Linear Regression: Loss function

Fitting an estimator/predictor/model involves solving for the Θ that minimizes the Loss function.

For a Regression task: our goal is to make the discrepancy (error) between $\mathbf{y}$ and $\hat{\mathbf{y}}$ "small".

- The discrepancy between $\mathbf{y}^{(\mathbf{i})}$ and $\hat{\mathbf{y}}^{(\mathbf{i})}$ is refered to as the *residual*, usually denoted by ϵ

$$\epsilon^{(\mathbf{i})} = \mathbf{y}^{(\mathbf{i})} - \hat{\mathbf{y}}^{(\mathbf{i})}$$

So

$$\begin{aligned} \mathbf{y} &= \hat{\mathbf{y}} + \epsilon \\ &= \mathbf{X}\Theta + \epsilon \end{aligned}$$

We define the per-example loss to be the residual *squared*

$$\mathcal{L}_{\Theta}^{(\mathbf{i})} = (\mathbf{y}^{(\mathbf{i})} - \hat{\mathbf{y}}^{(\mathbf{i})})^2$$

so that the average loss

$$\begin{aligned} \mathcal{L}_{\Theta} &= \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}_{\Theta}^{(\mathbf{i})} \\ &= \frac{1}{m} \sum_{i=1}^{m} (\mathbf{y}^{(\mathbf{i})} - \hat{\mathbf{y}}^{(\mathbf{i})})^2 \end{aligned}$$

This expression on the right is called the *Mean Squared Error (MSE)*.

$$\mathrm{MSE}(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{m}\sum_{i=1}^{m}(\mathbf{y}^{(\mathbf{i})} - \hat{\mathbf{y}}^{(\mathbf{i})})^2$$

- You will sometimes see *Root Mean Squared Error (RMSE)* which is the square root of the MSE

Notice that the Performance Metric and Loss Functions are identical in this case.

This will not always be true.

R^2 versus RMSE: Absolute versus relative error

One often sees the term R^2 in the context of Linear Regression.

Whereas RMSE is absolute error (in same units as $\mathbf{y}$), R^2 is a relative error (in units of percent).

The relationship is:

$$
\begin{aligned}
R^2 &= 1 - \left(\frac{\sum_{i=1}^m (\mathbf{y}_i - \hat{\mathbf{y}}_i)^2}{\sum_{i=1}^m (\mathbf{y}_i - \bar{\mathbf{y}}_i)^2} \right) \\
&= 1 - \left(\frac{m \cdot \mathrm{MSE}(\mathbf{y}, \hat{\mathbf{y}})}{\sum_{i=1}^m (\mathbf{y}_i - \bar{\mathbf{y}}_i)^2} \right) \\
&= 1 - \left(\frac{m \cdot \mathrm{RMSE}(\hat{\mathbf{y}}, \mathbf{y})^2}{\sum_{i=1}^m (\mathbf{y}_i - \bar{\mathbf{y}}_i)^2} \right)
\end{aligned}
$$

In addition to changing the units of error, the R^2 metric has an interesting interpretation.

Consider a naive "baseline" model for prediction

- predict $\bar{\mathbf{y}}$ for every value of $\mathbf{x}$
    - where $\bar{\mathbf{y}}$ is the average (over the training examples) of the target

The loss for the naive model is

$$\mathcal{L}_{\text{naive}} = \text{MSE}(\mathbf{y}, \bar{\mathbf{y}})$$

Then

$$\begin{aligned} R^2 &= 1 - \left(\frac{m \cdot \text{MSE}(\mathbf{y}, \hat{\mathbf{y}})}{m \cdot \text{MSE}(\mathbf{y}, \bar{\mathbf{y}})} \right) \\ &= 1 - \frac{\mathcal{L}}{\mathcal{L}_{\text{naive}}} \end{aligned}$$

Thus, R^2 is the *percent reduction in loss* achieved by our model compared to the naive model that always predicts $\bar{\mathbf{y}}$.

We now know our Loss function for the Linear Regression model.

Fitting the Linear Regression model solves for the Θ^* that minimizes average loss

$$\Theta^* = \underset{\Theta}{\operatorname{argmin}}\, \mathcal{L}_\Theta$$

which are the parameter values that minimizes MSE.

In [3]:
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print("Done")
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Done
```