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The Diffusion Speed of Good vs. Bad News in Geopolitics

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This article investigates the dissipation speed of positive and negative news in a geopolitical context. We perform a sentiment analysis of geopolitical news and measure the gamma of the corresponding sentiment scores per time unit in order to compare the travel speed of news with positive sentiment scores with news having negative sentiment scores. While prospect theory suggests that bad news is perceived as more impactful than good news, we show that this does not necessarily hold for the travel speed of news. On the contrary, we find that good news linked to keywords, which have usually a negative association, travel faster than bad news, and vice versa; a seeming repudiation of folk wisdom. Since our use cases were geopolitical crises, we associate phrases connected with conflict or the potential for conflict to have a broadly negative association. The implications of our insights suggest that the dissipation speed of news can be improved by framing and releasing positive news about events or entities with a negative association.

Keywords: sentiment analysis, sentiment score, sext mining, geo-politics, news flow

Introduction

Sentiment analysis (STA) is difficult because human language is complex. Consequently, individual analyses are untrustworthy. This does not, however, mean that STA is without worth. Individual outcomes may be corrupted, but it is in the large numbers and datasets where truth can be found. To this end, we analyze 7,022 English language publications divided into 23 country and keyword pairings connected to contemporary geopolitical crises. With this information, we seek to determine whether, as the idiom suggests, that news which contains negative sentiment dissipates faster than that which contains positive sentiment. Or, to speak plainly, does bad news travel faster than good?

We speak in hyperbole and metaphor, use sarcasm and colloquialism, and fall into anachronism and oxymoron. To draw sentiment from language is difficult; to do so perfectly is superhuman. A series of natural language processing (NLP) models have been built to do just that, to approximate the human ability to assign emotional value to word combinations, but to do so faster and cheaper than a hired hand might. The problem, evident in the STA literature, is that the results of analyses are often difficult to interpret. They appear stochastic to the naked eye. The imperfection of individual sentiment scores has proved a persistent barrier to applying sentiment analysis to the social sciences. For example, at this moment, sentiment analysis is too blunt a tool to be used for rhetorical criticism. However,

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there has been somewhat of a failure of imagination on this front. If a single sentiment analysis cannot be relied upon to tell us anything useful, then what about 100 analyses? Or 10,000? When dealing with a large data set, patterns emerge.

A solvable problem, pattern-wise, is how sentiment moves. A significant percentage of inputs are negative, another portion is positive, and that which is neither has no sentiment; it is neutral. As time progresses, and new language is available to analyze, the prevailing sentiment changes. One day all is sunshine and kittens, the next there is a dark and stormy night. Sentiment, like New England weather, changes frequently over even short periods of time. To test whether sentiment becomes less positive or more negative faster, we draw a sample of sentiment from contemporary geopolitical crises. While sentiment could have been drawn from English language publications on any topic, we were hopeful that STA could tell us about the crises as well as be studied on its own.

The keywords we used to find publications are based around four primary country pairs China-Taiwan, Saudi-Arabia-Iran, Turkey-Greece, and Germany-Ukraine. All four pairs have been associated with a headline-grabbing geopolitical crisis during the period where data was collected. Each pair was then associated with one unique keyword, and two shared keywords across all four pairs. China-Taiwan was linked to the term "Microchips." Saudi Arabia-Iran was linked to the term "OPEC." Turkey-Greece was linked to the term "Eastern Mediterranean." Germany-Ukraine was linked to the term "Natural Gas." Publications relating to "U.S. Aircraft Carrier Deployment" and "Nuclear" linked to the four country pairs were also collected. Each keyword- Microchips, OPEC, Eastern Mediterranean, Natural Gas, U.S. Aircraft Carrier Deployment, and Nuclear- was also analyzed separate from any country pair as a sort of control group. This allows us to test hypotheses such as if news on microchips generally changed sentiment differently from news directly connected to China-Taiwan. We also collected publications sans keyword on former Yugoslav Republics: Serbia, Kosovo, North Macedonia, Montenegro, Bosnia and Herzegovina, and Croatia. These countries were not looked at independently but as a sextuple pairing (as opposed to a country pair). Our country pairs all posed the possibility of violence during data collection, but our keyword pairings are split between terms connected with violence and those not. We associated "U.S. Aircraft Carrier Deployment" and "Nuclear" with violence. "Microchips," "OPEC," and "Natural Gas" were associated neutrally, and "Eastern Mediterranean" was associated positively (the impact of this association is indeterminate).

We organized our use cases like this for two reasons. The first, as previously stated, is to see whether positive sentiment diffuses at a slower rate than does negative sentiment, and if it does not do so universally, under which circumstances does it. The second, is to see if this type of research can be done. The crudity of sentiment analysis is an immense barrier to its use for anything but market research. By building a novel dataset and relating it to a social-scientific scenario (geopolitical crises), we hope to serve as a proof of concept for STA's application to broader issues. To accomplish the aforementioned tasks, we will first discuss previous uses of sentiment analysis and attempts to measure if bad news travels faster than good news in the next section, followed by our description of our methodology and data. We then present our results, and finally we conclude.

Sentiment Analysis

Sentiment Analysis as a Tool

We will next provide a short historical overview of the sentiment analysis (STA). Despite the topic's rapid growth, it is quite possible to summarize its application with appropriate parsimony; STA is quite new. Bibliometric analysis demonstrates that academic studies of or using STA are a mostly post-2010 phenomenon. It is also a largely Chinese specialty, with more publications coming out of the People's Republic than the U.S. (Micu et al., 2017). We will note that quantity is not necessarily indicative of quality.

STA is the "tools and other lexical resources for analyzing texts (Ahlgren, 2016)." It sits awkwardly at the intersection of radically diverse fields due to its newness, complexity, and broad, if not straightforward, applications. STA is an attempt to quantify the emotional context of communication; a task of interest to linguists, which requires the use of software, working on a set of problems most at home in mathematics and logic, which sees application in marketing (Rambocas & Pacheco, 2018). Research in both marketing and other areas of interest has often taken place through analyses of tweets on the microblogging site Twitter. For example, using a rudimentary sentiment coding process, Naveed et al. (2011) studies how positive or negative sentiment in a tweet affects the diffusion of that tweet through retweets. They found that tweets containing emotional value were more likely to be retweeted and that positive tweets were shared more often than negative ones (2011). In recent years, Twitter has become a hotbed for novel STAs, and we would recommend looking to Giachanou and Crestani's "Like It or Not: A Survey of Twitter Sentiment Analysis Methods" for a more complete breakdown of several dozen attempts at STA on Twitter (Giachanou & Crestani, 2016).

Aside from analyzing tweets, an obvious application of STA for the social sciences is quantitative rhetorical analysis, and an obvious subject of this analysis is State of the Union Addresses (SOTUs). Constitutionally mandated ("He shall from time to time give to Congress information of the State of the Union and recommend to their Consideration such measures as he shall judge necessary and expedient (U.S. Const. art. II, § 3)."), the annual addresses have been given both orally and through letters, but the addresses are ideal objects of study because they are digitized, connected to historical figures for whom there is significant public information, and connected to specific periods of US history where information on war, the economy, and public mood can be accessed. There is also a substantial enough dataset to be useful; there are well over 200 SOTUs. The exact number is controversial because of addresses given to congress outside of the modern late-January timeframe of SOTUs. President Bush's post-9/11 address is an example of this. He addressed a joint session of congress in late September of 2001, declaring

"In the normal course of events, Presidents come to this chamber to report on the state of the Union. Tonight, no such report is needed. It has already been delivered by the American people (Bush, 2001)." It is unclear whether the President's September 20th address fulfilled the constitutional mandate. Regardless, SOTUs make ideal subjects for STA.

We are aware of three sentiment analyses that have been conducted on complete SOTUs. The first, conducted in 2015, is from data-based-consultancy firm M&S Consulting. They have not publicly released the entirety of their results, although their Bush-era findings are consistent with the analysis of others. The second, from 2018, finds that SOTUs get more negative through a president's term; positive sentiment consistently dissipates over time (Rydeen, 2018). Most recently, Maria Kubara and Przemysław Mazurek (2021), applied STA to SOTUs, but their goal was to see if party affiliation can be determined algorithmically. To a high degree of accuracy, it can (2021). Only the 2018 STA drew meaningful results from the sentiment analysis itself, and those were quite limited in scope.

STA is still in its infancy, and large language models like ChatGPT show that there is a large demand for emotional literacy in software. We expect that below the surface of published research that there exists a flourishing market for professional sentiment analyses of customer reviews, performance evaluations, and candidate references. It is also of concern that the full extent of STAs use is largely hidden from public view. Firms can be sensitive about their use of software that has been characterized as invasive, and this sensitivity is a barrier for researchers.

Dualism

> "One of the problems has to do with the speed of light and the difficulties involved in trying to exceed it. You can't. Nothing travels faster than the speed of light with the possible exception of bad news, which obeys its own special laws. The Hingefreel people of Arkintoofle Minor did try to build spaceships that were powered by bad news but they didn't work particularly well and were so extremely unwelcome whenever they arrived anywhere that there wasn't really any point in being there" (Adams, 1993).

The above quote from Douglas Adams, writer of *The Hitchhikers Guide to the Galaxy* is a modern example of the folk wisdom that inspired this paper. 450 years earlier, when speaking of the fate of a captured prince in his pre-Shakespearean *Spanish Tragedy,* English Dramatist Thomas Kyd (1959) wrote that "if he lived, the news would soon be here. /Nay, evil news fly faster still than good." An instructive point in the evolution of the sentiment is that while Adams states the impossible speed of bad news as a given, something he expects the reader to be familiar enough with to understand the joke, Kyd (1959) presents his statement as a proposition to be accepted or rejected by the speaker's interlocutor. Over time, the idea has seeped more deeply into the public conscience. Kyd (1959) was likely not the first to posit this, that news which carries negative sentiment moves faster than positive news, but he was the first to write it down. Since the 1580s the perception of bad news' Mercurian speed has persisted in language and culture. The theory, always stated as fact, has become an inescapable piece of folk wisdom. Accordingly, researchers have sought to prove it. It must be noted that the relationship between positive and negative, what we call dualism, cannot be understood by speed alone, but the humans who propagate news must themselves be examined.

First, trying to prove the folk saying from a finance perspective Hong et al. (2000) test how analyst coverage (news) and stock momentum interact, with a gradual-information-diffusion model. They find that negative news (that which lowers stock prices) diffuses less effectively than does positive news. Notably, their study is not sentiment analysis. It is conceivable that news which carries negative sentiment could raise a stock price and thus be coded as positive within their model. Reporting on a deadly fire at a Coca-Cola plant might be explicitly "bad news," but still cause PepsiCo, Inc. to experience a bump. This is a broader issue with finance-based attempts to look at sentiment; they tend to use the results of information diffusion (stock movement), rather than any language contained within reporting. Consequently, even when asking the same question (Does bad news travel faster than good news?), it is possible to use dissimilar methods and reach dissimilar conclusions between sentiment analysis-based approaches and finance-based approaches. One insight from Hong, Lim, and Stein's paper is that "momentum strategies work better among stocks with low analyst coverage (p. 265)." This is a product of stocks with low coverage reacting to new information slower than the stocks of larger companies do. More broadly, this could imply that sentiment moves slower for less covered stories. This effect, however, is more observable with negatively coded information (Hong et al., 2000).

More recently, in 2012, Luís Miguel Serra Coelho used Hong and Stein's model and Chapter 11 bankruptcy filings in publicly traded companies to test reaction speeds to negative news. Coelho found a "statistically significant post-bankruptcy drift that lasts for at least 6 months (Coelho, 2015, p. 415)." Assuming that the negative drift represents a correction from inappropriately high valuations, then it often takes a full six months for the market to fully react to bad news. He found that the drift is worse for small, poorly covered firms. In fact, a large majority of publicly traded firms in the bottom quintile of the NYSE have zero assigned analysts (p. 430). This confirms Hong, Lim, and Stein's finding that bad news travels slowly, and slower still from smaller sources. It is also a case for the limited cognitive power of markets. Coelho (2015) contradicts both the folk wisdom that evil news travels faster still than good, and psychological considerations of dualism.

For example, Baumeister et al. (2001) bring the field of psychology down upon the nature of dualism in their exhaustive article "Bad Is Stronger Than Good." They find that in nearly every circumstance measured by psychology, negativity is "stronger" than positivity, that there exists an asymmetry between good and bad in the minds of man. In their words "when equal measures of good and bad are present,"…"the psychological effects of bad ones outweigh those of the good ones (p. 323)." Their theory rests upon three definitions which can be "understood even by creatures with limited linguistic capacity:" good, bad, and stronger (p. 324). The authors' explanation for why we are not all miserable wrecks, despite the potency of bad, is that in sufficient quantity, good experience can outweigh bad. With sufficient consumption, one may become drunker on merlot than they might on a lesser amount of absinthe. Even within the field of psychology, negativity far outstrips positivity. By coding 17,000 psychology publications, Janusz Czapiński (1985) found that there exists 69 publications on negative phenomena for every 31 on positive.

When grappling with how persons react to emotional stimulus, a necessary concept is the hedonic treadmill theory. First put forward in 1971 by Brickman and Campbell (1971) it suggests that people return to a base level of contentment. Just as one might run on a treadmill without getting anywhere, someone might increase their income, and will not be permanently happier. Further research found that the return to the base level was slower following a negative event (paralysis) and faster for a positive event (winning the lottery). This would suggest that sentiment ought to move from positive to less positive, neutral, or negative faster than it moves in the other direction. It seems psychologists and behavioral economists disagree with market researchers. It seems that studies of individual behavior and psyche are consistently at odds with market-based attempts at studying dualism and information behavior. This could be a function of methodological differences or an instance where institutions and organizations behave differently from their progenitors. Perhaps when someone complains that she hears of funerals before weddings, she is observing reality, not some personal bias.

Methodology & Data

We borrow insights gained from options trading, in particular from calculation of the option Greeks in order to measure the sensitivity of the option price to the underlying price. The only difference is that in our approach, we don't deal with prices, but instead with sentiment values, and not with underlying prices, but with time. Concretely, we utilize the calculation of Delta and Gamma of the sentiment values of the news in order to calculate their sensitivity on time. Larger impacts of change in sentiment scores induce that more sentiment was included per time interval. Since time intervals are constant, this means that more information was included per time unit, thus the travel speed of the news per time unit was faster.

The sentiment scores are calculated following Shukla and Unger (2022), where the authors use the FLAIR NLP framework, provided by Akbik et al. (2019), to facilitate training and distribution of state-of-the-art sequence labeling, text classification and language models. For the sentiment score we chose the currently most frequently discussed country pair combinations with a high probability of engagement in an open conflict. The sentiment score for all these country pair combinations is calculated in combination with corresponding hot topic keywords. The sentiment score is calculated for the following country pair relationships: China/Taiwan, Saudi Arabia/Iran, Turkey/Greece, Germany/ Ukraine, and former Yugoslavia, including Serbia, Kosovo, Macedonia, Montenegro, Bosnia and Herzegovina, and Croatia. We use following keywords in combination:

Microchip, US Aircraft carrier deployment, Nuclear, OPEC, Eastern Mediterranean, Natural Gas.

Table 1 highlights which keywords are used in which country pair combination.

Table 1. Keywords per Country Pair Combination

Country-pair Keyword		China/ Taiwan	Saudi Arabia/ Iran	Turkey/ Greece	Germany/ Ukraine	Former Yugoslavia
		✓	✓	✓	✓	✓
Microchip (+/-)		✓				
US Aircraft Carrier deployment (-)	✓	✓	✓	✓	✓	
Nuclear (-)	✓	✓	✓	✓	✓	
OPEC (+/-)	✓		✓			
Eastern Mediterranean (+)	✓			✓		
Natural Gas (+/-)	✓				✓	

We then retrieve historical news article available on Google news, covering from Dec 29, 2012- Jan 6, 2023. Most of the news articles (>90%) were retrieved within the past 3-8 months.

To test for robustness we also calculate the sentiment score for the keywords alone, which allows us to disentangle the relationship a keyword plays in combination with a country pair in a news article. In order to be able to draw conclusions about the impact of keyword sentiments on their dissipation speed we affiliate the level of violence associated with its keyword and categorize it into 2 categories: 1. Keywords associated with high level of violence, 2. Keywords with no or low level of violence. Ultimately, keywords associated with a high level of violence can be assumed to have a negative connotation and therefore provide a negative association. Conversely, keywords with a no or low level of violence can be viewed as positive associations, due to their positive connotation. Therefore, we assign a "-" sign to all keywords with a negative association and a "+/-" sign to all keywords with a positive or neutral association, indicating its positive or neutral connotation.

It is important to note that we distinguish between our subjective allocation of positive and negative associations with the keywords, and the sentiment values returned by our sentiment analyses, used for measuring the dissipation speed of news. Since the sentiment scores returned by our sentiment analyses are obtained by analyzing news articles, their values are time dependent. In contrast to that, our subjective keyword associations serve only for categorization purposes. The goal of the subjective keyword associations is to understand how the dissipation speed of news behaves in the context of negative or positive news flows. For this purpose we calculate the gamma of the sentiment scores.

We define S_t as the sentiment score of news at time t, consisting of the subsets S_t^+ for positive sentiment scores and S_t^- for negative sentiment scores, satisfying the condition $S_t \epsilon \{S_t^+, S_t^-\}$. We calculate the Gamma of the sentiment score, Γ_{S_t}, as

$$\Gamma_{S_t} = \frac{d\Delta_{S_t}}{dt}, \quad (1)$$

where

$$\Delta_{S_t} = \frac{dS_t}{dt} = \frac{S_t - S_{t-1}}{t-(t-1)}, \quad (2)$$

with Δ_{S_t} defining the change of the sentiment score over time. We then separate all positive and negative gammas into $\Gamma^+$and Γ^-subsets, satisfying $\Gamma_{S_t} \epsilon \{\Gamma^+, \Gamma^-\}$, and conduct a t-test to test the following hypotheses:

$$H_0: \Gamma^+ \geq |\Gamma^-|, \text{resp. } \Gamma^+ \leq |\Gamma^-|, \quad (3)$$
$$H_1: \Gamma^+ < |\Gamma^-|, \text{resp. } \Gamma^+ > |\Gamma^-|. \quad (4)$$

In our first hypothesis, we test if news with a positive sentiment score exhibit at least the same or a higher Gamma than news with an absolute negative Gamma. Then, we conduct the same hypothesis vice versa, i.e. if news with an absolute negative sentiment score exhibit the same or a higher Gamma than news with a positive sentiment score. The corresponding alternative hypotheses cover the respective inverted case.

Results

We summarize in Table 2 our results from all t-test combinations. We only conduct t-tests for country pair and keyword combinations for which combinations make sense. E.g., we test China/Taiwan and Microchip, while it wouldn't make sense to test Microchip with Saudi Arabia/Iran. We display the results where news with a positive sentiment travel faster than news with a negative sentiment with a "+", while we display the results where news with a negative sentiment travels faster than news with a positive sentiment with a "-".

We can see that out of 12 combinations, there are 9 cases where positive news travels faster than negative news. Out of these 9 cases, 5 are highly significant. There are only 3 cases in which negative news travels faster than positive news, out of which only 1 exhibits a high significance. We can summarize that in 75% of our cases, positive news travels faster than negative ones, out of which 41.67% are highly significant, measured against the total sample size. On the contrary, we find only a 25% chance that negative news travels faster than positive news, out of which only 8.33% are highly significant.

Looking at the singular evaluation of the country-pair relationship sentiments as well as the keyword sentiments, we find that no country pair relationship exhibits a significant superiority of news-sentiment travel speed, while the keywords “OPEC”, “Eastern Mediterranean” and “Natural Gas” show a highly significant travel speed of positive news over negative news. Interestingly, our results return only positive news speed superiority for all keywords, while the country-pair relationships exhibit mixed signals. This might be a coincidence due to the chosen time frame for testing, and doesn’t provide fundamental insights. What’s more interesting for us is the fundamental relationship that is revealed by the pattern of news speed superiority of country pairs and keywords combined.

The pattern we identify is that keywords with a connection to conflict or potential conflict, such as “Aircraft Carrier deployment,” exhibit a much more significant news speed dissipation of positive news sentiment scores than keywords with a more neutral or even positive association. For neutral or positive associations, we can’t find a clear pattern, also due to limitations of our sample size. Nevertheless, our small sample size indicates that the opposite might hold as well. We can find a clear superiority of news speed dissipation of news with positive sentiment scores in the cases of Saudi Arabia/Iran, Turkey/Greece, and Germany/Ukraine, in combination with “Aircraft Carrier deployment”. Our only extracted result for the combination “Eastern Mediterranean” and “Turkey/ Greece” suggests that keywords, news, or entities associated with a positive connotation spread negative news faster than positive news. Thus, the pattern we could extract from our results is an inverse relationship of keyword association with the dissipation speed of news according to their sentiment. Nevertheless, for more neutral words such as “Microchip” and “Natural Gas”, positive news seems to spread faster than negative news.

Table 2. Results

Country-pair Keyword		China/ Taiwan	Saudi Arabia/ Iran	Turkey/ Greece	Germany/ Ukraine	Former Yugoslavia
		+	-	-	+	+
Microchip (+/-)	+	+***				
US Aircraft Carrier deployment (-)	+	+	+***	+***	+***	
Nuclear (-)	+	+	-	+	+	
OPEC (+/-)	+***		-			
Eastern Mediterranean (+)	+***			-***		
Natural Gas (+/-)	+***				+***	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.10 ' ' 1.

Conclusion

Our research in this paper focuses on the dissipation speed of good news and bad news. It is broadly held that bad news spreads faster than good news. This popular assumption (folk wisdom) has been repeated or contested within diverse fields, including journalism, psychology, and finance. Prospect theory is one important tool for understanding reactions to sentiment. It alleges that negative outcomes have more impact on the human psyche than positive outcomes. Kahneman and Tversky (1972) showed that people evaluate situations in terms of expected utility relative to a reference point rather than absolute outcomes. When it comes to the relative evaluation of the impact of positive or negative news on the dissipation speed of the news, the relativity of biased information sets holds as well. However, the power of negativity seems to be overruled by the impact of positive sentiment scoring. This contradicts both the popular assumption of

The insights gained from our small but powerful sample size suggest an inverse relationship between negative keyword association and the dissipation speed of good news, and vice versa. We find a superiority of dissipation speed associated with good news over bad news on keywords or relations that are connoted to geopolitical conflict scenarios and a superiority of bad news traveling faster in association with positive connotation. The implications of these findings are very interesting as they raise further questions about both what makes positive news travel faster and at how granular a level might we understand dissipation speeds.

As we find, dissipation speed all depends on the context and the reference point. If the reference point has a negative or conflict association, then positive-related news will spread faster than negative-related news. However, if the reference point has a neutral or positive association, then the speed of dissipation of negative news can also be superior over the dissipation speed of positive news. However, the picture for the latter is not as straightforward or significant as it is for the former. Further research would need to focus on larger sample sizes to include more cases of neutral or positively associated keywords or relations and then measure the dissipation speed of good news and bad news for these cases in order to get a clearer picture.

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