An Examination of Influential Framing of Controversial Topics on Twitter

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I. INTRODUCTION

News sources are notorious for being biased, especially when it comes to international dealings. When it comes to news sources that talk about Sino-US Relations, Chinese news sources may portray one image and American news sources may portray another. Even Chinese and American news that get translated to the other language may portray a different image given the diction and syntax that news sources may deliberately use to paint a tweaked picture to foreigners.

The initial goal of this project was to gather articles in Chinese and English (primarily American) news sources that discuss particular topics of importance to Sino-US Relations and characterize each article first with the sentiment that article has towards the situation and the opposing actor. Further complexity can be added by investigating the social language dimension of formality and further expand into politeness, emotiveness, impartiality, and intimacy (Pavlick et al. 2016) to classify news articles by the type of source and article that is publishing the piece.

In short, the input of this first experiment was a large corpus of news articles across many different sources, both Chinese and English. The output of this research is a learned model that is able to classify news articles (in English and Chinese) with the sentiment the article has towards the situation - any by relation, the opposite state actor.

However, over time, I decided that it was best to use more open datasets, primarily the one made available by Twitter. This would give me more direction and the data would also be easier to capture. This solved some problems, but also created more problems as I discovered that there were many hidden parameters to the messy Twitter data and making a dataset was very time-consuming and not straightforward at all.

I will likely not be able to run the tests on Chinese articles in the course of my project this semester, but I will attempt to include that aspect of it in later versions of my project. My focus has thus moved from determining sentiment disparities between English and Chinese news sources to a focus on the layers of framing that Twitter uses may use to alter existing sentiments in news articles. As such, the following sections contain modified material from the project proposal and also includes information on what I have already done, my results, and my plans for the next step.

II. CHANGES FROM PROPOSAL

In the project proposal, I sought to gather my data directly through web crawling. After further examination and discussion with Dr. Wang, I have decided to first retrieve data through Twitter's Streaming and Search API. I will gather data on topics of particular controversial nature and only pay attention to the Tweets that allude to some news article and some additional comment. The comment that the user includes with the article will be seen as a "framing" statement, with a purpose of influencing their network to believe a certain way about the article or the topic. I will then head to the website alluded in the Tweet, and run language models to determine the nature of the article and how the statement is attempting to modify it.

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III. NEW PROBLEM

Entman (1993) states, in "Framing: Toward clarification of a fractured paradigm" that "to frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described."

This is an important issue because we are part of a society where invisible influential powers are taking over. We live in a digital age where every online user is constantly being exposed to the ideas of others in social media. Without even fully being aware, people can be affected by these ideas enough that their own values and decisions begin to morph. It is true that "you are the average of the five people you spend the most time with," but in an age where you can be exposed to exponentially more people and thoughts, any single entity can introduce ideas that make you change course.

Twitter is commonly used to voice political opinions and weigh in on current events. A capability in Twitter is to be able to share news articles (or other forms of news media) and also attach with it a personal thought. Be it obvious or not, these "attachments" usually are viewed as more important than the actual article itself, given that some people may not even bother to click on the article and read it. Normal opinions are weighted as heavily because they are seen, on default, as having no official evidence to support the thoughts. However, when a person attaches an article from a credible news source, like New York Times, and then adds a statement that may be a statement taken out of context from the article, a personal belief that seems to echo the article, or even a belief that appears to have nothing to do with the article, this makes a direct impact on the viewers of these posts.

The goal for this project would be identify the many ways people today are using Twitter and news hand in hand. Then, to qualify some nature of sentiment affect those users may have towards the particular topic, and measured numbers on what this means to social media "influence operations" in the future.

IV. DATASETS

While there are existing corpus available online for news articles, both in English and in Chinese, it may serve me for testing my model but will be less applicable when I extend my project. To get information on the particular topics I am interested in, I may use Information Retrieval techniques and web crawling to gather large relevant datasets. While Arruda et. al (2015) used Twitter as its political news source, we can also collect data in a similar fashion to how he does it, on a daily basis with only 20 of the day’s relevant Tweets chosen randomly. This dataset of news articles will serve as the main dataset that I will use for my project.

As for plans for annotating the data that I retrieve, it is likely that I may do a lot of it myself, ask help from friends, or even employ Amazon Mechanical Turk to handle a large piece of my dataset.

A big part of separating a variety of news sources will require a combination of using a set list of self-determined annotations for news sources as well as implementing formality detection on the actual news articles. Based on the papers mentioned in the ‘Related Work’ section, I can use existing labeled corpus made available by researchers to train a formality detection model to be used for classifying each of the news articles. Pavlick et. al (2016) released a new dataset of 6,574 sentences annotated for formality level. This, combined with the dataset of 2,775 news sentence-level formality annotations released by Lahiri (2015) and formality lexicon released by Brooke and Hirst (2014) should be a good start for implementing formality detection. Much of the work on formality will be replicating the experiment of Pavlick et. al (2016) and will be done as a later part of the project.

V. RELATED WORK


I looked into the media Frames Corpus that this research provided and am using it as a model to create my corpus of annotator data.


This article addresses two definitions - clickbaiting and sensationalism, which are factors that I may look for in my Twitter references. This is especially important if I follow the path of using annotators to check if my labels for my texts are in agreement. This literature review helped me formalize some of my definitions but did not provide any specific
methodologies to implement.


This research article was the most helpful article I got to read recently, providing detailed information and contrast between framing bias and epistemological bias and it helped me realize some of the features I may need to measure differences between pieces of data.


The pointwise mutual information metrics described in this research article will possibly be used as a future methodology. I am not fully sure how social bias and framing are connected just yet.


It is interesting to note that a lot of my model will depend on the training and any bias will be amplified over time. I read this about this kind of training in industry as well, when Google recently discovered that its sentiment analysis for ‘I am straight’ has a neutral sentiment whereas ‘I am gay’ has a sentiment of -0.2 and ‘I am homosexual’ having a sentiment of -0.4. This creates a wariness in me but I’m not sure how this will apply to my project just yet.

VI. DATA PRE-PROCESSING

The Twitter APIs took some while to get accustomed to. I primarily worked with the Streaming API, because it provides more options and data. However, I plan on also implementing parts of the Search API, although it important to note that the free usage of the API limits me to only query seven days back worth of data so it barely makes a difference.

So far I have only conducted experiments on the “climate change” controversial topic. I intend to include a few other topics as my process solidifies and is confirmed.

Many complications arose from this process. Some of the comments were used in a framing way, but many were just blatant opinions about the article. It was difficult at this step to separate those that are meant to be used as framing, and many that was obvious opinions. I decided to include all variations and to mention this in my later findings. The majority of the other complications arose from retweeting and the difference between adding a comment to a retweet, having an actual response posted by that specific Twitter user, or merely replying on someone else’s Twitter (or replies to other users’ replies to your own post). These kinds of interactions were hard to characterize and made for a lot of decision making on what would be included in my corpus.

On a later note, as for plans for annotating the data that I retrieve, it is likely that I may do a lot of it myself, ask help from friends, or even employ Amazon Mechanical Turk to handle a large piece of my dataset.

As such, currently my features are n-grams for the news articles, and I will run packaged sentiment analysis on the statements. Additionally, I may continue to implement some form of formality detection on those ”sentences” as well.

VII. METHODOLOGY

I have only put together features currently from the scraped news articles and the Twitter crawls during this time for
my project. However, my plan for methodology and model generation is coming to fruition in the near future. I intend to use Naive Bayes primarily and then continue on to the prominent sentiment analysis models. I also intend to try using neural networks to enhance my project.

Based on previous work, I have additional thoughts about possible methodology. Chesney (2017) suggests using novel methods of incongruence detection to explore the phenomenon of "incongruent headlines" which, in this case, would be "incongruent statements introducing articles through Twitter." I would need to extract key quotes or claims from the article, which is similar to other summarization techniques in NLP. I could also create the "statistically best headline for an article" or "statistically best summary of an article" and then compare how far that is from the given Twitter introduction. I would have to decide on the criteria to be deemed "far" including but not limited to lexical choices, syntactic structure, length, and tonality in sentiment or emotion. Augenstein et. al (2016) also uses stance detection to explore if headlines and the actual claims of the entire article are congruent.

Additionally, I can create a bag of words of "one-sided" or otherwise heavily opinionated and skewed words and create scores for statements on how strongly opinionated and in what way any certain statement is.

Lastly, Rudinger (2017) introduces pointwise-mutual-information which may be something to look into for measuring association and likelihood ratio tests of independence between lexical units.

VIII. Evaluation

I’ve recently been introduced to the evaluation metric of Krippendorff’s $\alpha$. This will help me decide on the validity of the inter-annotator agreement. It measures disagreement between two spans as the sum of the squares of the lengths of the parts which do not overlap (Card 2017).

I will use the main means of evaluation for most of the pieces of the project’s work-flow. When it comes to the model’s ability to classify news sources and articles by a specific type (possibly using an unsupervised clustering method), precision, recall, and F1 scores will all matter.

For the purpose of evaluating the sentiment analysis work, it is likely that I will need to manually assess and check the work. I may use a random sample of a few thousand of the articles and employ Amazon Mechanical Turk, do some assessing on my own, and also employ friends and family to check about a few hundred articles each. I will then combine accuracy scores and report the results. As such, I will continue to review past experiments and the research papers in order to see if there are other means for conducting evaluation.

IX. Conclusion

In conclusion, most of the work that I have been able to complete this semester is an extensive dive into data collection and cleaning as well as broadening my knowledge of the types of methodology I can implement. Since I started off with pretty ambitious in my goals, I fell heavily short due to a variety of reasons that stem from inability to define the problem. I learned a lot from my readings and while did not get a chance to implement the tests that I initially wanted to, came really close to putting together a decent dataset. I find that I am a lot more familiar with the entire research process and am optimistic that I will be able to complete something of more success in my future attempts.

REFERENCES