Crash Course in Machine Learning

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Features Check - What now?

- To this point:
  - Everything we have done is feature based!
  - This was a common trend for several decades
  - However, we can also do things based upon appearance (as we will soon see)
  - Good for us since this is complementary to feature-based approaches!
- **So where do we go from here???**

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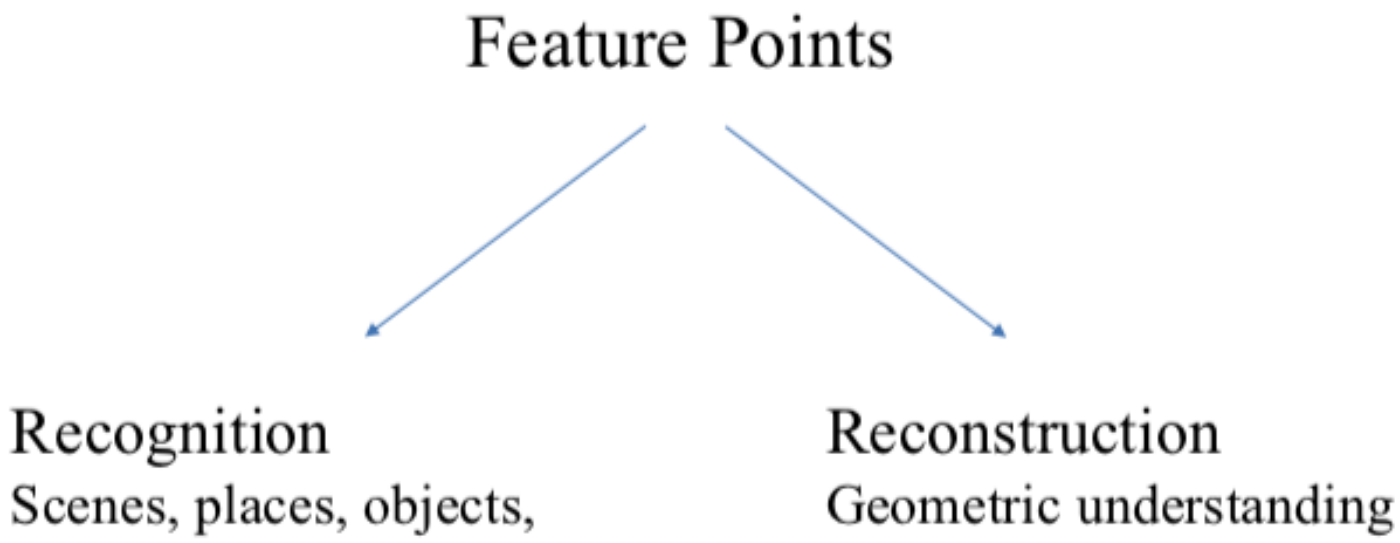
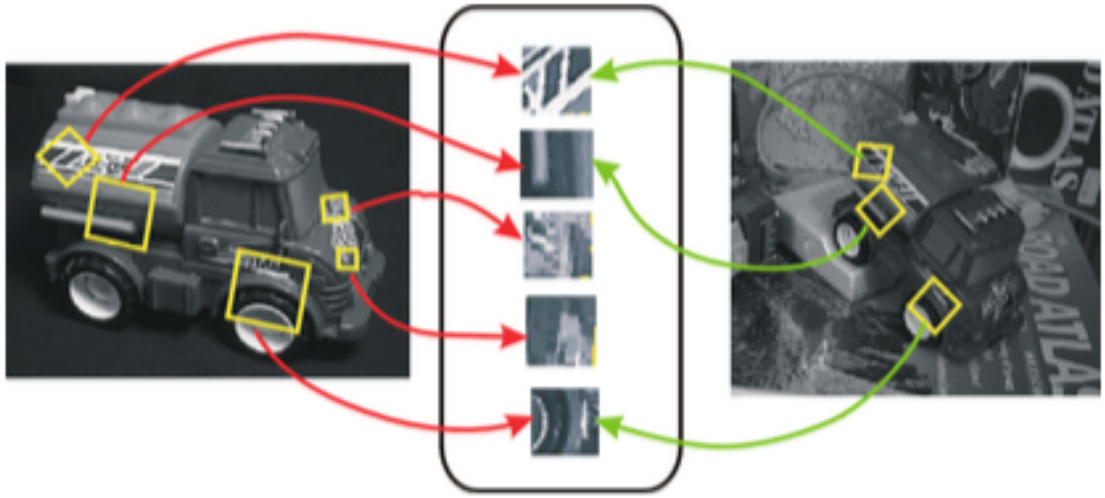


What we have done with features!

- Panoramic Stitching/Image Alignment!
- Can we use features to "understand" scenes?
- Are there other techniques for scene understanding?

What about object/scene recognition?

- Generally need machine learning techniques to "learn/describe" the visual world.

Scene recognition
- City/forest/factory/...

Find pedestrians

Amusing Satirical Aside

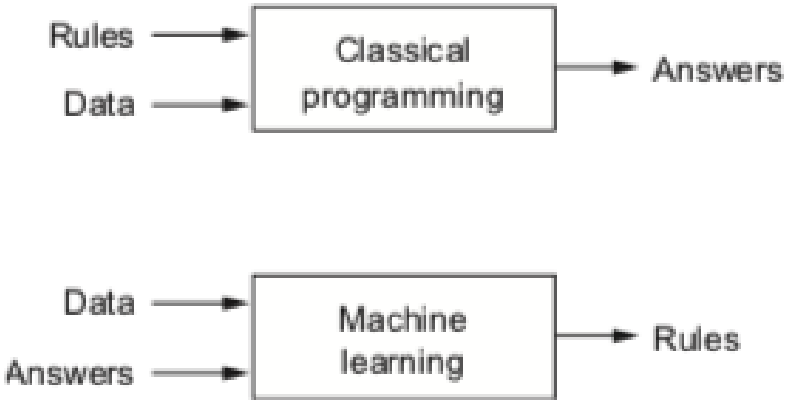
- CMU Machine Learning Department "protests" the G20! (Flickr)

Machine Learning (ML) as a Tool

- In this course we use ML as a tool and will NOT dive into the mathematical rigor (mostly)
- If you're interested in this stuff - the CSC department may be offering a ML course soon - per popular request!

What is Machine Learning?

- Learn from and make predictions on data:

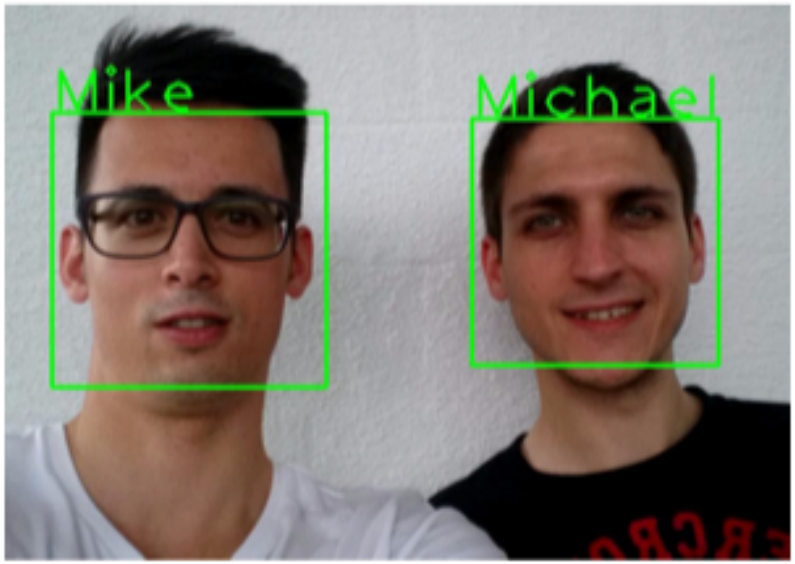


- One of the greatest exports from computing to other fields (and believe me when I say it's everywhere these days!)
- One of the fastest growing and hottest research areas in the world!

ML is applied in MANY different domains!

- In this course we're interested in ML for Computer Vision!

- Face Recognition
- Object Classification
- Scene Segmentation

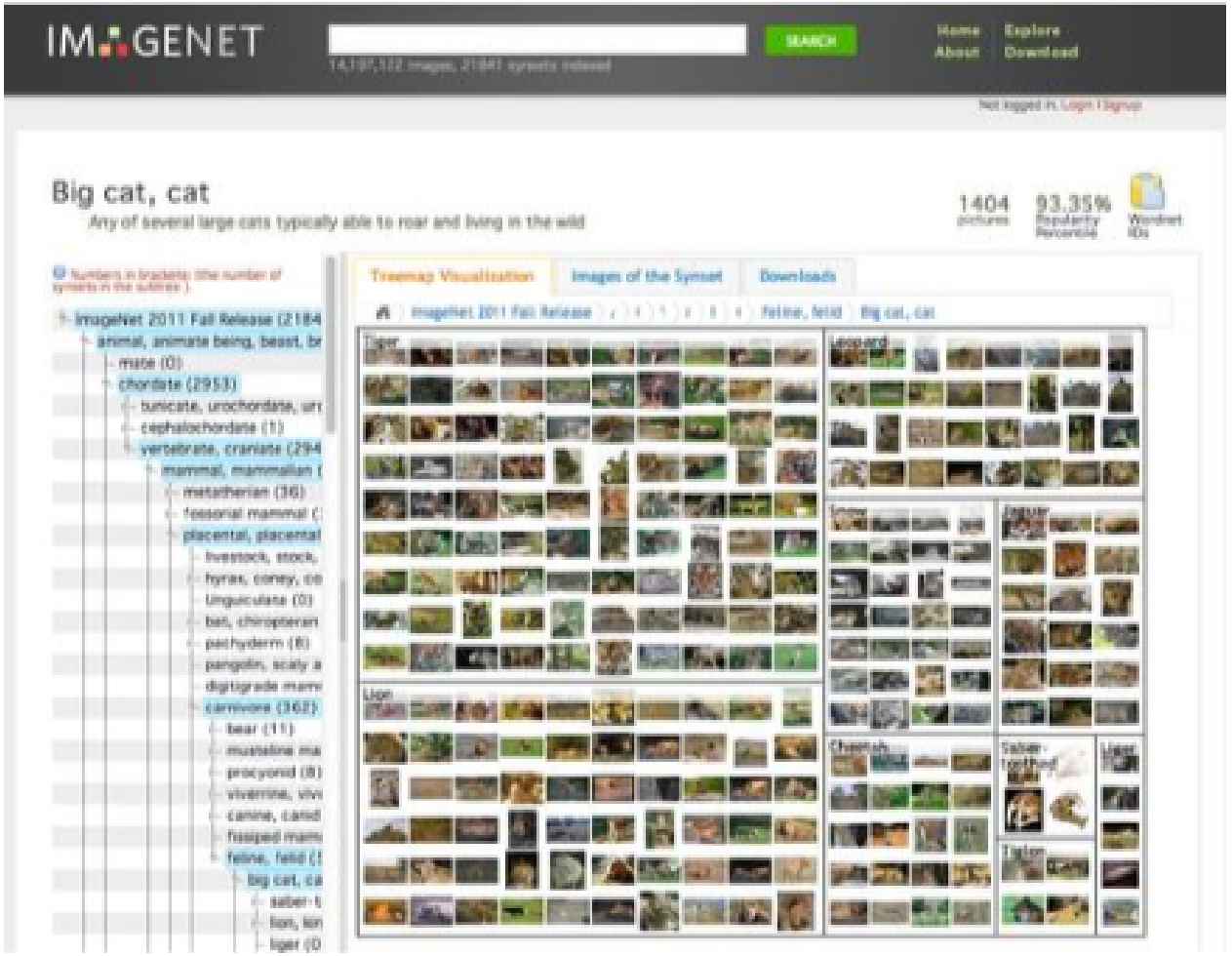


How exactly can machines "learn"?

- Lots and lots and lots and lots and lots of Data!
- Norvig – "The Unreasonable Effectiveness of Data" (IEEE Intelligent Systems, 2009)
  - "... invariably, simple models and a lot of data trump more elaborate models based on less data"

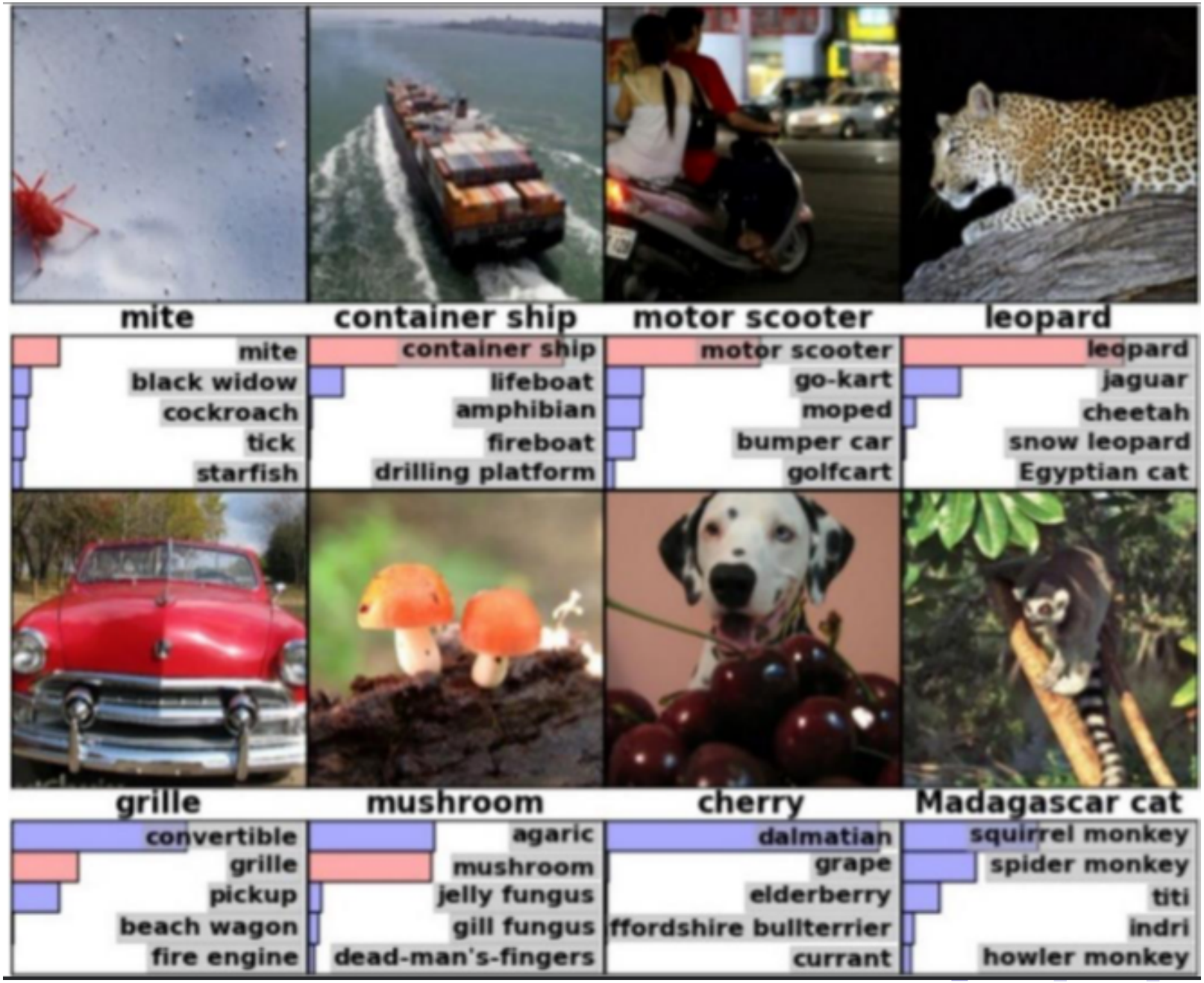
Classic Benchmark Challenge - ImageNet

- Images for each category of WordNet
- 1000 classes
- 1.2mil images
- 100k test
- Top 5 error



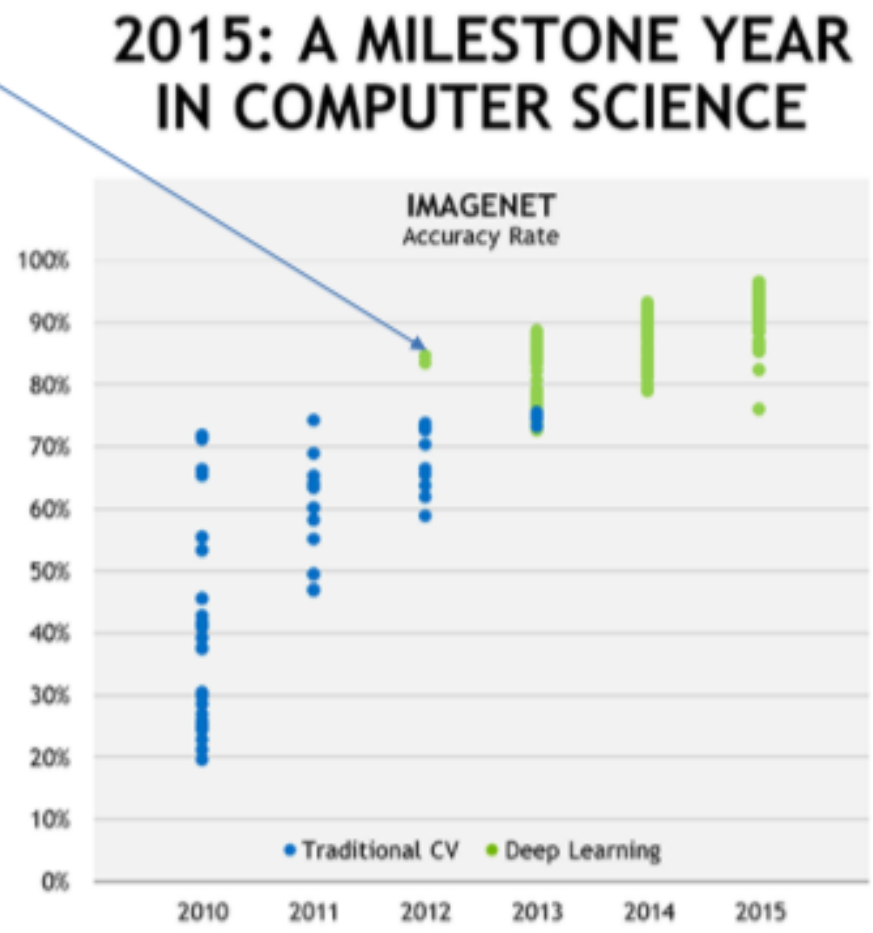
ImageNet = Lots and Lots and ... and Lots of Data

Example output (classification problem)



ImageNet Competition

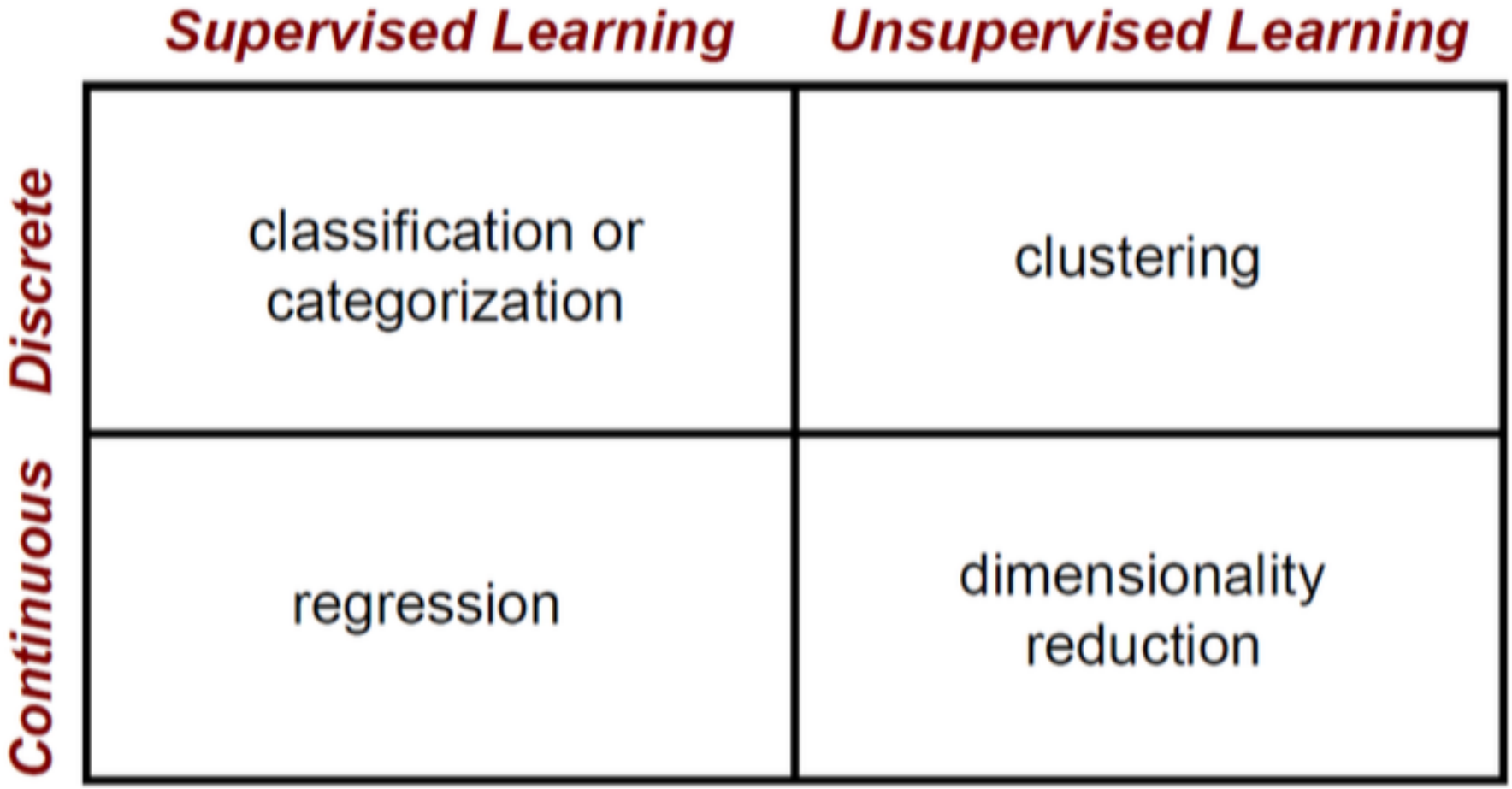
- Krizhevsky, 2012
- Google, Microsoft 2015
  - Beat the best human score in the ImageNet challenge.



NVIDIA

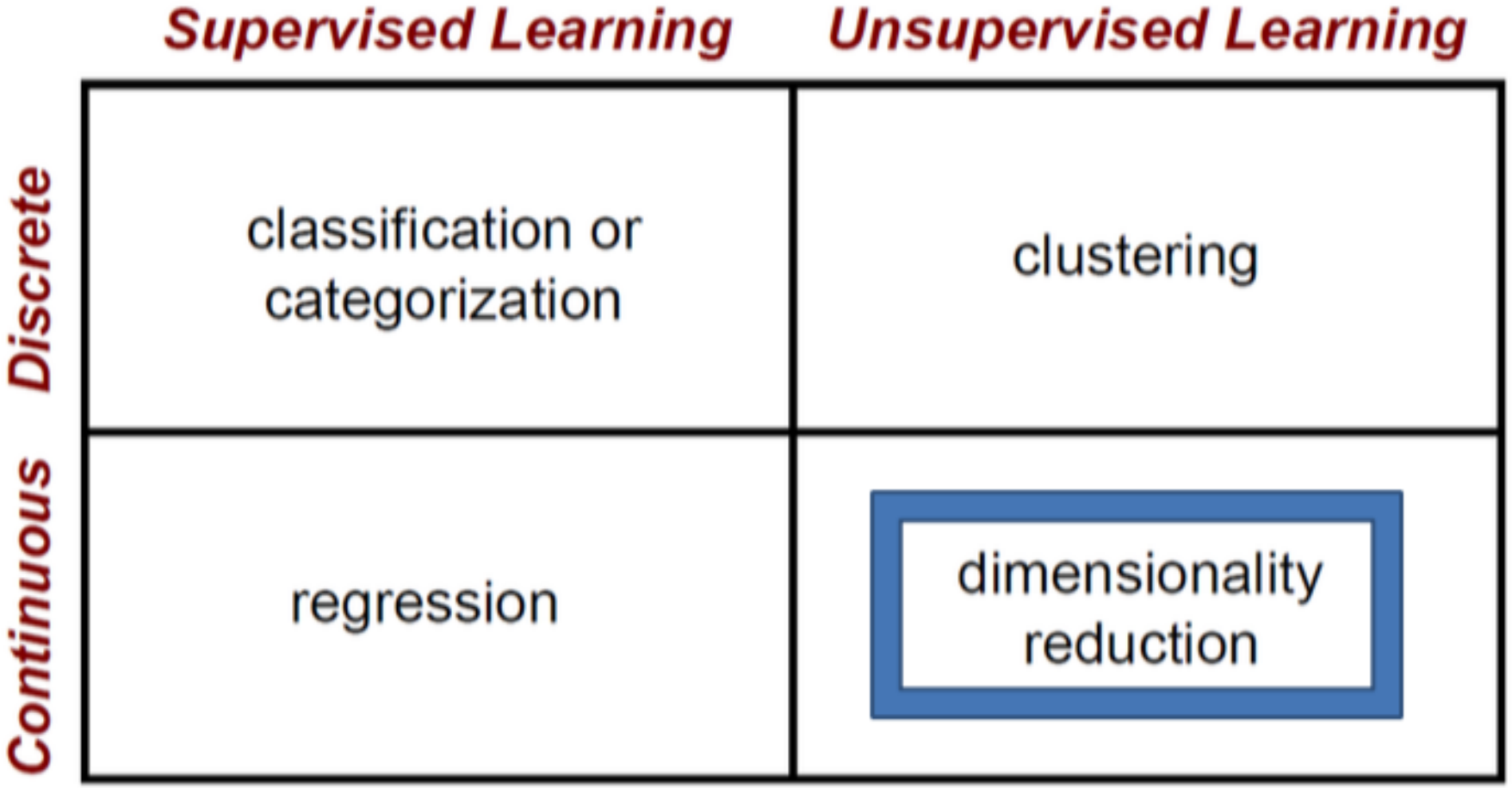
How can ML solve these types of problems? (or at a minimum help?)

- Four broad categories:



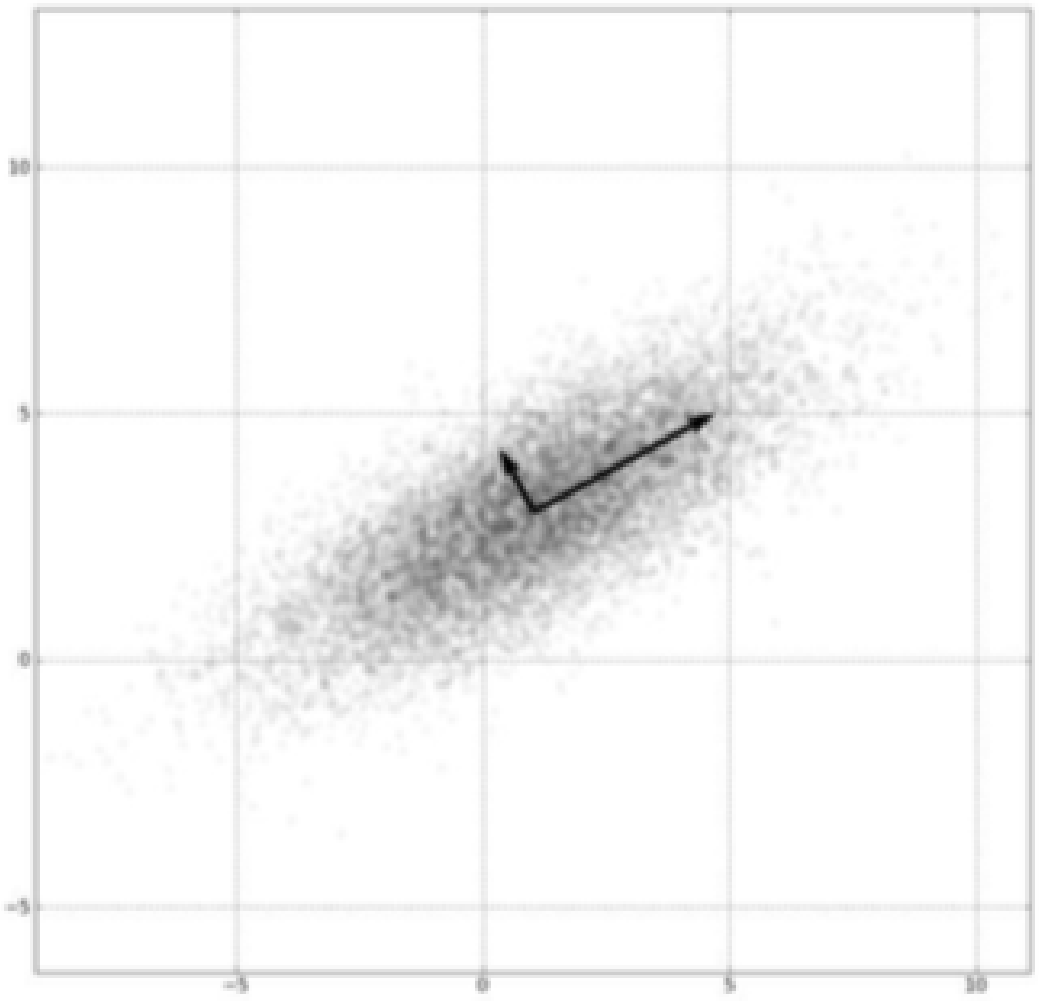
How can ML solve these types of problems? (or at a minimum help?)

- Dimensionality reduction (Closely related to Project 4 - more to come!)



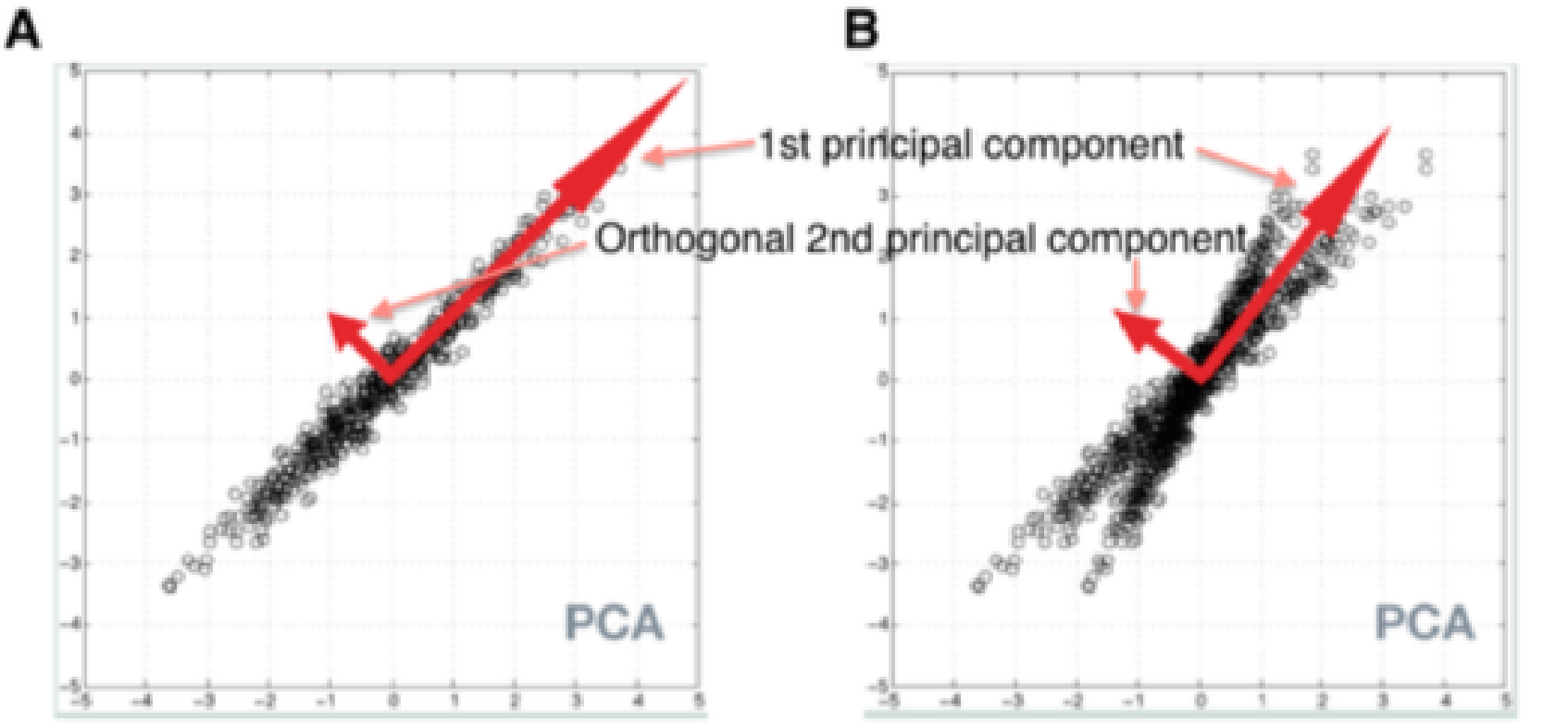
Many different approaches to Dimensionality Reduction

- **PCA**, ICA, LLE, ISOMAP, etc.
- Principal Component Analysis (PCA)
  - Arguably the most common approach (at least to start with)
  - Idea: Find a reduced dimensional subspace that maximizes the total variance in the data.
  - PCA finds an orthogonal subspace that finds correlation in the data: *best possible* low-dimensional subspace when using linear projections.



PCA

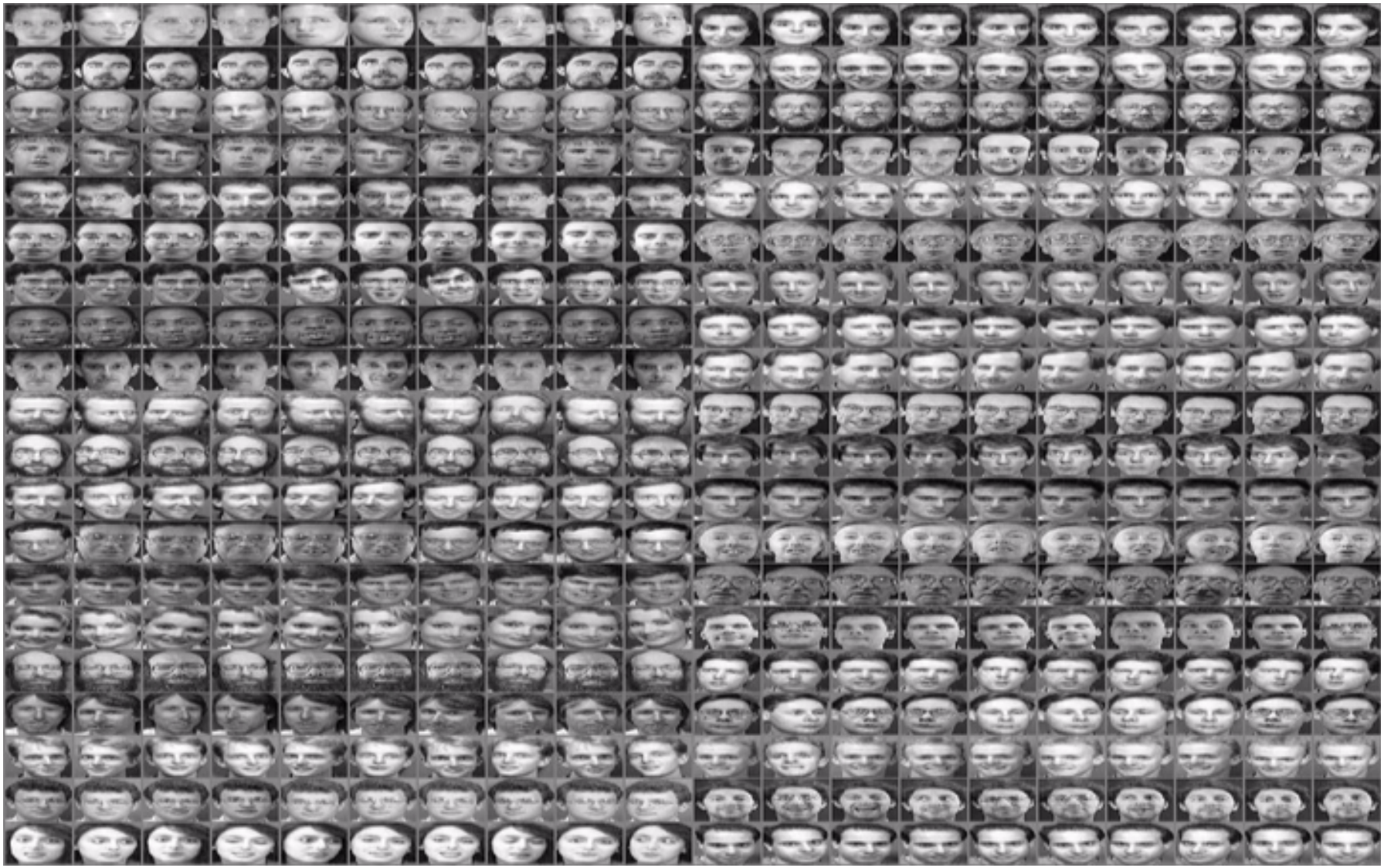
- We will dive into this in great detail in the next project!



(Figure adapted from C. Beckmann, Oxford FMRIB)

Application to Imaging: Eigenfaces for Recognition

- AT&T Face Database: 10 images of 40 different subjects.



Eigenfaces

Mean face

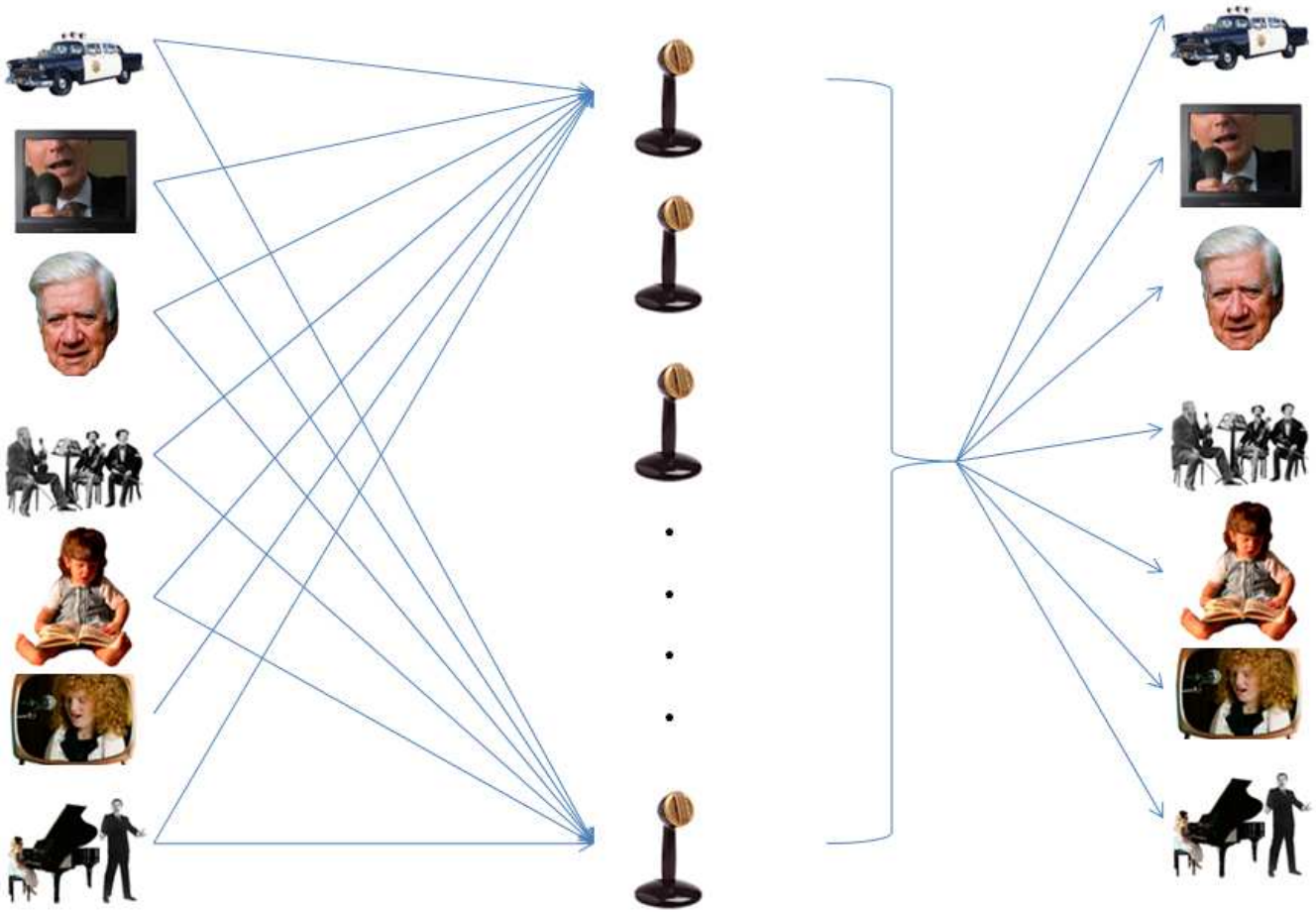
Basis of variance (eigenvectors)

M. Turk; A. Pentland (1991). "Face recognition using eigenfaces" (PDF).
Proc. IEEE Conference on Computer Vision and Pattern Recognition. pp. 586–591.

R.P.W. Duin

ICA - Blind Source Seperation

- Classically used to solve the "cocktail" party problem!



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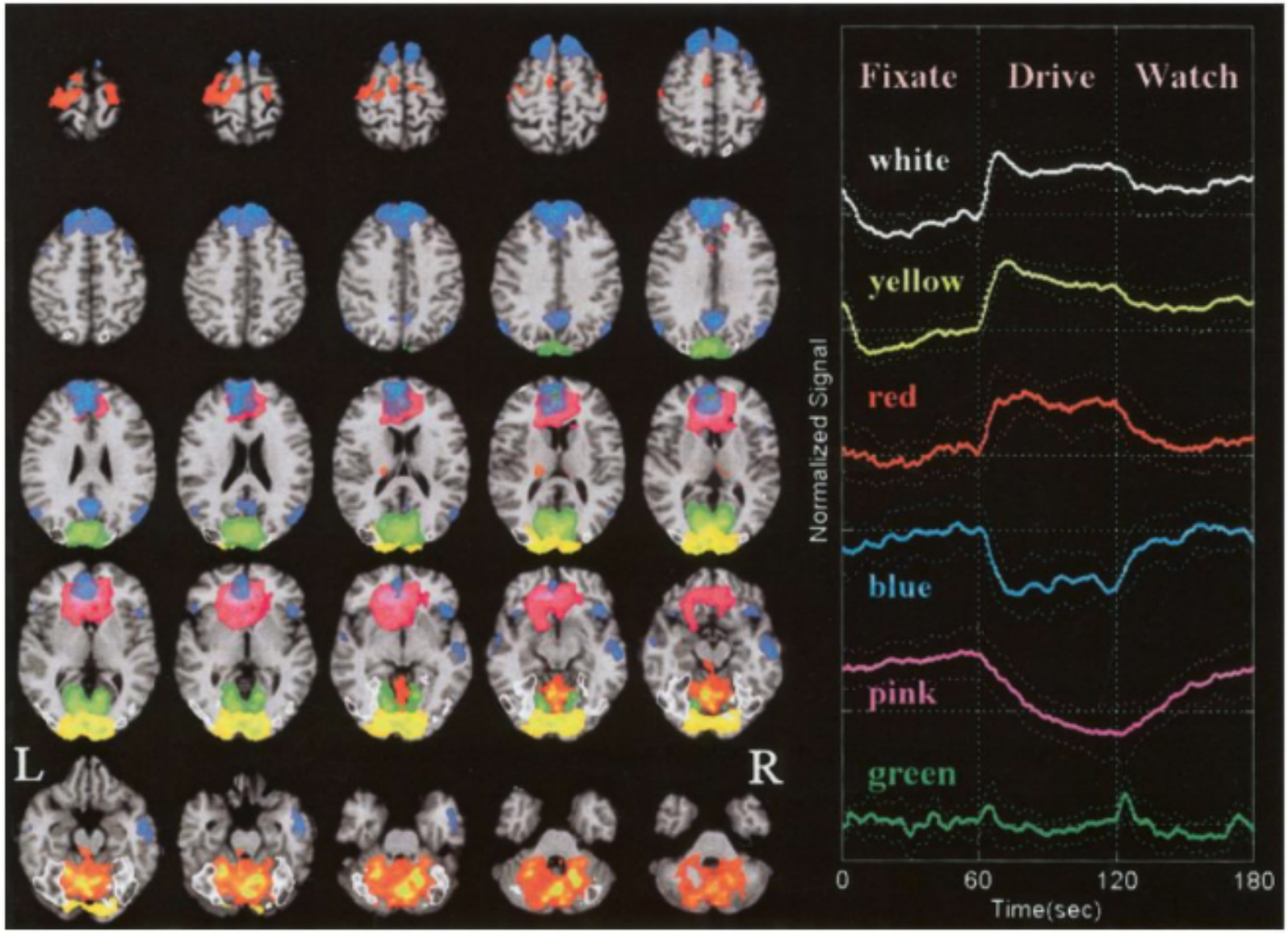
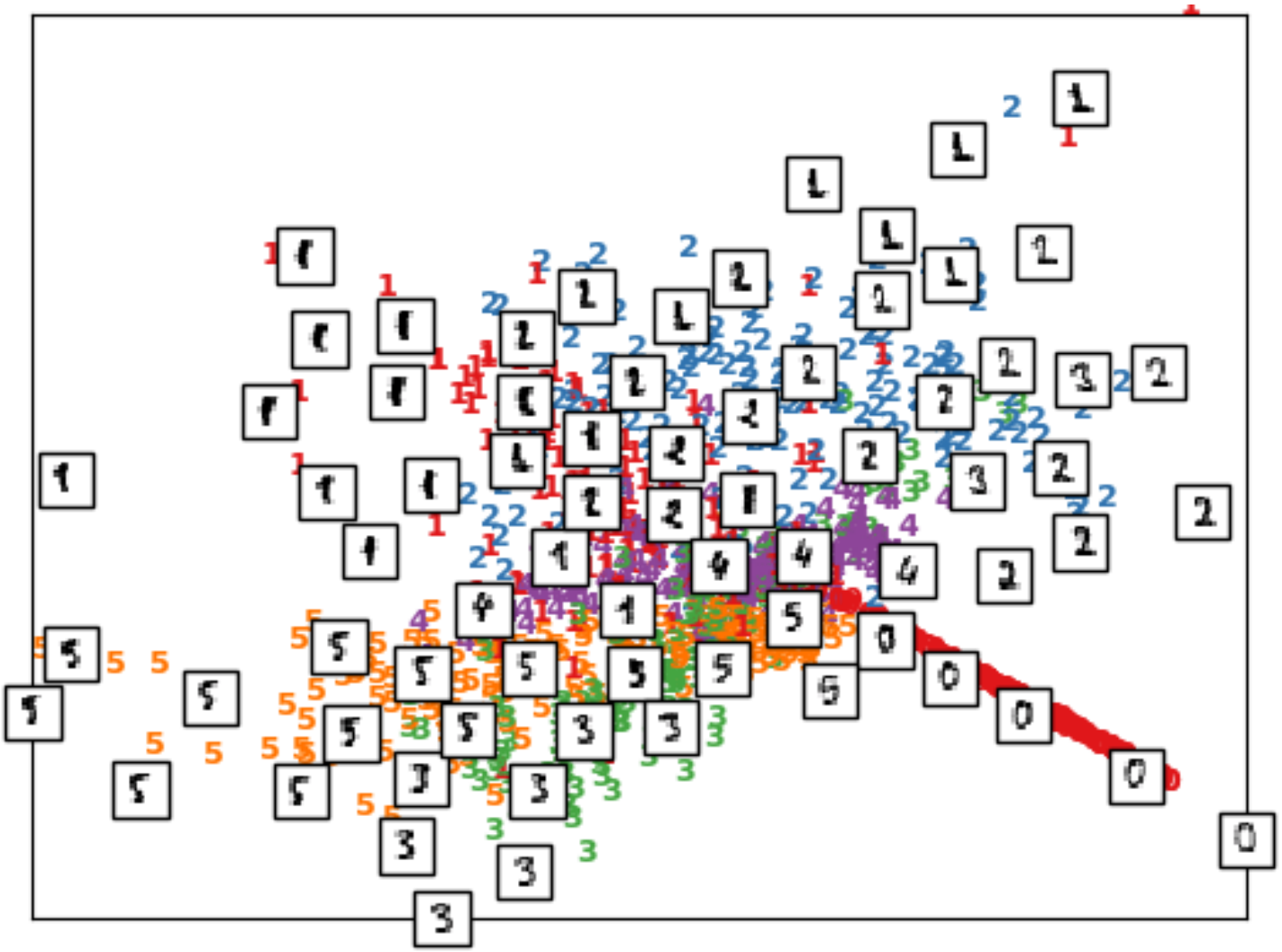


Local Linear Embedding (LLE)

- Think global - Fit local (Manifold learning approach)
- Looks at local linear planes in the data for "learning" manifold structure



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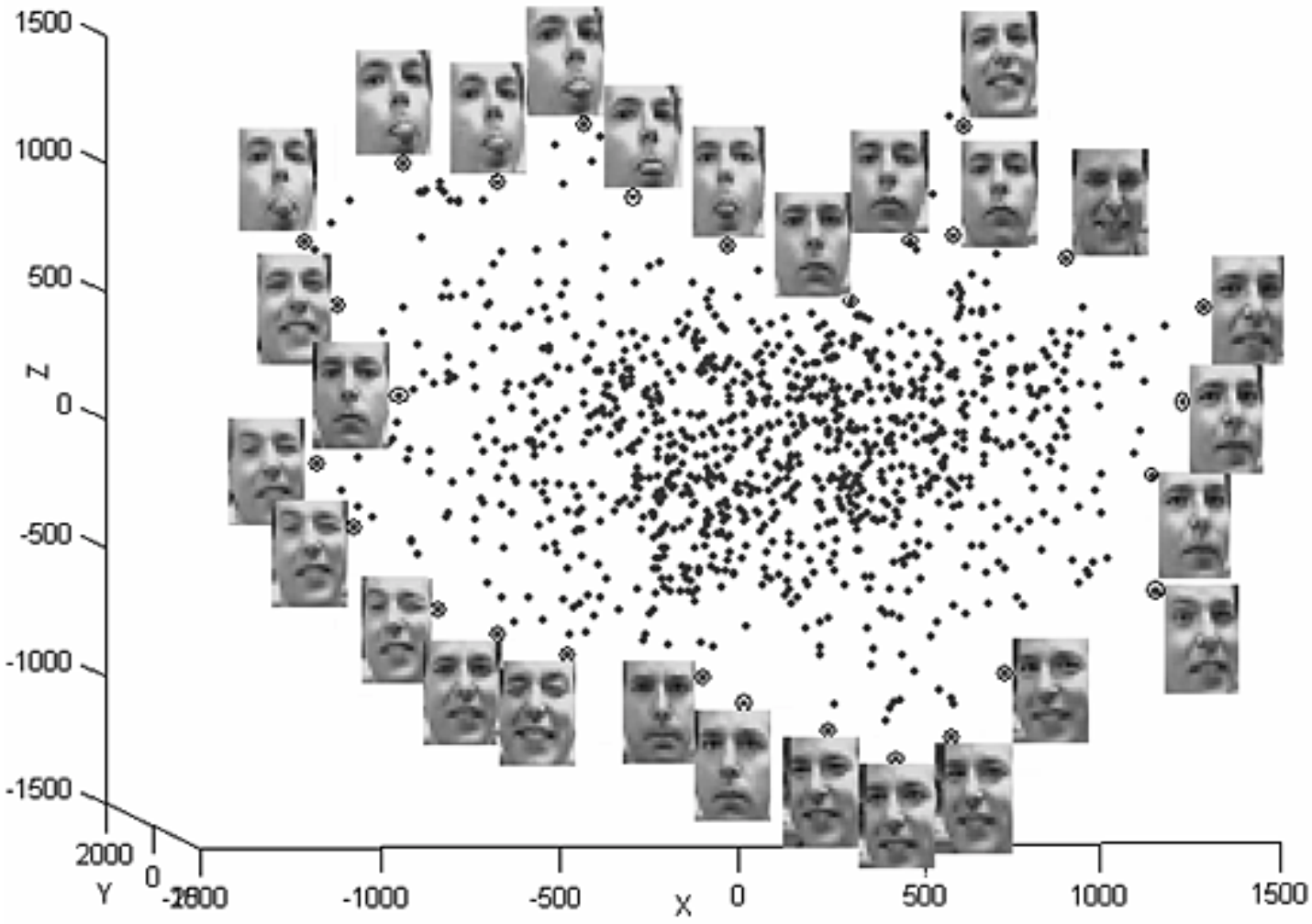
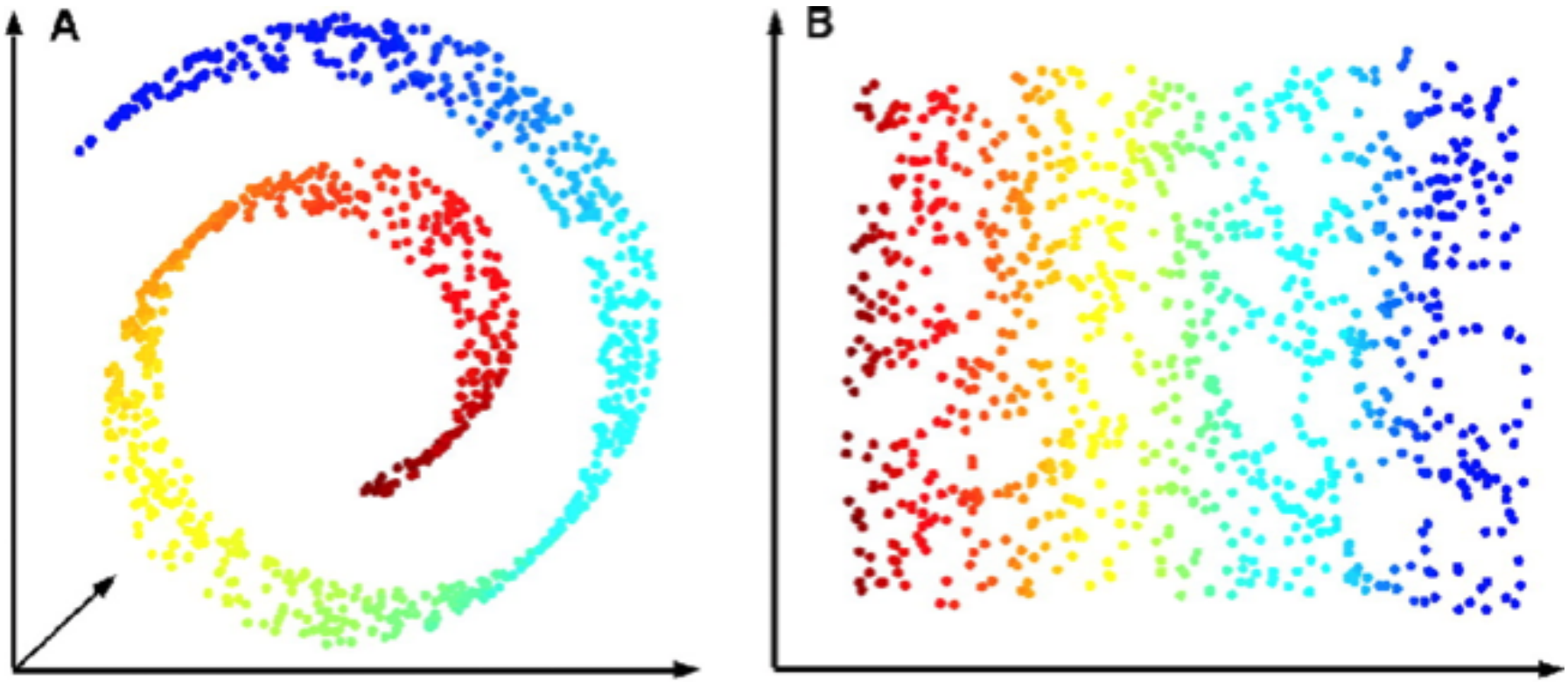


Isometric Mapping (ISOMAP)

- Maintain local isometries in the data (geodesic distance as opposed to Euclidean)



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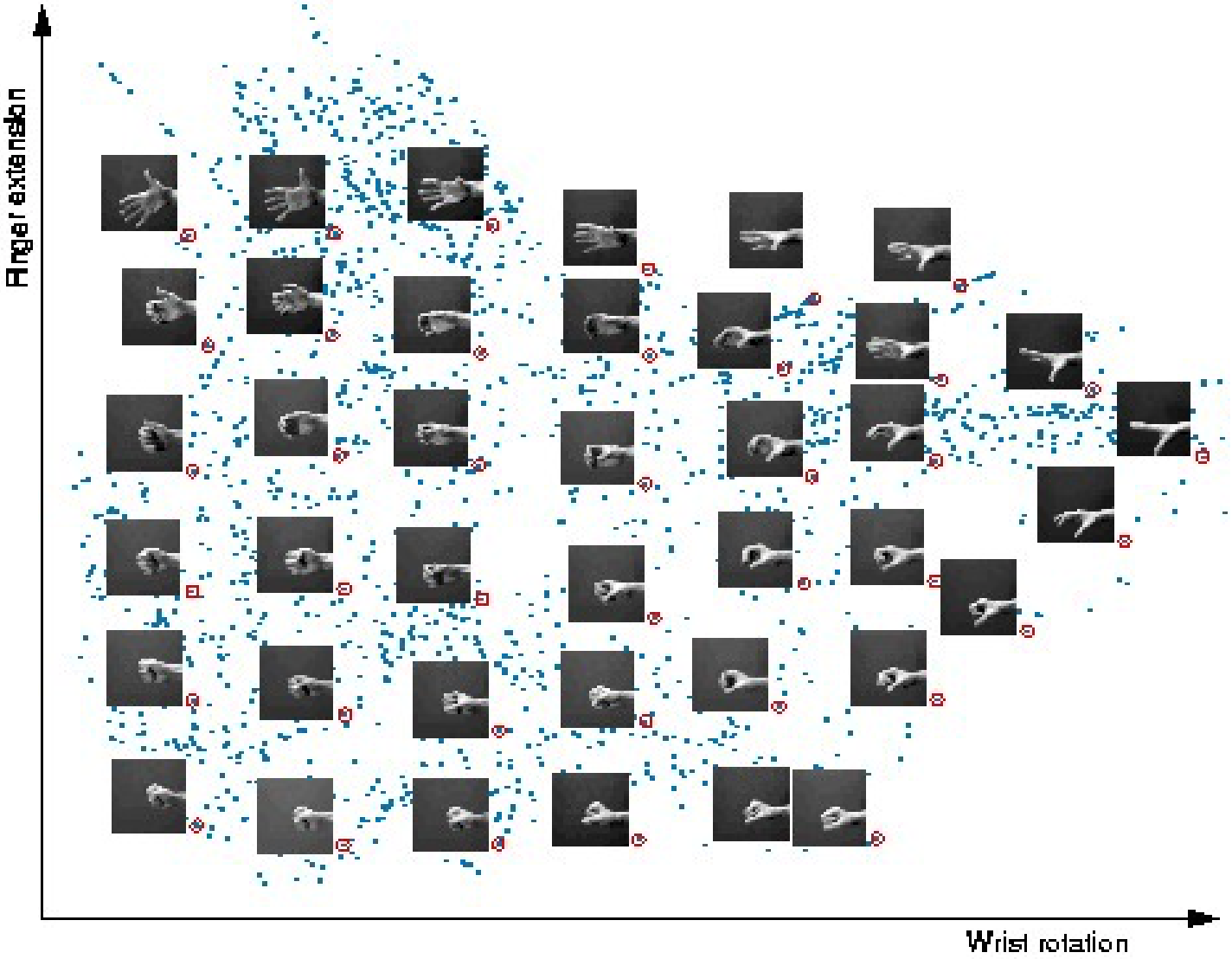
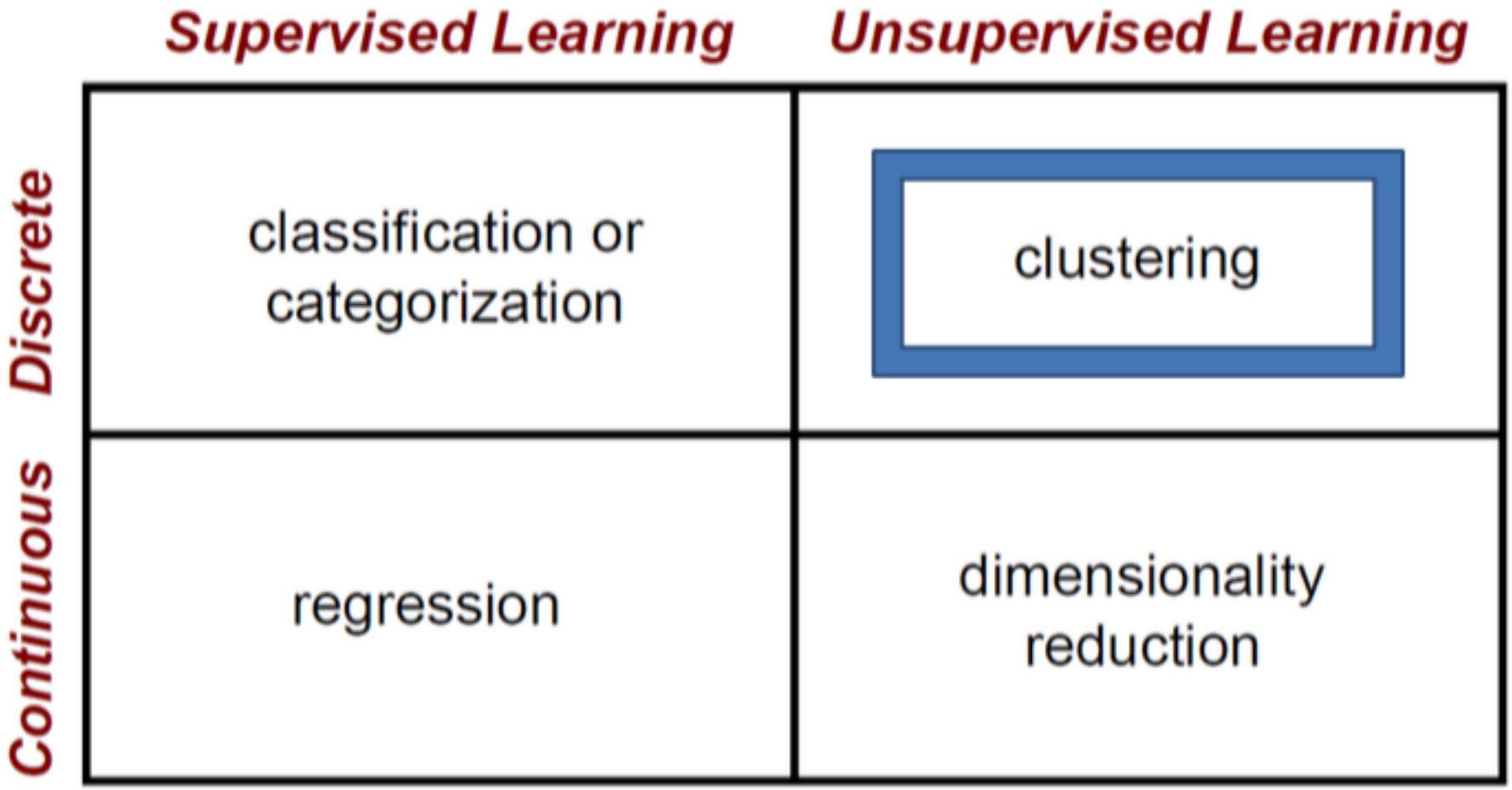


How can ML solve these types of problems? (or at a minimum help?)

- Data clustering



Example 1 - Mapping

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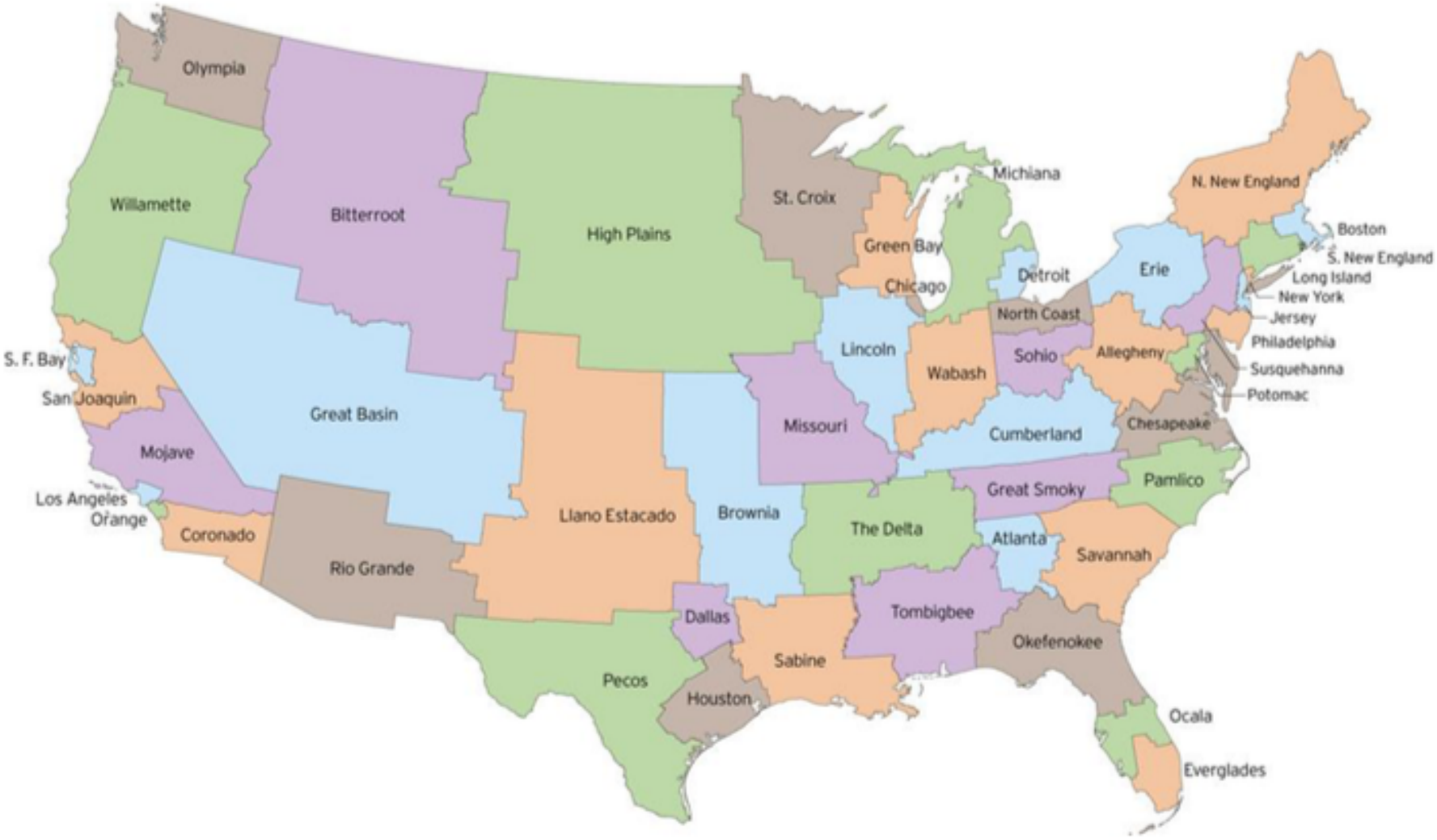


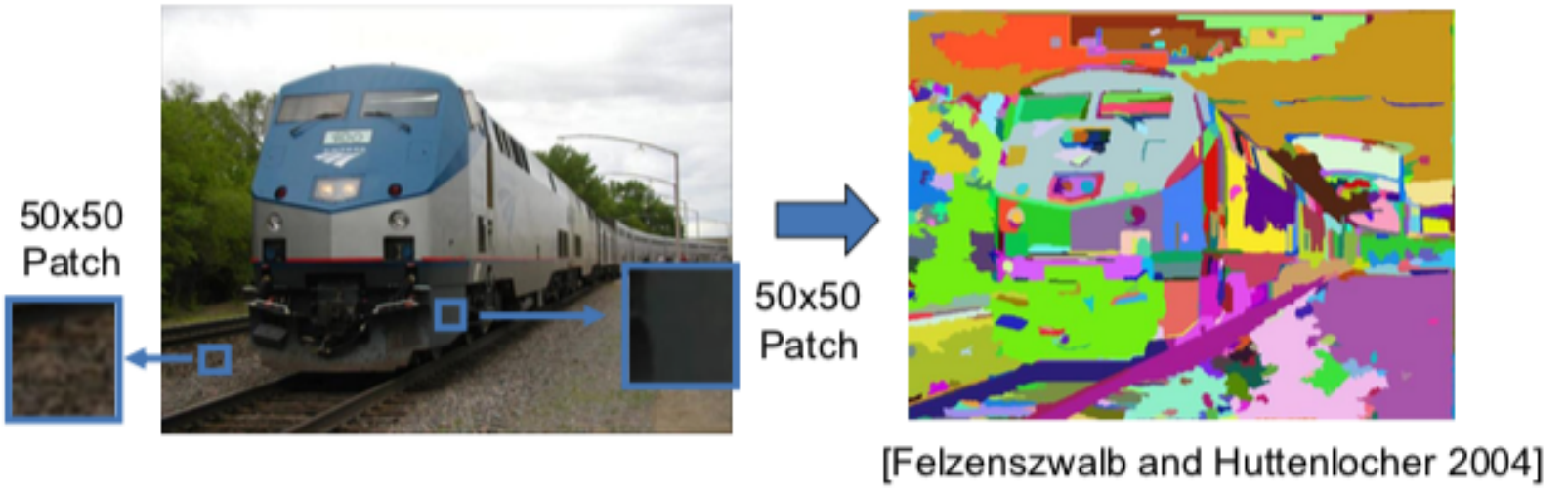
Example 1 - Mapping

Example 2 - Segmentation

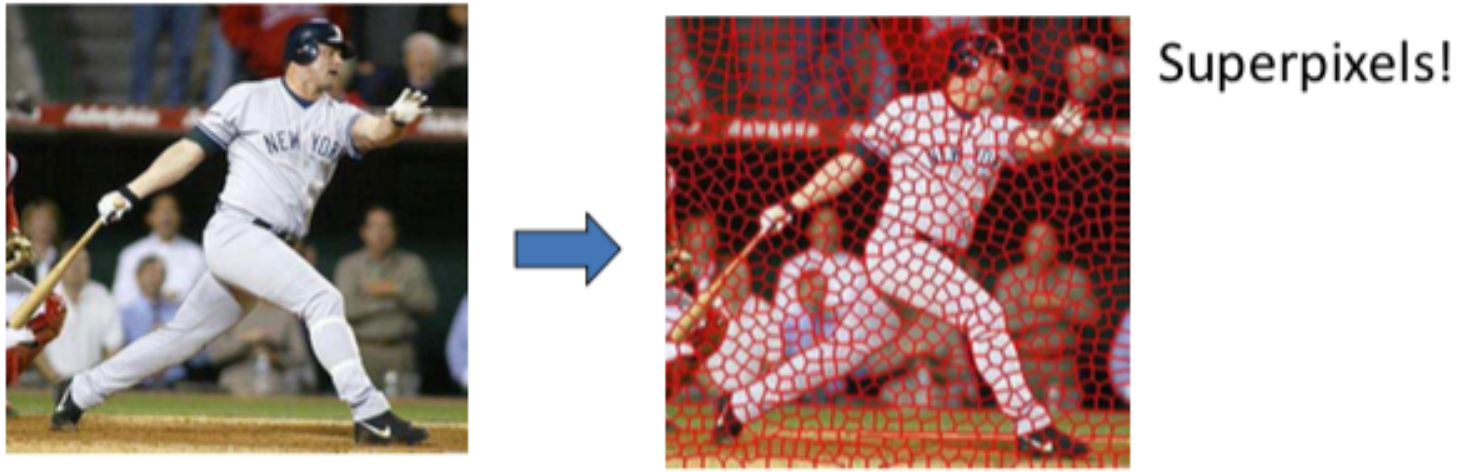
- Break up image into meaningful/similar regions.

Example 2 - Segmentation

- Can help feature support/region support.



[Felzenszwalb and Huttenlocher 2004]



[Hoiem et al. 2005, Mori 2005]

[Shi and Malik 2001]

Derek Hoiem

Example 2 - Segmentation

- Clean cropping (GrabCut: Rother *et al.*, 2004)




Clustering: Basic idea

- 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?

Clustering: Why do we Cluster?

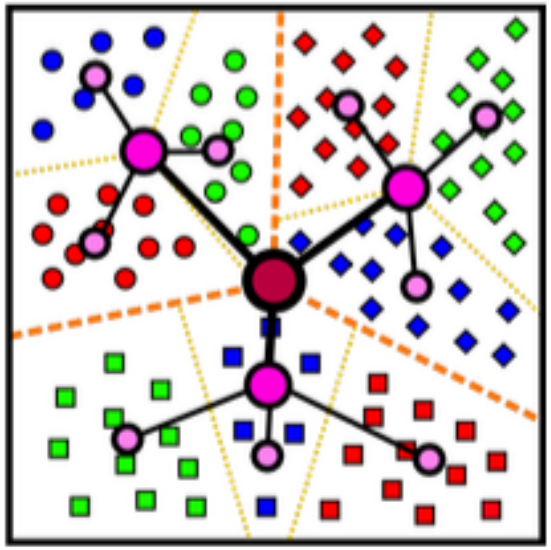
- Summarize/Visualize Data:
  1. Look at large amounts of data
  2. Patch-based compression or denoising
  3. Represent a large continuous vector with the cluster number
- Counting
  1. Histograms of texture, color, SIFT vectors
- Segmentation
  1. Separate the image into different regions
- Prediction/Classification
  1. Images in the same cluster may have the same labels

How do we cluster?

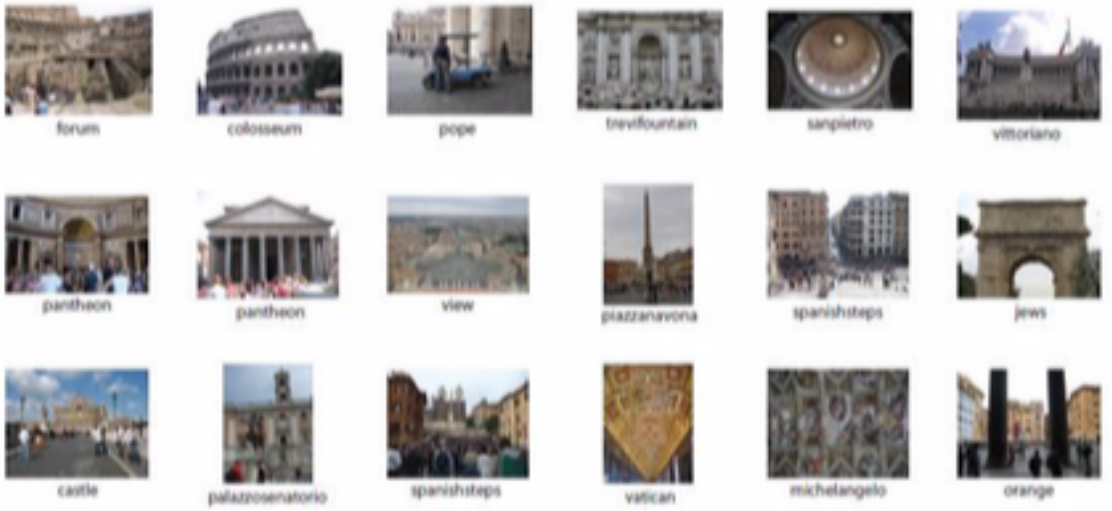
- K-means
  1. Iteratively re-assign points to the nearest cluster center
- Agglomerative clustering
  1. Start with each point as its own cluster and iteratively merge the closest clusters
- Mean-shift clustering
  1. Estimate modes of pdf
- Spectral clustering
  1. Split the nodes in a graph based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

Applications for each: K-Means

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



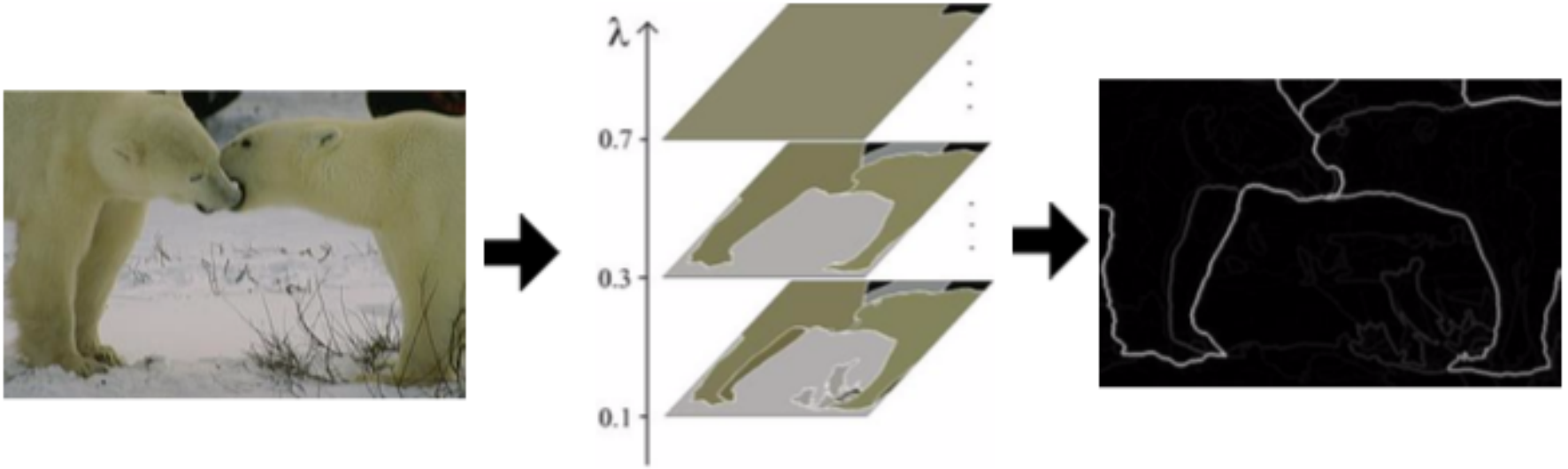
Quantization for computing histograms



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

Applications for each: Agglomerative

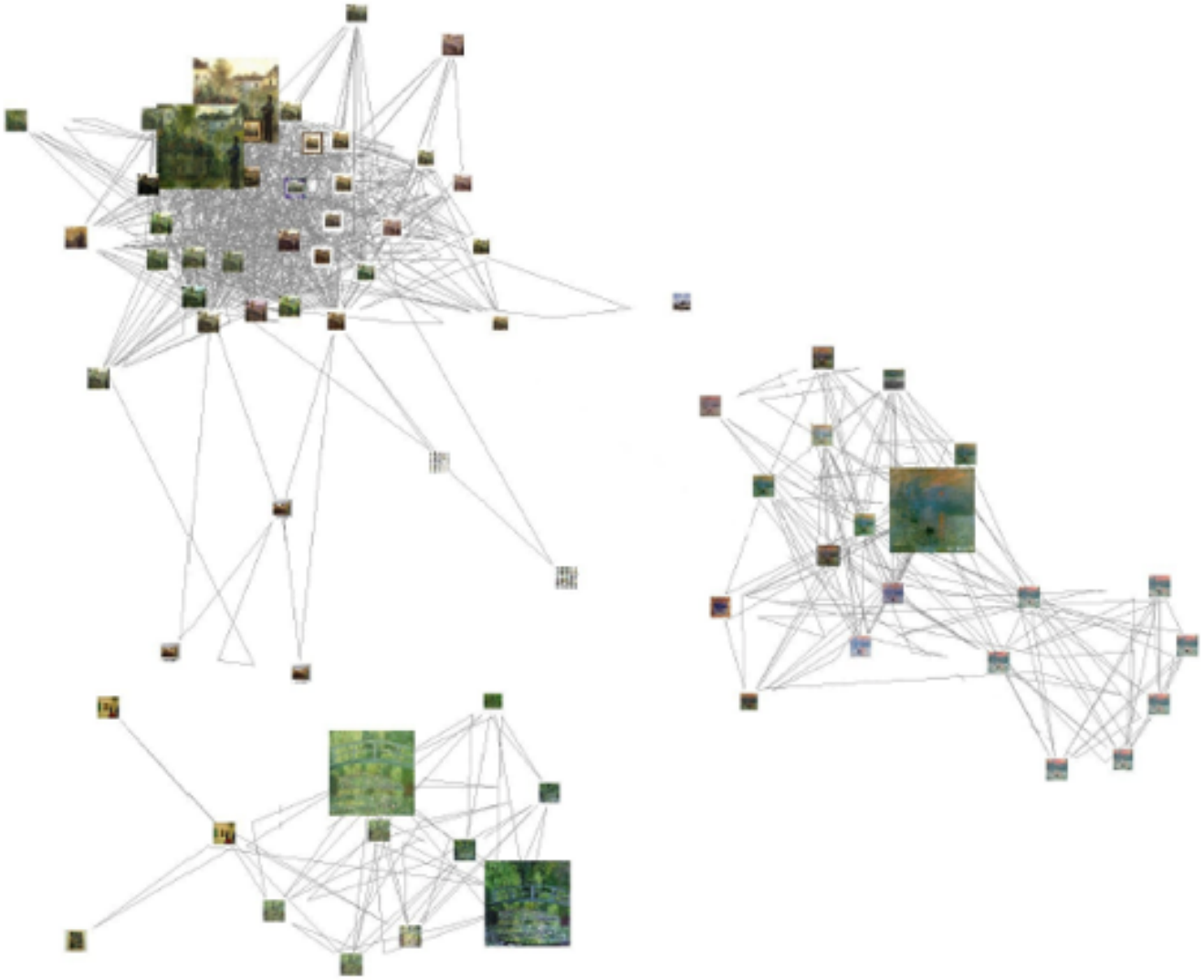
- Image segmentation: Agglomerative clustering
  1. More flexible with distance measures (e.g., can be based on boundary prediction)
  2. Adapts better to specific data
  3. Hierarchy can be useful



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

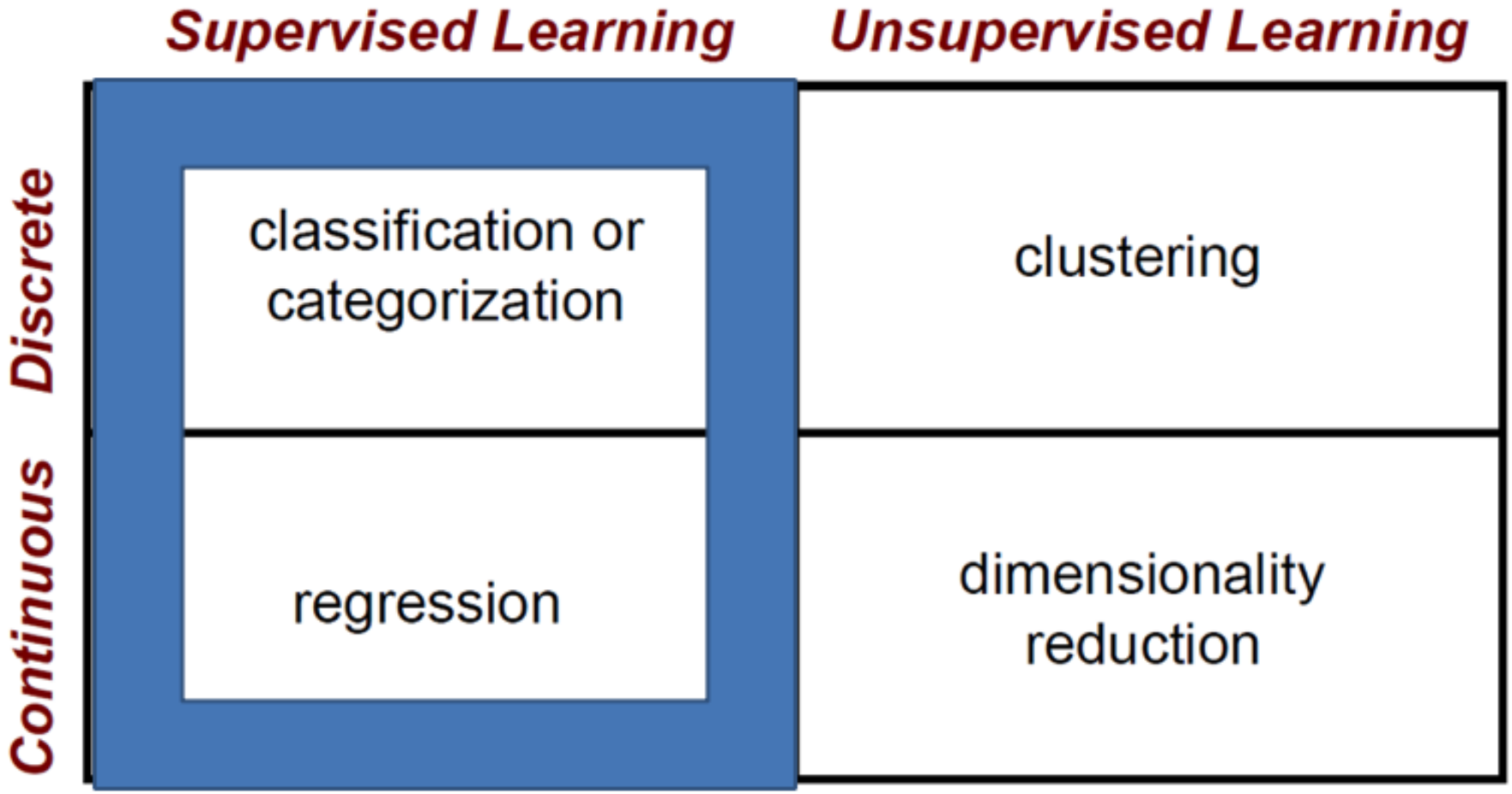
Applications for each: Spectral

- Image segmentation: Spectral clustering
  1. Useful for determining relevance of one object to another
  2. Segmentation



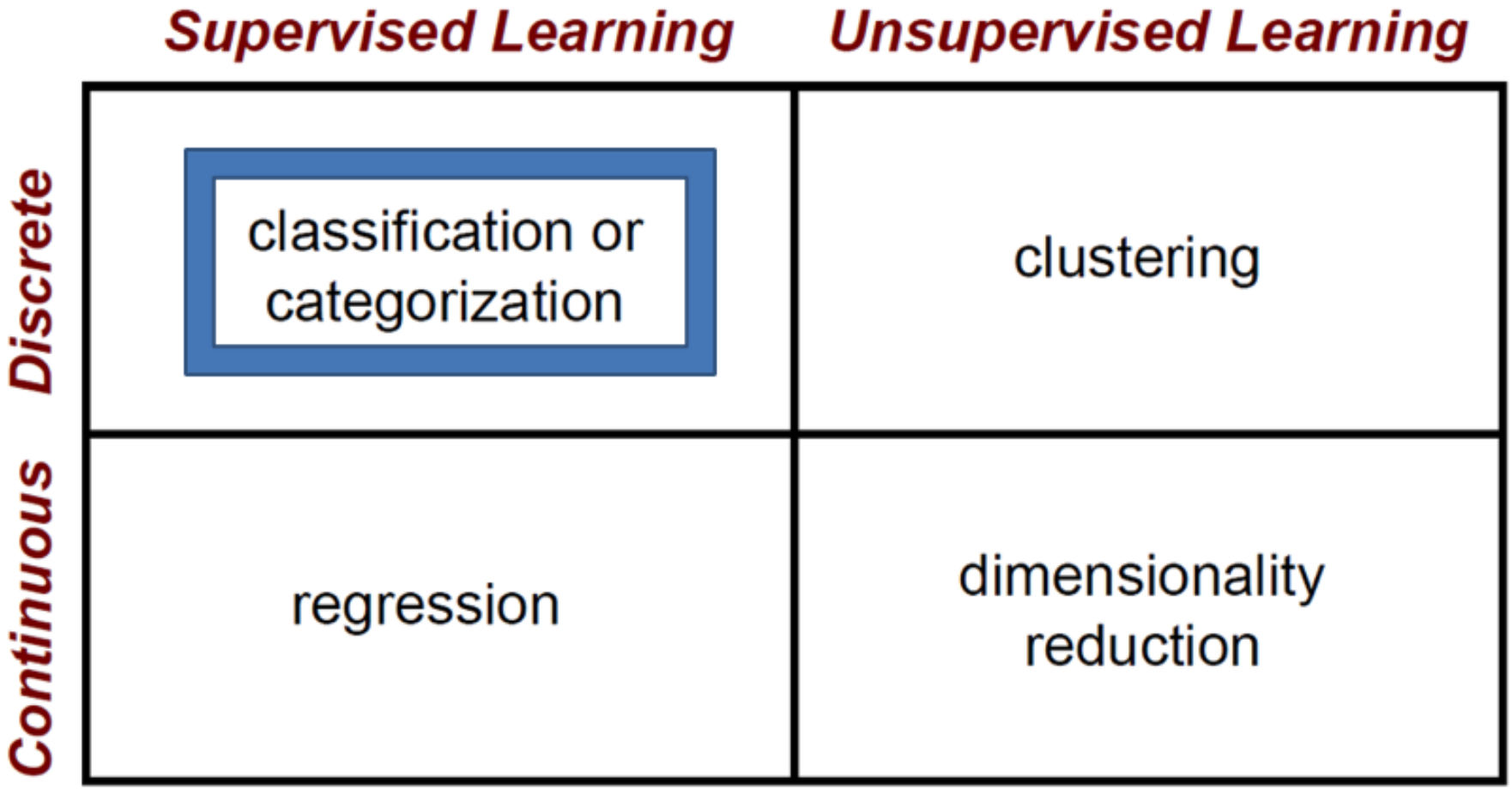
This is all unsupervised - what about supervised?

- What's the difference????



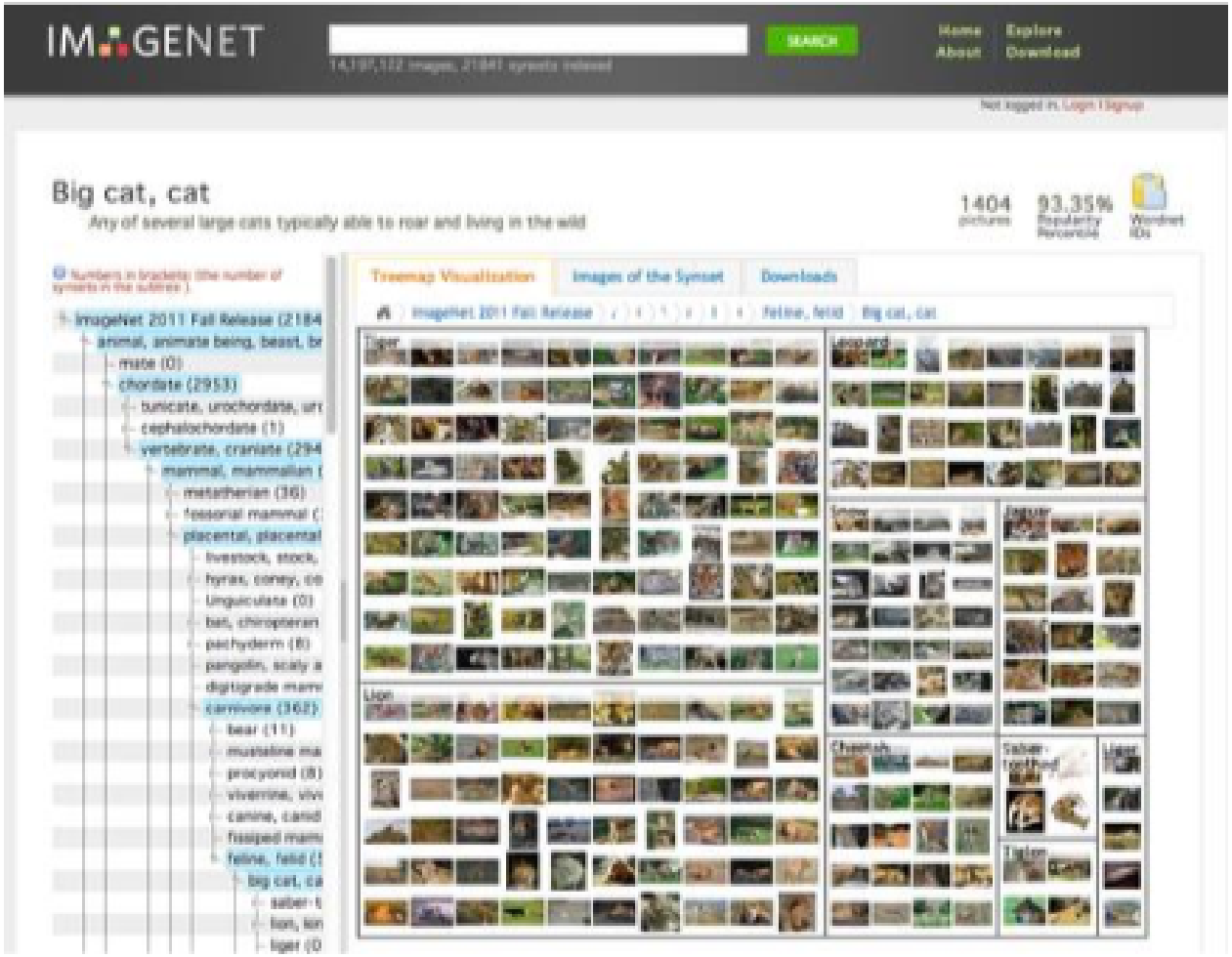
Let's have a look at classification

- Need some "additional" information: classes, labels, etc.



Recall: ImageNet

- Images for each category of WordNet
- 1000 classes
- 1.2mil images
- 100k test
- Top 5 error



Data Separation: Train, Validate, Test

- Need to separate the data into different categories for each class

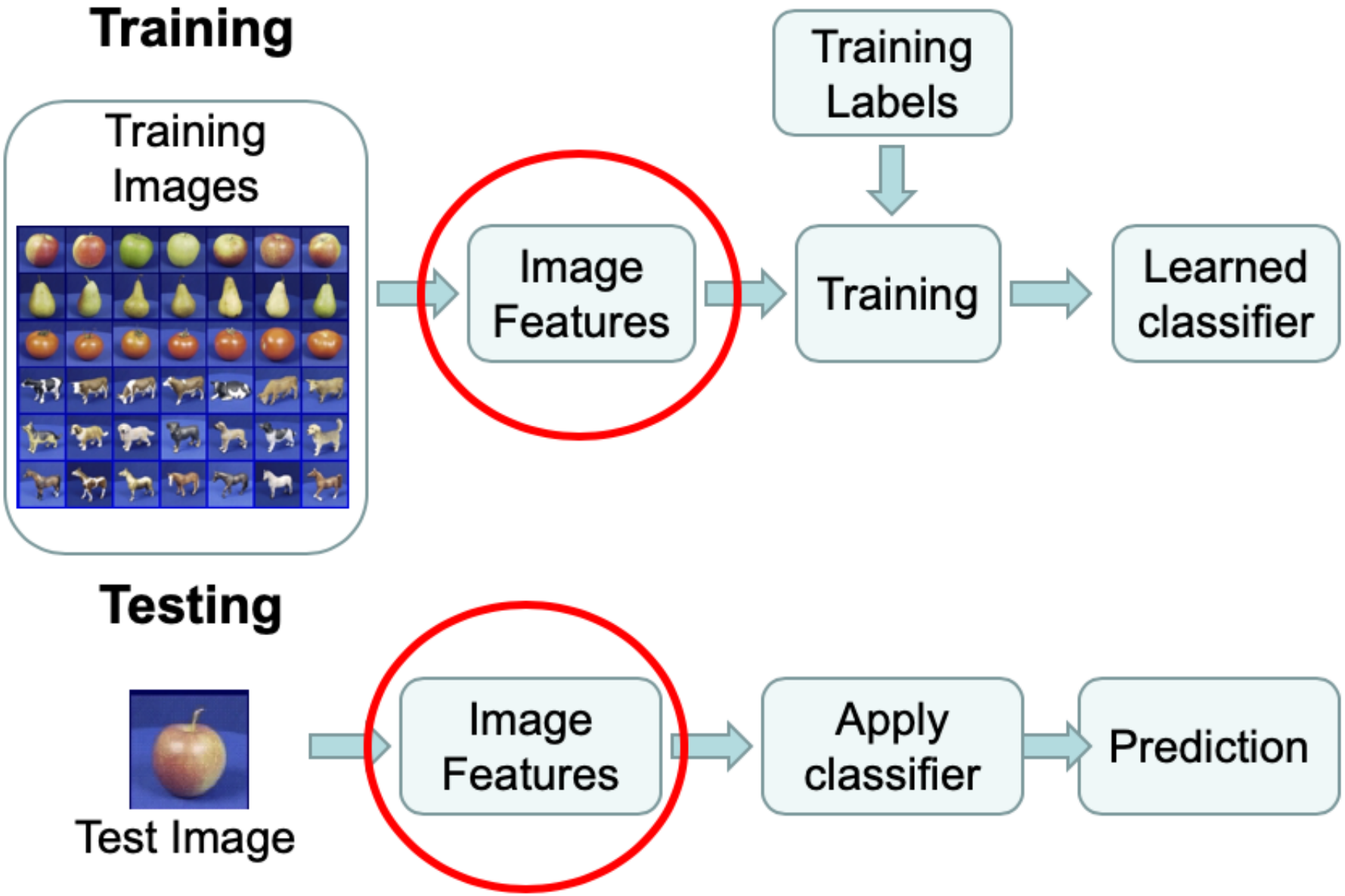
- Train classifier

- Measure error
- Tune model hyperparameters

- Secret labels
- Measure error

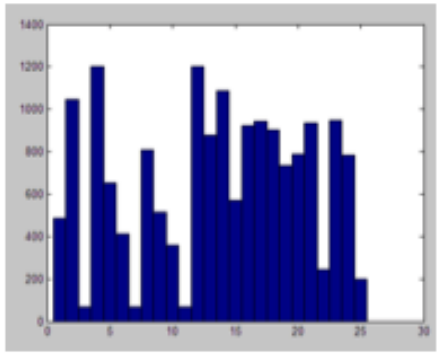
Random train/validate splits = cross validation

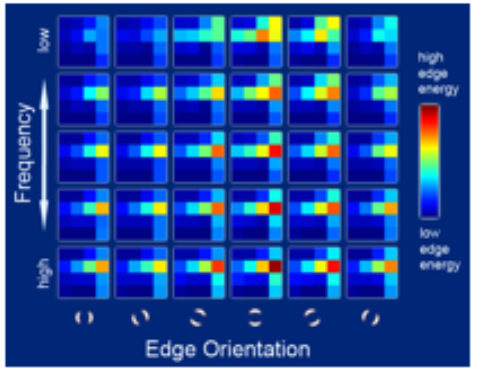
Classification Architecture: In General



What features???

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

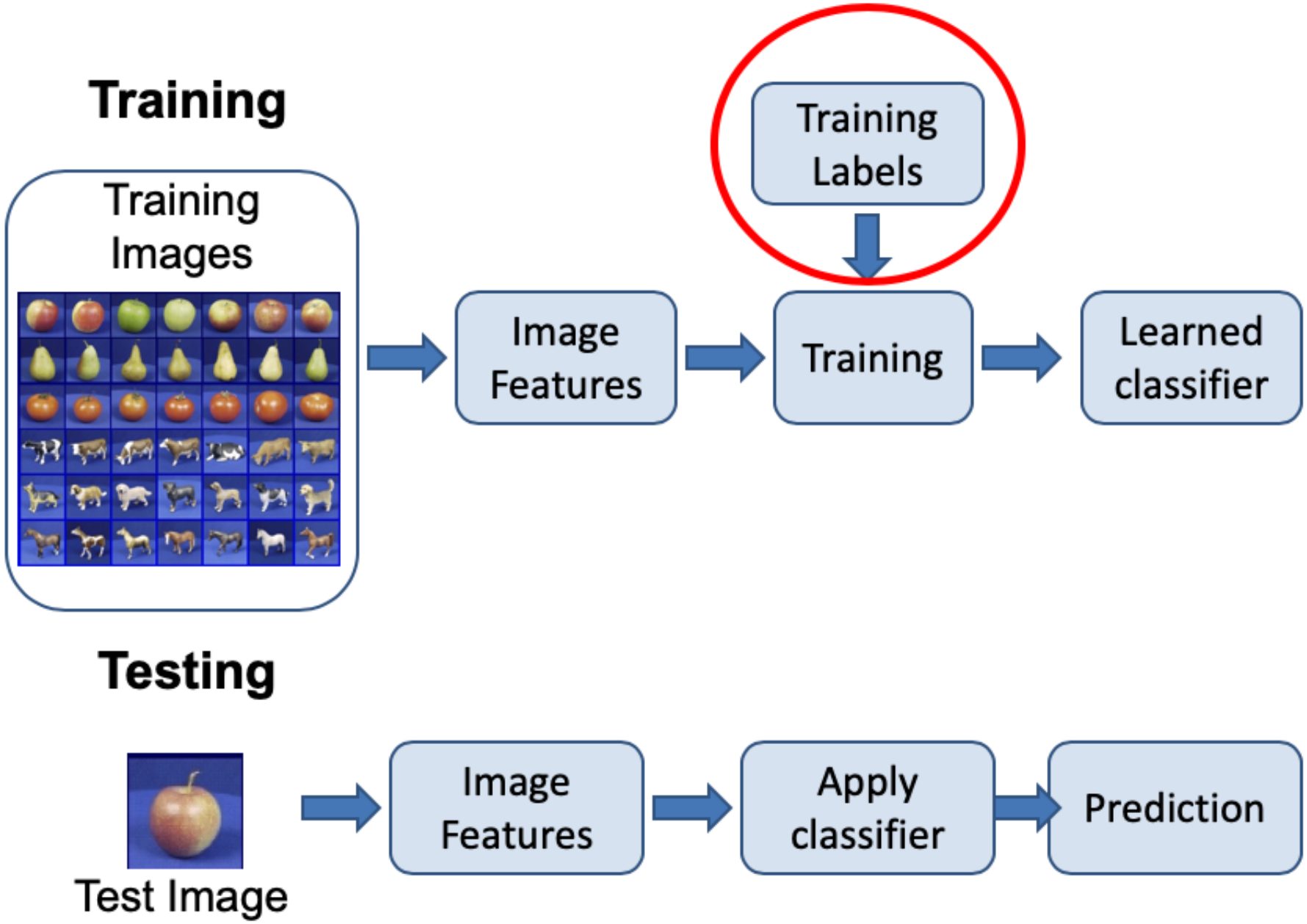




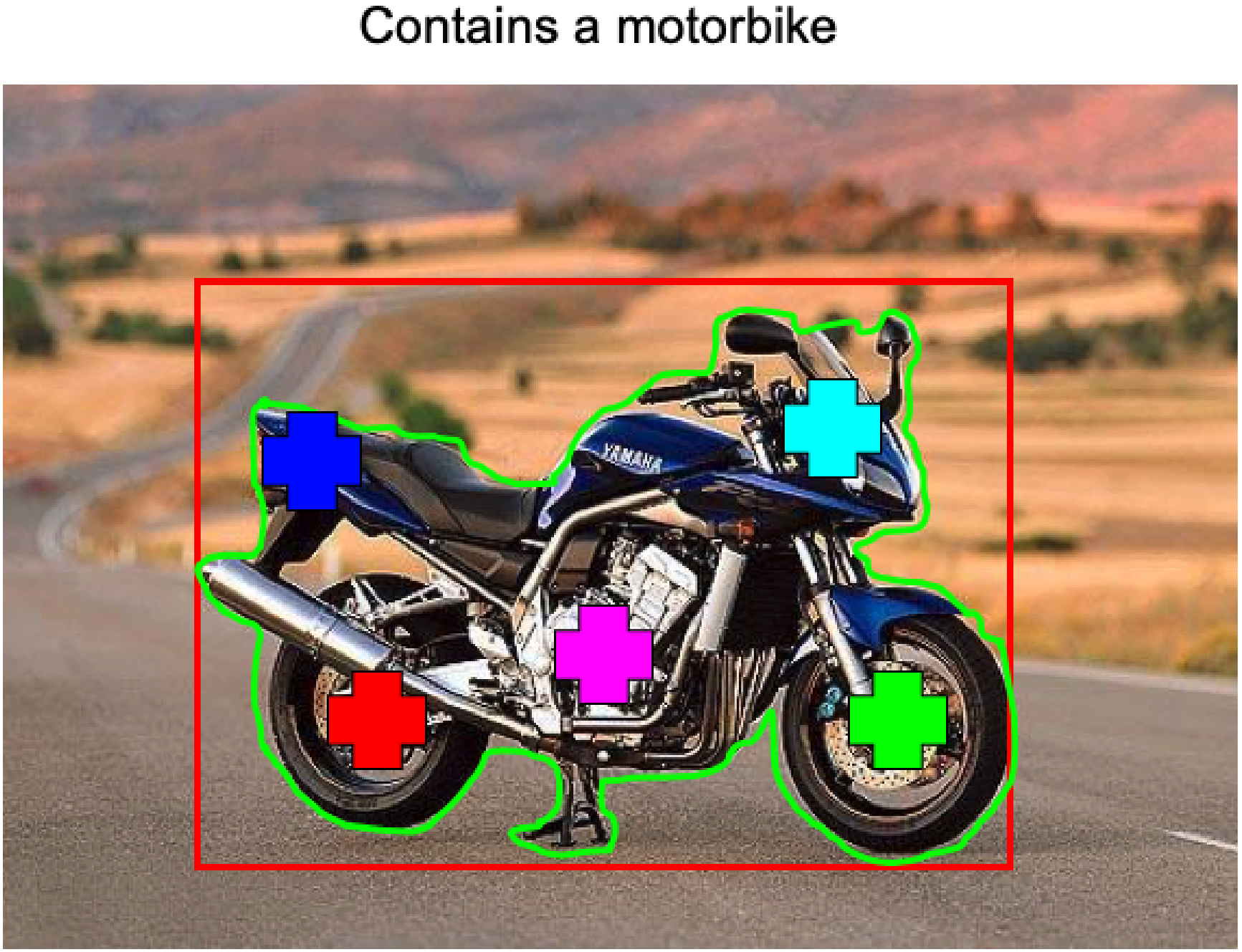
Data Representation for Classification

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

How do we "Label" classes?



Recognition $\rightarrow$ Data Association



Level of Supervision May Vary

'Semi-supervised': small partial labeling

Need to select "Good" training images

Good training example?

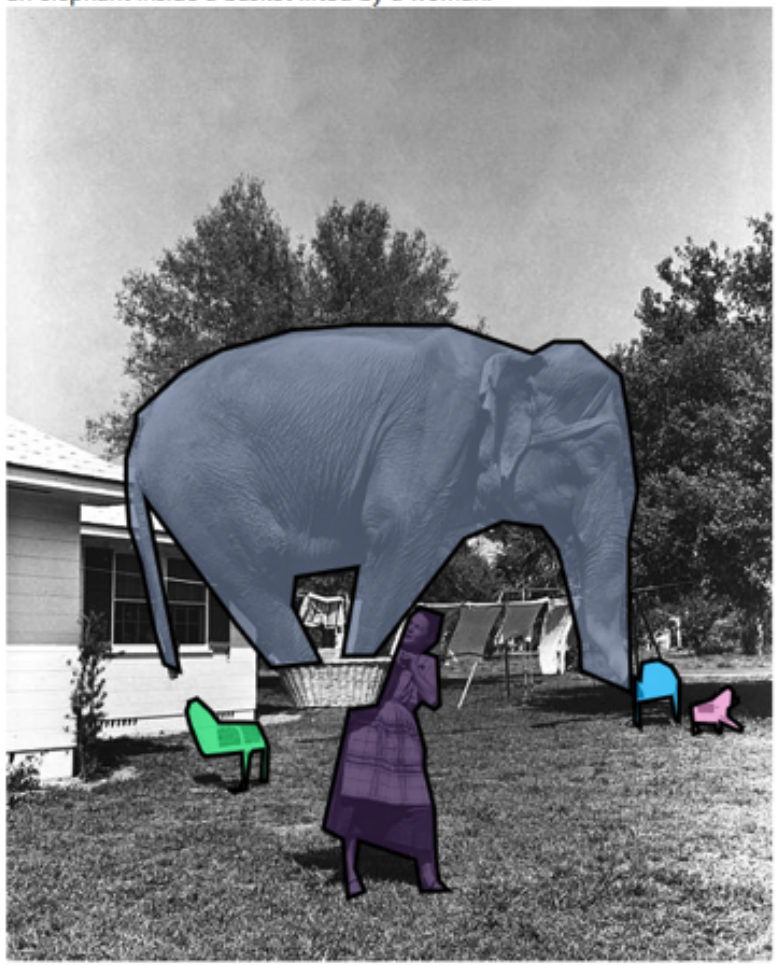
Need to select "Good" labels (MS-COCO)

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

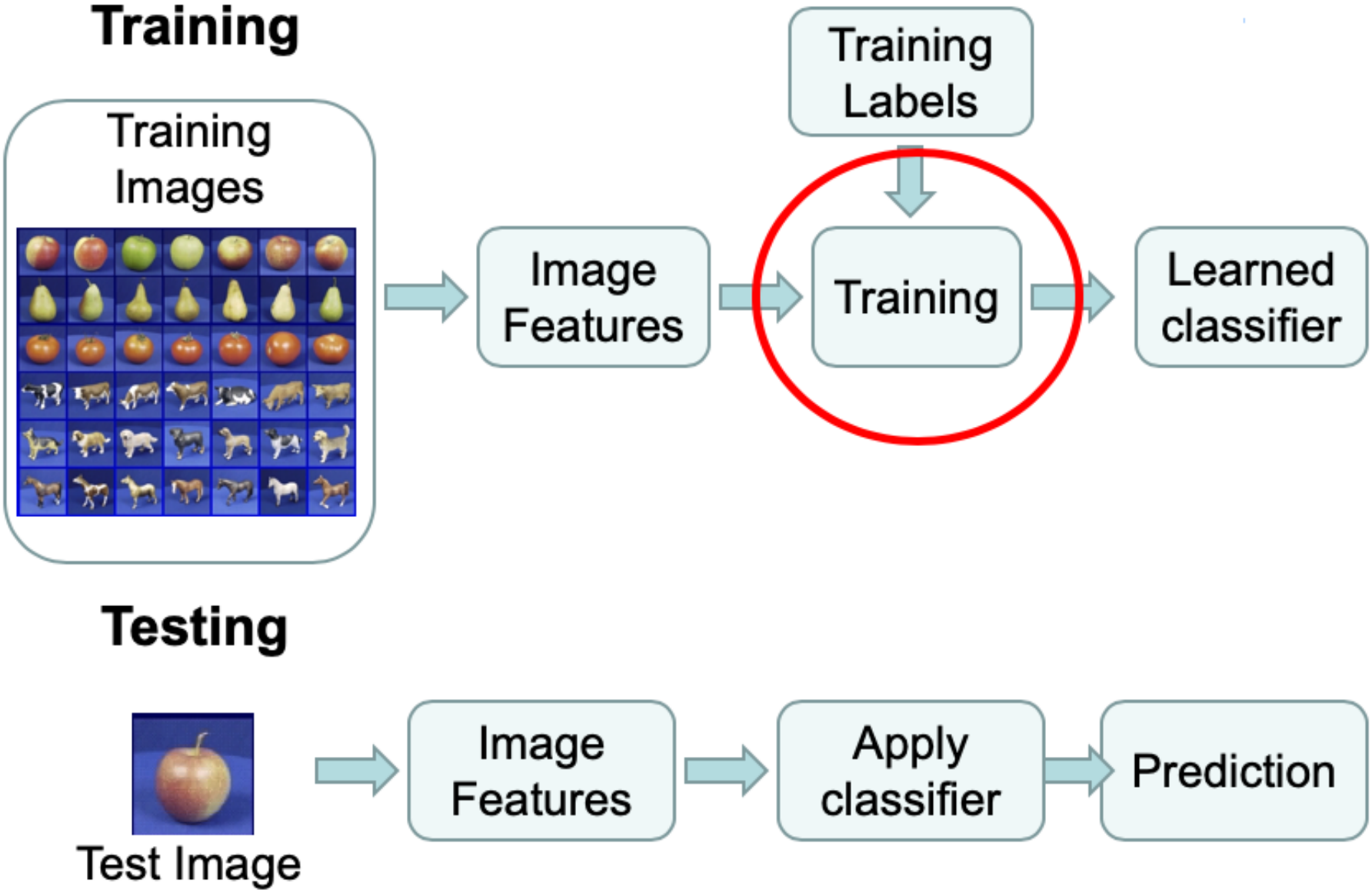
Good labels?

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.



ML Framework - Training



ML Framework

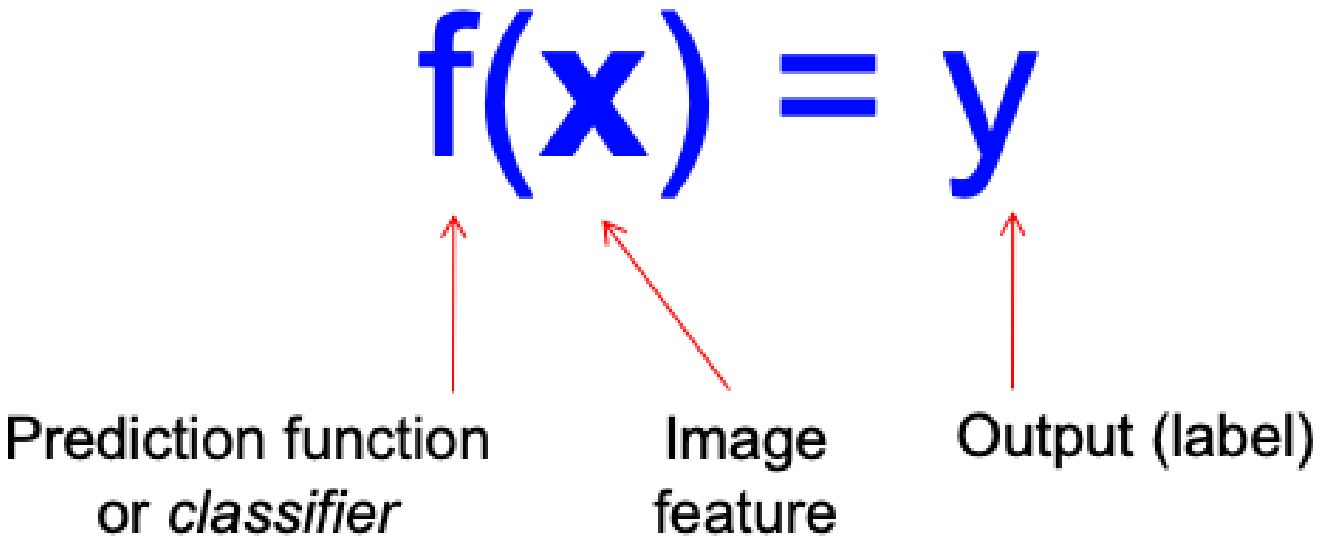
- Apply a prediction function to a feature representation of the image to get the desired output:

f() = “apple”

f() = “tomato”

f() = “cow”

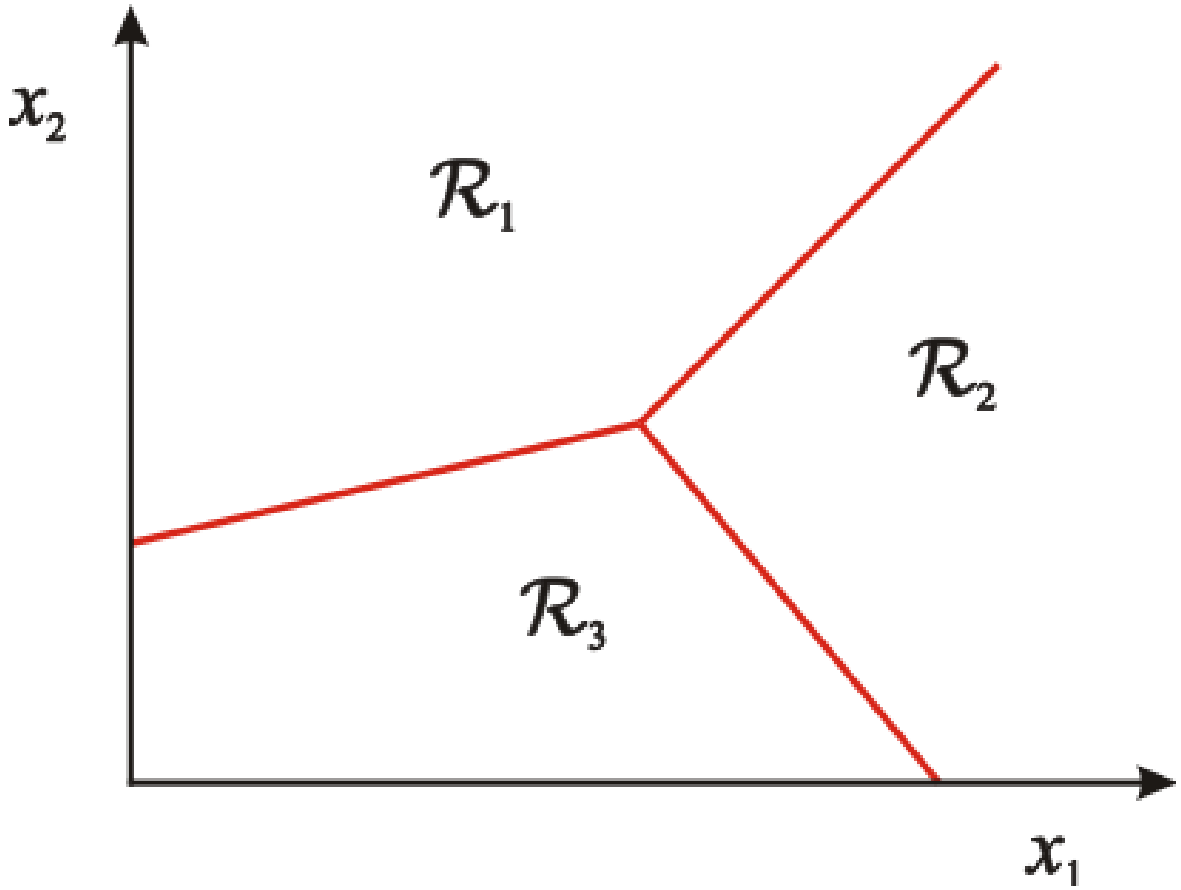
ML Framework



- **Training:** Given a *training set* of labeled samples $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$
  Estimate the prediction function $f(\cdot)$ by minimizing the prediction error on the training set.
- **Testing:**. Apply $f(\cdot)$ to some unseen *test sample* x_t and output the prediction $y_t = f(x_t)$ to classify x_t.

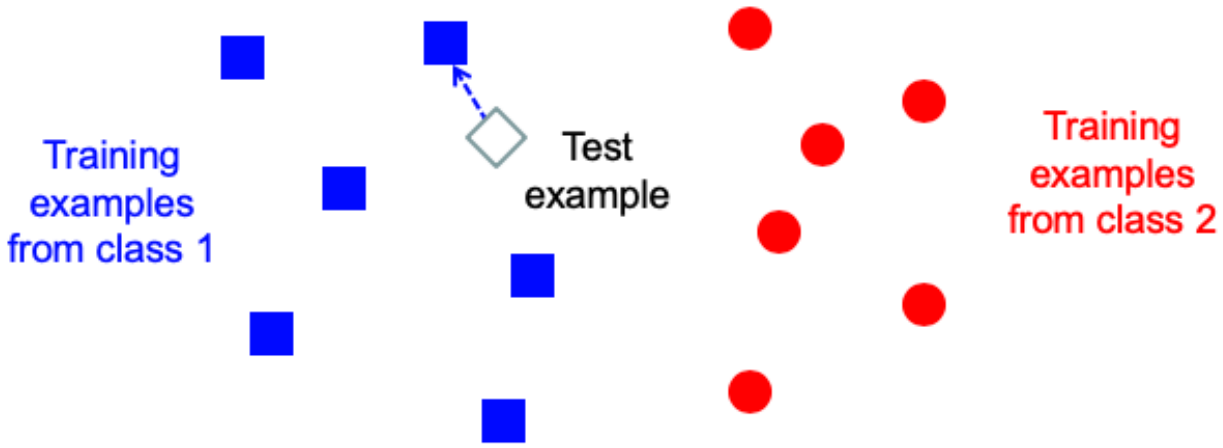
Classification

- Assign x_t to one (or more) classes.
- A decision rule divides input space into decision regions separated by decision boundaries.



Nearest Neighbor Search

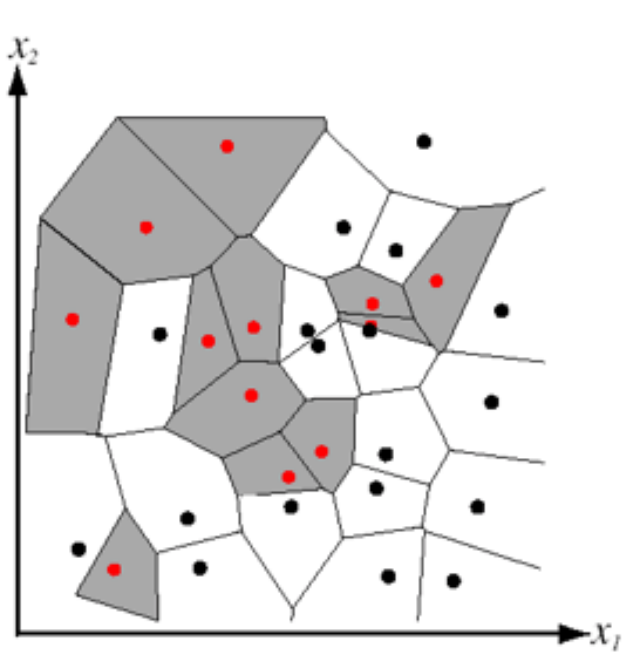
- Can range from simple to complex!
- Classify x_t as $y_t = f(x_t)$ that is "closest to" y_t in the predictor space.



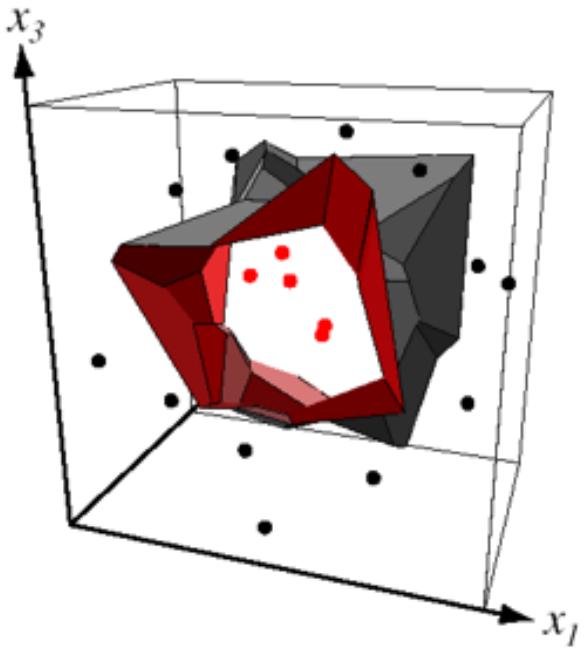
- Can visualize decision boundary via Voronoi diagram

Decision Boundary for NN Classifier

- Divides input space into decision regions separated by decision boundaries – Voronoi



from Duda *et al.*

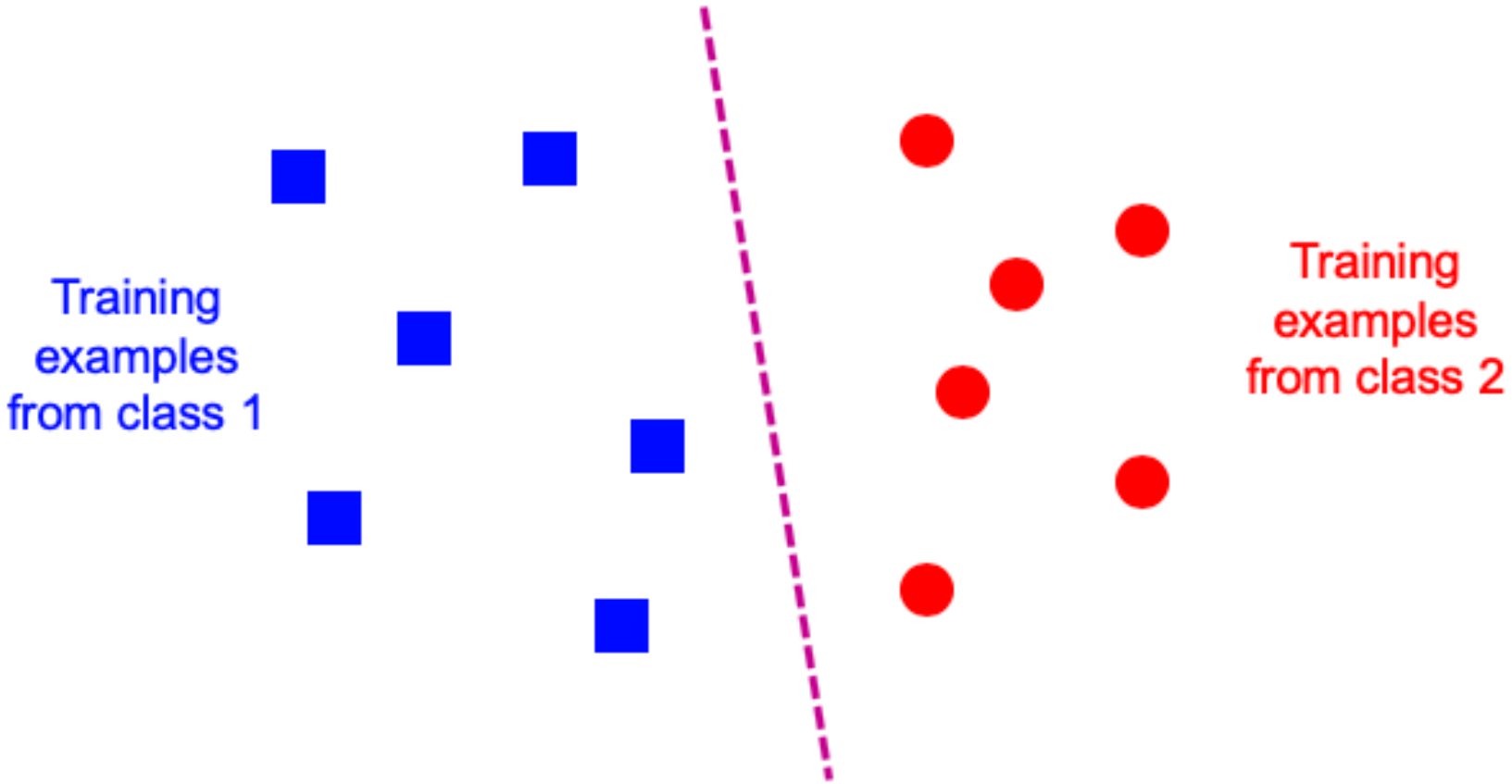


Voronoi partitioning of feature space for two-category 2D and 3D data

Source: D. Lowe

Examples: How to design other "Classifiers"

- Linear:
  - Find a linear function to separate the classes (PCA often works well here)



Examples: How to design other "Classifiers"

- Naive Bayes (more when we discuss Variational Autoencoders):
  - Define the conditional probability model over classes C_k

$$p(C_k|x_1, x_2, \ldots, x_n) = \frac{1}{Z} p(C_k) \prod_{i=1}^{n} p(x_i|C_k)$$

where Z is the evidence defined by

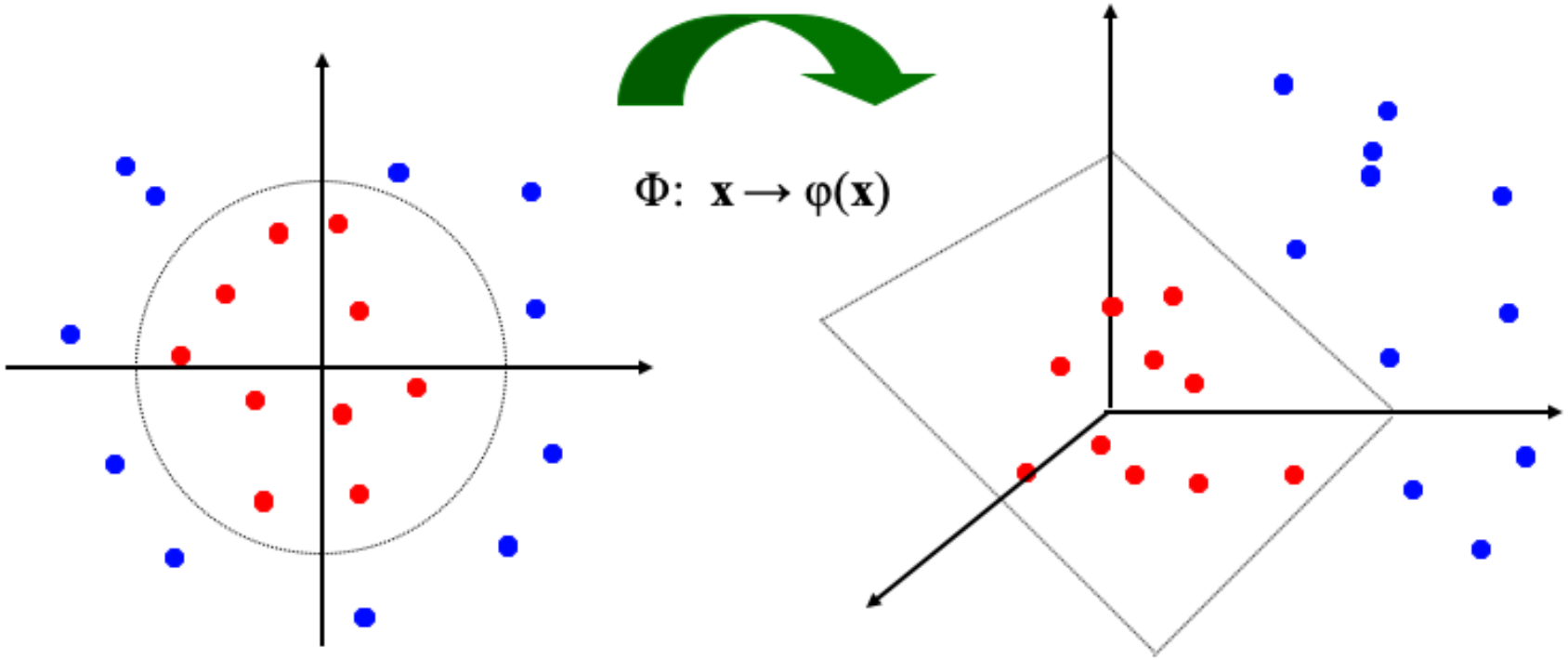
$$Z = p(\mathbf{x}) = \sum_k p(C_k) p(\mathbf{x}|C_k)$$

  - The classifier is then given by:

$$\hat{y} = \underset{k \in \{1,\ldots,K\}}{\operatorname{argmax}} \; p(C_k) \prod_{i=1}^{n} p(x_i|C_k)$$

Examples: How to design other "Classifiers"

- Nonlinear Support Vector Machine (SVM) (can also use Linear SVM on some data)
  - Map the original input space to some higher-dimensional feature space where the training set is separable



Examples: How to design other "Classifiers"

- Nonlinear Support Vector Machine (SVM) (can also use Linear SVM on some data)
  - So called *kernel trick* - Define a kernel function s.t.

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$$

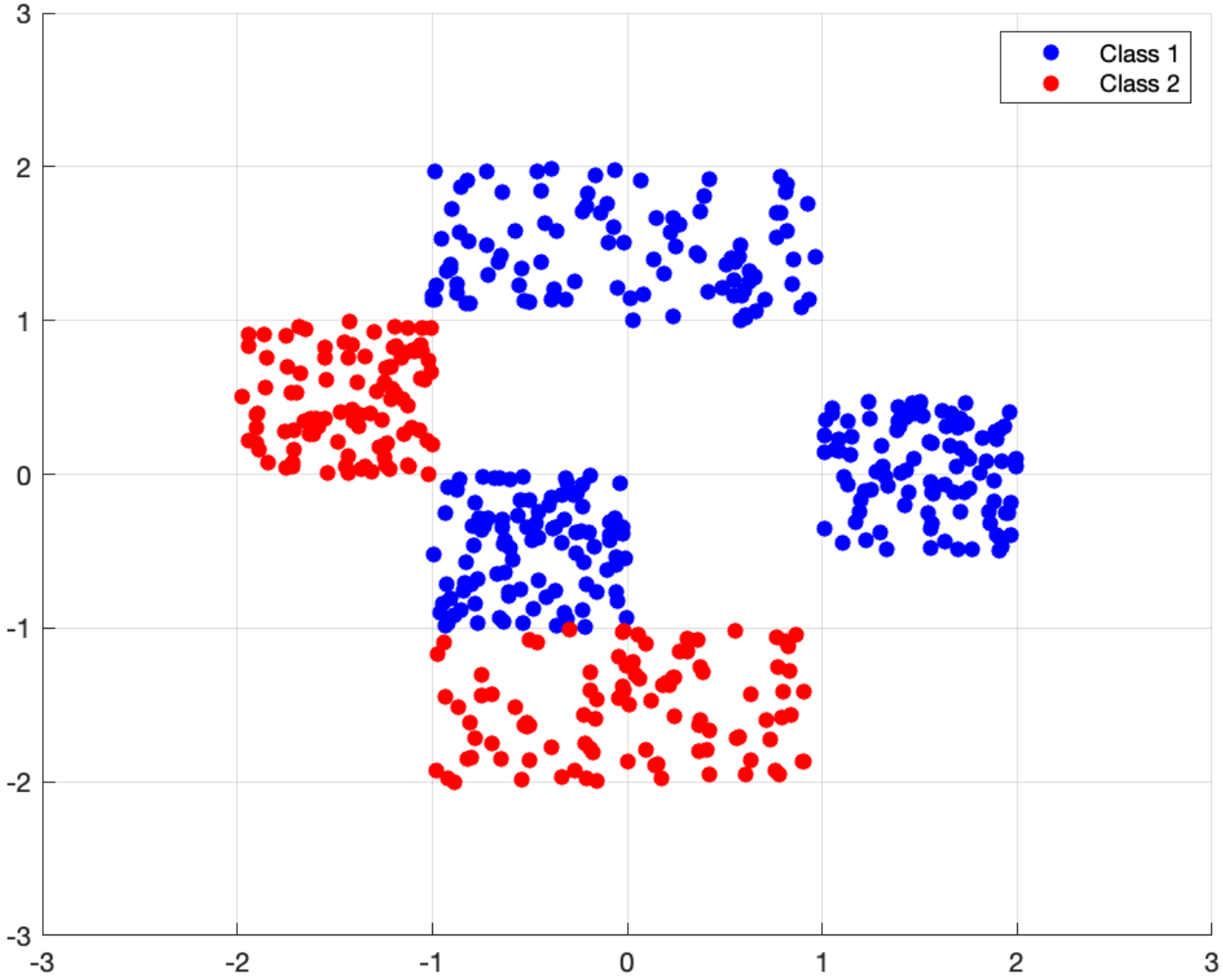
  - Produces a nonlinear decision boundary in the original feature space:

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

  - Generally use Radial-Basis functions for kernel

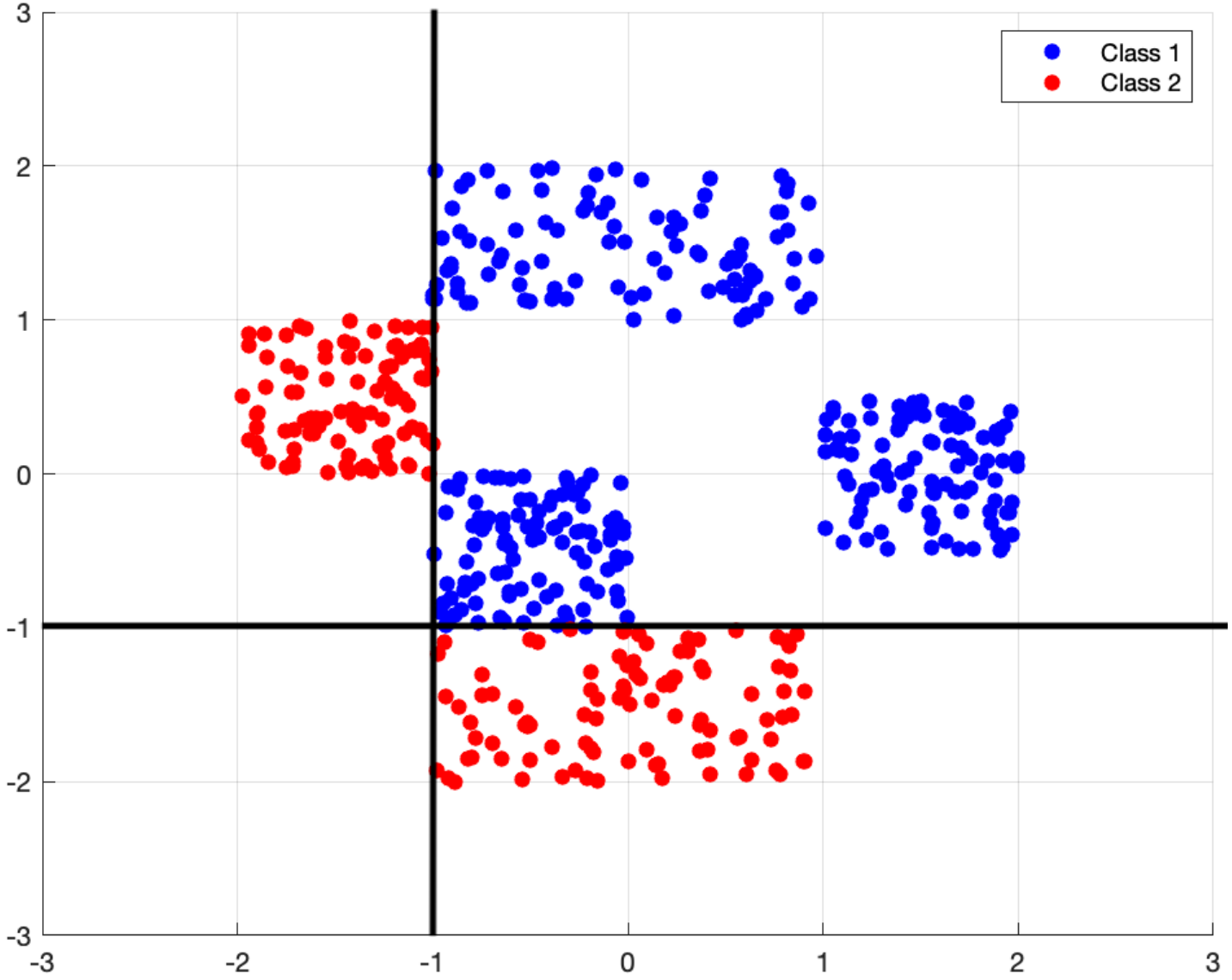
Examples: How to design other "Classifiers"

- Concrete example:



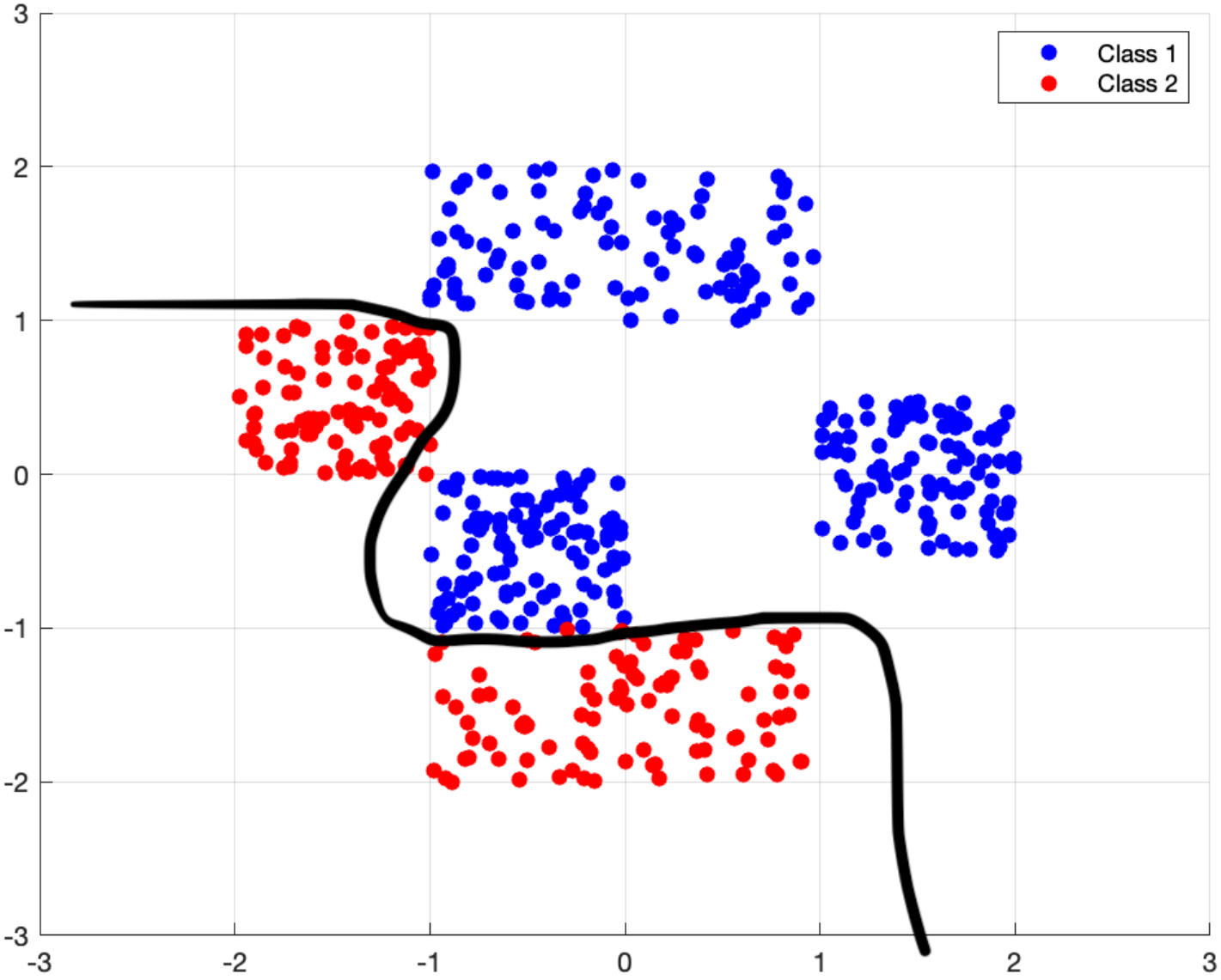
Examples: How to design other "Classifiers"

- Concrete example:



Examples: How to design other "Classifiers"

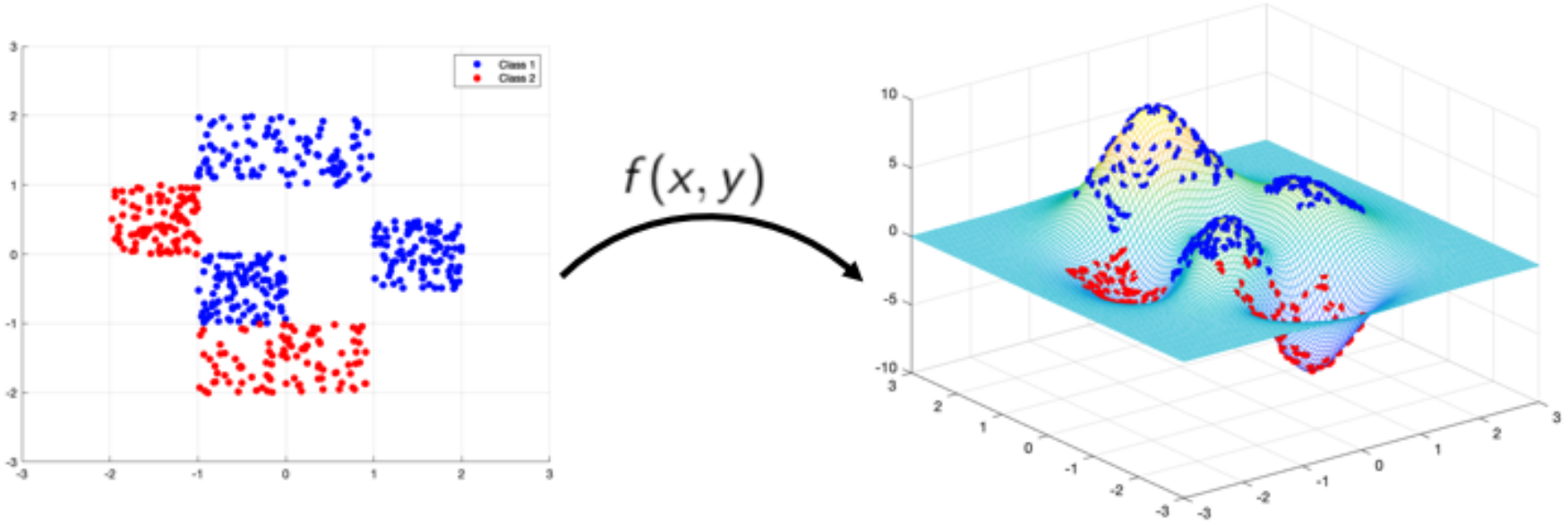
- Concrete example:



Examples: How to design other "Classifiers"

- Suppose we're "allowed" to increase the dimension by 1

$$f(x,y) = 3(1-x)^2 e^{(-(x^2)-(y+1)^2)} - 10\left(\frac{x}{5} - x^3 - y^5\right) e^{(-x^2-y^2)} - \frac{1}{3} e^{(-(x+1)^2-y^2)}$$



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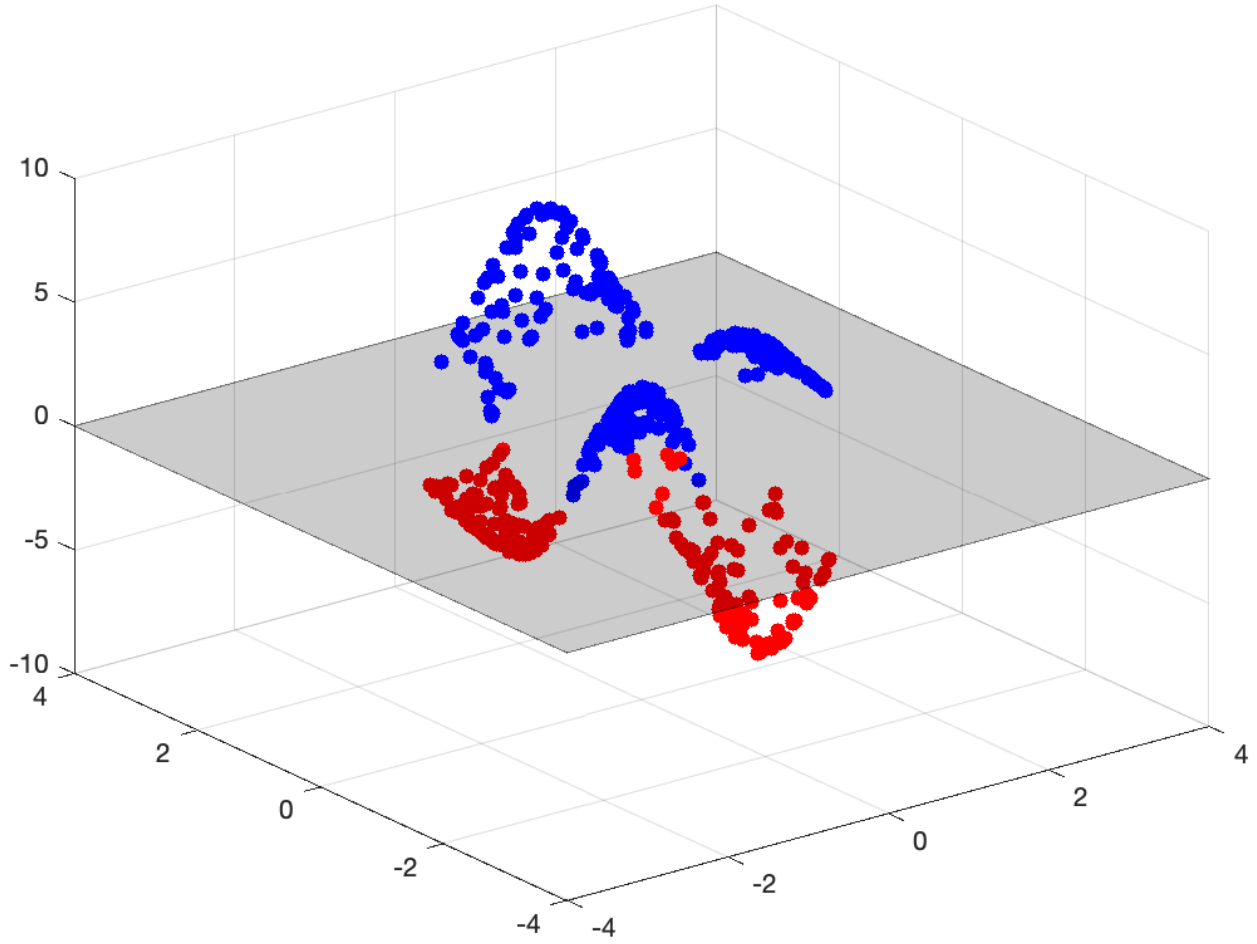


Multi-Class SVMs?

- As you might imagine, as the number of classes increases so does the complexity of "finding" a nonlinear mapping to do what we want:
  - We can " sort of " claim this is what neural networks attempt to accomplish
- Another approach is attempt to combine multiple two-class SVMs
  1. One vs. the other classes:
     - Training: learn an SVM for each class vs. the others
     - Testing: apply each SVM to test the input sample and assign to it the class of the SVM that returns the highest decision value
  2. One class vs. one class:
     - Training: learn an SVM for each pair of classes
     - Testing: each learned SVM "votes" for a class to assign to the test example

Classifiers in general (feature-based)

- **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)

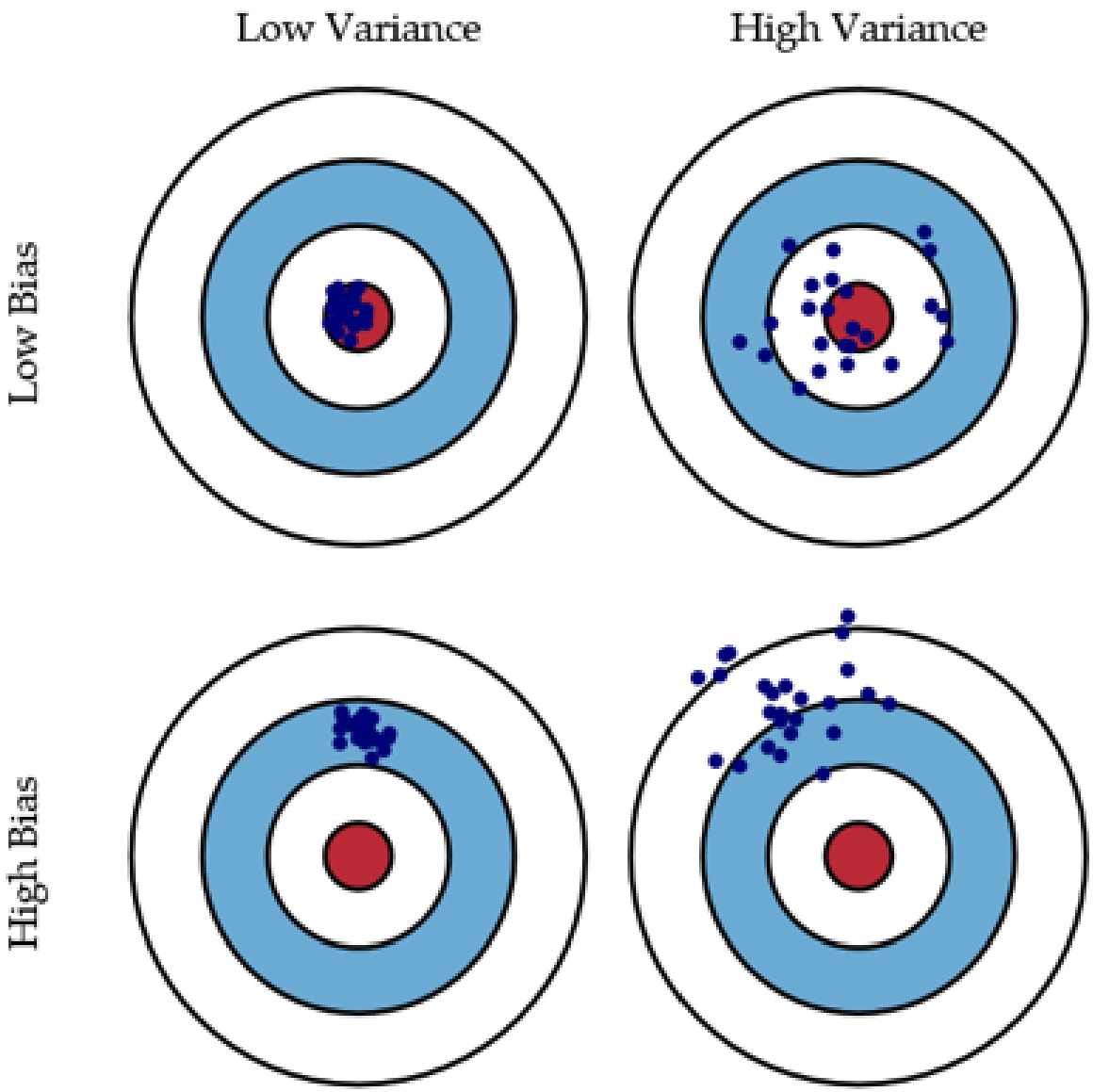
- How well does a learned model generalize from the data it was trained on to a new test set?

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

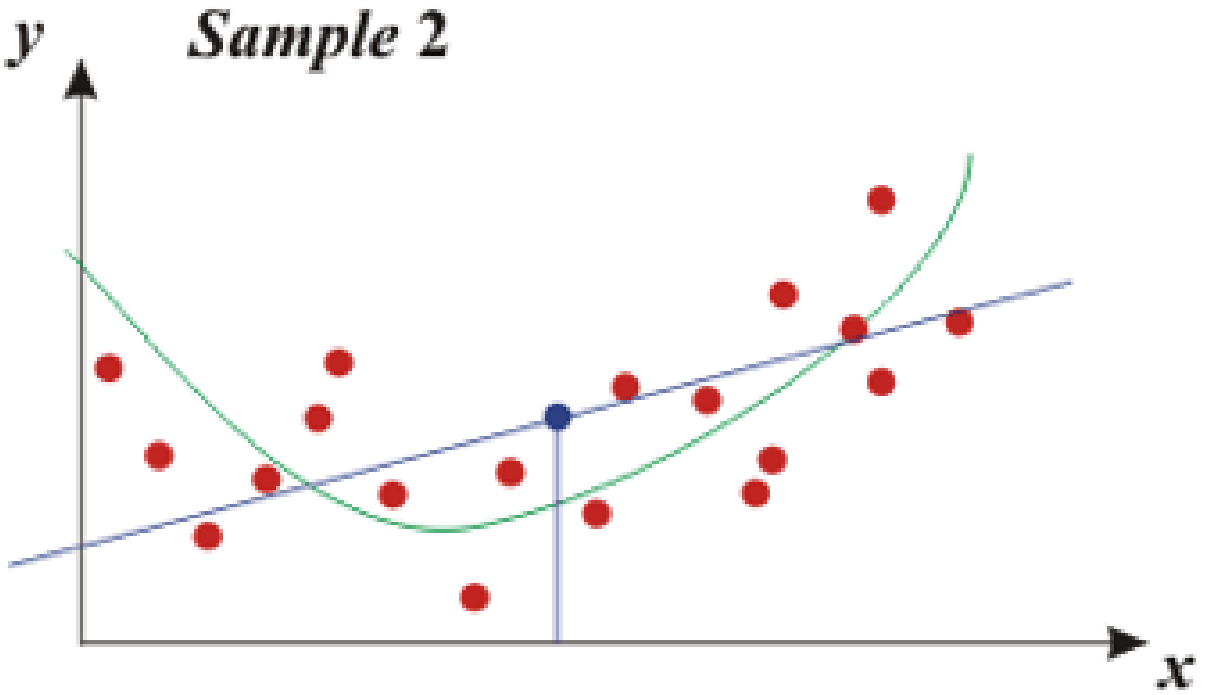


Bias = accuracy

Variance = precision

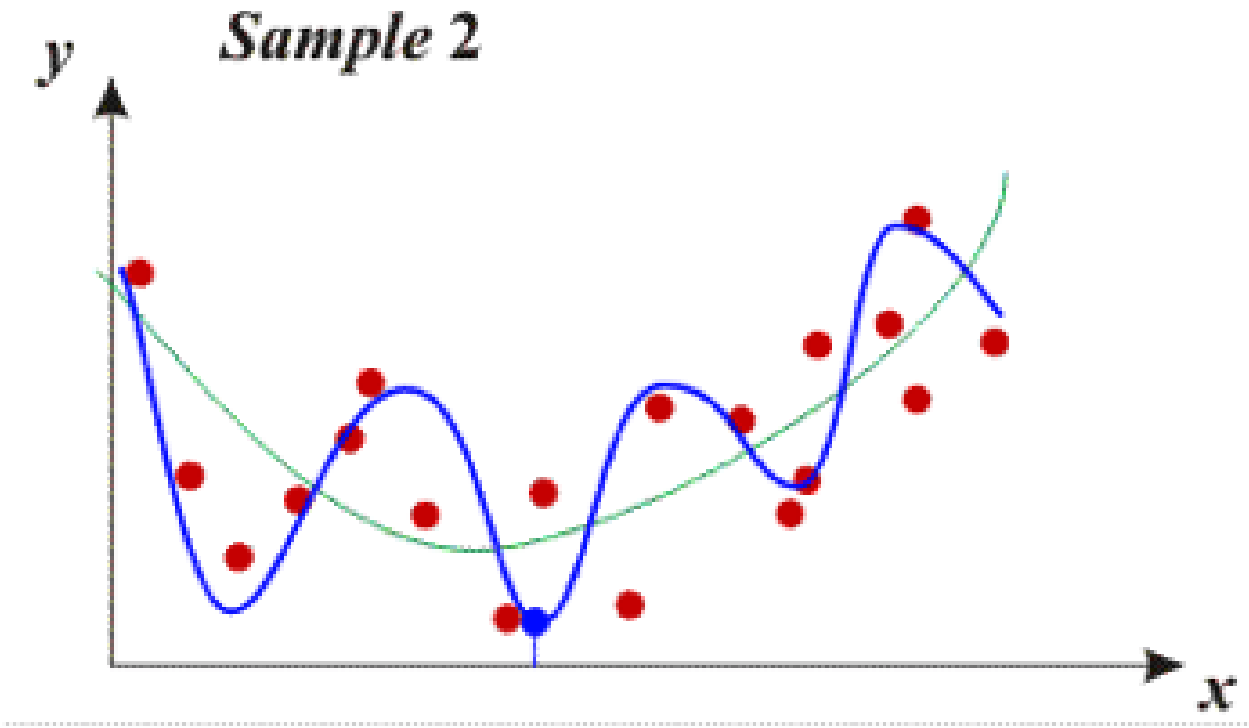
Generalization: Error effects

- **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

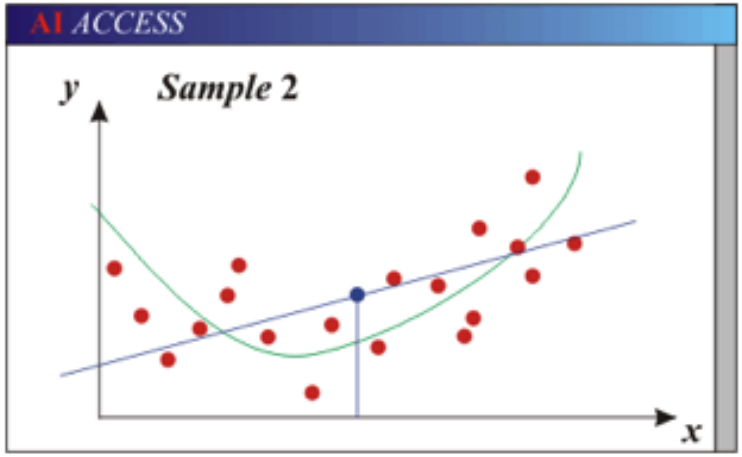


Generalization: Error effects

- **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

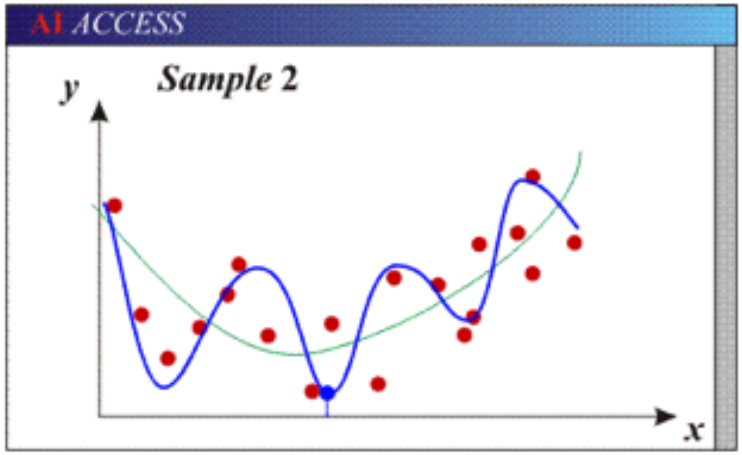


Generalization: Error effects



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

- Not enough flexibility!
- Too many assumptions



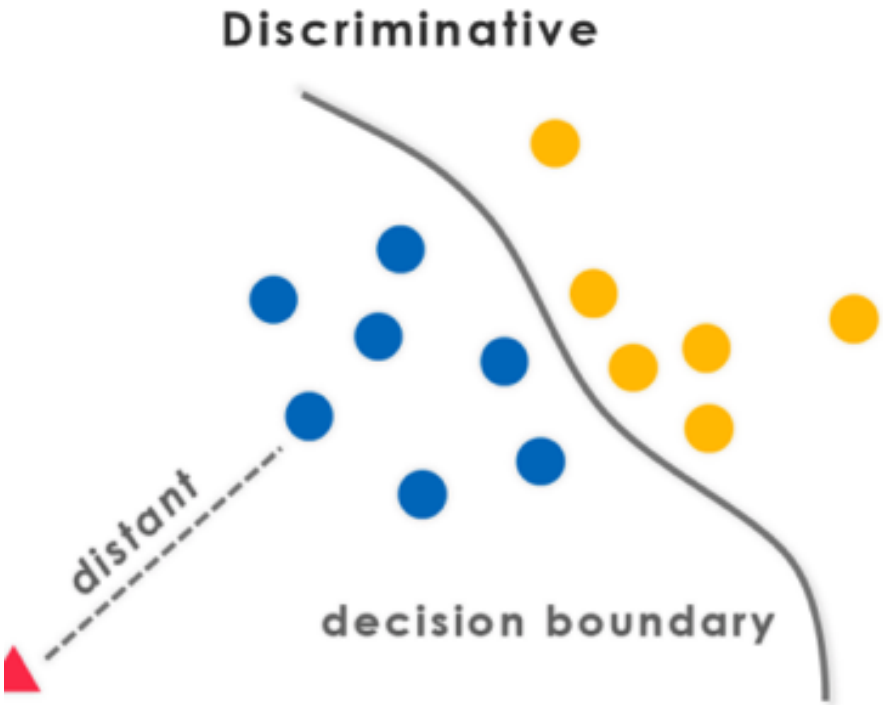
Models with too many parameters are inaccurate because of a large variance.

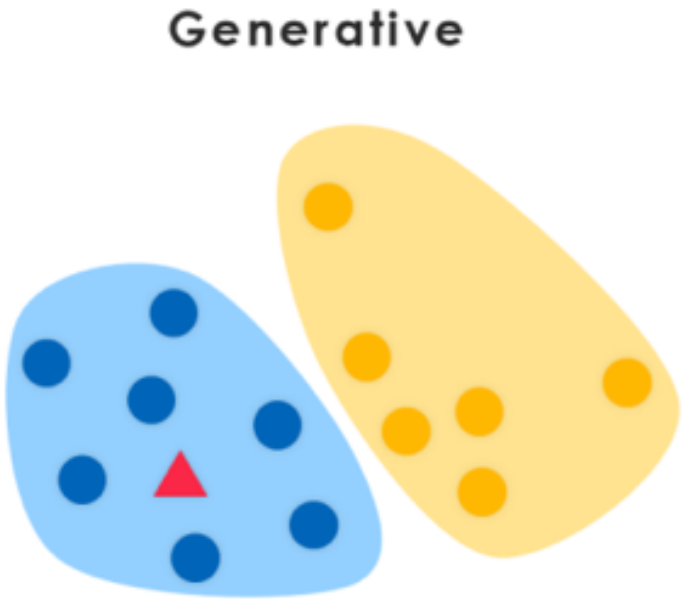
- Too much sensitivity to the sample.
- Slightly different data -> very different function.

Classifiers: Generative vs. Discriminative

- 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
- Generative Models
  - Represent both the data and the labels
  - Often, makes use of conditional independence and priors
  - Examples:
    - Naive Bayes classifier
    - Bayesian network
  - Models of data may apply to future prediction problems

Classifiers: Generative vs. Discriminative





"Learn the data boundary"

"Represent the data + boundary"

Bayesian methods:
Condition model on
data probabilistically

Classifiers

- We will really " dig in " to linear classifiers over the next couple weeks (PCA & LDA)
- What to keep in mind:
  - 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)