Embedding Arithmetic for Text-driven Image Transformation

Guillaume Couairon\textsuperscript{1,2} Matthieu Cord\textsuperscript{2} Matthijs Douze\textsuperscript{1} Holger Schwenk\textsuperscript{1}
\textsuperscript{1}Facebook AI \textsuperscript{2}Sorbonne Université
matthieu.cord@lip6.fr, \{gcouairon,matthijs,schwenk\}@fb.com

Abstract

Latent text representations exhibit geometric regularities, such as the famous analogy: queen is to king what woman is to man. Such structured semantic relations were not demonstrated on image representations. Recent works aiming at bridging this semantic gap embed images and text into a multimodal space, enabling the transfer of text-defined transformations to the image modality.

We introduce the SIMAT dataset to evaluate the task of text-driven image transformation. SIMAT contains 6k images and 18k “transformation queries” that aims at either replacing scene elements or changing their pairwise relationships. The goal is to retrieve an image consistent with the (source image, transformation) query. We use an image/text matching oracle (OSCAR) to assess whether the image transformation is successful. The SIMAT dataset will be publicly available.

We use SIMAT to show that vanilla CLIP multimodal embeddings are not very well suited for text-driven image transformation, but that a simple finetuning on the COCO dataset can bring dramatic improvements. We also study whether it is beneficial to leverage the geometric properties of pretrained universal sentence encoders (FastText, LASER and LaBSE).

1 Introduction

Many works aim at learning a multimodal space in which images and text can be embedded and compared (Wang et al., 2016; Faghri et al., 2018; Engilberge et al., 2018; Zheng et al., 2020b). This is especially useful for image and text retrieval tasks, i.e. given an input from one modality, find a corresponding sample of the other modality in a database. Such embeddings have other interesting applications. It has been shown in (Vo et al., 2019a; Jia et al., 2021) that textual input can be used to replace scene elements in images or change their properties with simple arithmetic operations in the latent space, combined with nearest neighbour search.

In this work, we aim at evaluating multimodal embeddings on the task of semantic image transformation: given an image and a transformation query formulated in the text domain, the task is to find an image that satisfies the transformation query while being semantically as similar as possible to the input image. For example, with the cat→dog transformation, an image showing a cat sitting in the grass should be transformed into an image with a dog sitting in the grass (Figure 1).

A dataset to evaluate text-driven image transformation must contain feasible (image, transformation-
tion) queries: the transformation \textit{man}$\rightarrow$dog can be applied to an image with “\textit{A man is running on the beach}”, but not to “\textit{A man is speaking on the phone}”. We create a corpus from Visual Genome images and annotations (Krishna et al., 2017) and ensure that this requirement is met. Evaluating semantic text-to-image transfer is challenging: First, we need to ensure that the requested transfer was performed (the cat was replaced by a dog). Then, we need to verify that the modification is minimal: the dog should be sitting on grass and ideally, all other visual elements should not be changed. We use OSCAR (Li et al., 2020b) as an external oracle to assess whether these two conditions are met.

We choose to transform images by encoding the transformation query as a \textit{delta vector} in the multimodal space, before adding it to an image embedding and retrieving the closest image in a database (see Figure 1). This procedure is applied at inference and solely relies on the image/text alignment without needing any transformation example. Are multimodal spaces like CLIP (Wang et al., 2016) structured well enough for this kind of operations? We know that word and sentence embeddings trained on vast amounts of data have been shown to possess geometric properties that can be useful for text transformation (Mikolov et al., 2013; Logeswaran and Lee, 2018). Therefore, we wanted to study whether it is necessary to consider independent text embeddings such as LASER (Artetxe and Schwenk, 2019) and LaBSE (Feng et al., 2020) as building blocks to multimodal embeddings better suited to text-driven image transformation. We evaluate our methods on the SIMAT database, as well as on the smaller SIC112 dataset (Vo et al., 2019b). The contribution of this work are:

- SIMAT, a dataset of 6 000 images and 18 000 transformation queries, to evaluate algorithms on the task of text-driven image transformation.
- A novel principled evaluation metric to use in conjunction with SIMAT.
- detailed experiments to measure which multimodal embeddings work best within the \textit{delta vectors} framework to transform images.

2 Related Work

The geometric properties of word embeddings have been observed notably in (Mikolov et al., 2013; Fournier et al., 2020), with the famous example king is to queen what man is to woman. These properties have also been studied for sentence embeddings (Logeswaran and Lee, 2018). Recent work has demonstrated that state-of-the art multimodal embeddings can be obtained by scaling up image-text alignment pretraining (Jia et al., 2021; Radford et al., 2021). It has been observed that such embeddings exhibit properties similar to word embedding analogies, allowing textual and image queries to be combined. A few examples are shown in (Jia et al., 2021), but without any quantified evaluation.

Text-to-image Retrieval. Semantic image transformation is a form of text-to-image retrieval where some textual inputs serve as instruction to modify an existing image through retrieval. The instruction is a simple word pair in our case, but it can also be a more complex instruction in natural language. Several datasets exist to tackle this problem: The CSS dataset (Vo et al., 2019b) which is a synthetic dataset with simple colored geometrical objects based on CLEVR (Johnson et al., 2017). The Fashion200k dataset (Han et al., 2017) provides around 200k images of fashion products, each annotated with a compact attribute description. Similarly, the Fashion-IQ dataset (Guo et al., 2019) was built to advance research on interactive fashion image retrieval. The MIT-States dataset (Isola et al., 2015), also commonly used, is a dataset of \approx 60k images, each annotated with an object/noun label and a state/adjective label such as new car or broken window. Those datasets are designed to evaluate text-driven image retrieval on narrow domains, which gives more control over what attributes can be changed and ensures that the transformation is always feasible. Another common characteristic is the focus on changing object properties rather than objects relationships. We focus on more realistic images, and study object transformations where an object should be replaced by another without changing the high-level subject-object interaction.

Methods for solving the text-driven image retrieval task (Vo et al., 2019b; Anwaar et al., 2021; Song and Soleymani, 2019) all focus on supervised learning: a fraction of the dataset is used for training and the remaining for testing. Instead, we want to measure if multimodal embeddings trained with an image/text matching objective can be used to solve this task without any transformation example.

Text-driven Image Editing. Some work focus on directly modifying the pixels of query images instead of performing the retrieval step (Shi et al.,
Zheng et al. (2020a) encode images as a graph of interacting objects which lets the user modify an image by editing its scene graph. GANs are also frequently used to modify images based on some natural language input (Nam et al., 2018; Li et al., 2020a; Xia et al., 2020). Lastly, CLIP (Radford et al., 2021) can be used in combination with a StyleGAN generator to make semantic edits in images, as exemplified in (Patashnik et al., 2021).

3 The SIMAT database

3.1 Requirements

To evaluate text-driven image transformation, we first need a list of images with some transformation queries (e.g. a man sleeping on the beach, with the query man → woman). We want simple images (so that the query is unambiguous) and relevant transformation queries.\(^1\) Second, a database of images that we will use for the retrieval step. And finally, a criterion to decide, based on the retrieved image, if the transformation is successful or not. It is the case if only the element designated by the transformation query has changed, while keeping the rest of visual elements as similar as possible.

Vo et al. (2019a) try to solve these requirements with a dataset of ≈1,500 images from Google Image Search queries, dubbed SIC112, with each image annotated with a actor-action-environment triplet, such as (woman, walking, street), among a set of 112 possible triplets. Transformation queries then consist in changing either the subject, action or environment. This set of images is also used as a database for retrieval, which has two advantages: (i) transformation queries are always possible by design of the dataset, and (ii) the quality of the retrieved image is measured by checking if its annotation triplet was indeed the one expected by the transformation query.

We scale this approach to a larger number of annotation triplets, that take the more general form of (subject, relationship, object). However, we observed that due to the larger triplet vocabulary, images can be accurately described by multiple such triplets, which skews the evaluation metric: an image would often be rejected for not being annotated with the expected triplet while still being visually correct. Therefore, we chose to use a different metric for evaluating the quality of transformed images:

\[^1\text{e.g. we do not want to change “man” into “mountain” as the transformation is not very semantic, it would be a simple object change in an image.}\]

we evaluate whether the semantic transformation is successful by querying OSCAR (Li et al., 2020b), a state-of-the-art image/text matching algorithm. OSCAR computes the probability \(P_O(I, T)\) that a caption \(T\) accurately described an image \(I\), based on the concatenation of the text tokens in \(T\) and the object tags and features detected by faster R-CNN on image \(I\) (we provide the triplet to OSCAR in the form of a caption written in natural language). Note that this OSCAR-based evaluation method does not involve image annotations in the retrieval database and thus could potentially be applied to a much larger database of non-annotated images, which we leave for future work.

3.2 Construction

Similarly to (Vo et al., 2019a), we create a list of images annotated with (subject, relationship, object) triplets, and perform the retrieval step inside the same list of images to ensure that transformation queries always have a valid solution in the dataset. We start from annotations from the Visual Genome dataset (Krishna et al., 2017). Each image in the dataset contains a list of such triplets with subject and object bounding boxes, which we use to crop square regions of images that minimally contain the subject and object in the image. We then filter this list and compute possible transformations:

Subject/Relation filtering. Only keep triplets for which the subject is a human or animal, and the relation is a non-positional relationship in Visual Genome. The full lists are shown in Figure 2.

Object filtering. Only keep objects \(O\) for which there exists at least two triplets \((S, R, O)\) and \((S', R, O)\) with \(R \neq R'\). This ensures that the selected objects have at least two different types of interaction in images. Then, only keep the 10 most frequent objects for a single (subject, relation) pair. This gives a list of 645 distinct triplets.

Building transformation queries. For each image \(I\) with associated triplet \((S, R, O)\), add in the list of transformation queries \((I, O \rightarrow O')\) if there is a triplet \((S, R, O')\) in the database. Do the same for \(S\) and \(R\). This ensures that transformation queries consists of pairs of objects that can have the same (subject, relation) pair, and symmetrically for subjects and relations.

Writing captions for OSCAR. For each of the 645 triplets, we manually wrote a caption in natural language, e.g. (man, sitting on, chair) → A man sitting on a chair.
Figure 2: Statistics for SIMAT database. All subjects and relationships are represented, but only 25 objects out of 131 are listed here.

We now have a database of images and transformation queries, but we have noticed some noise in the annotation procedure: an image can have a triplet annotation which does not well describe the main action in it, because the cropping procedure included an object that is more important than the extracted triplet. Also, transformation queries sometimes consisted in synonyms. We solve this problem using OSCAR to filter transformation queries: Given an image \( I \) with query triplet \( t_1 \) and target triplet \( t_2 \), we keep the corresponding transformation if \( P_O(I, t_1) > 0.9 \) and \( P_O(I, t_2) < 0.1 \). This ensures that not modifying the image is not a valid solution to the problem.

The distribution of images being quite skewed (see Figure 2), the transformation queries also have a bias towards the more frequent subjects, relations and objects. We alleviate this problem by using reweighting in the scoring metric (see below).

In summary, our SIMAT dataset (for Semantic IMage Transformation) consists of:

- 5,989 images, each annotated with a subject-relation-object triplet.
- 17,996 transformation queries on those images, with queries asking to change the subject, the relation, or the object.
- A list of 645 distinct subject-relation-object triplets with corresponding captions, each triplet having at least 2 corresponding images.

To allow hyperparameter selection, we make a 50-50 dev/set split on the list of images, and split the transformation queries accordingly.

3.3 Evaluation Metric

Let \( (I_i, w_1 \rightarrow w_2, T_i) \) be a sample in our dataset where \( w_1 \rightarrow w_2 \) is the transformation query and \( T_i \) is the caption associated to the target triplet of this sample. For this sample, we consider that a retrieved image \( J_i \) corresponds to a successful transformation if OSCAR outputs a probability \( P_O(J_i, T_i) > 0.5 \). The final score is simply a weighted accuracy over all dataset samples:

\[
S = \sum_{(I_i, T_i, \mu_i) \in S} \mu_i \mathbb{1}_{P_O(J_i, T_i) > 0.5}
\]

where the coefficients \( \mu_i \) are the contributions of each sample to the total score. We adopt an inverse square root reweighting to downsample the most frequent transformations.

4 Methods

Starting from semantic transformations in text, we show how text transformations can be transferred to images via multimodal embeddings. We then present our procedure for fine-tuning multimodal embeddings.

4.1 Text delta vectors for semantic transformations

Semantic properties in sentences can be modified by word replacement: in the sentence “A man walking on the beach”, the semantic property subject gender can be changed by replacing the word man with the word woman. In a latent space, where direct word replacement is not possible, we can apply semantic transformations by doing arithmetic operations. By encoding sentences as the sum of their word embeddings, applying a transformation \( w_1 \rightarrow w_2 \) on a sentence embedding \( E(s) \) amounts to adding the vector \( E(w_2) - E(w_1) \), which we call a delta vector. In principle, the textual form of the transformed sentence can be found by retrieving the sentence embedding closest to \( E(s) + E(w_2) - E(w_1) \) in a database.

However, there is some ambiguity in the process since bag of words representations do not take into account the order of words. That is why we consider more complex non-linear sentence embeddings which have been shown to display similar properties as above (Logeswaran and Lee, 2018), in addition to better reflecting the meaning of sentences (Artetxe and Schwenk, 2019).

We study four sentence embeddings: CLIP, obtained by a contrastive loss on a large set of im-
We consider multiple choices for the image and text encoders. We experiment with using two ImageNet-pretrained encoders: our default setup is to use the CLIP encoders (CLIP, ResNet) for the image encoder, and we freeze only the first three blocks of the ResNet encoder. The CLIP image embeddings are quite sparse due to the relatively small size of the image database, so we found it helpful to enforce the rule that the retrieved image should be different from the input image.

The scaling factor $\lambda$ is a hyper-parameter that can be adjusted to increase the strength of the transformation. The natural choice is $\lambda = 1$ but it has been noted that a higher value can help to better enforce the transformation (Jia et al., 2021). The image embeddings are quite sparse due to the relatively small size of the image database, so we found it helpful to enforce the rule that the retrieved image should be different from the input image.

# Finetuning multimodal embeddings

We consider multiple choices for the image and text encoders: Our default setup is to use the CLIP embeddings for both modalities (63M parameters for the text encoder, 87M for the image encoder), and we experiment with using two ImageNet-pretrained ResNets (RestNet50 and ResNet152, respectively 23M and 63M parameters) as image encoders, and FastText, LASER and LaBSE as text encoders. We can evaluate the vanilla CLIP embeddings without retraining; however, other encoding choices are not directly compatible and we have to fine-tune the encoders to be able to encode image and text into a shared latent space. We use a very simple fine-tuning scheme on COCO (Lin et al., 2014) where we train linear adaptation heads after the frozen encoders (Fig 3) for 30 epochs with a learning rate of 1e-3 and a batch size of 4096. Fine-tuning a model takes approx. 3 hours on 8 Tesla V100 GPUs.

When using the ResNet-based encoders, our initial study showed that only training a linear layer is not sufficient to get a reasonable performance on image-text retrieval, because the backbone network is only trained on image classification. Therefore, we freeze only the first three blocks of the ResNet models and add a simple 4-layer MLP architecture on top of the pooled features. We use an image-text InfoNCE (Sohn, 2016) contrastive loss (which was used for training CLIP):

$$C(I, T) = \frac{1}{n} \sum_{i=1}^{n} \frac{\exp(I_i \cdot T_i / \tau)}{\sum_{j=1}^{n} \exp(I_i \cdot T_j / \tau)}$$

$$\mathcal{L} = \frac{1}{2} C(I, T) + \frac{1}{2} C(T, I)$$

where $I$ and $T$ are normalized image and text embeddings, $\tau$ a temperature parameter which is learnable in CLIP. However, we choose to keep it fixed to study its impact on the transformation score.

## 5 Experiments on SIMAT database

In this section, we analyze the delta vector method for transferring text transformations to images.

### 5.1 Zero-shot CLIP

We first study the performance of the vanilla CLIP embeddings for transferring text transformations to images with delta vectors. To put our results in perspective, we also evaluate the following baselines:

**Text to Image:** We directly provide the target captions to the CLIP text encoder and retrieve the image closest to that embedding. This is the standard image retrieval task, which is easier because the target subject-relation-object features are given as input. Hence it can be considered as an upper bound of our SIMAT score.

**Image to Text to Image:** We first find among the SIMAT captions which one is closest to the query image. We then add the text delta vector corresponding to the transformation query and retrieve the closest image in the SIMAT database.
Table 1: SIMAT score for delta vectors in the original CLIP multimodal space. The default score considers the nearest neighbour in the retrieval step ($n = 1$). We also report the SIMAT score for the the best image using $n = 5$ nearest neighbours.

Results are shown in Table 1. The delta vector method works for 15.9% of the transformation queries. A higher value of $\lambda$ gives much better results (35.4%) which are nonetheless below the Image to Text to Image baseline (39%), and very far from the Text to Image upper bound (65.9%).

5.2 Fine-tuning CLIP on COCO

Here, we consider CLIP as image and text encoder, but we additionally train adaptation layers on COCO with different values for the temperature parameter $\tau$. Figure 5 shows the SIMAT score as a function of the scaling factor $\lambda$, on the SIMAT dev set. The same curve for the vanilla CLIP embeddings is shown in black. We can see that all curves have an optimal value for $\lambda$, which depends on $\tau$. This optimal value $\lambda^*(\tau)$ decreases as $\tau$ increases from 0.01 to 1, and the global optimum is reached for $\tau = 0.1$ and $\lambda = 1$. For these values, the SIMAT score is 48.2 which is a 33-point improvement over the zero-shot score.

We therefore conclude that the temperature parameter $\tau$ has a great importance for transferring text delta vectors to image, and the fine-tuned embeddings work best with delta vectors for $\tau = 0.1$ and $\lambda = 1$. Transformation examples on SIMAT obtained with this model are presented in Figure 4, while a detailed breakdown of transformation scores is shown in appendix A.

Note that the best image retrieval and text retrieval evaluations on COCO are obtained for $\tau = 0.01$, which hints towards the fact that smaller temperatures are better for image-text retrieval and higher temperatures ($\tau \sim 0.1$) are more compatible with the delta vector framework. In the rest of the paper, we use a fixed temperature of $\tau = 0.1$.

5.3 Using pretrained text encoders

We show in Figure 6, that a value of $\tau = 0.1$ which is optimal for CLIP, is also near-optimal for all other considered text embeddings, FastText, LASER and LaBSE. It seems to be a value that works well for delta vectors. In Table 2, we analyze our different choices for the image and text encoders. The Retrieval upper bound metric corresponds to the Text to Image baseline of section 5.1. The Text delta vector metric consists in checking if by taking the source caption embedding and adding the transformation delta vector, we get an embed-
If we fix the sentence encoder, the image encoder has an important influence on the image-text retrieval metrics but very little impact on the text delta vectors, SIMAT and Retrieval upper bound scores. Since COCO retrieval performance is higher for a training temperature of $\tau = 0.01$, we make the observation that multimodal embeddings better suited to image-text retrieval do not necessarily work better with delta vectors.

Also, quite unexpectedly, the SIMAT score does not seem correlated to the Text delta vector score, which measures how well delta vectors can transform text embeddings: the fine-tuned CLIP text embeddings have a text transformation accuracy of 82.4% whereas the fine-tuned FastText embeddings reach 94.4%. Yet they have very similar SIMAT scores (48.2% vs 47.5%). It seems to show that within our constraints, a slightly lower performance on text delta vector is not the current limitation.

Finally, we note that although the CLIP image embeddings are optimized to work well with the CLIP text embeddings, they are also compatible with FastText embeddings on our specific task since they can be adapted with linear layers with similar SIMAT scores (47.5 vs 48.2). The image/text retrieval performance is noticeably lower though, indicating that more complex sentence encoders are needed for this task.

### 5.4 Sentence-based delta vectors

In our default method for using text-based delta vectors, we used single words as input to the text encoder. This is particularly well suited for the FastText embeddings which are based on word embeddings, but not so much for the LASER and LaBSE sentence encoders which are built to encode sentences and not single words. This could explain the performance gap between FastText and LASER/LaBSE. To test this hypothesis, we changed our definition of delta vectors so that it is computed by encoding sentences rather than single words. We define the sentence average delta vector of transformation $w_1 \rightarrow w_2$ as the average of delta vectors $E(s_2) - E(s_1)$ where $s_1$ and $s_2$ go over all pairs of SIMAT captions such that $s_2$ is the result of the text transformation $w_1 \rightarrow w_2$ applied to $s_1$.

We show the results in Table 3. With this new method, the performance gap between the different text encoders is much smaller, the SIMAT score being higher for LASER and LaBSE, and smaller
for FastText. We observed that we can use a higher scaling factor to boost the SIMAT score, up to $\lambda = 1.5$ for CLIP. We suspect this is due to the fact that the second method produces more reliable delta vectors with a smaller norm.

Note that the role of this experiment is to shed light on the reasons behind the performance spread with respect to the text encoders. The captions of SIMAT should be reserved for evaluation only and not used within the algorithm. A better algorithm may use the COCO captions to create better sentence-based delta vectors, but we leave this for future work.

### 5.5 Validation on SIC112

In this final section, we use the SIC112 dataset (Vo et al., 2019a) to validate our delta vector-based transformation method. As explained in Section 3.1, the metric used is the accuracy of transformation success based on the original annotation of the retrieved image. They report a baseline accuracy of 26.6. We highlight the most important results in Table 4, where we use the same accuracy score and the same Image retrieval upper bound method as a point of comparison.

The zero-shot CLIP method reaches a lower score than the baseline with $\lambda = 1$ but a higher score with $\lambda = 3$, which is in accordance with our results on SIMAT. Fine-tuning with $\tau = 0.1$ dramatically improves the SIC112 score (although not shown here, the scores for $\tau = 0.01$ are lower). We also observe that using FastText embeddings yields even higher scores, although the Image retrieval Upper bound is much lower than that of the CLIP-only model. Note that our method with ResNet50 reaches the same accuracy as (Vo et al., 2019a) while not being trained with a transformation objective.

Figure 7 shows an ablation conducted on the image and text encoders used for transferring transformation on SIC112. Here, the choice of sentence embeddings has little influence while the CLIP image encoder outperforms its Resnet counterparts (45-50% accuracy vs 25-30%). This is probably because SIC112 images do not naturally belong to the image distribution of ImageNet or COCO, on which the Resnet are trained, whereas CLIP is trained on a much broader image distribution.

### 6 Conclusion and Future work

We introduce SIMAT, a novel dataset to study the task of text-driven image transformation. It is much larger in size and variety of transformations than existing approaches like SIC112. We emphasize the necessity of a novel evaluation metric and present a principled evaluation criterion to assess how well algorithms can transfer text-defined transformations to images. We use SIMAT to evaluate multimodal embeddings trained with an image-text alignment objective, without any transformation example. Transformations are computed at inference time using delta vectors, for which we present a detailed study. For future work, we would like to extend the tasks to richer semantic transformations: we expect that for transformations like young $\rightarrow$ old or dirty $\rightarrow$ clean, higher-level semantic knowledge embedded in language models will be critical to do meaningful transformations.

### Table 3: Comparison of two methods to calculate delta vectors: Single word and Sentence average. With the latter, all the encoders have very similar SIMAT scores.

| Sentence Encoder | Single word | Sentence Average $\lambda = 1$ | $\lambda = 1.2$ | $\lambda = 1.5$ |
|------------------|-------------|--------------------------------|----------------|----------------|
| CLIP             | 48.2        | 46.7                           | 51.5           | 53.5           |
| FastText         | 47.5        | 44.6                           | 46.5           | 45.8           |
| LASER            | 37.7        | 43.8                           | 45.0           | 44.2           |
| LaBSE            | 41.9        | 44.6                           | 46.5           | 45.5           |

### Table 4: Comparison of several algorithms for semantic image transformation on the SIC112 dataset.

| Method                          | SIC Score | Image retrieval Upper Bound |
|---------------------------------|-----------|-----------------------------|
| (Vo et al., 2019a)              | 26.6      | 39.6                        |
| CLIP zero shot ($\lambda=1$)    | 20.4      | 70.1                        |
| CLIP zero shot ($\lambda=3$)    | 31.7      | 70.1                        |
| CLIP                            | 47.4      | 71.8                        |
| CLIP FastText                   | 50.7      | 53.3                        |
| RN50 FastText                   | 26.7      | 52.5                        |

Figure 7: SIC score for multiple image/text encoders. Retrieval Upper bound is shown in transparency.
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A Supplementary Material

A.1 Transformation score by target

In Figure 8, we use the CLIP model finetuned with $\tau = 0.1$ and compute the SIMAT score by grouping transformations by their target values: for each word $w$, we compute the weighted accuracy of transformation success for all queries $w_1 \rightarrow w_2$ such that $w_2 = w$. The relative weight of each target value in the final SIMAT score is shown on the x-axis, and the y-axis represents the SIMAT score. We can see that overall, transforming object relations is harder than transforming the objects themselves, which is probably because relationship are less easily identifiable in images. Also, if we compare the SIMAT scores between objects, we can see that the best SIMAT scores are obtained for objects that are easy to recognize (sink, toilet, suitcase..) while the worst scores correspond to objects without a well defined shape that are harder to recognize (feeder, counter, wall, bus stop).