies have used the proposed method to examine how people’s ability to time travel influences how they evaluate events or rather how it influences the valence in their narratives. One of the strengths of the present study is that we analyzed data from two different domains and found the same overall pattern, that is, that the past is devaluated compared to the future. However, the effect sizes were between weak to moderate. Thus, further experimental and empirical data is needed to confirm or disprove our findings. For instance, it is plausible that narratives of events by non-journalists might give different results. Quoidbach (2013), for example, suggested that there are differences
between the cognitive processes that allow people to look forward and backward in time—imagine new things is generally more difficult than reconstructing old ones from one’s personal life. These researchers suggest that, because people find it difficult to imagine themselves changing in the future (e.g., their personality, preferences), people think that it is unlikely the they will actually change (see also Gärling and Gamble, 2012; Garcia et al., 2014).

In other words, if people in general find it difficult to change, it is possible that the future is as “rosy” as both the past and the present. In that case, the news and social media data presented here is only a reflection of a contagion of positive emotions for events placed in the future.

Moreover, auxiliary verbs (i.e., verbs that add functional or grammatical meaning and usually accompany a main verb in infinitive) sometimes have other meanings, than implying future tense. For example, “will” or “shall” can in conversational language be used in the present tense to express an ongoing activity that continuous in the near future. Although such exceptions may exist, the most common usage of “will” or “shall” is to describe future events or activities. Common for all verbs, that we used as temporal markers, is also that they are typically used within their denoted tense. Another limitation of the study is that predicting valence using the LSA method may introduce errors in the calculation. Although this is true, we still believe that the LSA is a powerful method that allows automatic measuring of valence with reasonable good accuracy.

Finally, we acknowledge the uneven proportions of extracted verbs and years in the Past, Present and Future conditions. At the most extreme, the years from the Facebook corpus was skewed in the sense that almost 87% of the extracted data was assigned to the Present condition. Most of the data showed the same type of skewness. The verbs from both data sets being the least skewed.

**Further Research and Concluding Remarks**

Our results open up a number of questions for future research. First, the choice of temporal markers can be further elaborated. Here we chose the time markers based on which words are commonly used as temporal markers in everyday language. Secondly, it would be interesting to replicate the results using different text corpora, such as, literature, novels and short stories, and political speeches. Moreover, there might be cultural differences in how we perceive and represent the past, the present, and the future. For instance, Chinese people seem to recall events from the past in greater detail compared to Canadians (Ji et al., 2009). Also in this line, one’s world view or conception of the world might influence our preference for past or future mental time travel (Ettlin and Hertwig, 2012).

All this being said, our results suggest that the evaluative communication of an event is temporal-valence asymmetrical (that is, valence of an event in time = past < present < future). The outcome, however, depends on whether it can function as incitement for future action or the promotion of behavior (higher valence) or feedback from past actions to avoid or prevent behavior in the future (lower valence): The Time Anchored Incitement Hypothesis (TAIH). We argue that, it might be self-beneficial to the one being the speaker to convey positive evaluative statements about the future that are in line with the legacy she/he envisions to leave for future generations, which in turn also makes the speaker to appear as more appealing and exciting to listeners. After all, we seem to have bias toward a “rosy future.” On the other hand, the negative value associated to past events might signal both danger and its proximity (Kyun, et al., 2010), thus, focusing attention on improving or even avoiding past behaviors.

**AUTHOR CONTRIBUTIONS**

DG and CA wrote the paper and revised drafts of the paper. KD and SS conceived and designed the experiments, performed the experiments, analyzed the data, contributed reagents, materials, and analysis tools, wrote the paper, prepared figures and/or tables, and reviewed drafts of the paper. MK, KD, SS, and CA reviewed drafts of the paper.

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