Data Science Institute COLUMBIA UNIVERSITY

Introduction

One way to model the sequence of a trader to help the decision making process in financial company is to use people's gaze information on multi-screens, which could be recorded by using some specialized device such as GazePoint. However, it's expensive and not scalable. Our project provided a convenient and scalable solution by directly using webcam to capture the face images and make real-time prediction. To simplify the problem, we built nine classification models to predict which part of the screen people is looking at. The prediction results are basically different time series sequence, which could be further used for decision making process.

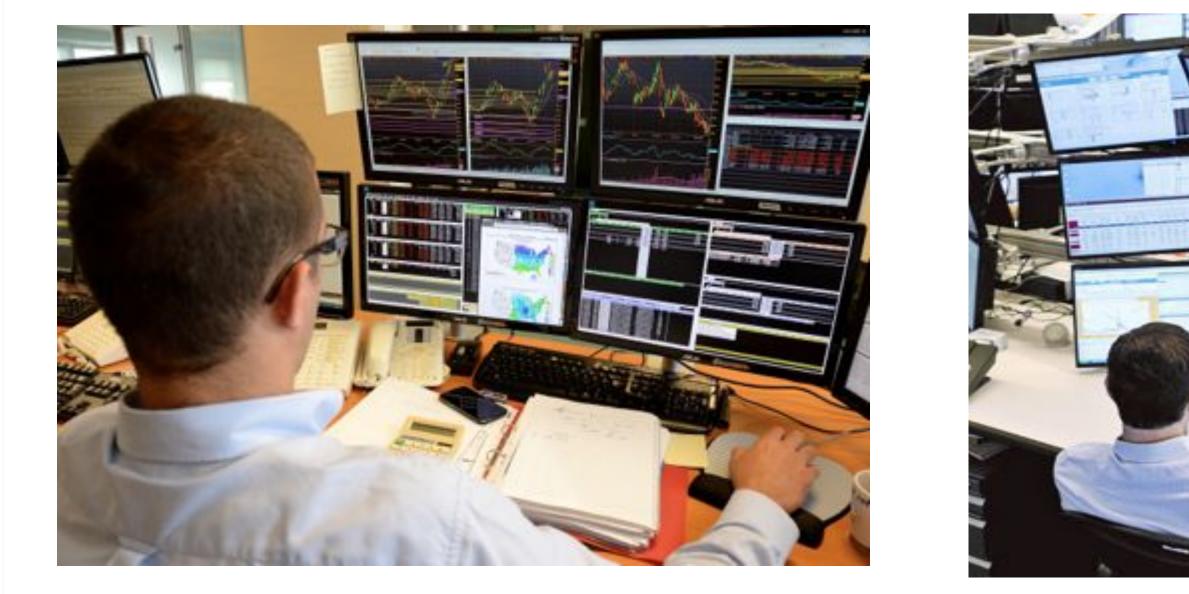


Figure 1. Two traders daily work

Model:

Architecture

The whole project pipeline consists of three parts: (1) Observer, it controls webcam to capture face images; (2) Eyegaze comparator, it uses gaze point

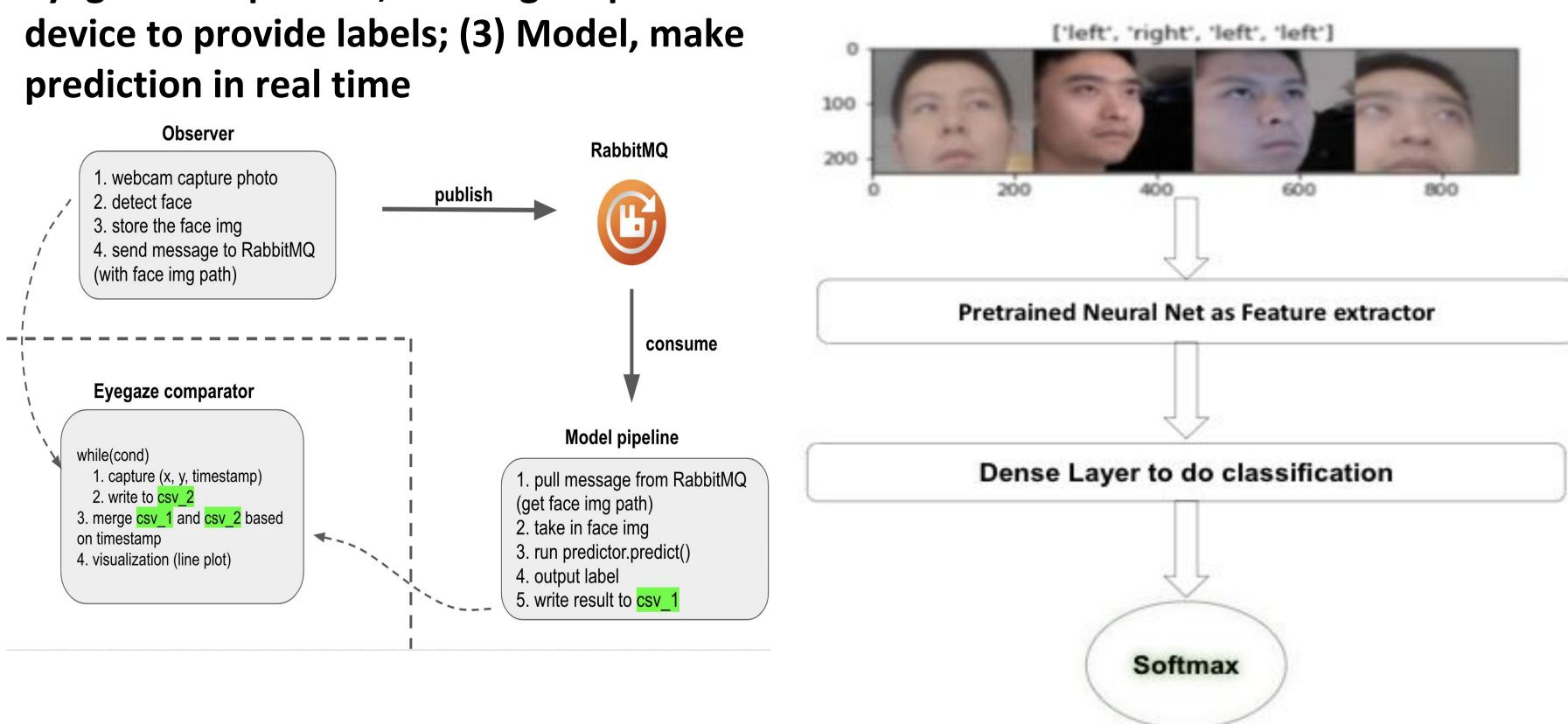
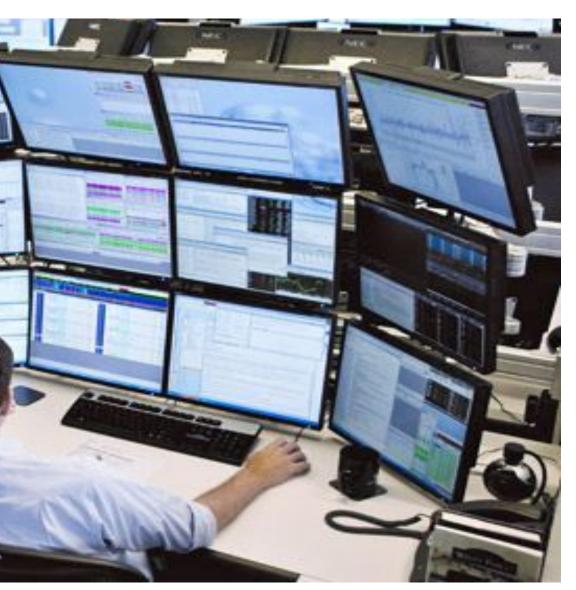


Figure 2. Project Pipeline

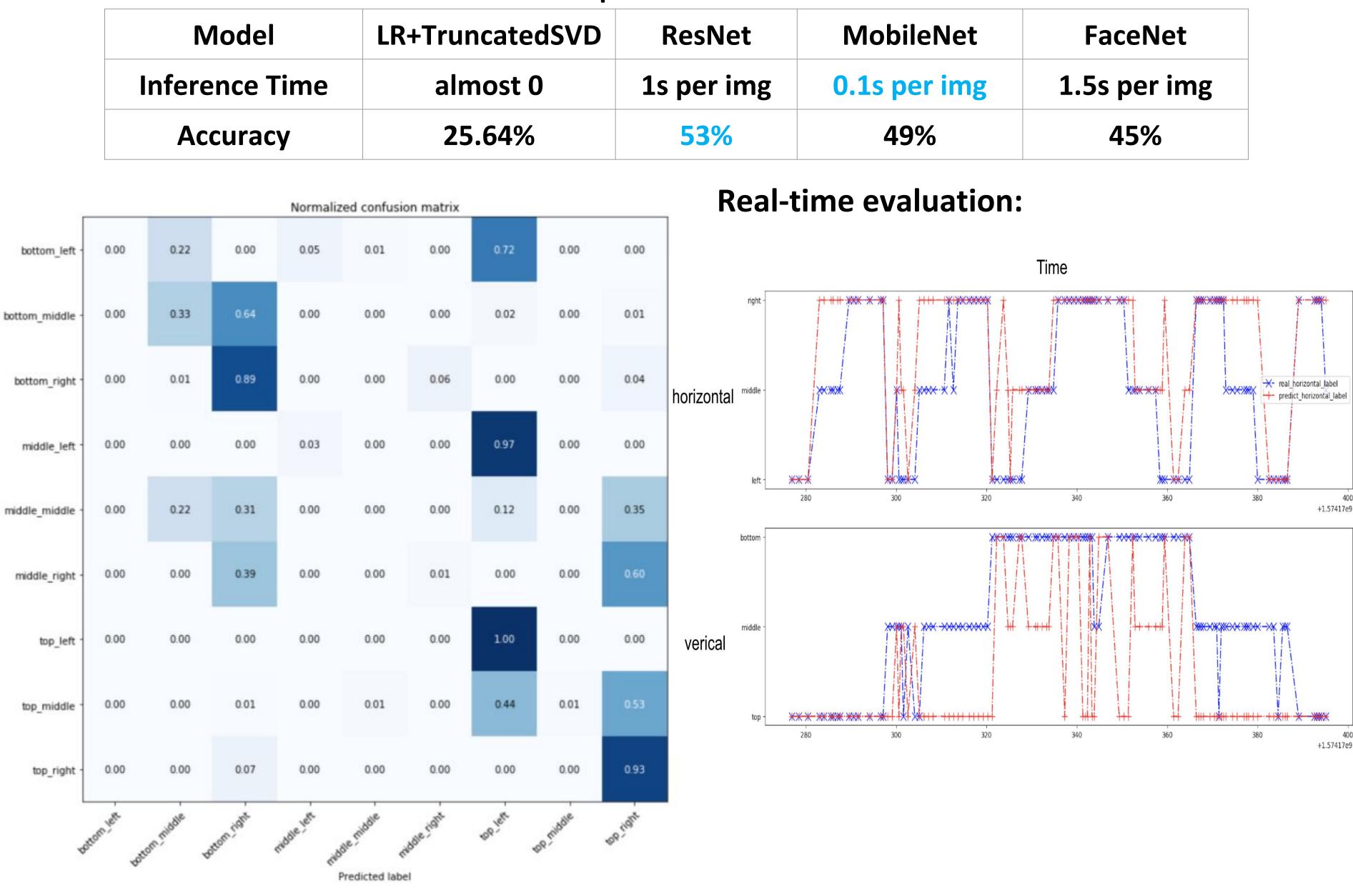
Knowing eye gaze through Webcam

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Evaluation

Model Performance:



We implement pre-trained neural nets, such as ResNet[1], MobileNet[2], FaceNet[3] with additional dense layers to do classification.

Conclusion

This project provides insights on capturing gazing point with webcams. Using transfer learning, which was proven useful given similar contexts and users, we model traders' eye gazing areas when looking at the screen. While our experiment tries different models, we decide to use MobileNet under the trade off between accuracy and inference time.

Acknowledgments

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References

Figure 3. Model Pipeline

Data Science Capstone Project with J.P. Morgan Al Research

Table 1. Experiment Result on our dataset			
LR+TruncatedSVD	ResNet	MobileNet	FaceNet
almost 0	1s per img	0.1s per img	1.5s per img
25.64%	53%	49%	45%

Figure 4. Confusion matrix on MobileNet Model

Figure 5. sample real-time evaluation result

[1] He et at. "Deep Residual Learning for Image Recognition",2015 [2] Sandler et at. "MobileNetV2: Inverted Residuals and Linear Bottlenecks", 2018 [3] Schroff et at." FaceNet: A unified embedding for face recognition and clustering", 2015





