BCIS 5110 Analysis of JD Data

In [103…

```
# This code appears in every demonstration Notebook.
# By default, when you run each cell, only the last output of the codes will show.
# This code makes all outputs of a cell show.
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

We will analyze JD Data in the rest of our assignments.

The objective: to build models to accurately predict delivery times for customer orders.
The data: We need the following tables from the JD.com data

```
1. Order<br>
2. User<br>
3. Delivery<br>
4. Inventory<br>
5. Network<br>
```

Assignment 8 include Q1 - Q10.

1. Import necessary packages.

In [104…

```
import pandas as pd
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from datetime import timedelta
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error
```

1. Read in the five csv files.

In [105…

```
order_df=pd.read_csv(r"C:\Assignments\BA\BAASSIGN\order.csv")
user_df = pd.read_csv(r"C:\Assignments\BA\BAASSIGN\user.csv")
delivery_df = pd.read_csv(r"C:\Assignments\BA\BAASSIGN\delivery.csv")
inventory_df = pd.read_csv(r"C:\Assignments\BA\BAASSIGN\inventory.csv")
network_df = pd.read_csv(r"C:\Assignments\BA\BAASSIGN\network.csv")
```

1. Display a sample of each data frame. How many observations? How many columns? What are the column names? (Use code to display such information.)

In [106…

```
print('Order DataFrame:')
display(order_df.head())
```

```
num_rows = order_df.shape[0]
num_cols = order_df.shape[1]
col_names = order_df.columns.tolist()

print(f"Number of observations: {num_rows}")
print(f"Number of columns: {num_cols}")
print("Column names:")
print(col_names)
print("\n")
```

Order DataFrame:

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type	promise	original_unit_p
0	d0cf5cc6db	0abe9ef2ce	581d5b54c1	2018-03-01	2018-03-01 17:14:25.0	1	2	-	
1	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
2	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
3	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
4	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	

```
Number of observations: 549989
Number of columns: 17
Column names:
['order_ID', 'user_ID', 'sku_ID', 'order_date', 'order_time', 'quantity', 'type', 'promi
se', 'original_unit_price', 'final_unit_price', 'direct_discount_per_unit', 'quantity_di
scount_per_unit', 'bundle_discount_per_unit', 'coupon_discount_per_unit', 'gift_item',
'dc_ori', 'dc_des']
```

In [107…

```
print('User DataFrame:')
display(user_df.head())

num_rows = user_df.shape[0]
num_cols = user_df.shape[1]
col_names = user_df.columns.tolist()

print(f"Number of observations: {num_rows}")
print(f"Number of columns: {num_cols}")
print("Column names:")
print(col_names)
print("\n")
```

User DataFrame:

	user_ID	user_level	first_order_month	plus	gender	age	marital_status	education	city_level
0	000089d6a6	1	2017-08	0	F	26-35	S	3	4
1	0000babd1f	1	2018-03	0	U	U	U	-1	-1
2	0000bc018b	3	2016-06	0	F	>=56	M	3	2
3	0000d0e5ab	3	2014-06	0	M	26-35	M	3	2
4	0000dce472	3	2012-08	1	U	U	U	-1	-1

```
Number of observations: 457298
Number of columns: 10
Column names:
['user_ID', 'user_level', 'first_order_month', 'plus', 'gender', 'age', 'marital_statu
s', 'education', 'city_level', 'purchase_power']
```

In [108…

```python
print('Delivery DataFrame:')
display(delivery_df.head())

num_rows = delivery_df.shape[0]
num_cols = delivery_df.shape[1]
col_names = delivery_df.columns.tolist()

print(f"Number of observations: {num_rows}")
print(f"Number of columns: {num_cols}")
print("Column names:")
print(col_names)
print("\n")
```

```
Delivery DataFrame:
```

	package_ID	order_ID	type	ship_out_time	arr_station_time	arr_time
0	dc3d6d2258	dc3d6d2258	1	2018-03-01 08:00:00	2018-03-01 15:00:00	2018-03-01 18:00:00
1	19802a570c	19802a570c	1	2018-03-01 10:00:00	2018-03-01 15:00:00	2018-03-01 17:00:00
2	e22627af66	e22627af66	1	2018-03-01 11:00:00	2018-03-01 15:00:00	2018-03-01 17:00:00
3	50d11a586d	50d11a586d	1	2018-03-01 10:00:00	2018-03-01 16:00:00	2018-03-01 19:00:00
4	a3bfe38bf4	a3bfe38bf4	1	2018-03-01 11:00:00	2018-03-01 16:00:00	2018-03-01 17:00:00

```
Number of observations: 293229
Number of columns: 6
Column names:
['package_ID', 'order_ID', 'type', 'ship_out_time', 'arr_station_time', 'arr_time']
```

In [109…

```python
print('Inventory DataFrame:')
display(inventory_df.head())

num_rows = inventory_df.shape[0]
num_cols = inventory_df.shape[1]
```

```
col_names = inventory_df.columns.tolist()

print(f"Number of observations: {num_rows}")
print(f"Number of columns: {num_cols}")
print("Column names:")
print(col_names)
print("\n")
```

Inventory DataFrame:

	dc_ID	sku_ID	date
0	9	50f6f91962	2018-03-01
1	9	7f0ddbcdde	2018-03-01
2	9	8ad5789d74	2018-03-01
3	9	468d34eda4	2018-03-01
4	9	460afaddb6	2018-03-01

```
Number of observations: 136079
Number of columns: 3
Column names:
['dc_ID', 'sku_ID', 'date']
```

In [110…

```
print('Network DataFrame:')
display(network_df.head())

num_rows = network_df.shape[0]
num_cols = network_df.shape[1]
col_names = network_df.columns.tolist()

print(f"Number of observations: {num_rows}")
print(f"Number of columns: {num_cols}")
print("Column names:")
print(col_names)
print("\n")
```

Network DataFrame:

	region_ID	dc_ID
0	2	57
1	2	43
2	2	42
3	2	66
4	2	20

```
Number of observations: 56
Number of columns: 2
Column names:
['region_ID', 'dc_ID']
```

1. Check for missing values of columns of each dataframe. You can use sum() (instead of any()) to find out the number of missing values. Which variables have missing values?

In [111…

```
dataframes = {
    "Order": order_df,
    "User": user_df,
    "Delivery": delivery_df,
    "Inventory": inventory_df,
    "Network": network_df
}
for name, df in dataframes.items():
    missing_values = df.isna().sum()
    print(f"Missing values in the {name} dataframe:")
    print(missing_values)

    total_missing = missing_values.sum()
    if total_missing == 0:
        print(f"No missing values in the {name} dataframe")
    else:
        print(f"Total missing values in the {name} dataframe: {total_missing}")
    print()
```

```
Missing values in the Order dataframe:
order_ID                       0
user_ID                        0
sku_ID                         0
order_date                     0
order_time                     0
quantity                       0
type                           0
promise                        0
original_unit_price            0
final_unit_price               0
direct_discount_per_unit       0
quantity_discount_per_unit     0
bundle_discount_per_unit       0
coupon_discount_per_unit       0
gift_item                      0
dc_ori                         0
dc_des                         0
dtype: int64
No missing values in the Order dataframe

Missing values in the User dataframe:
user_ID               0
user_level            0
first_order_month     0
plus                  0
gender                0
age                   0
marital_status        0
education             0
city_level            0
purchase_power        0
dtype: int64
No missing values in the User dataframe

Missing values in the Delivery dataframe:
package_ID           0
order_ID             0
```

```
type                0
ship_out_time       0
arr_station_time    0
arr_time            0
dtype: int64
No missing values in the Delivery dataframe

Missing values in the Inventory dataframe:
dc_ID     0
sku_ID    0
date      0
dtype: int64
No missing values in the Inventory dataframe

Missing values in the Network dataframe:
region_ID    0
dc_ID        0
dtype: int64
No missing values in the Network dataframe
```

1. Check the promise variable in orders table. What unusual values do you notice? What do you think it means?

In [112…

```python
data = order_df
unique_promise_values = data['promise'].unique()
print("Unique 'promise' values:")
print(unique_promise_values)
#The '-' character is an unusual value, usually suggesting the absence or lack of defin
#It is frequently employed as a placeholder when data is unavailable or irrelevant.
```

```
Unique 'promise' values:
['-' '2' '1' '3' '4' '5' '6' '7' '8']
```

1. How many observations for each value in 'promise' variable? What information can you draw from this?

In [113…

```python
promise_value_counts = data['promise'].value_counts()
print("Observations for each value in 'promise' variable:")
print(promise_value_counts)

# The 'promise' variable in the dataset has the following count of observations for eac

# '-' : 208,583 occurrences
# 1 : 157,509 occurrences
# 2 : 109,990 occurrences
# 3 : 33,176 occurrences
# 4 : 23,882 occurrences
# 5 : 10,054 occurrences
# 6 : 3,039 occurrences
# 7 : 1,382 occurrences
# 8 : 2,374 occurrences

#In the 'promise' field, the most frequently appearing value is "-", with 208,583 occur
#Values 1, 2, and 3 have relatively high counts, with 157,509, 109,990, and 33,176 obse
#Values 4, 5, 6, 7, and 8 have lower numbers, with values 4 and 5 having some but fewer
```

```
#To gain more detailed insights from the data, it's crucial to understand the context a
#Depending on the objectives, the distribution of promise values may impact the analysi
```

```
Observations for each value in 'promise' variable:
-    208583
1    157509
2    109990
3     33176
4     23882
5     10054
6      3039
8      2374
7      1382
Name: promise, dtype: int64
```

1. Select only two variables: 'type' and 'promise' from order table. Sort it by variable 'type' in descending order. What do you observe from the results? (check the first 10 and last 10 observations.) Think about the meaning of the type variable.

In [114…

```
df = order_df[['type', 'promise']]
df = df.sort_values(by='type', ascending=False)
print("First 10 observations:")
display(df.head(10))
print("\nLast 10 observations:")
display(df.tail(10))
#The 'type' variable categorizes from 2 to 1, with 2 as the highest. 'promise' indicate
#'type' may be a top-level category, and 'promise' might relate to delivery or commitme
```

First 10 observations:

	type	promise
0	2	-
308329	2	-
308358	2	-
308357	2	-
308356	2	-
308355	2	-
308354	2	-
308353	2	-
308352	2	-
308351	2	-

Last 10 observations:

	type	promise
334636	1	1
334633	1	1
334626	1	1
334632	1	1

	type	promise
334631	1	1
116820	1	2
116821	1	2
116822	1	1
334627	1	1
274994	1	2

1. Merge order and delivery tables, using inner merge. What does inner merge mean? How many observations are there in the merged dataset? Compared with the number of observations in the original order and delivery table, what can you say about the match between orders and deliveries?

In [115…

```
Inner_merged_data = pd.merge(order_df, delivery_df, on='order_ID', how='inner')
display(Inner_merged_data)
observations_merged = Inner_merged_data.shape[0]

observations_order = order_df.shape[0]
observations_delivery = delivery_df.shape[0]

print(f"Number of observations in the merged dataset: {observations_merged}")
print(f"Number of observations in the 'order' table: {observations_order}")
print(f"Number of observations in the 'delivery' table: {observations_delivery}")

if observations_merged == min(observations_order, observations_delivery):
    print("All orders have corresponding deliveries, and all deliveries have correspond
else:
    print("Some orders do not have corresponding deliveries, or some deliveries do not
#An inner merge (or inner join) combines rows from both dataframes only when there's a r
#The resulting merged dataset, 'Inner_merged_df,' contains 326,880 rows.
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origin
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15.0	1	1	1	

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origin
...	...	...	...	...	...	...	...	...	
326857	5fd298d448	165ee3e319	f7280c119d	2018-03-31	2018-03-31 12:42:35.0	1	2	3	
326858	9fa0694b3b	39933e9bc6	767ac490ed	2018-03-31	2018-03-31 19:51:43.0	1	1	2	
326859	c9d77a7ed0	18f92434cd	7f53769d3f	2018-03-31	2018-03-31 08:55:57.0	1	1	3	
326860	b9ad79338f	b5caf8a580	8dc4a01dec	2018-03-31	2018-03-31 13:31:01.0	1	1	2	
326861	02d31f05c9	f260895cbe	10d369ef96	2018-03-31	2018-03-31 18:21:16.0	1	2	4	

326862 rows × 22 columns

```
Number of observations in the merged dataset: 326862
Number of observations in the 'order' table: 549989
Number of observations in the 'delivery' table: 293229
Some orders do not have corresponding deliveries, or some deliveries do not have corresp
onding orders.
```

1. Merge order and delivery tables, using right merge. What does right merge mean? How many obervations are there in the merged dataset? Do all delivery records have matched order information?

In [116…

```
Right_merged_data = pd.merge(order_df, delivery_df, on='order_ID', how='right')
display(Right_merged_data)
observations_merged = Right_merged_data.shape[0]

# Check if all delivery records have matched order information
all_delivery_matched = Right_merged_data['order_ID'].notnull().all()

print(f"Number of observations in the merged dataset: {observations_merged}")
print(f"Do all delivery records have matched order information: {all_delivery_matched}"
#A right merge combines two DataFrames based on a common column or columns, but it incl
#The resulting merged dataset, 'Right_merged_df,' contains 326,880 rows.
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origin
0	dc3d6d2258	ee666e25c3	2e06817802	2018-03-01	2018-03-01 06:21:07.0	1	1	1	
1	19802a570c	845df5b5f2	5ae1bb1c76	2018-03-01	2018-03-01 09:10:09.0	1	1	1	

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origin
2	e22627af66	cae0d8c01f	b8c182c74f	2018-03-01	2018-03-01 10:50:41.0	1	1	1	
3	e22627af66	cae0d8c01f	c98d32ff09	2018-03-01	2018-03-01 10:50:41.0	3	1	1	
4	e22627af66	cae0d8c01f	c98d32ff09	2018-03-01	2018-03-01 10:50:41.0	3	1	1	
...	...	...	...	...	...	...	...	...	
326857	cb319102f1	df8c108eff	ac0cd64708	2018-03-31	2018-03-31 23:38:17.0	2	1	6	
326858	0fe3bbcfd8	b1fa95ae5e	068f4481b3	2018-03-22	2018-03-22 17:42:37.0	1	1	8	
326859	0fe3bbcfd8	b1fa95ae5e	fbce41fd82	2018-03-22	2018-03-22 17:42:37.0	1	1	8	
326860	0fe3bbcfd8	b1fa95ae5e	8dc4a01dec	2018-03-22	2018-03-22 17:42:37.0	2	1	8	
326861	d22fa05841	4032897ccb	50b53a8536	2018-03-24	2018-03-24 14:50:47.0	1	1	8	

326862 rows × 22 columns

```
Number of observations in the merged dataset: 326862
Do all delivery records have matched order information: True
```

1. Merge order and delivery tables, using left merge. What does left merge mean? How many obervations are there in the merged dataset? Compare the number of observations of the merged table with the original order table, what can you say about the match between orders and deliveries?

In [117…

```
Left_merged_data = pd.merge(order_df, delivery_df, on='order_ID', how='left')
display(Left_merged_data)
observations_merged = Left_merged_data.shape[0]
print(f"Number of observations in the merged dataset: {observations_merged}")
observations_order = order_df.shape[0]
if observations_merged == observations_order:
    print("All orders have corresponding delivery information.")
else:
    print("Some orders do not have corresponding delivery information.")
#A left merge combines two DataFrames based on a common column or columns, but it inclu
##The resulting merged dataset, 'Left_merged_df,' contains 550,027 rows.
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origir
0	d0cf5cc6db	0abe9ef2ce	581d5b54c1	2018-03-01	2018-03-01 17:14:25.0	1	2	-	
1	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
2	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
3	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
4	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	
...	...	...	...	...	...	...	...	...	
550012	3ad06b9fbe	a27b3ed4d4	a9109972d1	2018-03-31	2018-03-31 01:22:47.0	1	2	-	
550013	c9d77a7ed0	18f92434cd	7f53769d3f	2018-03-31	2018-03-31 08:55:57.0	1	1	3	
550014	b9ad79338f	b5caf8a580	8dc4a01dec	2018-03-31	2018-03-31 13:31:01.0	1	1	2	
550015	be3a9414b1	20ba6655f3	2dd6b818ec	2018-03-31	2018-03-31 12:51:18.0	1	2	-	
550016	02d31f05c9	f260895cbe	10d369ef96	2018-03-31	2018-03-31 18:21:16.0	1	2	4	

550017 rows × 22 columns

```
Number of observations in the merged dataset: 550017
Some orders do not have corresponding delivery information.
```

Assignment 9 starts here. Q11 - Q20.

In this part, we prepare the data for analysis.

1. First, we need to clean the merged order and delivery table.
   Identify the table from the inner merge in Q8. Take a look at it. You may find there are two variables: type_x and type_y, which were not in the original two tables.
   The reason is that there is a type variable in both orders and delivery tables. The merge keeps both and assigned x and y suffix to them.

Check the meaning of the two variables in our data description.
To make the two variables consistent, we can replace the values of one variable to match the other.

In [118…

```
#Resulting merged DataFrame, named Inner_merged_data, contains columns from both the "o
# Replace values of type_y with corresponding values from type_x
Inner_merged_data['type_y'] = Inner_merged_data['type_x']

# Compare values of type_x and type_y
same_values = Inner_merged_data['type_x'] == Inner_merged_data['type_y']
print("Number of observations in the merged dataset:", len(Inner_merged_data))

display(Inner_merged_data.head())
```

```
Number of observations in the merged dataset: 326862
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	original_uni
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15.0	1	1	1	

5 rows × 22 columns

Then compare the values of the two variables are the same.

In [119…

```
# Check if all values are same
if same_values.all():
    print("Values are same.")
else:
    print("Values are not same")
```

```
Values are same.
```

If they are, please drop one of them.

In [120…

```
#Check if values in 'type_x' and 'type_y' are the same
values_match = Inner_merged_data['type_x'].equals(Inner_merged_data['type_y'])

#If values are the same, drop one of the columns
if values_match:
```

```
    Inner_merged_data.drop(columns=['type_y'], inplace=True)
#Rename 'type_x' to a more meaningful name if needed


#Print the updated DataFrame
display(Inner_merged_data.head())
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	original_uni
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15.0	1	1	1	

5 rows × 21 columns

1. We need to remove the orders that
   1) has a single item;
   2) the item is a gift item;

The reason is that those orders might have come from other product categories and only use products from current category as a gift. We do not have information about those orders.

We first find orders with order_ID only appears once in the data, which indicates this order contains a single item.
Hint: you may use .duplicated() method to mark that. Think about which value of the argument 'keep' you want to choose. Consider saving the outcome as a variable.

In [121…

```
# Mark orders with a single item as duplicates
single_item_orders = Inner_merged_data.duplicated(subset='order_ID', keep=False)

# Print the first 5 rows of the variable indicating single-item orders
display(single_item_orders)

# Filter orders based on conditions (single item and not a gift item)
filtered_orders = Inner_merged_data[~(single_item_orders & (Inner_merged_data['gift_ite

# Print the first 5 rows of the filtered DataFrame
display(filtered_orders)
```

```
0         False
1         False
2         False
3         False
4         False
          ...
326857    False
326858    False
326859    False
326860    False
326861    False
Length: 326862, dtype: bool
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origin
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15.0	1	1	1	
...	...	...	...	...	...	...	...	...	
326857	5fd298d448	165ee3e319	f7280c119d	2018-03-31	2018-03-31 12:42:35.0	1	2	3	
326858	9fa0694b3b	39933e9bc6	767ac490ed	2018-03-31	2018-03-31 19:51:43.0	1	1	2	
326859	c9d77a7ed0	18f92434cd	7f53769d3f	2018-03-31	2018-03-31 08:55:57.0	1	1	3	
326860	b9ad79338f	b5caf8a580	8dc4a01dec	2018-03-31	2018-03-31 13:31:01.0	1	1	2	
326861	02d31f05c9	f260895cbe	10d369ef96	2018-03-31	2018-03-31 18:21:16.0	1	2	4	

312391 rows × 21 columns

Then we filter the data to remove those orders of a single gift item. Save the changes.

In [122…

```
# Filter orders to remove those with a single gift item
filtered_orders = Inner_merged_data[~(single_item_orders & (Inner_merged_data['gift_ite

# Save the changes to the DataFrame
Inner_merged_data = filtered_orders.copy()

# Print the first 5 rows of the updated DataFrame
display(Inner_merged_data.head())
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	original_uni
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15.0	1	1	1	

5 rows × 21 columns

1. Next, we remove orders with multiple packages. Hint: You may groupby order_ID, find the number of unique package_ID ('nunique') and then use transform() to broadcast the value to all record. Save the results as a new variable. Use the variable value to filter.

In [123…

```
# Group by 'order_ID' and count the number of unique 'package_ID'
package_counts = Inner_merged_data.groupby('order_ID')['package_ID'].transform('nunique

# Print the first 5 rows of the variable indicating package counts
display((package_counts))

# Filter orders to remove those with multiple packages
filter_orders = Inner_merged_data[package_counts == 1]

# Print the updated DataFrame
display(filter_orders)
```

```
0          1
1          1
2          1
3          1
4          1
          ..
```

```
326857    1
326858    1
326859    1
326860    1
326861    1
Name: package_ID, Length: 312391, dtype: int64
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origin
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40.0	1	1	2	
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26.0	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50.0	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37.0	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15.0	1	1	1	
...	...	...	...	...	...	...	...	...	
326857	5fd298d448	165ee3e319	f7280c119d	2018-03-31	2018-03-31 12:42:35.0	1	2	3	
326858	9fa0694b3b	39933e9bc6	767ac490ed	2018-03-31	2018-03-31 19:51:43.0	1	1	2	
326859	c9d77a7ed0	18f92434cd	7f53769d3f	2018-03-31	2018-03-31 08:55:57.0	1	1	3	
326860	b9ad79338f	b5caf8a580	8dc4a01dec	2018-03-31	2018-03-31 13:31:01.0	1	1	2	
326861	02d31f05c9	f260895cbe	10d369ef96	2018-03-31	2018-03-31 18:21:16.0	1	2	4	

312352 rows × 21 columns

1. Now we process time-related variables: order_date, order_time, ship_out_time, arr_station_time, and arr_time.
   First change all of them to Timestamp data type.
   Get the day of the month from the order_date and save it to a new variable 'order_day'.
   Get the hour of the order_time and save it to a new variable 'order_hour'.
   Caculate the delivery time by minus arr_time with order_time.

In [124…

```
time_columns = ['order_date', 'order_time', 'ship_out_time', 'arr_station_time', 'arr_t
Inner_merged_data[time_columns] = Inner_merged_data[time_columns].apply(pd.to_datetime)
```

In [125…

```
Inner_merged_data['order_day'] = Inner_merged_data['order_date'].dt.day
```

In [126…

```
Inner_merged_data['order_hour'] = Inner_merged_data['order_time'].dt.hour
```

In [127…

```
Inner_merged_data['delivery_time'] = Inner_merged_data['arr_time'] - Inner_merged_data[
display(Inner_merged_data)
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	origin
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40	1	1	2	
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15	1	1	1	
...	...	...	...	...	...	...	...	...	
326857	5fd298d448	165ee3e319	f7280c119d	2018-03-31	2018-03-31 12:42:35	1	2	3	
326858	9fa0694b3b	39933e9bc6	767ac490ed	2018-03-31	2018-03-31 19:51:43	1	1	2	
326859	c9d77a7ed0	18f92434cd	7f53769d3f	2018-03-31	2018-03-31 08:55:57	1	1	3	
326860	b9ad79338f	b5caf8a580	8dc4a01dec	2018-03-31	2018-03-31 13:31:01	1	1	2	
326861	02d31f05c9	f260895cbe	10d369ef96	2018-03-31	2018-03-31 18:21:16	1	2	4	

312391 rows × 24 columns

1. We will transform the delivery time to hours. Hint: You can use total_seconds() method to turn it into seconds and find hours. Use apply() to apply a function for the transformation.

In [128…

```
def convert_to_hours(td):
    return td.total_seconds() / 3600
Inner_merged_data['delivery_time_hours'] = Inner_merged_data['delivery_time'].apply(con
display(Inner_merged_data.head())
```

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	original_uni
0	7444318d01	33a9e56257	067b673f2b	2018-03-01	2018-03-01 11:10:40	1	1	2	

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type_x	promise	original_uni
1	f973b01694	4ea3cf408f	623d0a582a	2018-03-01	2018-03-01 09:13:26	1	1	2	
2	8c1cec8d4b	b87cb736cb	fc5289b139	2018-03-01	2018-03-01 21:29:50	1	1	2	
3	d43a33c38a	4829223b6f	623d0a582a	2018-03-01	2018-03-01 19:13:37	1	1	1	
4	e0f5386d87	0b07cae293	589c2b865b	2018-03-01	2018-03-01 21:09:15	1	1	1	

5 rows × 25 columns

1. Find the total number of packages between the origin distribution center and the destination center. What do you observe from those pairs of highest traffic?
   Hint: You may group by the distribution centers and count the unique number of packages. You can use reset_index() method to turn the groupby aggregation results into a regular dataframe for later operations.

In [129…

```
package_counts = Inner_merged_data.groupby(['dc_ori', 'dc_des'])['package_ID'].nunique(
package_counts.rename(columns={'package_ID': 'total_packages'}, inplace=True)
package_counts = package_counts.sort_values(by='total_packages', ascending=False)
display(package_counts)
```

	dc_ori	dc_des	total_packages
31	5	5	31624
6	2	2	23432
71	9	9	23067
23	4	4	20442
120	24	24	12640
...	...	...	...
326	56	18	1
379	57	19	1
322	56	14	1
4	1	46	1
287	54	13	1

627 rows × 3 columns

In [130…

```
#my observations are
#The package_counts DataFrame that is generated will display the overall count of packag
#The data will be arranged in descending order based on traffic volume, offering the opp
```

1. Now let's go back to the original orders table. Find the orders where gift_item equals to 1 (use filtering). What do you find about the orignal_unit_price and final_unit_price in the filtered dataset? Do we consider the 0 price as data errors?

In [131…

```
gift_orders = order_df[order_df['gift_item'] == 1]
display(gift_orders[['original_unit_price', 'final_unit_price']].describe())
zero_price_orders = gift_orders[(gift_orders['original_unit_price'] == 0) | (gift_order
display("Orders with 0 price:")
display(zero_price_orders)
#The descriptive statistics for 'original_unit_price' and 'final_unit_price' in the fil
#The consideration of 0 prices as they could indicate intentional free items, promotion
```

	original_unit_price	final_unit_price
count	94606.000000	94606.000000
mean	0.004334	-0.215242
std	0.544303	1.109574
min	0.000000	-32.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	69.000000	0.000000

'Orders with 0 price:'

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type	promise	original
6	89286e5fd9	79154d0001	6717b7c979	2018-03-01	2018-03-01 22:18:41.0	1	1	1	
10	9c65b6264b	2021a86702	d3e31fdd6e	2018-03-01	2018-03-01 00:12:07.0	2	1	1	
23	8b71aa6716	9bb8b4c04f	a0e49f9966	2018-03-01	2018-03-01 22:08:44.0	1	1	1	
25	67b8f778f6	53dc20e68d	a0e49f9966	2018-03-01	2018-03-01 23:17:02.0	1	1	1	
26	67b8f778f6	53dc20e68d	c98d32ff09	2018-03-01	2018-03-01 23:17:02.0	1	1	1	
...	...	...	...	...	...	...	...	...	

	order_ID	user_ID	sku_ID	order_date	order_time	quantity	type	promise	original
549939	6d882e746d	227f7204e8	cfe58e6b7f	2018-03-31	2018-03-31 06:03:08.0	2	2	-	
549980	a7c31a6da3	ecc9f60096	a9109972d1	2018-03-31	2018-03-31 21:02:09.0	1	2	-	
549981	ac748a8701	dbbace058c	a9109972d1	2018-03-31	2018-03-31 11:30:16.0	1	2	-	
549983	9fa0694b3b	39933e9bc6	767ac490ed	2018-03-31	2018-03-31 19:51:43.0	1	1	2	
549984	3ad06b9fbe	a27b3ed4d4	a9109972d1	2018-03-31	2018-03-31 01:22:47.0	1	2	-	

94606 rows × 17 columns

1. Still use the original order table. Filter the orders of a product (sku: 'a0e49f9966') on '2018-3-15'. Calculate the sales.
   Hint: we can multiply the quantity and final price columns together.
   The outcome will be a pandas series.
   The sum of the series will be the total sales.

In [132…

```
# Convert 'order_date' to datetime type if not already
order_df['order_date'] = pd.to_datetime(order_df['order_date'])

# Filter orders for the specific product on '2018-03-15'
filtered_orders = order_df[(order_df['sku_ID'] == 'a0e49f9966') & (order_df['order_date

# Calculate sales by multiplying quantity and final_unit_price columns
sales_series = filtered_orders['quantity'] * filtered_orders['final_unit_price']

# Display the sales series
print("Sales Series:")
print(sales_series)

# Calculate total sales
total_sales = sales_series.sum()
print("\nTotal Sales:", total_sales)
```

```
Sales Series:
Series([], dtype: float64)

Total Sales: 0.0
```

1. Now let's move to the user table.
   Create a pivot table that counts the customers based on their user_level and education.

In [133…

```
pivot_table_counts = pd.pivot_table(user_df, values='user_ID', index=['user_level', 'ed
pivot_table_counts.rename(columns={'user_ID': 'customer_count'}, inplace=True)
display(pivot_table_counts)
```

		customer_count
user_level	**education**	
-1	**-1**	2294
	3	9
0	**-1**	145
	2	7
	3	8
	4	1
1	**-1**	66391
	1	3001
	2	24182
	3	35486
	4	369
2	**-1**	28310
	1	3270
	2	32953
	3	75907
	4	1419
3	**-1**	8201
	1	1260
	2	13418
	3	68944
	4	4979
4	**-1**	4023
	1	629
	2	3606
	3	37548
	4	39922
10	**-1**	1005
	2	2
	3	6

		customer_count
user_level	education	
	4	3

1. Answer one of your descriptive questions using groupby or pivot table.

In [134…

```
# I used use a pivot table to analyze the average final_unit_price for each type of ord
pivot_table_avg_price = pd.pivot_table(order_df, values='final_unit_price', index='type
display(pivot_table_avg_price)
```

	final_unit_price
type	
1	85.135582
2	57.962828

Assignment 10 starts here. Q21-Q30.

We now further explore the data, especially with graphs. We do not require formatting details of graph. The basics are enough.

1. Let's first look at the user table. Use info() to display basic information about the table. Check the Dtype column. What is the data type for variable user_level? This data type does not fit our description about this variable:
   "taking on a value of 0, 1, 2, 3, or 4, where a higher user_level is associated with a higher total purchase value in the past. For users who are enterprise users (e.g., small shops in rural areas or small businesses), the corresponding user_level takes on a value of 10. However, for first-time purchasers, their user_level takes on the value −1."
   The numbers do not have a numeric meaning, but refer to categories of customers. So, we would like to change the data type to categorical. Please use .astype('string') to change the data type of user_level.
   You may find similar situation for variables: education, city_level and purchase_power. Change their data type too.

In [135…

```
user_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 457298 entries, 0 to 457297
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype 
---  ------            --------------   ----- 
 0   user_ID           457298 non-null  object
 1   user_level        457298 non-null  int64 
 2   first_order_month 457298 non-null  object
 3   plus              457298 non-null  int64 
 4   gender            457298 non-null  object
 5   age               457298 non-null  object
 6   marital_status    457298 non-null  object
```

```
 7   education          457298 non-null  int64
 8   city_level         457298 non-null  int64
 9   purchase_power     457298 non-null  int64
dtypes: int64(5), object(5)
memory usage: 34.9+ MB
```

In [136…

```
user_df['user_level'] = user_df['user_level'].astype('string')
user_df['education'] = user_df['education'].astype('string')
user_df['city_level'] = user_df['city_level'].astype('string')
user_df['purchase_power'] = user_df['purchase_power'].astype('string')
```

1. 1) The meaning of '-1' for user_level is new customer. We will replace '-1' with 'New' and '10' with 'Bus'. Notice that -1 now changes to a string '-1'.

In [137…

```
user_df['user_level'] = user_df['user_level'].replace({'-1': 'New', '10': 'Bus'})
```

2) The meaning of -1 in education, city_level and purchase_power is missing values. We will replace it with 'U', as missing value indicator of other variables like 'age', 'gender', etc.

In [138…

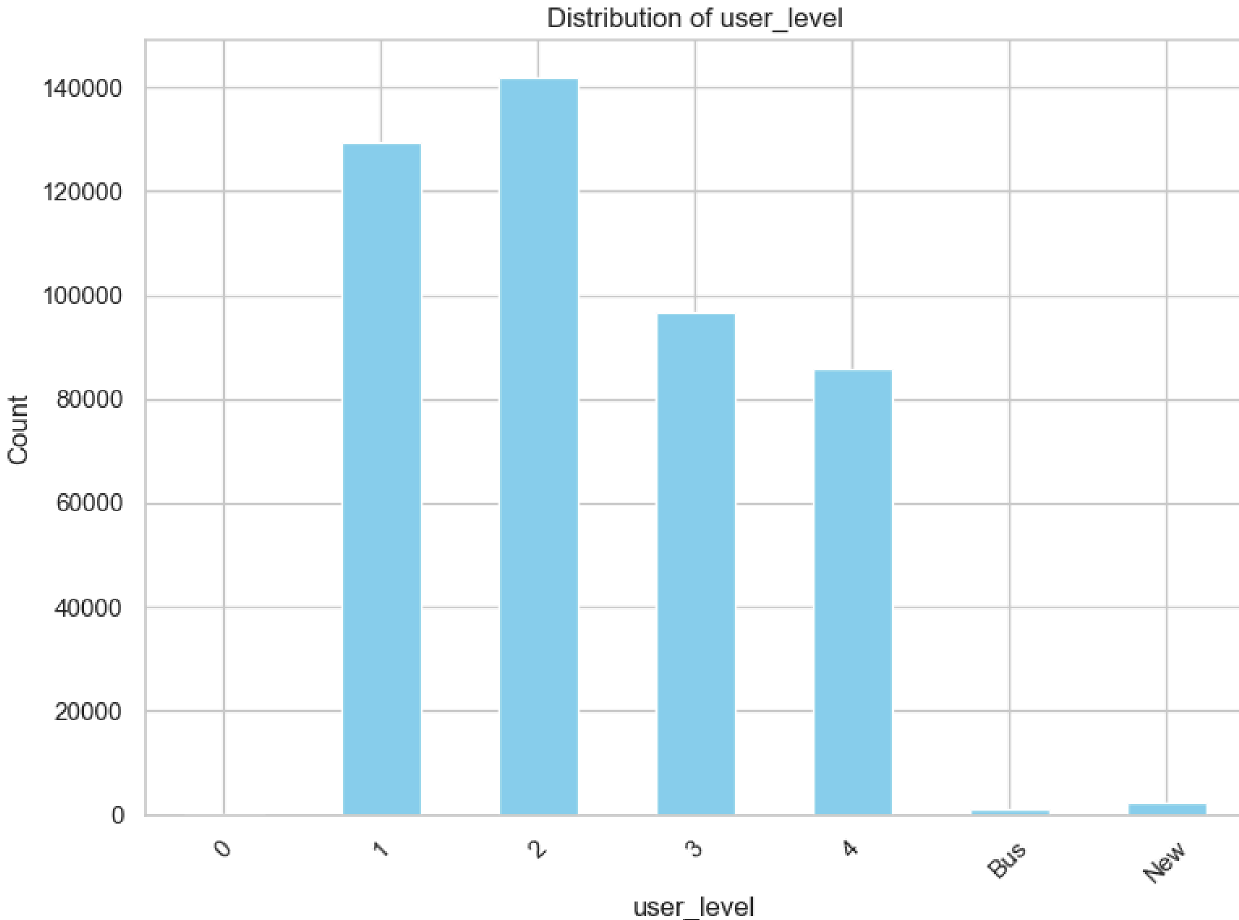
```
user_df['education'] = user_df['education'].replace({'-1': 'U'})
user_df['city_level'] = user_df['city_level'].replace({'-1': 'U'})
user_df['purchase_power'] = user_df['purchase_power'].replace({'-1': 'U'})
```

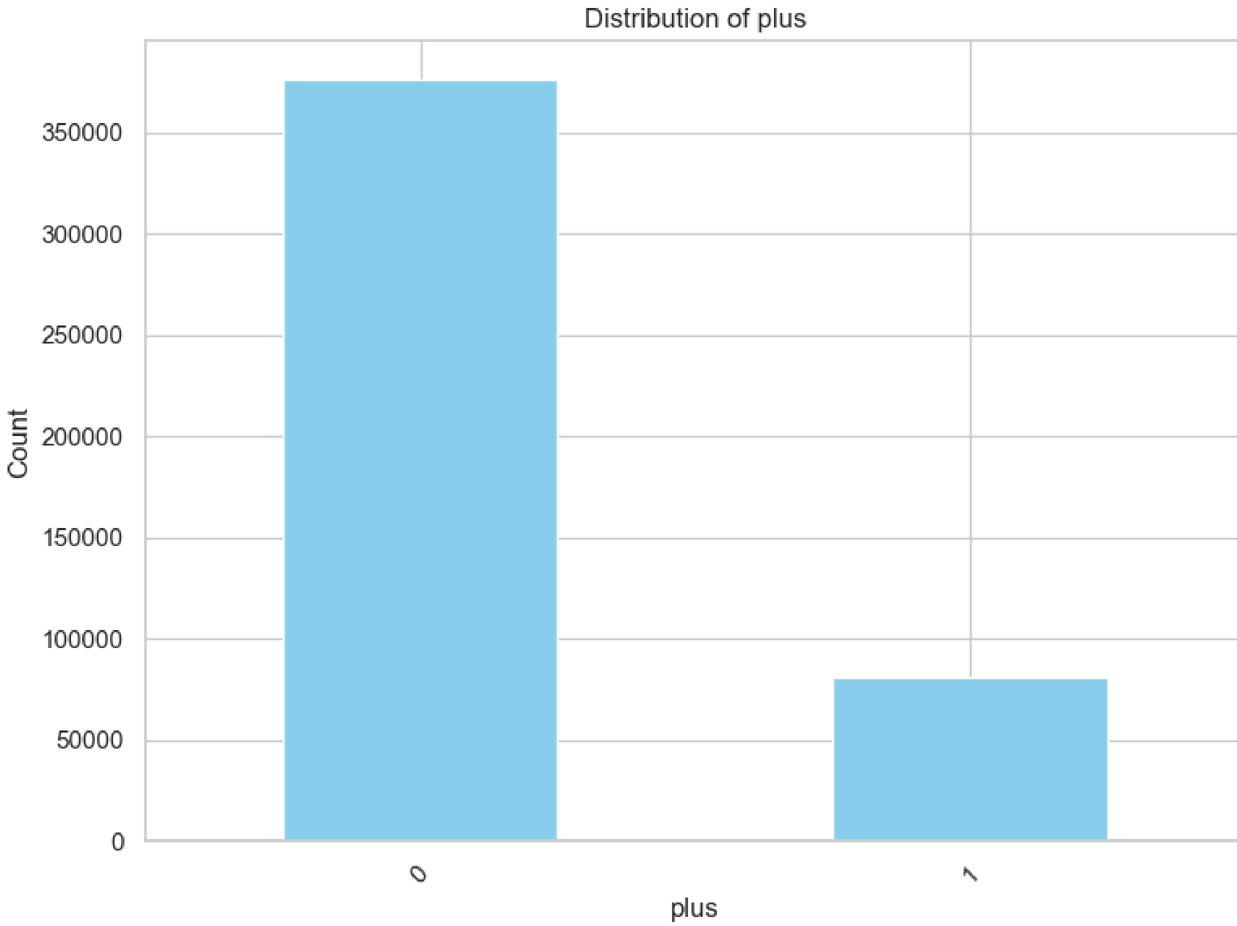
1. Let's move to the user table. Almost all user features are categorical variables. Make bar graphs to examine the distribution of "user_level', 'plus', 'gender', 'age', 'marital_status', 'education', 'city_level', and 'purchase_power'. You may consider using a loop. Based on the graphs, you may answer questions like these:
   A. What is the education level of the majority?
   B. Which age level has the most users?

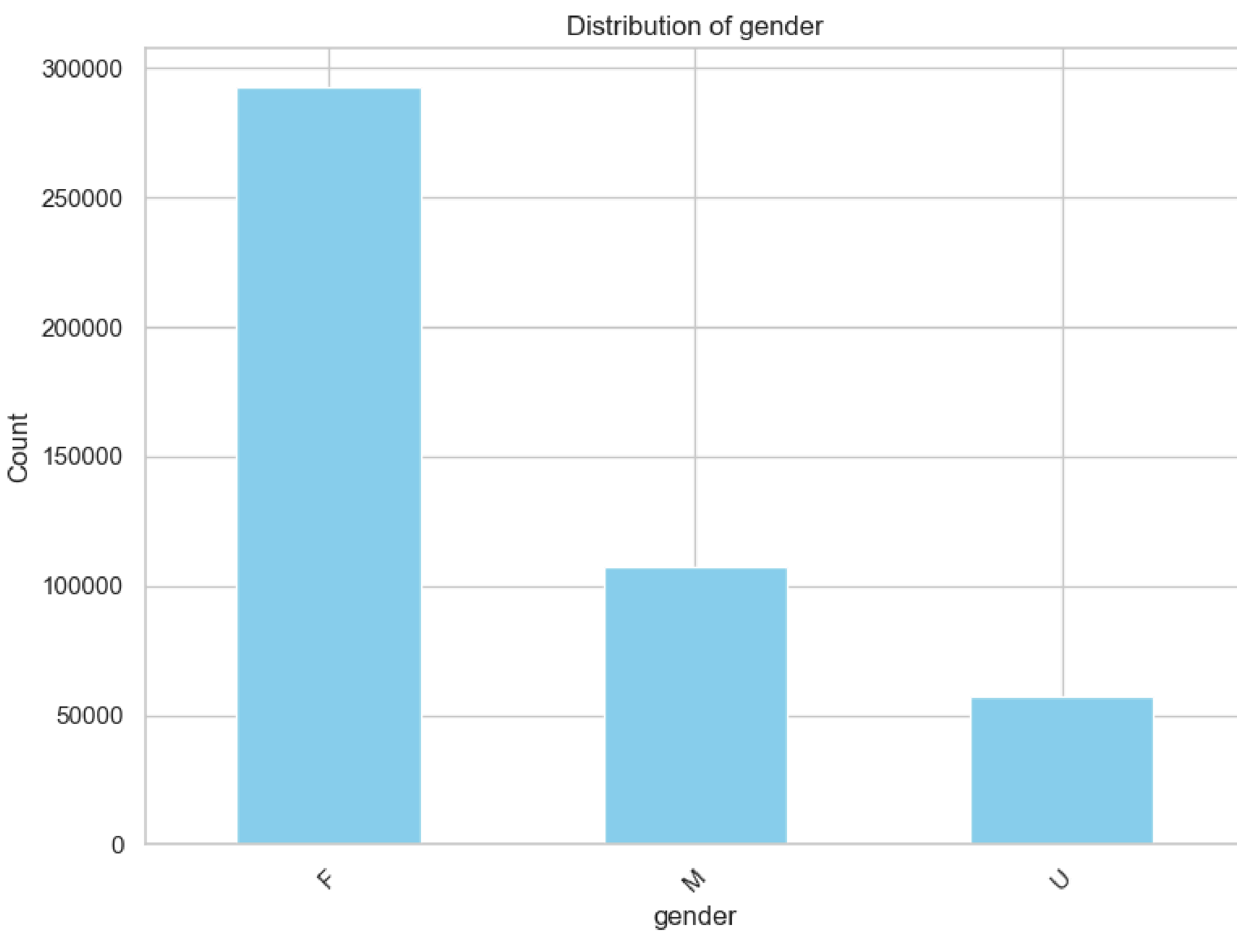
In [139…

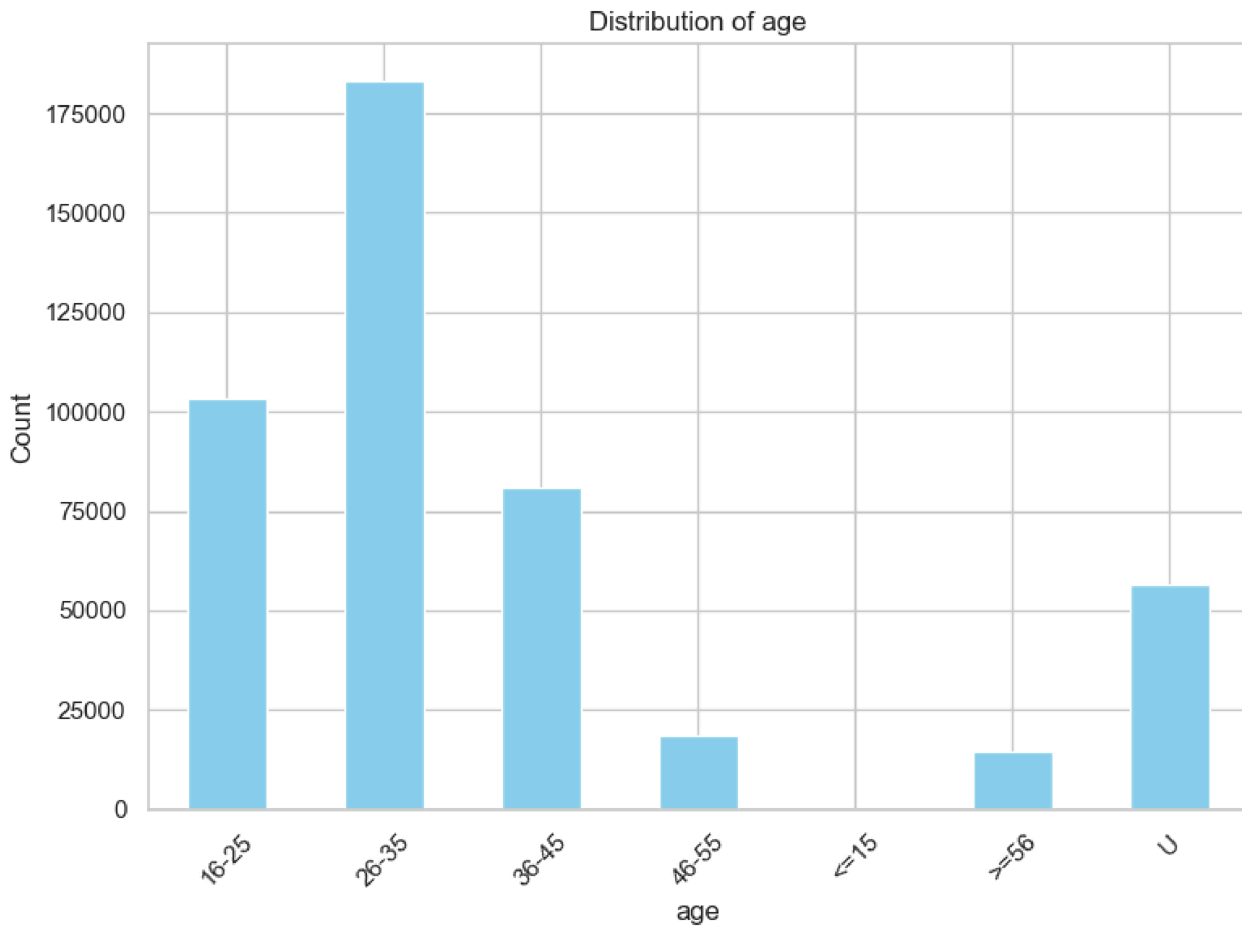
```
def plot_categorical_variable_distribution(dataframe, variable):
    plt.figure(figsize=(8, 6))
    dataframe[variable].value_counts().sort_index().plot(kind='bar', color='skyblue')
    plt.title(f"Distribution of {variable}")
    plt.xlabel(variable)
    plt.ylabel('Count')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

# List of categorical variables
categorical_variables = ['user_level', 'plus', 'gender', 'age', 'marital_status', 'educ

# Create bar graphs for each categorical variable
for var in categorical_variables:
    plot_categorical_variable_distribution(user_df, var)

# Find the most frequent education level
most_frequent_education = user_df['education'].value_counts().idxmax()
print(f"The education level of the majority is: {most_frequent_education}")

# Find the age level with the most users
```

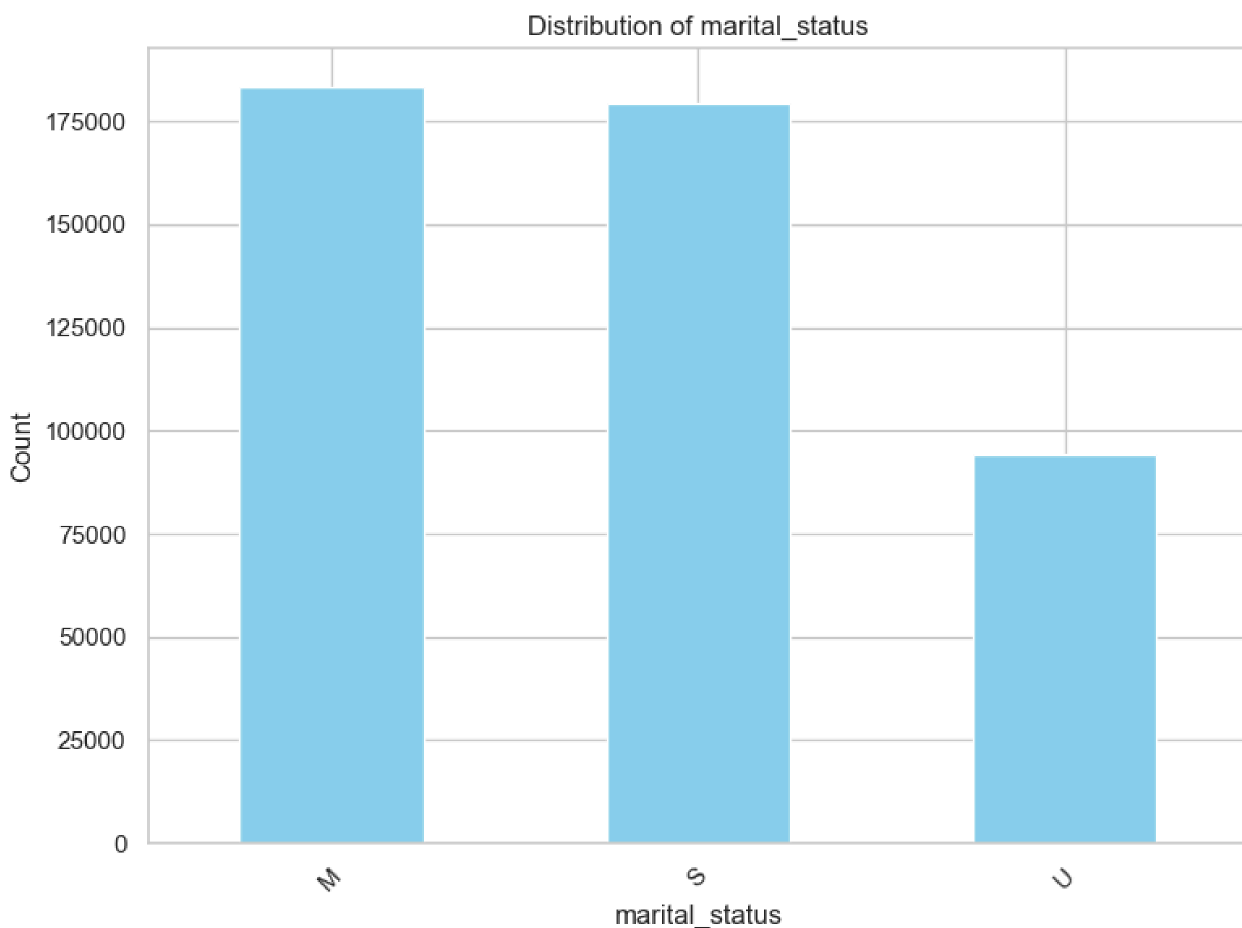
```
most_common_age_level = user_df['age'].value_counts().idxmax()
print(f"The age level with the most users is: {most_common_age_level}")
```

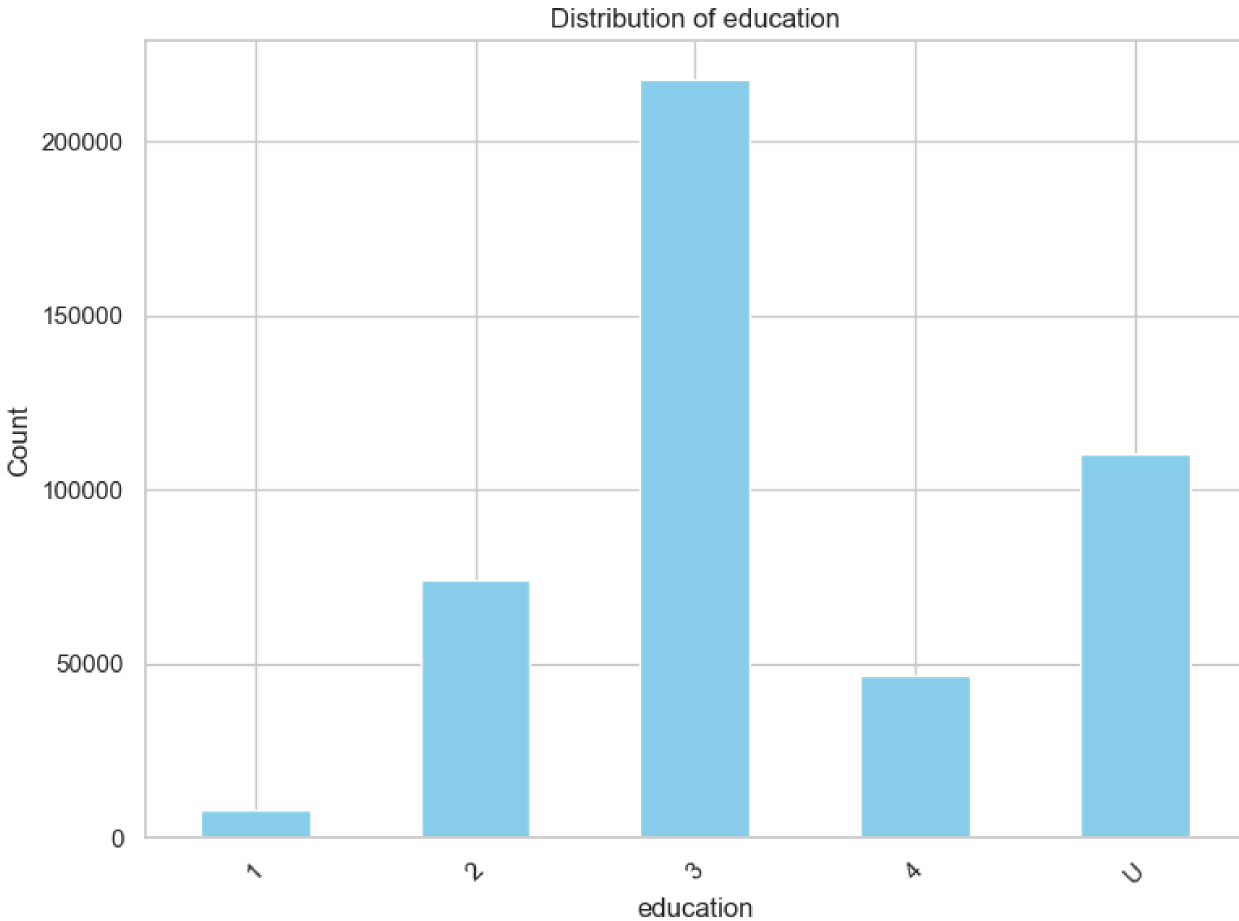


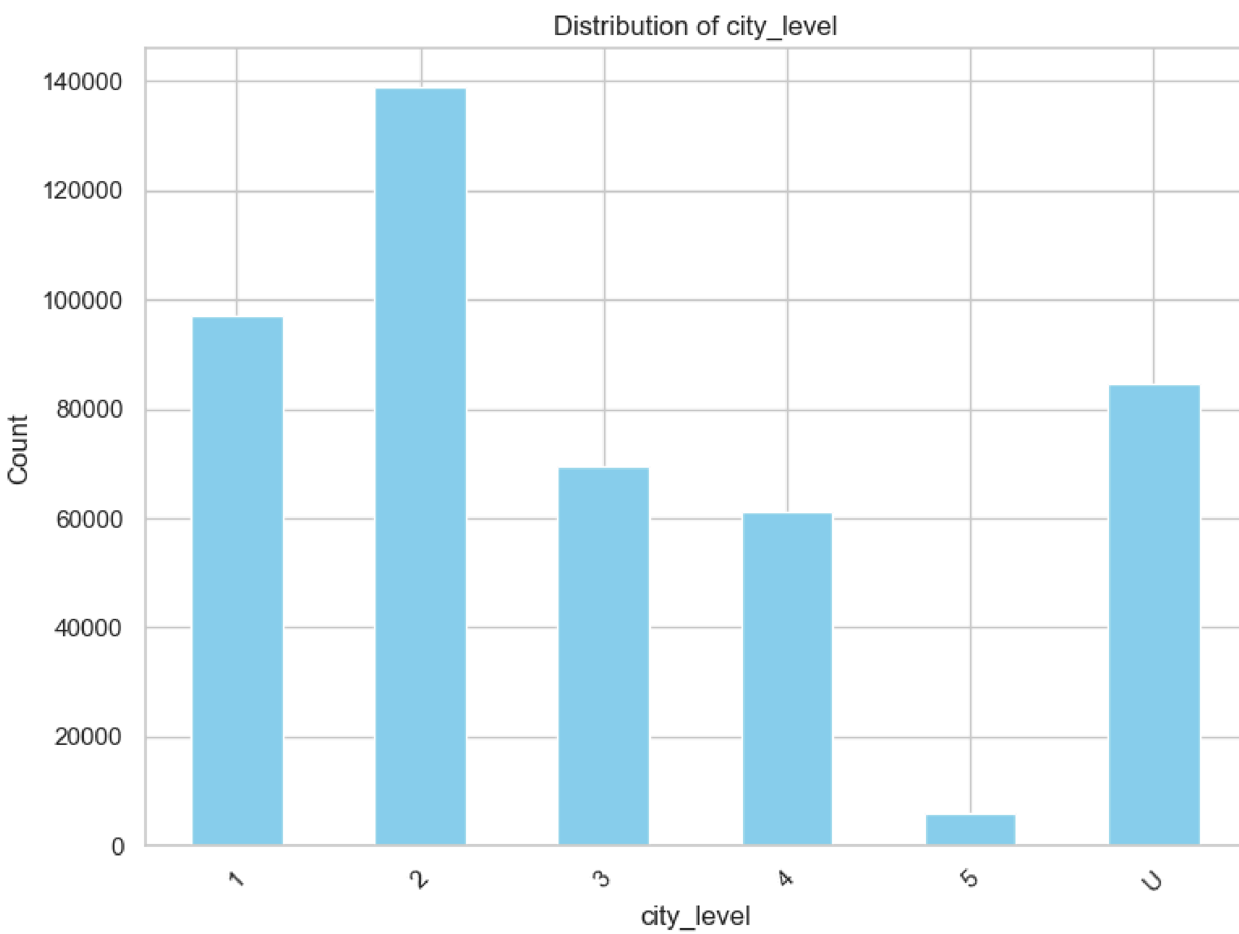

Distribution of plus
Count
350000
300000
250000
200000
150000
100000
50000
0
0
1
plus

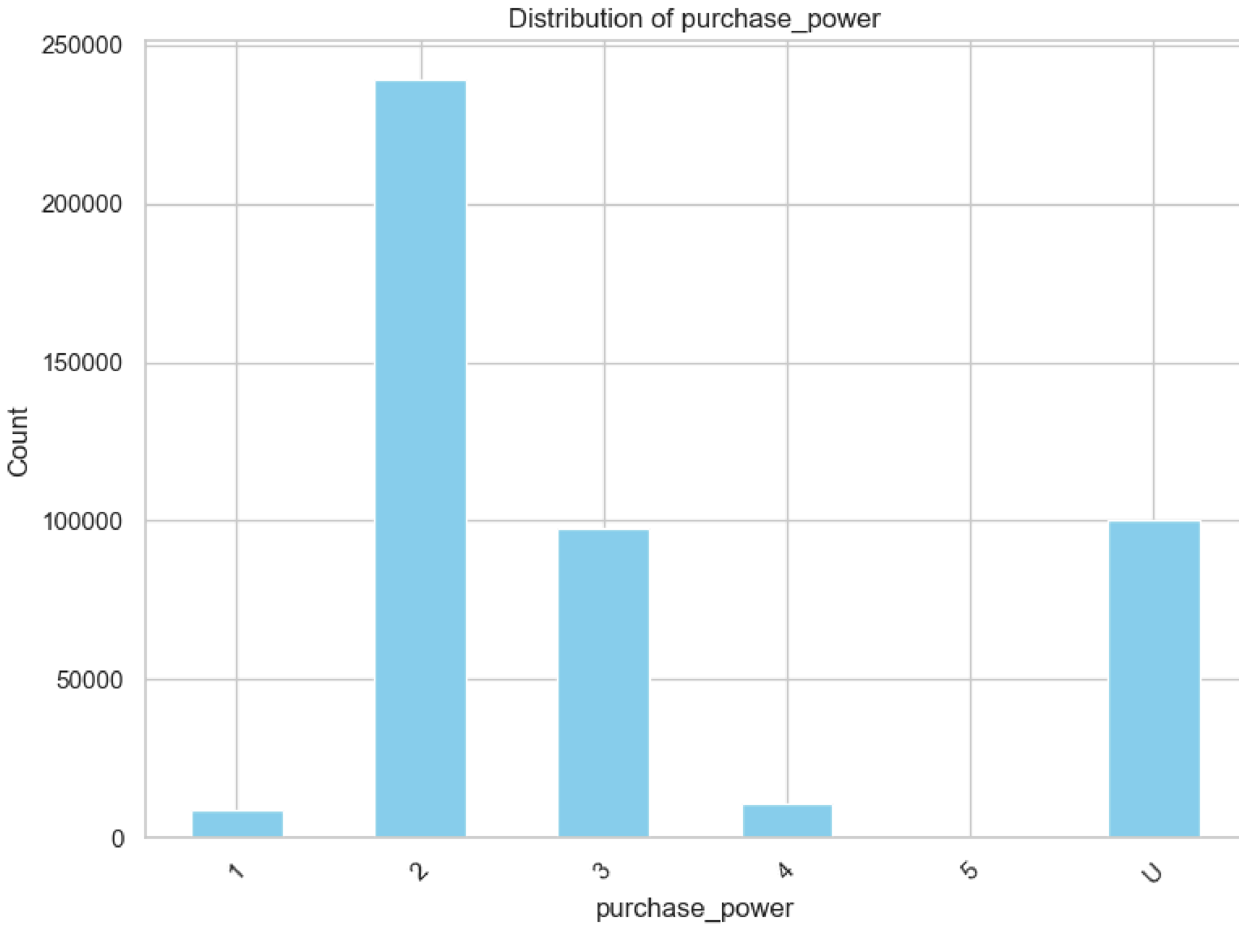

Distribution of gender
Count
300000
250000
200000
150000
100000
50000
0
F
M
U
gender


Distribution of age
Count
175000
150000
125000
100000
75000
50000
25000
0
16-25
26-35
36-45
46-55
<=15
>=56
U
age


Distribution of marital_status
Count
175000
150000
125000
100000
75000
50000
25000
0
M
S
U
marital_status


Distribution of education
Count
education
0
50000
100000
150000
200000
1
2
3
4
U


Distribution of city_level
Count
city_level
0
20000
40000
60000
80000
100000
120000
140000
1
2
3
4
5
U




```
The education level of the majority is: 3
The age level with the most users is: 26-35
```

1. Next we move to the table that resulted from Q11-Q15. Sum the quantity by day (we created this variable in Q14.) and save the results. Create a line graph based on it. Hint: The outcome of the sum is a Pandas Series. Use the .index to get the day and .values to get the sum for the plot. Or you may use reset_index() to turn the results to a dataframe. Which day has the most quantity sold?

In [140…

```
# Convert time-related variables to Timestamp data type
time_columns = ['order_date', 'order_time', 'ship_out_time', 'arr_station_time', 'arr_t
Inner_merged_data[time_columns] = Inner_merged_data[time_columns].apply(pd.to_datetime)

# Get the day of the month from 'order_date' and save it to a new variable 'order_day'
Inner_merged_data['order_day'] = Inner_merged_data['order_date'].dt.day

# Get the hour of the 'order_time' and save it to a new variable 'order_hour'
Inner_merged_data['order_hour'] = Inner_merged_data['order_time'].dt.hour

# Calculate the delivery time by subtracting 'arr_time' from 'order_time'
Inner_merged_data['delivery_time'] = Inner_merged_data['arr_time'] - Inner_merged_data[

# Print the first 5 rows of the updated DataFrame
print(Inner_merged_data.head())

# Sum the quantity by day
sum_by_day = Inner_merged_data.groupby('order_day')['quantity'].sum()  # Change 'filter
```

```
# Find the day with the most quantity sold
day_with_most_quantity = sum_by_day.idxmax()

print(f"The day with the most quantity sold is: {day_with_most_quantity}")

# Create a line graph based on the sum of quantity by day
sum_by_day.plot(kind='line', marker='o', figsize=(10, 6))
plt.title('Sum of Quantity Sold by Day')
plt.xlabel('Day')
plt.ylabel('Sum of Quantity')
plt.grid(True)
plt.show()
```

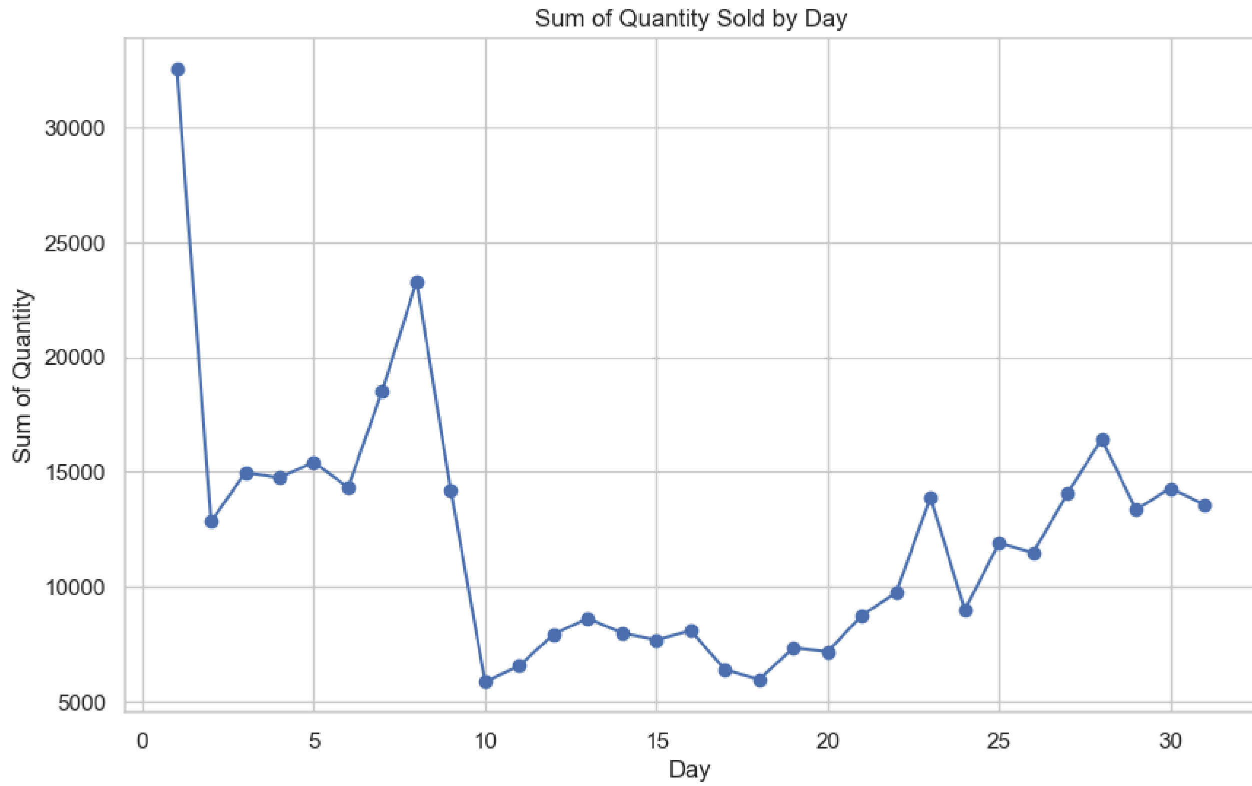
```
     order_ID     user_ID      sku_ID order_date          order_time  \
0  7444318d01  33a9e56257  067b673f2b 2018-03-01 2018-03-01 11:10:40
1  f973b01694  4ea3cf408f  623d0a582a 2018-03-01 2018-03-01 09:13:26
2  8c1cec8d4b  b87cb736cb  fc5289b139 2018-03-01 2018-03-01 21:29:50
3  d43a33c38a  4829223b6f  623d0a582a 2018-03-01 2018-03-01 19:13:37
4  e0f5386d87  0b07cae293  589c2b865b 2018-03-01 2018-03-01 21:09:15

   quantity  type_x promise  original_unit_price  final_unit_price  ...  \
0         1       1       2                 99.9              53.9  ...
1         1       1       2                 78.0              58.5  ...
2         1       1       2                 61.0              35.0  ...
3         1       1       1                 78.0              53.0  ...
4         1       1       1                 79.9              38.9  ...

   dc_ori  dc_des  package_ID       ship_out_time    arr_station_time  \
0      28      28  7444318d01 2018-03-01 13:00:00 2018-03-02 08:00:00
1      28      28  f973b01694 2018-03-01 14:00:00 2018-03-02 09:00:00
2       4      28  8c1cec8d4b 2018-03-02 09:00:00 2018-03-03 08:00:00
3       3      16  d43a33c38a 2018-03-01 20:00:00 2018-03-02 07:00:00
4       3      16  e0f5386d87 2018-03-01 22:00:00 2018-03-02 09:00:00

             arr_time  order_day order_hour   delivery_time  \
0 2018-03-02 14:00:00          1         11 1 days 02:49:20
1 2018-03-02 13:00:00          1          9 1 days 03:46:34
2 2018-03-04 11:00:00          1         21 2 days 13:30:10
3 2018-03-02 11:00:00          1         19 0 days 15:46:23
4 2018-03-02 12:00:00          1         21 0 days 14:50:45

  delivery_time_hours
0           26.822222
1           27.776111
2           61.502778
3           15.773056
4           14.845833

[5 rows x 25 columns]
The day with the most quantity sold is: 1
```

Out[140… `<Axes: xlabel='order_day'>`

Out[140… `Text(0.5, 1.0, 'Sum of Quantity Sold by Day')`

Out[140… `Text(0.5, 0, 'Day')`

Out[140… `Text(0, 0.5, 'Sum of Quantity')`



1. Repeat Q25 for variable 'order_hour' we created in Q14. When is the peak time for orders during a day? Can you describe the customer order trend over a day's time?

In [141…

```
# Sum the quantity by hour
sum_by_hour = Inner_merged_data.groupby('order_hour')['quantity'].sum()

# Find the hour with the most quantity ordered (peak time)
peak_order_hour = sum_by_hour.idxmax()

print(f"The peak time for orders during a day is: {peak_order_hour} o'clock")

# Create a line graph based on the sum of quantity by hour
sum_by_hour.plot(kind='line', marker='o', figsize=(10, 6))
plt.title('Sum of Quantity Sold by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel('Sum of Quantity')
plt.grid(True)
plt.show()
```

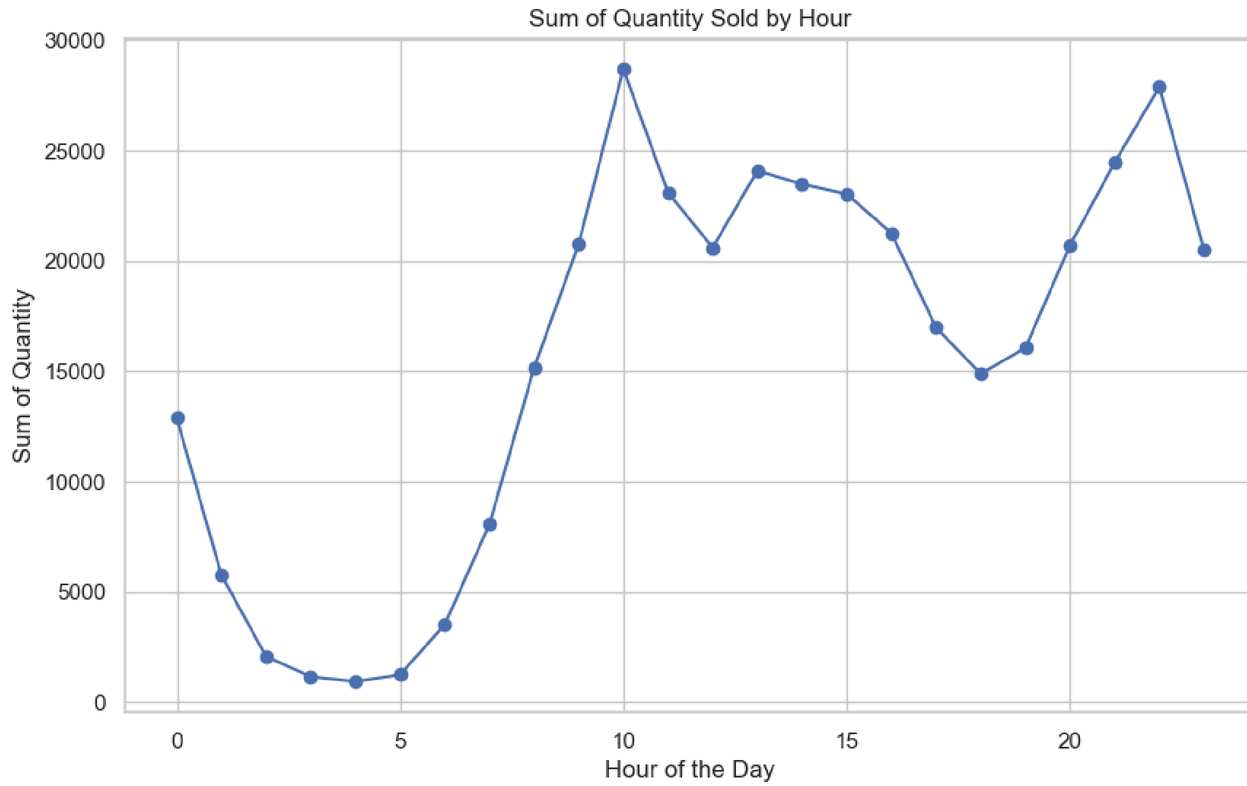
```
The peak time for orders during a day is: 10 o'clock
```

Out[141…
```
<Axes: xlabel='order_hour'>
```

Out[141…
```
Text(0.5, 1.0, 'Sum of Quantity Sold by Hour')
```

Out[141…
```
Text(0.5, 0, 'Hour of the Day')
```

Out[141…
```
Text(0, 0.5, 'Sum of Quantity')
```



1. Examine variable original_unit_price .

1) Using describe() to check the stastitics. What is min, max and median?

In [142…

```
# Use describe() to examine statistics of the 'original_unit_price' variable
price_stats = Inner_merged_data['original_unit_price'].describe()

# Print the statistics including min, max, and median
print("Statistics for 'original_unit_price':")
print(f"Minimum value: {price_stats['min']}")
print(f"Maximum value: {price_stats['max']}")
print(f"Median value: {price_stats['50%']}")  # '50%' corresponds to the median value
```

```
Statistics for 'original_unit_price':
Minimum value: 0.0
Maximum value: 7130.0
Median value: 85.0
```

2) Find out the percentage of observations whose original_unit_price is greater than 350. Delete those observations using filtering. We will use the filtered dataset from now on.

In [143…

```
# Calculate the percentage of observations where 'original_unit_price' is greater than .
percentage_greater_than_350 = (Inner_merged_data['original_unit_price'] > 350).mean() *

print(f"Percentage of observations with 'original_unit_price' > 350: {percentage_greate

# Filter the DataFrame to keep observations where 'original_unit_price' is not greater 
filtered_merged = Inner_merged_data[Inner_merged_data['original_unit_price'] <= 350].co

# Display the shape of the filtered DataFrame before and after filtering
print(f"Shape of original DataFrame: {Inner_merged_data.shape}")
print(f"Shape of filtered DataFrame: {filtered_merged.shape}")
```

```
# Now, 'filtered_merged' contains the dataset with observations where 'original_unit_pr
```

```
Percentage of observations with 'original_unit_price' > 350: 0.66%
Shape of original DataFrame: (312391, 25)
Shape of filtered DataFrame: (310335, 25)
```

3) Examine the distribution of original_unit_price, using bins range from 0 to 350, width 10. Which price range has the most orders?

In [144…

```
import matplotlib.pyplot as plt
import seaborn as sns

# Define bins ranging from 0 to 350 with a width of 10
bins = range(0, 360, 10)

# Set Seaborn style
sns.set(style="whitegrid")

# Create a histogram of 'original_unit_price' with specified bins
plt.figure(figsize=(12, 6))
plt.hist(filtered_merged['original_unit_price'], bins=bins, edgecolor='black', color='#
plt.title('Distribution of Original Unit Price', fontsize=16)
plt.xlabel('Original Unit Price', fontsize=14)
plt.ylabel('Number of Orders', fontsize=14)
plt.xticks(bins, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Count the number of orders in each price range (bin)
orders_per_bin = pd.cut(filtered_merged['original_unit_price'], bins=bins).value_counts
most_orders_range = orders_per_bin.idxmax()

print(f"The price range with the most orders is: {most_orders_range}")
```

Out[144…

```
<Figure size 1200x600 with 0 Axes>
```

Out[144…

```
(array([1.2330e+04, 3.6630e+03, 1.6820e+03, 4.5640e+03, 4.9670e+03,
        3.2929e+04, 3.1539e+04, 5.7251e+04, 1.9267e+04, 1.4141e+04,
        8.4430e+03, 5.5720e+03, 1.3104e+04, 1.6164e+04, 9.5820e+03,
        5.3300e+03, 2.4780e+03, 1.2135e+04, 3.3870e+03, 5.3610e+03,
        8.1100e+02, 6.3500e+02, 5.0000e+01, 2.6950e+03, 5.8090e+03,
        2.8450e+03, 2.0040e+03, 3.1800e+02, 4.3000e+02, 2.7036e+04,
        9.9100e+02, 3.2000e+01, 5.1800e+02, 2.2650e+03, 7.0000e+00]),
 array([  0.,  10.,  20.,  30.,  40.,  50.,  60.,  70.,  80.,  90., 100.,
        110., 120., 130., 140., 150., 160., 170., 180., 190., 200., 210.,
        220., 230., 240., 250., 260., 270., 280., 290., 300., 310., 320.,
        330., 340., 350.]),
 <BarContainer object of 35 artists>)
```

Out[144…

```
Text(0.5, 1.0, 'Distribution of Original Unit Price')
```

Out[144…

```
Text(0.5, 0, 'Original Unit Price')
```

Out[144…

```
Text(0, 0.5, 'Number of Orders')
```

Out[144…

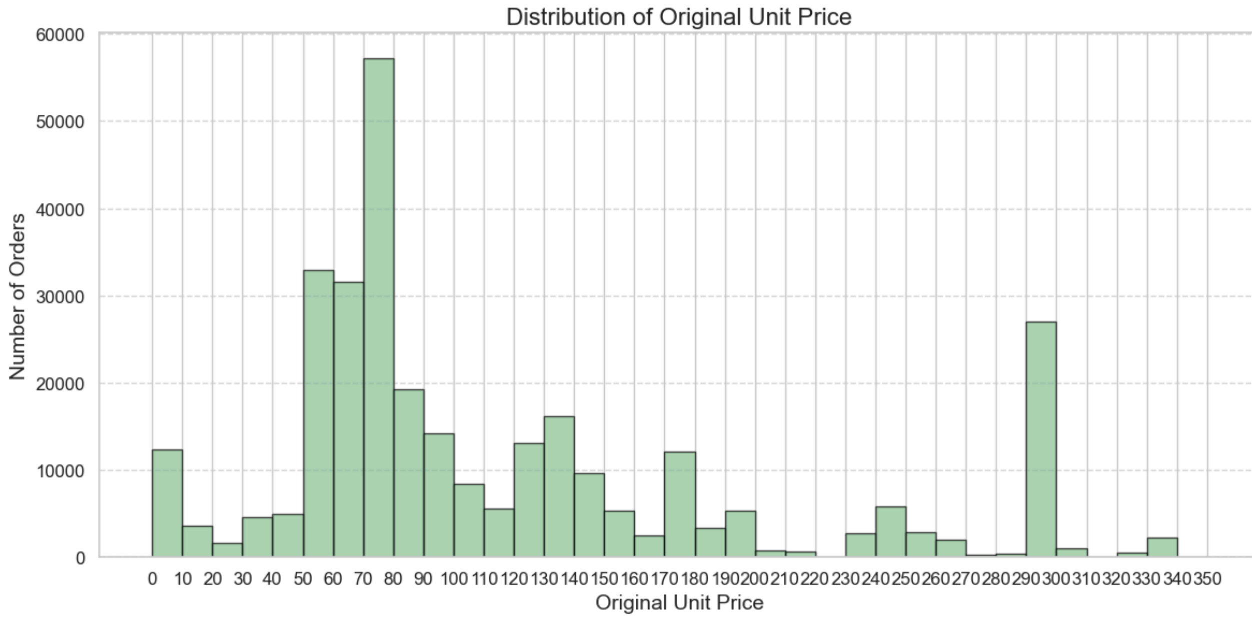
```
([<matplotlib.axis.XTick at 0x18588344750>,
  <matplotlib.axis.XTick at 0x18588374bd0>,
  <matplotlib.axis.XTick at 0x185883a5090>,
  <matplotlib.axis.XTick at 0x18588368790>,
```

```
 <matplotlib.axis.XTick at 0x1858828e290>,
 <matplotlib.axis.XTick at 0x18588287910>,
 <matplotlib.axis.XTick at 0x1858827e650>,
 <matplotlib.axis.XTick at 0x18588274ed0>,
 <matplotlib.axis.XTick at 0x1858826a190>,
 <matplotlib.axis.XTick at 0x185882602d0>,
 <matplotlib.axis.XTick at 0x18588285c10>,
 <matplotlib.axis.XTick at 0x18588255150>,
 <matplotlib.axis.XTick at 0x1858824c990>,
 <matplotlib.axis.XTick at 0x18588242090>,
 <matplotlib.axis.XTick at 0x18586697550>,
 <matplotlib.axis.XTick at 0x1858825a910>,
 <matplotlib.axis.XTick at 0x18586689650>,
 <matplotlib.axis.XTick at 0x185866809d0>,
 <matplotlib.axis.XTick at 0x18586676f50>,
 <matplotlib.axis.XTick at 0x18586672f90>,
 <matplotlib.axis.XTick at 0x18586685290>,
 <matplotlib.axis.XTick at 0x18586662190>,
 <matplotlib.axis.XTick at 0x18586658650>,
 <matplotlib.axis.XTick at 0x1858664fe10>,
 <matplotlib.axis.XTick at 0x18586646c90>,
 <matplotlib.axis.XTick at 0x1858665c290>,
 <matplotlib.axis.XTick at 0x185866392d0>,
 <matplotlib.axis.XTick at 0x18586630410>,
 <matplotlib.axis.XTick at 0x18586626ed0>,
 <matplotlib.axis.XTick at 0x1858661e090>,
 <matplotlib.axis.XTick at 0x18586653150>,
 <matplotlib.axis.XTick at 0x18586612d10>,
 <matplotlib.axis.XTick at 0x18586609950>,
 <matplotlib.axis.XTick at 0x185865ff650>,
 <matplotlib.axis.XTick at 0x185865fd410>,
 <matplotlib.axis.XTick at 0x18586601610>],
[Text(0, 0, '0'),
 Text(10, 0, '10'),
 Text(20, 0, '20'),
 Text(30, 0, '30'),
 Text(40, 0, '40'),
 Text(50, 0, '50'),
 Text(60, 0, '60'),
 Text(70, 0, '70'),
 Text(80, 0, '80'),
 Text(90, 0, '90'),
 Text(100, 0, '100'),
 Text(110, 0, '110'),
 Text(120, 0, '120'),
 Text(130, 0, '130'),
 Text(140, 0, '140'),
 Text(150, 0, '150'),
 Text(160, 0, '160'),
 Text(170, 0, '170'),
 Text(180, 0, '180'),
 Text(190, 0, '190'),
 Text(200, 0, '200'),
 Text(210, 0, '210'),
 Text(220, 0, '220'),
 Text(230, 0, '230'),
 Text(240, 0, '240'),
 Text(250, 0, '250'),
 Text(260, 0, '260'),
 Text(270, 0, '270'),
 Text(280, 0, '280'),
 Text(290, 0, '290'),
 Text(300, 0, '300'),
 Text(310, 0, '310'),
 Text(320, 0, '320'),
```

```
 Text(330, 0, '330'),
 Text(340, 0, '340'),
 Text(350, 0, '350')])
```

Out[144…

```
(array([    0., 10000., 20000., 30000., 40000., 50000., 60000., 70000.]),
 [Text(0, 0.0, '0'),
  Text(0, 10000.0, '10000'),
  Text(0, 20000.0, '20000'),
  Text(0, 30000.0, '30000'),
  Text(0, 40000.0, '40000'),
  Text(0, 50000.0, '50000'),
  Text(0, 60000.0, '60000'),
  Text(0, 70000.0, '70000')])
```




```
The price range with the most orders is: (70, 80]
```

1. Examine the distribution of final_unit_price, using bins range from -20 to 350, width 10. Comparing to original unit prices, how are the final prices different?

In [145…

```
# Define bins ranging from -20 to 350 with a width of 10
bins = range(-20, 360, 10)

# Set Seaborn style
sns.set(style="whitegrid")

# Create a histogram of 'final_unit_price' with specified bins
plt.figure(figsize=(12, 6))
plt.hist(filtered_merged['final_unit_price'], bins=bins, edgecolor='black', color='oran
plt.title('Distribution of Final Unit Price', fontsize=16)
plt.xlabel('Final Unit Price', fontsize=14)
plt.ylabel('Number of Orders', fontsize=14)
plt.xticks(bins, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Calculate the number of orders in each price range (bin)
orders_per_bin_final_price = pd.cut(filtered_merged['final_unit_price'], bins=bins).val

# Compare the distributions of original_unit_price and final_unit_price
plt.figure(figsize=(12, 6))
```

```
plt.hist(filtered_merged['original_unit_price'], bins=bins, edgecolor='black', alpha=0.
plt.hist(filtered_merged['final_unit_price'], bins=bins, edgecolor='black', color='oran
plt.title('Comparison of Original Unit Price and Final Unit Price', fontsize=16)
plt.xlabel('Price', fontsize=14)
plt.ylabel('Number of Orders', fontsize=14)
plt.legend(fontsize=12)
plt.xticks(bins, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

Out[145…

```
<Figure size 1200x600 with 0 Axes>
```

Out[145…

```
(array([8.9000e+01, 9.2200e+02, 1.6434e+04, 4.7890e+03, 1.0523e+04,
        3.7821e+04, 3.6635e+04, 4.2602e+04, 3.5412e+04, 1.9201e+04,
        9.4270e+03, 1.1270e+04, 1.1681e+04, 4.6090e+03, 1.0485e+04,
        5.0830e+03, 4.6640e+03, 5.4450e+03, 7.9960e+03, 1.7980e+03,
        2.1200e+03, 3.4790e+03, 1.0715e+04, 2.4290e+03, 8.0320e+03,
        2.4030e+03, 2.5380e+03, 6.8500e+02, 2.8700e+02, 2.3400e+02,
        1.3600e+02, 2.8800e+02, 7.1000e+01, 1.4000e+01, 5.0000e+00,
        1.3000e+01, 0.0000e+00]),
 array([-20., -10.,   0.,  10.,  20.,  30.,  40.,  50.,  60.,  70.,  80.,
         90., 100., 110., 120., 130., 140., 150., 160., 170., 180., 190.,
        200., 210., 220., 230., 240., 250., 260., 270., 280., 290., 300.,
        310., 320., 330., 340., 350.]),
 <BarContainer object of 37 artists>)
```

Out[145…

```
Text(0.5, 1.0, 'Distribution of Final Unit Price')
```

Out[145…

```
Text(0.5, 0, 'Final Unit Price')
```

Out[145…

```
Text(0, 0.5, 'Number of Orders')
```

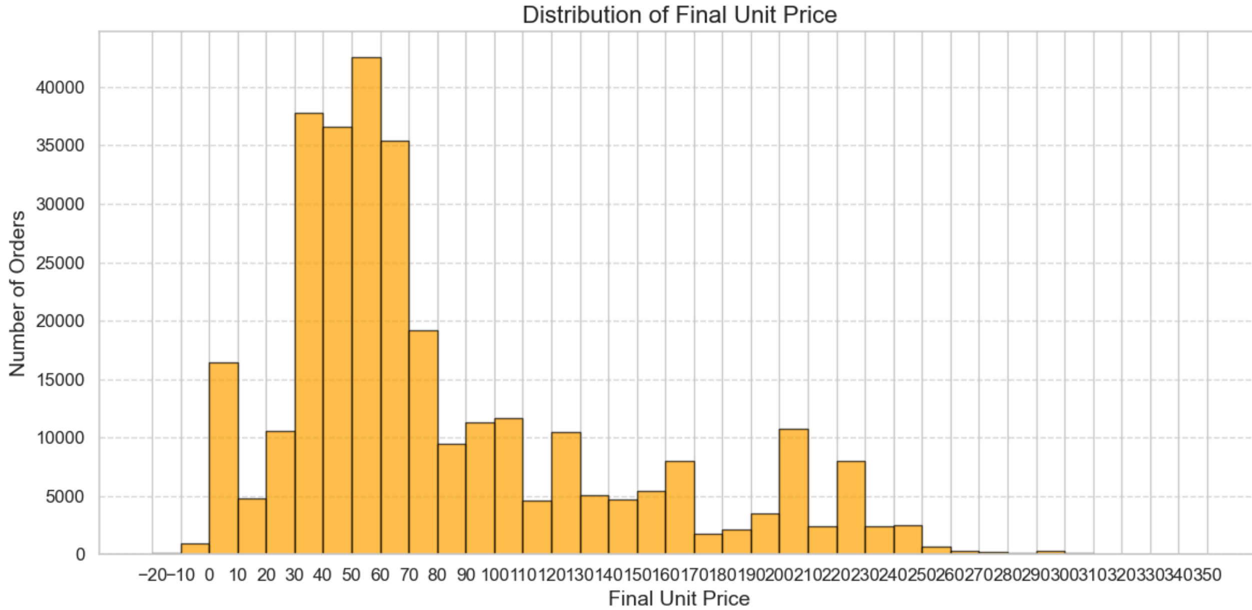
Out[145…

```
([<matplotlib.axis.XTick at 0x18586249b50>,
  <matplotlib.axis.XTick at 0x18588293050>,
  <matplotlib.axis.XTick at 0x185861efe10>,
  <matplotlib.axis.XTick at 0x18586678790>,
  <matplotlib.axis.XTick at 0x1858619cd90>,
  <matplotlib.axis.XTick at 0x18586192810>,
  <matplotlib.axis.XTick at 0x1858618d410>,
  <matplotlib.axis.XTick at 0x18586191190>,
  <matplotlib.axis.XTick at 0x185861faf90>,
  <matplotlib.axis.XTick at 0x18586174bd0>,
  <matplotlib.axis.XTick at 0x18586168850>,
  <matplotlib.axis.XTick at 0x1858615e850>,
  <matplotlib.axis.XTick at 0x18586166250>,
  <matplotlib.axis.XTick at 0x18586152390>,
  <matplotlib.axis.XTick at 0x18586147ad0>,
  <matplotlib.axis.XTick at 0x1858613e0d0>,
  <matplotlib.axis.XTick at 0x18586134450>,
  <matplotlib.axis.XTick at 0x1858613ae10>,
  <matplotlib.axis.XTick at 0x18586129ad0>,
  <matplotlib.axis.XTick at 0x18586120710>,
  <matplotlib.axis.XTick at 0x1858611c490>,
  <matplotlib.axis.XTick at 0x1858610cbd0>,
  <matplotlib.axis.XTick at 0x18586113e10>,
  <matplotlib.axis.XTick at 0x18586100350>,
  <matplotlib.axis.XTick at 0x185860f7510>,
  <matplotlib.axis.XTick at 0x185860ee710>,
  <matplotlib.axis.XTick at 0x185860e5590>,
  <matplotlib.axis.XTick at 0x185860ecb50>,
  <matplotlib.axis.XTick at 0x185860dab50>,
  <matplotlib.axis.XTick at 0x185860d2010>,
```

```
  <matplotlib.axis.XTick at 0x185860c8ad0>,
  <matplotlib.axis.XTick at 0x185860c0210>,
  <matplotlib.axis.XTick at 0x185860f2850>,
  <matplotlib.axis.XTick at 0x185860b4050>,
  <matplotlib.axis.XTick at 0x185860aaed0>,
  <matplotlib.axis.XTick at 0x185860a12d0>,
  <matplotlib.axis.XTick at 0x18586096c50>,
  <matplotlib.axis.XTick at 0x1858609e850>],
 [Text(-20, 0, '−20'),
  Text(-10, 0, '−10'),
  Text(0, 0, '0'),
  Text(10, 0, '10'),
  Text(20, 0, '20'),
  Text(30, 0, '30'),
  Text(40, 0, '40'),
  Text(50, 0, '50'),
  Text(60, 0, '60'),
  Text(70, 0, '70'),
  Text(80, 0, '80'),
  Text(90, 0, '90'),
  Text(100, 0, '100'),
  Text(110, 0, '110'),
  Text(120, 0, '120'),
  Text(130, 0, '130'),
  Text(140, 0, '140'),
  Text(150, 0, '150'),
  Text(160, 0, '160'),
  Text(170, 0, '170'),
  Text(180, 0, '180'),
  Text(190, 0, '190'),
  Text(200, 0, '200'),
  Text(210, 0, '210'),
  Text(220, 0, '220'),
  Text(230, 0, '230'),
  Text(240, 0, '240'),
  Text(250, 0, '250'),
  Text(260, 0, '260'),
  Text(270, 0, '270'),
  Text(280, 0, '280'),
  Text(290, 0, '290'),
  Text(300, 0, '300'),
  Text(310, 0, '310'),
  Text(320, 0, '320'),
  Text(330, 0, '330'),
  Text(340, 0, '340'),
  Text(350, 0, '350')])
```

Out[145…

```
(array([    0.,  5000., 10000., 15000., 20000., 25000., 30000., 35000.,
        40000., 45000.]),
 [Text(0, 0.0, '0'),
  Text(0, 5000.0, '5000'),
  Text(0, 10000.0, '10000'),
  Text(0, 15000.0, '15000'),
  Text(0, 20000.0, '20000'),
  Text(0, 25000.0, '25000'),
  Text(0, 30000.0, '30000'),
  Text(0, 35000.0, '35000'),
  Text(0, 40000.0, '40000'),
  Text(0, 45000.0, '45000')])
```



Out[145…
```
<Figure size 1200x600 with 0 Axes>
```

Out[145…
```
(array([0.0000e+00, 0.0000e+00, 1.2330e+04, 3.6630e+03, 1.6820e+03,
        4.5640e+03, 4.9670e+03, 3.2929e+04, 3.1539e+04, 5.7251e+04,
        1.9267e+04, 1.4141e+04, 8.4430e+03, 5.5720e+03, 1.3104e+04,
        1.6164e+04, 9.5820e+03, 5.3300e+03, 2.4780e+03, 1.2135e+04,
        3.3870e+03, 5.3610e+03, 8.1100e+02, 6.3500e+02, 5.0000e+01,
        2.6950e+03, 5.8090e+03, 2.8450e+03, 2.0040e+03, 3.1800e+02,
        4.3000e+02, 2.7036e+04, 9.9100e+02, 3.2000e+01, 5.1800e+02,
        2.2650e+03, 7.0000e+00]),
 array([-20., -10.,   0.,  10.,  20.,  30.,  40.,  50.,  60.,  70.,  80.,
         90., 100., 110., 120., 130., 140., 150., 160., 170., 180., 190.,
        200., 210., 220., 230., 240., 250., 260., 270., 280., 290., 300.,
        310., 320., 330., 340., 350.]),
 <BarContainer object of 37 artists>)
```

Out[145…
```
(array([8.9000e+01, 9.2200e+02, 1.6434e+04, 4.7890e+03, 1.0523e+04,
        3.7821e+04, 3.6635e+04, 4.2602e+04, 3.5412e+04, 1.9201e+04,
        9.4270e+03, 1.1270e+04, 1.1681e+04, 4.6090e+03, 1.0485e+04,
        5.0830e+03, 4.6640e+03, 5.4450e+03, 7.9960e+03, 1.7980e+03,
        2.1200e+03, 3.4790e+03, 1.0715e+04, 2.4290e+03, 8.0320e+03,
        2.4030e+03, 2.5380e+03, 6.8500e+02, 2.8700e+02, 2.3400e+02,
        1.3600e+02, 2.8800e+02, 7.1000e+01, 1.4000e+01, 5.0000e+00,
        1.3000e+01, 0.0000e+00]),
 array([-20., -10.,   0.,  10.,  20.,  30.,  40.,  50.,  60.,  70.,  80.,
         90., 100., 110., 120., 130., 140., 150., 160., 170., 180., 190.,
        200., 210., 220., 230., 240., 250., 260., 270., 280., 290., 300.,
        310., 320., 330., 340., 350.]),
 <BarContainer object of 37 artists>)
```

Out[145…
```
Text(0.5, 1.0, 'Comparison of Original Unit Price and Final Unit Price')
```

Out[145…
```
Text(0.5, 0, 'Price')
```

Out[145…
```
Text(0, 0.5, 'Number of Orders')
```

Out[145…
```
<matplotlib.legend.Legend at 0x18585c7ce10>
```

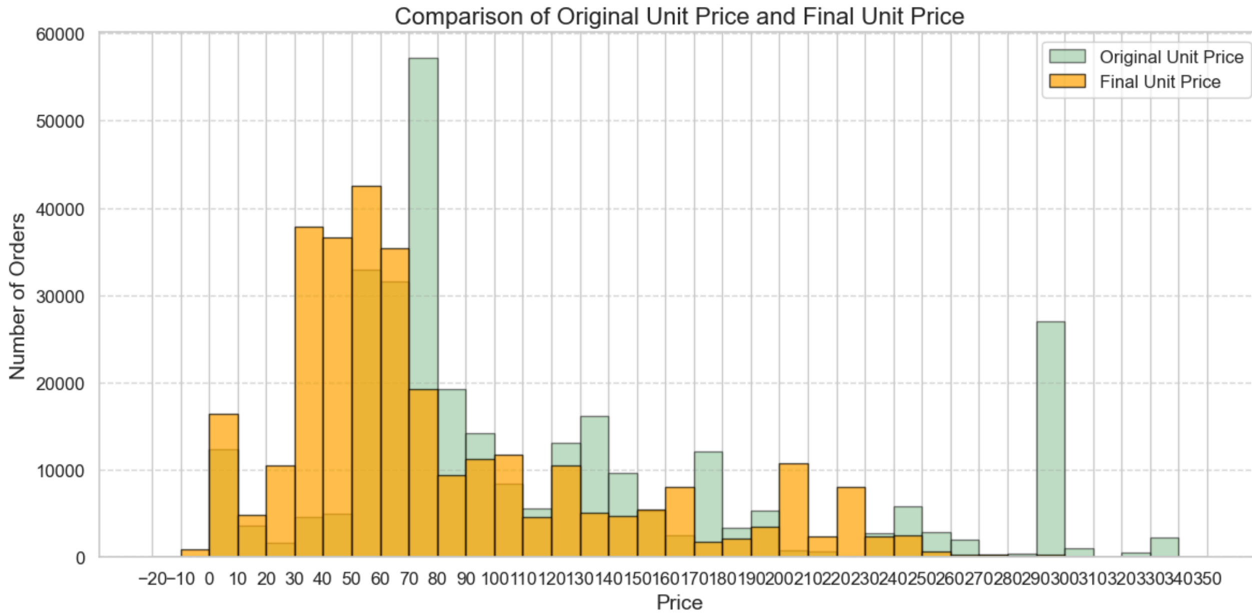
Out[145…
```
([<matplotlib.axis.XTick at 0x18585c8f790>,
  <matplotlib.axis.XTick at 0x18585cb6650>,
  <matplotlib.axis.XTick at 0x185860dea90>,
  <matplotlib.axis.XTick at 0x185846ac950>,
  <matplotlib.axis.XTick at 0x185846a2a90>,
  <matplotlib.axis.XTick at 0x1858469c550>,
  <matplotlib.axis.XTick at 0x185846940d0>,
```

```
 <matplotlib.axis.XTick at 0x1858468ad90>,
 <matplotlib.axis.XTick at 0x185846806d0>,
 <matplotlib.axis.XTick at 0x18584676f10>,
 <matplotlib.axis.XTick at 0x1858466d550>,
 <matplotlib.axis.XTick at 0x18584691050>,
 <matplotlib.axis.XTick at 0x18584661bd0>,
 <matplotlib.axis.XTick at 0x18584659750>,
 <matplotlib.axis.XTick at 0x18584653750>,
 <matplotlib.axis.XTick at 0x18584646990>,
 <matplotlib.axis.XTick at 0x18585c42490>,
 <matplotlib.axis.XTick at 0x1858463bc90>,
 <matplotlib.axis.XTick at 0x18584632650>,
 <matplotlib.axis.XTick at 0x1858462a2d0>,
 <matplotlib.axis.XTick at 0x18584621990>,
 <matplotlib.axis.XTick at 0x185835391d0>,
 <matplotlib.axis.XTick at 0x18585c944d0>,
 <matplotlib.axis.XTick at 0x1858352ed10>,
 <matplotlib.axis.XTick at 0x18583524c10>,
 <matplotlib.axis.XTick at 0x1858351ae50>,
 <matplotlib.axis.XTick at 0x18583511750>,
 <matplotlib.axis.XTick at 0x18585c9be10>,
 <matplotlib.axis.XTick at 0x18583506990>,
 <matplotlib.axis.XTick at 0x185834fd210>,
 <matplotlib.axis.XTick at 0x185834f3750>,
 <matplotlib.axis.XTick at 0x185834ead90>,
 <matplotlib.axis.XTick at 0x185834e1990>,
 <matplotlib.axis.XTick at 0x18583514850>,
 <matplotlib.axis.XTick at 0x185834d8990>,
 <matplotlib.axis.XTick at 0x185834ce710>,
 <matplotlib.axis.XTick at 0x185834c4950>,
 <matplotlib.axis.XTick at 0x185834ba210>],
[Text(-20, 0, '−20'),
 Text(-10, 0, '−10'),
 Text(0, 0, '0'),
 Text(10, 0, '10'),
 Text(20, 0, '20'),
 Text(30, 0, '30'),
 Text(40, 0, '40'),
 Text(50, 0, '50'),
 Text(60, 0, '60'),
 Text(70, 0, '70'),
 Text(80, 0, '80'),
 Text(90, 0, '90'),
 Text(100, 0, '100'),
 Text(110, 0, '110'),
 Text(120, 0, '120'),
 Text(130, 0, '130'),
 Text(140, 0, '140'),
 Text(150, 0, '150'),
 Text(160, 0, '160'),
 Text(170, 0, '170'),
 Text(180, 0, '180'),
 Text(190, 0, '190'),
 Text(200, 0, '200'),
 Text(210, 0, '210'),
 Text(220, 0, '220'),
 Text(230, 0, '230'),
 Text(240, 0, '240'),
 Text(250, 0, '250'),
 Text(260, 0, '260'),
 Text(270, 0, '270'),
 Text(280, 0, '280'),
 Text(290, 0, '290'),
 Text(300, 0, '300'),
 Text(310, 0, '310'),
```

```
 Text(320, 0, '320'),
 Text(330, 0, '330'),
 Text(340, 0, '340'),
 Text(350, 0, '350')])
```

Out[145…

```
(array([    0., 10000., 20000., 30000., 40000., 50000., 60000., 70000.]),
 [Text(0, 0.0, '0'),
  Text(0, 10000.0, '10000'),
  Text(0, 20000.0, '20000'),
  Text(0, 30000.0, '30000'),
  Text(0, 40000.0, '40000'),
  Text(0, 50000.0, '50000'),
  Text(0, 60000.0, '60000'),
  Text(0, 70000.0, '70000')])
```



1. Create a new variable 'sales', which is equal to the multiplication of quantity and final unit price. Make a graph for sales by day as in Q25.

In [146…

```python
# Create a new variable 'sales' by multiplying 'quantity' and 'final_unit_price'
filtered_merged['sales'] = filtered_merged['quantity'] * filtered_merged['final_unit_pr

# Group the data by 'order_day' and calculate the total sales for each day
sales_by_day = filtered_merged.groupby('order_day')['sales'].sum()

# Plot the sales by day
plt.figure(figsize=(10, 6))
sales_by_day.plot(kind='line', marker='o')
plt.title('Total Sales by Day')
plt.xlabel('Day')
plt.ylabel('Total Sales')
plt.grid(True)
plt.show()
```

Out[146…

```
<Figure size 1000x600 with 0 Axes>
```

Out[146…

```
<Axes: xlabel='order_day'>
```

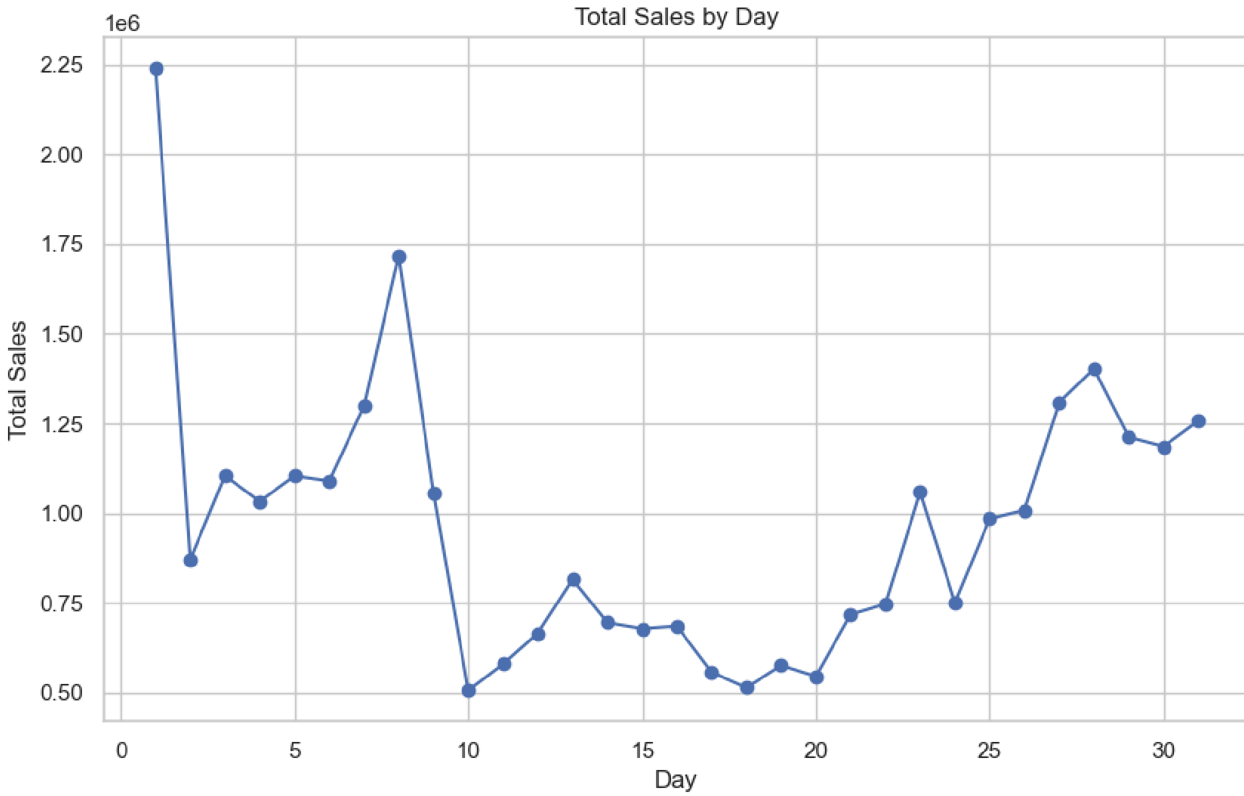
Out[146…

```
Text(0.5, 1.0, 'Total Sales by Day')
```

Out[146…

```
Text(0.5, 0, 'Day')
```

Out[146… Text(0, 0.5, 'Total Sales')



1. Try to answer one descriptive question you asked in your project initial report.

In [147…

```
#What is the most usual delivery time promised? This indicates the typical delivery spe


# Find the most common delivery time promised
most_common_delivery_time = filtered_merged['promise'].mode().values[0]
print(f"The most usual delivery time promised is: {most_common_delivery_time}")


#What is the typical order size in terms of item count? This shows how much money consu
#Calculate the average quantity of items per order
average_order_size = filtered_merged['quantity'].mean()

print(f"The typical order size in terms of item count is: {average_order_size:.2f}")
```

```
The most usual delivery time promised is: 1
The typical order size in terms of item count is: 1.21
```

Assignment 11 starts from here: Q31-Q40.

We only covered a small part of data exploration in Assignment 10. If you are interested, you can make many more graphs to understand the data.
Next we intend to build models to predict delivery times.

We want to use two sets of features to make predictions.

1. order effect: This class of predictors captures thevcharacteristics of an order that may impact deliveryvtime, such as the number of items (SKUs), order size (quantity), order type (1P or 3P),

discount rate and the number of gift items.
2. User effect: The process may prioritize certain customers over others, for example, customers with a PLUSmembership or higher past purchase values.
   Note: Actually, it will be better if we can include real-time workloads of distribution centers. It can be done with this dataset, but might be a little too much for us. So, we will leave that part out.

We need to further process the data to prepare the features.
Note: Here I have done this part. You need to change the name of DataFrame "order_delivery_inner' to your dataframe name that results from all the previous steps. Make sure you run the cells before you proceed.

1. The dataset we have so far is based on order-items. Each row is an item in an order. Now we need to aggregate by order to match order information with delivery information. Afterwards, each row is about one delivery / one order because we have already removed orders that have multiple deliveries.

First, let's calculate order values by multiply price and quantity.

In [148…

```
order_delivery_inner = Inner_merged_data

# Original value of items
order_delivery_inner['originValue'] = order_delivery_inner['original_unit_price'] \
                                    * order_delivery_inner['quantity']

# Final value of items
order_delivery_inner['finalValue'] = order_delivery_inner['final_unit_price'] \
                                   * order_delivery_inner['quantity']
order_delivery_inner.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 312391 entries, 0 to 326861
Data columns (total 27 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   order_ID                     312391 non-null  object
 1   user_ID                      312391 non-null  object
 2   sku_ID                       312391 non-null  object
 3   order_date                   312391 non-null  datetime64[ns]
 4   order_time                   312391 non-null  datetime64[ns]
 5   quantity                     312391 non-null  int64
 6   type_x                       312391 non-null  int64
 7   promise                      312391 non-null  object
 8   original_unit_price          312391 non-null  float64
 9   final_unit_price             312391 non-null  float64
 10  direct_discount_per_unit     312391 non-null  float64
 11  quantity_discount_per_unit   312391 non-null  float64
 12  bundle_discount_per_unit     312391 non-null  float64
 13  coupon_discount_per_unit     312391 non-null  float64
 14  gift_item                    312391 non-null  int64
 15  dc_ori                       312391 non-null  int64
 16  dc_des                       312391 non-null  int64
 17  package_ID                   312391 non-null  object
 18  ship_out_time                312391 non-null  datetime64[ns]
 19  arr_station_time             312391 non-null  datetime64[ns]
 20  arr_time                     312391 non-null  datetime64[ns]
```

```
 21  order_day                    312391 non-null  int64
 22  order_hour                   312391 non-null  int64
 23  delivery_time                312391 non-null  timedelta64[ns]
 24  delivery_time_hours          312391 non-null  float64
 25  originValue                  312391 non-null  float64
 26  finalValue                   312391 non-null  float64
dtypes: datetime64[ns](5), float64(9), int64(7), object(5), timedelta64[ns](1)
memory usage: 66.7+ MB
```

Next we aggregate by each order.

Please pay attention to the variable names. They should be consistent with yours. Make changes when necessary.

Variables that are the same across one order:

user_ID

order type - type_x

delivery time - delivery_time

order day - order_day

order hour - order_hour

Variables to be aggregated across one order:

sku_ID - to count to calculate the number of different products

quantity - to sum to calculate the order size

originValue - to sum to calculate sales value with the original price

finalValue - to sum to calculate final sales value

discount rate

gift_item - to sum to calculate the number of gift items

Therefore, we need to do the following:

1. For variables that are the same across one order, we can use the 'first' method to keep the value in the groupby result.
2. For variables to be aggregated, we specify aggregation for each of them.
3. We can use a dictionary to put all actions together.

In [149…

```
agg_dict = {
    'order_ID': 'first',
    'user_ID': 'first',
    'type_x': 'first',
    'delivery_time': 'first',
    'order_day': 'first',
    'order_hour':'first',
    'sku_ID': 'count',
    'quantity': 'sum',
    'originValue': 'sum',
    'finalValue': 'sum',
    'gift_item': 'sum'
}
```

```
order_agg = order_delivery_inner.groupby('order_ID',as_index=False).agg(agg_dict).reset
order_agg.head()
```

Out[149...

	index	order_ID	user_ID	type_x	delivery_time	order_day	order_hour	sku_ID	quantity	origi
0	0	0000095025	57648ed1fc	1	0 days 22:48:26	19	11	1	1	
1	1	00000e13eb	c113527e40	2	2 days 05:19:18	9	12	1	1	
2	2	0000132b39	c4f5626c0d	1	0 days 22:29:25	13	16	1	1	
3	3	000064fa67	99439045cb	1	0 days 08:03:43	2	10	1	1	
4	4	0000bde331	20d84fc11a	1	0 days 21:37:06	17	14	1	1	

1. Merge user table with this aggregated order table.

In [150...

```
order_user = pd.merge(order_agg, user_df, on = 'user_ID', how = 'inner')
```

1. We need to code a few more variables.

In [151...

```
# First we remove the orders with originValue is 0
order_user = order_user[order_user['originValue'] != 0]
```

In [152...

```
# Discount rate
order_user['dis_rate'] = (order_user['originValue'] - order_user['finalValue'])/order_u
# order_hour coded to be busy vs. not busy
order_user['busy_hour'] = order_user['order_hour'].apply(lambda h: 1 if 8<=h<=22 else 0
```

1. Prepare data for analysis. The target variable is 'delivery_time'.

   Features: 'type_x', 'sku_ID', 'quantity', 'finalValue', 'gift_item', 'plus', 'dis_rate', 'busy_hour'

In [153...

```
selected_features = ['type_x', 'sku_ID', 'quantity', 'finalValue', 'gift_item', 'plus',
target_variable = 'delivery_time'


data_for_analysis = order_user[selected_features + [target_variable]].copy()

print(data_for_analysis.isnull().sum())

data_for_analysis['delivery_time'].fillna(data_for_analysis['delivery_time'].mean(), in

print(data_for_analysis.isnull().sum())
```

```
type_x          0
sku_ID          0
quantity        0
```

```
finalValue       0
gift_item        0
plus             0
dis_rate         0
busy_hour        0
delivery_time    0
dtype: int64
type_x           0
sku_ID           0
quantity         0
finalValue       0
gift_item        0
plus             0
dis_rate         0
busy_hour        0
delivery_time    0
dtype: int64
```

1. Prepare the training and test datasets

In [154…

```
from sklearn.model_selection import train_test_split


X = data_for_analysis[selected_features]
y = data_for_analysis[target_variable]


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4


print("Training set shape - Features:", X_train.shape, "Target:", y_train.shape)
print("Test set shape - Features:", X_test.shape, "Target:", y_test.shape)
```

```
Training set shape - Features: (224124, 8) Target: (224124,)
Test set shape - Features: (56031, 8) Target: (56031,)
```

1. Train a Decision Tree regression model.

In [155…

```
reg = DecisionTreeRegressor()
reg.fit(X_train, y_train)
```

Out[155…

```
▾ DecisionTreeRegressor

DecisionTreeRegressor()
```

1. Make predictions on the testing data.

In [156…

```
predictions = reg.predict(X_test)
print(predictions)
```

```
[2.82476237e+14 1.20468500e+14 7.76892743e+13 ... 2.48103254e+14
 1.24056338e+14 3.19802937e+14]
```

In [157…

```
y_pred = reg.predict(X_train)

y_pred = reg.predict(X_test)
```

1. Evaluate the model using RMSE

In [159…

```
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print(f"Root Mean Squared Error: {rmse}")
```

```
Root Mean Squared Error (RMSE): 147.00503278045312
```

In [160…

```
# To understand the RMSE, We check the statistics of the target variable.
order_user['delivery_time'].describe()
# It seems the mean is about 34 hours. With RMSE being about 27,
# the prediction seems not very good.
# If you are interested to explore more, you may try some other prediction methods to s
# whether you can get better results.
```

Out[160…

```
count                       280155
mean     1 days 09:41:04.107469079
std      1 days 04:22:30.757980040
min             -1 days +07:25:00
25%               0 days 17:21:10
50%               0 days 23:33:42
75%               1 days 19:01:48
max              26 days 17:13:03
Name: delivery_time, dtype: object
```