The Language of Sketches

Xiaoyu Zhang

CMU-CS-22-111
May 2022

Computer Science Department
School of Computer Science
Carnegie Mellon University
Pittsburgh, PA 15213

Submitted in partial fulfillment of the requirements for the degree of Master of Science in Computer Science.

Keywords: multimodal machine learning, creative AI, text-to-image synthesis, sketch generation, sketch data collection

Abstract

Creative AI has seen much progress in recent years. Works like DALL-E 2 can generate inspiring art pieces from text descriptions. Instead of synthesizing realistic art works from language, we approach creativity from a different angle and investigate composition of semantic parts and visual concepts in sketches. For example, people can draw a circle to represent the moon, a scoop of ice-cream, or the face of a cat. Similarly, language descriptors can be composed to create new concepts. People can draw a large round cat face or a narrow oval cat face.

In order to study this reuse of abstract concepts, we construct a dataset of language annotated sketches. We examined current sketch datasets and found that they either lack language annotations or semantic part annotations. Therefore, we collect a dataset of 11,150 (sketch part, text) pairs for 572 face sketches and 787 angel sketches.

To understand the limits of current vision-language models, we fine-tuned CLIP, a model pre-trained with a contrastive objective on 400 million (image, text) pairs and can map (image, text) pairs into a joint vision-language embedding space. We observed that (1) CLIP cannot easily generalize to an unseen category on the task of pairing sketches with their descriptions even though similar shapes and descriptions have occurred in training; (2) through fine-tuning, average cosine distance has increased between a pair of descriptors used by annotators to differentiate two sketches. With insights gained about how language and sketches interact in the CLIP embedding space, our aim is to facilitate research into models that can generate sketches in a part-based manner satisfying descriptions given by users of the pictures they have on their minds.

Acknowledgements

I first and foremost thank my advisors, Professor Oliver Kroemer and Professor Yonatan Bisk, for advising me on this project. I am very grateful that I had the opportunity to explore the creative sketching domain with them during my Master's. Through working with them on this project, I have learned how humans use language creatively to describe sketches, and I am excited about building systems that can interact seamlessly with humans in the future. I want to thank Professor Jean Oh for serving on my committee.

I also want to thank my lab mates in the IAM and COMEDY lab (the name *COMEDY* was coined in April 2022 😄). Thank you guys for testing the numerous beta versions of my data collection interface and providing feedback without which the official deployment would not have been successful.

I thank my parents for encouraging me to pursue research topics that I enjoy. Thank you guys for listening to me all the time.

Contents

Chapter 1

Introduction

Creative AI, such as using deep learning models to generate paintings and music, has been a popular research domain. Since creative activities are hallmarks of human intelligence, numerous works have attempted to replicate the creative process on machines. For example, Pharmako-AI (Allado-McDowell & Okojie, 2020) is a book co-written by K Allado-McDowell and GPT-3 (Brown et al., 2020) through exchanges between the person and the language model. Works like DALL-E, GLIDE, and DALL-E 2 tackle the problem of synthesizing images from short language descriptions, and these generative models have produced many imaginative and inspiring art pieces (Ramesh et al., 2021; Nichol et al., 2021; Ramesh et al., 2022). These work are often motivated by the vision to create machines that can interact with people and augment human creativity. Our work is driven by a similar vision: how can we build systems that can be creative like humans so that AI agents and people can participate in creative activities together and inspire each other.

Instead of generating realistic art works from a wide variety of language like DALL-E, we approach creativity from a different angle and investigate composing basic visual concepts in object sketches. An example is illustrated in Figure 1.1: a triangle can be the sail of a boat, the cone of an ice-cream, the left/right ear of a cat, the roof of a house, the canopy of a tree, or the body of a mountain. The same triangle is adapted to become different parts in sketches of different objects. While sketches contain much fewer details compared to their natural images counterparts, people are not any less creative when sketching. One could say that the abstractness allows for more creativity.

Similarly, language descriptors can be composed to form new concepts applicable to different objects. For example, combining *large* and *round* or *narrow* and *oval* to describe different kinds of cat faces. Many other objects can be *large round* or *narrow oval*: angel halo, glasses, mirror, plate, necklace charm, table, etc. Moreover, there are multiple ways to describe the same sketch,

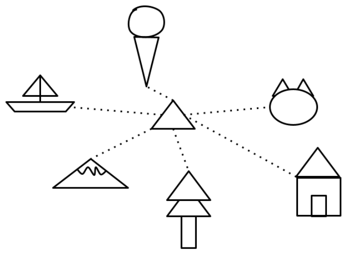


Figure 1.1: Triangle is adapted and composed with other shapes to create sketches of different objects. The objects are, from the top and in clockwise order: *ice-cream, cat, house, pine tree, mountain*, and *boat*.

depending on the person's viewpoint. *What features does this cat sketch have?* (Figure 1.2) Some people might pick up on its long pointy ears; others might notice its slightly edged chin, and there are still others that focus on the long whiskers curving upwards. People are likely to provide a variety of responses.

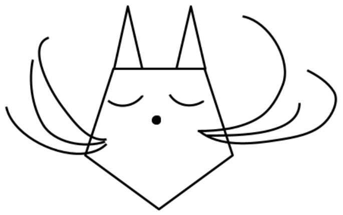


Figure 1.2: People are likely to provide a variety of descriptions when asked, *"What features does this cat sketch have?"*.

We want to build systems that can compose basic shapes in a creative manner and understand how words are combined and adapted to describe different objects. In this thesis, we are interested in semantic parts in sketches and how people describe them. For example, a face sketch may contain four semantic parts: eyes, nose, mouth, and face contour, that can be drawn using various geometric shapes with different features. After examining existing sketch datasets, we found that they do not contain either language annotations or semantic part annotations. We explain the details of related sketch datasets in Chapter 2. To fill the gap and study this reuse of abstract concepts, we construct a dataset of language-annotated face and angel sketches. We elaborate on the data collection process in Chapter 3.

Moreover, we hope to understand the limits of current vision-language models, such as Contrastive Language-Image Pre-Training, or CLIP, which is trained on millions of image-text pairs. CLIP has been used extensively to provide a loss function for optimizing text-to-image synthesis models (Frans et al., 2021; Ramesh et al., 2022; Gal et al., 2021; Patashnik et al., 2021). Despite the abundance of knowledge captured by CLIP's embedding space, we observed that CLIP, trained to associate natural images with their captions, has difficulty matching sketches from unseen categories with their part descriptions, suggesting that they might not understand that sketches from different categories are composed of parts different in semantics but share similar shapes and descriptions. We explain the details of CLIP and the fine-tuning process in Chapter 4. We analyze CLIP's performance and changes in its text embeddings after fine-tuning on our dataset in Chapter 5.

Chapter 2

Related Work

In this chapter, we survey two areas of related work: sketch datasets and sketch generation. There has been a proliferation of work on sketch representation learning (Ha & Eck, 2017; Eitz et al., 2012; Li et al., 2018; Yu et al., 2016; Ge et al., 2020; Kim et al., 2019; Aksan et al., 2020; Ribeiro et al., 2020; Chen et al., 2017; Lin et al., 2020). To study how humans compose descriptors and shapes in sketches, we look into what annotations current sketch datasets contain and found that they lack either semantic part labels or language descriptions of the parts (Section 2.1). These datasets were created to solve classical computer vision tasks, such as recognition, segmentation, retrieval, whole-sketch generation, etc. We will then look into generative models of sketches in Section 2.2. Although there have been many works on generating natural images, sketch generation has its own unique challenges: sketches contain sparse information and might bear little resemblance to their natural image counterparts; moreover, they illustrate features of the objects in an abstract way, such as a triangle as the house roof or a letter V as the ice-cream cone.

2.1 Sketch Dataset

TU-Berlin Eitz et al. (2012) is one of the first works to investigate the characteristics of free-hand sketches and attempt to extract local features based on orientation, which are later used in the task of sketch recognition. It also provides the TU-Berlin sketch dataset that contains $20,000$ sketches spanning 250 object categories with 80 samples in each. The TU-Berlin dataset is then extended for sketch-based 3D object retrieval to contain 1814 new sketches for 130 common household object categories. This additional set also contains hierarchical category labels; for example, in the label hierarchy, the descendant categories of the *animal* category are: *arthropod, biped, human, flying* *creature, quadruped,* and *underwater creature.* The TU-Berlin dataset contains some of the highest quality sketches for a wide range of categories, but they lack both text descriptions and semantic part annotations, and our dataset contains both types of annotations, although only for simpler sketches in the face and angel category.

Datasets with Text Descriptions The QMUL dataset contains sketches of shoes and chairs: 419 shoe sketches of various types of shoes, such as high heels, boots, and ballerina flats, and 297 chair sketches of different kinds (Yu et al., 2016). Although QMUL annotates for attributes of the sketches, they come from a fixed set of descriptions and are obtained from product tags, so these descriptions do not reflect how humans would creatively describe the drawings on their mind, which is a feature of our collected dataset. The Sketchy dataset contains $75,000$ sketches of 125 categories, and each sketch is paired with an image. Sketchy is additionally annotated with sketch validity metrics and short descriptions from annotators (Sangkloy et al., 2016). However, these descriptions are more like comments given by the participants, and the collecting process is not carefully designed, unlike our data collection process, where obtaining the text description is the main focus. Moreover, the short texts in Sketchy do not describe individual semantic object in the sketches.

QuickDraw Dataset The QuickDraw dataset is one of the largest sketch datasets, containing 50 million sketches distributed across 345 object categories. Each category has about 100,000 sketches (Ha & Eck, 2017). Annotators for the TU-Berlin dataset have 30 minutes to draw one sketch, and annotators for the QMUL dataset have reference photos for the sketches they are asked to draw; on the other hand, participants of Quick,Draw! have 20 seconds to create the sketches for a randomly assigned category without time to look for reference, so sketches in the QuickDraw dataset are the simplest. However, since sketches that failed to be recognized by a classification model are filtered, they are in general of good quality and are representative of the general population drawing skills. Moreover, many works on sketch representation learning use the QuickDraw dataset, so utilizing these sketches would allow us to adapt other pre-trained generative models to model our dataset. However, the QuickDraw dataset contains neither semantic part annotation nor language descriptions, and our collected dataset contains both.

Datasets with Semantic Part Annotations The sketches in our dataset come from the QuickDraw dataset, but the original QuickDraw dataset does not provide labels for semantic objects in the sketches. The Sketch Perceptual Grouping (SPG) dataset (Li et al., 2018) and the SketchSeg dataset (Qi & Tan, 2019) contain annotations for semantic segmentation, meaning that each stroke in a sketch is paired with a semantic label. For example, strokes in a face sketch are assigned one of the following labels: *eyes, nose, mouth, ear, hair, moustache, outline of face.* The SPG dataset annotates for $25,000$ QuickDraw sketches, belonging to 25 (out of 345) categories, and it selects

800 out of the original $100,000$ sketches in each category for annotation. The SketchSeg dataset builds upon the SPG dataset by using a recurrent neural work to generate additional sketches from one sketch in SPG; since each stroke in the generated sketch corresponds to a stroke in the original sketch, it automatically has part annotations. However, since the quality of the generated sketch is dependent upon the generative model, we choose the original SPG dataset, which is also publicly available. The SPG dataset does not contain text descriptions like our dataset, so we cannot study how people describe their sketches using SPG alone.

SketchCUB Yuan et al. (2021) collects a dataset, SketchCUB, of sketches and captions by transforming realistic images in the CUB dataset (Wah et al., 2011) into sketches with holistically-nested network (HED) (Xie & Tu, 2015). These sketches in the SketchCUB dataset are not done by humans and might not be representative of how the general population sketch, compared to those in QuickDraw. The SketchCUB dataset contains 10K sketches over 200 different categories of birds. Moreover, the original CUB dataset collects the captions by presenting to the annotators a fixed set of attributes and asking them to determine whether the bird has the attribute or not. There are a total of 312 binary attributes, and they are traditionally used to determine species of birds in nature. Therefore, the captions might not represent how people describe sketch parts. The SketchCUB text descriptions are also for the whole sketch and not for individual semantic part in sketches. In comparison, our dataset annotates for semantic parts in QuickDraw sketches, and we do not limit the annotators with a predefined list of words, so the descriptions tend to be more diverse and creative. There are a total of 1450 different words in our dataset.

2.2 Sketch Generation

Sketch-RNN Along with the QuickDraw dataset, Ha & Eck (2017) introduces Sketch-RNN and provides a web demo of collaborative drawing, where users can select a category and draw the first few strokes of a sketch, and the model will complete the rest of the sketch[1]. Sketch-RNN uses a variational autoencoder (VAE) with bidirectional RNN encoder and RNN decoder.

Ha & Eck (2017) uses a vector format to represent the sketches: each sketch is a set of strokes, and each stroke is a sequence of points, so the smooth curve is approximated with piecewise linear splines created by connecting adjacent points in the sequence. Works in sketch representation learning can be grouped into those that represent the input in this stroke-point vector format and those that treat the entire sketch as a raster image. Each point is a 5-component vector, $(\delta x, \delta y, p_1, p_2, p_3)$: the first two components represent changes in the (x, y) coordinate of the current point compared to the last one; the last three make up a one-hot vector representing current state of the sketch.

[1]You can access the demo from this website `https://magenta.tensorflow.org/sketch-rnn-demo`

Let $s = \begin{bmatrix} p_1 & p_2 & p_3 \end{bmatrix}$, if the current point will be connected with the next point, $s = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$; if the current point is the last point in the current stroke, so the pen is expected to be lifted next, then $s = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}$; if the current point is the last point in the sketch, then $s = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$. The RNN encoder takes this sequence as input and uses the final hidden state h of the RNN to parameterize Gaussian distributions of size N_z, from which a latent random variable $z \in \mathbb{R}^{N_z}$ is sampled. The latent z will be used to (1) initialize the hidden state h_0 of the RNN decoder and (2) be concatenated with the vector at each time step and fed as input into the decoder. The RNN decoder predicts parameters for distributions (Gaussian mixture model for sampling $\delta x, \delta y$ and categorical distribution for sampling p_1, p_2, p_2) at each time step from the hidden states of the RNN. Since the decoder works in an autoregressive manner, it can *encode* the first few strokes provided by the users into a hidden vector, which is conditioned on for later steps to produce distributions of points that make up the rest of the sketch.

Although our work uses the QuickDraw sketches, we render the vectors into raster images in order to use CLIP and its vision-language joint embeddings, since compared to Sketch-RNN, we need to incorporate text descriptions of the sketch parts. It is challenging to align semantic information in text with distributions of the x, y coordinates. While language gives high-level guidance on how strokes are organized on canvas to illustrate a particular concept, the coordinate information is too low level if directly used without an intermediate level of abstraction to aggregate these low-level sequence.

DoodlerGAN DoodlerGAN (Ge et al., 2020) is a recent work on creative sketching and represents sketches as raster images. It uses Generative Adversarial Network (GAN) to model the sketches[2]. Compared to Sketch-RNN, which can only complete the missing parts of sketches once users are done with their parts, DoodlerGAN generates sketches using a part-based approach. In this way, users and the system can take multiple turns to create sketches.

The part-based GAN has two networks: a part selector and a part generator. Given an incomplete sketch with some parts drawn (for example, a bird with its eyes and beak), the part selector determines what kind of part to draw next (for example, the bird wings). Then given the partial sketch and the category of the next part, the part generator produces a raster image of the part and its location on canvas. The part generator is a conditional GAN derived from StyleGAN2 (Karras et al., 2019), and it takes as input an image with number-of-parts+1 channels: one channel for each part and an additional channel for the whole partial sketch. The part selector uses the encoder of the part generator with an extra linear layer at the end as the classification head.

While the part-based generation aspect of DoodlerGAN aligns with our goal to study composition of shapes in sketches, there is no language associated with each part, and the generation process is

[2]Try the DoodlerGAN demo here: `http://doodlergan.cloudcv.org/`

not guided by language supervision. As indicated by Ge et al. (2020), compared to vector inputs, raster images can take better advantage of spatial structure of sketch parts. We believe that there is a shared abstractness in sketches and language, and we want to explore this aspect by first collecting a (semantic part, language description) dataset and then learning a part-based generative model from language.

SketchBird Along with SketchCUB, Yuan et al. (2021) introduces a GAN-based model that generates sketches of birds from captions. The model architecture is based on AttnGAN (Xu et al., 2017). A bidirectional long short-term memory (Bi-LSTM) network is used as the text encoder, which is trained with image-text pairs while minimizing the Deep Attentional Multimodal Similarity Model (DAMSM) loss, proposed in AttnGAN. This loss is calculated based on attention-driven text-image matching score, which is the dot-product similarity between words in the caption and image subregions.

Although SketchBird is one of the few works that look at sketch generation from language, it is limited by the dataset that it is trained and evaluated on: as explained earlier, the SketchCUB dataset does not contain human-drawn sketches, and the captions come from a list of predefined attributes. On the other hand, our work is motivated by how people can express high-level concepts, such as *circular*, through a variety of language, *round*, *moon-shaped*, *ringlike*, *disk-shaped*, and how these type of free-form language can be composed and used to generate abstract sketches, similar to those in the QuickDraw dataset.

Chapter 3

Data Collection

To study the composition of visual concepts, we need to collect a sketch dataset that contain both semantic part and language annotations. We tested two ways of collecting such dataset. Initially, in order to create a dataset with creative composition of shapes, such as the use of triangle in different sketches illustrated in Figure 1.1, we designed text prompts like *happy angel* and asked annotators to draw sketches in response to the prompts while annotating each step in their drawings. After deployment of pilot, although we collected many creative sketches, we saw major problems related to misalignment between the drawn parts and the text descriptions. We explain this prompt-guided design and its associated problems in Section 3.1.

After re-design, we leverage existing sketch datasets, QuickDraw and SPG (both explained in details in Section 2.1), to solve the problems of low-quality part and text annotations unusable for model learning. In the new version, we present two sketches at a time to annotators, where the sketches contain semantic parts that are visually contrasting to aid annotators in coming up with creative descriptions. We walk through the process of designing this *contrasting* interface in Section 3.2. After receiving satisfactory pilot results, we deployed this version full scale on Amazon Mechanical Turk (AMT); we present statistics of the dataset and explain how it allows us to study creative composition of abstract concepts in Section 3.3.

3.1 Prompt-Guided Sketch Text Dataset

3.1.1 Overview

When we first started designing our data collection interface, we wanted to collect sketches for prompts similar to the ones used in DALL-E (Ramesh et al., 2021): creative composition of attributes and objects that are not commonly associated. For example, *an evil cup of bubble tea* and *happy moon*. In addition to sketching, we require annotators to decompose their drawings into steps and provide descriptions for each step. We hope to discover combination of simple shapes like examples in Figure 1.1. Moreover, we expect that the imaginative prompts would result in creative sketches and diverse part descriptions.

We deployed the data collection interface on Amazon Mechanical Turk (AMT), which is a crowd-sourcing website that hosts different machine learning annotation tasks. In the remaining text, we use the word *turker* to refer to annotators we recruit on AMT; we will also use the word *HIT*, Human Intelligence Task, to refer to a task hosted on AMT. Please refer to AMT FAQs for more information on AMT.

For each HIT, we need to design: (1) the main interface for data collection; (2) instruction and requirements explaining the dos and don'ts; (3) qualification task to train turkers to provide high-quality annotations. After deploying the pilot, we realized a few major problems with this design. Firstly, due to the subjective nature of sketching, although the sketches are very creative, it is hard to understand how some annotators are illustrating the given prompts. Moreover, turkers are taking more than 30 minutes for each task, and, most importantly, many descriptions do not align with the drawn objects, making the data difficult to use for model learning. For example, in one step, an annotator drew the entire cat face, but they only annotated *big eyes*.

3.1.2 Interface Design

Main Task Interface

We illustrate a typical annotation process in Figure 3.1. The annotator draws a step on the canvas, enters text description for this step in the *Annotation* column, and hits *Add* to display it as a new row in the annotation table. For the annotator's convenience, we include an *Undo* button and a *Clear* button for erasing strokes and clearing the entire canvas. If the annotator wants to remove an entire step, including the drawing and the text description, they can use the *Delete* button. An example is shown in Figure 3.2. Repeat the drawing-and-adding process until the drawing is done.

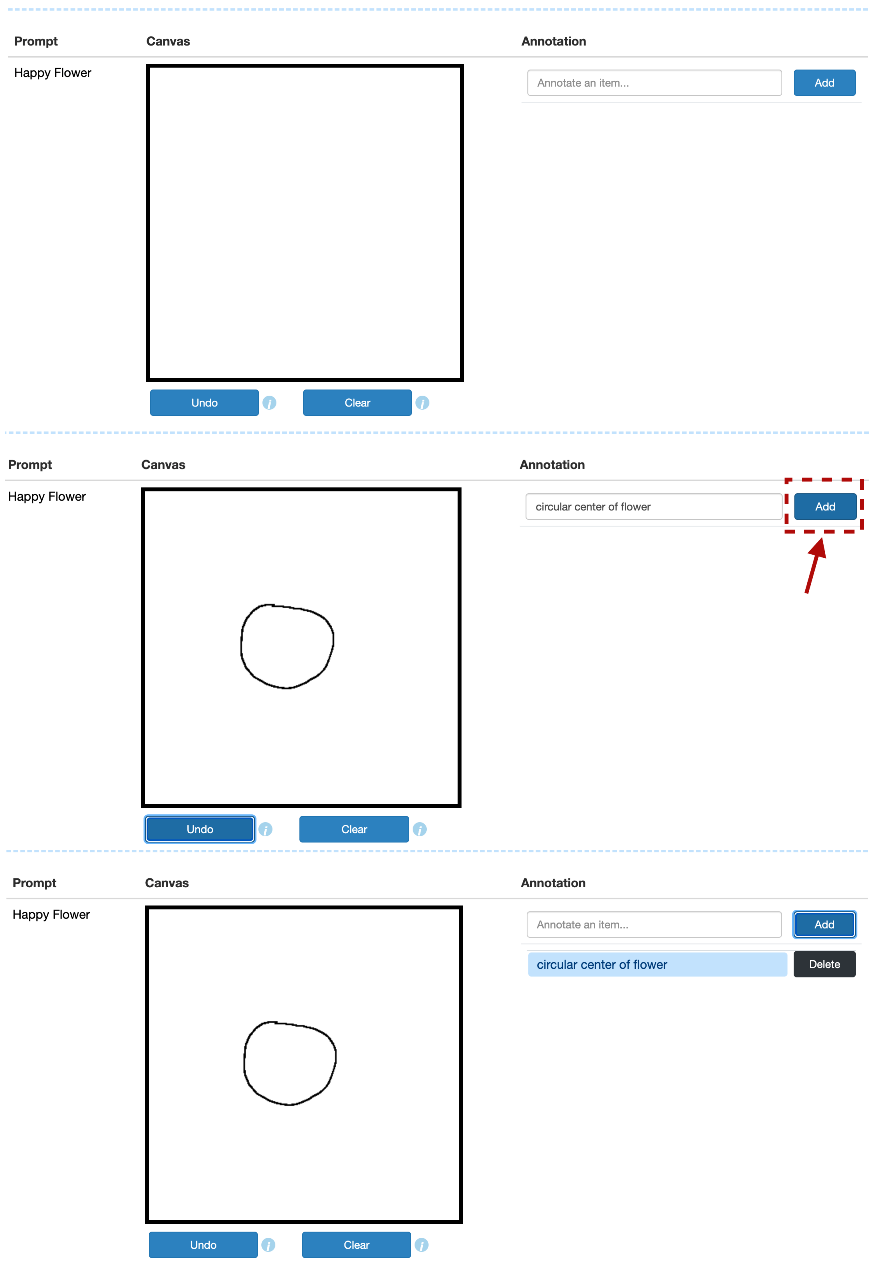


Figure 3.1: A typical annotation process. Top: interface at the start of annotation. Middle: before adding text descriptions for the drawing; red arrow and box show where to click to add text. Bottom: after adding text descriptions for the flower sketch.

This design encourages turkers to decompose their drawings into semantically meaningful parts.

We encountered some difficulties when implementing the *Delete* button. At the beginning, we treated erasing strokes as drawing the same strokes but in white; however, when strokes overlap each other, overwriting with white strokes breaks other strokes into segments. Therefore, we change the

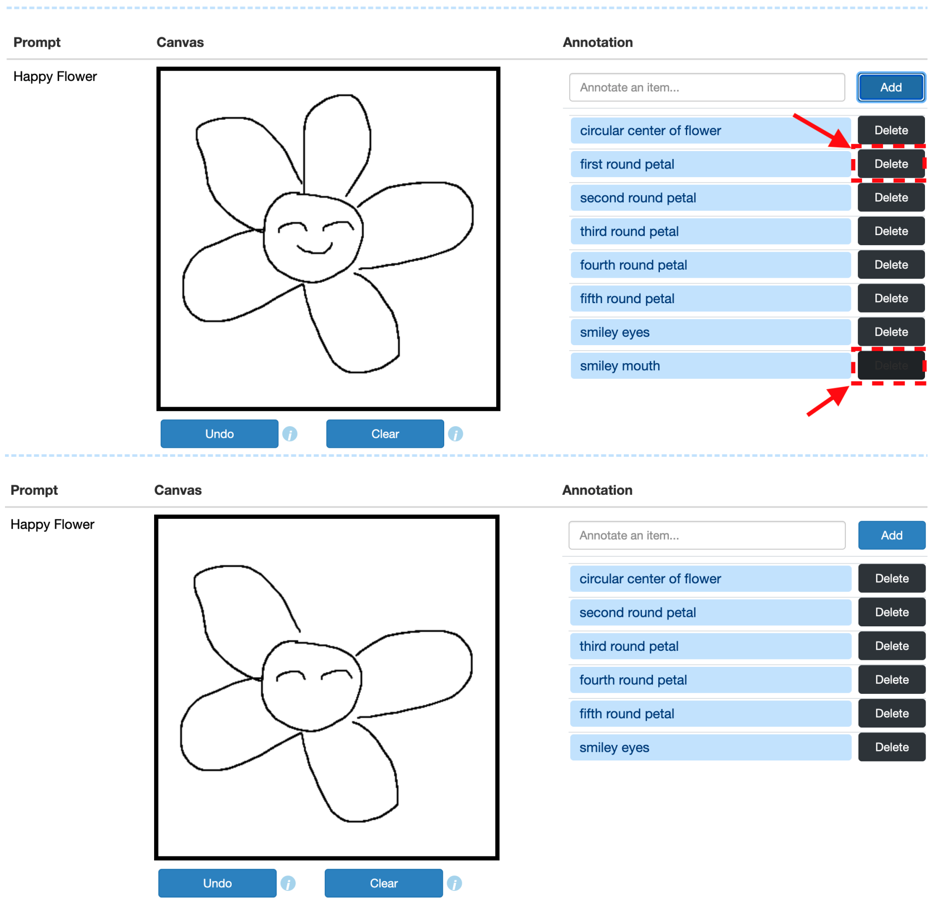
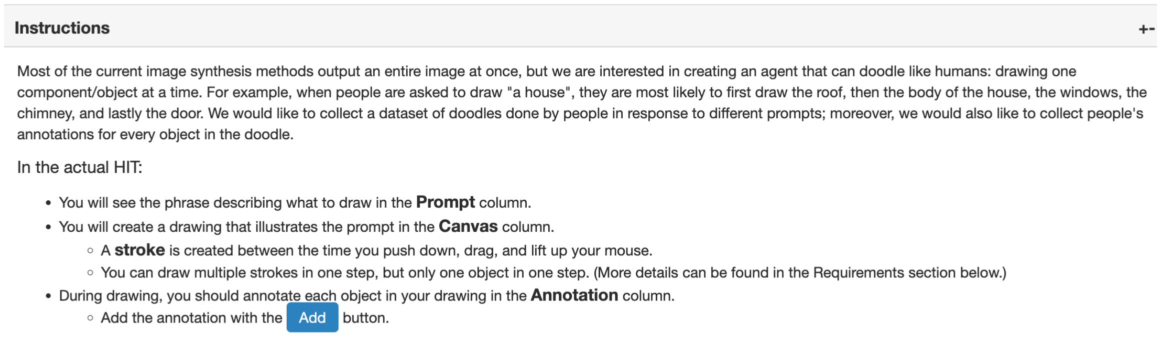


Figure 3.2: Top: the completed annotation for the prompt *Happy Flower*. Red arrows and boxes point to *Delete* buttons that can delete the text annotations along with their drawings. Bottom: after deleting the steps *first round petal* and *smiley mouth*.

drawing canvas to use layers like Photoshop, so that deleting strokes would be the same as deleting an entire layer, leaving other strokes intact.

Instruction and Requirement

To ensure that turkers understand the purpose of collecting the dataset, the instruction begins with the motivation behind this project (Figure 3.3). What we struggled the most when drafting the requirements was deciding what a single *step* in sketching was; how do we clearly explain this definition to the turkers? We considered providing a list of geometric shapes, such as rectangle, triangle, circle, etc., or asking annotations for each stroke, but these options could not reflect how people naturally sketch.


Instructions +-

Most of the current image synthesis methods output an entire image at once, but we are interested in creating an agent that can doodle like humans: drawing one component/object at a time. For example, when people are asked to draw "a house", they are most likely to first draw the roof, then the body of the house, the windows, the chimney, and lastly the door. We would like to collect a dataset of doodles done by people in response to different prompts; moreover, we would also like to collect people's annotations for every object in the doodle.

In the actual HIT:

- You will see the phrase describing what to draw in the **Prompt** column.
- You will create a drawing that illustrates the prompt in the **Canvas** column.
  - A **stroke** is created between the time you push down, drag, and lift up your mouse.
  - You can draw multiple strokes in one step, but only one object in one step. (More details can be found in the Requirements section below.)
- During drawing, you should annotate each object in your drawing in the **Annotation** column.
  - Add the annotation with the Add button.

Figure 3.3: The instruction section used in the prompt-guided sketch text dataset.

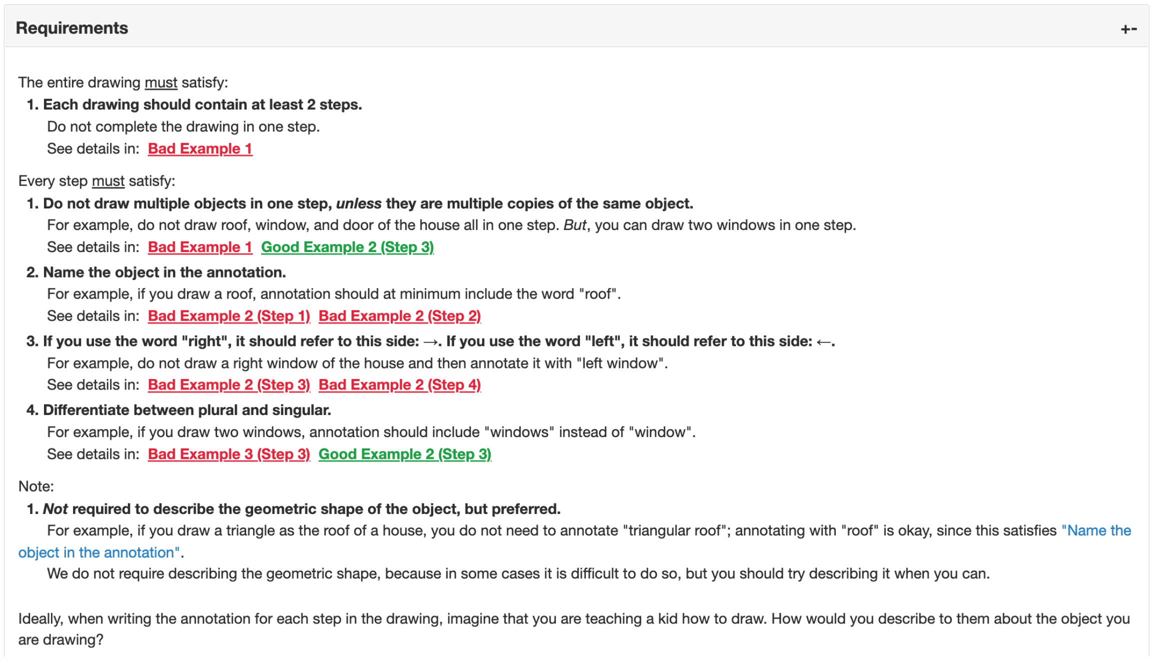
There is a wide spectrum of allowed annotations depending on how people sketch. For example, when drawing for the prompt *Happy Face*, one person might annotate 3 steps: *large u-shaped face*, *round eyes*, *big smiley mouth*. But for someone who likes to draw detailed eyes, they might describe the shape of the eye contour and the length of the eyelashes. The great variation in personal styles makes creative sketches fascinating to study but also challenging to collect a high-quality dataset.

We resorted to repeatedly testing the interface with lab mates to refine the requirements. The refinement process is explained in Appendix A. The requirements deployed in the final pilot is shown in Figure 3.4. Bad Example 2 is shown in Figure 3.5 and 3.6 as an instance of the examples used in the final requirements. To view all the examples, refer to: `https://erinzhang1998.github.io/portfolio/amazon_anno`.

Qualification

We set up a qualification test on AMT to (1) train turkers to have better understanding of the task and (2) to select turkers who can provide annotations that satisfy all the requirements. Similar to the process of writing the requirements, we went through several rounds of testing with students in the lab to come up with a set of questions that correspond well with the requirements. The qualification test starts with the same instruction and requirements in the final HIT, thus allowing turkers to familiarize themselves with the requirements and ask clarification questions before completing the actual annotation task. The test leads with a navigation bar (Figure 3.7) to make it convenient for turkers to switch between questions; originally, we displayed all questions on one page, but some found it time-consuming to scroll from the later questions back up to the instructions, so we decided to display one question at a time.

We show one question from the final qualification in Figure 3.8. Each question is a mock-up of the main task interface, and turkers need to determine whether every step satisfies all the requirements. We also include hints on which requirement the question is testing to encourage


Requirements +-

The entire drawing must satisfy:

1. **Each drawing should contain at least 2 steps.**
   Do not complete the drawing in one step.
   See details in: Bad Example 1

Every step must satisfy:

1. **Do not draw multiple objects in one step, *unless* they are multiple copies of the same object.**
   For example, do not draw roof, window, and door of the house all in one step. *But*, you can draw two windows in one step.
   See details in: Bad Example 1 Good Example 2 (Step 3)
2. **Name the object in the annotation.**
   For example, if you draw a roof, annotation should at minimum include the word "roof".
   See details in: Bad Example 2 (Step 1) Bad Example 2 (Step 2)
3. **If you use the word "right", it should refer to this side: →. If you use the word "left", it should refer to this side: ←.**
   For example, do not draw a right window of the house and then annotate it with "left window".
   See details in: Bad Example 2 (Step 3) Bad Example 2 (Step 4)
4. **Differentiate between plural and singular.**
   For example, if you draw two windows, annotation should include "windows" instead of "window".
   See details in: Bad Example 3 (Step 3) Good Example 2 (Step 3)

Note:

1. ***Not* required to describe the geometric shape of the object, but preferred.**
   For example, if you draw a triangle as the roof of a house, you do not need to annotate "triangular roof"; annotating with "roof" is okay, since this satisfies "Name the object in the annotation".
   We do not require describing the geometric shape, because in some cases it is difficult to do so, but you should try describing it when you can.

Ideally, when writing the annotation for each step in the drawing, imagine that you are teaching a kid how to draw. How would you describe to them about the object you are drawing?

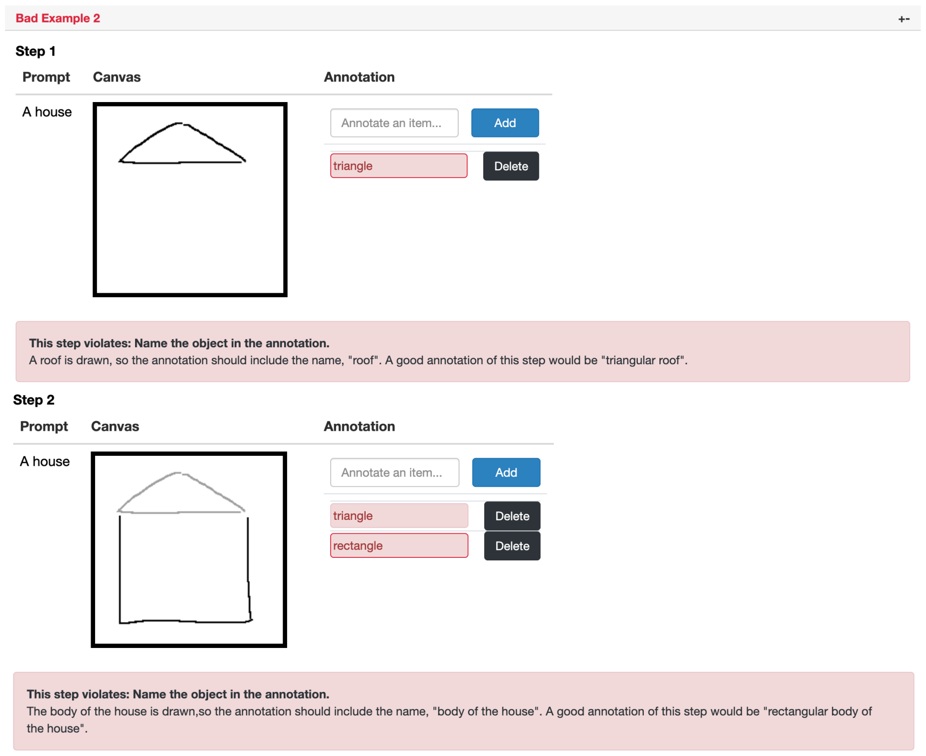
Figure 3.4: Final version of the requirements. The Bad Example links to counter-examples of the requirements, and Good Example links to good examples. When turkers click on the links, they are directed to the examples illustrating the corresponding requirement. This design helps them to understand the requirements better and provides high-quality annotations

turkers to revisit the requirements and form better understanding of the task. To see the full test, refer to: `https://erinzhang1998.github.io/portfolio/amazon_qual`.

3.1.3 Results

In our first pilot, we used prompts in the forms of *adjective*×*noun*. The list of adjectives includes: *happy, sad, surprised, sleepy, love-struck, evil*; the list of nouns includes: *person, kid, cat, bear, dog, sheep, jellyfish, cup of boba, apple, burger, sun, moon, star*. We wanted to see what sketches and text descriptions annotators would provide for prompts that ask for imaginative beings not in this world and include novel compositions of unrelated concepts, such as *evil apple* or *love-struck moon*. With these creative prompts, we hope to collect data that contain interesting compositions of the same geometric shapes and descriptions across different objects. We can then learn models that can, for example, generate circles to be different parts in different objects: eyes, moon, cherries, and angel halo.

Since we only collected 55 sketches, we were able to manually examine every sketch, and we found many creative sketches, such as a subset of the sketches that were collected for prompts with


Bad Example 2

Step 1

Prompt	Canvas	Annotation
A house		triangle

This step violates: Name the object in the annotation.
A roof is drawn, so the annotation should include the name, "roof". A good annotation of this step would be "triangular roof".

Step 2

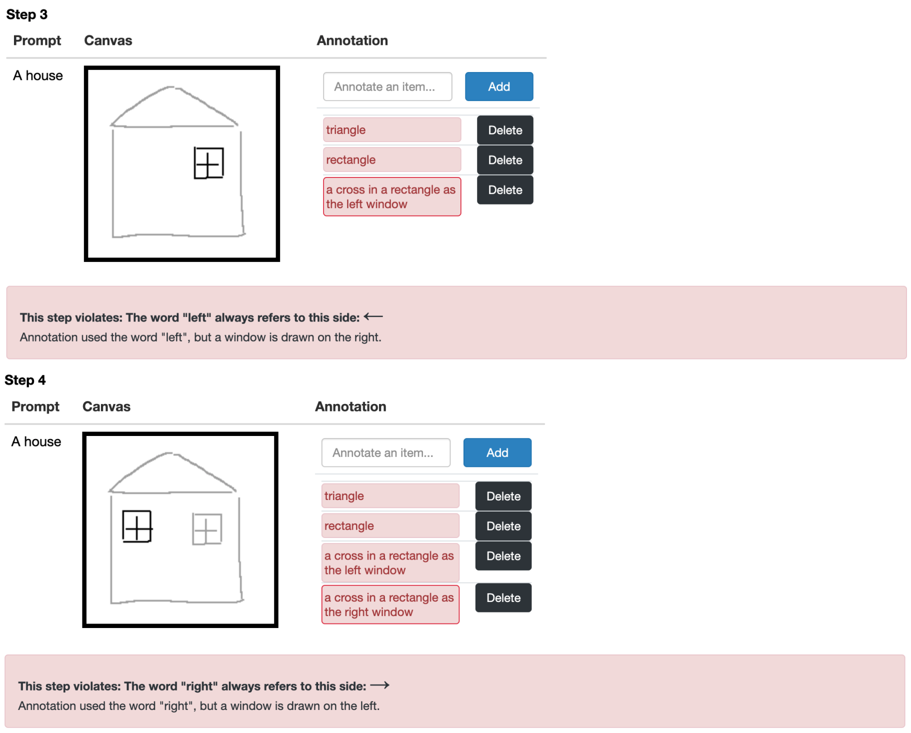
Prompt	Canvas	Annotation
A house		triangle rectangle

This step violates: Name the object in the annotation.
The body of the house is drawn,so the annotation should include the name, "body of the house". A good annotation of this step would be "rectangular body of the house".

Figure 3.5: Step 1 and 2 of an example used to explain the requirements to turkers.

the word *sleepy*, shown in Figure 3.9. From the pilot, we have learned that sketching was a good domain to study machine creativity. Examining the sketches in Figure 3.9, we saw that everybody had their own ways of illustrating *sleepy*: some people drew the letter *z* to symbolize sleeping; some drew a speech bubble with the word *yawn*; some drew sheep, cat, and dog lying down.

However, one issue was that turkers took a long time, on average 30 minutes, to complete one sketch and provide descriptions, and we did not have the resources to spend such long time on a single sketch. The second problem was that it was difficult to understand how some annotators interpreted the prompts through their sketches. We give 4 examples in Figure 3.10. Indeed, sketching is by its nature very subjective, a common challenge in creative AI. The third problem, the most concerning one, was that the part descriptions did not align well with the sketches: some annotators failed to describe every part they drew in a step, or they described parts not in the annotated step. An example is shown in Figure 3.11.


Step 3

Prompt	Canvas	Annotation
A house		triangle; rectangle; a cross in a rectangle as the left window

This step violates: The word "left" always refers to this side: ⟵
Annotation used the word "left", but a window is drawn on the right.

Step 4

Prompt	Canvas	Annotation
A house		triangle; rectangle; a cross in a rectangle as the left window; a cross in a rectangle as the right window

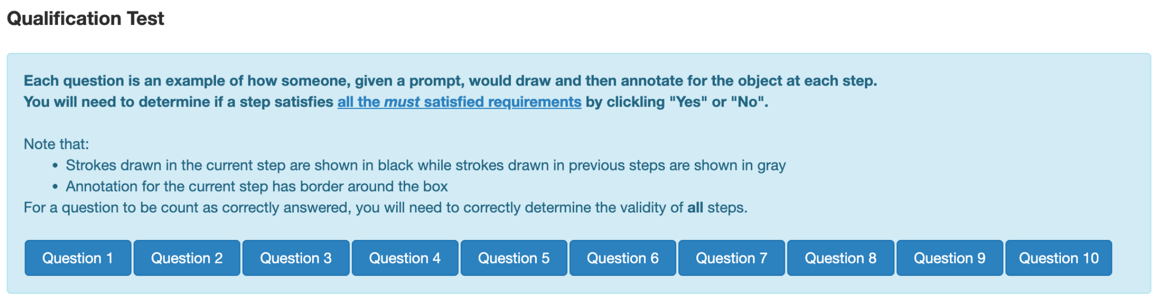
This step violates: The word "right" always refers to this side: ⟶
Annotation used the word "right", but a window is drawn on the left.

Figure 3.6: Step 3 and 4 of an example used to explain the requirements to turkers.

3.2 Contrasting Sketch Text Dataset

3.2.1 Overview

In response to the pilot results, we reconsider the data collection pipeline. We examined existing sketch datasets to see how their annotations could facilitate our data collection (dataset details are explained in Section 2). To shorten the time spent on sketching, we no longer asked annotators to sketch and instead only asked them to describe sketches in the QuickDraw dataset. Although

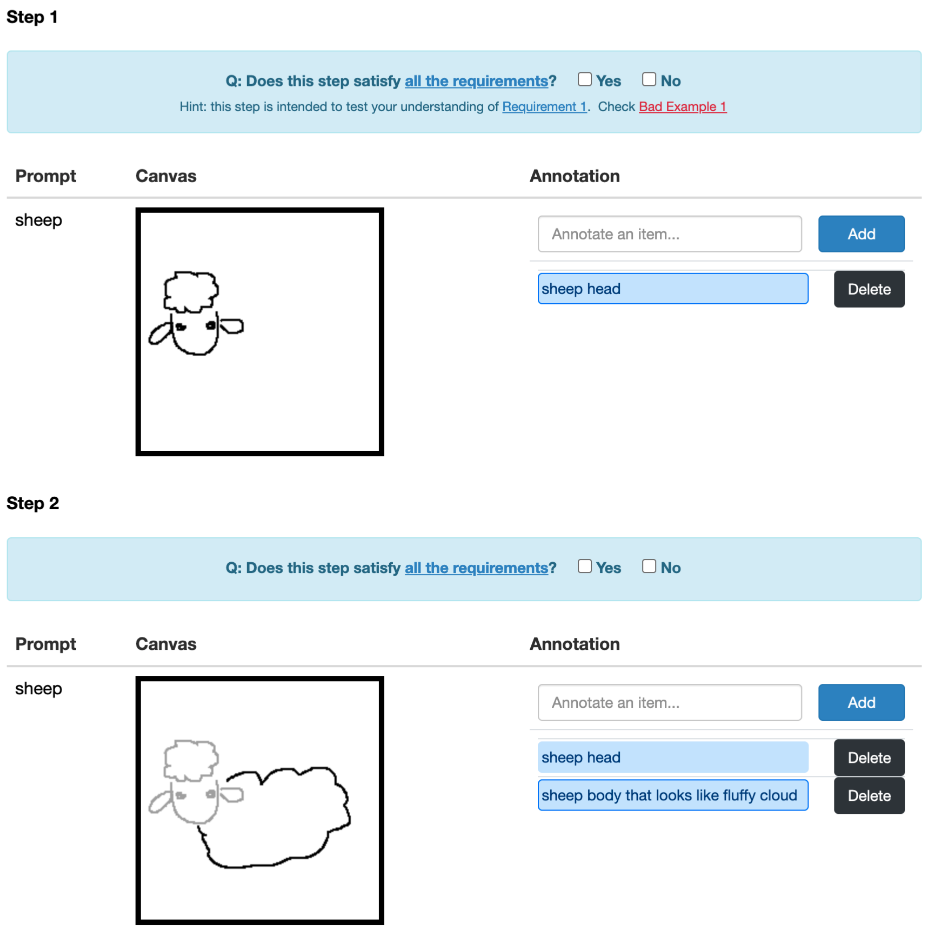

Qualification Test

Each question is an example of how someone, given a prompt, would draw and then annotate for the object at each step.
You will need to determine if a step satisfies all the *must* satisfied requirements by clickling "Yes" or "No".

Note that:
- Strokes drawn in the current step are shown in black while strokes drawn in previous steps are shown in gray
- Annotation for the current step has border around the box

For a question to be count as correctly answered, you will need to correctly determine the validity of **all** steps.

Figure 3.7: Navigation bar in the qualification test.



Step 1

Q: Does this step satisfy all the requirements? ☐ **Yes** ☐ **No**

Hint: this step is intended to test your understanding of Requirement 1. Check Bad Example 1

Prompt	Canvas	Annotation
sheep		sheep head

Step 2

Q: Does this step satisfy all the requirements? ☐ **Yes** ☐ **No**

Prompt	Canvas	Annotation
sheep		sheep head sheep body that looks like fluffy cloud

Figure 3.8: An example of the questions in the qualification test.

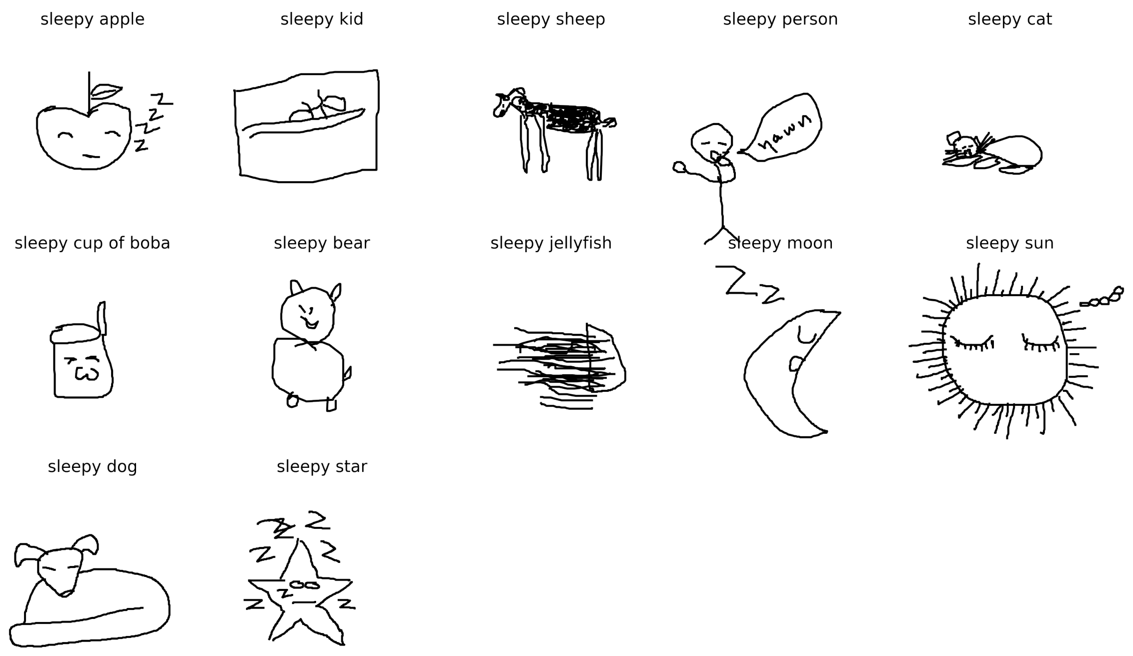


Figure 3.9: Sketches collected for prompts with the descriptor *sleepy* in the prompt-guided sketch text dataset. People were very creative and came up with various ways to illustrate the concept *sleepy* in their sketches.

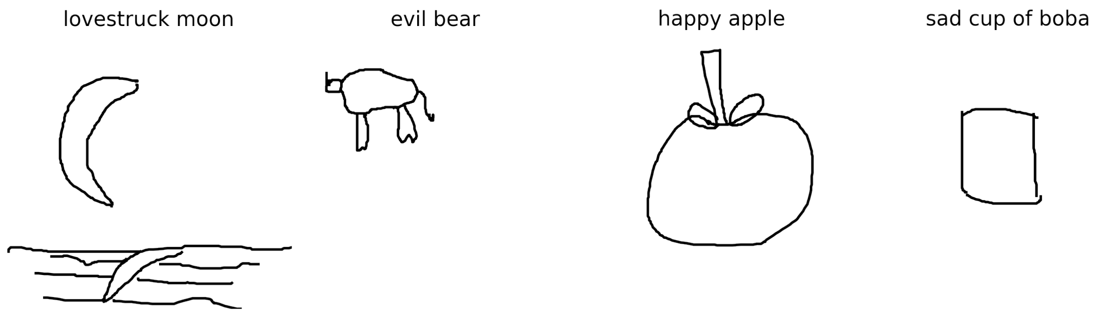


Figure 3.10: A challenge of studying creativity in humans: sketching is very subjective, and it is difficult to determine how some sketches illustrate the prompt and judge their annotation quality. This figure shows 4 examples from the prompt-guided sketch text dataset that are hard to interpret.

we could no longer design text prompts ourselves and collect creative sketches like the ones in the previous pilot, we solved the problem that it was difficult to understand how some sketches illustrated the given prompts.

The most important objective that this dataset should fulfill is allowing us to study how sketches share similar semantic parts and descriptions that are adapted to be used for different objects. We must resolve the issue that some text descriptions in the pilot do not match the drawing.

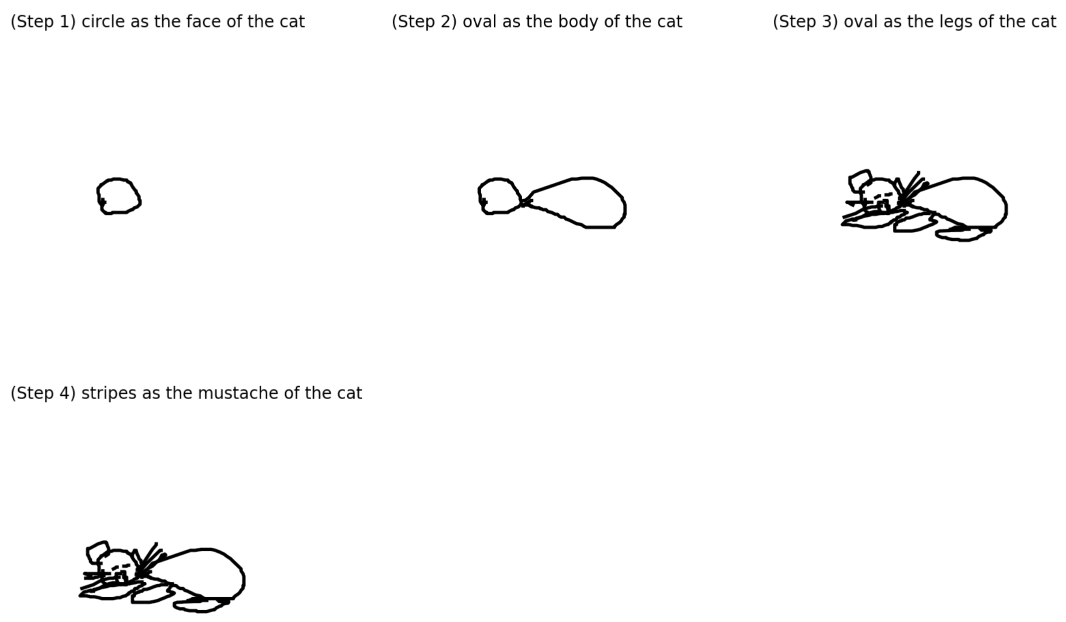

(Step 1) circle as the face of the cat
(Step 2) oval as the body of the cat
(Step 3) oval as the legs of the cat
(Step 4) stripes as the mustache of the cat

Figure 3.11: A major issue with the prompt-guided sketch text dataset: many text descriptions do not align with the drawings in each step. In this example, annotations for step 1 and 2 are correct, but in step 3, although the description says the sketch contains *legs of the cat*, the person have drawn the cat face, ears, whiskers, and legs. Moreover, in step 4, the annotator has annotated for parts drawn in the last step. Resolving this problem is very important because we need semantic part annotations and their corresponding text descriptions to study abstract concept composition.

Therefore, we use semantic part annotations from the Sketch Perceptual Grouping (SPG) dataset, which provides semantic part labels for each stroke in $20,000$ sketches from the QuickDraw dataset. In this way, annotators did not need to spend time thinking about how to segment sketches into parts themselves. Moreover, to help annotators coming up with creative ways to describe the semantic parts, in each task, we present a pair of sketches with contrasting features, implicitly priming them to describe the visual differences. (Note that all sketches in figures from this section on come from the QuickDraw dataset (Ha & Eck, 2017).)

3.2.2 Interface Design

Main Task Interface

When collecting the previous prompt-guided dataset, we relied on testing the interface with students in the lab to determine our design, but we observed performance differences between the students and turkers, such as amount of variety in the sketches, amount of time spent on the task, and common confusions related to understanding the requirements. Therefore, when collecting the contrasting sketch text dataset, we deployed several pilots on AMT to design the new interface. In Figure 3.12, we show how the main task interface progressed from the first pilot to the final version used to collect the entire dataset.

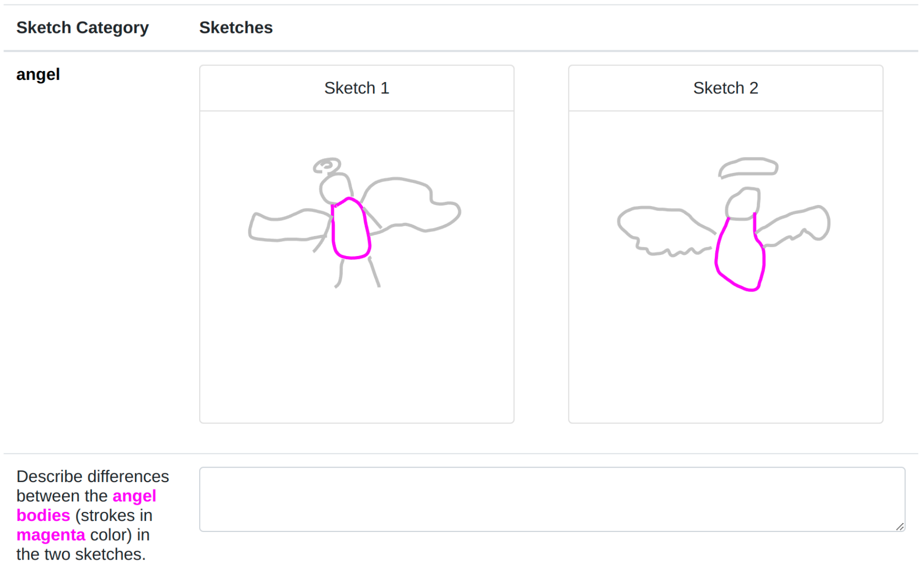
To better study how similar words are used differently across sketches, we changed to collect adjective phrases (Figure 3.12b, 3.12c) from collecting whole sentences (Figure 3.12a). We juxtaposed two sketches and highlighted the parts to be annotated in different colors to help annotators notice the contrasting features. Moreover, this design expedited the annotation process, since it was easier for people to perform contrasting tasks than to generate descriptions from a single sketch.

We chose the contrasting pairs by rendering each part in the sketches and encode the parts into image features using CLIP. For every part type, we iterate through the features and pair features that are the most distinct in terms of cosine distance. For example, to select a pair of sketches with contrasting *body*, we render the strokes that depict the *body* in all angel sketches; all these angel body sketches are encoded by CLIP, and pairs of bodies that are the most distinct are presented to the annotators in the format shown in Figure 3.12c.

Instruction and Requirement

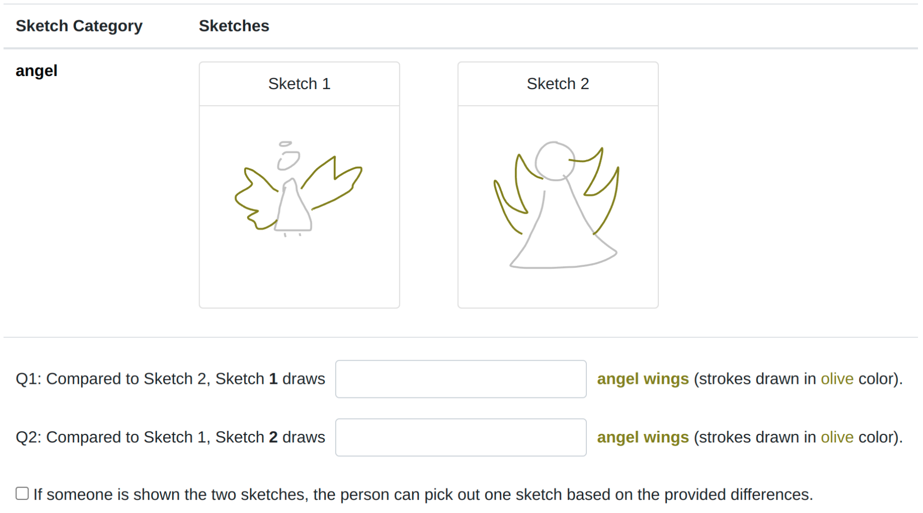
At the beginning, the instruction limited the annotators to provide three types of descriptions: shape, size, and position. However, in order to collect creative descriptions, we lifted restrictions on the type of words and only required annotators to fill in the blank with adjective phrases. We also provided some examples of adjective phrases in common sentences, unrelated to our task, for annotators to better understand their usage (Figure 3.13).

Since we simplified the HIT from 3 sub-tasks, sketching for the prompt, segmenting the sketches, and describing each step, to only asking for part descriptions, the requirements are much easier to write. We received less feedback from the annotators on being confused about the kind of sketches we wanted and the definition of semantic parts, which are now automatically highlighted in the sketches.



Sketch Category	Sketches	
angel	Sketch 1	Sketch 2
Describe differences between the **angel bodies** (strokes in **magenta** color) in the two sketches.		

(a) In the first pilot, we ask annotators to describe differences between the two sketches in full sentence.



Sketch Category	Sketches	
angel	Sketch 1	Sketch 2

Q1: Compared to Sketch 2, Sketch **1** draws [ ] **angel wings** (strokes drawn in olive color).

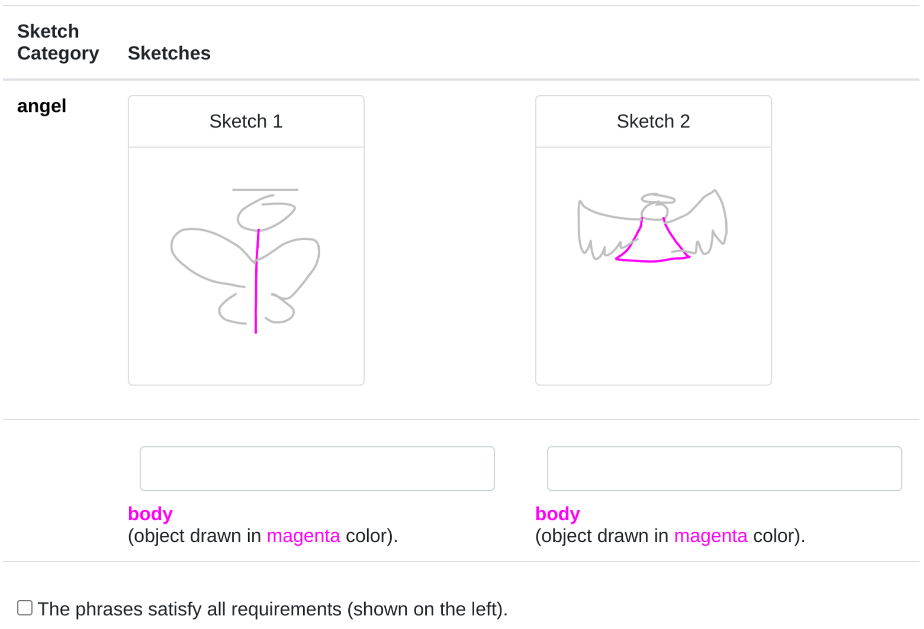
Q2: Compared to Sketch 1, Sketch **2** draws [ ] **angel wings** (strokes drawn in olive color).

☐ If someone is shown the two sketches, the person can pick out one sketch based on the provided differences.

(b) Compared to the previous pilot (3.12a), we still ask explicitly the differences between the sketches but limit annotations to adjective phrases.

We relied on the examples in the instruction to give annotators an idea of what descriptions we wanted. Some examples that we used in the tasks are shown in Figure 3.15. However, the downside was that, primed by the examples, annotators described the parts using words in the examples instead of coming up with a variety of descriptors, and we observed this behavior in the pilots. Therefore, we emphasized an additional requirement that asked the annotators to not limit themselves to words in the examples, and they should use any words that could illustrate the parts well.

Since in the future we want to use our dataset to learn models that can generate sketch parts



Sketch Category	Sketches	
angel	Sketch 1	Sketch 2
	body (object drawn in magenta color).	**body** (object drawn in magenta color).

☐ The phrases satisfy all requirements (shown on the left).

(c) Similar to the last pilot (3.12b), the final version asks for adjective phrases, but we do not state explicitly that annotators should describe the visual differences to allow for more creativity.

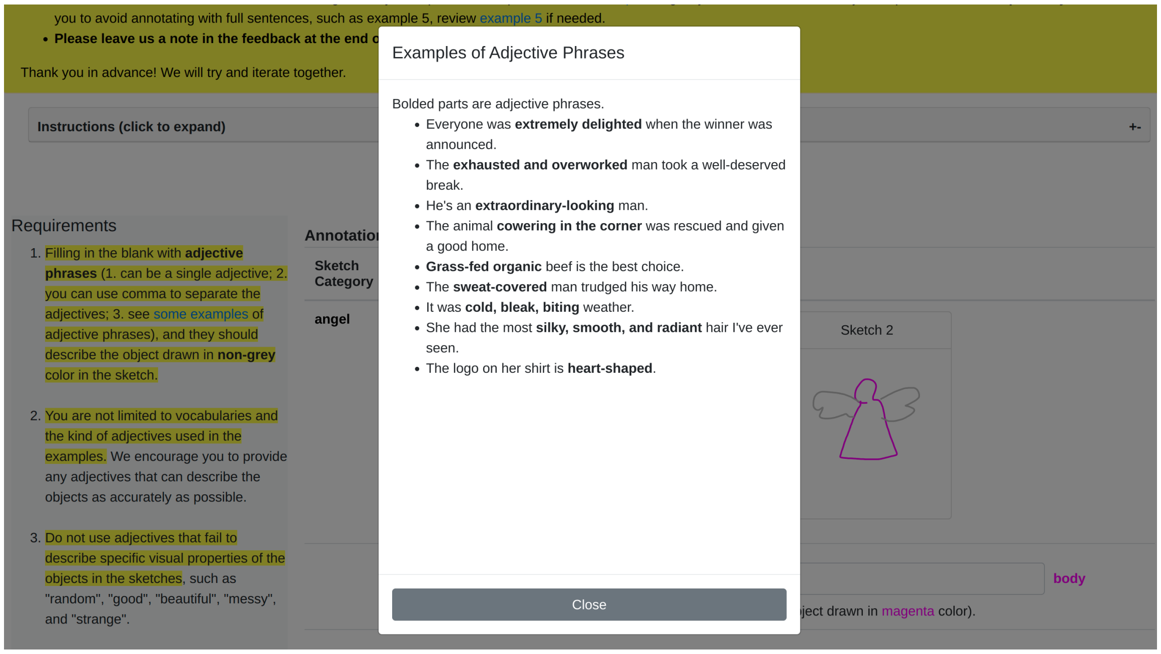
Figure 3.12: Different versions of the main task interface in chronological order. Final version used to collect the entire dataset is 3.12c.

from text descriptions, the text should pertain to visual properties of the parts, so we required that *Do not use adjectives that fail to describe specific visual properties of the objects in the sketches.* A caveat was that some annotators might consider descriptions about emotions expressed in the sketches unrelated to visual properties, since they are abstract compared to words like *rectangular* and *large*. We wanted to collect annotations for face sketches, and parts like *eyes* and *mouth* can be *smiley* or *sad*, so we added that adjectives describing emotions were allowed.

The requirements used in the final version is shown in Figure 3.14.

Qualification

We prepared 10 qualification questions; all are yes/no questions. We used the qualification test to train turkers to understand the requirements better. Each question had a hint that stated which requirement and examples were helpful for solving the question. The purpose of the qualification test was not to trick annotators but to ensure speed and quality of the annotation. We show one question from the qualification in Figure 3.16. To see the full test, refer to: `https://erinzhang1998.github.io/portfolio/v2qual`. At the end, we recruited 88 annotators to work on our task.


you to avoid annotating with full sentences, such as example 5, review example 5 if needed.

- **Please leave us a note in the feedback at the end o**

Thank you in advance! We will try and iterate together.

Instructions (click to expand) +-

Requirements

1. Filling in the blank with **adjective phrases** (1. can be a single adjective; 2. you can use comma to separate the adjectives; 3. see some examples of adjective phrases), and they should describe the object drawn in **non-grey** color in the sketch.
2. You are not limited to vocabularies and the kind of adjectives used in the examples. We encourage you to provide any adjectives that can describe the objects as accurately as possible.
3. Do not use adjectives that fail to describe specific visual properties of the objects in the sketches, such as "random", "good", "beautiful", "messy", and "strange".

Annotation

Sketch Category

angel

Sketch 2

body

ject drawn in magenta color).

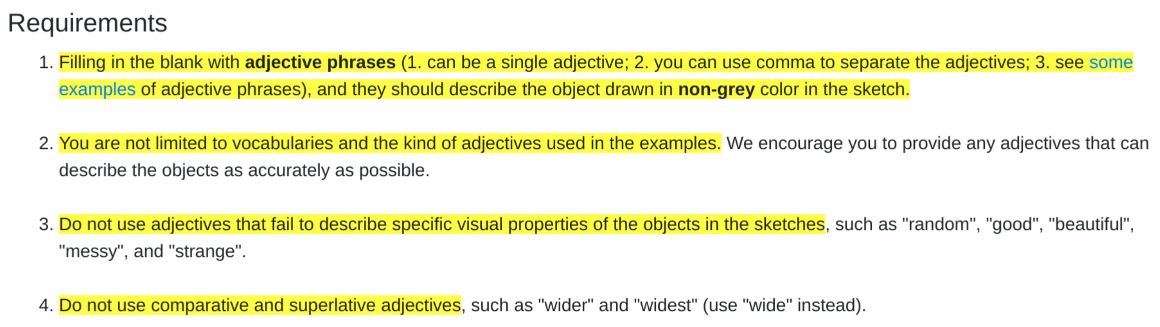
Examples of Adjective Phrases

Bolded parts are adjective phrases.

- Everyone was **extremely delighted** when the winner was announced.
- The **exhausted and overworked** man took a well-deserved break.
- He's an **extraordinary-looking** man.
- The animal **cowering in the corner** was rescued and given a good home.
- **Grass-fed organic** beef is the best choice.
- The **sweat-covered** man trudged his way home.
- It was **cold, bleak, biting** weather.
- She had the most **silky, smooth, and radiant** hair I've ever seen.
- The logo on her shirt is **heart-shaped**.

Close

Figure 3.13: A pop-up window containing examples of adjective phrases, used in collecting contrasting sketch text dataset in Section 3.2. It can be opened from the side panel by clicking on *some examples*. Note that we used examples that are unrelated to our task on purpose, because annotators tended to repeat words in examples, so we tried to not bias them.


Requirements

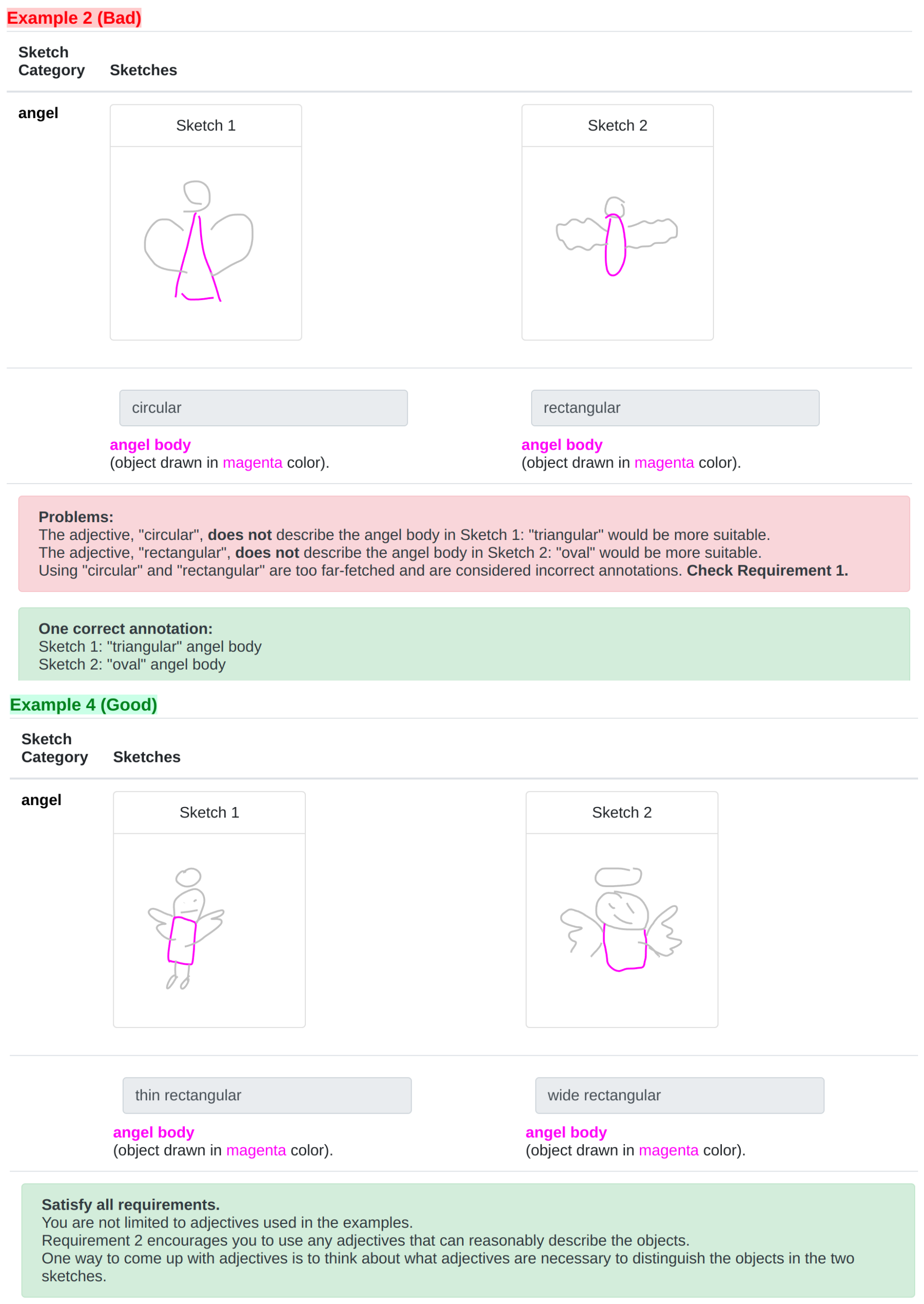
1. Filling in the blank with **adjective phrases** (1. can be a single adjective; 2. you can use comma to separate the adjectives; 3. see some examples of adjective phrases), and they should describe the object drawn in **non-grey** color in the sketch.
2. You are not limited to vocabularies and the kind of adjectives used in the examples. We encourage you to provide any adjectives that can describe the objects as accurately as possible.
3. Do not use adjectives that fail to describe specific visual properties of the objects in the sketches, such as "random", "good", "beautiful", "messy", and "strange".
4. Do not use comparative and superlative adjectives, such as "wider" and "widest" (use "wide" instead).

Figure 3.14: Requirements used in collecting the contrasting sketch text dataset (Section 3.2).

3.3 Dataset Summary

Our dataset contains sketches, their semantic part annotations, and descriptions for every part in a sketch. The sketches comes from the QuickDraw dataset (Ha & Eck, 2017), and the semantic part annotations come from the SPG dataset (Li et al., 2018); both datasets are explained in details in Section 2.

We annotated for 2 categories of sketches: face and angel. For angel sketches, we annotate for



Example 2 (Bad)

Sketch Category	Sketches	
angel	Sketch 1	Sketch 2
	circular	rectangular
	angel body (object drawn in magenta color).	**angel body** (object drawn in magenta color).

Problems:
The adjective, "circular", **does not** describe the angel body in Sketch 1: "triangular" would be more suitable.
The adjective, "rectangular", **does not** describe the angel body in Sketch 2: "oval" would be more suitable.
Using "circular" and "rectangular" are too far-fetched and are considered incorrect annotations. **Check Requirement 1.**

One correct annotation:
Sketch 1: "triangular" angel body
Sketch 2: "oval" angel body

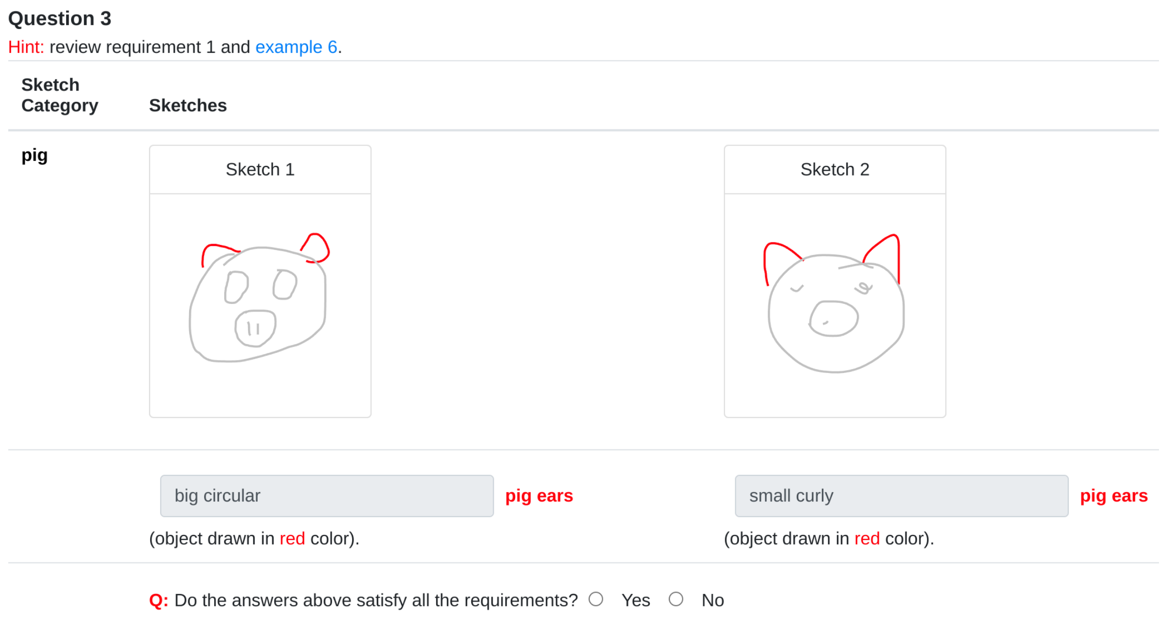
Example 4 (Good)

Sketch Category	Sketches	
angel	Sketch 1	Sketch 2
	thin rectangular	wide rectangular
	angel body (object drawn in magenta color).	**angel body** (object drawn in magenta color).

Satisfy all requirements.
You are not limited to adjectives used in the examples.
Requirement 2 encourages you to use any adjectives that can reasonably describe the objects.
One way to come up with adjectives is to think about what adjectives are necessary to distinguish the objects in the two sketches.

Figure 3.15: 2 examples used in the instructions to collect the contrasting sketch text dataset (Section 3.2).

the parts *halo*, *eyes*, *nose*, *mouth*, *body*, *outline of face*, and *wings*. For face sketches, we annotate for the parts *eyes*, *nose*, *mouth*, *hair*, *outline of face*.



Question 3

Hint: review requirement 1 and example 6.

Sketch Category	Sketches	
pig	Sketch 1	Sketch 2

big circular **pig ears**

(object drawn in red color).

small curly **pig ears**

(object drawn in red color).

Q: Do the answers above satisfy all the requirements? ○ Yes ○ No

Figure 3.16: Question 3 from the qualification test used to collect the contrasting sketch text dataset (Section 3.2). We show a hint at the beginning of each question telling the annotators which requirement this question is testing. In this way, we encourage them to review the requirements to have a good understanding of the task and can then provide high-quality annotations in the real HIT. The question interface is the same as the main task interface that annotators will see when they annotate. The 1-to-1 mock-up helps them to be familiar with the workflow.

	Face	Angel
Number of contrasting pairs	2515	3060
Number of distinct words	833	1107
Number of sketches	572	787

Table 3.1: Dataset statistics by category.

	Face					Angel						
	eyes	nose	mouth	hair	face	halo	eyes	nose	mouth	face	body	wings
Number of sketches	334	572	572	104	572	558	114	8	80	732	781	779
Number of distinct words	228	360	325	152	314	365	112	21	88	379	425	534
Number of contrasting pairs	689	401	687	126	612	559	114	8	80	733	785	781

Table 3.2: Dataset statistics by sketch parts. The phrase *contrasting pair* refers to a pair of sketches with contrasting features that are presented to the annotators.

In Table 3.2, we present dataset statistics broken down by semantic parts, and, in Table 3.1, we show the same statistics by sketch category. In Figure 3.17, we show 100 most frequently used words in our dataset.

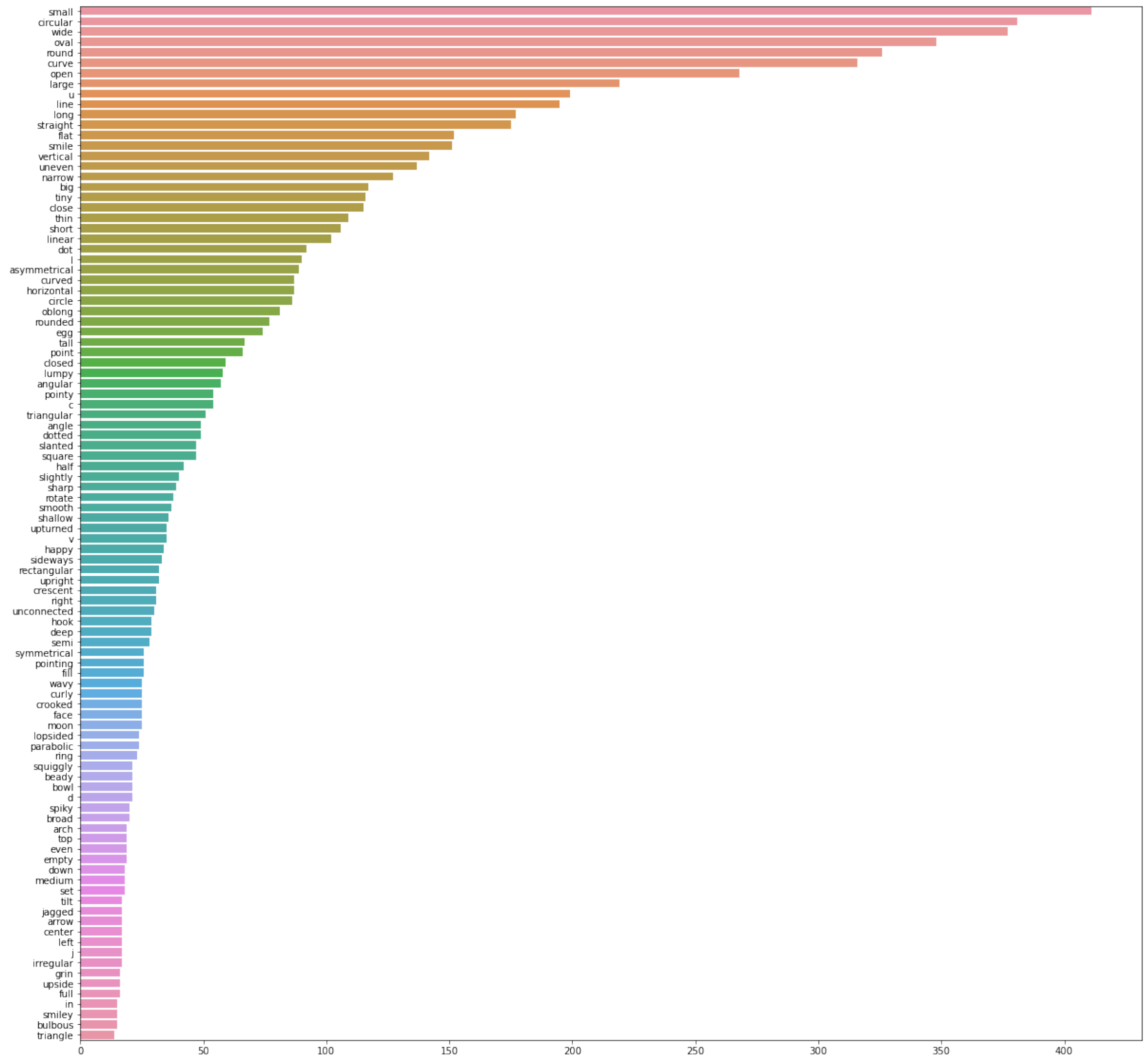


Figure 3.17: Top 100 most frequent words in the dataset corpus. X-axis: number of descriptions containing the word.

The *Creative Birds* and *Creative Creatures* datasets collected by DoodlerGAN (Ge et al., 2020) contain 2 categories, like ours, but there are 9k sketches in each category, and ours contains one tenth as many. Although we fall short on the number of sketches and the variety of sketching styles, we approach creativity from a completely different angle: we focus on how people compose similar basic shapes to create sketches of different categories and adapt similar language to describe different sketch parts, as explained in Section 1 and Figure 1.1.

Our face sketches contain 5 different parts, and angel sketches have 7 parts; there are 7 parts in Creative Birds and 16 parts in Creative Creatures. Again, we do not annotate for as many parts as DoodlerGAN. However, in our dataset, every part in every sketch has at least 2 different language

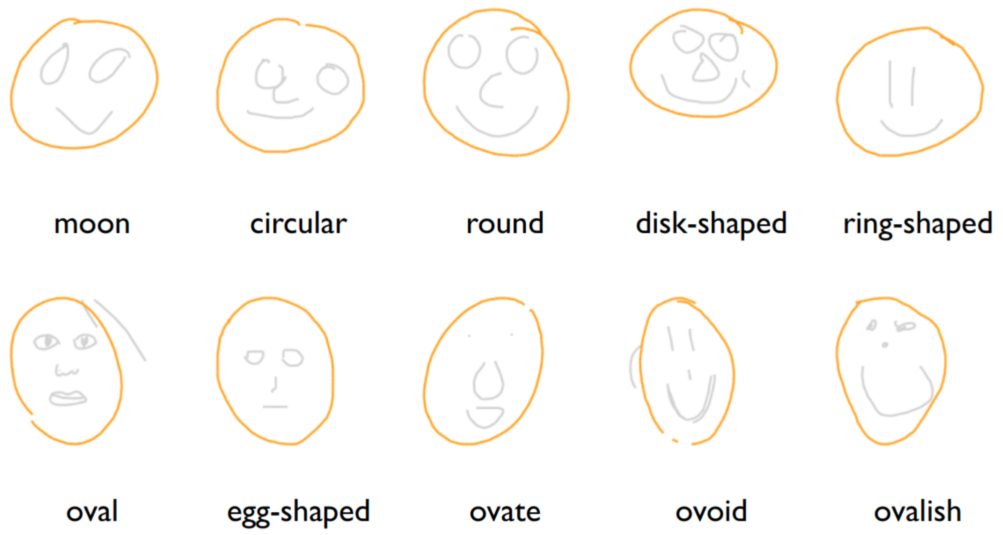


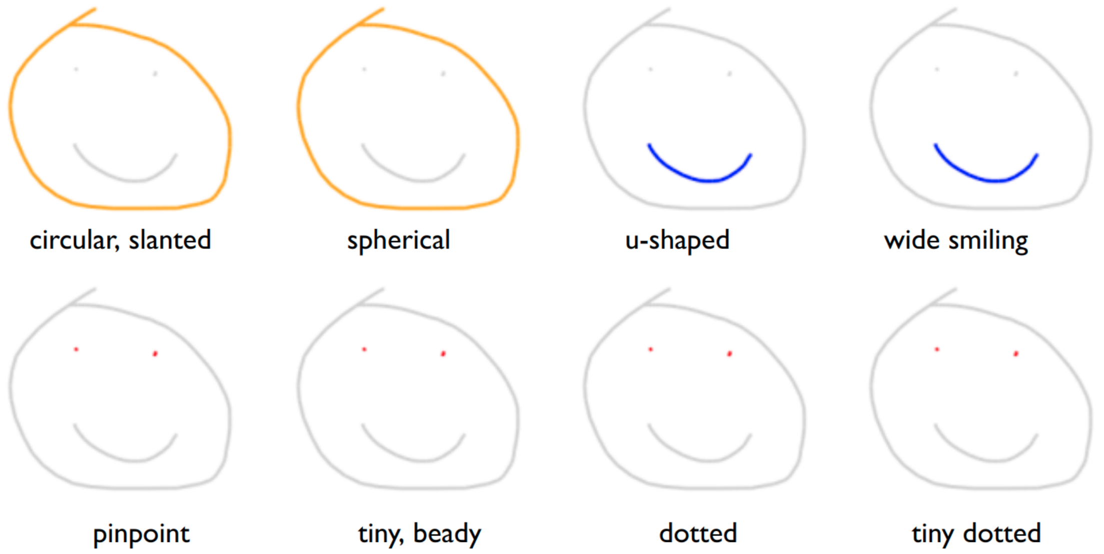
Figure 3.18: Different ways of describing circles (top) and ovals (bottom) in the dataset.

annotations describing the visual features, while DoodlerGAN has no language annotation. With text descriptions, in addition to part-based generative model, we can study how to generate similar shapes from different text descriptions. In Figure 3.18, we show how people describe *circles* using various descriptors (the figure only contains a subset of ways describing circles). In Figure 3.19a, we show the variety of language in describing a simple smiley face. Similarly, an example of creative description of different parts in angel sketches is shown in Figure 3.19b.

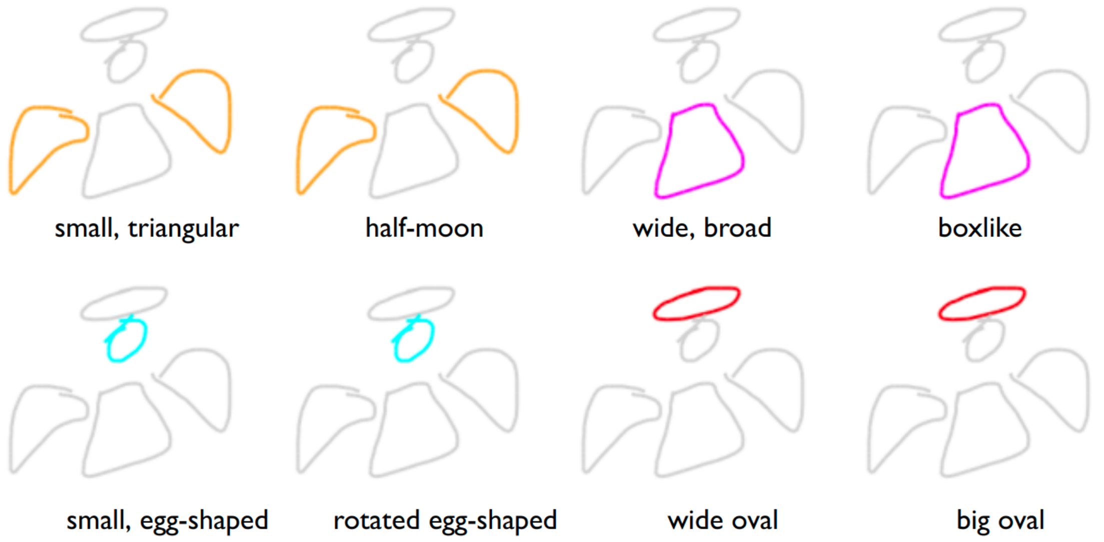
	Face					Angel						
	eyes	nose	mouth	hair	face	halo	eyes	nose	mouth	face	body	wings
small	192	143	65	2	9	150	53	8	25	202	64	47
oval	123	7	11		207	258	1			145	42	23
circular	164	12	11	2	192	80	14	1	2	276	10	11
round	175	18	2	1	130	91	8			268	22	45
wide	94	16	193		74	84	2		12	50	120	111
open	118	7	106		37	54	6		1	79	137	26
large	98	41	58		22	66	6			131	54	85
curve	23	52	221	3	17	18	9	1	27	10	58	101
triangular	9	20	9	2	11	10				14	294	42
line	92	27	56	19	1	15	22	3	14	3	93	9

Table 3.3: This table shows how many times each of the top-10 most frequently used word in the dataset is used to describe different parts in face and angel sketches. For example, *small* is used in 192 descriptions for eyes in face sketches, and it is used 150 times to describe angel halos. People use the same words differently depending on the sketching context.

Moreover, using this dataset, we can study how people compose concepts (e.g. *large+round*)



(a) Each part in this simple face sketch receives at least 2 descriptions from different annotators.



(b) An example of diverse descriptions for each part in the angel sketch.

Figure 3.19: Two examples from the face and angel categories that illustrate our dataset containing creative descriptions of sketches despite their simplicity. The caption at the bottom of each image is provided by annotators to describe the highlighted part in the sketch. For example, the wings are described as either *small, triangular* or *half-moon*.

and apply the same concepts to different semantic parts (e.g. *large round eyes* and *large round halo*). We observe that face and angel sketches share 486 words in total, and for the 200 words that occur most frequently in the dataset (all used in at least 13 part descriptions), 182 are shared across the two categories. Therefore, we believe that the datasets would allow us to study how people use similar words when sketching different objects. Although we cannot conclude in this project, we have already found some examples of the meaning of descriptors varied across sketches, after examining a few words. Figure 3.20 shows an example. In this example, *spiky* is used to mean either short hair in face sketches or pointy, edgy wings in angel sketches. Moreover, there is an implicit orientation change between the two categories of sketches: while *spiky hair* implies "spike" in the vertical direction, the phrase, *spiky wings*, implies jigsaws pointing out from the angel body, horizontally.

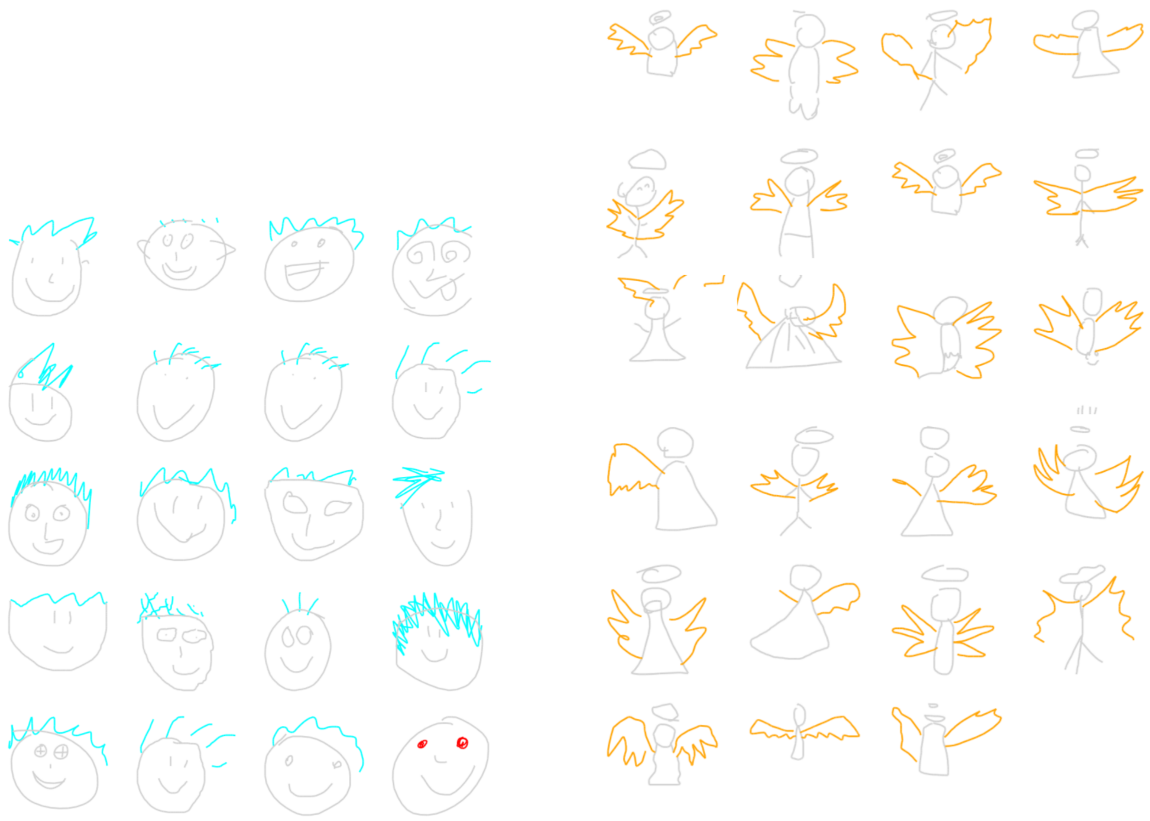


Figure 3.20: Left: face sketches whose hair descriptions contain the word *spiky*. In faces, the word refers to short and coarse texture of hair. Right: angel sketches whose wing description contains the word *spiky*, which is used to represent the pointy edges on wings.

Compare to the prompt-guided sketch text dataset, we no longer collect sketches that respond to prompts describing imaginary beings not in this world, such as *evil moon*; instead, the sketches belong to some category, face and angel. Therefore, the sketches are not as creative as the ones we received in the previous version, such as the ones in Figure 3.9. Since we are interested in how language can guide part-based sketch generation, we chose the contrasting sketch text dataset to ensure alignment between sketches and their descriptions.

Chapter 4

Modeling

In this chapter, we evaluate CLIP and test its performance on recognizing concepts expressed through natural language in sketches. We will first introduce the classification task used for evaluation in Section 4.1. We will elaborate on CLIP, its contrastive objective, image and text encoder, in Section 4.2.

4.1 Task Definition

Given two sketches (s_1, s_2) and their part annotations (t_1, t_2), such as the two pairs shown in Figure 4.1, the task is to match t_j with either s_1 or s_2. We use this task to evaluate the joint

(a) t_1: *wide triangular body* (b) t_2: *small rectangular body*

Figure 4.1: Two angel sketches, s_1 on the left and s_2 on the right, and their part annotations, t_1 and t_2. The task is to determine which sketch matches a given t_j.

vision-language embedding space of CLIP, which is often used as part of the objective function for models that generate image from text; the objective function often involves maximizing the cosine similarity between the generated image and the provided text (or some variants engineered to work for the particular latent space of the generator used) (Frans et al., 2021; Patashnik et al., 2021; Gal et al., 2021; Ramesh et al., 2022). Through this task, we can study how well CLIP can recognize different visual concepts in sketches, and the experiments can help us determine if CLIP can be used in similar ways to guide part-based sketch generation from language. Moreover, since we give CLIP the same pairs that were given to the annotators, we can learn if CLIP can understand how people are using language to describe the visual features of the sketches.

4.2 Method

CLIP stands for Contrastive Language-Image Pre-training, and it seeks to learn image representations that transfer to a wide range of downstream tasks such as image classification on datasets with a wide variety of source domains. To do so, it uses the task of pairing images with their corresponding captions for pre-training. CLIP has two main parts: a text encoder and an image encoder, and both can be transformers. To model our dataset, we fine-tune the pre-trained `ViT-B/32` CLIP model using the `clip` package (Radford et al., 2021).

In this section, we will first introduce the details of the CLIP contrastive objective (Section 4.2.1). We will then introduce the pre-trained transformer-based text and image encoders in Section 4.2.2 and 4.2.3, respectively. Lastly, in Section 4.2.4, we explain how we preprocess sketches and texts for fine-tuning and how we use CLIP to perform the task in Section 4.1.

4.2.1 Contrastive Objective

Pre-trained on 400 million pairs of image-caption data with a contrastive objective, CLIP is able to learn robust vision-language joint embedding that allows it to perform on par with state-of-the-art (SOTA) models learnt with supervised objectives (Radford et al., 2021). During pre-training, for a batch of N (text, image) pairs, CLIP obtains N image features, $I_1, \dots, I_N$, and N text features, $T_1, \dots, T_N$, from the encoders. It then calculates dot-product between each pair of normalized vectors, where there are $N \times N$ possible pairing in total, as shown in the grid in Figure 4.2. This grid is a logit matrix X of dimension $N \times N$ and $X_{ij} = I_i \cdot T_j$. If we normalize the i-th row ($i \in [N]$) through softmax ($\frac{\exp\{X_{i,i}\}}{\sum_{j=1}^{N} \exp\{X_{i,j}\}}$), we obtain a distribution over the captions representing the likelihood of pairing the j-th caption with the i-th image. Similarly, normalizing the j-th column through softmax gives a distribution over all the images of how likely an image pairs with the j-th caption.

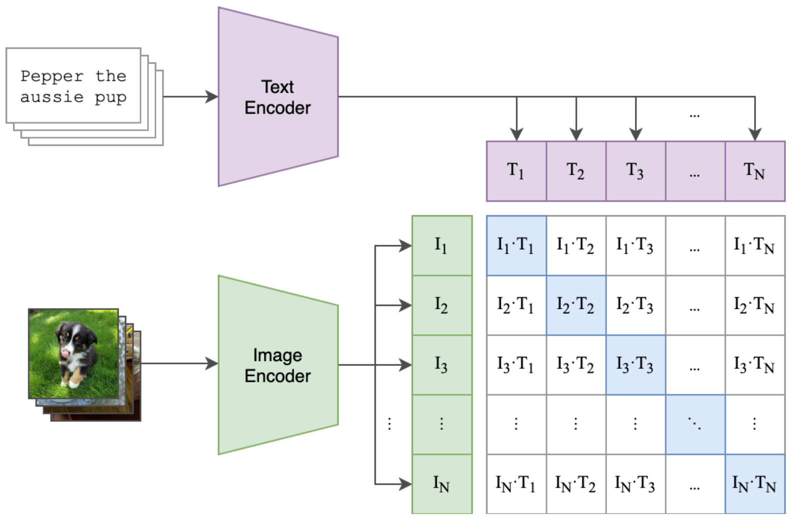

Pepper the aussie pup
Text Encoder
Image Encoder
T1 T2 T3 ... TN
I1 I2 I3 ⋮ IN
I1·T1 I1·T2 I1·T3 ... I1·TN
I2·T1 I2·T2 I2·T3 ... I2·TN
I3·T1 I3·T2 I3·T3 ... I3·TN
IN·T1 IN·T2 IN·T3 ... IN·TN

Figure 4.2: CLIP uses contrastive instead of generative objective for pre-training to learn joint vision-language embeddings. This image is taken from Figure 1 in the original CLIP paper (Radford et al., 2021). Each grid contains the dot-product of normalized image and text features.

As explained in Radford et al. (2021), we can treat each batch as containing N visual concepts expressed through language. By normalizing the rows and columns into distributions, we perform classification over the N captions for the images and classification over the N images for the captions. Moreover, we know that the ground-truth is pairing the i-th image with the i-th caption. Therefore, for classification over captions, we have the ground-truth vector Y_I; for classification over images, we have the ground-truth vector Y_T, and we know $Y_I = Y_T = \begin{bmatrix} 1 & 2 & \cdots & N \end{bmatrix}^T$. Similar to standard multi-class classification, we can use cross-entropy loss as our objective function. The loss $L_I(X, Y)$ of selecting the correct caption for each image:

$$L_I(X, Y) = \frac{1}{N} \sum_{i=1}^{N} -\log \frac{\exp\{X_{i,i}\}}{\sum_{j=1}^{N} \exp\{X_{i,j}\}} \tag{4.1}$$

The loss $L_T(X, Y)$ of selecting the correct image for each caption:

$$L_T(X, Y) = \frac{1}{N} \sum_{j=1}^{N} -\log \frac{\exp\{X_{j,j}\}}{\sum_{i=1}^{N} \exp\{X_{i,j}\}} \tag{4.2}$$

The final loss is defined as:

$$L = \frac{1}{2}(L_I(X, Y) + L_T(X, Y)) \tag{4.3}$$

In order to minimize the cross-entropy loss, the model has to increase the logits on the diagonal of X, which means that it has to learn an embedding space where the feature vectors of the i-th image and the i-th caption are similar and the feature vectors of the other pairs are far apart. The term *contrastive* in the title of CLIP comes from this objective to pull together the real pair in the joint embedding space.

4.2.2 Text Encoder

Overview of Transformer Architecture

The text encoder of CLIP is based on the transformer architecture introduced in Vaswani et al. (2017). Transformer relies only on self-attention mechanism to compute a representation for the input sequence. In this way, it alleviates the computation inefficiency and difficulty capturing long-range dependencies witnessed in recurrent layers.

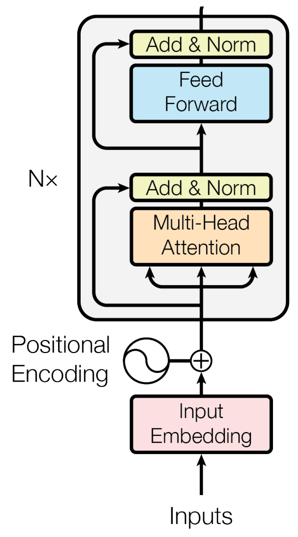
Figure 4.3a and 4.4 are the same figures used in Vaswani et al. (2017) to illustrate the transformer architecture. In Figure 4.3a, Vaswani et al. (2017) gives an overview of the encoder architecture. Firstly, tokenized texts go through an embedding layer; the input embeddings are summed with learned position embeddings that inject information on order of the sequence. The input is computed using Byte Pair Encoding (BPE) with a $49,152$ vocabulary. As explained in the GPT-2 paper, BPE, a sub-word tokenization scheme, strikes a good balance between word-level and character-level word embeddings, since one works well with common words and the other with rare sequences (Radford et al., 2019).

Next, the input is passed through stacked layers multi-head self-attention (MSA) mechanism followed by point-wise feed-forward networks (FFN). In the version of CLIP that we use, the text encoder is a 12-layer transformer, and the model dimenison is 512, $d_{model} = 512$, meaning that output of the initial embedding layers, MSA, FFN all have dimension 512.

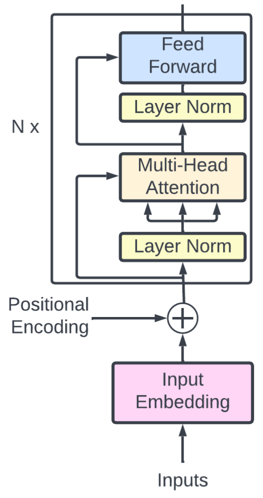
Compare to the formulation $LayerNorm(x + Sublayer(x))$ used in Vaswani et al. (2017) (Figure 4.3a), the CLIP text encoder uses $x + Sublayer(LayerNorm(x))$ (Figure 4.3b), where $Sublayer$ refers to either MSA or FFN. Each layer still contains residual connection and layer normalization, but the order is switched between Vaswani et al. (2017) and Radford et al. (2021).

Multi-Head Self-Attention

As illustrated in Figure 4.4, given query, key, value matricies Q, K, V (in our case, all three matrices equal to the input text embeddings), transformer uses different linear projections to create

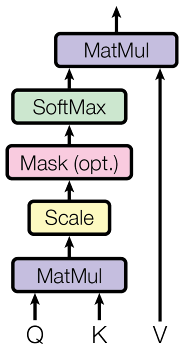


(a) Encoder architecture used in original Transformer paper; the figure is taken from Figure 1 in Vaswani et al. (2017).



(b) Encoder architecture of CLIP (Radford et al., 2021).

Figure 4.3: Text encoder architecture: the text encoder is a transformer with stacked layers of self-attention and feed-forward network sublayers. The main implementation difference between the original Transformer (on the left) and the transformer implemented by CLIP is the placement of layer normalization.



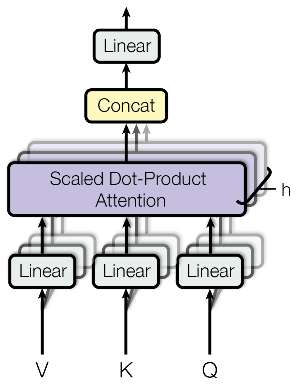


Figure 4.4: An illustration of the scaled dot-product attention on the left; on the right, an illustration of the multi-head self-attention mechanism (MSA) used in every layer of the transformer. Both figures are from the original Transformer paper (Vaswani et al., 2017).

multi-head attention, and Vaswani et al. (2017) explains the benefit of multi-head attention as allowing the model to attend simultaneously to multiple representation subspaces of the input.

$$\begin{aligned} MultiHead(Q,K,V) &= Concat(head_1,\ldots,head_h)W^O \\ head_i &= Attention(QW_i^Q, KW_i^K, VW_i^V) \\ Attention(Q,K,V) &= softmax(\frac{QK^T}{\sqrt{d_k}})V \end{aligned} \tag{4.4}$$

ViT-B/32 uses a version with $h = 8$ attention heads, so $W_i^Q, W_i^K \in \mathbb{R}^{d_{model} \times d_k}$ and $W_i^V \in \mathbb{R}^{d_{model} \times d_v}$, where $d_k = d_v = \frac{d_{model}}{h} = \frac{512}{8} = 64$. At the end of the multi-head attention mechanism, the weighted combination of values from each head is concatenated together and passed through a linear layer, represented here as $W^O \in \mathbb{R}^{(d_v \times h) \times d_v}$. CLIP uses the “Scaled Dot-Product Attention” in Vaswani et al. (2017), illustrated in details in Figure 4.4. The dot products between queries and keys determine the weights that are used to sum the values; in this way, we have a contextualized representation; compared to convolutions that use static kernels, attention weights are dynamic.

4.2.3 Image Encoder

The image encoder of CLIP uses Vision Transformer (ViT) introduced in Dosovitskiy et al. (2020). The architecture of ViT is based on the original transformer introduced in Vaswani et al. (2017). In order to reuse the transformer model, ViT needs to first turn an image of size $H \times W \times C$, (H, W, C stands for image height, width, channel size, respectively), into a sequence of “tokens”, similar to the text input. To do so, Dosovitskiy et al. (2020) reshapes the image to size $N \times (P^2 \cdot C)$, where N is the number of patches and P the patch size; the reshaped image can be seen as a sequence of N image tokens, each having a dimension of $P^2 \cdot C$. Each image token is then passed through a linear layer to be mapped to dimension D, similar to the model dimension d_{model} earlier.

In the version of CLIP that we used, all input images have dimension 224×224, the patch size $P = 32$, and the output of the initial embedding layers, MSA, FFN all have dimension 768 ($D = 768$). As explained in Dosovitskiy et al. (2020), before passing into the transformer, we also need to prepend a `[class]` token at the front of the sequence, whose embedding at the last layer of the transformer will be used as the representation for the entire image. In this way, each image is represented as a sequence of $7 \times 7 + 1 = 50$ tokens, illustrated as pink boxes in Figure 4.5. The purple boxes that are right next to the patch embeddings represent position embeddings, with a similar function to encoder sequence order information as in the text transformer. For the CLIP image encoder, layer normalization is applied to the input before passing into the transformer and to the output at the last layer.

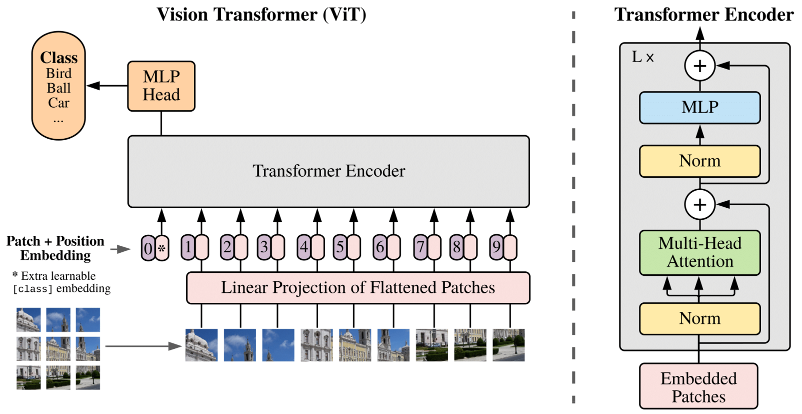


Figure 4.5: Vision Transformer (ViT) architecture (Dosovitskiy et al., 2020).

4.2.4 Fine-Tuning CLIP

We fine-tune CLIP with our dataset containing (sketch, part description) pairs. Our sketches come from the QuickDraw dataset (Ha & Eck, 2017), and the semantic part annotations come from the SPG dataset (Li et al., 2018). We collected text descriptions from turkers for every part in face and angel sketches; details of the data collection process are in Section 3.2, and we summarize the dataset in Section 3.3.

Sketch Preprocessing

The QuickDraw sketches are stored in vector format: each sketch is composed of a sequence of n strokes $S_i, i \in [n]$, and each stroke S_i is a sequence of vectors $(\delta x, \delta y, p, l)$. δx and δy are changes in the x, y coordinates with respect to the previous point; for the first point, its coordinate is with respect to the point $(25, 25)$. All points are assumed to be drawn on a 256×256 canvas. $p = 1$ if the point is the last point in the current stroke, and $p = 0$ otherwise. The SPG dataset provides annotation for semantic segmentation of the sketches (Li et al., 2018), and l is an integer representing which semantic part the current point belongs to. For face sketches, the parts can be *eyes*, *nose*, *mouth*, *hair*, or *outline of face*; for angel sketches, the parts can be *halo*, *eyes*, *nose*, *mouth*, *body*, *outline of face*, or *wings*.

During training, we render the sketches from the vector format into PNG images using the python package `cairocffi`. To augment the data, we did: (1) sample stroke width uniformly from the range $[2.5, 12.5]$; (2) rotate the sketches randomly by sampling an angle from the range $[-\frac{\pi}{4}, \frac{\pi}{4}]$; (3) scale the sketches with the scale factor sampled from the range $[0.75, 1.25]$; (4) translate the strokes vertically or horizontally with 0.15 as the maximum absolute fraction translation.

Text Preprocessing

We used the spaCy package to preprocess the text (Honnibal & Montani, 2017). spaCy provides trained natural language processing pipeline and includes models for, for example, token-to-vector and part-of-speech tagging. We use the `en_core_web_sm` pipeline and its lemmatizer to reduce words to their basic forms. Moreover, we lower-case all words and remove punctuation, a list of which is provided by `Python string` package, `string.punctuation`. We also remove words like *shaped*, *sized*, *and*, *like*, since they act like stop words and do not provide additional visual descriptions of the sketches. Text descriptions are also tokenized by CLIP's tokenizer before passing into CLIP text encoder.

Fine-tuning Objective

We used the same loss function and model pipeline as the one used for pre-training CLIP, explained in details in Section 4.2.1. In a batch of size N, we have N pairs of sketch and description for one of the semantic parts in the sketch. For example, Figure 4.1a is a pair of an angel sketch and description for the angel body, *wide triangular body.* Through fine-tuning, CLIP should adjust its embedding space so that text feature for *wide triangular body* and image feature for the sketch in Figure 4.1a are close in cosine similarity. During fine-tuning, we tried batch size $N \in \{64, 128\}$ and learning rate $\alpha \in \{1 \times 10^{-5}, 5 \times 10^{-6}, 2 \times 10^{-6}, 1 \times 10^{-6}, 7 \times 10^{-7}, 5 \times 10^{-7}, 1 \times 10^{-7}\}$. We present the best results in Chapter 5. To see all plots and parameters used in fine-tuning, refer to our Weights & Biases project page: `https://wandb.ai/erinz/clip-finetune/overview`.

Chapter 5

Results & Analysis

In this chapter, we present experiment results and analysis to understand the language used to describe sketch parts. We found the following:

1. CLIP, despite its large pre-trained corpus, cannot easily generalize to unseen category on the task of pairing sketches with their descriptions. This indicates that the relationship between natural images and language cannot be easily translated to sketches and their descriptions. (Section 5.1)

2. Average cosine distance has increased between a pair of descriptors that are used by annotators to differentiate two sketches, suggesting that word embeddings extracted from the fine-tuned CLIP can better reflect the contrasting nature of these pairs, compared to pre-trained CLIP. (Section 5.2)

5.1 Classification Experiment

As explained in Section 4.1, annotators provide descriptions (t_1, t_2) to differentiate the two sketches (s_1, s_2) presented to them, and from this process, we have the ground-truth pairing of (s_1, t_1) and (s_2, t_2). We use CLIP to decide which sketch should be paired with description t_j, and the results are reported in Table 5.1.

Compare to the zero-shot performance, fine-tuning on a single category would increase performance significantly on the category: for face, accuracy increased 16.3% on the test set after

Model	Face		Angel	
	Test	Dev	Test	Dev
zero-shot	53.8	54.6	56.4	57.2
finetuned on face	70.1	68.5	58.1	57.5
finetuned on angel	58.1	61.0	67.2	70.5
finetuned on face + angel	74.3	71.7	70.4	71.0

Table 5.1: Accuracy (%) of CLIP on choosing the correct sketch for a given text description from a pair of sketches. During annotation, the annotator is given the pair of sketches and provided descriptions of certain parts in the sketches for both sketches.

fine-tuning on face; performance increased 10.8% on the angel test set after fine-tuning on angel. The increase demonstrates that CLIP has adapted its embedding space and has learned to associate sketches with their part descriptions. However, CLIP fine-tuned on a single category cannot generalize easily to unseen category: only 1.7% increase on angel when fine-tuned on face, and 4.3% increase on face when fine-tuned on angel. The two categories share vocabulary, and similar shapes appear in the two categories, but CLIP does not generalize as easily as expected. Concepts like *big* and *small* appear in both categories, but it is not guaranteed that CLIP can recognize them in sketches from unseen category.

Transferring from angel to face results in slightly better performance compared to transferring from face to angel (+4.3% vs. +1.7%). One likely explanation is that the angel category contains more sketches (787 vs. 572) and a larger vocabulary (1107 vs. 833), so CLIP performed better because it has seen more sketches and has familiarized itself with the domain, and it has learned from a wider variety of ways that sketches can be described. A second explanation is that angels contain all face parts (*eyes, nose, face outline, mouth*) except *hair*, but face sketches do not contain *body, wings*, and *halo*, which are the most definitive features of angels. Therefore, CLIP, after learning how face parts are described through a few angel sketches that contain them, can recognize face sketches better. However, when it encounters angel sketches with unseen parts and new usage of words seen in the face category, it fails to transfer the learned concepts to angels.

Fine-tuning on both categories results in slightly better performance than fine-tuning on a single category. CLIP has the capacity to learn how different words are used in both categories, but it cannot transfer the learned concept across categories. Moreover, CLIP uses words in the WordNet synsets to search for images to construct the datasets used for pre-training, and 88% of all words in our datasets exist in WordNet, meaning that CLIP has seen them and how the visual concepts are demonstrated in images, but it cannot adapt the concepts to a different visual domain, sketches, without fine-tuning from sketches in both categories.

5.2 Word Similarity Experiment

In order to learn more about how have relationships between word embeddings changed through fine-tuning, we use cosine similarity as a metric to measure how close two words are. During annotation, we present two sketches with contrasting parts (for example, a face with big eyes and another with small eyes, like Figure 5.1) to the annotators and ask them for descriptions of the parts. We do not explicitly tell them that the eyes are different in sizes, yet it is highly likely that they would provide descriptors that can indicate this visual differences.

We extract all tuples of words from a pair of contrasting descriptions. In the case of Figure 5.1, one annotator provide the descriptions *large circular eyes* for the sketch on the left and *tiny solid eyes* for the other; from these two descriptions, we can extract 4 pairs of contrasting descriptors: (*large, tiny*), (*large, solid*), (*circular, tiny*), and (*circular, solid*). There are a total of $9,823$ pairs, and the top 20 most frequent pairs are shown in Table 5.2. For example, the pair *small* and *large* are use 228 times by annotators to contrast certain parts in the two sketches across face and angel sketches.

Figure 5.1: An example pair of sketches with different eyes that was presented to annotators. We do not pre-define a list of attributes and ask the annotators to determine whether the sketches are different in these attributes; instead, we highlight the parts in colors and implicitly prompt them to pick up on the differences. As expected, most annotations naturally include the size and shape differences. From the descriptions, we can extract pairs of *antonyms* used to indicate opposite visual concepts. In this case, the annotation was *large circular eyes* for the sketch on the left and *tiny solid eyes* for the one on the right.

We consider two words in each pair as “antonyms”, because they represent two *opposite* visual concepts in the two sketches. It is in cases like this that our common understanding of synonym and antonym falls short: (*large, tiny*) might align with most people’s idea of two words opposite in meaning, and (*large, solid*) do not appear as antithesis of each other, but the pair is used for the purpose of differentiating the sketches. Therefore, from a pragmatic perspective, these words are antonyms in our dataset.

After fine-tuning CLIP to learn to contrast sketches with these descriptions, we expect that the

word 1	word 2	#occurrences
small	large	228
circular	oval	142
wide	narrow	124
small	round	112
wide	small	108
oval	small	100
circular	small	94
oval	round	92
close	open	83
big	small	71
short	long	68
curve	wide	68
thin	wide	61
open	small	60
oval	wide	60
large	round	55
round	uneven	53
oval	open	51
open	circular	47
curve	small	46

Table 5.2: 20 pairs of descriptors most frequently used by annotators to differentiate parts in face and angel sketches. There are a total of 9823 pairs, and 7194, or 73.2%, pairs are used only once in the dataset.

similarity between contrasting words to decrease. Indeed, as shown in Table 5.3, we see a trend that as CLIP learns from more pairs of (sketch, part description) in our dataset, the word embeddings of contrasting words become dissimilar.

	avg cosine sim
zero-shot	0.833
finetuned on face	0.752
finetuned on face + angel	0.691

Table 5.3: Average cosine similarity.

Across the entire dataset, there are $\binom{1450}{2}$, about 1 million, pairs of words, whether they are used in contrasting descriptions or not, and 99.9% of the pairs decreased in cosine similarity, from pre-trained CLIP to CLIP fine-tuned on face and angel sketches. One possible explanation is that we collected our data by presenting two sketches with contrasting features, but it could also be a general trend of CLIP fine-tuning on additional datasets, and we need future studies to give an definitive answer.

We only see increase in cosine similarity in 824 pairs of words. When we look at the top 20 pairs of words with the most increase in cosine similarity, we see that 18 pairs include the word *slash*, which appears only once in our entire dataset. The increase is less than 0.06, compared to a decrease of 0.65 for the pair that has the largest decrease in similarity. If we only look at pairs of words that are among the 250 most frequent words, pairs whose cosine similarity has increased the most are *arrow, smiley*, *circle, arrow*, *trilateral, triangular*. However, the increase is still too marginal, ≈ 0.02, for us to conclude anything meaningful about the text embeddings of the fine-tuned CLIP model. Therefore, we cannot provide reasons for the marginal increase, and it is likely to be a chance event due to rare occurrences.

Chapter 6

Future Work

Firstly, there are many creative uses of language in our dataset, and in future work, we want to investigate what categories of creative usage are there and quantify how many cases are in each category. Most of our current characterization of the dataset are based on looking through a few examples in the datasets (there are a total of 11K!). As explained in Section 3.3, since we did not limit what language annotators could use during data collection, the dataset contains a variety of ways of describing the same concept. For example, for a nose that looks similar to the one in Figure 6.1, annotators describe it as *hook-shaped*, *c-shaped*, *inverted j*, *curved*, etc. We believe that this case is not the only one, and we want to quantify the diversity. In this way, we can evaluate how a multi-modal embedding space, such as the CLIP joint embedding, captures these relationships. Is the feature vector of the sketch collinear with the word features of every one of these words?

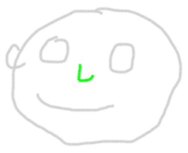


Figure 6.1: For the nose in this face sketch, our dataset contains a variety of descriptions: *hook-shaped*, *c-shaped*, *inverted j*, etc. We want to investigate how many of these creative usages are there in our dataset.

Secondly, we have observed that face and angel sketches share many visual concepts. These could be related to length (*long, short*), size (*big, small*), geometry (*circular, triangular*), direction (*horizontal, vertical*), and many more. We want to evaluate more thoroughly which concepts are shared and which ones are unique to each category. In this way, we can understand better the challenges around generalizing CLIP to unseen categories, indicated by results in Section 5.1.

Lastly, we want to learn a generative model that can produce sketches in a part-based manner, guided by language instructions. For example, people have experimented with DALL-E and have generated a wide variety of interesting images from captions, including sketches (Ramesh et al., 2021, 2022). However, none of the publicly available versions have the same power and cannot generate images as high-quality as those in the original DALL-E paper. Therefore, we could try training it using public repository, such as `https://github.com/lucidrains/DALLE-pytorch`, on our dataset, since some people have successfully done so. Another approach is experimenting with some variants of GAN guided by CLIP objective, similar to the models presented in Yuan et al. (2021); Gal et al. (2021); Karras et al. (2019).

Appendix A

Designing the Requirement Section

As explained in Section 3.1.2, when drafting requirements for collecting the prompt-guided sketch text dataset, we iterated through several versions, and here we show the progression. An excerpt from an old version of the instructions, in which we tried to explain a single *step* of the annotation:

> In each task, we show **1 prompt** from which we would like to get
>
> 1. A drawing containing 1 **entity** that you think illustrates the prompt.
> 2. Text annotation for every **"component"** that makes up the entity. The word "component" is intentionally vague, and it depends on how you compose your drawing. For example, in the above example, the prompt is "smiley face", and during the process of creating a "smiley face" entity, we used 4 components: a face, a left eye, a right eye, and a mouth. For each component, you can annotate with "face", "left eye", "right eye", "mouth", respectively; you can also annotate with more details describing the shapes of each component: "face that looks like an arc opening downwards", "a left eye that is an arc", "a right eye that looks exactly like the left eye", "an arc-like mouth". Try to use creative and descriptive languages. You can draw a component using multiple strokes.

Requirements and selected examples used in the first version of the requirement:

1. Do not draw entity that does not respond to the prompt. For example, given the prompt *Smiley Face*, the drawing should not contain irrelevant objects like a house.
2. Do not draw more than one entity that responds to the prompt. For example, One should not

draw two *Smiley Face* entities, although each *Smiley Face* entity is good. However, you can draw multiple tree objects to illustrate the prompt *Forest*.

3. Do not draw entity that is ambiguous in terms of illustrating the prompt. For example, the drawing (Figure A.1) looks more like a *Sad Face* than *Smiley Face*.

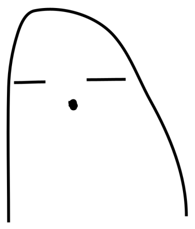
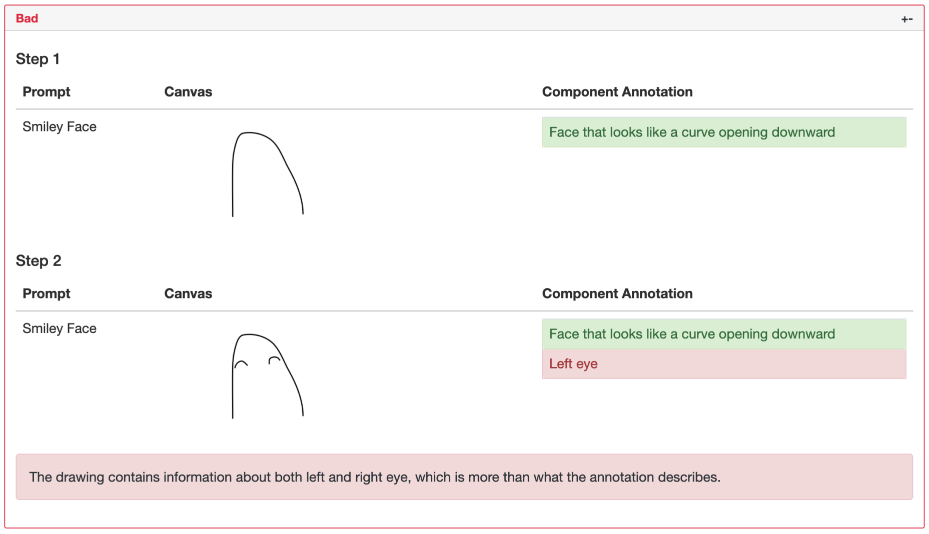


Figure A.1: An example included in the first version of the requirements.

4. Do not draw one component that contains more information/content than what the annotation for that component describes. (A counterexample is illustrated in Figure A.2.)



Bad

+-

Step 1

Prompt	Canvas	Component Annotation
Smiley Face		Face that looks like a curve opening downward

Step 2

Prompt	Canvas	Component Annotation
Smiley Face		Face that looks like a curve opening downward
		Left eye

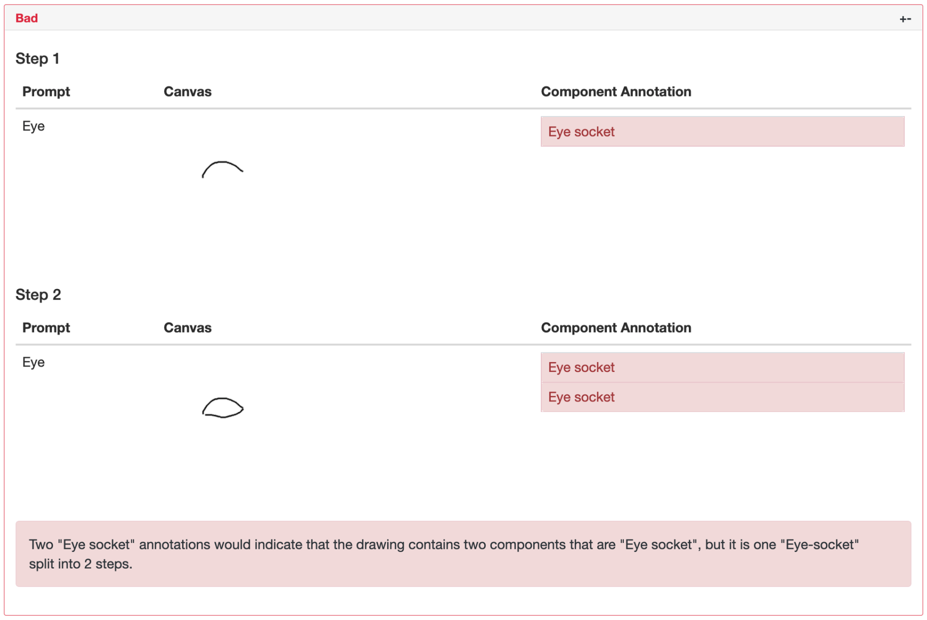
The drawing contains information about both left and right eye, which is more than what the annotation describes.

Figure A.2: An example of unaligned drawing and text description.

5. Do not split the drawing of a component into multiple steps, unless you can annotate each step separately. (A counterexample is illustrated in Figure A.3.)

6. Do not annotate a component more than once.

Second version of the requirement section in text-guided sketch text dataset:


Bad

+-

Step 1

Prompt	Canvas	Component Annotation
Eye		Eye socket

Step 2

Prompt	Canvas	Component Annotation
Eye		Eye socket Eye socket

Two "Eye socket" annotations would indicate that the drawing contains two components that are "Eye socket", but it is one "Eye-socket" split into 2 steps.

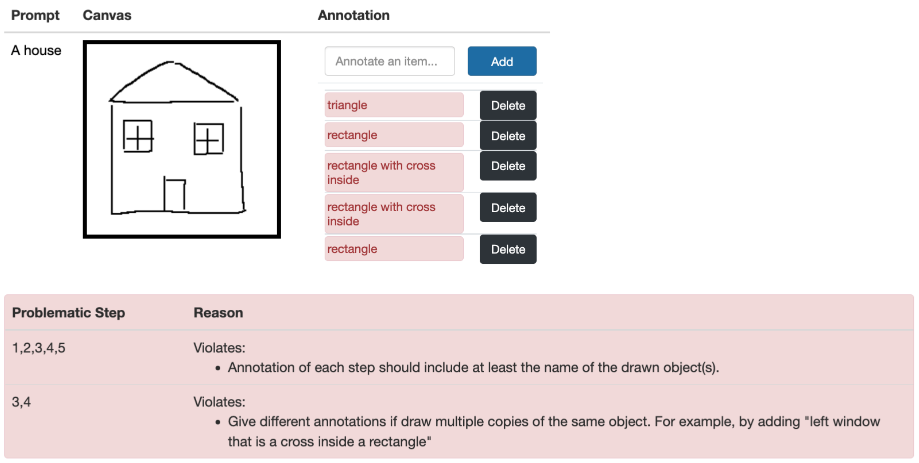
Figure A.3: An example of misalignment: text description *overflow* into multiple steps.

1. Draw *one* item at a time and provide its corresponding annotation. For example, the text annotation says "left eye", but two items are drawn: a left eye and a right eye.
2. The annotation should describe its corresponding item in the drawing *entirely*.
3. The annotation should name the item.
4. Desired properties of good drawings:
   - Contain as many items as possible, but be sure that they all contribute to illustrating the prompt. For example, draw more than just two eyes for a face.
   - Use shapes creatively. For example, draw a triangle for the left eye, and annotate accordingly with "triangular left eye that shows suspicion".
5. Desired properties of good annotations:
   - Use descriptive languages. For example, "a left eye that looks an arc facing downward".
   - Include the intention/purpose of drawing an item. Explain in the annotation reasons for drawing the item. For example, "thumbs-up next to the face that really shows how happy the face is".

Third version of the requirement section in text-guided sketch text dataset:

1. Each drawing should contain at least 2 steps.

2. Annotation of each step should include at least the name of the drawn object(s).
3. If draw multiple copies of the same object, draw each object in a separate step and give different annotations by using, for example, cardinal or ordinal numbers. (An example shown in Figure A.4)
4. Differentiate between plural and singular forms.
5. The name of the whole should not be used for its parts. (An example shown in Figure A.4)



Prompt	Annotation
A house	triangle
	rectangle
	rectangle with cross inside
	rectangle with cross inside
	rectangle

Problematic Step	Reason
1,2,3,4,5	Violates: • Annotation of each step should include at least the name of the drawn object(s).
3,4	Violates: • Give different annotations if draw multiple copies of the same object. For example, by adding "left window that is a cross inside a rectangle"

Figure A.4: A counterexample used in third version of the requirements.

6. The word ”right” always refers to this side: $\Longrightarrow$

Bibliography

Aksan, E., Deselaers, T., Tagliasacchi, A., & Hilliges, O. (2020). *Cose: Compositional stroke embeddings.*

Allado-McDowell, K., & Okojie, I. (2020). *Pharmako-ai.* Ignota.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... Amodei, D. (2020). *Language models are few-shot learners.* arXiv. Retrieved from `https://arxiv.org/abs/2005.14165` doi: 10.48550/ARXIV.2005.14165

Chen, Y., Tu, S., Yi, Y., & Xu, L. (2017). *Sketch-pix2seq: a model to generate sketches of multiple categories.* arXiv. Retrieved from `https://arxiv.org/abs/1709.04121` doi: 10.48550/ARXIV.1709.04121

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... Houlsby, N. (2020). *An image is worth 16x16 words: Transformers for image recognition at scale.* arXiv. Retrieved from `https://arxiv.org/abs/2010.11929` doi: 10.48550/ARXIV.2010.11929

Eitz, M., Hays, J., & Alexa, M. (2012). How do humans sketch objects? *ACM Trans. Graph. (Proc. SIGGRAPH)*, *31*(4), 44:1–44:10.

Frans, K., Soros, L. B., & Witkowski, O. (2021). *Clipdraw: Exploring text-to-drawing synthesis through language-image encoders.* arXiv. Retrieved from `https://arxiv.org/abs/2106.14843` doi: 10.48550/ARXIV.2106.14843

Gal, R., Patashnik, O., Maron, H., Chechik, G., & Cohen-Or, D. (2021). *Stylegan-nada: Clip-guided domain adaptation of image generators.* arXiv. Retrieved from `https://arxiv.org/abs/2108.00946` doi: 10.48550/ARXIV.2108.00946

Ge, S., Goswami, V., Zitnick, C. L., & Parikh, D. (2020). *Creative sketch generation.* arXiv. Retrieved from `https://arxiv.org/abs/2011.10039` doi: 10.48550/ARXIV.2011.10039

Ha, D., & Eck, D. (2017). *A neural representation of sketch drawings.*

Honnibal, M., & Montani, I. (2017). *spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing.* (To appear)

Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., & Aila, T. (2019). *Analyzing and improving the image quality of stylegan.* arXiv. Retrieved from `https://arxiv.org/abs/1912.04958` doi: 10.48550/ARXIV.1912.04958

Kim, J.-H., Kitaev, N., Chen, X., Rohrbach, M., Zhang, B.-T., Tian, Y., ... Parikh, D. (2019). *Codraw: Collaborative drawing as a testbed for grounded goal-driven communication.*

Li, K., Pang, K., Song, J., Song, Y.-Z., Xiang, T., Hospedales, T. M., & Zhang, H. (2018). *Universal perceptual grouping.* arXiv. Retrieved from `https://arxiv.org/abs/1808.02312` doi: 10.48550/ARXIV.1808.02312

Lin, H., Fu, Y., Jiang, Y.-G., & Xue, X. (2020). *Sketch-bert: Learning sketch bidirectional encoder representation from transformers by self-supervised learning of sketch gestalt.* arXiv. Retrieved from `https://arxiv.org/abs/2005.09159` doi: 10.48550/ARXIV.2005.09159

Nichol, A., Dhariwal, P., Ramesh, A., Shyam, P., Mishkin, P., McGrew, B., ... Chen, M. (2021). *Glide: Towards photorealistic image generation and editing with text-guided diffusion models.* arXiv. Retrieved from `https://arxiv.org/abs/2112.10741` doi: 10.48550/ARXIV.2112.10741

Patashnik, O., Wu, Z., Shechtman, E., Cohen-Or, D., & Lischinski, D. (2021). *Styleclip: Text-driven manipulation of stylegan imagery.* arXiv. Retrieved from `https://arxiv.org/abs/2103.17249` doi: 10.48550/ARXIV.2103.17249

Qi, Y., & Tan, Z.-H. (2019). Sketchsegnet+: An end-to-end learning of rnn for multi-class sketch semantic segmentation. *IEEE Access*, *7*, 102717-102726. doi: 10.1109/ACCESS.2019.2929804

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., ... Sutskever, I. (2021). *Learning transferable visual models from natural language supervision.* arXiv. Retrieved from `https://arxiv.org/abs/2103.00020` doi: 10.48550/ARXIV.2103.00020

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners..

Ramesh, A., Dhariwal, P., Nichol, A., Chu, C., & Chen, M. (2022). *Hierarchical text-conditional image generation with clip latents.* arXiv. Retrieved from `https://arxiv.org/abs/2204.06125` doi: 10.48550/ARXIV.2204.06125

Ramesh, A., Pavlov, M., Goh, G., Gray, S., Voss, C., Radford, A., ... Sutskever, I. (2021). *Zero-shot text-to-image generation.* arXiv. Retrieved from `https://arxiv.org/abs/2102.12092` doi: 10.48550/ARXIV.2102.12092

Ribeiro, L. S. F., Bui, T., Collomosse, J., & Ponti, M. (2020). *Sketchformer: Transformer-based representation for sketched structure.*

Sangkloy, P., Burnell, N., Ham, C., & Hays, J. (2016, jul). The sketchy database: Learning to retrieve badly drawn bunnies. *ACM Trans. Graph.*, *35*(4). Retrieved from `https://doi.org/10.1145/2897824.2925954` doi: 10.1145/2897824.2925954

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., . . . Polosukhin, I. (2017). *Attention is all you need.* arXiv. Retrieved from `https://arxiv.org/abs/1706.03762` doi: 10.48550/ARXIV.1706.03762

Wah, C., Branson, S., Welinder, P., Perona, P., & Belongie, S. (2011). *The Caltech-UCSD Birds-200-2011 Dataset* (Tech. Rep. No. CNS-TR-2011-001). California Institute of Technology.

Xie, S., & Tu, Z. (2015). *Holistically-nested edge detection.* arXiv. Retrieved from `https://arxiv.org/abs/1504.06375` doi: 10.48550/ARXIV.1504.06375

Xu, T., Zhang, P., Huang, Q., Zhang, H., Gan, Z., Huang, X., & He, X. (2017). *Attngan: Fine-grained text to image generation with attentional generative adversarial networks.* arXiv. Retrieved from `https://arxiv.org/abs/1711.10485` doi: 10.48550/ARXIV.1711.10485

Yu, Q., Liu, F., Song, Y.-Z., Xiang, T., Hospedales, T. M., & Loy, C. C. (2016). Sketch me that shoe. In *2016 ieee conference on computer vision and pattern recognition (cvpr)* (p. 799-807). doi: 10.1109/CVPR.2016.93

Yuan, S., Dai, A., Yan, Z., Guo, Z., Liu, R., & Chen, M. (2021). Sketchbird: Learning to generate bird sketches from text. In *2021 ieee/cvf international conference on computer vision workshops (iccvw)* (p. 2443-2452). doi: 10.1109/ICCVW54120.2021.00277