MAFS 6010Z Project 2: Paper Reproduction

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1. Introduction

In this project, we reproduce the paper “(Re)-Imag(in)ing Price Trends” paper[1], show that CNN can be used to predict price trend and achieves better performance than equal weight portfolio. Moreover, we propose different training target that can better improve model performance.

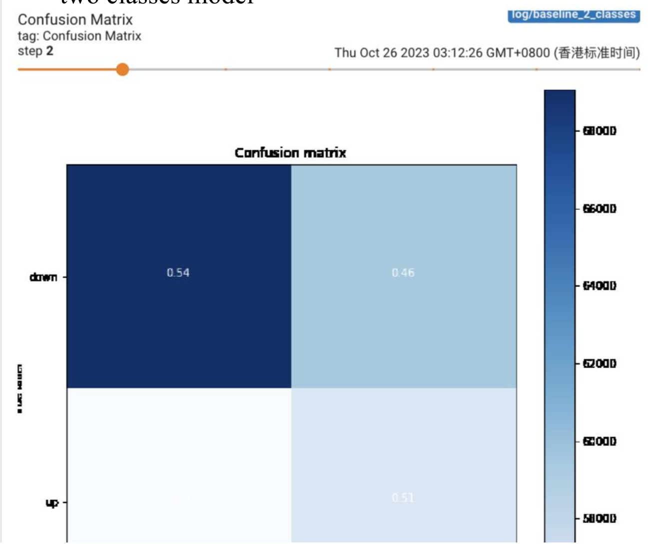
2. Data Preparation and Model Design

We use 20 days past OHLC(daily open, high, low, close price) chart with MA(moving average) and VB(volume bars) image as input and predict the 20 days price trend(Ret_20d). We design two ways of prediction:

1. Two labels: down(Ret_20d < 0) , up(Ret_20d > 0)
2. Three labels: down(Ret_20d < -0.04), oscillate (-0.04 < Ret_20d < 0.04), up (Ret_20d > 0.04)

For the Model, we use the same model as in the paper with same hyperparameter, expect we decrease the dropout rate of the fully connected(FC) layer from 0.5 to 0.25.

two classes model

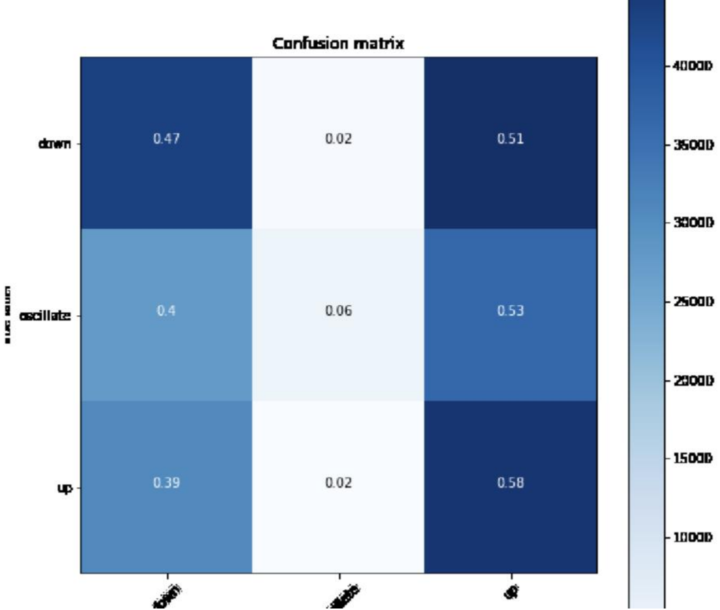


3. Experiment Design

We split the dataset into training, validation and testing splits. 1993-2001 data is used for training and validation, and the remaining are used as testing data. We do not randomly shuffle the data. Instead, we use the first 70% as training data and 30% as validation data. This splits ensures that validation data is later than training data, to avoid the leak of future information. We use cross-entropy loss as our loss function. Moreover, for the three labels task, we experiment different loss weight to encourage the model to predict up and down instead of oscillate. We will compare the equal weight setting (1.0, 1.0, 1.0) and weighted loss setting (1.2, 1.0, 1.2). For the optimizer, we choose AdamW optimizer.

For the implementation part, we refer to an open repository in GitHub3 and add our own modification. We record the training loss, validation loss, accuracy and confusion matrix of each epoch with tensorboard, and select the epoch with the best performance.

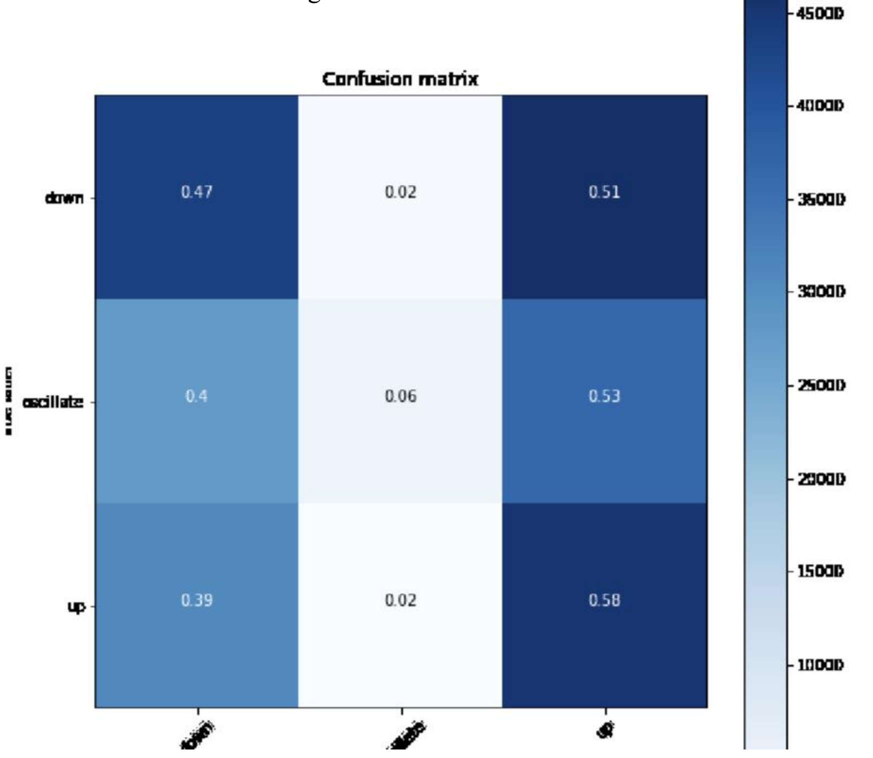
three-classes model



4. Performance Evaluation: Confusion Matrix

We first choose the best epoch based on Validation Loss. We can see that training loss drop to a slope within 10 epochs, while validation loss oscillate around their initial value. For two class classification, the prediction accuracy has no different from a random guess, but for three class classification we see a slightly improvement compared to a random guess (33% -> 40%). On test set, the improvement vanishes. From the confusion matrix, we cannot see the different in the distribution of predicted label condition on the true label.

three-classes weighted loss model



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5. Performance Evaluation:Portfolio Construction

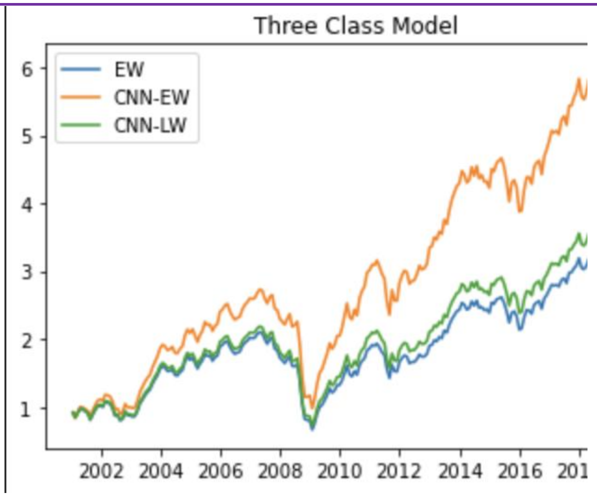
However, it is more appropriate to evaluate the model performance with backtesting rather than use statistical indicator. We use two ways to construct our portfolio:

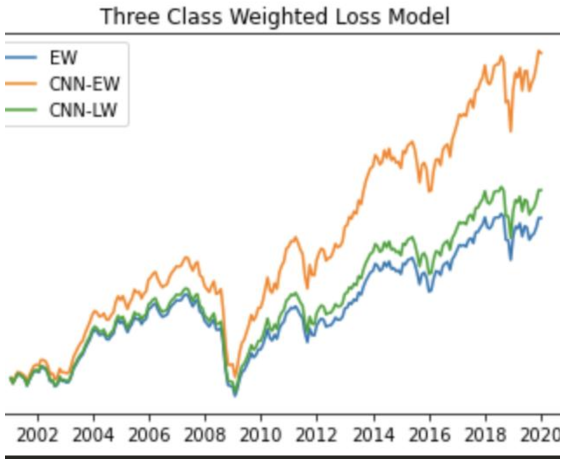
1. Long the stock with predicted label “up” with equal weight. (predict up portfolio)
2. Long all the stock with weight equal to there “up” logit. (logit weight portfolio)

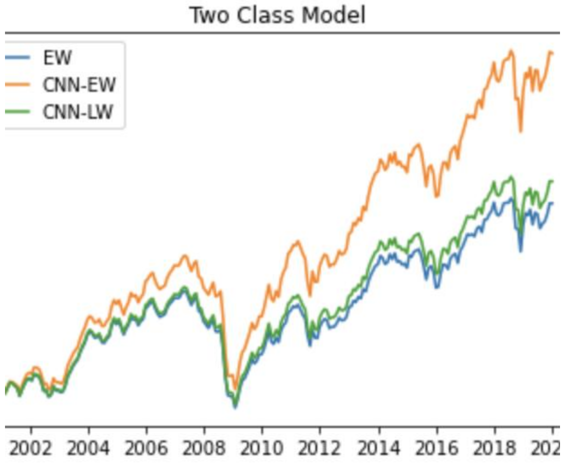
Then, we calculate their annualized return, Sharpe ratio, and maximum drawdown and compared to the equal weighted portfolio. The indicators are listed in the table. We conclude the following result:

1. The logit weight portfolio performs slightly better than equal weight portfolio.
2. The predict up portfolio outperform the equal weight portfolio significantly.
3. Despite the loss we set to different label in three class classification task, they seems to fall into the same local minimum, which can be proven from their confusion matrices and backtesting performance.

Model	Portfolio	Annualized Return	Sharpe Ratio	Maximum Drawdown
No	Equal Weighted Portfolio	6.28%	0.17	68.3%
Two Class Model	Predict Long Portfolio	8.87%	0.31	64.71%
	Logit Weight Portfolio	6.73%	0.2	67.11%
Three Class Model	Predict Long Portfolio	9.93%	0.35	64.15%
	Logit Weight Portfolio	6.92%	0.21	66.96%
Three Class Model With Weighted Loss	Predict Long Portfolio	9.39%	0.33	64.46%
	Logit Weight Portfolio	6.93%	0.21	66.95%







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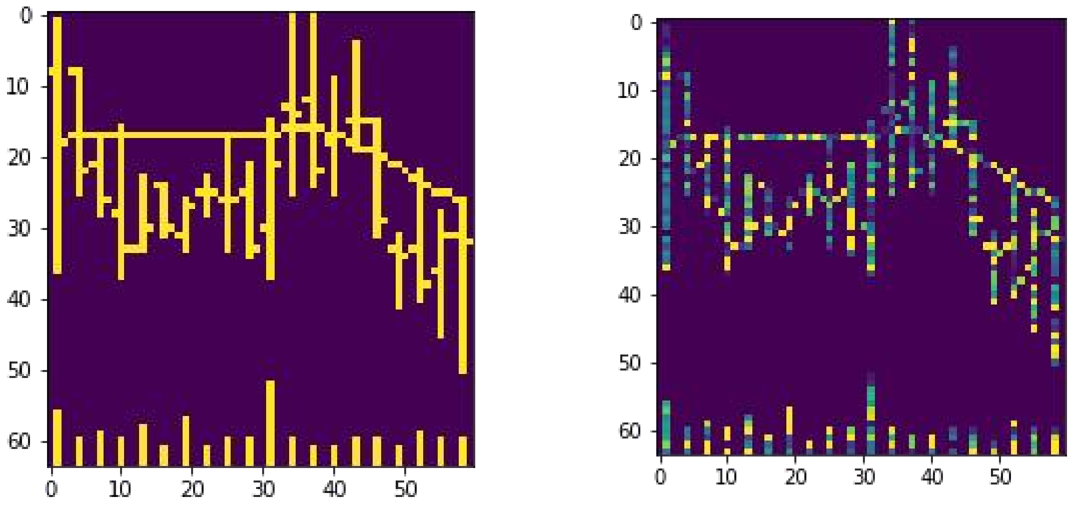
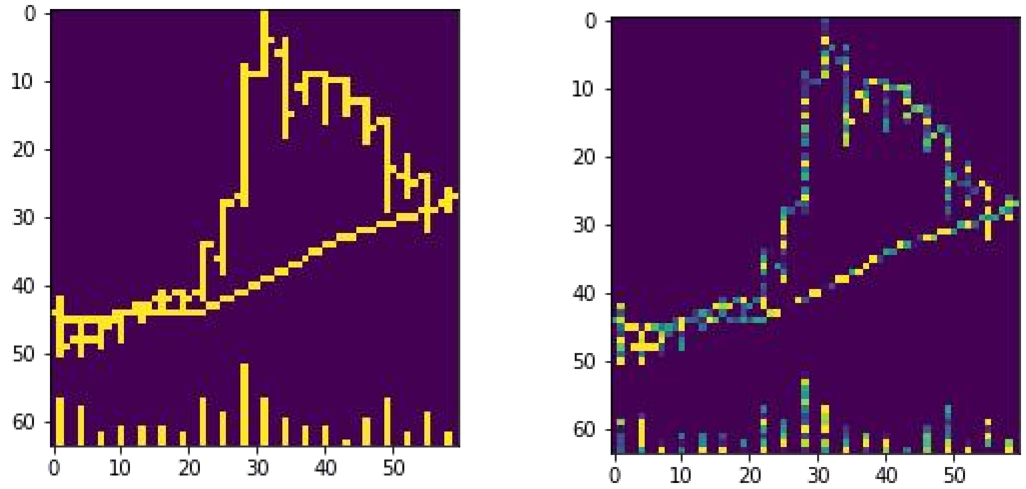
7. CNN Visualization

We try to analyzing the activation patterns of the CNN model at different levels layer by layer. We can understand the model's gradual abstraction and understanding process of the input image. Visualizing the activation patterns of different layers can reveal how well the model understands the image and observe how the model gradually transitions from low-level features to high-level features.

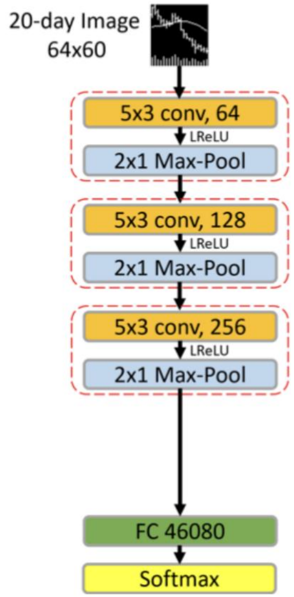
In this part, we selected two pictures, one representing falling and one representing rising; then we visualized each layer in CNN respectively using Guided GradCAM Technology. In this page, we also plot the attributions for the up and down.



down



up



8.Reference

1. Jiang, Jingwen, Bryan T. Kelly, and Dacheng Xiu. "(Re-) Imag (in) ing price trends." Chicago Booth Research Paper 21-01 (2020).
2. Loshchilov, Ilya, and Frank Hutter. "Decoupled weight decay regularization." arXiv preprint arXiv:1711.05101 (2017).
3. https://github.com/lich99/Stock_CNN

9.Contribution

Luo Xinyang: model training and evaluation
Sun Peiran: CNN visualization and interpretation

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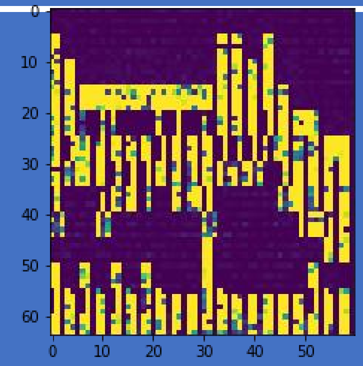
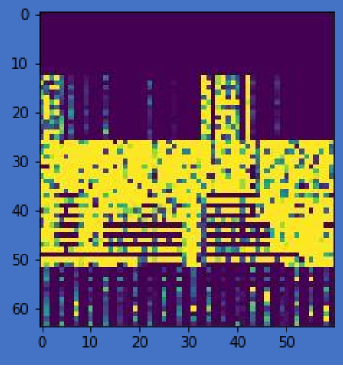
Two Classes

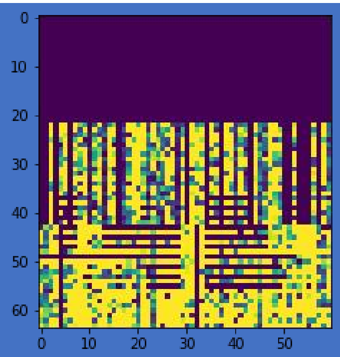
Layer 1



Layer 2

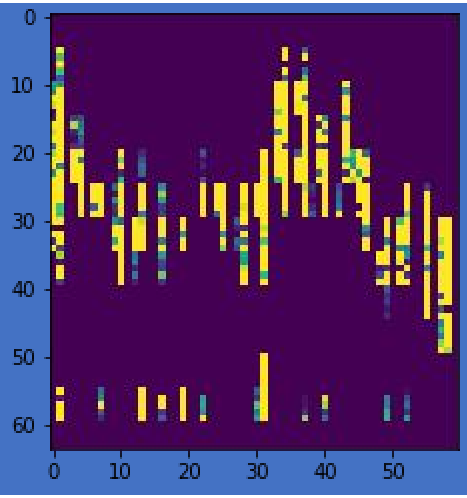


Layer 3



Three Classes

Layer 1



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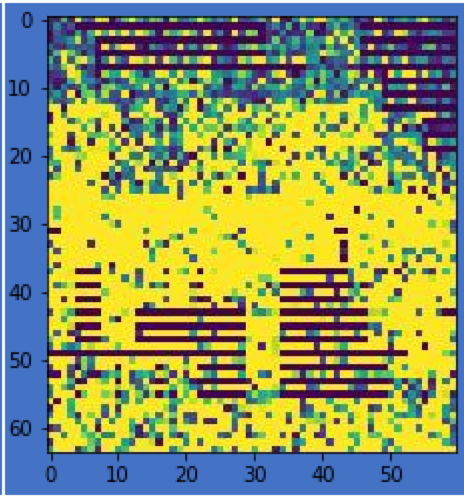
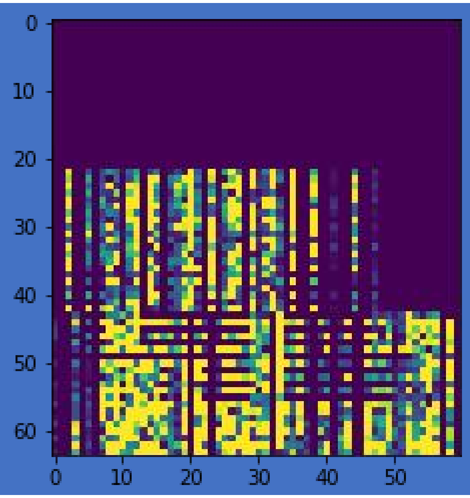
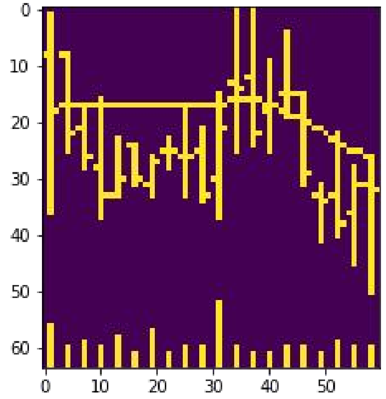


Layer 3





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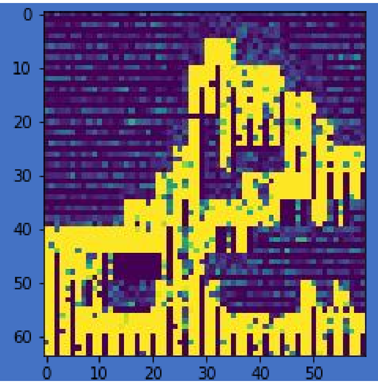

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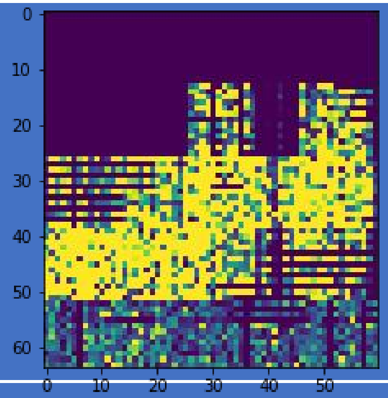

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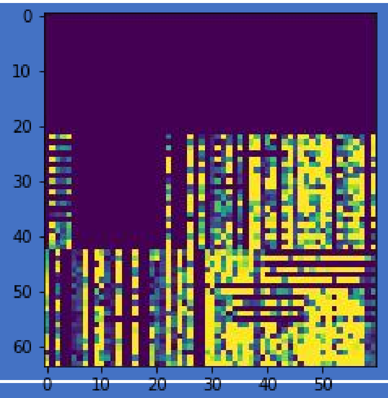

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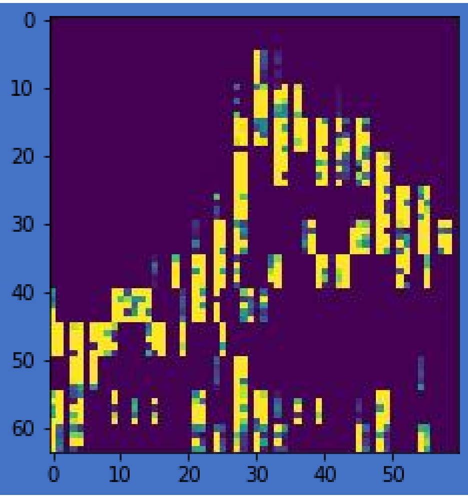
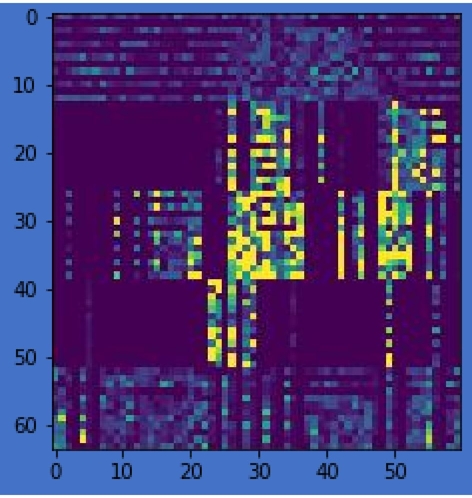


Layer 2



Layer 3