

# How to Create a Confusion Matrix in Google Sheets

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## Introduction to Classification Model Evaluation

The evaluation of a classification model is a fundamental step in data science, allowing users to assess how effectively a model predicts categorical outcomes. When dealing with binary outcomes, such as success/failure or 0/1, we frequently employ logistic regression. While measures like overall accuracy provide a basic understanding of performance, they often fail to capture the nuanced errors made by the model. This is where the Confusion Matrix becomes an indispensable tool.

A Confusion Matrix serves as a systematic, visual representation of a model's performance, contrasting the actual values against the values predicted by the model across a test dataset. By organizing the data in this manner, we can isolate specific types of errors, such as instances where the model incorrectly predicts a positive outcome (a **False Positive**) or incorrectly predicts a negative outcome (a **False Negative**). This deep dive into predictive errors is crucial for models where the cost of different types of misclassification varies significantly.

This detailed guide provides a practical, step-by-step methodology for constructing a fully functional Confusion Matrix directly within Google Sheets. Utilizing powerful built-in spreadsheet functions, particularly the **COUNTIFS** function, we can efficiently automate the calculation of all necessary components--True Positives, True Negatives, False Positives, and False Negatives--to provide a comprehensive performance evaluation without requiring specialized statistical software.

## 2. Understanding the Structure and Components

The use of logistic regression is generally reserved for scenarios where the response variable is **binary**, meaning it can only take one of two specified values, typically standardized as 0 or 1. To accurately evaluate the model's predictive quality, we must compare its predictions against the known actual values recorded in the test data set. This comparison forms the foundation of the 2x2 structure inherent in the Confusion Matrix.

The standard 2x2 table visually maps four critical outcomes, each representing a specific relationship between the actual and predicted classes. Understanding these four components--often referred to by their statistical acronyms--is essential for interpreting model performance metrics derived from the matrix. The matrix structure systematically segregates correct predictions (True outcomes) from incorrect predictions (False outcomes) based on the targeted class.

The four fundamental components that populate the matrix are defined based on the intersection of the actual and predicted classes:

**True Positives (TP):** These are instances where the model correctly predicted the positive class

(Actual = 1, Predicted = 1).

**True Negatives (TN):** These are instances where the model correctly predicted the negative class (Actual = 0, Predicted = 0).

**False Positives (FP):** Also known as a Type I Error, these are instances where the model incorrectly predicted the positive class when the actual result was negative (Actual = 0, Predicted = 1).

**False Negatives (FN):** Also known as a Type II Error, these are instances where the model incorrectly predicted the negative class when the actual result was positive (Actual = 1, Predicted = 0).

The visual representation below illustrates this conceptual layout, where the rows typically represent the actual values and the columns represent the predicted values, guiding the user to understand which cell corresponds to which metric.

		Predicted	
		0	1
Actual	0	30	12
	1	8	56

The following detailed, step-by-step methodology demonstrates the precise process of constructing this critical evaluation tool within the familiar environment of [Google Sheets](#).

## Step 1: Preparing and Entering the Data

The initial stage of generating any statistical analysis in a spreadsheet environment involves meticulously organizing the raw data. For constructing the Confusion Matrix, we require two primary columns of data: the observed **Actual Values** and the **Predicted Values** generated by your specific classification model. These values should typically be recorded using binary indicators (0s and 1s) representing the two classes.

It is crucial that these two columns are perfectly aligned row by row, ensuring that the predicted value in any given row corresponds directly to the actual outcome observed for that same data point. Discrepancies in alignment will lead to inaccurate calculation of the matrix components, rendering the subsequent evaluation metrics invalid. We will assume the data resides within a single sheet, starting from row 2 to accommodate descriptive headers.

For our working example, we will utilize a small data set comprising 20 observations, spanning rows 2 through 21. Column A will contain the Actual Values, and Column B will house the

Predicted Values. This layout facilitates easy referencing when writing the complex conditional counting formulas required for population. Maintaining data integrity through clear headers and contiguous ranges is key to spreadsheet efficiency.

	A	B	C	D
1	<b>Actual</b>	<b>Predicted</b>		
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				

## Step 2: Creating the Confusion Matrix Outline

Once the raw data is prepared and correctly formatted, the next task is to establish the visual framework for the confusion matrix itself. This matrix is essentially a 2x2 table that requires clearly labeled rows and columns to define the actual and predicted outcomes. While the precise location in the sheet can vary, placing the matrix adjacent to the raw data is often convenient for formula construction and quick review.

We will designate a specific area of the spreadsheet (e.g., columns D, E, and F) to construct the table headers. The column headers denote the **Predicted Class** (e.g., 0 and 1, placed in E2 and F2), and the row headers denote the **Actual Class** (e.g., 0 and 1, placed in D3 and D4). This structure ensures that each intersection point (E3, F3, E4, F4) corresponds unambiguously to one

of the four required metrics: True Positive, True Negative, False Positive, or False Negative.

A thoughtful setup of the header rows and columns simplifies the eventual calculation using array functions. It is highly recommended to explicitly label the cells to indicate which class (0 or 1) they represent, as these values will be dynamically referenced as criteria in the counting formula we are about to implement. This setup defines the location of our four core values: True Negatives (E3), False Positives (F3), False Negatives (E4), and True Positives (F4).

	A	B	C	D	E	F
1	<b>Actual</b>	<b>Predicted</b>			<b>Predicted</b>	
2	0	0		<b>Actual</b>	<b>0</b>	<b>1</b>
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				

### Step 3: Populating the Matrix using COUNTIFS

The core challenge in creating the Confusion Matrix is efficiently counting the occurrences that satisfy two simultaneous conditions: the specific actual value and the specific predicted value. Google Sheets provides the perfect tool for this task: the **COUNTIFS** function. This powerful function allows for accurate counting based on multiple criteria across multiple designated ranges.

For example, to calculate the number of **False Positives** (where Actual = 0 AND Predicted = 1), we need a single formula to simultaneously check the range of Actual Values for '0' and the range of Predicted Values for '1'. The standard syntax for the COUNTIFS formula is `=COUNTIFS(range1, criterion1, range2, criterion2, ...)`. By referencing the fixed data ranges and the dynamic row/column headers we set up in Step 2, we can create a single, robust formula that can be copied across all four cells of the matrix.

We begin by inputting the formula 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). This calculation yields the **True Negatives** count. The use of mixed absolute references (using the dollar sign, **\$**) is critical here to ensure that when the formula is dragged, the primary data ranges remain fixed,

while the criteria references shift correctly to pick up the corresponding row or column header.

The formula entered into cell **E3** is structured as follows, targeting the actual values in column A and the predicted values in column B:

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

In this formula, **\$A\$2:\$A\$21** is the fixed range of Actual Values, and **\$D3** is the criterion for the Actual Value (0 in this case), fixed on column D but allowed to change rows when dragged down. Similarly, **\$B\$2:\$B\$21** is the fixed range for Predicted Values, and **E\$2** is the criterion for the Predicted Value, fixed on row 2 but allowed to change columns when dragged right. By implementing this structure, we can efficiently click and drag this formula across to the remaining cells (F3, E4, and F4) to complete the matrix.

E3    fx =COUNTIFS(\$A\$2:\$A\$21, \$D3, \$B\$2:\$B\$21, E\$2)

	A	B	C	D	E	F
1	<b>Actual</b>	<b>Predicted</b>			<b>Predicted</b>	
2	0	0		<b>Actual</b>	<b>0</b>	<b>1</b>
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 4: Calculating Accuracy, Precision, and Recall

The completed Confusion Matrix serves as the raw data source for deriving standard performance metrics that allow for objective comparison between different classification models. These metrics quantify various aspects of the model's predictive skill, focusing on reliability and completeness in classification.

Once the counts for True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are secured in the matrix, we can calculate three of the most commonly cited metrics: **Accuracy**, **Precision**, and **Recall** (often referred to as Sensitivity). Each metric provides a distinct and valuable perspective on the model's overall effectiveness, making them essential for a

holistic evaluation.

The formulas for these metrics, translated into operations within Google Sheets, are defined as follows:

**Accuracy:** This measures the percentage of all observations that were correctly predicted, regardless of class. Formula:  $(TP + TN) / (TP + TN + FP + FN)$ .

**Precision:** This addresses the reliability of a positive prediction, calculated as the ratio of correct positive predictions relative to the total number of positive predictions made by the model. Formula:  $TP / (TP + FP)$ .

**Recall:** Also known as Sensitivity, this measures the model's ability to find all positive samples, calculated as the ratio of correct positive predictions relative to the total number of actual positive cases. Formula:  $TP / (TP + FN)$ .

By setting up dedicated cells below or adjacent to the matrix, we can input these formulas referencing the corresponding TP, TN, FP, and FN cells derived in Step 3.

	B	C	D	E	F	G
				<b>Predicted</b>		
<b>redicted</b>			<b>Actual</b>	<b>0</b>	<b>1</b>	
0			<b>0</b>	6	4	
1			<b>1</b>	2	8	
0						
0						
1			<b>Metric</b>	<b>Value</b>	<b>Formula</b>	
1			Accuracy	0.7	=SUM(E3,F4)/SUM(E3:F4)	
0			Precision	0.666666667	=F4/SUM(F3:F4)	
0			Recall	0.8	=F4/SUM(E4:F4)	
1						
0						
0						
1						
1						
1						

In this specific example, our model achieves an accuracy of **0.7**, which signifies that 70% of the observations in the test set were correctly classified. While a higher accuracy score is desirable, it is imperative to evaluate the scores for **Precision** and **Recall** as well. Accuracy can be misleading, particularly in situations involving imbalanced data sets. Comparing these comprehensive metrics

against those of other logistic regression models allows analysts to determine which statistical model provides the optimal balance of prediction reliability and coverage for the specific business or research need.

## Conclusion and Further Applications

Mastering the creation of the Confusion Matrix in Google Sheets provides a powerful, accessible methodology for rigorously evaluating the performance of any classification model. By leveraging the versatility of spreadsheet functions like COUNTIFS, complex statistical analyses become manageable without needing advanced programming environments. This matrix moves the evaluation beyond simple overall accuracy, delivering the detailed insights necessary to understand exactly where a model succeeds in its predictions and where specific types of critical errors occur.

This approach is particularly valuable for data practitioners who need to quickly prototype and test models, or for educational settings where the underlying mechanics of model evaluation must be transparently demonstrated. Furthermore, the foundational skills used here--data structuring, conditional counting, and formula referencing--are directly transferable to many other types of data analysis tasks routinely performed within the spreadsheet environment.

For those seeking to delve deeper into the theoretical underpinnings and advanced applications of this predictive technique, further exploration of topics such as the F1 Score (harmonic mean of Precision and Recall) and the Receiver Operating Characteristic (ROC) curve is highly recommended. These advanced metrics build directly upon the components derived from the confusion matrix.

The following resources provide additional information about logistic regression: