**\*\*Univariate Analysis\*\***

is a statistical method used to describe and analyze individual variables in a dataset. In this project, the univariate analysis is being done on the numerical columns of the dataset. Let's break down the code and the benefits of performing this analysis in this project:

Code Explanation:

- \*\*Excluded Columns\*\*: Some columns are excluded from the analysis because they are not relevant for this type of analysis or are not suitable for histogram and box plot visualization (e.g., 'Latitude', 'Longitude', 'Days for shipping (real)', 'Days for shipment (scheduled)').

- \*\*Filter Numeric Columns\*\*: The code selects only the numerical columns from the dataframe for the univariate analysis. These are columns with data types other than 'string'.

- \*\*Convert to Pandas\*\*: The PySpark DataFrame is converted to a Pandas DataFrame for easier plotting using seaborn.

- \*\*Plotting Histogram and Box Plot\*\*: For each selected numerical column:

- A histogram with kernel density estimation (kde=True) is plotted in the left column of each subplot.

- A box plot is plotted in the right column of each subplot.

- \*\*Plot Grid\*\*: The subplots are organized in a grid with rows and columns based on the number of numeric columns.

- \*\*Loop\*\*: The loop goes through each numeric column and plots its histogram and box plot in a separate subplot.

- \*\*Adjust Subplot Spacing\*\*: This adjusts the spacing between subplots for better visualization.

- \*\*Show Plot\*\*: Finally, the plots are displayed using `plt.show()`.

Benefits of Univariate Analysis:

1. \*\*Understanding Data Distribution\*\*: Univariate analysis helps in understanding the distribution of individual variables. This includes identifying the central tendency (mean, median) and dispersion (variance, range) of each variable.

2. \*\*Outlier Detection\*\*: Box plots are useful for identifying outliers in the data. Outliers can be important indicators of potential data issues or interesting patterns.

3. \*\*Data Cleaning Insights\*\*: Univariate analysis can reveal missing values, extreme values, or incorrect data entries that need to be cleaned or handled.

4. \*\*Feature Selection\*\*: Understanding the distribution of variables can help in deciding which features are important for the analysis. Features with low variability or features that are highly skewed may not provide much predictive power.

5. \*\*Assumptions for Further Analysis\*\*: It helps in checking assumptions required for further analysis like regression assumptions, normality assumptions, etc.

Outcome from Univariate Analysis in this Project:

- \*\*Histograms\*\*: These show the distribution of each numerical variable. It will provide insights into whether the variables are normally distributed, skewed, or have distinct patterns.

- \*\*Box Plots\*\*: These will indicate the presence of outliers in the data. Outliers in 'Order Item Discount', 'Order Item Discount Rate', etc., might suggest anomalies or interesting patterns that need further investigation.

- \*\*Data Cleaning Insights\*\*: If there are unexpected spikes or gaps in the histograms, it may indicate issues with the data that need to be addressed.

- \*\*Feature Importance\*\*: Based on the distribution and presence of outliers, decisions can be made on which features might be more important for predicting 'late delivery risk' or other target variables.

In summary, the univariate analysis provides a fundamental understanding of the distribution and characteristics of each numerical variable in the dataset. This understanding is crucial for making informed decisions during data preprocessing, feature engineering, and model building stages of the project.

**Categorical Analysis:**

In this project, categorical analysis is conducted on several categorical variables in the dataset. Each pie chart represents the distribution of a specific categorical variable, providing insights into the proportions of different categories within each variable.

Code Explanation:

- For each categorical variable:

- The value counts are calculated to understand the distribution of categories.

- A pie chart is plotted to visualize the distribution.

- Labels, colors, and other formatting options are applied to the pie chart for better readability.

**Benefits of Categorical Analysis:**

1. \*\*Understanding Class Imbalance\*\*:

- Analyzing the distribution of the target variable ('Late\_delivery\_risk') helps in understanding whether the classes are balanced or imbalanced.

- In this case, it was found that the classes are relatively balanced (54.83% class 1 and 45.17% class 0). This is beneficial as it ensures the model is exposed to a similar number of examples from each class during training.

2. \*\*Customer Insights\*\*:

- Analysis of 'Customer Country' distribution provides insights into the geographical distribution of customers.

- For example, the analysis revealed that the majority of customers (61.6%) are from the EE.UU country. This information can help in targeted marketing or business strategies.

3. \*\*Delivery Status\*\*:

- The 'Delivery Status' analysis shows the distribution of order delivery statuses.

- It was found that 54.8% of orders were delivered late, 23% were shipped in advance, 17.8% were shipped on time, and 4.3% were canceled. This can highlight areas for improvement in the delivery process.

4. \*\*Payment Type\*\*:

- Understanding the distribution of payment types ('Type') can provide insights into customer preferences and habits.

- The analysis revealed that 38.4% of people used debit payment, 27.6% used transfer system, 23.1% used payment system, and 10.9% used cash payment.

5. \*\*Customer Segment\*\*:

- Analyzing the 'Customer Segment' distribution helps in understanding the types of customers.

- It was found that 51.8% of customers are consumers, 30.4% are corporates, and 17.9% are from the home office category.

6. \*\*Market Type\*\*:

- The distribution of 'Market' type provides insights into the market regions where orders are coming from.

- For example, it was found that most orders (28.6%) are coming from LATAM, followed by EUROPE (27.8%), PACIFIC ASIA (22.9%), USCA (14.3%), and AFRICA (6.4%).

Outcome from Categorical Analysis:

- \*\*Understanding Customer Behavior\*\*: The analysis of customer-related variables like 'Customer Country', 'Payment Type', and 'Customer Segment' provides valuable insights into customer behavior and preferences. This information can be used to tailor marketing strategies, improve customer service, and enhance customer satisfaction.

- \*\*Operational Insights\*\*: Analysis of 'Delivery Status' gives insights into the efficiency of the delivery process. The high percentage of late deliveries indicates potential areas of improvement in shipping and logistics operations.

- \*\*Market Insights\*\*: The distribution of 'Market Type' provides information on which regions are contributing the most to orders. This can guide decisions on market expansion, localization of services, and allocation of resources.

- \*\*Modeling Considerations\*\*: Understanding the distribution of the target variable ('Late\_delivery\_risk') helps in model training. Balanced classes ensure that the model is not biased towards predicting one class over the other.

- \*\*Business Strategy\*\*: Overall, the categorical analysis helps in making data-driven business decisions. It provides a clearer picture of customer demographics, preferences, and operational efficiency, which can lead to more effective strategies and improvements in various aspects of the business.

In summary, conducting categorical analysis in this project provides valuable insights into customer behavior, operational efficiency, market distribution, and model training considerations. These insights can be leveraged to optimize business processes, improve customer satisfaction, and make informed decisions for business growth and success.

Categorical Analysis (Continued):

In the provided code, additional categorical analysis was performed on the columns 'Customer City' and 'Order Country'. Here's an explanation of the code and the outcomes:

### Code Explanation:

- \*\*List of Categorical Columns\*\*:

- Two categorical columns were selected for analysis: 'Customer City' and 'Order Country'.

- \*\*Value Counts Calculation\*\*:

- Value counts were calculated for each unique value in the 'Customer City' and 'Order Country' columns using PySpark's `groupBy` and `count` functions.

- The counts were then ordered in ascending order for the last 10 values and descending order for the top 20 values.

- \*\*Conversion to Dictionaries\*\*:

- The value counts for each column were converted to dictionaries for easier manipulation and plotting.

- \*\*Plotting\*\*:

- Subplots were created for each categorical column, with two columns per subplot:

- The left column shows the top 20 values for the 'Customer City' and 'Order Country' columns.

- The right column shows the last 10 values for the same columns.

- \*\*Bar Plots\*\*:

- Bar plots were used to visualize the distribution of counts for each unique value in the categorical columns.

- \*\*Outcome\*\*:

- The bar plots show the top 20 and last 10 values for 'Customer City' and 'Order Country', respectively.

- From the plots, it can be observed that:

- Most customers are situated in Caguas City, ordering the most.

- Customers from CA (likely California) are ordering the least.

- For 'Order Country', most orders are from Estados Unidos (United States), while very few orders are from Serbia and Burundi.

Insights from Categorical Analysis:

- \*\*Customer City Insights\*\*:

- The analysis reveals the distribution of customers across different cities.

- It is clear that Caguas City has a significantly higher number of customers compared to other cities.

- This information can be useful for targeted marketing campaigns, understanding customer demographics, and optimizing delivery routes.

- \*\*Order Country Distribution\*\*:

- The analysis of 'Order Country' shows where the majority of orders are coming from.

- Estados Unidos (United States) has the highest number of orders, which is expected given the market size.

- The presence of countries like Serbia and Burundi with very few orders could indicate potential areas for market expansion or targeted marketing efforts.

- \*\*Business Decision Making\*\*:

- Insights from this analysis can guide business decisions such as:

- Focusing marketing efforts on cities with a higher concentration of customers.

- Exploring opportunities for business expansion in countries with fewer orders.

- Optimizing shipping and logistics strategies based on customer locations.

- \*\*Modeling Considerations\*\*:

- For predictive modeling, these categorical variables can be encoded (e.g., one-hot encoding) to convert them into numerical form suitable for machine learning algorithms.

Conclusion:

The categorical analysis provides valuable insights into customer distribution across cities and the distribution of orders across countries. These insights can help in making informed business decisions, optimizing operations, and targeting specific customer segments. Additionally, this analysis lays the foundation for feature engineering and modeling in the later stages of the project.

Simple Random Sampling:

- \*\*Explanation\*\*:

- Simple random sampling is a type of probability sampling technique where each element of the population has an equal chance of being selected as part of the sample.

- In simple terms, every individual or item in the population has an equal opportunity to be chosen as part of the sample without any bias.

- This method is used to ensure that the sample is representative of the entire population, making it easier to generalize the findings from the sample to the entire population.

- \*\*Significance\*\*:

- Simple random sampling is crucial in statistical analysis and research because it helps in obtaining a sample that is unbiased and truly representative of the population.

- Significance lies in its ability to provide accurate and reliable results without introducing any systematic errors or biases.

- It simplifies the process of selecting a sample from a large population, making the analysis more manageable and efficient.

**Mann-Whitney U Test:**

- \*\*Explanation\*\*:

- The Mann-Whitney U test is a non-parametric statistical test used to compare two independent groups when the dependent variable is ordinal or continuous, but not normally distributed.

- It is an alternative to the t-test when assumptions of normality and equal variances are not met.

- The test assesses whether two independent samples have been drawn from the same population or not.

- The null hypothesis (H0) of the test is that there is no difference between the populations from which the two samples are drawn.

- \*\*Hypothesis\*\*:

- H0 (Null Hypothesis): The population mean of the two samples is equal.

- H1 (Alternate Hypothesis): The population mean of the two samples is not equal.

### Why Mann-Whitney U Test in this Project:

- \*\*Skewed Data\*\*:

- As observed during the numerical analysis, the data in all numerical variables is skewed and not normally distributed.

- Since the data is not normally distributed, it does not meet the assumptions required for parametric tests like the t-test.

- \*\*Alternative to Parametric Tests\*\*:

- The Mann-Whitney U test is chosen as an alternative to parametric tests like the t-test because it does not assume normality of data.

- It is robust to violations of normality assumptions and is suitable for use with skewed data.

- \*\*Purpose\*\*:

- The purpose of using the Mann-Whitney U test in this project is to compare two independent samples (population and sample) to determine if their means are significantly different.

- This test helps in understanding whether the characteristics observed in the sample are likely to be present in the population as a whole.

- \*\*Decision Making\*\*:

- By performing the Mann-Whitney U test, the project aims to make decisions about the significance of differences between population and sample means.

- If the p-value is greater than 0.05 (commonly chosen significance level), we fail to reject the null hypothesis, indicating that there is no significant difference between the population and sample means.

- If the p-value is less than 0.05, we reject the null hypothesis, suggesting that there is a significant difference between the population and sample means.

### Summary:

- \*\*Simple Random Sampling\*\* ensures that the sample is representative of the entire population and helps in obtaining unbiased results.

- \*\*Mann-Whitney U Test\*\* is chosen due to the non-normality of the data, providing a robust alternative to parametric tests.

- The test helps in determining if the observed characteristics in the sample are likely to be present in the entire population, aiding in decision-making and generalization of results.

**Chi-Square Goodness of Fit and Sampling Validation:**

In the provided code, the Chi-Square Goodness of Fit test is used along with sampling validation to ensure that the sample chosen is a good representation of the population. Here's an explanation of the code and its importance in the project:

### Chi-Square Goodness of Fit Test:

- \*\*Explanation\*\*:

- The Chi-Square Goodness of Fit test is a statistical test used to determine if there is a significant difference between the observed frequencies and the expected frequencies in one or more categories.

- In this context, it is used to check the distribution of all types in each categorical feature in the sample compared to the population.

- The null hypothesis (H0) states that there is no significant difference between the expected values (from population) and the observed values (from the sample).

- The alternative hypothesis (H1) states that there is a significant difference between the expected and observed values.

- \*\*Purpose\*\*:

- The Chi-Square test helps in evaluating whether the sample's categorical distribution is similar to that of the population.

- It ensures that the selected sample is not significantly different in terms of categorical distributions compared to the entire population.

Sampling Validation:

- \*\*Explanation\*\*:

- The `sampling\_validation` function is a user-defined function that takes in the data, start sample size, end sample size, and an increment value.

- It iteratively samples the data within the specified range of sample sizes and checks each column's validity using Mann-Whitney U-test for numerical columns and Chi-Square Goodness of Fit for categorical columns.

- The function returns a dictionary with sample sizes as keys and the average number of valid columns (passing both tests) as values.

- \*\*Purpose\*\*:

- \*\*Ensuring Representativeness\*\*:

- The function is crucial in ensuring that the chosen sample size represents the population accurately.

- By running statistical tests on each sampled dataset, it verifies if the sample's characteristics are similar to the population's characteristics.

- \*\*Determining Optimal Sample Size\*\*:

- The function helps in determining the optimal sample size that meets the criteria of passing both Mann-Whitney U-test and Chi-Square Goodness of Fit tests for all columns.

- It provides insights into how many samples are needed to get a representative dataset without introducing bias or errors.

- \*\*Statistical Robustness\*\*:

- Using both tests enhances the robustness of the sampling process.

- Mann-Whitney U-test handles numerical column validations, ensuring their statistical significance, while Chi-Square Goodness of Fit handles categorical column validations.

- \*\*Outcome\*\*:

- The `sampling\_validation` function outputs a dictionary where each key-value pair represents a sample size and the average number of columns that pass both tests.

- This information can guide the decision on the appropriate sample size for the project, ensuring that it is statistically valid and representative of the population.

Importance in the Project:

- \*\*Statistical Rigor\*\*:

- The Chi-Square Goodness of Fit test, along with Mann-Whitney U-test, ensures that the selected sample is statistically similar to the population.

- This is crucial for ensuring that any conclusions drawn from the sample are valid and can be generalized to the entire population.

- \*\*Sample Size Determination\*\*:

- The `sampling\_validation` function helps in determining the optimal sample size that meets the statistical criteria.

- This ensures that the sample is not too large or too small, balancing efficiency and accuracy in the analysis.

- \*\*Reducing Bias\*\*:

- By using statistical tests for sampling validation, the project aims to reduce bias in the sample selection process.

- The goal is to have a representative sample that reflects the diversity of the population, leading to more reliable and unbiased results.

- \*\*Enhancing Confidence\*\*:

- The tests and validation process enhance the confidence in the results obtained from the sample.

- Researchers and stakeholders can trust that the chosen sample size and characteristics accurately represent the larger population.

In conclusion, the Chi-Square Goodness of Fit test and the sampling validation process are essential steps in ensuring the statistical validity and representativeness of the sample chosen for analysis. These techniques enhance the rigor of the project's statistical analysis and reduce the potential for bias in the conclusions drawn from the data.

Simple random sampling is performed in this project for several important reasons:

1. Representative Sample:

- Simple random sampling ensures that each item or individual in the population has an equal chance of being selected for the sample.

- This method helps to create a sample that is representative of the entire population, which is crucial for making accurate inferences about the population as a whole.

2. Eliminates Bias:

- By using simple random sampling, we eliminate selection bias, which can occur when certain parts of the population are intentionally or unintentionally favored in the sample selection process.

- It ensures that every member of the population has an equal opportunity to be included in the sample, reducing the risk of bias.

3. Generalizability:

- A sample obtained through simple random sampling is more likely to be generalizable to the entire population.

- The results and conclusions drawn from the sample can be confidently extended to the broader population, making it valuable for making predictions or drawing insights.

4. Statistical Validity:

- Simple random sampling helps to ensure the statistical validity of the analysis.

- It provides a foundation for using statistical tests and making accurate statistical inferences about the population parameters.

5. Efficiency:

- Simple random sampling is straightforward and easy to implement, making it an efficient method for selecting a sample from a large population.

- It simplifies the sampling process without the need for complex sampling techniques, saving time and resources.

6. Unbiased Estimates:

- Simple random sampling leads to unbiased estimates of population parameters.

- The sample mean, variance, proportions, and other statistics calculated from the sample are unbiased estimators of the population parameters when using simple random sampling.

7. Ethical Considerations:

- Using simple random sampling ensures fairness and transparency in the selection process.

- It avoids favoritism or discrimination in selecting individuals or items for the sample.

Conclusion:

Simple random sampling is a fundamental and widely used sampling method in research and data analysis for its ability to provide representative, unbiased, and statistically valid samples. In this project, it ensures that the selected sample is a true reflection of the entire population, enabling reliable analysis and conclusions about the target variables such as late delivery risk, customer segments, order status, and more.

The function `selecting\_sample` is designed to select a sample from the given dataset (`data`) with a specified sample size (`sample\_size`). It ensures that the sample passes both the Mann-Whitney U-test for numerical columns and the Chi-Square Goodness of Fit test for categorical columns.

Here's a breakdown of the function:

1. \*\*Input\*\*:

- `data`: The dataset from which a sample needs to be selected.

- `sample\_size`: The size of the sample to be selected.

2. \*\*Output\*\*:

- `df\_new\_trial`: The selected sample dataframe that passes both tests.

3. \*\*Process\*\*:

- The function starts by separating the dataset into categorical and numerical columns using the `cat\_num\_cols` function.

- It initializes a counter `cnt` to track the number of iterations.

- Inside the `while` loop, a sample `df\_samp` of the specified `sample\_size` is generated from the original dataset using `data.sample(sample\_size)`.

- For each column in the dataset, it checks whether the sample passes the tests:

- If the column is numerical, it checks if the Mann-Whitney U-test (`mannwhitneyu\_test`) returns `True`.

- If the column is categorical, it checks if the Chi-Square Goodness of Fit test (`chi\_square\_goodness`) returns `True`.

- If any column fails the test, the loop breaks and the function moves to the next iteration.

- If all columns pass the tests, `valid\_col` is incremented.

- If `valid\_col` equals the total number of columns in the dataset (`len(df\_pd.columns)`), it means all columns passed the tests, and the function returns the selected sample `df\_samp`.

- The `while` loop ensures that the function keeps iterating until it finds a sample that satisfies the conditions.

Here's the function implementation:

```python

def selecting\_sample(data, sample\_size):

cat\_cols, num\_cols = cat\_num\_cols(data)

cnt = 0

while True:

cnt += 1

valid\_cols = 0

df\_samp = data.sample(sample\_size)

for col in data.columns:

if col in num\_cols:

if not mannwhitneyu\_test(data[col], df\_samp[col]):

break

else:

if not chi\_square\_goodness(data[col], df\_samp[col]):

break

valid\_cols += 1

if valid\_cols == len(data.columns):

print("Number of iterations:", cnt)

return df\_samp

# Call the function to select the sample

df\_new\_trial = selecting\_sample(df\_pd, 50000)

```

This function will continue to generate samples until it finds one where all columns pass the specified tests. The selected sample `df\_new\_trial` will be a good representation of the population for further analysis, ensuring that the statistical properties observed in the sample are reliable for making inferences about the entire dataset. The number of iterations taken to find a valid sample is also printed for reference.

Converting values into the `object` data type in the provided code snippet serves a specific purpose, typically related to how the data will be used or interpreted in downstream analysis. Here are some potential reasons why certain columns are being converted to the `object` data type:

1. \*\*Categorical Variables\*\*:

- Columns like "Late\_delivery\_risk," "Product Category Id," "Customer Id," "Department Id," "Order Item Cardprod Id," and "Customer Zipcode" might represent categorical variables.

- Converting these columns to `object` data type is a common practice when treating them as categorical variables, especially when they contain non-numeric or string-like values.

- Many machine learning algorithms and statistical tests require categorical variables to be encoded properly. Converting them to `object` data type ensures they are treated as categorical during encoding or analysis.

2. \*\*Preventing Misinterpretation\*\*:

- Sometimes numerical values might represent categories or identifiers rather than actual numeric quantities.

- For example, "Product Category Id," "Customer Id," and "Department Id" might be unique identifiers or codes for categories rather than continuous numerical values.

- By converting these columns to `object` data type, it helps prevent misinterpretation of these identifiers as continuous variables during analysis.

3. \*\*Downstream Operations\*\*:

- Certain operations or libraries might expect categorical variables to be in `object` format.

- For example, when using libraries like `scikit-learn` for machine learning, categorical variables are often required to be in `object` format for encoding using techniques like one-hot encoding or label encoding.

4. \*\*Consistency with Existing Data Types\*\*:

- Ensuring consistency in data types can also be a reason for the conversion.

- If other similar categorical columns are already in `object` data type, it's a good practice to maintain consistency across the dataset.

5. \*\*Analysis and Visualization\*\*:

- For some types of analysis or visualization, `object` data type might be more suitable.

- For instance, when creating plots or aggregating data by categories, `object` data type allows for more flexibility and readability in labels.

In summary, converting certain columns to the `object` data type is done to ensure proper treatment of categorical variables in the dataset. It helps in maintaining consistency, preventing misinterpretation, enabling proper encoding for machine learning algorithms, and facilitating various analysis and visualization tasks.

Bivariate analysis

Bivariate analysis is a statistical method used to determine if there is a relationship between two different variables. It is specifically focused on analyzing the relationship between two categorical or numerical variables. The main purpose of bivariate analysis is to discover patterns, trends, or relationships between the variables. Here are some benefits and reasons why bivariate analysis is used:

### Benefits and Purposes of Bivariate Analysis:

1. \*\*Identifying Relationships\*\*: Bivariate analysis helps to identify and understand the relationships between two variables. It determines whether changes in one variable are associated with changes in another variable.

2. \*\*Correlation\*\*: Bivariate analysis can measure the strength and direction of correlation between two numerical variables. For example, it can tell us if an increase in one variable corresponds to an increase, decrease, or no change in another variable.

3. \*\*Causal Relationships\*\*: While it cannot establish causation, bivariate analysis can provide insights into potential causal relationships between variables. It helps to identify if one variable might be influencing the other.

4. \*\*Data Exploration\*\*: It is an essential step in exploratory data analysis. By visualizing the relationship between variables, we can gain a better understanding of the data distribution and potential patterns.

5. \*\*Predictive Modeling\*\*: Bivariate analysis can help in feature selection for predictive modeling. Understanding how different variables interact can guide the selection of relevant features for building accurate models.

6. \*\*Decision-Making\*\*: For businesses, bivariate analysis aids in decision-making processes. For example, understanding the relationship between customer segment and late delivery risk can help in strategizing better shipping policies.

Examples of Bivariate Analysis in the Provided Code:

1. \*\*City Analysis\*\*:

- The code plots the count of late delivery risk for top cities in both 'Order City' and 'Customer City'. This helps in understanding if certain cities have higher or lower instances of late deliveries.

2. \*\*Shipping Mode Analysis\*\*:

- The countplot with percentage annotations shows the distribution of late delivery risk across different shipping modes. This provides insights into which shipping modes are associated with more or fewer late deliveries.

3. \*\*Customer Segment Analysis\*\*:

- Similar to the shipping mode, the code analyzes the distribution of late delivery risk across customer segments. This helps in understanding if certain customer segments have higher or lower rates of late deliveries.

4. \*\*Market Analysis\*\*:

- The countplot for market analysis shows the distribution of late delivery risk across different markets. This helps in understanding if the market type has an impact on late delivery rates.

5. \*\*Customer Country Analysis\*\*:

- The analysis of late delivery risk across different customer countries provides insights into which countries have higher or lower rates of late deliveries.

Outcome from Bivariate Analysis:

- From the provided code, we can see the percentage of late deliveries for various categories within each variable.

- For example, the analysis shows the percentage of late deliveries for different cities, customer segments, markets, and customer countries.

- This allows stakeholders to identify patterns and trends, such as which cities or customer segments are more prone to late deliveries.

- The annotations in the plots help in quickly understanding the distribution of late delivery risk across different categories.

- Ultimately, bivariate analysis helps in making informed decisions, such as focusing resources on improving delivery services in specific cities or customer segments with higher late delivery rates.

* Target encoding helps capture the relationship between categorical variables and the target, potentially improving the model's performance
* Dummy encoding is suitable for machine learning algorithms that cannot work directly with categorical data, converting them into a format that can be used for training predictive models
* It's important to handle categorical variables properly as they play a crucial role in model training and prediction accuracy

**Encoding**

In the provided code, we are preparing the data for Model 1 by encoding the categorical variables using different techniques:

### Target Encoding:

- Target encoding is a technique where categorical features are replaced with the average of the target variable for each category.

- This is done to capture the relationship between the categorical feature and the target variable.

### Dummy Encoding:

- Dummy encoding is used for the 'Type' and 'Shipping Mode' columns.

- Dummy encoding converts categorical variables into a series of zeros and ones, making it easier for machine learning models to process.

Here's a breakdown of the code:

### Target Encoding:

```python

# Define a function to calculate target encoding

def Target\_encode\_test(data, cols):

d\_map = {}

for col in cols:

cross = pd.crosstab(data[col], data["Late\_delivery\_risk"])

cross["prob"] = cross[1] / (cross[1] + cross[0])

d = {}

for cat in cross.index:

d[cat] = cross.loc[cat, "prob"]

d\_map[col] = d

return d\_map

# Apply target encoding to selected columns

en\_cols = df\_model\_1.columns.drop(["Late\_delivery\_risk", "Type", "Shipping Mode"])

Tar\_encode\_dict = Target\_encode\_test(df\_model\_1, en\_cols)

map\_categories\_encode(df\_model\_1, Tar\_encode\_dict)

```

In this section:

- The `Target\_encode\_test` function calculates the probability of late delivery for each category in the selected columns.

- It creates a dictionary `Tar\_encode\_dict` where keys are columns and values are dictionaries mapping categories to their respective probabilities.

- The `map\_categories\_encode` function applies the target encoding by mapping the dictionaries to the corresponding columns.

### Dummy Encoding:

```python

# Apply dummy encoding to 'Type' and 'Shipping Mode'

df\_final = pd.get\_dummies(df\_model\_1, drop\_first=True)

```

In this part:

- `pd.get\_dummies()` is used to convert the categorical variables 'Type' and 'Shipping Mode' into dummy variables.

- The `drop\_first=True` parameter drops the first level of each categorical variable to avoid multicollinearity.

### Outcome:

- After target encoding, the categorical columns (except 'Type' and 'Shipping Mode') now contain the probabilities of late delivery for each category.

- The 'Type' and 'Shipping Mode' columns are converted into dummy variables, creating new binary columns for each category.

- The `df\_final` DataFrame now contains the encoded features ready for Model 1, where the target variable 'Late\_delivery\_risk' is also encoded.

### Note:

- Target encoding helps capture the relationship between categorical variables and the target, potentially improving the model's performance.

- Dummy encoding is suitable for machine learning algorithms that cannot work directly with categorical data, converting them into a format that can be used for training predictive models.

- It's important to handle categorical variables properly as they play a crucial role in model training and prediction accuracy.

why we have done dummy encoding on type and shipping mode

In the encoding part of the model, dummy encoding was performed on the "Type" and "Shipping Mode" columns. Let's break down why dummy encoding was used for these columns:

1. \*\*Type Column\*\*:

- The "Type" column likely contains categorical values that represent different types of transactions or payment methods.

- Dummy encoding is used when dealing with categorical variables where the categories do not have a natural ordering or hierarchy.

- In this case, each category in the "Type" column (e.g., debit, transfer system, payment system, cash) is represented by a separate binary column.

- This allows the model to treat each category independently, without assuming any ordinal relationship between them.

2. \*\*Shipping Mode Column\*\*:

- The "Shipping Mode" column likely contains categorical values that represent different modes of shipping (e.g., standard, express, priority).

- Similar to the "Type" column, dummy encoding is used because these shipping modes do not have a natural ordering.

- Each category in the "Shipping Mode" column is represented by a separate binary column, enabling the model to distinguish between different shipping modes.

By using dummy encoding, the categorical variables "Type" and "Shipping Mode" are transformed into numerical format that the machine learning model can understand. This technique helps to prevent the model from assuming any ordinal relationship between the categories, which is important when dealing with categorical variables that do not have a clear numerical interpretation.

## **Train\_test\_split**

The `train\_test\_split` function from scikit-learn is used to split the dataset into training and testing sets. Here's the code snippet you provided:

```python

# Split the data into features (X) and target variable (y)

x = df\_final.drop("Late\_delivery\_risk", axis=1)

y = df\_final["Late\_delivery\_risk"]

# Split the data into training and testing sets

x\_train, x\_test, y\_train, y\_test = train\_test\_split(x, y, test\_size=0.20, random\_state=34)

# Print the shapes of the training and testing sets

print(f"x\_train {x\_train.shape}")

print(f"x\_test {x\_test.shape}")

print(f"y\_train {y\_train.shape}")

print(f"y\_test {y\_test.shape}")

```

Explanation:

- `x` contains all the features except the target variable "Late\_delivery\_risk".

- `y` contains the target variable "Late\_delivery\_risk".

- `train\_test\_split` is then used to split `x` and `y` into training and testing sets.

- The `test\_size` parameter specifies the proportion of the dataset to include in the test split (in this case, 20% for testing).

- `random\_state` is used to ensure reproducibility, so the same random split is generated each time.

The output will show the shapes of the training and testing sets:

- `x\_train` will have a shape of (number of samples, number of features) for the training features.

- `x\_test` will have a shape of (number of samples, number of features) for the testing features.

- `y\_train` will have a shape of (number of samples,) for the training target variable.

- `y\_test` will have a shape of (number of samples,) for the testing target variable.

This splitting process allows you to train your model on the `x\_train` and `y\_train` data and evaluate its performance on the `x\_test` and `y\_test` data.

why we choosen Late\_delivery\_risk as our target variable

In this project, "Late\_delivery\_risk" has been chosen as the target variable for several reasons:

1. \*\*Relevance to Business Objective\*\*:

- The business objective of this project might be related to optimizing delivery processes, reducing late deliveries, and improving customer satisfaction.

- "Late\_delivery\_risk" directly aligns with this objective as it indicates whether an order was delivered late or not.

- By predicting "Late\_delivery\_risk," the company can take proactive measures to ensure timely deliveries, potentially improving customer loyalty and satisfaction.

2. \*\*Actionable Insights\*\*:

- Predicting "Late\_delivery\_risk" can provide actionable insights for the company to optimize its supply chain and logistics.

- Insights from the analysis can help identify patterns or factors contributing to late deliveries, such as shipping modes, customer segments, or market types.

3. \*\*Binary Classification\*\*:

- "Late\_delivery\_risk" is a binary variable, making it suitable for binary classification tasks.

- This simplifies the problem into predicting whether an order will be late (class 1) or not (class 0), which is easier to model and interpret.

4. \*\*Balanced Target Variable\*\*:

- It's noted that the distribution of "Late\_delivery\_risk" is balanced in the dataset (around 55% class 1 and 45% class 0).

- A balanced target variable ensures that the model is exposed to a similar number of examples from each class during training, which helps prevent biases and leads to a more robust model.

5. \*\*Business Impact\*\*:

- Late deliveries can have a significant impact on customer satisfaction, brand reputation, and overall business performance.

- Predicting and preventing late deliveries can lead to improved customer retention, reduced costs associated with late deliveries, and increased efficiency in the supply chain.

In conclusion, choosing "Late\_delivery\_risk" as the target variable allows the company to build a predictive model that can provide valuable insights and actionable strategies to improve delivery performance, customer satisfaction, and business outcomes.

**Naive Bayes**

Naive Bayes is a classification algorithm based on Bayes' theorem, which assumes that features are independent of each other. Despite its simplicity, Naive Bayes is a powerful and efficient algorithm that is often used for text classification and other tasks. Here's an explanation of why Naive Bayes was used in the project, how it was implemented, and the outcomes:

### Why Naive Bayes in the Project?

1. \*\*Simplicity and Efficiency\*\*:

- Naive Bayes is known for its simplicity and efficiency. It's easy to implement and computationally efficient, making it suitable for large datasets.

2. \*\*Handling Categorical Data\*\*:

- In the project, after encoding categorical variables, we ended up with a dataset that had both categorical and numerical features.

- Naive Bayes can handle categorical data well, making it a good choice for our dataset.

3. \*\*Binary Classification\*\*:

- Since the project involves predicting whether an order will be late (class 1) or not (class 0), it's a binary classification problem.

- Naive Bayes is effective for binary classification tasks, particularly when the classes are well-separated.

4. \*\*Good Recall Score\*\*:

- The business objective prioritizes recall over accuracy. Recall is important because it focuses on minimizing false negatives (predicting an order as not late when it actually is).

- Naive Bayes can be effective in providing good recall scores, especially when the classes are imbalanced.

### Implementation of Naive Bayes:

1. \*\*Training the Naive Bayes Model\*\*:

- The `GaussianNB` class from `sklearn.naive\_bayes` was used to create a Gaussian Naive Bayes classifier.

- The model was trained on the training data (`x\_train` and `y\_train`) using the `fit()` method.

2. \*\*Prediction and Evaluation\*\*:

- After training, the model was used to make predictions on the test data (`x\_test`) using the `predict()` method.

- The recall scores for both the test and training sets were calculated using `recall\_score()` from `sklearn.metrics`.

- The `score()` method was used to calculate the accuracy score on the test data.

### Outcomes:

- \*\*Test Recall\*\*: The test recall score of approximately 0.956 indicates that the model correctly identified about 95.6% of the actual late deliveries in the test set.

- \*\*Train Recall\*\*: The training recall score of approximately 0.953 suggests that the model also performed well on the training data.

- \*\*Confusion Matrix Visualization\*\*: The confusion matrix provides a visual representation of the model's performance, showing the number of true positives, true negatives, false positives, and false negatives.

### Summary:

- \*\*Naive Bayes Usage\*\*: Naive Bayes was used due to its simplicity, efficiency, and ability to handle categorical data.

- \*\*Performance\*\*: The model achieved a high recall score, which is important for the project's business objective of minimizing false negatives (predicting late deliveries as non-late).

- \*\*Confusion Matrix\*\*: The confusion matrix visualization helps in understanding the model's performance in terms of true positives, true negatives, false positives, and false negatives.

In conclusion, Naive Bayes provided a good starting point for the project, showing promising results in terms of recall score, which aligns with the business objective of prioritizing the correct

identification of late deliveries.

on what basis you have decided to use naive bayes

Naive Bayes was chosen for our project based on several key factors. Firstly, our dataset contains a mix of categorical and numerical features, and Naive Bayes is well-suited for handling categorical data. Additionally, the algorithm is computationally efficient, making it ideal for our dataset size and resource constraints. Since our task is a binary classification problem - predicting late or non-late deliveries - Naive Bayes' effectiveness in binary classification tasks was another reason for its selection.

Furthermore, its simplicity and assumption of feature independence allow for easier implementation and interpretation. In our project, where we might have an imbalance between late and non-late deliveries, Naive Bayes' potential for good performance in imbalanced classes was a deciding factor. Finally, our business objective prioritizes a high recall score to minimize false negatives, and Naive Bayes has shown to be effective in achieving this.

So, considering these factors - handling categorical data, efficiency, suitability for binary classification, potential for good performance in imbalanced classes, and alignment with our business objective - Naive Bayes was the chosen model for our initial analysis."

This explanation provides a comprehensive overview of the reasons behind choosing Naive Bayes for the project, addressing its suitability for the dataset, efficiency, simplicity, and alignment with the project's objectives.

print(classification\_report(y\_test,y\_pred\_test))

outputs:-

precision recall f1-score support

0 0.90 0.50 0.64 4541

1 0.70 0.96 0.81 5459

accuracy 0.75 10000

macro avg 0.80 0.73 0.73 10000

weighted avg 0.79 0.75 0.73 10000

The `classification\_report` provides a comprehensive summary of the model's performance on the test data. Here's how to interpret the report:

### Interpretation of Classification Report:

1. \*\*Precision\*\*:

- Precision measures the accuracy of the positive predictions.

- For class 0 (non-late deliveries), the precision is 0.90, which means that when the model predicts a delivery is not late, it is correct 90% of the time.

- For class 1 (late deliveries), the precision is 0.70, indicating that when the model predicts a delivery is late, it is correct 70% of the time.

2. \*\*Recall\*\*:

- Recall (also called sensitivity or true positive rate) measures the ability of the classifier to find all the positive samples.

- For class 0, the recall is 0.50, indicating that the model is able to correctly identify 50% of the non-late deliveries.

- For class 1, the recall is 0.96, showing that the model can identify 96% of the late deliveries.

3. \*\*F1-Score\*\*:

- The F1-score is the harmonic mean of precision and recall. It balances between precision and recall.

- For class 0, the F1-score is 0.64.

- For class 1, the F1-score is 0.81.

4. \*\*Support\*\*:

- Support is the number of actual occurrences of the class in the test data.

- For class 0, there are 4541 instances.

- For class 1, there are 5459 instances.

5. \*\*Accuracy\*\*:

- The overall accuracy of the model is 0.75, which means that the model correctly predicts the class of 75% of the deliveries.

6. \*\*Macro Average\*\*:

- The macro average is the average of precision, recall, and F1-score across classes.

- The macro average precision is 0.80, recall is 0.73, and F1-score is 0.73.

7. \*\*Weighted Average\*\*:

- The weighted average takes into account the class imbalance by computing the average of metrics weighted by the support.

- The weighted average precision is 0.79, recall is 0.75, and F1-score is 0.73.

### Conclusion:

- The model performs relatively well in predicting late deliveries (class 1) with high precision (0.70) and recall (0.96).

- However, for non-late deliveries (class 0), the precision is good (0.90) but the recall is relatively low (0.50), indicating that the model struggles to correctly identify non-late deliveries.

- The overall accuracy of the model is 75%, but considering the business objective of minimizing false negatives (predicting a non-late delivery as late), the recall for class 0 should be improved.

### Recommendations:

- Since the business focus is on minimizing false negatives, further tuning the model to improve the recall for non-late deliveries (class 0) would be beneficial.

- Experimenting with different thresholds or using techniques like class weighting or resampling may help improve the model's performance, particularly for the minority class (class 0).

**Logistic Regression**

The Logistic Regression model you've fitted is a binary classification model, specifically used for predicting the probability of a binary outcome, in this case, whether a delivery is late or not.

### Interpretation of the Model Summary:

- \*\*Dependent Variable\*\*: Late\_delivery\_risk

- \*\*No. Observations\*\*: 40,000

- \*\*Method\*\*: Maximum Likelihood Estimation (MLE)

- \*\*Pseudo R-squared\*\*: 0.5564

- Pseudo R-squared is a measure of how well the model explains the variance in the dependent variable.

- In this case, 55.64% of the variance in late delivery risk is explained by the model.

### Coefficients:

- \*\*Customer City\*\*: The coefficient is -0.1189, but the p-value is high (0.750), indicating that this variable is not statistically significant in predicting late delivery.

- \*\*Customer Id\*\*: Positive coefficient of 6.2515, indicating that higher Customer Id is associated with a higher probability of late delivery.

- \*\*Customer Segment\*\*: Negative coefficient of -10.4364, indicating that certain customer segments are associated with a lower probability of late delivery.

- \*\*Customer Zipcode\*\*: The coefficient is -0.2337, but the p-value is high (0.415), suggesting it's not a significant predictor.

- \*\*Market\*\*: Negative coefficient of -4.0320, indicating certain markets are associated with a lower probability of late delivery.

- \*\*Order City\*\*: Positive coefficient of 4.9340, indicating certain order cities are associated with a higher probability of late delivery.

- \*\*Order Country\*\*: Negative coefficient of -1.0293, indicating certain countries are associated with a lower probability of late delivery.

- \*\*Order Region\*\*: The coefficient is -2.2896, but the p-value is relatively high (0.094), suggesting it's not highly significant.

- \*\*Order State\*\*: Not a significant predictor as the p-value is high (0.957).

- \*\*Order Status\*\*: Highly significant with a large positive coefficient of 19.9702, indicating certain order statuses are strongly associated with a higher probability of late delivery.

- \*\*Type\_DEBIT\*\*: Positive coefficient of 0.0849, indicating a slight association with a higher probability of late delivery, but not highly significant.

- \*\*Type\_PAYMENT\*\*: Negative coefficient of -0.0933, indicating a slight association with a lower probability of late delivery, but not highly significant.

- \*\*Type\_TRANSFER\*\*: Negative coefficient of -0.1121, indicating a slight association with a lower probability of late delivery, but not highly significant.

- \*\*Shipping Mode\_Same Day\*\*: Large negative coefficient of -7.6394, indicating that choosing "Same Day" shipping mode is strongly associated with a lower probability of late delivery.

- \*\*Shipping Mode\_Second Class\*\*: Negative coefficient of -6.1236, indicating that choosing "Second Class" shipping mode is associated with a lower probability of late delivery.

- \*\*Shipping Mode\_Standard Class\*\*: Negative coefficient of -7.8997, indicating that choosing "Standard Class" shipping mode is strongly associated with a lower probability of late delivery.

### Model Evaluation:

- The model has an overall significance with a LLR p-value of 0.000.

- It has a good fit with the data, as indicated by the converged optimization.

- The coefficients help understand the direction and strength of the relationship between each predictor and the probability of late delivery.

- A higher Customer Id, certain Customer Segments, specific Order Statuses, and choosing "Same Day" or "Standard Class" shipping modes are strongly associated with a higher probability of late delivery.

- On the other hand, certain markets, countries, and "Second Class" shipping mode are associated with a lower probability of late delivery.

### Recommendations:

- Focus on improving the prediction of late deliveries based on Customer Id, Customer Segment, Order Status, and Shipping Mode.

- Further investigation into the insignificant predictors may help refine the model.

- Consider feature engineering or incorporating additional relevant features to improve model performance.

Please note that the interpretation of coefficients may vary based on the specific domain and context of the data. It's also essential to consider practical implications and business requirements when interpreting and using the model.

The Logistic Regression model results in the following recall scores:

- \*\*Train Recall\*\*: 0.8641

- \*\*Test Recall\*\*: 0.8630

These scores indicate the proportion of actual late deliveries that were correctly predicted by the model. In other words:

- \*\*Train Recall\*\*: Out of all actual late deliveries in the training set, the model correctly identified 86.41%.

- \*\*Test Recall\*\*: Out of all actual late deliveries in the test set, the model correctly identified 86.30%.

The confusion matrix display provides a visual representation of the model's performance:

- True Positive (Top Left): The number of actual late deliveries correctly predicted as late deliveries.

- False Negative (Top Right): The number of actual late deliveries incorrectly predicted as not late deliveries.

- False Positive (Bottom Left): The number of actual not late deliveries incorrectly predicted as late deliveries.

- True Negative (Bottom Right): The number of actual not late deliveries correctly predicted as not late deliveries.

This matrix helps to understand the model's performance in terms of correct and incorrect predictions of late deliveries.

Please note that the recall scores are an essential metric, especially in scenarios where correctly identifying late deliveries is crucial, as discussed earlier. These scores indicate a relatively good performance of the logistic regression model in predicting late deliveries.

## **SUMMARY FOR ABOVE ALL MODELS FOR FIRST ENCODING :**

Certainly! Let's break down the outputs and what they indicate:

### Model Performance Metrics:

- \*\*Train Accuracy Score\*\*: The accuracy of the model on the training data. It tells us how often the model is correct on the training set.

- \*\*Test Accuracy Score\*\*: The accuracy of the model on the testing data. It tells us how often the model is correct on the testing set.

- \*\*Train Recall Score\*\*: The recall (also called sensitivity) of the model on the training data. It is the ratio of true positives to the sum of true positives and false negatives. It tells us the percentage of actual positive cases the model correctly predicted.

- \*\*Test Recall Score\*\*: The recall of the model on the testing data. Similar to train recall, it tells us how well the model predicts positive cases on unseen data.

### Analysis of Model Outputs:

1. \*\*GaussianNB\*\*:

- It has decent Test Accuracy (0.7491) and very high Test Recall (0.955670).

- This model is particularly good at identifying positive cases (late delivery risks) with high recall, but its accuracy is lower.

2. \*\*RandomForest\*\*:

- This model has high Test Accuracy (0.8988) and good Test Recall (0.907675).

- It performs well in both accuracy and recall, making it a strong contender.

3. \*\*BaggingRF\*\*:

- Similar to RandomForest, BaggingRF has high Test Accuracy (0.8935) and slightly lower but still good Test Recall (0.902729).

- It combines multiple Random Forest models to improve performance, and here it shows a good balance between accuracy and recall.

4. \*\*XGBoost, BaggingXGB, AdaBoost, BaggingAda, BaggingGB, GradientBoost\*\*:

- These models have varying performance but generally fall within the same range of Test Accuracy (around 0.85-0.86) and Test Recall (around 0.85-0.86).

**Model 2**

In the second set of models (Models 2), we are performing encoding and feature selection to prepare the data for training. Here's a breakdown of what we're doing:

### Encoding:

1. \*\*Target Encoding\*\*:

- We are using target encoding (probability encoding) for categorical variables except for "Order Status," "Shipping Mode," "Type," and "Market."

- Target encoding replaces each categorical value with the mean of the target variable (Late\_delivery\_risk) for that category.

- This encoding method helps capture the relationship between the categorical feature and the target variable.

2. \*\*Dummy Encoding\*\*:

- For the remaining categorical variables ("Order Status," "Shipping Mode," "Type," and "Market"), we are performing dummy encoding.

- Dummy encoding converts categorical variables into binary vectors (0s and 1s) where each category becomes a separate binary feature.

### Feature Selection:

- We are dropping the columns "Customer Segment," "Order Country," "Order State," "Market," and "Order Region."

- These columns are dropped based on some criteria such as business understanding, multicollinearity, or feature importance.

- Dropping irrelevant or redundant features helps improve model performance and reduces overfitting.

### Need for Encoding:

- Machine learning algorithms require numerical data for modeling.

- Categorical variables need to be converted into numerical form, hence the need for encoding.

- Target encoding captures the relationship between categorical variables and the target variable.

- Dummy encoding converts categorical variables into a format that can be used for modeling without implying any ordinal relationship between the categories.

### Steps Taken:

1. We dropped "Customer Segment," "Order Country," "Order State," "Market," and "Order Region" columns.

2. We performed target encoding on columns except for "Order Status," "Shipping Mode," "Type," and "Market."

3. For "Order Status," "Shipping Mode," "Type," and "Market," we used dummy encoding.

4. The resulting DataFrame `df\_final` is now ready for training our machine learning models.

This encoding and feature selection process ensures that the data is in a suitable format for various machine learning algorithms, enabling us to build and evaluate our models effectively.

The decision to drop certain columns such as "Customer Segment," "Order Country," "Order State," "Market," and "Order Region" from the dataset can be based on several factors:

1. \*\*Irrelevant Information\*\*:

- These columns may not have a significant impact on the target variable ("Late\_delivery\_risk").

- If the information they provide is not relevant to the prediction of late delivery risk, keeping them in the model could introduce noise.

2. \*\*Multicollinearity\*\*:

- Multicollinearity occurs when two or more features in a dataset are highly correlated with each other.

- Removing one of the correlated features can help reduce multicollinearity, which can improve the model's stability and interpretability.

3. \*\*Data Quality\*\*:

- If these columns have a lot of missing values or errors, it might be beneficial to drop them rather than trying to impute or correct the data.

4. \*\*Business Understanding\*\*:

- Based on domain knowledge or business requirements, certain columns may not be relevant for predicting late delivery risk.

- For example, "Order State" or "Order Country" might not directly impact late delivery risk in the context of this specific analysis.

5. \*\*Model Interpretability\*\*:

- Too many features can make it harder to interpret the model's results.

- Removing less important or redundant features can simplify the model and make it easier to understand.

So, in this case, dropping these columns may have been a strategic decision to improve the model's performance, reduce noise, and enhance interpretability. It's important to evaluate the impact of dropping these columns on the model's performance and adjust the feature selection strategy based on the specific goals of the analysis.

Difference between model 1 encoding and model 2 encoding

The main difference between Model 1 encoding and Model 2 encoding lies in the columns that were dropped and the type of encoding used:

### Model 1 Encoding:

- In Model 1, the following columns were dropped:

- `None`

- Encoding Used:

- Target Encoding for most categorical columns except "Type" and "Shipping Mode"

- Dummy Encoding for "Type" and "Shipping Mode"

### Model 2 Encoding:

- In Model 2, the following columns were dropped:

- "Customer Segment"

- "Order Country"

- "Order State"

- "Market"

- "Order Region"

- Encoding Used:

- Target Encoding for most categorical columns except "Order Status," "Shipping Mode," "Type," and "Market"

- Dummy Encoding for "Type" and "Shipping Mode"

### Explanation:

- \*\*Model 1 Encoding\*\*:

- Target encoded most categorical columns except "Type" and "Shipping Mode."

- Used dummy encoding for "Type" and "Shipping Mode."

- Did not drop any columns.

- \*\*Model 2 Encoding\*\*:

- Dropped "Customer Segment," "Order Country," "Order State," "Market," and "Order Region" columns.

- Target encoded most categorical columns except "Order Status," "Shipping Mode," "Type," and "Market."

- Used dummy encoding for "Type" and "Shipping Mode."

### Conclusion:

- Model 2's encoding strategy involved dropping additional columns that were deemed less relevant or potentially problematic for the prediction task.

- This approach aimed to improve model performance, reduce noise, and enhance interpretability by focusing on more relevant and informative features.

## **SUMMARY FOR ABOVE ALL MODELS FOR SECOND ENCODING :**

This code is evaluating various classification models using the second encoding strategy and reporting their performance metrics. Here's an explanation of the code and each model:

### Code Explanation:

- \*\*Models Evaluated\*\*:

- RandomForest

- AdaBoost

- GradientBoost

- XGBoost

- BaggingRF (Bagging with RandomForest base estimator)

- BaggingAda (Bagging with AdaBoost base estimator)

- BaggingGB (Bagging with GradientBoosting base estimator)

- BaggingXGB (Bagging with XGBoost base estimator)

- GaussianNB (Gaussian Naive Bayes)

- \*\*Metrics Reported\*\*:

- Train Accuracy Score

- Test Accuracy Score

- Train Recall Score

- Test Recall Score

- \*\*Model Evaluation\*\*:

- Each model is trained on the training data (x\_train, y\_train).

- Predictions are made on the test data (x\_test).

- Predicted probabilities are thresholded at 0.5 to get binary predictions.

- Metrics are calculated and stored in a DataFrame called `model\_report`.

- \*\*Sorting\*\*:

- The models are then sorted based on their Test Recall Score in descending order to identify the best-performing model.

### Model Explanation:

- \*\*RandomForest\*\*:

- Ensemble learning method using multiple decision trees.

- Combats overfitting and improves generalization.

- Generally performs well on a variety of datasets.

- \*\*AdaBoost\*\*:

- Adaptive boosting ensemble method.

- Focuses on instances that are hard to classify.

- Builds multiple weak learners sequentially to correct errors of previous models.

- \*\*GradientBoost\*\*:

- Gradient boosting ensemble method.

- Builds multiple decision trees sequentially, each correcting errors of its predecessor.

- Often achieves higher accuracy but can be prone to overfitting.

- \*\*XGBoost\*\*:

- Extreme Gradient Boosting.

- Optimized gradient boosting library.

- Often faster and more accurate than traditional Gradient Boosting.

- \*\*BaggingRF, BaggingAda, BaggingGB, BaggingXGB\*\*:

- Bagging with different base classifiers (RandomForest, AdaBoost, GradientBoost, XGBoost).

- Ensemble technique that builds multiple models in parallel and combines their predictions.

- Helps reduce variance and improve model stability.

- \*\*Gaussian Naive Bayes (GaussianNB)\*\*:

- Probabilistic classifier based on Bayes' theorem.

- Assumes that features are independent and follow a Gaussian distribution.

- Simple yet effective, especially for text classification and other similar tasks.

### Conclusion:

- The code evaluates a range of classification models using the second encoding strategy.

- The models are ranked based on their Test Recall Score, which is the metric of interest.

- The model with the highest Test Recall Score is considered the best-performing model for predicting late delivery risk in this scenario.

**Model3**

### Model 3 Overview:

#### Encoding:

- Target Encoding (Probability Encoding) for all features except 'Type' and 'Shipping Mode'.

- Dummy Encoding for 'Type' and 'Shipping Mode'.

- Dropped columns: 'Customer Segment', 'Order Country', 'Order State', 'Market', 'Order Region'.

#### Feature Engineering:

- The feature engineering part involves using KMeans clustering to create new features based on latitude and longitude data.

- KMeans clustering is used to cluster geographical locations (latitude and longitude) into different groups based on their proximity.

#### Steps:

1. \*\*Target Encoding\*\*:

- Probability encoding is performed on categorical features (except 'Type' and 'Shipping Mode').

- This replaces each category with the probability of the target variable being 1 for that category.

2. \*\*Dummy Encoding\*\*:

- Dummy encoding is used for 'Type' and 'Shipping Mode', creating binary columns for each category.

3. \*\*Dropping Columns\*\*:

- Certain columns such as 'Customer Segment', 'Order Country', 'Order State', 'Market', and 'Order Region' are dropped from the dataset.

4. \*\*Feature Engineering with KMeans\*\*:

- KMeans clustering is applied to the latitude and longitude data ('Latitude', 'Longitude') to create new cluster features.

- The Elbow Method is used to determine the optimal number of clusters (k) for KMeans. The plot shows the within-cluster sum of squares (WCSS) for different values of k.

- The number of clusters (k) where the WCSS starts to level off (the "elbow point") is often considered as the optimal number of clusters.

#### Importance of Feature Engineering:

- Feature engineering with KMeans can help in identifying geographical clusters or patterns in the data.

- This can potentially capture hidden relationships between locations that might affect the target variable, such as delivery times or risks.

#### Conclusion:

- Model 3 focuses on enhancing the dataset by creating new features using KMeans clustering.

- The combination of target encoding, dummy encoding, and feature engineering aims to improve the model's ability to capture important patterns and relationships in the data.

- The Elbow Method is used to select the optimal number of clusters for KMeans, providing a more informed approach to feature creation.

K MEANS

### K-Means Clustering in Depth:

#### Introduction:

- K-Means clustering is an unsupervised machine learning algorithm used for partitioning data into K distinct, non-overlapping clusters.

- The objective is to group similar data points together and discover underlying patterns or structures in the data.

#### Steps of K-Means:

1. \*\*Initial Centroid Assignment\*\*:

- K initial centroids are randomly chosen from the data points. These centroids represent the initial cluster centers.

2. \*\*Assigning Data Points to Clusters\*\*:

- Each data point is assigned to the nearest centroid based on a distance metric, commonly Euclidean distance.

- The distance between a data point and a centroid is calculated, and the data point is assigned to the cluster with the nearest centroid.

3. \*\*Updating Cluster Centroids\*\*:

- After assigning data points to clusters, the centroids are recalculated as the mean of all data points in the cluster.

- The new centroids become the center of their respective clusters.

4. \*\*Iterative Optimization\*\*:

- Steps 2 and 3 are repeated iteratively until convergence:

- Data points are reassigned to the nearest centroids.

- Centroids are recalculated based on the new cluster assignments.

- The algorithm converges when the cluster assignments and centroids no longer change significantly.

#### Key Points:

- \*\*Objective Function\*\*: K-Means aims to minimize the within-cluster sum of squares (WCSS), also known as inertia. It measures the sum of squared distances between each data point and its assigned centroid.

- \*\*WCSS Formula\*\*: \(\sum\_{i=1}^{K} \sum\_{x \in C\_i} ||x - \mu\_i||^2\)

- Where:

- \(K\) is the number of clusters.

- \(C\_i\) is the \(i\)th cluster.

- \(x\) is a data point.

- \(\mu\_i\) is the centroid of cluster \(C\_i\).

- \*\*Choosing K\*\*:

- The number of clusters, \(K\), needs to be specified in advance.

- The Elbow Method is a common approach to determine the optimal \(K\):

- Plot WCSS against different values of \(K\).

- The "elbow point" is where the WCSS starts to level off. This point indicates a good balance between minimizing WCSS and avoiding overfitting.

- However, the Elbow Method may not always give a clear answer, especially with complex or noisy data.

- \*\*Initialization\*\*:

- K-Means results can vary based on the initial random selection of centroids.

- To mitigate this, K-Means can be run multiple times with different initializations, and the best result in terms of WCSS can be chosen.

#### Advantages:

- \*\*Scalability\*\*: K-Means can handle large datasets efficiently.

- \*\*Simplicity\*\*: The algorithm is relatively easy to implement and understand.

- \*\*Versatility\*\*: Can be applied to a variety of data types and structures.

- \*\*Interpretability\*\*: Results in clear and non-overlapping clusters.

#### Disadvantages:

- \*\*Sensitive to Initialization\*\*: Different initial centroids can lead to different results.

- \*\*Assumes Spherical Clusters\*\*: Works well with spherical clusters but may struggle with irregular shapes.

- \*\*Requires Predefined K\*\*: The number of clusters must be specified in advance.

- \*\*Sensitive to Outliers\*\*: Outliers can significantly affect cluster centroids and results.

#### Applications:

- \*\*Customer Segmentation\*\*: Grouping customers based on behavior or preferences.

- \*\*Image Compression\*\*: Clustering pixels based on color similarity.

- \*\*Anomaly Detection\*\*: Identifying unusual patterns in data.

- \*\*Recommendation Systems\*\*: Grouping similar items or users.

#### Conclusion:

- K-Means clustering is a versatile and widely-used algorithm for unsupervised learning.

- Understanding its steps, strengths, and limitations is crucial for successful application.

- The Elbow Method helps in selecting an optimal number of clusters, and the algorithm iteratively optimizes cluster assignments and centroids to create meaningful clusters in the data.

**silhouette score**

The silhouette score is a measure used to evaluate the quality of clusters created by clustering algorithms like K-means. It provides a way to assess how well each data point fits into its assigned cluster and how distinct the clusters are from each other.

Here's why we used silhouette score:

### Why Silhouette Score?

1. \*\*Quantifies Cluster Quality\*\*: Silhouette score provides a single metric to understand how well each object lies within its cluster and how well-separated the clusters are from each other.

2. \*\*Validating Optimal Number of Clusters\*\*: By calculating the silhouette score for different numbers of clusters (K), we can determine the optimal number of clusters where the score is highest. A higher silhouette score indicates that the object is well-matched to its own cluster and poorly matched to neighboring clusters.

3. \*\*Avoids Need for Labels\*\*: Silhouette score is an unsupervised metric, meaning it does not rely on ground truth labels. This is valuable when working with unlabeled data, as it provides a way to evaluate the quality of clustering without knowing the true groupings.

### Interpretation of Silhouette Score:

- \*\*Score Range\*\*: The silhouette score ranges from -1 to 1. A score closer to 1 indicates that the sample is well-clustered, while a score closer to -1 indicates that the sample is likely in the wrong cluster.

- \*\*Interpretation\*\*:

- 0.71-1.0: A strong structure has been found.

- 0.51-0.70: A reasonable structure has been found.

- 0.26-0.50: The structure is weak and could be artificial.

- <0.25: No substantial structure has been found.

### How we used Silhouette Score:

In the code provided, we computed the silhouette score for a range of cluster numbers (3 to 13 clusters) to find the optimal number of clusters for our K-means clustering. The number of clusters with the highest silhouette score would be chosen as the optimal number of clusters. This helps us verify the elbow method's suggestion of 3 or 4 clusters by providing a more quantitative measure of cluster quality.

Apologies for the confusion. Let's revisit the comparison of Model 1, Model 2, and Model 3 considering XGBoost as the best model among Model 1.

### **Model Comparison**:

#### Model 1:

- \*\*XGBoost\*\*:

- Accuracy Score: 0.9055

- Recall Score: 0.8674

#### Model 2:

- \*\*XGBoost\*\*:

- Accuracy Score: 0.8979

- Recall Score: 0.8646

#### Model 3:

- \*\*RandomForest\*\*:

- Accuracy Score: 0.8880

- Recall Score: 0.8996

### Observations:

- \*\*Model 1\*\*:

- XGBoost had an accuracy of 0.9055 and a recall of 0.8674.

- \*\*Model 2\*\*:

- XGBoost had an accuracy of 0.8979 and a recall of 0.8646.

- \*\*Model 3\*\*:

- RandomForest had an accuracy of 0.8880 and a recall of 0.8996.

### Conclusion:

- Based on the updated comparison, \*\*XGBoost from Model 1\*\* is indeed the best among the three models.

- Model 1's XGBoost provides the highest accuracy and a competitive recall score, making it a good choice for predicting late delivery risk.

- Model 2's XGBoost is also performing well but slightly lower than Model 1.

- Model 3's RandomForest is consistent but has slightly lower performance compared to the XGBoost models in Model 1 and Model 2.

So, considering XGBoost as the best model among Model 1, it is indeed the best choice for predicting late delivery risk.

Hyperparameter tunning using XGBoost

Hyperparameter tuning is a crucial step in optimizing machine learning models for better performance. Boosting is an ensemble learning technique that combines multiple weak learners to create a strong learner. XGBoost (Extreme Gradient Boosting) is a popular and powerful implementation of gradient boosting.

### Hyperparameter Tuning:

- \*\*What is Hyperparameter Tuning?\*\*

- Hyperparameters are parameters that are not directly learned during the training process but are set before training. Tuning these hyperparameters involves searching for the optimal values that yield the best model performance.

- \*\*Significance of Hyperparameter Tuning:\*\*

- Improved Performance: Optimal hyperparameters can significantly improve the model's performance in terms of accuracy, precision, recall, etc.

- Generalization: Tuning helps in finding hyperparameters that generalize well to unseen data, reducing overfitting.

- Efficiency: Properly tuned hyperparameters lead to faster convergence and training times.

- \*\*Benefits of Hyperparameter Tuning:\*\*

- \*\*Better Model Performance:\*\* Finding the right combination of hyperparameters can result in a model that achieves higher accuracy and better generalization.

- \*\*Optimized Regularization:\*\* Hyperparameters like `max\_depth`, `gamma`, and `subsample` control overfitting. Tuning them ensures the model does not learn noise in the data.

- \*\*Improved Robustness:\*\* Tuning helps in making the model more robust to different types of data and unseen scenarios.

### XGBoost and Hyperparameter Tuning:

- \*\*XGBoost Advantages:\*\*

- \*\*Performance:\*\* XGBoost is known for its speed and performance due to its efficient implementation of gradient boosting.

- \*\*Regularization:\*\* It includes built-in regularization techniques to control overfitting.

- \*\*Flexibility:\*\* XGBoost allows tuning of various hyperparameters to customize the model for specific datasets and objectives.

- \*\*Why Use XGBoost for Hyperparameter Tuning?\*\*

- XGBoost is a state-of-the-art machine learning algorithm that often yields better performance compared to other algorithms.

- It provides a wide range of hyperparameters to tune, giving more control over the model.

- The RandomizedSearchCV method helps in efficiently exploring the hyperparameter space to find optimal values.

- \*\*Significance of Hyperparameter Tuning with XGBoost:\*\*

- \*\*Accuracy Improvement:\*\* By fine-tuning the hyperparameters, we can achieve higher accuracy and better performance on the test data.

- \*\*Avoid Overfitting:\*\* Tuning regularization hyperparameters like `max\_depth`, `gamma`, and `subsample` helps in preventing overfitting and improving generalization.

- \*\*Model Stability:\*\* Tuning makes the model more robust and stable, reducing the variance in predictions.

### Code Explanation:

- In the provided code:

- We are using `RandomizedSearchCV` with `xgb.XGBClassifier()` to perform hyperparameter tuning for XGBoost.

- The `param\_distributions` dictionary specifies the hyperparameters to search, along with their ranges.

- `RandomizedSearchCV` will search randomly within these ranges, and `n\_iter` specifies the number of parameter settings that are sampled.

- `cv=5` indicates 5-fold cross-validation.

- After fitting the model with training data (`rs.fit(x\_train, y\_train.values.ravel())`), the best hyperparameters and corresponding mean cross-validated score are printed.

This process allows us to find the best combination of hyperparameters for XGBoost, leading to an optimized and well-performing model for predicting late delivery risk.

The hyperparameters tuned using RandomizedSearchCV for the XGBoost model are as follows:

- \*\*Best Hyperparameters\*\*:

- `subsample`: 0.95

- `n\_estimators`: 100

- `max\_depth`: 3

- `gamma`: 3

- \*\*Best Score\*\*: 0.8575

These are the hyperparameters that were found to yield the best mean cross-validated score during the tuning process. Here's a brief explanation of each hyperparameter:

- `subsample`: Denotes the fraction of samples used to fit the individual base learners. A lower value leads to a more conservative model, while a higher value can improve generalization.

- `n\_estimators`: Specifies the number of boosting rounds or trees to build. Increasing this value may lead to a more complex model, potentially improving performance until it starts to overfit.

- `max\_depth`: Defines the maximum depth of each tree. A deeper tree can model more complex relationships in the data but also increases the risk of overfitting.

- `gamma`: Regularization parameter that controls the minimum loss reduction required to make a further partition on a leaf node. Higher values lead to more conservative models.

The best mean cross-validated score of 0.8575 indicates that the model, when trained with these hyperparameters, achieved an average accuracy score of approximately 85.75% during cross-validation. This suggests that the model's performance improved significantly after tuning the hyperparameters.

The XGBoost model was further tuned using the following hyperparameters:

- \*\*Best Hyperparameters\*\*:

- `n\_estimators`: 400

- `max\_depth`: 4

- `gamma`: 1

After training the XGBoost model with these hyperparameters, the recall scores on the test and train sets are as follows:

- \*\*Test Recall\*\*: 0.8611

- \*\*Train Recall\*\*: 0.8647

These recall scores indicate the proportion of correctly predicted "late delivery risk" instances out of all actual "late delivery risk" instances in the test and train sets, respectively.

The confusion matrix display for the test set shows how the model performed in terms of true positives, true negatives, false positives, and false negatives. This visualization helps in understanding the model's performance at different thresholds.

From these results, we can see that the XGBoost model with tuned hyperparameters achieved a test recall of approximately 86.11% and a train recall of approximately 86.47%. This suggests that the model is effectively capturing a high proportion of "late delivery risk" instances, both in the training and test sets.

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Here are the evaluation metrics for the XGBoost model with the tuned hyperparameters:

- \*\*Train Accuracy Score\*\*: 0.8604

- \*\*Test Accuracy Score\*\*: 0.8526

- \*\*Train Recall Score\*\*: 0.8647

- \*\*Test Recall Score\*\*: 0.8611

These scores indicate the performance of the model on the training and test sets:

- \*\*Accuracy Score\*\*:

- The accuracy score shows the proportion of correctly predicted instances out of all instances. The model achieved an accuracy of approximately 86.04% on the training set and 85.26% on the test set.

- \*\*Recall Score\*\*:

- Recall, also known as sensitivity, is the proportion of correctly predicted "late delivery risk" instances out of all actual "late delivery risk" instances. The model achieved a recall of approximately 86.47% on the training set and 86.11% on the test set.

These results suggest that the XGBoost model with tuned hyperparameters is performing consistently well on both the training and test sets. It's effectively capturing a high proportion of "late delivery risk" instances while maintaining good overall accuracy.

## **business Interpretation :**

* Here we got the consistent result for the Xg Boost after hyper parameter tunning and for business Interpretation recall is very important for us it like actual we late dilvery risk(1) but we predict not late delivery risk (0) so it is False negative that why we want recall score is good.
* Shipping mode: The shipping mode (standard class, same day, and second class) is the most important feature in predicting the risk of late delivery. This suggests that the choice of shipping mode plays a significant role in determining whether an order will be delivered on time or not. Businesses may need to focus on optimizing their shipping processes for different shipping modes to reduce the risk of delays and improve customer satisfaction.
* **Customer ID**: The customer ID is the second most important feature in predicting the risk of late delivery. This suggests that certain customers are more likely to experience delivery delays than others

Yes, your analysis is correct based on the feature importance plot of the XGBoost classifier. Let's break down your interpretation:

### Shipping Mode:

- \*\*Most Important Feature\*\*: The feature importance plot shows that "Shipping Mode" (including standard class, same day, and second class) is the most important feature in predicting the risk of late delivery.

- \*\*Business Implication\*\*: This suggests that the choice of shipping mode significantly impacts whether an order will be delivered on time or not. Different shipping modes have different delivery times and costs associated with them. For example:

- "Same day" shipping might be more expensive but ensures quick delivery, reducing the risk of late delivery.

- "Standard class" shipping might be more cost-effective but could take longer, increasing the risk of delays.

- "Second class" might fall in between in terms of cost and delivery time.

- \*\*Recommendation\*\*: Businesses should analyze their shipping modes' performance, customer preferences, and costs to optimize their shipping strategies. They can adjust shipping options, pricing, or carrier partnerships to reduce late deliveries and improve customer satisfaction.

### Customer ID:

- \*\*Second Most Important Feature\*\*: The feature importance plot also shows that "Customer ID" is the second most important feature in predicting late delivery risk.

- \*\*Business Implication\*\*: This indicates that certain customers are more likely to experience delivery delays than others. There could be various reasons for this, such as:

- Some customers might consistently place orders with tight deadlines.

- Certain customers might have specific delivery requirements or preferences that lead to delays.

- Customer location or shipping address could impact delivery times.

- \*\*Recommendation\*\*: Businesses should analyze the behaviors and patterns of customers with high late delivery risk. They can then tailor communication, service, or shipping options for these customers. For example:

- Proactively communicate shipping timelines and potential delays.

- Offer expedited shipping options or incentives for early ordering.

- Collect feedback from these customers to understand their specific needs and preferences.

### Business Interpretation:

- \*\*Focus on Reducing False Negatives\*\*: Since recall is crucial for the business (as you mentioned), the model's emphasis on shipping mode and customer ID is appropriate. A high recall means the model is effective at identifying most of the actual late delivery risks (True Positives).

- \*\*Mitigating Late Delivery Risks\*\*: The analysis highlights areas where the business can focus its efforts to reduce late deliveries:

- Optimize shipping modes and strategies.

- Tailor services and communication for customers with higher risk.

- Use customer data and feedback to improve delivery processes.

- \*\*Cost Considerations\*\*: While improving delivery times is important, businesses should also balance cost-effectiveness. For example, offering faster shipping might reduce late deliveries but increase costs. It's essential to find the right balance between customer satisfaction and operational costs.

In conclusion, your analysis correctly identifies the key features impacting late delivery risk and provides actionable insights for the business to optimize its shipping processes and customer services. By focusing on these areas, the business can reduce the risk of late deliveries, improve customer satisfaction, and ultimately drive better business outcomes.