

Data Mining Steps

1. Data Cleaning	Removal of noise and inconsistent records
2. Data Integration	Combining multiple sources
3. Data Selection	Only data relevant for the task are retrieved from the database
4. Data Transformation	Converting data into a form more appropriate for mining
5. Data Mining	Application of intelligent methods to extract data patterns
6. Model Evaluation	Identification of truly interesting patterns representing knowledge
7. Knowledge Presentation	Visualization or other knowledge presentation techniques

Data mining could also be called Knowledge Discovery in Databases (see kdnuggets.com)

Types of Attributes

Nominal	e.g., ID numbers, eye color, zip codes
Ordinal	e.g., rankings, grades, height
Interval	e.g., calendar dates, temperatures
Ratio	e.g., length, time, counts

Distance Measures

Euclidean Distance:

$$dist = \sqrt{\sum_{k=1}^n (p_k - q_k)^2}$$

Minkowski Distance:

$$dist = \left(\sum_{k=1}^n |p_k - q_k|^r \right)^{\frac{1}{r}}$$

$r=1$, City Block

$r=2$, Euclidean

$r \rightarrow \infty$, Chebyshev

Manhattan = City Block

Jaccard coefficient, Hamming, Cosine are a similarity / dissimilarity measures



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Measures of Node Impurity

GAIN = measure before split – measure after split

$$GINI(t) = 1 - \sum_j [p(j | t)]^2$$

$p(j | t)$ is the relative frequency of class j at node t

$$GINI_{split} = \sum_{i=1}^k \frac{n_i}{n} GINI(i)$$

where, n_i = number of records at child i,
 n = number of records at node p.

Pick the smallest

$$Entropy(t) = -\sum_j p(j | t) \log p(j | t)$$

Information Gain:

$$GAIN_{split} = Entropy(p) - \left(\sum_{i=1}^k \frac{n_i}{n} Entropy(i) \right)$$

Parent Node, p is split into k partitions;
 n_i is number of records in partition i

$$GainRatio_{split} = \frac{GAIN_{split}}{SplitINFO}$$

$$SplitINFO = -\sum_{i=1}^k \frac{n_i}{n} \log \frac{n_i}{n}$$

Parent Node, p is split into k partitions;
 n_i is number of records in partition i

$$Error(t) = 1 - \max_i P(i | t)$$

Model Evaluation

ACTUAL CLASS	PREDICTED CLASS		
		Class=Yes	Class>No
	Class=Yes	a (TP)	b (FN)
Class>No	c (FP)	d (TN)	

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F-measure} = \frac{2 \cdot TP}{2 \cdot TP + FN + FP}$$

$$\text{Cost} = TP \times Cost_{TP} + FN \times Cost_{FN} \\ + TN \times Cost_{TN} + FP \times Cost_{FP}$$

Sensitivity = Recall

$$\text{Specificity} = 1 - \frac{FP}{FP+TN} = \frac{TN}{TN+FP}$$

False Positive Rate = 1 - Specificity

Kappa = (observed agreement - chance agreement) / (1- chance agreement)

Kappa = (Dreal – Drandom) / (Dperfect – Drandom), where D indicates the sum of values in diagonal of the confusion matrix

K-Nearest Neighbor

- * Compute distance between two points
- * Determine the class from nearest neighbor list
 - * Take the majority vote of class labels among the k-nearest neighbors
 - * Weigh the vote according to distance



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K-Nearest Neighbor (cont)

> * weight factor, $w = 1 / d^2$

Rule-based Classification

Classify records by using a collection of "if...then..." rules

Rule: (Condition) --> y

where:

* Condition is a conjunction of attributes

* y is the class label

LHS: rule antecedent or condition

RHS: rule consequent

Examples of classification rules:

(Blood Type=Warm) \wedge (Lay Eggs=Yes) --> Birds

(Taxable Income < 50K) \wedge (Refund=Yes) --> Evade=No

Sequential covering is a rule-based classifier.

Rule Evaluation

$$\text{Accuracy} = \frac{n_c}{n}$$

$$\text{Laplace} = \frac{n_c + 1}{n + k}$$

$$\text{M-estimate} = \frac{n_c + kp}{n + k}$$

n : Number of instances covered by rule
 n_c : Number of instances of class c covered by rule
 k : Number of classes
 p : Prior probability (for the positive class)



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Bayesian Classification

$$\text{Conditional Probability: } P(C | A) = \frac{P(A, C)}{P(A)}$$

$$P(A | C) = \frac{P(A, C)}{P(C)}$$

Baye's theorem:

$$P(C | A) = \frac{P(A | C)P(C)}{P(A)}$$

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{normalizing constant}}$$

Naïve Bayes Classifier:

$$\text{Original: } P(A_i | C) = \frac{N_{ic}}{N_c}$$

$$\text{Laplace: } P(A_i | C) = \frac{N_{ic} + 1}{N_c + c}$$

$$\text{m-estimate: } P(A_i | C) = \frac{N_{ic} + mp}{N_c + m}$$

c: number of classes, p: prior probability, m: parameter

P(B|A), read as *the probability of B given A*.

$$P(B|A) = \frac{P(A \text{ and } B)}{P(A)} \quad P(A \text{ and } B) = P(A) \cdot P(B|A)$$

p(a,b) is the probability that both a and b happen.

p(a|b) is the probability that a happens, knowing that b has already happened.

Terms

Association Analysis	Min-Apriori, LIFT, Simpson's Paradox, Anti-monotone property
Ensemble Methods	Staking, Random Forest

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Terms (cont)

Decision Trees	C4.5, Pessimistic estimate, Occam's Razor, Hunt's Algorithm
Model Evaluation	Cross-validation, Bootstrap, Leave-one out (C-V), Misclassification error rate, Repeated holdout, Stratification
Bayes	Probabilistic classifier
Data Visualization	Chernoff faces, Data cube, Percentile plots, Parallel coordinates
Nonlinear Dimensionality Reduction	Principal components, ISOMAP, Multidimensional scaling

Rules Analysis

$$support = \frac{P(A, B)}{Total}$$

$$confidence = \frac{P(A, B)}{P(A)}$$

$$Lift = \frac{Confidence}{P(B)}$$

Example:
Rule {b} \rightarrow {c}

	a	c
b	3	4
b	2	1

$$support = 3/10 = 0.3$$

$$confidence = 3/7 = 0.4286$$

$$lift = \frac{3/7}{5/10}$$

Apriori Algorithm

Let k=1

Generate frequent itemsets of length 1

Repeat until no new frequent itemsets are identified

Generate length (k+1) candidate itemsets from

length k frequent itemsets

Prune candidate itemsets containing

subsets

of length k that are infrequent

Count the support of each candidate by scanning the DB

Eliminate candidates that are infrequent,

leaving only those that are frequent

Ensemble Techniques

AdaBoost Algorithm:

$$\alpha_t = \frac{1}{2} \ln \left(\frac{1 - \epsilon_t}{\epsilon_t} \right)$$

error (ϵ_t) = # of misclassified divided by total

$$w_i = w_1 = w_2 = \dots = w_{10} = \frac{1}{10} = 0.1$$

Re-weighting:

$$misclassified = w_i \times e^{+\alpha_t}$$

$$correct classified = w_i \times e^{-\alpha_t}$$

Manipulate training data: bagging and boosting ensemble of "experts", each specializing on different portions of the instance space

Manipulate output values: error-correcting output coding (ensemble of "experts", each predicting 1 bit of the {multibit} full class label)

Methods: BAGGing, Boosting, AdaBoost



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K-means Clustering

Select K points as the initial centroids

repeat

Form K Clusters by assigning all points to the closest centroid

Rec ompute the centroid of each cluster

until the centroids don't change

Closeness is measured by distance (e.g., Euclidean), similarity (e.g., Cosine), correlation.

Centroid is typically the mean of the points in the cluster

Hierarchical Clustering

Single-Link or MIN

Similarity of two clusters is based on the two most similar (closest / minimum) points in the different clusters

Determined by one pair of points, i.e., by one link in the proximity graph.

Complete or MAX

Similarity of two clusters is based on the two least similar (most distant, maximum) points in the different clusters

Determined by all pairs of points in the two clusters

Group Average

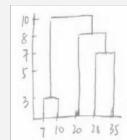
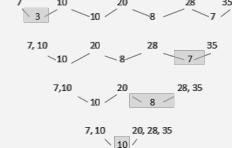
Proximity of two clusters is the average of pairwise proximity between points in the two clusters

Agglomerative clustering starts with points as individual clusters and merges closest clusters until only one cluster left.

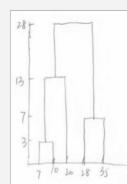
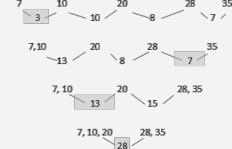
Divisive clustering starts with one, all-inclusive cluster and splits a cluster until each cluster only has one point.

Dendrogram Example

Single



Complete



Dataset: {7, 10, 20, 28, 35}

Density-Based Clustering

```
current_cluster_label <-- 1
for all core points do
    if the core point has no cluster label then
        current_t_c_lus_ter_label <-- current_t_c_lus_ter_label + 1
        Label the current core point with the cluster label
    end if
    for all points in the Eps-ne igh bor hood, except i-th the point itself do
        if the point does not have a cluster label then
            Label the point with cluster label
        end if
    end for
```



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Density-Based Clustering (cont)

> end for

DBSCAN is a popular algorithm

Density = number of points within a specified radius (Eps)

A point is a core point if it has more than a specified number of points (MinPts) within Eps

These are points that are at the interior of a cluster

A border point has fewer than MinPts within Eps, but is in the neighborhood of a core point

A noise point is any point that is not a core point or a border point

Other Clustering Methods

Fuzzy is a partitional clustering method. **Fuzzy clustering** (also referred to as **soft clustering**) is a form of clustering in that each data point can belong to more than one cluster.

Graph-based methods: Jarvis-Patrick, Shared-Near Neighbor (SNN, Density), Chameleon

Model-based methods: Expectation-Maximization

Regression Analysis (cont)

| Elastic Net

Anomaly Detection

Anomaly is a pattern in the data that does not conform to the expected behavior (e.g., outliers, exceptions, peculiarities, surprise)

Types of Anomaly

Point: An individual data instance is anomalous w.r.t. the data

Contextual: An individual data instance is anomalous within a context

Collective: A collection of related data instances is anomalous

Approaches

* Graphical (e.g., boxplots, scatter plots)

* Statistical (e.g., normal distribution, likelihood)

| Parametric Techniques

| Non-parametric Techniques

* Distance (e.g., nearest-neighbor, density, clustering)

Local outlier factor (LOF) is a density-based distance approach

Mahalanobis Distance is a clustering-based distance approach

Regression Analysis

- * Linear Regression
 - | Least squares
- * Subset selection
- * Stepwise selection
- * Regularized regression
 - | Ridge
 - | Lasso



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