CLICKBAIT AND EMOTIONAL LANGUAGE IN FAKE NEWS

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ABSTRACT

The detection of fake news is a modern challenge in journalism, computing, and natural language processing fields. Past work in detecting fake news have focused on both inherent textual features and the spread of these articles. This study explores two potential indicators in fake news, clickbait headlines and emotions in text. Clickbait is often used in news headlines to increase user engagement. This study, the first look into clickbait headlines as a sign against news source credibility, found consistent improvements in a fact checking system when clickbait-heavy news sources were discounted. Likewise, emotions have also been used as s manipulation tool in language. Using a feed-forward neural network to predict emotions in hyperpartisan news sources, right wing news and mostly false news are found to be more emotional.

***K*eywords** Misinformation · fake news · emotions

1 Introduction

In today's hyper-information age it is important to reserve a degree of cynicism for what we read on the internet. Information, while freely accessible, can also be cheaply and easily generated. In particular, fake news has the potential to dampen decision-making skills and leave readers susceptible to misinformation [1].

Fake news has some seriously damaging consequences for society [2]. In the last few years, fake news has caused public outrage that led to deaths [3], hampered response during terrorist activity [4], and delayed help to vulnerable areas during natural disasters [5]. Of course, fake news would not be problematic if readers didn't take them as fact. In a study with 320 pairs of hoax and real articles, humans were only able to correctly identify the hoax 66 percent of the time. Studies have repeatedly shown that humans perform very poorly when trying to discern hoax from real news [6]. Perhaps even more problematic is how quickly fake news spreads: fake news diffuses through social media faster than real news, aided by humans and bots intentionally and unintentionally dispersing the fake news as fact [7].

The notoriety of fake news can be partially attributed to clickbait. A clickbait is a vague and potentially misleading title that offers little or no information on actual news subjects. Clickbait can also be systematically outrageous and inciting [8]. For example: *"IT'S OVER: Hillary's ISIS Email Just Leaked It's Worse Than Anyone Could Have Imagined"* (Facebook), or *"He Changed His Name for a Horrible Reason, Now He's Telling Us Why"* (Upworthy). While a non-clickbait headline provides concrete information in the title, a clickbait leaves users hanging and entices them to click on the article to get information deliberately left out [9]. Clickbait employs a well-documented psychological phenomenon called the "curiosity gap", which use a reader's curiosity "as a form of cognitively induced deprivation that arises from the perception of a gap in knowledge or understanding" [10]. At best, readers are disappointed when the article's content does not live up to the excitement implied by the headline. At worst, the manipulation of the curiosity gap in clickbait aids the spread of fake news. Explorating of clickbait effects veracity of news sources is the first part of this study. Another manipulation tool in language is the use of emotions in text. The second part of my work focuses on the detection of fake and unreliable news through the lens of emotions conveyed in text. The goals are to 1) create a text model to predict not only the emotions in text but also the strength of these emotions and 2) to find differences between amount of emotional language in reliable and unreliable news.

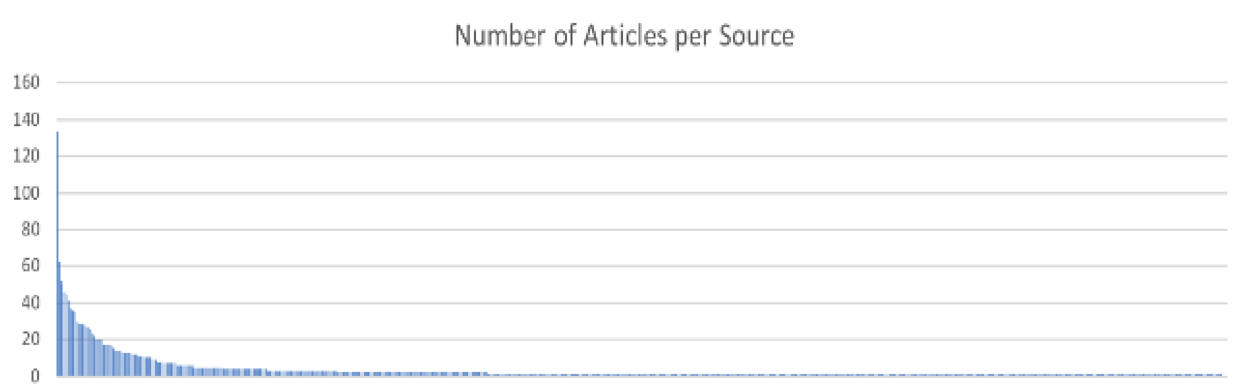


Figure 1: Long tailed graph showing num. articles per source. The vast majority of sources in the Emergent corpus do not have enough articles to reliably predict veracity.

2 Clickbait In News

2.1 Fact Checking Prototype

As a response to fake news, the Information Retrieval community has created various fact checking tools to combat the its rise [11] [12] [13] [14]. A number of these fact checking systems consider the stance of news articles to predict the veracity of claims made, thus filtering the fake news from the real news.

In 2018 Ngyuen et al. [12] created the veracity checking prototype shown in Figure 2. This fact checking system takes a claim as input and predicts how true that claim may be by "1) finding relevant articles (textual evidence); 2) assessing each article's reliability and its relative support for the claim in question; and 3) assessing claim validity based on this body of textual evidence" [15]. The stance of all articles aggregate to produce a truth value for the inputted claim. Naturally, each headline comes from a news source, such as CNN, Fox News, or Reuters. The credibility of this source directly affects its weight in veracity prediction. The more credible the source, the more weight the articles from that source possess.

2.2 Current Problems

Clearly, a robust model for predicting the credibility of a news source is crucial to the success of the fact checker. The current method of determining credibility aggregates the number of times the articles from a particular source has correctly predicted a claim. For example, an article taking a negative position against a wrong claim counts favorably for credibility [15]. This method, though logical in theory, is problematic in practice. The veracity prediction system uses the Emergent corpus [15] to create baseline predictions of source credibility. This corpus contains 2581 articles from 724 sources which holds the veracity of hundreds of claims. Yet 85.8% of the sources map to 5 articles or fewer, and 90% of the sources map to just 10 articles or fewer. As seen in Figure 1, the majority of sources rely on a scattered few number of articles to predict its overall credibility. There are simply not enough articles in the corpus to draw from for the current prediction method to perform as it should.

Currently, credibility prediction ignores the structure of the headline, a potentially valuable indicator of article credibility. This study programmatically identifies clickbait headlines with a support vector machine (SVM) text classifier and uses clickbait as an indicator to help predict the credibility of news sources. Using the prediction model of a fact checking system as baseline, the model is extended to consider clickbait to find potential improvements in predictive power. An improved model would signal a negative correlation between the credibility of a news source and the presence of clickbait in its headlines.

2.3 Related Research

Zhang et al. [16] identified a set of indicators for news source credibility as handpicked by journalists. "Content indicators" are analyzed by examining the text and title of the article and include title representativeness, clickbait title, and many others. The researchers found the presence of numerous clickbait titles detrimental to the perceived credibility of a source.

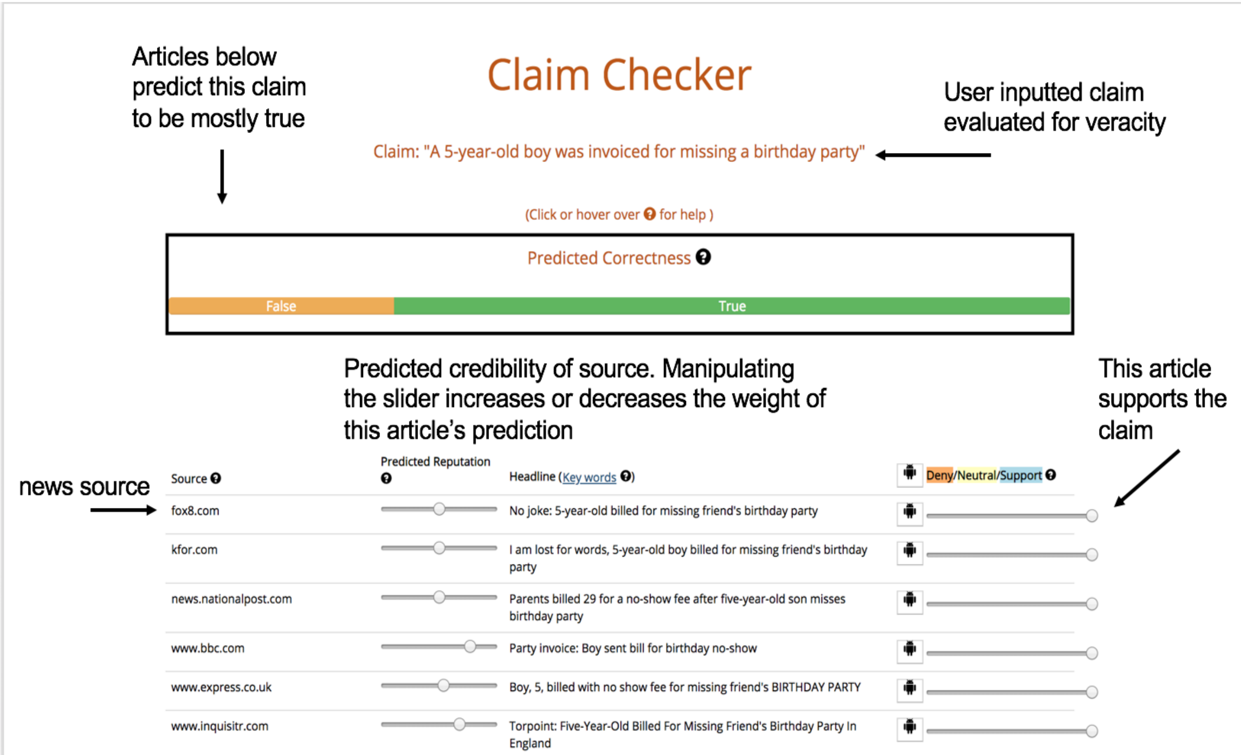


Figure 2: Veracity claim checker interface. The slide-bars under "Predicted Credibility" directly affect the predicted correctness of the claim.

Also spurred by the recent trend of misinformation, researchers have worked to detect clickbait headlines with various natural language processing methods. Contributions include a recursive neural net to classify clickbait from normal headlines [17] and linguistic differences identified between clickbait and non clickbait headlines [18].

While the studies above contributed common clickbait features and useful classification models, there's been little exploration on the application of those classifiers. This study applies text classification to identify clickbait to create a more comprehensive multivariate model of credibility prediction.

2.4 Implementation

The goal is to obtain the "clickbait-saturation" metric of each source and evaluate the predictive power of the claim checker system with and without considering that metric. This is done by:

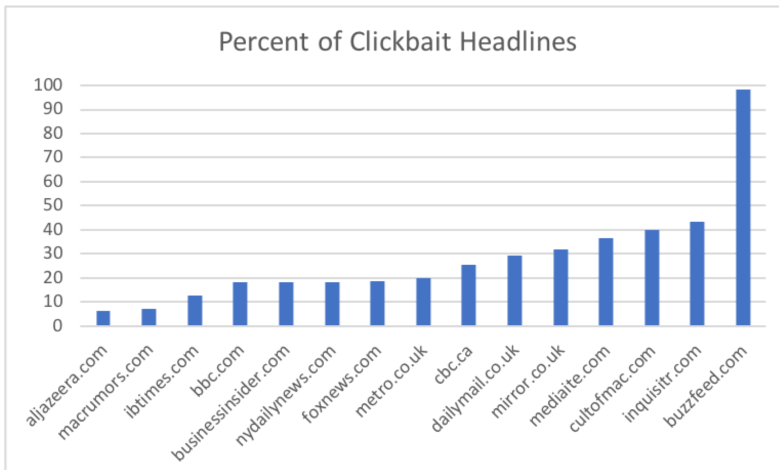
1. collecting a sample of headlines from each source
2. evaluating whether the sample is clickbait or non-clickbait
3. finding the percentage of each source's headlines that are clickbait
4. applying this metric to the credibility prediction model of the fact checking system
5. checking for a improvement in the fact checking system's predictions with and without the clickbait model

The Bing News API was used to collect exactly 100 headlines from each news source as clickbait testing data. Of 724 total sources represented, data for 533 sources was collected. The remaining sources were obscure blogs and low-profile websites whose articles were unsearchable by the API. Excluded articles account for only 6% of all articles.

The next step was to create a reliable text classifier. Data collected by [17], 21k rows of clickbait and non-clickbait headlines, was used as training data. A linear SVM classifier was chosen for high performance and high transparency. Optimizing the distance between clickbait and non-clickbait titles is intuitive for the purpose of this work. After experimenting with bag-of-words, term frequency (TF), and term frequency-inverse document frequency (TF-IDF), bag of words combined with TF-IDF yielded the highest performing classifier with 97% accuracy and a F1 (measuring both precision and recall) score of 0.995. The classifier was used to label each collected headline as clickbait or non-clickbait. Figure 3 shows the results for a sample of sources and the percentage of titles that are clickbait.

Table 1: Confusion matrix - testing clickbait classification

	classified as not clickbait	classified as clickbait
is not clickbait	3084	66
is clickbait	124	3126



In the Emergent corpus [15], each claim is classified as True, False, or Unknown. The three classes are roughly balanced. Naturally, reputable news sources will contain more True claims than less reputable sources. To test the predictive power of the model with consideration to clickbait, the predictive accuracy in the fact checking system is compared before and after multiplying the predictive weight of each source by 1-%clickbait. As a result, sources with many clickbait carry less weight in predicting veracity while sources with no clickbait are not affected. If clickbait is correlated with more False claims and fake news, then the model after considering clickbait will be more accurate in predicting claim veracity. The final predictive correctness results was found using a logistic regression model. Because the relationship between source credibility and clickbait may not be linear, I applied a softmax function to the clickbait data before using it to transform a source's predictive weight. The softmax function would lessen the impact for sources with extremely high and extremely low percentage of clickbait headlines.

2.5 Results

There is a consistent difference in predictive performance before and after applying the clickbait as an indicator. With the data randomly split into 8 folds, the baseline fact checking model correctly predicted claims 58.6% of the time and the clickbait model correctly predicted claims 60.7% of the time. As shown in Table II, the clickbait-modified model showed improvements over the initial model each time. Clearly, giving less weight to sources with more clickbait produced a more accurate model. Sources with more clickbait are more likely to spread fake news.

Table 2: results comparing predictive accuracy of model before and after accounting for clickbait

folds	initial model	modified model
8	mean: 58.6% | var: 0.009	mean: 61.3% | var: 0.013
4	mean: 58.4% | var: 0.003	mean: 60.0% | var: 0.003
2	mean: 56.3% | var: 0.003	mean: 58.7% | var: 8.88e-05

Sentence	V	A	D
We wish you and your family a new year full of joy and love.	4.3	3.6	2.9
I was feeling calm and private that night.	3.1	1.8	3.1
I shivered as I walked past the pale man's blank eyes.	2.0	3.0	1.8

Table 3: Representative sentences mapped to VAD dimensions.

3 Emotions in News

3.1 Related Research

3.1.1 Misinformation

Journalism and computer science researchers have been studying why and how fake news spreads with the hopes of curtailing its spread and mitigating its effects. In addition to studying the mechanisms, rationale, and impact of fake news, there have been many studies dedicated to creating algorithms for fake news detection. For fact-based news that tends to spread on social media platforms such as Twitter and Facebook, these algorithms fall in two camps: propagation-based or feature based. Propagation-based models inspect the spread of both real and fake news. Users or accounts are nodes while the exchange of some opinion or information (ie. sharing a news article) is an edge. The first propagation simulation model created by Acemoglu et al. [19] represented nodes as either normal or forceful. When two normal nodes interacted, each one takes on an average of the beliefs held by those nodes. But when two forceful nodes interacted, the normal node almost completely took on the beliefs of the forceful node. This model showed that belief about fake news or false information can be suppressed if many normal nodes are well connected to each other [19]. However, echo chambers can also form in the absence of well connected normal nodes, and false information can spread further and prevail.

Feature-based algorithms rely on some aspect of feature engineering, such as text length, n-grams, sentiment, syntactic similarity to other news, to determine if news contains false information. Notably, machine learning methods have made it possible to classify and detect fake news [20]. Beyond the basic bag-of-words approach, syntactical analysis has also been employed in the detection of fake news. For example, using Probabilistic Context Free Grammar and parse trees to rewrite sentences, Feng et al. [2] were able to achieve upwards of 91 percent accuracy in fake news detection.

3.1.2 Emotion Predictions

Emotion can be predicted from images of human faces, sounds of speech, and from also text [21]. There are two main ways to represent emotions: continuously or categorically. Categorical emotions are binned such as in Ekman's [22] 6 basic emotions of Anger, Disgust, Fear, Happiness, Sadness, and Surprise. Alternatively, emotions can be represented on a continuous basis. For example, Goel et al. [23] predicted the emotional intensity of Tweets between values of 0 and 1, 0 being the absense of emotion and 1 representing strong emotion.

Continuous predictions emotions can be represented in multiple axis of Valence (positive or negative sentiment), Arousal (emotionality and strength of feeling), and Dominance (degree of control over the situation)-VAD [24]. Each sentence or phrase has a corresponding rating in each axis, and when considered together, paints a picture of emotions represented (see Figure 3). This method was used to predict the emotions of English lemmas and analyze emotions represented in Facebook posts [25] [26].

Lastly, because they are different ways to represent the same emotional entities, continuous and dimensional representation of emotions can be easily mapped to represent the 6 basic emotions as seen in Figure 3 supplied by Buechel et al. [27].

3.2 Implementation

3.2.1 Training Data

The training data from Buechel et al. [27] maps sentences from news articles, blogs, and other sources to three dimensions of VAD on a continuous range between 1 and 5 [27]. 5 in Valence represents the most possibly positive sentence, 1 in Valence is the most negative, and so on. Table 1 shows examples of sentences represented in VAD dimesions. A continuous prediction, rather than a categorical one, captures a smoother and more fine grained representation of emotions with more flexibility. A categorical emotional assignment cannot tell us “which sentence is more emotionally intense”.

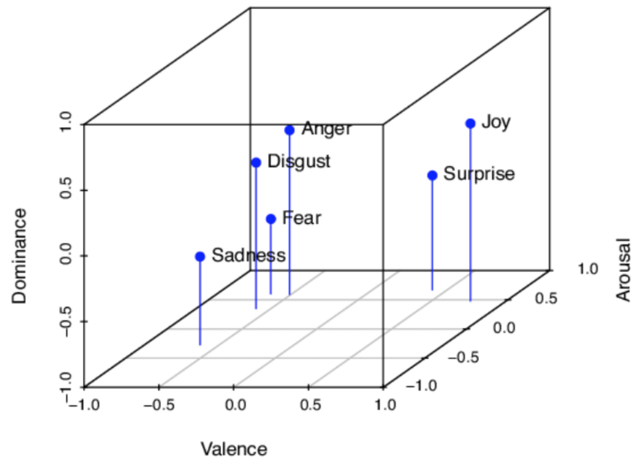


Figure 3: VAD dimensions map to Ekman's 6 Basic Emotions [27]

3.2.2 Predictive Model

The proposed predictive model is a feed-forward deep averaging network (FFDAN) built using Pytorch. FFDAN is an unordered model that has been proven to achieve state-of-the-art predictive accuracies comparable to that of much more complex architecture. Another advantage of the deep averaging model is its effectiveness on data with high syntactic variance. Small but meaningful differences are magnified through hidden layers, and error analysis shows that even syntactically aware models make similar errors to deep averaging models [28].

The input is a sentence from the Emobank corpus [27] and the sentence is parsed with Natural Language Tool Kit (nltk) word tokenizer [29]. Each word is then matched to its word vector using pre-trained 300 dimension Global Vectors (GloVe) [30]. The vectors of every word in a sentence are averaged and fed into the forward function, which consists of two linear layers and a nonlinear layer in between. Three outputs match each dimension of Valence, Arousal, and Dominance. The model is evaluated using the predicted values' Pearson correlation with the target values. A perfect model able to predict each sentence emotional values down to the last decimal point would theoretically have a correlation of 1.0 and a random model would have a correlation of 0.

After tuning, the best performing model is trained on a basic laptop in 60 seconds over 10 epochs.

3.2.3 Testing Data

Our test dataset [31] was created by journalists of Buzzfeed News in 2016 just prior to the presidential elections. It consists of over 2000 news articles shared on Facebook, each with a veracity and partisan orientation. The articles include all posts in the time frame of a week in September 2016 from nine Facebook news pages encompassing the left-leaning, right-leaning, and mainstream outlet orientations. Veracity assignments of mostly true, mostly false, mix of true and false, and no factual content, were assigned by journalists after fact-checking the articles. Preprocessing steps include transforming the xml files to a Pandas Dataframe and extracting sentences using nltk sentence tokenizer [29] to separate sentences from articles to feed into the predictive model.

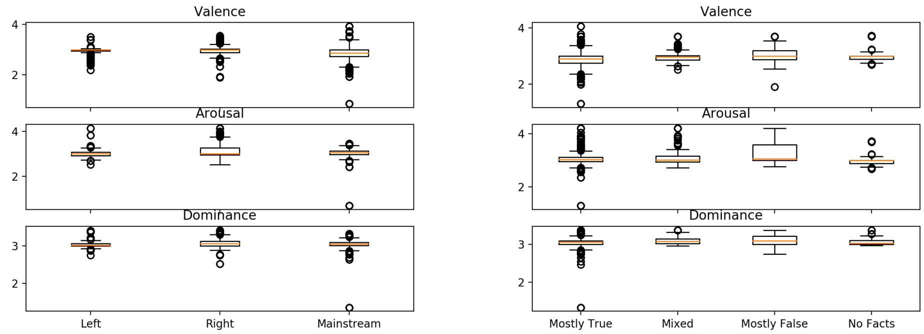
3.3 Results

Results were evaluated using Pearson correlation of predictions to target values. The baseline study was conducted by Akhtar et al. [32], who created a multi-task ensemble framework and used their model for continuous emotional predictions on the Emobank dataset [27]. The results shown in Table 2 from this study, using a much simpler network, was able to achieve comparable results for the Dominance dimension and superior results for the Arousal dimension, despite under-performing in the Valence dimension. Since Valence is the dimension that most closely represents emotions and strength of feeling, it is more important in our context to have strong prediction power for Valence.

To simplify the analysis the headlines of each article were used as a proxy of the emotionality in the news articles. The headlines were evaluated on two axes: orientation and veracity.

	Model	Correlation		
		V	A	D
Akhtar et. al	GRU	0.55	0.30	0.22
This study	DAN	0.48	0.44	0.22

Table 4: Comparable correlative results overall to more complex ensemble model

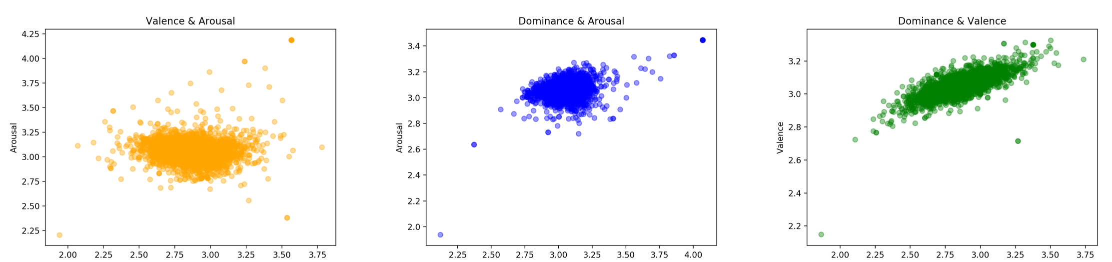


(a) VAD spread of headlines by orientation (b) VAD spread of headlines by veracity

Figure 4: Each row shows the spread of predictions for a single dimension across different groups of news, each column shows the spread of predictions for a single group of news for each dimension

Figure 4 above plot the spread for VAD predictions for each headline in the orientation and veracity axis, respectively. Each row shows the spread of predictions for a single dimension across different groups of news and each column shows the spread of predictions for a single group of news for each dimension. Right-leaning news articles tend to have a higher mean in addition to a wider spread for the Arousal axis. The same differences are more pronounced for the veracity axis. Mostly false news have the largest spread and overall higher Arousal. This is in line with the hypothesis that hyperpartisan news shows a higher degree of emotion to incite readers.

There is also some correlation between dimensions. Between Valence and Arousal there is almost zero correlation. This is likely because low and high valence is equally likely for high arousal sentences. For example, both Anger and Joy are emotions that occupy a higher Arousal level, but they are on opposite sides of the Valence dimension. Dominance and Arousal show a weaker correlation of about 0.2. Valence and Dominance have the highest correlation of 0.4.



(a) Valence Arousal Correlation (b) Dominance Arousal Correlation (c) Valence Dominance Correlation

Figure 5: V A shows no correlation while V D shows moderately strong correlation.

3.4 Error Analysis

Table 5 shows examples of some of the most accurate predictions. Due to the model and loss function used, sentences with predictions near the mean (approximately 3.0 for each dimension) tend to get more accurate predictions. These sentences also tend to be more straightforward with little surprises.

Table 6 highlights some of the least accurate predictions in the test set. There are four main reasons for inaccurate predictions:

	V		A		D	
	actual	pred	actual	pred	actual	pred
For some , it's a matter of weeks or months	2.7	**2.7**	3.1	**3.0**	2.7	**3.0**
Pleasant Run Children 's Homes ... 'where good kids get better.'	3.4	**3.3**	2.8	**3.0**	3.2	**3.2**
When asked why he explained that it is simply "something that I can't help".	3.0	**2.9**	3.2	**3.0**	3.0	**3.0**

Table 5: Examples of good predictions by the model

		actual	predicted	hypothesized reason
Valence	*Guinea capital largely calm under curfew, marital law.*	1.6	2.6	Typo in "marital" and "martial"
	Media cited for showing girls as sex objects.	2.3	3.2	Low valence is implied
	BA to charge $470 for an extra bag.	2.1	3.0	Outrage implied in the number
	Damn you.	1.7	3.1	Tendency towards mean
Arousal	*They jumped out and said 'Hollywood, Hollywood'.*	3.3	2.8	Arousal of "Hollywood" is implied
Dominance	*He began to cry.*	1.9	2.7	Tendency towards mean
	Mission accomplished: Out routine insouciance has been disrupted.	3.7	2.9	Satire

Table 6: Worst predictions by model show systematic errors

- **Typos**: In the case of the typo "martial" to "marital", the low valence usually captured by martial is replaced by a higher valence of marital.
- **Implied emotions**: one significant drawback of the deep averaging model is that it is unable capture semantic differences in sentence order. In many cases the emotions implied by how words are placed is stronger (or weaker) than just the words themselves.
- **Tendency towards the mean**: sentences whose actual target values lie on either side of the extreme will get predictions that are closer to the mean because of the model's tendencies to predict closer to the mean. This can be partially mitigated with more instances of extreme sentences. This is difficult to do naturally because extreme examples occur rarely in "nature".
- **Satire**: satirical phrases and sentences can carry significance and stronger emotions that the model cannot pick up on.

4 Conclusion

In the first part of this study, the clickbait model made better claim predictions when sources with more clickbait headlines were given less predictive weight. This result implies those same sources are also less credible and are more likely to report unreliable or false news. In the future, the clickbait model can be integrated into the fact checking system [12] to create a more robust credibility model. Clickbait is just one of 16 veracity indicators proposed to identify a potentially untrustworthy news source [16]. Other promising indicators include the number of advertisements and the placement of advertisements in a web page. This study calls for the consideration of a variety of indicators from the content and context of the news source and joins the fight against misinformation and fake news.

The second section studied emotional differences between news of two different axis: political orientation and veracity. Right-leaning news mostly false news showed stronger tendencies to use emotional language. There are several key implications for readers and consumers of news as well as for designers and developers of news platforms. Many readers of political news are not reading to necessarily gain new perspectives or learn novel information. Rather, it is often more satisfying to have one's own beliefs affirmed, further contributing to the formation and persistence of echo-chambers. Even so, readers should be more aware of potential emotional manipulation from the sources they have learned to trust, and be cautious of how their own emotions are affected after reading partisan news. For creator and curators who wish to combat misinformation, the next step in a development direction is to find predictive emotional markers in text for fake or emotionally manipulative news and create platform features to flag potential fake news.

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