

Lecture 4: 3 February, 2022

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Data Mining and Machine Learning
January–May 2022

Decision tree algorithm

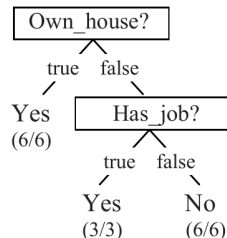
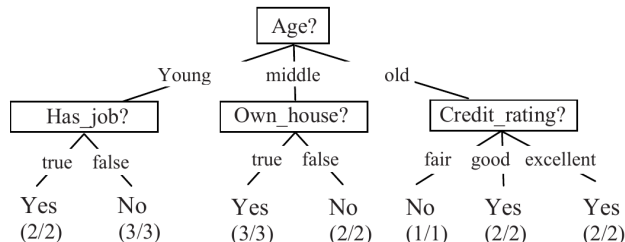
A : current set of attributes

Pick $a \in A$, create children corresponding to resulting partition with attributes $A \setminus \{a\}$

Stopping criterion:

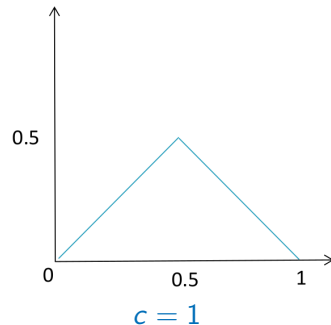
- Current node has uniform class label
- A is empty — no more attributes to query

If a leaf node is not uniform, use majority class as prediction



Building small decision trees

- Prefer small trees
- Goal: partition with uniform category
 - **pure** leaf
- Impure node — best prediction is majority value
- Minority ratio is **impurity**
- Heuristic: reduce impurity as much as possible
- For each attribute, compute weighted average impurity of children
- Choose the minimum

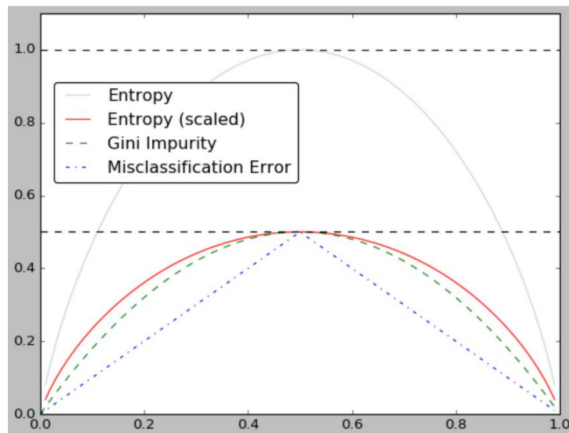


Misclassification rate is linear

- $c \in \{0, 1\}$
- x-axis: fraction of inputs with $c = 1$

Better impurity functions

- Impurity measure that increases more sharply performs better, empirically
- **Entropy**, information theory — [Quinlan]
 - n_0 with $c = 0$, $p_0 = n_0/n$
 - n_1 with $c = 1$, $p_1 = n_1/n$
 - $E = -(p_0 \log_2 p_0 + p_1 \log_2 p_1)$
- **Gini index**, economics — [Breiman]
 - n_0 with $c = 0$, $p_0 = n_0/n$
 - n_1 with $c = 1$, $p_1 = n_1/n$
 - $G = 1 - (p_0^2 + p_1^2)$



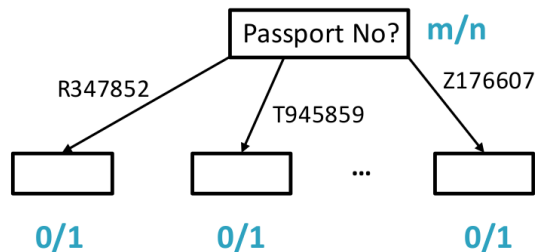
$c = 1$

Information gain

- Greedy strategy: choose attribute to maximize reduction in impurity — maximize **information gain**

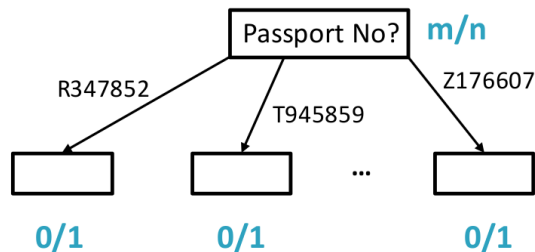
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 - Roll number, passport number, Aadhaar ...



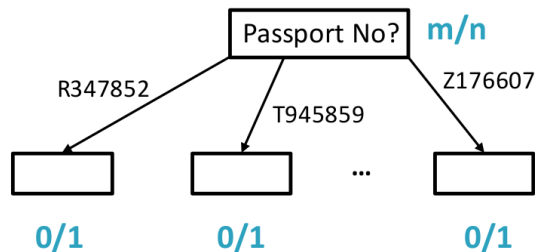
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 - New impurity is zero



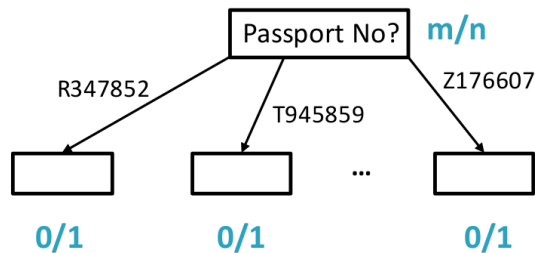
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- Maximum possible impurity reduction, but useless!



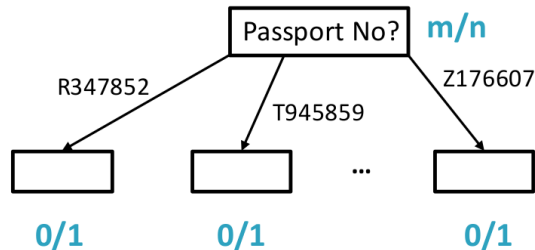
Information gain

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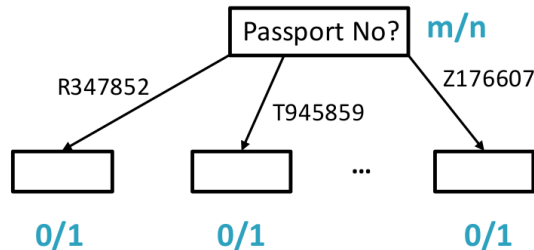
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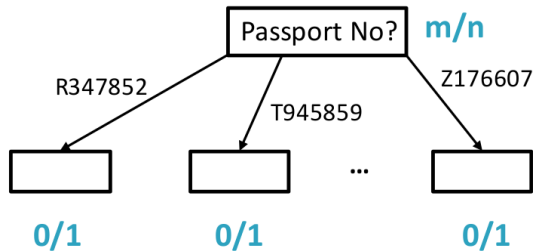
Information gain

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- Need a correction to penalize attributes with highly scattered attributes
- Extend the notion of impurity to attributes



Attribute Impurity

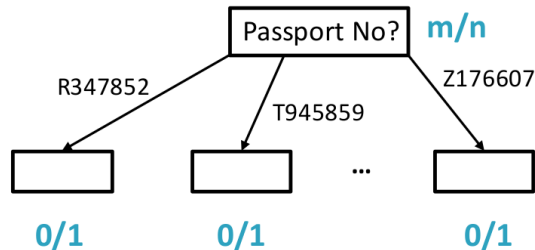
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- v_i appears n_i times across n rows
- $p_i = n_i/n$



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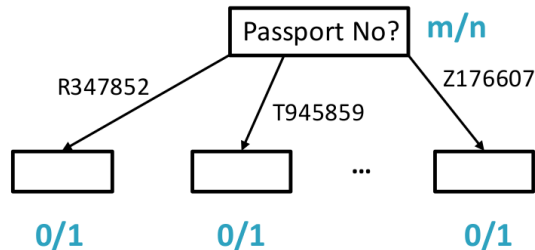
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- Gini index across k values

$$1 - \sum_{i=1}^k p_i^2$$



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Penalizing scattered attributes

- Divide information gain by attribute impurity
- **Information gain ratio(A)**

$$\frac{\text{Information-Gain}(A)}{\text{Impurity}(A)}$$

- Scattered attributes have high denominator, counteracting high numerator

Heuristics for building decision trees

- Can find better measures of impurity than misclassification rate
 - Non linear impurity function works better in practice
 - Entropy, Gini index
 - Gini index is used in most decision tree libraries

Heuristics for building decision trees

- Can find better measures of impurity than misclassification rate
 - Non linear impurity function works better in practice
 - Entropy, Gini index
 - Gini index is used in most decision tree libraries
- Blindly using information gain can be problematic
 - Attributes that are unique identifiers for rows produces maximum information gain, with little utility
 - Divide information gain by impurity of attribute
 - Information gain ratio

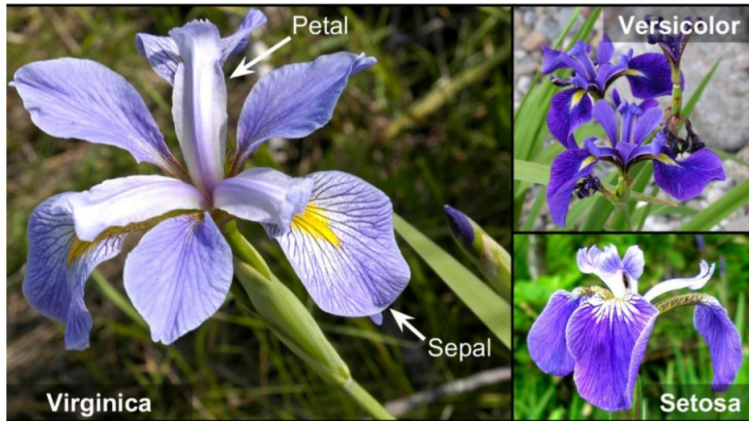
Categorical vs numeric attributes

- So far, all attributes have been categorical
- What age groups make up young, middle, old?
- How are these boundaries defined?
- How do we query numerical attributes?
 - Height, weight, length, income,

ID	Age	Has_job	Own_house	Credit_rating	Class
1	young	false	false	fair	No
2	young	false	false	good	No
3	young	true	false	good	Yes
4	young	true	true	fair	Yes
5	young	false	false	fair	No
6	middle	false	false	fair	No
7	middle	false	false	good	No
8	middle	true	true	good	Yes
9	middle	false	true	excellent	Yes
10	middle	false	true	excellent	Yes
11	old	false	true	excellent	Yes
12	old	false	true	good	Yes
13	old	true	false	good	Yes
14	old	true	false	excellent	Yes
15	old	false	false	fair	No

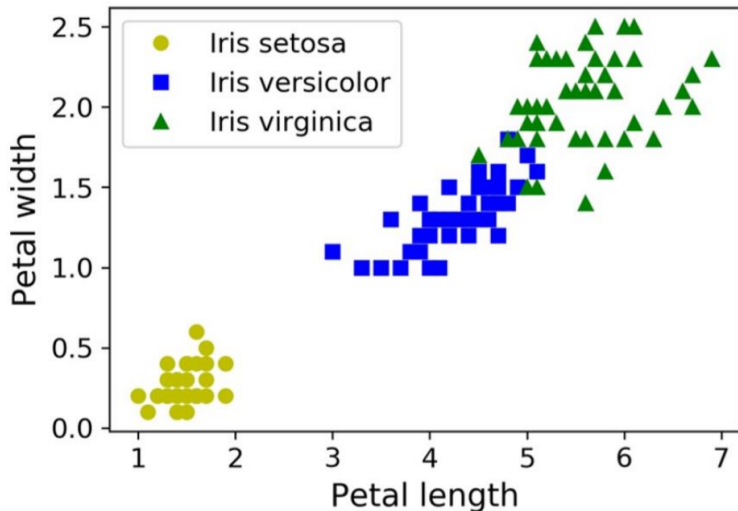
Iris dataset

- Iris is a type of flower
- Three species: *iris setosa*, *iris versicolor*, *iris virginica*
- Dataset has sepal length and width and petal length and width for 150 flowers



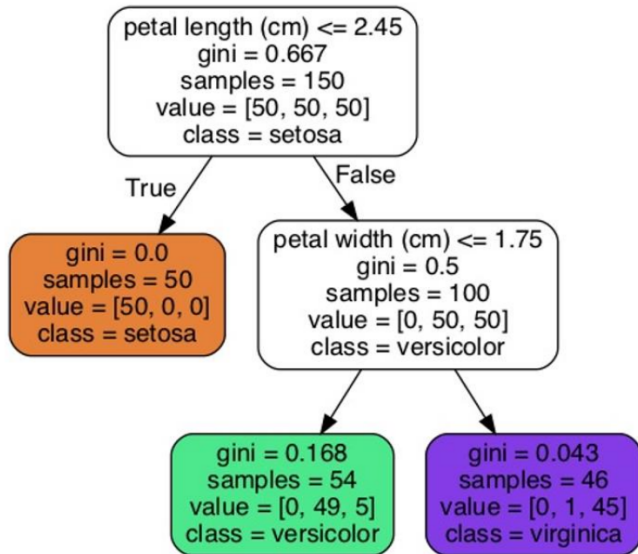
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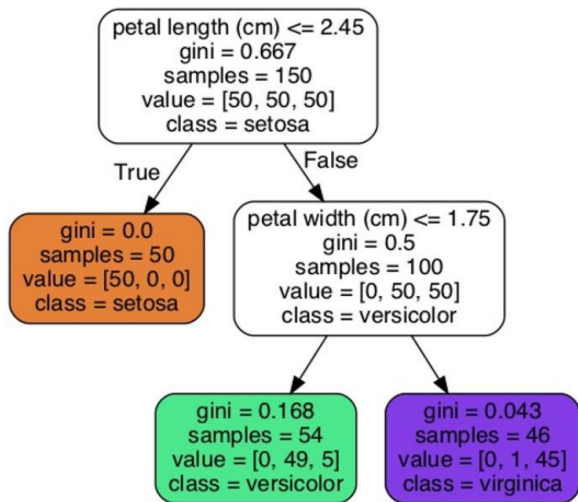
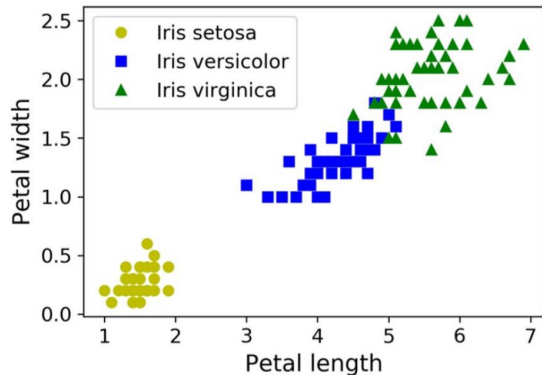
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- Decision tree for this data set



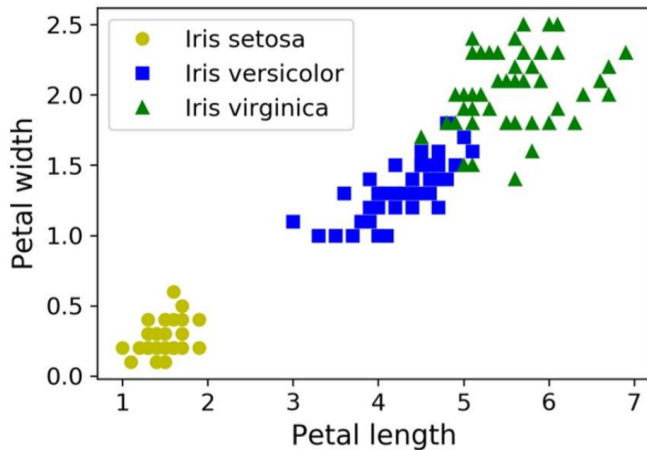
Decision tree for iris dataset

- Queries compare numerical attribute against a value
- How do we find these query values?



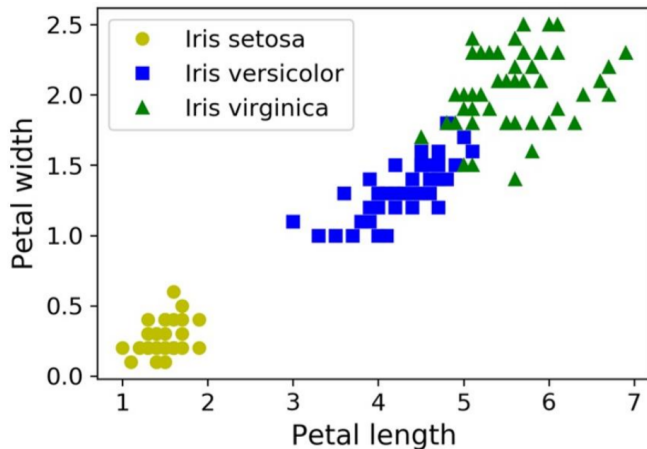
Querying numerical attributes

- Numerical attribute takes values in a range $[L, U]$
 - Petal length : $[1, 7]$
 - Petal width : $[0, 2.5]$



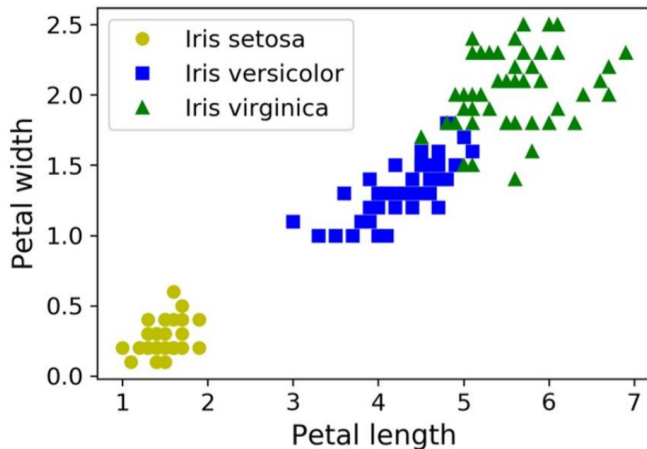
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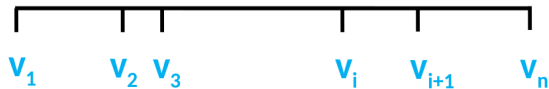
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- Infinitely many choices for v
- How do we pick a sensible one?



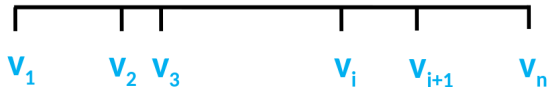
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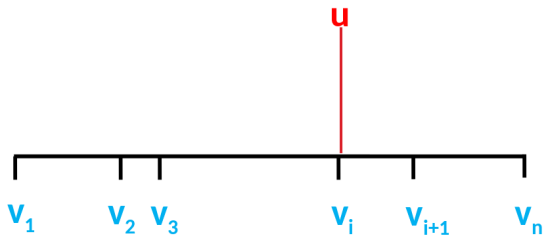
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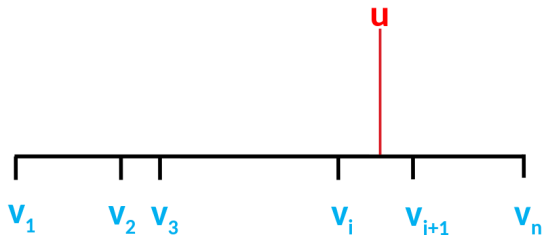
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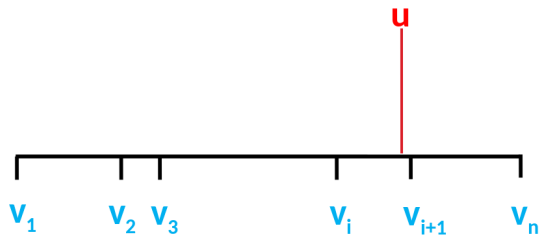
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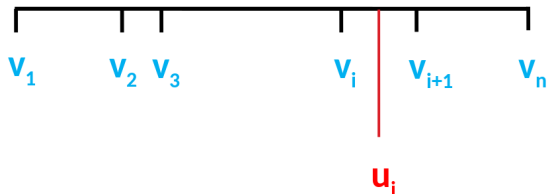
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- Any point within an interval can be used
- May prefer endpoints — midpoints may not be meaningful values

Building a decision tree

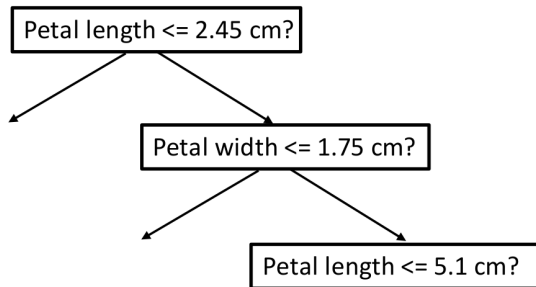
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Building a decision tree

- For each numerical attribute, choose query $A \leq v$ with maximum information gain
- Across all categorical and numerical attributes, choose the one with best information gain
- Categorical attributes can be queried only once on a path
- Numerical attributes can be queried repeatedly — interval to query keeps shrinking



Testing a supervised learning model

- How do we validate software?
 - Test suite of carefully selected inputs
 - Compare output with expected answers

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Testing a supervised learning model

- How do we validate software?
 - Test suite of carefully selected inputs
 - Compare output with expected answers
- What about classification models?
 - By definition, deploy on data where the outcome is unknown
 - If expected answer available, have a deterministic solution, model not needed!
- On what basis can we evaluate a supervised learning model?

Creating a test set

- Training data is labelled
 - No other source of inputs with expected answers

Creating a test set

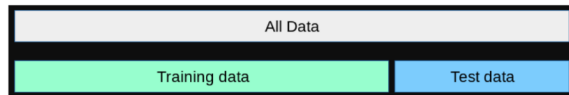
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 - Terminology: **training set** and **test set**
 - Build model using training set, evaluate on test set
- Creating the test set
 - Need to choose a random sample
 - Can further use **stratified sampling**, preserve relative ratios (e.g., age wise distribution)
 - ML libraries can do this automatically

Creating a test set

- How large should the test set be?
 - Typically 20-30% of labelled data
- Depends on labelled data available
 - Need enough training data to build the model

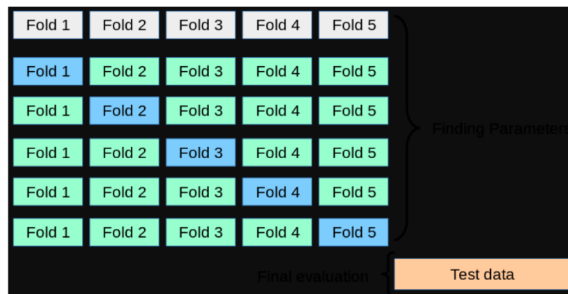
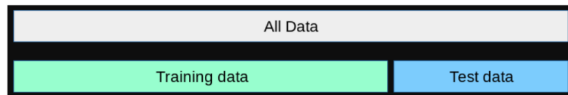


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Cross validation

- Partition labelled data into k chunks
- Hold out one chunk at a time
- Build k models, using $k-1$ chunks for training, 1 for testing
- Useful if labelled data is scarce

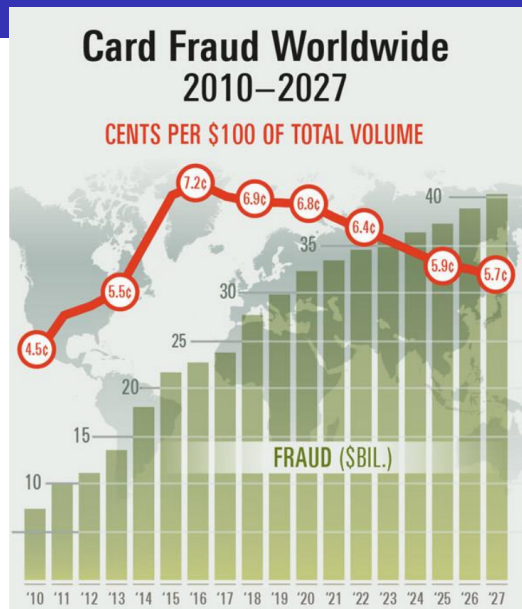


What are we measuring?

- Accuracy is an obvious measure
 - Fraction of inputs where classification is correct

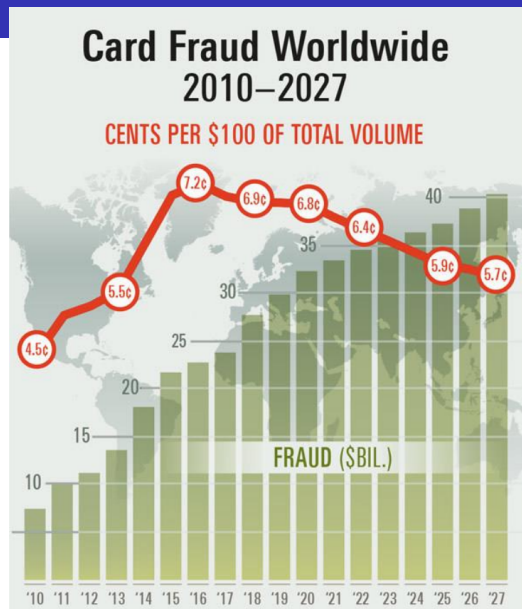
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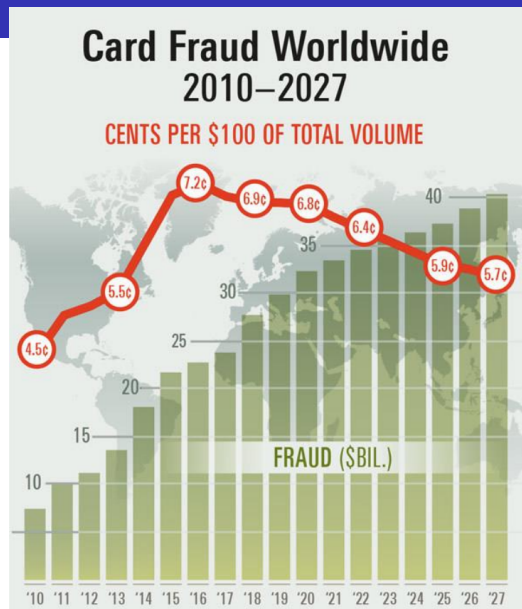
What are we measuring?

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- Classifiers are often used in asymmetric situations
 - Less than 1% of credit card transactions are fraud
- “Is this transaction a fraud?”
 - Trivial classifier — always answer “No”
 - More than 99% accurate, but useless!



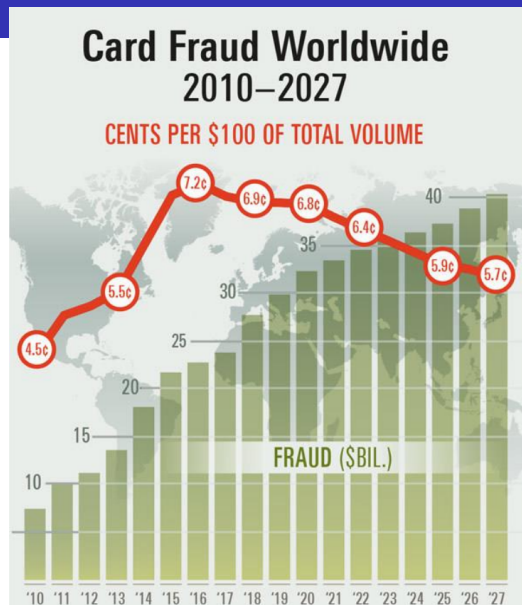
Catching the minority case

- The minority case is the useful case
 - Assume question is phrased so that minority answer is “Yes”
 - Want to flag as many “Yes” cases as possible



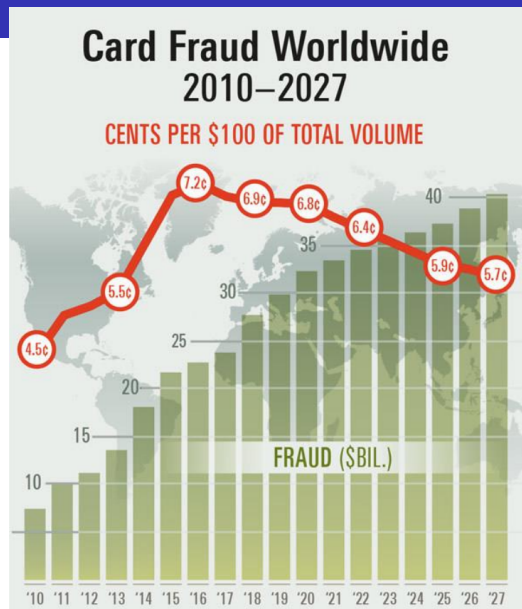
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- Aggressive classifier
 - Marks borderline “No” as “Yes”
 - False positives



Catching the minority case

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 - Assume question is phrased so that minority answer is “Yes”
 - Want to flag as many “Yes” cases as possible
- Aggressive classifier
 - Marks borderline “No” as “Yes”
 - False positives
- Cautious classifier
 - Marks borderline “Yes” as “No”
 - False negatives



Confusion matrix

- Four possible combinations
 - Actual answer: Yes / No
 - Prediction: Yes / No

Confusion matrix

- Four possible combinations
 - Actual answer: Yes / No
 - Prediction: Yes / No
- Record all four possibilities in **confusion matrix**
 - Correct answers
 - True positives, true negatives
 - Wrong answers
 - False positives, false negatives

	Classified positive	Classified negative
Actual positive	True Positive (TP)	False Negative (FN)
Actual negative	False Positive (FP)	True Negative (TN)

Performance measures

Precision

- What percentage of positive predictions are correct?

$$\frac{TP}{TP + FP}$$

Recall

- What percentage of actual positive cases are discovered?

$$\frac{TP}{TP + FN}$$

	Classified positive	Classified negative
Actual positive	True Positive (TP)	False Negative (FN)
Actual negative	False Positive (FP)	True Negative (TN)

Performance measures

- Precision 1, Recall 0.01

	Classified positive	Classified negative
Actual positive	1	99
Actual negative	0	900

Performance measures

- Precision 1, Recall 0.01
- Recall up to 0.4, but precision down to 0.29

	Classified positive	Classified negative
Actual positive	40	60
Actual negative	100	800

Performance measures

- Precision 1, Recall 0.01
- Recall up to 0.4, but precision down to 0.29
- Recall up to 0.99, but precision down to 0.165

	Classified positive	Classified negative
Actual positive	99	1
Actual negative	500	400

Performance measures

- Precision 1, Recall 0.01
- Recall up to 0.4, but precision down to 0.29
- Recall up to 0.99, but precision down to 0.165
- Precision-recall tradeoff
 - **Strict classifiers** : fewer false positives (high precision), miss more actual positives (low recall)
 - **Permissive classifiers** : catch more actual positives (high recall) but more false positives (low precision)

	Classified positive	Classified negative
Actual positive	99	1
Actual negative	500	400

Performance measures

- Which measure is more useful?

- Depends on situation

- Hiring

- Screening test:
high recall
- Interview:
high precision

- Medical diagnosis

- Immunization:
high recall
- Critical illness diagnosis:
high precision

	Classified positive	Classified negative
Actual positive	True Positive (TP)	False Negative (FN)
Actual negative	False Positive (FP)	True Negative (TN)

Other measures, terminology

- Recall is also called sensitivity
- Accuracy:
 $(TP+TN)/(TP+TN+FP+FN)$
- Specificity: $TN/(TN+FP)$
- Threat score:
 $TP/(TP+FP+FN)$
 - TN usually majority, ignore, not useful

	Classified positive	Classified negative
Actual positive	True Positive (TP)	False Negative (FN)
Actual negative	False Positive (FP)	True Negative (TN)

Other measures, terminology

- Recall is also called sensitivity
- Accuracy:
 $(TP+TN)/(TP+TN+FP+FN)$
- Specificity: $TN/(TN+FP)$
- Threat score:
 $TP/(TP+FP+FN)$
 - TN usually majority, ignore, not useful

	Classified positive	Classified negative
Actual positive	True Positive (TP)	False Negative (FN)
Actual negative	False Positive (FP)	True Negative (TN)

F Score

- A single combined score
- Harmonic mean of precision, recall

$$\frac{2pr}{p+r}$$