LOGICRANK:
Logic Induced Reranking for Generative Text-to-Image Systems

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Abstract

Text-to-image models have recently achieved remarkable success with seemingly accurate samples in photo-realistic quality. However, as state-of-the-art language models struggle evaluating precise statements consistently, so do language-based image generation processes. In this work, we showcase problems of state-of-the-art text-to-image models like DALL-E with generating accurate samples from statements related to the draw bench benchmark. Furthermore, we show that CLIP is not able to rerank those generated samples consistently. To this end, we propose LogicRank, a neuro-symbolic reasoning framework that can result in a more accurate ranking system for such precision-demanding settings. LogicRank integrates smoothly into the generation process of text-to-image models and moreover can be used to further fine-tune towards a more logical precise model.

Introduction

Transformer-based language models (LMs), such as BERT (Devlin et al. 2019) and GPT (Brown et al. 2020), have achieved success in several natural language understanding (NLU) tasks. However, there are growing concerns that these LMs cannot perform true logical reasoning (Sugawara et al. 2020; Contier et al. 2020). Naturally, these problems will be inherited in multi-modal setups, as the case of text-to-image generation tasks with models like DALL-E (Ramesh et al. 2021, 2022) or imagen (Saharia et al. 2022). The authors of DALL-E already mentioned this impairment in the context of geometric scene descriptions. Some approaches, such as DALL-E, suggest to sample several images within the forward pass and use text-image embedding models like CLIP to rerank generated images for best matching candidates to proceed with. This workflow is depicted in Fig. 1. After selection, the best ranked image may be further polished e.g. with supersizing or sharpening procedures. That post-processing is not discussed further in this work.

However, using CLIP as a reranker for DALL-E may not yield the expected performance for the following two reasons: 1) images generated with machine learning models can produce significant artifacts on other machine learning models, in particular as the generated data is out of training distribution 2) the generating and reranking models are both trained on a similar dataset and loss, therefore assumably

LogicRank as a Reasoned Reranker

As a reranker for logical statements, we propose LogicRank. It is an abstract framework that consumes a generative text-to-image model, object detectors, text prompts and their

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\textsuperscript{1}We used the huggingface version “dalle-mini/dalle-mega” (Dayma et al. 2021).
translation into logical rules, and outputs generated samples with their prompt-matching probabilities. The workflow is depicted in Fig. 2. In the following paragraphs we first give a motivating example before describing the separate components in more detail.

**Example.** In this study we use the DALL-E mini text-to-image model to evaluate the framework. The DALL-E approach (Ramesh et al. 2021) itself generates several samples, which are subsequently reranked. The iterative sample and rerank process is essential as it maximizes the evidence lower bound on the joint likelihood of the model distribution over images, captions and tokens. Fig. 1 depicts the original reranking process utilizing the pre-trained CLIP model as a reranker. CLIP embeds the generated images as well as the given text prompt and computes the similarity of both modalities. The similarity score is used for the final reranking. We observe that using CLIP as a reranker fails for many types of queries, e.g. positional precise statements. To encounter this drawback, we propose the workflow as follows.

The text statement and its translation into a logical rule is passed as input as depicted in Fig. 2. We first let the text-to-image model generate a set of corresponding samples to the text prompt. An object detection model generates an object-centric representation of the images. We found that little fine-tuning of DETR (Carion et al. 2020) works well for attribute detection in generated samples. Finally this object representation along with the logical statement rule is passed into the Neuro-Symbolic Forward Reasoner (NFSR) (Shindo, Dhami, and Kersting 2021) as described below, to derive the normalized probability estimate.

Fig. 3 shows an inference example. To evaluate the prompt “a blue sphere on top of a red cube”, we use the logical form: \( kp :- \) \text{shape(obj1, sphere)}, \text{color(obj1, blue)}, \text{shape(obj2, cube)}, \text{color(obj2, red)}, \text{position(obj1, obj2, above)}. The image shows an example of detected shape atoms with their probabilities thru DETR. For each bounding-box we further induce the color attributes and a positional relation. All derived attribute estimates are shown next to the figure. As a final result from the reasoner, we get the conclusion \( \hat{p}(kp|X) = 0.86 = \sqrt{0.46} \) for the rule in question.

This example already indicates a benefit of NFSR compared to CLIP-based reranking. We are not only confronted with the final result but also get detailed reasoned feedback, e.g. about dubious attributes to improve on.

**DETR.** As an object detector we use DETR (Carion et al. 2020). For the problem space of evaluating the performance of text-to-image models on placing objects in scenes properly, we further finetune DETR as follows: We use the CLEVR framework (Johnson et al. 2017) to generate 1000 images in a “DALL-E mini style”, with adjusted colors and proportions. CLEVR offers a dynamic framework for generating synthetic images and its text descriptions for scenes with randomly placed objects. We further modify Contrast and Brightness levels randomly, to obtain a more robust classifier. DETR is finetuned for 3000 steps on this dataset.
Neuro-Symbolic Forward Reasoner. The NSFR is an end-to-end differentiable reasoning framework. It factorizes the raw inputs into the object-centric representations, converts them into probabilistic ground atoms, and finally performs differentiable forward-chaining inference using weighted rules. NSFR works as follows, cf. Fig. 2.

**Step 1:** Let $X \in \mathbb{R}^{B \times N}$ be a batch of input images. Perception function $f_{\text{per}} : \mathbb{R}^{B \times N} \rightarrow \mathbb{R}^{B \times E \times D}$ factorizes input $X$ into a set of object-centric representations $Z \in \mathbb{R}^{B \times E \times D}$, where $E \in \mathbb{N}$ is the number of objects, and $D \in \mathbb{N}$ is the dimension of the object-centric vector.

**Step 2:** Let $G$ be a set of ground atoms. Convert function $f_{\text{con}} : \mathbb{R}^{B \times E \times D} \times G \rightarrow \mathbb{R}^{B \times G}$ generates a probabilistic vector representation of facts, where $G = |\mathcal{G}|$.

**Step 3:** Infer function $f_{\text{inf}} : \mathbb{R}^{B \times G} \rightarrow \mathbb{R}^{B \times C}$ computes forward-chaining inference using weighted clauses $C$.

**Step 4:** Predict function $f_{\text{pre}} : \mathbb{R}^{B \times C} \rightarrow \mathbb{R}^{B \times B}$ computes the probability of target facts. The probability of the labels $y$ of the batch of input $X$ is computed as:

$$p(y|X) = f_{\text{pre}}(f_{\text{inf}}(f_{\text{con}}(X; \Phi, \Theta; G; \Theta; C, W))).$$

where $\Phi, \Theta$, and $W$ are learnable parameters. Essentially, NSFR computes the logical entailment for given weighted clauses and probabilistic atoms in a differentiable way. As increasing number of attributes lead to vanishing probabilities, we normalize the final result taking the $n$-th square root: $p(y|X) = \sqrt[p_i]{p(y|X)} \approx \sqrt{p(y|X)}$, with $p_i$ being the $i$-th found attribute.

Next we will provide empirical evidence demonstrating that LogicRank enables text-to-image models like DALL-E to reliably generate images from precise statements.

**Empirical Evaluation**

We now compare the workflows of CLIP with its scores as a reranker (Fig. 1) and LogicRank with its probability estimates (Fig. 2) respectively. Inspired by the draw bench benchmark (Saharia et al. 2022), we consider three groups of tasks which require logical reasoning, namely coloring, positioning and counting. We start by comparing the reranking modules CLIP and LogicRank isolated from the generative model. To this end, we investigate the task of counting objects in given, i.e., not generated, real images. Next, we evaluate the complete pipeline: generating images with DALL-E mini and comparing the top reranked samples utilizing CLIP vs. LogicRank.

**Object Counting**

We start our evaluation with a simple counting benchmark comparing the CLIP ranking and the LogicRank ranking. For this evaluation we first group the images of the MS COCON dataset (Lin et al. 2014) by the number of dogs contained in their annotations. In the bottom row of Fig. 4, we show the produced CLIP scores (y-axis) on such groups (x-axis). The used text prompt for separation with CLIP is:

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prompt: a single dog
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Outliers, of which some are due to false annotations.

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prompt: two dogs
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We only show the best prompt out of several hand-crafted choices.

**Demanding Logical Reasoning**

Next, we move to more complex queries requiring logical reasoning in the text-to-image workflow and analyse the reranking within the generation process. For the entire pipelines of Fig. 1 and 2, we generate images with DALL-E mini and evaluate them with CLIP and LogicRank on the same statements respectively. To compare the ranking methods, we show the top-5 candidates for each method in Fig. 6 for 4 different statements. For each statement we generate 200 samples to also obtain enough qualitative images fitting the description. The candidates are then reranked, in the top rows with our proposed method on the logical rule, and in the bottom row with CLIP on the text-prompt.

For Task1-3, it can be observed that our LogicRank approach stays throughout consistent with the task description.
Figure 6: Top-5 (from left to right) results for several statements, each evaluated with NSFR (top-row) and CLIP (bottom-row) respectively, as described with the workflows Fig. 1 and 2 above. For each statement, 200 samples were generated, except for Task4, as described in text. One can observe that NSFR consistently matches the task description through all tasks, while CLIP confuses count, color, shape and positioning of objects.

while CLIP mixes up color to shape as in Task1 example 1 (from left to right) and 2, positioning as in Task2 example 3, or even the right amount of objects as in Task3 example 1. For the statement of Task4, DALL-E did not create any useful footage. We therefore generated 1500 samples with the statement of Task3, and just reranked them with CLIP and LogicRank respectively. Note that we did not explicitly ask DALL-E to generate images with more than 3 objects, even though we find some with NSFR. Comparing Task3 and 4, it can moreover be observed that CLIP favors the same samples over different statements disregarding the precise text-prompt. Example 1 even remains at the top position. For LogicRank, all 5 results match the description. Overall our method proofs more robust for selecting top samples, even for fairly complex rules.

The CLIP score clearly is not usable as a proper class separator. Throughout the top-5 candidates of all tasks, it remains within a small range giving no hint about the actual missing details, even though the quality differs a lot. As observed with Fig. 3 above, with the proposed LogicRank approach we can unravel the specific attributes and obtain their estimated probabilities. In the scenario of diffusion models, this precise feedback could potentially be used as guidance for specific re-sampling of object-attributes and locations.

**Conclusion**

In this work we demonstrated how language-image multimodels, in particular DALL-E and CLIP, suffer with accurate statements in generation processes as well as for similarity matching. For more accurate text-image similarity matching, we proposed LogicRank. It utilizes an object detector combined with Neuro-Symbolic Forward Reasoning to derive matching probability estimates. The latter approach is clearly able to fulfill the “counting”, “positional” and “colors” categories of the DrawBench prompts (Saharia et al. 2022). More complex rules could consistently be ranked, even for DALL-E generated images unseen before when fine-tuning the DETR model.

In ongoing research we first want build a benchmark dataset to evaluate DrawBench like precision capabilities utilizing LogicRank. We then plan to integrate the reasoner and its probability estimate as additional quality feedback during the diffusion process of DALL-E 2 (Ramesh et al. 2022). We believe it can be used to efficiently guide the model during training as well as inference towards a more precise and expected results. This method should prove more efficient, as it can directly refer to the image and attribute in question.

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7Even for Task1 and Task2, example 1 of Task3 scores the highest with 39.02 and 38.41 respectively- leaving some distance to the other, more precise samples.
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