Melbourne Bioinformatics
BIOINFORMATICS + DATA SERVICES + INFRASTRUCTURE, FOR LIFE SCIENCES TODAY

THE UNIVERSITY OF MELBOURNE

COMP90014

Algorithms for Bioinformatics

Week 11A: Supervised Learning

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

K-Nearest Neighbors (KNN)

Naive Bayes

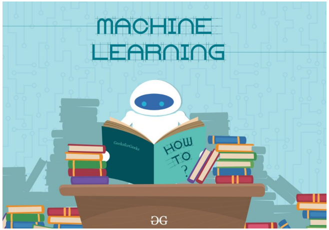
Association Rule Learning

Support Vector Machines (SVM)

Decision Trees

Ensemble Methods

Machine learning



Machine Learning is the field of study that gives computers the ability to learn without being explicitly programmed.

- Arthur Samuel, 1959.

Machine Learning is the study of algorithms that:

- *Improve their performance P*
- *at some task T*
- *with experience E.*

A well-defined learning task is given by $\langle P, T, E \rangle$

- Tom Mitchell, 1998.

Application of Unsupervised Clustering

GeoGuessr - Online Game

Google maps street view image is shown, player guesses the location.

Closer to the actual location = better score.

Difficult problem for AI

Images taken from anywhere, not uniformly sampled (cities vs rural)

Daytime / nighttime, varying weather, Illumination, season, traffic etc

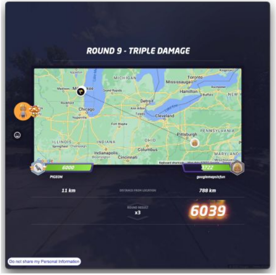
Predicting latitudes and longitudes directly = poor performance

Latitude / longitude not really good classification metric - regression.

Modern approaches use **geocells** to divide space into categories - classification

Unsupervised clustering used to define geocells

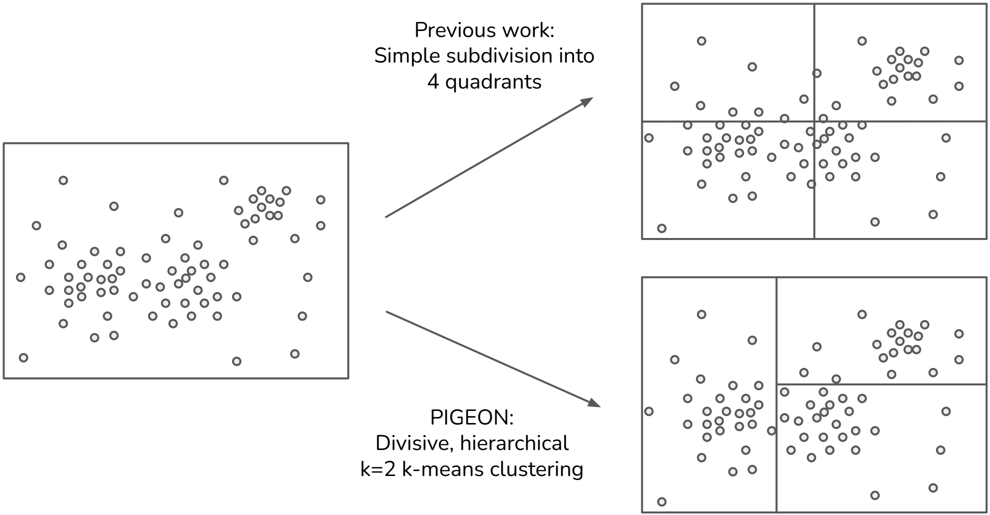
(a) Sample image in a Geoguessr location.



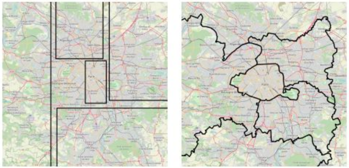
(b) Sample comparison of guesses between PIGEON and a human player.

Haas, L., Alberti, S., & Skreta, M. (2023). [PIGEON: Predicting Image Geolocations.]

PIGEON: Initial idea for Geocell Creation



PIGEON: Selected idea for Geocell Creation



(a) With rectangular geocells. (b) With our semantic geocells.

Figure 3. Voronoi tessellation applied in the process of geocell creation.

Algorithm 1 Semantic Geocell Division Algorithm

Input: geocell boundaries g, training samples x, OPTICS parameters p, minimum cell size MINSIZE.
Initialize $j = 1$.
repeat
  Initialize C = OPTICS(p_j).
  for g_i **in** g **do**
    Define $x_i = \{x_j | x_j \in x \wedge x_j \in g_i\}$.
    repeat
      Cluster $c = C(x_i)$.
      $c_{max} = c_k$ where $|x_{i,k}| \geq |x_{i,l}| \forall l$.
      if $|c_{max}| >$ MINSIZE and $|x \setminus x_{i,k}| >$ MINSIZE **then**
        New cell g_{new} = VORONOI($x_{i,k}$).
        $g_i = g_i \setminus g_{new}$.
        Assign x_i to cells i and new.
      end if
    until convergence
  end for
  $j = j + 1$
until j is $|p|$

Haas, L., Alberti, S., & Skreta, M. (2023). [PIGEON: Predicting Image Geolocations.]

PIGEON: Performance & Quirks

Works really well

On-par or better than human world champion

Neural net was analysed

Which features of an image was it paying **attention** to?

(a) Attention attribution map for an image in Canada.

PIGEON: Performance & Quirks

Works really well

- On-par or better than human world champion

Neural net was analysed

- Which features of an image was it paying **attention** to?

(a) Attention attribution map for an image in Canada.

PIGEON: Performance & Quirks

Works really well

- On-par or better than human world champion

Neural net was analysed

- Which features of an image was it paying **attention** to?

(a) Attention attribution map for an image in Canada.

PIGEON worked out an interesting feature to use - the car!

- Has time and location data for each image.
- Knows that images taken close in time & close in location were done by same car
- Could use features of the car / camera to identify a new image (eg smudges on the lens)

How do we feel about this?
Perhaps... **overfitting**?

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

K-Nearest Neighbors (KNN)

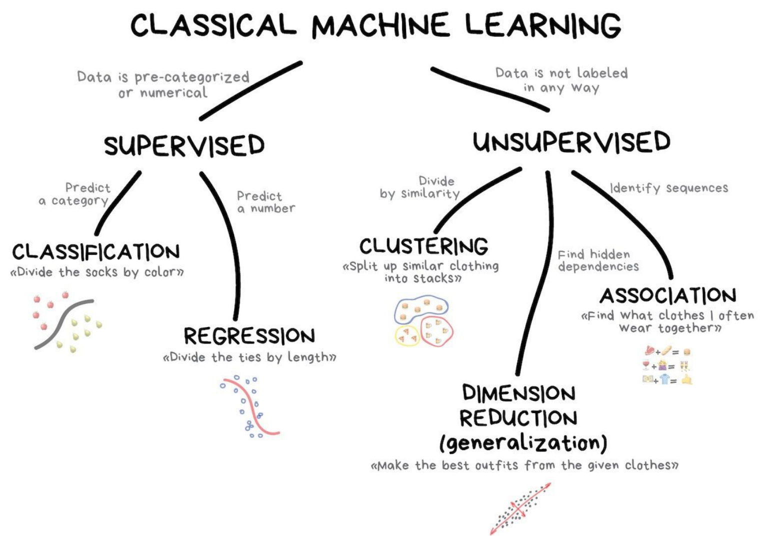
Naive Bayes

Association Rule Learning

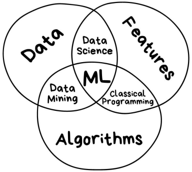
Support Vector Machines (SVM)

Decision Trees

Ensemble Methods


CLASSICAL MACHINE LEARNING
Data is pre-categorized or numerical
Data is not labeled in any way
SUPERVISED
UNSUPERVISED
Predict a category
Predict a number
Divide by similarity
Identify sequences
CLASSIFICATION
«Divide the socks by color»
REGRESSION
«Divide the ties by length»
CLUSTERING
«Split up similar clothing into stacks»
Find hidden dependencies
ASSOCIATION
«Find what clothes I often wear together»
DIMENSION REDUCTION (generalization)
«Make the best outfits from the given clothes»

Three components of **supervised** learning



vas3k

Data

- 🤖 labelled (historical / experimental)
- 🤖 representative and diverse
  - collection and curation is key
  - **A predictive model is as good as the training data**

Features

- 🤖 properties to be used as evidence to train a predictive model
- 🤖 requires knowledge of the problem

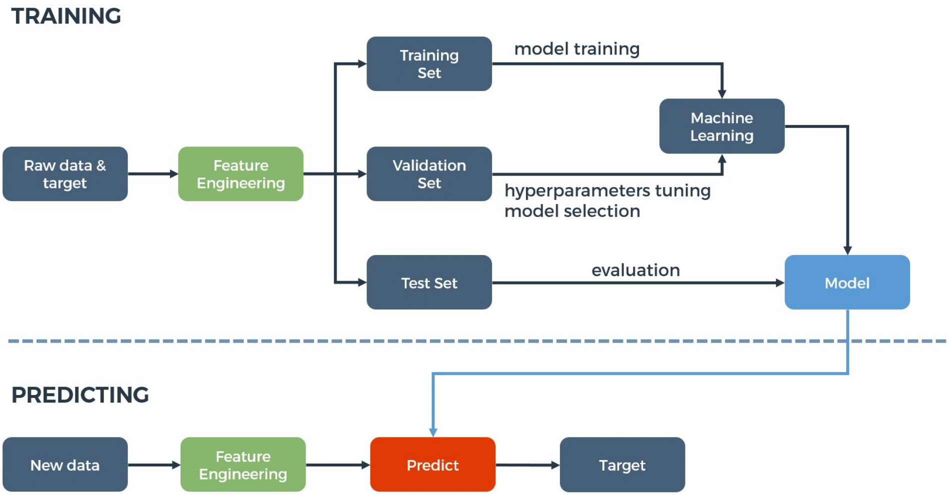
Learning Algorithms

- 🤖 which one?

Infer a function *f*:

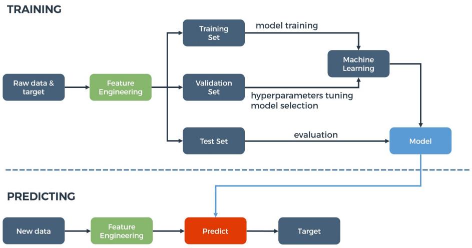
- 🤖 maps input (features) to an output (target)
- 🤖 experience (examples of input-output pairs)

Supervised Learning Pipeline



Julien Jouganous *et al.* via medium.com

Data



Julien Jouganous *et al.* via [medium.com]

Training set

- representative set of examples used for training, where the target value is known

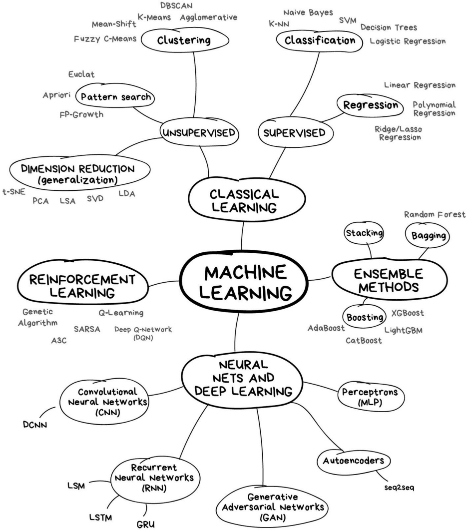
Validation set

- representative set of examples used to tune the architecture of a learning algorithm and estimate prediction errors

Independent test set (blind test)

- independently assess the performance of a predictive model
- never used during the training process
- error on the blind test provides an unbiased estimate of the generalization error

Learning algorithms



vas3k

There are tons of algorithms

- K-nearest neighbours (KNN)
- Naïve Bayes
- Support Vector Machines (SVMs)
- Decision Trees
- not an exhaustive list

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

<u>K-Nearest Neighbors (KNN)</u>

Naive Bayes

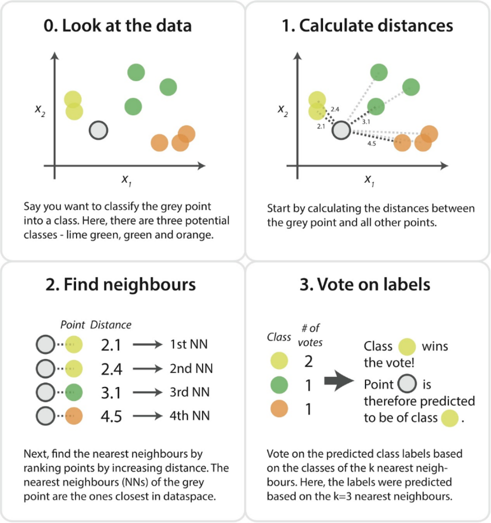
Association Rule Learning

Support Vector Machines (SVM)

Decision Trees

Ensemble Methods

K-nearest neighbours (KNN)

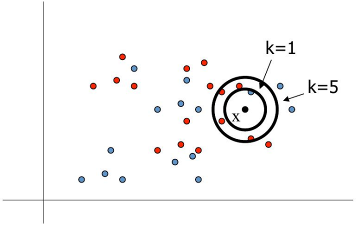


- given training data,
  $D = \{(x_1, y_1), ..., (x_N, y_N)\}$
  and a test point x_u
- prediction rule:
  look at the K most similar training examples to x_u
- for classification:
  assign the majority class label (majority voting)
- for regression:
  assign the average response
- The algorithm requires
  - parameter K: number of nearest neighbors to look for
  - distance function: to compute similarities between points

Jeorge Leonel via medium.com

KNN algorithm

Procedure KNN**:**
  foreach *test point* **do**
    Compute the distance to each training point
    Sort the distances in ascending order
    Select the K-nearest neighbors
    if *classification* **then** use majority rule
    if *regression* **then** use averaging



- KNN is called a non-parametric method
- Unlike other supervised learning algorithms, it doesn't learn an explicit mapping function f from the training data (no explicit model)
- It simply uses the training data at the test time to make predictions

David Sontag, New York University

KNN implementation

```python
# Locate the most similar neighbors
def get_neighbors(train, test_row, num_neighbors):
    distances = list()
    for train_row in train:
        dist = euclidean_distance(test_row, train_row)
        distances.append((train_row, dist))
    distances.sort(key=lambda tup: tup[1])
    neighbors = list()
    for i in range(num_neighbors):
        neighbors.append(distances[i][0])
    return neighbors

# Make a prediction with neighbors
def predict_classification(train, test_row, num_neighbors):
    neighbors = get_neighbors(train, test_row, num_neighbors)
    output_values = [row[-1] for row in neighbors]
    prediction = max(set(output_values), key=output_values.count)
    return prediction
```

Implementation: Jason Brownlee via machinelearningmastery.com

KNN implementation

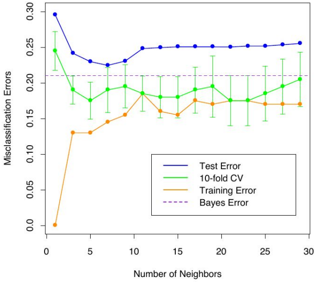
```python
# kNN Algorithm
def k_nearest_neighbors(train, test, num_neighbors):
    predictions = list()
    for row in test:
        output = predict_classification(train, row, num_neighbors)
        predictions.append(output)
    return(predictions)
```

- Time complexity?
- Space complexity?
- Would KNN be adequate for large-scale, real-time predictions?

Implementation: Jason Brownlee via machinelearningmastery.com

Properties of KNN

$$d(x_i, x_j) = \sum_{m=1}^{D} (x_{im} - x_{jm})^2$$



David Sontag, New York University

KNN requires computing distances

- several different distance metrics (*e.g.* Euclidean)

Features should be on the same scale

- *e.g.* kcal and kJ (we need to normalize them)

Choosing K

Pros:

- simple and intuitive, easily to implement/interpret

Cons:

- memory usage (store training data in memory)
- may perform badly in high dimensions
- sensitive to noisy features
- categorical attributes?

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

K-Nearest Neighbors (KNN)

<u>Naive Bayes</u>

Association Rule Learning

Support Vector Machines (SVM)

Decision Trees

Ensemble Methods

Naïve Bayes

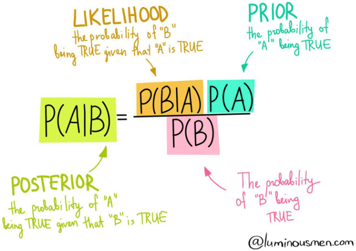
Conditional probability:

Probability of A and B

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

Probability of A given B

Probability of B



Data Science. Bayes theorem, luminousmen.com

Maximum a posteriori (MAP):

$$\arg\max P(A \mid B) \text{ for each class } A$$

$$\arg\max P(A \mid B) = \arg\max P(B \mid A) \times \frac{P(A)}{P(B)}$$
$$= \arg\max P(B \mid A) \times P(A)$$

- uses Bayes's rule
- $P(B)$ will be the same for all classes
- for a set of features x_i we calculate the joint probability: $B = (x_1, x_2, ..., x_n)$
- $\arg\max P(x_1, x_2, ..., x_n \mid A) \times P(A)$
  $P(x_1, x_2, ..., x_n \mid A) = \prod_i P(x_i \mid A)$
- simply the product of individual probabilities
- assumption: features are independent given a class

Naïve Bayes Algorithm

Cough	Sneezing	Fever	Flu
Yes	Yes	No	No
Yes	No	Yes	Yes
No	No	No	No
No	Yes	Yes	Yes

- Given this training data, if we have a new patient with only a cough, should we diagnose them with the flu?
- $P(? \mid \text{Cough, No Sneezing, No Fever})$
- $P(\text{Cough, No Sneezing, No Fever} \mid \text{Flu}) \times P(\text{Flu})$?
- $P(\text{Cough, No Sneezing, No Fever} \mid \text{No Flu}) \times (\text{No Flu})$?

Procedure `Naïve Bayes Learn`(*examples*):
- **foreach** *target value* v_j **do**
  - $\hat{P}(V_j) \leftarrow$ estimate $P(V_j)$
  - **foreach** *attribute value* a_i *of each attribute a* **do**
    - $\hat{P}(a_i \mid v_j) \leftarrow$ estimate $P(a_i \mid v_j)$

Procedure `Classify New Instance`(x):
- $v_{NB} = \arg\max_{v_j \in V} \hat{P}(v_j) \prod_{a_i \in x} \hat{P}(a_i \mid v_j)$

Naïve Bayes Algorithm

Procedure `Naïve Bayes Learn`(*examples*):
  foreach *target value* v_j **do**
    $\hat{P}(V_j) \leftarrow$ estimate $P(V_j)$
    foreach *attribute value* a_i *of each attribute a* **do**
      $\hat{P}(a_i \mid v_j) \leftarrow$ estimate $P(a_i \mid v_j)$

Procedure `Classify New Instance`(x):
  $v_{NB} = \arg\max_{v_j \in V} \hat{P}(v_j) \prod_{a_i \in x} \hat{P}(a_i \mid v_j)$

Type	Long	Not long	Sweet	Not sweet	Yellow	Not yellow	Total
Banana	400	100	350	150	450	50	**500**
Orange	0	300	150	150	300	0	**300**
Other	100	100	150	50	50	150	**200**
Total	500	500	650	350	800	200	**1000**

Step 1: Compute the 'Prior' probabilities for each of the classes.

- $P(\texttt{Banana}) = \frac{500}{1000} = 0.50$
- $P(\texttt{Orange}) = \frac{300}{1000} = 0.30$
- $P(\texttt{Other}) = \frac{200}{1000} = 0.20$

Naïve Bayes Algorithm

Procedure `Naïve Bayes Learn`(*examples*):
- **foreach** *target value* v_j **do**
  - $\hat{P}(V_j) \leftarrow$ estimate $P(V_j)$
  - **foreach** *attribute value* a_i *of each attribute a* **do**
    - $\hat{P}(a_i \mid v_j) \leftarrow$ estimate $P(a_i \mid v_j)$

Procedure `Classify New Instance`(x):

$$v_{NB} = \arg\max_{v_j \in V} \hat{P}(v_j) \prod_{a_i \in x} \hat{P}(a_i \mid v_j)$$

Type	Long	Not long	Sweet	Not sweet	Yellow	Not yellow	Total
Banana	400	100	350	150	450	50	**500**
Orange	0	300	150	150	300	0	**300**
Other	100	100	150	50	50	150	**200**
Total	500	500	650	350	800	200	**1000**

Step 2: Compute the 'Likelihood' probabilities for each feature/class combination.

- $P(\texttt{Long} \mid \text{Banana}) = \frac{400}{500} = 0.80$
- $P(\texttt{Sweet} \mid \text{Banana}) = \frac{350}{500} = 0.70$
- $P(\texttt{Yellow} \mid \text{Banana}) = \frac{450}{500} = 0.90$

Probability of A and B

$$\underbrace{P(A \mid B)}_{\text{Probability of A given B}} = \frac{P(A \cap B)}{P(B)}$$

Probability of B

Naïve Bayes Algorithm

Procedure `Naïve Bayes Learn`(*examples*):
  foreach *target value* v_j **do**
    $\hat{P}(V_j) \leftarrow$ estimate $P(V_j)$
    foreach *attribute value* a_i *of each attribute a* **do**
      $\hat{P}(a_i \mid v_j) \leftarrow$ estimate $P(a_i \mid v_j)$

Procedure `Classify New Instance`(x):
  $v_{NB} = \arg\max_{v_j \in V} \hat{P}(v_j) \prod_{a_i \in x} \hat{P}(a_i \mid v_j)$

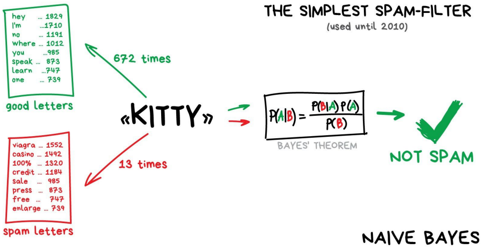
Type	Long	Not long	Sweet	Not sweet	Yellow	Not yellow	Total
Banana	400	100	350	150	450	50	**500**
Orange	0	300	150	150	300	0	**300**
Other	100	100	150	50	50	150	**200**
Total	500	500	650	350	800	200	**1000**

Step 3: Compute the 'Posterior' probabilities for each class given the features.

$P(\texttt{Y} \mid \texttt{Long, Sweet, Yellow})$?

$$
\begin{aligned}
P(\texttt{Banana} \mid \texttt{Long, Sweet, Yellow}) \\
&= (0.8 \times 0.7 \times 0.9) \times 0.5 = 0.252 \\
P(\texttt{Orange} \mid \texttt{Long, Sweet, Yellow}) \\
&= \ldots = 0.0 \rightarrow P(\texttt{Long} \mid \texttt{Orange}) = 0 \\
P(\texttt{Other} \mid \texttt{Long, Sweet, Yellow}) \\
&= \ldots = 0.019
\end{aligned}
$$

Naïve Bayes



Pros

- Easy to implement
- Very efficient

Cons

- Independence assumption doesn't always hold
- Loss of accuracy

vas3k

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

K-Nearest Neighbors (KNN)

Naive Bayes

Association Rule Learning

Support Vector Machines (SVM)

Decision Trees

Ensemble Methods

Association Rule Learning

Tries to find "interesting" **dependent** associations between variables.

Cough	Sneezing	Fever	Flu
Yes	Yes	No	No
Yes	No	Yes	Yes
No	No	No	No
No	Yes	Yes	Yes

Association Rule Learning

Tries to find "interesting" **dependent** associations between variables.

Transaction: $X \Longrightarrow Y$ (if X then Y)

- {Sneezing} $\Longrightarrow$ {Flu}
- {Cough} $\Longrightarrow$ {Flu}
- {Sneezing, Cough} $\Longrightarrow$ {Flu}

Cough	Sneezing	Fever	Flu
Yes	Yes	No	No
Yes	No	Yes	Yes
No	No	No	No
No	Yes	Yes	Yes

Association Rule Learning

Tries to find “interesting” **dependent** associations between variables.

Transaction: $X \Longrightarrow Y$ (if X then Y)

- {Sneezing} $\Longrightarrow$ {Flu}
- {Cough} $\Longrightarrow$ {Flu}
- {Sneezing, Cough} $\Longrightarrow$ {Flu}

Cough	Sneezing	Fever	Flu
Yes	Yes	No	No
Yes	No	Yes	Yes
No	No	No	No
No	Yes	Yes	Yes

Apply metrics known as **rules** on transactions to identify interesting relationships.

Association Rule Learning

Tries to find “interesting” **dependent** associations between variables.

Transaction: $X \Longrightarrow Y$ (if X then Y)

- {Sneezing} $\Longrightarrow$ {Flu}
- {Cough} $\Longrightarrow$ {Flu}
- {Sneezing, Cough} $\Longrightarrow$ {Flu}

Cough	Sneezing	Fever	Flu
Yes	Yes	No	No
Yes	No	Yes	Yes
No	No	No	No
No	Yes	Yes	Yes

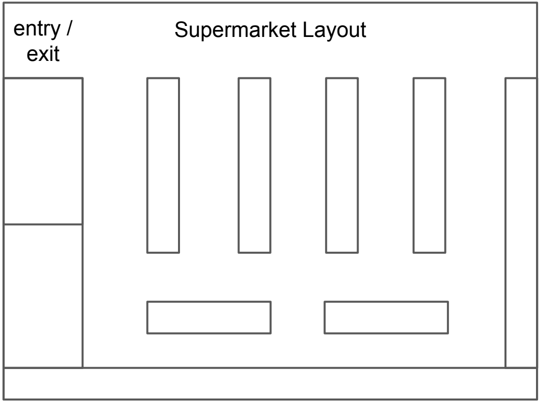
Apply metrics known as **rules** on transactions to identify interesting relationships.

Rule	Description
Support	How frequently does “X” appear in the dataset
Confidence	How many itemsets with “X” also contain “Y”
Lift	Ratio of observed support, to expected support if “X” and “Y” were independent
Conviction	How likely an association is genuine, not just random chance

Association Rule Learning

Application: Product placement in supermarkets

Transactions	
🍞 🥩 🧀 🥚 🥬	🍞 🥩 🥚 🥛
🍞 🥩 🧀 🥛	🍞 🍌 🥬 🧅
🍞 🍎 🍌 🍍	🍎 🥚
🥩 🧀 🥚	🍞 🥩 🧀 🥛
🍞 🥩 🧀 🥚 🥛	🧀 🥚 🥬 🧅 🥑

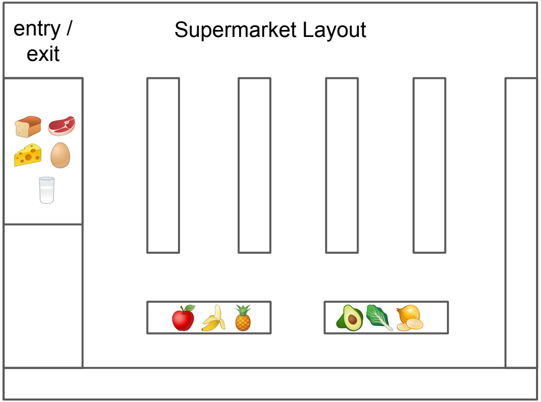


Association Rule Learning

Application: Product placement in supermarkets

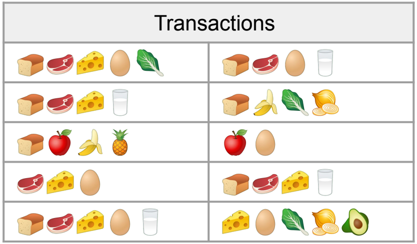
Transactions	
🍞🥩🧀🥚🥬	🍞🥩🥚🥛
🍞🥩🧀🥛	🍞🍌🥬🧅
🍞🍎🍌🍍	🍎🥚
🥩🧀🥚	🍞🥩🧀🥛
🍞🥩🧀🥚🥛	🧀🥚🥬🧅🥑

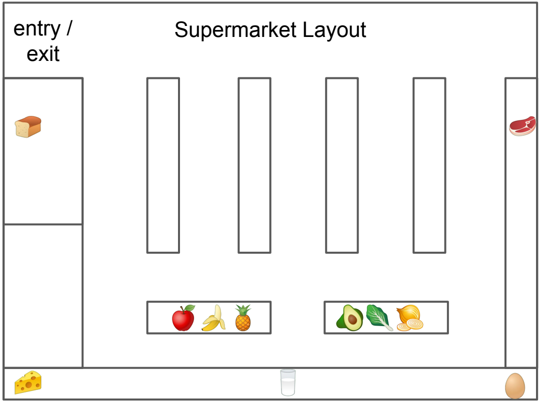
Easiest for customer



Association Rule Learning

Application: Product placement in supermarkets



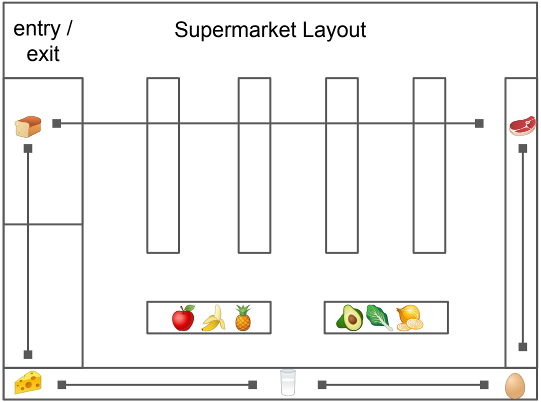


Association Rule Learning

Application: Product placement in supermarkets

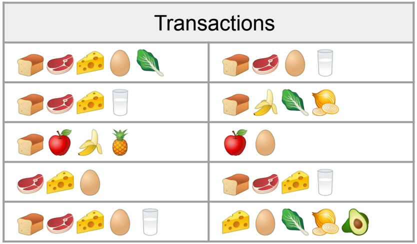
Transactions	
🍞 🥩 🧀 🥚 🥬	🍞 🥩 🥚 🥛
🍞 🥩 🧀 🥛	🍞 🍌 🥬 🧅
🍞 🍎 🍌 🍍	🍎 🥚
🥩 🧀 🥚	🍞 🥩 🧀 🥛
🍞 🥩 🧀 🥚 🥛	🧀 🥚 🥬 🧅 🥑

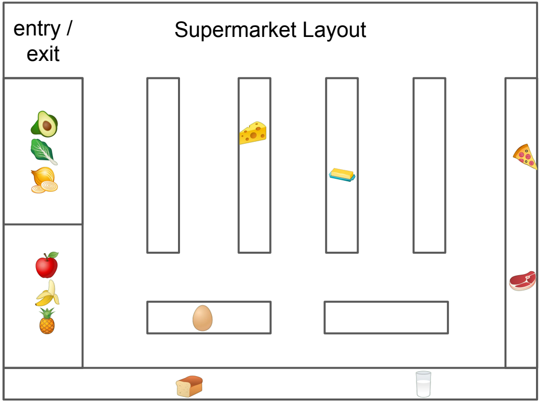
Max distance



Association Rule Learning

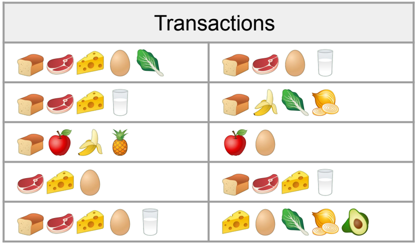
Application: Product placement in supermarkets



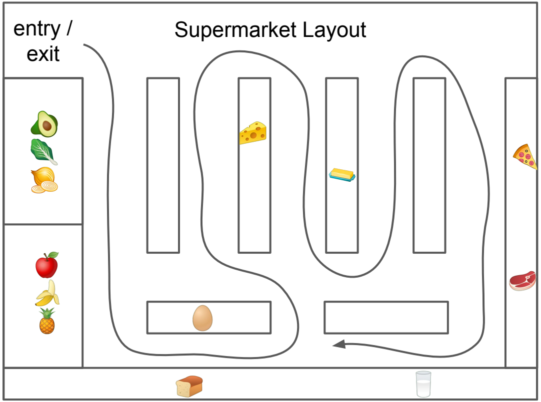


Association Rule Learning

Application: Product placement in supermarkets



Maximum walk



Association Rule Learning

Example: Apriori algorithm

Bottom up approach where subsets extended by 1 item at a time

Uses BFS to explore item sets efficiently

Identifies branches which will not meet **minimum cutoff criteria**

Cutoff Criteria

Min Support = 3

Transactions

Itemsets
{1,2,3,4}
{1,2,4}
{1,2}
{2,3,4}
{2,3}
{3,4}
{2,4}

1 item

Item	Support
{1}	3
{2}	6
{3}	4
{4}	5

2 items

Item	Support
{1,2}	3
~~{1,3}~~	~~1~~
~~{1,4}~~	~~2~~
{2,3}	3
{2,4}	4
{3,4}	3

3 items

Item	Support
{2,3,4}	2

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

K-Nearest Neighbors (KNN)

Naive Bayes

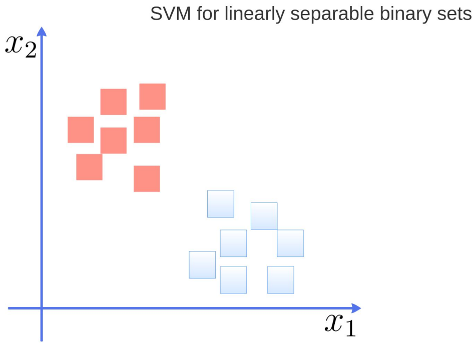
Association Rule Learning

<u>Support Vector Machines (SVM)</u>

Decision Trees

Ensemble Methods

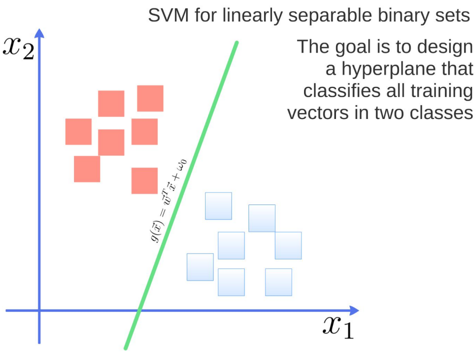
Support Vector Machines (SVM)



- consider linearly separable points
- for given training data, find decision boundaries separating classes (***hyperplane***)
- maximises the perpendicular distance to the nearest points
- ***maximum-margin hyperplane***
- gives a linear separator
- optimisation problem

Thales Sehn Körting, *How SVM (Support Vector Machine) algorithm works* on youtube

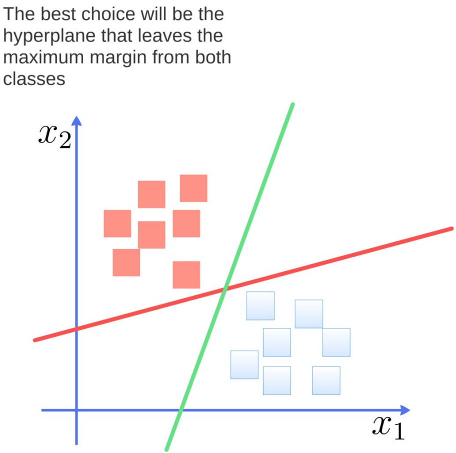
Support Vector Machines (SVM)



- consider linearly separable points
- for given training data, find decision boundaries separating classes (***hyperplane***)
- maximises the perpendicular distance to the nearest points
- ***maximum-margin hyperplane***
- gives a linear separator
- optimisation problem

Thales Sehn Körting, *How SVM (Support Vector Machine) algorithm works* on youtube

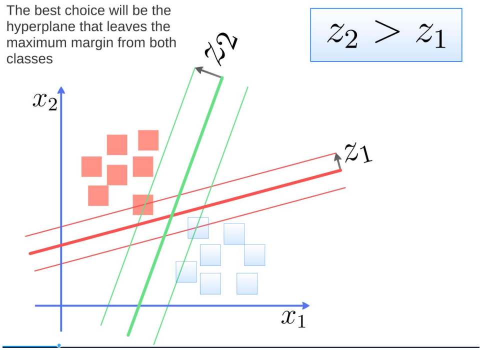
Support Vector Machines (SVM)



Thales Sehn Körting, *How SVM (Support Vector Machine) algorithm works* on youtube

- consider linearly separable points
- for given training data, find decision boundaries separating classes (***hyperplane***)
- maximises the perpendicular distance to the nearest points
- ***maximum-margin hyperplane***
- gives a linear separator
- optimisation problem

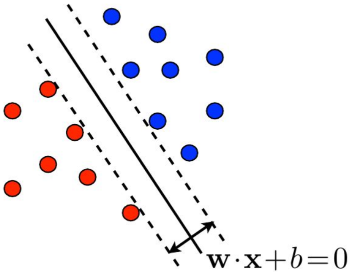
Support Vector Machines (SVM)



- consider linearly separable points
- for given training data, find decision boundaries separating classes (***hyperplane***)
- maximises the perpendicular distance to the nearest points
- ***maximum-margin hyperplane***
- gives a linear separator
- optimisation problem

Thales Sehn Körting, *How SVM (Support Vector Machine) algorithm works* on youtube

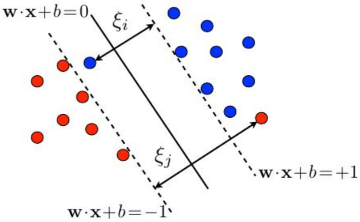
Support Vector Machines (SVM)

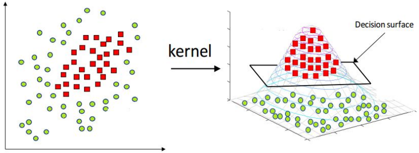


- finding maximum-margin hyperplane is a quadratic optimisation problem to find vector weights *w* and *b*
- *w* can be found as a linear combination of a subset of the training points
    - Points along the margins - the support vectors
- computationally straightforward
- minimising a convex function will find global optimum solution
- gives a linear boundary with maximum distance to points

Mohri 2012, *Foundations of machine learning*;

What if our data is not linearly separable?





- Use a soft SVM
  - Add terms to objective function to penalise points on the “wrong side” of boundary, but don’t forbid them
- Use a kernel function
  - Transform input data into a separable space
  - Kernel SVM allows non-linear boundaries in the original space and is a popular approach

$$
\begin{aligned}
\text{Polynomials of degree exactly } d\text{:}\quad & K(u,v) = (u\cdot v)^d \\
\text{Polynomials of degree up to } d\text{:}\quad & K(u,v) = (u\cdot v + 1)^d \\
\text{Gaussian kernels:}\quad & K(\vec{u},\vec{v}) = \exp\left(-\frac{\|\vec{u}-\vec{v}\|_2^2}{2\sigma^2}\right) \\
\text{Sigmoid:}\quad & K(u,v) = \tanh(\eta u\cdot v + v)
\end{aligned}
$$

Mohri 2012, *Foundations of machine learning*; *What is the kernel trick* via medium.com

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

K-Nearest Neighbors (KNN)

Naive Bayes

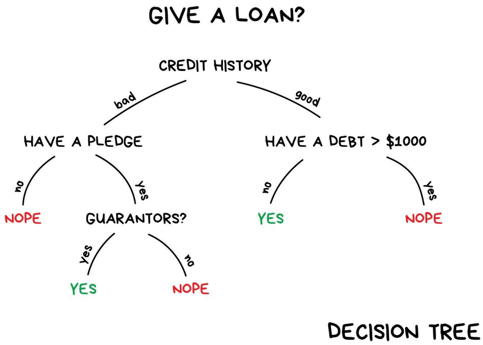
Association Rule Learning

Support Vector Machines (SVM)

<u>Decision Trees</u>

Ensemble Methods

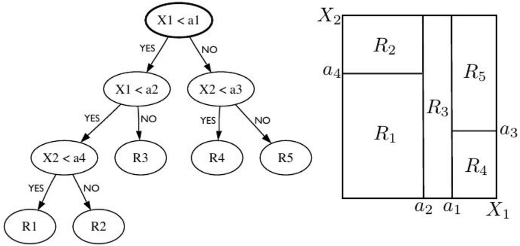
Decision Trees



- a decision tree consists of a hierarchy of rules for prediction
- we can visualise this as a tree where every node is either:
  - an internal node, with a decision criterion, with two children (binary)
  - a leaf node, which predicts an outcome
- trees can be built for classification or for regression

vas3k

How to build a decision tree from data?



1. Choose a decision point yielding best purity
2. Partition data into corresponding subsets
3. Reiterate with resulting subsets
4. Stop when regions are approximately pure

Impurity in classification

- misclassification
- Gini impurity: probability of incorrectly classifying a randomly chosen data point

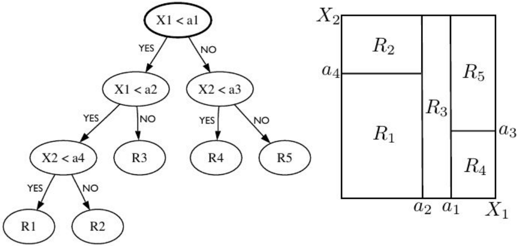
Impurity in regression

- mean squared error

$$F(R) = \sum_{x_i \in R} (y_i - \langle y \rangle)^2$$

Mohri 2012, *Foundations of machine learning*;

Recursive binary splitting is a greedy heuristic



Prediction

- a path from root to leaf based on the features

Pros

- decision trees facilitate explaining complex data
  - interpretable
- results can be easy to analyze and understand
- different types of variables: categorical, numerical

Cons

- large trees can easily overfit
- use a pruning criteria
  - minimize (impurity + tree size)

Mohri 2012, *Foundations of machine learning*;

Supervised Learning

Recap & brief detour about GeoGuessr

Supervised learning

K-Nearest Neighbors (KNN)

Naive Bayes

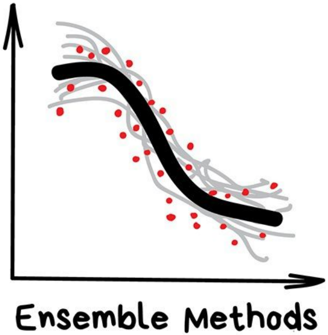
Association Rule Learning

Support Vector Machines (SVM)

Decision Trees

Ensemble Methods

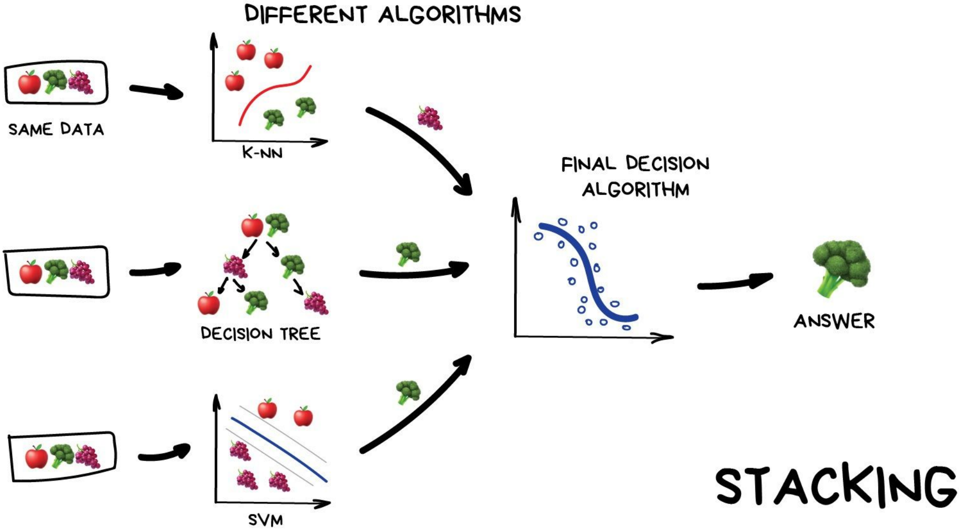
Ensemble methods



- rather than just one, combine multiple learning algorithms (or instances) into one predictive model
- ensemble methods are meta-algorithms aiming to:
  - decrease variance;
  - decrease bias;
  - improve predictions
- Stacking
- Bagging
- Boosting

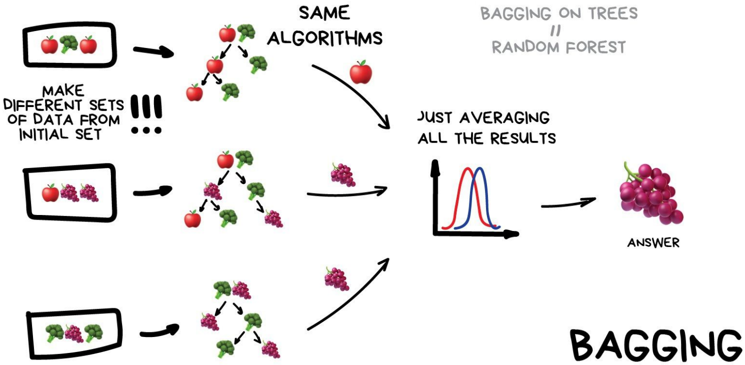
vas3k

Stacking



vas3k

Bagging

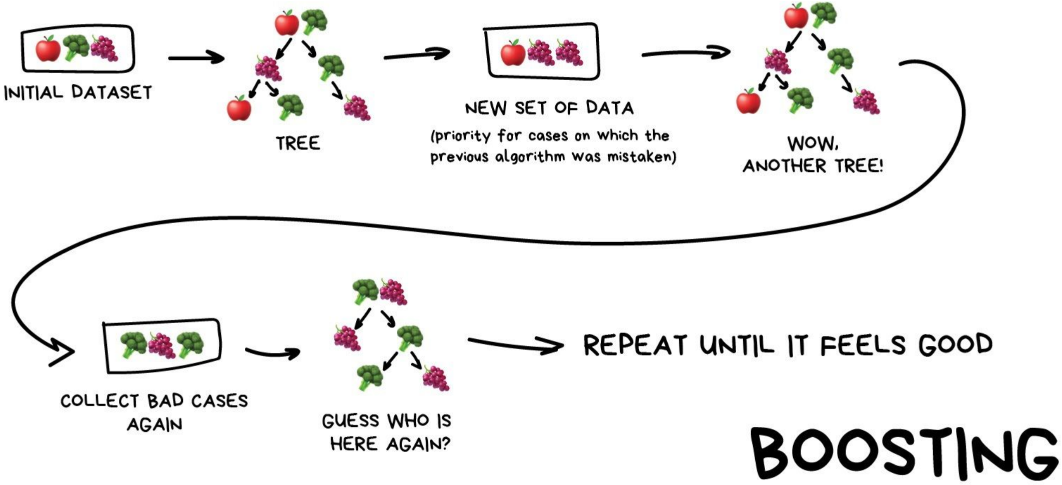


Random Forest (Breiman *et al.*, 2001)

- Very popular and effective
- Classification & regression
- Robust to outliers & feature importance

vas3k

Boosting



vas3k

Thank you!

Today: Supervised Learning

Next time: Model selection, tuning, validation