Part of the period will cover numerical examples as in 2-11-09. The rest will be devoted to the points below.

1. Important characterization of all points \((x, y)\) which lie on the line of regression:

\[
\frac{y - \bar{y}}{x - \bar{x}} = r \frac{s_y}{s_x}
\]

Slope = \(r \frac{s_y}{s_x} = r \frac{\hat{\sigma}_y}{\hat{\sigma}_x} = r \frac{\sqrt{y^2 - \bar{y}^2}}{\sqrt{x^2 - \bar{x}^2}}
\]

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2. Taking \( x = 0 \) in \( \frac{y - \bar{y}}{0 - \bar{x}} = r \frac{s_y}{s_x} \)
gives
   
   intercept = \( \bar{y} - \bar{x} \) slope

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3. For every \( x \), solving for \( y \) in
   \[
   \frac{y - \bar{y}}{x - \bar{x}} = r \frac{s_y}{s_x}
   \]
gives predicted \( y = \text{pt on regr line} : \)
   \[
   \text{pred } y = \bar{y} + (x - \bar{x}) \text{ slope}
   \]
4. For an approximately **ELLIPTICAL** plot, at a given x, the distribution of y is approximately **NORMAL** with

\[
\text{mean} = \text{predicted } y
\]

\[
\text{std dev} = \sqrt{1 - r^2} \ S_y
\]

Notice that the mean depends upon x but the std dev does not.

5. For an **ELLIPTICAL PLOT**

the regression predictor

\[
\bar{y} + (x - \bar{x}) \text{ slope}
\]

is optimal in the sense of least mean squared error of prediction.
5. \( r^2 \) is exactly the fraction of \( \hat{\sigma_y}^2 \) explained by the sample regression.

pp. 204-06 (Note text also uses R for r. The Greek "rho" \( \rho \) is also used for r).