Probing Text Models for Common Ground with Visual Representations

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Abstract
Vision, as a central component of human perception, plays a fundamental role in shaping natural language. To better understand how text models are connected to our visual perceptions, we propose a method for examining the similarities between neural representations extracted from words in text and objects in images. Our approach uses a lightweight probing model that learns to map language representations of concrete words to the visual domain. We find that representations from models trained on purely textual data, such as BERT, can be nontrivially mapped to those of a vision model. Such mappings generalize to object categories that were never seen by the probe during training, unlike mappings learned from permuted or random representations. Moreover, we find that the context surrounding objects in sentences greatly impacts performance. Finally, we show that humans significantly outperform all examined models, suggesting considerable room for improvement in representation learning and grounding.

1 Introduction
As humans, we learn language in rich perceptual environments. Our senses, and notably vision, are essential in shaping the meaning of many of our words, and as such are central for learning semantics (Harnad, 1990; McClelland et al., 2019; Bisk et al., 2020). While great strides have been made in learning representations from text (Devlin et al., 2019; Liu et al., 2019b; Lan et al., 2019; Raffel et al., 2019; Wang et al., 2019b,a, among others), how such representations relate to our visual perception remains an open research problem.

As illustrated in Figure 1, it is possible for representations learned from text to share structural similarities with those learned from visual inputs. For instance, a model that only observes text might find similarities between a ball and an apple in that both can be used as subjects of the verbs rolling or throwing. Similarly, a vision model might come to similar findings by learning that both these objects are usually associated with collections of pixels with similar shapes, colors or contexts. Undoubtedly, these similarities are not perfect, since not all visual information can be—or usually is—encoded in natural text. A pragmatic question then naturally arises: how much common ground do text models have with visual representations?

In this work, we study this question by probing language models, learning mappings from text to visual representations (Figure 2). Probing (Shi et al., 2016; Adi et al., 2016; Conneau et al., 2018b) has been widely used in recent literature for examining what is encoded in language representations (Peters et al., 2018; Tenney et al., 2019; Conneau...
There is a man in the park flying a kite.

An airplane on the runway near the roads.

A person flying a colorful kite on a beach.

A hand holding a cellphone above a checkered blanket.

Figure 2: To study natural language grounding, we train a probe that maps textual to visual representations. This probe allows retrieving visual patches (orange boxes in the right) from contextual representations of objects in text (bold orange words in the left). In each row, from left to right, we display the top 5 image patches retrieved from representations extracted by BERT base. All shown samples are from images and captions from MS-COCO with object categories previously unseen by the probe.

et al., 2018a). In essence, this paradigm consists of training a supervised model—the probe—to predict certain properties from frozen representations extracted by a trained model. Inspired by Oord et al. (2018), our probe is optimized to maximally preserve the mutual information between the distributions of textual and visual representations. In training, the probe learns to map textual representations of concrete objects (e.g. banana or tree) in sentences to visual representations from a semantically aligned image patch. Once trained, the probe is evaluated by retrieving image patches from its outputs.

We examine representations from multiple language models, including ones trained on purely textual data—GloVe, BERT, RoBERTa and ALBERT (Pennington et al., 2014; Devlin et al., 2019; Liu et al., 2019b; Lan et al., 2019)—and on vision and language—LXMERT, VL-BERT and VILBERT-MT (Tan and Bansal, 2019; Su et al., 2020; Lu et al., 2019a,b). Following common practice in recent language grounding literature, we use visual features from Faster R-CNN (Ren et al., 2015) trained on Visual Genome (Krishna et al., 2017). For all these models, we are able to learn nontrivial mappings from text to visual representations. Compared to models trained only on text, we find similar, but generally better results for vision and language models. Further, we show that contextual models that use the entire sentence when building representations significantly outperform non-contextual GloVe embeddings. By comparing recall from sentences where objects are accompanied or not by adjectives, we provide further evidence that context substantially affects performance. Our experiments are backed by control tasks with random or permuted outputs, where the probe fails to learn mappings that generalize to previously unseen objects.

Finally, we turn to human judgment to assess an upper-bound in performance. The examined models significantly under-perform humans in mapping text to visual inputs, exposing much room for improvement in representation learning and natural language grounding.

Our main contributions are to:

- Propose a probing procedure for examining similarities in text and visual representations;
- Find nontrivial mappings between text and visual representations from multiple models, that generalize to unseen object categories;
- Show that context substantially impacts probe performance;
- Find that vision and language models perform similarly or slightly better than text-only models;
- Expose ample headroom in retrieval through assessing human performance.
Figure 3: An overview of the proposed probing procedure. Semantically aligned pairs of words in text and objects in images are collected from image captioning data. A probe $\Psi_\theta$ is trained to map representations from text (green) to visual (blue) domains while maximally preserving mutual information. For a batch of aligned text and visual representations $L=(L_1, \ldots, L_B)$ and $V=(V_1, \ldots, V_B)$, the loss (Equation 2) drives the probe’s outputs $\hat{V}_i = \Psi_\theta(L_i)$ to be maximally useful in finding the aligned visual representation $V_i$ given all other visual representations $V_i^{\text{NEG}}$ in the batch, using pair-wise dot product similarities (red).

2 Probing

At a high level (Figure 3), we use a lightweight neural model that maps textual to visual representations, optimizing for maximally preserving their mutual information. Through minimizing an Information Noise Contrastive Estimation (InfoNCE) loss (Oord et al., 2018), the probe is driven to output features able to distinguish the correct visual representations from a set of distractors. Once trained, this probe can map arbitrary text representations to the visual space.

2.1 Representations

To train and evaluate the probe, we collect paired representations of words in text and objects in images. Concretely, we find pairs $(\ell, v)$ of continuous textual representations $\ell$ and visual representations $v$.

**Representations from text** Text representations $\ell$ are extracted from concrete words in text. Such representations $\ell$ are sequences of vectors with fixed dimension (i.e., $\ell = (\ell_1, \ldots, \ell_n)$, where each element $\ell_i$ is a vector of size $d_\ell$). As contextual models have become ubiquitous in NLP, we allow the full use of context surrounding an object when extracting text representations. Formally, we refer to models that extract representations from text as a function $\Lambda$ that maps a string $s$ in a larger textual context $c$ to a sequential representation $\ell = \Lambda(s \mid c)$. The length of the output sequence is determined by the tokenizer associated with the model, which might split a single word into multiple tokens. For instance, a model might take as inputs $s = \text{frisbee}$ and $c = \text{A dog chasing an orange frisbee}$ and output continuous representations $\ell \in \mathbb{R}^{3 \times d_\ell}$ if the tokenizer splits frisbee into three subword units. Note that this formalism also encompasses non-contextual models—e.g. GloVe embeddings—and vision and language models—e.g. LXMERT, VILBERT-MT—when extracting representations from text.

**Representations from images** To extract visual representations $v$ from objects in images, we use a trained object detection network $\Theta$ (e.g. Faster R-CNN). For simplicity, we will use $v = \Theta(o \mid i)$ to refer to the features extracted by the object detector corresponding to the detected object with highest confidence belonging to the object category $o$ in image $i$. Unlike text representations, the representations $\Theta(o \mid i)$ have fixed dimensions $\mathbb{R}^{dv}$. Moreover, note that a given object detection model implies a fixed set of object categories $O$ it is trained to detect, which will be used for constructing pairs of visual and textual representations.
Collecting paired data  Pairs \((\ell, v)\) of semantically aligned text and visual representations are collected from an image captioning dataset with pairs \((c, i)\) of captions \(c\) and images \(i\). For each image \(i\), and each object \(o\) detected by the object detector \(\Theta\), if \(o\) appears in some associated caption \(c\), we include the pair \((\ell = \lambda(o \mid c), v = \Theta(o \mid i))\). Especially in imaging captioning datasets with multiple captions per image (e.g. MS-COCO), it is possible that multiple captions contain an object \(o\) detected in the associated image. To avoid having multiple pairs \((\ell, v)\) associated with the same object instance, we ensure that at most one pair \((\ell, v)\) per object category in each image is included.

2.2 Training

While directly computing the mutual information (Equation 1).

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\text{ learning regime optimizes the model } \Psi_{\hat{\theta}}
\text{ to maximally preserve the mutual information between the}
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\mathcal{L} = -\mathbb{E}_\ell \left[ \log \frac{\exp((\Psi_{\hat{\theta}}(\ell), v_i))}{\sum_{v' \in \{v\} \cup \mathcal{V}_{\ell}^{\text{NEG}}} \exp((\Psi_{\hat{\theta}}(\ell), v'))} \right]
\]

(1)

In practice, the expectation in Equation 1 is estimated over a batch of size \(B\) with samples of text \(L = (L_1, \ldots, L_B)\) and visual representa-

tions \(V = (V_1, \ldots, V_B)\), where representations with the same index are associated. For effi-

ciency, we can define the set of negative distrac-

tors as all other visual representations in the batch \(\mathcal{V}_{i}^{\text{NEG}} = \{V_j \mid j \neq i\}\). Thus, only the pairwise dot products \((V_i, \Psi_{\hat{\theta}}(L_i))\) are needed to cal-

culate the loss matrix (Figure 3). The batch loss

\[
\mathcal{L}_B = -\frac{1}{B} \sum_{1 \leq i \leq B} \left[ \log \frac{\exp((\hat{V}_i, V_i))}{\sum_{1 \leq j \leq B} \exp((\hat{V}_i, V_j))} \right]
\]

(2)

Equation 2 is the final loss used for training the

\[
\text{parameters } \theta \text{ of the probe. Importantly, we note that the models used to extract representations are}
\text{ not trained or changed in any way during the probing procedure.}
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2.3 Evaluation

A natural evaluation procedure is to compute recall in retrieving image patches given objects in text. For such, we collect new pairs \((\ell, v)\) of text and visual representations from unseen images and captions. Concretely, let \(\mathcal{V}\) represent the set of all collected visual representations for evaluation. For each text representation \(\ell\), we use the trained probe to generate our estimate \(\hat{v} = \Psi_{\hat{\theta}}(\ell)\), and find the instances \(v' \in \mathcal{V}\) that maximize the dot product \((\hat{v}, v')\). Given an integer \(k\), we consider recall at \(k\) under two scenarios:

Instance Recall (IR@k)  is the percentage of pairs \((\ell, v)\) where the instance \(v\) is in the top \(k\) visual representations retrieved from \(\hat{v} = \Psi_{\hat{\theta}}(\ell)\).

Category Recall (CR@k)  is the percentage of pairs \((\ell, v = \Theta(o \mid i))\) where any of the top \(k\) retrieved visual representations \(v' = \Theta(o' \mid i')\) is associated with the same object category \(o\) as \(v\) (i.e. \(o' = o\)).

To avoid conclusions over specific sets of object categories, we evaluate our probe in two scenarios, where pairs \((\ell, v)\) are collected from object categories either seen or unseen by the probe during training. For both scenarios, images and captions have no intersection with those used in training. Finally, we create multiple seen/unseen splits from our data, training and testing on each. We then report average and standard deviation for recall scores.
3 Experimental settings

3.1 Text representation models

We examine representations from multiple models, trained purely textual inputs or multi-modal data. When applicable, we use representations extracted by the last layer of the models in question.

Models trained on text only  The majority of the models here examined are bi-directional contextual representation models based on the transformer architecture (Vaswani et al., 2017), trained on purely textual data. We examine the base ($d_L = 768$) and large ($d_L = 1024$) versions of BERT uncased, RoBERTa and ALBERT (Devlin et al., 2019; Liu et al., 2019b; Lan et al., 2019). For all these models, we use pre-trained weights from the HuggingFace Transformers library (Wolf et al., 2019)(1). Additionally, we examine non-contextual representations using GloVe embeddings (Pennington et al., 2014). For such, we use embeddings trained on 840 billion tokens of web data from Common Crawl, with $d_L = 300$ and a vocabulary size of 2.2 million(2).

Models trained on text and images  We examine multiple models trained on vision and language tasks, namely LXMERT, VL-BERT (base and large) and VILBERT-MT (Tan and Bansal, 2019; Su et al., 2020; Lu et al., 2019a,b)). LXMERT is trained on aggregated data from five image captioning and visual question answering datasets (Lin et al., 2014; Krishna et al., 2017; Antol et al., 2015; Hudson and Manning, 2019; Zhu et al., 2016); VL-BERT is trained on the large-scale Conceptual Captions (Sharma et al., 2018) along with text-only data (English Wikipedia and BookCorpus (Zhu et al., 2015)); VILBERT-MT is trained 12 datasets on four tasks, visual question answering, caption-based image retrieval, grounding referring expressions, and multi-modal verification. All of these are transformer-based models based on self-attention. When necessary, we adapt them to include only the language branches, restricting attention to the text inputs. For all models, we use the code and weights made public by the authors(3).

3.2 Visual representation models

As common practice in natural language grounding literature (Anderson et al., 2018; Tan and Bansal, 2019; Su et al., 2020; Lu et al., 2019b), we use a Faster-RCNN model (Ren et al., 2015) trained on Visual Genome (Krishna et al., 2017) to extract visual features. We use the trained network provided by Anderson et al. (2018)(4), and do not fine-tune during probe training. The vocabulary of this object detector includes 1600 categories in total, with some examples being bed, pizza and giraffe. The representations extracted by this network are 2048-dimensional (i.e. $d_V = 2048$).

3.3 Data

Our data is collected from image captions in MS-COCO 2015 Image Captioning Task (Lin et al., 2014), with over 120 thousand images and 600 thousand captions. We build disjoint training, validation and test sets from the aggregated training and validation sets of MS-COCO, following the procedure described in Section 2.1. We reserve 5000 images and their associated captions for building each of our validation and test sets, and use the remaining for training.

To examine how our findings generalize to new objects, we validate and test on representations from either seen or unseen object categories, all built new images and captions. We use 1400 out of the 1600 object categories for training and seen evaluation, and reserve the remaining 200 for unseen evaluation. Further, we perform cross-validation by using 5 different random 1400/200 splits of the object categories, training and validating once on each. While their exact size depends on specific object categories splits, the probe training sets contain at least 300 thousand pairs of representations. For consistency, the validation and test sets are truncated to 7000 and 1000 pairs for the seen and unseen scenarios, respectively.

3.4 Probing

Our probe consists of a lightweight neural model. To accommodate for the naturally sequential nature of text representations $\ell$, we use a single-layered model with LSTM cells (Hochreiter and Schmidhuber, 1997) with 512 hidden units and only unidirectional connections. The outputs are then projected by a linear layer to the visual representation space. The probe is trained using Adam optimizer(5).

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1 https://github.com/huggingface/transformers
2 https://nlp.stanford.edu/projects/glove/
3 LXMERT: https://github.com/airsplay/lxmert; VL-BERT (prec): https://github.com/jackroos/VL-BERT; VILBERT-MT (multi-task): https://github.com/facebookresearch/vilbert-multi-task
4 https://github.com/peteanderson80/bottom-up-attention
| Text repr. | IR@1 Seen | IR@5 Seen | CR@1 Seen | IR@1 Unseen | IR@5 Unseen | CR@1 Unseen |
|-----------|-----------|-----------|-----------|-------------|-------------|-------------|
| Random    | 0.1 ± 0.1 | 0.1 ± 0.1 | 0.1 ± 0.1 | 0.5 ± 0.2   | 1.2 ± 0.1   | 6.0 ± 2.0   |
| GloVe     | 6.0 ± 0.1 | 5.3 ± 0.6 | 21.6 ± 0.3 | 18.6 ± 1.6  | 96.6 ± 0.4  | 87.4 ± 5.4  |
| BERT base | 15.1 ± 0.6 | 12.3 ± 0.8 | 43.8 ± 0.9 | 36.4 ± 2.4  | 90.9 ± 0.4  | 87.7 ± 2.1  |
| BERT large| 14.5 ± 0.2 | 11.7 ± 0.8 | 42.8 ± 0.6 | 35.4 ± 2.7  | 90.3 ± 0.3  | 88.9 ± 2.6  |
| RoBERTa base | 13.9 ± 0.5 | 11.5 ± 0.9 | 41.1 ± 1.2 | 34.6 ± 1.9  | 91.0 ± 0.3  | 89.3 ± 1.2  |
| RoBERTa large | 12.3 ± 0.7 | 10.6 ± 0.8 | 38.3 ± 1.3 | 32.7 ± 2.8  | 90.0 ± 0.5  | 88.1 ± 3.7  |
| ALBERT base | 12.0 ± 0.3 | 9.0 ± 0.6  | 37.6 ± 0.5 | 29.5 ± 2.0  | 91.4 ± 0.1  | 84.6 ± 2.4  |
| ALBERT large | 12.0 ± 0.4 | 8.6 ± 0.8  | 37.6 ± 0.8 | 27.9 ± 1.5  | 92.2 ± 0.2  | 84.3 ± 3.8  |
| LXMERT*   | 16.3 ± 0.1 | 13.4 ± 0.8 | 46.2 ± 0.6 | 39.5 ± 3.6  | 90.9 ± 0.4  | 90.4 ± 1.3  |
| VL-BERT base | 16.4 ± 0.8 | 12.1 ± 0.7 | 46.4 ± 1.2 | 36.8 ± 1.7  | 91.9 ± 0.1  | 88.1 ± 2.0  |
| VL-BERT large | 17.1 ± 0.7 | 12.6 ± 1.0 | 47.1 ± 0.9 | 38.4 ± 2.3  | 91.4 ± 0.1  | 89.1 ± 2.1  |
| VILBERT-MT* | 17.8 ± 0.4 | 15.8 ± 0.9 | 48.2 ± 0.2 | 42.4 ± 1.2  | 90.7 ± 0.2  | 91.3 ± 2.1  |

Table 1: Nontrivial mappings can be learned from text to visual representations, which generalize well to unseen object categories. For each model, we train and evaluate 5 probes, using different sets of object categories seen in training. The table shows average instance recall (IR@k) or category recall (CR@k), plus or minus one standard deviation, on test seen (7000 samples from 1400 previously seen object categories) and test unseen scenarios (1000 samples from 200 previously unseen objects categories).

Figure 4: Object categories accompanied by at least one adjective can be better retrieved. Plots show instance recall at 1 using representations from BERT base and VILBERT-MT.

(Kingma and Ba, 2014) with a learning rate of 0.0002, weight decay of 0.0005 and default remaining coefficients ($\beta_1 = 0.9, \beta_2 = 0.999$ and $\epsilon = 10^{-8}$). We train with a batch size of 3072, for a total of 5 epochs.

4 Results and discussion

For all examined language models, nontrivial, generalizable mappings to visual representations can be learned (Table 1). For each model, we trained and evaluated probes 5 times, each with different splits of object categories seen in training and testing. For all examined models, recall scores are significantly better than random. Moreover, the learned mappings generalize well to the test set with unseen object categories. Interestingly, we note that there is no strong correlation between retrieval performance and performance on purely linguistic tasks for the examined text models (for instance, at SQuAD (Rajpurkar et al., 2018) or GLUE (Wang et al., 2019b)). This reinforces the intuition that text-only benchmarks are not the ideal landscape for studying language grounding.

Context matters Contrasting the performance of the non-contextual representations from GloVe with the remaining contextual models shows that context considerably affects instance recall (e.g. 6.0% vs 12.3% IR@1 for Glove vs BERT base with unseen object categories). This gap is not surprising, since a non-contextual representation of an object category should not be able to discern between distinct image patches depicting it. We observe higher category recall for GloVe, especially for seen object categories, which we hypothesize comes from the increased ease in correctly predicting the output object category if there is no intra-category noise in the inputs. More broadly, we investigate the influence of context by measuring performance of contextual models when the objects being queried have at least one adjective
Figure 5: More descriptive sentences lead to better instance recall, as illustrated with examples retrieved using representations mapped from BERT base. For all examples, contextual representations are extracted from the same word *cat*, yet the context encoded in them allows the retrieval of better matching image patches.

| Control  | IR@1  | IR@5  | CR@1  |
|----------|-------|-------|-------|
|          | Seen  | Unseen| Seen  | Unseen| Seen | Unseen |
| permuted | 1.5 ± 0.2 | 0.1 ± 0.1 | 7.2 ± 0.7 | 0.5 ± 0.3 | 37.0 ± 5.5 | 3.4 ± 2.7 |
| random   | 7.4 ± 0.4 | 0.1 ± 0.1 | 24.2 ± 0.4 | 0.5 ± 0.1 | 99.7 ± 0.1 | 1.9 ± 1.5 |

Table 2: Control tasks using random or permuted visual representations lead to poor retrieval performance for unseen object categories, indicating that the probe generalizes poorly in these scenarios. The table shows average recall (plus or minus one standard deviation) for BERT base, computed over 5 different object categories splits used for training and evaluation. Similar results are found for other models, complete tables can be found in the Appendix.

associated with them, as processed by the dependency parser from AllenNLP library (Gardner et al., 2018). These adjectives commonly include colors (e.g. *white*, *black*) and sizes (e.g. *big*, *small*). As shown in Figures 4 and 5, we observe conspicuous gains in instance recall for contextual models when objects are accompanied by adjectives.

**Grounded models** As shown in Table 1, text representations from models trained on vision and language also allow nontrivial mappings to be learned. Compared to models trained on text only, we find similar, but generally better performance. Larger differences are observed in instance retrieval, where representations need to be more comprehensive for mappings to be successful.

**Control tasks** Central to probing is the practice of contrasting performance with control tasks (Hewitt and Liang, 2019). In our experiments we examine two control tasks, where text representations are mapped either to 1) randomly *permuted* visual representations; or 2) *random* representations. For the *permuted* control task, we replace each visual representation \( v = \Theta(o \mid i) \) with another \( v' = \Theta(f(o) \mid i') \) from an object category \( o' = f(o) \) that deterministically depends on the original object category \( o \). For instance, all visual representations with the original category *cat* are replaced with representations from a second category *dog*. For the *random* control task, we sample representations with the same dimension \( d_V \), each dimension sampled independently from an uniform distribution \( \sim U(0, 1) \). Note that the permuted control task preserves some information on the original visual representations, while the random scenario does not. The results are shown in Table 2. In the experiments with random representations, the probe is able to learn a nontrivial mapping to object categories it has *seen* during training, and retrieves an image with the correct object category almost always. This is reasonable since, in this easier task, there are only a few fixed representations that need to be learned by the probe during training. However, as evidenced by the retrieval results with *unseen* object categories, there is no generalization. Moreover, we see on the *permuted* control tasks the mapping is harder for seen object categories, which is natural due to the fact that the visual representations are no longer fixed per object category. As in the *random* control task, no meaningful generalization to unseen object categories is observed. In summary, for unseen object categories, the probe is
Table 3: A sizable headroom in instance recall comparing human performance with examined models in a smaller test set with 100 samples.

Human BERT base VILBERT-MT
IR@1 76% 43% 53%

highly selective, and only yields good performance when visual representations are sensible.

Human performance Mappings from all examined models substantially under-perform humans. Similar to probe evaluation, we measure human performance in retrieving visual patches from words in sentences. In virtue of the limited human attention, we evaluate on a reduced test set of 100 samples of unseen object categories, asking subjects to choose out of 100 image patches the closest match to an object in a sentence. We collect over 1000 annotations from 17 subjects, with at least 30 annotations each. Our results (Table 3) show a large gap to mappings learned from the examined models: while humans retrieve the correct instance (IR@1) 76% of the time on average, the best performing model trained on text-only, BERT base, obtains only 43%, while the overall best model, VILBERT-MT obtains an IR@1 of 53%.

5 Related Work

What is encoded in language representations? Understanding what information state-of-the-art NLP models encode has gained increasing interest in recent years (Rogers et al., 2020). From factual (Petroni et al., 2019; Jawahar et al., 2019; Roberts et al., 2020) to linguistic (Conneau et al., 2018b; Liu et al., 2019a; Talmor et al., 2019) and common-sense (Forbes et al., 2019) knowledge, a wide set of properties have been previously analysed. A common approach in this literature is the use of probes (Shi et al., 2016; Adi et al., 2016; Conneau et al., 2018b; Hewitt and Liang, 2019), supervised models trained on top of frozen representations in some specific task of interest. Such models are typically used in settings were discrete, linguistic annotations are available. We refer to Belinkov and Glass (2019) and Rogers et al. (2020) for a more comprehensive literature review. Our approach differs from previous work in both scope and methodology, focusing on probing language representations for similarities with continuous, visual representations.

Natural language grounding A widely investigated research direction aims to connect natural language to the physical world (Bisk et al., 2020; McClelland et al., 2019), typically through training and evaluating multi-modal models (Tan and Bansal, 2019; Su et al., 2020; Lu et al., 2019a,b; Chen et al., 2019) in multi-modal tasks (Antol et al., 2015; Hudson and Manning, 2019; Suhr et al., 2018; Zellers et al., 2019). Closer to our motivations of understanding what already is encoded by trained text models are the works of (Lucy and Gauthier, 2017) and (Scialom et al., 2020). Lucy and Gauthier (2017) evaluate how representations from non-contextual word embeddings can predict discrete, human-generated perceptual features drawn from semantic norm datasets. Our work focuses instead on examining the semantic overlap with representations from trained vision models, as they bear a direct, instance-specific connection to raw visual inputs. Scialom et al. (2020) examines cross-modal transferability of text models when using multi-modal inputs for text generation, finding that semantic abstractions from BERT generalize well to the visual domain. While our conclusions are generally aligned, our methodology differs substantially—instead of encoding visual representations into text models, we map purely textual representations to the visual domain.

6 Conclusion

In this work we propose a probing procedure for evaluating structural similarities between latent representations extracted by language and by vision models. Examining a wide range of models, we find that nontrivial mappings can be learned from text to visual representations. Moreover such mappings generalize well to unseen object categories, unlike in control experiments. We emphasize that these results are not a claim that text and visual models learn representations with perfect (or close to perfect) similarity, nor that language grounding is trivial because of the commonalities that do exist. By investigating and measuring such common ground, our intentions are to better understand the landscape of representation learning and natural language grounding, and in so, foment further progress. As suggested by human retrieval performance, there remains an appreciable headroom for building better, more grounded representations.
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### Appendix

| Text repr. | IR@1 Seen | IR@1 Unseen | IR@5 Seen | IR@5 Unseen | CR@1 Seen | CR@1 Unseen |
|------------|-----------|-------------|-----------|-------------|-----------|-------------|
| GloVe      | 1.9 ± 0.1 | 0.2 ± 0.1   | 8.6 ± 0.4 | 0.5 ± 0.4   | 44.8 ± 3.8 | 2.6 ± 3.1   |
| BERT base  | 1.5 ± 0.2 | 0.1 ± 0.1   | 7.2 ± 0.7 | 0.5 ± 0.3   | 37.0 ± 5.5 | 3.4 ± 2.7   |
| BERT large | 1.4 ± 0.2 | 0.1 ± 0.1   | 7.3 ± 0.5 | 0.6 ± 0.2   | 40.7 ± 4.3 | 3.1 ± 3.3   |
| RoBERTa base | 1.5 ± 0.1 | 0.0 ± 0.0   | 7.4 ± 0.4 | 0.3 ± 0.1   | 39.9 ± 3.0 | 1.1 ± 0.7   |
| RoBERTa large | 1.5 ± 0.1 | 0.1 ± 0.1   | 6.7 ± 0.4 | 0.6 ± 0.2   | 40.0 ± 5.8 | 3.3 ± 0.8   |
| ALBERT base | 1.6 ± 0.1 | 0.0 ± 0.0   | 7.3 ± 0.6 | 0.5 ± 0.3   | 36.4 ± 3.8 | 1.9 ± 1.0   |
| ALBERT large | 1.5 ± 0.1 | 0.1 ± 0.1   | 7.0 ± 0.4 | 0.4 ± 0.4   | 38.5 ± 4.3 | 1.6 ± 1.5   |
| LXMERT^1   | 1.6 ± 0.1 | 0.1 ± 0.1   | 7.4 ± 0.3 | 0.5 ± 0.1   | 41.5 ± 3.5 | 1.1 ± 1.0   |
| VL-BERT base | 1.6 ± 0.3 | 0.1 ± 0.1   | 7.5 ± 0.5 | 0.4 ± 0.1   | 37.6 ± 2.9 | 2.9 ± 1.2   |
| VL-BERT large | 1.6 ± 0.2 | 0.1 ± 0.0   | 8.0 ± 0.5 | 0.5 ± 0.1   | 41.2 ± 3.6 | 4.0 ± 4.7   |
| VILBERT-MT^1 | 1.7 ± 0.1 | 0.1 ± 0.1   | 7.8 ± 0.7 | 0.4 ± 0.2   | 40.5 ± 5.3 | 1.9 ± 1.2   |

Table 4: Control tasks using permuted visual representations lead to poor retrieval performance for unseen object categories, indicating that the probe generalizes poorly in these scenarios. The table shows average recall (plus or minus one standard deviation) for all studied models, computed over 5 different object categories splits used for training and evaluation.

| Text repr. | IR@1 Seen | IR@1 Unseen | IR@5 Seen | IR@5 Unseen | CR@1 Seen | CR@1 Unseen |
|------------|-----------|-------------|-----------|-------------|-----------|-------------|
| GloVe      | 7.4 ± 0.1 | 0.0 ± 0.0   | 24.2 ± 0.3 | 0.2 ± 0.2   | 99.8 ± 0.0 | 2.2 ± 3.2   |
| BERT base  | 7.4 ± 0.4 | 0.1 ± 0.1   | 24.2 ± 0.4 | 0.5 ± 0.1   | 99.7 ± 0.1 | 1.9 ± 1.5   |
| BERT large | 7.4 ± 0.2 | 0.2 ± 0.1   | 24.3 ± 0.5 | 0.5 ± 0.2   | 99.6 ± 0.1 | 2.8 ± 2.4   |
| RoBERTa base | 7.4 ± 0.3 | 0.0 ± 0.1   | 24.2 ± 0.7 | 0.4 ± 0.4   | 99.5 ± 0.0 | 1.8 ± 2.8   |
| RoBERTa large | 7.3 ± 0.1 | 0.1 ± 0.1   | 24.2 ± 0.4 | 0.2 ± 0.2   | 99.6 ± 0.0 | 0.2 ± 0.1   |
| ALBERT base | 7.5 ± 0.2 | 0.1 ± 0.1   | 24.2 ± 0.4 | 0.3 ± 0.2   | 99.4 ± 0.0 | 1.9 ± 2.1   |
| ALBERT large | 7.6 ± 0.2 | 0.1 ± 0.0   | 24.3 ± 0.6 | 0.5 ± 0.3   | 99.7 ± 0.0 | 2.4 ± 2.2   |
| LXMERT^1   | 7.5 ± 0.1 | 0.1 ± 0.0   | 24.3 ± 0.2 | 0.6 ± 0.2   | 99.7 ± 0.0 | 1.1 ± 0.9   |
| VL-BERT base | 7.6 ± 0.2 | 0.1 ± 0.0   | 24.4 ± 0.4 | 0.5 ± 0.2   | 99.7 ± 0.0 | 0.9 ± 1.1   |
| VL-BERT large | 7.4 ± 0.1 | 0.2 ± 0.1   | 24.4 ± 0.3 | 0.7 ± 0.4   | 99.7 ± 0.0 | 1.2 ± 1.2   |
| VILBERT-MT^1 | 7.7 ± 0.2 | 0.2 ± 0.1   | 24.6 ± 0.6 | 0.8 ± 0.5   | 99.5 ± 0.1 | 2.8 ± 2.3   |

Table 5: Control tasks using random visual representations lead to poor retrieval performance for unseen object categories, indicating that the probe generalizes poorly in these scenarios. The table shows average recall (plus or minus one standard deviation) for all studied models, computed over 5 different object categories splits used for training and evaluation.