EEP 596: Adv Intro ML || Lecture 6

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Univ. of Washington, Seattle

January 24, 2023

Logistics

1. **Lightning Presentation Slot:** Please pick a slot for your 5 minute lightning presentation this quarter if not done already. Spreadsheet available on discord
2. **Conceptual 2:** Assigned and due the coming Sunday
3. **Programming 3:** Will be assigned today and will be a mini-project based on Kaggle contest - Due in about 2 weeks on February 4 (Saturday)
4. Anything else?

Last class

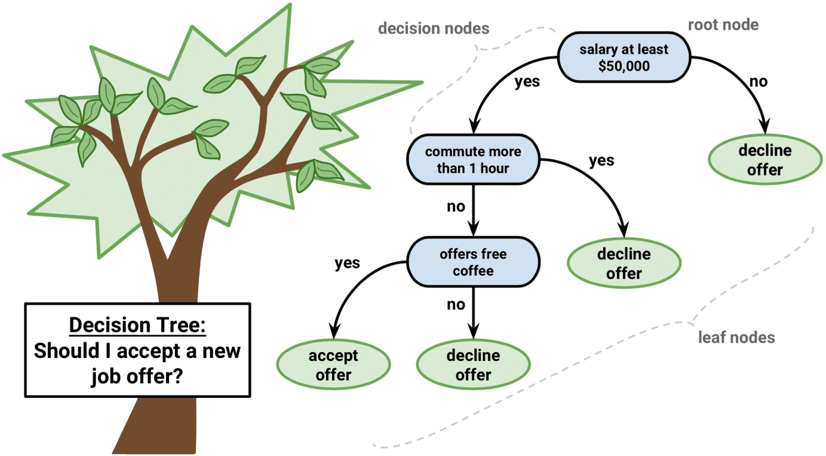
1. How Logistic Regression differs from Linear Regression?
2. Evaluation metrics for Binary Classification
3. Pre-processing and Feature engineering for Spam Classification
4. Bag of words model
5. TF-IDF

Today!

Decision Trees

Next Topic: Decision Trees Classifier

Decision Trees Motivation



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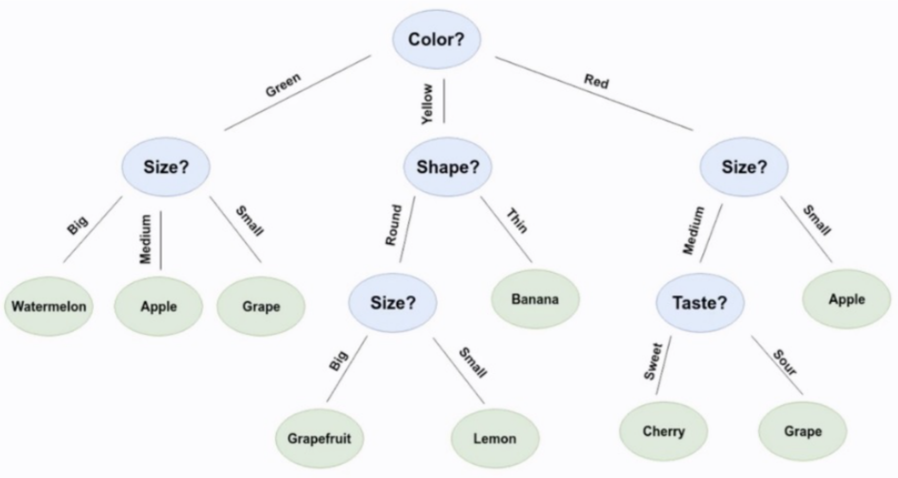
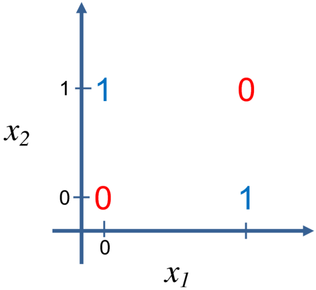


ICE #1

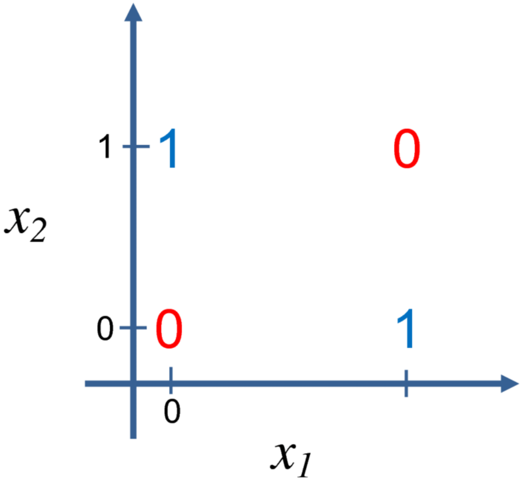
Can Logistic Regression learn to separate the 0's from the ones exactly?



1. Yes
2. No
3. Maybe

XOR Function

Linearly Separable?



XOR Function

Can XOR be modeled by Decision Tree?

Why Decision Trees?

1. **Human-like:** We usually make decisions based on if/then and else/or scnearios. **Example:** If it is raining outside, it's not too cold and it's summer time - Let's go hiking. **Example:** If it's raining and it's winter, let's skip hiking.

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5. **Robustness to noise:** A few noisy examples in the data set may not through a decision tree prediction off - Based on majority votes.

Learning Decision Trees

Learning

The `learning` for Decision Trees boils down to how to build the tree. Which feature to split on first? Second? And so on... Also, when to stop building the tree

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Intuition behind building Decision Trees

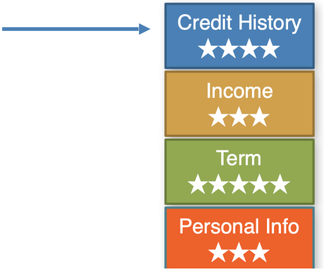
Start splitting on features that give the maximum information gain or reduce the uncertainty in prediction/reduce the classification error. This is done iteratively and hence can be thought of as a greedy procedure.

Case Study: What makes a loan risky?

Features: Credit History

Did I pay previous loans on time?

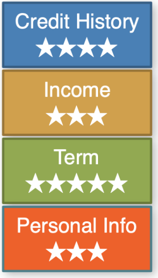
Example: excellent, good, or fair



Features: Income

What's my income?

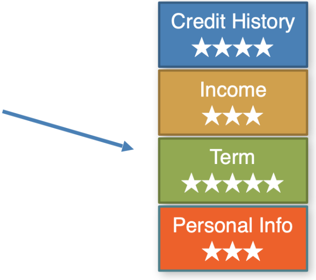
Example:
$80K per year



Features: Loan Terms

How soon do I need to pay the loan?

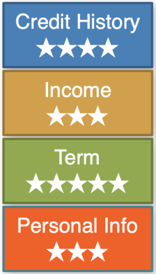
Example: 3 years, 5 years,…



Features: Personal Information

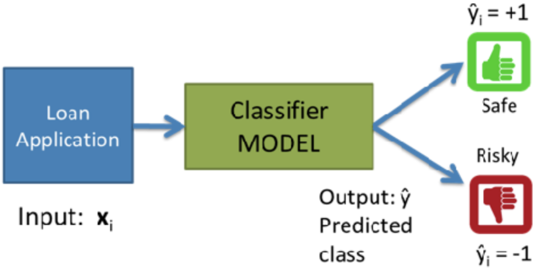
Age, reason for the loan, marital status,…

Example: Home loan for a married couple



Intelligent Loan Review System

Loan Classifier

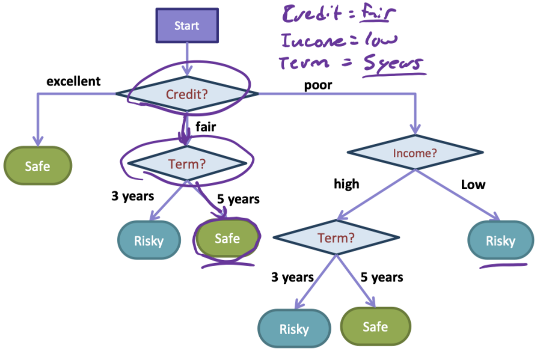


Sample Data

Data (N observations, 3 features)

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	5 yrs	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	safe
fair	5 yrs	low	safe
poor	3 yrs	high	risky
poor	5 yrs	low	safe
fair	3 yrs	high	safe

Decision Trees



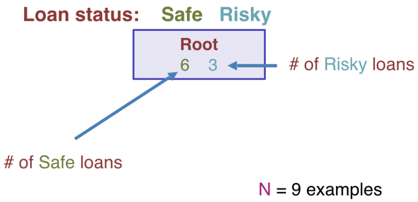
- **Branch/Internal node:** splits into possible values of a feature
- **Leaf node:** final decision (the class value)

Growing Trees

Questions

- Which features are "good"?
- When to stop growing a tree?

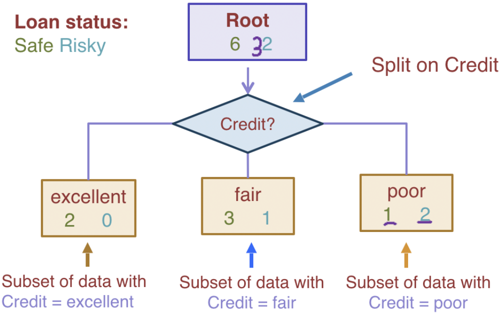
Visual Notation



Decision stump 1

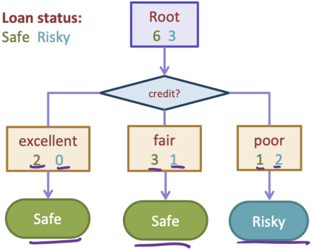
Data (N observations, 3 features)

Credit	Term	Income	y
excellent	3 yrs	high	safe
fair	5 yrs	low	risky
fair	3 yrs	high	safe
poor	5 yrs	high	risky
excellent	3 yrs	low	safe
fair	5 yrs	low	safe
poor	3 yrs	high	risky
poor	5 yrs	low	safe
fair	3 yrs	high	safe



Making predictions

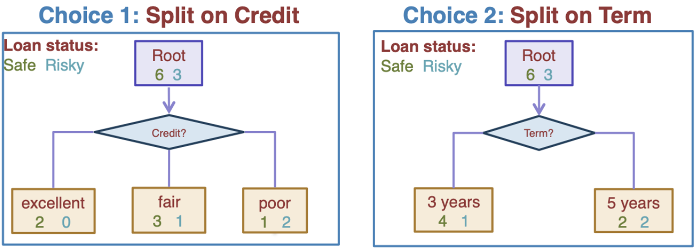
For each leaf node, set ŷ = majority value



Split selection

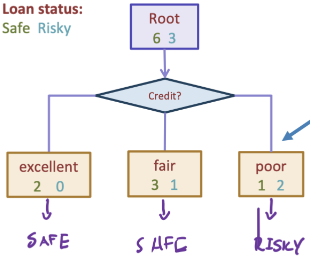
How do we select the best feature?

Select the split with lowest classification error



Split Effectiveness

How do we measure effectiveness of a split?



Idea: Calculate classification error of this decision stump

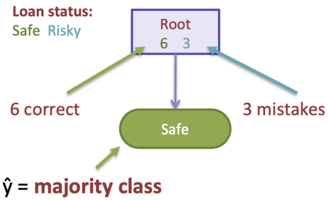
$$\text{Error} = \frac{\text{\# mistakes}}{\text{\# data points}}$$

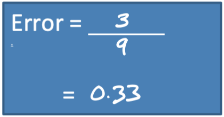
Calculate Classification Error

Calculating classification error

Step 1: $\hat{y}$ = class of majority of data in node

Step 2: Calculate classification error of predicting $\hat{y}$ for this data

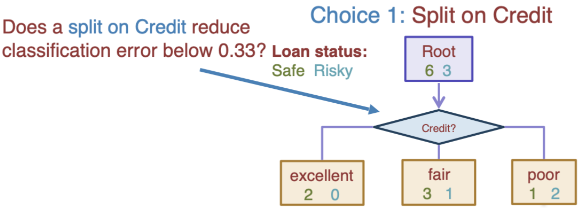




Tree	Classification error
(root)	0.33

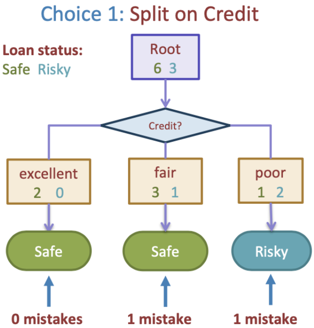
Split on Credit

Choice 1: Split on Credit history?



Split on Credit

Split on Credit: Classification error

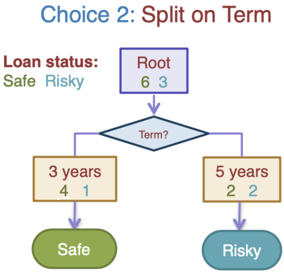


$$\text{Error} = \frac{0+1+1}{9} = \frac{2}{9} = 0.22$$

Tree	Classification error
(root)	0.33
Split on credit	0.22

Split on Term

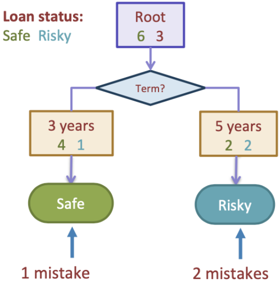
Choice 2: Split on Term?



Split on Term

Evaluating the split on Term

Choice 2: Split on Term



$$\text{Error} = \frac{1 + 2}{9} = \frac{3}{9}$$
$$= 0.33$$

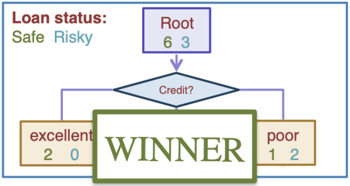
Tree	Classification error
(root)	0.33
Split on credit	0.22
Split on term	0.33

Split Winner

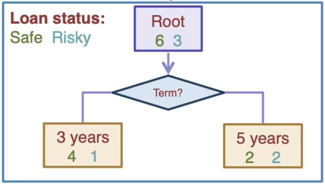
Choice 1 vs Choice 2:
Comparing split on credit vs term

Tree	Classification error
(root)	0.33
split on credit	0.22
split on loan term	0.33

Choice 1: Split on Credit



Choice 2: Split on Term



Split selection

Split selection procedure

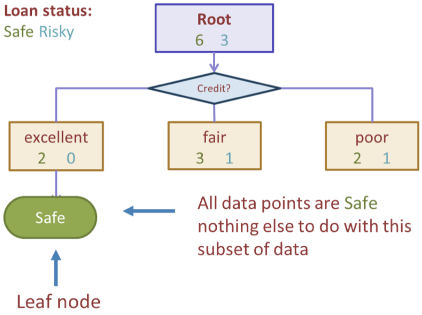
- Given a subset of data set, M at a node
- For each remaining feature $h_i(x)$, split M by feature $h_i(x)$ and compute classification error
- Pick the feature i to split with minimum classification error

Decision Tree Classification as a Greedy Procedure

DT Classifier Training procedure

If classification splits satisfy criteria (e.g. low classification error), stop,
Else, split further using split selection procedure.

Stopping



Loan status:
Safe Risky
Root
6 3
Credit?
excellent
2 0
fair
3 1
poor
2 1
Safe
All data points are Safe
nothing else to do with this
subset of data
Leaf node

Stopping criteria in practice

1. **Splits with few data points** can lead to over-fitting. Example

Stopping criteria in practice

A. **Splits with few data points** can lead to over-fitting. Example
B. **Max tree depth** can be a stopping criteria to prevent over-fitting.

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Stopping criteria in practice

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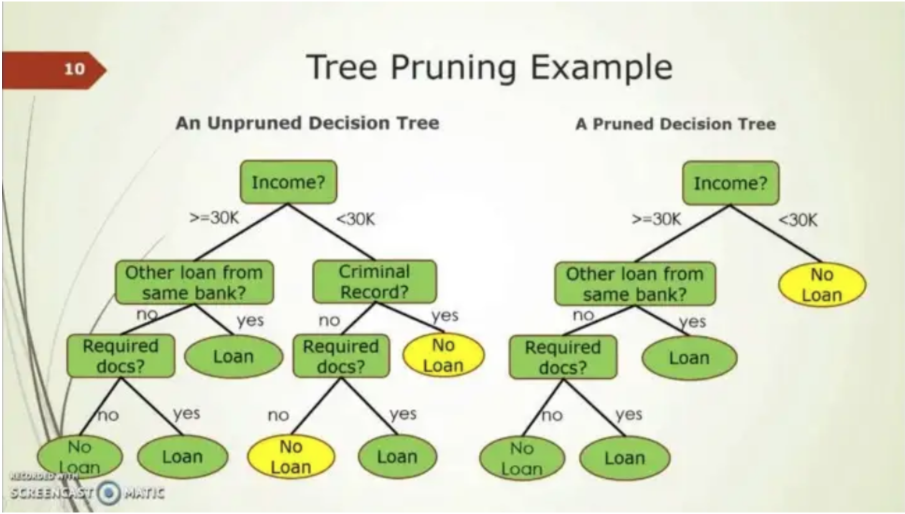
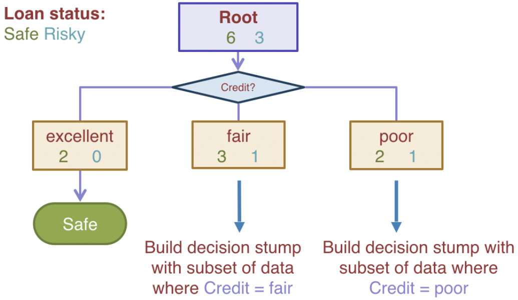
C. Although theoretically, can aim for 0 classification error - This would lead to over-fitting. Use above 2 to stop earlier.
D. No standard 'regularization' for DTs like for Logistic Regression. Why?
E. **Pruning** - Can be done to prune branches that lead to over-fitting

Decision Trees Pruning

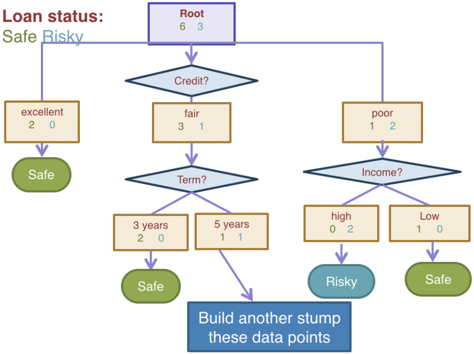


Tree Pruning Example Reference

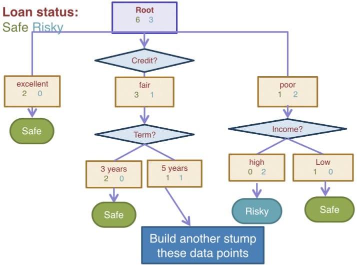
Recursive Splits



Second level DT



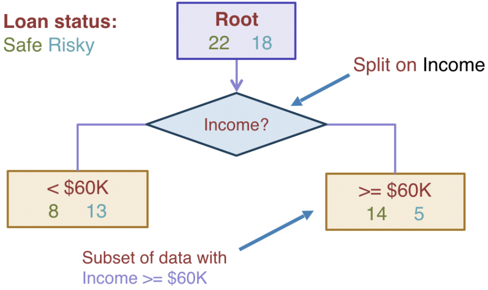
Classification error



The classification error for the DT above is:

a. 0.33
b. 0.11
c. 0.22
d. 0

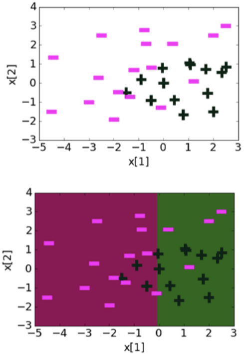
Threshold splits for real valued features

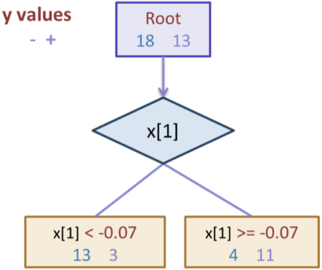


Choosing Split Threshold for Numeric Features

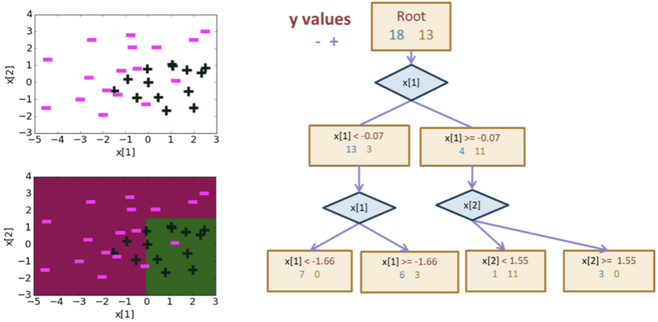
1. Grid search?
2. Numeric vs Categorical Features: Can recurse more than once on a numeric feature. Can't do the same for categorical feature. Why?

Decision Boundary level 1 || Numeric Features



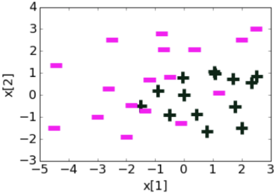


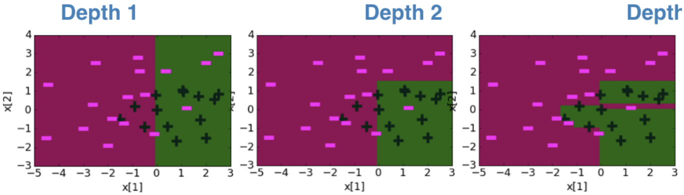
Decision Boundary level 2 || Numeric Features



Decision Boundary level 3 || Numeric Features

- Decision boundaries can be complex!





Decision Trees Summary

Summary

- Intuitive way to classify by making decsisions by walking down the tree
- Can learn complex **non-linear decision boundaries** (unlike logistic regression)
- Prone to **overfit** as tree depth increases (unlike logistic regression)
- Splitting at nodes with few data points can lead to overfitting
- Over-fitting can be avoided by early stopping (depth or error)
- Improve Decision Trees - Random Forests - Next Lecture!

Decision Trees vs Logistic Regression

1. Both are **interpretable** in different ways

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3. Decision Trees can easily learn **non-linear decision boundaries** while Logistic Regression learns linear decision boundary
4. Decision Tree has a higher model complexity as compared to Logistic Regression
5. Logistic Regression is less prone to **over-fitting** than Decision Trees with large number of features

Pitfalls of Decision Trees

1. **Overfitting**

Pitfalls of Decision Trees

1. **Overfitting**
2. **Feature Engineering**

Pitfalls of Decision Trees

1. **Overfitting**
2. **Feature Engineering**
3. **Not suitable for Regression**

Overcoming pitfalls of Decision Trees - Random Forests

Random Forests Introduction

A **Random Forest** is a collection of T Decision Trees. Each decision tree casts a "vote" for a prediction and the ensemble predicts the majority vote of all of its trees.