Transcript

Slide 1

This is a presentation for my project, titled “Forecasting daily Closing Prices for Equity symbols using Artificial Neural Networks”. I would like to point out that the project is still under way and results have not been published yet.

Slide 2

Firstly, a brief outline of what we’re going to talk about in this presentation. The project is an attempt to predict the stock market so a quick explanation on why forecasting is important in general comes first. Followed by a short description of other closely related works and then the methodology and data collection for this project. We will have some time for Q&A at the end.

Slide 3

Forecasting. Why do we need to know the prices of stocks beforehand? The goal is to build diverse portfolios based on robust trading logic and strategies. We also want to trust our computers to trade autonomously for us. The bottom line is we want to take decisions not founded in chance. We want to make money with as little risk involved as possible.

What stops us from already doing that? The Efficient Market Hypothesis states that stock prices reflect all available information in the market and since stock prices only react to new information which appear to be random, that means that prices also behave randomly. Literature is mixed on the efficiency of the market however, with multiple studies showcasing that markets are not perfectly efficient. The second problem is that traditional methods for modelling asset returns are not as accurate as we would like them to be.

Slide 4

Neural networks have been used to solve a wide variety of problems due to their universal approximator status. They’re flexible and we’ve seen a multitude of architectures employed. In the context of finance, we have seen simple Multi-Layered Perceptrons, Recurrent nets (LSTM, GRU), Convolutional nets, Generative Adversarial nets (GANs) used to predict the stock market that rival more traditional numerical approaches like autoregressive integrated moving averages, heteroscedastic models and so on. In fact, several studies show lower error values for neural networks than ARIMA models in predicting stock prices.

Other aspects of statistics seem to make an appearance in the design of Artificial Neural Networks for finance, like data mining and natural language processing. It’s been shown that analysis of finance related news, from articles and even tweets, has a noticeable impact on the accuracy of stock market prediction methods.

Slide 5

Moving on to our project, which is about forecasting the closing price of symbols using historical data as well as constructed features. We implement a 3-layer Sequential model with 2 Long Short-Term Memory layers and 1 Dense layer. LSTMs are powerful time series modelling networks and have been widely used in this context since their invention in 1997. We will be using the Keras API to create, train and test our model against the datasets prepared. The model will then be benchmarked against an appropriate ARIMA model, with error rates and accuracy metrics presented.

A graph is also provided in the slide that shows the training and testing values generated by the model plotted against the historical closing price of a New York Stock Exchange stock.

Why did we choose LSTMs? They are a type of artificial Recurrent Neural Network architecture and was chosen for the model because of their feedback connections, unlike the standard fully connected feedforward nets, this allows them to keep track of long-term dependencies in the input time series. This characteristic makes them perfectly suited to deal with time series. The network is trained and tested using Root Mean Square Error as its loss function and optimized using the Adam optimisation algorithm. We chose Adam for its popularity. The model will then be compared with an ARIMA model, using MSE. Hyperparameters will be tuned through manual search at first, hopefully we’ll have time to implement a better tuning method.

Slide 6

Moving on to the data used in the model. We have selected several stocks from the New York Stock Exchange (NYSE) for the trading year 2018. We take their daily open, high, low, close and volume values and construct rolling averages for the closing price with a standard window size of 14 days.

A few other features are then created, like an exponential moving average with the same window size, a Stochastic Oscillator index and upper and lower Bollinger bands. The data are then scaled down, split into training (80%) and testing sets (20%) and the most recent 160 rows are selected for the network to process.

The model would then predict future closing prices based on its training and testing and (hopefully) outperform the ARIMA model.

Slide 7

That’s the end of the presentation. I would like to thank my supervisor for her support.

Slide 8

Let’s move on to some questions.

Appendix

A stochastic oscillator is a momentum indicator comparing a closing price of a security to a range of its prices over a certain period. The sensitivity of the oscillator to market movements is reducible by adjusting that time period or by taking a moving average of the result. It is used to generate overbought and oversold trading signals, utilizing a 0-100 bounded range of values.

An exponential moving average (EMA) is a type of moving average (MA) that places a greater weight and significance on the most recent data points. The exponential moving average is also referred to as the exponentially weighted moving average. An exponentially weighted moving average reacts more significantly to recent price changes than a simple moving average (SMA), which applies an equal weight to all observations in the period.

Bollinger Bands are a highly popular technique. Many traders believe the closer the prices move to the upper band, the more overbought the market, and the closer the prices move to the lower band, the more oversold the market.

A time series is homoscedastic when the variance of the error term (random variable, noise) is constant. Heteroscedastic models don’t assume this.

Keras API, TensorFlow Backend, numpy, pandas, sklearn

Error metrics: RMSE, MSE Misc. Features: Directional Movement index, Relative Strength