Project Phase 3 Report: Data Presentation & Visualization

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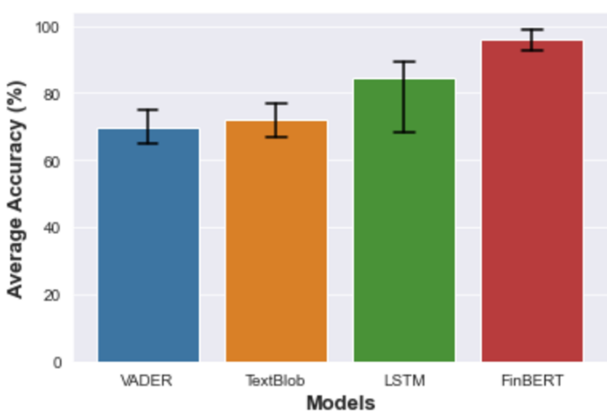
Our GitHub repository can be found here.

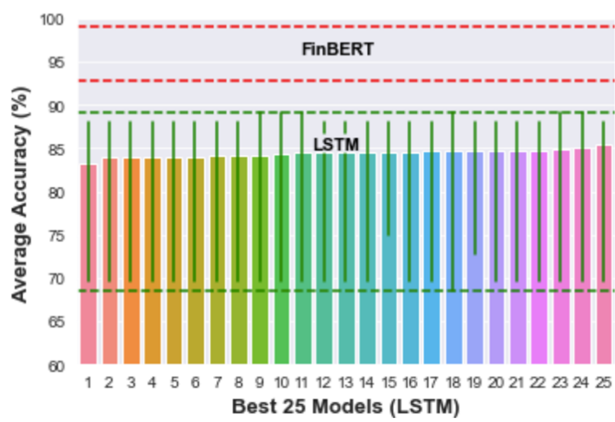
What was our initial problem and goal?

With the onset of the pandemic back in early 2020, many aspects of our lives began to fluctuate and change rapidly. One major thing that was affected by it was the realm of finance and economics. Stocks began to change drastically, cryptocurrency shot up, and people even organized to buy shares of a certain company to crash other people's purchases. People who trade these assets often painstakingly stay up to date on news relevant thereto, many make a morning ritual out of scanning financial news headlines to get a sense of how the market was feeling, what the word on the Wall Street was, so to speak. This sort of process is time consuming, must be done on a near daily basis, and becomes increasingly time consuming in proportion to the number of assets one wishes to keep track of. This problem was the inspiration for our project. Our ultimate goal for this project was to develop a tool that could be given a search phrase relevant to a financial asset and return back a gauge of market sentiment. This would provide a helpful initial insight when making a decision, and could be used in a number of ways to assist in financial planning and asset trading. In this paper, we'll discuss the initial stages of our development, the data analysis we performed, the performance of each of the models we employed, and how to utilize the tool we built.

Data Analysis Process

Initially, in order to begin development on this idea, we needed a good dataset to use for our future stages in training a model. After doing some research, we were able to find three separate sets of data that each listed out an article's headline, and paired with it, its sentiment score or value which would display that a headline was either positive, negative, or neutral. We combined these three datasets and pre-processed them such that the sentiment scores they each had were compatible with a simple numeric representation to allow for easy data management and model training. In addition, we removed all unnecessary words and characters from the resulting dataset so the models would determine sentiment scores based only on words and characters it understands and that are not inherently neutral. For example, an excess of words such as ‘the’, ‘a’, and ‘what’, which are known as stopwords, weigh down the specificity of the sentiment values, and could cause a sentiment score prediction to be much more neutral than it should be. Furthermore, many words can be reduced to a simpler form with a process known as lemmatization. For example “simpler” and “simplest” would both be reduced to just the word “simple”. This helps the model treat several words as if they were just one, thus reducing the model’s complexity and increasing the model’s understanding of those very similar words by effectively grouping them together. Once we finished with this step of pre-processing, we began the next phase of our development: determining a model for our project.

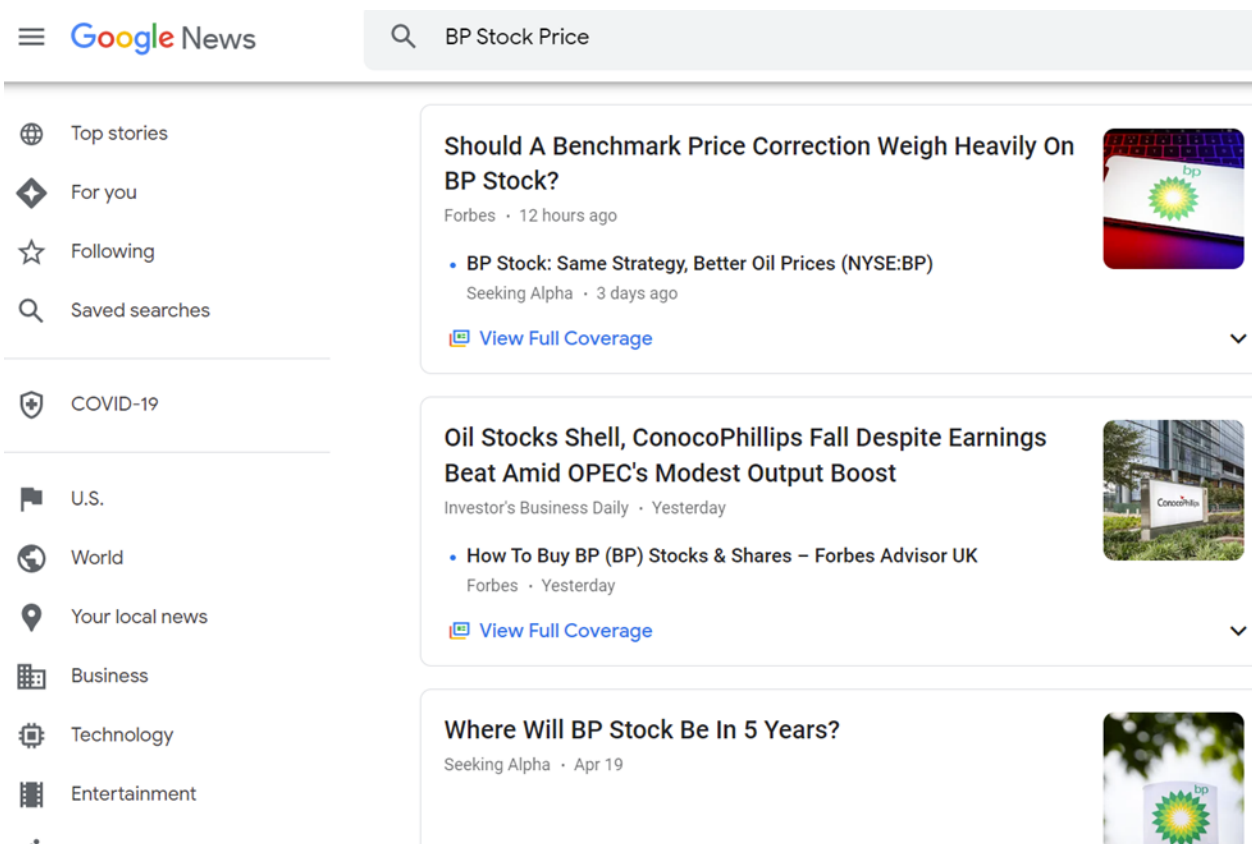




Going through this phase of our project, we wanted to test four different methods of determining financial headline sentiment. Two of these models were VADER from NLTK and TextBlob, both of which are text analysis libraries that determine sentiment with a rule-based method and built for more general forms of sentiment analysis. And, as our results demonstrate, when they were used to determine sentiment in the financial sector, they were notably less accurate than the other two, more complex, models which both use neural networks. VADER and TextBlob were only able to reach an average accuracy of 69.81% and 71.97%, respectively. These results confirm what we had initially suspected, that rule-based methods are not as powerful nor as applicable. The second best model (LSTM) was a neural network which we constructed and trained 2916 times to achieve an average accuracy of 85.435% for its best model. This was a significant increase than the previous two, however we were able to find an even better option. The FinBERT neural network, which was specifically trained on financial data and was produced in a master's thesis by Dogu Tan Araci in 2019, was able to achieve an average predictive accuracy of approximately 96%. This proved to be the best option for our final system due to its impressive accuracy, so we decided to move forward with implementing this neural network into our tool's sentiment determination.

How does our tool work?

The *simple_average_sentiment_score* function is essentially the tool we set out to build in this project. It utilizes a function called *getHeadlines* which itself utilizes the requests and BeautifulSoup libraries to retrieve headlines from Google News.



Thereafter, FinBERT models and tokenizers are generated and used to assign polarity values to each headline such that each headline receives a positive, neutral, and negative polarity score which sum to 1 for each headline. Whereupon, depending on the parameters passed, the overall sentiment score is calculated in different ways. The *numHeadlinesConsidered* parameter has a default maximum of 100 headlines to consider - this can be reduced to consider only the first *x* number of headlines. Since the results are returned from Google in the order in which they are listed this is a way of looking at only the *x* most relevant headlines, as determined by Google.

The *argMax* has a default of *True* meaning that the highest polarity score 'wins' and assigns either 1, 0, or -1 accordingly - if *argMax* is set to *False* then each headline is given a sentiment score equal to its positive polarity score minus its negative polarity score. The third parameter *allow_neutrals* is by default *True* and therefore considers headlines with neutral values in the calculation of the final simple average, if this is set to *False* then only headlines with negative or positive sentiments will be considered, the purpose of this is to allow the possibility of forcing the tool to give a clear indication of market sentiment since often financial news reports can be very cautious about taking too clear a position on a particular asset. As such, results achieved by setting *allow_neutrals* to *False* should be compared with the results obtained by setting it to *True* and must be understood in context.

What do the predictions mean in the domain of analysis?

The predictions our tool was able to deduce have a wide array of applications, and could mean a number of things that can be helpful to a business or analyst. We were able to try a number of financial topics and retrieved a final result that was polarized in one sentiment direction.

Example Results

Below, we've listed some specific sentiment analysis examples, their search query, its average sentiment score, and the date the search was performed. These were produced by utilizing FinBERT to judge present sentiment. These values range from 1 to -1, with 1 being the most positive sentiment and -1 being the most negative.

Positive Sentiment Examples

Our first example comes from the search result of the Occidental Petroleum Corporation (OXY) with a rating of +0.6 (As of 5/5/2022). After running this through our program a few times, in the recent media, it seems as though the company has had a very positive financial outlook. Specifically, a major CEO in the oil field purchased $350 million buys this past week. Additionally, the company recently announced that they are beginning work for a Gulf Coast CO2 transportation and sequestration project back on 4/25/22. These two major news stories definitely could be a cause of the upsurgence in positive sentiment, however, this provides a numeric value to the companies' sentiment in current day press.

	Headline	Positive	Neutral	Negative	Pos-Neg	Argmax
0	Berkshire buys more Occidental shares, boosts ...	0.883639	0.100412	0.015949	0.867690	1
1	Occidental Petroleum Corporation (OXY) is high...	0.945074	0.028696	0.026230	0.918844	1
2	Occidental Petroleum Corporation (OXY) Soars t...	0.806940	0.150478	0.042582	0.764358	1
3	Occidental Petroleum Corp. stock rises Wednesd...	0.907295	0.029045	0.063660	0.843635	1
4	Occidental, Hess, and 3 Other Oil Companies Wi...	0.822971	0.168045	0.008984	0.813987	1
5	Oil stocks in broad rally as crude futures sur...	0.629618	0.130457	0.239925	0.389693	1
6	Is Invesco Dynamic Energy Exploration & Produc...	0.737522	0.250534	0.011944	0.725578	1
7	Diamondback Energy Inc. stock rises Wednesday,...	0.913792	0.028722	0.057486	0.856306	1
8	EOG Resources Inc. stock underperforms Wednesd...	0.063951	0.015127	0.920922	-0.856971	-1
9	Booming offset industry could cut CO2 -- or ju...	0.051364	0.218986	0.729650	-0.678287	-1

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0.6
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As a secondary example of a positive sentiment score, we found that the Silicon Motion Technology Corporation had recent press that lead to them having a +0.4 overall sentiment score. After some additional research, we believe this was due to the fact that the chipmaking company MaxLinear had purchased the company for $3.8 billion, causing the stock to increase by 17.19%.

	Headline	Positive	Neutral	Negative	Pos-Neg	Argmax
0	Silicon Motion Technology stock gains amid tak...	0.858754	0.101590	0.039656	0.819099	1
1	Mid-Afternoon Market Update: Nasdaq Drops 650 ...	0.125210	0.037444	0.837346	-0.712136	-1
2	Silicon Motion (SIMO) Reports Strong Prelimina...	0.948671	0.030861	0.020469	0.928202	1
3	Silicon Motion Launches World's Fastest Single...	0.589126	0.395467	0.015407	0.573719	1
4	Hot Stocks: TWTR near deal with Musk; SIMO con...	0.020404	0.073256	0.906340	-0.885936	-1
5	Silicon Motion: Good Potential At A Reasonable...	0.686778	0.305770	0.007452	0.679326	1
6	Silicon Motion Announces World's First Merchan...	0.530421	0.459644	0.009936	0.520485	1
7	US STOCKS-Wall St slides on global slowdown fears	0.012022	0.025690	0.962288	-0.950267	-1
8	The Global NAND Flash Market is expected to gr...	0.945804	0.038122	0.016074	0.929731	1
9	Brookfield Infrastructure Is Benefitting From ...	0.948464	0.036650	0.014886	0.933578	1

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0.4
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Negative Sentiment Examples

In regards to a good example for negative sentiment score, we found that many popular companies or services tend to come out more negative. This may be due to the fact that the overall press of these companies get more attention when painted in a negative light, however, the results are very clear when looking at recent news articles. For this specific example, Netflix received an overall sentiment score of -0.6 as of 5/6/22. These results had been tied around the fact that Netflix recently had a class action lawsuit against them, combined with their decision to cancel popular new shows and their actively decreasing subscriber count.

	Headline	Positive	Neutral	Negative	Pos-Neg	Argmax
0	Netflix tried and failed to build fandom with ...	0.612573	0.338577	0.048849	0.563724	1
1	Netflix's stumbles cause rivals to rethink str...	0.008981	0.028406	0.962613	-0.953632	-1
2	Frank Langella Blames 'Cancel Culture' After F...	0.034904	0.279168	0.685929	-0.651025	-1
3	Netflix's Movie Library Has Shrunk By More Tha...	0.020890	0.040406	0.938704	-0.917815	-1
4	Netflix Is Being Sued By Its Own Shareholders ...	0.010398	0.034752	0.954850	-0.944453	-1
5	Along for the Ride review – Netflix teen roman...	0.108044	0.329839	0.562117	-0.454073	-1
6	13% of U.S. Netflix subs would cancel if charg...	0.010720	0.086403	0.902878	-0.892158	-1
7	Had enough streaming? Netflix and CNN woes sho...	0.085328	0.052770	0.861903	-0.776575	-1
8	Media mogul Byron Allen says Netflix is a 'gre...	0.890866	0.100264	0.008871	0.881995	1
9	Netflix cancels Meghan Markle series 'Pearl' a...	0.009341	0.046429	0.944230	-0.934889	-1

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-0.6
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Additionally, we had done research into Apple and it seemed they also had a very negative sentiment score, coming in at a rating of -0.8. When digging deeper into this, we found out that there had been rumors in regards to the Apple iPhone 14 launch being delayed, and being slated to be at a higher price point. Along with this, Apple has been known to have been drastically impacted by the supply chain problems stemming from the pandemic, which continues to cause issues with Apple manufacturing.

	Headline	Positive	Neutral	Negative	Pos-Neg	Argmax
0	Apple, Google, and Microsoft commit to expande...	0.922927	0.066454	0.010619	0.912308	1
1	iPhone users complain Apple Music is installin...	0.012962	0.177599	0.809439	-0.796477	-1
2	Apple drops trade-in value for Mac, iPad, and ...	0.026302	0.035811	0.937887	-0.911585	-1
3	Apple Reaches Settlement to Pay $15 to Some iP...	0.027649	0.026782	0.945569	-0.917919	-1
4	Meta Partly Blames Apple's iOS Privacy Changes...	0.019026	0.025121	0.955854	-0.936828	-1
5	Employees at an Apple store in Maryland join t...	0.015747	0.074342	0.909911	-0.894164	-1
6	EU Plans to Regulate Apple Delayed to Spring 2...	0.040007	0.368593	0.591401	-0.551394	-1
7	Why Apple, Meta Platforms, and Salesforce.com ...	0.023512	0.137159	0.839329	-0.815817	-1
8	Supply-Chain Woes Hitting Apple for Billions	0.011841	0.056847	0.931312	-0.919471	-1
9	Apple sues chip startup Rivos for alleged trad...	0.019941	0.104572	0.875487	-0.855546	-1

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-0.8
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Neutral Sentiment Example

For neutral sample results, we found out that the BP Stock Price had a wide array of neutral values. When we reviewed the specific sentiment score, the results for BP came out to be a +0.14 score, much more neutral than the previous scores listed. This was most likely due to the lack of public interest this company may have received. Specifically, in the articles found, it mostly discusses BP in regards to future developments and its involvement with other companies, rather than BP being the sole source of a negative or positive influence.

	Headline	Positive	Neutral	Negative	Pos-Neg	Argmax
0	Should A Benchmark Price Correction Weigh Heav...	0.052490	0.237453	0.710057	-0.657567	-1
1	Oil Stocks Shell, ConocoPhillips Fall Despite ...	0.023276	0.010993	0.965732	-0.942456	-1
2	Where Will BP Stock Be In 5 Years?	0.030861	0.943608	0.025531	0.005330	0
3	Fossil fuel companies like Shell and BP are ra...	0.059291	0.840839	0.099870	-0.040580	0
4	BP boosts buybacks on soaring energy prices af...	0.815004	0.081407	0.103589	0.711415	1
5	Is BP Stock a Solid Long Term Investment?	0.350892	0.640028	0.009079	0.341813	0
6	Stocks making the biggest moves midday: Chegg,...	0.110404	0.846819	0.042776	0.067628	0
7	BP (NYSE:BP) Price Target Raised to $36.00 at ...	0.882799	0.096121	0.021080	0.861719	1
8	Stocks Higher, Tesla, Twitter, Logitech, BP An...	0.180021	0.797487	0.022492	0.157528	0
9	JPMorgan says this is the only sector seeing '...	0.940641	0.046540	0.012819	0.927821	1

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0.14326520189642905
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This result, when compared to a much larger sample size, continues to reign true, as in the following search results, the overall sentiment score decreases to a value of 0.9.

	Headline	Positive	Neutral	Negative	Pos-Neg	Argmax
0	Should A Benchmark Price Correction Weigh Heav...	0.052490	0.237453	0.710057	-0.657567	-1
1	Oil Stocks Shell, ConocoPhillips Fall Despite ...	0.023276	0.010993	0.965732	-0.942456	-1
2	Where Will BP Stock Be In 5 Years?	0.030861	0.943608	0.025531	0.005330	0
3	Fossil fuel companies like Shell and BP are ra...	0.059291	0.840839	0.099870	-0.040580	0
4	BP boosts buybacks on soaring energy prices af...	0.815004	0.081407	0.103589	0.711415	1
...	...	...	...	...	...	...
95	BP PLC share price and latest news	0.022592	0.917987	0.059422	-0.036830	0
96	Brits face a massive increase in energy bills....	0.085362	0.134326	0.780312	-0.694949	-1
97	BP stock price hits new 52-week low - Jun. 24,...	0.012025	0.037007	0.950969	-0.938944	-1
98	Why BP Stock Will Likely Work Over the Next Fe...	0.116146	0.868966	0.014887	0.101259	0
99	Is New Leadership a Reason to Expect Gains in ...	0.229810	0.738392	0.031798	0.198011	0

100 rows × 6 columns

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0.08986836474388837
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Notice that when we include more headlines (100 vs 10) the result becomes slightly more neutral. This phenomenon was observed many times and it is our belief that this comes from the tendency of financial reporters to be, as a general rule, rather cautious in their tone and sentiment such that including more results generally moves the sentiment closer to a neutral average sentiment. Furthermore, the more headlines that are considered, the more holistic is the insight into the asset searched, as opposed to considering only the most recent and popular articles. These factors should be kept in mind by the user when using the tool.

Conclusion

This project was extremely informative in terms of integrating data from different sources as well as developing LSTM neural networks and comparing them to pretrained language analysis models. This project made clear both how useful pretrained models are while also illustrating how competitive LSTM neural networks are, even in comparison to cutting edge techniques which have been further fine-tuned (FinBERT). If we were to carry this project further we'd like to develop more complex methods to compute weighted average sentiment scores, such as by giving higher weights to more recent publications, giving higher weights to publications from more well respected sources, and giving higher weights to headlines which have had many recent views.