

An introduction to classification

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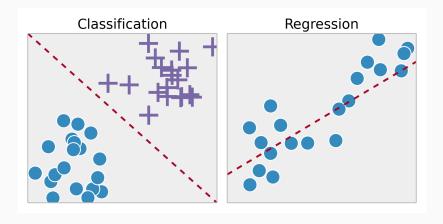
Regression

- · Predict a continuous value
- Minimise a loss function that measures how 'off' (numerically) our predictions are

Classification

- Predict a class
- Minimise a loss function that measures how 'inaccurate' the predicted classes are

Regression versus classification

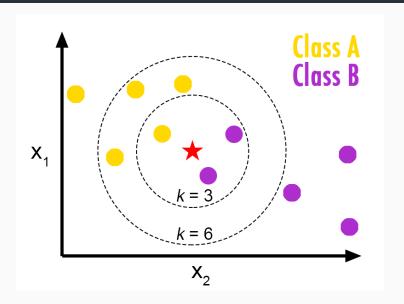


Given a new observation...

- Find the k 'most similar' training sample(s)
- · Predict the most common class among them

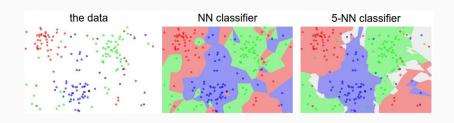
Questions

- · How do we define similarity?
- How many neighbours do we use?



Choice of k

- Larger $k \to \text{smoother boundaries}$, less noisy
- If k = N, we always predict the majority class



Distance metrics

Euclidean distance

$$\sqrt{\sum_{i} (x_i - y_i)^2}$$

KNeighborsClassifier(..., metric='euclidean', ...)

Manhattan distance

$$\sum_{i} |x_i - y_i|$$

KNeighborsClassifier(..., metric='manhattan', ...)

Distance metrics

Minkowski distance

$$\left(\sum_{i}|x_{i}-y_{i}|^{p}\right)^{1/p}$$

KNeighborsClassifier(..., metric='minkowski', ...)

- $p = 1 \rightarrow Manhattan distance$
- $p = 2 \rightarrow$ Euclidean distance

Weight of neighbours

Uniform weights

- · All k neighbours contribute equally to the prediction
- · Actual distance to each is ignored
- KNeighborsClassifier(..., weights='uniform', ...)

Distance weights

- Contributions are weighted by 1/distance
- · Closer neighbours influence the prediction more
- KNeighborsClassifier(..., weights='distance', ...)

Curse of dimensionality

As the number of variables (coordinates) increases...

- The volume of the space increases
- Pairwise distances become more similar → sparsity
- \cdot Some samples have huge neighbourhoods o 'hubs'



Classification accuracy

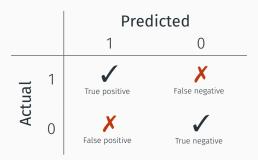
Classification accuracy

- Percentage of correct predictions
- Higher is better

Classification error (inverse of accuracy)

- Percentage of incorrect predictions
- · Lower is better

Confusion matrix



- · Gives a better understanding of behaviour
- Can be used to define multiple performance metrics

Sensitivity

(a.k.a. true positive rate or recall)

$$\frac{\sum \text{True positive}}{\sum \text{Actual} = 1}$$

Specificity

(a.k.a. true negative rate)

$$\frac{\sum \text{True negative}}{\sum \text{Actual} = 0}$$

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Perfect sensitivity:

- All sick are identified as sick
- Negative test result definitely rules out disease

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Perfect specificity:

- No healthy are identified as sick
- Positive test result useful for ruling in disease

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Perfect specificity:

- No healthy are identified as sick
- Positive test result useful for ruling in disease

Can we maximise both at the same time?

100% sensitivity

'Everyone is a terrorist!'

100% sensitivity

- 'Everyone is a terrorist!'
- All terrorists are stopped \rightarrow 100% sensitivity

100% sensitivity

- 'Everyone is a terrorist!'
- All terrorists are stopped \rightarrow 100% sensitivity
- No one can enter the country!

100% sensitivity

- 'Everyone is a terrorist!'
- All terrorists are stopped \rightarrow 100% sensitivity
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100% specificity

· 'No one is a terrorist!'

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- 'Everyone is a terrorist!'
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100% specificity

- · 'No one is a terrorist!'
- · All non-terrorists are allowed in ightarrow 100% specificity

100% sensitivity

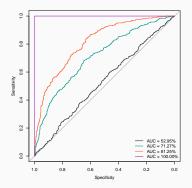
- 'Everyone is a terrorist!'
- All terrorists are stopped \rightarrow 100% sensitivity
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100% specificity

- · 'No one is a terrorist!'
- All non-terrorists are allowed in ightarrow 100% specificity
- · All terrorists are also allowed into the country!

ROC and AUC

Receiver Operating Characteristic (ROC) curve

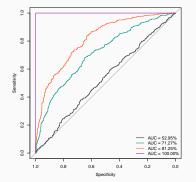


Sensitivity vs (1 - specificity)

 \rightarrow TP rate vs FP rate

ROC and AUC

Receiver Operating Characteristic (ROC) curve



Sensitivity vs (1 - specificity) \rightarrow TP rate vs FP rate

Area Under the Curve (AUC)

- Probability of Prediction(actual 1) > Prediction(actual 0)
- Random guess
 → AUC = 50% (diagonal)
- Higher is better
- Can be used for model selection

Precision

(a.k.a. positive predictive ratio)

$$\frac{\sum \text{ True positive}}{\sum \text{ Predicted} = 1}$$

Recall

(a.k.a. true positive rate or sensitivity)

$$\frac{\sum \text{True positive}}{\sum \text{Actual} = 1}$$

Precision

(a.k.a. positive predictive ratio)

$$\frac{\sum \text{True positive}}{\sum \text{Predicted} = 1}$$

- How 'useful' the search results are
- Perfect precision: only relevant results

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- How 'complete' the search results are
- Perfect recall: all relevant results

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- How 'useful' the search results are
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- How 'complete' the search results are
- Perfect recall: all relevant results

Can be summarised into an F_1 or F_β score

Cost-benefit analysis

- Assume that the four possible outcomes of the classification have costs and benefits
- · In economics, this is the 'utility function'
 - > 0 desirable
 - = 0 neutral
 - < 0 undesirable
- Utilities needn't be symmetrical

EXERCISE: planning an outdoor activity

- You have 20 people enrolled in an outdoor activity costing £30 per participant
- The day before the activity, you check the weather forecast and decide to either:
 - · If sunny, go ahead, which costs you £5 per participant
 - · If rainy, cancel and refund the participants
- The day of the activity, it will either:
 - · Be sunny, in which case you get to keep the profit
 - · Rain, in which case you'll refund the participants

Question: what is the utility (profit) matrix?

EXERCISE: planning an outdoor activity

The first weather forecast you consider is free, and has the following confusion matrix:

		Forecast	
		*	////
Actual	*	20%	20%
	//// ////	10%	50%

Questions

- What are the sensitivity, specificity, and recall?
- What is the expected profit?

EXERCISE: planning an outdoor activity

The second weather forecast costs £15, and has the following confusion matrix:

		Forecast	
		*	<i>''''</i>
Actual	*	30%	5%
	////	10%	55%

Questions

- What are the sensitivity, specificity, and recall?
- What is the expected profit?