UnrealText: Synthesizing Realistic Scene Text Images from the Unreal World

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Abstract

Synthetic data has been a critical tool for training scene text detection and recognition models. On the one hand, synthetic word images have proven to be a successful substitute for real images in training scene text recognizers. On the other hand, however, scene text detectors still heavily rely on a large amount of manually annotated real-world images, which are expensive. In this paper, we introduce UnrealText, an efficient image synthesis method that renders realistic images via a 3D graphics engine. 3D synthetic engine provides realistic appearance by rendering scene and text as a whole, and allows for better text region proposals with access to precise scene information, e.g. normal and even object meshes. The comprehensive experiments verify its effectiveness on both scene text detection and recognition. We also generate a multilingual version for future research into multilingual scene text detection and recognition. The code and the generated datasets are released at: https://jyouhou.github.io/UnrealText/.

1. Introduction

With the resurgence of neural networks, the past few years have witnessed significant progress in the field of scene text detection and recognition. However, these models are data-thirsty, and it is expensive and sometimes difficult, if not impossible, to collect enough data. Moreover, the various applications, from traffic sign reading in autonomous vehicles to instant translation, require a large amount of data specifically for each domain, further escalating this issue. Therefore, synthetic data and synthesis algorithms are important for scene text tasks. Furthermore, synthetic data can provide detailed annotations, such as character-level or even pixel-level ground truths that are rare for real images due to high cost.

Currently, there exist several synthesis algorithms [45, 10, 6, 49] that have proven beneficial. Especially, in scene text recognition, training on synthetic data [10, 6] alone has become a widely accepted standard practice. Some researchers that attempt training on both synthetic and real data only report marginal improvements [15, 19] on most datasets. Mixing synthetic and real data is only improving performance on a few difficult cases that are not yet well covered by existing synthetic datasets, such as seriously blurred or curved text. This is reasonable, since cropped text images have much simpler background, and synthetic data enjoys advantages in larger vocabulary size and diversity of backgrounds, fonts, and lighting conditions, as well as thousands of times more data samples.

On the contrary, however, scene text detection is still heavily dependent on real-world data. Synthetic data [6, 49] plays a less significant role, and only brings marginal improvements. Existing synthesizers for scene text detection follow the same paradigm. First, they analyze background images, e.g. by performing semantic segmentation and depth estimation using off-the-shelf models. Then, po-
tential locations for text embedding are extracted from the segmented regions. Finally, text images (foregrounds) are blended into the background images, with perceptive transformation inferred from estimated depth. However, the analysis of background images with off-the-shelf models may be rough and imprecise. The errors further propagate to text proposal modules and result in text being embedded onto unsuitable locations. Moreover, the text embedding process is ignorant of the overall image conditions such as illumination and occlusions of the scene. These two factors make text instances outstanding from backgrounds, leading to a gap between synthetic and real images.

In this paper, we propose a synthetic engine that synthesizes scene text images from 3D virtual world. The proposed engine is based on the famous Unreal Engine 4 (UE4), and is therefore named as UnrealText. Specifically, text instances are regarded as planar polygon meshes with text foregrounds loaded as texture. These meshes are placed in suitable positions in 3D world, and rendered together with the scene as a whole.

As shown in Fig. 1, the proposed synthesis engine, by its very nature, enjoys the following advantages over previous methods: (1) Text and scenes are rendered together, achieving realistic visual effects, e.g. illumination, occlusion, and perspective transformation. (2) The method has access to precise scene information, e.g. normal, depth, and object meshes, and therefore can generate better text region proposals. These aspects are crucial in training detectors.

To further exploit the potential of UnrealText, we design three key components: (1) A view finding algorithm that explores the virtual scenes and generates camera viewpoints to obtain more diverse and natural backgrounds. (2) An environment randomization module that changes the lighting conditions regularly, to simulate real-world variations. (3) A mesh-based text region generation method that finds suitable positions for text by probing the 3D meshes.

The contributions of this paper are summarized as follows: (1) We propose a brand-new scene text image synthesis engine that renders images from 3D world, which is entirely different from previous approaches that embed text on 2D background images, termed as UnrealText. The proposed engine achieves realistic rendering effects and high scalability. (2) With the proposed techniques, the synthesis engine improves the performance of detectors and recognizes significantly. (3) We also generate a large scale multilingual scene text dataset that will aid further research.

2. Related Work

2.1. Synthetic Images

The synthesis of photo-realistic datasets has been a popular topic, since they provide detailed ground-truth annotations at multiple granularity, and cost less than manual annotations. In scene text detection and recognition, the use of synthetic datasets has become a standard practice. For scene text recognition, where images contain only one word, synthetic images are rendered through several steps [45, 10], including font rendering, coloring, homography transformation, and background blending. Later, GANs [5] are incorporated to maintain style consistency for implanted text [50], but it is only for single-word images. As a result of these progresses, synthetic data alone are enough to train state-of-the-art recognizers.

To train scene text detectors, SynthText [6] proposes to generate synthetic data by printing text on background images. It first analyzes images with off-the-shelf models, and search suitable text regions on semantically consistent regions. Text are implanted with perspective transformation based on estimated depth. To maintain semantic coherency, VISO [49] proposes to use semantic segmentation to filter out unreasonable surfaces such as human faces. They also adopt an adaptive coloring scheme to fit the text into the artistic style of backgrounds. However, without considering the scene as a whole, these methods fail to render text instances in a photo-realistic way, and text instances are too outstanding from backgrounds. So far, the training of detectors still relies heavily on real images.

Although GANs and other learning-based methods have also shown great potential in generating realistic images [47, 16, 12], the generation of scene text images still require a large amount of manually labeled data [50]. Furthermore, such data are sometimes not easy to collect, especially for cases such as low resource languages.

More recently, synthesizing images with 3D graphics engine has become popular in several fields, including human pose estimation [42], scene understanding/segmentation [27, 23, 32, 34, 36], and object detection [28, 41, 8]. However, these methods either consider simplistic cases, e.g. rendering 3D objects on top of static background images [28, 42] and randomly arranging scenes filled with objects [27, 23, 34, 8], or passively use off-the-shelf 3D scenes without further changing it [32]. In contrast to these researches, our proposed synthesis engine implements active and regular interaction with 3D scenes, to generate realistic and diverse scene text images.

2.2. Scene Text Detection and Recognition

Scene text detection and recognition, possibly as the most human-centric computer vision task, has been a popular research topic for many years [48, 20]. In scene text detection, there are mainly two branches of methodologies: Top-down methods that inherit the idea of region proposal networks from general object detectors that detect text instances as rotated rectangles and polygons [18, 52, 11, 51, 46]; Bottom-up approaches that predict local segments and local geometric attributes, and compose them into in-
individual text instances [37, 21, 2, 39]. Despite significant improvements on individual datasets, those most widely used benchmark datasets are usually very small, with only around 500 to 1000 images in test sets, and are therefore prone to over-fitting. The generalization ability across different domains remains an open question, and is not studied yet. The reason lies in the very limited real data and that synthetic data are not effective enough. Therefore, one important motivation of our synthesis engine is to serve as a stepping stone towards general scene text detection.

Most scene text recognition models consist of CNN-based image feature extractors and attentional LSTM [9] or transformer [43]-based encoder-decoder to predict the textual content [3, 38, 15, 22]. Since the encoder-decoder module is a language model in essence, scene text recognizers have a high demand for training data with a large vocabulary, which is extremely difficult for real-world data. Besides, scene text recognizers work on image crops that have simple backgrounds, which are easy to synthesize. Therefore, synthetic data are necessary for scene text recognizers, and synthetic data alone are usually enough to achieve state-of-the-art performance. Moreover, since the recognition modules require a large amount of data, synthetic data are also necessary in training end-to-end text spotting systems [17, 7, 29].

3. Scene Text in 3D Virtual World

3.1. Overview

In this section, we give a detailed introduction to our scene text image synthesis engine, UnrealText, which is developed upon UE4 and the UnrealCV plugin [30]. The synthesis engine: (1) produces photo-realistic images, (2) is efficient, taking about only 1-1.5 second to render and generate a new scene text image and, (3) is general and compatible to off-the-shelf 3D scene models. As shown in Fig. 2, the pipeline mainly consists of a Viewfinder module (section 3.2), an Environment Randomization module (section 3.3), a Text Region Generation module (section 3.4), and a Text Rendering module (section 3.5).

Firstly, the viewfinder module explores around the 3D scene with the camera, generating camera viewpoints. Then, the environment lighting is randomly adjusted. Next, the text regions are proposed based on 2D scene information and refined with 3D mesh information in the graphics engine. After that, text foregrounds are generated with randomly sampled fonts, colors, and text content, and are loaded as planar meshes. Finally, we retrieve the RGB image and corresponding text locations as well as text content to make the synthetic dataset.

3.2. Viewfinder

The aim of the viewfinder module is to automatically determine a set of camera locations and rotations from the whole space of 3D scenes that are reasonable and non-trivial, getting rid of unsuitable viewpoints such as from inside object meshes (e.g. Fig. 3 bottom right).

Learning-based methods such as navigation and exploration algorithms may require extra training data and are not guaranteed to generalize to different 3D scenes. Therefore, we turn to rule-based methods and design a physically-constrained 3D random walk (Fig. 3 first row) equipped with auxiliary camera anchors.

3.2.1 Physically-Constrained 3D Random Walk

Starting from a valid location, the physically-constrained 3D random walk aims to find the next valid and non-trivial location. In contrast to being valid, locations are invalid if they are inside object meshes or far away from the scene boundary, for example. A non-trivial location should be not too close to the current location. Otherwise, the new viewpoint will be similar to the current one. The proposed 3D random walk uses ray-casting [35], which is constrained by physically, to inspect the physical environment to determine valid and non-trivial locations.

In each step, we first randomly change the pitch and yaw values of the camera rotation, making the camera pointing to a new direction. Then, we cast a ray from the camera location towards the direction of the viewpoint. The ray stops when it hits any object meshes or reaches a fixed maximum length. By design, the path from the current location to the stopping position is free of any barrier, i.e. not inside of any object meshes. Therefore, points along this ray path are all valid. Finally, we randomly sample one point between the $\frac{1}{3}$-th and $\frac{2}{3}$-th of this path, and set it as the new location of the camera, which is non-trivial. The proposed random walk algorithm can generate diverse camera viewpoints.

3.2.2 Auxiliary Camera Anchors

The proposed random walk algorithm, however, is inefficient in terms of exploration. Therefore, we manually select a set of $N$ camera anchors across the 3D scenes as starting points. After every $T$ steps, we reset the location of the camera to a randomly sampled camera anchor. We set $N = 150-200$ and $T = 100$. Note that the selection of camera anchors requires only little carefulness. We only need to ensure coverage over the space. It takes around 20 to 30 seconds for each scene, which is trivial and not a bottleneck of scalability. The manual but efficient selection of camera is compatible with the proposed random walk algorithm that generates diverse viewpoints.
Figure 2: The pipeline of the proposed synthesis method. The arrows indicate the order. For simplicity, we only show one text region. From left to right: scene overview, diverse viewpoints, various lighting conditions (light color, intensity, shadows, etc.), text region generation and text rendering.

Figure 3: In the first row (1)-(4), we illustrate the physically-constrained 3D random walk. For better visualization, we use a camera object to represent the viewpoint (marked with green boxes and arrows). In the second row, we compare viewpoints from the proposed method with randomly sampled viewpoints.

3.3. Environment Randomization

To produce real-world variations such as lighting conditions, we randomly change the intensity, color, and direction of all light sources in the scene. In addition to illuminations, we also add fog conditions and randomly adjust its intensity. The environment randomization proves to increase the diversity of the generated images and results in stronger detector performance. The proposed randomization can also benefit sim-to-real domain adaptation [40].

3.4. Text Region Generation

In real-world, text instances are usually embedded on well-defined surfaces, e.g. traffic signs, to maintain good legibility. Previous works find suitable regions by using estimated scene information, such as gPb-UCM [1] in SynthText [6] or saliency map in VISD [49] for approximation. However, these methods are imprecise and often fail to find appropriate regions. Therefore, we propose to find text regions by probing around object meshes in 3D world. Since inspecting all object meshes is time-consuming, we propose a 2-staged pipeline: (1) We retrieve ground truth surface normal map to generate initial text region proposals; (2) Initial proposals are then projected to and refined in the 3D world using object meshes. Finally, we sample a subset from the refined proposals to render. To avoid occlusion among proposals, we project them back to screen space, and discard regions that overlap with each other one by one in a shuffled order until occlusion is eliminated.

3.4.1 Initial Proposals from Normal Maps

In computer graphics, normal values are unit vectors that are perpendicular to a surface. Therefore, when projected to 2D screen space, a region with similar normal values tends to be a well-defined region to embed text on. We find valid image regions by applying sliding windows of $64 \times 64$ pixels across the surface normal map, and retrieve those with smooth surface normal: the minimum cosine similarity value between any two pixels is larger than a threshold $t$. We set $t$ to 0.95, which proves to produce reasonable results. We randomly sample at most 10 non-overlapping valid image regions to make the initial proposals. Making proposals from normal maps is an efficient way to find potential and visible regions.

3.4.2 Refining Proposals in 3D Worlds

As shown in Fig. 4, rectangular initial proposals in 2D screen space will be distorted when projected into 3D
Generating Text Images: Given text regions as proposed and refined in section 3.4, the text generation module samples text content and renders text images with certain fonts and text colors. The numbers of lines and characters per line are determined by the font size and the size of refined proposals in 2D space to make sure the characters are not too small and ensure legibility. For a fairer comparison, we also use the same font set from Google Fonts \(^2\) as SynthText does. We also use the same text corpus, Newsgroup20. The generated text images have zero alpha values on non-stroke pixels, and non zero for others.

1. When the distances from the rectangular proposals’ corners to the nearest point on the underlying surface exceed certain threshold
2. https://fonts.google.com/

Rendering Text in 3D World: We first perform triangulation for the refined proposals to generate planar triangular meshes that are closely attached to the underlying surface. Then we load the text images as texture onto the generated meshes. We also randomly sample the texture attributes, such as the ratio of diffuse and specular reflection.

3.6. Implementation Details

The proposed synthesis engine is implemented based on UE4.22 and the UnrealCV plugin. On a ubuntu workstation with an 8-core Intel CPU, an NVIDIA GeForce RTX 2070 GPU, and 16G RAM, the synthesis speed is 0.7-1.5 seconds per image with a resolution of 1080 \(\times\) 720, depending on the complexity of the scene model.

We collect 30 scene models from the official UE4 marketplace. The engine is used to generate 600K scene text images with English words. With the same configuration, we also generate a multilingual version, making it the largest multilingual scene text dataset.

4. Experiments on Scene Text Detection

4.1. Settings

We first verify the effectiveness of the proposed engine by training detectors on the synthesized images and evaluating them on real image datasets. We use a previous yet time-tested state-of-the-art model, EAST \([52]\), which is fast and accurate. EAST also forms the basis of several widely recognized end-to-end text spotting models \([17, 7]\). We adopt an opensource implementation \(^3\). In all experiments, models are trained on 4 GPU with a batch size of 56. During the evaluation, the test images are resized to match a short side length of 800 pixels.

Benchmark Datasets We use the following scene text detection datasets for evaluation: (1) ICDAR 2013 Focused Scene Text (IC13) \([14]\) containing horizontal text with zoomed-in views. (2) ICDAR 2015 Incidental Scene Text (IC15) \([13]\) consisting of images taken without carelessness with Google Glass. Images are blurred and text are small. (3) MLT 2017 \([26]\) for multilingual scene text detection, which is composed of scene text images of 9 languages.

4.2. Experiments Results

Pure Synthetic Data We first train the EAST models on different synthetic datasets alone, to compare our method with previous ones in a direct and quantitative way. Note that ours, SynthText, and VISP have different numbers of images, so we also need to control the number of images used in experiments. Results are summarized in Tab. 1.

Firstly, we control the total number of images to 10K, which is also the full size of the smallest synthetic dataset.

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3. https://github.com/argman/EAST
VISD. We observe a considerable improvement on IC15 over previous state-of-the-art by +0.9% in F1-score, and significant improvements on IC13 (+3.5%) and MLT 2017 (+2.8%). Secondly, we also train models on the full set of SynthText and ours, since scalability is also an important factor for synthetic data, especially when considering the demand to train recognizers. Extra training images further improve F1 scores on IC15, IC13, and MLT by +2.6%, +2.3%, and +2.1%. Models trained with our UnrealText data outperform all other synthetic datasets. Besides, the subset of 10K images with our method even surpasses 800K SynthText images significantly on all datasets. The experiment results demonstrate the effectiveness of our proposed synthetic engine and datasets.

Table 1: Detection results (F1-scores) of EAST models trained on different synthetic data.

| Training Data | IC15 | IC13 | MLT 2017 |
|---------------|------|------|----------|
| SynthText 10K | 46.3 | 60.8 | 38.9     |
| VISD 10K (full) | 64.3 | 74.8 | 51.4     |
| Ours 10K | 65.2 | 74.8 | 54.2     |
| SynthText 800K (full) | 58.0 | 67.7 | 44.8     |
| Ours 600K (full) | 67.8 | 80.6 | 56.3     |
| Ours 5K + VISD 5K | 66.9 | 80.4 | 55.7     |

Complementary Synthetic Data One unique characteristic of the proposed UnrealText is that, the images are generated from 3D scene models, instead of real background images, resulting in potential domain gap due to different artistic styles. We conduct experiments by training on both UnrealText data (5K) and VISD (5K), as also shown in Tab. 1 (last row, marked with *italics*), which achieves better performance than other 10K synthetic datasets. This result demonstrates that, our UnrealText is complementary to existing synthetic datasets that use real images as backgrounds. While UnrealText simulates photo-realistic effects, synthetic data with real background images can help adapt to real-world datasets.

Combining Synthetic and Real Data One important role of synthetic data is to serve as data for pretraining, and to further improve the performance on domain specific real datasets. We first pretrain the EAST models with different synthetic data, and then use domain data to finetune the models. The results are summarized in Tab. 2. On all domain-specific datasets, models pretrained with our synthetic dataset surpasses others by considerable margins, verifying the effectiveness of our synthesis method in the context of boosting performance on domain specific datasets.

Pretraining on Full Dataset As shown in the last rows of Tab. 2, when we pretrain the detector models with our full dataset, the performances are improved significantly, demonstrating the advantage of the scalability of our engine. Especially, The EAST model achieves an F1 score of 74.1 on MLT17, which is even better than recent state-of-the-art results, including 73.9 by CRAFT[2] and 73.1 by LOMO [51]. Although the margin is not great, it suffices to claim that the EAST model revives and reclaims state-of-the-art performance with the help of our synthetic dataset.

4.3. Module Level Ablation Analysis

One reasonable concern about synthesizing from 3D virtual scenes lies in the scene diversity. In this section, we address the importance of the proposed view finding module and the environment randomization module in increasing the diversity of synthetic images.

Ablating Viewfinder Module We derive two baselines from the proposed viewfinder module: (1) Random Viewpoint + Manual Anchor that randomly samples camera locations and rotations from the norm-ball spaces centered around auxiliary camera anchors. (2) Random Viewpoint Only that randomly samples camera locations and rotations from the whole scene space, without checking their quality. For experiments, we fix the number of scenes to 10 to control scene diversity and generate different numbers of images, and compare their performance curve. By fixing the number of scenes, we compare how well different view finding methods can exploit the scenes.

Ablating Environment Randomization We remove the environment randomization module, and keep the scene models unchanged during synthesis. For experiments, we fix the total number of images to 10K and use different
number of scenes. In this way, we can compare the diversity of images generated with different methods.

We train the EAST models with different numbers of images or scenes, evaluate them on the 3 real datasets, and compute the arithmetic mean of the F1-scores. As shown in Fig. 5 (a), we observe that the proposed combination, i.e. Random Viewpoint + Manual Anchor, achieves significantly higher F1-scores consistently for different numbers of images. Especially, larger sizes of training sets result in greater performance gaps. We also inspect the images generated with these methods respectively. When starting from the same anchor point, the proposed random walk can generate more diverse viewpoints and can traverse much larger area. In contrast, the Random Viewpoint + Manual Anchor method degenerates either into random rotation only when we set a small norm ball size for random location, or into Random Viewpoint Only when we set a large norm ball size. As a result, the Random Viewpoint + Manual Anchor method requires careful manual selection of anchors, and we also need to manually tune the norm ball sizes for different scenes, which restricts the scalability of the synthesis engine. Meanwhile, our proposed random walk based method is more flexible and robust to the selection of manual anchors. As for the Random Viewpoint Only method, a large proportion of generated viewpoints are invalid, e.g. inside other object meshes, which is out-of-distribution for real images. This explains why it results in the worst performances.

From Fig. 5 (b), the major observation is that environment randomization module improves performances over different scene numbers consistently. Besides, the improvement is more significant as we use fewer scenes. Therefore, we can draw a conclusion that, the environment randomization helps increase image diversity and at the same time, can reduce the number of scenes needed. Furthermore, the random lighting conditions realize different real-world variations, which we also attribute as a key factor.

5. Experiments on Scene Text Recognition

In addition to the superior performances in training scene text detection models, we also verify its effectiveness in the task of scene text recognition.

5.1. Recognizing Latin Scene Text

5.1.1 Settings

Model We select a widely accepted baseline method, ASTER [38], and adopt the implementation\(^4\) that ranks top-1 on the ICDAR 2019 ArT competition on curved scene text recognition (Latin) by [19]. The models are trained with a batch size of 512. A total of 95 symbols are recognized, including an End-of-Sentence mark, 52 case sensitive alphabets, 10 digits, and 32 printable punctuation symbols.

Training Datasets From the 600K English synthetic images, we obtain a total number of 12M word-level image regions to make our training dataset. Also note that, our synthetic dataset provide character level annotations, which will be useful in some recognition algorithms.

Evaluation Datasets We evaluate models trained on different synthetic datasets on several widely used real image datasets: IITT [24], SVT [44], ICDAR 2015 (IC15) [13], SVTP [31], CUTE [33], and Total-Text [4].

Some of these datasets, however, have incomplete annotations, including IITT, SVT, SVTP, CUTE. While these datasets contain punctuation symbols, digits, upper-case and lower-case characters, the aforementioned datasets only provide case-insensitive annotations and ignore all punctuation symbols. In order for more comprehensive evaluation of scene text recognition, we re-annotate these 4 datasets in a case-sensitive way and also include punctuation symbols. We also publish the new annotations and we believe that they will become better benchmarks for scene text recognition in the future.

5.1.2 Experiment Results

Experiment results are summarized in Tab. 6. First, we compare our method with previous synthetic datasets. We have to limit the size of training datasets to 1M since VISD only publishes 1M word images. Our synthetic data achieves consistent improvements on all datasets. Especially, it surpasses other synthetic datasets by a considerable margin on datasets with diverse text styles and complex backgrounds such as SVTP (+2.4%). The experiments verify the effectiveness of our synthesis method in scene text recognition especially in the complex cases.

Since small scale experiments are not very helpful in how researchers should utilize these datasets, we further train models on combinations of Synth90K, SynthText, and ours. We first limit the total number of training images to 9M. When we train on a combination of all 3 synthetic datasets, with 3M each, the model performs better than the model trained on 4.5M × 2 datasets only. We further observe that training on 3M × 3 synthetic datasets is com-

\(^4\)https://github.com/Jyouhou/ICDAR2019-ArT-Recognition-Alchemy
Experiment results are shown in Tab. 3. When we only use synthetic data and control the number of images to 1.2M, ours result in a considerable improvement of 1.6% in overall accuracy, and significant improvements on some scripts, e.g. Latin (+7.6%) and Mixed (+21.6%). Using the whole training set of 4.1M images further improves overall accuracy to 39.5%. When we train models on combinations of synthetic data and our training split of MLT19, as shown in the bottom of Tab. 3, we can still observe a considerable margin of our method over SynthText by 3.2% in overall accuracy. The experiment results demonstrate that our method is also superior in multilingual scene text recognition, and we believe this result will become a stepping stone to further research.

### 5.2.2 Experiment Results

Experiment results are shown in Tab. 3. When we only use synthetic data and control the number of images to 1.2M,
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A. Scene Models

In this work, we use a total number of 30 scene models which are all obtained from the Internet. However, most of these models are not free. Therefore, we are not allowed to share the models themselves. Instead, we list the models we use and their links in Tab. 5.

B. New Annotations for Scene Text Recognition Datasets

During the experiments of scene text recognition for English scripts, we notice that among the most widely used benchmark datasets, several have incomplete annotations. They are IIIT5K, SVT, SVTP, and CUTE-80. The annotations of these datasets are case-insensitive, and ignore punctuation marks.

The common practice for recent scene text recognition research is to convert both prediction and ground-truth text strings to lower-case and then compare them. This means that the current evaluation is flawed. It ignores letter case and punctuation marks which are crucial to the understanding of the text contents. Besides, evaluating on a much smaller vocabulary set results in over-optimism of the performance of the recognition models.

To aid further research, we use the Amazon mechanical Turk (AMT) to re-annotate the aforementioned 4 datasets, which amount to 6837 word images in total. Each word image is annotated by 3 workers, and we manually check and correct images where the 3 annotations differ. The annotated datasets are released via GitHub at https://github.com/Jyouhou/Case-Sensitive-Scene-Text-Recognition-Datasets.

B.1 Samples

We select some samples from the 4 datasets to demonstrate the new annotations in Fig. 6.

B.2 Benchmark Performances

As we are encouraging case-sensitive (also with punctuation marks) evaluation for scene text recognition, we would like to provide benchmark performances on those widely used datasets. We evaluate two implementations of the ASTER models, by Long et al.\textsuperscript{6} and Baek et al.\textsuperscript{7} respectively. Results are summarized in Tab. 6.

The two benchmark implementations perform comparably, with Baek’s better on straight text and Long’s better at curved text. Compared with evaluation with lower case + digits, the performance drops considerably for both models when we evaluate with all symbols. These results indicate that it may still be a challenge to recognize a larger vocabulary, and is worth further research.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
Dataset & Sample Image & Original Annotation & New Annotation \\
\hline
CUTE80 & \includegraphics[height=1cm]{CUTE80_image.png} & TEAM & Team \\
\hline
IIIT5K & \includegraphics[height=1cm]{IIIT5K_image.png} & 15 & 15\% \\
\hline
SVT & \includegraphics[height=1cm]{SVT_image.png} & DONALD & Donald’ \\
\hline
SVTP & \includegraphics[height=1cm]{SVTP_image.png} & MARLBORO & Marlboro \\
\hline
\end{tabular}
\caption{Examples of the new annotations.}
\end{table}

\textsuperscript{6}https://github.com/Jyouhou/ICDAR2019-ArT-Recognition-Alchemy
\textsuperscript{7}https://github.com/clovaai/deep-text-recognition-benchmark
| Scene Name                | Link                                                                 |
|--------------------------|----------------------------------------------------------------------|
| Urban City               | https://www.unrealengine.com/marketplace/en-US/product/urban-city   |
| Medieval Village         | https://www.unrealengine.com/marketplace/en-US/product/medieval-village |
| Loft                     | https://ue4arch.com/shop/completed-projects/archviz/loft/             |
| Desert Town              | https://www.unrealengine.com/marketplace/en-US/product/desert-town   |
| Archinterior 1           | https://www.unrealengine.com/marketplace/en-US/product/archinteriors-vol-2-scene-01 |
| Desert Gas Station       | https://www.unrealengine.com/marketplace/en-US/product/desert-gas-station |
| Modular School           | https://www.unrealengine.com/marketplace/en-US/product/modular-school-pack |
| Factory District         | https://www.unrealengine.com/marketplace/en-US/product/factory-district |
| Abandoned Factory        | https://www.unrealengine.com/marketplace/en-US/product/modular-abandoned-factory |
| Buddhist                 | https://www.unrealengine.com/marketplace/en-US/product/buddhist-monastery-environment |
| Castle Fortress          | https://www.unrealengine.com/marketplace/en-US/product/castle-fortress |
| Desert Ruin              | https://www.unrealengine.com/marketplace/en-US/product/modular-desert-ruins |
| HALArchviz               | https://www.unrealengine.com/marketplace/en-US/product/hal-archviz-toolkit-v1 |
| Hospital                 | https://www.unrealengine.com/marketplace/en-US/product/modular-act-f1-hospital |
| HQ House                 | https://www.unrealengine.com/marketplace/en-US/product/hq-residential-house |
| Industrial City          | https://www.unrealengine.com/marketplace/en-US/product/industrial-city |
| Archinterior 2           | https://www.unrealengine.com/marketplace/en-US/product/archinteriors-vol-4-scene-02 |
| Office                   | https://drive.google.com/file/d/0B_mjKk7NOcnEUWZuRDVFQ9STED/view |
| Old Village              | https://www.unrealengine.com/marketplace/en-US/product/old-village    |
| Modular Building         | https://www.unrealengine.com/marketplace/en-US/product/modular-building-set |
| Modular Home             | https://www.unrealengine.com/marketplace/en-US/product/supergenius-modular-home |
| Dungeon                  | https://www.unrealengine.com/marketplace/en-US/product/top-down-multistory-dungeons |
| Old Town                 | https://www.unrealengine.com/marketplace/en-US/product/old-town       |
| Root Cellar              | https://www.unrealengine.com/marketplace/en-US/product/root-cellar    |
| Victorian                | https://www.unrealengine.com/marketplace/en-US/product/victorian-street |
| Spaceship                | https://www.unrealengine.com/marketplace/en-US/product/spaceship-interior-environment-set |
| Top-Down City            | https://www.unrealengine.com/marketplace/en-US/product/top-down-city  |
| Scene Name               | https://www.unrealengine.com/marketplace/en-US/product/urban-city    |
| Utopian City             | https://www.unrealengine.com/marketplace/en-US/product/utopian-city   |

Table 5: The list of 3D scene models used in this work.

| Implementation | Case                  | IIIT | SVT  | IC13 | IC15 | SVTP | CUTE80 | Total |
|----------------|-----------------------|------|------|------|------|------|--------|-------|
| Long et al.    | All                   | 81.2 | 71.2 | 86.9 | 62.0 | 62.3 | 65.1   | 44.7  |
| Baek et al     | All                   | 81.5 | 71.7 | 88.9 | 62.1 | 62.6 | 64.9   | 41.5  |
| Long et al.    | lower case + digits   | 89.5 | 84.1 | 89.9 | 68.8 | 73.5 | 76.3   | 58.2  |
| Baek et al     | lower case + digits   | 86.5 | 83.5 | 93.0 | 70.3 | 75.1 | 68.4   | 46.0  |

Table 6: Results on English datasets (word level accuracy). *All* indicates that the evaluation considers lower case characters, upper case characters, numerical digits, and punctuation marks.