Abstract

Understanding human actions is a key problem in computer vision. However, recognizing actions is only the first step of understanding what a person is doing. In this paper, we introduce the problem of predicting why a person has performed an action in images. This problem has many applications in human activity understanding, such as anticipating or explaining an action. To study this problem, we introduce a new dataset of people performing actions annotated with likely motivations. However, the information in an image alone may not be sufficient to automatically solve this task. Since humans can rely on their lifetime of experiences to infer motivation, we propose to give computer vision systems access to some of these experiences by using recently developed natural language models to mine knowledge stored in massive amounts of text. While we are still far away from fully understanding motivation, our results suggest that transferring knowledge from language into vision can help machines understand why people in images might be performing an action.

1. Introduction

Recognizing human actions is an important problem in computer vision. However, recognizing actions is only the first step of understanding what a person is doing. For example, you can probably tell that the people in Figure 1 are riding bicycles. Can you determine why they are riding bicycles? Unfortunately, while computer vision systems today can recognize actions well, they do not yet understand the intentions and motivations behind people’s actions.

Humans can often infer why another person performs an action, in part due to a cognitive skill known as the theory of mind [39]. This capacity to infer another person’s intention may stem from the ability to impute our own beliefs onto others [3, 32]. For example, if we needed to commute to work, we might choose to ride our bicycle, similar to the top right in Figure 1. Since we would be commuting to work in that situation, we might assume others in a similar situation would do the same.
ing large-scale language models [11] estimated on billions of web pages [5], we can acquire knowledge about people’s experiences, such as their interactions with objects, their environments, and their motivations. We present an approach that integrates these signals from text with computer vision to better infer motivations. While we are still a long way from incorporating human experiences into a computer system, our experiments suggest that we can predict motivations with some success. By transferring knowledge acquired from text into computer vision, our results suggest that we can predict why a person is engaging in an action better than a simple vision only approach.

The primary contribution of this paper is introducing the problem of predicting the motivations of actions to the computer vision community. Since humans are able to reliably perform this task, we believe that answering “why” for human actions is an interesting research problem to work on. Moreover, predicting motivations has several applications in understanding and forecasting actions. Our second contribution is to use knowledge mined from text on the web to improve computer vision systems. Our results suggest that this knowledge transfer may be beneficial for predicting human motivation. The remainder of this paper describes this approach in detail. Section 2 first reviews related work. Section 3 then introduces a new dataset for this task. Section 4 describes our model that uses a factor graph composed of visual classifiers and pairwise potentials estimated from text. Section 5 presents experiments to analyze the approaches to predict motivation.

2. Related Work

Motivation in Vision: Perhaps the most related to our paper is work that predicts the persuasive motivation of the photographer who captured an image [14]. However, our paper is different because we seek to infer the motivation of the person inside the image, and not the motivation of the photographer.

Action Prediction: There have been several works in robotics that predicts a person’s imminent next action from a sequence of images [3, 24, 16, 9, 19]. In contrast, we wish to deduce the motivation of actions in a single image, which may be related to what will happen next. There also has been work in forecasting activities [3, 37], inferring goals [40], and detecting early events [12], but they are interested in predicting the future in videos while we wish to explain the motivations of actions of people in images. We believe insights into motivation can help further progress in action prediction.

Action Recognition: There is a large body of work studying how to recognize actions in images [27, 1]. Our problem is related since in some cases the motivation can be seen as a high-level action. However, we are interested in understanding the motivation of the person engaging in an action rather than the recognizing the action itself. Our work complements action recognition because we seek to infer why a person is performing an action.

Commonsense Knowledge: There are promising efforts in progress to acquire commonsense knowledge for use in computer vision tasks [43, 6, 7, 10, 42]. In this paper, we also seek to put commonsense knowledge into computer vision, but we instead attempt to extract it from written language.

Language in Vision: The community has recently been incorporating natural language into computer vision, such as generating sentences from images [20, 15, 30], producing visual models from sentences [44, 38], and aiding in contextual models [26, 22]. In our work, we seek to mine language models trained on a massive text corpus to extract some knowledge that can assist computer vision systems.

Visual Question Answering: There have been several efforts to develop visual question and answering systems in both images [2, 35] and videos. One could view answering why a person performs an action as a subset of the more general visual QA problem. However, we believe understanding motivations is an important subset to study specifically since there are many applications, such as action forecasting. Moreover, our approach is different from most visual question answering systems, as it jointly infers the actions with the motivations, and also provides a structured output that more suitable for machine consumption.

3. Dataset

On the surface, it may seem difficult to collect data for this task because people’s motivations are private and not directly observable. However, humans do have the ability to think about other people’s thinking [3, 32]. Consequently, we instruct crowdsourced workers to examine images of people and predict their motivations, which we can use as both training and testing data.

We compiled a dataset of images of people by selecting 10, 191 people from Microsoft COCO [23], and annotating motivations with Mechanical Turk. In building this dataset, we found there were important choices for collecting good annotations of motivations. We made sure that these images did not have any person looking at the camera (using [31]), as otherwise the dominant motivation would be “to take photo.” We wish to study natural motivations, and not ones where the person is aware of the photographer. We instructed workers on Amazon Mechanical Turk to annotate each person with their current action, the scene, and their motivation. We originally required workers to pick actions from a pre-defined vocabulary, but we found this was too restrictive for workers. We had difficulty coming up with a vocabulary of actions, possibly because the set of human actions may not be well-defined. Consequently, we decided to allow workers to write short phrases for each concept. Specifically, we had workers fill in the blanks for
Figure 2: **Motivations Dataset:** We show some example images, actions, and motivations from our dataset. Below each image we write a sentence in the form of "**action in order to motivation.**" We use this dataset to both train and evaluate models that predict people’s motivations. The dataset consists of around 10,000 people. Notice how the motivations are often outside the image, either in space or time.

We show examples from our dataset in Fig. 2. The images in the dataset cover many different natural settings, such as indoor activities, outdoor events, and sports. Since workers could type in any short phrase for motivations, the
motivations in our dataset vary. In general, the motivations tend to be high-level activities that people do, such as “celebrating” or “looking nice”. Moreover, while the person’s action is usually readily visible, people’s motivations are often outside of the image, either in space or time. For example, many of the motivations have not happened yet, such as raising one’s hands because they want to catch a ball.

Since we instructed workers to type in simple phrases, workers frequently wrote similar sentences. To merge these, we cluster each concept. We first embed each concept into a feature space with skip-thoughts [17], and cluster with k-means. For actions and scenes, we found $k = 100$ to be reasonable. For motivations, we found $k = 256$ to be reasonable. After clustering, we use the member in each cluster that is closest to the center as the representative label for a cluster. Fig.5 shows the distribution of motivations in our dataset. This class imbalance shows one challenge of predicting motivations because we need to acquire knowledge for many categories. Since collecting such knowledge manually with images (e.g. via annotation) would be expensive, we believe language is a promising way to acquire some of this knowledge.

We are interested in analyzing the link between actions and motivations. Can motivations be predicted from the action alone? To explore this, we calculate the distribution of motivations conditioned on an action, and plot the en-

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**Figure 3: Statistics of Dataset** We show a histogram of frequencies of the actions, motivations, and scenes in our dataset. There are 100 actions, 256 motivations, and 100 scenes. Notice the class imbalance. On the vertical axis, not all categories are shown due to space restrictions.

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**Figure 4: Are motivations predictable from just actions?** We calculate the probability of a motivation conditioned on the action, and plot the entropy for each action. If motivations could be perfectly predicted from actions, the curve would be a straight line at the bottom of the graph (entropy would be 0). If motivations were unpredictable from actions, the curve would be at the top (maximum entropy of 8). This plot suggests that actions are correlated to the motivations, but it is not possible to predict the motivations only given the action. To predict motivations, we likely need to reason about the full scene.

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**Figure 5: Which images have consistent motivations?** On the left, we show some images from our test set where all workers disagreed on the motivation. On the right, we show images where all workers agreed.
4. Predicting Motivations

In this section, we present our approach to predict the motivations behind people’s actions. We first describe a vision-only approach that estimates motivation from image features. We then introduce our main approach that combines knowledge from text with visual recognition to infer motivations.

4.1. Vision Only Model

Given an image \( x \) and a person of interest \( p \), a simple method can try to predict the motivation using only image features. Let \( y \in \{1 \ldots M\} \) represent a possible motivation for the person. We experimented with using a linear model to predict the most likely motivation:

\[
\arg\max_{y \in \{1 \ldots M\}} w_y^T \phi(x, p)
\]

(1)

where \( w_y \in \mathbb{R}^D \) is a classifier that predicts the motivation \( y \) from image features \( \phi(x) \in \mathbb{R}^D \). We can estimate \( w_y \) by training an \( M \)-way linear classifier on annotated motivations. We use one versus rest for multi-class classification. In our experiments, we use this model as a baseline.

4.2. Extracting Commonsense from Text

We seek to transfer some knowledge from text into the visual classifier to help predict motivation. Our main idea is to create a factor graph over several concepts (actions, motivations, and scenes). The unary potentials come from visual classifiers, and the potentials for the relationships between concepts can be estimated from large amounts of text.

Let \( x \) be an image, \( p \) be a person in the image, and \( y_i \in \{1 \ldots k_i\} \) be its corresponding labels for \( 1 \leq i \leq K \). In our case, \( K = 3 \) because each image is annotated with a scene, action, and motivation. We score a possible labeling configuration \( y \) of concepts with the function:

\[
\Omega(y|x, p; w, u) = \sum_{i=1}^{K} w_{y_i}^T \phi_i(x, p) + \sum_{i=1}^{K} u_{y_i} L_i(y_i) + \sum_{i<j} u_{ij} L_{ij}(y_i, y_j) + \sum_{i<j<k} u_{ijk} L_{ijk}(y_i, y_j, y_k)
\]

(2)

where \( w_{y_i} \in \mathbb{R}^{D_i} \) is the unary term for the concept \( y_i \), \( \phi_i(\cdot) \) and \( L(y_i, y_j, y_k) \) are potentials that scores the relationships between the visual concepts \( y_i, y_j, \) and \( y_k \). The terms \( u_{ijk} \in \mathbb{R} \) calibrate these potentials with the visual classifiers. We will learn both \( w \) and \( u \), while \( L \) is estimated from text. Our model forms a third order factor graph, which we visualize in Fig.6.

In order to learn about the relationships between concepts, we mine large amounts of text. Recent progress in natural language processing has created large-scale language models that are trained on billions of web-pages [5, 11]. These models work by ultimately calculating a probability that a sentence or phrase would exist in the training corpus. Since people usually do not write about scenarios that are rare or impossible, we can query these language models to score the relationship between concepts. Fig.2 shows some pairs of actions and motivations, sorted by the score from the language model. For example, the language
Table 2: Example Language Potentials: By mining billions of web-pages, we can extract some knowledge about the world. This table shows some pairs of concepts, sorted by the score from the language model.

<table>
<thead>
<tr>
<th>Action</th>
<th>Motivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>watching</td>
<td>see</td>
</tr>
<tr>
<td>reading</td>
<td>learn</td>
</tr>
<tr>
<td>talking</td>
<td>listen</td>
</tr>
<tr>
<td>talking</td>
<td>learn</td>
</tr>
<tr>
<td>running</td>
<td>play</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>watching</td>
<td>type on laptop</td>
</tr>
<tr>
<td>skiing</td>
<td>look at truck</td>
</tr>
<tr>
<td>sleeping</td>
<td>see a giraffe</td>
</tr>
<tr>
<td>reading</td>
<td>cut wedding cake</td>
</tr>
<tr>
<td>riding skateboard</td>
<td>get cake</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

We often require the n-best solutions, which can be done efficiently with approximate approaches such as n-best MAP estimation \([4, 21]\) or sampling techniques \([28, 25]\). However, we found that, in our experiments, it was tractable to evaluate all configurations with a simple matrix multiplication, which gave us the exact n-best solutions in a few seconds on a high-memory server.
4.5. Indicating Person of Interest

Finally, to predict somebody’s motivation, we must specify the person of interest. To do this, we crop the person, and extract visual features for the close-up crop. We then concatenate these features with the full image features. We use this concatenation to form $\phi(x, p)$.

5. Experiments

In this section, we evaluate the performance at inferring motivations in images from our models. We first describe our evaluation setup, then we present our results.

5.1. Experimental Setup

We designed our experiments to evaluate how well we can predict the motivation of people from our dataset. We assumed the person-of-interest is specified since the focus of this work is not person detection. We computed features from the penultimate layer ($fc7$) in the VGG-16 convolutional neural network trained on Places \cite{zhou2017places} due to their strong performance on other visual recognition problems \cite{donahue2014decaf, krizhevsky2012imagenet}. We concatenate the features for both the full image and a close-up crop of the person of interest (giving a $8 \times 192$ dimensional feature vector). We experimented with a few different $C$ values, and report the best performing (0.001). To compute the chance performance, we evaluate median rank against a list sorted by the frequency of motivations.

5.2. Evaluation

We evaluate our approach on an image by finding the median rank of a ground truth motivation in the max-marginals on all states for the motivation concept. This is equivalent to the rank of ground truth motivation in the list of motivation categories, sorted by their best score among all possible configurations. We use median rank because motivation prediction may have multi-modal solutions, and we seek an evaluation metric that allows for multiple predictions. We report the median rank of our full approach and the baseline in Tab.3.

Our results suggest that incorporating knowledge from text can improve performance at predicting motivations, compared to a vision-only approach. Our interpretation is that text acts as a regularizer that helps the model perform better on novel images during inference time. The baseline appears prone to over-fitting, since the baseline performs slightly worse when we specify the person. Moreover, our approach is significantly better than chance, suggesting that the learning algorithm is able to use the structure in the data to infer motivations. As one might expect, performance for our model improves when we specify the person of interest in the image.

5.3. Diagnostics

For diagnostic purposes, the bottom of Tab.3 shows the performance of our approach if we had ideal recognition systems for each visual concept. To give ideal detectors to our system, we can constrain the unary potentials for the corresponding concept to the ground truth. Our results suggest that if we had perfect vision systems for actions and scenes, then our model would only slightly improve, and it would still not solve the problem. This suggests that motivations are not the same as scenes or actions. Rather, in order to improve performance further, we hypothesize integrating additional visual cues such as human gaze \cite{battaglia2014video} and clothing will yield better results, motivating work in high-level visual recognition.

To evaluate the impact of the language model, we also experimented with using an alternative language model trained on text from Wikipedia instead of the web. Here, the language model is estimated with much less data. Interestingly, using the Wikipedia language model performs
sitting at a table in order to eat in a restaurant

holding a racket in order to hit the ball in a tennis court

drinking wine in order to eat dinner in a dining room

sitting at a table in order to get information in a dining room

sitting down in order to rearrange food in a classroom

standing in order to play video game in a living room

playing video game in order to get information in a dining room

swinging a bat in order to hit a ball in a baseball field

hitting a ball in order to hit the ball in a baseball field

holding a bat in order to hit a ball in a baseball field

playing video game in order to get information in a dining room

Figure 7: Example Results: We show the top three predictions for some people in our evaluation set. The sentences are shown only to visualize results: we do not generate free-form captions. Even when the model is wrong, it usually predicts concepts that have plausible relations to other, which is possible because of the language model.

6. Conclusion

While computers can recognize the actions of people in images with good performance, predicting the motivations behind actions is a relatively less explored problem in computer vision. This problem is important both for developing a full understanding of actions, as well as in applications, such as anticipating future actions. We have released a new dataset to study this problem, and we have investigated how to transfer some knowledge from text to help predict motivations.

Our experiments indicate that there is still significant room for improvement. We suspect that advances in high-level visual recognition can help this task. However, our results suggest that visual information alone may not be sufficient for this challenging task. We hypothesize that incorporating common knowledge from other sources can help, and our results imply that written language is one valuable source. Our framework only transfers some of the commonsense knowledge into vision models, and we hypothesize that continued work in commonsense reasoning for vision will help machines infer motivations. We believe that progress in natural language processing is one way to advance such high-level reasoning in computer vision.

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References


