Machine Learning Crash Course

Computer Vision

Jia-Bin Huang, Virginia Tech

Many slides from D. Hoiem, J. Hays

Administrative stuffs

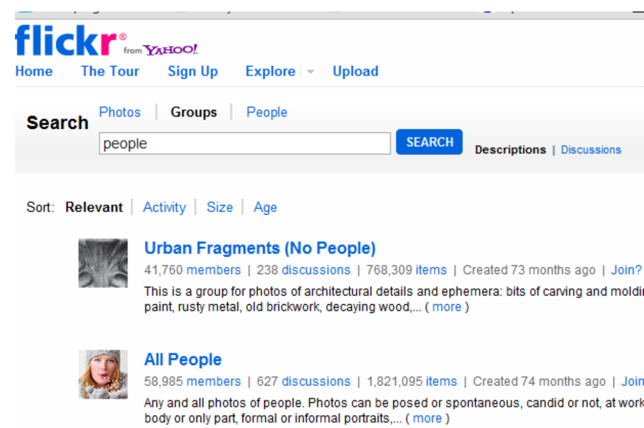
- HW 4
  - Due 11:59pm on Wed, November 2^{nd}

- What is a category?

- Why would we want to put an image in one?

    To predict, describe, interact. To organize.

- Many different ways to categorize



Examples of Categorization in Vision

- Part or object detection
  - E.g., for each window: face or non-face?
- Scene categorization
  - Indoor vs. outdoor, urban, forest, kitchen, etc.
- Action recognition
  - Picking up vs. sitting down vs. standing …
- Emotion recognition
- Region classification
  - Label pixels into different object/surface categories
- Boundary classification
  - Boundary vs. non-boundary
- Etc, etc.

Image Categorization

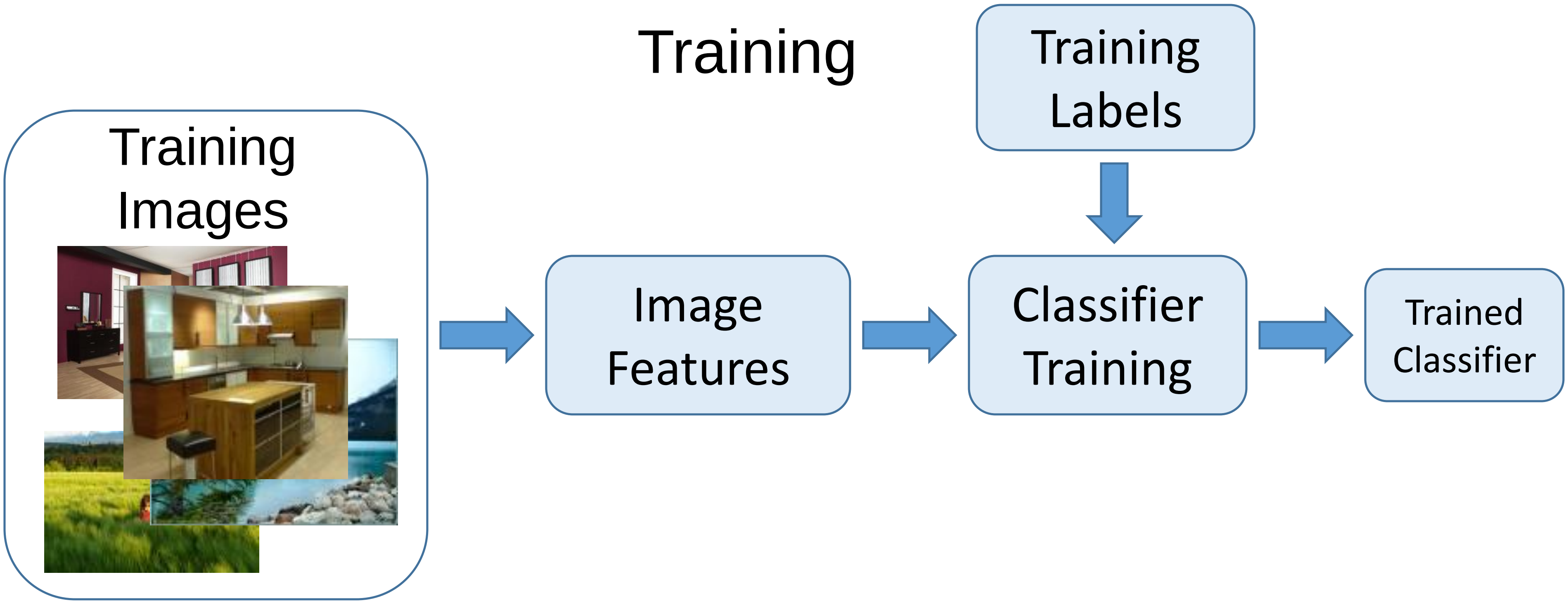
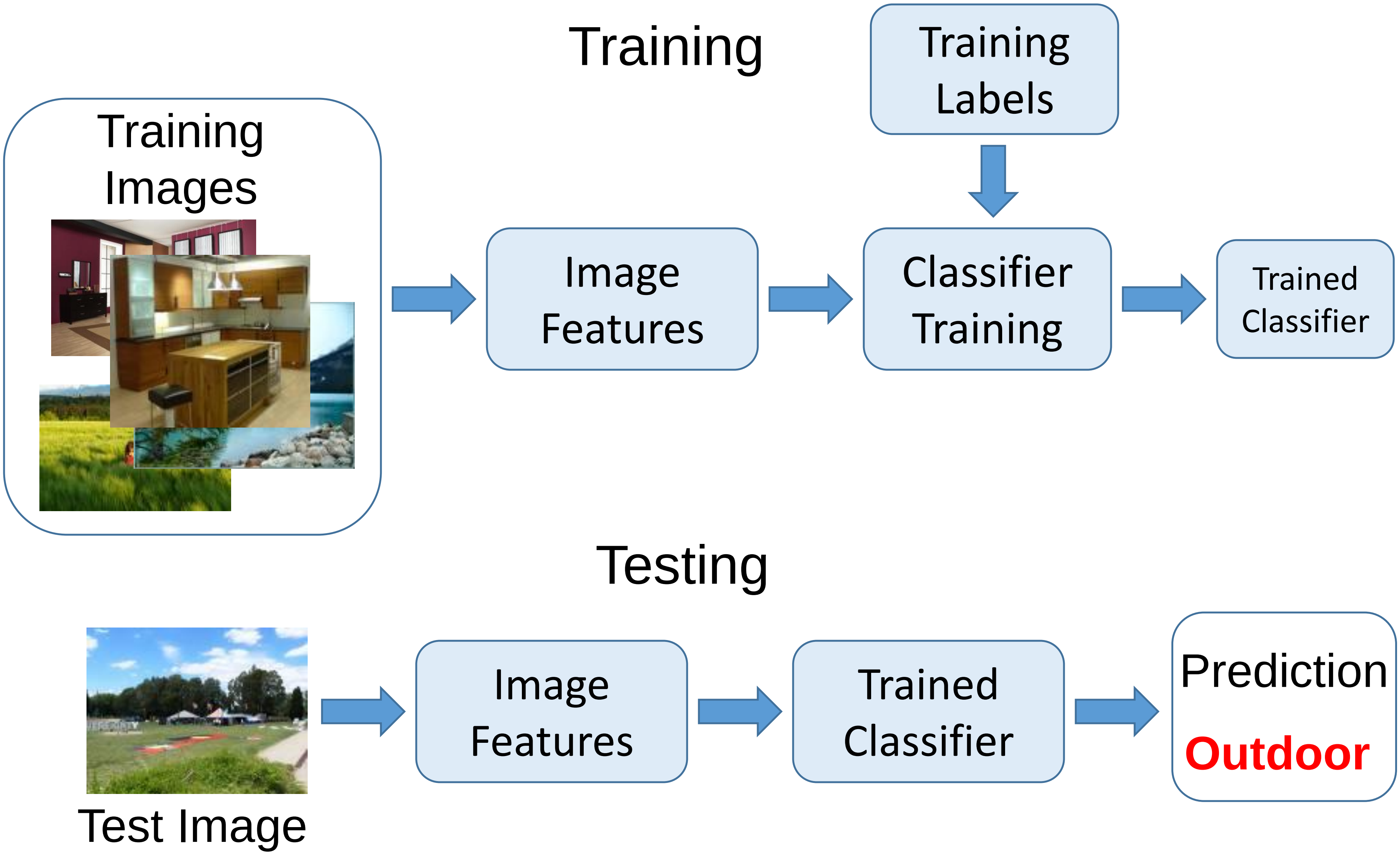


Image Categorization



Feature design is paramount

- Most features can be thought of as templates, histograms (counts), or combinations
- Think about the right features for the problem
  - Coverage
  - Concision
  - Directness

Today’s class: Machine Learning

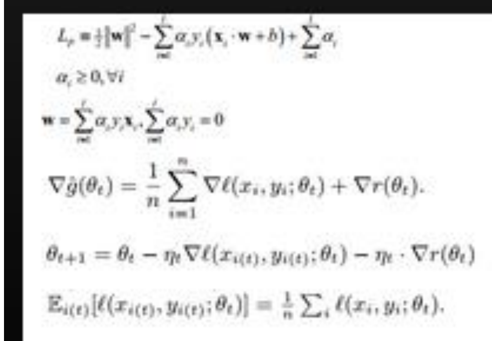
- Machine learning overview
- Unsupervised Learning
  - Dimensionality reduction
  - Clustering
- Supervised Learning
  - Classification
  - Regression

Machine Learning

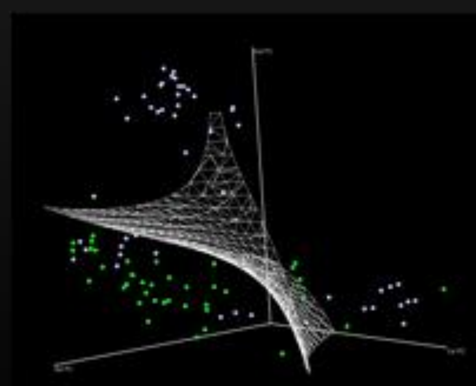
what society thinks I do

what my friends think I do

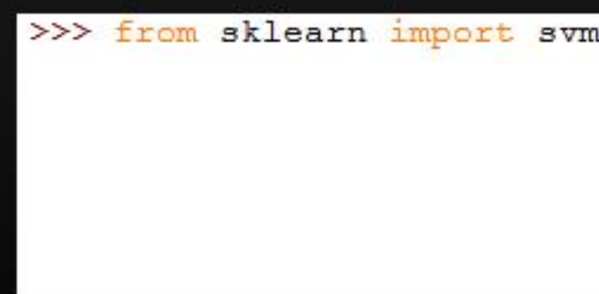
what my parents think I do



what other programmers think I do



what I think I do



what I really do

- “If you were a current computer science student what area would you start studying heavily?”
  - Answer: Machine Learning.
  - “The ultimate is computers that learn”
  - Bill Gates, Reddit AMA

- “Machine learning is the next Internet”
  - Tony Tether, Director, DARPA

- “Machine learning is today’s discontinuity”
  - Jerry Yang, CEO, Yahoo

Slide Credit: Pedro Domingos, Tom Mitchel, Tom Dietterich

Google snaps up object recognition startup DNNr

Google has ac
Toronto, who

by Josh Lowensohn

2 / 0

Google has acqui
research compan

« Search needs a shake-up

Songbirds use grammar rules »

Machine Learning Startup Acquired by ai-one

Press Release

For Immediate Release: August 4, 2011

San Diego artificial intelligence startup acquired by leading
ing SDKs as market for advanced

day that it acquired Auto-Semantics, a local start-up
es to corporate IT departments. The acquisition is the
nd acquisitions by ai-one that consolidates its
ing market for machine learning technologies.

Topic: Cloud

Follow via:

Microsoft acquires legal-focused machine-learning vendor Equivio

Summary: *Microsoft has purchased Equivio, maker of a machine-learning platform for the legal industry, for an undisclosed amount.*

By Mary Jo Foley for All About Microsoft | January 20, 2015 -- 16:24 GMT (08:24 PST)

Follow @maryjofoley 95.6K followers *Get the ZDNet Cloud newsletter now*

Microsoft has purchased Equivio, an eDiscovery/compliance vendor with a specialization in text analysis, for an undisclosed amount.

Microsoft officials announced the acquisition of the Israeli company -- its first acquisition of 2015 using more of its offshore cash -- on January 20.

Update: The Wall Street Journal reported back in October last year that Microsoft planned to buy Equivio for $200 million.

Update No. 2: A Microsoft spokesperson said the $200 million estimate was inflated and incorrect, but declined to provide a different figure.

FOUNDED
2011

OVERVIEW
DeepMind is a cutting edge artificial intelligence company. We combine the best techniques from machine learning and systems neuroscience to build powerful general-purpose learning algorithms. Founded by Demis Hassabis, Shane Legg and Mustafa Suleyman, the company is based in London and supported by some of the most iconic technology entrepreneurs and investors of the past decade. Our first commercial ...

Machine Learning:

Making predictions or decisions from Data

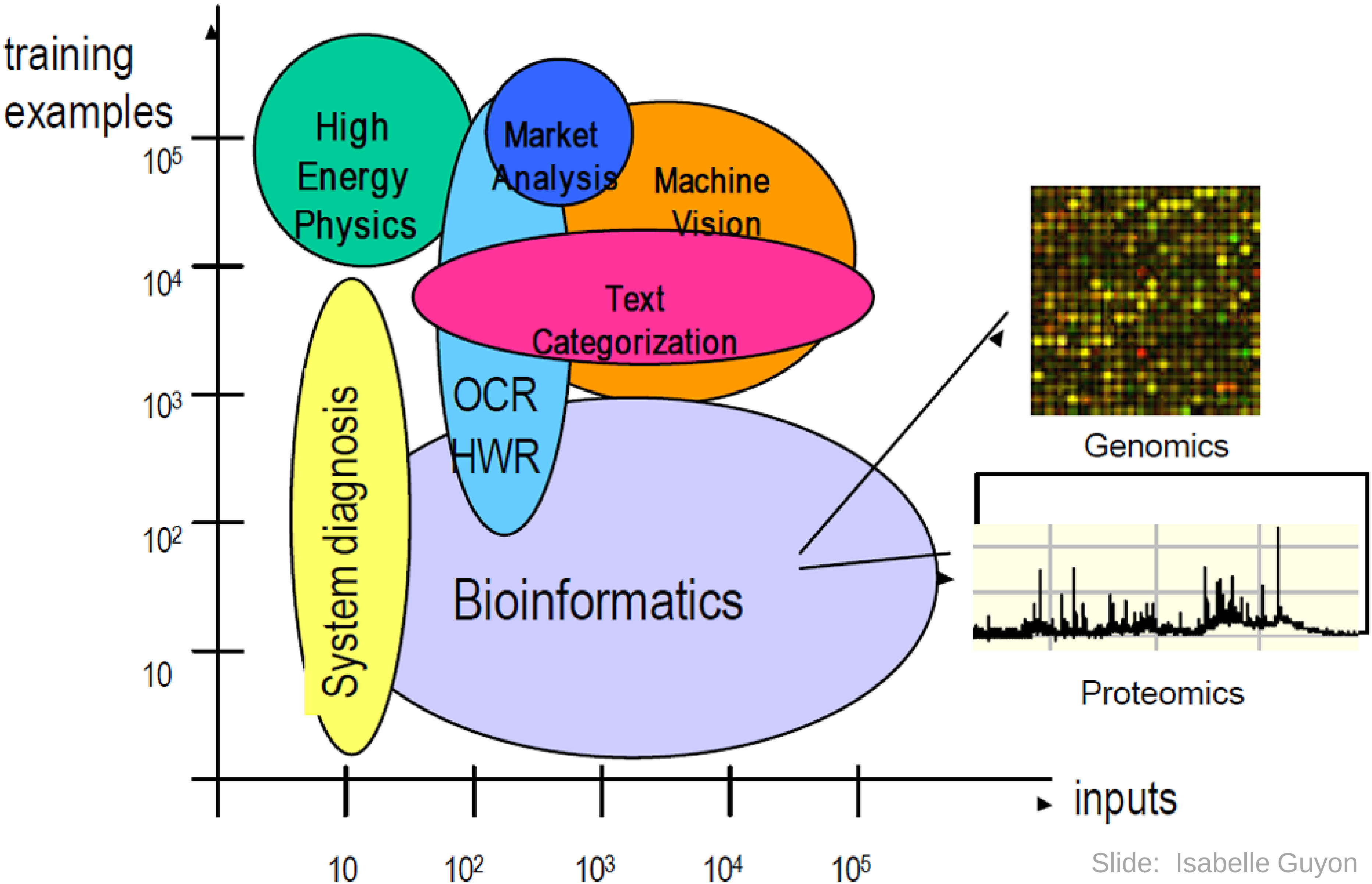
Resources

- Disclaimer:
  - This overview will not cover statistical underpinnings of learning methods. We've looking at ML as a tool.
- ML related courses at Virginia Tech
  - ECE 5424 / 4424 - CS 5824 / 4824 Introduction to Machine Learning
  - CS 4804 Introduction to Artificial Intelligence
  - ECE 6504 Neural Networks and Deep Learning
- External courses
  - Machine Learning by Andrew Ng
    https://www.coursera.org/learn/machine-learning
  - Learning from Data by Yaser S. Abu-Mostafa
    https://www.edx.org/course/learning-data-introductory-machine-caltechx-cs1156x

Impact of Machine Learning

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

Machine Learning Applications



Slide: Isabelle Guyon

Machine Learning Problems

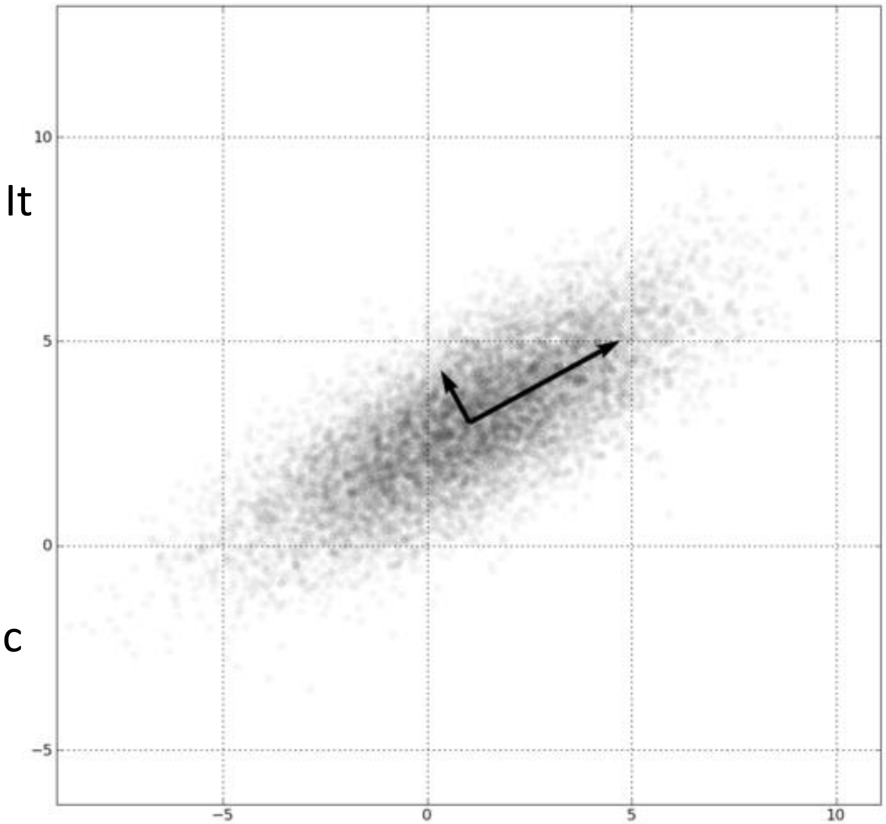
	Supervised Learning	***Unsupervised Learning***
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

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 based on linear projections (minimizes reconstruction error).

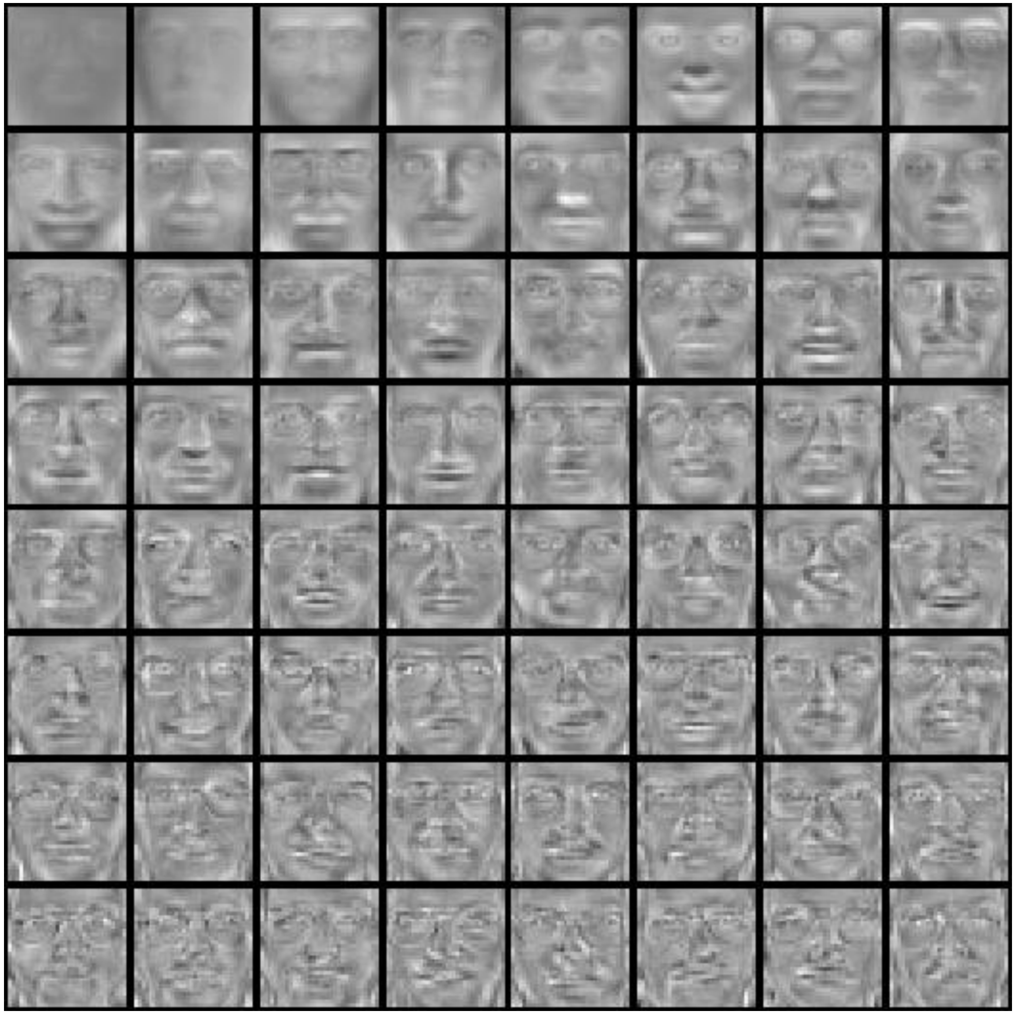
- PCA should be used for dimensionality reduction, not for discovering patterns or making predictions. Don't try to assign semantic meaning to the bases.



Eigenfaces example

Mean: μ

Top eigenvectors: $u_1,\ldots u_k$



Machine Learning Problems

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

Clustering

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

- Key Challenges:
  - What makes two points/images/patches similar?
  - How do we compute an overall grouping from pairwise similarities?

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

Slide: Derek Hoiem

Machine Learning Problems

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

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

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

output

prediction function

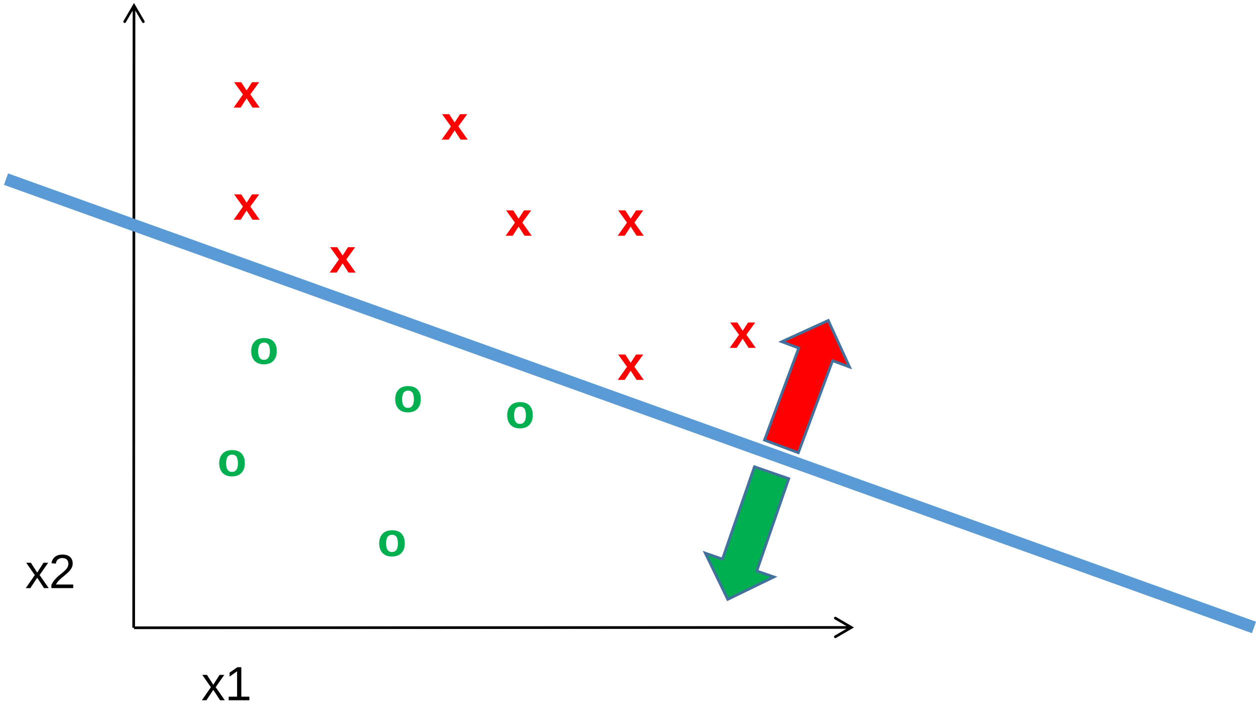
Image feature

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

Classifier

A classifier maps from the feature space to a label



Different types of classification

- **Exemplar-based**: transfer category labels from examples with most similar features
  - What similarity function? What parameters?
- **Linear classifier**: confidence in positive label is a weighted sum of features
  - What are the weights?
- **Non-linear classifier**: predictions based on more complex function of features
  - What form does the classifier take? Parameters?
- **Generative classifier**: assign to the label that best explains the features (makes features most likely)
  - What is the probability function and its parameters?

Note: You can always fully design the classifier by hand, but usually this is too difficult. Typical solution: learn from training examples.

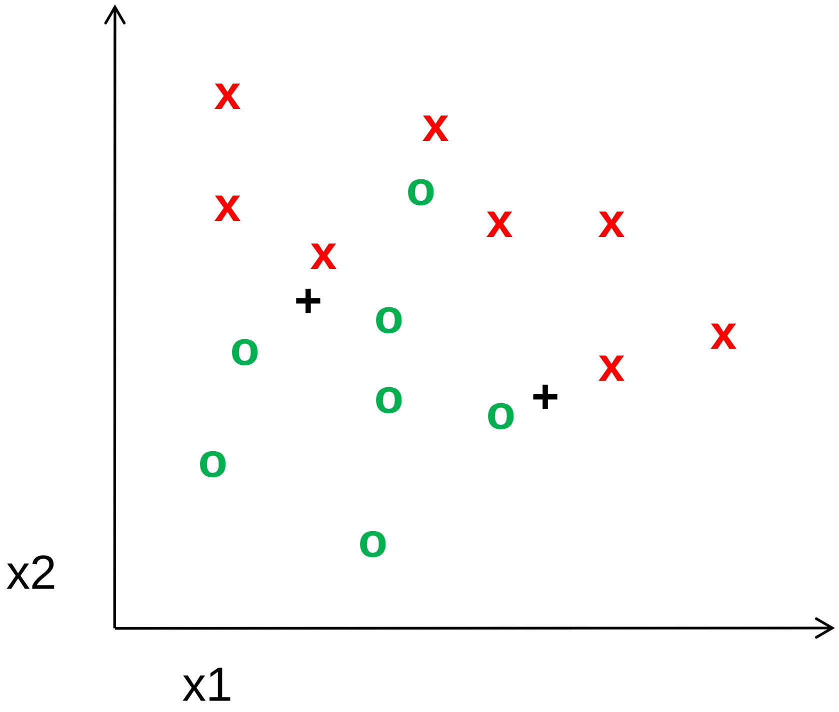
One way to think about it…

- Training labels dictate that two examples are the same or different, in some sense
- Features and distance measures define visual similarity
- Goal of training is to learn feature weights or distance measures so that visual similarity predicts label similarity
- *We want the simplest function that is confidently correct*

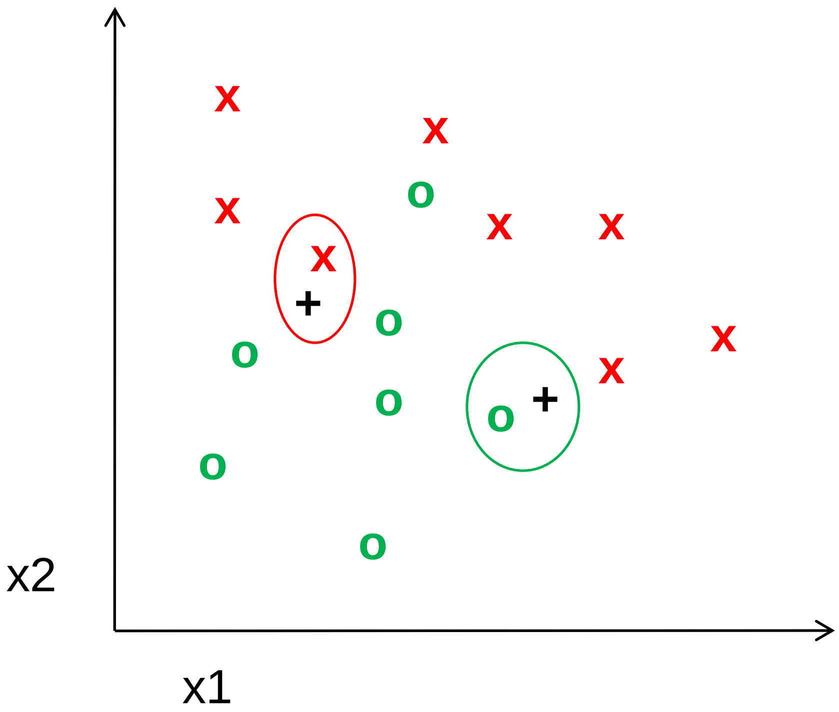
Exemplar-based Models

- Transfer the label(s) of the most similar training examples

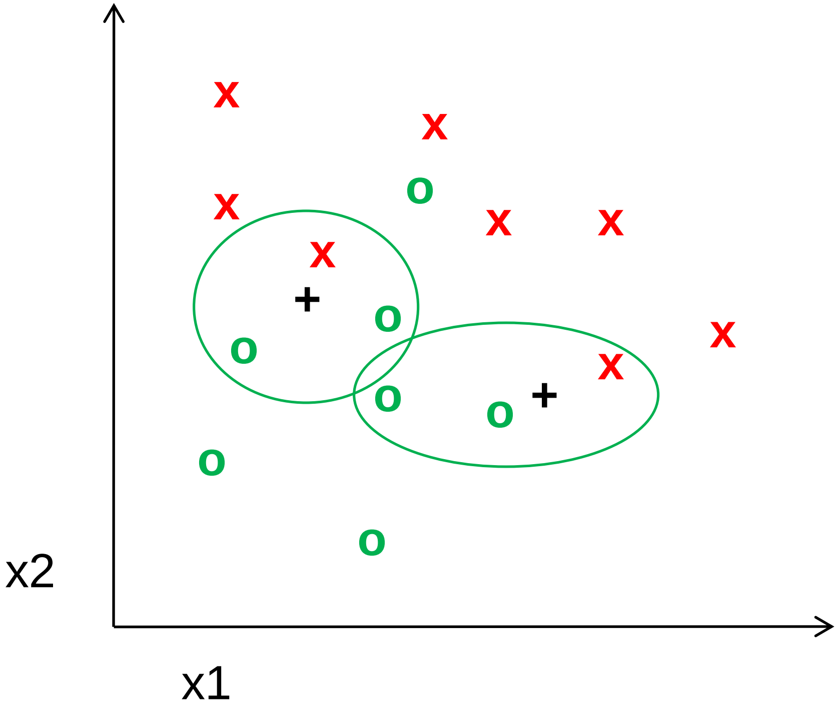
K-nearest neighbor classifier



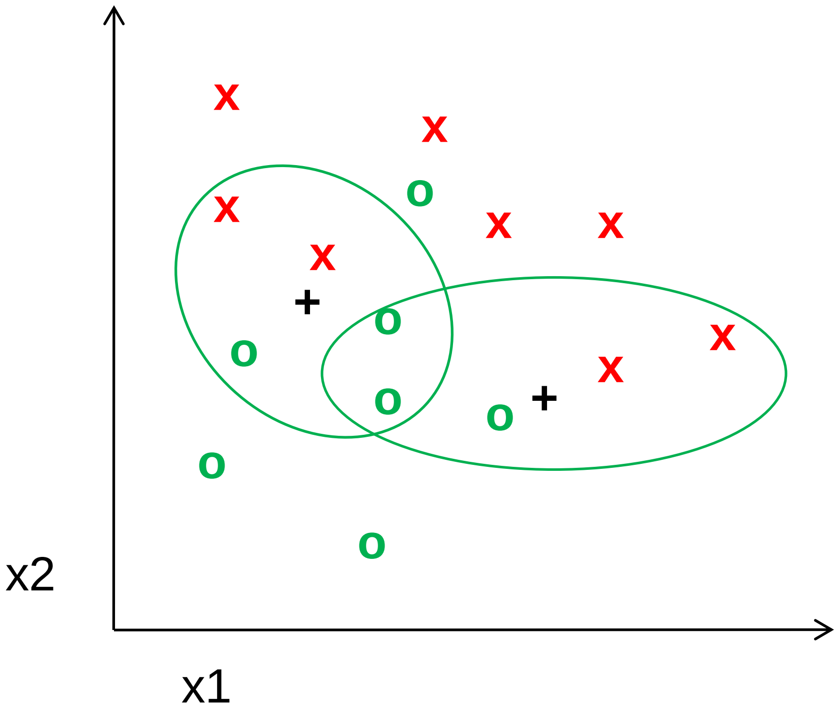
1-nearest neighbor



3-nearest neighbor



5-nearest neighbor



Using K-NN

- Simple, a good one to try first
- Higher K gives smoother functions
- No training time (unless you want to learn a distance function)
- With infinite examples, 1-NN provably has error that is at most twice Bayes optimal error

Discriminative classifiers

Learn a simple function of the input features that confidently predicts the true labels on the training set

$$y = f(x)$$

Training Goals

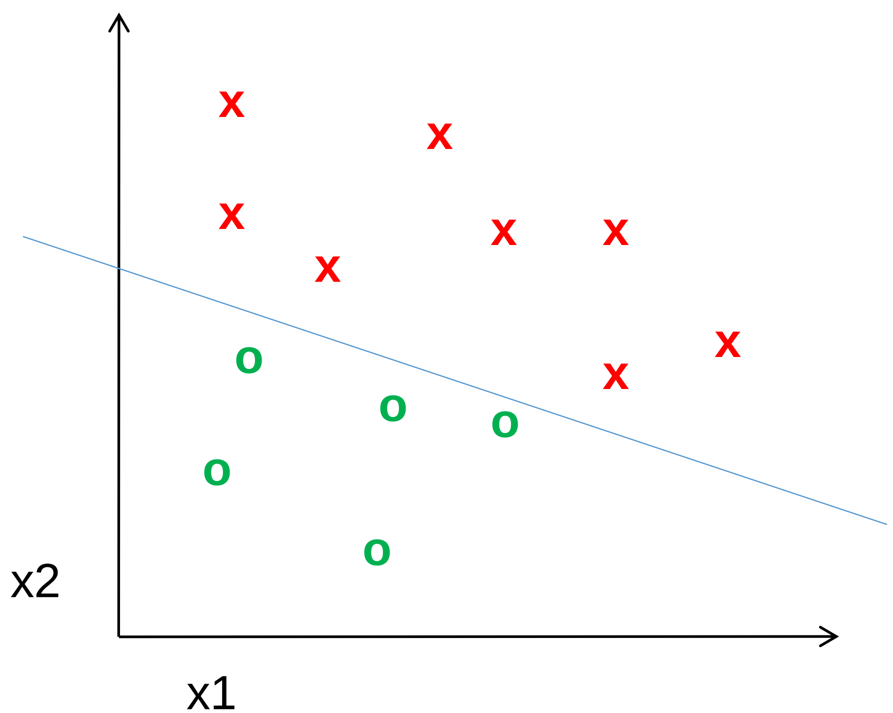
1. Accurate classification of training data
2. Correct classifications are confident
3. Classification function is simple

Classifiers: Logistic Regression

- Objective
- Parameterization
- Regularization
- Training
- Inference

$$\log \frac{P(x_1, x_2 \mid y=1)}{P(x_1, x_2 \mid y=-1)} = \mathbf{w}^T \mathbf{x}$$

$$P(y=1 \mid x_1, x_2) = 1/\left(1+\exp\left(-\mathbf{w}^T \mathbf{x}\right)\right)$$



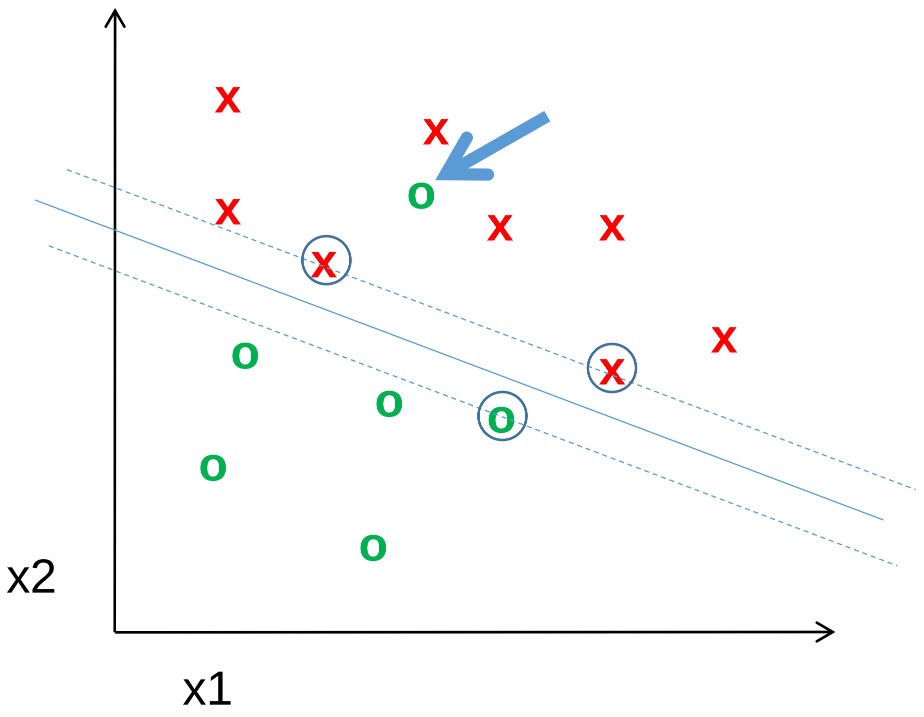
The **objective function** of most discriminative classifiers includes a **loss term** and a **regularization term**.

Using Logistic Regression

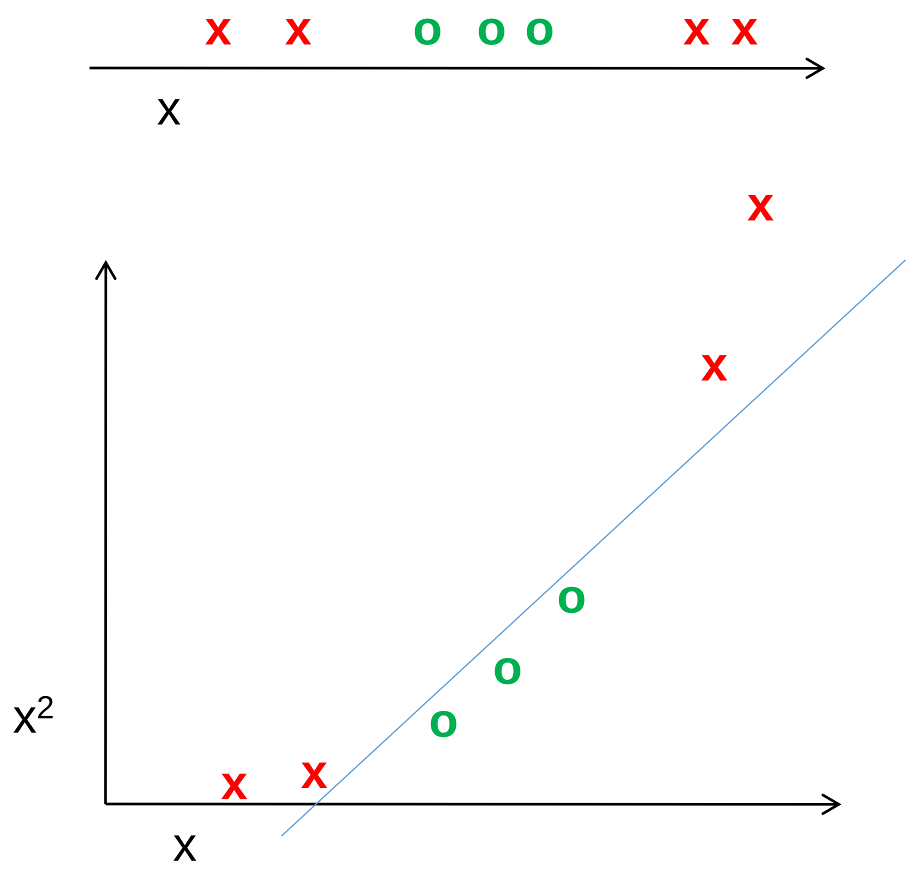
- Quick, simple classifier (good one to try first)

- Use L2 or L1 regularization
  - L1 does feature selection and is robust to irrelevant features but slower to train

Classifiers: Linear SVM



Classifiers: Kernelized SVM

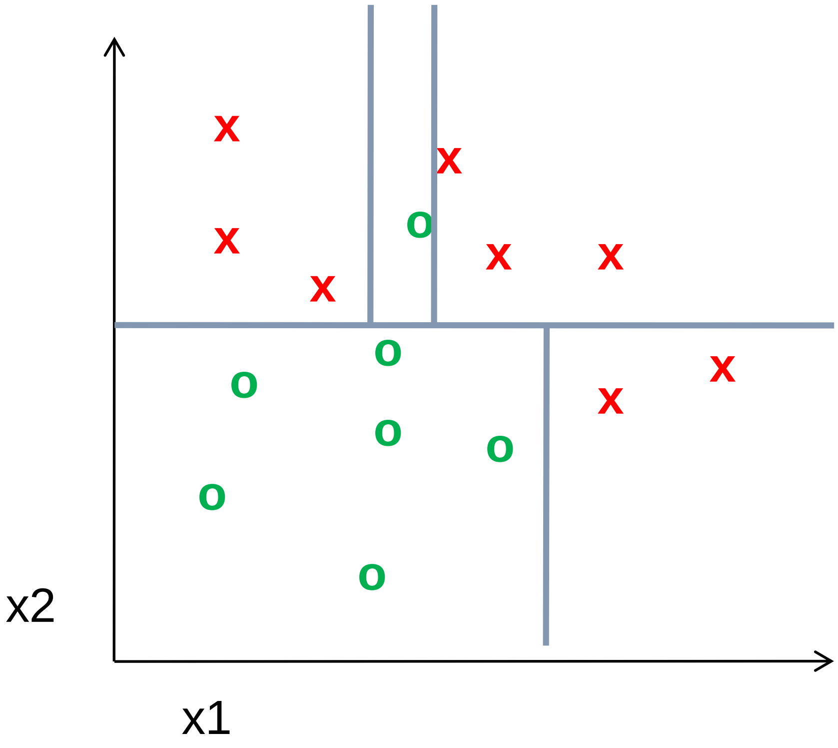


Using SVMs

- Good general purpose classifier
  - Generalization depends on margin, so works well with many weak features
  - No feature selection
  - Usually requires some parameter tuning

- Choosing kernel
  - Linear: fast training/testing – start here
  - RBF: related to neural networks, nearest neighbor
  - Chi-squared, histogram intersection: good for histograms (but slower, esp. chi-squared)
  - Can learn a kernel function

Classifiers: Decision Trees



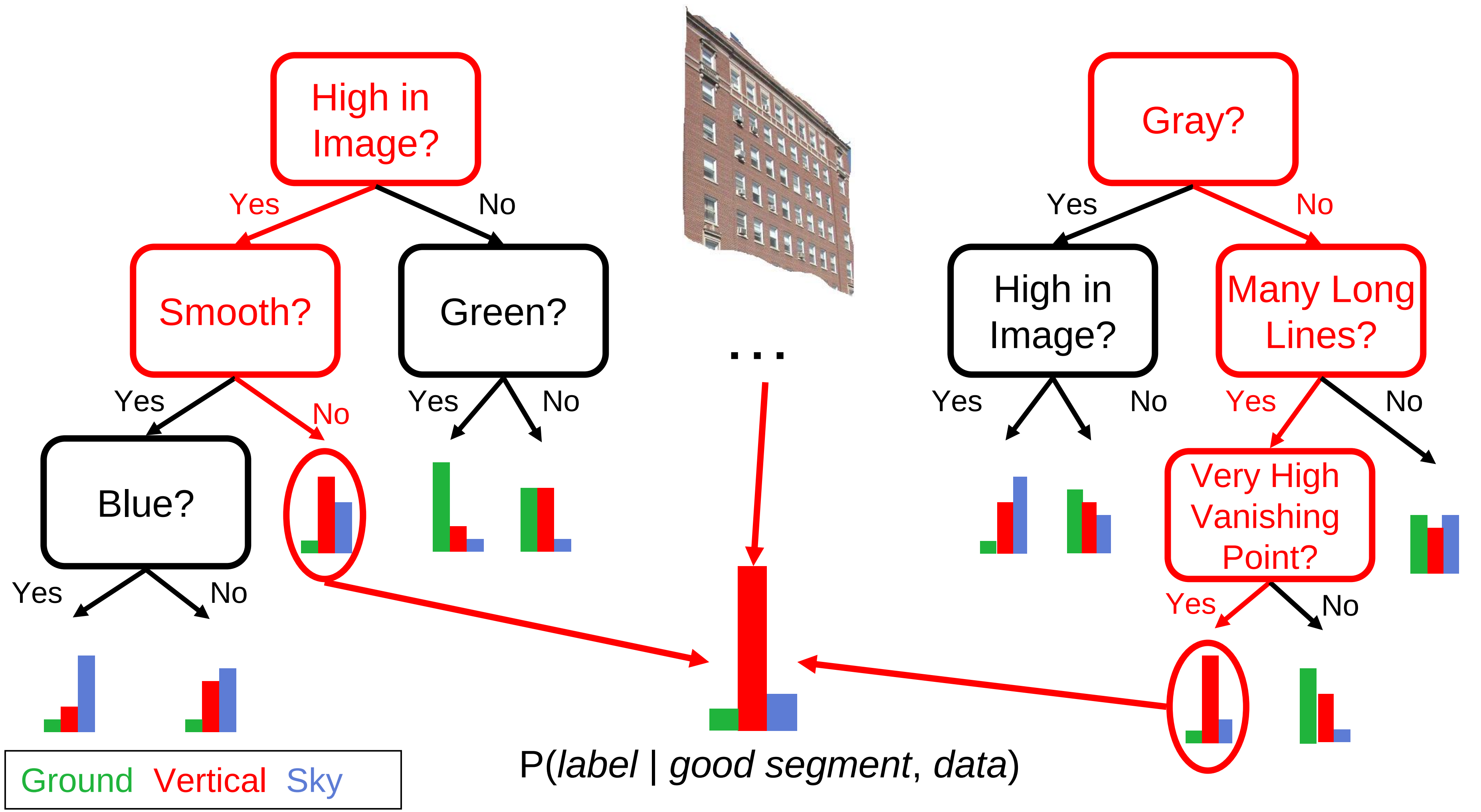
Ensemble Methods: Boosting

Discrete AdaBoost(Freund & Schapire 1996b)

1. Start with weights $w_i = 1/N$, $i = 1, \ldots, N$.
2. Repeat for $m = 1, 2, \ldots, M$:
   (a) Fit the classifier $f_m(x) \in \{-1, 1\}$ using weights w_i on the training data.
   (b) Compute $\mathrm{err}_m = E_w[1_{(y \neq f_m(x))}]$, $c_m = \log((1 - \mathrm{err}_m)/\mathrm{err}_m)$.
   (c) Set $w_i \leftarrow w_i \exp[c_m \cdot 1_{(y_i \neq f_m(x_i))}]$, $i = 1, 2, \ldots N$, and renormalize so that $\sum_i w_i = 1$.
3. Output the classifier $\mathrm{sign}[\sum_{m=1}^{M} c_m f_m(x)]$

figure from Friedman et al. 2000

Boosted Decision Trees



[Collins et al. 2002]

Using Boosted Decision Trees

- Flexible: can deal with both continuous and categorical variables
- How to control bias/variance trade-off
  - Size of trees
  - Number of trees
- Boosting trees often works best with a small number of well-designed features
- Boosting “stubs” can give a fast classifier

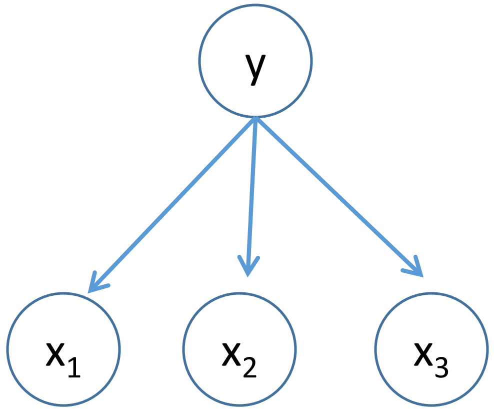
Generative classifiers

- Model the joint probability of the features and the labels
  - Allows direct control of independence assumptions
  - Can incorporate priors
  - Often simple to train (depending on the model)

- Examples
  - Naïve Bayes
  - Mixture of Gaussians for each class

Naïve Bayes

- Objective
- Parameterization
- Regularization
- Training
- Inference



Using Naïve Bayes

- Simple thing to try for categorical data
- Very fast to train/test

Many classifiers to choose from

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

Which is the best one?

No Free Lunch Theorem

Generalization Theory

- It’s not enough to do well on the training set: we want to also make good predictions for new examples

Bias-Variance Trade-off

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

Unavoidable error

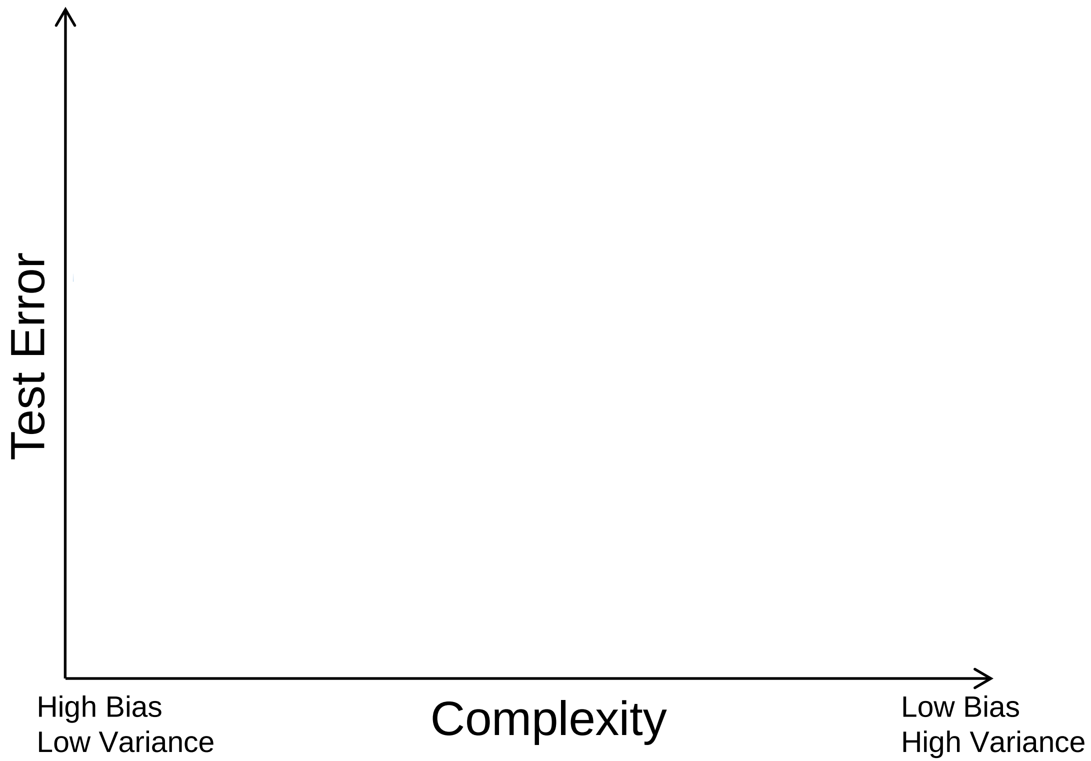
Error due to incorrect assumptions

Error due to variance parameter estimates from training samples

See the following for explanation of bias-variance (also Bishop's "Neural Networks" book): http://www.inf.ed.ac.uk/teaching/courses/mlsc/Notes/Lecture4/BiasVariance.pdf

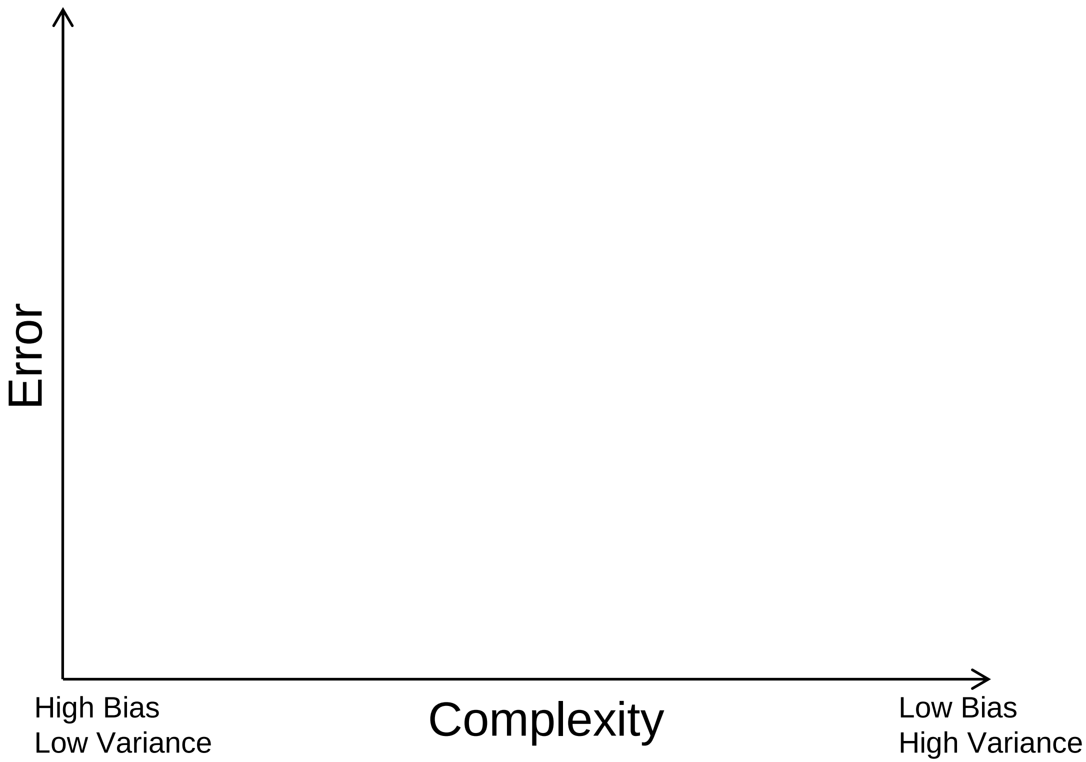
Bias and Variance

$$\text{Error} = \text{noise}^2 + \text{bias}^2 + \text{variance}$$



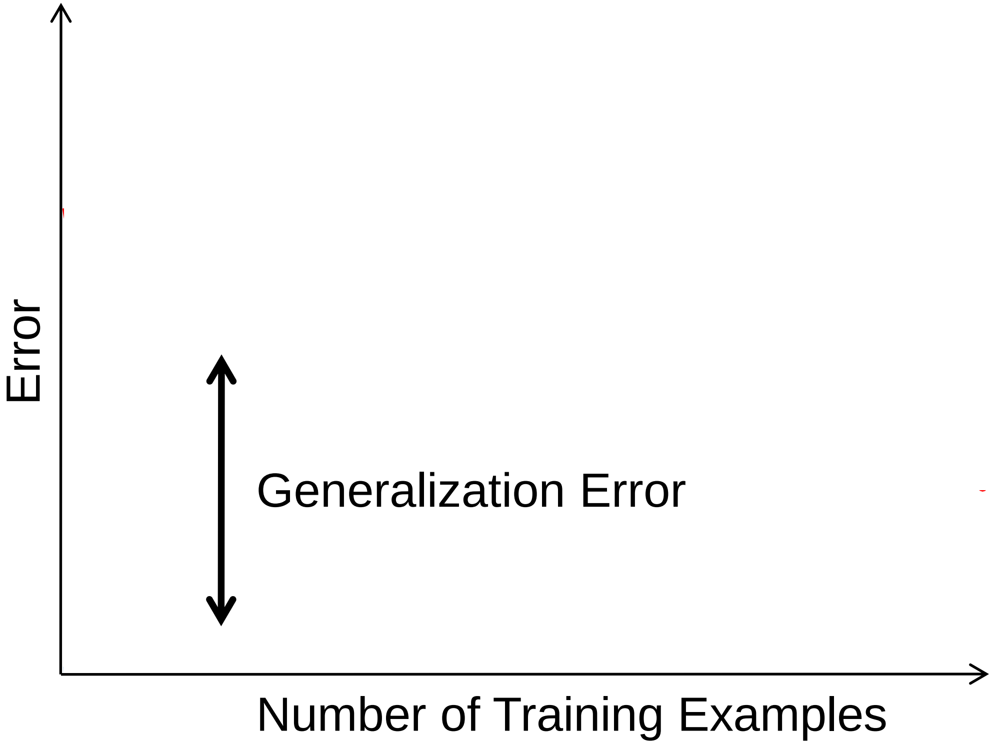
Choosing the trade-off

- Need validation set
- Validation set is separate from the test set



Effect of Training Size

Fixed classifier



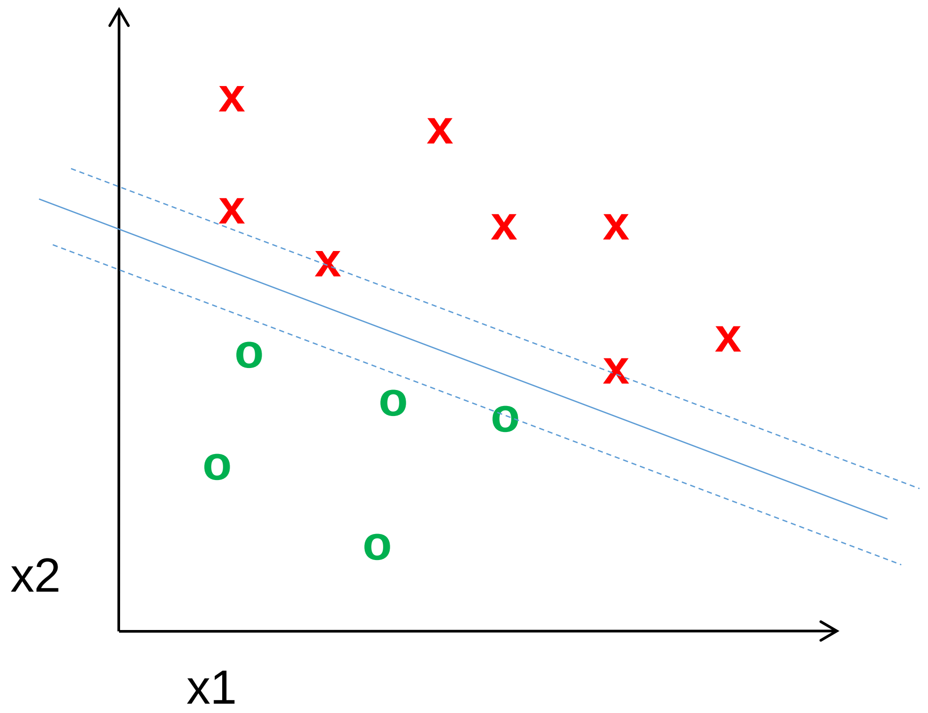
How to reduce variance?

- Choose a simpler classifier
- Regularize the parameters
- Use fewer features
- Get more training data

Which of these could actually lead to greater error?

Reducing Risk of Error

- Margins



The perfect classification algorithm

- Objective function: encodes the right loss for the problem
- Parameterization: makes assumptions that fit the problem
- Regularization: right level of regularization for amount of training data
- Training algorithm: can find parameters that maximize objective on training set
- Inference algorithm: can solve for objective function in evaluation

Comparison

assuming x in {0 1}

	Learning Objective	Training	Inference
Naïve Bayes	$\text{maximize} \sum_i \left[\sum_j \log P(x_{ij} \mid y_i; \theta_j) + \log P(y_i; \theta_0) \right]$	$\theta_{kj} = \dfrac{\sum_i \delta(x_{ij} = 1 \wedge y_i = k) + r}{\sum_i \delta(y_i = k) + Kr}$	$\boldsymbol{\theta}_1^T \mathbf{x} + \boldsymbol{\theta}_0^T (1 - \mathbf{x}) > 0$ where $\theta_{1j} = \log \dfrac{P(x_j = 1 \mid y = 1)}{P(x_j = 1 \mid y = 0)}$, $\theta_{0j} = \log \dfrac{P(x_j = 0 \mid y = 1)}{P(x_j = 0 \mid y = 0)}$
Logistic Regression	$\text{maximize} \sum_i \log(P(y_i \mid \mathbf{x}, \boldsymbol{\theta})) + \lambda \lVert \boldsymbol{\theta} \rVert$ where $P(y_i \mid \mathbf{x}, \boldsymbol{\theta}) = 1/(1 + \exp(-y_i \boldsymbol{\theta}^T \mathbf{x}))$	Gradient ascent	$\boldsymbol{\theta}^T \mathbf{x} > t$
Linear SVM	$\text{minimize } \lambda \sum_i \xi_i + \frac{1}{2} \lVert \boldsymbol{\theta} \rVert$ such that $y_i \boldsymbol{\theta}^T \mathbf{x} \geq 1 - \xi_i \quad \forall i,\ \xi_i \geq 0$	Quadratic programming or subgradient opt.	$\boldsymbol{\theta}^T \mathbf{x} > t$
Kernelized SVM	complicated to write	Quadratic programming	$\sum_i y_i \alpha_i K(\hat{\mathbf{x}}_i, \mathbf{x}) > 0$
Nearest Neighbor	most similar features → same label	Record data	y_i where $i = \underset{i}{\text{argmin}}\ K(\hat{\mathbf{x}}_i, \mathbf{x})$

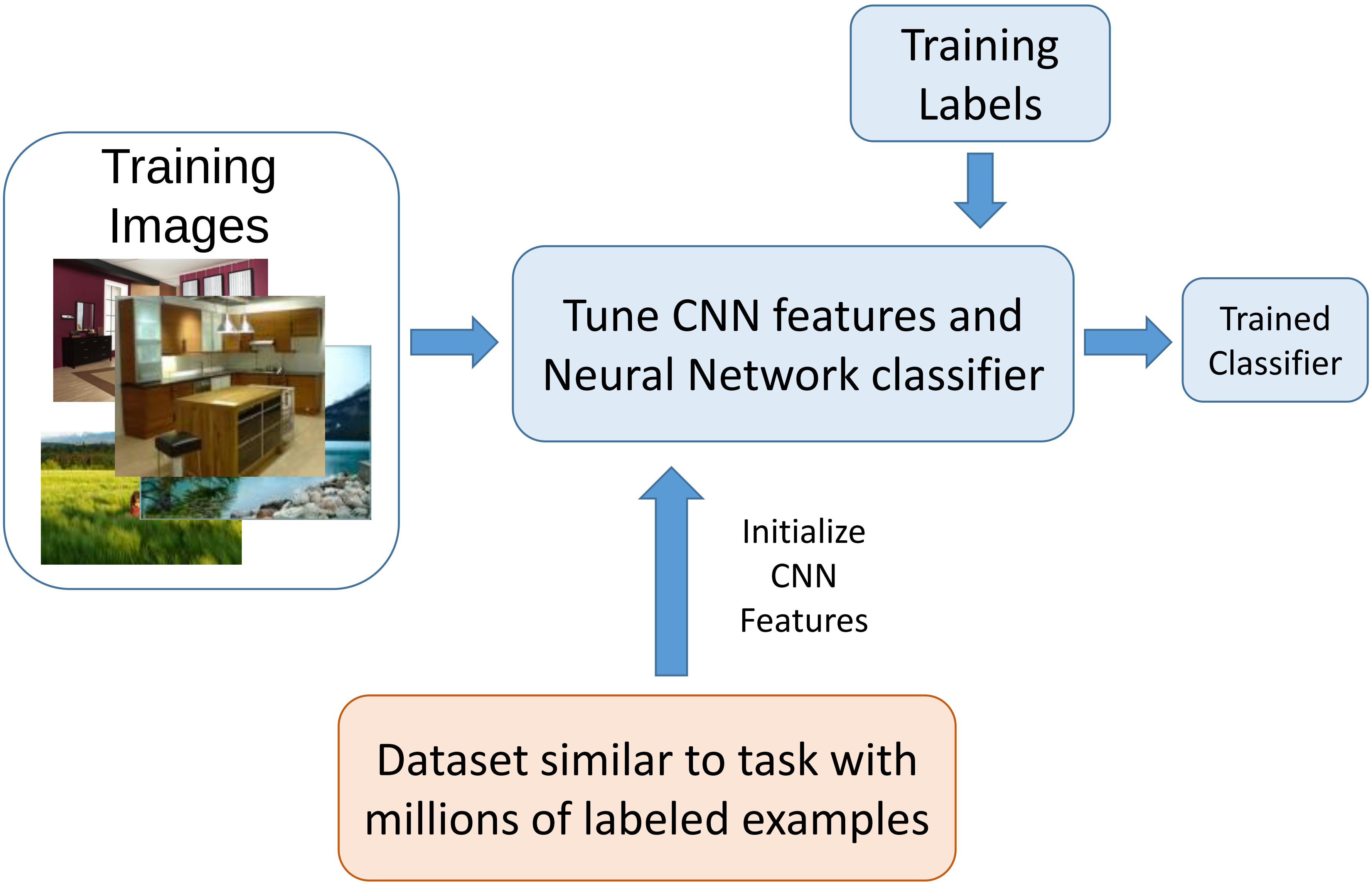
Characteristics of vision learning problems

- Lots of continuous features
  - E.g., HOG template may have 1000 features
  - Spatial pyramid may have ~15,000 features
- Imbalanced classes
  - often limited positive examples, practically infinite negative examples
- Difficult prediction tasks

When a massive training set is available

- Relatively new phenomenon
  - MNIST (handwritten letters) in 1990s, LabelMe in 2000s, ImageNet (object images) in 2009, …
- Want classifiers with low bias (high variance ok) and reasonably efficient training
- Very complex classifiers with simple features are often effective
  - Random forests
  - Deep convolutional networks

New training setup with moderate sized datasets



Practical tips

- Preparing features for linear classifiers
  - Often helps to make zero-mean, unit-dev
  - For non-ordinal features, convert to a set of binary features

- Selecting classifier meta-parameters (e.g., regularization weight)
  - Cross-validation: split data into subsets; train on all but one subset, test on remaining; repeat holding out each subset
    - Leave-one-out, 5-fold, etc.

- Most popular classifiers in vision
  - *SVM*: linear for when fast training/classification is needed; performs well with lots of weak features
  - *Logistic Regression*: outputs a probability; easy to train and apply
  - *Nearest neighbor*: hard to beat if there is tons of data (e.g., character recognition)
  - *Boosted stumps or decision trees*: applies to flexible features, incorporates feature selection, powerful classifiers
  - *Random forests*: outputs probability; good for simple features, tons of data
  - *Deep networks / CNNs*: flexible output; learns features; adapt existing network (which is trained with tons of data) or train new with tons of data

- Always try at least two types of classifiers

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.

Things to remember

- No free lunch: machine learning algorithms are tools

- Try simple classifiers first

- Better to have smart features and simple classifiers than simple features and smart classifiers
  - Though with enough data, smart features can be learned

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

Some Machine Learning References

- General
  - Tom Mitchell, *Machine Learning*, McGraw Hill, 1997
  - Christopher Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, 1995

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  - Friedman, Hastie, and Tibshirani, "Additive logistic regression: a statistical view of boosting", Annals of Statistics, 2000

- SVMs
  - http://www.support-vector.net/icml-tutorial.pdf

- Random forests
  - http://research.microsoft.com/pubs/155552/decisionForests_MSR_TR_2011_114.pdf