

★ 1. Simple Linear Regression

Used when one independent variable predicts one dependent variable.

Equation:

$$Y=a+bXY=a+bX$$

- $aa \rightarrow Intercept$ (constant term).
- $bb \rightarrow Slope$ (shows change in YY for one unit change in XX).
- **Example:** Predict salary (YY) based on experience (XX).
- Evaluation Metric: R-squared (R2R^2), Mean Squared Error (MSE).
- **Assumption:** Linear relationship, normally distributed residuals.

★ 2. Multiple Linear Regression

Used when two or more independent variables predict one dependent variable.

Equation:

$$Y=a+b1X1+b2X2+...+bnXnY = a+b$$
 1X 1+b 2X 2+...+b nX n

- X1,X2,...XnX 1, X 2, ... X n \rightarrow Multiple independent variables.
- Example: Predict house price based on bedrooms, square footage, and distance to city.
- **Assumptions:** Linearity, No multicollinearity, Homoscedasticity, Normality of errors.

★ 3. Least Squares Regression Line (LSRL)

- Used to find the best-fit line that minimizes errors in prediction.
- Equation: Y=a+bXY = a + bX
- "Least squares" minimizes the sum of squared residuals (difference between actual & predicted values).
- Used in both Simple & Multiple Regression.

★ 4. Pearson Correlation Coefficient (rr)

• Measures linear relationship strength between two variables.

$$r = \sum (X - X^{-})(Y - Y^{-}) \sum (X - X^{-}) 2 \sum (Y - Y^{-}) 2r = \frac{(X - X^{-})(Y - bar\{Y\})}{(X - bar\{X\})^{2} \sum (Y - bar\{Y\})^{2}}$$

- Value Range:
 - \circ r=1r = 1 → Perfect positive correlation
 - \circ r=0r = 0 → No correlation
 - \circ r=−1r = -1 \rightarrow Perfect negative correlation
- **Example:** Relationship between study time & exam score.

★ 5. Spearman's Rank Correlation Coefficient

• Measures monotonic relationships (not necessarily linear).

$$rs=1-6\sum di2n(n2-1)r$$
 s = 1 - \frac{6 \sum d i^2}{n(n^2 - 1)}

- Based on rankings instead of actual values.
- Best for ordinal data (ranked data, not continuous).
- Example: Relationship between customer satisfaction rank & product sales rank.

★ 6. Poisson Distribution

- Used for counting events in a fixed interval (time/space).
- Formula:

$$P(X=k)=\lambda ke-\lambda k!P(X=k) = \frac{\lambda e^{\lambda k}P(X=k)}{k!}$$

- $\lambda = A$ Average rate of occurrence.
- kk = Number of occurrences.
- **Example:** Number of calls received at a call center per hour.

📌 7. Normal Distribution & CDF

• Bell-shaped symmetric distribution where most values cluster around the mean.

- Properties:
 - Mean = Median = Mode
 - 68-95-99.7 Rule (Empirical Rule)
 - 68% of data within 1 standard deviation
 - 95% within 2 standard deviations
 - 99.7% within 3 standard deviations
- Cumulative Distribution Function (CDF): $P(X \le x) = 12[1 + erf(x \mu\sigma 2)]P(X \le x) = \frac{1}{2} \cdot \left[1 + \text{crf} \left(\frac{x \mu\sigma 2}{2}\right)\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \text{crf} \left(\frac{x \mu\sigma 2}{2}\right)\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{\pi\sigma 2}{2}\right]P(X \le x) = \frac{1}{2} \cdot \left[1 + \frac{$
 - o **Example:** Heights of people, IQ scores.

★ 8. Central Limit Theorem (CLT)

- If we take multiple random samples from any distribution, the sample means will follow a Normal Distribution, regardless of the original distribution.
- Formula for sample mean distribution:

$$\mu X^- = \mu, \sigma X^- = \sigma n \cdot \{ \{X\} \} = \mu, \quad \{sigma_{\{X\}} \} = frac_{\{sigma\}} \{ \{n\} \} = \pi \cdot \{x\} \}$$

- $\mu X \setminus mu \{ bar\{X\} \} = Mean of sample means.$
 - $\sigma X \setminus sigma \{ bar\{X\} \} = Standard deviation of sample means.$
- **Example:** The average height of students in different classrooms will be normally distributed.

🖈 9. Regression Line & Pearson Correlation Connection

- If two regression equations are: $Y=byxX+a, X=bxyY+cY=b_{yx}X+a$, $Y=b_{yx}Y+a$, $Y=b_{xx}Y+a$, $Y=b_{xx}Y+a$
- Example:
 - Regression of **Y** on **X**: $3X+4Y+8=03X+4Y+8=0 \implies byx=-3/4b \{yx\} = -3/4$.
 - o Regression of **X on Y**: $4X+3Y+7=04X+3Y+7=0 \implies bxy=-3/4b \{xy\} = -3/4$.
 - o **Pearson's rr**: r= $(-34)\times(-34)=34=0.75$ r = \sqrt{\left(-\frac{3}{4}\right) \times \left(-\frac{3}{4}\right)} = \frac{3}{4} = 0.75
 - Indicates strong positive correlation.

Final Summary Table

Concept Key Takeaways

Simple Linear Regression One independent variable predicts a dependent variable.

Multiple Linear Regression More than one independent variable predicts a dependent variable.

Least Squares Regression Line Best-fit line minimizes squared residuals.

Pearson Correlation (rr) Measures linear relationship strength $(-1 \le r \le 1-1 \ \text{leq r } \text{leq 1})$.

Spearman Correlation (rsr s) Measures ranked (monotonic) relationships.

Poisson Distribution Probability of discrete events in fixed intervals.

Normal Distribution Bell-shaped curve, mean = median = mode.

CDF of Normal Distribution Calculates probability up to a given value.

Central Limit Theorem (CLT) Sample means follow a normal distribution, regardless of population.

Regression-Pearson Connection $r=byx \times bxyr = \sqrt{b_{yx} \times b_{xyr}}$.

★ Why These Topics Are Important?

- **✓** Used in **Data Science**, **Machine Learning**, **Finance**, **Marketing**, **Engineering**.
- **✓** Helps in **prediction**, **hypothesis testing**, and decision-making.
- Pearson & Spearman correlations help understand relationships between variables.
- **CLT** is **foundation for statistical inference**.