

# What You See is What You Read? Improving Text-Image Alignment Evaluation

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## Abstract

Automatically determining whether a text and a corresponding image are semantically aligned is a significant challenge for vision-language models, with applications in generative text-to-image and image-to-text tasks. In this work, we study methods for automatic text-image alignment evaluation. We first introduce SeeTRUE: a comprehensive evaluation set, spanning multiple datasets from both text-to-image and image-to-text generation tasks, with human judgements for whether a given text-image pair is semantically aligned. We then describe two automatic methods to determine alignment: the first involving a pipeline based on question generation and visual question answering models, and the second employing an end-to-end classification approach by finetuning multimodal pretrained models. Both methods surpass prior approaches in various text-image alignment tasks, with significant improvements in challenging cases that involve complex composition or unnatural images. Finally, we demonstrate how our approaches can localize specific misalignments between an image and a given text, and how they can be used to automatically re-rank candidates in text-to-image generation.<sup>1</sup>

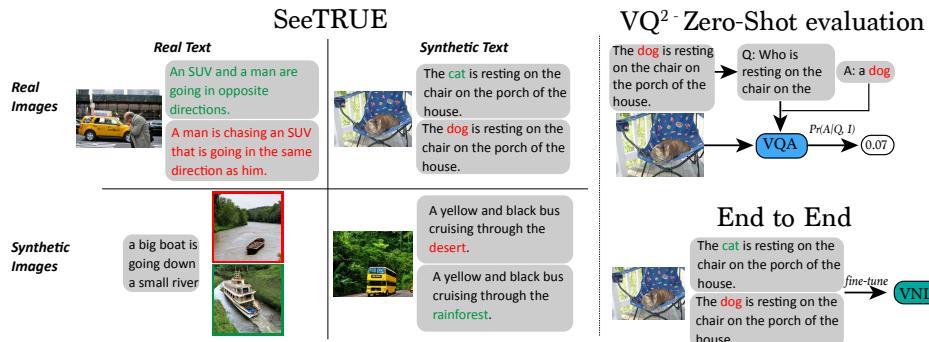


Figure 1: Overview of our approach to text-image alignment evaluation using SeeTRUE. We curate diverse pairs of real and synthetic text and images and use automatic contradiction generation and human evaluation to create a benchmark dataset. We propose two methods for text-image alignment evaluation: VQ<sup>2</sup> and VNLI, demonstrated with example pairs.

\*Equal contribution. Yonatan participated in this work as part of an internship at Google Research.

<sup>1</sup>Data and code are attached to this submission.

## 1 Introduction

The recent success and proliferation of multi-modal large language models (LLMs) for text-to-image and image-to-text generation [1–8] make such technology increasingly useful for a wide range of creative applications. However, such models still struggle in generating semantically-aligned image-text pairs; in text-to-image generation, models do not cope with complex specifications [9, 10] or fail to map words in the prompt to visual entities [11, 12]. In image captioning, object hallucination is a long-standing challenge [13] with generated captions still being inferior to human-written ones [14].

Given the above, the task of automatically determining whether a given text-image pair is semantically aligned is highly important, as it is useful both for *evaluating* and for *improving* text-to-image and image-to-text models. However, existing evaluation approaches are still far from ideal; common methods like CLIP [15] or BLIP [6, 7] are based on encoding the image and text as fixed-size embeddings, making it hard to model complex semantics [16]. In addition, while the task is relevant both to text-to-image and image-to-text generation, it is usually studied in silo while considering only one of the applications, thus impeding progress.

In this work, we promote a comprehensive approach to evaluating image-text alignment. We introduce SeeTRUE, a diverse evaluation suite which includes a wide range of image-text pairs with human judgments that determine if the image and text are semantically aligned. SeeTRUE encompasses both real and synthetic images and text, allowing the assessment of text-image alignment models’ generalization capabilities across various tasks and 31,855 labeled examples from diverse sources. As part of constructing SeeTRUE, we also introduce a novel method for generating contradicting captions from existing ones by prompting a large language model with tailored instructions.

We present two approaches for automatic image-text alignment evaluation. The first, VQ<sup>2</sup>, utilizes question generation and visual question answering by generating questions related to the text [17] and ensuring that the correct answer is obtained when asking these questions with the provided image. The second method, Visual Entailment<sup>2</sup> (VNLI), involves directly fine-tuning a large pretrained multimodal model to predict if a given image-text pair is semantically aligned. Both strategies are inspired by recent studies on evaluating factual consistency between two texts [18–21].

We conduct comprehensive experiments on SeeTRUE, demonstrating that both our VQ<sup>2</sup> and VNLI methods outperform a wide range of strong baselines, including various versions of CLIP [15], COCA [22], BLIP [6, 7], and OFA [23]. While previous work showed that vision-and-language models tend to exhibit sub-optimal “bag-of-words” behavior [16], the VQ<sup>2</sup> method particularly excels on datasets with compositional challenges, achieving state-of-the-art results on the Winoground dataset [24] e.g. by improving the *group score* from 16% to 30.5%. Our methods also demonstrate improved performance when evaluating synthetic images (e.g. on DrawBench [5] and EditBench [25]). Finally, we showcase how VQ<sup>2</sup> can identify specific sources of misalignment for a given text-image pair and how our methods can re-rank generated image candidates for a given prompt.

To summarize, our contributions are as follows: (1) We introduce the SeeTRUE benchmark for meta-evaluation of image-text alignment. (2) We introduce a novel method to generate contradicting image captions from given captions with LLMs. (3) We suggest two reference-free metrics for image-text alignment evaluation: VQ<sup>2</sup>, based on question generation and visual question answering, and VNLI, based on fine-tuning large multimodal language models. (4) We conduct extensive evaluation of the above approaches against strong baselines, demonstrating superior performance over multiple datasets. (5) We release our evaluation suite, models and code to foster future work.

## 2 SeeTRUE: A Comprehensive Text-Image Alignment Benchmark

We begin by introducing SeeTRUE, a diverse benchmark for meta-evaluation of image-text alignment methods, covering the 4-way combinations of real and synthetic text-and-image pairs. It addresses limitations in current benchmarks, which mainly focus on natural images and often lack challenging negative captions. SeeTRUE allows to better assess the generalization abilities of text-image alignment models across various tasks.

Defining how image-text alignment is assessed has a direct impact on the construction of evaluation datasets. As images can display more details than described in their caption or text prompt, we define

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<sup>2</sup>We use the terms Entailment and Natural Language Inference (NLI) interchangeably.

Table 1: SeeTRUE: a benchmark for image-text alignment encompassing 31,855 real and synthetic image-text pairs from diverse datasets and tasks. An example from each dataset is presented below.

	Real Text + Real Images		Real Text + Synthetic Images			Synthetic + Real	Synthetic + Synthetic
Dataset Name	SNLI-VE	Winoground	DrawBench	EditBench	COCO t2i	COCO-Con	
# Test Examples	17,901	1,600	1,968	3,827	2,586	1,992	1,981
% Positive / Total	33.3%	50%	55.7%	36.9%	63.6%	52.7%	44.1%
Labeled in this work?	X	X	✓	✓	✓	✓	✓
Image							
Text	the player swings his bat	the heavy oncoming traffic is contrasted with the light outgoing traffic	A blue cup and a green cell phone	a few pink candles and some cream on top of a cake.	A person on a snow board high up in the air.	A giraffe leaned over in a plush field next to some cows	a doctor wearing a white coat in the middle of a street
Human Label	True	True	False	True	False	False	True

image-text alignment as the case where all the details described in the text are accurately represented within the image. Inspired by the Textual Entailment task [26] which judges for two pieces of text whether one (the “hypothesis”) can be inferred given the other (the “premise”), our definition maps the image to the premise and the text to the hypothesis, resulting in the task of predicting whether the information in the text can be inferred from the given image.

## 2.1 Datasets

We describe the datasets included in our benchmark, with a high-level overview in Table 1.

**Real text and real images.** For pairs of human-written text and real (non-generated) images, we include the SNLI-VE [27] and Winoground [24] datasets. SNLI-VE is a widely adopted VNLIN dataset containing an image, a text, and a label of the alignment between the two – entailment, contradiction, or neutral. Winoground is a challenging dataset for compositional understanding, where each example includes two images and two text captions, where the task is to match each text to its corresponding image. The captions only differ in a few words, which should result in distinct visual interpretations. For example, “some plants surrounding a lightbulb” vs. “a lightbulb surrounding some plants”.

**Real text and synthetic images.** For datasets that represent text-to-image generation tasks we use EditBench [25] which offers prompts and images generated by various text-to-image models given those prompts, accompanied by alignment ratings. To encourage more diversity in the data, we also create new datasets by generating images using Stable Diffusion models [3] (V1.4 and V2.1) and Imagen [5] by prompting them with COCO [28] captions and text prompts from DrawBench [5], creating the COCO text-to-image (“COCO t2i”) and the DrawBench text-to-image datasets.

**Synthetic text and real images.** This category includes a new dataset which we name COCO-Con. COCO-Con is generated using a novel automatic method which we describe in detail in Section 2.3. Specifically, we generate synthetic contradicting captions for COCO images based on their original captions by prompting a large language model, and verify the resulting captions with human raters.

**Synthetic text and synthetic images.** We utilize PickaPic [29], a source of user-generated and ranked synthetic images. We create synthetic captions using BLIP2 [7] and employ our automatic contradiction generation method (Section 2.3) to produce unaligned captions. This category evaluates synthetic text that is generated by image captioning models, e.g. for improving textual image search.

We note that some of the datasets are only used for testing (e.g., Winoground, DrawBench, EditBench) while others include both training and test sets (e.g., SNLI-VE, COCO t2i, COCO-Con, PickaPic-Con). This allows us to investigate different training configurations and their effect on performance.

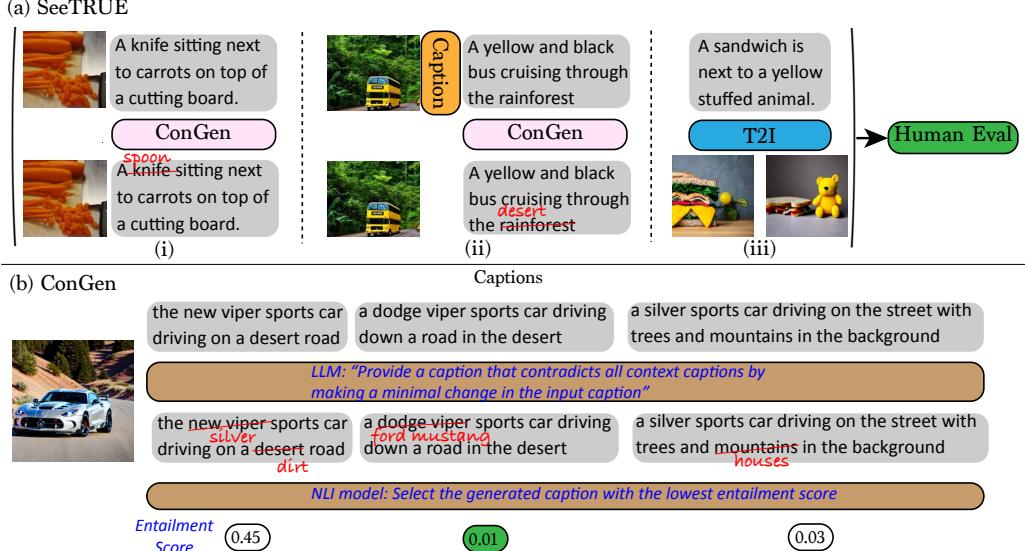


Figure 2: (a) The SeeTRUE generation process. (i) An image-text pair from a dataset is used to generate a contradicting caption using ConGen. (ii) An image (real or synthetic) is passed through a captioning model to generate a caption, which is then passed to ConGen to generate a contradicting caption. (iii) A text-to-image model is applied on captions from the dataset to create multiple image-text pairs. All the resulting examples are evaluated by human raters to create SeeTRUE. (b) The contradiction generation process (ConGen) takes a caption as input and instructs an LLM to generate variants that contradict it. An NLI model is used to select the variant with the lowest entailment score.

## 2.2 Human Annotation and Evaluation

To standardize the labeling scheme across datasets, we follow TRUE [19] and use binary annotations for alignment/misalignment. In datasets with three-way annotations (e.g. Entailment, Contradiction, Neutral) we convert the labels to binary labels by collapsing all non-entailment/non-alignment labels to a single negative label.

Some datasets, such as COCO-Con and PickaPic-Con, start with automatically generated labels, while others lack annotations entirely (e.g. DrawBench). To make sure we have high quality labels we conduct human annotation for all test examples in such datasets. We ask three crowd-workers from Amazon Mechanical Turk (AMT) to evaluate whether a given image-text pair is aligned, by answering the question: “Does the image present all the details described in the text correctly?” with “Yes” or “No”. If the answer is “No”, the workers are also requested to describe the main misalignment to enhance the annotation quality. While the random chance of agreement is 25%, the annotators reached consensus in 80% of cases. Furthermore, we measured a Fleiss-Kappa [30] score of 0.722, showing a good level of agreement between the annotators. Full annotation details, AMT user interface example, and agreement numbers per dataset can be found in appendix A.2.

The datasets we annotated include DrawBench, COCO t2i, COCO-Con and PickaPic-Con, with statistics presented in Table 1. These datasets vary in their positive/negative distribution, with COCO t2i having the highest percentage of positives (63.6%) and DrawBench having the lowest (36.9%). The agreement with the auto-label is 94% for COCO-Con and 77% for PickaPic-Con. To prevent the inclusion of offensive images, particularly those that are synthetically generated, annotators are asked to mark any images that may be considered offensive and these were discarded.

## 2.3 ConGen: Generating Contradicting Captions by Prompting LLMs

We propose an automatic method for generating unaligned captions from existing, aligned image-and-text pairs, with the goal of creating challenging examples for evaluation and training. Our method is inspired by the concept of contrast sets: given an original example with a corresponding label, we create a minimally perturbed example where the perturbation changes the corresponding

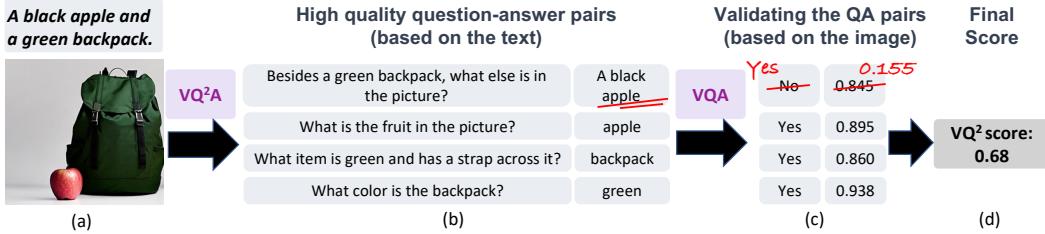


Figure 3: The  $VQ^2$  pipeline: (a) given a text and an image, (b) generate question and answer pairs from the text, (c) re-write each pair as a yes-no question and obtain the ‘yes’ answer probability from the image as an alignment score. (d) Finally, average all alignment pair scores as the final  $VQ^2$  score.

label [31–34]. Contrast sets address the issue of supervised models exploiting data artifacts in i.i.d. train/test splits to achieve high test scores, while their performance degrades significantly on samples outside their training distribution.

To create contrast sets for image-text alignment, we go over the text captions from the image-text pairs in the COCO and PickaPic datasets, covering both natural and synthetic images. For each caption we instruct PaLM [35], a large language model, to generate several contradicting captions via few-shot inference with 7 positive and 8 negative examples. For instance, for the caption “*a knife sitting next to carrots on top of a cutting board*”, the model replaces the word *knife* with *spoon* (see Fig. 2, left). We then use a Natural Language Inference (NLI) model [18] to score whether the generated caption is indeed contradicting the original, and select the generated caption with the highest contradiction score. Figure 2 illustrates this process. Human annotators verified that the resulting contradicting captions are of high quality, with 94% agreement with human labels in COCO and 77% agreement with human labels in PickaPic (more details in section 2.2).

### 3 Methods

Using our SeeTRUE benchmark, we would like to reassess the performance of multimodal alignment approaches. In this section we introduce two image-text alignment methods. In Section 4 we will compare their performance against established, previously published methods.

#### 3.1 $VQ^2$ : Zero-Shot Alignment via Question Generation and Visual Question Answering

Inspired by recent work on factual consistency evaluation in text-to-text tasks [36, 18, 37], we propose a zero-shot approach for automatically evaluating image-text alignment based on question generation and question answering. Figure 3 provides an overview of the method. For a given image-text pair  $\{I, T\}$ , we first extract a set of candidate answer spans  $\{a_j\}_{j=1}^N$  from the given text  $T$ . Then, we use a question generation (QG) model to generate a question for each answer candidate  $q_j = QG(a_j, T)$ . Each generated question-answer pair  $(q_j, a_j)$  is scored with a question answering (QA) model, and if  $QA(q_j, a_j, T)$  returns a low score, we filter out the corresponding pair. This results in a subset of  $M$  question-answer pairs  $\{(q_j, a_j)\}_{j=1}^M$ .

Each generated question-answer pair  $(q_j, a_j)$  is then independently validated based on the image  $I$  using a visual question answering (VQA) model, obtaining an answer alignment score  $s_j = VQA(q_j, a_j, I)$  (more details on how this score is computed are given in 3.1). The overall alignment score for a image-text pair, denoted as the  $VQ^2$  score, is the average over all  $s_j$  scores for all the generated  $(q_j, a_j)$  pairs. We next describe each step in more detail.

**Generating question-answer pairs.** We follow the  $VQ^2A$  method [17] to generate question and answer pairs given an image caption in three steps. First, answer spans are extracted from text  $T$  using SpaCy [38], based on Part-of-Speech (POS) and dependency parse tree annotations. Then, for each answer span, a question  $q_j$  is generated given the answer span and the full caption as input using a T5-XXL model fine-tuned on SQuAD1.1 [39]. Finally, each candidate question-answer pair  $(q_j, a_j)$  is validated by answering  $q_j$  on  $T$  using a QA model, which is trained by fine tuning a T5-XXL model on SQuAD2.0 [40] and Natural Questions [41]. Finally, we match the output answer  $a'_j$  to the expected answer  $a_j$  using token-level F1 comparison. As suggested in [17], if the answer comparison F1 score is lower than 0.54 the question-answer pair is filtered out.

**Assessing question-answer pair alignment against the image.** To determine if the information conveyed by the text  $T$  is presented correctly in the image  $I$ , we use a VQA model based on PaLI-17B [42] as follows. We reformulate each question and answer candidate pair  $(q_j, a_j)$  into a new yes-no predicate question  $q'_j$  using the format “*is { $a_j$ } true for { $q_j$ } in this image?*”. For example, for the text “*two girls are sitting on some grass*”, and the automatically induced question-answer pair {“*what are the girls sitting on?*”, “*some grass*”}, the reformulated question is “*is on some grass true for what are the girls sitting on? in this image?*”. The VQA model is then invoked to answer the predicate question ( $q'_j$ ) over image  $I$ . We define the alignment score  $s_j$  as the probability of the model for answering “yes”. We note that we also experimented with other answer alignment methods, e.g. ones that directly ask the generated question without formulating it as a yes/no question. However, the yes-no approach worked best. More details can be found in appendix A.3.

### 3.2 End-to-end VNLI Models

Another approach is to train end-to-end Visual NLI models (VNLI) that receive an image and text as input, and directly predict an alignment score. We do so by fine-tuning multimodal pretrained models while formatting the examples as yes/no questions using the prompt: “Does this image entail the description: {text}?", followed by a binary “yes” or “no” answer. In inference time we measure the probabilities of predicting “yes” or “no”, and use the relative ratio between the two as the alignment score. Specifically, we finetune BLIP2 [7] and PaLI-17B [42] using a dataset comprising 110K text-image pairs labeled with alignment annotations. This includes 44K examples from COCO-Con, 3.5K from PickaPic-Con, 20K from COCO t2i and 40K from the training split of the SNLI-VE dataset. We generate COCO-Con and COCO t2i based on the COCO train split and PickaPic-Con with a distinct set of images, to ensure that there is no overlap with samples in the SeeTRUE benchmark. More technical details and training hyperparameters are described in appendix A.4.

## 4 Experiments

### 4.1 Models and Metrics

We evaluate  $VQ^2$  and fine-tuned VNLI models based on PaLI and BLIP2 (Section 3) against several state-of-the-art multimodal models: (a) CLIP [15] and two larger versions - CLIP RN50x64 and CLIP ViT-L 14 [43], (b) CoCa [22], (c) BLIP Large [6], (d) BLIP2 FlanT5-XXL [7], and (e) OFA Large [23], and (f) TIFA [44]. First five models were typically trained with either a contrastive objective or an image-text matching objective that samples positive or negative caption-label pairs. TIFA, like  $VQ^2$ , employs a VQA model with generated question-answer pairs. However, TIFA contrasts textual and visual answer candidates provided by the model, while our method checks if the textual answer is accurate given the image.

We assess each method’s ability to detect misalignments in each dataset in SeeTRUE. We use a binary labeling scheme and report the Area Under the ROC Curve (ROC AUC) for each method. For Winoground, we use existing metrics: (1) *text score*: accuracy in selecting the right caption for an image; (2) *image score*: accuracy in choosing the correct image given a caption; (3) *group score*: accuracy requiring all four image-caption pairs to be correct for a successful example.

### 4.2 Results

We present our main results in Table 2. Notably, our  $VQ^2$  approach excels as the top-performing zero-shot model across all datasets, surpassing other zero-shot baselines and even outperforming most of the fine-tuned models while achieving the highest score on the challenging Winoground dataset. This shows the robustness of the  $VQ^2$  approach, which decomposes the alignment decision by generating multiple yes/no verification questions.

When looking at finetuned models, the PaLI variant finetuned on all the available datasets outperforms all the rest with an average score of 82.9, achieving the best results on 3 out of 7 datasets. The SNLI-VE-only variant is behind with an average score of 79.7, while achieving the highest scores for 2 out of 7 datasets. This shows that integrating synthetic training data leads to notable improvements on synthetic images on DrawBench (+4%), EditBench (+11.7%), COCO t2i (+5.5%), PickaPic-Con (+2.2%). Nevertheless, the inclusion of synthetic training data did not enhance performance on the COCO-Con dataset, comprised solely of natural images. This indicates that the variation in

Table 2: Main Results on SeeTRUE, split into zero-shot and end-to-end fine-tuned methods across the real and synthetic image-text eval-sets. The numbers in the table are ROC AUC.

Text & Images Model	Real + Real		Real + Synthetic			Synthetic + Real	Synthetic + Synthetic	Avg.	
	SNLI-VE	Winoground	DrawBench	EditBench	COCO t2i	COCO-Con	PickaPic-Con		
zero-shot	CLIP RN50x64	66.6	53.6	59.2	67.1	58.8	71.1	66.8	63.3
	CLIP ViT-L14	65.8	53.3	60.5	62.1	58.8	70.7	66.8	62.6
	COCA ViT-L14	68.5	53.1	67.4	66.3	62.1	74.2	68.1	65.7
	COCA ViT-L14 (f.t. on COCO)	70	53.1	66.2	68.3	66.2	76.5	67.2	66.8
	BLIP	75.2	58.2	60.5	68	70.7	84.2	76.6	70.5
	BLIP2	76.4	56.9	58.5	67.5	66.9	84.3	76.9	69.6
	BLIP 2 (f.t. COCO)	75.9	60	65.7	70	73.3	85.8	78	72.7
	PaLI	65.4	53.6	60.2	56.7	53.3	65.5	60.5	59.3
f.t. snli+ve	TIFA	—	58.0	73.4	67.8	72.0	—	—	—
	VQ <sup>2</sup> (Ours)	88.0	<b>63.5</b>	82.6	73.6	<b>83.4</b>	87.1	81.7	<b>80.0</b>
	OFA Large	80.5	53.3	77.6	70.9	67.5	75.4	69.5	70.7
	BLIP2	82.3	58.5	64.3	58.7	60.5	82.6	66.9	67.7
PaLI + Synthetic Data	PaLI	<b>95.1</b>	61.7	82.8	65.5	77.7	<b>91.2</b>	83.7	79.7
	PaLI + Synthetic Data	94.2	61.8	<b>86.8</b>	<b>77.2</b>	83.2	91	<b>85.9</b>	<b>82.9</b>
Avg(VQ <sup>2</sup> , PaLI+Syn)		93.9	<b>63.5</b>	<b>87.8</b>	<b>78.4</b>	<b>85.1</b>	<b>93</b>	<b>87.3</b>	<b>84.1</b>

Table 3: Results on the Winoground dataset, reporting text score, image score, and group score.

Model	Text Score	Image Score	Group Score
VQ <sup>2</sup> (Ours)	<b>47.00</b>	<b>42.20</b>	<b>30.50</b>
PaLI (ft SNLI-VE + Synthetic Data)	46.5	38	28.75
PaLI (ft SNLI-VE)	45.00	41.50	28.70
BLIP2 (f.t. COCO)	44.00	26.00	23.50
IAISlarge [45]	42.50	19.75	16.00
VinVL [24]	37.75	17.75	14.50
TIFA	19.00	12.50	11.30
CLIP RN50x64	26.50	13.75	10.25
OFA Large (f.t. SNLI-VE)	27.70	14.30	9.00
COCA ViT-L14 (f.t. on COCO)	28.25	11.50	8.25
Random Chance [24]	25.00	25.00	16.67
Humans [24]	89.50	88.50	85.50

image types could be a contributing factor that calls for additional exploration. Notably, the last row shows a simple average between VQ<sup>2</sup> and our leading fine-tuned PaLI model, that produces higher performance, suggesting that they complement each other effectively.

**Winoground Results.** Table 3 shows the performance of the different methods on the challenging Winoground dataset, which requires strong visual reasoning and compositional understanding skills. Our zero-shot approach, VQ<sup>2</sup>, achieves state-of-the-art results on this dataset, surpassing other strong baselines, with a group score of 30.5%. This again indicates that VQ<sup>2</sup>’s approach that decomposes the alignment task into multiple question-answer pairs is a promising path for image-text alignment.

**Contradiction Generation.** We assessed the VQ<sup>2</sup> method’s capacity to detect image-text contradictions, as shown in fig. 4. Contradiction generation relies on identifying the question-answer pair with

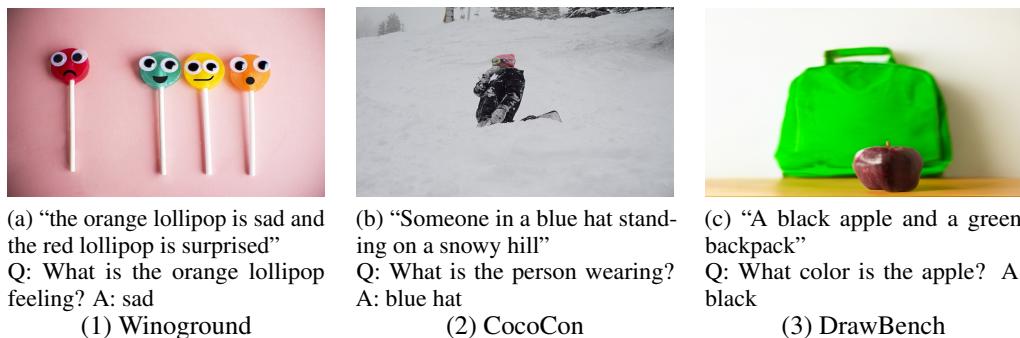


Figure 4: Contradicting captions and the question/answer pairs with lower VQ<sup>2</sup> alignment score, indicating the contradiction reason.

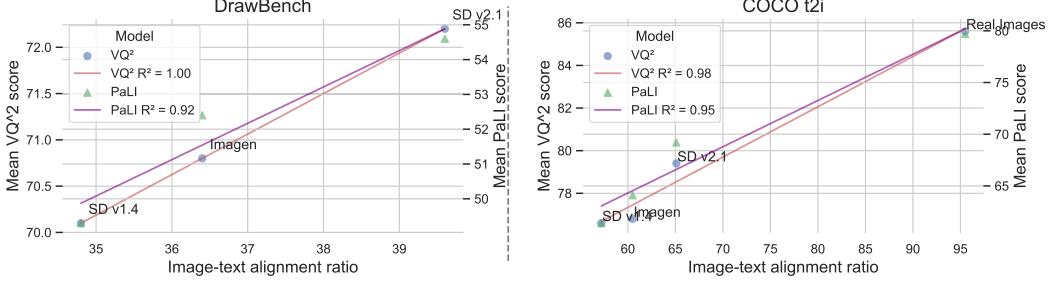


Figure 5: Highly correlated  $VQ^2$  and PaLI scores vs. human rankings of text-to-image models the lowest VQA score, signaling the least likely alignment between the image and the text. Three paper authors evaluated whether a particular contradiction (consisting of a question and an answer) accurately represents the primary discrepancy between the image and the text. The majority vote among the authors determined the final outcome, yielding the following accuracy rates: 88% for Coco-Con, 74% for DrawBench, and 80% for Winoground. This indicates that our method is capable of identifying these contradictions by investigating the structure and content of the given caption and image. As a result, our method can achieve strong results, particularly on datasets that require compositional understanding.

**Comparing Generative Models.**  $VQ^2$ 's ability to compare between generative models is demonstrated on the results of DrawBench and COCO-t2i, which include generated images from different models, together with human quality ratings. fig. 5 shows that the  $VQ^2$  and our fine-tuned PaLI ranking correlates very well with human ranking ( $R^2 > 0.92$ ). In addition, since unlike human annotations, the  $VQ^2$  score is consistent across datasets, it offers a way to evaluate dataset difficulty on an absolute scale.

Table 4: Comparison of human-labeled quality scores for top-ranked images with model breakdown

Dataset	Model	Random	CLIP	PaLI	$VQ^2$
COCO t2i	SD 1.4	68.6	74.6	88.2	86.4
	SD 2.1	71.3	81.2	84.5	87.3
DrawBench	SD 1.4	66.7	77.4	77.4	87.1
	SD 2.1	59.0	78.0	87.0	82.0

**Reranking Using Alignment Assessment.** Alignment scores can also be used for reranking candidate generations, on top of evaluation. To demonstrate this, we re-rank the image candidate per prompt in the DrawBench and COCO-t2i datasets. We do so using  $VQ^2$  and CLIP and measure the human-labeled quality of the top-ranked image for each method. The results, presented in table 4, show that ranking with  $VQ^2$  consistently achieves higher quality scores when compared to ranking with CLIP. One such example is shown in fig. 6, where both  $VQ^2$  and our top-performing fine-tuned PaLI model demonstrate superior ranking by placing the brown-and-white cats above the white-only cats. This consistency between  $VQ^2$  and PaLI highlights their alignment evaluation models' potential for enhancing text-to-image systems, which contrasts with the divergent ranking exhibited by CLIP.



Figure 6: Four COCO-t2i text-to-image model outputs ranked by VQ2 scores, correlating with top PaLI model. Image order and CLIP (RN50x64) similarity scores given, but not aligned with VQ<sup>2</sup>/PaLI ranks.

## 5 Related Work

Our work advances research in visual entailment (VE) [27], visual question answering (VQA) [46], text-to-image alignment evaluation, and cross-task consistency for multi-modal models, with a focus on enhancing the semantic understanding of image-caption relationships.

Textual Entailment (TE) [26, 47] evaluates the truthfulness of a textual hypothesis given a textual premise, providing a key benchmark for the semantic capabilities of neural network models [48–50, 35]. Recently, TE has been adapted to the multimodal domain as Visual Entailment (VE) [27] to assess the semantic alignment between images and text. Vision-and-language models like CLIP [15], CoCa [22], BLIP [6], BLIP2 [7] and OFA [23] often act as bag-of-words models, lacking a deep comprehension of language compositionality [16]. Our approach addresses this by generating multiple questions probing diverse semantic aspects, thereby improving performance on challenging compositional tasks like Winoground [24] and unnatural images as in Drawbench [5].

Unlike DrawBench [5] and DALL-Eval [51] which depend on human feedback and operate within a discrete set of alignments, our approach produces automated scores for a broader range of text-image alignments, facilitating efficient evaluation of vision-and-language models. Our approach also surpasses the recently proposed TIFA [44], which may be due to employing more question-answer pairs and tailored models for question generation and answering.

Several works have explored cross-task consistency in multi-modal models across various modalities. VQA studies have tackled inconsistencies and enhanced consistency using data augmentation and contrastive loss. NLP researchers have improved consistency across tasks or within a single task by employing counterfactual instances or contrast sets [26, 47]. Our research aligns with studies that evaluate natural text and images [52]; however, extending the focus to synthetic images and texts, and aligning with synthetic image understanding research [53–58]. We introduce two unique approaches to address the complexities of image-text alignment.

Another related effort is PickScore [29], which predicts human preferences for image quality and aesthetics by ranking or choosing between two images. In contrast, our methods independently score a single image and focus specifically on image-text alignment.

## 6 Limitations

We recognize that in some cases, making a binary decision for whether a text and an image are aligned may be difficult, also for humans. To tackle this limitation, we provided human annotators with comprehensive guidelines, which resulted in a high inter-annotator agreement (Fleiss-Kappa score of 0.722 with 80% of the cases where all annotators agreed on the entailment label).

Although many images in our datasets were obtained by others and not created by us, we made an effort to ensure that they do not contain harmful or potentially harmful content, such as NSFW or biased imagery. During the annotation process, three individuals examined each image and indicated if it could be considered offensive. Additionally, two of the authors manually reviewed the images

for any harmful content. However, we understand that the perception of harmful or offensive content may vary among individuals and may be subject to personal interpretation.

## 7 Conclusion

We addressed the task of image-text alignment evaluation, which we find very close to the Visual Entailment (VNL) task. We first introduced the SeeTRUE benchmark, which covers the mix of real and synthetic text and image pairs in text-to-image and image-to-text generation tasks, and includes challenging cases based on generated contradictions. We then proposed two methods, VQ<sup>2</sup> and end-to-end VNL, which outperform strong baselines on SeeTRUE and can serve as a starting point for future research on the task.

In future work, we would like to employ our automatic evaluation models for guiding the training of text-to-image and image-to-text models towards more aligned outputs, following recent trends in text-to-text generation [59, 60]. For example, such models may be useful either for filtering training examples or as a reward when training models using reinforcement learning.

## References

- [1] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. In *International Conference on Machine Learning*, pages 8821–8831. PMLR, 2021.
- [2] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022.
- [3] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. 2022 iee. In *CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10674–10685, 2022.
- [4] Jiahui Yu, Yuanzhong Xu, Jing Yu Koh, Thang Luong, Gunjan Baid, Zirui Wang, Vijay Vasudevan, Alexander Ku, Yinfei Yang, Burcu Karagol Ayan, et al. Scaling autoregressive models for content-rich text-to-image generation. *arXiv preprint arXiv:2206.10789*, 2022.
- [5] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily Denton, Seyed Kamyar Seyed Ghaseipour, Burcu Karagol Ayan, S Sara Mahdavi, Rapha Gontijo Lopes, et al. Photorealistic text-to-image diffusion models with deep language understanding. *arXiv preprint arXiv:2205.11487*, 2022.
- [6] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. BLIP: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *International Conference on Machine Learning*, pages 12888–12900. PMLR, 2022.
- [7] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. BLIP-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *arXiv preprint arXiv:2301.12597*, 2023.
- [8] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *Advances in Neural Information Processing Systems*, 35: 23716–23736, 2022.
- [9] Gary Marcus, Ernest Davis, and Scott Aaronson. A very preliminary analysis of dall-e 2. *arXiv preprint arXiv:2204.13807*, 2022.
- [10] Nan Liu, Shuang Li, Yilun Du, Josh Tenenbaum, and Antonio Torralba. Learning to compose visual relations. *Advances in Neural Information Processing Systems*, 34:23166–23178, 2021.
- [11] Royi Rassin, Shauli Ravfogel, and Yoav Goldberg. Dalle-2 is seeing double: flaws in word-to-concept mapping in text2image models. *arXiv preprint arXiv:2210.10606*, 2022.

- [12] Hila Chefer, Yuval Alaluf, Yael Vinker, Lior Wolf, and Daniel Cohen-Or. Attend-and-excite: Attention-based semantic guidance for text-to-image diffusion models. *arXiv preprint arXiv:2301.13826*, 2023.
- [13] Anna Rohrbach, Lisa Anne Hendricks, Kaylee Burns, Trevor Darrell, and Kate Saenko. Object hallucination in image captioning. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4035–4045, Brussels, Belgium, October–November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1437. URL <https://aclanthology.org/D18-1437>.
- [14] Jungo Kasai, Keisuke Sakaguchi, Lavinia Dunagan, Jacob Morrison, Ronan Le Bras, Yejin Choi, and Noah A. Smith. Transparent human evaluation for image captioning. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3464–3478, Seattle, United States, July 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.nacl-main.254. URL <https://aclanthology.org/2022.nacl-main.254>.
- [15] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR, 2021.
- [16] Mert Yuksekgonul, Federico Bianchi, Pratyusha Kalluri, Dan Jurafsky, and James Zou. When and why vision-language models behave like bags-of-words, and what to do about it? In *The Eleventh International Conference on Learning Representations*, 2022.
- [17] Soravit Changpinyo, Doron Kukliansky, Idan Szpektor, Xi Chen, Nan Ding, and Radu Soricut. All you may need for VQA are image captions. In *NAACL*, 2022.
- [18] Or Honovich, Leshem Choshen, Roee Aharoni, Ella Neeman, Idan Szpektor, and Omri Abend.  $Q^2$ : Evaluating factual consistency in knowledge-grounded dialogues via question generation and question answering. *arXiv preprint arXiv:2104.08202*, 2021.
- [19] Or Honovich, Roee Aharoni, Jonathan Herzig, Hagai Taitelbaum, Doron Kukliansky, Vered Cohen, Thomas Scialom, Idan Szpektor, Avinatan Hassidim, and Yossi Matias. TRUE: Re-evaluating factual consistency evaluation. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3905–3920, Seattle, United States, July 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.nacl-main.287. URL <https://aclanthology.org/2022.nacl-main.287>.
- [20] Philippe Laban, Tobias Schnabel, Paul N. Bennett, and Marti A. Hearst. SummaC: Re-Visiting NLI-based Models for Inconsistency Detection in Summarization. *Transactions of the Association for Computational Linguistics*, 10:163–177, 02 2022. ISSN 2307-387X. doi: 10.1162/tacl\_a\_00453. URL [https://doi.org/10.1162/tacl\\_a\\_00453](https://doi.org/10.1162/tacl_a_00453).
- [21] Liyan Tang, Tanya Goyal, Alexander R Fabbri, Philippe Laban, Jiacheng Xu, Semih Yahvuz, Wojciech Kryściński, Justin F Rousseau, and Greg Durrett. Understanding factual errors in summarization: Errors, summarizers, datasets, error detectors. *arXiv preprint arXiv:2205.12854*, 2022.
- [22] Jiahui Yu, Zirui Wang, Vijay Vasudevan, Legg Yeung, Mojtaba Seyedhosseini, and Yonghui Wu. Coca: Contrastive captioners are image-text foundation models. *arXiv preprint arXiv:2205.01917*, 2022.
- [23] Peng Wang, An Yang, Rui Men, Junyang Lin, Shuai Bai, Zhikang Li, Jianxin Ma, Chang Zhou, Jingren Zhou, and Hongxia Yang. OFA: Unifying architectures, tasks, and modalities through a simple sequence-to-sequence learning framework. In *International Conference on Machine Learning*, pages 23318–23340. PMLR, 2022.
- [24] Tristan Thrush, Ryan Jiang, Max Bartolo, Amanpreet Singh, Adina Williams, Douwe Kiela, and Candace Ross. Winoground: Probing vision and language models for visio-linguistic compositionality. *ArXiv preprint*, abs/2204.03162, 2022. URL <https://arxiv.org/abs/2204.03162>.

- [25] Su Wang, Chitwan Saharia, Ceslee Montgomery, Jordi Pont-Tuset, Shai Noy, Stefano Pellegrini, Yasumasa Onoe, Sarah Laszlo, David J Fleet, Radu Soricut, et al. Imagen editor and editbench: Advancing and evaluating text-guided image inpainting. *arXiv preprint arXiv:2212.06909*, 2022.
- [26] Ido Dagan, Bill Dolan, Bernardo Magnini, and Dan Roth. Recognizing textual entailment: Rational, evaluation and approaches—erratum. *Natural Language Engineering*, 16(1):105–105, 2010.
- [27] Ning Xie, Farley Lai, Derek Doran, and Asim Kadav. Visual entailment: A novel task for fine-grained image understanding. *arXiv preprint arXiv:1901.06706*, 2019.
- [28] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision—ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014.
- [29] Yuval Kirstain, Adam Polyak, Uriel Singer, Shahbuland Matiana, Joe Penna, and Omer Levy. Pick-a-pic: An open dataset of user preferences for text-to-image generation, 2023.
- [30] Joseph L Fleiss. Measuring nominal scale agreement among many raters. *Psychological bulletin*, 76(5):378, 1971.
- [31] Matt Gardner, Yoav Artzi, Victoria Basmova, Jonathan Berant, Ben Bogin, Sihao Chen, Pradeep Dasigi, Dheeru Dua, Yanai Elazar, Ananth Gottumukkala, et al. Evaluating models’ local decision boundaries via contrast sets. *arXiv preprint arXiv:2004.02709*, 2020.
- [32] Yonatan Bitton, Gabriel Stanovsky, Roy Schwartz, and Michael Elhadad. Automatic generation of contrast sets from scene graphs: Probing the compositional consistency of GQA. *arXiv preprint arXiv:2103.09591*, 2021.
- [33] Chuanrong Li, Lin Shengshuo, Zeyu Liu, Xinyi Wu, Xuhui Zhou, and Shane Steinert-Threlkeld. Linguistically-informed transformations (LIT): A method for automatically generating contrast sets. In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 126–135, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.blackboxnlp-1.12. URL <https://aclanthology.org/2020.blackboxnlp-1.12>.
- [34] Shachar Rosenman, Alon Jacovi, and Yoav Goldberg. Exposing Shallow Heuristics of Relation Extraction Models with Challenge Data. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 3702–3710, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.302. URL <https://aclanthology.org/2020.emnlp-main.302>.
- [35] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.
- [36] Alex Wang, Kyunghyun Cho, and Mike Lewis. Asking and answering questions to evaluate the factual consistency of summaries. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5008–5020, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.450. URL <https://aclanthology.org/2020.acl-main.450>.
- [37] Thomas Scialom, Paul-Alexis Dray, Sylvain Lamprier, Benjamin Piwowarski, Jacopo Staiano, Alex Wang, and Patrick Gallinari. QuestEval: Summarization asks for fact-based evaluation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6594–6604, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.529. URL <https://aclanthology.org/2021.emnlp-main.529>.
- [38] Matthew Honnibal and Ines Montani. spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing. To appear, 2017.

- [39] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. SQuAD: 100,000+ questions for machine comprehension of text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2383–2392, Austin, Texas, November 2016. Association for Computational Linguistics. doi: 10.18653/v1/D16-1264. URL <https://aclanthology.org/D16-1264>.
- [40] Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don’t know: Unanswerable questions for SQuAD. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 784–789, Melbourne, Australia, July 2018. Association for Computational Linguistics. doi: 10.18653/v1/P18-2124. URL <https://aclanthology.org/P18-2124>.
- [41] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. Natural questions: A benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:452–466, 2019. doi: 10.1162/tacl\_a\_00276. URL <https://aclanthology.org/Q19-1026>.
- [42] Xi Chen, Xiao Wang, Soravit Changpinyo, AJ Piergiovanni, Piotr Padlewski, Daniel Salz, Sebastian Alexander Goodman, Adam Grycner, Basil Mustafa, Lucas Beyer, Alexander Kolesnikov, Joan Puigcerver, Nan Ding, Keran Rong, Hassan Akbari, Gaurav Mishra, Linting Xue, Ashish Thapliyal, James Bradbury, Weicheng Kuo, Mojtaba Seyedhosseini, Chao Jia, Burcu Karagol Ayan, Carlos Riquelme, Andreas Steiner, Anelia Angelova, Xiaohua Zhai, Neil Houlsby, and Radu Soricut. PaLI: A jointly-scaled multilingual language-image model. In *ICLR*, 2023.
- [43] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.
- [44] Yushi Hu, Benlin Liu, Jungo Kasai, Yizhong Wang, Mari Ostendorf, Ranjay Krishna, and Noah A Smith. Tifa: Accurate and interpretable text-to-image faithfulness evaluation with question answering. *arXiv preprint arXiv:2303.11897*, 2023.
- [45] Shuhuai Ren, Junyang Lin, Guangxiang Zhao, Rui Men, An Yang, Jingren Zhou, Xu Sun, and Hongxia Yang. Learning relation alignment for calibrated cross-modal retrieval. *arXiv preprint arXiv:2105.13868*, 2021.
- [46] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In *Proceedings of the IEEE international conference on computer vision*, pages 2425–2433, 2015.
- [47] Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 632–642, Lisbon, Portugal, September 2015. Association for Computational Linguistics. doi: 10.18653/v1/D15-1075. URL <https://aclanthology.org/D15-1075>.
- [48] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1423. URL <https://aclanthology.org/N19-1423>.
- [49] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21(1), jan 2020.
- [50] Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton,

Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback, 2022.

- [51] Jaemin Cho, Abhay Zala, and Mohit Bansal. Dall-eval: Probing the reasoning skills and social biases of text-to-image generative transformers. *arXiv preprint arXiv:2202.04053*, 2022.
- [52] Adyasha Maharana, Amita Kamath, Christopher Clark, Mohit Bansal, and Aniruddha Kembhavi. Exposing and addressing cross-task inconsistency in unified vision-language models. *arXiv preprint arXiv:2303.16133*, 2023.
- [53] Tejas Gokhale, Hamid Palangi, Besmira Nushi, Vibhav Vineet, Eric Horvitz, Ece Kamar, Chitta Baral, and Yezhou Yang. Benchmarking spatial relationships in text-to-image generation. *arXiv preprint arXiv:2212.10015*, 2022.
- [54] Hang Li, Jindong Gu, Rajat Koner, Sahand Sharifzadeh, and Volker Tresp. Do dall-e and flamingo understand each other? *arXiv preprint arXiv:2212.12249*, 2022.
- [55] Nitzan Bitton-Guetta, Yonatan Bitton, Jack Hessel, Ludwig Schmidt, Yuval Elovici, Gabriel Stanovsky, and Roy Schwartz. Breaking common sense: Whoops! a vision-and-language benchmark of synthetic and compositional images. *arXiv preprint arXiv:2303.07274*, 2023.
- [56] Xiaoshi Wu, Keqiang Sun, Feng Zhu, Rui Zhao, and Hongsheng Li. Better aligning text-to-image models with human preference. *arXiv preprint arXiv:2303.14420*, 2023.
- [57] Ali Borji. Generated faces in the wild: Quantitative comparison of stable diffusion, midjourney and dall-e 2. *arXiv preprint arXiv:2210.00586*, 2022.
- [58] Andreas Stöckl. Evaluating a synthetic image dataset generated with stable diffusion. *arXiv preprint arXiv:2211.01777*, 2022.
- [59] Hannah Rashkin, David Reitter, Gaurav Singh Tomar, and Dipanjan Das. Increasing faithfulness in knowledge-grounded dialogue with controllable features. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 704–718, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.58. URL <https://aclanthology.org/2021.acl-long.58>.
- [60] Roei Aharoni, Shashi Narayan, Joshua Maynez, Jonathan Herzog, Elizabeth Clark, and Mirella Lapata. mFACE: Multilingual summarization with factual consistency evaluation, 2022.

## A Appendix

### A.1 Dataset Supplementary Materials

1. Dataset documentation, metadata, and download instructions: anonymous.
2. Intended uses: we hope SeeTRUE will be used by researchers to evaluate image-text matching models.
3. Author statement: We bear all responsibility in case of violation of right in using our benchmark.
4. Each dataset’s license is described below. Our additional human annotations and generated images are licensed under CC-BY 4.0 license <https://creativecommons.org/licenses/by/4.0/legalcode>.
5. Hosting & preservation: the dataset will be hosted in Huggingface Datasets, accessible and available for open research.
6. SeeTRUE fields are presented in table 5.

Additional licensing details: we do publish the datasets we annotated in this work, and do not re-publish the existing SNLI-VE and Winoground datasets. Full licenses:

1. MS COCO [28]: <https://cocodataset.org/#termsofuse>
2. EditBench [25]: <https://research.google/resources/datasets/editbench/>, <https://www.apache.org/licenses/LICENSE-2.0>
3. DrawBench [5]: <https://Imagen.research.google/>, <https://docs.google.com/spreadsheets/d/1y7nAbmR4FREi6npB1u-Bo3GFwdOPYJc617rB0xIRHY/edit#gid=0>
4. Pick-a-Pick [29]: [https://huggingface.co/datasets/yuvalkirstain/pickapic\\_v1](https://huggingface.co/datasets/yuvalkirstain/pickapic_v1)
5. SNLI-VE [27]: <https://github.com/necla-ml/SNLI-VE>
6. Winoground [24]: <https://huggingface.co/datasets/facebook/winoground>

Table 5: SeeTRUE Rows Examples

image	text	label	original_dataset_id	dataset_source
img1	A zebra to the right of a fire hydrant.	0	text_133_image_1228	drawbench
img2	A group of people standing next to bags of luggage.	1	text_105_image_1377	coco_t2i
img3	a tiny figurine is surrounded by cell phones on a table.	1	3786	editbench

### A.2 Human Annotation Process

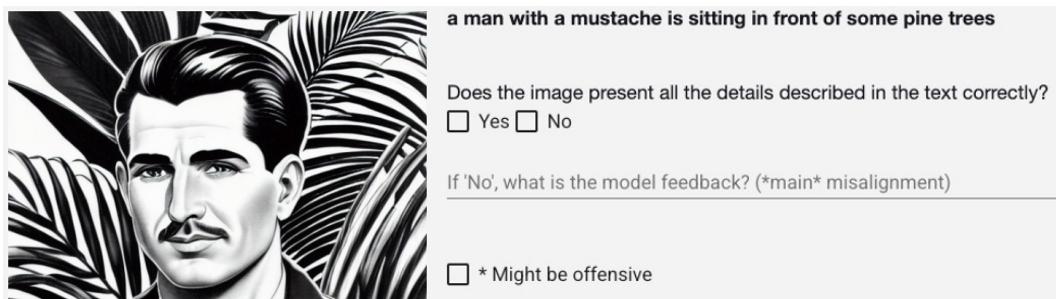


Figure 7: Annotation interface for determining whether a given image-text pair are aligned.

In order to provide reliable human labels for our datasets, we conducted an annotation process using the SeeTRUE platform. The process comprised several steps, including setting qualification requirements, providing instructions, and evaluating annotator agreement.

We set the basic requirements for our annotation task as follows: a percentage of approved assignments above 98%, more than 5,000 approved HITs, and annotator locations limited to the US, UK, Australia, or New Zealand. We selected 5 examples from our dataset for a qualification test and screened the annotators’ results. fig. 7 displays a sample of the Mechanical Turk user interface. The payment for the crowd-workers was 15-18 USD hourly.

The instructions provided were as follows:

*Evaluate the given image and text to determine if they match, selecting either “Yes” or “No”. Some images may be synthetically generated by a text-to-image model. To assess the match, mentally generate a textual description for the image (no need to write it down) and compare this generated description to the given text. If the descriptions closely resemble each other, mark “Yes”. If not, mark “No” and provide feedback on the specific issue causing the misalignment, focusing on the primary issue if multiple misalignments are present. If you encounter an image or text that may be offensive due to bias, race, NSFW content, etc., mark the checkbox to indicate this issue.*

Full agreement metrics are presented in table 6. As shown in the table, the percentage of cases where all annotators agreed and the Fleiss-Kappa scores vary across the datasets, with COCO-Con exhibiting the highest level of agreement and Drawbench the lowest. These differences highlight the varying levels of complexity within the datasets.

Table 6: Agreement metrics for different datasets.

Dataset	Full	Drawbench	COCO t2i	COCO-Con	PickaPic-Con
# Items	8,527	1,968	2,586	1,992	1,981
% all agreed	80	76	78	86	77
Fleiss-Kappa	0.72	0.66	0.68	0.81	0.69

### A.3 Comparing $VQ^2$ variants

$VQ^2$  consists of two main parts: generating question-answer pairs and assessing question-answer pair alignment against the image. We have experimented with different variants of the  $VQ^2$  zero-shot method.

**Assessing question-answer pair alignment methods** Given a question-answer pair, we would like to assess the question based on the image and compare it to the information in the text. We experimented with several configurations for answer alignment:

1. Type A: Given a question-answer pair  $(q_j, a_j)$  generated from the text, we answer the question using a VQA model and obtain an answer based on the image  $a_j^I = VQA(q_j, I)$ . We compare a pair of  $(q_j, a_j)$  with a pair of  $(q_j, a_j^I)$  using an Natural Language Inference (NLI) model, where the pair based on the text serves as the premise and the other as the hypothesis. We define the alignment score  $s_j$  as the probability of the NLI model for answering “entailed”.
2. Type B: As done in type A, we answer the question using a VQA model and obtain the answer  $a_j^I = VQA(q_j, I)$ . We use the VQA model again to compare the the two answers and determine whether they are the same. The question is formulated as “Is  $\{a_j\} == \{a_j^I\}$  in this image?”. We define the alignment score  $s_j$  as the probability of the VQA model for answering “yes”.
3. Type C: We reformulate each question and answer candidate pair  $(q_j, a_j)$  into a new yes-no predicate question  $q'_j$  using the format “is  $\{a_j\}$  true for  $\{q_j\}$  in this image?”. The VQA model is then invoked to answer the predicate question  $(q'_j)$  over image  $I$ . We define the alignment score  $s_j$  as the probability of the model for answering “yes”.

**Generating question-answer pairs** To produce question-answer pairs from the text, we first extract informative spans in the text  $T$ . We extract as answer candidates all named entities and noun phrases in  $T$  using spaCy. We noticed that for short text  $T$ , this method doesn’t produce enough question-answer pairs to assess the alignment between the text and the image. Thus, we extend the answer

candidates by adding multi-word spans, such as adjectives ("black and white") and location "in the air". We use the extended answer candidate extraction in all of our experiments.

Table 7 summarize the results of the  $VQ^2$  variants on the EditBench dataset. Our zero-shot  $VQ^2$  method is  $VQ^2$  type C, it outperforms other configurations and it is more efficient, since it requires a single run of the VQA model for the question-answer pair assessment.

Table 7: Comparing  $VQ^2$  configurations on all EditBench categories

Method	Models used for assessment	EditBench					
		Color	Count	Material	Shape	Size	Mean
$VQ^2$ (A)	VQA & NLI	75.7	63.6	71.9	67.6	75.9	70.9
$VQ^2$ (B)	VQA & VQA	<b>80.2</b>	72.3	75.6	<b>73.5</b>	75.4	75.4
$VQ^2$ (C) w.o. multi-word answers	VQA	77.2	71.5	73.6	71.9	75.5	73.9
$VQ^2$ (C)	VQA	78.5	<b>73.5</b>	<b>76.9</b>	71.7	<b>78.2</b>	<b>75.8</b>

#### A.4 Reproducibility

To fine-tune BLIP2, we adjust only the Q-former parameters of the model using the Adam optimizer. We train the model for two epochs and designate 10% of the training set as a validation set for early stopping and use learning rate selection between {1e-5, 5e-5}. A single training took 5 hours on a linux server with one A6000 GPU. All experiments took <2 days.

Zero-shot  $VQ^2$ : For 10,000 text-image pairs, the inference time of every step is as follows. Answer candidate generation: when using extended answer candidates – about 1 day. Otherwise, 12 hours. Question generation and filtering: When using extended answer candidates, about 2 days, otherwise, 1 day. The last step only takes a few minutes.