1st Place Solution to ECCV 2022 Challenge on Out of Vocabulary Scene Text Understanding: Cropped Word Recognition

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Abstract

This report presents our winner solution to ECCV 2022 challenge on Out-of-Vocabulary Scene Text Understanding (OOV-ST): Cropped Word Recognition. This challenge is held in the context of ECCV 2022 workshop on Text in Everything (TiE), which aims to extract out-of-vocabulary words from natural scene images. In the competition, we first pre-train SCATTER on the synthetic datasets, then fine-tune the model on the training set with data augmentations. Meanwhile, two additional models are trained specifically for long and vertical texts. Finally, we combine the output from different models with different layers, different backbones, and different seeds as the final results. Our solution achieves an overall word accuracy of 69.73% when considering both in-vocabulary and out-of-vocabulary words.

1. Introduction

This report focuses on scene text recognition, which aims to recognize a sequence of characters from a cropped image. The task is evaluated in both in-vocabulary (IV) and out-of-vocabulary (OOV) words, where “IV” refers to the text instances has been seen in the training set and “OOV” means the text instances are unseen accordingly.

ECCV 2022 challenge on Out-of-Vocabulary Scene Text Understanding (OOV-ST)¹, held together with ECCV 2022 workshop on Text in Everything (TiE)², favors the recognition of OOV words. In this competition, the training, validation and test sets are composed of several commonly used datasets, including ICDAR13 [3], ICDAR15 [2], MLT19 [7], COCO-Text [9], TextOCR [8], HierText [6], and OpenImagesText [4]. Additionally, participants are allowed to generate synthetic data with a provided dictionary of the 90k most frequent English words. Since the competition emphasizes on OOV instances but does not wish to drop IV words completely, two leaderboards are recognized, including 1) on OOV words only and 2) on both IV and OOV words by averaging the IV and OOV scores.

In this report, we describe our solution to the Cropped Word Recognition track in this challenge. Our solution achieves 69.73% in word accuracy when considering both in-vocabulary and out-of-vocabulary words, which ranked 1st in the competition. Meanwhile, it also ranked 2nd when considering out-of-vocabulary words only with a word accuracy of 59.45%. Details are given below.

2. Methods

Our solution is based on SCATTER [5], with the following improvements:

2.1. Synthetic Data

To improve the generalization of the model, we generate 60M synthetic data with the provided dictionary of the 90k most frequent English words. We pre-train SCATTER on the synthetic data to accelerate the model convergence.

2.2. Data Augmentation

In both pre-training stage and fine-tuning stage, multiple data augmentations are employed. Specifically, we follow ABINet [1] and use geometry transformation (i.e., rotation, affine and perspective transformations), image quality deterioration (i.e., gaussian noise, motion blur and JPEG compression), color jitter, etc.

2.3. Long Texts and Vertical Texts

It is observed that the baseline model does not perform well over long texts and vertical texts, which is caused by sample imbalance in the training set. Since the proportion of long texts and vertical texts is too small, models tend to focus more on regular texts. Therefore, we train two more SCATTER-based models especially for better recognition of long texts and vertical texts.

Long Texts. We consider images with large aspect ratios (i.e. larger than 9:1) as long images and texts in such images are denoted as long texts. We set the maximum length of texts in long-text model to 50 and train on long images only.

1. https://rrc.cvc.uab.es/?ch=19
2. https://sites.google.com/view/tie-eccv2022/challenge
### 2.3. Ensemble

#### Internal Ensemble.

According to [5], the output sequence of characters is from the final selective decoder during inference, but the training loss consists of all five selective decoder blocks with the same weight. Therefore, we combine internal results by averaging the output probabilities of all five blocks at each time step.

#### External Ensemble.

We train SCATTER models with different backbones and different seeds, and finally combine their outputs together as the way in internal ensemble.

| Method | IV CRW | OOV CRW | IV&OOV CRW |
|--------|--------|---------|------------|
|        | ED     | ED      |            |
| Our solution | 80.0 | 136484 | 59.5 | 43890 | 69.7 |

Table 4. Final results in the test set over IV, OOV, and IV&OOV words.

### 3. Experiments

#### 3.1. Evaluation Metrics

The results are evaluated in terms of two metrics, i.e., Correctly Recognized Words (CRW) and Edit Distance (ED)\(^3\). If not specified otherwise, all the ablation studies are done in the out-of-vocabulary (OOV) validation set.

#### 3.2. Experiment Results

Table 1 shows the ablation results of using data augmentation, synthetic data, and long&vertical texts. In this study, we take grayscale images as input and choose ResNet18 as backbone. As Table 1 shows, both data augmentation and synthetic data bring an improvement by 2.3% in Correctly Recognized Words (CRW), validating that they can enhance the generalization of the model. By assembling two extra models specifically for long and vertical texts, CRW is improved by 0.7% overall in the validation set, even though long and vertical texts only account for only 5% in the validation set.

We also tried different image types and backbones. As shown in Table 2, it leads to an improvement of 1.8% in terms of CRW by using RGB images and ResNet-50 as the backbone. As Table 1 shows, both data augmentation and synthetic data bring an improvement by 2.3% in Correctly Recognized Words (CRW), validating that they can enhance the generalization of the model. By assembling two extra models specifically for long and vertical texts, CRW is improved by 0.7% overall in the validation set, even though long and vertical texts only account for only 5% in the validation set.

Furthermore, Table 3 demonstrates the effectiveness of two ensemble strategies. As Table 3 shows, we obtain an improvement of 0.2% in terms of CRW by internally combining all five blocks together. Additionally, external ensemble improves the CRW score from 62.0% to 63.9%.

The final results of IV, OOV, IV+OOV words in the test set are shown in Table 4. Moreover, we combine our recognizer with our oCLIP-based [10] text detector and obtain the best performance in the end-to-end recognition track for OOV words.

### 4. Conclusion

This report summarizes the details of our solution that won the ECCV 2022 Challenge on Out of Vocabulary Scene Text Understanding in the track of Cropped Word Recognition.

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\(^3\)https://rrc.cvc.uab.es/?ch=19&com=tasks
References

[1] Shancheng Fang, Hongtao Xie, Yuxin Wang, Zhendong Mao, and Yongdong Zhang. Read Like Humans: Autonomous, Bidirectional and Iterative Language Modeling for Scene Text Recognition. In CVPR, 2021. 1

[2] Dimosthenis Karatzas, Lluis Gomez-Bigorda, Anguelos Nicolaou, Suman Ghosh, Andrew Bagdanov, Masakazu Iwamura, Jiri Matas, Lukas Neumann, Vijay Ramaseshan Chandrasekhar, Shijian Lu, et al. ICDAR 2015 competition on Robust Reading. In ICDAR, 2015. 1

[3] Dimosthenis Karatzas, Faisal Shafait, Seiichi Uchida, Masakazu Iwamura, Lluis Gomez i Bigorda, Sergi Robles Mestre, Joan Mas, David Fernandez Mota, Jon Almazan Almazan, and Lluis Pere De Las Heras. ICDAR 2013 Robust Reading Competition. In ICDAR, 2013. 1

[4] Ilya Krylov, Sergei Nosov, and Vladislav Sovrasov. Open images v5 text annotation and yet another mask text spotter. In ACML, 2021. 1

[5] Ron Litman, Oron Anschel, Shahar Tsiper, Roee Litman, Shai Mazor, and R Manmatha. SCATTER: Selective Context Attentional Scene Text Recognizer. In CVPR, 2020. 1, 2

[6] Shangbang Long, Siyang Qin, Dmitry Panteleev, Alessandro Bissacco, Yasuhiisa Fujii, and Michalis Raptis. Towards End-to-End Unified Scene Text Detection and Layout Analysis. In CVPR, 2022. 1

[7] Nibal Nayef, Yash Patel, Michal Busta, Pinaki Nath Chowdhury, Dimosthenis Karatzas, Wafa Khelif, Jiri Matas, Umapada Pal, Jean-Christophe Burie, Cheng-lin Liu, et al. ICDAR2019 Robust Reading Challenge on Multi-lingual Scene Text Detection and Recognition – RRC-MLT-2019. In ICDAR, 2019. 1

[8] Amanpreet Singh, Guan Pang, Mandy Toh, Jing Huang, Wojciech Galuba, and Tal Hassner. TextOCR: Towards large-scale end-to-end reasoning for arbitrary-shaped scene text. In CVPR, 2021. 1

[9] Andreas Veit, Tomas Matera, Lukas Neumann, Jiri Matas, and Serge Belongie. COCO-Text: Dataset and Benchmark for Text Detection and Recognition in Natural Images. arXiv:1601.07140, 2016. 1

[10] Chuhui Xue, Yu Hao, Shijian Lu, Philip Torr, and Song Bai. Language Matters: A Weakly Supervised Vision-Language Pre-training Approach for Scene Text Detection and Spotting. In ECCV, 2022. 2