dm24s1

Topic 02 : Motivating Example

Part 01 : Introduction to Classification

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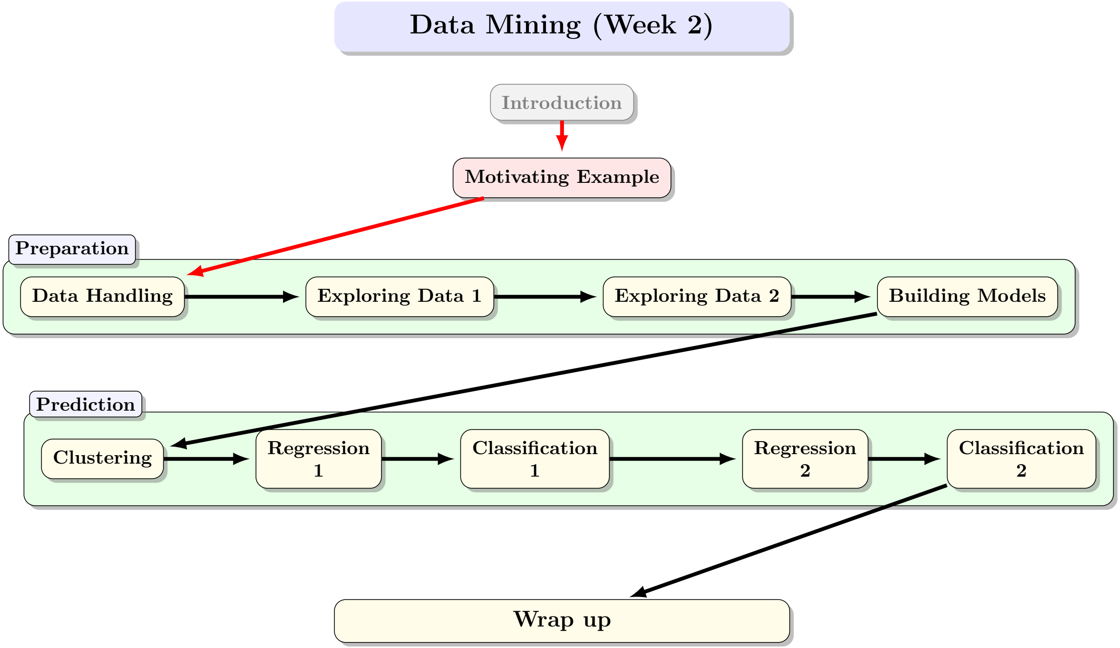
Autumn Semester, 2024

Outline

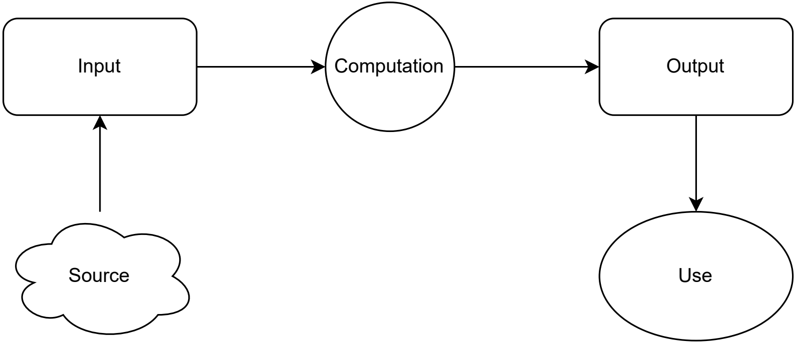
- How classification differs from regression
- Classification metrics
- Lazy vs Eager learners



Data Mining (Week 2)
Introduction
Motivating Example
Preparation
Data Handling
Exploring Data 1
Exploring Data 2
Building Models
Prediction
Clustering
Regression 1
Classification 1
Regression 2
Classification 2
Wrap up

Outline

What does it mean to learn from data?



Programmed Computation

- Explicit, detailed programming logic

Learned Computation

- Implicit, learning from examples

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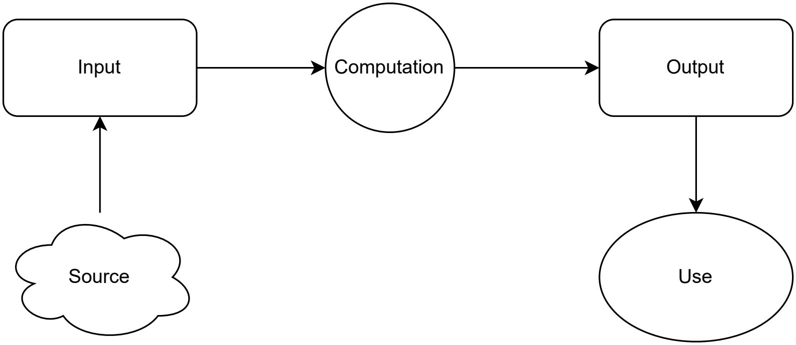

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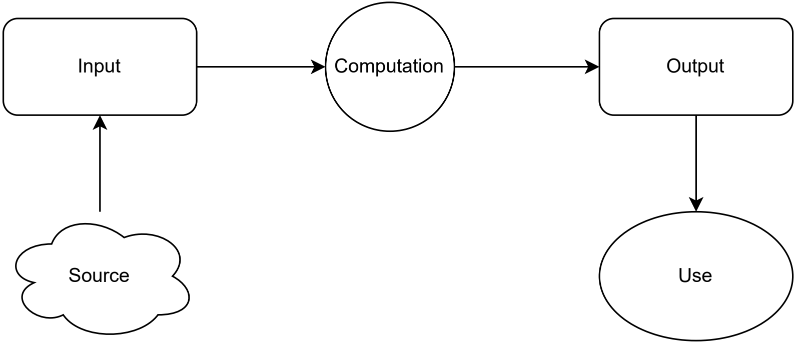

Programmed Computation

- 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

Benefits

- Less programming effort
- Subtle rules are inferred
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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

Lazy learner

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Eager learner

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

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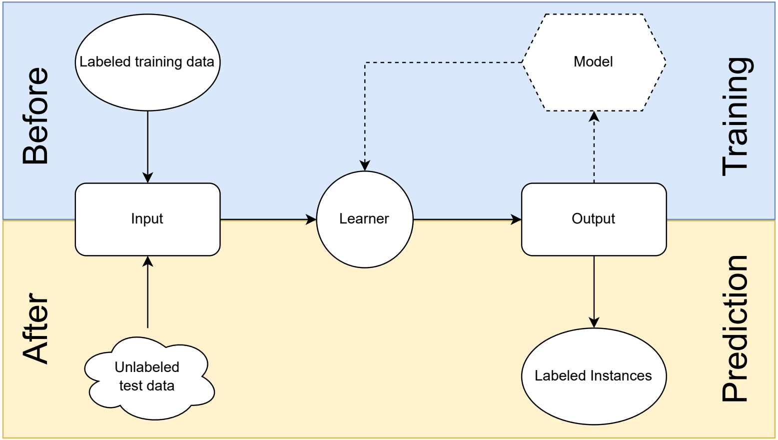
- Some *classifiers* generate class membership probabilities en route to predicting class membership (of the most likely class), so the predicted class can be defined by a set of numbers rather than a simple label.
- There are many classification algorithms!
- We choose one of the simplest today, which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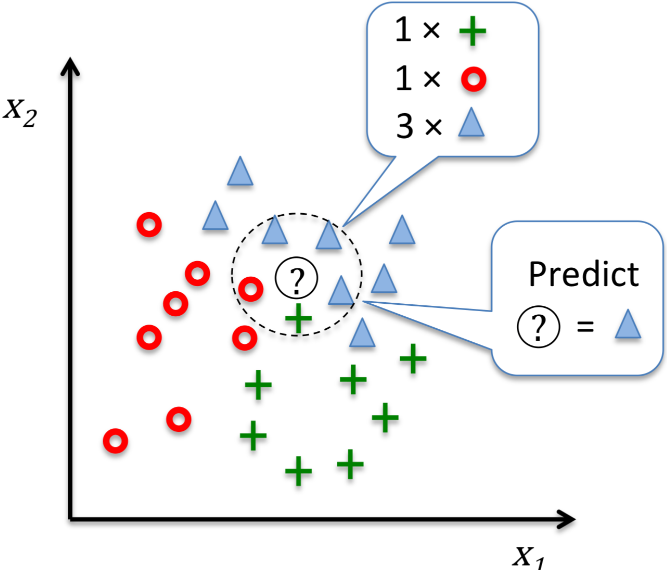
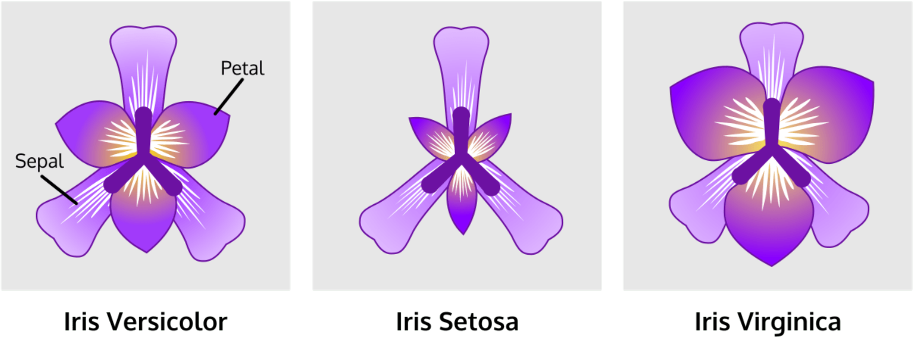
K-Nearest Neighbours: Example prediction

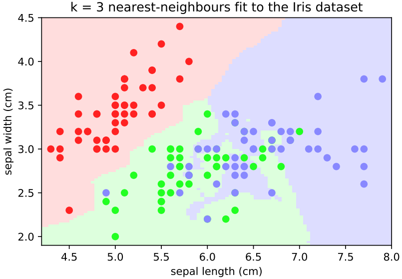


Classifying iris species



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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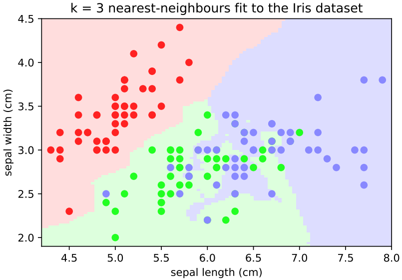

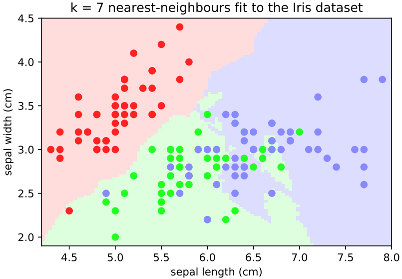

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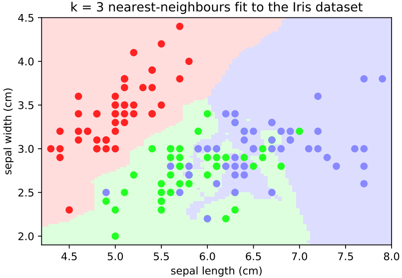

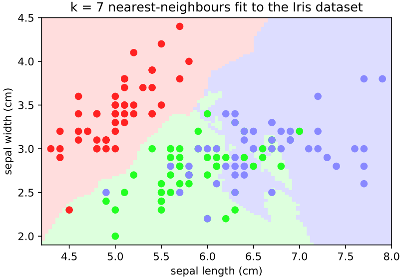

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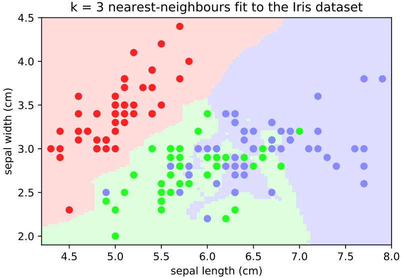

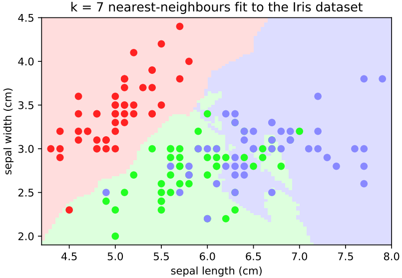

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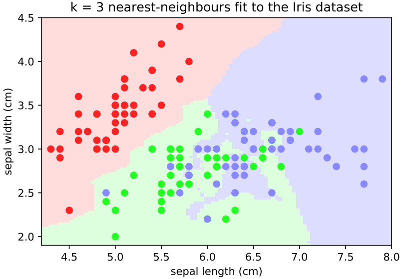

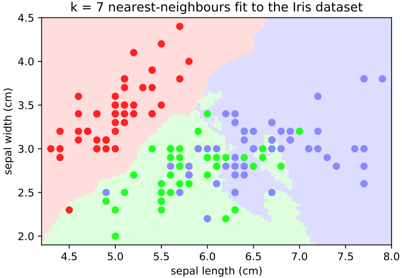

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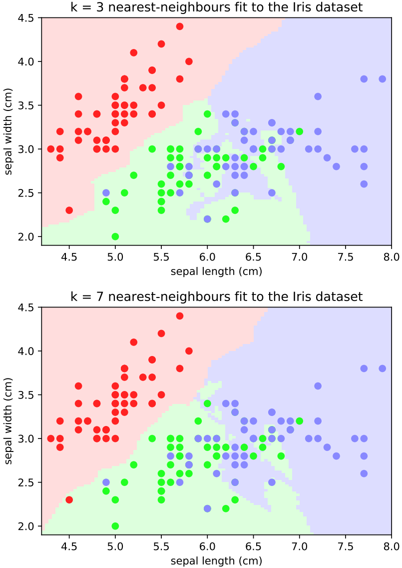

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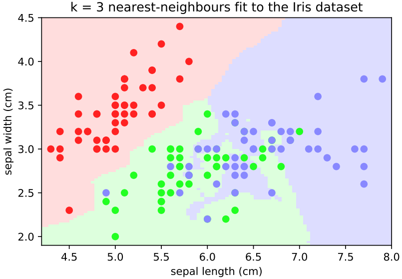

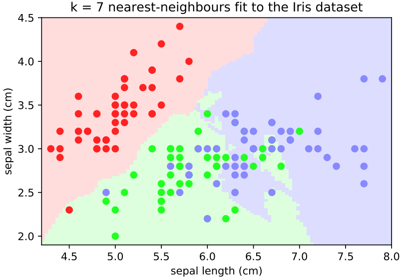

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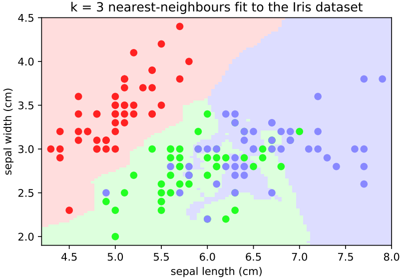

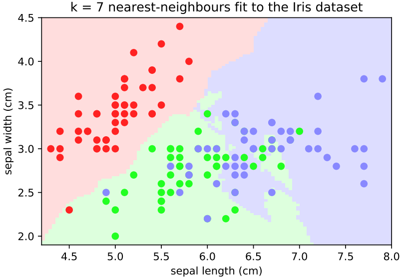

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- $k = 7$ has lower variance, pays less attention to “outliers”, so region boundaries are smoother

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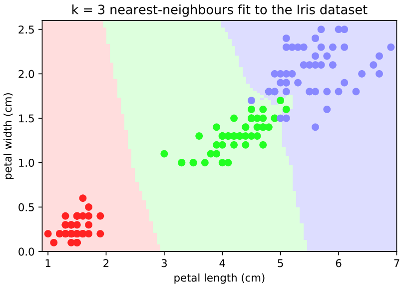

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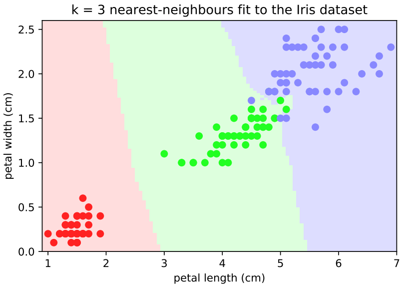

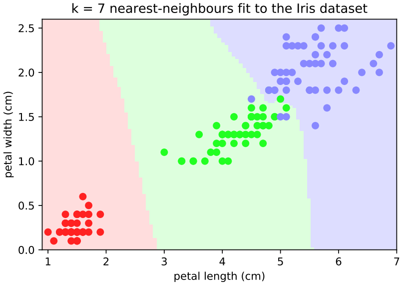

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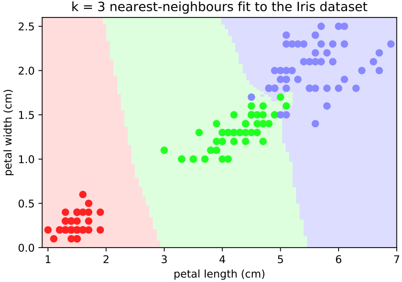

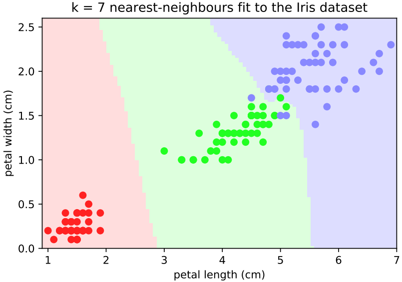

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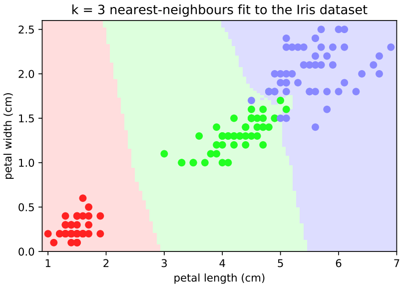

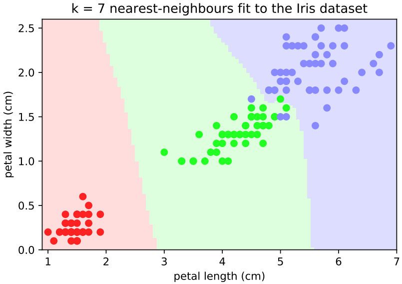

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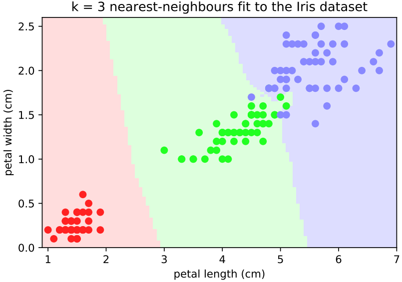

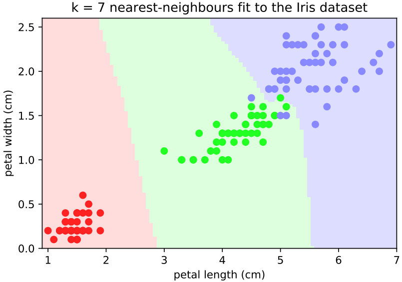

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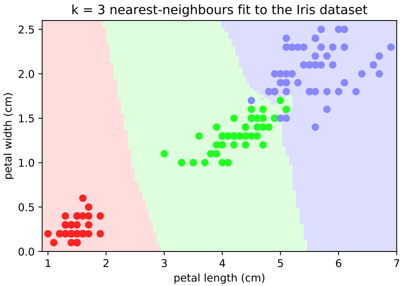

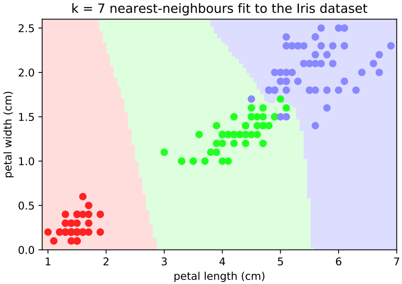

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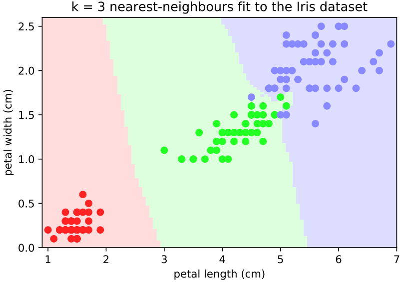

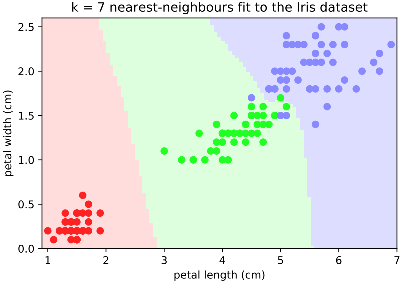

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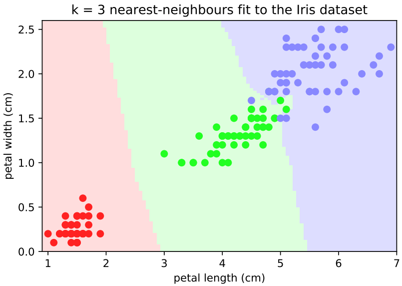

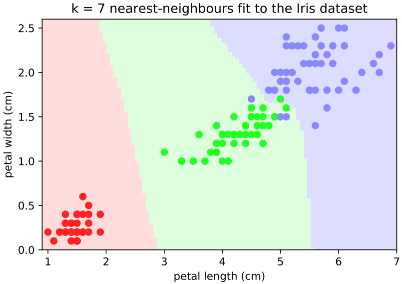

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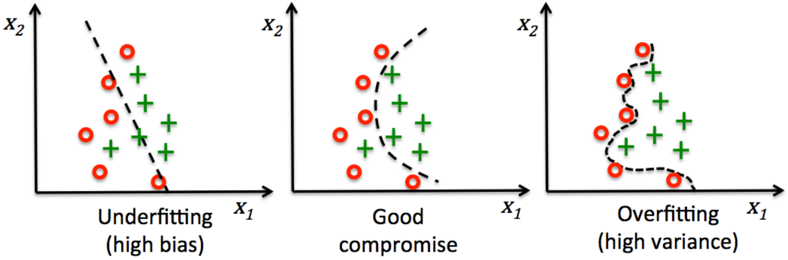
- The distance function D depends on the number of dimensions p
- If the regions are well separated, as here, adding more dimensions rarely helps
- Over- and under-fitting is largely down to the choice of k

Sidebar: Classification over- and under-fitting



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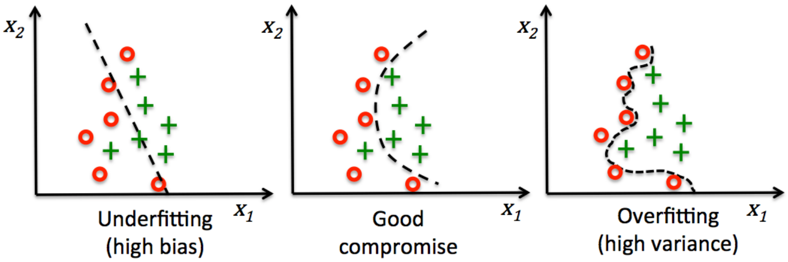

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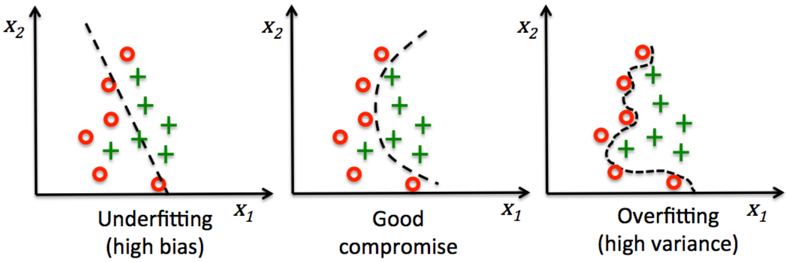

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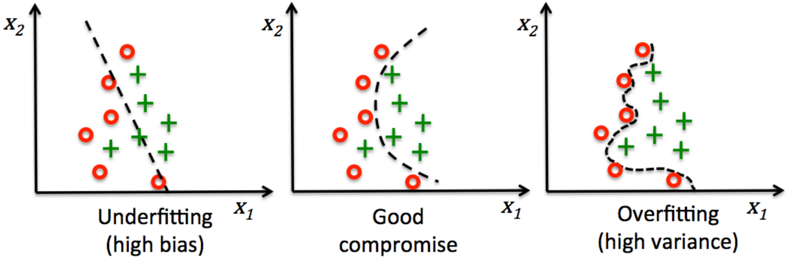

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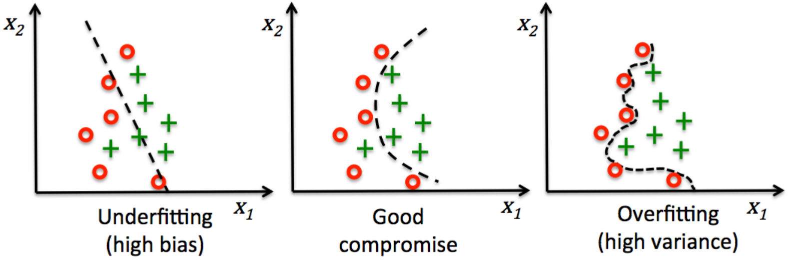

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As k increases the boundary becomes smoother. Often that is what you need.

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		
		S	**V1**	**V2**
predicted	**S**	50	0	0
	V1	0	50	0
	V2	0	0	50

k = 3, training

		Actual		
		S	**V1**	**V2**
predicted	**S**	50	0	0
	V1	0	47	3
	V2	0	3	47

k = 3, test

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(Columns: *Actual*)

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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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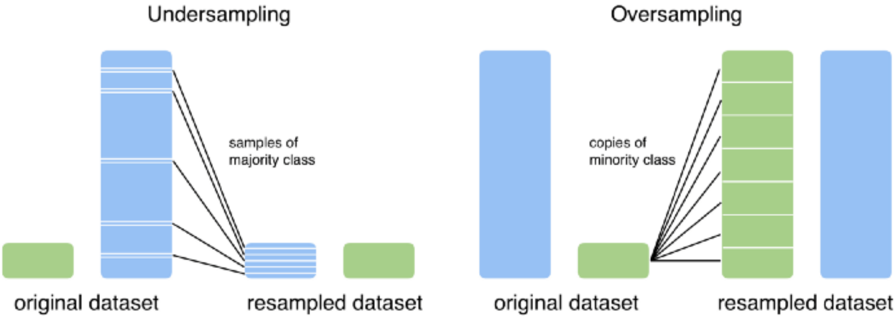
Very few lines of code are needed!

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*)