Human Evaluation of Text-to-Image Models on a Multi-Task Benchmark

Abstract

We provide a new multi-task benchmark for evaluating text-to-image models. We perform a human evaluation comparing the most common open-source (Stable Diffusion) and commercial (DALL-E 2) models. Twenty computer science AI graduate students evaluated the two models, on three tasks, at three difficulty levels, across ten prompts each, providing 3,600 ratings. Text-to-image generation has seen rapid progress to the point that many recent models have demonstrated their ability to create realistic high-resolution images for various prompts. However, current text-to-image methods and the broader body of research in vision-language understanding still struggle with intricate text prompts that contain many objects with multiple attributes and relationships. We introduce a new text-to-image benchmark that contains a suite of thirty-two tasks over multiple applications that capture a model’s ability to handle different features of a text prompt. For example, asking a model to generate a varying number of the same object to measure its ability to count or providing a text prompt with several objects that each have a different attribute to identify its ability to match objects and attributes correctly. Rather than subjectively evaluating text-to-image results on a set of prompts, our new multi-task benchmark consists of challenge tasks at three difficulty levels (easy, medium, and hard) and human ratings for each generated image.
1 Introduction

Spurred by large-scale pretraining on billions of image-text pairs, vision-language models have seen rapid progress in recent years. Large-scale models like CLIP [8] and Flamingo [1] have reported remarkable performance on dozens of benchmarks using a single model, even when using few or no task-specific training samples. Generating high-resolution images given a text prompt has improved in quality to such an extent with models like Stable Diffusion [10], Imagen [12], and DALL-E 2 [9] that their influence has affected popular culture as illustrated in their use to generate magazine covers.[1]

There has been much recent progress in improving text-to-image models, allowing the synthesis of objects within novel contexts [11] such as different backgrounds, illumination, and poses. However, these methods still need help generating images in complex scenes or where compositionality is essential. A critical bottleneck in further progress is the need for rigorous evaluation protocols, as current evaluation methods focus on prompts that do not fully account for the diverse settings these models must support [12].

We propose a new text-to-image generation benchmark covering thirty-two tasks over multiple applications, each targeting a different capability of text-to-image generation models as shown in Table 2. For example, we may ask a model to produce varying numbers of an object to identify its ability to count or to generate an image with an object of a specified shape. We divide each task into three difficulty levels: easy, medium, and hard. For example, suppose the task is to synthesize different numbers of objects. In that case, the task may be easy: generating 1-3 objects, medium - generating 4-10 objects, and hard - generating more than ten objects. Next, we provide ten different instances for each task difficulty level. These instances are specific prompts that implement the tasks. We score text-to-image models on each of the thirty instances (ten for each of the three difficulty levels) for each of the fifty tasks and applications. Specifically, we run our benchmark on DALL-E 2 [9], and Stable Diffusion [10].

We can quantify and compare any new text-to-image generation model with our new benchmark. In this work, we perform a human evaluation of three tasks. Note, however, that many of the tasks may also be evaluated automatically, e.g. by a neural network. For instance, incorporating spatial-aware methods ensures that prompts with spatial relationships and compositional elements are correctly generated. Using OCR mechanisms ensures that quoted text is legible and accurate.

Our key contributions are: (i) developing challenge tasks for state-of-the-art text-to-image generative models, (ii) defining human evaluation procedures, and (iii) Performing a human evaluation for a subset of tasks with 3,600 human ratings, comparing the performance of two of the most common open source (Stable Diffusion) and commercial (DALL-E 2) models.

2 Related Work

Text-to-image models may be roughly split into two types: autoregressive transformer-based models [14] and diffusion-based models [12]. Prior state-of-the-art [2, 4, 5, 11] handles specific limitations of text-to-image models, such as generating an image within the context or modifying object attributes automatically. A comprehensive and quantitative multi-task benchmark for text-to-image synthesis does not exist that covers a diverse set of tasks with varying difficulty levels. Our goal is to develop a benchmark that will become the gold standard in the field for evaluating text-to-image models that will endure time.

Text-to-image models are commonly evaluated by the Inception Score (IS) and the Fréchet Inception Distance (FID). Both of these metrics are based on Inception v3 classifier. These measures, therefore, are designed for the unconditional setting and are primarily trained on single-object images. We have seen several approaches which rectify these shortcomings. Imagen [12] introduced DrawBench, a benchmark with 11 categories with approximately 200 prompts total. Human raters (25 participants) were asked to choose a better set of generated images from two models regarding image fidelity and image-text alignment. Categories are: colors counting, conflicting, DALL-E 2, description, misspellings, positional, rare words, Reddit, text.

DALL-Eval [3] proposed PaintSkills to test skills of the generative models — specified object generation, counting, color, and spatial relations. It utilizes the Unity engine to test these tasks.

https://www.cosmopolitan.com/lifestyle/a40314356
Table 1: Normalized ratings (%) for human evaluation of Stable Diffusion and DALL-E 2 across the three tasks of counting, shapes, and faces. DALL-E 2 outperforms Stable Diffusion on Counting and Faces tasks, and Stable Diffusion shows a minor advantage on the shapes task. On 6 out of 9 sub-tasks, DALL-E 2 produces better images.

Using predefined sets of objects, a subset of MS-COCO [6] objects, colors, and spatial relations. We propose a more comprehensive benchmark of tasks at a finer level of detail, with three difficulty levels. Localized Narratives [7] is a multi-modal image captioning approach that can be adapted to benchmarking images. Text captions are first generated by human annotators whose cursor movement and voice commentary hover their cursor over the image to provide richness and accuracy. PartiPrompts, a holistic benchmark of 1,600 English prompts [13], compared to Localized Narratives, is better in probing model capabilities on open-domain text-to-image generation. The 1,600 prompts span 12 different categories and 11 challenge aspects. The 12 categories are artifacts, animals, indoor scenes, produce and plants, abstract, arts, food & beverage, vehicles, illustrations, outdoor scenes, people, and world knowledge, while the 11 challenge aspect are basic, fine-grained detail, properties & positioning, linguistic structures, perspective, quantity, writing & symbols, complex, imagination, style & format and simple detail. The image quality and the alignment of the generated image with the input text are evaluated.

3 Methods

We create a comprehensive multi-task text-to-image generation benchmark of thirty-two diverse tasks, as shown in Table 2. The motivation behind selecting benchmark tasks is to cover a wide range of downstream applications that benefit from high-quality text-to-image models, including: (1) graphic design (generating new designs for websites), (2) e-Commerce (generating personalized ads), (3) architectural planning and design (generating new renderings of buildings, interior design, and creative home design), (4) real-estate listings (generating furnished versions of unfurnished apartment and house photos for advertisement), (5) education (generating personalized digital learning interfaces with customized enhancements), (6) user interface and user experience (generating design templates for mobile and desktop applications), (7) stop-motion video (generating frames for short animations), (8) cosmetics (generating realistic images showcasing products), (9) stock photos (generating large amounts of stock images for general audiences), (10) product design (quickly prototyping digital and physical products), (11) illustrations (generating professional artwork for custom purposes), (12) synthetic data (generating synthetic data for boosting training samples size), (13) social media (generating memes and shareable content), (14) image recommendation (generating recommendations based on user preferences), (15) gaming (using natural language to create complex scenes for video games), (16) proteomics (designing new proteins visualizing existing structures), (17) material science (designing new crystals).

We use the benchmark to compare different models, comparing Stable Diffusion [10] and DALL-E 2 [9], and identify their limitations. Our evaluation protocol consists of human ratings between 1 (worst) and 5 (best) of tasks at three difficulty levels. The three difficulty levels are currently assigned heuristically based on the experience with failure modes of generative models. Examples of cases in which human evaluation is required are: (i) concepts that are difficult to define, such as successfully combining objects that are rarely co-occurring in the real world; (ii) complex tasks, such as images that require common sense; and (iii) cases where human expertise is essential such as generating images without racial or gender bias. We obtained 3,600 human ratings: twenty graduate students, two models, three difficulty levels, and ten prompts each. The images were all generated with identical default model parameters and evaluated on the same scale, scoring between 1 (worst) and 5 (best).

Publicly available [https://beta.dreamstudio.ai/]
Table 2: Multi-task text-to-image benchmark and applications: we propose a series of tasks on which text-to-image models could be evaluated. The tasks are selected to cover a multitude of downstream applications.

| Id | Task |
|----|------|
| 1  | Generating a specified number of objects |
| 2  | Generating objects with specified spatial positioning |
| 3  | Combining objects very rarely co-occurring in the world |
| 4  | Generating images obeying physical rendering rules of shadows, reflections, and acoustics |
| 5  | Generating objects with specified colors |
| 6  | Generating conflicting interactions between objects |
| 7  | Understanding complex and long text prompts describing objects |
| 8  | Understanding misspelled prompts |
| 9  | Handling absurd requests |
| 10 | Understanding rare words |
| 11 | Incorporating quoted text with correct spelling |
| 12 | Understanding negation and counter-examples |
| 13 | Understanding anaphora and phrases that refer to other parts of the prompt |
| 14 | Aligning text as specified in the prompt |
| 15 | Generating common-sense images |
| 16 | Removing objects without needing manual annotation |
| 17 | Removing content that is not child-safe |
| 18 | Editing the color of objects without marking them manually |
| 19 | Replacing objects without marking them manually |
| 20 | Generating objects with abstract shapes |
| 21 | Objects obeying physics rules |
| 22 | Generating images without racial or gender bias |
| 23 | Understanding comparative concepts like fewer and more |
| 24 | Photo-realistic faces |
| 25 | Understanding prompts regarding weather |
| 26 | Handling multi-lingual prompts |
| 27 | Duplicating objects perfectly |
| 28 | Generating multiple camera viewpoints of the same scene |
| 29 | Generating realistic faces with a specific emotion |
| 30 | Generating well-known faces |
| 31 | Generating a thumbnail summary for text and video |
| 32 | Changing dimensions of an image without losing information |

4 Results

We survey twenty students that evaluate the performance of Stable Diffusion and DALL-E 2. Each student evaluated the three tasks at three levels of difficulty and ten prompts each, providing a rating between 1 (worst) and 5 (best). We collected a total of 3,600 scores. The results are summarized in Table 1 and a detailed breakdown of the evaluations by prompts are available in Table 3 of the Appendix. Our human evaluation shows that DALL-E 2 (65.7%) performs better on the counting task than Stable Diffusion (54.4%). On the Faces tasks, both models perform very well, and DALL-E 2 (81.7%) performs better than Stable Diffusion (70.2%), and on the Shapes task, both models perform equally well (56.8% compared to 57.6%). Performance gracefully degrades as the tasks are more difficult, except for DALL-E 2, which performs slightly better on the hard than on the medium Shapes task.

5 Conclusion

We propose a new quantitative way of evaluating text-to-image generative models using a benchmark covering many model competencies and applications. Initial human evaluation on a subset of benchmark tasks shows a slight advantage of DALL-E 2 over Stable Diffusion. Our proposed benchmark allows for testing individual competencies and limitations of the different generative models. Understanding the limitations is critical for picking the suitable model for each task and application, advancing the quality of generative models, and aligning their performance with human goals.
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## Appendix

| Difficulty  | Easy DALL-E 2 | Medium DALL-E 2 | Hard DALL-E 2 |
|-------------|---------------|----------------|--------------|
| Prompt / Model | SD  | SD  | SD  | SD  |
| 1           | 96 | 69 | 30 | 57 |
| 2           | 93 | 62 | 28 | 52 |
| 3           | 49 | 34 | 22 | 61 |
| 4           | 87 | 38 | 37 | 44 |
| 5           | 51 | 77 | 46 | 57 |
| 6           | 97 | 54 | 35 | 82 |
| 7           | 92 | 51 | 47 | 48 |
| 8           | 67 | 38 | 37 | 45 |
| 9           | 43 | 43 | 30 | 55 |
| 10          | 73 | 56 | 49 | 39 |

| Difficulty  | Easy DALL-E 2 | Medium DALL-E 2 | Hard DALL-E 2 |
|-------------|---------------|----------------|--------------|
| Prompt / Model | SD  | SD  | SD  | SD  |
| 1           | 69 | 79 | 66 | 73 |
| 2           | 82 | 83 | 70 | 69 |
| 3           | 76 | 76 | 68 | 80 |
| 4           | 97 | 70 | 91 | 91 |
| 5           | 23 | 81 | 58 | 90 |
| 6           | 75 | 71 | 74 | 77 |
| 7           | 60 | 91 | 53 | 95 |
| 8           | 58 | 76 | 41 | 81 |
| 9           | 96 | 74 | 59 | 51 |
| 10          | 89 | 74 | 62 | 65 |

| Difficulty  | Easy DALL-E 2 | Medium DALL-E 2 | Hard DALL-E 2 |
|-------------|---------------|----------------|--------------|
| Prompt / Model | SD  | SD  | SD  | SD  |
| 1           | 93 | 73 | 36 | 41 |
| 2           | 94 | 49 | 67 | 64 |
| 3           | 89 | 32 | 44 | 62 |
| 4           | 85 | 48 | 44 | 50 |
| 5           | 49 | 69 | 30 | 66 |
| 6           | 89 | 45 | 47 | 71 |
| 7           | 52 | 65 | 34 | 70 |
| 8           | 37 | 32 | 49 | 47 |
| 9           | 79 | 84 | 51 | 37 |
| 10          | 41 | 71 | 49 | 65 |

Table 3: Normalized ratings (%) for human evaluation of Stable Diffusion and DALL-E 2 across the three tasks of counting, shapes, and faces for each of the ten prompts.
### Counting Task

#### Easy (1-3 typical number of objects)

| Task Description |
|-------------------|
| 1. Lioness hiding in the grass |
| 2. Tennis ball on the court |
| 3. Park alley with a single streetlight |
| 4. Three people crossing the street |
| 5. Desert road with two cars on it |
| 6. Person holding three toy pyramids |
| 7. Two giraffes eating leaves off a tree |
| 8. Cup with three spoons sticking out of it |
| 9. Bench in a park with two backpacks on it |
| 10. Three people having a conversation in a restaurant |

#### DALL-E 2

| Task Description |
|-------------------|
| 1. Computer desk with six laptops |
| 2. Four chopsticks laying by the plate |
| 3. Person juggling four rings in a circus |
| 4. Configuration of six bowling pins on a bowling lane |
| 5. Seven fire hydrants in a row by the street |
| 6. Five photographs prints are hanging to dry in a dark room |
| 7. Pencil drawing of a table with eight chairs around it |
| 8. Close-up photo of seven grains of buckwheat on a plate |
| 9. Grocery store parking lot with eight empty spaces |
| 10. Clip art of nine children doing a circle dance around a Christmas tree |

#### Medium (4-10 atypical number of objects)

| Task Description |
|-------------------|
| 1. Painting of seventeen horses in a field |
| 2. Person carrying a stack of twelve books |
| 3. Drawing of a pyramid of ten champagne glasses |
| 4. Coffee table with a five-by-five chess board on it |
| 5. Architectural render of twenty-story building in the city |
| 6. Two people juggling ten balls together |
| 7. Birthday cake with exactly seventy candles on it |
| 8. Office room with five desks and seven chairs |
| 9. Drone photo of twelve boats arranged in three rows |
| 10. Aquarium with fourteen golden fish in a hotel lobby |

#### Hard (10+ objects with other numerical concepts in prompt)

| Task Description |
|-------------------|
| 1. Lioness hiding in the grass |
| 2. Tennis ball on the court |
| 3. Park alley with a single streetlight |
| 4. Three people crossing the street |
| 5. Desert road with two cars on it |
| 6. Person holding three toy pyramids |
| 7. Two giraffes eating leaves off a tree |
| 8. Cup with three spoons sticking out of it |
| 9. Bench in a park with two backpacks on it |
| 10. Three people having a conversation in a restaurant |

Figure 1: Evaluation of image generation on a counting task at various difficulties. Each panel contains tasks with different difficulties. The columns correspond to the text prompt, and the rows correspond to the model used to generate the image: (i) Stable Diffusion and (ii) DALL-E 2. The prompts used to generate the images are classified into three different difficulties: (i) easy difficulty tasks consisting of generating 1–3 objects, e.g., two cars, three people; (ii) medium difficulty tasks consisting of generating 4–10 objects, including uncommon combinations of quantities and objects, e.g., six bowling pins, seven fire hydrants; (iii) hard difficulty tasks consisting of 10 or more objects with other numerical concepts in the prompt, e.g., twelve boats arranged in three rows.
### Shapes Task

#### Easy (simple shapes)

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|-----|
| Star shape | Circle shape | Triangle shape | Rectangle shape | Square shape | Oval shape | Diamond shape | Semicircle shape | Hexagon shape | Pentagon shape |

#### Medium (entity in the form of a shape)

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|-----|
| Diamond shaped bush | TV shaped like an octagon | Triangular shaped cell phone | A rug in the shape of a trapezoid | Pyramid shaped waterfall | Hexagonal maze made of sand | Lamp shaped like a diamond | A brick in the shape of a semicircle | Cake in the shape of a five-pointed star | Eraser in the shape of a parallelogram |

#### Hard (multiple entities with specified shapes)

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|-----|
| Conical green toy in a triangular maze | A dodecahedron made of wood in a glass sphere | Five-pointed star medal and a cubic chair | Pyramid shaped cake and a cylindrical sandcastle | Guitar with a rectangular shape by a hexagon shaped window | A triangular tree with heart shaped leaves | Square shaped water bottle next to a semicircular orange | Rectangular hat decorated with circles and hexagons | An octagon shaped cookie on a heart shaped plate | A pear-shaped sponge floating in a square plastic basin with water |

Figure 2: Evaluation of image generation on a shape task at various difficulties. Each panel contains tasks at different difficulties where the columns correspond to the text prompt, and the rows correspond to the model used to generate the image: (i) Stable Diffusion and (ii) DALL-E 2. The prompts used to generate the images are classified into three different difficulties: (i) easy difficulty tasks consisting of generating simple shapes, e.g., circle, star; (ii) medium difficulty tasks consisting of generating entities in the form of a shape, e.g., hexagonal maze, octagonal TV; (iii) hard difficulty tasks consisting of multiple entities, each of a specified shape, e.g., square-shaped water bottle next to a semicircular orange.
Figure 3: The prompts used to generate the images are classified into three different difficulties: generating photo-realistic faces given (i) easy: 1 to 2 features for an individual; (ii) medium: different 1 to 3 features for each individual in a group of 1 to 2 people with easy angle and posture; (iii) hard: given more than two features for each individual in a group of more than two people with challenging angle, posture, lighting or occlusion. Asterisk (∗) indicates a failure to generate an image because of the model’s content filters.