

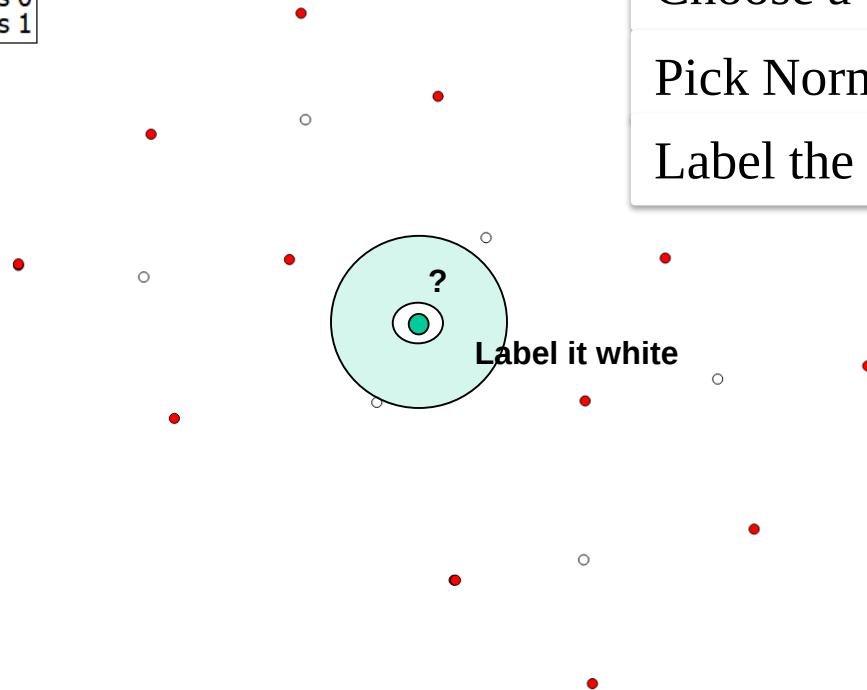
# APPLIED MACHINE LEARNING

## *Classification with K-nearest Neighbors (KNN)*

# Nearest Neighbor Classifier

- One of the simplest of all machine learning classifiers
- Simple idea: label a new point with the same label as that of the closest known point

○ Class 0  
● Class 1



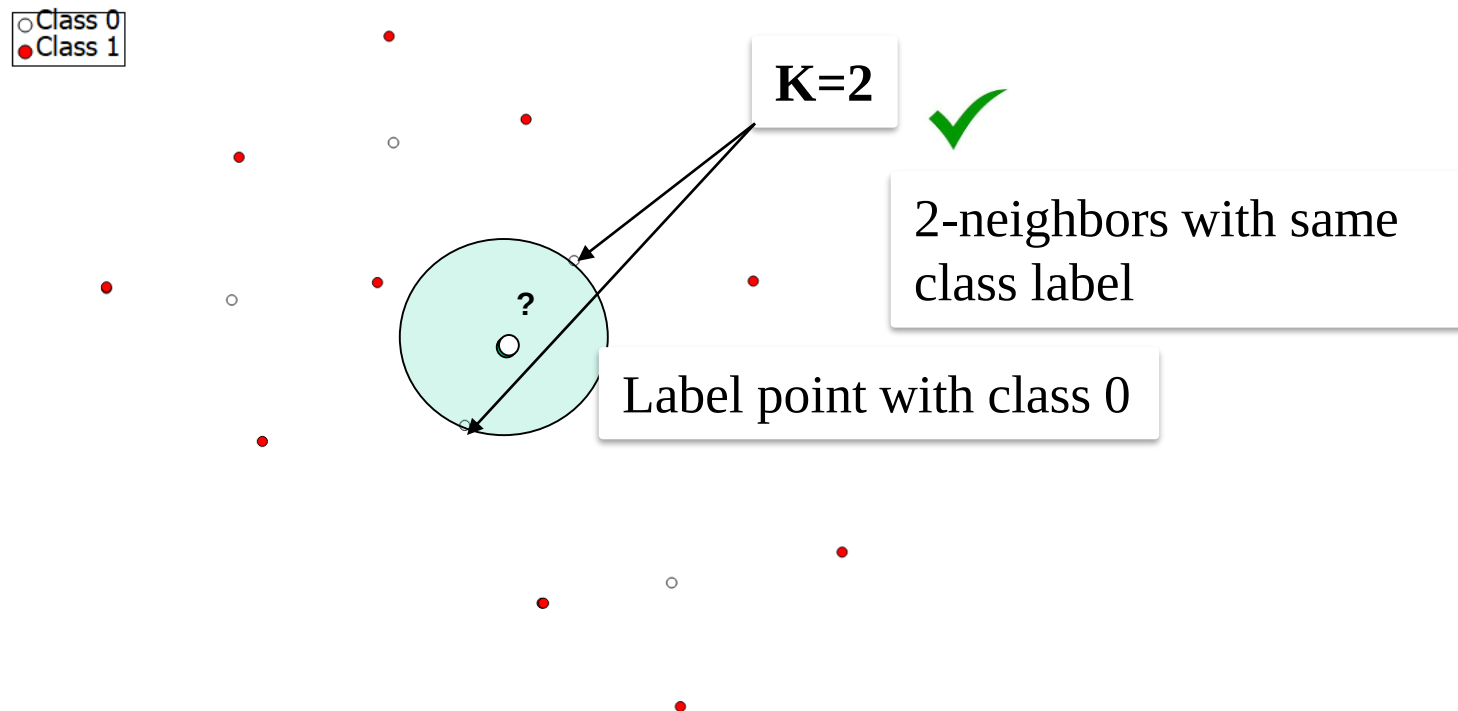
Choose a distance measure

Pick Norm-2

Label the point with class 0

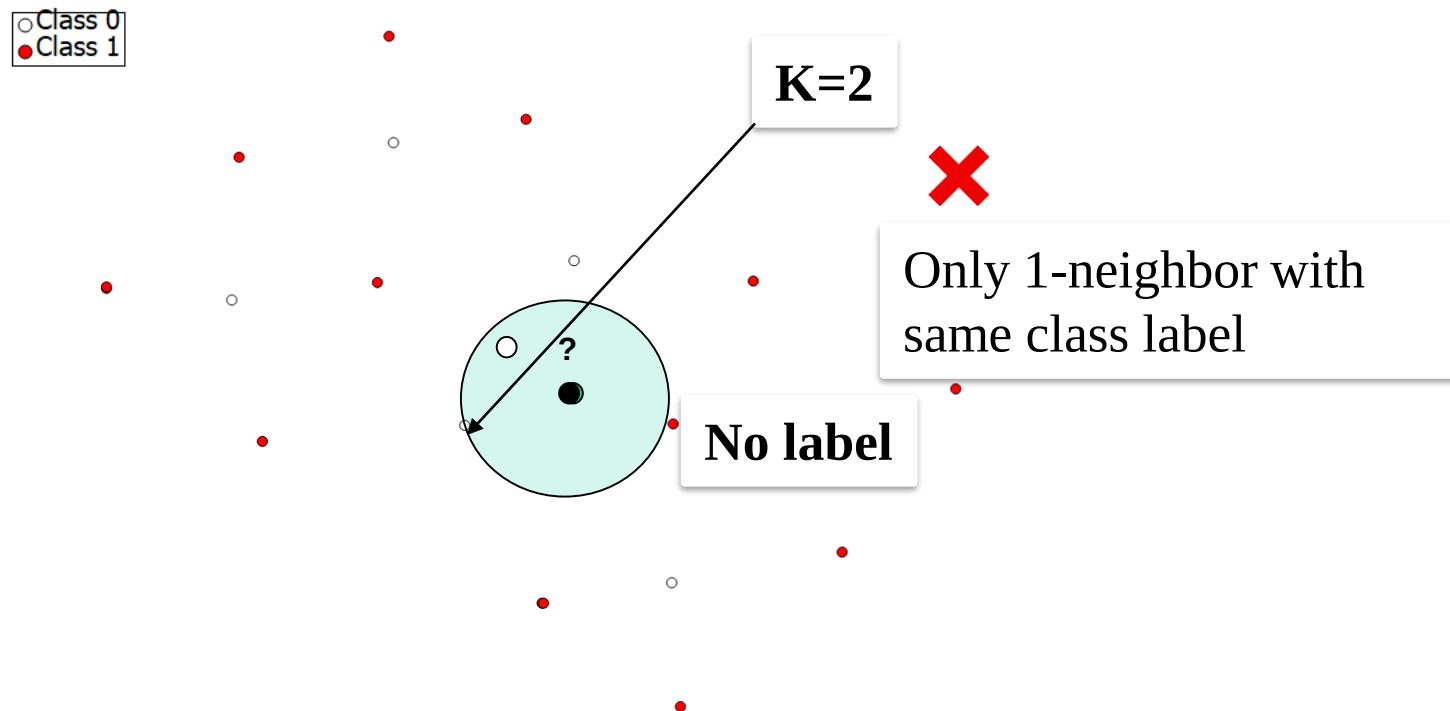
# Nearest Neighbors Classifier

- Label a new point with the same label as that of the closest known group of data points
- $K$ =number of neighbors



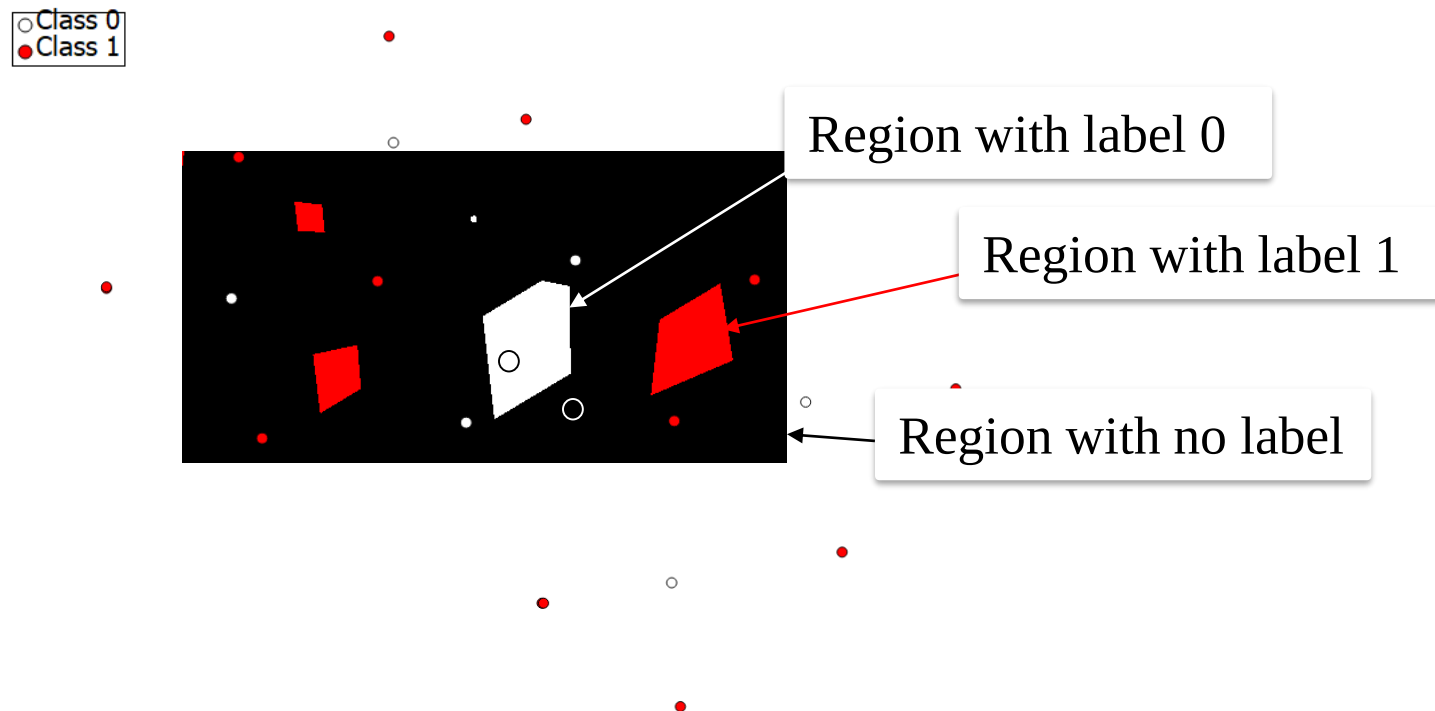
# Nearest Neighbors Classifier

- Label a new point with the **same label as that of the closest known group of data points**
- K=number of neighbors**



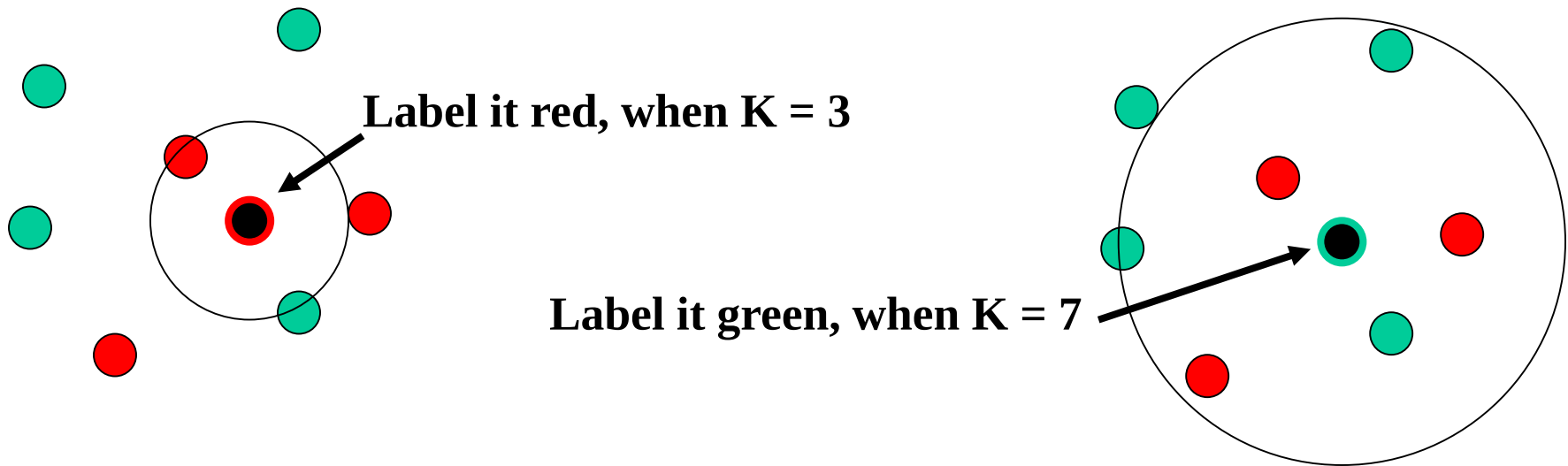
# Nearest Neighbors Classifier

- Label a new point with the **same label as that of the closest known group of data points**
- K=number of neighbors**



## Nearest Neighbors Classifier

- Probabilistic approach to smooth away noise in the labels
- A new point is now assigned **the most frequent label of its  $K$  nearest neighbors**



## Classification with K- Nearest Neighbors (K-NN)

Probability to be classified with label of class  $c$  :

$$p(y = c \mid x, K) = \frac{N_{c,K}}{K}$$

$K$  : Number of nearest neighbors

$N_{c,K}$  : Number of samples of class  $c$  included in  $K$  nearest neighbors

# Classification with k- Nearest Neighbors (K-NN)

## Summary

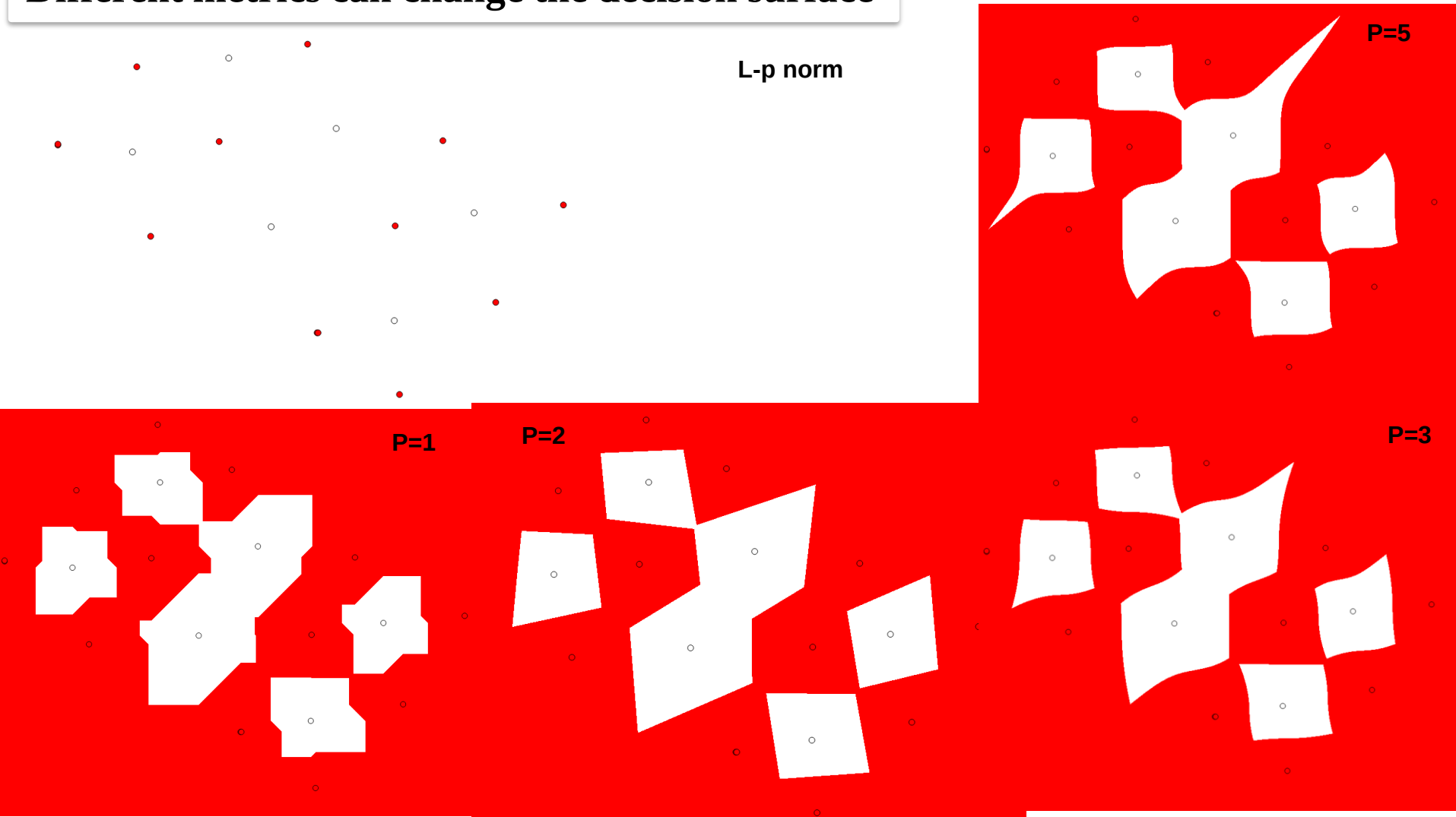
### Algorithm:

- Pick hyperparameters: K, Distance metric
- Training: **No training!** Save simply dataset
- Testing: x sample to be classified
  1. Calculate distance between x and all the other samples
  2. Pick the K samples closest to x
  3.  $N_{c,K}$   $\rightarrow$  Count number of samples of each class c in K
  4. Get probability of each class:
$$p(y = c | x, K) = \frac{N_{c,K}}{K}$$
  5. Assign label of most likely class

# Classification with k- Nearest Neighbors (K-NN)

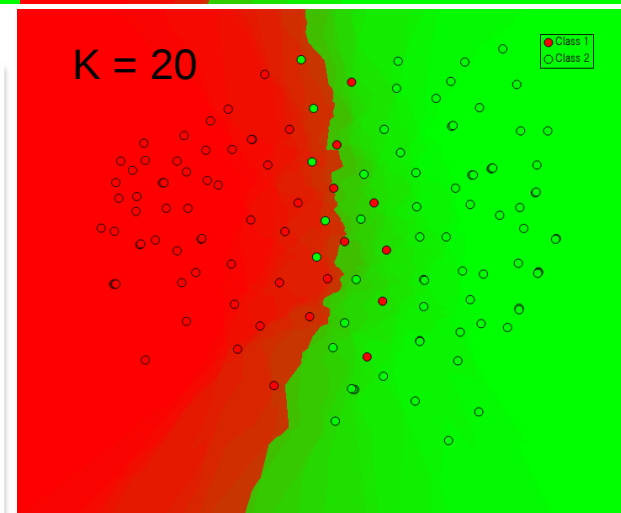
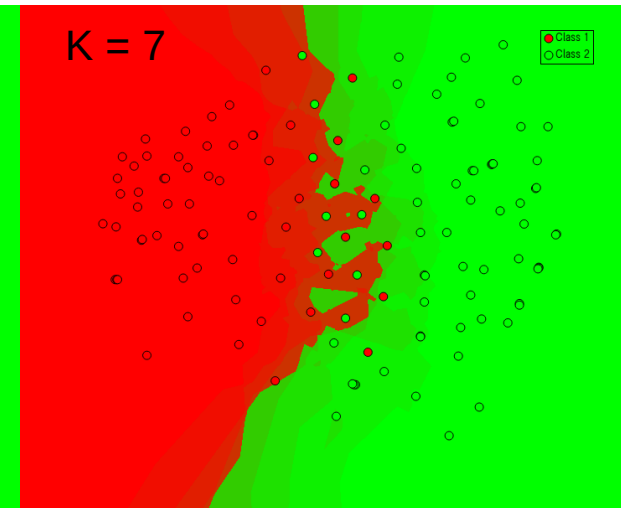
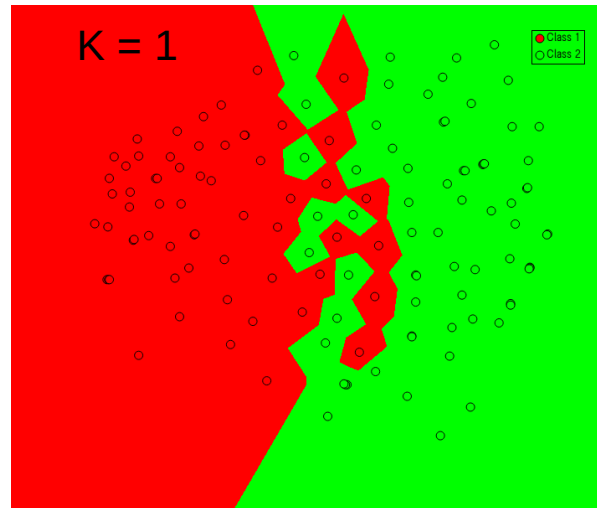
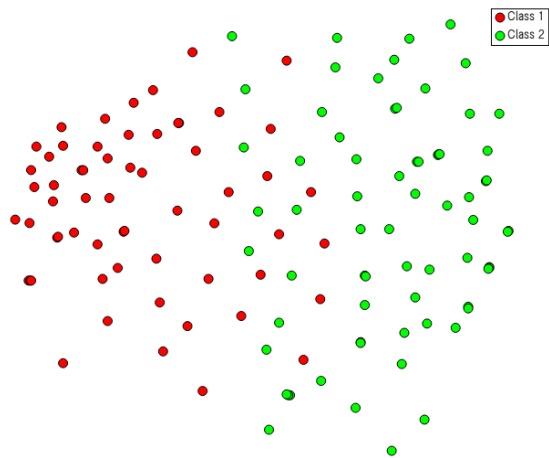
## Impact of metric

Different metrics can change the decision surface



# Classification with k- Nearest Neighbors (K-NN)

## Impact of K selection



- ❖ Large  $K$ :
  - Makes KNN less sensitive to noise
- ❖ Small  $K$ :
  - Allows capturing finer structure of space
- ❖ Pick  $K$  not too large, but not too small (depends on data)

# Classification with k- Nearest Neighbors (K-NN)

## Summary

### Advantages:

- Simplicity
- No assumptions regarding the distribution of data
- **Does not need a model for data distribution**

### Disadvantages:

- Curse of dimensionality (*stores the entire dataset*)
- High computational complexity (*pass through the entire dataset for each classification; prohibitive for large data sets.*)
- Large Impact of choice of K and of metric
- **Does not learn a model**

### Possible Improvements:

- *Weighting* examples from the neighborhood
- Measuring “closeness”
- Finding “close” examples in a large training set *quickly*