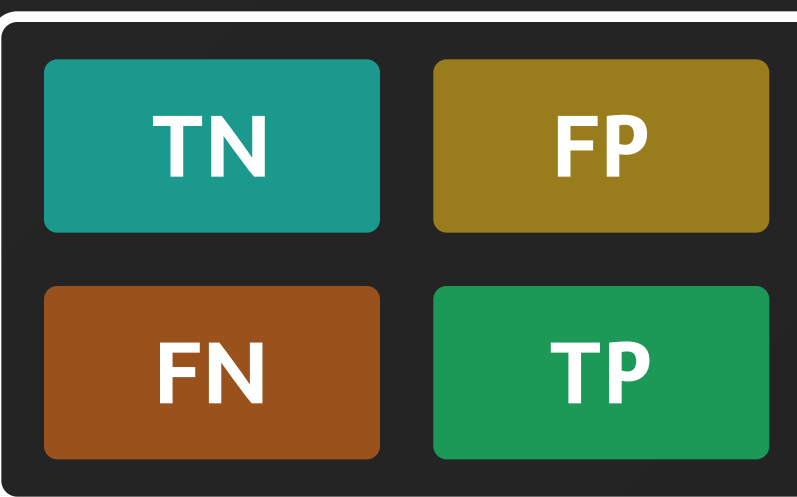


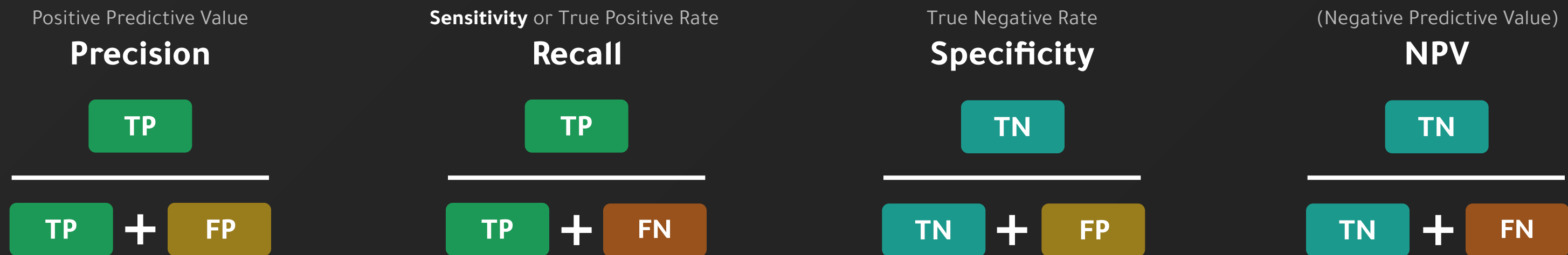
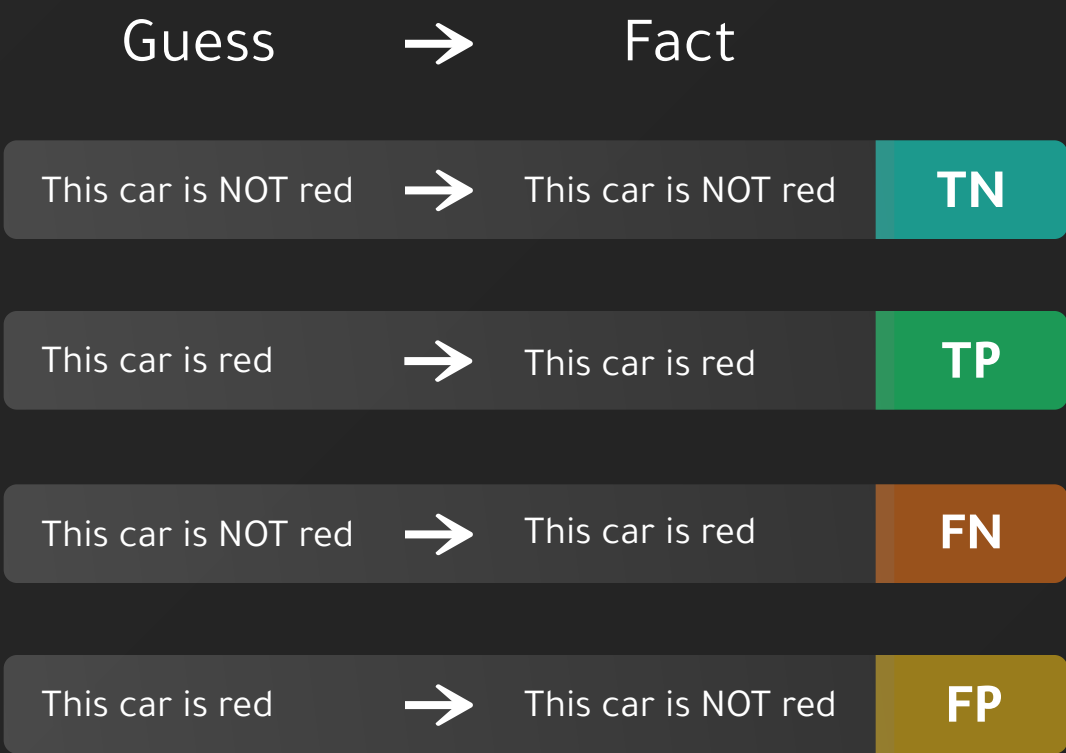
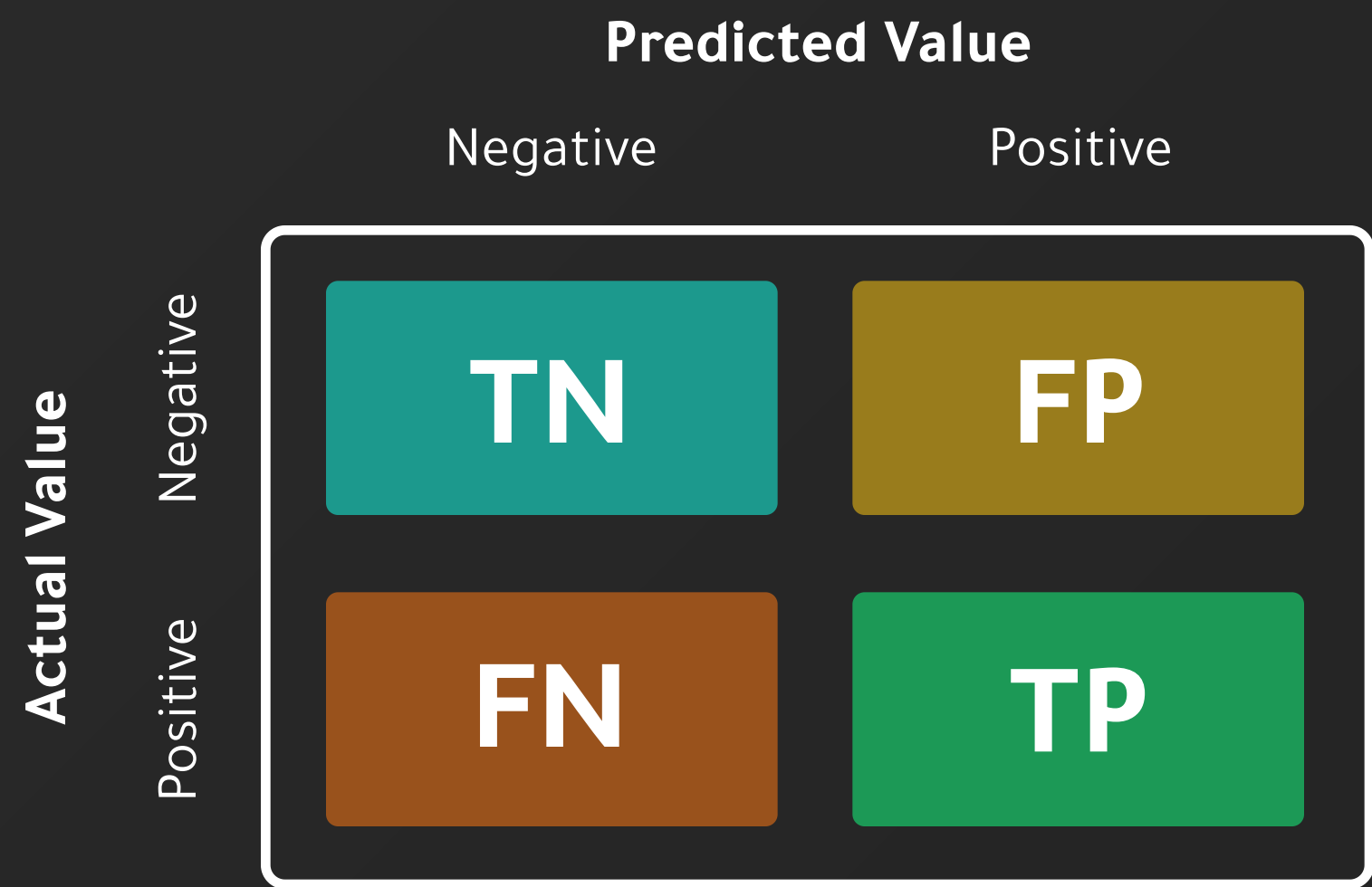
Confusion Matrix



and Classification Evaluation Metrics

Trust is a must when a decision-maker's judgment is critical. To give such trust, we summarize all possible decision outcomes into four categories: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) to serve an outlook of how confused their judgments are, namely, the confusion matrix. From the confusion matrix, we calculate different metrics to measure the quality of the outcomes. These measures influence how much trust we should give to the decision-maker (classifier) in particular use cases. This document will discuss the most common classification evaluation metrics, their focuses, and their limitations in a straightforward and informative manner.

Confusion Matrix



Matthews Correlation Coefficient (MCC)

$$\frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}$$

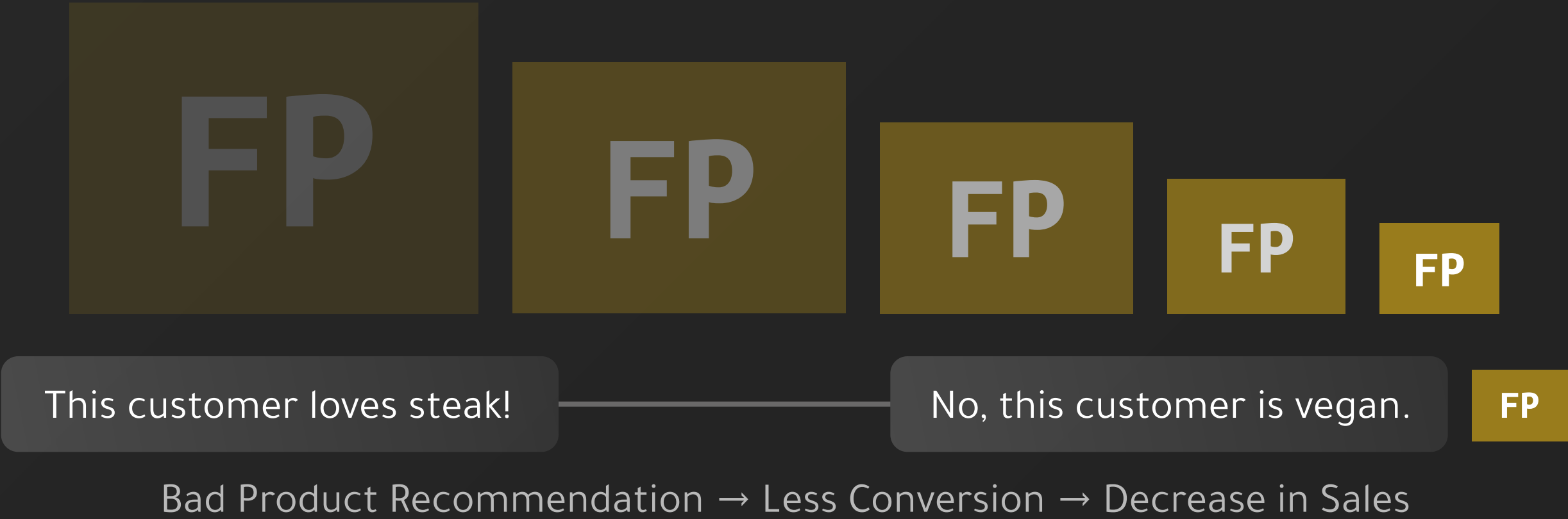
Precision & Recall

Common Goal

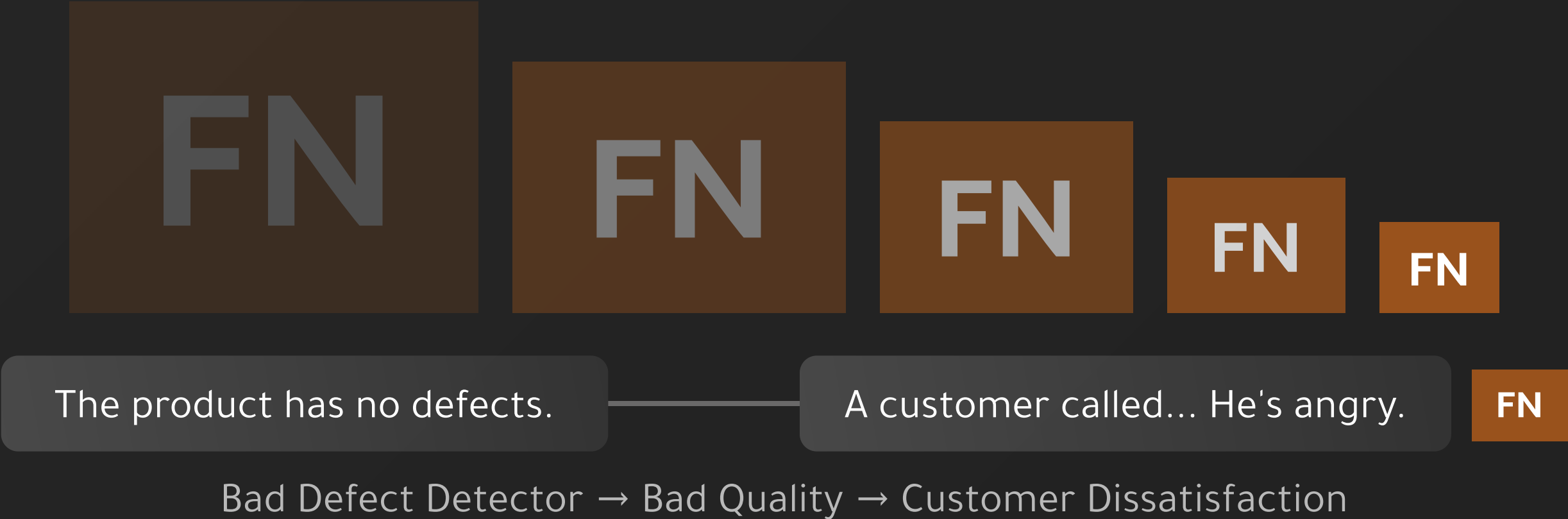


We use both metrics when actual negatives are less relevant. For example, googling "Confusion Matrix" will have trillions of unrelated (negative) web pages, such as the "Best Pizza Recipe!" web page. Accounting for whether we have correctly predicted the latter webpage and alike as negative is impractical.

Precision Goal



Recall Goal



Specificity & NPV

Common Goal



We use both metrics when actual positives are less relevant. In essence, we aim to rule out a phenomenon. For example, we want to know how many healthy people (no disease detected) there are in a population. Or, how many trustworthy websites (not fraudulent) is someone visiting.

Specificity Goal



This person is a criminal.

They were detained for no reason.

FP

Bad Predictive Policing → Injustice

NPV Goal



They don't have cancer.

No, they should be treated!

FN

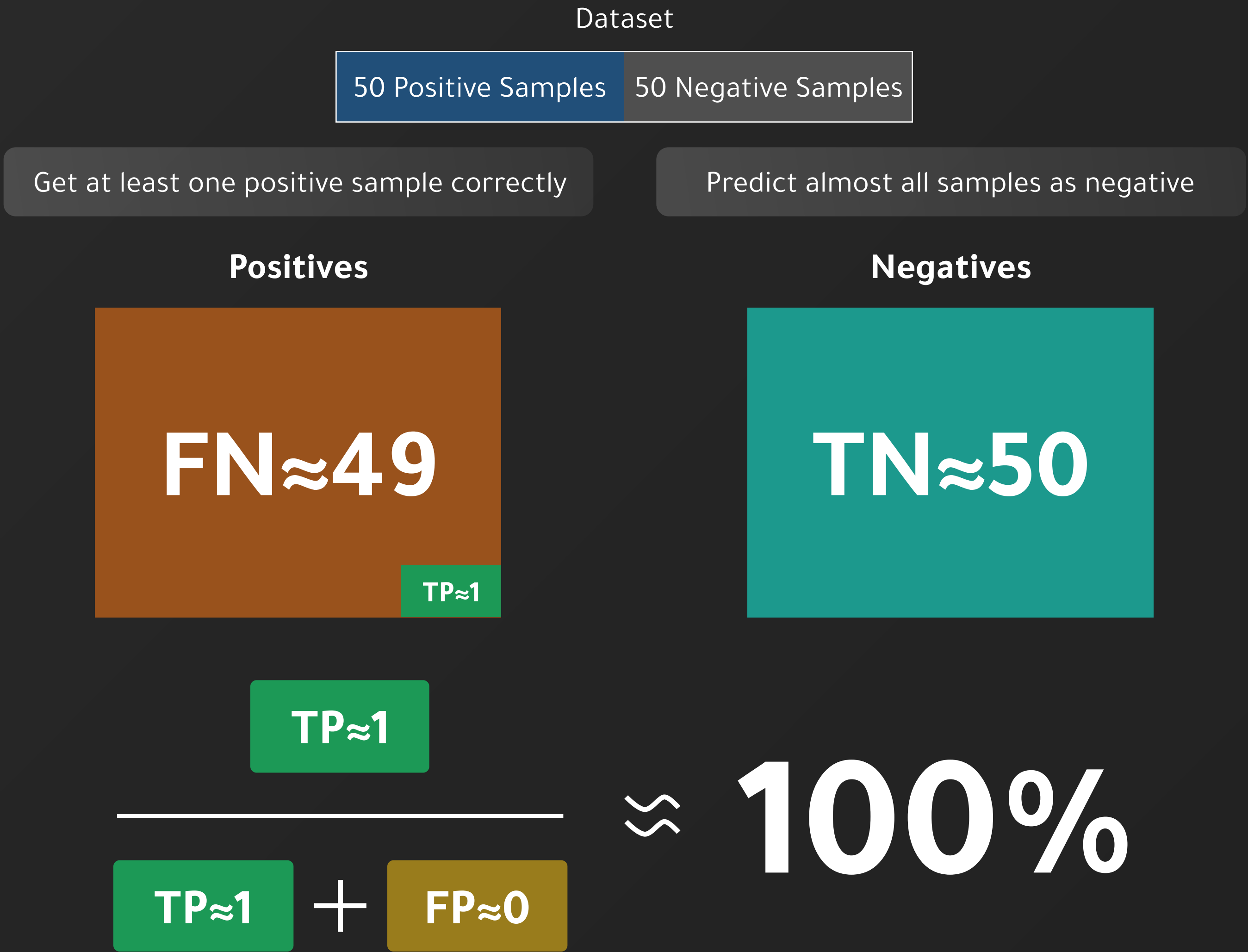
Bad Diagnosis → No Treatment → Consequences

Hacks

Previously explained evaluation metrics, among many, are granular, as they focus on one angle of prediction quality which can mislead us into thinking that a predictive model is highly accurate. Generally, these metrics are not used solely. Let us see how easy it is to manipulate the aforementioned metrics.

Precision Hacking

Precision is the ratio of correctly classified positive samples to the total number of positive predictions. Hence the name, Positive Predictive Value.



Predicting positive samples with a high confidence threshold would potentially bring out this case. In addition, when positive samples are disproportionately higher than negatives, false positives will probabilistically be rarer. Hence, precision will tend to be high.

Recall **Hacking**

Recall is the ratio of correctly classified positive samples to the total number of actual positive samples. Hence the name, True Positive Rate.

Dataset

50 Positive Samples 50 Negative Samples

Predict all samples as positive

Positives

TP=50

Negatives

FP=50

TP=50

TP=50

+

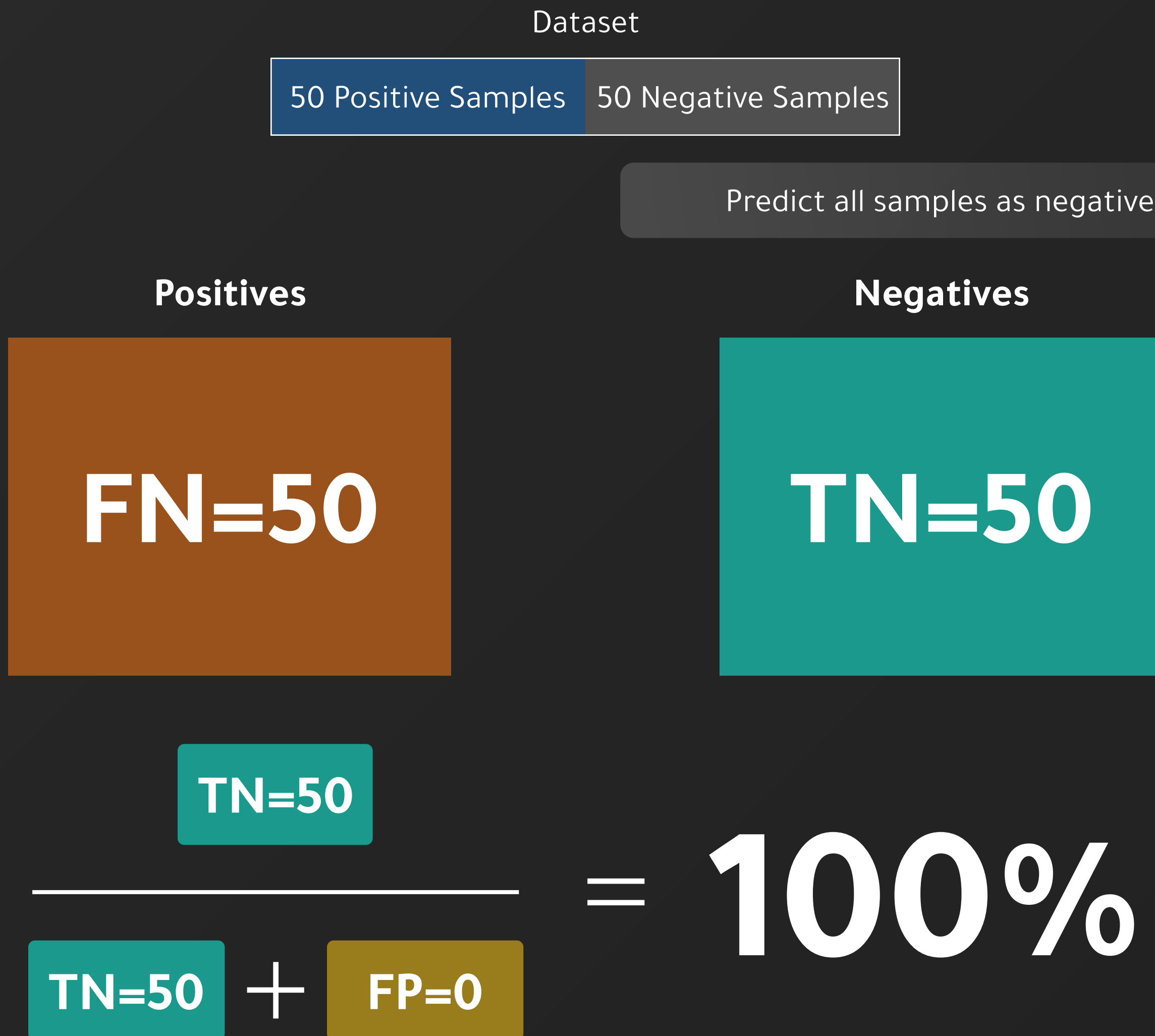
FN=0

= **100%**

Similar to precision, when positive samples are disproportionately higher, the classifier would generally be biased towards positive class predictions to reduce the number of mistakes.

Specificity **Hacking**

Specificity is the ratio of correctly classified negative samples to the total number of actual negative samples. Hence the name, True Negative Rate.



Contrary to Recall (Sensitivity), Specificity focuses on the negative class. Hence, we face this problem when negative samples are disproportionately higher. Notice how the Balanced Accuracy metric intuitively solves this issue in subsequent pages.

NPV Hacking

Negative Predictive Value is the ratio of correctly classified negative samples to the total number of negative predictions. Hence the name.

Dataset

50 Positive Samples 50 Negative Samples

Predict almost all samples as positive

Get at least one negative sample correctly

Positives



Negatives



TN ≈ 1

TN ≈ 1 + FN ≈ 0

≈ 100%

Predicting negative samples with a high confidence threshold has this case as a consequence. Also, when negative samples are disproportionately higher, false negatives will probabilistically be rarer. Thus, NPV will tend to be high.

Comprehensive Metrics

As we have seen above, some metrics can misinform us about the actual performance of a classifier. However, there are other metrics that include more information about the performance. Nevertheless, all metrics can be “hacked” in one way or another. Hence, we commonly report multiple metrics to observe multiple viewpoints of the model's performance.

Accuracy

Accuracy treats all error types (false positives and false negatives) as equal. However, equal is not always preferred.

$$\frac{\text{TP} + \text{TN}}{\text{FP} + \text{TP} + \text{TN} + \text{FN}}$$

Accuracy Paradox



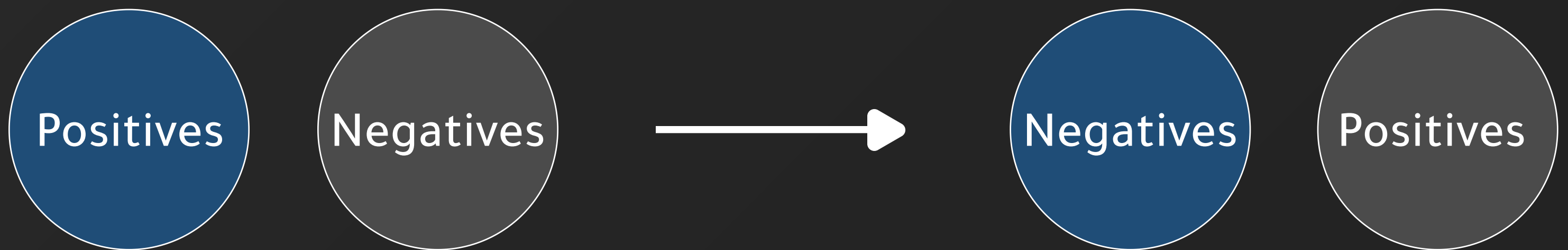
Since accuracy assigns equal cost to all error types, having significantly more positive samples than negatives will make accuracy biased towards the larger class. In fact, the Accuracy Paradox is a direct “hack” against the metric. Assume you have 99 samples of class 1 and 1 sample of class 0. If your classifier predicts everything as class 1, it will get an accuracy of 99%.

F1-Score

F1-Score will combine precision and recall in a way that is sensitive to a decrease in any of the two (Harmonic Mean). Note that the issues mentioned below do apply to F_β score in general.

$$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Asymmetric Measure



F1-Score is asymmetric to the choice of which class is negative or positive. Changing the positive class into the negative one will not produce a similar score in most cases.

True Negatives Absence

F1-Score does not account for true negatives. For example, correctly diagnosing a patient with no disease (true negative) has no impact on the F1-Score.

Balanced Accuracy

Balanced Accuracy accounts for the positive and negative classes independently using Sensitivity and Specificity, respectively. The metric partially solves the Accuracy paradox through independent calculation of error types and solves the true negative absence problem in F_β -Score through the inclusion of Specificity.

$$\frac{\text{Sensitivity} + \text{Specificity}}{2}$$

Relative Differences in error types

TN 9	FP 1
FN 1000	TP 9000

TN 9000	FP 1000
FN 1	TP 9

Balanced Accuracy is commonly robust against imbalanced datasets, but that does not apply to the above-illustrated cases. Both models perform poorly at predicting one of the two (positive P or negative N) classes, therefore unreliable at one. Yet, Balanced Accuracy is 90%, which is misleading.

Matthews Correlation Coefficient (MCC)

MCC calculates the correlation between the actual and predicted labels, which produces a number between -1 and 1. Hence, it will only produce a good score if the model is accurate in all confusion matrix components. MCC is the most robust metric against imbalanced dataset issues or random classifications.

$$\frac{(\text{TP} \times \text{TN}) - (\text{FP} \times \text{FN})}{\sqrt{(\text{TP} + \text{FP}) \times (\text{TP} + \text{FN}) \times (\text{TN} + \text{FP}) \times (\text{TN} + \text{FN})}}$$

MCC faces an issue of it being undefined whenever a full row or a column in a confusion matrix is zeros. However, the issue is outside the scope of this document. Note that this is solved by simply substituting zeros with an arbitrarily small value.

Conclusion

We have gone through all confusion matrix components, discussed some of the most popular metrics, how easy it is for them to be "hacked", alternatives to overcome these problems through more generalized metrics, and each one's limitations. The key takeaways are:

Recognize the hacks against granular metrics as you might fall into one unintentionally. Although these metrics are not solely used in reporting, they are heavily used in development settings to debug a classifier's behavior.

Know the limitations of popular classification evaluations metrics used in reporting so that you become equipped with enough acumen to decide whether you have obtained the optimal classifier or not.

Never get persuaded by the phrase "THE BEST" in the context of machine learning, especially evaluation metrics. Every metric approached in this document (including MCC) is the best metric only when it best fits the project's objective.

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Reviewer



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THANK YOU!

For any feedback, issues, or inquiries, contact yousefalghofaili@gmail.com

F_{β} Score

F_{β} Score is the generalized form of F1 Score ($F_{\beta=1}$ Score) where the difference lies within the variability of the β Factor. The β Factor skews the final score into favoring recall β times over precision, enabling us to weigh the risk of having false negatives (Type II Errors) and false positives (Type I Errors) differently.

$$\frac{(1 + \beta^2) \times \text{Precision} \times \text{Recall}}{(\beta^2 \times \text{Precision}) + \text{Recall}}$$



Precision is β times **Less** important than Recall



$\beta = 1$

Balanced F1-Score

$\beta = 1$



Precision is β times **More** important than Recall



F_{β} Score has been originally developed to evaluate Information Retrieval (IR) systems such as Google Search Engine. When you search for a webpage, but it does not appear, you are experiencing the engine's low Recall. When the results you see are completely irrelevant, you are experiencing its low Precision. Hence, search engines play with the β Factor to optimize User Experience by favoring one of the two experiences you have had over another.