

# Worked example

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## Example Scenario: Fraud Detection

Imagine we have a dataset of credit card transactions where only 1% of the transactions are fraudulent (positive class), and the remaining 99% are legitimate transactions (negative class).

### Dataset Characteristics:

- Total transactions: 10,000
- Fraudulent transactions (positive class): 100
- Legitimate transactions (negative class): 9,900

## Model Performance Evaluation

Let's consider a machine learning model trained to classify these transactions as fraudulent or legitimate. After training, the model is evaluated using a confusion matrix, which breaks down the model's predictions as follows:

- **True Positives (TP):** Predicted as fraudulent and actually fraudulent.
- **True Negatives (TN):** Predicted as legitimate and actually legitimate.
- **False Positives (FP):** Predicted as fraudulent but actually legitimate (Type I error).
- **False Negatives (FN):** Predicted as legitimate but actually fraudulent (Type II error).

Assume the model's predictions are as follows:

- TP = 80 (correctly identified fraudulent transactions)
- TN = 9,800 (correctly identified legitimate transactions)
- FP = 100 (legitimate transactions incorrectly identified as fraudulent)
- FN = 20 (fraudulent transactions incorrectly identified as legitimate)

### Confusion Matrix:

	Predicted Fraudulent	Predicted Legitimate
Actual Fraudulent	80 (TP)	20 (FN)
Actual Legitimate	100 (FP)	9,800 (TN)

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## Calculating Metrics

### Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{80 + 9,800}{80 + 9,800 + 100 + 20} = \frac{9,880}{10,000} = 0.988$$
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### Recall (Sensitivity):

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{80}{80 + 20} = \frac{80}{100} = 0.8$$
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Recall is 80%.

## Interpretation

- **Accuracy:** The model shows high accuracy (98.8%), which might initially suggest good performance. However, this high accuracy is mainly driven by the large number of identified legitimate transactions (TN). It does not reflect the model's performance in identifying fraudulent transactions effectively.
- **Recall:** The recall score is 80%, indicating that the model correctly identifies 80% of the fraudulent transactions. This metric is crucial in fraud detection because missing fraudulent transactions (false negatives) can be costly. A recall score of 80% means that the model catches 80% of the fraudulent activities, which is often more important than overall accuracy.

## Conclusion

In the context of imbalanced classes like fraud detection, where the positive class (fraudulent transactions) is rare compared to the negative class (legitimate transactions), using Recall provides a more meaningful evaluation of the model's effectiveness. It directly measures the model's ability to detect instances of the minority class (fraudulent transactions) accurately, which is critical for decision-making in such applications. Therefore, despite high accuracy, the focus should be on Recall to ensure that the model performs well where it matters most — identifying fraudulent activities to prevent financial losses.

$\text{Accuracy} = \frac{9,880}{10,000} = 98.8\%$   
Accuracy is 98.8%.

$$0 + 20 = \frac{80}{100}$$

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