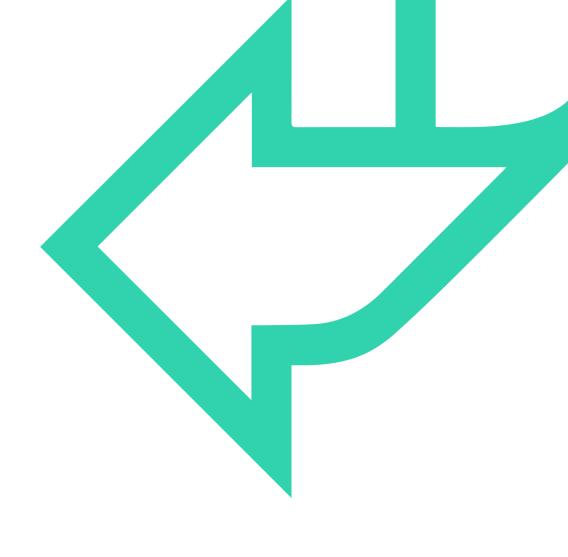


## **Linear Regression**





## Line Fitting



#### MODELING NUMERICAL VARIABLES

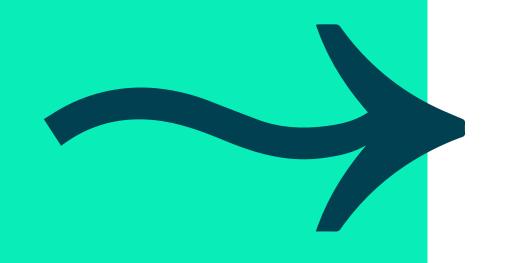


- quantify the relationship between two numerical variables
- modelling numerical response variables using a numerical or categorical explanatory variable

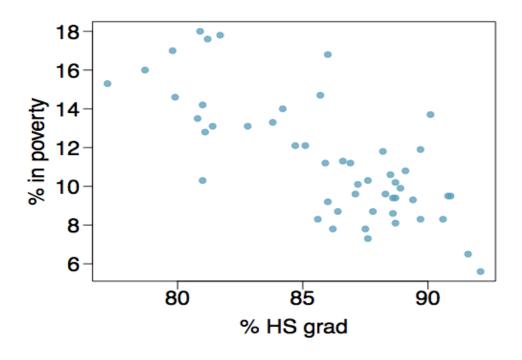




#### **SCATTERPLOT**

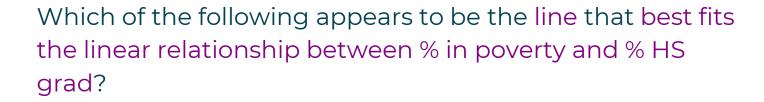


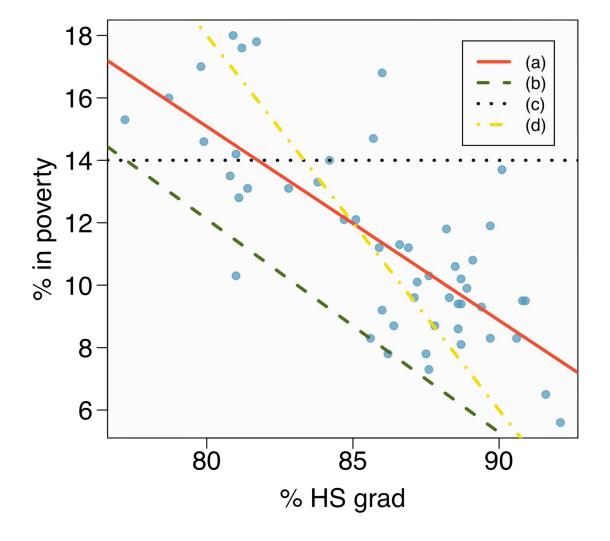
#### Poverty vs. HS graduate rate





# EYEBALLING THE LINE







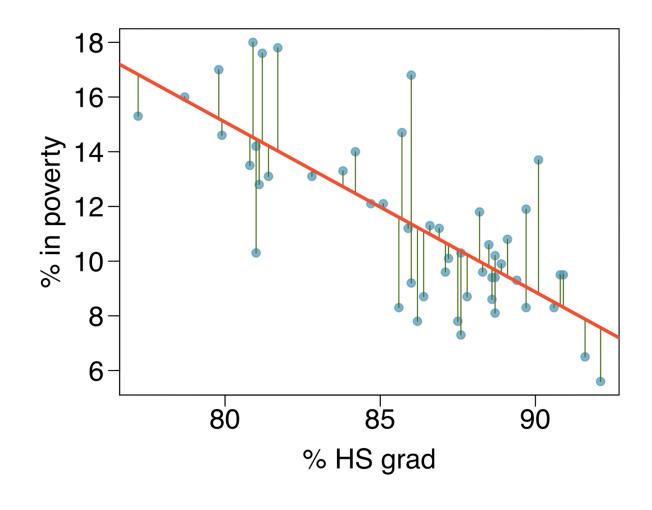
## Residuals



#### RESIDUALS

Leftovers from the model fit:

Data = Fit + Residual



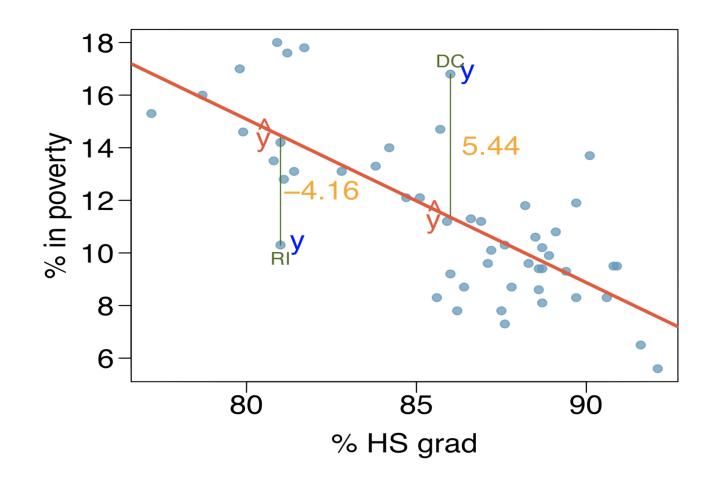


#### **RESIDUALS**

% living in poverty in RI is 4.16% less than predicted

$$e_i = y_i - \hat{y}_i$$

Difference between the observed  $(y_i)$  and predicted  $\hat{y}_i$ 





## Correlation



#### Quantifying the relationship

- CORRELATION DESCRIBES THE STRENGTH OF THE LINEAR ASSOCIATION BETWEEN TWO VARIABLES.
- IT TAKES VALUES BETWEEN -1 (PERFECT NEGATIVE) AND +1 (PERFECT POSITIVE).
- A VALUE OF 0 INDICATES NO LINEAR ASSOCIATION.



#### COVARIANCE

#### Quantifying the relationship

$$\frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{n}$$



#### CORRELATIO N

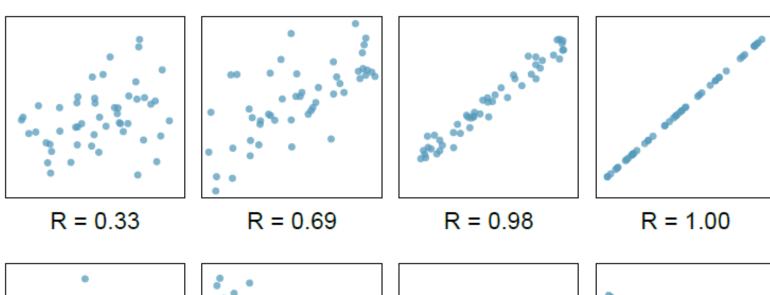
#### Quantifying the relationship

$$\rho_{xy} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{m}$$

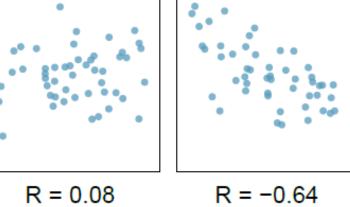
$$\sigma_x \sigma_y$$

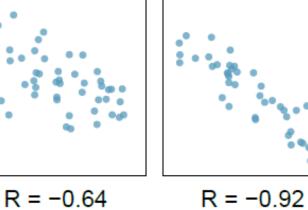


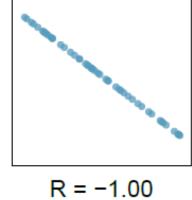
### QUANTIFYING THE RELATIONSHIP





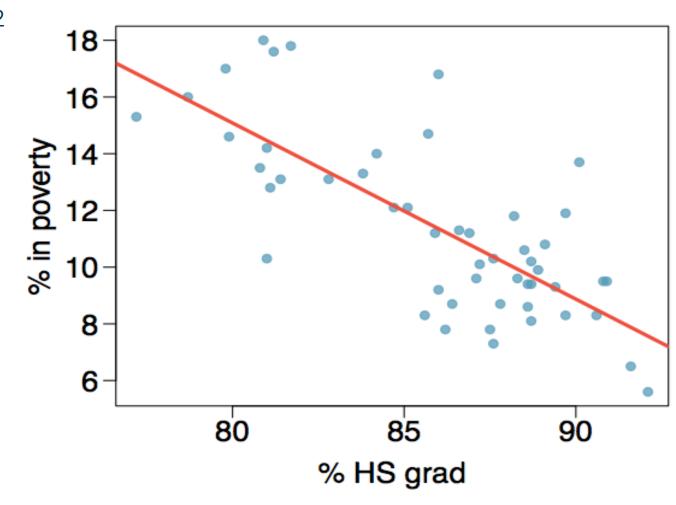








- (a) 0.6
- (b)-0.75
- (c) 0.1
- (d)0.02
- (e) 1.5







Which of the following is the best guess for the correlation between percent in poverty and percent HS grad?

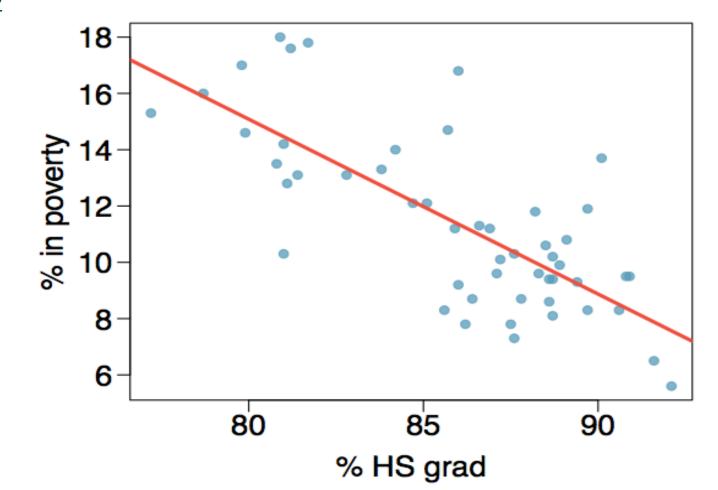
(a) 0.6

(b)-0.75

(c) - 0.1

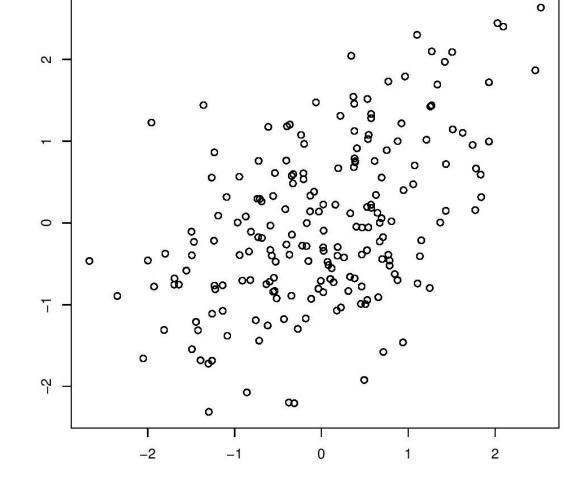
(d)0.02

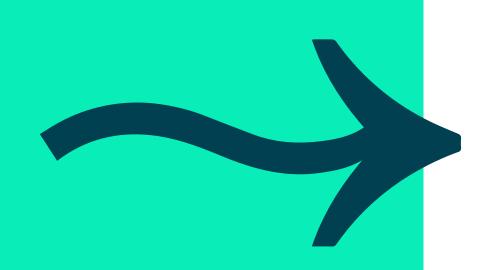
(e)-1.5





- (a) 0.1
- (b)-0.6
- (c) 0.4
- (d)0.9
- (e)0.5

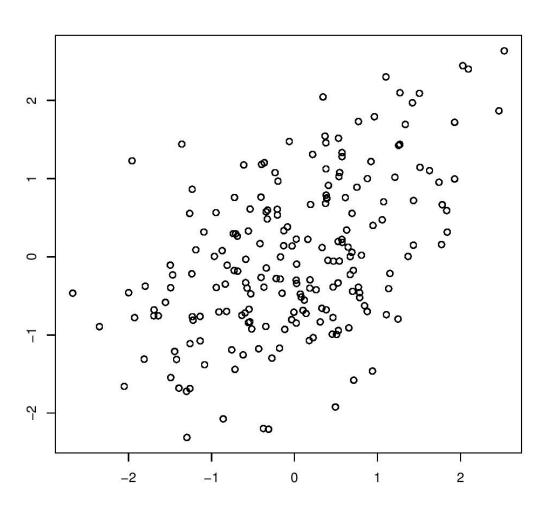






- (a) 0.1
- (b)-0.6
- (C) 0.4
- (d)0.9
- (e)0.5

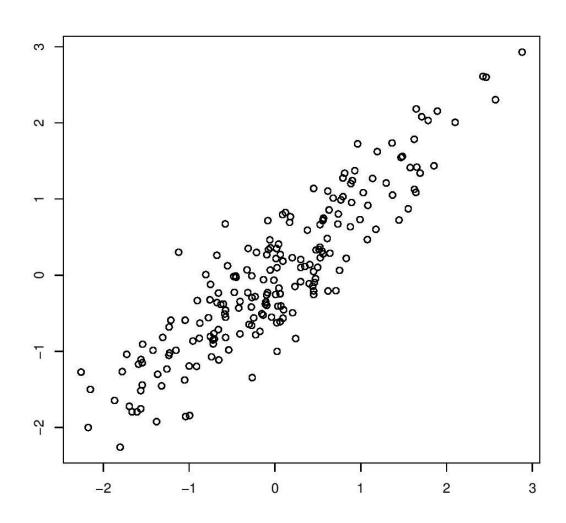






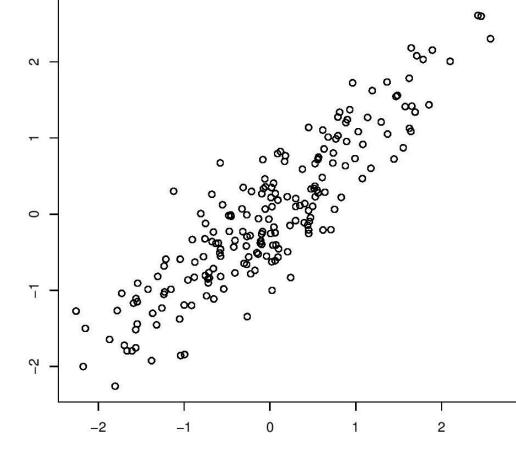
- (a) 0.1
- (b)-0.6
- (c) 0.4
- (d)0.9
- (e)0.5

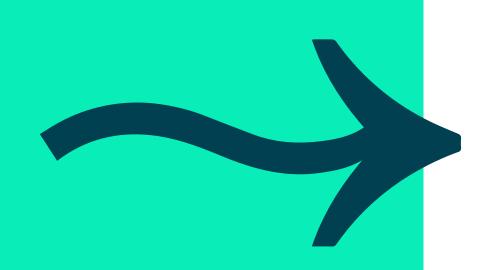






- (a) 0.1
- (b)-0.6
- (c) 0.4
- (d)0.9
- (e)0.5

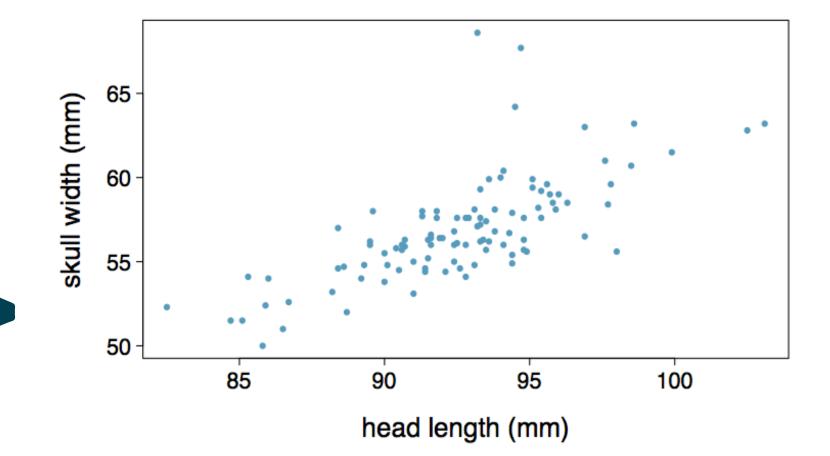






# POSSUMS: TRUE/FALSE?

- (a) There is no relationship between head length and skull width, i.e. the variables are independent.
- (b) Head length and skull width are positively associated.
- (c) Skull width and head length are negatively associated.
- (d) A longer head causes the skull to be wider.
- (e) A wider skull causes the head to be longer.



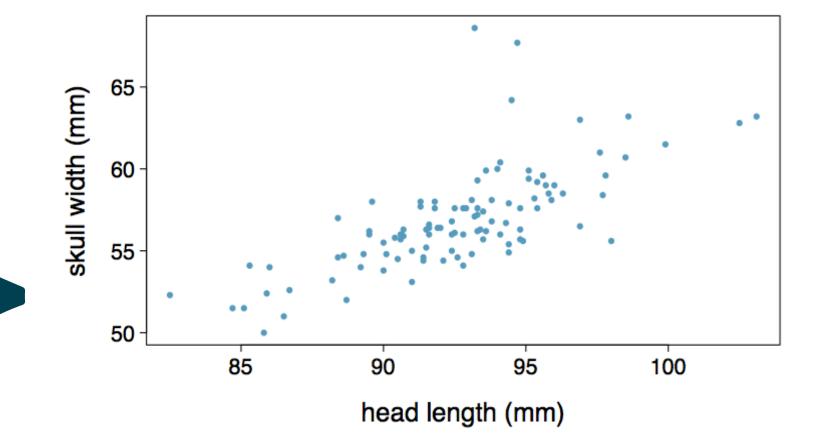


# POSSUMS: TRUE/FALSE?

(a) There is no relationship between head length and skull width, i.e. the variables are independent.

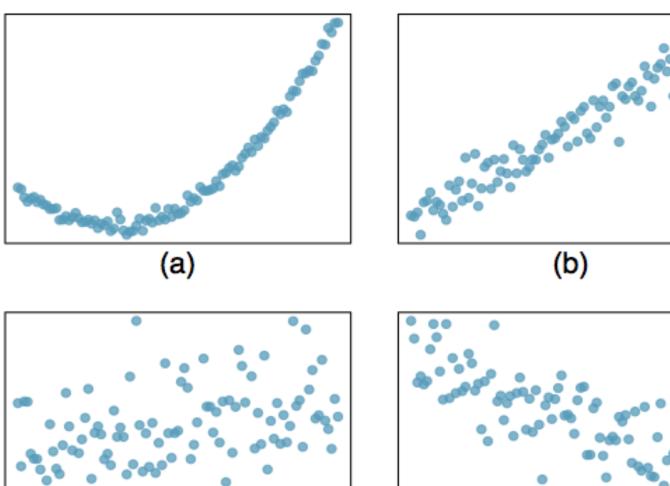
#### (b) Head length and skull width are positively associated.

- (c) Skull width and head length are negatively associated.
- (d) A longer head causes the skull to be wider.
- (e) A wider skull causes the head to be longer.

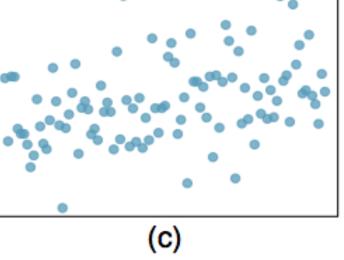


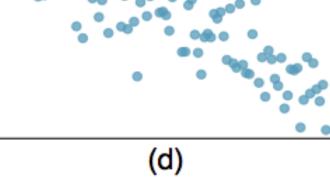


## **ASSESSING** THE CORRELATION



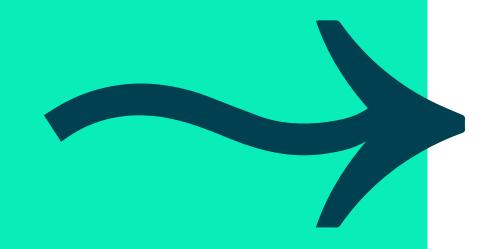


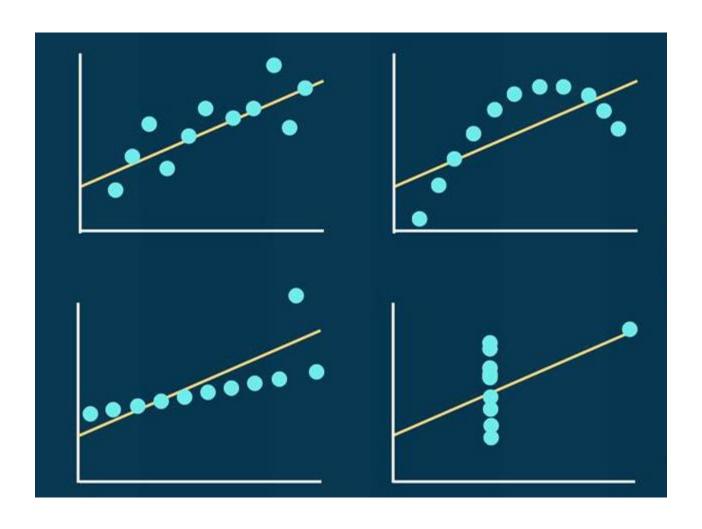






BE CAREFUL
WHEN MAKING
CONCLUSIONS
BASED ON
STATISTICS





ref: The Anscombe's Quartet, 1973



Fitting a line by least squares regression



#### FITTING



We want a line that has small residuals

Option 1: Minimize the sum of magnitudes (absolute values) of residuals

$$|e_1| + |e_2| + ... + |e_n|$$

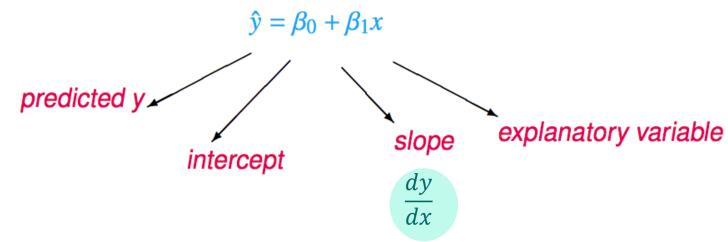
Option 2: Minimize the sum of squared residuals – "least squares"

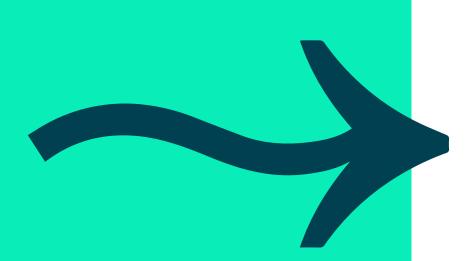
$$e_1^2 + e_2^2 + ... + e_n^2$$

- Why least squares?
  - 1. Most commonly used
  - 2. Easier to compute by hand and using software
  - 3. In many applications, a residual twice as large as another is usually more than twice as bad



#### **EQUATION**

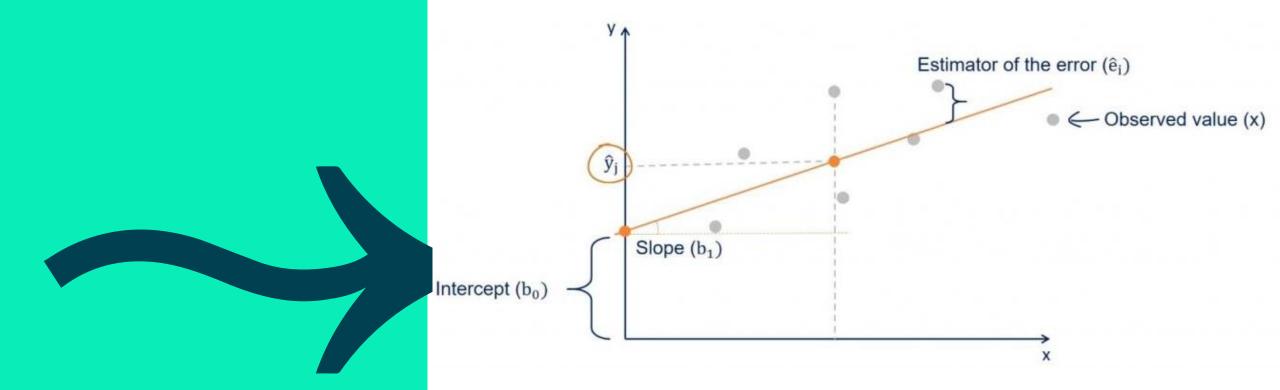






# REGRESSION COEFFICIENTS

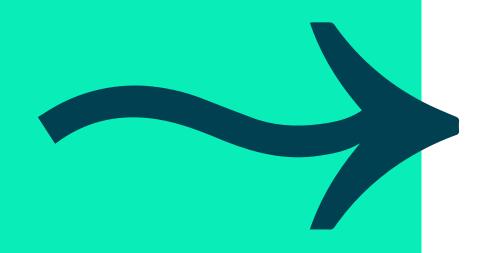
$$Y_i = \beta_0 + \beta_1 X_i + \hat{\mathbf{e}}_i$$





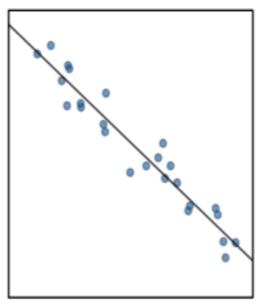
# LEAST SQUARES LINE: CONDITIONS

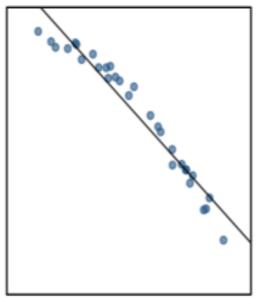
- 1. Linearity
- 2. Nearly normal residuals
- 3. Constant variability

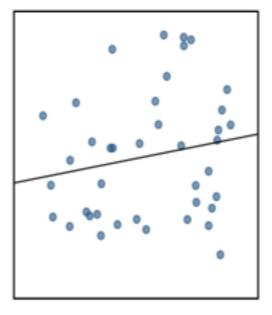


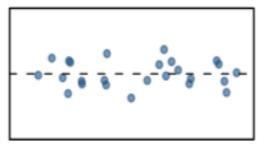


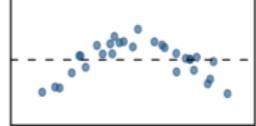
## LS LINE: CONDITION: LINEARITY

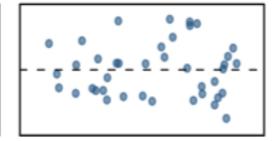








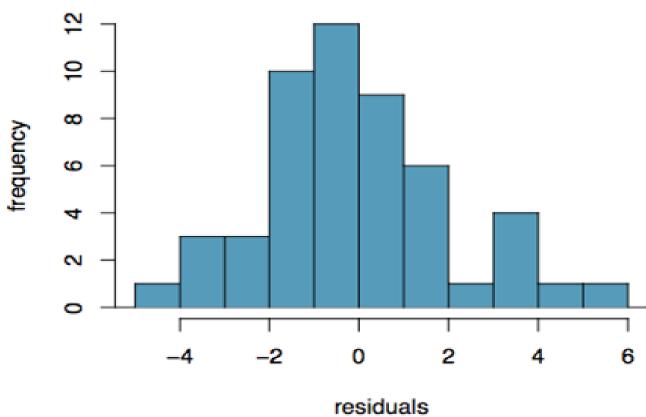






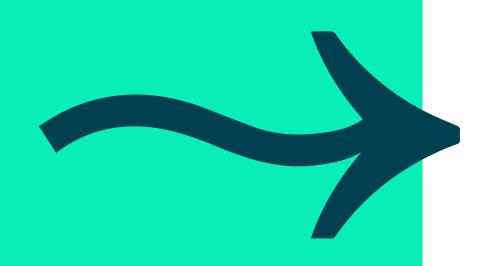
# LS LINE: CONDITION: NORMAL $\varepsilon_i$

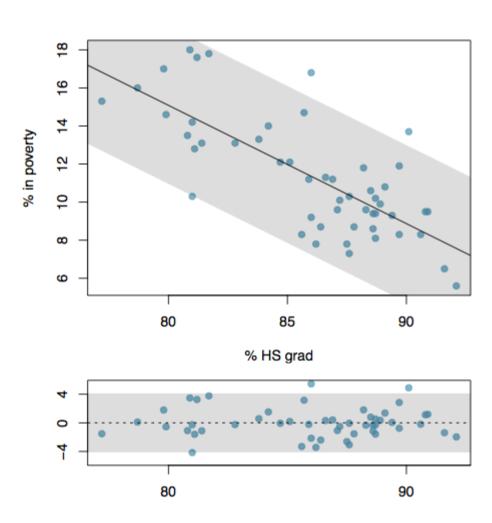






# LS LINE: CONDITION: CONSTANT $\sigma^2$

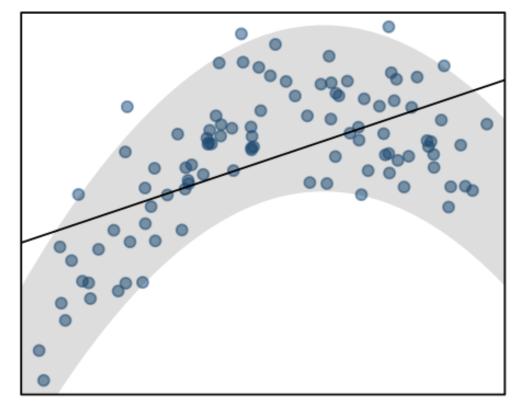




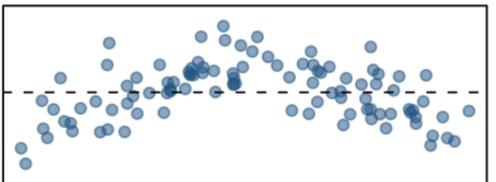




- (a) Constant variability
- (b) Linear relationship
- (C) Normal residuals
- (d)No extreme outliers



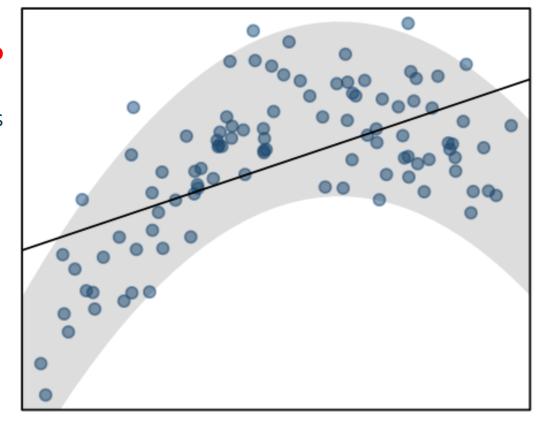




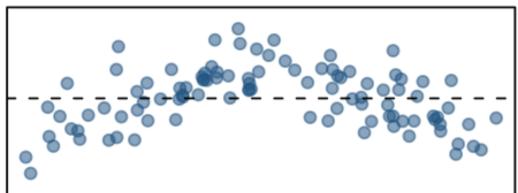


What condition is this linear model obviously violating?

- (a) Constant variability
- (b)Linear relationship
- (C) Normal residuals
- (d) No extreme outliers



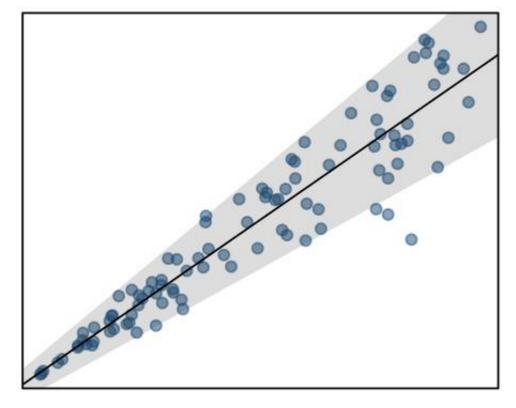


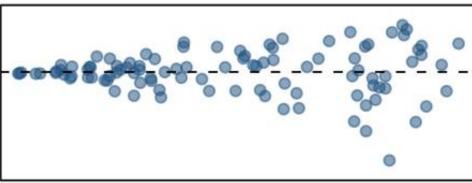




What condition is this linear model obviously violating?

- (a) Constant variability
- (b)Linear relationship
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- (d) No extreme outliers





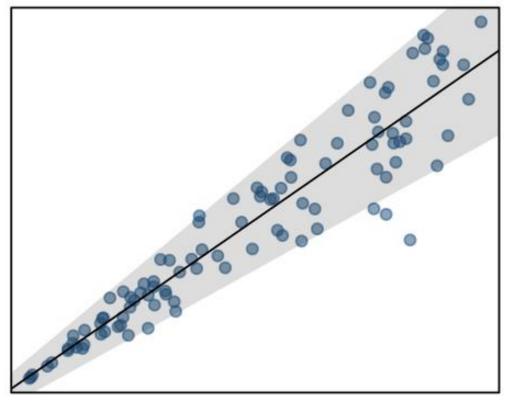


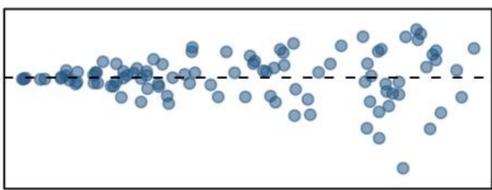




#### (a)Constant variability

- (b)Linear relationship
- (C) Normal residuals
- (d) No extreme outliers



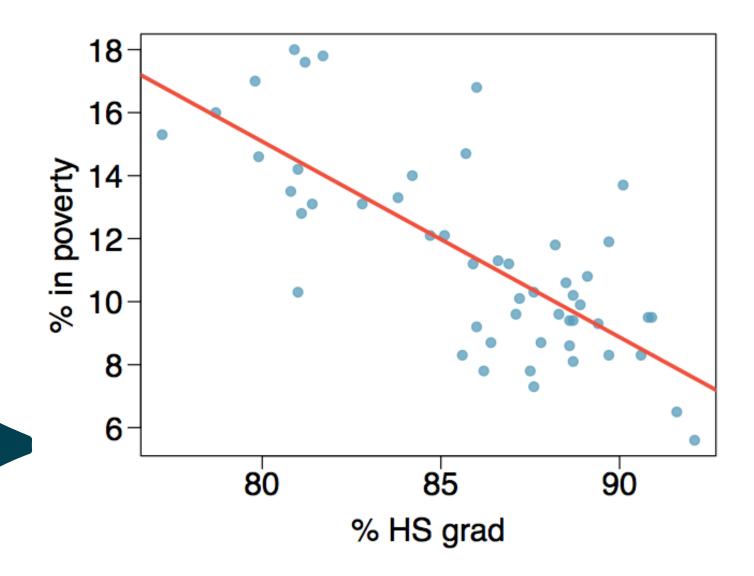






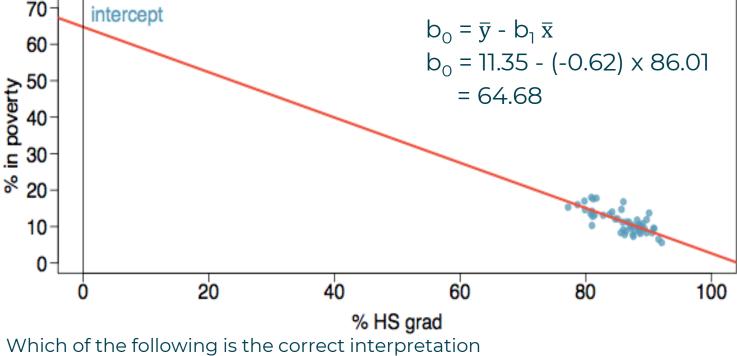
# REGRESSION LINE

 $\% \ \widehat{in \ poverty} = 64.68 - 0.62 \% \ HS \ grad$ 



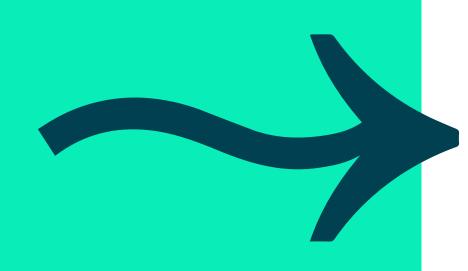
# Q٨

# INTERCEPT



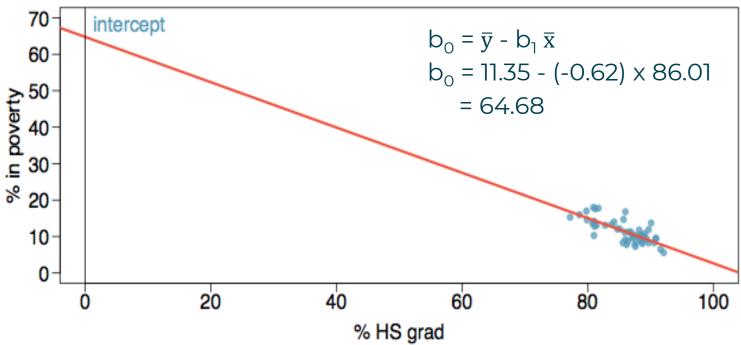
Which of the following is the correct interpretation of the intercept?

- (a) For each % point increase in HS graduate rate, % living in poverty is expected to increase on average by 64.68%.
- (b) For each % point decrease in HS graduate rate, % living in poverty is expected to increase on average by 64.68%.
- (C) Having no HS graduates leads to 64.68% of residents living below the poverty line.
- (d)States with no HS graduates are expected on average to have 64.68% of residents living below the poverty line
- (e) In states with no HS graduates % living in poverty is expected to increase on average by 64.68%.





# INTERCEPT



Which of the following is the correct interpretation of the intercept?

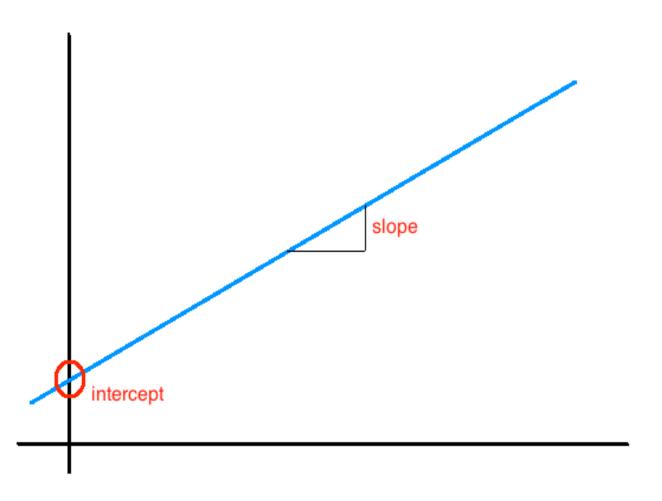


(d)
States with no HS graduates are expected on average to have 64.68% of residents living below the poverty line



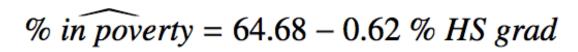
# INTERPRETATION

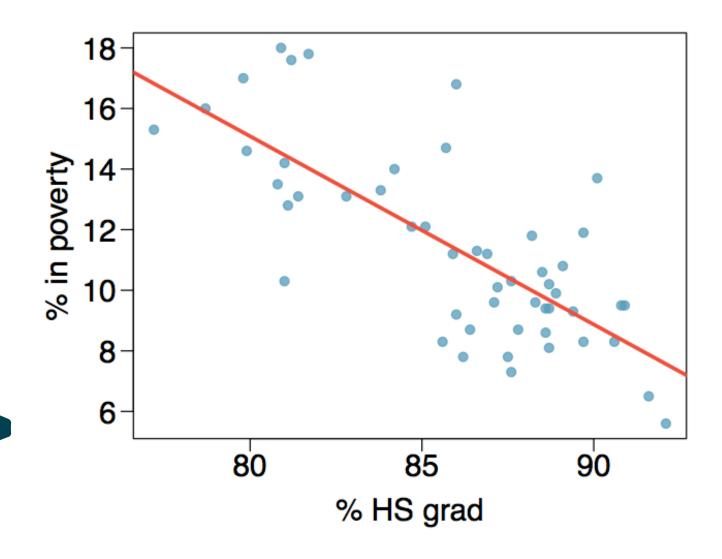






# **PREDICTION**



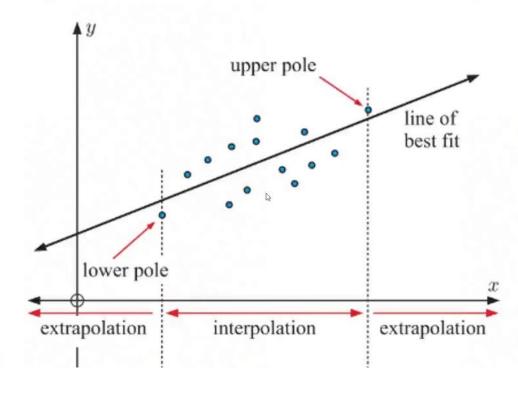




# Interpolation / Extrapolation

In between the points = reliable

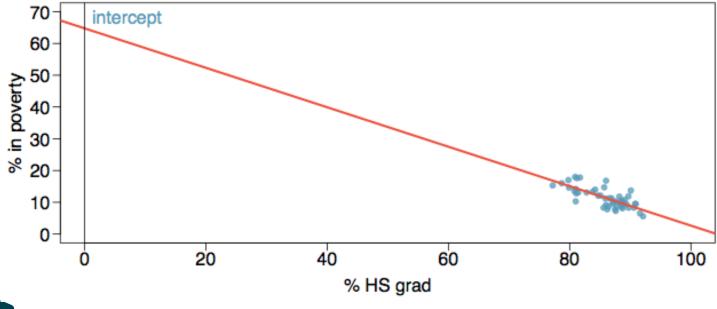
Outside the points = unreliable







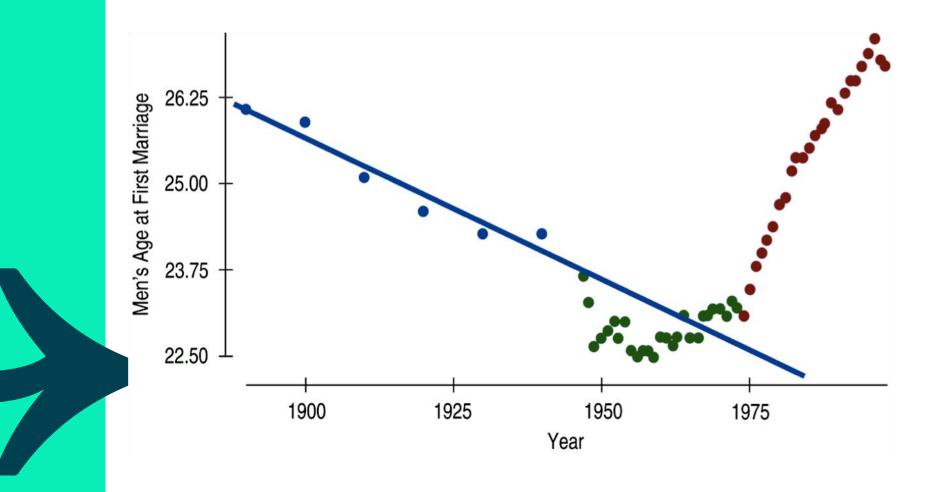
# Our Example of finding the intercept







Applying a model estimate to values outside of the realm of the original data – if a linear model was built in 1950





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#### Printable version

### Women 'may outsprint men by 2156'

Women sprinters may be outrunning men in the 2156 Olympics if they continue to close the gap at the rate they are doing, according to scientists.

An Oxford University study found that women are running faster than they have ever done over 100m.



Women are set to become the dominant sprinters

At their current rate of improvement, they should overtake men within 150 years, said Dr Andrew Tatem.

The study, comparing winning times for the Olympic 100m since 1900, is published in the journal Nature.

However, former British Olympic sprinter Derek Redmond told the BBC: "I find it difficult to believe.

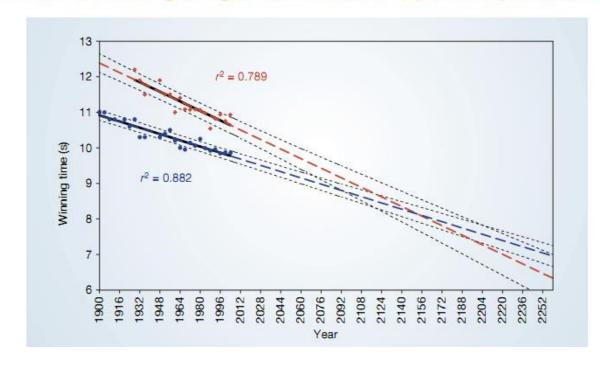
"I can see the gap closing between men and women but I can't necessarily see it being overtaken because mens' times are also going to improve."





# Momentous sprint at the 2156 Olympics?

Women sprinters are closing the gap on men and may one day overtake them.







# WHAT IS R<sup>2</sup>?

What is  $\mathbb{R}^2$ ?

R<sup>2</sup> evaluates the strength of the fit of a linear model

**R**<sup>2</sup> = square of the correlation coefficient

R<sup>2</sup> = "coefficient of determination"

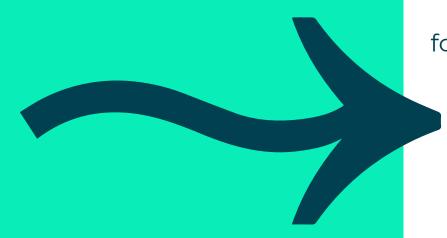
What does R<sup>2</sup> tell us?

The percent of variability in the response variable is **explained** by the model

What about the remainder of the variability?

Remainder is explained by variables NOT included in the model or by inherent randomness in the data

for the model (% in poverty vs % HS grad),  $R^2 = (-0.62)^2 = 0.38$ 

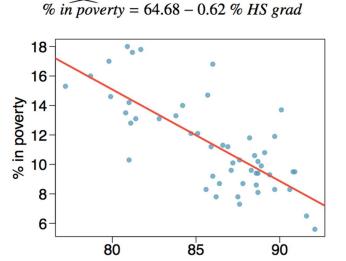




# R<sup>2</sup> = 0.38 INTERPRETATION?

- a) 38% of the variability in the % of HS graduates among the 51 states is explained by the model.
- b) 38% of the variability in the % of residents living in poverty among the 51 states is explained by the model.
- c) 38% of the time % HS graduates predict % living in poverty correctly.
- d) 62% of the variability in the % of residents living in poverty among the 51 states is explained by the model





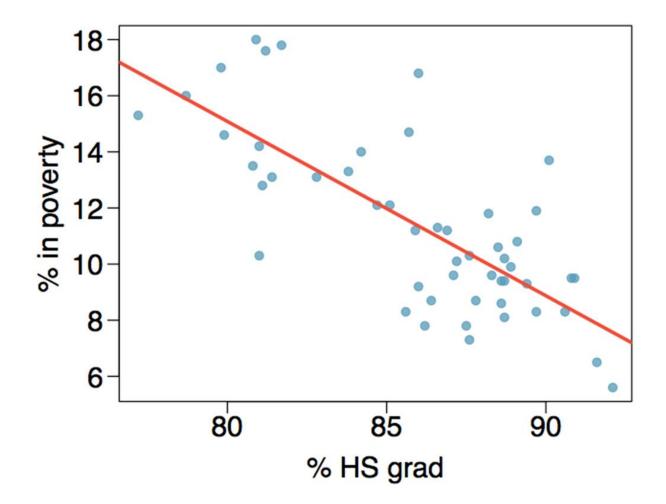
% HS grad



# R<sup>2</sup> = 0.38 INTERPRETATION?

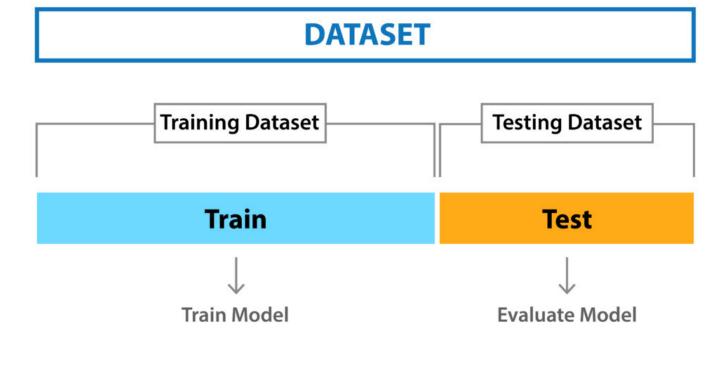


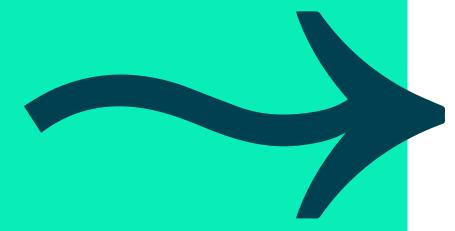
% 
$$\widehat{in \ poverty} = 64.68 - 0.62 \% \ HS \ grad$$





# IN MACHINE LEARNING







# COMMON METRICS FOR REGRESSION

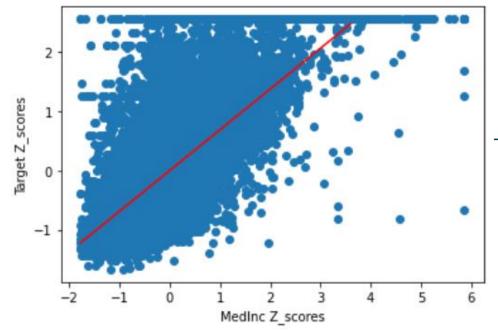
We have 3 main metrics for regression models:

- 1. Mean Absolute Error (MAE)
- 2. Mean Squared Error (MSE)
- 3. Root Mean Squared Error (RMSE)



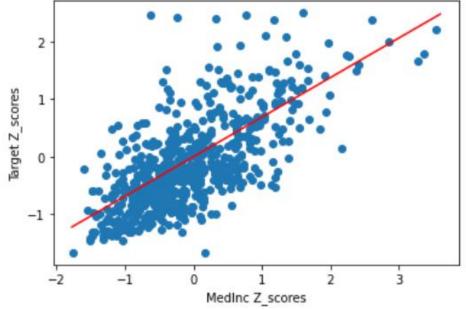


## **EXAMPLE**



Training Data





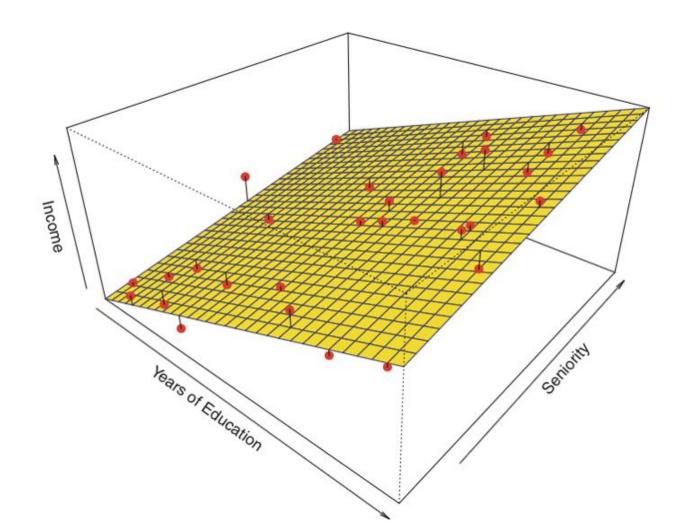
Test Data



# MULTI DIMENSIONAL



As we increase beyond 3 dimensions the model becomes impossible to visualise.





### THE MATHS

It is impossible to visualize as we increase dimension, but it is very easy and intuitive to display mathematically

In 2 dimensions, 1 target and 1 feature our regression model was:

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

In 3 dimensional space, 1 target and 2 features:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

In 4 dimensional space, 1 target and 3 features:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

And so forth





# CURSE OF DIMENSIONALITY

## More Dimensions

More problems





# DEMO AND EXERCISES

Open the linear regression notebook

We will go through a demo, building a linear regression model, first with one feature then with more.