ICTSS00120 - Artificial Intelligence Skill Set

Evaluation Metrics

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Learning Objectives

- Understand the key evaluation metrics for machine learning models.
- Learn how to calculate and interpret each metric.
- Relate the metrics to the spam detection example from the lab.
- Appreciate the importance of different metrics in different contexts.

Key Evaluation Metrics: An Overview

1. **Accuracy**
2. **Precision**
3. **Recall**
4. **F1 Score**
5. **Confusion Matrix**

These metrics are essential for evaluating the performance of your machine learning models. Let's dive into each one in detail.

Starting definitions

- TP (True Positives): The number of instances correctly predicted as positive.
- TN (True Negatives): The number of instances correctly predicted as negative.
- FP (False Positives): The number of instances incorrectly predicted as positive.
- FN (False Negatives): The number of instances incorrectly predicted as negative.

Accuracy

Definition:

- The ratio of correctly predicted instances to the total instances.

Formula:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

Usage:

- Provides a single measurement of the model's performance.
- Useful when the class distribution is balanced.

Precision

Definition:

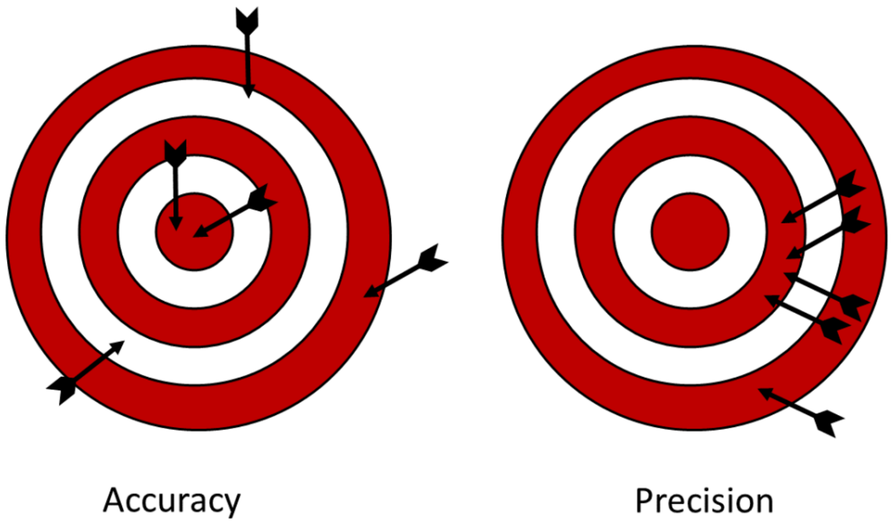
- The ratio of true positive predictions to the sum of true positive and false positive predictions.

Formula:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Usage:

- Indicates how many positive predictions were actually correct.
- Important in contexts where the cost of false positives



Recall (Sensitivity, True Positive Rate)

Definition:

- The ratio of true positive predictions to the sum of true positive and false negative predictions.

Formula:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Usage:

- Indicates how many actual positives were captured by the model.
- Critical in contexts where catching all positive cases is important.

F1 Score

Definition:

- The harmonic mean of precision and recall.

Formula:

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Usage:

- Provides a single metric that balances precision and recall.
- Useful when you need a balance between precision and recall.

Confusion Matrix

Definition:

- A table used to describe the performance of a classification model on a set of test data for which the true values are known.

Components:

- **True Positive (TP)**: Correctly predicted positive instances.
- **True Negative (TN)**: Correctly predicted negative instances.
- **False Positive (FP)**: Incorrectly predicted as positive (Type I error).
- **False Negative (FN)**: Incorrectly predicted as negative (Type II error).

Example: Confusion Matrix in Spam Detection

Initial SVM Result:

```
Confusion Matrix:
[[1200  195]
 [  43  168]]

Precision: 0.46
Recall: 0.80
F1 Score: 0.59
```

- **TN (1200)**: Ham correctly identified as Ham.
- **FP (195)**: Ham incorrectly identified as Spam.
- **FN (43)**: Spam incorrectly identified as Ham.
- **TP (168)**: Spam correctly identified as Spam.

Accuracy in Spam Detection

Formula:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

Result:

$$\text{Accuracy} = \frac{1200+168}{1200+168+195+43} \approx 0.85$$

Interpretation:

85% of the time, the classifier made correct predictions, but this metric alone does not provide a full picture, especially with imbalanced classes.

Precision in Spam Detection

Formula:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Result:

$$\text{Precision} = \frac{168}{168+195} \approx 0.46$$

Interpretation:

Only 46% of the messages identified as spam were actually spam. Indicates high false positive rate.

Recall in Spam Detection

Formula:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Result:

$$\text{Recall} = \frac{168}{168+43} \approx 0.80$$

Interpretation:

80% of the actual spam messages were correctly identified as spam. Indicates high sensitivity to capturing spam.

F1 Score in Spam Detection

Formula:

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Result:

$$\text{F1 Score} = \frac{2 \cdot 0.46 \cdot 0.80}{0.46 + 0.80} \approx 0.59$$

Interpretation:

Balances the precision and recall. Useful in this context where both false positives and false negatives are important.

Why Use Multiple Metrics?

- **Accuracy**: Good for balanced datasets but not informative for imbalanced classes.
- **Precision**: Important when the cost of false positives is high.
- **Recall**: Critical when the cost of false negatives is high.
- **F1 Score**: Provides a balance between precision and recall.
- **Confusion Matrix**: Offers a complete view of model performance.

Using multiple metrics provides a more comprehensive evaluation of the model's performance and helps in understanding its strengths and weaknesses.

Questions & Discussion

Q&A:

- Any questions about the evaluation metrics?
- How would you apply these metrics to other types of classification problems?

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