Introduction to Classification, an example of Supervised Machine Learning

Classification: Definition

- Given a collection of examples (*training set*)
 - Each example is represented by a set of *features*,
 sometimes called *attributes*
 - Each example is to be given a label or class
- Find a *model* for the label as a function of the values of features.
- Goal: <u>previously unseen</u> examples should be assigned a label as accurately as possible.
- A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.

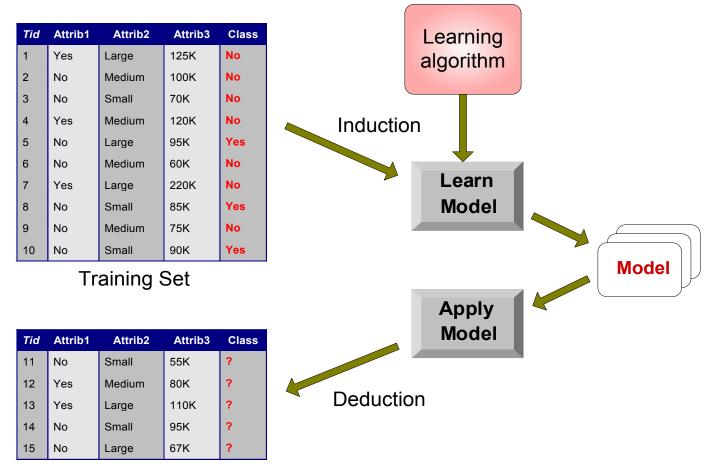
Supervised vs. Unsupervised Learning

- Supervised learning (classification and other tasks)
 - Supervision: The training data (observations, measurements, etc.)
 are accompanied by labels indicating the class of the observations
 - New data is classified based on the training set
- Unsupervised learning (includes clustering)
 - The class labels of training data is unknown
 - Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data

NLP Tasks

- Many NLP tasks can be accomplished either through
 - unsupervised techniques, sometimes also called rule-based or symbolic techniques
 - Supervised techniques, where the task is defined automatically from a training set
- In both cases, the evaluation of the task will most likely use a **training set** to define the technique and a **test set** for evaluation
 - POS tagging uses Hidden Markov Models
 - Parsing uses statistical lexicalized parsers
 - Sentiment analysis uses classification
- The evaluation of these tasks often uses ideas from the evaluation of classification

Illustrating Classification Task



Test Set

Classification Techniques

- There are a number of different classification algorithms to build a model for classification
 - Decision Tree based Methods
 - Rule-based Methods
 - Memory based reasoning, instance-based learning
 - Neural Networks
 - Genetic Algorithms
 - Naïve Bayes and Bayesian Belief Networks
 - Support Vector Machines
- In this introduction, we illustrate classification tasks using Decision Tree methods
- Features can have numeric values (continuous) or a finite set of values (categorical/nominal), including boolean true/false

Example of a Decision Tree

| 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 |

Training Data

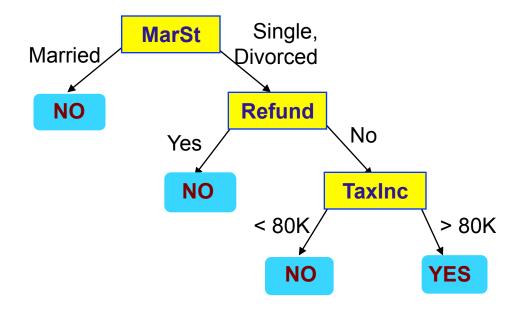
Model: Decision Tree

Example task: Given the marital status, refund status, and taxable income of a person, label them as to whether they will cheat on their income tax.

Another Example of Decision Tree

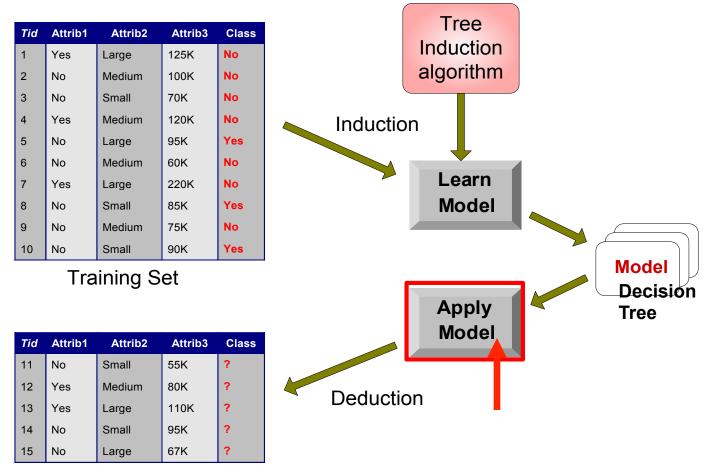
boolean categorical continuous

| Tid | Refund | Marital Status | Taxable Income | Cheat |
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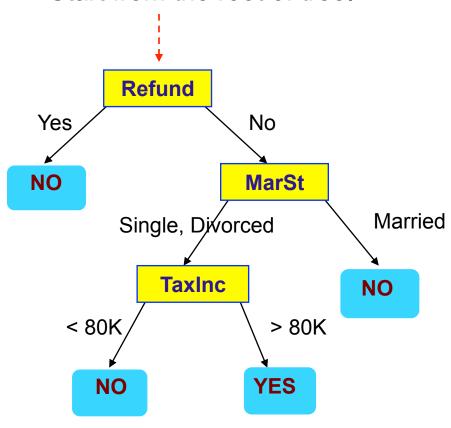
There could be more than one tree that fits the same data!

Decision Tree Classification Task



Test Set

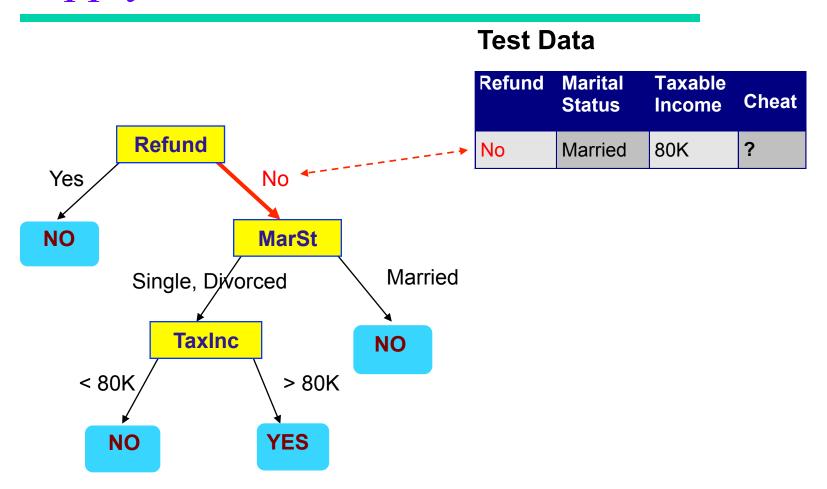
Start from the root of tree.

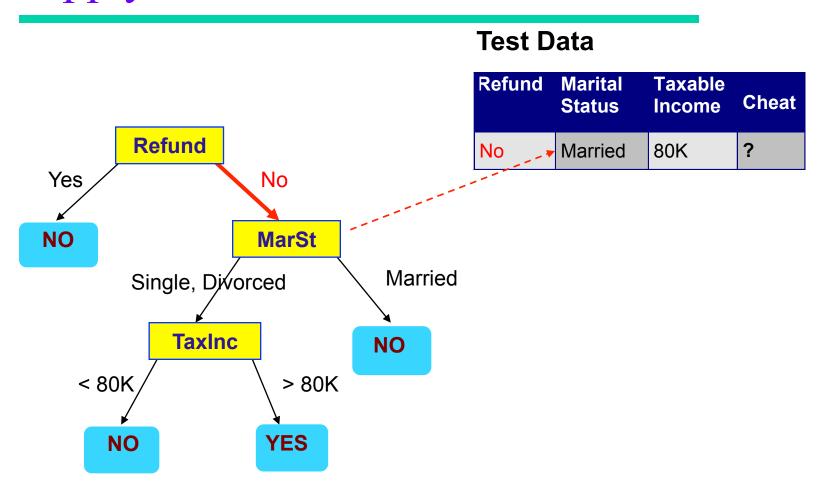


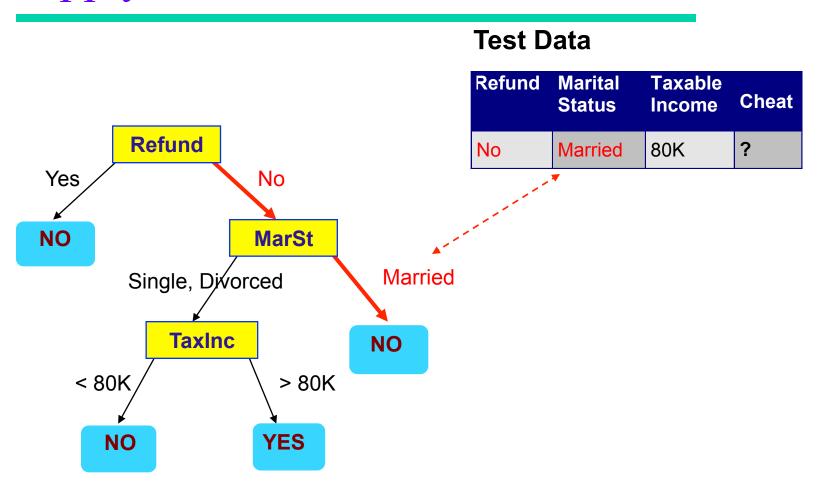
Test Data

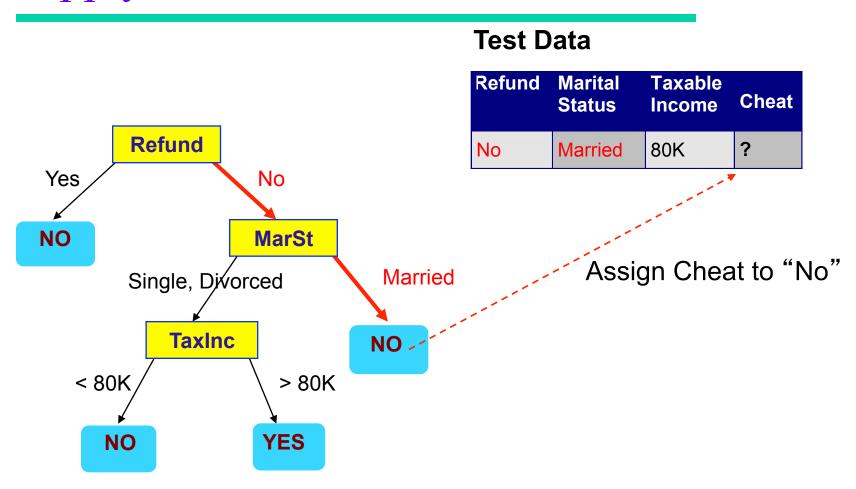
| Refund | | Taxable Income | Cheat |
|--------|---------|-------------------|-------|
| No | Married | 80K | ? |

Test Data Refund **Marital Taxable** Cheat **Status** Income Refund ? No Married 80K Yes No NO **MarSt** Married Single, Divorced **TaxInc** NO < 80K > 80K YES NO

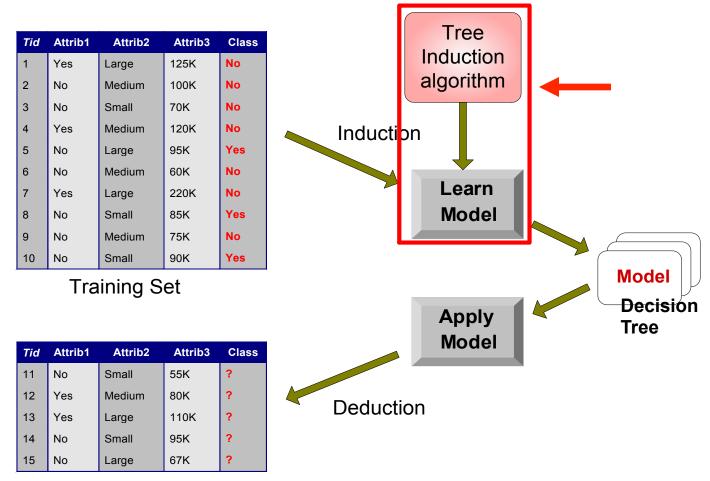








Decision Tree Classification Task



Test Set

Metrics for Performance Evaluation

- Focus on the predictive capability of a model
 - Rather than how fast it takes to classify or build models, scalability, etc.
- Confusion Matrix for a binary classifier (two labels) on test set:

| | PREDICTED CLASS | | | |
|--------|-----------------|-----------|----------|--|
| | | Class=Yes | Class=No | |
| ACTUAL | Class=Yes | a | b | |
| CLASS | Class=No | С | d | |

a: TP (true positive)

b: FN (false negative)

c: FP (false positive)

d: TN (true negative)

Classifier Accuracy Measures

• Another widely-used metric: Accuracy of a classifier M is the percentage of test set that are correctly classified by the model M

Accuracy =
$$\frac{a+d}{a+b+c+d} = \frac{TP+TN}{TP+TN+FP+FN}$$

| | Yes - C ₁ | No - C ₂ |
|----------------------|----------------------|---------------------|
| Yes - C ₁ | a: True positive | b: False negative |
| No - C ₂ | c: False positive | d: True negative |

| classes | buy_computer = yes | buy_computer = no | total |
|--------------------|--------------------|-------------------|-------|
| buy_computer = yes | 6954 | 46 | 7000 |
| buy_computer = no | 412 | 2588 | 3000 |
| total | 7366 | 2634 | 10000 |

Other Classifier Measures

• Alternative accuracy measures (e.g., for cancer diagnosis or information retrieval)

```
sensitivity = t-pos/pos /* true positive recognition rate */
specificity = t-neg/neg /* true negative recognition rate */

precision = t-pos/(t-pos + f-pos)

recall = t-pos/(t-pos + f-neg )

accuracy = sensitivity * pos/(pos + neg) + specificity * neg/(pos + neg)
```

Multi-Class Classification

- Most classification algorithms solve binary classification tasks, while many tasks are naturally multi-class, i.e. there are more than 2 labels
- Multi-Class problems are solved by training a number of binary classifiers and combining them to get a multiclass result
- Confusion matrix is extended to the multi-class case
- Accuracy definition is naturally extended to the multi-class case
- Precision and recall are defined for the binary classifiers trained for each label