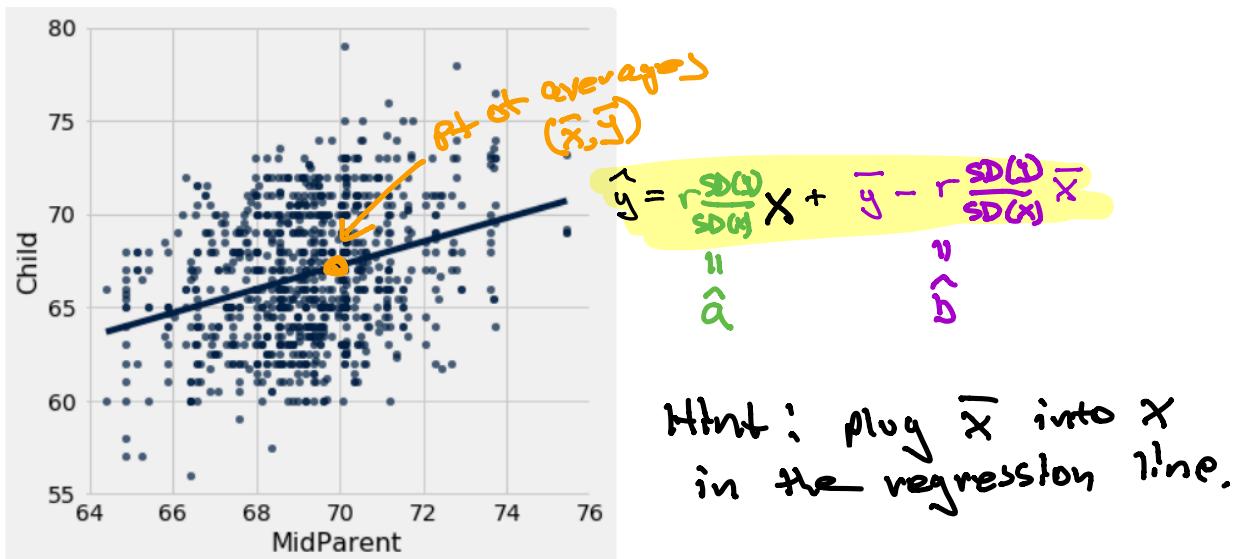


Stat 88 Lec 37

warm up 2:00-2:10

let $(x_1, y_1), \dots, (x_n, y_n)$ be random pairs. The average of these pairs (\bar{x}, \bar{y}) is called the point of averages in the scatter diagram. Show that the point of averages lies on the regression line.



$$\hat{y} = r \cancel{\frac{SD(y)}{SD(x)} x} + \bar{y} - r \cancel{\frac{SD(y)}{SD(x)}} \bar{x} = \bar{y}$$

Last time

Sec 11.3 and 11.4 linear regression.

For a sample of pairs $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ the regression line is the best fitting line through your scatter plot:

$$\hat{y} = r \frac{SD(y)}{SD(x)} X + \bar{y} - r \frac{SD(y)}{SD(x)} \bar{x}$$

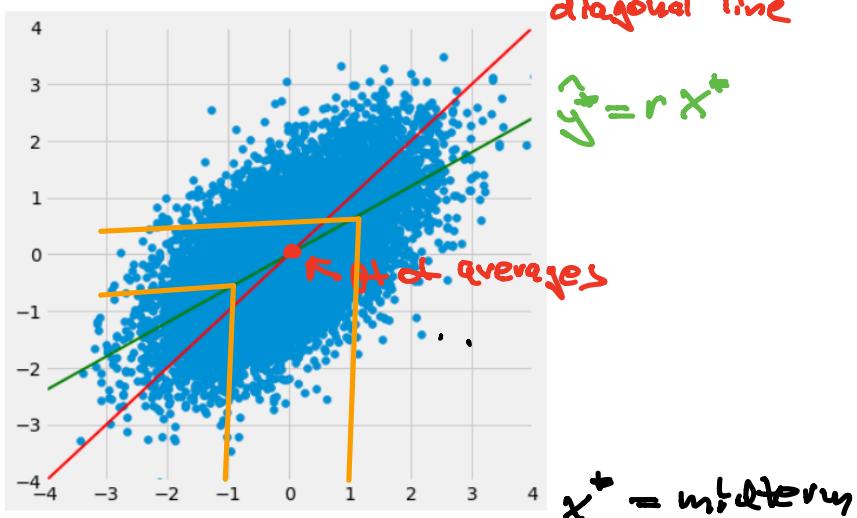
\hat{a} \hat{b}

where $r = E(X^* Y^*) = \frac{1}{n} \sum_{i=1}^n x_i^* y_i^*$ where x^* is x in std units,

The regression line for (x^*, y^*) is much simpler

$$\hat{y}^* = r x^* \quad \text{so some people prefer to work in std units.}$$

$y^* = \text{final}$



regression effect: if you are above the median on the midterm (x), you can expect to do relatively worse on the final,

If you are below the median on the midterm, you can expect to do better on the final,

Today ① Sec 11.5 The error in regression
② Sec 12.1 The simple linear regression model

② Sec 11.5 the error in regression

The error in the regression estimate is called the **residual** and is defined as

$$D = y - \hat{y}$$

It is useful to write this in terms of the deviations $D_x = x - \bar{x}$ and $D_y = y - \bar{y}$.

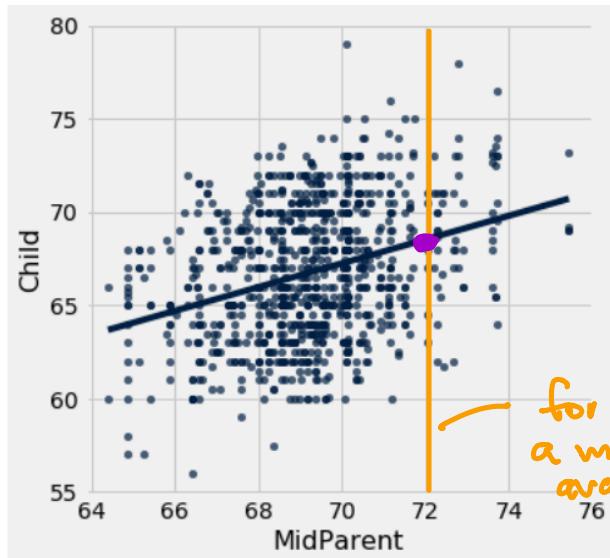
$$\hat{y} = \hat{\alpha}x + \hat{b} = \hat{\alpha}x + \mu_y - \hat{\alpha}\mu_x$$

$$= \hat{\alpha}(x - \mu_x) + \mu_y$$

$$\begin{aligned}
 D = y - \hat{y} &= y - \left[\hat{\alpha} (x - \bar{x}) + \bar{y} \right] \\
 &= y - \bar{y} - \hat{\alpha} (x - \bar{x}) \\
 &= D_y - \hat{\alpha} D_x \quad \leftarrow
 \end{aligned}$$

What is $E(D)$? $E(D) = E(D_y) - \hat{\alpha} E(D_x) = 0$

This says for a fixed $X = x$, the average deviation of Y from \bar{Y} is 0.



for those parents with a midparent ht = 72, the avg child ht is the pt on the regression line at $x=72$,

$$\text{what is } E(D_x^2) ? \quad E(D_x^2) = \text{Var}(D_x) + (E(D_x))^2 = [\sigma_x^2]$$

$$E(D_X D_Y) ? \quad \text{Var}(X \sim M_x) \quad \text{Var}(Y \sim M_y)$$

$$\Rightarrow r = \frac{E(D_X D_Y)}{\sigma_x \sigma_y} \Rightarrow E(D_X D_Y) = [r \sigma_x \sigma_y] \quad \text{Var}(X) = \sigma_x^2$$

$$Var(D) = E(D^2) - (E(D))^2$$

$$D^2 = (D_Y - \hat{a}_X D_X)^2 = E(D_Y^2) - 2\hat{a}E(D_X D_Y) + \hat{a}^2 E(D_X^2)$$

$$= \sigma_Y^2 - 2r \underbrace{\frac{\sigma_Y}{\sigma_X} r \sigma_X \sigma_Y}_{?} + r^2 \frac{\sigma_Y^2}{\sigma_X^2} \sigma_X^2$$

= ?

$$= \sigma_Y^2 - 2r^2 \sigma_Y^2 + r^2 \sigma_Y^2$$

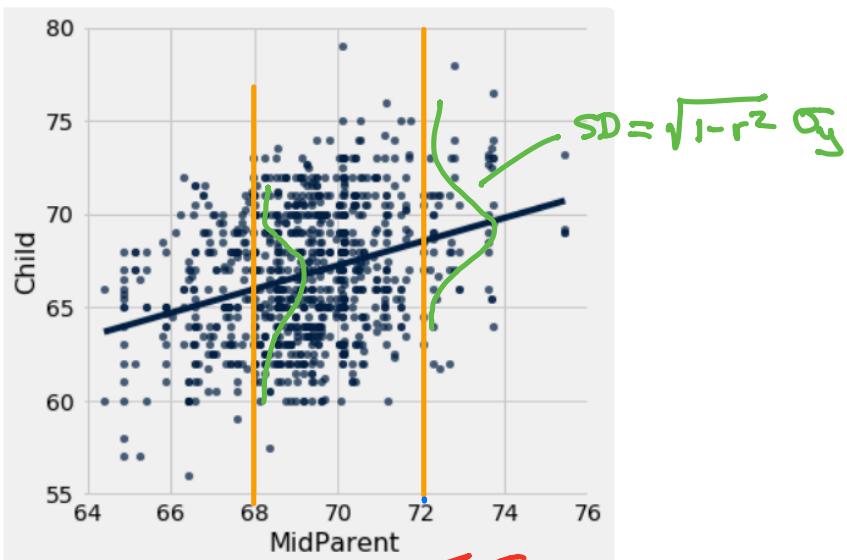
$$= \sigma_Y^2 - r^2 \sigma_Y^2 = [(1 - r^2) \sigma_Y^2]$$

$$\Rightarrow SD(D) = \sqrt{1-r^2} \sigma_y$$

The residuals are normally distributed
so

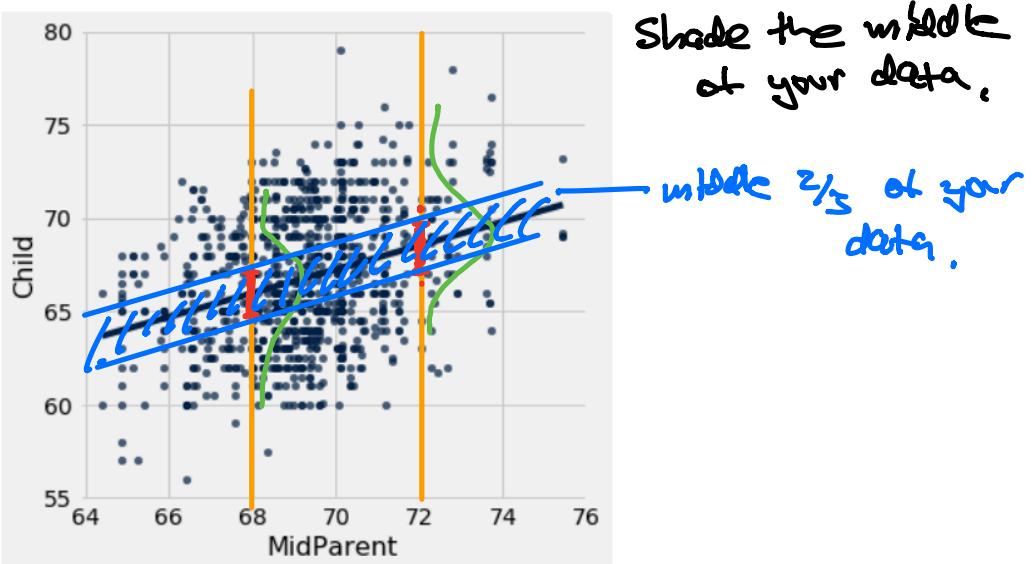
$$D \sim N(0, (1-r^2)\sigma_y^2)$$

Picture



I have marked $1SD = \sqrt{1-r^2} \sigma_y$ on either side of \hat{y} below.

Shade the middle $2/3$ of your data.



Ex

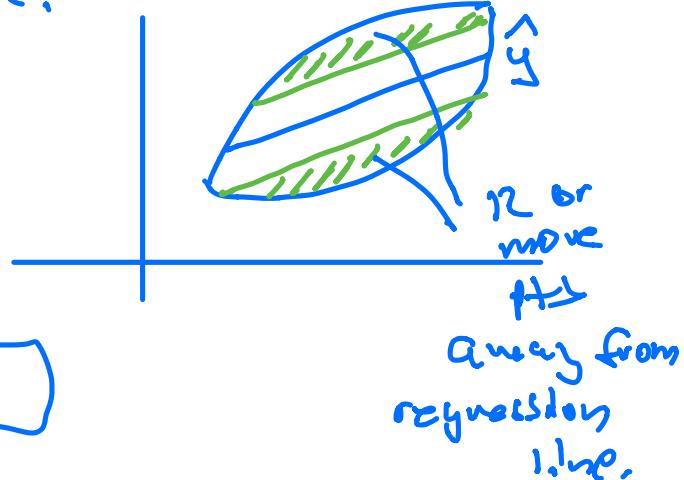
- . For about 1/3 of the students, the prediction for the final score was off by more than how many points?

- average midterm score ≈ 50 , $SD \approx 25$
 average final score ≈ 55 , $SD \approx 15$, $r \approx 0.60$

- a 6 pts
b 9 pts
 c 12 pts
d 15 pts

$\frac{1}{3}$ of your data is at least 1 SD away from regression line.

$$\begin{aligned} SD(D) &= \sqrt{1 - r^2} \sigma_y \\ &= \sqrt{1 - 0.6^2} (15) \\ &= (0.8)(15) = 12 \end{aligned}$$

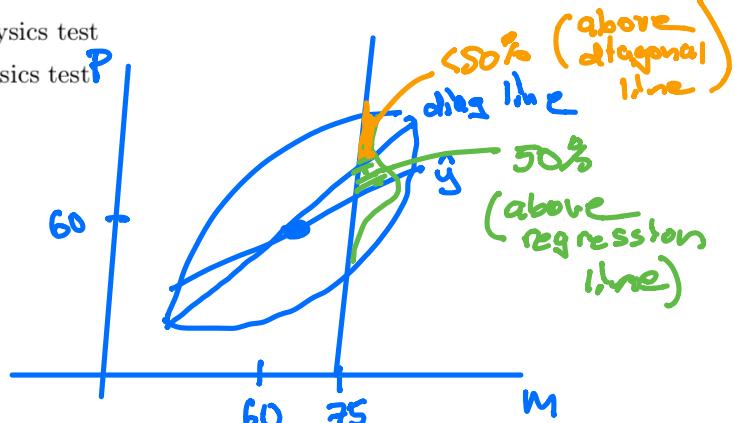


Ex

At Cal's engineering school, students are required to take aptitude tests in various subjects, including mathematics and physics. Students who do well on the mathematics test also tend to score high on the Physics tests. On both tests, the average is 60, and the spreads are about the same for both tests. The scatter diagram is football shaped. Of the students scoring about 75 on the Mathematics test:

- i just about half scored over 75 on the Physics test
ii more than half scored over 75 on the Physics test
 iii less than half scored over 75 on the Physics test

Choose one option and explain.



② Sec 12.1 The Simple Regression Model

x = Predictor variable
 y = response variable
 ϵ = error term (random)

Assumption:

Formally, for individuals $i = 1, 2, 3, \dots, n$, the response is assumed to be

$$Y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$

(signal) random error
response

where:

- β_0 and β_1 are unobservable constant parameters.
- x_i is the value of the predictor variable for individual i and is assumed to be constant (that is, not random).
- The errors $\epsilon_1, \epsilon_2, \dots, \epsilon_n$ are i.i.d. normal $(0, \sigma^2)$ random variables.
- The error variance σ^2 is an unobservable constant parameter, and is assumed to be the same for all individuals i .

we see the responses y_1, y_2, \dots, y_n
and we want to pick out the signals

$$y_1 = \beta_0 + \beta_1 x_1,$$

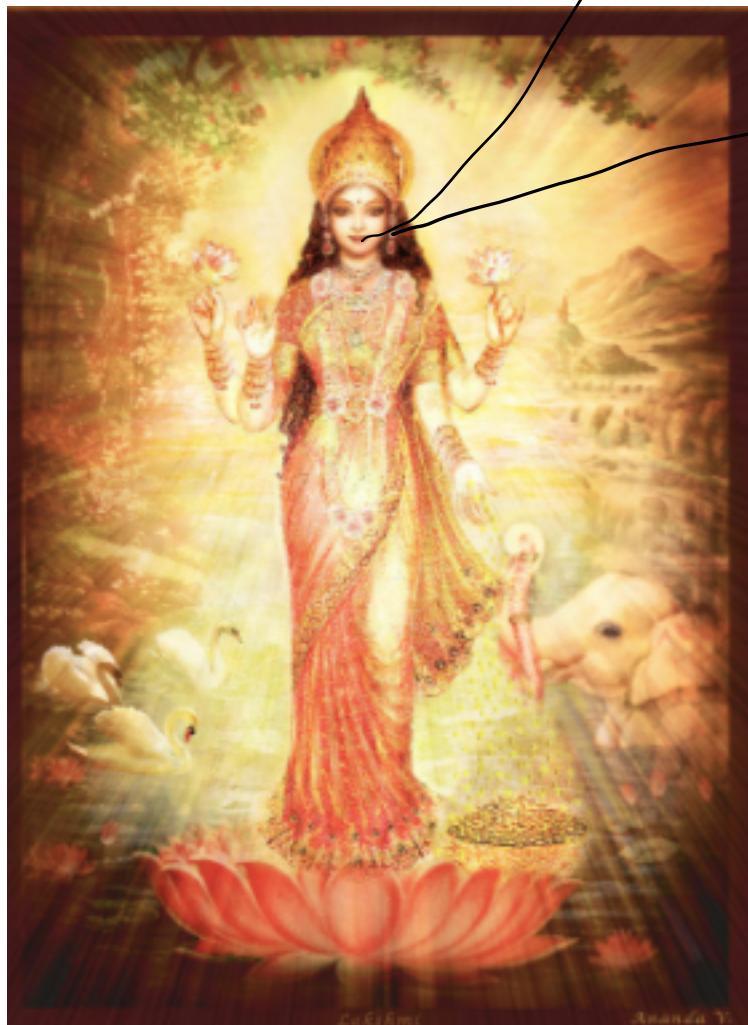
$$y_2 = \beta_0 + \beta_1 x_2$$

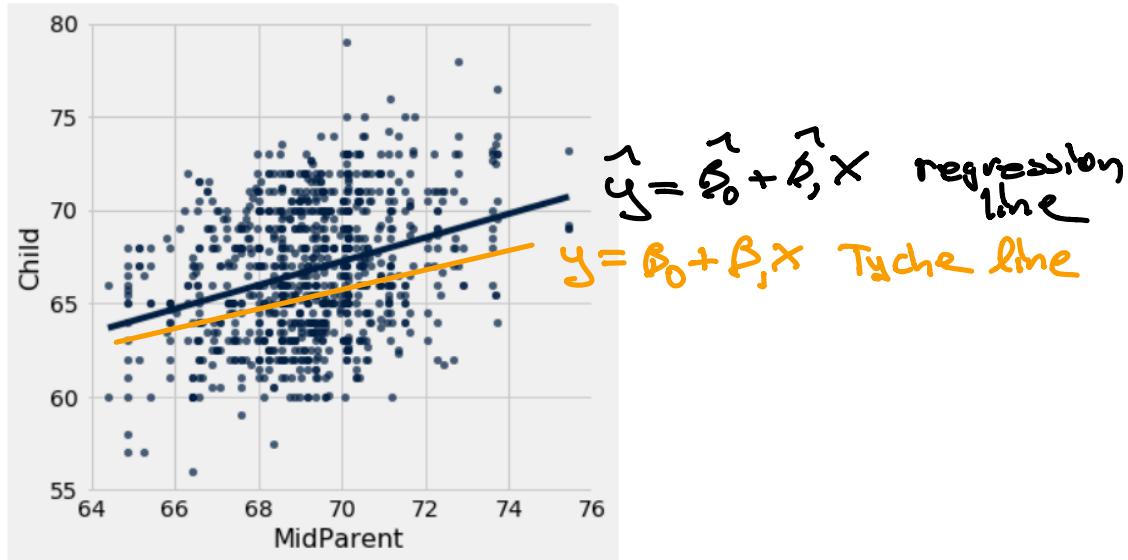
:

$$y_n = \beta_0 + \beta_1 x_n$$

I call the line $y = \beta_0 + \beta_1 x$ the True line

Image of Tyche the goddess of fortune.
Only Tyche knows β_0, β_1 .





\hat{y} is an estimator of y

using $\hat{\beta}_1$, we can hypothesize whether β_1 is zero (i.e whether y and x are uncorrelated),

For example is the height of parents related to the height of their child?