

Understanding Confusion Matrices for Logistic Regression in Google Sheets

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Understanding the performance of a classification model is crucial in data science. We typically use [logistic regression](#) when the outcome or [response variable](#) is **binary** (e.g., Yes/No, 0/1, Success/Failure). Evaluating how well this model predicts outcomes requires robust statistical tools.

One of the most essential tools for assessing classification quality is the [confusion matrix](#). This standardized 2x2 table provides a clear visualization of the model's performance by comparing the predicted values against the true, **actual values** observed in the test dataset. It forms the foundation for calculating critical performance metrics.

		Predicted	
		0	1
Actual	0	30	12
	1	8	56

This comprehensive, step-by-step guide demonstrates how to efficiently construct and interpret a [confusion matrix](#) directly within Google Sheets, turning raw classification data into actionable insights using simple functions.

Step 1: Prepare and Enter the Classification Data

The first step requires organizing the raw results generated by your classification model. We need two primary columns of data: the **Actual Values** (the true outcomes from your test set) and the **Predicted Values** (the outcomes generated by your [logistic regression](#) model). For this example, we assume the outcomes are binary, represented by 0s and 1s.

Enter the data, ensuring the columns are clearly labeled to avoid confusion during the matrix construction phase. Our sample dataset includes 20 observations, as shown below:

	A	B	C	D
1	Actual	Predicted		
2	0	0		
3	0	0		
4	0	1		
5	0	0		
6	0	0		
7	0	1		
8	0	1		
9	0	0		
10	0	0		
11	0	1		
12	1	0		
13	1	0		
14	1	1		
15	1	1		
16	1	1		
17	1	1		
18	1	1		
19	1	1		
20	1	1		
21	1	1		
22				

Once the actual and predicted values are correctly aligned in Columns A and B, we can proceed to set up the structure that will house the confusion matrix calculations.

Step 2: Construct the Confusion Matrix Structure and Formula

A standard [confusion matrix](#) is a 2x2 grid that categorizes observations into four types: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Before inputting the counting logic, establish the matrix outline, typically labeling the rows with Actual values (0 and 1) and columns with Predicted values (0 and 1).

Set up the matrix structure starting in column D, resembling the image provided. This structure helps map the cell locations to the specific performance categories (e.g., Actual 1 and Predicted 1 will represent the True Positives).

	A	B	C	D	E	F
1	Actual	Predicted			Predicted	
2	0	0		Actual	0	1
3	0	0		0		
4	0	1		1		
5	0	0				
6	0	0				
7	0	1				
8	0	1				
9	0	0				
10	0	0				
11	0	1				
12	1	0				
13	1	0				

To populate this matrix, we utilize the powerful [COUNTIFS](#) function in Google Sheets. This function allows us to count cells that satisfy multiple specified criteria simultaneously--in this case, matching both the actual value in Column A and the predicted value in Column B. The formula must be entered into cell **E3**, which corresponds to the count where the Actual value is '0' (referenced from D3) AND the Predicted value is '0' (referenced from E2).

The specific formula utilizing absolute referencing (dollar signs) to lock the data ranges and semi-absolute referencing for the criteria rows/columns is:

=COUNTIFS(\$A\$2:\$A\$21, \$D3, \$B\$2:\$B\$21, E\$2)

We can then click and drag this formula to each remaining cell (E4, F3, F4) in the confusion matrix. This efficiently calculates the total counts for True Positives, True Negatives, False Positives, and False Negatives based on the model's output.

E3 `=COUNTIFS(A2:A21, $D3, B2:B21, E$2)`

	A	B	C	D	E	F
1	Actual	Predicted			Predicted	
2	0	0		Actual	0	1
3	0	0		0	6	4
4	0	1		1	2	8
5	0	0				
6	0	0				
7	0	1				
8	0	1				
9	0	0				
10	0	0				
11	0	1				
12	1	0				
13	1	0				

Step 3: Calculate Key Model Evaluation Metrics (Accuracy, Precision, and Recall)

Once the confusion matrix is populated, the counts within the 2x2 grid (TP, TN, FP, FN) allow for the calculation of critical evaluation metrics that provide a nuanced view of model efficacy. These metrics help determine not just if the model is correct overall, but how it performs specifically regarding positive and negative classifications.

The three most common metrics derived from the confusion matrix are defined as follows:

Accuracy: Percentage of correct predictions relative to the total number of observations. It is a measure of overall correctness.

Precision: Measures the quality of positive predictions; specifically, the correct positive predictions relative to all instances classified as positive by the model.

Recall (Sensitivity): Measures the model's ability to find all positive cases; specifically, the correct positive predictions relative to the total number of actual positives.

Implement the formulas for these metrics adjacent to the matrix, referencing the appropriate cells for the counts to derive the final performance scores, as shown in the example below:

B	C	D	E	F	G
redicted			Predicted		
0		Actual	0	1	
0		0	6	4	
1		1	2	8	
0					
0					
1		Metric	Value	Formula	
1		Accuracy	0.7	=SUM(E3,F4)/SUM(E3:F4)	
0		Precision	0.6666666667	=F4/SUM(F3:F4)	
0		Recall	0.8	=F4/SUM(E4:F4)	
1					
0					
0					
1					
1					
1					

The higher the **accuracy** score, the better a model is able to correctly classify observations into their respective binary categories. In this example, our model has an accuracy of **0.70**, which tells us that it successfully classified 70% of the observations in the test set.

When developing models, it is standard practice to compare the accuracy, precision, and recall of different [logistic regression](#) models to determine which one is optimally suited for classifying observations into categories of 0 or 1, depending on the specific business or scientific objective.

Additional Resources for Classification Analysis

Mastering the evaluation metrics derived from the **confusion matrix** is fundamental to robust data analysis. The following tutorials and resources provide additional information about [logistic regression](#) and advanced classification assessment techniques.

These resources will help deepen your understanding of how these metrics translate into real-world model performance and reliability.