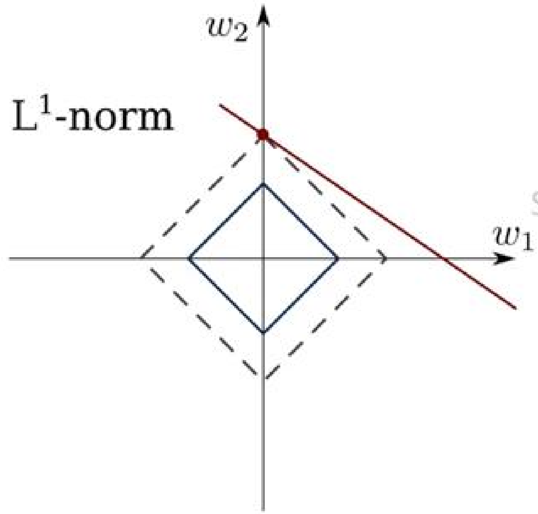
Siddhardhan

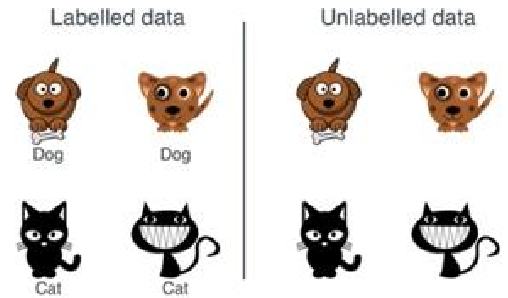
Lasso Regression
- intuition

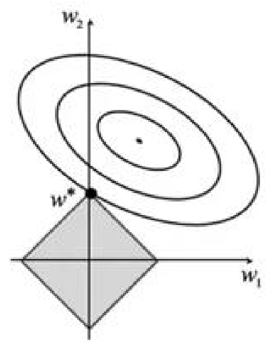


Lasso Regression

About Lasso Regression:

1. Supervised Learning Model
2. Regression model
3. **L**east **A**bsolute **S**hrinkage and **S**election **O**perator
4. Implements Regularization (L1) to avoid Overfitting





L1

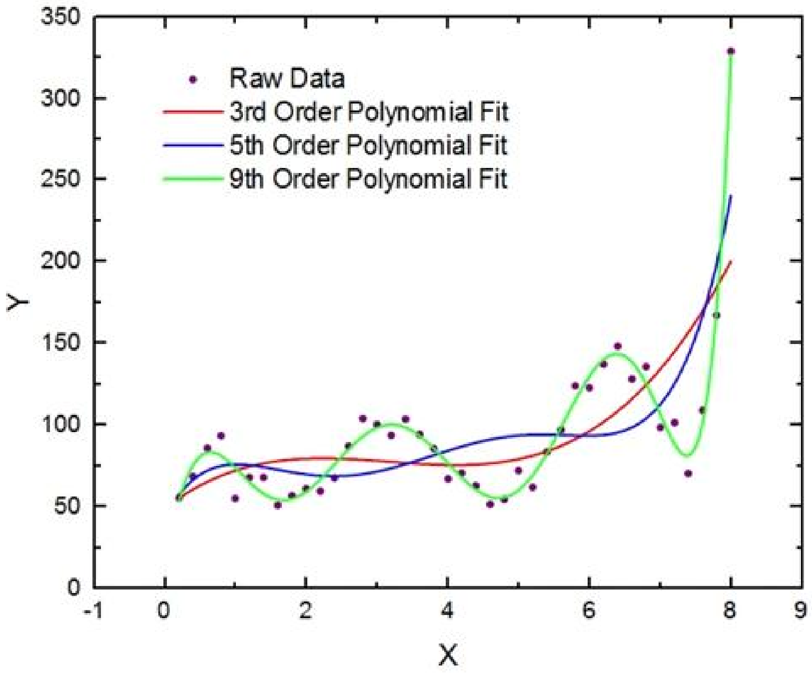
Linear Regression

Experience in Years	0	2	4	5	6
Salary	2,00,000	4,00,000	8,00,000	10,00,000	12,00,000

What would be the **salary** of a person with **3 years of Experience?**

~ ₹ 650000 per Year

Polynomial Equations



1st order Polynomial equation : $y = ax + d$

2nd order Polynomial equation : $y = ax^2 + bx + d$

3rd order Polynomial equation : $y = ax^3 + bx^2 + cx + d$

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y --> Dependent Variable

x --> Independent Variable

a, b, c --> coefficients

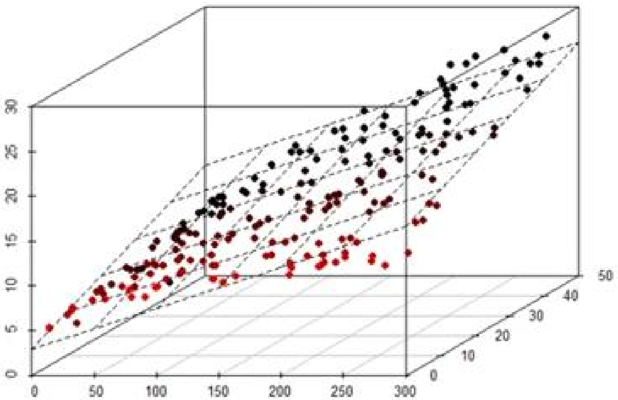
d --> constant term

Inference: As the complexity of the model increases,
It tends to Overfit with the data.

What if there are more than 2 Variables?

Multiple Linear Regression

Multiple linear regression is a model for predicting the value of one dependent variable based on two or more independent variables.



Simple Linear Regression $Y = w_1 X_1 + b$

Multiple Linear Regression $Y = w_1 X_1 + w_2 X_2 + w_3 X_3 + b$

Regularization

Regularization is used to reduce the overfitting of the model by adding a penalty term (λ) to the model. Lasso Regression uses L1 regularization technique.

The "penalty" term reduces the value of the coefficients or eliminate few coefficients, so that the model has fewer coefficients. As a result, overfitting can be avoided.

3rd order Polynomial equation : $y = ax^3 + bx^2 + cx + d$

This Process is called as Shrinkage.

LASSO --> Least **A**bsolute **S**hrinkage and **S**election **O**perator

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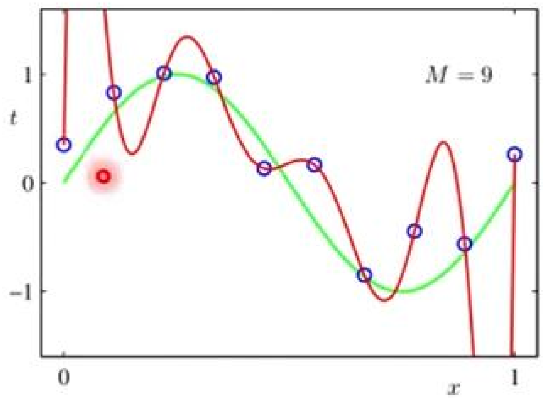

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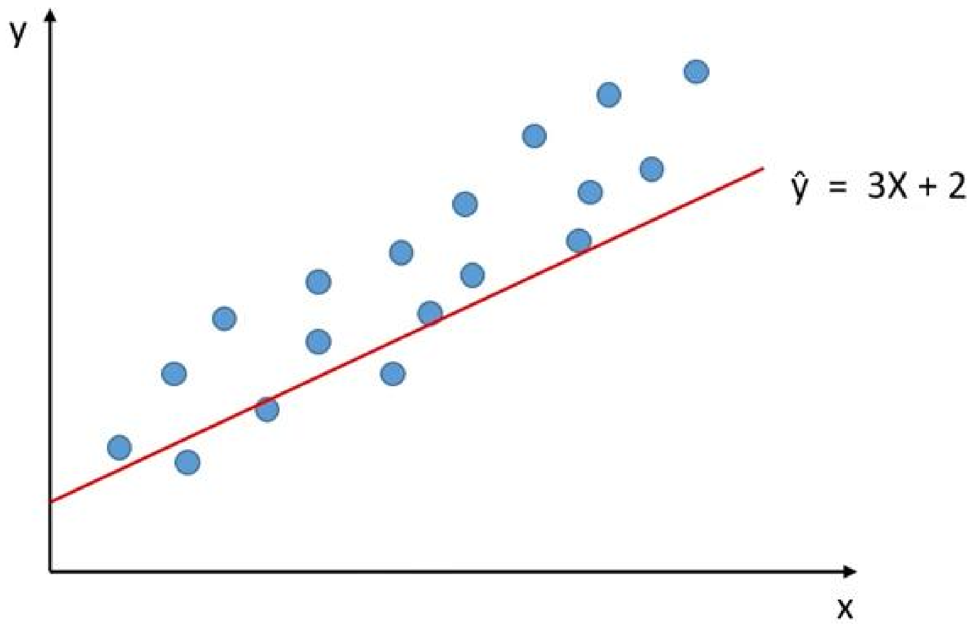
Linear Regression

Randomly assigned Parameters: w = 3; b = 2



x	y	ŷ
2	10	8
3	14	11
4	18	14
5	22	17
6	26	20

Cost Function

x	y	ŷ
2	10	8
3	14	11
4	18	14
5	22	17
6	26	20

$$\textbf{Cost (J)} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Cost $= [\ (10 - 8)^2 + (14 - 11)^2 + (18 - 14)^2 + (22 - 17)^2 + (26 - 20)^2\ ]\ /\ 5$

Cost $= [\ 4 + 9 + 16 + 25 + 36]\ /\ 5$

Cost $= 18$

Low Cost value → High Accuracy

Lasso Regression

Cost Function for Lasso Regression :

$$J = \frac{1}{m}\left[\sum_{i=1}^{m}\left(y^{(i)} - \hat{y}^{(i)}\right)^2 + \lambda \sum_{j=1}^{n} w_j\right]$$

m --> Total number of Data Points

n --> Total number of input features

$y^{(i)}$ --> True Value

$\hat{y}^{(i)}$ --> Predicted Value

λ --> Penalty Term

w --> Parameter of the model

Boston House Price Dataset

The dataset used in this project comes from the UCI Machine Learning Repository. This data was collected in 1978 and each of the 506 entries represents aggregate information about 14 features of homes from various suburbs located in Boston.

crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat	price
0.00632	18	2.31	0	0.538	6.575	65.2	4.09	1	296	15.3	396.9	4.98	24
0.02731	0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.9	9.14	21.6
0.02729	0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
0.03237	0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4

$$J = \frac{1}{m}\left[\sum_{i=1}^{m}\left(y^{(i)} - \hat{y}^{(i)}\right)^2 + \lambda\sum_{j=1}^{n} w_j\right]$$

Gradient Descent

Gradient Descent is an optimization algorithm used for minimizing the cost function in various machine learning algorithms. It is used for updating the parameters of the learning model.

$$w_2 = w_1 - L * \frac{dJ}{dw}$$

$$b_2 = b_1 - L * \frac{dJ}{db}$$

w --> weight
b --> bias
L --> Learning Rate

$\frac{dJ}{dw}$ --> Partial Derivative of cost function with respect to w

$\frac{dJ}{db}$ --> Partial Derivative of cost function with respect to b

Gradients for Lasso Regularization

if $(w_j > 0)$:

$$\frac{dJ}{dw} = \frac{-2}{m}\left[\left[\sum_{i=1}^{m} x_j \cdot \left(y^{(i)} - \hat{y}^{(i)}\right)\right] + \lambda\right]$$

else $(w_j \leq 0)$:

$$\frac{dJ}{dw} = \frac{-2}{m}\left[\left[\sum_{i=1}^{m} x_j \cdot \left(y^{(i)} - \hat{y}^{(i)}\right)\right] - \lambda\right]$$

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$$\frac{dJ}{db} = \frac{-2}{m}\left[\sum_{i=1}^{m} \left(y^{(i)} - \hat{y}^{(i)} \right)\right]$$

$$w_2 = w_1 - L^* \frac{dJ}{dw}$$

$$b_2 = b_1 - L^* \frac{dJ}{db}$$

Gradients for Lasso Regularization

if $(w_j > 0)$:	***else*** $(w_j \leq 0)$:
$\frac{dJ}{dw} = \frac{-2}{m}\left[\left[\sum_{i=1}^{m} x_j \cdot \left(y^{(i)} - \hat{y}^{(i)}\right)\right] + \lambda\right]$	$\frac{dJ}{dw} = \frac{-2}{m}\left[\left[\sum_{i=1}^{m} x_j \cdot \left(y^{(i)} - \hat{y}^{(i)}\right)\right] - \lambda\right]$

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$$w_2 = w_1 - L^* \frac{dJ}{dw}$$

$$b_2 = b_1 - L^* \frac{dJ}{db}$$

$$y = w.x + b$$