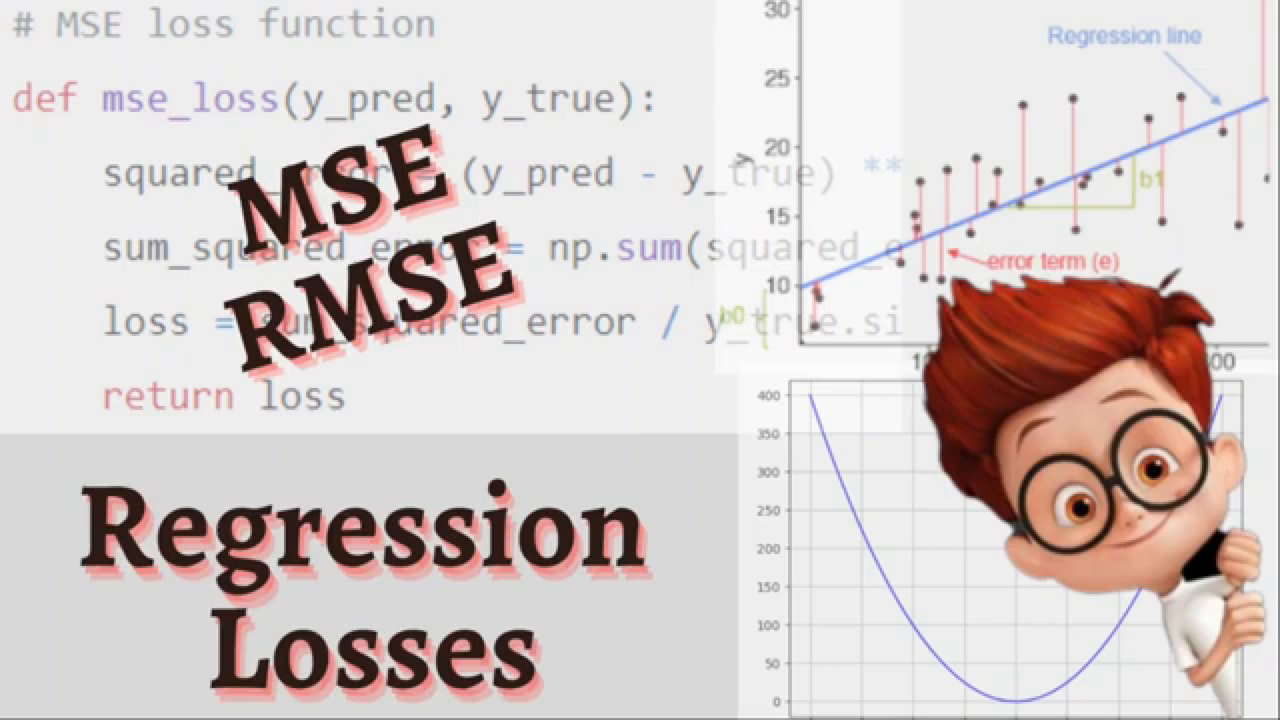
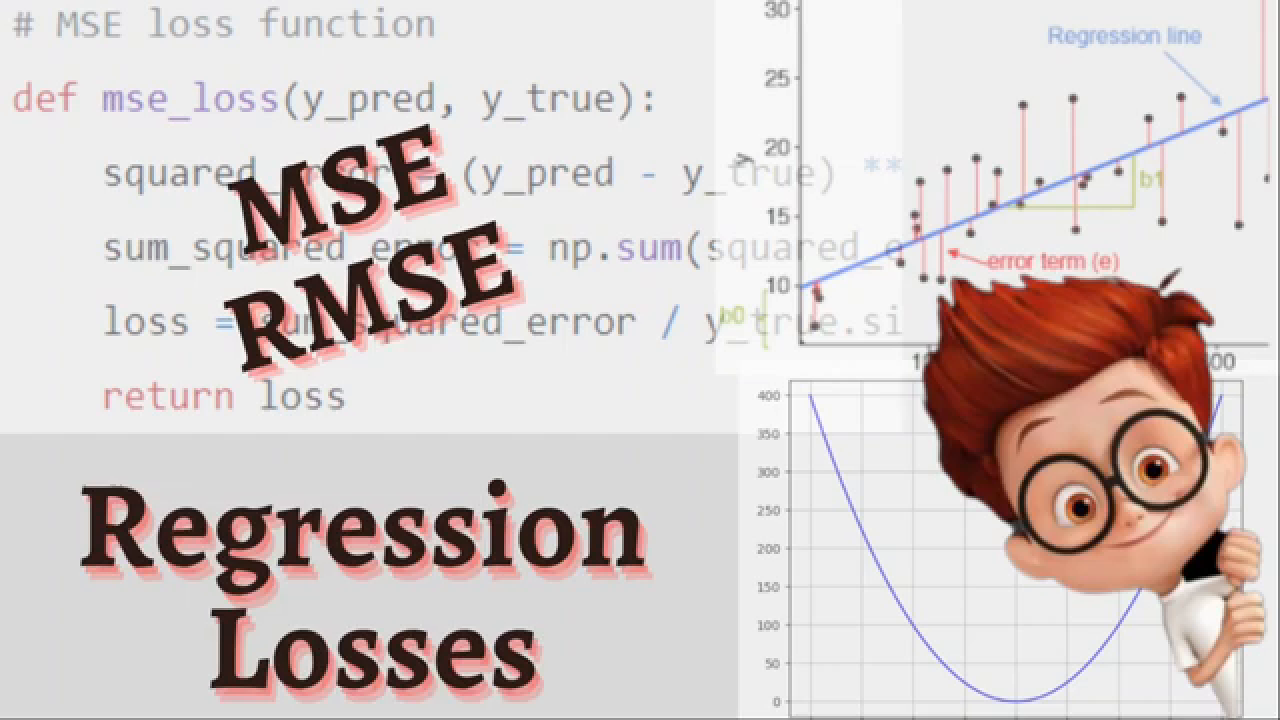


# MSE loss function
def mse_loss(y_pred, y_true):
return loss
MSE
RMSE
Regression
Losses
Regression line
error term (e)
b1
b0



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Mean Squared Error

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Mean Squared Error

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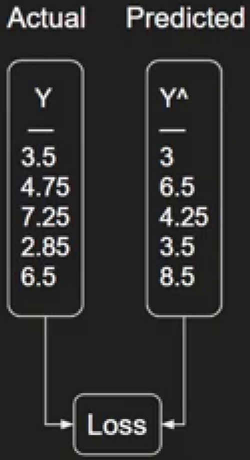

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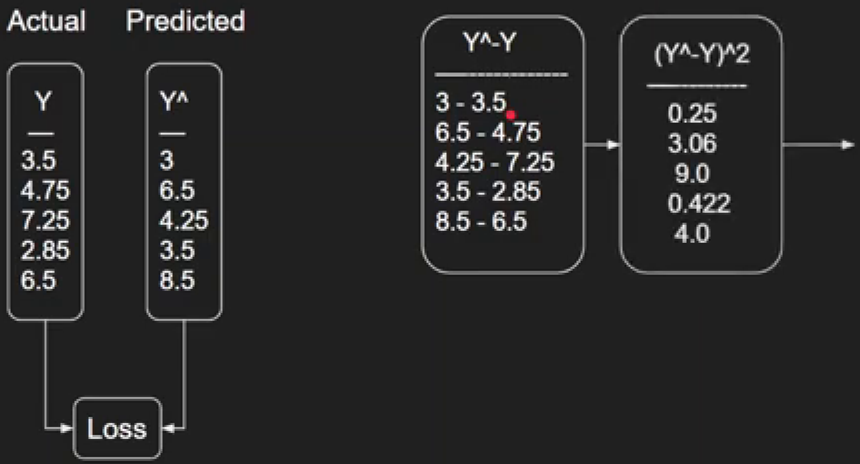

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$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_{ip} - y_i)^2$$

Actual	Predicted
Y	Y^
3.5	3
4.75	6.5
7.25	4.25
2.85	3.5
6.5	8.5

Actual (Y) and Predicted (Y^) → Loss

Y^-Y	(Y^-Y)^2
3 - 3.5	0.25
6.5 - 4.75	3.06
4.25 - 7.25	9.0
3.5 - 2.85	0.422
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→ Sum: 16.732 → Mean: 3.34

L2 loss

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L2 loss

Python Implementation

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# MSE loss function
def mse_loss(y_pred, y_true):
    squared_error = (y_pred - y_true) ** 2
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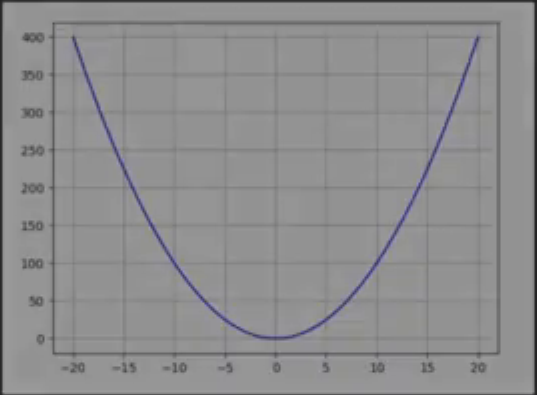
Error Surface



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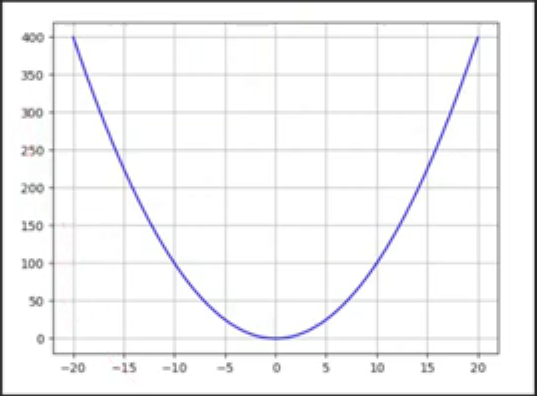

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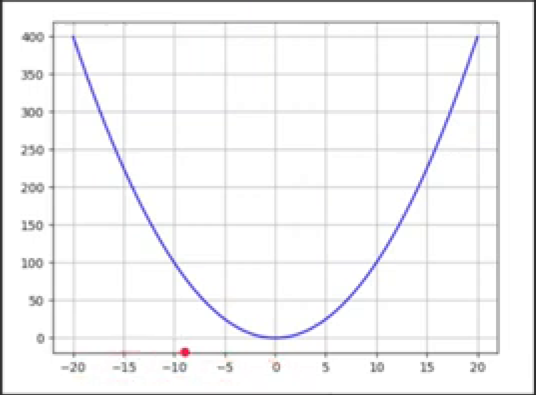

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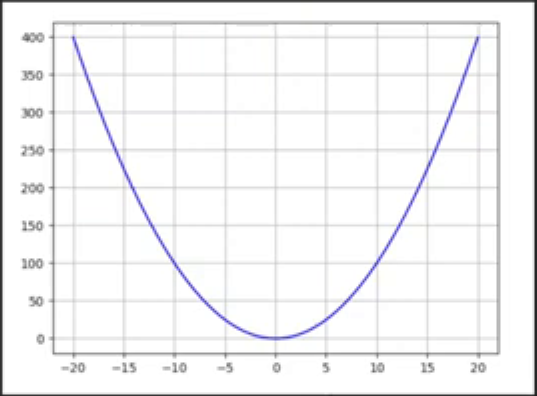

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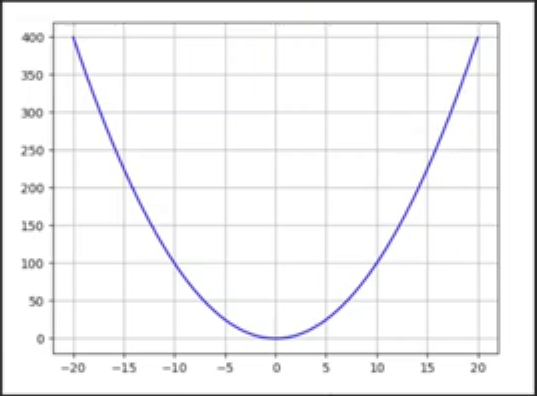

y-y^

Features

- No positive-negative value cancellation
- Weighted errors
- Smooth loss function
- Prefered to MAE
- High loss in case of outliers

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