Feature Importance in Decision Trees:

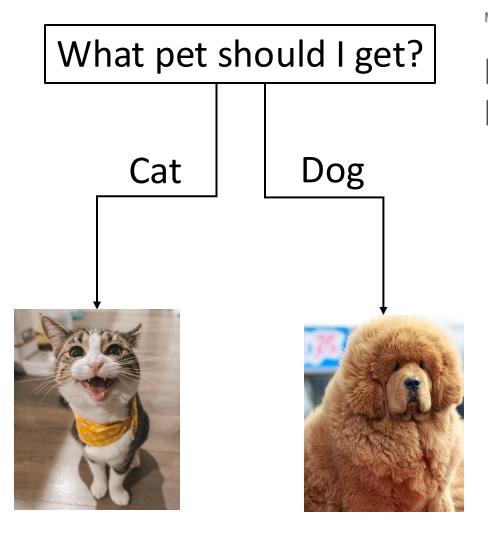
Impurity-based Importance Calculations & Explainable AI

Dr. Franziska Boenisch





You already interact(ed) with decision trees!



May 11, 2023 2m read

Random Forests: Netflix Customer Recommendations Improved by 20%



... watching Netflix ...

Spotify — Decision Trees with Music Taste

7 min read · Nov 26, 2020



Jinkim



... or listening to music.



Outline for Today

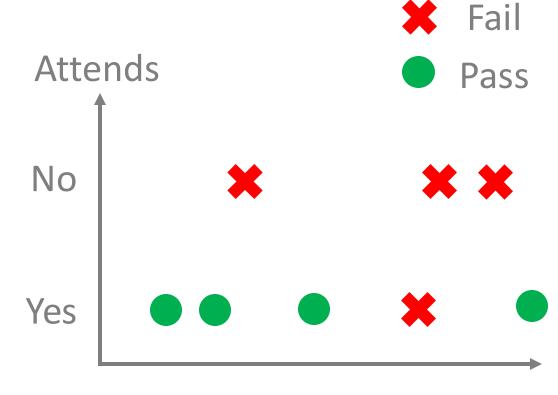
Intuition on classification with decision tree

- Impurity-based feature importance metrics
- Building decision trees based on impurity reduction
- Feature importance and explainable AI

Datasets and Tree-based Classification

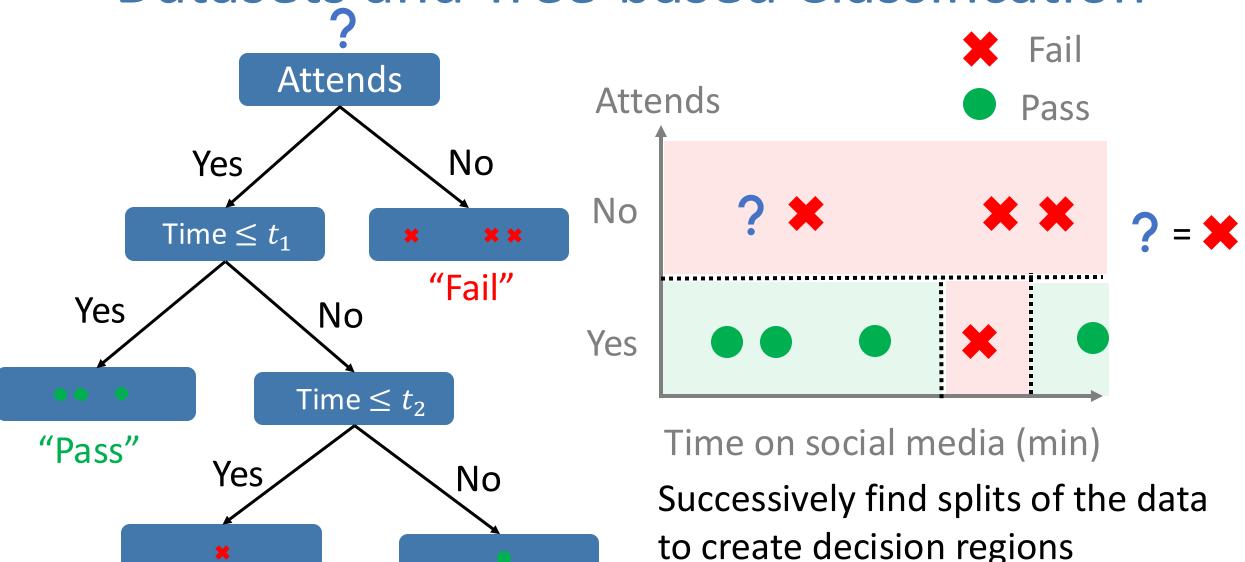
Dataset from my Lecture

Social Media Time (min)	Attends Class	Passed the Midterm
30	Yes	Pass
80	Yes	Pass
140	Yes	Pass
50	Yes	Pass
110	No	Fail
60	No	Fail
100	Yes	Fail
120	No	Fail
Continuous	Categorica	al
Features		Label



Time on social media (min)

Datasets and Tree-based Classification



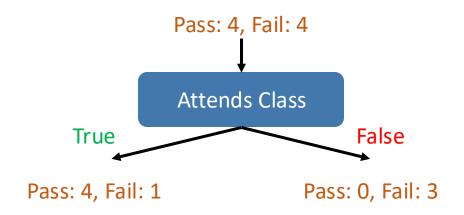
"Pass"

"Fail"

Greedy, recursive partitioning

Finding the Best Split Criterion

Social Media Time (min)	Attends Class	Passed the Midterm	
30	Yes	Pass	—
80	Yes	Pass	-
140	Yes	Pass	—
50	Yes	Pass	-
110	No	Fail	←
60	No	Fail	-
100	Yes	Fail	-
120	No	Fail	—



Impure split

Pure split

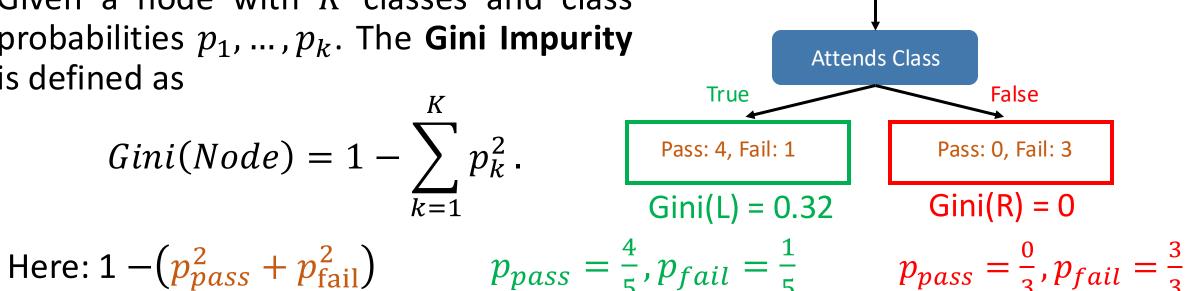
Is attendance our best spilt?

Gini Impurity: Definition

Given a node with K classes and class probabilities p_1, \dots, p_k . The **Gini Impurity** is defined as

$$Gini(Node) = 1 - \sum_{k=1}^{K} p_k^2.$$

Here:
$$1 - (p_{pass}^2 + p_{fail}^2)$$



Pass: 4, Fail: 4

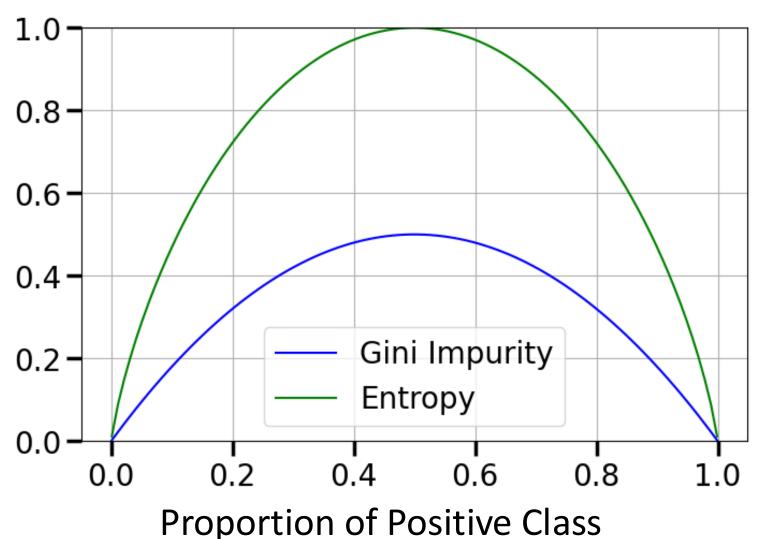
In our example:

- True branch: Gini(L) =
$$1 - \left(\frac{4}{5}\right)^2 - \left(\frac{1}{5}\right)^2 = 0.32$$

- False branch:
$$Gini(R) = 1 - (0)^2 - (1)^2 = 0$$

Gini Impurity and Entropy

Impurity



Alternative to Gini:

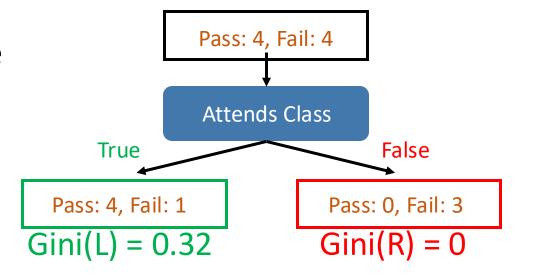
 $\mathsf{Entropy} = -\sum_k p_k \log_2 p_k \,,$

with p_k : proportion of data from class k in the node.

Gini Impurity of the Entire Split

When evaluating a split, we compute the weighted Gini of the children:

$$Gini_{split} = \frac{n_L}{n}Gini(L) + \frac{n_R}{n}Gini(R)$$



 $Gini_{split} = 0.2$

n: total number of data points in split \rightarrow 8

 n_I : number of points in L(eft) node

 n_R : number of points in R(right) node \rightarrow 3

$$n_R$$
: number of points in R(right) node \rightarrow 3

$$Gini_{split} = \frac{5}{8} * 0.32 + \frac{3}{8} * 0 = 0.2$$

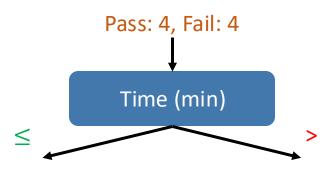
Gini Impurity on Continuous Values

Goal: Identify the best splitting threshold

Social Media Time (min)	Passed the Midterm	
30	Pass	
50	Pass	
60	Fail	
80	Pass_	4
100	Fail	
110	Fail	
120	Fail	
140	Pass	

2. Identify where class changes

3. Take average as threshold



≤ 55

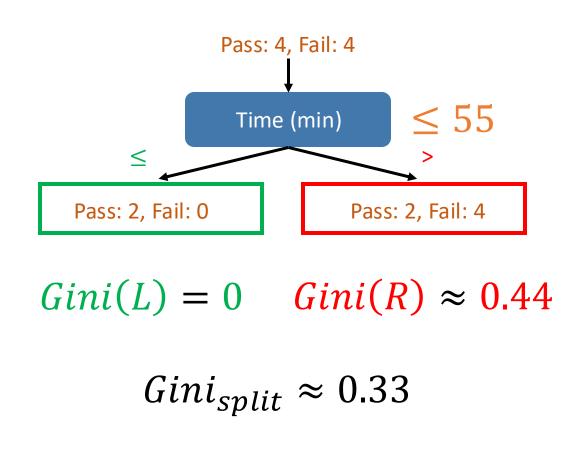
 ≤ 70

 ≤ 90

 ≤ 130

Gini Impurity on Continuous Values

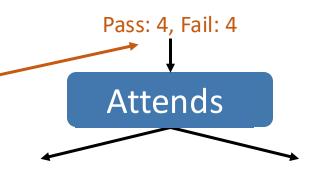
Social Media Time (min)	Passed the Midterm	
30	Pass	
50	Pass	→ 0.33
60	Fail	$\rightarrow 0.33$ $\rightarrow 0.48$
80	Pass	$\rightarrow 0.38$
100	Fail	, 0.30
110	Fail	
120	Fail	$\longrightarrow 0.44$
140	Pass	, 0.44



Impurity Reduction to Choose the Best Split

Choose the split that causes the maximum impurity reduction $\Delta i(split)$:

$$\Delta i (split) = \max(Gini_{parent} - Gini_{split})$$



Gini_{parent} =
$$1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2 = 0.5$$
(is fixed \rightarrow find lowest Gini_{split}

$$\Delta i \ (Attends) = 0.5 - 0.2 = 0.3$$

Gini impurity over all possible splits:

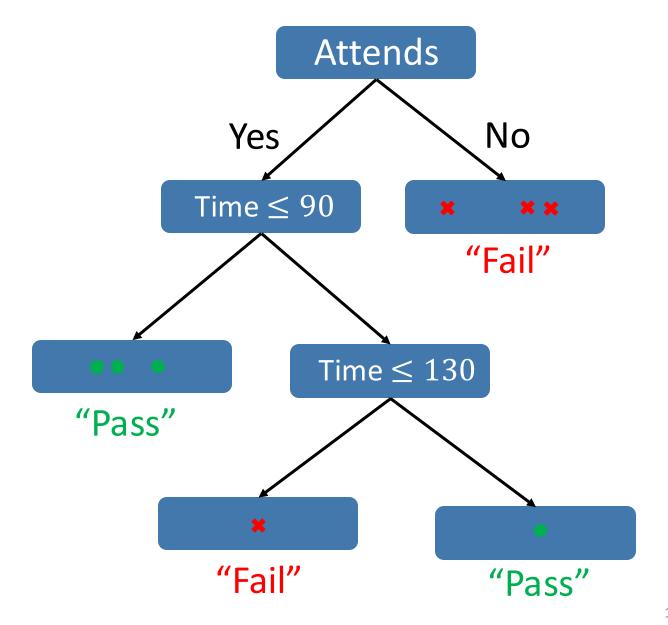
$$Gini_{Attends} = 0.2$$
 $Gini_{Time \le 55} = 0.33$
 $Gini_{Time \le 70} = 0.48$
 $Gini_{Time \le 90} = 0.38$
 $Gini_{Time \le 120} = 0.44$

$$Gini_{Time \le 130} = 0.44$$

From Trees to Explainable Al

Decisions in the tree are:

- Human-interpretable
- Verifiable
- We can ask "What if?" (Counterfactuals)



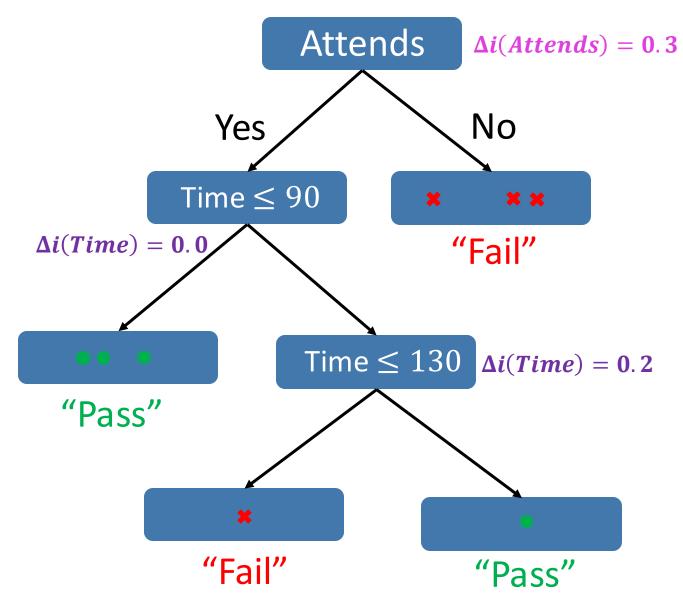
Impurity-based Feature importance

We calculate the **importance** of a feature f in a tree as:

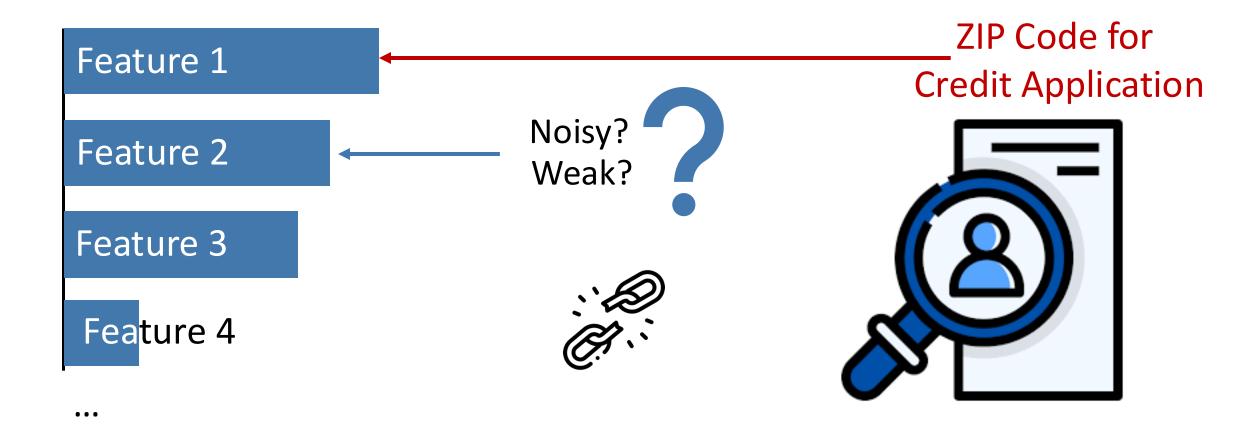
Importance(f) =
$$\frac{\sum_{t \in Splits \ on \ f} \Delta i(t)}{\sum_{s \in All \ splits} \Delta i(s)}.$$

Importance(Attends)
$$= \frac{0.3}{0.3 + 0.0 + 0.2} = 0.6 = 60\%$$

$$Importance(Time) = \frac{0.0 + 0.2}{0.3 + 0.0 + 0.2} = 0.4 = 40\%$$



Feature Importance for Explainability

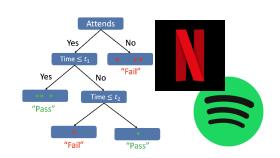


Understanding predictions

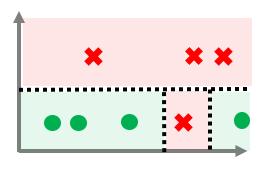
Model debugging

Identifying biases

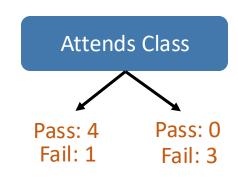
Summary & Lecture Materials



Decision Trees: Omnipresent



Divide Data in Regions



Impurity-based Feature Splits



Serve Explainable AI

Lecture Materials:

