

MATH 5470 Final Project: (Re-)Imag(in)ing Price Trends

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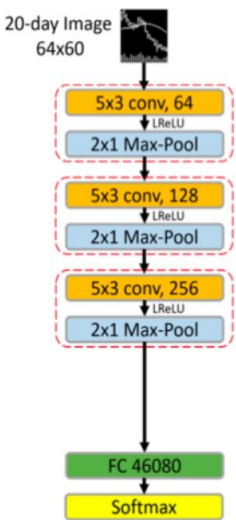
1. Introduction

Many literature has proven the feasibility of using past stock prices to predict future returns. In this project, we replicate the paper “(Re-)Imag(in)ing Price Trends” by Jiang et al.¹ which uses the convolutional neural network (CNN) to learn about the behavior of price-based predictive patterns. First we embed the 1D historical price time series into 2D images depicting past market information, and then we feed the training samples into CNN model to forecast the trend of future stock returns. We further investigate the sensitivity of CNN architecture for prediction, and explore the interpretability of the CNN model using Grad-CAM method. Besides simple binary classification, a CNN regression model is also constructed to predict the detailed return values. Finally, we briefly evaluate and analyze the model performance.

2. Data Preprocessing and CNN Baseline Model

Data: We investigate the 20-day return with image data which are of size 64x60 and each one features moving average line (MA) and volume bar (VB). The labels are the returns of the next time horizon with 1 indicating positive return and 0 otherwise.

Model: A variety of CNNs are trained to do the bi-classification. The loss is measured by cross-entropy between labels. Each training step minimizes the cross-entropy loss. Consistent with the paper, we use 70% of data from 1993 to 2000 for training and 30% for validation. The remaining twenty years of data are used for testing. The right figure shows an example of input image and the structure of baseline model.



3. Sensitivity Analysis of Model Structure

We study the model performance sensitivity of various CNN structures. The sensitivity is reported in terms of validation and testing accuracies. The variations of model structures include the dropout probability, number of convolutional layers, use of batch normalization, activation function, etc. As shown in the table, the highest validation accuracy appears when the dropout probability equals to 0.75, which indicates the robustness of CNN, while decreasing the number of layers meaningfully reduces the model performance. From the perspective of testing accuracy, the optimal structure is when we transition from leaky ReLU to ReLU. We can also see that the model performance is fairly sensitive to the use of batch normalization.

Model		Validation Acc	Test Acc
Baseline		0.546	0.528
Dropout (0.50)	0.00	0.545	0.518
	0.25	0.547	0.533
	0.75	0.548	0.531
Layers (3)	2	0.526	0.533
BN (yes)	no	0.544	0.445
Activation (LReLU)	ReLU	0.540	0.551

6. References

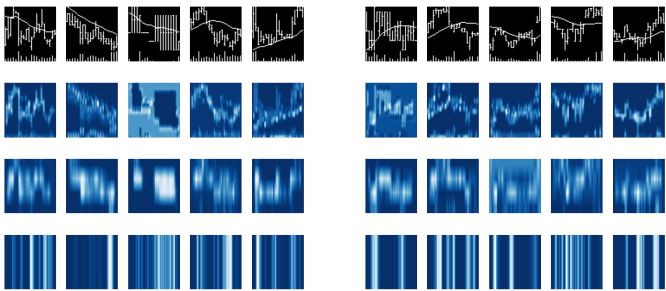
1. Jiang, Jingwen, et al. (Re-)Imag(in)ing Price Trends. Chicago Booth Research Paper No. 21-01. 2020.

7. Contribution

Hu, Mingyun: Data preprocessing, sensitivity analysis of models
Ma, Wanteng: Model adjustment, visualization and interpretation
Zhang, Jiaxin: CNN regression model

4. CNN Model Interpretation

The figures below show the Grad-CAM results of CNN model. Brighter regions of the heatmap correspond to regions with the higher activation. The input samples are classified as 0 and 1. From the results we conclude that (1) the first layer can capture the inflection points of the trends; (2) Open and close prices are of interest by model; (3) The volume information can be reflected in the last layer.



5. CNN Regression Model

We also build a regression model with CNN, since the labels of the data are numerical numbers. We set mean square error (MSE) as the loss function to help early stop, and try using the R^2 to present the accuracy. However, the R^2 is negative. Since the predicted value is not precise enough, we analyze the MSE directly. From the table we can see that, similar to the binary classification, the optimal structure is the one using ReLU instead of leaky ReLU.

Regression Model		Validation Loss	Test Loss
Baseline		0.05248	0.02665
Dropout(0.5)	0.00	0.05231	0.02669
	0.25	0.05262	0.02668
	0.75	0.05260	0.02650
BN(yes)	no	0.05239	0.02663
Activation(LReLU)	ReLU	0.05242	0.02649