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DIGITAL TALENT
INCUBATOR 2020

Modul 5: Classification

Organized by:
CAE

Module Objectives

- Understand what is classification and its application
- Understand how classification algorithm work
- Understand how to build classification model

Module Overview

Topics

- Classification Model
- Decision Tree
- Random Forest
- Naive Bayes
- KNN
- Build Classification Model using Python

Activities

- Group Discussion
- Coding Practice

Classification

- In machine learning and statistics, classification is the problem of identifying to which of a set of categories (sub-populations) a new observation belongs, based on a training set of data containing observations (or instances) whose category membership is known.
- Examples are assigning a given email to the "spam" or "non-spam" class, and assigning a diagnosis to a given patient based on observed characteristics of the patient (sex, blood pressure, presence or absence of certain symptoms, etc.)

Use of Classification

- **Handwriting recognition:** used to interpret intelligible handwritten input from sources such as paper documents, photographs, touch-screens and other devices
- **Web search engine:** used to classify information on World Wide Web
- **Speech recognition:** used for recognition and translation of spoken language into text by computers.

Use of Classification (Cont.)

- **Biological classification:** used for classifying biological organism based on shared characteristics (taxonomy)
- **Credit scores:** used to determine who qualifies for a loan, at what interest rate, and what credit limits.

Classification Algorithm

- Decision Tree
- Random Forest
- Bayesian
- Lazy Learner (kNN)

Decision Tree

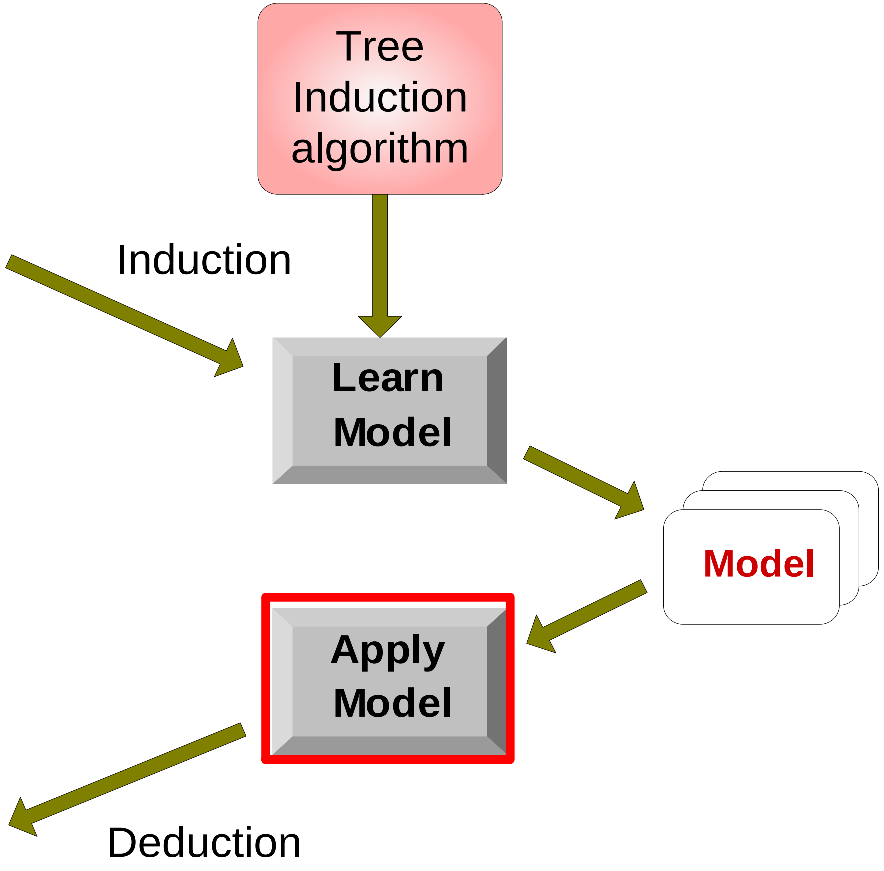
- Decision tree is a tree shaped diagram used to determine a course of action. Each branch of the tree represents a possible decision, occurrence or reaction

- Important Terms
  - Entropy : measure of randomness in the dataset
  - Information gain : measure of decrease in entropy after dataset is split
  - Leaf node : carries the classification or decision
  - Root node: top most decision node

Decision Tree Classification Task

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
6	No	Medium	60K	No
7	Yes	Large	220K	No
8	No	Small	85K	Yes
9	No	Medium	75K	No
10	No	Small	90K	Yes

Training Set

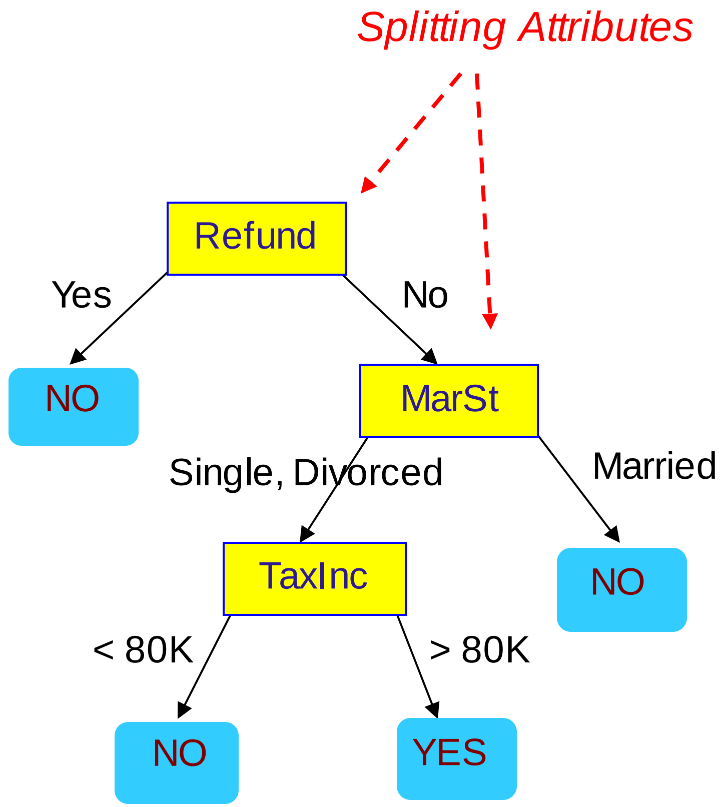


Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	No	Small	95K	?
15	No	Large	67K	?

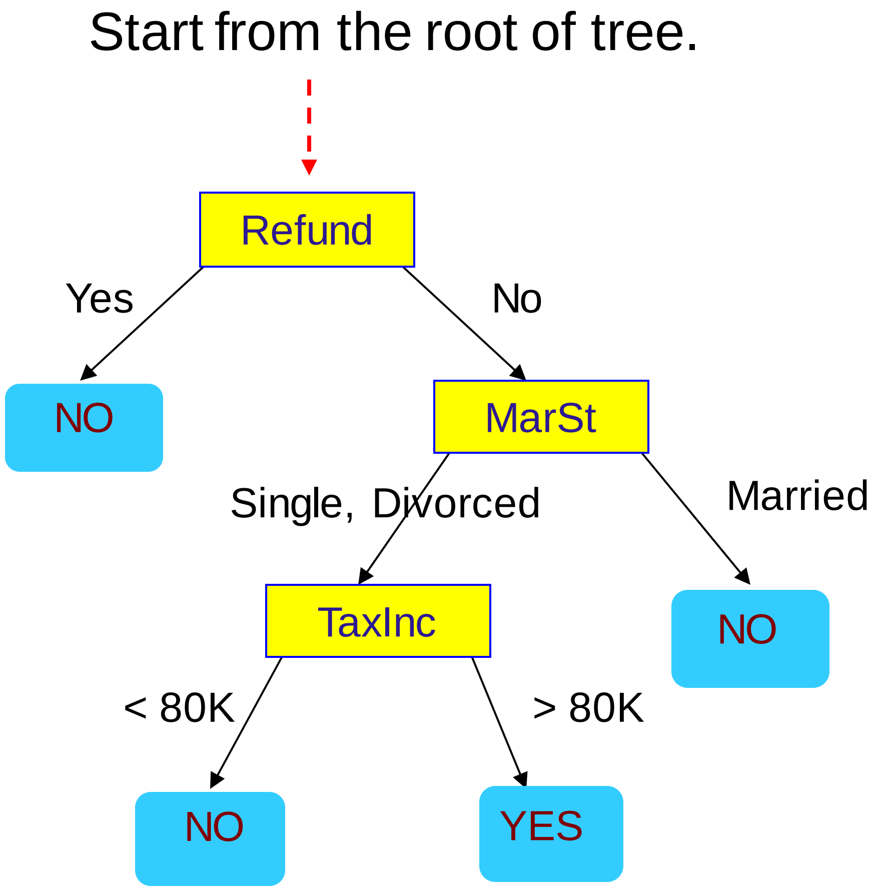
Test Set

Decision Tree Classification Task

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



Apply Model on Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

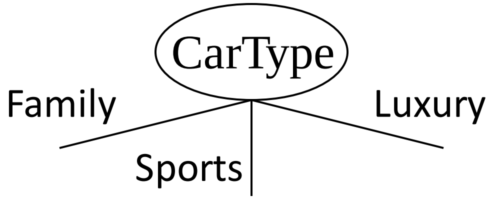
Specify Attribute Test Condition

- Depends on attribute types
  - Discrete
    - Nominal
    - Ordinal
  - Continuous

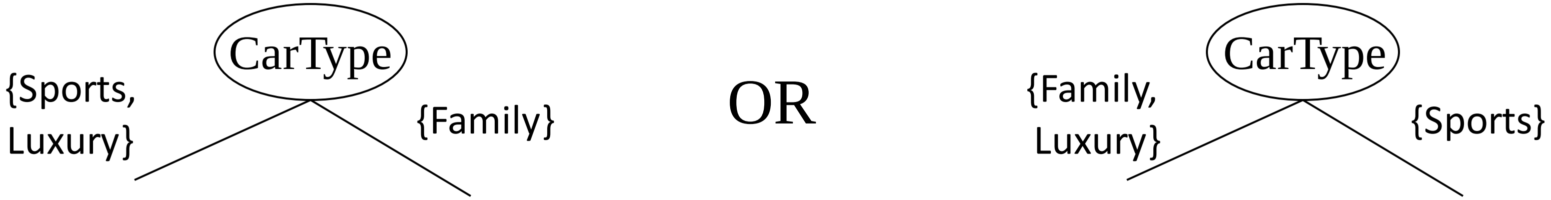
- Depends on number of ways to split
  - Multi-way split
  - Binary split

Splitting Based on Nominal Attributes

- Multi-way split: Use as many partitions as distinct values.

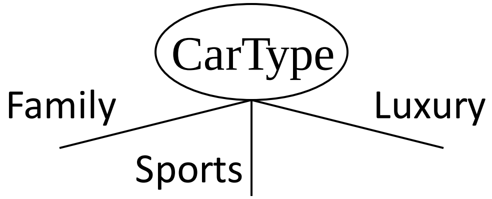


- Binary split: Divides values into two subsets. Need to find optimal partitioning.

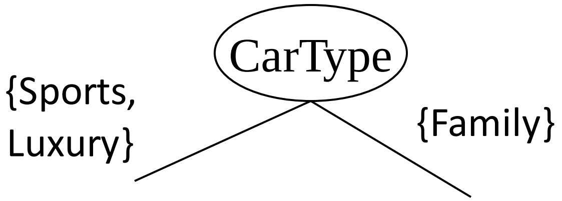


Splitting Based on Ordinal Attributes

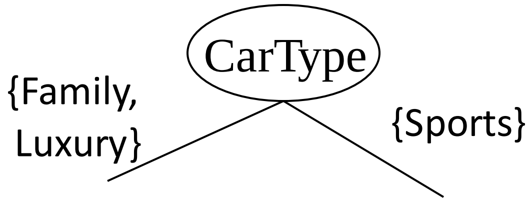
- Multi-way split: Use as many partitions as distinct values.



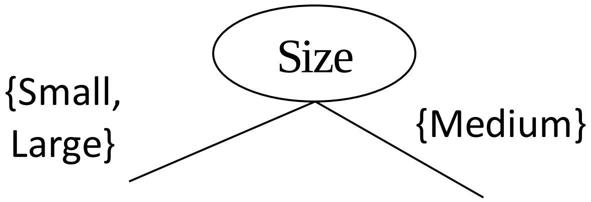
- Binary split: Divides values into two subsets.
  Need to find optimal partitioning.



OR

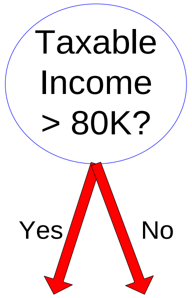


- What about this split?

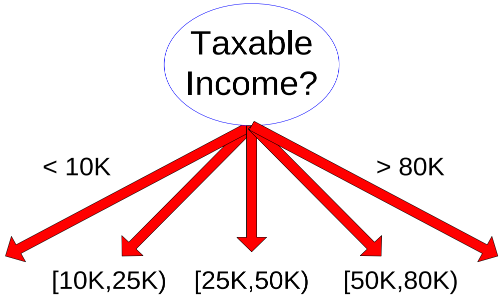


Splitting Based on Continuous Attributes

- Different ways of handling
  - Discretization to form an ordinal categorical attribute
    - Static – discretize once at the beginning
    - Dynamic – ranges can be found by equal interval bucketing, equal frequency bucketing (percentiles), or clustering.
- Binary Decision: (A < v) or (A v)
  - consider all possible splits and finds the best cut
  - can be more compute intensive



(i) Binary split



(ii) Multi-way split

Decision Tree Summary

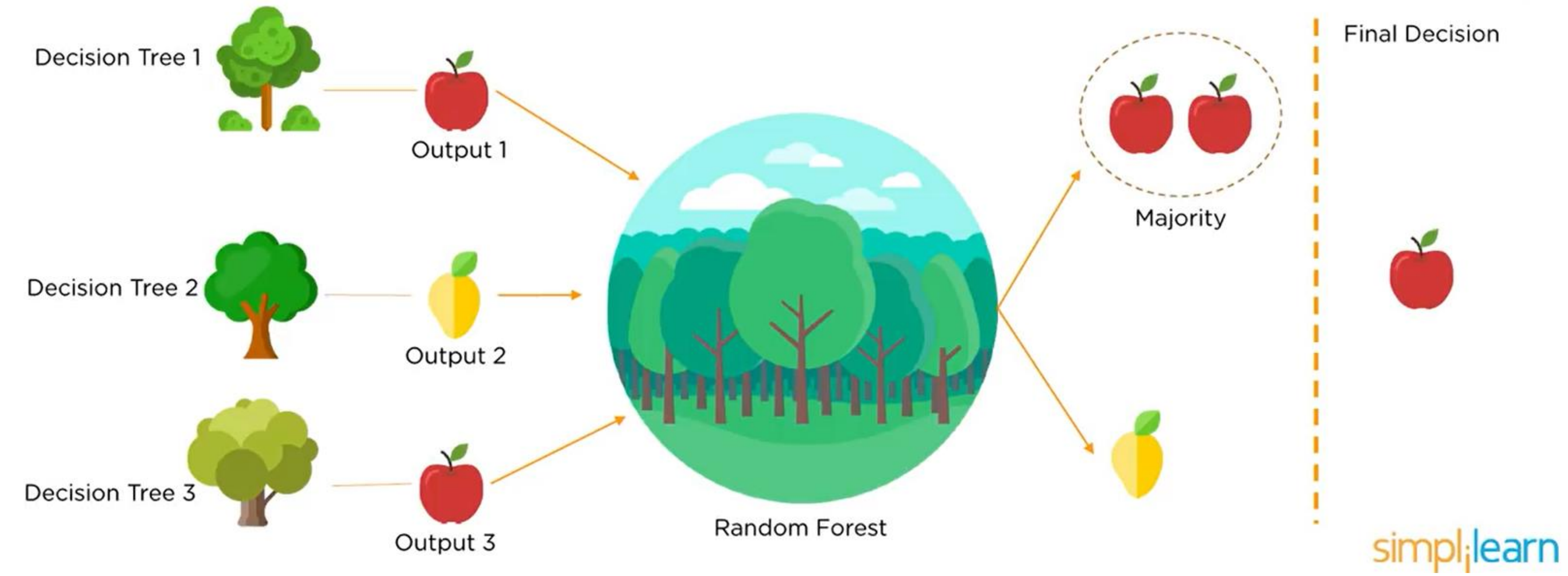
- Advantages:
  - Inexpensive to construct
  - Extremely fast at classifying unknown records
  - Easy to interpret for small-sized trees
  - Accuracy is comparable to other classification techniques for many simple data sets

- Disadvantages:
  - Overfitting when algorithm capture noise in the data
  - The model can get unstable due to small variation of data
  - Low biased tree: difficult for the model to work with new data

Random Forest

- Random forest or Random Decision Forest is a method that operates by constructing multiple decision trees during training phases
- The Decision of the majority of the trees is chosen as final decision.

Random Forest



Random Forest Summary

- Random Forest:
  - Each classifier in the ensemble is a decision tree classifier and is generated using a random selection of attributes at each node to determine the split
  - During classification, each tree votes and the most popular class is returned
- Two Methods to construct Random Forest:
  1. Forest-RI (random input selection): Randomly select, at each node, F attributes as candidates for the split at the node. The CART methodology is used to grow the trees to maximum size
  2. Forest-RC (random linear combinations): Creates new attributes (or features) that are a linear combination of the existing attributes (reduces the correlation between individual classifiers)
- Insensitive to the number of attributes selected for consideration at each split, and faster than bagging (grouping based on frequency) or boosting

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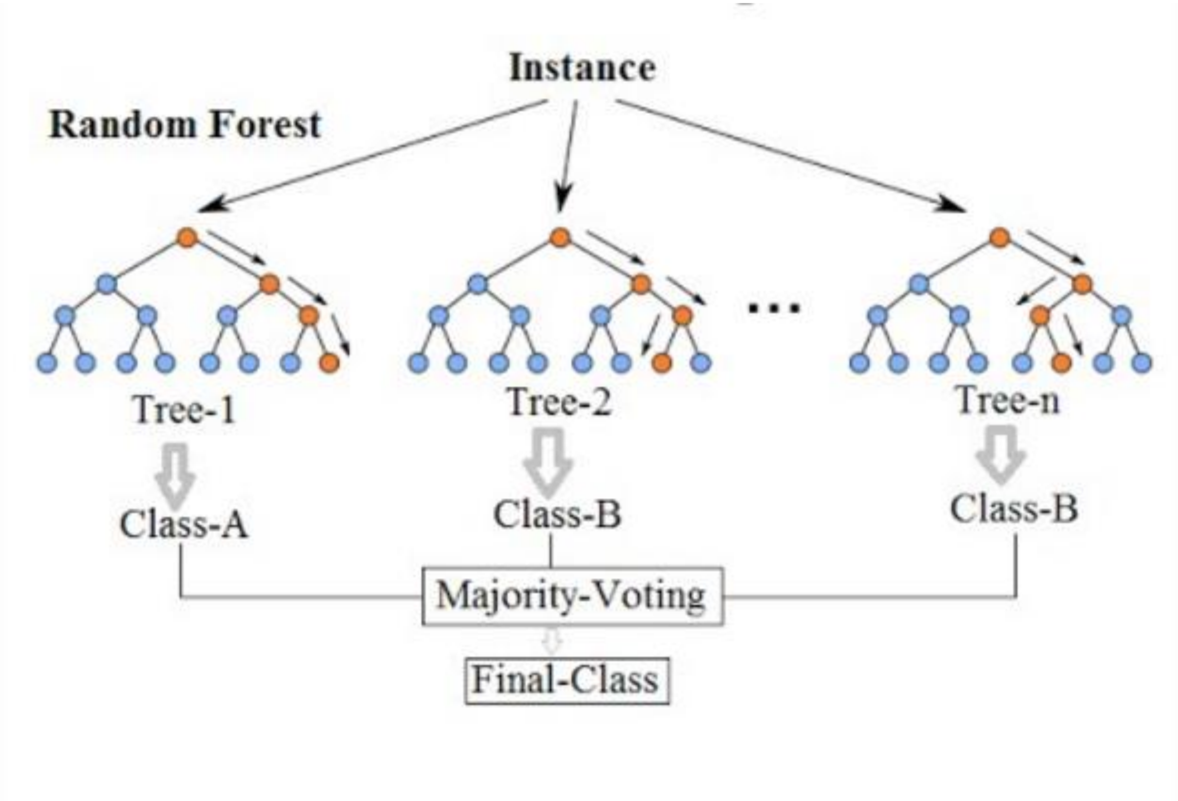
How Random Forest Work



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Random Forest Summary

- Advantages:
  - It can be used for both regression and classification tasks and that it's easy to view the relative importance it assigns to the input features.
  - It is also considered as a very handy and easy to use algorithm, because it's default hyper-parameters often produce a good prediction result.
- Disadvantages:
  - Many trees can make the algorithm to slow and ineffective for real-time predictions. A more accurate prediction requires more trees, which results in a slower model.
  - It is a predictive modeling tool and not a descriptive tool.

Naive Bayes Classifier

- Naive Bayes is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set.
- There is not a single algorithm for training such classifiers, but a family of algorithms based on a common principle: all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable.

Naive Bayes Classifier

A probabilistic framework for solving classification problems

- Conditional Probability:

$$P(C \mid A) = \frac{P(A,C)}{P(A)}$$

$$P(A \mid C) = \frac{P(A,C)}{P(C)}$$

- Bayes theorem:

$$P(C \mid A) = \frac{P(A \mid C)P(C)}{P(A)}$$

Example of Naive Bayes Classifier

Given:

- A doctor knows that meningitis causes stiff neck 50% of the time
- Prior probability of any patient having meningitis is 1/50,000
- Prior probability of any patient having stiff neck is 1/20

If a patient has stiff neck, what's the probability he/she has meningitis?

$$P(M \mid S) = \frac{P(S \mid M)P(M)}{P(S)} = \frac{0.5 \times 1/50000}{1/20} = 0.0002$$

Bayesian Classifiers

- Consider each attribute and class label as random variables
- Given a record with attributes (A1, A2,…,An)
  - Goal is to predict class C
  - Specifically, we want to find the value of C that maximizes P(C| A1, A2,…,An)
- Can we estimate P(C| A1, A2,…,An) directly from data?

Bayesian Classifiers

- Approach:
  - compute the posterior probability P(C | A1, A2, …, An) for all values of C using the Bayes theorem

$$\boxed{P(C \mid A_1 A_2 \ldots A_n) = \frac{P(A_1 A_2 \ldots A_n \mid C) P(C)}{P(A_1 A_2 \ldots A_n)}}$$

  - Choose value of C that maximizes
    P(C | A1, A2, …, An)
  - Equivalent to choosing value of C that maximizes
    P(A1, A2, …, An|C) P(C)
- How to estimate P(A1, A2, …, An | C)?

Naïve Bayes Classifier

- Assume independence among attributes Ai when class is given:
  - P(A1, A2, …, An |C) = P(A1| Cj) P(A2| Cj)… P(An| Cj)
  - Can estimate P(Ai| Cj) for all Ai and Cj.
  - New point is classified to Cj if P(Cj) P(Ai| Cj) is maximal.

How to Estimate Probabilities from Data?

- Class: P(C) = Nc/N
  - e.g., P(No) = 7/10,
    P(Yes) = 3/10

- For discrete attributes:

  P(Ai | Ck) = |Aik|/ Nc

  - where |Aik| is number of instances having attribute Ai and belongs to class Ck
  - Examples:

P(Status=Married|No) = 4/7
P(Refund=Yes|Yes)=0

- For continuous attributes:
- Discretize the range into bins
- one ordinal attribute per bin
- violates independence assumption
- Two-way split: (A < v) or (A > v)
- choose only one of the two splits as new attribute
- Probability density estimation:
- Assume attribute follows a normal distribution
- Use data to estimate parameters of distribution
  (e.g., mean and standard deviation)
- Once probability distribution is known, can use it to estimate the conditional probability P(Ai|c)

Naive Bayes Summary

Name	Give Birth	Can Fly	Live in Water	Have Legs	Class
human	yes	no	no	yes	mammals
python	no	no	no	no	non-mammals
salmon	no	no	yes	no	non-mammals
whale	yes	no	yes	no	mammals
frog	no	no	sometimes	yes	non-mammals
komodo	no	no	no	yes	non-mammals
bat	yes	yes	no	yes	mammals
pigeon	no	yes	no	yes	non-mammals
cat	yes	no	no	yes	mammals
leopard shark	yes	no	yes	no	non-mammals
turtle	no	no	sometimes	yes	non-mammals
penguin	no	no	sometimes	yes	non-mammals
porcupine	yes	no	no	yes	mammals
eel	no	no	yes	no	non-mammals
salamander	no	no	sometimes	yes	non-mammals
gila monster	no	no	no	yes	non-mammals
platypus	no	no	no	yes	mammals
owl	no	yes	no	yes	non-mammals
dolphin	yes	no	yes	no	mammals
eagle	no	yes	no	yes	non-mammals

Give Birth	Can Fly	Live in Water	Have Legs	Class
yes	no	yes	no	?

A: attributes

M: mammals

N: non-mammals

$$P(A|M) = \frac{6}{7} \times \frac{6}{7} \times \frac{2}{7} \times \frac{2}{7} = 0.06$$

$$P(A|N) = \frac{1}{13} \times \frac{10}{13} \times \frac{3}{13} \times \frac{4}{13} = 0.0042$$

$$P(A|M)P(M) = 0.06 \times \frac{7}{20} = 0.021$$

$$P(A|N)P(N) = 0.004 \times \frac{13}{20} = 0.0027$$

P(A|M)P(M) > P(A|N)P(N)

=> Mammals

How to Estimate Probabilities from Data?

Tid	Refund	Marital Status	Taxable Income	Evade
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

- Normal distribution:

$$P(A_i \mid c_j) = \frac{1}{\sqrt{2\pi\sigma_{ij}^2}} e^{-\frac{(A_i-\mu_{ij})^2}{2\sigma_{ij}^2}}$$

  – One for each (A_i,c_i) pair

- For (Income, Class=No):
  – If Class=No
    - sample mean = 110
    - sample variance = 2975

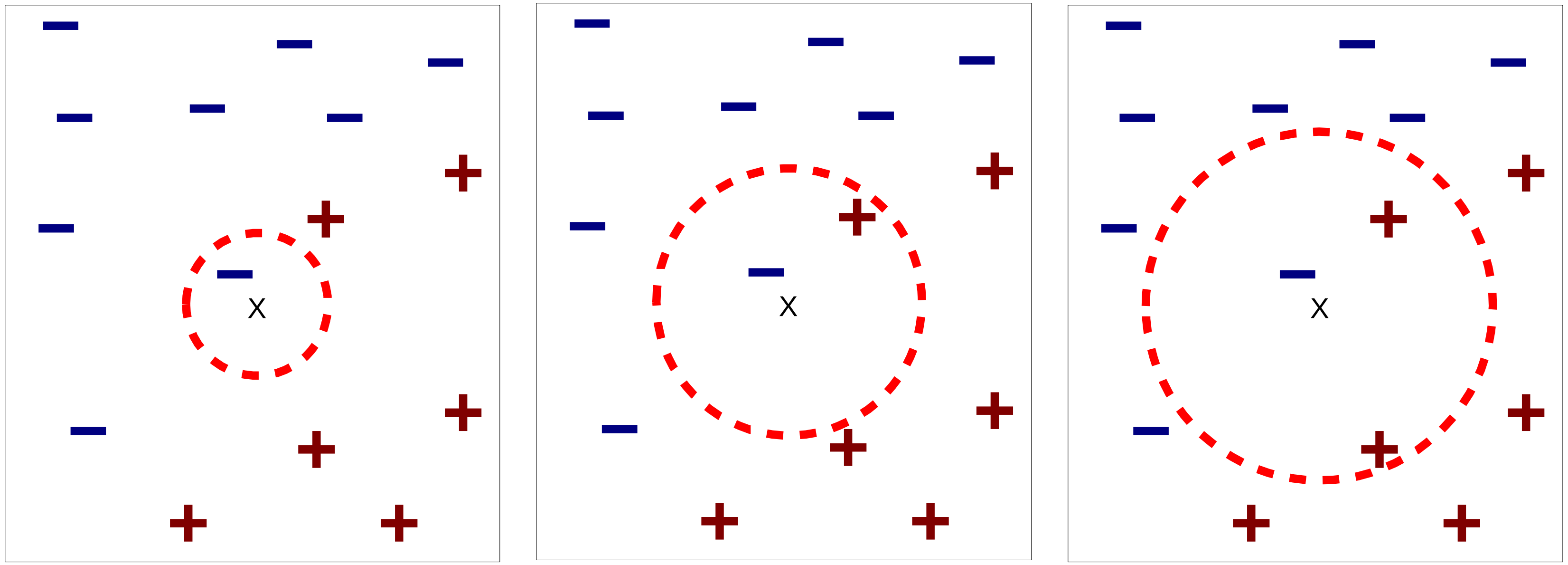
$$P(Income = 120 \mid No) = \frac{1}{\sqrt{2\pi}(54.54)} e^{-\frac{(120-110)^2}{2(2975)}} = 0.0072$$

Naive Bayes Summary

- Robust to isolated noise points
- Handle missing values by ignoring the instance during probability estimate calculations
- Robust to irrelevant attributes
- Independence assumption may not hold for some attributes
- Use other techniques such as Bayesian Belief Networks (BBN)

K Nearest Neighbourhood

- K-nearest neighbors of a record x are data points that have the k smallest distance to x.

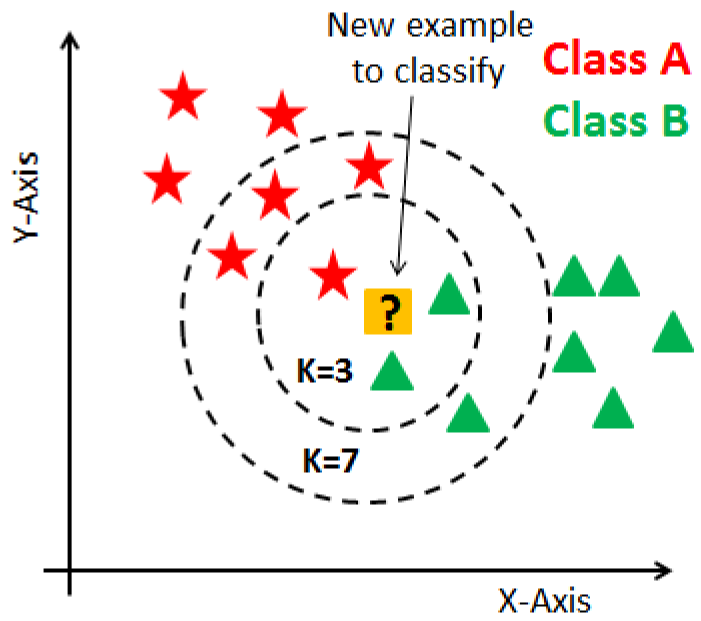


(a) 1-nearest neighbor (b) 2-nearest neighbor (c) 3-nearest neighbor

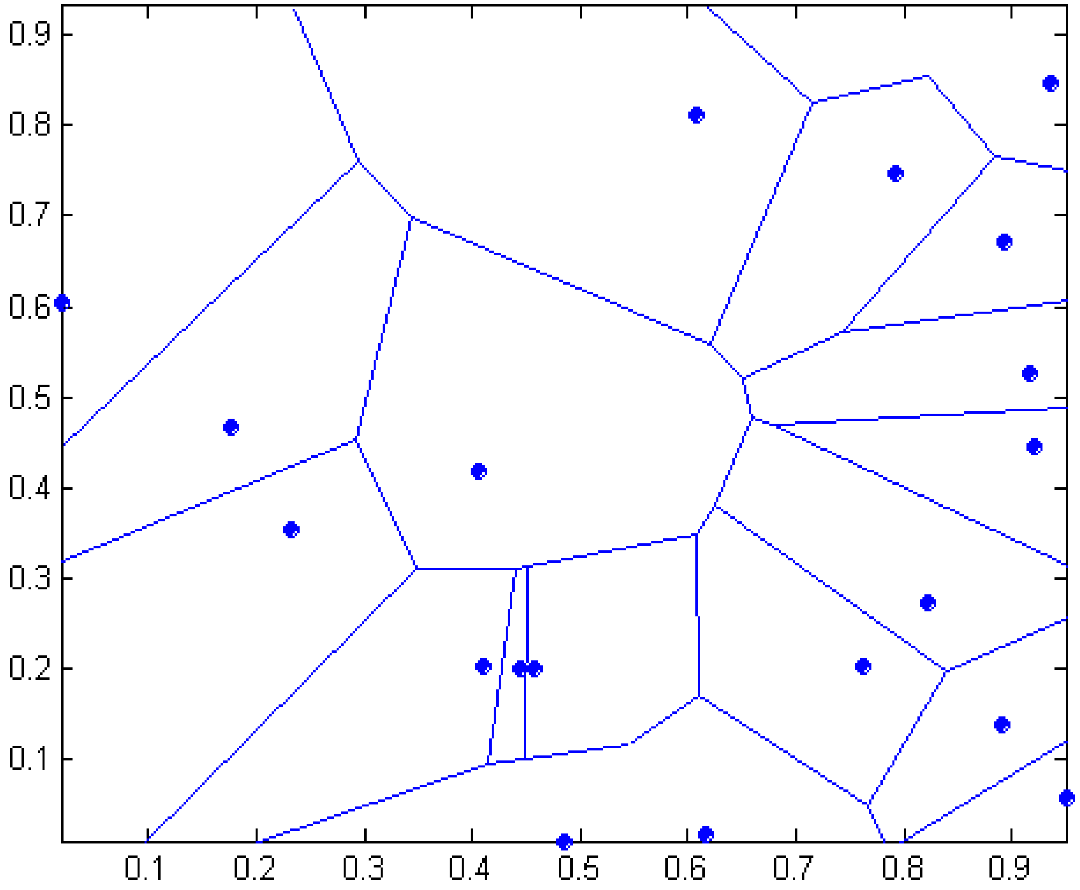
Nearest-Neighbor Classifiers

- Requirement
  - The set of stored records
  - Distance Metric to compute distance between records
  - The value of k, the number of nearest neighbors to retrieve

- To classify an unknown record:
  - Compute distance to other training records
  - Identify k nearest neighbors
  - Use class labels of nearest neighbors to determine the class label of unknown record



Voronoi Diagram



KNN Summary

- Advantages:
  - Simple technique that is easily implemented
  - Building model is cheap
  - Extremely flexible classification scheme
- Disadvantages:
  - Classifying unknown records are relatively expensive
  - Requires distance computation of k-nearest neighbors
  - Computationally intensive, especially when the size of the training set grows
  - Accuracy can be severely degraded by the presence of noisy or irrelevant features

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:

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a	b
	Class=No	c	d

a: TP (true positive)

b: FN (false negative)

c: FP (false positive)

d: TN (true negative)

Metrics for Performance Evaluation

- Most widely-used metric:

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

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	A (TP)	B (FN)
	Class=No	C (FP)	D (TN)

Limitation of Accuracy

- Consider a 2-class problem
  - Number of Class 0 examples = 9990
  - Number of Class 1 examples = 10

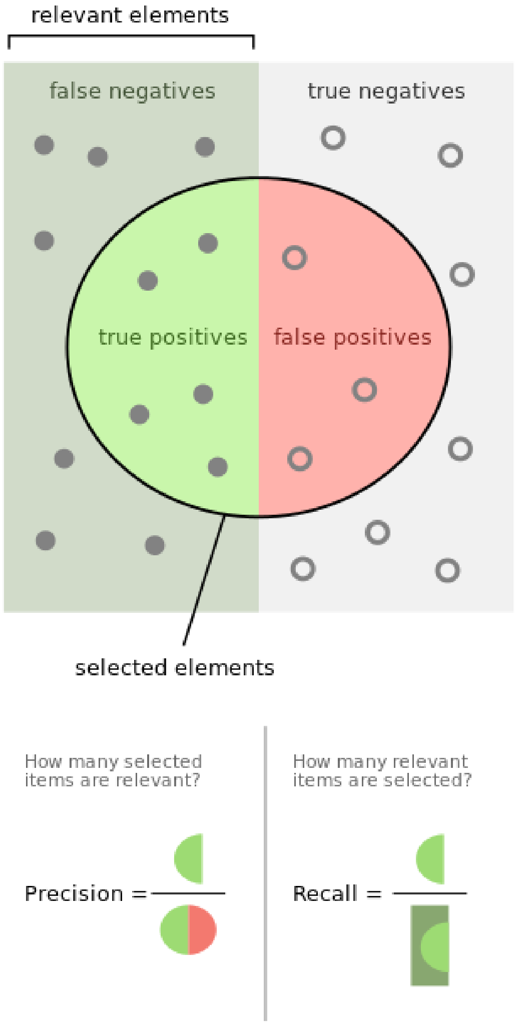
- If model predicts everything to be class 0, accuracy is 9990/10000 = 99.9 %
  - Accuracy is misleading because model does not detect any class 1 example

Cost-Sensitive Measures

$$\text{Precision (p)} = \frac{a}{a+c}$$

$$\text{Recall (r)} = \frac{a}{a+b}$$

$$\text{F - measure (F)} = \frac{2rp}{r+p} = \frac{2a}{2a+b+c}$$



Practice with Python

- Practice Link:
- https://github.com/rc-dbe/dti

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Assignment

- Create a classification model using “bank-marketing.csv” dataset from Kaggle https://www.kaggle.com/janiobachmann/bank-marketing-dataset
- Choose minimal 2 algorithm
- Compare performance of algorithm by using appropriate metric
- Use Google Collab (or Jupyter Notebook if you want)
- Put the code in your GitHub
- Make it informative as possible

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