Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representation

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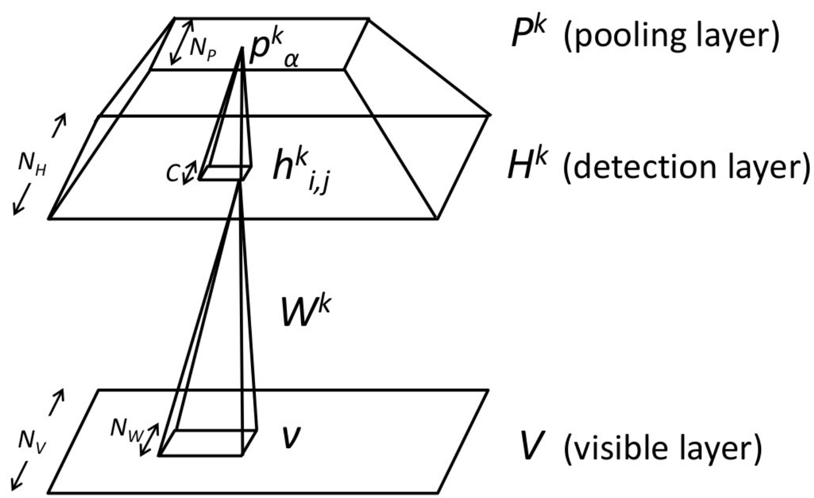
Motivation

- DBN's don't scale well to realistically sized images:
  - Images are high dimensional
  - Objects can appear anywhere in an image
- Both of these problems can be addressed by introducing a degree of translation invariance

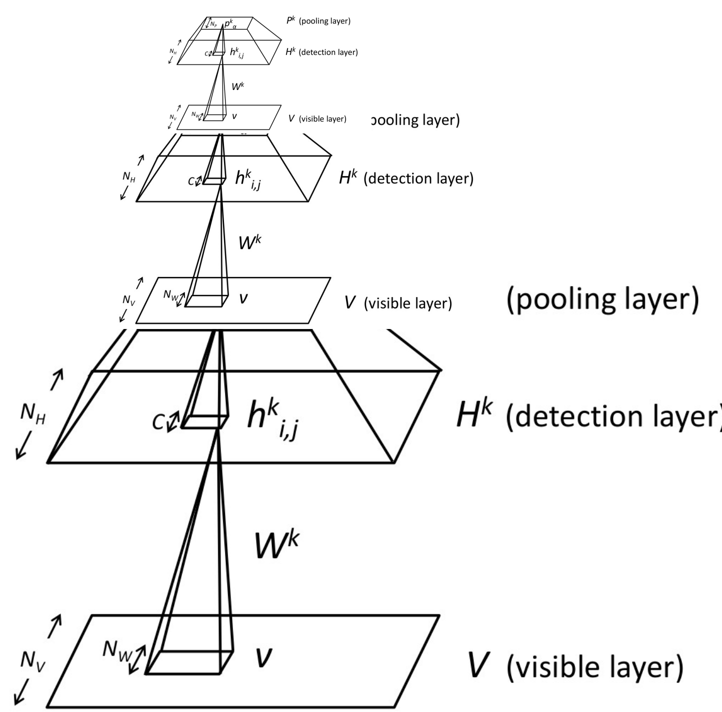
Convolutional RBM (CRBM)

- Two layers:
  - Input layer V
    - N_V X N_V array of real-valued units
  - Hidden layer H
    - K "groups"
      - N_H X N_H arrays of real-valued units



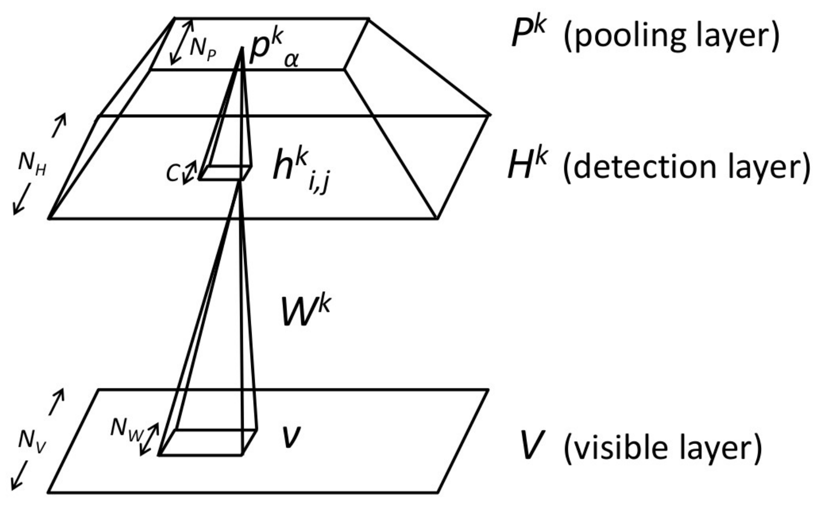
Convolutional RBM (CRBM)

- Like DBNs, stack several max-pooling CRBM on top of each other
- Train with efficient greedy, layer-wise algorithm



Probabilistic Max-Pooling

- In general, each layer requires progressively larger inputs
- Add a third layer to reduce complexity shrinking representation, without sacrificing significant features
- Feed forward only the “best match” by adding the constraint that only one unit in each C X C block is activated



Hierarchical probabilistic inference

- Lee and Mumford proposed that visual cortex performs hierarchical Bayesian inference
  - Use posterior computed at each layer to improve feature detection (especially disambiguation) in lower layers
  - This extends to feature inference
- e.g, from an observation of half of a face, we can infer the rest of the face by combining observation with prior knowledge of faces

Experiment

1) Learning hierarchical representations from natural images
2) Self-taught learning for object recognition
3) Handwritten digit classification
4) Unsupervised learning of object parts
5) Hierarchical probabilistic inference

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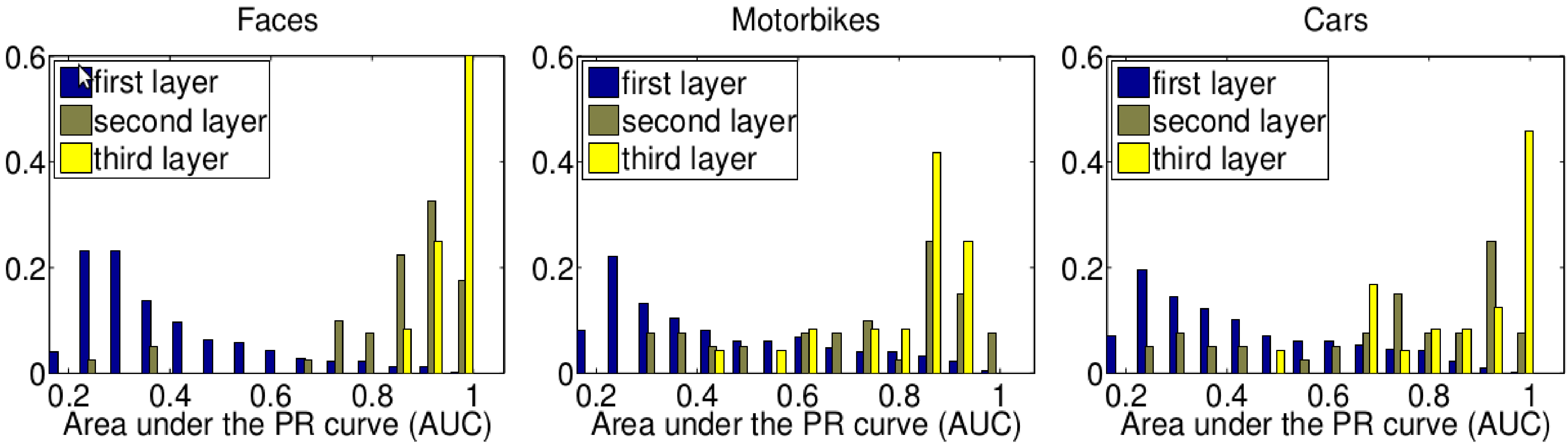
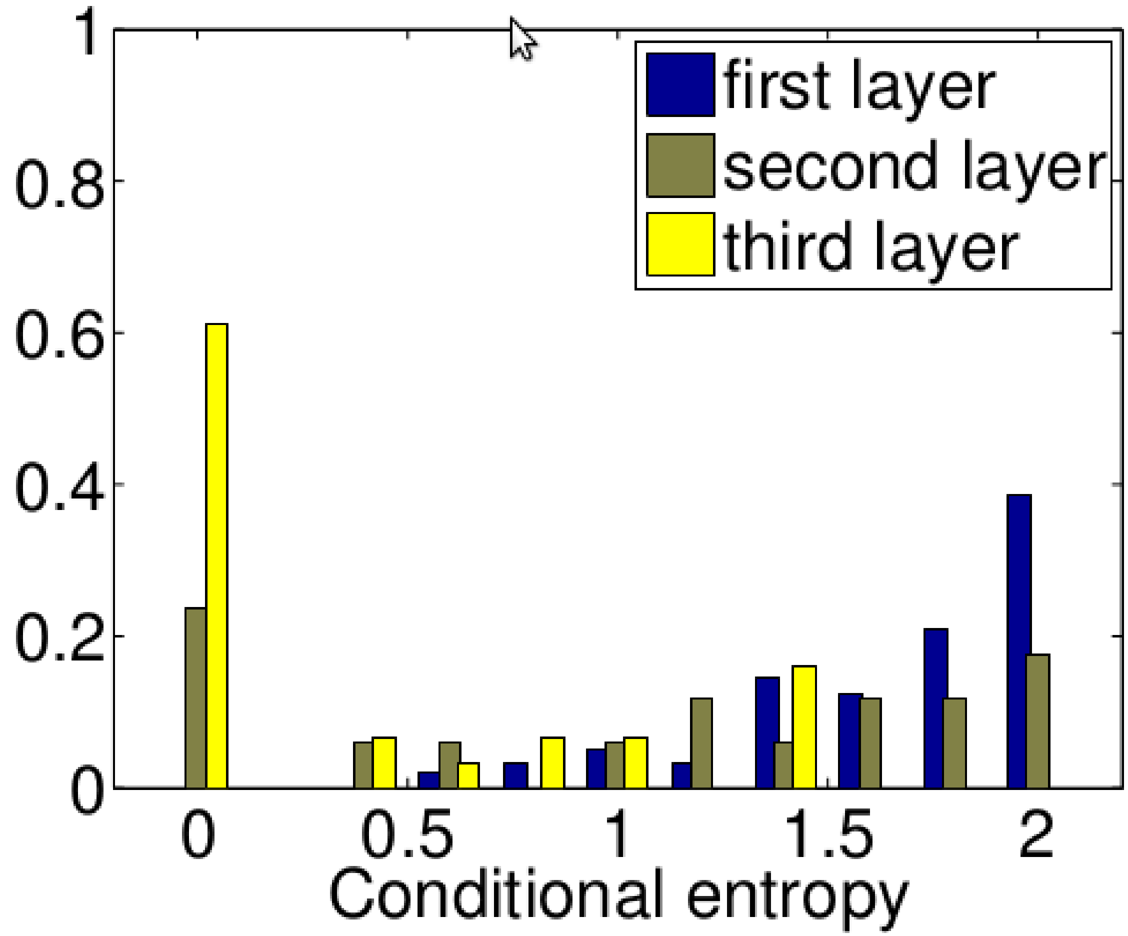
Unsupervised learning of object parts



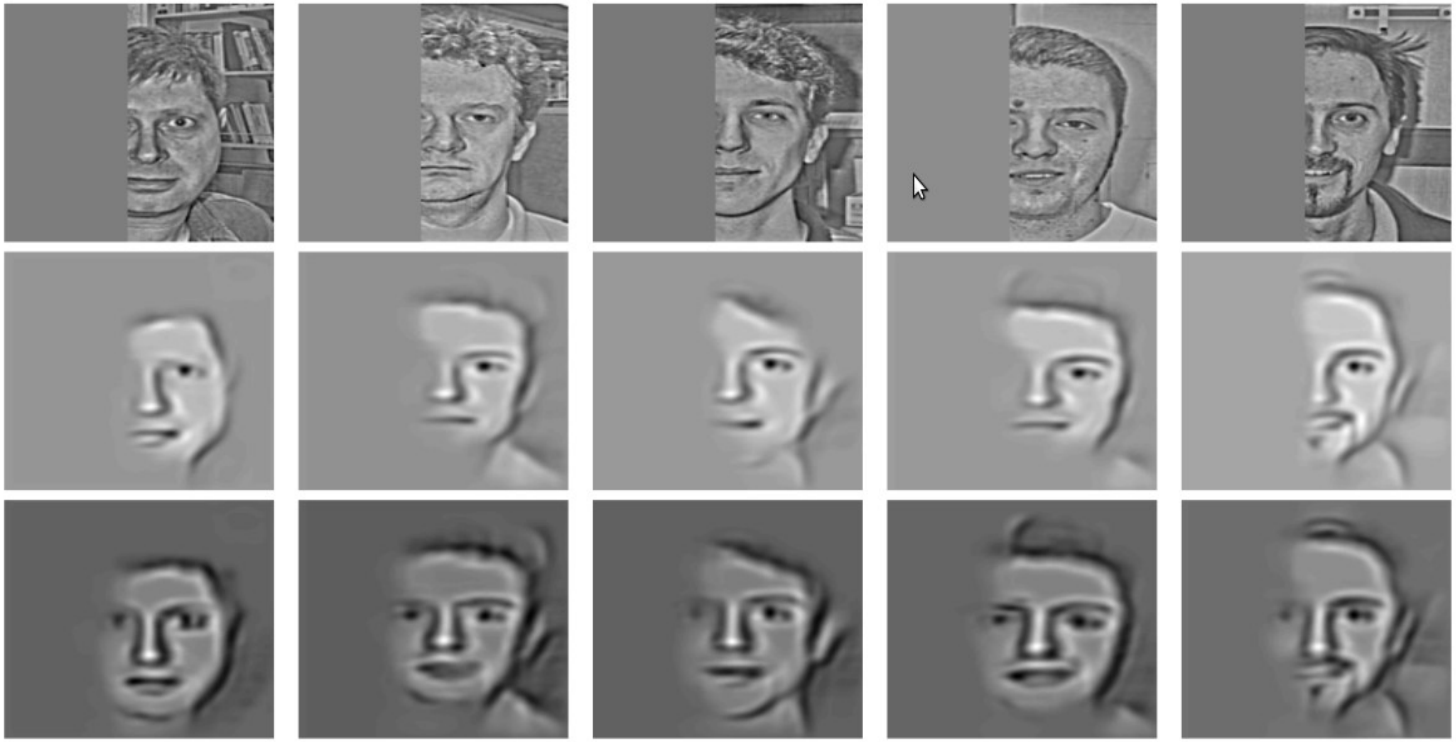
Features	Faces	Motorbikes	Cars
First layer	0.39 ± 0.17	0.44 ± 0.21	0.43 ± 0.19
Second layer	0.86 ± 0.13	0.69 ± 0.22	0.72 ± 0.23
Third layer	0.95 ± 0.03	0.81 ± 0.13	0.87 ± 0.15

Unsupervised learning of object parts



Hierarchical probabilistic inference

- Original image
- Control (bottom-up)
- Top-down and Bottom-up



Conclusions

- Probabilistic Max-Pooling significantly reduces computational overhead
- Incorporating top-down information flow reduces stimulus ambiguity and allows inference of unobserved stimulus
    - Similar to hierarchical Bayesian inference