LINEARLY MAPPING FROM IMAGE TO TEXT SPACE

Anonymous authors
Paper under double-blind review

ABSTRACT

The extent to which text-only language models (LMs) learn to represent the physical, non-linguistic world is an open question. Prior work has shown that pretrained LMs can be taught to "understand" visual inputs when the models' parameters are updated on image captioning tasks. We test a stronger hypothesis: that the conceptual representations learned by text-only models are functionally equivalent (up to a linear transformation) to those learned by models trained on vision tasks. Specifically, we show that the image representations from vision models can be transferred as continuous prompts to frozen LMs by training only a single linear projection. Using these to prompt the LM achieves competitive performance on captioning and visual question answering tasks compared to models that tune both the image encoder and text decoder (such as the MAGMA model). We compare three image encoders with increasing amounts of linguistic supervision seen during pretraining: BEIT (no linguistic information), NF-ResNET (lexical category information), and CLIP (full natural language descriptions). We find that all three encoders perform equally well at transferring visual property information to the language model (e.g., whether an animal is large or small), but that image encoders pretrained with linguistic supervision more saliently encode category information (e.g., distinguishing hippo vs. elephant) and thus perform significantly better on benchmark language-and-vision tasks. Our results indicate that LMs encode conceptual information structurally similarly to vision-based models, even those that are solely trained on images.

1 INTRODUCTION

Much recent work in NLP has revolved around studying the limits on representational capacity incurred by training on form-only text data, as discussed in Bender & Koller (2020). Tied to this argument is the idea that without explicit *grounding*, language models are not inclined to learn conceptual representations of language that reflect the rich conceptual knowledge that humans gain from interacting with the physical, non-linguistic world. Despite this, there have been remarkable findings in large language models' abilities to generalize to and reason about non-linguistic phenomena (Tsimpoukelli et al., 2021; Eichenberg et al., 2021; Li et al., 2021; Patel & Pavlick, 2022). Thus, an open question in the field is to what extent (if at all) a language model trained on text-only data can be a model of the world. In this paper, we test a specific hypothesis about the relationship be-

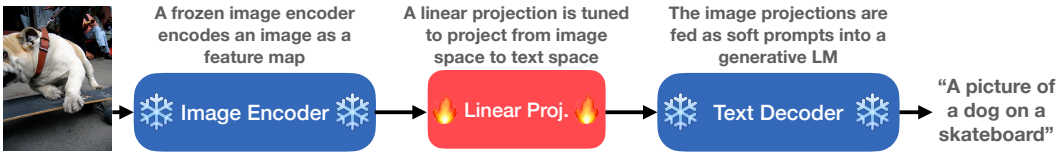


Figure 1: We train linear projections from image representations into the input space of a language model to produce captions describing images. We find that LMs can describe the contents of most image representations, but performance varies based on the type of image encoder used.

tween language model and image encoder representations: that these conceptual representations are functionally equivalent (up to a linear transformation). To do this, we train a single linear layer to project from the representation space of images into the language space of a generative LM without

tuning any other model parameters, which we call `LiMBeR`: Linearly Mapping Between Representation spaces. That is, we linearly transform an image representation into "soft prompts"–vector(s) in the embedding space that do not correspond to discrete language tokens (Lester et al., 2021). The weights of this linear projection are tuned for an image captioning task (illustrated in Figure 1). We can then evaluate its performance on 'understanding' different kinds of images at test time by exploring the text the LM generates. Because a linear projection is a distance-preserving transformation, we would expect that if the conceptual representation spaces of the two models are structured similarly, this transfer will be successful and the LM will have little trouble describing the contents of images.

We use three different image encoders with increasing levels of linguistic supervision in pretraining: BEIT (Bao et al., 2021), Normalizer Free Resnet50 (NFRN50) (Brock et al., 2021), and CLIP (Radford et al., 2021) to train different projections into the LM. By *linguistic supervision*, we refer to the extent to which the image encoder was exposed to language data during its pretraining, thus influencing the expected representational similarity between it and an LM. While CLIP was pretrained to align images with full natural language captions in a shared image-text representation space, BEIT had no exposure to language and was trained by predicting the contents of masked out sections of images. NFRN50 falls somewhere between these extremes: having been pretrained on an image classification task for identifying the subject of an image over the set of classes in ImageNet1k Russakovsky et al. (2015). Although there is no natural language in this task, the pretraining objective encourages the model to map visual features along lexical categorical concepts (the image classes) derived from the WordNet hierarchy (Miller, 1995).

We show that prompting an LM with any of the three image encoders effectively transfers semantic content in the image that the LM describes with natural language. However, performance also appears proportional to the strength of the linguistic supervision the image encoder had. While CLIP and NFRN50 perform competitively with tuning the models freely (e.g., Tsimpoukelli et al. (2021), Eichenberg et al. (2021)), BEIT appears to transfer mostly coarse-grained visual *properties* and struggles with encouraging the LM to generate exact lexical *categories*. We interpret this as evidence that LMs learn conceptual spaces that are structurally very similar to those learned by models trained directly on image data, but that the exact degree of similarity depends on the type of supervision the image encoder receives. In summary, we show: (1) that visual semantic information can be linearly mapped to language models in the form of soft prompts without tuning any model parameters. (2) That this mapping allows generative models to describe images and answer questions about images at a level that is comparable to what is achieved by multimodal models which tune image and language representations jointly. And (3) by training our prompting pipeline with different image encoder backbones, we demonstrate that linguistic supervision in pretraining plays a key role in concept formation in models and thus, the transferability of visual features from vision to text spaces.

2 Related Work

Our approach takes inspiration from recent work in adapting pretrained language models for accepting representations of images as inputs. Particularly, the Frozen and MAGMA models (Tsimpoukelli et al., 2021; Eichenberg et al., 2021), as well as Sung et al. (2022); Alayrac et al. (2022); Mokady et al. (2021); Luo et al. (2022); Lin et al. (2021); Zhai et al. (2022), which show that pretrained image and text networks can be tuned together on an image captioning task and applied to downstream vision-language (VL) tasks. These approaches either fine-tune the pretrained models, or train non-linear MLP projection/fusion networks between modalities, making interpretation of the representations difficult compared to our approach. Scialom et al. (2020) show a learned linear transformation is sufficient for BERT to encode image region representations which are then fed to a text decoder to generate questions about the image, but it is not well understood what abstractions LMs are able to transfer from a transformation of this type, or if a text decoder can operate on linear transformations of visual encodings directly.

Pretrained/from scratch LMs have typically been used in the past for image captioning applications in which an image representation is fed into the LM as input (Desai & Johnson, 2021; Shen et al., 2021; Devlin et al., 2015). Gui et al. (2022); Yuan et al. pretrain vision-language models from scratch using image-caption data. Zeng et al. (2022); Xie et al. (2022); Wang et al. (2022) augment

multimodal performance by feeding text prompts derived from VL models into an LM, in order to incorporate knowledge learned by LM training. These show LMs can interface with visual inputs described in text; our work questions whether the visual input can be fed directly into the LM, without bridging through language first. The success of aforementioned models on VL tasks indicates there is a representational similarity learned by text and image models independently, which we investigate in this paper.

Our work is also highly related to the idea of model "stitching" (Lenc & Vedaldi, 2015) in which two different models are attached at a certain layer. `LiMBeR` can be described as stitching the output of an image encoder to the input of an LM in the form of soft prompts (Lester et al., 2021). Stitching offers distinct advantages in evaluating the representational similarity between two models, as described in Bansal et al. (2021), over other conventional methods like RSA and CKA (Kriegeskorte et al., 2008; Kornblith et al., 2019). For example, `LiMBeR` allows us to show not just that CLIP encodings are *more similar* to text encodings than BEIT representations, but that BEIT representations are nevertheless equivalently able to transfer *visual property* information to the LM (§5.3).

There has been considerable interest in recent work in establishing if LMs model aspects of the non-linguistic world in order to model language, i.e. learn a 'world model'. Lu et al. (2021) show that the weights of a pretrained LM can generalize to tasks with different modalities and argue that LMs may become useful as "universal computation engines" which can learn non-language tasks. Li et al. (2021) show that models of entities and situations can be derived from contextual word representations. Patel & Pavlick (2022) show that very large LMs (GPT-3 scale (Brown et al., 2020)) can learn in-context non-linguistic conceptual domains depicted in text. Our work differs from these in that we have an LM interface directly with non-text data without changing model weights and show that, although fundamentally different, the representation space of a text-only LM shares non-trivial similarities to that of several vision-based models.

3 METHOD: LINEARLY MAPPING FROM IMAGE TO TEXT REPRESENTATIONS

While previous work has shown success in mapping images to language model soft prompts as a method for multimodal pretraining (e.g., Frozen, Magma; see Section 2), there have been no attempts to restrict the mechanism behind this mapping and understand how it works. Our basic approach is to train a single linear layer P to project from the hidden size h_I of a pretrained image encoder into the input space e_L of a generative language model for an image captioning task. The projected inputs do not correspond to discrete language tokens, and can be thought of as soft prompts (Lester et al., 2021) representing the image. For brevity, we refer to training P as **Li**nearly **M**apping **Be**tween **R**epresentation spaces (i.e., `LiMBeR`)[1]. Our approach can also be viewed as paring down the method used in Tsimpoukelli et al. (2021) and Eichenberg et al. (2021), such that the only trained parameters reside in the projection P. By freezing the image encoder E and LM on either side of the projection, we can examine the similarities between the representation spaces of the two as a function of the ability of the LM to describe an image input or perform some task relating to it. We expect that, if a language model represents visual conceptual information structurally similarly to that learned by a vision encoder, then a simple distance-preserving transformation to the language space is all that is required to transfer visual features into the language model. Before describing the training procedure, we will describe the basic components of the model, and the variations we chose.

Language Model LM & Image Encoders E We hypothesize that the conceptual representations learned by an LM are equivalent, up to a linear transformation, to the representations from an image encoder E. The language model used is the 6 billion parameter decoder-only GPT-J model (Wang & Komatsuzaki, 2021). P is trained to project from h_I to the input space $e_L = 4096$ of the LM. We train several models with different E's to determine the compatibility between encodings from E and the LM. We also test how the choice of E influences performance on this task, specifically, with regards to the degree of linguistic supervision E saw in pretraining, as described in Section 1.

From E we extract an image encoding of dimensionality h_I representing the image. We then project that encoding to a $e_L * k$ sequence of soft prompts, which we hereafter refer to as *image prompts*.

[1]We avoid specifying images or text in our backronym because one could linearly map between any two representation spaces of any modalities (e.g. video-to-text or text-to-text)

k is determined by the architecture of the E. For example, for consistency with the MAGMA model, we use the 12x12x3072d feature map before pooling from CLIP, which we flatten to $k = 12 * 12 = 144$. The encoders we experiment with are (1) **CLIP RN50x16** (Radford et al., 2021), $k = 144$, $h_I = 3072$. Because CLIP is trained to learn multimodal image-text embeddings, we expect that it will be easier for the model to learn a projection into language space than a vision only encoder. (2) **NFRN50** (Brock et al., 2021), $k = 2$, $h_I = 2048$. We train three variants using NF-Resnet50: one pretrained and frozen during caption training (NFRN50), one tuned during caption training (NFRN50 Tuned; note that the LM is still frozen), and one randomly initialized (NFRN50 Random). The NFRN50 models are pretrained on an image classification task on data that is labeled according to WordNet hypo/hypernym structure. This signal trains the model to separate object classes according to these words. For this reason, we consider it to have indirect access to linguistic supervision. (3) **BEIT-Large** (Bao et al., 2021), $k = 196$, $h_I = 1024$. BEIT is pretrained using a self-supervised masked visual token modeling task and does not have access to any labeled data which may give the model an inductive bias towards a linguistic structure. We use the 16-pixel patch version that was pretrained only on ImageNet22k. We additionally test two variants of this model: BEIT Random, is randomly initialized, and BEIT FT, which was pretrained on the same task and then finetuned for image classification on the same dataset. We use this model to show that it is indeed the linguistic supervision of the pretraining objective which induces better performance in the captioning task.

3.1 Training Procedure

Following the MAGMA and Frozen models (Eichenberg et al., 2021; Tsimpoukelli et al., 2021), we train a projection on an image captioning task so that we can learn to align the representation spaces of E and the LM. All models are trained with the same basic hyperparameters and settings as described in the MAGMA paper (see Appendix A for details) on the Conceptual Captions 3M dataset (CC3M, Sharma et al. (2018)) for 15,000 training steps.

Baselines As baselines, we use NFRN50 Random, NFRN50 Tuned, and train our own instance of MAGMA$_{base}$. Please note that NFRN50 Tuned is a stand-in for the Frozen model: it is architecturally the same, but differs in that we use the hyperparameters used to train the MAGMA model. NFRN50 Random allows us to test the efficacy of `LiMBeR` when the image encoder backbone has not learned any useful visual features. The MAGMA we train uses the CLIP RN50x16 image encoder (Radford et al., 2021), GPT-J as the LM, and adapters in sequence in the attention blocks with a downsample factor of 4.

3.2 Limitations

`LiMBeR` allows us to compare the representation spaces of two models of different modalities without changing either model's parameters and behaviors, but is not free from all confounding variables. Due to computational constraints, we did not control for the prompt length (k) for each image encoder. Tsimpoukelli et al. (2021) experiment with the value of k for the Frozen model and show that while there are some differences, k is mostly a factor in hyperparameter tuning and should not strongly affect the comparison between models.

We consider *LM runoff* another potential confound. In some cases, if the LM recognizes and generates a relevant word for one concept (e.g., "the beach"), it might continue generating relevant information due to a strong linguistic prior for that info showing up (e.g., "building a sandcastle"), giving the illusion it is recognizing every element in an image (even if it never saw "the sandcastle"). Regardless, the scope of this problem is very limited, and across multiple large datasets our results show that recovery of *any* image information is still possible, even if the full and precise extent of which is impossible to know. We also include a 'blind' model in visual question answering analysis to further control for this.

4 Performance on Vision-Language Tasks

We first verify that image representations that are linearly projected into the input space of the LM carry semantic information about the content of the image that the LM can make sense of. Since we

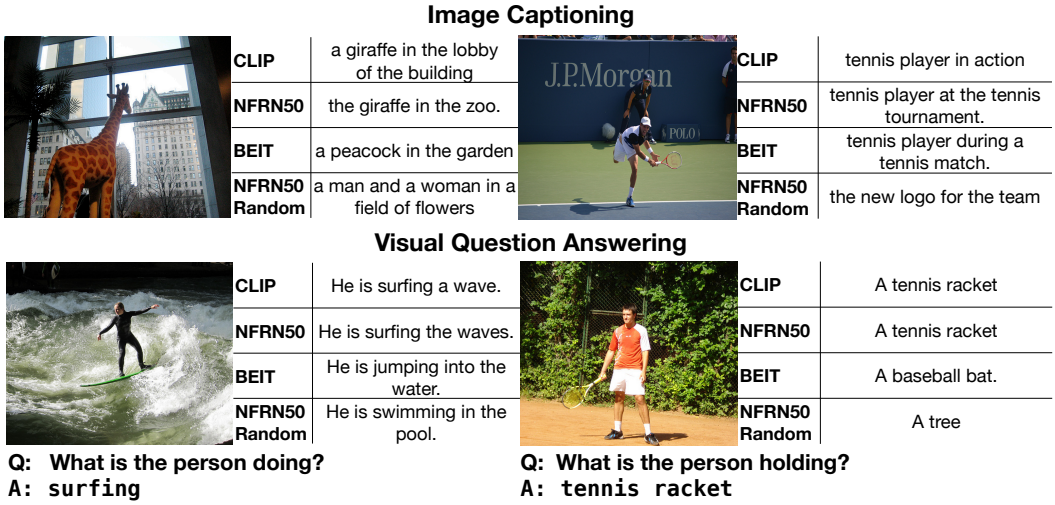


Figure 2: Curated examples of captioning and zero-shot VQA illustrating the ability of each model to transfer information to the LM without tuning either model. We use these examples to also illustrate common failure modes for BEIT prompts of sometimes generating incorrect but conceptually related captions/answers.

only tune a single projection between the image encoder and text decoder, the prompt tokens in the LM are equivalent to the image representation up to that linear transformation. If LMs are learning a conceptual space that reflects that of the non-linguistic, purely visually grounded space of the image encoder, the LM should be able to capture the image information and describe it in text.

Data We evaluate on image prompts generated by each image encoder on multiple image captioning datasets: MSCOCO (Lin et al., 2014) and NoCaps (Agrawal et al., 2019), as well as the VQA2 (Goyal et al., 2017) visual question-answering dataset. Following convention from *SimVLM* and MAGMA, we input the prefix "A picture of" after every image to prompt the model. Like in previous work, we find that this is a favorable prompt which tends to increase performance.

Metrics For image captioning, we report CIDEr-D (Vedantam et al., 2015), CLIPScore, and Ref-CLIPScore (Hessel et al., 2021). CIDEr-D rewards generating accurate words which are more likely to be visually informative, and CLIPScore can evaluate similarity between an image and caption without references, which helps us give credit for captions that vary greatly from the ground truth, but similar in semantic content (e.g. describing a pool as a lake). We report additional captioning metrics in Appendix B. For visual question answering, we follow the few-shot procedure used in Eichenberg et al. (2021) in which we prompt the models with the "[image] Q: [q] A:" format. We take the first word of the generation and, like in the MAGMA paper, truncate to the length of the longest ground truth answer. We also use the normalization procedure and accuracy metric described in the VQA repo[2]

Results Our main results can be seen in Table 1. As evidenced by comparing MAGMA and CLIP, and NFRN50 tuned and frozen, we find that there is relatively little benefit in training parameters in either encoder or decoder. Note that the MAGMA model we implemented is identical to the frozen CLIP model, with the exceptions that MAGMA tunes the image encoder and LM. On captioning and VQA tasks, performance of the jointly-tuned models (MAGMA, NFRN50 Tuned) is not consistently better, and is often worse, than just training the projection with frozen models. This trend persists across over 10 automatic captioning metrics, which are described in Appendix B. Our results indicate that there is in fact a relationship between the linguistic supervision of the pretraining task and performance on transferring to the LM. That is, CLIP outperforms NFRN50, which outperforms BEIT. To confirm this, we apply `LiMBeR` to a BEIT model finetuned on image classification

[2]https://github.com/GT-Vision-Lab/VQA

Image Captioning	NoCaps - CIDEr-D				NoCaps (All)		**CoCo**	CoCo	
	In	Out	Near	All	CLIP-S	Ref-S	CIDEr-D	CLIP-S	Ref-S
🔥NFRN50 Tuned	20.9	30.8	25.3	27.3	66.5	72.5	35.3	69.7	74.8
🔥MAGMA (released)	18.0	12.7	18.4	16.9	63.2	68.8	**52.1**	76.7	79.4
🔥MAGMA (ours)	**30.4**	**43.4**	**36.7**	**38.7**	74.3	78.7	47.5	75.3	**79.6**
❄️BEIT Random	5.5	3.6	4.1	4.4	46.8	55.1	5.2	48.8	56.2
❄️NFRN50 Random	5.4	4.0	4.9	5.0	47.5	55.7	4.8	49.5	57.1
❄️BEIT	20.3	16.3	18.9	18.9	62.0	69.1	22.3	63.6	70.0
❄️NFRN50	21.3	31.2	26.9	28.5	65.6	71.8	36.2	68.9	74.1
❄️BEIT FT.	**38.5**	**48.8**	**43.1**	**45.3**	73.0	78.1	51.0	74.2	78.9
❄️CLIP	34.3	48.4	41.6	43.9	**74.7**	**79.4**	**54.9**	**76.2**	**80.4**
VQA n-shots	0				1		**2**	4	
Blind	20.60				35.11		36.17	36.99	
🔥NFRN50 Tuned	27.15				37.47		38.48	39.18	
🔥MAGMA (ours)	24.62				39.27		40.58	41.51	
🔥MAGMA (reported)	32.7				40.2		**42.5**	43.8	
❄️NFRN50 Random	25.34				36.15		36.79	37.43	
❄️BEIT	24.92				34.35		34.70	31.72	
❄️NFRN50	27.63				37.51		38.58	39.17	
❄️CLIP	33.33				39.93		**40.82**	40.34	

Table 1: Captioning Performance and Visual Question Answering (VQA) accuracy for all variations on model architecture and image encoders used. On captioning, we see a consistent increasing trend in performance that correlates with an increase in linguistic supervision. However BEIT (the only vision-only model), performs far above a randomly initialized NFRN50 model and is on par with the other models on CLIPScore (CLIP-S) and RefCLIP Score (Ref-S) (Hessel et al., 2021). We see that BEIT performs at the level of our random baselines on VQA, suggesting there is a deficiency in relating visual information to more complex visual-linguistic reasoning tasks

(BEIT FT.), and find that this model improves performance drastically, even outperforming CLIP on NoCaps, and improving over BEIT on all metrics, including CLIP-Score by 9-10 points.

Notably, we find that even BEIT, which has no linguistic supervision in pretraining, still transfers well to the LM for captioning, far outperforming random NFRN50 across the board, which had no pretraining to learn visual features. We do find that BEIT captions using vaguer language, and/or semantically related-but-incorrect descriptions of objects (Figure 2; more examples in Appendix B). We see this reflected in the CLIPScores of the captions as well, which reward semantic similarity rather than precise lexical overlap with a reference caption. BEIT captions score 62 and 63.6 for NoCaps and COCO respectively; on average only 4.5 points behind NFRN50 but 14.3 ahead of random NFRN50. Perhaps we see the greatest failure of BEIT prompts in the inability to transfer details that the LM can use to answer questions about images (At 4-shot VQA, BEIT scores 31.72% while a 'blind' LM with no image input scores 36.99%). We hypothesize this is because BEIT representations do not encode visual information that corresponds well to lexical categories. In Section 5, we provide evidence in favor of this hypothesis, and investigate the granularity of detail prompts from each frozen encoder transfer to the LM.

5 Transfer of Visual Concepts

Examining the conditions that cause an image prompt to succeed or fail to transfer to the LM can help us understand the differences between the text and image representation spaces. Doing so can also help us understand why BEIT prompts perform so poorly for VQA despite performing decently for captioning. In Section 5.1, we analyze the ability to accurately generate specific lexical categories in captions when they appear in images (e.g., mentioning "squirrel" when given a picture of one). Following that, in Section 5.3 we focus on mistakes the models make: when the LM generates a bad caption, does it generate a caption that describes entities with similar visual *properties*? For example, a caption generated from an image of a "small", "woodland", and "furry" animal might not mention the actual animal depicted (e.g., a squirrel); but does it instead mention a different

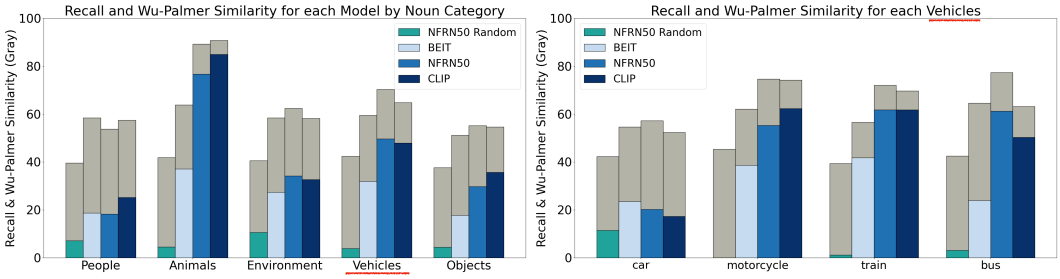


Figure 3: On average, recall of nouns in generated captions follows the standard pattern (CLIP>NFRN50>BEIT). However, judging by Wu-Palmer similarity, BEIT performs nearly the same or better than NFRN50 and CLIP on 4/5 of the noun categories. This indicates that although BEIT struggles to transfer the exact correct concept, it is transferring a related one based on visual similarity. On the right we show this effect for individual vehicle words. BEIT may have never learned to distinguish the 'bus' concept, but the LM still understands to generate a highly related concept, i.e., another vehicle. Average random Wu-Palmer similarity is around .4 consistently.

but similar furry animal (e.g., a rabbit)? We find that only linguistically informed image encoders (NFRN50, CLIP) tend to strongly encode concepts aligning to lexical *categories*, but all pretrained models including BEIT encode property information approximately equally well, and far better than a randomly initialized image encoder baseline.

5.1 Transfer of Lexical Categorical Concepts

Using the COCO validation set, we count the top 50 nouns, modifiers (e.g., adjectives), and relations (e.g., verbs, prepositional phrases) that appear in the ground truth captions and calculate how often they appear in the generated captions that were used to calculate the scores in Table 1.

Metrics We calculate the precision/recall/F1 for each word, broken down along conceptual categories. To test our hypothesis that BEIT transfers coarser information, we also report the Wu-Palmer similarity (Wup) (Wu & Palmer, 1994) between the ground truth word and the most similar word in the generated caption. The Wup score works by calculating the distance between the ground truth word and the generated word in the WordNet taxonomy, offering a way to measure 'how close' a word was to the correct answer.

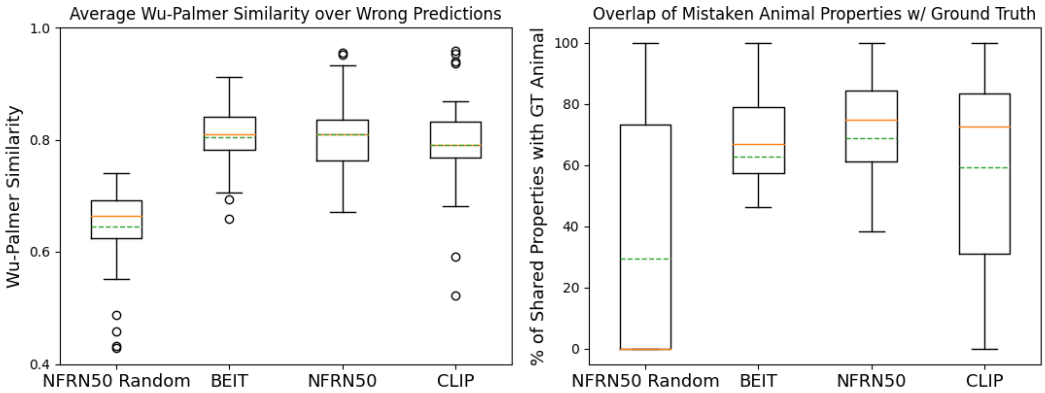
Results In Figure 3, we show that BEIT's recall for nouns in categories like 'people', 'environment', 'vehicles', and 'objects' is lower than NFRN50 or CLIP, but is comparable in terms of Wup similiarity in many categories. Unlike NFRN50 and CLIP's pretraining, BEIT's pretraining does not encourage it to learn conceptual differences between two similar looking objects that use different words. Compared to prompts from a randomly initialized NFRN50, for which very few consistent patterns emerge, the LM can still extract the broad conceptual meaning behind BEIT prompts, as evidenced by high Wup similarity (and CLIPScore results in Table 1). We interpret these results as supporting the hypothesis that BEIT prompts transfer conceptual information from the purely visual to purely text space, but only in terms of coarse-grained conceptual information corresponding to visual properties, not lexical categories. Our full analysis, including additional metrics and results for each individual word from the top 50 nouns, modifiers, and relations can be found in Appendix B.

5.2 Probing

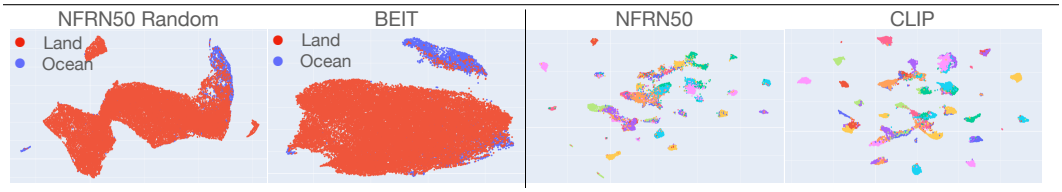
To rule out the possibility that BEIT representations *are* encoding lexical concept information, but are merely unable to linearly transfer it to the LM due to representational differences, we train linear probes on several datasets for image classification. We find that BEIT typically does not encode fine-grained information as well as NFRN50 or CLIP, though it far outperforms the randomly initialized NFRN50 baseline. We discuss training details and results in Appendix E.

5.3 TRANSFER OF COARSE-GRAINED PERCEPTUAL CONCEPTS

To better understand what BEIT encodes, if not word category information, we further investigate where errors arise, and how the structures of the embedding spaces for each frozen image encoder differ. For the sake of this analysis, we constrain the task to generating captions for pictures of animals. The reason for this narrower scope is that the captions are easier to analyze: the caption describing a picture of an animal should virtually always mention the name of that animal, and the word used to describe the animal is mostly unambiguous.



(a) **Left**: Wu-Palmer Similarity for captions in which the models made mistakes show that BEIT, NFRN50, and CLIP all similarly far off from the correct animal, meaning that even if they predict the wrong animal, it is on average very taxonomically similar. **Right**: When the model mistakes one animal for another in the dataset, how similar are the AWA properties for the true animal and the one it mistakes it most for? The average number of overlapping properties show that animals predicted from BEIT are at least as similar to the real animal as NFRN50 and CLIP. Median is shown as the solid orange line while the dashed green line shows the mean.



(b) **UMAP projections of AWA images:**While NFRN50 and CLIP cluster tightly along lexical categories (color coded by animal), BEIT clusters the most distinctly along animals that live in water/the ocean; the randomly initialized NFRN50 mostly randomly overlap in one cluster.

Figure 4

Data For this task we use the Animals With Attributes 2 (AWA) dataset (Xian et al., 2019) which contains 37k total images covering 50 animal classes. Each animal class also comes with annotations for 85 properties describing the animals (e.g., 'claws', 'stripes', 'jungle'), which allow us to analyze if prompts from certain encoders consistently make mistakes along any of these dimensions.

Metrics When an image prompt produces a caption, we can measure the similarity of any animals mentioned to the WordNet synset of the ground truth animal label. We can also measure similarity using the annotated properties provided by the AWA dataset. For a given animal (e.g., "squirrel"), we can look at the other animal in the dataset that it is most often mistaken for (e.g., "rabbit") and compare the proportion of properties that they share.

Results We generate captions for each image using prompts from each frozen image encoder. We consider a caption to be 'correct' if it contains the name of the animal the image depicts. CLIP and NFRN50 are correct most often: 59% and 43% of the time respectively. BEIT and the randomly initialized NFRN50 only achieve 13% and 0.4% accuracy, respectively. This aligns with previous observations that BEIT struggles with encoding fine-grained lexical level concepts. By looking at

failure cases for each model, we can establish whether each model is predicting the presence of a similar animal or not. In Figure 4a, we show that when captions generated from each model mistake one animal for another, the mistaken animals are highly similar to the ground truth animal when measuring both Wu-Palmer similarity (Averages: BEIT: 0.8, NFRN50: 0.81, CLIP: 0.8) and overlap of AWA properties (Averages: BEIT: 0.62, NFRN50: 0.68, CLIP: 0.59). Although BEIT prompts do not transfer the exact animal concept to the LM, the coarse grained perceptual information is transferred and 'understood' by the LM. In Figure 4b we create UMAP projections of the encodings for each image in AWA and indeed find that NFRN50 and CLIP cluster according to tight lexical categories (the animal types), BEIT clusters most tightly by perceptual features, such as habitat, having flippers, etc.

6 Discussion & Future Work

Because `LiMBeR` only tunes a linear transformation between image and text spaces, we interpret the success of generating text relevant to an image as indicative of a linear relationship between the representation spaces of vision and text models. For example, the relative positions which a vision model encodes the concepts 'animal' and 'inside building', as well as their compositions (see Figure 2) must be similar to the structure a language model encodes those concepts under. Further work is necessary to understand the nature of this relationship, and how well it generalizes. We find an LM which uses a linguistically supervised image encoder (NFRN50, CLIP) as the vision backbone in `LiMBeR` does in fact make use of fine-grained conceptual information in the image representations. Using a vision-only encoder (BEIT) leads to generations from the LM that are often incorrect but close under measures of perceptual relatedness. BEIT has no inductive bias in pretraining to distinguish concepts over some threshold of perceptual similarity that we would normally distinguish with language. However, we see that performance improves if BEIT was finetuned on image classification before `LiMBeR` is applied. This suggests interesting future work on the role of language in category formation. Although it appears that the LM encodes aspects of non-linguistic visual similarity, we believe the linguistically-informed and vision-only representations are fundamentally different and require modeling a more sophisticated relationship between linguistic and visual concepts. For this reason, `LiMBeR` is also a strong baseline for future VL models, as it provides a point of comparison for a minimal mapping between vision and language. We are also excited by future work using `LiMBeR` as a tool to probe for what information is encoded in a vision or language model. There are many questions related to this that we could not address in this paper. For example, how does the scale of an LM or vision encoder affect transferability? What about reporting bias (Paik et al., 2021) in an LM's training corpus? Answering these questions can help us understand the limits of text-only pretraining, as well as how to better 'ground' LMs to non-linguistic data.

7 Conclusion

In this paper, we test the whether image and text representations are equivalent under a linear transformation such that an LM can describe the contents of an image representation without tuning either the vision or language model. We show through `LiMBeR` (Linearly Mapping Between Representation spaces) that training such a transformation to connect image features to an LM's input space is competitive on image captioning and visual question answering benchmarks with similar models like MAGMA that tune both image and text networks. However, we also find that such transfer is highly dependant on the amount of linguistic supervision the image encoder backbone had during its pretraining phase. BEIT, which is a vision-only image encoder underperforms compared to CLIP, which was pretrained with natural language captions. We explore what conceptual information transfers successfully, and find through probing, clustering, and analysis of generated text that the representational similarity between LMs and vision-only image representations is mostly restricted to coarse-grained concepts of perceptual features, while linguistically supervised vision models can transfer lexical concepts. Our findings indicate that LMs and vision models learn conceptually similar representation spaces, but it is unclear why this would be the case. This finding is consistent with the idea that LMs learn a model of the world in order to model language, but may also be explained by some property of the training process of deep neural networks that is not well understood. We are excited by future work applying `LiMBeR` to other domains and modalities as a behavioral tool for understanding the representations of LMs and other networks.

8 REPRODUCIBILITY STATEMENT

We are committed to making all of our results reproducible. For training all of our models, we open source all of our code and the random seeds used. We also release the weights of the linear projections that were trained for `LiMBeR`. Because we froze the image and text models attached to the projection, the weights can be used to quickly reproduce our results with the corresponding off-the-shelf pretrained models with no other tuning necessary. We use the default data splits for all datasets we used and release the random seeds used for all tasks that require generation from the LM in our codebase as well. For the AWA tasks that require matching Wordnet synsets, we document the exact animal synsets that we used as the 'ground truth' for the animal labels in Appendix D, Table 6.

REFERENCES

Harsh Agrawal, Karan Desai, Yufei Wang, Xinlei Chen, Rishabh Jain, Mark Johnson, Dhruv Batra, Devi Parikh, Stefan Lee, and Peter Anderson. Nocaps: Novel object captioning at scale. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 8948–8957, 2019.

Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katie Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *arXiv preprint arXiv:2204.14198*, 2022.

Yamini Bansal, Preetum Nakkiran, and Boaz Barak. Revisiting model stitching to compare neural representations. *Advances in Neural Information Processing Systems*, 34:225–236, 2021.

Hangbo Bao, Li Dong, Songhao Piao, and Furu Wei. Beit: Bert pre-training of image transformers. In *International Conference on Learning Representations*, 2021.

Emily M. Bender and Alexander Koller. Climbing towards NLU: On meaning, form, and understanding in the age of data. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 5185–5198, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.463. URL `https://aclanthology.org/2020.acl-main.463`.

Andy Brock, Soham De, Samuel L Smith, and Karen Simonyan. High-performance large-scale image recognition without normalization. In *International Conference on Machine Learning*, pp. 1059–1071. PMLR, 2021.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

Karan Desai and Justin Johnson. Virtex: Learning visual representations from textual annotations. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 11162–11173, 2021.

Jacob Devlin, Hao Cheng, Hao Fang, Saurabh Gupta, Li Deng, Xiaodong He, Geoffrey Zweig, and Margaret Mitchell. Language models for image captioning: The quirks and what works. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pp. 100–105, 2015.

Constantin Eichenberg, Sid Black, Samuel Weinbach, Letitia Parcalabescu, and Anette Frank. Magma - multimodal augmentation of generative models through adapter-based finetuning. *ArXiv*, abs/2112.05253, 2021.

Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the V in VQA matter: Elevating the role of image understanding in Visual Question Answering. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.

Liangke Gui, Qiuyuan Huang, Alex Hauptmann, Yonatan Bisk, and Jianfeng Gao. Training vision-language transformers from captions alone. *arXiv preprint arXiv:2205.09256*, 2022.

Jack Hessel, Ari Holtzman, Maxwell Forbes, Ronan Le Bras, and Yejin Choi. CLIPScore: a reference-free evaluation metric for image captioning. In *EMNLP*, 2021.

Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton. Similarity of neural network representations revisited. In Kamalika Chaudhuri and Ruslan Salakhutdinov (eds.), *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pp. 3519–3529. PMLR, 09–15 Jun 2019. URL https://proceedings.mlr.press/v97/kornblith19a.html.

Nikolaus Kriegeskorte, Marieke Mur, and Peter A Bandettini. Representational similarity analysis-connecting the branches of systems neuroscience. *Frontiers in systems neuroscience*, pp. 4, 2008.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Karel Lenc and Andrea Vedaldi. Understanding image representations by measuring their equivariance and equivalence. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 991–999, 2015.

Brian Lester, Rami Al-Rfou, and Noah Constant. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 3045–3059, Online and Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.emnlp-main.243. URL https://aclanthology.org/2021.emnlp-main.243.

Belinda Z Li, Maxwell Nye, and Jacob Andreas. Implicit representations of meaning in neural language models. 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)*, pp. 1813–1827, 2021.

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 *European conference on computer vision*, pp. 740–755. Springer, 2014.

Xudong Lin, Gedas Bertasius, Jue Wang, Shih-Fu Chang, Devi Parikh, and Lorenzo Torresani. Vx2text: End-to-end learning of video-based text generation from multimodal inputs. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7005–7015, 2021.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *International Conference on Learning Representations*, 2018.

Kevin Lu, Aditya Grover, Pieter Abbeel, and Igor Mordatch. Pretrained transformers as universal computation engines. *CoRR*, abs/2103.05247, 2021. URL https://arxiv.org/abs/2103.05247.

Ziyang Luo, Yadong Xi, Rongsheng Zhang, and Jing Ma. A frustratingly simple approach for end-to-end image captioning, 2022. URL https://arxiv.org/abs/2201.12723.

George A Miller. Wordnet: a lexical database for english. *Communications of the ACM*, 38(11): 39–41, 1995.

Ron Mokady, Amir Hertz, and Amit H Bermano. Clipcap: Clip prefix for image captioning. *arXiv preprint arXiv:2111.09734*, 2021.

Cory Paik, Stéphane Aroca-Ouellette, Alessandro Roncone, and Katharina Kann. The world of an octopus: How reporting bias influences a language model's perception of color. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 823–835, 2021.

Roma Patel and Ellie Pavlick. Mapping language models to grounded conceptual spaces. In *International Conference on Learning Representations*, 2022. URL https://openreview.net/forum?id=gJcEM8sxHK.

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*, pp. 8748–8763. PMLR, 2021.

S Rajbhandari, J Rasley, O Ruwase, and Y He. Zero: memory optimization towards training a trillion parameter models. arxiv e-prints arxiv: 11910.02054 (2019), 2019.

Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. doi: 10.1007/s11263-015-0816-y.

Thomas Scialom, Patrick Bordes, Paul-Alexis Dray, Jacopo Staiano, and Patrick Gallinari. What bert sees: Cross-modal transfer for visual question generation. In *Proceedings of the 13th International Conference on Natural Language Generation*, pp. 327–337, 2020.

Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 2556–2565, Melbourne, Australia, July 2018. Association for Computational Linguistics. doi: 10.18653/v1/P18-1238. URL https://aclanthology.org/P18-1238.

Sheng Shen, Liunian Harold Li, Hao Tan, Mohit Bansal, Anna Rohrbach, Kai-Wei Chang, Zhewei Yao, and Kurt Keutzer. How much can clip benefit vision-and-language tasks? In *International Conference on Learning Representations*, 2021.

Yi-Lin Sung, Jaemin Cho, and Mohit Bansal. Vl-adapter: Parameter-efficient transfer learning for vision-and-language tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 5227–5237, 2022.

Maria Tsimpoukelli, Jacob Menick, Serkan Cabi, S. M. Ali Eslami, Oriol Vinyals, and Felix Hill. Multimodal few-shot learning with frozen language models. In A. Beygelzimer, Y. Dauphin, P. Liang, and J. Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems*, 2021. URL https://openreview.net/forum?id=WtmMyno9Tq2.

Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4566–4575, 2015.

Ben Wang and Aran Komatsuzaki. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. https://github.com/kingoflolz/mesh-transformer-jax, May 2021.

Zhenhailong Wang, Manling Li, Ruochen Xu, Luowei Zhou, Jie Lei, Xudong Lin, Shuohang Wang, Ziyi Yang, Chenguang Zhu, Derek Hoiem, et al. Language models with image descriptors are strong few-shot video-language learners. *arXiv preprint arXiv:2205.10747*, 2022.

Zhibiao Wu and Martha Palmer. Verbs semantics and lexical selection. In *Proceedings of the 32nd annual meeting on Association for Computational Linguistics*, pp. 133–138, 1994.

Yongqin Xian, Christoph H. Lampert, Bernt Schiele, and Zeynep Akata. Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 41(9):2251–2265, 2019. doi: 10.1109/TPAMI.2018.2857768.

Yujia Xie, Luowei Zhou, Xiyang Dai, Lu Yuan, Nguyen Bach, Ce Liu, and Michael Zeng. Visual clues: Bridging vision and language foundations for image paragraph captioning. *arXiv preprint arXiv:2206.01843*, 2022.

Lu Yuan, Dongdong Chen, Yi-Ling Chen, Noel Codella, Xiyang Dai, Jianfeng Gao, Houdong Hu, Xuedong Huang, Boxin Li, Chunyuan Li, et al. Florence: A new foundation model for computer vision.

Andy Zeng, Adrian Wong, Stefan Welker, Krzysztof Choromanski, Federico Tombari, Aveek Purohit, Michael S Ryoo, Vikas Sindhwani, Johnny Lee, Vincent Vanhoucke, et al. Socratic models: Composing zero-shot multimodal reasoning with language. 2022.

Xiaohua Zhai, Xiao Wang, Basil Mustafa, Andreas Steiner, Daniel Keysers, Alexander Kolesnikov, and Lucas Beyer. Lit: Zero-shot transfer with locked-image text tuning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18123–18133, 2022.

A LiMBeR Training Details

A.1 Training Details

We mimic the MAGMA pretraining process for each of our models as outlined in Eichenberg et al. (2021). As described above, the training task is caption generation. For each training example, an image and caption pair (x, y) is fed into the model. The image encoder E encodes the image into a $i_1, ..., i_k$ of dimensionality h_I and length k. For the CLIP Encoder, for example, we extract (12,12,3072) feature patches, which we resize to (144,3072) and feed into the projection layer P. The output of P is fed as tokens representing the image into the language model LM. The caption y is tokenized as $t_1, ..., t_m$ where m is the variable length of the caption. LM is given the encoded image tokens and starting with t_1 learns to minimize the next token log probability of t_i for timestep i conditioned on $i_1, ..., i_k$ and $t_1, ...t_{i-1}$.

During training, we minimize the loss with the AdamW (Loshchilov & Hutter, 2018) optimizer per mini-batch, with the help of ZeRO stage 2 (Rajbhandari et al., 2019). We use a dropout probability of 0.1, a weight decay of 0, betas = (0.9, 0.95), and gradient clipping = 1.0. All models are trained for 15,000 training steps across 16 A100 GPUs for approximately 1.75 days. Our effective batch size was 2048. We use a learning rate of $8 * 10^-4$ for the projection layer P. For models where we tune E as well, we tune its parameters with a learning rate of $2 * 10^-6$.

Model	Prompt Length (k)	Hidden size (h_I)	Pretraining
CLIP RN50x16	144	3072	Contrastive Image-caption matching
NFRN50	2	2048	Image Classification
BEIT	196	1024	Self-supervised

Table 2: Summary of image encoders used for pretraining. Prompt length refers to the number of the tokens fed into the language model representing the image.

B Captioning Performance

To get a better idea of the kinds of captions LiMBeR produces, see Figure 6, which includes 15 images that were randomly selected from the COCO validation set (2017) and the generated captions for all models we test. We include a greater range captioning metric results in Table 3 for the COCO dataset. Overall, we find the same trends that we report in the main paper, which are that 1.) the greater amount of linguistic supervision that an image encoder has, the better its captioning performance and 2.) unfreezing the image encoder does not seem to lead to consistently significant improvements. We also include the breakdown of the SPICE metric across the associated subcategories such as relations, attributes, and objects. Of the LiMBeR models, we find that CLIP based models do the best across the board (12.1 for CLIP vs. 9.28 for NFRN50). Besides the random baseline, BEIT performs the worst overall except in the color category (0.45 vs. 0.42 for NFRN50). We also include heatmaps with recall/precision/F1/Wu-Palmer similarity metrics comparing the captions generated by each model and the top 50 nouns (objects), modifiers, and relations from the ground truth captions from the COCO validation set (Figures 7, 8, 9).

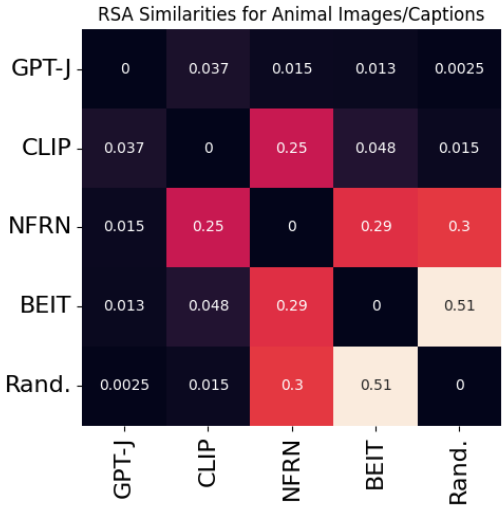


Figure 5: RSA similarity scores between representations of images of animals and the ground truth captions describing them. GPT-J is has very low correlation with image encoder representations

Model	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGE	CIDER	SPICE	CLIPScore	RefCLIPScore
NFRN50 Tuned	0.375	0.229	0.134	0.080	0.127	0.316	0.353	0.091	0.697	0.748
MAGMA (Ours)	0.309	0.216	0.145	0.097	0.146	0.341	0.475	0.110	0.753	**0.796**
MAGMA (Released)	**0.432**	**0.300**	**0.203**	**0.137**	**0.159**	**0.376**	**0.521**	**0.117**	**0.767**	0.794
BEIT Random	0.288	0.132	0.052	0.022	0.068	0.232	0.052	0.022	0.488	0.562
NFNRN Random	0.261	0.115	0.044	0.018	0.062	0.208	0.048	0.021	0.495	0.571
BEIT	0.319	0.187	0.105	0.060	0.106	0.299	0.223	0.064	0.636	0.697
NFRN50	0.409	0.254	0.149	0.088	0.132	0.334	0.362	0.093	0.689	0.741
BEIT FT.	**0.420**	**0.283**	0.182	0.116	0.155	0.367	0.510	0.116	0.742	0.789
CLIP	0.400	0.278	**0.187**	**0.126**	**0.161**	**0.376**	**0.549**	**0.121**	**0.762**	**0.804**

Table 3: All of the caption metrics for the models. For all scores, higher is better

We also use COCO images and captions to measure the similarity between vision and text encodings of the same concepts. That is, if there is a structural similarity between image and text encodings, do typical representational similarity metrics reflect this? For this experiment we want to encode a large number of images and captions that depict a set of concepts, and compare the relative representational similarity between the concepts for the image and text representations. The intuition is that if image and text models are representing concepts in a similar structure, then two concepts that are represented similarly in an image model should be similar within text representations as well. We sample a small subset of images depicting 10 different animals from the COCO dataset, and encode each image with each of our four image encoders (without a `LiMBeR` projection), and the ground truth captions with GPT-J. We use the last hidden state of the last token as the representation of the caption. We choose animals because it is easy for humans to intuitively compare how similar two animals are. In total, we collect 939 images and captions for each animal class and compare the representational similarity of the subset of encodings using the representational similarity analysis (RSA) technique from Kriegeskorte et al. (2008). The similarity matrix between each representation for each set is calculated, and then the upper triangular matrix for each similarity matrix is used to calculate the Pearson correlation. The results of this can be seen in Figure 5. We zero out the diagonal for visibility of the other values, since the diagonal is always equal to 1. RSA does not seem to capture similarity in a way that reflects the transfer performance to the LM. For example, similarity between the BEIT and randomly initialized NFRN50 model are unusually high given differences in performance in our experiments. Further analysis on the geometry of these representation spaces is required to make stronger statements about how (dis)similar they are. We leave this for future work.

Model	SPICE (All)	Relations	Cardinality	Attributes	Size	Color	Object
NFRN50 tuned	9.1	1.12	0.02	1.64	0.33	0.40	19.9
MAGMA (ours)	11.0	1.37	0.00	3.94	0.36	1.31	22.6
MAGMA (released)	**11.7**	**1.99**	**1.30**	**3.95**	**0.50**	**1.32**	**23.8**
NFRN50 random	2.14	0.06	0.00	0.22	0.00	0.12	4.93
BEIT	6.4	0.61	0.0	1.26	0.21	0.45	14.1
NFRN50	9.28	1.28	0.02	1.70	0.27	0.42	20.2
CLIP	**12.1**	**1.83**	**0.08**	**3.76**	**0.39**	**0.75**	**25.08**

Table 4: F-scores (x100) for each fine-grained category of the SPICE metric, evaluated on the 2017 COCO validation dataset. The top and bottom divide separates models where the image encoder is either tuned of frozen, respectively. Models that use CLIP as their image encoder show a large jump in improvement over other models (even compared to tuned ResNet), especially in the Attributes (e.g. adjectives) and Object (e.g. nouns) categories.

C VISUAL QUESTION ANSWERING PERFORMANCE

The VQA accuracies are broken down by question type and model for the 4-shot case in Table 5. We don't notice any significant patterns in the per question type breakdown. It does seem perhaps NFRN50 is better at questions that require counting objects in an image. Future work is needed to determine if this is just noise or a significant trend.

Q Type	# Q's	Blind	RN Tune	MAGMA	RN Rand	BEIT	RN	CLIP
how many	20462	33.6	34.7	32	33	18.8	**34.8**	23.3
is the	17265	64.1	64.7	**65.3**	64.8	58.9	64.6	61.1
what	15897	17.4	19.9	22.4	16.7	8.9	20.3	**26.9**
what color is the	14061	30.5	33.7	36.7	33.1	28.9	34	**40.3**
what is the	11353	15.5	18.7	23.2	16.1	11.9	18.7	**29.5**
none of the above	8550	38.5	**40.1**	36	38.7	26.8	39.9	37.4
is this	7841	62.4	64.1	**65.8**	64.2	57.7	63.7	57.1
is this a	7492	63.3	63.8	**67.6**	63.4	59.5	63.5	58.5
what is	6328	9.3	12.9	21.2	10	6.6	13.2	**24.1**
what kind of	5840	15	22.5	29.5	15.8	11.1	22.5	**36.9**
are the	5264	63	64.2	**64.3**	63.9	59.4	63.8	58.9
is there a	4679	60.6	61.6	**63.8**	61.7	60.2	61.5	58.6
what type of	4040	16.4	23	30.7	17.2	12.8	23	**38.2**
where is the	3716	2	1.1	2.4	0.9	1.0	1.3	**3.1**
is it	3566	**63.6**	60.3	62.3	60	57.5	60.4	58.3
what are the	3282	13.4	17.3	23.1	14.7	9.8	18	**28.6**
does the	3183	66.6	67.6	66	67.4	63.0	**67.6**	64.6
is	3169	63.8	63.4	**65.0**	63.1	56.6	62.6	58.5
is there	3120	62.4	62.3	**64.6**	61.7	59.2	63.1	54.5
what color are the	3118	32	36.3	35.8	34.6	29.4	36	**39.7**
are these	2839	62.3	65.1	**66.8**	64.1	60.3	64.9	56.6
are there	2771	60.1	60.2	**62.8**	60.1	57.5	60.1	55.4
what is the man	2663	10	16.7	30.1	11.4	10.3	15.6	**34.7**
is the man	2511	61.9	61.7	**64.6**	62.2	58.9	61.5	59.2
which	2448	23.8	26	**27.9**	22.7	7.1	26.1	26
how	2422	**12.2**	10.2	7.5	9.7	4.0	10.8	9.8
are	2359	60.6	62.9	**63.5**	62.4	57.1	62.5	56.8
does this	2227	66.3	67.2	66.2	67.6	62.7	**67.7**	61.3
what is on the	2174	11.5	14.9	17.8	13.2	7.3	15.2	**23.0**
how many people are	2005	27.2	**28.0**	26.7	27	10.6	27.7	18.7
what does the	1970	7	7.6	12	6.8	2.7	7.4	**14.2**
what time	1746	15.4	18.9	13.4	16.6	16.0	19.1	**22.4**
what is in the	1733	9.8	13.7	23.8	10.8	6.8	13.8	**30.1**
what is this	1696	9.6	21.7	35.2	9.6	11.6	21.8	**41.3**
what are	1556	9.2	16.8	28.6	10.4	8.7	17.4	**36.0**
do	1503	68.8	70.1	65.9	**70.2**	61.4	69.7	64.9
why	1438	**3.2**	2	2.8	1.5	0.6	1.9	2.8
what color	1428	26.9	28.5	32.1	28.4	23.8	27.8	**35.0**
are they	1335	60.8	61.2	**65.8**	62.5	59.8	61.4	59.4

Q Type	# Q's	Blind	RN Tune	MAGMA	RN Rand	BEIT	RN	CLIP
what color is	1335	25.4	26.5	35.8	26.1	29.1	26.6	**36.4**
are there any	1330	59.1	58.3	**61.6**	58.7	54.4	58	52.7
where are the	1313	2.8	1.7	2.4	1.2	0.9	1.7	**3.3**
is he	1087	61.8	62.2	**64.2**	61.6	59.8	63.1	61.2
what sport is	1086	22	37.1	63.4	24.9	36.6	36.7	**67.6**
who is	1070	13.6	14.4	14.3	13.7	5.3	**14.8**	9.6
is the woman	992	63.2	62.2	**66.6**	61	59.3	61.5	60.9
has	946	64	65.3	65.5	65.5	62.7	**66.3**	63.5
what brand	935	**20.0**	16.5	4.4	17.8	6.3	17.8	12.4
how many people are in	905	23.9	28.3	**29.0**	25.8	15.8	26.9	17.4
what is the person	900	8.2	16.3	32.2	9.2	12.4	17.7	**38.0**
is this an	890	65.1	67.6	**68.2**	67.7	61.4	67.4	59.2
can you	872	59.5	58.9	**62.3**	59.9	58.8	59.6	59.5
what is the woman	853	8.5	15	28.5	10.2	6.7	14.6	**32.6**
what animal is	833	10.2	28.5	56.1	10.8	16.8	28.6	**63.6**
what is the color of the	826	35.4	40.4	39.3	36.8	34.3	39.3	**44.7**
was	818	62.6	61.8	**63.8**	62.1	59.9	60.9	59.5
is the person	794	61.9	61.7	61.3	**62.4**	57.5	62	57.1
what is the name	780	3.4	4.4	8	3.8	1.5	4.5	**9.0**
what room is	762	15	43.4	62.9	19.9	24.0	39.3	**65.9**
is this person	734	62	61.3	**63.3**	62.5	60.2	61.9	57.5
do you	724	61.7	**62.1**	60.1	60.8	55.6	62	58.3
is that a	714	60.9	**63.1**	62.7	61.5	57.5	62.4	59.6
what number is	673	8.8	7.6	**12.6**	7.5	0.5	8.9	10.2
could	618	72.3	71.8	67.5	**73.6**	67.4	71.5	58.9
why is the	514	1.6	1.9	2.5	1.3	0.5	1.6	**2.6**

Table 5: Average 4-shot accuracies of models on every question type from the VQA2.0 dataset. Note that NFRN50, NFRN Random, and NFRN Tuned are renamed to save space. MAGMA refers to our version of the model.

D ANIMALS WITH ATTRIBUTES

AWA2 The Animals with Attributes 2 Dataset contains 37k images of 50 animal classes annotated with 85 properties (e.g. 'stripes', 'tough'). For each image encoder we generate captions using image projections into the LM for each image in the dataset and identify any animals mentioned using overlapping WordNet synsets with the ground truth labels. We report the animal synsets that we used as the 'ground truth' synsets. For example, to calculate accuracy, etc. we split generated captions on white space and check the possible synsets of each word and check if there is any overlap with our list. Each label synset is listed in Table 6.

We report two AWA experiments here: (1) the first appears in the main paper, and investigates how similar the most similar words mentioned in the generated captions are to the ground truth animal in terms of Wu-Palmer similarity *for the generated captions in which the ground truth animal does not appear* – i.e., mistakes. The per animal results can be found in Table 7. (2) We also report the average precision (AP) of the average animal properties vector for the animals predicted to the ground truth for each model. This experiment is similar to the properties-overlap experiment reported in the paper but is a measure of how often the predicted animal properties are similar vs. very different from the ground truth. If the LM mentions an animal in the dataset, we add that animal's property vector to a running list. If the LM does not mention an animal in the dataset, we ignore that caption. For each image-caption pair, we take the average of the properties vectors that correspond to the animals mentioned in the captions, and calculate the AP against the ground truth binary properties vector. Results per animal class are in Table 8. We exclude any entries for which a model makes fewer than 50 mistakes for an animal class. For example, for all of the images labeled as depicting a tiger in the AWA dataset, CLIP based captions fail to mention a tiger a *single* time.

Animal Name	**WordNet Synset**
antelope	antelope.n.01
grizzly+bear	grizzly.n.01

killer+whale	killer_whale.n.01
beaver	beaver.n.07
dalmatian	dalmatian.n.02
persian+cat	persian_cat.n.01
horse	horse.n.01
german+shepherd	german_shepherd.n.01
blue+whale	blue_whale.n.01
siamese+cat	siamese_cat.n.01
skunk	skunk.n.04
mole	mole.n.06
tiger	tiger.n.02
hippopotamus	hippopotamus.n.01
leopard	leopard.n.02
moose	elk.n.01
spider+monkey	spider_monkey.n.01
humpback+whale	humpback.n.03
elephant	elephant.n.01
gorilla	gorilla.n.01
ox	ox.n.02
fox	fox.n.01
sheep	sheep.n.01
seal	seal.n.09
chimpanzee	chimpanzee.n.01
hamster	hamster.n.01
squirrel	squirrel.n.01
rhinoceros	rhinoceros.n.01
rabbit	rabbit.n.01
bat	bat.n.01
giraffe	giraffe.n.01
wolf	wolf.n.01
chihuahua	chihuahua.n.03
rat	rat.n.01
weasel	weasel.n.02
otter	otter.n.02
buffalo	american_bison.n.01
zebra	zebra.n.01
giant+panda	giant_panda.n.01
deer	deer.n.01
bobcat	bobcat.n.01
pig	hog.n.03
lion	lion.n.01
mouse	mouse.n.01
polar+bear	ice_bear.n.01
collie	collie.n.01
walrus	walrus.n.01
raccoon	raccoon.n.02
cow	cow.n.01
dolphin	dolphin.n.02

Table 6: To aid with reproducibility, we report all animal synsets that were used for experiments that require disambiguating words in captions to animal classes. This allows us to correctly count a mention of "tigress" in a caption as a mention of the "tiger" animal type without relying on unreliable string matching techniques.

	Random	**NFRN50 Random**	**BEIT**	**NFRN50**	**CLIP**
polar+bear	0.79	0.60	0.86	0.95	0.96
buffalo	0.73	0.64	0.84	0.93	0.95

	Random	NFRN50 Random	BEIT	NFRN50	CLIP
bobcat	0.72	0.71	0.83	0.90	0.94
grizzly+bear	0.76	0.70	0.88	0.95	0.94
blue+whale	0.73	0.43	0.69	0.76	0.87
dalmatian	0.77	0.72	0.79	0.83	0.85
chihuahua	0.74	0.70	0.84	0.85	0.85
leopard	0.77	0.70	0.82	0.81	0.85
collie	0.72	0.70	0.85	0.85	0.85
german+shepherd	0.72	0.67	0.84	0.85	0.85
siamese+cat	0.75	0.69	0.85	0.85	0.84
persian+cat	0.74	0.67	0.85	0.85	0.84
ox	0.73	0.69	0.82	0.84	0.84
seal	0.77	0.55	0.77	0.74	0.82
spider+monkey	0.74	0.65	0.81	0.80	0.81
antelope	0.75	0.72	0.78	0.80	0.81
skunk	0.79	0.65	0.84	0.79	0.81
mole	0.79	0.64	0.79	0.84	0.80
lion	0.77	0.74	0.82	0.80	0.79
rat	0.80	0.67	0.79	0.85	0.78
hamster	0.80	0.66	0.79	0.80	0.78
walrus	0.78	0.56	0.72	0.76	0.78
wolf	0.80	0.69	0.85	0.83	0.77
killer+whale	0.71	0.46	0.71	0.73	0.77
humpback+whale	0.73	0.43	0.66	0.67	0.77
chimpanzee	0.72	0.64	0.85	0.74	0.76
moose	0.75	0.60	0.81	0.79	0.74
fox	0.80	0.72	0.84	0.84	0.74
weasel	0.79	0.68	0.81	0.83	0.73
hippopotamus	0.79	0.58	0.76	0.74	0.73
deer	0.77	0.66	0.81	0.80	0.73
otter	0.79	0.60	0.80	0.82	0.72
pig	0.76	0.67	0.83	0.75	0.71
cow	0.71	0.65	0.78	0.78	0.70
sheep	0.76	0.65	0.84	0.82	0.68
horse	0.75	0.62	0.77	0.75	0.59
giant+panda	0.79	0.70	0.87	0.90	0.52
beaver	0.80	0.55	0.77	0.76	–
tiger	0.77	0.74	0.82	–	–
elephant	0.79	0.64	0.79	–	–
gorilla	0.72	0.60	0.91	0.84	–
squirrel	0.80	0.67	0.80	0.83	–
rhinoceros	0.78	0.67	0.80	0.76	–
rabbit	0.76	0.69	0.82	0.81	–
bat	0.82	0.67	0.74	0.74	–
giraffe	0.78	0.70	0.79	0.76	–
zebra	0.76	0.68	0.78	–	–
mouse	0.79	0.64	0.75	0.83	–
raccoon	0.79	0.64	0.83	0.81	–
dolphin	0.73	0.49	0.72	0.68	–
Mean=	**0.76**	**0.64**	**0.80**	**0.81**	**0.79**

Table 7: Wu-Palmer Similarity for mistakes. Animals for which a model made fewer than 50 mistakes are dashed out

Animal/Model	Random	NFRN50 Random	BEIT	NFRN50	CLIP
hamster	0.70	0.74	0.83	1.00	1.00
rat	0.79	0.83	0.81	0.99	1.00

Animal/Model	Random	NFRN50 Random	BEIT	NFRN50	CLIP
squirrel	0.76	0.70	1.00	1.00	1.00
rhinoceros	0.48	0.41	0.81	0.96	1.00
rabbit	0.75	0.76	0.85	1.00	1.00
bat	0.59	0.58	0.58	0.99	1.00
giraffe	0.66	0.73	0.92	1.00	1.00
wolf	0.87	0.84	0.94	1.00	1.00
chihuahua	0.80	0.80	0.79	0.91	1.00
zebra	0.79	0.86	1.00	1.00	1.00
chimpanzee	0.86	0.84	0.83	1.00	1.00
giant+panda	0.71	0.74	0.76	1.00	1.00
deer	0.83	0.91	1.00	1.00	1.00
bobcat	0.72	0.79	0.80	1.00	1.00
lion	0.74	0.93	0.93	1.00	1.00
mouse	0.77	0.69	0.81	0.98	1.00
polar+bear	0.72	0.76	1.00	1.00	1.00
raccoon	0.76	0.77	0.85	1.00	1.00
grizzly+bear	0.70	0.68	1.00	1.00	1.00
dolphin	0.55	0.69	1.00	1.00	1.00
tiger	0.77	0.84	1.00	1.00	1.00
leopard	0.79	0.86	0.95	1.00	1.00
horse	0.88	1.00	1.00	1.00	1.00
german+shepherd	0.87	0.86	0.76	1.00	1.00
blue+whale	0.42	0.34	1.00	1.00	1.00
siamese+cat	0.83	1.00	1.00	1.00	1.00
killer+whale	0.42	0.56	0.88	1.00	1.00
beaver	0.68	0.66	0.77	1.00	1.00
hippopotamus	0.47	0.41	0.80	1.00	1.00
persian+cat	0.75	1.00	1.00	1.00	1.00
spider+monkey	0.79	0.77	0.99	1.00	1.00
humpback+whale	0.43	0.82	0.97	1.00	1.00
elephant	0.61	0.61	1.00	1.00	1.00
gorilla	0.76	0.75	0.89	1.00	1.00
moose	0.77	0.82	0.88	1.00	1.00
cow	0.74	0.82	1.00	1.00	1.00
fox	0.80	0.77	0.96	1.00	1.00
seal	0.57	0.51	0.95	1.00	1.00
sheep	0.59	0.70	0.98	1.00	1.00
pig	0.72	0.70	0.98	1.00	1.00
otter	0.66	0.72	0.73	0.76	1.00
mole	0.72	0.68	0.88	0.82	1.00
walrus	0.39	0.38	0.70	0.72	0.99
antelope	0.81	0.85	0.94	0.97	0.98
ox	0.74	0.69	0.89	0.93	0.95
collie	0.84	0.87	0.80	0.93	0.91
weasel	0.85	0.77	0.86	0.90	0.90
buffalo	0.64	0.69	0.91	0.74	0.85
skunk	0.70	0.79	0.83	0.83	0.84
dalmatian	0.86	0.86	0.83	0.72	0.73
Mean=	**0.71**	**0.74**	**0.89**	**0.96**	**0.98**

Animal/Model	Random	NFRN50 Random	BEIT	NFRN50	CLIP

Table 8: Per animal average precision (AP) for properties of mentioned animal in captions per model for the Animals with Attributes 2 (AWA2) dataset. BEIT, which tends to do worse at captioning and question answering consistently predicts animals which share similar properties, and considerably better than randomly initialized NFRN50 and randomly selecting animals as baselines. This suggests that BEIT representations encode similar animals into broad conceptual categories (e.g. large savanna animals) which are able to linearly transfer to the LM. Without linguistic supervision, BEIT does not naturally distinguish these by the words we use to describe them, as NFRN50 and CLIP do.

Animal/Model	NFRN50 Random	BEIT	NFRN50	CLIP
giraffe	0.00	0.16	0.96	1.00
zebra	0.00	0.77	1.00	1.00
tiger	0.00	0.75	0.98	1.00
elephant	0.00	0.37	0.96	0.99
dolphin	0.00	0.37	0.58	0.98
rabbit	0.00	0.13	0.85	0.98
rhinoceros	0.00	0.04	0.30	0.98
squirrel	0.00	0.41	0.88	0.97
gorilla	0.00	0.20	0.93	0.96
sheep	0.00	0.27	0.91	0.96
raccoon	0.00	0.00	0.73	0.95
bat	0.00	0.00	0.28	0.94
horse	0.09	0.85	0.94	0.92
humpback+whale	0.00	0.21	0.56	0.92
hippopotamus	0.00	0.06	0.59	0.92
fox	0.00	0.15	0.91	0.91
cow	0.00	0.41	0.82	0.90
giant+panda	0.00	0.00	0.76	0.90
moose	0.00	0.01	0.41	0.89
deer	0.02	0.41	0.79	0.87
pig	0.00	0.15	0.76	0.86
leopard	0.00	0.42	0.92	0.86
seal	0.00	0.27	0.73	0.86
wolf	0.00	0.03	0.76	0.85
hamster	0.00	0.00	0.69	0.83
mouse	0.00	0.01	0.25	0.82
beaver	0.00	0.01	0.49	0.80
rat	0.00	0.00	0.37	0.78
chimpanzee	0.00	0.00	0.44	0.76
lion	0.08	0.14	0.40	0.66
killer+whale	0.00	0.00	0.10	0.53
otter	0.00	0.03	0.06	0.48
mole	0.00	0.01	0.02	0.40
walrus	0.00	0.00	0.00	0.36
bobcat	0.00	0.00	0.16	0.33
grizzly+bear	0.00	0.00	0.06	0.15
chihuahua	0.00	0.00	0.04	0.14
antelope	0.00	0.00	0.07	0.05
collie	0.00	0.00	0.06	0.04
weasel	0.00	0.00	0.03	0.03
buffalo	0.00	0.04	0.02	0.02
dalmatian	0.00	0.00	0.00	0.02
ox	0.00	0.00	0.00	0.01
skunk	0.00	0.00	0.00	0.01
siamese+cat	0.00	0.00	0.00	0.00
german+shepherd	0.00	0.00	0.00	0.00

Animal/Model	NFRN50 Random	BEIT	NFRN50	CLIP
persian+cat	0.00	0.00	0.00	0.00
polar+bear	0.00	0.00	0.00	0.00
spider+monkey	0.00	0.00	0.00	0.00
blue+whale	0.00	0.00	0.00	0.00
Mean=	**0.00**	**0.13**	**0.43**	**0.59**

Table 9: Accuracy for each model and each animal class in Animals with Attributes 2. A caption is considered correct if the animal name is mentioned in the caption for the image.

E PROBING VISUAL REPRESENTATIONS

We train probes on the image encodings from each of our image encoders to classify fine-grained lexical and coarse grained categorical concepts on several datasets: COCO (Lin et al., 2014), and CC3M (Sharma et al., 2018), and CIFAR-100 (Krizhevsky et al., 2009). The architecture is a single linear layer which takes an image encoding of dimension h_I (see Table 2) and projects to the number of classes for the classification task. For single label classification, we use a softmax activation on the logits and train with cross entropy as the loss function. For multilabel classification tasks, we use a sigmoid activation layer on top of the logits and train with a binary cross entropy loss function. We consider a certain class predicted if the value of the class after the sigmoid is ¿0.5.

Hyperparameters For simplicity, all probes are trianed with the same hyperparameters (with a few exceptions for the CC3M probes): learning rate: 1e-4, optimizer: AdamW (Loshchilov & Hutter, 2018), betas=(0.9, 0.999), batch size: 48 for CC3M probes; 32 for all others, max epochs: 300 for CC3M probes; 300 for all others.

Object Supercategory	Objects within class
accessory	*backpack, umbrella, handbag, tie, suitcase*
animal	*bird, cat, dog, horse, sheep, cow, elephant, bear, zebra, giraffe*
appliance	*microwave, oven, toaster, sink, refrigerator*
electronic	*tv, laptop, mouse, remote, keyboard, cell phone*
food	*banana, apple, sandwich, orange, broccoli, carrot, hot dog, pizza, donut, cake*
furniture	*chair, couch, potted plant, bed, dining table, toilet*
indoor	*book, clock, vase, scissors, teddy bear, hair drier, toothbrush*
kitchen	*bottle, wine glass, cup, fork, knife, spoon, bowl*
outdoor	*traffic light, fire hydrant, stop sign, parking meter, bench*
person	*person*
sports	*frisbee, skis, snowboard, sports ball, kite, baseball bat, baseball glove, skateboard, surfboard, tennis racket*
vehicle	*bicycle, car, motorcycle, airplane, bus, train, truck, boat*

Table 10: All individual object labels and supercategories they fall under as annotated in the COCO dataset.

E.1 COCO OBJECT CLASSES PROBE

The COCO dataset contains labels for 80 objects in images, typically used for object detection or segmentation tasks. Because one image can be labeled for multiple objects, we train the probe as a multi-label classification task.

In addition to having fine-grained labels for each type, COCO provides labels for each broad category that each object belongs to, called the *supercategory*. In Table 10, we show which supercategory each object label falls under.

E.1.1 COARSE-GRAINED SUPERCATEGORY PROBES

We train a multilabel classification probe to classify the object category seen in a given image. We report F1 for each `LiMBeR` model in Figure 11. We find that BEIT does a bit worse than NFRN50 and CLIP overall, but is able to classify some categories (images with accessories, vehicles, and 'outdoor' objects) well.

E.1.2 FINE-GRAINED OBJECT LABEL PROBES

Next, we look at the probe results for probes trained to identify individual objects by type. Our results can be found in Figure 12d. We find the same pattern emerges, and that BEIT does not seem to be significantly closer to the other pretrained models in terms of F1 on the coarse-grained vs. fine-grained patterns as we might expect. However, we do show that BEIT encodes strong, but weaker lexical concept categories than the other two models, and that the finding that BEIT transfers coarser grained information is not due to irreconcilable representational differences between BEIT space and the LM space.

E.2 CC3M PROBES

We also *train* the same set of probes on image data from CC3M, but *evaluate* on the same validation set from COCO (i.e., the same evaluation as used in Section E.1.2). The purpose of this experiment is to create a setting for a linear probe that better matches the `LiMBeR` setup we use in the main paper. If there are concepts that the probe has no trouble with, but rarely appear in captions, that could be an indicator that the LM and the image encoder represent that concept very differently in representation space.

Data To align the CC3M images with the object labels in COCO, we create labels by looking for exact string matches of the object label words (e.g. "teddy bear") in CC3M captions. Of the 80 object classes, we cut out any that have fewer than 1000 images. This leaves us with 782,794 training images for the probes across 53 object classes; fewer than the CC3M dataset used to train `LiMBeR`, but far more than the previous datasets we used for probing.

Results Because, in this setting, we train our probes on the same distribution as the `LiMBeR` models, we compare the F1 of the probes identifying objects in images to the F1 of those concepts appearing in the generated captions. Our results can be seen in Figure 13. It appears that if the image encoder encodes the lexical concept, it generally also transfers to the LM with `LiMBeR`. Limitations of this approach are that (1) the BEIT probe appears much worse at the domain shift from CC3M to COCO (e.g., F1 for animals drops 0.3 compared to when the probes are trained on COCO) and (2) some words in the label space are often substituted for more common words in generated captions (e.g. "person" could be generated as "man", "woman", etc.). This makes it difficult to recognize cases where the probe succeeds but the transfer fails. An interesting problem for future work is better understanding which concepts are encoded in an image encoder's representations, but do not transfer well with a linear map to the LM.

E.3 CIFAR-100 PROBES

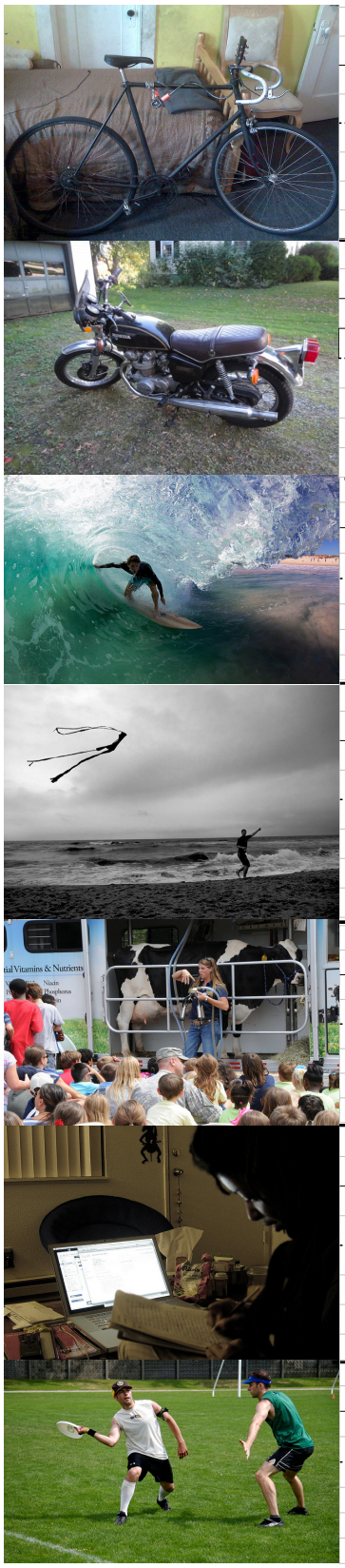
CIFAR-100 (Krizhevsky et al., 2009) is a dataset of 60,000 32x32 images balanced across 100 object classes. Like COCO, the 100 object labels are also annotated for coarse-grained object categories including 'aquatic mammals' and 'household furniture'. For CIFAR data, we train a classifier which classifies an image for a *single* object label. Like with COCO, we train a set of probes for the fine and coarse labels. We were surprised to find that for CIFAR images, BEIT representations tended to better than NFRN50 in terms of average F1 (for the fine-grained probe, BEIT: 0.57, NFRN50: 0.47); a first for any of the experiments we ran. Given the majority of evidence shows NFRN50 encodes lexical category information stronger than BEIT, we hypothesize this is not because of BEIT encoding lexical concepts more strongly, but due to the small resolution of images: because BEIT uses visual tokens, it may be more robust to extremely blurry images, which are out of distribution for both NFRN50 and BEIT.

E.3.1 COARSE-GRAINED PROBES

In Figure 14 we show the F1 results for the coarse-grained image labels probes trained on image encodings from each model. Each coarse-grained class in the testing set has 500 images each.

E.3.2 FINE-GRAINED PROBES

In Figure 15d we show the per object class F1 results for the image encodings from each model. Each class in the testing set has 100 images each. Similar to the COCO probe we do not see significant intra-model changes between the coarse-grained and fine-grained probe results.

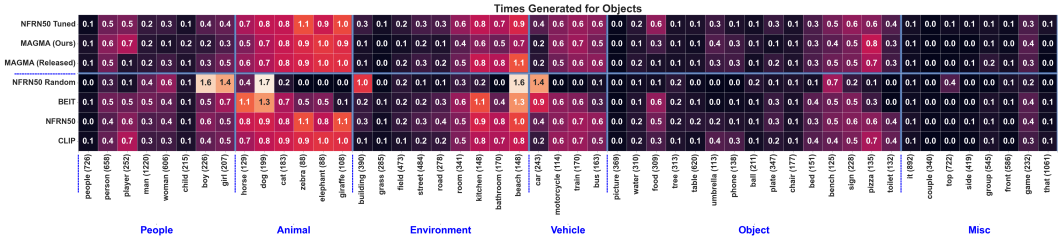


Ground Truth:	A bicycle is standing next to a bed in a room.
NFRN50 Tuned :	my bike with a basket.
MAGMA (Ours) :	my bike
MAGMA (Rel.) :	a vintage bike vintage bike
NFRN Random:	a young boy in a blue shirt and a red hat on a bicycle
BEIT:	the bike.
NFRN50:	my bicycle with a basket on the front.
CLIP:	my bike, which is a fixed gear bike.
Ground Truth:	A black Honda motorcycle parked in front of a garage
NFRN50 Tuned :	my motorcycle
MAGMA (Ours) :	my bike
MAGMA (Rel.) :	a 1973 Honda CB750
NFRN Random:	the car on the road
BEIT:	the bike.'
NFRN50:	a motorcycle on a motorcycle.
CLIP:	my motorcycle.
Ground Truth:	A man riding a wave on top of a white surfboard.
NFRN50 Tuned :	a surfer in the water
MAGMA (Ours) :	a surfer riding a wave.
MAGMA (Rel.) :	a surfer riding a wave
NFRN Random:	the view from the top of the mountain
BEIT:	a surfer riding a wave.
NFRN50:	a surfer in the water.
CLIP:	a surfer riding a wave.
Ground Truth:	A person standing on top of a beach flying a kite.
NFRN50 Tuned :	a man standing on the beach with a surfboard.
MAGMA (Ours) :	a kite on a beach.
MAGMA (Rel.) :	a man running on the beach
NFRN Random:	the new car in the garage
BEIT:	a man standing on a rock in the sea.
NFRN50:	a man surfing on the beach.
CLIP:	a man flying a kite on the beach.
Ground Truth:	A lady explains the process of milking a cow.
NFRN50 Tuned :	a horse and rider at the fair.
MAGMA (Ours) :	a woman on a stage with kids in the audience.
MAGMA (Rel.) :	a woman milking a cow in front of a group of children.
NFRN Random:	the new restaurant.
BEIT:	the crowd at the event.
NFRN50:	a crowd of people at a festival
CLIP:	the dairy cows.
Ground Truth:	A woman is taking notes in front of her laptop
NFRN50 Tuned :	the man who was shot and killed in the lobby of the building.
MAGMA (Ours) :	a student studying.
MAGMA (Rel.) :	a student working on a paper
NFRN Random:	the man who was killed in the attack.
BEIT:	the room where the meeting took place.
NFRN50:	the room where the meeting took place.
CLIP:	a student working on his laptop.
Ground Truth:	A couple of men standing on top of a field together.
NFRN50 Tuned :	the team before the match
MAGMA (Ours) :	men playing a game of sport.
MAGMA (Rel.) :	a men's lacrosse game at the University of New England
NFRN Random:	the new home of the football team
BEIT:	football player and football player during a training session.
NFRN50:	the team before the game.
CLIP:	the team during a practice session.

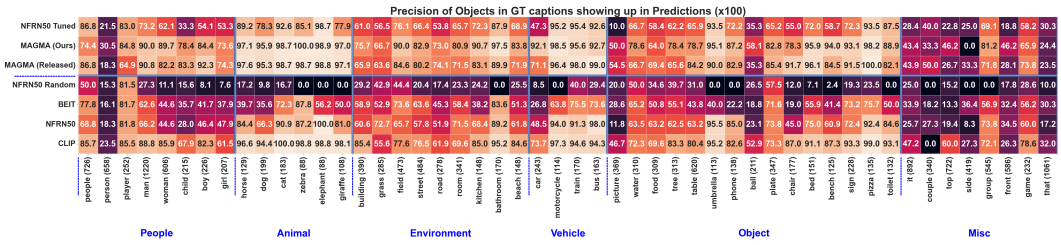
Figure 6: 15 randomly selected images from the COCO 2017 validation dataset and the generated captions from all models.

Ground Truth:	The vegetable are laid out neatly at the table.
NFRN50 Tuned :	vegetables and fruits for sale at a market in the city
MAGMA (Ours) :	fresh produce.
MAGMA (Rel.) :	a farmers market
NFRN Random:	a woman and her child in a garden
BEIT:	the garden
NFRN50:	the vegetables and fruits available at the farmers market.
CLIP:	the farm stand with a variety of vegetables
Ground Truth:	A woman standing in front of a box handing a woman a bag of food.
NFRN50 Tuned :	a woman with a box of food on her head.
MAGMA (Ours) :	a volunteer distributing food to the homeless.
MAGMA (Rel.) :	a woman in a white shirt and black pants handing out food to a man in a
NFRN Random:	a young girl with a flower in her hair and a smile on her face
BEIT:	a woman cooking in her kitchen.
NFRN50:	a woman selling fruit and vegetables in a market
CLIP:	person, a volunteer at the food distribution.
Ground Truth:	A man lies on the beach while someone else holds a kite.
NFRN50 Tuned :	the beach with a person lying on the sand.
MAGMA (Ours) :	person and i braiding a kite on the beach.
MAGMA (Rel.) :	a man and a woman playing on the beach.
NFRN Random:	a man and a woman sitting on a bench in the park
BEIT:	a man and woman doing a handstand on the beach.
NFRN50:	a young man sitting on the beach.
CLIP:	a man playing with a kite on the beach.
Ground Truth:	The young boy is playing in the living room of his house.
NFRN50 Tuned :	a little girl with a doll and a toy
MAGMA (Ours) :	person with a prosthetic finger
MAGMA (Rel.) :	a toddler boy standing up and holding his head.
NFRN Random:	the artist with his son.
BEIT:	a boy in a wheelchair.
NFRN50:	a little girl with a toy airplane
CLIP:	person with his new toy
Ground Truth:	A white toilet sitting in a corner of a room.
NFRN50 Tuned :	the toilet in the bathroom.
MAGMA (Ours) :	actor and a toilet
MAGMA (Rel.) :	the bathroom in the <PERSON>'s suite.
NFRN Random:	the bride and groom at the wedding
BEIT:	a white and black cat on a black background.
NFRN50:	a toilet in a public restroom.
CLIP:	the toilet in the room
Ground Truth:	Several different pieces of electronic equipment and computers on a desk.
NFRN50 Tuned :	my desk at work.
MAGMA (Ours) :	my desk with a laptop and various devices
MAGMA (Rel.) :	my desk
NFRN Random:	a man and a woman sitting on a bench in a park.
BEIT:	the computer i use.
NFRN50:	my computer desk at work.
CLIP:	my desk as it looked after a few days of working.
Ground Truth:	A living room filled with furniture and a table.
NFRN50 Tuned :	the living room.
MAGMA (Ours) :	the living room
MAGMA (Rel.) :	the living room.
NFRN Random:	the living room in the house
BEIT:	the living room.
NFRN50:	the living room in the house.
CLIP:	the living room.
Ground Truth:	A row of cows standing behind a metal fence.
NFRN50 Tuned :	a cow in a pen with a calf
MAGMA (Ours) :	dairy cows on a dairy farm.
MAGMA (Rel.) :	a dairy farm
NFRN Random:	the interior of the church
BEIT:	a horse being led through the streets.
NFRN50:	a horse and a cow in a barn
CLIP:	a dairy farm.

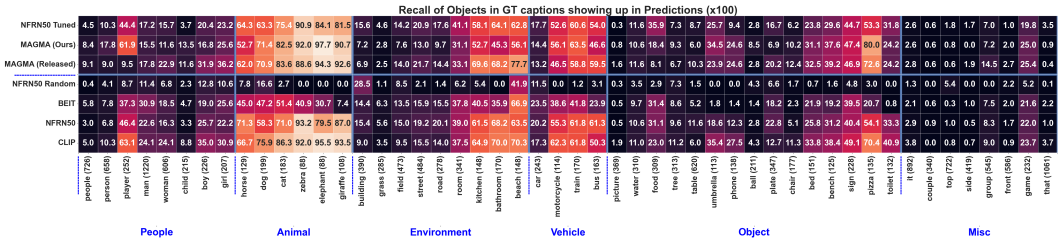
Figure 6: 15 randomly selected images from the first random seed taken from the COCO 2017 validation dataset with the generated captions from all models.



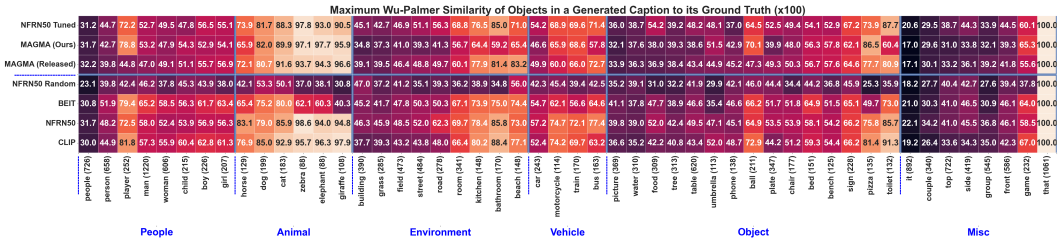
(a) times generated / # of times in ground truth



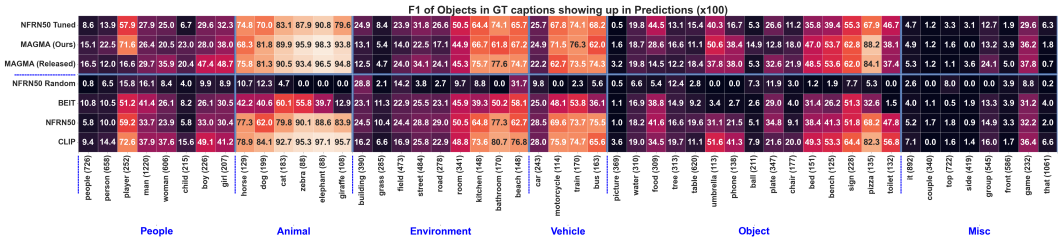
(b) precision



(c) recall

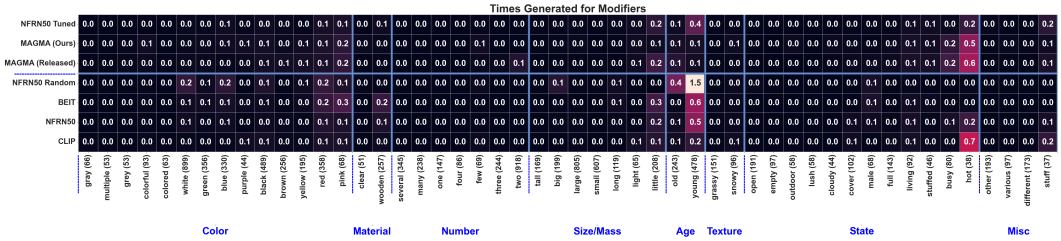


(d) The Wu-Palmer Similarity between the ground truth word and the most similar word in the generated captions.

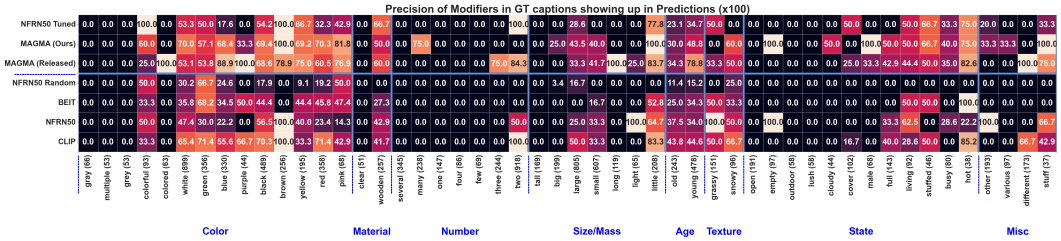


(e) f1

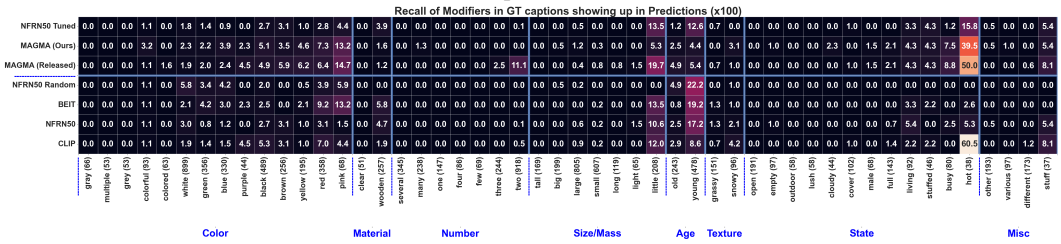
Figure 7: The top 50 nouns that appear in the ground truth captions of the COCO validation set and how often each model generates them



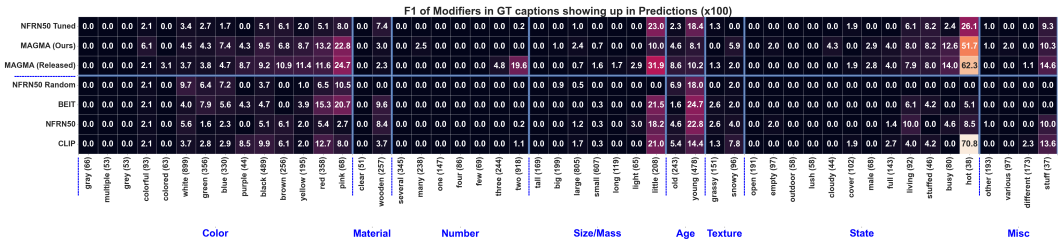
(a) times generated / # of times in ground truth



(b) precision

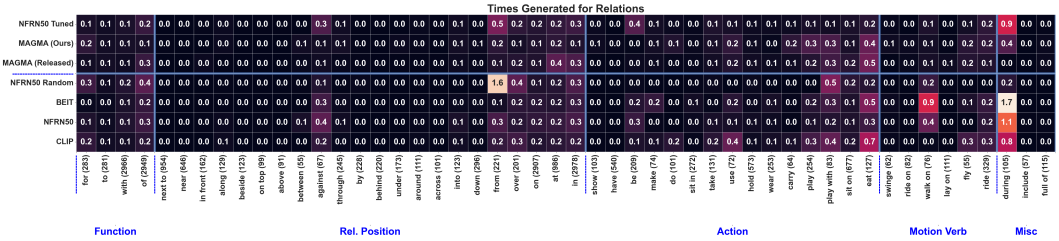


(c) recall

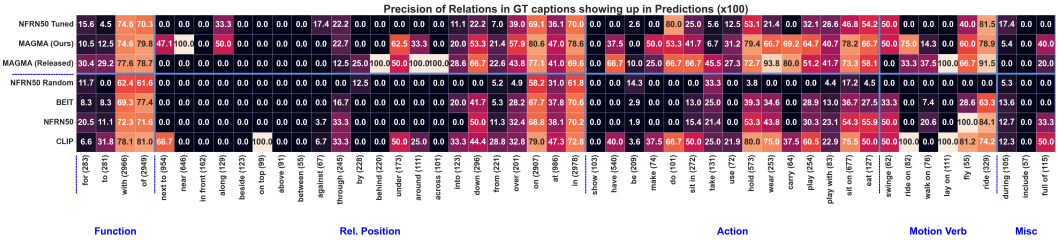


(d) f1

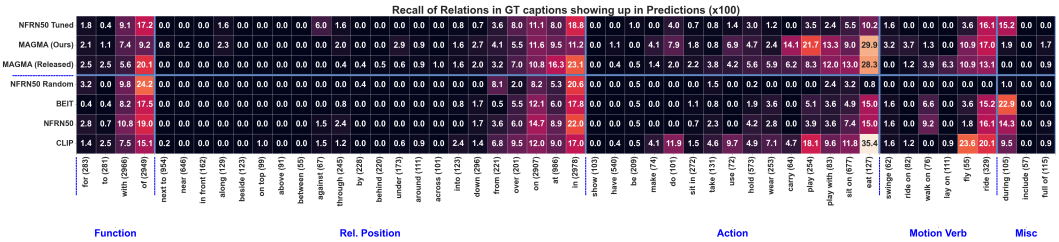
Figure 8: The top 50 modifiers that appear in the ground truth captions of the COCO validation set and how often each model generates them



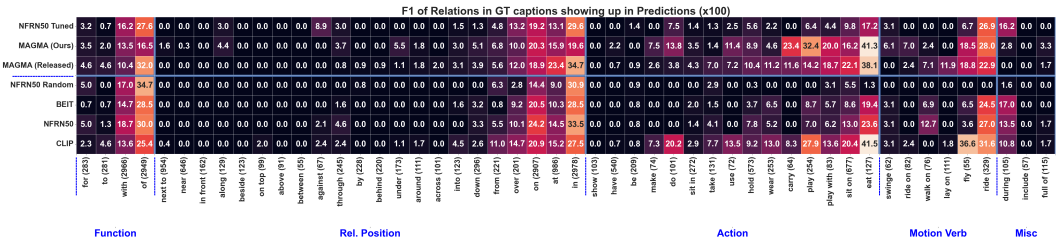
(a) times generated / # of times in ground truth



(b) precision



(c) recall



(d) f1

Figure 9: The top 50 relations that appear in the ground truth captions of the COCO validation set and how often each model generates them

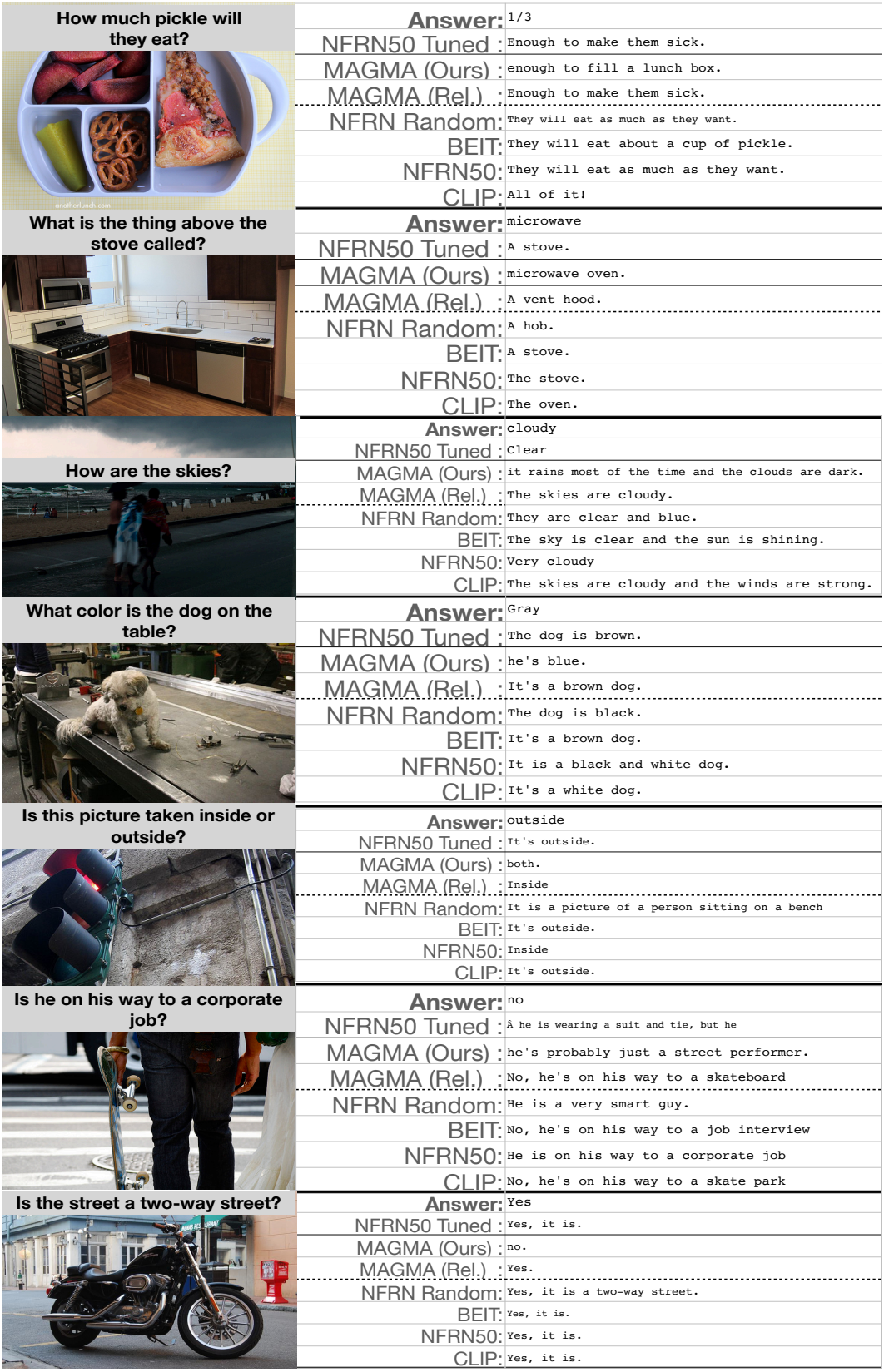
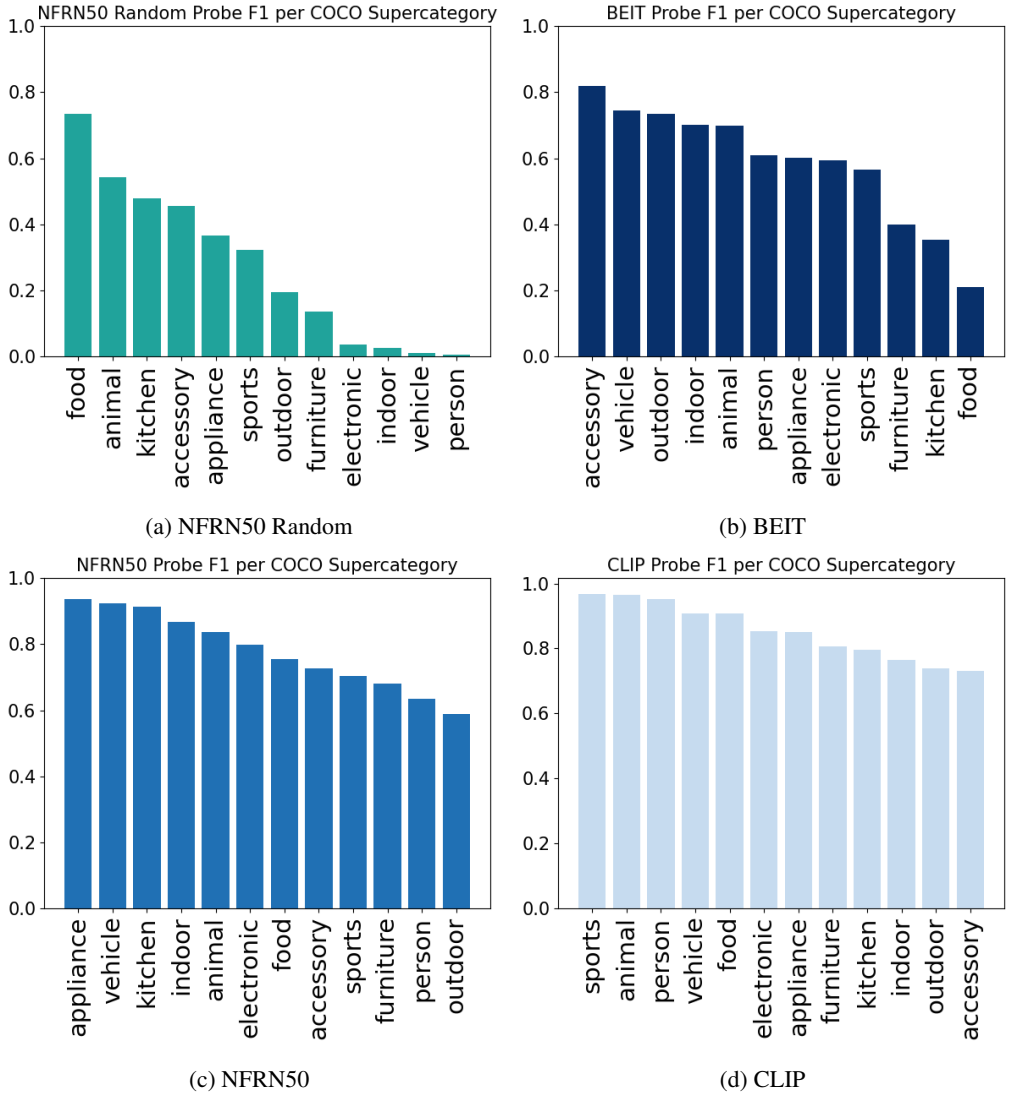


Figure 10: 15 randomly selected images from the VQA2 validation set and the generated answers from all models.

Figure 10: 15 randomly selected images from the VQA2 validation set and the generated answers from all models.



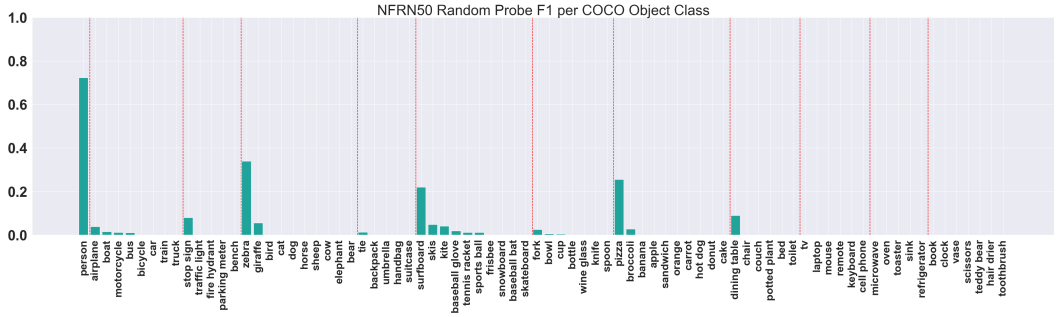
(a) NFRN50 Random

(b) BEIT

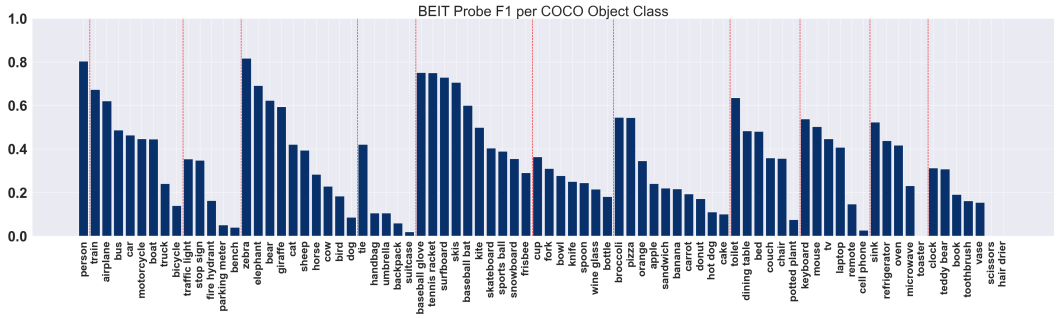
(c) NFRN50

(d) CLIP

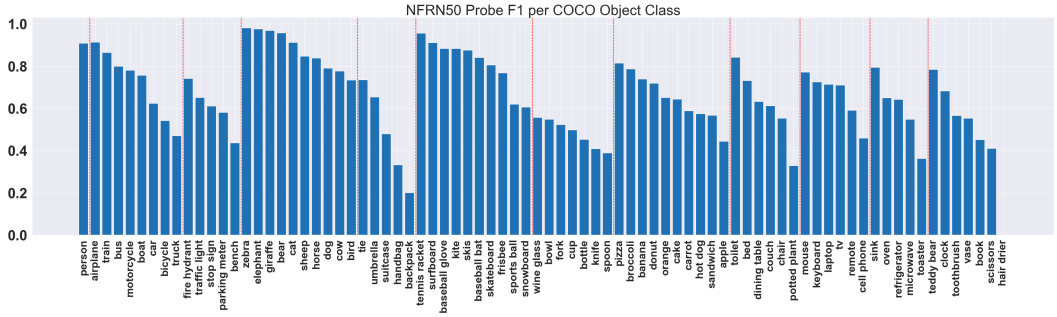
Figure 11: Probes trained on COCO images to classify the supercategories of the objects in the images



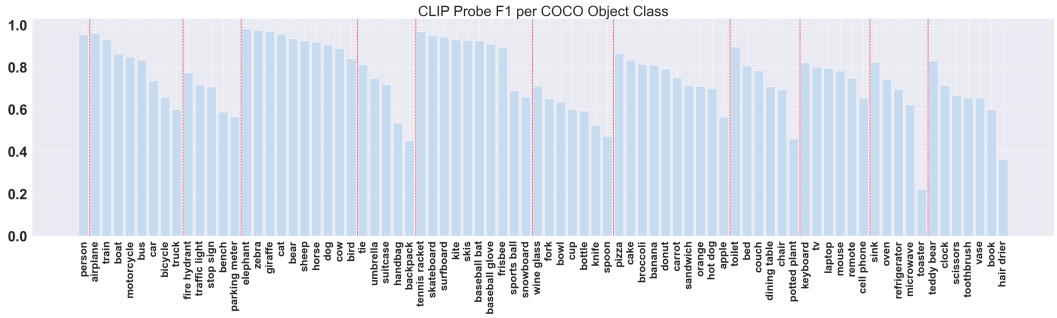
(a) NFRN50 Random Per COCO object label probe F1 results



(b) BEIT Per COCO object label probe F1 results



(c) NFRN50 Per COCO object label probe F1 results



(d) CLIP Per COCO object label probe F1 results

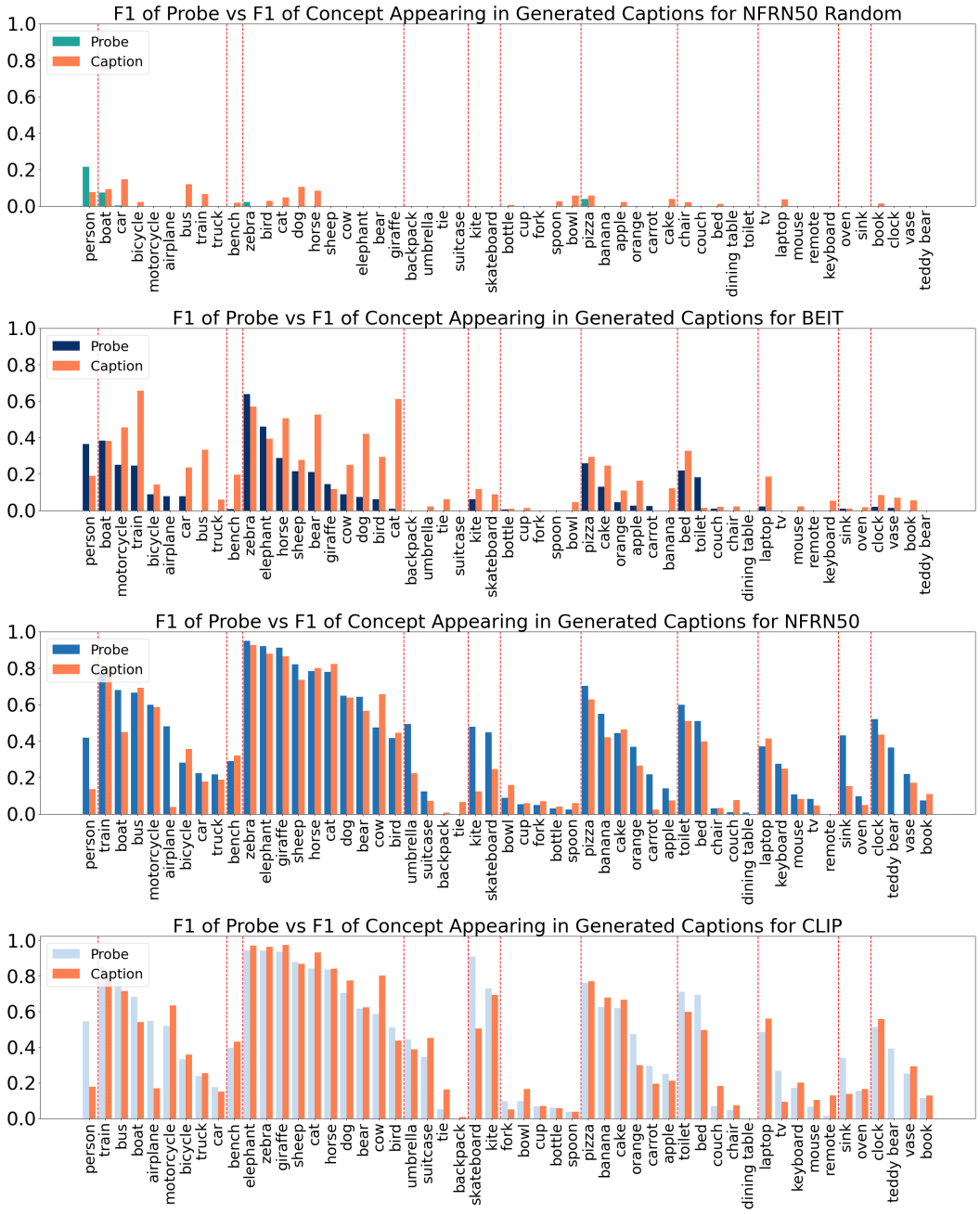
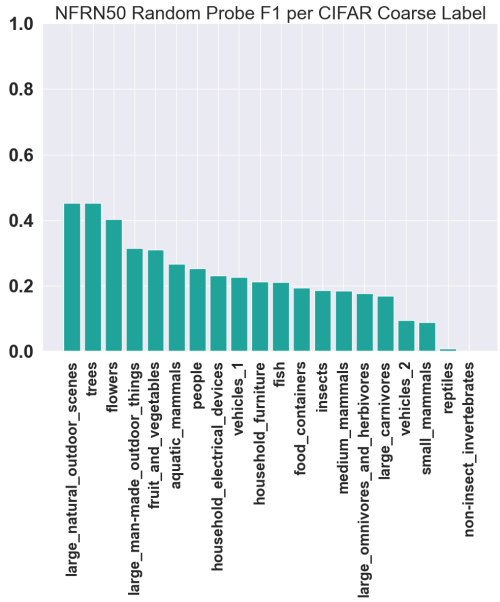
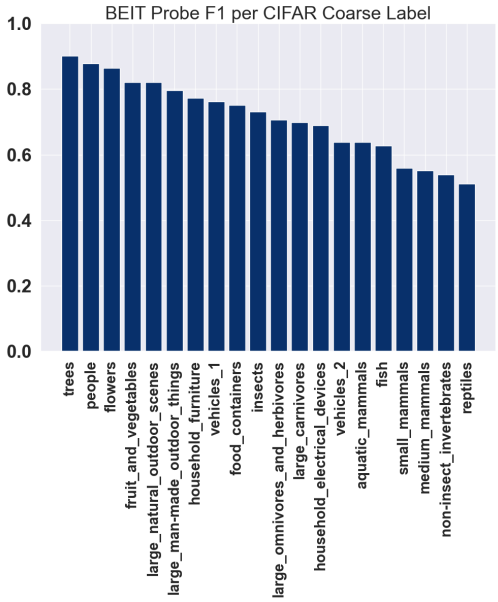


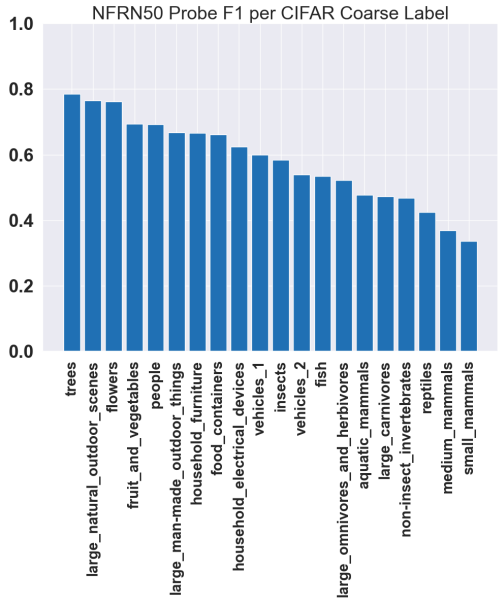
Figure 13: F1 of image encoder probes trained on CC3M and evaluated on COCO. We find that F1 of captions by object category tend to follow those of probe performance. Notably the BEIT probe is much worse at transferring from CC3M to COCO, and the captioning F1 tends to be consistently higher which makes it difficult to draw conclusions for this model. Generally, it appears the ability to *encode* lexical information into the image representation entails being able to *transfer* that information to the LM with a linear map.



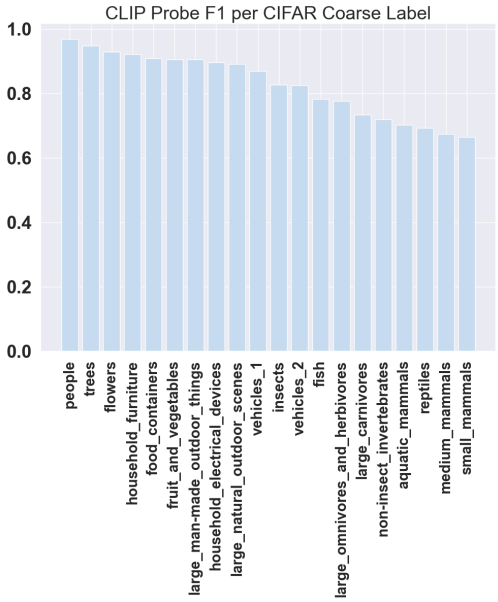
(a) NFRN50 Random



(b) BEIT

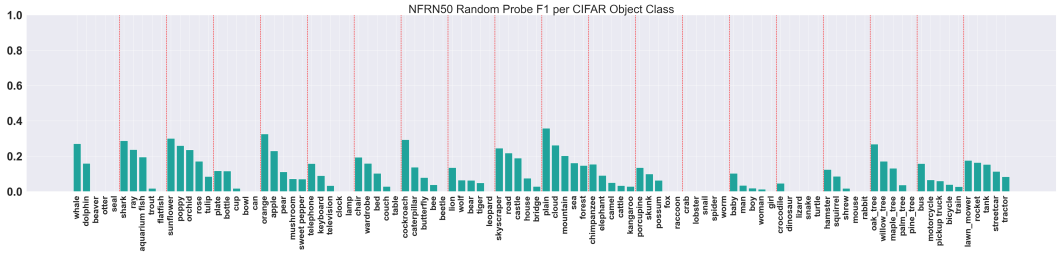


(c) NFRN50

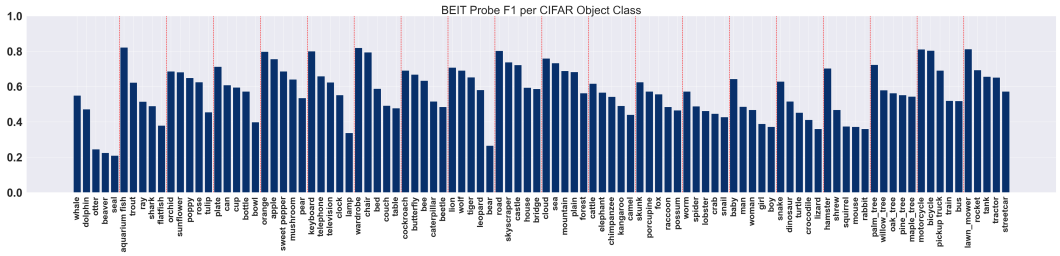


(d) CLIP

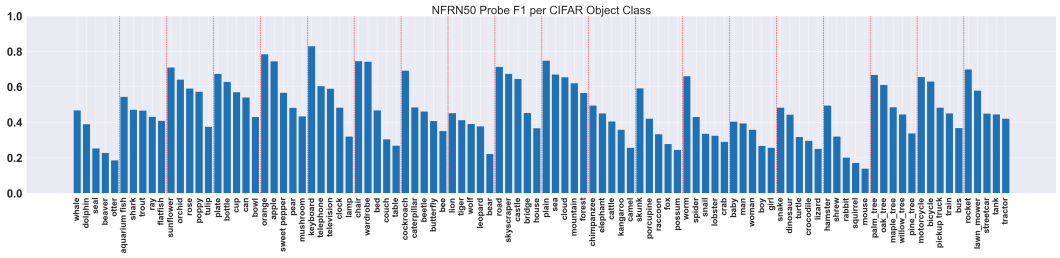
Figure 14: Probes trained on CIFAR images to classify the coarse labels of the objects in the images



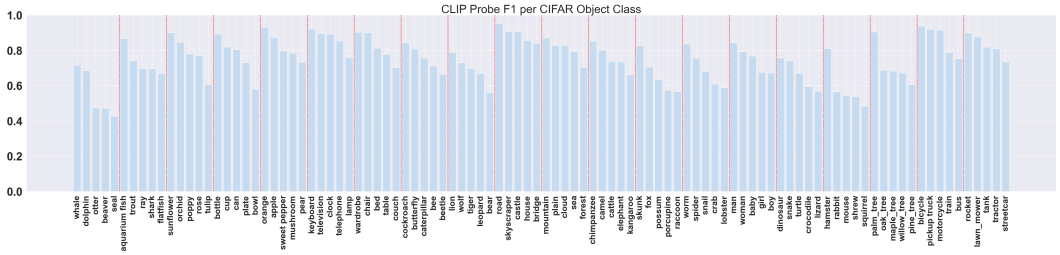
(a) NFRN50 Random Per CIFAR object label probe F1 results



(b) BEIT Per CIFAR object label probe F1 results



(c) NFRN50 Per CIFAR object label probe F1 results



(d) CLIP Per CIFAR object label probe F1 results