News Sentiment vs. Social Media Sentiment in Algorithmic Trading

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***Abstract*—Analyzing sentiment related to financial markets helps investors gain an understanding of the outlook toward a given security. Algorithmic trading is ubiquitous, but a generally accepted, effective implementation remains unsolved. Using sentiment data, assessment of future financial security movement is possible. By analyzing multiple papers from the field of algorithmic trading, the benefits and drawbacks of different sources of sentiment were assessed. News sentiment is effective because of its quality, but ineffective regarding its quantity, timeliness, and journalism themes. Social media sentiment can be effective due to its size and speed of release with the drawback of a significant data filtering requirement. The choice between the two is dependent on the goal of the strategy. For a long-term trading strategy, news sentiment is good because the drawback of timeliness will not be detrimental. For fast, short-term trading strategies, social media sentiment is a better option.**

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I. INTRODUCTION

Algorithmic trading[1] (AT) is the most used method of exchanging securities and currency. For example, in 2011 alone, AT accounted for more than 73% of all United States equity volume. [13]

The significance of AT is due to its already close ties with the public and its ability to return a profit. Financial accounts like pensions, 401ks, and Roth IRAs of the public are invested using AT. On a smaller scale, successful implementations of AT by retail investors lead to financial gain.

Just as with regular security/currency trading, the success of AT depends on the strategy. Without significant strategy planning, trading is as good as gambling. A successful strategy is one that may not work the first time, but through extensive testing, paper trading, and revisions, returns a profit. In the field of AT, factors like data quality and the source of sentiment can lead to lackluster results even with intensive planning and revision.

The difficulty with previous solutions is that with many places to gather user sentiment[2] data, it can be difficult to figure out what works best without testing everything which would take too much time.

[1] Algorithmic trading (AT), sometimes called algo trading or black box trading [12], refers to any form of trading using sophisticated algorithms (programmed systems) to automate all or some part of the trade cycle. AT usually involves learning, dynamic planning, reasoning, and decision-making. [13]

[2] User Sentiment is scraped from many places on the internet (blogs, news, social media, etc.) to gather an overall gauge of the feeling about something (in our case, a security or digital currency). [13]

The solution is researching data sourcing and usage to trade. Through analysis of previous research, it is possible to narrow down the best potential candidate to gather sentiment data.

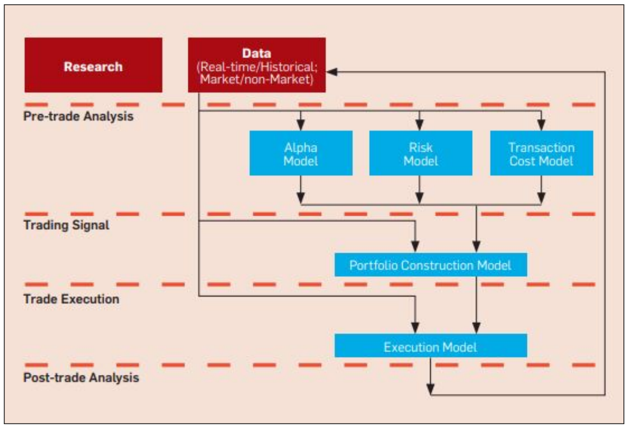

Fig. 1. This shows a basic visual model flow chart for an AT strategy. The algorithms and decisions are made in the top two rows. Trade processing is completed in the following two. Finally, data generated from the final row can be reused in the data and pre-trade analysis.
[13]

II. Background on Algorithmic Trading

The components of an AT strategy are as follows:

1) **Research and data:** Research/data consists of what you intend on trading, generating historical data for testing, and variable data (user sentiment, technical analysis, etc.) to base your trades on. This data is broken down into raw data[3], cleaned data[4], and analyzed data[5].
2) **Pre-trade analysis:** Secondly, pre-trade analysis analyzes opportunities with the supplied data/variables. The primary actor is the alpha model[6] which is supported by the risk model[7] and transaction cost model[8]. In the case of user sentiment, we will use a theory-driven alpha model which will predict market moves, compared to an empirical data-driven that mines market data. 2
3) **Trading signal** Third, the combination of data gathered, and models generated creates a trading signal[9]. While normally given to people for processing, this will be sent to the computer instead.

[3]Data taken straight from a source containing errors and a lack of analysis. [13]

[4]Data that has been edited to remove errors caused by any number of failures in the extraction process. [13]

[5]"Context-specific features of raw and cleaned data that emphasize principal components of underlying data. These data sources, real-time and historic, are the cornerstone of the research, design, and back-testing of trading algorithms and drive the decision-making of all AT system components. Buying (raw and especially, cleaned) data is hugely expensive, and cleaning data is highly time-consuming, but essential due to the sensitivity of trading algorithms." [13]

[6]This model analyzes real-time and historical data to identify opportunities. [13]

[7]Risk models attempt to quantify the risk associated with individual instruments and the portfolio. While not involved in the analysis of a security/currency, they are used to determine risk appetite which is how much risk someone is willing to take on. [13]

[8]The transaction cost model calculates all transaction costs when executing a certain signal and optimizes the portfolio accordingly. [13]

[9]Identifies the assets to be purchased (and when) based on the pre-trade analysis. [13]

4) **Trade execution** The execution model[10]will then determine the location, price, and type of order to be placed (ex: NYSE, buy $AAPL 100 shares at $150/share).
5) **Post-trade analysis** Finally, the trade will be examined in a post-trade analysis which will compare the expected result to the actual result. This analysis can also be used as data for future trades by adding the results into the research/data for alpha model analysis. The cycle then repeats for new trades with the goal of optimizing the data provided and increasing profit from each signal.

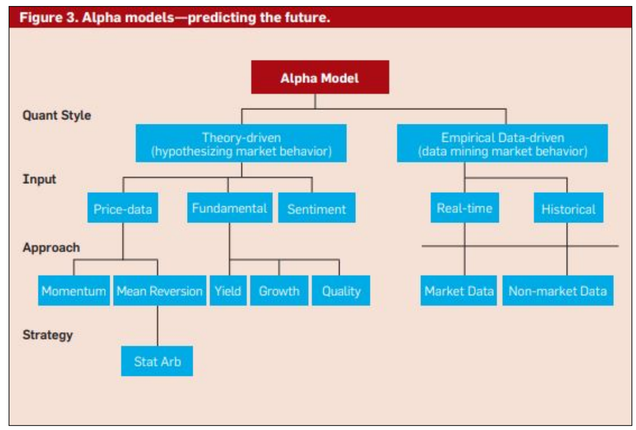

Fig. 2. This is an abstraction of possible alpha models usable in AT. User sentiment based AT will follow a theory-driven model (shown on the left side) which will attempt to predict market behavior. However, a more robust strategy not focused specifically on the effects of a single variable (user sentiment) may utilize both theory and empirical data-driven models.
[13]

Using this basic structure and tweaking the alpha model while obtaining more and better data is the process of developing/implementing an AT strategy. The most important part of this for creating a unique and effective user sentiment-based trading strategy is focusing on the data collection and alpha model implementation which is the purpose of this paper.

III. User Sentiment

The source selection of user sentiment data for the purpose of AT is the most investigated and debated. The two primary forms of sentiment data are news sources and social media. The news is often peer-reviewed with less chance of fake/error-causing data when chosen from reputable publishers. Social media has more data at the cost of more erroneous information. In this section, the pros and cons of both will be further evaluated to determine the best source for a new user sentiment-based trading strategy.

A. News Sentiment

News sentiment data is popular among sentiment-based AT for a good reason: reliability. Provided the news is from reputable outlets, there is little chance of inaccurate titles or

[10]Model for determining trade execution. Consists of where the asset will be purchased (NYSE, NASDAQ, crypto wallet, etc.), the order type (aggressive, passive, large, small, scheduled, etc.), and whether the asset will be purchased at the market (current price) or limit (a price set by a human or the program). [13]

poor grammar, for example. This reduces the amount of effort spent on data processing.

In work by Nan et al., news headlines from Twitter were used as part of their sentiment analysis. They found that they could use “sentiment analysis to assess whether a news headline is favorable or admonitory to the company” [5] they were deciding to trade. Additionally, they obtained the data from Reuters, a well-known news agency. Finally, through knowledge graphs, a positive, neutral, or negative outlook of a headline toward a certain security could be assessed. In this case, dealing with a headline meant no sifting through article data while also ensuring a definitive positive, neutral, or negative result.

Authors Francisco et al. found similar ease with using news headlines as they contained more straightforward information. Furthermore, this group had the benefit of a group of news headlines pre-labeled with their sentiment status such that training an identifier was easier. The news came from reputable sources like the Wall Street Journal so the information did not require analysis for validity. One concern with the news sentiment was that ”although some companies can be quite popular, the news used for SA (Sentiment Aware) only matches some of the data points in the price time series, meaning not all data points in the price time series display a corresponding news release. There is therefore a news coverage issue.” [7] For the S&P 500, for example, there was more data, but as the analyzed securities decreased in mentions, compensation methods were required to display understandable results. Another contributor to lackluster results was tech news. The

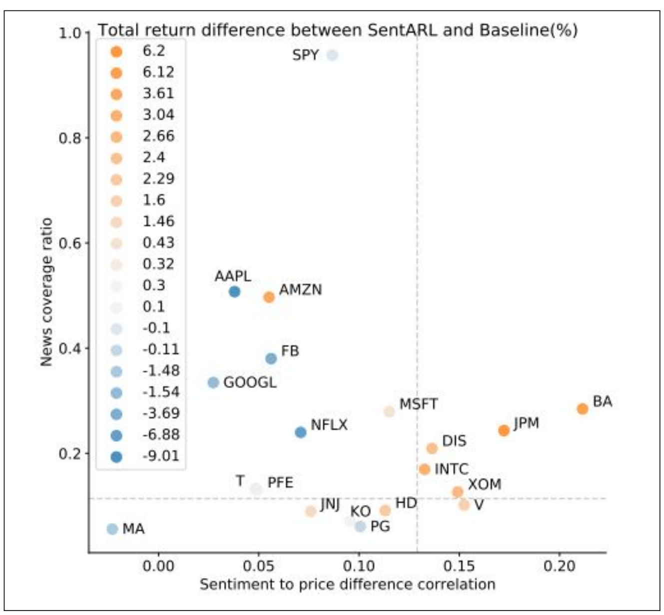

Fig. 3. This chart shows the results of the sentiment analysis for each security analyzed. The amount of news coverage increases along the x-axis while the sentiment-to-price difference increases along the y-axis.
[7]

authors noted ”some of the assets with the worst correlation that led to the worst SentARL[11] performance are mainly from the tech segment. It seems to indicate that news regarding tech companies, even though more popular and common, could be more speculative and lead to a false perception of the prevalent market mood.” 3 Not only does the source of the news matter but even the type of company referenced must be considered.

[11]Sentiment-aware reinforcement learning.

Tech news was not the only kind of news with external influences. Researchers at the Stevens Institute of Technology explored several implications of using news sentiment for their trading algorithm. The first of which is that they believe most news data is full of muddled/inaccurate results. [14] While they acknowledge efforts by others to filter this data, they proposed and created a reward-based system that would generate signals only when positive or negative market swings were observed. On the other hand, if the market does not react to news sentiment signals, the model will ignore the information. This strategy performed best out of the assessed and baseline. 4 Another discovery was that ”when the financial market is

Fig. 4. This chart shows the performance of analyzed strategies from trading on the S&P 500. The reward, score, and trend strategies performed significantly better than shock or the baseline ”buy and hold” strategy.
[14]

optimistic, stocks attracting optimists and speculators; like small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks usually have low returns in the following periods.” [14] This conclusion means that when market optimism as a whole is high, headlines may skew towards optimistic outlooks. This adds further difficulty for both news sentiment and social media sentiment because the tipping point between an optimistic and pessimistic headline could vary depending on the overall sentiment of the market.

The combination of this research along with another paper that reinforced these ideas [10] demonstrates the flaws and benefits of using a news sentiment-based strategy. News sentiment is popular in AT research as it does not require the same data processing as social media. Additionally, if reputable sources are chosen, filtering further decreases. While it is true that the quality and trustworthiness of the information will not need the same scrutiny as social media sentiment, a lack of popularity, unreliable industry, non-moving headlines, or general market sentiment influence are all shortcomings of this strategy. Overall, if designing a strategy based around popular digital currency or well-discussed securities is the goal, news sentiment is good for gathering sentiment data.

B. Social Media Sentiment

Social media is the other option when deciding to trade on user sentiment. Social media provides a vast amount of data on both popular and niche topics. However, due to high data-processing costs and the risk of bots, misleading information, and sometimes unusable material, it can be difficult to implement.

Researchers Oliveira et al. remark on several reasons why social media sentiment (referred to as micro-blogging) is useful for AT. The first of which is the quantity of data accessible as "the community of users that utilizes these services to communicate and share information about stock market issues has grown and is potentially more representative of all investors." [6] 5 The number of active participants on popular social media platforms has the potential for data mining. A unique claim this paper makes is that "the small size of the message (maximum 140 characters) and the usage of cashtags (a hashtag identifier for financial stocks [ex: $AAPL]) can make it a less noisy source of data." [6] Unlike most prospective AT designers, the authors of this paper believe there is less noise than would otherwise be created from more in-depth sources like blogs or news articles. However, it is inarguable that the use of what these authors call "cashtags" is advantageous for deciphering the main focus of a social media post. Finally, the time frame of social media posts has a significant advantage over that of the news because "users post very frequently, reacting to events in real-time. This regularity allows a real-time sentiment assessment that can be exploited during the trading day." [6] In contrast to news articles that take longer to publish, social media posts are fast and constant. Social media sentiment is a strong option for building an AT strategy with Twitter being at the forefront of this analysis.

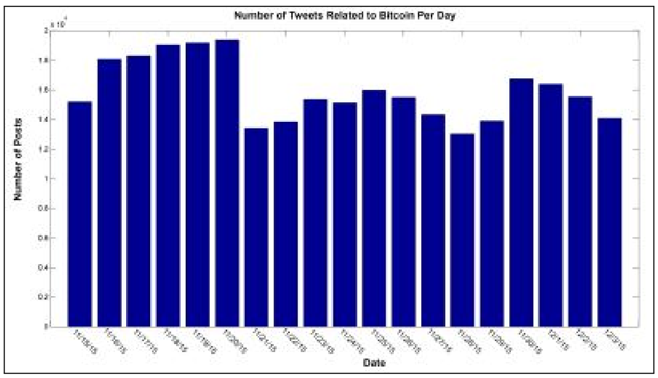

Fig. 5. As an example, this chart shows the number of tweets related to bitcoin over a one-month period. This is also representative of both the positive and negative of using social media for gathering sentiment data.
[14]

A common trait among social media posts is the lack of confidence in the contents of each message. Researchers Huang et al. attempt to solve the issue of untrustworthy posts (tweets from Twitter specifically) to improve their sentiment analysis. To do so, four filters were used: expertise, experience, reputation, and authority. Each is described as follows: "Expertise measures a user's involvement in the subject of interest. Experience is the difference between a user's Expertise and the average Expertise in the network. Authority is the number and quality of social media links a user receives from Hubs as an Authority. Reputation is the number and quality of social media links to a user." [4] The results were that the trust filters outperformed both baselines indicating that analyzing social media sentiment with filters is beneficial for accuracy.

A difficulty noted in [3] is that due to bots, there are a significant amount of duplicate posts that would skew data if not dealt with. The solution was to compute the Levenshtein distance[12] from each tweet to the other after removing unnecessary characters from the string. In doing so, not only was their data set reduced by roughly 50% but also yielded a higher classification accuracy. [3] Another tool researchers in [3] used was the premade sentiment analyzer from text-processing.com which when combined with logistic regression (statistical model for event probability), performed at "a day to day accuracy of 86.00% and an hour to hour accuracy of 98.58%" [3] This paper not only provides a solution to duplicate/non-human data which would otherwise skew results, but also effective sentiment analysis tools that do not require any external modification.

Finally, researchers Birbeck et al. used stock prices as ground truth while assessing user sentiment after. The methodology is: "the classification does not refer to the sentiment expressed in the tweet's content, but is simply an indication of whether or not the stock referred to should be bought or sold, as determined by whether the price rose or fell in the hour following the tweet." [2] From this point, using the labeled tweets, they could analyze future posts for their likelihood to be representative of a stock rising or falling. In doing so, they were able to realize a test profit of 5.18%. An observation from their work was that "the creation of stock-specific dictionaries for individual companies along with basic quantitative measures relating to stock performance produce a classifier that can label tweets with accuracies consistently above the 50% baseline for random guessing." [2] In terms of my experiment, looking into stock/currency-specific subreddits may be more worthwhile than using generic financial subreddits. This unique approach to sentiment analysis is grounds for further investigation in my own experimentation as the results from this method of analyzing twitter are better than the other papers mentioned.

Social media sentiment data has strong support for its timeliness, quantity, and promising research. While as a developer it may be difficult/time-consuming to develop ways to manage misleading, duplicate, or nonsensical data, the sentiment information potential of the millions of users cannot be denied. Furthermore, as with the factors previously mentioned, even small communities can be analyzed to predict currency/security. There is no need to only target large currencies/popular stocks which would be mandatory for news sentiment.

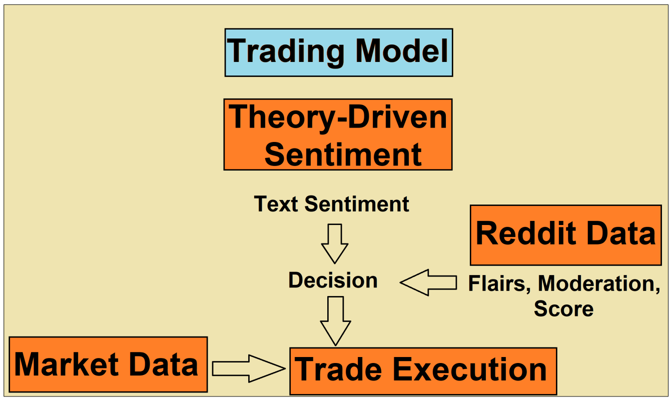

Fig. 6. This is the mental model used for my trading strategy. It uses the theory-driven aspect from Figure 2 in addition to the inclusion of my chosen data source.

[14]

IV. Trading Algorithm Implementation

For the algorithmic aspect of the trading strategy, I decided on a momentum trading[13] demonstration. Throughout the course of the day, this algorithm will gather Reddit posts filtering by tag (the type of content posted for example meme, due diligence, profits/loss) and score (likes to dislikes). From here, the sentiment of both the post header and post body is assessed using OpenAI's API. When a stock ticker symbol is gathered from the post title it is then placed in an array to be assessed for momentum. From this point, if more posts are found with the same ticker symbol, meet the filter requirements, and have positive sentiment in the title/body, the ticker has positive momentum. A trade will then be executed with the intention to sell a week from the position's purchase. This process will repeat for any number of stocks with a positive momentum based on the subreddit provided.

V. Future Trends

For the future trends of sentiment-based AT, there are three possible outlets I identified both in the space of sentiment analysis and in the field of algorithmic trading. For sentiment analysis, as the field continues to improve, trading on the type of sentiment will become more specific. Additionally, as artificial intelligence (AI), machine learning (ML), and natural language processing (NLP) improve so will sentiment-based trading. However, there are many ways to trade via algorithms and as such, with more experimentation, one strategy may outperform another.

Specific sentiment: Current sentiment analysis tools like OpenAI, for example, have four outputs: positive, negative, neutral, or no sentiment assessed (or something to that effect). As the ability to assess sentiment improves, however, the quality and quantity of data able to be extracted from the text will increase. [11] For example, one future capability in the field of sentiment assessment is the ability to detect bias. [9] Poria et al. further predict that the cause of bias, bias evaluation, and even a bias-removal system are all future possibilities. [9] This is just one area of nine researchers identified as areas for improvement in sentiment detection.

Improvements to AI/ML/NLP: NLP technologies are improving, which will make sentiment-based algorithmic trading strategies more advanced in their understanding and analysis of online content sentiment. This will allow traders to make better, more precise trading decisions by considering a wide range of online sources. Furthermore, as AI/ML technologies continue to improve, sentiment-based algorithmic trading strategies will incorporate more advanced AI techniques like deep learning and reinforcement learning in order to enhance their accuracy and efficiency. [1]

Other trading strategies: High-frequency trading (HFT) is another popular trading strategy employed by larger bodies like banks or investment firms due to its high execution costs. HFT has gained popularity in recent years due to advancements in technology and communication infrastructure that enable it to exploit small price discrepancies and temporary market inefficiencies. According to Laurent Bernut, CEO at Alpha Secure Capital, current HFT strategies have their drawbacks in addition to the strategy itself facing more strict government regulation. However, as these algorithms continue to improve, they may become more profitable than sentiment trading causing the latter to fade out of practice. [1]

The future of sentiment analysis is bright. From detailed analyses to more accurate assessments, all fields which implement sentiment will improve in the coming years. However, despite improvements to the core of sentiment-based AT, there are other popular trading strategies gaining traction. Whether or not sentiment-based trading will exist in the future depends not only on how profitable its implementation capability ceiling is compared to its competing algorithms but also on how governments will regulate these new financial instruments.

VI. Conclusion

The difficulty of AT on user sentiment is the selection of data. News sources often have less "noise" than social media sentiment, fewer headlines, delays in release, and industries that have speculative journalism can make this data tough to work with. Social media, while larger and less manageable, provides analysis in real-time, and while the potential for misleading/useless posts is possible, previous research demonstrates the ability to filter this out. Additionally, sources like [3] and [8] provide third-party analysis tools that should ease the burden of labeling the data. For these reasons, I used Reddit.com for my user-sentiment trading experiment because it provides quantity and timeliness and gives unique indicators on each post (theme tags, number of upvotes vs downvotes, popularity, and moderation teams). The combination of these factors provides a solution to the flaws of both news and social media sentiment.

Algorithmic trading requires many fields of expertise for effective implementation. Current research demonstrates,

[12] "The Levenshtein distance is the edit distance between two strings. This value can be leveraged to prove that any pair of tweets is dissimilar by at least some threshold value." [3]

[13] A typical momentum trading strategy for stocks aims at capturing trends in stock prices. It uses the contention that stocks with an upward momentum will continue rising and should be bought and stocks with downward momentum will continue falling and should be sold.[13]

through testing, profitable solutions given proper sentiment assessed, and reliability of data. While some AT strategies are more difficult to execute as a retail investor (high-frequency trading, for example) it is possible to develop algorithms not reliant on their execution speed, but on the accuracy of their analyses.

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VII. RELEVANT COURSEWORK ACKNOWLEDGEMENT

To complete this course project I used information and experience from both inside and outside of the classroom. This was not just from computer science classes either, I believe I integrated what I learned from other disciplines into this paper as well. Throughout the course of my work over the semester, I believe I gained a better understanding of previous work via this project.

From a programming aspect, courses like CS200, CS230, and CS330 all played a role in my demonstration. Additionally, high school courses like AP Computer Science Principles and AP Computer Science A laid the foundation for my success in college software development courses. The classes I have taken over the past six years gave me the ability to lay out a plan for executing my demonstration. Although learning python and the APIs I used were all new, it was easier because of my experience in both high school and college classes.

Other classes that played a role in my final project (presenting and paper) would be AP Seminar, AP English, First Year Seminar, Ethics, French, and Japanese. In my AP classes in high school, I worked on both my writing and presenting skills which I then used for this final project. I furthered my writing and speaking abilities in my First Year Seminar and computer science ethics course. I also believe that my long-term study of foreign languages (both related to English and not) helped me portray my ideas, get out of a mistake in what I meant to say vs what I said, and become more comfortable presenting in front of an audience (though I still have a lot of work to do on that last point).

From outside the classroom, I had two summer research projects and an internship that all enhanced my coding skills and ability to work independently. Working with Jeremy by myself, I had to learn how to code on my own to meet the expectations of the project. Similarly, working on the Nursing Simulation team with Peter and Jodie taught me how to learn coding concepts applicable to real-world applications. Finally, my internship at USAA taught me what it meant to write ”enterprise-level” code. Code that was free of unnecessary lines, unused imports, and was readable. Although the code in my demonstration was not up to this standard due to time constraints, I still feel accomplished knowing that I have the ability to recognize the difference between ”good” and ”bad” code and can work on that in the future.

Finally, this project has deepened my understanding of all the coursework and experience above by tying it together. The classes and experiences above all focused on a specific idea/skill and the combination of all of these parts is what makes up the computer science capstone. As a result of this class, I was able to make the connection between academic writing and presentation found in my non-computer science/AP classes and the technicality of ideas in computer science. Furthermore, I was able to demonstrate my understanding via my demo which not only shows off my ability as a software developer but also my ability to understand my area of research. This class was the capstone of my academic career and tied my liberal arts education together.