

Learn How to Calculate the Matthews Correlation Coefficient (MCC) in R for Evaluating Classification Models

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Why the Matthews Correlation Coefficient is Essential

Evaluating the performance of [classification models](#) is a critical and foundational step in any robust [machine learning](#) or [data science](#) workflow. While accessible metrics like [accuracy](#) are frequently employed, they often present a misleading picture of model efficacy, particularly when dealing with [imbalanced datasets](#). In these common real-world scenarios, the **Matthews correlation coefficient** (MCC) emerges as a highly robust, informative, and essential alternative that addresses the shortcomings of simpler metrics.

The [Matthews correlation coefficient](#) (MCC) is a holistic metric designed specifically to assess the quality of [binary classification](#) models. Its primary strength lies in its comprehensive consideration of all four fundamental outcomes derived from the [confusion matrix](#): **True Positives** (TP), **True Negatives** (TN), **False Positives** (FP), and **False Negatives** (FN). This inclusive approach ensures that MCC provides a balanced evaluation that is proportionate to the size of all classes, making it reliable even when one class vastly outnumbers the other.

Unlike standard [accuracy](#), which can yield deceptively high values for models that simply predict the majority class in imbalanced data, MCC offers a more truthful representation of a model's true predictive capability. Essentially, MCC quantifies the correlation between the observed and predicted binary classifications. The resulting single value effectively summarizes the model's overall predictive power, reflecting its performance across both the positive and negative class instances simultaneously.

The Mathematical Formulation and Components of MCC

The reliability of the **Matthews correlation coefficient** stems directly from its sophisticated mathematical formulation, which systematically incorporates every type of prediction error and success. This formula is notable for its inherent symmetry, meaning the resulting MCC score remains valid and consistent regardless of which class is arbitrarily designated as "positive" or "negative." This characteristic makes MCC exceptionally valuable for objective model comparison and critical steps like [model selection](#).

The core mathematical relationship defining MCC is as follows:

$$\text{MCC} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$$

To fully appreciate this formula, we must clarify the role of the four components derived from the classification's [confusion matrix](#):

TP (True Positives): Represents the number of instances where the model correctly identified the positive class. This is often the primary measure of success for the target outcome.

TN (True Negatives): Represents the number of instances where the model correctly identified the negative class. This indicates the model's ability to reject irrelevant cases.

FP (False Positives): Represents the number of instances where the model incorrectly predicted the positive class when the actual class was negative (a Type I error).

FN (False Negatives): Represents the number of instances where the model incorrectly predicted the negative class when the actual class was positive (a Type II error).

The denominator serves a crucial function: it is the geometric mean of four distinct factors, effectively normalizing the score. This mathematical normalization ensures that the final [Matthews correlation coefficient](#) value is strictly constrained within the range of -1 and +1. This standardization provides a clear, consistent scale for interpretation, independent of the overall dataset size or the specific distribution of the classes.

Interpreting the MCC Score Range

The **Matthews correlation coefficient** provides an easily interpretable range of values, offering instantaneous insight into a model's predictive quality, which is one of its major advantages over other metrics:

MCC = -1: This score indicates total disagreement, signifying that the model's predictions are consistently opposite to the actual classes. The model performs worse than random guessing.

MCC = 0: A score of **0** implies that the model's predictions are equivalent to completely random guessing. There is no correlation between the observed and predicted outcomes.

MCC = 1: A perfect score of **1** denotes total agreement between the predicted and actual classes. This represents flawless performance, where the model achieves 100% [accuracy](#) in identifying both positive and negative instances without error.

This metric is particularly valuable when the two classes within the dataset are significantly [imbalanced](#)--meaning one class appears much more frequently than the other. In such scenarios, relying solely on simple [accuracy](#) can be highly misleading. For example, if 95% of observations belong to the negative class, a naive model that always predicts the negative class will achieve 95% [accuracy](#). However, this model is utterly uninformative regarding the minority class.

MCC, conversely, would yield a score close to zero for such a naive model, accurately highlighting its poor ability to distinguish between the two classes. Its inherent robustness to class imbalance makes it the preferred evaluation metric for tasks where errors of both types (false positives and false negatives) carry significant and comparable weight in the overall assessment of performance.

Case Study: Predicting NBA Draft Outcomes

To solidify our understanding of how MCC is applied and why it is superior for skewed data, let us

examine a detailed practical example. Imagine a professional sports analyst developing a sophisticated [statistical model](#) designed to predict whether 400 unique [college basketball](#) players will successfully be drafted into the [NBA](#). This setup represents a classic [binary classification](#) challenge, where "drafted" is designated as the positive class, and "not drafted" is the negative class.

After executing the [predictive model](#), the analyst summarizes the results using a [confusion matrix](#). This matrix clearly breaks down the model's correct and incorrect assessments for each class. Crucially, in this real-world scenario, the data is highly skewed: out of 400 players, only 20 were actually drafted, leaving 380 who were not. The following image illustrates the performance summary provided by the model:

		Predicted	
		Drafted = Yes	Drafted = No
Actual	Drafted = Yes	15 (True Positive)	5 (False Negative)
	Drafted = No	5 (False positive)	375 (True Negative)

From this [confusion matrix](#), we extract the four essential counts required for the MCC calculation:

True Positives (TP): 15 (The model correctly predicted 15 players would be drafted).

True Negatives (TN): 375 (The model correctly predicted 375 players would not be drafted).

False Positives (FP): 5 (The model incorrectly predicted 5 players would be drafted when they were not).

False Negatives (FN): 5 (The model incorrectly predicted 5 players would not be drafted when they actually were).

We observe that the actual positive cases (20) are dwarfed by the negative cases (380). This severe class imbalance confirms that the **Matthews correlation coefficient** will offer a significantly more reliable and unbiased evaluation compared to simpler metrics like overall [accuracy](#).

Calculating the Matthews Correlation Coefficient Manually

Armed with the specific values derived from our NBA draft prediction [confusion matrix](#), we now proceed with a manual, step-by-step calculation of the **Matthews correlation coefficient**. This detailed process is invaluable for truly understanding how the metric integrates all four components of the prediction outcomes and how sensitive it is to trade-offs between false positives and false negatives.

Using the formula $MCC = (TP \cdot TN - FP \cdot FN) / \sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}$, and substituting the values established in the previous section:

TP = 15

TN = 375

FP = 5

FN = 5

We first calculate the Numerator and the Denominator components separately:

Numerator Calculation: $(15 * 375) - (5 * 5) = 5625 - 25 = \mathbf{5600}$

Denominator Factor Calculations:

$(TP + FP) = (15 + 5) = 20$

$(TP + FN) = (15 + 5) = 20$

$(TN + FP) = (375 + 5) = 380$

$(TN + FN) = (375 + 5) = 380$

Denominator Product: $20 * 20 * 380 * 380 = 57,760,000$

Square Root of Denominator: $\sqrt{57,760,000} \approx \mathbf{7600}$

Final MCC Calculation: $5600 / 7600 \approx \mathbf{0.7368}$

The resulting **Matthews correlation coefficient** for this model is approximately **0.7368**. Since this value is significantly closer to one than to zero, it strongly suggests that the model performs well, exhibiting a strong positive correlation between its predictions and the actual draft outcomes. This confirms that the model's predictive power is substantially better than random chance, even when dealing with the highly [imbalanced](#) nature of NBA draft statistics.

Implementing MCC in R: Using Actual and Predicted Vectors

While manual calculation provides clarity, real-world data science requires programmatic solutions for efficiency, especially when handling large datasets. The statistical [programming language R](#) provides excellent tools for this purpose. The [mltools package](#) is widely used in machine learning for metric calculation, offering a highly convenient dedicated [function](#) for computing MCC.

Before proceeding, ensure the [mltools package](#) is installed in your [R](#) environment (using `install.packages("mltools")` if necessary). Once available, the [package](#) must be loaded into your active session. We will demonstrate how to replicate the exact NBA draft example using the [mcc\(\)](#) [function](#), defining separate [vectors](#) to store the actual and predicted classes.

```
library(mltools)
```

```
# Define the vector of actual classes (20 drafted (1), 380 not drafted (0))
actual <- rep(c(1, 0), times=c(20, 380))

# Define the vector of predicted classes based on the confusion matrix (TP=15, FN=5, FP=5,
TN=375)
preds <- rep(c(1, 0, 1, 0), times=c(15, 5, 5, 375))

# Calculate the Matthews correlation coefficient using the mcc function
mcc(preds, actual)

0.7368421
```

The output confirms that the **Matthews correlation coefficient** calculated programmatically by the `mcc()` [function](#) is precisely **0.7368421**. This result matches our painstaking manual calculation, validating the consistency and reliability of the library [function](#). Utilizing this approach significantly streamlines the metric calculation process, making it feasible for analyzing large-scale predictive models.

Alternative R Method: Calculating MCC from a Confusion Matrix

The `mcc()` [function](#) within the [mltools](#) [package](#) offers valuable flexibility by allowing users to calculate the **Matthews correlation coefficient** directly from a pre-computed [confusion matrix](#). This feature is highly advantageous when integrating MCC computation into existing workflows where model summaries are already provided in matrix format, or when working with outputs from other [R functions](#) that generate confusion tables.

To employ this functionality, the [confusion matrix](#) must be passed via the `confusionM` argument. It is essential that the matrix adheres to the expected structure, typically arranging rows by actual classes and columns by predicted classes. We recreate our NBA draft prediction [confusion matrix](#) directly in [R](#) and demonstrate the MCC calculation using this specialized matrix input:

library(mltools)

```
# Create confusion matrix: (TP, FN; FP, TN) using byrow=TRUE
conf_matrix <- matrix(c(15, 5, 5, 375), nrow=2, byrow = TRUE) # Row 1: Actual Positive (TP, FN),
Row 2: Actual Negative (FP, TN)

# View the structure of the R confusion matrix
conf_matrix

15 5
```

5 375

```
# Calculate Matthews correlation coefficient using the confusion matrix input  
mcc(confusionM = conf_matrix)
```

0.7368421

The MCC score of approximately **0.7368** is consistently reproduced using this matrix input method. This reinforces the utility and consistency of the [mltools package](#), confirming that researchers can reliably compute this critical metric whether they start with raw prediction [vectors](#) or pre-aggregated confusion matrices. Choosing the **Matthews correlation coefficient** ensures your model evaluation is robust, especially when tackling the complexities of real-world [imbalanced data](#).

Additional Resources

For those interested in exploring further aspects of model evaluation and [R](#) programming, the following tutorials explain how to perform other common tasks and delve deeper into related concepts. Understanding MCC is a valuable addition to your data analysis toolkit, especially when tackling real-world problems with complex data distributions.