# Learning from Infinite Data: Object Recognition on CIFAR-10

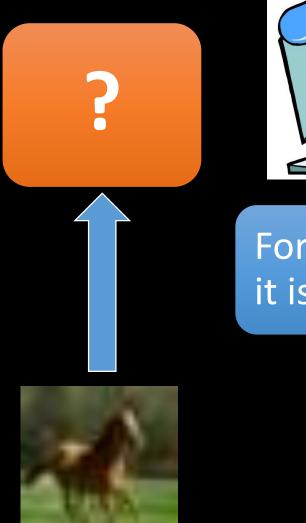
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# Object Classification





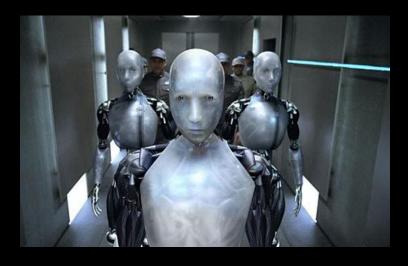


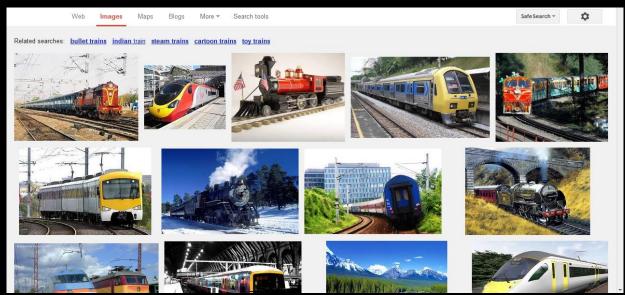
For computers it is hard!

# But it is essential



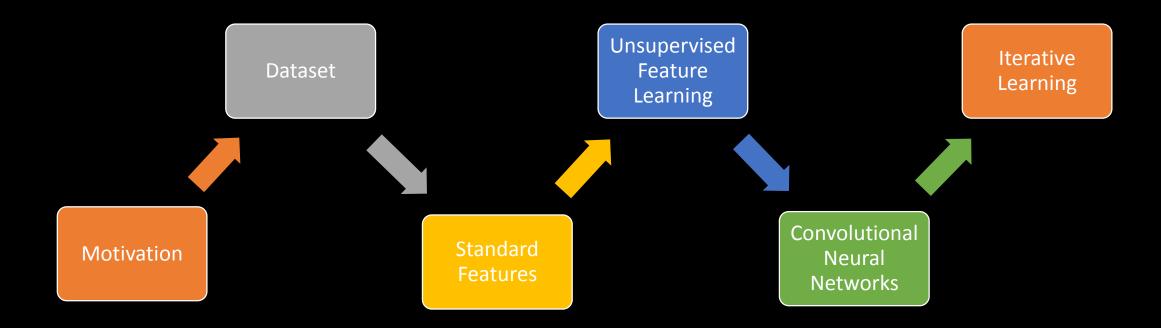




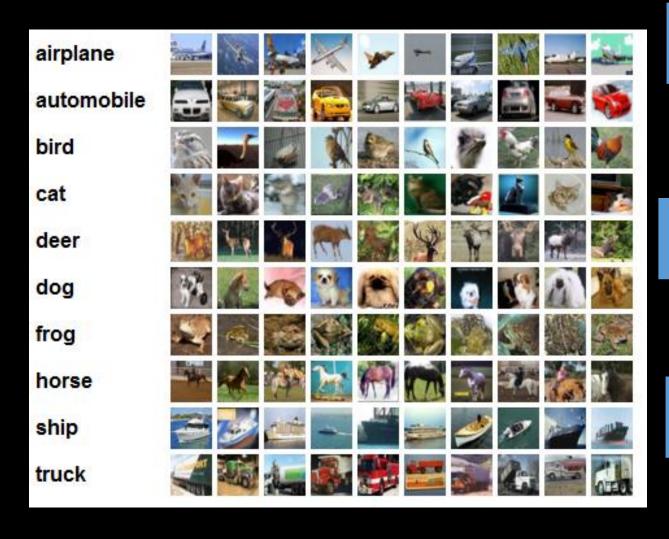




# Outline



#### Dataset Used: CIFAR-10



Train Data

•50,000

**Test Data** 

10,000

No Of Classes

•10

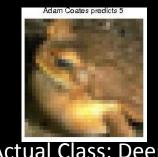
#### Why this dataset is hard?

Objects within a class are extremely varied

Distractors and Occlusions in images

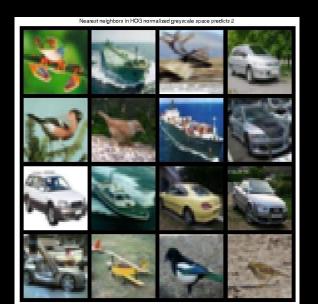
Many Images require "High-Level Reasoning"

# Simple starters

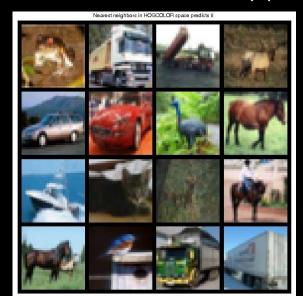


Actual Class: Deer(5)

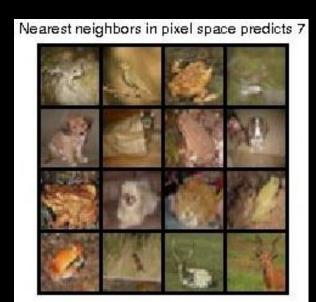
Normalized HOG Feature Space Predicted Class: Automobile(2)



**HOG** Feature Space Predicted Class: Horse(8)



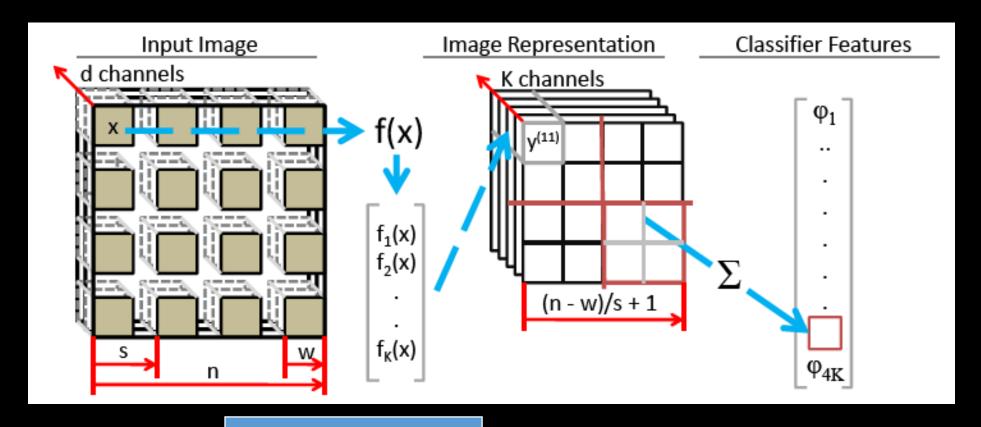
Pixel Feature Space Predicted Class: Frog (4)



# Inadequacy of classical descriptors

Types of feature	Accuracy
Raw Pixels	32.4%
HOG Descriptors	35.7%
Normalized HOG Descriptors	43.8%

#### Unsupervised Feature learning Framework

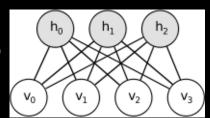


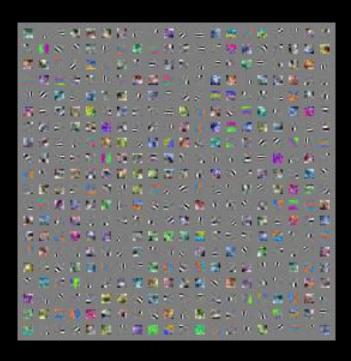
S: Stride Length

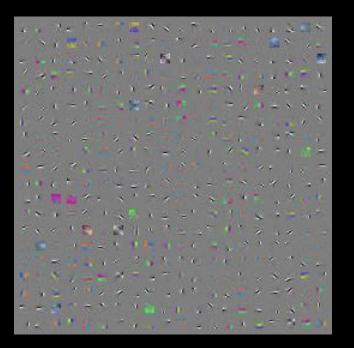
W: Receptor Field Size

#### Restricted Boltzmann Machines (RBM)

RBM are undirected graphical models with a layer(H) of K hidden variables used to learn a different feature representation of the data

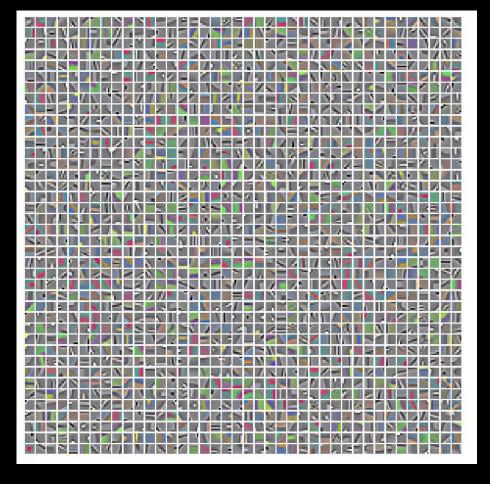






#### K-means Clustering (Triangle)

 Triangle Kmeans Clustering is a variation of the standard Kmeans Clustering algorithm is which the data is represented by a Kdimensional vector(K is the number of clusters) whose each component is a measure of the distance from the respective cluster centroids



Learned Cluster Centers using 1600 clusters and a 6 \* 6 receptor field size

#### Results

Receptor Size: 6, Stride Length: 1

Number of Clusters	Accuracy
400	72.5
900	75.75
1600	77.35

Number of clusters: 400, Stride Length: 1

Receptor Field Size	Accuracy
4	71.13
6	72.5
8	72.83

Number of clusters: 400, Receptor Size: 6

Stride Length	Accuracy
1	72.5
3	69.48
5	64.43

Number of clusters: 400, Receptor Size: 6, Stride Length: 1

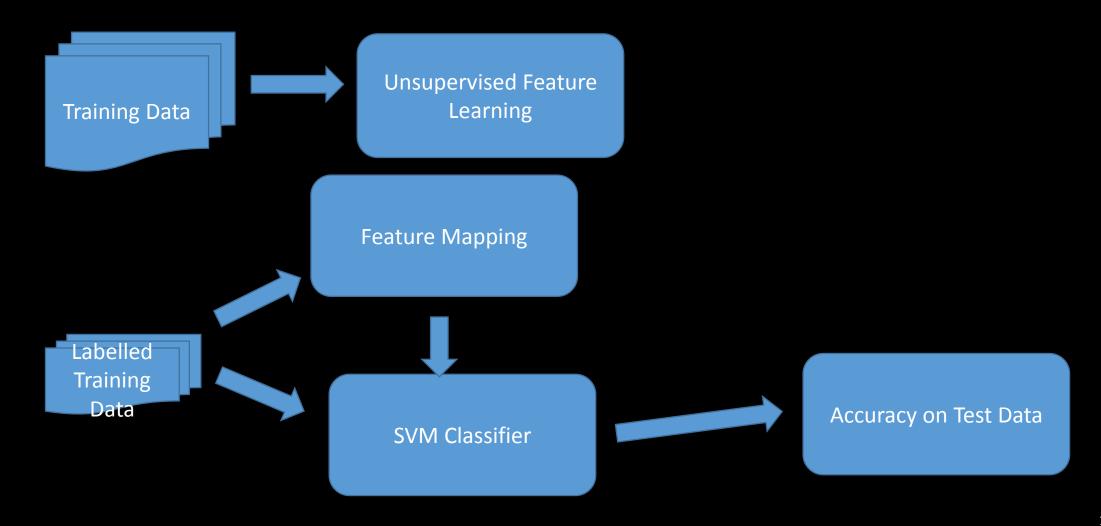
Effect of Whitening	Accuracy
Without Whitening	64.3
With Whitening	72.5

#### Increasing Layers: Convolutional Nets

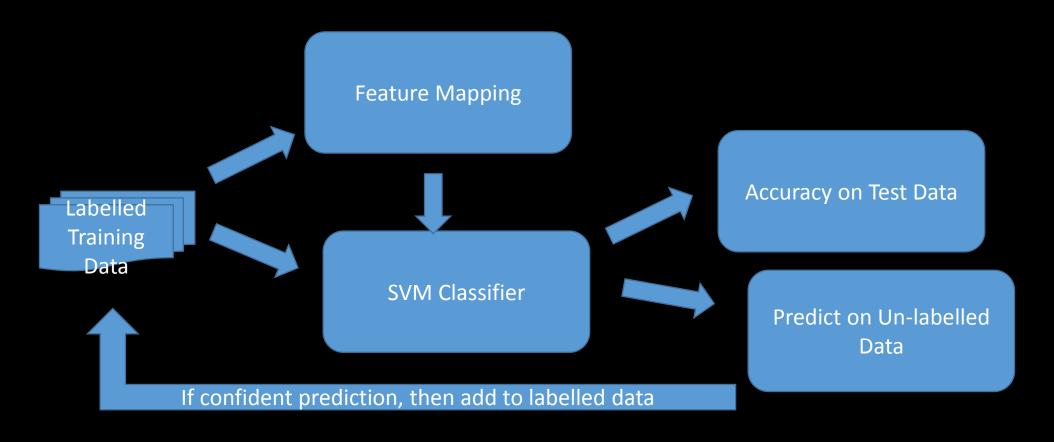
Number of Layers	Accuracy
2	72.86
3	73.24

However, this increases complexity and computational requirements.

# Current Flow Diagram



# Learning from unlabeled data: Iterative Learning



# Experiments on Iterative Learning

Experiment	Result
CIFAR-10 (2 labeled batches) one-step	62.8%
CIFAR-10 (5 labeled batches) one-step	72.5%
CIFAR-10 (2 labeled + 3 unlabeled) Iterative Learning	63.7%

#### Experiments on Iterative Learning

If conf(i) > mean(conf) + D \* sqrt(var(conf)), transfer point from unlabeled dataset to labeled dataset.

Experiment	Number of points transferred	Accuracy of transferred points	Test Results
D = 1	14568	48.3%	59.6%
D = 3	4937	84.74%	63.7%
D = 5	237	88.60%	62.2%
D = 7	46	89.13%	62.6%

#### Iterative Learning: Conclusions

- Choose only very high confidence points to avoid poisoning data
- But, less fraction of unlabeled data would be transferred to labeled data
- Solution: Get large corpus of unlabeled data!
- Not a problem in today's world.

#### Iterative Learning: Size of Datasets

Increase in unlabeled data => gradual increase in test results

# of batches	Number of points transferred	Accuracy of transferred points	Test Results
1	1578	81.32%	62.7%
2	3113	82.79%	62.9%
3	4937	84.74%	63.7%

#### Summary

- We studied feature learning algorithms, supervised and unsupervised
- We ran experiments with state-of-the-art algorithms, and noted their tradeoffs, advantages and disadvantages.
- We found that there has not been much work in using unlabeled data, apart from feature learning.
- We develop and implement an Iterative Learning algorithm which takes advantage of large corpus of unlabeled data not just for feature learning, but also for supervised classification.