

## **CLASSIFICATION: THE NEAREST-NEIGHBORS ALGORITHM (K-NN)**

AP

# FROM THE INTRODUCTION:

## 1. Classification and class probability

### Instance:

- a collection (dataset) of datapoints from  $\mathbf{X}$
- a classification system  $C = \{c_1, c_2, \dots, c_r\}$

**Solution:** classification function  $\gamma : \mathbf{X} \rightarrow C$

**Measure:** misclassification

# MISCLASSIFICATION WHEN R=2

- it's described by the *confusion matrix*, which scores the result of classification against labeled examples.
- often one class is of more interest than the other: better measures are needed.
- accuracy on the given examples *does not automatically translate* into accuracy on new, previously-unseen data

negative class	TN	FP
positive class	FN	TP
	predicted negative	predicted positive

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

# BINARY CLASSIFICATION IN 2D

With just two numerical dimensions, datapoint similarity can be interpreted as simple Euclidean distance.

Being very close  $\iff$  being very similar

Q: are 4 and 6 more similar to each other than -1 and +1?

Assumption: small changes in the values won't alter the classification, close points will receive the same classification

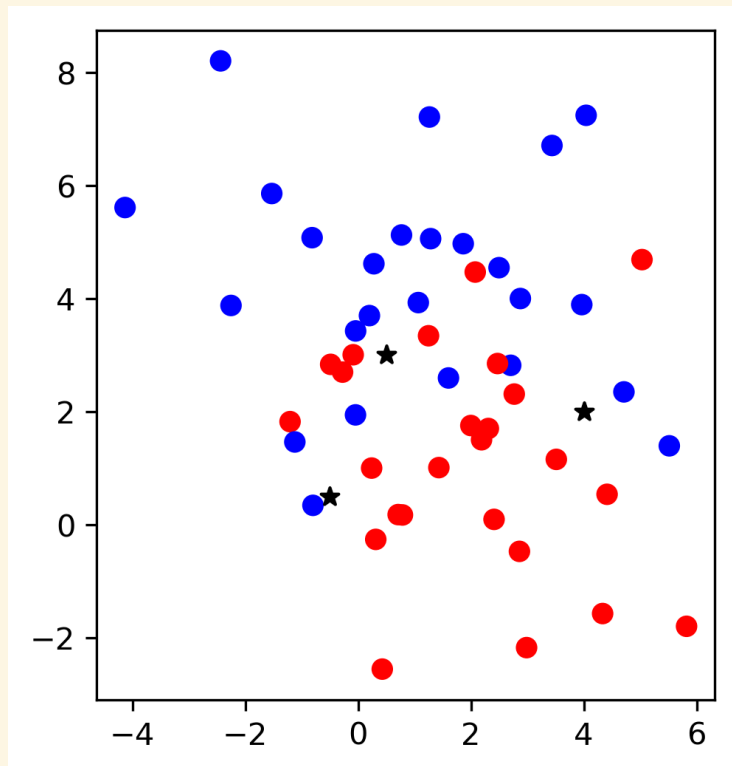
if a point is in close distance to a labeled one then assign the same class

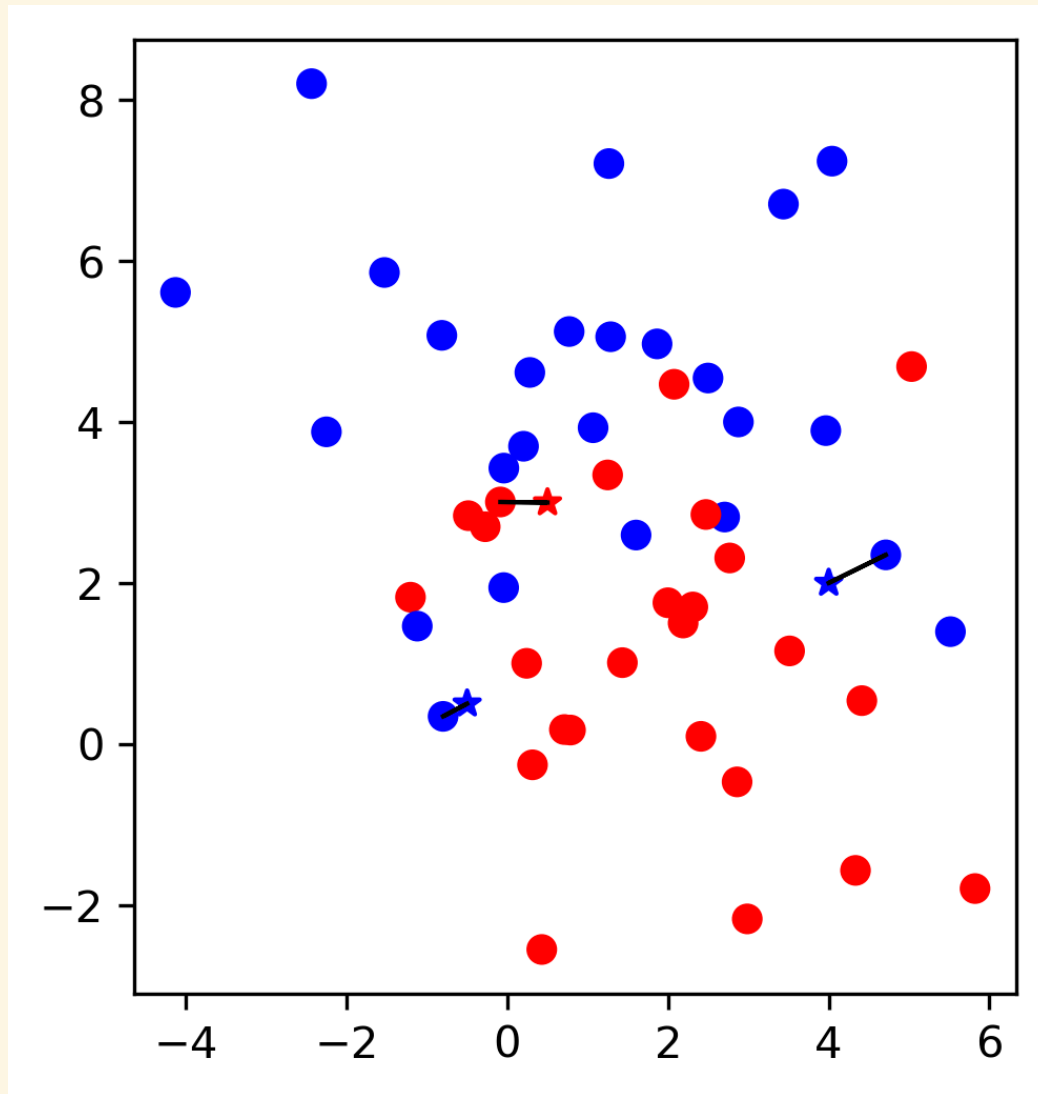
# THE NEAREST NEIGH. ALGORITHM

Take a set of labeled points (the examples), all others are *blank* at the moment.

Whenever a blank point has a nearest neighbor datapoint which is labeled, give it the same label

This is the NN, or 1-NN algorithm.





$$\gamma(\mathbf{x}) = y_i, i = \operatorname{argmin}_j ||\mathbf{x}_j - \mathbf{x}||$$

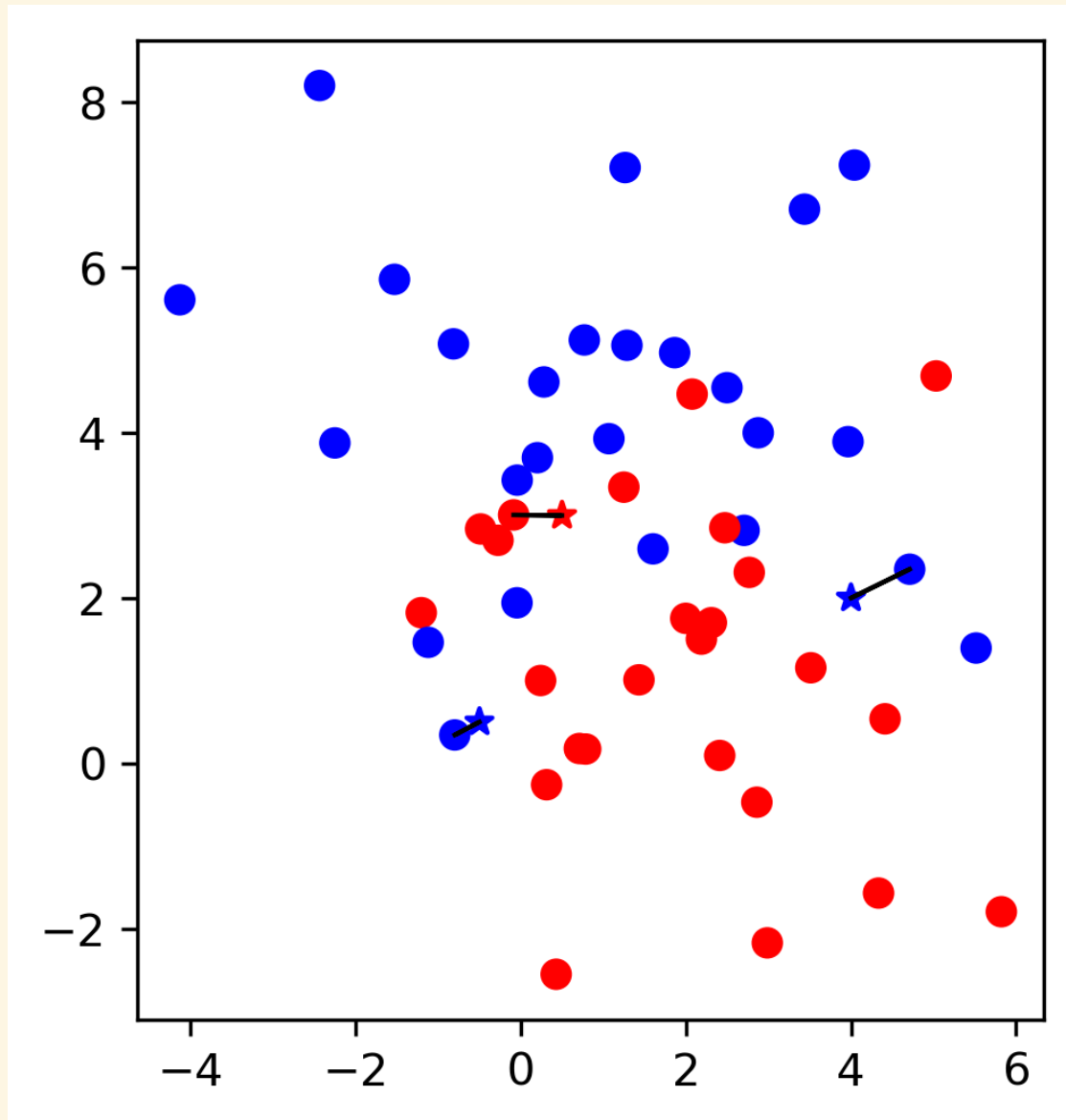
# FROM 1-NN TO K-NN

Consider the  $k$  nearest neighbors

Assign the class that is the most common among them

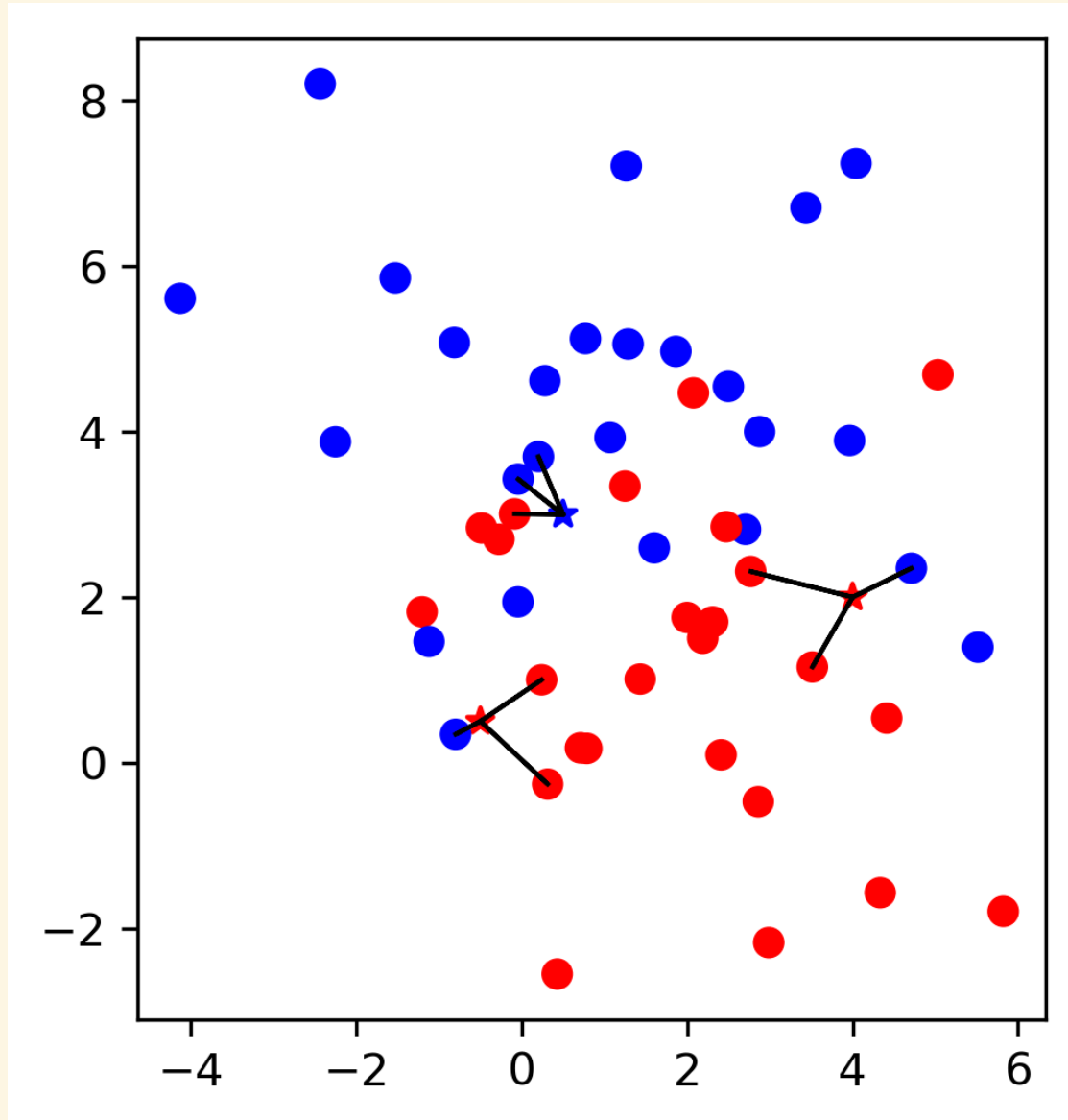
Variation: consider each label relative to the effective distance of the neighbor.

# 1-NN

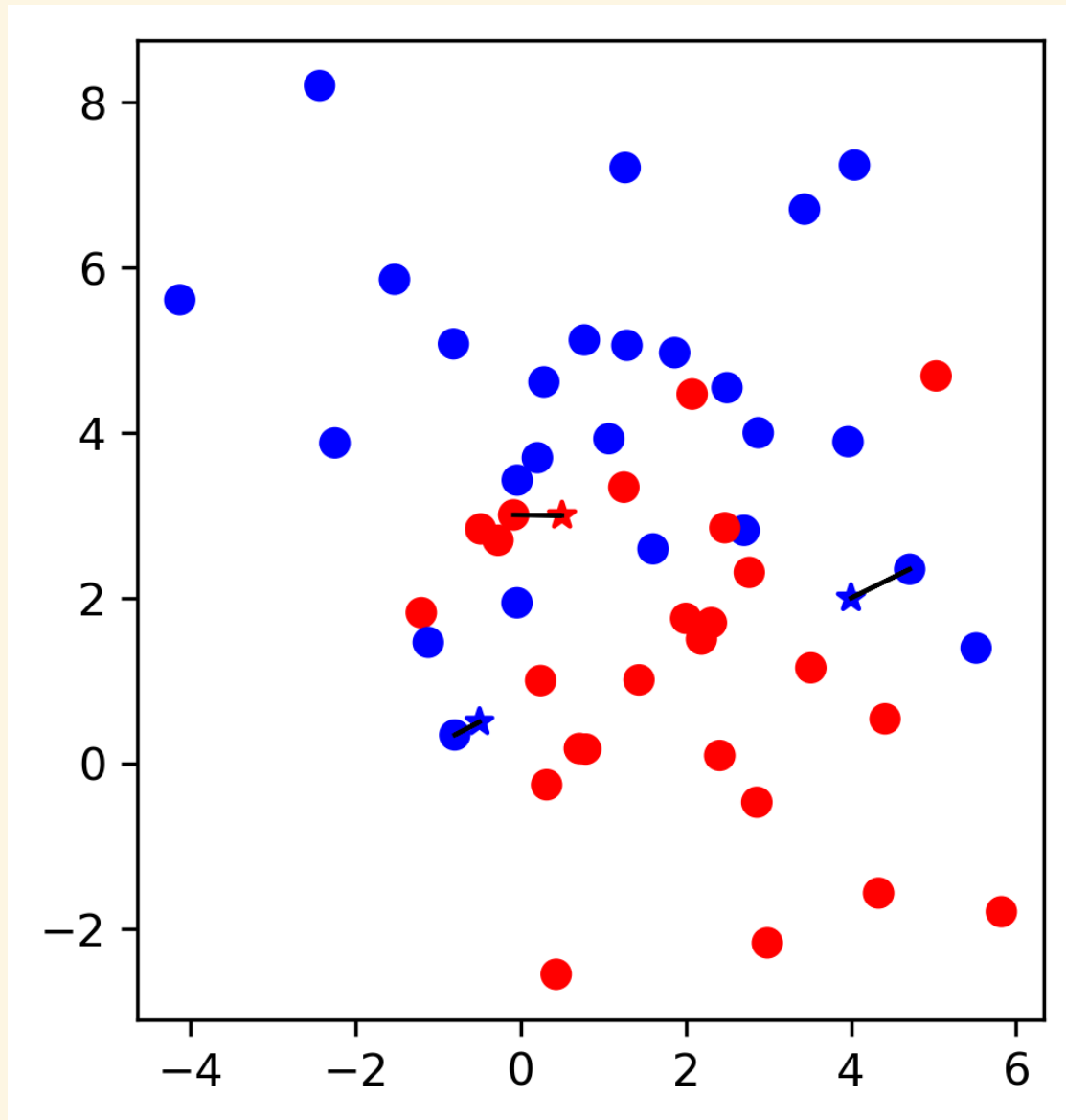




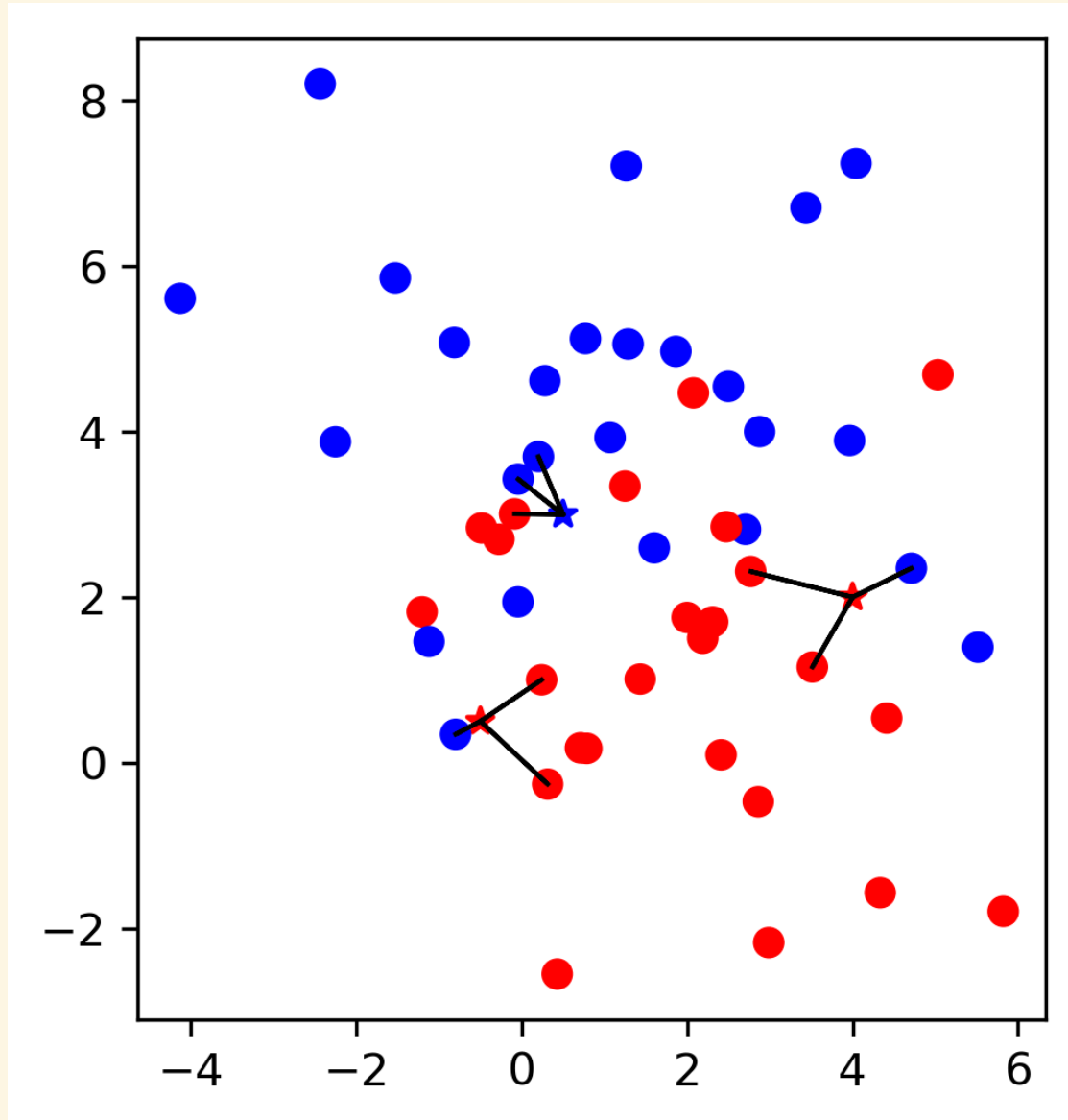
# 3-NN



# 1-NN



# 3-NN



# LEARNING

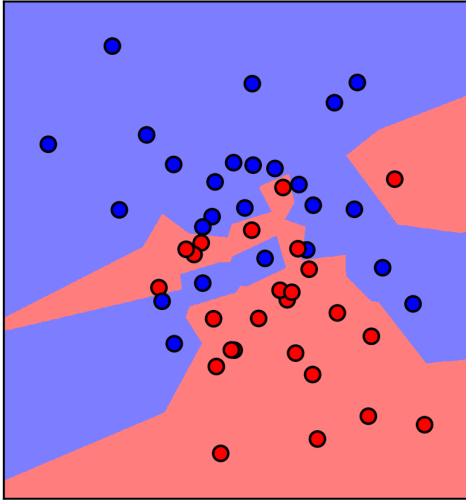
Given the labeled examples, k-NN determines the areas around each example which give a certain class.

k-NN learns an area or *surface* and applies it in classification

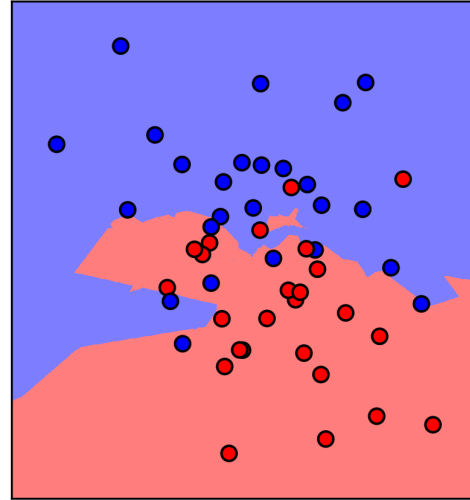
A larger k does not always mean a better classification

# INFLUENCE OF K

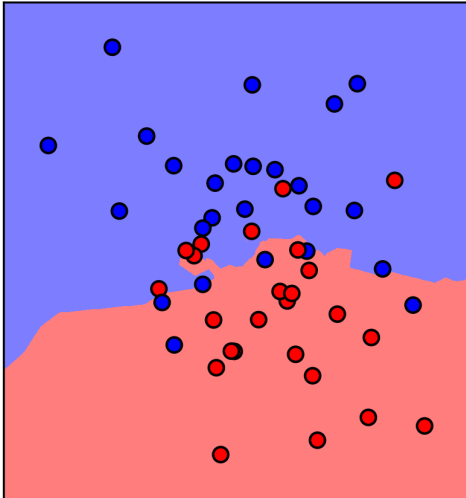
n\_neighbors=1



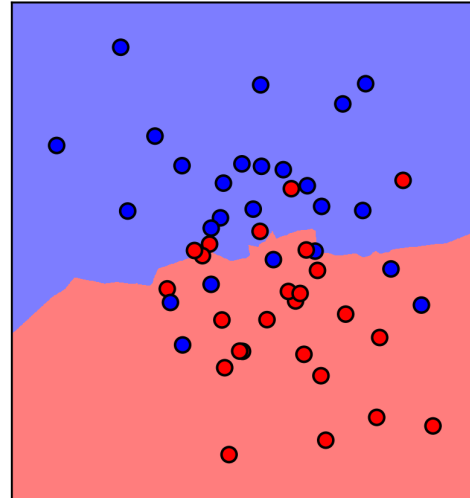
n\_neighbors=5



n\_neighbors=10



n\_neighbors=30



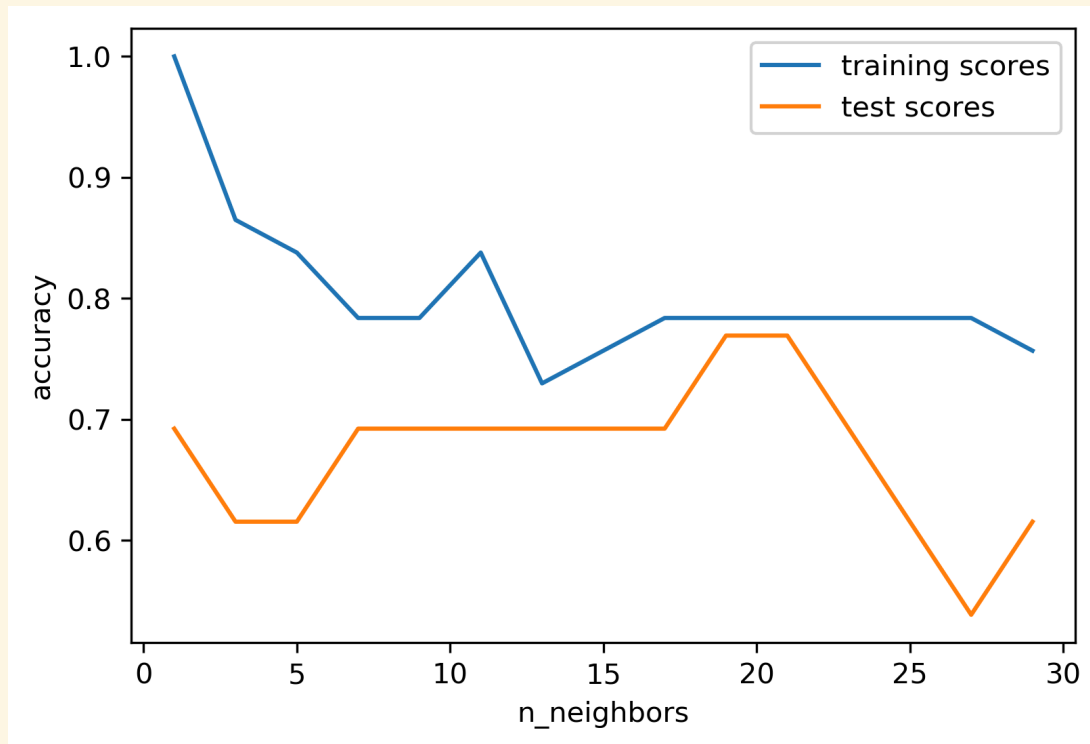
# OBSERVATIONS

## k-NN

- introduces us to *voting systems*
- is effective when the two classes are balanced, i.e., not *skewed*, in the dataset
- there is no standard way to choose  $k$ , yet it may greatly influence the outcome:
  - we face hyperparameter optimization.
- on large training data, even 1-NN approaches the *irreducible\_error\_rate* (2x).

# TRADE-OFFS

Sometimes improving accuracy on the training data does not translate into improved accuracy in testing against *unseen* data



1-NN is perfect on training but 0.7 on test.

Increasing k does not improve much and *overfitting* creeps in.