Academic Research Review

Algorithmic Trading using Deep Neural Networks

EXECUTIVE SUMMARY

In this paper, we attempt to use a deep learning algorithm to find out important features in financial market data pertaining to a set of equities and forex which will then be fed into an AI system to make an optimal trade decision. The data for the deep neural network is collected on basis of three parameters namely fundamental analysis, technical analysis and sentiment analysis thereby mimicking the way in which discretionary traders make their trading decisions.

INTRODUCTION

Deep Learning (or Deep Neural Networks (DNN)) is a branch of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. This algorithm attempts to model high-level abstractions in data by using a deep graph with multiple processing layers. One of the real world applications of deep learning algorithms is the in area of image recognition where these algorithms have revolutionized this field with its ability to find distinctive patterns and features from noisy data. Unlike other machine learning algorithms which tend to plateau in performance with more data, Deep Neural Networks shows higher performance as dimension of data increases.

DATA FORMULATION AND MODEL PARAMETERS

- We resorted to a popular machine learning quote, “Don’t model the World; Model the Mind.” for data formulation. We wanted to emulate the way in which discretionary traders work and hence we explored different indicators they take into consideration while making a trading decision. There were three aspects that stood out and we formulated the data for our system based on these:
- Fundamental Analysis (FA), which refers to the core financials of the company
- Technical Analysis (TA), which refers to different ways in which a stock is moving in the market with indicators like trend, momentum etc., and
- Sentiment Analysis (SA), which refers to the positive/negative sentiment that is prevalent for a company or a country usually obtained from news/social media
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- For this study, we are considering the following asset classes:
- Equities - 7 stocks from different sectors in S&P 500 were sampled based on market capitalization
- Forex - 3 currency pairs namely EURUSD, USDJPY, GBPUSD were chosen

METHODOLOGY

The system described below is used to generate the optimal trading decision (buy, hold, sell) for a single security. The system can be generalized to trading a basket of securities.

System Overview

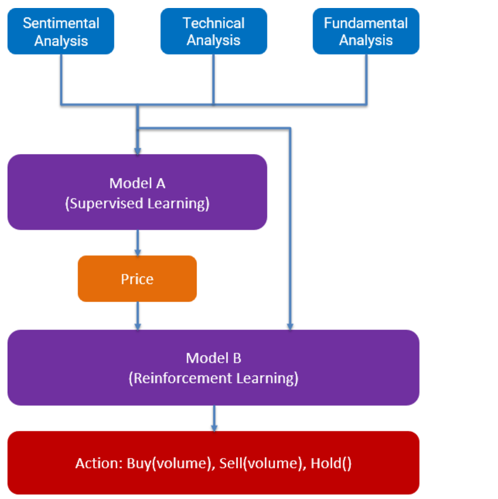

Figure 1: Simplified overview

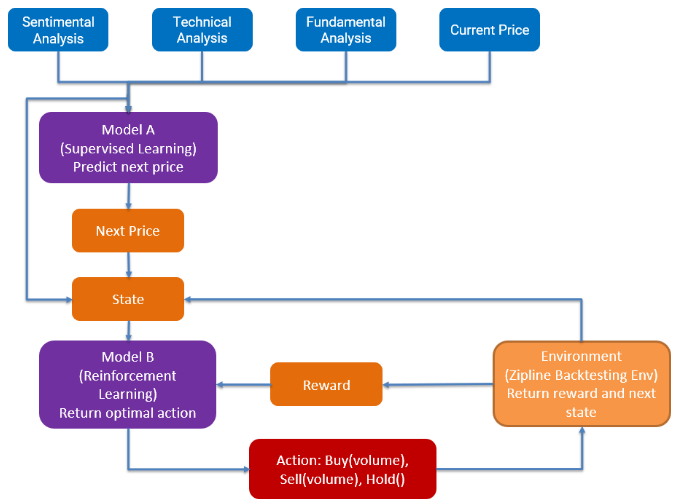

Figure 2: More detailed overview

Model A

The role of model A is to generate a prediction for the security's price in the next time step(minute). Model A will be trained with supervised learning algorithms using historical pricing data. While having a prediction of the next price is useful, it does not tell us the optimal action to take. A simple strategy based on model A would be to buy when price is predicted to rise and sell otherwise. However, we can do better by providing the prediction to another model which decides on the optimal action for us. This brings us to model B.

Model B

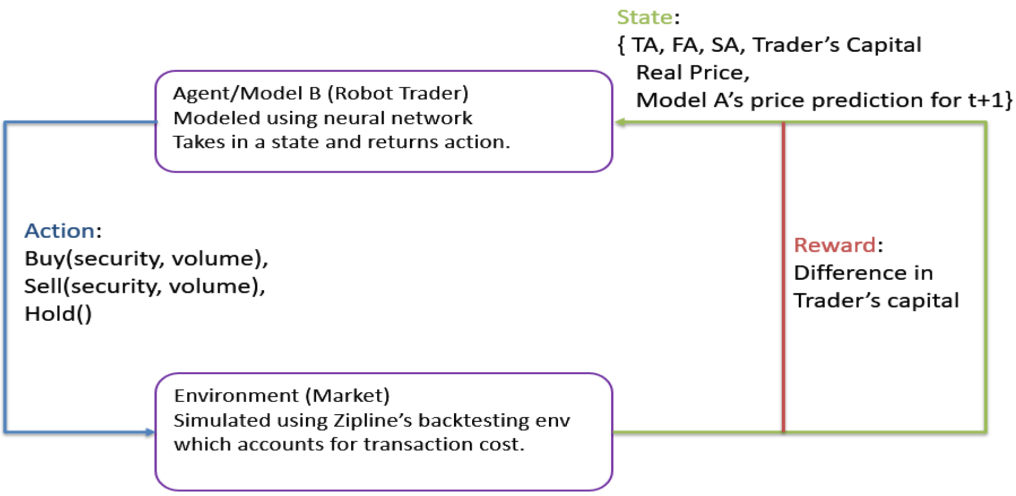

Figure 3: Interaction between model B and the environment

Unlike the training of model A, we cannot train model B (the AI agent) using supervised learning approach as it is not possible to know the correct action to take in any given state. Therefore, the agent has to be trained using reinforcement learning where the agent can learn the optimal action to take by interacting with the environment. We will be using Quantopian's Zipline backtesting to simulate the environment as it provides a realistic trading conditions for our agent to learn the optimal actions. The next state returned by the environment will be augmented with model A's prediction of the next price, the agent's current capital and the features from the three feature classes (technical analysis, fundamental analysis and sentimental analysis).

In reinforcement learning, the agent's goal is to learn an optimal policy that allows it to collect as much reward as possible in the long run. Therefore, it is very important that the reward is defined such that it aligns with our goal of maximizing profit. As of now, the reward is defined as the difference in trader's capital from the current time to the next time step.

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