Temasek POLYTECHNIC

SCHOOL OF INFORMATICS & IT

Machine Learning for Decision Making

Predicting competitive selling price for products

Student Name (Matric Number): Javen Lai Le Yu (2202934B)

Tutorial Group: P03

Tutor: Zaw Htet Wai

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Declaration of Originality

I am the originator of this work and I have appropriately acknowledged all other original sources used as my references for this work.

I understand that Plagiarism is the act of taking and using the whole or any part of another person's work, including work generated by AI, and presenting it as my own.

I understand that Plagiarism is an academic offence

and if I am found to have committed or abetted the offence of plagiarism in relation to this submitted work, disciplinary action will be enforced.

Describe how you have used Generative AI tools such as ChatGPT or Dall.E-2 in your assignment.

Show snapshots of the conversations with the AI tool (i.e., the prompts you used and the response you get from the AI tool).

1. Problem framing with ChatGPT:

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Problem Statement: "As a data scientist at a retail hypermarket in Singapore, you are tasked with developing predictive models to understand the key drivers of customer engagement and their financial impact for the upcoming quarter. The model should help the business make informed decisions on strategic planning."
Data Dictionary: The dataset contains the following columns:
datetime: The date and time the transaction was made.
customer_id: The ID of the customer who made the transaction.
product_id: The ID of the product involved in the transaction.
category: The category of the product.
unit_price: The unit price of the product.
quantity: The quantity of the product sold // improve the improve statement to be quantifiable and clear and specific

Problem Statement: "As a data scientist at a retail hypermarket in Singapore, your objective is to develop predictive models aimed at comprehending the primary factors influencing customer engagement and assessing their financial implications for the forthcoming quarter. This model should offer actionable insights that assist the business in making well-informed decisions regarding strategic planning."

Data Dictionary: The dataset comprises the following columns:

1. datetime: The date and time at which the transaction occurred.
2. customer_id: The unique identifier of the customer conducting the transaction.
3. product_id: The distinct identifier for the product involved in the transaction.
4. category: The product's category to which it belongs.
5. unit_price: The cost per unit of the product.
6. quantity: The quantity of the product sold during the transaction, expressed as a numeric value, to enable precise measurement and analysis.

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Task: Target for model training and goal for deployment.

For Model Training: "The objective for model training is to optimize predictive accuracy and effectively capture patterns in the data."

For Deployment Goal: "The goal for model deployment is to provide real-time predictions and insights that can support data-driven decision-making for the business."

2. Quality check + Grammar improvements and phrasing to make explanations fluent:

22 does it completely answer the problem statement

The revised problem statement provides a more detailed and specific focus on predicting customer spending behavior and product purchases, which is a key aspect of the original problem statement. However, it doesn't explicitly address the "key drivers of customer engagement" and their "financial impact" as mentioned in the original statement. To fully align with the original problem statement, you should include the analysis of key drivers of customer engagement and how these drivers relate to the financial impact on the business. Here's a more comprehensive revision:

"Develop predictive models to understand the key drivers of customer engagement and their financial impact by analyzing customer spending behavior across various product categories. These models aim to predict the quantity and financial value of products customers will buy for the upcoming quarter. The insights generated should help the business make informed decisions for strategic planning, considering both customer engagement and financial implications."

22 To develop models that predict the quantity that will be bought by a customer for a product. The models should help business analysts gauge the performance of a product before launch, thereby allowing strategic planning and informed decision making. rephrase

Revised Statement: "Our goal is to create predictive models that estimate the quantity of a product a customer will purchase. These models will empower business analysts to assess a

3. Fact checking:

22 B) One-way ANOVA: Nominal-Ratio what would my hypotheses be

In a one-way ANOVA with a nominal independent variable (e.g., categories or groups) and a ratio-dependent variable (e.g., quantity, unit price), you typically have the following hypotheses:

Null Hypothesis (H0):

- H0: There is no significant difference in the means of the dependent variable (e.g., quantity or unit price) among the different categories or groups.

Alternative Hypothesis (Ha):

- Ha: There is a significant difference in the means of the dependent variable among at least one pair of categories or groups.

In other words, the null hypothesis assumes that all category means are equal, while the alternative hypothesis suggests that at least one pair of category means is significantly different from each other.

4. Generating Code to solve data structures and algorithms problem + Debugging:

```
def evaluate_model(model, X, y):
  y_pred = model.predict(X)  # Predict using the model and predictors

  print(f"R-squared (Goodness of Fit): {r2_score(y, y_pred):.2f}")

  # for Linear Regression
  if hasattr(model, 'intercept_') and hasattr(model, 'coef_'):
    intercept = model.intercept_[0]
    coefficients = model.coef_[0]

    print(f"Intercept: {intercept:.2f}")
    print("Coefficients:")
    # print the intercept name: value // this part isnt working as intended
    for feature, coef in zip(X, coefficients):
      print(f"{feature}: {coef:.2f}")

  # for Decision Tree Regressor
  elif hasattr(model, 'feature_importances_'):
    feature_importance = model.feature_importances_

    print("Feature Importance:")
    for feature, importance in zip(X.columns, feature_importance):
      print(f"{feature}: {importance:.2f}")

  # catch error
  else:
    print("Model type not supported for obtaining coefficients or feature importance.")
```

1. Introduction

1.0 Business Context

Retail Hypermarket is a Singapore-based thrift store, operating on a unique business model that customizes prices of products for different customers. Their strategy focuses on competitive pricing to attract customers and build customer relationships. They **offer customized prices based on factors like customer loyalty, bulk purchasing, and buying multiple products simultaneously**.

However, the **fairness of their pricing methods is questioned by some customers** after they saw other customers buying the same product for a cheaper price. This sparked outrage, causing them to boycott the store for biases towards certain people, and insisting on a discount or abandoning the purchase. After receiving such threats, Retail Hypermarket is worried about a potential loss of customers and decreased revenue.

Hence, I am engaged as a data scientist to build predictive models that:

- Understands how Retail Hypermarket sets their prices for different customers and products.
- Estimates the most reasonable pricing of a product for a customer, free from any bias.

This model allows my client to justify to customers on how the prices are derived, allowing for a fair and data-driven way for setting prices. This initiative aims to retain customers who might consider boycotting the store due to perceived pricing bias, ultimately maintaining the store's financial performance.

1.1 Problem Statement

To develop predictive models that account factors like product type, customer type, volume of purchase, and market trends to **determine the most optimal price for a product**. The model will be implemented in the next quarter, aiming to provide consistent and unbiased pricing for products.

1.2 Objective

The models are trained to **predict the unit price of a product for a transaction** based on customer behavior (bulk purchaser, loyal customer, buys multiple different products at once) and market trends.

1.3 Goal for deployment

1.3.1 Whitebox:

- Highly interpretable
- Rationale behind how the model derives a prediction can be clearly understood.

1.3.2 Blackbox:

- Predictions are highly accurate.
- Rationale behind how the model derives its prediction can be understood.

1.4 Inputs for Models

Target: Unit Price

Potential predictors:

- Product category
- Product type
- Customer type
- Quantity of purchase
- How many different products are bought
- Season (Month, Quarter): To capture market trend for different periods of the year.

1.5 Considerations

- Predictors should be readily available before occurrence of prediction.
- Data used to train models should be recent, to ensure the patterns and intricacies the model works on matches the current trend. This makes the model usable as the predictions are reliable.
- Models should be well-generalized to predict unseen future occurrences with similar accuracy as training dataset; no overfitting on training data.
- Models should adhere to AI ethics and regulations, ensuring transparency, fairness, absence of bias, and non-discrimination.

1.6 Metrics for Model Evaluation

1.6.1 **Goodness of Fit: R^2** to analyse how well to predictions can be explained by the predictor values, to assess if the patterns and intricacies of how customers engage in purchase of various products has been captured by model.

1.6.2 **Accuracy: Mean Absolute Percentage Error (MAPE)** to assess the accuracy percentage of an average prediction compared to the actual value.

As unit price can range from cents to thousands of dollars, MAPE is the most suitable measure for assessing the accuracy of a model's prediction in a clear and meaningful way for the nature of the models' target because it provides a relative measure of prediction accuracy, rather than a definitive error value to fit all ranges of prediction.

1.7 Success Criteria for Project

- Deploy **1** predictive model to be presented to Retail Hypermarket for usage.
- Before deployment, a model's MAPE should be below 20%, indicating a prediction accuracy of at least 80% to be considered as 'good forecasting' hence acceptable for business usage. The accuracy should not be 100% as this likely indicates overfitting.
- Model fit should be above 85%, to affirm model is explainable and its decisions are closely based off truth of historical data; no underfitting, hence reliable.
- Goal of deployment (1.3) should be fulfilled.
- The black-box model should outperform the white-box model by a noticeable margin of minimally 5% if chosen for deployment, to ensure the choice of the more complex model is justified by significantly improved accuracy.
- The models **should NOT be prone to underpredict prices** as this could lead to financial losses for my client when they have to sell a product underpriced.
- Overpredictions are not an issue. In fact, it could be beneficial because Retail Hypermarket Staff could reduce a predicted price if possible. Deducting a discount from the predicted price would make customers feel like they are getting a better deal, making them satisfied. However, I should not intentionally modify my model to overpredict as this may lead to customers questioning the trustability of the model.

1.8 Environment

- New Products and Customers: The model should also work for new products and customers not in training dataset. This ensures usability of models sustainable for future usage.
- Economic Status: Customer interests and spending behaviour may change during recessions or economic boom. These trends may not be captured and identified if they are not within the training dataset.
- Market Trends: The market trend and customers' spending behavior can change rapidly in this fast-paced society, and may differ from the training data.
- Seasonal changes: Unprecedented events like a virus outbreak, unexpected intense rainfall or scorching weather period, may deter customers from visiting Retail Hypermarket, resulting financial performance that cannot be explained by the models.
- Competition: New retail companies may emerge in the future and influence customers' decision on whether to patronize Retail Hypermarket, and the models are unable to account for such external factors.

In summary:

1. The training dataset must be recent and reflective of current trends and customer behaviour.
2. The Model's code and documentations should be clear, easy to understand, and adaptable for future modifications (e.g. changing dataset, random_state).

1.9 Target leakage

Do not include:

- **Features not available at the time of prediction** as this makes the model unusable as the business would not have access to such information when making pricing decisions. E.g. Year.
- **Features directly related unit price** to prevent multicollinearity issues.
- **Features with unrealistically high collinearity with unit price**, which could be derived from the target and bias the model.
- **High cardinality columns** like ID to prevent overfitting and ensure model generalization with new, unseen data.
- **Multicollinearity should be avoided** as it leads to reduced model interpretability, unstable coefficient estimates, increased standard errors, misleading feature importance, and difficulty in identifying the true drivers of a prediction.

2. Data Attributes

2.1 Data Understanding

The dataset 'synthetic_data.csv' was provided by Retail Hypermarket, which contains the company's transaction records from 2022 onwards. A data dictionary, attached below, has also been provided for understanding what each column represents.

Data Dictionary: The dataset contains the following columns:

datetime: The date and time the transaction was made.
customer_id: The ID of the customer who made the transaction.
product_id: The ID of the product involved in the transaction.
category: The category of the product.
unit_price: The unit price of the product.
quantity: The quantity of the product sold.

2.2 Data Inspection

2.2.1 Importing libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

SEED = 2202934 # admin number for random_state
```

2.2.2 Loading csv into DataFrame

In [2]:
```
df = pd.read_csv('synthetic_data.csv')
print("Number of observations: ", len(df)) # count rows in df
```

```
Number of observations:  331664
```

There is sufficient data of 300K+ rows for train test splitting.

2.2.3 Exploring Dataset

In [3]:
```
pd.set_option('display.float_format', '{:.10f}'.format) # show full unit_price
df.head()
```

Out[3]:

	Datetime	Product_ID	Category	Quantity	Unit_Price	Customer_ID
0	2022-01-07	10106959	Stationery	9	1.5798753892	a225207859
1	2022-01-09	90097406	Sports	4	196.2533774599	a225207859
2	2022-01-10	10010465	Electronics	1	825.3742907058	a225207859
3	2022-01-14	10010510	Electronics	2	325.9650346646	a225207859
4	2022-01-16	40049430	Books	1	22.6019194627	a225207859

In [4]:
```
df.tail()
```

Out[4]:

	Datetime	Product_ID	Category	Quantity	Unit_Price	Customer_ID
331659	2022-12-18	20026116	Groceries	5	5.3781616834	c891387366
331660	2022-12-23	10018925	Electronics	1	1193.8285186999	c891387366
331661	2022-12-27	20022820	Groceries	3	5.1754917125	c891387366
331662	2022-12-27	40042985	Books	2	38.5985362367	c891387366
331663	2022-12-31	20025163	Groceries	3	5.3977440791	c891387366

Evaluation:

1. **Datetime is missing time**. There is nothing that can be done about missing time as I am only provided with this dataset.

2. There is **no columns like Quarter or Month**. However, these seasonality features can be derived from the date in Datetime.

3. Unit_Price is a non-terminating number, which is strange as its unconventional for prices at supermarkets to go beyond cents. Hence, **Unit_Price should be rounded off to 2 d.p.**

4. The records seem to be in **time-series**, and ends at 31 December 2022? (Continued at 2.3.2.b)

2.2.4 Are there duplicated records?

In [5]:
```
df.duplicated(subset=['Datetime', 'Customer_ID']).sum() # sum up number of dup
```

Out[5]:
```
29362
```

This indicates that **there are customers who make multiple transactions a day**. To check if there are duplicated records, I should factor in Product_ID as a customer probably wouldn't buy the same product again on same day.

In [6]:
```
df.duplicated(subset=['Datetime', 'Customer_ID', 'Product_ID']).sum() # sum up
```

Out[6]:
```
0
```

There are **no duplicated records in dataset**.

2.2.5 Check for data types and missing values

In [7]:
```
pd.set_option('display.float_format', '{:.3f}'.format) # revert df to round of
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 331664 entries, 0 to 331663
Data columns (total 6 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Datetime     331664 non-null  object 
 1   Product_ID   331664 non-null  int64  
 2   Category     331664 non-null  object 
 3   Quantity     331664 non-null  int64  
 4   Unit_Price   331664 non-null  float64
 5   Customer_ID  331664 non-null  object 
dtypes: float64(1), int64(2), object(3)
memory usage: 15.2+ MB
```

Takeaways:

1. No missing values for any columns.
2. Datetime column is not in date format.

2.2.6 Summary statistics

In [9]:
```
df.describe().loc[['min', 'mean', 'max']]
```

Out[9]:

	Product_ID	Quantity	Unit_Price
min	10010000.000	1.000	1.001
mean	30263284.237	9.125	124.090
max	90099999.000	20.000	1199.947

In [10]:
```
df.nunique()
```

Out[10]:
```
Datetime          368
Product_ID      75781
Category           10
Quantity           20
Unit_Price     331664
Customer_ID      2648
dtype: int64
```

Takeaways:

1. All Product_IDs are 8 char.
2. Every transaction can only involve 1 to 20 of the same product.
3. Cheapest product is 1 dollar and most expensive is 1200 dollars. An average product costs 124 dollars per unit.
4. There are 10 types of product Category.

2.2.7 Do Products have a fixed unit price

In [11]:
```
Product = df.sort_values(by=['Product_ID'])
Product.head(4)
```

Out[11]:

	Datetime	Product_ID	Category	Quantity	Unit_Price	Customer_ID
126708	2022-05-22	10010000	Electronics	2	850.915	a704811449
326206	2022-05-26	10010000	Electronics	2	357.381	c567078712
173955	2022-09-06	10010000	Electronics	1	495.939	c849466466
105432	2022-11-07	10010000	Electronics	1	791.225	d703549797

Analysis:

Price of product changes over time. This validates the business context that the prices change

2.3 Data Cleaning

2.3.0 Rectifications based on Data Inspection:

1. Round off Unit_Price to 2 d.p.
2. Parse Datetime into date format.
3. Features extraction on Date to create Quarters.

2.3.1 Unit_Price:

In [12]:
```
df['Unit_Price'] = round(df['Unit_Price'], 2)
```

2.3.2.a Parsing Datetime:

In [13]:
```
df['Datetime'] = pd.to_datetime(df['Datetime'])
```

2.3.2.b Confirmation in data is in time-series

In [14]:
```
df.sort_values(by='Datetime', inplace=True)
df.tail(8)
```

Out[14]:

	Datetime	Product_ID	Category	Quantity	Unit_Price	Customer_ID
48824	2023-01-03	50056627	Furniture	1	927.850	a793237418
150571	2023-01-03	70070603	Toys	9	24.140	d407005726
151609	2023-01-03	40041605	Books	3	5.020	a166502882
77889	2023-01-03	90093200	Sports	2	33.040	a253267567
200653	2023-01-03	70077230	Toys	3	8.880	a731741739
115899	2023-01-03	50050749	Furniture	2	985.720	a555546365
229742	2023-01-03	10012069	Electronics	1	1112.050	d112052977
95489	2023-01-03	30030537	Clothing	5	24.710	b004263214

Analysis:

- It's strange that these transactions were placed randomly within the 2022 dataset rather than at the end of the dataset as expected.
- This raises concerns about the reliable of the Datetime column, especially when the time values are missing from this column.

Evaluation:

- The Datetime for 2023 records may be incorrect as these records do not follow the typical pattern of transactional record systems where new transactions are found at the end of the dataset.
- Since there are 300K rows of data, sufficient for training and validating the model, I shall exclude the 2023 records and train my model solely on 2022 data due to suspicions in reliability of 2023 records: because time is missing from Datetime, its possible that this column has problems.
- However, 2023 records could be used for testing of models.

In [15]:
```
df_test = df[df['Datetime'].dt.year == 2023]
df = df[df['Datetime'].dt.year != 2023]
```

In [16]:
```
len(df_test)
```

Out[16]:
```
386
```

2.3.3 Quarter:

Customer spending behavior can varies across seasons, hence I will create this column to allow user to predict prices for different quarters of the year.

In [17]:
```
df['Quarter'] = df['Datetime'].dt.to_period('Q').astype(str).str[-1]
# Only need the Quarter number, hence index last number in Quarter
```

2.4 Exploratory Data Analysis (EDA)

2.4.1 Examine df:

In [18]:
```
df.sample(12) # randomly sample df to analyse data
```

Out[18]:

	Datetime	Product_ID	Category	Quantity	Unit_Price	Customer_ID	Quarter
198868	2022-11-25	10011523	Electronics	1	584.240	b640406944	4
268551	2022-09-16	80085024	Health & Beauty	10	15.810	c811621255	3
296265	2022-04-20	20022061	Groceries	20	13.630	a802312729	2
302813	2022-01-27	20027605	Groceries	4	7.110	c743592899	1
197759	2022-10-01	20020395	Groceries	12	15.070	a468927639	4
182543	2022-03-21	20024903	Groceries	2	8.860	a064716817	1
28099	2022-02-07	20026802	Groceries	16	16.670	a827822986	1
272796	2022-06-01	70078756	Toys	5	12.940	c431059167	2
285446	2022-06-29	20025031	Groceries	14	10.470	b319666381	2
124281	2022-03-27	20029923	Groceries	3	8.250	c027999838	1
271003	2022-05-06	20025219	Groceries	12	7.580	b852893984	2
185703	2022-03-19	10018720	Electronics	1	480.650	d109852895	1

2.4.2 EDA Graph Plotter:

In [19]:
```
def eda_plot(df, category, measure, plot_type='line', measurement='sum'):
    category_revenue = df.groupby(category)[measure].agg(measurement)     # Aggı
    plt.figure(figsize=(16, 6))                                           # Set

    # Toggle to the selected chart
    if plot_type == 'line':
        plt.plot(category_revenue.index, category_revenue.values, marker='o', ]
        plt.grid(True)                                                    # turı

    elif plot_type == 'bar':
        category_revenue = category_revenue.sort_values(ascending=False) # Sor
        plt.bar(category_revenue.index, category_revenue.values)

    else:
        print("Invalid plot_type. Please use 'line' or 'bar'.")          # err
        return

    # Remove '_' for easier readibility of legends
    measure = measure.replace('_', ' ')
    category = category.replace('_', ' ')

    # Add labels above the data points
    for x, y in zip(category_revenue.index, category_revenue.values):
        plt.text(x, y, f'{y:.2f}', ha='center', va='bottom')

    plt.title(f'{measurement.capitalize()} {measure} per {category}')
    plt.xlabel(category)
    plt.ylabel(measure)
    plt.xticks(category_revenue.index)
    plt.show()
```

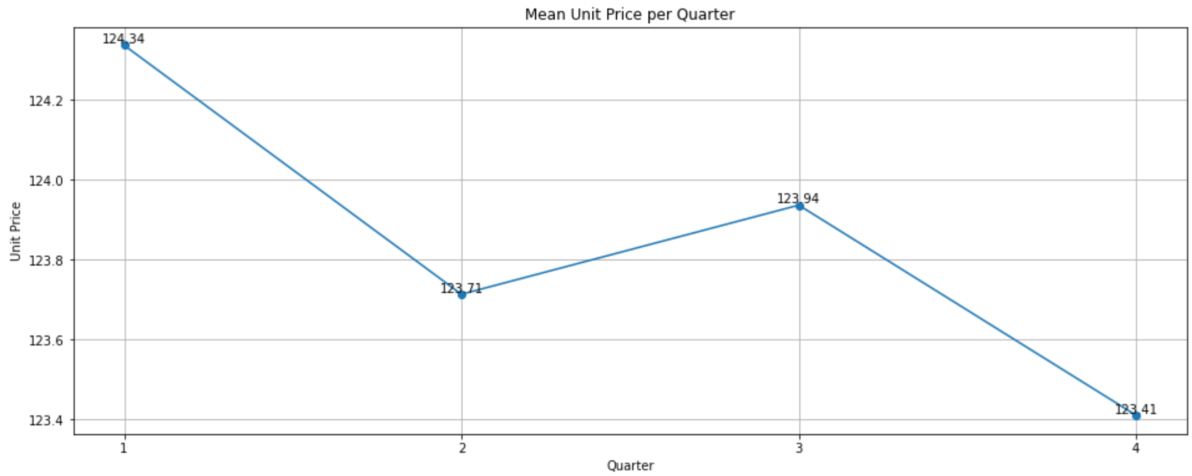
Usage:

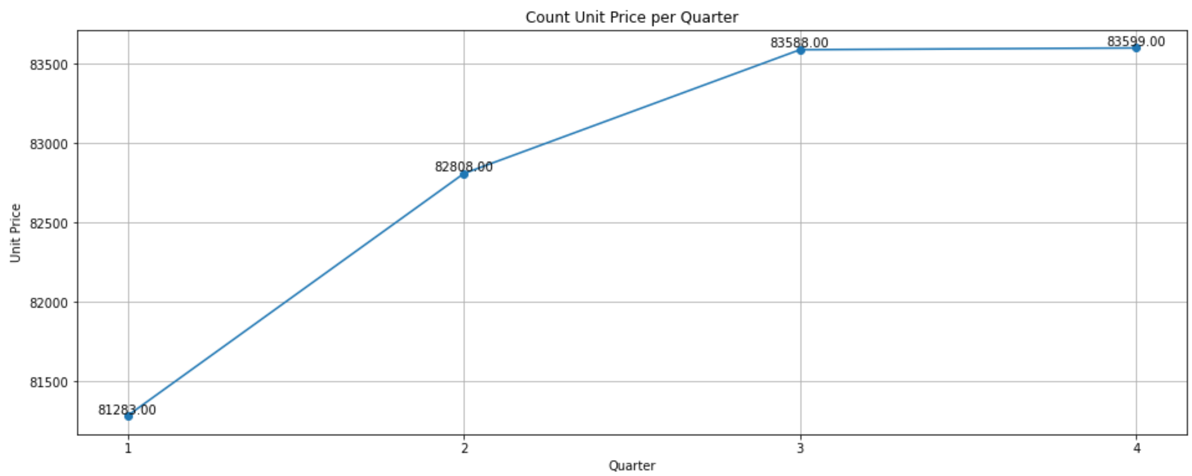
> eda_plot(DataFrame, [Column in df], [measure, must be numerical], plot_type=[Type of Plot, line or bar, default=line], measurement=[measurement, sum/mean/median. default=sum])

2.4.3 Average Unit Price per Quarter

- Is there a discernable spending pattern for each quarter?

In [20]:
```
eda_plot(df, 'Quarter', 'Unit_Price', measurement='mean')
eda_plot(df, 'Quarter', 'Unit_Price', measurement='count')
```





A) Analysis:

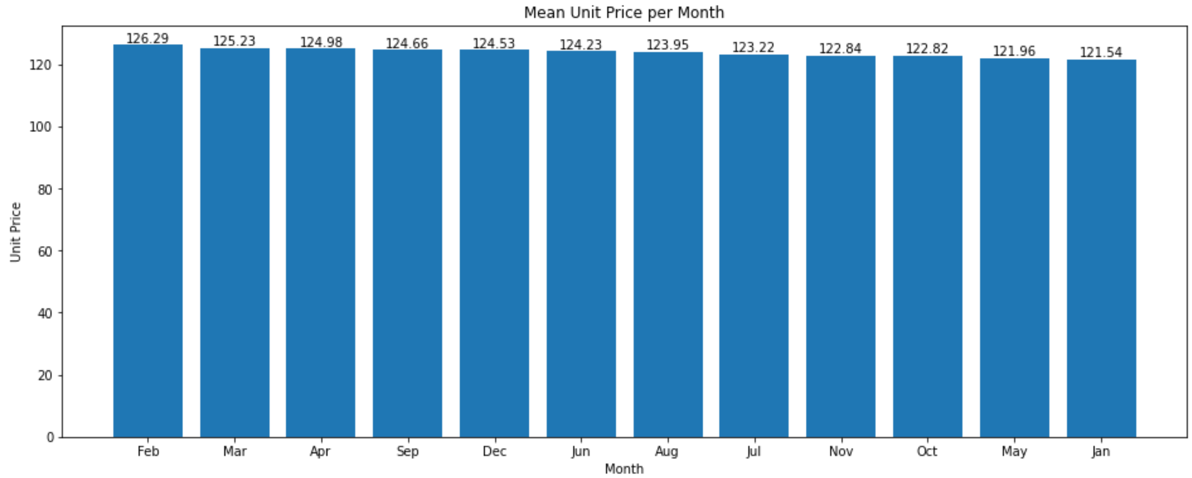
1. There are variation in average unit price for all quarters are very minimal (1 dollars range).
2. There are more transactions during Q3 and Q4.

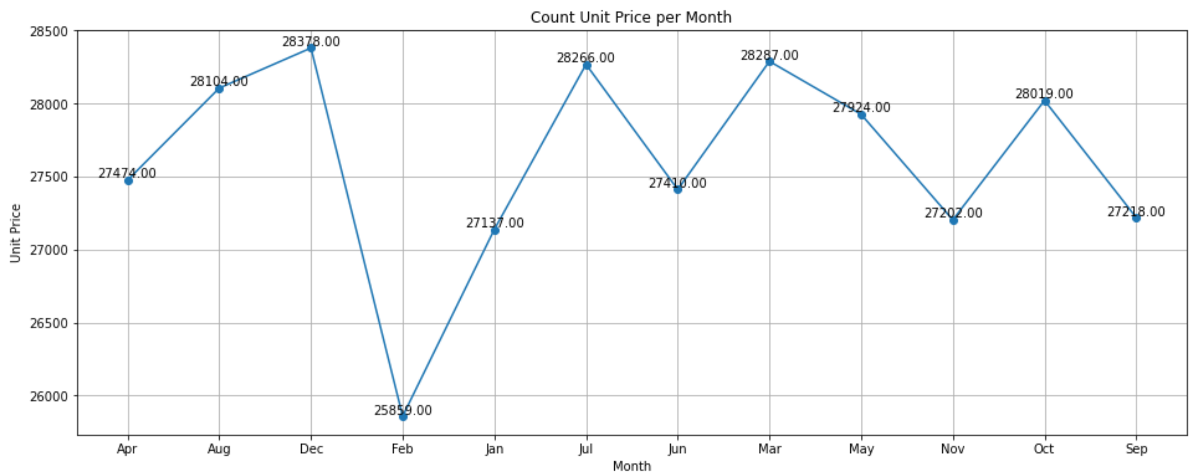
B) Evaluation:

There can be an argument that there are lesser customers during Q1 due to higher prices. To validate this assumption, I need to delve deeper.

C) Further Investigation:

In [21]:
```
# Create the 'YY-MMM' column
df['Month'] = df['Datetime'].dt.strftime('%b')
eda_plot(df, 'Month', 'Unit_Price', 'bar', measurement='mean')
eda_plot(df, 'Month', 'Unit_Price', measurement='count')
```





D) Analysis:

- Customers buy expensive products on Feb, but Feb has the least customer transactions.
- August, December, July, and March are the months Retail Hypermarket can expect the most customer activities.

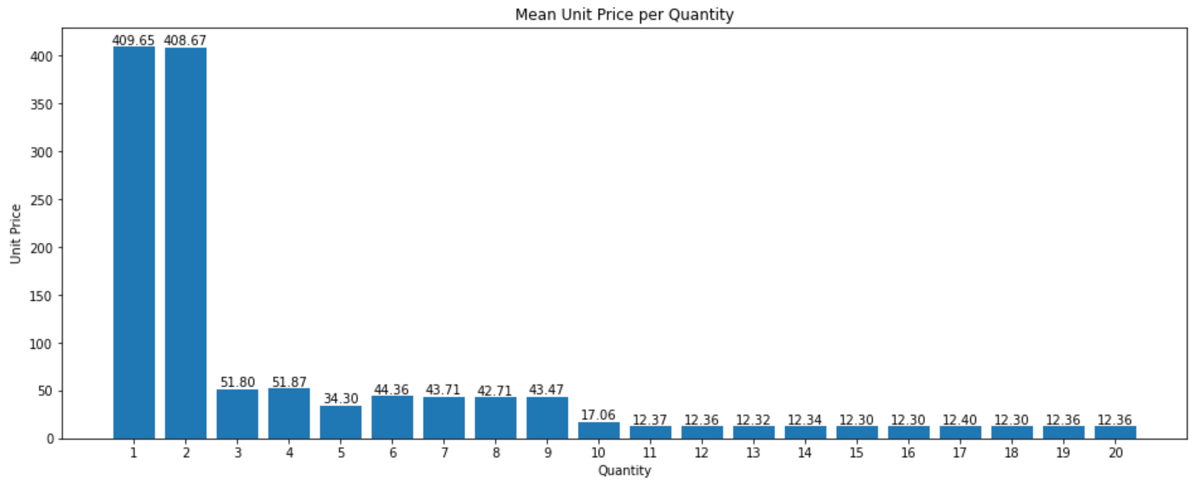
E) Conclusion:

- Higher prices could deter customers from engaging with purchases as proven by Feb.
- Quarter is quite a weak predictor, but month could be a strong predictor.

2.4.4 Relationship between quantity and quality

- Do customers purchase more when products are cheaper or buy fewer when prices are higher?

In [22]:
```
eda_plot(df, 'Quantity', 'Unit_Price', 'bar', measurement='mean')
```



A) Analysis:

1. Each transaction can have a quantity of 1 to 20 of a product.
2. 3 Classes observed:
    - Customers usually only buy 1-2 of an expensive product.
    - Customers buy 3-9 of a mid-range priced product.
    - Customers buy cheap products below 20 dollars in bulks of 10-20.

B) Evaluation:

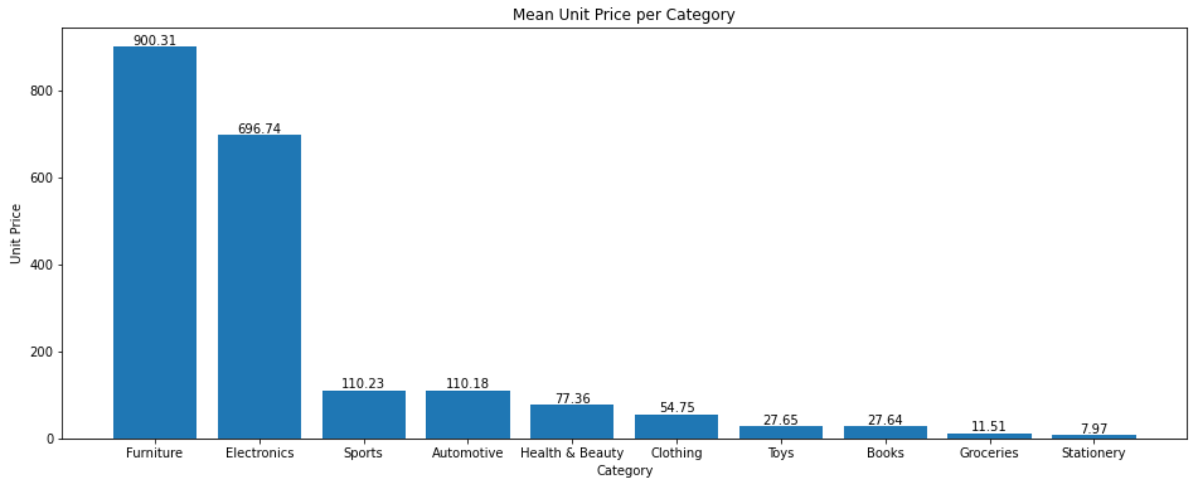
Discounts isn't the explanation for customers to buy more of a product as a discount of 88% (350/400) is illogical.

C) Conclusion:

- Quantity is a potential predictor because there is a distinguishable pattern.
- My hypothesis is that the product is the most significant determiner for the price. To validate this assumption, I shall perform EDA for Product Category.

2.4.5 Price of products across categories

In [23]:
```
eda_plot(df, 'Category', 'Unit_Price', 'bar', 'mean')
```



A) Analysis

It's clear that Furniture an Electronic products are significantly more expensive on average.

B) Evaluation

- The previous graph now makes sense. It's logical for Customers to purchase groceries and stationery in bulk, Clothing and Toys in moderate volume, and just 1-2 Furniture or Electronics at a time.
- A potential concern is that there may be low-cost items like earpieces within the electronics category. To address this, a robust feature is needed to distinguish affordable products within expensive categories or vice versa.
- It's worth noting that there may be multicollinearity between the quantity of items purchased and the product category since the behavioural patterns explain each other.

C) Conclusion

Category is a useful predictor because there is an observable pattern.

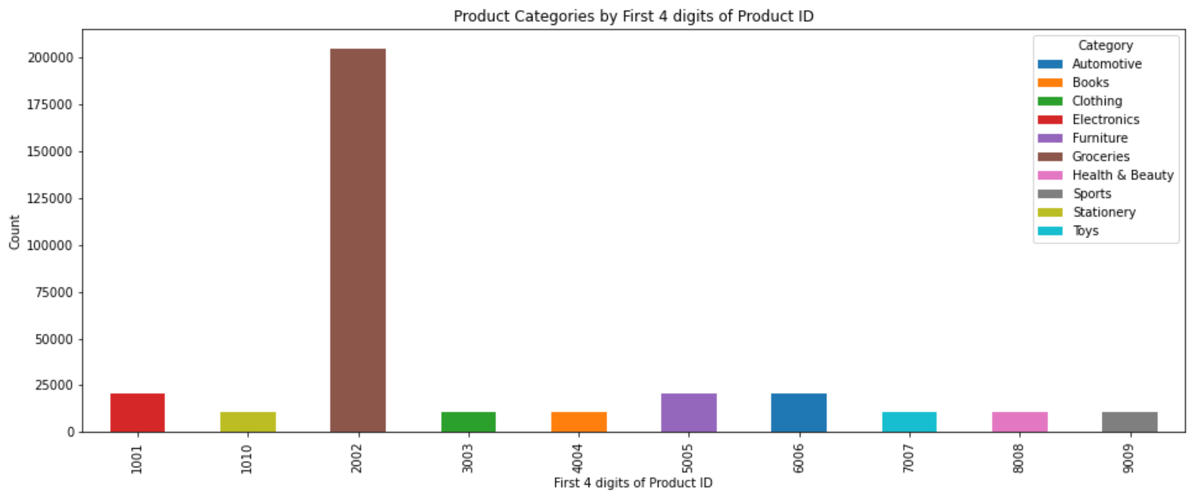
2.4.6.a Exploring relationship between Category and Product_ID

From 2.4.1, I discovered that the first 4 digits could represent something. To clarify my assumption, I shall investigate through visualisation.

In [24]:
```
# Extract the first digit from 'Product_ID' and create a new column 'First_Dig
df['4_digits'] = df['Product_ID'].astype(str).str[0:4]

# Group data by 'First_Digit' and 'Category' and count the occurrences
grouped = df.groupby(['4_digits', 'Category']).size().unstack(fill_value=0)

# Create a bar plot to visualize the relationship
grouped.plot(kind='bar', stacked=True, figsize=(16, 6))
plt.title("Product Categories by First 4 digits of Product ID")
plt.xlabel("First 4 digits of Product ID")
plt.ylabel("Count")
plt.show()
```



In [25]:
```
df.Product_ID.nunique() # count of distinct values
```

Out[25]: 75725

A) Analysis

- First 4 digits of Product ID represents the category.
- Groceries are the most common products sold in Retail Hypermarket.

B) Evaluation

- There is no anomalous products that do not belong to a category.
- There are too many product IDs; high cardinality column.

2.4.6.b Could Product Type be within Product_ID?

Since product category could be found within Product_ID, could the Product_ID also tell us what type of product it is?

In [26]:
```
df['Product_ID'].nunique() # how many product ids are there
```

Out[26]: 75725

In [27]:
```
# Extract the 5th to 6th digits from the 'Product_ID'
df['Product_Type_1'] = df['Product_ID'].astype(str).str[4:6]

# Extract the 5th to 6th digits from the 'Product_ID'
df['Product_Type_2'] = df['Product_ID'].astype(str).str[6:9]
```

In [28]:
```
df['Product_Type_1'].nunique()
```

Out[28]: 100

In [29]:
```
df['Product_Type_2'].nunique()
```

Out[29]: 100

In [30]:
```
# How unique variations of products
df['Product_Type_3'] = df['Product_ID'].astype(str).str[4:9]
df['Product_Type_3'].nunique()
```

Out[30]: 10000

C) Assumptions

1.

- Product_Type_1 could represent the product type; what the product is.
- Product_Type_2 could represent the brand of the brand.

2.

Last 4 numbers could just be random variations to identify a product.

D) Conclusion

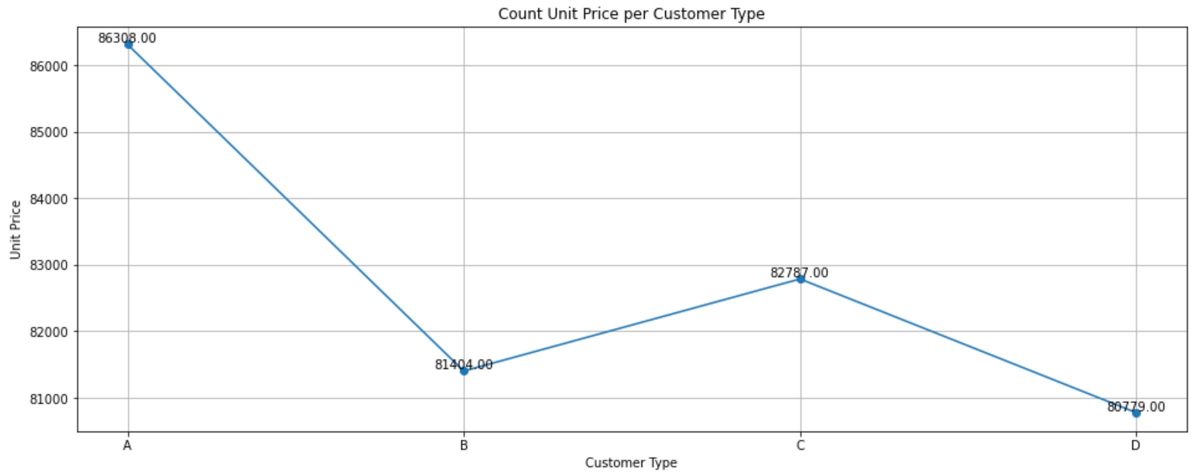
- Do not use Product ID as it could overfit model due to high cardinality.
- **Risky to use Product Types** as I'm unable to validate what they represent. Hence, it could violate the requirements of 'Need to be usable for new products' and it could also potential overfit the model due to high cardinality.

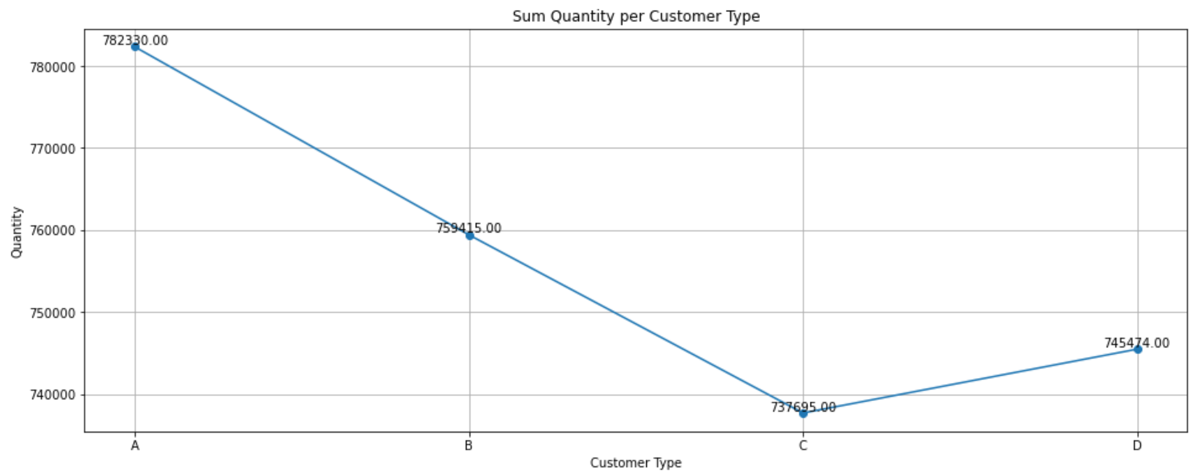
2.4.7 Customer analysis

- I suspect a similar pattern with Customer ID where Retail Hypermarket labels their customer and puts the customer type as the header of the ID. Hence, I investigated each customer class.

In [31]:
```
# Extract the first letter from 'Customer_ID' and create a new column 'Customer
df['Customer_Type'] = df['Customer_ID'].str[0].str.capitalize()

eda_plot(df, 'Customer_Type', 'Unit_Price', 'line', 'count')
eda_plot(df, 'Customer_Type', 'Quantity', 'line', 'sum')
```





A) Analysis

- Around 80K customers for each customer type; no class imbalance in customer type.
- First letter of Product ID represents the customer class.
- There is a discernable pattern between Customer Type and the quantity of products they buy.

B) Evaluation

- Type A customers are clearly the most loyal group of customers who frequent Retail Hypermarket and buy the most products, while type C customers buy the least products.
- D seems to represent customers who are not yet grouped, which could indicate that they are newer customers.

C) Conclusion

- Customers are grouped based on how much products they buy, customers who buy a lot are valued higher with A type, and customers who buys few products are labelled as C. D

represents new customers who are yet to be assigned into a group.
- Type A customers are the best customers in loyalty and buying the most products.
- Customer Type has interesting trends, and could be a useful predictor for models to study the intricate patterns of each customer type.

3. Modelling

3.0 Reusable Methods

3.0.1 Importing libraries

In [32]:
```
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_squared_error
from sklearn import tree
import numpy as np
```

3.0.2 Partitioner

To split dataset into train-test sets

Usage:

Provide DataFrame, target column, train size, and whether the predictors should be normalized for interepretability.

In [33]:
```
def partition(X, y, train_size=0.7, SEED=SEED, normalize=True):
    if normalize:
        scaler = StandardScaler()   # init scaler
        X = scaler.fit_transform(X)

    # Split the normalized data into train and test sets
    X_train, X_val, y_train, y_val = train_test_split(X, y, train_size=train_s

    return X_train, X_val, y_train, y_val
```

3.0.3 Model Evaluator

Report on model's fit and how predictors explain prediction.

Usage:

Provide the trained model, Predictors DataFrame, Target DataFrame, original Predictors DataFrame (to obtain column names), are you evaluating with model's training dataset? [True/False] default=False, max_depth=[display branches to which level].

In [34]:
```
def evaluate_model(model, X, y, cols, training=False, max_depth=3):
    y_pred = model.predict(X)  # Predict using the model and predictors

    # Only runs for Linear Regression, when intercept_ is found in model
    if hasattr(model, 'intercept_') and training:
        print(f"Intercept: {model.intercept_:.2f}")
        print(pd.DataFrame(model.coef_, cols.columns, columns=["Coefficient"])

    # for black-box models like DTR
    elif hasattr(model, 'feature_importances_') and training:
        # visualize Tree
        plt.figure(figsize=(16,20))
        tree.plot_tree(model, feature_names=list(X_train.columns), max_depth=m

    elif hasattr(model, 'intercept_') or hasattr(model, 'feature_importances_'
        pass  # if testing set, no need to report on features

    # catch error
    else:
        print("Model type not supported for obtaining coefficients or feature 


    # Visualize the fit
    plt.figure(figsize=(16, 6))
    plt.scatter(y, y_pred, alpha=0.2)
    plt.xlabel("Actual Values")
    plt.ylabel("Predicted Values")
    plt.title("Actual vs Predicted Values")
    plt.grid(True)
    plt.show()

    print(f"R-squared (Goodness of Fit): {r2_score(y, y_pred):.2f}")
```

3.0.4 Accuracy Evaluator

Creates relevant assessments to report on a model's performance.

Usage:

Provide the trained model, Predictors DataFrame, Target DataFrame, sample size for visualization.

In [35]:
```
def evaluate_accuracy(model, X, y, sample_size=0):
    y_pred = model.predict(X)  # Predict using the model and predictors

    # formula to calculate MAPE
    n = len(y)
    mape = (1/n) * sum(abs((y - y_pred) / y) * 100)
    print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")

    # Visualize Accuracy
    if sample_size > 0:
        y = y.iloc[:sample_size] # subset y into sample size specified
        y_pred = y_pred[:sample_size]

    else:
        return # if no sample size = no need sampling analysis, end the functi

    print("Sampled Analysis:")
    plt.figure(figsize=(16, 6))
    plt.plot(y.reset_index(drop=True), "red", label='Actual Data')
    plt.plot(y_pred, 'blue', label='Predicted Data', alpha=0.5)

    plt.ylabel('Unit_Price')
    plt.title('Actual Vs Predicted')
    plt.legend()
    plt.show()

    # formula to calculate MAPE
    n = len(y)
    mape = (1/n) * sum(abs((y - y_pred) / y) * 100)

    print(f"MAPE for sample: {mape:.2f}%")
```

3.1 Data Pre-processing

3.1.0 Encoders

Original columns will be dropped after encoding.

1. One-Hot Encoder:

In [36]:
```
# One-Hot Encoding
def one_hot_encode(df, columns_to_encode):
    one_hot = pd.get_dummies(df[columns_to_encode])         # Create new col fo
    df = pd.concat([df, one_hot], axis=1)                   # Concatenate enco
    df = df.drop(columns=columns_to_encode)                 # Drop cols after 

    return df
```

Input: DataFrame, [encode_col1, encode_col2]

2.a Label Encoder:

In [37]:
```
from sklearn.preprocessing import LabelEncoder

def label_encode(df, columns_to_encode):
    label_encoders = {}     # Dictionary to store label encoders for each colu
    df_encoded = df.copy()  # Create a copy of the DataFrame to avoid modifyin

    for col in columns_to_encode:
        label_encoder = LabelEncoder()                               # Init th
        encoded_data = label_encoder.fit_transform(df_encoded[col])  # Fit and
        df_encoded[col + '_encoded'] = encoded_data                  # Add the

        label_encoders[col] = label_encoder                          # Store t
        df_encoded.drop(col, axis=1, inplace=True)                   # Drop th

    return df_encoded, label_encoders
```

Input: DataFrame, [encode_col1, encode_col2]

2.b Label Decoder:

In [38]:
```
def label_decoder(label_encoders):
    for col, encoder in label_encoders.items():
        print(f"Label values for {col}: {encoder.classes_}") # map out cols an
```

3.1.1 Extract relevant features for Model's DataFrame:

In [39]:
```
df.head(1)
```

Out[39]:

	Datetime	Product_ID	Category	Quantity	Unit_Price	Customer_ID	Quarter	Month	4_d
269220	2022-01-01	20028680	Groceries	15	10.140	c918818917	1	Jan	

Do not use columns:

1. Datetime:

- Target Leakage: future value.
- High cardinality and leads to overfitting.

2. Product_ID:

- Violates business requirement: Model must work for new unseen values.
- High cardinality and leads to overfitting.

3. Customer ID:

- Violates business requirement: Model must work for new unseen values.
- High cardinality and leads to overfitting.

4. First 4 digits of Product_ID:

- Same meaning and value as category, leading to multicollinearity.

5. Quarter and Month:

- For baseline model, it's common to start with a simpler model without engineered features to establish a baseline model's performance before adding complexity.

In [40]:
```
# Subset a predictors and Target into DataFrames for modelling
X = df[['Category', 'Quantity', 'Customer_Type']] # predictors
y = df['Unit_Price']                               # Target
```

3.1.2 Encoding predictors

I selected one-hot encoding as its easy to interpret and is the most common encoding method used.

In [41]:
```
X = one_hot_encode(X, ['Category', 'Customer_Type'])
```

In [42]:
```
X.columns # Check all columns in predictors DataFrame
```

Out[42]:
```
Index(['Quantity', 'Category_Automotive', 'Category_Books',
       'Category_Clothing', 'Category_Electronics', 'Category_Furniture',
       'Category_Groceries', 'Category_Health & Beauty', 'Category_Sports',
       'Category_Stationery', 'Category_Toys', 'Customer_Type_A',
       'Customer_Type_B', 'Customer_Type_C', 'Customer_Type_D'],
      dtype='object')
```

3.1.3 Data Partitioning

Splitting dataset into train-test sets where 70% of data is for training and 30% is for validation. Normalization not needed as all features are 0 or 1 except for quantity because their are derived from one-hot encoding. Hence, the model can be interpreted fairly without normalization.

In [43]:
```
X_train, X_val, y_train, y_val = partition(X, y, train_size=0.7, normalize=Fal
```

3.2 Linear Regression

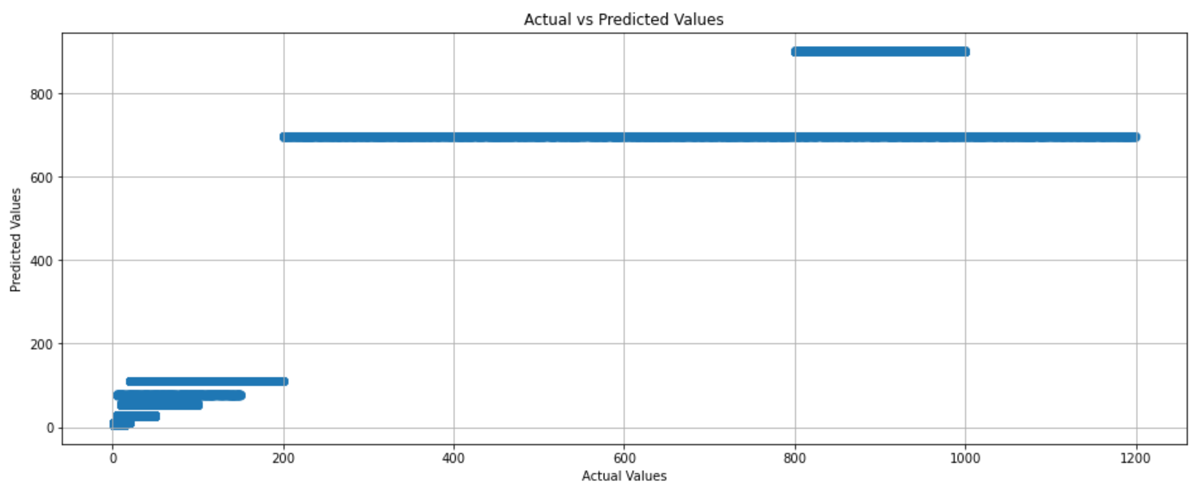
In [44]:
```
from sklearn.linear_model import LinearRegression
LR_model = LinearRegression()        # init model
LR_model.fit(X_train, y_train)       # train model
```

Out[44]:
```
LinearRegression()
```

Evaluate Model explanability on training set:

In [45]:
```
evaluate_model(LR_model, X_train, y_train, X, training=True)
# Model, training predictors, training targets, predictors, isTraining
```

```
Intercept: -28798949266935.46
                                 Coefficient
Quantity                               0.276
Category_Automotive         -20535972079.382
Category_Books              -20535972162.301
Category_Clothing           -20535972135.150
Category_Electronics        -20535971493.200
Category_Furniture          -20535971288.558
Category_Groceries          -20535972181.002
Category_Health & Beauty    -20535972112.980
Category_Sports             -20535972079.253
Category_Stationery         -20535972183.964
Category_Toys               -20535972163.035
Customer_Type_A           28819485239124.391
Customer_Type_B           28819485239125.141
Customer_Type_C           28819485239124.090
Customer_Type_D           28819485239124.305
```




```
R-squared (Goodness of Fit): 0.92
```

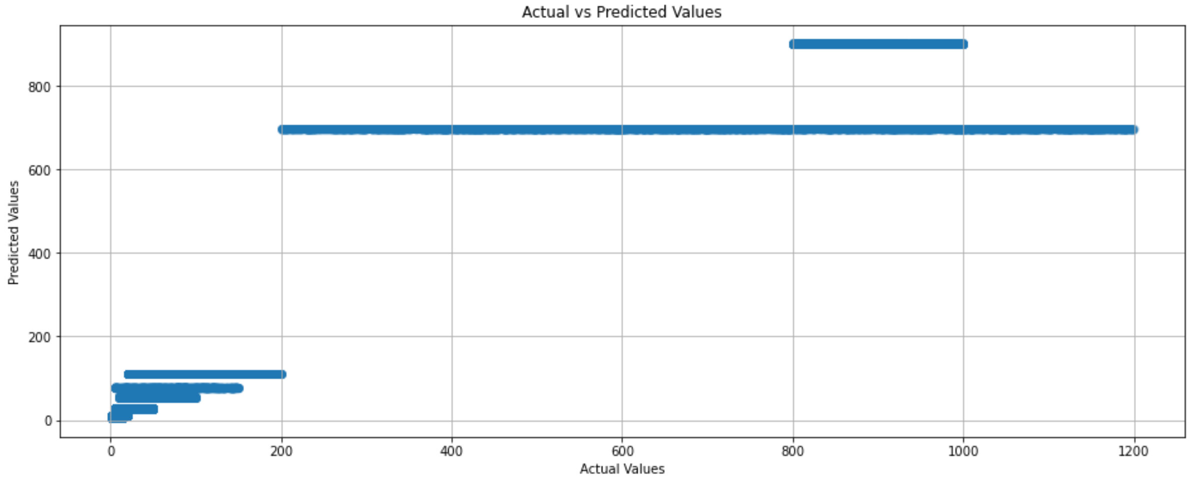
Model performance on training set:

In [46]:
```
evaluate_accuracy(LR_model, X_train, y_train)
```

```
Mean Absolute Percentage Error (MAPE): 44.25%
```

Evaluate Model explanability on validation set:

In [47]:
```
evaluate_model(LR_model, X_val, y_val, X)
```

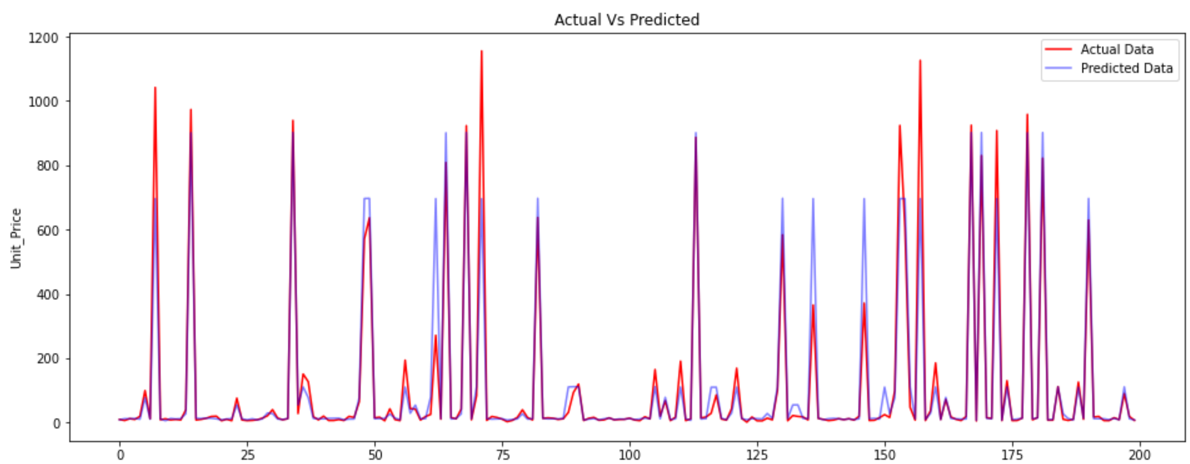



```
R-squared (Goodness of Fit): 0.92
```

Model performance on training set:

In [48]:
```
evaluate_accuracy(LR_model, X_val, y_val, sample_size=200) # edit sample_size 
```

```
Mean Absolute Percentage Error (MAPE): 44.02%
Sampled Analysis:
```




```
MAPE for sample: 45.60%
```

Analysis:

1. LR Model able to closely follow the pattern of actual unit prices.

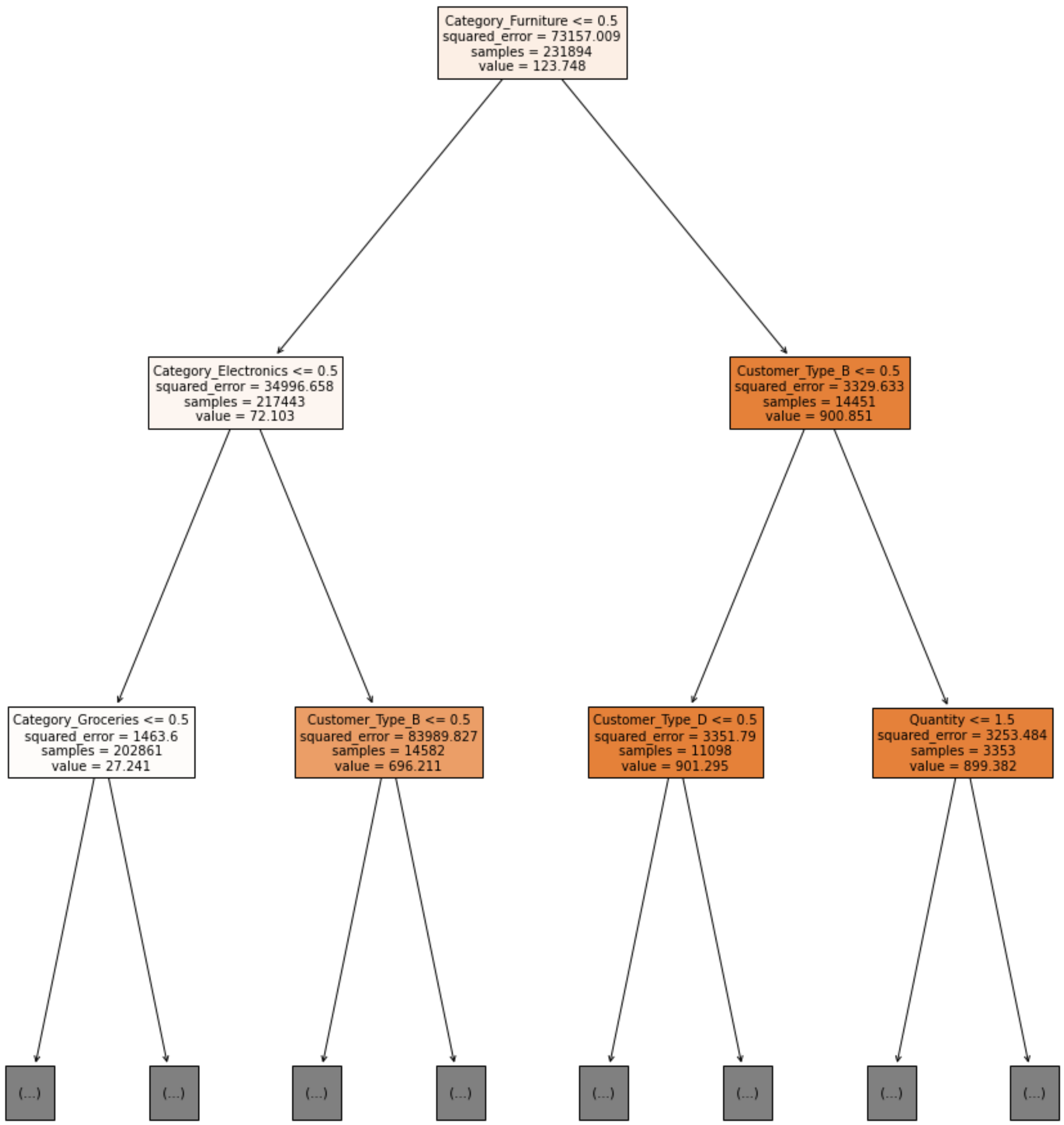
2. LR Model has tendency of significantly underpredicting expensive products, which is NOT GOOD as this means Retail Hypermarket must sell an expensive product for cheap, potentially inccuring a loss, when customers see the prediction of the model as their calculated price.
3. Model is exhibits a high degree of explanatory power with an R-squared (R^2) value of 92%.

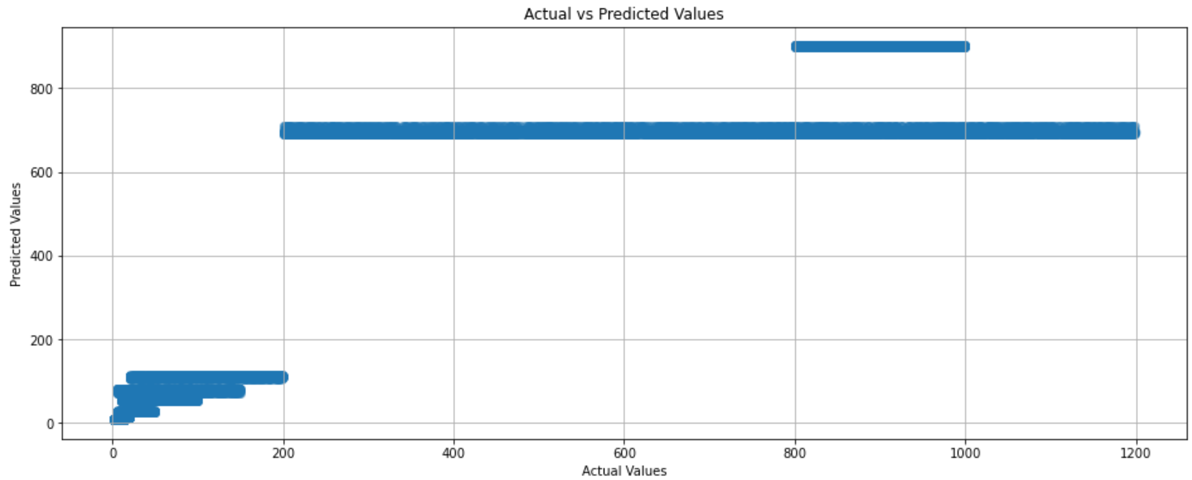
3.3 Decision Tree Regression

In [49]:
```
#Build DTR model
from sklearn.tree import DecisionTreeRegressor
DTR_model = DecisionTreeRegressor(random_state=SEED).fit(X_train , y_train) # 
```

Evaluate Model explanability on training set:

In [50]:
```
evaluate_model(DTR_model, X_train, y_train, X, training=True, max_depth=2)
```





R-squared (Goodness of Fit): 0.92

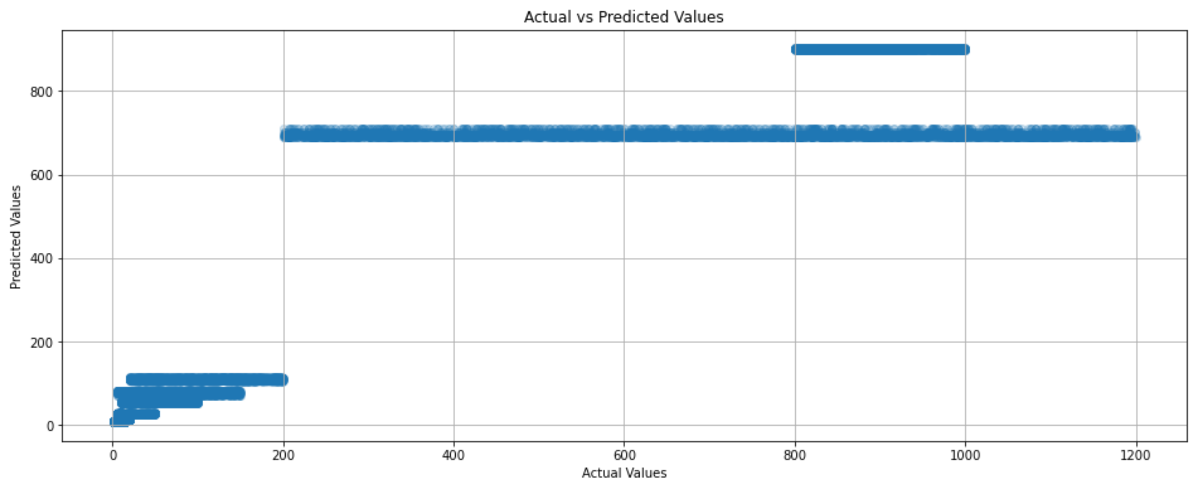
Model performance on training set:

In [51]:
```
evaluate_accuracy(DTR_model, X_train, y_train)
```

Mean Absolute Percentage Error (MAPE): 43.30%

Evaluate Model explanability on validation set:

In [52]:
```
evaluate_model(DTR_model, X_val, y_val, X)
```

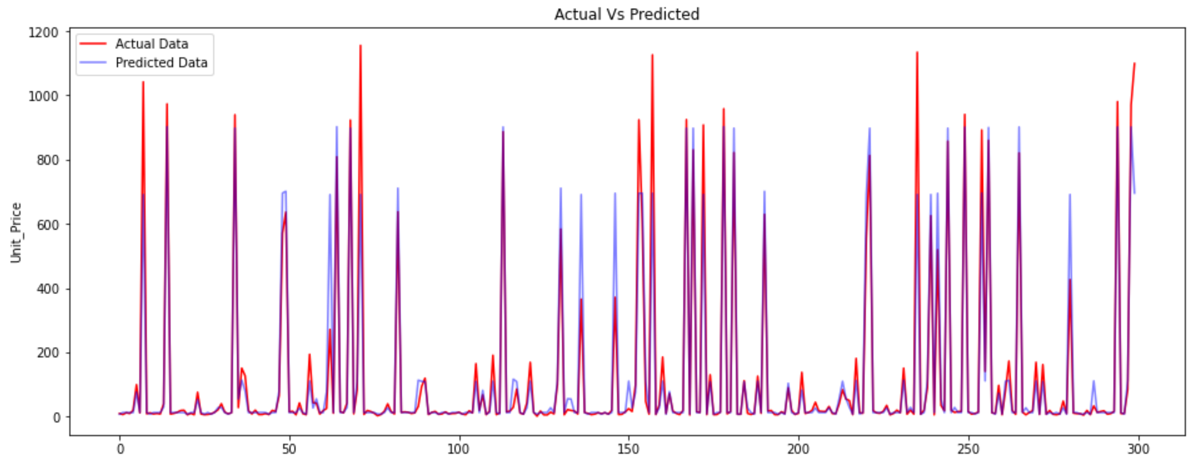


R-squared (Goodness of Fit): 0.92

Model performance on training set:

In [53]:
```
evaluate_accuracy(DTR_model, X_val, y_val, sample_size=300) # edit sample_size
```

```
Mean Absolute Percentage Error (MAPE): 43.12%
Sampled Analysis:
```




```
MAPE for sample: 42.26%
```

Analysis:

1. The DTR Model seems to capture the general trend of prices better than the LR Model, closely following the actual data line.
2. MAPE for DTR is better than LR by around 1%.
3. DTR Model also underpredicts expensive products.

Conclusion:

Although **both models meet requirements for explainability of model** (high R^2) and **no overfitting** (performs equally well for validation set), the **accuracy requirement is NOT met**.

Hence, improvements are needed to bring down the MAPE; increase the accuracy of model. As DTR performed slightly better, I will focus on black-box models as they are known for their ability to capture non-linear trends and complex patterns, hence able in producing impressively high accuracy.

References for part 1:

- 1.0 Problem Framing: Creating Week 03 Workshop 05: Problem Framing. Temasek Polytechnic.
- 1.6 Metrics for evaluating models. Week 02 Workshop 04: Model Scoring
- 1.6 Understanding MAPE for evaluating model accuracy for businesses. https://www.statology.org/what-is-a-good-mape/ (https://www.statology.org/what-is-a-good-mape/)
- 1.7 Acceptable ranges for MAPE. https://www.researchgate.net/figure/MAPE-CRITERIA-FOR-MODEL-EVALUATION_tbl1_27219891 (https://www.researchgate.net/figure/MAPE-CRITERIA-FOR-MODEL-EVALUATION_tbl1_27219891)

- 1.8 Considering environmental factors: Ideas were improved upon suggestions from ChatGPT.
- 1.9 Formulating potential Target Leakages, Week 03 Workshop 06: Target Leakage
- 2.1 Data Dictionary is taken from project specifications.
- 2.4.2 EDA Graph Plotter is built with ChatGPT. OpenAI. (2023, October 30). Re: Python Code for Creating Line and Bar Plots in EDA [Online Forum Comment]. ChatGPT by OpenAI. https://www.chatgpt.com (https://www.chatgpt.com)
- 2.4.6 Graph of Total Revenue per Product is adapted from ChatGPT's code. OpenAI. (2023, October 30). Re: Python Code for Creating Line and Bar Plots in EDA [Online Forum Comment]. ChatGPT by OpenAI. https://www.chatgpt.com (https://www.chatgpt.com)
- 3.0 Reusable methods are built with ChatGPT. OpenAI. (2023, October 31).
- 3.0.3 Coefficient of predictors table adapted from P01_RecapML 4.4 Model Interpretation#Coefficients. Temasek Polytechnic.
- 3.0.4 Sampled analysis graph is adapted from P01_RecapML 4.4 Model Interpretation#Plot of y_pred and y_test. Temasek Polytechnic.
- 3.1.0 One-Hot encoder built with ChatGPT. OpenAI. (2023, October 31). Re: # One-Hot Encoding def one-hot(): // create a one-hot encoder function. input: df, columns to be encoder [Online Forum Comment]. ChatGPT by OpenAI. https://www.chatgpt.com (https://www.chatgpt.com)
- 3.1.0 Label encoder and decoder built using One-Hot encoder and Lab P01_RecapML#3. Data Preparation
- 3.3 Code to visualize Decision Tree Regressor is taken from Lab

End of Part 1