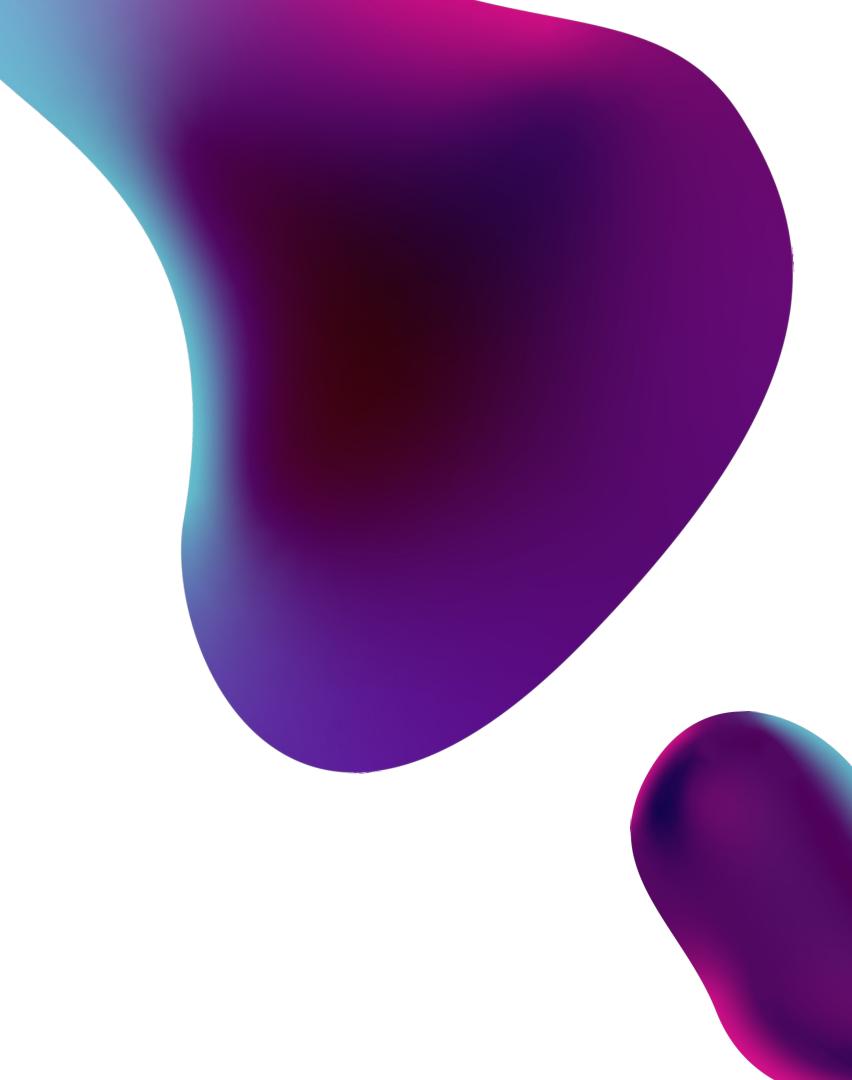
K-Nearest Neighbor

Data Mining Lê Công Minh Khôi – 519H0181



Introduction

Simple algorithm

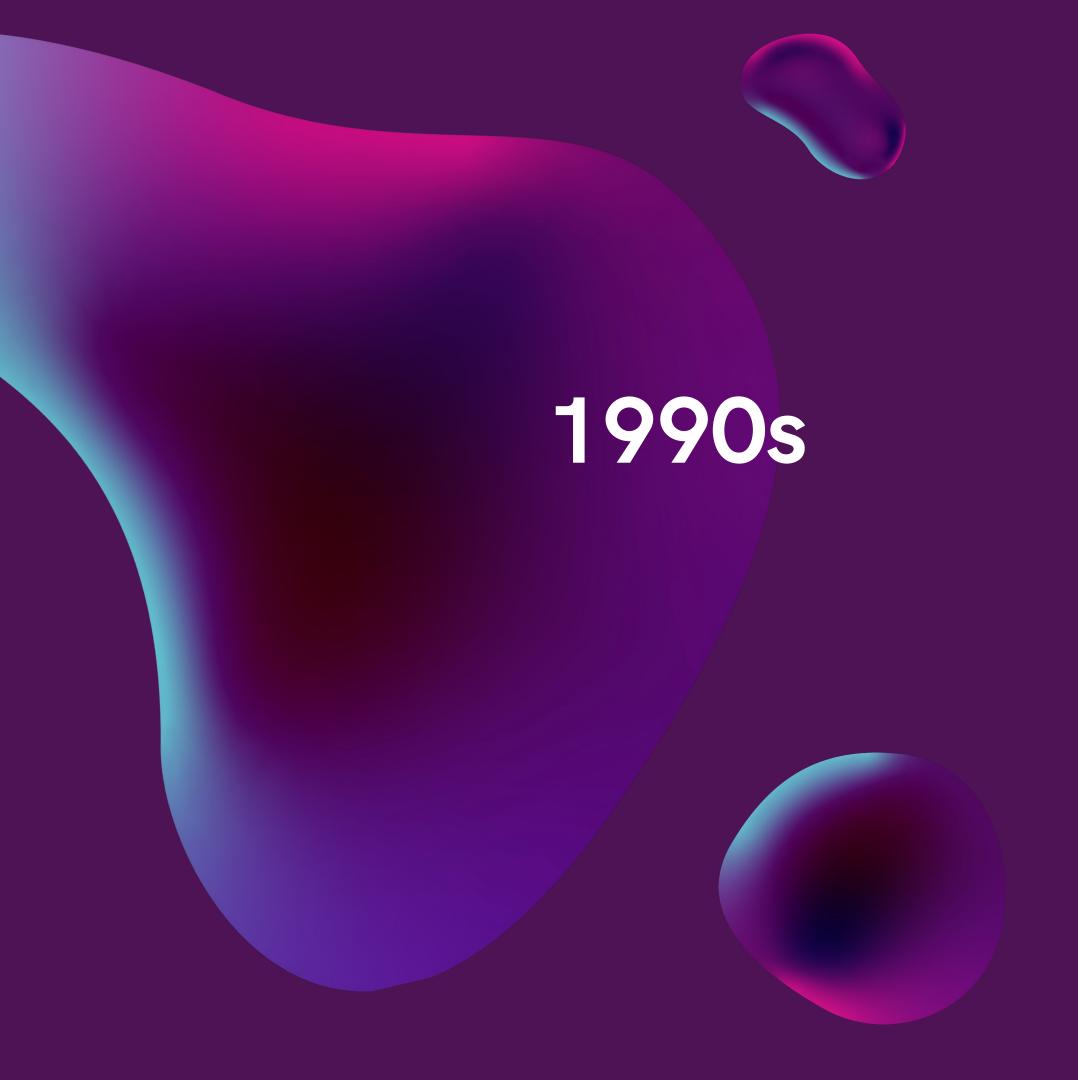
Classification/R egression

Based on a similarity measure

1970s

Statistical estimation

Pattern recognition



Popular in machine learning

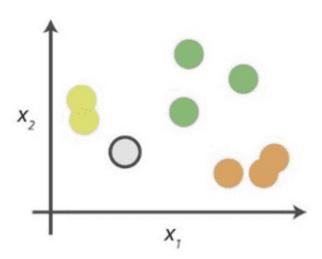
Why do we need a kNN algorithm?

kNN

Simple To Implement Versatile

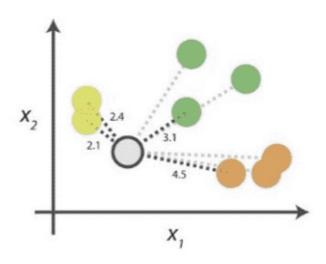
Effective

0. Look at the data



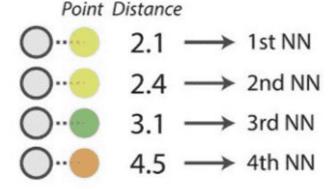
Say you want to classify the grey point into a class. Here, there are three potential classes - lime green, green and orange.

1. Calculate distances



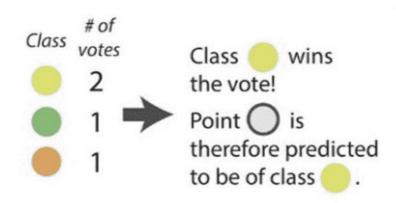
Start by calculating the distances between the grey point and all other points.

2. Find neighbours



Next, find the nearest neighbours by ranking points by increasing distance. The nearest neighbours (NNs) of the grey point are the ones closest in dataspace.

3. Vote on labels



Vote on the predicted class labels based on the classes of the k nearest neighbours. Here, the labels were predicted based on the k=3 nearest neighbours.

How does the kNN algorithm work?

The kNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other.

Step by step explanation

- 1. Load the data
- 2. Choose k
- 3. For each point in the data
 - 1. Calculate the distance between current point and the point we try to predict
 - 2. Add the distance and the index of the example to an ordered collection
- 4. Sort the ordered collection of distances and indices from smallest to largest (in ascending order) by the distances
- 5. Pick the first k entries from the sorted collection
- 6. Get the labels of the selected k entries
- 7. Return prediction
 - 1. If regression, return the mean of the k labels
 - 2. If classification, return the mode of the k labels



How to choose the value of k?

Usually odd

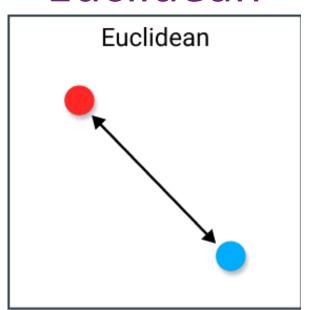


Try different k value

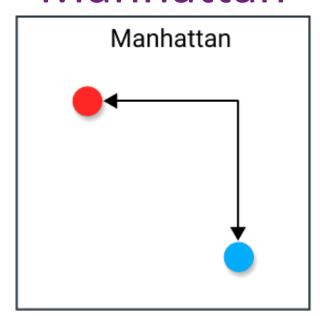
Pick the best result

Calculating the distance

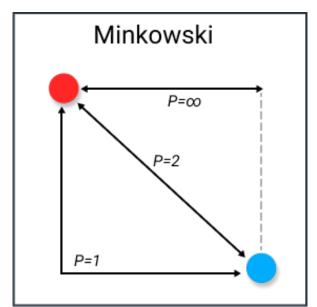
Euclidean



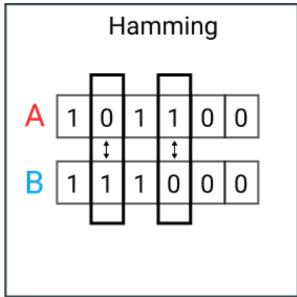
Manhattan



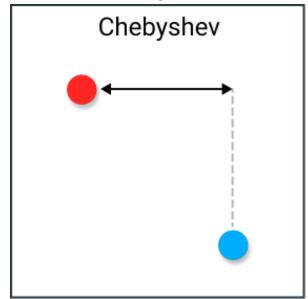
Minkowski

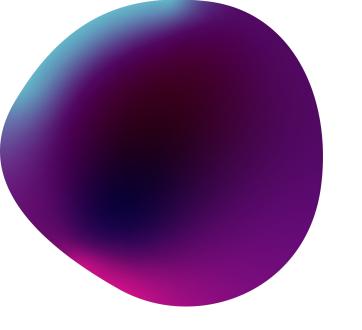


Hamming



Chebyshev





Advantages



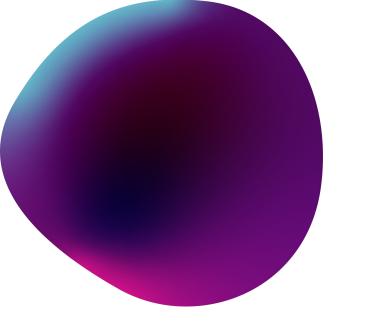
Simple to implement

Versatile

Training is trivial

Works with any number of classes

Effective if the training data is large



Disadvantages

Computationally expensive

High memory requirement

Prediction stage might be slow with a large testing dataset



Does not work well with high dimensional data

One-hot encoding is required for categorical features

