

1. Linear regression is a supervised machine learning algorithm use to predict a continuous variable by using the training data that is fed into the model.

Linear regression assumes a linear relationship between the input features $X \in \mathbb{R}^d$ and output y . Goal is to find parameter β such that \hat{y} (prediction) are closest to y (actual outputs).

- * Squaring penalizes large errors more than small ones
- * ensure the fn is differentiable, hence able to take gradient
- * Direct summation may ~~lead to~~ allow +ve & -ve errors to cancel each other. Squaring ensures all errors are +ve

$$(b). J = \frac{1}{2} \|y - X\beta\|^2$$

$$= \frac{1}{2} (y - X\beta)^T (y - X\beta)$$

$$= \frac{1}{2} (y^T - \beta^T X^T) (y - X\beta)$$

$$= \frac{1}{2} (y^T y - \underbrace{y^T X \beta}_{\text{scalar}} - \underbrace{\beta^T X^T y}_{\text{scalar}} - \beta^T X^T X \beta)$$

$$\therefore (y^T X \beta)^T = \beta^T X^T y = \text{scalar}$$

$$\nabla J(\beta) = \nabla \left(\frac{1}{2} (y^T y - 2\beta^T X^T y + \beta^T X^T X \beta) \right)$$

$$\frac{\partial (x^T a)}{\partial x} = a \quad \Rightarrow \quad \frac{\partial J(\beta)}{\partial \beta} = \frac{1}{2} (-2X^T y + 2X^T X \beta)$$

$$\Rightarrow -X^T y + X^T X \beta = 0$$

$$X^T X \beta = X^T y$$

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

$$y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1} \quad X = \begin{bmatrix} x_1 & \dots & x_d \\ \vdots & & \vdots \\ x_n & \dots & x_d \end{bmatrix}_{n \times d+1} \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_d \end{bmatrix}_{d+1 \times 1}$$

- Q. Direct conversion of XTX in the normal equation can be problematic as taking inverse of a high dimensional matrix is computationally expensive as it takes both time & memory.

Gradient descent takes small steps rather than take inverse of whole matrix at once, updates the model parameters of model constantly without starting calculation from start.

2. (a). Backpropagation is an algorithm used to calculate gradients by propagating the error backward from output to the input layer.
- Chain rule helps us to break down complex derivatives of loss fn into simple steps.

(b). $\frac{\partial L}{\partial z_2} = a_2 - y$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial z_2} \cdot \frac{\partial z_2}{\partial w_2}$$

$$\because z_2 = w_2 a_1 + b_2$$

$$\frac{\partial z_2}{\partial w_2} = a_1$$

$$= (a_2 - y) a_1$$

$$\frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial z_2} \cdot \frac{\partial z_2}{\partial b_2}$$

$$z_2 = w_2 a_1 + b_2$$

$$\frac{\partial z_2}{\partial b_2} = 1$$

$$\frac{\partial L}{\partial b_2} = a_2 - y$$

$$\frac{\partial L}{\partial z_1} = \frac{\partial L}{\partial z_2} \cdot \frac{\partial z_2}{\partial a_1} \cdot \frac{\partial a_1}{\partial z_1}$$

$$\frac{\partial a_1}{\partial z_1} = a_1 (1 - a_1)$$

$$= (a_2 - y) w_2$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial z_1} \frac{\partial z_1}{\partial w_1}$$

$$= (a_2 - y) w_2 a_1 (1 - a_1) x$$

$$\frac{\partial L}{\partial b_1} = \frac{\partial L}{\partial z_1} \frac{\partial z_1}{\partial b_1}$$

$$= (a_2 - y) w_2 a_1 (1 - a_1)$$

©: To update the weights we subtract a fraction of the gradient from the current value

$$w_1' = w_1 - \alpha \frac{\partial L}{\partial w_1}$$

$$w_2' = w_2 - \alpha \frac{\partial L}{\partial w_2}$$

$$b_1' = b_1 - \alpha \frac{\partial L}{\partial b_1}$$

$$b_2' = b_2 - \alpha \frac{\partial L}{\partial b_2}$$

$\alpha \rightarrow$ controls the step size

If α ~~is~~ too small
 \rightarrow convergence very slow

If α too large
 \rightarrow may overshoot the minimum

Q3

① (a). RNN \rightarrow RNN processes input sequentially if ⁱⁿ it contains a hidden state (memory) the output at step t depends both on current input & step $t-1$.

b). ANN \rightarrow process inputs independently

②. Simple RNN's struggle with long term dependencies due to the problem of vanishing gradient.

Q4 - LSTMs uses gates to ^{regulate} information flow unlike RNNs.
 Forget gate \rightarrow decides what information to throw away
 Input gate \rightarrow decides what new important info to store
 Output gate \rightarrow decides what info is relevant of immediate prediction

(1) LSTM uses cell state to address the problem of vanishing gradient

- (2)
- ANN → House Price Prediction
 - RNN → Time Series Forecasting
 - LSTM → Machine Translation

Q4,

Example of long range dependency

(a). The boys who play soccer in the main are is

The model must connect the neural subject boys at the start the neural verb are at the end

A standard RNN would struggle, by the time it processes the sentence the vanishing gradient problem ~~it~~ would cause ^{it} to forget that the subject was "boys". It might incorrectly predict "is".

(b). LSTM use a memory cell that carries relevant context across time steps. Gated ^{into} control flow, input gate decides what new info to store, forget gate decides what old info to drop, the output gate decides what to give as output. This gating prevents vanishing gradients & enables long term dependency learning