Performance Metrics, Neural Networks II

Machine Learning 1 UE (INP.33761UF)

Thomas Wedenig

May 22, 2024

Institute of Theoretical Computer Science
Graz University of Technology, Austria

Table of contents

Performance Metrics

- **Regression:** $y^{(i)} \in \mathbb{R}$
  - **Note:** In the following, $\mathbf{x}^{(i)}, y^{(i)}$ come from the **test set**
- **Mean Squared Error** (MSE):

$$MSE(\boldsymbol{\theta}) = \frac{1}{N_{\text{test}}} \sum_{i=1}^{N_{\text{test}}} \left(f_{\boldsymbol{\theta}}(\mathbf{x}^{(i)}) - y^{(i)} \right)^2$$

- **Root Mean Squared Error** (RMSE):

$$RMSE(\boldsymbol{\theta}) = \sqrt{MSE(\boldsymbol{\theta})}$$

- **Mean Absolute Error** (MAE):

$$MAE(\boldsymbol{\theta}) = \frac{1}{N_{\text{test}}} \sum_{i=1}^{N_{\text{test}}} | f_{\boldsymbol{\theta}}(\mathbf{x}^{(i)}) - y^{(i)} |$$

- Prefer RMSE and MAE, since they have the **same unit as the target**

- **Binary classification:** $y^{(i)} \in \{0, 1\}$. A model's prediction can be:
  - **True Positive** (TP): $y = 1$ and model correctly said $\hat{y} = 1$
  - **True Negative** (TN): $y = 0$ and model correctly said $\hat{y} = 0$
  - **False Positive** (FP): $y = 0$ but model incorrectly said $\hat{y} = 1$
  - **False Negative** (FN): $y = 1$ but model incorrectly said $\hat{y} = 0$

- **Binary classification:** $y^{(i)} \in \{0, 1\}$. A model's prediction can be:
  - **True Positive** (TP): $y = 1$ and model correctly said $\hat{y} = 1$
  - **True Negative** (TN): $y = 0$ and model correctly said $\hat{y} = 0$
  - **False Positive** (FP): $y = 0$ but model incorrectly said $\hat{y} = 1$
  - **False Negative** (FN): $y = 1$ but model incorrectly said $\hat{y} = 0$
- Say the test data has P positive and N negative examples: $N_{\text{test}} = P + N$
- **Accuracy:**

$$ACC = \frac{TP + TN}{N_{\text{test}}} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:**

$$PREC = \frac{TP}{TP + FP}$$

- **Recall:**

$$REC = \frac{TP}{P} = \frac{TP}{TP + FN}$$

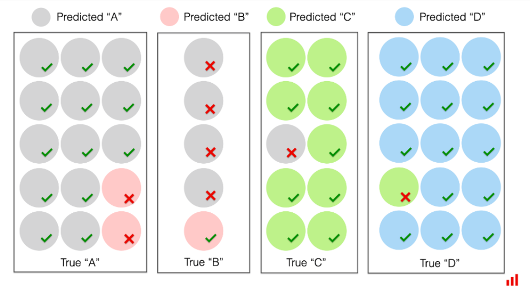
- F_1 **Score**:

$$F_1 = 2 \cdot \frac{PREC \cdot REC}{PREC + REC}$$

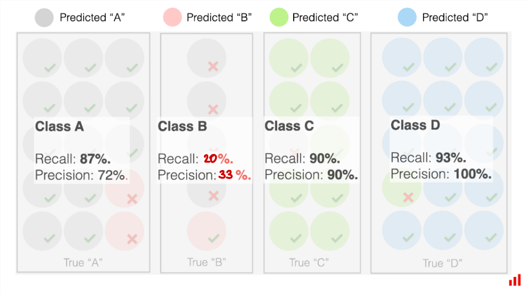
- F_1 is the **harmonic mean** of **precision** and **recall**
  - Balances precision and recall
- Accuracy, Precision, Recall, F_1 are all $\in [0, 1]$

What about **multiclass** classification?

- Report metric **per class**
  - Precision, Recall, F_1

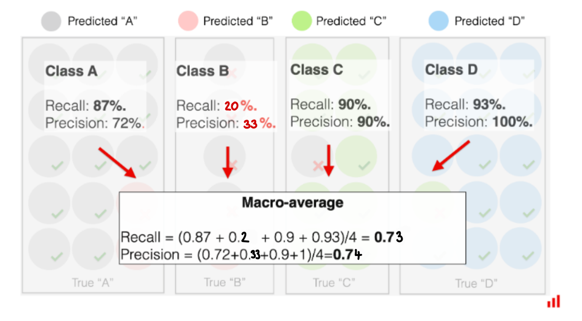


https://www.evidentlyai.com/classification-metrics/multi-class-metrics



https://www.evidentlyai.com/classification-metrics/multi-class-metrics

- We can also **average** the individual per-class metric (**macro** average)
  - Gives equal weight to each class



https://www.evidentlyai.com/classification-metrics/multi-class-metrics

- We can also globally count true predictions and false predictions (**micro** average)
  - Gives a global type of **accuracy**

Demo: Classification Report & Automatic Differentiation

Assignment 2 Questions