

A Deep Learning Method for Mathematical Formulas Detection in PDF Documents

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Abstract—Write the abstract here.
Index Terms—

I. INTRODUCTION

II. RELATED WORKS

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In this section, we will describe the implementation of our mathematical formula detection system and dataset in detail.

A. Dataset

Our data is from the [IBEM dataset](#). This originally comprises 600 documents, with 8273 pages in total. Those documents are parsed from mathematical papers, then each page is annotated with a bounding box of 2 types: isolated and embedded. The dataset is then split into various sets for IC-DAR 2021 Competition on Mathematical Formula Detection, including Training, Test, and Validation sets.

Training

- Tr00: 4082 pages.
- Tr01: 760 pages.
- Tr10: 329 pages.

Test

- Ts00: 736 pages.
- Ts01: 380 pages.
- Ts10: 699 pages.
- Ts11: 329 pages.

Validation

- Va00: 577 pages.
- Va01: 380 pages.

Our experiment uses Tr01, Tr10, Ts01 for training, Va01 for validation, and Ts11 for testing with 2178 pages in total ($\sim 26.33\%$ of the original dataset), and an approximate ratio of 4.47 : 1.16 : 1. The reason for this small subset is for

the purpose of evaluating the ability of the model on small subsets, and the performance it gives (F1-score) through time (minutes).

B. Implementation Details

Our baseline model is Faster R-CNN with ResNet50 as the backbone. We have trained on Kaggle with a 4-core CPU, 12GB RAM, and a NVIDIA Tesla P100 GPU ¹. The images are resized to 1447×2048 with the same ratio. The size of the region crops from the image is 1200×1120 to fit the limitation of the machine. They are also flipped and padded for data augmentation. For the feature aggregation, we use FPN (2-6). The loss function for the classifier is Cross-Entropy Loss and for the bounding box is L1 Loss. Test images are resized to 1583×2048 due to the distribution of the test dataset, flip augmentation is also applied. For post-processing, Non-Maximum Suppression (NMS) with 0.5 IoU threshold to remove redundant boxes. All models are trained based on the MMDetection toolbox and config given by [Yuxiang Zhong](#). The optimizer for this baseline is Stochastic Gradient Descent (SGD) with a learning rate of 0.02.

C. Remarks

We have tested on 3 configs: Faster R-CNN with schedule 1x (12 epochs), [Dynamic R-CNN](#) with schedule 1x (12 epochs) to check if it is better than the faster one and Faster R-CNN with schedule 2x (24 epochs) to check if the model is underfitting with low epochs.

¹<https://www.kaggle.com/docs/notebooks>

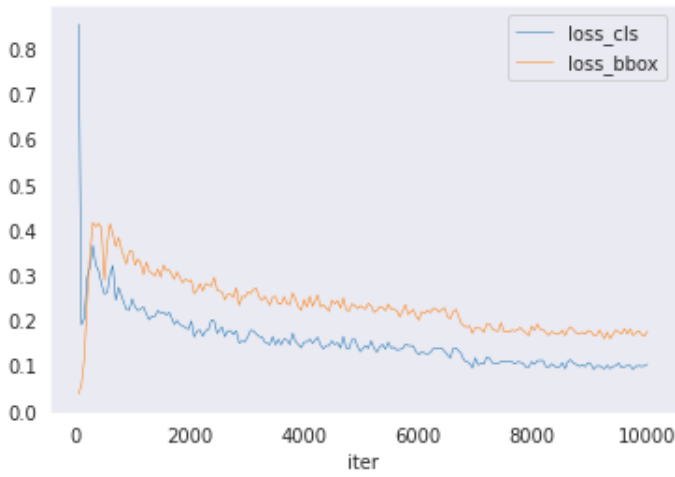


Fig. 1. Faster R-CNN with schedule 1x

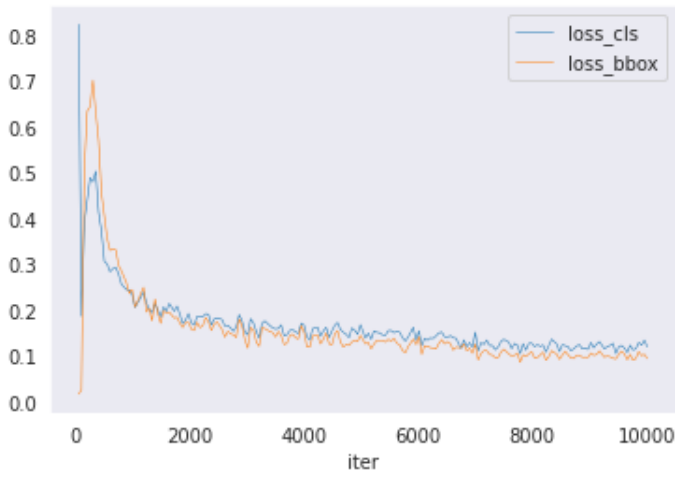


Fig. 2. Dynamic R-CNN with schedule 1x

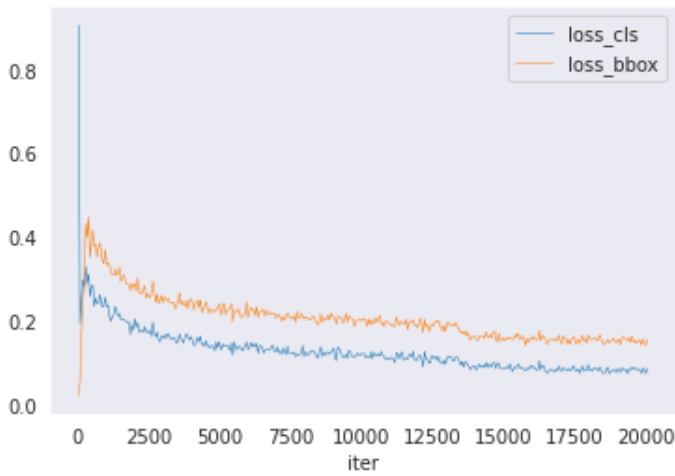


Fig. 3. Faster R-CNN with schedule 2x

The F1-score gained from the model is as follow.

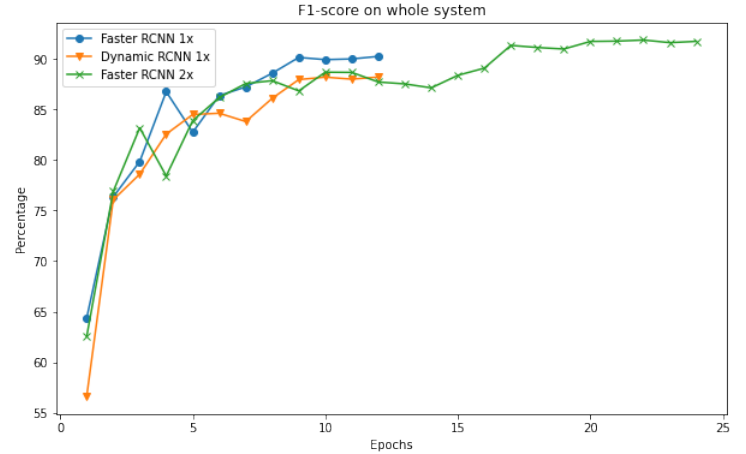


Fig. 4. F1-score on whole system

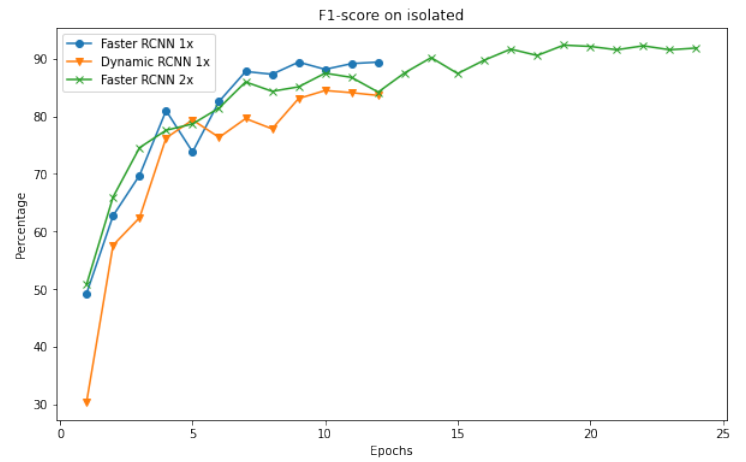


Fig. 5. F1-score with isolated bounding box

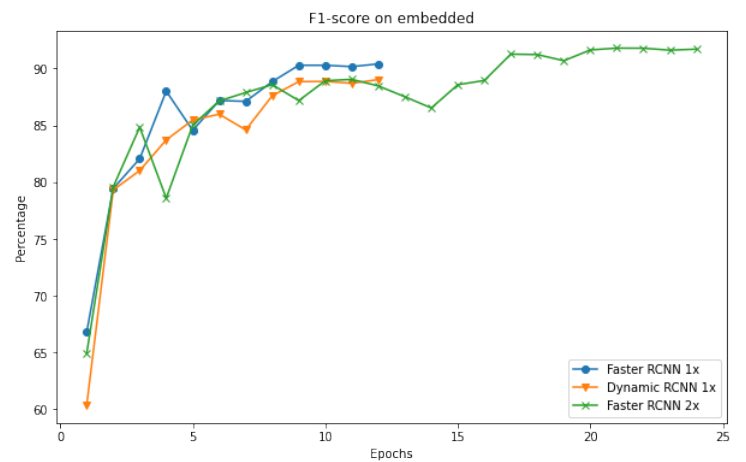


Fig. 6. F1-score with embedded bounding box

V. FUTURE WORKS

VI. CONCLUSION

ACKNOWLEDGMENT

REFERENCES

- [1] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," *Phil. Trans. Roy. Soc. London*, vol. A247, pp. 529–551, April 1955.
- [2] J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.