Evaluation

Evaluation

- How do we know:
  - If our results are any good?
  - Which system is better?
  - If a change is for the better?

- Learning task T is any process by which a system improves performance **measured by P** from experience E.

- Example:
  - **T:** predict housing price
  - **E:** houses with known prices and independent variables
  - **P:** ?

- Measure the performance for a system:
  - Wrt to the task for which the system was built
  - Using a **TEST SET** for that task
  - Against a known **GROUND TRUTH**
  - Using **METRICS** that measures performance

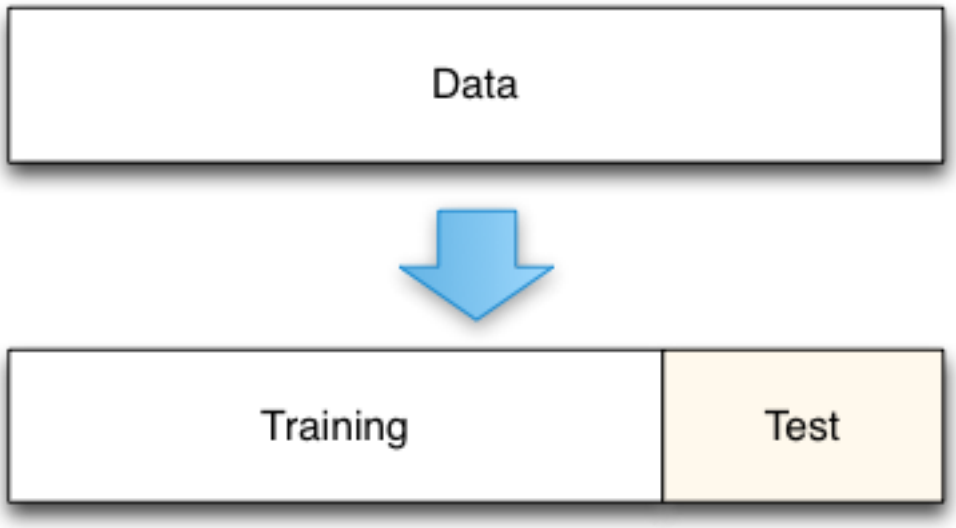
Test Set

- Using a **TEST SET** for that task
  - Test cases:
    - Houses with known features
    - Images of cars
  - Against known **GROUND TRUTH** labels
    - House prices
    - Car brand/Driving direction/Right of way

- We can use a test set to evaluate how close to the truth we are
- **Never train on your test data!**

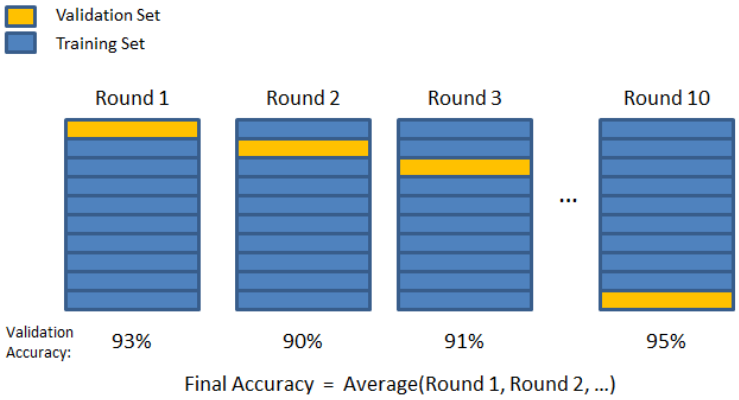
- Goal:
  - Learn a model for **unseen** (future) cases
  - Having learned to predict the test cases you can no longer use them to evaluate the performance on unseen cases

- **Split your data** in Training and Test set



- Example:
  - 80%-20% split
  - The test set size corresponds to confidence in the evaluation

- **Cross validation:**
  - Commonly used
    - N-fold cross validation (small data sets)



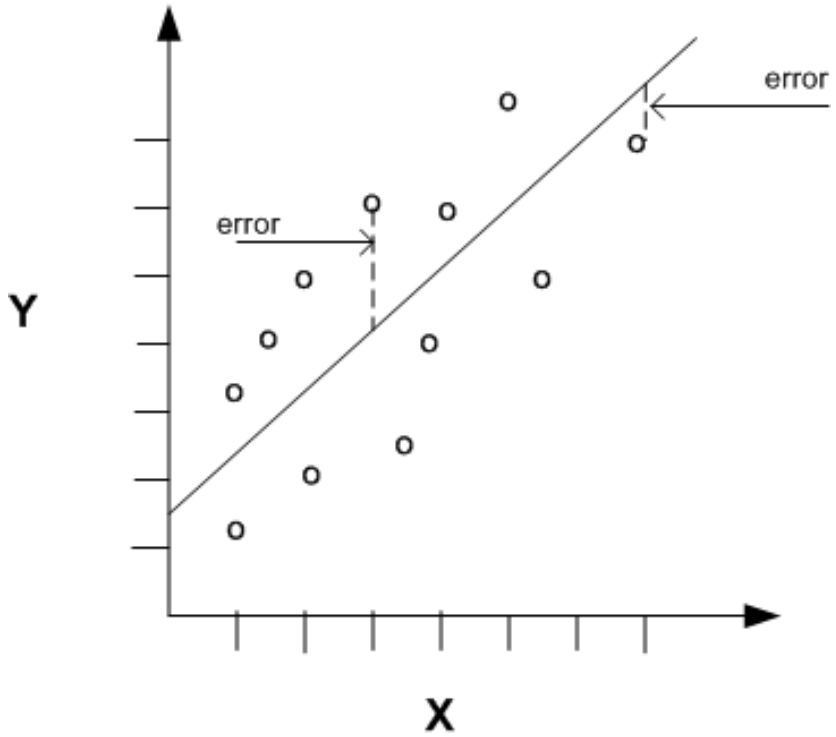
    - Leave-one-out (for very small data sets)

Metrics

- Think of metrics as:
  - An (imperfect) indication of improvement
- Many different metrics
  - **Effectiveness:**
    - Accuracy
  - **Efficiency:**
    - Speed, memory usage

- Type of task:
  - Regression
- Metric: **RMSE**
  - Root Mean Squared Error

- Weakness:
  - Outliers!



- Type of task:
  - Classification
  - **Confusion matrix**

	Guilty	Innocent
Predicted Guilty	True Positives 👍	False Positives 👎
Predicted Innocent	False Negatives 👎	True Negatives 👍

- **Accuracy:**
    - The fraction of correctly classified cases
- Accuracy = (TP + TN) / total
- System A = (10 + 65) / 100 = 0.75
- System B = (5 + 75) / 100 = 0.80

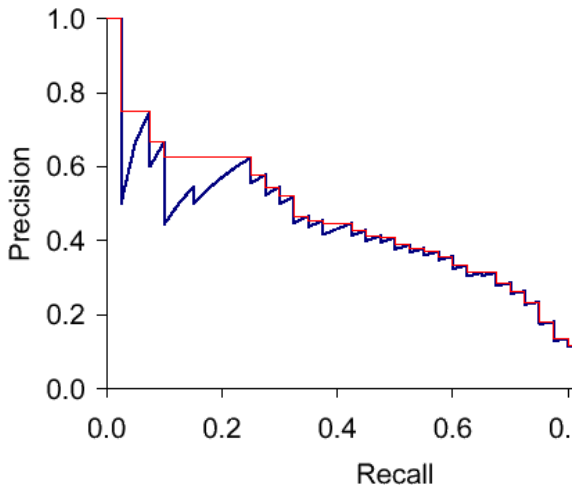
System A	Guilty	Innocent
Predicted Guilty	10	20
Predicted Innocent	5	65

System B	Guilty	Innocent
Predicted Guilty	5	10
Predicted Innocent	10	75

- **Recall:**
    - The fraction of positives that is identified
- Recall = TP / (TP + FN)
- System A = 10 / (10 + 5) = 0.67
- System B = 5 / (5 + 10) = 0.33

- **Precision:**
    - The fraction of the identified cases that is indeed positive
- Precision = TP / (TP + FP)
- System A = 10 / (10 + 20) = 0.33
- System B = 5 / (5 + 10) = 0.33

- Classic **tradeoff between metrics:**
    - The 'same' system can only improve one metric by sacrificing another



- There is a classic **tradeoff between metrics**
    - The 'same' system can improve on metric by sacrificing another
        - If you wish to convict more truly guilty persons you will also convict more innocent (higher recall → lower precision)
        - If you wish faster results you sacrifice accuracy
- True improvement is when you improve one metric without sacrificing another

- What metric to choose for our project?
    - Use what is commonly used in literature
    - The metric is beyond debate, reproducible, your results comparable to other work

- What if we think of a better metric?
    - That is one of the most common pitfalls.

Confidence

- How confident are we that B is better than A?
    - System A has RMSE = 0.8999
    - System B has RMSE = 0.8888
- Lower RMSE is better!

System A	System B
0.8999	0.8888
0.8500	0.8555
0.9200	0.9100
0.8800	0.8700

- We can statistically test whether B is **significantly** better than A:
    - Hypothesis 0: B is not better than A
    - Hypothesis 1: B is better than A
    - Based on the estimated probability of rejecting H0 when it is true.