MSE (Mean Squared Error)

Mean Squared Error (MSE) is the average squared error between actual and predicted values. The mean squared error is calculated by:

$$\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

MSE

MSE should be interpreted as an error metric where the closer your value is to 0, the more accurate your model is. However, there is no general rule for how to interpret given MSE values. It is an absolute value which is unique to each dataset and can only be used to say whether the model has become more or less accurate than a previous run.

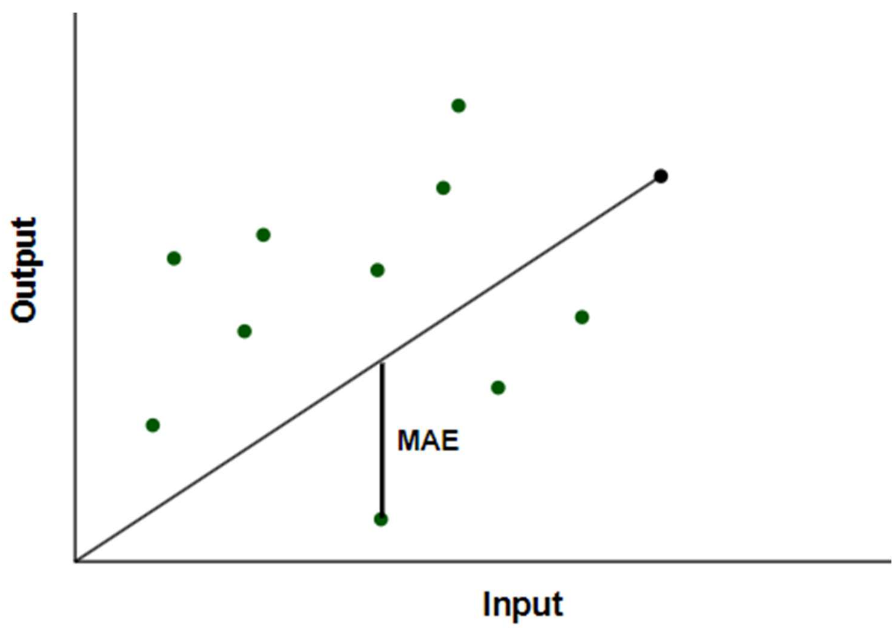
MAE (Mean Absolute Error)

MAE is the average of the absolute value between predicted and actual values. The mean absolute error is calculated by:

$$\frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

MAE

The Mean Absolute Error (MAE) serves as an indicator of the accuracy of a predictive model. A lower MAE suggests a more accurate model. However, it's important to note that the interpretation of MAE is specific to the scale of the target variable being predicted. Unlike some other metrics, MAE is returned in the same units as the target variable, making its interpretation dataset-dependent.



MAE Visualization

Choosing Between MSE and MAE

The key difference between squared error and absolute error is that squared error punishes large errors to a greater extent than absolute error, as the errors are squared instead of just calculating the difference.

Let's explore situations where Mean Squared Error (MSE) is more suitable than Mean Absolute Error (MAE), and vice versa:

Use MSE when:

- MSE penalizes larger errors more heavily due to the squaring of differences. If your project is particularly concerned about minimizing the impact of large errors and is more tolerant of small errors, MSE may be more appropriate.
- When using optimization algorithms to train machine learning models, MSE can offer better numerical stability in certain cases. The squared term often leads to smoother and more well-behaved optimization landscapes.
- MSE amplifies the differences between small and large errors. This can be beneficial when you want a metric that reflects and magnifies the variations in performance, making it easier to distinguish between models with subtle differences.

Use MAE when:

- If your dataset contains outliers and you want the metric to be less influenced by extreme values, MAE is a better choice at that situation.
- MAE provides error values in the same units as the target variable, making it more interpretable. If clear communication of the error in a way that stakeholders can easily understand is crucial, MAE is often preferred.