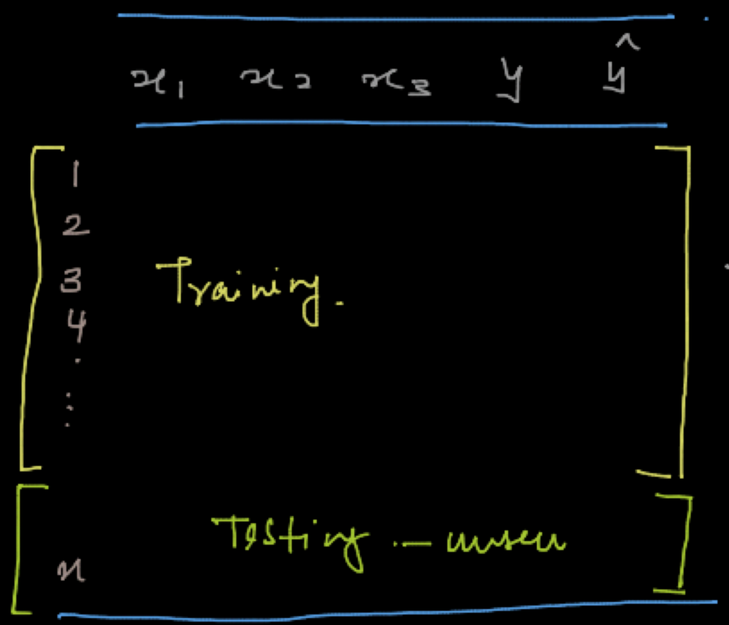
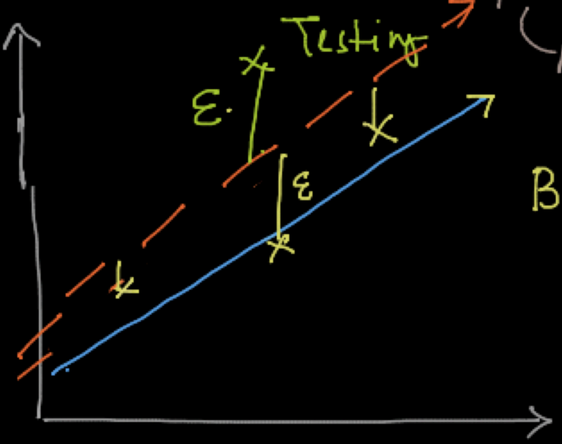
Bias → Training Error Variance → Testing Error

↓

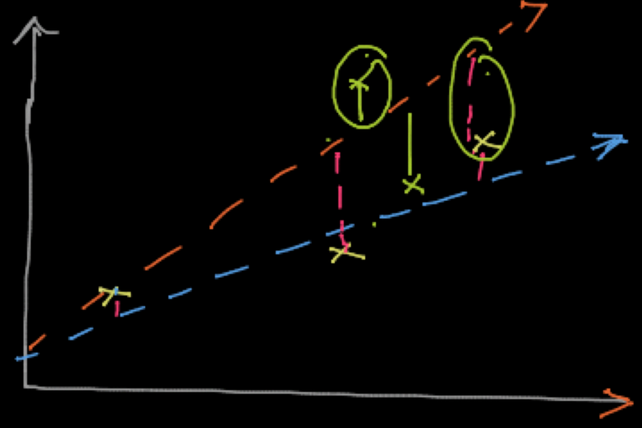
Bias ↓ Variance -



→ Model is trained on training Data → Estimating the model parameters (β_0, β_1) → Find the line of Best fit.



Bias ↓ 0 - ↑ ↓



$$SSE = (y - \hat{y})^2$$

$$\checkmark \ SSE = \sum_{i=1}^{n} \left[y_i - (\beta_0 + \beta_1 x_i) \right]^2$$

Minimum = (SSE + (Additional))

↳ Regularization

Lasso Regularization: (L1 - Regularization)

$$\text{Obj. fu} = \text{SSE} + \lambda \sum_{i=1}^{d} \beta_i$$

↳ Hyperparam

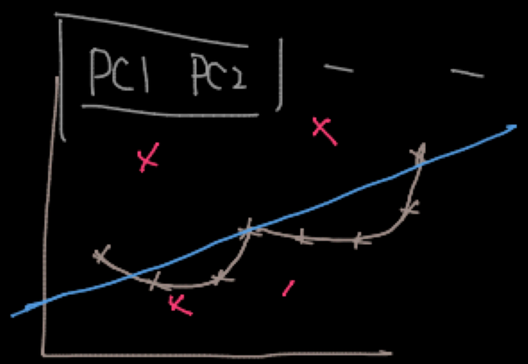
Regularization term → Introduce Bias into the model, but will reduce the Variance.

$\beta_3 = 0$

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

100 (1000) 3.5

← d = 3 →			
x_1	x_2	x_3	y
-	-	-	
-	-	-	
-	-	-	



x_1	x_2	y

Bias ⇅ Variance

Training Error ≅ Testing Error → Good fit.

Training Error (Bias) ↓ 0 ; Testing Error (Variance) ⇒ Very high → overfitting.

Feature Eng.

→ PCA.

Ridge Regularization:

$$\text{Obj Fn} = \text{SSE} + \alpha \sum_{i=1}^{d} \beta_i^2$$

L2 - Regularization.

↳ $\alpha = 0$

↓

Elastic Net:

$$\text{Obj. Fn} = \text{SSE} + \cdot \lambda \sum_{i=1}^{d} \beta_i + \cdot \alpha \sum_{i=1}^{d} \beta_1^2 \cdot$$

↓ β's = 0.

↓ β ↓

✓ Lasso Regression →

✓ Ridge Regression →

∴ [objective + Regula.]

→ minimize (or) maximize.

training Error → 0.5L.
0.8L.

→ 0.5L.
5 Lakhs
} Overfit.

Accuracy → 98%.
test → 97%.
} Rt.

30%.

y y

Yes ~~No~~ = No ∴
No ~~No~~ Yes ∴

→ Binary Executables

: exe
: dmg

#@-1- ..

model = LinearRegression( )

model.fit (X train, Y train) → testing.

Pickling. → pickle.

: sav. → Client.

Developers.

model.sav

Cursor selected