Measuring Success: Accuracy and Precision

Picture this: You're in the world of prediction modeling, whether it's forecasting future trends, leveraging machine learning algorithms, or crafting models in a familiar tool like Excel. After making predictions, the next logical step is to evaluate their quality. When assessing predictions, three terms frequently come into play: accuracy, precision, and bias. The way you wield these terms can significantly influence the reliability of your predictions. In this article, we will delve into the practical applications of accuracy and precision as evaluation metrics, with a brief consideration of bias.

Accuracy, like many words, can have different meanings for different people. Some may view accuracy as a composite of precision and bias, while others may use it interchangeably with bias. In contrast, accuracy and bias are often distinct metrics. To avoid some confusion in the case of this article, we will use accuracy as a stand-alone evaluation metric.

Before going any deeper, let's set some boundaries and define accuracy and precision:

- Accuracy: A measure of how close a prediction is to the true value. This measure can be calculated in various ways, such as by averaging the differences, taking the median, or other statistical methods.
- Precision: A measure of the consistency and similarity between multiple predictions, disregarding the true value. It focuses on how well the predictions align with each other.

Now that we've established a clear understanding of accuracy and precision, let's explore the critical role they play in ensuring the quality of predictions.

Accuracy:

It is important to try and avoid some common pitfalls when measuring the reliability of a prediction. The first pitfall that I see to be the most common is to not take the absolute value of the error before using their favorite evaluation metric. Usually, the argument for this is that the direction of the error is important. The consequences of overlooking the use of the absolute value of the error can be serious. This oversight can lead to a misleading phenomenon that I call ‘Phantom Accuracy’. To showcase this impact, let's explore an example.

For these examples, we will just use a simple mean error evaluation for our accuracy metric.

Let's imagine a simple prediction model like this:

Prediction	True Value	Error
100	80	20
80	100	-20
100	70	30
80	90	-10
75	105	-30
90	80	10

When we apply mean error ME, $ME = \frac{1}{n}\sum_{i=1}^{n}(x_i - \widehat{x_i})$. This will be:

$$ME = \frac{(100-80)+(80-100)+(100-70)+(80-90)+(75-105)+(90-80)}{6}$$

$$ME = \frac{0}{6}$$

$$ME = 0$$

Now this is an exaggerated example meant to illustrate how the accuracy of a prediction model can result in 'Phantom Accuracy' giving the impression of good predictions even when the actual predictions fall short. If we instead take the absolute value by using

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \widehat{x_i}|,$$

we will get an MAE=20 a much more telling measurement.

If you do want to measure the direction of a prediction, I would recommend measuring the bias of the prediction. This is usually most prevalent when doing forecasting, to check whether you are under-forecasting or over-forecasting. There are a plethora of ways to measure bias. However, the main takeaway from bias is that it exists what direction is it pointing, and how significant it is. The bias number should not be used to make a systematic adjustment, such as we have an ME of -10 so we adjust all our forecasts to add 10. This would insert an artificial bias without finding the root cause of the bias.

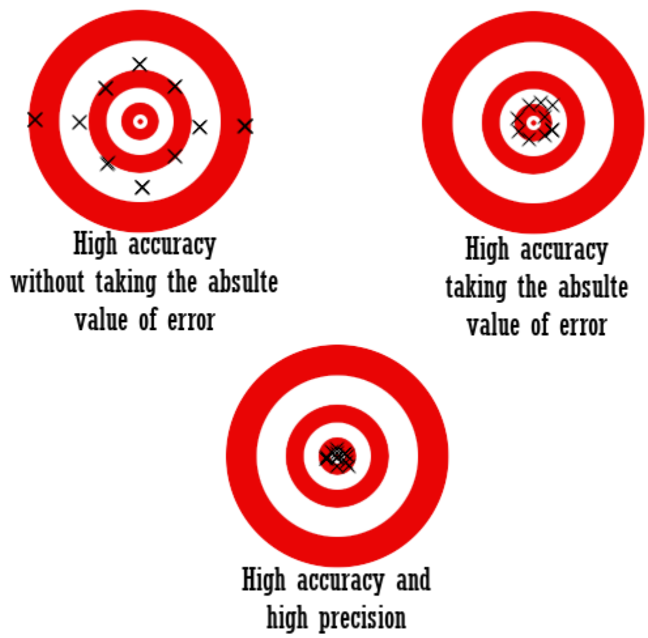
Precision:

Precision is sometimes an afterthought when reviewing a prediction. People tend to ask how accurate something is and stop after that. While precision alone may not be the most useful metric in isolation, using precision alongside other metrics such as accuracy can give much-needed insight. So, if precision is not helpful on its own then what benefit does it have? I'm glad you asked in terms of precision in forecasting a lower precision will indicate more variation in the forecasts. While a high precision score will minimize the error in a forecast. So, if we had a forecast with high accuracy and low precision that forecast would have errors that are not consistent. A forecast with high accuracy and high precision will have to be both accurate on the aggregate and have consistently low errors. With high precision we can more easily track down those problem forecasts and adjust the forecast model, this is due to less noise to work through if the precision is low. This is also true for regression machine learning models.

When we look at precision from the machine learning perspective that is not regression i.e. classification models the meaning is slightly different. Precision in this case will be the true positive predictions over all predicted positives. This measures how consistently the model correctly predicts the positive classification. Some examples of how precision is important in this case could be fraud detection or medical diagnoses. For fraud detection, precision would be more important than accuracy because banks do not want to consistently flag transactions as fraudulent that are not. Banks would want to flag fraudulent transactions with as few false positives as possible to not anger customers. Similarly, with medical diagnoses a false positive is detrimental to the patient, so it is critical to minimize those false alarms.

Combining Concepts:

Some concepts just make more sense when seeing them visually. We can show the difference between measuring accuracy using the absolute value of the error and not.



We can see that when do not take the absolute value, the errors that are on opposite sides can cancel each other out, resulting in the earlier 0 we obtained. In order to guarantee our predictions are closer to the center of the target we need to take the absolute value of the error before calculating accuracy. Then once we measure precision into the equation, we can find those problem predictions and fix them to get a precise and accurate forecast/prediction. Taking the absolute value of the error is crucial to ensure our predictions align with the center of the target. Moreover, when we introduce precision into the equation, we gain the ability to identify and rectify problematic predictions, ultimately striving for both precision and accuracy. In some cases, prioritizing precision over accuracy becomes necessary, making both crucial factors when evaluating predictions. As analysts let’s try and make our jobs easier not harder.