# Topic 8 - Metrics for Performance Evaluation

# Aims of the Session

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- Learn different metrics used to evaluate classification frameworks

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- Learn different metrics used to evaluate classification frameworks
- Understand some alternatives to design proper tests

# Resources for the Lecture

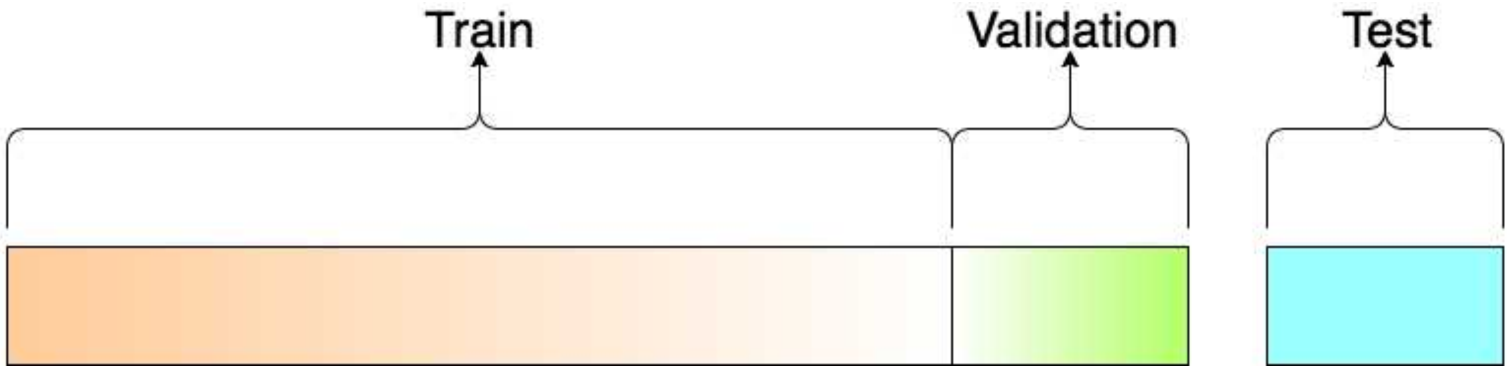
## Websites


- https://towardsdatascience.com/understanding-the-bias-variance-tradeoff-165e6942b229
- https://en.wikipedia.org/wiki/Precision_and_recall
- https://en.wikipedia.org/wiki/Sensitivity_and_specificity
- https://en.wikipedia.org/wiki/Confusion_matrix
- https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5
- https://towardsdatascience.com/multi-class-metrics-made-simple-part-i-precision-and-recall-9250280bddc2
- https://machinelearningmastery.com/k-fold-cross-validation/
- https://pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/
- https://medium.com/mlearning-ai/understanding-evaluation-metrics-in-medical-image-segmentation-d289a373a3f

## Online Courses

- Deep Learning Specialization by Andrew NG (Coursera)

# Some important concepts


Train
Validation
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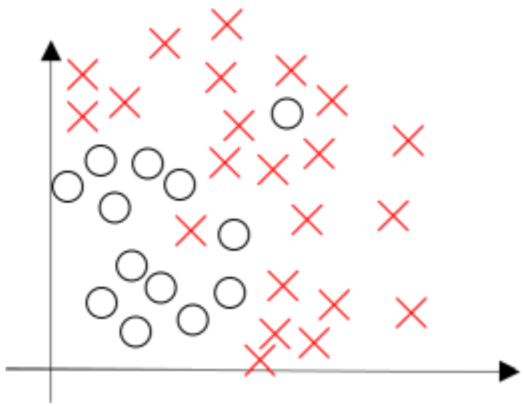

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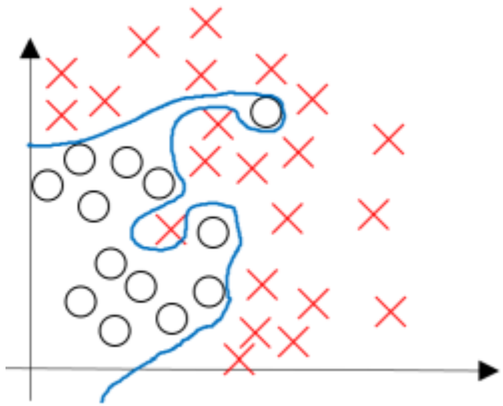

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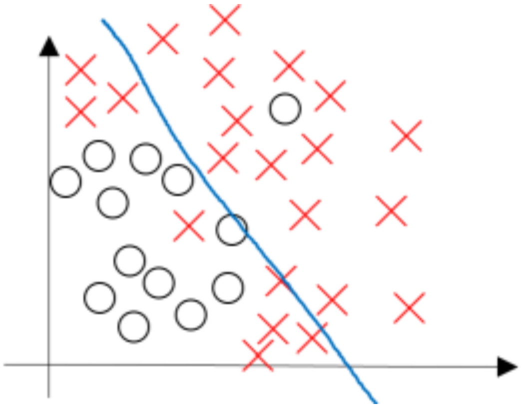
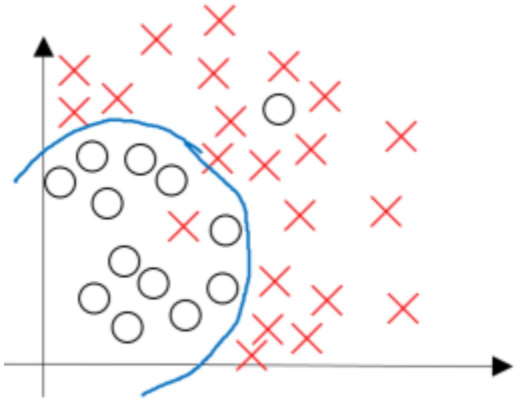


- What do we expect?

- What do we expect?



“just right”

# The bias-variance trade-off

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- As you can see, a model can either have high bias or high variance

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- As you can see, a model can either have high bias or high variance
- The main objective of machine learning is to find a function $h(x)$ that maps feature $X$ to class/target $y$ minimising:
    - bias error
    - variance error
    - irreducible error (noise in the data)

Typically[1], the **Error** of a learner/classifier is modelled using the following equation:

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$$Err(x) = Bias^2 + Variance + Irreducible\ Error$$

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**Why $Bias^2$?**

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    - Samples from the *positive class* that are classified correctly

# Performance Measures

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- `True Positives` (TP): This is what many people understand as *accuracy* (but is not!)
    - Samples from the *positive class* that are classified correctly
- `True Negatives` (TN): How many samples from the negative class are **NOT** classified as being from the positive one

- `False Positives` (FP): How many samples from the negative class are classified as being from the positive class
    - Also known in statistics as **False alarms** or **Type I Error**

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- `False Negatives` (FN): How many samples from the positive class are classified as being from the negative class
    - Also known in statistics as **Type II Error**

# Accuracy

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- Recall that we said that this is **not** a good measure for imbalanced datasets

- **WHY?**

# Error Rate

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- Also must be **between** $0$ **and** $1$
- **Do you think this one is good for imbalanced datasets?**

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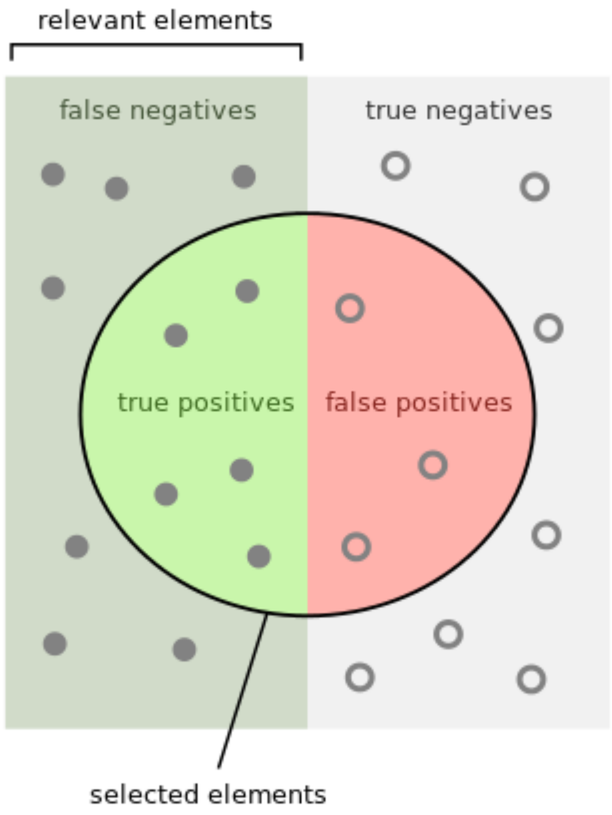

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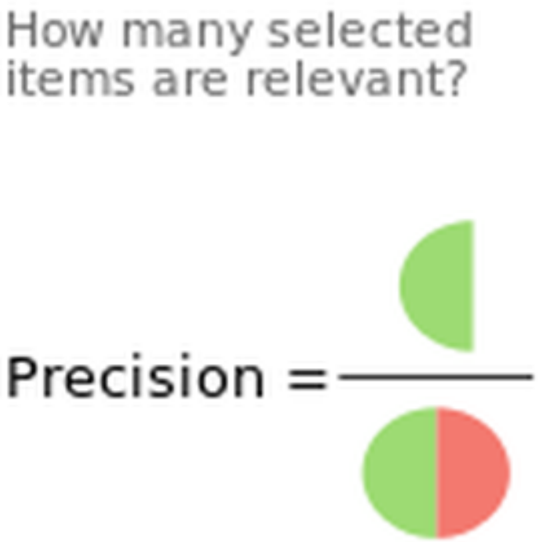

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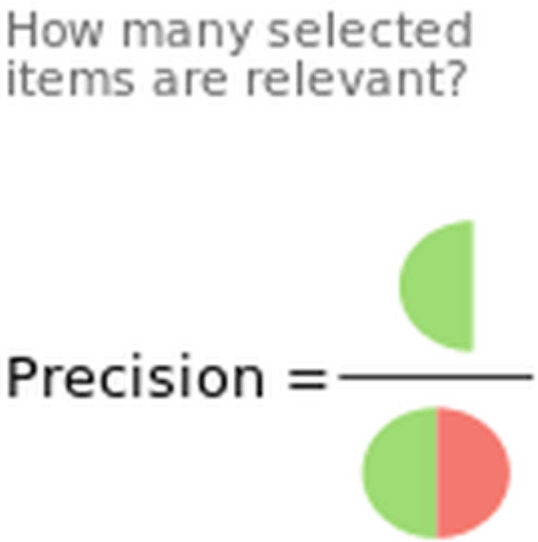


- How much of what I **have** I **need**?

Recall

## Recall

- $Recall = \frac{TP}{TP+FN}$

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- How much of what I **need** I **have**?

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- Most systems are known to have a precision/recall trade-off

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- Most systems are known to have a precision/recall trade-off
- **Which is better?**

F1-score (or F1-measure)

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- Harmonic mean between precision and recall

F1-score (or F1-measure)

- Harmonic mean between precision and recall
- $F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{2 \times TP}{(2 \times TP) + FP + FN}$

# Sensitivity and Specificity

## Sensitivity and Specificity

- Similar to precision and recall, but used more in the health sciences domain

# Sensitivity

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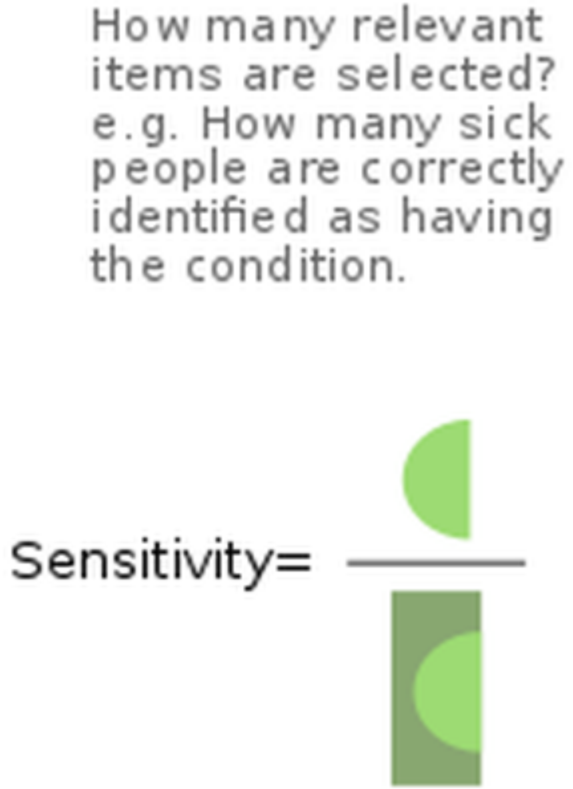

# Specificity

## Specificity

- The precision for the negative class

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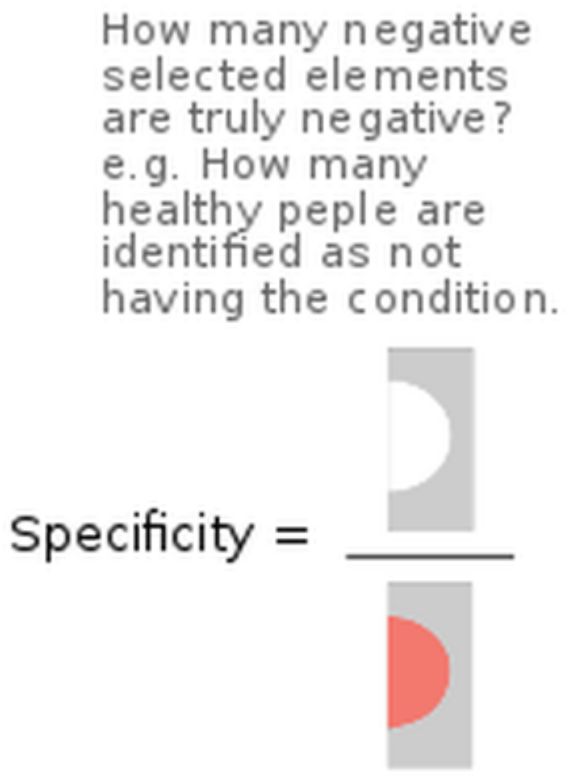

**Is there any "F-measure" for these two?**

# The Confusion Matrix

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Example

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- Also known as *error matrix*
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## Example

- A classifier has been trained to distinguish cats from dogs

- Assuming a sample of 13 animals (8 cats and 5 dogs), you get the following confusion matrix

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| | | Actual class | |
|---|---|---|---|
| | | **Cat** | **Dog** |
| **Predicted class** | **Cat** | **5** | 2 |
| | **Dog** | 3 | **3** |

- This table can also be interpreted with respect to the previously seen terms

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| | | Actual class | |
|---|---|---|---|
| | | **Cat** | **Non-cat** |
| **Predicted class** | **Cat** | 5 True Positives | 2 False Positives |
| | **Non-cat** | 3 False Negatives | 3 True Negatives |

Area under the Receiving Operating Characteristic (ROC) Curve

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- It is a probability curve that tells you how much your model is able to distinguish between classes
- Higher the AUC, better the model is capable of performing the distinction

- The curve plots **False Positive Rate** (x-axis) vs **True Positive Rate** (y-axis)
    - $FPR : 1 - Specificity$
    - $TPR : Recall\ (also\ known\ as\ Sensitivity)$

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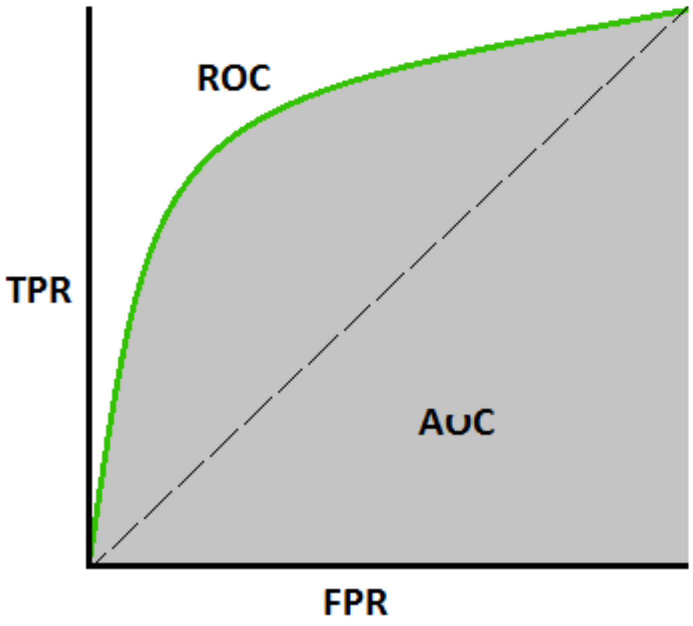

# Runtime

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- Not very "accepted" in the academic world, but extremely useful in the industrial one!
- You can import the `time` module in Python and use the `perf_counter()` function to calculate the time of processes running
    - Just be very careful where in your code you calculate the time!

In [1]:

```
import time

t = time.perf_counter()
# do stuff
x=0
for i in range(1000):
    x=x+i
# stuff has finished
print('Elapsed time: ',time.perf_counter() - t)
```

```
Elapsed time:  0.00035020000007079943
```

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- So far, we have only spoken of metrics in the context of binary datasets
- However, in most cases you will deal with multi-class datasets
- There are many ways to adapt the aforementioned metrics to these scenarios, the most common one being the **One vs All** approach
    - Comparing a metric of one class against the rest as if these were a single class

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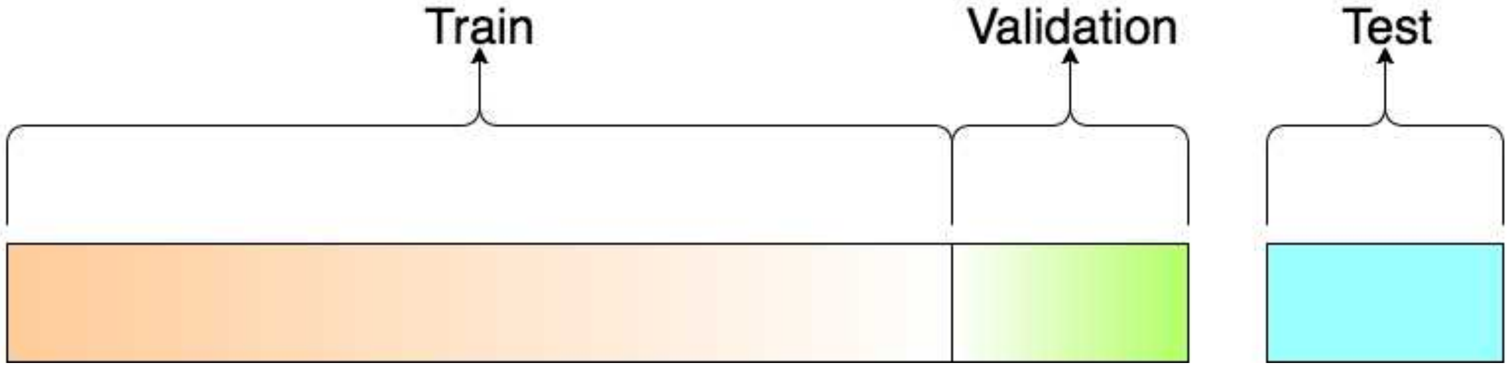
- `Micro` is the harmonic mean of all metrics, which derives in the system's accuracy
- To see an example of this, I recommend you to visit this site

# Validation Frameworks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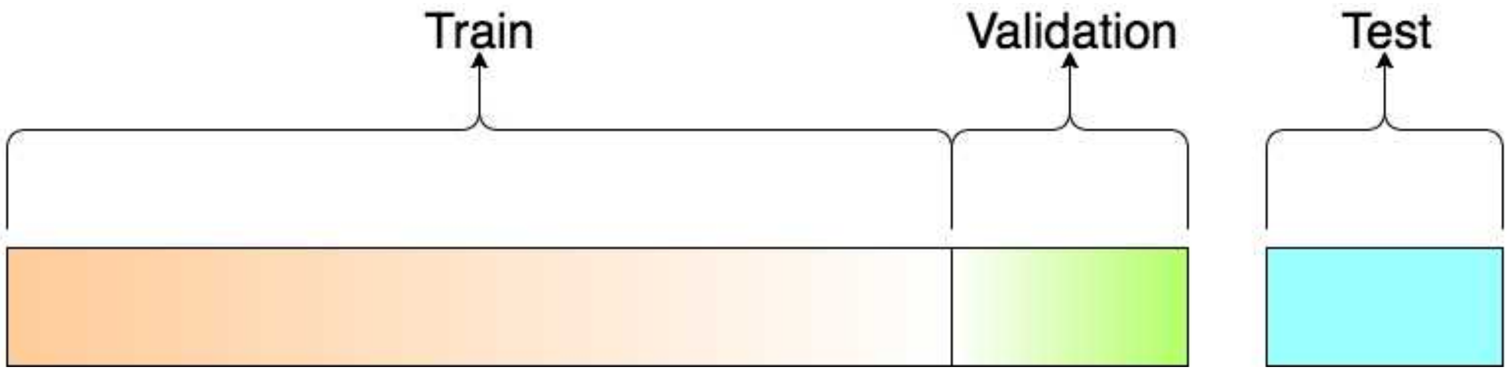


- Technically this is not the only way to split the data!

- Even when you split uniformly using train/val/test approach, you are still not considering that maybe some train/val data is better/worse for testing and vice versa!

- Even when you split uniformly using train/val/test approach, you are still not considering that maybe some train/val data is better/worse for testing and vice versa!
- To address this issue, there are some iterative validation frameworks which let you split data in different ways and perform multiple tests of the same model

# Cross validation

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- Simple to understand
- Reduces "bias"
    - i.e. over-optimistic results that may be caused due to chance
- Based on a single parameter $k$ which defined the number of times that the dataset will be *folded*

# How it works

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1. Shuffle the dataset

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2. Split the dataset into $k$ groups

3. For each group
    - Take that group as the test data
    - Take the remaining groups as the training data
    - Fit the model
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4. Once you are done, average/summarise all results

Which $k$ to choose?

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- Representative for the model: Large enough to be statistically significant!
- $k = 5$ and $k = 10$ are the usual standard, but it depends on how many samples you have!

- If you do $k = n$ ($n$ being the number of samples in the dataset) then you will test every sample as the test against the rest as the training set

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- This is also known as the **Leave-One-Out** approach

- Some datasets (like the one you will use in the bonus part of the lab) already are partitioned in the $k$ folds

# Metrics used in Computer Vision

# IoU (A.K.A. Jaccard Index)

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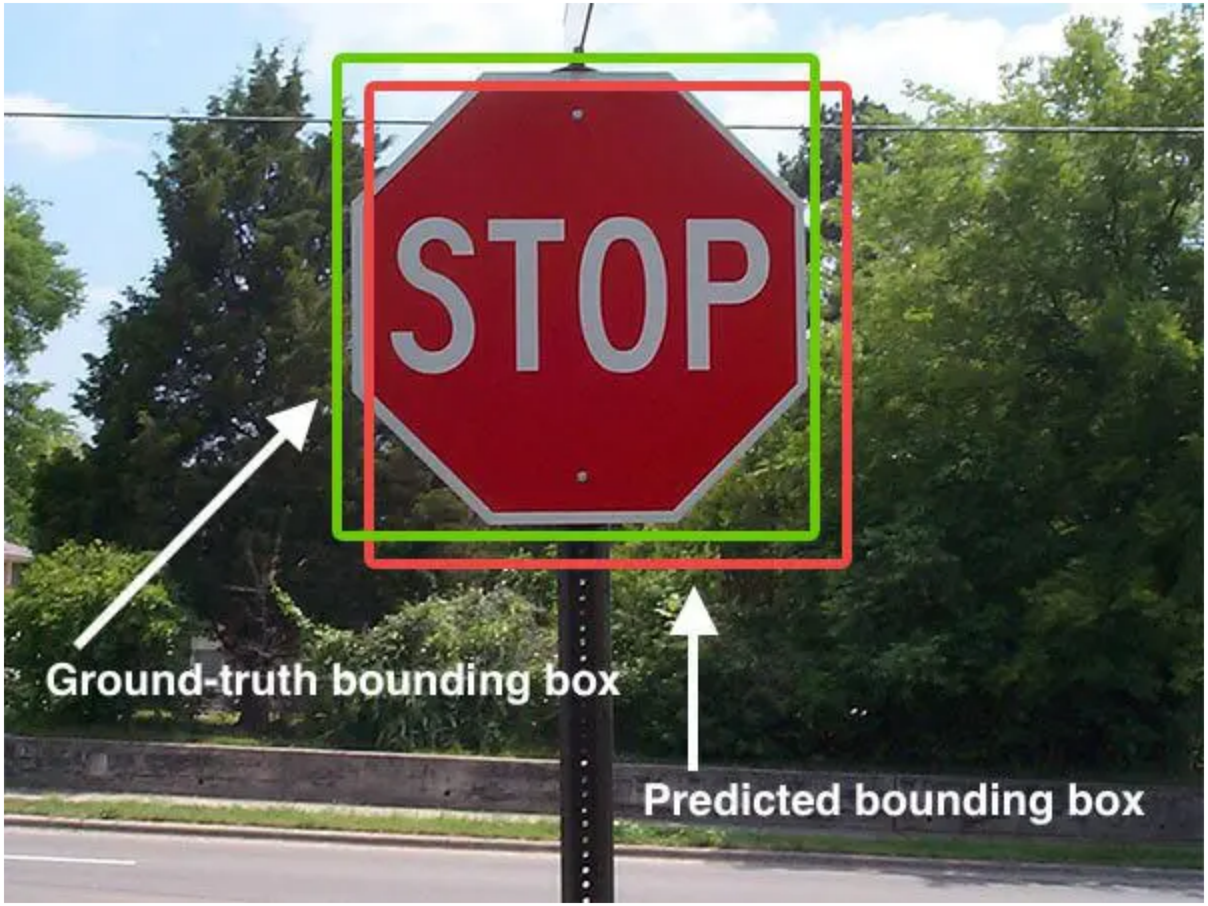

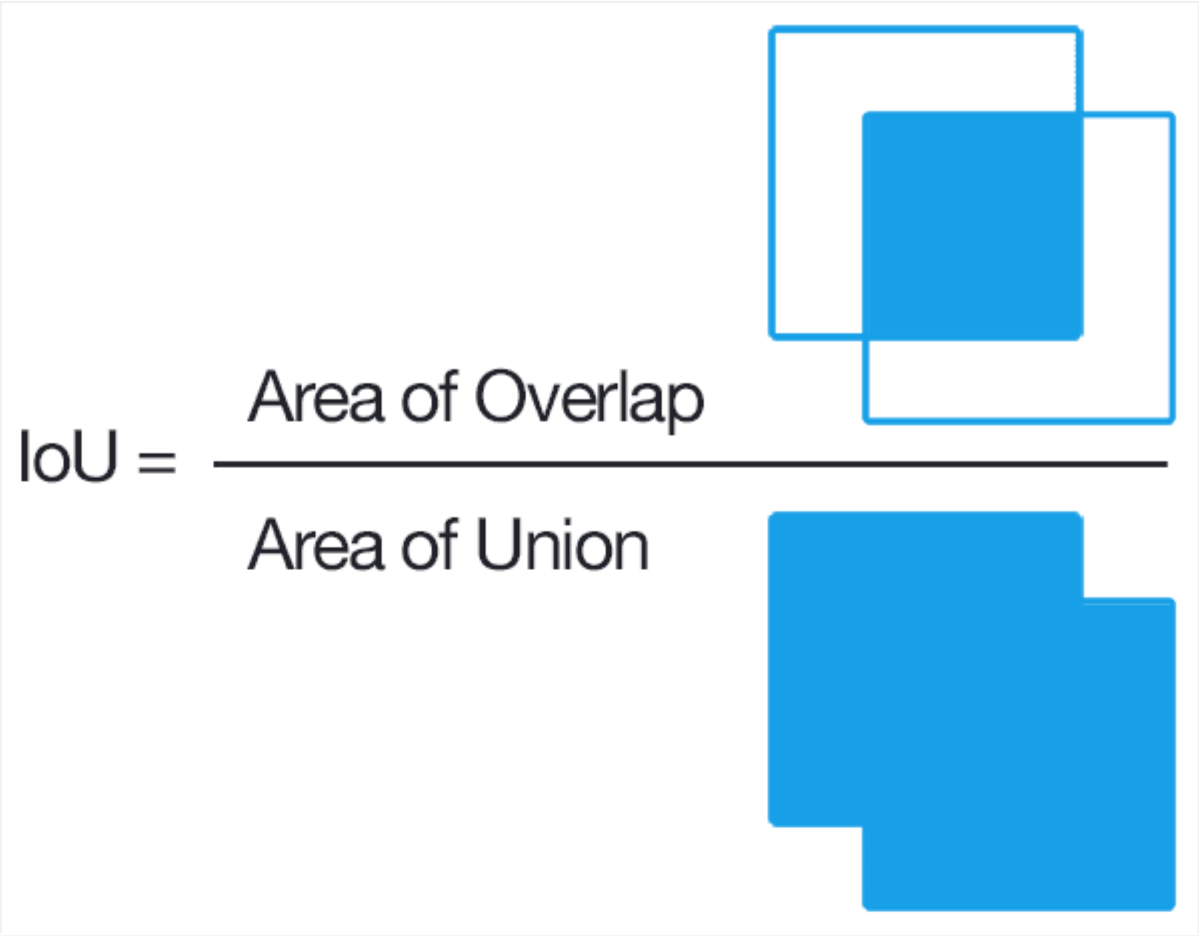
Area of Overlap
IoU =
Area of Union

- Normally, $IoU \geq 0.5$ is considered good, while $1$ is perfect!

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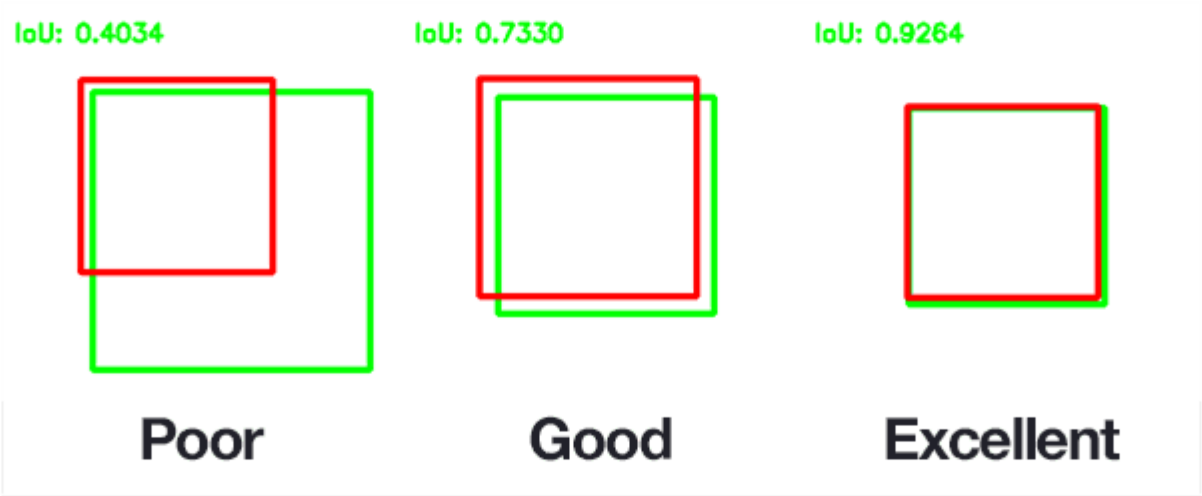

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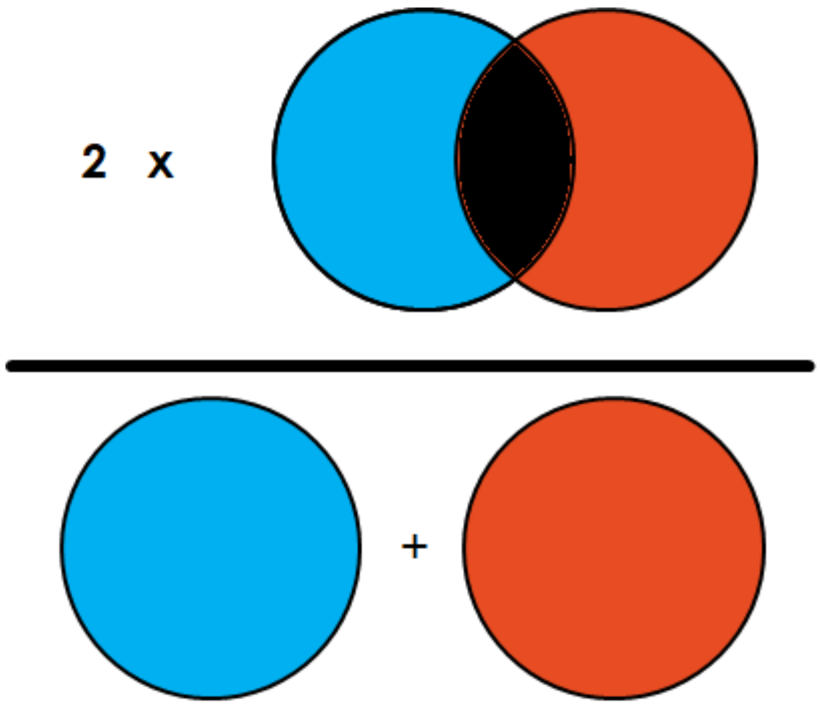

## What is the difference between IoU and Dice?

**What is the difference between IoU and Dice?**

- IoU is more like recall, so it is good to use when you want to detect if a larger amount of the object pixels are outside the area of interest, but also if the detection is **overestimating** where the object is!

**What is the difference between IoU and Dice?**

- IoU is more like recall, so it is good to use when you want to detect if a larger amount of the object pixels are outside the area of interest, but also if the detection is **overestimating** where the object is!
- Dice coefficient penalises false positives, which is better for high imbalanced datasets or when the segmentations are not correct

# LAB: PERFORMANCE MEASURES FOR BINARY DATASETS