Recap: Multiple Views and Motion

- Epipolar geometry
  - Relates cameras in two positions
  - Fundamental matrix maps from a point in one image to a line (its epipolar line) in the other
  - Can solve for F given corresponding points (e.g., interest points)
- Stereo depth estimation
  - Estimate disparity by finding corresponding points along scanlines
  - Depth is inverse to disparity
- Motion Estimation
  - By assuming brightness constancy, truncated Taylor expansion leads to simple and fast patch matching across frames
  - Assume local motion is coherent
  - "Aperture problem" is resolved by coarse to fine approaches and iterative refinement

$$\nabla I \cdot \begin{bmatrix} u & v \end{bmatrix}^T + I_t = 0$$

Machine Learning

Computer Vision
James Hays, Brown

Photo: CMU Machine Learning Department protests G20

Slides: Isabelle Guyon, Erik Sudderth, Mark Johnson, Derek Hoiem

It is a rare criticism of elite American university students that they do not think big enough. But that is exactly the complaint from some of the largest technology companies and the federal government.

At the heart of this criticism is data. Researchers and workers in fields as diverse as bio-technology, astronomy and computer science will soon find themselves overwhelmed with information.

The next generation of computer scientists has to think in terms of what could be described as Internet scale.

New York Times
Training to Climb an Everest of Digital Data.
By Ashlee Vance.
Published: October 11, 2009

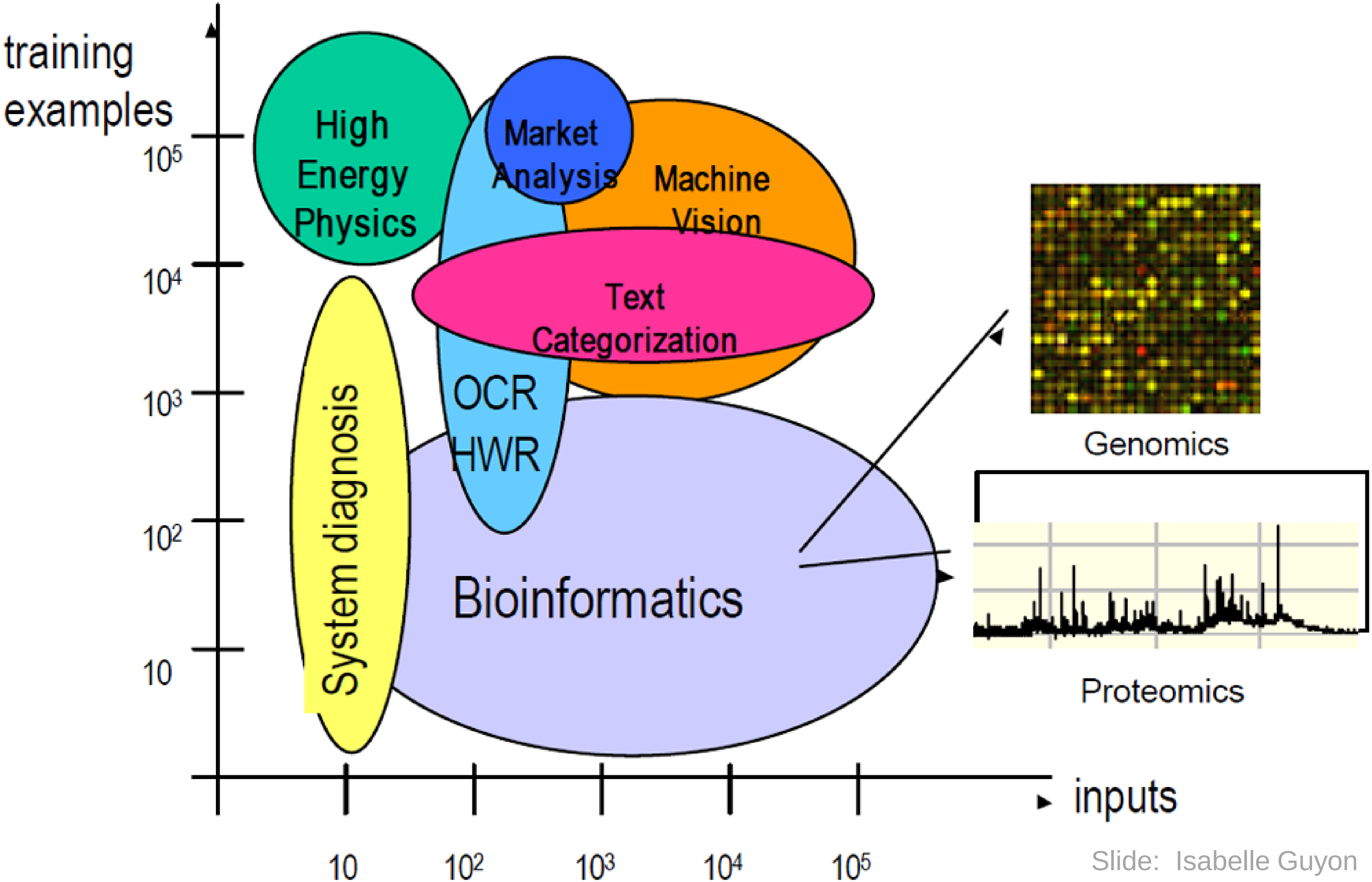
Machine learning: Overview

- Core of ML: Making predictions or decisions from Data.
- This overview will not go in to depth about the statistical underpinnings of learning methods. We're looking at ML as a tool. Take *CS 142: Introduction to Machine Learning* to learn more.

Impact of Machine Learning

- Machine Learning is arguably the greatest export from computing to other scientific fields.

Machine Learning Applications



Slide: Isabelle Guyon

Image Categorization

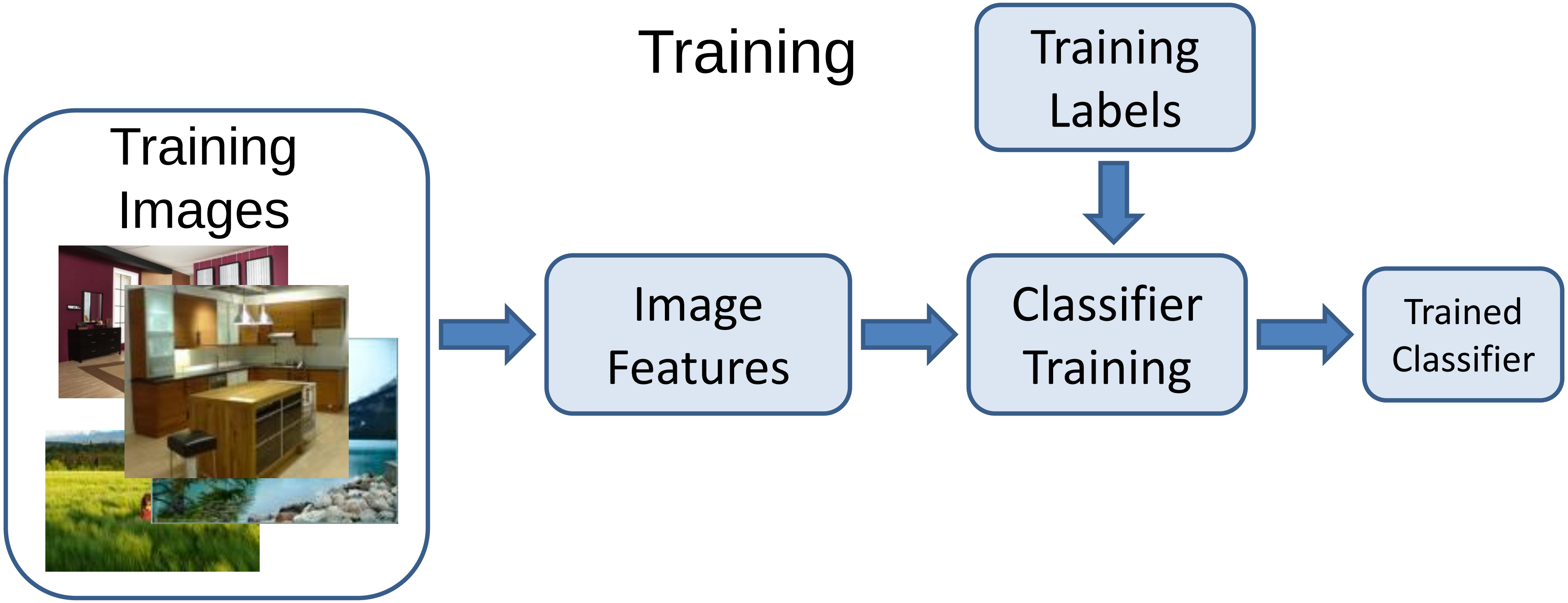
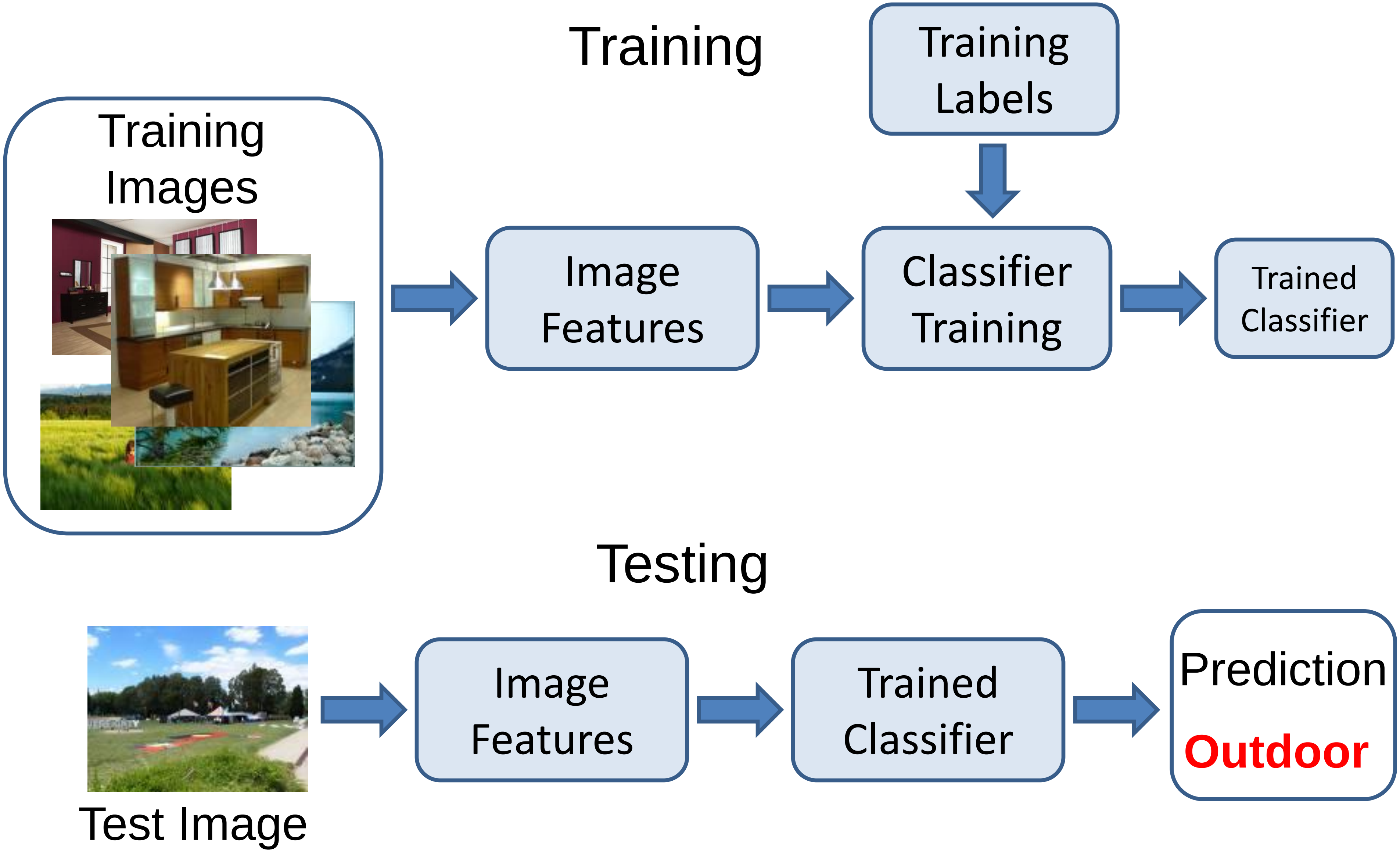


Image Categorization

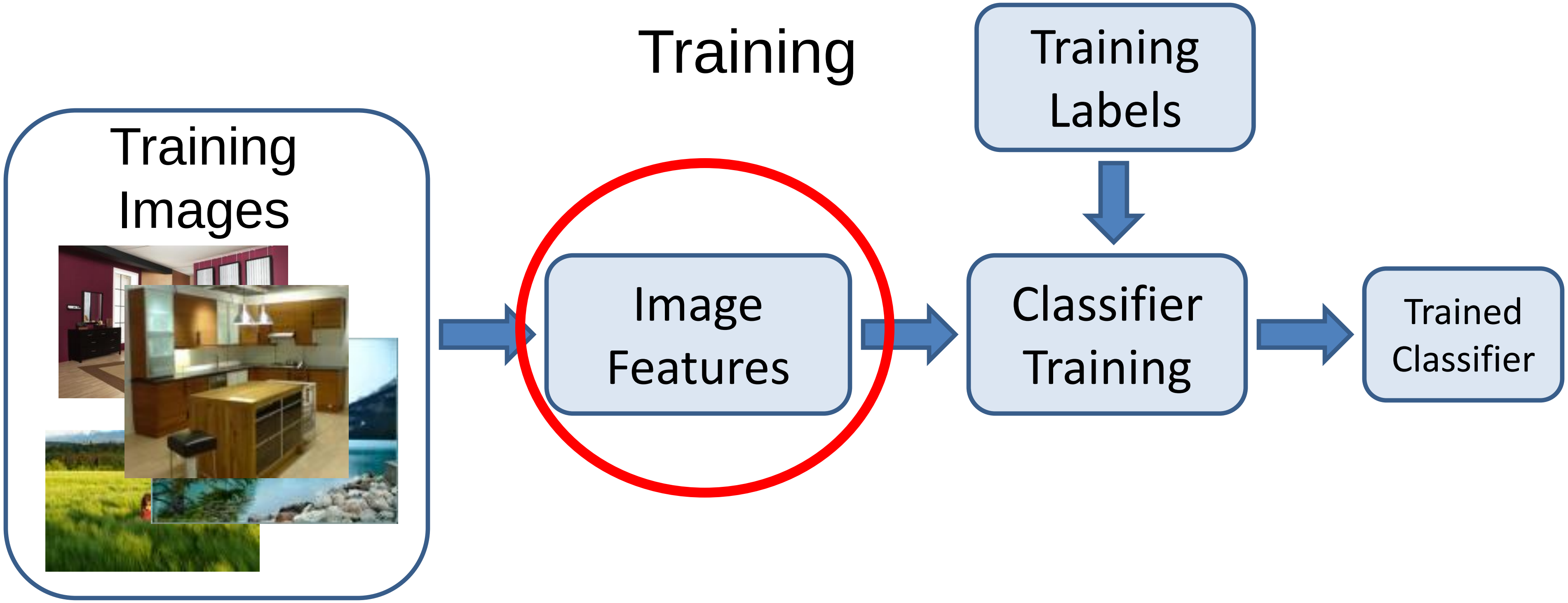


Example: Scene Categorization

- Is this a kitchen?



Image features



General Principles of Representation

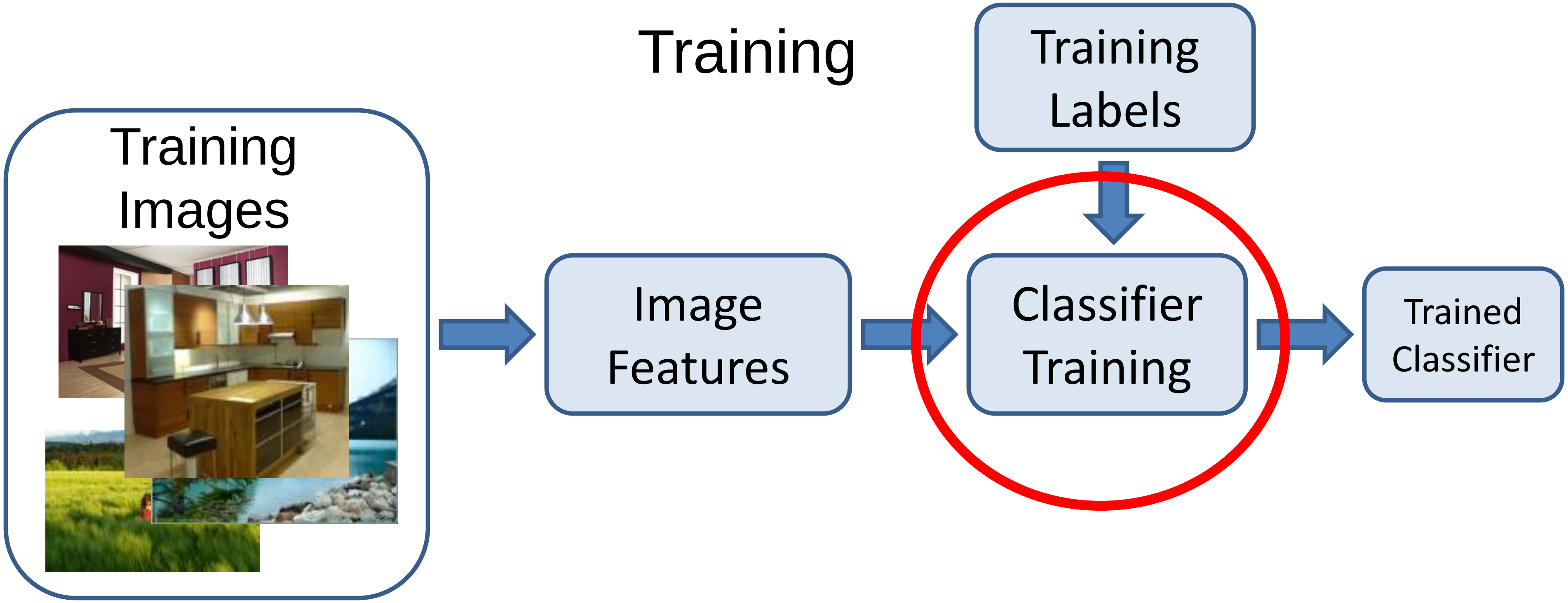
- Coverage
  - Ensure that all relevant info is captured
- Concision
  - Minimize number of features without sacrificing coverage
- Directness
  - Ideal features are independently useful for prediction

Image representations

- Templates
  - Intensity, gradients, etc.

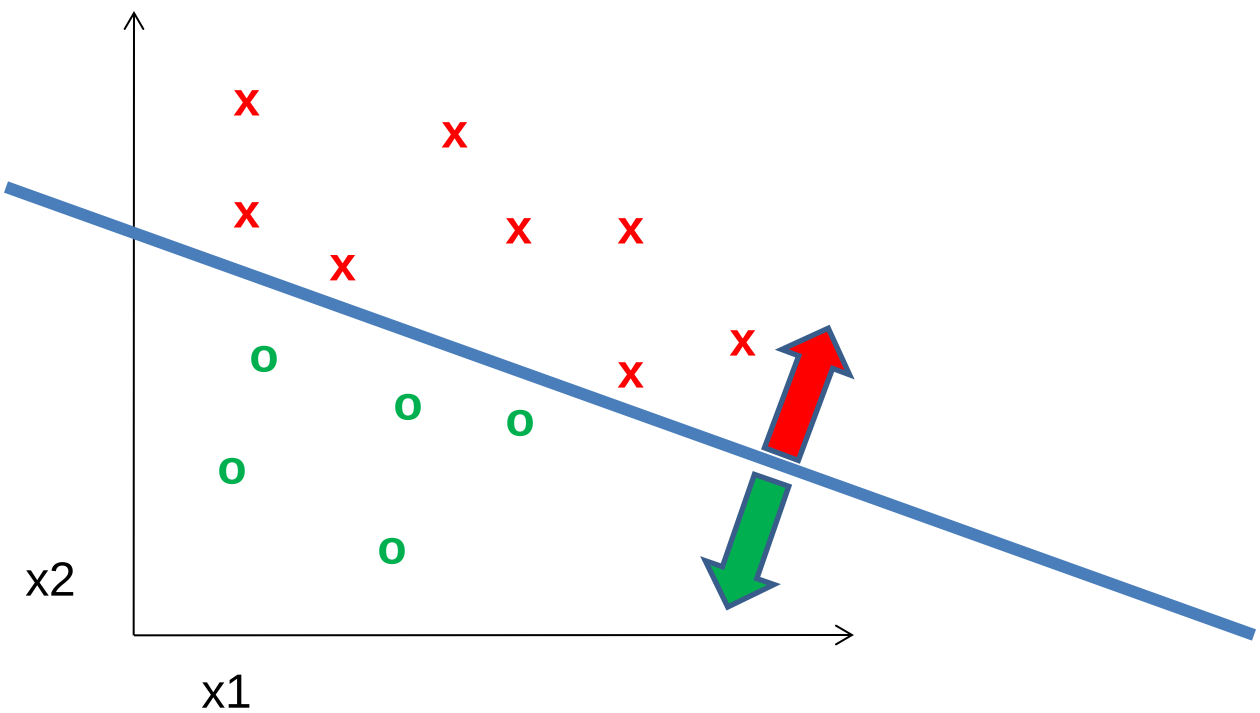
- Histograms
  - Color, texture, SIFT descriptors, etc.

Classifiers



Learning a classifier

Given some set of features with corresponding labels, learn a function to predict the labels from the features



Many classifiers to choose from

- SVM
- Neural networks
- Naïve Bayes
- Bayesian network
- Logistic regression
- Randomized Forests
- Boosted Decision Trees
- K-nearest neighbor
- RBMs
- Etc.

Which is the best one?

One way to think about it…

- Training labels dictate that two examples are the same or different, in some sense
- Features and distance measures define visual similarity
- Classifiers try to learn weights or parameters for features and distance measures so that visual similarity predicts label similarity

Claim:

The decision to *use* machine learning is more important than the choice of a *particular* learning method.

If you hear somebody talking of a specific learning mechanism, be wary (e.g. YouTube comment "Oooh, we could plug this in to a Neural network and blah blah blah“)

Machine Learning Problems

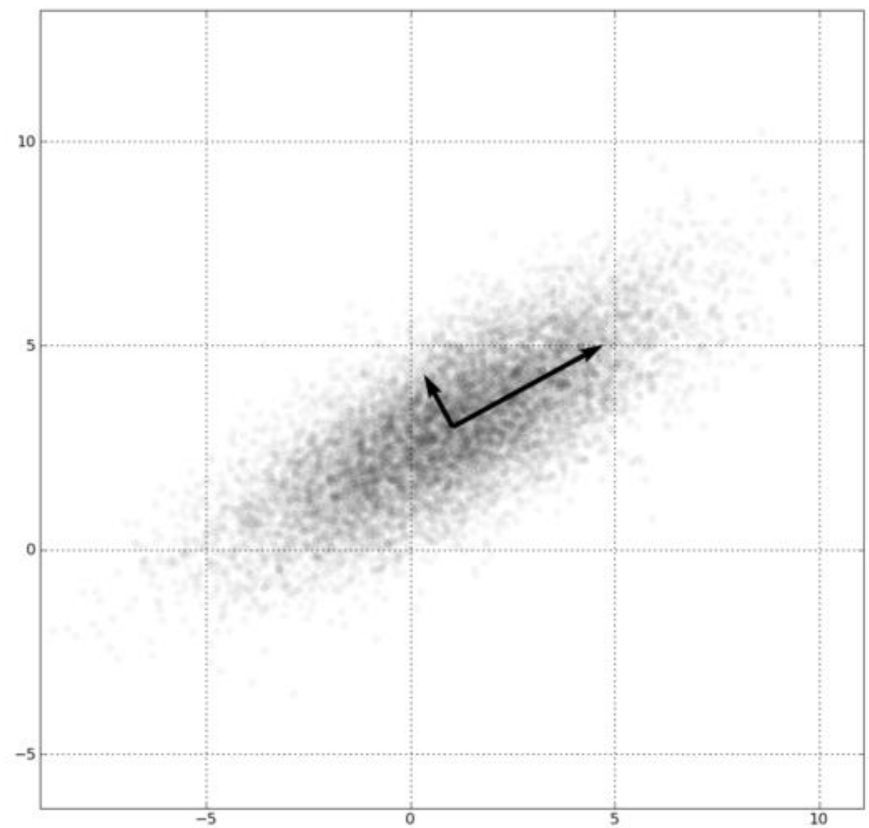
	Supervised Learning	Unsupervised Learning
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

Dimensionality Reduction

- **PCA**, ICA, LLE, Isomap

- PCA is the most important technique to know. It takes advantage of correlations in data dimensions to produce the best possible lower dimensional representation, according to reconstruction error.

- PCA should be used for dimensionality reduction, not for discovering patterns or making predictions. Don't try to assign semantic meaning to the bases.



Machine Learning Problems

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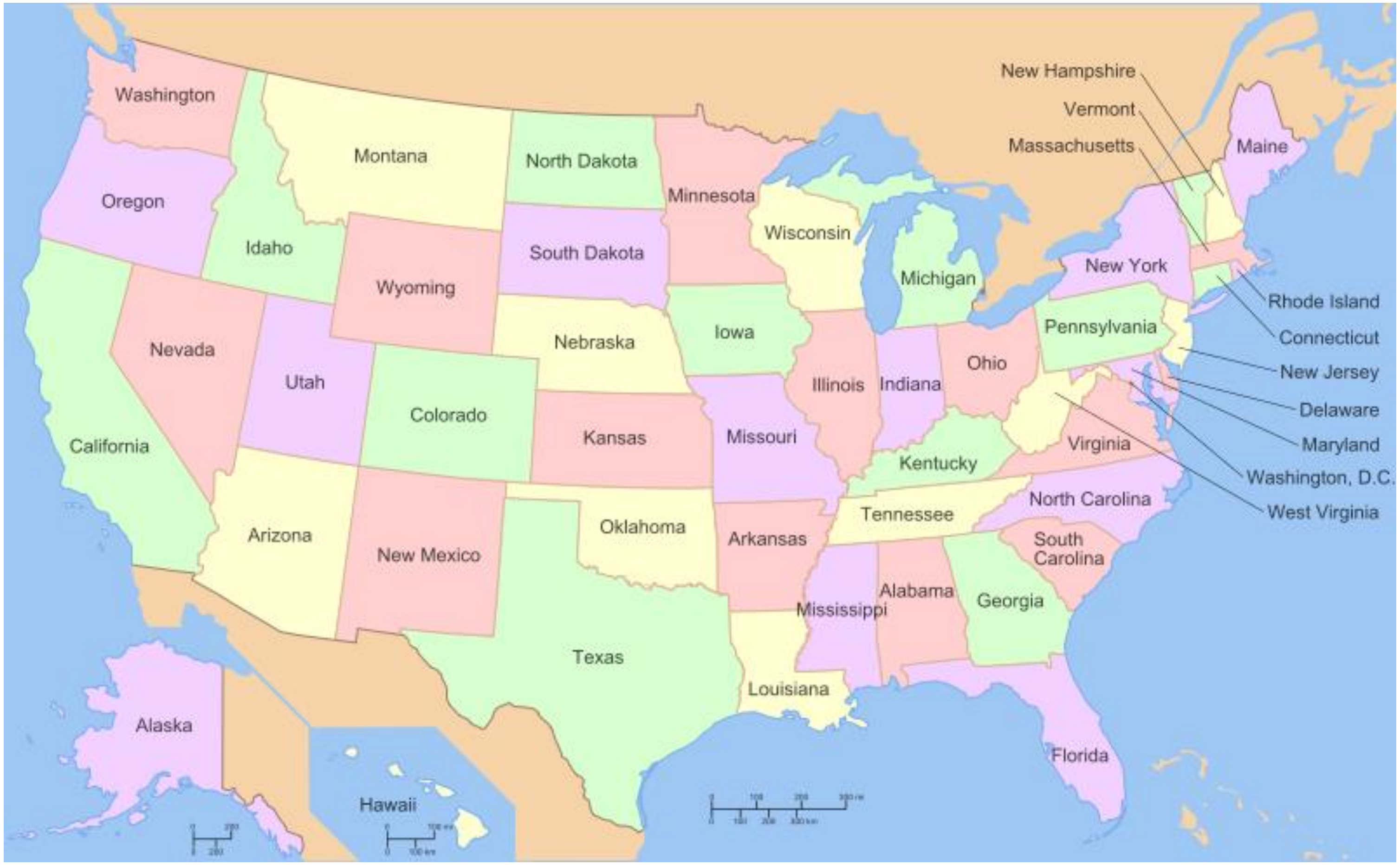

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New Hampshire
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Connecticut
Pennsylvania
New Jersey
Delaware
Maryland
Washington, D.C.
West Virginia
Nevada
Utah
Colorado
Nebraska
Iowa
Illinois
Indiana
Ohio
California
Kansas
Missouri
Kentucky
Virginia
Arizona
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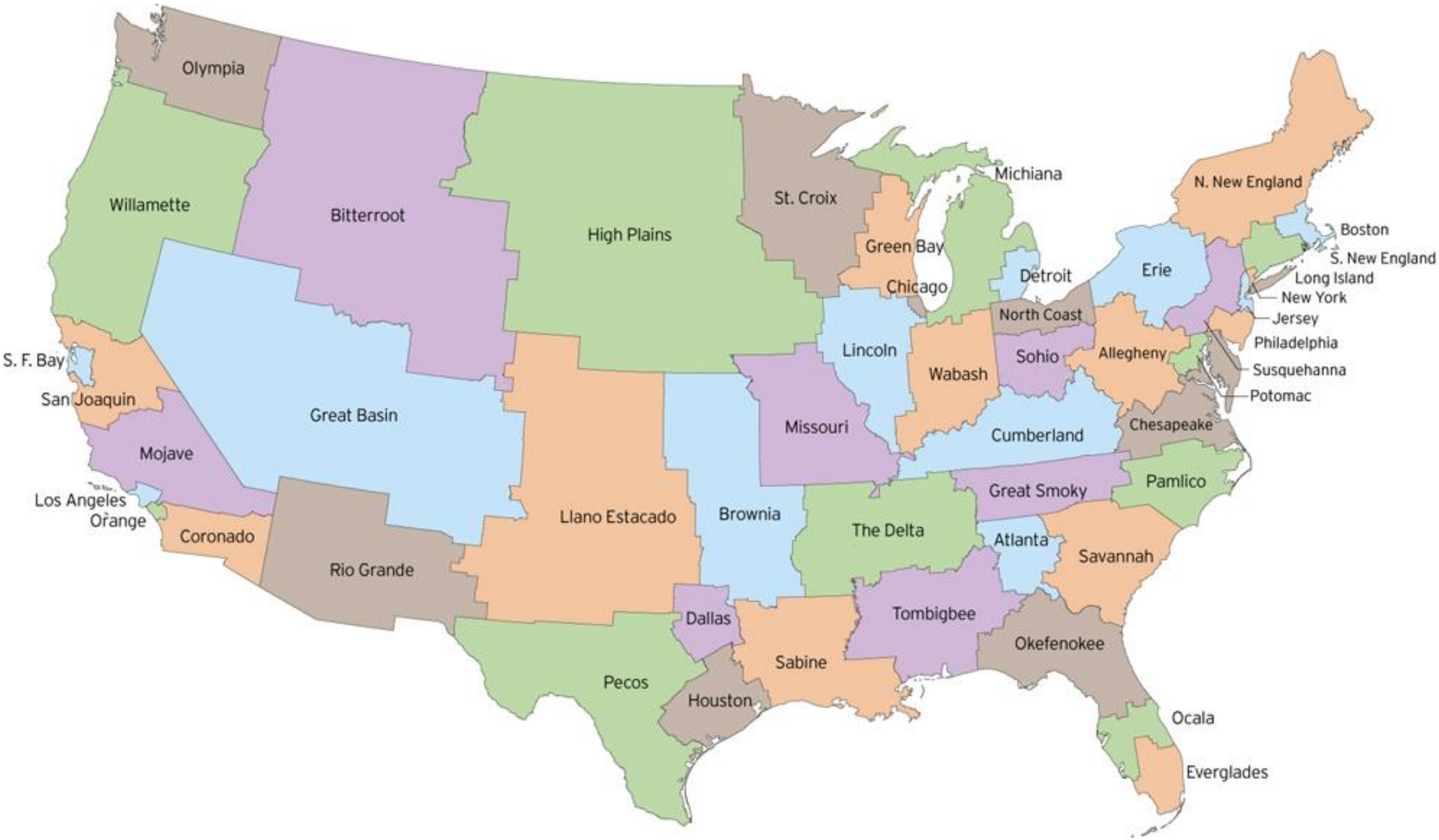
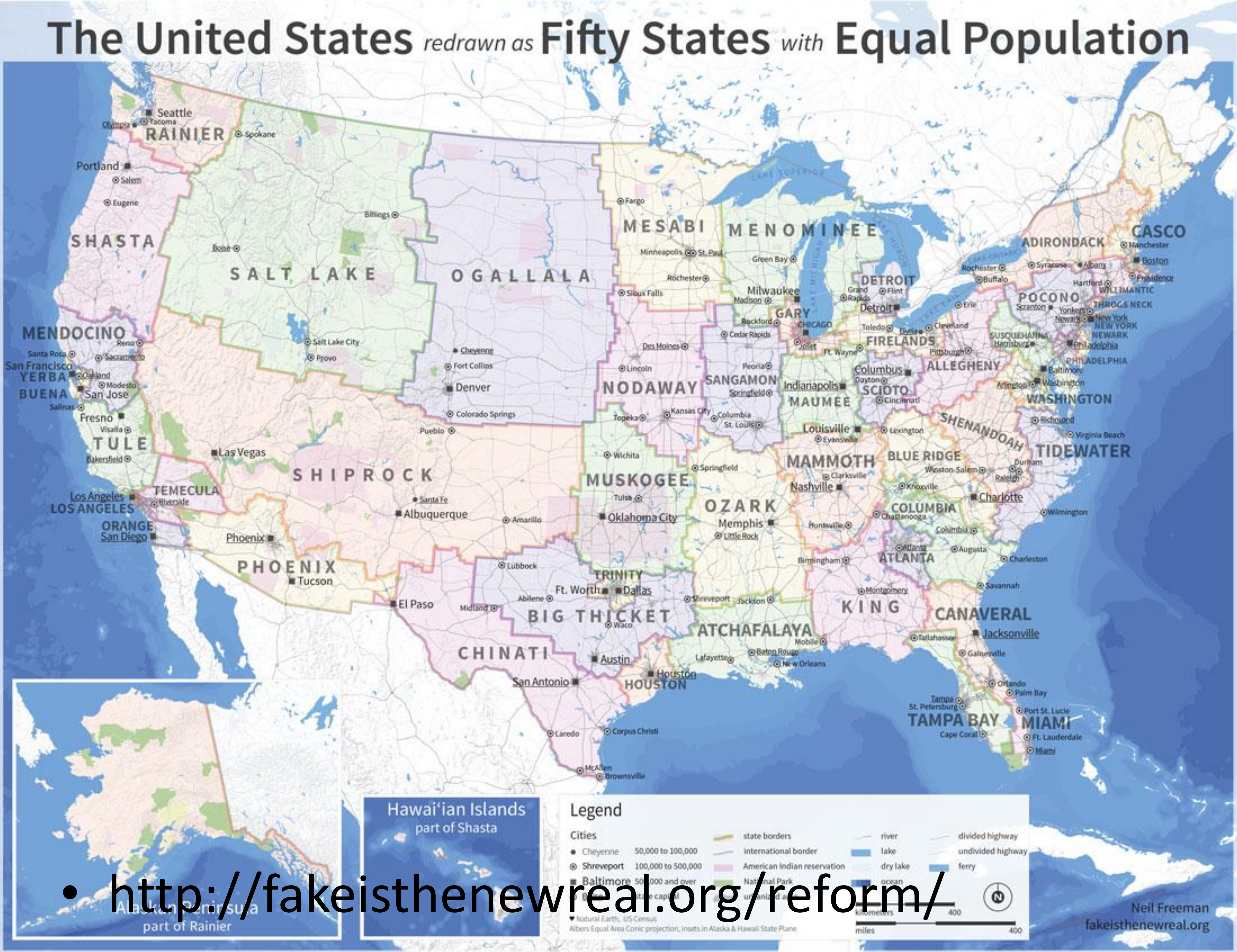
North Carolina
South Carolina
Mississippi
Alabama
Georgia
Texas
Louisiana
Florida
Alaska
Hawaii



- http://fakeisthenewreal.org/reform/



- http://fakeisthenewreal.org/reform/

Clustering example: image segmentation

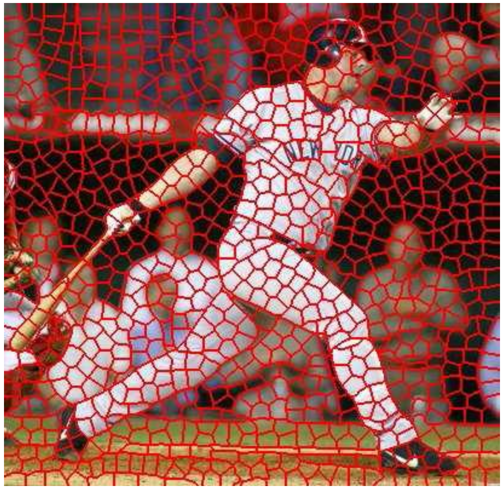
Goal: Break up the image into meaningful or perceptually similar regions

Segmentation for feature support

Slide: Derek Hoiem

Segmentation for efficiency

[Felzenszwalb and Huttenlocher 2004]



[Shi and Malik 2001]

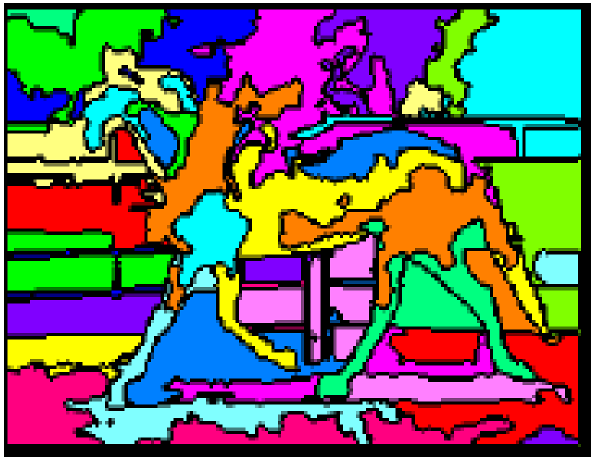
[Hoiem et al. 2005, Mori 2005]

Slide: Derek Hoiem

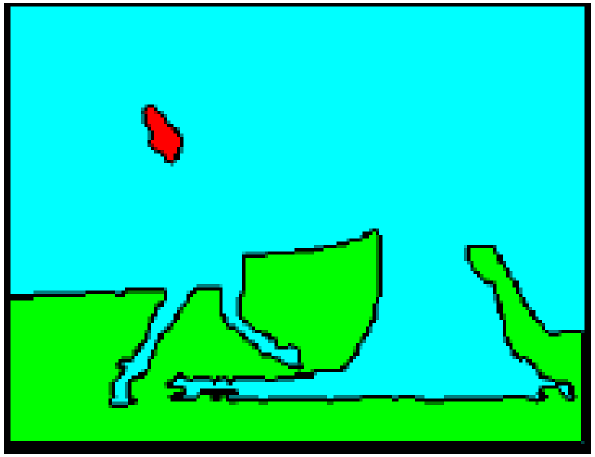
Segmentation as a result

Rother et al. 2004

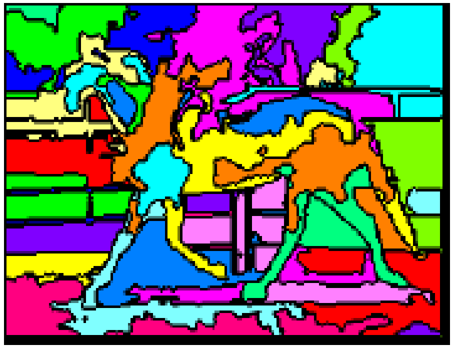
Types of segmentations

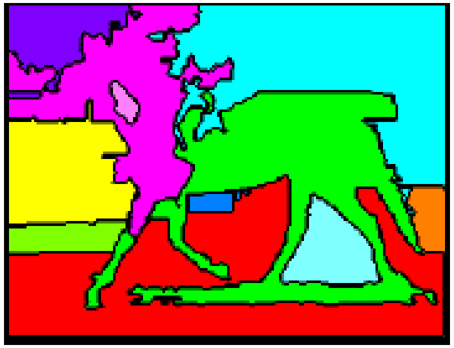


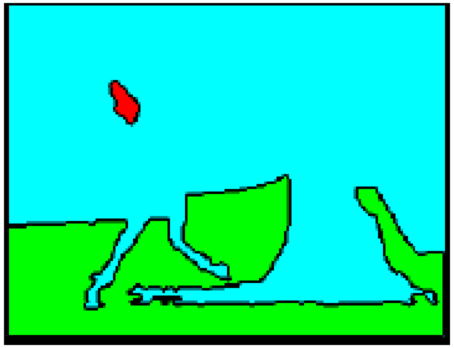
Oversegmentation



Undersegmentation







Multiple Segmentations

Clustering: group together similar points and represent them with a single token

Key Challenges:

1) What makes two points/images/patches similar?

2) How do we compute an overall grouping from pairwise similarities?

Slide: Derek Hoiem

Why do we cluster?

- **Summarizing data**
  - Look at large amounts of data
  - Patch-based compression or denoising
  - Represent a large continuous vector with the cluster number
- **Counting**
  - Histograms of texture, color, SIFT vectors
- **Segmentation**
  - Separate the image into different regions
- **Prediction**
  - Images in the same cluster may have the same labels

Slide: Derek Hoiem

How do we cluster?

- K-means
  - Iteratively re-assign points to the nearest cluster center
- Agglomerative clustering
  - Start with each point as its own cluster and iteratively merge the closest clusters
- Mean-shift clustering
  - Estimate modes of pdf
- Spectral clustering
  - Split the nodes in a graph based on assigned links with similarity weights

Clustering for Summarization

Goal: cluster to minimize variance in data given clusters

– Preserve information

Cluster center

Data

$$\mathbf{c}^*, \boldsymbol{\delta}^* = \underset{\mathbf{c},\boldsymbol{\delta}}{\operatorname{argmin}} \tfrac{1}{N} \sum_{j}^{N} \sum_{i}^{K} \delta_{ij} \left(\mathbf{c}_i - \mathbf{x}_j \right)^2$$

Whether x_j is assigned to c_i

Slide: Derek Hoiem

K-means algorithm

1. Randomly select K centers

2. Assign each point to nearest center

3. Compute new center (mean) for each cluster

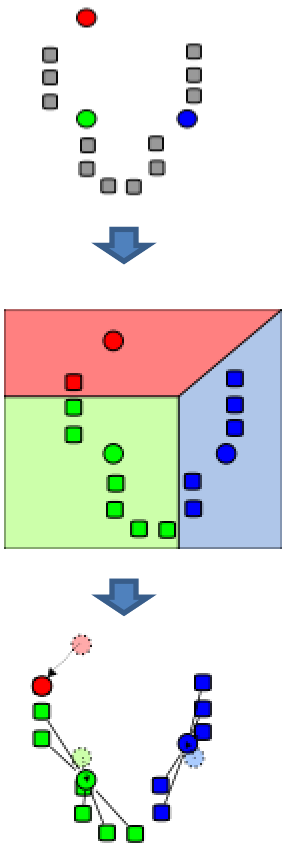
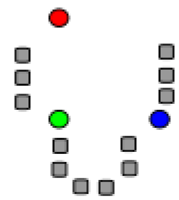


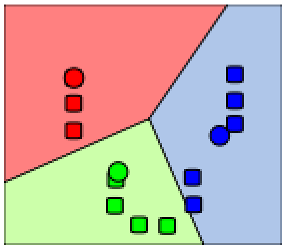
Illustration: http://en.wikipedia.org/wiki/K-means_clustering

K-means algorithm

1. Randomly select K centers



2. Assign each point to nearest center



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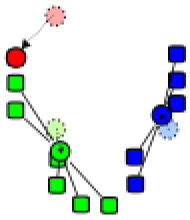


Back to 2

Illustration: http://en.wikipedia.org/wiki/K-means_clustering

K-means

1. Initialize cluster centers: $\mathbf{c}^0$; t=0

2. Assign each point to the closest center

$$\boldsymbol{\delta}^t = \underset{\boldsymbol{\delta}}{\operatorname{argmin}} \tfrac{1}{N} \sum_j^N \sum_i^K \delta_{ij} \left(\mathbf{c}_i^{t-1} - \mathbf{x}_j\right)^2$$

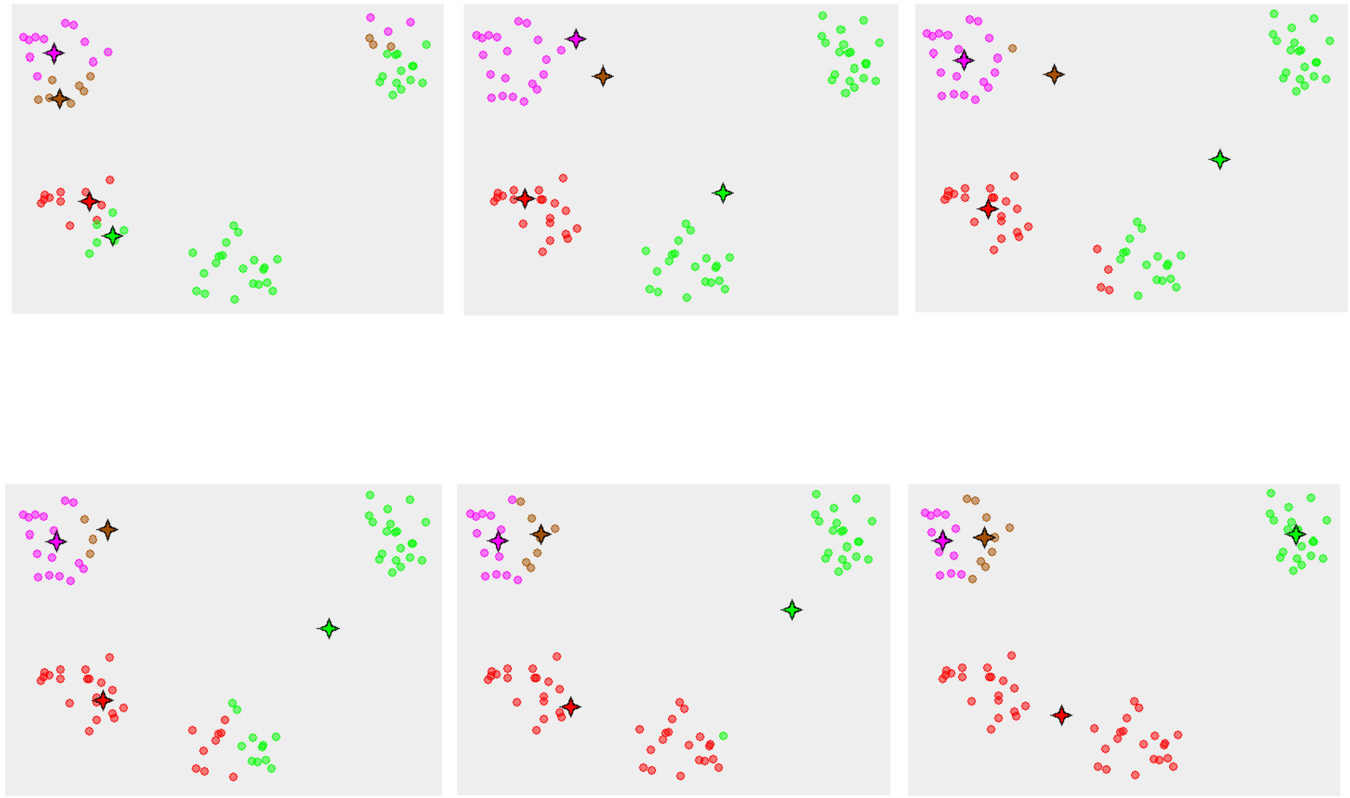
3. Update cluster centers as the mean of the points

$$\mathbf{c}^t = \underset{\mathbf{c}}{\operatorname{argmin}} \tfrac{1}{N} \sum_j^N \sum_i^K \delta_{ij}^t \left(\mathbf{c}_i - \mathbf{x}_j\right)^2$$

4. Repeat 2-3 until no points are re-assigned (t=t+1)

Slide: Derek Hoiem

K-means converges to a local minimum



K-means: design choices

- Initialization
  - Randomly select K points as initial cluster center
  - Or greedily choose K points to minimize residual
- Distance measures
  - Traditionally Euclidean, could be others
- Optimization
  - Will converge to a *local minimum*
  - May want to perform multiple restarts

How to evaluate clusters?

- Generative
  - How well are points reconstructed from the clusters?
- Discriminative
  - How well do the clusters correspond to labels?
    - Purity
  - Note: unsupervised clustering does not aim to be discriminative

Slide: Derek Hoiem

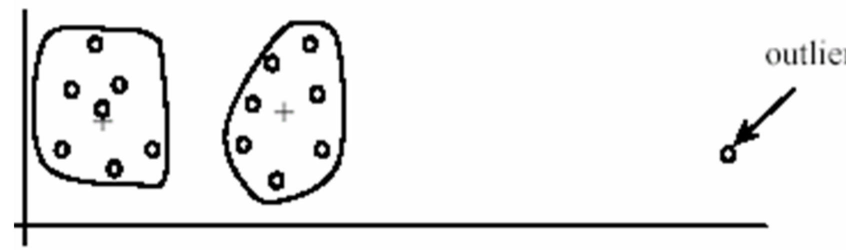
How to choose the number of clusters?

- Validation set
  - Try different numbers of clusters and look at performance
    - When building dictionaries (discussed later), more clusters typically work better

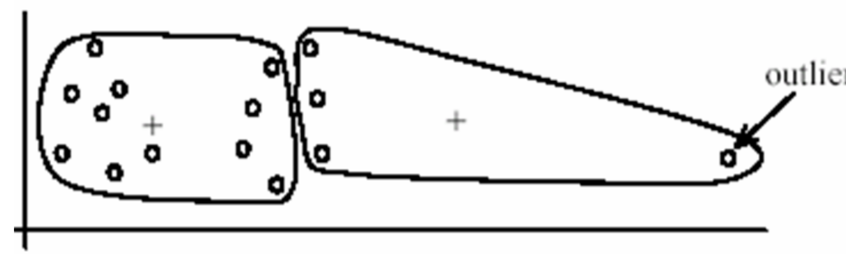
Slide: Derek Hoiem

K-Means pros and cons

- Pros
  - Finds cluster centers that minimize conditional variance (good representation of data)
  - Simple and fast*
  - Easy to implement
- Cons
  - Need to choose K
  - Sensitive to outliers
  - Prone to local minima
  - All clusters have the same parameters (e.g., distance measure is non-adaptive)
  - *Can be slow: each iteration is O(KNd) for N d-dimensional points
- Usage
  - Rarely used for pixel segmentation



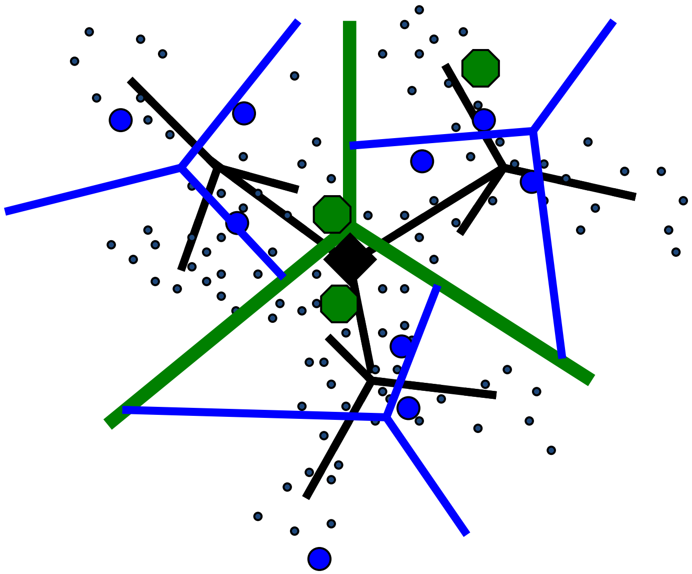
(B): Ideal clusters



Building Visual Dictionaries

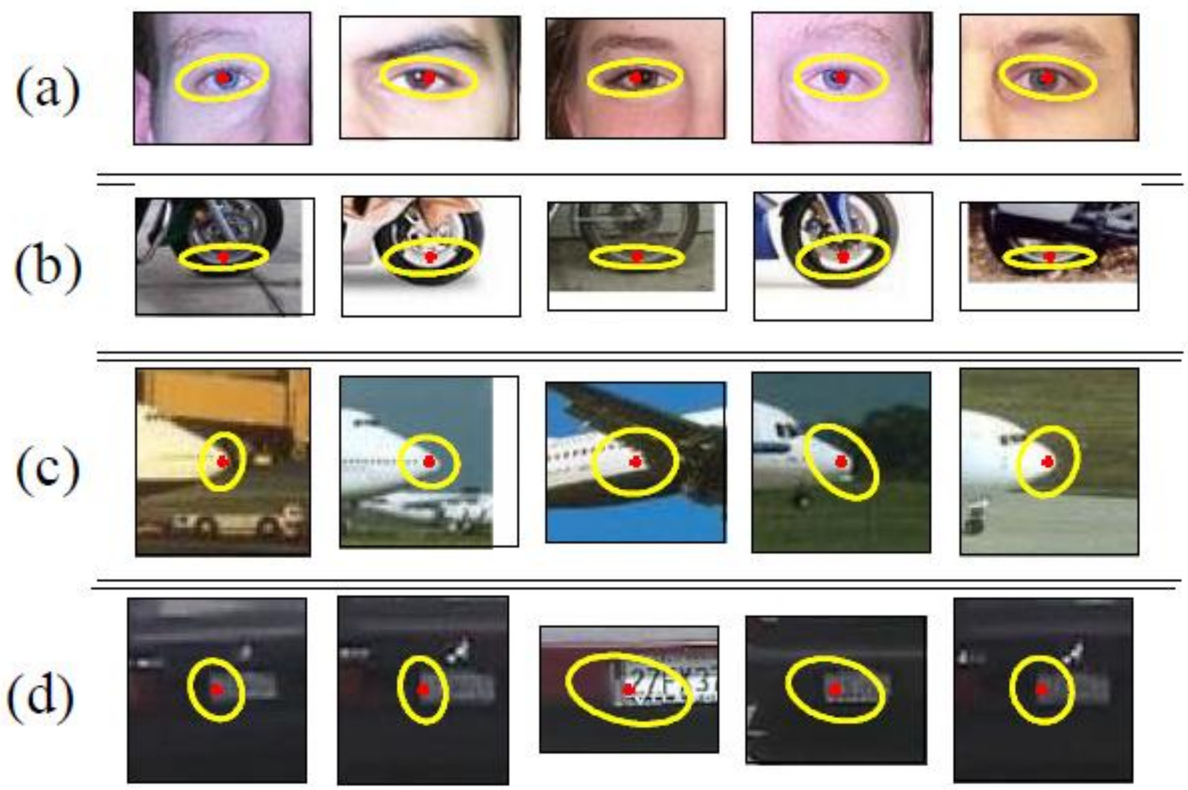
1. Sample patches from a database
   – E.g., 128 dimensional SIFT vectors

2. Cluster the patches
   – Cluster centers are the dictionary



3. Assign a codeword (number) to each new patch, according to the nearest cluster

Examples of learned codewords



Most likely codewords for 4 learned "topics"
EM with multinomial (problem 3) to get topics

http://www.robots.ox.ac.uk/~vgg/publications/papers/sivic05b.pdf Sivic et al. ICCV 2005