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| **Mean Absolute Error (MAE)**  The average of the absolute differences between the predicted and actual values. | MAE gives a clear, intuitive measure of the average magnitude of errors, but it does not penalize larger errors more than smaller ones.  **Use Case**: When you want a model that treats all errors equally. |
| **Mean Squared Error (MSE)**  The average of the squared differences between the predicted and actual values. | MSE penalizes larger errors more than smaller ones due to the squaring of differences. It's sensitive to outliers.  **Use Case**: When larger errors need to be penalized more heavily, and the dataset doesn't contain too many outliers. |
| **Root Mean Squared Error (RMSE)**  The square root of the Mean Squared Error, providing a metric in the same units as the target variable. | RMSE provides a more interpretable error measure because it is in the same unit as the original data. Like MSE, it penalizes large errors.  **Use Case**: When the model should focus on large errors and a more interpretable metric is needed. |
| **R-squared (R²) - Coefficient of Determination**  A measure of how well the model’s predictions explain the variance in the target variable. | Where yˉ​ is the mean of the actual values.  R² ranges from 0 to 1, where 1 indicates perfect predictions, and 0 indicates that the model does not explain any variance.  **Use Case**: When you want to understand how well the model is fitting the data and how much variance is explained. |
| **Adjusted R-squared**  A modified version of R² that adjusts for the number of predictors in the model. It helps to prevent overfitting when there are multiple features. | Where n is the number of data points and ppp is the number of predictors.  Unlike R², it penalizes the addition of irrelevant features, making it a better metric when comparing models with different numbers of predictors.  **Use Case**: When comparing models with different numbers of features. |
| **Mean Absolute Percentage Error (MAPE)**  The average of the absolute percentage differences between the predicted and actual values. | MAPE expresses the error as a percentage, making it easy to interpret. However, it can be undefined if any actual value (yi​) is zero.  **Use Case**: When relative error is important and the target values are non-zero. |
| **Explained Variance Score**  Measures the proportion of variance in the target variable that is explained by the model. | A value close to 1 indicates a good model fit, and a value close to 0 indicates a poor fit.  **Use Case**: When you need to understand how much of the target's variance is captured by the model. |
| **Huber Loss**  A loss function that combines MSE and MAE, penalizing large errors less than MSE but more than MAE. | It’s robust to outliers, similar to MAE, but less sensitive than MAE when the error is small.  **Use Case**: When you want a balance between penalizing large errors and robustness to outliers. |
| **Quantile Loss**  Used for quantile regression, it measures the difference between predicted and actual values in terms of a quantile. | It is useful when predicting specific quantiles (e.g., median or 90th percentile) instead of the mean.  **Use Case**: For models that focus on predicting specific quantiles (e.g., the median). |

Each metric provides different insights into how well the regression model is performing, so the choice of metric depends on the specific goals of the model and the characteristics of the data.