Evaluating Text to Image Synthesis:
Survey and Taxonomy of Image Quality Metrics

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Abstract—Recent advances in text-to-image synthesis have been enabled by exploiting a combination of language and vision through foundation models. These models are pre-trained on tremendous amounts of text-image pairs sourced from the World Wide Web or other large-scale databases. As the demand for high-quality image generation shifts towards ensuring content alignment between text and image, novel evaluation metrics have been developed with the aim of mimicking human judgments. Thus, researchers have started to collect datasets with increasingly complex annotations to study the compositionality of vision-language models and their incorporation as a quality measure of compositional alignment between text and image contents. In this work, we provide a comprehensive overview of existing text-to-image evaluation metrics and propose a new taxonomy for categorizing these metrics. We also review frequently adopted text-image benchmark datasets before discussing techniques to optimize text-to-image synthesis models towards quality and human preferences. Ultimately, we derive guidelines for improving text-to-image evaluation and discuss the open challenges and current limitations.

Index Terms—Artificial Intelligence, Surveys, Machine learning, Text analysis, Image Generation

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1 INTRODUCTION

THE rapidly evolving landscape of text-conditioned image generation has emerged as a pivotal area in computer vision and natural language processing [3]–[5]. As the demand for seamless integration between textual and visual information intensifies, understanding the intricate mechanisms behind accurate text-to-image (T2I) alignment becomes imperative. Furthermore, robust metrics for T2I alignment are essential for objectively evaluating the performance of models, facilitating advancements in research and technology for high-quality image generation that aligns with human judgment. In modern text-conditioned applications, such as text-to-video [6]–[8] where multiple frames are generated for a single text prompt and text-to-3D where image-based NeRF approaches and diffusion models produce 3D representations for textual scene descriptions [9]–[13] the measurement of alignment between text and image content is fundamental. Moreover, an increasing number of web-based applications, like DALL-E, ImageFX, DreamStudio, Midjourney, and civitai.com, offer simple user interfaces and capable hardware, making modern generative AI accessible not only to researchers but also to novices. After the release of Stable Diffusion [14], a large community developed that uses and publishes their generated images along with corresponding prompts online [15]. Even a Stable Diffusion WebUI [16] was developed by the community, enabling even novice users to apply Stable Diffusion by providing an iterative human-in-the-loop workflow. In these scenarios, the integration of automatic T2I quality metrics could foster semi-automated processes.

In this work, we consider the process T2I synthesis as a black box, where for a given textual input, a model produces an image (see Figure 1). Furthermore, we define the quality of an image as equal to a combination of image quality and alignment quality, with the latter correlating to the degree of alignment between the text and the image. Consequently, this is fulfilled only if all details described by a text prompt are visually represented in the image. Humans possess the fundamental ability to leverage multiple modalities of perceived data to properly engage with the world under dynamic, unconstrained circumstances [17]. This leads us to the assumption that human judgments in evaluating T2I alignment are the gold standard, necessitating proper validation of proposed metrics against human ratings [18]–[21]. Before the invention of CLIP [22], the evaluation of T2I alignment was considered to be captured by solving image-text retrieval/matching tasks [23]. However, measuring the similarity between a query and the target text turned out to be not as effective as measuring the distance between text and image embeddings [24].

This survey delves into the current state of research on measuring T2I alignment, exploring the strengths and limitations of existing metrics, surveying benchmark datasets, reviewing T2I optimization methods, and ultimately aiming to contribute guidelines that propel advancements in the synergy between measurement and optimization of T2I alignment. Through a comprehensive analysis of recent developments, we endeavor to elucidate key challenges and avenues for future exploration in the dynamic field of text-conditioned image generation.

Within the remainder of this work, we systematically address essential components to provide a comprehensive overview of evaluation strategies for T2I synthesis. Therefore, we first derive a taxonomy in Section 2, which is based on the current state of the art (SOTA) for T2I evaluation. Next, we categorize recently published metrics utilizing our proposed taxonomy in Section 3, before providing an overview of the text-image datasets (see Section 4), which are frequently used to construct text-image quality metrics

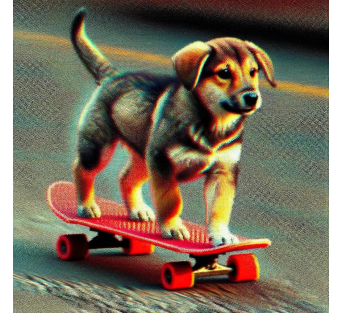An astronaut floating in the ocean holding a piña colada

DAScore: 0.80

Aesthetic: 6.43

DAScore: 0.81

Aesthetic: 6.27

A dog riding a skateboard

DAScore: 0.88

Aesthetic: 6.68

DAScore: 0.89

Aesthetic: 5.92

The ray is chasing the fish

DAScore: 0.77

Aesthetic: 6.39

DAScore: 0.49

Aesthetic: 6.45

A computer is standing below the table

DAScore: 0.68

Aesthetic: 6.09

DAScore: 0.36

Aesthetic: 6.04

Fig. 1. Examples of text-conditioned image synthesis are presented. We use four prompts, and for each prompt, we synthesize two images. Beneath each image, the DA-Score and Aesthetic Score are displayed. The DA-Score [1] measures text-to-image alignment, and the Aesthetic Score [2] assesses image quality. In the top row, we show two images that depict accurate compositions for a given prompt, whereas in the bottom row, only one image demonstrates a correctly aligned object relation.

and benchmark datasets enabling comprehensive evaluation of text-conditioned image generators and their ability of visio-linguistic compositionality. Since the assessment of text-image synthesis also enables for the optimization of T2I, we discuss promising approaches in Section 5. Finally, we address the remaining challenges of current evaluation frameworks in Section 6, and propose guidelines for comprehensive and consistent evaluation of future frameworks in Section 7. We conclude our survey in Section 8.

2 TAXONOMY

The main contribution of our work is the proposition of a taxonomy for T2I evaluation metrics, derived from the current state of the literature. Even before the rise of diffusion-based image generation, the field of text-conditioned image generation strived for methods to evaluate such models [25]–[28]. Inception Score (IS) [29] and Fréchet Inception Distance (FID) [30] are two of the most frequently used image quality measures for image synthesis evaluation, with many more techniques proposed in recent years. To provide a comprehensive overview and spot open challenges and derive research guidelines, we developed a taxonomy

to categorize existing methods based on their operating data structure, measurable aspects, scope, and conditions used. Defining requirements for metrics that can benchmark image synthesis models is not straightforward. Realism is undoubtedly the major aspect targeted by researchers [31]. Other aspects contributing to high-quality images include aesthetics [2], human preferences [32]–[34], naturalism, and the principles of photography, such as balance, harmony, closure, movement, color, pattern, contrast, negative space, and grouping. While some of these aspects may be quantitatively measurable, many are abstract, complex, and therefore hard to measure. However, natural language can describe such aspects in great detail, and there are many talented human authors who generate creative descriptions of sceneries. Hence, detecting and measuring the quality of these abstract, yet well-described aspects, presents a challenge to researchers in the field of text-conditioned image synthesis. Evaluation of T2I synthesis quantifies the quality of generated images, which depends on the measured aspect and human subjective perception, and most frequently is measured for an entire image. Hence, this taxonomy defines *general quality* as quantifying a certain aspect globally for a single image, e.g., realism, aesthetics, human preferences,
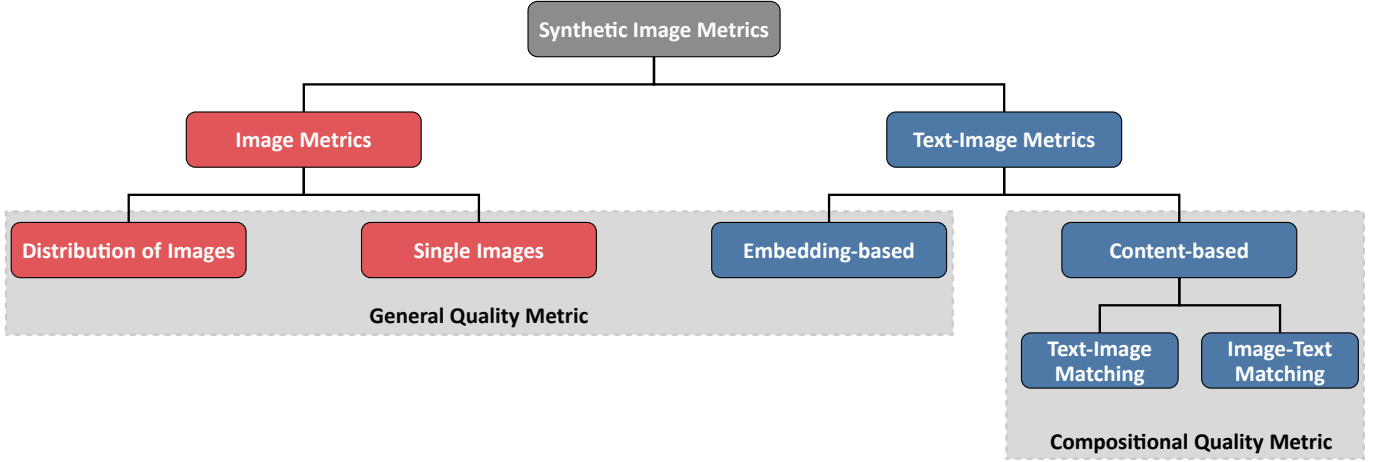
Fig. 2. Proposed taxonomy for text-to-image (T2I) evaluation metrics. In general, two categories of metrics needs to be distinguished: pure image-based and text-conditioned image quality metrics. Additionally, synthetic image metrics can measure two different qualities: general image quality and compositional quality.

which is determined by asking human raters for their judgments. Usually, this is done by conducting a large-scale crowd-sourced study where images are ranked by a large group of human observers, which naturally can be considered a high effort endeavor. Ultimately, acquired human annotations enable the development of deep learning based models, which are capable to learn and imitate such human judgments, e.g., PickScore [33], ImageReward [32], Human Preference Score [34]–[36]. When human judgment is not the primary target or only implicitly required, such data can be acquired from diverse publicly available databases. Foundation models like CLIP, BLIP and BLIP-2 are (pre-)trained on tremendous amounts of image-text pairs collected from such publicly available sources on the Internet. Alternatively, frozen feature extractors can be utilized, which are pre-trained on human curated sources, e.g., BooksCorpus [37] or the English Wikipedia.

In addition to general image quality, this taxonomy defines a second type of quality, *compositional quality*, which is measured by dissecting prompt and image into multiple text-image pairs and measure the alignment quality of such pairs. In particular, individual quality is measured between content specified in the text and content depicted in the image, e.g., spatial relations, semantic object accuracy, attribute alignment, or counting alignment [38]–[40]. Usually, the prompt is composed of multiple distinct pieces of information describing different parts of a scenery, which accumulate to a rich scene description. In this context Winoground [41] introduces the term visio-linguistic compositional reasoning. It refers to the task of understanding and reasoning about the relationships between visual and textual components in a way that requires combining them to form a coherent understanding or to make inferences. This involves tasks that require not just recognizing objects or elements in images and understanding text, but also understanding how the textual and visual elements interact and compose to convey a particular meaning. We refer to methods, that can measure the quality of such individual components and interactions as compositional quality metrics. Specifically, given a complex prompt, it can

be decomposed into a set of disjoint assertions describing different parts of the content, e.g., single or multiple objects, relations between objects, object attributes, lighting, style, artistic reference. Thus, the composition of assertions must be known or extracted from the prompt. As a result, the proposed taxonomy considers the compositional quality metric to measure text-image alignment with a finer granularity, whereas general quality metrics provide an averaged score of relations between text and image.

However, high compositional quality does not automatically result in high general image quality and vise versa. Thus, in our taxonomy, we consider pure image-based evaluation metrics from the image synthesis domain, which are designed to measure image quality, and text-image evaluation metrics. In particular, the input to a T2I evaluation metric are a (human written or synthetic) prompt together with an image. While the pure image-based evaluation metrics solely judge the generated image indicated by a score, the text-conditioned metrics output a score providing information about the alignment quality, of a certain aspect, for the generated image with respect to the input text prompt.

2.1 Image Metrics

We include the palette of pure image-based quality measures in our taxonomy, despite the absence of textual condition. As described above, quality assessment of T2I synthesis incorporates general image quality, which does not necessarily rely on text-condition. Moreover, image quality is evaluated independently of text-image quality, e.g., an image that looks photorealistic but ignores textual facts contributes to a high image quality score but a low alignment score. Also, an image that exactly depicts all objects and their relations described by the prompt can simultaneously look artificial, resulting in low image quality but high alignment quality. In the upper row of Figure 1, we present two examples where compositional quality is identical, while image quality is rated unequally. The proposed taxonomy divides image quality metrics that rely solely on images into distribution-based metrics and single image-based metrics.

2.1.1 Distribution-based Metrics

Distribution-based metrics fundamentally rely on statistical measures to evaluate the differences between the distribution of generated data and the distribution of given, usually real-world, data providing a quality score indicating performance of a generator, e.g., Inception Score (IS) [30] and Fréchet Inception Distance (FID) [29]. This class of metrics considers the image generator as a black box and bases its quality computation on sample distribution. In general these metrics target to benchmark models on a general level, rather than providing quality scores for individual output samples.

2.1.2 Single Image Metrics

Single image metrics infer quality from the image itself, analyzing it based on its structural and semantic composition through feature extraction and subsequent quality inference. In contrast to distribution-based metrics, single image-based metrics are computed without the existence of any target image or distribution. Recent approaches of such metrics often rely on a fine-tuned image network that learned to predict human judgments when trained on a large-scale human annotated dataset, e.g., LAION Aesthetic Predictor [2], perceptual artifact localization (PAL) [42], [43] or human viewpoint preferences (HVP) [35].

2.2 Text-Image Alignment Metrics

In contrast to image metrics, text-image metrics consider high-quality to correlate with high alignment between text and image. This taxonomy, distinguishes between embedding-based metrics, which quantify general image quality based on text-image alignment, and content-based metrics which examine compositional quality.

2.2.1 Embedding-based Metrics

In the context of embedding-based metrics, the evaluation of quality is based on learned embedding representations for vision and language inputs. To do so, text prompts get tokenized by a tokenizer and are then transformed to an embedding vector using a text encoder model, e.g., a transformer model [44]. Likewise, the image gets transformed into an image embedding representation using an image encoder model, e.g., ViT [45]. These embedding vectors have a fixed size and carry compressed information of both representations. Such foundation models are trained via representation learning in order to output meaningful embeddings, which can be utilized to compute cosine similarity between text and image embeddings. Aligning embedding vectors for text-image pairs is done via vision-and-language pre-training strategies, e.g., CLIP [22], BLIP [46], BLIP-2 [47]. Extracted embedding vectors encode valuable information, resulting in superior performance for multiple zero-shot scenarios [46]–[48]. However, several works have shown, that pre-trained representations can be utilized to further adapt such representation learning models by fine-tuning them on human annotated data. Through this, individual human judgments can be incorporated into models, tweaking estimations towards missing nuances of human judgments, as done for instance by PickScore [33] and ImageReward [32].

2.2.2 Content-based Metrics

Content-based metrics analyze language and visual representations with respect to their semantic content, whereby the actual measurements of such metrics are computed for the decomposed components separately. Content-based metrics are based on the way how humans would compare content across text and image domain, e.g., words read in a prompt and matching them to regions depicted in the image, and vise versa. Hence, content-based quality metrics are comprehensible for human observers due to such similar behavior.

Text-Image Content Matching. To relate parts of the text prompt to image regions, the text prompt needs to be dissected into substrings, where each substring describes distinct details, e.g., description of an object, relation between two objects, scene settings, etc. This decomposition into distinct assertions is elementary for text-image content matching. Some approaches [49] synthetically compose prompts utilizing prompt templates in order to generate object relations, e.g., "{objectA} {spatial relation} {objectB}". Based on the prompt dissection, the resulting set of assertions is compared to corresponding regions in the image. This can be done by utilizing a visual question answer model (VQA) [47], [50], where questions are generated based on the assertions and together with the image, the VQA model is interrogated for the presence or absence of specific relations, objects, attributes etc. Another way is to extract meaningful regions from the image. Therefore, candidate regions need to be found in the image. This is usually done via object detection [51] or semantic segmentation [52].

Image-Text Content Matching. Starting the dissection from the image side and match image regions to corresponding positions of the prompt, can be seen as the inverse to text-image content matching. However, text-image and image-text content matching is not bijective, since there might be parts in the image not mentioned in the text and vise versa. Although, the process is quite similar, object detection and segmentation models facilitate finding meaningful regions, which then are used to match with corresponding parts of the prompt. Additionally, image caption models can be used to generate captions [50], [53], which describe the presented scene in the image. Image captioning is an ongoing topic within the vision-language model community, and for the evaluation of such models, image caption metrics are utilized [54]–[59].

3 METRICS

Measuring the quality of an image has been an important research area in recent decades, especially in the field of computer vision, computer graphics and visualization [60], and it is referred to as image quality assessment (IQA). However, these metrics are designed to measure quality difference between an image x to a reference image y, where y functions as a ground truth (with perfect quality), which is commonly needed for image-to-image tasks, e.g., noise removal [61], [62] or super resolution [63], [64]. Since the

advent of generative AI, initially mostly fueled by generative adversarial networks (GANs), researchers were striving for methods to measure the quality of their proposed image generators [65]. When image quality measures like peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM) [60] failed to capture "high quality", "photo-realism", or "cinematic" properties, the need for dedicated metrics arose. Initial work in this direction, resulted in the development of metrics that measure distribution fidelity, e.g., inception score (IS) [30] and Fréchet inception score (FID) [29]. These metrics are designed to compare the image distribution of a target image dataset to the image output distribution of an image generator.

However, they are based solely on images without adopting any text-condition. In the following, we discuss two types of text-conditioned image quality metrics, i.e. embedding-based and content-based quality measures and for each we provide details on the most adopted metrics in context of T2I synthesis. Afterwards, image captioning metrics and closely related metrics, which have been utilized for evaluation of T2I alignment, are discussed. Finally, we summarize the field of pure image-based metrics, that have been adopted for assessing image quality for text-condition image generation. See Table 1, for an overview of the reviewed metrics.

3.1 Embedding-based Metrics

Text-conditioned image quality assessment represents a novel and evolving paradigm in the field of T2I generation. In these approaches, the perceived quality of an image is assessed not only based on its visual characteristics, but also in the context of accompanying textual information. However, existing image-only measures (Section 3.4) are unable to integrate textual cues that describe the content associated with an image. Text-to-image alignment acknowledges the intrinsic relationship between language and visual perception, allowing for a more nuanced evaluation that aligns with human judgment. In applications where text and image synergy is crucial, such as T2I synthesis, image captioning, content-based image retrieval, and human-computer interaction-based image generation, quantitatively measuring the alignment between text and image is mandatory. The incorporation of textual information introduces a dynamic dimension to image quality assessment, reflecting the evolving needs of multimodal systems and fostering advancements in the understanding and evaluation of visual content. In the following, we provide an overview of recent developments in quality assessment for T2I alignment.

One of the first reference-free approaches, that were used for measuring the distance between a textual and an image representation is CLIPScore [24], which is based on Contrastive Language-Image Pre-training (CLIP) [22]. The CLIP distance is computed through the cosine similarity between the text embedding vector and the image embedding vector. By pre-training on vast and diverse datasets, CLIP exhibits a remarkable capacity to generate meaningful and contextually rich embeddings for images and corresponding textual descriptions. CLIPScore was introduced as reference-free evaluation metric for image caption generation tasks together with its reference-based version RefCLIPScore.

Multimodal mixture of Encoder-Decoder (MED) was proposed by Li *et al.* [46]. It is used for multi-task pre-training and flexible transfer learning from image-text pairs collected from the web, and it is incorporated into BLIP, a framework which enables a wider range of downstream tasks such as T2I retrieval on COCO Captions [89] and Flickr30K [90], [91]. In the same manner as CLIPScore, the textual and image embedding vector returned by BLIP can be used to compute the cosine similarity, when it is referred to as BLIPScore.

One year later, BLIP is followed by BLIP-2 in 2023, which is introduced as an efficient approach for vision-language pre-training, utilizing pre-trained image encoders and large language models (LLMs) with minimal trainable parameters. It sets new benchmarks across different vision-language tasks and exhibits advanced zero-shot capabilities for generating text from images. It utilizes a two stage pre-training of a query transformer (Q-Former), where the first stage bootstraps vision-language representation learning from a frozen image encoder. The second stage applies a frozen LLM for bootstrapping vision-to-language generative learning, enabling zero-shot instructed image-to-text generation. Again, the learned embedding vectors are utilized to compute an alignment score between text and image called BLIP2Score.

Singh et al. [92] additionally employ scene graphs and propose a graph decomposition and augmentation framework to learn text-image representation. They derive a pseudo image scene graph from the text caption by diving the text-based graph into multiple subgraphs and matching them with the image. They further extend the common vision-language component of the loss by an image-to-multi-text loss, to train their model MosaiCLIP.

LXMERT was introduced by Tan et al. [93], a transformer consisting of three encoders which model separate tasks, namely object relationship, language and cross-modality encoding. The model takes as input text and image, but only uses the image encoding that belong to objects recognized by a separate object detection module. Following this, the relationship of the two modalities is learned in the cross-modality encoding through a cross-attention module. A disadvantage of their approach is the reliance on a separate object detection module, which can fail at correctly localizing all objects in the scene, therefore excluding information in the learning process.

The Unified Transformer (UniT), proposed by Hu et al. [94], learns multiple visual perception and language understanding tasks simultaneously. Each forward pass through the model has an input the text-image pair along with a task specific index, which the model embeds. The output from the text and image encoders are concatenated and further fed into a multi-head cross attention module. At the end of the process, the output representations are fed into task specific output heads. This design alleviates the need for task-specific finetune of the model, since it learns to jointly solve all tasks.

A mixture of four pre-training tasks in image and text space is proposed by Chen et al. [95] in their work on UNITER. As pre-training tasks, they use Masked Language Modeling with image information added, Masked Region Modeling with text information added Image-Text Match-

Metric	General Image Quality Metric	OA	S	NS	AB	Human Evaluated	Rationale
Embedding-based							
CLIPScore [24]	✓	✗	✗	✗	✗	✓	✗
BLIP-ITC [46]	✓	✗	✗	✗	✗	✗	✗
BLIP-ITM [46]	✓	✗	✗	✗	✗	✗	✗
BLIP2-ITC [47]	✓	✗	✗	✗	✗	✗	✗
BLIP2-ITM [47]	✓	✗	✗	✗	✗	✗	✗
CLIP-IQA [66]	✓	✗	✗	✗	✗	✗	✗
MID [67]	✓	✗	✗	✗	✗	✓	✗
NegCLIP [48]	✓	✗	✗	✗	✗	✗	✗
CLoVe [68]	✓	✗	✗	✗	✗	✗	✗
PickScore [33] (fine-tuned)	✓	✗	✗	✗	✗	✓	✗
ImageReward [32] (fine-tuned)	✓	✗	✗	✗	✗	✓	✗
HPSv1 [36] (fine-tuned)	✓	✗	✗	✗	✗	✓	✗
HPSv2 [34] (fine-tuned)	✓	✗	✗	✗	✗	✓	✗
CLIP-R-Precision [69] (fine-tuned)	✓	✗	✗	✗	✗	✓	✗
RAHF [70]	✓	✗	✗	✗	✗	✓	(image-based rationale)
COBRA [71] (fine-tuned)	✓	✗	✗	✗	✗	✓	✗
R-Precision [72] (fine-tuned)	✓	✗	✗	✗	✗	✗	✗
Text-Image							
VNLI [73] (fine-tuned)	✓	VQA	VQA	VQA	VQA	✓	✓
MQ [40]	✓	✗	✗	✗	✗	✓	(text-based rationale) + (image-based rationale)
VQ² [73]	✓	VQA	VQA	VQA	VQA	✓	(text-based rationale)
DA-Score [1]	✗	VQA	VQA	VQA	VQA	✓	(text-based rationale)
SOA [74]	✗	DET	✗	✗	✗	✓	(image-based rationale)
TIAM [75]	✗	SEG	✗	✗	SEG	✓	(image-based rationale)
VISOR [49]	✗	DET	DET	✗	✗	✓	(image-based rationale)
VISOR$_N$ [49]	✗	DET	DET	✗	✗	✓	(image-based rationale)
VISOR$_{cond}$ [49]	✗	✗	DET	✗	✗	✓	(image-based rationale)
PA [38]	✗	✗	✓	✗	✗	(✓)	✗
CA [38]	✗	COUNT	✗	✗	COUNT	(✓)	✗
ViCE [76]	✗	LLM	LLM	LLM	LLM	✓	(text-based rationale)
TIFA [77]	✗	VQA	VQA	VQA	VQA	✓	(text-based rationale)
B-VQA [78]	✗	✗	✗	✗	VQA	✓	✗
3-in-1 [78]	✗	DET	DET	✗	VQA	✓	(image-based rationale)
Image-Text							
VIEScore [79]	✗	MLLM	MLLM	MLLM	MLLM	✓	(text-based rationale)
LLMScore [80]	✗	VQA	VQA	VQA	VQA	✓	(text-based rationale)
UniDet [78]	✗	DET	DET	✗	✗	✓	(image-based rationale)
ViLBERTScore [59]	✗	DET	DET	✗	✗	✓	✗
VIFIDEL [58]	✗	DET	DET	✗	✗	✓	✗
TIGEr [57]	✓	✗	✓	✗	✓	✓	✗
Distribution							
IS [30]	✓	✗	✗	✗	✗	✗	✗
FID [29]	✓	✗	✗	✗	✗	✗	✗
MiFID [81]	✓	✗	✗	✗	✗	✗	✗
KID [82]	✓	✗	✗	✗	✗	✗	✗
C2ST [83]	✓	✗	✗	✗	✗	✗	✗
PRD [84]	✓	✗	✗	✗	✗	✗	✗
I-PRD [85]	✓	✗	✗	✗	✗	✗	✗
GMM-GIQA [86]	✓	✗	✗	✗	✗	✗	
Aesthetic Predictor [2]	✓	✗	✗	✗	✗	✓	✗
Single Image							
PAL4VST [43]	✓	✗	✗	✗	✗	✓	(image-based rationale)
PAL4InPaint [42]	✓	✗	✗	✗	✗	✓	(image-based rationale)
PPL [87]	✓	✗	✗	✗	✗	✗	✗
PR [84]	✓	✗	✗	✗	✗	✗	✗
KPR [85]	✓	✗	✗	✗	✗	✗	✗
CAS [88]	✓	✗	✗	✗	✗	✗	✗

Compositional aspect: **OA**: Object accuracy, **S**: Spatial relations, **NS**: Non-spatial relations, **AB**: Attribute binding
Reasoning: **SEG**: segmentation, **DET**: object detection, **VQA**: visual question answering, **LLM**: large language model, **MLLM**: multimodal large language model, **COUNT**: counting model

🏋 : fine-tuned, 📝 : text-based rationale, 🖼 : image-based rationale

TABLE 1

ing and Word-Region Alignment. They also combine four different datasets and train on the combined data. Similar to LXMERT, the image encoder is an object detector tasked with producing encodings of recognized objects. This comes with similar drawbacks of reliance on the detector. Gan et al. [96] extend the UNITER approach by employing large-scale task-agnostic adversarial pre-training along with task-specific adversarial finetuning, both on the embedding space. When combined with KL-divergence-based regularization, their model yields an embeddings space that is more invariant than the one of UNITER.

Zhang et al. [97] revisit vision-language models by improving individual components of an existing vision-language framework by Li et al. [98]. Their approach scales up the training data by combining four different datasets. With this, they improve the object detection model used as part of their approach, a design choice also made by UNITER and LXMERT, and show this improves the downstream vision-language representations. But contrary to UniT, their approach requires task-specific finetuning.

Vision-and-Language Transformer (ViLT) is proposed by Kim et al. [99] as a simplistic but effective method for vision-language pre-training. Contrary to the previously described approaches, their model does not operate on region features extracted from an object detection model. Instead, it uses a vision transformer encoder which produces representations at patch granularity, alleviating the reliance on the detector for feature extraction. This design also reduces the model size and increases its speed. The approach also uses a shared transformer encoder with modality tokens for the model to differentiate between text and image input as well as separate token and patch positional embeddings respectively.

Li et al. [100] propose the Visual Semantic Reasoning Network (VSRN), which uses bottom-up attention to reason about relevant regions in the image. This information is further processed by a graph convolution network that generated features with semantic relationships. The output is further paired with the text encoding where the model jointly optimizes the encoding and text generation to learn the alignment of the modalities.

Another relevant metric for evaluating text-image alignment is R-Precision. Xu et al. [72] were the first to apply it for text-image alignment. For this, they aim to identify the top r relevant text captions for a given image with caption candidates R, to compute R-Precision as r/R. This is achieved by first extract global feature vectors from their pre-trained encoders for generated images and given text captions. The cosine similarity is computed between image and text vectors, and then used to rank the captions in descending similarity to identify the r most similar candidates. Park et al. [69] extend this approach by using CLIP as the encoder for images and texts, and show this leads to a more human-aligned judgement and prohibits the bias that might come from using a custom model.

With CLIP at the center, Wang et al. [66] propose the CLIP Image Quality Assessment (CLIP-IQA) benchmark. In their work, they improve CLIP's ability to asses text-image alignment through antonym prompt pairing and removing the positional embedding from the image encoder. The resulting model is significantly better for evaluating quality and abstract perception.

Kim et al. [67] propose Mutual Information Divergence (MID), a unified metric for multimodal generation, calculated through the negative Gaussian cross-mutual information between real and generated samples. Broadly formulated, their metric quantitatively measures how well one modality is aligned with the other, where both modalities are represented as encodings generated by their respective CLIP encoders. MID is shown to have consistent behavior across a variety of datasets where cosine-similarity-based techniques have shown weaknesses, especially for narrow domains like images of human faces. Kirstain et al. [33] train a scoring function, PickScore, to estimate the user's satisfaction for a particular generated image by finetuning CLIP-H using a large dataset comprised of generated images along with human preferences. Their objective function is designed to maximize the likelihood of a preferred image picked over an unpreferred one. Finally, they combine everything into a comprehensive benchmark they call Pick-a-Pic, which contains 500k examples with 35k distinct prompts that better represent what humans image to be contained in the image generation.

Xu et al. [32] build a T2I human preference reward model. To train the network, they gather and annotate 137k text-image pairs that go through a thorough annotation pipeline. The authors go one step further as PickScore and use the output of their reward model is further used to as a target to enable Reward Feedback Learning on top of a diffusion model to then optimize its image generations. With this, they are able to create a generative diffusion model that creates images which are more human-preference-aligned.

A similar approach is taken by Wu et al. in both their first [36] and second [34] iteration of their human preference score (HPS). In the first version, they first collect a large dataset of human choices from images that have been generated by the same prompt, comprised of roughly 98k images with 25k prompts. Each prompt is assigned multiple image choices, for which the dataset contains annotations which image the user preferred. With this, they finetune a CLIP-L model a mechanism similar to the original CLIP training: The objective is to maximize the similarity between the prompt and the image chosen by the user, by minimizing the similarity to images rejected by the user. After training, the score is defined as the re-scaled cosine similarity between text and image embedding. Using their dataset, they also tune a diffusion model to generate images that are more aligned to human preferences by adding a preference identifier to the text prompt and incentivizing the model to output images in accordance to their HPS. The second version of HPS [34] introduces an even larger dataset of 798,090 human preference annotations for 433,760 image-text pairs. The HPS v2 finetuned CLIP model improves the human aligned scoring of the first version. Further, it is demonstrated to be sensitive to algorithmic improvements of the underlying T2I models.

Fu et al. [101] propose DreamSim, an extensive benchmark for evaluation of generated image w.r.t. human preference alignment. Their dataset is composed of 20k synthetic image triplets with a reference image as well as two other images, where the user decided which is more similar to the reference. Their dataset covers various aspects of similarity, such as pose, perspective, foreground color, number of

items, and object shape. Using this dataset, they learn their perceptual metric using an ensemble of networks to encode each of the triplet images, calculate the cosine similarity between each image to the reference, followed by a triplet loss. They show their learned network is able to make more human-aligned judgements, compared to e.g., CLIP. On the other hand, previous methods did not rely on an ensemble configuration, increasing the computational cost of DreamSim.

In DreamBooth [102] a combination of three metrics is used to evaluate a multi-view generation of an object. To assess the image quality they compare a generated image with the ground truth image from the same view using cosine similarity of CLIP [22] and DINO [103]. Hereby the CLIP-based metric only requires the images to show the same subject to return high similarities, whereas the DINO-based metric was included to measure more fine-grained differences. Lastly they use the cosine similarity of CLIP embeddings of the generated image and the according text prompt to measure prompt fidelity.

3.2 Content-based Metrics

Content based metrics evaluate the generated image directly based on its content, rather than the images projection into an embedding space (see Section 2.2.1). This also allows for a decomposition of the evaluation of single aspects of the image quality like object accuracy (OA), spatial relationships (S), non-spatial relationships (NS) or attribute bindings (AB). In the following we will discuss multiple content-based metrics.

3.2.1 Text-Image Content Matching

The *SeeTRUE(VNLI)* metric was introduced by [73]. It relies on fine-tuning multi-modal models (like BLIP2 [47], PaLI-17B [104]). The training dataset consists of 110K text-image pairs labeled with binary alignment annotations. The model receives the image as well as a text prompt consisting of "Does this image entail the description: prompt?" The model is trained to answer the question with "yes"/"no". During inference the relative ratio between predicting "yes" or "no" is used to compute the alignment score. The more "yes" is predicted by the fine tuned model, the better the alignment is assumed to be. A major limitation of this fine-tuned approach is its black box nature, making improvements of the validated model difficult as well as trust in the evaluation hard.

Mismatch Quest [40] especially tackles this issue by introducing an end-to-end trainable approach for providing visual and textual feedback in T2I models, aiming to identify and explain alignment discrepancies between generated images and textual prompts. They introduce a method for generating a comprehensive training set that includes aligned image-text pairs and negative examples with misalignment. This is achieved by LLMs and visual grounding models to create synthetic examples with misalignment, based on aligned image-text pairs, and corresponding textual and visual feedback. To generate this dataset the authors use Part-of-Speech (POS) Tagging by labeling each word with its grammatical category (such as noun, verb, adjective). Based on the POS tags misaligned text-image pairs are

then generated based on aligned ones. The authors use this approach to generate a training set (TV-Feedback) to fine tune feed back models in such way that they are able to provide visual (bounding box) as well as textual explanation for misalignment. For evaluation the authors introduce a SeeTRUE Feedback dataset with 2,008 human annotated instances highlighting textual and visual feedback. The authors also show in a study that the proposed model aligns well with human judgements. However, the authors found that the proposed model possibly struggles with the detection of multiple misalignments.

In difference to the fine-tuned metrics of *Mismatch Quest* and *SeeTRUE(VNLI)*, other metrics are utilizing VQA models to generate an evaluation score for generated images. They especially utilize these VQA models for evaluation disjoint parts of the image prompt, making them belong to the category of compositional metrics.

Yarom *et al.* [73] propose the *SeeTRUE(VQ^2)* metirc: First, the authors extract answers from the image prompt using SpaCy [105], which is based on POS and dependency parse tree annotations. For each answer a_j a question q_j is generated leading to a set of question-answer pairs. Next, the generated pairs are reformulated to match yes-no questions, following the schema of "is a_j true for q_j in this image?". The assumption is that if the VQA model is able to answer all question answer pairs with yes, the semantic alignment is perfect. Hence, the final score is computed by an average over all 'yes' answer probabilities.

Similar to the *SeeTRUE(VQ^2)* metric, *Decompositional-Alignment-Score* (DA-Score), by [1], decomposes the image prompt to evaluate the T2I alignment. The authors found that misalignment's are often left undetected by pre-trained multi-modal models, such as CLIP, especially when there are more complex prompts. Hence, DA-Score decomposes the prompt into a set of disjoint assertions using a LLM. Each assertion is then evaluated individually using a VQA model (BLIP). Finally, the scores are combined to give the T2I alignment score. The individual evaluation of the assertion allows to draw conclusions about the strength and weaknesses of the generative model. Moreover it allows the optimization during the forward diffusion process by iteratively increasing the cross-attention strength of low scoring assertions. The authors show a higher correlation with human ratings over prior evaluation metrics, like CLIP [24], BLIP [46] and BLIP2 [47] especially when the prompt becomes more complex.

However, in order for the VQA based compositional metrics like *SeeTRUE(VQ^2)* or *DA-Score* to be applicable to the defined image aspects like object accuracy (OA), spatial relationships (S), non-spatial relationships (NS) or attribute bindings (AB), thoughtful prompt-engeneering is required, which means that a prompt needs to capture different image aspects.

Hinz *et al.* [74] propose the usage of their Semantic Object Alignment (SOA) metric which is able to specifically address the challenges posed by multi-object and other complex scenes represented by the generated images. The authors propose to use a pre-trained detection model to infer the existence of prompted objects in an input image. To do so, the authors sample image captions from the COCO validation set, explicitly mentioning one of the 80 main

object categories. They use a pre-trained object detector to check if the generated images contain the objects specified in the captions. The paper conducts a user study comparing several T2I models using SOA and demonstrates that SOA aligns well with human rankings. In contrast, other metrics like Inception Score do not exhibit the same alignment.

In the work of Grimal *et al.* [39], they follow a similar approach introducing their Text-Image Alignment Metric (TIAM). It captures the alignment between image and prompt by characterizing the contents of a set of generated image based on a pre-trained segmentation model. For generating prompts the authors propose to follow a simple template that is enriched by word labels (like "elephant" or "cat") and additionally optional attributes (like color). For the evaluation of the attribute color, the authors propose to count a correct assignment when at least 40% of the attribute color is detected within the segmentation mask of the object. The authors propose the usage of YoloV8 which was trained on 80 COCO classes. In order to make the segmentation model perform well on the generated images, they require to be realistic looking, as COCO was used for training YoloV8. Hence, to bias the generator towards the generation of realistic looking images, the authors propose to use a text prompt, which starts with "a photo of", to bias the generation process towards realistic looking images. They also evaluate the correlation to human evaluation and show their superiority compared to [22] and [46].

Limitations of the two previous works [39], [74] include their applicability to generative models which are trained to produce different styled images like cartoons or sketches. Additionally, the pretrained models are limited to detecting classes which have been presented during training, and evaluation of domain specific generative models is thus not possible. Additionally, another significant drawback of metrics relying on pretrained models is the potential overlap between the models used for generation and evaluation. A recent study highlighted this issue [38], revealing that SOA employs the same pretrained detector as CPGAN [106] during image generation. This overlap can result in overfitting during evaluation, giving CPGAN an unfair advantage (even over real images) when assessed using the SOA metric. To address this problem, an effective solution is to swap the detection model used in the evaluation process.

In the realm of T2I generation metrics, the conventional focus has been on assessing semantic accuracy and the realism of generated images. However, [49] venture beyond these norms by introducing the *VISOR* (Verifying Spatial Object Relationships) metric. Unlike other metrics, VISOR specifically targets the accuracy of spatial relationships between two or more objects specified within the text prompt. Using this metric, the authors found that many existing models struggle with the challenge of generating multiple objects, and even when successful, they often fall short in capturing spatial relationships described in the input text prompts. The authors propose three variants of the VISOR metric: $VISOR$, $VISOR_N$, and $VISOR_{cond}$. These metrics first rely on detecting objects that have been mentioned in the text prompt. This is done either through a pretrained model or human feedback. Furthermore, the metrics evaluate the spatial relationships between objects using a pretrained object detector and the centroids of detected bounding boxes for deriving depicted relationships. The *VISOR* metric returns 1 if all objects are present in the image with correct spatial relationships, otherwise it returns 0. $VISOR_N$ adopts a distribution-based approach, assessing the model's capability to generate at least n spatially correct images based on the *VISOR* score for a given text prompt mentioning spatial relationships. Finally, $VISOR_{cond}$ evaluates the conditional probability of generating correct spatial relationships, given that all objects are generated accurately. This means that the object accuracy does not influence the $VISOR_{cond}$ metric.

[38] also propose a metric for evaluating the *Positional Alignment* (PA). The metric evaluates how well the generated images align with the positional information conveyed in text descriptions. Therefore, they define a set of positional words (W) that convey positioning information, such as "above," "below," "on top of," etc. For each word in W, the authors filter captions in the evaluation set of the COCO dataset containing that word to create a matched caption set (Q_w). A mismatched caption (P_w) is then created by replacing the positional word with its antonym while keeping other words unchanged. For each word in W, a set (D_w) is created, including triplets (R_{wi}, P_{wi}, Q_{wi}), where R_{wi} is a generated image from the matched caption P_{wi}. The authors use these sets to query the input captions from the binary query set [Q_{wi}, P_{wi}], marking a query as successful if the matched caption is correctly identified using CLIP.

Additionally, the authors introduce *Counting Alignment* (CA), which quantifies how accurately a T2I synthesis model aligns with counting aspects in input text descriptions, specifically focusing on the number of objects in generated images. The evaluation process begins by constructing a test dataset, filtering captions from the MS-COCO validation set that mention counting using terms like "a", "one", "two", etc. Ground truth counting information is annotated for each selected caption, emphasizing countable object types to avoid penalizing uncountable categories. Text-to-image models then generate images from each caption in the counting test set. An off-the-shelf object counting model is utilized to count objects for each class in the generated images. The CA value is computed by comparing predicted and ground truth counts, measuring counting errors with root mean squared error, and averaging over all test images and object classes.

[38] state that the evaluation of T2I generation should be evaluated based on a variety of criteria. They hence propose a framework to combine multiple aspects for the image evaluation which they call *bag of metrics*. In their study they are able to show a more consistent ranking with real images and human evaluation, using the proposed *bag of metrics*. The authors further provide a python package called *TISE* for direct application.

In a similar vein, [78] put forward the innovative *3-in-1 metric*, designed specifically to assess attribute bindings, spatial relations, and non-spatial relations, such as "look at," "hold," and "play with," in text-to-image generation models. As its name implies, this metric amalgamates three distinct evaluation criteria to comprehensively analyze the entirety of image content. To evaluate attribute bindings, the authors introduce the *Disentangled BLIP-VQA* approach, recognizing that conventional VQA-based assessments often yield inaccurate results due to the model's inabil-

ity to discern correct object-attribute relationships. Consequently, they decompose complex prompts into independent questions, ensuring each question pertains to only one attribute-object pair, thus circumventing confusion in the VQA model's understanding. For assessing spatial relations, they propose the *UniDet-based metric*, leveraging a detection model akin to [49], employing the UniDet model to evaluate relations like "next to," "near," "on the side of," as well as directional relations such as "left," "right," "top," and "bottom." Finally, they employ CLIPScore to evaluate non-spatial relations, completing the triad of evaluations in the 3-in-1 metric framework.

In their paper Yuksekgonul et al. [48], the authors aim to elucidate how Visual Language Models (VLMs) encode the compositional relationship between objects and attributes. To achieve this goal, they introduce the Attribution, Relation, and Order benchmark. This benchmark evaluates the VLM's comprehension of object properties and relations using the Visual Genome Attribution and Visual Genome Relation datasets, respectively. They evaluate the order sensitivity using COCO [107] and Flicker30k [108]. The authors emphasize a critical issue regarding contrastive pretraining in VLMs, which tends to prioritize learning low-level features over higher-level compositional structures. To tackle this challenge, the authors propose composition-aware hard negatives, which they integrate into CLIP's contrastive objective [22]. These hard negatives are generated by altering linguistic elements such as nouns and phrases in negative captions. During training, when assembling a batch of images and their corresponding captions, the authors include not only the original images but also strong alternatives. Through their evaluations, the authors assert that integrating the proposed alternatives improves VLMs' comprehension of composition and order.

The Visual Instruction-guided Explainable Score (VIEScore) proposed by Ku *et al.* [79] is composed of the perceptual quality (PQ) and the semantic consistency (SC) score. Both scores are based on instructing a LLM using handcrafted prompt templates to reason about a given image. In their experiments LLaVA [109] and GPT-4v [50] are utilized for image analysis. Perceptual quality is measured by two sub-scores, the first is measuring image naturalness and the second measures degree of distortions / artifacts. Note, that PQ is based on the image only, the VLM is not informed about the prompt. Also, SC is composed of sub-scores, which depend on the evaluation objective. SC is demonstrated for 5 objectives: text-guided image generation, text/mask-guided image editing, control-guided image generation, subject-driven image generation and subject-guided image editing.

The first method leveraging LLMs for automatic T2I evaluation is called LLMScore and was proposed by Lu *et al.* [80], which is applied in an image-to-text manner. First, they utilize BLIP2 for image captioning and producing a global image description followed by an object-centric local reasoning. Therefore, Grit [53] detects image crops of objects and generates a textual description of that particular region. In order to fuse global and local text description, GPT-4 [50] transforms them into an object-centric visual description. Finally, the evaluation objective of LLMScore can be retargeted and in their work Lu *et al.*demonstrate overall score and

error counting objectives. The visual description together with the evaluation instruction are forward to GPT-4 and the final LLMScore with rational is returned. However, LLM-generated captions may contain additional details fabricated by the LLM rather than originating from the image captioning process, which may lead to not sufficiently incorporating requirements and inputs from the original prompt.

Visual concept evaluation (ViCE) is a metric that was designed to possess an understanding of visual concepts in a similar fashion as humans do, who are able to directly generate the visual concepts once they receive a prompt to inspect. Similar to other VQA-based methods, ViCE initially generates questions-answer pairs using GPT-3.5-turbo [50] based on the prompt. An initial set of 15 questions are questioned to an LLM in order to parse visual concepts from the prompt. A unique feature of this method is, that the model may seek additional information to refine its understanding of the image. Therefore, after the initial response phase, the LLM is asked in an iterative process whether it requires further information until the model is satisfied with its comprehension of the image. In such a way, the model is able to validate whether if the objects are in a correct semantic relationship. Finally, the actual visual image analysis is then performed by a BLIP2-based VQA model assessing the image based on the previous generated question-answer pairs.

In the work of Hu *et al.* [77] they propose a metric called TIFA leveraging VQA models to measure the faithfulness of a generated image. To do so, they generate multiple-choice question-answer pairs utilizing GPT-3 [110] via in-context learning and apply verification of generated questions using a multi-task question-answering model called UnifiedQA [111]. TIFA adopt an open-domain pre-trained vision-language models (the authors recommend to use mPLUG-large [112]) as VQA model, rather than closed-class classification models fine-tuned on VQAv2 [113] enabling it to perform well on diverse set of visual elements. However, limitations of TIFA is the dependency to 12 categories: object, activity, animal, food, counting, color, material, spatial, location, shape, attribute, and other, which are considered to generated question-answer pairs.

3.3 Image Captioning Metrics

Finally, delving into the evaluation of T2I alignment one needs to look into its inversion. In the time before the invention of CLIP, T2I alignment was measured in reversed manner, the so called image-to-text alignment, which is a closely related task found in the field of image caption generation (or image description generation), where for a given image a generated textual description needs to be evaluated. There are several datasets like Flickr8K [114], Flickr30K [90], MS-COCO [89], [107] or Pascal 50S [54], that provide human ratings of captions for a given image functioning as benchmark datasets for image to text evaluation, and several visio-linguistic metrics were developed. In the following, we provide an overview of image captioning metrics and machine translation metrics that shaped the field of text-conditioned image synthesis evaluation before compositional quality metrics emerged.

TIGEr (Text-to-Image Grounding for Image Caption Evaluation) [57] is a metric specifically designed for the

evaluation of image captioning models. In contrast to the previous mentioned metrics it is not purely lexical based but also takes the image content directly into account. This is done via a process called text-image grounding. TIGEr compares text and image representations in vector space. In their ablations the authors show that TIGEr achieves a higher correlation with human judgement than BLEU, ROUGE and METEOR.

Moreover, there are several metrics based on the comparison between detected objects in the image and the textual description of such in an image description [79], [115]. Visual fidelity of image descriptions is measured by VIFIDEL [58], which is based on the word's mover distance (WMD) [116], measured between objects in the image, and its corresponding description in the text. VIFIDEL is specified by the inverse of the minimum cumulative cost required to move semantic labels (e.g., object categories) from an image to words in the description. This converts WMD from a distance measure to a similarity measure. Category names of detected objects in the image are compared to the words from the description. Additionally, object importance can be applied to weight more frequently used words in the reference descriptions.

In the work of Lee *et al.* [59] they propose a metric called ViLBERTScore, which similar to BERTScore [117] that computes textual embeddings for a reference and a generated caption. Additionally, the computation of textual embeddings is conditioned with the target image using the model proposed by Lu *et al.* [118]. Hereby, contextual embeddings are computed by applying an object detector to the target image and feeding pairs of image region features and text embeddings to the pre-trained ViLBERT model. Finally, the ViLBERTScore is defined by the cosine similarity between reference caption embeddings and candidate caption embeddings.

The BLEU (bilingual evaluation understudy) metric [119] was initially used to evaluate the performance of machine translation systems. BLEU measures the precision of n-grams between a machine generated candidate translation and a corpus of high quality human translations. It is important to know that only the count of matching n-grams is taken into account and the order of n-grams is ignored. The BLEU metric is always between 0 and 1, where a score of 1 would indicate that the candidate translation would directly match a translation from the text corpus. Therefore it is highly unlikely to achieve a score of 1. Nevertheless the BLEU metric has been shown to have a high correlation with human judgments. Because of this and because it is an inexpensive metric it still remains popular to date.

ROUGE [120] is a software package as well as a set of metrics that was originally intended for the evaluation of text summaries. The paper introduces 4 metrics that also show high correlation with human judgments. ROUGE-N is very similar to the BLEU metric but instead of precision it measures recall between n-grams. ROUGE-L measures the "Longest Common Subsequence" (LCS) between the candidate and a reference text. It thus also takes the sentence structure into account. ROUGE-W is a weighted version of ROUGE-L that gives a higher weight to consecutive LCSes. ROUGE-S measures the co-occurence of skip-bigrams. A skip-bigram is a bigram that allows for an arbitrary gap between the pair of words. A weakness of this metric is that it does not give credit to candidate sentences that do not share a skip-bigram with any reference candidate. Therefore the metric can be extended to ROUGE-SU, that also counts unigrams. ROUGE-1 (ROUGE-N with N=1), ROUGE-L, ROUGE-W, ROUGE-SU4 and ROUGE-SU9 (the maximum skip distances where 4 and 9 respectively.) have show great performance in evaluation very short, headline-like, summaries. We therefore would recommend them over other ROUGE metrics in the field of image captioning.

METEOR (Metric for Evaluation of Translation with Explicit ORdering) [121] is another machine translation metric that tries to improve on the BLEU metric. It works by matching unigrams between a candidate machine translation and a corpus of reference translations. As has been shown in previous work [122], including the recall and not only using precision yields a higher correlation with human judgement. Additionally, METEOR uses different modules where the unigram matches are not only done based on direct matches but also on stemmed versions and synonyms. The authors of the METEOR paper show in an ablation study that METEOR achieves a higher correlation with human judgement than the BLEU metric.

BertScore [117] is a metric used to evaluate the quality of machine-generated text, particularly in the context of natural language generation tasks such as text summarization or machine translation. It is based on BERT (Bidirectional Encoder Representations from Transformers) [123]. BertScore evaluates the similarity between a reference text and a generated text by computing the cosine similarity of their contextualized word embeddings obtained from BERT. This method allows BertScore to capture not only the semantic similarity between words but also their context within the sentence. BertScore has been shown to correlate well with human judgments of text quality. It provides a quantitative measure of how closely a generated text matches a reference text, which is valuable for assessing the performance of text generation systems.

3.4 Pure Image-based Metrics

One set of popular evaluation metrics assumes the generative model to be a black box and operates only on samples of the generated distribution q and compares it to samples from the target distribution p. The most commonly used metrics then rely on comparing features produced by pre-trained neural networks. Inception Score (IS) [30] uses an Inception network pre-trained on ImageNet to compare class predictions for a set of generated samples $x \sim q$. Hereby the score rewards low entropy in class predictions $p(y|x)$, i.e. generated images that can be clearly classified as one of the classes, as well as high entropy in marginal class distribution $p(y)$, i.e., a large diversity among generated samples. Due to its short-comings [124], the IS has recently lost popularity. The MODE score [125] improves upon the IS by adding another term that rewards similar distribution of class predictions for the generated and target images. IS-based metrics are not suited for T2I, as the marginal class distribution $p(y)$ is typically not available.

The Fréchet Inception Distance (FID) [29] compares the means and co-variances of the features, extracted by the

Inception network from samples of the generated and target distributions, using the Fréchet (or Wasserstein-2) distance. FID proved to be a more consistent quality measure than IS and is still commonly used. MiFID [81] extends FID by incorporating a term that penalizes memorization of training samples, by computing the minimum cosine distance of Inception features to the training dataset. This penalty was introduced to avoid bogus submissions for an image generation competition.

All of the Inception-based metrics share the downside of relying on the weights of the Inception network. Those weights are the result of supervised ImageNet classification training and many of the Inception metrics are not robust to different sets of weights obtained from similar trainings [124]. Further, with the increasing scale of modern T2I models and datasets [2] far beyond the ImageNet domain, features trained to classify this comparatively narrow domain may be insufficient for quality assessment. Adoption of a more capable and general feature extractor, such as semi-supervised models, could improve the reliability of metrics like FID, especially for models exceeding the ImageNet domain.

The distributions p and q can also be compared using kernel embedding of distributions, such as with the popular maximum mean discrepancy (MMD) metric, which measures the distance between kernel embeddings of samples. Unlike information theoretic approaches, MMD has the benefit of not requiring density estimation or bias correction. Most implementations use a fixed kernel for MMD, which introduces problems with complex natural images. The parzen window estimate [126] can be seen as an MMD approach. The Kernel Inception Distance (KID) [82] computes the squared MMD between Inception representations, eliminating FID's bias for the amount of samples.

Another common means of comparing two distributions is using two-sample tests. Lopez-Paz and Oquab introduce C2ST [83] and propose using a binary classifier to distinguish between samples of the generated and target distribution. This binary classifier should achieve an accuracy of $\approx 50\%$ for large numbers of samples. Using a nearest neighbor classifier allows for further insights in the generated data. For example, if the majority of nearest neighbors for generated images are also generated images, this indicates possible mode collapse. C2ST can be used with both, nearest neighbor classifiers and neural network based classifiers, including such based on pre-trained feature extractors like ResNet-34 [127].

The previously mentioned image-based metrics reduce the problem of evaluating generated images to a scalar score. Sajjadi et al. [84] find that such evaluation benefits from a separate notion of precision and recall for the distributions (PRD). Hereby precision measures the fraction of generated images that are in the support of the target distribution p. Recall measures the fraction of real images that are in the support of the generated distribution q. Sajjadi et al. cluster Inception embeddings of samples from p and q using k-means, before comparing the histogram over cluster assignments. Finding meaningful clusters that are mostly occupied by only generated samples would therefore decrease precision and clusters mostly occupied by target distribution samples decrease recall. They use multiple randomized clusterings to compute final precision and recall of the distributions. Kynkäänniemi et al. [85] further improve on this idea by changing how the support of a distribution is estimated (I-PRD). While Sajjadi et al. reduce this estimation of support to a one dimensional histogram comparison, the improved method explicitly models the support manifold. The support is estimated by placing hyperspheres around each of the sample embeddings with a radius equal to the distance to its nearest neighbor within the distribution. After finding the portion of samples from p and q lying in each others' supports, the precision and recall can be directly computed.

Gu et al. [86] propose GMM-GIQA, which models the embeddings of the target distribution p using a Gaussian mixture model. A generated image can then be assigned a score based on the probability density of its embedding. The authors note however, that the metric may fail for too complex distributions, as they cannot be sufficiently modeled using a Gaussian mixture model.

Karras et al. [87] introduce the perceptual path length, a metric for latent variable models. The idea is to pair-wise compare subsequent images in a latent space interpolation using a perceptual image metric. This metric measures if any drastic changes appear for close latent codes and rewards smooth transitions within the interpolation, which is an indicator for a good disentanglement.

With the introduction of the LAION Aesthetics dataset [2], the authors trained models[1] to predict how aesthetic humans would rate a given generated image, resulting in an image quality metric that is aligned with human preferences.

Zhang et al. [43] collect a dataset containing human annotated segmentation of artifacts. They then train binary segmentation models to automatically detect such artifacts in images. They further propose a related metric for evaluating in-painting using generative models, the Perceptual Artifact Ratio (PAR) [42], also known as PAL4InPainting, which measures the relative area occupied by artifacts. This metric is also generally applicable to full images, not just regions for in-painting.

4   DATASETS

This section provides an overview of datasets used to evaluate text-conditioned image synthesis, see Table 2. First, we discuss datasets that origin from the image captioning research community, which were used first to evaluate text-image generation systems. With recent developments of vision-language models, researchers started to seek for increasing complexity of evaluation data resulting in the emergence of the term, visio-linguistic compositionality. It describes the task and datasets for evaluating the ability of vision and language models to conduct reasoning of image and text which are subject to compositionality, meaning they are ensembles of several contents. Second, we discuss existing visio-linguistic compositionality benchmark datasets, and finally we inspect specifically designed datasets for development of text-image metrics and their verification on human judgments.

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1. https://github.com/christophschuhmann/improved-aesthetic-predictor

4.1 Image Caption Datasets

The development of image generators requires tremendous amounts of image data [128], [129] in order to learn data statistics and fitting the output distribution of the generator to real image distributions. In the context of evaluation text-conditioned image synthesis, the necessity of text-image pairs arises. Fortunately, there already exist such datasets collected from researchers of the image captioning research domain, e.g., MS-COCO Captions [89], Flickr30K [90], [91], PASCAL-50S [54], Abstrac-50S [54], which curate one to fifty human generated descriptions per image.

UIUC Pascal Sentence Dataset [130] and Flickr8K [114] are the first popular image caption datasets, featuring multiple image descriptions per image. The work of Hodosh *et al.* [114], that frames the evaluation of image description as ranking task and describes the collection of $8,092$ images from Flickr and $1,000$ from PASCAL VOC-2008 [131] having human annotators describe each image. The crowdsource instructions and quality control mechanism are adopted from Rashtchian *et al.* [130] in order to collect five image descriptions per image from human annotators utilizing the Amazon Turk Platform. Users were asked to describe images they see, using a single sentence while focusing on the main characters, settings and object relations. Further, they were asked to use adjectives for color, spacing, emotion or quantity, utilizing no more than 100 characters. A separate set of users were asked to perform quality control by conducting spelling and grammar checks in order to ensure high quality textual descriptions of images. Later, Young *et al.* [90] extend the size of the Flickr8K dataset incorporating $158,915$ image captions, which correspond to $31,783$ referring to it as Flickr30K. Another extension was proposed by Plummer *et al.* [91]. They collect cross-caption coreference chains, that link same entities mentioned in different captions of the same image, and meanwhile bounding boxes localize such entities in image space.

The SBU Captioned Photo Dataset [132] collects one million images from Flickr.com ensuring some quality requirements, in particular they filter the collected data for textual descriptions with satisfactory length of visual description, at least two words belonging to (objects, attributes, actions, stuff, and scenes) and at least one preposition indicating visible spatial relation. While the dataset poses a tremendous amount of image-text pairs, the content of image captions may be visual descriptive but lacks human supervised verification resulting in many image captions being only comprehensible with personal knowledge of the caption's author, e.g., using the given name of a dog for describing a dog playing with a ball.

Based on Microsoft COCO [107], which is a large-scale dataset consisting of images acquired through Flickr showing multiple objects in their natural context, the frequently used COCO Captions [89] dataset was created. It supplements MS-COCO by collecting $1,026,459$ captions for $164,062$ images, including five captions for each image in MS-COCO and a subset of $5,000$ images were annotated with 40 reference sentences. Together with the actual dataset the authors released an evaluation protocol, in particular they deploy an evaluation server ensuring consistent evaluation computing numerous metrics like BLEU [119],

ROGUE [120], METEOR [121] and CIDEr [54].

In the work of Vedantam *et al.* [54] two datasets are collected, PASCAL-50S and ABSTRACT-50S based on the UIUC Pascal Sentence Dataset and the Abstract Scenes Dataset [133], respectively. Annotations for these datasets were collected with the goal to investigate consensus between humans annotators, in particular the similarity between a candidate image description and several reference descriptions. While PASCAL-50S feature real images, ABSTRACT-50S consists of images in a clip-art style designed by humans in a different crowdsource study [133]. For both datasets, 50 human generated sentences are collected while annotators are instructed to provide descriptions that should help others recognize the image from a collection of similar images. Having a large set of fifty reference sentences per image facilitates research of text-image alignment, however the amount and variety of images provided by both datasets seems too few in order to provide complexity for profound text-image evaluation.

Increasing the number of object classes is achieved by the image dataset called, nocaps. It consists of over 600 object classes, and it is presented in the work of Agrawal *et al.* [134], which is based on OpenImages V4 [135] a large-scale human-annotated object detection dataset. Nocaps was acquired by filtering Open Images and excluding images with non-zero or unknown image rotations, instances from a single object category, less than six unique object classes and finally they apply a balancing scheme to have an even distribution of images depicting two to six unique object classes avoiding frequently occurring object classes.

Mao et al.'s [136] introduction of the Pinterest40M dataset represents a significant advancement in multimodal word embeddings, featuring over 40 million images and 300 million sentences from Pinterest.com. Far exceeding the scale of existing datasets like MS COCO, Pinterest40M's unique blend of visual and textual data enables the development of richer word embeddings. Further, this dataset serves as a vital resource for exploring vision-language pre-training methods [137]–[139].

The Conceptual Captions [140] dataset is programmatically acquired through web-crawling billions of webpages utilizing the JavaScript framework Flume [141] developed to build efficient data-parallel pipelines. In such a way, a tremendous amount of image-text pairs can be downloaded, however stringent filtering is necessary in order to keep only high quality images and captions. Therefore, they excluded images based on encoding format, size, aspect ratio, and offensive content. Since the accompanying Alt-text harvested from the HTML webpages are not restricted to be good image descriptions, filtering was applied by analyzing part-of-speech, sentiment/polarity, pornography/profanity annotations using the Google Cloud Natural Language APIs. To further increase textual quality, several heuristics based on the count of nouns, prepositions, token repetition, word capitalization, English Wikipedia token likelihood and predefined boilerplate prefix, e.g., "click to enlarge picture", "stock photo". Ultimately, image-text based filtering through Google Cloud Vision APIs is applied, which tries to map text tokens to content of the image, as well as text transformation with hypernymization replaces proper names by its hypernym. The intention of this dataset, con-

sisting of over 3 million image-text pairs, is to serve different downstream tasks of image captioning, however it trends to be frequently utilized for vision-language pre-training [142].

To facilitate image-text pre-training, Conceptual 12M [142] was acquired by relaxing filter criteria of the collection pipeline used for Conceptual Captions. This strategy trades precision of image descriptions for increased scale of the data corpus, in particular they increase the recall of visual concept descriptions by lowering requirements of word repetitions, caption size ranges, image aspect ratios and hypernymization. Just as Conceptual Captions and Pinterest40M, such web sourced image descriptions enable vision-language pre-training but lack the quality and complexity for proper evaluation of T2I synthesis methods.

4.2 Visual Question Answering

The Visual Question Answering (VQA) dataset [143], a pioneering resource in the field, combines 123,287 MS COCO images and 50,000 abstract scenes with over 760K million questions and 10 million answers crowdsourced via Amazon Mechanical Turk. Designed to challenge VQA models in understanding complex visual content, the dataset covers a broad spectrum of question types and answers, reflecting real-world diversity and the intricacies of human language. Each image is associated with five open-ended questions, requiring detailed visual recognition, commonsense knowledge, and inferential reasoning, with ten distinct answers per question to capture the variability of human responses.

The Visual Commonsense Reasoning (VCR) dataset [144] is specifically designed to move beyond mere recognition tasks to test models on cognition-level visual understanding. It features 290,000 question-answer-rationale (QAR) triples across 110,000 unique movie scenes. Each QAR triple challenges models to not only identify objects within a scene but also to understand complex interactions and motivations. The dataset focuses on deep visual comprehension, requiring models to infer and rationalize about unseen aspects of the image, thus bridging the gap between visual perception and commonsense reasoning. VCR is frequently used as downstream task for evaluating representation learning of visual-linguistic approaches [59], [95], [145], [146].

4.3 Compositionality Benchmarks

The work of Thrush *et al.* [41] introduces Winoground, a novel task and dataset designed to evaluate vision and language models' capabilities in visio-linguistic compositional reasoning. This involves matching two images with two captions, each containing the same set of words but in a different order, requiring precise comprehension of both modalities. Despite testing state-of-the-art models, the study finds that none significantly outperform chance, highlighting a significant gap in current models' understanding of compositional reasoning. This work not only reveals the limitations of existing models but also sets a new benchmark for advancing visio-linguistic comprehension in AI.

[147] The Visual Genome dataset [67], is a dataset for comprehensive scene understanding. It contains more than 108k images, each with an average of 35 objects delineated by a bounding box. However bounding box annotated objects are not sufficient for a compressive scene understanding. Object attributes and their relationships are also needed. To obtain these, about 50 overlapping image subregions per image have been captured by human annotators. From those, object attributes and relationships could be extracted, which turn are used to create image scene graphs and additional question answer pairs. Object attributes and relationships are canonicalized on Word-Net synsets [148].

T2I-CompBench [78] is a compositional dataset targeting to provide complex prompt compositions in order to study attribute binding, object relations and complex compositions skills of image generation models. Therefore, they acquire a dataset consisting of 6,000 text-image pairs (1,000 for each sub-category: color, shape, texture, spatial relation, non-spatial relation, complex composition). Text prompt for color attribute binding are gathered from CC500 [149] and COCO [89], while for the remaining sub-classes prompts are generated by GPT [50] or handcrafted using prompt templates.

Rich human feedback, in short RichHF-18K [70], is a dataset consisting of 18K image-text pairs collected from Pick a Pic dataset [33]. For each image human annotations are crowdsourced consisting of two heatmaps localizing artifacts/implausibility and misalignment, four scores, i.e. plausibility, alignment, aesthetic, overall quality and one text sequence indicating misaligned keywords. In order to filter for photorealisitc images and balance classes across images they adopt PaLI visual question answering model, which assesses realism and selects images of five classes: *animal*, *human*, *object*, *indoor scene* and *outdoor scene*. Heatmaps are derived from averaged key point positions across annotators for artifact and misalignment annotations. The dataset provides complex annotations enabling fine-tuning a scoring model on human feedback, however the collected annotations origin from only 27 individual annotators which took around 3,000 rater-hours, which questions the quality of annotations as well as consensus of such a small group of raters.

The goal of the SeeTRUE benchmark is to study text-image alignment evaluation. The dataset builds on top of several existing vision-language datasets: COCO Captions [89], SNLI-VE [150], DrawBench [151], EditBench [12], Winoground [41] and Pick a Pic [33]. It includes $31,855$ real and synthetic image-text pairs and corresponding human annotations, where each binary annotation indicates alignment or misalignment of text and image.

5 OPTIMIZATION

While T2I quality metrics are developed in order to judge the quality of single T2I samples or entire T2I models, other techniques can also be used in order to optimize the synthesized output. In this section we will review some of these techniques, whereby we differentiate between those which require a training process (see Section 5.1), and those which can be used without additional training (see Section 5.2).

5.1 Finetuning Image Generators

The StyleT2I framework [153], which utilizes a CLIP-guided contrastive loss, a semantic matching loss, and a spatial

Dataset	#Images	#Text	#Words	Image Content	Image Source	Text Source	Annotations / Task
UIUC Pascal Sentence Dataset [130]	1,000	5		Images of twenty object categories	VOC2008	crowdsourced	Image Caption
SBU Captioned Photo Dataset [132]	1,000,000	1		Photographs of everyday activities, events and scenes	Flickr.com	web-scraped	Image Caption
Flickr8K [114]	8,092	5		People or animals performing some action	Flickr.com	crowdsourced	Image Caption
Flickr30K [90]	31,783	5		Photographs of everyday activities, events and scenes	Flickr.com	crowdsourced	Image Caption
COCO Captions [89]	204,721	5 to 40	11	Common Objects	Flickr.com	crowdsourced	Image Caption
PASCAL-50S [54]	1,000	50	8.8	Images of twenty object categories	VOC2008	crowdsourced	Image Caption
ABSTRACT-50S [54]	500	50	10.59	Cartoon-like Images	Abstract Scenes Dataset [133]	crowdsourced	Image Caption
Pinerest40M [136]	40,000,000	7	10	DIY crafts, fashion, home decor, recipes, travel, and more, from both professionals and hobbyists	Pinerest.com	web-scraped	VLM Pre-Training
Conceptual Captions [140]	3,369,218	1	10.3	Wide variety (natural, product images, professional photos, cartoons, drawings, etc.)	World Wide Web	web-scraped	Image Caption
nocaps [134]	15,100	11	10	Multiple objects per image	Open Images V4 (Flickr.com)	web-scraped	Image Caption
Conceptual 12M [142]	12,423,374	1	20.2	Wide variety (natural, product images, professional photos, cartoons, drawings, etc.)	World Wide Web	web-scraped	VLM Pre-Training
VQA [143]	254,721	30	< 2	Common Objects & Cartoon-like Images	MS COCO & Abstract Images similar to [133]	crowdsourced	VQA
VQAv2.0 [113]	204,721	54	-	Common Objects	MS COCO	crowdsourced	VQA
VCR [144]	110.000	5.3	11.8	Movie Scenes	Large Scale Movie Description Challenge [152] & YouTube	crowdsourced	VQA

TABLE 2

constraint to refine attribute manipulation within intended spatial regions, trains a StyleGAN [154] model to increase compositional accuracy. This approach ensures more disentangled latent representations, that can be decoded into a high-fidelity image aligned with the input text. In order to find optimal latent codes, a Text-to-Direction module is employed to predict the sentence direction that is aligned with the input text, which is trained using a CLIP-guided contrastive loss. To enhance attribute alignment a *Attribute-to-Direction module* gets optimized by the semantic matching loss that strives to identify attribute directions of the latent codes. To mitigate the issue of changing multiple regions during attribute alignment, a spatial constraint avoids spatial variations outside of a pseudo-ground-truth mask generated by a segmentation model.

In the work of Dong *et al.* [155], called RAFT, a Stable Diffusion model is fine-tuned on high quality samples ranked by a reward model. In a decoupled data generation process high-quality training data is sampled from the generator by discarding low-quality data points, which is done by utilizing a reward model to filter out those that exhibit undesired behavior. In their experiments they adopt CLIPScore and LAION Aesthetic Predictor as reward models, however fine-tuning on training data produced by the generator hinders the model to overcome problems within distribution towards high-quality compositionality, which remains concealed outside of the generators distribution. After training a reward model utilizing their proposed dataset, see Section 3.2, Liang *et al.* [70] demonstrate to fine-tune a Muse image generator and comparing it to the pre-trained Muse version based on 100 generated test prompts. In their experiments, they utilize Muse to generate a set of 100,512 images for 12,564 generated prompts, then they apply their reward scores to filter out images below a certain threshold, and fine-tune Muse. Finally, they quantify the gain from Muse finetuning by conducting a study, where they present the two images side-by-side originating from the baseline and finetuned model. They were able to show, that the plausibility finetuned model produces significantly fewer artifacts/implausibility than the original Muse. A

similar approach by Lee *et al.* [156] collects binary decisions from human annotators for a large set of synthetic images to train a reward model. Thus, they are able to finetune Stable Diffusion via reward-weighted likelihood maximization to better align it to human feedback using 27K image-text pairs. Also, AlignProp [157] is following the idea of utilizing a reward model to supervise finetuning of Stable Diffusion with human feedback.

After such recent developments of reward models opening a way towards incorporating human feedback into the diffusion process, further approaches adopted reward models, applying supervision during reinforcement learning. Thus, Fan *et al.* [158] propose *DPOK*, diffusion policy optimization with KL regularization, which utilizes KL regularization to stabilize RL finetuning and aligning T2I. Unlike traditional supervised finetuning, which often degrades image quality, the RL finetuning with DPOK optimizes ImageReward [32] a feedback-trained reward model online, leading to better alignment between text prompts and generated images while maintaining high image fidelity. The paper demonstrates that DPOK outperforms supervised fine-tuning methods in experiments, showcasing its effectiveness in enhancing T2I diffusion models. However, their work studies KL-regularization and primarily focuses on training a different diffusion model for each prompt. Denoising diffusion policy optimization (DDPO), proposed by Black *et al.* [159] broadens the approach by training using multiple prompts and showcasing the model's ability to generalize to unseen prompts. The adaptability of DDPO to various reward functions, including those derived from vision-language models, marks its advance in enhancing prompt-image alignment beyond the scope of human feedback optimization.

5.2 Training free Optimization

In their work, Liu *et al.* [160] introduce an approach called Composable Diffusion Models, targeting the challenge of accurately align compositional text prompts to their image representation. Their method proposes a structured strategy where an image is generated through the composition of a

set of diffusion models, each modeling different visual concepts. By treating diffusion models as energy-based models, they enable the explicit combination of data distributions defined by these models. This approach assumes the visual concepts are conditionally independent given the image. Sampling from the resultant distribution involves using a composed score function that integrates the contributions of each concept to the denoising process, allowing for the generation of images that faithfully represent the composed concepts. This allows for the generation of scenes that are more complex than those encountered during training, effectively combining object relations, and attributes accurately.

Feng *et al.* [149] introduce *Structured Diffusion Guidance*, a method aimed to enhance compositional T2I synthesis through the use of scene graphs, which are derived from the prompt. Instead of computing a text embedding for a single sequence, this method extracts noun phrases from the prompt corresponding to visual concepts and entities, and encode such noun phrases separately to achieve region-wise semantic guidance. Finally, for each cross-attention map the average of all noun phrase activations denotes the corresponding output.

The method *Attend and Excite* by Chefer *et al.* [161] proposes a training-free concept, which they call *Generative Semantic Nursing* (GSN) exploiting cross-attention maps of a Stable Diffusion model [14] to incorporate all subject tokens in the prompt and strengthen their activations, ultimately steering the model to better represent objects and their attributes and relations in the image. GSN is applied during inference, in particular at each denoising step attention values are maximized at the subject's corresponding region in the attention map. This results in following denoising steps to better incorporate subject tokens into the latent representation. The maximization of attention values is based on a loss objective that enforces high activations for at least one patch in the attention map per subject token. However, the authors observe, that the timing of the optimization is crucial, since during the final timesteps of denoising the spatial locations of objects in the generated image do not alter anymore. Also, at each denoising step an iterative latent refinement is adopted, and the authors show that a gradual refinement helps to prevent frequent updates of latent updates which would lead to degraded images. While the proposed strategy provides promising results for simple prompts, its efficacy declines for prompts with increasing complexity, e.g., multiple entities with bound attributes.

A follow-up work, named *Divide and Bind* [162] by Li *et al.*, picks up the idea of *GSN* and applies total variation maximization, which opens the room for activated regions and increases the amount of local changes in the attention maps. As a result, diverse object regions are encouraged to emerge, enabling concurrently competing objects during the generation process. Therefore, they introduce two novel objectives, one that attends to the object tokens and the other for attribute binding regularization. The formulation of the attendance loss is based on the finite differences approximation of the total variation along the spatial dimension, which enables activations of neighboring locations in the attention maps resulting in activation patterns effectively dividing the image in to different regions. In order to realize attribute binding, object tokens and attribute tokens, which tend to share large overlapping regions in the attention map, are normalized. Thus, the normalized attention maps are considered as two probability mass functions, whose symmetric similarity is then maximized by minimizing the Jensen-Shannon divergence [163].

The metric proposed by Singh *et al.* [1], see Section 3.2 for further details, is able to detect parts of the image that are not aligned with the prompt, and when passing relative importance of such parts to a modified reverse diffusion process, it becomes possible to improve T2I alignment. In their experiment, they can show that by incorporating such relative importance in the form of weighting factors through a combination of prompt weighting and cross-attention guidance (*Attend and Excite*), they can optimize T2I alignment.

Layout control with cross-attention guidance is achieved by Chen *et al.* [164], by introducing two techniques to incorporate object bounding boxes to steer the diffusion process optimizing for spatial relation alignment. This method enables to control image generation by providing object bounding boxes to encourage the diffusion model to generate corresponding objects within the bounding box region of the image. The work proposes two ways of layout guidance: forward and backward guidance. The former method applies a smoothed window function to the cross-attention maps, which increase activation for corresponding object tokens inside the bounding box. The second method, backward guidance applies an energy-loss function which is computed via back-propagation to update the latent vector and therefore indirectly alter the cross-attention maps. During image generation they alternate between denoising steps and gradient updates. While this technique improves overall layout and provides control over spatial relations, problems of standard diffusion approaches for object attribution remain and the question of manual bounding box placement needs to be considered.

6 CHALLENGES

Measuring text-image alignment focuses on relations between objects described by a text. That includes spatial and non-spatial relations between objects and their bound visual attributes. However, these alignment-focused metrics are targeted to sense the presence or absence of certain compositions in image space, but are unable to quantify the quality of such detected components (if present). Quality scores provided by VLM-based metrics are defined on their visio-linguistic capability providing quantitative reasoning in form of class probabilities for *Yes* or *No* answers of closed questions. However, such probability score merely indicates the degree of uncertainty rather than actual alignment quality. Future measures should be designed to compute quantities for detected compositions enabling to rank alignment quality on an component-level rather than on a basis of uncertainty scores. Also, VLMs tend to behave like bags-of-words [48], which is a phenomenon that describes a model's insensibility of word order and permutations of object relations, e.g. the text-image alignment of the sentences "the gold fish is swimming in the aquarium" and "the aquarium is swimming in the gold fish" are scored similarly.

Such behavior is caused by the training objective applied to pre-train VLMs. The contrastive pre-training optimizes for image-text retrieval on large datasets, which does not acknowledge compositional information and thus fails to learn unique representations [48]. A step towards a solution of this problem are hard negative samples [48], [68], where existing prompts are transformed to represent negative compositional semantics by word or relation swapping, and are included to the training set for fine-tuning. Many of the content-based T2I metrics rely on the outputs of VLMs or LLMs that may contain additional details fabricated by a language model rather than actually represented by the image. Additionally, VLMs show limited capability of understanding inputs of multiple images, which may result in low correlation scores on image editing tasks [79]. VLMs are good at generation task evaluation, but fail at image to image evaluation due to high level feature focus [79].

Existing T2I datasets [90], [107], [136], [140], [142] mainly originate from various online sources, where image-text pairs are collected by applying heuristics to filter the data, thereby often trading quality for quantity. Otherwise, high quality image descriptions need to be crowdsourced by human annotators, which is time consuming and costly. With increasing focus towards the evaluation of visio-linguistic compositionality the necessity of compositional datasets intensifies [41], [165]–[167]. While the evaluation on such complex datasets fosters the development of compositional metrics, the active research in this field seems to stick to a limited set of four compositional aspects: object accuracy, spatial relations, non-spatial relations and attribute binding. However, we consider this to be a subset of a greater set which is yet to be explored, thus, in the work of Dehouche [168] they apply GPT-3 [50] to explore a set of 20 topics, e.g. medium, technique, genre, mood, tone, lighting, artistic reference, which are derived from human generated prompts taken from Lexica[2].

Benchmarking image synthesis is lacking of comparability due to evaluation on individually proposed datasets providing insights on specific topics. Although, there are widely adopted compositional datasets [41], the size of such datasets limits the assumptions that can be made regarding generalizability. However, creating a comprehensive benchmark for compositionality evaluation should be targeted in the near future.

7 GUIDELINES

7.1 Define Reasoning Skills of Metrics

Benchmarking T2I synthesis involves measuring general image quality and compositional quality, as described in the beginning of Section 2. However, the understanding of image quality might change for different underlying domains depending on the application for which they are evaluated for. For instance, in the domain of artistic image synthesis, like comics, anime, mangas, paintings, high image quality is considered to reflect certain art styles, drawing characteristics, shapes and colors rather than photo-realism and naturalism. In order to capture and measure such large variety of abstract concepts, there have been developed

2. https://lexica.art/

many visual quality metrics, see Table 1, each equipped with unique reasoning capabilities such as aesthetic and human preference prediction, perceptual artifact localization, object recognition, object counting, spatial relations, object attribute recognition, etc. Hence, selecting reasoning skills for evaluation needs to be done carefully, and the calibration of such priority is crucial. Considering the use case of generating synthetic images for pre-training object detection networks of real images, one would need to ensure, that the image generator produces correct visual representation of described objects necessitate metrics with strong object recognition and object counting skills, and ultimately some priority to measuring photo-realism is required as well. As shown in Section 3, the current state-of-the-art does not include a general purpose metric satisfying a comprehensive evaluation of T2I synthesis.

7.2 Selection of Evaluation Prompts

Fundamental for evaluating T2I image synthesis are the underlying text prompts forming the input to the image generator. In Section 7.1 essential reasoning skills of the metrics are defined, which in their entirety indicate performance of the examined generator. However, evaluation prompts are required to include rich descriptions covering an overall set of visual concepts, in order to exhaust reasoning capabilities and thus provide comprehensive benchmark results. In Section 4, we provide an overview for the state-of-the-art datasets containing image-text pairs with different levels of complexity. Textual descriptions originating from image captioning datasets usually lack the range of visual concepts to be useful in the evaluation context of text-image synthesis. Applying image generators to inappropriate prompts, that do not cover descriptions whose visual depictions are measured, can lead to outperforming other methods, however, rendering test results meaningless. Therefore, the collection of evaluation prompts must include a strategy to ensure authenticity, complexity, compositionality and representativity of textual descriptions incorporated in the test dataset.

7.3 Prompt Normalization

Recent advances of diffusion-based image generation models [169] prove the ability of such models to synthesize real looking images of impressive quality. These models utilize or are based on pre-trained vision-language models that were trained on dataset that may be subject to language biases resulting in the image generator being sensible to such biases, e.g., specific sentence formats, absence of grammatical structure, certain keywords constellations, artist name known only by some models, etc. In order to mitigate such behavior and thus to avoid linguistic advantages of some models, the evaluation prompts need to be cleaned. This can be achieved by adopting LLMs, which feature strong capabilities for rephrasing, summarizing and completion of text. After this process, prompts are considered to be freed of any bias, in particular prompts are now considered to be natural language, complete sentences and freed of any keywords, and further normalization protocols may be applied. For some applications it may be beneficial to normalize prompt length since some text encoder networks have limited token

vector lengths. Hypernymization, where a word is replaced by its hypernym, another word that describes it in a more general way, e.g., daisy and rose would be replaced by flower, is a method to semantically normalize prompts, however it may reduce variety of evaluation prompts. Also, the representation of numbers and dates can be brought into a consistent format, e.g., *Two dogs are playing with a ball.* and *2 dogs are playing with a ball.*

7.4 Image Synthesis

As diffusion-based image generation is sensitive to the selected seed for the initial noise sampling during the early diffusion steps, it is crucial to fix such seeds to guarantee reproducibility. Further, some benchmarks compare image generators sharing an identical training protocol and differing only in small architectural changes or vise versa, where utilizing identical seeds clarify the contribution of these changes. The image resolution used during training might have a strong influence on image quality, and should be configured appropriately and consistently throughout all evaluated methods, this extends to sampling method, sampling steps and guidance parameters. When the image generation pipelines are properly configured, for each prompt in the evaluation set, a fixed number of N images is generated, where N is equal to the number of used seeds. Higher numbers for N provide increasingly robust performance results in exchange with computational costs.

7.5 Performance Measurement

After generating images using the pipeline configured in Section 7.4, evaluation performance is computed by applying metrics defined in Section 7.1 to each synthesized image. Some measures are defined for the image distribution of the entire test dataset, see Section 2.1, while most of the metrics are computed for individual images. Ultimately, recently developed compositional quality metrics are able to provide not only score associated with image quality, and additionally output a rationale for deeper explainability of the score, see Section 3.2. In order to extract comprehensive benchmark results, a close inspection of individual compositional aspects is necessary. Thus, both general image quality and compositional quality should be captured and investigated separately by the selected evaluation metrics. Drawing conclusions from results based on a single metric lacks sufficient variation in perspective, leaving research questions only partially answered.

8 CONCLUSION

This survey provides an overview of the current state-of-the-art (SOTA) in evaluation metrics for text-to-image synthesis. First, we introduce our taxonomy to categorize quality measures based on the conditions they use (images or text-conditioned images), their scope (distribution of images or a single image), their operating data structure (embeddings or content), and what they measure (general quality or compositional quality). Second, we collect, review, and compare both established and emerging evaluation metrics, acknowledging the trend towards compositional quality metrics. These metrics are sensitive to different

aspects of a prompt and can detect and judge their alignment quality with the text. Third, we highlight the shortcomings of existing text-image datasets, where large-scale databases lack compositional attributes and datasets specifically tailored to benchmark visio-linguistic compositionality possess an insufficient amount of data for comprehensive text-to-image synthesis evaluation. Fourth, we review and discuss optimization-based approaches aimed at increasing text-to-image alignment by fine-tuning the generators or optimizing cross-attention layers during inference. Finally, we provide guidelines for the development of comparable and meaningful evaluation protocols, enabling consistent quality assessment and thus, representative text-to-image synthesis evaluation.

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