Assignment-based Subjective Questions

1. **From your analysis of the categorical variables from the dataset, what could you infer about their effect on the dependent variable?**

Answer:

	coef	std err	t	P>|t|	[0.025	0.975]
const	4491.3033	34.329	130.832	0.000	4423.856	4558.751
yr	997.6089	34.887	28.596	0.000	929.065	1066.152
holiday	-144.8060	34.690	-4.174	0.000	-212.963	-76.649
temp	1112.3380	49.328	22.550	0.000	1015.421	1209.255
hum	-212.4803	47.214	-4.500	0.000	-305.244	-119.717
windspeed	-283.8038	37.482	-7.572	0.000	-357.446	-210.162
season_summer	283.1647	40.838	6.934	0.000	202.928	363.401
season_winter	477.0212	42.462	11.234	0.000	393.594	560.448
mnth_Jan	-96.0523	42.706	-2.249	0.025	-179.960	-12.145
mnth_Jul	-102.0844	41.107	-2.483	0.013	-182.849	-21.320
mnth_Sep	218.8248	37.512	5.833	0.000	145.123	292.526
weekday_Sun	-139.8040	34.658	-4.034	0.000	-207.899	-71.709
weathersit_Cloudy	-224.2329	42.849	-5.233	0.000	-308.421	-140.045
weathersit_Rainy	-357.1103	38.329	-9.317	0.000	-432.417	-281.804

Above snapshot shows relationship between independent variable (features above) and dependent variable

Dissecting on Monthly basis:

- September (mnth_Sep) : had a positive correlation with 218.8248
- January(mnth_Jan) : had a slight negative correlation with -96.0523
- July(mnth_Jul) : had a slight negative correlation with -102.0844

Dissecting on Seasonal basis:

- Winter(season_winter) : had a positive correlation with 477.0212
- Summer(season_summer) : had a positive correlation with 283.1647

Dissecting on weather basis:

- Cloudy(weathersit_cloudy) : had a negative correlation with -224.2329
- Rainy(weathersit_rainy) : had a negative correlation with -357.1103

Dissecting wind speed, temperature & humidity:

Temperature has positive correlation with 1112.3380, wind speed is negatively correlated with coefficient as -283.8038 and humidity also having negative correlation with -212.4803

2. Why is it important to use drop_first=True during dummy variable creation?

Answer:

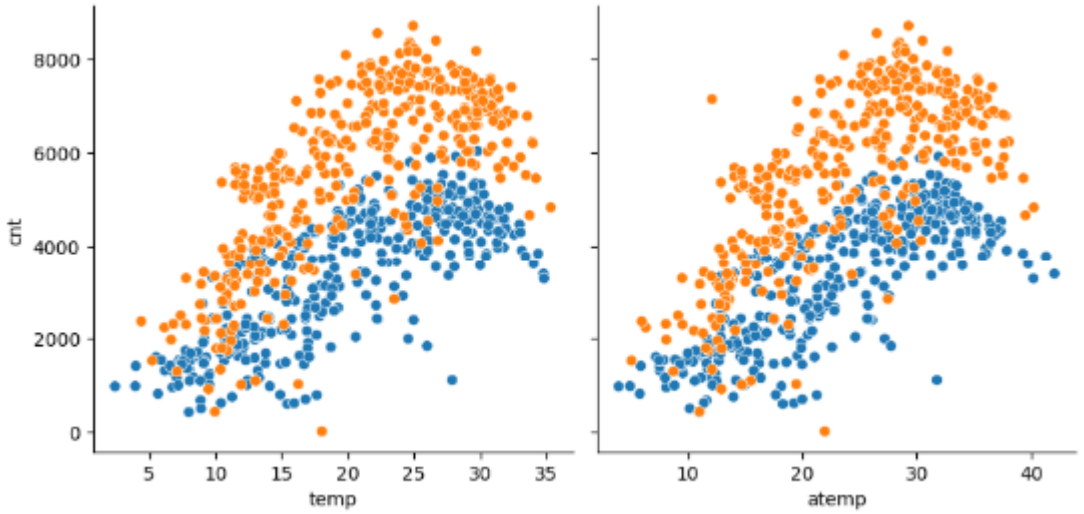
To avoid multicollinearity we use drop_first=True when creating dummy variables. Multicollinearity happens when one variable can be perfectly predicted from others, which can confuse the model and make it hard to understand the impact of each variable.

By setting drop_first=True, we drop one category from each set of dummy variables. This ensures that the model doesn't include redundant information, making it easier to interpret the results and keeping the analysis mathematically correct.

3. Looking at the pair-plot among the numerical variables, which one has the highest correlation with the target variable?

Answer:

temp and atemp has highest correlation with cnt target variable and they are also highly correlated with each other thus both can be assumed too similar.



4. How did you validate the assumptions of Linear Regression after building the model on the training set?

Answer:

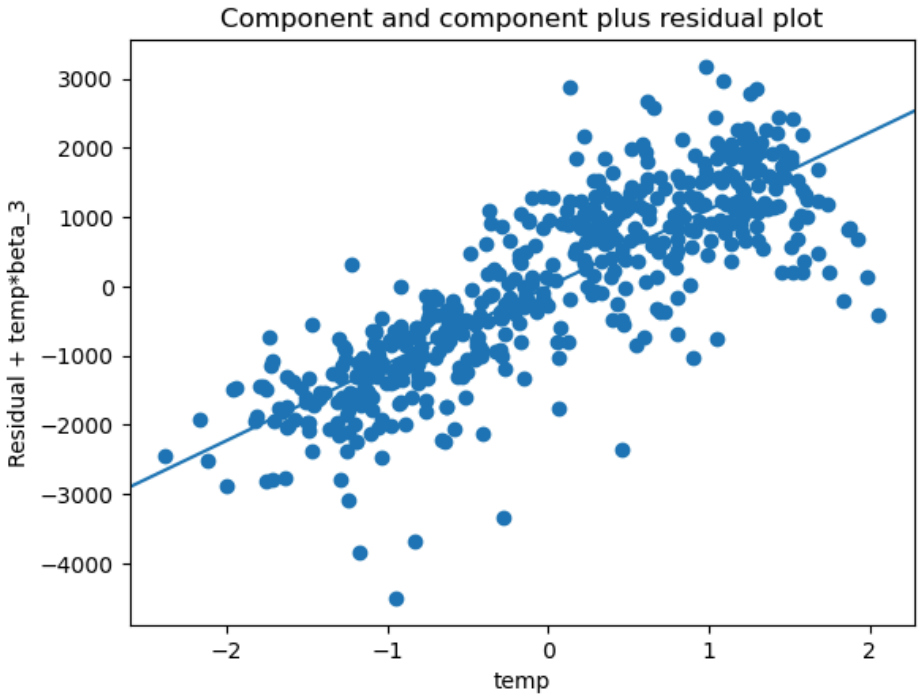
The assumptions of linear regression is validated against below mentioned conditions as follows:

• Linear Relationship

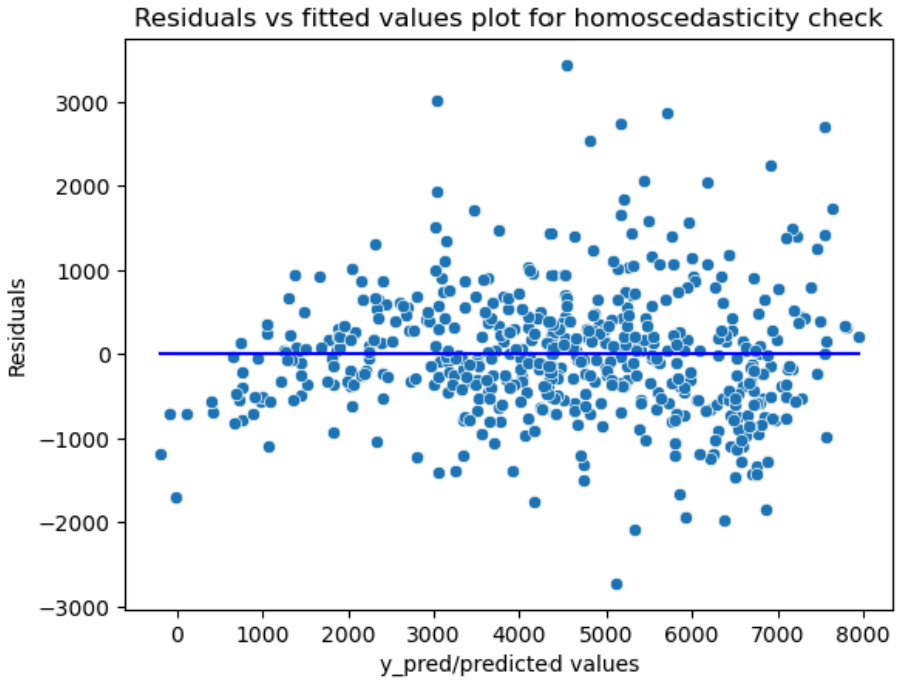
• Homoscedasticity
• Absence of Multicollinearity
• Independence of residuals (absence of auto-correlation)
• Residuals are normally distributed

The evidence are as follows:

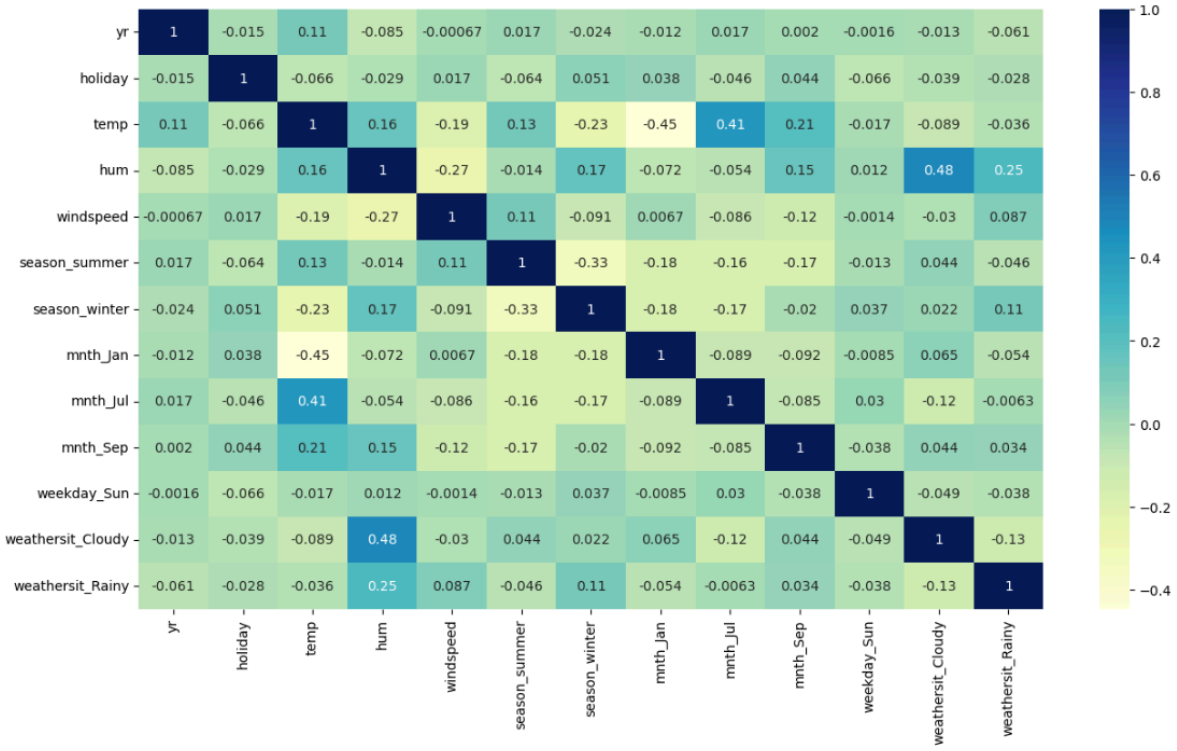
The linear relationship was assessed using a partial residual plot (CCPR) from the statsmodels library. The CCPR plot allows us to evaluate the impact of a single regressor on the response variable while accounting for the influence of other independent variables. In this case, we plotted the target variable against 'temp' to demonstrate their linear relationship, considering all other variables.



Homoscedasticity was tested by plotting residual vs predicted values and it shows no pattern in scatter plot thus verifying Homoscedasticity

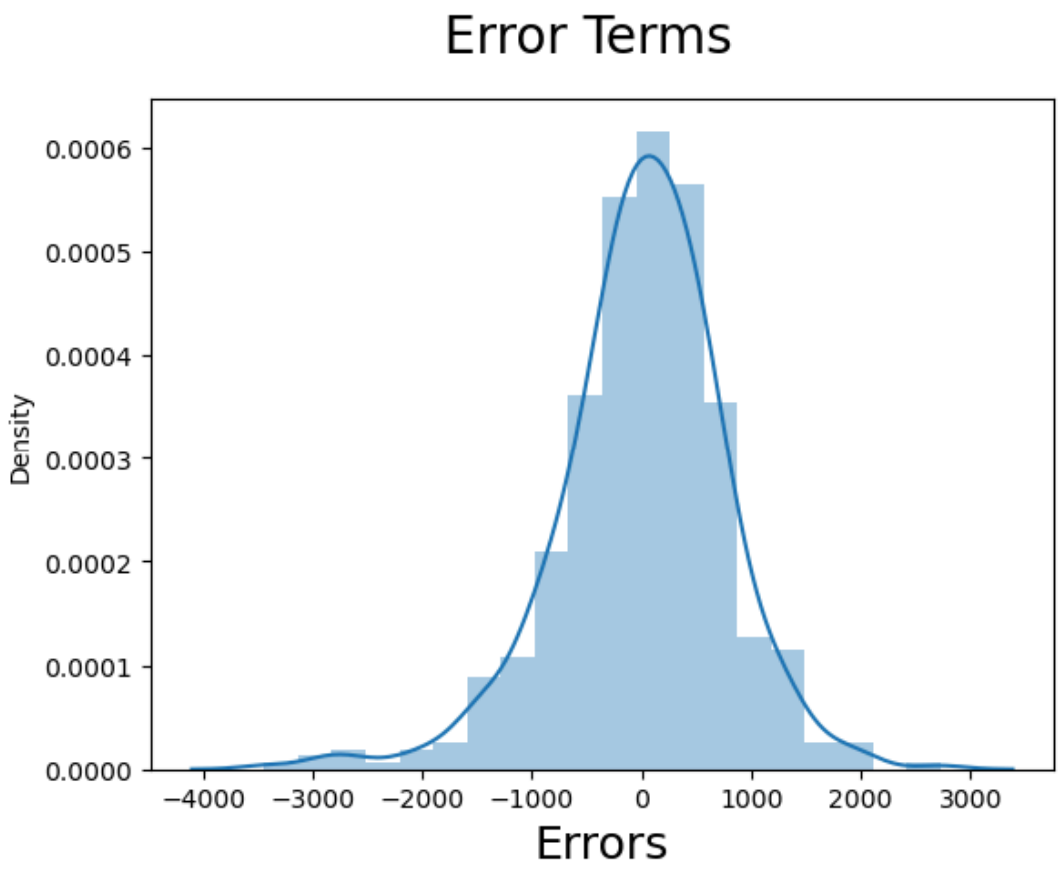


Multicollinearity was checked via heatmap and VIF where no column had high correlation or VIF.



Independence of residuals was verified by Durbin-Watson statistics where the value of the final model is 2.0858 which is almost 2 which indicates non-autocorrelation.

The distribution of residual was checked using histogram which is normally distributed.



5. Based on the final model, which are the top 3 features contributing significantly towards explaining the demand of the shared bikes?

Answer:

Top 3 features based upon below snapshot of final model is :

	coef	std err	t	P>|t|	[0.025	0.975]
const	4491.3033	34.329	130.832	0.000	4423.856	4558.751
yr	997.6089	34.887	28.596	0.000	929.065	1066.152
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1. Temperature(temp) - With a coefficient of 1112.3380, temperature has the most substantial positive impact on bike demand.
2. Year (yr): The year variable has a positive coefficient of 997.6089, indicating a notable increase in demand over time.
3. Winter(season_winter): Winter has a positive coefficient of 477.0212, indicating a notable increase in demand during the winter season.

General Subjective Questions

1. Explain the linear regression algorithm in detail.
Answer:

Linear regression is a simple yet powerful algorithm used to model the relationship between a dependent variable and one or more independent variables. The goal is to predict the dependent variable based on the independent variables.

• Equation: The model is represented as $y=\beta0+\beta1x1+\beta2x2+\cdots+\beta nxn+\epsilon$, where $\beta0$ is the intercept, $\beta1$, $\beta2$, … are the coefficients, and ϵ is the error term.

• Assumptions: Linearity, independence of observations, homoscedasticity (constant variance of errors), normality of residuals, and no multicollinearity among predictors.

• Coefficient Estimation: The coefficients are estimated using Ordinary Least Squares (OLS), which minimizes the sum of squared errors between observed and predicted values.

• Interpretation: Coefficients represent the change in the dependent variable for a one-unit change in an independent variable.

• Model Evaluation: R-squared measures how well the model explains the variability in the data. P-values indicate the significance of each predictor.

• Limitations: Sensitive to outliers, assumes linear relationships, and can overfit with too many predictors.

To conclude, linear regression is widely used for predictive modelling, trend analysis, and understanding relationships between variables due to its simplicity and interpretability.

2. Explain the Anscombe's quartet in detail.

Answer:

Anscombe's quartet is a collection of four datasets that have nearly identical simple statistical properties—such as mean, variance, correlation, and linear regression line—but differ significantly when graphed. The quartet was created by statistician Francis Anscombe in 1973 to illustrate the importance of visualising data before analysing it.

• Identical Statistics: All four datasets share similar summary statistics (e.g., mean, variance, correlation, and linear regression line).

• Different Graphs: When plotted, each dataset reveals very different patterns:

1. The first dataset shows a typical linear relationship.
2. The second dataset shows a nonlinear relationship.
3. The third dataset has a clear outlier that affects the regression line.
4. The fourth dataset shows a vertical line, where most data points have the same xvalue.

• Lesson: Anscombe's quartet demonstrates that relying solely on numerical summaries can be misleading, and emphasises the importance of data visualisation for a complete understanding of data.

To conclude, Anscombe's quartet highlights the critical role of graphical analysis in statistical data interpretation**.**

3. What is Pearson's R?

Answer:

Pearson's R, or Pearson's correlation coefficient, is a statistical measure that evaluates the strength and direction of a linear relationship between two variables. It ranges from -1 to 1:

- 1 indicates a perfect positive linear relationship,
- -1 indicates a perfect negative linear relationship,
- 0 indicates no linear relationship.

A positive R value means that as one variable increases, the other tends to increase as well. A negative R value means that as one variable increases, the other tends to decrease. Pearson's R is commonly used in various fields, including psychology, social sciences, and data analysis, to assess correlations between variables.

4. What is scaling? Why is scaling performed? What is the difference between normalized scaling and standardized scaling?

Answer:

Scaling in data analysis refers to the process of transforming data to fit within a specific range or to have particular statistical properties. It's often performed to prepare data for various algorithms or models that assume or benefit from data being on a common scale.

Scaling can help in:

1. Improving Model Performance: Many machine learning algorithms, like gradient descentbased methods or distance-based models (e.g., k-nearest neighbours), perform better when features are on a similar scale.
2. Ensuring Consistency: In datasets where features have different units or ranges, scaling ensures that no feature disproportionately affects the outcome due to its scale.
3. Enhancing Convergence Speed: Algorithms can converge faster if the data is scaled appropriately, especially when using methods that involve optimization.

Types of Scaling:

1. Normalized Scaling (Min-Max Scaling):
    - o Purpose: Transforms data to fit within a specific range, usually [0, 1].
    - o Method: For a feature x, the normalized value x′ is computed as

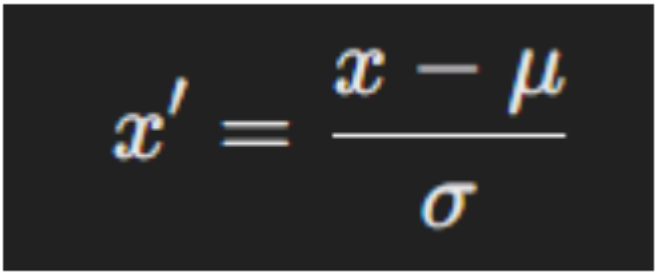
$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

o Use Case: Useful when you need to bound the values within a specific range, often required for neural networks and algorithms that use distance metrics.

2. Standardized Scaling (Z-score Normalization):

o Purpose: Centers the data around the mean with a standard deviation of 1.

o Method: For a feature xxx, the standardized value x′ is computed as



$$x' = \frac{x - \mu}{\sigma}$$

where μ is the mean of x and σ is the standard deviation of x.

o Use Case: Useful when you need features with zero mean and unit variance, commonly used in algorithms assuming normally distributed data or when comparing features with different units.

In a nutshell, normalization rescales data to a fixed range, while standardisation shifts and scales data to have a mean of zero and a standard deviation of one. The choice between them depends on the specific requirements of your analysis or machine learning model.

5. You might have observed that sometimes the value of VIF is infinite. Why does this happen?

Answer:

The Variance Inflation Factor (VIF) measures how much the variance of a regression coefficient is inflated due to multicollinearity with other predictors. It is calculated for each predictor in a regression model, and a high VIF indicates that the predictor is highly correlated with other predictors.

A VIF value can become infinite in cases where there is perfect multicollinearity. This occurs when:

1. Perfect Multicollinearity: One predictor variable is a perfect linear combination of other predictor variables. In this scenario, the matrix used to estimate regression coefficients becomes singular, meaning it cannot be inverted. This results in the VIF calculation producing an infinite value.

2. Deterministic Relationships: If one predictor is entirely determined by a linear combination of other predictors, it creates a situation where the predictor’s variance is infinitely inflated.

In practical terms, when you encounter an infinite VIF, it indicates that there is a redundancy in your predictors, and you may need to address multicollinearity by removing or combining predictors to resolve the issue.

6. What is a Q-Q plot? Explain the use and importance of a Q-Q plot in linear regression.

Answer:

A Q-Q plot (Quantile-Quantile plot) is a graphical tool used to assess if a dataset follows a specific theoretical distribution, typically the normal distribution. It plots the quantiles of the data against the quantiles of the theoretical distribution. Here's a brief explanation:

How It Works:

- Quantiles: The Q-Q plot compares the quantiles of the sample data against the quantiles of a specified theoretical distribution. For a normal Q-Q plot, it compares the quantiles of the data with the quantiles of the standard normal distribution.
- Plot: Points are plotted on a scatter plot where the x-axis represents the theoretical quantiles and the y-axis represents the sample quantiles. If the data follows the theoretical distribution, the points will approximately lie on a straight line (often a 45-degree line).

Use and Importance in Linear Regression:

- Assess Normality of Residuals: In linear regression, one of the key assumptions is that the residuals (the differences between observed and predicted values) are normally distributed. A Q-Q plot helps to visually assess this assumption by showing how well the residuals match the normal distribution.
- Model Validation: If the residuals deviate significantly from the straight line, it suggests that the normality assumption may be violated, which could affect the validity of hypothesis tests and confidence intervals derived from the model.
- Detect Outliers: Deviations from the straight line in the Q-Q plot can also indicate the presence of outliers or data points that do not conform to the normal distribution.

In summary, a Q-Q plot is a valuable diagnostic tool for validating the normality of residuals in linear regression, helping to ensure that model assumptions are met and that the results are reliable.