MACHINE LEARNING IN AVIATION

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Toulouse, July 11, 2013

Outline

Outline

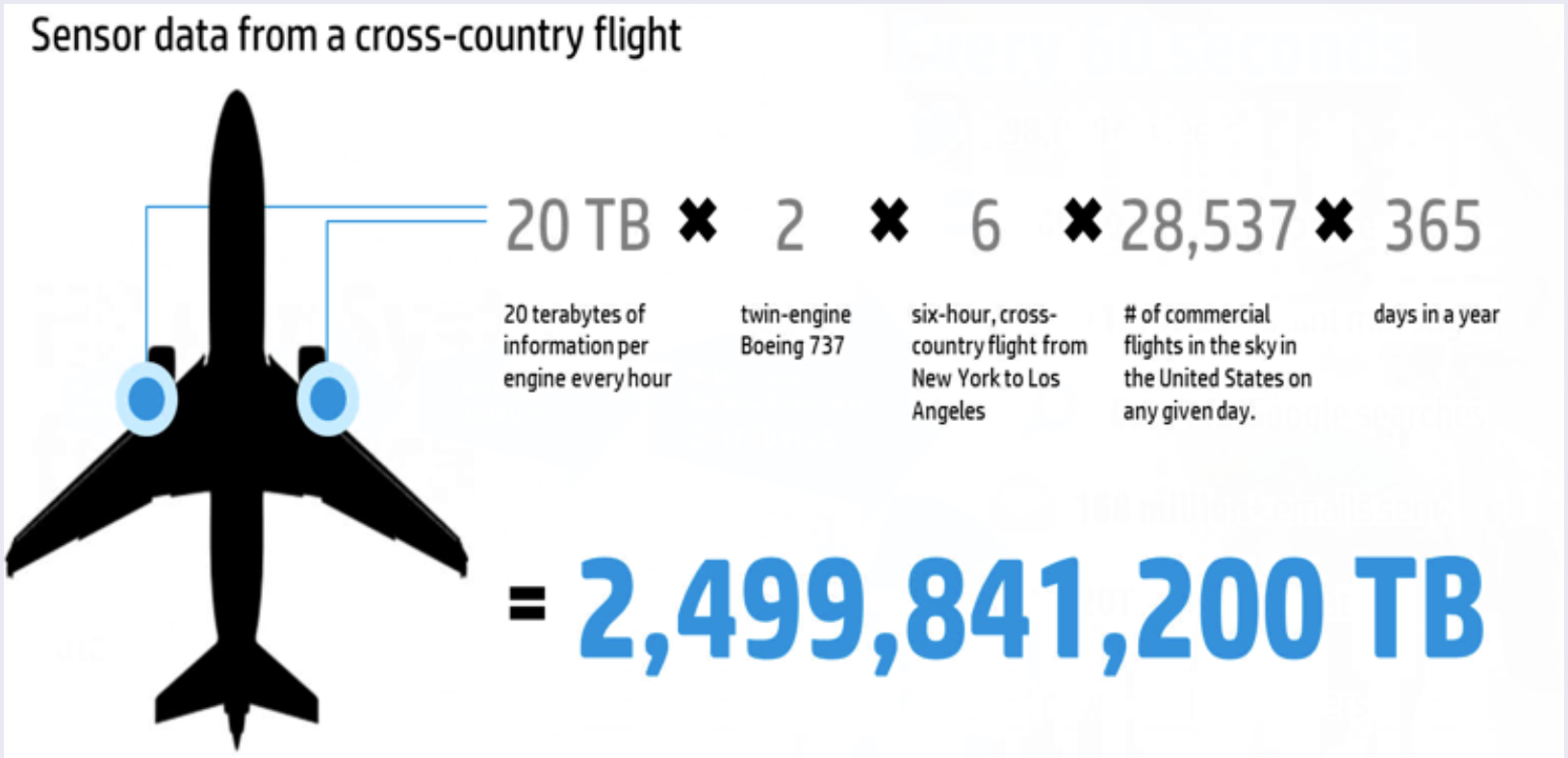
Introduction

Data in aviation

- Data in our world: smartphones, social networks, atmospheric readings, financial data, medical records, bioinformatics, airplane instrumentation, etc.
- Estimation of 2.5 exabytes of data generated on the planet every day
- Data in aviation:
  - Flight tracking
  - Weather conditions
  - Airport information
  - Airline information
  - Market information
  - Passenger information
  - Air safety reports
  - Aircraft data

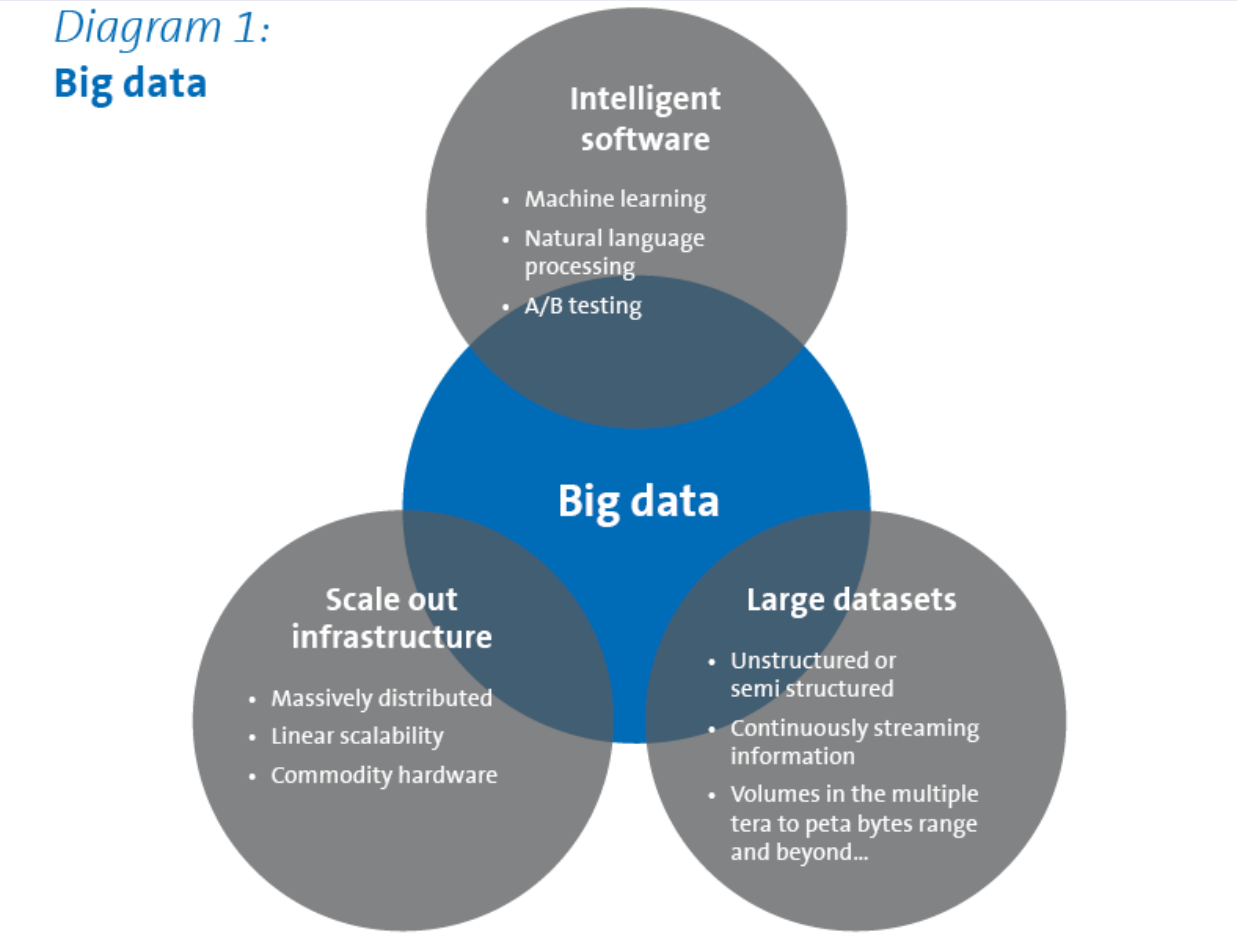
Introduction

Data in USA cross-country commercial flights



Introduction

Big Data. The five V's: volume, variety, velocity, viability and value



DAVENPORT, TH (2013). *At the Big Data Crossroads: Turning Towards a Smarter Travel Experience*. Amadeus IT Group

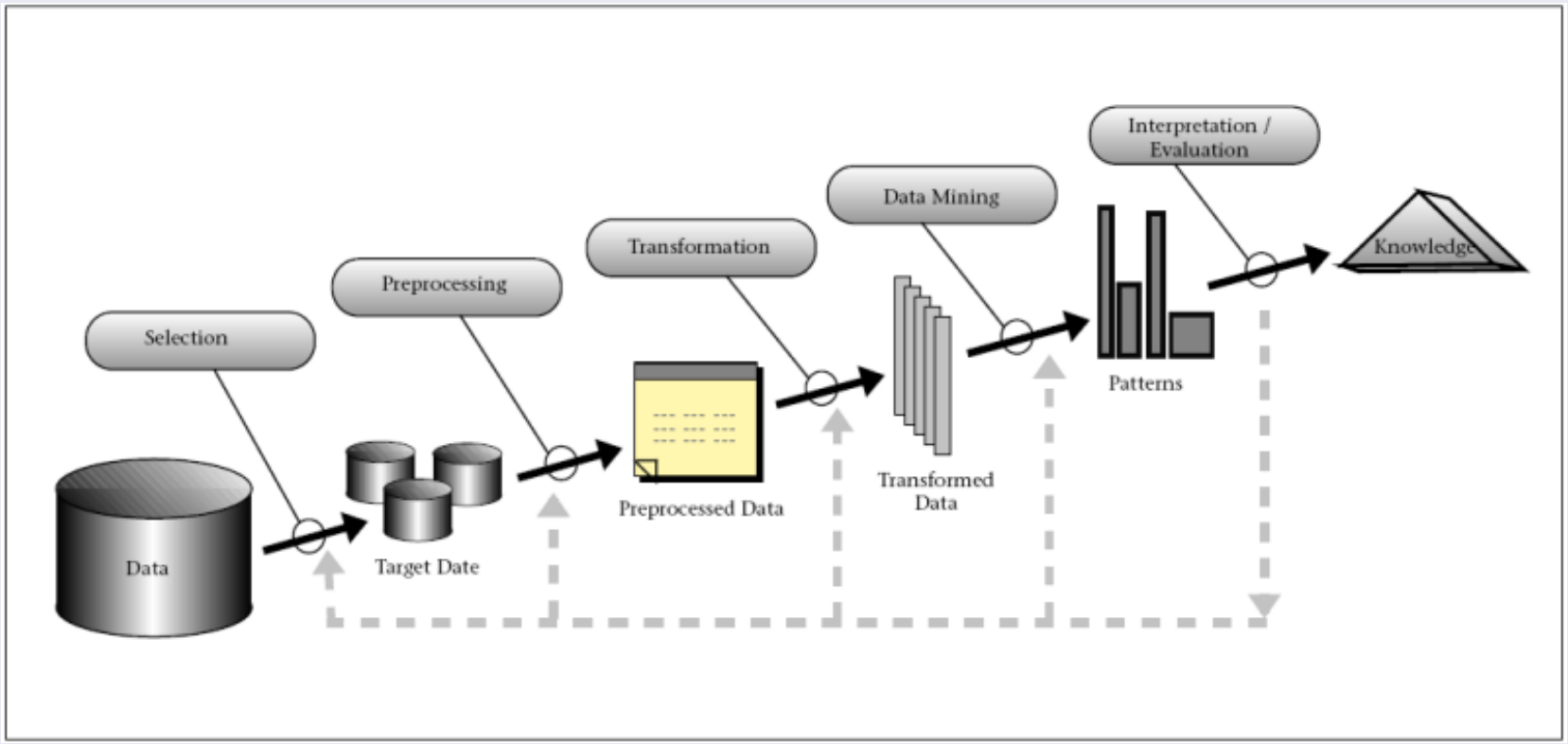
Introduction

Aviation industry

- Characteristics: Large scale and unstructured mixture of data in a variety of data formats
  - Radar
  - Weather (spatial-temporal)
  - Terrain (spatial)
  - Infrastructure
  - Text
- Benefits:
  - Help airlines increase sales
  - Customer loyalty
  - Improve fuel management and efficiency
  - Manage fleets more effectively
  - Improve customer service

Pattern recognition (PR) a step in knowledge discovery in databases (KDD)

PR a part of KDD



Outline

Supervised classification

Supervised: From labelled data to classification models

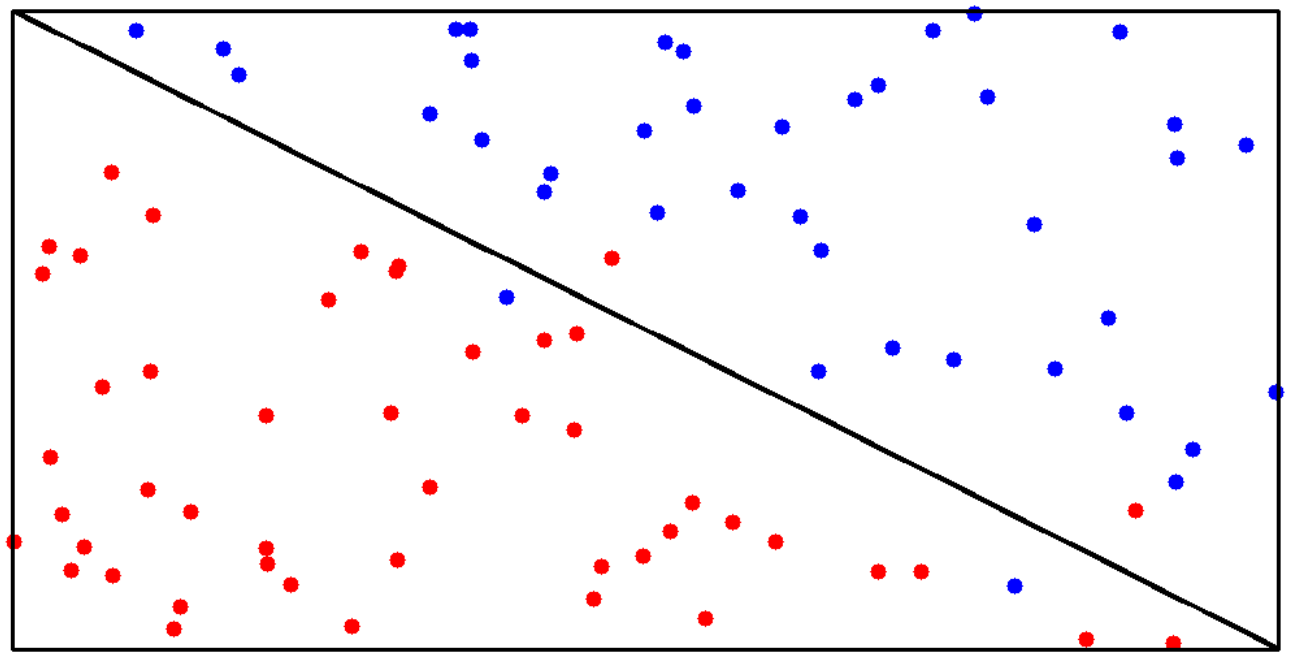
Predictor variables (attributes) and one labelled (class) variable:

	X_1	$\ldots$	X_n	C
$(\boldsymbol{x}^{(1)}, c^{(1)})$	$x_1^{(1)}$	$\ldots$	$x_n^{(1)}$	$c^{(1)}$
$(\boldsymbol{x}^{(2)}, c^{(2)})$	$x_1^{(2)}$	$\ldots$	$x_n^{(2)}$	$c^{(2)}$
$\ldots$		$\ldots$		$\ldots$
$(\boldsymbol{x}^{(N)}, c^{(N)})$	$x_1^{(N)}$	$\ldots$	$x_n^{(N)}$	$c^{(N)}$
$\boldsymbol{x}^{(N+1)}$	$x_1^{(N+1)}$	$\ldots$	$x_n^{(N+1)}$	???

Construct a classification model that predicts with high accuracy the class of a new instance only characterized by the predictor variables

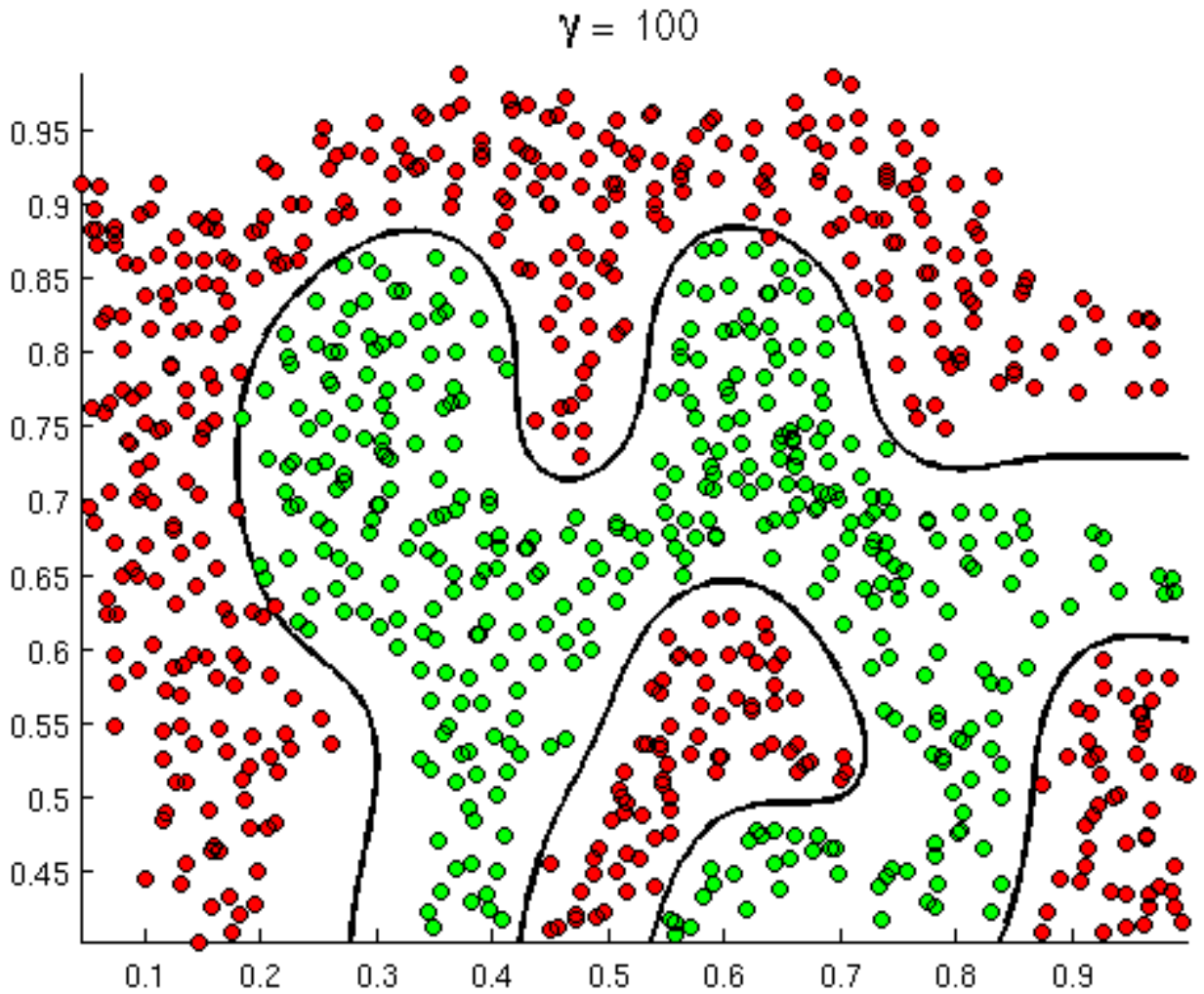
Supervised classification

Linear decision boundary



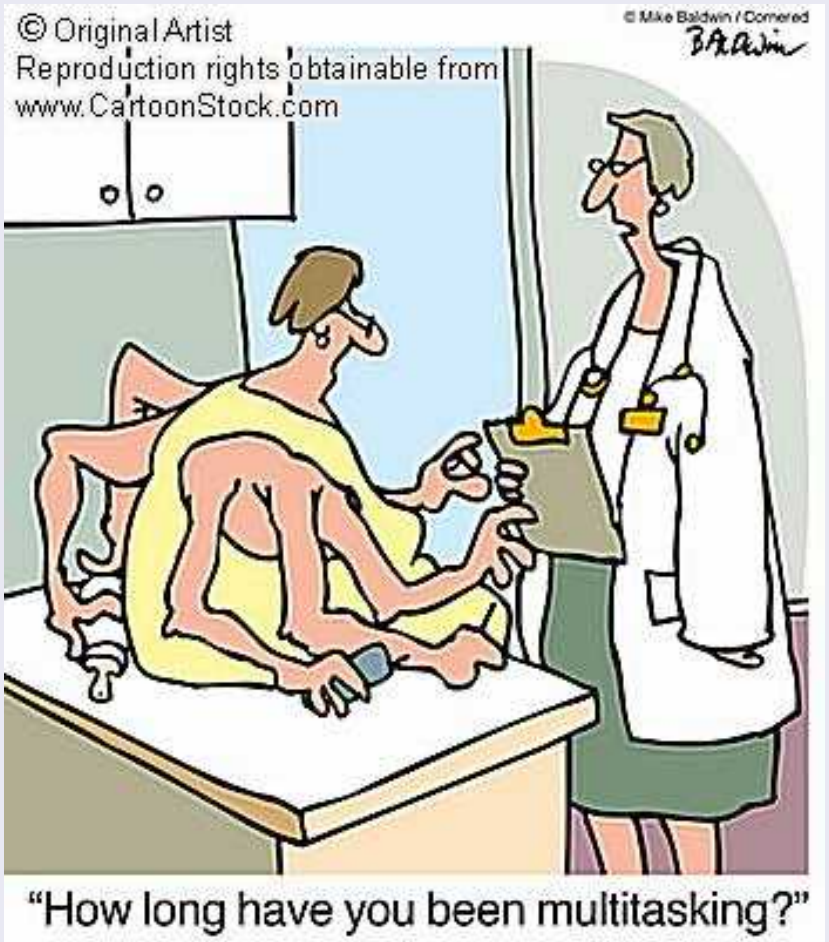
Supervised classification

Non linear decision boundary



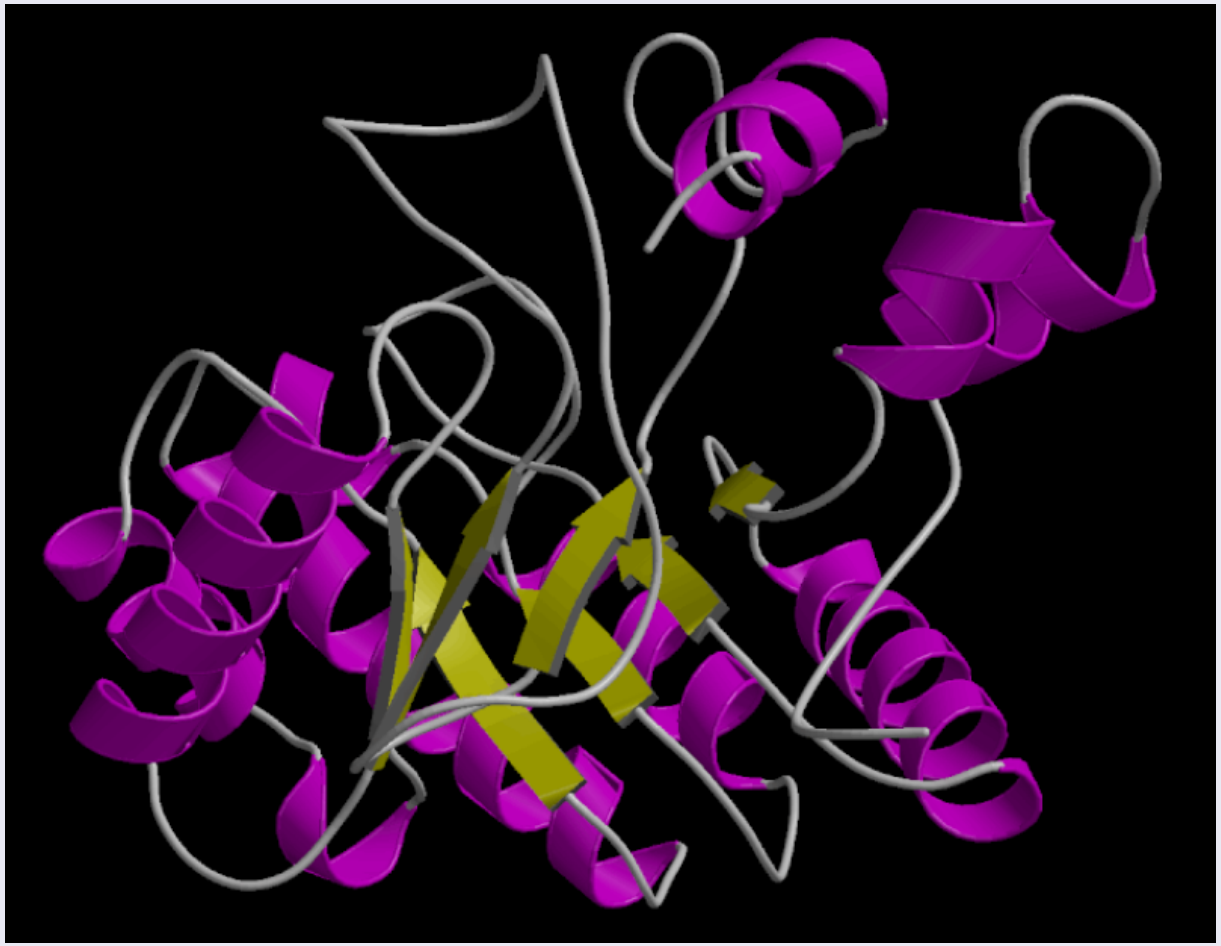
Supervised classification

Disease diagnosis



Supervised classification

Prediction of the secondary structure of proteins



Supervised classification

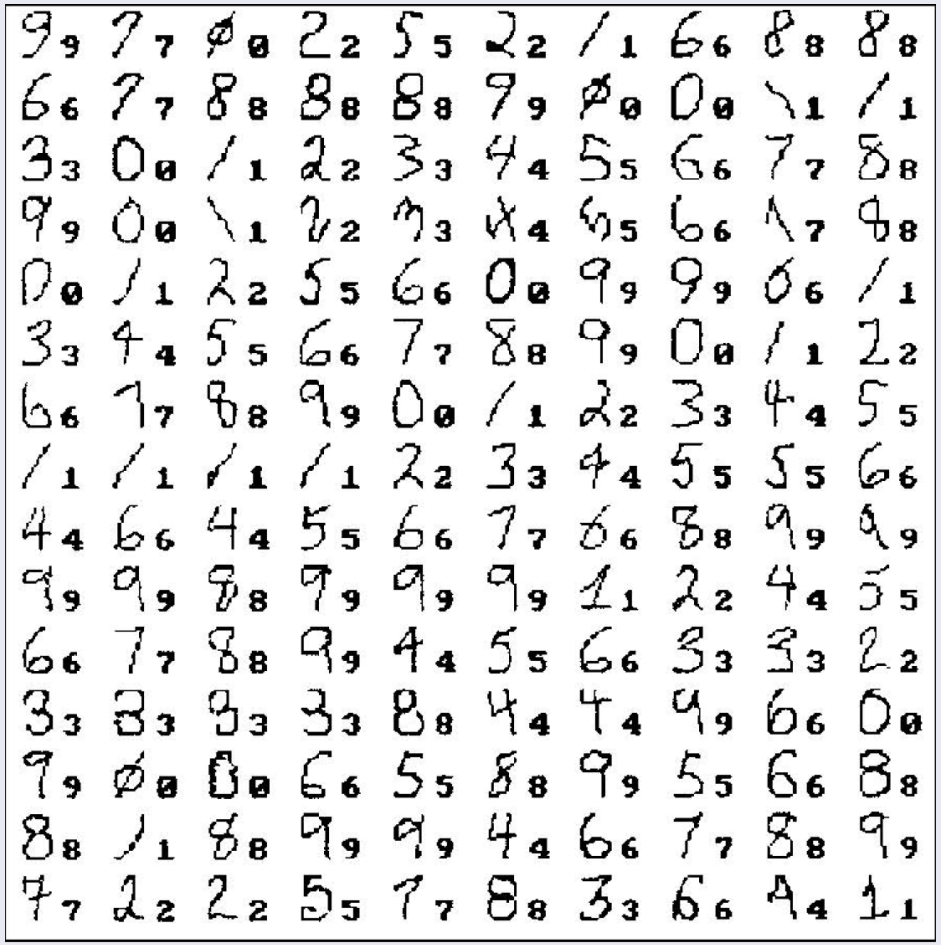
Fraudulent use of credit cards

Supervised classification

Spam email

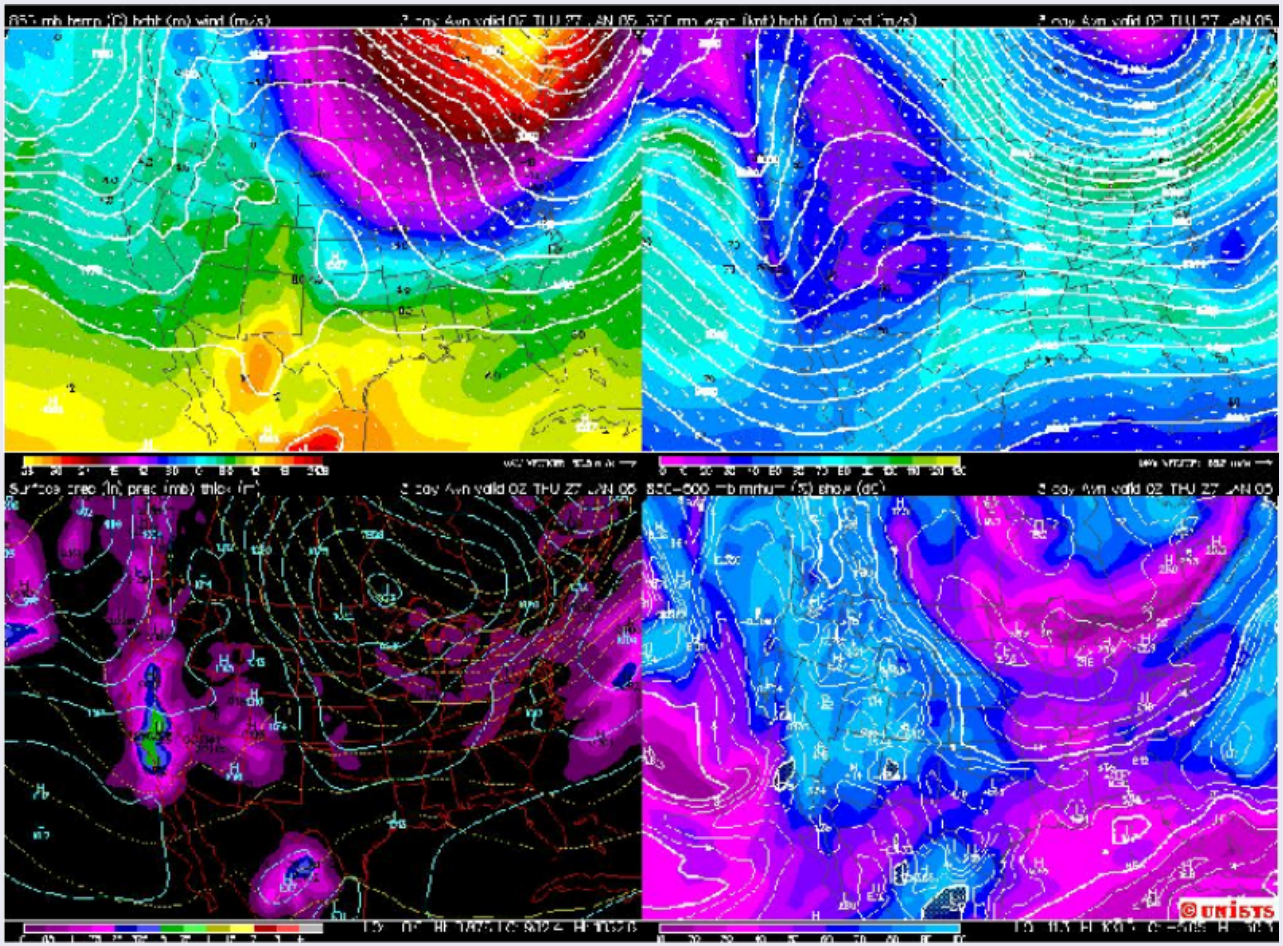
Supervised classification

Handwritten character recognition



Supervised classification

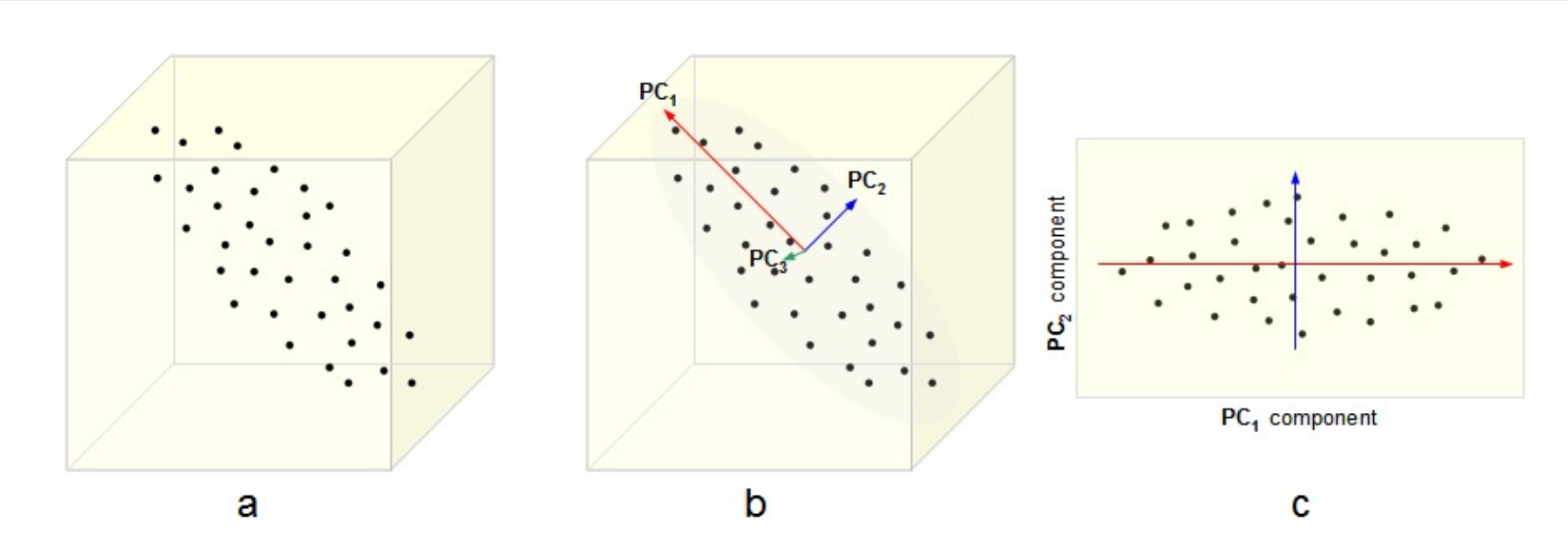
Weather forecasting



Supervised classification

Less is more. Dimensionality reduction with principal component analysis (PCA)

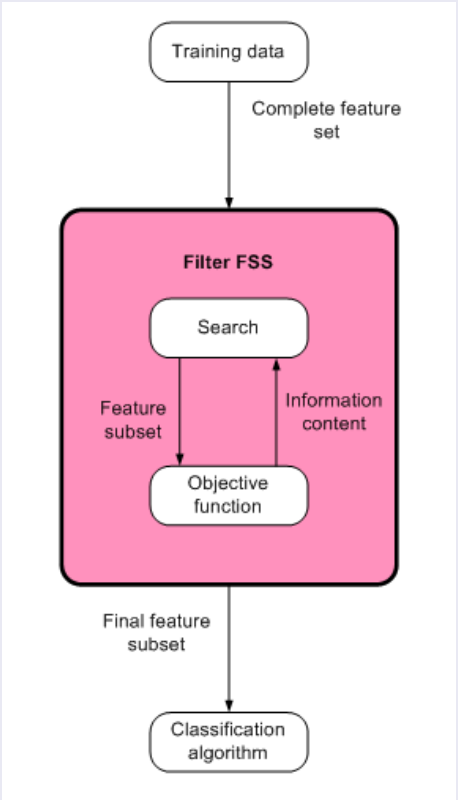
- Directions of max variance of the data
- 3-D data, but distributed mostly on a 2-D surface $\Rightarrow$ Find it

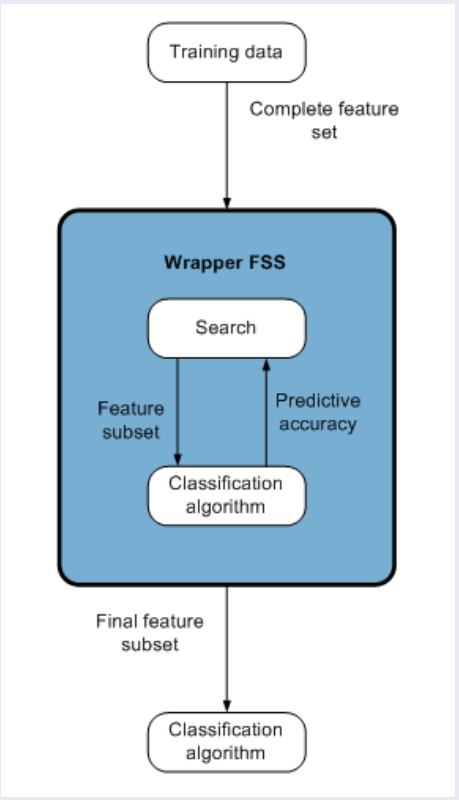


Supervised classification

Less is more. Feature subset selection (FSS)

- Requirement: Scoring function to measure the quality of a subset
- Filter approach: intrinsic characteristics of the data
- Wrapper approach: knowledge about the classifier

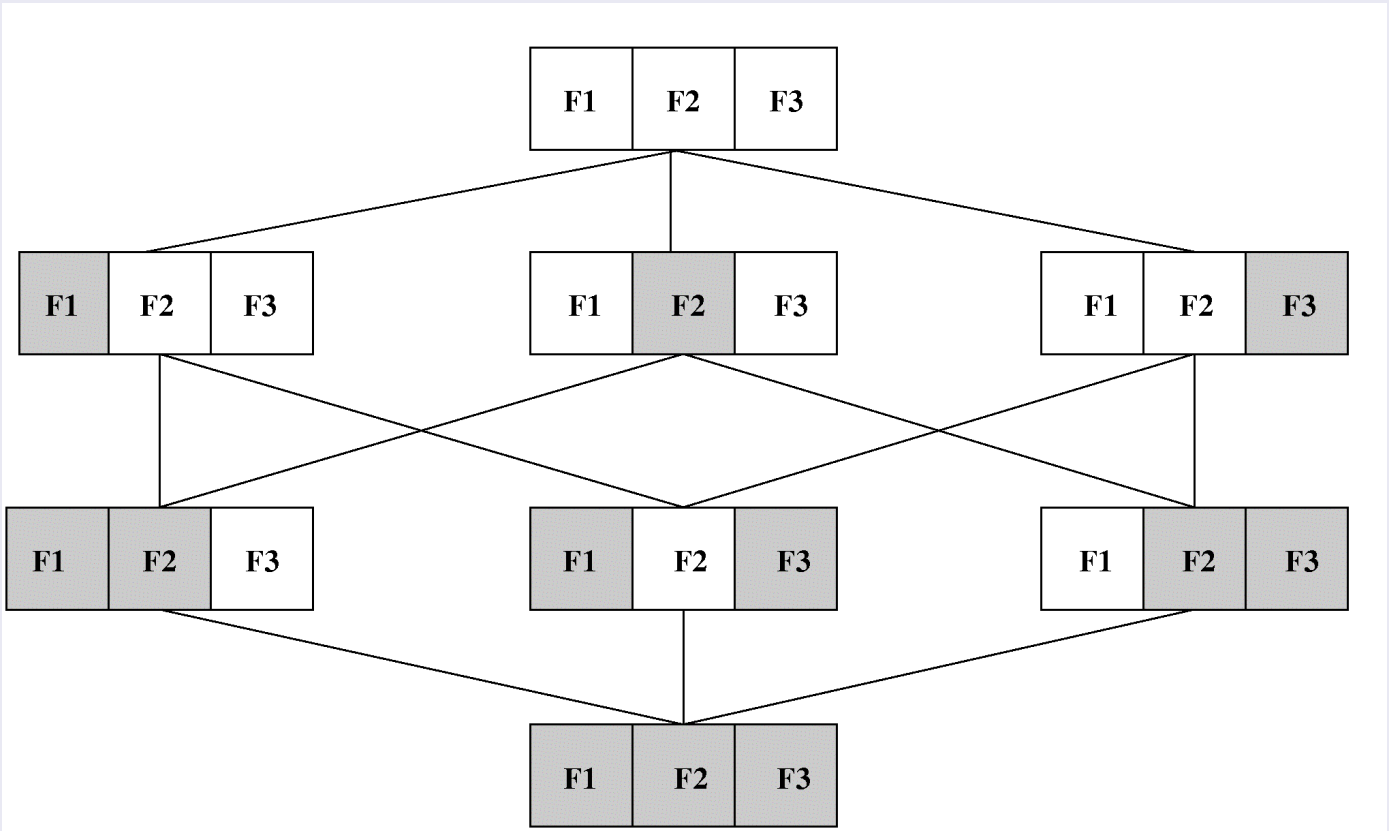




Supervised classification

Less is more. Feature subset selection (FSS)

- FSS as a combinatorial optimization problem: search strategies (forward, backward, genetic algorithms, ...)
- Cardinality of the search space: 2^n



Supervised classification

Measuring the performance. Confusion matrix

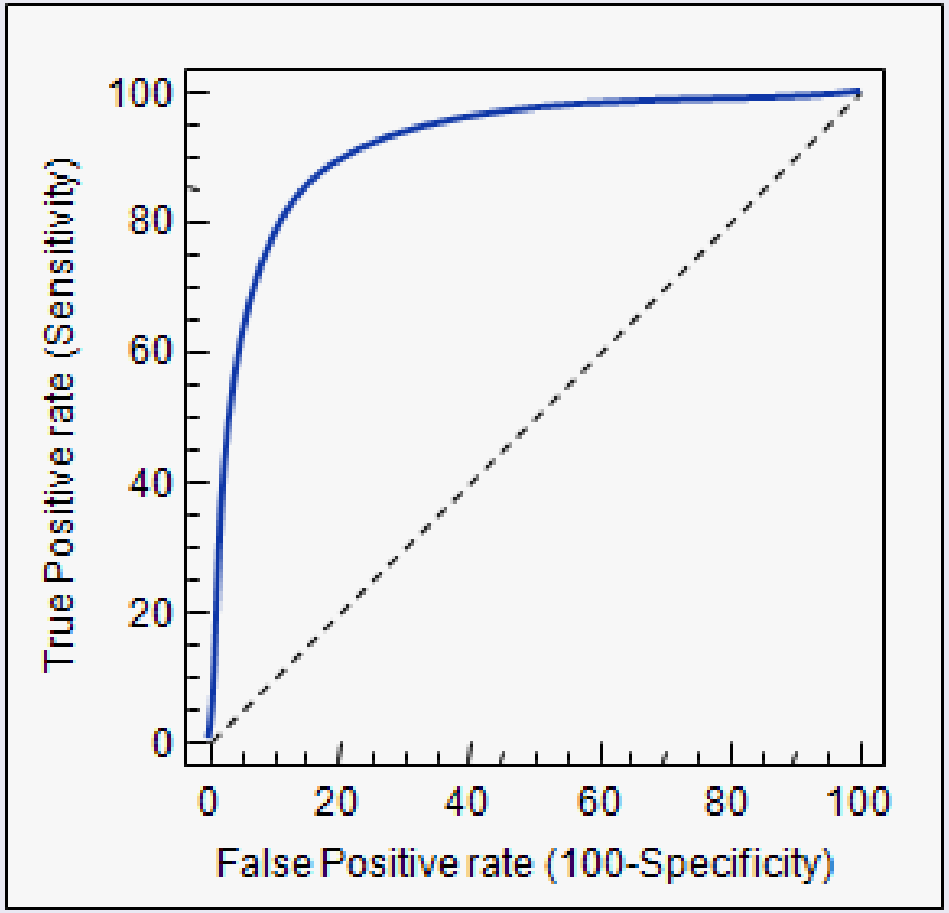
		C True class +	C True class -
C_M Predicted class	+	a	b
	-	c	d

Figures of merit

- Accuracy: $\frac{a+d}{a+b+c+d}$
- Error rate: $\frac{c+b}{a+b+c+d}$
- Rate of true positives (sensitivity): $\frac{a}{a+c}$
- Rate of true negatives (specificity): $\frac{d}{b+d}$

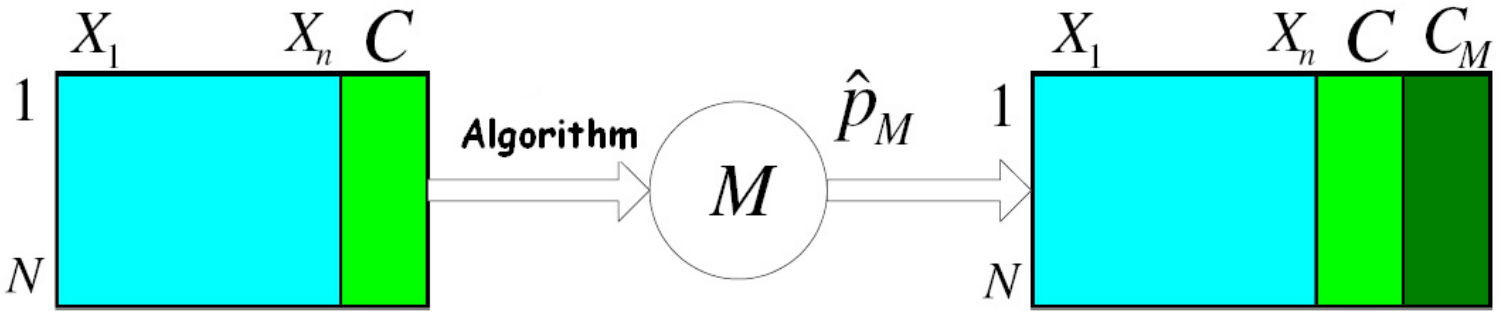
Supervised classification

ROC curve. Area under the ROC curve (AUC)



Supervised classification

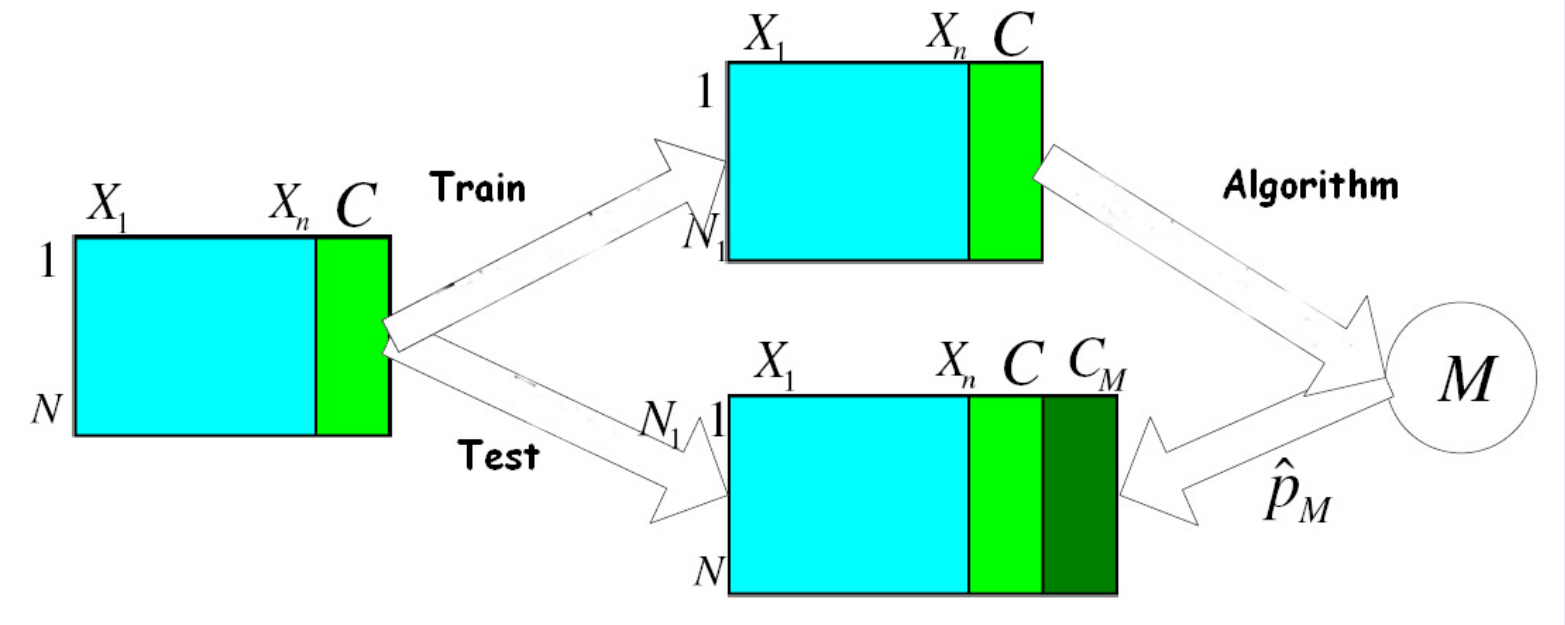
Estimation methods. No honest



$$\hat{p}_M = \frac{1}{N} \sum_{i=1}^{N} \delta(c^{(i)} = c_M^{(i)})$$

Supervised classification

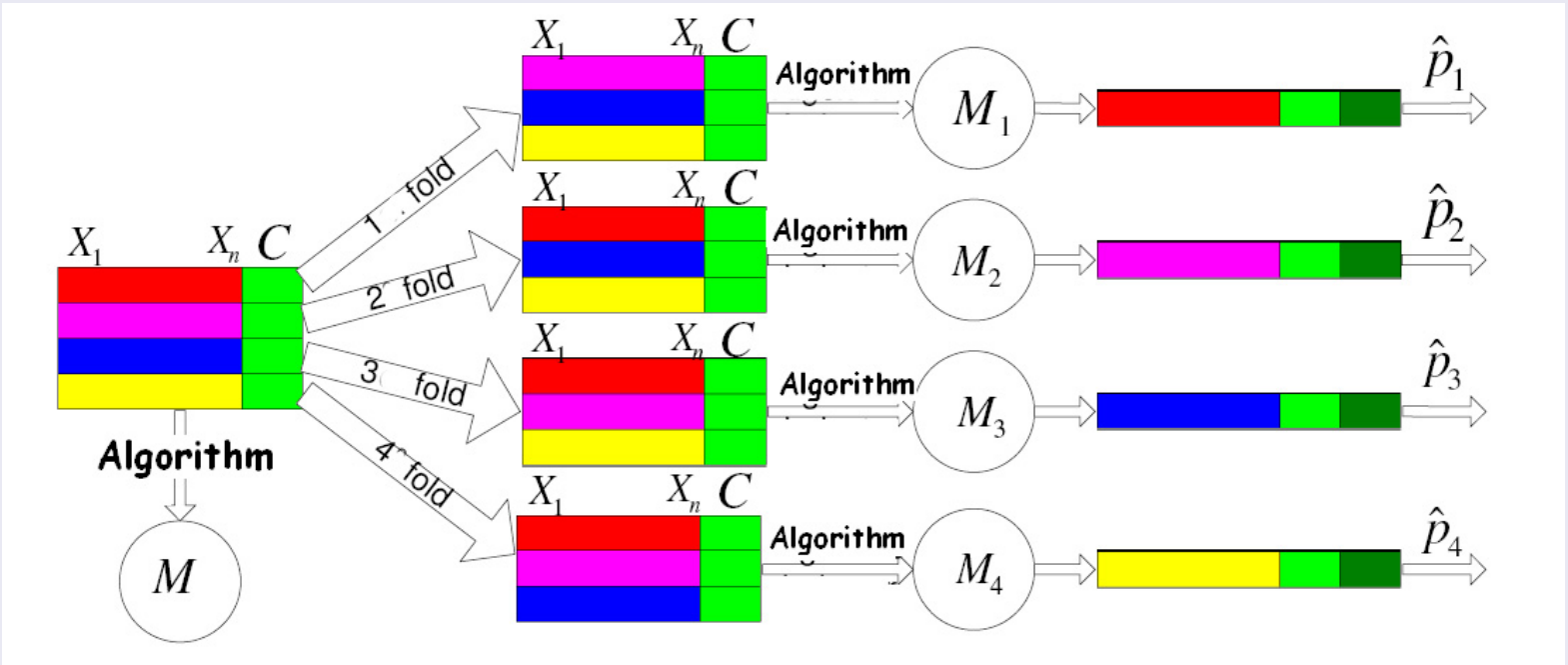
Estimation methods. Train and test



$$\hat{p}_M = \frac{1}{N - N_1} \sum_{i=1}^{N-N_1} \delta(c^{(N_1+i)} = c_M^{(N_1+i)})$$

Supervised classification

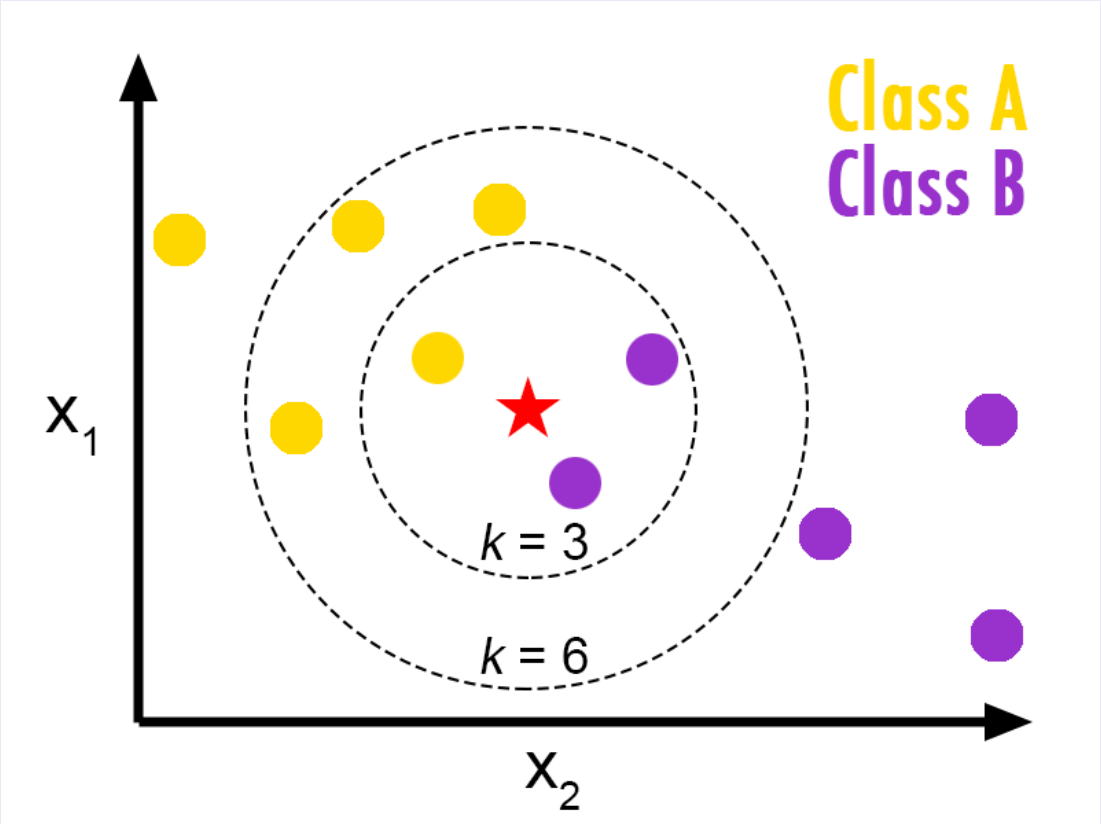
Estimation methods. k–fold cross validation



$$\hat{p}_M = \frac{1}{k} \sum_{i=1}^{k} \hat{p}_i$$

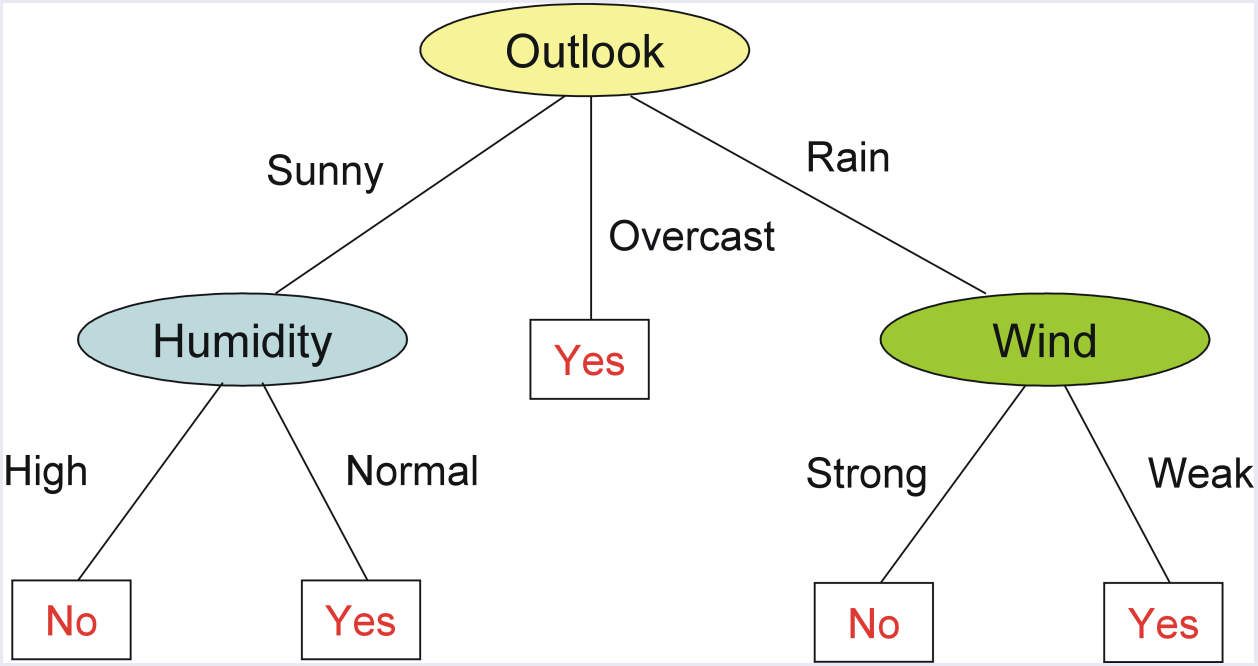
Supervised classification

Classifiers. k-NEAREST NEIGHBORS



Supervised classification

Classifiers. CLASSIFICATION TREE



- Equivalent set of rules:

R1: If (*Outlook*=Sunny) and (*Humidity*=High) then PLAYTENNIS=No
R2: If (*Outlook*=Sunny) and (*Humidity*=Normal) then PLAYTENNIS=Yes
R3: If (*Outlook*=Overcast) then PLAYTENNIS=Yes
R4: If (*Outlook*=Rain) and (*Wind*=Strong) then PLAYTENNIS=No
R5: If (*Outlook*=Rain) and (*Wind*=Weak) then PLAYTENNIS=Yes

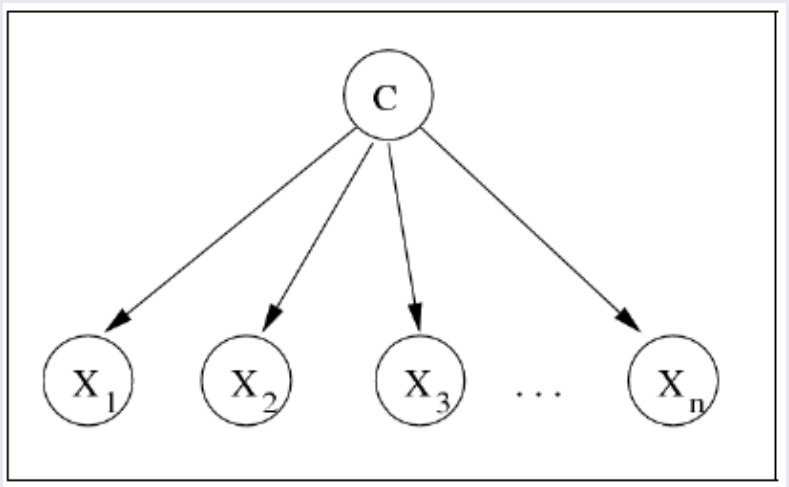
Supervised classification

Classifiers. NAIVE BAYES

Predictor variables are conditionally independent given C

$$P(c|x_1,...,x_n) \propto P(C=c)\prod_{i=1}^{n} P(X_i=x_i|C=c)$$

$$\Rightarrow \qquad c^* = arg \;\; max_c P(C=c)\prod_{i=1}^{n} P(X_i=x_i|C=c)$$

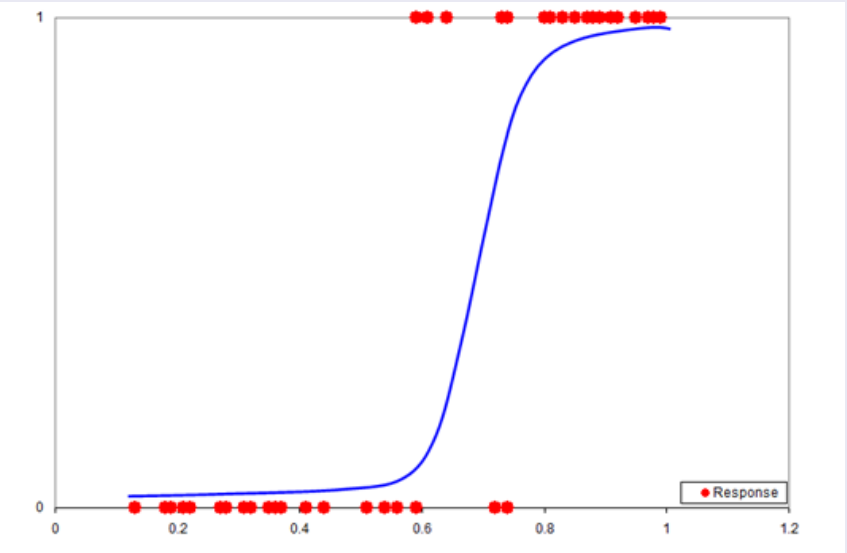


Supervised classification

Classifiers. LOGISTIC REGRESSION

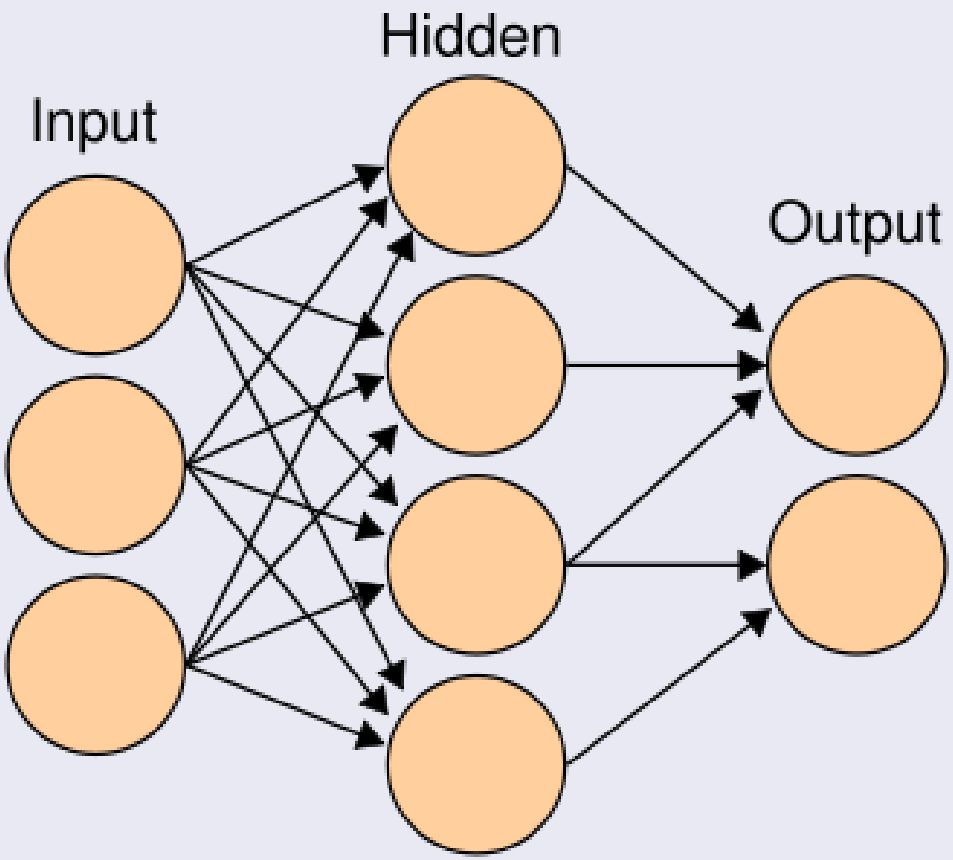
$$\pi_j = P(C = 1|\mathbf{x}_j) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_{j1}+\cdots+\beta_n x_{jn})}}$$

$$\Rightarrow \; 1 - \pi_j = P(C = 0|\mathbf{x}_j) = \frac{1}{1+e^{(\beta_0+\beta_1 x_{j1}+\cdots+\beta_n x_{jn})}}$$



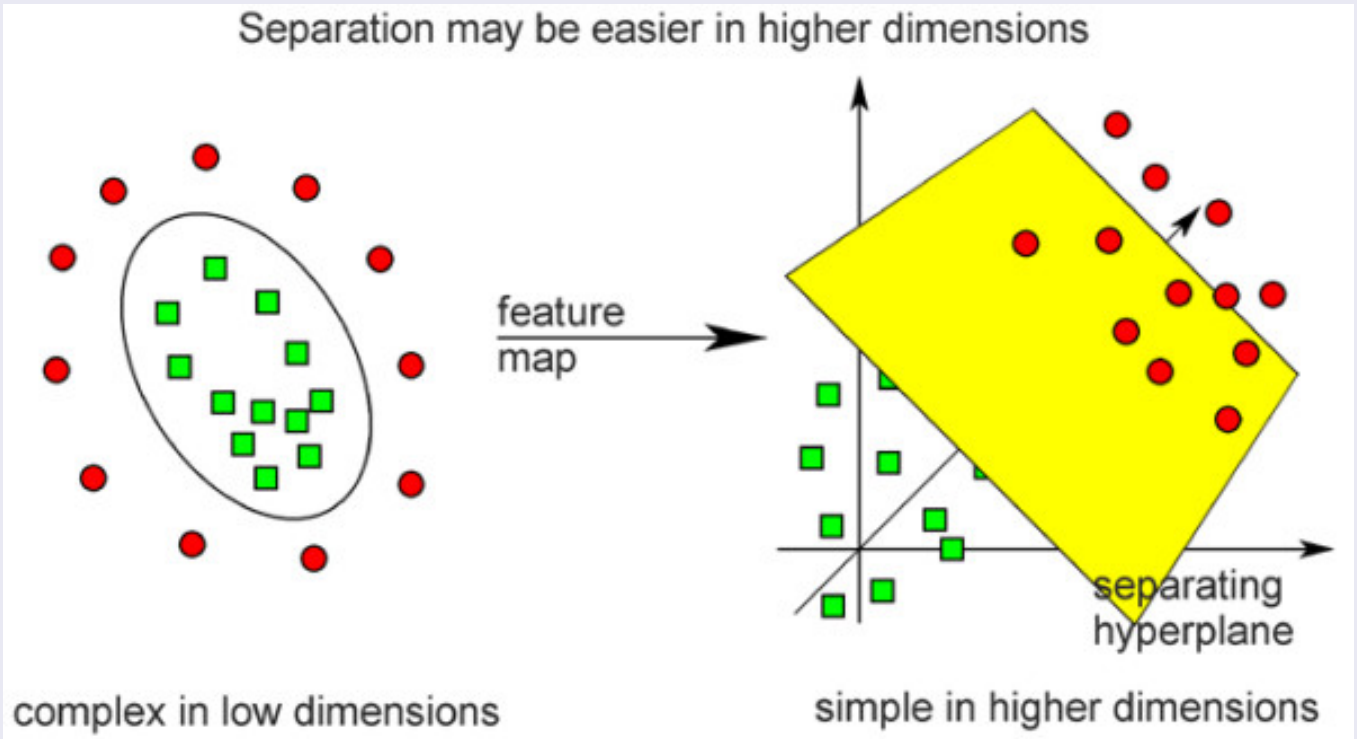
Supervised classification

Classifiers. NEURAL NETWORK



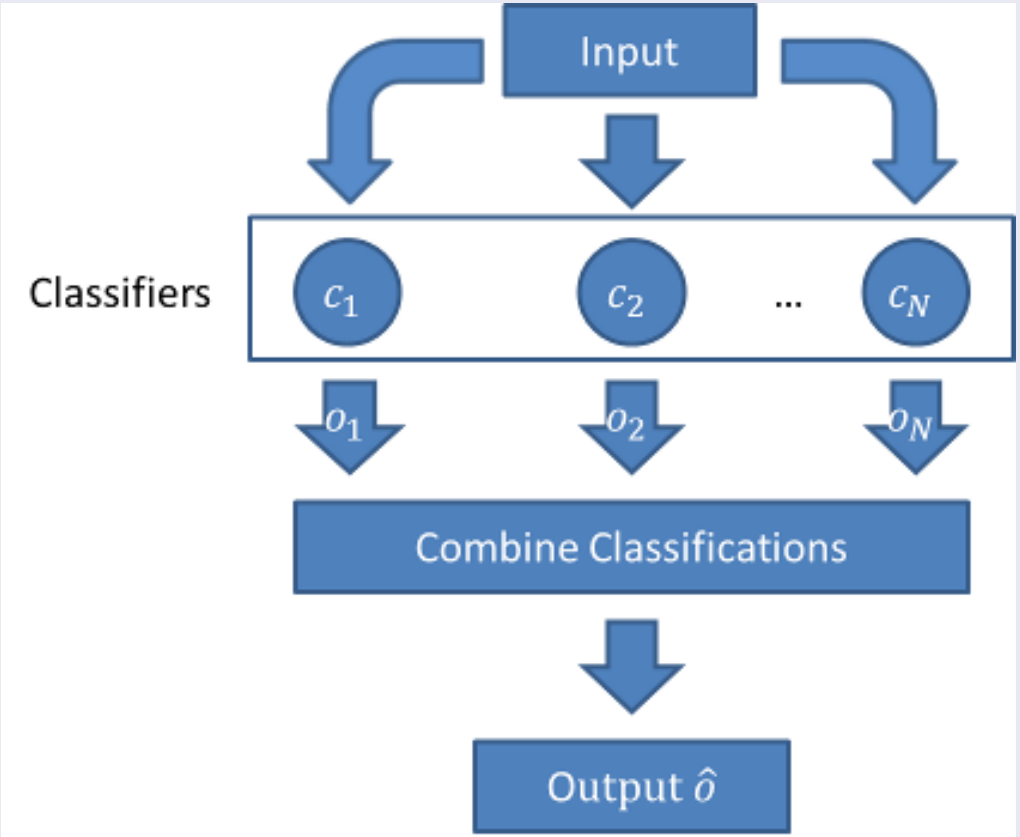
Supervised classification

Classifiers. SUPPORT VECTOR MACHINE



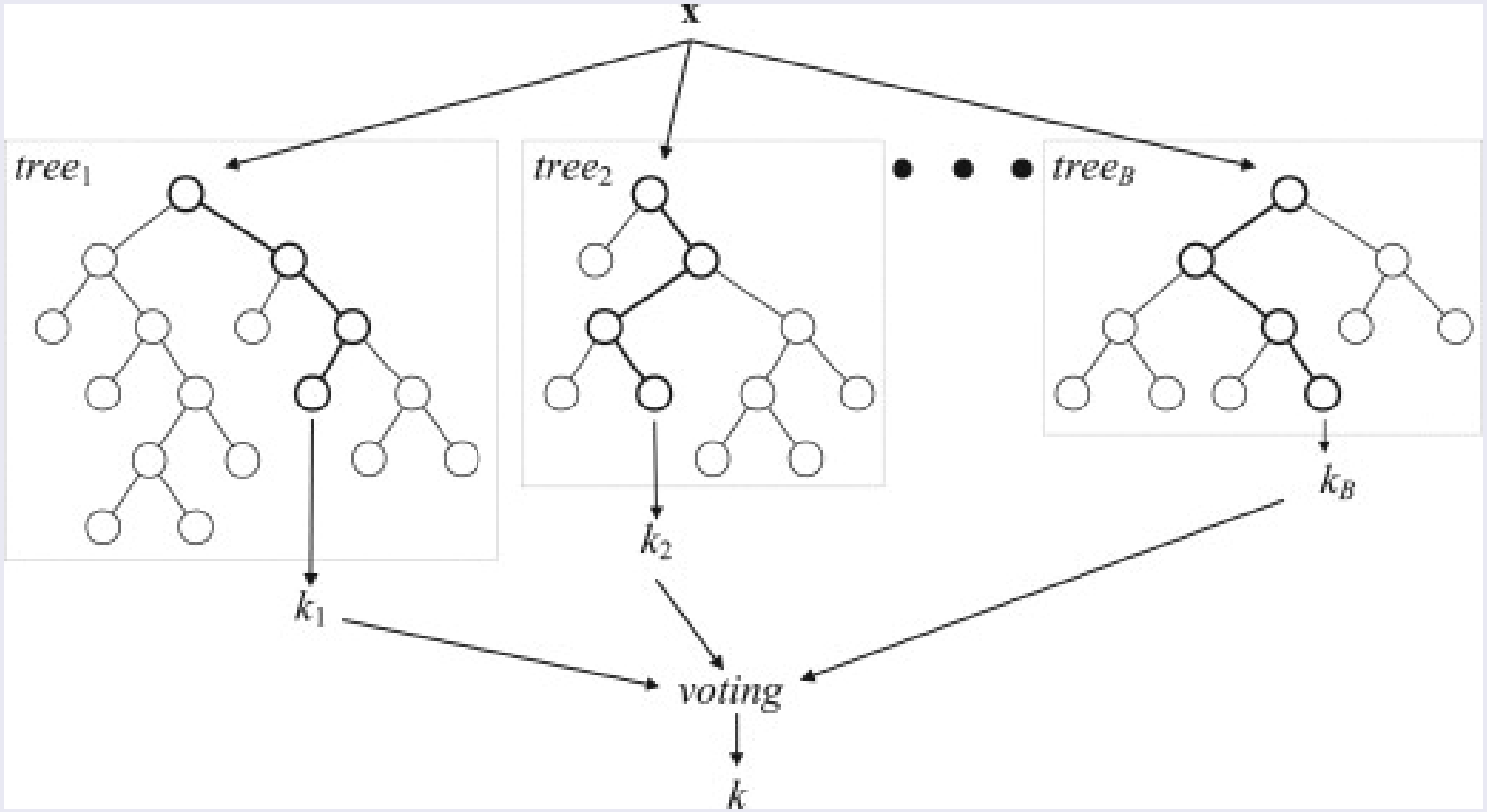
Supervised classification

Classifiers. METACLASSIFIERS



Supervised classification

Classifiers. METACLASSIFIERS. RANDOM FOREST



Supervised classification

Case study on diagnose aviation turbulence

- Predominant cause of accidents and injuries
- Costing airlines millions of euros per year in compensation: aircraft damage, and delays due to post-event inspections and repairs
- Attempts to avoid turbulent airspace cause: flight delays and en route deviations, increasing air traffic controller workload, disrupt schedules of air crews and passengers and use extra fuel

WILLIAMS JK (2013). Using random forest to diagnose aviation turbulence. *Machine Learning*, in press

Supervised classification

Case study on diagnose aviation turbulence

- Data sets (March 10 to November 4, 2010)
  - UAL from 95 United Airlines, Boeing 757: 5,623,738 instances
  - DAL from 80 Delta Air Lines, Boeing 737: 6,595,922 instances
  - Predictor variables: Numerical weather predictors, Dopller radar, Geostationary satellite images, Lightning detection network, Derived fields and features
  - Class variable: Eddy dissipation rate (EDR) an aircraft-independent atmospheric turbulence metric
- Feature subset selection: wrapper forward/backward selection guided by the AUC
- Supervised classification methods: k-nearest neighbor ($k = 100$); logistic regression; and random forest (200 trees)
- Validation: 10-fold cross-validation repeated 32 times with AUC as performance metric

Supervised classification

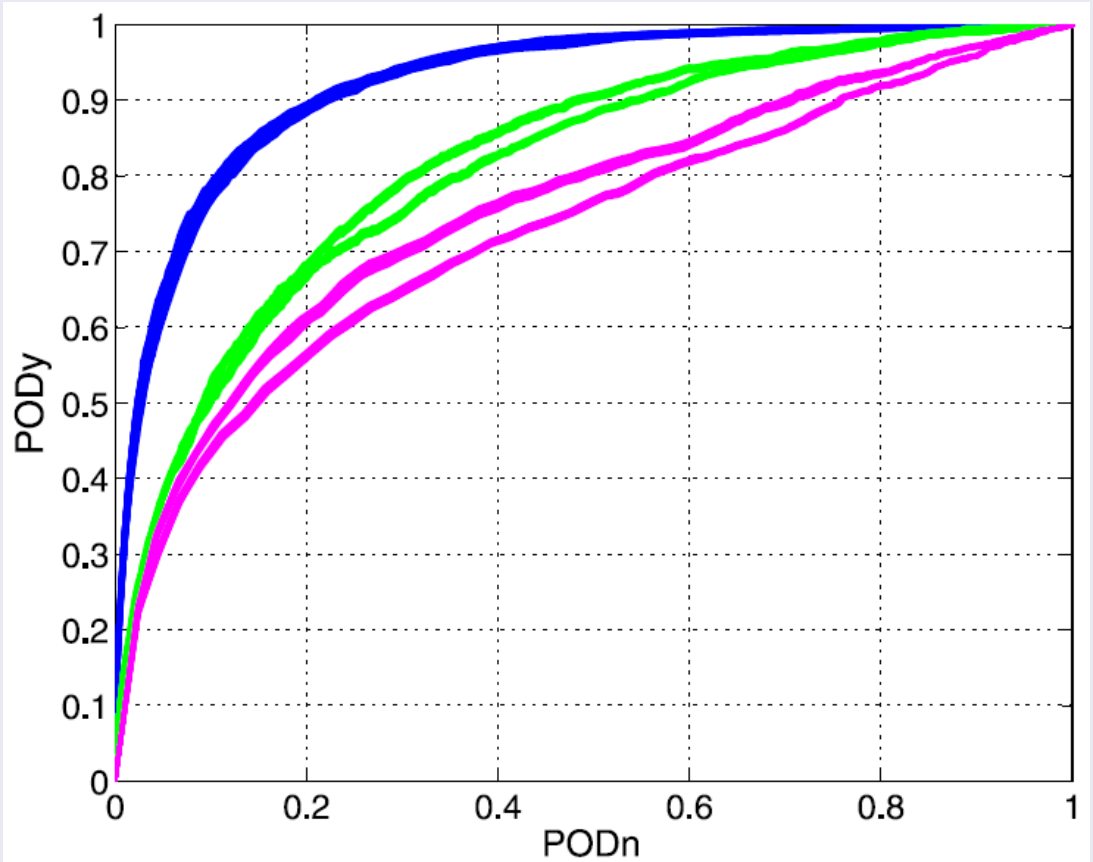
Case study on diagnose aviation turbulence

Table 2 Forward/backward selection procedure results for RF and logistic regression

Random forest (8)			Logistic regression (8)		
Rank	Mean occ.	Predictor name	Rank	Mean occ.	Predictor name
1	115	Dist. to NSSL echo top > 10 kft	1	135	Model FRNTGTHRI
2	114	Model FRNTGTHRI	2	134	Diff. Alt. to 80-km max NTDA sev. top
3	104	Model RITW	3	127	Dist. to NSSL echo top > 10 kft
4	89	Model ELLROD2	4	126	10-km max of NSSL echo top
5	88	Diff. Alt. to 80-km max NTDA sev. top	5	121	Model ELLROD2
6	85	Model MWT2	6	111	Model RITW
7	79	Model ELLROD1	7	107	Model BROWN2
8	78	160-km mean of Satellite Ch. 6	8	94	Diff. Alt. to 20-km max NTDA mod. top
9	69	Model F2DTW	9	92	Model BROWN1
10	68	Model MWT3	10	89	Model ELLROD1
11	68	40-km min of Satellite Ch. 6	11	88	Model MWT3
12	67	Model Atm. Pressure	12	87	Model EDRRI
13	66	Model BROWN2	13	85	Model DTF3
14	65	Satellite Ch. 4 minus Model temp.	14	83	20-km no. of good NTDA dBZ points
15	64	Model DUTTON	15	77	10-km no. of good NTDA dBZ points
16	63	Satellite Ch. 4 minus Satellite Ch. 3	16	76	10-km mean of NTDA composite EDR
17	58	Model NGM2	17	74	10-km max of NTDA composite EDR
18	56	160-km mean of Satellite Ch. 4	18	74	10-km min of Satellite Ch. 3
19	53	Model RICH	19	73	10-km mean of NSSL echo top
20	52	Diff. Model pres. to Mod. surf. pres.	20	69	Model IAWINDRI

Supervised classification

Case study on diagnose aviation turbulence



PODy= TPR; PODn= FPR; Random forest (blue) with AUC=0.924; k-NN (green) with AUC=0.915; logistic regression (green) with AUC=0.915; Graphical turbulence guidance (magenta) with AUC=0.816; storm distance (magenta) with AUC=0.743

Multi-label classification

X_1	X_2	X_3	X_4	X_5	C
3.2	1.4	4.7	7.5	3.7	1
2.8	6.3	1.6	4.7	2.7	0
7.7	6.2	4.1	3.3	7.7	1
9.2	0.4	2.8	0.5	3.9	0
5.5	5.3	4.9	0.6	6.6	1

X_1	X_2	X_3	X_4	X_5	C_1	C_2	C_3	C_4
3.2	1.4	4.7	7.5	3.7	1	0	1	1
2.8	6.3	1.6	4.7	2.7	0	0	1	0
7.7	6.2	4.1	3.3	7.7	1	0	1	1
9.2	0.4	2.8	0.5	3.9	0	1	0	0
5.5	5.3	4.9	0.6	6.6	1	1	0	1

Multi-label classification

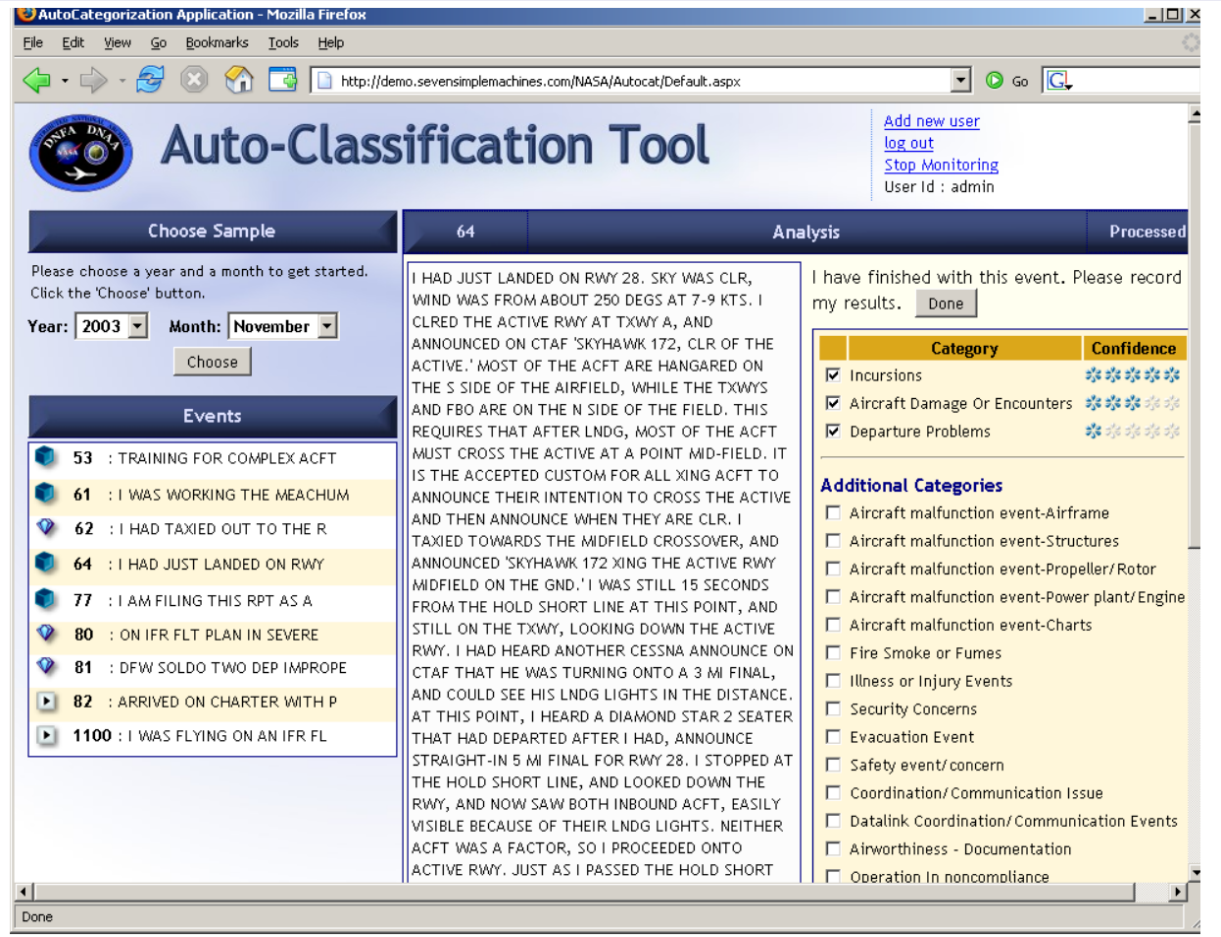
Case study on the ASRS database

- The Aviation Safety Reporting System (ASRS) database spans 30 years and contains over 700,000 aviation safety reports in free text form
- Primary concern is system health and safety: detection, diagnosis, prediction, mitigation, and prevention of ongoing and future system problems
- ARSR reports are publicly available and are written by pilots, flight controllers, technicians, flight attendants, and others including passengers
- Predictor variables, X_1 to $X_{25,729}$: 25,729 terms that occur in at least one document
- Class variables to be predicted, C_1 to C_{60}: 60 problem types that appear during flights
- A subset of 28,596 documents containing 22 classes was used

OZA N, ET AL. (2009). Classification of aeronautics system health and safety documents. *IEEE Transactions on Systems, Man, and Cybernetics, Part C*, 39(6), 670-680

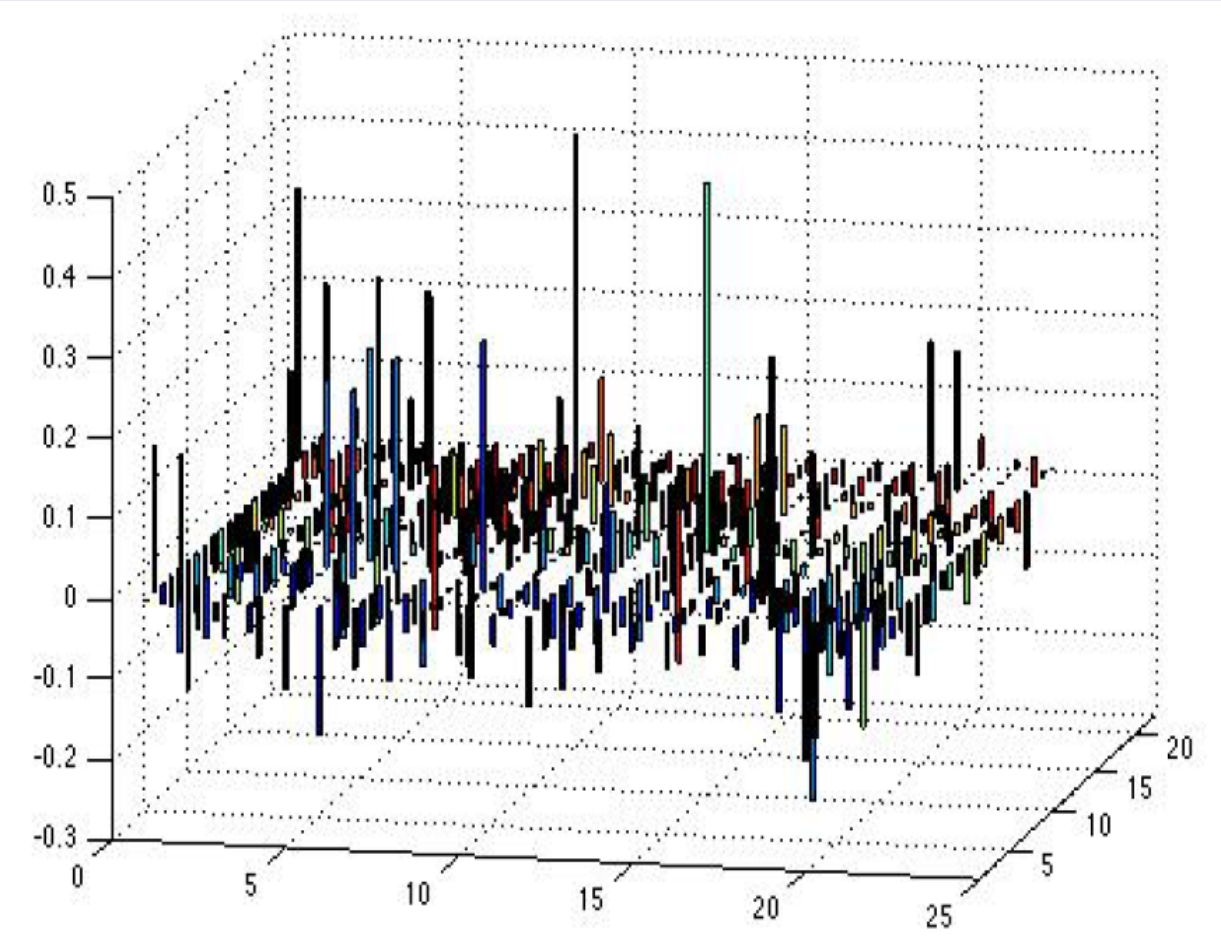
Multi-label classification

Case study on the ASRS database



Multi-label classification

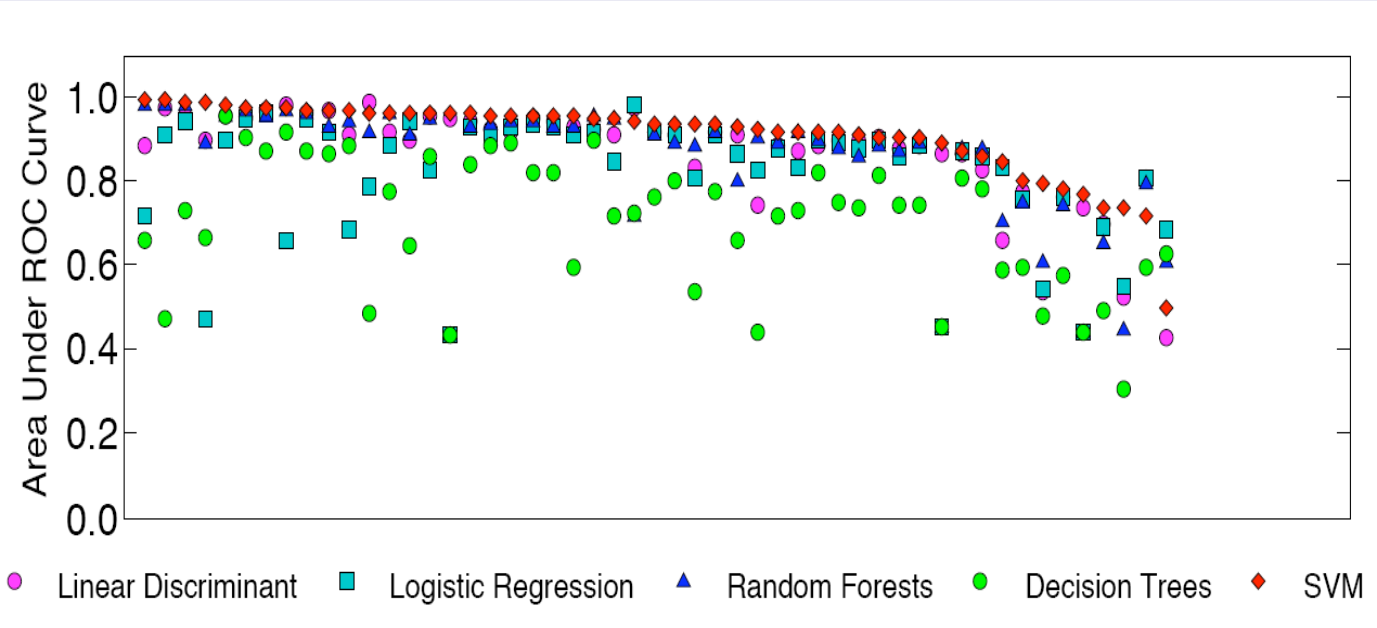
Case study on the ASRS database



Correlations between pairs of class variables

Multi-label classification

Case study on the ASRS database



AUC performances over the 60 univariate classification problems

Outline

Clustering

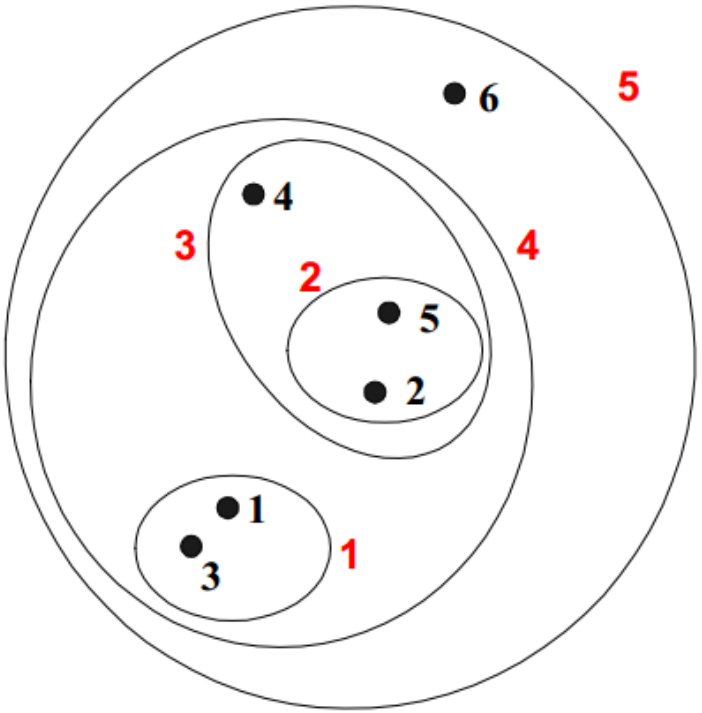
A general dataset

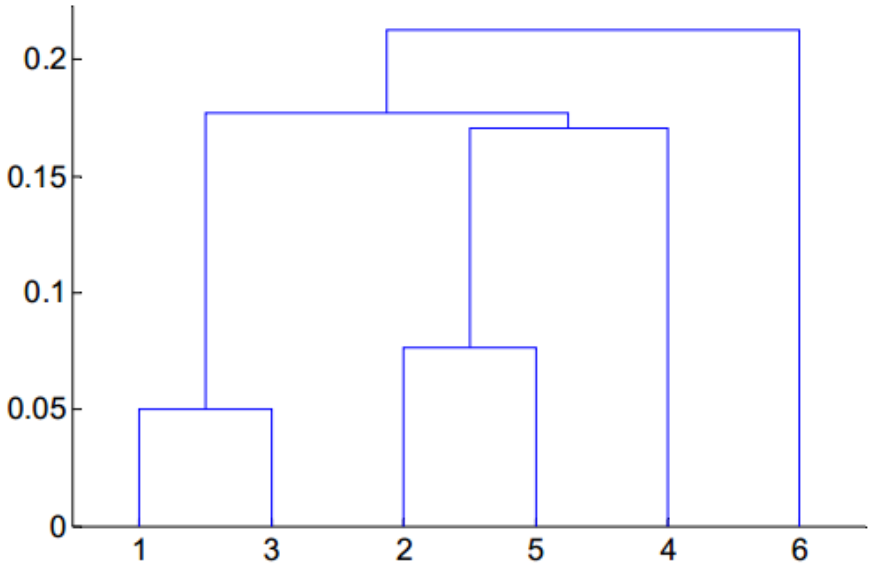
	X_1	$\ldots$	X_n
$\boldsymbol{x}^{(1)}$	$x_1^{(1)}$	$\ldots$	$x_n^{(1)}$
$\ldots$		$\ldots$	
$\boldsymbol{x}^{(N)}$	$x_1^{(N)}$	$\ldots$	$x_n^{(N)}$

- Grouping objects in clusters
- High similarity within each cluster
- High dissimilarity between the different clusters
- Main methods:
  - Hierarchical clustering
  - Partitional clustering
  - Probabilistic clustering

Clustering

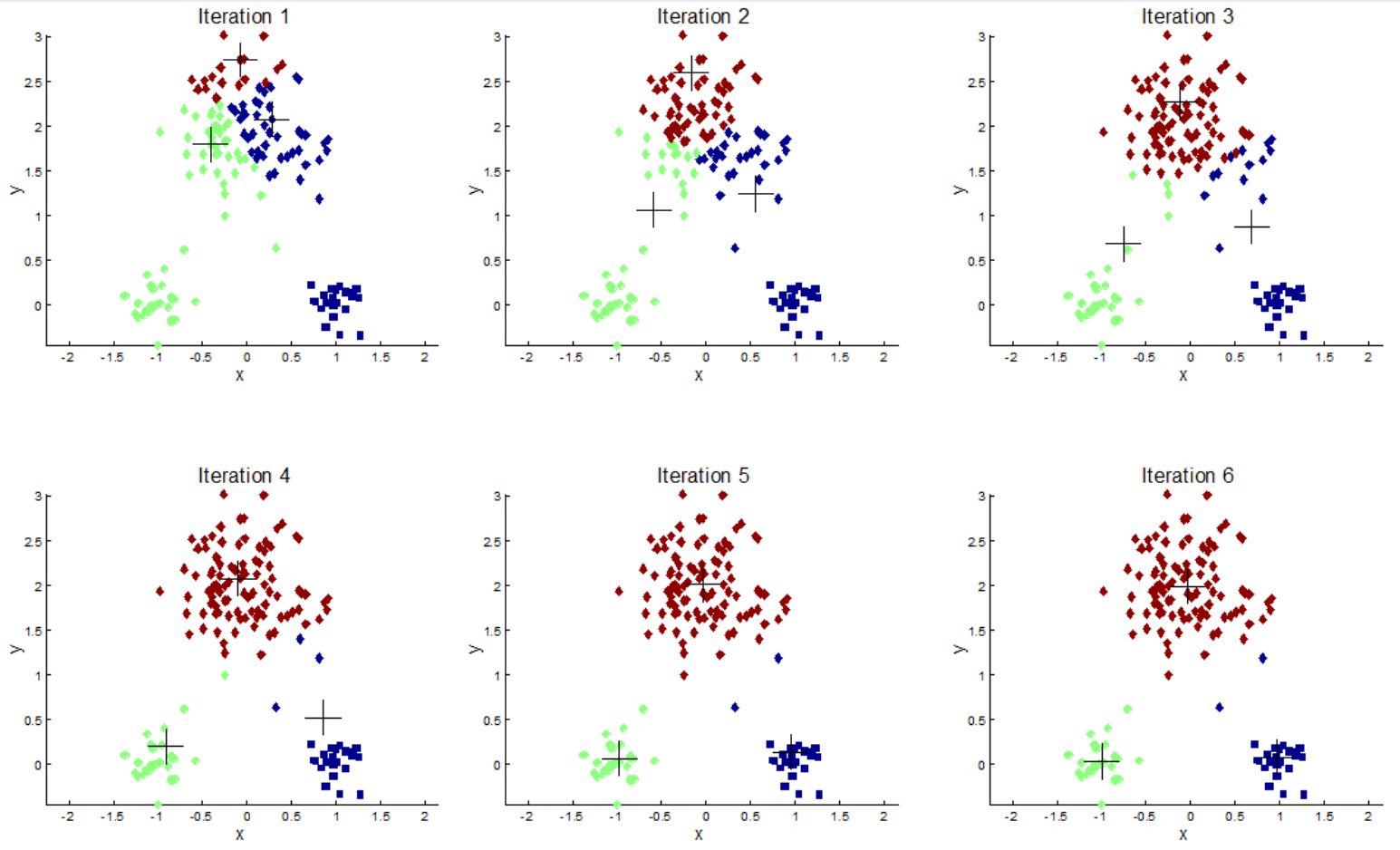
Hierarchical Clustering





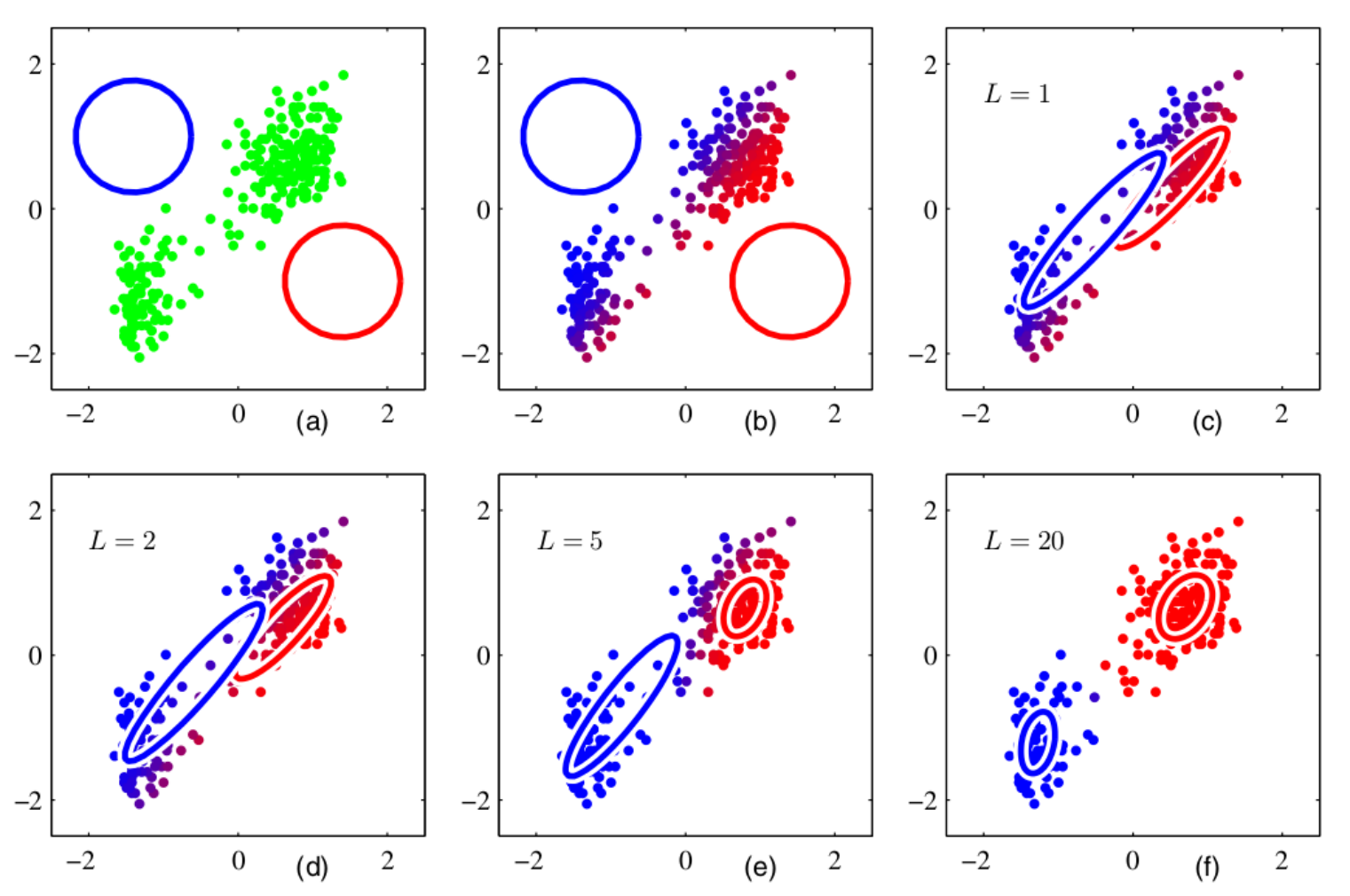
Clustering

PARTITIONAL CLUSTERING: k-means



Clustering

PROBABILISTIC CLUSTERING: finite mixture models with EM



Clustering

Case study on detecting anomalous landing

- A key question on the aviation safety domain
- For a specific aircraft make and model at a specific airport
- Variables: sequence of switches that a pilot flips during the course of the landing phase of the flight
- Data set: N= 2,200 flights, and n= 1,500 possible switches
- Cluster algorithm: k-medoids
- Anomalous landing: a sequence that is far away from the cluster centroid

BUDALAKOTI ET AL. (2009). Anomaly detection and diagnosis algorithms for discrete symbol sequences with applications to airline safety. *IEEE Transactions on Systems, Man, and Cybernetics, Part C*, 39(1), 101-113

Outline

Conclusions

Machine learning in aviation

- Aviation industry generates large scale data
- Transform these data sets into knowledge
- Machine learning methods:
  - Supervised classification
  - Clustering
- Advances in the safety, security, and efficiency of civil aviation

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MACHINE LEARNING IN AVIATION

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Toulouse, July 11, 2013