Attention as Grounding: Exploring Textual and Cross-Modal Attention on Entities and Relations in Language-and-Vision Transformer

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Abstract

We explore how a *multi-modal transformer* trained for generation of longer image descriptions learns syntactic and semantic representations about entities and relations grounded in objects at the level of masked self-attention (text generation) and cross-modal attention (information fusion). We observe that cross-attention learns the visual grounding of noun phrases into objects and high-level semantic information about spatial relations, while text-to-text attention captures low-level syntactic knowledge between words. This concludes that language models in a multi-modal task learn different semantic information about objects and relations cross-modally and uni-modally (text-only). Our code is available here: https://github.com/GU-CLASP/attention-as-grounding.

1 Introduction

In this paper, we examine what kind of knowledge is encoded in the multi-modal transformer. Existing work has mostly looked at the knowledge captured in models that operate with **a single modality** (text). For instance, previous research has shown that the attention weights in large-scale models, e.g. BERT (Devlin et al., 2019), implicitly encode knowledge of sentence structure (Raganato and Tiedemann, 2018; Ravishankar et al., 2021), part-of-speech tags, syntactic dependencies (Clark et al., 2019; Vig and Belinkov, 2019), subject-verb agreement between words (Goldberg, 2019), and even information about textual co-reference (Tenney et al., 2019). Only a few papers have inspected what is captured by **multi-modal architectures**. Cao et al. (2020) demonstrate that the attention heads in image-and-text transformers effectively encode linguistic and cross-modal knowledge. Ilinykh and Dobnik (2021) provide the analysis of how language representations are indirectly affected by visual information in language-and-vision model.

Here we inspect what the model learns about two types of words in the multi-modal setting: (i) words denoting objects in the scene (e.g. "a red chair"), (ii) words depicting spatial relations between objects (e.g. "a chair *next to* the table"). While it is relatively simple to associate nouns with specific image regions, words describing relations are much harder to ground (Lu et al., 2017), possibly because visual representations are typically designed to capture objects without any explicit knowledge of relations. Secondly, grounded relations depend on knowledge from *both* vision and language modalities which contains information about the objects and their mode of interaction (*what*) as well as their physical location (*where*) (Ghanimifard and Dobnik, 2019). Ideally, each relation (and also other types of words) should be grounded in both modalities, but to a different degree.[1] However, studies of language-and-vision models indicate that they are frequently biased towards one modality, most often to language (Goyal et al., 2017). Therefore, *the main research challenge* is to develop architectures that learn to utilise an appropriate ratio of visual and language knowledge for generation (or understanding) of each word in its context. Towards this goal we investigate grounding of different semantic types and answer the following questions:

Q1: Does attention across two modalities learn visually grounded semantics of nouns?

Q2: What syntactic knowledge is encoded in attention on text in the multi-modal set-up?

Q3: What does cross-modal attention learn about grounded semantics of spatial relations?

We use a two-stream multi-modal transformer (Herdade et al., 2019), which first attends to each modality independently and then learns to attend cross-modally. This architecture uses rich relative

[1] Of course, in uni-modal word-embeddings the semantics of words are grounded in word-contexts only but such representations give us only common sense knowledge not linked to particular situations.

geometry between objects, while many other two-stream models (Tan and Bansal, 2019; Lu et al., 2019) simply use either coordinates of bounding boxes or their spatial location. We train the model for *image paragraph generation* (Ilinykh et al., 2019; Krause et al., 2017), allowing examination of the knowledge of semantic types in extensive contexts. Our experiments show how language and vision are bridged in the multi-modal transformer. In addition, our work provides insights into how multi-modal representations are learned for different word types.

2 Experimental Set-Up

Model We train a multi-modal transformer for image paragraph generation. The model is based on the image captioning transformer proposed by Herdade et al. (2019)[2]. We use the object detector provided by Anderson et al. (2018a)[3]. This model comes pre-trained on object annotations from Visual Genome (Krishna et al., 2016). We extract features of N objects per image, resulting in the set $\mathbf{V} = \{v_1, \ldots, v_N\}$ with $v_n \in \mathbb{R}^{1\times D}$. We set $N = 36$ and $D = 2048$. The object extractor also provides us with labels ("table") and attributes ("round") for the objects, which will be used in our experiments. Following Herdade et al. (2019), we also extract geometry information about each object $\mathbf{G} = \langle x, y, w, h\rangle$ (centre coordinates, width, height) and use it as an additional input along with visual features. Figure 1 describes the architecture of the model. In this model, each attention mechanism consists of six layers with eight attention heads in them. The *image encoder* (orange box) learns to combine visual and geometric features[4] and passes them through the standard self-attention block, consisting of multi-head self-attention, feed-forward network, residual connections and layer-normalisation. Due to uni-directional nature of description generation, the *text decoder* (blue box) produces representation of the current token w_i, based on previously generated tokens $(w_1, \ldots, w_{i-1})$, while $(w_{i+1}, \ldots, w_W)$ are replaced with $[MASK]$. Finally, the *cross-attention* (red box) uses information from both textual and visual streams to output a probability of the next word in the sequence.

[2]https://github.com/yahoo/object_relation_transformer

[3]https://github.com/peteanderson80/bottom-up-attention

[4]For more information on how image encoder employs both visual and geometric information, we refer the reader to the original implementation by Herdade et al. (2019).

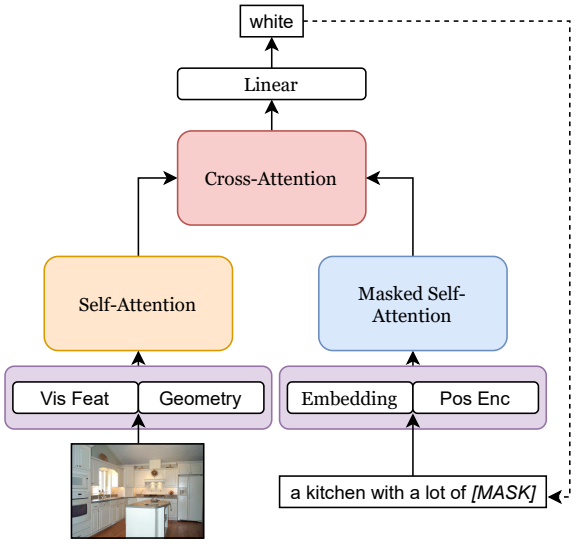


Figure 1: Multi-modal image description transformer. Every next generated word is concatenated with the previously generated words and passed to the model to output the next word prediction.

Figure 2: **Ground truth description of the image**: It's a room with a bar on the side. There is a pink couch in the center. There's a coffee table in front of the couch. It has a light purple rug. There are three chairs at the bar.
Generated description of the image: This appears to be a bonus room that is red and white. There is a wooden table in the center of the room. There is a red couch. There is a large plant in the corner.

Dataset We train our model on Tell-Me-More (Ilinykh et al., 2019), a dataset of natural multi-sentence descriptions of real-world images of rooms in the house setting (Zhou et al., 2017). The descriptions in this dataset are paragraphs produced by human describers in an image captioning task which are different from annotated relationships between object pairs in the Visual Genome (Krishna et al., 2016) which were examined in earlier work (Ghanimifard and Dobnik, 2019). Figure 2

Model Type	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	CIDEr	WMD
CNN+LSTM+LSTM (Ilinykh and Dobnik, 2020)	25.10	13.88	8.11	4.61	11.30	**26.38**	7.61
Multi-Modal Transformer (this paper)	**39.68**	**24.12**	**14.71**	**8.33**	**14.97**	17.54	**8.66**

Table 1: Automatic evaluation of image paragraphs generated by two different model architectures.

shows an example of the ground truth text and generated paragraph. For training, we use train and extra splits, providing us with 4820 image-sequence pairs, while for validation and testing we use 441 and 441 pairs respectively. We use beam search to generate sequences with beam width $bw = 2$. The model is trained with standard cross-entropy loss. The best model's checkpoint is chosen based on the highest CIDEr score (Vedantam et al., 2015) for the test set after training for 100 epochs. As Table 1 shows, our model achieves higher scores across most of the standard automatic metrics compared to the baseline architecture (CNN + LSTM + LSTM). Although our transformer performs slightly worse in terms of CIDEr score, note that different from previous work on multi-sentence image description generation (Krause et al., 2017; Chatterjee and Schwing, 2018; Ilinykh and Dobnik, 2020), we do not restrict the model to generate a specific number of sentences, instead stopping the generation when either the END token is encountered or the maximum number of words has been generated ($W = 150$). In addition, our dataset is much smaller than the Stanford image paragraph dataset (Krause et al., 2017), that the first model has been trained on.

3 Methods and Metrics

We extract the attention weights from both cross-modal attention and masked self-attention. Here, we could examine attention of the model while it is generating a new description or attention of the model receiving a ground truth description using teacher-forcing. Since our task is a validation task where we want to examine the behaviour of the model under fixed conditions we opted for ground truth descriptions. Using generated descriptions could produce identifiable attention patterns but the descriptions are not guaranteed to contain entities and relations that are in the image and we are interested in. If the model has approximated the training data well, then the unseen ground truth descriptions will not be far off from its predictions. Using ground truth descriptions that are not the model's predictions imposes more uncertainty for the model and therefore harsher conditions for evaluation of attention patterns. Identifying interpretable attention patterns under these conditions therefore makes the conclusions stronger.

For every generated word w_i, the attention weight α per head h in each layer ℓ is extracted. In transformers the attention weights are computed as the scaled dot-product of the query matrix Q with all the keys in K followed by a $\mathrm{softmax}$ operation. These weights are focusing on either previously generated words (masked self-attention *MSA*, Equation 1) or image objects (cross-attention *CA*, Equation 2).

$$\alpha_{\ell,h}(w_i \mid w_1, \ldots, w_{i-1}) = \mathrm{softmax}(\frac{Q_{MSA} K_{MSA}^T}{\sqrt{d_k}}) \quad (1)$$

$$\alpha_{\ell,h}(w_i \mid v_1, \ldots, v_N) = \mathrm{softmax}(\frac{Q_{CA} K_{CA}^T}{\sqrt{d_k}}) \quad (2)$$

We inspect how much attention is focused on specific parts of the input sequence when particular parts of the target sequence are generated. We refer to this measure as the **attention focus** or **attention proportion**. In our experiments, we calculate the proportion of total attention from a specific head that is focused on specific parts of the source sequence, e.g. previously generated words or image objects. Attention proportions are generally calculated as follows:

$$\boldsymbol{P}_{\ell,h}(\alpha \mid S, T) = \frac{\sum_{u \in \mathbf{U}} \sum_{i=1}^{|S|} \sum_{t=1}^{|T|} \alpha(s_i, S | t_j, T)}{\sum_{u \in \mathbf{U}} \sum_{i=1}^{|S|} \sum_{t=1}^{|T|} \alpha(s_i, t_j, T)}, \quad (3)$$

where $\boldsymbol{P}_{\ell,h}$ is the attention proportion for a specific head, S and T are the specific conditions imposed on the source and target sequences unique for every experiment (described below), $\mathbf{U}$ is the set of image descriptions sequences, t_j is the text span for either a noun phrase or relation from the target (generated) sequence T, s_i is the particular object or a text span from the source sequence S.

Conditions on $\boldsymbol{P}$ for Q1 For our experiments on visual grounding in cross-modal attention, T limits the target sequence to the text span of a noun phrase, while S defines the ground truth object that this noun phrase depicts. The attention proportion

is calculated by computing the accumulated attention weight from the words in the noun phrase towards the corresponding object and then divided by the overall attention on all objects attended when this noun phrase is generated. We use spaCy (Honnibal et al., 2020) to extract noun phrases from image paragraphs which might introduce some errors, see Appendix A for examples. We skip any phrases which contain at least one word from the list specified in Appendix B. We keep determiners and adjectives in the noun phrases and any numerals if they occur. Some of the paragraphs might contain noun phrases that cannot be grounded in the bounding boxes in the image; either because the bounding boxes are not identified or because the noun phrases refer to abstract concepts. These phrases typically contain words such as "room", "image" or "photo" and are generally placed at the beginning of the description (e.g., "the image is of a kitchen with ..."). In future experiments, we plan to investigate how the model grounds general descriptions of the scene ("the nursery room").

Conditions on P for Q2 For the experiments on word-to-word attention, T is set to the generated word at the specific time-step t_j, while S accumulates attention on words of specified part-of-speech tags when the target word t_j is generated. Ilinykh and Dobnik (2021) show that masked self-attention on text is indirectly affected by vision in the multimodal set-up. Nouns that often describe objects are attended to a greater extent than some other words of specific part-of-speech tag (e.g., verbs) even though this model has never seen the image directly. Interestingly, the same phenomenon is not observed in text-only models such as `distilgpt-2`: its attention is much more local, focusing on the words that surround the target word instead of attending to more distant nouns. This finding suggests that a multi-modal transformer can learn *semantic* differences between words of various part-of-speech tags not just their structural arrangement which would be their syntax. Therefore, we construct two sets of part-of-speech tags, which reflect semantic differences between words in terms of the possibility of their grounding. The first set contains determiners, adjectives and nouns used in descriptions of objects, while the second set includes verbs and adpositions used in descriptions of relations between objects.

Conditions on P for Q3 To examine grounding of spatial relations, both S and T are determined based on the set of static spatial relations extracted from the texts. We extracted $target - relation - landmark$ triplets from each description (there are likely to be multiple relations mentioned in a single image description sequence), based on the annotation schema described in Kolomiyets et al. (2013) and publicly available tool[5]. We obtained 1015 relations of *region* type ("clothes on hangers"), 239 relations of *direction* type ("a gold chandelier above the table"), and 6 relations of *distance* type ("a large vase in the middle of the table"). Each of these relations consists of three spatial elements: a target (*a cup*), a landmark (*a table*) and a relation (*on*) in "a cup on the table". Given that the word order describing relations is typically a $target - relation - landmark$ sequence, the attention proportion for masked self-attention can be extracted only in following directions: $relation \rightarrow target$, $landmark \rightarrow relation$, $landmark \rightarrow target$, and $landmark \rightarrow target + relation$. For example, a possible T could restrict currently generated word to $relation$ (typically expressed with adpositions), while S could limit the calculation of the attention focus to $target$ (expressed as a noun phrase) in case of $relation \rightarrow target$ experiment.

4 Linking Nouns and Objects

To inspect attention heads for visual grounding, we require ground truth annotations of correct linking between image objects and noun phrases. We construct such links automatically using semantic similarity between noun phrases and object labels provided by the object feature extractor. First, we use spaCy (Honnibal et al., 2020) and extract noun phrases on different levels of nesting. For example, a noun chunk "a window with white lace curtains" and the nested chunk "white lace curtains" are identified as two different noun phrases. Potentially, this design choice allows for more accurate linking between noun phrases focusing on different objects ("window" and "curtains") and corresponding fine-grained object detections. In addition, noun phrases with specific details potentially disambiguate linking when multiple objects of the same type are in the image, e.g., several windows. As for object labels, for every detected object in every image, we take the predicted label and its attribute if the extractor's confidence for this attribute is higher

[5] https://github.com/mmxgn/sprl-spacy

Combination Method	*Measure*	*mAP@K*	*Acc*
GloVe Multiply	cos	0.095	13.78
GloVe Add	cos	0.276	41.84
BERTScore	F_1	0.232	41.84
Sentence Transformer	cos	**0.313**	**44.39**

Table 2: Results of the search for the optimal method of linking noun phrases and object descriptions.

than 0.1. We determined this threshold manually allowing a lower degree of confidence to generate a sufficient number of adjectival attributes in order to disambiguate objects, e.g. "a brown chair" vs "a black chair".

Noun phrases and object descriptions typically include multiple words, Therefore, we compute semantic similarity between phrases. We examine several methods for linking noun phrases and object descriptions and compare them against the small subset of image paragraphs with manually annotated linking. Specifically, we randomly sample ten image-text pairs, consisting of 196 detected noun phrases. Then, 158 noun phrases were manually linked with image objects by the first author. The subset of the remaining 38 noun phrases included pronouns and abstract descriptions, too ambiguous to be linked with the specific object in the scene. In addition, we found that some noun phrases describe either a non-detected object or were extracted by mistake. A fraction of noun phrases that were not linked with any object is shown in Appendix A.

Table 2 shows the results of our search for the best linking method. We use GloVe embeddings (Pennington et al., 2014) to represent each word in a phrase and combine them by either element-wise multiplication (*GloVe Multiply*) or addition (*GloVe Add*), inspired by methods for phrase meaning representation (Mitchell and Lapata, 2008). The resulting vectors for a noun phrase and object description were compared based on cosine similarity. For *BERTScore* we follow Zhang et al. (2020) and use contextual word embeddings (Devlin et al., 2019) to represent every word. Words in a noun phrase and object description are then matched against each other by cosine similarity, and the F1 score can be used to examine the similarity. Finally, for *Sentence Transformer* we represent each word with the embedding from Sentence Transformer (Reimers and Gurevych, 2019). This model fine-tunes BERT embeddings for numerous NLI tasks and applies a mean pooling operation to get the fixed-size vector representing embedding of a whole phrase. We report accuracy *Acc* against manual annotations of ten image-text pairs. We also compute mean average precision *mAP@K*, a metric that allows us to see whether a particular combination method generally rates relevant object descriptions more similar to a noun phrase:

$$AP@K = \sum_{k=1}^{m} P_k(R_k - R_{k-1}), \qquad (4)$$

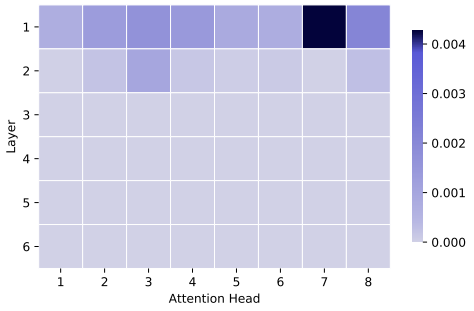
where P_k and R_k are the precision and recall at cut-off k, *m* is the number of noun phrases detected in an image paragraph. K is set to the number of objects (36) since we inspect the linking of noun phrases with the whole set of objects. The final *mAP@K* score is the mean of average precisions for noun phrases in descriptions of images. Our search results for the linking method demonstrate that using embeddings from Sentence Transformer and comparing them for cosine similarity performs the best in terms of both metrics. Interestingly, simply using BERT embeddings and match them for similarity (*BERTScore*) is not enough to achieve a high *mAP@K* score, and this method also performs worse than a simple addition of non-contextualised embeddings (*GloVe Add*). A more complex fusion of information from different words is required to represent a phrase. When examining attention heads for visual grounding of nouns and relations, we thus use the best performing linking method (*Sentence Transformer*). Noun phrases might describe a group of objects in the scene ("six chairs"), corresponding to multiple object detections (several chairs). Labels of such objects are often identical, which makes their cosine similarity scores also identical. Therefore, we link a noun phrase with multiple objects on top of the similarity ranking if they have the same cosine score. Otherwise, a noun phrase is linked with the object that is ranked the highest.

5 Experiments and Results

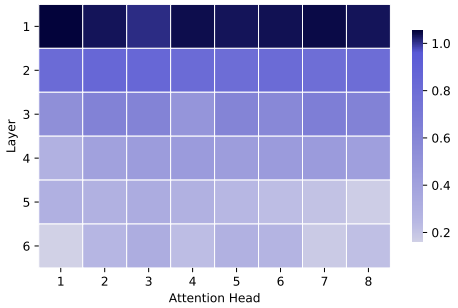
Attention Entropy We compute entropy of the attention weights in both modules for each attention head. Specifically, the entropy E of an attention head h in layer ℓ is defined as follows:

$$E_{\ell,h}(t_j) = -\sum_{i=1}^{|S|} \alpha(s_i, t_j) \log(\alpha(s_i, t_j)) \qquad (5)$$

where s_i and t_j are specific source and target sequence items and α is the attention weight between



(a) MSA entropy



(b) CA entropy

Figure 3: Normalised entropy of attention heads in different layers for masked-self attention (MSA) and cross-attention (CA). The darker the colour, the higher the entropy. All values were normalised by the maximum achievable entropy $-log_2(O)$. Note that the range of values is different between the graphs.

them. As Figure 3 shows, the entropy pattern is similar across both attention modules. Attention heads have lower entropy in deeper layers, focusing more on specific parts of the source sequence. In contrast, surface layers scatter attention across many items (either objects or previously generated words). Intuitively, such progressive increase of attention focus from surface to deeper levels indicate that both modules first learn to generalise over low-level features, gradually moving to capture more specialised, high-level conceptual knowledge (Ullman, 1984). Here, a fair question to ask is *what kind of low-level and high-level knowledge do masked and cross-modal attention learn in different layers with different entropy?*

As Ghader and Monz (2017) show for the task of machine translation, lower attention entropy is mainly observed when looking at nouns and adjectives, while higher entropy is witnessed when attending to adpositions and verbs. This finding demonstrates that attending to nouns in purely textual syntactic dependencies is less complex than focusing on verbs. In the context of our task, adpositions and verbs would be used when generating spatial relations, while objects are described with nouns and adjectives. Learning nouns in a multi-modal setting implies their visual grounding, a more complex task that requires knowledge of the scene. Similarly, in general, understanding spatial relations is a much more sophisticated task for the multi-modal transformer. It requires higher-level semantic knowledge and identification of objects and relations, compared to simple attention on verbs and adpositions as part-of-speech tags in a uni-modal setting. It has also been shown that attention on highly complex phenomena (named entities) would happen in deeper layers of the model, while low-level constructs (determiners) are attended much earlier in the layers of both uni-modal (Vig and Belinkov, 2019), and multi-modal (Ilinykh and Dobnik, 2021) architectures. Therefore, in our experiments, we examine how attention heads in different layers of masked and cross-modal attention capture either **syntactic knowledge** (nouns and relation phrases as words) or **semantic information** (visually grounded nouns and spatial relations).

Visual Grounding in Cross-Attention Here we investigate whether the high focus of cross-attention heads in deeper layers can be attributed to their specialisation in visual grounding of nouns. Specifically, *based on the linking method*, we compute the proportion of attention that radiates from words in a noun phrase towards **corresponding objects** described by this noun phrase. Figure 4 shows the results. We can see that attention heads

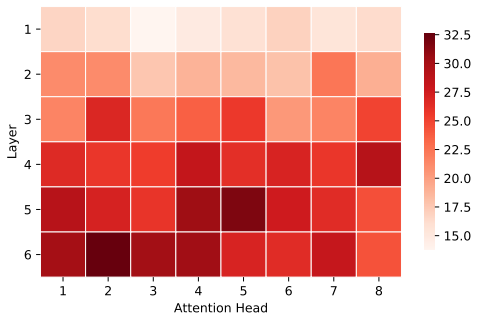
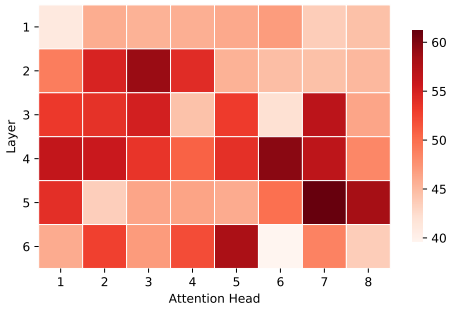
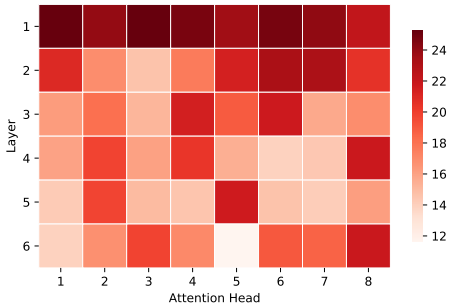


Figure 4: Attention proportions $\boldsymbol{P}$ on correct noun-object pairs (as determined by linking) for each attention head in the cross-modal attention. The darker the colour, the **bigger** the proportion. The proportions are averaged over the noun phrases in descriptions.



(a) $\boldsymbol{P}$ on DET, ADJ, NOUN



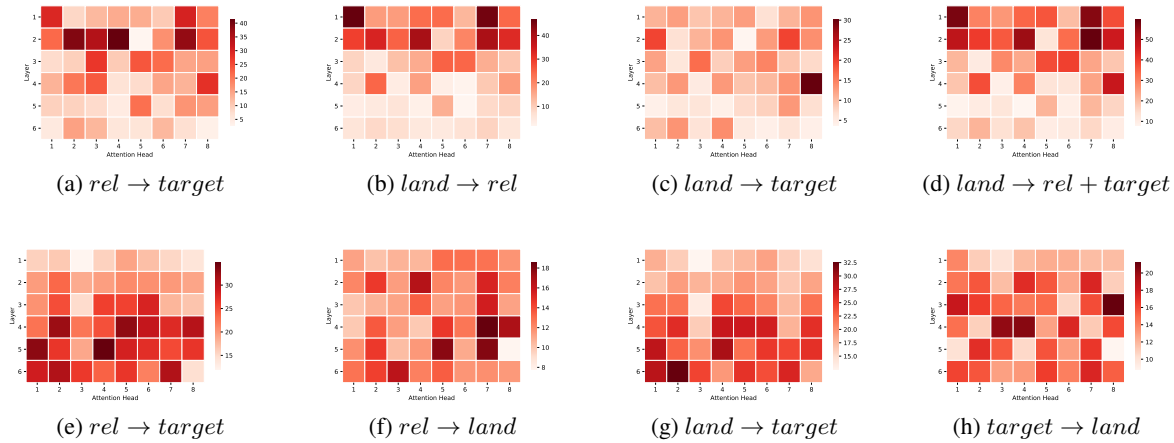
(b) $\boldsymbol{P}$ on VERB, ADP

Figure 5: Attention proportions on words of specific part-of-speech tags for every head in the masked self-attention module. The proportions are averaged over the samples in the test set.

in deeper layers concentrate on linking bounding boxes of detected objects with noun phrases that describe them when these phrases are generated. Specifically, while in the first layer, attention heads pay on average 16% of their attention to the linked objects, in the deeper layers, the average attention focus reaches 29%. The most activated head is the second head in the sixth layer, which places 33% of its attention on connecting noun phrases with the bounding boxes of objects linked with this phrase. These findings show that the model captures complex visually grounded semantics of nouns in deeper layers of cross-attention. In addition, lower entropy observed in these layers (Figure 3b) also indicates that deeper heads are strongly focused and specialised in grounding of nouns.

Masked Self-Attention on Specific Part-of-Speech Tags Figure 5 demonstrates the attention focus on previously generated words of specific POS tags. We separate between tags which either describe objects ⟨DET, ADJ, NOUN⟩ or relations ⟨VERB, ADP⟩. Based on the heat-maps, we can see that previously generated determiners, adjectives and nouns are more attended in all layers except the first one, in which the focus is on relation part-of-speech tags. At the same time, according to Figure 3a, the attention in the first layer is more dispersed, which means that when attending to verbs and adpositions, attention is also looking at other words to a lesser degree, possibly such words which are involved in the action described by the verb. We calculated the Pearson correlation coefficient between both heat-maps in Figure 5. The test has shown a significant negative correlation ($r = -0.71, p = 1.7e-08$), indicating that there is a clear separation in attention focus on two types of words in masked self-attention. Overall, text-to-text attention is able to capture local and non-grounded syntactic knowledge of objects and relations between them.

Masked Self-Attention on Spatial Relations Figures 6a–6d show the attention focus in masked self-attention for several possible directions between parts of the phrase describing spatial relation. For example, $rel \rightarrow target$ shows the attention on the noun phrase describing the target object when a phrase describing relation is generated. Note that in masked self-attention, we are not able to look into the future; thus, we cannot inspect attention on $rel \rightarrow landmark$ or $target \rightarrow landmark$. The first important observation is a clear difference between attention on the word depicting the target object depending on where this attention is coming from. Numerous attention heads in the first layers focus on the target when relation is generated (Figure 6a), while only a few heads are looking at the target when landmark is generated. According to Figure 6b, relation is more important for landmark since it is widely attended by many heads, compared to only a few heads in Figure 6c and only a single head (head 8, layer 4) being highly active. In addition, there are three attention heads in the second layer (2, 3, 4) in Figure 6a, which are also highly activated in Figure 5a. This might indicate that these heads do not simply look at the words depicting objects but specialise in such words, which are playing the part of the "target" object in spatial relations. Therefore, we can identify particular heads that learn knowledge of syntactic dependencies between words describing spatial relations in the textual encoder. Also, based on Figure 6b, we can see that the focus on relation phrases is mostly captured in surface layers, which supports our statement that the model first needs to



(a) $rel \rightarrow target$ (b) $land \rightarrow rel$ (c) $land \rightarrow target$ (d) $land \rightarrow rel + target$

(e) $rel \rightarrow target$ (f) $rel \rightarrow land$ (g) $land \rightarrow target$ (h) $target \rightarrow land$

Figure 6: Heat-map visualisations of $\boldsymbol{P}$ for masked self-attention (**the top row**) and cross-attention (**the bottom row**) for different possible configurations of attention between words constituting spatial relations. All attention proportions are normalised by the number of spatial relations in the test set.

learn general knowledge about existing relations in the scene, later starting to exploit it for better focus on correct target and landmark nouns.

Cross-Attention on Spatial Relations Figures 6e–6h show how much each head looks at the specific object that corresponds to a target or a landmark in spatial relations. Similar to our experiment on visual grounding, we linked every noun phrase describing either a target or a landmark with a bounding box of the detected object by computing semantic similarity between the noun phrase and the label of every object. Note that here we look at how words of *semantic categories* describing relations between objects are grounded in *visual representations* (objects) rather than other words, as in the case of the masked self-attention. One noticeable difference between the top and bottom rows in the Figure 6 is that the attention focus in the cross-modal part of the architecture is much more distributed across heads.

Given that, according to Figure 4, while multimodal grounding of nouns into objects is clearly observed in the deeper parts of the model, grounding of relations in objects is much less interpretable. First, relations cannot be straightforwardly linked to the visual features of objects in a scene. When grounding relations the system needs to rely on several sources of knowledge, both linguistic and visual, and here systems tend to rely on linguistic knowledge more than on visual information (Ghanimifard and Dobnik, 2019). Learning is further complicated by the fusion of information in cross-attention. For example, the model needs to simultaneously rely on the semantic information from the language representations and identify objects that are targets and landmarks in spatial relations. Therefore, cross-modal attention activates several attention heads when trying to learn about spatial relations, which require attention on multiple sources of knowledge.

Interestingly, as Figure 6f and Figure 6h show that attention on landmark in cross-attention is distributed across multiple layers. However, the first layer of $rel \rightarrow land$, which generally has the highest entropy (cf. Figure 3b), is more activated compared to the first layer of the $target \rightarrow land$ attention map. This shows that certain attention heads in the first layer specialise to identify landmarks from relations (Figure 6f), whereas there are less such heads that identify landmarks from targets (Figure 6h). This can be attributed to the fact that the model learns to confidently attend targets only in the deeper layers of the network because targets require much more complex inference. Landmarks are intuitively semantically closer to relations as in descriptions they are used together to identify targets. For example, Dobnik et al. (2018) show that there is a strong asymmetry between knowledge about targets and landmarks. Landmarks are generally much easier to predict, and they contribute less to the perplexity of the model than targets. Intuitively, a speaker would like to describe the target, and they need to find a suitable contextually salient landmark, which then selects an appropriate relation and finally produce a full description including the target. Therefore, it might happen

that the model first distributes its attention between heads in surface and deeper layers to identify landmarks in the context of particular relation, and then learns to strongly map this relation-landmark context with the specific target in deeper layers. This idea is also supported by strongly localised and focused attention on the target object in deeper layers when either a relation or a landmark are generated (Figure 6g and Figure 6e).

Note the differences between attention patterns in Figure 6a and Figure 6e for the $relation \rightarrow target$ direction. Surface layers in masked self-attention, as we have shown, seem to learn local syntactic dependencies between words in the source input (text). This is different from the multi-modal scenario, where deeper layers are much more activated for visual and language inputs. This indicates that spatial relations are much more sophisticated in the language-and-vision context: they need to capture semantic dependencies between words and objects in the scene. Also, the complexity of information might be the reason why $rel \rightarrow target$ attention is much more scattered across many heads in deeper layers in cross-modal attention, compared to more focused attention in specific heads in surface layers for masked self-attention.

6 Conclusion

We have shown that the language model in a multi-modal task captures linguistic phenomena of different kind depending on the source knowledge (text or objects) and semantic type of the output words (noun phrases or spatial relations). Cross-modal attention visually grounds objects and, therefore, semantic dependencies in its deeper layers (addresses **Q1**). Text-only attention learns low-level linguistic phenomena, e.g. local syntactic dependencies (addresses **Q2**). This is also exemplified for target-relation-landmark descriptions which are attended in a sequential order that they appear in the text. We have also shown that there is a difference in a way objects and relations are grounded cross-modally and such grounding is particularly challenging for relations (addresses **Q3**). The grounding of landmarks depends on relations to a greater degree than on targets in both masked and cross-modal self-attentions. This could be attributed to the auto-regressive nature of the image paragraph generation task. However, there are important differences in terms of activations across attention layers for different semantic pairs. Deeper heads in the cross-modal attention tend to be activated more than the surface heads which is the opposite tendency compared to masked self-attention. Overall, our work demonstrates that attention on vision and language captures considerably more diverse linguistic knowledge, *both syntactic and semantic* which is not *linearly aligned*, compared to uni-modal (language only) architectures.

One possible follow-up experiment is to use attention as input to the probing classifier and identify a specific knowledge encoded by the weights. However, the performance of the probing model does not tell us whether the original model utilises acquired knowledge since it is *detached* from the original architecture (Belinkov, 2022). Although attention is not necessarily an explanation (Jain and Wallace, 2019), inferring linguistic properties from attention weights does not require learning a new set of parameters. Other methods include fine-grained analysis of features preferred by specific neurons in the model architecture by examining their maximum activation values (Rethmeier et al., 2020). This method would identify the neurons that are active at each step of generation, but would not straightforwardly tell us how words and objects are linked together, which is clearly expressed in attention. Our results indicate that the way relations are grounded in a transformer model is not completely transparent. Future research should focus on examining the effect of different feature representations that are relevant for spatial relations (e.g., RGB-D and different models of geometry, common sense knowledge about objects' affordances) as well as the models that can be built around them. In another follow-up study we could examine grounding of relations in a different task, for example in vision-and-language navigation (Anderson et al., 2018b) which is rich with descriptions of relations between objects and compare whether the same observations also hold for those models.

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A Appendix A

Pronouns such as `it` and `his` were not linked with any object in the scene. Noun phrases depicting spatial descriptions or locations were also ignored, e.g. `the right`, `the background`, `the corner`. Some noun phrases are describing properties of objects in the scene (e.g., `color`, `the overall color of the room`) or positional arrangement (`a straight line` in `three paintings hang in a straight line`). Other noun phrases describe

a general understanding of the image, and not a single bounding box could cover it (`a beachside hotel` in `a room that looks like inside a beachside hotel`). Some noun phrases were incorrect either due to an error made by spaCy or human producing the original description, e.g. `the walls floor sofa`.

B Appendix B

When extracting noun phrases for the experiment on visual grounding we ignore all pronouns and spatial phrases found on this list: `right`, `a right`, `the right`, `left`, `a left`, `the left`, `top`, `the top`, `bottom`, `the bottom`, `back`, `the back`, `front`, `the front`, `far`, `the far`, `close`, `the close`, `side`, `each side`, `background`, `the background`, `foreground`, `the foreground`, `middle`, `the middle`, `corner`, `a corner`, `the corner`.