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Project: Stock Movement Prediction

ML Final Project Proposal

Description

For our final project, we will be using various machine learning algorithms to predict the optimal times to buy and sell stock shares. Ours is an **application project**. In essence, we want to predict local maxima and minima for time series data. Existing literature employs a wide array of methods for local extrema prediction, including (and certainly not limited to) random forest, support vector machines (SVMs), reinforcement learning, and long short-term memory neural networks (LSTMs). We plan to implement several of these and compare the investment strategies that they produce using the foundational evaluation metric of our field: profit. We would also like to explore ways to use sentiment analysis techniques on company news or tweet data; we would integrate this as another feature for our other models. In the end, we would like to devise a machine learning-informed portfolio allocation strategy that adheres to

Roles:

The division of the first phase of our project will be based on algorithms: each of us will work simultaneously and (mostly) individually on incorporating one of the following approaches with our data: reinforcement learning, support vector machines (SVMs), artificial neural networks (ANN), long short term memory (LSTM), Naïve Bayes, random forest, KNN, and logistic regression. After those are completed, we will collaborate on merging our algorithms with the NLP, fleshing out those elements as much as we can before the final deadline.

- Daniel
    - Individual assignment tentatively set as building reinforcement learning model and Naïve Bayes classifier
        - Use *Yang et. al* for reinforcement learning agent performance benchmark
        - Compare Naïve Bayes results to those obtained by *Nabipour et al.*
    - Contribute to NLP component (sentiment analysis on tweets)
        - Reconcile project ideas with Tweet Catcher library methods and other existing NLP techniques
- Yaroslava
    - Individual assignment tentatively set as building KNN, LSTM/ANN
        - Compare to results obtained by *Patel et al.* and *Nabipour et al.*
    - Contribute to NLP component
        - Focus on theoretical basis from *Bing et. al*
- Jonathan

- Individual assignment tentatively set as building SVM, random forest, logistic regression
    - Compare to results obtained by *Hiba Sadia et al.*
- Contribute to NLP component
    - Emphasis on coding and evaluation using results from *Bing et. al*

Related Topics

1. LSTM (ANN) - long short-term memory is an artificial recurrent neural network architecture that can be used for classifying and making predictions using time series data. Since LSTM can store past information (previous stock prices), we hope to use it to predict the local minima and maxima of future prices.

2. Random Forest algorithms construct decision trees, which allow them to output classifications based on the mode or the average of the classes that make up a tree. Randomly generating decision trees and averaging their values will help us build out a model that does not overfit on one (type of) stock or one time period.

3. Support Vector Machine (SVM) algorithms build out a decision function using support vectors—a subset of training samples—and produce binary classifications. Our SVM will predict whether the stock price will decrease or increase on a given day. Each "direction change" implies a local extreme: a point at which we will buy or sell.

4. Reinforcement learning is predicated on maximizing a reward function, which we will develop by measuring the accuracy of our extrema predictions and by applying our profit metric.

5. Natural language processing involves quantifying and analyzing features of textual data. We will use NLP methods to explore the relationship between relevant tweet sentiments and concurrent stock movements.

Data

The best freely available historical stock price data set that we could find is this one from Kaggle. It is a CSV file consisting of daily price data from over 5,800 stocks, dated between 1980 and April 2020. We will use only a small segment of it (probably less than five years worth) to test and train our models. If we can get library access to more detailed proprietary data—which would ideally have more features or include hourly prices—then we may look to use that instead.

As for the tweet sentiment analyzer, we will use Tweet Catcher, a Python package that accesses historical tweets based on user-entered keywords. We will use company names or stock tickers as keywords and analyze the top results.

Novel Approach

For our novel approach, we would like to weigh the daily price changes based on the stock's average volatility. This could help to improve performance by predicting major ebbs and flows before they happen. Some simple trading strategies involve selling or buying after a predefined jump or fall in the stock price (a reasonable choice is 10%). We can expand upon this by weighting a set percentage by the average volatility, encouraging the algorithms to avoid buying during short price falls (hoping for a larger decrease), and conversely, avoid selling during short price jumps (hoping for a larger increase).

Our more ambitious novel idea involves creating a user-specified parameter for acceptable risk tolerance and capital constraints. Higher risk tolerance would permit less frequent buying and selling, in which the investor would hope for larger price decreases or increases, respectively, as marginal (10 percent?) changes occur. Investors with more funding may be drawn to higher-risk strategies, while investors with less funding may prefer a more conservative approach. We can limit purchases and adjust the number of shares of each stock that are bought and sold based on the constraint (the size of the investor's account), allowing our algorithm to make *comprehensive portfolio recommendations*. None of our reference papers appeared to devise specific portfolio allocation strategies. We can superimpose the stock price charts and local extrema on a single time series graph, telling the user when to buy or sell a certain amount of shares of each stock.

Timeline

We would like to complete our "individual" algorithm assignments within four weeks. If we can complete our implementations of the selected algorithms and compare their performance evaluations to those of our references and to each other by late November, then we will use our remaining weeks to apply tweet sentiments as features in our existing models and incorporate our novel performance boosting strategy. Our current timeline is:

Week 1: Attempt to apply familiar algorithms (KNN, Naïve Bayes, SVM) to dataset, look further into methods and variables provided by selected libraries (Tweet Catcher, etc.)

Week 2: Yaroslava will create the initial version of ANN and LSTM code, define the key aspects of novelty in data mining applicable for the project. Daniel will start to train the reinforcement learning agent on the dataset. Jonathan will finish the SVM code, begin work on Random Forest, and gather Twitter data for the NLP component.

Week 3: Flesh out code from Week 2 (LSTM/ANN for Yaroslava, RL for Daniel, Random Forest for Jonathan), run preliminary NLP analyses on Twitter data

Week 4: Complete LSTM/ANN, RL, and RF code, work collectively to complete Twitter sentiment analysis and look for ways to integrate it with the other algorithms

Week 5: Fix any bugs or issues in the code, begin evaluation comparison for each algorithm and its related paper(s), explore novel performance boosting and portfolio allocation strategy

Week 6: Complete evaluation, compare with reference literature, put together basic slides for final presentation

Week 7: Polish final presentation, work on written report

Demo

For our demo, we plan to display and compare the results (predicted local minima and maxima) generated by each of our models. We will include the total return yielded by following the investment strategy informed by each model. Finally, we will compare the performances of each algorithm on our data (using standard and trading-specific evaluation metrics) to those reached by the implementations in our reference papers.

Evaluation

Our goal is to develop a trading strategy that will maximize return for a stock trader. Thus, our models will be evaluated on how much profit would be generated by buying at their identified local minima and selling at their identified local maxima. We can easily calculate the profit using our daily stock price data and with these extrema.The algorithms will be measured against each other, as well as against the actual maximum profit (calculated from the global minimum and maximum) over a specified time period. Separately, we will evaluate the individual performance of our models using standard evaluation metrics (F1 score, ROC curve, etc.) to those reached by the implementations in our reference papers.

We will also run the same evaluation metrics on our algorithms with the novel approaches that we will be exploring which include volatility weighting, risk tolerance, and portfolio recommendations. In addition, we will need to combine the standard algorithmic predictions with the NLP sentiment analysis in order to get a final prediction. For this, we will likely categorize certain sentiments as being on either extreme (positive or negative) and make adjustments to the expected stock value relative to historic data for similar sentiments.

References

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