

Linear Regression Formula Sheet

1. Beta Definitions

- **β_0** : The y intercept of the population regression line
 - **β_1** : The slope of the population regression line
 $\beta_1 = \text{Cov}(x,y) / \text{Var}(x) = \text{Slope of the true model}$
 - **$\hat{\beta}_0$ ($\beta_{\text{hat } 0}$)**: The estimated intercept of the regression line based on the sample data.
 $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$
 - **$\hat{\beta}_1$ ($\beta_{\text{hat } 1}$)**: The estimated slope of the regression line based on the sample data. This is calculated by minimizing the sum of squared errors.
 $\hat{\beta}_1 = S_{xy} / S_{xx} = \sum (x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=1}^n (x_i - \bar{x})^2$
 - **$\bar{\beta}_0$ & $\bar{\beta}_1$** : The population averages of β_0 & β_1 across different samples.
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2. Sigma Definitions

- **σ** : The standard deviation of the error term ϵ - this measures the spread of the errors around the regression line.
 $\sigma = \sqrt{\text{Var}(\epsilon)}$
 - **σ^2 (σ squared)**: The variance of the error term, representing the average squared deviation from the true regression line.
 $\sigma^2 = \{ \sum ((y_i - \beta_0 - \beta_1 x_i)^2) \} / n$
 - **$\hat{\sigma}^2$ (σ hat squared)**: The estimated variance of the error term, calculated using sample data.
 $\hat{\sigma}^2 = S_{yy} / (n-2) = (\sum (y_i - \hat{y}_i)^2) / (n-2)$
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3. Epsilon Definitions

- ϵ : The error term in the population model, the difference between real & predicted
 $\epsilon_i = y_i - (\beta_0 + \beta_1 x_i)$
 - ϵ^\wedge (ϵ hat): The residual in the sample model, representing the difference between the observed y_i and the predicted y^\wedge_i (y hat i).
 $\epsilon^\wedge_i = y_i - y^\wedge_i = y_i - (\beta^\wedge_0 + \beta^\wedge_1 x_i)$
 - ϵ^- (ϵ bar): The mean of the error terms, which we assume to be zero
 $\epsilon^- = E(\epsilon) = 0$
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4. Key Regression Concepts

- **Linear Regression Model:** $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$
- **Fitted (Predicted) Values y^\wedge_i :** $y^\wedge_i = \beta^\wedge_0 + \beta^\wedge_1 x_i$

SST:

- **Sum of Squares Total (SST):** $SST = \sum (y_i - y^-)^2$
- **Total Sum of Squares (TSS):** $TSS = \sum (y_i - y^-)^2$

SSE:

- **Sum of Squares Explained (SSE):** $SSE = \sum (y_i - y^\wedge_i)^2$
- **Explained Sum of Squares (ESS):** $ESS = \sum (y_i - y^\wedge_i)^2$

SSR:

- **Sum of Squared Residual (SSR):** $SSR = \sum (y^\wedge_i - y^-)^2$
 - **Residual Sum of Squares (RSS):** $RSS = \sum (y^\wedge_i - y^-)^2$
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5. Other things

- **Sum of Residuals:** $\sum \epsilon^i = 0$
This ensures that the residuals sum to zero in a least-squares regression.
 - **Sum of Residuals Weighted by X:** $\sum x_i \epsilon^i = 0$
This ensures that the weighted sum of the residuals, using x_i , is zero.
 - **Sum of Fitted Values and Residuals:** $\sum y^i \epsilon^i = 0$
This ensures that there is no correlation between the fitted values and the residuals.
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How to Prove things

- **Estimating β^0 & β^1 (β^0 & β^1 hat):**
 - Use the formula $\beta^1 = S_{xy}/S_{xx}$ to find the slope
 - Use the formula $\beta^0 = \bar{y} - \beta^1 \bar{x}$
- **Proof of Zero Residual Sum:**
 - Show that $\sum \epsilon^i = 0$ follows from the least-squares estimation process.
- **Variance of β^1 :**
 - From the formula for β^1 (hat)
 - $\text{Var}(\beta^1) = \sigma^2/S_{xx}$