Why You Should Try the Real Data for the Scene Text Recognition

Loginov Vladimir
Intel Corporation vladimir.loginov@intel.com

Abstract. Recent works in the text recognition area have pushed forward the recognition results to the new horizons. But for a long time a lack of large human-labeled natural text recognition datasets has been forcing researchers to use synthetic data for training text recognition models. Even though synthetic datasets are very large (MJSynth and SynthText, two most famous synthetic datasets, have several million images each), their diversity could be insufficient, compared to natural datasets like ICDAR and others. Fortunately, the recently released text recognition annotation for OpenImages V5 dataset has comparable with synthetic dataset number of instances and more diverse examples. We have used this annotation with a Text Recognition head architecture from the Yet Another Mask Text Spotter and got comparable to the SOTA results. On some datasets we have even outperformed previous SOTA models. In this paper we also introduce a text recognition model. The model’s code is available.

Keywords: Domain Shift · Open Images · Scene Text Recognition.

1 Introduction

The text recognition plays an important role in people’s lives. It can be used for digitalizing old documents and helping blind people read. Also, the text recognition could be utilized in a variety of automation algorithms; one of the most common use-cases is the license plate recognition.

Since the release of the synthetic datasets (MJSynthJaderberg et al. (2014), SynthTextGupta et al. (2016)), a common approach to the model training was the following: use synthetic data for training and real data for evaluation. This was caused by a lack of labeled large text recognition datasets. From the very first deep learning text recognition architectures such as Shi et al. (2015) to the modern works like Cai et al. (2021), Cui et al. (2021) researchers have followed this pattern. Even though real datasets have train splits, their size is significantly less than the size of synthetic datasets.

Due to the lack of real data for training, previous works aimed mainly at tuning an architecture of the model rather than using different data. Baek et al. (2019) suggested the idea of differentiating a text recognition model into 4 stages:

1 https://github.com/openvinotoolkit/training_extensions
transformation, feature extraction, sequence modelling and prediction. Many of the existing text recognition model architectures fit into this scheme. We follow the same approach: in our work we use TPS [Jaderberg et al. (2015)] for transformation, ResNeXt [Xie et al. (2016)] for feature extraction, convolutional encoder-recurrent decoder from YAMTS [Krylov et al. (2021)] with 2D attention mechanism the sequence modelling and the prediction.

The rest of the paper is organized as follows:

– In the Section 2 we briefly discuss other works in this field.
– In the Section 3 we describe in details the suggested model architecture.
– In the Section 4 we show the results of our experiments.
– In the Section 5 we make conclusions and do some call to action for other researchers.

Our main contributions are as follows:

– Developing the idea of using real data together with synthetic data for training text recognition models.
– Suggesting text recognition model which performs on par with other models and even outperforms current state-of-the-art approaches on some datasets.

2 Related Works

MJSynth [Jaderberg et al. (2014)], SynthText [Gupta et al. (2016)] are two large (each has several million images with text) text recognition datasets. These two datasets contain images generated in the certain pipeline. In MJSynth, image generation process is the following: first, certain font is picked and text in this font is rendered; second, using the image from the previous step, borders and shadows are colored and composed together; third, projective distortion is applied to the image; and the last step is natural image blending. See Jaderberg et al. (2014) for details. SynthText’s pipeline takes into account depth of the image regions and uses segmentation network to predict suitable positions to put the text. See the corresponding publication Gupta et al. (2016) for details.

These two works play an important role in text recognition area, and their contribution could hardly be overestimated. However, even though images from MJSynth and SynthText look like real, in some cases it is clear that the specific image is manually generated. Moreover, real world images are sometimes so various and rich in texture, curvature, color and other visual features that it is hard to generate them using a set of predefined rules. Thus, there is a problem: there are datasets used for training with great number of examples, but these examples are not diverse enough; and there are testing datasets with more complex, real images on which the model is evaluated. This causes a misalignment between training and testing samples. The problem is also known as domain shift [Michieli et al. (2020); Zhang et al. (2019)]. Model fits to the training images and, without augmentations, shows poorer performance on the testing ones. If a researcher decides to use augmentation to deal with the overfitting
problem, model spends its capacity to learn augmented training samples which are still different from testing. This results in model performance drop on the testing dataset.

Baek et al. (2021) was one of the first works which suggested the idea of using real datasets for training text recognition models, but in unsupervised manner, since large annotated datasets were not available then. Recently released text spotting annotation for OpenImagesV6 Krylov et al. (2021) and TextOCR Singh et al. (2021) made training text recognition models on real data in a supervised manner possible.

ASTER Shi et al. (2019) is one of the works which utilizes Thin Plate Spline transformation for automatic image rectification. Experiments from Shi et al. (2019) show that this technique helps to boost the recognition accuracy.

ResNeXt Xie et al. (2016) and ResNet-like He et al. (2016) backbones are widely used as feature extractors for many text recognition models Shi et al. (2019), Cai et al. (2021), Qiao et al. (2020), Baek et al. (2019). We have experimented extensively with the configuration of the backbone and found that standard configuration without the last stage pretrained on the ImageNetRussakovsky et al. (2014) performs the best.

Attention mechanism Bahdanau et al. (2016) was first introduced as a novel technique for the machine translation. Recently, the attention mechanism have become a standard for text recognition models.

Alongside with annotation for text spotting we also use the text recognition head from Krylov et al. (2021). It performs well for text spotting task and our experiments show that it also performs well for text recognition task.

3 Model Architecture

3.1 Overall Architecture

We follow the same approach as in Baek et al. (2019) but do not divide the last two stages. Thus, the text recognition head consists of sequence modelling and final prediction. We utilize TPS Jaderberg et al. (2015) as in ASTER Shi et al. (2019) for image rectification, since this stage has become one of the standard building blocks for modern text recognition models. We use ResNeXt Xie et al. (2016) for feature extraction due to its good performance/accuracy trade-off. In our work we have utilized the same text recognition head as in Krylov et al. (2021). You can see the full model in the Figure 1.

3.2 Thin Plate Spline

Thin Plate Spline (TPS) Jaderberg et al. (2015) was first proposed for image recognition in the rectification task. Later, this module was utilized in some text recognition models Shi et al. (2019), Qiao et al. (2020).

The spatial transformer mechanism is split into three parts. In order of computation, first a localization network takes the image and generates parameters
for spatial transformation. Using the predicted parameters, a sampling grid is generated, which is a set of points where the input map should be sampled to produce the transformed output. This is done by the grid generator. Finally, the sampler generates output image using the grid and input image.

Thin plate spline is designed in such way that it does not require letter level annotation. Thus, it can be utilized as is in many text recognition architectures and its parameters can be learned in an end-to-end manner.

3.3 Backbone

Since the release of the ResNet [He et al., 2016] this network has become popular for many computer vision tasks due to its simplicity of learning and capacity. During the past years, ResNet-like networks showed their effectiveness and were used in many other text recognition models: ASTER [Shi et al., 2019], CSTR [Cai et al., 2021], SEED [Qiao et al., 2020], Baek et al. [2019]. The ResNeXt-101 consists of 5 stages. We use ResNeXt-101 without the last stage. We find this configuration to have a good accuracy/performance trade-off. In our model we utilize pretrained on ImageNet [Russakovsky et al., 2014] weights as initial for the ResNeXt-101.

3.4 Text Recognition Head

Our network heavily utilizes the text recognition head from [Krylov et al., 2021] with minor changes. First, we increase the number of channels to 1024 in the convolutional encoder since this is the exact number of the output channels from the ResNext-101 (without the last stage). Convolutional encoder of the head also produces 1024 output channels. Second, for the same reason, we have changed the size of the feature map to $3 \times 12$. For the rest of the parameters, we use the same architecture, including the depth of the encoder part and the type of the recurrent decoder (GRU [Cho et al., 2014]).
4 Experiments

4.1 Datasets

Training Datasets

There are two large synthetic datasets:

- MJSynth is a synthetically generated text recognition dataset \cite{jaderberg2014}. It has about 9M images.
- SynthText is also a synthetic dataset, but it has an annotation for text detection and text recognition. It consists of about 800k images with approximately 8M word instances.

Recently there were released two large natural text recognition datasets: TextOCR \cite{singh2021} and OpenImages V5 text spotting \cite{krylov2021}.

- TextOCR has about 900k instances of annotated words.
- OpenImages V5 text spotting dataset has about 2M text instances.

In our work we have used a combination of synthetic and real data: MJSynth and OpenImages V5 text spotting. We did not use any specific technique to balance samples from different datasets in the batch.

Testing Datasets

In the text recognition task, datasets could be divided into two groups: Regular and Irregular datasets. In the regular datasets, like ICDAR03, ICDAR13, IIIT5k, SVT, text is mainly horizontally oriented without curvatures and perspective distortions. Irregular datasets, like ICDAR15, SVT-P, CUTE, mostly consist of curved texts, which could be with some perspective distortions. Images from irregular datasets are usually more challenging for text recognition models to make the prediction.

We perform evaluation of our model on the testing parts of the following datasets:

Regular datasets:

- ICDAR2003 \cite{lucas2003} consists of 1156 images for training and 1110 images for evaluation. A common practice for text recognition models is to ignore all images which contain non-alphanumeric symbols and are less than 3 symbols in length. This results in 867 images for evaluation.
- ICDAR2013 \cite{karatzas2013} is inherited from ICDAR2003. Its train and test split have 848 and 1095 images, respectively. Ignoring non-alphanumeric words results in the dataset of size 1015.
- IIIT5k \cite{mishra2012} is collected from Google image search. It has 2k images for training and 3k for testing.
- SVT \cite{wang2011} has 257 images for training and 647 images for evaluation. Its name stands for Street View Text and consists of outdoor street images.

Irregular datasets:
ICDAR2015 [Karatzas et al. (2015)] was created for the ICDAR 2015 Robust Reading competition and contains 4468 images for training and 2077 images for evaluation. All evaluation subset is used for the evaluation, even though it consists of some examples with non-alphanumeric instances. Unlike the previous datasets, this has examples with irregular text.

SVT-P [Phan et al. (2013)] is also collected from Google Street View and has many examples with perspective distortions. Dataset size is 645.

Both training and evaluation of the model were performed in case-insensitive mode. The vocabulary of our experiments consists of 10 digits, 26 letters and 4 special symbols: start token, end token, pad token and unknown token. Pad token is used in training phase for numeric representations of the texts to be equal length and further concatenate them into one batch. Unknown token is used to represent symbol that is not in the vocabulary (e.g., question mark). Thus, the final stage of our model predicts every character among 40 classes. We do not use any lexicon or beam search to boost the recognition accuracy.

### 4.2 Image Preprocessing

Image preprocessing and augmentation plays an important role in many deep learning algorithms. We resize all input images to $64 \times 256$ fixed resolution. TPS preprocessing of our network produces image of fixed size $48 \times 192$. We also use color jittering (from torchvision [Marcel and Rodriguez (2010)]) and Gaussian blurring (from opencv [Bradski (2000)]) as augmentations. In the end of the augmentation pipeline we convert all images to grayscale and scale images to be in $[0;1]$ interval.

### 4.3 Loss Function

Standard Negative Loglikelihood loss function is used as cost function. We use Adam [Kingma and Ba (2017)] optimizer with a constant learning rate $1e^{-4}$. Other parameters are default for PyTorch’s Adam optimizer, including zero weight decay. The model was trained for 15 epochs.

### 4.4 Environment

All experiments were performed on a server with 8 NVIDIA® Tesla P100 GPUs with 16 GB VRAM. We use PyTorch 1.8.1 as our training framework. Batch size was set to 48.

### 4.5 Evaluation Results

We compare our model with current state-of-the-art approaches in the Table 1. Standard text recognition accuracy is used as a metric of quality.
Table 1. Evaluation results and comparison with other models. Results in bold are the best in every dataset.

| Model | IC03 | IC13 | IC15 | IIIT5K | SVT | SVT-P |
|-------|------|------|------|--------|-----|-------|
| CSTR Cai et al. (2021) | 94.8 | 93.2 | 81.6 | 90.1 | 93.7 | 85.0 |
| ASTER Shi et al. (2019) | 94.8 | 93.2 | 81.6 | 90.1 | 93.7 | 85.0 |
| SEED Qiao et al. (2020) | - | 92.8 | 80.0 | 93.8 | 89.6 | 81.4 |
| RCEED Cui et al. (2021) | - | 94.7 | **82.2** | **94.9** | 91.8 | 83.6 |
| SATRN Lee et al. (2020) | 96.7 | 94.1 | 79.0 | 92.8 | 91.3 | 86.5 |
| Back et al. Baek et al. (2019) | 94.4 | 92.3 | 71.8 | 87.9 | 87.9 | 79.2 |
| **Our model** | **97.1** | **96.8** | 80.2 | 93.5 | **94.7** | **89.9** |

4.6 Ablation Study

Results Using Different Train Datasets During our research, we have experimented with different datasets used in training. You can see experiments’ results in the Table 2. All experiments were performed under the same conditions: ResNeXt-101 backbone, YAMTS text recognition head, case-insensitive training, case-insensitive evaluation. We did not use TPS module for this experiment.

Table 2. Comparison of the recognition accuracy using different training datasets.

| Dataset | IC03 | IC13 | IC15 | IIIT5K | SVT | SVT-P |
|---------|------|------|------|--------|-----|-------|
| MJSynth | 92.7 | 88.9 | 64.2 | 84.2 | 86.2 | 78.1 |
| MJSynth + SynthText | 95.2 | 93.5 | 69.3 | 87.5 | 88.1 | 82.9 |
| MJSynth + OpenImagesV5 | 95.6 | 95.2 | **75.3** | **92** | **91.8** | **87.1** |
| OpenImages V5 | 94.1 | 94.2 | 73.2 | 91.1 | 89.0 | 82.9 |

It is clear from the table, that having only synthetic data is insufficient to train a robust text recognition model. It is also interesting that using only real data drops recognition accuracy a bit. Possible explanation for this fact is that since the training examples are more difficult, the model should be trained on a longer schedule (possibly with lower learning rate) like in case of strong augmentations.

Influence of Case Sensitive Learning As it was stated in the previous section, our first models were trained in case-sensitive mode while evaluation was performed in case-insensitive mode, like in Lee et al. (2020). This was caused by the overfitting problem, and case-sensitive training could be thought as a special augmentation type. Since the OpenImagesV5 dataset is more challenging than synthetic dataset, augmentation could be reduced, allowing model to spend its capacity on learning features of the target dataset, and not augmentations. We have compared two training setups, the only difference is case mode (and, thus, number of output classes). The results are reported in the Table 3.
Table 3. Comparison of the recognition accuracy using different case mode.

| Case Mode    | IC03  | IC13  | IC15  | IIIT5K | SVT   | SVT-P |
|--------------|-------|-------|-------|--------|-------|-------|
| Case-Sensitive | 95.6  | 95.2  | 82.0  | 91.8   | 87.1  |       |
| Case-Insensitive | 97.0  | 96.5  | 83.2  | 93.5   | 91.6  |       |

Note, these two experiments are performed without TPS module.

4.7 Experiments with ViTSTR

Transformer models have become very popular during the past months for many deep learning problems, and scene text recognition is not an exception. We have tried to train ViTSTR [Atienza (2021)] using the OpenImagesV5 annotation. The results can be seen in the table. We have trained the models in the same framework, but, for an honest comparison, we have disabled filtering non-alphanumeric symbols during the test. Numbers near the name of the datasets mean portion of the dataset in the batch. Thus, 0.5 ST + 0.5 MJ means balanced batch containing examples from both MJSynth and SynthText. Baseline model is ViTSTR-Tiny, both models were trained using random data augmentation from the source framework.

Table 4. Comparison of the recognition accuracy using different training datasets for ViTSTR-Tiny+Aug.

| Training Dataset | IC03  | IC13  | IC15  | IIIT5K | SVT   | SVT-P |
|------------------|-------|-------|-------|--------|-------|-------|
| 0.5MJ + 0.5 ST (baseline) | 93.7  | 89.8  | 66.6  | 85.1   | 85.9  | 78.5  |
| 0.4MJ + 0.2 OpenImagesV5 + 0.4 ST | 95.6  | 94.2  | 77.0  | 91.7   | 90.7  | 86.7  |

The intention of this experiment was not to train the best model, but to show that the model actually have higher capacity and could perform better on the validation datasets, if trained on the real data. The more difficult is the dataset (e.g. IC15 and SVT-P), the higher is the accuracy gain. It is clear from the table that even though large augmentation was applied to train the baseline model, not full capacity of the model was utilized.

5 Conclusion

In this paper we have shown that training on natural text recognition datasets could be more efficient than on synthetically generated images. Our experiments have proven the fact that training with more challenging data and less augmentations is more efficient in terms of accuracy on the testing dataset. We have also introduced a text recognition model which achieves state-of-the-art results on some common text recognition benchmarks. We encourage other researchers to try to use the real data to train their models, because as we have shown in
this can help to boost the recognition accuracy, especially, for the
attention-based and transformer models.
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