

# DATA-DRIVEN PROBLEM SOLVING IN MECHANICAL ENGINEERING

## K Nearest Neighbors

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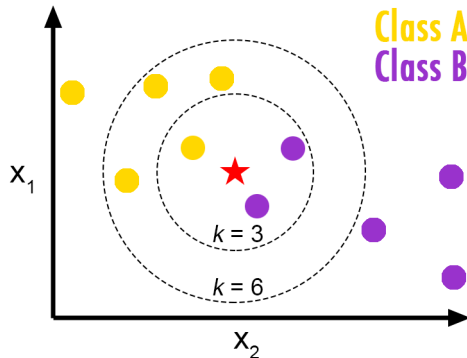
# K Nearest Neighbors



Given a set of labeled training examples, we seek the training example which is most similar to an unlabeled point  $p$ , and then take the class label for  $p$  from its nearest labeled neighbors.

**K-Nearest Neighbors** is an algorithm for supervised learning, where the model is ‘trained’ with data points corresponding to their classes.

Once a point is to be predicted, it takes into account the ‘K’ nearest points to determine its class.

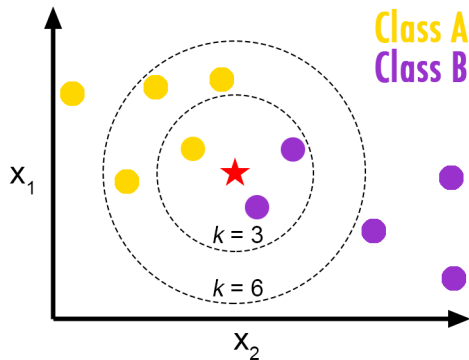


# Implementation



Here is how this algorithm works:

- (1) Pick a value for  $k$
- (2) Calculate the distance of unknown case from all cases.
- (3) Select the  $k$  points in the training data that are “nearest” to the unknown data point.
- (4) Make a prediction using the most popular target variable class from the  $k$ -nearest neighbors.



# Implementation



There are multiple options to find the distance in step (3), which measures the distance between points  $x^{(1)}$  and  $x^{(2)}$  for all  $n$  features.

- Euclidean distance

$$d = \sqrt{\sum_{i=1}^n (x_i^{(1)} - x_i^{(2)})^2}$$

- Manhattan distance

$$d = \sum_{i=1}^n |x_i^{(1)} - x_i^{(2)}|$$

- Minkowski distance

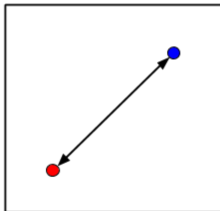
$$d = (\sum_{i=1}^n |x_i^{(1)} - x_i^{(2)}|^p)^{\frac{1}{p}}$$

- Chebyshev distance

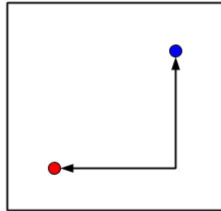
$$d = \max(|x_i^{(1)} - x_i^{(2)}|)$$

$$= \lim_{p \rightarrow \infty} (\sum_{i=1}^n |x_i^{(1)} - x_i^{(2)}|^p)^{\frac{1}{p}}$$

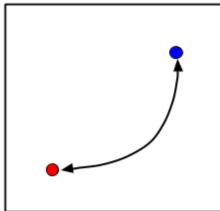
Euclidean



Manhattan



Minkowski



Chebyshev

