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An application of sentiment analysis with transformer models on online news articles covering the Covid-19 pandemic

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An application of sentiment analysis with transformer models on online news articles covering the Covid-19 pandemic

A thesis submitted in partial satisfaction of the requirements for the degree Master of Applied in Statistics

by

Prakul Asthana

2021

ABSTRACT OF THE THESIS

An application of sentiment analysis
with transformer models on online news
articles covering the Covid-19 pandemic

by

Prakul Asthana
Master of Applied in Statistics
University of California, Los Angeles, 2021
Professor Yingnian Wu, Chair

The Covid-19 pandemic has had a devastating impact on lives across the world, with tremendous human socio-economic costs, while exposing and exacerbating several fault lines in our society. It has also caused a rapid rise in misinformation and erosion of trust in established news outlets amid allegations of political bias and censorship. In this paper we use the processes of sentiment analysis to study the coverage of the Covid-19 pandemic in news outlets. By comparing the coverage from news sources with opposing political leanings, we quantitatively establish political bias. We also repeat this process on news articles mentioning specific topics like Masks, Social Distancing etc., to check for any bias present in the sentiment towards them. Lastly, we compare sentiment in Covid-19 news coverage in the United States, the United Kingdom and Australia to contrast the political bias in news articles on the pandemic in these three countries.

The thesis of Prakul Asthana is approved.

Hongquan Xu

Rick Paik Schoenberg

Yingnian Wu, Committee Chair

University of California, Los Angeles

2021

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CHAPTER 1

Introduction

The Covid-19 pandemic has been an unforeseen and unprecedented catastrophe across the globe. Along with the dramatic loss of human life, it has posed tremendous challenges to the public health, food security and people's livelihoods. The economic and social implications of the pandemic are devastating with tens of millions of people at the risk of falling into extreme poverty and an additional 132 million possibly falling into the undernourished category. [1] Within this tumultuous and unprecedented crisis, we have also witnessed a rapid rise in misinformation, false reporting and hate speech through the internet. While suspicions of bias and partisanship have long been raised against various small or big news agencies, the Covid-19 pandemic has greatly exacerbated all such claims, sending the trust and credibility of established media outlets at an all time low among people belonging to both sides of the political spectrum.[2, 3] This void created from the traditional media outlets was filled in by a hodgepodge of small players, amplifying their reach through social media, and often further fueling conspiracy theories about the origin of the virus or pseudo-scientific claims about the severity of the Covid-19 disease. Furthermore, in the United States, the 2020 elections have served to exacerbate the issue in a highly charged and polarized environment. The net effect of this has been a general disbelief among large sections of the society about the grave nature of the pandemic and reduced confidence in preventive measures like masks, social distancing or vaccinations.[4, 5]

Sentiment analysis is a fundamental task in the fields of natural language processing, text mining and computational linguistics. It aims to systematically identify, extract, quantify, and study affective states and subjective information in free form text. Fundamentally, this involves detecting and quantifying positive or negative sentiment in text. It's often used by businesses to detect sentiment in social data, gauge brand reputation, and understand the voice of customers. Over the years, sentiment analysis has moved from rule based rigid methods to modern machine learning based classification methods. These machine learning methods either classify sentiment into discrete categories ranging from strongly negative to strongly positive, or give a continuous metric representing positive sentiment in the text. [6, 7]

In recent years, transformer based natural language models have established themselves as the front-runners in all natural language processing tasks. Driven by an attention based architecture at their core, large scale transformer models have revolutionized all language related tasks including translation, text generation, next word prediction, natural language inference, question answering and of course sentiment based classification. The Bidirectional Encoder Representations from Transformers model, colloquially known as BERT, was the first major transformer model, which became popular due to its state of the art performance on various natural language tasks. It consolidated the various advancements made in the self-attention process for long short-term and recurrent models, while laying out the groundwork for all future refinements of transformer models.[8, 9] Distilled BERT or DistilBERT is another such refinement which focuses on reducing the size of the BERT transformer to allow for faster inference and training, while retaining nearly identical performance in all key benchmark tasks. This is achieved through the process of knowledge distillation, where a smaller model is trained to reproduce the behaviour of a larger model or an ensemble.[10]

Thus, this paper aims to use this DistilBERT model to perform sentiment analysis on the Covid-19 news coverage, to compare and contrast the positivity seen in articles covering the Covid-19 pandemic across major media outlets. Using a dataset being compiled and maintained by the Global Database of Events, Language, and Tone or the (GDELT project), we aim to quantify the varying levels of positivity seen in right leaning and left leaning media outlets, about the Covid-19 pandemic since the start of the year 2020. Further, as previously discussed the massive amount of misinformation prevalent among the public regarding the Covid-19 disease can be traced back to some source on the internet. Hence, we will also look specifically at the sentiment around mentions of masks, social distancing and other facets of the pandemic to quantify the differences if any. Lastly, we will also have a look at the media coverage in few other countries like the United Kingdom and Australia to see whether the trends observed in media coverage in the United States corroborate with those observed across the world.

The remainder of this thesis is organized as follows. Section 2 deals with establishing the background into working of transformers, and then shares some salient features of the DistilBERT model used for analysis here. Section 3 gives a brief overview of the sentiment analysis process and how the transformer model was fine-tuned to perform this task. Section 4 covers an exploratory analysis of the online news article dataset, and reports some of the most interesting results observed during the sentiment analysis of this dataset. Finally, section 5 discusses these results in detail and section 6 concludes the work and outlines possible future improvements.

CHAPTER 2

Transformer models

2.1 Early models in Natural Language Processing

The earliest Natural Language Processing (NLP) systems followed a rule based rigid IF <condition> THEN <action> architecture. With the progress of computing power and increasing availability of large text corpus, statistical NLP models started coming to the fore in the 1990's - 2000's period. Powered by rich feature sets constructed from document-term matrices, these models are regarded as the beginning of the machine learning era in text processing. Some of the early models in this era like Decision Trees, produced systems of large and complex if-then rules, which were similar to previous era of hand written rule based models. However, these models were capable of making soft, probabilistic decisions. Hidden Markov models were introduced from part of speech tagging around the same time period while Latent Dirichlet Allocation was introduced as a probabilistic generative model for collections of discrete data such as text corpora.[11, 12]

In the late 1990's, work on using neural network based models for NLP tasks also started to pick up steam. Due to the sequential nature of unstructured text, recurrent neural networks (RNN) had the most success in language tasks, compared to other neural network architectures. The long short-term memory model (LSTM) was also introduced around the same time, as an upgraded version of the vanilla RNN model with better ability to predict sequences of longer durations thanks to better handling of the vanishing gradient problem.[13] In 2001, the first neural "language" model was proposed, using a feed-forward neural network and later improved in 2003 giving the first neural probabilistic language model which improved the benchmarks set by n-gram models while utilizing a novel distributed learning approach to tackle the curse of dimensionality. By mid 2010's, there was a wide variety of such natural language models most of which used powerful word embeddings at their core and were geared towards specific tasks like sequence to sequence model for machine translation, which utilizes an encoder - decoder based structure, and used either LSTM or gated recurrent units (GRU's) as a building block to avoid the vanishing gradient problem associated with RNNs.[14]

2.2 Attention process

To Further improve the performance of these models, a novel "attention" mechanism was proposed.[15] Attention allowed the model to focus on the relevant parts of the input sequence as needed. As a result, instead of mindlessly aligning the first word at the output with the first word from the input, the model actually learns from the training phase how to align words in that language pair. Soon afterwards, a new architecture based on these encoder decoder blocks, but without any RNN/LSTM/GRU units was proposed.[16] This new so-called Transformer model, was able to achieve state of the art performance on language translation tasks and provided lots of flexibility for future growth and easy parallelization for scaling up in size. One of the keys to the success of the Transformer model was its self-attention mechanism in which makes the encoder look at other words in the input sentence as it encodes a specific word. This bakes in the "understanding" of other relevant words into the one we're currently processing.

This is achieved by using three vectors for each word in the input - a Query vector (Q), a Key vector (K), and a Value vector (V). A score is calculated by taking the dot product of Key and Query vectors and determines how much focus to place on other parts of the input sentence as we encode a word at a certain position. Scores are then divided by 8 to

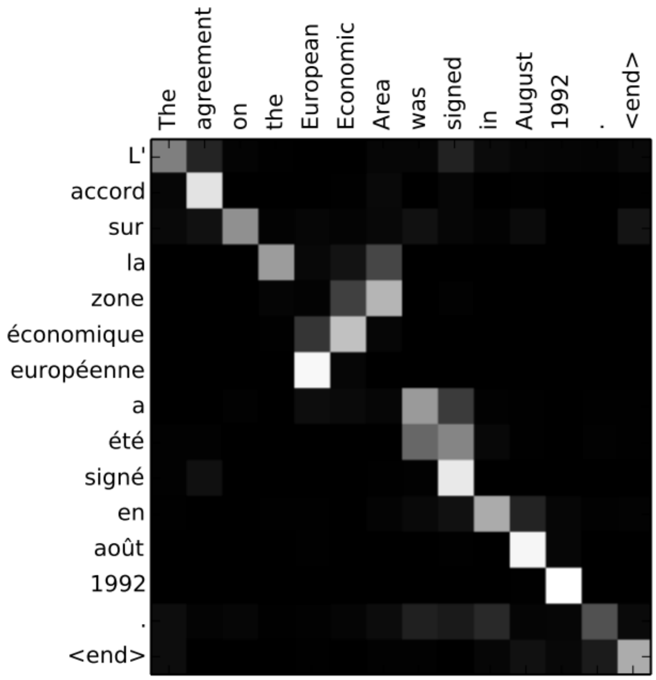


Figure 2.1: Attention matrix showing the relative weights or importance given to words in a sentence during machine translation task from English to French

stabilize gradients and passed through a softmax operation to make sure they're all positive and add up to 1. This softmax score determines how much each word will be expressed at this position. Finally, each value vector is multiplied by the softmax score, to keep intact the values of the word(s) we want to focus on, drowning-out irrelevant words and weighted value vectors are summed up together to give the output of the self attention layer. Transformers usually contain "multi headed" attention which expands the model's ability to focus on different positions and gives the attention layer multiple "representation sub-spaces".

2.3 BERT

Bidirectional Encoder Representations from Transformers or BERT as its widely known was a model released in 2018 which builds on several clever ideas from the NLP community and

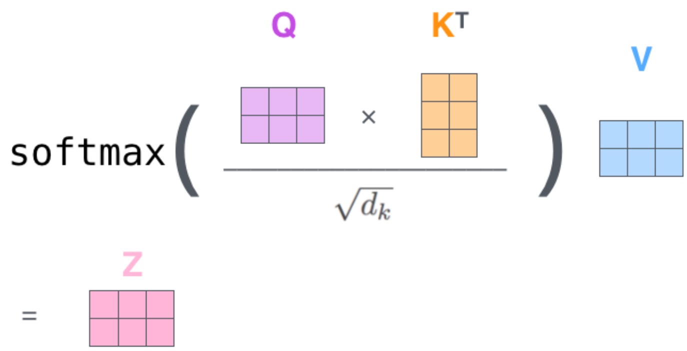


Figure 2.2: The process of calculation of self attention represented by the z vector) in matrix form. Here, d_k represents the dimension of the key vector used.

centered around the Transformer architecture which we have just discussed. BERT kick started the era of transfer learning in NLP as the model could be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task specific architecture modifications.[8] In terms of model size, BERT was much bigger than a plain transformer with a large number of encoder layers, larger feedforward-networks and more attention heads. It also uses contextual word embeddings instead of fixed embeddings like Glove or word2vec used earlier. As a result of these, and several other improvements made in BERT, it achieved new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement).

BERT was trained using two key tasks - Masked Language Model (MLM) and Next Sentence Prediction (NSP). In a MLM task, 15% of words in text are replaced with the [MASK] token, and the model is made to predict these missing words. The loss function only considers predictions for these masked words, and as such the model converges slower than directional models, however it gains through an increased context awareness. In NSP the model is given a pair of sentences, and is made to predict if the second sentence is the next subsequent sentence of the first sentence. 50% of training data is a pair of subsequent sentences from the corpus while the other half is randomly chosen non-subsequent sentences.

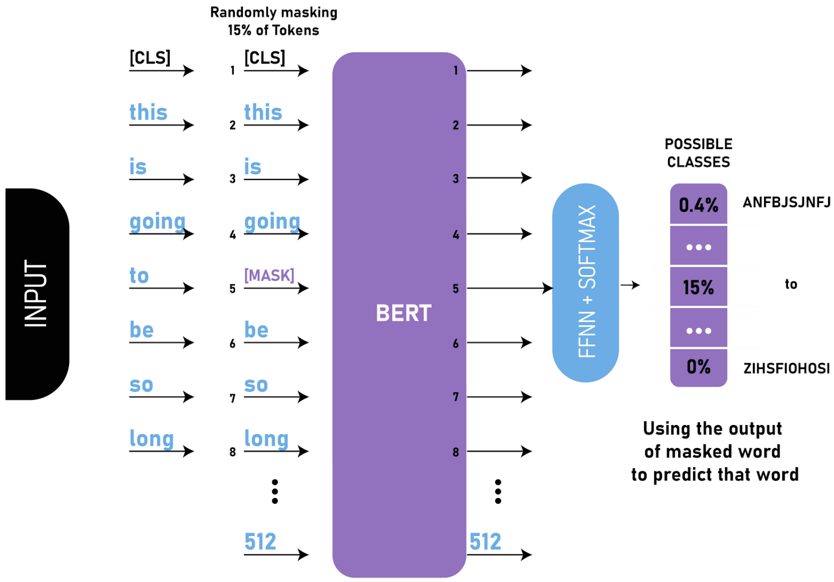


Figure 2.3: Training BERT as a language model to predict masked words. During the training process, 15% of words are masked randomly.

This task helps the model understand the relationship between sentences.

2.4 DistilBERT

DistilBERT is a smaller version of BERT developed and open sourced by the team at the company HuggingFace. It's a lighter and faster version of BERT that roughly matches its performance.[10] Knowledge distillation, also referred to as teacher-student learning, is a compression technique in which a small model is trained to reproduce the behavior of a larger model. It uses the so-called "dark knowledge" of the model or the uncertainty which exists when models have non-zero probabilities for incorrect classes in classification problems. This uncertainty is a measure of the generalizability of the model.

Thus, in such teacher-student training, a student model is trained to mimic the full output distribution of the teacher network, i.e. its knowledge. Instead of conventional training

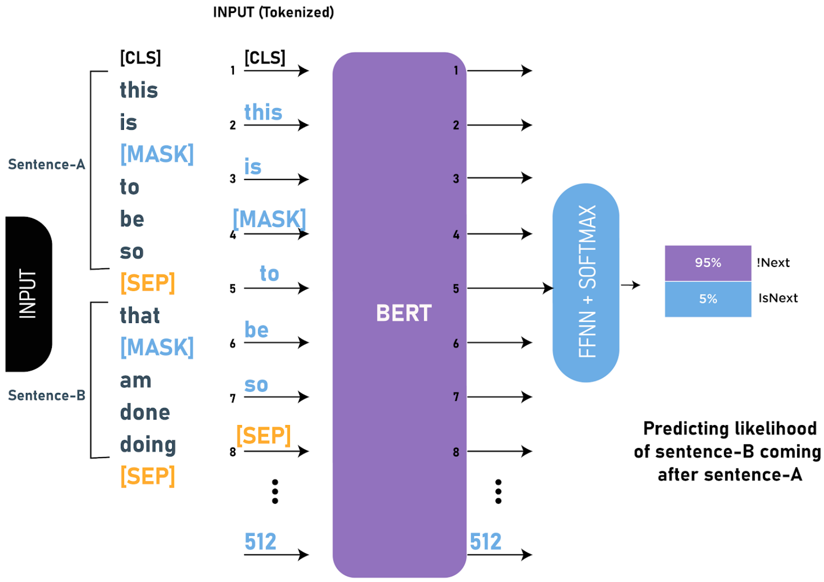


Figure 2.4: Training BERT to predict if the second sentence of the given sentence pairs is the next subsequent sentence or not.

through cross-entropy over hard targets (one-hot encoded gold class), it is trained through cross-entropy over soft targets (probabilities of teacher model). This allows for a richer loss as a single training example enforces much more constraint than a single hard target.[17, 18] Thus, the training loss can be given by the equation below, where t_i are the logits from the teacher model and s_i are the logits from the student model, with L representing the training loss.

$$L = -\Sigma_i(t_i * log(s_i))$$

Another parameter, called softmax-temperature was also introduced to expose the mass of distribution over classes. When $T \to 0$, the distribution becomes a Kronecker and is equivalent to the one-hot target vector. Whereas, when $T \to +\infty$, it becomes a uniform distribution. The same temperature parameter is applied both to the student and the teacher at training time, giving more signals for each training example. During inference, T is set to

1 and recover the standard softmax. Thus the modified softmax function can be represented as shown below, with T being the softmax-temperature, and z_i, z_j being the activation's of the final layer. This gives us the probability distribution among classes as represented by p_i.

$$p_i = \frac{exp(z_i/T)}{\Sigma_j(exp(z_j/T))}$$

Distillation loss is computed using the Kullback-Leibler loss since the optimizations are equivalent. The KL loss is used as a measure of how one probability distribution is different from the other, and can be calculated using the equation below. Here p and q represent two probability distributions, between which we are trying to calculate the divergence.

$$KL(p \parallel q) = E_p(log(\frac{p}{q})) = \Sigma_i(p_i * log(p_i)) - \Sigma_i(p_i * log(q_i))$$

The overall training loss is a linear combination of the distillation loss (KL loss) and the masked language modeling loss as seen earlier in training process of BERT.

As shown in the table, DistilBERT's performances compare favorably with the baseline (BERT and pre-BERT state of the art models) while having respectively about half and one third the number of parameters. In terms of inference time, DistilBERT is more than 60% faster and smaller than BERT and 120% faster and smaller than ELMo+BiLSTM.

Models	No. of parameters (millions)	Inference time (s)	SST-2 (acc)
Baseline - ELMo + BiLSTM	180	895	91.5
BERT	110	668	92.1
DistilBERT	66	410	92.7

Table 2.1: Comparing the size, inference time and relevant performance metrics of BERT and DistilBERT with previous SoTA benchmark.

CHAPTER 3

Sentiment Analysis

Sentiment Analysis, also called Opinion Mining, is one of the most recent research topics within the field of Information Processing. Facts have an objective component; however, there are other textual elements which express subjective characteristics. These elements are mainly opinions, sentiments, appraisals, attitudes, and emotions, which are the focus of sentiment analysis.

3.1 Types of sentiment analysis

Broadly speaking, sentiment analysis methods can be divided into two main categories - machine learning approaches and lexicon-based approaches. Machine learning approaches depend on the selection and extraction of the appropriate set of features used to detect sentiment. Some of the most important features used are for example: (1) terms (words or n-grams) and their frequency; (2) part of speech information; (3) negations can change the meaning of any sentence; and (4) syntactic dependencies (tree parsing). On the other hand, lexicon-based approaches mainly rely on a sentiment lexicon, i.e., a collection of known and precompiled sentiment terms, phrases and even idioms, developed for traditional genres of communication. Two subcategories can be found here: Dictionary-based and Corpus-based approaches. The former is usually based on the use of an initial set of terms (seeds) that are usually collected and annotated in a manual way. While, the corpus-based techniques arise with the objective of providing dictionaries related to a specific domain. These dictionaries are generated from a set of seed opinion terms that grows through the search of related words by means of the use of either statistical or semantic techniques.[6] Depending on whether the target of study is a whole text or document, one or several linked sentences, or one or several entities or aspects of those entities, different NLP and sentiment analysis tasks can be performed. Thus there are three distinct types of sentiment analysis: (i) document level, (ii) sentence level and (iii) entity/aspect level. Document level considers that a document is an opinion on an entity or aspect of it. However, if a document presents several sentences dealing with different aspects or entities, then the sentence level is more suitable. Finally, when more precise information is necessary, then the entity/aspect level arises. It is the finest-grained level, it considers a target on which the opinion holder expresses a positive or negative opinion.[6]

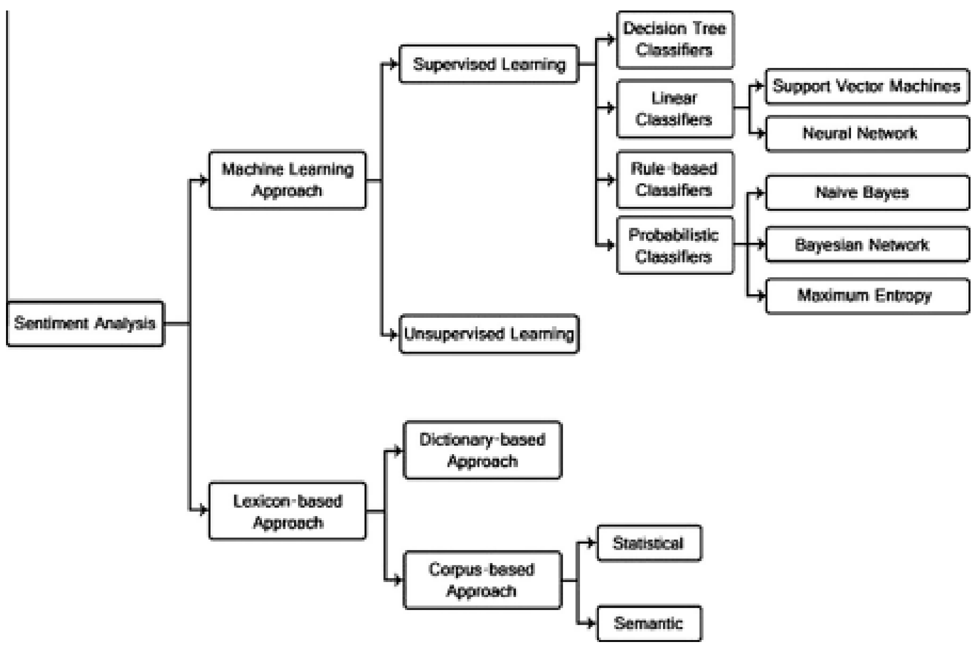


Figure 3.1: Various types of sentiment analysis based upon machine learning or lexicon based approaches. In this paper, we will be using supervised machine learning approach using a neural network classifier which is fed by a transformer model.

3.2 Sentiment analysis with Transformers

As mentioned previously, one of the defining features of transformer models is their unique adaptability towards a variety of NLP tasks, utilizing their vast language model knowledge through transfer learning. We can add a two layer classifier over the usual transformer architecture and then train those two layers on a labelled sentiment dataset. One such data set is the Stanford Sentiment Treebank (SST), which consists of 11,855 single sentences extracted from movie reviews. These were parsed by the Stanford parser and used to create a total of 215,154 unique phrases from those parse trees. These phrases were annotated by 3 human judges into categories. In SST-5 or SST fine-grained, these categories are positive, somewhat positive, neutral, somewhat negative and negative. While, the binary SST-2 dataset contains just two categories - (positive and somewhat positive vs negative and somewhat negative, with neutral phrases discarded).[19]

This dataset has become a benchmark for measuring the performance of language models on classification tasks and is one of the tasks in the comprehensive General Language Understanding Evaluation (GLUE) benchmark.[9] Given the generalized nature of the SST dataset, a model pre-trained on SST can be used directly as a sentiment classifier without much performance impact. The DistilBERT model is able to achieve approximately 92.7% accuracy on the SST-2 dataset while BERT achieves 92.1% accuracy on the same dataset.[10]

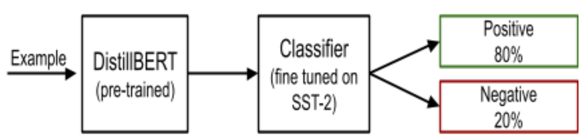


Figure 3.2: Sentiment analysis setup used in this paper. We have a pre-trained DistilBERT model, on which we attached a classifier which has been fine tuned on the SST-2 dataset. This model achieves 92.7% accuracy on the SST-2 dataset and is well suited to serve as a general purpose binary sentiment classifier in an unsupervised setting.

CHAPTER 4

Experiments

As discussed above, we used a pre-trained DistilBERT model, with a classifier fine tuned on the binary SST-2 dataset to classify the sentiment of a given piece of text. The model output was the probabilities of given text being positive and negative. For our analysis, we have renamed the probability of the given text having positive sentiment as the “Positivity score”.

4.1 Covid-19 news dataset

We will use a comprehensive dataset created and maintained by the Global Database of Events, Language, and Tone (GDELT) project, founded by Kalev Leetaru and Georgetown University. This daily updated dataset contains over 53.19.77 Mn articles as of Jan 26 2021, pertaining to Covid-19 coverage in online news media and is accessible publicly through a Google BigQuery engine. For the purposes of this analysis, we will be looking at 10 newspapers and news portals in the United States to dissect the sentiment in news articles covering the Covid-19 pandemic from the period starting 1 January 2020 to 31 December 2020. These selected sources are -

- CNN
- New York Times
- Washington Post

- Los Angeles Times
- National Public Radio
- Fox News
- Breitbart
- New York Post
- Wall Street Journal
- USA Today

These news sources can also be roughly grouped into two categories based on if they lean politically towards right wing or left wing, as seen in the figure below. Given the vastness of the political spectrum and the fact that often news organizations try to include articles, from commentators on both sides of the political divide, this binary classification of political leaning can be considered an oversimplification. However, as 2020 was a key election year in the country, the coverage of Covid-19 pandemic was also heavily influenced by political considerations. By studying and contrasting the sentiment of articles covering the pandemic, we will be able to better estimate and understand the political bias if any in Covid-19 news coverage.

4.2 Exploratory analysis

We can start by looking at some of the key features of the dataset we have selected that is Covid-19 news articles of the aforementioned ten sources for the year 2020.

As we can see in Figure 4.1, some news outlets are way more prolific than others in sheer volume of articles covering the pandemic. This can be assumed to be the function of organization size, resources and revenue capacities, all of which may impact the coverage.

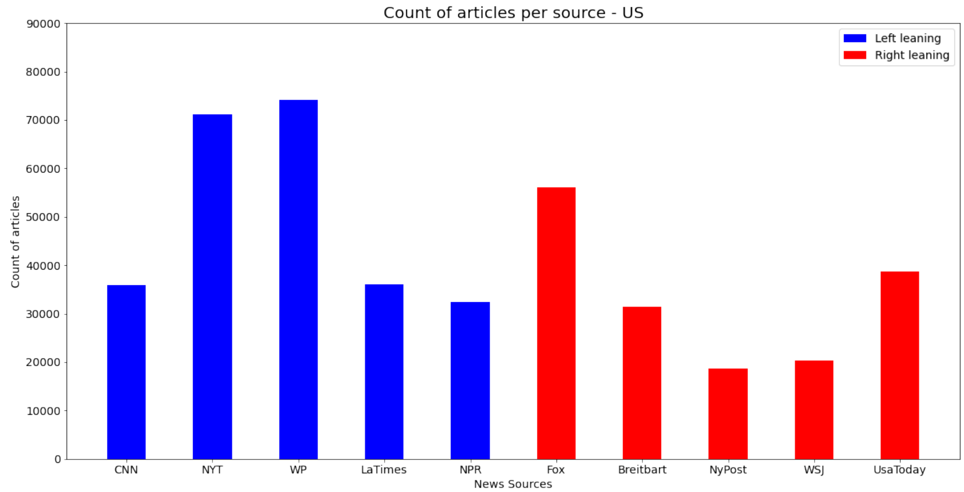


Figure 4.1: Count of articles covering the Covid-19 pandemic from our selected 10 sources, during the period 1^{st} January 2020 to 31^{st} December 2020

Further, New York Times and Washington Post clearly have the most number of articles covering the pandemic, while Wall Street Journal has the lowest. This can also be attributed to the editorial outlook at Wall Street Journal which is more business-focused.

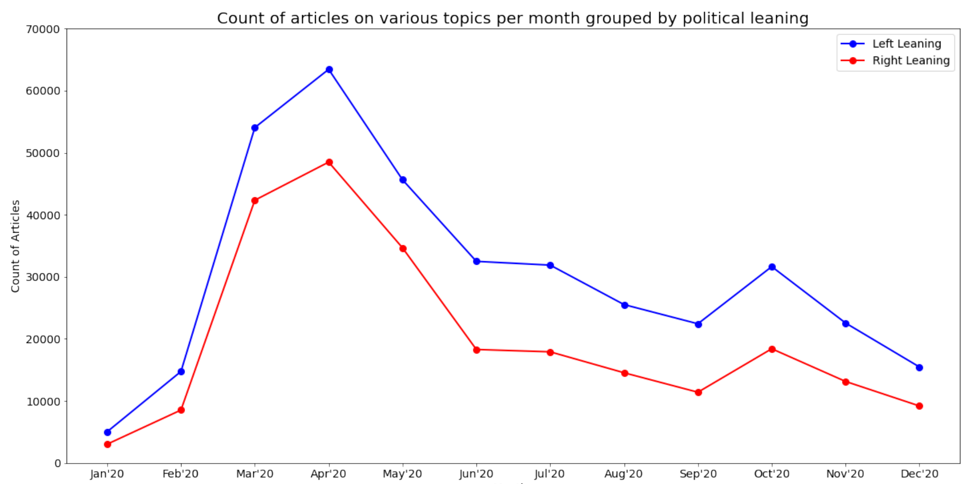


Figure 4.2: Monthly count of articles covering the Covid-19 pandemic in left leaning and right leaning news outlets

Again, we can see in Figure 4.2 that left leaning news outlets are more prolific. We can also see that both right leaning and left leaning media followed the same trend in coverage throughout the year, as evidenced by their almost parallel lines. The Covid-19 coverage in the media peaked around April 2020, which was the peak of initial panic and mass hysteria caused by disease. Also, interestingly the coverage of Covid-19 went up in both right and left leaning media in October 2020, just before the presidential elections, and has been in decline since then even as the US faced a record number of cases per day in December.

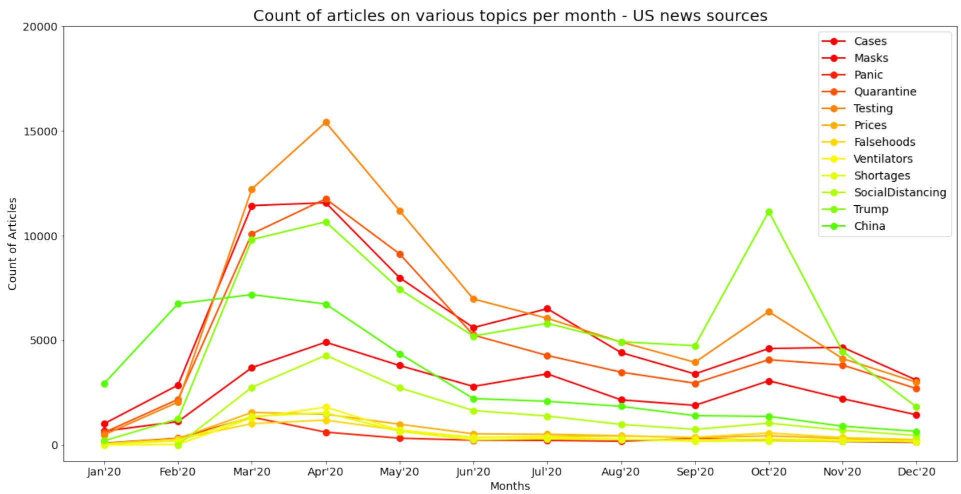


Figure 4.3: Monthly count of articles covering various sub-topics within the Covid-19 pandemic

In the dataset, we also get tags on articles indicating various sub-topics being covered in the given article. It's important to note that a given article can cover multiple sub-topics and thus have multiple tags. In Figure 4.3 we are looking at the count of articles covering various sub-topics. We can see that articles covering Testing, Prices, Shortages peaked in April 2020 and have been in decline ever since. However, articles covering Cases show a double humped curve as has been seen in the actual progression of the Covid-19 pandemic where an initial summer peak was followed by a stronger fall-winter second wave. Further, articles covering former President Trump get a spike before the election in October 2020, around the same time when he himself had contracted the disease.

News Sources	CNN	NYT	WP	LaTimes	NPR	Fox	Breitbart	NyPost	WSJ	UsaToday
Topic tags	Left	Left	Left	Left	Left	Right	Right	Right	Right	Right
Cases	6657	13309	12392	6345	6058	7800	4126	2555	2502	5431
China	3364	8219	6683	1717	2030	4758	5731	1943	2109	1905
Covid19	15760	38574	37765	17919	16643	27890	18665	11152	14219	19595
Falsehoods	595	1002	1332	383	330	614	855	207	93	630
Masks	3433	4992	5750	3148	2762	3615	2034	1128	934	3370
Panic	416	669	871	348	256	452	346	224	107	481
Prices	535	1730	1486	501	381	450	375	259	844	678
Quarantine	5823	11403	10372	5388	4365	7254	4885	2791	2673	5343
Shortages	569	928	1177	444	388	504	318	251	230	586
SocialDistancing	2012	2135	2950	1772	1383	2288	1059	648	339	2186
Testing	6919	12469	12848	7024	5795	14546	4768	2948	2678	6756
Trump	6410	9700	16013	3771	4655	10333	7096	1786	2024	5703
Ventilators	672	1044	1178	505	474	656	317	263	165	539

Table 4.1: Comprehensive view of the dataset under consideration with category wise article count for each news source selected for the analysis

Finally, in Table 4.1 we can look at the comprehensive summary of the dataset, in terms of the number of articles per individual news source and sub-topic tags. The dataset overall appears to be somewhat well balanced, with some sub-topics being more popular with certain news sources than others.

4.3 Overall sentiment analysis

As we can see the overall sentiment around Covid-19 news coverage has been steadily improving, i.e. turning more positive. We are using bootstrap methodology to construct 95% confidence intervals around the monthly average of sentiment calculated from the data. For the bootstrap calculation, we are using 1000 iterations and using the 2.5^{th} percentile and 97.5^{th} percentile values to construct the confidence intervals.

As we can see in Figure 4.5, in March, July and August 2020, we can say with 95% confidence that the coverage of the Covid-19 pandemic was more positive in right leaning media outlets than in the left leaning media outlets. Overall, we can see that the average sentiment around Covid-19 coverage has always been more positive in right leaning news

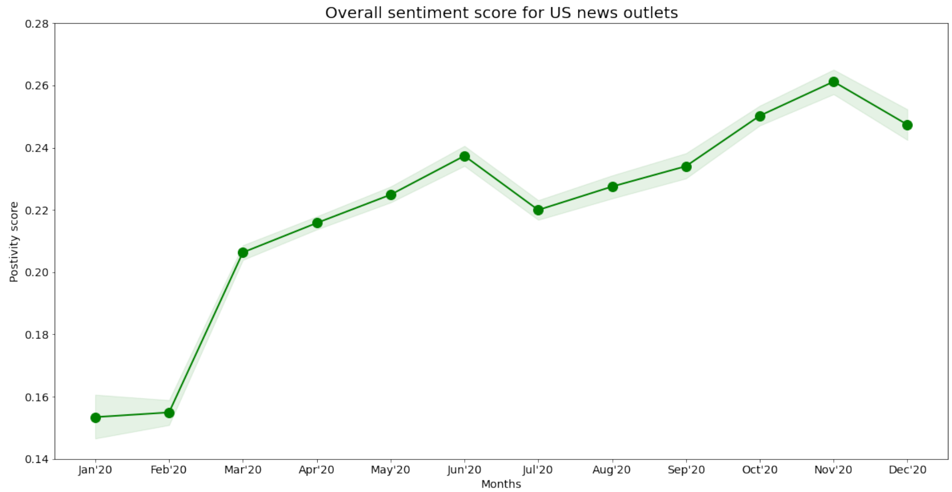


Figure 4.4: Overall sentiment in Covid-19 news coverage over time, as measured by the monthly average of 'Positivity score' or the monthly average probability of the text being classified as positive by our model.

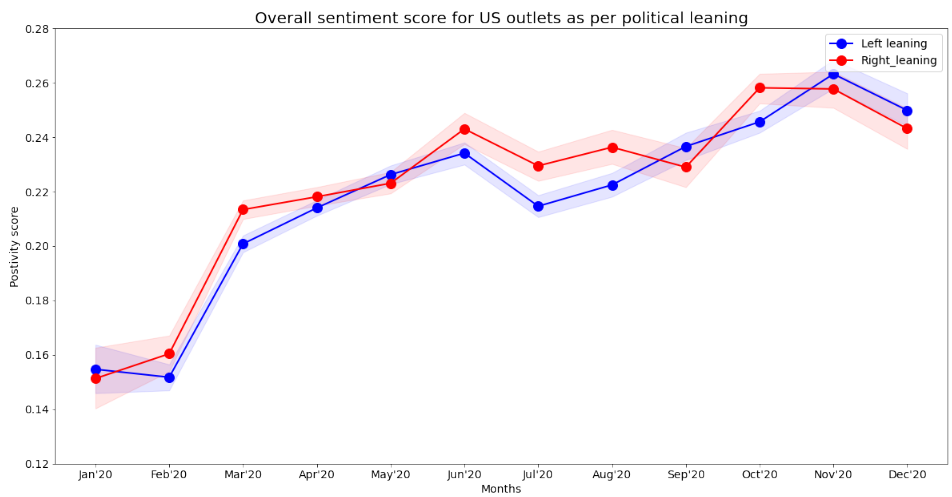


Figure 4.5: Overall sentiment in Covid-19 news coverage over time grouped by political leaning of the news sources.

sources, until November 2020, where the trend flipped. This reversal may be related to the 2020 Presidential elections which took place on 4^{th} November 2020.

To further validate the right wing - left wing trend observed before, we look at the most

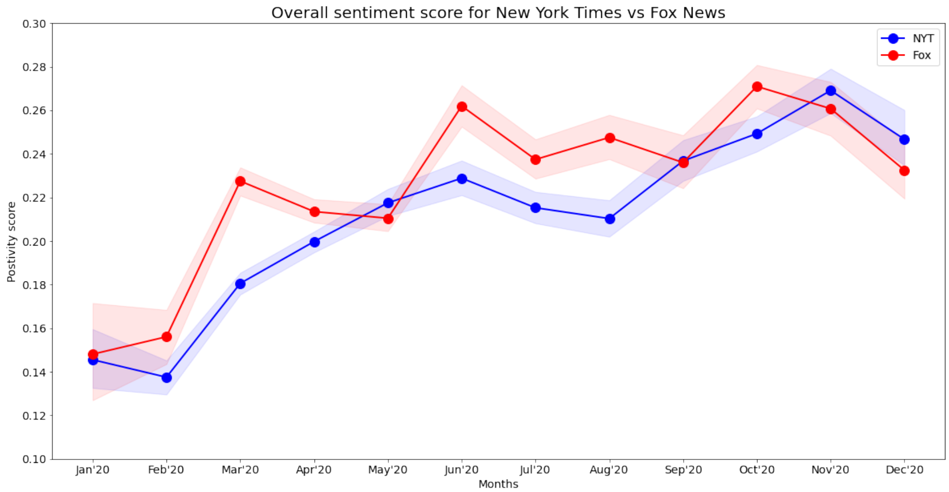


Figure 4.6: Overall sentiment in Covid-19 news coverage over time - New York Times vs Fox News.

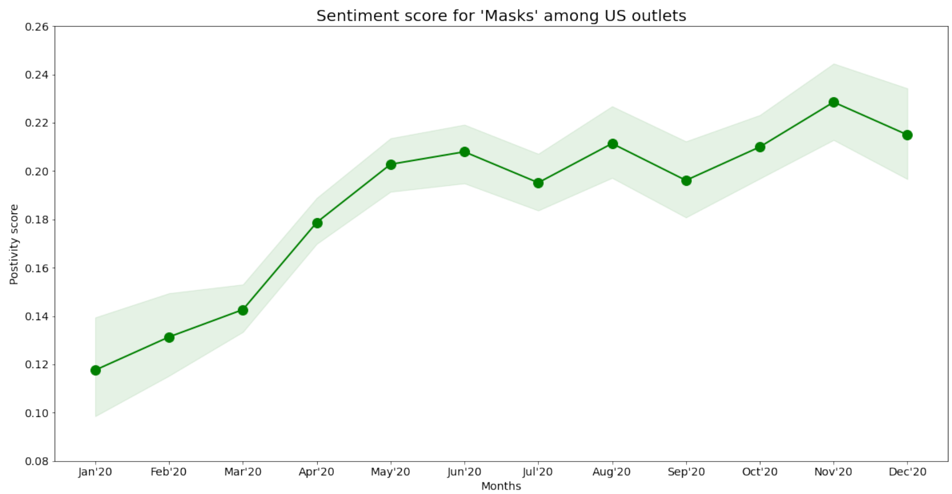
prominent right leaning and left leaning news outlets, i.e. New York Times and Fox News. Due to the non-overlapping confidence intervals, we can conclude with statistical significance that the coverage of the pandemic by Fox News was much better than the same in New York TImes in the months of March, April, June, July, August and October 2020. Overall, we observe that Fox news has consistently had much more positive coverage of the Covid-19 pandemic than the New York Times, and that this trend flipped after the November 2020 elections.

4.4 Sentiment analysis in articles on various sub-topics

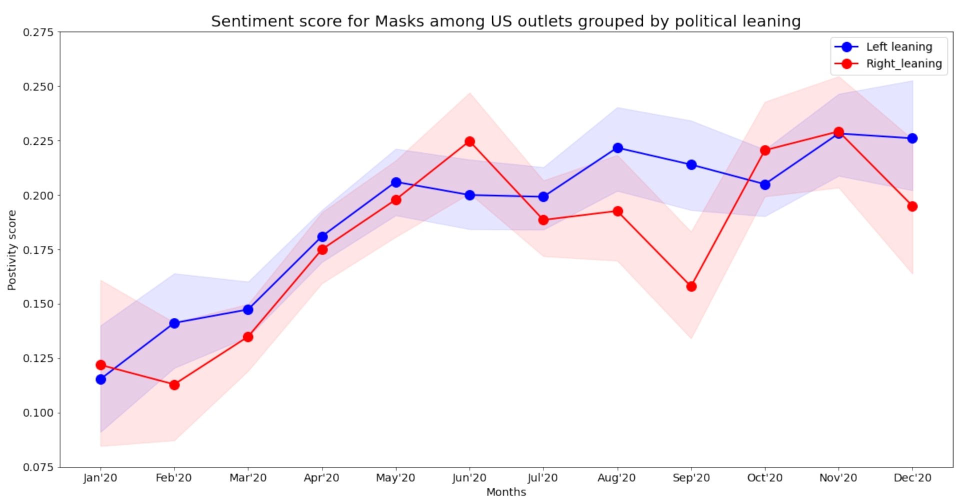
We can also look at the sentiment in articles focused on certain sub-topics covered in our dataset.

4.4.1 Sub-topic : Masks

Throughout the pandemic, we have seen a growing anti-masks movement, especially among people who politically lean towards the right wing. We can look at the sentiment around Masks, in Covid-19 news articles to validate this theory with statistical evidence.



(a) Overall sentiment score for articles covering the sub-topic of Masks



(b) Sentiment score for articles covering the sub-topic of Masks, grouped by political leaning of the news source

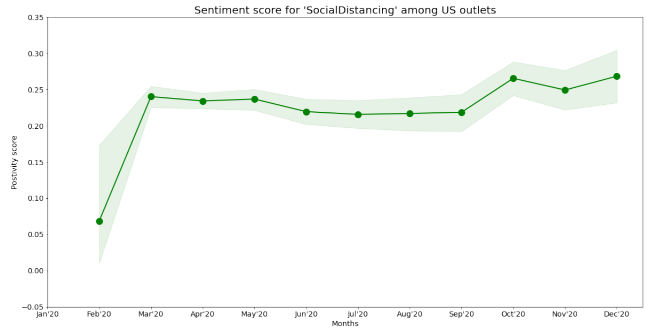
Figure 4.7: Sentiment analysis for articles covering the sub-topic of masks.

As we can see in Figure 4.7 (a), overall, the sentiment around Masks, has been increasing in Covid-19 related news articles. While the initial rapid rise can be attributed to usage of masks being encouraged by CDC guidelines, and the after June 2020 the positivity score appears to have plateaued. In Figure 4.7 (b), we see that only in the month of September 2020, we can conclude that sentiment around masks was significantly better in left leaning news media as compared to right leaning news media, as evidenced by non-overlapping confidence intervals. Overall, the general trend has been that average positivity score around Masks is better left leaning news outlets, though not by statistically significant margins.

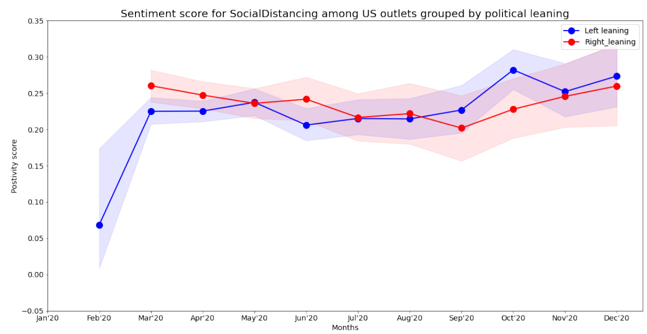
4.4.2 Sub-topic : Social Distancing

Another key preventive measure in the fight against Covid-19 has been social distancing. However, unlike masks the attitudes towards social distancing have not become a point of contention across political lines.

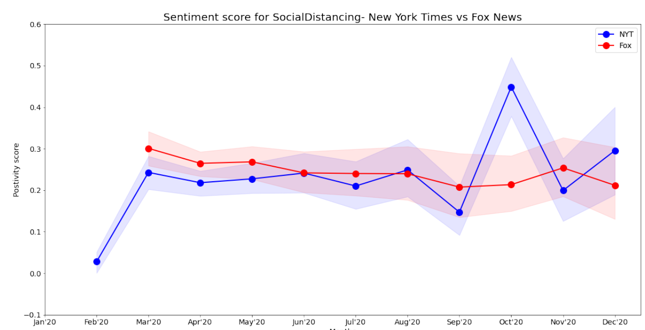
Figure 4.8 confirms our beliefs that in terms of preventive measures to counter the spread of Covid-19, social distancing was far less divisive politically than masks. In Figure 4.7 (a) we can see that overall sentiment around social distancing has remained almost constant throughout the year. When grouped by political leaning, Figure 4.7 (b), we see that there is no month where a statistically significant difference in sentiment is present between left leaning and right leaning news outlets. Lastly, in Figure 4.7 © we are looking at the most prolific right leaning and left leaning news outlets, Fox News and New York Times, we again see that for most of the year the average sentiment around social distancing has been pretty much the same, except for October 2020. This may have been related again with the presidential elections, where one candidate held socially distanced car based events while the other held traditional in-person events.



(a) Overall sentiment score for articles covering the sub-topic of Masks



(b) Sentiment score for articles covering the sub-topic of social distancing, grouped by political leaning of the news source

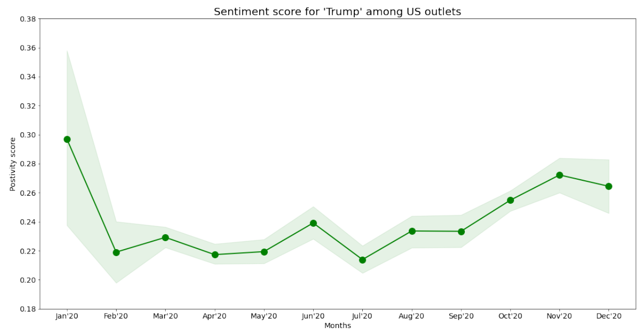


(c) Sentiment score for articles covering the sub-topic of social distancing, Fox News vs New York Times

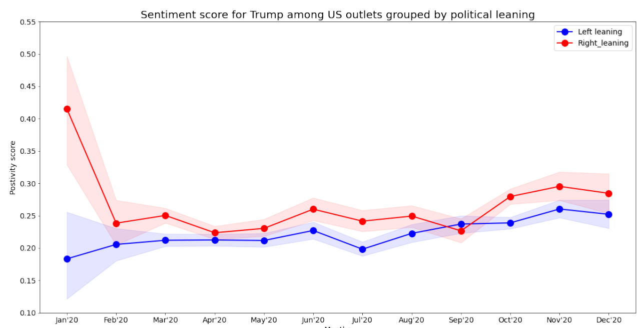
Figure 4.8: Sentiment analysis for articles covering the sub-topic of social distancing

4.4.3 Sub-topic : Trump

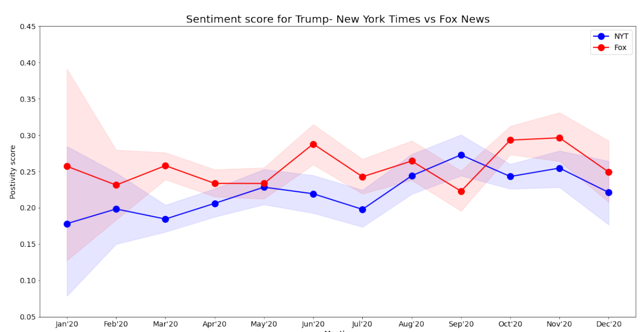
One of the most hotly debated topics during the year 2020 was, whether the federal government led by President Trump was able to adequately handle the Covid-19 pandemic. Given the highly political nature of this topic, we expect to see significant differences in sentiment around the sub-topic of Trump, in news articles covering the Covid-19 pandemic from various sources.



(a) Overall sentiment score for articles covering the sub-topic of Trump



(b) Sentiment score for articles covering the sub-topic of Trump, grouped by political leaning of the news source



(c) Sentiment score for articles covering the sub-topic of Trump, Fox News vs New York Times

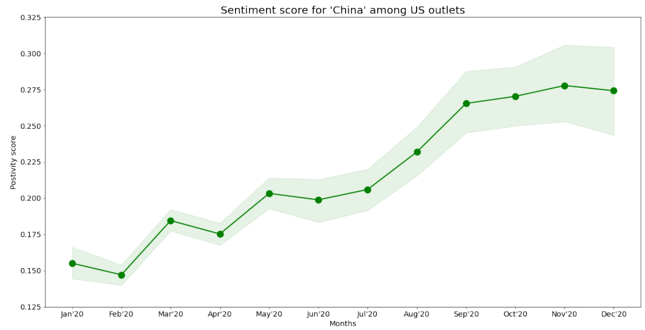
Figure 4.9: Sentiment analysis for articles covering the sub-topic of Trump

As we can see in Figure 4.9, our initial hypothesis of significant divergence in sentiment of articles mentioning former President Trump has been sufficiently met. In Figure 4.9 (b) we can see that the right leaning news media has consistently had much more positive sentiment than the left leaning news media, in its coverage of President Trump. This difference was statistically significant during the months of January, March, July and October 2020, at a 95% confidence level. Further, in Figure 4.9 (c) on comparing the most prominent news outlets on both sides of the political divide, we again observe that the coverage around President Trump was significantly more positive in Fox News than New York Times. Again, we observe a statistically significant difference, as evidenced by the non-overlapping confidence intervals was present during the months of March, June and October 2020.

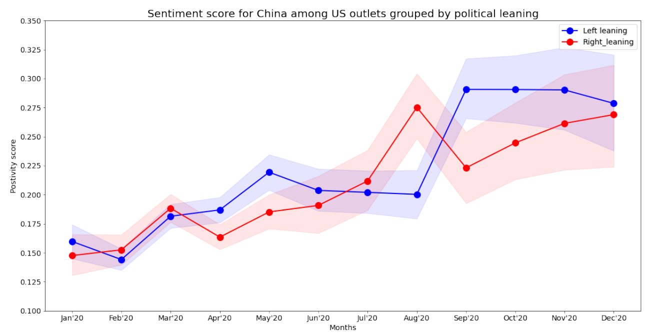
4.4.4 Sub-topic : China

Another bone of contention during the year 2020, has been the attitude towards China. Its widely documented that the pandemic began in China, with the first major outbreak being reported in the city of Wuhan. However, it's believed that after some initial subterfuge regarding the extent of the outbreak, China was able to successfully control and stem the spread of the pandemic within its borders. In the United States media, the general sentiment towards China suffered greatly especially early on in the pandemic, but has been recovering since then.

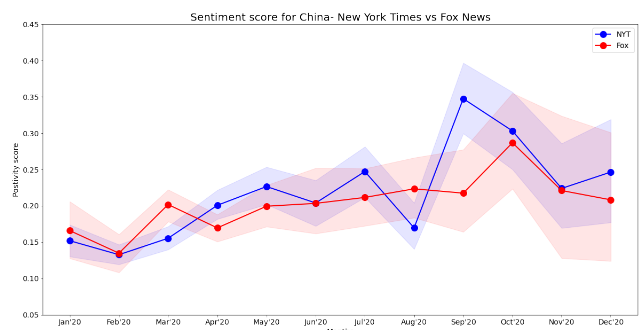
As we can see in Figure 4.10 (a), the sentiment in articles mentioning China has been steadily recovering in the online news articles, from the harm suffered early on in the pandemic. The widening confidence intervals towards the later half of the year suggest that the number of articles containing China have been declining leading to a greater variance in the monthly average positivity scores. Looking at the news sources, grouped by political leaning we observe that sentiment towards China has undergone multiple shifts. While early on in the pandemic right leaning media was more negative on China, it became more positive around the months of July and August, and went back to being more negative in September. A similar crisscross trend is also observed when directly comparing sentiment in articles from



(a) Overall sentiment score for articles covering the sub-topic of China



(b) Sentiment score for articles covering the sub-topic of China, grouped by political leaning of the news source



(c) Sentiment score for articles covering the sub-topic of China, Fox News vs New York Times

Figure 4.10: Sentiment analysis for articles covering the sub-topic of China

Fox News and New York Times. Overall we can conclude that the sentiment towards China shows no sustained significant differences between right leaning and left leaning news outlets.

4.5 International Sentiment

We can also look at the sentiment in news outlets from other English speaking countries and compare the same to that observed in news outlets from the US. For our analysis we will be considering two other English speaking countries which are culturally and socio-economically very close to the United States - United Kingdom and Australia. Within these countries we have selected the following news outlets for comparison against the 10 news outlets from United States -

News Outlet	Country	Political Leaning
The Guardian	United Kingdom	Left
The Independent	United Kingdom	Left
Daily Mail	United Kingdom	Right
Sydney Morning Herald	Australia	Left
Daily Telegraph	Australia	Right
The Australian	Australia	Right

Table 4.2: News sources from Australia and United Kingdom selected for comparison with the ones from United States.

Another important factor aiding in the selection of Australia and the United Kingdom is that both these countries like the United States had a right wing government in charge for the whole of 2020, with Boris Johnson in UK and Scott Morrison in Australia being the respective heads of state. However unlike the US, UK and Australia did not have any elections during 2020. Still, we can expect right leaning media to be more accommodating of governments efforts to control the Covid-19 pandemic in both the United Kingdom and Australia, just like the US.

4.5.1 Overall Sentiment - US vs UK vs Australia

We can start by comparing the overall sentiment in Covid-19 news coverage in the UK and Australia as against what we have observed in the US.

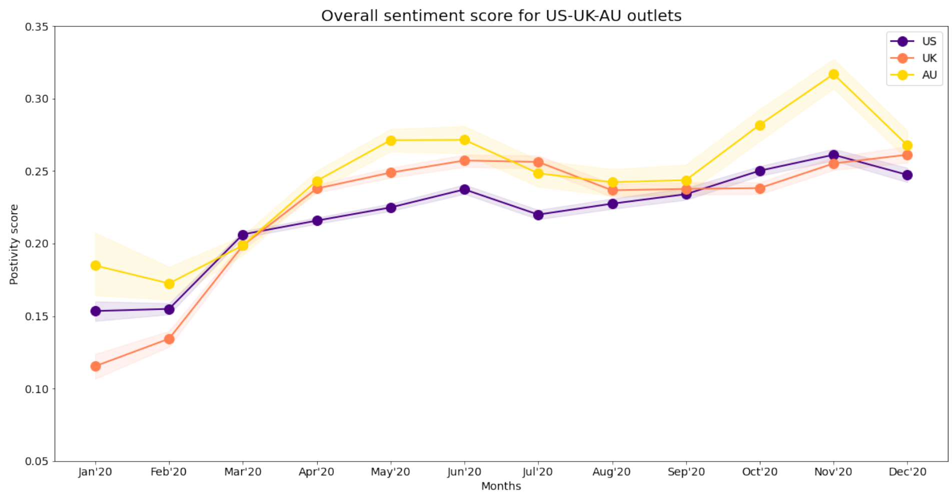


Figure 4.11: Overall sentiment in Covid-19 news coverage over time - comparison between US, UK and Australia.

As we can see above, overall the sentiment in Covid-19 news coverage has been much more positive in Australia as compared to the United Kingdom and the United States. This reflects the fact that Australia also has been much more successful in stemming the spread of the disease, than the US and UK. For the United Kingdom, the sentiment was much more positive during the initial spread of the disease during Summer of 2020, and decreased during the second wave of the pandemic in Fall - Winter of 2020. This makes sense as the second wave of the pandemic has proven to be more deadly than the initial outbreak in summer, especially with the appearance of mutant, more infectious strains in the UK. On the other hand, in the US the sentiment has steadily improved through the year 2020, even though like the UK, the second wave of the pandemic was much more deadlier.

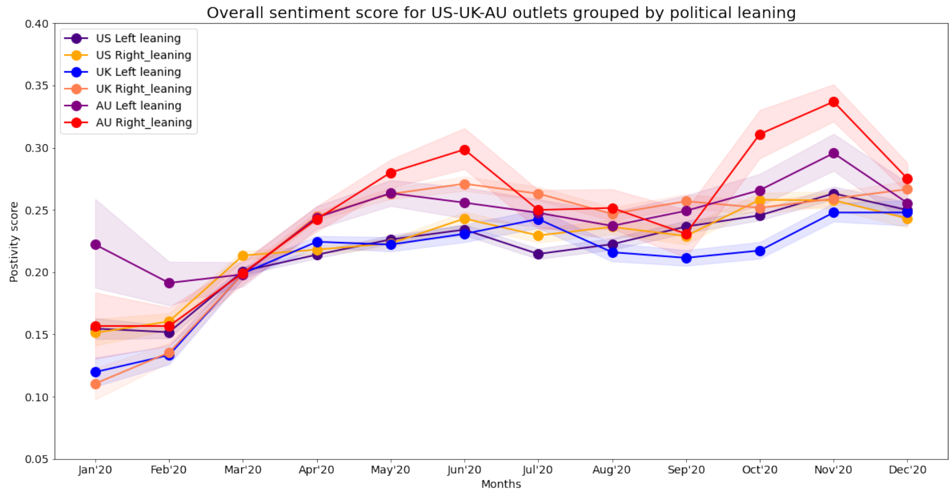


Figure 4.12: Sentiment grouped by political leaning in Covid-19 news coverage over time, comparison between US, UK and Australia

4.5.2 Sentiment grouped by political leaning

In Figure 4.12, we can observe that overall, Australia's both right and left leaning news media outlets have been more positive in their coverage of the Covid-19 pandemic than their counterparts in the US and UK, especially in the last couple of months of 2020. This corroborates well with our earlier observation on Australia being much more successful in dealing with the pandemic than most other countries of the world. In the UK, we also observe that the right leaning news media has had a much more positive sentiment in the Covid-19 news coverage than the left leaning news outlets. This is similar to the behavior we had witnessed earlier in our analysis of the United States.

CHAPTER 5

Conclusion

The objective of this paper is to use the tools of sentiment analysis to objectively analyze the coverage of the Covid-19 news articles in news outlets. We started with analyzing the sentiment of all articles related to Covid-19 appearing in the selected 10 US news outlets from the period of 1st January 2020 to 31 December 2020. We found that the sentiment as measured by the positivity score, has steadily been increasing in the news coverage in spite of the rapid rise in cases observed during the last few months of the year during the second wave of the pandemic. This improving sentiment can be linked to the rapid progress made in the process of vaccine development, along with a general atmosphere of indifference towards the pandemic due to the so-called pandemic fatigue. Next, we looked at these same articles but grouped them based on whether the news source is considered to be a "right leaning" news organization or a "left leaning" news organization. Looking at the monthly average positivity score in these two groups, we concluded that right leaning news outlets had more positive sentiment in covering the Covid-19 pandemic than left leaning news outlets. This difference was statistically significant in the months of March, July, August and October 2020 at 95% confidence level. On comparing the most prominent right leaning and left leaning news outlets, we observe a similar trend where the coverage of the pandemic was more positive in Fox News than in the New York Times. This difference was also statistically significant at the 95% level in the months of March, April, June, July, August and October 2020. Thus, we can conclude that there has been significant bias in reporting around the Covid-19 pandemic where right leaning news outlets have reported on the pandemic with more positive sentiment than their left leaning counterparts. Given that the pandemic in

2020 took hold under the administration of a Republican president and during an election year, this bias in reporting is along expected lines.

Next, we looked to analyze the sentiment around various topics associated with the Covid-19 pandemic. These include preventive measures like masks and social distancing, whose use has unfortunately been politicised in the US, along with more contentious and divisive topics like former President Trump and China. These sub-topic based sentiment analysis were used to analyze and quantify any possible bias in news reports around the Covid-19 pandemic, which mention these sub-topics. We started with news articles mentioning masks, and observed that the overall sentiment in news articles mentioning masks has been steadily increasing. Looking at news outlets grouped by their political leanings, we observe that only for October 2020, we can conclude that sentiment around masks was more positive in left leaning news outlets than right leaning news outlets by a statistically significant margin. For the rest of the year, while average monthly sentiment on masks remained more positive in left leaning outlets than their right leaning counterparts, the difference was not large enough to be statistically significant. Unlike the previous case, this analysis does not provide enough evidence to help conclusively prove the theory that right leaning news outlets have consistently against use of masks as we have statistically significant results in only one month.

Similarly, we looked at the sentiment in articles mentioning social distancing. Here we found that the sentiment has been almost constant throughout the year, and shows no noticeable difference between the left leaning and right leaning news outlets or even between Fox News and New York Times. We only noticed a sudden spike in sentiment around social distancing in the New York Times in October 2020, which may be attributed to the Presidential elections where political events and polling processes were generating some minor debate around the issue. Next we looked at the more divisive issue of sentiment in articles mentioning former President Trump. Here we observed that overall, after an initial dip, sentiment in articles mentioning Trump had been steadily becoming more positive.

Furthermore, on grouping news outlets by political leanings, we observed that right leaning news media had more positive sentiment in articles mentioning Trump than left leaning news media. This difference was statistically significant in January, March, July and October 2020 at 95% confidence level. On repeating the same experiment with just Fox News and New York Times, we notice that a statistically significant difference in sentiment is observed in March, June and October 2020. Thus, we can conclude through our analysis that right leaning media has had more positive sentiment in their Covid-19 news coverage when they mention President Trump, as compared to left leaning media. This confirms our intuitive hypothesis where we would expect President Trump to get favourable coverage in right leaning news outlets due to his political affiliation to the Republican party.

Lastly, we also looked at sentiment in news articles in the United Kingdom and Australia, in order to compare them with those observed here in the United States. Apart from being English speaking western high-income democracies, both the UK and Australia were also under the leadership of right wing governments during 2020. This not only allowed us to compare sentiment in coverage of Covid-19 pandemic in three similar countries, but also provided us an opportunity to compare the relative political bias in news reporting in these three countries. We observed that overall, the sentiment in Australia was much more positive than the UK or the US, which makes sense as Australia has done much better than the other two countries in stemming the spread of the pandemic within its borders. Peculiarly, in the UK the sentiment became more negative as the second wave of the pandemic took hold in the country in winter of 2020. This is in sharp contrast to the US where overall sentiment around Covid-19 kept becoming more positive throughout the year even as the second/third wave of the pandemic proved to be much more deadly. This indicates that the news coverage of the pandemic in the UK was more closely correlated with the cases count and deaths from the pandemic, when compared with the US. Similarly, looking at the sentiment grouped by political leaning of news outlets in these three countries we see similar trends where the right leaning media is much more positive in its coverage of the pandemic than their left leaning counterparts. This result is expected, since as we have previously explained, all three countries were under the leadership of right wing governments throughout 2020. Furthermore, the difference in sentiment between right leaning and left leaning news outlets is statistically significant in all three countries, confirming the presence of political bias in news reporting in each of them.

5.1 Future Work

In this work we have been able to confirm the presence of political bias in coverage of the Covid-19 pandemic. The next step in this process will be to detect the presence of other kinds of bias in news articles. Using the powerful language modelling capabilities of latest transformer models, we can build machine learning systems which can detect discrimination based on upon race/sex/religion etc. Such applications of machine learning systems can make the world more equitable to people from diverse backgrounds while raising the quality of discussions in public life. We can also expand this current work to include more news outlets and countries in the analysis, while keeping the analysis up to date and publicly available to ensure that the general public is always aware of any hidden biases present in the news content they are consuming.

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