Masters of Technology

Project Report

Sentiment analysis of new media to predicting stock returns

TEAM MEMBERS

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Contents

1. Background

The Efficient Market Hypothesis (EMH) states that stock prices are efficiently valued at any given time in a highly liquid market to reflect all available information. However, several studies in the field of behavioural finance have contradicted this hypothesis and shown that various psychological factors also influence investor decisions.

One of the key ideas of behavioural finance is to study the herd behaviour, where financial decisions are informed by the majority of the herd. Increasingly, people rely on social media for news and information, and it has become a common medium to express opinions on financial markets.

The underlying belief is that social media influences investor sentiment, which in turn drives financial decisions and affects the stock price movement. Predicting the stock returns based on the sentiment can help investors make more informed decisions in the financial markets.

2. Objective

New media sentiment provides valuable insights for investors. These computer-driven readings of the social media mood can analyze huge numbers of posts while sifting out unreliable information. With sentiment analysis on new media Stocktwits & Twitter, the aim of this project is to develop conversational UI to provide stock movement from transaction date t up to t+5 investment advisory to the investors.

The github link for the project is at https://github.com/vidur6789/lucy-fin-bot. Our Chatbot name in telegram is LucyLewBot.

3. System Architecture

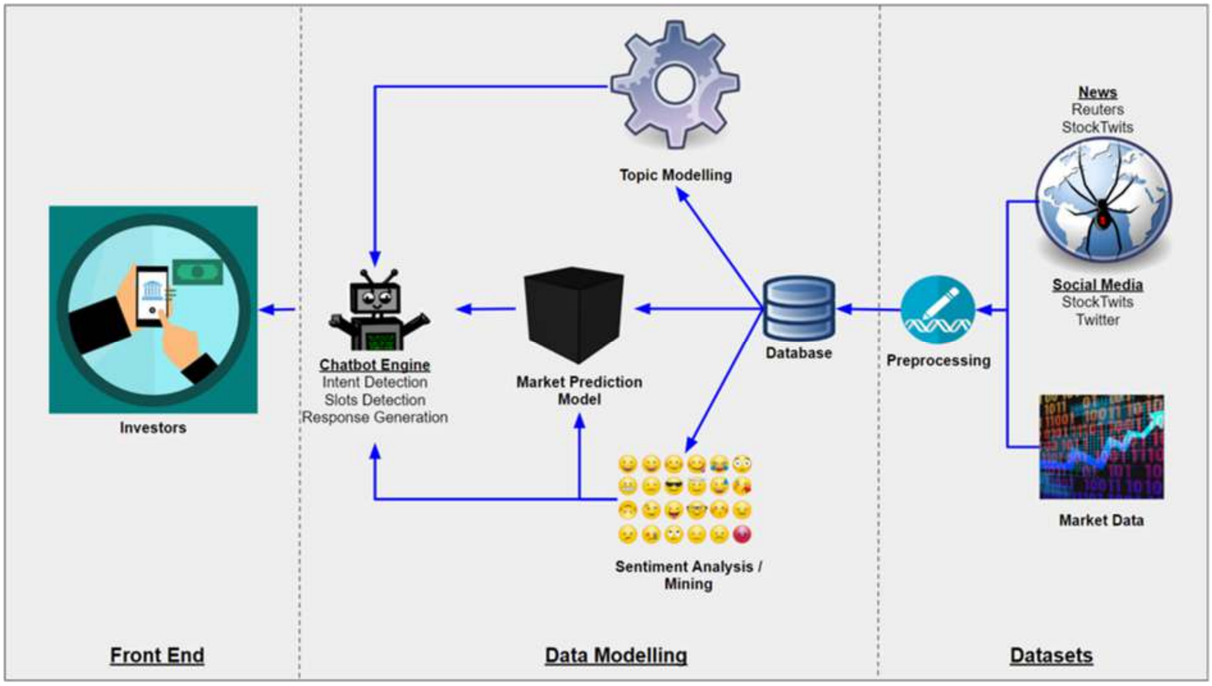


Figure 3-1: System Architecture Diagram

• Datasets

In datasets, the team has already retrieved social media posts and news articles related to financial markets for offline analysis. In this part, Data cleaning, pre-processing would be done.

• Data Modelling

In data modelling, there are three parts would be done:

- classify the posts into positive and negative sentiment to find underlying emotions of investors
- Predict the short-term stock price movements based on sentiment score and attention attributes such as no of likes, retweets, followers on new media
- Engine chatbot to process the intent detection, slots detection and response generation

- ## Front End

In front end, the model has been deployed in the form of chatbot in telegram. When a user enters a message related to the designated stocks in telegram, the chatbot would return stock movement and investment advisory to the user.

4. Data Understanding

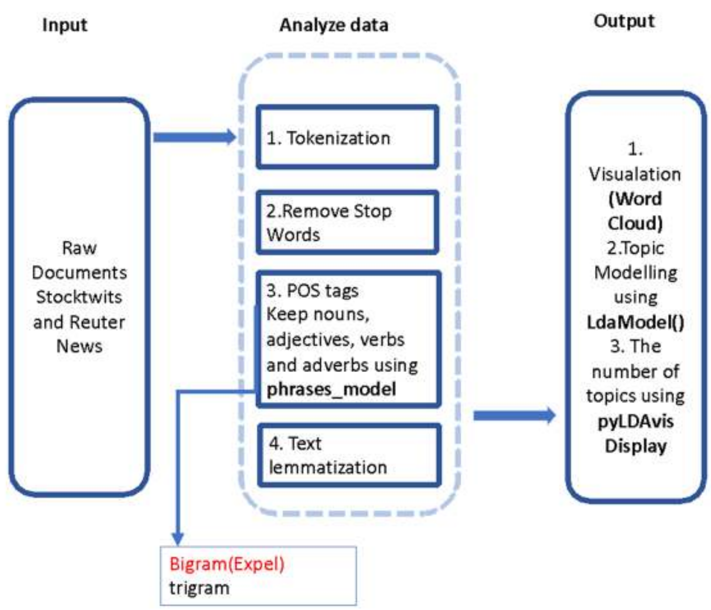
Focusing on ten tech stocks as below table shown, we collected text data of financial news articles from Google New and posts from two social media platforms (Twitter and StockTwits).

S/N	Company Name	Symbol
1	Apple	AAPL
2	Google	GOOGL
3	Facebook	FB
4	Amazon	AMZN
5	Microsoft	MSFT
6	Alibaba	BABA
7	AMD	AMD
8	Intel	INTC
9	Tesla	TSLA
10	Twitter	TWTR

5. Topic Modelling

The Topic Modelling aims to provide investors an insight of news in Stocktwits and Reuter News through key words. The chatbot would return the trending topics related to the specific company when investors enter keyword: trending news/topics + company name. The details of the topic modelling would be described in this section.

5.1 Trending news/topics processing pipeline



In the analysis part, Comparing top 10 common bigram and trigram words in Stocktwits and Reuter respectively, trigram words has more meaning in terms of whole context. Figure 5-1 and figure 5-2 shows the top 10 common bigram and trigram words in Stocktwits.

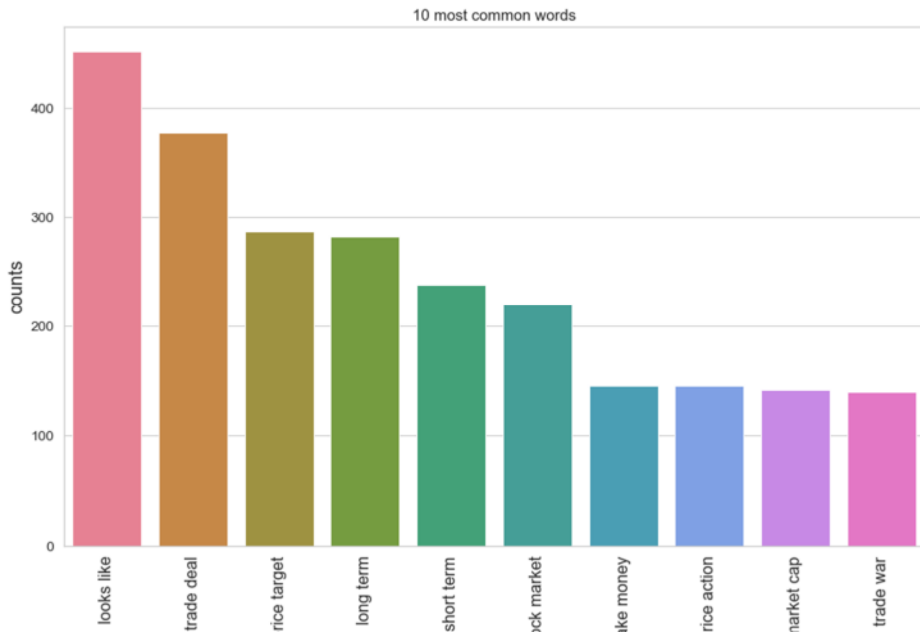


Figure 5-1: Top 10 common bigram words for words for Stocktwits

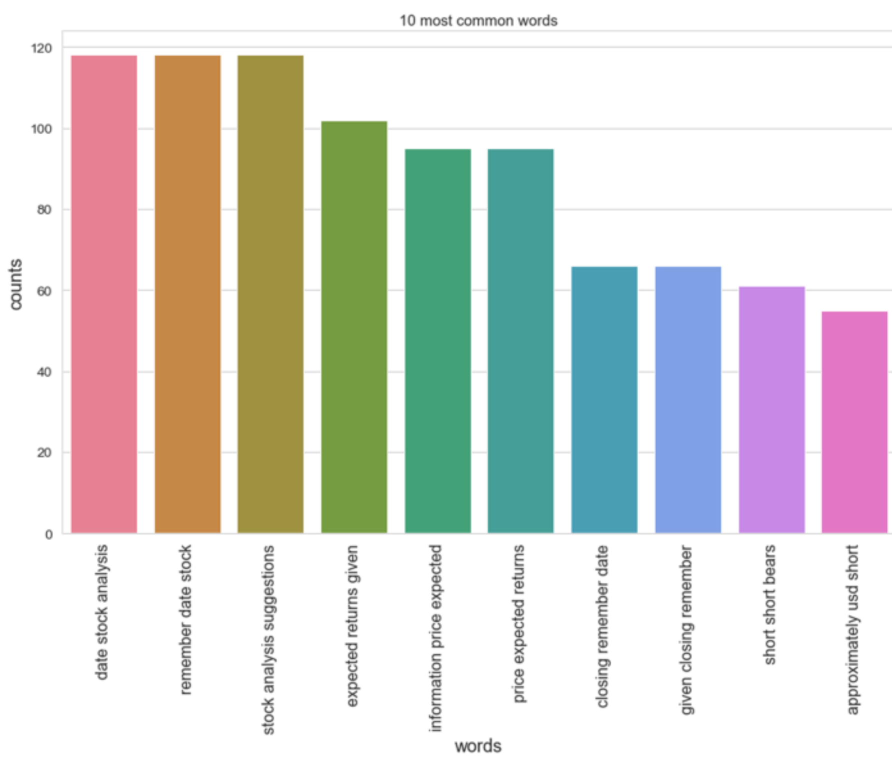


Figure 5-2: Top 10 common Trigram words for Stocktwits

5.2 Visualisation - Wordcloud

Wordclouds are generated for both Stocktwits and Reuter News dataset to note the most recurrent terms in the document as figure 5-3 and figure 5-4.

Figure 5-3: WordCloud for Stocktwits trigram dataset

Figure 5-4: WordCloud for Reuter News trigram dataset

5.3 Trending news/Topics

The topic numbers are 3 for in both Stocktwits and Reuter.

When we have 4 topics for Stocktwits as figure 5-5 shown, we can see certain topics are clustered together, this indicates the similarity between topics. Hence we have selected the 3 topics as figure 5-6 for our dataset.

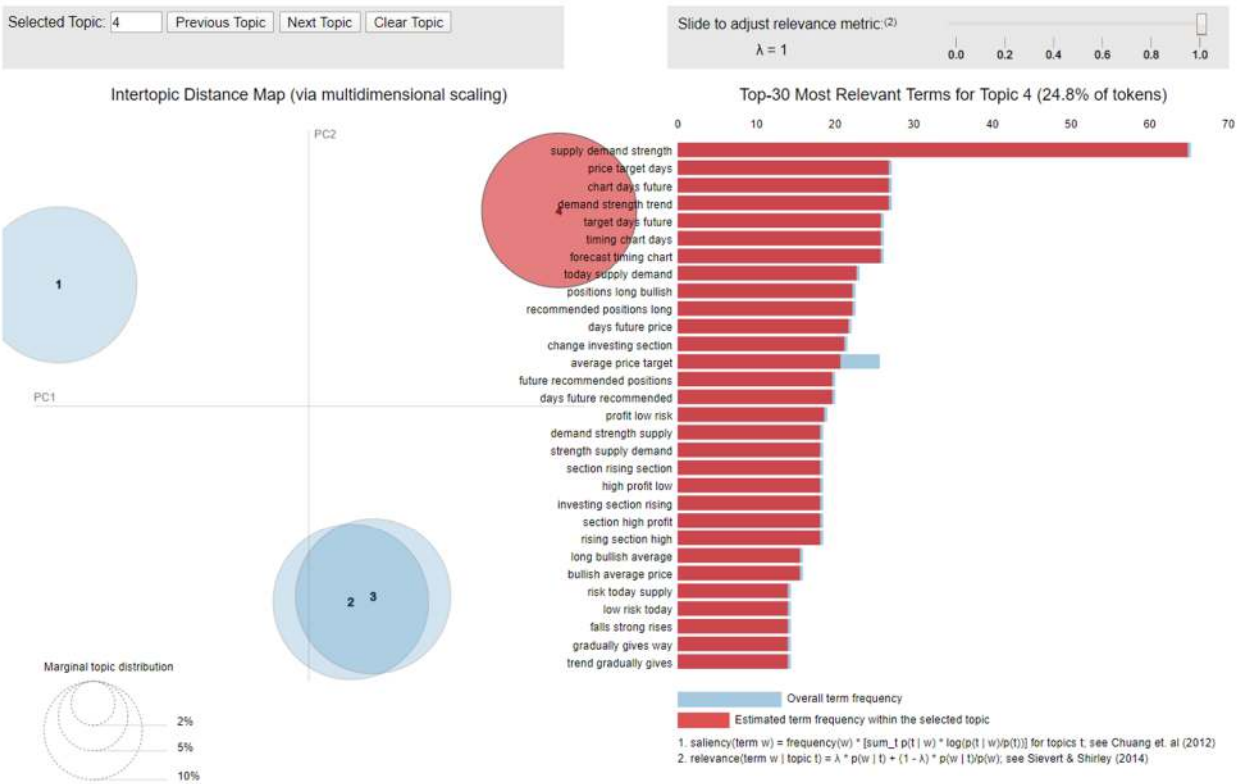


Figure 5-5: pyLDAvis Display for Stocktwits trigram with 4 topics

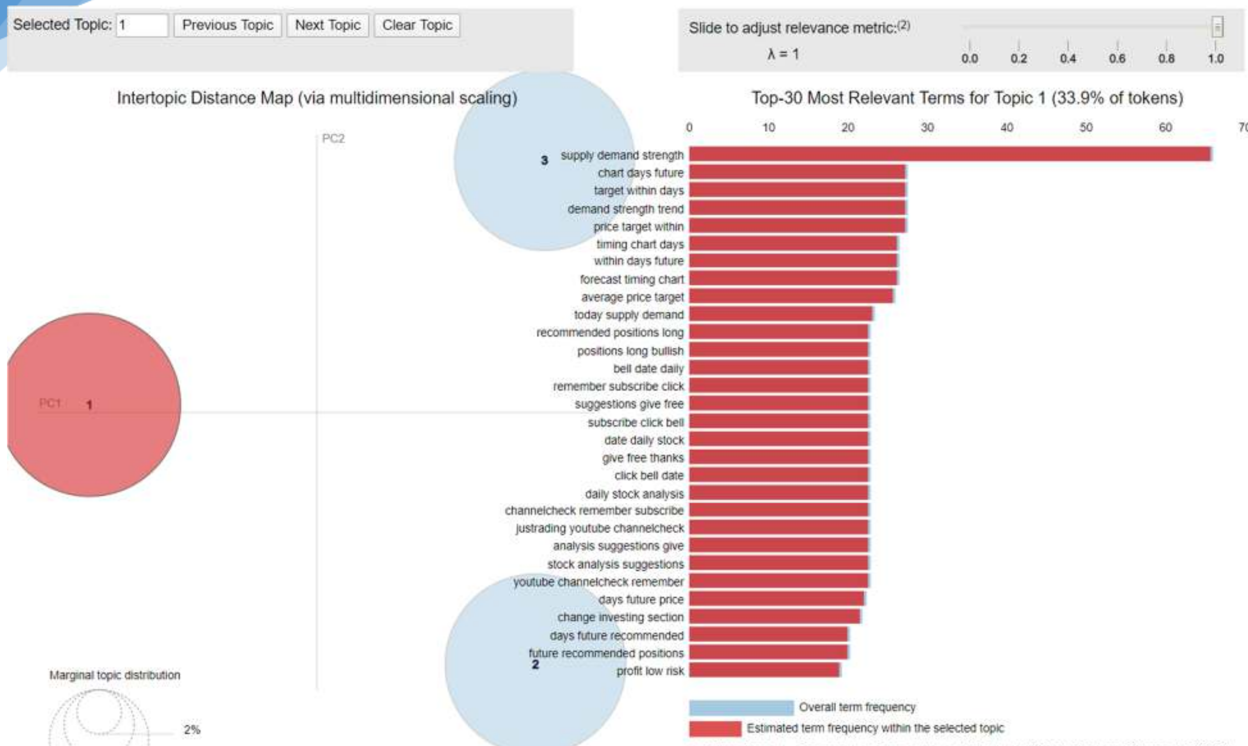


Figure 5-6: pyLDAvis Display for Stocktwits trigram

In Stocktwits, the topics are related to the supply, demand in the market, price and price charts recommendations/targets Electric cars, tech revolution, Trump, trade deal as figure 5-6 and figure 5-7 shown.

Figure 5-7: Stocktwits 3 topics Trigram wordcloud

In Reuter, the topics are related to the economic, recession, business, market, forecast as Figure 5-8 and figure 5-9 shown.

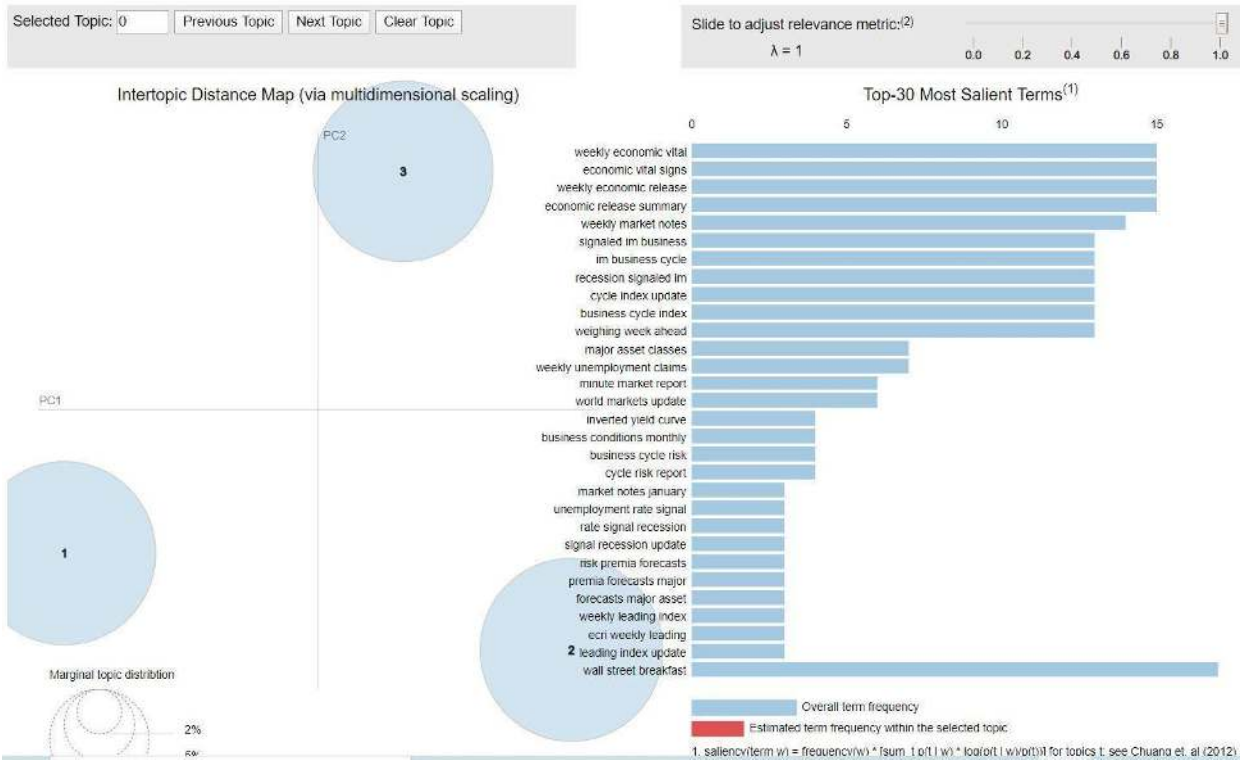


Figure 5-8: pyLDAvis Display for trigram for Reuter News

Figure 5-9: Reuters 3 topics Trigram wordcloud

6. Sentiment Classification

The project classifies the posts in twitter and Stocktwits related to stock market into two market sentiments **Bullish and Bearish** using various machine learning techniques and finding their effectiveness on providing sentiment.

6.1 Dataset

Training set:

1. 1,308 labelled sentiment Twitter data from the GitHub site "twitter-stock-sentiment : Stock market sentiment analysis using twitter" :

   link: https://github.com/poojathakoor/twitter-stock-sentiment
2. for Stocktwits data, 46,289 out of 135,026 are labelled and hence are used

Test set:

1. 66,257 unlabelled one-week Twitter data as shown in Figure 6-1

```
Number of tweets for $AAPL is 7690
Number of tweets for $goog is 1573
Number of tweets for $FB  is 3414
Number of tweets for $amzn is 5203
Number of tweets for $MSFT is 2799
Number of tweets for $baba is 1697
Number of tweets for $AMD is 2447
Number of tweets for $intc is 3370
Number of tweets for $tsla is 19973
Number of tweets for $dia is 1496
Number of tweets for $spy is 12895
Number of tweets for $twtr is 1804
Number of tweets for $vix is 1896
```

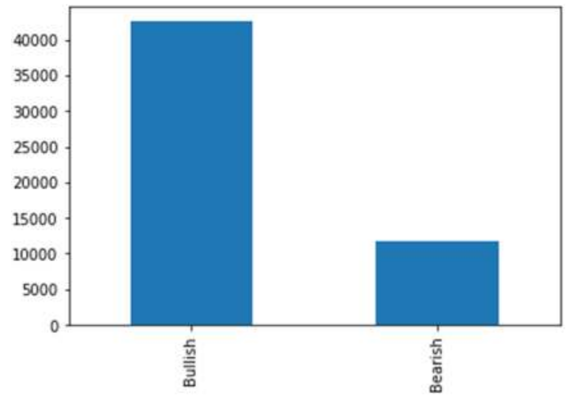
Figure 6-1: Twitter Data collected

88,737 out *of* 135,026 unlabelled Stocktwits data

6.2 Imbalanced Classification

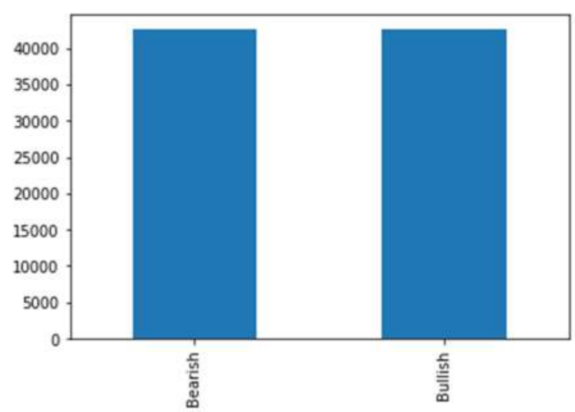
The sentiment classes **Bullish and Bearish** in the **training set** have a highly unequal number of samples as table 6-2 shown. Primarily, two approaches were explored in this project to deal with imbalance in the classes:

1. Random Sampling with Replacement
2. Synthetic minority over-sampling technique (SMOTE)



Tabel 6-2: Balancing Classes

Experimenting with the two approaches of balancing classes showed that both approaches worked equally well in improving precision and recall metrics over the minority class as compared to using the imbalanced data. As a result, random oversampling with replacement was chosen to evaluate the different classification techniques discussed in the subsequent section. Therefore, it can be assumed for the rest of the report that all classification models were evaluated on this balanced dataset.



Tabel 6-3: Balancing Classes

6.3 Classification Methods

In this project, several classification methods were experimented with to classify the sentiments of social media posts related to financial markets. These methodologies have been discussed in more detail in this section.

3a. Machine Learning Methods on TF-IDF

The baseline approach used in this project utilised tf-idf features to generate the document term matrix. These features were then fed into a variety of machine learning models to compare the performance across different methodologies. Naive Bayes, Logistic Regression, K-nearest neighbour and Support Vector Machine. Each of the mentioned machine learning models were optimised using GridSearch and cross validation to get the most reliable estimate of model performance. The results are shown in Figure 6-5.

3b. Deep Learning on one-hot encoding

The social media posts were each encoded using one-hot vector strategy such that the feature values indicate the presence of a given word. Since neural networks can work as universal function approximators, these features were then trained to **predict the sentiment label with a sequence of dense layers.** The optimal architecture was obtained by experimenting with different numbers of layers, hidden neurons in each layer and optionally introducing dropout layers. Figure 6-4 shows the architecture of the feedforward neural network used to compare with other approaches. This model was trained using binary cross-entropy as the loss function and Adam as the optimizer for back-propagating errors.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 64)                2240064
_________________________________________________________________
dense_2 (Dense)              (None, 32)                2080
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_3 (Dense)              (None, 256)               8448
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_4 (Dense)              (None, 2)                 514
=================================================================
Total params: 2,251,106
Trainable params: 2,251,106
Non-trainable params: 0
_________________________________________________________________
```

Figure 6-4: Feedforward Neural Network architecture

3c. Deep Learning on Word2Vec

The third approach mentioned here used Word2Vec feature encoding to predict the sentiment. The word vectors were obtained using a pre-trained language model from the NLP library spacy. Each social media post was transformed into a sequence of vectors, where each vector represented a word in the semantic space of the English language. The sequence of vectors were aggregated into a single vector by taking the mean. Similar to the previous approach, these features were then trained using a sequential feedforward neural network model consisting of multiple Dense layers. Binary cross-entropy and Adam were selected as the loss function and optimizer in this case as well. Additionally, bayesian optimization was used to find the optimal architecture and parameters for this model using third party library hyperas.

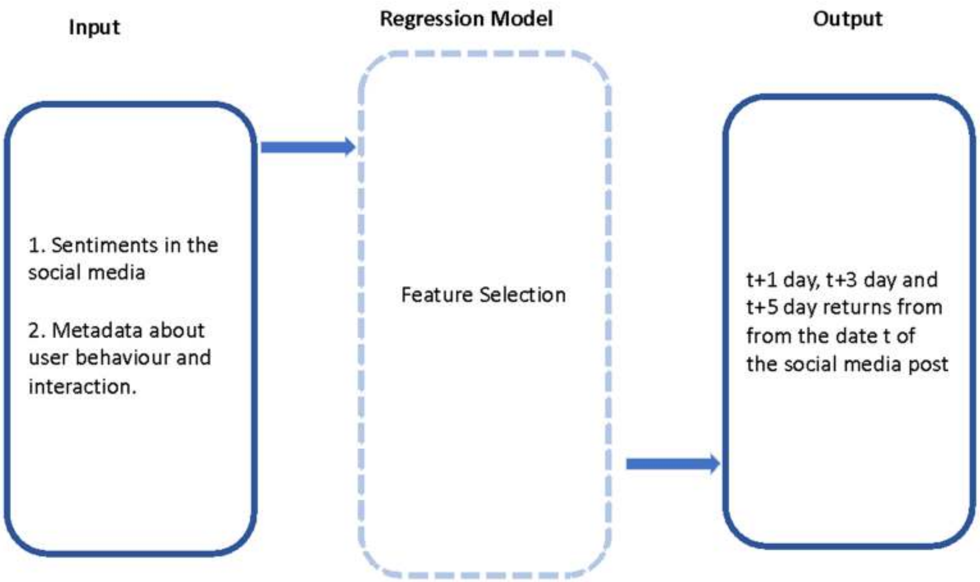
Support Vector Machine (SVM) and deep learning models provide the best results for sentiment classification as Figure 6-5 illustrated.

	Sentiment	**Precision**	**Recall**	**F1-score**	**Support**	**Accuracy**
Naive Bayes	Bullish	79.00%	85.00%	82.00%	7314	81.00%
	Bearish	84.00%	77.00%	80.00%	7285	
Logistic Regression	Bullish	81.00%	81.00%	81.00%	7314	81.00%
	Bearish	81.00%	80.00%	81.00%	7285	
K-Nearest neighbor	Bullish	78.00%	**97.00%**	86.00%	7314	85.00%
	Bearish	**96.00%**	72.00%	83.00%	7285	
Support Vector Machine	Bullish	**98.00%**	94.00%	**96.00%**	7314	**96.00%**
	Bearish	94.00%	**98.00%**	**96.00%**	7285	
Dense Feedforward (one-hot features)						**93.49%**
Dense Feedforward (Word2Vec)						**95.85%**

Figure 6-5: Sentiment Classification results

7. Financial Predictive Modelling

Financial predictive modelling aims to predicting the percentage change of the closing price in stock movement from the date t of the social media post to t+1 day, t+3 day and t+5 day returns. The details of the financial Predictive modelling would be analysed in this section.



○

7.1 Dataset

The dataset used for prediction short term financial returns primarily consisted of the sentiment predicted in the earlier stages of the project. In addition to the sentiment data, the team experimented with additional metadata that captures information about user behaviour and interaction. The output label i.e. near term future returns were generated by fetching closing price data for all stocks from available open source financial market APIs like Tiingo.

The input dataset was grouped by the date of the social media post and the stock symbol. This transformed dataset then calculated aggregate feature values for each of the variables in the dataset. This was done with the reasonable assumption that a single social media post is unlikely to be a significant driver of price movements. Instead, aggregated feature values are more likely to accurately reflect the sentiment in the market.

As alluded to in the previous section, the team experimented with a variety of features to evaluate their predictive power for financial returns. These features have been described in more detail in this section:

1a. Sentiment features:

The sentiment features refer to the bullish and the bearish score calculated from the deep learning model described in the *Sentiment Classification* section. The sentiment scores were aggregated by calculating both the sum and the mean of the scores on the transformed dataset.

1b. User metadata:

These set of features aim to capture some features quantifying the reliability and authenticity of the social media profile using metadata available on the social media platforms. Specifically, this metadata included features about whether the user's social media profile has been verified, number of days since the user joined and the number of social media handles followed by this user.

1c. Attention features:

The idea behind this group of features is to reflect the audience of a given social media post. This included variables such as number of likes, number of followers, number of replies and number of reshares of a given social media post.

7.2 Modelling - Regression and Feature Selection

A simple multi-layer-perceptron was used here to regress the features described above with the generated financial returns. This was modelled as a multi-out regression problem with three output neurons, each corresponding to the 1-day, 3-day and 5-day returns. A multi-output single model approach was chosen over a multi-model single output approach to enable knowledge transfer for predicting multiple outputs. In other words, using a single neural network incentivises the model to learn shared representations of the features that can predict multiple outputs. This can be especially useful in improving generalization in cases where there is limited data such as this project. Similar to previous sections where neural network models were used, hyperas library was used for bayesian optimisation of the network architecture. In this case, the model used mean squared error as the loss function and adam as the optimizer. Figure 7-1 shows the model and Figure 7-2 shows the results of the given model for the variation in features used.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 10)                110
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 55
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 18
=================================================================
Total params: 183
Trainable params: 183
Non-trainable params: 0
_________________________________________________________________
```

Figure 7-1: Regression Model

Features	Mean Squared Error
Sentiment	0.0412
Sentiment + Attention	0.0336
Sentiment + User	0.0476
All features	0.0503

Figure 7-2: Regression Results

The results above in *Figure 7-2* show that sentiment and attention features give the best results for this given dataset.

8. Chatbot Front End (Telegram)

The front-end used in this project is Telegram, one of the most secure messaging services in the world. Telegram has open-APIs which allows chatbot to be implemented and also has readily available wrappers which integrate with codes of different languages.

Telegram bots support bot commands, which allows bot settings to be altered. In the case of our project, we are using bot commands handler to start the bot and also to enter simulation mode to bring us back to past dates to simulate and showcase a proof of concept since the backend engine is not running live to scrape news and active tweets.

We used the Python-Telegram-Bot wrapper as our webhook service to Telegram.

8.1 User Utterance Dataset

To fulfill the knowledge base for slots and intent detection, we manually handcrafted likely utterances that are likely to be asked during a conversation and defined 14 intents to handle Finance Related Information and Advisories. We have also extracted small talk utterances from Google Dialogflow to have a natural interaction and to anticipate smooth flowing back-and-forth conversation. These smalltalk enhances usability and a personality to the chatbot to instill users with a greater sense of connection. By including small talks, the total number of intents extended to 104.

Table in the appendices shows the intents of each Financial Topics and also the sample utterances and responses for detection.

8.2 Intent and Slots Detection

The intent categorizes the user's conversation intent for the conversation turn. It is important for the chatbot to detect the correct intent for each user utterance. In order to correctly answer queries, the accuracy for intent detection is paramount. Therefore, we explore 4 different methods in search of the best classifier to realize this objective.

2a. Logistic Regression & Support Vector Machine

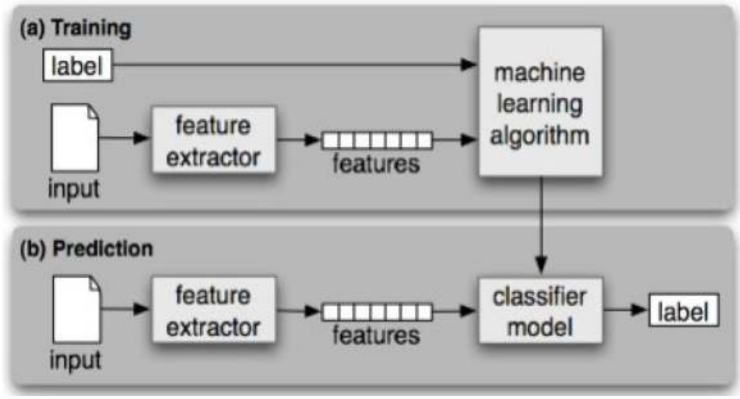


Figure 8-1: Typical Machine Learning Model for Intent Detection

User utterance dataset is first pre-processed and vectorized. Important features are then extracted using the KBest to reduce complexity following the training using Logistic Regression (LR) and Support Vector Machine (SVM) models. The results of LR and SVM methods achieved 82% and 92% on the test samples respectively. However, due to our large sets of intent for this project, misclassification rates are severe and the algorithm fails mostly when we enquire for questions related to the finance topics which utterances are typically similar across the intents. Therefore, we seek a better classification method using Deep Recurrent Neural Network in our next section.

2b. GRU Attention with PyTorch

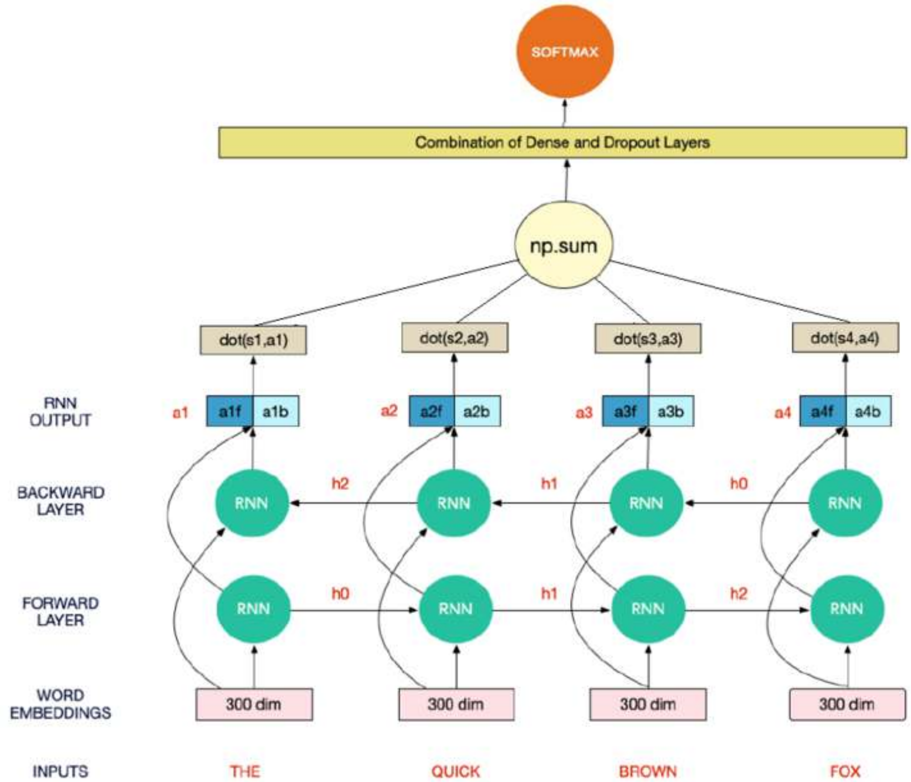


Figure 8-2: Attention Network Diagram

Our project attempts to build an encoder and decoder network with Gated Recurrent Unit (GRU). Simple preprocessing will be done on the user utterance and converted to a one-hot vector. We also denote the Start of Sentence and End of Sentence using the <SOS > and <EOS> tags. To manage robustness to cater for unknown words, we denote a special tag <UNK> for words that is not within the one-hot dictionary.

After conversion, the utterance vector will then be fed into an encoder, compressed into a single vector and then fed into a decoder which returns an output and a hidden state. We then do a batch multiplication between the encoder and decoder key and query vector pairs in the following feed-forward network. This mechanism allows the decoder network to learn and weigh the importance of word relationship within a sentence with regards to the output training labels.

Our trained model achieved performance similar to the SVM model with about 91% accuracy for the same test set.

2c. Multi-Level Intent Detection

To further improve on the detection for intent, we made a final attempt to redesign our intent names and groupings, segregating intents in accordance to the domains and queries at different levels. We build classifiers at different levels creating classification tasks at Macro and Micro scale based on the different groups of intents. (ie. applied algorithm dynamically handles and groups based on intents of specialized domains.) This method proved its superiority compared to the previous methods (Logistic Regression, SVM, Attention) and achieved a 99% classification score on the same test set used on previous methods.

c1. Methodology

We created an algorithm to group and split intent based on the intent naming convention. In this way, the intent detection can be dynamic to adapt to any number of intent added or removed from the utterance dataset. For example, given an intent name "Finance_Predictions_Sentiments_SingleStock", the algorithm would be able to break up based on the '_' symbol. In this way, it also helps to construct a parent-child relationship between each node shown below:

← **Backwards Chaining**

$Finance <-> Predictions \mid Predictions <-> Sentiments \mid Sentiments <-> SingleStock$

Forward Chaining →

Legend:

$Parent <-> Child$: **Parent and Child Relationship**

| : **Separator**

Figure 8-3: Parent – Child Relationship Illustration

By constructing the relationships, we can easily group parents with their children using forward and backwards chaining methods to build into a tree graph as shown in the Figure 8-4 (Finance tree shown in this example, click here for the full tree):

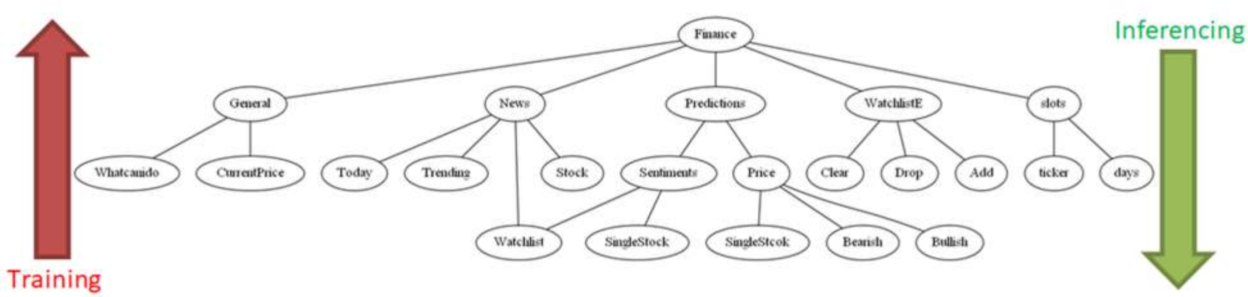


Figure 8-4: Tree Diagram of Finance Nodes, click here for the full tree

Given this arrangement, the algorithm uses backwards chaining to identify nodes of different children with the same parent and automatically groups and trains each parent node with a classifier (SVM in this context) from leaf nodes to root nodes (direction of red arrow). This results in building a total of 17 classifiers for 104 intents, extending from root nodes, Finance and Small talk, to all its leaf nodes.

Inferencing or Utterance Prediction is done on a forward chaining where the user utterance is parsed from the root nodes to the respective leaf nodes by the node with the highest classification score. The path of each node is recorded and concatenated together to form a function string to be called for further actions.

2d. Results and Conclusion

We have observed that the SVM and Logistic Regression algorithm is capable of handling small sets of intent (14 intents) and the performance degrades when more intent is injected.

Attention DNN requires a relatively large utterance dataset for results to be stable. However, we should not take Attention Network results in this project to be conclusive as the DNN is built from scratch without the use of transfer learning. We should expect better results when transfer learning is used as a model learnt on a very large dataset would be able to generalize better.

The Multi-level method achieved an impressive 99% percent accuracy on the test set shown in the Table 8-5.

This showcases the performance of traditional machine learning methods outperforming NLP advanced deep learning (Attention). In addition, training of Attention Networks can be time consuming and resource costly to train a network which in return might not provide a better classification outcome.

Detection of macro and micro scale, re-assigning classification jobs to its lower layer is an intuition from the work organisation hierarchical charts where job is correctly channelled to different teams of experts from a macro to a micro scale. Given that tree-like structure, Multi-level method is advantageous not only because of its high accuracy, but also interpretability and traceability at different spilt of each node to identify misclassification. The quick training times also enabled the suitability of doing hot-reloading of training as intents and utterances change compared to the Attention Network.

	Precision	Recall	F1-score	Support
Multi-Level Support Vector Machine				
Accuracy			**0.99**	437
Macro	**0.95**	**0.94**	**0.94**	437
Weighted	**0.99**	**0.99**	**0.99**	437
Support Vector Machine				
Accuracy			0.92	437
Macro	0.75	0.74	0.73	437
Weighted	0.93	0.92	0.92	437
Logistic Regression				
Accuracy			0.82	437
Macro	0.39	0.38	0.36	437
Weighted	0.77	0.82	0.78	437
RNN - Attention				
Accuracy			0.91	437
Macro	0.71	0.71	0.69	437
Weighted	0.91	0.91	0.89	437

Table 8-5: Intent Detection Classification Score of Various Methods
(Click on each model to see detailed Classification Scores)

8.3 Slots detection

In this project, we utilized the Classic Conditional Random Field to tackle our sequential labelling problem for slots detection and labelling. This model attempts to compute the conditional probability distribution for a sequence of words. Natural Language is full of interrelated grammatical structures, which is known to us. Therefore, in order for machines to understand the language rules and structures, we need to manually include them as features to learn from. This is why pre-processing was first done to include some important features, Part-of-Speech (POS) Tags, uppercase, lowercase and titles, which is linguistically useful for detecting the sequential events within a sentence to identify useful slots.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Utterance	What	is	the	extected	price	movement	for	DOW	Jones	for	the	next	3	days
Slot Label	O	O	O	O	O	O	O	B-Stockname	I-Stockname	O	O	O	B-numberofdays	O
Segment	O	O	O	O	O	O	O	B	I	O	O	O	B	O
POS Tag	WP	VBZ	DT	JJ	NN	NN	IN	NN	NN	IN	DT	JJ	CD	NNS
Lower	N	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	N	Y
Title	Y	N	N	N	N	N	N	N	Y	N	N	N	N	N
Upper	N	N	N	N	N	N	N	Y	N	N	N	N	N	N
Digit	N	N	N	N	N	N	N	N	N	N	N	N	Y	N

Table 8-6: Example of POS tagging and labelling of user utterance

For identifying slot names of multiple tokens, we included a BIO tagging for Beginning of Slots, Inside and Outside to increase the robustness of the model when handling such scenarios.

		Precision	Recall	F1-score	Support
Conditional Random Field					
B-numberofdays		1.00	0.75	0.86	4
B-Stockname		0.99	1.00	1.00	548
Micro	avg	0.99	1.00	1.00	552
Macro	avg	1.00	0.88	0.93	552
Weighted	avg	0.99	1.00	1.00	552
Samples	avg	0.13	0.13	0.13	552

Table 8-7: Slots Detection Classification Score using CRF

This results in a weighted average accuracy score of 0.93.

8.4 Intent & Slot Detection Improvements/Work in Progress:

Due to restrictions in time, we are in the midst of working on a CRF model using attention for both slots and intent detection on a single model (Refer to Figure 8-8). We are looking at creating an attention model for slots output based on the Attention model shown in the table below. We can then use the same attention layer for the intent detection based by including and training a linear layer at the top of the attention layer.

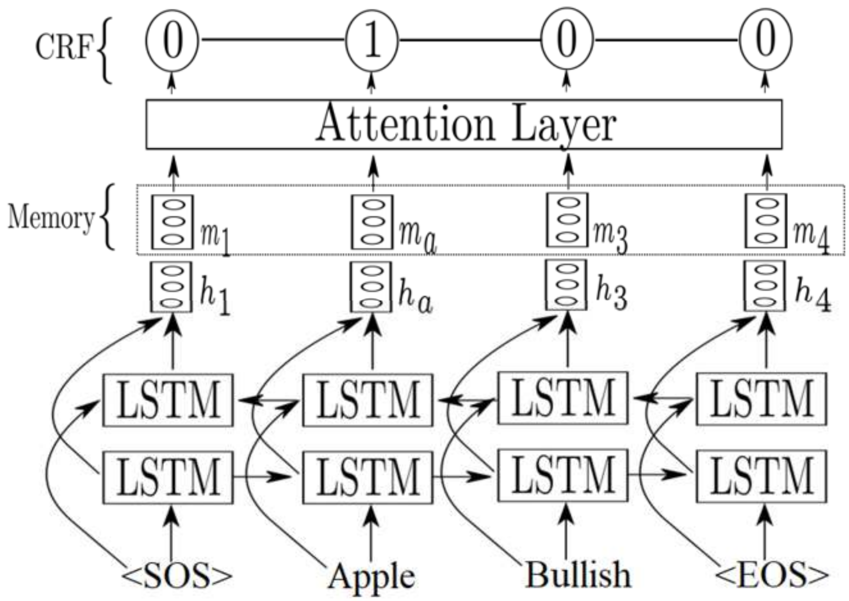


Figure 8-8: Architecture in progress, for Slots detection.
(Diagram omitted using same attention layer for intent detection)

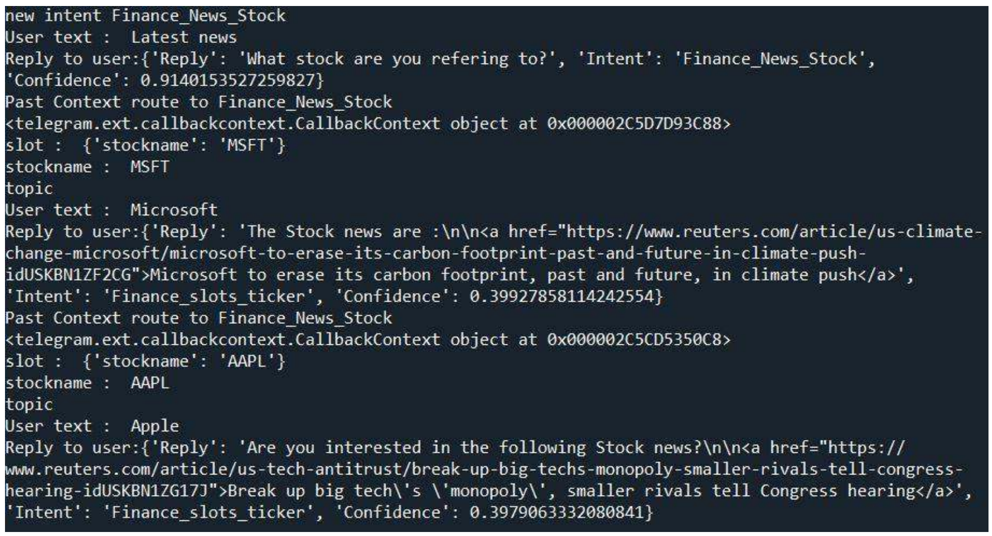
9. Conclusion

In this project, a retrieval-based backend chatbot system is developed to aid investors in their search for good stock to invest. We defined a limited scope for the chatbot, which is to search for popular technology stocks or obtain detailed news information on a specific stock as chatbots tend to work well for specific tasks.

It has been a steep learning curve, and our team picked up valuable skills in the process, learning how to build a chatbot backend engine and using deep learning and stocks sentiment to predict the stock price direction, web scrapping, calling external APIs, using various Machine learning methods for intent and slot detection.

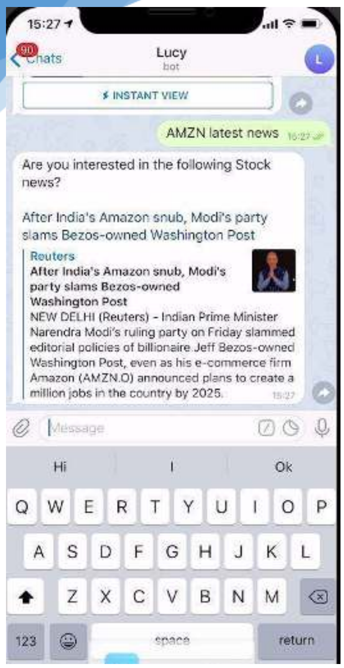
10. Appendix A : Test Case

1. Test Case 1 : Intent - Finance_news_stock

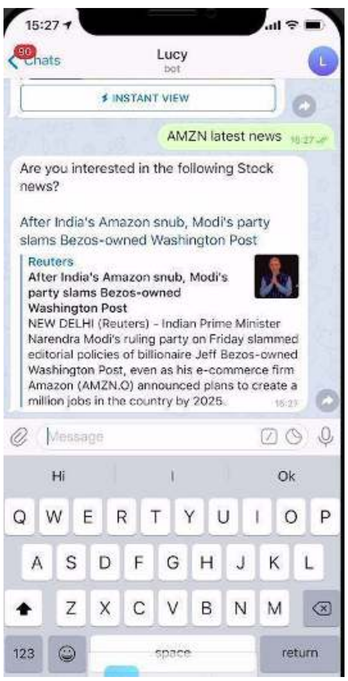


```
new intent Finance_News_Stock
User text :  Latest news
Reply to user:{'Reply': 'What stock are you refering to?', 'Intent': 'Finance_News_Stock',
'Confidence': 0.9140153527259827}
Past Context route to Finance_News_Stock
<telegram.ext.callbackcontext.CallbackContext object at 0x000002C5D7D93C88>
slot :  {'stockname': 'MSFT'}
stockname :  MSFT
topic
User text :  Microsoft
Reply to user:{'Reply': 'The Stock news are :\n\n<a href="https://www.reuters.com/article/us-climate-
change-microsoft/microsoft-to-erase-its-carbon-footprint-past-and-future-in-climate-push-
idUSKBN1ZF2CG">Microsoft to erase its carbon footprint, past and future, in climate push</a>',
'Intent': 'Finance_slots_ticker', 'Confidence': 0.39927858114242554}
Past Context route to Finance_News_Stock
<telegram.ext.callbackcontext.CallbackContext object at 0x000002C5CD5350C8>
slot :  {'stockname': 'AAPL'}
stockname :  AAPL
topic
User text :  Apple
Reply to user:{'Reply': 'Are you interested in the following Stock news?\n\n<a href="https://
www.reuters.com/article/us-tech-antitrust/break-up-big-techs-monopoly-smaller-rivals-tell-congress-
hearing-idUSKBN1ZG17J">Break up big tech\'s \'monopoly\', smaller rivals tell Congress hearing</a>',
'Intent': 'Finance_slots_ticker', 'Confidence': 0.3979063332080841}
```

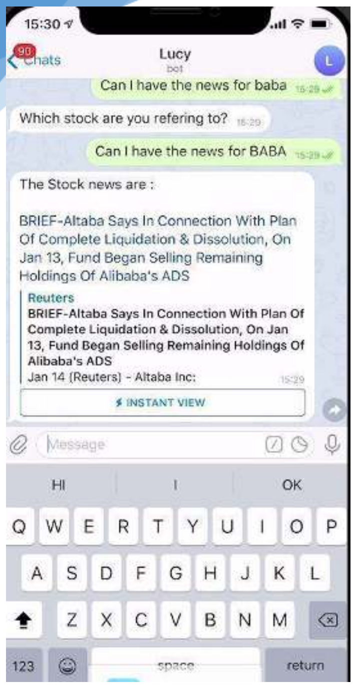
```
'Intent': 'Finance_slots_ticker', 'Confidence': 0.3979063332080841}
<telegram.ext.callbackcontext.CallbackContext object at 0x000002C5CD5B1908>
slot :  {'stockname': 'GOOGL'}
stockname :  GOOGL
topic
new intent Finance_News_Stock
User text :  News feed for google
Reply to user:{'Reply': 'The following are the Stock news :\n\n<a href="https://www.reuters.com/
article/us-alphabet-marketcap/alphabet-public-market-capitalization-tops-1-trillion-
idUSKBN1ZF2S2">Alphabet public market capitalization tops $1 trillion</a>', 'Intent':
'Finance_News_Stock', 'Confidence': 0.7660109400749207}
```




```
'Intent': 'Finance_slots_ticker', 'Confidence': 0.3979063332080841}
<telegram.ext.callbackcontext.CallbackContext object at 0x000002C5CD5B1908>
slot :  {'stockname': 'GOOGL'}
stockname :  GOOGL
topic
new intent Finance_News_Stock
User text :  News feed for google
Reply to user:{'Reply': 'The following are the Stock news :\n\n<a href="https://www.reuters.com/
article/us-alphabet-marketcap/alphabet-public-market-capitalization-tops-1-trillion-
idUSKBN1ZF2S2">Alphabet public market capitalization tops $1 trillion</a>', 'Intent':
'Finance_News_Stock', 'Confidence': 0.7660109400749207}
```

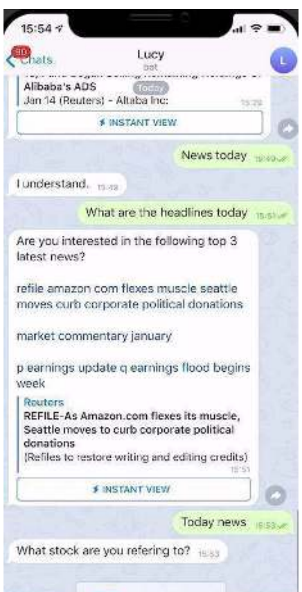



```
slot :  {'stockname': 'AMZN'}
stockname :  AMZN
topic
new intent Finance_News_Stock
User text :  AMZN latest news
Reply to user:{'Reply': 'Are you interested in the following Stock news?\n\n<a href="https://
www.reuters.com/article/us-amazon-com-india/after-indias-amazon-snub-modis-party-slams-bezos-owned-
washington-post-idUSKBN1ZG0KU">After India\'s Amazon snub, Modi\'s party slams Bezos-owned Washington
Post</a>', 'Intent': 'Finance_News_Stock', 'Confidence': 0.9986709356307983}
```



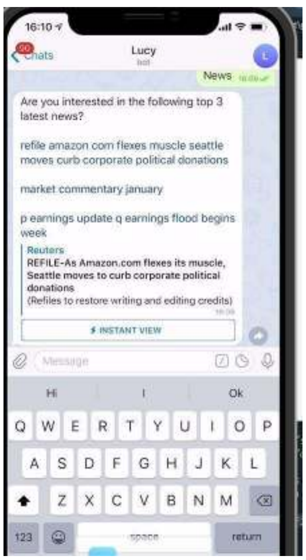

```
slot :  {'stockname': ''}
stockname :
new intent Finance_News_Stock
User text :  Can I have the news for baba
Reply to user:{'Reply': 'Which stock are you refering to?', 'Intent': 'Finance_News_Stock',
'Confidence': 0.9978622794151306}
<telegram.ext.callbackcontext.CallbackContext object at 0x000002C5DCEC4388>
slot :  {'stockname': 'BABA'}
stockname :  BABA
topic
new intent Finance_News_Stock
User text :  Can I have the news for BABA
Reply to user:{'Reply': 'The Stock news are :\n\n<a href="https://www.reuters.com/article/brief-
altaba-says-in-connection-with-pla/brief-altaba-says-in-connection-with-plan-of-complete-liquidation-
dissolution-on-jan-13-fund-began-selling-remaining-holdings-of-alibabas-ads-idUSFWN29J0FE">BRIEF-
Altaba Says In Connection With Plan Of Complete Liquidation & Dissolution, On Jan 13, Fund Began
Selling Remaining Holdings Of Alibaba\'s ADS</a>', 'Intent': 'Finance_News_Stock', 'Confidence':
0.9952440857887268}
```

2. Test Case 2 : Intent - Finance_news_today

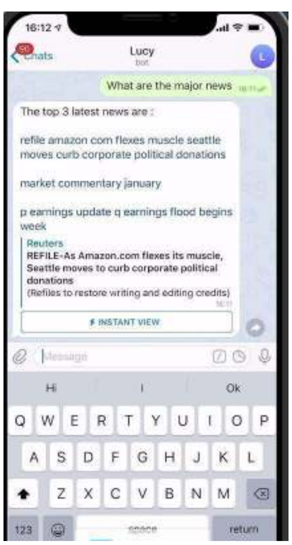



```
User text :  News today
Reply to user:{'Reply': 'I understand.', 'Intent': 'smalltalk_confirmation_no', 'Confidence':
0.38807135820388794}
Date :  01/13/2020
today:  01/13/2020
new intent Finance_News_Today
User text :  What are the headlines today
Reply to user:{'Reply': 'Are you interested in the following top 3 latest news?\n\n<a href="https://
www.reuters.com/article/usa-politics-seattle/refile-as-amazon-com-flexes-its-muscle-seattle-moves-to-
curb-corporate-political-donations-idUSL4N29F3EM">refile amazon com flexes muscle seattle moves curb
corporate political donations</a>\n\n<a href="https://www.reuters.com/article/
idUSSeekingAlpha431635920200112">market commentary january</a>\n\n<a href="https://www.reuters.com/
article/idUSSeekingAlpha431635720200112">p earnings update q earnings flood begins week</a>\n\n',
'Intent': 'Finance_News_Today', 'Confidence': 0.895670473575592}
<telegram.ext.callbackcontext.CallbackContext object at 0x000002C5E6B42648>
slot :  {'stockname': ''}
stockname :
new intent Finance_News_Stock
User text :  Today news
Reply to user:{'Reply': 'What stock are you refering to?', 'Intent': 'Finance_News_Stock',
'Confidence': 0.913058876991272}
```


```
User text :  Today news
Reply to user:{'Reply': 'What stock are you refering to?', 'Intent': 'Finance_News_Stock',
'Confidence': 0.913058876991272}
Date :  01/13/2020
today:  01/13/2020
new intent Finance_News_Today
User text :  Top news today
Reply to user:{'Reply': 'Found top 3 latest news :\n\n<a href="https://www.reuters.com/article/usa-
politics-seattle/refile-as-amazon-com-flexes-its-muscle-seattle-moves-to-curb-corporate-political-
donations-idUSL4N29F3EM">refile amazon com flexes muscle seattle moves curb corporate political
donations</a>\n\n<a href="https://www.reuters.com/article/idUSSeekingAlpha431635920200112">market
commentary january</a>\n\n<a href="https://www.reuters.com/article/idUSSeekingAlpha431635720200112">p
earnings update q earnings flood begins week</a>\n\n', 'Intent': 'Finance_News_Today', 'Confidence':
0.9794290661811829}
```

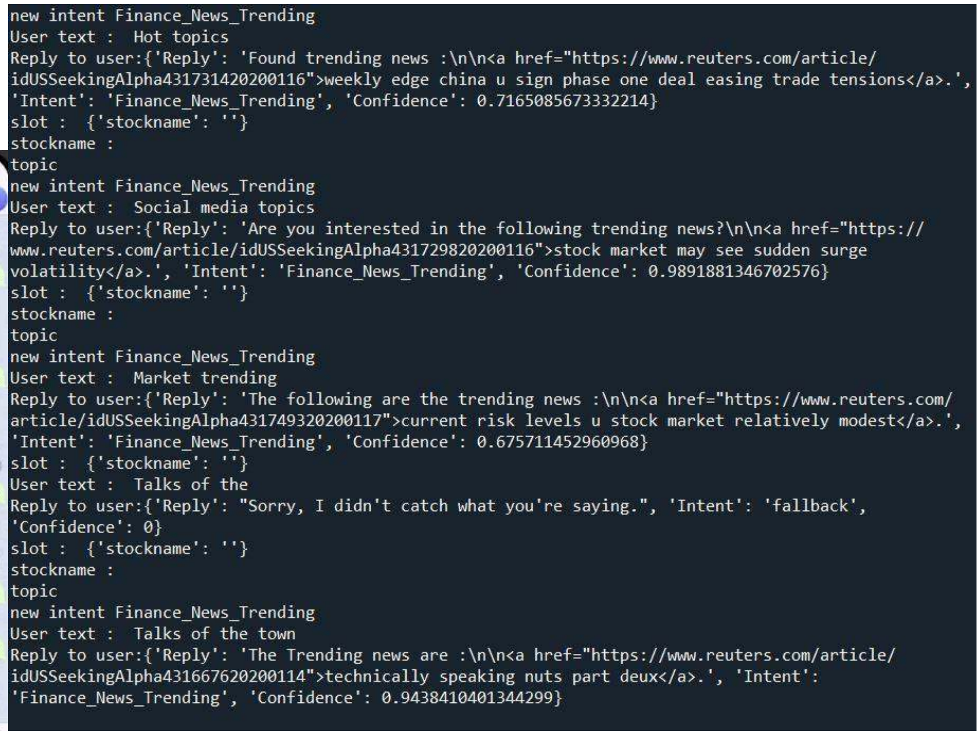



```
Past Context route to Finance_News_Today
Date :  01/13/2020
today:  01/13/2020
User text :  News
Reply to user:{'Reply': 'Are you interested in the following top 3 latest news?\n\n<a href="https://
www.reuters.com/article/usa-politics-seattle/refile-as-amazon-com-flexes-its-muscle-seattle-moves-to-
curb-corporate-political-donations-idUSL4N29F3EM">refile amazon com flexes muscle seattle moves curb
corporate political donations</a>\n\n<a href="https://www.reuters.com/article/
idUSSeekingAlpha431635920200112">market commentary january</a>\n\n<a href="https://www.reuters.com/
article/idUSSeekingAlpha431635720200112">p earnings update q earnings flood begins week</a>\n\n',
'Intent': 'Finance_slots_ticker', 'Confidence': 0.39745065569877625}
```

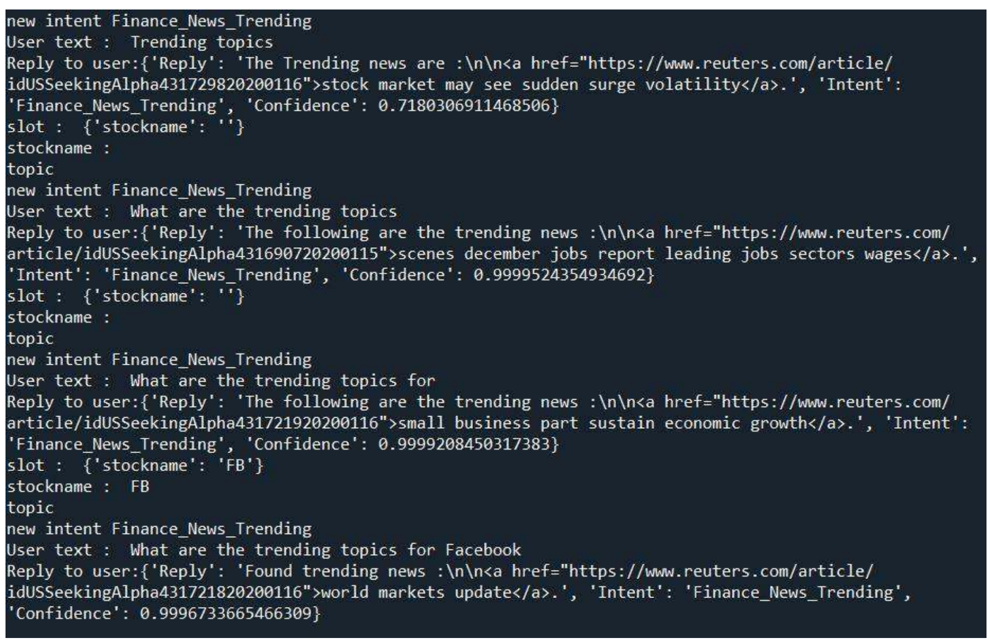



```
Date :  01/13/2020
today:  01/13/2020
new intent Finance_News_Today
User text :  What are the major news
Reply to user:{'Reply': 'The top 3 latest news are :\n\n<a href="https://www.reuters.com/article/usa-
politics-seattle/refile-as-amazon-com-flexes-its-muscle-seattle-moves-to-curb-corporate-political-
donations-idUSL4N29F3EM">refile amazon com flexes muscle seattle moves curb corporate political
donations</a>\n\n<a href="https://www.reuters.com/article/idUSSeekingAlpha431635920200112">market
commentary january</a>\n\n<a href="https://www.reuters.com/article/idUSSeekingAlpha431635720200112">p
earnings update q earnings flood begins week</a>\n\n', 'Intent': 'Finance_News_Today', 'Confidence':
0.9440336227416992}
```

3. Test Case 3 : Intent - Finance_news_trending



```
new intent Finance_News_Trending
User text :  Hot topics
Reply to user:{'Reply': 'Found trending news :\n\n<a href="https://www.reuters.com/article/
idUSSeekingAlpha431731420200116">weekly edge china u sign phase one deal easing trade tensions</a>.',
'Intent': 'Finance_News_Trending', 'Confidence': 0.7165085673332214}
slot :  {'stockname': ''}
stockname :
topic
new intent Finance_News_Trending
User text :  Social media topics
Reply to user:{'Reply': 'Are you interested in the following trending news?\n\n<a href="https://
www.reuters.com/article/idUSSeekingAlpha431729820200116">stock market may see sudden surge
volatility</a>.', 'Intent': 'Finance_News_Trending', 'Confidence': 0.9891881346702576}
slot :  {'stockname': ''}
stockname :
topic
new intent Finance_News_Trending
User text :  Market trending
Reply to user:{'Reply': 'The following are the trending news :\n\n<a href="https://www.reuters.com/
article/idUSSeekingAlpha431749320200117">current risk levels u stock market relatively modest</a>.',
'Intent': 'Finance_News_Trending', 'Confidence': 0.675711452960968}
slot :  {'stockname': ''}
User text :  Talks of the
Reply to user:{'Reply': "Sorry, I didn't catch what you're saying.", 'Intent': 'fallback',
'Confidence': 0}
slot :  {'stockname': ''}
stockname :
topic
new intent Finance_News_Trending
User text :  Talks of the town
Reply to user:{'Reply': 'The Trending news are :\n\n<a href="https://www.reuters.com/article/
idUSSeekingAlpha431667620200114">technically speaking nuts part deux</a>.', 'Intent':
'Finance_News_Trending', 'Confidence': 0.9438410401344299}
```



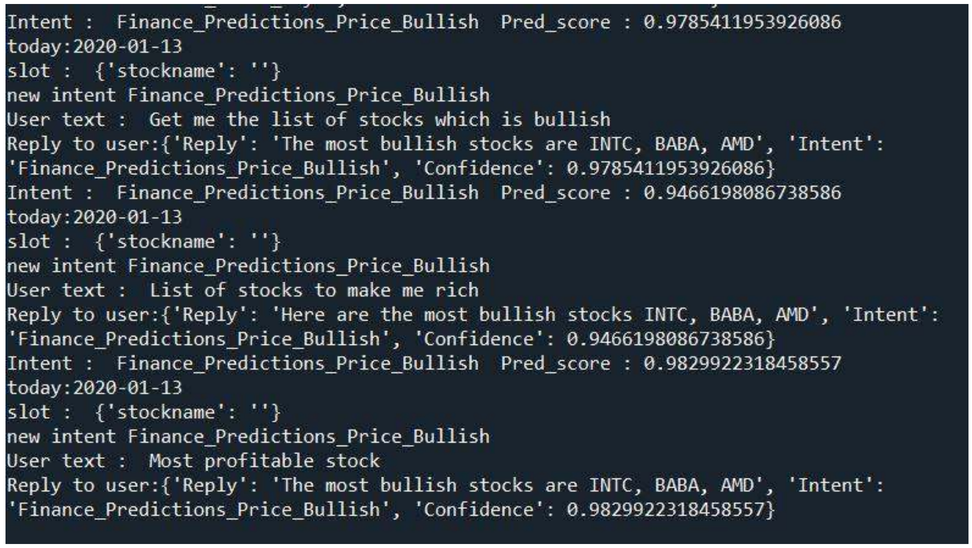
```
new intent Finance_News_Trending
User text :  Trending topics
Reply to user:{'Reply': 'The Trending news are :\n\n<a href="https://www.reuters.com/article/
idUSSeekingAlpha431729820200116">stock market may see sudden surge volatility</a>.', 'Intent':
'Finance_News_Trending', 'Confidence': 0.7180306911468506}
slot :  {'stockname': ''}
stockname :
topic
new intent Finance_News_Trending
User text :  What are the trending topics
Reply to user:{'Reply': 'The following are the trending news :\n\n<a href="https://www.reuters.com/
article/idUSSeekingAlpha431690720200115">scenes december jobs report leading jobs sectors wages</a>.',
'Intent': 'Finance_News_Trending', 'Confidence': 0.9999524354934692}
slot :  {'stockname': ''}
stockname :
topic
new intent Finance_News_Trending
User text :  What are the trending topics for
Reply to user:{'Reply': 'The following are the trending news :\n\n<a href="https://www.reuters.com/
article/idUSSeekingAlpha431721920200116">small business part sustain economic growth</a>.', 'Intent':
'Finance_News_Trending', 'Confidence': 0.9999208450317383}
slot :  {'stockname': 'FB'}
stockname :  FB
topic
new intent Finance_News_Trending
User text :  What are the trending topics for Facebook
Reply to user:{'Reply': 'Found trending news :\n\n<a href="https://www.reuters.com/article/
idUSSeekingAlpha431721820200116">world markets update</a>.', 'Intent': 'Finance_News_Trending',
'Confidence': 0.9996733665466309}
```


```
slot :  {'stockname': 'TWTR'}
stockname :  TWTR
topic
new intent Finance_News_Stock
User text :  Popular news for twitter
Reply to user:{'Reply': 'The Stock news are :\n\n<a href="https://www.reuters.com/article/us-usa-fed-trump/boneheads-no-more-feds-rate-cuts-appear-to-defuse-trumps-twitter-rage-idUSKBN1YG2FF">\'Boneheads\' no more? Fed\'s rate cuts appear to defuse Trump\'s Twitter rage</a>', 'Intent': 'Finance_News_Stock', 'Confidence': 0.9995924830436707}
```

4. Test Case 4 : Intent - Finance_Predictions_price_bearish

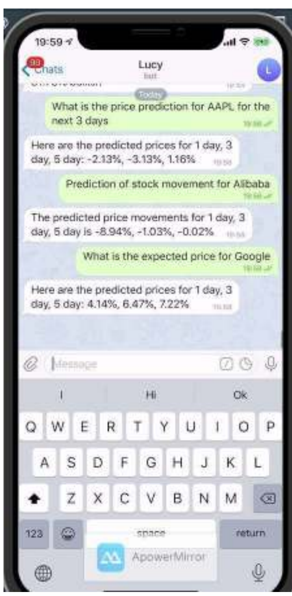

```
Intent :  Finance_Predictions_Price_Bearish  Pred_score : 0.8477271199226379
today:2020-01-13
slot :  {'stockname': ''}
new intent Finance_Predictions_Price_Bearish
User text :  Which stock to short sell 5
Reply to user:{'Reply': 'The most bearish stocks are AAPL, AMZN, TWTR', 'Intent': 'Finance_Predictions_Price_Bearish', 'Confidence': 0.8477271199226379}
Intent :  Finance_Predictions_Price_Bearish  Pred_score : 0.8476213812828064
today:2020-01-13
slot :  {'stockname': ''}
new intent Finance_Predictions_Price_Bearish
User text :  Which stock can I short
Reply to user:{'Reply': 'Here are the most bearish stocks AAPL, AMZN, TWTR', 'Intent': 'Finance_Predictions_Price_Bearish', 'Confidence': 0.8476213812828064}
Intent :  Finance_Predictions_Price_Bearish  Pred_score : 0.9630482792854309
today:2020-01-13
slot :  {'stockname': ''}
new intent Finance_Predictions_Price_Bearish
User text :  Which brings me the max profit if I short sell
Reply to user:{'Reply': 'The most bearish stocks are AAPL, AMZN, TWTR', 'Intent': 'Finance_Predictions_Price_Bearish', 'Confidence': 0.9630482792854309}
```

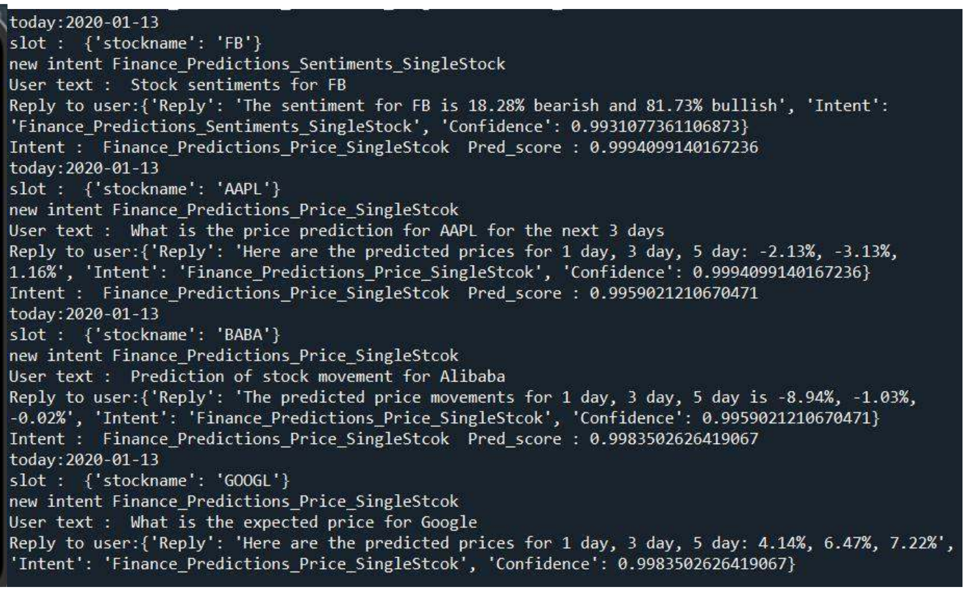
5. Test Case 5 : Intent - Finance_Predictions_price_bullish



```
Intent :  Finance_Predictions_Price_Bullish  Pred_score : 0.9785411953926086
today:2020-01-13
slot :  {'stockname': ''}
new intent Finance_Predictions_Price_Bullish
User text :  Get me the list of stocks which is bullish
Reply to user:{'Reply': 'The most bullish stocks are INTC, BABA, AMD', 'Intent':
'Finance_Predictions_Price_Bullish', 'Confidence': 0.9785411953926086}
Intent :  Finance_Predictions_Price_Bullish  Pred_score : 0.9466198086738586
today:2020-01-13
slot :  {'stockname': ''}
new intent Finance_Predictions_Price_Bullish
User text :  List of stocks to make me rich
Reply to user:{'Reply': 'Here are the most bullish stocks INTC, BABA, AMD', 'Intent':
'Finance_Predictions_Price_Bullish', 'Confidence': 0.9466198086738586}
Intent :  Finance_Predictions_Price_Bullish  Pred_score : 0.9829922318458557
today:2020-01-13
slot :  {'stockname': ''}
new intent Finance_Predictions_Price_Bullish
User text :  Most profitable stock
Reply to user:{'Reply': 'The most bullish stocks are INTC, BABA, AMD', 'Intent':
'Finance_Predictions_Price_Bullish', 'Confidence': 0.9829922318458557}
```

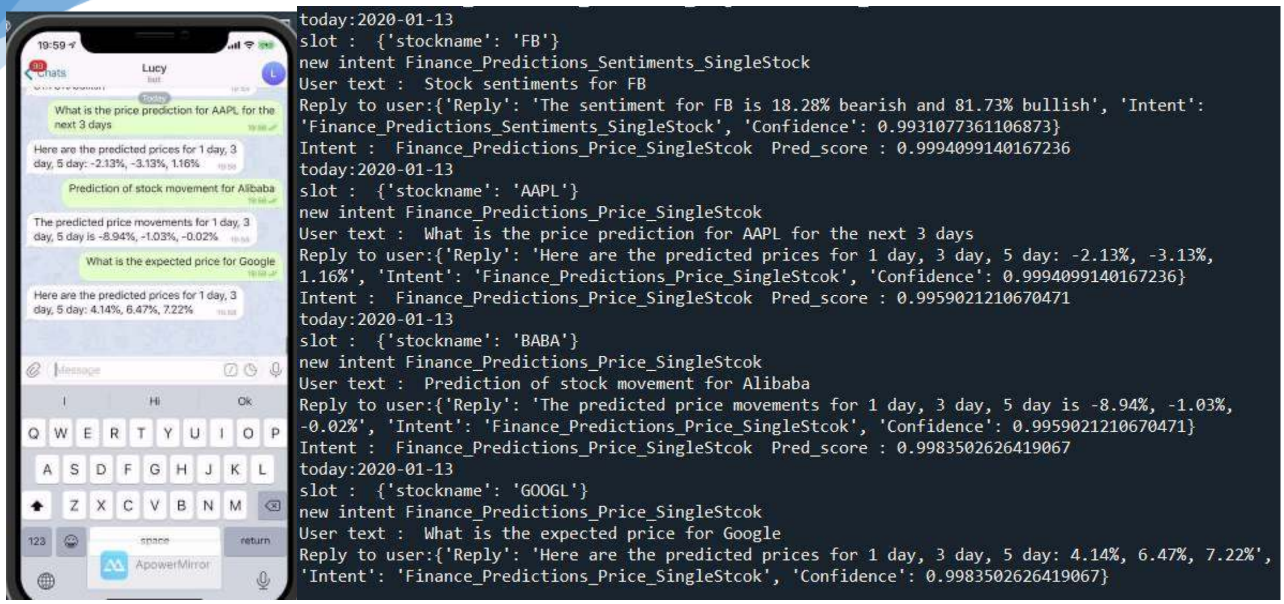
6. Test Case 6 : Intent - Finance_Predictions_price_SingleStcok





```
today:2020-01-13
slot :  {'stockname': 'FB'}
new intent Finance_Predictions_Sentiments_SingleStock
User text :  Stock sentiments for FB
Reply to user:{'Reply': 'The sentiment for FB is 18.28% bearish and 81.73% bullish', 'Intent':
'Finance_Predictions_Sentiments_SingleStock', 'Confidence': 0.9931077361106873}
Intent :  Finance_Predictions_Price_SingleStcok  Pred_score : 0.9994099140167236
today:2020-01-13
slot :  {'stockname': 'AAPL'}
new intent Finance_Predictions_Price_SingleStcok
User text :  What is the price prediction for AAPL for the next 3 days
Reply to user:{'Reply': 'Here are the predicted prices for 1 day, 3 day, 5 day: -2.13%, -3.13%,
1.16%', 'Intent': 'Finance_Predictions_Price_SingleStcok', 'Confidence': 0.9994099140167236}
Intent :  Finance_Predictions_Price_SingleStcok  Pred_score : 0.9959021210670471
today:2020-01-13
slot :  {'stockname': 'BABA'}
new intent Finance_Predictions_Price_SingleStcok
User text :  Prediction of stock movement for Alibaba
Reply to user:{'Reply': 'The predicted price movements for 1 day, 3 day, 5 day is -8.94%, -1.03%,
-0.02%', 'Intent': 'Finance_Predictions_Price_SingleStcok', 'Confidence': 0.9959021210670471}
Intent :  Finance_Predictions_Price_SingleStcok  Pred_score : 0.9983502626419067
today:2020-01-13
slot :  {'stockname': 'GOOGL'}
new intent Finance_Predictions_Price_SingleStcok
User text :  What is the expected price for Google
Reply to user:{'Reply': 'Here are the predicted prices for 1 day, 3 day, 5 day: 4.14%, 6.47%, 7.22%',
'Intent': 'Finance_Predictions_Price_SingleStcok', 'Confidence': 0.9983502626419067}
```

7. Test Case 7 : Intent - Finance_Sentiments_SingleStock



8. Test Case 8 : Intent - Finance_Whatcanido

Appendix B : User Utterance/Response Table

Intent	Sample utterence	Sample response	Description	Status
Finance_News_Stock	- '[stockname](AAPL) news' - news for [stockname](AAPL) - related news for [stockname](AAPL)	- The Stock news are :, - The following are the Stock news :, - Found the Stock news :	To get respective Stock news	Completed
Finance_News_Today	- news today - what are the headlines today - news headlines today	- The top 3 latest news are : - The following are top 3 today news : - Found top 3 latest news :	To get current today news	Completed
Finance_News_Trending	- trending topics for the past [numberofdays] days - hot topics - recent topics on social media	- The Trending news are : - The following are the trending news : - Found trending news :	To get the trending news	Completed
Finance_Predictions_Sentiments_SingleStock	- stock sentiments for [stockname](AAPL) - what are the sentiments for [stockname](AAPL) - social media sentiments for [stockname](AAPL)	- The sentiment for {stock_slot} is {bear_sent} bearish and {bull_sent} bullish', - '{stock_slot} is {bull_sent} bullish', - 'Overall sentiment for {stock_slot} is currently {sentiment_label}'	Retrieve sentiment predictions for particular stock	Completed
Finance_Predictions_Price_SingleStock	- stock prediction for [stockname](AAPL) - prediction for [stockname](AAPL) - movement prediction for [stockname](AAPL)	- The {col_names_str} returns predicted for {stock_slot} are {returns_str}', - 'The predicted price movements for {col_names_str} is {returns_str}', - 'Here are the predicted prices for {col_names_str}: {returns_str}'	Retrieve price predictions for particular stock	Completed
Finance_Predictions_Price_Bearish	- What stock should i sell [numberofdays]? - Which stock should i sell	- 'The most bearish stocks are {symbols_str}', - 'Here are the most bearish stocks	To list the stocks which have	Completed

	[numberofdays]? - which stock to short sell [numberofdays]?	{symbols_str}', - '{symbols_str} are the most bearish stocks in the market currently	bearish sentiment	
Finance_Predictions_Price_Bullish	- what should i buy for the next [numberofdays] days? - what is bullish for the next [numberofdays] days? - what stock should i consider for the next [numberofdays] days?	- 'The most bullish stocks are {symbols_str}', - 'Here are the most bullish stocks {symbols_str}', - '{symbols_str} are the most bullish stocks in the market currently'	To list the stocks which have bullish sentiment	Completed
Finance_WatchlistE_Add				For improvement
Finance_WatchlistE_Drop				For improvement
Finance_WatchlistE_Clear	- Clear my watchlist - Remove all from my watchlist - Remove all stocks from my watchlist			For improvement
Finance_Predictions_Sentiments_Watchlist			Retrieve watchlist predicted sentiment	For improvement
Finance_General_Whatcanido	- What does this bot do? - What does this chatbot do?	- I can help you with Technology Stock price direction predictions, the stock trending news or create your favourite watchlist. - OK, To get started, let me know which stock are you interested in ? To end the conversation just say Bye		Completed

Fallback		I'm sorry, I didn't understand that. You could ask me about news or price prediction on the following technology stocks : apple,google,Facebook,amazon,Microsoft,Alibaba,tesla, dow Jones,spider,tweeter,volatility index Sorry, I'm afraid I can't understand as I can only help you to search for news or price prediction on the following technology stocks : apple,google,Facebook,amazon,Microsoft,Alibaba,tesla, dow Jones,spider,tweeter,volatility index. Is there any particular stock that you would like to check ?		Completed	