Stock Prediction Using Artificial Neural Networks

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Introduction

In the trading environment, high-quality onestep forecasting is usually of great concern to market makers for risk assessment and management. We aim to forecast the price movement of individual stocks, based only on their historical price information.

Existing Solutions

RNN One of the existing solutions is using Recurrent Neural Network alone in order to estimate the next time sequence using LSTM or GRU neural units.

CNN Another solution is creating images from the stock and feeding them into a forward Convolutional Neural Network. Which works like extracting important features from such images, and prediction the next time sequence according to the extracted features

Let Xt represent a set of basic indicators and Yt denote the closing price of one stock for a one minute interval at time t (t = 1,2,...,T), where T is the maximum lag of time. Given the historical basic indicators information X ($X = \{X_1, X_2,...,X_T\}$) and the past closing price Y ($Y = \{Y_1, Y_2,...,Y_T\}$), our goal is to predict the closing price $Y_T + 1$ for the next one minute time interval.

Proposed Solutions

For the purpose of our experiment, We have two solutions proposed that were not implemented before. So we decided to run them versus, the already implemented architectures, CNN, RNN.

- 1. The first proposed solution is to implement an architecture that can extract features from the sequence of inputs to the network, and then use the extracted features to predict the next time sequence based on a window of the extracted features.
- 2. The second proposed solution is to implement a Generative Adversarial Network. This model is based on the intuition that a trader predicts the upcoming sequence, and then he tries to verify and adjust his prediction.

Dataset

For the purpose if this experiment, we used the publicly available stock market dataset from Kaggle, which contains over 14 million stock market closing data point. However, we used only the 4 stocks of Google, Amazon, Facebook, and Netflix, as they have a closely related data points which would make the experiment run smoothly.

Experimental Results

To ensure fairness in our experiment, we used the same dataset for all the models we trained. We tried several window sizes for the model. And, we finally choose the window size to be 8 for all models.

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m Mean~Squared~Error}=rac{1}{n}\Sigma_{t=1}^n(Y_t$ - $Y_{t+1})^2$

We used the MSE to be our loss function as we are comparing continuous values together.

Architecture	MSE
RNN	13.25
CNN	8.61
C-RNN	6.46
GAN	0.0000

Table 1: MSE of each experiment

Architectures Used

CNN We used 2 stacks of ConvNets. Each stack consists of 2 size 3 filters to have a receptive field of 5 while having lower number of parameters and average pooling at the end as we are dealing with a sequence of numbers. We increase the number of filters as we go down the network to extract more features as we go along.

RNN We added a sequence of Recurrent Units. We ended up choosing the GRU units as they lead to faster convergence and performance.

C-RNN In this architecture, we combined both of the convolution to extract features from the sequence and then feed those features into the GRU units for past input dependence.

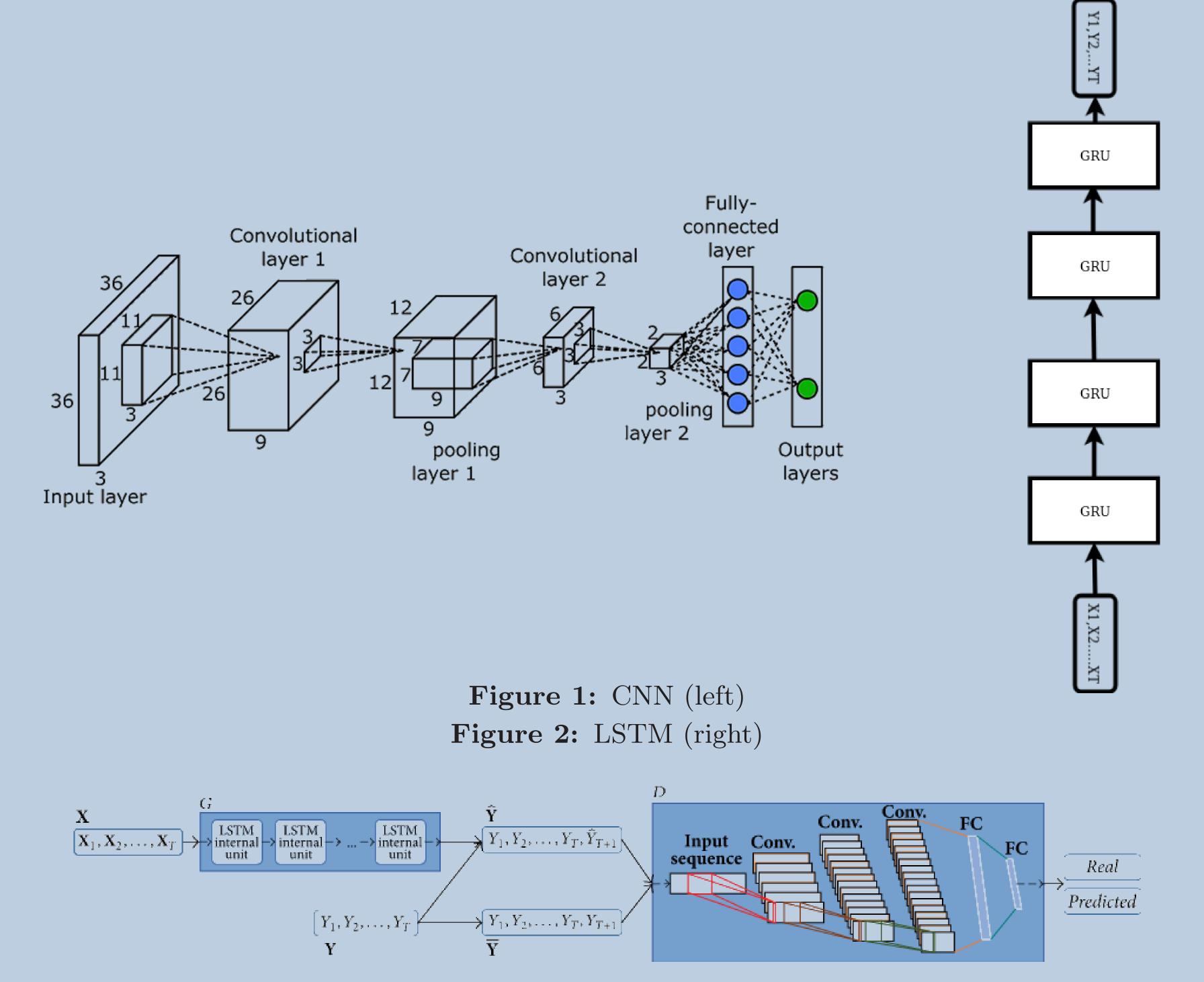


Figure 3: GAN Architecture

GAN Our GAN architecture is as follows, we have our generator as a Recurrent Neural Network which takes the stock dataset as input and predicts on that sequence. We then train the discriminator based on the real dataset and the fake dataset. We then freeze the discriminator, and train the whole model on the real dataset.

References

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