

Q1. Simple Linear Regression vs Multiple Linear Regression

Aspect	Simple Linear Regression	Multiple Linear Regression
Definition	Predicts a dependent variable (Y) from one independent variable (X)	Predicts a dependent variable (Y) from two or more independent variables (X1, X2, ...)
Equation	$Y = \beta_0 + \beta_1 X + \epsilon$ $Y = \beta_0 + \beta_1 X + \epsilon$	$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon$ $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon$
Use case	Predicting house price based on square footage	Predicting house price based on square footage, number of bedrooms, age of house, and location

Example:

- Simple: Predict **salary** based on **years of experience**
- Multiple: Predict **salary** based on **years of experience, education level, and location**

Q2. Assumptions of Linear Regression

1. **Linearity:** Relationship between independent and dependent variables is linear.
 - **Check:** Scatter plots, residual plots
2. **Independence of errors:** Residuals are independent.
 - **Check:** Durbin-Watson test
3. **Homoscedasticity:** Constant variance of errors.
 - **Check:** Residual vs predicted value plot
4. **Normality of errors:** Residuals are normally distributed.

- **Check:** Histogram or Q-Q plot of residuals
 - 5. **No multicollinearity (for multiple regression):** Independent variables are not highly correlated.
 - **Check:** Correlation matrix, VIF (Variance Inflation Factor)
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Q3. Interpreting Slope and Intercept

- **Intercept ($\beta_0 \backslash beta_0 \beta_0$):** Predicted value of Y when all X = 0
- **Slope ($\beta_1 \backslash beta_1 \beta_1$):** Change in Y for a 1-unit increase in X

Example:

- Model: $\text{Salary} = 30000 + 5000 \times \text{Years of Experience}$
 $\text{Salary} = 30000 + 5000 \times \text{Years of Experience}$
 - Intercept = 30000 → Base salary with 0 years experience
 - Slope = 5000 → Each additional year of experience increases salary by 5000
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Q4. Gradient Descent

- **Concept:** Iterative optimization algorithm to **minimize the loss function** (e.g., Mean Squared Error in regression)
- **How it works:**
 1. Start with random coefficients ($\beta_0, \beta_1 \backslash beta_0, \backslash beta_1 \beta_0, \beta_1$)
 2. Compute gradient (slope) of the loss function with respect to coefficients
 3. Update coefficients in the opposite direction of the gradient
$$\beta = \beta - \alpha \frac{\partial J}{\partial \beta}$$

4. Repeat until convergence
 - **Use in ML:** Finds optimal parameters for regression, logistic regression, and neural networks
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Q5. Multiple Linear Regression

- **Model:** Predicts Y using multiple independent variables.
$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon$$
$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon$$
- **Difference from Simple Regression:** Multiple predictors instead of one; allows capturing more complex relationships.

Example: Predicting house price using:

- Square footage
 - Number of bedrooms
 - Age of house
 - Location rating
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Q6. Multicollinearity in Multiple Linear Regression

- **Definition:** High correlation between two or more independent variables
- **Problem:** Inflates standard errors, unstable coefficients, reduces interpretability
- **Detection:**
 - Correlation matrix (look for $r > 0.8$)
 - Variance Inflation Factor (VIF > 10 indicates serious multicollinearity)

- **Solutions:**
 - Remove correlated variables
 - Combine features using PCA
 - Regularization (Ridge or Lasso regression)
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Q7. Polynomial Regression

- **Concept:** Extends linear regression by including **polynomial terms of the independent variable(s)**
- **Equation:**
$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \dots + \beta_n X^n + \epsilon$$
$$Y = \beta_0 + \beta_1 t + \beta_2 t^2 + \dots + \beta_n t^n + \epsilon$$
- **Difference from linear regression:** Captures **non-linear relationships**

Example: Predicting **growth of bacteria** over time: $Y = \beta_0 + \beta_1 t + \beta_2 t^2$

Q8. Advantages and Disadvantages of Polynomial Regression

Advantages:

- Captures non-linear relationships
- Flexible in fitting curved data

Disadvantages:

- Prone to overfitting if degree is high

- Coefficients may lose interpretability
- Sensitive to outliers

When to use:

- Use when **scatter plots show a curved pattern** between X and Y
 - Example: Predicting **temperature variation over the day**
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