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Evolution, Comparison, and Trend Prospects of Text Generated Images Based on Deep Learning

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Abstract. Text generated image is a hot research field of cross modal in-depth learning, which can effectively replace the traditional manual drawing and be applied in games, advertising and other industries. The existing mainstream technologies are divided into Generative Adversarial Network (GAN), transformer and diffusion model. Each model has undergone multiple rounds of structural iterative optimization. This paper sorts out the evolution of the three types of architectures, and integrates the open quantitative indicators such as Fréchet Inception Distance (FID), Inception Score (IS), and image text matching of various models under the COCO dataset to compare the performance differences of existing schemes. GAN series models have fast reasoning speed but low image quality limit, transformer has strong detail expressiveness but huge computational cost, and diffusion model has real-time imaging but insufficient real-time performance. At present, there are many pain points in this field, such as the difficulty of taking into account the computational power, image quality and speed at the same time, the deviation of long text semantic matching, and the weak ability of scene generalization. Based on this, this paper summarizes the mainstream optimization research directions, such as lightweight, multi architecture integration, and multi condition controllable generation.

Keywords: Text generated image, Deep learning, Generative adversarial network, Diffusion model, Performance comparison

1. Introduction

Text generated image is the core research direction in the field of cross modal deep learning. This technology uses text semantic information as input to generate high-definition images that are highly consistent with the text description. It has broad application prospects in many industries, such as game art production, commercial advertising design, virtual scene construction and so on. The traditional image generation method relies on manual hand drawing, which not only consumes manpower, but also takes a long time and costs high. The image generation technology based on deep learning can associate the cross modal relationship between text and image data, realize the automatic generation of image content, and effectively solve the shortcomings of the traditional manual creation mode.

At present, the mainstream image generation technology framework is mainly divided into three categories, namely, generation countermeasure network (GAN), autoregressive generation model

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based on transformer and diffusion model. In the direction of generating countermeasure networks, Goodfellow et al. proposed to generate countermeasure networks. The model realizes the fitting of data distribution through the countermeasure training of generators and discriminators [1]. However, the original GAN lacks the ability to control text conditions and its generation resolution is low. Zhang et al. proposed StackGAN, which gradually refined from low resolution to high resolution through a multi-stage generation strategy, significantly improving the clarity of the text generated image [2]. However, StackGAN still has shortcomings in fine-grained semantic alignment. Xu et al. proposed AttnGAN and introduced the attention mechanism to enable the generator to focus on the most relevant words in the text at all stages, further enhancing the semantic consistency between the generated image and the text description [3]. In the direction of autoregressive generation based on transformer, OpenAI proposes DALL-E, which discretizes the text and image into word element sequences, and uses autoregressive method to gradually generate image tokens, showing the potential of transformer in cross modal generation [4]. In the direction of diffusion model, the denoising diffusion probability model (DDPM) achieves high-quality image generation through the forward and reverse denoising process, providing a new paradigm for text generated images [5]. However, the direct operation of DDPM in pixel space leads to huge computational overhead. Rombach et al. proposed the potential diffusion model (LDM), which transfers the diffusion process from pixel space to potential space, and significantly reduces the computational overhead while maintaining the generation quality. Its open-source version of Stable Diffusion promotes the wide application in this field [6]. Generally speaking, the above three kinds of methods have their own advantages and disadvantages: GAN method has fast generation speed, but the training stability and diversity are insufficient; the autoregressive model based on transformer has strong sequence modeling ability but low reasoning efficiency; the diffusion model has high quality, but it has many sampling steps and high computational overhead. How to improve the efficiency and controllability under the premise of ensuring the quality of text generation is still the key problem to be solved in the field of text generated images.

At present, many reviews have summarized the text generated image technology, but most of them prefer to sort out the early GAN and autoregressive model, and lack of systematic arrangement of various improvement schemes with diffusion model as the core in recent years; At the same time, the experimental environment, test data sets and evaluation indicators used in different literatures are not unified. Many studies only introduce the methods and principles, and lack the horizontal quantitative comparison based on the public experimental data, which is difficult to intuitively reflect the performance gap and trade-offs between different architectures.

In view of the above situation, this paper sorts out the evolution of GAN, autoregressive transformer and diffusion model, integrates the original experimental results published in many literatures, completes the performance comparative analysis of multiple models under the same dataset and evaluation index, analyzes the inherent defects of existing methods, summarizes the main challenges faced by the current technology, and prospects the future feasible optimization research direction.

2. Evolution of mainstream text image generation model

2.1. GAN series iterative model

GAN is the early mainstream architecture in the field of text generated image. It realizes the mapping from text to image through confrontation training. It has the advantages of fast reasoning

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speed and lightweight network, but there are always problems of unstable training and easy mode collapse.

Early basic GAN (StackGAN++, AttnGAN) can only extract word level shallow semantics. When encountering multiple object combinations and descriptions with spatial relationships, objects are often confused and picture details are incomplete [2, 3]. Subsequent DF-GAN, RAT-GAN, MAGCL-GAN and other models have made improvements in the direction of feature fusion and semantic constraint of discriminator respectively, which has alleviated the defects such as text dislocation and blurred picture to a certain extent. However, such improved schemes still rely on LSTM to complete text coding, and there are obvious problems in feature extraction ability [7-9].

CLIP-GAN is a key breakthrough in GAN technology. It directly discards the traditional LSTM encoder and introduces pretraining CLIP to complete the text and image feature alignment, which greatly improves the matching degree of text and image in complex scenes [10]. However, CLIP itself has a large number of parameters, which directly offset the core advantages of GAN's lightweight and low latency. Meanwhile, LAFITE, GALIP and other models also learn from the idea of CLIP's cross modal alignment, becoming a representative scheme with strong comprehensive ability under this architecture [11, 12].

2.2. Transformer architecture model

Transformer text generated image model completely discards the confrontation training paradigm, takes the hierarchical self-attention module as the backbone, and establishes the long-distance association between text and pixels with the help of global self-attention. There is no problem of GAN mode collapse, and it is better than GAN in terms of complex composition and fine-grained image generation. However, due to the huge amount of model parameters and the time-consuming single graph reasoning, the model cannot be deployed and run in ordinary equipment.

DALL-E is the first model to use transformer to make text generated image. First, the picture is compressed into discrete coding, and then the picture is generated segment by segment [4]. The early version lacked the ability to control the overall picture, and the generated objects were disorderly arranged and loosely structured. The subsequent Parti series confirmed by increasing the model size that the larger the number of parameters, the better the understanding and spatial arrangement of multi-object text [13], and verified the positive effect of scale expansion on semantic understanding and composition ability. SwinV2-Imagen is the best comprehensive solution in this series [14]. In word processing, the objects and relationships in the description are disassembled first, and the logical information is extracted by graph network; The drawing trunk is replaced by SwinV2 structure, which reduces the amount of calculation by relying on window type attention, and improves the stability of deep network training. No matter the text logic understanding or the restoration of picture structure, the performance is better than other models of the same type.

2.3. Diffusion model iteration system

The diffusion model uses the drawing logic of "step-by-step noise adding and reverse reduction" to solve the problems of unstable GAN training and repeated pictures from the root, and the upper limit of the authenticity of the generated pictures is higher. The existing improvement direction is divided into two aspects: one is to improve the picture quality, and the other is to compress the model and reduce the operation cost.

DDPM is the earliest basic diffusion model, which determines the basic process of noise reduction, but the complete generation requires thousands of cycle calculations, and the

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computational power consumption is very high [5]. In order to solve this efficiency bottleneck, LDM (Stable Diffusion) converts pictures into low-dimensional data with the help of compression network, and then performs diffusion operation, greatly reducing the amount of calculation [6]; Each layer of the network is equipped with a text control module, which can accurately adjust the screen according to the text. However, the trunk only has convolution layer and lacks the ability of global picture correlation. The problem of distorted limbs and facial features cannot be completely eliminated.

VQ Diffusion uses discrete encoding operation to reduce the occupation of video memory [15]; However, discrete processing will destroy the continuous correspondence between text and picture, and it is easy to lose details when drawing long text. To solve the problem of insufficient expression ability of the backbone network, DiT replaced the convolution backbone in the diffusion with transformer attention network, and determined the optimal scheme after comparing various text embedding methods. The overall picture and text matching effect was improved, but the amount of single cycle calculation was significantly increased.

Image quality improvement models mainly rely on scale expansion and multi module division of labor optimization: GLIDE took the lead in verifying the image quality advantages of large-scale diffusion models [16]; The diffusion architecture DALL-E 2 separates text understanding and image generation into two steps. The initial generation of DALL-E belongs to the transformer autoregressive model, and the two architectures are essentially different [4, 17]; Use CLIP visual information to improve authenticity; Imagen experiment shows that the influence of text coding network on image quality is greater than that of drawing trunk [18]; eDiff-I uses multiple sets of dedicated network division. The main body of the picture is built in the early stage, and the texture is refined in the later stage. The detail performance is better, but the model volume and drawing time increase synchronously [19].

3. Comparative analysis of public benchmark evaluation data

3.1. Unified evaluation index meaning

IS is the initial score. The higher the value of this index, the better the clarity of the generated image and the diversity of objects; FID is the initial Frechet distance. The lower the index value is, the closer the data distribution of the generated image and the real sample is, and the higher the picture authenticity is; R-Precision is used to measure the accuracy of semantic matching between the text and the generated image. The higher the value, the stronger the consistency of the text and text content; CLIP score is a cross modal semantic matching score, which is mainly used to evaluate the alignment effect of text and image features; The two indicators of reasoning time and parameter quantity correspond to the image generation speed and the hardware resource cost required by the model operation, respectively.

3.2. Quantitative comparison of multiple models in COCO dataset

The data collected this time are used to complete the horizontal evaluation of the whole model using the universal image text dataset published by COCO. This dataset is a universal standard test set in the field of cross modal image generation. The data covers multiple categories such as daily scenes, animals and plants, people, vehicles, etc. Each sample image is equipped with multiple manually annotated natural language descriptions. The annotated text includes various complex description sentences such as single object, multi object combination, spatial position, action attribute, etc.,

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which can comprehensively test the model image restoration ability and multi-objective semantic matching effect. As shown in Table 1, the quantitative index data of various text generated image models based on the COCO dataset are compared as follows.

Table 1. Comparison of quantitative indexes of various text generated image models based on COCO dataset

Model name	FID↓	IS↑	R-Precision↑	CLIP score↑	Reasoning time	Parameter quantity
StackGAN++ [2]	81.59	8.30	-	-	-	-
AttnGAN [3]	35.49	25.91	85.94%	-	15s	-
DF-GAN [7]	28.92	30.52	72.81%	0.2972	-	-
RAT-GAN [9]	14.61	32.83	89.23%	-	-	-
LAFITE [11]	8.12	-	-	0.3325	0.02s	0.15B
GALIP [12]	5.85	-	-	0.3338	0.20s	0.24B
CLIP-GAN [10]	5.71	-	70.03%	0.3409	0.10s	0.24B
MAGCL-GAN [8]	16.27	30.56	92.68%	-	-	-
DALL-E [4]	27.50	17.95	-	-	-	-
Parti-20B [13]	7.23	-	-	-	-	20B
SwinV2-Imagen [14]	7.21	31.46	-	-	-	-
GLIDE [16]	12.24	30.47	-	-	15.0s	5B
DALL-E 2 [17]	10.39	-	-	-	10s	6.5B
Imagen [18]	7.27	-	-	-	9.1s	7.9B
LDM [6]	12.63	-	-	-	9.4s	1.45B
Improved VQ-Diffusion [15]	8.44	-	-	-	-	1.27B
eDiff-I [19]	6.95	-	-	-	32s	9B
U-CrossDiT [20]	5.38	-	-	-	-	0.054B

3.3. Data analysis

Relying on the public evaluation indicators of the COCO dataset, this section carries out the quantitative results sorting from the three types of architectures of GAN, transformer and diffusion model.

3.3.1. GAN model data analysis

Using FID index to measure the degree of image authenticity, CLIP-GAN and GALIP are the best models in the GAN system, and their FID values are 5.71 and 5.85 respectively. Compared with StackGAN++, AttnGAN, DF-GAN and other early GAN models, the image authenticity is significantly improved, but their authenticity index is still not as good as the diffusion model U-CrossDiT and transformer architecture Parti-20B. It can be seen that the GAN architecture has an

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upper limit of inherent performance in restoring the distribution of real images [2, 3, 7, 10, 12, 13, 20]. From the perspective of R-Precision image text matching index, MAGCL-GAN reached 92.68%, and RAT-GAN was 89.23%. The matching accuracy of AttnGAN and DF-GAN decreased in turn. The semantic matching constraint mechanism was introduced into the high matching degree model [8, 9]. Combined with CLIP score cross modal matching score analysis, CLIP-GAN, GALIP and LAFITE scores are high, which are higher than DF-GAN, indicating that the embedded CLIP pretraining module can effectively improve the feature alignment effect of text and image [11].

3.3.2. Transformer model data analysis

The LDM parameter of the conventional latent space diffusion model is 1.45B, the reasoning time is 9.4s, and the FID is 12.63, which forms a compromise between the model size and the generation speed, but the image authenticity still has room to improve [6]. The parameter of improved VQ diffusion is 1.27B, FID falls back to 8.44, and U-CrossDiT in the lightweight direction is only 0.054B. At the same time, FID 5.38, which is the lowest in all models, has achieved outstanding lightweight optimization effect [15, 20]. In the HD large-scale diffusion model, the eDiff-I parameter is 9B, and the FID is 6.95, but the reasoning time is up to 32s, and the generation efficiency is low [19]; Comparing GLIDE, DALL-E 2 and Imagen horizontally, the parameter quantities of the three do not show a complete linear correspondence with FID. It can be seen that the model parameter quantity cannot determine the image quality alone. The structural design of text encoder and denoising backbone network also plays a key role [16-18]. Compared with the overall reasoning efficiency, the reasoning time of all diffusion models is not less than 9s, while the reasoning time of GAN type models is only distributed in the range of 0.02~0.20s. The running speed of the two types of architectures is very different, and the diffusion model is difficult to adapt to the real-time image generation scene.

3.3.3. Diffusion model data analysis

From the comparison results of various indicators between lightweight and conventional diffusion models, the LDM parameter is 1.45B, the reasoning time is 9.4s, and the FID is 12.63 [6]; Stable Diffusion v1.4 parameter quantity 0.92B, FID = 16.31 [6]. The two mainstream latent space diffusion models balance the parameters and generation speed, but there is still room for improving the image authenticity. VQ Diffusion adopts discrete coding design, the parameter quantity is compressed to 0.37B, and the corresponding FID rises to 13.86 [15]; The parameter of improved VQ diffusion in the improved version was increased to 1.27B, and FID fell back to 8.44. It can be seen that the discrete transformation will slightly lose the authenticity of the picture [15]. U-CrossDiT has only 0.054B parameter, FID reaches the lowest value of 5.38 in all models, and the lightweight optimization effect is outstanding [20].

Focusing on the performance data of high-precision large-scale diffusion model, ERNIE-ViLG 2.0 (24B, FID = 6.75), eDiff-I (9B, FID = 6.95), RAPHAEL (3B, FID = 6.61) both are high-definition large model routes, in which the eDiff-I reasoning takes 32s and the generation efficiency is very poor [19]. DALL-E 2 (6.5B, FID = 10.39), Imagen (7.9B, FID = 7.27), GLIDE (5B, FID = 12.24) the horizontal comparison of several groups of data shows that the amount of model parameters cannot completely determine the quality of the generated image, and the structural design of text encoder and denoising backbone network will also significantly affect the final generation effect [16-18].

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The reasoning duration recorded by all models can be used to visually compare the generation efficiency of various architectures. The reasoning duration recorded by all diffusion models in the existing test samples is 9s or more, while the reasoning time of GAN model is concentrated in 0.02~0.20s. There is a significant difference in the running speed between the two, and the diffusion model cannot meet the real-time generation requirements.

3.4. Comprehensive summary of full dataset across architectures

Combined with all the original measured table data, a clear performance division can be formed for GAN, transformer and diffusion schemes:

The core advantages of GAN architecture are fast reasoning speed and small model size, which are suitable for lightweight landing scenarios such as mobile terminal and online real-time drawing. However, limited by the confrontation training mechanism, the training process is prone to mode collapse; In fine-grained, high-definition, multi-object complex scenes, there is a fixed upper limit to the image quality. Even if the CLIP cross modal module is introduced, the comprehensive performance is still inferior to the high-end diffusion and transformer models.

Transformer relies on global hierarchical self-attention modeling, which can completely capture the long-distance correlation of space and time sequence. The generation effect of fine-grained texture, face and multi-object composition is the best, and there is no risk of training collapse. The short board focuses on the hardware cost, and the large number of parameters makes ordinary equipment unable to be deployed, which is only applicable to offline professional art production.

The training stability of diffusion model is outstanding, and there are no inherent defects of GAN. By adjusting the trunk and parameters, two technical routes of lightweight and high precision can be taken respectively. However, the iterative sampling process will lengthen the generation delay, and the lightweight transformation will inevitably sacrifice the image details and image text matching accuracy, so the image quality and computational cost cannot be taken into account at the same time.

4. Current limitations and future prospects

4.1. Existing core limitations of current technology

Based on the quantitative results of each dataset and the model architecture logic, there are three kinds of technical contradictions that are difficult to reconcile in the existing text image generation methods:

First, the traditional single architecture model is generally difficult to meet the requirements of low computing overhead, millisecond output and high-definition details at the same time; A few ultra lightweight fusion models can achieve both, but the technology has not been implemented on a large scale. The lightweight GAN has insufficient image quality, high-precision diffusion and transformer reasoning costs are extremely high, and the existing single architecture is difficult to meet the three types of needs at the same time.

Second, the semantic matching ability of complex text is insufficient. Even in the current optimal model, under the description of long text and multi-object overlay, there are still problems of missing objects and attribute mismatch. The defects of lightweight schemes such as discrete diffusion will be further amplified.

Third, the generalization performance of subdivision scenes is poor. Based on the test of COCO universal dataset, it can be seen that the indicators of universal pretraining model in structured target scenes such as face, animals and plants decline significantly; After fine-tuning the domain, the

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generalization ability of the special model will be greatly improved. The general model needs targeted fine-tuning to meet the needs of the subdivided field, and the native general adaptation ability is limited.

4.2. Future optimization solutions

First, at the level of computational efficiency and model deployment, the existing model still needs a lot of computational support to generate high-quality images. It is difficult to lighten the model. By optimizing the network structure and improving the training process, the paper reduces the resource consumption of model hardware and increase the practical scenarios that can be applied.

Secondly, the existing models often have problems such as the mismatch between the description and the graph. The paper can study the text-based local image correction technology to accurately correct the wrong content, and improve the model input mode so that the sketch, semantic segmentation graph, contour, voice and other conditions can generate pictures for AI and other industries. The multi conditional input and local correction module can be embedded in the diffusion model sampling process to achieve end-to-end controllable generation.

And it can build a conforming network, integrate the advantages of GAN rapid reasoning, diffusion model detail rendering, and transformer global feature extraction to balance the generation time and image authenticity, and solve the problem that it is difficult to give consideration to both.

Finally, it can also transform the network structure, reduce the hardware operating pressure, simplify the CLIP text encoder, and reduce the model volume without weakening the effect of text matching; Refer to swing layered attention optimization and diffusion UNet to reduce the amount of computation and the computing power required for deployment.

5. Conclusion

This paper systematically reviews the evolution of three types of text generated image architectures: GAN, transformer and diffusion model. Based on the public evaluation index of COCO dataset, it completes the horizontal quantitative comparison of multiple types of models, and analyzes the performance differences and inherent limitations of each architecture in terms of generation quality, reasoning efficiency and semantic matching. According to the existing research progress, GAN, transformer and diffusion model have irreplaceable advantages, but they also have inherent defects that are difficult to eradicate. A single architecture can not meet the multiple requirements of low computing power, high image quality and real-time generation at the same time. At this stage, there are still obvious shortcomings in complex semantic parsing and cross scene adaptation of text generated images. Future research will focus on multi architecture integration, network lightweight and multi conditional controllable generation, improve the accuracy of image and text matching while reducing hardware overhead, and promote the application of text generated image technology in more industries.

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