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Abstract

The trend of financial reports, news and publications have grown over recent years. Assessing the relevance of financial information in making informed investment decisions has become an important aspect to modern investors. Mining financial text documents and understanding the sentiments of individual investors, institutions and markets is an important and challenging problem in financial markets. In this research project, an NLP model has been proposed for opinion mining in financial text documents or new headlines based on multiple features. This report shows that sentiments classified as positive, neutral, and negative plays a significant role in stock market analysis. The proposed model(s) has been evaluated based on the performance parameters of the precision, recall and polarity-based accuracy assessment, which gives the overall perspective of the overall accuracy. The proposed model has been clearly defined as being better than other models, when assessed on the given parameters.

INTROCUDUTION

Mining financial text documents and understanding the sentiments of individual investors, institutions and markets is an important and challenging problem in the literature. The Wall Street Journal and a limited number of finance-related publications attempted to collect business news and spread it to others, but this news moved to the greater public at the speed of print – if at all. Now, even obscure companies produce a constant stream of information, from the daily price fluctuations in the stock to announcements and posts on dedicated message boards. When information floods in, it can be difficult to pick out what is important. Current approaches to mine sentiments from financial texts largely rely on domain-specific dictionaries. However, dictionary-based methods often fail to accurately predict the polarity of financial texts. The above problem formulate the basis of this research project.

Objectives

The aim is to build a predictive model and find whether the news may have positive, negative, or neutral influence on the stock price. As a result, sentences which have a sentiment that is not relevant from an economic or financial

Acknowledgements

1. https://www.datasciencecentral.com viewed 25/05/202
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perspective are considered neutral. Using this model, the financial phrase bank will help prospective investor to know which news headlines will have an impact on the stock market prices.

Hypothesis

Financial Sentiment Hypothesis Criteria

Positive sentiments: news headlines containing positive sentiments are on average less verbose (contain words < 50 on average). Investors tend to take a buy or sell position, speculating for future gains or some take a sell position to reap the cumulative gains.

Key investments decision/strategy is: buy **or sell position**

Negative sentiments: Negative reports, negative profits, decline in earnings per share and negative news reports results in negative sentiments hence decline in stock market prices. Investors will recommend to sell or to liquidate the asset.

Key investments decision/strategy is: liquidate **or hold**

Neutral sentiments: generally financial news with no impact on stock prices are more verbose and contain more words (greater than 100), Investors tend to take wait and see scenario or just a hold on position.

Key investments decision/strategy is: **irrelevant, no effect**

Data set

The data covers release of the financial phrase bank with a collection of 4846 sentences in the form of financial news headlines. The study is focused only on financial and economic domains. The selected collection of phrases was annotated by 16 people with adequate background knowledge on financial markets. Three of the annotators were researchers and the remaining 13 annotators were master's students at Aalto University School of Business with majors primarily in finance, accounting, and economics. The study has 2 variables, the class (mapped as the label column/target variable) variable with opinion 3 levels i.e. positive, negative, or neutral sentiments and the financial text heading (mapped as the predictor variable)

Data Preprocessing and Exploration.

The data preprocessing entailed cleaning the financial text using regular expression programming tool. Some of the cleaning tasks was to change numeric values to read as money, year of figures, changing phone numbers to be read as just phone numbers and replacing a variety of money symbols. After this, special characters and white space in the text was removed. Stemming and lemmatization was applied.

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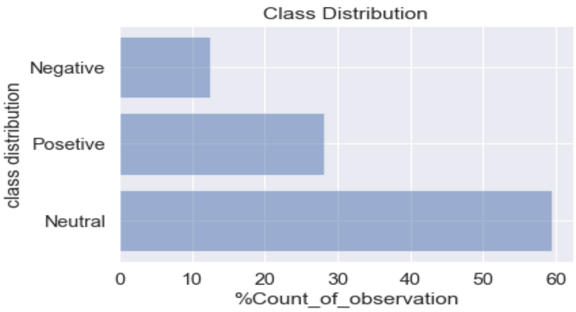
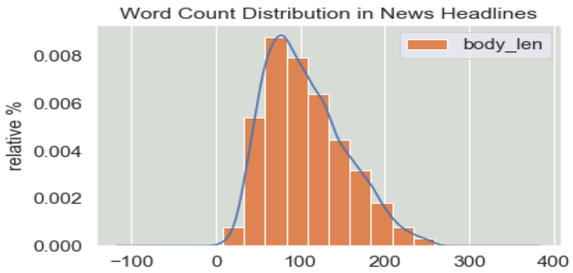
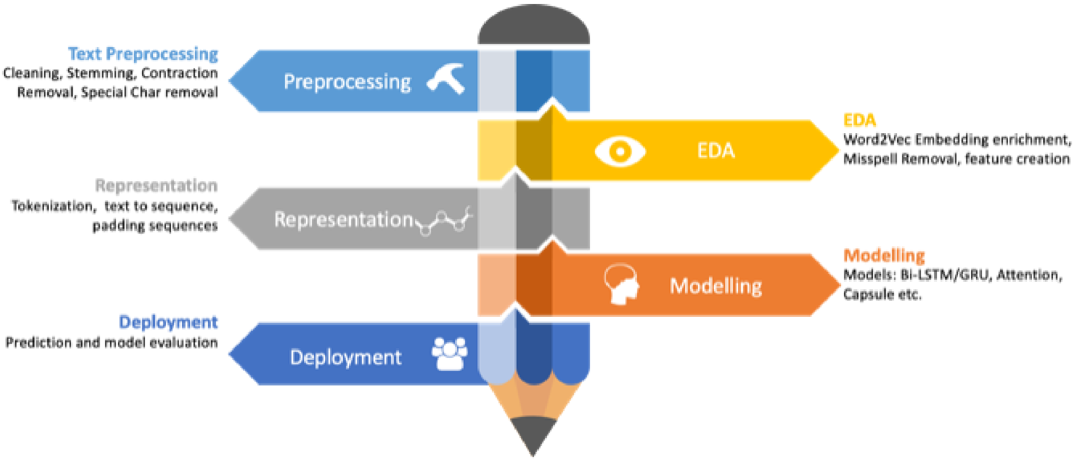
FINANCIAL TEXT MINGING (NLP) PROJECT_MUWANI_ROBSON





Neutral sentiments constitute 59% of the total dataset while negative sentiments took baseline record of 12% from the data set. Negative news headlines contained more words than the rest of the class. Negative class top for most news headlines with words exceeding 50. Neutral statements top for news headlines less than 50. Negative news headlines contained more words than the rest of the class.

NLP TEXT CLEANING AND MODEL PROCESS


Text Preprocessing
Cleaning, Stemming, Contraction Removal, Special Char removal
Preprocessing
EDA
Word2Vec Embedding enrichment, Misspell Removal, feature creation
EDA
Representation
Tokenization, text to sequence, padding sequences
Representation
Modelling
Models: Bi-LSTM/GRU, Attention, Capsule etc.
Modelling
Deployment
Prediction and model evaluation
Deployment

Feature Engineering: creating a bag of words

After cleaning the data, we tokenized and encoded the text, converted the words into a sequence or padding sequence. This was basically encoding the given texts using internal vocabulary with optionally applied encoding options. Now that we have tokenized our data and have a word to numeric representation mapping of our vocabulary. Since neural networks work by performing computation on numbers, passing in a bunch of words, the algorithm will not understand it. Training data set was created and separated from the test data set, test sample size was set 25%.

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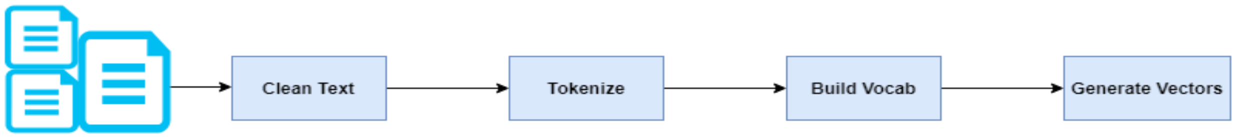
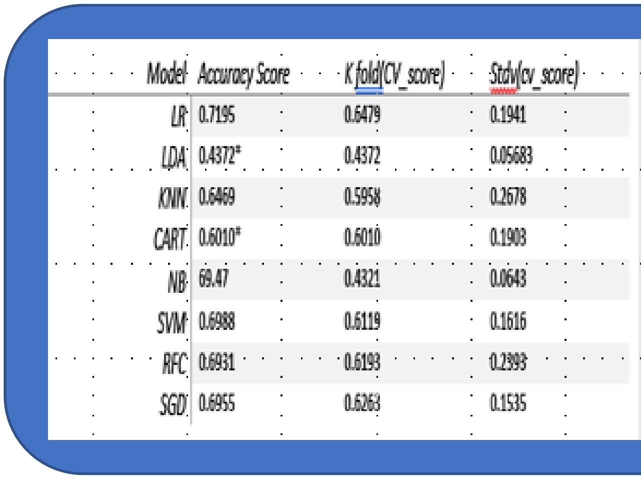
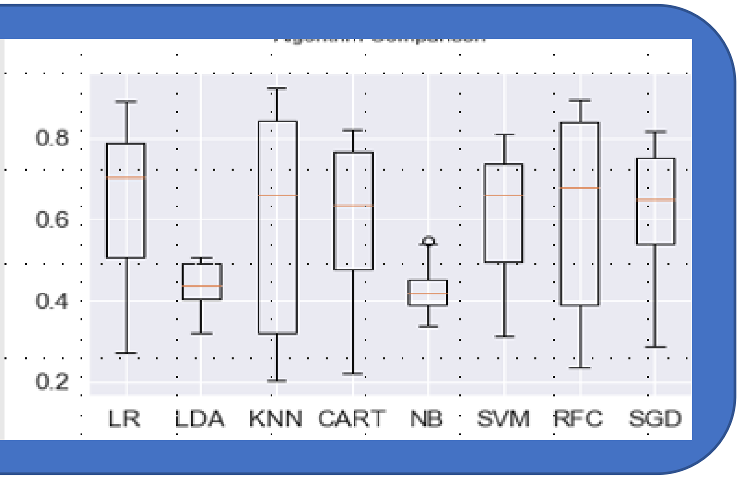


The above is a summary of the feature engineering steps.

Model Results:



Model	Accuracy Score	K fold(CV_score)	Stdv(cv_score)
LR	0.7195	0.6479	0.1941
LDA	0.4372*	0.4372	0.05683
KNN	0.6469	0.5958	0.2678
CART	0.6010*	0.6010	0.1903
NB	69.47	0.4321	0.0643
SVM	0.6988	0.6119	0.1616
RFC	0.6931	0.6193	0.2393
SGD	0.6955	0.6263	0.1535

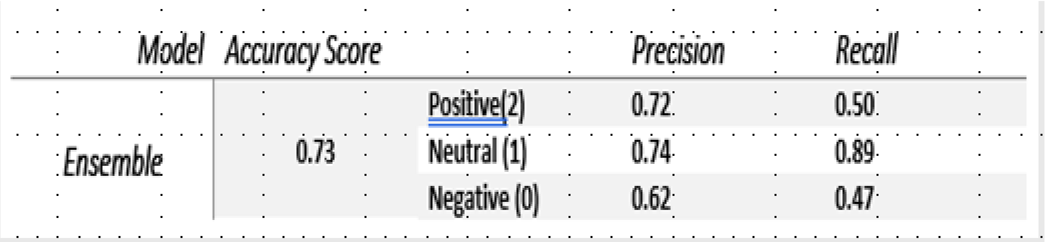


- Logistic regression performed better than all the models, recording an accuracy of ~72%.
- SVM, SGD, Random Forests and KNN all recorded an accuracy of ~70%~70%,~69% and ~65% respectively
- Worst performing models were LDA and NB, all below
- There was greater variability in model performance as read from k fold model stdv, the validation was set at cv=10 for all the models that performed better.

Model improvement:

To improve the model, an ensemble method was applied. Ensemble methods are **meta-algorithms that combine several machine learning techniques into one predictive model** in order to decrease variance (bagging), bias (boosting), or improve predictions (stacking).

Ensemble Results:



Model	Accuracy Score		Precision	Recall
Ensemble	0.73	Positive(2)	0.72	0.50
		Neutral (1)	0.74	0.89
		Negative (0)	0.62	0.47

Model results improved to 73%, precision as a measure of relevant and correct classifications by the model was 62% and recall i.e. a measure all relevant/ correct classifications for Negative sentiments was very low at 47%.

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Findings

- Irrelevant financial text /news or document are more verbose, contain more words on average exceeding 100 words compared to financial text with positive sentiments.
- Logistic regression presented as a better model in predicting the polarity of financial news headlines. However, the score signifies need for improvement through use of best hyper parameters (Gridsearch).
- Model improvement was applied via ensemble method, score went up to 73%.
- NB, SGD, RFC and SVC presented alternative accuracy scores but needs great improvement.
- Great variability was observed in K-fold accuracy scores in all models that performed better, test scores and accuracy score almost the same for all the models.
- K fold score stdv was too high for all models that performed better (variance between the k-fold scores, for cv=10).
- LDA, KNN and CART models proved to be the worst models in predicting the financial text sentiments. The model accuracy score was 100% and thus not acceptable models.

Recommendations

- The obtaining results show suitability of Logistic regression as a better model in predicting the polarity of financial text for this data set. Therefore, I recommend using this model with great caution to avoid overfitting. The model accuracy can further be improved by selecting best parameters and hyper parameters.
- **Use of ensemble:** thus, select all models with average score of 70% and run an ensemble method with only better models (L R,NB,SGD ,RFC and SVC).
- **Add more data**-for models with high variance high variance of predictions it is ideal to increase the training set size. Try increasing your sample by providing new data, which could translate into new cases or new features.
- **Data Preprocessing & Feature engineering**-apart from transformations, creating more new variables out of existing variables is also extremely helpful to improve the model performance.
- **Sample size -**upscale or downscale sample to create a balance between classes (sentiment opinions) also helps to improve model performance.
- **Re-validate the model at proper time frequency.** It is necessary to score the model with new financial text data every day, every week or month based on changes in the data. If required rebuild the models periodically with different techniques to challenge the model present in the production.

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