# Supervised Learning

@cambridgespark

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# Fitting a response to data

**Classification**

- Training data: (point, class)
- Ex: Reading digits (image, {0, 1, ...9})

**Regression**

- Training data: (point, value)
- Ex: Predict salary (characteristics, salary)

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# Building a supervised model

True relationship between x and y represented by a function **f**:

$$X \rightarrow f(x) = y$$

You want to build a model **f'**:

$$X \rightarrow f'(x) \approx y$$

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Neural Networks can, in theory, represent any function.

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# Training and testing a model

Workflow

- **TRAINING**: Consider some of the data (training data):
  - Build a model **f’** which works well on it
- **TESTING**: Consider the rest of the data (test data)
  - Check how **f’** is performing on that

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The test data is necessarily distinct from the training data in order to assess how your model generalises

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# Train-test split

- Usually around 70%-30% split
- Randomised for representativity
- Can be stratified if the data is imbalanced

When doing one hot encoding, what if the test set has new labels? Common source of bugs!

# Evaluating a model

**Loss function**: Measure of performance of a specific model evaluated on a given set of points S (usually training/test points)

E.g.: Mean Squared Error (MSE) for regression:

$$L_{\mathrm{MSE}}(\widehat{f}) = \sum_{i \in S} (\widehat{f}(x_i) - y_i)^2$$

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# Training a model = Minimising the loss

Consider a parametric model **f'** defined by a vector of parameters β

Best β is such that the loss is minimised

# Training a model = Minimising the loss

Consider a parametric model f’ defined by a vector of parameters $\beta$

Best $\beta$ is such that the loss is minimised

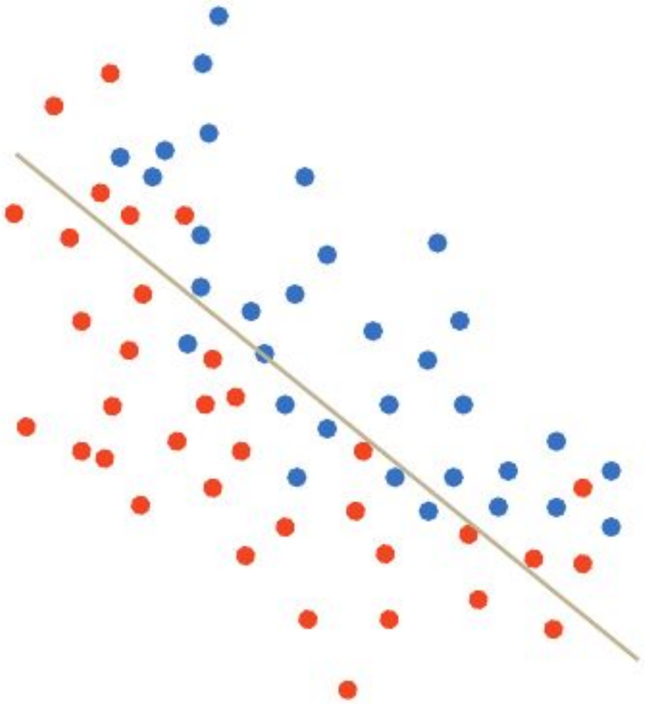
Training problem:

**Find $\beta^* \in \arg\min L(f')$**

# Training and testing: the cases

- Poor on training: **underfitting**

# Underfitting



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# Training and testing: the cases

- Poor on training: **underfitting**
- Good on training but poor on testing: **overfitting**

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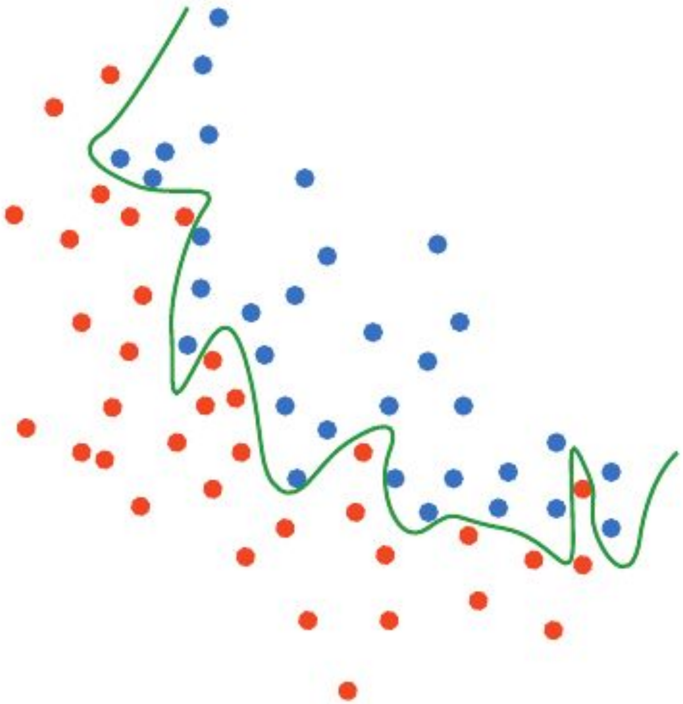
# Overfitting



# Training and testing: the cases

- Poor on training: **underfitting**
- Good on training but poor on testing: **overfitting**
- Good on training and good on testing: **job done**

More about this later, now how do you build a model in Python?

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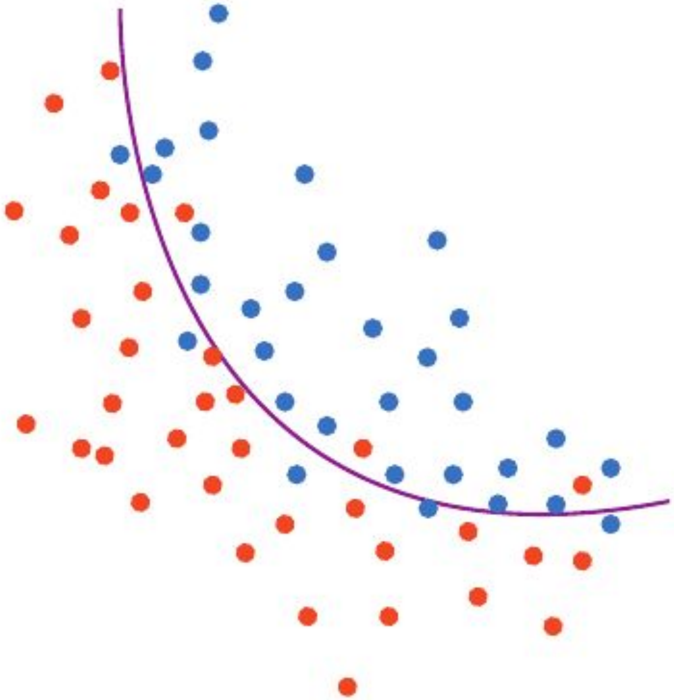
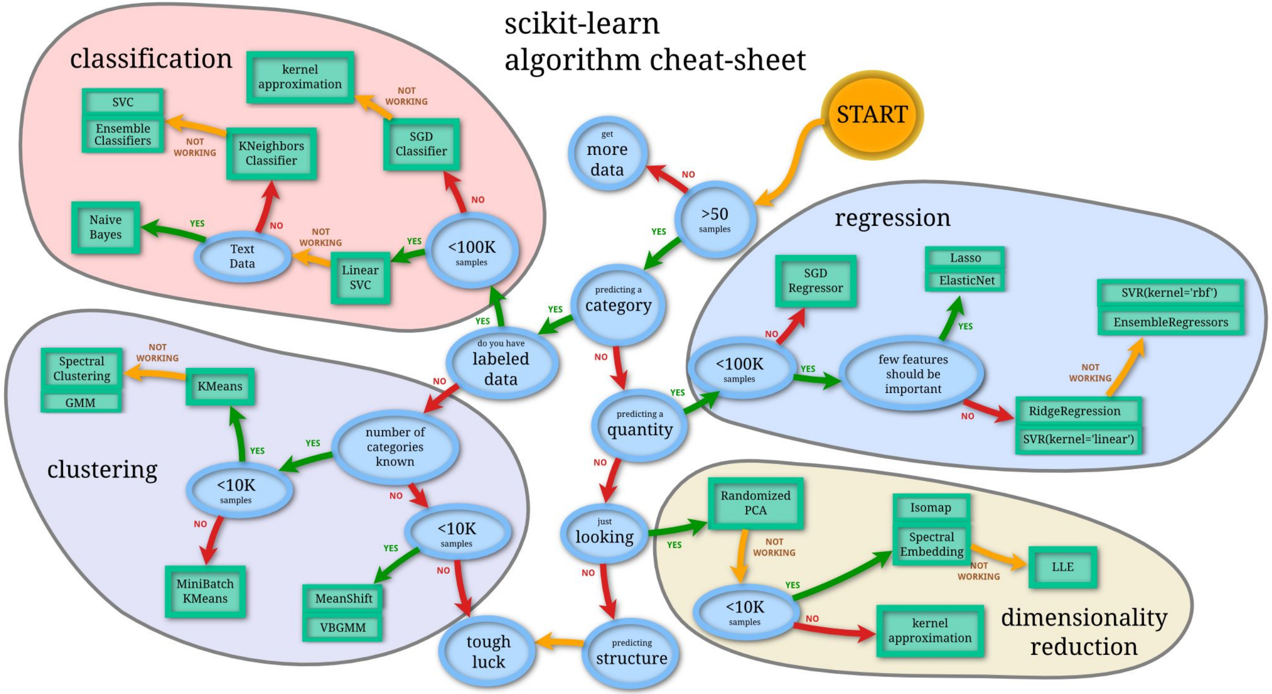
# Good fit



# Scikit-learn algorithm map

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Hands-on session

*01-supervised_learning.ipynb*
*Part 1: Preparing the data*

# A simple classifier: K-Nearest-Neighbours

Basic Idea:

- Consider the K training points closest to a test point
- Majority vote over which class the point should belong to

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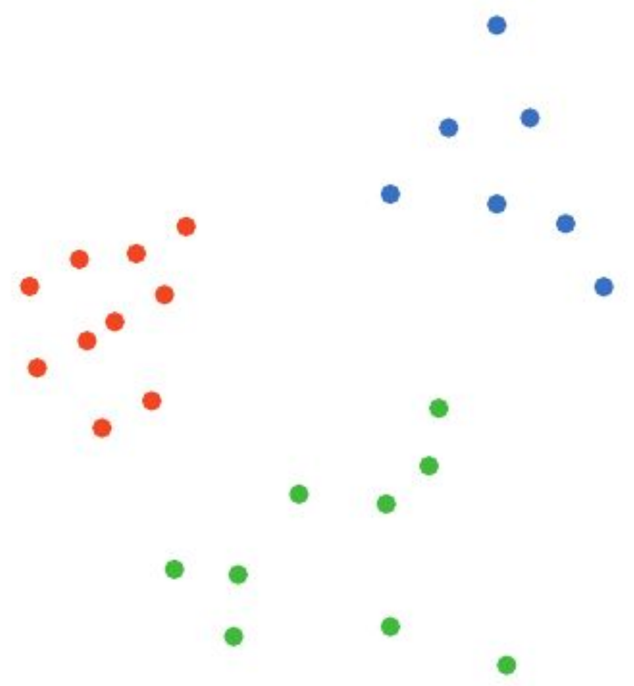
Let’s see...

# K-Nearest-Neighbours



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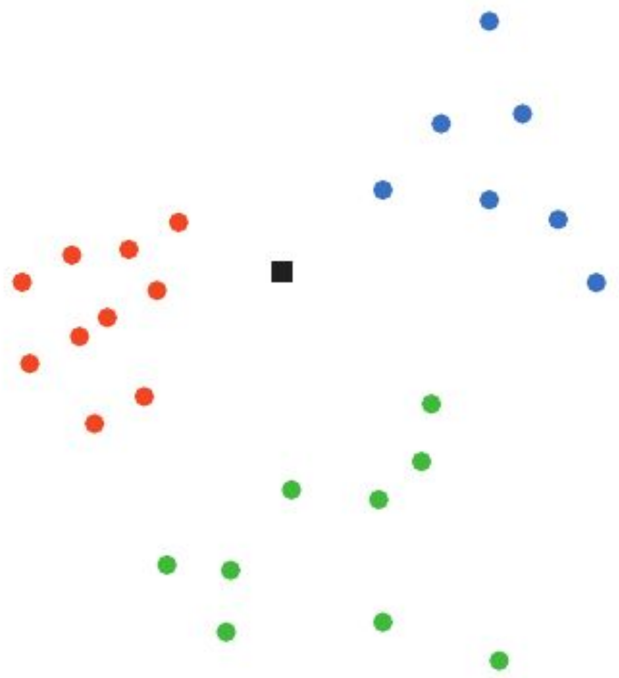
# K-Nearest-Neighbours



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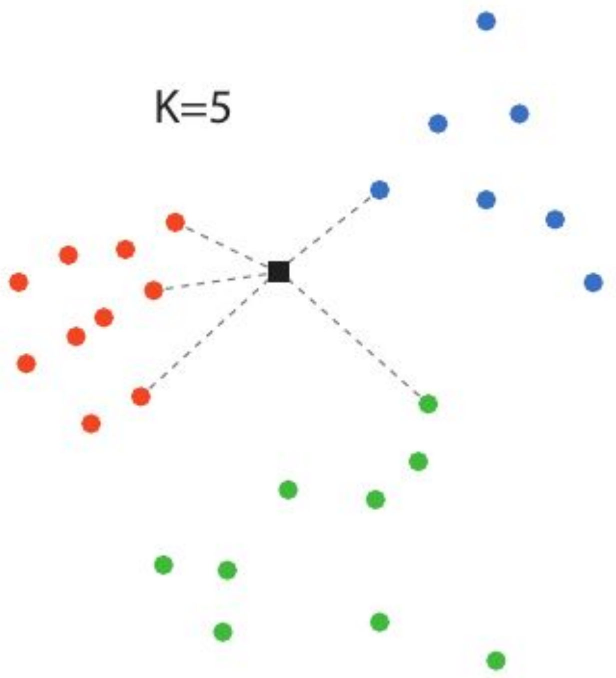

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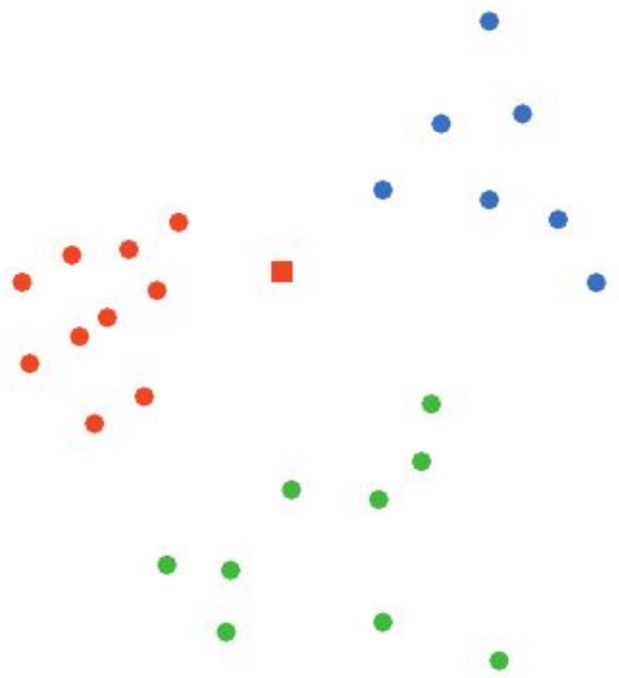

# Hyperparameter tuning

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You should only use the training set to adjust the model...

You should only use the test set for a final assessment of the model...

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# Training-Validation-Testing

1. Take a slice of the training data -> validation set
2. Apply the same procedure as before to adjust the model but using the smaller training set and validation set
3. Report performance on the untouched test set

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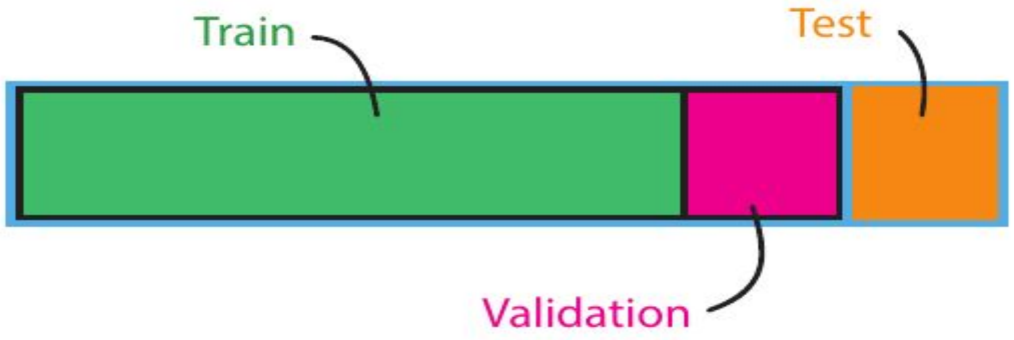

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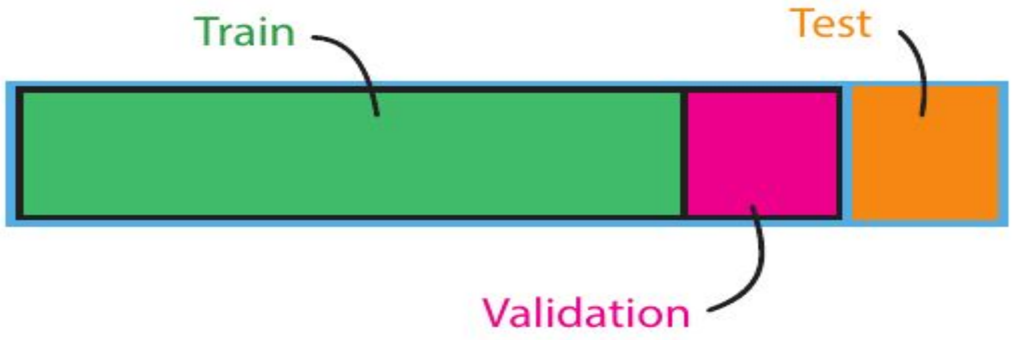


Nice but we're not using the whole training data...

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# From validation to cross-validation

We would like to:

- Use something like validation to tune our model without looking at the test set
- Exploit all the data from the initial training set

**WARNING**: There will be a lot of K's in the following slides, those are **not** referring to the k in kNN but for k-fold cross validation.

# K-fold cross validation

1. Shuffle the training set and slice it in k batches

For each model to train and evaluate:

2. Pick one slide s of the k batches
3. Use the rest of the batches to train the model
4. Compute accuracy on slice s (validation)

# K-fold cross validation

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For each model to train and evaluate:

2. Pick one slide s of the k batches
3. Use the rest of the batches to train the model
4. Compute accuracy on slice s (validation)
5. Go back to 2) and repeat for all slices
6. Report the average accuracy

Pick the model with the highest average accuracy

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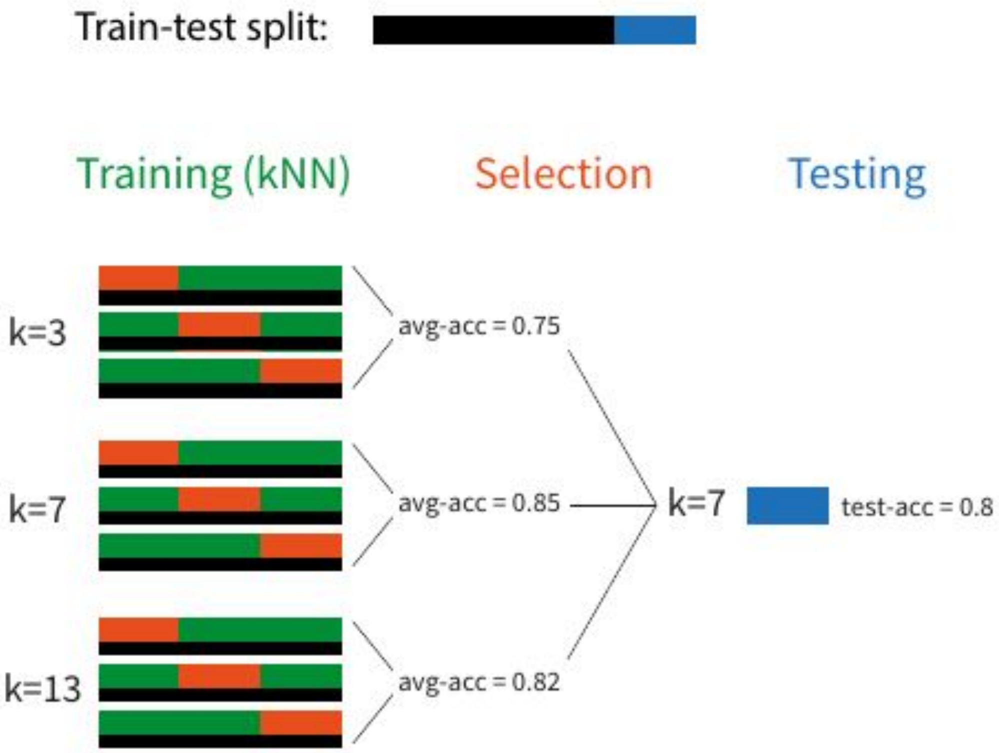
# K-fold cross validation

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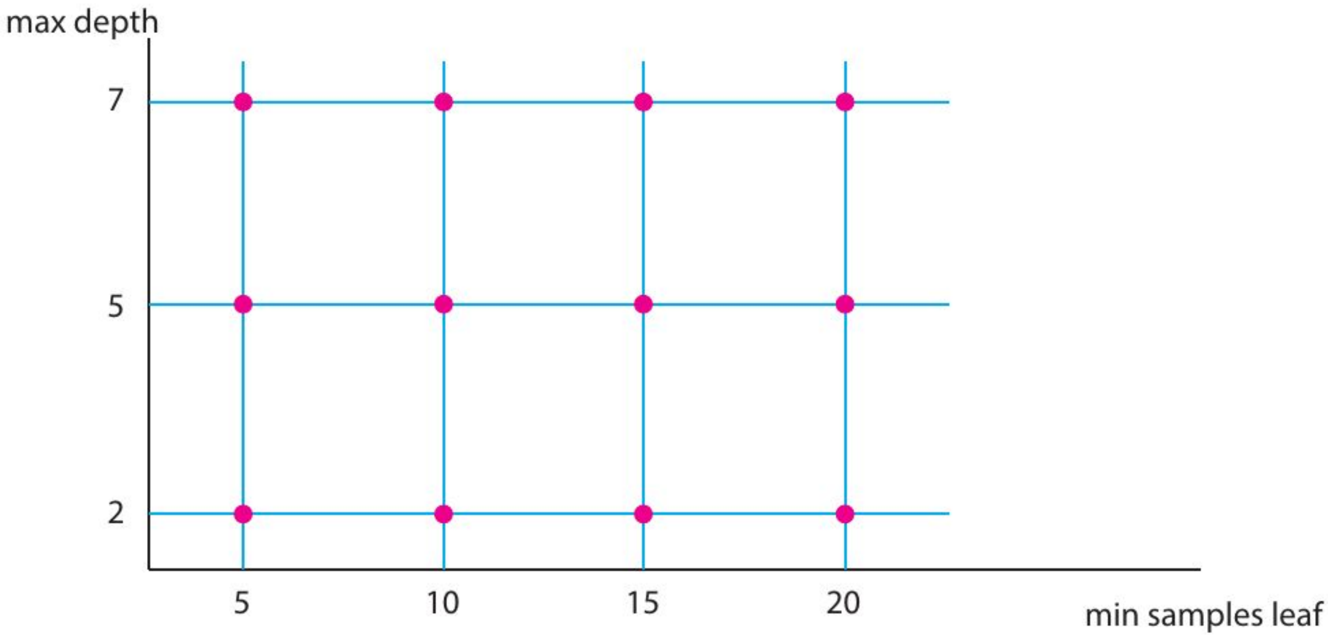
# K-fold cross validation

Now that we have a way to evaluate models with different parameters, how do we choose the parameters we want to test?

# Grid Search

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# Testing a binary classifier

On the test data, compare the predicted responses y' = f'(x) to the actual response y.

| | | PREDICTED | |
|---|---|---|---|
| | | Positive | Negative |
| ACTUAL | Positive | TP | FN |
| | Negative | FP | TN |

# Testing a binary classifier

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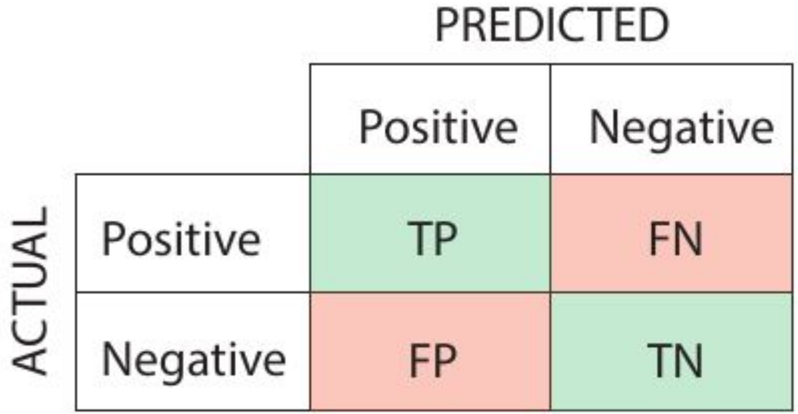


- Predicted Jargon from clinical trials, positive/negative defined by context
- This is the confusion matrix

# Testing a binary classifier

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| ACTUAL | Positive | TP | FN |
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**Accuracy**: (TP + TN) / N
**Sensitivity/Recall**: TP / (TP + FN)
**Precision**: TP / (TP + FP)

The metric of importance is usually dictated by context.

**Example**: Fraud

- Flagging a clean transaction as fraudulent (OK)
- Not flagging a fraudulent transaction (bad)

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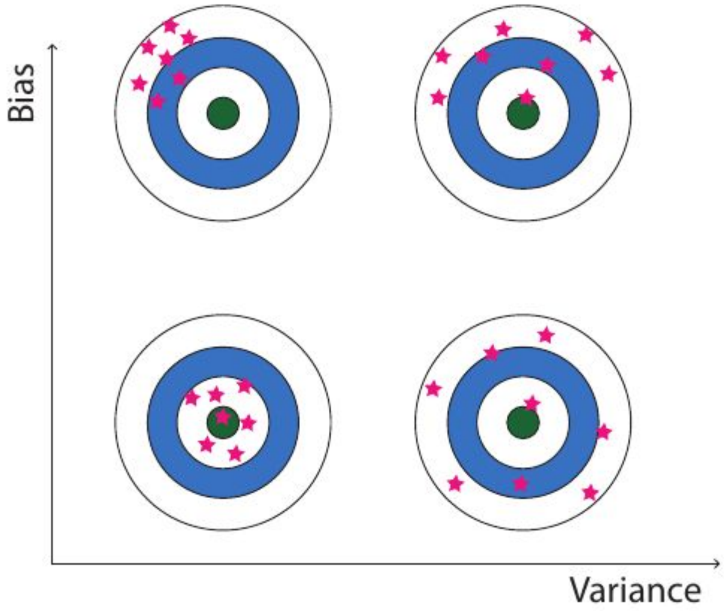
Hands-on session

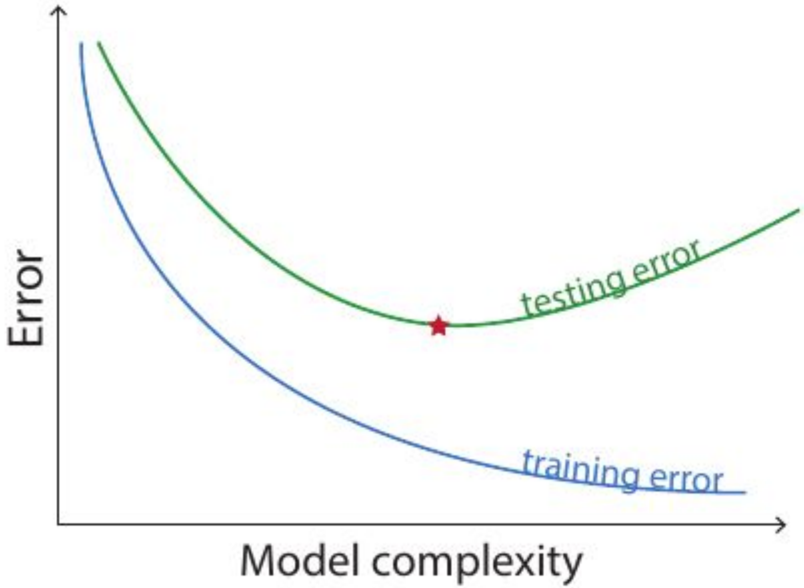
*02-supervised_learning.ipynb*
*Part 2: Training a model*

# Bias and Variance

One way of visualising the performances achieved by a model is to imagine that it corresponds to a dart thrower.



# Bias-Variance Tradeoff

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