Exploiting Commonsense Knowledge about Objects for Visual Activity Recognition

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Abstract

Situation recognition is the task of recognizing the activity depicted in an image, including the people and objects involved. Previous models for this task typically train a classifier to identify the activity using a backbone image feature extractor. We propose that commonsense knowledge about the objects depicted in an image can also be a valuable source of information for activity identification. Previous NLP research has argued that knowledge about the prototypical functions of physical objects is important for language understanding, and NLP techniques have been developed to acquire this knowledge. Our work investigates whether this prototypical function knowledge can also be beneficial for visual situation recognition. We build a framework that incorporates this type of commonsense knowledge in a transformer-based model that is trained to predict the action verb for situation recognition. Our experimental results show that adding prototypical function knowledge about physical objects does improve performance for the visual activity recognition task.

1 Introduction

Physical objects play an important role in our daily lives. People use different tools to achieve different goals in all kinds of situations. For example, we use a toothbrush to clean our teeth, a microwave oven to heat food, and a camera to take photos. The functions of physical objects is a type of commonsense knowledge that has been recognized to play an important role in natural language processing (Burstein, 1979; Jiang and Riloff, 2021).

Physical objects play an important role in computer vision as well. There are well-established computer vision tasks that aim to identify the objects in an image, such as object detection (Lin et al., 2014) and image classification (Deng et al., 2009; Krizhevsky, 2009). Recently, attention has been paid to more comprehensive image understanding, such as identifying the salient event depicted in an image as well as relevant people and objects. Situation recognition (Yatskar et al., 2016) is the task of producing a structured summary of an image that describes the main activity and the entities that fill semantic roles for that activity. The task was originally defined using frame structures from FrameNet (Baker et al., 1998; Ruppenhofer et al., 2016) as the activity representation. For example, given the image shown in Figure 1, a system should identify a baking event (which is indexed in FrameNet as a type of Cooking_creation activity), and recognize the corresponding semantic role/value pairs associated with FrameNet’s Cooking_creation frame. Models for this task usually follow a two-step pipeline: (1) predict a verb that describes the activity depicted in the image, and (2) identify the entities associated with each semantic role. Previous systems have relied solely on features extracted from the image and have not yet exploited any external commonsense knowledge.

Our work focuses on the activity recognition (verb prediction) part of the situation recognition task. We hypothesize that (a) correctly identifying the activity in an image strongly depends on recognizing the objects that appear in the image, and (b) explicit commonsense knowledge about physical objects can also be beneficial. More specifically, our work is motivated by recent research emphasizing the importance of commonsense knowledge...
about the prototypical functions of physical objects for language understanding (Jiang and Riloff, 2021, 2022). An intuitive extension to visual reasoning is that if an object appears in an image, especially when it is used by a person, the activity depicted in the image is likely to be the prototypical function associated with the object. For example, a woman holding a comb is probably brushing her hair, and a man holding a cookie sheet (as shown in Figure 1) is probably baking.

We explore these hypotheses by creating a transformer-based model that incorporates commonsense knowledge about the prototypical functions of physical objects for visual activity recognition. Our experimental results confirm that correctly identifying the objects in an image is very important for activity recognition, and we show that providing explicit knowledge about the prototypical functions of objects can improve performance for this task.

2 Related Work

Commonsense knowledge about physical objects has long been recognized to be important for natural language understanding (Burstein, 1979). Within the NLP community, a variety of recent projects have focused on acquiring and using different types of knowledge about physical objects, including relative physical knowledge (Forbes and Choi, 2017), relative spatial relations (Collell et al., 2018), semantic plausibility (Wang et al., 2018), object affordances (Persiani and Hellström, 2019), and object usage status (Jiang and Riloff, 2022). The work most relevant to our research is Jiang and Riloff (2021), which developed a NLP method to learn the most typical way that people use human-made physical artifacts. They used FrameNet frames as a representation for object functions and they created a dataset of physical objects paired with their prototypical function frames to evaluate their results. Our research incorporates their prototypical function data into a transformer-based model for visual activity recognition.

Visual reasoning tasks, such as visual question answering (Antol et al., 2015) and image captioning (Young et al., 2014), have been widely explored for understanding images and videos. Previous work has proposed to use external knowledge for visual tasks, such as image classification (Marino et al., 2017), object detection (Singh et al., 2018), and visual question answering (Wu et al., 2016).

Situation recognition is a task of recognizing the activity depicted in an image, including the people and objects involved in the activity and the roles these participants play. Yatskar et al. (2016) introduced the imSitu dataset, which associates images with a verb that describes the main action, and a set of semantic roles derived from FrameNet (Ruppenhofer et al., 2016). They tackled this problem by first applying the VGG network (Simonyan and Zisserman, 2014) to extract features from the image and then building a CRF model to jointly predict the verb and semantic roles. Several research efforts have further explored this task. Suhail and Sigal (2019) used a graph neural network to capture the relations between semantic roles. Pratt et al. (2020) used an LSTM to jointly classify verbs and semantic roles. Cooray et al. (2020) cast situation recognition as a query-based visual reasoning problem and further handled inter-dependencies between queries to overcome the sparsity issues of semantic roles. Recently, Cho et al. (2022) proposed a collaborative framework using two transformer modules, and Li et al. (2022) used contrastive learning to distinguish the correct activities from negative examples. All of these prior efforts have relied solely on features extracted directly from the image. Our work aims to show that explicitly providing commonsense knowledge about objects can also be beneficial for visual activity recognition.

3 Methods

Given an image, the visual activity recognition task predicts a verb that describes the main activity in the image. Figure 2 shows the framework of our model called ARF (Activity Recognition with Functions), which takes 3 sources of input: 1) the image, 2) nouns corresponding to the objects in the image, and 3) the names of FrameNet frames that describe the prototypical functions of the objects. We use the CLIP (Radford et al., 2021) model, which has been pre-trained on both images and text, to generate an encoding for each of the 3 types of input. Finally, we give the concatenated representation vectors as input to a transformer model that is trained to predict a verb for activity recognition.

3.1 Notation

The task can be denoted as given the $i$th image $I_i$ ($i = 1...n$), the system should predict the correct activity verb $v_i^*$. The score for the $j$th candidate
verb being the activity for image $I_i$ is defined as:

$$
\Pr(v_j^i | I_i) = \frac{\exp(g(I_i, v_j^i))}{\sum_{k=1}^m \exp(g(I_i, v_k^i))}
$$

(1)

where $g(\cdot)$ is a function produced by our model for scoring the assignment of a verb to the image, and $m$ is the total number of candidate verbs. We use negative log likelihood as our loss function:

$$
\mathcal{L} = -\sum_{i=1}^n \log \Pr(v_i^* | I_i)
$$

(2)

### 3.2 Object Recognition

Ideally, we would use an Object Detector to identify the objects in an image for our experiments. However, the object detectors that are most readily available use categories that do not cover the range of object types that we need. For example, object detection datasets often contain a number of animate objects such as people and animals. As an alternative, we turned to image captioning systems. For our first set of experiments, we used a state-of-the-art image captioning model called OFA (Wang et al., 2022) to generate 10 different sentences that describe the image. We set beam size 10 and diversity 10. We then extracted the nouns from these sentences to create a set of words that (hopefully) include the objects.

However, even though the image captioning system often generated reasonable captions, the most relevant objects were frequently omitted from the caption, or misidentified.\footnote{One likely reason is that the images are in low resolution and many objects are small, such as a pencil.} Since the goal of our research is to determine whether adding explicit knowledge about an object improves performance, we cannot truly assess the value of such knowledge when we do not know what objects appear in the image. Developing better methods to identify specific objects in an image is an important direction for future research in computer vision. For now, we continued our investigation by performing additional experiments with the gold nouns in the imSitu dataset. These experiments essentially evaluate the impact of adding object knowledge when the objects have been perfectly identified by an oracle.

### 3.3 Prototypical Function Knowledge

We obtained the knowledge of what an object is typically used for from a dataset created by (Jiang and Riloff, 2021). Their data contains a list of physical objects represented as WordNet synsets (Miller, 1995), and each object is paired with a human-annotated frame from FrameNet that represents its prototypical function. For example, knife is paired with the Cutting frame.

For each object in an image, we aim to use its function frame to help with activity identification. However, Jiang and Riloff (2021) and imSitu (Yatskar et al., 2016) used different subsets of frames from FrameNet. We felt that it made sense to align them, so we used the inter-frame relations provided by FrameNet to map the prototypical function frames to imSitu’s frames. For each function frame, we create a mapping to all of the imSitu frames that are within one hop via any frame relation. Finally, we associate each object with its corresponding imSitu frames.

### 3.4 Activity Recognition Model

We use CLIP ViT-B/32 (Radford et al., 2021) as the backbone model to encode the image and text. For each example, we first apply CLIP’s image encoder to produce an image feature vector. Then we use CLIP’s text encoder to generate an embedding for each object (noun) and average the object vectors. For each object, we also collect its prototypical function frames and use CLIP’s text encoder again to generate embeddings for each frame’s name, then average those vectors. If there is no object, or no associated frame, then we encode an empty string.

Next, we build a transformer model consisting of 6 encoding layers and a classification layer on...
<table>
<thead>
<tr>
<th>Model</th>
<th>Dev Acc</th>
<th>Test Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yatskar et al. (2016)</td>
<td>32.3</td>
<td>32.3</td>
</tr>
<tr>
<td>Cooray et al. (2020)</td>
<td>38.0</td>
<td>38.2</td>
</tr>
<tr>
<td>Pratt et al. (2020)</td>
<td>39.6</td>
<td>39.9</td>
</tr>
<tr>
<td>Suhail and Sigal (2019)</td>
<td>43.2</td>
<td>43.3</td>
</tr>
<tr>
<td>Cho et al. (2022)</td>
<td>44.4</td>
<td>44.7</td>
</tr>
<tr>
<td>Li et al. (2022)</td>
<td>-</td>
<td>45.6</td>
</tr>
<tr>
<td>ARF</td>
<td>46.2</td>
<td>46.4</td>
</tr>
<tr>
<td>ARF+nounsC</td>
<td>46.6</td>
<td>46.5</td>
</tr>
<tr>
<td>ARF+nounsC+func</td>
<td>46.9</td>
<td>47.2</td>
</tr>
<tr>
<td>ARF+nounsG</td>
<td>69.2</td>
<td>69.5</td>
</tr>
<tr>
<td>ARF+nounsG+func</td>
<td>72.0</td>
<td>71.9</td>
</tr>
</tbody>
</table>

Table 1: Experimental results.

top. As input, the model takes the concatenation of all 3 vectors (corresponding to image, objects and functions). The classifier then selects the most probable action verb from all 504 candidate verbs used in the imSitu dataset.

4 Evaluation

The imSitu data contains 126,102 images, with manually annotated activity verbs and frame structures. We follow the same data split (train 75,702, development 25,200, test 25,200) as Yatskar et al. (2016). We report verb prediction accuracy on both the development and test sets. When fine-tuning the transformer, we use batch size 32, hidden vector dimension 512, AdamW optimizer with learning rate 1e-4 and train for 10 epochs.

4.1 Experimental Results

Table 1 compares our model with six previous methods described in Section 2. The ARF row shows the performance of our basic model using only image input. Our model performs a little better than previous systems, probably due to the CLIP model which is quite good. Also, the other models are trained for the full situation recognition task, whereas our model is trained solely for the verb prediction task.

The next two rows show results when adding embeddings for the nouns extracted from the captioning system (nounsC) and when using the nouns as well as their function frames (nounsC+func). The nouns alone produce just a tiny improvement, but adding the function frames improves a bit more. We believe that these results are primarily due to the limitations of the captioning system.

The last two rows in Table 1 show the performance when using the gold nouns (nounsG) and when using the gold nouns plus their associated function frames (nounsG+func). These results show a huge performance boost simply from correctly identifying all the objects in the image. And providing the external knowledge about their prototypical functions further improves performance. In the next section, we try to better understand the role that objects play.

4.2 Analysis

Figure 3 shows some examples of how the functions of objects in the image can help identify the main activity. Consider subfigure (a), we see a hand-held spoon in front of the baby’s mouth; the baby is expressing their like or dislike by making a grimace; there is some green substance (probably food) both on the face and spoon. We don’t see a series of continuous actions, yet we know it is a feeding event because of our commonsense knowledge. Similarly for the other images in Figure 3, from the shields, we can infer Protecting; looking at the canoe, we know it is Motion; and the knife is a good indicator for Cutting.

Images with and without Objects However, not all images contain “salient” physical objects. For example, imagine a picture showing a man running on a trail. The man is wearing clothes, which usually does not help with identifying the running activity (people generally wear clothes). In order to tease apart the images with and without salient ob-
Table 2: Comparing performance on images with and without physical objects that have function frames.

<table>
<thead>
<tr>
<th>Model</th>
<th>w/ Func</th>
<th>w/o Func</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARF</td>
<td>46.0</td>
<td>46.4</td>
</tr>
<tr>
<td>ARF+nouns&lt;sub&gt;G&lt;/sub&gt;</td>
<td>70.4</td>
<td>68.5</td>
</tr>
<tr>
<td>ARF+nouns&lt;sub&gt;G&lt;/sub&gt;+func</td>
<td>75.1</td>
<td>70.4</td>
</tr>
</tbody>
</table>

Table 3: Performance with and without the nouns for specific semantic roles.

<table>
<thead>
<tr>
<th>People</th>
<th>Locations</th>
<th>Objects</th>
</tr>
</thead>
<tbody>
<tr>
<td>with Nouns</td>
<td>69.3</td>
<td>69.2</td>
</tr>
<tr>
<td>without Nouns</td>
<td>61.4</td>
<td>64.4</td>
</tr>
</tbody>
</table>

The per-
formance dropped to 37.2% accuracy on those same images without the nouns. In contrast, providing the gold nouns had much less impact on the other sets of images, which contain People or Locations but not necessarily Objects.

**Salient Objects** Another challenge is how to find the “salient” objects that play important roles in the image, and from which we have a better chance of identifying the main activity. We count the number of physical objects (not in the People or Locations semantic category) for all images. We find that nearly 40% of images are annotated with two or more objects. In our ARF model, when there are multiple objects in the image, we simply use the average of each object’s embedding, which could potentially be improved by giving more weight to the most salient object. This issue may be even more important when using object detection systems because they may identify more objects (the gold annotation only contains objects that belong to a pre-defined semantic role)! This is an important issue to study in future work.

**5 Conclusion**

The prototypical functions of physical objects is a type of commonsense knowledge that is important for NLP. In this work, we showed that it can be a useful source of information for image understanding as well. Specifically, we tackled the situation recognition task by building a transformer model that incorporates the functions of objects to predict the activity in an image. The experiments show that knowledge of the objects and their prototypical functions can improve performance on this task. However, automatically recognizing the objects in an image remains a challenge, and exploiting better object detection methods is an important direction for future work.
6 Limitations

For image captioning, we used the pre-trained OFA model for zero-shot inference. We did not explore every state-of-the-art model or fine-tune OFA specifically on the imSitu dataset. Other image captioning systems could yield better results. The gap between automatic object recognition and using gold nouns confirms that correctly identifying the objects in an image is very important for activity recognition. Also, we are not certain that mapping the Jiang and Riloff (2021) function frames to the imSitu frames is strictly necessary.

Acknowledgements

We thank the Utah NLP group for their constructive comments. We also thank the anonymous ACL reviewers for their valuable suggestions and feedback.

References


ACL 2023 Responsible NLP Checklist

A For every submission:

✅ A1. Did you describe the limitations of your work?
   Section 6

✗ A2. Did you discuss any potential risks of your work?
   I don’t see any risk.

✅ A3. Do the abstract and introduction summarize the paper’s main claims?
   Section 1.

✗ A4. Have you used AI writing assistants when working on this paper?
   Left blank.

B ✅ Did you use or create scientific artifacts?
   Section 3.

✅ B1. Did you cite the creators of artifacts you used?
   Section 3.

✗ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
   Left blank.

☐ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
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   Not applicable. Left blank.

☐ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
   Not applicable. Left blank.

✅ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
   Section 4.

C ✅ Did you run computational experiments?
   Section 4.

✗ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
   Left blank.

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C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
Section 4.

C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
Left blank.

C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
Section 3.

D  X Did you use human annotators (e.g., crowdworkers) or research with human participants?
Left blank.

□ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
Not applicable. Left blank.

□ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants’ demographic (e.g., country of residence)?
Not applicable. Left blank.

□ D3. Did you discuss whether and how consent was obtained from people whose data you’re using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
Not applicable. Left blank.

□ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
Not applicable. Left blank.

□ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
Not applicable. Left blank.