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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IV. Experiments

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 ICDAR 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 bouding 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.
The results are given in the figures below.

[1]https://www.kaggle.com/docs/notebooks

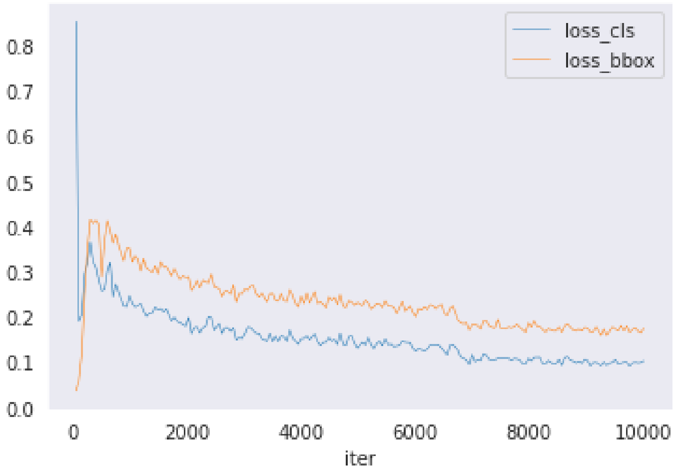

Fig. 1. Faster R-CNN with schedule 1x

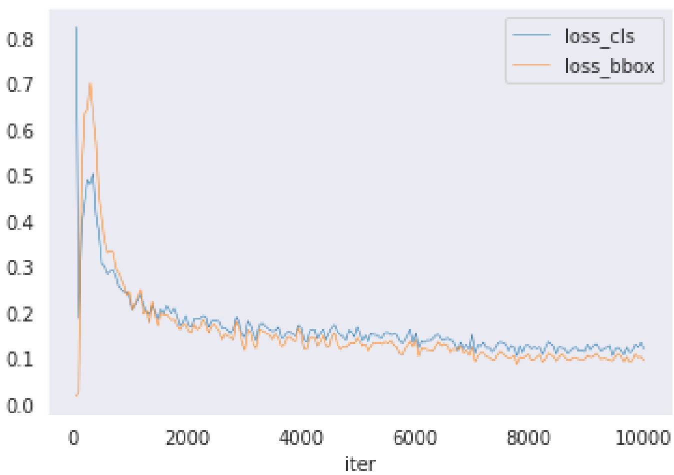

Fig. 2. Dynamic R-CNN with schedule 1x

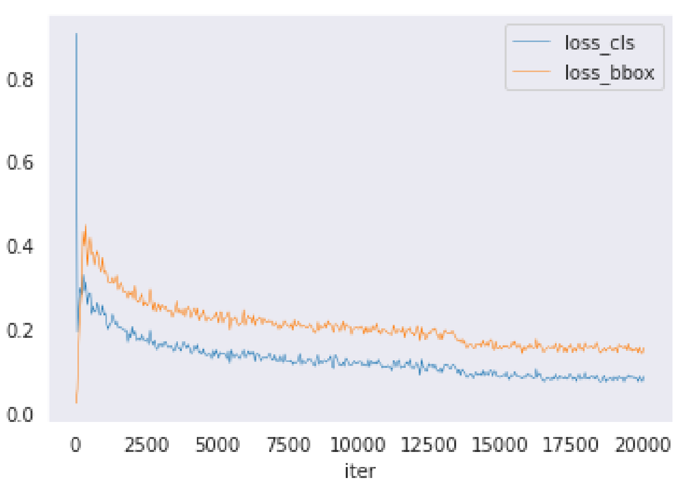

Fig. 3. Faster R-CNN with schedule 2x

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

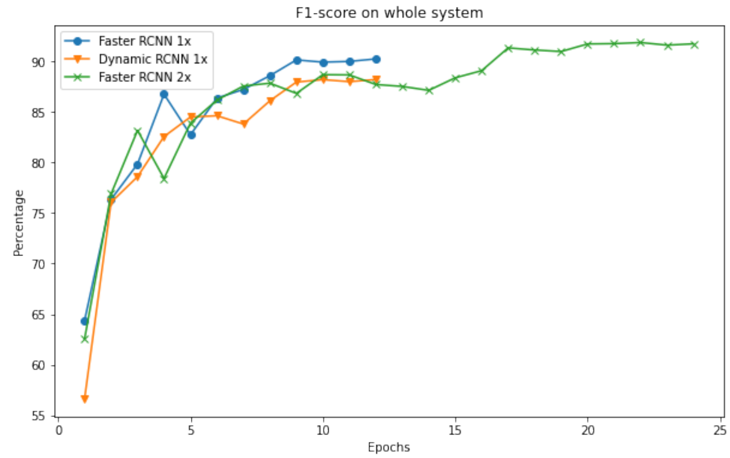

Fig. 4. F1-score on whole system

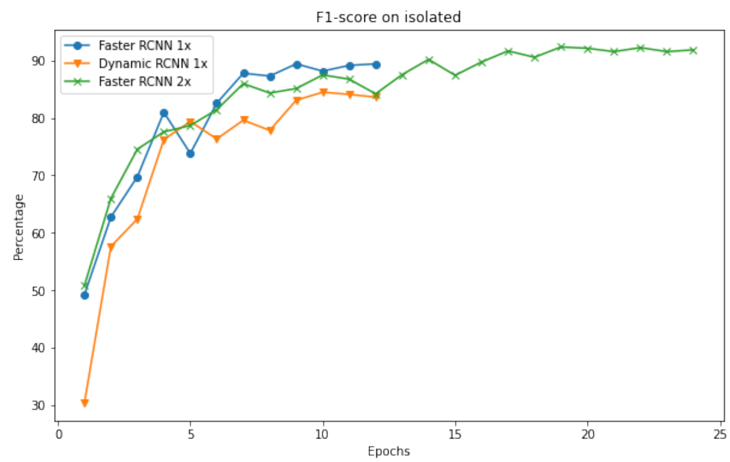

Fig. 5. F1-score with isolated bounding box

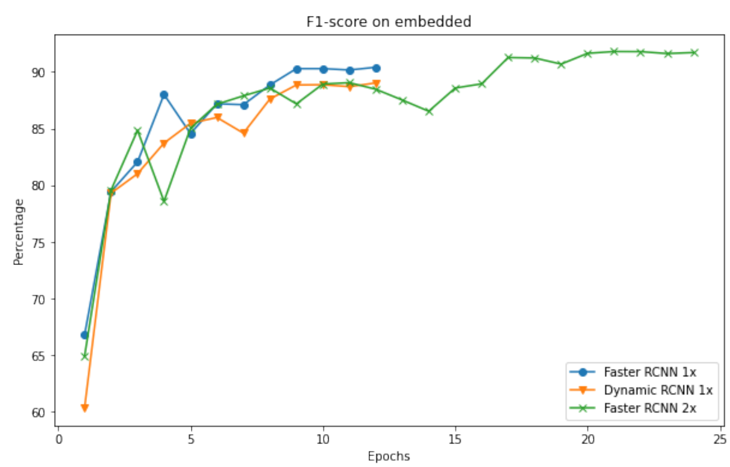

Fig. 6. F1-score with embedded bounding box

It can be seen from the graphs that on the whole system, with the same schedule 1x, the F1-scores given by the Faster R-CNN model are higher than the one by Dynamic R-CNN if we use the same number of epochs, except in the case of 5 epochs. The difference gets higher when we increase the number of epochs. Compared to the scores by Faster R-CNN with schedule 2x (24 epochs), although it gives a lower percentage when trained with a small number of epochs, the score becomes increasing to around 90%. Moreover, on the isolated bounding box, the Faster R-CNN model shows its benefit when compared with the number of Dynamic R-CNN, the F1-score of Faster R-CNN is nearly 90% while the one of Dynamic R-CNN reaches about 80% when they are both trained with 12 epochs. Considering the Faster R-CNN with schedule 2x, it gives the same F1-score with Dynamic R-CNN 1x at the point of 12 epochs, however, the score is about 90% at the point of 24 epochs. Besides that, it can be inferred from the figures of the embedded bounding box that with the same number of epochs (12 epochs), the Faster R-CNN model always provides better results than the Dynamic R-CNN, in spite of the fact that the difference is not large. When we increase the number of epochs to 24, we can observe that the F1-score of Faster R-CNN can reach the milestone of nearly 95%.

From the result given above, we can conclude that the Faster R-CNN model gives better F1-score than the Dynamic R-CNN model.

V. Future Works

VI. Conclusion

Acknowledgment

References

[1] Zhong, Y., Qi, X., Li, S., Gu, D., Chen, Y., Ning, P., and Xiao, R. (2021). 1st Place Solution for ICDAR 2021 Competition on Mathematical Formula Detection. Available: http://arxiv.org/abs/2107.05534.