

Data Science and Artificial Intelligence

Machine Learning



Regression

Lecture No. 04



By- SIDDHARTH SABHARWAL SIR



Class/Notes/DPP

Recap of Previous Lecture



Topic

β Formulae

Topic

Representation X, Y

Topic

2D data \rightarrow attributes
features.

Topic

Topic

Topics to be Covered



Topic

Gradient descent

Topic

loss fn in matrix

Topic

R^2 : Coeff of determination

Topic


Topic

About the Faculty

- AIR 1 GATE 2021, 2023 (ECE).
- AIR 3 ESE 2015 ECE.
- M.Tech from IIT Delhi in VLSI.
- Published 2 papers in field of AI-ML.
- Paper 1 : Feature Selection through Minimization of the VC dimension.
- Paper 2 : Learning a hyperplane regressor through a tight bound on the VC dimension.



By- SIDDHARTH SABHARWAL SIR

A vibrant red, billowing cloud of smoke or fire, resembling an explosion, centered in the frame.

DON'T LIMIT YOUR
CHALLENGES
CHALLENGE YOUR LIMIT



How the data is represented in matrix format

D dimension data

Data Point	D_1	D_2	...	D_D	y
1	x_1^1	x_1^2		x_1^D	y_1
2	x_2^1	x_2^2		x_2^D	y_2
3	\vdots	\vdots		\vdots	\vdots
4	\vdots	\vdots		\vdots	\vdots
\vdots	\vdots	\vdots		\vdots	\vdots

$$X = \begin{bmatrix} 1 & x_1^1 & x_1^2 & \dots & x_1^D \\ 1 & x_2^1 & x_2^2 & \dots & x_2^D \\ \vdots & \vdots & \vdots & \ddots & \vdots \end{bmatrix}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_D \end{bmatrix}$$



The final expression of Beta matrix..

$$\beta = (X^T X)^{-1} (X^T Y) \Rightarrow \text{imp}$$

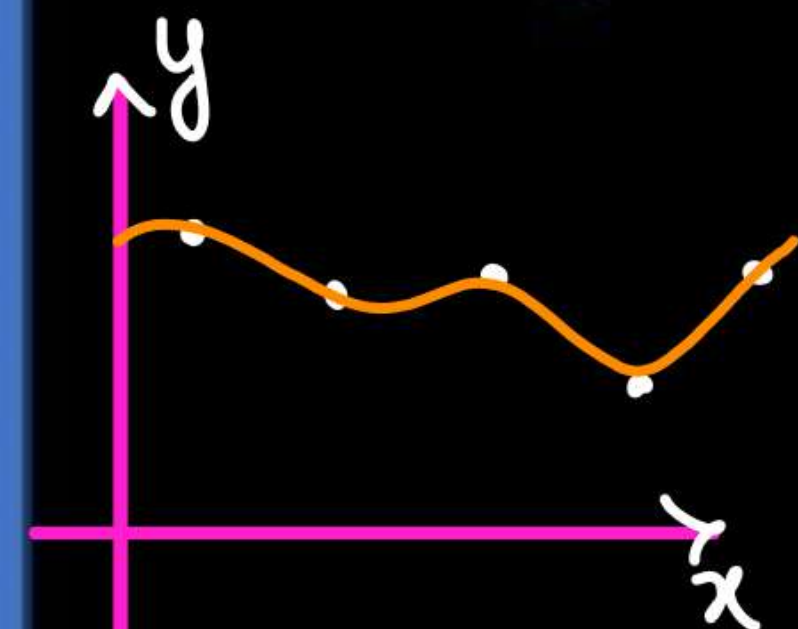


Regression.

Regression and Classification...

2 Type of data

Humidity	Temp	Wind speed	Amt of Rain	label Y
40	30	15	25	• Numbers
30	40	20	33	• Real values
10	15	20	42	
⋮	⋮	⋮	41	
⋮	⋮	⋮	46	



• Here we want a fcn Relating Y and x



Classification

Regression and Classification...

2 Type of data

Humidity	Temp	Wind speed	Rain
40	30	15	Yes
30	40	20	No
10	15	20	Yes
⋮	⋮	⋮	Yes
⋮	⋮	⋮	No

label
Y: Yes/No

Categorical Nature

Here we want a line
that **seperates**.



Regression :- Since we are finding a linear
relation b/w y and x
$$y = \beta_0 + \beta_1 x^1 + \beta_2 x^2 + \dots$$

So this is linear Regression



Basics of Machine Learning



What is the primary goal of linear regression in the context of 1D data?

A) To classify data into categories

☒ B) To predict a continuous output variable based on an input feature

C) To reduce the dimensionality of the data

D) To cluster data points into groups

→ Find linear relation b/w y and x , and



In simple linear regression (1D), the relationship between the independent variable x and the dependent variable y is modeled as:

- A) $y = mx + c + \epsilon$
- B) $y = mx^2 + c$
- C) $y = \sin(x) + c$
- D) $y = \log(x) + c$

data

x	y
x_1	y_1
x_2	y_2
x_3	y_3
\vdots	\vdots

Relation by y and x

$\Rightarrow y = mx + c \rightarrow$ Predicted value fcn

$y = mx + c + \epsilon$

(error term which is very small)



What does the term "residual" represent in linear regression?

A) The slope of the regression line

☒ B) The difference between the predicted value and the actual value

C) The intercept of the regression line

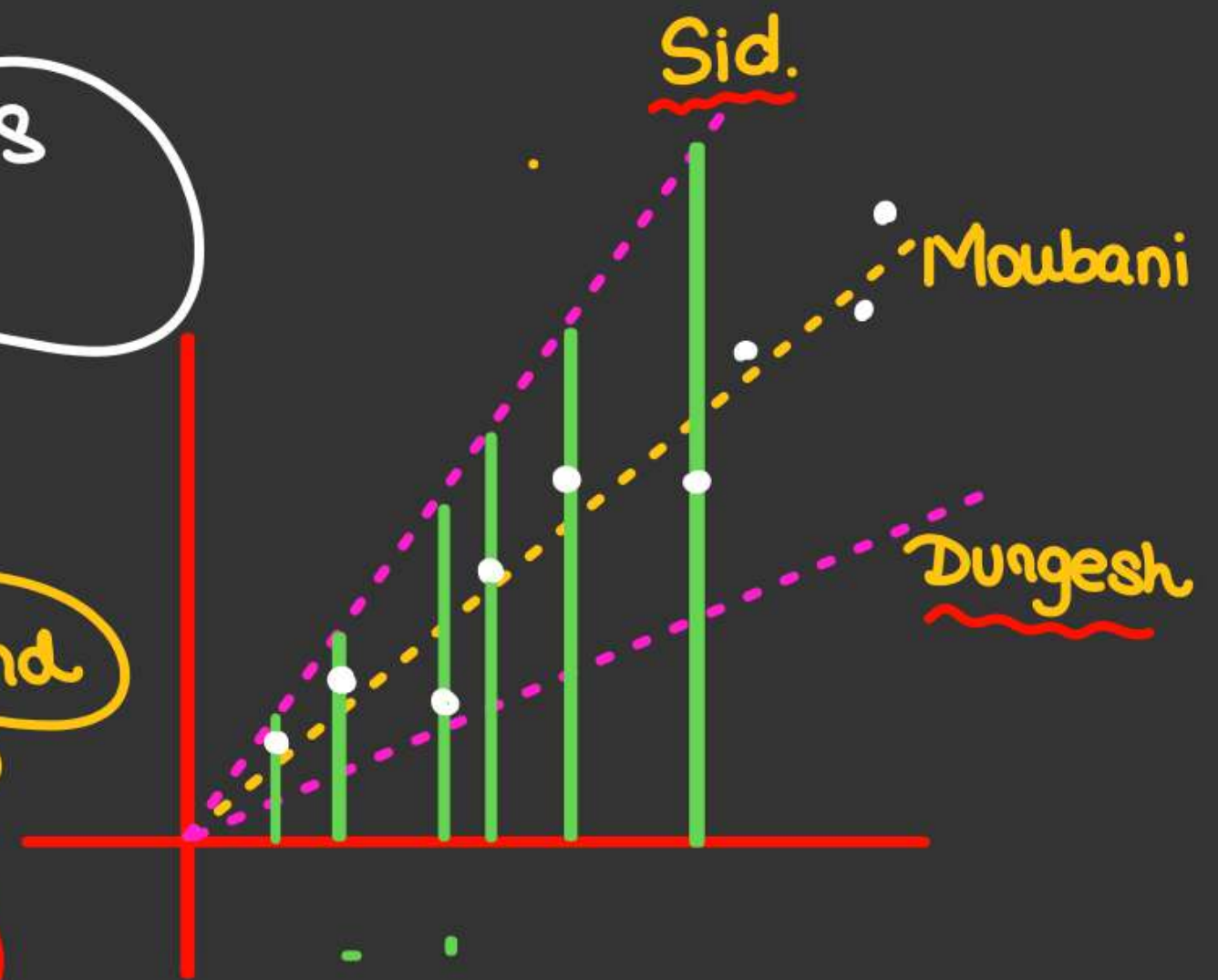
D) The correlation coefficient

Best line: data Ke beech \hat{y} cross
Kare, Residual \pm ve.

Q.

Which is best :-

Yellow line: Best understand
data Pattern



Residual: (Actual - Predicted)

Sid: Residual always -ve

Dungesh: Residual always +ve

Moubani: Residual \pm ve



Skip

In the context of linear regression, what does R^2 (R-squared) measure?

- A) The slope of the regression line
- B) The proportion of variance in the dependent variable explained by the independent variable
- C) The residual error
- D) The intercept of the regression line



What happens to the regression line if all the data points lie exactly on a straight line?

- ☒ A) The residuals will be zero
- B) The slope will be zero
- C) The intercept will be zero
- D) The R^2 value will be zero



Skip

Which of the following is a limitation of linear regression?

- A) It cannot handle categorical variables
- B) It assumes a linear relationship between variables
- C) It is sensitive to outliers
- D) All of the above



Given the following data points for x and y :

x	y
1	2
2	3
3	5
4	6

H.W

We min sum of Residual².

$$\beta = (X^T X)^{-1} (X^T Y)$$

$$\text{loss fcn} = \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

→ we use this eq

$$\frac{\partial L}{\partial m} = 0, \frac{\partial L}{\partial c} = 0 \text{ eq form}$$

Find the slope (m) and intercept (c) of the best-fit line $y = mx + c$ using the least squares method.



For a linear regression model, the following statistics are given:

- Mean of x (\bar{x}) = 5
- Mean of y (\bar{y}) = 10
- Variance of x (σ_x^2) = 4
- Covariance between x and y ($\text{Cov}(x, y)$) = 6

Find the slope (m) and intercept (c) of the regression line.



Basics of Machine Learning



For a linear regression model, the sum of squared residuals (SSR) is 50, and the total sum of squares (TSS) is 200. What is the value of R^2 ?

Skip



Basics of Machine Learning



A dataset has the following properties:

1D data with x, y as data values.

- Number of data points (n) = 10

- $\sum x = 30, \sum y = 50$

- $\sum xy = 200, \sum x^2 = 120$

Find the slope (m) of the regression line.

1D data

$$[X^T X] \beta = (X^T Y)$$

$$\rightarrow \begin{bmatrix} \sum 1 & \sum x \\ \sum x & \sum x^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} \sum y \\ \sum xy \end{bmatrix}$$

$$\begin{bmatrix} 10 & 30 \\ 30 & 120 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 50 \\ 200 \end{bmatrix}$$

$$[X^T X] \beta = (X^T Y)$$

$$\begin{bmatrix} \sum 1 & \sum x \\ \sum x & \sum x^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} \sum y \\ \sum xy \end{bmatrix}$$

$$\begin{bmatrix} 10 & 30 \\ 30 & 120 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 50 \\ 200 \end{bmatrix}$$

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \left(\frac{1}{120 \times 10 - 30 \times 30} \right) \begin{bmatrix} 120 - 30 \\ -30 & 10 \end{bmatrix} \begin{bmatrix} 50 \\ 200 \end{bmatrix} \Rightarrow \frac{1}{300} \begin{bmatrix} 0 \\ 500 \end{bmatrix}$$

$$\beta_0 = 0, \beta_1 = \frac{5}{3}$$



1D data

- $\beta_0 = c = 0$
- $\beta_1 = m = \frac{5}{3}$

1D data

x_1 y_1
 x_2 y_2
 x_3 y_3
 x_4 y_4
 \vdots \vdots
 x_{10} y_{10}

$$X = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ 1 & x_3 \\ \vdots & \vdots \\ 1 & x_{10} \end{bmatrix}$$

$$X^T X = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ x_1 & x_2 & x_3 & \dots & x_{10} \end{pmatrix} \begin{bmatrix} 1 & x_{1.} \\ 1 & x_{2.} \\ 1 & x_{3.} \\ \vdots & \vdots \\ 1 & x_{10.} \end{bmatrix}$$

$$X^T = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ x_1 & x_2 & x_3 & \dots & x_{10} \end{bmatrix} \Rightarrow \left\{ \begin{array}{l} \sum_{i=1}^{10} 1 \\ \sum_{i=1}^{10} x_i \\ \sum_{i=1}^{10} x_i^2 \end{array} \right\}$$



How to represent the Loss function in the matrix format

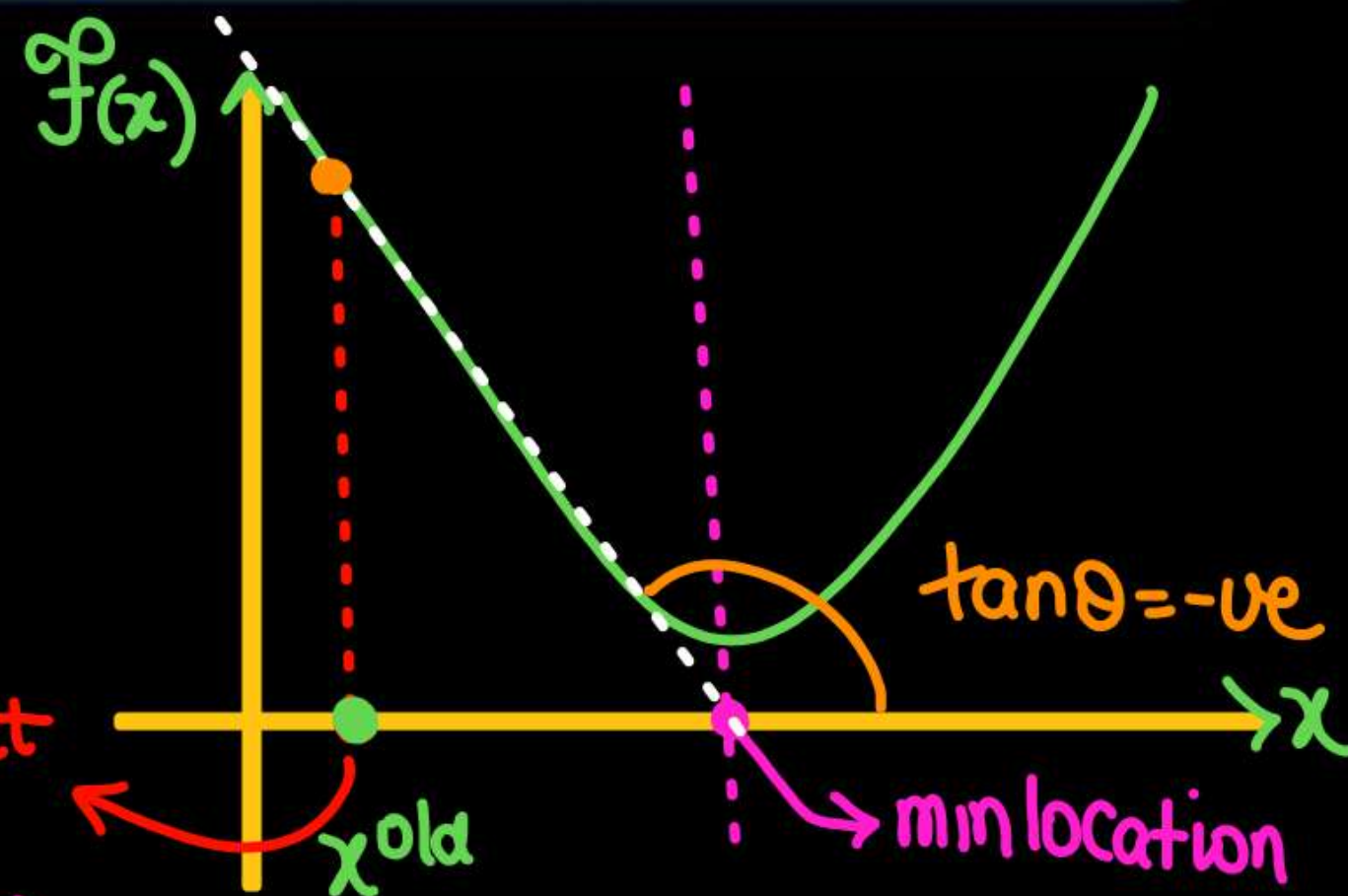
Gradient Descent

Maths

We start to find min location:

1) we start @ any Random x location

$$\rightarrow x_{\text{next}} = x_{\text{old}} - \eta \left(\frac{dF(x)}{dx} \Big|_{x_{\text{old}}} \right)$$





Linear Regression

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How to represent the Loss function in the matrix format

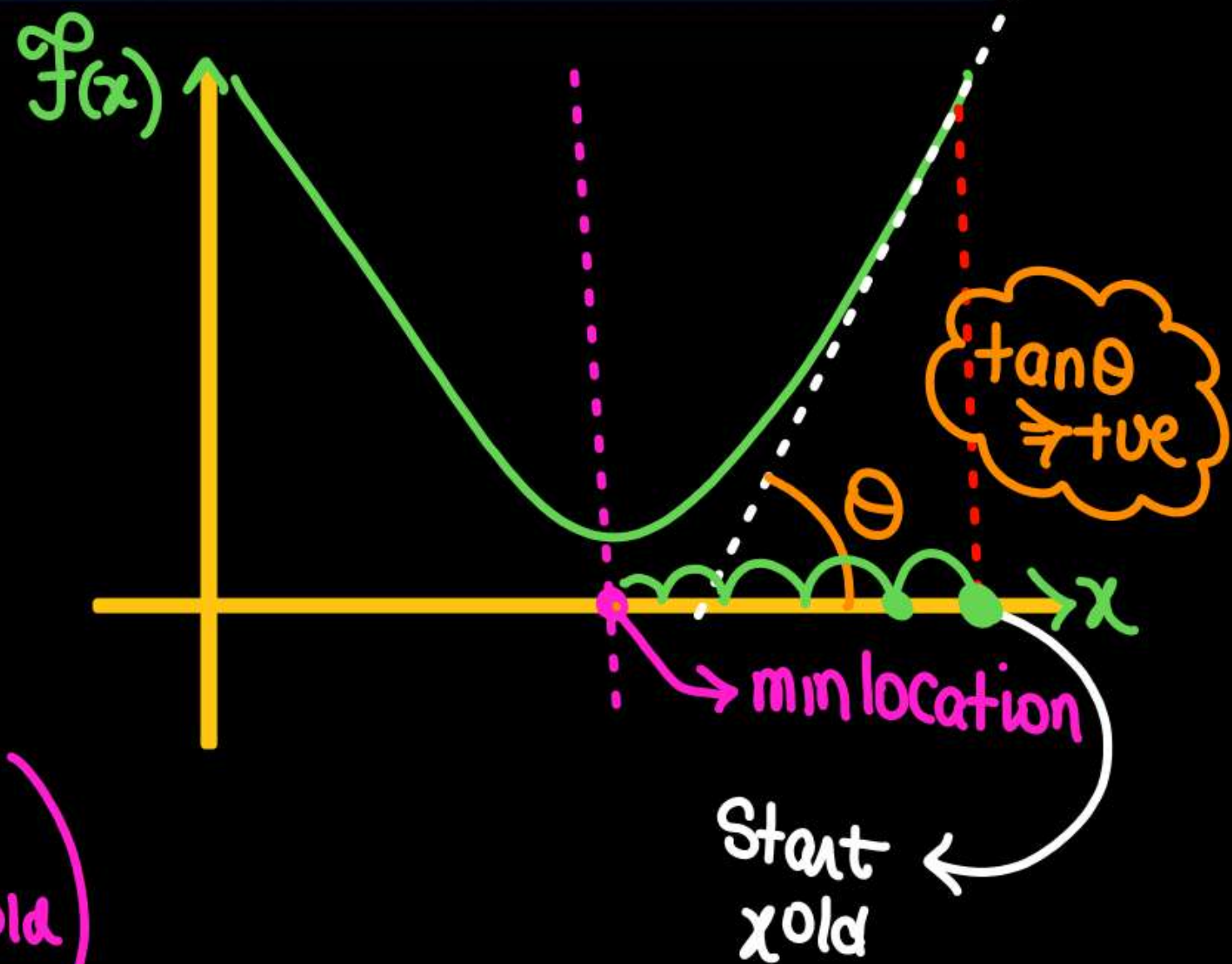
Gradient Descent

Maths

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$$\rightarrow x_{\text{next}} = x_{\text{old}} - \underset{\text{Const}}{\eta} \left(\frac{dF(x)}{dx} \bigg|_{x_{\text{old}}} \right)$$





Linear Regression

How to represent the Loss function in the matrix format

Gradient descent

↳ maths Concept to find min of a fxn.

we have a fxn $f(x)$

Step 1 : we start with any Random x Value

Step 2 : Iteration 1 : $x^{\text{old}} = \text{Value}$

$$x^{\text{new}} = x^{\text{old}} - \eta \left(\frac{\partial F(x)}{\partial x} \Big|_{x^{\text{old}}} \right)$$

learning Rate



Linear Regression

How to represent the Loss function in the matrix format

Step 3 Iteration 2

Here iteration 1 Result x^{old}

$$\Rightarrow \left(x^{new} = x^{old} - \eta \left. \frac{\partial F(x)}{\partial x} \right|_{x^{old}} \right)$$

So on

@min algorithm stops: @min $df(x)/dx = 0$



Linear Regression

How to represent the derivative of L by Beta in matrix format

Happy Mode





Linear Regression

How to represent the derivative of L by Beta in matrix format

1D data

$$\begin{array}{cc} x & y \\ x_1 & y_1 \\ x_2 & y_2 \\ x_3 & y_3 \\ x_4 & y_4 \end{array} \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$$
$$y = \beta_0 + \beta_1 x$$

$$L = \sum_{i=1}^4 (y_i - y_i')^2$$

$$L = \sum_{i=1}^4 (y_i - (\beta_0 + \beta_1 x_i))^2$$

$$\frac{\partial L}{\partial \beta} = \begin{bmatrix} \frac{\partial L}{\partial \beta_0} \\ \frac{\partial L}{\partial \beta_1} \end{bmatrix} \Rightarrow \begin{bmatrix} -2 \left(\sum_{i=1}^4 y_i - \beta_0 - \beta_1 x_i \right) \\ -2 \left(\sum_{i=1}^4 y_i x_i - \beta_0 \sum_{i=1}^4 x_i - \beta_1 \sum_{i=1}^4 x_i^2 \right) \end{bmatrix}$$

$$\frac{\partial L}{\partial \beta} = \begin{bmatrix} \partial L / \partial \beta_0 \\ \partial L / \partial \beta_1 \end{bmatrix} \Rightarrow \begin{bmatrix} -2 \left(\sum_{i=1}^4 y_i - \beta_0 - \beta_1 x_i \right) \\ -2 \left(\sum_{i=1}^4 y_i x_i - \beta_0 x_i - \beta_1 x_i^2 \right) \end{bmatrix}$$

$$\frac{\partial L}{\partial \beta} = -2 \begin{bmatrix} \sum_{i=1}^4 y_i - \beta_0 \sum_{i=1}^4 1 - \beta_1 \sum_{i=1}^4 x_i \\ \sum_{i=1}^4 x_i y_i - \beta_0 \sum_{i=1}^4 x_i - \beta_1 \sum_{i=1}^4 x_i^2 \end{bmatrix}$$

$$\begin{aligned}
\frac{\partial L}{\partial \beta} &= -2 \begin{bmatrix} \sum_{i=1}^4 y_i - \beta_0 \sum_{i=1}^4 1 - \beta_1 \sum_{i=1}^4 x_i \\ \sum_{i=1}^4 x_i y_i - \beta_0 \sum_{i=1}^4 x_i - \beta_1 \sum_{i=1}^4 x_i^2 \end{bmatrix} \\
&= -2 \left\{ \begin{bmatrix} \sum y_i \\ \sum x_i y_i \end{bmatrix} - \begin{bmatrix} \sum 1 & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} \right\} \\
\frac{\partial L}{\partial \beta} &= \begin{bmatrix} \partial L / \partial \beta_0 \\ \partial L / \partial \beta_1 \end{bmatrix} = -2 \left\{ X^T Y - (X^T X) \beta \right\}
\end{aligned}$$



Linear Regression

What is gradient descent method

Q $f(x) = 3x^2 + 4x + 6$

$x^{\text{start}} = 3$

$\eta = 0.1$

find x @ end of 1st and 2nd iteration

$\rightarrow \frac{df(x)}{dx} = 6x + 4$

It 1: $x^{\text{old}} = 3$

$$\begin{aligned} x^{\text{new}} &= x^{\text{old}} - \eta \left. \frac{df(x)}{dx} \right|_{x^{\text{old}}} \\ &= 3 - (0.1) [6x + 4]_{x=3} \\ &= 0.8 \end{aligned}$$

It 2: $x^{\text{old}} = 0.8$

$$\begin{aligned} x^{\text{new}} &= x^{\text{old}} - \eta \left. \frac{df(x)}{dx} \right|_{x^{\text{old}}} \\ &= 0.8 - (0.1) [6x + 4]_{x=0.8} \\ &= -0.08 \end{aligned}$$

loss fn

$$\Rightarrow \mathcal{L} = (15 + 20\beta_0^2 + 15\beta_1^2 + 30\beta_0\beta_1)$$

Randomly Question

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$$

let we start $(\beta_0 = \beta_1 = 1)$, $\eta = 0.1$, find β_0, β_1 after 2 iteration

Sol.

$$\beta^{\text{new}} = \beta^{\text{old}} - \eta \left. \frac{\partial \mathcal{L}}{\partial \beta} \right|_{\beta^{\text{old}}}$$

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{new}} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{old}} - \eta \begin{bmatrix} \partial \mathcal{L} / \partial \beta_0 \\ \partial \mathcal{L} / \partial \beta_1 \end{bmatrix}_{\beta^{\text{old}}}$$

$$\frac{\partial \mathcal{L}}{\partial \beta_0} = 40\beta_0 + 30\beta_1$$

$$\frac{\partial \mathcal{L}}{\partial \beta_1} = 30\beta_1 + 30\beta_0$$



Sol. $\beta^{\text{new}} = \beta^{\text{old}} - \eta \left. \frac{\partial L}{\partial \beta} \right|_{\beta^{\text{old}}}$

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{new}} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{old}} - \eta \begin{bmatrix} \partial L / \partial \beta_0 \\ \partial L / \partial \beta_1 \end{bmatrix}_{\beta^{\text{old}}}$$

$$\frac{\partial L}{\partial \beta_0} = 40\beta_0 + 30\beta_1$$

$$\partial L / \partial \beta_1 = 30\beta_1 + 30\beta_0$$

$$\mathcal{I}_{t1} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{old}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{new}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} - \cdot 1 \begin{bmatrix} 70 \\ 60 \end{bmatrix} \Rightarrow \begin{bmatrix} -6 \\ -5 \end{bmatrix}$$

$$\mathcal{I}_{t2}: \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{old}} = \begin{bmatrix} -6 \\ -5 \end{bmatrix}, \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}^{\text{new}} = \begin{bmatrix} -6 \\ -5 \end{bmatrix} - \cdot 1 \begin{bmatrix} -390 \\ -330 \end{bmatrix} \Rightarrow \begin{bmatrix} 33 \\ 28 \end{bmatrix}$$

#Q. Let's consider regression in one dimension, so our inputs $x^{(i)}$ and outputs $y^{(i)}$ are in \mathbb{R} .

(a) (4 points) Linny uses regular linear regression. Given the following dataset, **1D data**

(Home work)

$$D = \{((1), 1), ((2), 2), ((3), 4), ((3), 2)\}$$

What value of θ and θ_0 optimize the mean squared error of hypotheses of the form $h(x; \theta, \theta_0) = \theta x + \theta_0$?

θ
 θ_0

Linear Regression

$$y = (\beta_0 + \beta_1 x^1 + \beta_2 x^2 \dots)$$

* β_0 : Intercept
• Bias
Term

↓
Coeff of 1st dimen

u u 2nd u

⋮

#Q. Consider a one-dimensional regression problem with training data $\{x_i, y_i\}$. We seek to fit a linear model with ~~no bias term~~ Only Bias term.

Sol



data

$x_1 \ y_1$

$x_2 \ y_2$

\vdots

\vdots

$x_N \ y_N$

model $y = \beta_0$

→ we start from Beginning

$$L = \sum_{i=1}^N (y_i - \beta_0)^2 \quad \frac{\partial L}{\partial \beta_0} = 0, \quad \cancel{2 \sum_{i=1}^N (y_i - \beta_0)} = 0$$

$$\Rightarrow \sum_{i=1}^N y_i - \sum_{i=1}^N \beta_0 = 0$$

$$\Rightarrow \sum_{i=1}^N y_i - \beta_0 \sum_{i=1}^N 1 = 0$$

$$\left\{ \beta_0 = \frac{\sum_{i=1}^N y_i}{N} \right\}$$

#Q. Consider a one-dimensional regression problem with training data $\{x_i, y_i\}$. We seek to fit a linear model with no bias term:

Sol \Rightarrow

data

$x_1 \quad y_1$

$x_2 \quad y_2$

$\vdots \quad \vdots$

$\vdots \quad \vdots$

$x_N \quad y_N$

model $y = \cancel{\beta_0} + \beta_1 x$
 $y = \beta_1 x$

\rightarrow we start from beginning

$$L = \sum_{i=1}^N (y_i - \beta_1 x_i)^2$$

$$\min L : \frac{\partial L}{\partial \beta_1} = 0 \Rightarrow \cancel{2} \sum_{i=1}^N (y_i - \beta_1 x_i) x_i = 0$$

So. $\sum_{i=1}^N (y_i x_i^0 - \beta_1 x_i^2) = 0$

$$\beta_1 \sum_{i=1}^N x_i^2 = \sum_{i=1}^N y_i x_i$$

$$\Rightarrow \beta_1 = \frac{\sum_{i=1}^N x_i y_i^0}{\sum_{i=1}^N x_i^2}$$



#Q. Consider the following 4 training examples:

X	Y
-1	1
0	2
1	4
2	6

We want to learn a function $f(x) = ax + b$ which is parametrized by (a, b) . Using squared error as the loss function, which of the following parameters would you use to model this function.

HPW

#Q. The linear regression model $y = a_0 + a_1x_1 + a_2x_2 + \dots + a_px_p$ is to be fitted to a set of N training data points having p attributes each. Let X be $N \times (p + 1)$ matrix of input values (augmented by 1's), Y be $N \times 1$ vector of target values, and θ be $(p + 1) \times 1$ vector of parameter values $(a_0, a_1, a_2, \dots, a_p)$. If the sum squared error is minimized for obtaining the optimal regression model, which of the following equation holds?

P.w.

(a) $X^T X = X Y$

(b) $X \theta = X^T Y$

(c) $X^T X \theta = Y$

(d) $X^T X \theta = X^T Y$

Consider the function $J(w) = w_1^2 + w_2^2 - 6w_1 + 8w_2 - 9$. Answer questions (1-6):

gradient descent. \Rightarrow $\begin{pmatrix} w_1 \\ w_2 \end{pmatrix}^{\text{new}} = \begin{pmatrix} w_1 \\ w_2 \end{pmatrix}^{\text{old}} - \eta \begin{pmatrix} \partial J / \partial w_1 \\ \partial J / \partial w_2 \end{pmatrix} @ \text{old } w_1, w_2$

4) Start with the initial guess of $[w_1, w_2] = [5, 5]$. Take the value of learning rate = 0.3. The value of w_1 after 2 iterations of gradient descent will be _____.

THANK - YOU