UDACITY MACHINE LEARNING ENGINEERING CAPSTONE PROJECT

QUALIFYING GOOGLE TREND TERMS' VOLUMES AS A SIGNIFICANT CONTRIBUTOR TO INCORPORATE IN FINANCIAL TRADING STATEGIES

REVISITING PREIS' GOOGLE TRENDS TRADING STRATEGY WITH UPDATED SUPERVISED AND RNN LEARNING

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Domain Background

There are two schools of thought on whether collective decision-making precedes or is already incorporated into financial market pricing. One school of thought is well represented by an Economic Nobel Prize winning Eugene Fama. Mr. Fama is known as "The Father of Finance". Fama' University of Chicago PHD thesis concluded that short-term price movements are unpredictable and approximate a random walk. The futility of trying to gain advantages over Fama's efficient-market hypothesis was later widely reinforced by Princeton University economist Burton Malkiel's in his book "A Random Walk Down Wall Street" who posits: " A blindfolded monkey throwing darts at a newspaper's financial pages could select a portfolio that would do just as well as one carefully selected by experts". Per Fama, "the past history of a series of cannot be used to predict the future in any meaningful way and that the future path of a security's price is no more predictable than the path of a series of random numbers.

The other school of thought is well represented by Fama's nemesis Robert J. Shiller who famously won and shared winning his own Nobel Prize the same year with Fama. Shiller wrote a book entitled "Animal Spirits" about the impact of human psychology on the market and believes Fama incorrectly minimizes the role of investor psychology and emotion in financial markets. Also supporting the idea that financial markets are not information efficient is Herbert Simon, an Economic Nobel Prize and computer science Turing Prize winner. Simon posited that an actor begins their decision-making processes by attempting to gather information. Both economists inspire a good question: If you can measure the information gathering process before making a decision, can you use it successfully to predict short-term financial market movements?

In 2013, Tobais Preis (Warwich Business School), Helen Susannah Moat and Eugene Stanley (Boston University Physics Department) submitted a paper to www.nature.com entitled "Quantifying Trading Behavior in Financial Markets Using Google Trends" (https://www.nature.com/articles/srep01684). This paper posits that by using Google Trends within an investigated time period their "Google Trends Theory" not only reflected the current state of the market but could have anticipated future trends. They summarize by saying, in retrospect (from 2004 to 2011), their Google Trends Strategy could have been used in the construction of a profitable trading strategy.

This recurrent neural network (RNN) machine-learning Capstone Project will analyze Preis' Google Trends Trading strategy by using its methodology, Dow Jones Industrial Average (DJIA) 2004 to 2011 training data and DJIA 2012 to 2016 test data. This Capstone's mission is to learn if key financial terms (Google Trend terms) along with term search volumes are worthy predictors to financial market price movements.

This Capstone's null hypothesis is the market-efficiency hypothesis (Fama) is correct and that all information is already factored into financial market pricing. To test this hypothesis, the Google Trends Strategy will be implemented and its results (both statistics and profitability) will be compared to both a DJIA random market and buy and hold investment strategy.

While testing this null hypothesis is the central focus on this capstone, this capstone also gathers insights on any correlative relationships between the financial results from Google Trends with Google Search Volumes for each DJIA stock, and selected technical indicators such as stock price moving averages and standard deviation bands breakout technique which uses standard deviations from the moving average to identify price breakouts.

Problem Statement

Simon's observation that "an actor begins their decision-making processes by attempting to gather information before making it" makes sense. People do engage information before acting upon it. *The problem is the difficulty of figuring out if you can capitalize on the chasm between investors engaging information and then their acting upon it in financial markets.*

This capstone will answer if you can capitalize on investors engaging information before they trade by using supervised learning to classify input data (Google trend search terms volumes) that delivers its predictive output (0 or 1 signal) for either buying or shorting the DJIA. All trades signaled from 2004 to 2017 will be compared to pricing predictions made from a LSTM RMM model that reviews all trading data.

Before getting into how the Google Trends Strategy (GTS) works, it is important to review the important questions it raises that underscore the importance of this capstone inquiry:

- Can you predict short-term stock movements (up/down) based upon search terms combined with its search-term volumes?
- Are notable drops in the market traceably preceded by investor concern and are notable increases in the market traceable preceded by investor confidence?
- Do the majority of trades implemented by machine learning algorithms today completely reinforce the efficient market hypothesis or is there a significant negation to be found in a time delay impact between those researching information and then acting on it?
- If you can predict short-term stock movements using sentiment search key words volumes:
    - Is the DJIA the best index for profit?
    - What are the best key terms to use for profit per index?
    - What are the best methods for determining key word efficiency?
    - Is there an optimal combination of key word, search volumes, and technical indicators?
    - What is the most profitable methodology for getting into and out of financial trades using this Google Trends Strategy?
- Does a RNN analysis confirm or deny that search-term volumes are statistically significant predictive indictors or the existence of a relationship of important factors that can be used to predict DJIA price movements?
- Is there a relationship between search term volume and trading volume?

Datasets and Inputs

Here are the three main dataset sources to be utilized for this capstone project:

The first dataset is Yahoo finance (https://finance.yahoo.com). This dataset contains all Open, High, Low, Close, Trade Volume, and Adjusted Close prices for the DJIA index on each trading day from January 1st 2011 to November 1st 2017. The ML algorithm will use the DJIA daily open price as its categorical strike price (for either buy or short buy) and the daily closing price as its categorical selling price. In the training set (DJIA trading summaries from 2004 to 2011) Preis' study implemented 105 trades and we expect to confirm them. This capstone will discover how many trades will be made during the testing set timeframe (DJIA trading history from 2012 to 2017). There will be a accumulative profit/loss feature as well.

The second dataset consists of 98 search terms documented in Preis' report: (https://www.nature.com/articles/srep01684). Twenty of the top buy and short keywords listed in Figures 3 and 4 will be used to compare Google Trends search volumes to determine when to buy or shorting the DJIA. When search volumes are at a three-week high or low a categorical 0 or 1 will signal to either buy or short.

The third dataset will be the financial keywords taken from the Financial Times (www.financialtimes.com) and Wall Street Journal (www.wsj.com) that are deemed as relevant key words to be used in this capstone research project. We will look for key words that have the highest occurrence and meaning relevance during 2012 to 2017. For example, the word "debt" had tremendous relevance in 2008 during the financial crisis but other words may prove more relevant between 2012 and 2017. Words that signal trades are ranked by those with the highest accumulated profits made by the end of November 2017.

Solution Statement

To determine if there is an opportunity to create profitable market investment strategies by discovering predictive key word searches before financial market price movements, I will test these two null hypotheses:

1) Taking long/short positions following the decrease in the key Google trend search term volumes does not provide better returns than a random investment strategy.

2) Taking long/short positions following the increase in key Google trend search term volumes does not provide better returns than a random investment strategy.

In essence, this capstone seeks to prove the efficient-market hypothesis still holds true and to disprove there is a statistical significant impact to be found trading profitably based upon search term volumes as predictive indicators.

This report will use supervised learning to select the right day to trade by signaling its time to take a long or short position in the DJIA. The first output label indicates buy (1) or doing nothing (0). The second output label (sell) indicates sell (1) or doing nothing (0). Look ahead bias is avoided by mimicking a cognitive computing or human-thought process that makes decisions based upon clear signals.

If this report finds profitable and statistical merit using GTS within an investment trading strategy, then this report will conclude with next step recommendations.

Benchmark Model
This capstone will use this python DataFrame with following rows:

- Top 20 Financial Indicator Search Terms – terms like "debt"
- Index Name – DJIA
- Date – of all DJIA trading activity from 1/1/04 to 11/30/17
- Open ~ High ~ Low ~ Close ~ Adjusted Close ~ Volume
- Enter Long Price ~ Exit Long Price ~ Enter Short Price ~ Exit Short Price
- DJIA Price Adjusted Close Moving Average (MA)
- DJIA MA +1/-1 Standard Deviation Buy/Sell Signals – T or F
- 30 Dow Stock Names
- 30 Dow Stock Adjusted Close Moving Average (MA)
- Dow Stock MA +1/-1 Standard Deviation Buy/Sell Signals – T or F
- 30 Dow Stock Name Search Volume Moving Average (MA)
- Dow Stock Name Search Volumes MA +1/-1 Standard Deviation Buy/Sell Signals – T or F

The Google Trends Strategy Model
There are four components to the Google Trends Strategy (GTS)'s model. They are search-term performance, search-term selection, using search terms as financial predictors to buy or short an index, and executing a consistent trade purchase/sell timing methodology.

Search-term performance
This capstone will use the top twenty search terms in Preis' Google Trends Strategy. These tested key-search terms will be analyzed and ranked per stock market index performance as the cumulative returns of the top twenty search terms on both the training data (2004 – 2011) and the test data (2012 to 2017).

Profit is realized when a future change in the market price is correctly anticipated. Search terms are ranked in order of most profitable. This will be implemented (with the benefit of hindsight) as follows:

- Selling (shorting the market) the DJIA index is done by selling at the closing price p(t) and buying back at price p(t+1) with the cumulative return R changing by log(p(t)) – log(p(t+1).
- Buying the DJIA index is the reverse: buying at the closing price p(t) and selling back at price p(t+1) with the cumulative return R changing by log(p(t+1) – log(p(t)).

Search-term relevance
In Preis' study, the search term "debt" was deemed the most profitable for both buying and shorting the DJIA index. This research was done during the financial market melt down of 2007 and 2008. Therefore, testing for search-term relevance during different investment eras makes sense.

Financial relevance is calculated by the frequency of each search term in the online editions of the Wall Street Journal (www.wsj.com) and the Financial Times (www.ft.com).

Search-term volume as short or buy indicators
Leveraging significant relative change in search term volumes when using search terms as predictors to buy or short an index such as the DJIA, in most likely most effective when the sentiment of the word logically makes sense as an indicator. For example, Preis found the term "debt" to be the most effective search term indicators for both shorting and buying profitably.

The logic here is: If worldwide or US domestic Google searches using the term 'debt' goes up substantially up compared to three weeks before, then this indicates concern which signals a good time to short because selling is likely to occur. If worldwide or US domestic Google searches use of the term "debt" goes down substantially compared to three weeks before, then this can indicate a lack of concern which signals a good time to buy so the indexes are expected to rise.

Timing short and buy trades
The trickiest challenge influencing this capstone's effectiveness is to establish an effective timing for purchasing and selling indexes as soon as key search term indicator signals are sent.

This capstone revises Preis' timing methodology from purchasing and selling on the first day of the week to the current or next day of the week:

- The short strategy was implemented by selling the DJIA at the closing price p (t) on the current or next trading day of week t, if the change in profit * (t-1, change in t) > 0 and buying the DJIA at price p(t+1) and the end of current or next day of the following week.

- The buy strategy was implemented by selling the DJIA at the closing price p (t) on the current or next trading day of week t, if the change in profit * (t-1, change in t) < 0 and buying the DJIA at price p(t+1) and sell the end of the current or next trading day of the following week.

Buy and Hold (Warren Buffet) Strategy
GTS' success will be determined in comparison to profits made by a buy and hold the DJIA strategy. The buy and hold strategy is to buy the DJIA on January 1st 2012 (its price is $12,221.19) and sell it on the day of writing this report, November 14th, 2017, its closing price is $23,432.71. In other words, the returns from the GTS must be higher than approximately $11,211.52 to be deemed worthy of incorporating into a trading strategy and system.

Random (Walk on Wall Street) Strategy
GTS' success will also be determined in comparison to profits made by randomly buying a stock or shorting one week and selling it the next week. There will be 10,000 of these random trade simulations and the standard deviation of these trades will be used as the baseline for evaluation metrics.

Evaluation Metrics
To determine if the Google Trend Strategy is a valued component to include within a profitable trading strategy, the first evaluation metric is the profit realized per each trading strategy. The cumulative profit/loss realized from using the Google Trend Strategy will be visually compared to the Random and Buy/Hold Strategies. The accumulative profit/loss will be calculated by adding up the results from each trade for each strategy made during the testing data (2012 to 2017).

There will also be cumulative return visualization that shows profits made from the twenty search terms used and compares these results in terms of standard deviations to the random strategy returns. The random strategy has a zero standard deviation and other strategy results will vary from this standard deviation. Therefore, comparing how these results compare to this standard deviation tells an interesting story on the strategies merit. For example, if using the search term "debt" realizes a profit that is 2.31 standard deviations larger than the random strategy, the term debt will be visualized with a 2.31 value that surpasses the two horizontal axis marking that signifying two standard deviations.

The benchmark model has its own predictive performance metrics such as the F-score, accuracy score and time.

Project Design (hybrid supervised and recurrent neural network (RNN) deep learning)
The Supervised learning process to explore all features during DJIA buying and selling
- Data exploration
- Logarithmic transformation separating highly skewed feature distributions from strategy gains and losses.
- Normalizing Numerical Features
- One-Hot Encoding for Existing Features during buy and sells
- Evaluating model clarity – Precision and Recall
- Comparing supervised learning models
- Create a training and predicting pipeline
- Model Evaluations (SGDC, Ensemble Methods (Gradient Boosting & Random Forest Classifiers)
- Grid Search Optimization (tuning for optimized final accuracy and F-scores)
- Final model analysis
- Feature importance ranking ~ Extracting feature importance

The neural network (RNN) deep learning process to explore all features during buy and sell process
A RNN will be used to predict the test data DJIA stock prices when Google Trend terms indicate to buy or sell.
- Data is loaded and normalized to improve convergence
- Build the model
    - Sequential model

- LSTM first layer ~ true sequence ~ 20% dropout
- LSTM second layer ~ false sequence ~ 20% dropout
- Linear dense layer to produce one single value
- Compile model with MSE and Gradient descent optimizer

- Train the model ~ comparing predictions to actuals
- Test for predictions
- Visualize

The supervised learning process is used to analyze features and the RNN is used to predict DJIA index prices when this Google Trend Strategy is implemented to buy and sell the DJIA.

Presentation
All profit and loss results will be visually summarized by comparing each of these three strategies (Google Trends, long term buy and hold, and random buying) within a horizontal x axis yearly timeframe and vertical y-axis highlighting the comparative percentage of profit or loss.

If these results show that the Google Trends strategy has profitable competitive merit than the results from the top ten terms will be shown in comparison to all strategies with a discussion on the Google Trends Strategy results.

All significant findings from the supervised learning and RNN processes will be summarized. If the null hypothesis is proven not true, then recommendations on how to incorporate the Google Trends Strategy into a financial trading strategy based upon all significant findings and areas for further research will be summarized.