MATH5470 Final Project: (Re-)Imag(in)ing Price Trends

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https://www.youtube.com/watch?v=vJF3vGip9LE

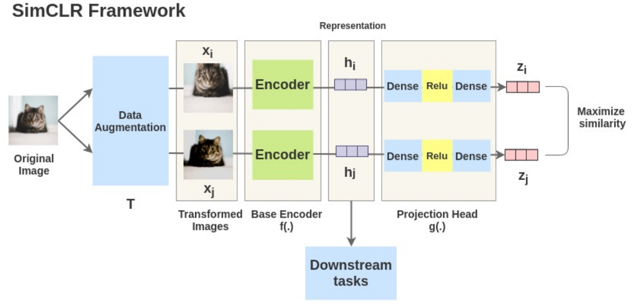
1. Introduction

We have replicated the paper which explore CNN to learn price patterns as image that are most predictive of future returns. We treat it as image binary classification task.
Instead of simply applied the same CNN model as stated in the original paper, we additionally applied pre-trained RESNET50 as our new backbone and applied self-supervised learning before proceeding to the classification step.
Our accuracy has slightly increased compared with the original paper.

2. Self-Supervised Contrastive Learning

Contrastive Learning aims to learn general features of a dataset to create a better latent representation in the model latent space. The idea is to pull closer data points together in the embedding space.
Recent research in Google AI blog, which combined Self-Supervised Learning before Supervised fine-tuning on labeled medical images have achieved higher accuracy.
We want to explore the same training technique on this price trends dataset to see if this technique can achieve higher accuracy.
We applied **SimCLR** Framework before training the down-stream task.

SimCLR Framework



Youtube Link

https://www.youtube.com/watch?v=vJF3vGip9LE

3. Transfer Learning with RESNET50

Transfer Learning usually fast converge and boost accuracy through transferring the pre-trained knowledge in previous task to new downstream task. Deeper model usually perform better in image classification task. Therefore, we attempted a deeper architecture **RESNET50** in this price trend prediction. However, as stated in original paper, the image dataset for pretraining look rather different from ImageNet, the performance of this transfer learning in this downstream task is yet to be observed.

4. Training Method

We applied the same **training strategy**, including

1. Randomly select 70% images for training and 30% for validation
2. 50% Dropout
3. Adam Optimizer
4. Xavier Initialization
5. Early Stopping
6. Batch Normalization

Additionally, we applied self-supervised pre-training and pre-trained RESNET50 for comparison

5. Prediction on Price Trends

Model	V Acc.	T Acc.	V Loss	T Loss
Baseline	0.542	0.533	0.687	0.690
Our Replicated Baseline	0.522	0.517	0.697	0.705
RESNET50	0.552	0.541	0.679	0.682
SimCLR + RESNET50	0.549	0.543	0.681	0.683

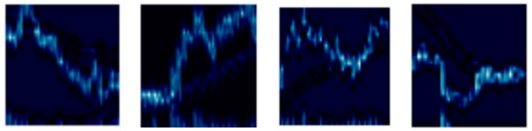
Each model have been trained for at least 3 times with different parameter setting and obtained the best as the result.

5. Result

Our replicated model perform slightly poor than the paper. However, with RESNET50, this deeper pre-trained model can boost the accuracy. **Deeper Model with pretraining** can again achieve better result than simple model.
However, the effect of contrastive learning **does not have significant improvement** in this downstream task.
Overall, the accuracy is always above 0.5, which CNN perform better than random guess and indeed learn some price pattern.

6. CNN Visualization with Grad-CAM

We visualize the activation using Grad-CAM. The main activation area is the price, rather than the moving average line in the middle of the price or the Volume Bar in the bottom.
CNN learn to predict by mainly reading the price movement. The volume bar in the bottom have little effect for the prediction.



7. References

Self-Supervised Learning Advances Medical Image Classification
https://ai.googleblog.com/2021/10/self-supervised-learning-advances.html

8. Contribution

Coding, Model Architecture, CNN Visualization

- Wong Wing Kin

Parameter Tuning

- Wan Ho Yin