PANDA: Pose Aligned Networks for Deep Attribute Modeling

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Abstract

We propose a method for inferring human attributes (such as gender, hair style, clothes style, expression, action) from images of people under large variation of viewpoint, pose, appearance, articulation and occlusion. Convolutional Neural Nets (CNN) have been shown to perform very well on large scale object recognition problems [14]. In the context of attribute classification, however, the signal is often subtle and it may cover only a small part of the image, while the image is dominated by the effects of pose and viewpoint. Discounting for pose variation would require training on very large labeled datasets which are not presently available. Part-based models, such as poselets [4] and DPM [12] have been shown to perform well for this problem but they are limited by flat low-level features. We propose a new method which combines part-based models and deep learning by training pose-normalized CNNs. We show substantial improvement vs. state-of-the-art methods on challenging attribute classification tasks in unconstrained settings. Experiments confirm that our method outperforms both the best part-based methods on this problem and conventional CNNs trained on the full bounding box of the person.

1. Introduction

Recognizing human attributes, such as gender, age, hair style, and clothing style, has many applications, such as facial verification, visual search and tagging suggestions. This is, however, a challenging task when dealing with non-frontal facing images, low image quality, occlusion, and pose variations. The signal associated with some attributes is subtle and the image is dominated by the effects of pose and viewpoint. For example, consider the problem of detecting whether a person wears glasses. The signal (glasses wireframe) is weak at the scale of the full person and the appearance varies significantly with the head pose, frame design and occlusion by the hair. Therefore, localizing object parts and establishing their correspondences with model parts can be key to accurately predicting the underlying attributes.

Deep learning methods, and in particular convolutional nets [20], have achieved very good performance on several tasks, from generic object recognition [14] to pedestrian detection [25] and image denoising [6]. Moreover, Donahue *et al.* [8] show that features extracted from the deep convolutional network trained on large datasets can benefit related tasks because they provide good generic visual features. However, as we report below, they may underperform compared to conventional methods which exploit explicit pose or part-based normalization. We conjecture that available training data, even ImageNet-scale, is presently insufficient for learning pose normalization in a CNN, and propose a new class of deep architectures which explicitly incorporate such representations. We combine a part-based representation with convolutional nets in order to obtain the benefit of both approaches. By decomposing the input image into parts that are pose-specific we make the subsequent training of convolutional nets drastically easier, and therefore, we can learn very powerful pose-normalized features from relatively small datasets.

Part-based methods have gained significant recent attention as a method to deal with pose variation and are the state-of-the-art method for attribute prediction today. For example, spatial pyramid matching [18] incorporates geometric correspondence and spatial correlation for object recognition and scene classification. The DPM model [12] uses a mixture of components with root filter and part filters capturing viewpoint and pose variations. Zhang *et al.* proposed deformable part descriptors [27], using DPM part boxes as the building block for pose-normalized representations for fine-grained categorization task. Poselets [5, 3] are part detectors trained on positive examples clustered using keypoint annotations; they capture a salient pattern at a specific viewpoint and pose. Several approaches [11, 26] have used poselets as a part localization scheme for fine-grained categorization tasks which are related to attribute prediction. Although part-based methods have been successful on several tasks, they have been limited by the choice of the

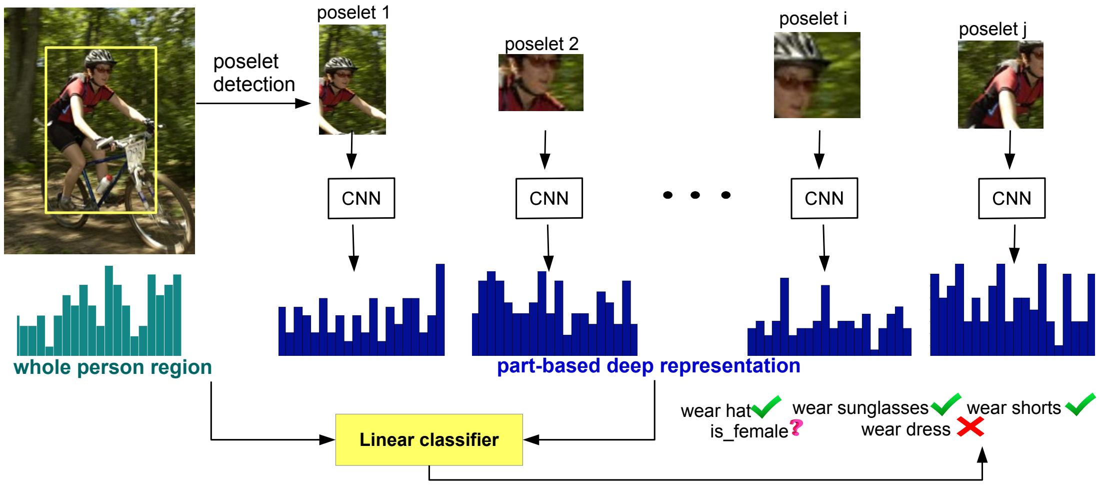


Figure 1: **Overview of Pose Aligned Networks for Deep Attribute modeling (PANDA)**. One convolutional neural net is trained on semantic part patches for each poselet and then the activations of all nets are concatenated to obtain a pose-normalized deep representation. The final attributes are predicted by linear SVM classifier using the pose-normalized representations.

low-level features applied to the image patches.

We propose the PANDA model, Pose Alignment Networks for Deep Attribute modeling, which augments deep convolutional networks to have input layers based on semantically aligned part patches. Our model learns features that are specific to a certain part under a certain pose. We then combine the features produced by many such networks and construct a pose-normalized deep representation. In this work, we use poselets, but the method can also be generalized to other part-based models, such as DPM [12]. We demonstrate the effectiveness of PANDA on attribute classification problems and present state-of-the-art experimental results on three datasets, a large-scale attribute dataset from the web, the Berkeley Attributes of People Dataset [4] and the Labeled Faces in the Wild dataset [15].

2. Related work

2.1. Attribute classification

Attributes are used as an intermediate representation for knowledge transfer in [17, 10] on object recognition tasks. By representing the image as a list of human selected attributes enables it to recognize unseen objects with few or zero examples. Other related work on attributes includes that by Parikh *et al.* [22] exploring the relative strength of attributes by learning a rank function for each attribute, which can be applied to zero-shot learning as well as generating richer textual descriptions. There are also some related work in automatic attribute discovery. Berg *et al.* [1] proposed automatic attribute vocabularies discovery by mining unlabeled text and image data sampled from the web. Duan *et al.* [9] proposed an interactive crowd-sourcing method to discover both localized and discriminative attributes to differentiate bird species.

In [15, 16], facial attributes such as gender, mouth shape, facial expression, are learned for face verification and image search tasks. Some of the attributes used by them are similar to what we evaluate in this work. However, the difference is that all of their attributes are about human faces and most of images in their dataset are just frontal face subjects while our dataset is much more challenging in terms of image quality and pose variations.

A very closely related work on attribute prediction is Bourdev *et al.* [4], which is a three-layer feed forward classification system and the first layer predicts each attribute value for each poselet type. All the predicted scores of first layer are combined as a second layer attribute classifier and the correlation between attributes are leveraged in the third layer. Our method is also built on poselets, from which the part correspondence is obtained to generate a pose-normalized representation.

2.2. Deep learning

The most popular deep learning method for vision, namely the convolutional network, has been pioneered by LeCun and collaborators [20] who initially applied it to OCR [21] and later to generic object recognition tasks [13].

As more labeled data and computational power has become recently available, convolutional nets have become the most accurate method for generic object category classification [14] and pedestrian detection [25].

Although very successful when provided very large labeled datasets, convolutional nets usually generalize poorly on smaller dataset because they require the estimation of millions of parameters. This issue has been addressed by using unsupervised learning methods leveraging large amounts of unlabeled data [23, 13, 19]. In this work, we take instead a different perspective: we make the learning task easier by providing the network with pose-normalized inputs and we also train on a related task using a larger dataset.

While there has already been some work on using deep learning methods for attribute prediction [7], in this work we explore many more ways to predict attributes, we incorporate the use of poselets in the deep learning framework and we perform a more extensive empirical validation which compares against conventional baselines and deep CNNs evaluated on the whole person region.

3. Pose Aligned Networks for Deep Attribute modeling (PANDA)

We explore part-based models, specifically poselets, and deep learning to obtain pose-normalized representation for attribute classification tasks. Our goal is to use poselets for part localization and incorporate these normalized parts into deep convolutional nets in order to extract pose-normalized representations. Towards this goal, we leverage both the power of convolutional nets for learning discriminative features from data and the ability of poselets to simplify the learning task by decomposing the objects into their canonical poses. We develop Pose Aligned Networks for Deep Attribute modeling (PANDA), which incorporates part-based and whole-person deep representations.

While convolutional nets have been successfully applied to large scale object recognition tasks, they do not generalize well when trained on small datasets. In this work, we propose a part-based deep convolutional neural nets, using poselets based part model (but DPM could also be used). Starting from well-aligned poselet patches, a deep net is trained on patches from each poselet yielding highly localized and discriminative feature representations.

Specifically, we start from aligned poselet patches and resize each patch to 64x64 pixels and some example poselet patches are shown in Figure 3. The overall convolutional net architecture is shown in Figure 2. First, we randomly jitter the image and flip it horizontally with probably 0.5 in order to improve generalization. The network consists of four convolutional, max pooling, local response normalization stages, then followed by a fully connected layer with 576 hidden units. After that, the network branches out one fully connected network with 128 hidden units for each attribute and each of the branch outputs a binary classifier of the attribute. The last two layers are split to let the network develop customized features for each attribute (e.g., detecting whether a person wears a "dress" or "sunglasses" presumably reuqires different features) while the bottom layers are shared to a) reduce the number of parameters and b) to leverage common low-level structure.

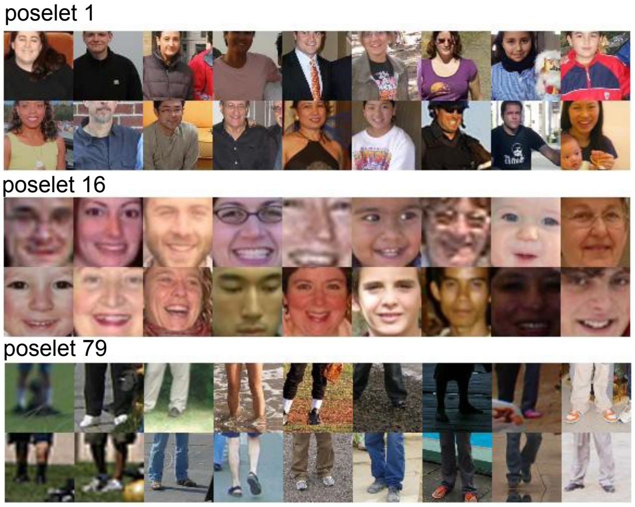


Figure 3: **Poselet Input Patches.** For each poselet, we use the detected patches to train a convolution neural net. Here are some examples of input poselet patches and we are showing poselet patches with high scores for poselet 1,16 and 79.

The whole network is trained jointly by standard backpropagation of the error [24] and stochastic gradient descent [2] using as a loss function the sum of the log-losses of each attribute for each training sample. The details of the layers are given in Figure 2, further implementation details can be found in [14]. To deal with noise and inaccurate poselet detections, we train on patches with high poselet detection scores and then we gradually add more low confidence patches.

Different parts of the body may have different signals for each of the attributes and sometimes signals coming from one part cannot infer certain attributes accurately. For example, deep net trained on person leg patches contains little information about whether the person wears a hat. Therefore, we first use deep convolutional nets to generate discriminative image representations for each part separately and then we combine these representations for the final classification. Specifically, we extract the activations from fc_attr layer in Figure 2, which is 576 dimensional, for the CNN at each poselet, and concatenate the activations of all poselets together into 576*150 dimensional feature. If a poselet does not activate for the image, we simply leave the

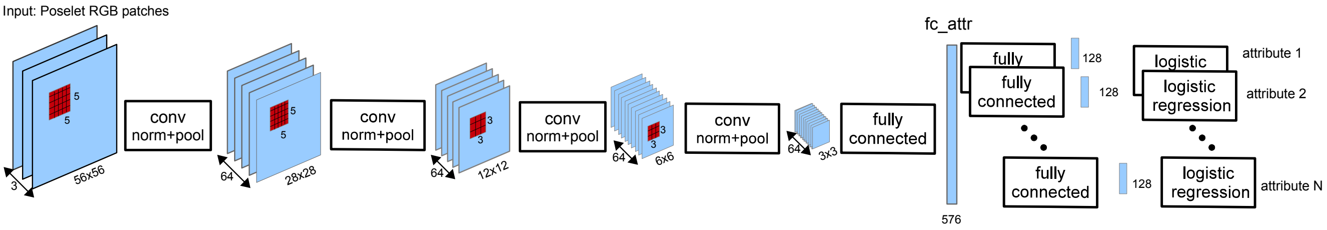


Figure 2: **Part-based Convolutional Neural Nets.** For each poselet, one convolutional neural net is trained on patches resized 64x64. The network consists of 4 stages of convolution/pooling/normalization and followed by a fully connected layer. Then, it branches out one fully connected layer with 128 hidden units for each attribute. We concatenate the activation from fc_attr from each poselet to obtain the pose-normalized representation. The details of filter size, number of filters and stride we used are depicted above.

feature representation to zero.

The part-based deep representation mentioned above leverages both the discriminative deep convonvolutional features and part correpondence. However, poselet detected parts may not always cover the whole image region and in some degenerate cases, images may have few poselets detected. To deal with that, we also incorporate a deep network covering the whole-person bounding box region as input to our final pose-normalized representation.

Based on our experiments, we find a more complex net is needed for the whole-person region than for the part regions. We extract deep convolutional features from the model trained on Imagenet [14] using the open source package provided by [8] as our deep representation on whole image patch.

As shown in Figure 1, we incorporate both part-based deep representation and deep representation on whole image patch in our model to obtain the deep pose-normalized representation. A linear SVM classifier is trained using the pose-normalized representation for each of the attribute to get the final prediction.

4. Datasets

4.1. The Berkeley Human Attributes Dataset

We tested our method on the Berkeley Human Attributes Dataset [4]. This dataset consists of 4013 training, and 4022 test images collected from PASCAL and H3D datasets. The dataset is challenging as it includes people with wide variation in pose, viewpoint and occlusion. About 60% of the photos have both eyes visible, so many existing attributes methods that work on frontal faces will not do well on this dataset.

4.2. Attributes 25K Dataset

Unfortunately the training portion of the Berkeley dataset is not large enough for training our deep-net models (they severely overfit when trained just on these images). We collected an additional dataset from the web of 24963 people split into 8737 training, 8737 validation and 7489 test examples. We made sure the images do not intersect those in the Berkeley dataset. The statistics of the images are similar, with large variation in viewpoint, pose and occlusions.

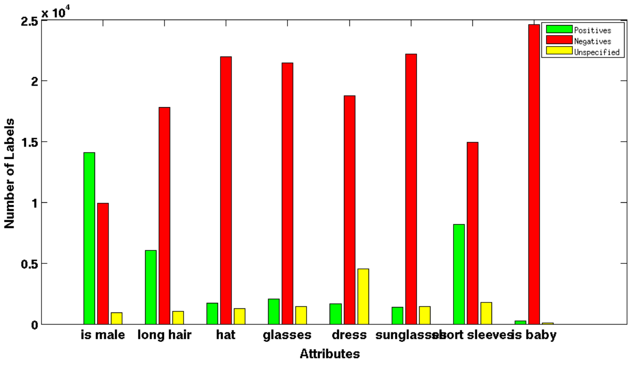


Figure 4: Statisitcs of the number of groundtruth labels on Attribute 25k Dataset. For each attribute, green is the number of positive labels, red is the number of negative labels and yellow is the number of uncertain labels.

We train on our large training set and report results on both the corresponding test set and the Berkeley Attributes test set. We chose to use a subset of the categories from the Berkeley dataset and add a few additional categories. This will allow us to explore the transfer-learning ability of our system.

Not every attribute can be inferred from every image. For example, if the head of the person is not visible, we cannot enter a label for the ”wears hat” category. The statistics of ground truth labels are shown on Figure 4.

5. Results

In this section, we will present a comparative performance evaluation of our proposed methods.

5.1. Results on the Berkeley Attributes of People Dataset

On Table 1 we show the results on applying our system on the publicly available Berkeley Attributes of People dataset. **Poselets** and **DPD** rows show the results on that dataset as reported by [4] and [27]. For our method, **PANDA**, we use Attributes25K dataset to train the poselet-level CNNs of our system, and we used the Berkeley dataset validation examples to train the SVM.

As the table shows, our system outperforms all the prior methods across most attributes. In the case of t-shirt, [4] performs slightly better, perhaps due to the fact that they use skin-tone channel and part masks. It should be noted that our method is conceptually very simple: We feed the raw RGB pixels to each poselet CNN, then we concatenate the features extracted from each CNN and train a linear SVM classifier. In contrast, [4] uses a combination of HOG features, color histogram features, skin channels, and part-dependent soft masks and combines the results using context by training a polynomial SVM. [27] use gradient, LBP, RGB and normalized RGB combined in Spatial Pyramid Match Kernel.

Note also that the attributes t-shirt, shorts, jeans and long pants are not present in the Attributes25K dataset. In Figure 5, we show the attribute prediction results returned by PANDA by generating queries of several attributes. To search for person images wearing both hat and glasses, we return the images with the largest cumulative score for those attributes.

In Figure 6, we show the top failure cases for wear tshirts and wear long sleeves on the test dataset. In the case of wearing tshirt, the top failure cases are picking the sleeveless, which look very similar to tshirts. And for the case of wearing long sleeves, some of failures are due to the occlusion of the arms and presence of jacket.

5.2. Results on the Attributes25K Dataset

Table 2 shows results on the Attributes25K-test Dataset.

Poselets150. shows the performance of our implementation of the three-layer feed-forward network proposed by [4]. Instead of the 1200 poselets in that paper we used the 150 publicly released poselets, and instead of multiple aspect ratios we use 64x64 patches. Our system underperforms [4] and on the Berkeley Attributes of People dataset yields mean AP of 60.6 vs 65.2[1], but it is faster and simpler and we have adopted the same setup for our CNN-based poselets. This allows us to make more meaningful comparisons between the two methods.

DPD and **DeCAF** We used the publicly available implementations of [27] based on deformable part models and [8] based on CNN trained on ImageNet. The results in this table confirm that our method performs very well.

5.3. Component Evaluation

We now explore the performance of individual components of our system as shown on Table 3 using the Berkeley dataset. Our goal is to get insights into the importance of using deep learning and the importance of using parts.

How well does a conventional deep learning classifier perform? We first explore a simple model of feeding the raw RGB image of the person into a deep network. To help with rough alignment and get signal from two resolutions we split the images into four 64x64 patches – one from the top, center, and bottom part of the person's bounds, and one from the full bounding box at half the resolution.

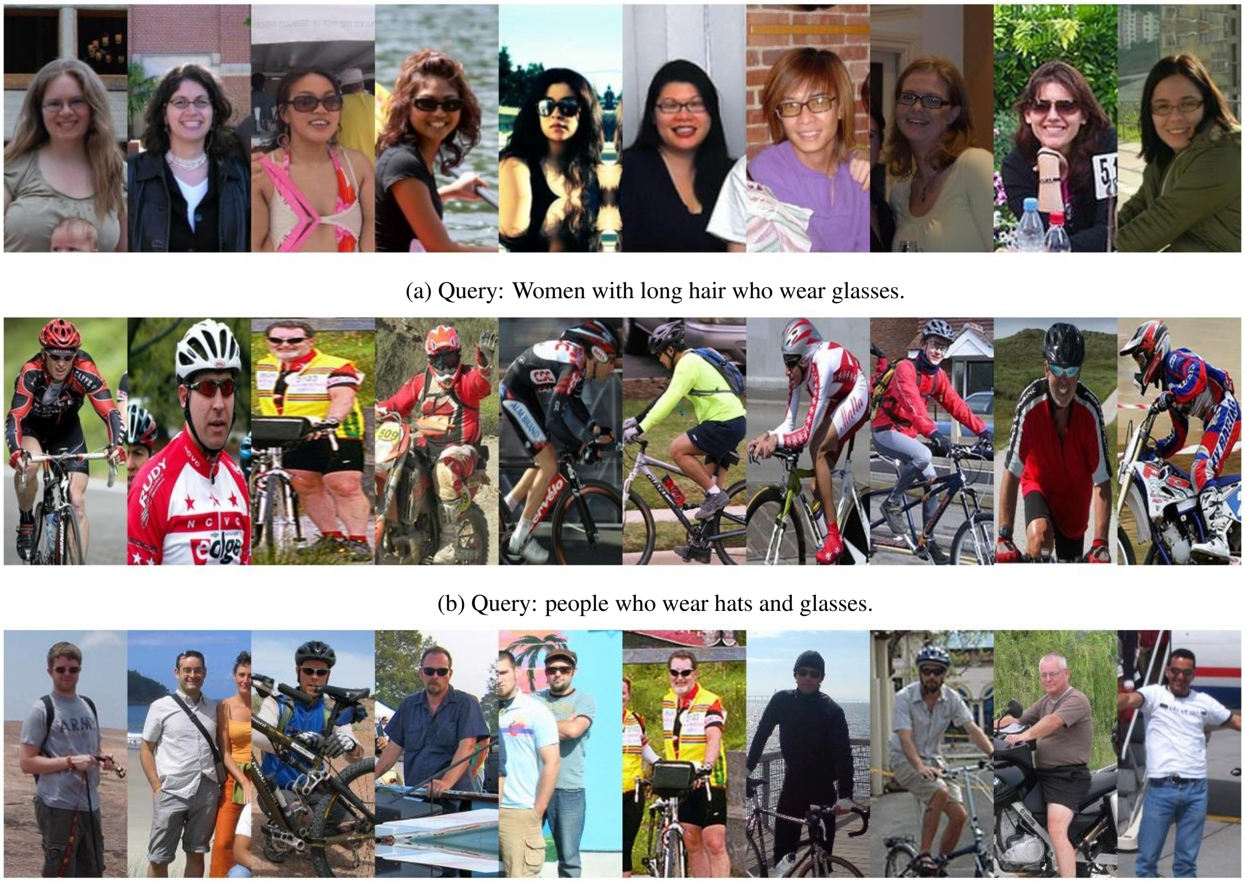
We resize each image to 64x128 pixels and crop it into three overlapping 64x64 squares (top, middle and bottom). We also resize the input image to 64x64 pixels to provide the network with information about the whole image at a coarser scale. In total we have 4 concatenated 64x64 square color images as input (12 channels). We train a CNN on this 12x64x64 input on the full Attributes-25K dataset. The structure we used is similar to the CNN in Figure 2 and it consists of two convolution/normalization/pooling stages, followed by a fully connected layer with 512 hidden units followed by nine columns, each composed of one hidden layer with 128 hidden units. Each of the 9 branches outputs a single value which is a binary classifier of the attribute. We then use the CNN as a feature extractor on the validation set by using the features produced by the final fully connected layer. We train a logistic regression using these features and report its performance on the ICCV test set as **DL-Pure** on Table 3.

We also show the results of our second baseline – DeCAF, which is the global component of our system. Even though it is a convolutional neural net originally trained on a completely different problem (ImageNet classification), it has been exposed to millions of images and it outperforms **DL-Pure**.

How important is deep learning at the part level?. By comparing the results of **Poselets150L2** and **DLPoselets** we can see the effect of deep learning at the part level. Both methods use the same poselets, train poselet-level attribute classifiers and combine them at the person level with a linear SVM. The only difference is that Poselets150L2 uses the features as described in [4] (HOG features, color histogram, skin tone and part masks) whereas DLPoselets uses features trained with a convolutional neural net applied to the poselet image patch. As our table shows, deep-net poselets result in increased performance.

PANDA shows the results of our proposed system which combines DeCAF and DLPoselets. As Table shows, our part and holistic classifiers use complementary features and

[1] see supplementary material for more



(a) Query: Women with long hair who wear glasses.

(b) Query: people who wear hats and glasses.

(c) Query: men with short pants and glasses.

Figure 5: **Example of PANDA queries.** Top results returned by our proposed method PANDA on Berkeley Attributes of People Dataset for query about multiple attributes. The prediction scores of multiple attributes are computed as a linear combination of attribute prediction scores.

Attribute	male	long hair	glasses	hat	tshirt	longsleeves	shorts	jeans	long pants	Mean AP
Poselets[4]	82.4	72.5	55.6	60.1	**51.2**	74.2	45.5	54.7	90.3	65.18
DPD[27]	83.7	70.0	38.1	73.4	49.8	78.1	64.1	78.1	93.5	69.88
PANDA	**91.7**	**82.7**	**70.0**	**74.2**	49.8	**86.0**	**79.1**	**81.0**	**96.4**	**78.98**

Table 1: Attribute classification results on Berkeley Attributes of People Dataset as compared to the methods of Bourdev *et al*. [4] and Zhang *et al*. [27] .

combining them together further boosts the performance.

5.4. Robustness to viewpoint variations

In Table 4, we show the performance of our method as a function of the viewpoint of the person. We considered as *frontal* any image in which both eyes of the person are visible, which includes approximately 60% of the dataset. *Profile* views are views in which one eye is visible and *Back-facing* are views where both eyes are not visible. As expected, our method performs best for front-facing people because they are most frequent in our training set. However, the figure shows that PANDA can work well across a wide range of viewpoints.

5.5. Results on the LFW Dataset

We also report results on the Labeled Faces in the Wild dataset [15]. The dataset consists of 13233 images of cropped, centered frontal faces. Such constrained environment does not leverage the strengths of our system in its ability to deal with viewpoint, pose and partial occlusions. Nevertheless it provides us another datapoint to com-

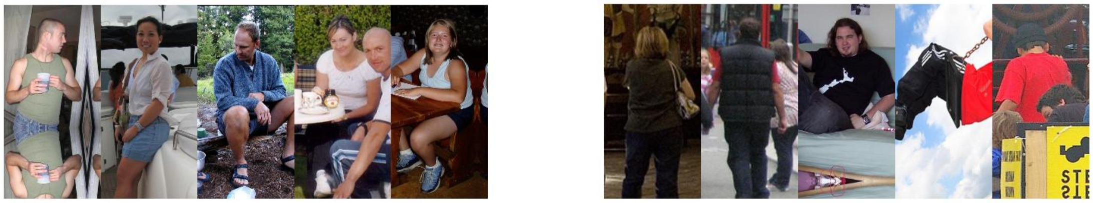


Figure 6: Example of failure cases on Berkeley Attributes of People Dataset. On the left we show highest scoring failure cases for ”wears t-shirt” and on the right – for ”wears long sleeves”.

Attribute	male	long hair	hat	glasses	dress	sunglasses	short sleeves	baby	mean AP
Poselets150[4]	86.00	75.31	29.03	36.72	34.73	50.16	55.25	41.26	51.06
DPD[27]	85.84	72.40	27.55	23.94	48.55	34.36	54.75	41.38	48.60
DeCAF [8]	82.47	65.03	19.15	14.91	44.68	26.91	56.40	50.19	44.97
PANDA	**94.10**	**83.17**	**39.52**	**72.25**	**59.41**	**66.62**	**72.09**	**78.76**	**70.74**

Table 2: Average Precision on the Attributes25K-test dataset.

Method	Gender AP
Simile [15]	95.52
FrontalFace poselet	96.43
PANDA	**99.54**

Table 5: Average precision of PANDA on the gender recognition of the LFW dataset.

pare against other methods. This dataset contains many attributes, but unfortunately the ground truth labels are not released. We used crowd-sourcing to collect ground-truth labels for the gender attribute only. We split the examples randomly into 3042 training and 10101 test examples with the only constraint that the same identity may not appear in both training and test sets. We used our system whose features were trained on Attribute-25K to extract features on the 3042 training examples. Then we trained a linear SVM and applied the classifier on the 10101 test examples. We also used the publicly available gender scores of [15] to compute the average precision of their system on the test subset. The results are shown on Table 5.

PANDA’s AP on LFW is 99.54% using our parts model, a marked improvement over the previous state of the art. Our manual examination of the results shows that roughly 1 in 200 test examples either had the wrong ground truth or we failed to match the detection results with the correct person. Thus PANDA shows nearly perfect gender recognition performance in LFW. This experiment also shows the difficulty of the Berkeley Attributes of People and the Attributes25K datasets.

One interesting observation is that, even though the dataset consists of only frontal-face people, the performance of our frontal-face poselet is significantly lower than the performance of the full system. This suggests that our system benefits from combining the signal from multiple redundant classifiers, each of which is trained on slightly different set of images.

6. Conclusion

We presented a method for attribute classification of people that improves performance compared with previously published methods. It is conceptually simple and leverages the strength of convolutional neural nets without requiring datasets of millions of images. It uses poselets to factor out the pose and viewpoint variation which allows the convolutional network to focus on the pose-normalized appearance differences. We concatenate the deep features at each poselet and add a global deep feature. Our feature representation is generic and we achieve state-of-the-art results on the Berkeley Attributes dataset and on LFW even if we train our features on a dataset with very different statistics. We believe that our proposed hybrid method using mid-level parts and deep learning classifiers at each part will prove effective not just for attribute classification, but also for problems such as detection, pose estimation, action recognition.

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Attribute	male	long hair	glasses	hat	tshirt	longsleeves	short	jeans	long pants	Mean AP
DL-Pure	80.65	63.23	30.74	57.21	37.99	71.76	35.05	60.18	86.17	58.11
DeCAF	79.64	62.29	31.29	55.17	41.84	78.77	**80.66**	**81.46**	96.32	67.49
Poselets150 L2	81.70	67.07	44.24	54.01	42.16	71.70	36.71	42.56	87.41	58.62
DLPoselets	**92.10**	82.26	**76.25**	65.55	44.83	77.31	43.71	52.52	87.82	69.15
PANDA	91.66	**82.70**	69.95	**74.22**	**49.84**	**86.01**	79.08	80.99	**96.37**	**78.98**

Table 3: Relative performance of baselines and components of our system on the Berkeley Attributes of People test set.

Partition	male	long hair	glasses	hat	tshirt	longsleeves	shorts	jeans	long pants	Mean AP
Frontal	92.55	88.40	77.09	74.40	51.69	86.84	78.00	79.63	95.70	80.47
Profile	91.42	59.38	37.06	69.47	49.02	84.61	85.57	82.71	98.10	73.04
Back-facing	88.65	63.77	72.61	72.19	55.20	84.32	74.01	86.12	96.68	77.06
All	91.66	82.70	69.95	74.22	49.84	86.01	79.08	80.99	96.37	78.98

Table 4: Performance of PANDA on front-facing, profile-facing and back-facing examples of the Berkeley Attributes of People test set.

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