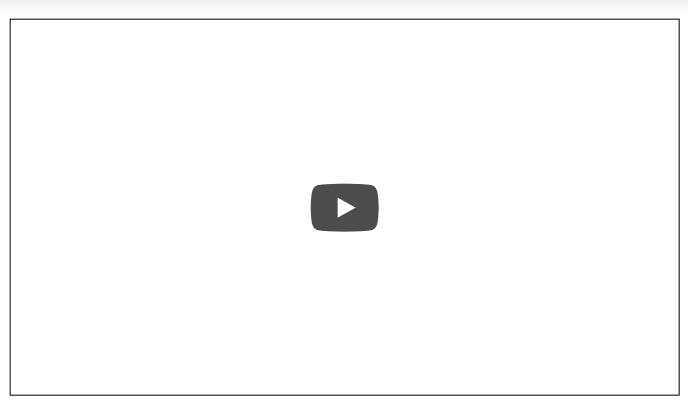


Minimizing Error Functions



NOTE: From 2:22 onward, the slide title should say "Mean Absolute Error".

Development of the derivative of the error function

Notice that we've defined the squared error to be

$$Error = \frac{1}{2}(y - \hat{y})^2.$$

Also, we've defined the prediction to be

$$\hat{y}=w_1x+w_2.$$

So to calculate the derivative of the Error with respect to w_1 , we simply use the chain rule:

$$_{\partial w_{1}}^{\partial}Error=_{\partial\hat{y}}^{\partial Error}_{\partial\hat{y}}_{\partial w_{i}}.$$

The first factor of the right hand side is the derivative of the Error with respect to the prediction \hat{y} , which is $-(y-\hat{y})$.

The second factor is the derivative of the prediction with respect to w_1 , which is simply x.



Minimizing Error Functions

$$\frac{\partial}{\partial w_1} Error = -(y - \hat{y})x$$

Exercise

Calculate the derivative of the Error with respect to w_2 and verify that it is precisely $-(y-\hat{y})$.

NEXT