Logistic Regression Evaluation Metrics

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When dealing with classification tasks like predicting Titanic survival, it's important to evaluate how well your model performs. Below are key evaluation metrics used for logistic regression:

1. Accuracy

- Measures the ratio of correctly predicted instances to the total.
- Formula: Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Good for balanced datasets, but misleading for imbalanced classes.

2. Confusion Matrix

- A 2x2 table for binary classification:

	Predicted No	Predicted Yes
Actual No	TN	FP
Actual Yes	FN	TP

- TP: True Positives correctly predicted survival
- TN: True Negatives correctly predicted deaths
- FP: False Positives predicted survival, but didn't
- FN: False Negatives predicted death, but survived

3. Precision, Recall, and F1 Score

- Precision = TP / (TP + FP)
  -> How many predicted survivors actually survived?
- Recall = TP / (TP + FN)
  -> How many actual survivors did we identify?
- F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

-> Balance between precision and recall

4. ROC Curve

- ROC: Receiver Operating Characteristic
- Plots True Positive Rate (Recall) vs. False Positive Rate
- Helps visualize model performance across thresholds

5. AUC Score (Area Under Curve)

- Area under the ROC Curve
- Range: 0 to 1
- AUC = 1.0 perfect model, AUC = 0.5 random guessing
- Higher AUC = better model ability to distinguish classes

Example:

If we use `predict_proba()` in scikit-learn to compute probabilities:

```python
from sklearn.metrics import roc_curve, roc_auc_score
fpr, tpr, _ = roc_curve(y_test, y_prob)
auc = roc_auc_score(y_test, y_prob)
```

Then plot:

```python
plt.plot(fpr, tpr, label=f'AUC = {auc:.2f}')
```

Summary:

- Use Accuracy for quick checks

- Confusion Matrix, Precision, Recall, and F1 Score for deeper insight
- Use ROC and AUC for probability-based performance comparison