Machine Learning Algorithms

1. Ridge and Lasso Regression ← {Overfitting, Bias, Variance, Underfitting}
2. Elastic Net Regression
3. Logistic Regression

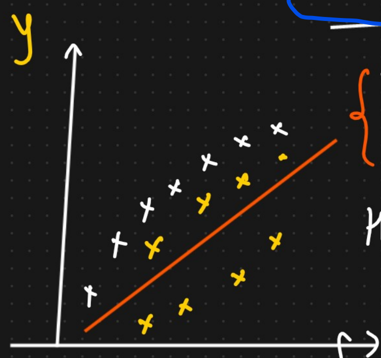
{ Bias = Training Data
Variance = Test Data }

Training Data

Test Data ↓↓↓
Acc

Model 1

Underfitting



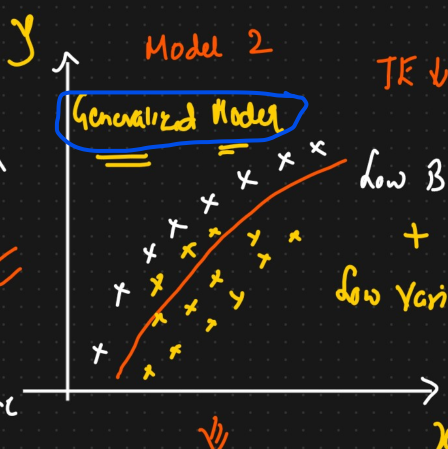
{ Training Error ↑↑

High Bias ✓
+
Low Variance
or
High Variance }

Model 2

Generalized Model

TE ↓↓



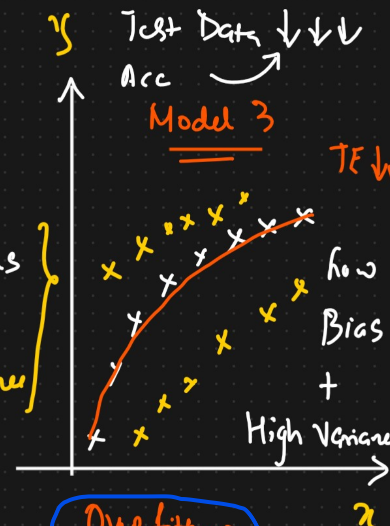
{ Low Bias
+
Low Variance }

⇓

Generalized Model

Model 3

TE ↓↓



Low Bias
+
High Variance

Overfitting

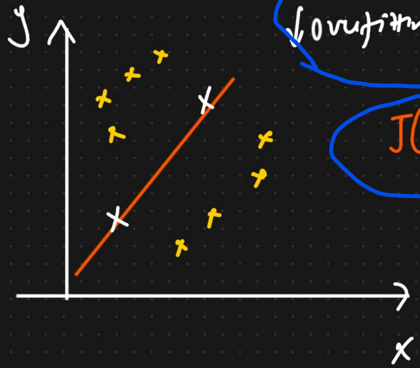
{ Training Data → Train our Model ✓ }

Test Data → Check the performance of the Model ✓
↳ Validation Data

② Ridge and Lasso Regression

Train Error ↓ + Test Error ↑↑

{Low Bias + High Variance}



Overfitting

Cost function

$$J(\theta_0,\theta_1) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2 = 0$$

Reduce overfitting

Ridge Regression ($L2$ Regularization) $\boxed{\lambda = 1}$

Hyperparameter

$$J(\theta_0,\theta_1) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2 + \underbrace{\lambda\,(\text{slope})^2}$$

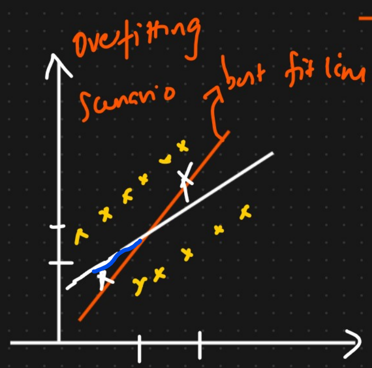
penalty

Slope

$h_\theta(x) = \theta_0 + \theta_1 x_1$

$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3$

$(\theta_1^2 + \theta_2^2 + \theta_3^2 + \theta_4^2)$



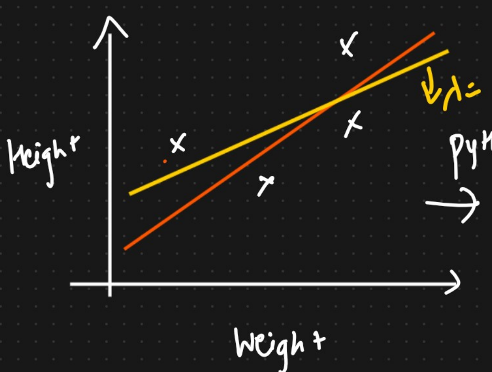
$= 0 + (1)(1.5)^2$

$= 2.25 \downarrow\downarrow \downarrow\downarrow$

$= \text{Small value} + (1)(0.9)^2$

$\approx 0.81 \downarrow\downarrow$

Relationship between λ and $(\text{Slope})^2$ $\quad \lambda\uparrow\uparrow$



$\downarrow\lambda =$

python $\rightarrow \boxed{\lambda} \rightarrow$ Hyperparameter Tuning } Cost

Penalty

$$J(\theta_0,\theta_1) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2 + \lambda\,(\text{Slope})^2\}$$

λ = Different λ values

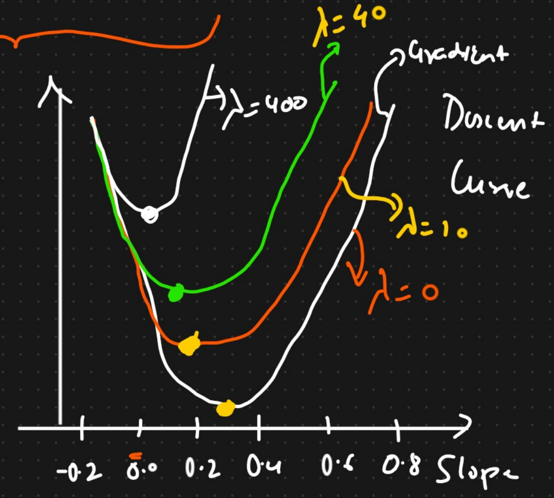
Will get intilized

$\Downarrow$

Hyperparameter

$\lambda = 10$

$\boxed{\lambda\uparrow\uparrow}$ $\boxed{\text{Slope}\downarrow\downarrow}$



$\boxed{\theta_1}$

Global Minima Is Shifting

$\lambda\uparrow\uparrow$ Slope $\downarrow\downarrow$

{ Reduce Overfitting } $\Downarrow \Downarrow \Downarrow$

$h_\theta(x) = \theta_0 + \theta_1 x \rightarrow$ neglecting this feature. ($\theta_1 \rightarrow 0$)

Reduce Overfitting

Lasso Regression (L_1 Regularization) ⇒ Feature Selection

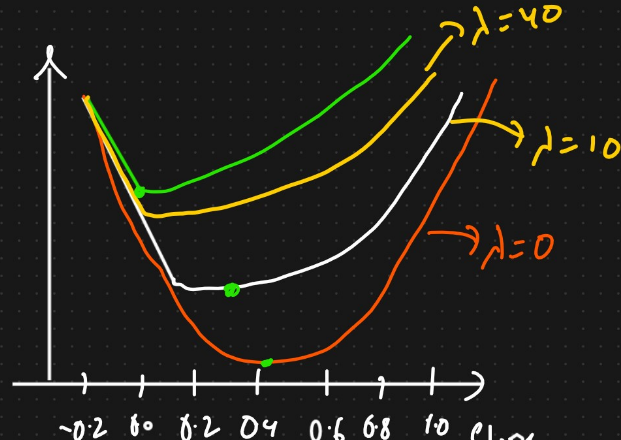
Cost function $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{i}) - y^{(i)} \right)^2 + \lambda |\text{Slope}|$

$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \dots + \theta_n x_n$

$\theta_3 \to 0.13 \to 0$

$\lambda \uparrow\uparrow$ Slope $\downarrow\downarrow$

{1 unit X, 0.13 unit Y}



⇒ feature selection }

$\lambda \uparrow\uparrow$ Slope $\downarrow\downarrow$

Not at all correlated ≈ 0 → feature neglected ⇒ feature selection.

Final Conclusion

{ Ridge = Reduce Overfitting, Lasso = Feature Selection } ⇒ Overall

Elastic Net Regression

Reducing overfitting ⇑ Feature Selection ⇑

$$\boxed{J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x_i) - y^{(i)} \right)^2 + \lambda_1 (\text{slope})^2 + \lambda_2 |\text{slope}|}$$

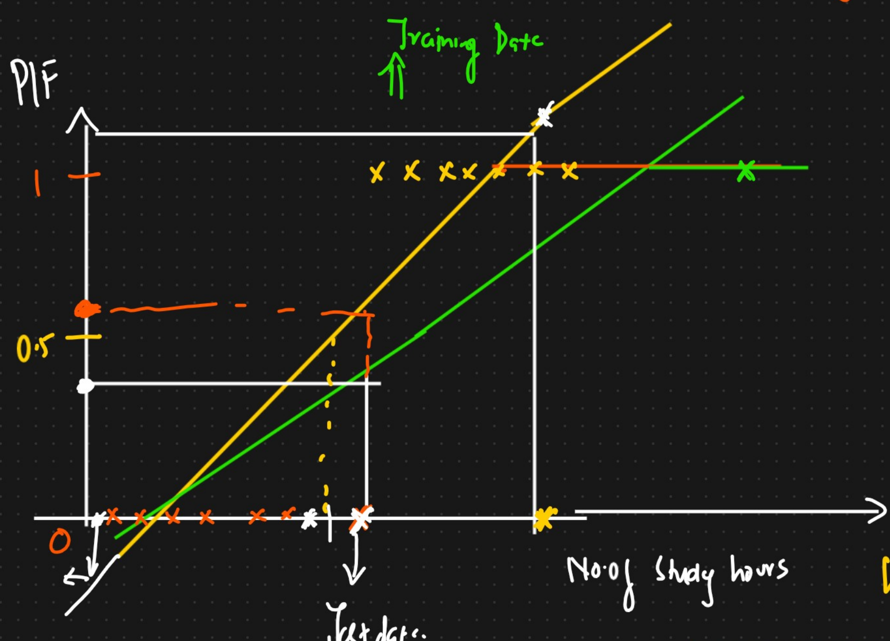
Multicollineanity

$f_1 \longleftrightarrow f_2 \quad f_3 \quad O/P$

0.95%   -0.95

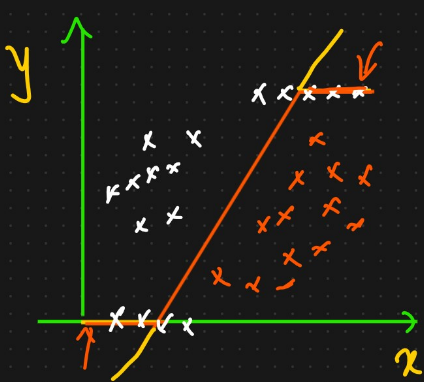
600 features ⇒ Lasso

② Logistic Regression (Classification) → { Binary classification }



No of study	No of play	P/F
—	—	P
—	—	F

$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \dots + \theta_n x_n$



$$\boxed{h_\theta(x) = \theta_0 + \theta_1 x_1}$$

⇓

$h_\theta(x) = g(\theta_0 + \theta_1 x_1)$

⇓

Let $z = \theta_0 + \theta_1 x_1$

$h_\theta(x) = g(z)$ → function on z

⇓

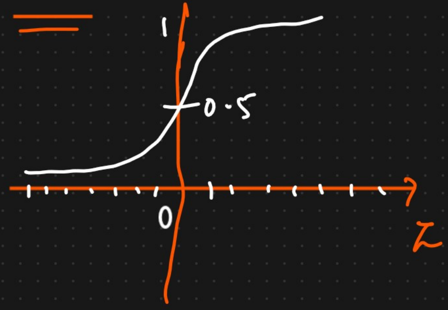
{ Activation function }

Sigmoid Activation fn

$$h_\theta(x) = \frac{1}{1+e^{-z}}$$

O { 0 to 1 }

exponential



$$\boxed{h_\theta(x) = \frac{1}{1+e^{-(\theta_0+\theta_1 x_1)}}}$$

$\Downarrow$

Best fit line + Squashing

$$\boxed{h_\theta(x) = \theta_0 + \theta_1 x_1}$$

Training Set

$$\{(x^1,y^1), (x^2,y^2), (x^3,y^3) \ldots (x^n,y^n)\}$$

$y = \{0,1\} \rightarrow$ 2 Output $\rightarrow$ Binary classification

$$h_\theta(z) = \frac{1}{1+e^{-z}} \qquad z = \theta_0 + \theta_1 x_1 \qquad \theta_0 = 0 \qquad \text{intercept} = 0$$

Aim : Change θ_1 $\rightarrow$ It classifies points.

Costfunction

Logistic Regression

$$J(\theta_1) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta(x)^i - y^{(i)}\right)^2$$

$\hat{y}$ MSE

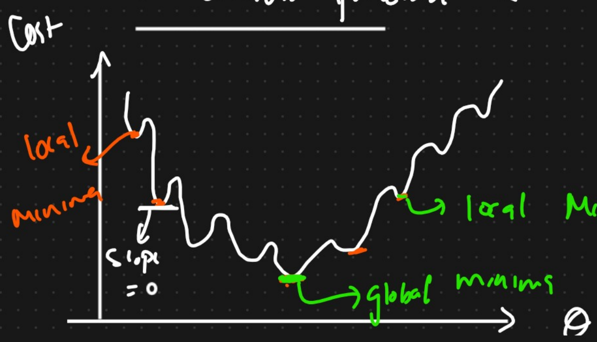
$h_\theta(x) = \theta_1 x_1$

$\Downarrow$

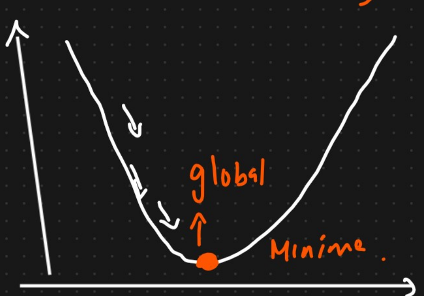
Gradient Descent

$$h_\theta(x) = \frac{1}{1+e^{-(\theta_1 x)}}$$

Non Convex function

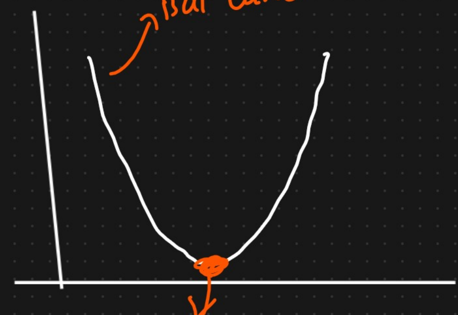


{ Convex function }



Logistic Regression Cost function (Log Loss)

$$J(\theta_1) = \begin{cases} \boxed{-\log(h_\theta(x))} \;\; \underbrace{}_{\hat{y}} & y=1 \\ \boxed{-\log(1-h_\theta(x))} \;\; \underbrace{}_{\hat{y}} & y=0 \end{cases}$$



$y=1$

Cost function

$$J(\theta_0,\theta_1) = -y\log(h_\theta(x^i)) - (1-y)\log(1-h_\theta(x))$$ {log loss cost function}

Cost function for Logistic Regression

$$J(\theta_1) = -\frac{1}{2m}\sum_{i=1}^{m}\left[\left(y^i\log(h_\theta(x^i)) + (1-y^{(i)})\log(1-h_\theta(x^i)\right)\right]$$

$$\boxed{h_\theta(x^i) = \frac{1}{1+e^{-(\theta_1 x_1)}}} \Rightarrow \text{hypothesis.}$$

θ_1

repeat until Convergence

{

$$\theta_j := \theta_j - \alpha\frac{\partial}{\partial\theta_j}(J(\theta_1)).$$

}

Performance Metrics (Binary Classification).

x_1	x_2	Act y	predi $\hat{y}$
–	–	0	1
–	–	1	1
–	–	0	0
–	–	1	1
–	–	1	1
		0	1
		1	0

{Actual}

{Predicted}	1	0
1	3	2
0	1	1

⇒ Confusion matrix

Predicted \ Actual	1	0
1	↑TP	FP↓
0	FN↓	TN↑

TP & TN Are correct predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} = \frac{3+1}{3+2+1+1} = \frac{4}{7}$$

$= 57\%$

Training

1000 datapoint points

0 → 900 datapoint
1 → 100 datapoint } Imbalanced Dataset

0 → 600 datapoints
1 → 400 datapoints } Balanced

Not Spam

Predicted \ Actual	1	0
1	TP	FP
0	FN	TN

→ FP ↓↓
→ FN ↓

① Precision

$$= \frac{TP}{TP+FP\downarrow\downarrow}$$

② Recall (TPR).

$$\frac{TP}{TP+FN}$$

③ F-Score

Spam Classification {FP↓↓} → Precision

HAS CANCER OR NOT {FN↓↓} → Recall

Company ⇒ FP

People ⇒ FN

Tomorrow Stock market is going to crash $\left\{ \begin{array}{l} \text{Both FP} \downarrow\downarrow \\ \text{\& FN} \downarrow\downarrow \end{array} \right\}$.

F-Beta Score : $(1+\beta^2) \dfrac{\text{Precision} * \text{Recall}}{\beta^2 * [\text{Precision} + \text{Recall}]}$

↓✓↓
$\boxed{\text{FP \& FN}}$ ✓

$\boxed{\beta = 1}$ $= (1+1) \dfrac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$ } Harmonic Mean

$\beta \downarrow\downarrow$

$\boxed{FP >> FN}$

$\beta = 0.5$ $= (1+0.25) \dfrac{P \times R}{(0.25)[P+R]}$

$\boxed{FN >> FP}$

$\boxed{\beta = 2}$ $= \boxed{(1+(2)^2) \dfrac{PR}{(4)[P+R]}}$.