

Accuracy vs recall

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In machine learning, both accuracy and recall are important metrics used to evaluate the performance of models, but they serve different purposes and are chosen based on the specific requirements of the task.

Accuracy

Accuracy is a straightforward metric that measures the proportion of correctly classified instances (both true positives and true negatives) out of the total number of instances evaluated. It is calculated as:

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

When to Use Accuracy:

- Accuracy is typically used when the classes in the dataset are balanced, meaning there is a similar number of instances for each class.
- It provides a general idea of how well the model is performing overall in terms of correctness.

Example Scenario:

- In a scenario where correctly predicting all classes equally matters, such as sentiment analysis where both positive and negative sentiments are equally important.

Recall

Recall (also known as sensitivity or true positive rate) measures the proportion of actual positive instances correctly identified by the model. It focuses specifically on the model's ability to correctly detect positive instances out of all actual positive instances (true positives + false negatives). It is calculated as:

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

When to Use Recall:

- Recall is particularly useful when the cost of false negatives (missed positive instances) is high, and correctly identifying all positive cases (even at the expense of more false positives) is crucial.
- It is important in applications where the goal is to minimize the number of false negatives, such as medical diagnostics or fraud detection.

Example Scenario:

- In medical diagnostics, where the priority is to correctly identify all patients with a disease (minimizing false negatives), even if it means some healthy patients might be incorrectly identified as having the disease (false positives).

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Choosing Between Accuracy and Recall

- **Balanced Classes:** If the classes are balanced (roughly equal number of instances for each class), accuracy can provide a good overall measure of performance.
- **Imbalanced Classes:** When dealing with imbalanced classes (where one class significantly outnumbers the other), accuracy can be misleading. In such cases, recall (or other metrics like precision-recall) is more informative, especially for the minority class.
- **Cost Considerations:** The choice between accuracy and recall also depends on the specific costs of false positives and false negatives in the application domain. If missing positive instances (false negatives) is more costly than incorrectly labeling negative instances (false positives), recall becomes more important.

In summary, while accuracy gives a general measure of correct predictions across all classes, recall focuses on the ability to detect positive instances correctly. The choice between these metrics depends on the specific requirements and costs associated with the problem being solved.

why does imbalanced classes mean it is better to use recall score

Imbalanced classes in a classification problem refer to a situation where one class (typically the minority class) is significantly less frequent than another (the majority class). For example, in fraud detection, the number of fraudulent transactions is much lower than the number of legitimate transactions. In medical diagnosis, the number of patients with a rare disease might be much smaller compared to those without the disease.

Challenges with Imbalanced Classes

When faced with imbalanced classes, accuracy as a metric can be misleading and not reflect the model's performance. This is because:

1. **Skewed Performance Evaluation:** Accuracy can be high even if the model predicts the majority class correctly most of the time, while performing poorly on the minority class. For instance, if 90% of the data belongs to the majority class, a model that simply predicts everything as the majority class can achieve 90% accuracy.
2. **Focus on Minority Class:** In many real-world applications, correctly identifying instances of the minority class (positive instances, such as fraudulent transactions or patients with a rare disease) is more important than identifying the majority class. The cost of missing a positive instance (false negatives) is often much higher than the cost of incorrectly classifying a negative instance (false positives).

Why Recall Score is Preferable

Recall (or sensitivity) focuses directly on the model's ability to correctly identify positive instances. It is calculated as the number of true positives divided by the sum of true positives and false negatives. In imbalanced classes scenarios, recall is often more beneficial because:

- **Prioritizes Minority Class:** It explicitly measures how well the model identifies instances of the minority class. A high recall indicates that the model is effective in capturing most of the positive instances, which is often the primary goal in applications where the minority class is of greater interest.
- **Handles Class Imbalance:** Unlike accuracy, which can be misleading due to class imbalance, recall provides a more meaningful measure of performance for the minority class.

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Minority class imbalances can mislead accuracy, which can be misleading due to class imbalance. This provides a more complete picture of the model's performance on the positive class, which is typically the class of interest in many real-world scenarios.

- **Decision Support:** In applications such as fraud detection or medical diagnostics, high recall ensures that a high proportion of actual positive cases are correctly identified, providing more reliable decision-making support.

Conclusion

In summary, imbalanced classes often necessitate the use of recall (or sensitivity) as a metric to evaluate model performance. This metric addresses the challenges posed by the rarity of the minority class. By focusing on the model's ability to correctly identify instances of the minority class, recall provides a more meaningful evaluation of performance in scenarios where the number of positive instances is high. Therefore, in imbalanced classification problems, prioritizing recall score over accuracy is often more appropriate for assessing the model's effectiveness in correctly identifying instances of the minority class, with significant implications for real-world applications.

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