Comprehensive Studies for Arbitrary-shape Scene Text Detection

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Abstract

Numerous scene text detection methods have been proposed in recent years. Most of them declare they have achieved state-of-the-art performances. However, the performance comparison is unfair, due to lots of inconsistent settings (e.g., training data, backbone network, multi-scale feature fusion, evaluation protocols, etc.). These various settings would dissemble the pros and cons of the proposed core techniques. In this paper, we carefully examine and analyze the inconsistent settings, and propose a unified framework for the bottom-up based scene text detection methods. Under the unified framework, we ensure the consistent settings for non-core modules, and mainly investigate the representations of describing arbitrary-shape scene texts, e.g., regressing points on text contours, clustering pixels with predicted auxiliary information, grouping connected components with learned linkages, etc. With the comprehensive investigations and elaborate analyses, it not only cleans up the obstacle of understanding the performance differences between existing methods, but also reveals the advantages and disadvantages of previous models under fair comparisons.

1. Introduction

Reading texts in the natural image is a hot topic, due to its wide practical applications, e.g., robot navigation [11], image caption [28], image retrieval [12], etc. Scene text detection, as the prerequisite of reading text system, has attracted increasing attention in the computer vision community over the past few years. However, due to the uneven illumination, the perspective distortion and the complex backgrounds in natural scenes, they result in the difficulties of detecting scene texts. Moreover, the specific characteristics of texts (e.g., various scales, diverse aspect ratios, different fonts, arbitrary-shape layouts, etc.) also increase the challenge of the detection.

To address these challenges, some existing methods [39, 15, 50, 10, 52, 14] adopt axis-aligned rectangles, rotated rectangles or quadrangles to localize scene texts. Despite their progress on horizontal or multi-oriented texts, these methods may fall short, when handling arbitrary-shape texts that are ubiquitous in the real life, as shown in Figure 1 (a)(b)(c). To accurately localize arbitrary-shape text contours in the natural image (Figure 1 (d)), two kinds of methods are prevalent in the field of scene text detection. One is top-down based methods. They perform the binary segmentation or the regression of arbitrary-shape text contour points on the proposals. The other is bottom-up based methods. They first predict local units (e.g., pixels, connected components) and their auxiliary information, and then group them into different text instances.

However, it is hard to affirm whether and how a newly proposed model has the improvement in performance and speed, when comparing with previous same-type methods. It is because existing methods adopt different training settings and testing environments. As shown in Table 1 and Table 2, existing methods usually employ different backbone networks and utilize different external data to pre-train the model. We also observe that different testing scales would distinctly influence the performance and speed of the model. Moreover, some methods even claim they have achieved the state-of-the-arts based on the reported performance using different evaluation protocols (Table 2). These inconsistent-
cies hinder the fair comparisons between the proposed core techniques of existing methods.

In this paper, we make comprehensive studies for the bottom-up based methods, as this kind of methods has excellent speeds and owns more flexible representations for describing arbitrary-shape scene texts compared with top-down based methods. To reveal the advantages and disadvantages of the core techniques in existing methods, we propose a unified framework for the bottom-up based arbitrary-shape scene text detection, providing a common perspective for existing methods. Specifically, the proposed framework consists of five consecutive operation modules. The first module is image pre-processing, which mainly refers to the data augmentation in the training stage and the image resizing in the testing stage. The second module is extracting visual features, using the backbone network pre-trained on ImageNet [27]. The third is the feature fusion module, which fuses multi-scale features to obtain better feature representations. The fourth module is the prediction head, which outputs estimated parameters of describing arbitrary-shape texts. The fifth module refers to the post-processing, which is only utilized in the testing stage. We thus could use this unified framework to support all existing bottom-up based scene text detectors. Based on the proposed framework, we investigate the influence of the fourth module (namely, the prediction head) under the unified experimental settings (e.g., the same image pre-processing, backbone network and feature fusion strategy), as almost bottom-up based arbitrary-shape scene text detectors pay attention on this module. With this investigation, we can clearly understand the strengths and weaknesses of existing bottom-up based arbitrary-shape scene text detection methods. Meanwhile, it also exposes some overlooked explorations and challenges, which could guide more flourishing studies in the future works.

The contributions of this paper are summarized as follows: i) We reveal the inconsistencies between previous arbitrary-shape scene text detection methods, which help readers to perceive the advances and challenges in the field of the arbitrary-shape scene text detection. ii) A unified framework is introduced, which would facilitate comprehensive investigations for better understanding the pros and cons of existing detectors. iii) We provide a fair comparison toolkit, which would clean up the obstacle on the current comparisons.

2. Related Work

Arbitrary-shape scene text detection methods [21, 2] with deep learning can be roughly grouped into top-down methods and bottom-up methods.

**Top-down arbitrary-shape scene text detectors:** These detectors either carry out the binary segmentation or regress key contour points based on proposals. For the segmentation-based methods, they usually perform the pixel-wise semantic segmentation for all pixels in the proposals, inspired by the framework of MaskRCNN [7], and mainly focus on enriching the feature representations or obtaining better segmentation [42, 19, 13, 46, 41, 4, 17]. For example, MS-CAFA [4] exploits a pyramid ROI pooling attention mechanism to learn robust features for proposals with various scales. Mask-TTD [17] adopts a tightness prior to adjust text proposals for better covering the entire text region, and utilizes the text frontier information to improve the text mask prediction. Moreover, in ContourNet [38], the authors only perform the segmentation for text contours on the adaptive proposals. For the regression-based methods [18, 3, 37], they directly or dynamically regress the key points on text contours. For example, CTD-CLOC [18] predicts the offsets of key points to the top-left points, and utilizes the Long Short-Term Memory (LSTM) to smooth the offsets. Instead of the static regression, ATRR [37] adaptively outputs the point pair using LSTM.

However, the tow-down based methods usually require the artificial design of anchors, which would limit the generalization abilities of models for texts with various scales and aspect ratios. Besides, these methods involve multiple pipelines and complex networks, making them hard to achieve the promising speed.

**Bottom-up Arbitrary-shape Scene Text Detectors:** These detectors can be divided into pixel-wise based methods and component-wise based methods. The former ones [35, 30, 45, 36, 16, 34, 51, 31, 44, 47] predict the auxiliary information of each pixel or the specific pixel in the entire/shrunk text region to better formulate different text instances. For example, PSENet [35] introduces a progressive scale expansion algorithm to fuse multi-shrunk segmentation maps with the help of text region kernels. Similarly, PAN [36] estimates the embedding vectors of pixels to measure the distances to different text kernels. Besides, MSR [45] and TextField [44] learn the offset field of each pixel in text regions for better linking neighbor pixels. Furthermore, TextRay [31] predicts the text center heatmap and multiple rays rooted at the specific text center pixels, which can directly reconstruct the text instances and thus avoid the clustering process.

Differently, the component-wise based methods [22, 1, 29, 48, 23] first generate the local components based on the pixel-wise predictions, and then focus on exploring the grouping strategies (e.g., heuristic rules, linkage estimation, relationship reasoning, etc.). For example, TextSnake [22] reconstructs entire text instances by sliding a circle along the central axis. Instead of the offline reconstruction, ICG [29] regards the linkages between the estimated rotated squares as a binary classification, to dynamically formulate the entire text instance. Moreover, DRRGN [48] and ReLaText [23] further deduce the relationships between local
### Inconsistencies Analyses

In this section, we illustrate the different settings between prior works in details.

**Backbones:** As shown in Table 1 and Table 2, previous methods utilize different backbone networks (e.g., VGG16, ResNet50, ResNet101, etc.) pre-trained on ImageNet [27] to extract visual features. Stronger ones usually bring better performances. For example, in DB [16], using ResNet50 with deformable convolution networks (termed as ‘ResNet50-DCN’) as the backbone has the improvement of 2.4% in F-measure, compared with ResNet18-DCN. Similarly, using ResNet101 also increases the F-measure of 1.2% than using ResNet50 in TextFuseNet [46]. Even though some works adopt the same backbone networks, different versions of networks may also influence the performance. For example, PAN [36] uses the ResNet-v2 [9] while other methods usually adopt ResNet-v1 [8].

#### Training Data:
Some existing methods directly train components with the graph convolution network.

These bottom-up based methods have more flexible representation of describing texts, and can usually achieve competitive performances and decent speed. Thus, they have become more and more prevalent. In this paper, we present a unified framework for the bottom-up arbitrary-scene text detectors, which is helpful to the fair comparison in the field of scene text detection.

#### Table 1: Comparisons between existing methods on the dataset CTW [18]. \(\triangle\), \(\circ\) and \(\ast\) denote the short side, the long side and the height, respectively, when resizing the image with keeping the aspect ratio. \((s_{min}, s_{max})\) indicates the short side is set to \(s_{min}\) if it is less than \(s_{min}\), and keep the longer side is not larger than \(s_{max}\). \(\dagger\) means using the recognition branch to optimize the detection in an end-to-end framework. ‘MS’ represents the multi-scale testing. The red italic and the blue bold denote the optimal value for top-down based methods and bottom-up based methods respectively.

| Type                      | Method                  | Venue     | Backbone                  | Pretrain data                  | training data | testing size | R (%) | P (%) | F (%) | FPS | GPUs (#) |
|---------------------------|-------------------------|-----------|---------------------------|--------------------------------|---------------|--------------|-------|-------|-------|-----|----------|
| Bottom-up based methods   |                         |           |                           |                                |               |              |       |       |       |     |          |
| Top-down based methods    |                         |           |                           |                                |               |              |       |       |       |     |          |

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1. We found this from their official code: [https://github.com/zhongqianli/pan_pp.pytorch](https://github.com/zhongqianli/pan_pp.pytorch)
the model on the real-world training data. Differently, some methods first utilize the synthetic dataset SynText [49] or the large-scale real-world dataset (e.g., MLT17 [24], COCO-Text [6], etc.) to pre-train the model, and then the model is fine-tuned on the real-world training data. Table 1 and Table 2 have shown that pre-training on external data can bring obvious performance improvements. For example, pre-training on MLT17 achieves the improvement of 4.2% in F-measure for PSENNet-1s [35] (Table 1). Similarly, pre-training SynText has elevated the F-measure of about 2.9% in PAN [36] (Table 2). Besides, different pre-training data and epochs may also result in different detection performances obviously, but existing methods usually does not care about these inconsistencies, when comparing with other methods.

**Testing Scales:** In the inference stage, various testing sizes of the input image can obviously affect the performance and speed of the model, as displayed in Table 1 and Table 2. For example, in PAN [36] that does not pre-train on SynText, with the increase of the short size of the input image, the F-measure increases by 3.8% and 5.1% on the datasets CTW and TOT, respectively. Moreover, some methods even use the multi-scale testing strategy to promote the performance. However, they may only have a slight improvement on performance but consequently bring the decrease in speed. For example, the recent work CRNet [51].

Table 2: Comparisons between existing methods on the dataset TOT [3]. ♠ and ♦ denote evaluating the performance with the metric [3] IOU@0.5 and DetEval-v2 respectively.
with the multi-scale testing strategy (Table 1) only increases 0.3% in F-measure, compared with the previous method ContourNet [38] using the single-scale testing strategy.

**Evaluation Protocols:** When evaluating on TOT [3], it involves three kinds of evaluation protocols (e.g., IOU@0.5, DetEval-v1 and DetEval-v2). However, some of existing methods do not indicate which kind of the evaluation protocol they use, which makes the comparison confusing. Moreover, prior works report the performances (Table 2) under different evaluation protocols, and make comparisons with each other. Thus, these comparisons are unreasonable, making the assertion of achieving state-of-the-arts unbelievable for some methods.

**Data Augmentation:** Scene text detection methods with deep neural networks are data-driven. Data augmentation thus plays significant roles in learning robust models. However, different data augmentation strategies may cause the performance change of the model in complex scenarios. For example, previous methods randomly crop the sub-image from the input image with different sizes (e.g., 512×512 [34], 640×640 [30, 35, 16], 768×768 [44], 960×960 [31], etc.), which may make the model have different generalization abilities to the scales of texts. Meanwhile, some existing methods randomly rotate the input image with different angles (e.g., {0°, 90°, 180°, 270°} [34], [-10°, 10°] [35, 16], etc.), pursuing the robustness to the rotated arbitrary-shape scene texts.

**Multi-scale Feature Fusion:** Deep arbitrary-shape scene text detectors usually involve fusing multi-scale features generated by the backbone network, before feeding into the prediction head. This fusion between low-level and high-level features could enrich the feature representations, facilitating the model to detect texts with various scales. However, existing methods usually introduce different fusion techniques, which further make trouble for fairly investigating the representations of describing texts. These different fusion techniques not only influence the performance, but also result in different memory and speed. Besides, even though the module adopts similar fusion strategies, it could still bring different performance gains, due to different resolutions of the output maps. For example, in PSENet [35], when the resolution of the output map is 1/4 of the input image (termed as ‘PSENet-4s’), it decreases by 2.3% and 1.3% in F-measure for the datasets CTW and TOT respectively, compared with ‘PSENet-1s’.

### 4. Proposed Unified Framework

In this section, we propose a unified framework for the bottom-up arbitrary-shape scene text detection methods, as shown in Figure 2. This framework mainly consists of five modules: image pre-processing, backbone, multi-scale feature fusion, prediction head and post-processing.

Specifically, the original image \( I \in \mathbb{R}^{H \times W \times 3} \) is first fed into the image pre-processing module to generate the network input \( \tilde{I} \in \mathbb{R}^{H \times W \times 3} \), formulated as:

\[
\tilde{I} = \mathcal{N}(\mathcal{P}(I)),
\]

where \( \mathcal{N} \) means the image normalization; \( \mathcal{P} \) refers to the data augmentation and the test image resizing strategy for the training and testing stage respectively. Due to the differences of \( \mathcal{P} \) in existing methods, we thus unify the settings of \( \mathcal{P} \) for fair comparisons following [48]. In the training stage, the data augmentation mainly involves four steps: i) Randomly scale the original image via the aspect ratio ranging in [0.75, 2.5]; ii) Randomly crop the image patch with the scale of 640×640.; iii) Randomly rotate the cropped image patch with the angle of [-90°, 90°]. iv) Randomly flip the image in the horizontal direction with the probability of 0.5. In the testing stage, the test image resizing strategy indicates the short size of \( I \) is set to \( s \) if it is less than \( s \), while the longer side is not larger than 2\( s \). In the experiments, \( s \) is set to 512 in default, and we also investigate the influence of performance against the change of \( s \).

In the backbone module, we utilize the backbone network pre-trained on ImageNet [27] to extract multi-scale visual feature representations, which can be formulated as:

\[
\{F_i\}_{i=1}^{L} = \mathcal{B}(I; \Theta_b),
\]

where \( F_i \in \mathbb{R}^{(H/2^i + 1) \times (W/2^i + 1) \times D_i} \) denotes the feature map generated by the \( i \)-th stage of the backbone network \( \mathcal{B} \) with the pre-trained weights of \( \Theta_b \); \( L \) is the number of multi-scale features; \( I \) means the indicator function. \( D_i \) is the dimension of the feature. In the framework, we adopt the frequently-used backbone network ResNet50 [8] like most existing scene text detection models.

Next, the feature fusion module \( \phi \) combines low-level and high-level features for generating a more representative feature \( F^e \in \mathbb{R}^{(H/\sigma) \times (W/\sigma) \times D_e} \). It can be expressed as,

\[
F^e = \phi(\{F_i\}_{i=1}^{L}; \Theta_f),
\]

where \( \sigma \) and \( D_e \) denote the downsampling factor and dimension of feature maps; \( \Theta_f \) indicates the learnable parameters in \( \phi \). Additionally, \( \phi \) usually adopts a top-down fusion strategy. That is, it gradually fuses feature maps from deep semantic representations to shallow local cues. However, \( \phi \) in most previous methods has obvious differences (More details can be seen in Section ?? of Appendix), which can result in different performances. To avoid the influence of different \( \phi \), we set the frequently-used fusion strategy like those in [22, 48], where \( \sigma \) is equal to 1.

After that, the enhanced feature \( F^e \) is fed into a single prediction head module \( \varphi \) to estimate the local unit categories and their auxiliary information, termed as \( Q \in \mathbb{R}^{\mathcal{R} \times \mathcal{C}} \), which can be formulated as:

\[
Q = \mathcal{U}_\varphi(\varphi(F^e; \Theta_p)),
\]
where $U_{\omega} \phi$ indicates upsampling the resolution of the output with the factor of $\omega$. $\Theta_p$ denotes the learnable parameters in $\varphi$. $C_o$ is the number of the prediction (e.g., categories and auxiliary information). For example, in PSENet [35], $Q$ consists of $C_o$ segmentation masks for the text instances at different shrunk scales. It is worth noting that PSENet-1s ($\omega'/\omega = 4/4 = 1$) achieves better performance than PSENet-4s ($\omega'/\omega = 1/4$), due to different resolutions of the outputs. Similarly, $Q$ in DB [16] contains the predicted shrunk text region map and the estimated threshold map, and its resolution is also upsampled to the same as that of the network input ($\omega'/\omega = 4/4 = 1$) (More examples can be seen in Section ?? of Appendix). For a fair comparison, we set $\omega' = \omega$ in experiments.

After obtaining the network output $Q$, it is directly fed into the loss function to calculate the loss in the training stage, or is post-processed to generate final detection results in the testing stage. Generally, most existing bottom-up arbitrary-shape scene text detectors mainly focus on the exploration of representations of describing text instances, which reflects at the prediction head module $\varphi$ and its corresponding loss function.

5. Experiments and Analyses

With the unified framework, we emphatically investigate the prediction head module of several previous methods, for profoundly disclosing the advances and shortages of current researches on arbitrary-shape scene text detection.  

5.1. Datasets and Evaluation Protocols

CTW [18] is a prevalent arbitrary-shape scene text detection benchmark. It contains 1500 images (1000 images for training and 500 images for testing) in total. The annotation of the text instance is line-level, and is labeled by a polygon with 14 key points.

TOT [3] is also a frequently-used dataset for arbitrary-shape scene text detection. It consists of 1,255 training images and 300 testing images. The text instance in the image is annotated by the word-level polygon with unfixed number of key points.

For each dataset, we adopt two evaluation protocols, e.g., IOU@0.5 utilized in [18] and DetEval-v2 proposed in [3], for better revealing the performance differences.

5.2. Implementation details

Based on the official open codes, we adopt the same settings for the image pre-processing, backbone and feature fusion module to make a fair comparison. Other settings keep the same with the corresponding original methods. Additionally, the model is directly trained for 600 epochs on the training set of the corresponding dataset. The batch size is fixed to 6 in the training stage. When testing, the batch size is set to 1 in a single thread. All experiments...
are conducted with the deep learning framework Pytorch 1.4, and on a workstation with a single RTX 2080Ti GPU, a 4.00GHz Intel(R) Xeon(R) W-2125 CPU, and 15G RAM.

5.3. Comparisons of Performance and Speed

Table 3 shows that PSENet [35] and PAN [36] achieve the optimal \( F\)-measure on CTW under the evaluation protocols IOU@0.5 and DetEval-v2 respectively. On the dataset TOT, DB [16] and PAN [36] have obtained the best \( F\)-measure under IOU@0.5 and DetEval-v2, respectively. In the terms of the speed, DB [16] significantly outperforms other methods. Meanwhile, the speed of the component-wise based methods TextSnake [22] and DRRGN [48] is distinctly slower than the pixel-wise based methods (e.g., PSENet [35], PAN [36], DB [16], etc.). Some visualized detection results are presented in Figure 3. These quantitative and qualitative experimental results indicate that an older method can be better than a newer method in performance or speed under fair comparisons. It is because the improvements in the original methods mainly come from some tricks (e.g., more training data, stronger backbone, well-designed feature fusion strategies, etc.). To further verify the ability of accurately localizing the text contours, we use stricter thresholds under the evaluation protocol IOU. As show in Figure 4, we observe that PAN [36] is more robust to the change of IOU threshold than other methods. Similarly, the qualitative results in Figure 3 have also shown that PAN [36] can achieve more accurate text contours.

5.4. Influence of Testing Scale

To investigate the robustness of scales, we validate several kinds of testing scales like those in [36]. As shown in Figure 5, it shows that different testing scales can result in obviously different performances. Even through the short size \( s \) of the test image is consistent with the size \( (640 \times 640) \) of the training image, it also can not ensure achieving the optimal performance. Under many conditions, it achieves the best performance, when using a smaller size (e.g., 512). The reason may be ascribed to the domain shift of the scale between the training data and the testing data. In effect, existing methods usually utilize the testing scale with no evidence. Sometimes, when we only change the testing scale, it would also bring an obvious performance improvement. In the past few years, learning a scale-robust detector for the arbitrary-shape scene texts with diversified scales and aspect ratios nearly draws little attention in the field of scene text detection.

5.5. Exploration of Generalization Ability

To verify the generalization ability of existing methods, we conduct cross-dataset experiments. Specifically, we train the models on the training set of CTW and then test on the testing set of TOT (CTW \( \rightarrow \) TOT), and vice versa (TOT \( \rightarrow \) CTW).
| Method        | Venue | CTW $\rightarrow$ TOT | TOT $\rightarrow$ CTW |
|---------------|-------|-------------------------|------------------------|
|               |       | IOU@0.5 | DetEval-v2 | R (%) | F (%) | R (%) | F (%) | R (%) | F (%) |
| TextSnake [22]| ECCV'18 | 29.6 | 36.6 | 32.7 | 65.3 | 47.9 | 55.3 | 57.3 | 44.8 | 50.3 | 73.5 | 71.8 | 72.6 |
| PSENet [35]   | CVPR'19 | 30.9 | 55.8 | 39.8 | 61.9 | 67.1 | 64.4 | 51.5 | 37.0 | 43.1 | 59.6 | 59.6 | 59.6 |
| PAN [36]      | ICCV'19 | 27.8 | 59.1 | 37.8 | 65.7 | 78.9 | 71.7 | 45.6 | 37.1 | 40.9 | 65.3 | 72.3 | 68.6 |
| DB [16]       | AAAI'20 | 29.2 | 60.0 | 39.3 | 45.1 | 65.0 | 53.3 | 53.4 | 35.4 | 42.6 | 65.6 | 71.3 | 68.3 |
| DRRGN [48]    | CVPR'20 | 32.4 | 55.3 | 40.9 | 64.6 | 66.1 | 65.3 | 50.9 | 36.0 | 42.2 | 56.8 | 57.9 | 57.3 |

Table 4: Generalization Ability.

![Figure 5: Effect of testing scales. The experiments are conducted on the datasets CTW and TOT for DRRGN [48], DB [16], PAN [36], PSENet [35] and TextSnake [22].](image)

As shown in Table 4, we find that DRRGN [48] and PAN [36] can achieve the best $F$-measure on CTW $\rightarrow$ TOT, under IOU@0.5 and DetEval-v2 respectively. Meanwhile, the older detector TextSnake [22] shows better generalization abilities on TOT $\rightarrow$ CTW than other methods. These experiments further reveal that some older methods may still surpass the newly proposed methods in some aspects under fair comparisons.

### 5.6. Analyses of Convergence

As shown in Figure 6, it indicates that TextSnake [22] and PAN [36] can achieve more stable convergence, when evaluating under both IOU@0.5 and DetEval-v2. Meanwhile, TextSnake [22] also shows faster convergence than other methods. Figure 6 also shows that the convergence of the model is dependent on the evaluation protocol. For example, DRRGN [48] can achieve more stable convergence after about 200 epochs under IOU@0.5 than DetEval-v2. Generally speaking, the stability and speed of the model convergence also reflect the advantages of the model to some extent, which is usually ignored by existing scene text detectors.

![Figure 6: Illustration of the model convergence. The experiments are conducted on the dataset CTW for DRRGN [48], DB [16], PAN [36], PSENet [35] and TextSnake [22]. Best view in color.](image)

6. Conclusions

In this paper, we reveal the inconsistencies between existing arbitrary-shape scene text detectors. These inconsistencies bring difficulties in determining the advantages of the newly proposed core techniques compared with previous methods. To clean up the hindrance on fair comparisons, we present a unified framework for bottom-up arbitrary-shape scene text detection models. With this framework, we have provided a fair comparison for several well-known methods. We also provide comprehensive analyses on these methods for better disclosing their strengths and weaknesses. Thus, these profound studies suggest multiple directions to explore in the future. Firstly, it is necessary to propose more robust representations of describing arbitrary-shape scene texts with various scales and aspect ratios for more accurate localizations. Secondly, it is very meaningful to explore more efficient online data augmentation strategies by considering the intrinsic characteristics of scene texts. Thirdly, it is useful to study the scene text detector with a tradeoff between performance and speed on resource-constrained circumstances.
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