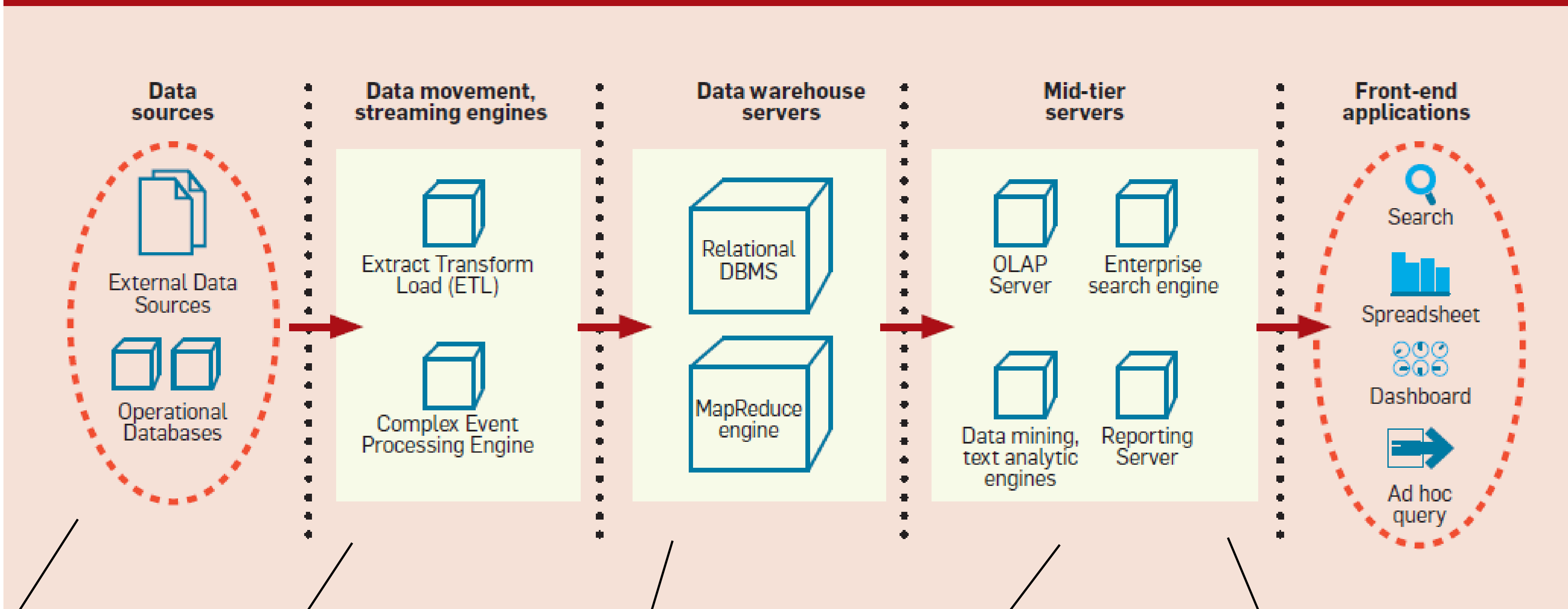
LABORATORY OF DATA SCIENCE

Reminds on Data Mining

BI Architecture

Figure 1. Typical business intelligence architecture.



6 lessons – data access

4 lessons – data quality & ETL

1 lessons – analytic SQL

5 lessons – OLAP and reporting

4 lessons – data mining

Data Mining Techniques

Preprocessing and visualization

- Classification/Regression
- Association Rule Discovery
- Clustering
- Sequential Pattern Discovery
- Deviation Detection
- Text Mining
- Web Mining
- Social Network Analysis
- …

Tools for data mining

- From **DBMS**
  - SQL Server Analysis Services
  - Oracle Data Miner
  - IBM DB2 Intelligent Miner (discontinued)
- From **Statistical analysis**
  - IBM Modeler (formerly SPSS Clementine)
  - SAS Miner
- From **Machine-Learning**
  - Knime
  - Weka
- An updated list
  - http://www.kdnuggets.com/software/index.html

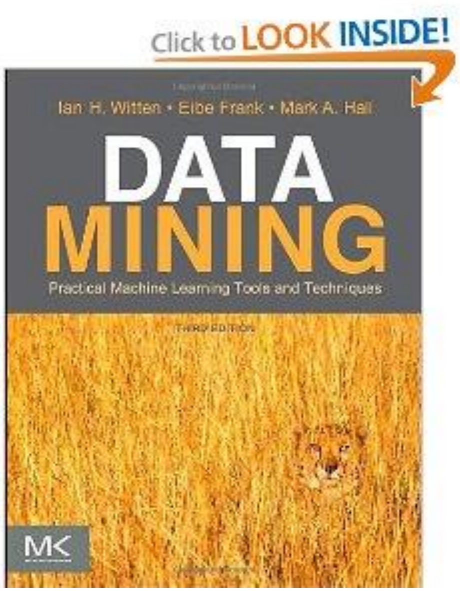
Standards

- XML representation of data mining models
  - Predictive Modelling Markup Language: PMML
- API for accessing data mining services
  - Microsoft OLE DB for DM
  - Java JDM
- SQL Extensions for data mining
  - Standard SQL/MM Part 6 Data Mining
  - Oracle, DB2 & SQL Server have non-standard extensions
    - SSAS DMX query language and Data Mining queries

Weka

Weka

- Suite for machine learning / data mining
- Developed in Java
  - Distributed with a GNU GPL licence
  - Since 2006 it is part of the BI Pentaho suite
- References
  - "Data Mining" by Witten & Frank, 3rd ed., 2011
  - On line docs http://www.cs.waikato.ac.nz/ml/weka/index.html
- Features / limits:
  - A complete set of tools for pre-processing, classification, clustering, association rules, visualization
  - Extensible (documented APIs)
  - Not very efficient / scalable (data are maintained in main memory)

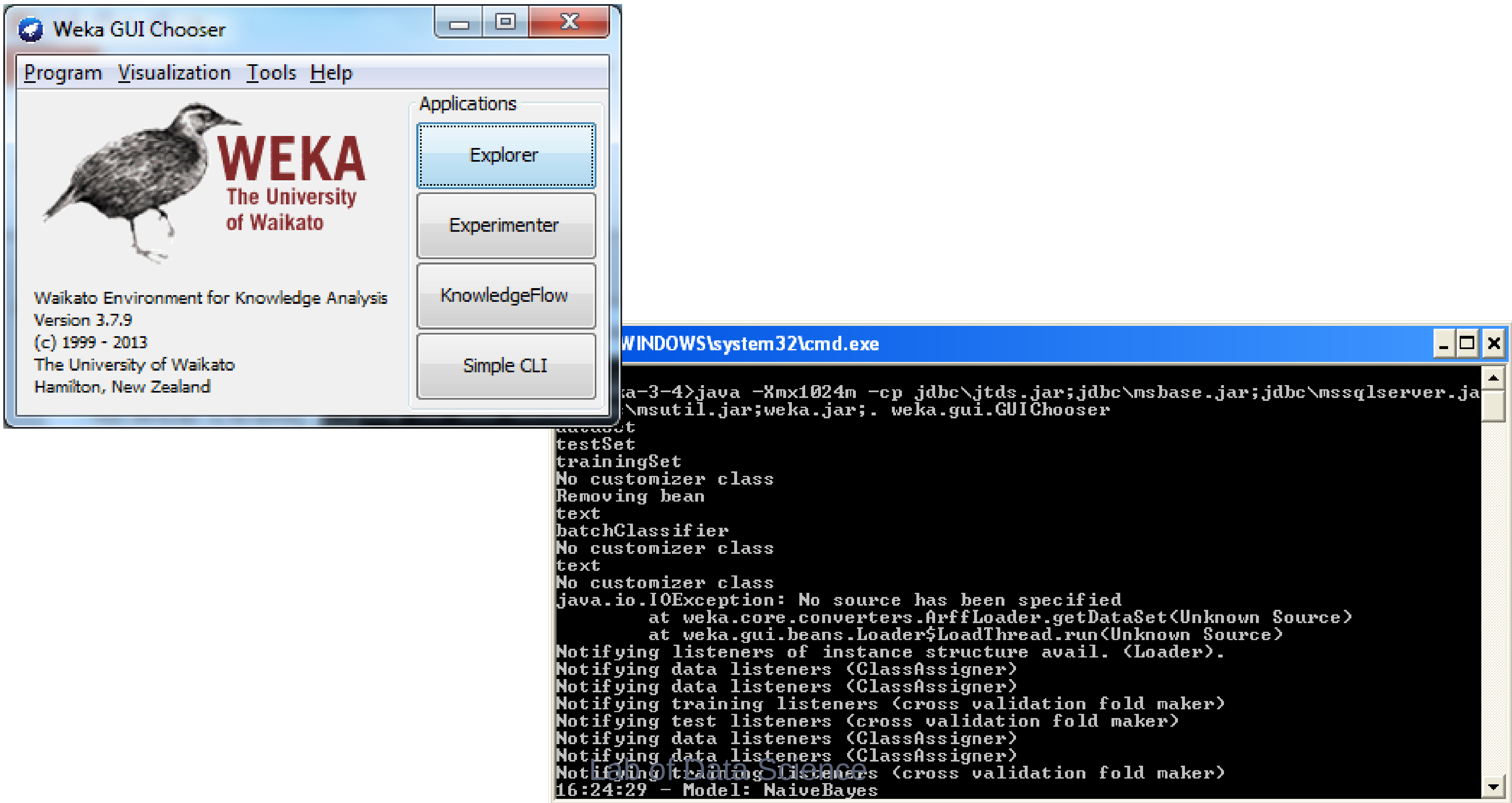


Weka versions

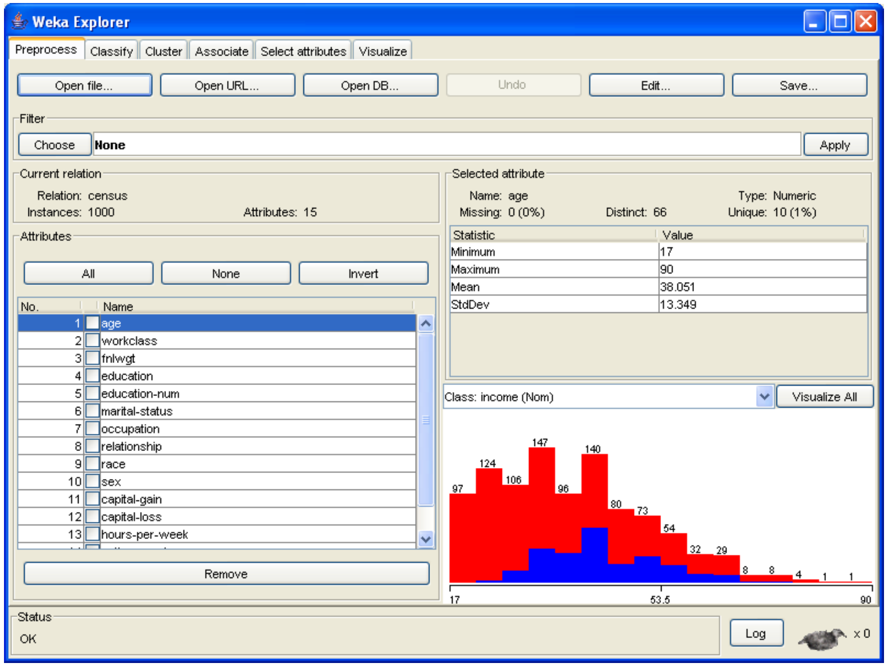
- Download: http://www.cs.waikato.ac.nz/~ml/weka
- May 2015, Weka 3.7.12 (developer version)
- Patch distributed by the teacher
  - To be copied in the Weka installation directory
  - It includes setting for:
    - Larger memory occupation (Java default is 80Mb)
    - Data types for SQL Server RDBMS
    - Driver JDBC
- Weka Light
  - Minimal version 3.7.12, patch already included

Weka interfaces

- GUI chooser and console with errors/warnings

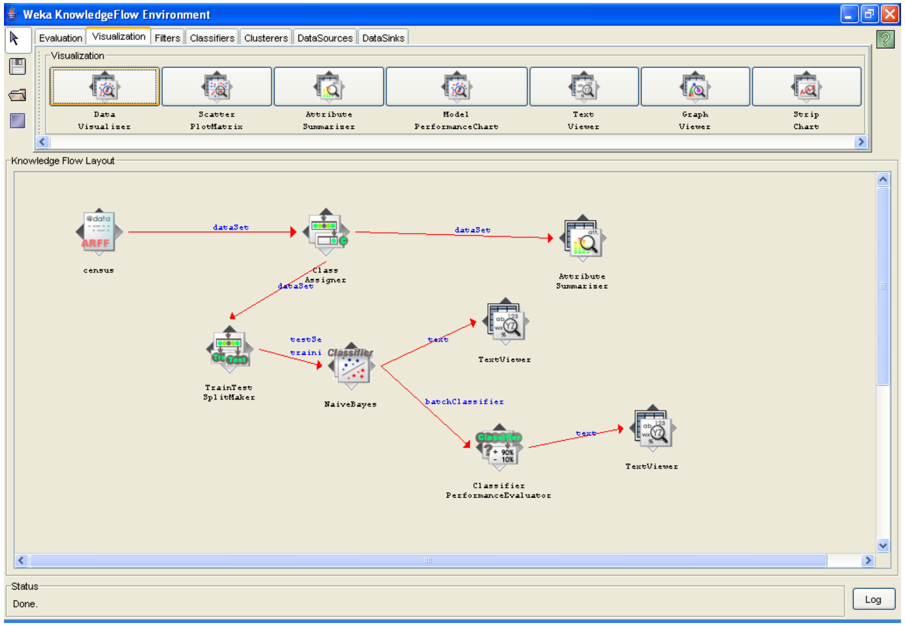


Weka interfaces: Explorer



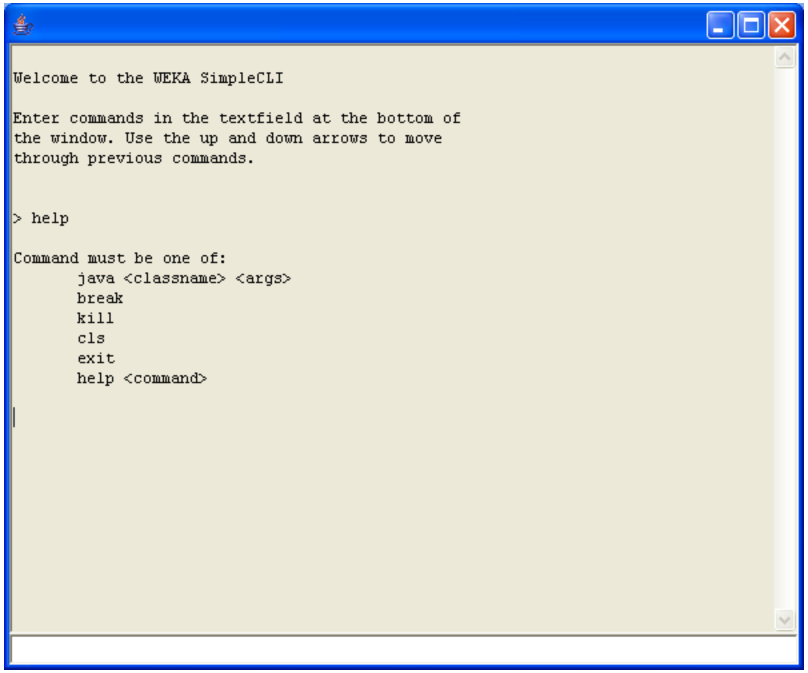
Explorer: GUI with distinct panels for pre-processing, classification, clustering, …

Weka interfaces: KnowledgeFlow



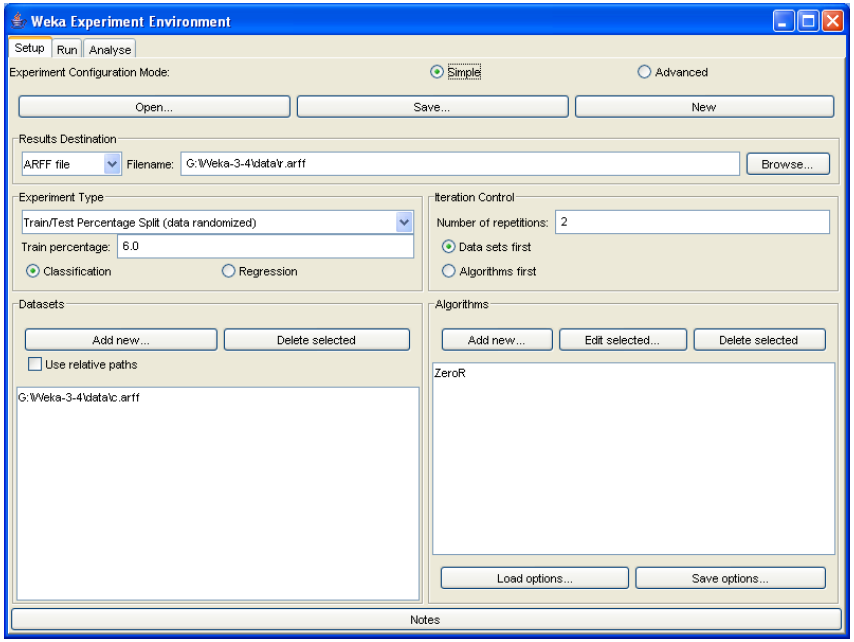
KnowledgeFlow: GUI with data flow

Weka interfaces: Simple CLI



Simple CLI (Call Level Interface): command line interface

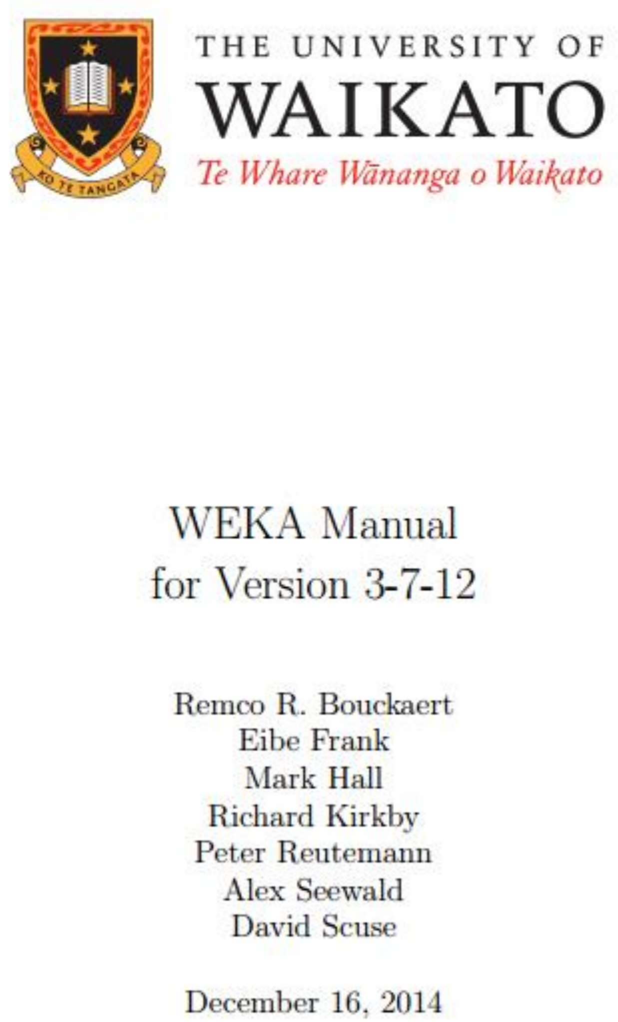
Weka interfaces: Experimenter



Experimenter: automation of large experiments by varying datasets, algorithms, parameters, ..

Details

- Weka manual
  - Installation directory, or at the weka website



THE UNIVERSITY OF WAIKATO

Te Whare Wānanga o Waikato

WEKA Manual
for Version 3-7-12

Remco R. Bouckaert
Eibe Frank
Mark Hall
Richard Kirkby
Peter Reutemann
Alex Seewald
David Scuse

December 16, 2014

Filters

- Conversions

  MakeIndicator, NominalToBinary, NumericToBinary, NumericToNominal
- Selections

  RemovePercentage, RemoveRange, RemoveWithValues, SubSetByExpression
- Sampling

  Resample, SpreadSubSample, StratifiedRemoveFolds
- Transformation

  Add, AddExpression, AddNoise, AddValues
- Normalization

  Center, Normalize, Standardize
- Discretization

  Discretize
- Cleaning

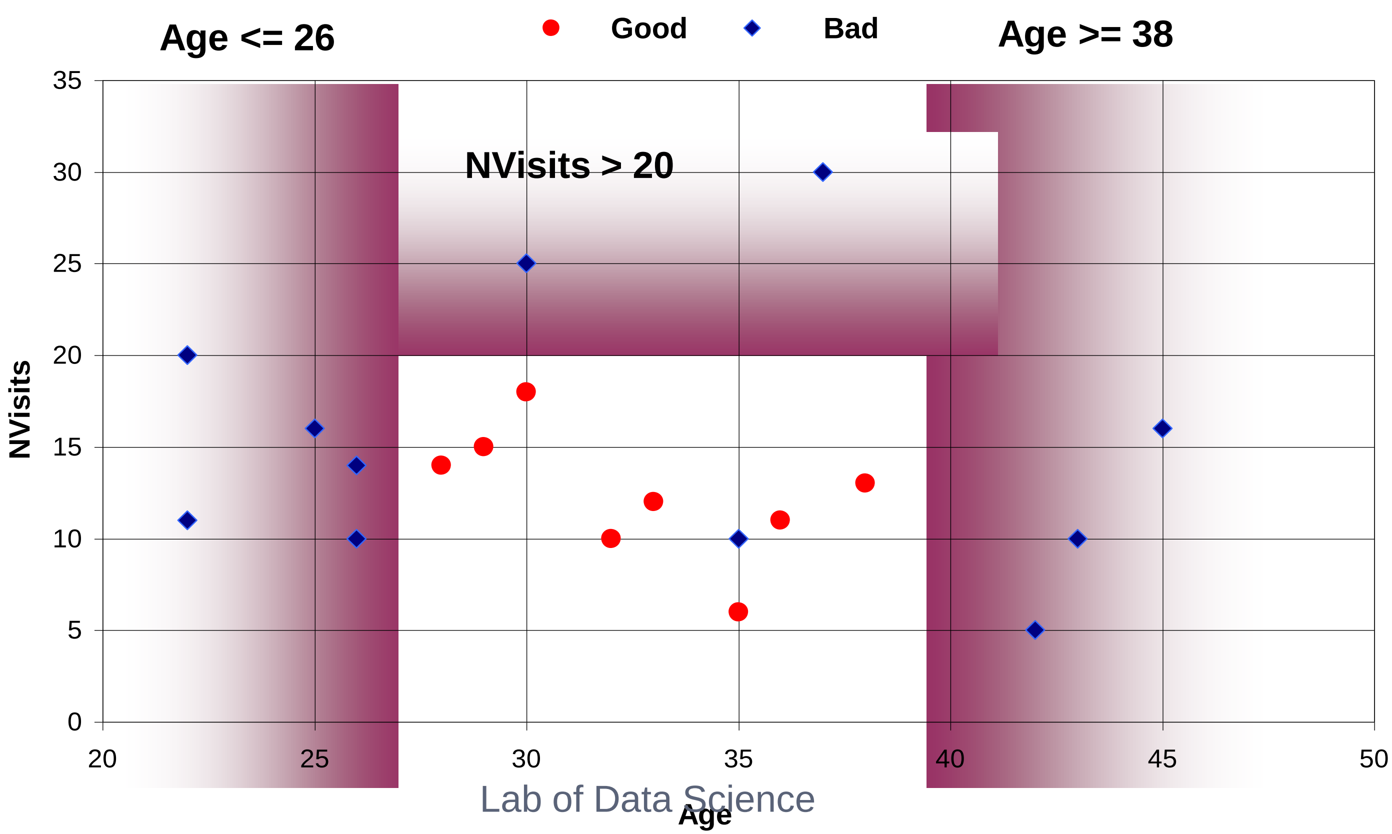
  NumericCleaner, Remove, RemoveByType, RemoveUseless
- Missing Values

  ReplaceMissingValues

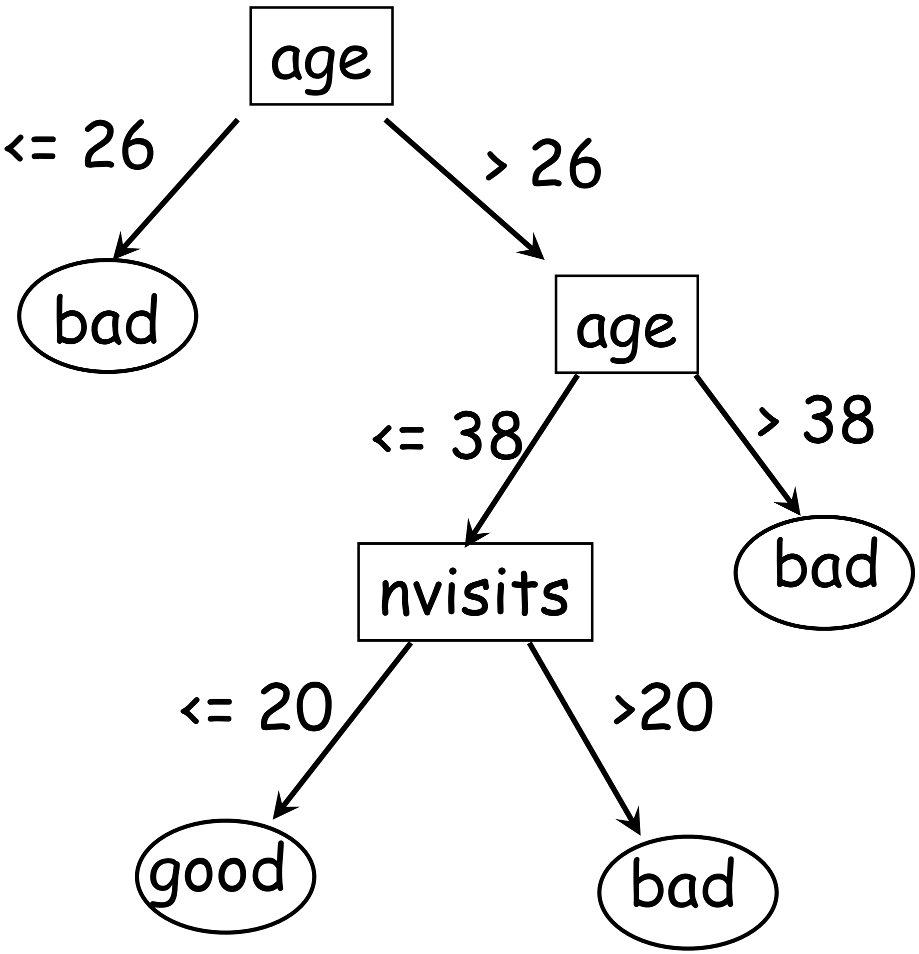
Reminds on classification

Who are my best customers?

- … given their age and frequency of visit !
- Good customers = top buyers, buy more than X, …



… described with a decision tree!



Classification: input

A set of examples (or instances or cases) which described a concept or event (**class**) given predictive **attributes** (or **features**)

- **Attributes** can be either continuous or discrete (maybe discretized)
- The **class** is discrete

outlook	temperature	humidity	windy	class
sunny	85	85	false	Don't Play
sunny	80	90	true	Don't Play
overcast	83	78	false	Play
rain	70	96	false	Play
rain	68	80	false	Play
rain	65	70	true	Don't Play
overcast	64	65	true	Play
sunny	72	95	false	Don't Play
sunny	69	70	false	Play
rain	75	80	false	Play
sunny	75	70	true	Play
overcast	72	90	true	Play
overcast	81	75	false	Play
rain	71	80	true	Don't Play

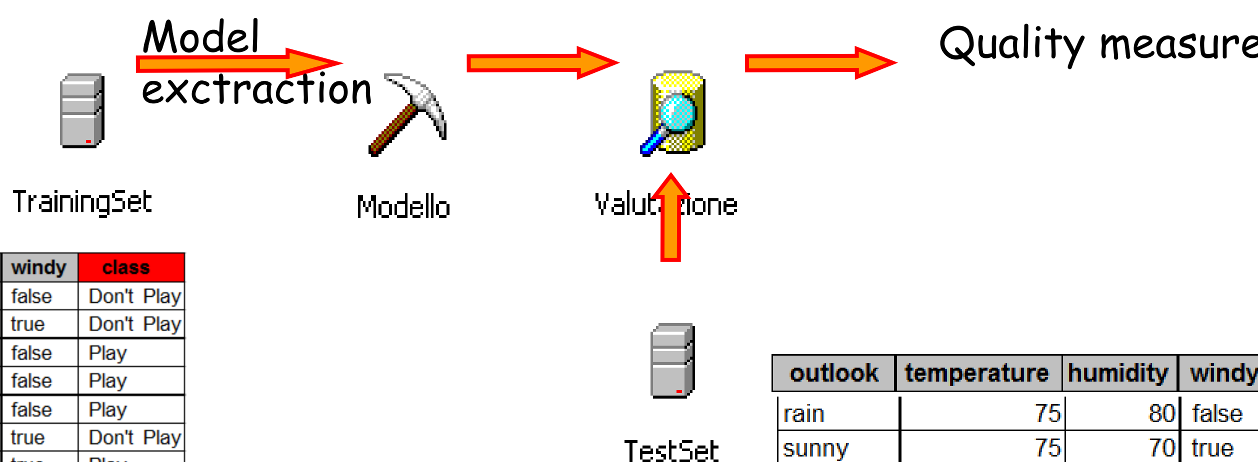
Classification: output

A function *f(sample)* = *class*, called a **classification model**, that describes/predict the class value given the feature values of a sample obtained by generalizing the samples of the training set

- Usage of a classification model:
  - **descriptively**
    - Which customers have abandoned?
  - **predictively**
    - Over a **score set** of samples with unknown class value
    - Which customers will respond to this offer?

How to evaluate a class. model?

- **Holdout method**
  - Split the available data into two sets
  - Training set is used to build the model
  - Test set is used to evaluate the interestingness of the model
    - Typically, training is 2/3 of data and test is 1/3



outlook	temperature	humidity	windy	class
sunny	85	85	false	Don't Play
sunny	80	90	true	Don't Play
overcast	83	78	false	Play
rain	70	96	false	Play
rain	68	80	false	Play
rain	65	70	true	Don't Play
overcast	64	65	true	Play
sunny	72	95	false	Don't Play
sunny	69	70	false	Play

outlook	temperature	humidity	windy	class
rain	75	80	false	Play
sunny	75	70	true	Play
overcast	72	90	true	Play
overcast	81	75	false	Play
rain	71	80	true	Don't Play

How good is a classification model?

- Stratified holdout
  - Available data is divided by stratified sampling wrt class distribution

- (Stratified) n-fold cross-validation
  - Available data divided into n parts of equal size
  - For i=1..n, the i-th part is used as test set and the rest as training set for building a classifier
  - The average quality measure of the n classifiers is statistically more significative than the holdout method
  - The FINAL classifier is the one training from all the available data
    - Cross-validation is useful when data is scarce or attribute distributions are skewed

Quality measures: accuracy

- **Accuracy**: percentage of cases in the test set that is correctly predicted by the model
  - E.g., accuracy of 80% means that in 8 cases out of 10 in the test set the predicted class is the same of the actual class
- Misclassification % = (100 – accuracy)
- Lower bound on accuracy: **majority classifier**
  - A trivial classifier for which f(case) = majority class value
  - Its accuracy is the percentage of the majority class
  - E.g., two classes: fraud 2% legal 98%
  - Its hard to beat the 98% accuracy

Quality measures: confusion matrix


```
Correctly Classified Instances          42               73.6842 %
Incorrectly Classified Instances        15               26.3158 %
Total Number of Instances               57

=== Confusion Matrix ===

  a  b   <-- classified as
 14  6 |  a = bad
  9 28 |  b = good
```

Predicted class

Actual class

Misclassified cases

Quality measures: precision

Precision: accuracy of predicting "C"

$$\frac{\text{\# Cases predicted Class=C and with real Class=C}}{\text{\# Cases predicted Class=C}}$$

```
Root mean squared error                  0.3213
Relative absolute error                 53.8362 %
Root relative squared error             75.46   %
Coverage of cases (0.95 level)          97.8923 %
Mean rel. region size (0.95 level)      73.3048 %
Total Number of Instances            16606

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0,594    0,058    0,760      0,594    0,667      0,586    0,881     0,748     >50K
                 0,942    0,406    0,881      0,942    0,910      0,586    0,881     0,943     <=50K
Weighted Avg.    0,859    0,323    0,852      0,859    0,852      0,586    0,881     0,896

=== Confusion Matrix ===

     a     b   <-- classified as
  2346  1605 |     a = >50K
   740 11915 |     b = <=50K
```

76% of times predictions >50K are correct

Quality measures: recall

Recall: coverage of predicting "C"

$$\frac{\#\text{ Cases predicted Class=C and with real Class=C}}{\#\text{ Cases with real Class=C}}$$

```
Root mean squared error                  0.3213
Relative absolute error                 53.8362 %
Root relative squared error             75.46   %
Coverage of cases (0.95 level)          97.8923 %
Mean rel. region size (0.95 level)      73.3048 %
Total Number of Instances            16606

=== Detailed Accuracy By Class ===
```

59,4% of real class >50K are found by predictions

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,594	0,058	0,760	0,594	0,667	0,586	0,881	0,748	>50K
	0,942	0,406	0,881	0,942	0,910	0,586	0,881	0,943	<=50K
Weighted Avg.	0,859	0,323	0,852	0,859	0,852	0,586	0,881	0,896	

```
=== Confusion Matrix ===

     a     b   <-- classified as
  2346  1605 |     a = >50K
   740 11915 |     b = <=50K
```

Measures: lift chart

- Classifier: f(sample, class) = confidence
  - and then f(sample) = argmax_{class} f(sample, class)
  - E.g., f(sample, play) = 0.3 f(sample, don't play) = 0.7
- Samples in the test set can be ranked according to a fixed class
  - Rank customers on the basis of the classifier confidence **they will respond** to an offer
- **Lift chart**
  - X-axis: ranked sample of the test set
  - Y-axis: percentage of the total cases in the test set with the actual class value included in the ranked sample of the test set (i.e., recall)
  - Plots: performance of a classifier vs random ranking
  - Useful when resources (e.g., budget) are limited

Contacting only 50% of customer will reach 80% of those who respond. Lift = 80/50 = 1.6

Lift Chart - variants

- Lift(X) = recall(X)
  - Estimation of random classifier lift
  - Previous example, Lift(50%) = 80%
- LiftRatio(X) = recall(X) / X
  - Ratio of lift over random order
  - Previous example, LiftRatio(50%) = 80% / 50% = 1.6
- Profit chart
  - Given a cost/benefit model, the Y axis represent the total cost/gain when contacting X and not contacting TestSet\X

The unbalancing problem

- For unbalanced class values, it is difficult to obtain a good model
  - Fraud = 2% Normal = 98%
    - The majority classifier is accurate at 98% but it is not useful

- Oversampling and Undersampling
  - Select a **training** set with a more balanced distribution of class values A and B
    - 60-70% for class A and 30-40% for class B
    - By increasing the number of cases with class B (oversampling) or by reducing those with class A (undersampling)
  - The training algorithm has more chances of distinguishing characteristics of A VS B
    - The test set MUST have the original distribution of values

- Cost Sensitive Classifier, Ensembles (bagging, boosting, stacking)
  - Weights errors, build several classifiers and average their predictions

Rule based classification

Rule-Based Classifier

- Classify records by using a collection of "if…then…" rules
- Rule: $(Condition) \rightarrow y$
  - where
    - *Condition* is a conjunctions 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) $\rightarrow$ Birds
    - (Taxable Income < 50K) $\wedge$ (Refund=Yes) $\rightarrow$ Evade=No

Rule-based Classifier (Example)

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
human	warm	yes	no	no	mammals
python	cold	no	no	no	reptiles
salmon	cold	no	no	yes	fishes
whale	warm	yes	no	yes	mammals
frog	cold	no	no	sometimes	amphibians
komodo	cold	no	no	no	reptiles
bat	warm	yes	yes	no	mammals
pigeon	warm	no	yes	no	birds
cat	warm	yes	no	no	mammals
leopard shark	cold	yes	no	yes	fishes
turtle	cold	no	no	sometimes	reptiles
penguin	warm	no	no	sometimes	birds
porcupine	warm	yes	no	no	mammals
eel	cold	no	no	yes	fishes
salamander	cold	no	no	sometimes	amphibians
gila monster	cold	no	no	no	reptiles
platypus	warm	no	no	no	mammals
owl	warm	no	yes	no	birds
dolphin	warm	yes	no	yes	mammals
eagle	warm	no	yes	no	birds

R1: (Give Birth = no) $\wedge$ (Can Fly = yes) $\rightarrow$ Birds

R2: (Give Birth = no) $\wedge$ (Live in Water = yes) $\rightarrow$ Fishes

R3: (Give Birth = yes) $\wedge$ (Blood Type = warm) $\rightarrow$ Mammals

R4: (Give Birth = no) $\wedge$ (Can Fly = no) $\rightarrow$ Reptiles

R5: (Live in Water = sometimes) $\rightarrow$ Amphibians

Application of Rule-Based Classifier

- A rule *r* covers an instance **x** if the attributes of the instance satisfy the condition of the rule

R1: (Give Birth = no) $\wedge$ (Can Fly = yes) $\rightarrow$ Birds

R2: (Give Birth = no) $\wedge$ (Live in Water = yes) $\rightarrow$ Fishes

R3: (Give Birth = yes) $\wedge$ (Blood Type = warm) $\rightarrow$ Mammals

R4: (Give Birth = no) $\wedge$ (Can Fly = no) $\rightarrow$ Reptiles

R5: (Live in Water = sometimes) $\rightarrow$ Amphibians

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
hawk	warm	no	yes	no	?
grizzly bear	warm	yes	no	no	?

The rule R1 covers a hawk => Bird

The rule R3 covers the grizzly bear => Mammal

Rule Coverage and Accuracy

- **Coverage of a rule:**
  - Fraction of records that satisfy the antecedent of a rule
- **Accuracy of a rule:**
  - Fraction of records that satisfy both the antecedent and consequent of a rule

Tid	Refund	Marital Status	Taxable Income	Class
1	Yes	**Single**	125K	**No**
2	No	Married	100K	**No**
3	No	**Single**	70K	**No**
4	Yes	Married	120K	**No**
5	No	Divorced	95K	**Yes**
6	No	Married	60K	**No**
7	Yes	Divorced	220K	**No**
8	No	**Single**	85K	**Yes**
9	No	Married	75K	**No**
10	No	**Single**	90K	**Yes**

(Status=Single) $\rightarrow$ No

Coverage = 40%, Accuracy = 50%

How does Rule-based Classifier Work?

R1: (Give Birth = no) $\wedge$ (Can Fly = yes) $\rightarrow$ Birds

R2: (Give Birth = no) $\wedge$ (Live in Water = yes) $\rightarrow$ Fishes

R3: (Give Birth = yes) $\wedge$ (Blood Type = warm) $\rightarrow$ Mammals

R4: (Give Birth = no) $\wedge$ (Can Fly = no) $\rightarrow$ Reptiles

R5: (Live in Water = sometimes) $\rightarrow$ Amphibians

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
lemur	warm	yes	no	no	?
turtle	cold	no	no	sometimes	?
dogfish shark	cold	yes	no	yes	?

A lemur triggers rule R3, so it is classified as a mammal

A turtle triggers both R4 and R5

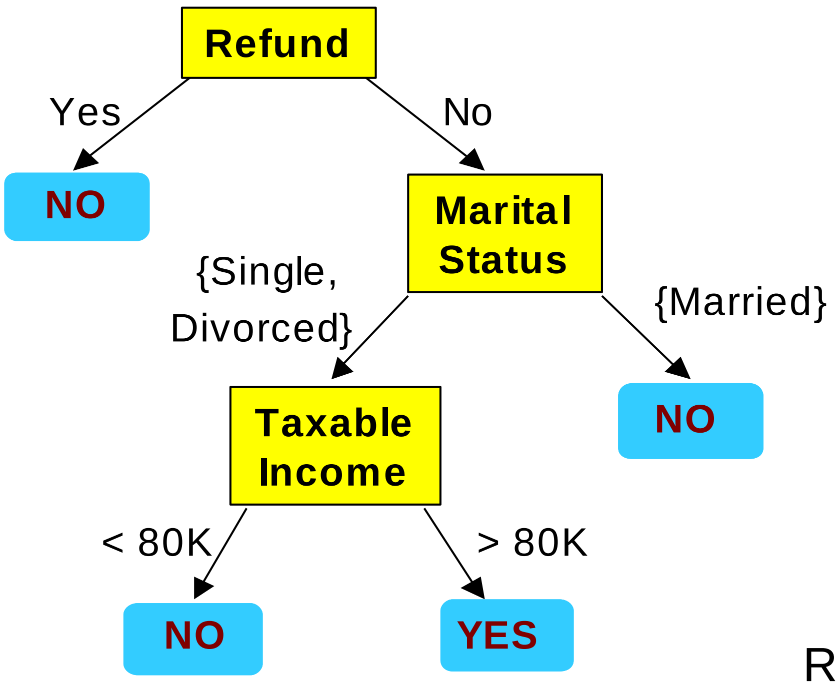
A dogfish shark triggers none of the rules

Characteristics of Rule-Based Classifier

- Mutually exclusive rules
  - Classifier contains mutually exclusive rules if the rules are independent of each other
  - Every record is covered by **at most** one rule

- Exhaustive rules
  - Classifier has exhaustive coverage if it accounts for every possible combination of attribute values
  - Each record is covered by **at least** one rule

From Decision Trees To Rules



Classification Rules

(Refund=Yes) ==> No

(Refund=No, Marital Status={Single,Divorced}, Taxable Income<80K) ==> No

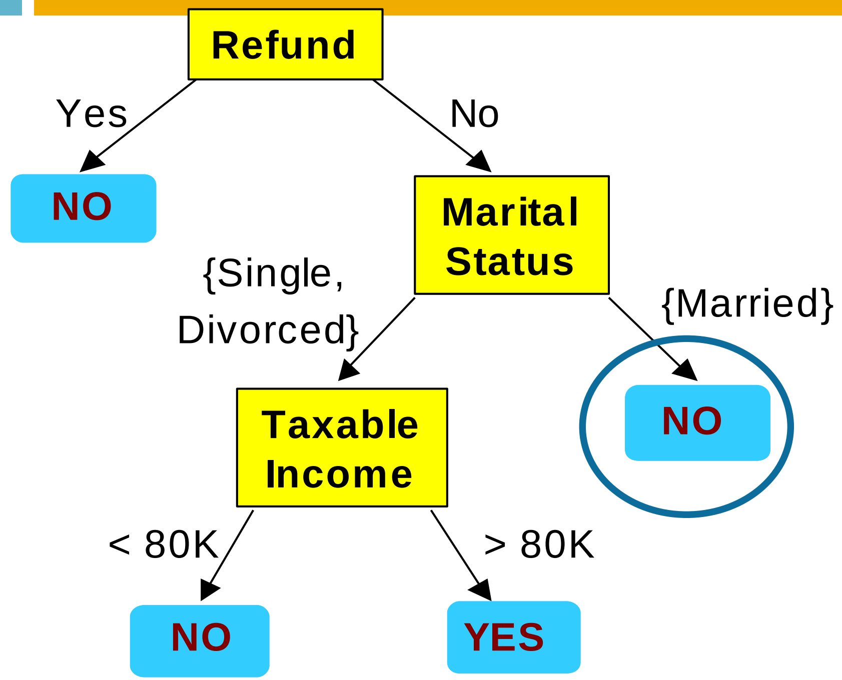
(Refund=No, Marital Status={Single,Divorced}, Taxable Income>80K) ==> Yes

(Refund=No, Marital Status={Married}) ==> No

Rules are mutually exclusive and exhaustive

Rule set contains as much information as the tree

Rules Can Be Simplified



Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Initial Rule: (Refund=No) $\wedge$ (Status=Married) $\rightarrow$ No

Simplified Rule: (Status=Married) $\rightarrow$ No

Effect of Rule Simplification

- Rules are no longer mutually exclusive
  - A record may trigger more than one rule
  - Solution?
    - Ordered rule set
    - Unordered rule set – use voting schemes
- Rules are no longer exhaustive
  - A record may not trigger any rules
  - Solution?
    - Use a default class

Building Classification Rules

- Direct Method:
  - Extract rules directly from data
  - e.g.: RIPPER, CN2, Holte's 1R

- Indirect Method:
  - Extract rules from other classification models (e.g. decision trees, neural networks, etc).
  - e.g: C4.5rules