

# IMAGE CLASSIFICATION USING SELF-TAUGHT LEARNING FOR FEATURE DISCOVERY

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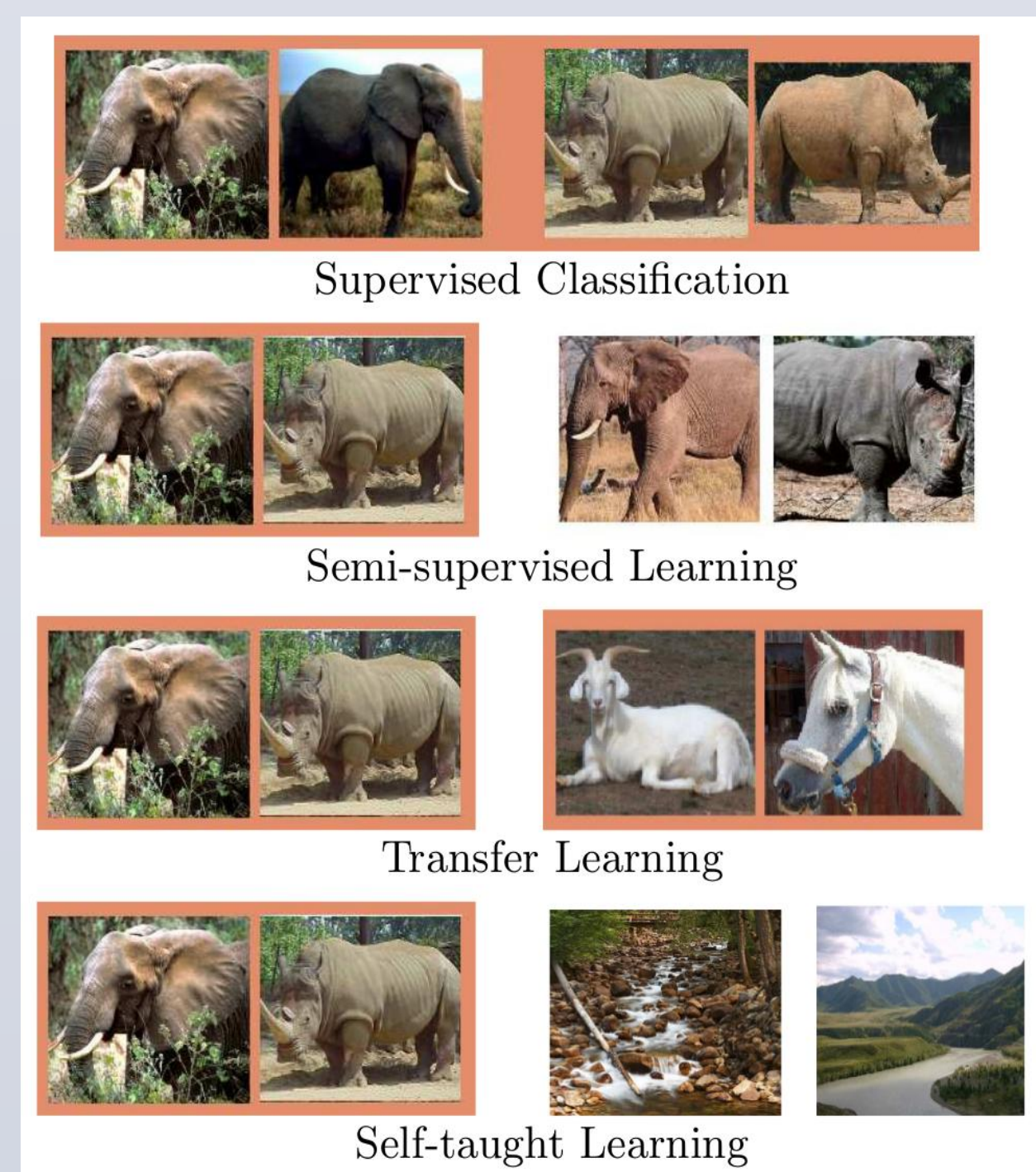
## ABSTRACT

Deep Learning has produced results which match the benchmark results in many object classification tasks. Deep Belief Networks are a class of deep neural-networks, composed of numerous hidden layers with connections across layers and no connections between neurons in the same layer. Convolutional deep belief networks<sup>[1]</sup> with probabilistic max pooling provide a translational invariant hierarchical generative model supporting both top-down and bottom-up inference. The advantages of CDBN are used for image classification using a new semi-supervised technique called Self-Taught Learning<sup>[2]</sup>. In our project, we experiment with CDBNs for classification of Caltech 101 dataset.

## INTRODUCTION

- **Convolutional Neural Networks** are known for their ability to exploit the 2-D nature of images in contrast to neural networks and **Deep Belief Networks** make use of Pre-training phase to improve results while classification.
- Convolutional deep belief networks combine the positives of both the state of the art models to get even better performance. Probabilistic max pooling provides a translational invariant hierarchical generative model supporting both top-down and bottom-up inference.
- Raina et al. proposed the concept of Self-Taught Learning in 2007.
  - Labeled data – generally, difficult to obtain
  - Unlabeled data – abundant and cheap
- Self Taught learning makes use of unlabeled data to learn a generic representation of images using Sparse coding which can be later used to learn features from the labeled images.

## CLASSIFICATION TECHNIQUES



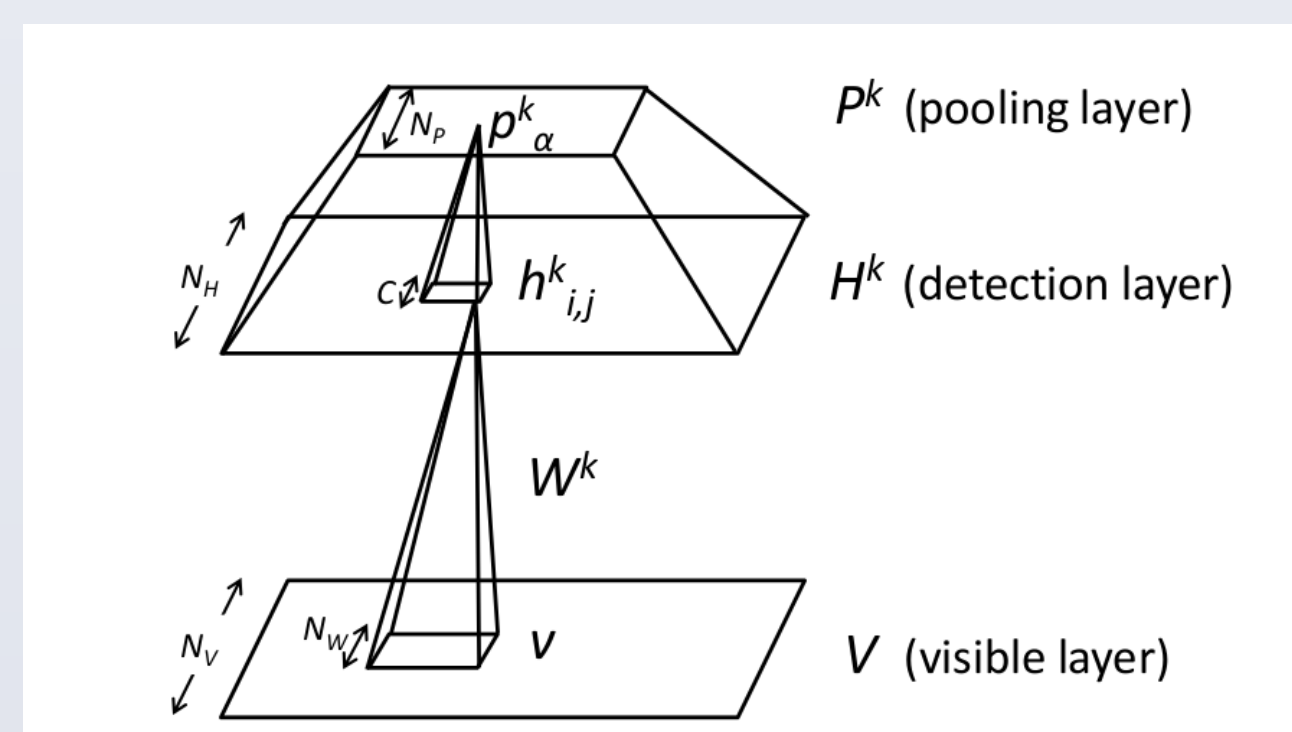
Raina R., Battle A., Lee H., Packer B., & Ng

## PREVIOUS WORK

In 2007, Raina et al.<sup>[2]</sup> used it to match many state of the art results in different domains like image classification, music genre classification and UseNet article classification. Lee et al.<sup>[1]</sup> used CDBNs to match the best results on Caltech 101 dataset using a model which was very generic in nature and used limited training examples. The state of the art results for Caltech 101 is 67% overall, averaged on all classes.

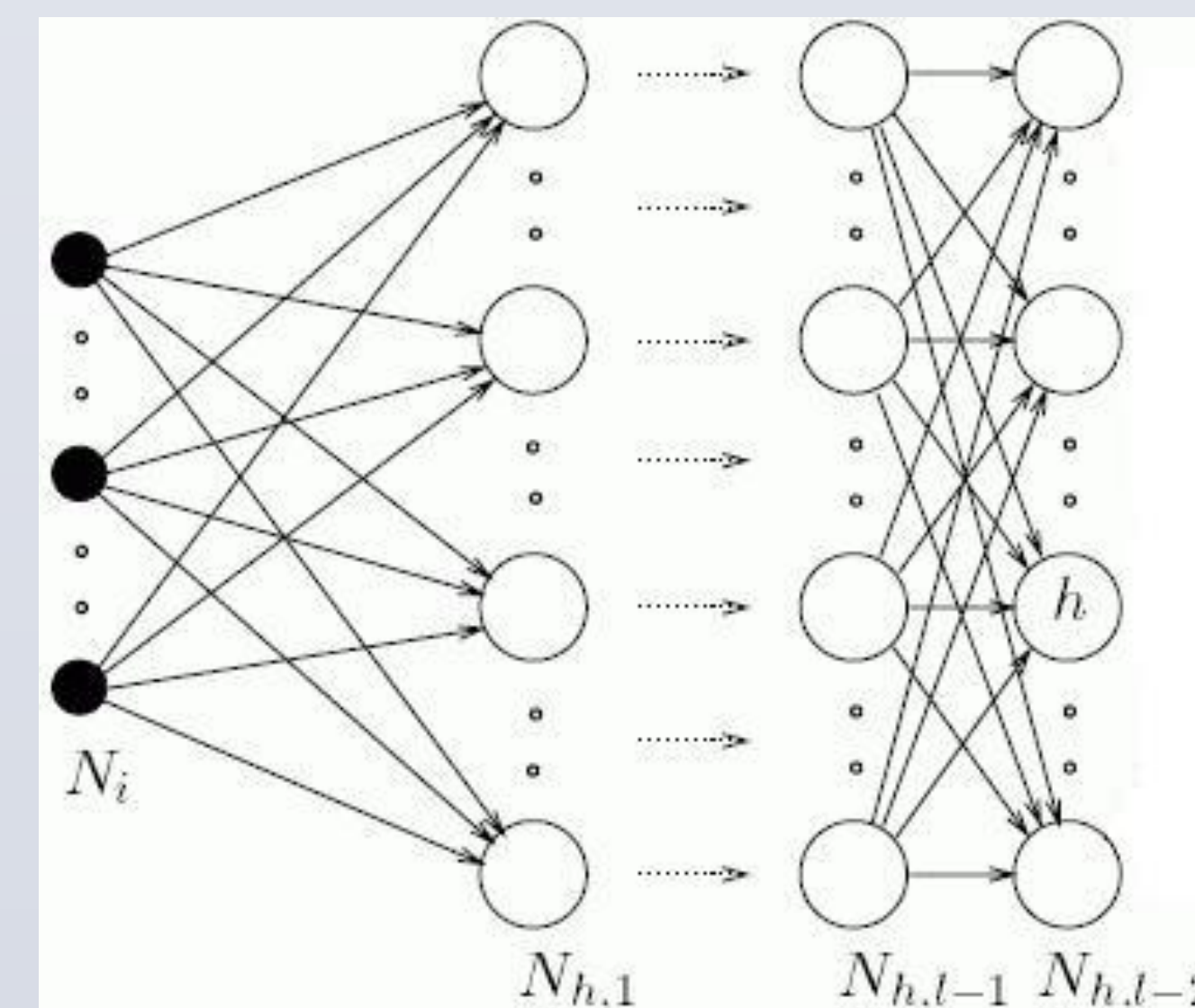
## CONVOLUTIONAL DEEP BELIEF NETWORK

Multiple layers of CRBMs



H. Lee, R. Grosse, R. Ranganath and A. Ng

## Single Unit of RBM



<http://www.codeproject.com/Articles/19323/Image-Recognition-with-Neural-Networks>

$$E(\mathbf{v}, \mathbf{h}) = - \sum_k \sum_{i,j} \left( h_{i,j}^k (\tilde{W}^k * v)_{i,j} + b_k h_{i,j}^k \right) - c \sum_{i,j} v_{i,j}$$

subj. to  $\sum_{(i,j) \in B_\alpha} h_{i,j}^k \leq 1, \forall k, \alpha.$

## DATASET

ImageNet<sup>[7]</sup> Natural Objects Dataset as source of unlabeled data

- Cropped to Uniform Size 150 X 200

Caltech 101<sup>[8]</sup> dataset for labeled images - 5 objects

- Elephant
- Leopard
- Car
- Motorbike
- Airplane

30 images were used as labeled images of each class

- 20 were used for training
- 10 were used for testing

## ALGORITHM

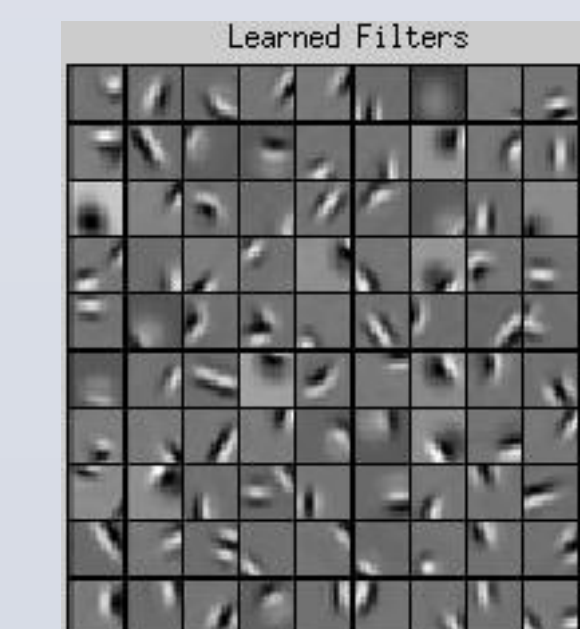
Using only labeled data

1. Train CDBN on labeled dataset
2. Use learnt weights to extract features
3. Classify using SVM (linear kernel).

Self-taught learning

1. Train CDBN on unlabeled dataset of natural images
2. Use learnt weights to extract features from labeled dataset
3. Classify using SVM

## RESULTS



|          | Car | Airplane | Elephant | Leopard | Bike |
|----------|-----|----------|----------|---------|------|
| Car      | 5   | 1        | 1        | 0       | 3    |
| Airplane | 1   | 6        | 0        | 1       | 2    |
| Elephant | 1   | 1        | 7        | 0       | 1    |
| Leopard  | 1   | 2        | 2        | 4       | 1    |
| Bike     | 2   | 0        | 1        | 0       | 7    |

## ACCURACY

| CDBN with Self Taught Learning | CDBN |
|--------------------------------|------|
| 58 %                           | 52 % |

## CONCLUSIONS

- Self Taught Learning is a very effective technique when the size of labeled datasets is very small.
- Convolutional Deep Belief Networks are known for learning very good hierarchical representations of inputs at different levels.
- The complexity of implementing CDBNs is high, and generally different implementations end up producing different results.
- There are a lot of hyper parameters which need to be initialized and can play an influencing role in the results.

## REFERENCES

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6. Tutorial on CDBN : [http://ufldl.stanford.edu/wiki/index.php/Feature\\_extraction\\_using\\_convolution](http://ufldl.stanford.edu/wiki/index.php/Feature_extraction_using_convolution)
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