The line of best fit via transformations

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In this note, we will show how transformations can be used to obtain a radically simple derivation of the equation of the line of best fit. Our approach also gives a simple geometric interpretation of the Pearson correlation coefficient.

Given a sequence of n points in the plane $(X_1, Y_1), \ldots, (X_n, Y_n)$ we seek the linear equation $y = a + bx$ that approximates the points as closely as possible, in the sense that the sum of the squared errors $E = \sum_{i=1}^{n}(Y_i - a - bX_i)^2$ is minimized.

We assume that not all of the points lie on a single horizontal or vertical line. In that case, we can apply a *transformation* to the points so that $\sum x_i = \sum y_i = 0$ and $\sum x_i^2 = \sum y_i^2 = 1$. The transformation is defined by

$$x_i = \frac{X_i - \overline{X}}{\sqrt{\sum(X_i - \overline{X})^2}} \quad \text{and} \quad y_i = \frac{Y_i - \overline{Y}}{\sqrt{\sum(Y_i - \overline{Y})^2}}.$$

This transformation is linear, so it maps lines to lines. If we transform a line fitted to the data, the sum of squared errors is multiplied by a positive constant factor. Therefore, the transformation preserves the line of best fit.

Let $r = \sum x_i y_i$. Then

$$\begin{aligned}
E &= \sum(y_i - a - bx_i)^2 \\
&= \sum(y_i^2 + a^2 + b^2x_i^2 - 2ay_i - 2bx_iy_i + 2abx_i) \\
&= \sum y_i^2 + \sum a^2 + \sum b^2x_i^2 - \sum 2ay_i - \sum 2bx_iy_i + \sum 2abx_i \\
&= 1 + na^2 + b^2 - 2br \\
&= (1 - r^2) + na^2 + (b - r)^2 \ .
\end{aligned}$$

The sum is minimized when $a = 0$ and $b = r$, so the line of best fit is $y = rx$. What a simple equation! Unfortunately, the equation is a bit messier when expressed in terms of the original variables.

$$\begin{aligned}
\frac{y - \overline{Y}}{\sqrt{\sum(Y_i - \overline{Y})^2}} &= \left(\frac{\sum(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum(X_i - \overline{X})^2 \sum(Y_i - \overline{Y})^2}}\right)\left(\frac{x - \overline{X}}{\sqrt{\sum(X_i - \overline{X})^2}}\right) \\
y - \overline{Y} &= \left(\frac{\sum(X_i - \overline{X})(Y_i - \overline{Y})}{\sum(X_i - \overline{X})^2}\right)(x - \overline{X}) \ .
\end{aligned}$$

Note that r is the Pearson correlation coefficient of the sample. This shows that the correlation coefficient can be interpreted geometrically as the slope of the line of best fit when the x and y values are standardized.