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Master Thesis

Master in Language Analysis and Processing

Grounding Language Models for Spatial Reasoning

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Abstract

Humans are able to learn to understand and process the distribution of space, and one of the initial tasks of Artificial Intelligence has been to show machines the relationships between space and the objects that appear in it. Humans naturally combine vision and textual information to acquire spatial relationships among objects, and when reading a text, we are able to mentally depict the spatial relationships that may appear in it. Thus, the visual differences between images depicting "a person sits and a dog stands" and "a person stands and a dog sits" are obvious for humans, but still not clear for automatic systems. In this project, we propose to build grounded Neural Language models that are able to perform this kind of spatial reasoning. Neural Language models (LM) have shown impressive capabilities on many NLP tasks but, despite their success, they have been criticized for their lack of meaning. Vision-and-Language models (VLM), trained jointly on text and image or video data, have been offered as a response to such criticisms, but recent work has shown that these models struggle to ground spatial concepts properly. In the project we propose to build spatially-aware language models that ground spatial concepts in images. We propose to use a variety of methods that involve the creation of synthetic datasets specially focused on spatial reasoning capabilities, as well as the use of multi-task learning. We expect the new models to improve the state of the art in spatial reasoning. Code is released at `https://github.com/juletx/spatial-reasoning` and models are released at `https://huggingface.co/juletxara`.

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1 Introduction

This chapter is an introduction of the master thesis and includes background, objectives and research questions.

1.1 Objectives

Despite the impressive performance of pretrained vision and language models (VLMs) on a wide variety of multimodal tasks, they remain poorly understood. One important question is to what extent such models are able to conduct unimodal and multimodal compositional reasoning and spatial reasoning. For example, the visual differences between images depicting "a person sits and a dog stands" and "a person stands and a dog sits" are clamorously obvious for humans, but still not clear for current state-of-the-art VLMs. To perform well on tasks where compositional and spatial reasoning is required, the models do not only need a proper encoding of text and images, but also to be able to **ground meaning across the two modalities** (spatial grounding).

Thus the main objective of the project is to **learn language models for spatial reasoning via the grounding of LMs with spatial concepts and relations**. One of the main goals of the project is to investigate ways to acquire grounded representation for spatial reasoning. In that sense, we will define suitable ways to incorporate spatial information into pre-trained vision and language models. Towards this goal, this project will focus on using the latest advances in deep-learning techniques, pre-trained LMs for effective zero and few-shot transfer learning.

We have defined the following specific objectives in the scope of spatial reasoning:

1. **Investigate the use of synthetic datasets to overcome the lack of annotated datasets for spatial grounding**. As to avoid the scarcity of multimodal datasets that explicitly describe spatial relations, we propose to automatically construct synthetic datasets on spatial relations and use them to train existing language models in a self-supervised way, with the final aid of obtaining spatially grounded language models. In particular, we propose two alternatives to produce the synthetic datasets:

   a) **Explicit verbalization** of spatial relations in images. Given an image in an existing dataset, we propose to use an object detector to identify the entities in the images, as well as hand-designed verbalization templates to automatically generate textual descriptions of the spatial relations among them.

   b) **Using large generative VLMs**, which are known to obey spatial relations as described in the text, to obtain realistic images with entities that are arranged following certain spatial relations.

2. **Investigate the use of multi-tasking and multi-sourcing to improve generalization properties**. In a multi-task training paradigm, the model is forced to learn more than one task simultaneously, therefore improving its generalization capabilities. We will investigate multi-task settings to combine the verbalized dataset, the images produced by the generative VLMs, as well as traditional training data to obtain spatial-aware language models.

3. **Improve zero-shot and few-shot generalization of VLM models** to obtain effective models in small data regimes of the spatial reasoning domain without the necessity of explicitly annotating big quantities of spatial relations.

4. **Improve the state of the art in spatial reasoning**. Improve the state of the art in spatial reasoning. The final goal is to apply the findings learnt from previous objectives to improve the state-of-the-art in multiple datasets. We plan to evaluate our models at least on two vision and language datasets. The first one is the Winoground dataset [1], which presents a novel task for evaluating the ability of vision and language models to conduct visio-linguistic compositional reasoning. The second one is the VSR benchmark [2] for investigating VLMs capabilities in recognising 65 types of spatial relationships in natural text-image pairs.

1.2 Research Questions

Research Tasks (RT) and Questions (RQ) are based on the objectives from the previous section.

RT0. Prepare the research scenario. The initial task is related to **gathering corpora, exploring different datasets**, **Language Models** (LM) and **building a baseline prototype**. We have already identified some important datasets on spatial reasoning but we will check if there is any new appropriate dataset to evaluate our models. At the same time, we will examine and reimplement (if needed) state-of-the-art systems in order to further understand the task to be solved. This leads us to the following research questions: **RQ0.A) Are the available datasets appropriate to evaluate the spatial abilities of current LMs? RQ0.B) Which is the best pre-trained LMs for spatial reasoning?** We will conduct a quantitative and qualitative analysis of the existing text-only LMs and vision-language LMs in order to 1) measure the appropriateness of probing evaluations of the datasets and 2) explain the limitations of different types of pre-trained LMs.

RT2: Perform synthetic data generation using generative models to learn spatial grounding. We will focus on using large generative VLMs to construct high quality synthetic images that depict a fixed set of spatial relations. In that sense, we want to answer the following research questions. **RQ2.A) Which is the right way to make explicit the implicit information encoded in generative VLMs? RQ2.B) Can we improve the state-of-the-art of vision and language models in tasks that require spatial reasoning?**

RT3: Perform multi-task and multi-source learning in few-shot settings. In this task we will focus on finding ways of applying multi-task learning using multiple sources of information in order to force LMs to ground spatial relations into text without the necessity of explicitly annotating big quantities of spatial relations. This leads us to the following research questions: **RQ3.A) What kind of tasks and information sources are relevant to learn spatial information effectively? RQ3.B) What is the best way to combine the task in a multi-task setting? RQ3.C) Can we effectively minimize annotated data to obtain state-of-the-art results in tasks that require spatial reasoning?**

2 Related Work

This chapter introduces related work that was used in the development of this project. This chapter includes: Grounding Language Models Section 2.1. Vision Language Models Section 2.2. Spatial Reasoning Datasets Section 2.5. Multimodal Transformers in Section 2.6. Diffusion Models in Section 2.7.

2.1 Grounding Language Models

Neural Language Models (LM) have shown **impressive capabilities** on many Natural Language Processing (NLP) tasks [3, 4, 5]. LMs are pretrained on large corpora in order for them to learn universal language representations, which are beneficial for downstream NLP tasks and can avoid training a new model from scratch. The pretrained models are then fine-tuned in specific downstream tasks, using annotated data that is orders of magnitude smaller than the text used in the pretraining phase. Following this transfer learning methodology, researchers have extended the state of the art on a wide array of tasks as measured by leaderboards on specific benchmarks for English [6, 3].

Despite the impressive results of LMs for different language-related tasks, many authors criticize them for their **lack of meaning** [7, 8]. In their opinion, language models trained exclusively on linguistic form (i.e. words) are unable to learn meaning. Those authors suggest that **grounding is one of the key elements to bring human-like language understanding**. However, language grounding is a very broad area that covers a great diversity of techniques, modalities and concepts. In this project, we will focus on spatial reasoning, that is, **grounding LMs with spatial concepts**. We choose spatial reasoning because it is one of the most fundamental capabilities for both humans and LMs. Such relations are crucial to how humans organize the mental space and make sense of the physical world, and therefore fundamental for a grounded theory of semantics [9]. However, spatial reasoning has been found to be particularly challenging (much more challenging than capturing properties of individual entities) for current models [10].

2.2 Vision Language Models

Vision Language Models (VLM), which are trained jointly on text and image, have been proposed as a general solution to the lack of grounding in language models [11, 12, 13, 14]. Vision-language pre-training aims to improve performance of downstream vision and language tasks by pretraining the model on many image-text pairs. These pre-trained models can then be fine-tuned on each downstream task.

VLMs have been used in tasks that require grounding spatial concepts, such as VQA [15] or NLVR2 [16], but recent work has shown that **VLMs struggle to ground spatial concepts properly** [17]. Large generative VLMs trained on massive amounts of data like DALLE-2 [13] or IMAGEN [14] are known to possess visual-reasoning skills [18], but they are not publicly available and only accessible to large companies.

There are several **works that try to ground language models to spatial relations**. For example, [19, 20] focus on the acquired commonsense knowledge of models about object scales, e.g. do they know that a person is bigger than an ant? However, they ask about generic object scale relations, without providing any context. Some other authors [21, 22] work on implicit and explicit spatial relations of objects, given some descriptive texts. The proposed benchmark datasets are designed for object bounding box generation.

2.3 Synthetic Visual Reasoning Datasets

Multimodal training datasets with images and descriptions that include spatial relations tend to be small. Synthetic visual reasoning datasets have been proposed to overcome this problem. These datasets enable full control of dataset generation, easing spatial reasoning capability probing on VLMs. Some examples of synthetic datasets include SHAPES [23], CLEVR [24], NLVR [25] and SPARTQA [26].

SHAPES is a dataset of synthetic images designed to benchmark understanding of spatial and logical relations among multiple objects [23]. The dataset consists of complex yes or no questions about arrangements of colored shapes. Each image is a 3×3 grid of objects. Each object is characterized by shape (circle, square, triangle), colour (red, green, blue) and size (small, big).

CLEVR was one of the pioneering works on testing **compositional language and elementary visual reasoning** [27]. However, it presents two major drawbacks: i) questions not only cover spatial grounding but some other concepts such as compositional language and attribute identification, and ii) spatial relations are limited to four, i.e. left, right, behind and in front.

NLVR containins natural language sentences grounded in images [25]. The task is to determine whether a sentence is true about a visual input. The data was collected through crowdsourcing, and solving the task requires reasoning about sets of objects, comparisons, and spatial relations.

SPARTQA provides a synthetic **question-answering** dataset that is specially focused on spatial reasoning capabilities [26]. SPARTQA is built on NLVR's images containing more objects with richer spatial structures. However, it contains only text and no images, and therefore it does not provide any means to ground spatial concepts.

A very recent work proposes a method called **Pseudo-Q** to **automatically create synthetic datasets** that can be used to train visually grounded models [28]. Their method consists of leveraging an off-the-shelf object detector to identify visual objects from unlabeled images, and then creating language queries for these objects that are obtained in an unsupervised fashion with a pseudo-query generation module.

The major drawback of synthetic datasets is that they do not always accurately reflect the challenges of reasoning in the real world. Some aspects that are very important in the real world are not taken into account in synthetic images. For example, the orientations of objects, their context and the viewpoint can affect their spatial relation.

2.4 Natural Visual Reasoning Datasets

Many vision-language datasets with natural images also contain spatial relations. For example, NLVR2 [16], MS COCO [29], and VQA [15].

NLVR2 is a dataset for joint reasoning about natural language and images, with a focus on semantic diversity, compositionality, and visual reasoning challenges [16]. There are 9 prevalent linguistic challenges in NLVR2 among which are spatial relations. The examples in Fig. 2.1 require addressing challenging semantic phenomena.

VQA [15] is a popular vision and language task. Given an image and a question about the image, the task is to provide an accurate answer. VQA is commonly used as a benchmark to evaluate VQA systems. Questions are generally open-ended but multiple choices are provided for some questions. Some examples are shown in Fig. 2.2.

The problem of these datasets is that many different challenges are mixed. Sentences have complex lexical and syntactic information. This makes it hard to identify the exact challenges, preventing categorised analysis.

With the objective of **evaluating spatial relations**, a recent work provides new unified datasets [17]. As the objective of such work is to evaluate whether VLMs learn more spatial commonsense than

(a) The left image contains twice the number of dogs as the right image, and at least two dogs in total are standing.

(b) One image shows exactly two brown acorns in back-to-back caps on green foliage.

Figure 2.1: Two examples from NLVR2, where each caption is paired with two images. The first caption is True and the second one is False.

Figure 2.2: Example images, questions and answers from VQA.

LMs, the datasets are purely textual, so they do not provide any means to ground spatial concepts. Interestingly, authors find that VLMs, and more concretely text-to-image systems, perform much better than text-only LMs.

2.5 Visual Spatial Reasoning Datasets

The **Winoground** dataset [1] is focused on **evaluating visio-linguistic compositional reasoning** in VLMs. Each instance in the dataset is composed of two images and two captions, but crucially, both captions contain a completely identical set of words, only in a different order. The task is then to match them correctly, which requires the systems to properly deal with composition in natural language. Previous works have shown that language transformers have **difficulties in learning word order** [30, 31]. Winoground provides a means to test whether this is also true for multimodal models.

Another very recent dataset named **Visual Spatial Reasoning (VSR)** [2], whose objective is to test spatial grounding capabilities by covering 65 different spatial relations over natural images collected from COCO [29]. Given an image, VSR provides a caption which describes a spatial relation between two of the objects that appear in the image. That relation can be real or fake, and that is precisely what the model has to infer, i.e. whether the caption is correct with respect to the given image. Another advantage of this dataset is that it is annotated by humans. Given its features, **we believe VSR is a**

good candidate to evaluate spatial grounding in LMs.

2.6 Multimodal Transformers

Multimodal transformers are state-of-the-art in many vision-language tasks, and that includes spatial reasoning. Most of the models tested in Winoground [1] and VSR [2] are multimodal transformers. Those transformers differ in embedding, architecture and pretraining objectives and cross-modal attention.

Embedding. Most models use a pretrained BERT tokenizer for text encoding. For image embedding, there are more different options. Some models use Convolutional Neural Networks (CNN) to extract features from images. Another common approach is to use Vision Transformer (ViT).

Architecture. Depending on their architecture, they can mainly be classified into two types: single-stream and dual-stream transformers. On the one hand, in **single-stream** transformers the image and text embeddings are concatenated and then jointly encoded. On the other hand, **dual-stream** transformers have two separate modality-specific encoders with optional cross-modality fusion.

Pretraining Objectives. Vision-language transformers use a different pretraining objectives including **masked language modeling** (MLM), image-conditioned **language modeling** (LM), **image-text contrastive** learning (ITC), **image-text matching** (ITM). For example, BLIP [32] is jointly pre-trained with three vision-language objectives: ITC, ITM and LM.

Cross-Modal Attention. There are different types of multimodal attention as presented in [33]. In **modality-specific attention**, the language and visual input attend to their modality. In **merged attention**, the language and visual input attend to both themselves and the other modality. In **co-attention**, the language and visual input only attends to the other modality input.

2.7 Diffusion Models

Diffusion models are machine learning systems trained to denoise random gaussian noise step by step, to get to a sample image. Neural networks are trained to predict a way to slightly denoise the picture in each step. As we can see in Fig. 2.3, after a certain number of steps, a sample is obtained.

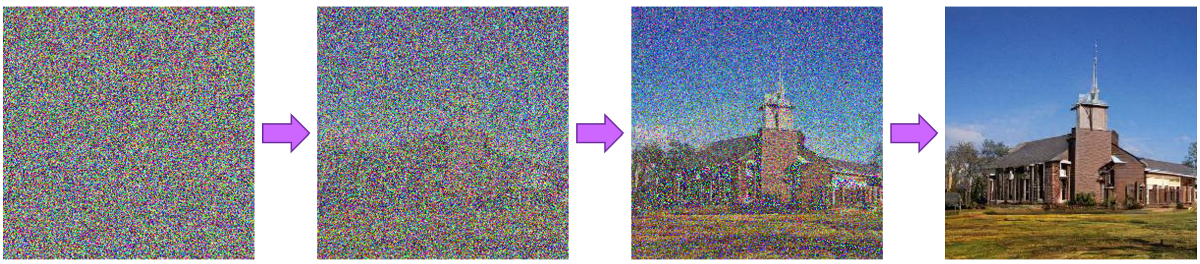


Figure 2.3: In the diffusion process random images are denoised in multiple steps to get a sample image. Source: https://github.com/huggingface/notebooks/blob/main/diffusers/diffusers_intro.ipynb

Diffusion models have obtained SOTA results on image generation. However, one downside of diffusion models is that the reverse denoising process is slow. In addition, these models consume a lot of memory because they work in pixel space. Therefore, it is challenging to train these models and also to use them for inference.

Consequently, most of the recent diffusion models, e.g. DALLE-2 [13] and IMAGEN [14], are unfortunately not accessible to the community. The most popular exception is Stable Diffusion [34], which has been open sourced and can be used on a single GPU.

2.7.1 Stable Diffusion

Stable Diffusion is based on a type of diffusion model called Latent Diffusion [34]. Latent diffusion reduces the memory and compute complexity by applying the diffusion process over a lower dimensional latent space. There are three main components in latent diffusion: an autoencoder (VAE), a U-Net and a text-encoder (CLIP).

The autoencoder (VAE) [35]. The VAE has two parts, an encoder and a decoder, as we can see in Fig. 2.4. During latent diffusion training, the encoder maps the images to a latent space for the forward diffusion process, which applies more noise at each step. During inference, the decoder maps the latents generated by the reverse diffusion process back to the images. The encoder and decoder are trained jointly to minimize the reconstruction error.

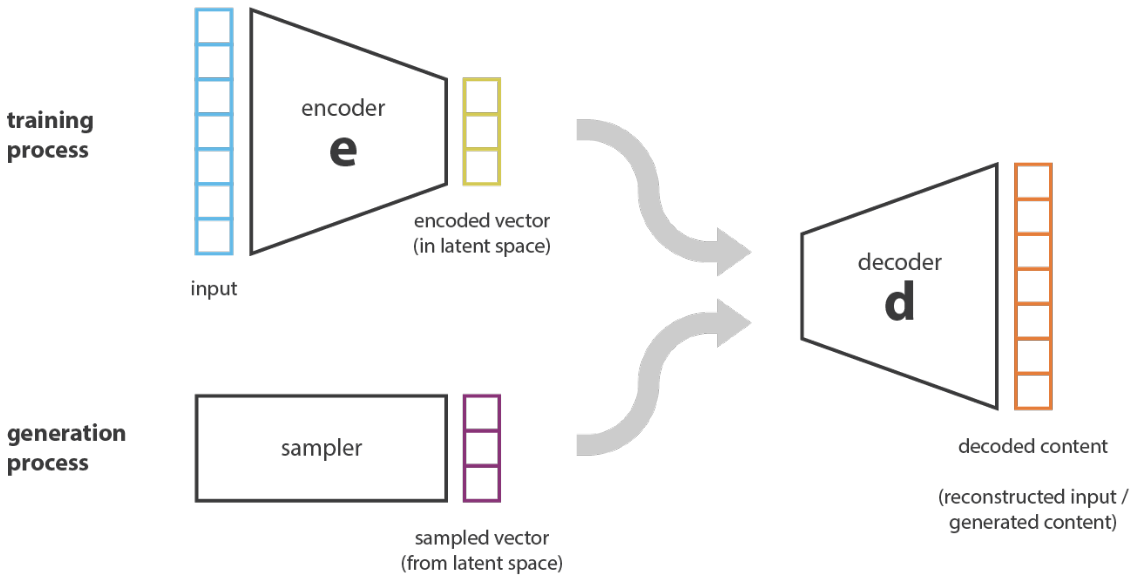


Figure 2.4: Variational Autoencoder (VAE) training and generation processes. Source: https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

The U-Net [36]. The U-Net also has an encoder part and a decoder part, as shown in Fig. 2.5. The encoder has several ResNet blocks which half the image size by 2. The decoder does the opposite process to upsample the image to the initial size. The U-Net outputs the noise residual which can be used to compute the denoised image representation. To prevent the U-Net from losing important information while downsampling, shortcut connections are usually added from the downsample path to the corresponding layers in the upsample path. Moreover, the output of the stable diffusion U-Net is conditioned on text-embeddings via cross-attention layers.

The text-encoder (CLIP) [37]. The text-encoder transforms the input prompt into an embedding for the U-Net. Stable Diffusion does not train the text-encoder during training and uses an already trained CLIP text encoder, which is shown in Fig. 2.6.

With the previous components we nearly have the full Stable Diffusion inference architecture Fig. 2.7. The stable diffusion model takes a latent seed and a text prompt as input. The latent seed is used to generate initial random latents. The output of the U-Net is used to compute a denoised image representation with a scheduler algorithm. This process is repeated many to get better representations in each iteration. Finally, the latent image representation is decoded by the VAE decoder.

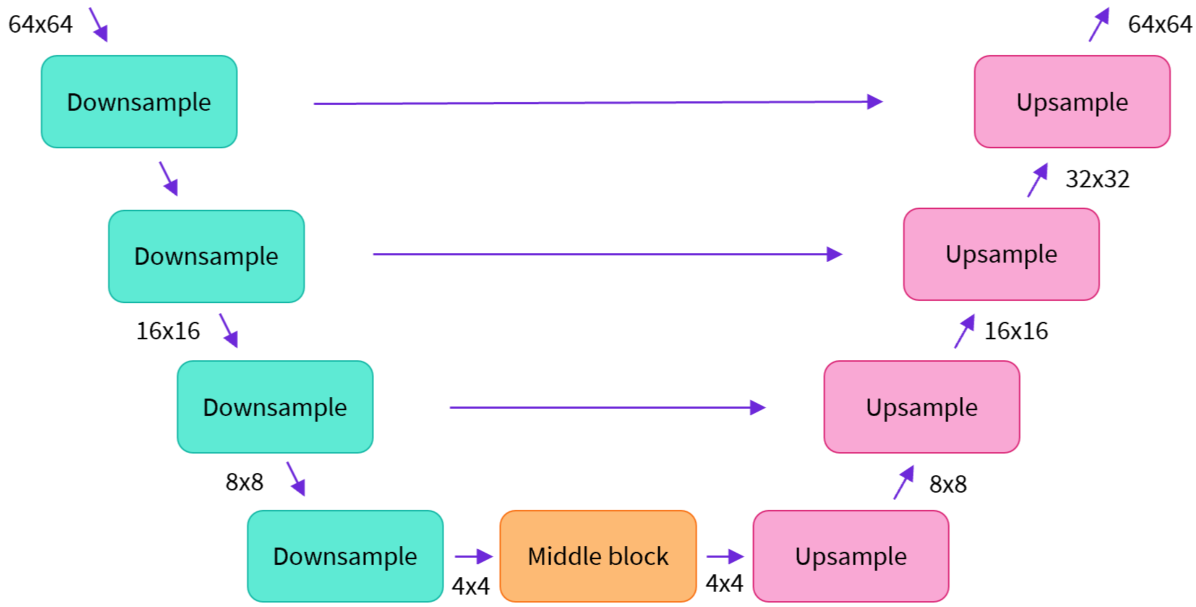


Figure 2.5: The architecture of the U-Net model. Source: https://github.com/huggingface/notebooks/blob/main/diffusers/diffusers_intro.ipynb

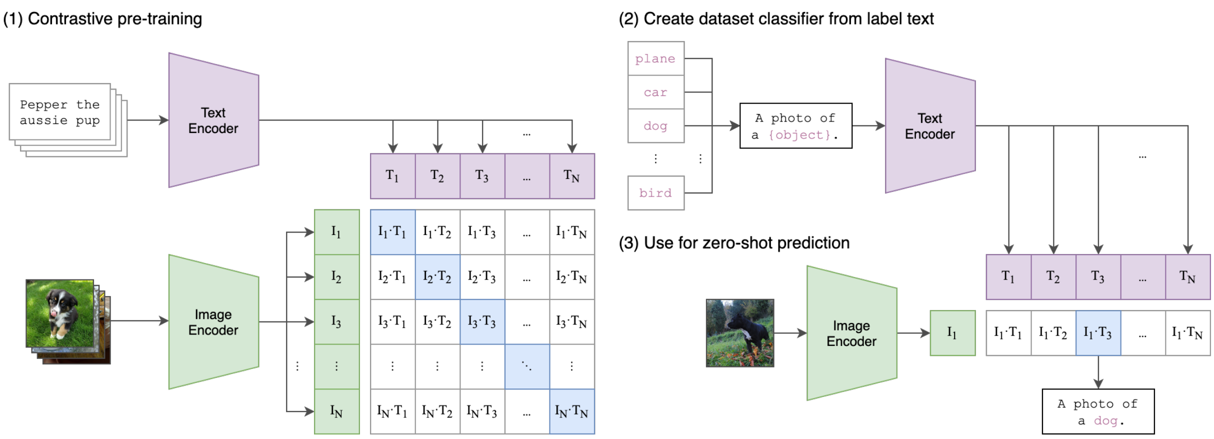


Figure 2.6: CLIP model architecture. Source: https://github.com/openai/CLIP

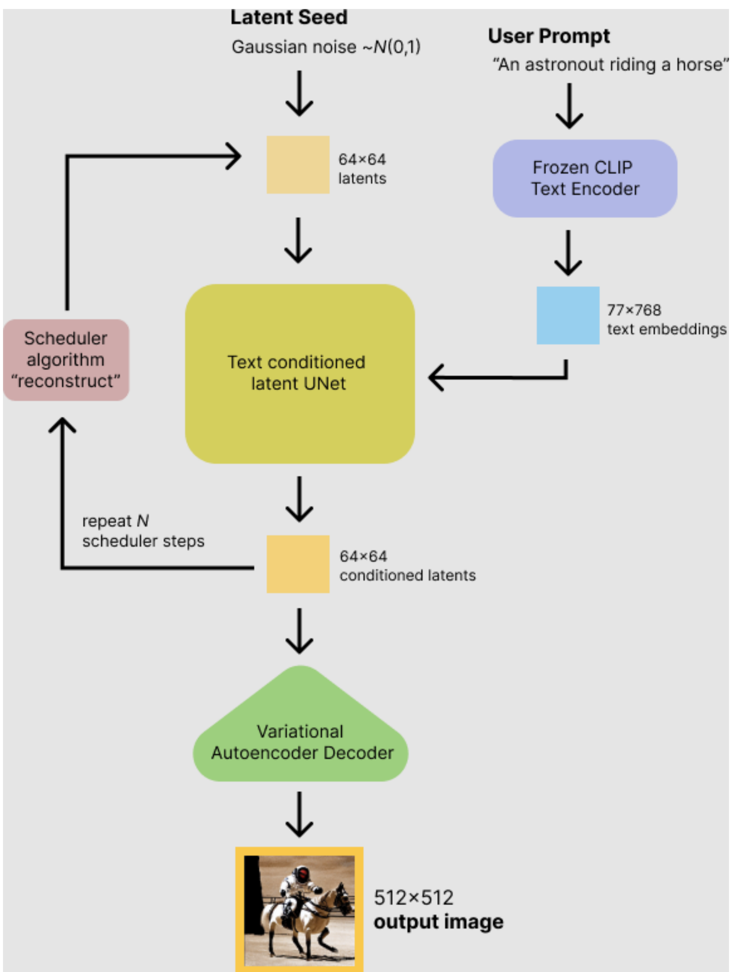


Figure 2.7: Stable Diffusion inference architecture. Source: https://github.com/huggingface/notebooks/blob/main/diffusers/stable_diffusion.ipynb

3 Datasets

This chapter introduces the datasets and metrics we used.

3.1 Winoground

3.1.1 Dataset

See Table 3.1

See Fig. 3.1, Fig. 3.2 and Fig. 3.3

3.1.2 Metrics

3.1.2.1 Score

Performance on Winoground [1] is computed according to three different metrics that evaluate different aspects of the models' visio-linguistic reasoning abilities.

The first metric is the **text score**, which measures whether a model can select the correct caption, given an image. Given images I_0 and I_1 and captions C_0 and C_1, the text score for an example (C_0, I_0, C_1, I_1) is computed according to:

$$ts(C_0, I_0, C_1, I_1) = \begin{cases} 1 & \text{if } s(C_0, I_0) > s(C_1, I_0) \\ & \quad \text{and } s(C_1, I_1) > s(C_0, I_1) \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

where $s(\cdot)$ is the model's score for the image/caption pair.

The second metric is the **image score**, which measures whether a model can select the correct image, given a caption. The image score for an example is computed according to:

$$is(C_0, I_0, C_1, I_1) = \begin{cases} 1 & \text{if } s(C_0, I_0) > s(C_0, I_1) \\ & \quad \text{and } s(C_1, I_1) > s(C_1, I_0) \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

Category	Tag	Count
Linguistic$_{\text{swap-dep.}}$	Object	141
	Relation	233
	Both	26
Linguistic$_{\text{swap-indep.}}$	1 Main Pred	293
	2 Main Preds	108
Visual	Symbolic	41
	Series	31
	Pragmatics	24

Table 3.1: Linguistic and visual tag counts in the Winoground dataset. Every example has a linguistic tag; only examples that contain the visual phenomena have visual tags.

(a) [some plants] surrounding [a light-bulb]

(b) [a lightbulb] surrounding [some plants]

(c) a [brown] dog is on a [white] couch

(d) a [white] dog is on a [brown] couch

(e) [circular] food on [heart-shaped] wood

(f) [heart-shaped] food on [circular] wood

Figure 3.1: Examples from the dataset for the swap-dependent linguistic tags *Object*, *Relation* and *Relation* from left to right. The linguistic examples are additionally tagged with 1 main predicate.

(a) there is [a mug] in [some grass]

(b) there is [some grass] in [a mug]

(c) a person [sits] and a dog [stands]

(d) a person [stands] and a dog [sits]

(e) it's a [truck] [fire]

(f) it's a [fire] [truck]

Figure 3.2: Examples from the dataset for the swap-dependent linguistic tags *Object*, *Relation* and *Both* from left to right. The linguistic examples are additionally tagged with 2, 1, and 1 main predicates from left to right.

(a) the kid [with the magnifying glass] looks at them []

(b) the kid [] looks at them [with the magnifying glass]

(c) the person with the ponytail [packs] stuff and other [buys] it

(d) the person with the ponytail [buys] stuff and other [packs] it

(e) there are [three] people and [two] windows

(f) there are [two] people and [three] windows

Figure 3.3: Examples from the dataset for the swap-dependent visual tags *Pragmatics*, *Series* and *Symbolic* from left to right. The visual examples are additionally tagged with the *Relation* tag, and 1, 2, and 1 main predicates from left to right.

Our final metric **group score** combines the previous two, which measures if every combination for a given example is correctly scored by the model. The group score for an example is computed according to:

$$gs(C_0, I_0, C_1, I_1) = \begin{cases} 1 & \text{if } ts(C_0, I_0, C_1, I_1) \\ & \quad \text{and } is(C_0, I_0, C_1, I_1) \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

3.1.2.2 Accuracy

We also add three additional accuracy metrics. These are similar to the previous ones, but accuracy is 0.5 when one of the pairs is correct.

Given images I_0 and I_1 and captions C_0 and C_1, the **text accuracy** for an example (C_0, I_0, C_1, I_1) is computed according to:

$$ta(C_0, I_0, C_1, I_1) = \begin{cases} 1 & \text{if } s(C_0, I_0) > s(C_1, I_0) \\ & \quad \text{and } s(C_1, I_1) > s(C_0, I_1) \\ 0.5 & \text{if } s(C_0, I_0) > s(C_1, I_0) \\ & \quad \text{xor } s(C_1, I_1) > s(C_0, I_1) \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

where $s(\cdot)$ is the model's score for the image/caption pair.

The **image accuracy** for an example is computed according to:

$$ia(C_0, I_0, C_1, I_1) = \begin{cases} 1 & \text{if } s(C_0, I_0) > s(C_0, I_1) \\ & \quad \text{and } s(C_1, I_1) > s(C_1, I_0) \\ 0.5 & \text{if } s(C_0, I_0) > s(C_0, I_1) \\ & \quad \text{xor } s(C_1, I_1) > s(C_1, I_0) \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

The **group accuracy** in our framework is computed according to:

$$ga(C_0, I_0, C_1, I_1) = (ta(C_0, I_0, C_1, I_1) + ia(C_0, I_0, C_1, I_1))/2 \tag{3.6}$$

3.2 Visual Spatial Reasoning

3.2.1 Dataset

See Table 3.2

Category	Spatial Relations
Adjacency	Adjacent to, alongside, at the side of, at the right side of, at the left side of, attached to, at the back of, ahead of, against, at the edge of
Directional	Off, past, toward, down, deep down*, up*, away from, along, around, from*, into, to*, across, across from, through*, down from
Orientation	Facing, facing away from, parallel to, perpendicular to
Projective	On top of, beneath, beside, behind, left of, right of, under, in front of, below, above, over, in the middle of
Proximity	By, close to, near, far from, far away from
Topological	Connected to, detached from, has as a part, part of, contains, within, at, on, in, with, surrounding, among, consists of, out of, between, inside, outside, touching
Unallocated	Beyond, next to, opposite to, after*, among, enclosed by

Table 3.2: The available 71 spatial relations. 65 of them appear in our final dataset. Relations with $*$ are not used.

4 Methods

This chapter explains the methods we used for evaluation in each dataset. This includes model configurations and other settings.

4.1 Winoground

We introduce baseline models and our models in Section 4.1.1 and then provide an overview of all the models.

4.1.1 Models

Baselines. Winoground authors [1] evaluate various configurations of the following multimodal transformers: CLIP [37], FLAVA [38], LXMERT [12], UniT [39], UNITER [40], VILLA [41], VinVL [42], ViLT [43], VisualBERT [44] and ViLBERT [11]. They also evaluate several configurations of two types of RNN-based models: VSE++ [45] and VSRN [46].

Ours. We evaluate various configurations of the following multimodal transformers: OFA [47], BLIP [32], CLIP [37], FLAVA [38] and ViLT [43]. OFA and BLIP were not included in the baseline evaluation. The other models were already included but we test more configurations. For example, we test models that are finetuned on Flickr30k, COCO, NLVR2 and VSR. We try different model sizes when they are available.

Overview. We provide a high-level overview of the differences between the models in Table 4.1 which includes pretraining datasets, architecture, and attention mechanisms between the modalities. We omit datasets that were only used to train backbones. We exclude the language embedding from this table as every model uses a pretrained BERT tokenizer, except CLIP, VSE++, and VSRN. The pretraining datasets include COCO [29], Visual Genome (VG) [48], Conceptual Captions (CC) [49], SBU Captions [50], Flickr30k [51], VQA 2.0 [52], VCR [53], NLVR2 [54], SNLI-VE [55], QNLI [56], MLNI-mm [57], QQP [58], Localized Narratives (LN) [59], Wikipedia Image Text (WIT) [60], Conceptual Captions 12M (CC 12M) [61], Red Caps (RC) [62], YFCC100M [63], SST-2 [64], and LAION [65]. CLIP uses their own dataset for pretraining.

Model	Datasets	# Images, Captions	Architecture	Attention
VinVL [42]	VQA, GQA, VG-QA, COCO, Flickr30k, CC, SBU	1.89, 4.87	single-stream	merged
UNITER [40]	COCO, VG, CC, SBU	4.20, 9.58	single-stream	merged
ViLLA [41]	COCO, VG, CC, SBU	4.20, 9.58	single-stream	merged
VisualBERT [44]	COCO, NVLR2	0.30, 0.52	single-stream	merged
ViLT [43]	COCO, VG, SBU, CC	4.10, 9.85	single-stream	merged
LXMERT [12]	COCO, VG	0.18, 9.18	dual-stream	modality-specific, co-attn, merged
ViLBERT [11]	CC	3.30, 3.30	dual-stream	modality-specific, co-attn, merged
UniT [39]	COCO detect., VG detect., VQAv2, SNLI-VE QNLI, MNLI-mm, QQP, SST-2	0.69, 1.91	dual-stream	modality-specific, merged
FLAVA $_{ITM}$ [38]	COCO, SBU, LN, CC, VG, WIT, CC 12M, RC, YFCC100M	70.00, 70.00	dual-stream	modality-specific, merged
FLAVA $_{Contrastive}$ [38]	COCO, SBU, LN, CC, VG, WIT, CC 12M, RC, YFCC100M	70.00, 70.00	dual-stream	modality-specific
CLIP [37]	–	400.00, 400.00	dual-stream	modality-specific
OFA [47]	CC 12M, CC 3M, SBU, COCO, VG-Cap	20.00, 20.00	single-stream	modality-specific, merged
BLIP $_{ITM}$ 14M [32]	COCO, VG, SBU, CC, CC 12M	14.00, 15.00	dual-stream	modality-specific, merged
BLIP $_{ITC}$ 14M [32]	COCO, VG, SBU, CC, CC 12M	14.00, 15.00	dual-stream	modality-specific
BLIP $_{ITM}$ 129M [32]	COCO, VG, SBU, CC, CC 12M, LAION	129.00, 130.00	dual-stream	modality-specific, merged
BLIP $_{ITC}$ 129M [32]	COCO, VG, SBU, CC, CC 12M, LAION	129.00, 130.00	dual-stream	modality-specific

Table 4.1: A high-level overview of the differences between the models we evaluate by the pretraining datasets, architecture, and attention mechanisms between the modalities.

4.2 Visual Spatial Reasoning

We first introduce how the dataset is split for experiments in Section 4.2.1, and then baseline and our models in Section 4.2.2.

4.2.1 Dataset Splits

The VSR dataset has two types of splits [2], random and zero-shot. The statistics of the two splits are shown in Table 4.2.

split	train	dev	test	total
random	7,083	1,012	2,024	10,119
zero-shot	5,440	259	731	6,430

Table 4.2: Data statistics of the *random* and *zero-shot* splits.

Random split. We split the dataset randomly into train/dev/test with the ratio of 70%/10%/20%. All the validated data points are used in this split.

Zero-shot split. We create another concept zero-shot split where train/dev/test have no overlapping concepts. That is, each concept can only appear in one of the sets. This is done by randomly grouping concepts into three sets with the ratio of 50%/20%/30%. This is a more challenging setup because the model has to learn concepts and relations in a compositional way instead of remembering the co-occurrence of the two. Moreover, having less training data is a disadvantage for the models, since not all the data can be used in this setting.

4.2.2 Models

Baselines. VSR authors [2] test three popular VLMs: VisualBERT [44], LXMERT [12], and ViLT [43]. All three models are stacked Transformers [66] that take image and text pairs as input. The difference mainly lies in how or whether they encode position information of objects. Checkpoints are saved every 100 iterations and the best checkpoint on the dev set is used for testing. All models are run three times using three random seeds.

Ours. We first test the same baseline models. We also evaluate a ViLT model that has only been finetuned on NLVR2. We evaluate BLIP [32] trained on VSR and NLVR2.

5 Experiments

5.1 Winoground

We perform various experiments on Winoground. Appart from image-text matching 5.1.1, we perform more experiments to gain more insight about the dataset and the tested models.

5.1.1 Image-Text Matching

This is the original Winoground task, given two captions and two images the aim is to match them correctly.

5.1.2 Text-to-Image Generation

We used Stable Diffusion to generate images 9 images for each Winoground caption. This results in a total of $800 * 9 = 7200$ images. This way we can test the compositional reasoning capabilities of a SOTA diffusion model.

We used Label Studio to annotate images generated by Stable Diffusion. As annotating all the images would take a very long time, we choose to annotate a subset of examples, and only one image per caption.

In each annotation there are two captions from Winoground and two images generated with Stable Diffusion. Each image is created from one caption but the order of the images is random. The annotators have to choose which text corresponds to each image: the first caption, the second caption, both or none. An screenshot of the annotation interface can be seen in...

There were 5 annotators in total and each one annotated 50 examples, for a total of 250 annotated examples. There are 400 examples in total, so we decided that it is a big enough subset.

The general conclusion is that Stable Diffusion is not good at this task. Most of the images do not match any of the captions. There are a few images that match both captions. The remaining images match one caption or the other, but there are many that match the incorrect caption. If we take into account image pairs, there are only a few correct ones.

5.1.3 Image Captioning

We used OFA [47] and BLIP [32] models of different sizes to generate captions for all Winoground images. We chose these models because they are SOTA in image captioning and we also use them in other evaluations. Our intention was to compare them with the real captions. We calculated BLEU scores for all models and we found out that they are very low. This indicates that the captions generated by these models are very far from the real captions.

One reason for this could be that the real Winoground captions are not typical captions. They are hand-crafted so that they contain the same words in a different order, and that conditions the captions. Another reason could be that these models are not good at describing these types of images that require compositional reasoning. As these models are not very good at matching Winoground images with captions.

Analysing the captions manually would be necessary to know how good they really are. If these captions are good enough they could also be used to improve the results of the models by incorporating them in the evaluation process. They could provide extra information about the images to the models, that is not included in the original captions.

5.1.4 Image Retrieval

We used CLIP retrieval[1] to retrieve images from LAION-5B dataset. We used Winoground captions and images to get similar images. For each caption and image, we compute its embeddings using CLIP ViT-L-14. Then the system uses a KNN algorithm to retrieve images that have similar embeddings. We can also compute the mean of caption and image embeddings to retrieve images that match both the image and the caption.

The system also has an aesthetic score that can be used to retrieve better looking images. It can also remove duplicate images and images that contain unsafe content and violence.

This system can be used to increase the size of our dataset. We can retrieve many similar images. The number of retrieved images and the similarity score can also be used as a measure of how common an image is. If there are very few similar images in the dataset, that means that the image is uncommon.

[1] https://github.com/rom1504/clip-retrieval

6 Results

This chapter introduces baseline results and our results.

6.1 Winoground

6.1.1 Compared To Humans

6.1.1.1 Baseline

We show baseline results in Table 6.1, which includes the following multimodal transformers: CLIP [37], FLAVA [38], LXMERT [12], UniT [39], UNITER [40], VILLA [41], VinVL [42], ViLT [43], VisualBERT [44] and ViLBERT [11]. They also evaluate several configurations of two types of RNN-based models: VSE++ [45] and VSRN [46].

	Score			Accuracy		
Model	Text	Image	Group	Text	Image	Group
MTurk Human	**89.50**	**88.50**	**85.50**	**93.75**	**93.88**	**93.81**
Random Chance	25.00	25.00	16.67	50.00	50.00	50.00
VinVL	**37.75**	17.75	14.50	**62.75**	**57.75**	**60.25**
UNITER$_{large}$	**38.00**	14.00	10.50	**63.25**	**55.75**	**59.50**
UNITER$_{base}$	**32.25**	13.25	10.00	**60.62**	**55.50**	**58.06**
ViLLA$_{large}$	**37.00**	13.25	11.00	**62.62**	**55.25**	**58.94**
ViLLA$_{base}$	**30.00**	12.00	8.00	**59.62**	**55.00**	**57.31**
VisualBERT$_{base}$	15.50	2.50	1.50	**50.50**	49.88	**50.19**
ViLT (ViT-B/32)	**34.75**	14.00	9.25	**60.50**	**55.38**	**57.94**
LXMERT	19.25	7.00	4.00	**52.12**	**51.88**	**52.00**
ViLBERT$_{base}$	23.75	7.25	4.75	**57.25**	**52.50**	**54.87**
UniT$_{ITM Finetuned}$	19.50	6.25	4.00	**50.25**	**50.75**	**50.50**
FLAVA$_{ITM}$	**32.25**	20.50	14.25	**62.75**	**59.13**	**60.94**
FLAVA$_{Contrastive}$	**25.25**	13.50	9.00	**59.25**	**55.12**	**57.19**
CLIP (ViT-B/32)	**30.75**	10.50	8.00	**60.38**	**53.25**	**56.81**
VSE++$_{COCO}$ (ResNet)	22.75	8.00	4.00	**51.38**	**50.88**	**51.12**
VSE++$_{COCO}$ (VGG)	18.75	5.50	3.50	**50.38**	49.75	**50.06**
VSE++$_{Flickr30k}$ (ResNet)	20.00	5.00	2.75	**51.50**	**50.25**	**50.88**
VSE++$_{Flickr30k}$ (VGG)	19.75	6.25	4.50	**52.75**	**51.00**	**51.88**
VSRN$_{COCO}$	17.50	7.00	3.75	**50.38**	**51.12**	**50.75**
VSRN$_{Flickr30k}$	20.00	5.00	3.50	**53.25**	**51.75**	**52.50**

Table 6.1: Results on the Winoground dataset across the text, image and group score and accuracy metrics. Results above random chance in **bold**.

6.1.1.2 Ours

We show our results in Table 6.2, which includes various configurations of the following multimodal transformers: OFA [47], BLIP [32], CLIP [37], FLAVA [38] and ViLT [43].

We test 4 different versions of ViLT. The first one is the pre-trained only version, without finetuning. Two others are finetuned for retrieval on COCO and Flickr30k. The last one is finetuned for visual reasoning on NLVR2. The best one is the one trained on NLVR2, which shows that finetuning on that task helps perform better on Winoground. Finetuning for retrieval is also helpful and improves the results of the pre-trained model. The score of the pre-trained model is lower than the baseline one.

For FLAVA and CLIP we manage to replicate baseline results. We also test 3 other CLIP models with different configurations and find that they all perform similar to the baseline configuration.

We test the 5 model sizes of OFA. Taking into account that this model gets state-of-the-art performance on many tasks, the performance is not very good. Even the biggest model is not better than the best baseline model. OFA is trained to generate "yes" or "no" when given an image and the text "Does the image describe <caption>?". This might explain why it does not perform that well on retrieval and Winoground.

We test many configurations of BLIP, which include different training sizes, scoring, vision transformer sizes and finetuning datasets. ITM score is better than ITC score in all the cases. Even the 14M pretrained only model is better than all the previously tested models. Finetuning for retrieval on COCO and Flickr30k improves the results even more, reaching nearly above random performance in text, image and group scores.

However, even the best model is still far from human performance in text, image and group scores. If we look at accuracy metrics, the gap is reduced, but the difference is still very big. Image score remains much lower than text score for all the models.

6.1.2 Results By Linguistic Tag

6.1.2.1 Baseline

See Table 6.3

6.1.2.2 Ours

See Table 6.4

6.1.3 Results By Visual Tag

6.1.3.1 Baseline

See Table 6.5

6.1.3.2 Ours

See Table 6.6

6.2 Visual Spatial Reasoning

6.2.1 Compared To Humans

6.2.1.1 Baseline

See Table 6.7. The gap between dev and tests becomes much greater on zero-shot split likely due to the smaller size of both dev and test sets.

Model	Score Text	Score Image	Score Group	Accuracy Text	Accuracy Image	Accuracy Group
MTurk Human	**89.50**	**88.50**	**85.50**	**93.75**	**93.88**	**93.81**
Random Chance	25.00	25.00	16.67	50.00	50.00	50.00
ViLT (ViT-B/32)	**27.50**	8.75	6.00	**56.88**	**53.12**	**55.00**
ViLT$_{COCO}$ (ViT-B/32)	**32.75**	13.50	11.25	**61.88**	**56.00**	**58.94**
ViLT$_{Flickr30k}$ (ViT-B/32)	**35.00**	11.50	9.75	**61.62**	**54.50**	**58.06**
ViLT$_{NLVR2}$ (ViT-B/32)	**38.00**	15.25	12.00	**58.75**	**55.62**	**57.19**
ViLT$_{VSR}$ Random (ViT-B/32)	**30.50**	14.50	8.00	**59.00**	**55.75**	**57.38**
ViLT$_{VSR}$ Zero-shot (ViT-B/32)	**29.50**	14.00	9.25	**58.38**	**54.75**	**56.56**
FLAVA$_{ITM}$	**32.25**	20.50	14.25	**62.75**	**59.13**	**60.94**
FLAVA$_{ITC}$	**25.25**	13.50	9.00	**59.25**	**55.12**	**57.19**
CLIP (ViT-B/32)	**30.75**	10.25	8.25	**60.38**	**53.12**	**56.75**
CLIP (ViT-B/16)	25.00	10.25	7.00	**57.88**	**53.75**	**55.81**
CLIP (ViT-L/14)	**28.50**	11.00	8.00	**60.38**	**54.62**	**57.50**
CLIP (ViT-L/14-336)	**27.50**	12.00	8.00	**59.38**	**55.12**	**57.25**
OFA$_{Tiny}$	20.50	8.00	3.75	**53.50**	**52.00**	**52.75**
OFA$_{Base}$	**26.50**	10.50	7.00	**58.88**	**54.00**	**56.44**
OFA$_{Medium}$	22.75	9.00	5.50	**54.25**	**52.75**	**53.50**
OFA$_{Large}$	**26.00**	8.75	5.75	**58.38**	**52.88**	**55.62**
OFA$_{Huge}$	**36.25**	15.50	13.50	**64.38**	**56.62**	**60.50**
BLIP$_{ITM14M}$ (ViT-B/16)	**39.25**	19.00	15.00	**65.88**	**58.25**	**62.06**
BLIP$_{ITC14M}$ (ViT-B/16)	**32.25**	13.75	10.50	**62.25**	**56.50**	**59.38**
BLIP$_{ITM}$ (ViT-B/16)	**40.50**	20.50	16.50	**66.25**	**59.00**	**62.62**
BLIP$_{ITC}$ (ViT-B/16)	**29.75**	14.50	9.50	**59.88**	**56.12**	**58.00**
BLIP$_{ITM}$ (ViT-B/16) (CapFilt-L)	**37.50**	18.50	14.00	**65.00**	**59.13**	**62.06**
BLIP$_{ITC}$ (ViT-B/16) (CapFilt-L)	**31.50**	10.50	8.50	**61.38**	**53.62**	**57.50**
BLIP$_{ITM}$ (ViT-L/16)	**42.50**	18.25	15.50	**66.88**	**57.25**	**62.06**
BLIP$_{ITC}$ (ViT-L/16)	**33.25**	12.00	9.00	**61.75**	**55.00**	**58.38**
BLIP$_{ITMCOCO}$ (ViT-B/16)	**48.00**	24.50	**20.00**	**69.88**	**61.25**	**65.56**
BLIP$_{ITCCOCO}$ (ViT-B/16)	**37.75**	15.75	12.75	**65.00**	**56.88**	**60.94**
BLIP$_{ITMFlickr30k}$ (ViT-B/16)	**46.25**	24.25	**21.25**	**69.25**	**60.62**	**64.94**
BLIP$_{ITCFlickr30k}$ (ViT-B/16)	**38.25**	15.00	12.25	**65.38**	**56.12**	**60.75**
BLIP$_{ITMCOCO}$ (ViT-L/16)	**46.75**	24.00	**20.50**	**68.88**	**61.00**	**64.94**
BLIP$_{ITCCOCO}$ (ViT-L/16)	**37.75**	13.75	10.50	**64.88**	**55.75**	**60.31**
BLIP$_{ITMFlickr30k}$ (ViT-L/16)	**45.00**	24.75	**20.50**	**68.62**	**60.50**	**64.56**
BLIP$_{ITCFlickr30k}$ (ViT-L/16)	**36.00**	16.25	13.50	**63.38**	**56.75**	**60.06**
BLIP$_{NLVR2}$ (ViT-B/16)	**40.25**	25.00	**18.50**	**64.62**	**61.62**	**63.12**

Table 6.2: Results on the Winoground dataset across the text, image and group score and accuracy metrics. Results above random chance in **bold**.

6.2.1.2 Ours

6.2.2 Results By Relation

6.2.2.1 Baseline

See Fig. 6.1

Model	Object Text	Object Image	Object Group	Relation Text	Relation Image	Relation Group	Both Text	Both Image	Both Group	1 Main Pred Text	1 Main Pred Image	1 Main Pred Group	2 Main Preds Text	2 Main Preds Image	2 Main Preds Group
MTurk Human	**92.20**	**90.78**	**88.65**	**89.27**	**90.56**	**86.70**	**76.92**	**57.69**	**57.69**	**87.33**	**85.62**	**82.53**	**95.37**	**96.30**	**93.52**
VinVL	**36.88**	17.73	14.18	**37.77**	17.60	14.16	**42.31**	19.23	**19.23**	**39.38**	21.23	**17.47**	**33.33**	8.33	6.48
UNITER$_{large}$	**39.01**	12.77	9.93	**36.05**	14.16	9.87	**50.00**	19.23	**19.23**	**40.07**	16.44	13.36	**32.41**	7.41	2.78
UNITER$_{base}$	**34.04**	11.35	9.22	**30.04**	14.16	10.30	**42.31**	15.38	11.54	**35.27**	14.73	11.99	24.07	9.26	4.63
ViLLA$_{large}$	**36.88**	14.89	11.35	**37.34**	12.88	11.16	**34.62**	7.69	7.69	**39.73**	17.12	14.38	**29.63**	2.78	1.85
ViLLA$_{base}$	**33.33**	15.60	9.93	**27.04**	9.01	6.01	**38.46**	19.23	15.38	**33.22**	14.04	10.27	21.30	6.48	1.85
VisualBERT$_{base}$	19.15	2.13	0.71	12.88	2.15	1.72	19.23	7.69	3.85	16.44	2.74	1.71	12.96	1.85	0.93
ViLT (ViT-B/32)	**31.91**	15.60	9.22	**36.91**	11.59	8.15	**30.77**	**26.92**	**19.23**	**35.27**	17.12	11.64	**33.33**	5.56	2.78
LXMERT	22.70	9.22	6.38	17.60	5.58	2.58	15.38	7.69	3.85	19.18	8.56	5.14	19.44	2.78	0.93
ViLBERT$_{base}$	**29.08**	10.64	7.09	19.31	3.00	1.72	**34.62**	**26.92**	**19.23**	23.97	8.90	5.82	23.15	2.78	1.85
UniT$_{ITM finetuned}$	17.73	5.67	2.13	18.03	4.72	3.43	**42.31**	23.08	**19.23**	21.58	6.85	4.11	13.89	4.63	3.70
FLAVA$_{ITM}$	**31.91**	23.40	14.89	**30.04**	16.31	12.02	**53.85**	**42.31**	**30.77**	**36.30**	24.66	**17.81**	21.30	9.26	4.63
FLAVA$_{Contrastive}$	23.40	19.15	11.35	23.61	8.58	5.58	**50.00**	**26.92**	**26.92**	26.37	16.44	10.62	22.22	5.56	4.63
CLIP (ViT-B/32)	**34.75**	7.80	6.38	22.75	8.58	5.58	**80.77**	**42.31**	**38.46**	**35.27**	13.01	10.27	18.52	3.70	1.85
VSE++$_{COCO}$ (ResNet)	21.99	6.38	1.42	23.61	9.01	5.58	19.23	7.69	3.85	25.00	9.59	4.79	16.67	3.70	1.85
VSE++$_{COCO}$ (VGG)	17.73	2.13	2.13	18.45	7.30	3.86	**26.92**	7.69	7.69	18.49	4.79	2.74	19.44	7.41	5.56
VSE++$_{Flickr30k}$ (ResNet)	20.57	6.38	3.55	18.88	4.29	2.15	**26.92**	3.85	3.85	21.58	6.51	3.42	15.74	0.93	0.93
VSE++$_{Flickr30k}$ (VGG)	17.73	4.96	2.84	19.74	6.87	5.15	**30.77**	7.69	7.69	20.55	6.16	4.79	17.59	6.48	3.70
VSRN$_{COCO}$	15.60	4.96	2.13	18.88	7.73	4.72	15.38	11.54	3.85	17.12	7.19	3.77	18.52	6.48	3.70
VSRN$_{Flickr30k}$	16.31	4.96	2.13	21.03	4.29	3.86	**30.77**	11.54	7.69	20.89	5.82	3.77	17.59	2.78	2.78

Table 6.3: The results by linguistic tag. Results above chance are in **bold**.

Model	Object Text	Object Image	Object Group	Relation Text	Relation Image	Relation Group	Both Text	Both Image	Both Group	1 Main Pred Text	1 Main Pred Image	1 Main Pred Group	2 Main Preds Text	2 Main Preds Image	2 Main Preds Group
MTurk Human	**92.20**	**90.78**	**88.65**	**89.27**	**90.56**	**86.70**	**76.92**	**57.69**	**57.69**	**87.33**	**85.62**	**82.53**	**95.37**	**96.30**	**93.52**
ViLT (ViT-B/32)	**29.08**	10.64	4.96	**26.18**	7.73	6.44	**30.77**	7.69	7.69	**30.14**	10.62	7.53	20.37	3.70	1.85
ViLT$_{COCO}$ (ViT-B/32)	**33.33**	15.60	12.77	**30.90**	10.73	9.01	**46.15**	**26.92**	**23.08**	**36.64**	15.75	14.04	22.22	7.41	3.70
ViLT$_{Flickr30k}$ (ViT-B/32)	**32.62**	14.89	11.35	**35.62**	8.15	7.73	**42.31**	23.08	**19.23**	**36.99**	14.38	11.99	**29.63**	3.70	3.70
ViLT$_{NLVR2}$ (ViT-B/32)	**39.01**	16.31	14.18	**36.48**	14.59	10.30	**46.15**	15.38	15.38	**39.73**	18.15	15.07	**33.33**	7.41	3.70
ViLT$_{VSR}$ Random (ViT-B/32)	**34.75**	17.73	9.93	**27.47**	11.16	6.01	**34.62**	**26.92**	15.38	**32.53**	16.44	9.59	25.00	9.26	3.70
ViLT$_{VSR}$ Zero-shot (ViT-B/32)	**34.75**	19.86	14.18	**26.18**	10.73	6.44	**30.77**	11.54	7.69	**32.19**	15.75	11.30	22.22	9.26	3.70
FLAVA$_{ITM}$	**31.91**	23.40	14.89	**30.04**	16.31	12.02	**53.85**	**42.31**	**30.77**	**36.30**	24.66	**17.81**	21.30	9.26	4.63
FLAVA$_{ITC}$	23.40	19.15	11.35	23.61	8.58	5.58	**50.00**	**26.92**	**26.92**	26.37	16.44	10.62	22.22	5.56	4.63
CLIP (ViT-B/32)	**35.46**	7.80	6.38	22.32	7.73	5.58	**80.77**	**46.15**	**42.31**	**35.62**	13.01	10.62	17.59	2.78	1.85
CLIP (ViT-B/16)	**27.66**	10.64	5.67	19.31	6.44	4.29	**61.54**	**42.31**	**38.46**	**30.14**	11.99	8.90	11.11	5.56	1.85
CLIP (ViT-L/14)	**27.66**	8.51	5.67	**25.75**	9.87	6.44	**57.69**	**34.62**	**34.62**	**30.14**	13.01	9.93	24.07	5.56	2.78
CLIP (ViT-L/14-336)	**32.62**	12.77	9.22	21.03	8.15	4.29	**57.69**	**42.31**	**34.62**	**30.48**	14.04	10.62	19.44	6.48	0.93
OFA$_{Tiny}$	22.70	6.38	2.13	17.17	6.87	3.43	**38.46**	**26.92**	15.38	23.97	8.22	4.45	11.11	7.41	1.85
OFA$_{Base}$	**25.53**	14.18	7.09	24.46	6.87	5.15	**50.00**	23.08	**23.08**	**28.77**	12.67	8.56	20.37	4.63	2.78
OFA$_{Medium}$	19.86	7.80	4.26	22.32	7.73	4.72	**42.31**	**26.92**	**19.23**	24.32	10.96	6.85	18.52	3.70	1.85
OFA$_{Large}$	**26.24**	10.64	5.67	24.03	5.15	3.86	**42.31**	**30.77**	**23.08**	**29.45**	10.96	7.53	16.67	2.78	0.93
OFA$_{Huge}$	**40.43**	18.44	15.60	**30.90**	11.59	9.87	**61.54**	**34.62**	**34.62**	**39.73**	19.18	**16.78**	**26.85**	5.56	4.63
BLIP$_{ITM14M}$ (ViT-B/16)	**41.84**	23.40	**17.73**	**36.05**	14.59	11.59	**53.85**	**34.62**	**30.77**	**43.84**	23.63	**18.49**	**26.85**	6.48	5.56
BLIP$_{ITC14M}$ (ViT-B/16)	**34.04**	13.48	9.93	**28.33**	12.02	9.44	**57.69**	**30.77**	**23.08**	**37.67**	16.44	13.01	17.59	6.48	3.70
BLIP$_{ITM}$ (ViT-B/16)	**46.10**	22.70	**17.73**	**35.62**	17.60	14.16	**53.85**	**34.62**	**30.77**	**45.89**	**25.34**	**20.55**	**25.93**	7.41	5.56
BLIP$_{ITC}$ (ViT-B/16)	**34.75**	14.18	9.22	**25.32**	13.73	8.58	**42.31**	23.08	**19.23**	**33.56**	16.10	10.62	19.44	10.19	6.48
BLIP$_{ITM}$ (ViT-B/16) (CapFilt-L)	**39.01**	19.86	12.77	**34.76**	15.88	12.45	**53.85**	**34.62**	**34.62**	**41.10**	22.60	**17.12**	**27.78**	7.41	5.56
BLIP$_{ITC}$ (ViT-B/16) (CapFilt-L)	**36.88**	12.77	9.22	**26.18**	8.58	7.30	**50.00**	15.38	15.38	**35.96**	13.36	10.96	19.44	2.78	1.85
BLIP$_{ITM}$ (ViT-L/16)	**41.84**	19.86	**17.02**	**40.77**	16.31	13.73	**61.54**	**26.92**	**23.08**	**45.55**	23.29	**20.21**	**34.26**	4.63	2.78
BLIP$_{ITC}$ (ViT-L/16)	**34.04**	14.18	11.35	**30.90**	9.01	6.01	**50.00**	**26.92**	**23.08**	**36.99**	14.04	10.96	23.15	6.48	3.70
BLIP$_{ITMCOCO}$ (ViT-B/16)	**42.55**	**26.95**	**19.15**	**49.79**	21.89	**19.31**	**61.54**	**34.62**	**30.77**	**48.97**	**29.79**	**24.66**	**45.37**	10.19	7.41
BLIP$_{ITCCOCO}$ (ViT-B/16)	**36.88**	19.15	14.18	**36.05**	11.59	10.30	**57.69**	**34.62**	**26.92**	**41.78**	18.84	15.07	**26.85**	7.41	6.48
BLIP$_{ITMFlickr30k}$ (ViT-B/16)	**49.65**	**28.37**	**22.70**	**42.49**	19.74	**18.45**	**61.54**	**42.31**	**38.46**	**51.03**	**28.42**	**26.03**	**33.33**	12.96	8.33
BLIP$_{ITCFlickr30k}$ (ViT-B/16)	**36.88**	17.02	10.64	**36.48**	12.02	11.16	**61.54**	**30.77**	**30.77**	**40.75**	17.12	13.70	**31.48**	9.26	8.33
BLIP$_{ITMCOCO}$ (ViT-L/16)	**48.94**	**25.53**	**20.57**	**44.64**	22.32	**20.60**	**53.85**	**30.77**	**19.23**	**51.03**	**28.42**	**23.97**	**35.19**	12.04	11.11
BLIP$_{ITCCOCO}$ (ViT-L/16)	**36.88**	14.18	11.35	**36.05**	11.16	7.30	**57.69**	**34.62**	**34.62**	**41.10**	16.44	13.36	**28.70**	6.48	2.78
BLIP$_{ITMFlickr30k}$ (ViT-L/16)	**46.10**	22.70	16.31	**42.06**	24.89	**21.46**	**65.38**	**34.62**	**34.62**	**50.34**	**29.11**	**24.66**	**30.56**	12.96	9.26
BLIP$_{ITCFlickr30k}$ (ViT-L/16)	**39.01**	19.86	15.60	**30.47**	11.59	9.44	**69.23**	**38.46**	**38.46**	**39.38**	20.55	**17.12**	**26.85**	4.63	3.70
BLIP$_{NLVR2}$ (ViT-B/16)	**42.55**	23.40	**19.86**	**36.48**	**25.32**	**16.74**	**61.54**	**30.77**	**26.92**	**42.47**	**27.74**	**21.23**	**34.26**	17.59	11.11

Table 6.4: The results by linguistic tag. Results above chance are in **bold**.

6.2.2.2 Ours

See Fig. 6.2

See Table 6.8 and Table 6.9

Model	Symbolic			Pragmatics			Same Image Series		
	Text	Image	Group	Text	Image	Group	Text	Image	Group
MTurk Human	**96.43**	**92.86**	**92.86**	**58.82**	**41.18**	**41.18**	**95.65**	**91.30**	**91.30**
VinVL	25.00	17.86	14.29	**29.41**	5.88	5.88	**34.78**	17.39	13.04
UNITER$_{large}$	**39.29**	**28.57**	**17.86**	**35.29**	0.00	0.00	4.35	8.70	0.00
UNITER$_{base}$	**46.43**	14.29	14.29	**29.41**	17.65	11.76	8.70	8.70	0.00
ViLLA$_{large}$	**39.29**	14.29	10.71	17.65	0.00	0.00	17.39	4.35	0.00
ViLLA$_{base}$	**42.86**	17.86	14.29	**29.41**	5.88	5.88	13.04	8.70	4.35
VisualBERT$_{base}$	**28.57**	0.00	0.00	5.88	0.00	0.00	13.04	0.00	0.00
ViLT (ViT-B/32)	**28.57**	17.86	10.71	**35.29**	0.00	0.00	**26.09**	0.00	0.00
LXMERT	**28.57**	3.57	3.57	17.65	5.88	0.00	8.70	4.35	0.00
ViLBERT$_{base}$	**28.57**	10.71	7.14	**29.41**	5.88	5.88	13.04	0.00	0.00
UniT$_{ITM finetuned}$	14.29	10.71	7.14	17.65	5.88	5.88	21.74	4.35	4.35
FLAVA$_{ITM}$	25.00	**28.57**	**17.86**	17.65	**29.41**	11.76	17.39	8.70	0.00
FLAVA$_{Contrastive}$	17.86	10.71	10.71	11.76	23.53	5.88	17.39	4.35	4.35
CLIP (ViT-B/32)	**39.29**	3.57	3.57	**35.29**	5.88	5.88	8.70	0.00	0.00
VSE++$_{COCO}$ (ResNet)	**32.14**	10.71	10.71	23.53	11.76	0.00	13.04	4.35	4.35
VSE++$_{COCO}$ (VGG)	17.86	14.29	7.14	17.65	0.00	0.00	13.04	4.35	4.35
VSE++$_{Flickr30k}$ (ResNet)	21.43	3.57	0.00	23.53	0.00	0.00	17.39	4.35	0.00
VSE++$_{Flickr30k}$ (VGG)	**28.57**	10.71	10.71	11.76	0.00	0.00	13.04	4.35	0.00
VSRN$_{COCO}$	7.14	3.57	0.00	11.76	0.00	0.00	13.04	0.00	0.00
VSRN$_{Flickr30k}$	21.43	3.57	3.57	**35.29**	11.76	5.88	8.70	4.35	4.35

Table 6.5: The results by visual tag. Results above chance are in **bold**.

6.2.3 Results By Relation Meta Category

6.2.3.1 Baseline

See Fig. 6.3

6.2.3.2 Ours

See Fig. 6.4

See Table 6.10 and Table 6.11

Model	Symbolic Text	Symbolic Image	Symbolic Group	Pragmatics Text	Pragmatics Image	Pragmatics Group	Same Image Series Text	Same Image Series Image	Same Image Series Group
MTurk Human	**96.43**	**92.86**	**92.86**	**58.82**	**41.18**	**41.18**	**95.65**	**91.30**	**91.30**
ViLT (ViT-B/32)	21.43	7.14	3.57	17.65	5.88	5.88	17.39	8.70	4.35
ViLT$_{COCO}$ (ViT-B/32)	21.43	10.71	10.71	**29.41**	17.65	5.88	21.74	8.70	4.35
ViLT$_{Flickr30k}$ (ViT-B/32)	**28.57**	7.14	7.14	23.53	0.00	0.00	**26.09**	4.35	4.35
ViLT$_{NLVR2}$ (ViT-B/32)	**42.86**	10.71	10.71	**41.18**	0.00	0.00	17.39	13.04	4.35
ViLT$_{VSR}$ Random (ViT-B/32)	**28.57**	14.29	7.14	**29.41**	11.76	5.88	**30.43**	21.74	8.70
ViLT$_{VSR}$ Zero-shot (ViT-B/32)	25.00	10.71	7.14	**35.29**	23.53	11.76	**30.43**	8.70	0.00
FLAVA$_{ITM}$	25.00	**28.57**	**17.86**	17.65	**29.41**	11.76	17.39	8.70	0.00
FLAVA$_{ITC}$	17.86	10.71	10.71	11.76	23.53	5.88	17.39	4.35	4.35
CLIP (ViT-B/32)	**35.71**	3.57	3.57	**35.29**	5.88	5.88	13.04	0.00	0.00
CLIP (ViT-B/16)	21.43	3.57	3.57	**29.41**	11.76	11.76	4.35	4.35	0.00
CLIP (ViT-L/14)	**28.57**	10.71	3.57	23.53	17.65	11.76	13.04	8.70	4.35
CLIP (ViT-L/14-336)	**28.57**	14.29	7.14	17.65	17.65	5.88	13.04	4.35	0.00
OFA$_{Tiny}$	21.43	7.14	7.14	11.76	17.65	0.00	21.74	8.70	0.00
OFA$_{Base}$	**28.57**	10.71	10.71	23.53	5.88	5.88	21.74	13.04	4.35
OFA$_{Medium}$	**28.57**	10.71	7.14	17.65	5.88	5.88	13.04	8.70	4.35
OFA$_{Large}$	**28.57**	14.29	10.71	**29.41**	0.00	0.00	13.04	0.00	0.00
OFA$_{Huge}$	**39.29**	14.29	14.29	11.76	11.76	5.88	17.39	4.35	4.35
BLIP$_{ITM14M}$ (ViT-B/16)	**46.43**	17.86	**17.86**	**35.29**	11.76	11.76	17.39	4.35	0.00
BLIP$_{ITC14M}$ (ViT-B/16)	**32.14**	14.29	10.71	**29.41**	0.00	0.00	13.04	0.00	0.00
BLIP$_{ITM}$ (ViT-B/16)	**50.00**	17.86	**17.86**	**29.41**	5.88	5.88	13.04	4.35	0.00
BLIP$_{ITC}$ (ViT-B/16)	**39.29**	10.71	7.14	5.88	11.76	0.00	4.35	8.70	0.00
BLIP$_{ITM}$ (ViT-B/16) (CapFilt-L)	**42.86**	17.86	14.29	23.53	17.65	**17.65**	17.39	4.35	0.00
BLIP$_{ITC}$ (ViT-B/16) (CapFilt-L)	**42.86**	0.00	0.00	17.65	0.00	0.00	4.35	0.00	0.00
BLIP$_{ITM}$ (ViT-L/16)	**53.57**	25.00	**25.00**	**29.41**	5.88	0.00	**26.09**	4.35	0.00
BLIP$_{ITC}$ (ViT-L/16)	**39.29**	17.86	14.29	**41.18**	11.76	11.76	8.70	4.35	4.35
BLIP$_{ITMCOCO}$ (ViT-B/16)	**53.57**	17.86	**17.86**	**58.82**	17.65	**17.65**	**39.13**	8.70	0.00
BLIP$_{ITCCOCO}$ (ViT-B/16)	25.00	10.71	7.14	**35.29**	5.88	5.88	17.39	8.70	4.35
BLIP$_{ITMFlickr30k}$ (ViT-B/16)	**53.57**	21.43	**21.43**	**35.29**	11.76	11.76	**26.09**	4.35	4.35
BLIP$_{ITCFlickr30k}$ (ViT-B/16)	**35.71**	10.71	10.71	23.53	17.65	11.76	17.39	4.35	0.00
BLIP$_{ITMCOCO}$ (ViT-L/16)	**39.29**	**35.71**	**25.00**	**58.82**	23.53	**17.65**	**26.09**	4.35	0.00
BLIP$_{ITCCOCO}$ (ViT-L/16)	**46.43**	14.29	14.29	17.65	5.88	5.88	13.04	0.00	0.00
BLIP$_{ITMFlickr30k}$ (ViT-L/16)	**39.29**	**28.57**	**25.00**	**47.06**	11.76	5.88	**30.43**	8.70	4.35
BLIP$_{ITCFlickr30k}$ (ViT-L/16)	**39.29**	14.29	14.29	**47.06**	5.88	5.88	21.74	13.04	13.04
BLIP$_{NLVR2}$ (ViT-B/16)	**57.14**	21.43	10.71	**41.18**	5.88	5.88	21.74	17.39	4.35

Table 6.6: The results by visual tag. Results above chance are in **bold**.

model↓	random split dev	random split test	zero-shot split dev	zero-shot split test
human	95.4			
VisualBERT	59.2$_{\pm 0.9}$	57.4$_{\pm 0.9}$	57.4$_{\pm 2.2}$	54.0$_{\pm 1.3}$
LXMERT	**73.8**$_{\pm 1.2}$	**72.5**$_{\pm 1.4}$	**69.2**$_{\pm 1.0}$	**63.2**$_{\pm 1.7}$
ViLT	71.9$_{\pm 1.3}$	71.0$_{\pm 0.7}$	66.7$_{\pm 1.7}$	62.4$_{\pm 1.5}$

Table 6.7: Model performance on VSR. Results of both random and zero-shot splits, both validation and tests are listed.

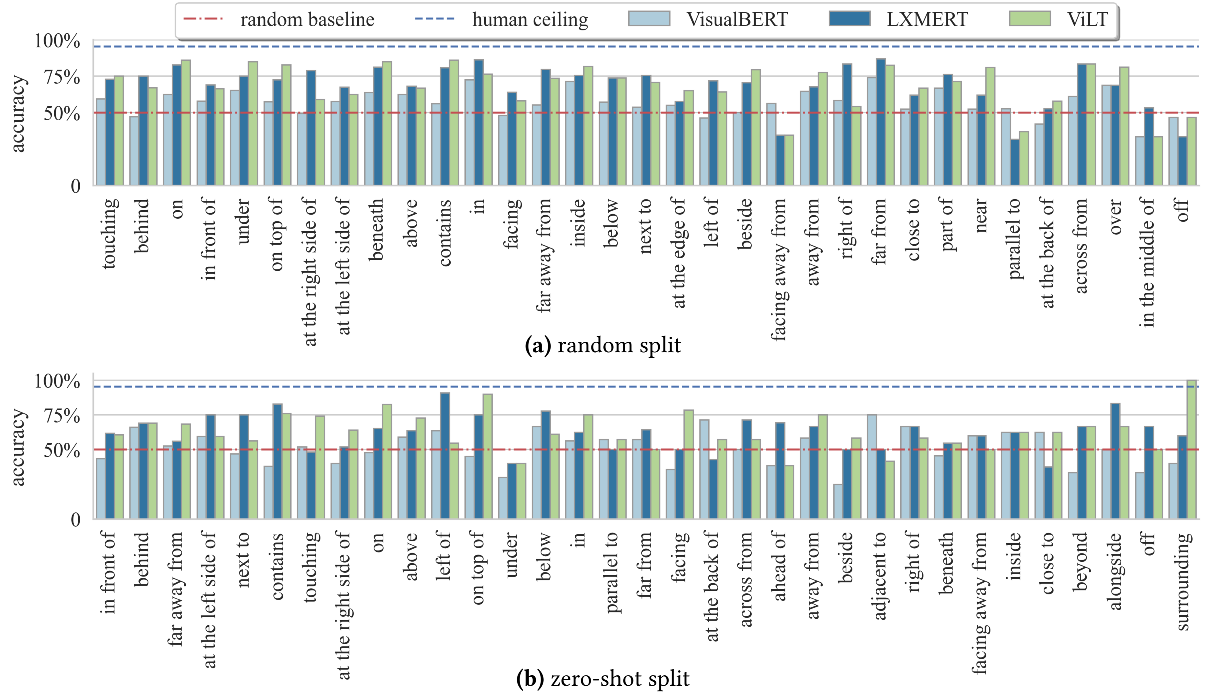


Figure 6.1: Performance by relation on the random (upper) and zero-shot (lower) split test sets. Relation order sorted by frequency (high to low from left to right). Only relations with more than 15 and 5 occurrences on the random and zero-shot tests respectively are shown.

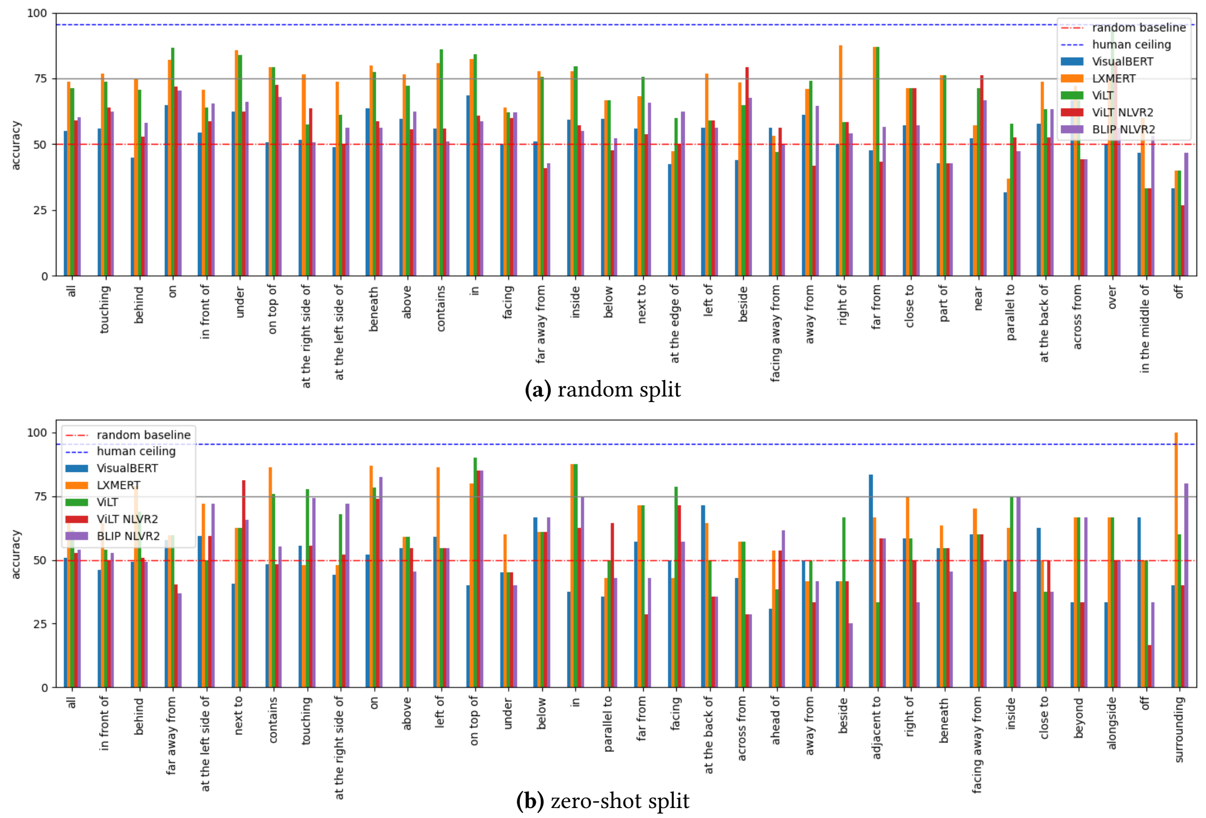
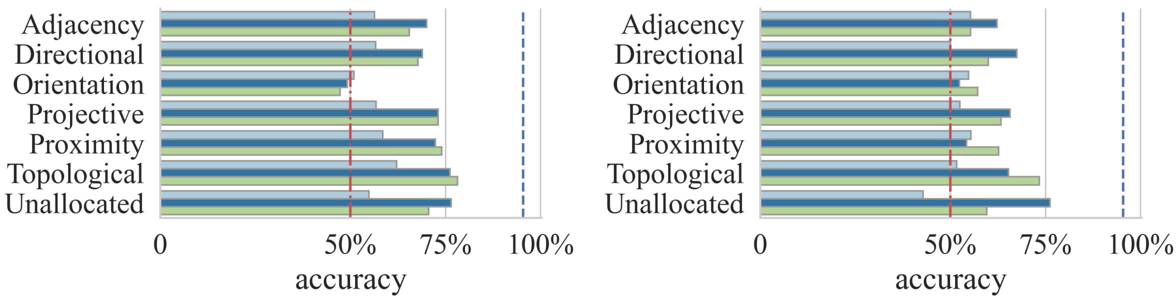


Figure 6.2: Performance by relation on the random (upper) and zero-shot (lower) split test sets. Relation order sorted by frequency (high to low from left to right). Only relations with more than 15 and 5 occurrences on the random and zero-shot tests respectively are shown.

relation	number	VisualBERT	LXMERT	ViLT	ViLT NLVR2	BLIP NLVR2
all	2024	55.1	73.9	71.2	59.1	60.1
touching	236	55.9	76.7	73.7	64.0	62.3
behind	136	44.9	75.0	70.6	52.9	58.1
on	128	64.8	82.0	86.7	71.9	70.3
in front of	116	54.3	70.7	63.8	58.6	65.5
under	112	62.5	85.7	83.9	62.5	66.1
on top of	87	50.6	79.3	79.3	72.4	67.8
at the right side of	85	51.8	76.5	57.6	63.5	50.6
at the left side of	80	48.8	73.8	61.3	50.0	56.2
beneath	80	63.7	80.0	77.5	58.8	56.2
above	72	59.7	76.4	72.2	55.6	62.5
contains	57	56.1	80.7	86.0	56.1	50.9
in	51	68.6	82.4	84.3	60.8	58.8
facing	50	50.0	64.0	62.0	60.0	62.0
far away from	49	51.0	77.6	75.5	40.8	42.9
inside	49	59.2	77.6	79.6	57.1	55.1
below	42	59.5	66.7	66.7	47.6	52.4
next to	41	56.1	68.3	75.6	53.7	65.9
at the edge of	40	42.5	47.5	60.0	50.0	62.5
left of	39	56.4	76.9	59.0	59.0	56.4
beside	34	44.1	73.5	64.7	79.4	67.6
facing away from	32	56.2	53.1	46.9	56.2	50.0
away from	31	61.3	71.0	74.2	41.9	64.5
right of	24	50.0	87.5	58.3	58.3	54.2
far from	23	47.8	87.0	87.0	43.5	56.5
close to	21	57.1	71.4	71.4	71.4	57.1
part of	21	42.9	76.2	76.2	42.9	42.9
near	21	52.4	57.1	71.4	76.2	66.7
parallel to	19	31.6	36.8	57.9	52.6	47.4
at the back of	19	57.9	73.7	63.2	52.6	63.2
across from	18	66.7	72.2	66.7	44.4	44.4
over	16	50.0	75.0	93.8	81.2	56.2
in the middle of	15	46.7	60.0	33.3	33.3	53.3
off	15	33.3	40.0	40.0	26.7	46.7

Table 6.8: Number and performance by relation on the random split test. Only relations with more than 15 occurrences are shown.



(a) random split

(b) zero-shot split

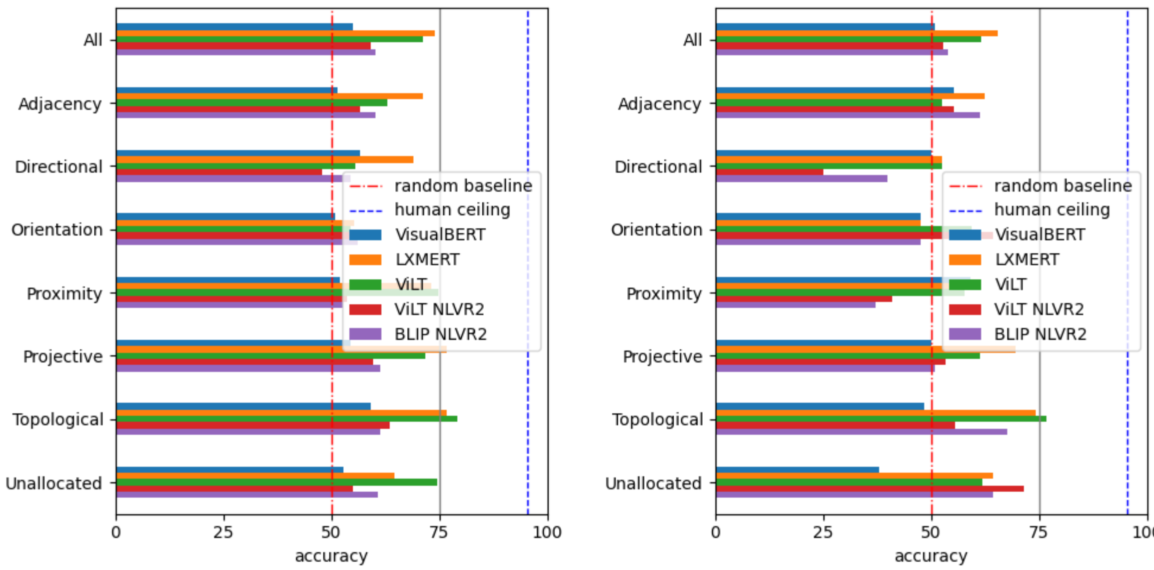
Figure 6.3: Performance by meta categories of relations, on the random (left) and zero-shot (right) split test sets. For legend information, see Figure 6.1.

relation	number	VisualBERT	LXMERT	ViLT	ViLT NLVR2	BLIP NLVR2
all	731	50.8	65.5	61.6	52.8	53.9
in front of	76	46.1	64.5	53.9	50.0	52.6
behind	71	49.3	78.9	69.0	50.7	49.3
far away from	57	57.9	59.6	59.6	40.4	36.8
at the left side of	32	59.4	71.9	50.0	59.4	71.9
next to	32	40.6	62.5	62.5	81.2	65.6
contains	29	48.3	86.2	75.9	48.3	55.2
touching	27	55.6	48.1	77.8	55.6	74.1
at the right side of	25	44.0	48.0	68.0	52.0	72.0
on	23	52.2	87.0	78.3	73.9	82.6
above	22	54.5	59.1	59.1	54.5	45.5
left of	22	59.1	86.4	54.5	54.5	54.5
on top of	20	40.0	80.0	90.0	85.0	85.0
under	20	45.0	60.0	45.0	45.0	40.0
below	18	66.7	61.1	61.1	61.1	66.7
in	16	37.5	87.5	87.5	62.5	75.0
parallel to	14	35.7	42.9	50.0	64.3	42.9
far from	14	57.1	71.4	71.4	28.6	42.9
facing	14	50.0	42.9	78.6	71.4	57.1
at the back of	14	71.4	64.3	50.0	35.7	35.7
across from	14	42.9	57.1	57.1	28.6	28.6
ahead of	13	30.8	53.8	38.5	53.8	61.5
away from	12	50.0	41.7	50.0	33.3	41.7
beside	12	41.7	41.7	66.7	41.7	25.0
adjacent to	12	83.3	66.7	33.3	58.3	58.3
right of	12	58.3	75.0	58.3	50.0	33.3
beneath	11	54.5	63.6	54.5	54.5	45.5
facing away from	10	60.0	70.0	60.0	60.0	50.0
inside	8	50.0	62.5	75.0	37.5	75.0
close to	8	62.5	50.0	37.5	50.0	37.5
beyond	6	33.3	66.7	66.7	33.3	66.7
alongside	6	33.3	66.7	66.7	50.0	50.0
off	6	66.7	50.0	50.0	16.7	33.3
surrounding	5	40.0	100.0	60.0	40.0	80.0

Table 6.9: Number and performance by relation on the zero-shot split test. Only relations with more than 5 occurrences are shown.

category	number	VisualBERT	LXMERT	ViLT	ViLT NLVR2	BLIP NLVR2
All	2024	55.1	73.9	71.2	59.1	60.1
Adjacency	284	51.4	71.1	63.0	56.7	60.2
Directional	90	56.7	68.9	55.6	47.8	54.4
Orientation	112	50.9	55.4	54.5	55.4	56.2
Proximity	123	52.0	73.2	74.8	53.7	52.8
Projective	773	54.5	76.7	71.7	59.8	61.4
Topological	591	59.2	76.8	79.2	63.5	61.4
Unallocated	51	52.9	64.7	74.5	54.9	60.8

Table 6.10: Number and performance by relation meta category on the random split test.



(a) random split

(b) zero-shot split

Figure 6.4: Performance by meta categories of relations, on the random (left) and zero-shot (right) split test sets. For legend information, see Fig. 6.2.

category	number	VisualBERT	LXMERT	ViLT	ViLT NLVR2	BLIP NLVR2
All	731	50.8	65.5	61.6	52.8	53.9
Adjacency	114	55.3	62.3	52.6	55.3	61.4
Directional	40	50.0	52.5	52.5	25.0	40.0
Orientation	42	47.6	47.6	59.5	64.3	47.6
Proximity	83	59.0	59.0	57.8	41.0	37.3
Projective	286	50.0	69.6	61.2	53.5	51.0
Topological	124	48.4	74.2	76.6	55.6	67.7
Unallocated	42	38.1	64.3	61.9	71.4	64.3

Table 6.11: Number and performance by relation meta category on the zero-shot split test.

7 Discussion

7.1 Winoground

7.1.1 Capabilities of Encoders

7.1.1.1 Baseline

See Table 7.1

	Perplexity		Caption Length					
	Text-Image		Text		Image		Group	
Model	Corr.	p-value	Corr.	p-value	Corr.	p-value	Corr.	p-value
MTurk Human	0.05	0.07	**0.11**	**0.03**	**0.20**	**0.00**	**0.20**	**0.00**
VinVL	**-0.05**	**0.04**	**-0.11**	**0.03**	**-0.18**	**0.00**	**-0.20**	**0.00**
UNITER$_{large}$	-0.01	0.57	-0.08	0.13	-0.06	0.20	**-0.16**	**0.00**
UNITER$_{base}$	-0.03	0.22	**-0.15**	**0.00**	**-0.11**	**0.03**	**-0.14**	**0.00**
ViLLA$_{large}$	-0.02	0.39	-0.05	0.32	**-0.13**	**0.01**	**-0.12**	**0.01**
ViLLA$_{base}$	-0.04	0.13	**-0.14**	**0.01**	**-0.12**	**0.01**	**-0.11**	**0.03**
VisualBERT$_{base}$	-0.04	0.15	-0.09	0.07	-0.07	0.14	-0.06	0.22
ViLT (ViT-B/32)	-0.04	0.16	-0.09	0.06	**-0.20**	**0.00**	**-0.16**	**0.00**
LXMERT	-0.04	0.12	-0.00	0.97	-0.05	0.32	**-0.11**	**0.02**
ViLBERT$_{base}$	-0.04	0.11	-0.09	0.09	**-0.15**	**0.00**	**-0.14**	**0.00**
UniT$_{ITM Finetuned}$	-0.01	0.73	-0.03	0.53	-0.05	0.32	-0.02	0.73
FLAVA$_{ITM}$	-0.03	0.22	**-0.21**	**0.00**	**-0.22**	**0.00**	**-0.23**	**0.00**
FLAVA$_{Contrastive}$	**-0.06**	**0.01**	**-0.15**	**0.00**	**-0.25**	**0.00**	**-0.19**	**0.00**
CLIP (ViT-B/32)	-0.04	0.09	**-0.27**	**0.00**	**-0.19**	**0.00**	**-0.22**	**0.00**
VSE++$_{COCO}$ (ResNet)	**-0.05**	**0.04**	-0.03	0.60	-0.02	0.74	0.01	0.90
VSE++$_{COCO}$ (VGG)	-0.04	0.08	-0.02	0.65	0.03	0.50	0.03	0.56
VSE++$_{Flickr30k}$ (ResNet)	-0.02	0.43	-0.01	0.80	0.01	0.91	0.02	0.67
VSE++$_{Flickr30k}$ (VGG)	0.01	0.74	-0.09	0.07	-0.07	0.18	**-0.10**	**0.04**
VSRN$_{COCO}$	**-0.07**	**0.01**	-0.03	0.60	-0.05	0.30	-0.05	0.36
VSRN$_{Flickr30k}$	-0.02	0.32	-0.03	0.60	-0.10	0.06	-0.05	0.29

Table 7.1: (left) The correlation between model image-caption scores and the caption perplexity from GPT2. (right) The correlation between the model text, image and group scores and the caption length.

7.1.1.2 Ours

See Table 7.2

7.1.2 By Multimodal Pretraining Dataset Size

7.1.2.1 Baseline

See Table 7.3 and Fig. 7.1

7.1.2.2 Ours

See Table 7.4 and Fig. 7.2

Model	Perplexity Image-Caption Corr.	Perplexity Image-Caption p-value	Caption Length Text Corr.	Caption Length Text p-value	Caption Length Image Corr.	Caption Length Image p-value	Caption Length Group Corr.	Caption Length Group p-value
MTurk Human	0.05	0.07	**0.11**	**0.03**	**0.20**	**0.00**	**0.20**	**0.00**
ViLT (ViT-B/32)	-0.04	0.08	**-0.12**	**0.02**	-0.07	0.17	-0.05	0.35
ViLT$_{COCO}$ (ViT-B/32)	-0.05	0.06	**-0.21**	**0.00**	**-0.16**	**0.00**	**-0.17**	**0.00**
ViLT$_{Flickr30k}$ (ViT-B/32)	**-0.05**	**0.03**	**-0.11**	**0.03**	**-0.17**	**0.00**	**-0.14**	**0.01**
ViLT$_{NLVR2}$ (ViT-B/32)	0.00	0.95	**-0.13**	**0.01**	**-0.11**	**0.03**	**-0.12**	**0.02**
FLAVA$_{ITM}$	-0.03	0.22	**-0.21**	**0.00**	**-0.22**	**0.00**	**-0.23**	**0.00**
FLAVA$_{ITC}$	**-0.06**	**0.01**	**-0.15**	**0.00**	**-0.25**	**0.00**	**-0.19**	**0.00**
CLIP (ViT-B/32)	-0.04	0.10	**-0.28**	**0.00**	**-0.21**	**0.00**	**-0.23**	**0.00**
CLIP (ViT-B/16)	-0.04	0.11	**-0.26**	**0.00**	**-0.22**	**0.00**	**-0.23**	**0.00**
CLIP (ViT-L/14)	-0.03	0.22	**-0.22**	**0.00**	**-0.17**	**0.00**	**-0.18**	**0.00**
CLIP (ViT-L/14-336)	-0.04	0.11	**-0.23**	**0.00**	**-0.22**	**0.00**	**-0.23**	**0.00**
OFA$_{Tiny}$	-0.01	0.66	**-0.17**	**0.00**	-0.06	0.24	**-0.12**	**0.02**
OFA$_{Base}$	-0.02	0.43	**-0.15**	**0.00**	**-0.12**	**0.02**	**-0.10**	**0.05**
OFA$_{Medium}$	-0.01	0.77	**-0.11**	**0.03**	**-0.14**	**0.00**	**-0.12**	**0.01**
OFA$_{Large}$	**-0.16**	**0.00**	**-0.18**	**0.00**	**-0.20**	**0.00**	**-0.17**	**0.00**
OFA$_{Huge}$	0.01	0.75	**-0.15**	**0.00**	**-0.17**	**0.00**	**-0.16**	**0.00**
BLIP$_{ITM14M}$ (ViT-B/16)	-0.00	0.85	**-0.22**	**0.00**	**-0.23**	**0.00**	**-0.21**	**0.00**
BLIP$_{ITC14M}$ (ViT-B/16)	-0.00	0.97	**-0.24**	**0.00**	**-0.17**	**0.00**	**-0.17**	**0.00**
BLIP$_{ITM}$ (ViT-B/16)	**-0.05**	**0.04**	**-0.24**	**0.00**	**-0.23**	**0.00**	**-0.22**	**0.00**
BLIP$_{ITC}$ (ViT-B/16)	**-0.06**	**0.02**	**-0.19**	**0.00**	**-0.17**	**0.00**	**-0.13**	**0.01**
BLIP$_{ITM}$ (ViT-B/16) (CapFilt-L)	**-0.10**	**0.00**	**-0.20**	**0.00**	**-0.28**	**0.00**	**-0.23**	**0.00**
BLIP$_{ITC}$ (ViT-B/16) (CapFilt-L)	**-0.10**	**0.00**	**-0.25**	**0.00**	**-0.17**	**0.00**	**-0.15**	**0.00**
BLIP$_{ITM}$ (ViT-L/16)	**-0.07**	**0.01**	**-0.17**	**0.00**	**-0.21**	**0.00**	**-0.19**	**0.00**
BLIP$_{ITC}$ (ViT-L/16)	**-0.08**	**0.00**	**-0.22**	**0.00**	**-0.17**	**0.00**	**-0.17**	**0.00**
BLIP$_{ITMCOCO}$ (ViT-B/16)	-0.04	0.11	**-0.17**	**0.00**	**-0.26**	**0.00**	**-0.22**	**0.00**
BLIP$_{ITCCOCO}$ (ViT-B/16)	**-0.06**	**0.02**	**-0.18**	**0.00**	**-0.26**	**0.00**	**-0.22**	**0.00**
BLIP$_{ITMFlickr30k}$ (ViT-B/16)	-0.04	0.11	**-0.25**	**0.00**	**-0.28**	**0.00**	**-0.28**	**0.00**
BLIP$_{ITCFlickr30k}$ (ViT-B/16)	**-0.07**	**0.00**	**-0.20**	**0.00**	**-0.19**	**0.00**	**-0.18**	**0.00**
BLIP$_{ITMCOCO}$ (ViT-L/16)	**-0.06**	**0.02**	**-0.24**	**0.00**	**-0.23**	**0.00**	**-0.23**	**0.00**
BLIP$_{ITCCOCO}$ (ViT-L/16)	**-0.10**	**0.00**	**-0.21**	**0.00**	**-0.21**	**0.00**	**-0.21**	**0.00**
BLIP$_{ITMFlickr30k}$ (ViT-L/16)	**-0.05**	**0.04**	**-0.27**	**0.00**	**-0.25**	**0.00**	**-0.23**	**0.00**
BLIP$_{ITCFlickr30k}$ (ViT-L/16)	**-0.09**	**0.00**	**-0.24**	**0.00**	**-0.19**	**0.00**	**-0.16**	**0.00**

Table 7.2: (left) The correlation between model image-caption scores and the caption perplexity from GPT2. (right) The correlation between the model text, image and group scores and the caption length.

Pretraining	Score	Corr.	p-value
Image	Text	**0.84**	**0.00**
	Image	**0.76**	**0.00**
	Group	**0.75**	**0.00**
Caption	Text	**0.77**	**0.00**
	Image	**0.75**	**0.00**
	Group	**0.71**	**0.00**

Table 7.3: Correlations between the number of pretraining images and captions and the model text, image, and group scores. CLIP and FLAVA are excluded as outliers.

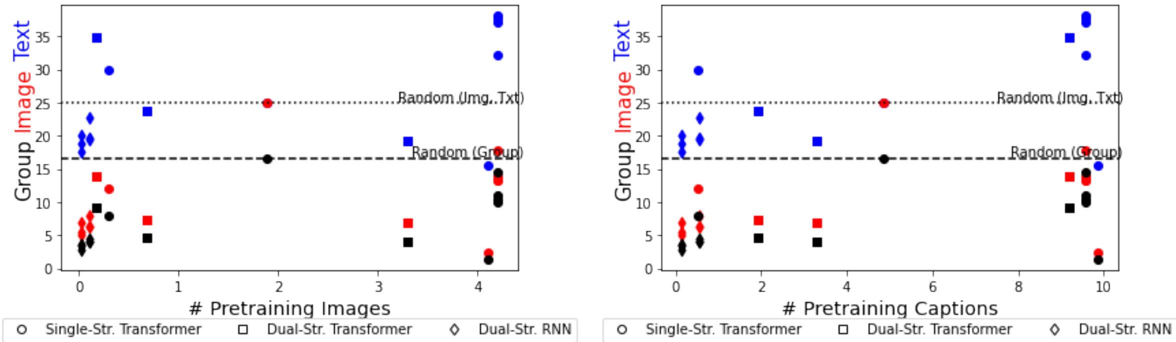


Figure 7.1: Graphs of the model performance on Winoground for each model by the number of pretraining images (left) and pretraining captions (right).

Pretraining	Score	Corr.	p-value
	Text	-0.09	0.65
Image	Image	-0.16	0.44
	Group	-0.13	0.53
	Text	-0.09	0.66
Caption	Image	-0.15	0.44
	Group	-0.12	0.54

Table 7.4: Correlations between the number of pretraining images and captions and the model text, image, and group scores. Only BLIP, CLIP and FLAVA are included.

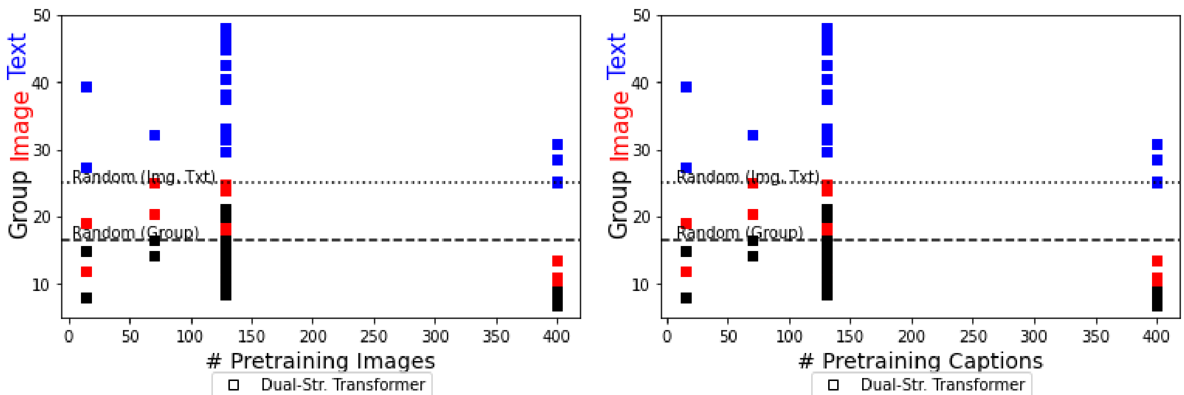


Figure 7.2: Graphs of the model performance on Winoground for each model by the number of pretraining images (left) and pretraining captions (right).

8 Conclusions

8.1 Future Work

8.1.1 Image-to-Image Generation

Stable Diffusion could be used to generate new images as a data augmentation technique. For example, multiple image variations can be generated from an input image, to get similar images that still match the original caption. We could also change the caption if we are interested in getting similar images with different object. In painting could also be used to change an specific part of the image.

Appendix

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