EE5600 Introduction to AIFML OTheorey (1) Simplest case of Linear regres own Lounthon Linear regression is where the expression for finding the Labels from input is lineary in Barrameter and Labels are from a continuous set in linear regression Ýz X w 7 - estimated labels from infact and weights where X - Matire containing N input 30 vectors

{[i e place, N] N- natural numbers } w - weights ictor

There gi) is ground truth babel consciously with 
$$x^{(i)}$$
 is ground truth babel consciously with  $x^{(i)}$  is ground truth babel consciously in Matrix Notation,

B(w) = 
$$(y - xw)^{2}(y - yw)^{2}(xw)^$$

The lest estimate for y welld be Gest XWA where w' = (xTx) xTy (25 Using basis function with (N+1) Bonomotion J = [ D; (70) w 0 where  $\phi(\vec{x}^{ij}) = 1$  forall in  $C_{ij}, \vec{N}$  ie  $\vec{N}$ we can responsement to in Nativial punto W z [wo] Confunction (8SE).'
[E(W) = [(yi) - yi)] = [(yi) - [

AIn most general cours No of observations N) will be loss than the total dimension (d+1) N=(0+1) which Leads to overfitting. Thus the model Borforms poorly on unsendata. By using L2 regularisation by tryingto fur a constraint on the squared norm of weights voctor, along with SSE we generate weights as close to origin as possible. [ Note: - We do this often subtracting the mean from the Loubels By varing I, we can regulate the shounkage of weights. + a frigher value of A should chosen to ensure both Lear error and Lesser squared norm

b) 
$$\frac{1}{2}$$
  $\frac{1}{2}$   $\frac$ 

$$\omega = \begin{bmatrix} \omega_0, & \omega_{02} & \cdots & \omega_{1K} \\ \omega_{11}, & \omega_{12}, & \cdots & \omega_{1K} \end{bmatrix}$$

$$\psi = \begin{bmatrix} y_1 & y_2 & \cdots & y_{2K} \\ y_2 & y_2 & \cdots & y_{2K} \\ y_{2K} & y_{2K} & \cdots & y_{2K} \end{bmatrix}$$

$$\chi = \begin{bmatrix} \chi_1^{(1)} & \chi_2^{(2)} & \cdots & \chi_{2K}^{(N)} \\ \chi_1^{(N)} & \cdots & \chi_{2K}^{(N)} \end{bmatrix}$$

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$$\mathcal{L} = \left\{ \begin{array}{c} \mathcal{L} \\ \mathcal{L}$$

on taking the V(E(W) = U Sumularlepos) Dese get  $[W^* = (X^T \times)^T X^T Y$ For Bousis function, M+1 Parameters For maltidemential Labels. Giz = EDJONE WIK 140) = 2 B; (xi) w; K The weights matrix is of dimension (d+1)×(k) w, 4 are bundar matrix notion as about -) GiDERK 

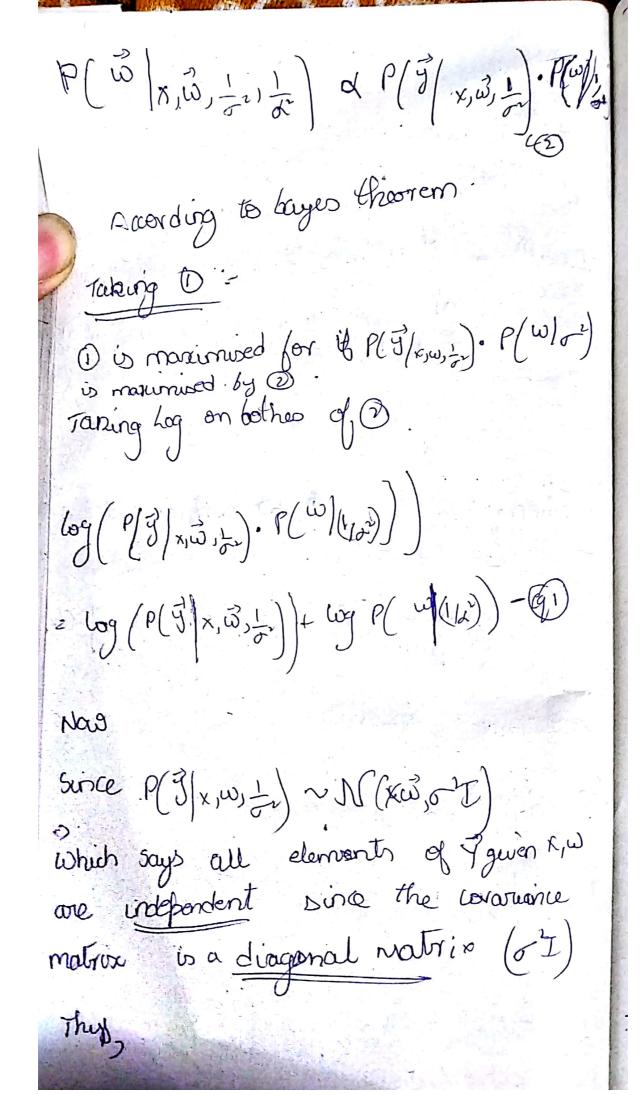
Now q= pw (Fau) = E & Cyin-Bi(n;))2 = # [ (y- pw) (4-xp)] Minimisting this is similar to minimising prob(2) for each whem of y notice on taking \(\tau(\tau(\w))^20\) is conclored to prob@ we get wh = (DTD) DTY (7) Now  $X_{ij} = x_{ij}^{(i)} + n_{ij} \rightarrow 0$ # 121 to N. (i) + n;

$$L(\vec{\omega}) = \sum_{i=1}^{N} (y^{i}) - \omega_{0} - \sum_{j=1}^{d} \hat{x}_{j}^{(i)} \omega_{j})^{2}$$

$$L(\vec{\omega}) = \sum_{i=1}^{N} (y^{i}) - \omega_{0} - \sum_{j=1}^{d} \hat{x}_{j}^{(i)} \omega_{j} - \sum_{j=1}^{d} n_{ij} \omega_{j}^{(i)}$$

$$= \sum_{i=1}^{N} (y^{i}) - \omega_{0} - \sum_{j=1}^{d} \hat{x}_{j}^{(i)} \omega_{j} - \sum_{j=1}^{d} n_{ij} \omega_{j}^{(i)}$$

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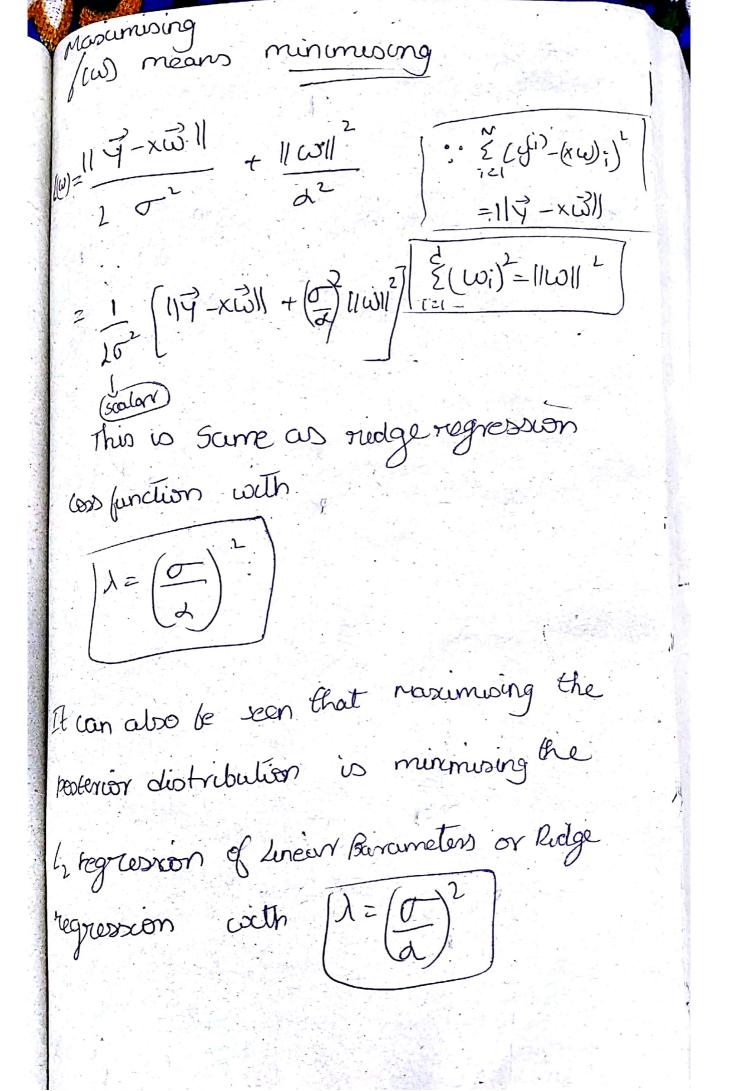
Similarly,

$$P(\vec{\omega}||k|) \sim N(0d^{2}z)$$
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Which bout all elements of  $\vec{\omega}$  are independent the Geometric matrice is adiagnod.

Matrior (2<sup>1</sup>I).

P( $\vec{\omega}||\vec{k}|$ ) =  $\vec{1}$  |  $\vec{l}$  |



$$fanhx = \frac{e^{x} - e^{x}}{e^{x} + e^{x}} = \frac{e^{x} \left[1 - e^{2x}\right]}{e^{x} \left[1 + e^{x}\right]} = \frac{1 - e^{x}}{1 + e^{x}}$$

$$\sigma(x) = \frac{1}{1 + e^{x}}$$

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$$2\sigma(x) = \frac{2}{1 + e^{x}}$$

$$2\sigma(x) = \frac{1 - e^{x}}{1 + e^{x}} = fanh(x)$$

$$\frac{1}{1 + e^{x}} = \frac{1}{1 + e^{x}}$$

$$fanh(x) = 2\sigma(x) - 1$$

$$\frac{1}{1 + e^{x}} = \frac{1}{1 + e^{x}}$$

$$\frac{1}{2} \left(x + \frac{M}{2} u\right) \left(x - \frac{1}{2} u\right) - \frac{M}{12}$$

$$\frac{1}{2} \left(x - \frac{M}{2} u\right) + \frac{M}{12} \left(x - \frac{1}{2} u\right) - \frac{M}{12}$$

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$$\frac{1}{2} \left(x - \frac{M}{2} u\right) = \frac{1 - e^{x}}{1 + e^{x}}$$

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$$\frac{1}{2} \left(x - \frac{M}{2}$$

