BETTING ON THE STOCK MARKET

MMA 823 | Analytics for Financial Markets

The intersection of analytics and financial markets

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MMA 823
Analytics for Financial Markets

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Order of files:

Filename	Pages	Comments and/or Instructions
Team Jarvis_MMA 823 Team Project.pdf	16	

Additional Comments:

Please find attached link for the code and model result files related to the project:

https://queensuca-my.sharepoint.com/:f:/g/personal/19udp_queensu_ca/EgU9gLrq15NEo5C2INgxWsMBO1jytBpoNugfjExV5dgceQ?e=uhb7ja

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Business Rationale

Incorporating AI with Investment Management:

Will robots replace human investment managers? As the investment industry rests on the cusp of its greatest technological advancements that are AI and ML, it is important to understand the many ways that AI can be incorporated into Investment Management.

Some of the examples being:

- Arriving at buy or sell decisions based on macro, fundamentals, or market input variables using classification
- Determining sentiment via natural language processing of news, Twitter, transcripts, etc.
- Predicting asset price direction or finding signals from noisy data (e.g., using support vector machines to do supervised classification).

Artificial Intelligence and Human Intelligence Model

AI techniques can augment human intelligence which allows investment professionals to attain higher level of performance. As a result, it enables smarter decision making by alleviating the routine tasks by leveraging the collective intelligence of machines and humans.

Applying AI to predict stock market movement

Accurately predicting a chaotic system like a stock market is next to impossible. But with AI and ML we can try predicting the asset price direction or finding signals from noisy data. It is significant if we can lower the risk of loss and raise the probability of success with Artificial Intelligence and Machine Learning.

Current State of AI application in Investment Management

The CFA institute conducted interviews in March 2019 with investment industry professionals (Equity sell-side/buy-side Analysts, Portfolio Managers, Chief Investment Officers etc.) around the world regarding the use of analytics in their field of work. According to the survey around 95% of the portfolio managers still relied on Excel and desktop market data tools for their investment strategies and processes. On the other hand, very few of them used advanced analytical tools like R, Python and MATLAB. The prevalence of AI/ML techniques in trading strategies is low, according to this survey. As shown in Figure 1 (Appendix), 69% of portfolio manager respondents reported not using any AI/ML techniques for creating trading algorithms in the past 12 months. Those professionals who are using these techniques indicate a wide range of use cases, including arriving at buy or sell decisions based on various input variables (15%), building signals (14%), and determining sentiment based on NLP (10%).

Project Idea

Our team's project idea came largely from the efficient- market hypothesis that states: " share prices reflect all information", which is to mean that newly revealed information about a company obtained through news outlets will directly impact that company's stock price. As a result, we found it intriguing to monitor stock price movement from specific pieces of news releases.

We focused on analyzing a series of company's earnings-related news to predict the direction of stock price movement and ultimately develop investment strategies by leveraging our predictive capabilities on

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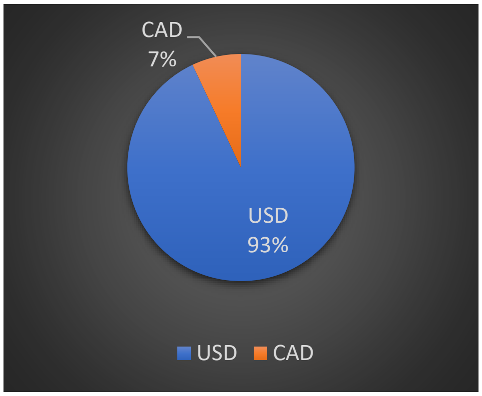
stock movement. Our tool is geared towards helping institutional portfolio managers by granting essential earnings news on specific companies in a matter of minutes.

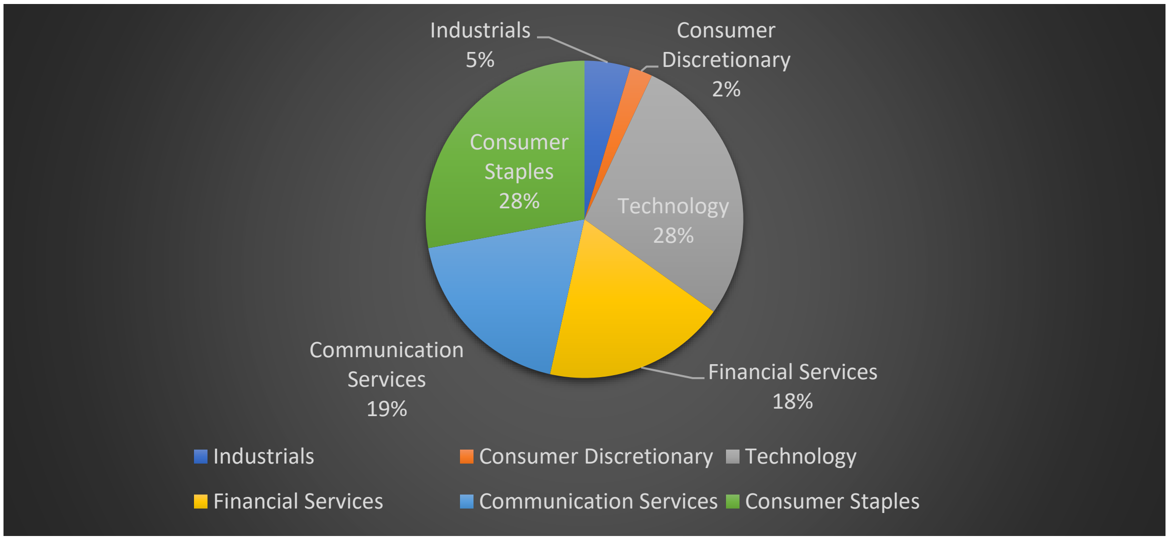
Our project rests on three main pillars to deliver on an outcome. Upon gathering the news items and snippets that pertain to a company's earnings, we then integrate Natural Language Processing techniques to determine the sentiment of the text. Once the sentiment is determined, we can make predictions on the direction of the stock market movement. Lastly, our outcome is to use the predictions along with our investment strategies and apply them to the market to generate profits.

Data Acquisition

Data acquisition for the sentiment analysis was sourced from news outlets, primarily from CNBC. First, 43 publicly traded companies across 24 industries and 6 sectors were identified. Next, for the 43 companies, Q3 2019 earnings reports were gathered from the news outlets. Finally, using Yahoo Finance API, stock prices for each of the 43 stock tickers were gathered for model validation purposes and prices were captured on the day of the news release as well as the following day until the end of Q4 2019.

Currency and Industry Exposure:





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List of Stocks:

Consumer Staples	Technology	Communication Services	Financial Services	Industrials	Consumer Discretionary
BYND	AAPL	DIS	BAC	BA	AMZN
CMG	ADBE	FB	BNS.TO	GE	
DIN	AMD	GOOGLE	C		
GM	DBX	PINS	MA		
KSS	ABM	ROKU	MS		
LOW	INTC	SNAP	POW.TO		
LULU	LYFT	T	RY.TO		
M	MSFT	TWTR	TRV		
NKE	MU				
TGT	QCOM				
TSLA	UBER				
WMT	WORK				

Validation Pipeline

STEP 1 - Pre-processing

In the data preprocessing stage of the model pipeline. The investment earnings news data are collected and read into the pipeline. It is then preprocessed using python regular expression to clean the text-based data, where further Natural Language Toolkit (NLTK) functions and methods are applied.

Within the preprocessing stage, the following character manipulations are performed: Using a combination of steps of finding and replacing characters in the text data, the text feature data is transformed. Python replace functions are applied, along with filtering logic based on regular expression patterns on the data frame to achieve the action required.

```
In [65]: df['Earnings Report'].replace({ r'\A\s+|\s+\Z': '', '\n' : ' '}, regex=True, inplace=True)
         df['Earnings Report'] = df['Earnings Report'].str.replace('\d+', '')
         df["Earnings Report"] = df['Earnings Report'].str.replace('[^\w\s]','')
         df["Earnings Report"] = df['Earnings Report'].str.replace('\s+',' ',regex = True)
```

The preprocessing pipeline then stores the data type as a string and sets all characters to lower case. Next stopwords are removed using the NLTK English stop words and lastly the remaining words are stemmed to resolve the word back to their root forms.

```
In [66]:
from nltk.stem.porter import PorterStemmer
df['Earnings Report'] = df['Earnings Report'].astype(str)
df['Earnings Report'] = df['Earnings Report'].apply(lambda x: " ".join(x.lower() for x in x.split()))
stop = stopwords.words('english')
df['Earnings Report'] = df['Earnings Report'].apply(lambda x: " ".join(x for x in x.split() if x not in sto
st = PorterStemmer()
df['Earnings Report'] = df['Earnings Report'].apply(lambda x: " ".join([st.stem(word) for word in x.split()
```

The following table below describes in further detail the code and actions performed at each of the steps mentioned above in the data preprocessing stage.

Step #	Code	Action Performed
1	replace({ r'\A\s+|\s+\Z': '', '\n' : ' '}, regex=True, inplace=True)	Remove all leading and trailing whitespace at the start or end of a string. Replace newline with a space
2	str.replace('\d+', '')	Replace numeric text (0-9) with space
3	str.replace('[^\w\s]','')	Replace non-word, and non-space characters with space
4	str.replace('\s+',' ',regex = True)	Replace trailing white spaces with only 1-character length white space
5	astype(str)	Convert to string
6	apply(lambda x: " ".join(x.lower() for x in x.split())) stop = stopwords.words('english')	Transform all text to lower case. Remove english stopwords from text string by applying NLTK stopwords
7	apply(lambda x: " ".join(x for x in x.split() if x not in stop)) st = PorterStemmer()	Apply NLTK PorterStemmer() function to resolve words back to their root word format/context

STEP 2 - Sentiment Scoring Model

The VADER sentiment package was used to determine the sentiment of the statements within the investment earnings news data. VADER (Valence Aware Dictionary for Sentiment Reasoning) is a model used for text sentiment analysis that is sensitive to both polarity (positive/negative) and intensity which is nothing but strength of emotion. VADER sentimental analysis relies on a dictionary that maps lexical features to emotion intensities known as sentiment scores.

The preprocessing steps were deliberately minimal, as VADER sentiment requires context found in punctuations (ie. commas, exclamation marks, and periods) along with words within the statements. With the preprocessed and cleansed text data from Step 1. The VADER Sentiment package is then applied to the investment earnings news data. VADER has the unique feature of utilizing 4 sentiment scoring method

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which apply polarity ratios to the likelihood of the sentiment category. Four scores can be determined from this model – Negative, Positive, Neutral and Compound Scores. The Compound score is the score which is computed by normalizing the above scores.

```
In [67]: from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
         analyzer= SentimentIntensityAnalyzer()

In [68]: df['compound'] = [analyzer.polarity_scores(x)['compound'] for x in df['Earnings Report']]
         df['neg'] = [analyzer.polarity_scores(x)['neg'] for x in df['Earnings Report']]
         df['neu'] = [analyzer.polarity_scores(x)['neu'] for x in df['Earnings Report']]
         df['pos'] = [analyzer.polarity_scores(x)['pos'] for x in df['Earnings Report']]
```

Selecting a Threshold Value

Once sentiment scores for all the company's earnings news are determined, the model establishes an appropriate threshold for the compound score to classify overall sentiment of the text in two categories (Negative or Positive).

The threshold set for the model's compound scores are 0.8. If the compound score for a text is greater than 0.8 the model will classify that the earnings report as having a positive sentiment, whereas if the compound score for the text is less than 0.8 the model will classify the earnings report as having negative sentiment. The reason for setting a threshold for the compound score is because the percentage of neutral words in financial texts is very high, thus using this threshold mechanism manages the proportions of positive and negative scores.

```
In [69]: def f(row):
             if row['compound'] > 0.80:
                 val = "Positive"
             else:
                 val = "Negative"
             return val

         df['Sentiment'] = df.apply(f, axis=1)
         df
```

STEP 3 - Investment Strategy

Strategy 1 (Ideal Strategy)

At the third stage, we used the sentiment classification (positive/negative) to determine the direction of the stock price movement. If the sentiment was considered to be positive from the sentiment model, our strategy would be to purchase a long call option of the underlying stocks. If the sentiment was considered to be negative, our strategy was to purchase a long put option of the underlying stocks. (Please refer to Appendix Table 1)

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Investment Strategy for Positive Sentiment Result

Based on the sentiment analysis on companies earning report, a positive sentiment indicates that the stock prices are expected to rise. If the stock prices do rise as expected, then investors will benefit from purchasing Long Call Option.

The profit will be generated by exercising the call option which allows the investor to purchase the underlying shares at a price lower than the market price. Moreover, if the prices move in the opposite direction, investors can choose not to exercise the option and let the option expire. Hence, under this situation, the only loss to investors is the option premium.

Investment Strategy for Negative Sentiment Result

Based on the sentiment analysis on companies' earnings reports, a negative sentiment indicates that the stock prices are expected to fall. If the stock prices do fall as expected, then investors will benefit from purchasing a Long Put Option.

The profit will be generated by exercising the put option which allows the investor to sell the underlying shares at a price higher than the market price. Moreover, if the prices move in the opposite direction, investors can choose not to exercise the option and let the option expire. Hence, under this situation, the only loss to investors is the option premium.

Strategy 2

Since option prices are not easily available on the market due to either thinly traded or opaque records, we decided to implement another investment strategy through which the profit for our model can be calculated. The strategy is to take simple long position in the stock when the sentiment result is positive and short position in the stock when the sentiment result indicates a negative signal.

The detailed strategy and profit metric computed around this strategy will be explained in the next section along with analysis of accuracy matrix. (Refer to Appendix – Table 2)

STEP 4 - Signals for Testing Profit

After Market Movement

The after-market movement of stock price is defined as the price change between next-day opening price (i.e. day after the earnings announcement) and release-day close price.

Next Day Market Movement

On the other hand, the next-day movement is defined as price change between next-day closing price (i.e. day after the earnings announcement) and release-day close price.

Hence, compared with next day-market movement, the testing window for price change on after market movement is shorter. The accuracy matrix is then compared between these two testing signals, in order to determine which testing method of capturing stock movements have better performance.

STEP 5 - Accuracy

Using the above two signals for testing, the sentiment model mentioned above could be compared against real data to validate if the model predicted the direction of the stock movements correctly

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(Positive/Negative). Considering this was simply a classification problem, a confusion matrix was developed for the two testing signals and various evaluation metrics were computed.

**Please Note – As mentioned above since option prices are hard to acquire, we decided to use the [Strategy 2](#) for calculating the Accuracy metrics and Profit metric.

<u>Evaluation metrics:</u>

Accuracy- shows how accurate our model was while predicting the correct classes of TP and TN

Precision- measures of all the "positive" predictions, how many were correct?

Recall/Sensitivity - measures how many true "positives" were correctly predicted to be 'positive'?

F1 Score – Is a combination of precision and recall. In order to have a high F1 Score, both precision and recall must be high

Specificity - Measures how well the classifier is able to detect the "negative" cases

<u>Sample Confusion Matrix</u>

A confusion matrix is a table that compares a models prediction to the truth labels.

		Predicted	
		Yes	No
Actual	Yes	2	2
	No	1	2

**From Stephen Thomas MMA 869 Class Notes*

In this scenario, actual would imply the direction of price movement /strategy that should have been applied based on real aftermarket/next day movement prices whereas predicted is the direction of price movement/strategy determined by the model.

<u>Confusion Matrix for After Market Movement</u>

	Predicted Position was Long (Rise in Prices)	**Predicted Position was Short (Drop in Prices)**
Actual Long Position (Rise in Prices)	19	4
Actual Short Position (Drop in Prices)	14	6

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Accuracy	58%	(TP+TN)/(TP+FP+FN+TN)
Precision	58%	TP/(TP+FP)
Recall/ Sensitivity	83%	TP/(TP+FN)
F1 Score	68%	(2 * Precision * Recall)/(Precision + Recall)
Specificity	30%	TN/(TN+FP)

Confusion Matrix for Next Day Market Movement

	Predicted Position was Long (Rise in Prices)	**Predicted Position was Short (Drop in Prices)**
Actual Long Position (Rise in Prices)	15	5
Actual Short Position (Drop in Prices)	18	5

Accuracy	47%	(TP+TN)/(TP+FP+FN+TN)
Precision	45%	TP/(TP+FP)
Recall/ Sensitivity	75%	TP/(TP+FN)
F1 Score	57%	(2 * Precision * Recall)/(Precision + Recall)
Specificity	22%	TN/(TN+FP)

Clearly it is extremely difficult to accurately predict the direction of the stock price movement and hence the long/short strategy. The sentiment model performed just as well as random guessing. However, when comparing both these testing signals, we can see the aftermarket movement model is better at predicting the stock price movement.

STEP 6 - Profit

Before we deep dive into the profit metric, we will broadly explain the long and short positions theories. Investors maintain long security positions in the expectation that the stock will rise in price in the future. So, having a "long position" in security means that investors own the security at lower price and will sell it at a higher price in order to make a profit. (Refer to Appendix Table 3)

However, a short position is the sale of a stock investors do not own. Investors who hold short positions expect the price of the security will decrease in value and they can buy the stock back at a lower price in order to make a profit. If the price of stock rises and investors buy it back at a higher price, then the investors will incur a loss.

In our project, if the sentiment analysis shows a positive sentiment, we hold a long position to purchase the stock and sell it later; if not, we hold a short position to sell the stock and buy it back later. We then calculated profit for after-market movement and next day movement scenarios.

For example, Stock - PINS:

Stock Ticker	PINS
Sentiment	**Negative**
Check	Correct
After market movement	
BUY/SELL (on the day of earnings)	Sell

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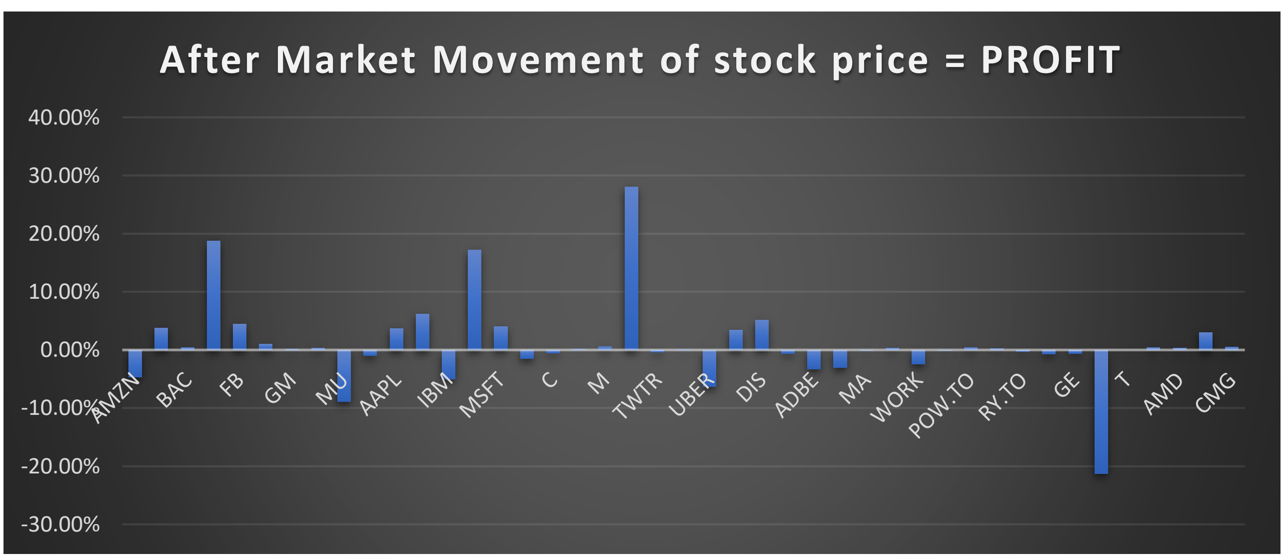
Closing Price on day of earnings report	$25.14
BUY/SELL (Next Day after earnings)	Buy
Opening Price (next day after the news announcement)	$19.63
Profit	**28% = 25.14/19.63 -1**
Next day movement	
BUY/SELL (on the day of earnings)	Sell
Closing Price on day of earnings report	$25.14
BUY/SELL (Next Day after earnings)	Buy
Closing Price (next day after the news announcement)	$20.86
Profit	**21% = 25.14/20.86 -1**

What we can see from this example, since the sentiment is predicted correctly, the profit is generated at a positive way, where the after-market movement profit is much higher than the next day movement profit.

Additionally, the sum of profit based on after-market movement and next day movement scenarios is as follows. When comparing the profit testing signals, we can see the aftermarket movement model is significantly better at generating profit.

	After Market Movement	Next Day Movement
Total Profit	41.72%	2.03%
Average Profit (out of 43 stocks)	0.97%	0.05%

The charts below demonstrate the profit for each stock under both after-market movement and next day movement scenarios:



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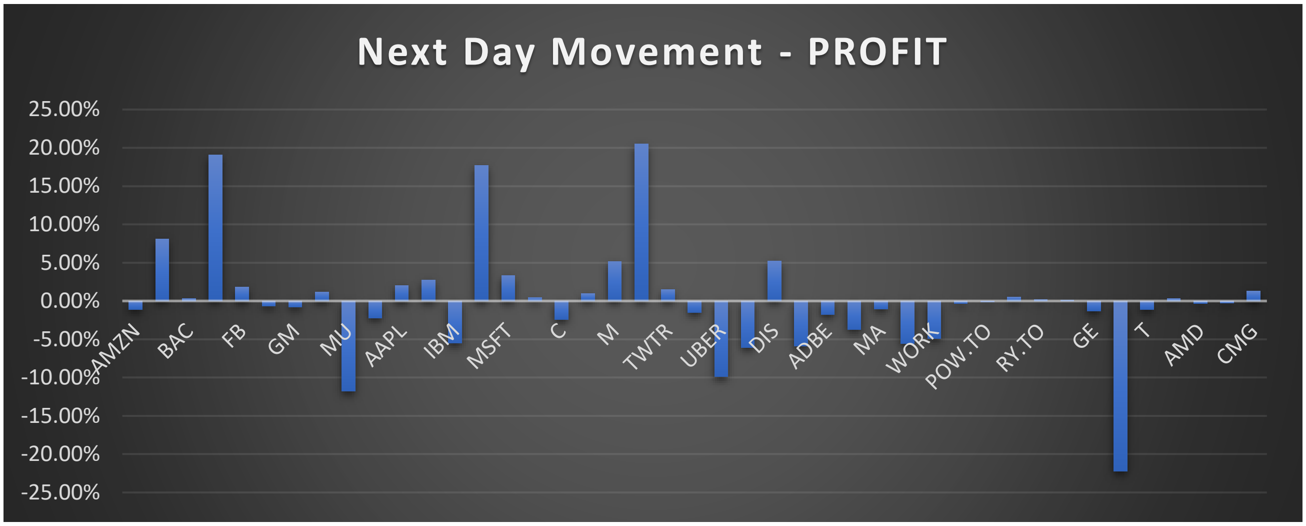

Recommendations

After looking at the accuracy of the model we would recommend not use this model solely to predict the movement of the stock price direction. This model can be further enhanced by adding company's financial ratios like net income, earnings per share, total asset, total equity, total revenue, EPS surprise to predict the direction of stock movement.

Additionally, the NLP model can be enhanced to seek fundamental drivers of future returns before selecting stocks for investment. This model can further be used to analyze the earnings calls by dissecting the language coming from management. The model can be comprised of 4 components; omission (failure to disclose key details), spin (exaggeration from management and overly scripted language), mystification (overly complicated storytelling), and blame (deflection of responsibility). Once the earnings calls are dissected, Machine Learning (ML) can be used to analyze historical earnings recordings relative to a stock's performance (good or bad). The ML can then generate insights like dependability of forecasts of stocks performance on CEO's statements and correlations in performance of firms in the same sector or operating in similar geographies

The sentiment model and options strategy model built by our team are more applicable for institutional investors like pension funds, mutual funds etc. as even a small increase in basis points (bps) for the returns can result into a large magnitude of profit. Additionally, this model is useful for such investors to zip through large amount of earnings in no time.

Lastly, it is recommended for companies to have a streamlined data pipeline. Having systematic ways of getting SEDAR earnings reports, financial ratios and news through API's that are easy to use and free of cost will make the data acquisition task much simpler.

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Appendix

Table 1

Date	Stock Ticke	Industry	Earnings R	compound	neg	neu	pos	Sentiment	Option Strategy
10/24/2019	AMZN	Consumer Discretionary	amazon st	0.9935	0.028	0.779	0.193	Positive	Long Call
10/24/2019	INTC	Technology	intel stock	0.9868	0.022	0.843	0.135	Positive	Long Call
10/16/2019	BAC	Financial Services	bank amer	0.9952	0.01	0.818	0.172	Positive	Long Call
11/6/2019	ROKU	Communication Services	roku stock	0.4767	0.053	0.882	0.065	Negative	Long Put
10/30/2019	FB	Communication Services	facebook s	0.9878	0.032	0.861	0.107	Positive	Long Call
11/20/2019	LOW	Consumer Staples	low wedne	0.9848	0.053	0.832	0.116	Positive	Long Call
10/29/2019	GM	Consumer Staples	gener mot	0.9888	0.105	0.707	0.188	Positive	Long Call
10/23/2019	BA	Industrials	boe report	0.8349	0.084	0.817	0.099	Positive	Long Call
6/25/2019	MU	Technology	share men	-0.7717	0.112	0.793	0.095	Negative	Long Put
10/28/2019	GOOGL	Communication Services	googl pare	0.9957	0.024	0.836	0.14	Positive	Long Call
7/30/2019	AAPL	Technology	appl repor	0.9953	0.035	0.819	0.146	Positive	Long Call
7/31/2019	QCOM	Technology	qualcomm	0.6486	0.05	0.856	0.094	Negative	Long Put
10/16/2019	IBM	Technology	ibm share	0.9823	0.037	0.832	0.131	Positive	Long Call
10/23/2019	TSLA	Consumer Staples	tesla deliv	0.8583	0.065	0.838	0.097	Positive	Long Call
4/24/2019	MSFT	Technology	microsoft	0.9829	0.024	0.844	0.132	Positive	Long Call
11/19/2019	KSS	Consumer Staples	kohl share	0.9948	0.062	0.739	0.199	Positive	Long Call
10/15/2019	C	Financial Services	citigroup t	0.9942	0.032	0.723	0.245	Positive	Long Call
11/20/2019	TGT	Consumer Staples	target earr	0.9949	0.007	0.823	0.169	Positive	Long Call
11/21/2019	M	Consumer Staples	maci thurs	0.9423	0.084	0.786	0.13	Positive	Long Call
10/31/2019	PINS	Communication Services	pinterest s	0.7506	0.046	0.85	0.104	Negative	Long Put
10/24/2019	TWTR	Communication Services	twitter sha	0.7269	0.044	0.896	0.06	Negative	Long Put
10/22/2019	TRV	Financial Services	share trav	-0.34	0.11	0.799	0.091	Negative	Long Put

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Table 2

Date	Stock Tick	Industry	Earnings F	compoun	neg	neu	pos	Sentim	Strategy
2019-10-24	AMZN	Consumer Discretionary	amazon s	0.9935	0.028	0.779	0.193	Positive	Long Position
2019-10-24	INTC	Technology	intel stock	0.9868	0.022	0.843	0.135	Positive	Long Position
2019-10-16	BAC	Financial Services	bank ame	0.9952	0.01	0.818	0.172	Positive	Long Position
2019-11-06	ROKU	Communication Services	roku stock	0.4767	0.053	0.882	0.065	Negative	Short Position
2019-10-30	FB	Communication Services	facebook	0.9878	0.032	0.861	0.107	Positive	Long Position
2019-11-20	LOW	Consumer Staples	low wedn	0.9848	0.053	0.832	0.116	Positive	Long Position
2019-10-29	GM	Consumer Staples	gener mo	0.9888	0.105	0.707	0.188	Positive	Long Position
2019-10-23	BA	Industrials	boe repor	0.8349	0.084	0.817	0.099	Positive	Long Position
2019-06-25	MU	Technology	share mer	-0.7717	0.112	0.793	0.095	Negative	Short Position
2019-10-28	GOOGL	Communication Services	googl pare	0.9957	0.024	0.836	0.14	Positive	Long Position
2019-07-30	AAPL	Technology	appl repo	0.9953	0.035	0.819	0.146	Positive	Long Position
2019-07-31	QCOM	Technology	qualcomn	0.6486	0.05	0.856	0.094	Negative	Short Position
2019-10-16	IBM	Technology	ibm share	0.9823	0.037	0.832	0.131	Positive	Long Position
2019-10-23	TSLA	Consumer Staples	tesla deliv	0.8583	0.065	0.838	0.097	Positive	Long Position
2019-04-24	MSFT	Technology	microsoft	0.9829	0.024	0.844	0.132	Positive	Long Position
2019-11-19	KSS	Consumer Staples	kohl share	0.9948	0.062	0.739	0.199	Positive	Long Position
2019-10-15	C	Financial Services	citigroup	0.9942	0.032	0.723	0.245	Positive	Long Position
2019-11-20	TGT	Consumer Staples	target ear	0.9949	0.007	0.823	0.169	Positive	Long Position
2019-11-21	M	Consumer Staples	maci thur	0.9423	0.084	0.786	0.13	Positive	Long Position
2019-10-31	PINS	Communication Services	pinterest	0.7506	0.046	0.85	0.104	Negative	Short Position
2019-10-24	TWTR	Communication Services	twitter sh	0.7269	0.044	0.896	0.06	Negative	Short Position
2019-10-22	TRV	Financial Services	share trav	-0.34	0.11	0.799	0.091	Negative	Short Position
2019-11-04	UBER	Technology	uber anno	0.8773	0.089	0.772	0.139	Positive	Long Position
2019-10-30	LYFT	Technology	compani r	0.872	0.08	0.787	0.132	Positive	Long Position
2019-08-06	DIS	Communication Services	disney mi	0.7717	0.068	0.837	0.096	Negative	Short Position
2019-10-22	SNAP	Communication Services	snap shar	0.8779	0.084	0.796	0.12	Positive	Long Position

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Table 3

				After Market Movement of stock price = PROFIT					Next Day Movement - PROFIT				
Stock Tick	Industry	Sentim	Strategy	BUY/SELL (on the day of earnings)	Closing Price on day of earnings report	BUY/SELL (Next Day after earnings)	Opening Price (next day after the news annoucement)	Profit	BUY/SELL (on the day of earnings)	Closing Price on day of earnings report	BUY/SELL (Next Day after earnings)	Closing Price (next day after the news annoucement)	Profit
AMZN	Consumer Discretionary	Positive	Long Position	Buy	$ 1,780.78	Sell	$ 1,697.55	-4.67%	Buy	$ 1,780.78	Sell	$ 1,761.33	-1.09%
INTC	Technology	Positive	Long Position	Buy	$ 52.23	Sell	$ 54.19	3.75%	Buy	$ 52.23	Sell	$ 56.46	8.10%
BAC	Financial Services	Positive	Long Position	Buy	$ 30.17	Sell	$ 30.30	0.43%	Buy	$ 30.17	Sell	$ 30.26	0.30%
ROKU	Communication Services	Negative	Short Position	Sell	$ 141.05	Buy	$ 118.75	18.78%	Sell	$ 141.05	Buy	$ 118.46	19.07%
FB	Communication Services	Positive	Long Position	Buy	$ 188.25	Sell	$ 196.70	4.49%	Buy	$ 188.25	Sell	$ 191.65	1.81%
LOW	Consumer Staples	Positive	Long Position	Buy	$ 117.83	Sell	$ 118.99	0.98%	Buy	$ 117.83	Sell	$ 117.02	-0.69%
GM	Consumer Staples	Positive	Long Position	Buy	$ 38.21	Sell	$ 38.26	0.13%	Buy	$ 38.21	Sell	$ 37.91	-0.79%
BA	Industrials	Positive	Long Position	Buy	$ 340.50	Sell	$ 341.70	0.35%	Buy	$ 340.50	Sell	$ 344.55	1.19%
MU	Technology	Negative	Short Position	Sell	$ 32.68	Buy	$ 35.87	-8.89%	Sell	$ 32.68	Buy	$ 37.04	-11.77%
GOOGL	Communication Services	Positive	Long Position	Buy	$ 1,288.98	Sell	$ 1,276.00	-1.01%	Buy	$ 1,288.98	Sell	$ 1,260.66	-2.20%
AAPL	Technology	Positive	Long Position	Buy	$ 52.19	Sell	$ 54.10	3.66%	Buy	$ 52.19	Sell	$ 53.26	2.04%
QCOM	Technology	Negative	Short Position	Sell	$ 73.16	Buy	$ 68.88	6.21%	Sell	$ 73.16	Buy	$ 71.20	2.75%
IBM	Technology	Positive	Long Position	Buy	$ 142.11	Sell	$ 135.00	-5.00%	Buy	$ 142.11	Sell	$ 134.26	-5.52%
TSLA	Consumer Staples	Positive	Long Position	Buy	$ 50.94	Sell	$ 59.67	17.15%	Buy	$ 50.94	Sell	$ 59.94	17.67%
MSFT	Technology	Positive	Long Position	Buy	$ 125.01	Sell	$ 130.06	4.04%	Buy	$ 125.01	Sell	$ 129.15	3.31%
KSS	Consumer Staples	Positive	Long Position	Buy	$ 47.02	Sell	$ 46.33	-1.47%	Buy	$ 47.02	Sell	$ 47.22	0.43%
C	Financial Services	Positive	Long Position	Buy	$ 71.22	Sell	$ 70.82	-0.56%	Buy	$ 71.22	Sell	$ 69.50	-2.42%
TGT	Consumer Staples	Positive	Long Position	Buy	$ 126.43	Sell	$ 126.58	0.12%	Buy	$ 126.43	Sell	$ 127.65	0.96%
M	Consumer Staples	Positive	Long Position	Buy	$ 14.67	Sell	$ 14.75	0.55%	Buy	$ 14.67	Sell	$ 15.43	5.18%
PINS	Communication Services	Negative	Short Position	Sell	$ 25.14	Buy	$ 19.63	28.07%	Sell	$ 25.14	Buy	$ 20.86	20.52%
TWTR	Communication Services	Negative	Short Position	Sell	$ 30.75	Buy	$ 30.87	-0.39%	Sell	$ 30.75	Buy	$ 30.30	1.49%
TRV	Financial Services	Negative	Short Position	Sell	$ 130.15	Buy	$ 130.07	0.06%	Sell	$ 130.15	Buy	$ 132.16	-1.52%
UBER	Technology	Positive	Long Position	Buy	$ 31.08	Sell	$ 29.13	-6.27%	Buy	$ 31.08	Sell	$ 28.02	-9.85%
LYFT	Technology	Positive	Long Position	Buy	$ 44.11	Sell	$ 45.63	3.45%	Buy	$ 44.11	Sell	$ 41.44	-6.05%
DIS	Communication Services	Negative	Short Position	Sell	$ 141.87	Buy	$ 134.93	5.14%	Sell	$ 141.87	Buy	$ 134.86	5.20%
SNAP	Communication Services	Positive	Long Position	Buy	$ 14.00	Sell	$ 13.91	-0.64%	Buy	$ 14.00	Sell	$ 13.18	-5.86%

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Python Code – Sentiment Model

Please note the python code for the Sentiment Model and Python code which we used to pull prices from Yahoo Finance is saved at the below location:

ONE DRIVE LINK:

https://queensuca-my.sharepoint.com/:f:/g/personal/19udp_queensu_ca/EgU9gLrq15NEo5C2INgxWsMBO1jytBpoNugfjExV5dgceQ?e=uhb7ja