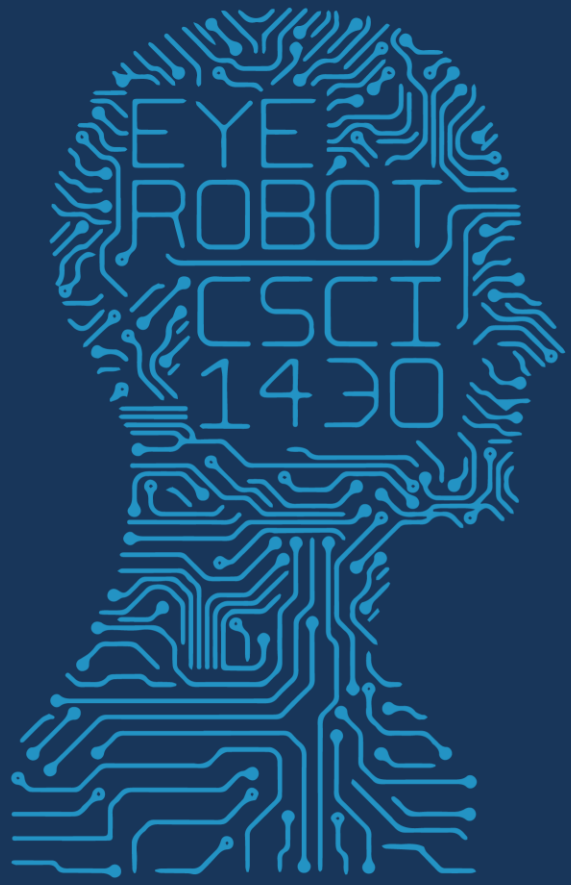
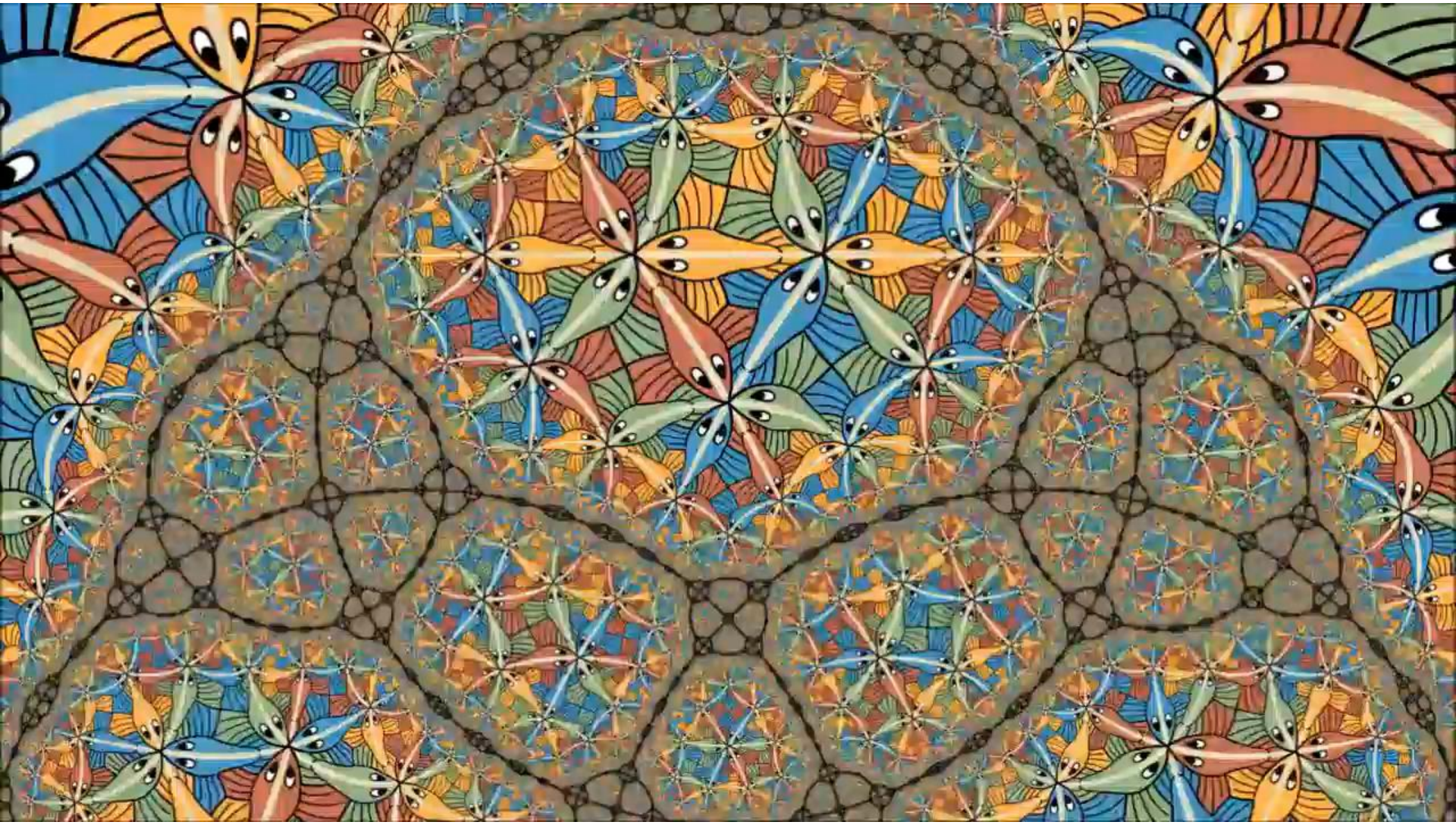
1950

Future Vision

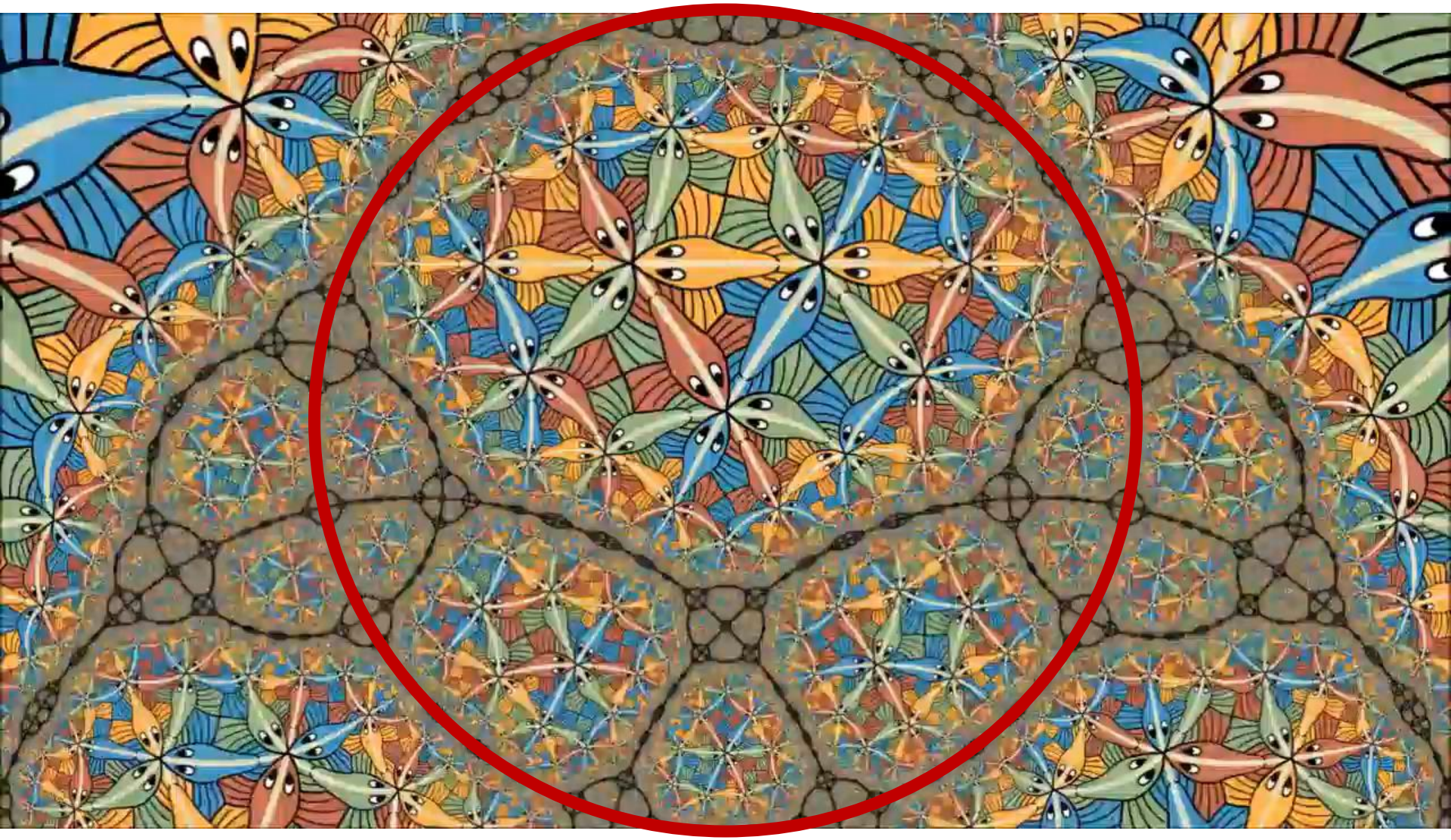


13 February 2019

Computer Vision

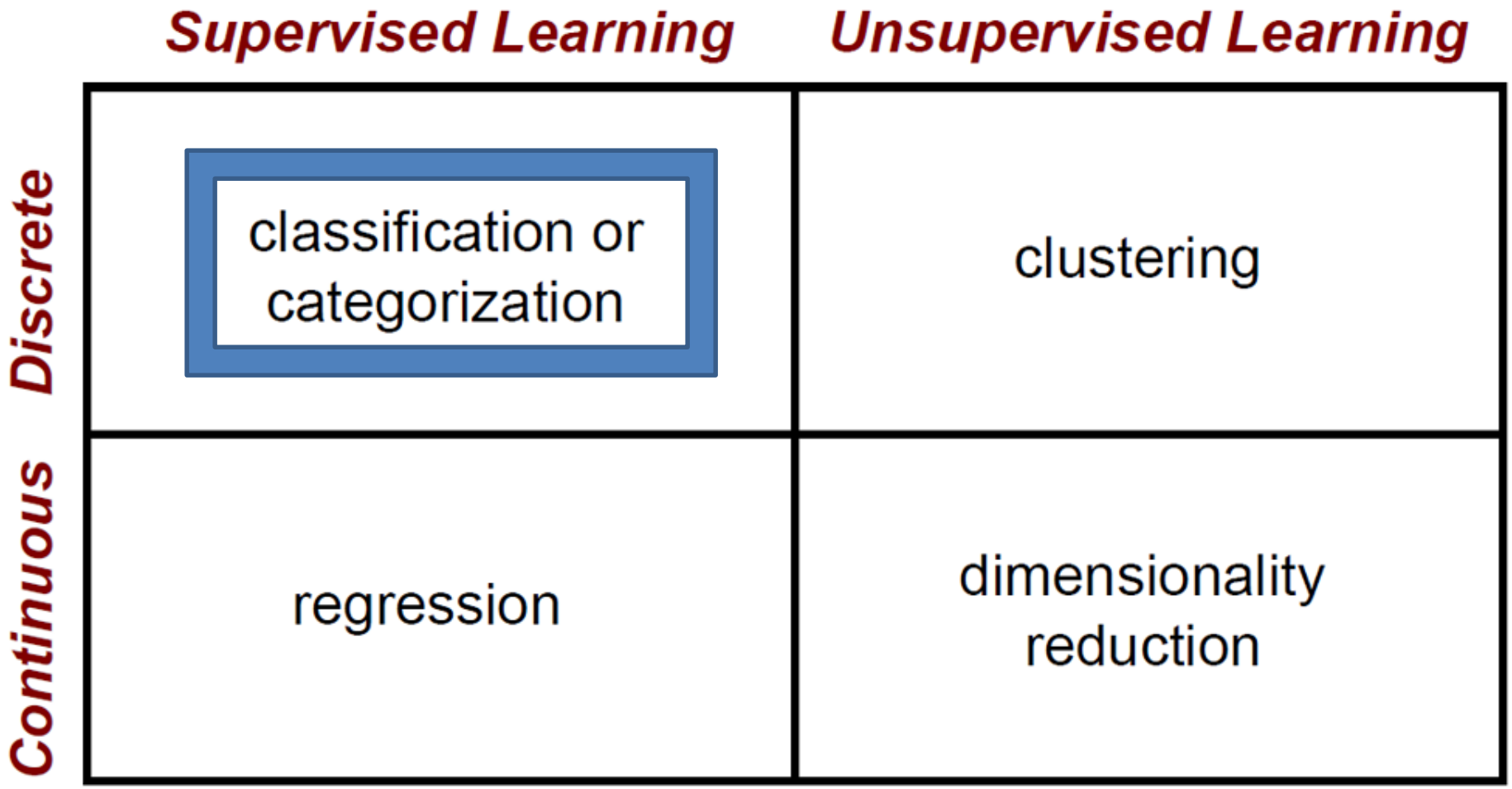


Escher’s Circle Limit III



Escher’s Circle Limit III

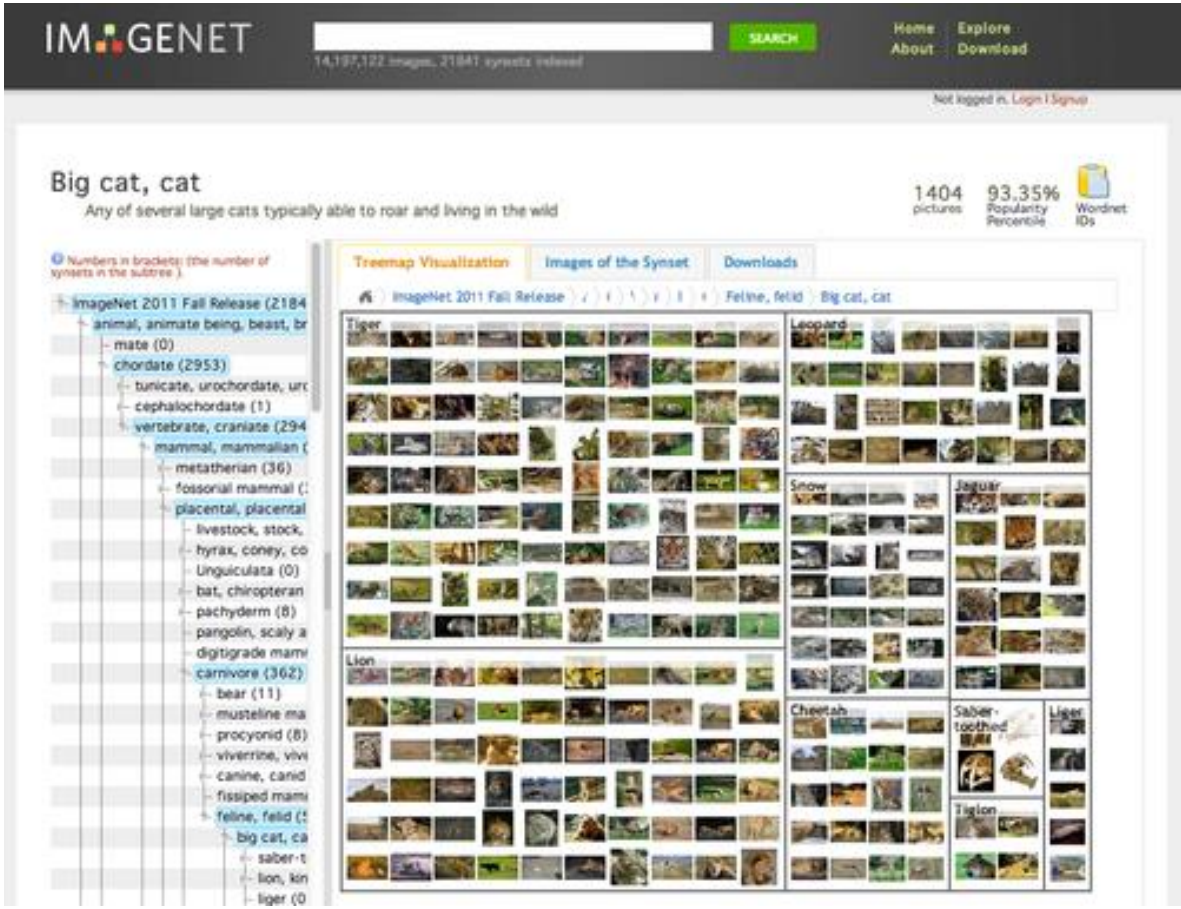
Machine Learning Problems



ImageNet

- Images for each category of WordNet
- 1000 classes
- 1.2mil images
- 100k test

- Top 5 error



Dataset split

Training Images

- Train classifier

Validation Images

- Measure error
- Tune model hyperparameters

Testing Images

- Secret labels
- Measure error

Random train/validate splits = cross validation

Training

Images

Labels

Image Features

Training

Trained classifier

Testing

Image *not in training set*

Image Features

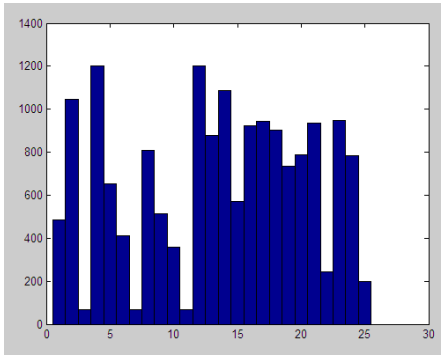
Apply classifier

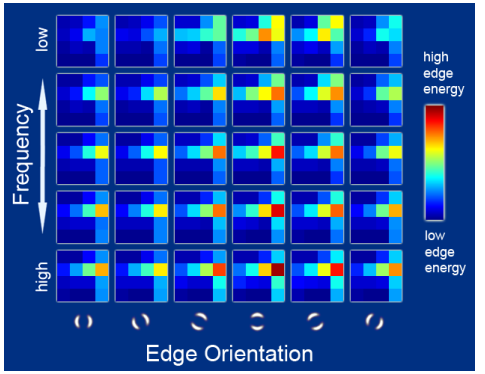
Prediction

Slide credit: D. Hoiem and L. Lazebnik

Features

- Raw pixels
- Histograms
- Templates
- SIFT descriptors
  - GIST
  - ORB
  - HOG….





Training

Images

Labels

Image Features

Training

Trained classifier

Testing

Image *not in training set*

Image Features

Apply classifier

Prediction

Slide credit: D. Hoiem and L. Lazebnik

Recognition task and supervision

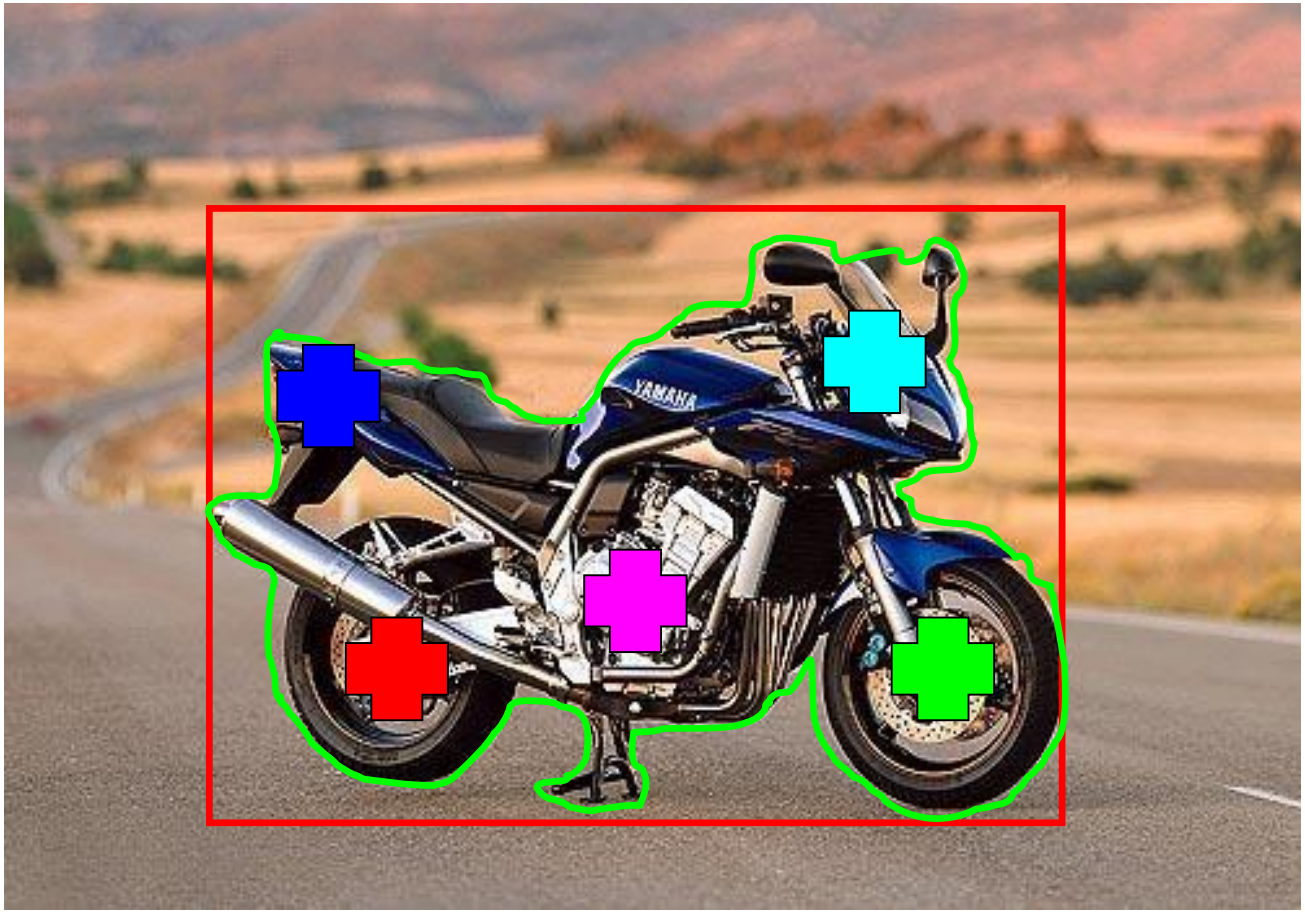
Think-Pair-Share

What are all the possible supervision (‘label’) *types* to consider?

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



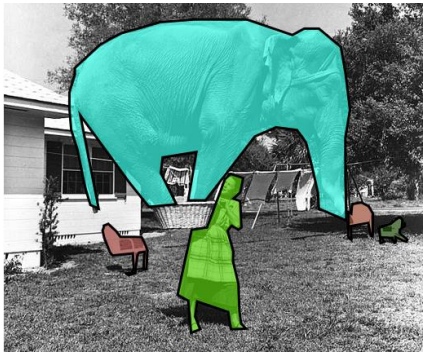
Spectrum of supervision

Less

More

E.G., ImageNet

E.G., MS Coco



Unsupervised

"Weakly" supervised

Fully supervised

Fuzzy; definition depends on task

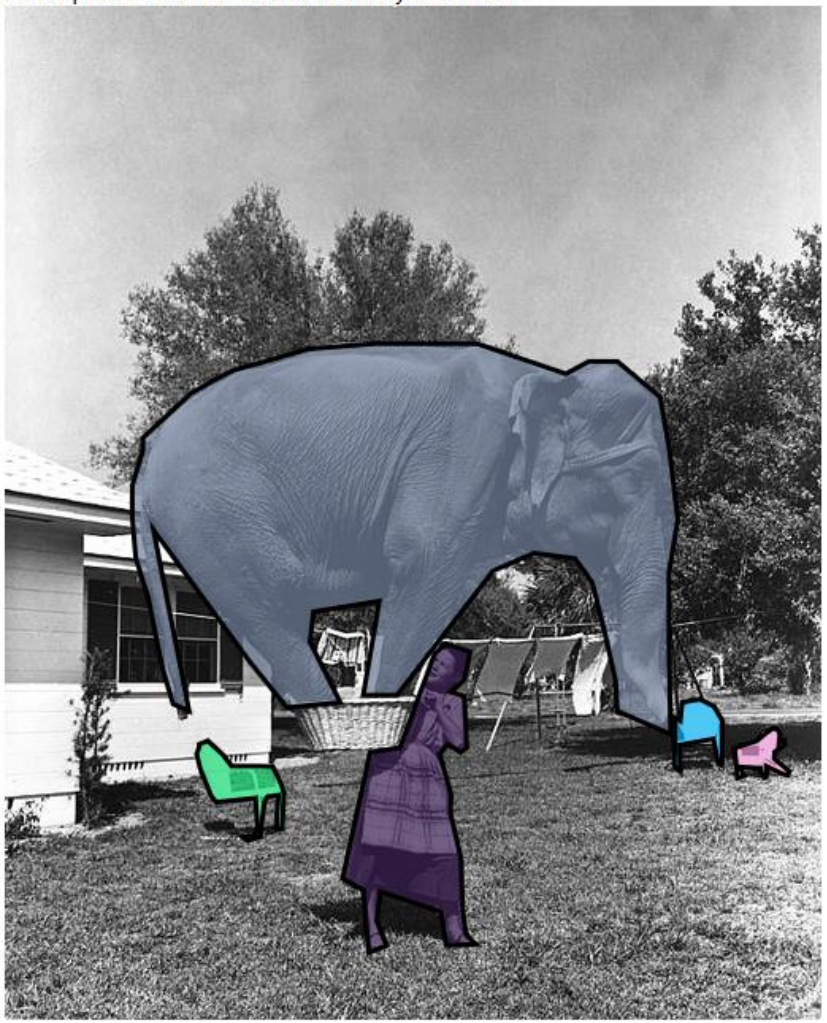
'Semi-supervised': small partial labeling

Good training example?

Good labels?

URL

an elephant standing on top of a basket being held by a woman.
a woman standing holding a basket with an elephant in it.
a lady holding an elephant in a small basket.
a lady holds an elephant in a basket.
an elephant inside a basket lifted by a woman.



http://mscoco.org/explore/?id=134918

Google guesses from the 1st caption

Training

Images

Labels

Image Features

Training

Trained classifier

Testing

Image *not in training set*

Image Features

Apply classifier

Prediction

Slide credit: D. Hoiem and L. Lazebnik

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”

The machine learning framework

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

Prediction function or *classifier*

Image feature

Output (label)

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 unseen *test example* $\mathbf{x}_u$ and output the predicted value $y_u = f(\mathbf{x}_u)$ to *classify* $\mathbf{x}_u$.

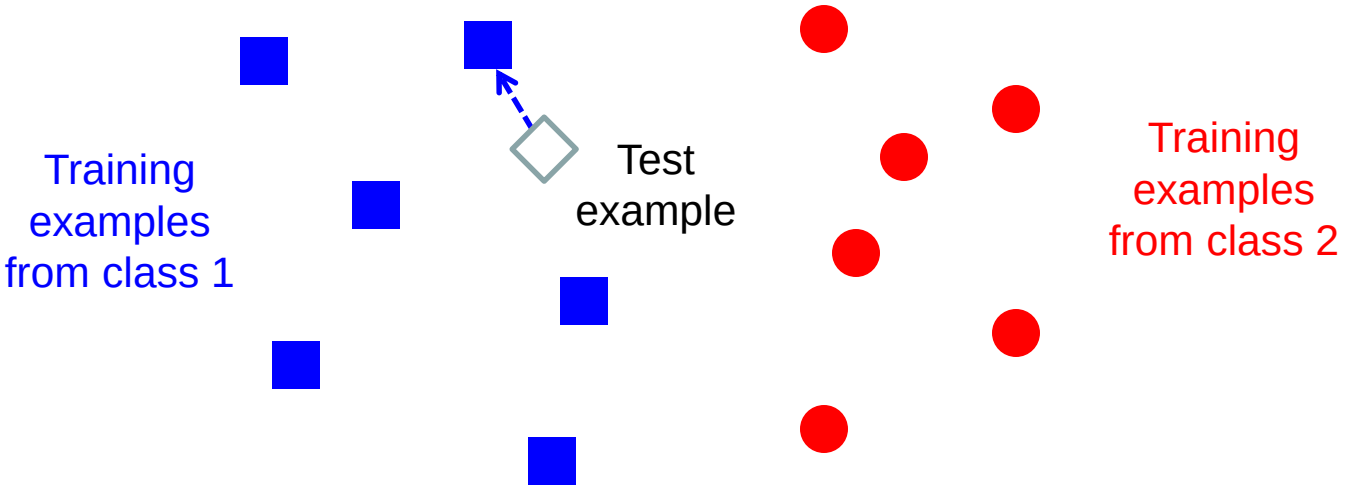
Slide credit: L. Lazebnik

Classification

Assign **x** to one of two (or more) classes.

A decision rule divides input space into *decision regions* separated by *decision boundaries* – literally boundaries in the space of the features.

Classifiers: Nearest neighbor



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

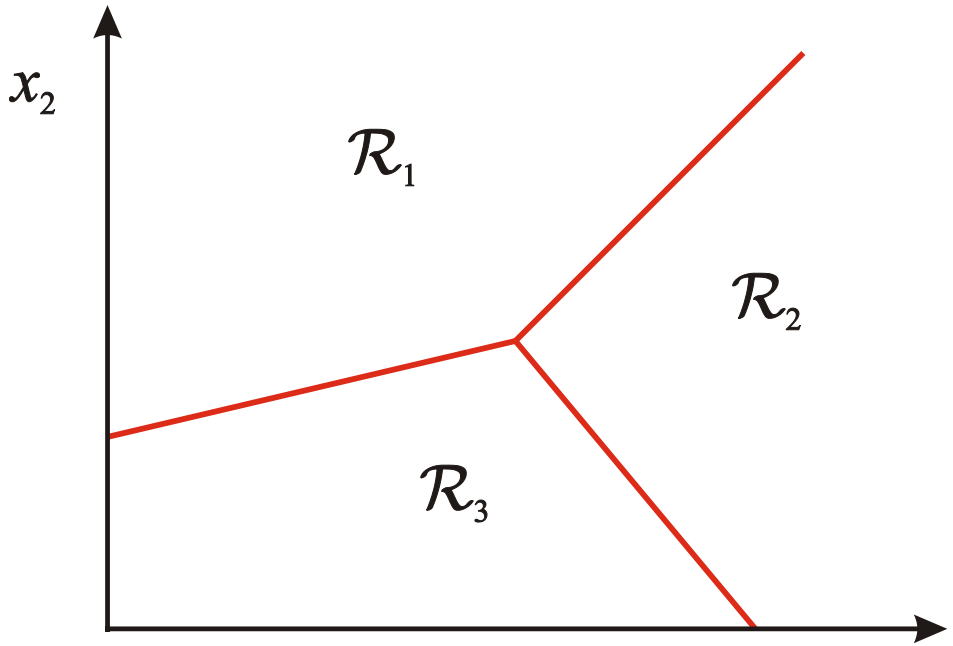
- All we need is a distance function for our inputs
- No training required!

Quickie Think-Pair-Share: What does the decision boundary look like?

Classification

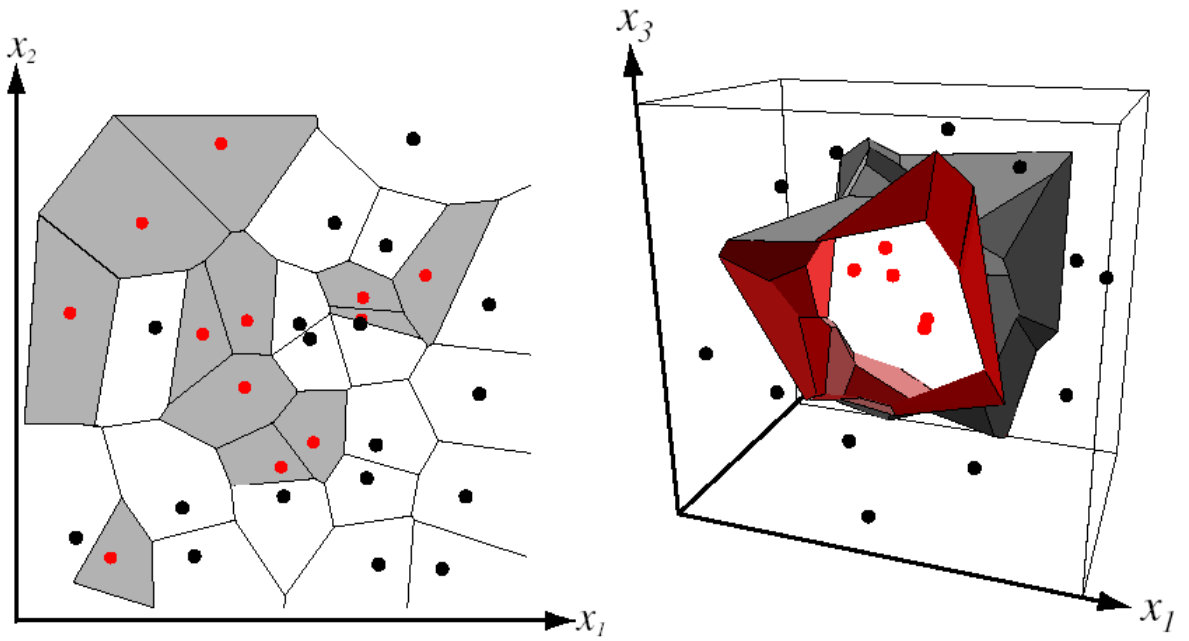
Assign **x** to one of two (or more) classes.

A decision rule divides input space into *decision regions* separated by *decision boundaries* – literally boundaries in the space of the features.



Decision boundary for Nearest Neighbor Classifier

Divides input space into *decision regions* separated by *decision boundaries – Voronoi.*

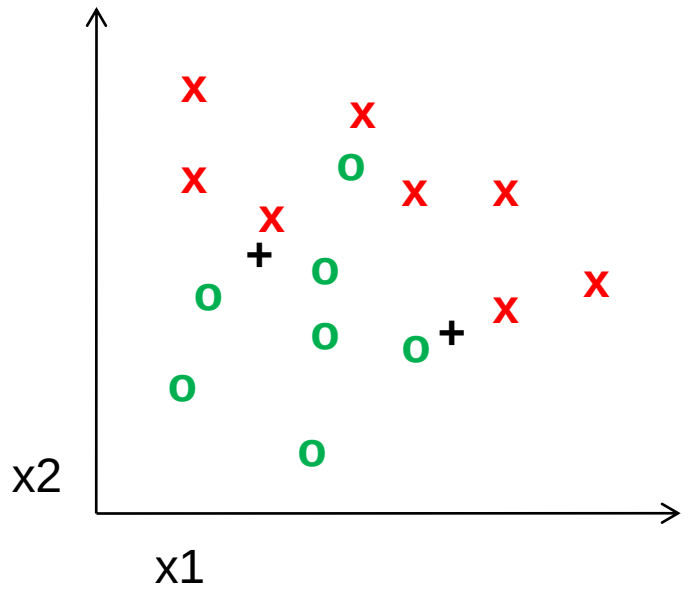


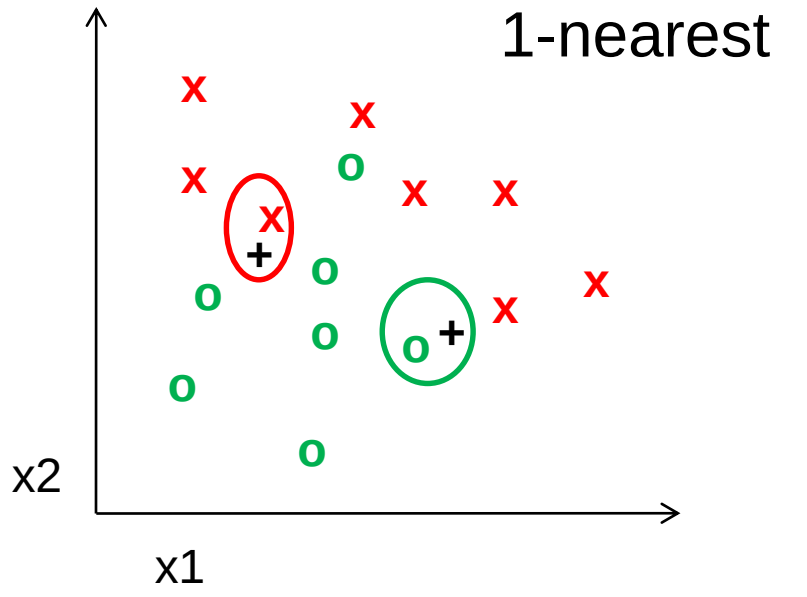
from Duda *et al.*

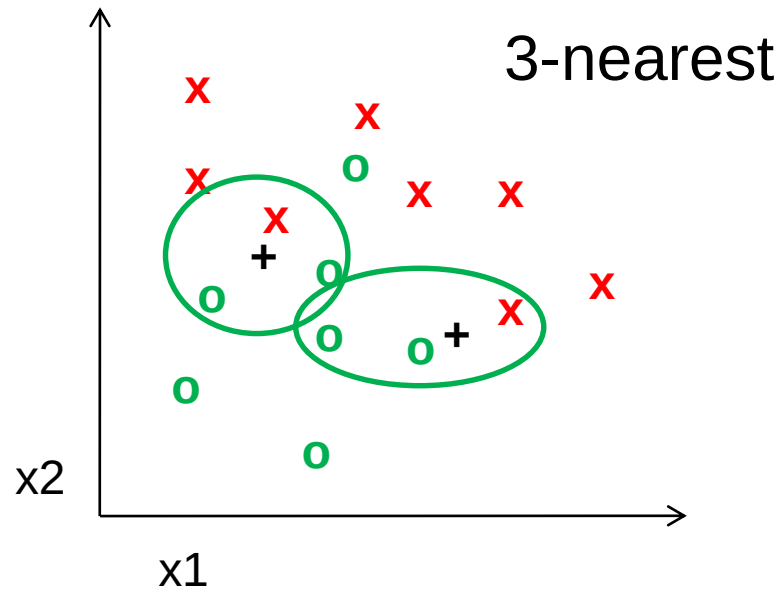
Voronoi partitioning of feature space for two-category 2D and 3D data

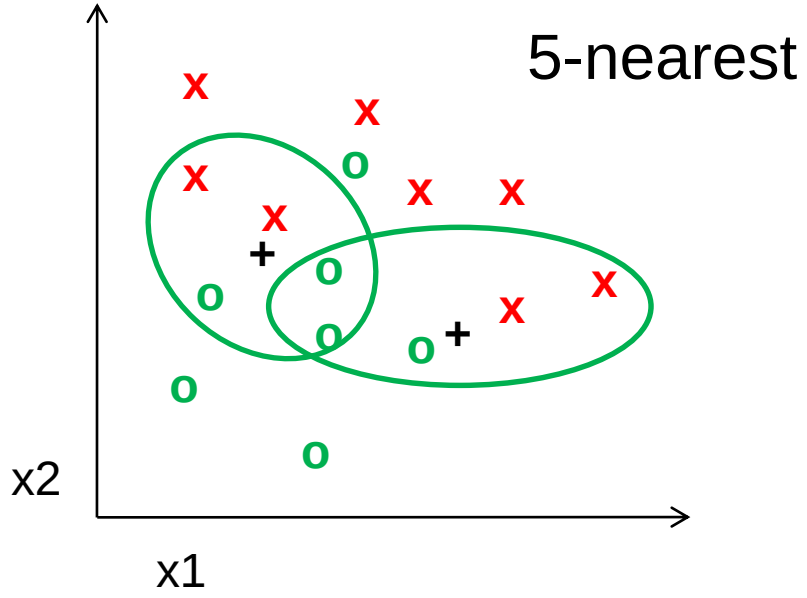
Source: D. Lowe

k-nearest neighbor

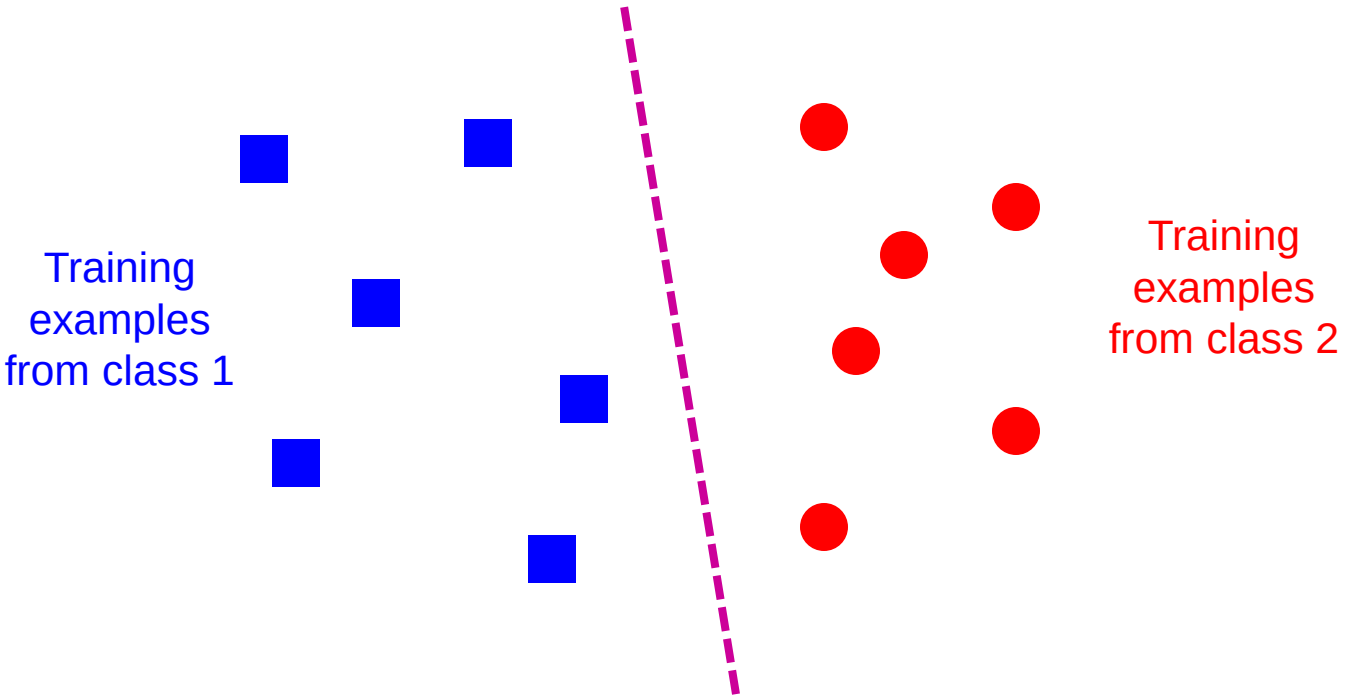








Classifiers: Linear

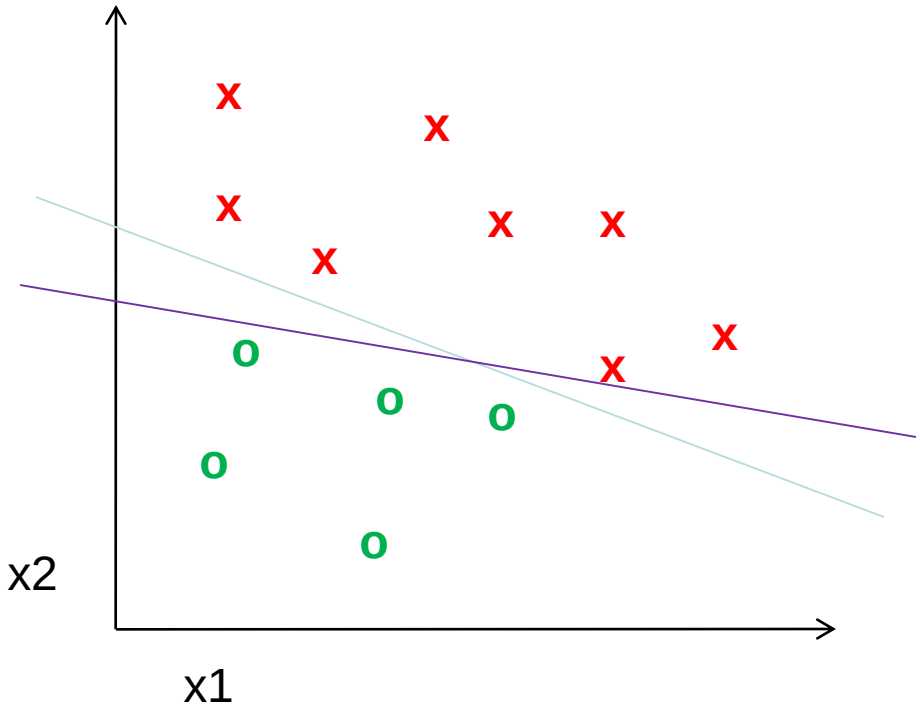


Find a *linear function* to separate the classes

Classifiers: Linear SVM

Find a *linear function* to separate the classes:

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



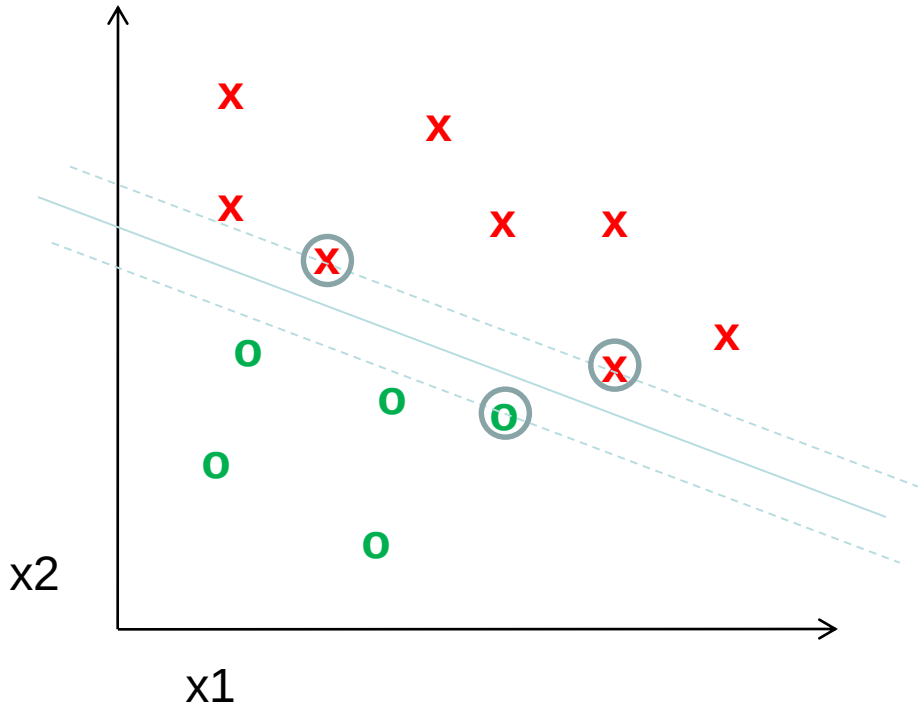
Classifiers: Linear SVM

Find a *linear function* to separate the classes:

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

How?

X = all data points



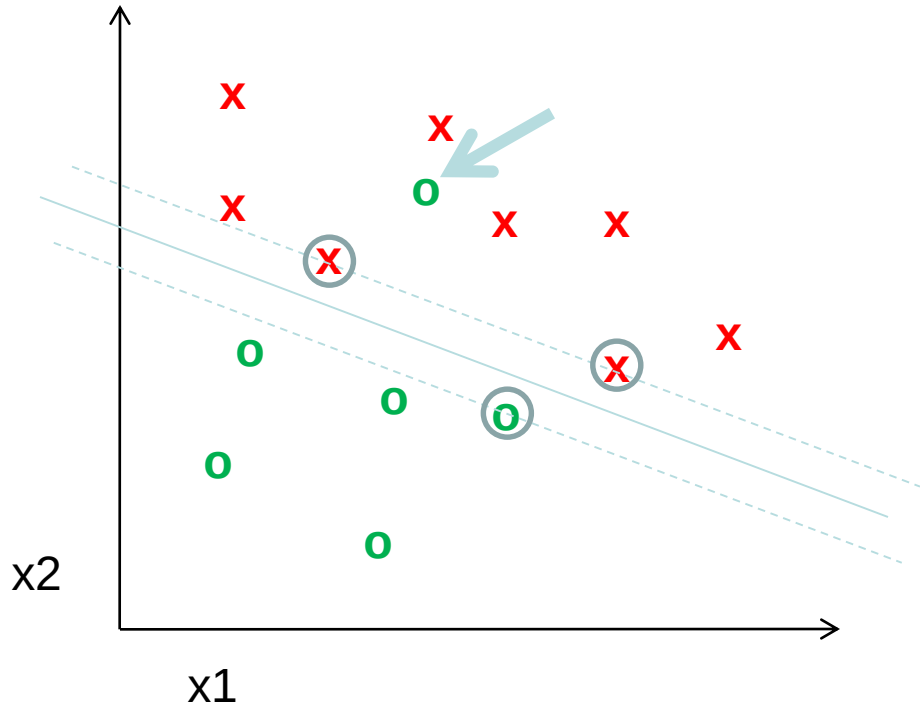
Define *hyperplane* **tX-b = 0**, where **t** is tangent to hyperplane.

Minimize **||t||** s.t. **tX-b** produces correct label for all **X**

Classifiers: Linear SVM

Find a *linear function* to separate the classes:

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

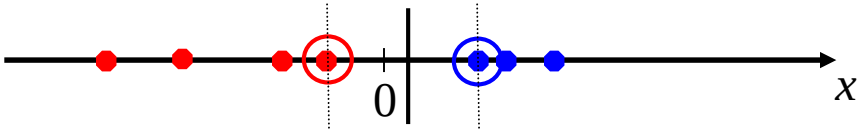


What if my data are not linearly separable?

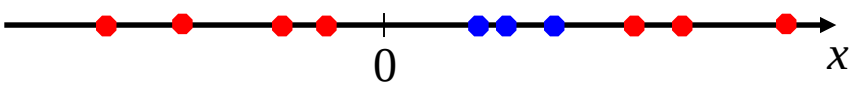
Introduce flexible ‘hinge’ loss (or ‘soft-margin’)

Nonlinear SVMs

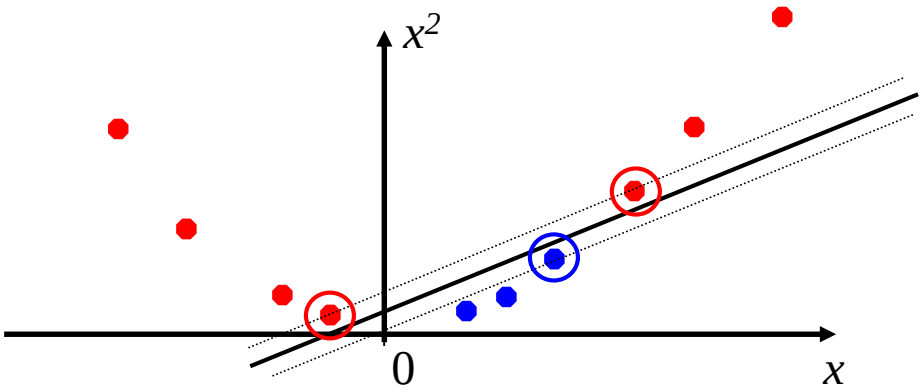
- Datasets that are linearly separable work out great:



- But what if the dataset is just too hard?

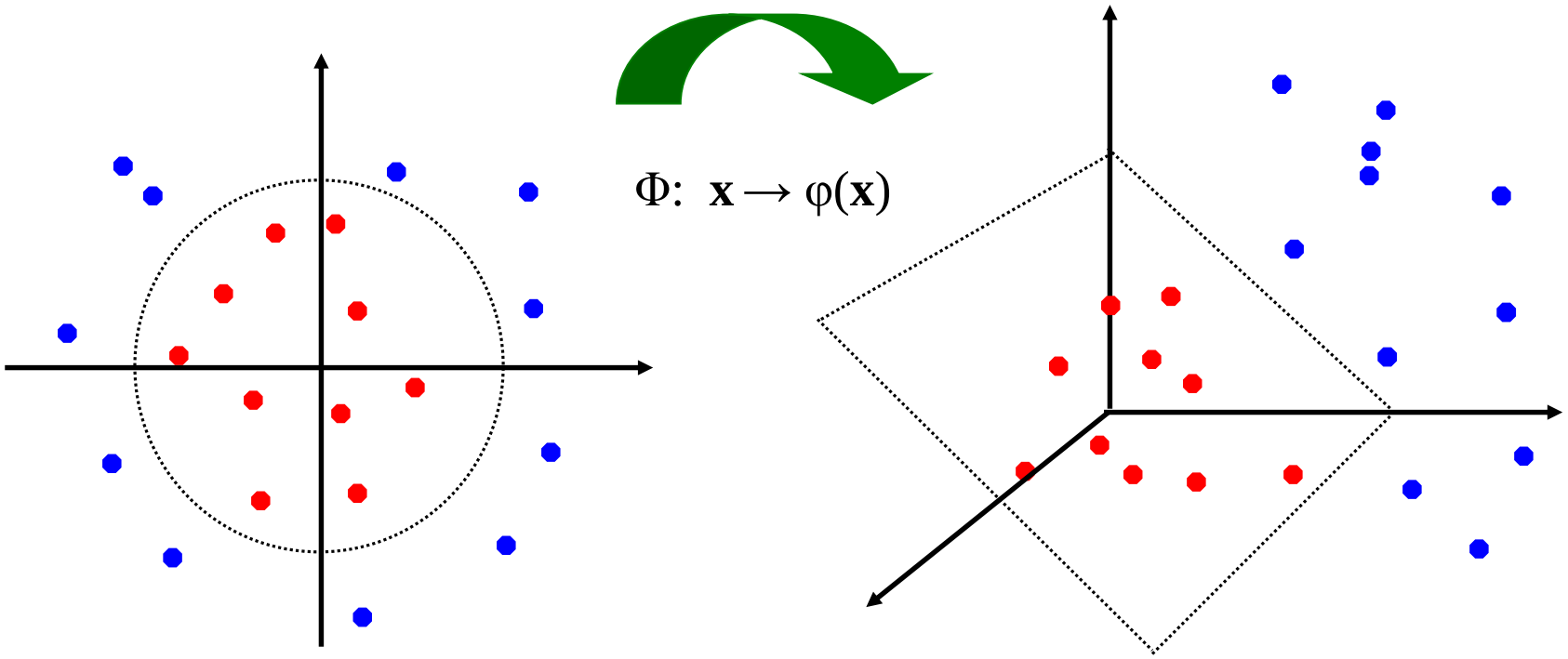


- We can map it to a higher-dimensional space:



Nonlinear SVMs

Map the original input space to some higher-dimensional feature space where the training set is separable:



Slide credit: Andrew Moore

[Additional info]

Nonlinear SVMs

The kernel trick: instead of explicitly computing the lifting transformation $\varphi(\mathbf{x})$, define a kernel function K such that:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i) \cdot \varphi(\mathbf{x}_j)$$

This gives a *non-linear* decision boundary in the original feature space:

$$\sum_i \alpha_i y_i \varphi(\mathbf{x}_i) \cdot \varphi(\mathbf{x}) + b = \sum_i \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b$$

But…we only transformed the distance function *K!*

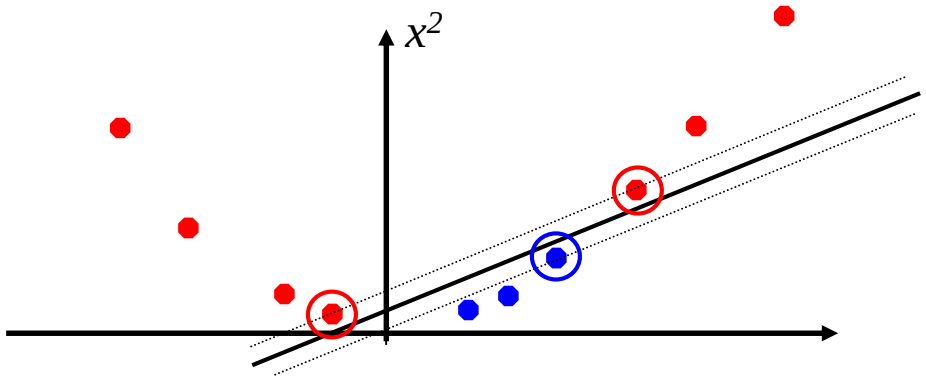
Common kernel function: Radial basis function kernel

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition
Data Mining and Knowledge Discovery, 1998

[Additional info]

Nonlinear kernel: Example

Consider the mapping $\varphi(x) = (x, x^2)$



$$\varphi(x) \cdot \varphi(y) = (x, x^2) \cdot (y, y^2) = xy + x^2 y^2$$

$$K(x, y) = xy + x^2 y^2$$

[Additional info]

Kernels for bags of features

- Histogram intersection kernel:

$$I(h_1, h_2) = \sum_{i=1}^{N} \min(h_1(i), h_2(i))$$

- Generalized Gaussian kernel:

$$K(h_1, h_2) = \exp\left(-\frac{1}{A} D(h_1, h_2)^2 \right)$$

D can be (inverse) L1 distance, Euclidean distance, χ^2 distance, etc.

J. Zhang, M. Marszalek, S. Lazebnik, and C. Schmid, IJCV 2007
Local Features and Kernels for Classifcation of Texture and Object Categories: A Comprehensive Study

What about multi-class SVMs?

Unfortunately, there is no “definitive” multi-class SVM.

In practice, we combine multiple two-class SVMs

One vs. others

- Training: 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
  - 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

Training

Training Images

Training Labels

Image Features

Training

Learned classifier

Testing

Test Image

Image Features

Apply classifier

Prediction

Slide credit: D. Hoiem and L. Lazebnik

Features and **distance measures**

define visual similarity.

Training labels

dictate that examples are the same or different.

Classifiers

learn weights (or parameters) of features and distance measures…
so that visual similarity predicts label similarity.

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 Error

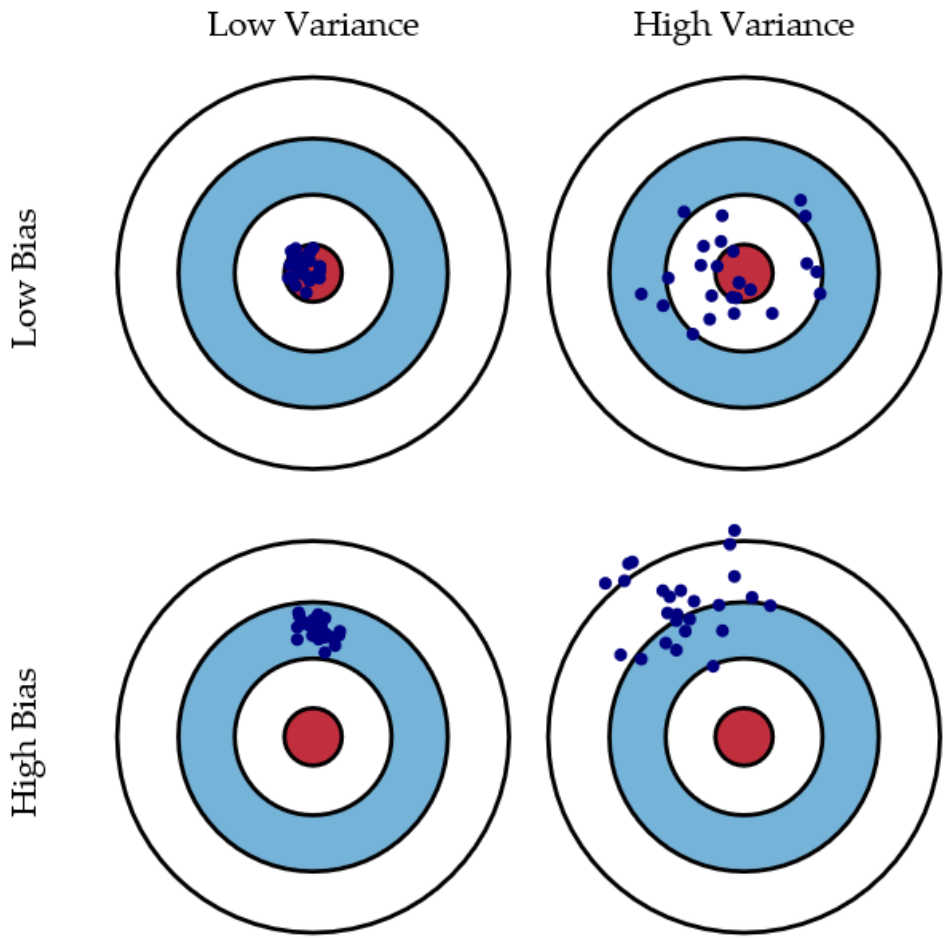
Bias:

- Difference between the expected (or average) prediction of our model and the correct value.
- Error due to inaccurate assumptions/simplifications.

Variance:

- Amount that the estimate of the target function will change if different training data was used.

Bias/variance trade-off



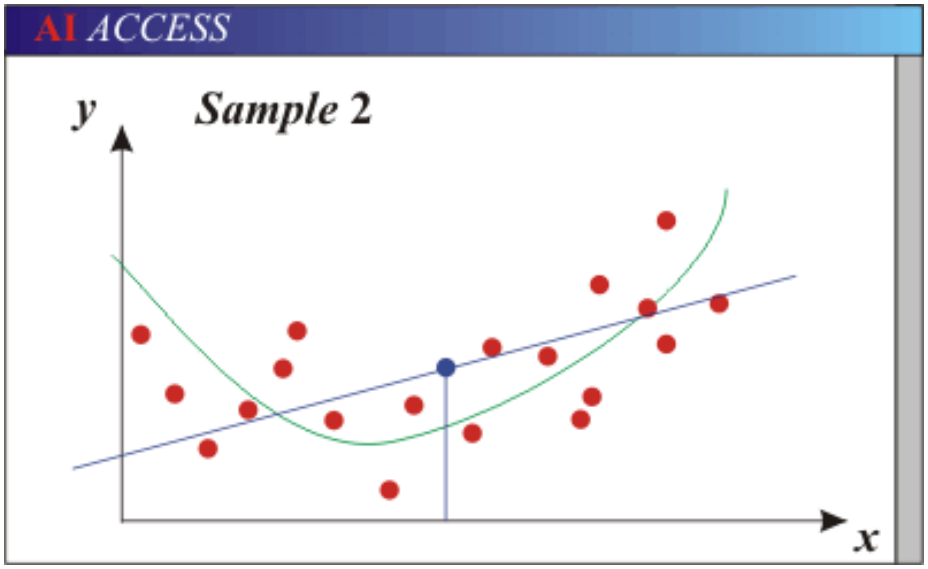
Bias = accuracy
Variance = precision

[Scott Fortmann-Roe]

Generalization Error Effects

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



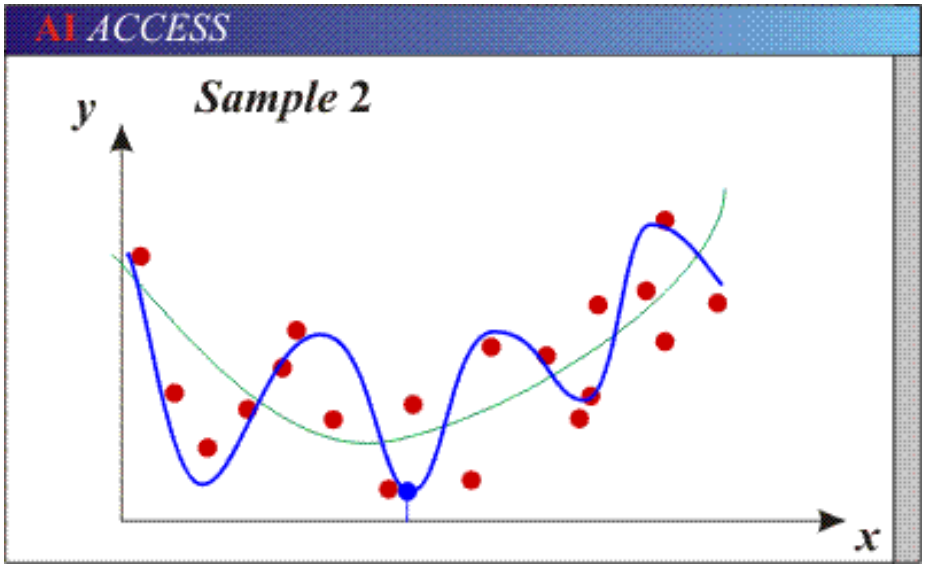
Green line = true data-generating function without noise
Blue line = data model which underfits

Slide credit: L. Lazebnik

Generalization Error Effects

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



Green line = true data-generating function without noise
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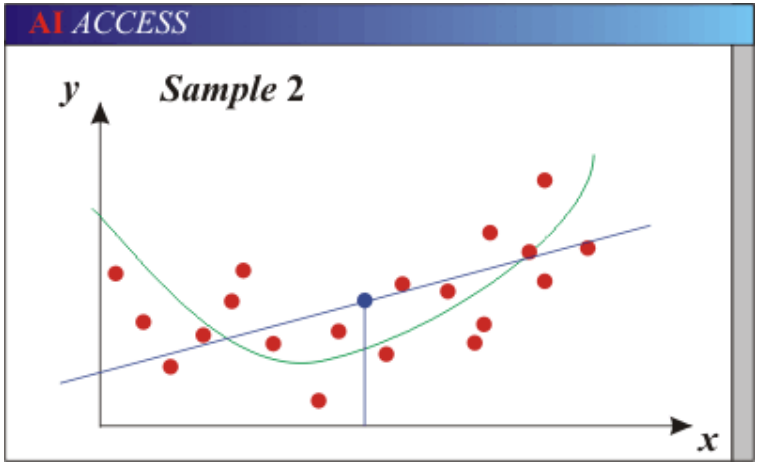
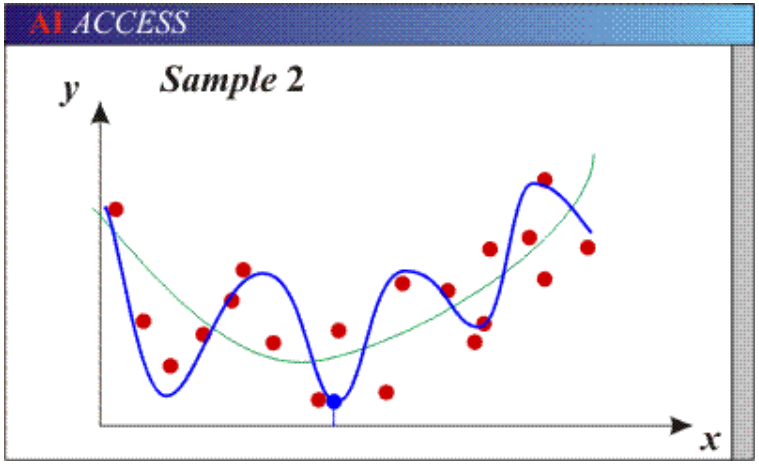
Slide credit: L. Lazebnik

Bias-Variance Trade-off



Models with too few parameters are inaccurate because of a large bias.

- Not enough flexibility!
- Too many assumptions



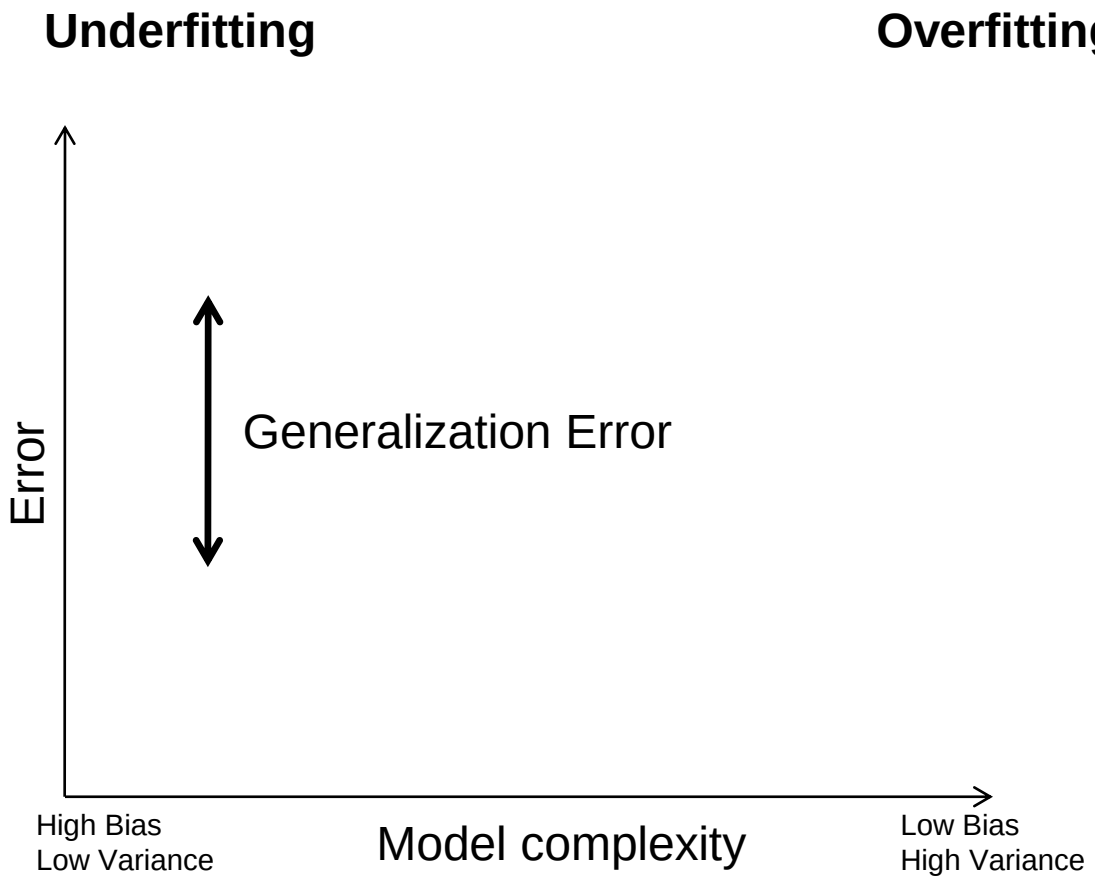
Models with too many parameters are inaccurate because of a large variance.

- Too much sensitivity to the sample.
- Slightly different data -> very different function.

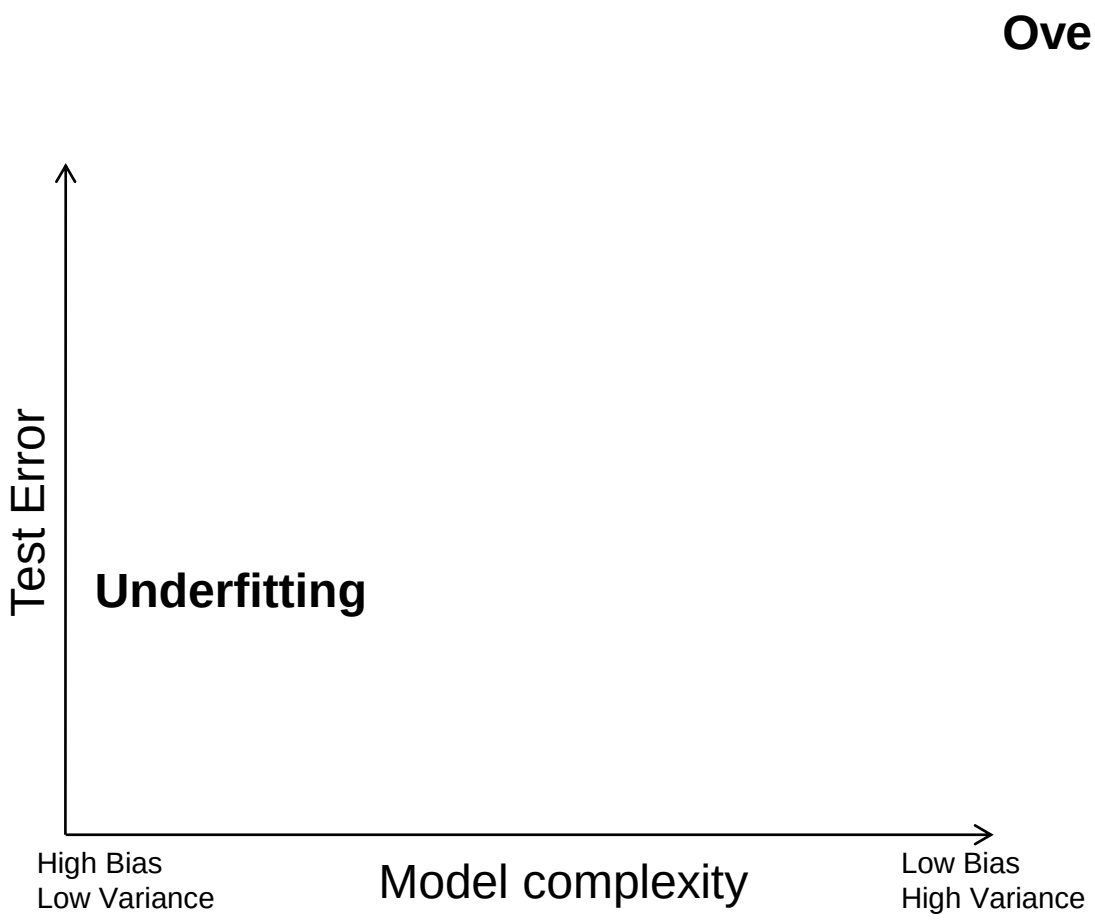
Slide credit: D. Hoiem

Bias-variance tradeoff

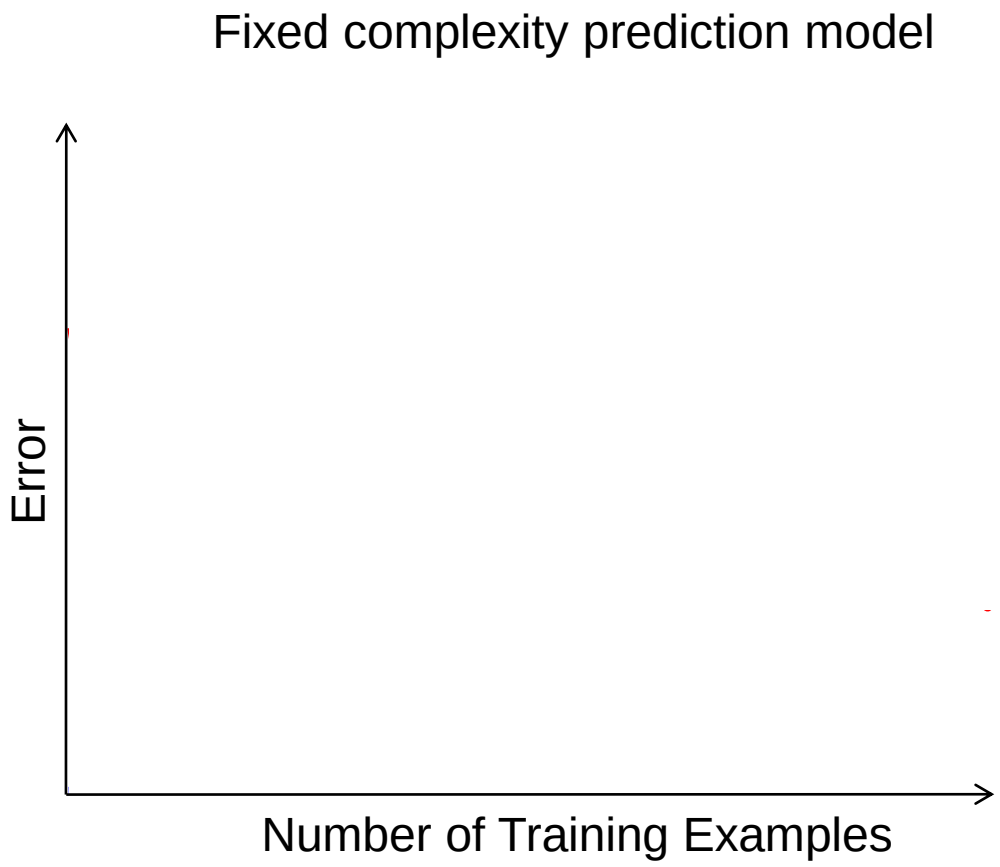
Fixed number of training examples



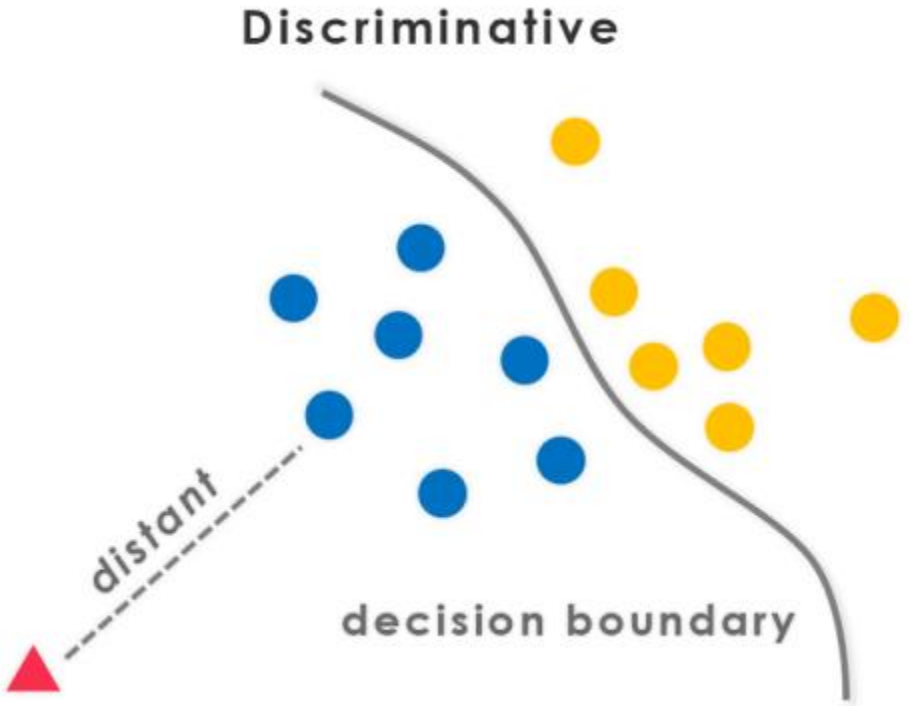
Bias-variance tradeoff

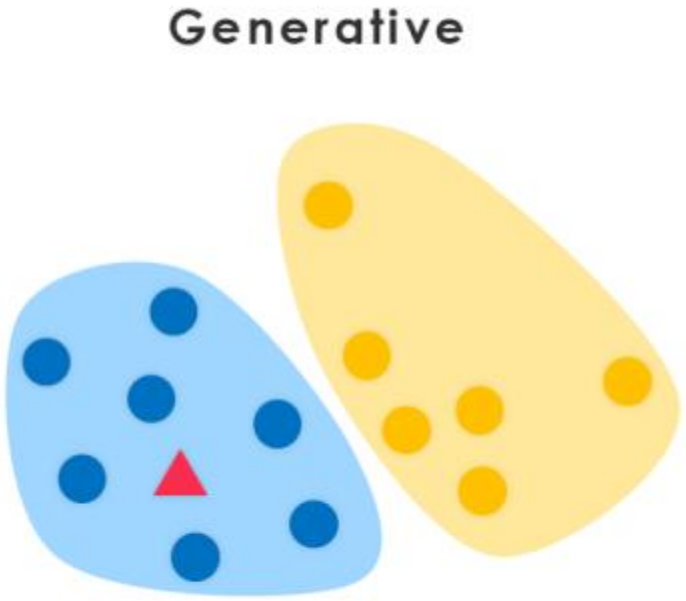


Effect of Training Size



[evolvingai.org]





"Learn the data boundary"

Given:
Observations X
Targets Y

Learn conditional distribution:
$P(Y|X = x)$

"Represent the data and then define boundary"

Given:
Observations X
Targets Y

Learn joint distribution:
$P(X, Y)$

Photo: CMU Machine Learning Department Protests G20

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

Many classifiers to choose from…

- K-nearest neighbor
- SVM
- Naïve Bayes
- Bayesian network
- Logistic regression
- Randomized Forests
- Boosted Decision Trees
- Restricted Boltzmann Machines
- Neural networks
- Deep Convolutional Network
- …

Which is the best?

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, currently, because it learns the feature representation.

Claim:

It is more important to have more or better labeled data than to use a different supervised learning technique.

*Again, deep learning may be an exception here for the same reason, but deep learning _needs_ a lot of labeled data in the first place.

“The Unreasonable Effectiveness of Data” - Norvig

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