Predicting the Category and Attributes of Mental Pictures
Using Deep Gaze Pooling

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Abstract

Previous work focused on predicting visual search targets from human fixations but, in the real world, a specific target is often not known, e.g. when searching for a present for a friend. In this work we instead study the problem of predicting the mental picture, i.e. only an abstract idea instead of a specific target. This task is significantly more challenging given that mental pictures of the same target category can vary widely depending on personal biases, and given that characteristic target attributes can often not be verbalised explicitly. We instead propose to use gaze information as implicit information on users' mental picture and present a novel gaze pooling layer to seamlessly integrate semantic and localized fixation information into a deep image representation. We show that we can robustly predict both the mental picture's category as well as attributes on a novel dataset containing fixation data of 14 users searching for targets on a subset of the DeepFashion dataset. Our results have important implications for future search interfaces and suggest deep gaze pooling as a general-purpose approach for gaze-supported computer vision systems.

1. Introduction

The cognitive process of mind as well as thoughts and intentions are reflected in human gaze behavior [4, 17, 19]. In his seminal work, Yarbus showed that gaze behavior is also closely related to the task that people perform [37]. The work triggered a large number of follow-up works in various fields, including artificial intelligence, neuroscience, as well as human and computer vision.

These works demonstrated that gaze behavior can be used to infer users' tasks [2, 13, 39], activities [5, 31], as well as cognitive [6] and abstract thought processes [8, 23], or it can be used for interactive image retrieval [7, 14, 27].

Most recently, gaze information was successfully used to predict the target of a visual search task [3, 12, 28, 30, 39].

Said prediction is challenging given that the target is only in the mind of the users. Borji et al. showed the possibility of search target prediction in a closed-set (all the search target were in the training set) [3] while Zelinsky et al. predicted categorical search targets from user fixations [39].

To overcome this limitation, Sattar et al. more recently introduced a method that extended search target prediction to an open-set [30]. Their method was able to predict the search target over an unknown set of targets. Al thought they did not train explicitly for all the targets but they still required a defined set of targets to measure the similarities of fixations to them.

While all of these works underline the significant potential of search target prediction using gaze, they tried to predict the specific instance of the target, which had to be
shown to users beforehand. This represents a rather strong requirement given that, in the real world, a specific target is often not known a priori, e.g. when searching for a suitable dress for a friend’s upcoming birthday party. Instead, users often only have a mental picture in mind, i.e. only an abstract idea of what they are looking for. In addition, they might only be able to verbalise individual desired properties of a that mental picture while other properties remain unspecific. Considering the birthday example again, a user might be looking for a dress that “is flowery because I like flowers” and “it is long as I want to be classic” or “I would like it made from lace or silk”.

As a proxy to the real world, similar to prior work [30], we study prediction of the mental picture during visual search in image collages. As shown in Figure 1, a user has a mental picture of what she is looking for. While she is looking at the collage, part of one image might be compatible with her mental picture while others are unrelated. As in the example, one of the dresses has the same material as observers mental picture and other has similar pattern. We then aim to predict the mental picture. This task is significantly more challenging given that mental pictures of the same target category can vary widely depending on personal biases, and given that characteristic target attributes can often not be verbalised explicitly.

The specific contributions of this work are three-fold. First, we present the first method to predict the categories and attributes of mental picture from gaze and image information. Second, we propose a novel gaze-pooling layer that seamlessly integrates fixation data with state-of-the-art deep learning architectures. We show that it is possible to add gaze information into a CNN formulation without a need to train the CNN for gaze data. Third, we present a new data set for attribute and category prediction of mental pictures, which contains fixation data of 14 users, during searching for clothing categories and attributes. We report on a series of experiments on this dataset that demonstrate both the feasibility of the task as well as the effectiveness of our method. Our results have important implications for future search interfaces and suggest deep gaze pooling as a general-purpose approach for gaze-supported computer vision systems.

2. Related Work

Our method for predicting the mental picture using gaze is related to previous works on gaze-supported computer vision, most importantly the prediction of visual search targets, as well as previous efforts to get at the mental picture. Gaze-Supported Computer Vision. Accessibility of the eye tracking instruments increases the interest of using gaze informations to aid computer vision tasks. Vision research shown that human tend to fixate on salient objects in the visual scene [11, 26]. Using this motivation, gaze cues were used to infer the object locations. In [20, 36] they used the correlation of fixations and object in the context of saliency predictions. In [27, 16] they used fixation data to to perform weakly supervised training of object detectors, or in [22] they inferred scene semantics. Gaze information has been used to analyze pose estimation tasks [32] as well as detecting actions [24]. Gaze has been used in segmentation as well. [25] used human fixations to do an active segmentation. Fixation information is also used for localizing important objects in egocentric videos [34, 9]. Recently, [33], studied the possibility of integrating human gaze information into an attention-based long short-term memory architecture. They showed the effectiveness of gaze in image captioning and complementing the machine attention for semantic scene understanding task.

Predicting Search Targets Using Gaze. Gaze informations has been used to predict the target of visual search task. Zelinsky et al. predicted search targets from subjects’ gaze patterns during a categorical search task [39]. In their experiments, participants were asked to find two categorical search targets among four visually similar distractors. Borji et al. focused on predicting search targets from fixations [3]. They used a binary pattern and 3-level luminance patterns as target and participants were asked to find targets out of a set of other patterns. In a recent study Sattar et al. predicted search targets of users in an open and closed-world setting [30]. They introduced a method, which measured the compatibility of the gaze data and search targets. Participants were asked to find a target image in synthesized collages of images. All of these works, however, only focused on predicting a specific instance of search target fixations data.

In contrast, our work is first to address the prediction of the semantic concepts and properties of mental picture using gaze. It removes the need of seeing specific stimulus.

Getting at Mental Pictures. Visual attributes can be considered as semantic properties that users can use to address their mental picture [10, 29, 35]. Kovashka et al. introduced a novel explicit feedback method to assess the mental picture of users [1]. In their method, a user described which attributes of exemplar images should be modified via semantic language to communicate with the system. Their method updates its relevance function iteratively and re-ranks the database of images until they match the mental-picture.

Most recently, Yu et al. proposed to use free-hand human sketches as queries to perform instance-level retrieval of images [38]. They considered these sketches to be manifestations of users’ mental pictures. They developed a deep triplet-ranking model for instance-level SBIR.

To overcome the insufficient fine-grained training data, they introduced a novel data augmentation and staged pre-training strategies. Both works are related to ours as they tried to predict the mental picture of users. However, [1]
required users to define their mental picture with a set of attributes and assumed that they have a large enough vocabulary to describe their mental picture. For [38], sketching may not be easy for everyone and sketching concepts like texture, color, material, style is difficult if not impossible. In contrast, in our work, we are not using any feedback loop our explicit user input and we do not require any explicit initial description of the mental picture. We, for the first time, instead use fixation information that can be acquired implicitly during the search task itself.

3. Data Collection and Collage Synthesis

To evaluate our method we used the DeepFashion dataset [21]. DeepFashion is a clothes dataset consisting of 289,222 images annotated with 46 different categories, 1000 attributes. We used the top 10 categories and attributes in our study. The training set of DeepFashion dataset was used to train the our image model for categories and attributes predictions. We used the validation set of deepfashion dataset, to train users for each category and attributes. Finally, the test set is used to build up image collages, which we record human gaze data while searching for specific categories and attributes. In the following our data collection is explained in more details.

3.1. Participants and Apparatus

We collected data from 14 participants (six females), aged between 18 and 30 years and with different nationalities. All participants had normal or corrected to normal vision. For gaze data collection we used a stationary Tobii TX300 eye tracker that provides binocular gaze data at a sampling frequency of 300Hz. Parameters for fixation detection were left at their defaults: fixation duration was set to 60ms while the maximum time between fixations was set to 75ms. The stimuli were shown on a 30-inch screen with a resolution of 2560x1600 pixels. Before the recording, we calibrated the eye tracker using a standard 9-point calibration, followed by a validation of eye tracker accuracy. Participants were assigned to search for ten different categories and attributes in two different sessions: training and testing.

3.2. User Training

We first trained participants so they could familiarized themselves with the categories and attributes. To this end, for each category, each participant was first shown nine randomly selected samples of that category. They were then shown four randomly selected samples, two of which belonged to the category they were currently being trained for and the other two from the remaining categories. For each sample, participants had to answer whether it belonged to the current category or not. After entering their response, participants received visual feedback on the right answer.

Participants had to provide at least five correct answers before proceeding to the next category or attribute. In addition to these binary answers, participants had to complete several multiple-choice questions. Participants were shown five samples from each category or attributes and had to select the right category. This step is repeated two times for all of the categories and attributes.

3.3. User Testing

Afterwards, we recorded participants’ gaze while they searched for each of the categories or attributes in image collages. For each category and attribute we generated 10 image collages, each containing 20 images. Each category or attribute appeared only twice in each collage at a random location (see Figure 2 for an example). Collages were shown full screen. Participants were then shown three different samples of the first out of 10 categories or attributes. Participants had a maximum of 10 seconds to find the target category or attribute in the collage. To determine more easily on which images participants fixated on, all images were placed on a grey background and had a margin to neighboring images of at least 60 pixels. As soon as participants found the target they were asked to press a key. Afterwards they were
4. Prediction of Mental Pictures Using Gaze

In this work we are interested in predicting the category and attributes of mental pictures. Previous works either required users’ explicit input to get their mental picture [38,1] or only predicted a specific search target instance shown to the users beforehand [3,30,39]. In contrast, we introduce a novel approach that uses gaze input as implicit information on the mental picture. We address this task by introducing the Gaze Pooling Layer (GPL). In the following, we describe the four major components of our method in detail: The image encoder, human gaze encoding, the Gaze Pooling Layer, and Classification. Finally, we also discuss different integration schemes across multiple images.

4.1. Image Encoder

We build on the recent success of deep learning and use a convolutional neural network (CNN) to encode image information [15,18]. Given a raw image $I$, a CNN is used to extract image feature map $F(I)$.

$$F(I) = \text{CNN}(I)$$

Due to the end-to-end training properties of these networks, this allows us to obtain domain specific features. In our case, the network will be trained with data and labels relevant to the fashion domain.

As we are interested in combining spatial gaze features with the image features, we use features $F(I)$ of the last convolutional layer that still has a spatial resolution. This results in a task-dependent representation with spatial resolution. In addition, to gain a higher spatial resolution we used a similar architecture as describe in [41]. For AlexNet the last layers after conv5 are removed. The resulting resolution is $13 \times 13$. For VGGnet, layers after conv5-3 are removed to gain a mapping resolution of $14 \times 14$.

4.2. Human Gaze Encoding

Given a mental picture, participant $P \in \mathbb{P}$ look at image $I$ and performs fixations $G(I,P) = (x_i, y_i), i = 1, ..., N$ in screen coordinates. We aggregate these fixations into attention masks that capture the spatial density $A(G)$ of fixations over the full image. Therefore, we represent the attention mask $A(g)$ for a single fixations $g \in G(I, P)$ by a Gaussian:

$$A(g) = \mathcal{N}(g, \sigma_{\text{fix}})$$
, centered at the coordinates of the fixation, with a fixed standard deviation \( \sigma_{\text{fix}} \) – the only parameter of our representation. The attention mask for all fixations \( A(G) \) is obtained by coordinate-wise summation:

\[
A(G) = \sum_{g \in G} A(g)
\]

This corresponds to an average pooling integration. We also propose a max pooling version as follows:

\[
A(G) = \max_{g \in G} A(g)
\]

4.3. Gaze Pooling Layer

We combine the visual features \( F(I) \) with attention mask \( A(G) \) in a Gaze Pooling Layer. The integration is performed by element-wise multiplication between both to obtain a gaze-weighted feature map (GWFM)

\[
\text{GWFM}(I, G) = F(I) \otimes A(G).
\]

In spirit of [41], we then perform Global Average Pooling (GAP) on each feature channel separately in order to yield a vector-valued feature representation.

\[
\text{GAP}_{\text{GWFM}}(I, G) = \sum_{x,y} \text{GWFM}(I, G)
\]

We finish our pipeline by classification with a fully connected layer and a softmax layer.

\[
p(C|I, G) = \text{softmax}(W \cdot \text{GAP}_{\text{GWFM}}(I, G) + b),
\]

where \( W \) are the learned weights and \( b \) is the bias. The classes represent either categories or attributes depending on the experiment and we decide for the class with the highest class posterior.

4.4. Integration across Images

In our study, a stimulus is a collage with a set of images \( I_i \in \mathbb{I} \). During the search task, participants are free to fixate on multiple images in the collage, which generates fixations \( G_i \in \mathbb{G} \) for each image \( I_i \). Hence, we need a mechanism to aggregate information across images. To do this, we propose a simple but effective weighted average scheme of the computed posteriors:

\[
p(C|\mathbb{I}, \mathbb{G}) = \sum_i \left( \frac{w_i}{\sum_j w_j} \right) p(C|I_i, G_i).
\]

We consider for the weights \( w_i \) the total fixations duration on image \( I_i \) as well as fixed \( w_i \), which leads, again, to plain averaging.

## Table 1. Evaluation of vision-only methods.

| Vision-Only       | Category Top1 | Category Top3 | Category Top5 | Attributes Accuracy |
|-------------------|---------------|---------------|---------------|-------------------|
| Alexnet-GAP       | 62%           | 86%           | 94%           | 75%               |
| VGGnet-GAP        | 68%           | 89%           | 96%           | 79%               |

4.5. Vision-Only Performance

To obtain vision-only models with higher spatial feature map resolution, we followed [41] and built on the Alexnet-GAP and VGGnet-GAP models. For our categorization experiments we fine-tuned on a 10 class classification problem on the DeepFashion dataset [21]. For attribute prediction, we fine-tuned a model with 10 times 2-way classification in the final layer. In Table 1, we report the obtained accuracies. As the VGG-based version gives superior performance across all metrics in both tasks, we used it in all further experiments.

We also performed a validation of our model in the same setting as [21] and obtained comparable results (±5%). Please note that all of these results are on a 10 class subset relevant to our main experiments. It also has to be noted that those numbers are not comparable to the results in the main experimental section as they represent recognition of the image content and are not related to the mental picture of the observer – which is the task in the following section. In fact, we conducted sanity checks that the vision-only baselines performed at chance level on all following experiments on category and attribute prediction of mental pictures.

5. Experiments

To evaluate our method for mental picture category and attribute prediction, we performed a series of experiments on the recorded dataset. We first evaluated the effectiveness of our Gaze-Pooling Layer, the effect of using a local vs a global representation, and of using a weighting by fixation duration. We then evaluated the gaze encoding that encompasses the pooling scheme of the individual fixation as well as the \( \sigma_{\text{fix}} \) parameter to represent a single fixation. Finally, we evaluated the robustness of our method with respect to noise in the eye tracking data, which sheds light on different possible deployment scenarios and hardware that our approach is amendable to. Across the results, we present Top-N accuracies denoting correct predictions if the correct answer is among the top N predictions.

5.1. Evaluation of Gaze-Pooling Layer (GPL)

Fixation information enters our GPL in two places: The attention masks and the weighted average across images in the form of fixation duration. We first evaluated the effect of both on overall performance. We refer to the approach that
uses the attention masks as local (using spatial fixation information), while the global approach instead uses a uniform and therefore uninformative attention mask. In addition to weighting by fixation duration we considered treating each fixation equally.

Table 2 shows the result of this evaluation, with the first column denoting if local or global information was used and the second column whether fixation duration was used. Absolute performance of our best model using local information and fixation duration were 57%, 74%, and 84% on top1-3 accuracy respectively for the categorization task and 77% accuracy for attributes. The results show a consistent improvement (16 to 18 pp for categories, 13 pp for attributes) across all measures and tasks going from a global to a local representation (first to second row). Adding the weighting by fixation duration yields another consistent improvement for both local and global approach (another 6 to 21 pp for categories). Our best method, improves overall by 22 to 26 pp on the categorization task and 18 pp on the attributes. The global method without fixation duration (first row) is top1-3 accuracy and analyzed here the influence on the overall performance by varying this parameter in a sensible range (given eye tracker accuracy and coarseness of feature map) from 1 to 2 as shown in Table 3. As can be seen from the Table, our method is largely insensitive to the investigated range of reasonable choices of this parameter and our choice of 1.6 is on average a valid choice within that range.

### Fixation Pooling Strategies

We evaluated two options for how to integrate single fixations into an attention mask: Either using average or max pooling. The results are shown in Table 4. As the Table shows, while both options perform well, average pooling consistently improves over the max pooling option.

#### 5.3. Noise Analysis

While our gaze data is recorded with a highly-accurate stationary eye tracker, there are different modalities and types of eye trackers available. One key characteristic in which they differ is the error at which they can record gaze data – typically measured in degrees of visual angle. While our controlled setup provides us with an accuracy of about 0.7 degrees of error, state-of-the-art eye trackers based on webcams, tablets or integrated into glasses can have up to 4 degrees depending also on the deployment scenario [40]. Therefore, we finally investigated the robustness of our approach w.r.t. different per-fixation $\sigma_{\text{fix}}$.

Table 2. Evaluation of global vs. local gaze pooling with and without weighting based on the fixation duration $\bullet$.

| Fixation Pooling Strategies | Category | Attribute |
|-----------------------------|----------|-----------|
| Max                         | 54%±8    | 73%±9    | 83%±6    | 76%±11 |
| Average                     | 57%±8    | 74%±7    | 84%±4    | 77%±9  |

Table 3. Evaluation of different fixation encoding schemes using average or max pooling.

| Fixation Pooling Strategies | Category | Attribute |
|-----------------------------|----------|-----------|
| Max                         | 54%±8    | 73%±9    | 83%±6    | 76%±11 |
| Average                     | 57%±8    | 74%±7    | 84%±4    | 77%±9  |
Figure 4. Accuracy for different amounts of noise added to the eye tracking data. Our method is robust to this error which suggests that it can also be used with head-mounted eye trackers or learning-based methods that leverage RGB cameras integrated into phones, laptops, or public displays.

drop of 5 to 10pp for Top3 to Top1 accuracy, respectively – even at the highest noise level. In particular, all the results are consistently above the performance of the corresponding global methods shown as dashed lines in the plot.

6. Discussion

In this work we studied the problem of predicting the mental picture during visual search task from fixations. Table 2 shows that we can predict the mental picture significantly above chance for categories (Top3 = 84%) and attributes (77%). Our Gaze Pooling Layer achieves a modular integration of visual and gaze features that is compatible with modern deep learning architectures. Beyond this capability, we would like to highlight three features that are of particular practical importance.

Parameter Free Integration Scheme First, our proposed integration scheme is parameter-free. We introduce a single parameter $\sigma_{\text{fix}}$ but the gaze encoding is only input to the integration scheme and, in addition, the method turns out to be not very sensitive to the choice (see experiments in subsection 4.2).

Training from Vision-Only Input Second, fixing the attention masks to uniform maps yields a deep architecture similar to a GAP network that is well-suited for various classification tasks. While this no longer addresses the task of predicting categories and attributes intended by the human in the loop, it allows us to train the remaining architecture for the task at hand and on vision-only data, which is typical easier to obtain in larger quantities than gaze data. This type of training results in a domain-specific image encoding as well as task-specific classifier.

Training Free Gaze Deployment Gaze data is time consuming to acquire – which makes it rather incompatible with today’s data hungry deep learning models. However, in our model, the attention masks computed from the gaze data can be understood as spatially localized feature importance that are used to weight feature importance in the spatial image feature maps. It turns out that this re-weighting scheme does not require re-training with gaze data (see experiments), so that the approach can be instantly deployed based on the vision-only model without any gaze-specific training. We believe this is a key feature to that makes the use of gaze information in deep learning practical.

Visualizing Effect of Gaze Pooling Layer We provide further insights into the working of our Gaze Pooling Layer by showing visual examples of the classification process and associated attention mask. Figure 5 shows results for the categorization task and Figure 6 for the attribute task.

Each of these figures shows the output of the “vision only” method that does not use gaze information and is therefore “unaware” of the mental picture of the participant. Consequently, all predictions are wrong, as they do not related to the mental picture. Instead, we observe that in each case a prominent part of the image is correctly classified as the contained category or attribute.

Next to the “vision only” prediction, we show the prediction using gaze information via our proposed Gaze Pooling Layer. We observe that in all cases we manage to predict the correct category of the mental picture and in 3 out of 4 cases at least one relevant attribute. Key to our success is the attention masks visualized in the left half of the images. It shows the selectiveness towards more relevant parts in the image that in turn re-weight visual features in our Gaze Pooling Layer.

In order to illustrate the challenges our Gaze Pooling Layer has to deal with in terms of the variations in the observed gaze data, we show example fixation data in Figure 7. In each image, fixation data of two participants (red and green dots) is overlaid over a presented collage. Although both participants had the same mental picture (top: attribute ‘Floral’; bottom: category ‘Cardigan’), we observe a drastically different fixation behaviour. Despite this strong variation in the gaze information, our Gaze Pooling Layer allows to predict the correct answer in all 4 cases. The key to this success is aggregating relevant local visual feature across all images in the collage, that in turn represent one consistent mental picture in terms of categories and attributes.

7. Conclusion

In this work we demonstrated how to predict the mental picture of users from their fixations data during visual search. To this end we proposed a novel gaze pooling layer to seamlessly integrate semantic and localized fixation information
into a deep image representation. Our work is fundamentally
different to previous ones as we no longer require partici-
pants to find specific instance of an object. Also, we are not
training on gaze data which makes our method generic and
generalizable to deployments in which gaze is not available.
Our work paves the way for new applications in different ar-
eas, including gaze-assisted computer vision, visual question
answering, attention-based convolutional neural networks,
and context-based image retrieval.

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