

Lec: 04  
01.29.24

## "Linear Regression"

LR → simple approach to  
↓  
supervised learning

It makes some assumptions:

- i) All predictors are Independent  
↑  
each of the features will affect independently
- ii)  $Y \rightarrow$  the label / target depends on the predictors.  
(There is a relationship between  $X$  and  $Y$ )
- iii) The relationship is linear.

the form of LR → equation of a line

$$\hat{Y} = c + mx$$

↓  
this form we assume for  $\epsilon$

$$Y = \beta_0 + \beta_1 x + \epsilon$$

↓      ↓      ↓  
Intercept    Slope    error terms  
↓  
Coefficient / parameters

$\beta_0$  and  $\beta_1 \rightarrow$  we estimate for those values so that output can be predicted

Linear reg assumes = Linear funct  
(Straight line)

$$y = c + mx$$

$$\Rightarrow y = f(x)$$

$$\Rightarrow y = \beta_0 + \beta_1 x + \epsilon$$

Estimate  $\hat{\beta}_0$  and  $\hat{\beta}_1$  to predict  $\hat{y}$

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

need to find these values.

$$\hat{\beta}_0 = ? \quad \hat{\beta}_1 = ?$$

Least square method  $\rightarrow$  efficient method for finding the values of  $\beta_0$  and  $\beta_1$ .

$$y = f(x)$$

$$\hat{y} = \hat{\beta}_0 + \beta_1 x$$

$$e_i^r = (\hat{y} - \hat{y})^r =$$

$$e_2^r, e_3^r, e_4^r, \dots, e_n^r$$

All of these errors together:

Residual Sum Square

$$(RSS) = e_1^r + e_2^r + \dots + e_n^r$$

$$(\hat{y}_1 - \hat{\beta}_0 + \hat{\beta}_1 x_1)^r$$

$\hat{\beta}_0 = ?$   $\hat{\beta}_1 = ?$  what are the estimates?  
→ or finding ↗ ↘

$$RSS = \sum_{i=1}^n (\hat{y}_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^r$$

Partial derivative of RSS, with respect  
to  $\hat{\beta}_0$  and  $\hat{\beta}_1$ , and set it equal  
zero.

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Where,  $\bar{x}, \bar{y}$  = sample means of  $x$  and  $y$

$$f(x) = \hat{\beta}_0 + \hat{\beta}_1 x$$

## # Evaluation of Linear regression:

- i) Standard Error: will give us values  
→ how close  $\hat{\beta}_0, \hat{\beta}_1$  estimates to  
the true value → 0 to  $\infty$   
→ the lower, the better

confidence intervals :

$$[\pm 2, \pm 10]$$

95% sure that we are in the  
right track. → true value will  
be inside this range.

#  $R^2$  = proportion of variance  
↓ explained.

(Accuracy equivalence) in the model  
How much explanation  
can give us?

$$[0, 1]$$

$$[0\%, 100\%]$$

$$R^2 = 1 - \frac{RSS}{TSS}$$

TSS = Total sum squared  
 $= \sum_{i=1}^n (y_i - \bar{y})^2$

Hypothesis

Assumption that needs to be tested.

null hypothesis  $\rightarrow$  no relation

alternative  $\rightarrow$  some  $\neq 0$

# null hypothesis

$\downarrow$  train and test a model

$\downarrow$   
Accept / reject based on this model

ex:

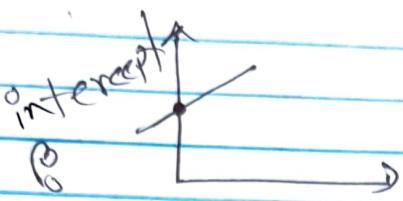
$$\begin{cases} f(x) = \beta_0 + (\beta_1 x) & \text{if } \beta_1 = 0 \\ & = \beta_0 \end{cases}$$

t-statistic  $\rightarrow$  way to reject / accept the hypothesis

Some form of relationship

which  $\neq$  coefficient has relation individually.

f-statistic: At least 1 co-efficient has the relationship



$$f(n) = \hat{\beta}_0 + \hat{\beta}_1 n$$

$$= 7.0325 + 0.10475(n)$$

P-value  $\rightarrow$  P < 0.05

All the results we have  
Shows  $\downarrow$  is statistically significant coefficient.

Loc: 05  
01.31.23 ("coding session")

writing code to implement. Least  
regression  
↓  
data

## Databases in ISLP

Boston talk

## Simple LR:

just 1

$$f(n) = \Theta_0 + \Theta_1 n$$

30

$\beta_0 \times 1$

result: last : -0.9500  $\Rightarrow$

(negative relationship)

$$t \rightarrow -24.528$$

A hand-drawn diagram illustrating a Multiple Linear Regression (MLR) model. At the top, the acronym "MLR" is written in large, bold letters. Below it, a vertical line separates the dependent variable "y" from the independent variables "x<sub>0</sub>", "x<sub>1</sub>", and "x<sub>2</sub>". A horizontal line labeled "mode" is positioned above the "y" variable. The entire set of variables is enclosed in a bracket, indicating they are part of a single model. A regression line is drawn through the points, representing the relationship between the independent variables and the dependent variable.

positive relat<sup>n</sup>:

1st stat: age

doesn't matter how old

At first without  
interaction → individually  
→ then together

qualitative - data:

0 = No

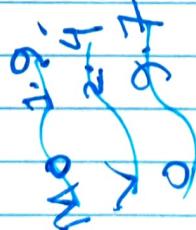
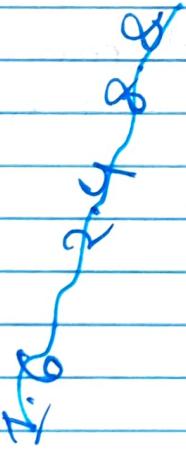
1 = Yes

$$f(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

$$\left. \begin{aligned} & \frac{1}{n} \sum_{i=1}^n I(y_i \neq \hat{y}_i) \\ & \text{Ave}(I(y_i \neq \hat{y}_i)) \end{aligned} \right\} \begin{array}{l} y_i \neq \hat{y}_i \rightarrow 1 \\ y_i = \hat{y}_i \rightarrow 0 \end{array}$$

$$\# \text{ Pro}(Y = j | X = x_0) = \frac{1}{K} \sum_{i \in N_0} I(y_i = j)$$

$$CV_{(1)} = \sqrt{\frac{1}{n} \sum_{i=1}^n \text{Error}_i}$$



lec: 06  
02-05-24

# i) Is there a relationship between X and Y?

→ t-statistics / f-statistic

whether/ not reject null hypothesis

ii) How strong is the relationship between X and Y?

co-efficient > impact

→  $R^2$  ( $0-1 \rightarrow \uparrow\uparrow \rightarrow \text{better}$ )

iii) Which of the predictors are associated with Y? → P-value,  $< 0.05$

iv) Is there synergy among the predictors?

→ P-value,  $< 0.05$

examine the 1) associated with each predictor t-star

v) How accurate is the model for future prediction?

→ co-efficient within the confidence interval

# classification:  
predicting classification problem

feature vector  $X \rightarrow Y$   
qualitative response

no quantitative  
try to predict the probability  
of label  $y$ .

e.g.:  $P(x)$

$$P(X \mid \text{brown}) = ? \quad 0.5 \quad \checkmark$$

$$P(X \mid \text{blue}) = ? \quad 0.2$$

$$P(X \mid \text{green}) = ? \quad 0.3$$

$$P(X \mid y_n) = ?$$

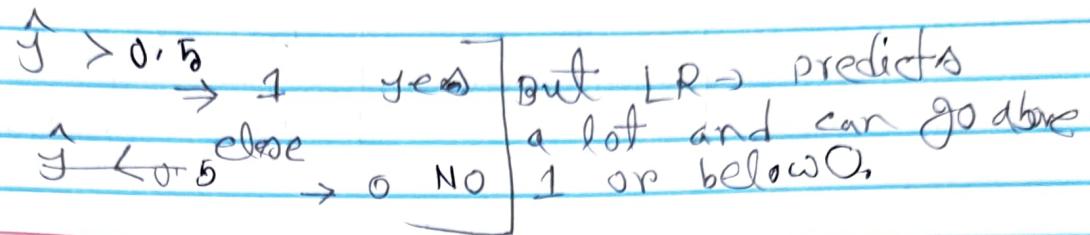
imbalanced default

-	-	No
-	-	No
-	-	-

$\downarrow$   
 $\square$  co-efficient  
 $\square$  of balance  
needs to be in  
 $\uparrow \uparrow$  but lower in  
ignore

Linear regression

Why not LGR model?

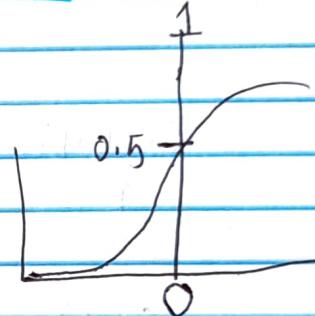


## # Logistic Regression:

→ parametric method  
 → \* \* Data of a certain form  
functional form \* \*

$$\begin{aligned}y &= c + mx \\y &= \beta_0 + \beta_1 x\end{aligned}$$

→ Assume sigmoid functn ≈ [0, 1]



above 0.5 → yes  
 below → no

$$\begin{aligned}s(x) &= \frac{1}{1 + e^{-x}} \\&= \frac{1}{1 + (2.71)}\end{aligned}$$

Euler constant  
2.71

any value we provide, will be in the range of [0 - 1]

$$P(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

[value within 0 and 1]

$$1 + e^{-\alpha_0 + \alpha_1 x + \alpha_2 y}$$

$$\begin{array}{c|c|c|c} x_0 & x_1 & y_1 & \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}} \end{array}$$

we are gonna predict  
 $\beta_0$  and  $\beta_1$  co-efficient

# we have funct<sup>n</sup>:

$$P(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

How do we find this estimates:

\* Maximum Likelihood: find the probability of predictor giving y/label

= 1.

$$\# S(x) = \frac{1}{1 + e^{-x}} = \frac{1}{1 + \frac{e^x}{e^x}}$$

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

=

$$\prod_{i=1}^n P(x_i) \cdot (1 - P(x_i))$$

likelihood  
of predicting  
1 and 0

Predictor will tell  
which one is more  
likely

Maxi likelihood for each of the predictor

F - statistic  $\rightarrow$  overall relationship (1 predictor has it)  
t - statistic  $\rightarrow$  individual predictor relationship  
 $\Rightarrow$  individual predictor relationship

# Making Pred :  $\hat{\beta}_0 + \hat{\beta} x$

$$\hat{P}(Y) = \frac{e}{1 + e^{\hat{\beta}_0 + \hat{\beta} x}}$$

$$\hat{P}(X) = \hat{P}(x)$$

comparing whether they are same/not

g)  $\uparrow\downarrow$  balance  $\rightarrow$  predicting good.

co-efficient

0.4099  $\rightarrow$  can be any number

Stu(yes)  $\rightarrow$  has  $\uparrow\downarrow$  magnitude than the balance predictor.

# multiple predictors:

slide 11 →

student → neg. coefficient

not a good sign which is fooling  
the model

opposite prediction of model.