# Machine Learning

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#### Clustering vs. Classification

Clustering = unsupervised learning

- Classes: unknown a priori
- Goal: discover classes from the data

Classification = supervised learning

- Classes: known/predefined
- Goals: understand the basis for the classes and build a predictor (classify new data)
- Prediction with a categorical outcome variable

# **Clustering in Bioinformatics**



Worm orthologs of co-expressed genes in fly are some times also co-expressed.

#### Yan et al. (2014) Genome Biology

### **Classification in Bioinformatics**



Presence of histone modifications at promoters can be predicted from transcription factor binding and (to a lesser degree) sequence motifs.

#### Benveniste et al. (2014) PNAS

DISTANCES

#### Distances

Machine learning algorithms require a notion of pairwise distance between objects.

- Dissimilarity
  - Non-negative:  $d(x,y) \ge 0$
  - Symmetric: d(x,y)=d(y,x)
  - Monotone: d(x,y) > d(x,z) if z more similar to x

-Metric (additional conditions)

Definite: d(x,y)=0 iff x=y

Triangle inequality:  $d(x,y)+d(y,z) \ge d(x,z)$ 

#### **Distance Metrics**

• Manhattan distance

$$d(x,y) = \sum_{i} |x_i - y_i| \in (0,\infty)$$

• Euclidean distance

$$d(x,y) = \sqrt{\sum_{i} (x_i - y_i)^2} \in (0,\infty)$$

#### Examples of the Minkowski metric

### **Correlation Distances**

$$d(x,y) = 1 - r(x,y) \in (0,2)$$

Sample correlation measures r(x,y):

- Pearson
- Uncentered (cosine-angle distance)
- Spearman
- Kendall's Tau
- Maximal Information Coefficient

(Correlation measure from Reshef et al. Science 2011 – not used for clustering yet!)

#### More on Distances

- Minkowski metrics: magnitude
- Correlation distances: pattern (or both)
- The absolute value of any distance can also be used, e.g.

$$d(x,y) = 1 - |r(x,y)| \in (0,1)$$

Distances between distributions are a different concept, e.g., Kullback-Leibler D<sub>KL</sub>(p(X),q(X))= - Σ<sub>x</sub> p(x) log{p(x)/q(x)}

#### **Perfectly Correlated**



## **Perfectly Anti-Correlated**



#### Same Mean, Uncorrelated



#### Same Mean, No Variation



# CLUSTERING

# **Cluster Analysis**

Exploratory data analysis methods for:

- Discovering patterns
- Grouping
  - -Variables
  - -Samples
  - -Both simultaneously
- Dimension reduction

   How many distinct patterns?
- Ordering and organizing

# **Clustering Methods**

Two main components:

- 1. Distance measure
- 2. Algorithm

These produce a mapping from data to parameters of interest:

- -Cluster labels, sizes, profiles
- -Hierarchical tree structure, ordering
- -Number of groups

## **Clustering Algorithms**

- Model-based (AUTOCLASS,SNOB) vs. Non-parametric
- Partitioning (SOMs, PAM, KMEANS) vs. Hierarchical
  - -Agglomerative (CLUSTER, AGNES)
    - Linkage: single, complete, average
  - Devisive (SOTA, DIANA, TSVQ)
  - -Hybrid (HOPACH, MUTUAL CLUSTERS)

# Partitioning vs. Hierarchical



Cho *et al.* (1998) Molecular Cell, 2: 65-73 Tamayo *et al.* (1999) PNAS, 96: 2907-2912

Alizadeh et al. (2000) Nature, 403: 503-511



#### **Distance Between Clusters**





#### Single (maximum)



#### **Effects of Outliers**



# How Many Clusters?

- Relevant for both partitioning and hierarchical algorithms (with pruning)
- Level of structure: global vs. detailed
- Two main approaches:
  - Direct Methods (criteria)
    - e.g. sums of squares, silhouettes
  - Resampling Methods (testing)
    - e.g. Clest, gap statistic, bootstrap

# **Inference for Clustering**

- How reliable and repeatable are cluster results from a single data set?
- Can view output (e.g. gene cluster labels) as a parameter estimate.
- Use resampling methods to estimate the variability of this estimator (since no closed form typically).

#### Example: Bootstrap cluster memberships

# Issues in Cluster Analysis

- Results can be very sensitive to input (i.e., pre-processing and filtering).
- What method fits your application?
  - Distance: capture what "close" means
  - Algorithm: the kind of clusters you seek
- Clustering methods will <u>always</u> return some output, but is it <u>meaningful</u>?
  - Evaluate variability
  - Assess biological relevance
  - Confirm hypotheses with experiments

# CLASSIFICATION

### Classification

- <u>Training</u>: build a model for the known class labels of samples as a function of (a subset of) the large set of measured variables.
- <u>Evaluation</u>: quantify how well the model performs on held out or independent data.
- <u>Prediction</u>: model <u>predicts</u> unknown class labels of future samples.

# **Classification Methods**

- K nearest neighbors (KNN)
- Discriminant analysis
  - -linear (LDA)
  - -non-linear (quadratic, logistic)
- Naïve Bayes
- Support vector machines (SVM)
  - Multi-Kernel Learning: linear combination of SVM kernels for subsets of variables.
- Neural networks (CNNs, deep learning)
- Classification trees (CART, random forests)
- Gradient boosting machine (GBM)

## **Ensemble Classifiers**

Build a collection of "weak learners" and combine them for better prediction.

- Random Forests: subset of variables.
- **Boosting:** resample and aggregate using weights based on previous misclassifications.
- Bagging: classifier for bootstrap samples, aggregate by majority vote.
- Super Learner: weighted (via cross validation) combo of different classifiers.

# **Training Decisions**

- Feature selection (very important in omics)
  - -Correlations with metadata
  - Recursive feature elimination (permutations of outof-bag observations in random forests)
  - -Gradient boosting machine
- Parameters
  - -KNN: how many neighbors?
  - -NNET: how many hidden states?
  - -SVM: kernel?
  - -Class priors
- <u>Must</u> account for these in performance evaluation

# **Evaluating Performance**

- Evaluate performance on held out test data.
  - -Generalizability
  - -Over-fitting
- Estimate classification error rates by bootstrap (out-of-bag) or cross-validation.
- Must avoid bleeding of information between the training and test sets!
- Prediction error is measured with a loss function. Many choices...



Specificity = TNR = TN/(FP+TN) Fall out = FPR = FP/(FP+TN) Sensitivity = TPR = recall = power = TP/(TP+FN) Miss rate = FNR = FN/(TP+FN)

Precision = positive predicted value = TP/(FP+TP) False discovery rate = FP/(FP+TP) Negative predicted value = TN/(TN+FN) False omission rate = FN/(TN+FN)

#### Summary Performance Measures

Accuracy = (TP+TN)/(FP+TN+TP+FN)

F-score = (I+b^2)(precision x recall)/ (b^2 precision + recall) FI = 2TP/(2TP+FP+FN)

FI is harmonic mean of precision and recall F2 weights recall higher F0.5 weight precision higher

Area under the curve:



#### Other Issues...

- Human input for training, not prediction
- Multi-class problems
  - -all vs. one and other binary reductions
  - -Bagging trees, random forests OK
- Standardization of variables
- Variable importance

EXTRA SLIDES

# **Comparing Clustering Methods**

- Any distance measure?
- Reaction to noise: robust vs. efficient
- Results reproducible?
- Biological relevance

Partitioning Variety of cluster sizes Overlapping clusters

<u>Hierarchical</u>

Sensible ordering

### Hybrid tree of partitions

#### HOPACH: Pruned hierarchical tree produces nested clusters





## **Bootstrap Fuzzy Clustering**

#### boothopach function

		(Ren	Name	
	1.0	PAE2848	C,C : PROD: pyruvate dehydrogenase E2 (dhydrolipoamide acetytransferase); CAT: Energy metabolism;Gkcolysis/gluconeogenesis; HMM-ID: 2-oxoacid_dh	
	0.999	PAE2505	R : PROD: conserved hypothetical protein; CAT: Hypothetical; Conserved; HMMHD: Głyowalase	
	0.998	PAE0201	S : PRICE : conserved hypothetical protein; CAT: Hypothetical;Conserved; HMM-ID: NA	
	0.983	PAE1408	NA: PROD: hypothetical protein; CAT: Hypothetical;Hypothetical; HMM-ID: NIA	
	0.974	PAE2687	ER,R,R : PROD: alcohol dehydrogenase (Zin(); CAT: Energy metabolism/Fermentation; HMM-ID: adh_zinc	
	0.97	PAE0956	NA: PROD: amidutransferase (hisH); CAT: Amino acid biosynthesis Histickine family; HMM-ID: GATase	
	0.963	PAE (724	NA: Between teatures PAE1365 and PAE1365 Length: 139 bp	
	0.94B	PAE3562	K: PROD: DNA-directed RNA polymerase subunit E'(poE1); CAT: Transcription,DNA-dependent RNA.polymerase; HMM-ID: S1	
	0.945	PAE1302	NA: PROD: tricom protease; CAT: Protein fate;Degradation of proteins, peptides, and glycopeptides; HMM-ID: NVA	
	0.945	PAE0284	S : PRICD: conserved hypothetical protein; CAT: Hipothetical;Conserved; HMM-D: filament	
	0.943	PAE2450	E.E.: PROD. typtophan synthase alpha suburit ; CAT. Amino acid biosynthesis, Aromatic amino acid family, HMM-ID: trp_synA.	
	0.94	PAE0152	NA: PROD: conserved hypothetical protein; CAT: Hypothetical ;Conserved; HMM+ID: NA	
	0.939	PAE/1035	NA: Between teatures PAE1B31 and PAE1B32 Length: 170 bp	
	0.931	PAE2258	K: PROD: DNA-directed RNA polymerase suburit; CAT: Transcription;DNA-dependent RNA polymerase; HMM-ID: NA	
	0.922	PAE2564	NA: PROD: ademylylsuffate reductase alpha subunit part 2, authentic frameshift, CAT: Central Intermediany metabolism;Suffur metabolism; HMMHD: NA	
	0.917	PAE0958	E,E,E,E : PROD: histidinol-phosphate aminotransferase (hisC) ; CAT: Amino acid biosynthesis (Histidine family, HMM-ID: aminotran_2;aminotran_1	
	0.911	PAE3612	C, C : PROD: nitrate reductase beta subunit (nari-l); CAT: Energy metabolism;Electron transport; HMM-ID: feril	
	0.909	PAE2584	NA: PROD: citrate synthase part 1, authentic frameshift, CAT. Energy metabolism,TCA cycle; HMM-ID: citrate_synt	
	0.893	PAE0325	NA: PROD: possible protein; CAT: may not code; HMM-ID: NA	
the second se	0.B73	PAE3595	NA: PROD. RNA 3/terminal phosphate cyclase; CAT: Transcription (RNA processing, HMM-ID: RCT	
	0.866	PAE1856	NA: PROD: hypothetical protein; CAT: Hypothetical; Hypothetical; HMM-ID: NIA	
	0.856	PAE3488	W: PROD: UDP-N-acehiglucosamine-dolichyl-phosphate N-acehiglucosaminephosphotransferase; CAT: Cell envelope;Biosynthesis and degradatation of surface polysarcharide	
	0.849	PAE2597	NA: PROD: suffixe reductase beta subunit; CAT: Central Intermediary metabolism; Suffur metabolism; HMM-D: fer4	
	0.829	PAE2296	H : PROD: riboflawin synthese; CAT: Biosynthesis of cofactors, prosthetic groups, and carriers; Riboflawin, FMN, and FAD; HMM-ID: DMRL_synthese	
	0.023	PAE/203	NA: Detwoen testures PAE0499 and PAE0500 Length: 193 bp	
	0.B12	PAE22220	NA: PROD. hypothetical protein; CAT: Hypothetical; HMMHD: NA	
	0.809	PAE2254	NA: PROD. hypothetical protein; CAT: Hypothetical; HWMHD: bZIP	
	0.80B	PAE2034	NA: PROD. hypothetical protein; CAT: Hypothetical; HWMHD: NA	

Pyrobaculum aerophilum array data from Lowe Lab (UCSC)

#### Silhouette-based Criteria

• The silhouette for j'th object (e.g., gene):



- Average silhouette (AS): overall mean
- Median split silhouette (MSS): split each cluster and see if silhouettes get smaller

#### MSS vs. AS



PAM clustering Euclidean distance

# Distances in R

Function	Package	Distances
dist	stats	Euclidean, Manhattan, Canberra, max, binary
daisy	cluster	Euclidean,
	bioDist	Manhattan
distancematrix distancevector	hopach	Euclidean, cor, cosine-angle (abs versions)

# **Clustering Algorithms in R**

Package	Functions	Туре
stats	kmeans	partitioning
	hclust	divisive
class	SOM	partitioning
cluster	pam	partitioning
	agnes	agglomerative
	diana	divisive
hopach	hopach	hybrid

Other packages: cclust, e1071, flexmix, fpc, mclust

### **Classification Methods in R**

Package	Functions
e1071	naiveBayes, svm
glmnet	glmnet, cv.glmnet
ipred	lda, bagging
nnet	nnet
rpart	rpart
gbm	gbm, summary
randomForest	randomForest
pamr	knn, cv

caret, MLInterfaces: frameworks to interface with methods