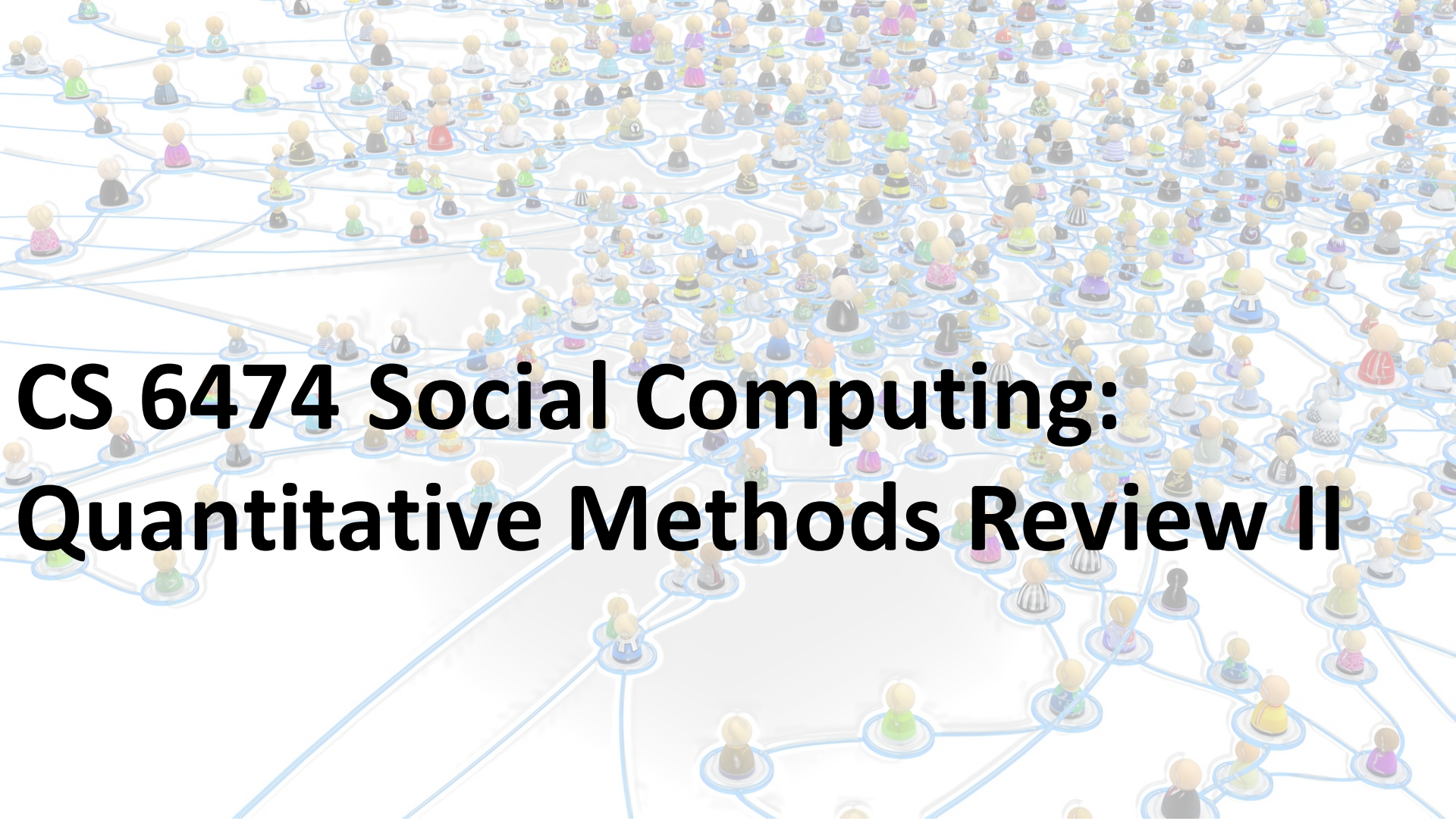

CS 6474 Social Computing: Quantitative Methods Review II

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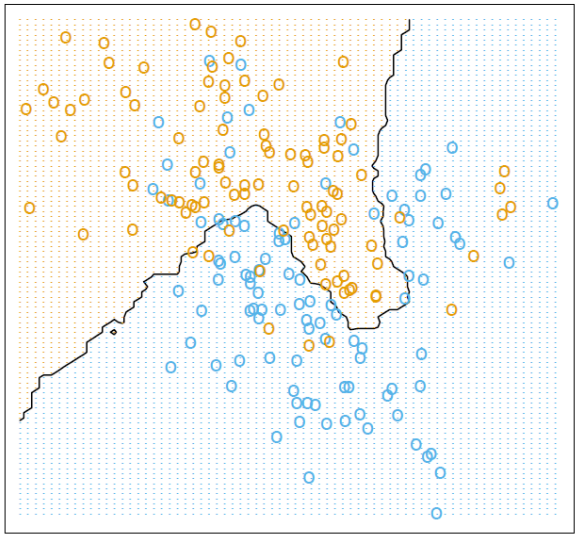
Week 7 | October 1, 2018

Different tasks

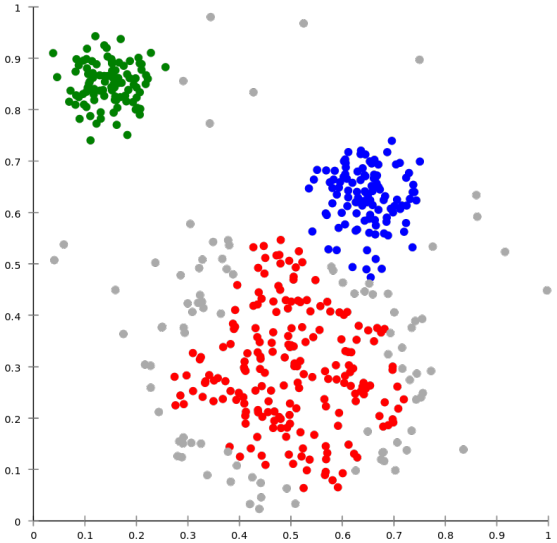
- *Supervised learning:* We're predicting a target variable for which we get to see examples. (regression, classification)
- *Unsupervised learning:* We're predicting a target variable for which we never get to see examples. (clustering)

Class Exercise I

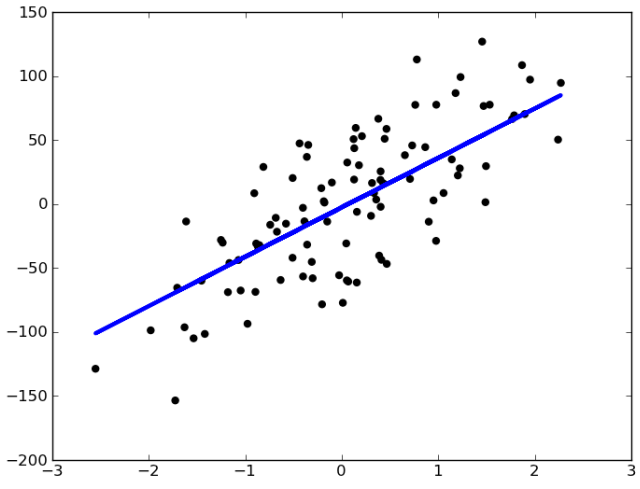
What we will cover…



Classification



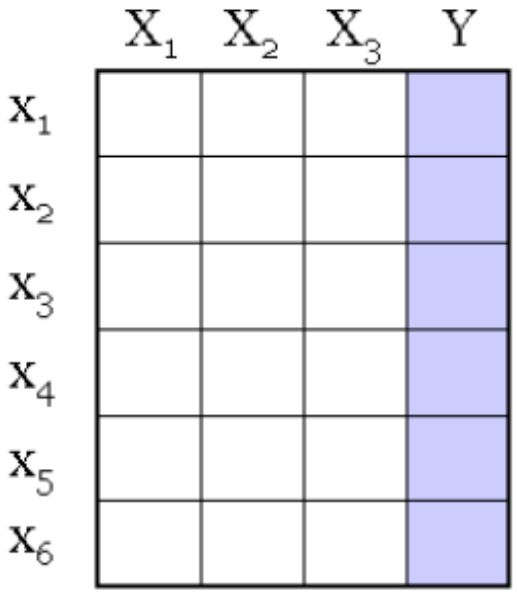
Clustering



Regression

Representing data

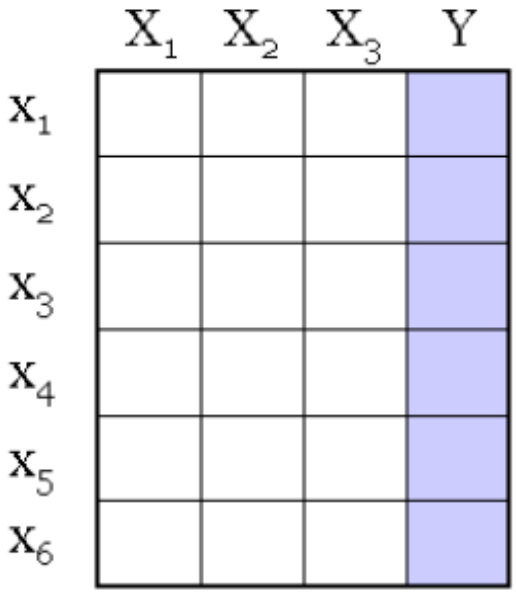
- *Data/points/instances/examples/samples/records*: rows
- *Features/attributes/dimensions/independent variables/covariates/predictors/regressors*: columns
- *Target/outcome/response/label/dependent variable*: special column to be predicted



Representing data

Continuous: a number, like #followers, #tweets

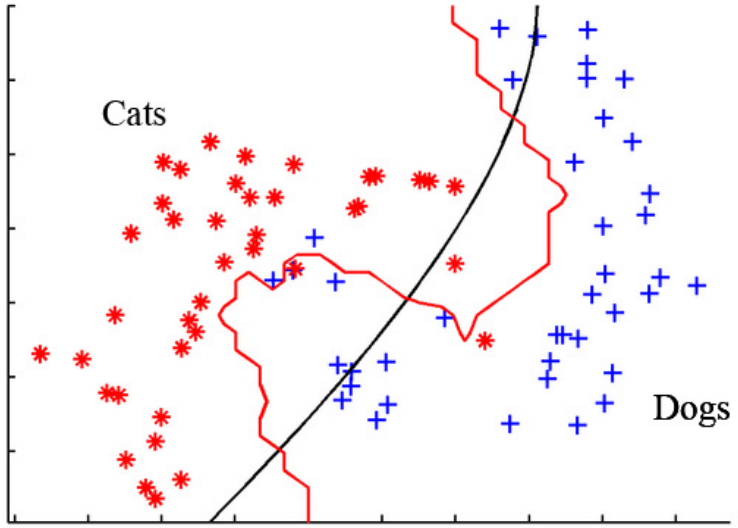
Discrete: a symbol, like gender, sentiment type

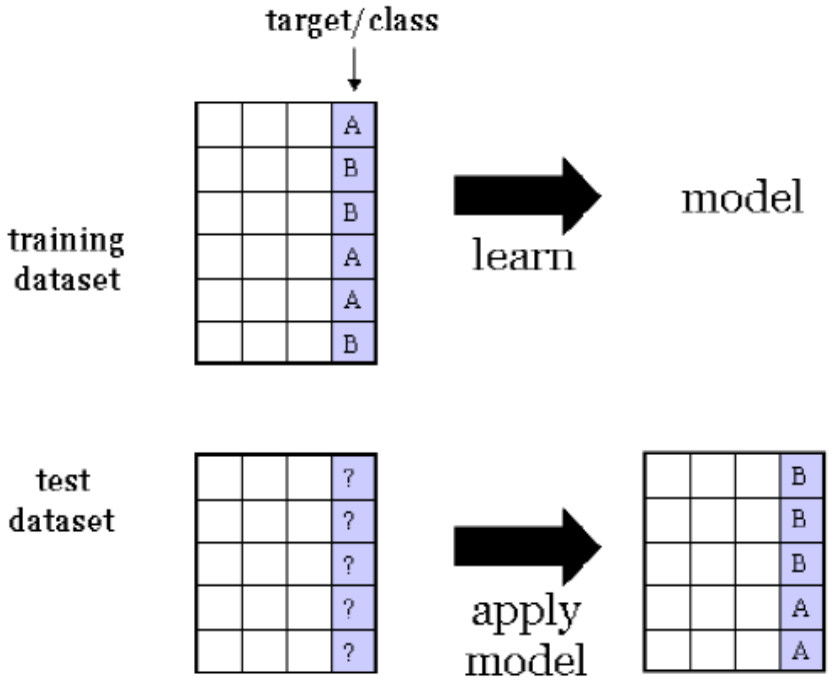


Classification (supervised learning)

Classification

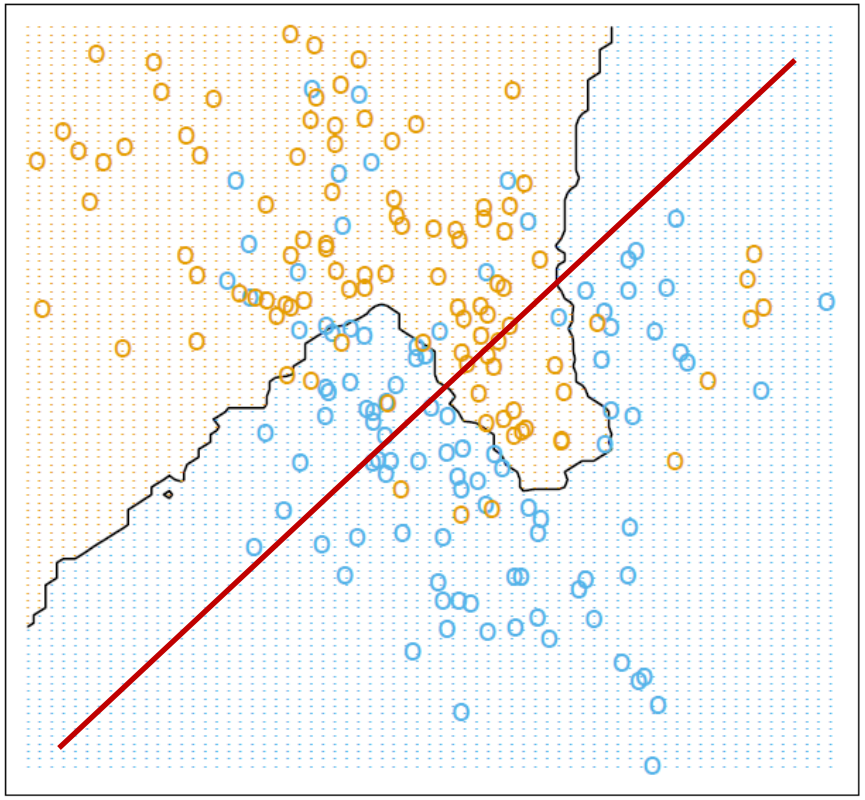
- The setup:
  - You obtain some kind of model based on some examples, or *training data*, through a process called *learning* (also *estimation*).
  - Then you use that model to *predict* something about data you haven't seen before, but that comes from the same distribution as the training data, called *test data*.





Classification

- However your prediction of classification may not always be correct—each data point is different!
- Typical error measurement—accuracy



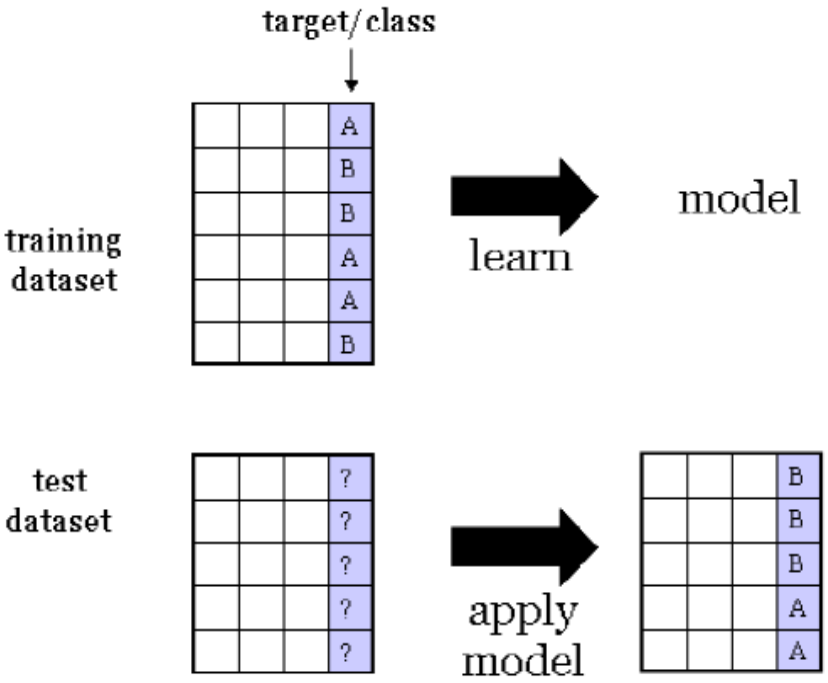
Classification Accuracy: Estimating Error Rates

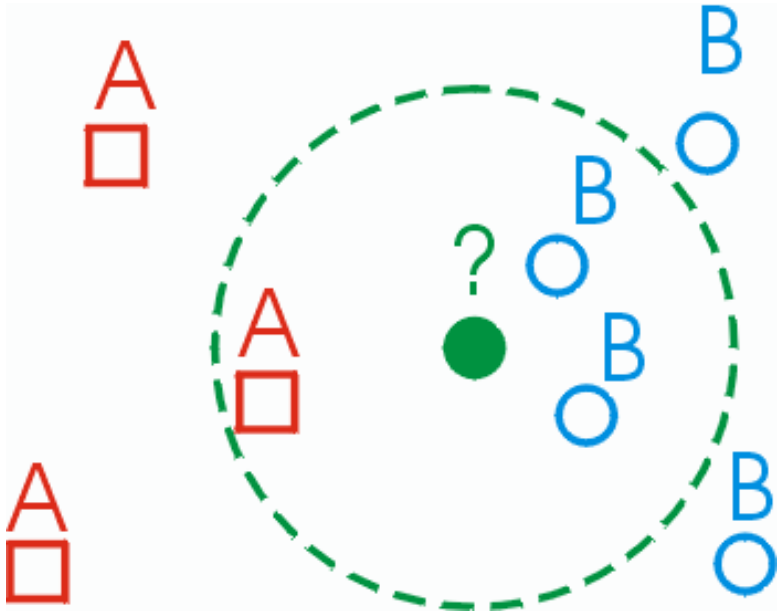
- Partition: Training-and-testing
  - use two independent data sets, e.g., training set (2/3), test set(1/3)
  - used for data set with large number of samples
- Cross-validation
  - divide the data set into *k* subsamples
  - use *k-1* subsamples as training data and one sub-sample as test data—*k*-fold cross-validation
  - for data set with moderate size
- Bootstrapping (leave-one-out)
  - for small size data

Classification

Simple example of a classification model ("classifier"):

- Use the label of the past training point which is most similar to the new test point, and return that as the prediction ("*k* nearest-neighbor").





Classification: *k*-NN Algorithm

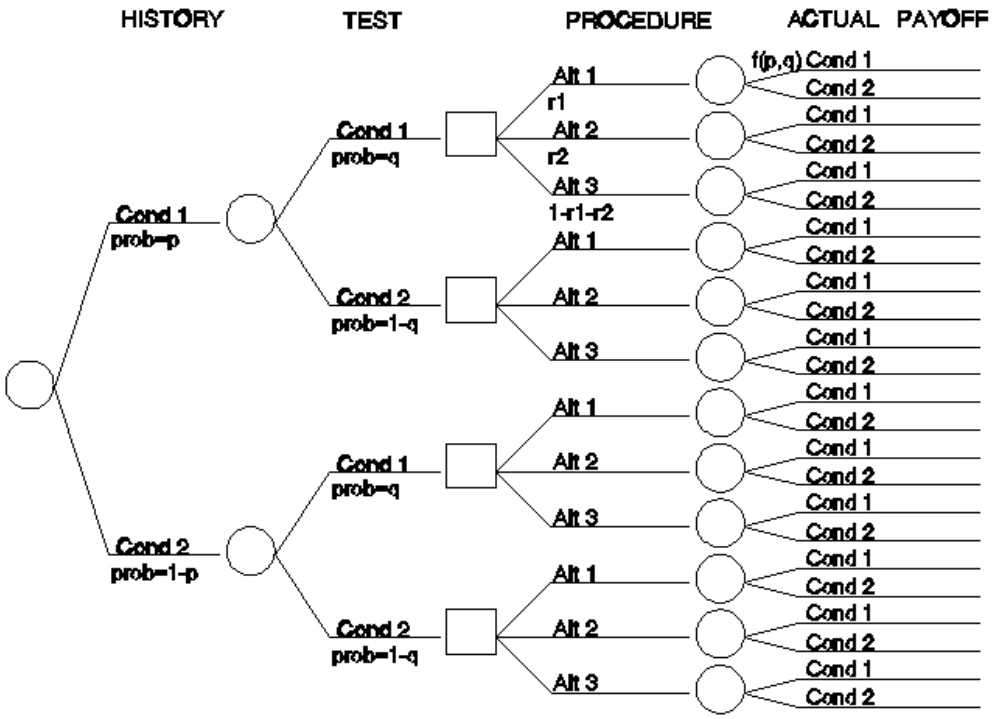
- The *k*-NN algorithm for *continuous-valued target functions*
- Calculate the mean values of the *k* nearest neighbors
- Distance-weighted nearest neighbor algorithm
- Weight the contribution of each of the k neighbors according to their distance to the query point x_q
  - giving greater weight to closer neighbors
- Similarly, for real-valued target functions
- Robust to noisy data by averaging k-nearest neighbors
- Curse of dimensionality: distance between neighbors could be dominated by irrelevant attributes.
- To overcome it, axes stretch or elimination of the least relevant attributes.

Classification: Decision trees

- A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.
- A decision tree is a flowchart-like structure in which internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test and each leaf node represents a class label (decision taken after computing all attributes).
- The paths from root to leaf represents classification rules.

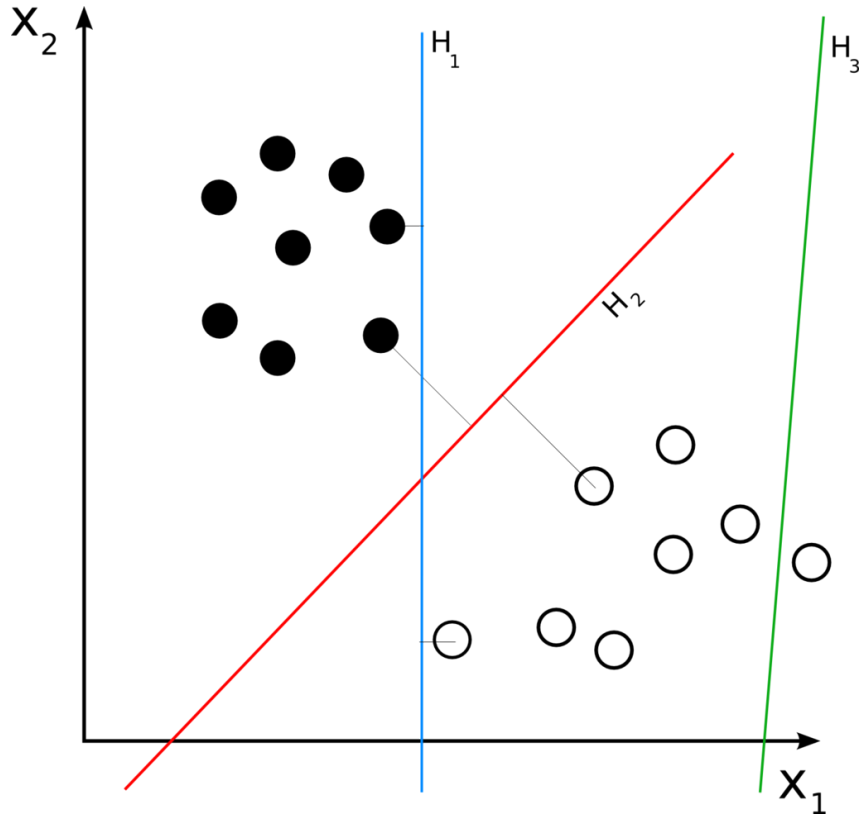
Classification: Decision trees

- A decision tree consists of 3 types of nodes:
  - Decision nodes - commonly represented by squares
  - Chance nodes - represented by circles
  - End nodes - represented by triangles
- Example: Should you recommend smoking cessation content to B?



Classification: linear classifier

- A linear classifier achieves this by making a classification decision based on the value of a linear combination of the characteristics.



Classification: linear classifier

- **Naive Bayes classifiers** are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features.
- A naive Bayes classifier assumes that the value of a particular feature is unrelated to the presence or absence of any other feature, given the class variable.

- Example: a fruit may be considered to be an apple if it is red, round, and about 3" in diameter. A naive Bayes classifier considers each of these features to contribute independently to the probability that this fruit is an apple, regardless of the presence or absence of the other features.

Classification: linear classifier

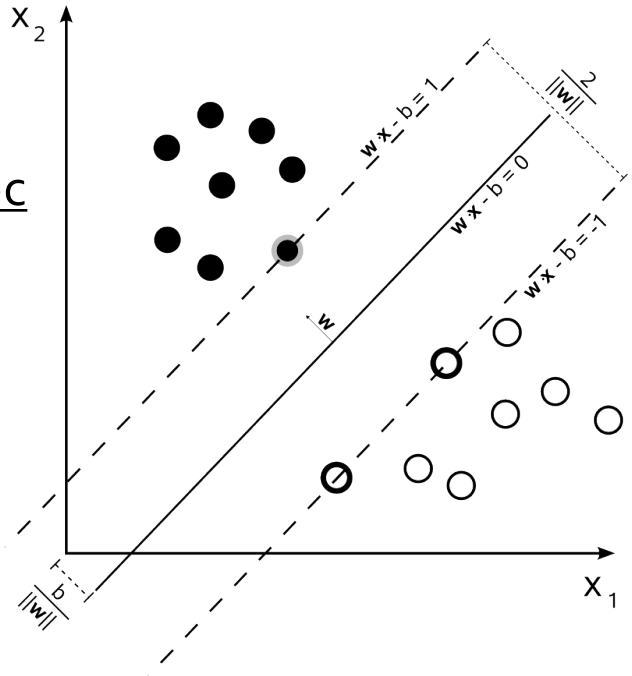
- A **logistic regression** model predicts a binary response from a binary predictor
- It is used for predicting the outcome of a categorical dependent variable (i.e., a class label) based on one or more predictor variables (features). That is, it is used in estimating the parameters of a qualitative response model.
- The probabilities describing the possible outcomes of a single trial are modeled, as a function of the explanatory (predictor) variables, using a logistic function.

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}.$$

Classification: Support Vector Machine

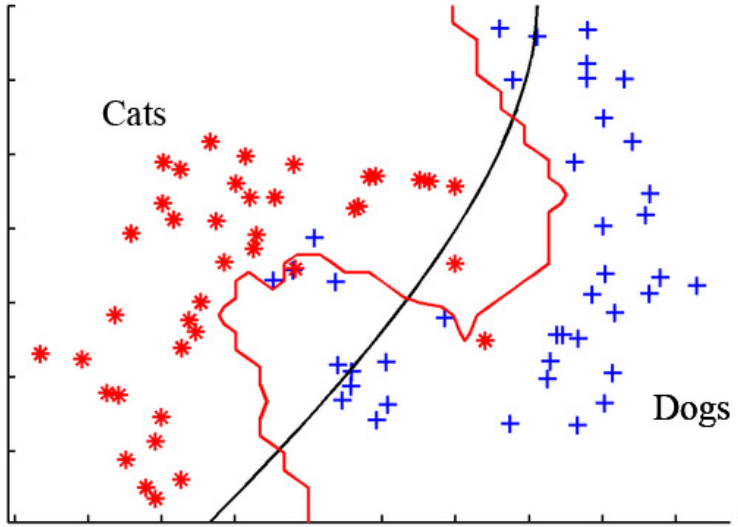
- A support vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks.
- Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

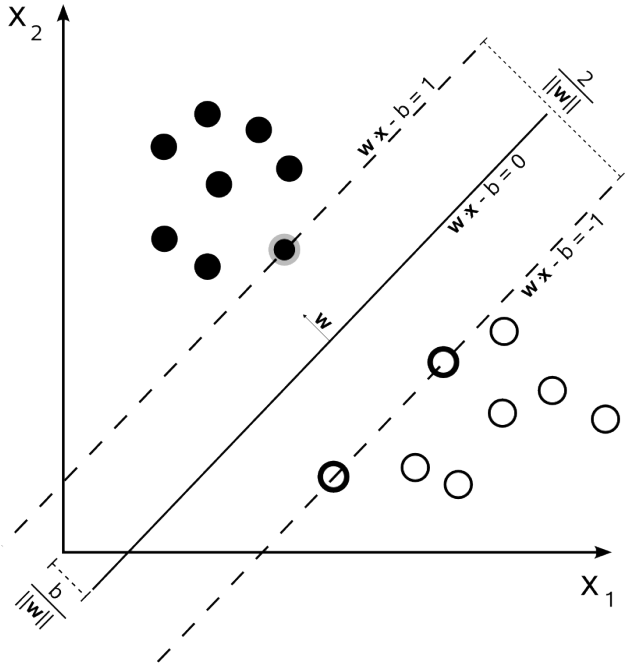
- Video explaining how SVM works (in detail): https://www.youtube.com/watch?v=1NxnPkZM9bc



Classification: Support Vector Machine

- But data is not always linearly separable!
- SVMs can efficiently perform a non-linear classification using what is called the *kernel trick*, implicitly mapping their inputs into high-dimensional feature spaces.
- How it works: https://www.youtube.com/watch?v=3liCbRZPrZA





Performance Evaluation

- $precision = \frac{tp}{tp+fp}$
- $recall = \frac{tp}{tp+fn}$
- $f1score = 2\frac{precision \times recall}{precision+recall}$

- sklearn.metrics
  - precision_score
  - recall_score
  - f1_score

	actual class (observation)	
predicted class (expectation)	**tp** (true positive) Correct result	**fp** (false positive) Unexpected result
	fn (false negative) Missing result	**tn** (true negative) Correct absence of result

Cross Validation

- When tuning the parameters of model, let each article as training and testing data alternately to ensure the parameters are not dedicated to some specific articles.
  - from sklearn.cross_validation import KFold
  - for train_index, test_index in KFold(10, 2):
    - train_index = [5 6 7 8 9]
    - test_index = [0 1 2 3 4]

How to choose the right classifier?

- Predictive accuracy
- Speed and scalability
  - time to construct the model
  - time to use the model
- Robustness
  - handling noise and missing values
- Scalability
  - efficiency for high dimension, large-scale data
- Interpretability
  - understanding and insight provided by the model
- Goodness of rules
  - decision tree size
  - compactness of classification rules

Class Exercise II and III

Clustering (unsupervised learning)

Clustering

- "Show me the sub-groups in the data."
- Why show sub-groups in the data? Sometimes:
  - Computational reasons (e.g. use cluster centers instead of the dataset)
  - Statistical reasons (e.g. identify/remove outliers)
  - Mainly: Visualization/understanding reasons

- Cite examples where you'll apply clustering to study a social computing problem?

Clustering: *K* means

- The *K*-means method is as follows:
  - First initialize the means μ_k somehow, for example by choosing *K* different points randomly. Then:
  - Assign each point according to

    $C(i) = \arg\min_k ||x_i - \mu_k||$.

  - Recompute each μ_k according to the new assignments.
  - Stop when no assignments change.
  - However, it does not necessarily obtain the global optimum. In practice, this is done, say, 10 times and the result with the lowest sum-of-squares is used.

Clustering: how to choose *K*?

- A (heuristic) approach (out of many that have been proposed) uses the *gap statistic* – it chooses the *K* where the data look most clustered when compared to uniformly-distributed data.
  - For each value of *K*, compute the log of within-cluster scatter, $\log W_K$ for the best clustering using that *K*.
  - For each value of *K*, also compute this quantity for *m* clusterings using uniformly-distributed data – call this $\log W'_K$ and its standard deviation s_K. it the next cluster center.
  - Compute $G(K) = |\log W_K - \log W'_K|$.
  - Choose the *K* such that $G(K) \geq G(K+1) - s_K \sqrt{(1 + 1/m)}$, i.e. the smallest *K* producing a gap within one standard deviation of the gap at $K + 1$.

Clustering: hierarchical clustering

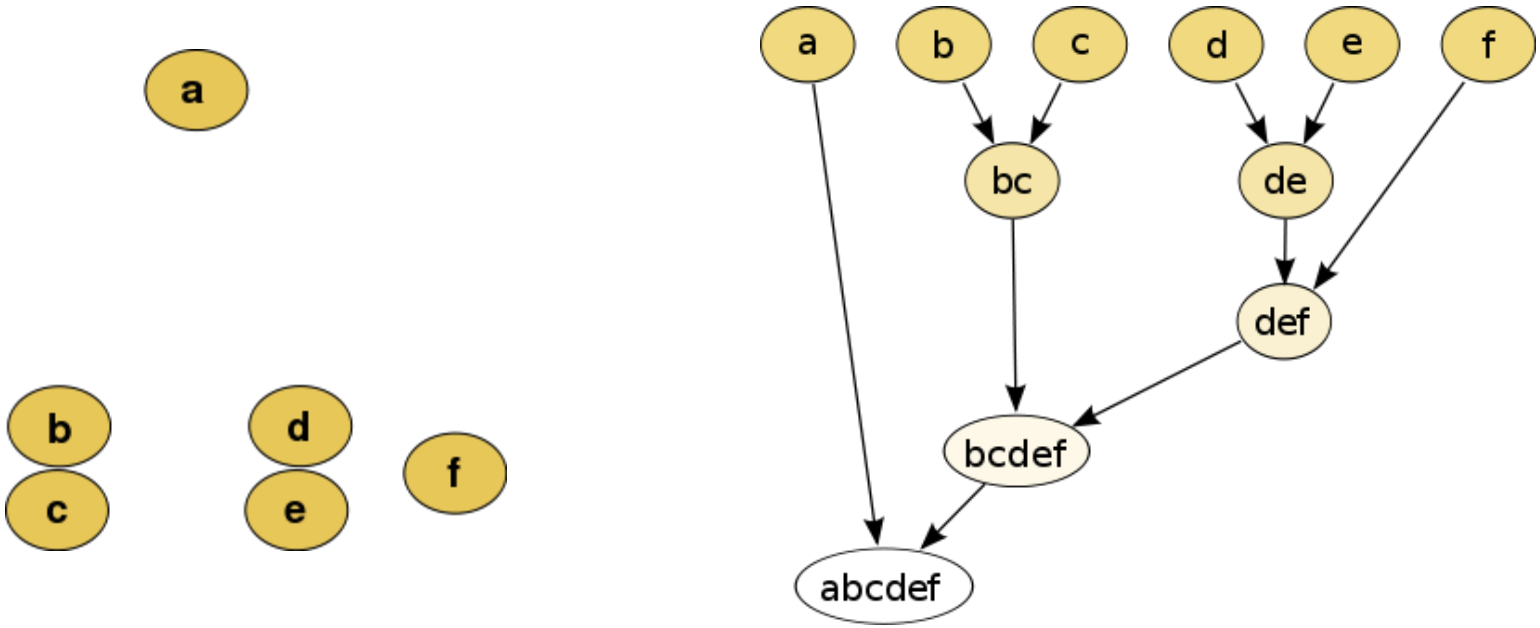
- Hierarchical clustering is a method of cluster analysis which seeks to build a hierarchy of clusters. Strategies for hierarchical clustering generally fall into two types:
  - Agglomerative: This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy.
  - Divisive: This is a "top down" approach: all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy.

Clustering: hierarchical clustering

In order to decide which clusters should be combined (for agglomerative), or where a cluster should be split (for divisive), a measure of dissimilarity between sets of observations is required.

Euclidean distance $\|a-b\|_2 = \sqrt{\sum_i (a_i - b_i)^2}$

Cosine similarity $\frac{a \cdot b}{\|a\|\|b\|}$



Feature extraction

Practical Issues

- Tokenization
  - Convert document to word counts = “bag of words”
  - word token = “any nonempty sequence of characters”
  - for HTML (etc) need to remove formatting

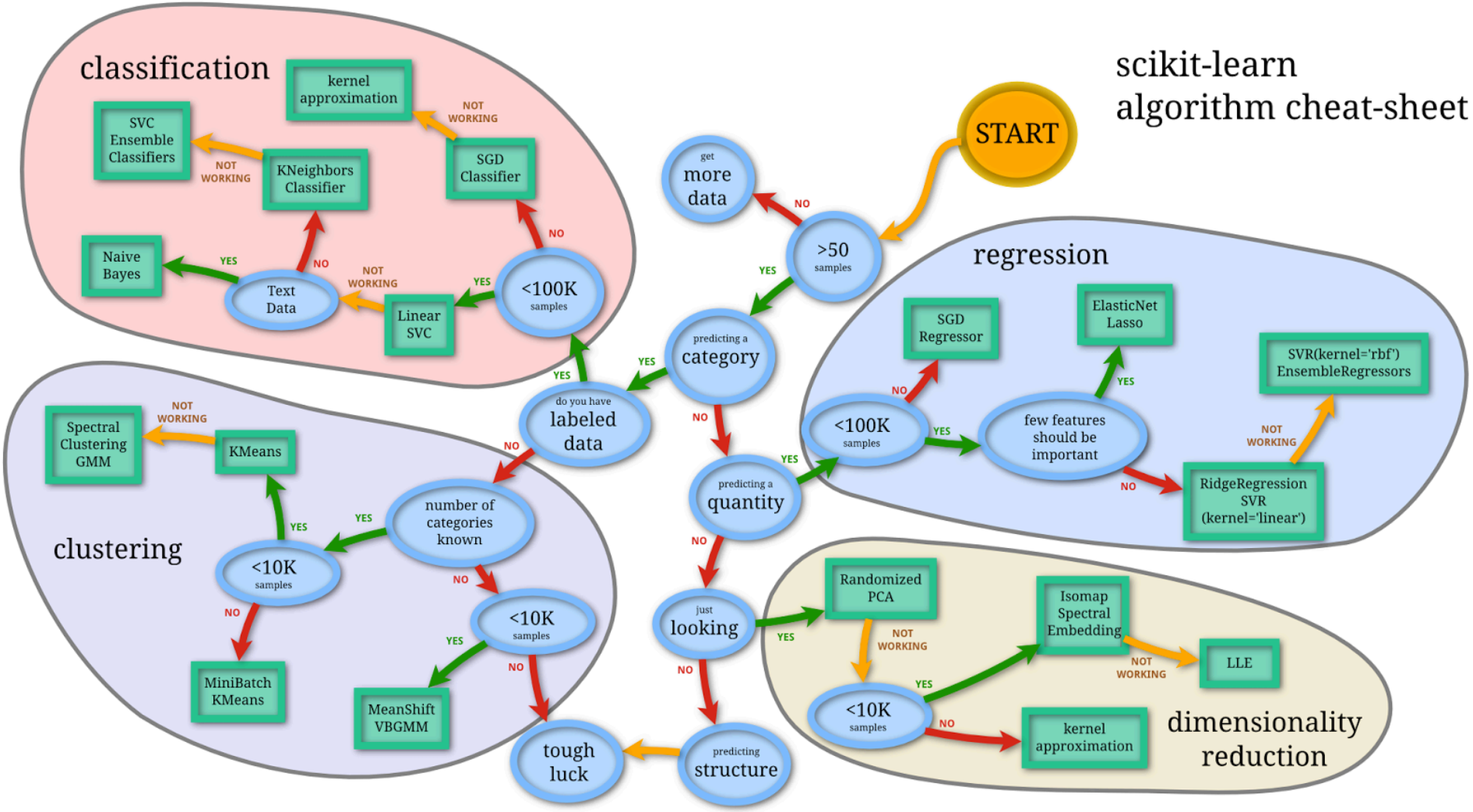
- Canonical forms, Stopwords, Stemming
  - Remove capitalization
  - Stopwords
    - » remove very frequent words (a, the, and…) – can use standard list
    - » Can also remove very rare words, e.g., words that only occur in k or fewer documents, e.g., k = 5
- Stemming
- Data representation
  - e.g., sparse 3 column for bag of words: <docid termid count>
  - can use inverted indices, etc.

Text Feature extraction in sklearn

- sklearn.feature_extraction.text
- CountVectorizer
  - Transform articles into token-count matrix
- TfidfVectorizer
  - Transform articles into token-TFIDF matrix
- Usage:
  - fit(): construct token dictionary given dataset
  - transform(): generate numerical matrix

Feature Selection

- Decrease the number of features:
  - Reduce the resource usage for faster learning
  - Remove the most common tokens and the most rare tokens (words with less information):
    - Parameter for Vectorizer:
      - max_df
      - min_df
      - max_features


scikit-learn
algorithm cheat-sheet
START
get more data
NO
>50 samples
YES
predicting a category
YES
do you have labeled data
YES
<100K samples
YES
Linear SVC
NOT WORKING
Text Data
NO
Naive Bayes
YES
KNeighbors Classifier
NO
SVC Ensemble Classifiers
NOT WORKING
kernel approximation
NOT WORKING
SGD Classifier
NO
classification
NO
predicting a quantity
YES
<100K samples
NO
SGD Regressor
YES
few features should be important
YES
ElasticNet Lasso
NO
RidgeRegression SVR (kernel='linear')
NOT WORKING
SVR(kernel='rbf') EnsembleRegressors
regression
NO
just looking
YES
Randomized PCA
NOT WORKING
<10K samples
YES
Isomap Spectral Embedding
NOT WORKING
LLE
NO
kernel approximation
dimensionality reduction
NO
predicting structure
tough luck
NO
number of categories known
YES
<10K samples
YES
KMeans
NOT WORKING
Spectral Clustering GMM
NO
<10K samples
YES
MeanShift VBGMM
NO
MiniBatch KMeans
clustering