Algorithmic Trading: High Frequency & Low Frequency Trading

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Abstract

Algorithmic trading is defined as the mathematical models that are programmed to give computerized trading orders. The broad subject is categorized into high frequency trading and low frequency trading. The sub category, high frequency trading, is addressed using a presentation by the founder of investor's exchange (IEX) and how proximity and fast connections are essential to optimize high frequency trading algorithms. The paper then shifts to how algorithmic trading facilitates liquidity in a small scope. Low frequency trading is then explained using different approaches to build an algorithm. Furthermore, four stocks from the US equities market are chosen to analyze how sentiment scores and the distance between short-term/long-term moving averages impact on the stock's price trend. The analysis indicates that sentiment scores from a previous week, impact on the four stock's prices the following week with respect to the positive (negative) distance between their moving averages.

1. Introduction:

In a fast-evolving world where markets are shaped everyday and the only constant is change, data reached its highest peak in human history in the year 2016 (Esteves 2017). The amount of data available in the capital markets is more than what any trader or investor can anticipate, whereby an edge in technology is the ultimate competitive advantage to perceive future trends and harvest profits faster than other market practitioners. All that taken to fact have led to the existence of algorithmic trading (AT) among exchanges and between quant traders that are more efficient than institutional dealers in executing trades in a timely and accurate manner. The term AT is the residual of the fast-evolving technological innovations and is the use of computer algorithms to make trading decisions in order to manage and submit these orders (Hendershott, Jones and Menkveld (2011)). In comparable literature, Foucault (2012), concludes that AT depends on the trading strategies developed and the investment in innovations and technologies. This paper sheds light on the investment in technologies and data centers that US stock exchanges are implementing. AT is categorized, however, in to high frequency trades (HFL) and low frequency trading (LFT), were each differs to a vast extent in technological sophistication and implementation.

In this paper, the objective will be to define AT and its subcategories which are HFT and LFT. In addition, the paper addresses how AT is prevailing in the US equities markets through flash trades (FT) that stock exchanges are facilitating to HFT firms. Furthermore, the literature will define a sample of an LFT strategy that can be implemented by a trader through a new view to moving averages depicted by Avramov, Kaplanski and Subrahmanyam (2018) where sentiment is added to the rationale anchoring bias of investors. This strategy can be mixed with sentiment analysis to capture the anchor bias and take advantage of investors underreaction.

The first objective is to define AT and its subcategories. A framework presented by Brad Katsuyama (2016), the founder of investor's exchange (IEX), in a discussion on a book named Flash Boys written by author Michael Lewis, reveals how HFT is a major part of todays trades especially in the US equities markets that has the largest stock exchanges in the world. HFT is used only by sophisticated firms that have ultra-fast connections and are co-located near the data centers where data is exchanged (Boehmer, Fong and Wu (2012)). HFT is triggered when large orders, through institutional traders, are sent to several exchanges to be partially filled. The order is spread over all exchanges where the portfolio's underlying assets or stock is listed. Nevertheless, the paper addresses the important role that HFT firms are taking part of all market transactions.

The next objective is to show how AT improves liquidity in the market at some days in an unbiased definition. Liquidity is defined by having matching orders fulfilled at the least time. The orders are either market or limit orders. Boehmer, Fong and Wu (2012) show how number of quotes and trade messages of various global stock exchanges have increased between 2001 and 2009.

Moreover, the last objective is to define LFT which is more common among quant investors or institutions with limited arbitrage latency abilities. A variety LFT strategies are discussed and how to incorporate each one in an AT. The three approaches to constructing an LFT lie in sentiment analysis, technical analysis and machine learning techniques that learn market trend and volatility and try to beat market return in the future through past data fed to the designed AT model.

2. Algorithmic Trading Definition:

Trading started from the early ages where a commodity is transferred between individuals on the principal of supply and demand. A supply of a commodity is exchanged for another fungible asset that is in demand. In the stock market, that is foreshadowed by the exchange of stock shares for currency. The emergence of new technological initiatives has developed AT in an expanding manner after the introduction of electronic trading. In addition, trading floor specialists are swapped with automatic quote updates (auto quote) since the year 2003 where examples such as NYSE have implemented such changes (Boehmer, Fong, and Wu (2012)). AT is the automation of computerized algorithm based on mathematical models that execute book orders, market orders and strategic trading preference based on a programing language that is developed into to a trading robot. The programmed code or what is known as algorithm trades on behalf of the trader in a faster and more efficient manner. AT can be constructed on special platforms such as Quantopian that uses Python language to back test algorithms or inside applications that have their tailored coding language such as MetaTrader, which is written in meta quotes language (MQL), and these are just two examples. Nevertheless, the rise of AT has changed the US Equity market in such a way that trades do not happen on trading floors anymore but at data warehouses that are in other geographical areas separate from the stock exchange's (Katsuyama. 2016). Taking an example is the NASDAQ, where the stock exchange's data warehouse is in Cratered, NJ not in Times Square, NY. However, a new definition to AT currently not just depends on faster orders but also on the proximity to the data warehouses and the sophistication of the AT algorithms that are based on mathematical models. Limit and market orders that took days to be done by traders are being executed by microseconds and even milliseconds at top stock exchanges such as BATS (Katsuyama 2016).

[Please insert Figure 1 here]

AT can cause decline in depth that hamper investors ability to trade large amounts without substantial cost or higher prices for each partial order filled (Hendershott, Jones and Menkveld (2011)). In context, the book, "Flash boys: A wall street revolt" written by bestselling author Michael Lewi's narrates a story about an institutional investor at Royal bank of Canada who tries to buy a certain number of shares available in the market but only a fraction of the order is executed at a pre-displayed price (CBSN, (2014)). When the trader goes back to fill the rest of the order, the price would have changed. The author of "Flash boys" then addresses the issue of HFT that is becoming a more critical AT technique that puts firm's with efficient technologies at a competitive edge built on inefficiencies of other investors that lack such technologies. One of the biggest advantages of HFT firms is that they place their co-located servers physically near exchanges' computer hardware's (Boehmer, Fong and Wu (2012)). Moreover, HFT occurs when a big market order is sent out to the market, and the order gets divided by a smart order router among all exchanges that list the underlying traded security or portfolio (Foucault and Menkveld, (2008)). The closest exchange in geographical distance fills part of the order, and simultaneously an HFT firm catches the signal and races to cancel their matching orders (i.e. sell orders if the market order of the counter financial institution is a buy order) from other exchanges. HFT is also known and documented to increase trading volume which highly compensates market makers (Boehmer, Fong and Wu (2012)). The HFT firms then buys shares at a lower price and sell the rest of the market order at a higher price (Katsuyama, (2016)). This process, as Brad Katsuyama addresses in a public presentation takes about 2 milliseconds before the order reaches from the first to the last stock exchange in terms of proximity or location. However, it would only take the HFT firms that caught the order, 476 microseconds (millionth of a second) to race to other exchanges. Brad Katsuyama while working at Royal Bank of Canada (RBC) found a way to counter the effect of HFT firms by slowing the fastest connections through sending orders to the farthest stock exchange first and to the closest exchange last. Another approach would be to search for counterparties to settle large trades via "dark pools", which are hidden markets that can settle transaction without hitting exchanges (Bessembinder and Venkataraman (2004)). The technique of countering HFT firms is out of the scope of the paper but is worth mentioning how limited technological institutions can cope with AT on a big scale to limit their opportunity costs.

On the other hand, individuals using computerized trading that are located far from stock exchange data center's or have limited algorithms capacity in executing fast and sophisticated trades strategies use LFT rather than HFT.

[Please insert Figure 2 here]

3.AT and Liquidity issues:

AT no doubt increases liquidity among market players, but that role is not consistent on all trading days. HFT firms step out of the market when trading becomes costly for them (Boehmer, Fong, and Wu, (2012)). Some instances are related to low priced stocks, small market cap traded shares or have high volatility are considered unrewarding to AT using HFT. However, for large stocks, AT reduces the bid-ask spread which in turn reduces cost of trading such stocks and price discovery (Hendershott, Jones and Menkveld, (2011)). In addition, Hendershott, Jones and Menkveld (2011) statistically presented, in their paper, how AT lowers the cost of trading and increases price discovery.

The literature on algorithmic trading in any market, especially the US stock market is not yet fully exploited to an extent works cited can appear more frequently in several studies that precede them. Furthermore, each study adheres to the importance of AT on liquidity in exchange markets, but two opinions are present in defining the importance or the manipulation of AT and liquidity issues. Chaboud, Chiquoine, Hjalmarsson and Vega (2012) show that AT has small yet positive impact on market liquidity. They also suggest that AT facilitates more efficient price discovery through eliminating triangular arbitrage and incorporating faster macroeconomic news to traded assets' prices. The latter part is explained by sentiment analysis which screens news from credible sentiment datasets and is tailored into an algorithm. The sentiment scores in the dataset can be very viable with respect to their credible sources and provoke AT to react much faster to news then human traders. This transparency helps induce trading liquidity through the efficiency in price discovery. In addition, in the next objective the paper addresses, the notion of how macroeconomic news or sentiment incorporates to stocks traded in the US equities, is explained and an observation is presented of how an approximate 7-day delay in sentiment affects a stocks price with respect to the stock's moving averages. However, this observation does not suggest that stocks prices will always follow a martingale process.

Kozhan and Wah Tham (2012) show that algorithmic traders executing simultaneous trades causes a crowding effect, which deviates prices away from fundamentals. This also suggests that traded assets don't always reflect sentiment since sentiment scores are based on fundamental news such as earnings, dividend payouts, stock splits or public offering and the such. In a similar viewpoint other authors argue that AT hinders liquidity since it has negative effect on price informativeness due to the common AT strategies and the common trigger signal of such strategies (Jarrow and Protter (2011)). The trigger signal is validated through the addressed HFT framework presented by Brad Katsuyama at a public presentation in 2016, which was discussed in the previous section. Thus, in the following section, both concerns have been isolated by discussing a LFT algorithm design theory based on a new strategy that reflects the soundness of the anchor bias theory and the impact of the overall market news on each of the underlying stocks chosen for that purpose. The anchor bias theory is as stated earlier, suggests that investors are anchored to the long term MA (Avramov, Kaplanski and Subrahmanyam (2018)).

4. LFT Strategies:

A more convenient way to implement AT by limited technology and proximity users, is LTF that can be modeled by quant traders, experienced programmers and financial institutions with adequate technological capabilities. HFT is measured in milliseconds and microseconds and is optimized via proximity to data centers of stock exchanges, however, LFT is in minutes to seconds and is augmented based on a design theory The LFT algorithm can be based on filtering from the whole stock market special preferences such as the most liquid securities in the top 95 percentile or the largest market capitalized stocks, for example. An algorithm is coded in a back-testing engine to develop a return/risk metric that match a trader’s strategy. The program can be linked to an interface on a broker’s platform, through an artificial programming interface (API) after the strategy is tested and ready for live trading.

Algorithms implementing LFT can be done on special back testing platforms. Since the focus of the paper is on US equity market, the quantopian platform is the most relevant back testing engine. After choosing the platform, data should be accessed easily, such as daily closing prices, market cap, volume and other attributes that stocks are traded based on. Quantopian is a free open source company that gives free access to financial market data and free back testing services. The third part of the LFT is the design theory. The design theory can be separated into three parts that range from technical indicators such as moving averages, machine learning techniques and sentiment analysis (Roy and Nayeem, (2015)).

Technical indicators have had the most attention in the past years in forecasting future trends of prices. Moving averages (MA) are the most used indicators in perceiving price changes. A new research that viewed MA in a new perspective, were only two moving averages are used, the short term 21-day MA and the long term 200-day MA and the spread between them is an indicator of shorting or longing a stock. The research showed that investors always underreact to fundamentals and future price trends based on the rationale anchoring theory (Avramov, Kaplanski and Subrahmanyam, (2018)). Avramov, Kaplanski and Subrahmanyam (2018) build their theory on investors underreaction to price changes in stock using different return models, investment time horizons and factor models. Investors underreaction to the moving average distance (MAD) is the source of return in the strategy. They suggest that this is the case since most investors rely on easily accessible information to make investing decisions which can sometime be irrelevant. The anchor bias, as they name it, is when these investors start to deviate from the 200 Day MA, due to news on their underlying asset (Tversky and Kahneman, (1974)). In addition, the research ends in concluding that when the spread between the short-term MA and long-term MA is large and positive (21-day MA above 200-day MA) positive sentiment impacts on price to go up while negative sentiment has minimal impact on the price to go down due to investors anchoring to the lower long-term MA. Whereas in a negative spread (200-day MA is above 21-day MA) bad sentiment (i.e.: negative earnings surprises, sell recommendation announcements, and seasoned equity issues) impacts more on price drifting down while positive announcements have less invoke on the price since underreaction is minimal. This technique can be used to construct a LFT algorithm on a single stock or portfolio of stocks through examining how returns are rewarding in such a strategy. An algorithm concept will be presented to reflect the soundness of implementing technical indicators approach in the overall strategy.

Another technique that can be used to build an LFT algorithms, is machine learning. This approach is fed a large sample of data, in our case is historical market prices (time series) and the algorithm will learn how to ride the volatility (price fluctuations) of the data after being trained for an adequate amount of time. Machine Learning techniques require time before initial investment to learn the pattern in mimicking and beating the market represented by an index (Roy and Nayeem, (2015)). On the quantopian platform, the index is the Spyder (SPR) ETF(Exchange Traded Fund) index that replicates the S&P 500 market index. An advantage that different machine learning techniques delivers is that it rides market volatility after being trained as stated earlier. In a study, using three approaches to forecasting security prices, Roy and Nayeem (2015) show via the quantopian platform, that MA have rewarding profits at first but lag in the end and vice versa for machine learning. However, in their research paper, Roy and Nayeem (2015) conclude a combination of sentiment analysis and machine learning have the most rewarding return/risk framework. Sentiment analysis, scores rich viable texts from the Sentdex database accessed through quantopian platform and delivers appropriate buy strategy for scores above 3 and sell signal for scores under -1. Whereas, the machine learning technique will prevent exposure to risk (Roy and Nayeem 2018).

Several AT strategies have shown quiet rewarding return compared to risk. This paper proposes an LFT based on the anchoring bias theory and MAD factor in Avramov, Kaplanski and Subrahmanyam (2018) paper. Sentiment analysis is a critical factor since the total time it takes a human to read one article and derive sentiment, an algorithm can read millions of articles and identify a specific sentiment score or attitude for each security (Aroomoogan (2015)). In addition, the Sentdex free sentiment database version is used to analyze the proposed algorithm model. The importance of Sentdex is that it yields, via a score between -3 and 6, rich but also relevant information through articles published by credible sources such as Wall Street Journal, CNBC and Forbes... To illustrate both approaches in the proposed strategy, four active stocks are chosen for the simplicity of the model. The stocks are Nasdaq, Apple, Facebook and Amazon. These stocks differ in market cap, volatility and to an extent in liquidity but the scope is to address an observed strategy through an empirical study that can be further expanded in the future.

The time span of the observation is 2 months, from 30/07/2018 till 01/10/2018. Quantopian research notebook is used as the workspace for research since it provides direct access to securities historical prices and historical sentiment scores timestamped for each day of the underlying security.

For each stock, after historical closing prices are obtained, the 21-day MA and the 252-day MA are graphed to represent respectively the short term and long-term MA. The distance between the MA is positive (negative) when the 21-day MA is above (under) the 252-day MA. Then the sentiment scores and closing prices for the stocks are graphed respectively for the months of August and September 2018. The aim is to observe when does a sentiment impact on the stock's price. The four stocks show that the security's price adjusts approximately 7 days after a given sentiment score. In example, the sentiment scores graph between 11/10/2018-11/14/2018 have an identifiable correlation with the trend of the closing stock prices between 11/17/2018-11/21/2018 for any of the chosen stocks. However, not all stocks react the same to a sentiment score, for instance, Facebook stock has a reversal in the positive spread of the MA where in the month of September the Long-term 252 MA is above the 21 MA. In addition, the positive spread for Nasdaq's MA is converging to zero near the end of the month. As such, negative sentiment has more impact on the price to drop for these two stocks more than positive sentiment has on the price to go up, which is the case in the two stated stocks. On the contrary, the Apple and Amazon stocks, have a large positive spread which indicates that positive sentiment will impact more on the price to go up than negative sentiment impacts on prices to go down.

This validates Avramov, Kaplanski and Subrahmanyam (2018) notion that with positive MA spreads tend to be underpriced while negative MA spreads tend to be overpriced. Figures 3-6 depict the findings and reveal the approximate 7-day delay to adjust to sentiment and how each sentiment score impacts on the stocks prices in respect to the stocks positive (negative) MA spread.

[Please insert Figures 3-6 here]

The observations show that an LFT algorithm can be modeled based on the MA spread and the delay in the impact of the sentiment signal score, which may reflect the change and trend of a stock's price. Thus, a series of conditions are to be set in the algorithm that must be satisfied in order to execute a buy or sell order. One way in implementing such a strategy is using a filter in the back-testing engine (ie. Pipline in Quantopian) to go through all US listed and actively traded stocks and give back stock's with highest spreads in their short- or long-term MA. The stocks with largest positive and negative spreads are selected and added to the portfolio, however the portfolio can be limited to one stock or as many stock's with respect to the constraint the algorithm filter yields. After the stocks are categorized into either a positive or negative MA spread, another filter can be applied based on the capital asset pricing model (CAPM). This step is required to allocate the portfolio weights among the highest alpha stocks or in other words the best performing stocks with respect to the market index, which is the SPR ETF in our case. Furthermore, once the most liquid and highest spread stocks are obtained, the buy or sell strategy will be executed after reading the Sentdex sentiment score 7 days before the market opens on any trading day. If the algorithm read a sentiment score of above 3 and the stock lies in the large positive spread category, a buy order will be executed once market open. Whereas, if the algorithm obtained a sentiment score below -1 for any stock in the negative spread filtered category 7 days before markets open, a sell signal will be executed after 7 days have lapsed. The challenging factor is to incorporate the algorithm to read the sentiment score 7 days prior to executing the orders with respect to the MA spreads.

The algorithm is left with two loose ends that need to be addressed to optimize the efficiency without human intervention. The first is the exit strategy for each order executed to prevent downside risk and exposure to adverse price changes or minimization of profit. A proposed exit strategy is to exit any open position before daily market close in few minutes in order to allow a new valuation of the sentiment score that was registered 7 days previously, before market opens the following trading day. The order execution will follow same routine described earlier. One concern is that exiting daily from an order will minimize profits since the stock will be bought or sold at a different price the next trading. However, this comes with a reward that is captured by the emphasized MA spread and 7-day prior sentiment score which will have the same impact on the stocks price with respect to all the factors mentioned. Profits will be minimized but will be guaranteed based on the anchor bias theory and this paper's 7-day delay findings. In addition, the algorithm evaluates the spread between the MA once per month since the short-term MA is a 21-day MA, reflecting 21 trading days per month. Once the spread starts to decrease below a prescribed threshold, which is passed to the algorithm, the stock is dropped out of it's category and not traded anymore by the algorithm and can be replaced a new stock with a larger spread above the mentioned threshold (the threshold can be above 1.2 for positive MA spreads and below 0.8 for negative MA spreads). The threshold is defined by the 21-day MA over (divided) by the 252-day MA (Avramov, Kaplanski and Subrahmanyam, (2018)).

Although out of the scope of the study, the second issue that needs to be tied down is the portfolio weights which will constitute of longed and shorted stocks. Since the orders are closed and opened daily, the stock's weights are also evaluated daily after the algorithm decides which stock or stocks to include in any trading day portfolio. This criterion is an open-ended constraint that can be based on weights that add up to 1, where the number of longed stocks is twice the number of the shorted stocks. The algorithm can even add up the weights of the longed and shorted stocks to 0, where the same weight of longed and shorted stocks is executed. This criterion is as stated an open-ended constraint that depends on the initial capital and leverage the algorithm will be working based on. However, the higher the alpha value in the CAPM of each stock the higher that stocks weight will be assigned to different stocks in each of the two defined classes (positive and negative spreads).

This is an example of an LFT strategy that can be further addressed with a complete empirical and statistical approach. However, from the small sample of stocks selected, the findings show a design theory for an LFT algorithm to work on in the future.

5. Conclusion:

AT is increasing throughout the whole world, and specifically in the US, which constitutes the largest stock exchanges globally. The emergence of AT is not new but can be at least traced back to the introduction of autoquotes by the NYSE in 2003, which facilitated faster quoting of securities prices (Hendershott, Jones and Menkveld (2011)). AT expands to other markets such as the foreign exchange (FX) and the derivative market, but the scope of the paper focused on a small part of the US equity market. The broad spectrum of AT is linked to the new innovation’s in technology, were the faster firm or trader in light speed measure, is the one with the most advantage.

The paper featured a holistic and unbiased explanation of the two types of AT, which are HFT and LFT. The former executes AT that are dependent on ultra-fast connections to monitor the market quotes and adjust orders accordingly. Whereas, the latter is based on a slower time frame yet still faster than a nonalgorithmic trader or trading floor specialist. LFT focuses on the design theory more than the speed and proximity to data centers, where market orders are relayed.

In the end, the paper addresses a small framework of a design theory to implement a LFT strategy. Four stocks from the US equity market where chosen and studied based on their short rum/long run MA spread and the impact of sentiment signal, derived from a large database (Sentdex), on the stocks prices for a time frame of 2 months. The observation showed a delay of approximately 7 days for a sentiment score to reflect on the stocks price, and how magnitude of impact changes with respect to the stocks MA spread. This study leaves a statistical approach for future implementation and an algorithm to be back tested to check soundness.

Appendix

Figure 1:

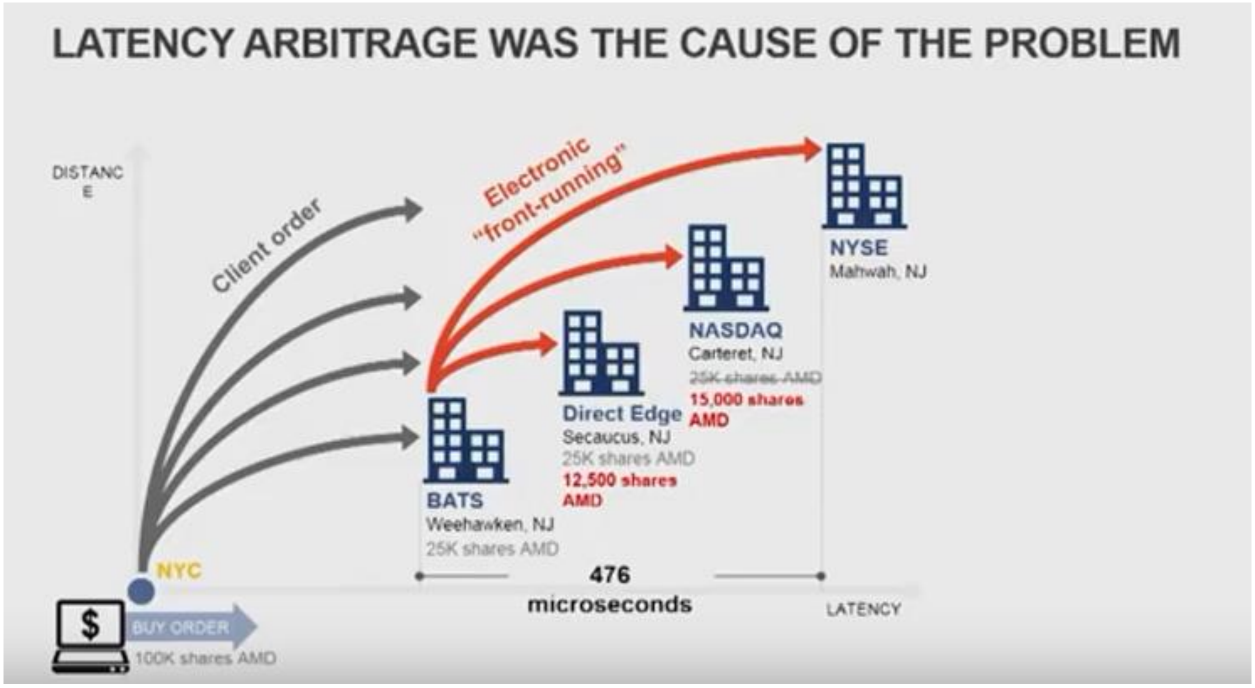


Figure 1: HFT Orders Schema; Katsuyama, Brad. *Brad Katsuyama - The Stock Market had become an Illusion. Brad Katsuyama*. 2016: Youtube, 2016. https://youtube.com/watch?v=0eqqCwhPlyU.

Figure 2:

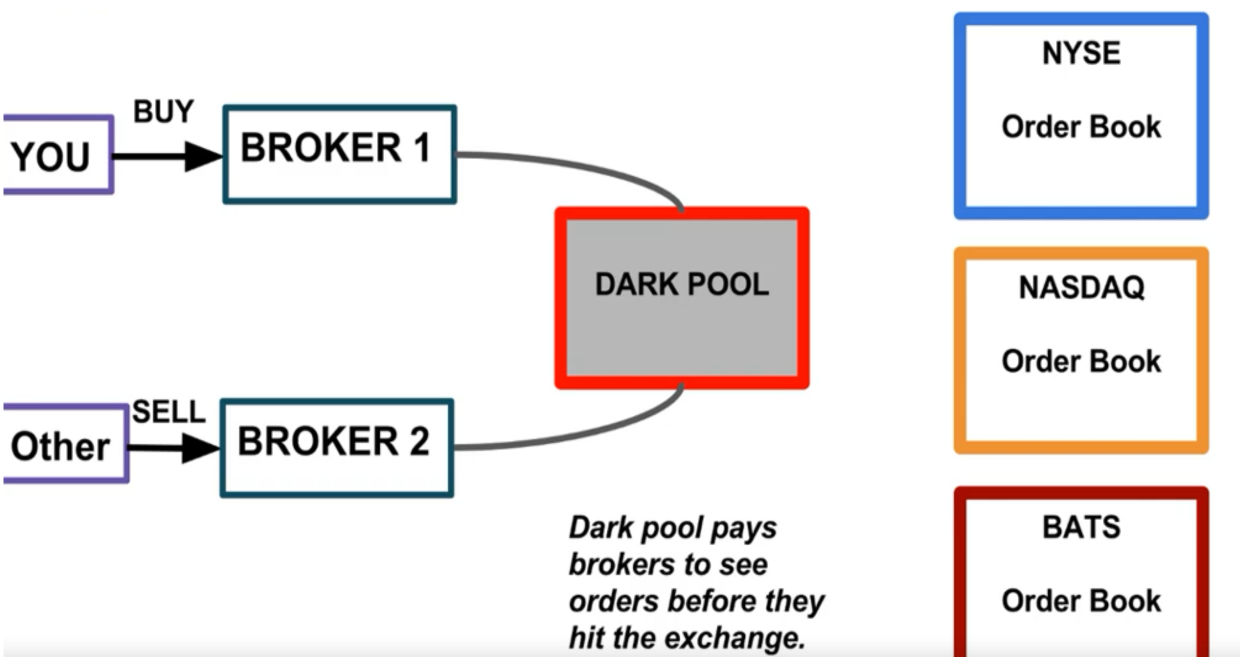
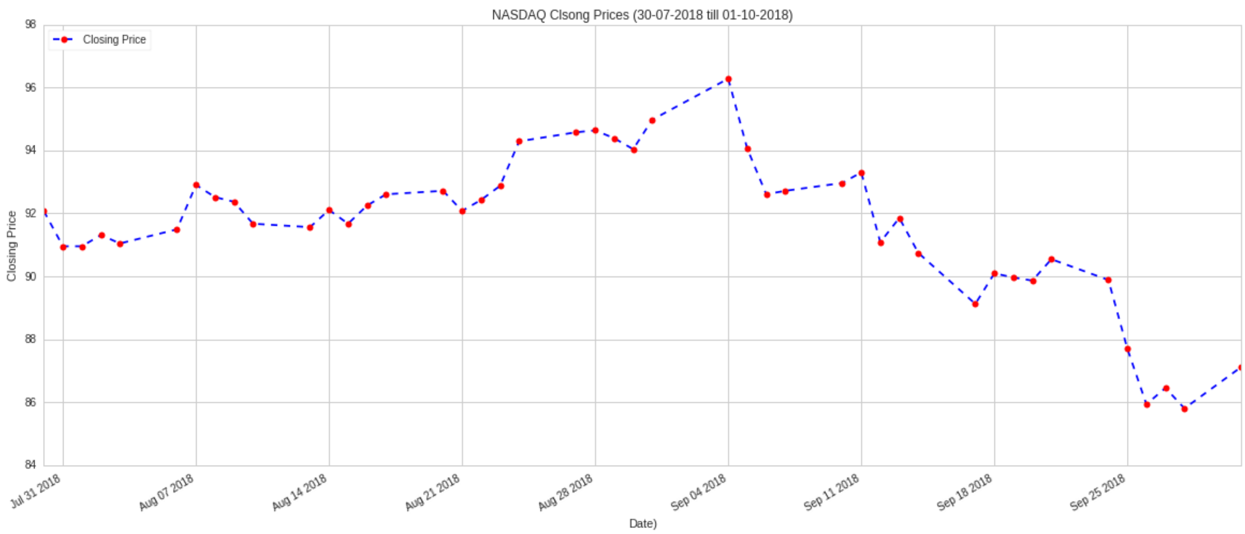


Figure 3: Nasdaq (Time series and sentiment scores graphed using quantopian research IDE notebook)



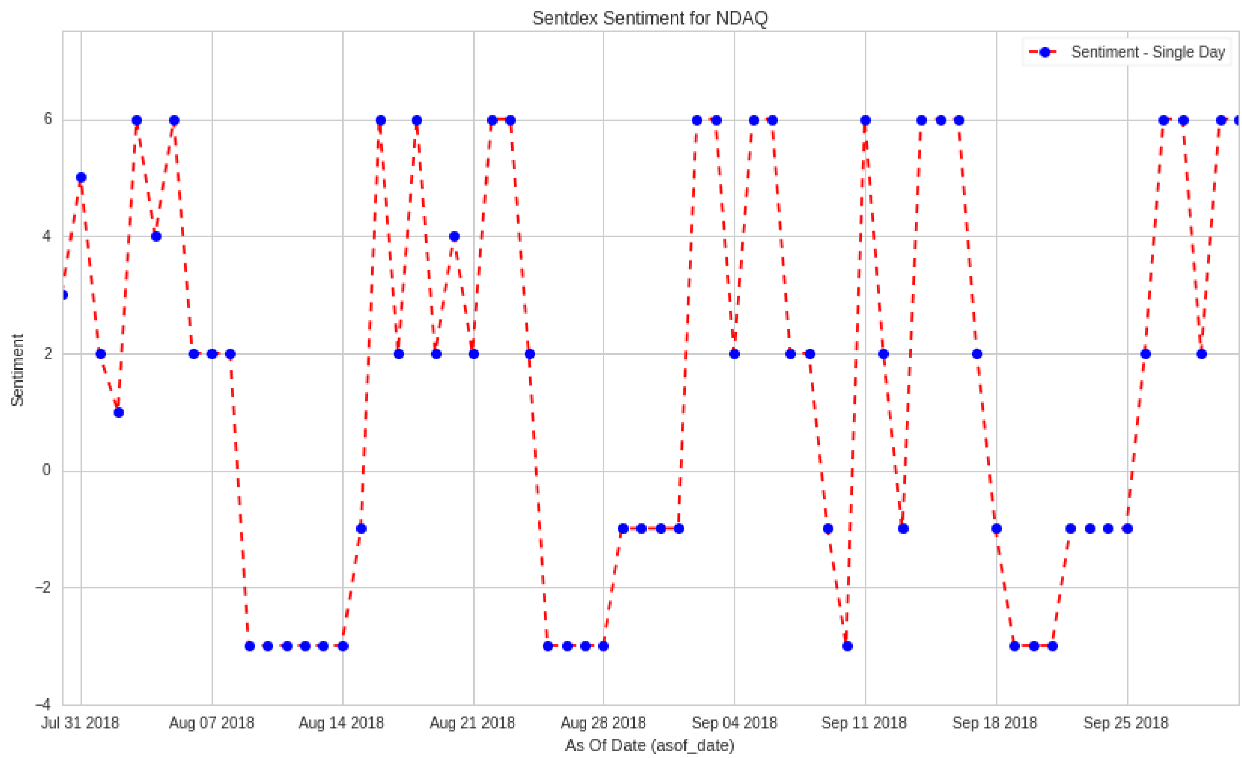


Figure 4: Facebook (Time series and sentiment scores graphed using quantopian research IDE notebook)

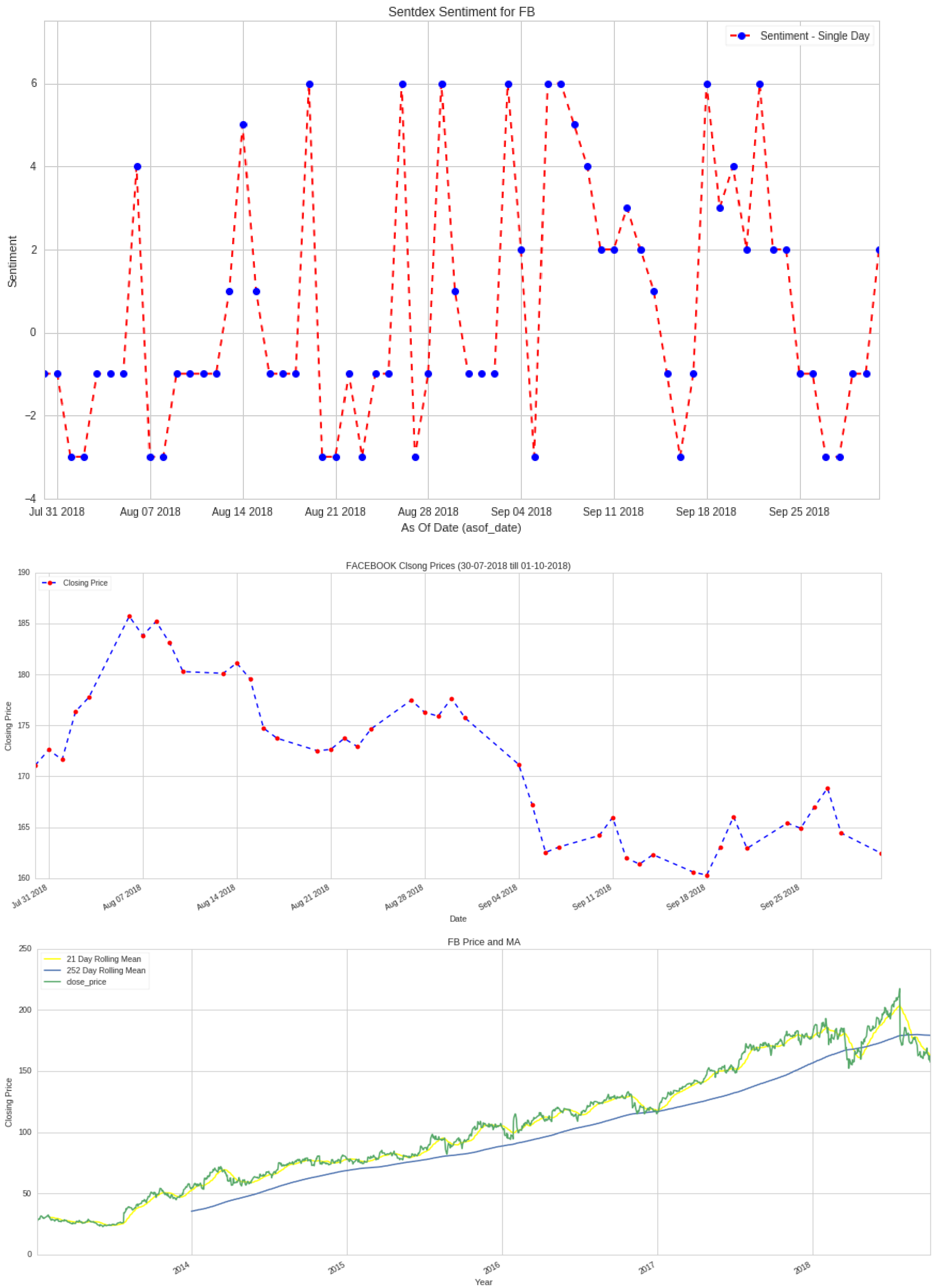
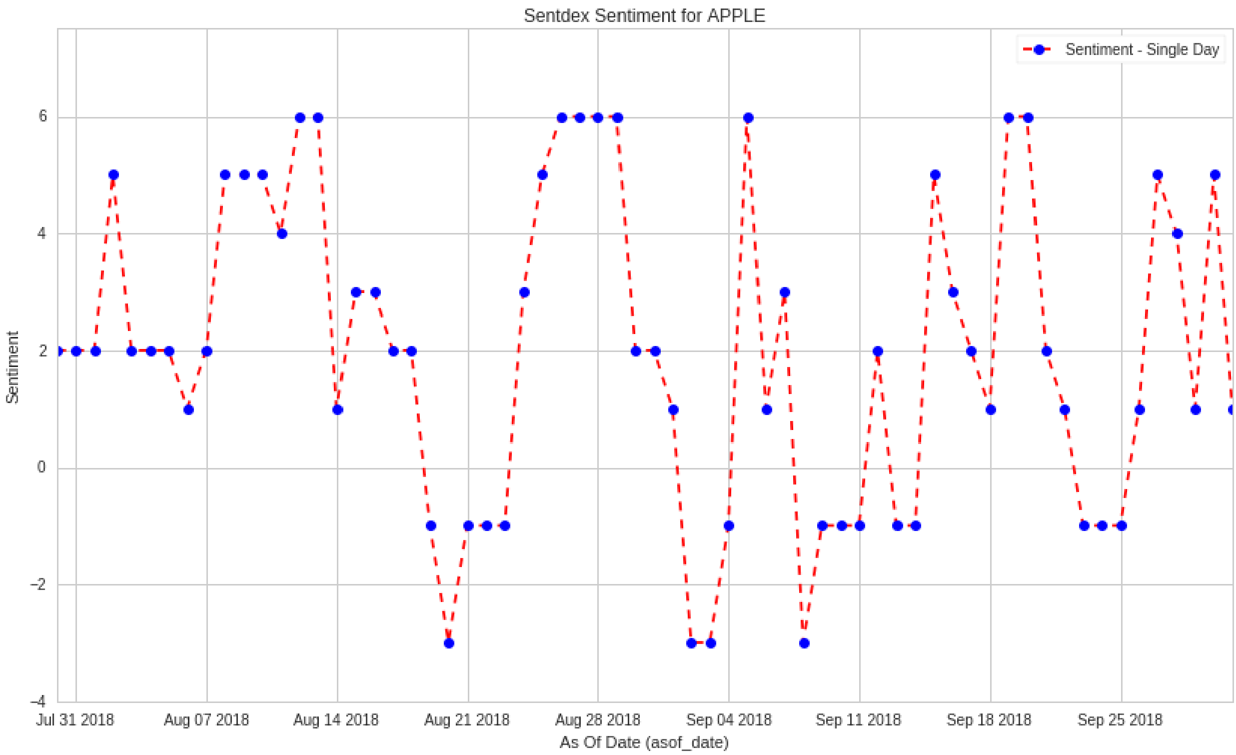


Figure 5: Apple (Time series and sentiment scores graphed using quantopian research IDE notebook)



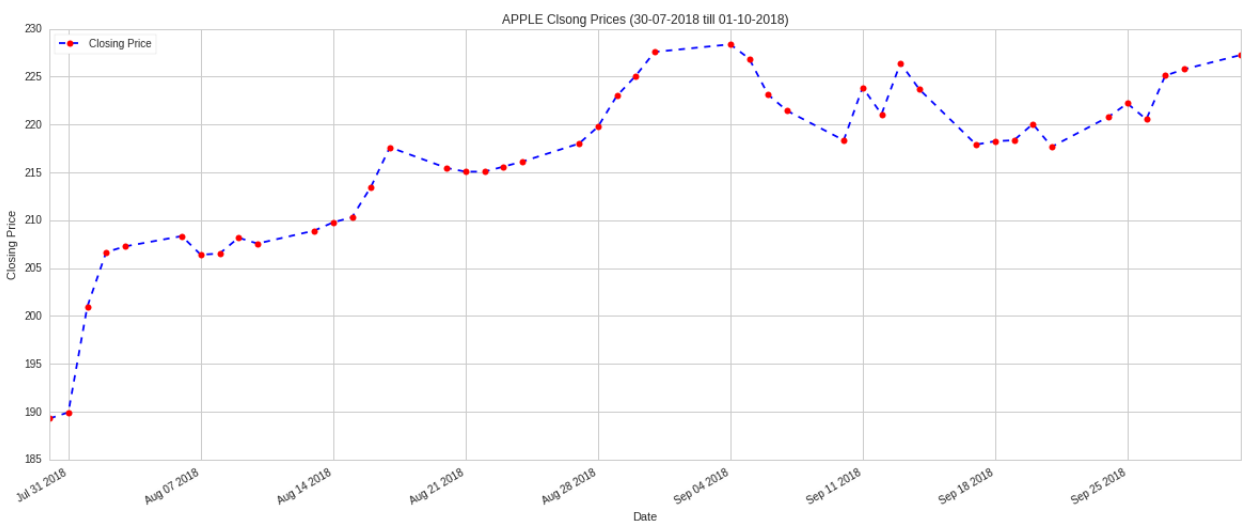
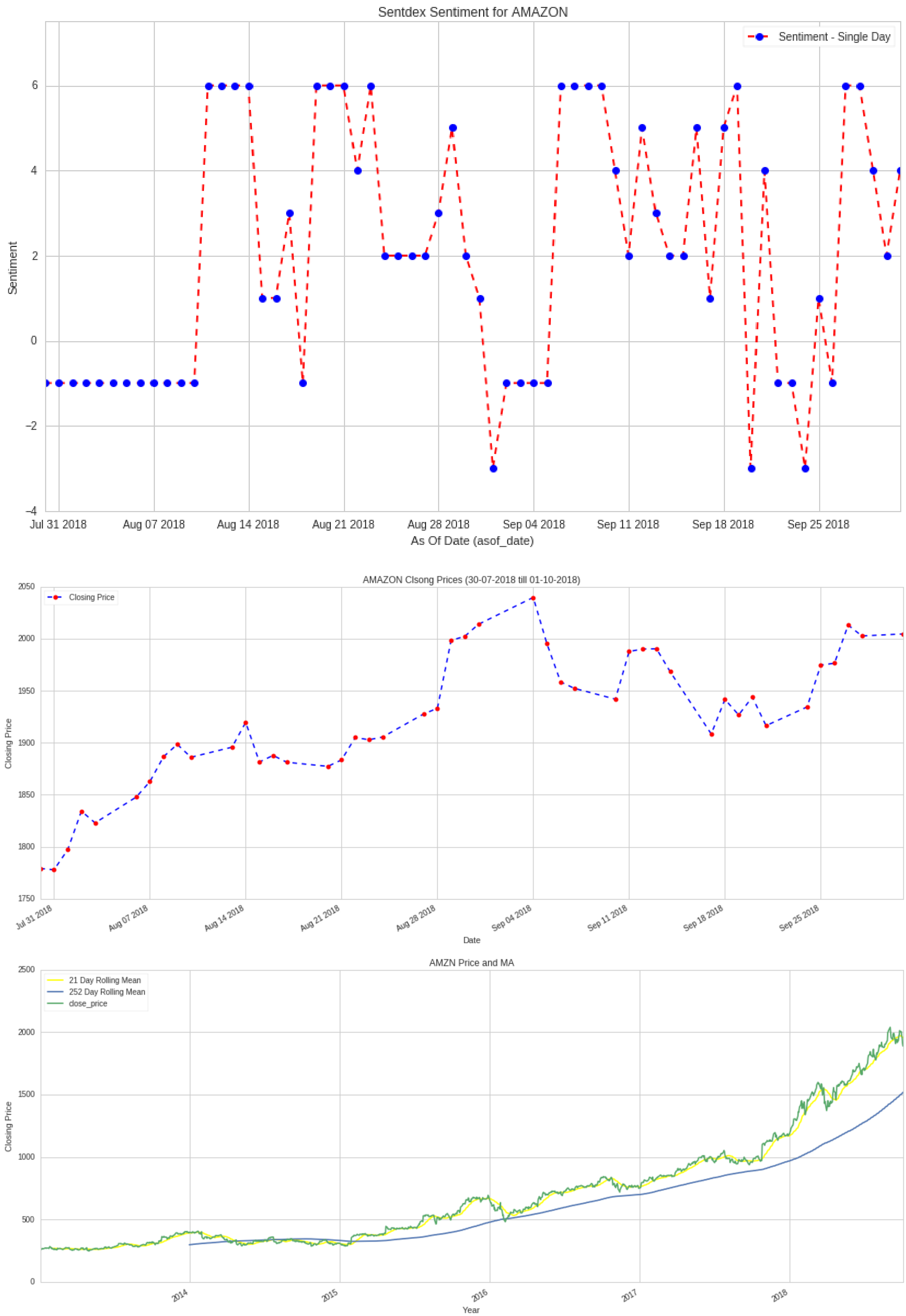


Figure 6: Amazon (Time series and sentiment scores graphed using quantopian research IDE notebook)



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