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Digital Adventure Ride to the Future


7 – 18 January, 2024



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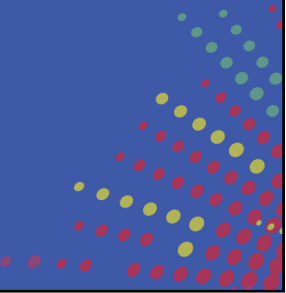


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Regression and Demand Forecasting


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Utrecht University




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Today







Classification



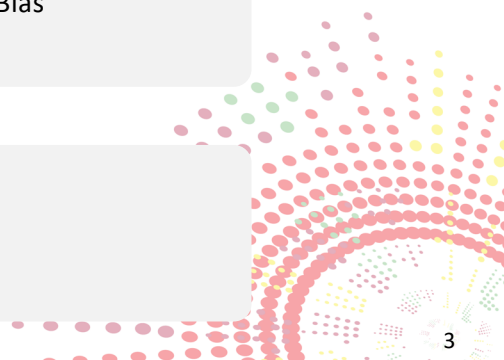
Model and Data Bias



Fairness




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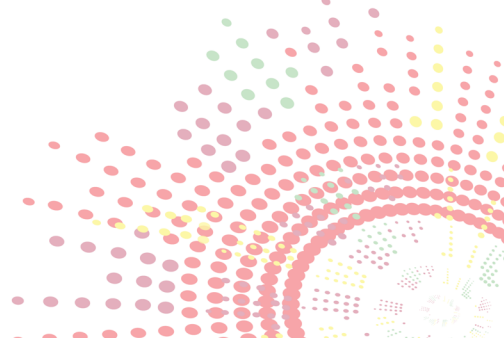
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Classification





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Topics

- Classification
 - Train-Test Split
 - Classification Algorithms
 - Evaluation
- Evaluation



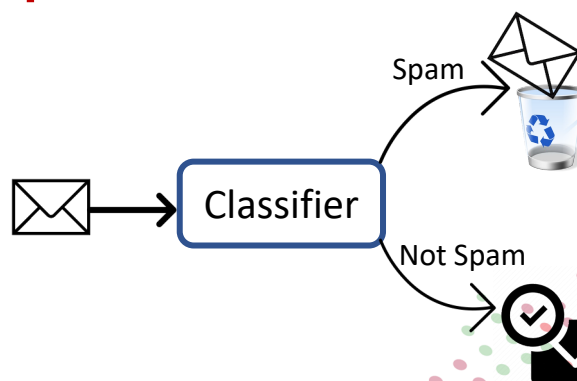
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Real World Examples

- Credit/loan approval
- Medical diagnosis
- Fraud detection
- Web page categorization
- Spam detection in emails
- Image classification
- Text sentiment



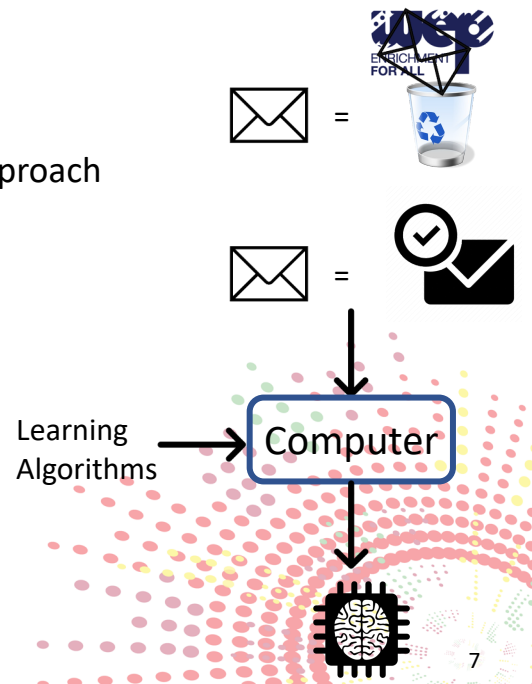
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How Classifiers Work?

- Classification is a supervised learning approach
 - Labeled dataset is needed
 - Features/Examples: X
 - Outcomes/Labels: Y
 - Learn the patterns
 - Use them to predict the labels



Classification techniques

- Include:
 - Logistic Regression
 - Learning from the neighbors
 - Decision tree-based methods
 - Support vector machines
 - Neural networks
 - Bayesian classification

Building a Classification Model



- Split the data into training and testing
- Train the classifier on the training data
- Select a set of performance measures
 - Accuracy, Balanced Accuracy, Precision, Recall, F-Score, ...
- Evaluate the classifier on the test set

NOTE: NEVER USE THE TEST SET FOR TRAINING!

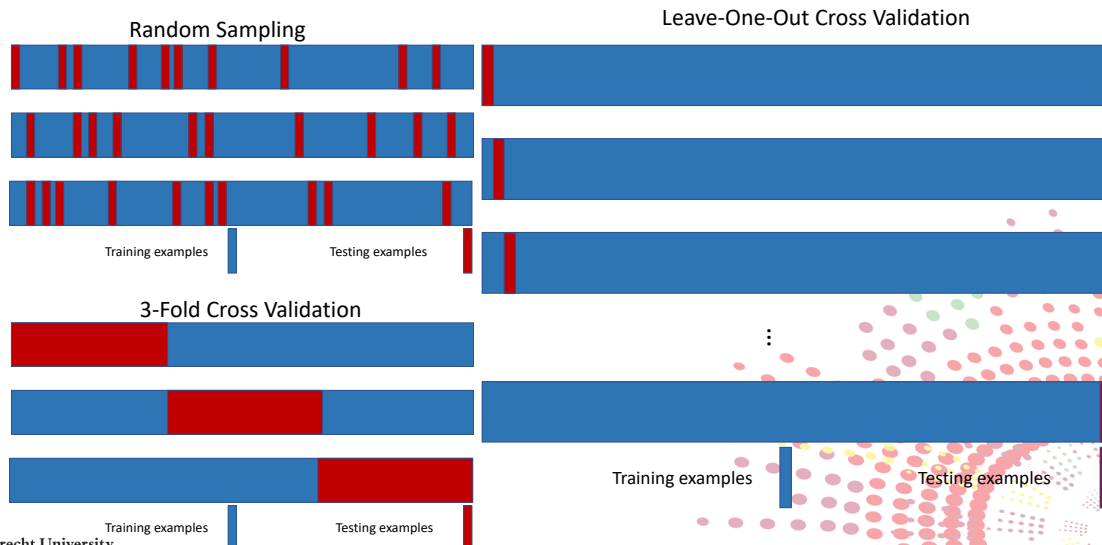


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Train-Test Split



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Train-Test Split



- Problem
 - The training/testing set may not include examples from one of the classes
- Solution
 - Split with stratification
 - Ensures that each class is represented with approximately equal proportions in both subsets



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Classification – A Three-Step Process



- Model construction
 - describing a set of predetermined classes
- Model evaluation
 - testing if the model will perform well on unseen data
 - labels are available but not provided to the model (classifier)
- Model usage
 - for classifying future or unknown objects

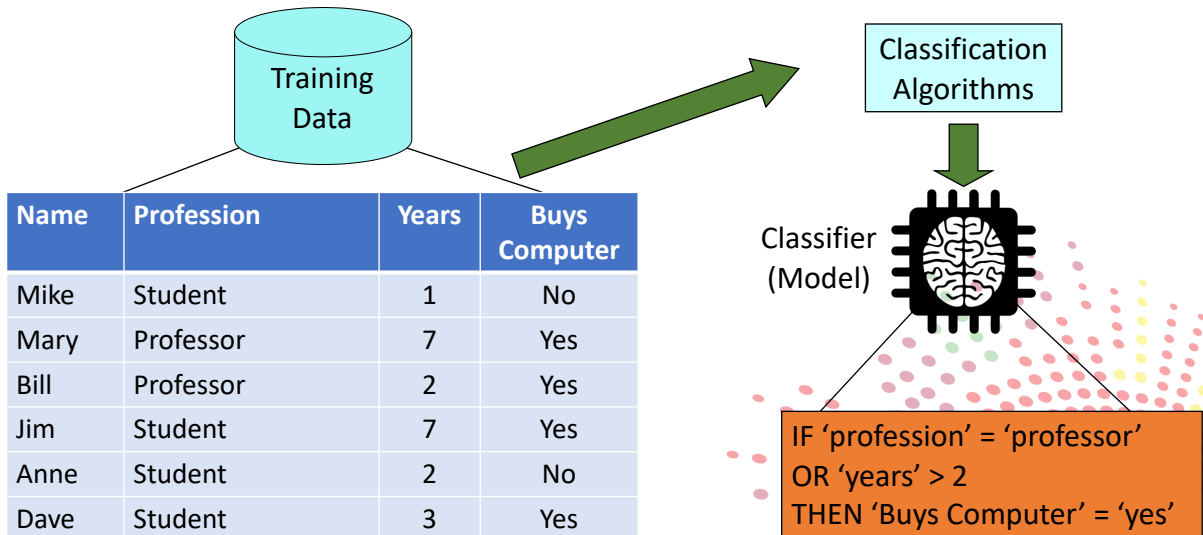


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Model Construction

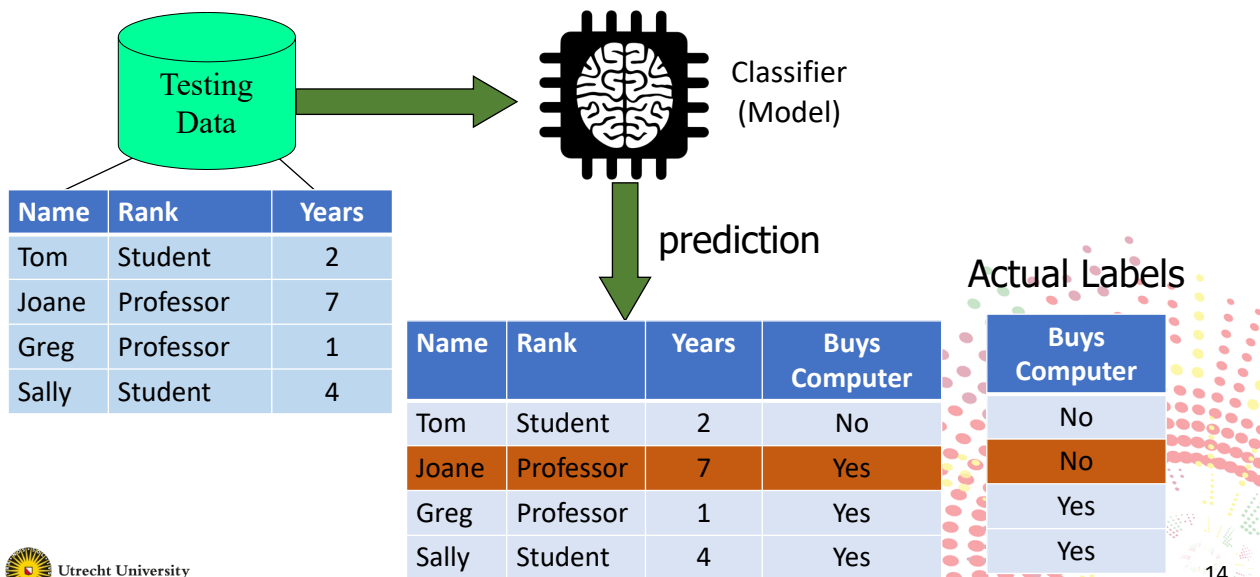


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Step (2): Evaluating the Model

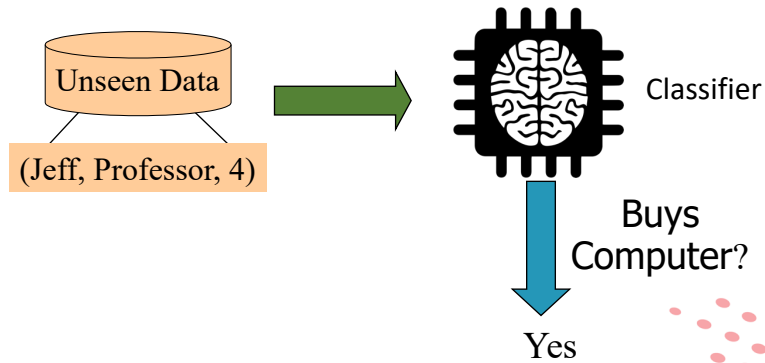


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Step (3): Using the Model in Prediction



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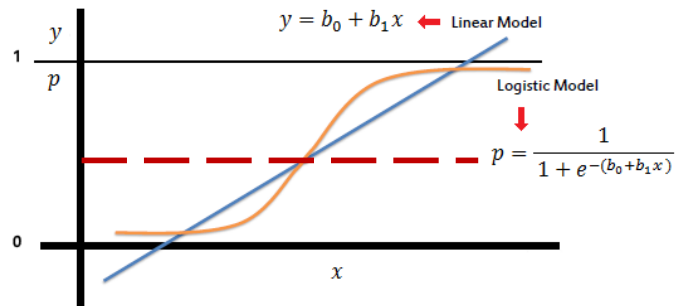
Classification Techniques



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Logistic Regression



A sigmoid function that assumes values in the range $[0,1]$

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

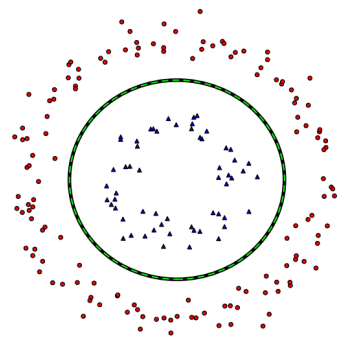
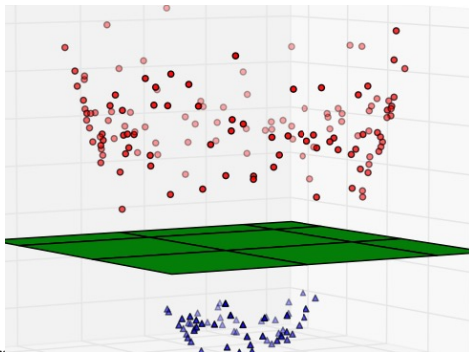
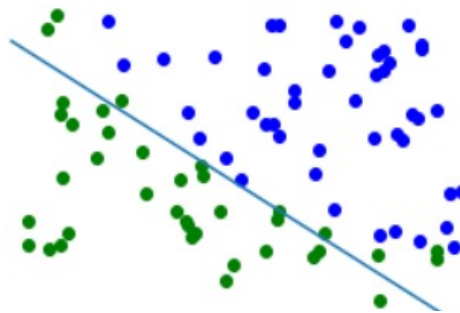


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Decision Boundaries



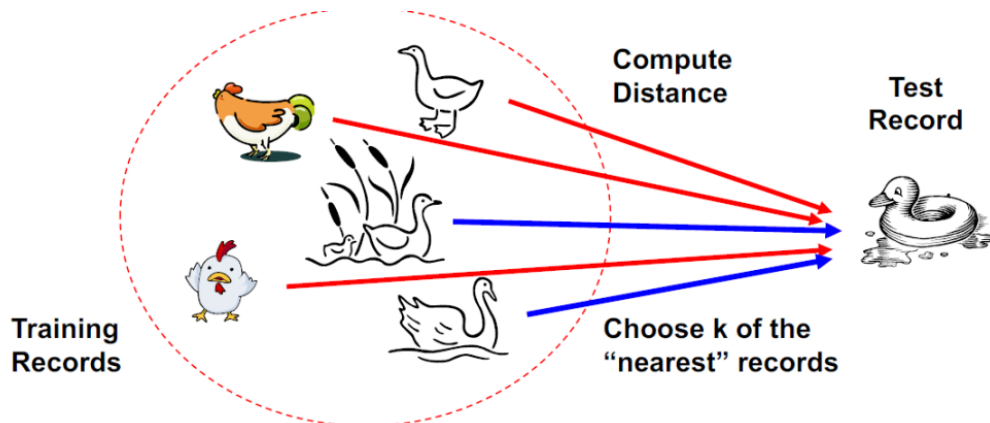
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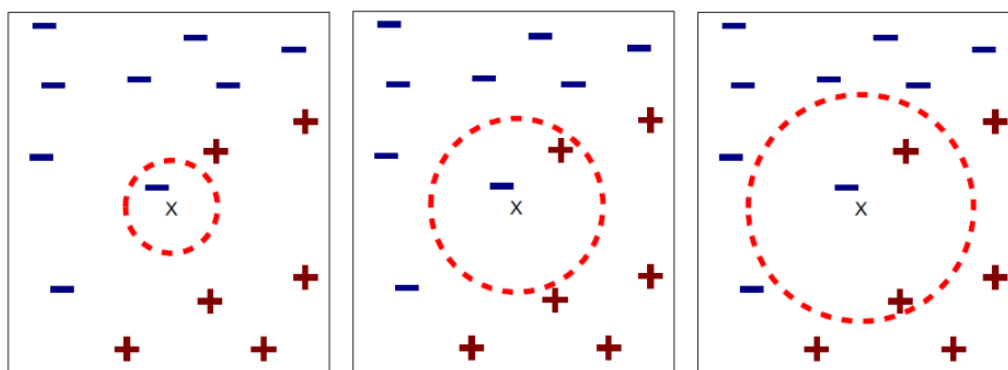
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Nearest Neighbors Classifiers

Basic idea: if it walks like a duck, quacks like a duck, then it is probably a duck



Nearest Neighbors Classifiers (Cont.)



1- nearest neighbor

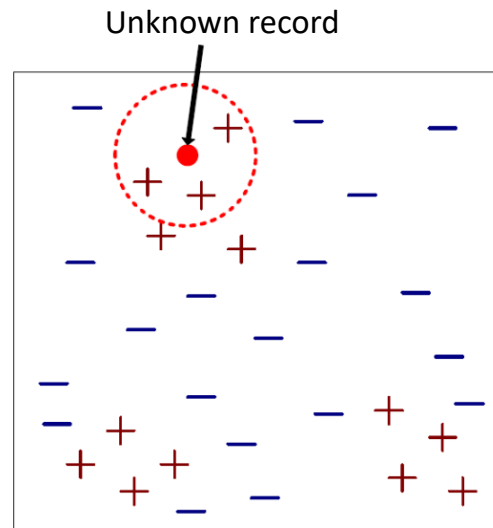
2- nearest neighbors

3- nearest neighbors

Nearest Neighbors Classifiers (Cont.)



- Three requirements:
 - Set of records (training set)
 - Distance metric
 - The number of neighbors to be considered k
- Classifying unknown record x :
 - Compute the distance from x to the other training records
 - Identify the k -Nearest Neighbors ($kNN(x)$)
 - Use class labels of the kNN records to determine the class of x .. How?



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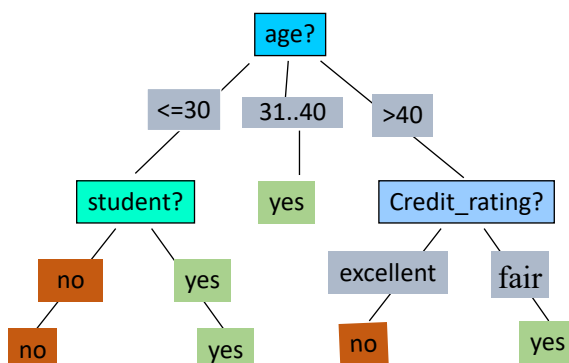
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Decision Trees



- Outcome: Buys_computer
- Resulting tree:



age	income	student	credit rating	buys computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31...40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no

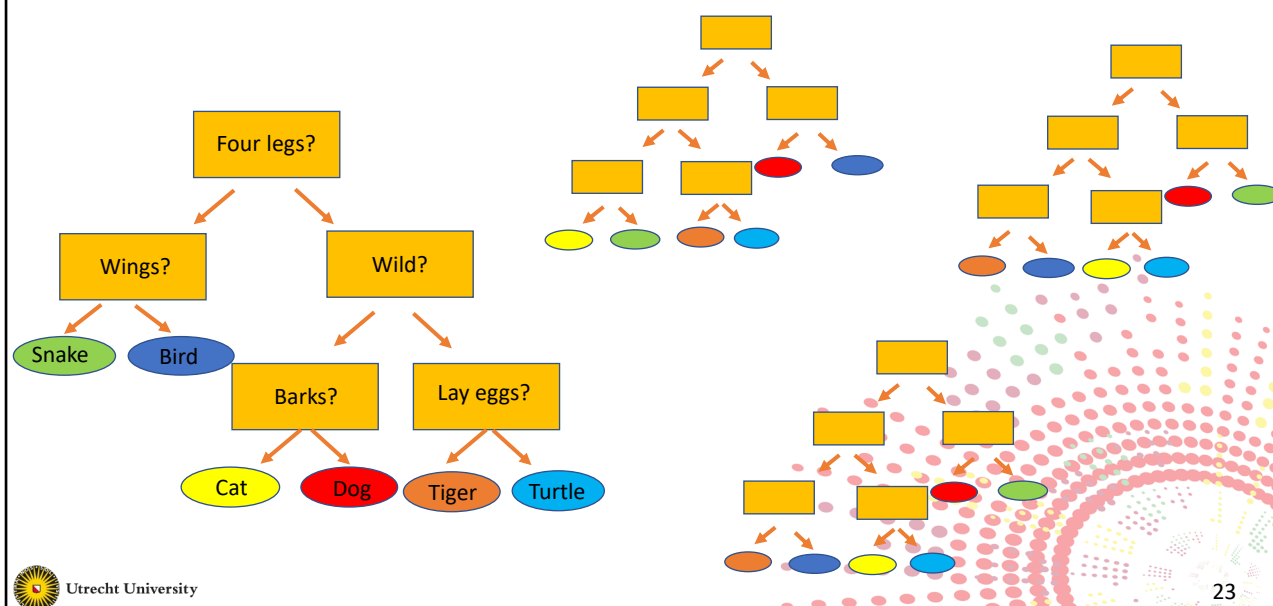


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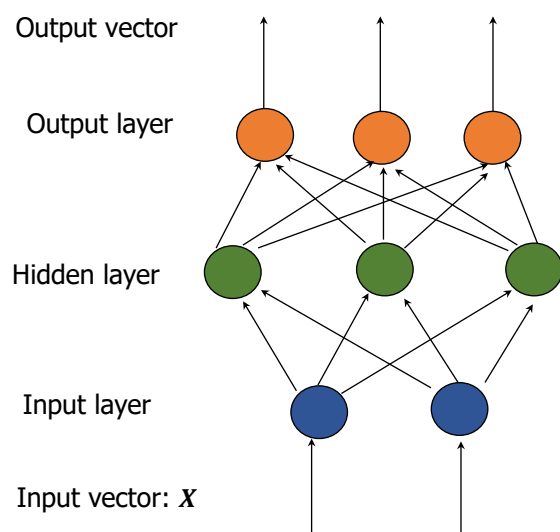
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Random Forests



Neural Network

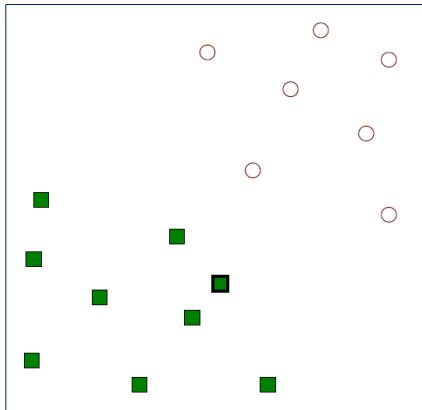


$$w_j^{(k+1)} = w_j^{(k)} + \lambda (y_i - \hat{y}_i^{(k)}) x_{ij}$$

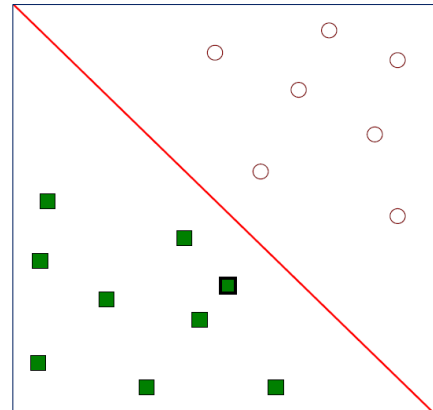
Support Vector Machines (SVM)



Find linear hyperplane (decision boundary) that will separate the data



One possible separators



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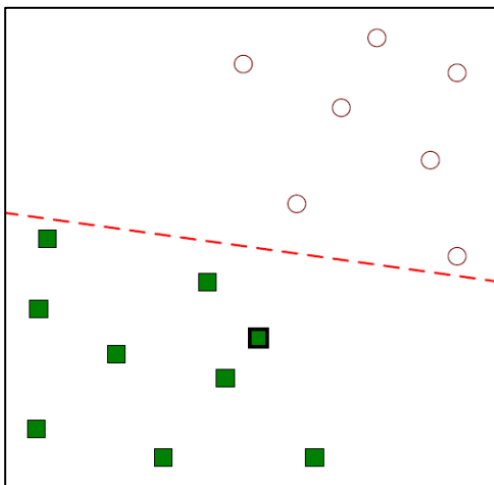
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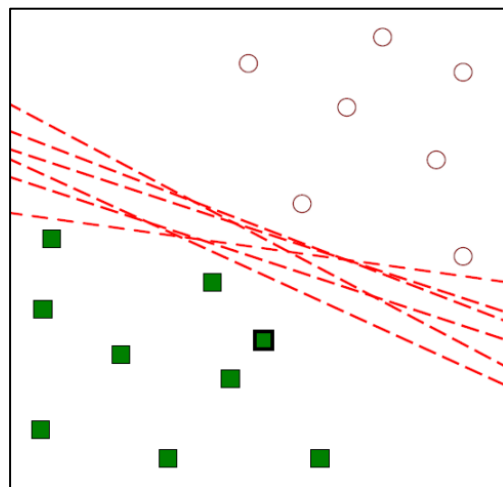
Support Vector Machines (SVM) (Cont.)



Another possible separator



Other possible separators



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Support Vector Machines (SVM) (Cont.)

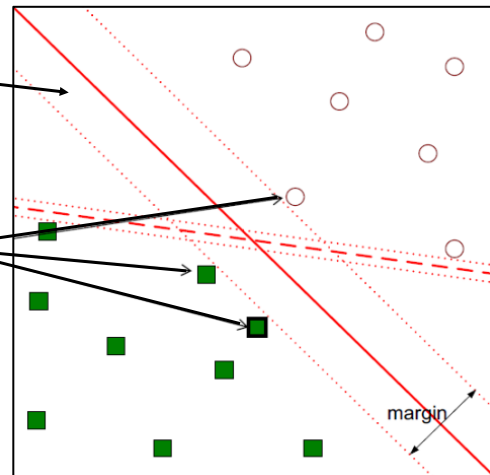


Find the hyperplane that maximizes the margin

Better separator

Support Vectors

are the points that the margin is pushed up against



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Evaluation: Confusion Matrix



- Focus on the predictive capability of a model

Confusion Matrix:

	Predicted Label		
		Class = Y	Class = N
Actual Label	Class = Y	TP	FN
	Class = N	FP	TN

TP = True Positive
 FP = False Positive
 FN = False Negative
 TN = True Negative

- The basic used metric:

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



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Evaluation Measures



Measure	Formula
Accuracy (acc.)	$\frac{TP + TN}{TP + FP + TN + FN}$
Precision (P)	$\frac{TP}{TP + FP}$
Recall (R)	$\frac{TP}{TP + FN}$
F1-Score	$2 \frac{P \times R}{P + R}$
Sensitivity (TPR)	Recall (TPR)
Specificity (TNR)	$\frac{TN}{TN + FP}$
Balanced Accuracy (BA)	$\frac{\text{Sensitivity} + \text{Specificity}}{2}$



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Accuracy



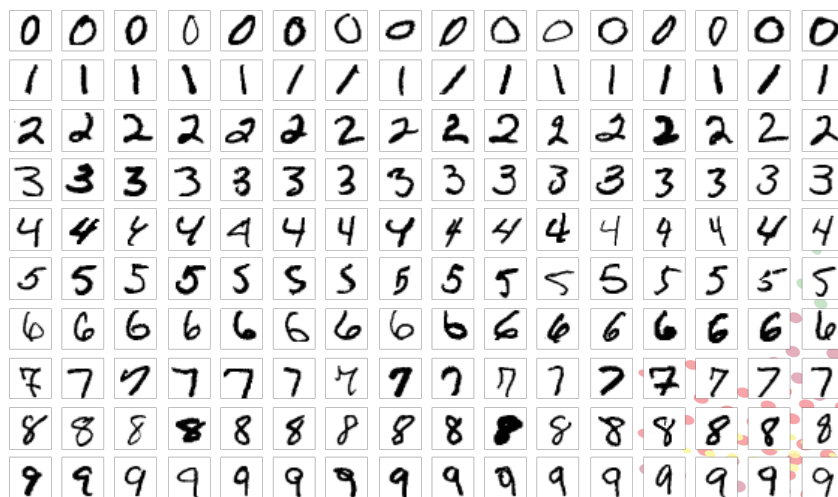
- Limitation of accuracy metric:
 - The problem of **unbalanced classes**
 - Consider a 2-class problem
 - Number of class 1 examples = 9990
 - Number of class 0 examples = 10
 - If the model predict everything as class 1
 - $Accuracy = \frac{9990}{10000} = 99.9\%$
- Accuracy is misleading because the classifier didn't predict any class 0 examples
- $Weighted Accuracy = \frac{w_1 TP + w_4 TN}{w_1 TP + w_2 FN + w_3 FP + w_4 TN}$



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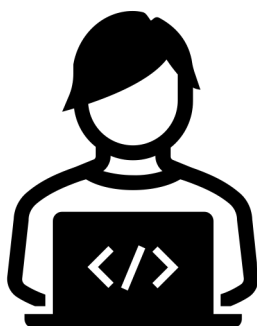
Example: Classifying hand-written digits



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Coding Time






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Coffee Break



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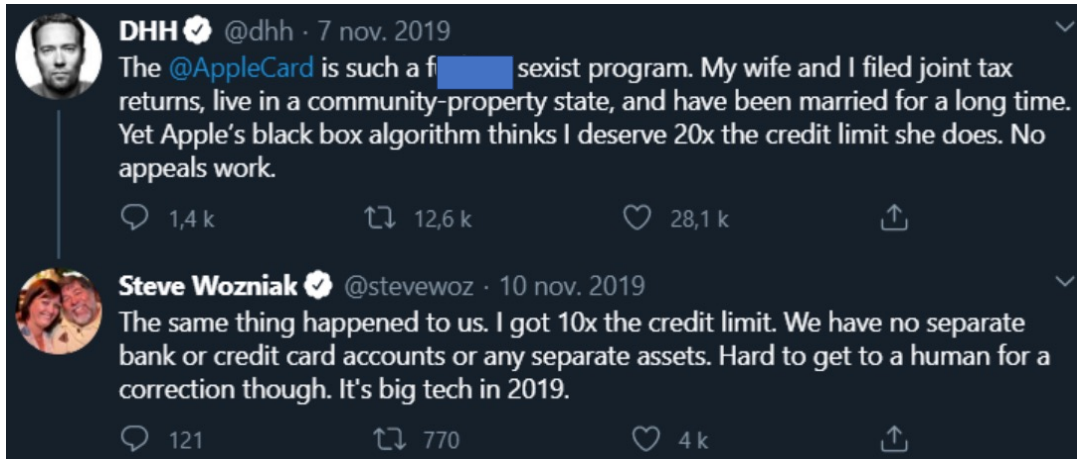
Model and Data Bias



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Unfair Algorithms – Apple Card



<https://www.bloomberg.com/opinion/articles/2019-11-11/is-the-apple-and-goldman-sachs-credit-card-sexist>,
<https://www.theguardian.com/technology/2019/nov/10/apple-card-issuer-investigated-after-claims-of-sexist-credit-checks>



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Who's Paid the Biggest Worker Abuse Fines? The Answer May Surprise You.

Big banks not only mistreat customers. They've also faced some of the heaviest fines for mistreating their employees.

RESEARCH & COMMENTARY
 JANUARY 25, 2019
 by Phil Mattera

Parent Companies with the Highest Disclosed Discrimination Penalties

Rank	Parent	Penalty Total	Cases
1	Bank of America	\$210,296,593	8
2	Coca-Cola	\$200,616,000	9
3	Novartis	\$183,000,000	2
4	Morgan Stanley	\$150,385,000	6
5	Abercrombie & Fitch	\$90,115,600	4
6	FedEx	\$80,035,138	15
7	Boeing	\$79,935,059	7
8	Verizon Communications	\$71,504,891	6
9	Wells Fargo	\$68,099,000	5
10	SoftBank (parent of Sprint)	\$62,852,756	3

<https://inequality.org/research/penalties-workplace-abuse/>



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Reasons

- Historical bias in the decision variable
- Limited / less informative features
- Biased data collection
- Imbalanced representation of different demographic groups



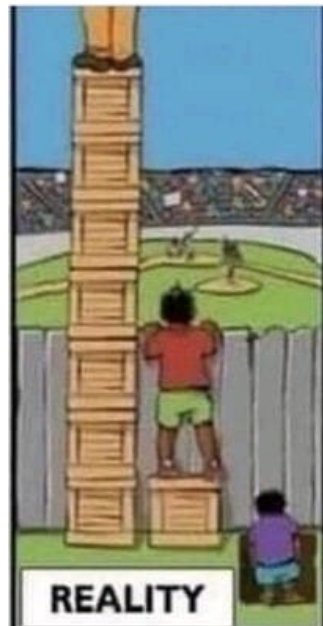
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Consequences

- One gets more than is needed
- Huge disparity is created



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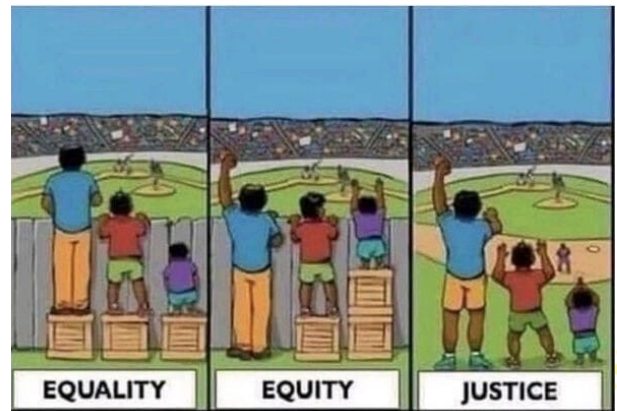
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What Should be Done?



- Equality: everyone benefits from the same support
- Equity: everyone gets the needed support
- Justice: remove the causes of inequity



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Algorithmic Fairness



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What do you think is fair?

“Fairness is the absence of any prejudice or favoritism towards an individual or a group based on their intrinsic or acquired traits in the decision-making context”



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Fairness Through Unawareness

- What if you do not even collect sensitive data?
 - Useful to have the sensitive features to check for fairness
- Removing the protected attributes does not always work
 - Proxy attributes



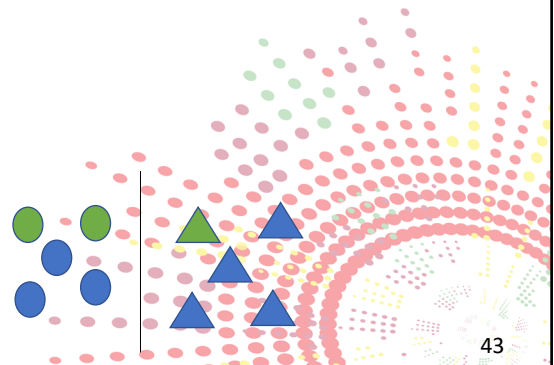
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Statistical Parity

- People of different groups should have the same probability of getting the positive outcome
- Disparate Impact Ratio
 - Base rate unprivileged / base rate privileged
 - Should be between 0.8 and 1.25



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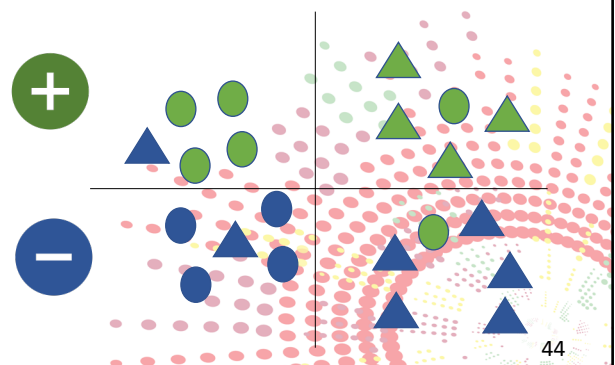
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Consistency

- An individual fairness measure
- Determines how similar the labels are for the similar instances in a dataset based on the k-neighbors of the instance
- This Metric: takes values between 0 and 1 with 1 is the optimal

- Priv. Pos.
- Priv. Neg.
- ▲ Un-Priv. Neg.
- ▲ Un-Priv. Pos.



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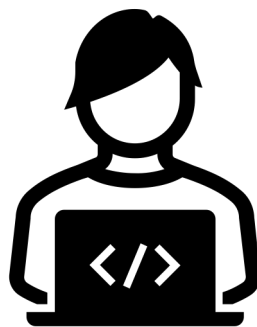
Bias Mitigation Algorithms

- Pre-Processing Algorithms
- In-Processing Algorithms
- Post-Processing Algorithms



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Coding Time

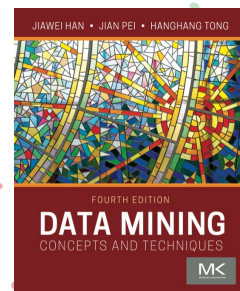
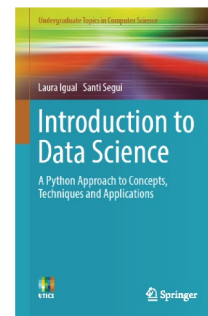


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Reading Material for Interested Students

- Introduction to Data Science, Ch 5.
[Supervised Learning](#)
- Data Mining: Concepts-and-Techniques
Ch 6. Classification

Acknowledgement: parts of the material were prepared by Xiangliang Zhang, Fenna Woudstra and Begum Hattatoglu



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Thank You



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