What Vision-Language Models ‘See’ when they See Scenes

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Abstract
Images can be described in terms of the objects they contain, or in terms of the types of scene or place that they instantiate. In this paper we address to what extent pretrained Vision and Language models can learn to align descriptions of both types with images. We compare 3 state-of-the-art models, VisualBERT, LXMERT and CLIP. We find that (i) V&L models are susceptible to stylistic biases acquired during pretraining; (ii) only CLIP performs consistently well on both object- and scene-level descriptions. A follow-up ablation study shows that CLIP uses object-level information in the visual modality to align with scene-level textual descriptions.

1 Introduction
Grounding symbols in perception (Harnad, 1990) is a crucial step towards achieving full understanding of natural language (Bender and Koller, 2020; Bisk et al., 2020). This endeavour has received new impetus through the development of pretrained Vision and Language (V&L) models (e.g. Lu et al., 2019; Tan and Bansal, 2019; Li et al., 2019; Chen et al., 2020; Li et al., 2020a; Luo et al., 2020; Su et al., 2020; Wang et al., 2020; Luo et al., 2020; Li et al., 2021; Huang et al., 2021; Radford et al., 2021). Similarly to unimodal language models such as BERT (Devlin et al., 2019), V&L models are intended to be task-agnostic and are extensively pretrained on paired image-text data, achieving good performance on several tasks after finetuning (e.g. Lu et al., 2020; Li et al., 2020c; Kim et al., 2021). Pretraining usually includes an image-text alignment task to discover implicit cross-modal relationships. Although the importance of this task is widely recognized and adopted during model pretraining, it is unclear how the models perform on it, since they are usually evaluated on downstream tasks.

The data used for V&L pretraining usually contains highly descriptive text which mentions objects and their spatial relationships. For instance, the COCO (Chen et al., 2015) and Localized Narratives (LN; Pont-Tuset et al., 2019) captions for Figure 1 are of this type, though they differ stylistically. By contrast, the third caption in the figure, from the novel HL1K dataset introduced in Section 3 below, is what we refer to as ‘scene-level’, focusing on what type of scene or location is depicted. Note that both the object- and scene-level descriptions in the Figure describe the picture, albeit in different ways. Indeed, it would be expected that, for a V&L model to display true grounding capabilities, it should be able to identify both types of descriptions as true of a scene. For models which do display this capability, a natural follow-up question is whether their representations capture interesting connections between scenes on the one hand, and the objects within them on the other.

Research on human perception suggests that humans do not perceive scenes exclusively in terms of the objects they contain, and that visual salience is not exclusively determined by bottom-up features such as colour and texture. Rather, visual stimuli are considered ‘scenes’ because their elements con-
stitute a meaningful whole, both in terms of their contents (e.g. one expects an oven in a kitchen, but not in a living room) and in terms of their spatial arrangement (e.g. ovens do not typically hang from the ceiling) (Malcolm et al., 2016). These observations gave impetus to work showing that violations of scene ‘semantics’ (content) and ‘syntax’ (spatial arrangement) exact a cognitive cost during perception (e.g. Biederman et al., 1982; Võ and Wolfe, 2013). A related strand of modeling research in computer vision has also shown that scene-level priors generate expectations about objects and their configurations, impacting the salience of objects in a way that classical, feature-based models of attention (e.g. Itti and Koch, 2001) would not predict (Torralba et al., 2006; Oliva and Torralba, 2007). Indeed, the problem of linking low-level features with high-level semantic information is an instance of the problem referred to as the ‘semantic gap’ in computer vision (Ma et al., 2010).

In this paper we investigate whether V&L models are able to handle object-level and scene-level descriptions equally well. A positive answer to this question would suggest that such models are learning useful associations between the elements of a scene and the overall scene type, as captured in the textual descriptions.

We perform an analysis in a zero-shot setting on three state-of-the-art pretrained Vision and Language models. To our knowledge, this is the first systematic comparison of model capabilities on object- versus scene-level grounding. The goal of this study is therefore not to establish new SOTA results, but to further our understanding of what V&L models learn, as a function of the data they are pre-trained on and the model architecture. Therefore we choose three models differing in many settings, (including training set size, architecture, number of parameters and model size). All of the models are however optimized on the image-sentence alignment task.

We find that only one of the models under comparison, CLIP (Radford et al., 2021), performs consistently well on both object- and scene-level image-text matching. We then investigate this model’s abilities in depth, using an ablation method to identify the elements of a text and/or an image which contribute to these abilities.

| Model | Training size (# image-sentence pairs) | Model size (# parameters) | Pretraining Objectives |
|-------|---------------------------------------|---------------------------|------------------------|
| CLIP  | 400M                                  | 151M                      | ISA                    |
| VisualBERT | 330k                                | 112M                      | ISA, MLM               |
| LXMert | 9.18M                                 | 228M                      | ISA, MLM MOP, VQA      |

Table 1: Comparison of training settings for the three models (ISA: Image-Sentence Alignment, MLM: Masked Language Modeling, MOP: Masked Object Prediction, VQA: Visual Question Answering)

2 Models

Current V&L models typically combine textual and visual features in a single or a dual-stream architecture. Though the two architectures have been found to perform roughly at par Bugliarello et al. (2020), in this paper we include representatives of both. We also include a third model which differs in structure and is trained on a much larger and more varied dataset. Table 1 gives an overview of some of the properties of the models we consider.

LXMERT (Tan and Bansal, 2019) is a dual-stream model, which encodes text and visual features in parallel, combining them using cross-modal layers. LXMERT is trained on COCO captions (Chen et al., 2015) as well as a variety of VQA datasets, with an image-text alignment objective, among others.

VisualBERT (Li et al., 2019) is a single-stream, multimodal version of BERT (Devlin et al., 2019), with a Transformer stack to encode image regions and linguistic features and align them via self-attention. It is pretrained on COCO captions (Chen et al., 2015). Image-text alignment is conceived as an extension of the next-sentence prediction task in unimodal BERT. Thus, VisualBERT expects an image and a correct caption, together with a second caption, with the goal of determining whether the second caption matches the ⟨image, correct caption⟩ pair.

CLIP (Radford et al., 2021) combines a transformer encoder for text with an image encoder based on Visual Transformer (Dosovitskiy et al., 2020), jointly trained using contrastive learning to maximise scores for aligned image-text pairs. CLIP is trained on around 400M pairs sourced from the Internet, a strategy similar to the web-scale training approach used for unimodal models such as GPT-3 (Brown et al., 2020). We note that the visual backbone for this model differs from that of LXMERT.
and VisualBERT, both of which use Faster-RCNN (Ren et al., 2015).

3 Data

We use four different datasets for our experiments. Dataset statistics are provided in the Appendix.

**Localized Narratives** Localized Narratives (LN) Pont-Tuset et al. (2019) is a V&L dataset harvested by transcribing speech from annotators who were instructed to give object-by-object descriptions as they moved a mouse over image regions. LN captions tend to be highly detailed and stylistically similar to speech. We use LN as a source of object-level captions. The images in LN come from preexisting datasets; this allows us to align LN captions with images and captions from datasets such as COCO and ADE20K.

**ADE20K** ADE20K (Zhou et al., 2017) is a computer vision dataset containing 20k images comprehensively annotated with objects, parts and scene labels. We use ADE20K as a source of scene-level captions. For our experiments, we filter out images with scenes which in the dataset are labelled as unknown. We produce captions for each image using a simple template-based generation method (see Appendix). We align ADE20K images and their scene-level descriptions, to the corresponding object-level captions in LN.

**COCO** COCO (Lin et al., 2014) consists of images paired with captions and object annotations. LN captions are also available for the same images. We use images and captions from the 2017 COCO validation split, as well as the corresponding LN captions.

**HL1K** High Level Scenes - 1k (HL1K) is a new dataset and part of an ongoing data collection effort. HL1K is composed of 1k images, each depicting at least one person, sampled from the 2014 COCO train split. We crowd-sourced three annotations per image on Amazon Mechanical Turk, showing crowd workers the image and asking them to write a description in response to the question Where is the picture taken? It was made clear to annotators that the answer to this question should bring to bear their knowledge of typical, or common, scenes. Descriptions were corrected for typos using the Neuspell Toolkit (Jayanthi et al., 2020). Finally, we paired our scene-level HL1K captions with the previously available COCO and LN object-level captions. Figure 1 is an example; further examples are provided in the Appendix.

4 Experiments

We first test models in the image-text alignment task on both object- and scene-level descriptions. We then delve more deeply into the performance of the best model, using an ablation task. Since we are interested in the capabilities of the pretrained models, we do not finetune them.

4.1 Image-sentence alignment

For the image-text alignment task, we use the models’ pretrained alignment head to predict whether a scene-level or object-level caption correctly describes an image, or not. Table 2 shows that LXMERT and VisualBERT perform adequately on object-level COCO Captions, though performance is lower than expected given that they were pretrained on this dataset. In the case of LXMERT, one possible explanation is catastrophic forgetting, arising from the fact that this model is pretrained for its final ten epochs on VQA (similar observations are made by Parcabalescu et al., 2021). For both models, performance drops dramatically on LN captions. This is likely due to a stylistic difference: LN captions are longer than COCO, more discursive and contain disfluencies. In contrast, CLIP performs close to ceiling on all three datasets, possibly reflecting the benefits accrued from the size and diversity of its pretraining data.

|                | LXMERT | CLIP | VisualBERT |
|----------------|--------|------|------------|
| Object         |        |      |            |
| ADE20k + LN    | 28.4   | **96.8** | 39.0       |
| COCO + LN      | 59.1   | **98.7** | 65.2       |
| COCO Cap.      | 79.3   | **99.1** | 64.4       |
| Scene          |        |      |            |
| ADE20k         | 58.0   | **97.6** | 17.3       |
| HL1K           | 45.5   | **91.5** | 55.3       |

Table 2: Image-sentence alignment accuracies on object-level and scene-level captions. Chance performance is at 50%. (LN = Localized Narratives)

On scene-level captions, performance is somewhat above chance for LXMERT on ADE20k template-based descriptions, and for VisualBERT on HL1K. Otherwise, performance is below 50% for both models. Once again, CLIP performs above 90%, though there is a drop in performance from the template-based ADE20k descriptions to human-authored HL1K scene-level captions, possibly due to the stylistic difference between the datasets.

1Note that this setting is the same used by the models is their pretraining.
to the more predictable nature of the former.

4.2 Ablation experiments on CLIP

Since CLIP is the only one of the three models which is successful at matching scene-level and object-level captions to images, we probe its capabilities further, paying particular attention to the question whether CLIP links scene types (e.g. kitchen) to scene contents (e.g. oven, pizza) in image-text matching.

Whereas a standard image-text alignment setup compares the model’s success at identifying actual versus random captions, here we directly compare the preference of the model for scene- versus object-level descriptions, as a function of (i) the entities mentioned in the object-level caption; (ii) the entities visible in an image. To this end, we use textual and visual ablation, described below (see Appendix for further examples and details).

Textual ablation A textual ablation is performed by removing noun phrases (NPs) in the object-level caption. For example, for the COCO caption in Figure 1, one ablated version would remove the NP a baseball player resulting in getting ready to swing at a baseball game . . . . For a given image $i$ with object-level caption $o$ and scene-level caption $s$, we compare how $P(o|i)$ – CLIP’s estimate of the probability that $o$ matches $i$ – changes as NPs are removed from $o$, and to what extent this causes CLIP to assign higher probability $P(s|i)$, to $s$ as the match for $i$. We report two comparisons, one on LN captions versus ADE20K scene template descriptions; and one on COCO captions against HL1K scene-level descriptions.

To control for possible loss of grammaticality after ablation, we score ablated captions with GRUEN (Zhu and Bhat, 2020), a BERT-based model which has been shown to yield scores that correlate highly with human judgments. CLIP probabilities for ablated textual captions yielded a very low correlation with grammaticality (Pearson’s $r = 0.1, p < .01$) suggesting that grammaticality did not affect the scores.

Visual ablation Given an image, we detect the bounding regions of entities which are also mentioned in the corresponding object-level caption, and occlude them with a greyscale mask. Once again, we are interested in whether CLIP’s estimate of the alignment probability of object- versus scene-level captions, changes as elements of the visual input are masked.

Vision vs text Without ablation, the model assigns higher probability to object-level descriptions, suggesting that CLIP assigns higher confidence to an image-text pair when the text focuses on objects. This preference is far more marked for COCO/HL1K, in line with the observation (Table 2) that HL1K scene descriptions are somewhat more challenging for this model. As entity-level information is removed from the object-level caption (row T), the model’s preference swings to the scene-level caption, suggesting that the model leverages the visual information to align with the scene description. Visual ablation (V), by contrast, results in the opposite tendency: when entities are occluded in the image, the model shows greater preference for object-level captions. This suggests that the way CLIP ‘understands’ scene-level descriptions depends on which entities are visible. If both sources of information are ablated (V+T), the preference once again veers towards object-level captions.

Scenes vs. entities These findings suggest that CLIP reasons about scenes on the basis of salient objects within them. To investigate this further, we use scene labels extracted from the HL1K captions and the object detections produced for the visual ablation. For a scene label $s$ and entity label $e$, we compute $P(s|e)$. Details of this computation are given in the Appendix. For example, Table 4 shows the most likely entities in park scenes. For all images with at least three detected entities, we consider the image-sentence alignment probability assigned by CLIP to the scene-level description, when the top 1, 2 or 3 most likely entities in the

|          | ADE20k |       | HL1K |       |
|----------|--------|-------|------|-------|
|          | LN     | Scene | COCO | Scene |
| No ablation | 55.6   | 44.4  | 95.7 | 4.3   |
| T        | 22.0   | 78.0  | 67.2 | 32.8  |
| V        | 74.9   | 25.1  | 71.2 | 28.8  |
| V+T      | 68.4   | 31.6  | 63.3 | 36.7  |

Table 3: Preference expressed in percentage for object-level versus scene-level (sub-columns), where there is no ablation, T(ex) textual ablation, V(visual) ablation, or both (V+T) for a each dataset (columns).
scene are masked. Figure 2 displays a linear trend, with the probability assigned by CLIP to the scene-level description dropping as more likely entities are removed.\textsuperscript{3} Thus, when CLIP aligns images with scenes, it is relying on object-level information in the visual modality. This explains why the removal of object mentions in text results in higher preference for scene-level descriptions, since the objects are detectable in the image. By the same token, masking objects in images causes the model to rely more on the entity-level information in the text.

\textbf{Single word comparison} So far, our analysis suggests that CLIP reasons about scenes based on object-level information. However, the length of the caption might be a possible confounding factor. Some of our results might simply be due to the model assigning a higher alignment probability to a caption which is longer or more informative. This would be an alternative explanation for the changes observed above in the alignment probabilities after textual ablation. To account for this, we replicate the alignment experiment using single words. We use the scene labels extracted from HL1K scene-level descriptions and identify the top three most likely entities in a given scene, as identified in the previous experiment (see Figure 2). Given an image, we compare image-text alignment probabilities in CLIP for single-word object labels (e.g. \textit{motorbike}) and single-word scene labels (e.g. \textit{road}).

In this setting, CLIP displays a moderate preference for scene labels (63%), suggesting that such labels are more informative than object-level labels, for the one-word alignment task. Moreover, a qualitative analysis shows that CLIP prefers object labels when the images have strongly foregrounded entities with little background visibility, as shown in Fig 3.

\section{Related work}

Large, pretrained models are often analysed via probe tasks or through an investigation of their attention heads (see Belinkov and Glass, 2019, for a survey). For example, Li et al. (2020b) consider VisualBERT’s attention heads in a manner similar to Clark et al. (2019), showing that it is able to ground entities and syntactic relations (see also Ilharco et al., 2020; Dahlgren Lindström et al., 2020). Hendricks and Nematzadeh (2021) similarly seek to obtain an in-depth understanding of the representations learned by V&L models, finding that they

\begin{table}[h]
\centering
\begin{tabular}{ |l|c| }
\hline
\textbf{ENTITY} & \textbf{$P(s|e)$} \\
\hline
skateboard & 0.28 \\
bench & 0.22 \\
frisbee & 0.11 \\
kite & 0.11 \\
orange & 0.11 \\
umbrella & 0.09 \\
person & 0.07 \\
\hline
\end{tabular}
\caption{Top entities in park scenes.}
\end{table}

\textsuperscript{3}A one-way ANOVA comparing the change in log probability as 1, 2 or 3 entities are removed showed that the difference is significant ($F(2, 156) = 4.25, p < 0.05$).
fail to ground verbs in visual data, compared to other morphosyntactic categories.

The ability of V&L models to reason with a combination of linguistic and visual cues is explored through tasks such as VCR (Zellers et al., 2019), SWAG (Zellers et al., 2018) and NLVR (Suhr et al., 2017, 2019). Pezzelle et al. (2020), in work complementary to our own, address the relationship between visual and textual modalities, exploring a task in which the text does not provide an object-level description of an image. In work presented concurrently with our own, Frank et al. (2021) propose an ablation-based methodology to evaluate the extent to which multimodal models rely on visual and/or textual information to perform grounding.

Although scene recognition is a central task in computer vision, there has been little work exploring the capabilities of models to link scene- and object-level representations. Some precedent for the concerns addressed in this paper are found in the image captioning literature. For example, an influential proposal by (Anderson et al., 2018) combines top-down and bottom-up attention to improve the quality of image descriptions, while CapWAP (Fisch et al., 2020) conditions image captioning on questions that determine which information is relevant to current communicative needs, going beyond object-level description. Closer to the scope of the work presented here, a recent pretrained V&L model, SemVLP (Li et al., 2021), combines single- and dual-streams for feature-level and high-level semantic alignment. We plan to investigate this model further in future work.

6 Conclusions

Grounding language in vision requires V&L models to capture the relation between ‘high-level’ characterisations of scenes and the entities they contain. The experiments in this paper suggest that when models do this, they rely on object-level information in the visual modality, to link images to scene descriptions in the textual modality. This is partly dependent on the probability of entities occurring in scenes.

However, this is not an ability that all models have: LXMERT and VisualBERT perform poorly on scene-level descriptions and also on object-level captions which are stylistically different from the ones they were pretrained on, whereas CLIP handles both object- and scene-level captions. We note that for LXMERT and VisualBERT, testing on ADE20k, Localized Narratives and HL1K amounts to a zero-shot setting. With the exception of HL1K, a new dataset, it is an open question whether this is true of CLIP. Since this model is trained on web-scale data, it is difficult to ascertain that the training and test data in our experiments are disjoint; as Bender et al. (2021) recently argued, with such pre-training strategies, training data is often unfaithful. On the other hand, our findings also show that, at least as far as object and scene-level grounding is concerned, model size is not a determining factor. As shown in Table 1, CLIP is smaller in terms of number of parameters than LXMERT.

Apart from the sheer volume of pre-training data used in CLIP, we believe that two additional factors contribute to its success. First, its contrastive learning objective may result in greater sensitivity to fine-grained distinctions between captions, when the model computes the likelihood with which a text matches a given image. A second important feature of CLIP is its visual backbone, which (in the version used in this paper) is based on Visual Transformer (ViT Dosovitskiy et al., 2020). By contrast, the visual component in LXMERT and VisualBERT is CNN-based. Recent work by Tuli et al. (2021) has shown that the attention-based ViT architecture may be more consistent with characteristics of human vision than a convolutional network. This could partially underlie the model’s ability to use object-level information in an image to align to scene-level captions. The extent to which the visual backbone of V&L models impacts their grounding capabilities is a topic that should be further explored.

7 Ethical considerations

For the studies presented here, we used a new dataset, HL1K, collected using the Amazon Mechanical Turk crowdsourcing platform. For the data collection, participants were shown images and asked to answer questions such as *Where is the picture taken?* Answers took the form of short statements. Workers were paid at the rate of €0.03 per item, an amount we consider equitable for the work involved, and in line with rates for similar tasks. No sensitive or identifying information was collected. All other data and models used are publicly available. The HL1K dataset will be made available upon publication.
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A Dataset details

Table 5 gives the sizes of the ADE20k, HL1K and COCO datasets. For ADE20k, the numbers are for images which are not labelled as having an unknown scene. For COCO captions, there are five captions associated with each image. For the purposes of the present study, a single caption is randomly selected for each.

|                      | ADE20k | HL1K | COCO |
|----------------------|--------|------|------|
| images               | 19733  | 1000 | 5000 |
| COCO captions        | 19733  | 3000 | 5000 |
| Localized Narratives  | 19733  | 1000 | 5000 |

Table 5: Datasets sizes

Table 6 provides the number of ablations analysed in the study. For both ADE20k and HL1k we obtain a number of ablated captions which is greater than the respective dataset sizes in Table 5, because for each example we generate all the possible combinations of noun phrases. For the Visual and Visual+Textual ablations, the number of ablated instances is lower than the dataset size, because we skip all the images where no object is detected.

|          | ADE20k | HL1K |
|----------|--------|------|
| T        | 205k   | 10027|
| V        | 10788  | 625  |
| T+V      | 1078   | 625  |

Table 6: Total number of ablations generated per dataset, across all the ablations experiments

A.1 Scene description templates

ADE20K scene labels are converted to textual descriptions using three different templates:

- it is a SCENE
- this is a SCENE
- it is located in SCENE

A scene label is rendered into a description using a randomly selected template from the above. For example:

- bathroom -> it is a bathroom
- bedroom -> this is a bedroom
- airport -> it is located in an airport

A.2 HL1K Examples

HL1K is collected by asking crowd workers to consider an image, and answer the question Where is the picture taken? Crowd workers are asked to respond using full sentences, as far as possible. Since images are selected from the COCO 2014 train split, they are also accompanied by their object-level COCO captions and Localized Narratives. An example image with corresponding HL1K scene-level descriptions is shown below.

Where is the picture taken?

- in a bedroom
- the picture is taken in a bedroom
- this is the bedroom

Figure 4: COCO image with corresponding scene descriptions in HL1K

B Experiment details

B.1 Image-sentence alignment

Results for image-sentence alignment experiments in the paper are averages over three separate runs for each model.

For LXMERT, we use the image-sentence alignment head.\(^4\) CLIP and LXMERT are tested on the standard alignment task: given an image and either the correct caption, or a random caption, the model needs to determine whether the caption correctly aligns with the image.

We use the publicly available implementation of VisualBERT.\(^5\) The image-sentence alignment setting for this model is somewhat different, since alignment is modelled as an extension of the next-sentence prediction task in unimodal BERT. VisualBERT takes an image and a correct caption.

\(^4\)github.com/huggingface/transformers
\(^5\)https://github.com/uclanlp/visualbert
together with a second caption, which may be correct or randomly selected. The task is to predict whether the second caption correctly aligns with the image+caption pair.

For all experiments, we truncate textual captions to a maximum length of 50 tokens, following standard practice for such models, including CLIP.

B.2 Ablation

Ablation is performed on object-level captions, and on images. Results for ablation are reported based on a single run of CLIP. Figure 5 shows an original image and its object-level caption, together with the visual and textual ablations. Below, we explain the process of ablation in more detail.

Textual ablation Given an object-level caption, we identify all the NPs in the caption and create new versions by removing each possible subset of the set of NPs, with the restriction that the resulting caption must always contain at least one NP. When NP removal results in dangling predicates, we remove them to preserve grammaticality. NPs are detected using Spacy v.3 pipeline for English using the *en_core_web_md* pretrained models.

Visual ablation Given an object-level caption and an image, we extract all nouns from the caption and extract the embedding vector for each noun using the pretrained FastText embeddings.6 We pass the image through the Faster-RCNN object detector7 to detect entities. We extract embeddings for each entity label. Then, we identify regions to be masked by comparing embeddings for entity labels \( l_e \) against embeddings for nouns \( n_e \) in the caption, considering them a match if \( \text{cosine}(l_e, n_e) \geq 0.7 \). Bounding box regions corresponding to matched entities are occluded with a greyscale mask.

C Scene-entity probabilities

Entity probabilities are computed on the basis of the entities detected in the image and object-level caption, using the process described above for visual ablation. Let \( e \) be an entity detected \( n_e \) times in the dataset, of which \( n_{e,s} \) times in images depicting scene \( s \). We compute:

\[
P(s|e) = \frac{n_{e,s}}{n_e}
\]

6We use the model with 2m word vectors trained with subword information from common Crawl [https://fasttext.cc/docs/en/english-vectors.html](https://fasttext.cc/docs/en/english-vectors.html)

7Faster R-CNN ResNet-50 FPN pre-trained on COCO, available from the torchvision module in Pytorch

Figure 5: The original image at the top, in the middle the visually ablated imaged and at the bottom the original caption and all the cases generated by the constituent textual ablation.

Figure 6 shows visualisations for entities detected in four different scene types, from the HL1K
Figure 6: Visualisations of entities in four different scene types. For a given entity $e$ in scene $s$, font size is proportional to $P(s|e)$.

dataset. To compute the mean probabilities assigned by CLIP to scene-level descriptions after entities are visually ablated, we average over those images containing at least three detected entities (53/174 total scenes).