# dm25s1

## Topic 02 : Motivating Example

## Part 01 : Introduction to Classification

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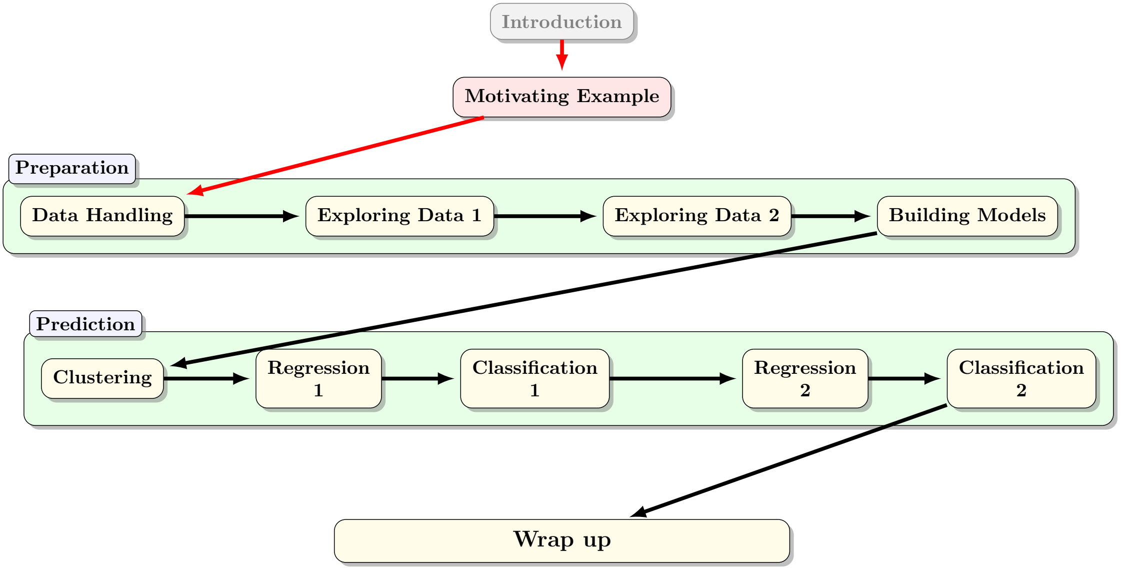
Autumn Semester, 2025

### Outline

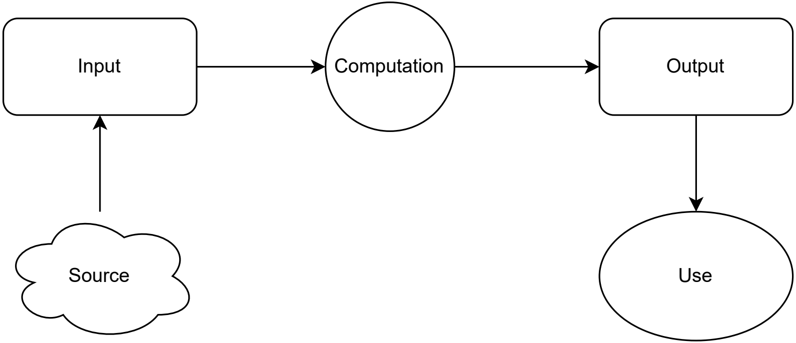
- How classification differs from regression
- Classification metrics
- Lazy vs Eager learners

# Data Mining (Week 2)



# Outline

# What does it mean to learn from data?

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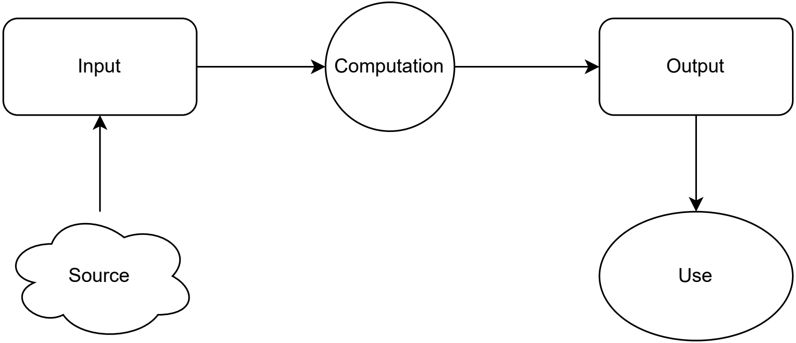


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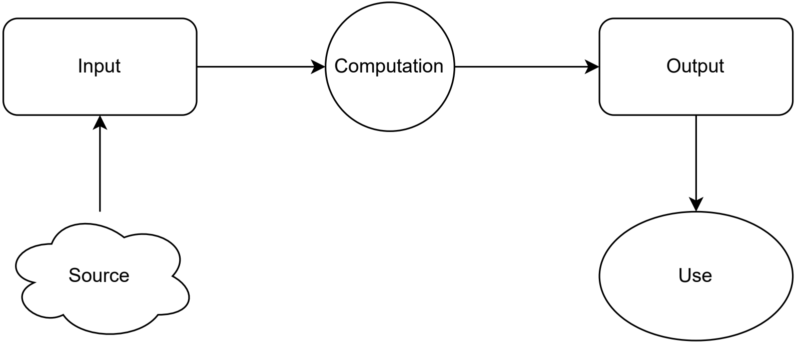


## Programmed Computation

- Explicit, detailed programming logic
- Handle edge cases, messy data
- Software engineering - unit testing, etc.

## Learned Computation

- Implicit, learning from examples
- Less brittle, but harder to test
- New paradigms - iterative model building

# Machine learning pros and cons

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## Challenges

- Need (lots of) data for training
- Training data (sample) needs to represent population
- Algorithms have many configuration settings
- Need to understand and validate
- Prediction error needs to be minimised

# Lazy vs Eager Learners

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Usually an (eager) model requires much less memory than a (lazy) training set.

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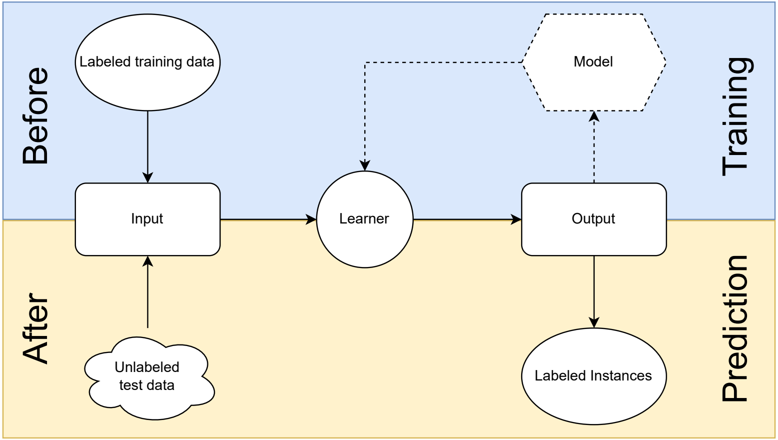
- Some *classifiers* generate class membership probabilities en route to predicting class membership (of the most likely class), so the predicted class can be defined by a set of numbers rather than a simple label.
- There are many classification algorithms!
- We choose one of the simplest today, which works by *voting for the most likely label*.

# Classification Overview




Today's classifier is a lazy learner and so uses local approximantion, not a model

# Example Applications

In 5 minutes, identify 3 possible applications for classification

# Outline

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**Example 2 (Spam Detection)**

A new email arrives. Is it spam? We have a large database of previous emails that have been labeled "Spam" or "Ham". Can we use this information *directly* to say whether the new email is spam or not?

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2. distance function $D : d(x_i, x_j) : \mathbb{R}^{p \times p} \rightarrow \mathbb{R}$ where $d(x_i, x_j) > 0$ if $x_i \neq x_j$ and is zero otherwise

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6. function $L$ that applies this representative label to the incoming instance

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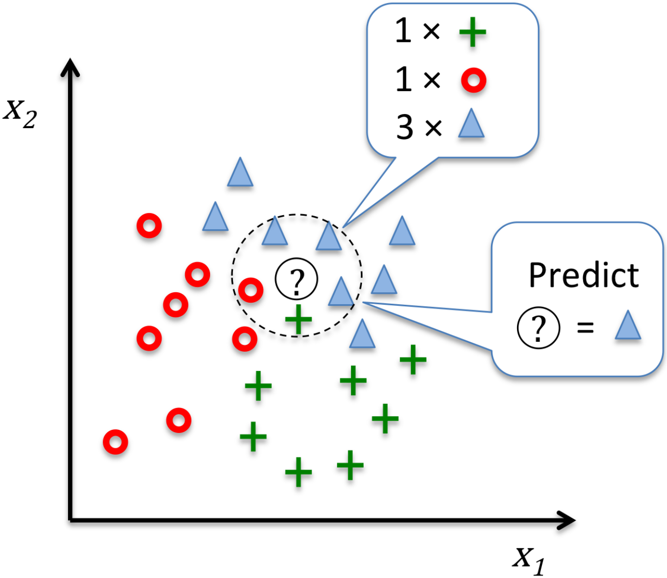
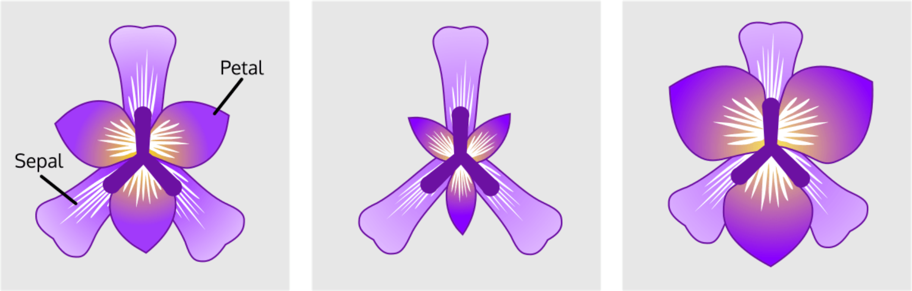
# K-Nearest Neighbours: Example prediction



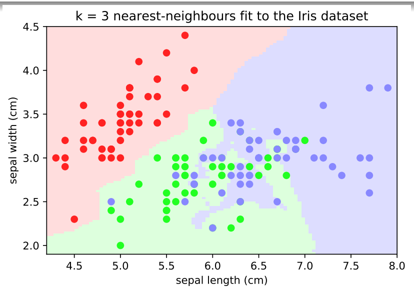
# Classifying iris species




Iris Versicolor Iris Setosa Iris Virginica

Given measurements of sepal and petal lengths and widths, can we distinguish between the 3 species?

# K-Nearest Neighbours: Iris SW-SL



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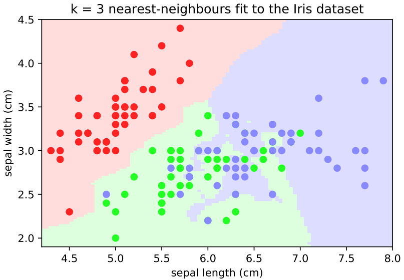


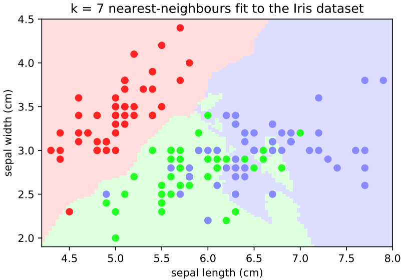

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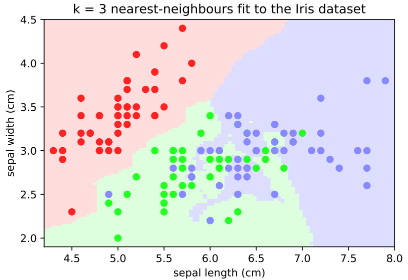


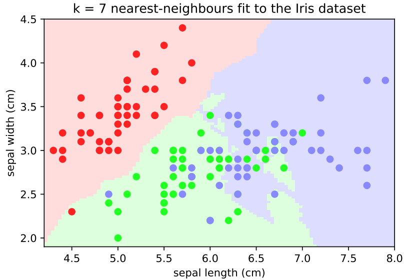


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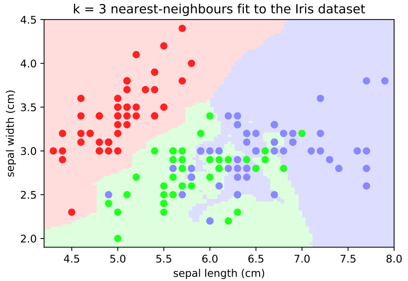


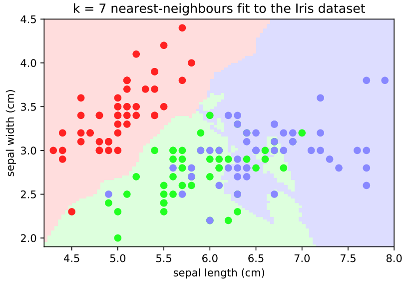


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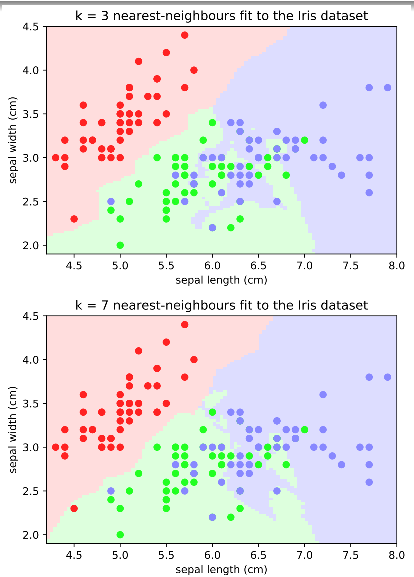


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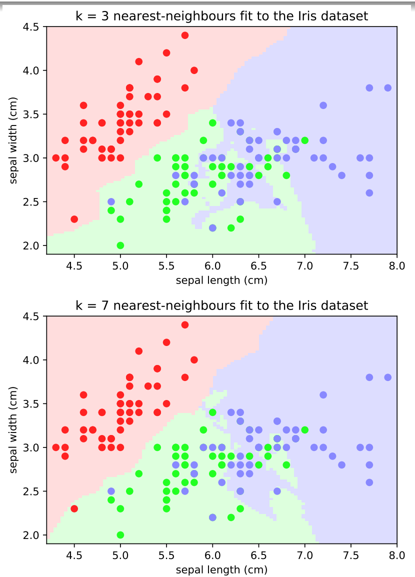


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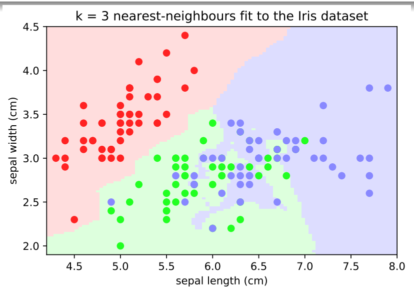


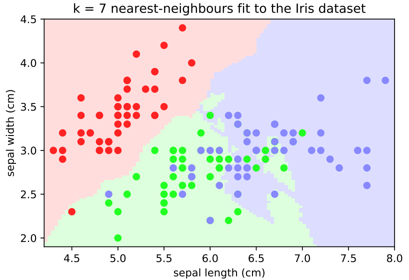


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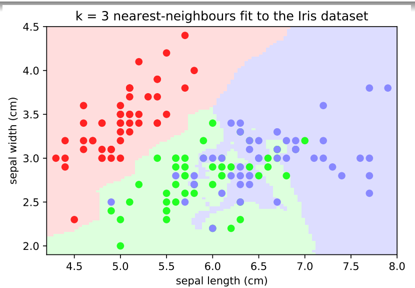


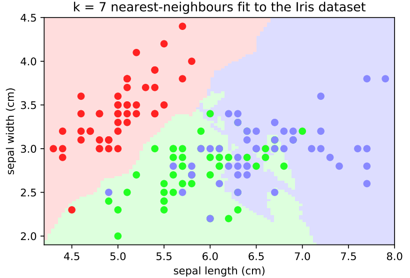


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- $k = 7$ has lower variance, pays less attention to "outliers", so region boundaries are smoother

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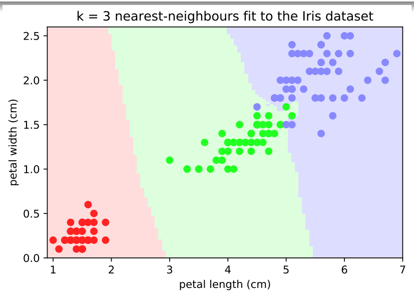

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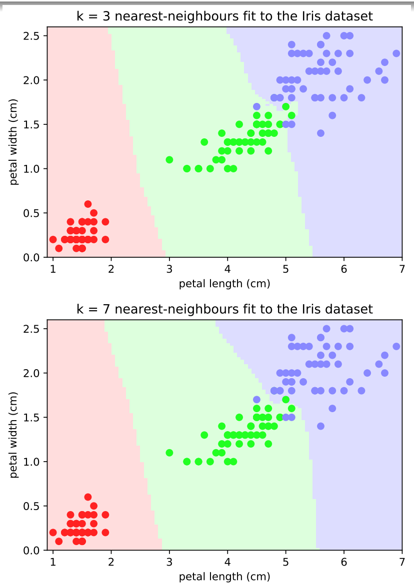

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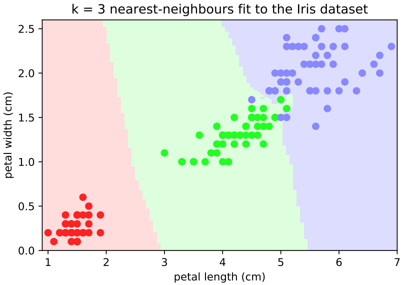


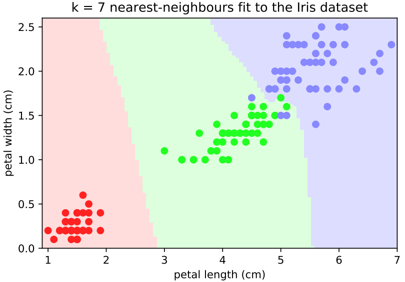


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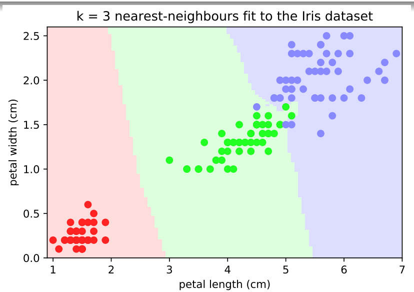


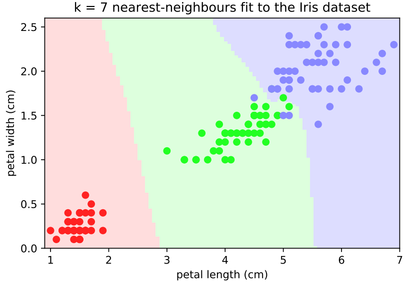


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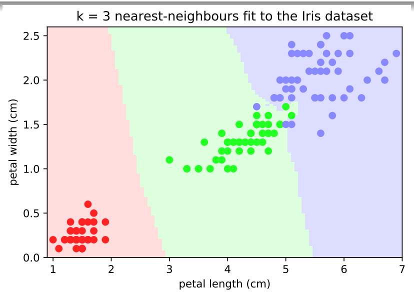


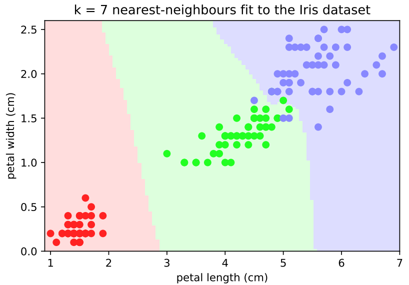


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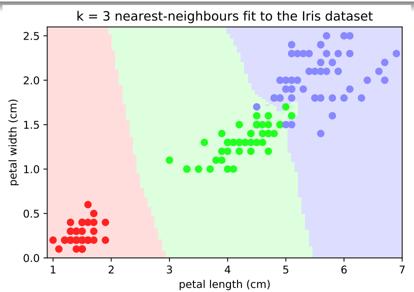


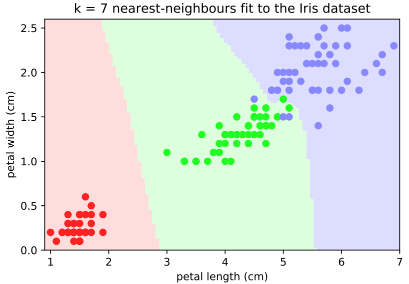


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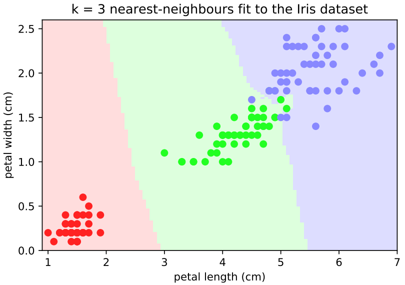


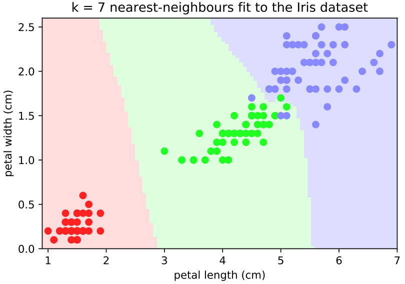


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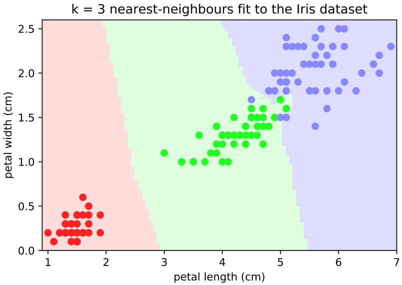


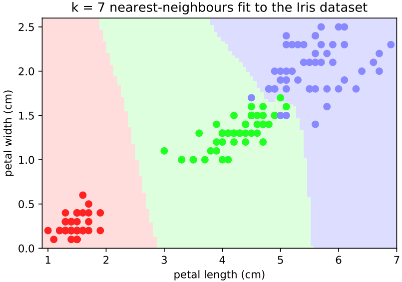


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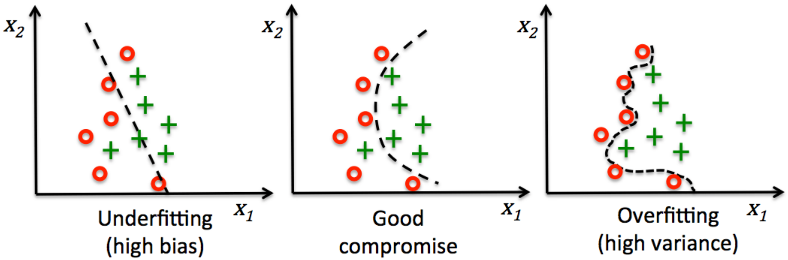
- The distance function $D$ depends on the number of dimensions $p$
- If the regions are well separated, as here, adding more dimensions rarely helps
- Over- and under-fitting is largely down to the choice of $k$

# Sidebar: Classification over- and under-fitting



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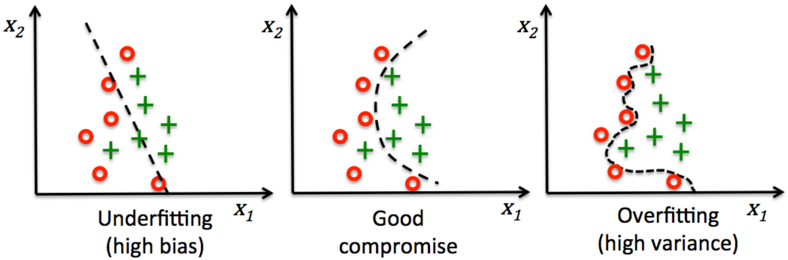


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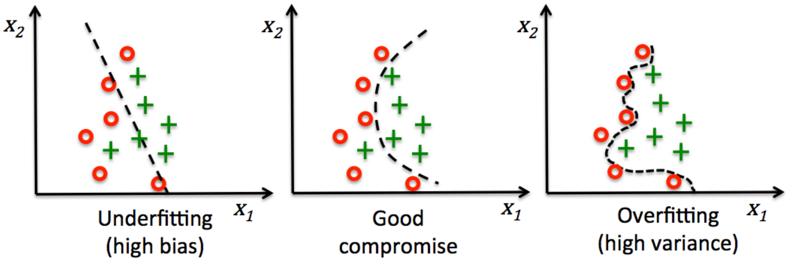


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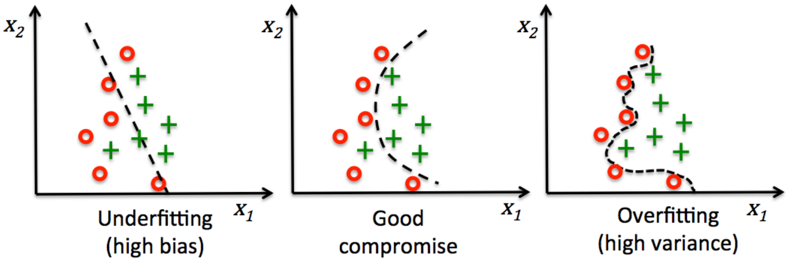


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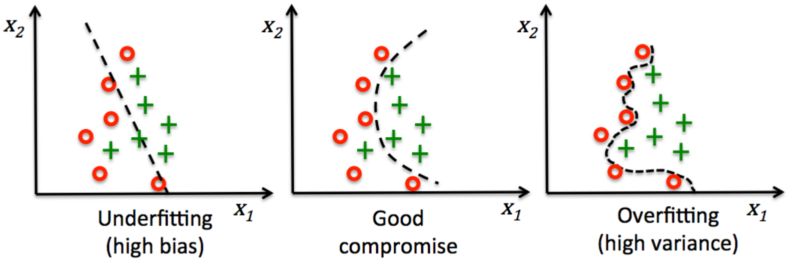


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As $k$ increases the boundary becomes smoother. Often that is what you need.

# Sidebar: Classification result summary: Confusion Matrix

### k = 1, training

### k = 3, training

### k = 3, test

# Sidebar: Classification result summary: Confusion Matrix

## k = 1, training

| | | *Actual* | | |
|---|---|---|---|---|
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| *predicted* | **S** | 50 | 0 | 0 |
| | **V1** | 0 | 50 | 0 |
| | **V2** | 0 | 0 | 50 |

## k = 3, training

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|---|---|---|---|---|
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- Unlike most other techniques, decision boundaries are implicit, not explicit.
- If the decision boundary is also needed, might be better to use a different algorithm.

# k-nearest-neighbours in python

**Python's `scikit-learn` libraries provide a general interface to model fitting that abstracts away most of the details.**

## Method (Identifying the Iris species)

```
# create the model
knn = neighbors.KNeighborsClassifier(n_neighbors=5)

# fit the model
knn.fit(X, y)

# What kind of iris has 3cm x 5cm sepal and 4cm x 2cm petal?
result = knn.predict([[3, 5, 4, 2],])

# it is a versicolor...
print(iris.target_names[result])

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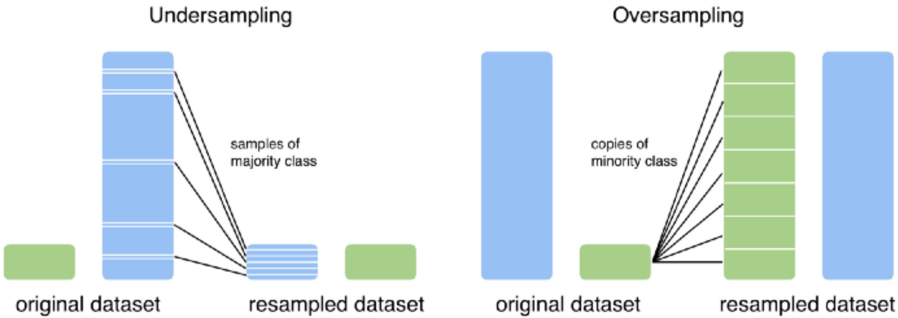
Very few lines of code are needed!

# How might things go wrong?




K nearest neighbors is very sensitive to unbalanced data, so need to be careful!!

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- We can use such metrics to validate our classifier choice and search for optimal hyperparameters (*hyperparameter tuning*)