ASSIGNMENT: REGRESSSION

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1) What is Simple Linear Regression?
   - Simple Linear Regression is a statistical technique that models the relationship between a dependent variable (target) and a single independent variable (predictor) using a straight line. The model assumes the form:

     $$\boldsymbol{Y = mX + c + \varepsilon}$$

     where Y is the dependent variable, X is the independent variable, m is the slope, c is the intercept, and ε is the error term.

2) What are the key assumptions of Simple Linear Regression?
   The key assumptions are:
   - **Linearity**: The relationship between X and Y is linear.
   - **Independence**: Observations are independent of each other.
   - **Homoscedasticity**: Constant variance of residuals/errors across values of X.
   - **Normality**: The residuals (errors) are normally distributed.
   - **No multicollinearity**: Since it's simple linear regression, there's only one independent variable, so this isn't a concern.

3) What does the coefficient m represent in the equation $Y = mX + c$?
   - The coefficient $\boldsymbol{m}$ represents the **slope** of the line, which indicates the change in the dependent variable $\boldsymbol{Y}$ for a one-unit change in the independent variable $\boldsymbol{X}$.

4) What does the intercept c represent in the equation $Y = mX + c$?
   - The intercept **c** is the value of $\boldsymbol{Y}$ when $\boldsymbol{X = 0}$. It indicates the point where the regression line crosses the Y-axis.

5) How do we calculate the slope m in Simple Linear Regression?
   - The slope $\boldsymbol{m}$ is calculated using the formula:

     $$m = \frac{\Sigma[(X_i - \bar{X})(Y_i - \bar{Y})]}{\Sigma[(X_i - \bar{X})^2]}$$

     This formula computes how much Y changes with respect to X, by correlating deviations of X and Y from their means.

6) What is the purpose of the least squares method in Simple Linear Regression?
   - The **least squares method** minimizes the sum of the squared differences between the observed values and the predicted values (errors). This method ensures the best-fitting line by reducing the total error in prediction.

7) How is the coefficient of determination (R^2) interpreted in Simple Linear Regression?

- **R^2 (R-squared)** measures the proportion of the variance in the dependent variable that is predictable from the independent variable.
  a) $R^2 = 1$ means perfect prediction.
  b) $R^2 = 0$ means no predictive power.
  Higher values indicate a better fit of the model to the data.

8) What is Multiple Linear Regression?
   - **Multiple Linear Regression** is an extension of simple linear regression where two or more independent variables are used to predict the dependent variable. The equation is:

$$Y = b^0 + b^1X^1 + b^2X^2 + \ldots + bnXn + \varepsilon$$

   where b^0 is the intercept, b^1 to bn are the coefficients for each independent variable, and ε is the error term.

9) What is the main difference between Simple and Multiple Linear Regression?
   - **Simple Linear Regression** involves **one** independent variable.
   - **Multiple Linear Regression** involves **two or more** independent variables.
   This allows Multiple Linear Regression to model more complex relationships.

10) What are the key assumptions of Multiple Linear Regression?
   - **Linearity**: The relationship between independent variables and the dependent variable is linear.
   - **Independence of errors**: Observations should be independent.
   - **Homoscedasticity**: Constant variance of residuals.
   - **Normality of residuals**: Errors should be normally distributed.
   - **No multicollinearity**: Independent variables should not be highly correlated with each other.

11) What is heteroscedasticity, and how does it affect the results of a Multiple Linear Regression model?
   - Heteroscedasticity refers to the circumstance in which the variance of residuals (errors) is not constant across all levels of the independent variables. It violates one of the key assumptions of regression and can lead to:
     a) Inefficient estimates of coefficients
     b) Biased standard errors
     c) Invalid hypothesis tests (t-tests, F-tests)

12) How can you improve a Multiple Linear Regression model with high multicollinearity?
   To address multicollinearity:
   - Remove highly correlated predictors

- **Combine correlated variables** through techniques like PCA
- **Use regularization techniques** like Ridge or Lasso regression
- **Center or standardize variables** to reduce correlation

13) **What are some common techniques for transforming categorical variables for use in regression models?**
- **One-Hot Encoding**: Creates binary columns for each category
- **Label Encoding**: Assigns a unique integer to each category (used cautiously)
- **Binary Encoding** or **Target Encoding**: Useful for high-cardinality categorical features

14) What is the role of interaction terms in Multiple Linear Regression?
- Interaction terms allow the effect of one independent variable to depend on the level of another. They model **non-additive relationships** and capture more complex dependencies between variables.

15) How can the interpretation of intercept differ between Simple and Multiple Linear Regression?
- In **Simple Linear Regression**, the intercept is the expected value of Y when $X = 0$.
- In **Multiple Linear Regression**, it is the expected value of Y when **all independent variables are zero**, which might not always be meaningful, especially if Xs can't be zero in real life.

16) What is the significance of the slope in regression analysis, and how does it affect predictions?
- The slope represents the **rate of change** in the dependent variable for a one-unit change in the independent variable.
  It helps determine:
  a) The direction (positive or negative) of the relationship
  b) The strength of influence on the outcome

17) How does the intercept in a regression model provide context for the relationship between variables?
- The intercept serves as a **baseline value** of the dependent variable when all predictors are zero. It can contextualize predictions and model behavior in edge cases but should be interpreted with caution when "zero" isn't meaningful.

18) What are the limitations of using R^2 as a sole measure of model performance?
- **R^2 increases with more variables**, even if they don't improve the model
- It doesn't indicate if a model is appropriate
- Doesn't reveal bias or residual patterns

- **Adjusted R^2** is a better metric as it accounts for model complexity

19) How would you interpret a large standard error for a regression coefficient?
A large standard error suggests:
- High variability in the estimate
- Weak evidence that the corresponding predictor influences the response variable
- Possible multicollinearity or small sample size

20) How can heteroscedasticity be identified in residual plots, and why is it important to address it?
- In a residual vs. fitted plot, heteroscedasticity appears as a **funnel or cone shape**.
  Addressing it is crucial because it:
  a) Affects standard errors and p-values
  b) Leads to unreliable confidence intervals and hypothesis tests
  Solutions include using log transformations or robust standard errors.

21) What does it mean if a Multiple Linear Regression model has a high R^2 but low adjusted R^2?
- This means that the model includes predictors that do **not contribute meaningfully** to explaining the variance in Y. Adjusted R^2 penalizes the model for adding irrelevant variables, signaling potential **overfitting**.

22) Why is it important to scale variables in Multiple Linear Regression?
- Scaling ensures that all variables contribute equally to the model, especially when:
  a) Using **regularization (Ridge/Lasso)**
  b) Comparing **coefficients** for importance
  c) Avoiding **numerical instability** during optimization

23) What is polynomial regression?
- Polynomial Regression is a type of regression that models the relationship between the independent variable and the dependent variable as an **nth degree polynomial**, such as:

$$\boldsymbol{Y = b^0 + b^1X + b^2X^2 + \ldots + bnX^n + \varepsilon}$$

24) How does polynomial regression differ from linear regression?
- **Linear Regression** fits a straight line; it assumes a linear relationship
- **Polynomial Regression** fits a curve; it allows for nonlinear relationships by adding powers of the independent variable(s)

25) When is polynomial regression used?

- It's used when data shows a **nonlinear trend** that can't be captured by linear regression. Common in:
  a) Modeling curved relationships
  b) Fitting data with turning points
  c) Improving fit in a flexible way without using complex algorithms

26) What is the general equation for polynomial regression?

The general form of a polynomial regression equation is:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \cdots + \beta_n x^n + \epsilon$$

Where:

- y is the dependent variable
- x is the independent variable
- $\beta_0, \beta_1, \ldots, \beta_n$ are coefficients
- ϵ is the error term

This equation allows the model to fit curves instead of straight lines.

27) Can polynomial regression be applied to multiple variables?

- Yes, polynomial regression can be extended to **multiple variables** (multivariate polynomial regression). In that case, the model includes not just powers of each variable, but also **interaction terms**, e.g.:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_1 x_2 + \beta_5 x_2^2 + \cdots$$

This enables modeling of complex surfaces in multidimensional space.

28) What are the limitations of polynomial regression?

- **Overfitting**: High-degree polynomials may fit the noise, not the trend
- **Extrapolation risk**: Behavior outside the data range can be erratic
- **Computational complexity**: Larger polynomials require more computation
- **Interpretability**: Difficult to explain and understand higher-degree models
- **Multicollinearity**: Powers of variables can be highly correlated

29) What methods can be used to evaluate model fit when selecting the degree of a polynomial?

- **Cross-validation**: Helps in choosing a degree that generalizes well
- **Adjusted R^2**: Penalizes for too many predictors
- **AIC/BIC** (Akaike/Bayesian Information Criterion): Model comparison criteria
- **Residual plots**: Help assess whether residuals are randomly distributed
- **Learning curves**: Visualize performance on training vs. validation sets

30) Why is visualization important in polynomial regression?

- Visualization helps to:

a) **Detect overfitting** or underfitting
b) Understand how well the curve fits the data
c) Reveal model behavior in different regions of the input space
d) Communicate findings clearly to stakeholders
It's particularly useful when dealing with low-dimensional data (1D or 2D).

31) How is polynomial regression implemented in Python?

– In Python, polynomial regression can be implemented using **scikit-learn**:

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
import numpy as np

# Example for degree 3
model = make_pipeline(PolynomialFeatures(degree=3), LinearRegression())

X = np.array([[1], [2], [3], [4], [5]])
y = np.array([1.2, 1.9, 3.2, 4.1, 5.3])

# Fit model
model.fit(X, y)

# Predict
y_pred = model.predict(X)
y_pred
```

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```
array([1.17571429, 1.99714286, 3.05428571, 4.19714286, 5.27571429])
```