


Regression model evaluation metrics

Réda DEHAK
<http://ismil.dehak.org>


1



Deciding an Evaluation Metric for a Regression Model

- Evaluating the model accuracy is an essential part of the process in creating machine learning models to describe how well the model is performing in its predictions. Evaluation metrics change according to the problem type.
- The errors represent how much the model is making mistakes in its prediction. The basic concept of accuracy evaluation is to compare the original target with the predicted one according to certain metrics.


2




Rule of evaluation metrics (loss value)

- **A Smaller Loss Value**
If the total difference between the predicted values and the actual ones is relatively small, the total error/loss will be smaller value and thus, signify a good model.
- **A Larger Loss Value**
If the difference between the actual and predicted values is large, the total error/value of loss function will be relatively larger as well to imply that the model is not trained well.

3



Loss Functions



- The Goal of Training a Regression Model**
The goal of training a Regression Model is to find those values of weights against which loss function can be minimized i.e difference between the predicted values and the true labels is minimized as much as possible.
- Mean Squared Error (MSE):


$$MSE = \frac{1}{N} \sum_i (y_i - \hat{y}_i)^2$$
- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N} \sum_i (y_i - \hat{y}_i)^2}$$
- Mean Absolute Error (MAE)


$$MAE = \frac{1}{N} \sum_i |y_i - \hat{y}_i|$$
- Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{N} \sum_i \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$
- R-squared

4




Mean Squared Error (MSE)




- Mean Squared Error (MSE):

$$MSE = \frac{1}{N} \sum_i (y_i - \hat{y}_i)^2$$
- differentiable, so you can easily use it as a loss function.
- The MSE penalizes large errors: It is not Robust to outliers.
- Not interpretable in the scale of the target

5




Root Mean Squared Error (RMSE)



- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N} \sum_i (y_i - \hat{y}_i)^2}$$
- differentiable, so you can easily use it as a loss function.
- The RMSE penalizes large errors: It is not Robust to outliers.
- Interpretable in the scale of the target

6



Mean Absolute Error (MAE)

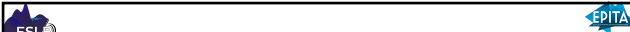
- Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum_i |y_i - \hat{y}_i|$$

- In the same unit as the output variable.
- It is most Robust to outliers.
- MAE is not differentiable so we have to apply various optimizers (convergence problem)

Réda DEHAQ 7

7



Mean Absolute Percentage Error (MAPE)


- Mean Absolute Percentage Error:

$$MAPE = \frac{1}{N} \sum_i \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

- Most commonly used in time series problems.
- Intuitive interpretation in terms of relative error.
- MAPE has some troubles dealing with values equals or near 0.

Réda DEHAQ 8

8



R-squared

- R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression.

R-squared = Explained variation / Total variation

- R-squared is always between 0 and 100%:
 - 0% indicates that the model explains none of the variability of the response data around its mean.
 - 100% indicates that the model explains all the variability of the response data around its mean.

In general, the higher the R-squared, the better the model fits your data.

Réda DEHAQ 9

9

R-squared

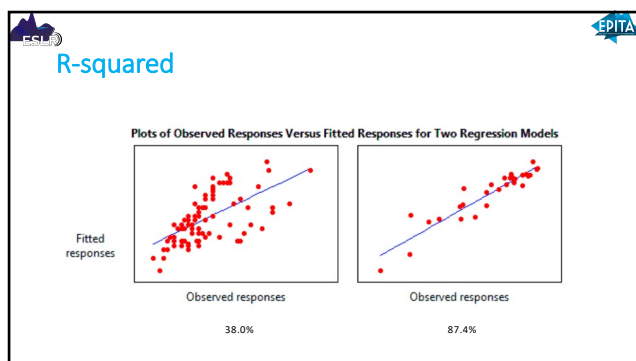
- total sum of squares (Variance of the data):

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 \quad \text{where } \bar{y} = \frac{1}{N} \sum_i y_i$$
- Residual sum of squares:

$$SS_{res} = \sum_i (y_i - \hat{y}_i)^2$$
- Coefficient of determination:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

10



11
