# Machine Learning Crash Course

Computer Vision
James Hays

Photo: CMU Machine Learning Department protests G20

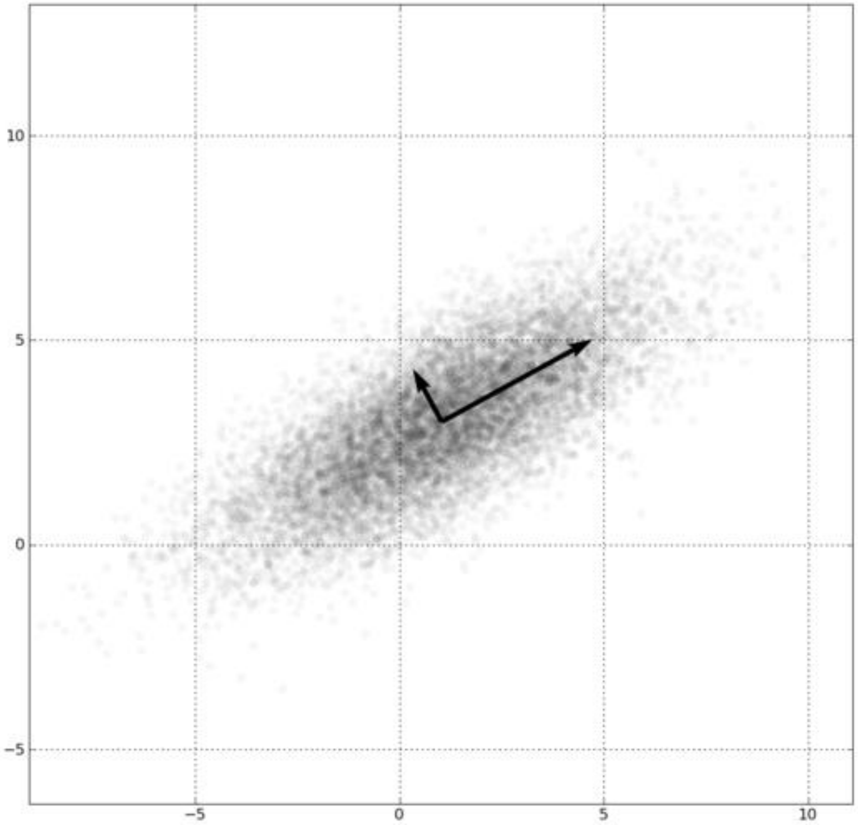
Slides: Isabelle Guyon, Erik Sudderth, Mark Johnson, Derek Hoiem

# Machine Learning Problems

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

# Dimensionality Reduction

- **PCA**, ICA, LLE, Isomap, *Autoencoder*
- PCA is the most important technique to know.  It takes advantage of correlations in data dimensions to produce the best possible lower dimensional representation based on linear projections (minimizes 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.



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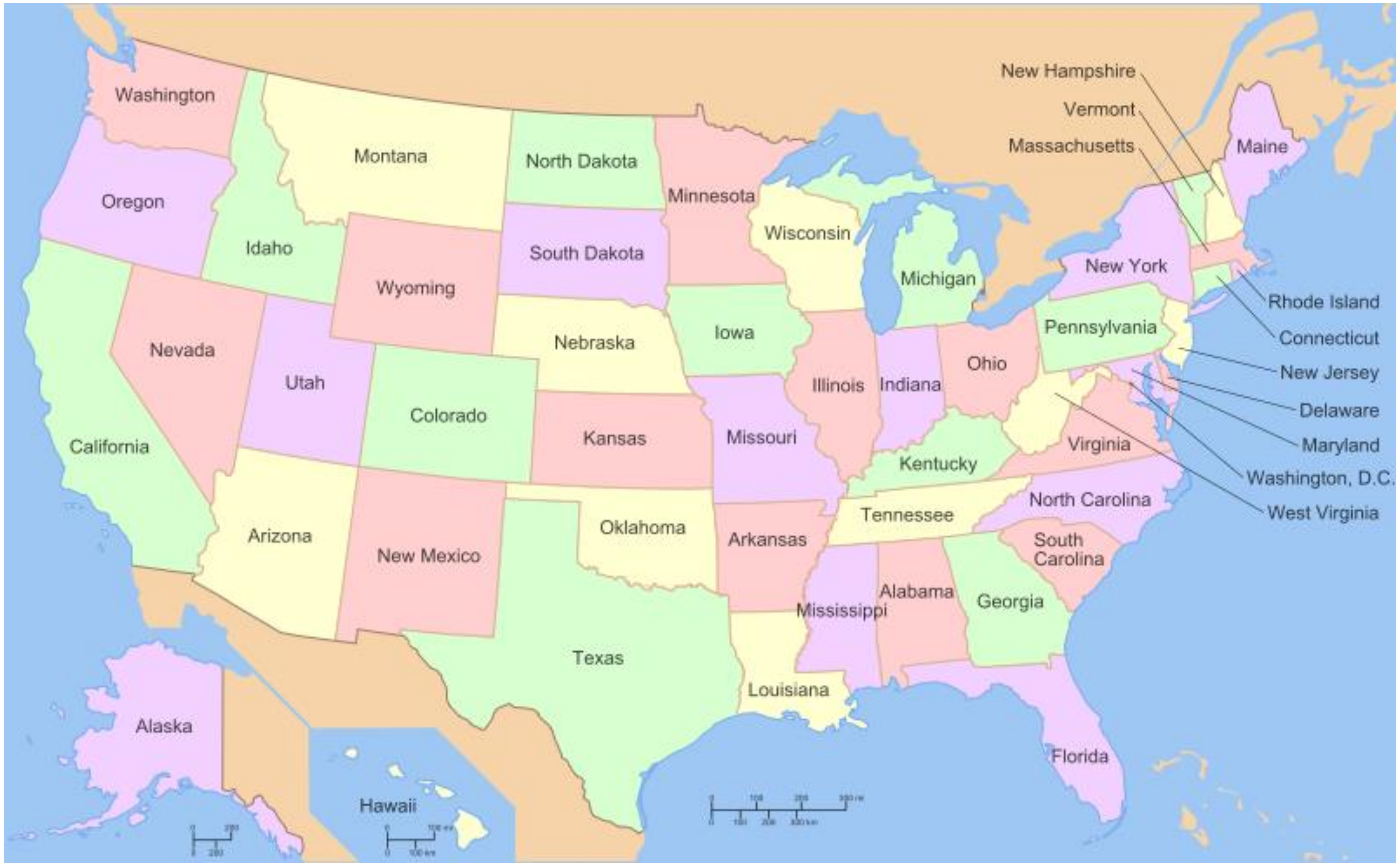
New Hampshire
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Connecticut
Pennsylvania
Iowa
Nebraska
Nevada
Utah
Ohio
New Jersey
Illinois
Indiana
Delaware
Colorado
Kansas
Missouri
California
Virginia
Maryland
Kentucky
Washington, D.C.
North Carolina
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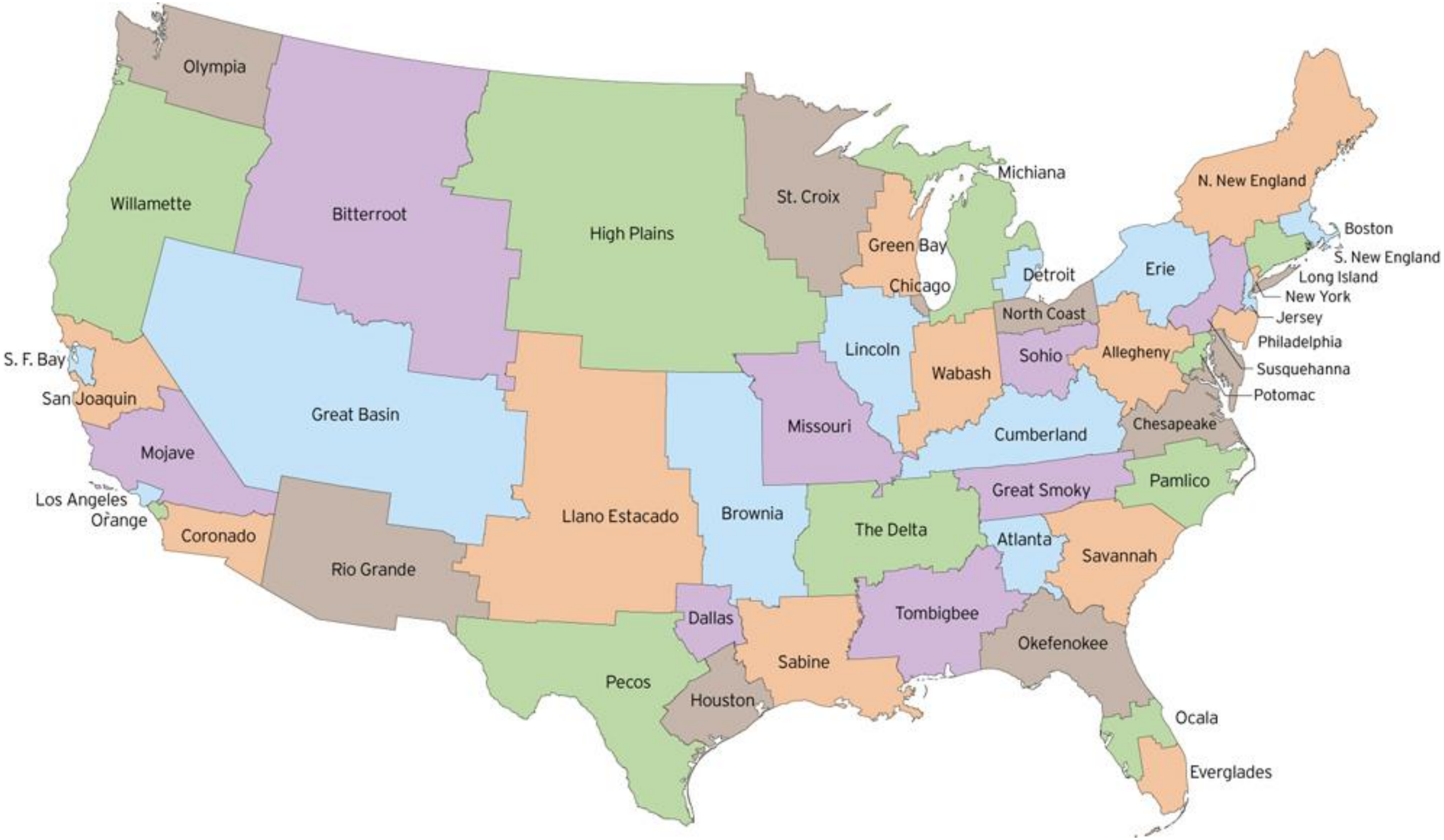
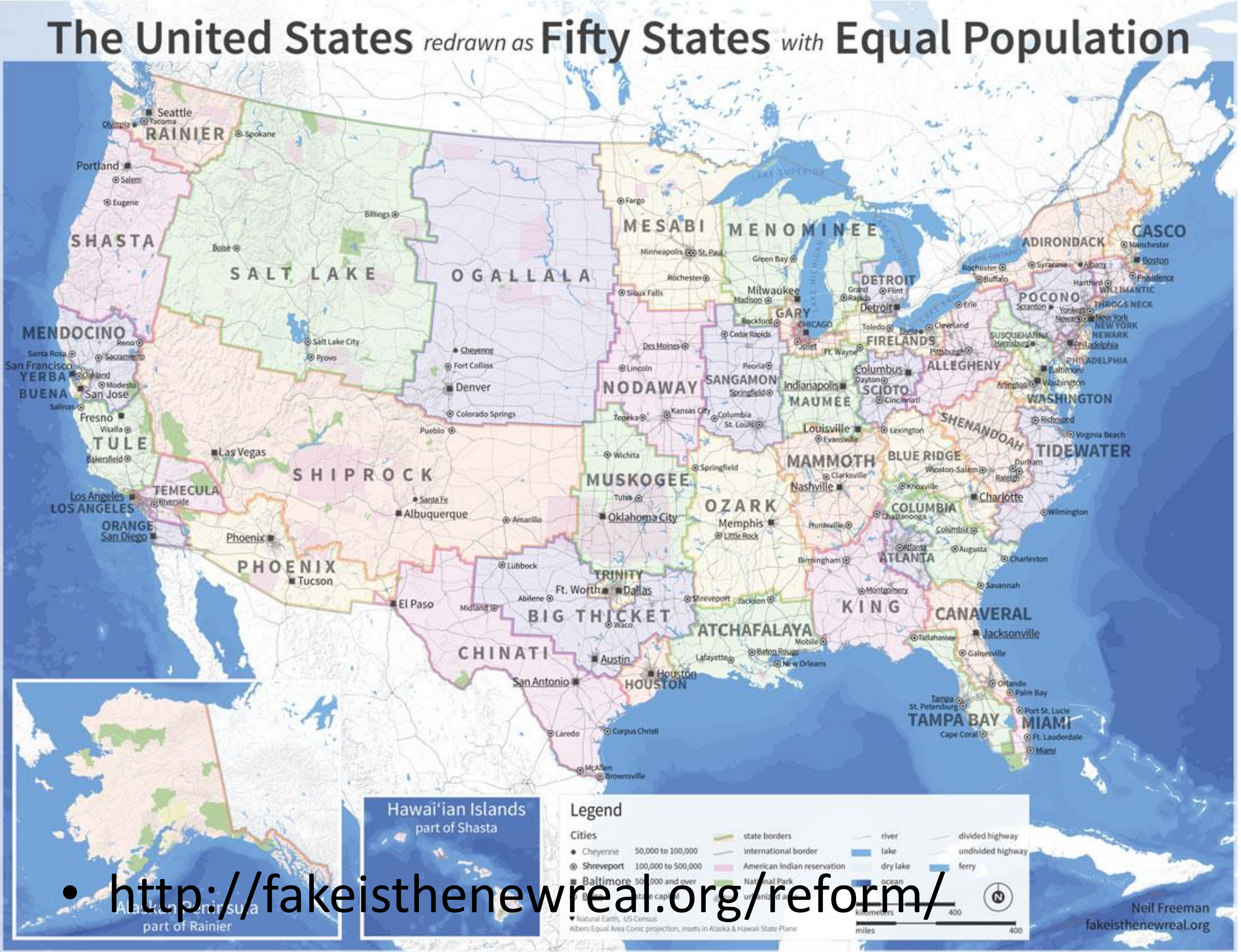


- http://fakeisthenewreal.org/reform/

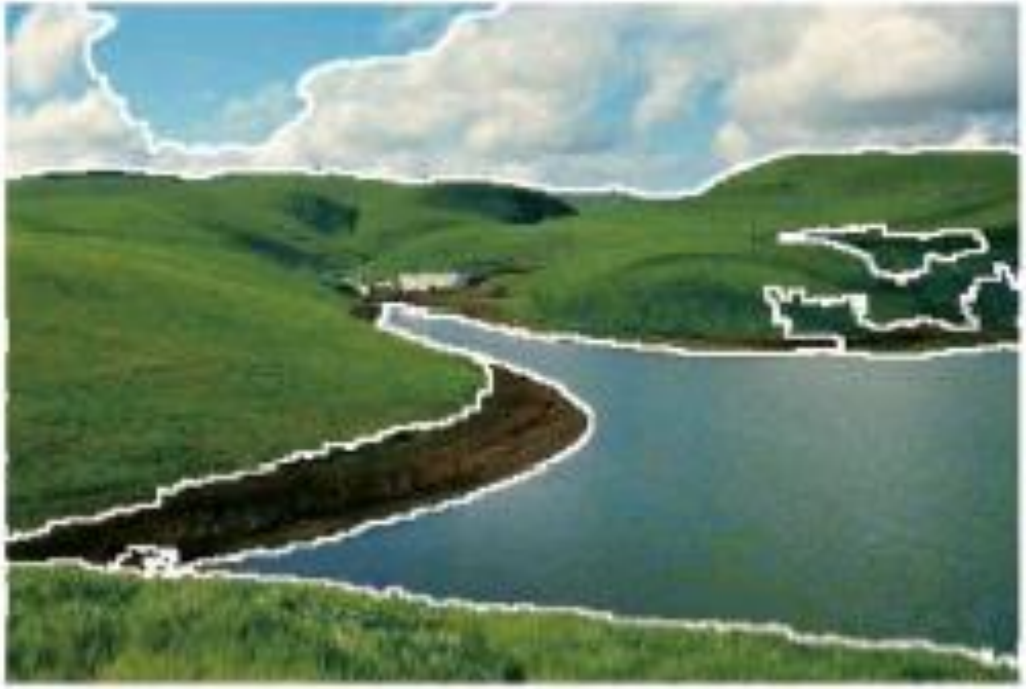
# The United States *redrawn as* Fifty States *with* Equal Population



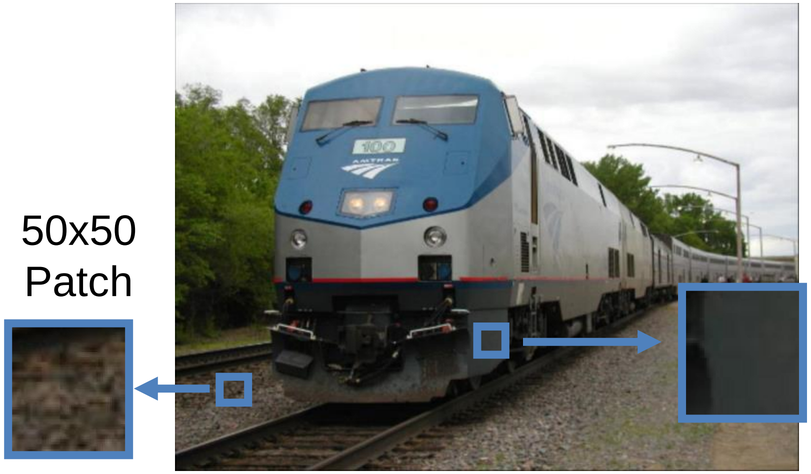
- http://fakeisthenewreal.org/reform/

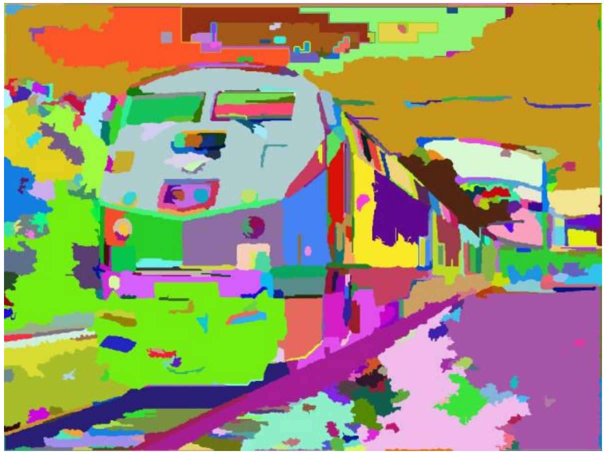
# Clustering example: image segmentation

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

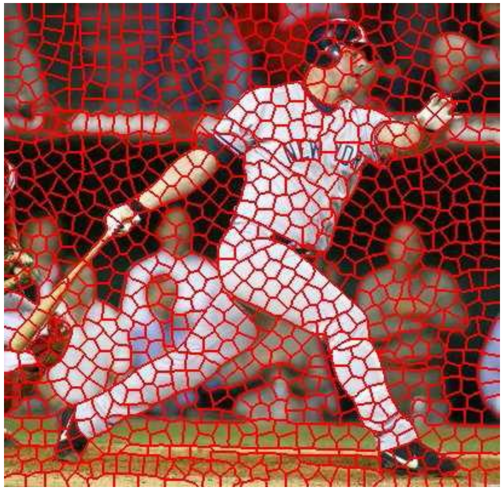


# Segmentation for feature support or efficiency





[Felzenszwalb and Huttenlocher 2004]

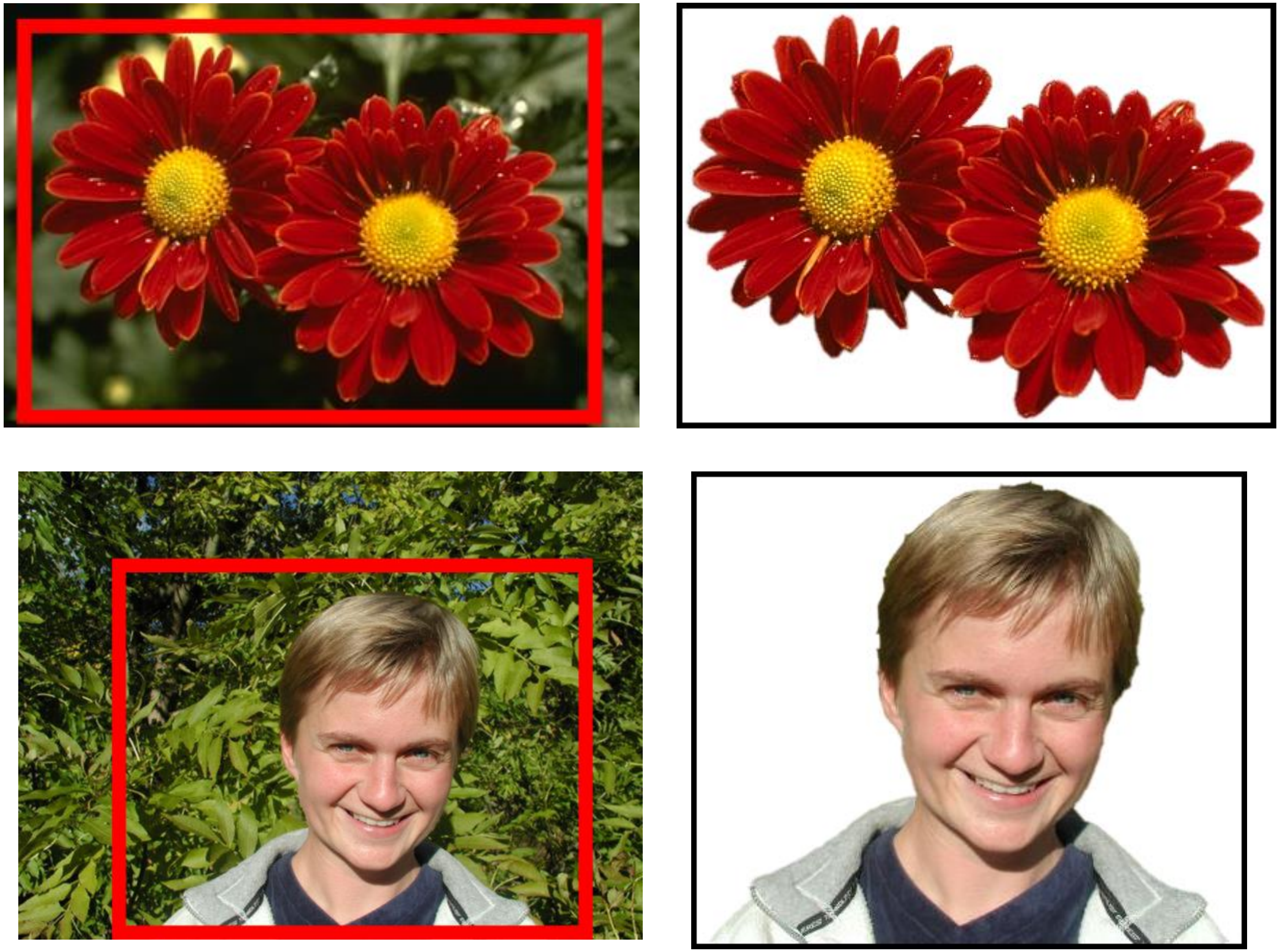


[Shi and Malik 2001]

[Hoiem et al. 2005, Mori 2005]

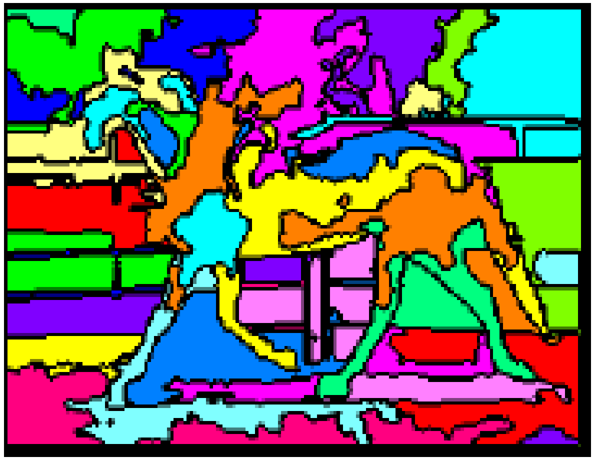
Slide: Derek Hoiem

# Segmentation as a result

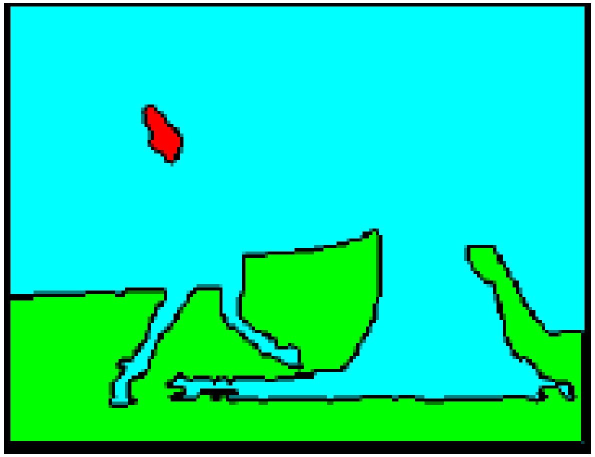


Rother et al. 2004

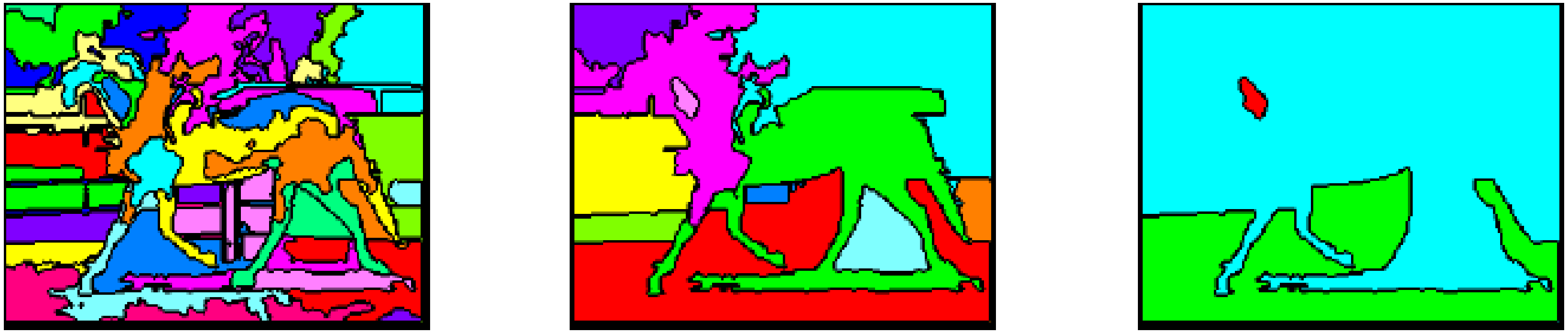
# Types of segmentations



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

# 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

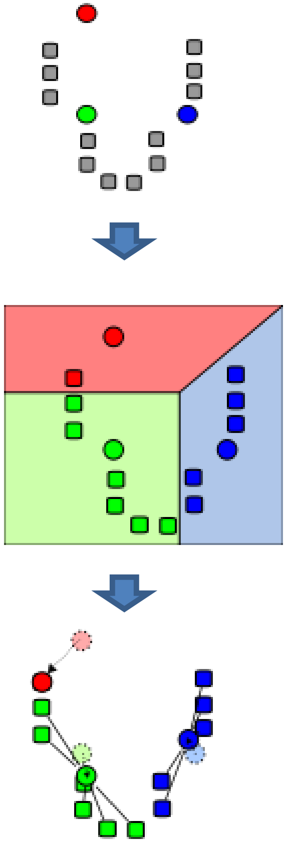
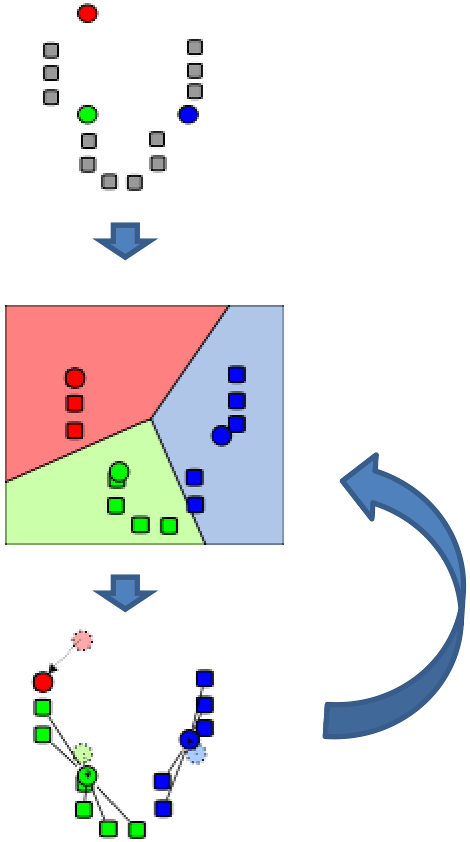


Illustration: http://en.wikipedia.org/wiki/K-means_clustering

# K-means algorithm



1. Randomly select K centers

2. Assign each point to nearest center

3. Compute new center (mean) for each cluster

Back to 2

Illustration: [http://en.wikipedia.org/wiki/K-means_clustering](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)

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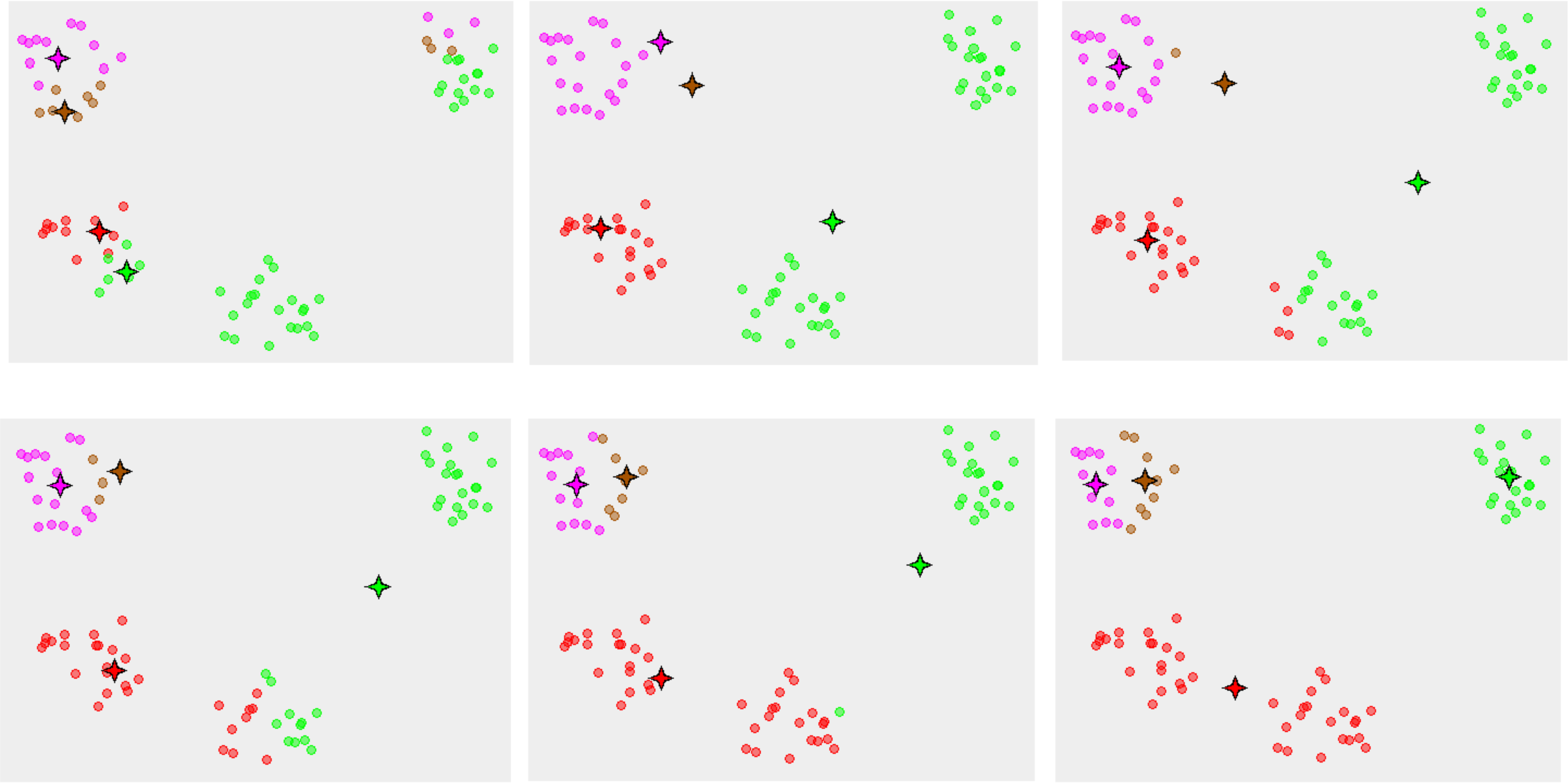
# K-means converges to a local minimum

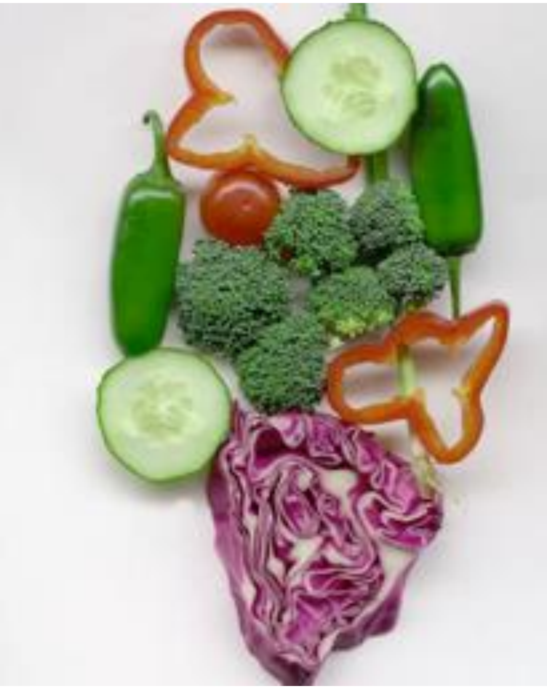


# K-means: design choices

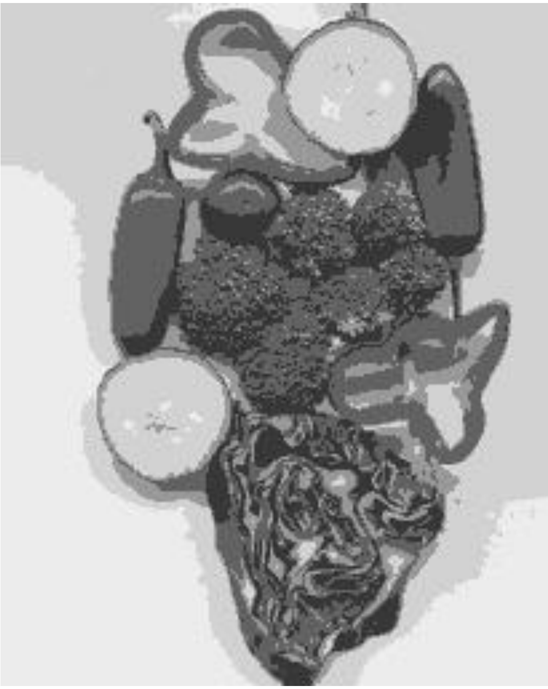
- Initialization
  - Randomly select K points as initial cluster center
  - Or greedily choose K points to minimize residual
- Distance measures
  - Traditionally Euclidean, could be others
- Optimization
  - Will converge to a *local minimum*
  - May want to perform multiple restarts

# K-means clustering using intensity or color

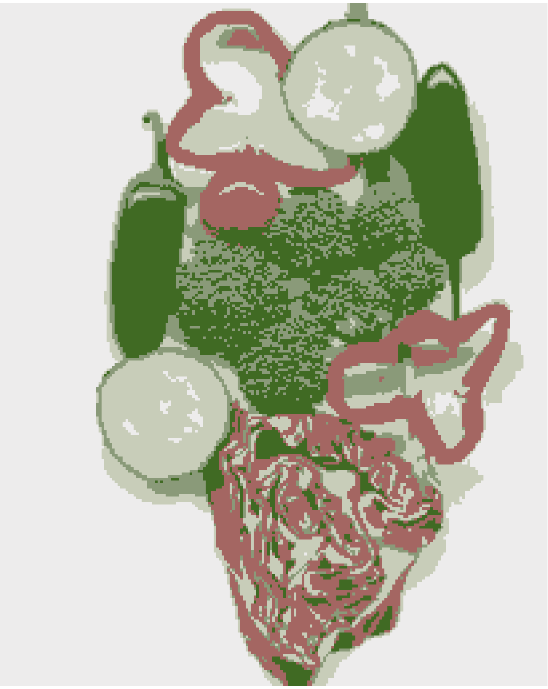
Image



Clusters on intensity



Clusters on color



# 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

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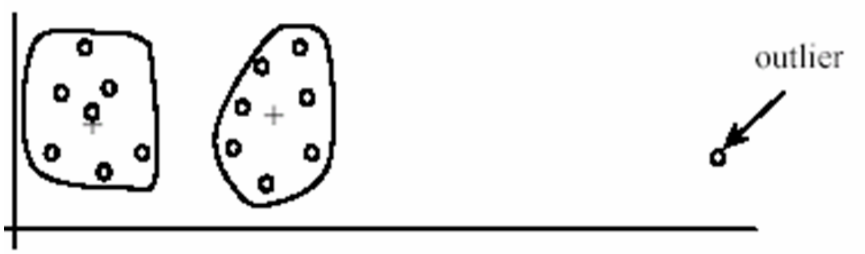
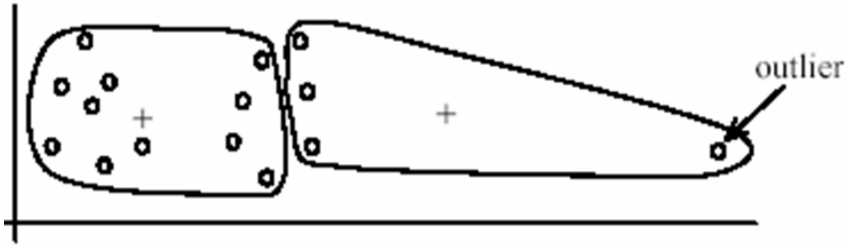
# K-Means pros and cons

- 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

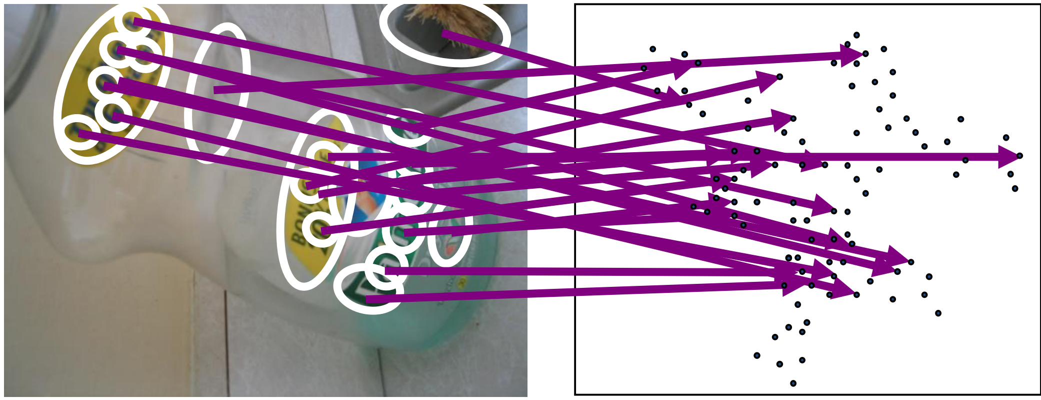


(B): Ideal clusters

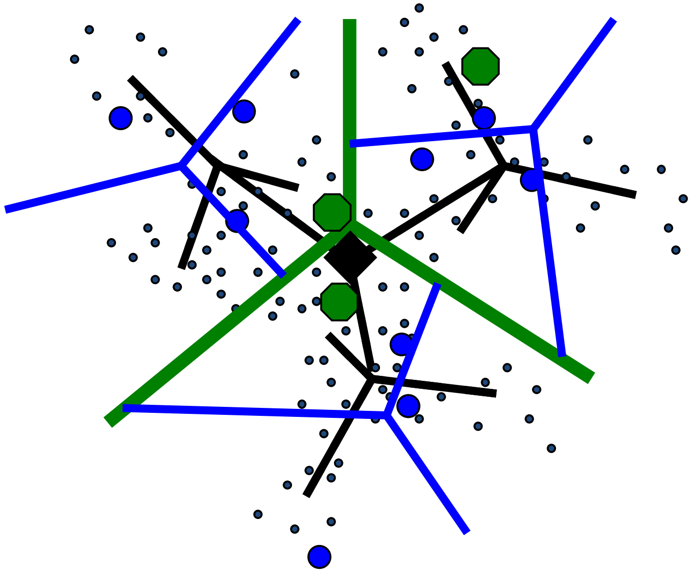


# Building Visual Dictionaries

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

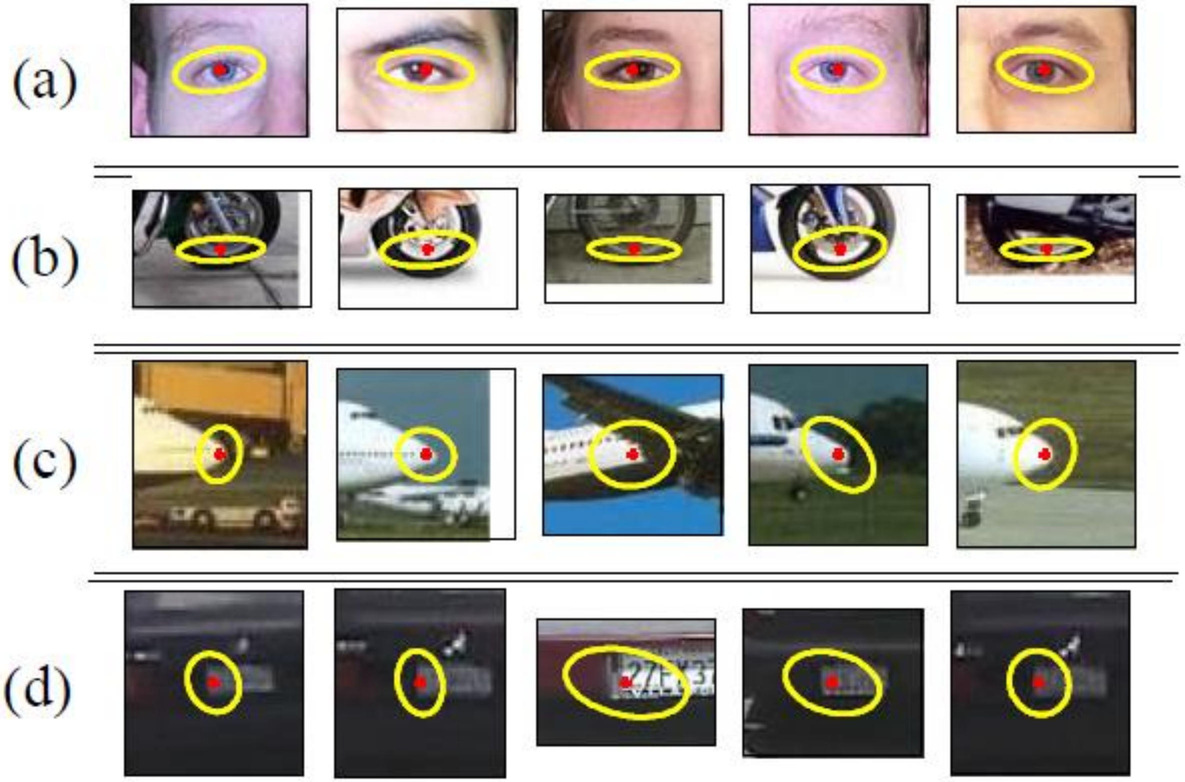


2. Cluster the patches
   - Cluster centers are the dictionary



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

# Examples of learned codewords

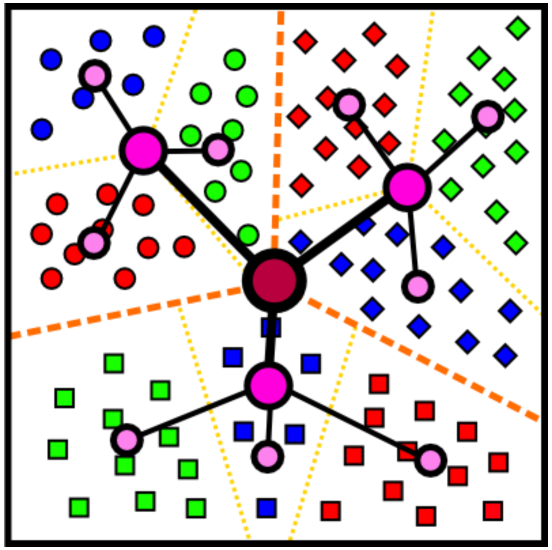


Most likely codewords for 4 learned “topics”
EM with multinomial (problem 3) to get topics

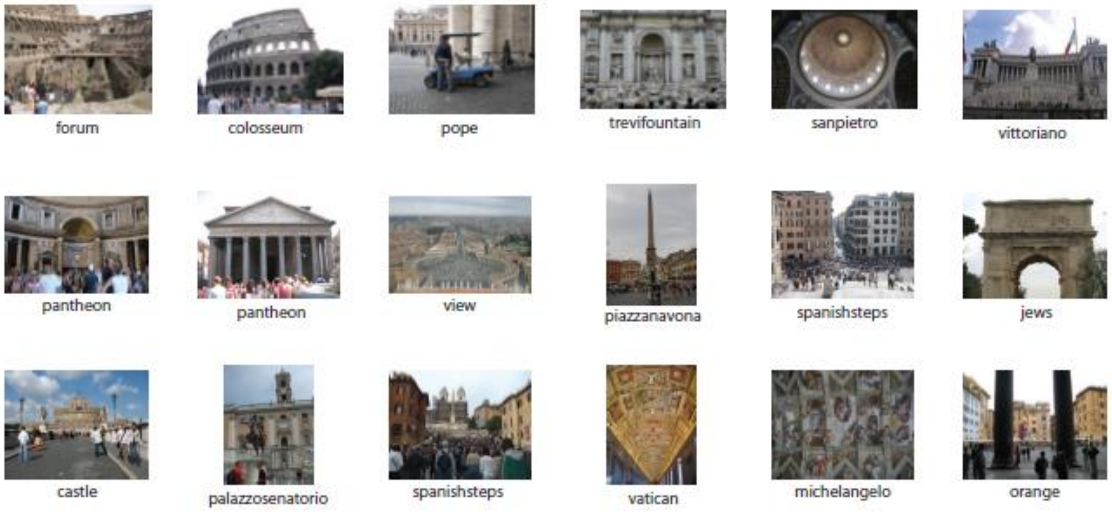
[http://www.robots.ox.ac.uk/~vgg/publications/papers/sivic05b.pdf](http://www.robots.ox.ac.uk/~vgg/publications/papers/sivic05b.pdf) Sivic et al. ICCV 2005

# Which algorithm to use?

- Quantization/Summarization: K-means
  - – Aims to preserve variance of original data
  - – Can easily assign new point to a cluster



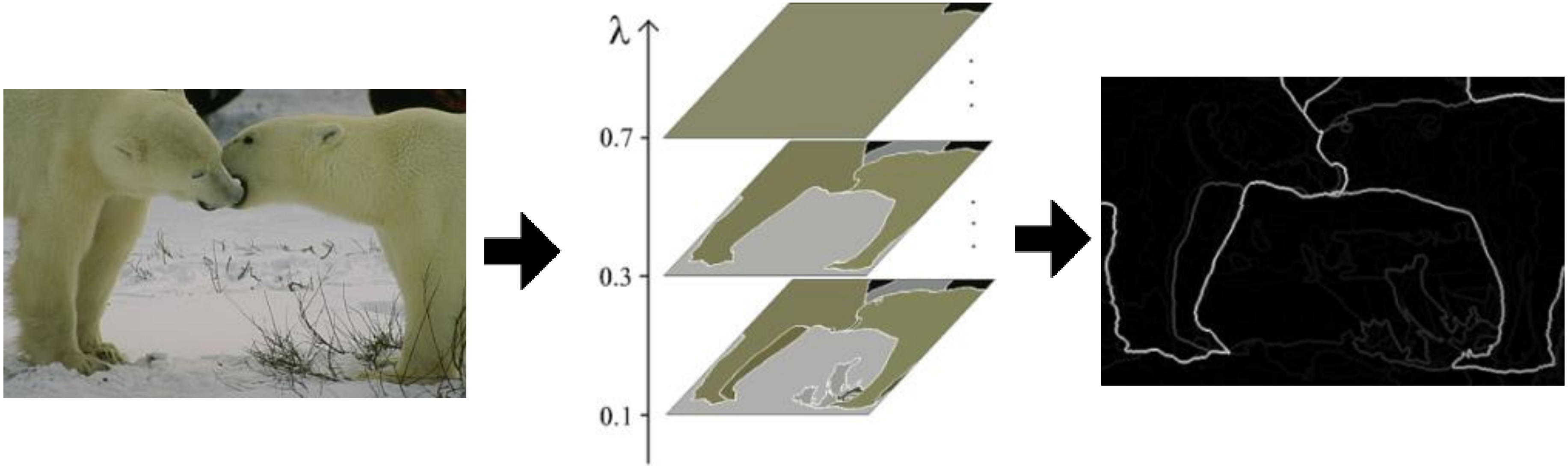
Quantization for computing histograms



Summary of 20,000 photos of Rome using "greedy k-means"
http://grail.cs.washington.edu/projects/canonview/

# Which algorithm to use?

- Image segmentation: agglomerative clustering
  - More flexible with distance measures (e.g., can be based on boundary prediction)
  - Adapts better to specific data
  - Hierarchy can be useful



http://www.cs.berkeley.edu/~arbelaez/UCM.html

# Machine Learning Problems

| | *Supervised Learning* | *Unsupervised Learning* |
|---|---|---|
| *Discrete* | classification or categorization | clustering |
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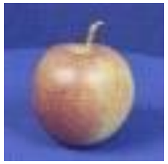
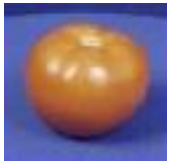
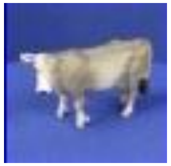
# The machine learning framework

- Apply a prediction function to a feature representation of the image to get the desired output:

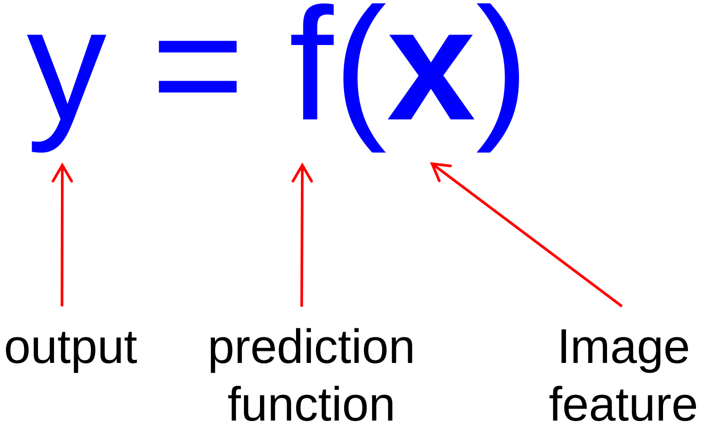
f(  ) = “apple”

f(  ) = “tomato”

f(  ) = “cow”

Slide credit: L. Lazebnik

# The machine learning framework



$$y = f(\mathbf{x})$$

output

prediction function

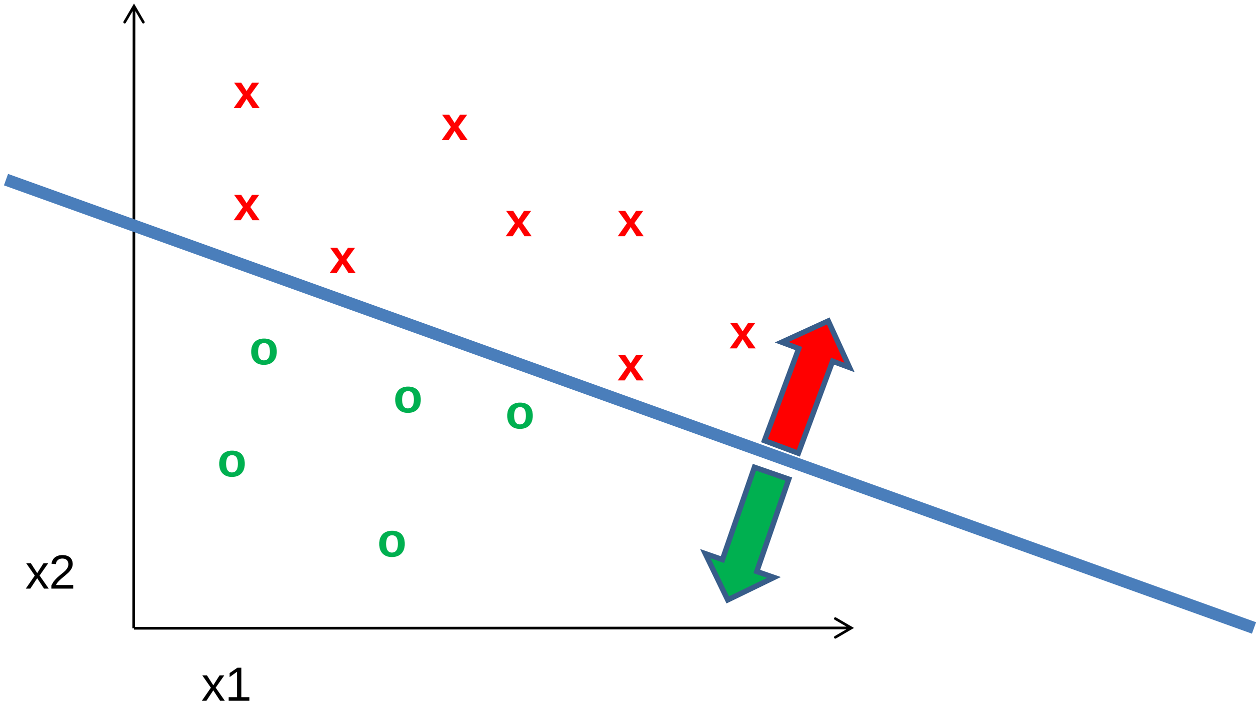
Image feature

- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the prediction function $f$ by minimizing the prediction error on the training set
- **Testing:** apply $f$ to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

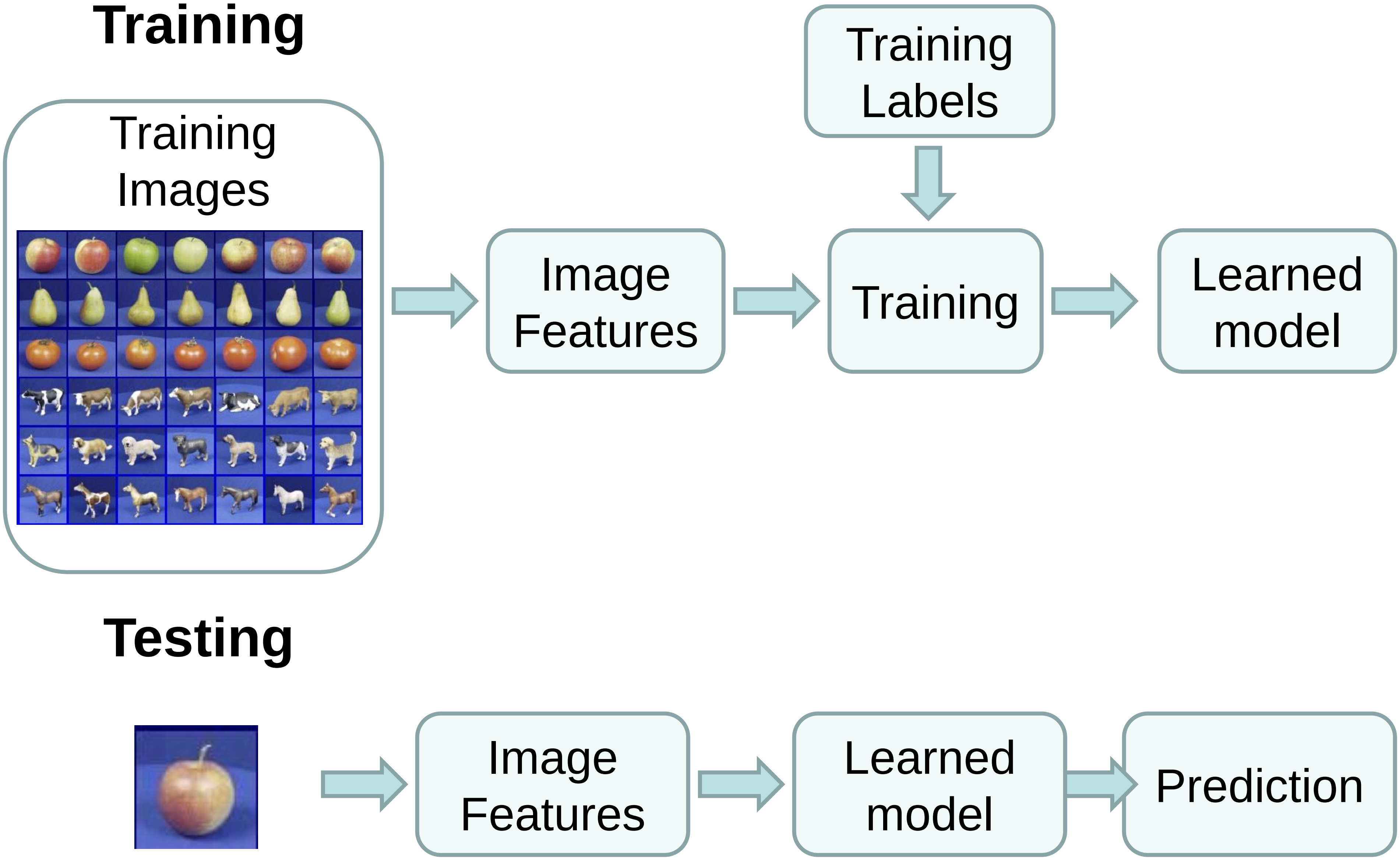
Slide credit: L. Lazebnik

# Learning a classifier

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



# Steps



**Training**

Training Images → Image Features → Training → Learned model

Training Labels → Training

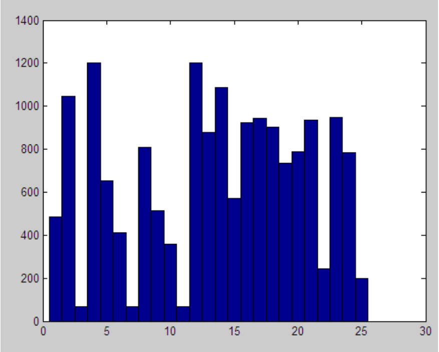
**Testing**

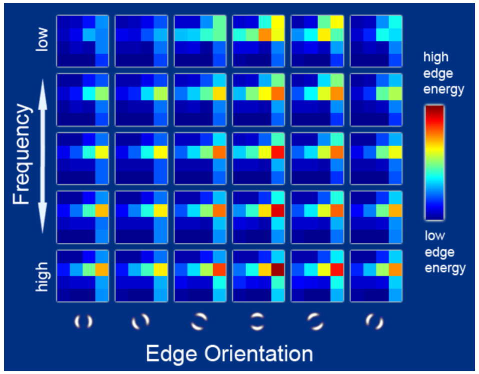
Test Image → Image Features → Learned model → Prediction

Slide credit: D. Hoiem and L. Lazebnik

# Features

- Raw pixels
- Histograms
- GIST descriptors
- …





Slide credit: L. Lazebnik

# 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

# Many classifiers to choose from

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

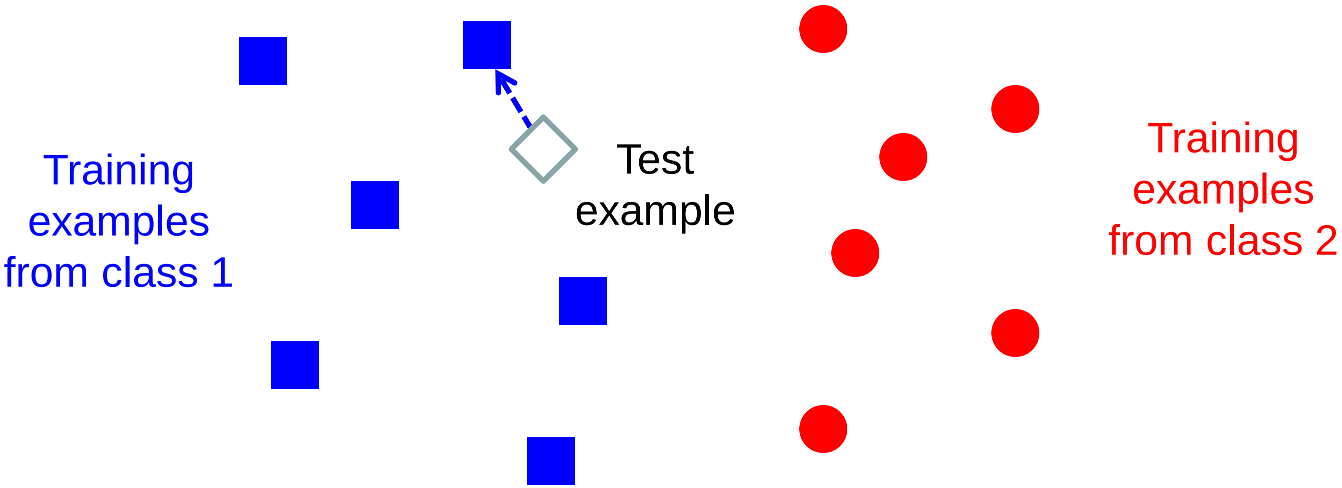
Which is the best one?

Claim:

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

*Deep learning seems to be an exception to this, at the moment, probably because it is learning the feature representation.

# Classifiers: Nearest neighbor

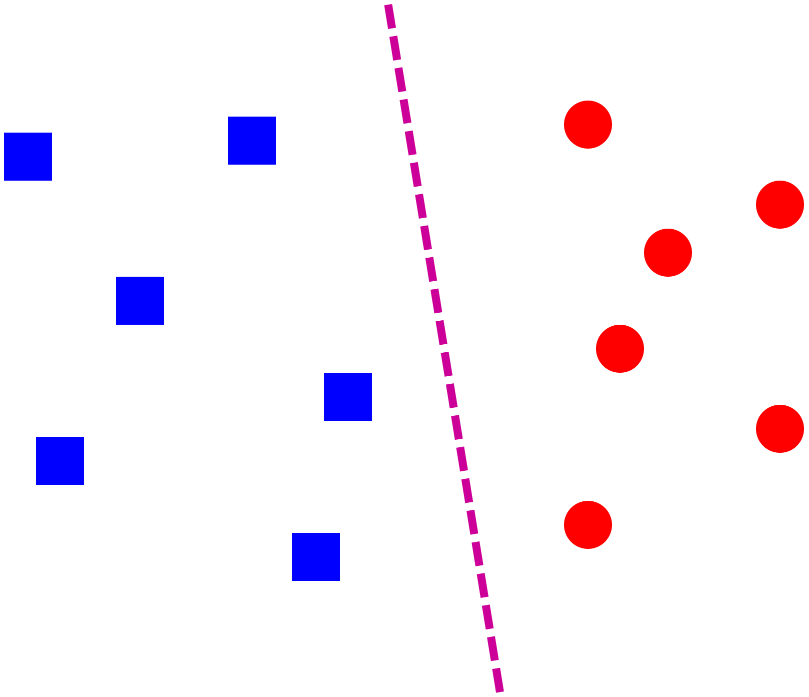

Training examples from class 1
Test example
Training examples from class 2

f(**x**) = label of the training example nearest to **x**

- All we need is a distance function for our inputs
- No training required!

Slide credit: L. Lazebnik

# Classifiers: Linear



- Find a *linear function* to separate the classes:

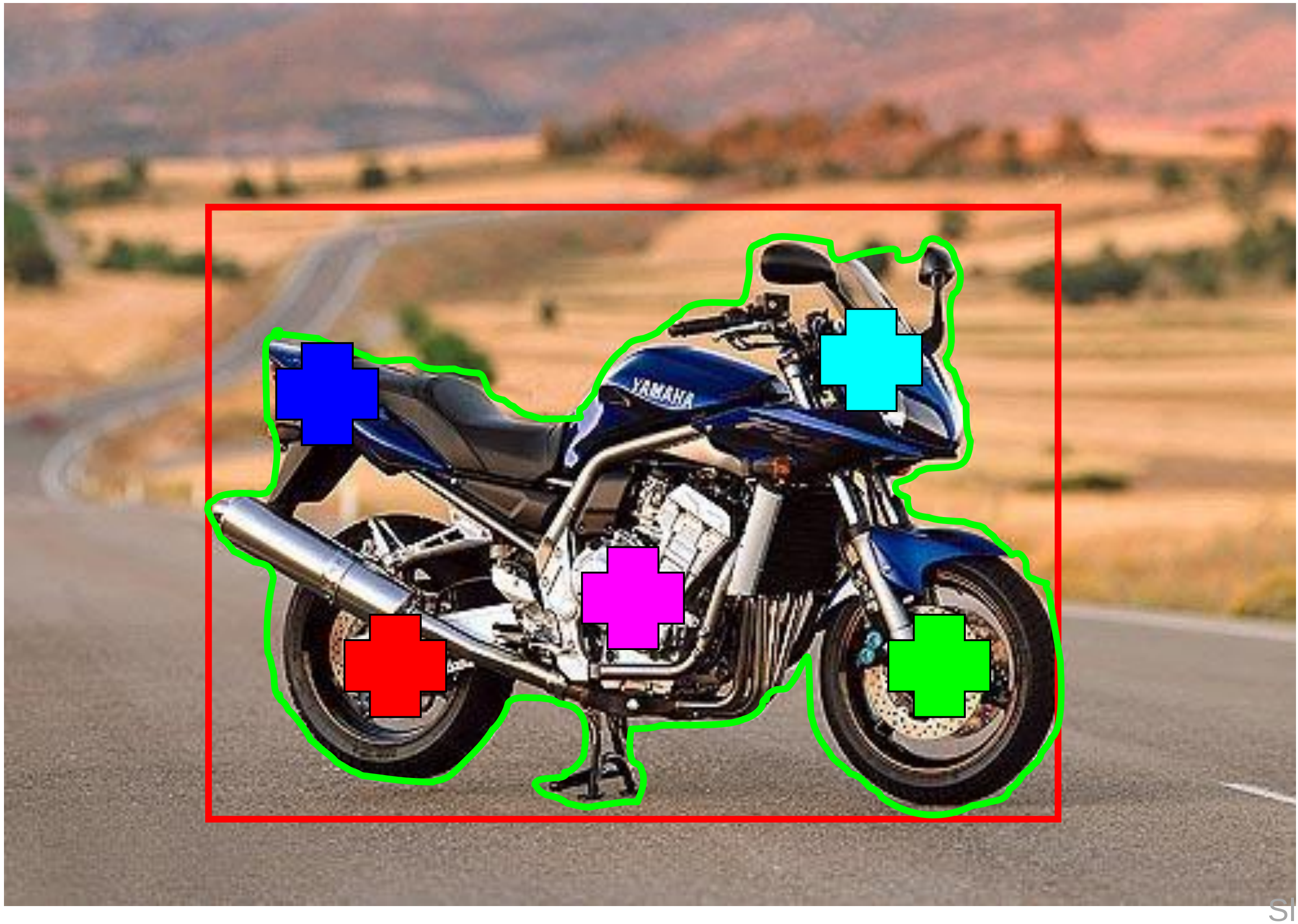
$$f(\mathbf{x}) = \mathrm{sgn}(\mathbf{w} \cdot \mathbf{x} + b)$$

Slide credit: L. Lazebnik

# Recognition task and supervision

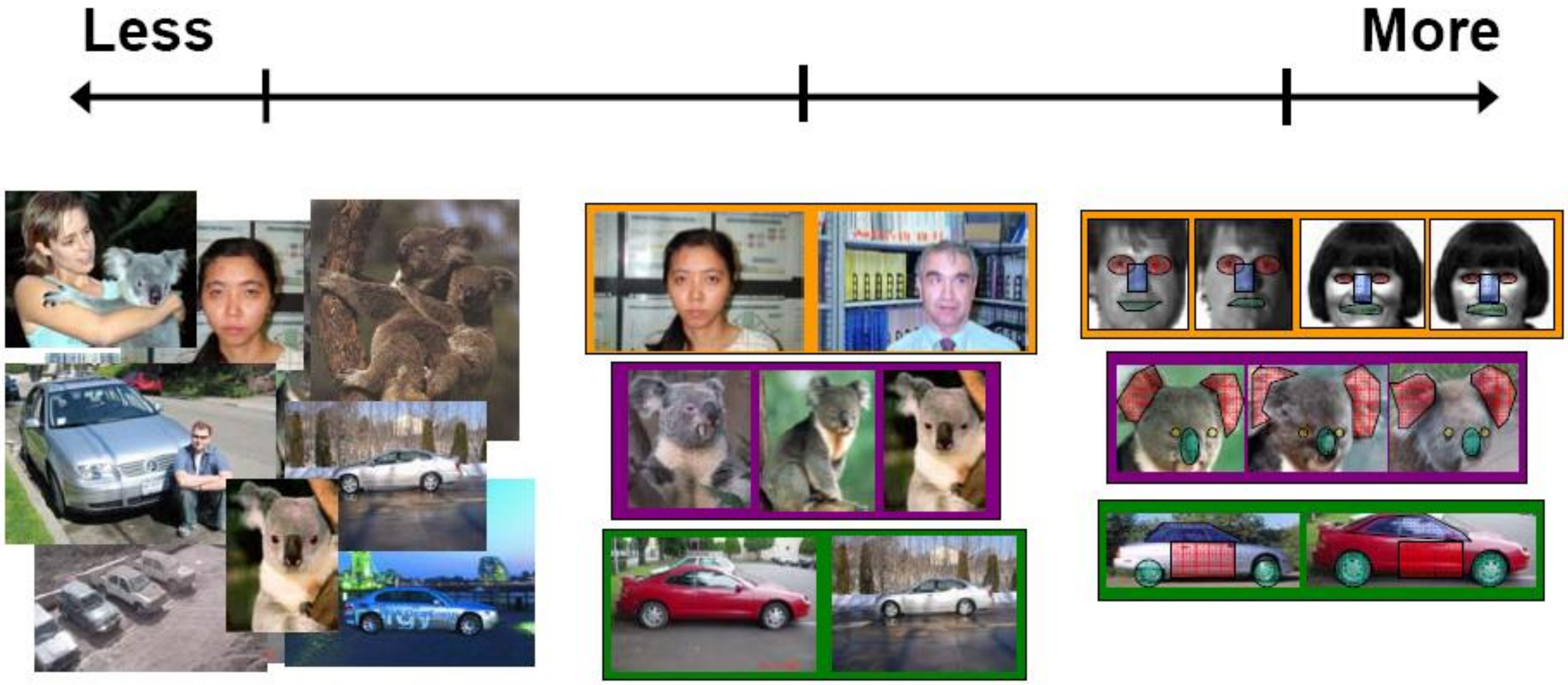
- Images in the training set must be annotated with the “correct answer” that the model is expected to produce

Contains a motorbike



Slide credit: L. Lazebnik

# Spectrum of supervision



Unsupervised

“Weakly” supervised

Fully supervised

Definition depends on task

Slide credit: L. Lazebnik

# Generalization

Training set (labels known)

Test set (labels unknown)

- How well does a learned model generalize from the data it was trained on to a new test set?

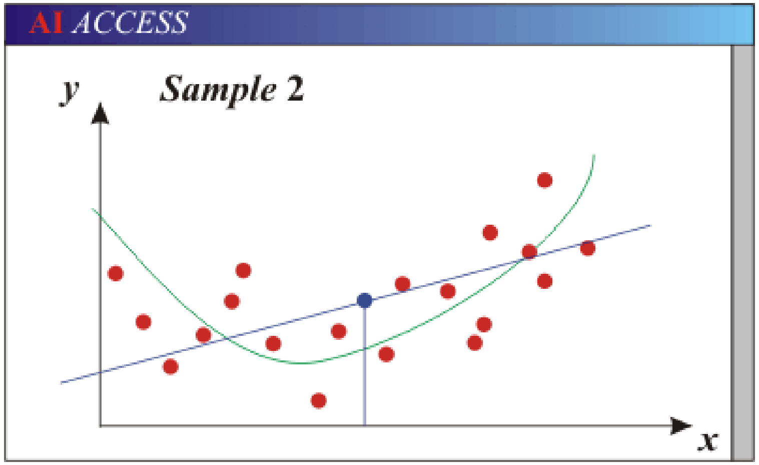
Slide credit: L. Lazebnik

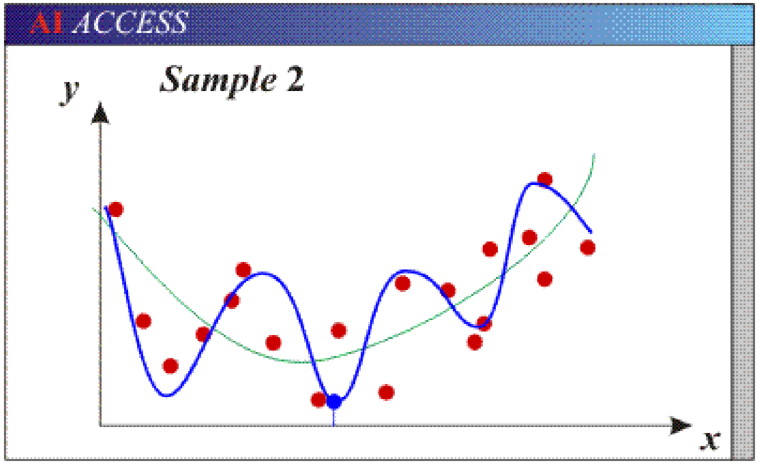
# Generalization

- Components of generalization error
  - **Bias:** how much the average model over all training sets differ from the true model?
    - Error due to inaccurate assumptions/simplifications made by the model.
  - **Variance:** how much models estimated from different training sets differ from each other.
- **Underfitting:** model is too “simple” to represent all the relevant class characteristics
  - High bias (few degrees of freedom) and low variance
  - High training error and high test error
- **Overfitting:** model is too “complex” and fits irrelevant characteristics (noise) in the data
  - Low bias (many degrees of freedom) and high variance
  - Low training error and high test error

Slide credit: L. Lazebnik

# Bias-Variance Trade-off





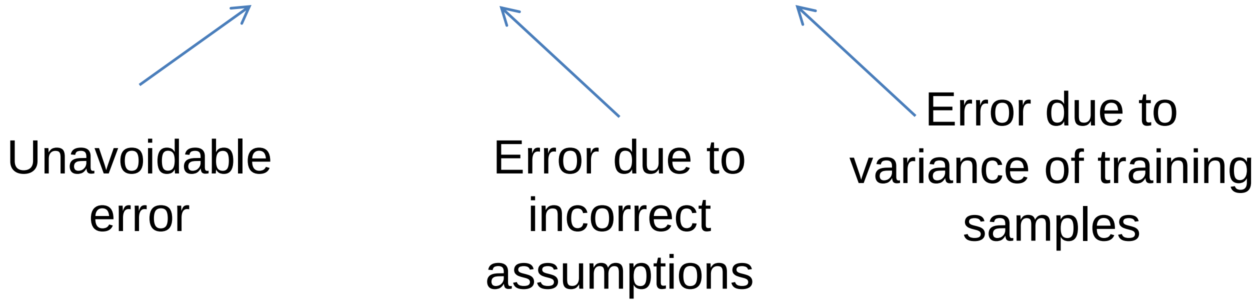
- Models with too few parameters are inaccurate because of a large bias (not enough flexibility).

- Models with too many parameters are inaccurate because of a large variance (too much sensitivity to the sample).

Slide credit: D. Hoiem

# Bias-Variance Trade-off

$$E(MSE) = noise^2 + bias^2 + variance$$



Unavoidable error

Error due to incorrect assumptions

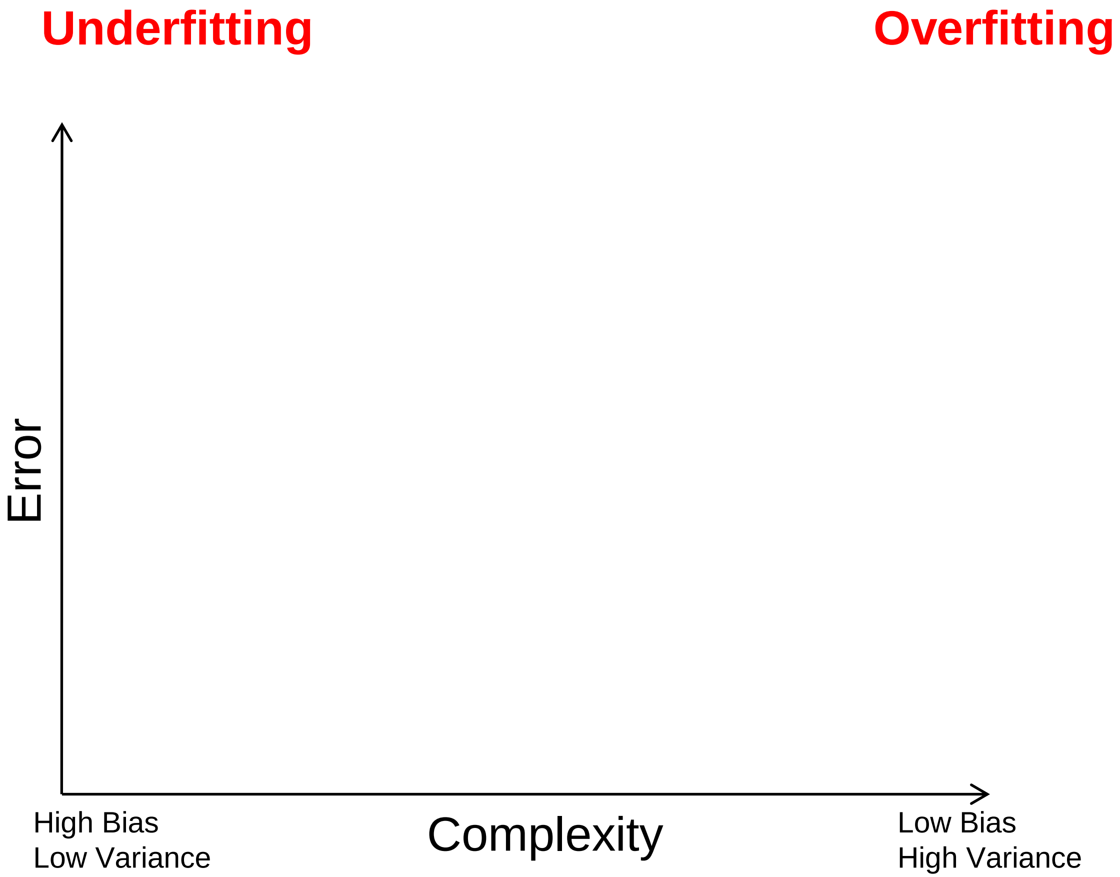
Error due to variance of training samples

See the following for explanations of bias-variance (also Bishop's "Neural Networks" book):

•http://www.inf.ed.ac.uk/teaching/courses/mlsc/Notes/Lecture4/BiasVariance.pdf

Slide credit: D. Hoiem

# Bias-variance tradeoff



Underfitting

Overfitting

Error

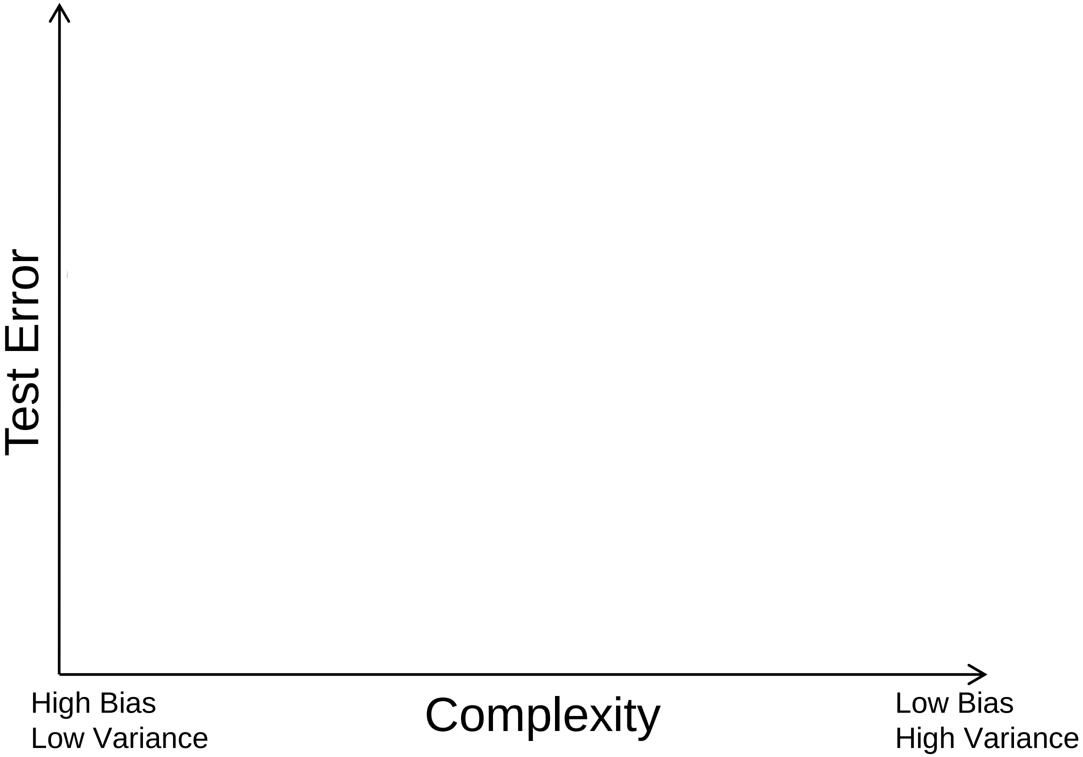
Complexity

High Bias
Low Variance

Low Bias
High Variance

Slide credit: D. Hoiem

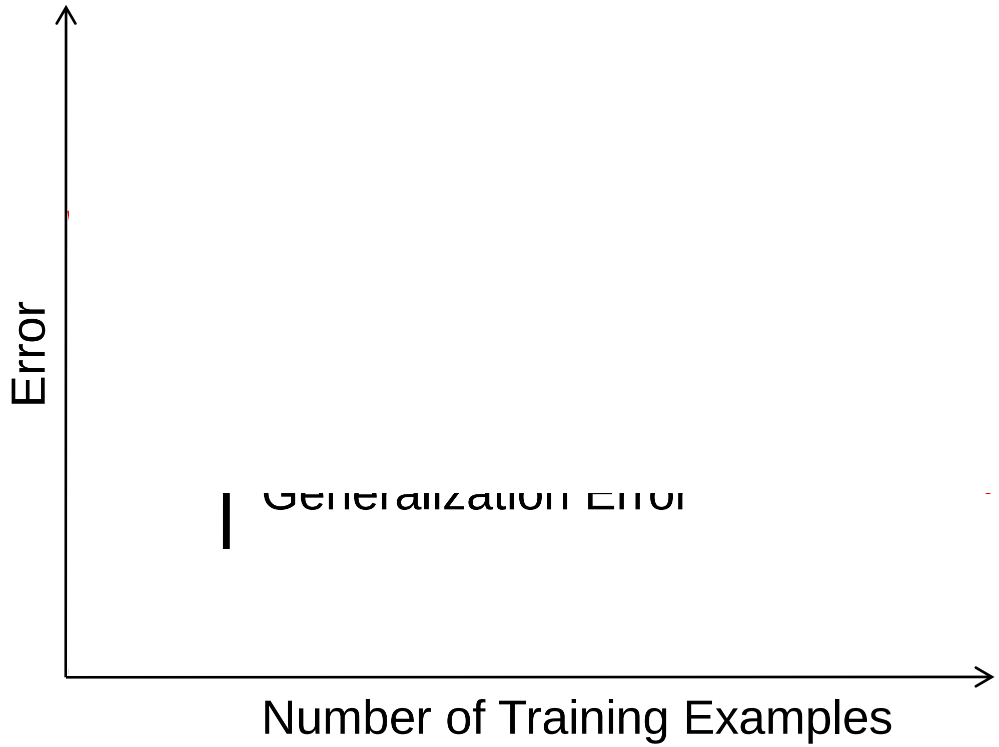
# Bias-variance tradeoff



Slide credit: D. Hoiem

# Effect of Training Size

Fixed prediction model



Slide credit: D. Hoiem

# Remember…

- No classifier is inherently better than any other: you need to make assumptions to generalize

- Three kinds of error
  - Inherent: unavoidable
  - Bias: due to over-simplifications
  - Variance: due to inability to perfectly estimate parameters from limited data

Slide credit: D. Hoiem

# How to reduce variance?

- Choose a simpler classifier

- Regularize the parameters

- Get more training data

Slide credit: D. Hoiem

# Very brief tour of some classifiers

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

# Generative vs. Discriminative Classifiers

## Generative Models

- Represent both the data and the labels
- Often, makes use of conditional independence and priors
- Examples
  - Naïve Bayes classifier
  - Bayesian network

- Models of data may apply to future prediction problems

## Discriminative Models

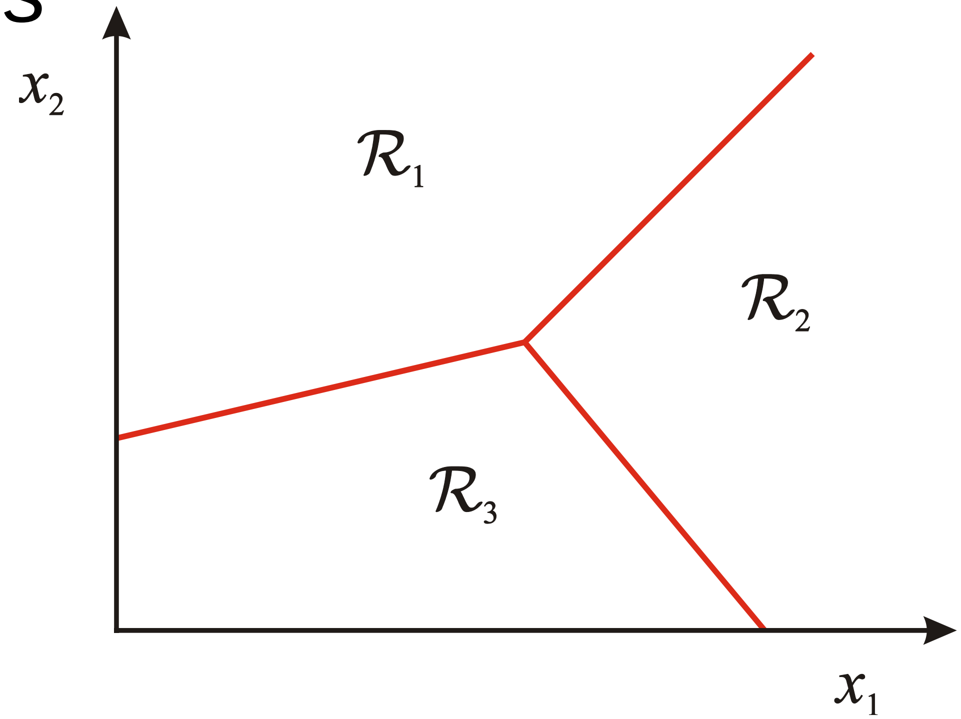
- Learn to directly predict the labels from the data
- Often, assume a simple boundary (e.g., linear)
- Examples
  - Logistic regression
  - SVM
  - Boosted decision trees

- Often easier to predict a label from the data than to model the data

Slide credit: D. Hoiem

# Classification

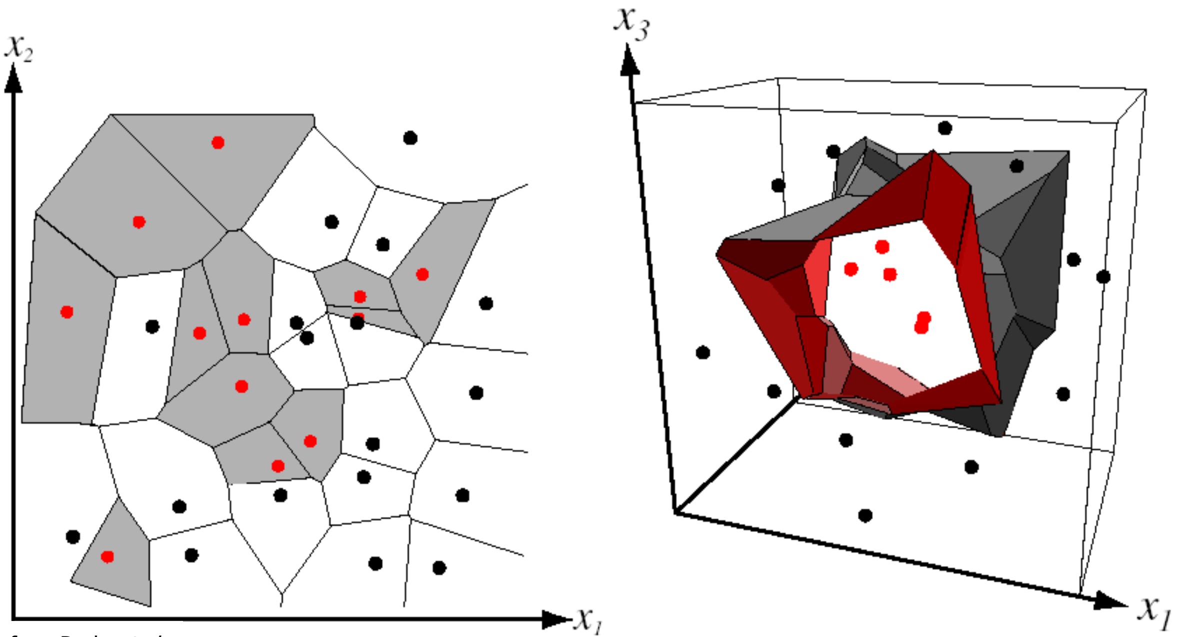
- Assign input vector to one of two or more classes
- Any decision rule divides input space into *decision regions* separated by *decision boundaries*



Slide credit: L. Lazebnik

# Nearest Neighbor Classifier

- Assign label of nearest training data point to each test data point

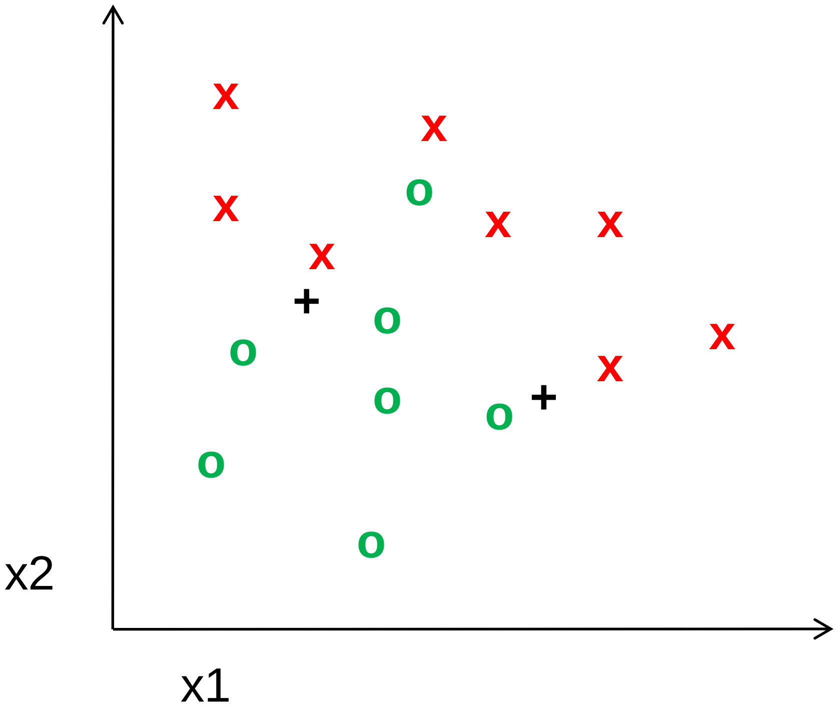


from Duda *et al.*

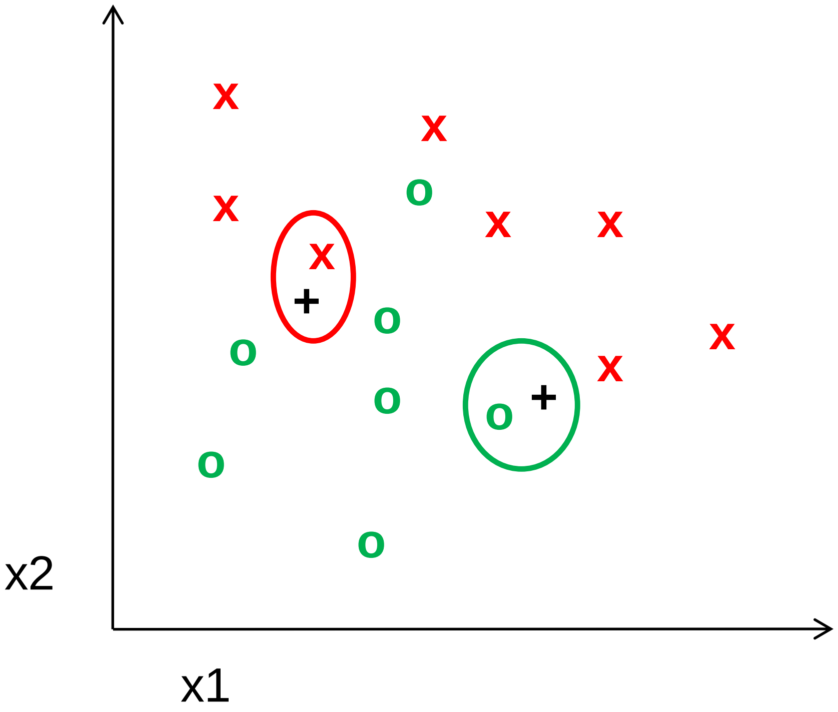
Voronoi partitioning of feature space
for two-category 2D and 3D data

Source: D. Lowe

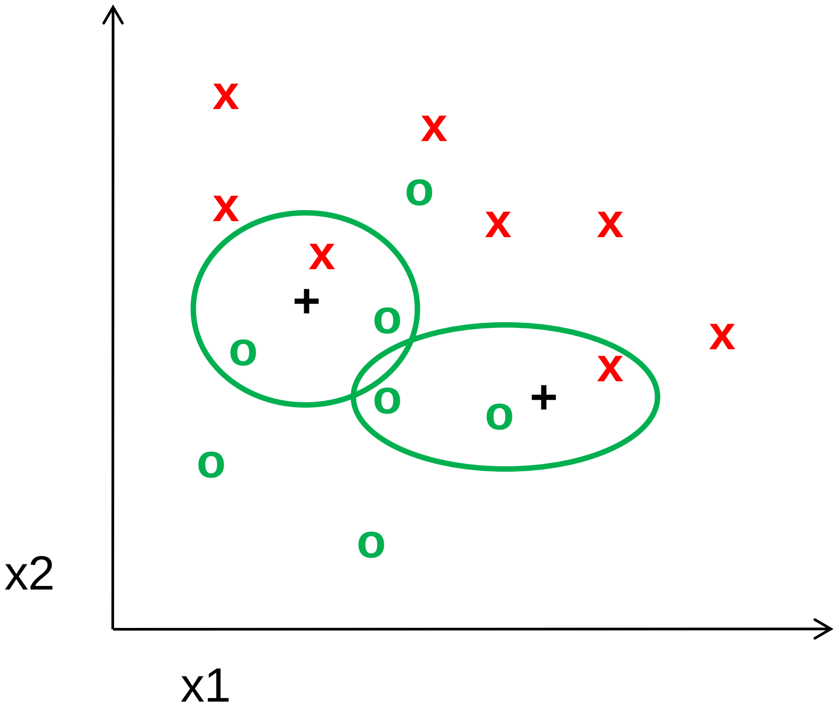
# K-nearest neighbor



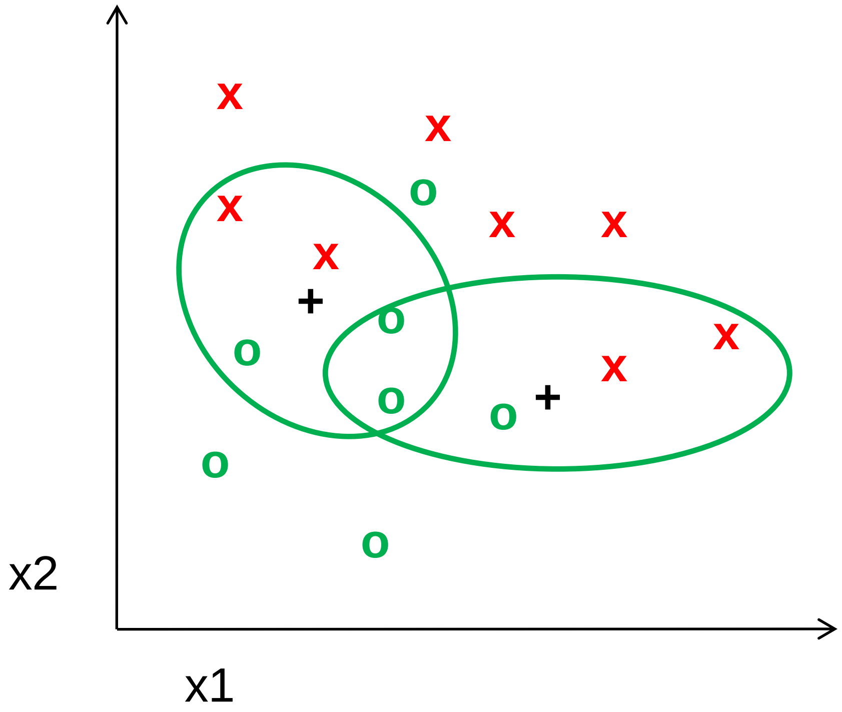
# 1-nearest neighbor



# 3-nearest neighbor



# 5-nearest neighbor

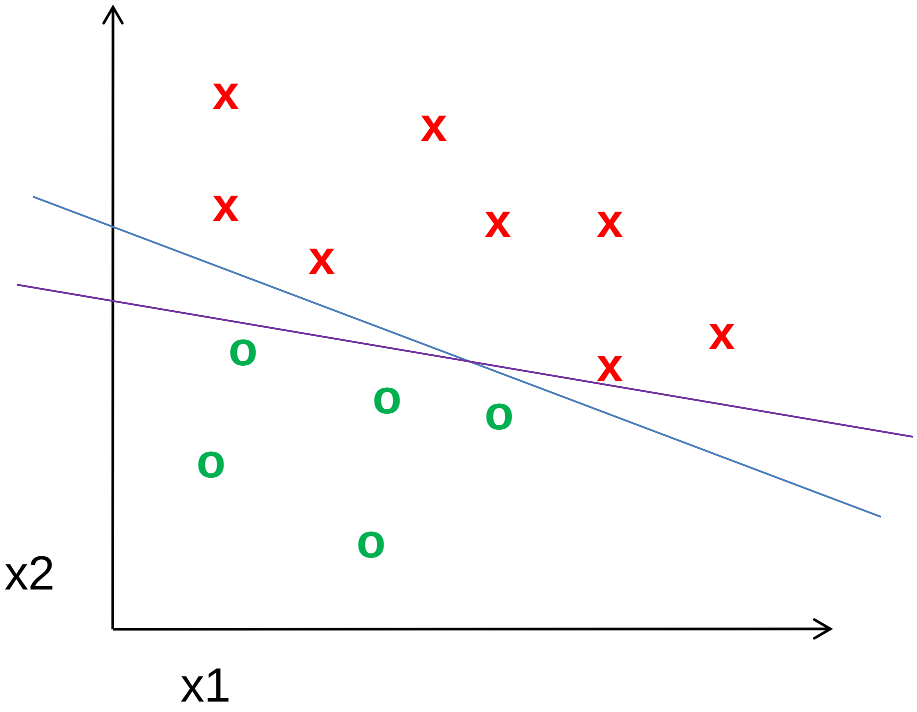


# Using K-NN

- Simple, a good one to try first

- With infinite examples, 1-NN provably has error that is at most twice Bayes optimal error

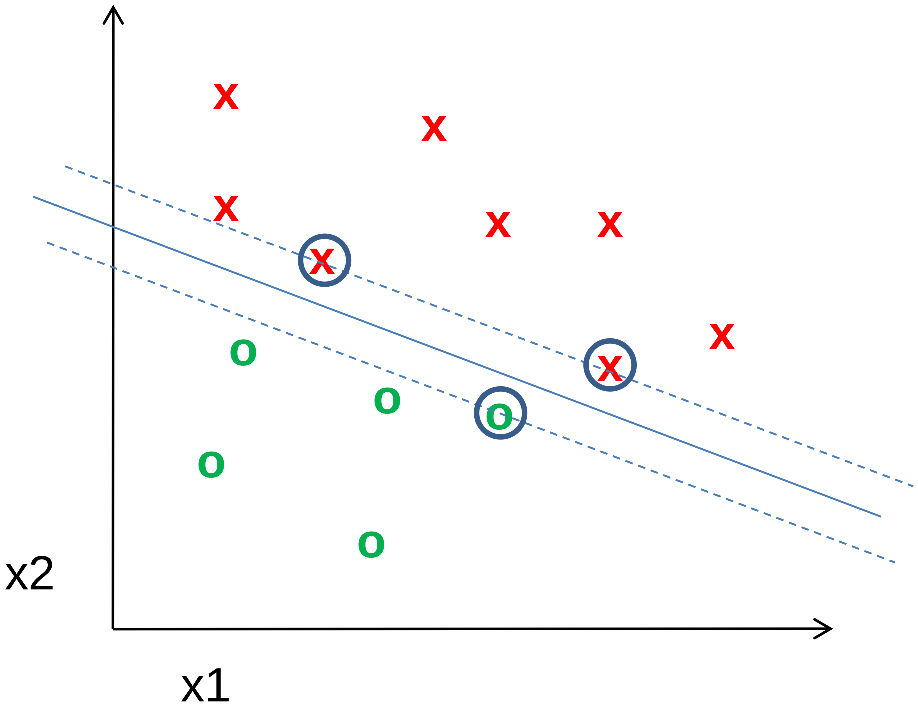
# Classifiers: Linear SVM



- Find a *linear function* to separate the classes:

$$f(\mathbf{x}) = \mathrm{sgn}(\mathbf{w} \cdot \mathbf{x} + b)$$

# Classifiers: Linear SVM



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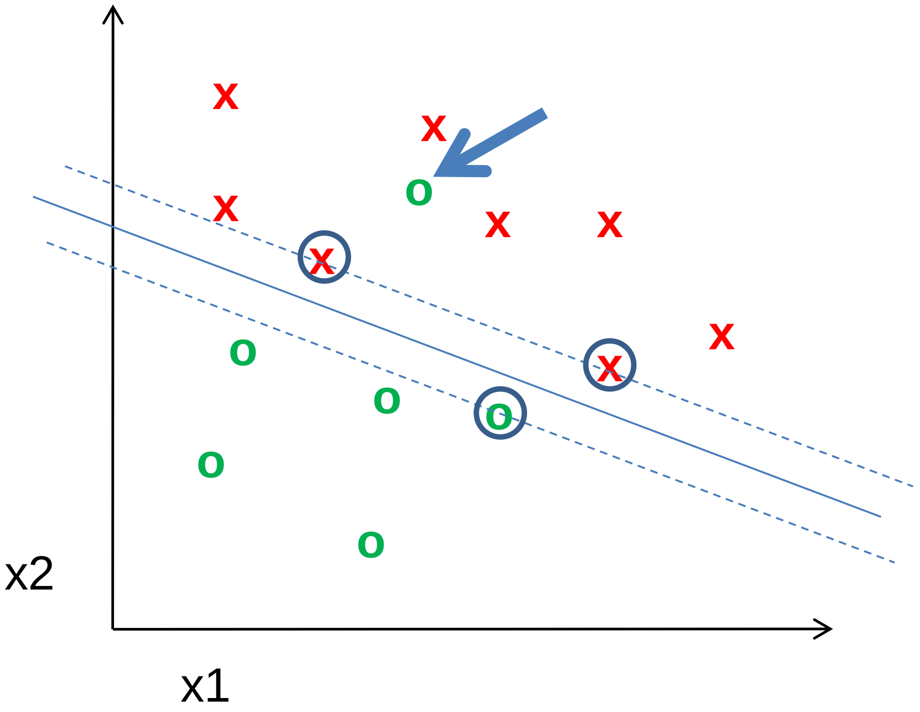
# Classifiers: Linear SVM



- Find a *linear function* to separate the classes:

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# What about multi-class SVMs?

- Unfortunately, there is no “definitive” multi-class SVM formulation
- In practice, we have to obtain a multi-class SVM by combining multiple two-class SVMs
- One vs. others
  - Traning: learn an SVM for each class vs. the others
  - Testing: apply each SVM to test example and assign to it the class of the SVM that returns the highest decision value
- One vs. one
  - Training: learn an SVM for each pair of classes
  - Testing: each learned SVM “votes” for a class to assign to the test example

Slide credit: L. Lazebnik

# SVMs: Pros and cons

- Pros
  - Many publicly available SVM packages: [http://www.kernel-machines.org/software](http://www.kernel-machines.org/software)
  - Kernel-based framework is very powerful, flexible
  - SVMs work very well in practice, even with very small training sample sizes

- Cons
  - No "direct" multi-class SVM, must combine two-class SVMs
  - Computation, memory
    - During training time, must compute matrix of kernel values for every pair of examples
    - Learning can take a very long time for large-scale problems

# What to remember about classifiers

- No free lunch: machine learning algorithms are tools, not dogmas

- Try simple classifiers first

- Better to have smart features and simple classifiers than simple features and smart classifiers

- Use increasingly powerful classifiers with more training data (bias-variance tradeoff)

Slide credit: D. Hoiem

# Making decisions about data

- 3 important design decisions:

  1) What data do I use?

  2) How do I represent my data (what feature)?

  3) What classifier / regressor / machine learning tool do I use?

- These are in decreasing order of importance
- Deep learning addresses 2 and 3 simultaneously (and blurs the boundary between them).
- You can take the representation from deep learning and use it with any classifier.