Content

- **F-beta score**
  - F-2 score
  - F-0.5 score

Revision

Let's recall what we studied in lecture:

- F1-measure balances the precision and recall.
- Precision is a metric that quantifies the number of correct positive predictions made.
  - $Precision = \frac{TruePositives}{TruePositives+FalsePositives}$
- Recall is a metric that quantifies the number of correct positive predictions made out of all positive predictions that could have been made.
  - $Recall = \frac{TruePositives}{TruePositives+FalseNegatives}$

F-beta score

But On some problems, we might be interested in an F-measure with more attention put on precision, such as when false positives are more important to minimize.

The solution is the **Fbeta-measure.**

- Defined as Fbeta = $\frac{((1+beta^2)*Precision*Recall)}{(beta^2*Precision+Recall)}$

F-2 Score

When it is more important to optimise **recall than precision**

- we use the **F2 score**
- Defined as: $F2 = \frac{(1+2^2)*precision*recall}{(2^2)*precision+recall}$

F-0.5 Score

Now what if we might be interested in an F-measure with **more attention put on precision**,

- such as when **false positive are more important to minimize**

- We use the **F0.5 score**
- $F0.5 = \frac{(1+0.5^2)*precision*recall}{(0.5^2)precision+recall}$