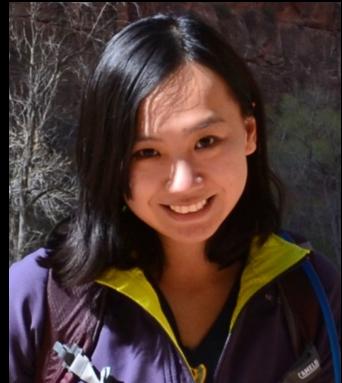


PANDA: Pose Aligned Networks for Deep Attribute Modeling



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men who wear helmet and sunglasses



Why is attribute classification challenging?

Low resolution



Occlusion



Pose variations



Toward attribute classification

Transfer knowledge

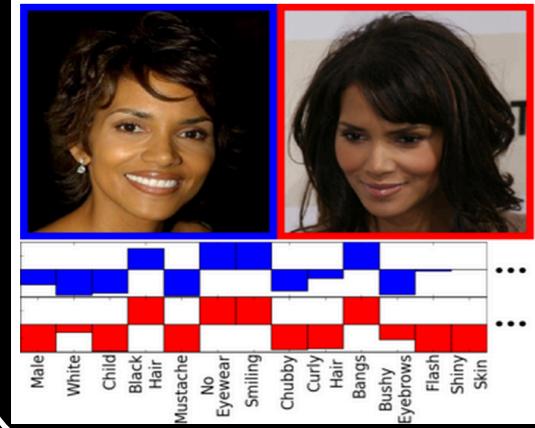
polar bear

black: no
white: yes
brown: no
stripes: no
water: yes
eats fish: yes



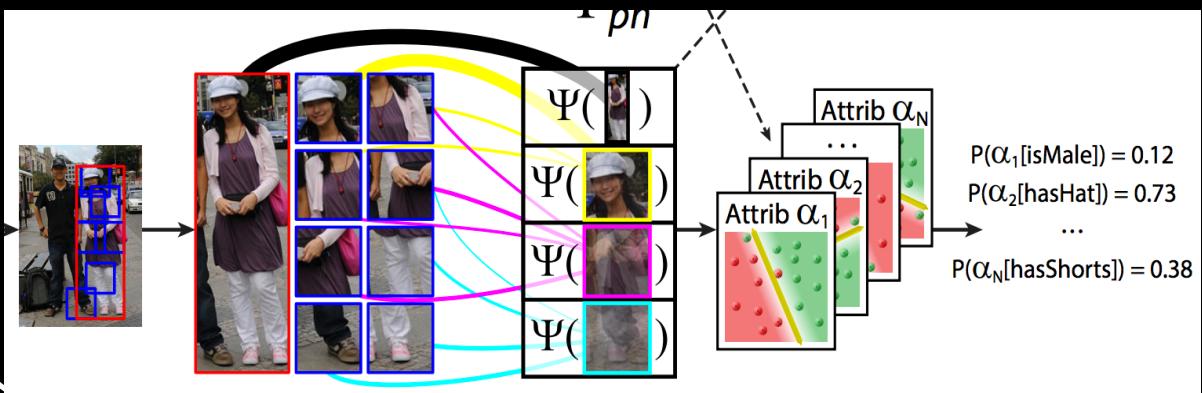
[Lampert et al. (CVPR 09), Farhadi et al. (CVPR 09)]

Facial Attribute

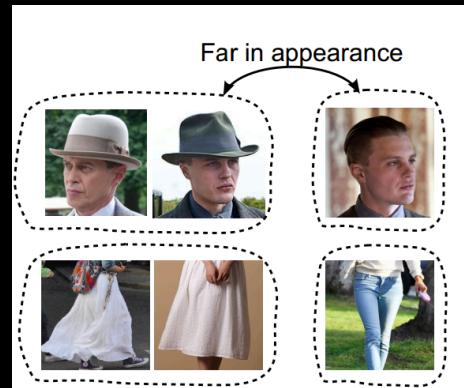


[Kumar et al. (ICCV 09)]

Part-based approach



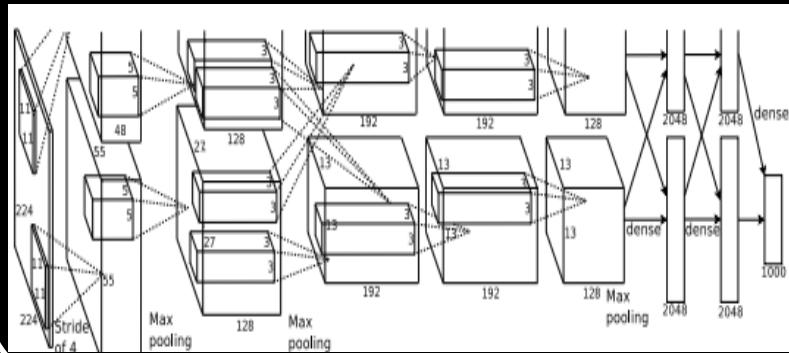
Far in appearance



[Bourdev et al. (ICCV11), Zhang et al. (ICCV 13) Joo et al. (ICCV 13)]

Progress in deep learning

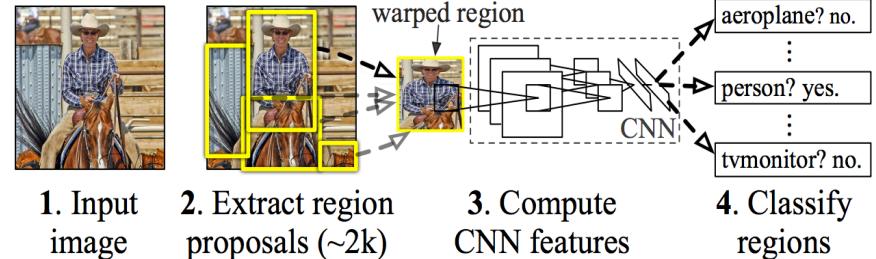
image classification



[Krizhevsky et al. NIPS 12, Zeiler et al. ICLR 14]

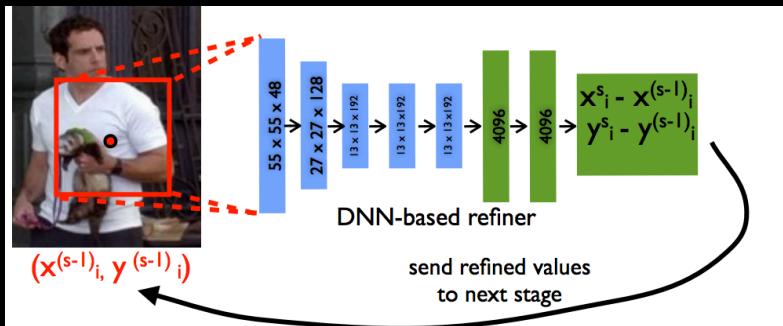
object detection

R-CNN: Regions with CNN features



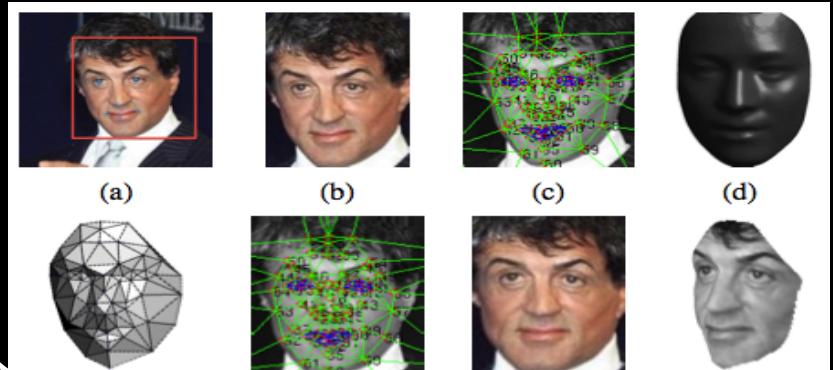
[Girshick et al. CVPR 14]

human pose estimation



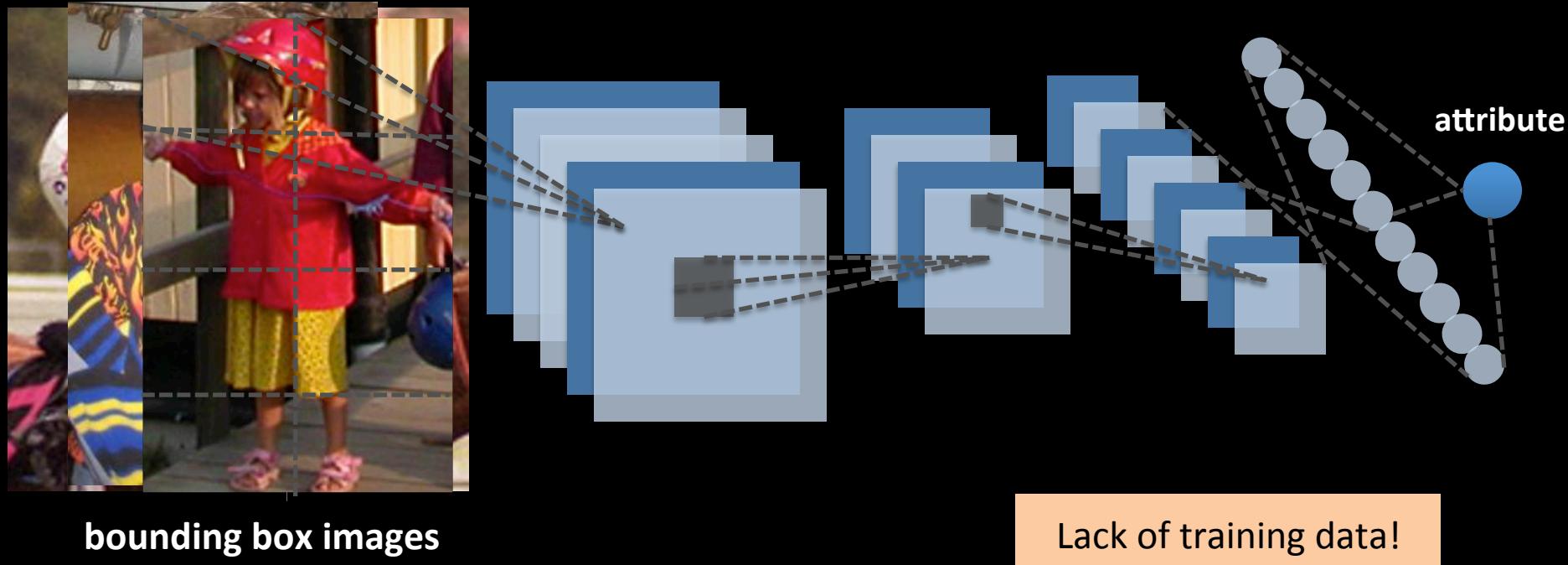
[Toshev et al. CVPR 14]

face verification



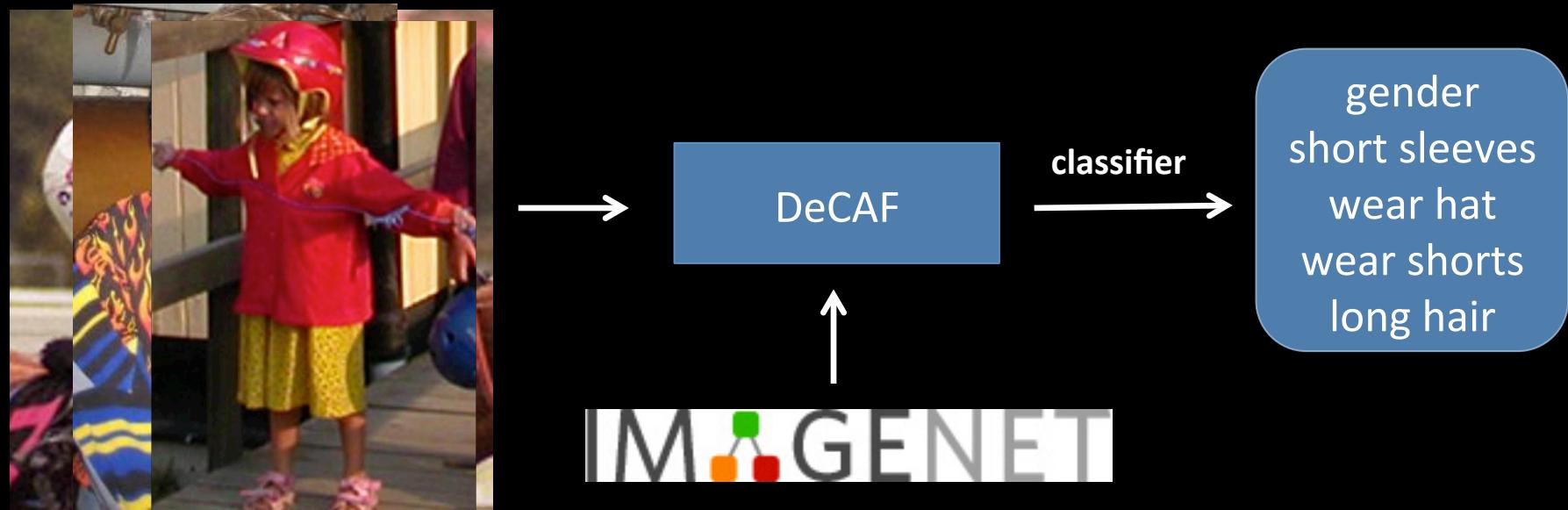
[Taigman et al. CVPR 14]

Can we train CNN from scratch?



method	Joo et al. ICCV 2013	CNN from scratch
mean AP	70.7	58.11

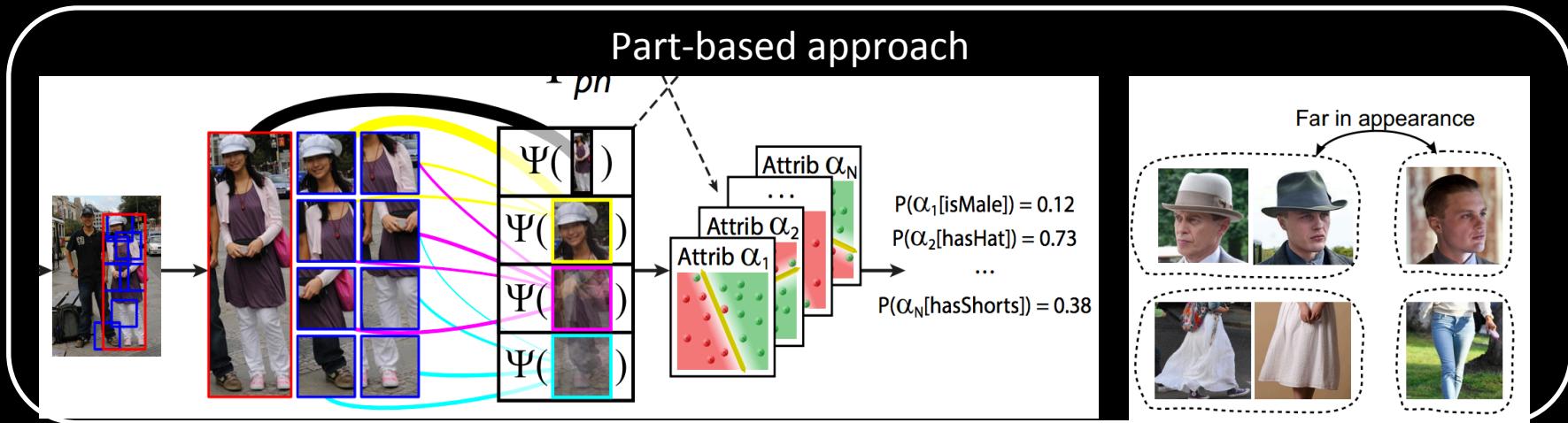
What if we finetune from ImageNet?



method	Joo et al	from scratch	from ImageNet
mean AP	70.7	58.11	67.49

How can we simplify the task?

Decompose the image into parts



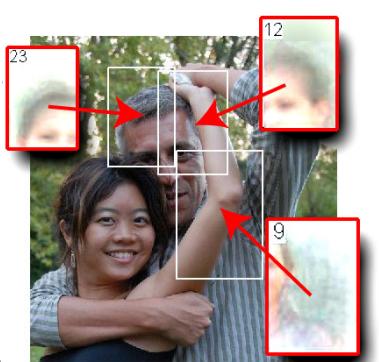
[Bourdev et al. (ICCV11), Zhang et al. (ICCV 13) Joo et al. (ICCV 13)]

Decompose the image into parts



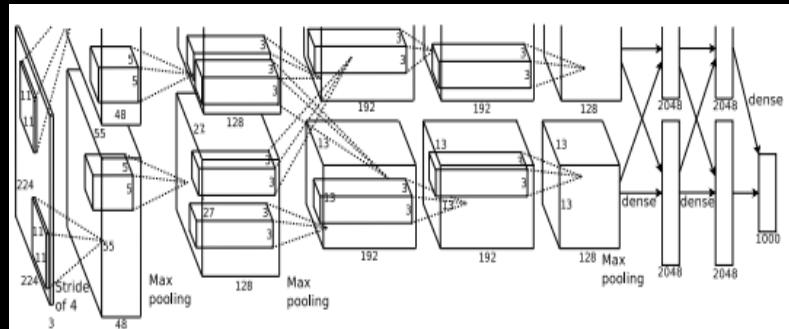
Our approach

Part-based models



Pose normalization

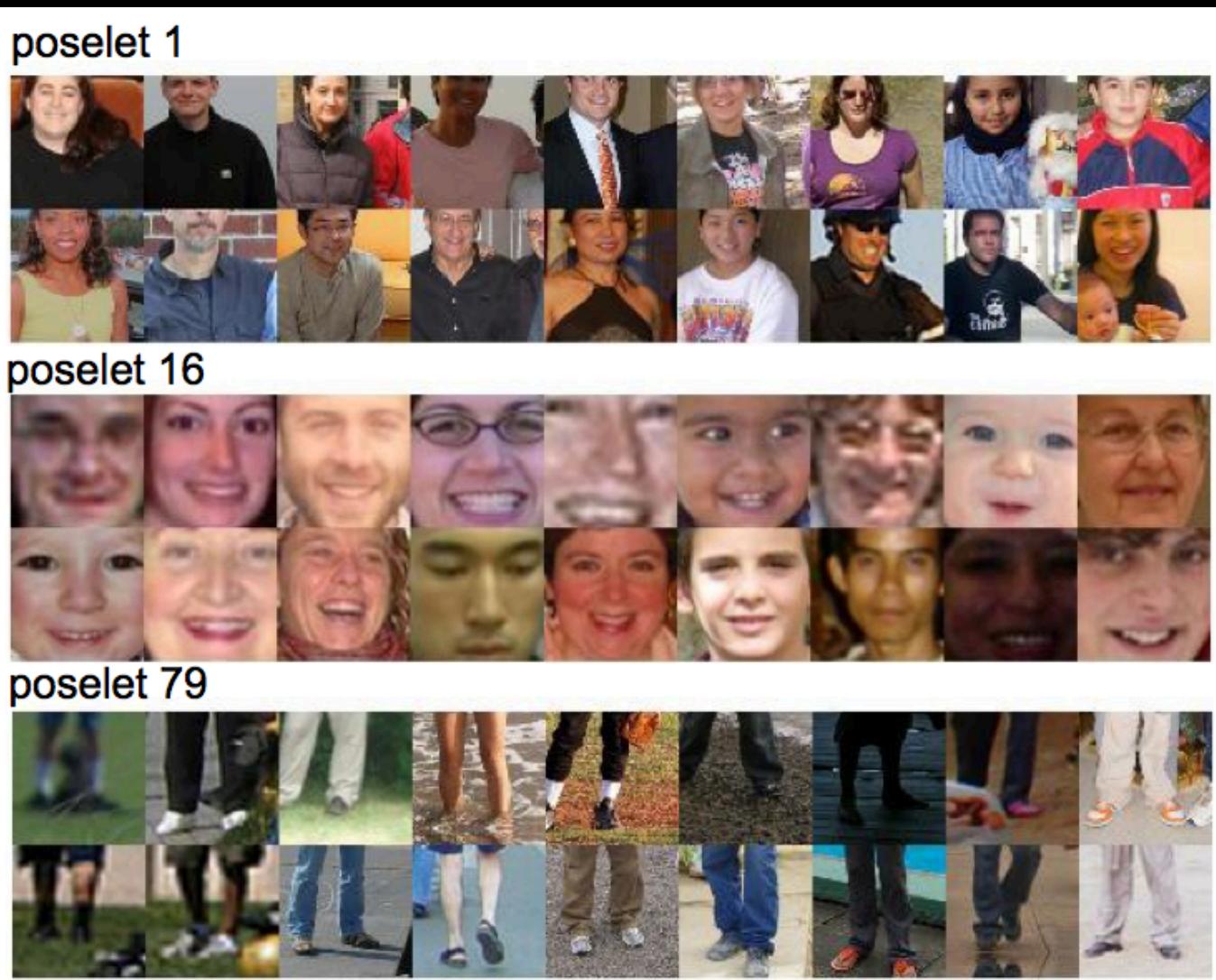
Deep convolutional networks



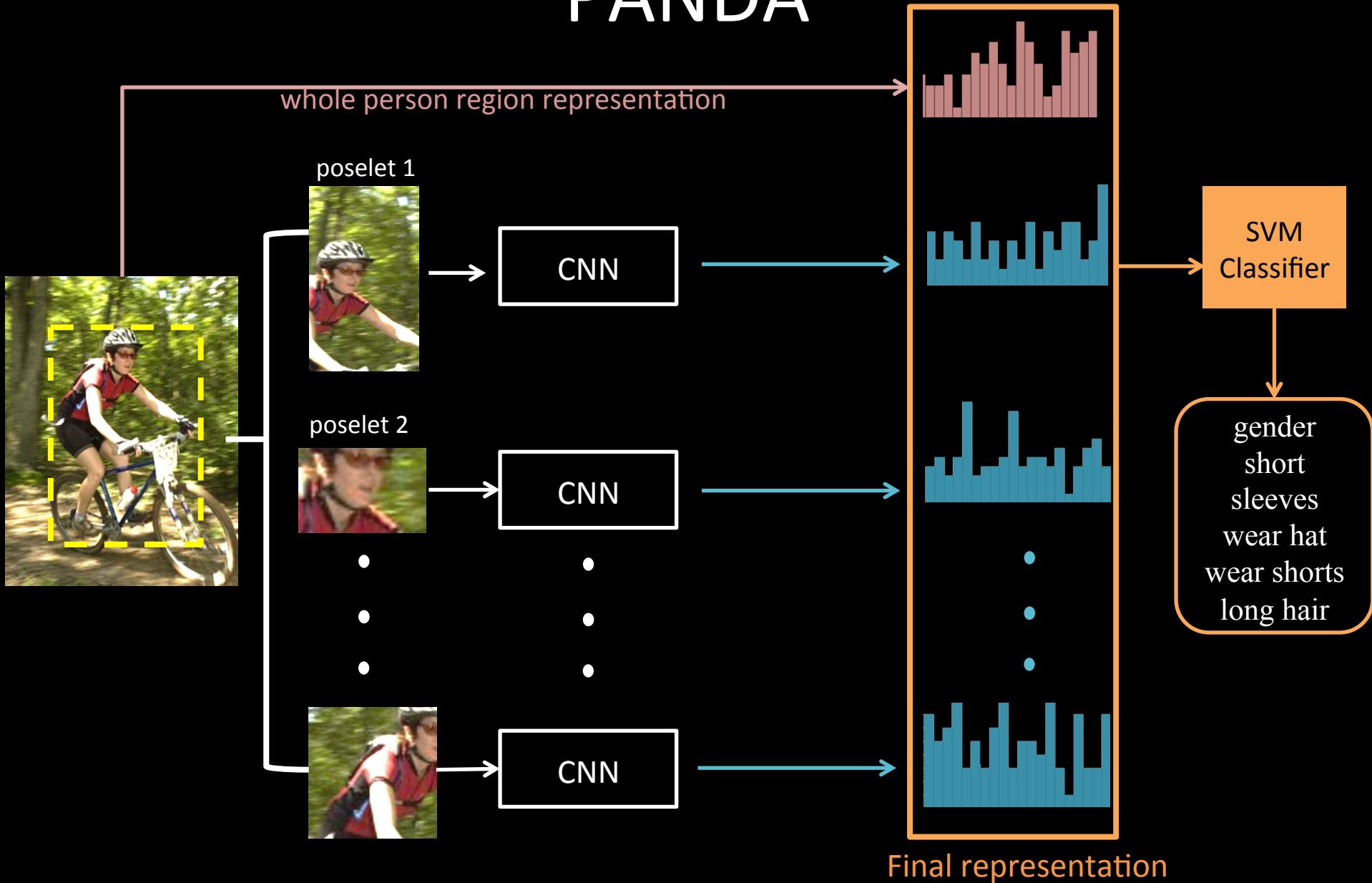
Discriminative feature representation

Pose Aligned Networks for Deep
Attribute modeling (PANDA)

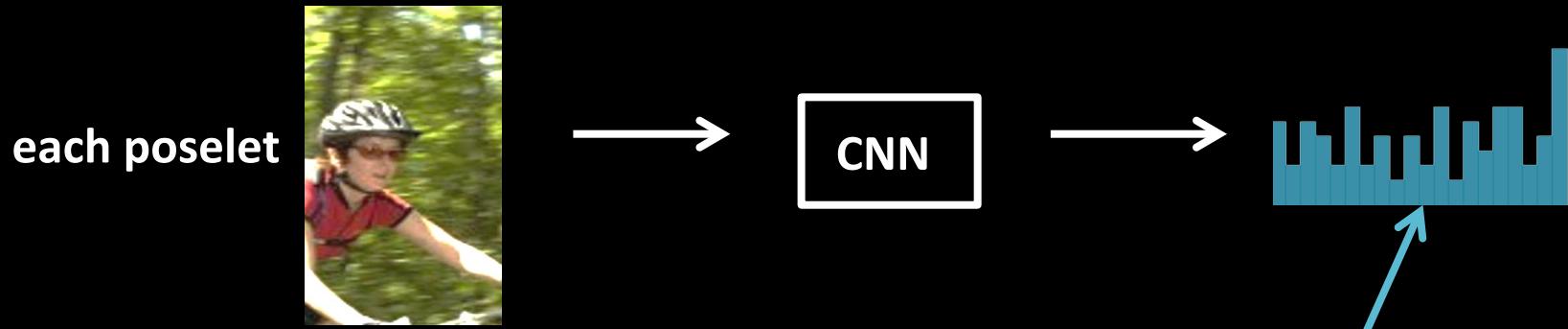
Poselets capture part of the pose from a given viewpoint



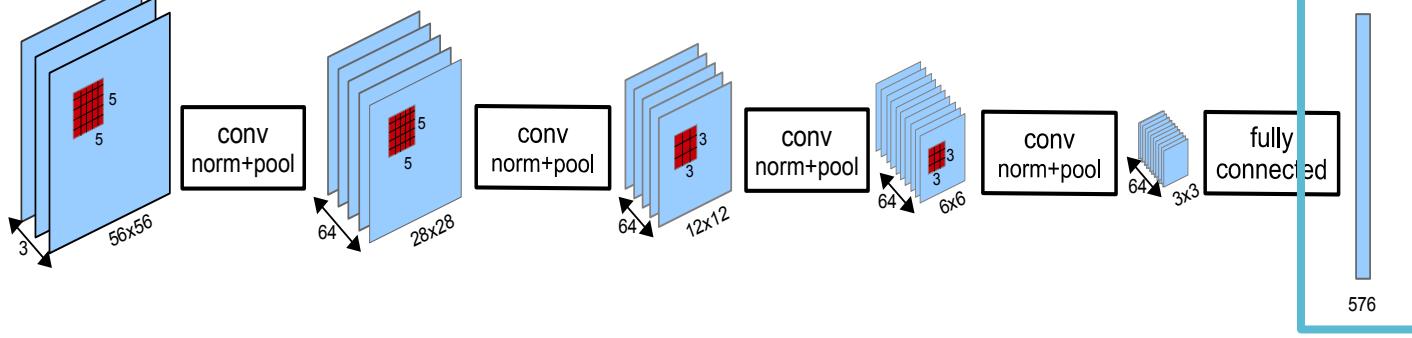
PANDA



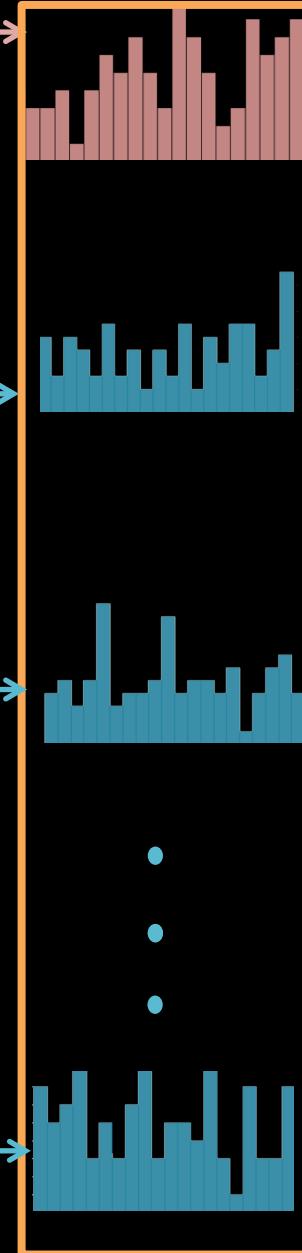
Part-Level CNN



Input: Poselet RGB patches



Final Representation

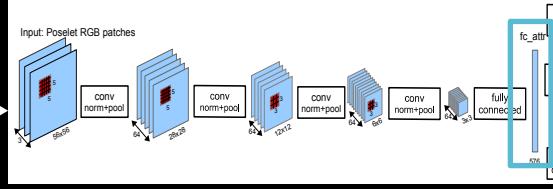
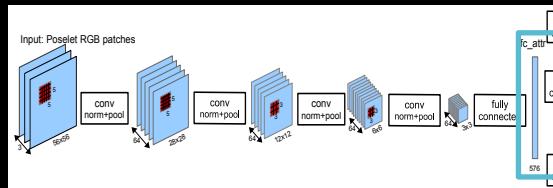
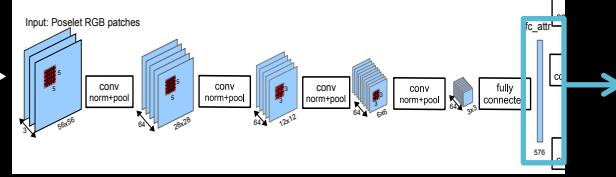


Holistic

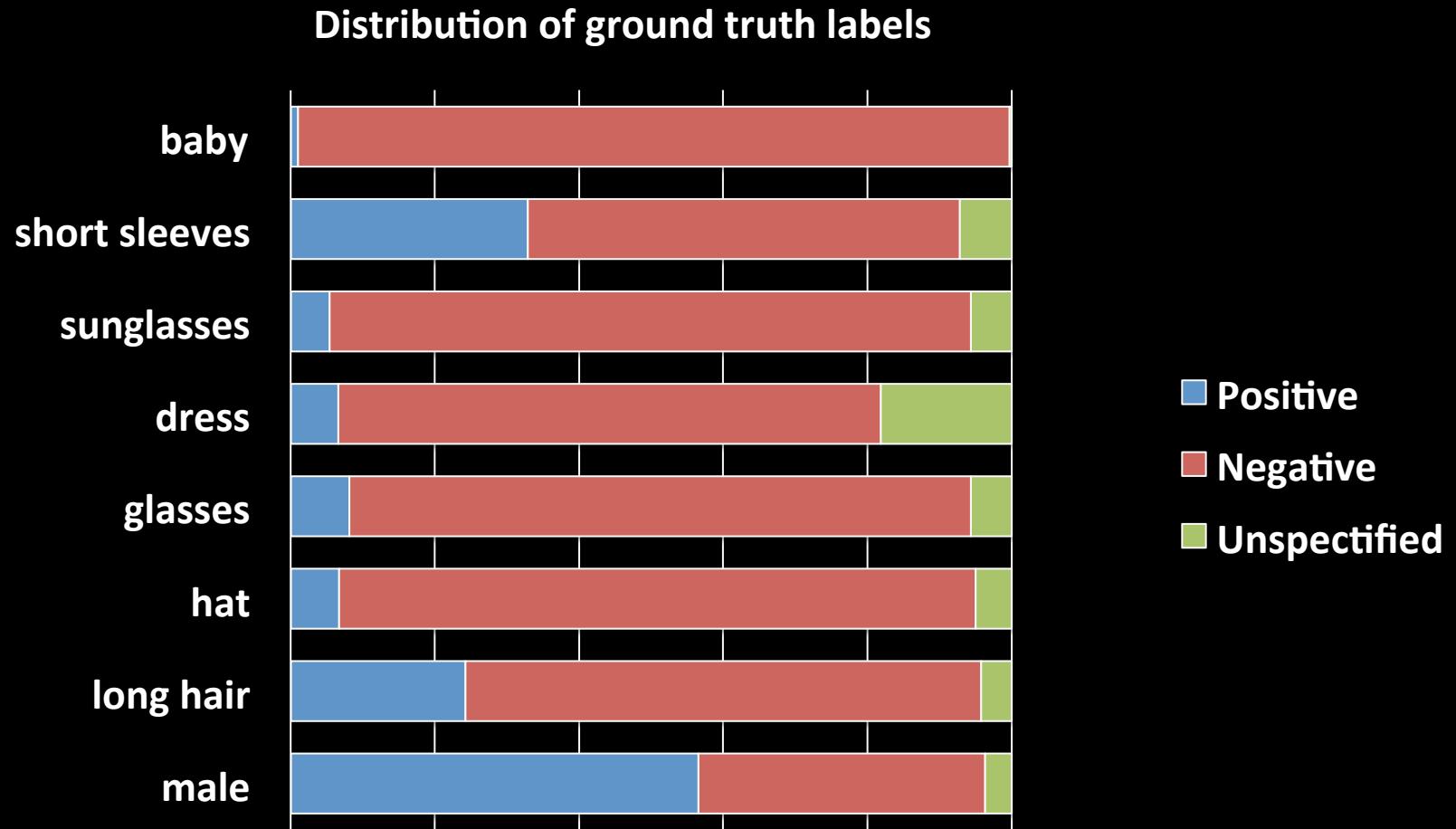
IMAGENET

Linear SVM

gender
short
sleeves
wear hat
wear shorts
long hair



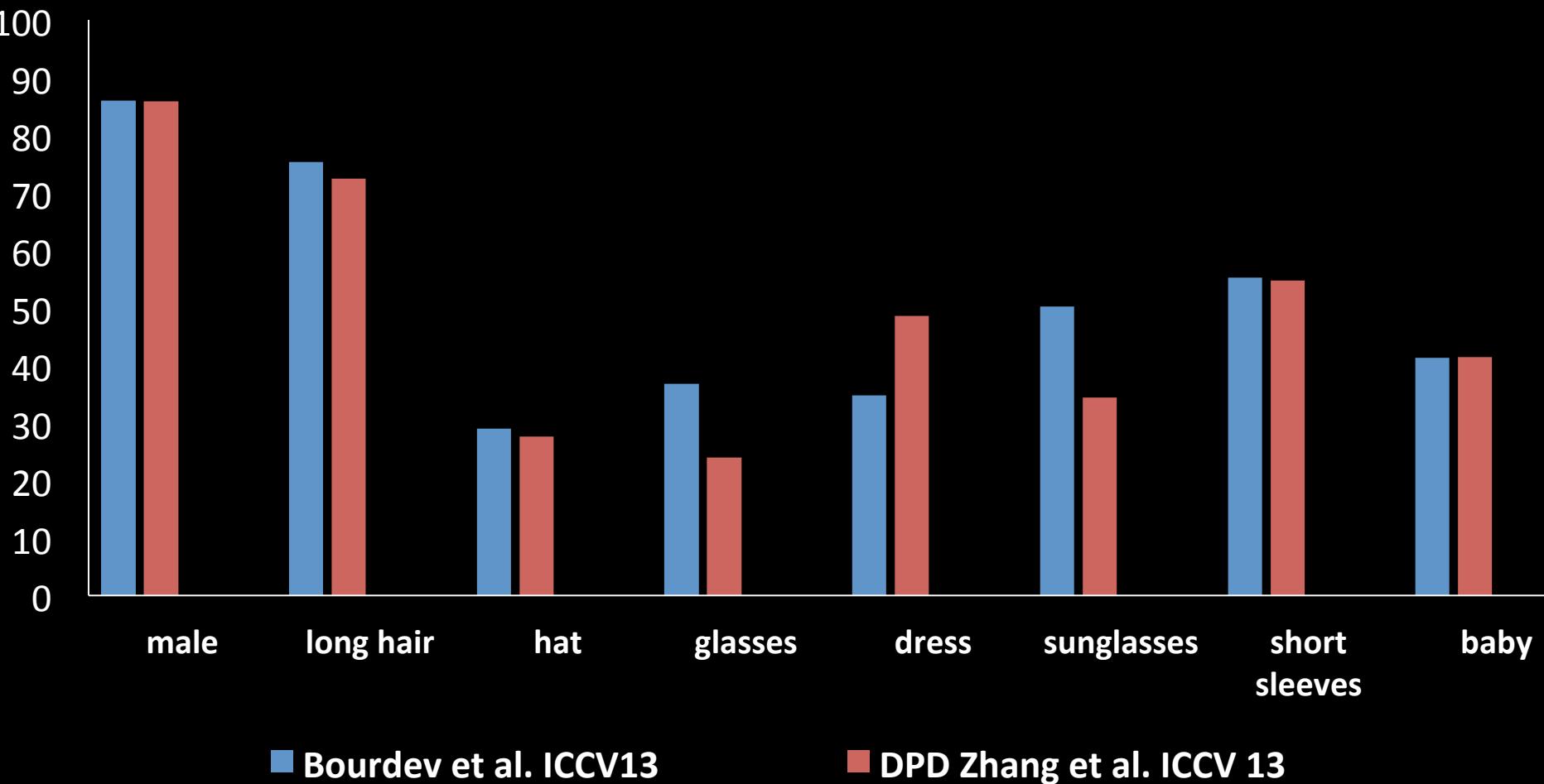
Dataset: Attribute 25k



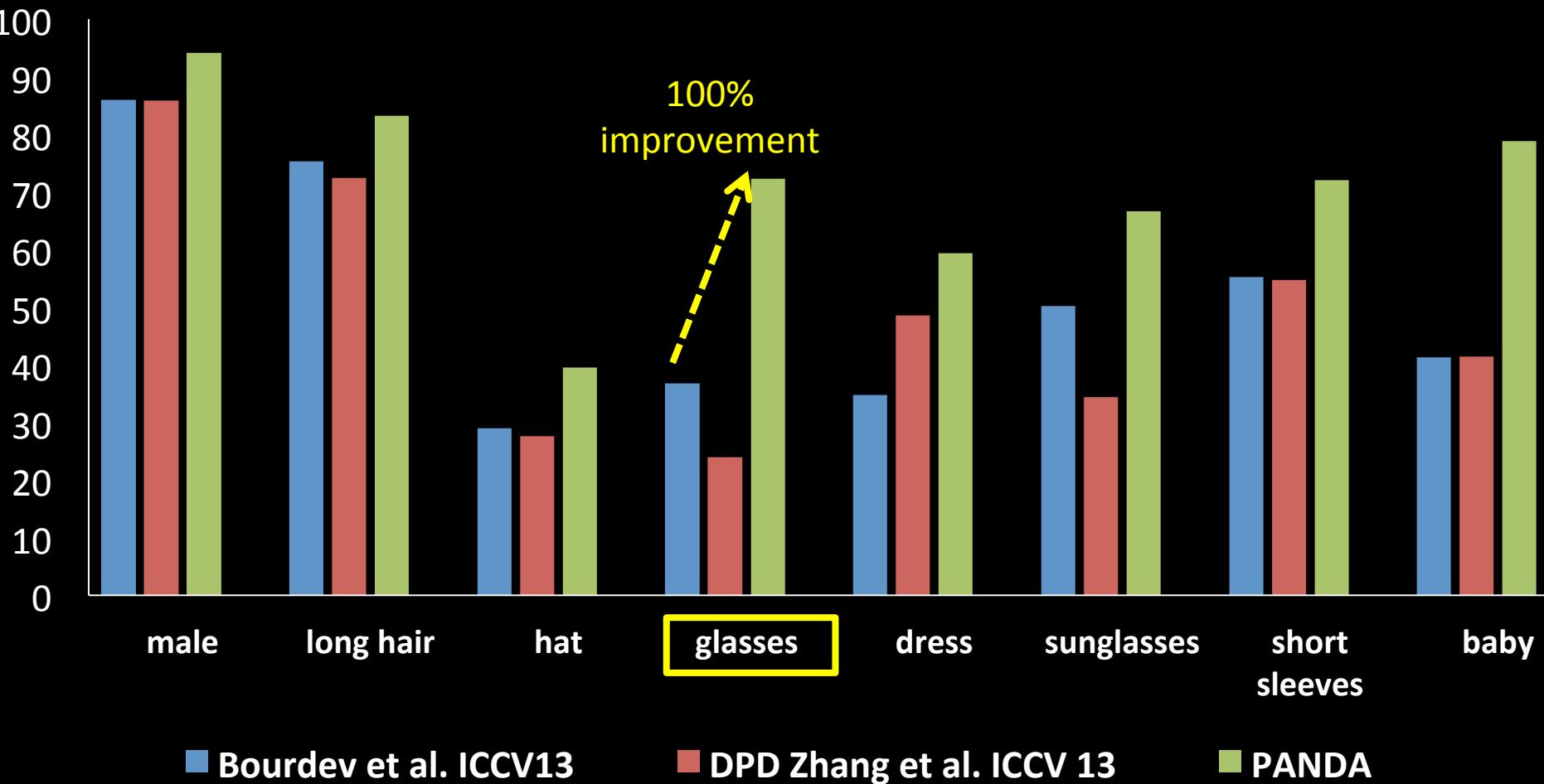
2061 training examples per poselet on average

RESULTS

Average Precision (AP) on Attribute 25k



Average Precision (AP) on Attribute 25k



Component Evaluation

method	mean AP
PANDA (Holistic + Poselets)	70.74

Component Evaluation

method	mean AP
PANDA (Holistic + Poselets)	70.74
Holistic only	44.97
Poselets only	64.72

Component Evaluation

method	mean AP
PANDA (Holistic + Poselets)	70.74
Holistic only	44.97
Poselets only	64.72
Holistic + DPM	61.20

Poselets vs DPM

Frontal face poselet



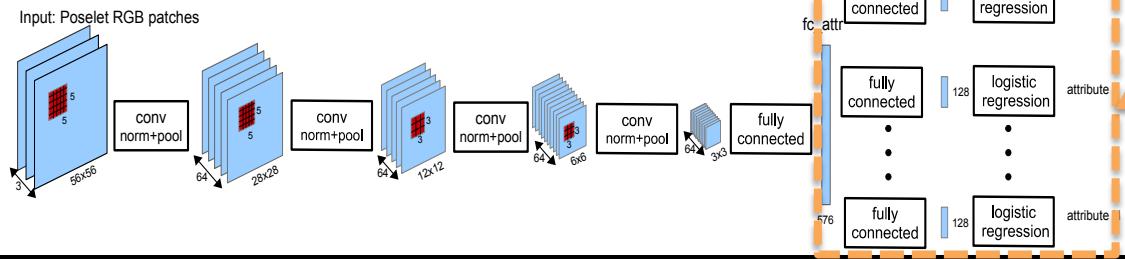
Head DPM



Mixes different poses

Alignment noise

Transfer learning



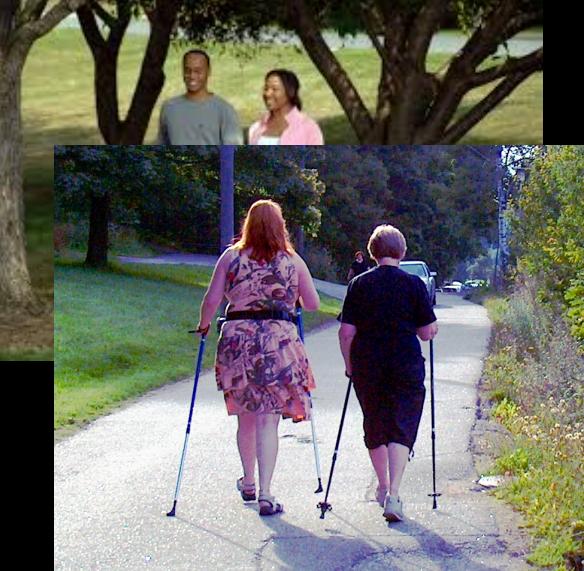
Adding new attributes
and retrain CNNs

Use the same CNNs only
retrain SVM classifier

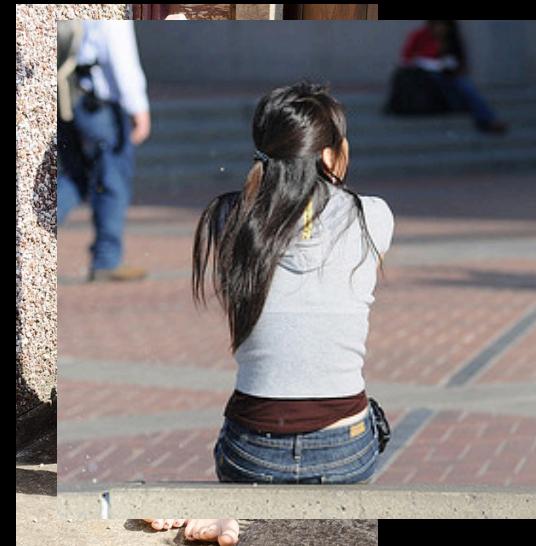
smiling: AP 84.7%
(frequency baseline 40.67%)



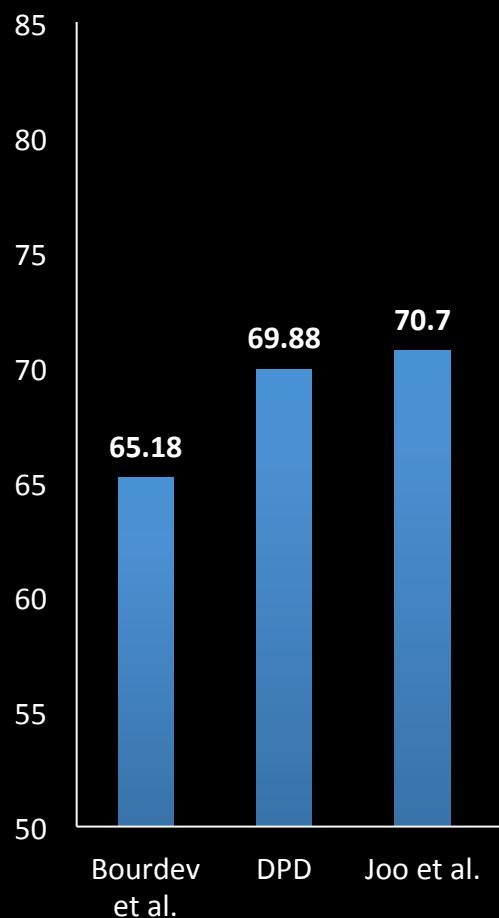
walking: AP 26.0%
(frequency baseline 4.34%)



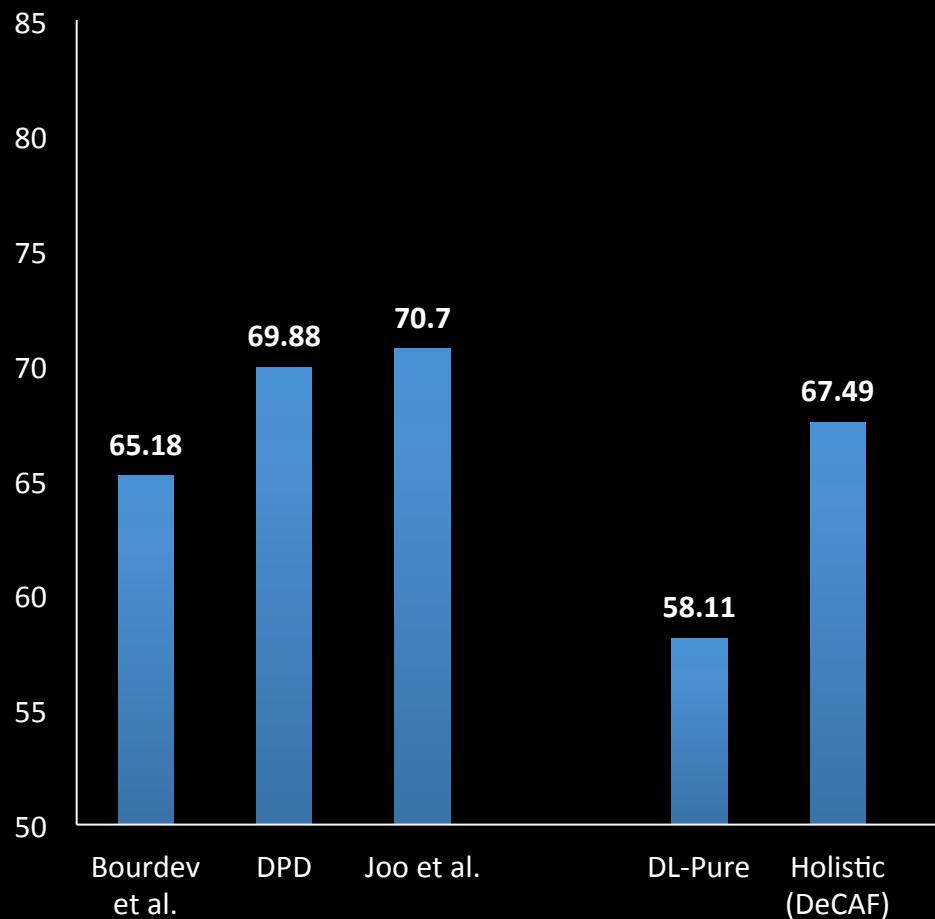
sitting: AP 25.70%
(frequency baseline 7.65%)



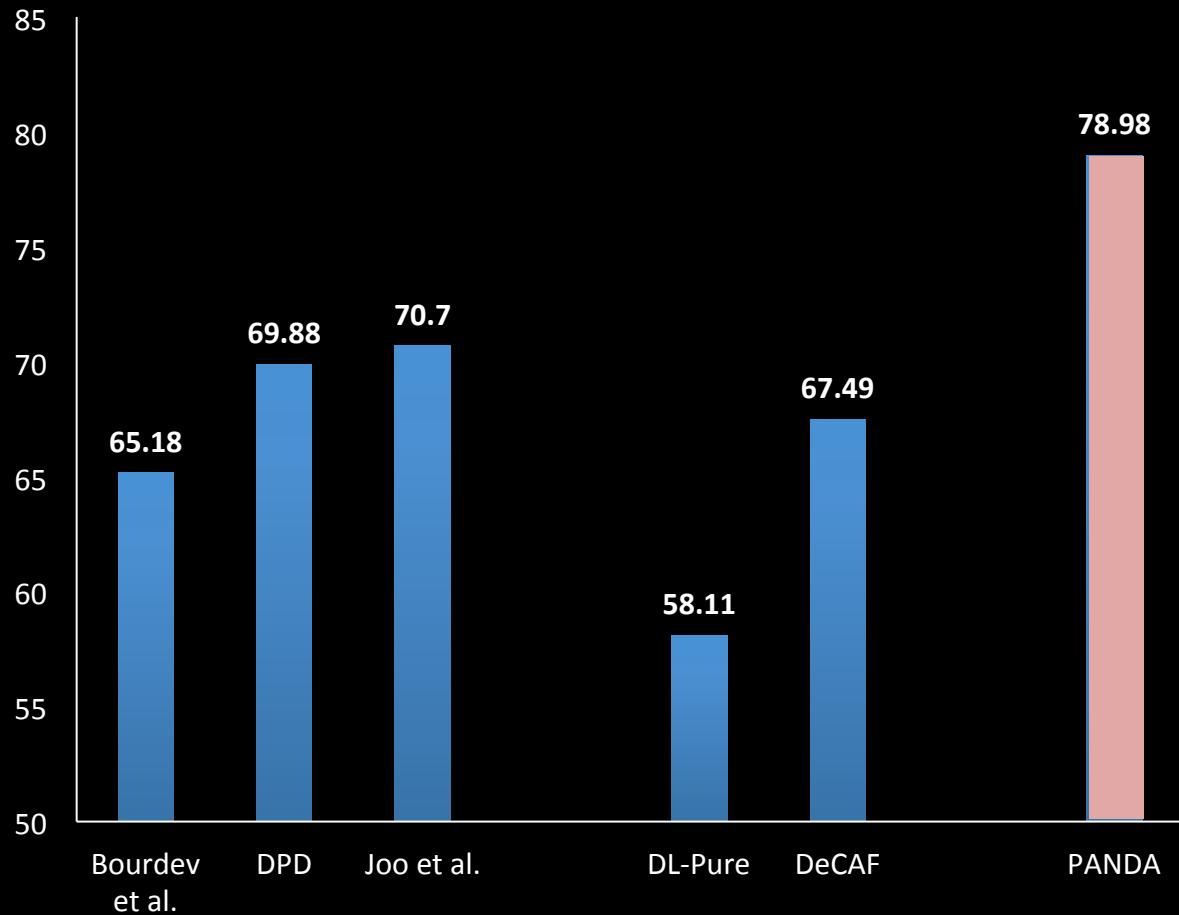
AP on Berkeley Attributes of People Dataset



AP on Berkeley Attributes of People Dataset



AP on Berkeley Attributes of People Dataset



The part-level CNNs
are trained using
Attribute 25k data.

Top scoring examples

wear glasses



short hair



female



Top scoring examples

wear hat



wear shorts



wear jeans



Hard to see skin

Failure Cases

Unusual pose

Predicted: Long sleeves, Ground truth: short sleeves



Predicted: short pants, ground truth: Long pants

Annotation errors

ambiguous



Gender Recognition on Labeled Faces in the Wild



Much easier dataset – no occlusion, high resolution, centered frontal faces

Method	Gender AP
Kumar et al	95.52
Frontal face poselet	96.43

[Kumar et al, ICCV 2009]

Gender Recognition on Labeled Faces in the Wild



Much easier dataset – no occlusion, high resolution, centered frontal faces

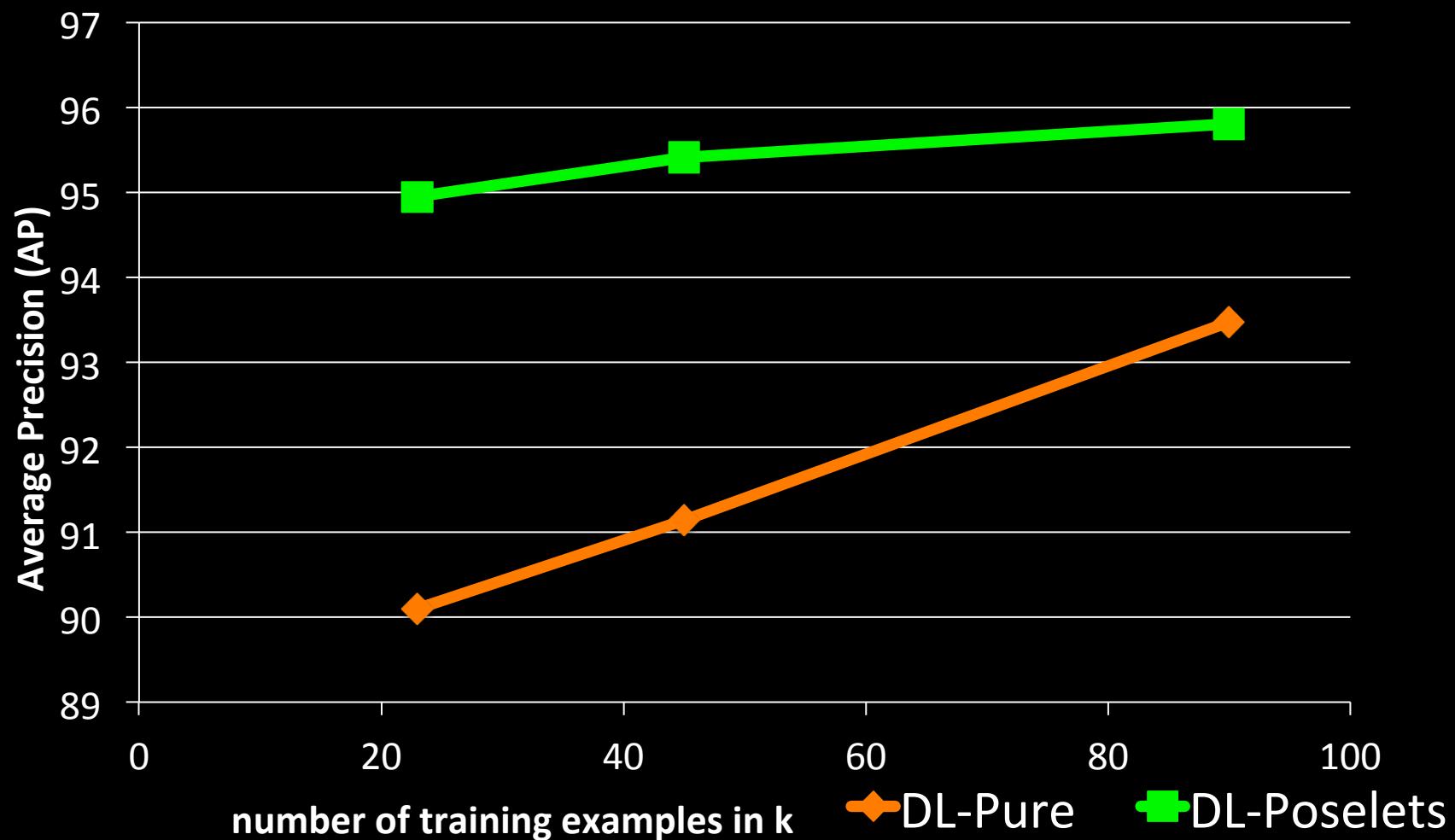
Method	Gender AP
Kumar et al	95.52
Frontal face poselet	96.43
PANDA	99.54



Male or female?

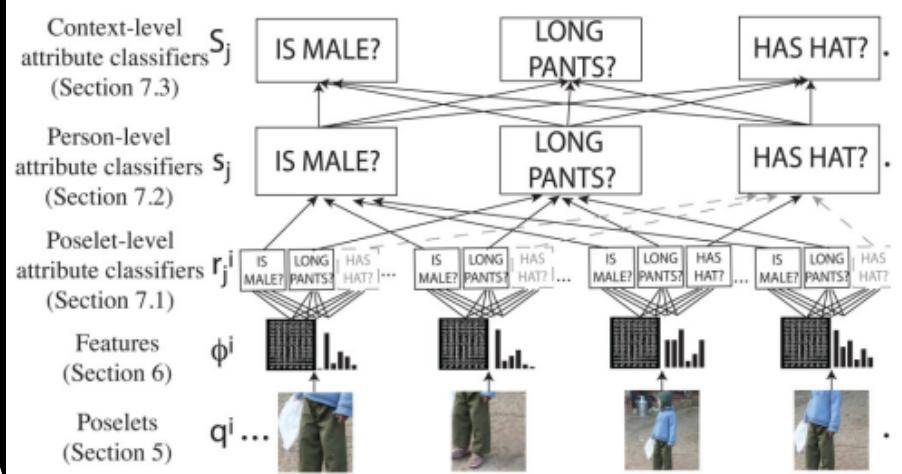
[Kumar et al, ICCV 2009]

Does more data help?

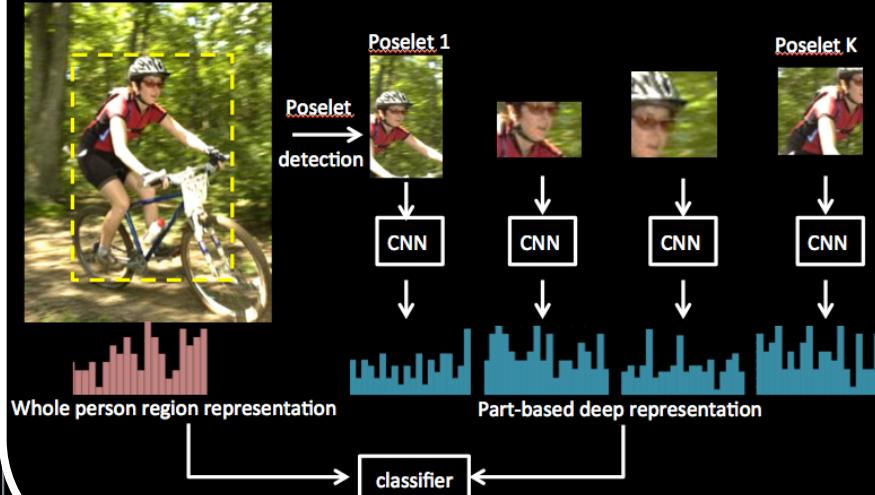


Comparison

Bourdev et al. ICCV 11



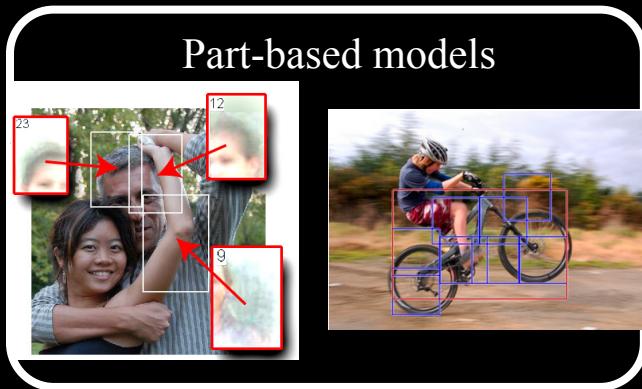
PANDA



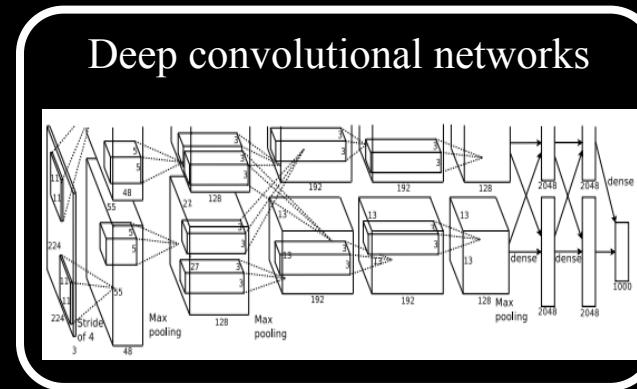
- Use poselet as part-based model
- Has context-level attribute classifier
- Use HOG+color+skin+part masks

- Use poselets as part-based model
- Attributes are jointly trained
- Training part-level CNN for powerful discriminative feature
- Generalized much better to new attributes

Conclusion



Pose normalization



Discriminative feature representation

- Pose-normalization significantly helps deep convolutional networks in the task of attribute classification.
- Mid-level parts remain important in the context of CNNs.



Thanks!

- Code and pre-trained models will be released soon.



*None of the images in this slides are taken from Facebook.

Running time

- Single CPU
- 13s (poselet detection) +2s(feature extraction)