MachineLearnAthon - Microlecture Evaluation metrics

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MachineLearnAthon
A project Co-funded by the Erasmus+ programme of the European Union

Learning outcomes of today

After successfully completing this micro-lecture, you are able to….

- Explain the significance of evaluation metrics in assessing model performance
- Assess the suitability of specific metrics for different types of machine learning problems (e.g., classification vs. regression)
- Interpret classification metrics such as Accuracy, Precision, and Recall using confusion matrix values
- Calculate classification performance using TP, FP, TN, and FN values
- Apply regression metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to quantify model prediction errors

Agenda for today

- Evaluation metrics in Machine learning
- Classification Metrics
  - Accuracy
  - Precision, Recall
- Regression Metrics
  - Mean Absolute Error (MAE)
  - Mean Squared Error (MSE)
  - Root Mean Squared Error (RMSE)

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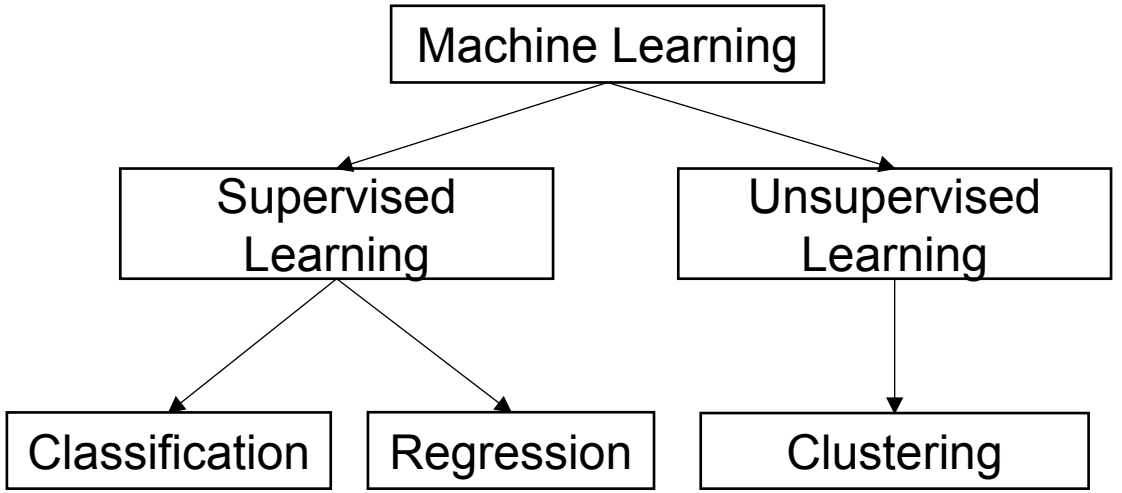
Evaluation metrics in Machine learning

- Evaluation metrics are essential in machine learning for assessing model performance. These metrics help determine how well a model is likely to perform in real-world application.
- Different tasks like classification, regression, and clustering each have unique metrics tailored to their requirements and objectives.
- Classification metrics typically evaluate accuracy and balance; regression metrics focus on error magnitude, while clustering metrics assess grouping quality.
- Evaluation metrics should be applied on a test set, which was not used for training the machine learning model.



Zheng, A. (2015)

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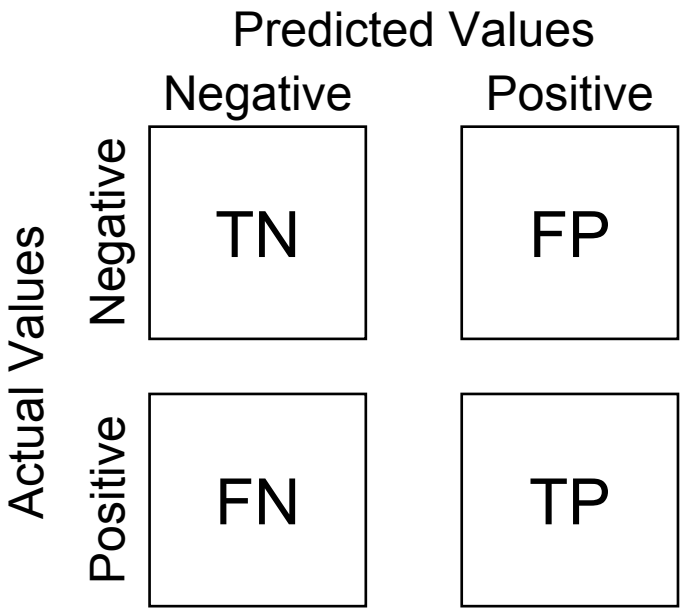
Classification Metrics - Accuracy

Accuracy measures the proportion of correct predictions over total predictions, often used in balanced datasets for a clear view of correct classifications.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$



Zheng, A. (2015)

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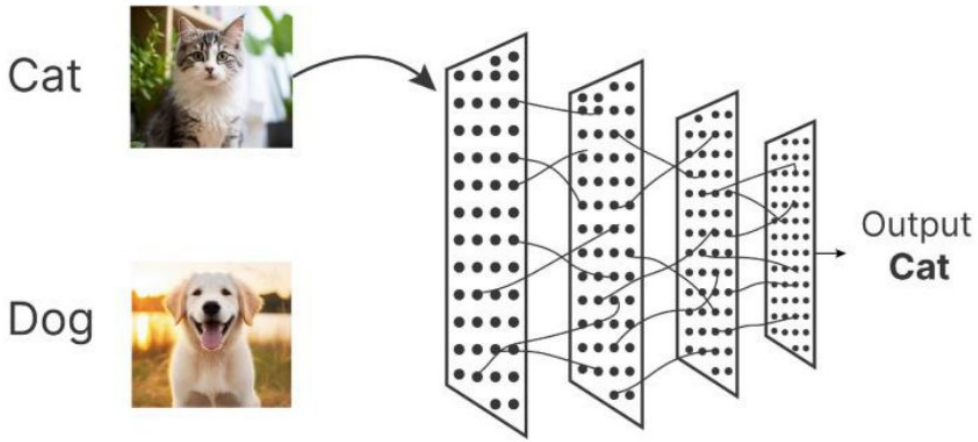
Classification Metrics - Accuracy

In an example, a model examines 100 images to classify dogs and cats: 59 are dogs (48 correctly identified, 11 misclassified) and 41 are cats (37 correctly identified, 4 misclassified)

$$\text{Accuracy} = \frac{48+37}{37+9+6+48} = 0.85 = 85\%$$



Actual Values \ Predicted Values	Cat	Dog
Cat	37	4
Dog	11	48

Naidu et al (2023), Zheng, A. (2015)

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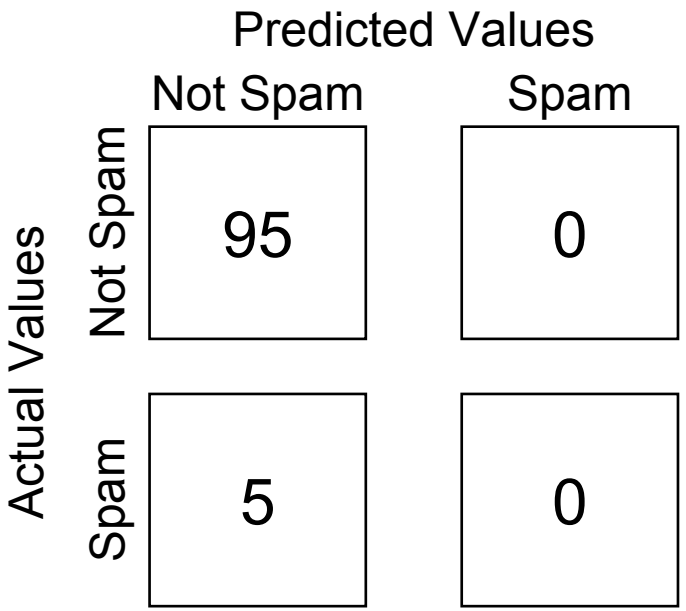
Classification Metrics - Accuracy

- In another example, our model predicts whether an email is spam or not. Out of 100 emails, 95 are 'Not Spam' and 5 are 'Spam' in the dataset.

$$\text{Accuracy} = \frac{95+0}{0+5+95+0} = 0.95 = 95\%$$



- In imbalanced datasets, accuracy can mislead; alternative metrics like precision and recall may provide a better insight

Rainio et al (2024)

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Classification Metrics - Precision, Recall

- Precision measures the proportion of true positive predictions out of all the positive predictions made by the model.

$$\text{Precision} = \frac{TP}{TP+FP}$$

- Back to the example for predicting spam and not spam Emails:

$$\text{Accuracy} = \frac{90+3}{90+3+5+2} = 0.93 = 93\%$$

$$\text{Precision} = \frac{3}{2+3} = 0.6 = 60\%$$

		Predicted Values: Negative	Predicted Values: Positive
Actual Values	Negative	TN = 90	FP = 2
Actual Values	Positive	FN = 5	TP = 3

Naidu et al (2023), Rainio et al (2024)

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Classification Metrics - Precision, Recall

- Recall, also known as sensitivity is the proportion of true positives out of all actual positive cases.

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

- Back to the example for predicting spam and not spam Emails:

$$\text{Accuracy} = 93\%$$

$$\text{Precision} = 60\%$$

$$\text{Recall} = \frac{3}{3+5} = 0.375 = 37.5\%$$

- Recall is extremely important in such cases that missing a positive instance is extremely costly. E.g. Fraud Detection

Actual Values \ Predicted Values	Negative	Positive
Negative	TN = 90	FP = 2
Positive	FN = 5	TP = 3

Naidu et al (2023), Rainio et al (2024)

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Regression Metrics

- Difference to classification is a numeric target value, therefore other evaluation metrics are needed to measure the model performance
- Variety of metrics with different approaches and therefore other advantageous use cases
- Here: Mean Absolute Error, Mean Squared Error, Root Mean Squared Error

Tatachar (2021)

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Regression Metrics - Mean Absolute Error (MAE)

- Mean Absolute Error (MAE) measures the average of the absolute difference between the observed and the predicted values

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left| Y_i - \hat{Y}i \right|$$

  - n: Number of predictions
  - Y_i : Observed values
  - $\hat{Y}i$: Predicted values

- Example: weather prediction

$$MAE = \frac{(|28 - 27| + |30 - 28| + |28 - 24| + |25 - 21|)}{4} = 2.75$$

	Actual temperature in °C	Predicted temperature in °C
1	28	27
2	30	28
3	28	24
4	25	21

Tatachar (2021)

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Regression Metrics – Mean Squared Error (MSE)

- Mean Squared Error (MSE) measures the average squared difference between the observed and the predicted values

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}i\right)2$$

  - n: Number of predictions
  - Y_i : Observed values
  - $\hat{Y}i$: Predicted values

- Example: weather prediction

$$MSE = \frac{((28-27)2+(30-28)2+(28-24)2+(25-21)2)}{4} = 9.25$$

	Actual temperature in °C	Predicted temperature in °C
1	28	27
2	30	28
3	28	24
4	25	21

Plevris et al (2022), Tatachar (2021)

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Regression Metrics – Root Mean Squared Error (RMSE)

- Root Mean Squared Error (RMSE) is the square root of the MSE

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}i\right)2}$$

  - n: Number of predictions
  - Y_i : Observed values
  - $\hat{Y}i$: Predicted values

- Example: weather prediction

$$RMSE = \sqrt{MSE} = \sqrt{9.25} \approx 3.041$$

	Actual temperature in °C	Predicted temperature in °C
1	28	27
2	30	28
3	28	24
4	25	21

Plevris et al (2022), Tatachar (2021)

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Recap this lecture

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