Classical Machine Learning: Classification and Regression (I)

Learning Objectives

- Learn some techniques to understand your data and prepare your data for ML.
- Learn the basic concepts of a few interesting classifiers.

Techniques to Understand Your Data

Understand Your Data

- **Machine learning is all about the data.**
- **If data quality is poor, even the most sophisticated analysis would generate only lackluster (乏善可陳) results.**
- **A tale (see Know_Your_Data.pdf)**

Understand Your Data with Descriptive Statistics

Data_understand.ipynb

- Take a peek at your raw data.
- Review the dimensions of your dataset.
- Review the data types of attributes in your data.
- Summarize the distribution of instances across classes in your dataset.
- Summarize your data using descriptive statistics.
- Understand the relationships in your data using correlations.
- Review the skew of the distributions of each attribute.

Understand Your Data with Visualization

- **Histograms.**
- **Density Plots.**
- **Box and Whisker Plots.**

jupyterlab

Data_understand.ipynb

Prepare your data for machine learning

Data Preparation

Data_prepare.ipynb

- Rescale data.
- Standardize data.
- Normalize data.
- Binarize data.

Scikit-Learn Recipe

- Load the data.
- Split the dataset into the input feature matrix and output target vector for machine learning.
- Apply a pre-processing transform to the input variables.
- Summarize the data to show the change.

Classification algorithm walkthrough

Fun Time

Which learning problems below is likely NOT a classification problem?

1. **Given an image, try to predict whether it is dog or cat.**
2. **Given an applicant information, try to predict whether we should issue a credit card to her/him.**
3. **Given a rainfall, try to predict the water level of a dam.**
4. **Given a X-ray, try to predict whether it is a cancer.**

Classification

Classification uses models called classifiers to predict categorical (discrete, unordered) class labels.

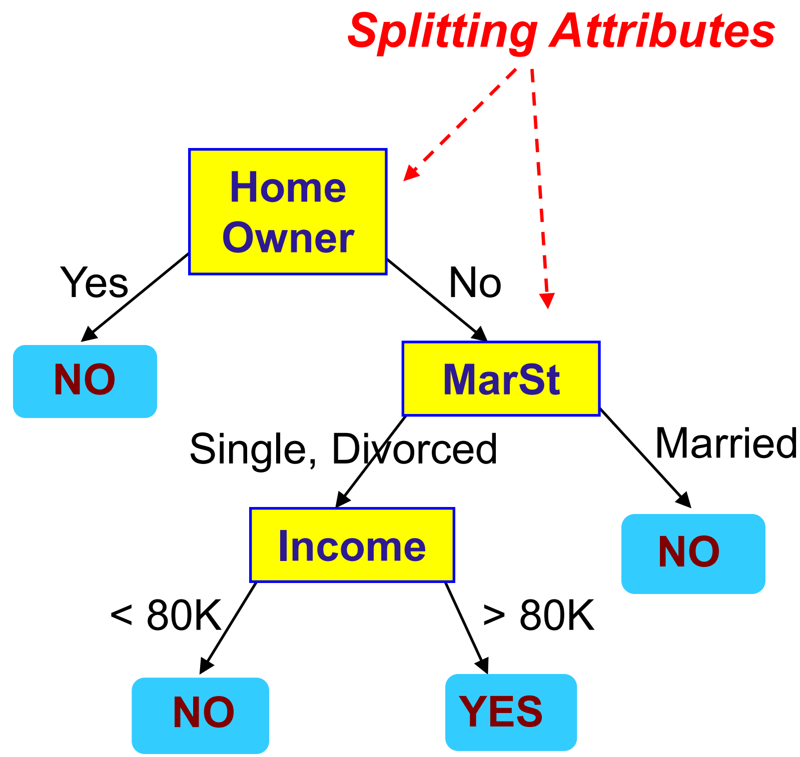
Task	Feature set, **x** (or attribute set)	Class label, *y*
Spam filtering	Features extracted from email message header and content	spam or non-spam
Tumor identification	Features extracted from MRI scans	malignant or benign
Bridge warning	Features extracted from river velocity and depth	danger or safe

Classification Algorithm Walkthrough: Decision Tree

Example of a Decision Tree

	categorical	categorical	continuous	class
ID	**Home Owner**	**Marital Status**	**Annual Income**	**Defaulted Borrower**
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

Another Example of Decision Tree

categorical categorical continuous class

ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
1	Yes	Single	125K	No
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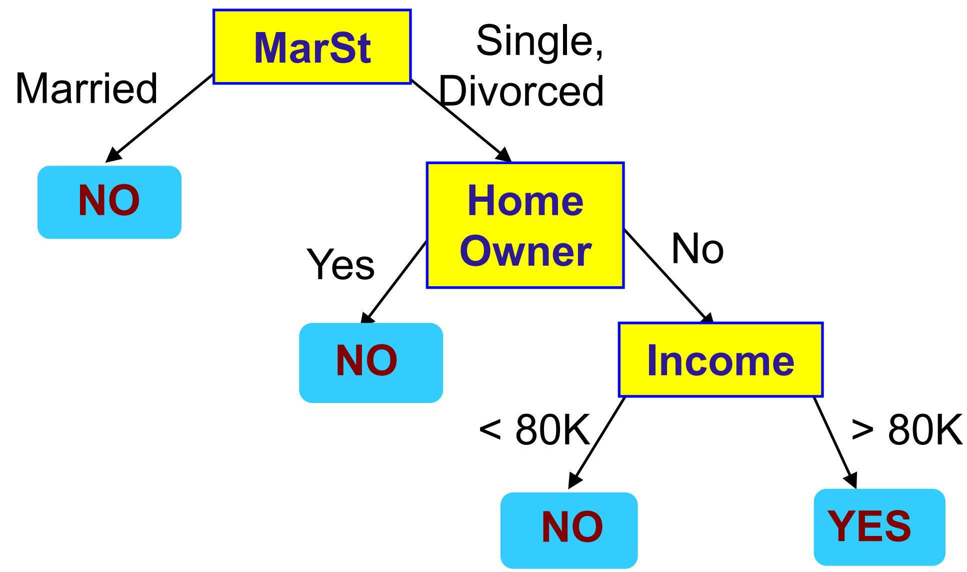
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes



There could be more than one tree that fits the same data!

Decision Tree Induction

- Many Algorithms:
  - Hunt’s Algorithm (one of the earliest)
  - CART
  - ID3, C4.5
  - SLIQ,SPRINT

General Structure of Hunt's Algorithm

- Let D_t be the set of training records that reach a node t

- General Procedure:
  - If D_t contains records that belong the same class y_t, then t is a leaf node labeled as y_t
  - If D_t contains records that belong to more than one class, use an attribute test to split the data into smaller subsets. Recursively apply the procedure to each subset.

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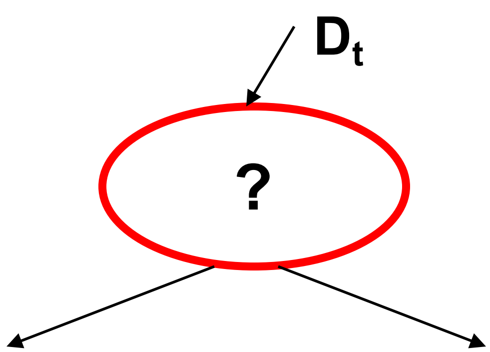

Hunt's Algorithm

Defaulted = No

(7,3)

(a)

ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
1	Yes	Single	125K	**No**
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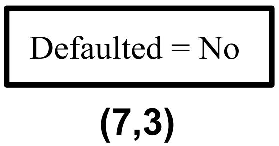
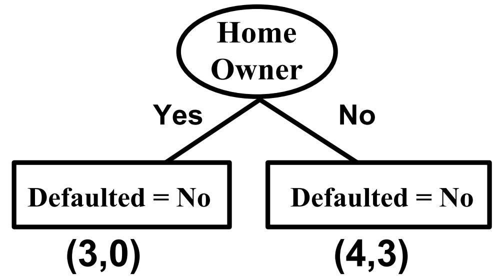
Hunt’s Algorithm



(a)



(b)

ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
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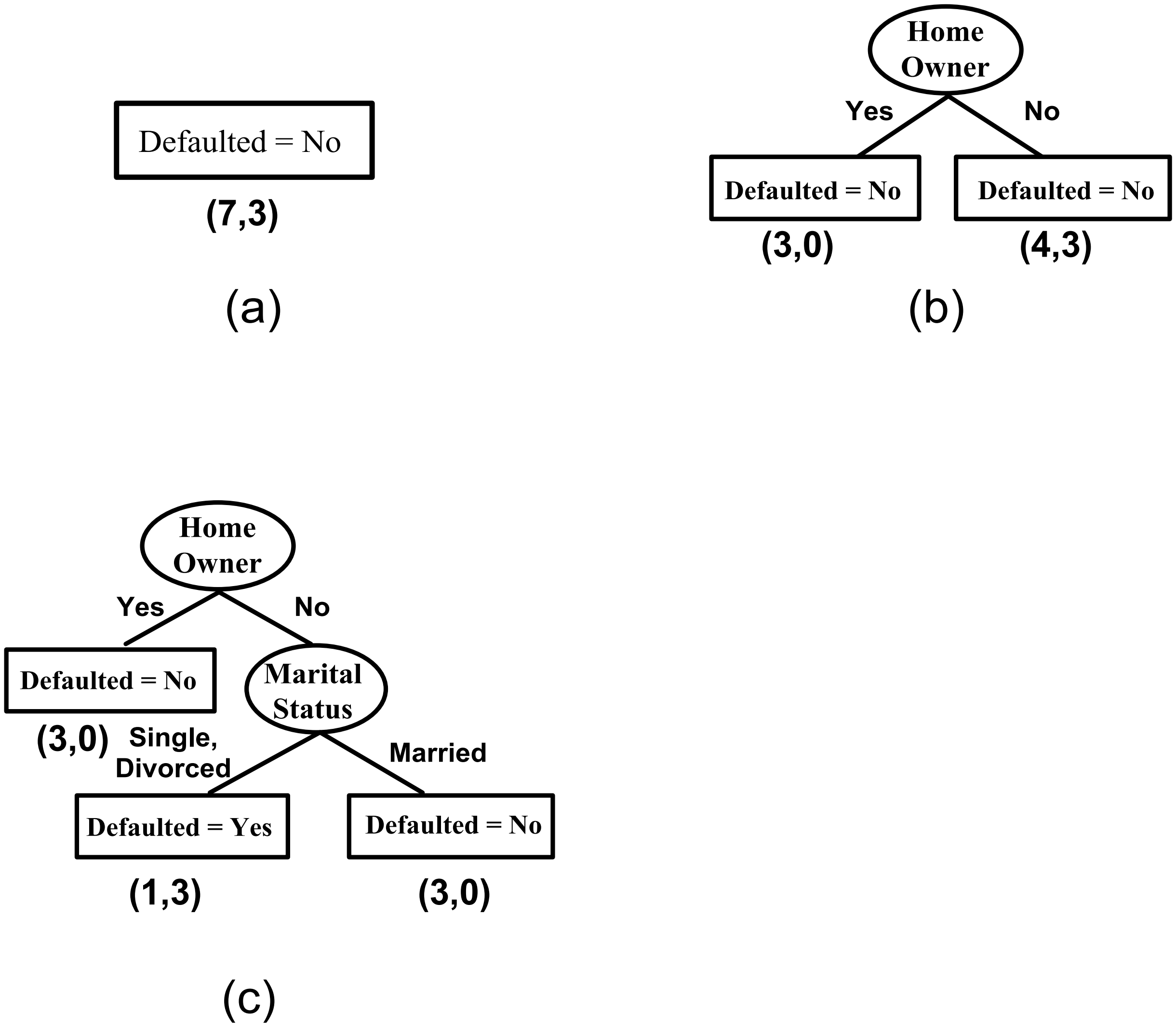
Hunt's Algorithm



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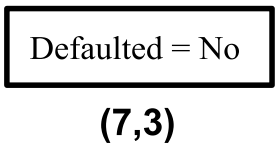
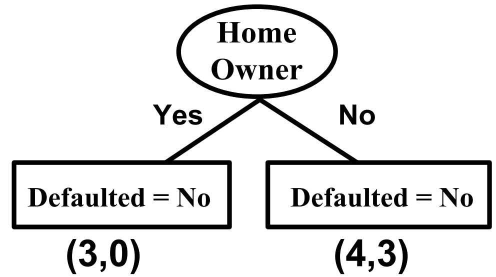
Hunt's Algorithm



(a)



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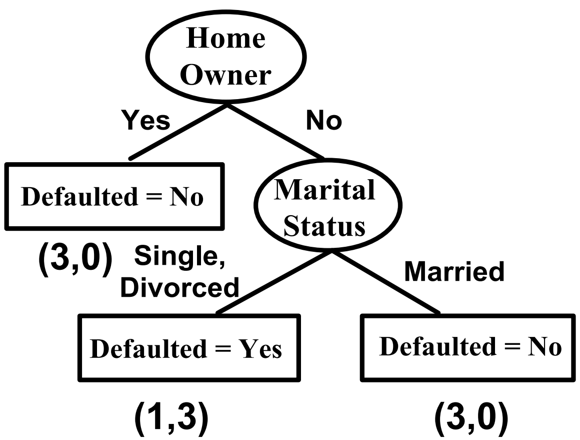
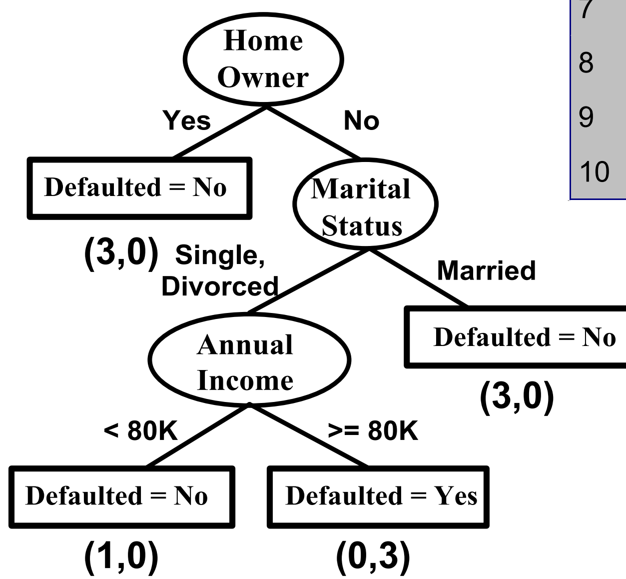


(c)



(d)

Decision Tree: theoretical minimum and example

- The phrase “theoretical minimum” is taken from a very successful book series written by Leonard Susskind, a great physicist at Stanford University.

- “Theoretical minimum” means just the minimum theories and equations you need to know in order to proceed to the next level.

- See Decision_Tree.pdf

Summary

Classification Algorithm Walkthrough: Decision Tree

- Decision tree is simple and useful for interpretation.
- Decision tree uses a greedy algorithm with a best-split attribute to recursively split the tree.
- The "Gini" criteria, or the "Entropy" criteria is the most commonly used index to determine the best split.
- Shallow decision trees are weak learners and are not competitive in terms of prediction accuracy
- Deep decision trees tend to overfit data.
- An ensemble of randomized decision trees such as random forests is a powerful algorithm for classification. This will be covered in the sequel.