In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
```

In [282…

```
df = pd.read_csv('dataset.csv')
```

In [283…

```
df.head()
```

Out[283]:

|  | market_id | created_at | actual_delivery_time | store_id | store_primary_category | ord |
|---|---|---|---|---|---|---|
| **0** | 1.0 | 2015-02-06 22:24:17 | 2015-02-06 23:27:16 | df263d996281d984952c07998dc54358 | american |  |
| **1** | 2.0 | 2015-02-10 21:49:25 | 2015-02-10 22:56:29 | f0ade77b43923b38237db569b016ba25 | mexican |  |
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | f0ade77b43923b38237db569b016ba25 | NaN |  |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | f0ade77b43923b38237db569b016ba25 | NaN |  |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | f0ade77b43923b38237db569b016ba25 | NaN |  |

# Generic data about datasets

In [284…

```
df.shape
```

Out[284]:

```
(197428, 14)
```

In [285…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 197428 entries, 0 to 197427
Data columns (total 14 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   market_id                 196441 non-null  float64
 1   created_at                197428 non-null  object 
 2   actual_delivery_time      197421 non-null  object 
 3   store_id                  197428 non-null  object 
 4   store_primary_category    192668 non-null  object 
 5   order_protocol            196433 non-null  float64
 6   total_items               197428 non-null  int64  
 7   subtotal                  197428 non-null  int64  
 8   num_distinct_items        197428 non-null  int64  
 9   min_item_price            197428 non-null  int64  
 10  max_item_price            197428 non-null  int64  
 11  total_onshift_partners    181166 non-null  float64
 12  total_busy_partners       181166 non-null  float64
 13  total_outstanding_orders  181166 non-null  float64
dtypes: float64(5), int64(5), object(4)
memory usage: 21.1+ MB
```

# NULL Values check

In [286…

```
df.isna().sum()
```

Out[286]:

```
market_id                     987
created_at                      0
actual_delivery_time            7
store_id                        0
store_primary_category       4760
order_protocol                995
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners      16262
total_busy_partners         16262
total_outstanding_orders    16262
dtype: int64
```

# EDA

In [287…

```
df.loc[df['market_id'].isna()]
```

Out[287]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category |
|---|---|---|---|---|---|
| **45** | NaN | 2015-02-09 03:27:37 | 2015-02-09 04:22:18 | ea119a40c1592979f51819b0bd38d39d | italian |
| **182** | NaN | 2015-02-01 05:32:34 | 2015-02-01 06:01:21 | a87ff679a2f3e71d9181a67b7542122c | mediterranean |
| **970** | NaN | 2015-02-17 02:17:43 | 2015-02-17 03:15:14 | fe8c15fed5f808006ce95eddb7366e35 | NaN |
| **1126** | NaN | 2015-02-18 03:50:52 | 2015-02-18 04:15:09 | aa2a77371374094fe9e0bc1de3f94ed9 | sandwich |
| **1625** | NaN | 2015-02-17 03:49:46 | 2015-02-17 04:21:27 | 86311dbe35f1b6c5166365165602f54d | pizza |
| **...** | ... | ... | ... | ... | ... |
| **196027** | NaN | 2015-01-24 02:59:19 | 2015-01-24 04:16:30 | 84d9ee44e457ddef7f2c4f25dc8fa865 | NaN |
| **196561** | NaN | 2015-02-02 20:49:57 | 2015-02-02 21:26:34 | 07042ac7d03d3b9911a00da43ce0079a | NaN |
| **197170** | NaN | 2015-02-01 01:29:54 | 2015-02-01 01:50:18 | 17e62166fc8586dfa4d1bc0e1742c08b | vietnamese |
| **197171** | NaN | 2015-02-16 19:16:44 | 2015-02-16 19:56:03 | 17e62166fc8586dfa4d1bc0e1742c08b | vietnamese |
| **197259** | NaN | 2015-02-10 01:32:37 | 2015-02-10 02:02:09 | 959776b99b006e5785c3a3364949ce47 | NaN |

987 rows × 14 columns

In [288…

```
df[['market_id','store_id']]
```

Out[288]:

| | market_id | store_id |
|---|---|---|
| **0** | 1.0 | df263d996281d984952c07998dc54358 |
| **1** | 2.0 | f0ade77b43923b38237db569b016ba25 |
| **2** | 3.0 | f0ade77b43923b38237db569b016ba25 |
| **3** | 3.0 | f0ade77b43923b38237db569b016ba25 |
| **4** | 3.0 | f0ade77b43923b38237db569b016ba25 |
| **...** | ... | ... |
| **197423** | 1.0 | a914ecef9c12ffdb9bede64bb703d877 |
| **197424** | 1.0 | a914ecef9c12ffdb9bede64bb703d877 |
| **197425** | 1.0 | a914ecef9c12ffdb9bede64bb703d877 |
| **197426** | 1.0 | c81e155d85dae5430a8cee6f2242e82c |
| **197427** | 1.0 | c81e155d85dae5430a8cee6f2242e82c |

197428 rows × 2 columns

Loading [MathJax]/extensions/Safe.js

In [289…

```
# df.loc[df['store_id']=='a914ecef9c12ffdb9bede64bb703d877'][['market_id','store_id']].v
```

In [290…

```
store_id_market_id_mapping = df[['store_id','market_id']]
store_id_market_id_mapping = store_id_market_id_mapping.dropna()
store_id_market_id_mapping
```

Out[290]:

| | store_id | market_id |
|---|---|---|
| **0** | df263d996281d984952c07998dc54358 | 1.0 |
| **1** | f0ade77b43923b38237db569b016ba25 | 2.0 |
| **2** | f0ade77b43923b38237db569b016ba25 | 3.0 |
| **3** | f0ade77b43923b38237db569b016ba25 | 3.0 |
| **4** | f0ade77b43923b38237db569b016ba25 | 3.0 |
| **...** | ... | ... |
| **197423** | a914ecef9c12ffdb9bede64bb703d877 | 1.0 |
| **197424** | a914ecef9c12ffdb9bede64bb703d877 | 1.0 |
| **197425** | a914ecef9c12ffdb9bede64bb703d877 | 1.0 |
| **197426** | c81e155d85dae5430a8cee6f2242e82c | 1.0 |
| **197427** | c81e155d85dae5430a8cee6f2242e82c | 1.0 |

196441 rows × 2 columns

In [291…

```
store_id_market_id_mapping
```

Out[291]:

| | store_id | market_id |
|---|---|---|
| **0** | df263d996281d984952c07998dc54358 | 1.0 |
| **1** | f0ade77b43923b38237db569b016ba25 | 2.0 |
| **2** | f0ade77b43923b38237db569b016ba25 | 3.0 |
| **3** | f0ade77b43923b38237db569b016ba25 | 3.0 |
| **4** | f0ade77b43923b38237db569b016ba25 | 3.0 |
| **...** | ... | ... |
| **197423** | a914ecef9c12ffdb9bede64bb703d877 | 1.0 |
| **197424** | a914ecef9c12ffdb9bede64bb703d877 | 1.0 |
| **197425** | a914ecef9c12ffdb9bede64bb703d877 | 1.0 |
| **197426** | c81e155d85dae5430a8cee6f2242e82c | 1.0 |
| **197427** | c81e155d85dae5430a8cee6f2242e82c | 1.0 |

196441 rows × 2 columns

In [292…

```
# tmp = store_id_market_id_mapping.loc[store_id_market_id_mapping['store_id']=='f0ade77b

# tmp.groupby('store_id')['market_id'].apply(lambda x : x.mode().iloc[0]).iloc[0]
```

In [293…

```
from tqdm import tqdm
```

In [294…

```
# def get_store_and_market_id_mapping(store_ids):
#     store_id_and_market_id_mapping = {}
             re_id in tqdm(store_ids):
```

```
#         tmp_store_id = store_id_market_id_mapping.loc[store_id_market_id_mapping['stor
#         max_value_market_id = tmp_store_id.groupby('store_id')['market_id'].apply(lamb
#         if(store_id not in store_id_and_market_id_mapping.keys()):
#             store_id_and_market_id_mapping[store_id] = max_value_market_id
#     return store_id_and_market_id_mapping
```

In [295…

```
# get_store_and_market_id_mapping = get_store_and_market_id_mapping(set(store_id_market_
```

In [296…

```
# list(get_store_and_market_id_mapping.keys())
```

In [297…

```
df_store_id_and_market_id_mapping = pd.read_csv('get_store_and_market_id_mapping.csv')
```

In [298…

```
df_store_id_and_market_id_mapping
```

Out[298]:

| | store_id | market_id |
|---|---|---|
| **0** | 8e200fc779d0a8e7eaba42e877f0a5c0 | 5.0 |
| **1** | 1b9e43c170cd3fc59624a18663b8d4d2 | 2.0 |
| **2** | e0d2fe50debfaec6b2d7bafdd9d936c8 | 2.0 |
| **3** | 84f5ddd735176becc72c3b1ff424149e | 6.0 |
| **4** | e57edfc7529f0c7b21788231308caeab | 3.0 |
| **...** | ... | ... |
| **6735** | 0e4e946668cf2afc4299b462b812caca | 1.0 |
| **6736** | 939b9fed93c76ce9339b8aa1b2d5c57c | 6.0 |
| **6737** | 1690bccd010b308cd33989d3819ed96a | 3.0 |
| **6738** | 57cd30d9088b0185cf0ebca1a472ff1d | 1.0 |
| **6739** | 59990206aa06fc1de0b921c4320f332c | 5.0 |

6740 rows × 2 columns

In [299…

```
df['market_id'][197171]
```

Out[299]:

```
nan
```

In [300…

```
df_store_id_and_market_id_mapping.loc[df_store_id_and_market_id_mapping['store_id']=='ea
```

Out[300]:

```
4.0
```

# Now Fixing the Missing Market_id

In [301…

```
df.head()
```

Out[301]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category | ord |
|---|---|---|---|---|---|---|
| **0** | 1.0 | 2015-02-06 22:24:17 | 2015-02-06 23:27:16 | df263d996281d984952c07998dc54358 | american | |
| **1** | 2.0 | 2015-02-10 21:49:25 | 2015-02-10 22:56:29 | f0ade77b43923b38237db569b016ba25 | mexican | |
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | f0ade77b43923b38237db569b016ba25 | NaN | |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | f0ade77b43923b38237db569b016ba25 | NaN | |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | f0ade77b43923b38237db569b016ba25 | NaN | |

In [302…

```
df.loc[df['market_id'].isna()]
```

Out[302]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category |
|---|---|---|---|---|---|
| **45** | NaN | 2015-02-09 03:27:37 | 2015-02-09 04:22:18 | ea119a40c1592979f51819b0bd38d39d | italiar |
| **182** | NaN | 2015-02-01 05:32:34 | 2015-02-01 06:01:21 | a87ff679a2f3e71d9181a67b7542122c | mediterranear |
| **970** | NaN | 2015-02-17 02:17:43 | 2015-02-17 03:15:14 | fe8c15fed5f808006ce95eddb7366e35 | Na |
| **1126** | NaN | 2015-02-18 03:50:52 | 2015-02-18 04:15:09 | aa2a77371374094fe9e0bc1de3f94ed9 | sandwicl |
| **1625** | NaN | 2015-02-17 03:49:46 | 2015-02-17 04:21:27 | 86311dbe35f1b6c5166365165602f54d | pizz |
| **...** | ... | ... | ... | ... | .. |
| **196027** | NaN | 2015-01-24 02:59:19 | 2015-01-24 04:16:30 | 84d9ee44e457ddef7f2c4f25dc8fa865 | Na |
| **196561** | NaN | 2015-02-02 20:49:57 | 2015-02-02 21:26:34 | 07042ac7d03d3b9911a00da43ce0079a | Na |
| **197170** | NaN | 2015-02-01 01:29:54 | 2015-02-01 01:50:18 | 17e62166fc8586dfa4d1bc0e1742c08b | vietnamese |
| **197171** | NaN | 2015-02-16 19:16:44 | 2015-02-16 19:56:03 | 17e62166fc8586dfa4d1bc0e1742c08b | vietnamese |
| **197259** | NaN | 2015-02-10 01:32:37 | 2015-02-10 02:02:09 | 959776b99b006e5785c3a3364949ce47 | Na |

987 rows × 14 columns

In [303…

```
def get_new_market_id(market_id,store_id):
    """
```

Loading [MathJax]/extensions/Safe.js

```
    This Function is helping to get fix market_id
    """
    new_market_id = []
    for market_id,store_id in zip(market_id,store_id):
        if(pd.isna(market_id)==True):
            if(len(df_store_id_and_market_id_mapping.loc[df_store_id_and_market_id_mappi
                new_market_id.append(df_store_id_and_market_id_mapping.loc[df_store_id_a
            else:
                new_market_id.append(np.nan)
        else:
            new_market_id.append(market_id)
    return new_market_id


new_market_id = get_new_market_id(df['market_id'],df['store_id'])

print(len(new_market_id))
```

```
197428
```

In [304…

```
df['new_market_id'] = new_market_id
```

In [305…

```
df['market_id'] = new_market_id
```

In [306…

```
df.drop('new_market_id',axis=1,inplace=True)
```

# We have fixed market_id upto some extent

In [307…

```
df.isna().sum()
```

Out[307]:

```
market_id                    3
created_at                   0
actual_delivery_time         7
store_id                     0
store_primary_category    4760
order_protocol             995
total_items                  0
subtotal                     0
num_distinct_items           0
min_item_price               0
max_item_price               0
total_onshift_partners   16262
total_busy_partners      16262
total_outstanding_orders 16262
dtype: int64
```

In [308…

```
from sklearn.impute import SimpleImputer
```

In [309…

```
imputer = SimpleImputer(missing_values=np.nan,strategy='most_frequent')
```

In [310…

```
df['market_id'] = imputer.fit_transform(pd.DataFrame(df['market_id']))
```

In [311…

```
df.head()
```

Out[311]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category | ord |
|---|---|---|---|---|---|---|
| **0** | 1.0 | 2015-02-06 22:24:17 | 2015-02-06 23:27:16 | df263d996281d984952c07998dc54358 | american | |
| **1** | 2.0 | 2015-02-10 21:49:25 | 2015-02-10 22:56:29 | f0ade77b43923b38237db569b016ba25 | mexican | |
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | f0ade77b43923b38237db569b016ba25 | NaN | |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | f0ade77b43923b38237db569b016ba25 | NaN | |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | f0ade77b43923b38237db569b016ba25 | NaN | |

In [312…

```
df.isna().sum()
```

Out[312]:

```
market_id                       0
created_at                      0
actual_delivery_time            7
store_id                        0
store_primary_category       4760
order_protocol                995
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners      16262
total_busy_partners         16262
total_outstanding_orders    16262
dtype: int64
```

In [313…

```
df.loc[df['actual_delivery_time'].isna()]
```

Out[313]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category |
|---|---|---|---|---|---|
| **109** | 3.0 | 2015-02-10 21:51:54 | NaN | da353f402faf6cf475d4abd1450b0882 | sandwich |
| **7670** | 2.0 | 2015-02-08 02:54:42 | NaN | 140f6969d5213fd0ece03148e62e461e | japanese |
| **78511** | 4.0 | 2015-02-15 02:15:45 | NaN | 1f0e3dad99908345f7439f8ffabdffc4 | catering |
| **115982** | 4.0 | 2015-02-16 01:52:49 | NaN | b92894e4589f652dc3116cb3a8c48c08 | pizza |
| **140635** | 2.0 | 2015-02-15 02:21:42 | NaN | 0d73a25092e5c1c9769a9f3255caa65a | dessert |
| **158967** | 2.0 | 2015-02-01 01:21:29 | NaN | faacbcd5bf1d018912c116bf2783e9a1 | mexican |
| **170416** | 5.0 | 2015-02-01 01:36:33 | NaN | 6c7a107981f9c2a0ed55efce297bd1e2 | fast |

# Fixing actual delivery time NAN Values

In [314…

```
df['actual_delivery_time'] = df['actual_delivery_time'].ffill(axis=0)
```

In [315…

```
df.isna().sum()
```

Out[315]:

```
market_id                       0
created_at                      0
actual_delivery_time            0
store_id                        0
store_primary_category       4760
order_protocol                995
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners      16262
total_busy_partners         16262
total_outstanding_orders    16262
dtype: int64
```

In [316…

```
df.loc[df['store_primary_category'].isna()]
```

Loading [MathJax]/extensions/Safe.js

Out[316]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category |
|---|---|---|---|---|---|
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | f0ade77b43923b38237db569b016ba25 | NaN |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | f0ade77b43923b38237db569b016ba25 | NaN |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | f0ade77b43923b38237db569b016ba25 | NaN |
| **5** | 3.0 | 2015-01-28 20:30:38 | 2015-01-28 21:08:58 | f0ade77b43923b38237db569b016ba25 | NaN |
| **6** | 3.0 | 2015-01-31 02:16:36 | 2015-01-31 02:43:00 | f0ade77b43923b38237db569b016ba25 | NaN |
| **...** | ... | ... | ... | ... | .. |
| **197210** | 1.0 | 2015-02-15 02:17:39 | 2015-02-15 03:21:16 | 77c493ec14246d748db3ee8fce0092db | NaN |
| **197211** | 1.0 | 2015-02-03 01:58:27 | 2015-02-03 02:32:07 | 77c493ec14246d748db3ee8fce0092db | NaN |
| **197212** | 1.0 | 2015-02-12 02:42:13 | 2015-02-12 03:39:29 | 77c493ec14246d748db3ee8fce0092db | NaN |
| **197259** | 5.0 | 2015-02-10 01:32:37 | 2015-02-10 02:02:09 | 959776b99b006e5785c3a3364949ce47 | NaN |
| **197363** | 1.0 | 2015-02-12 20:44:22 | 2015-02-12 21:30:44 | a914ecef9c12ffdb9bede64bb703d877 | NaN |

4760 rows × 14 columns

# Fixing NAN value for store primary category

In [317…

```
store_id_and_store_primary_cate = df[['store_id','store_primary_category']]
```

In [318…

```
store_id_and_store_primary_cate.dropna(inplace=True)
```

```
C:\Users\gaura\AppData\Local\Temp\ipykernel_14360\4249315177.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  store_id_and_store_primary_cate.dropna(inplace=True)
```

In [319…

```
store_id_and_store_primary_cate.head()
```

Out[319]:

|  | store_id | store_primary_category |
|---|---|---|
| **0** | df263d996281d984952c07998dc54358 | american |
| **1** | f0ade77b43923b38237db569b016ba25 | mexican |
| **8** | f0ade77b43923b38237db569b016ba25 | indian |
| **14** | ef1e491a766ce3127556063d49bc2f98 | italian |
| **15** | ef1e491a766ce3127556063d49bc2f98 | italian |

In [320…

```
store_id_and_store_primary_cate.groupby(['store_id'])['store_primary_category'].apply(la
```

Out[320]:

```
store_id
0004d0b59e19461ff126e3a08a814c33         american
00053f5e11d1fe4e49a221165b39abc9          mexican
0006aabe0ba47a35c0b0bf6596f85159            other
000a91f3e374e6147d58ed1814247508          mexican
0029f088c57ad3b6ec589f9ba4f7a057           burger
                                         ...
ffbd6cbb019a1413183c8d08f2929307          chinese
ffc58105bf6f8a91aba0fa2d99e6f106         sandwich
ffd52f3c7e12435a724a8f30fddadd9c            irish
ffeabd223de0d4eacb9a3e6e53e5448d        breakfast
ffedf5be3a86e2ee281d54cdc97bc1cf    mediterranean
Name: store_primary_category, Length: 6569, dtype: object
```

In [321…

```
def get_store_and_store_primary_category_mapping(store_ids):
    """
    Get store and store primary category mapping

    """
    store_and_store_primary_category = {}
    for store_id in tqdm(store_ids):
        tmp_store_id = store_id_and_store_primary_cate.loc[store_id_and_store_primary_ca
        max_value_market_id = tmp_store_id.groupby('store_id')['store_primary_category']
        if(store_id not in store_and_store_primary_category.keys()):
            store_and_store_primary_category[store_id] = max_value_market_id
    return store_and_store_primary_category

get_store_and_store_primary_category_mapping = get_store_and_store_primary_category_mapp
```

```
  0%|          | 0/6569 [00:00<?, ?it/s]  2%|▏         | 119/6569 [00:01<01:11, 90.74it/
s]
```

Loading [MathJax]/extensions/Safe.js

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[321], line 14
     11             store_and_store_primary_category[store_id] = max_value_market_id
     12     return store_and_store_primary_category
---> 14 get_store_and_store_primary_category_mapping = get_store_and_store_primary_categ
ory_mapping(set(store_id_and_store_primary_cate['store_id']))

Cell In[321], line 8, in get_store_and_store_primary_category_mapping(store_ids)
      6 store_and_store_primary_category = {}
      7 for store_id in tqdm(store_ids):
----> 8     tmp_store_id = store_id_and_store_primary_cate.loc[store_id_and_store_primar
y_cate['store_id']==store_id]
      9     max_value_market_id = tmp_store_id.groupby('store_id')['store_primary_catego
ry'].apply(lambda x : x.mode().iloc[0]).iloc[0]
     10     if(store_id not in store_and_store_primary_category.keys()):

File c:\Users\gaura\anaconda3\envs\tf_gpu\lib\site-packages\pandas\core\indexing.py:119
1, in _LocationIndexer.__getitem__(self, key)
   1189 maybe_callable = com.apply_if_callable(key, self.obj)
   1190 maybe_callable = self._check_deprecated_callable_usage(key, maybe_callable)
-> 1191 return self._getitem_axis(maybe_callable, axis=axis)

File c:\Users\gaura\anaconda3\envs\tf_gpu\lib\site-packages\pandas\core\indexing.py:141
3, in _LocIndexer._getitem_axis(self, key, axis)
   1411     return self._get_slice_axis(key, axis=axis)
   1412 elif com.is_bool_indexer(key):
-> 1413     return self._getbool_axis(key, axis=axis)
   1414 elif is_list_like_indexer(key):
   1415     # an iterable multi-selection
   1416     if not (isinstance(key, tuple) and isinstance(labels, MultiIndex)):

File c:\Users\gaura\anaconda3\envs\tf_gpu\lib\site-packages\pandas\core\indexing.py:121
0, in _LocationIndexer._getbool_axis(self, key, axis)
   1208 labels = self.obj._get_axis(axis)
   1209 key = check_bool_indexer(labels, key)
-> 1210 inds = key.nonzero()[0]
   1211 return self.obj._take_with_is_copy(inds, axis=axis)

KeyboardInterrupt: 
```

In [ ]:

```
get_store_and_store_primary_category_mapping

get_store_and_store_primary_category_mapping_df = pd.DataFrame()

get_store_and_store_primary_category_mapping_df['store_id'] = list(get_store_and_store_p

get_store_and_store_primary_category_mapping_df['store_primary_category'] = list(get_sto
```

In [ ]:

```
get_store_and_store_primary_category_mapping_df
```

Loading [MathJax]/extensions/Safe.js

Out[ ]:

| | store_id | store_primary_category |
|---|---|---|
| **0** | 46e0eae7d5217c79c3ef6b4c212b8c6f | sandwich |
| **1** | e4d78a6b4d93e1d79241f7b282fa3413 | cafe |
| **2** | 248e844336797ec98478f85e7626de4a | alcohol |
| **3** | 670c26185a3783678135b4697f7dbd1a | fast |
| **4** | 021b8947656eb84e4c641506215777c8 | japanese |
| **...** | ... | ... |
| **6564** | 0b61a4e863c0f5e7e20001aea1c33962 | alcohol |
| **6565** | 9b40aee76034c9543ceacba5df759a1d | burger |
| **6566** | d79f7940be5afa4e3fa70cd73295878f | thai |
| **6567** | 6a8018b3a00b69c008601b8becae392b | thai |
| **6568** | 09c78e5e092faab26c371b2c3f13f514 | fast |

6569 rows × 2 columns

In [ ]:

```
df.head()
```

Out[ ]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category | orde |
|---|---|---|---|---|---|---|
| **0** | 1.0 | 2015-02-06 22:24:17 | 2015-02-06 23:27:16 | df263d996281d984952c07998dc54358 | american | |
| **1** | 2.0 | 2015-02-10 21:49:25 | 2015-02-10 22:56:29 | f0ade77b43923b38237db569b016ba25 | mexican | |
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | f0ade77b43923b38237db569b016ba25 | NaN | |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | f0ade77b43923b38237db569b016ba25 | NaN | |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | f0ade77b43923b38237db569b016ba25 | NaN | |

In [ ]:

```
def get_new_store_primary_category():
    store_primary_category=[]
    for store_primary_cate,store_id in zip(df['store_primary_category'],df['store_id']):
        if(pd.isna(store_primary_cate)==True):
            if(len(get_store_and_store_primary_category_mapping_df.loc[get_store_and_sto
                store_primary_category.append(get_store_and_store_primary_category_mappi
            else:
                store_primary_category.append(np.nan)
        else:
            store_primary_category.append(store_primary_cate)
    return store_primary_category



get_new_store_primary_category = get_new_store_primary_category()
len(get_new_store_primary_category)
```

Out[ ]:

```
197428
```

Loading [MathJax]/extensions/Safe.js

In [ ]:
```python
df['get_new_store_primary_category'] = get_new_store_primary_category
```

In [ ]:
```python
df.isna().sum()
```

Out[ ]:
```
market_id                              0
created_at                             0
actual_delivery_time                   0
store_id                               0
store_primary_category              4760
order_protocol                       995
total_items                            0
subtotal                               0
num_distinct_items                     0
min_item_price                         0
max_item_price                         0
total_onshift_partners             16262
total_busy_partners                16262
total_outstanding_orders           16262
get_new_store_primary_category       867
dtype: int64
```

In [ ]:
```python
pd.DataFrame(df['get_new_store_primary_category'])
```

Out[ ]:

| | get_new_store_primary_category |
|---|---|
| **0** | american |
| **1** | mexican |
| **2** | indian |
| **3** | indian |
| **4** | indian |
| **...** | ... |
| **197423** | fast |
| **197424** | fast |
| **197425** | fast |
| **197426** | sandwich |
| **197427** | sandwich |

197428 rows × 1 columns

In [ ]:
```python
valus = SimpleImputer(missing_values=np.nan,strategy='most_frequent').fit_transform(pd.D

get_new_store_primary_category = []
for v in valus:
    get_new_store_primary_category.append(v[0])
df['get_new_store_primary_category'] = get_new_store_primary_category
df['store_primary_category'] = df['get_new_store_primary_category']
df.drop('get_new_store_primary_category',axis=1,inplace=True)
```

In [ ]:
```python
df['order_protocol'] = imputer.fit_transform(pd.DataFrame(df['order_protocol']))
```

In [ ]:
```python
df.isna().sum()
```

Loading [MathJax]/extensions/Safe.js

Out[ ]:

```
market_id                       0
created_at                      0
actual_delivery_time            0
store_id                        0
store_primary_category          0
order_protocol                  0
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners      16262
total_busy_partners         16262
total_outstanding_orders    16262
dtype: int64
```

In [ ]:

```
df.loc[df['total_onshift_partners'].isna()]
```

Out[ ]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category |
|---|---|---|---|---|---|
| **160** | 6.0 | 2015-02-06 01:11:56 | 2015-02-06 01:42:51 | 45d38ce7f5231602e24a2103a0300ae6 | breakfast |
| **161** | 6.0 | 2015-02-14 02:07:47 | 2015-02-14 03:17:37 | 45d38ce7f5231602e24a2103a0300ae6 | breakfast |
| **162** | 6.0 | 2015-01-31 21:58:30 | 2015-01-31 22:55:32 | 45d38ce7f5231602e24a2103a0300ae6 | breakfast |
| **163** | 6.0 | 2015-02-08 03:28:59 | 2015-02-08 05:32:11 | 45d38ce7f5231602e24a2103a0300ae6 | breakfast |
| **164** | 6.0 | 2015-01-23 19:29:17 | 2015-01-23 20:25:25 | 45d38ce7f5231602e24a2103a0300ae6 | breakfast |
| **...** | ... | ... | ... | ... | ... |
| **197196** | 3.0 | 2015-02-10 19:55:29 | 2015-02-10 20:33:13 | 084afd913ab1e6ea58b8ca73f6cb41a6 | indian |
| **197197** | 3.0 | 2015-02-06 03:05:38 | 2015-02-06 03:58:16 | 084afd913ab1e6ea58b8ca73f6cb41a6 | indian |
| **197198** | 3.0 | 2015-01-23 03:57:56 | 2015-01-23 04:43:17 | 084afd913ab1e6ea58b8ca73f6cb41a6 | indian |
| **197199** | 3.0 | 2015-01-24 03:15:41 | 2015-01-24 04:04:19 | 084afd913ab1e6ea58b8ca73f6cb41a6 | indian |
| **197421** | 1.0 | 2015-01-30 03:35:01 | 2015-01-30 04:42:19 | a914ecef9c12ffdb9bede64bb703d877 | fast |

16262 rows × 14 columns

In [ ]:

```
df['total_onshift_partners'] = SimpleImputer(missing_values=np.nan,strategy='median').fi
df['total_busy_partners'] = SimpleImputer(missing_values=np.nan,strategy='median').fit_t
df['total_outstanding_orders'] = SimpleImputer(missing_values=np.nan,strategy='median').
```

In [ ]:

```
df.describe()
```

Loading [MathJax]/extensions/Safe.js

Out[ ]:

|  | market_id | order_protocol | total_items | subtotal | num_distinct_items | min_item_price | max_i |
|---|---|---|---|---|---|---|---|
| **count** | 197428.000000 | 197428.000000 | 197428.000000 | 197428.000000 | 197428.000000 | 197428.000000 | 1974 |
| **mean** | 2.978296 | 2.872865 | 3.196391 | 2682.331402 | 2.670791 | 686.218470 | 11 |
| **std** | 1.524646 | 1.505888 | 2.666546 | 1823.093688 | 1.630255 | 522.038648 | 5 |
| **min** | 1.000000 | 1.000000 | 1.000000 | 0.000000 | 1.000000 | -86.000000 |  |
| **25%** | 2.000000 | 1.000000 | 2.000000 | 1400.000000 | 1.000000 | 299.000000 | 8 |
| **50%** | 3.000000 | 3.000000 | 3.000000 | 2200.000000 | 2.000000 | 595.000000 | 10 |
| **75%** | 4.000000 | 4.000000 | 4.000000 | 3395.000000 | 3.000000 | 949.000000 | 13 |
| **max** | 6.000000 | 7.000000 | 411.000000 | 27100.000000 | 20.000000 | 14700.000000 | 147 |

# Fixed all NAN value issues.

In [ ]:

```
df.isna().sum()
```

Out[ ]:

```
market_id                   0
created_at                  0
actual_delivery_time        0
store_id                    0
store_primary_category      0
order_protocol              0
total_items                 0
subtotal                    0
num_distinct_items          0
min_item_price              0
max_item_price              0
total_onshift_partners      0
total_busy_partners         0
total_outstanding_orders    0
dtype: int64
```

In [583…

```
# saving fixed data for futher analysis and ML modeling
# df.to_csv('market.csv',index=False)
```

In [586…

```
df = pd.read_csv('market.csv')
```

In [587…

```
df.shape
```

Out[587]:

```
(197421, 15)
```

In [588…

```
df.isna().sum()
```

Loading [MathJax]/extensions/Safe.js

Out[588]:

```
market_id                          0
created_at                         0
actual_delivery_time               0
store_id                           0
store_primary_category             0
order_protocol                     0
total_items                        0
subtotal                           0
num_distinct_items                 0
min_item_price                     0
max_item_price                     0
total_onshift_partners             0
total_busy_partners                0
total_outstanding_orders           0
delivery_time_gt_created_at_check  0
dtype: int64
```

In [589…

```
df
```

Out[589]:

| | market_id | created_at | actual_delivery_time | store_id | store_primary_category |
|---|---|---|---|---|---|
| **0** | 1.0 | 2015-02-06 22:24:17 | 2015-02-06 23:27:16 | df263d996281d984952c07998dc54358 | american |
| **1** | 2.0 | 2015-02-10 21:49:25 | 2015-02-10 22:56:29 | f0ade77b43923b38237db569b016ba25 | mexican |
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | f0ade77b43923b38237db569b016ba25 | indian |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | f0ade77b43923b38237db569b016ba25 | indian |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | f0ade77b43923b38237db569b016ba25 | indian |
| **...** | ... | ... | ... | ... | ... |
| **197416** | 1.0 | 2015-02-17 00:19:41 | 2015-02-17 01:24:48 | a914ecef9c12ffdb9bede64bb703d877 | fast |
| **197417** | 1.0 | 2015-02-13 00:01:59 | 2015-02-13 00:58:22 | a914ecef9c12ffdb9bede64bb703d877 | fast |
| **197418** | 1.0 | 2015-01-24 04:46:08 | 2015-01-24 05:36:16 | a914ecef9c12ffdb9bede64bb703d877 | fast |
| **197419** | 1.0 | 2015-02-01 18:18:15 | 2015-02-01 19:23:22 | c81e155d85dae5430a8cee6f2242e82c | sandwich |
| **197420** | 1.0 | 2015-02-08 19:24:33 | 2015-02-08 20:01:41 | c81e155d85dae5430a8cee6f2242e82c | sandwich |

197421 rows × 15 columns

In [590…

```
df['created_at'] = pd.to_datetime(df['created_at'])
df['actual_delivery_time'] = pd.to_datetime(df['actual_delivery_time'])
```

# QC on created_at and actual_delivery_time

In [591…
```
# df_created_at_and_actual_delivery_time = df[['created_at','actual_delivery_time']]
```

In [592…
```
# df_created_at_and_actual_delivery_time
# df_created_at_and_actual_delivery_time['check'] = (df_created_at_and_actual_delivery_t
```

In [593…
```
# df_created_at_and_actual_delivery_time
```

In [594…
```
# df_created_at_and_actual_delivery_time['check'].value_counts()
```

In [595…
```
# df_created_at_and_actual_delivery_time.loc[df_created_at_and_actual_delivery_time['che
```

In [596…
```
# df['delivery_time_gt_created_at_check'] = (df['created_at']<=df['actual_delivery_time'
```

In [597…
```
# df = df.loc[df['delivery_time_gt_created_at_check']==True]
```

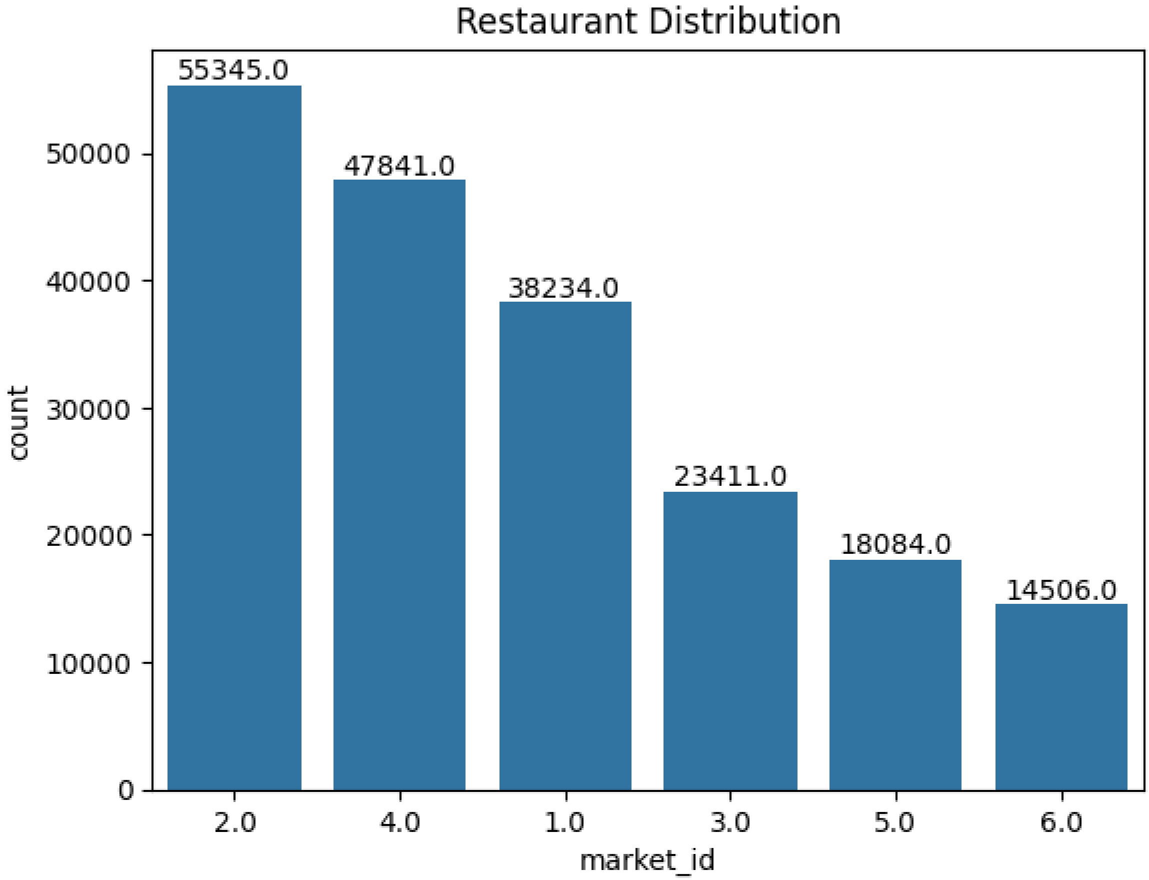
In [598…
```
# df.to_csv('market.csv',index=False)
```

In [599…
```
df.shape
```

Out[599]:
```
(197421, 15)
```

# Univariate Data Analysis

In [600…
```
# Create the countplot
ax = sns.countplot(x=df['market_id'],order=df['market_id'].value_counts().index)

# Add numbers above the bars
for p in ax.patches:
    ax.annotate(f"{p.get_height()}", (p.get_x() + p.get_width() / 2., p.get_height()), h

# Set the title
plt.title('Restaurant Distribution')

# Show the plot
plt.show()
```



```
It is observed that most of the restaurants are located in market 2
```

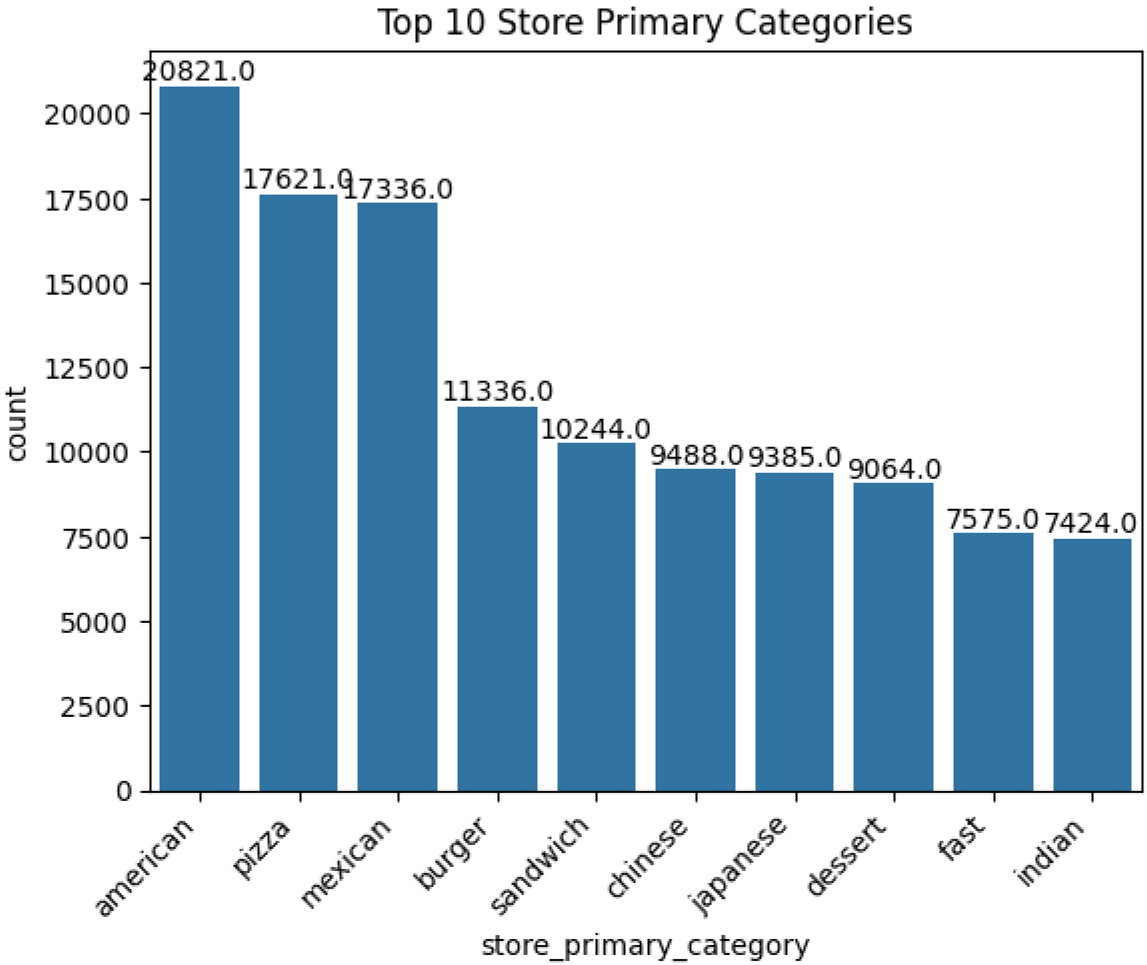
# Top 10 Store Primary Categories

In [601…

```
ax = sns.barplot(x=df['store_primary_category'].value_counts()[:10].index,
                 y=df['store_primary_category'].value_counts()[:10])

# Rotate x labels to 30 degrees
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')

for p in ax.patches:
    ax.annotate(f"{p.get_height()}", (p.get_x() + p.get_width() / 2., p.get_height()), h

# Set the title
plt.title('Top 10 Store Primary Categories')

# Show the plot
plt.show()
```

```
C:\Users\gaura\AppData\Local\Temp\ipykernel_26344\2251548322.py:5: UserWarning: set_tick
labels() should only be used with a fixed number of ticks, i.e. after set_ticks() or usi
ng a FixedLocator.
  ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
```

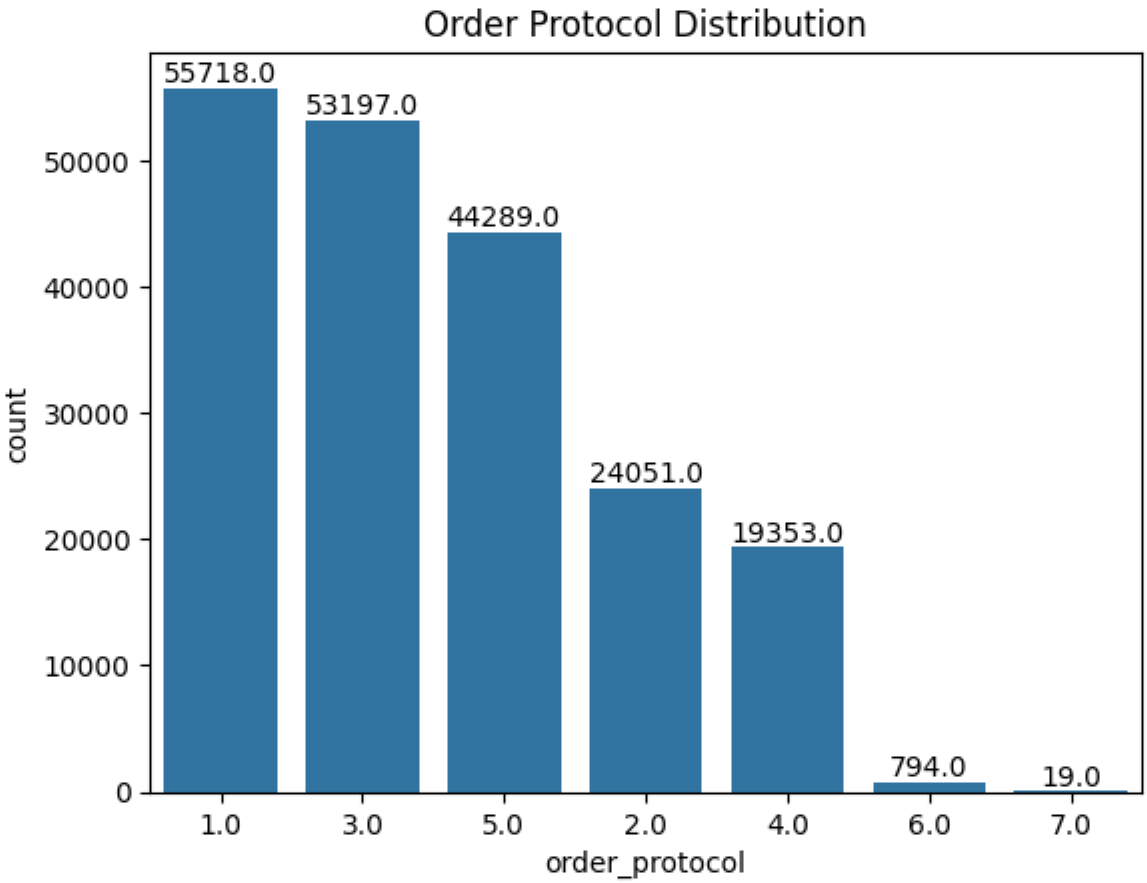
Loading [MathJax]/extensions/Safe.js



## Order Protocol Distribution

In [602…

```
# Create the countplot
ax = sns.countplot(x=df['order_protocol'],order=df['order_protocol'].value_counts().inde

# Add numbers above the bars
for p in ax.patches:
    ax.annotate(f"{p.get_height()}", (p.get_x() + p.get_width() / 2., p.get_height()), h

# Set the title
plt.title('Order Protocol Distribution')

# Show the plot
plt.show()
```



```
Maximum order have got from 1 followed by 3 and 5
```

In [603…

```
df.head()
```

Out[603]:

|   | market_id | created_at | actual_delivery_time | store_id | store_primary_category | ord |
|---|---|---|---|---|---|---|
| **0** | 1.0 | 2015-02-06 22:24:17 | 2015-02-06 23:27:16 | df263d996281d984952c07998dc54358 | american |  |
| **1** | 2.0 | 2015-02-10 21:49:25 | 2015-02-10 22:56:29 | f0ade77b43923b38237db569b016ba25 | mexican |  |
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | f0ade77b43923b38237db569b016ba25 | indian |  |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | f0ade77b43923b38237db569b016ba25 | indian |  |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | f0ade77b43923b38237db569b016ba25 | indian |  |

In [604…

```
df['delivery_time_minutes'] = round((df['actual_delivery_time'] - df['created_at']).dt.t
```

In [605…

```
df['day_of_week']  = df['created_at'].dt.day_of_week
```

In [606…

```
df['order_created_month'] = df['created_at'].dt.month

df['order_created_hour'] = df['created_at'].dt.hour

df['order_delivery_hour'] = df['actual_delivery_time'].dt.hour
```

```
df['time_taken_to_delivery_hour'] = abs(df['order_delivery_hour'] - df['order_created_ho
```

In [607…

```
df.drop(['store_id','delivery_time_gt_created_at_check'],axis=1,inplace=True)
```

In [608…

```
df.head()
```

Out[608]:

|  | market_id | created_at | actual_delivery_time | store_primary_category | order_protocol | total_items | subtotal | nu |
|---|---|---|---|---|---|---|---|---|
| **0** | 1.0 | 2015-02-06 22:24:17 | 2015-02-06 23:27:16 | american | 1.0 | 4 | 3441 |  |
| **1** | 2.0 | 2015-02-10 21:49:25 | 2015-02-10 22:56:29 | mexican | 2.0 | 1 | 1900 |  |
| **2** | 3.0 | 2015-01-22 20:39:28 | 2015-01-22 21:09:09 | indian | 1.0 | 1 | 1900 |  |
| **3** | 3.0 | 2015-02-03 21:21:45 | 2015-02-03 22:13:00 | indian | 1.0 | 6 | 6900 |  |
| **4** | 3.0 | 2015-02-15 02:40:36 | 2015-02-15 03:20:26 | indian | 1.0 | 3 | 3900 |  |

In [609…

```
df.drop(['created_at','actual_delivery_time'],axis=1,inplace=True)
```

# EDA for Numeric Columns

In [610…

```
df.describe()
```

Out[610]:

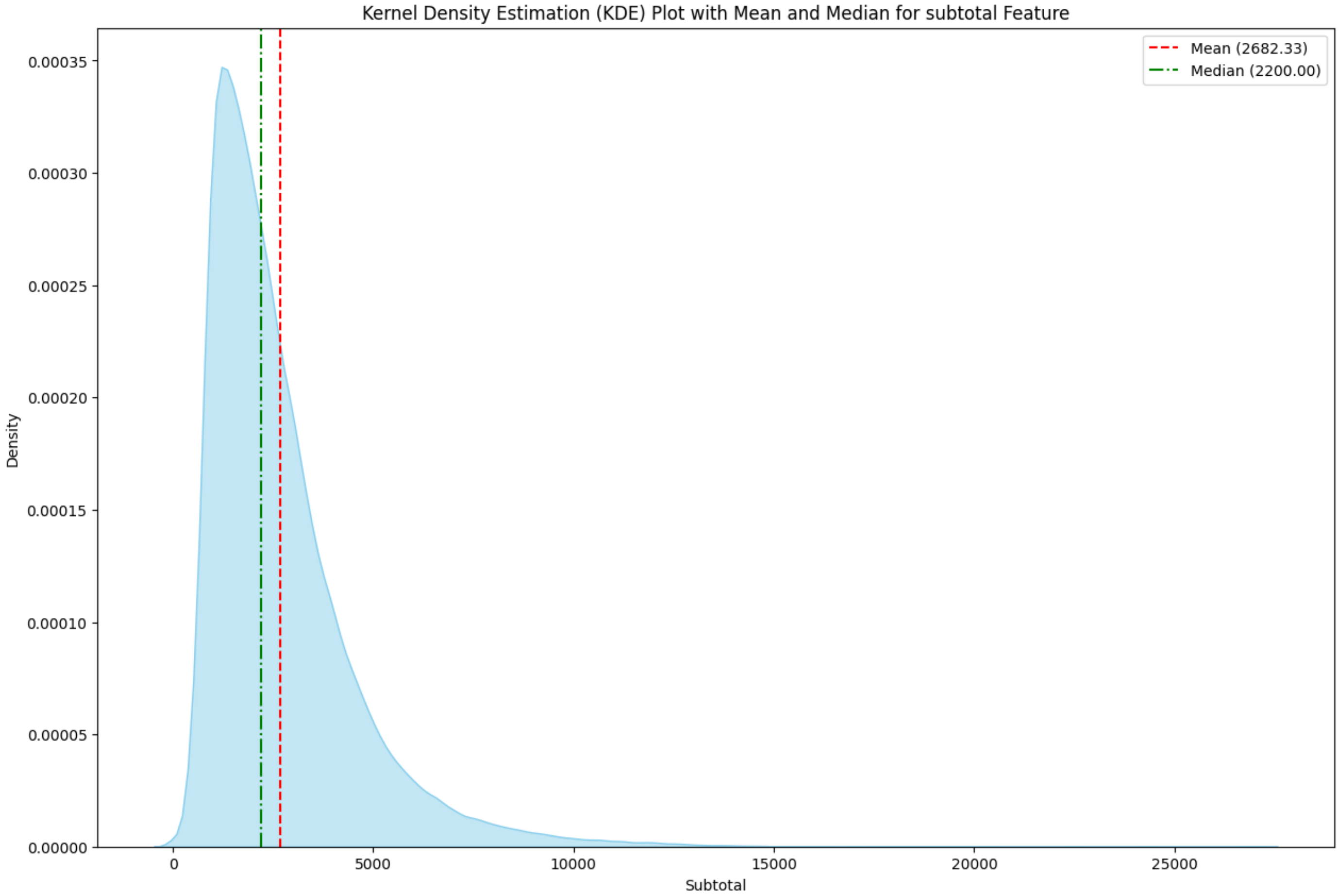
|  | market_id | order_protocol | total_items | subtotal | num_distinct_items | min_item_price | max_ |
|---|---|---|---|---|---|---|---|
| **count** | 197421.000000 | 197421.000000 | 197421.000000 | 197421.000000 | 197421.000000 | 197421.000000 | 1974 |
| **mean** | 2.978290 | 2.872871 | 3.196367 | 2682.326379 | 2.670780 | 686.224596 | 1 |
| **std** | 1.524658 | 1.505892 | 2.666552 | 1823.106256 | 1.630261 | 522.044061 | 5 |
| **min** | 1.000000 | 1.000000 | 1.000000 | 0.000000 | 1.000000 | -86.000000 |  |
| **25%** | 2.000000 | 1.000000 | 2.000000 | 1400.000000 | 1.000000 | 299.000000 | 8 |
| **50%** | 3.000000 | 3.000000 | 3.000000 | 2200.000000 | 2.000000 | 595.000000 | 10 |
| **75%** | 4.000000 | 4.000000 | 4.000000 | 3395.000000 | 3.000000 | 949.000000 | 13 |
| **max** | 6.000000 | 7.000000 | 411.000000 | 27100.000000 | 20.000000 | 14700.000000 | 147 |

# Skewness Analysis for Subtotal Feature

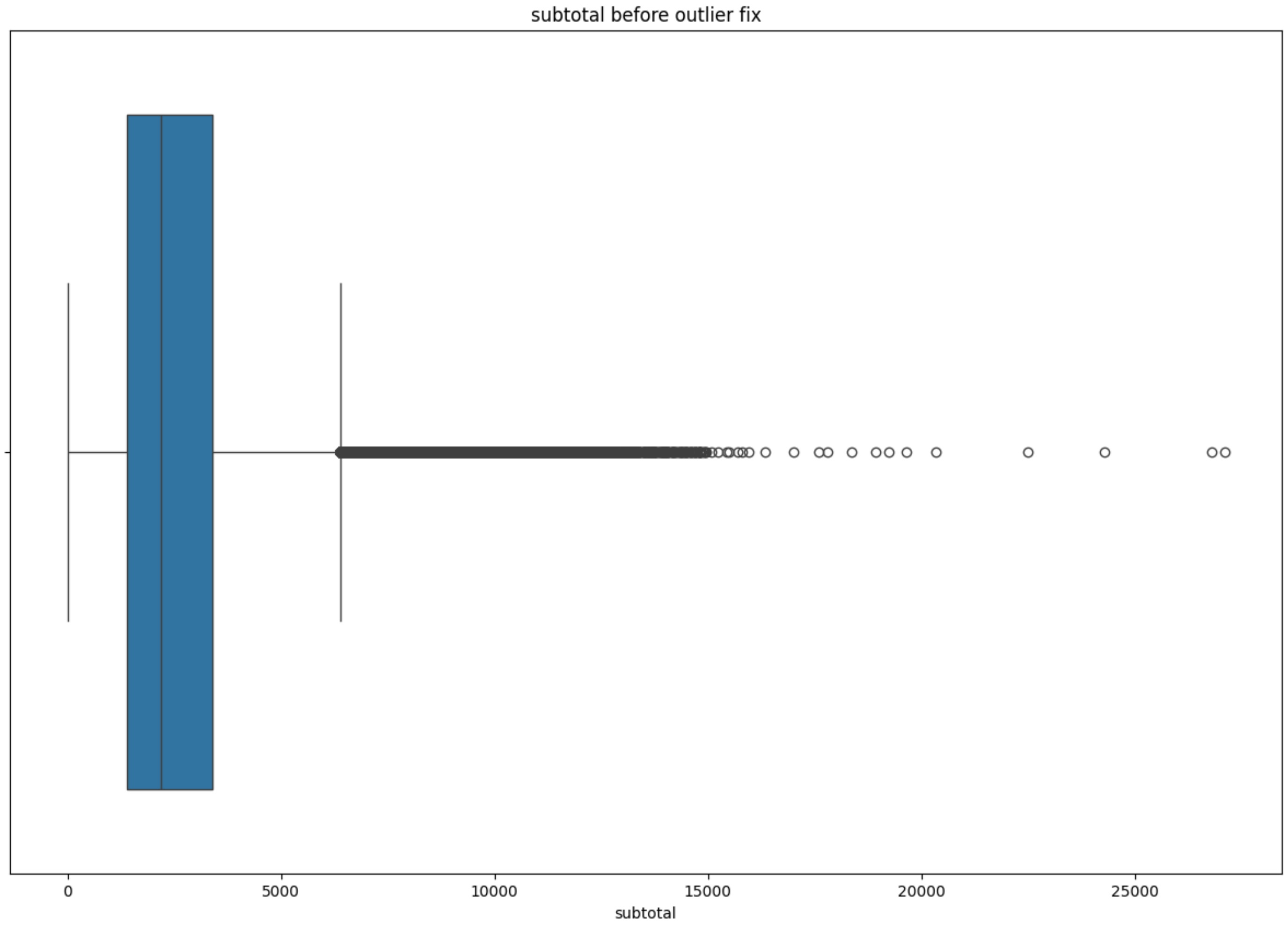
In [611…

```
# Create the KDE plot
plt.figure(figsize=(15,10))
ax = sns.kdeplot(data=df, x='subtotal', fill=True, color='skyblue', alpha=0.5)

# Calculate mean and median
mean_val = np.mean(df['subtotal'])
median_val = np.median(df['subtotal'])
```

```
# Add vertical lines for mean and median
ax.axvline(mean_val, color='red', linestyle='--', label=f'Mean ({mean_val:.2f})')
ax.axvline(median_val, color='green', linestyle='-.', label=f'Median ({median_val:.2f})'

# Set labels and title
plt.xlabel('Subtotal')
plt.ylabel('Density')
plt.title('Kernel Density Estimation (KDE) Plot with Mean and Median for subtotal Featur

# Show legend
plt.legend()

# Show the plot
plt.show()

plt.figure(figsize=(15,10))
plt.title('subtotal before outlier fix')
sns.boxplot(x=df['subtotal'])
plt.show()
```



Loading [MathJax]/extensions/Safe.js



# Using IQR Method to remove outliers

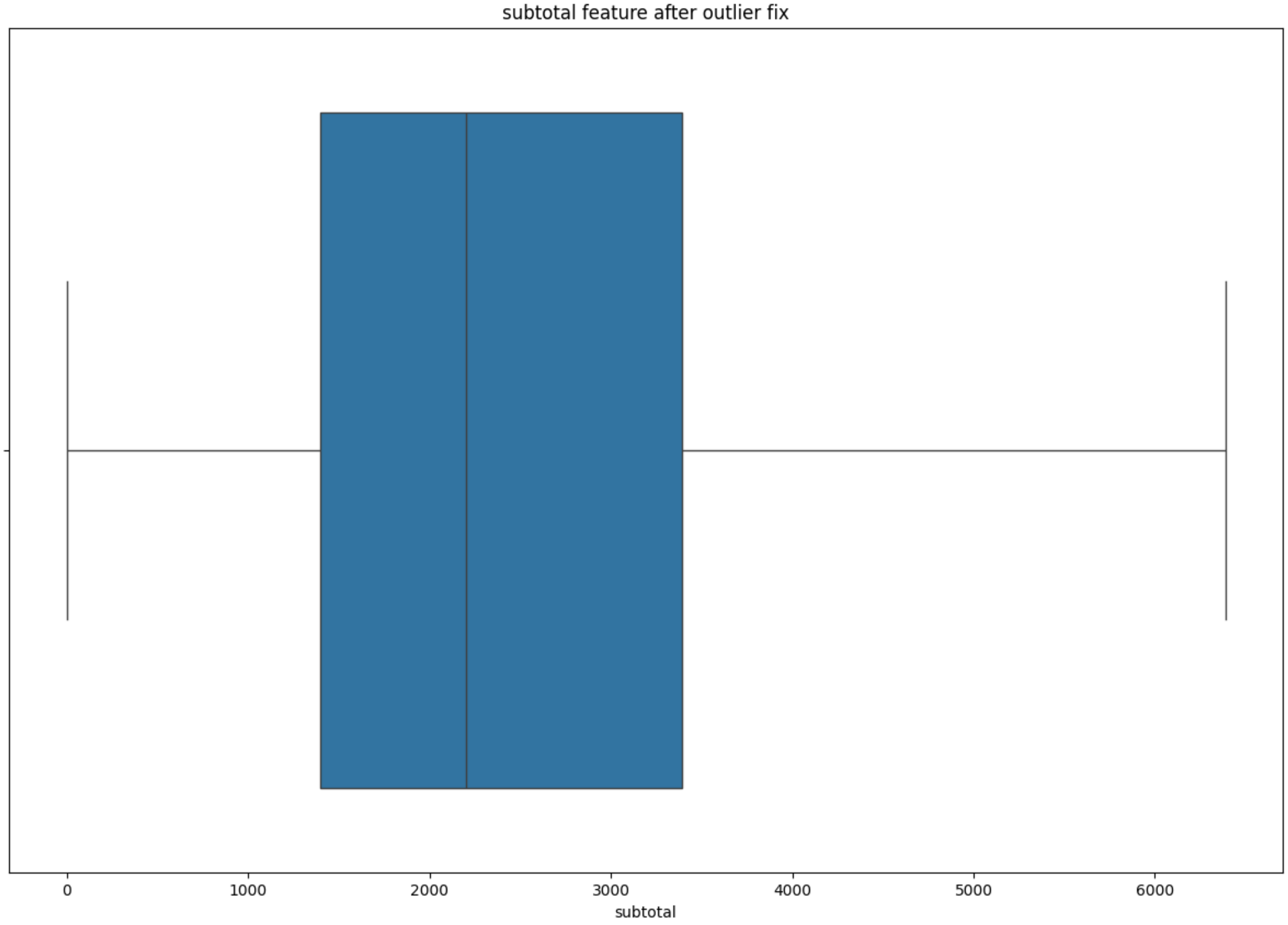
In [612…

```
q1 = df['subtotal'].quantile(0.25)
q3 = df['subtotal'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['subtotal'] = np.where(df['subtotal']>right_wisker,right_wisker,df['subtotal'])
```

```
left, right wisker : (-1592.5, 6387.5)
```

In [613…

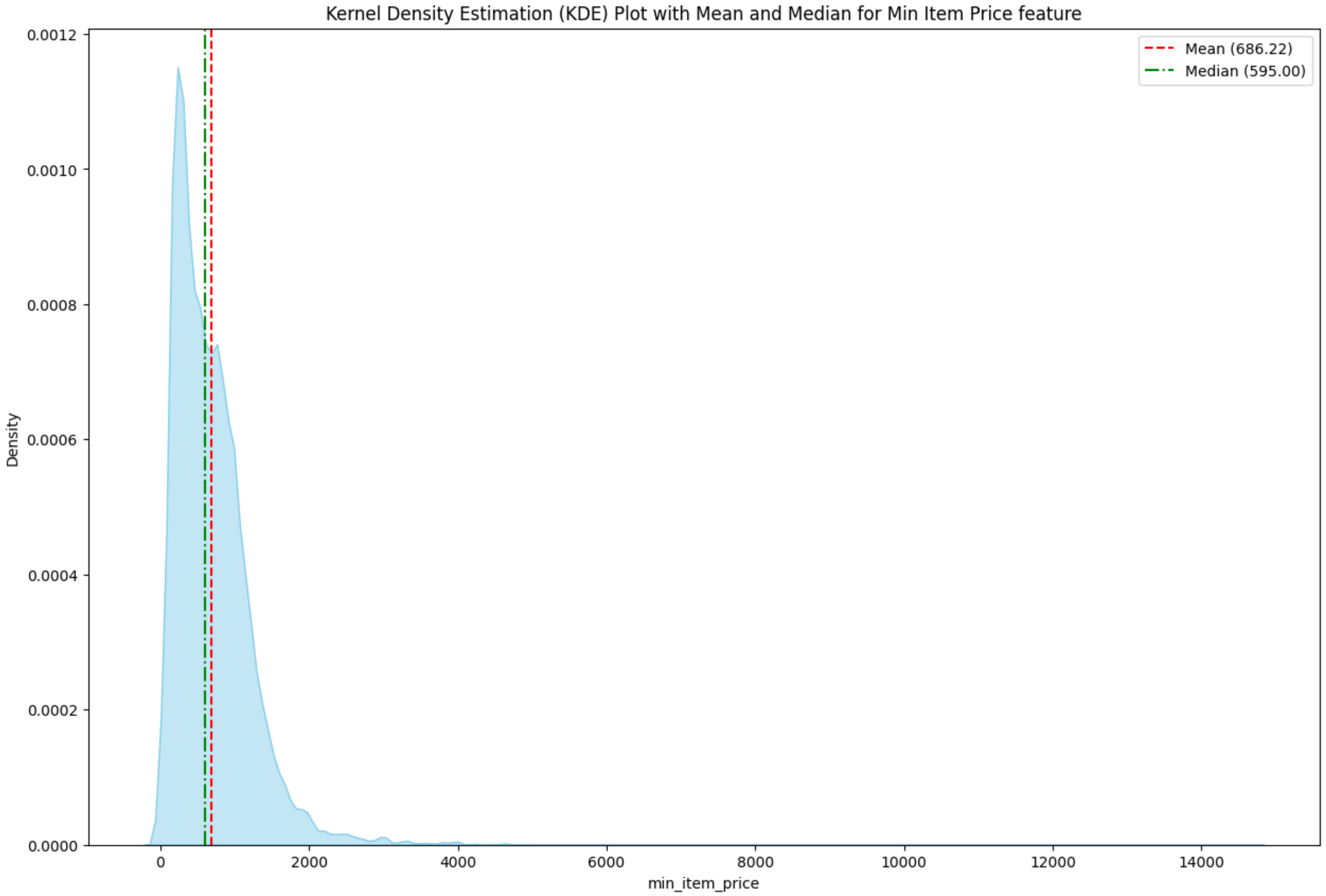
```
plt.figure(figsize=(15,10))
plt.title('subtotal feature after outlier fix')
sns.boxplot(x=df['subtotal'])
plt.show()
```

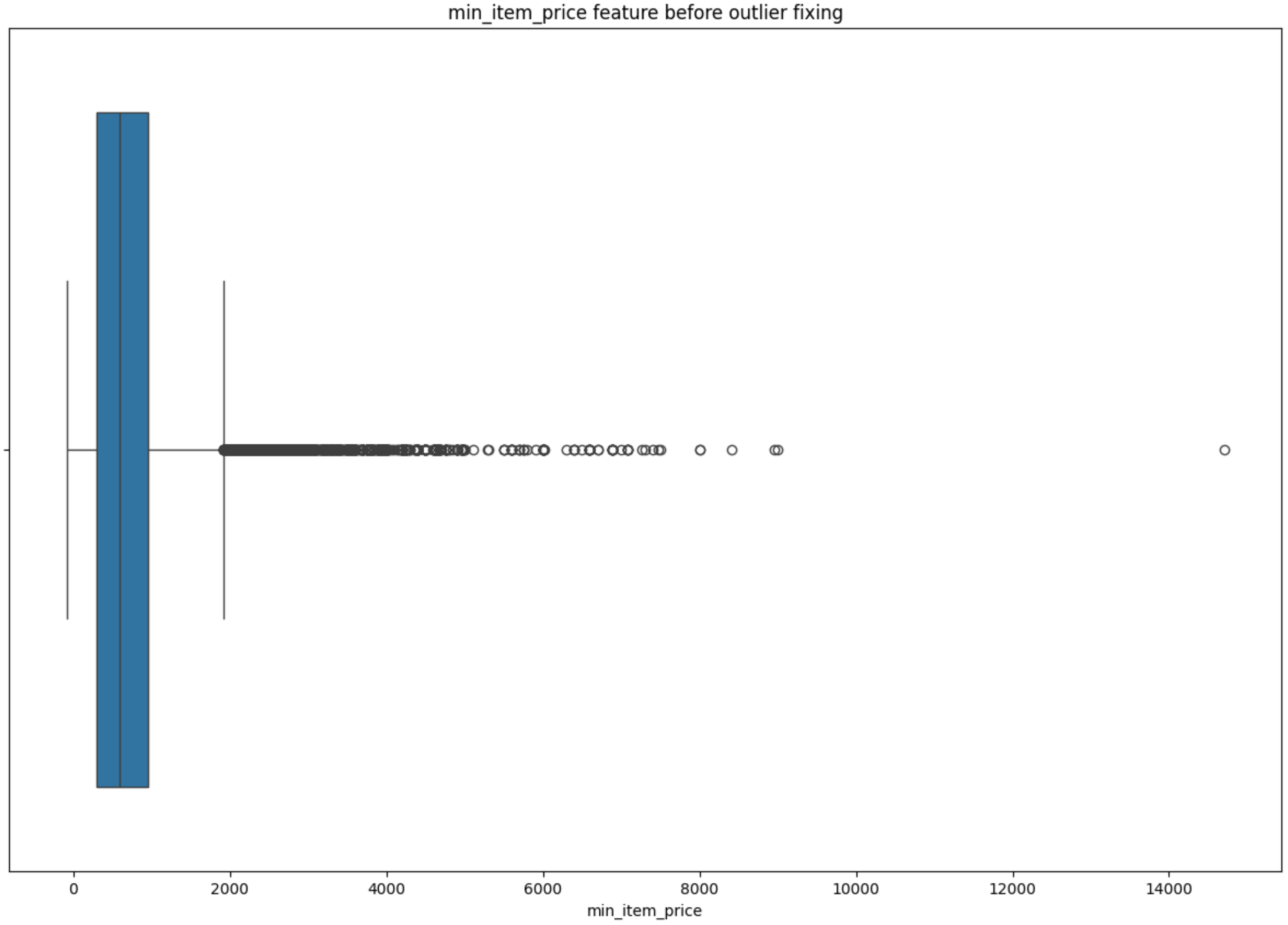

subtotal feature after outlier fix

## Skewness Analysis for Min Item Price Feature

In [614…

```
# Create the KDE plot
plt.figure(figsize=(15,10))
ax = sns.kdeplot(data=df, x='min_item_price', fill=True, color='skyblue', alpha=0.5)

# Calculate mean and median
mean_val = np.mean(df['min_item_price'])
median_val = np.median(df['min_item_price'])

# Add vertical lines for mean and median
ax.axvline(mean_val, color='red', linestyle='--', label=f'Mean ({mean_val:.2f})')
ax.axvline(median_val, color='green', linestyle='-.', label=f'Median ({median_val:.2f})'

# Set labels and title
plt.xlabel('min_item_price')
plt.ylabel('Density')
plt.title('Kernel Density Estimation (KDE) Plot with Mean and Median for Min Item Price

# Show legend
plt.legend()

# Show the plot
plt.show()

plt.figure(figsize=(15,10))
plt.title('min_item_price feature before outlier fixing')
sns.boxplot(x=df['min_item_price'])
plt.show()
```





In [615…

```
q1 = df['min_item_price'].quantile(0.25)
q3 = df['min_item_price'].quantile(0.75)
IQR = q3-q1
```

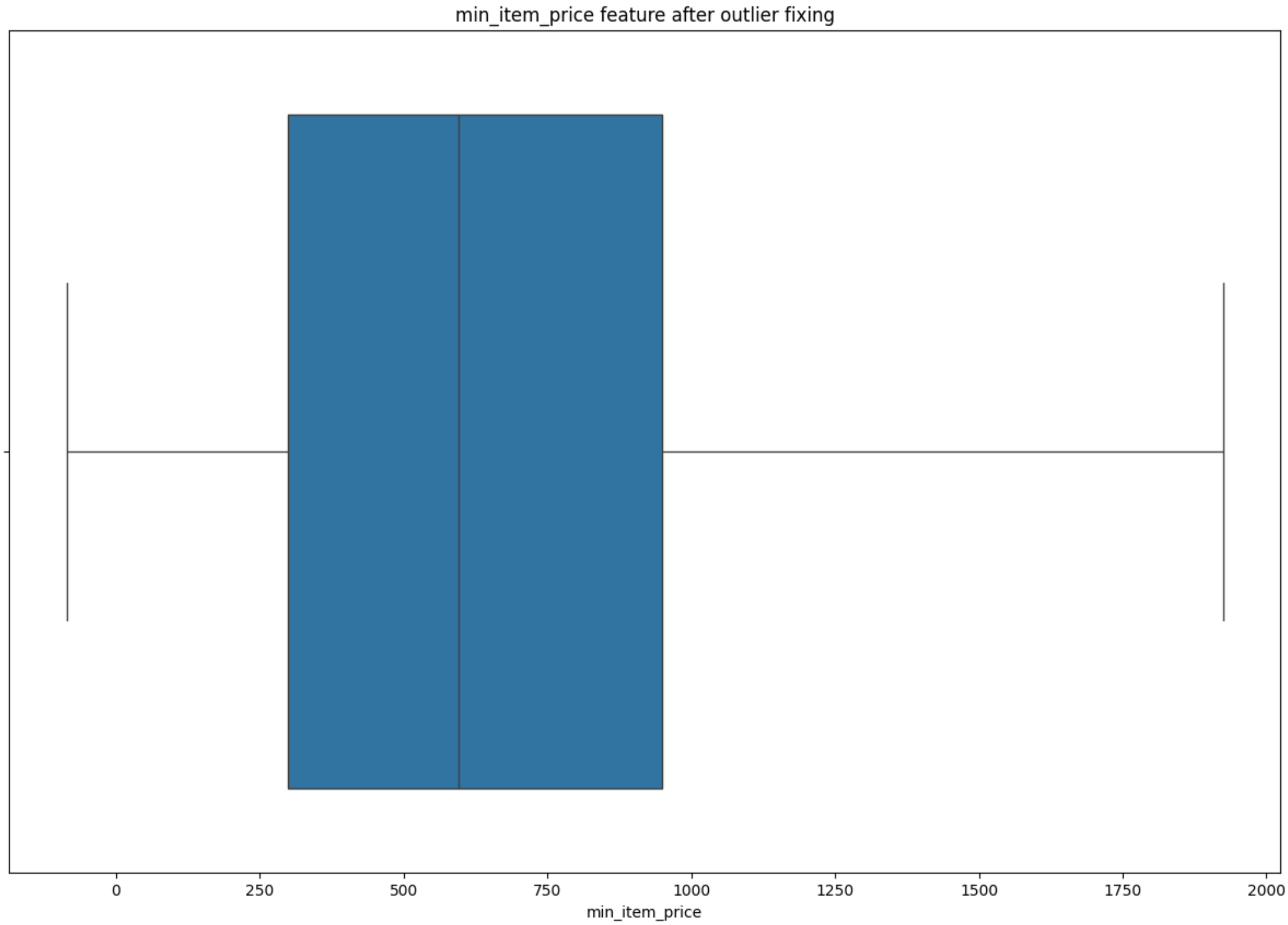
Loading [MathJax]/extensions/Safe.js

```
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['min_item_price'] = np.where(df['min_item_price']>right_wisker,right_wisker,df['min_i
```

```
left, right wisker : (-676.0, 1924.0)
```

In [616…

```
plt.figure(figsize=(15,10))
plt.title('min_item_price feature after outlier fixing')
sns.boxplot(x=df['min_item_price'])
plt.show()
```

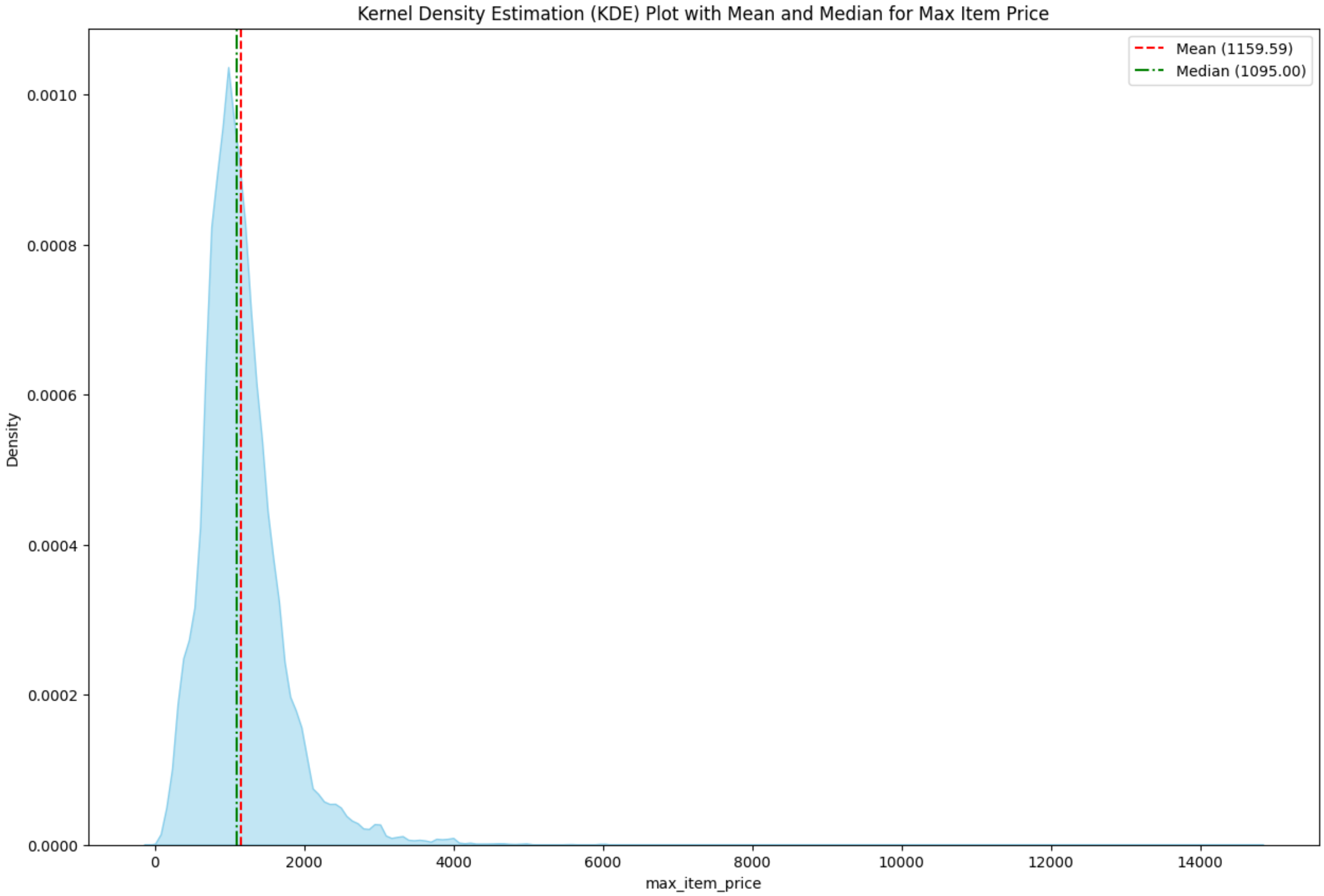


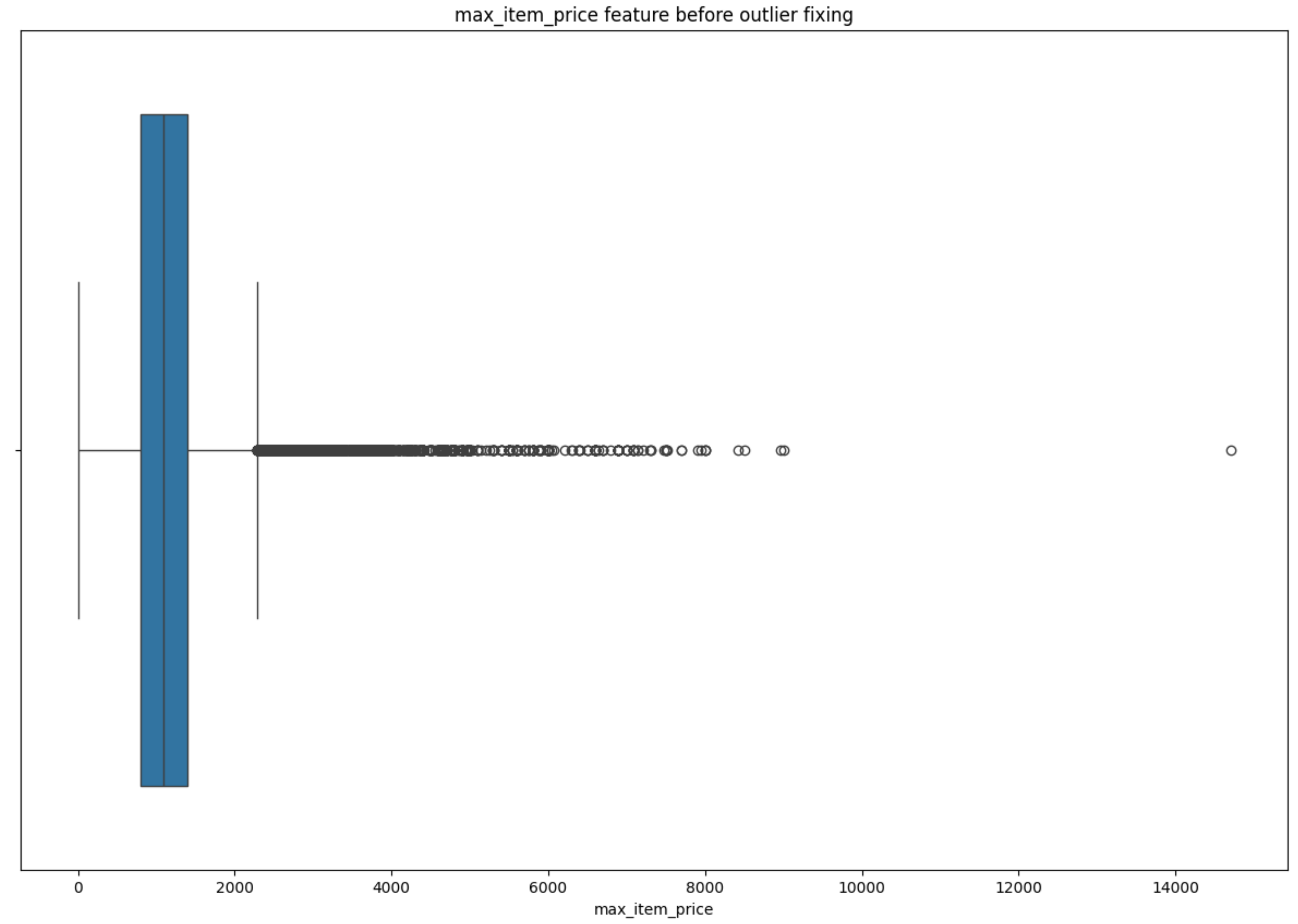
## Skewness Analysis for Max Item Price Feature

In [617…

```
# Create the KDE plot
plt.figure(figsize=(15,10))
ax = sns.kdeplot(data=df, x='max_item_price', fill=True, color='skyblue', alpha=0.5)

# Calculate mean and median
mean_val = np.mean(df['max_item_price'])
median_val = np.median(df['max_item_price'])

# Add vertical lines for mean and median
ax.axvline(mean_val, color='red', linestyle='--', label=f'Mean ({mean_val:.2f})')
ax.axvline(median_val, color='green', linestyle='-.', label=f'Median ({median_val:.2f})'

# Set labels and title
plt.xlabel('max_item_price')
plt.ylabel('Density')
plt.title('Kernel Density Estimation (KDE) Plot with Mean and Median for Max Item Price'
```

```python
plt.legend()

# Show the plot
plt.show()

plt.figure(figsize=(15,10))
plt.title('max_item_price feature before outlier fixing')
sns.boxplot(x=df['max_item_price'])
plt.show()
```





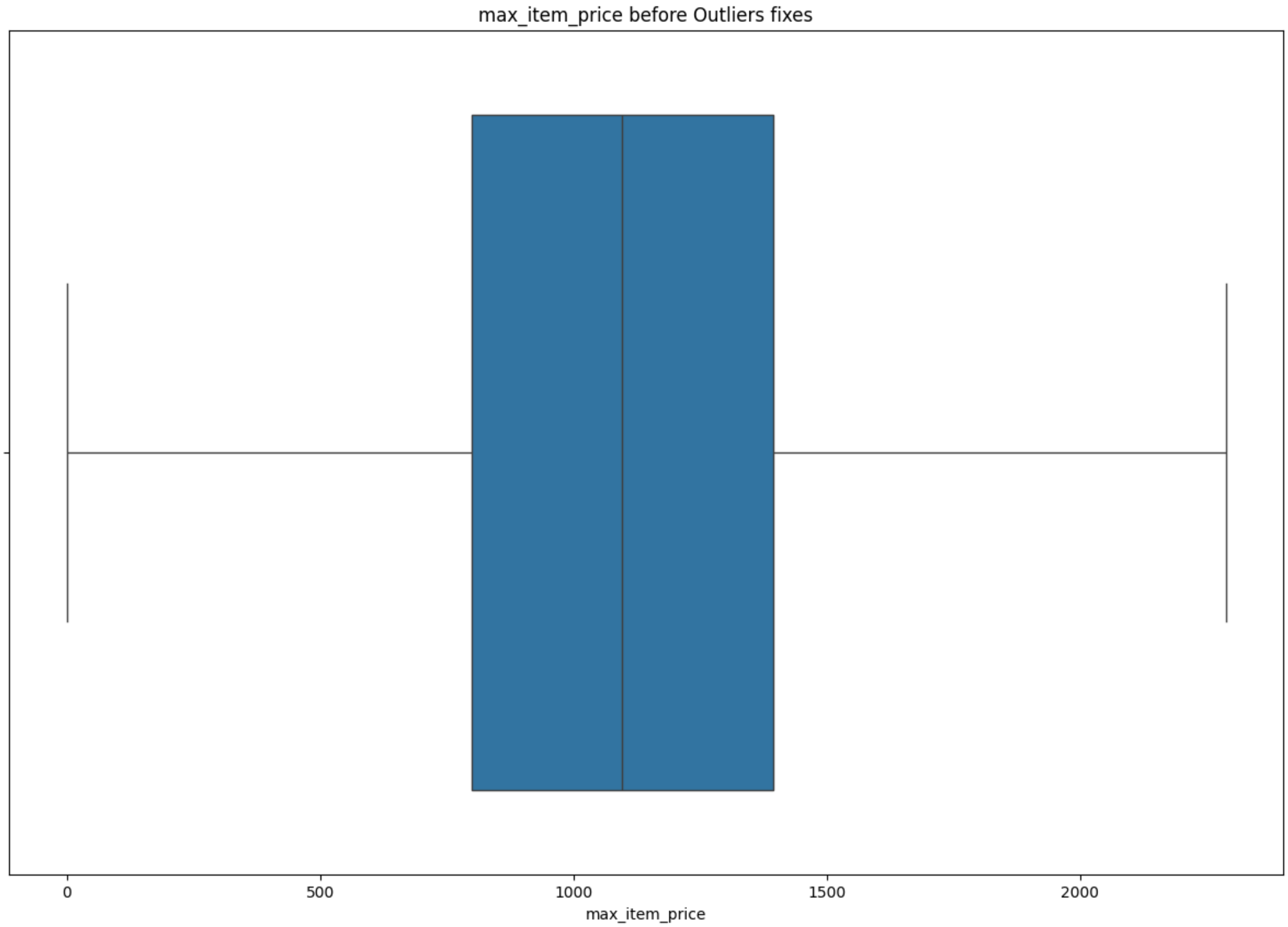
In [618…

```
q1 = df['max_item_price'].quantile(0.25)
q3 = df['max_item_price'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['max_item_price'] = np.where(df['max_item_price']>right_wisker,right_wisker,df['max_i
```

```
left, right wisker : (-92.5, 2287.5)
```

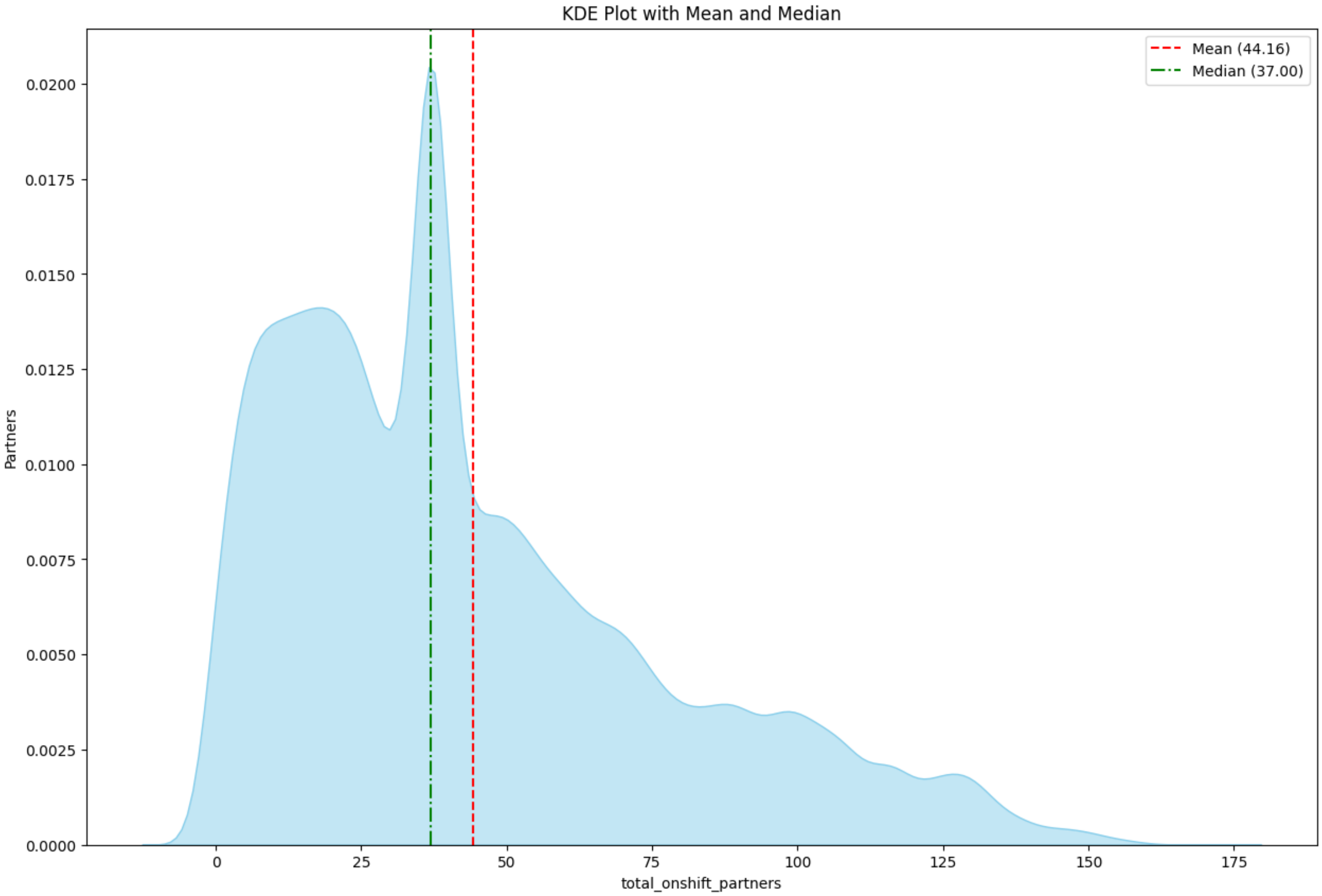
In [619…

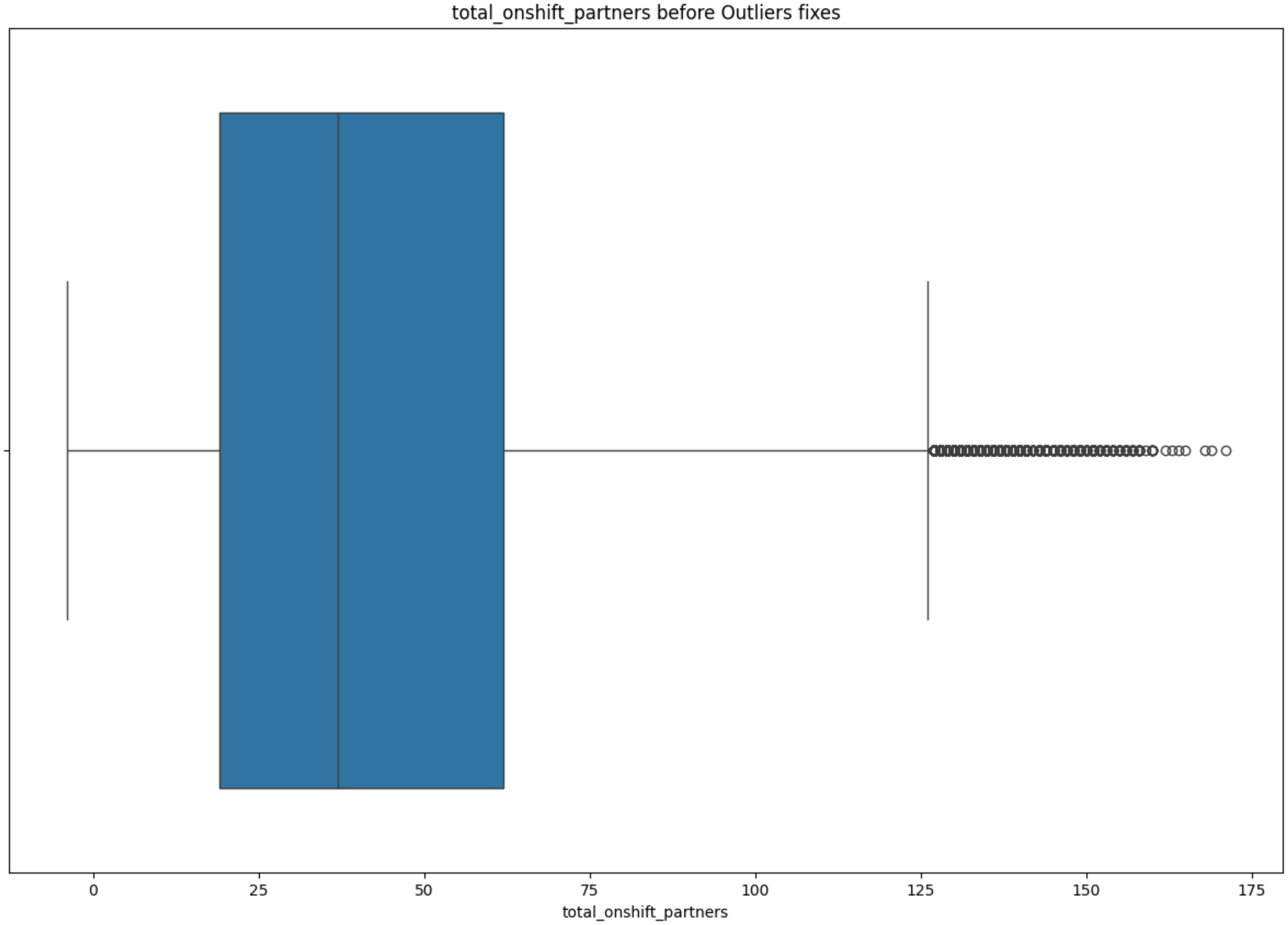
```
plt.figure(figsize=(15,10))
plt.title('max_item_price before Outliers fixes')
sns.boxplot(x=df['max_item_price'])
plt.show()
```



In [620…

```
# Create the KDE plot
plt.figure(figsize=(15,10))
ax = sns.kdeplot(data=df, x='total_onshift_partners', fill=True, color='skyblue', alpha=

# Calculate mean and median
mean_val = np.mean(df['total_onshift_partners'])
median_val = np.median(df['total_onshift_partners'])

# for p in ax.patches:
#     ax.annotate(f"{p.get_height()}", (p.get_x() + p.get_width() / 2.0, p.get_height())


# Add vertical lines for mean and median
ax.axvline(mean_val, color='red', linestyle='--', label=f'Mean ({mean_val:.2f})')
ax.axvline(median_val, color='green', linestyle='-.', label=f'Median ({median_val:.2f})'

# Set labels and title
plt.xlabel('total_onshift_partners')
plt.ylabel('Partners')
plt.title('KDE Plot with Mean and Median')

# Show legend
plt.legend()

# Show the plot
plt.show()

plt.figure(figsize=(15,10))
plt.title('total_onshift_partners before Outliers fixes')
sns.boxplot(x=df['total_onshift_partners'])
plt.show()
```





In [621…

```
q1 = df['total_onshift_partners'].quantile(0.25)
q3 = df['total_onshift_partners'].quantile(0.75)
IQR = q3-q1
```

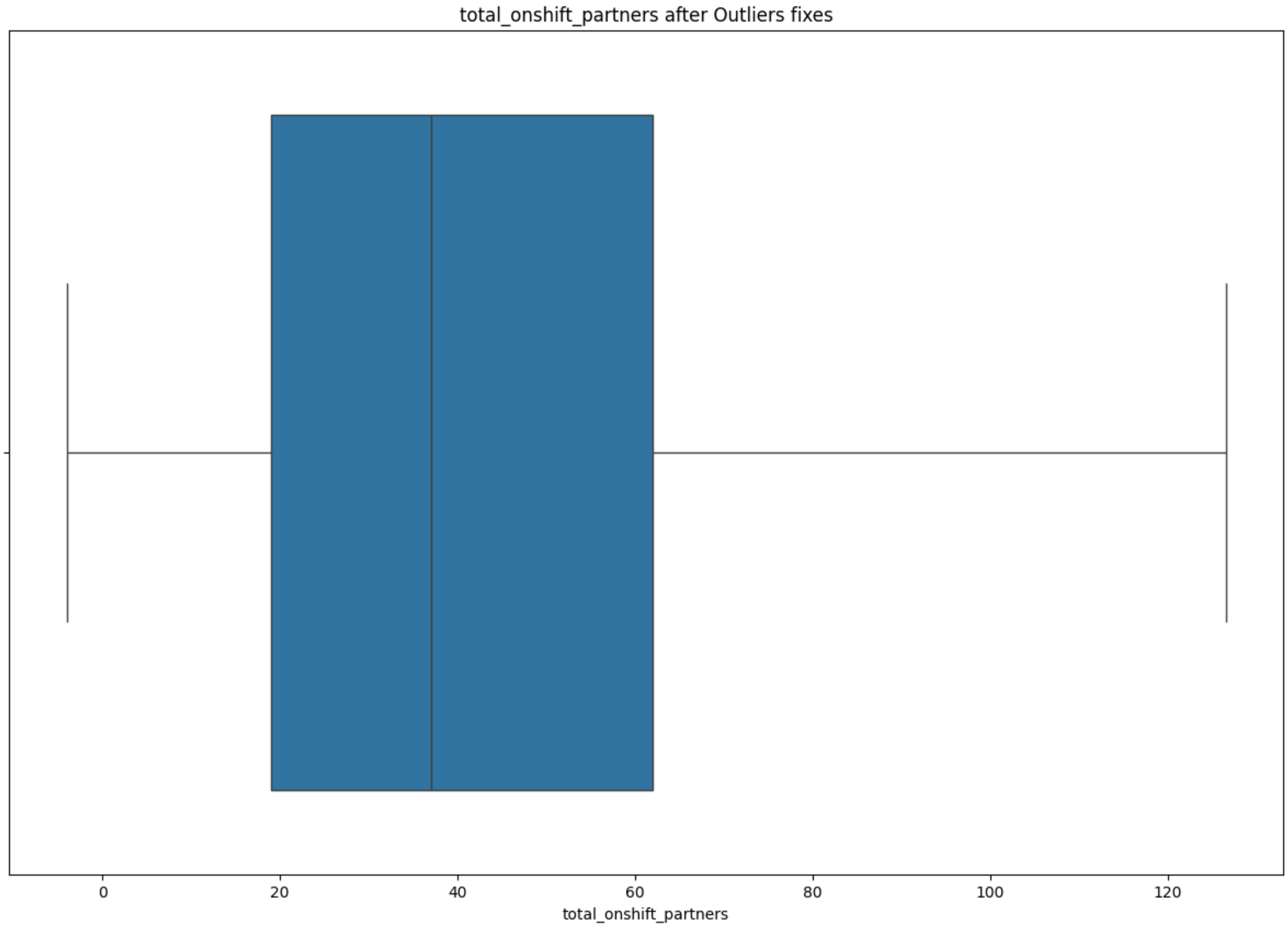
Loading [MathJax]/extensions/Safe.js

```
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['total_onshift_partners'] = np.where(df['total_onshift_partners']>right_wisker,right_
```

```
left, right wisker : (-45.5, 126.5)
```

In [623…

```
plt.figure(figsize=(15,10))
plt.title('total_onshift_partners after Outliers fixes')
sns.boxplot(x=df['total_onshift_partners'])
plt.show()
```

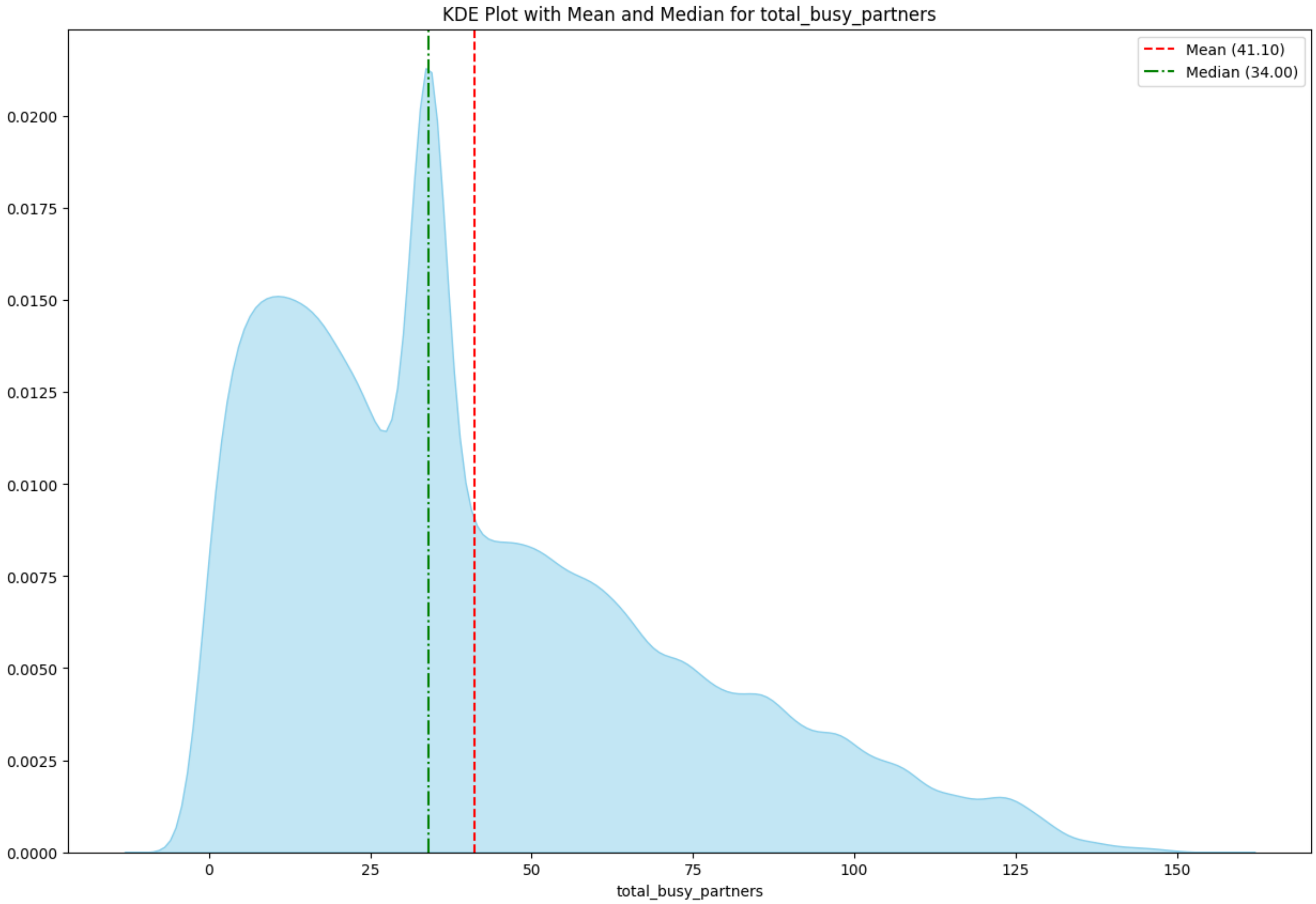


In [624…

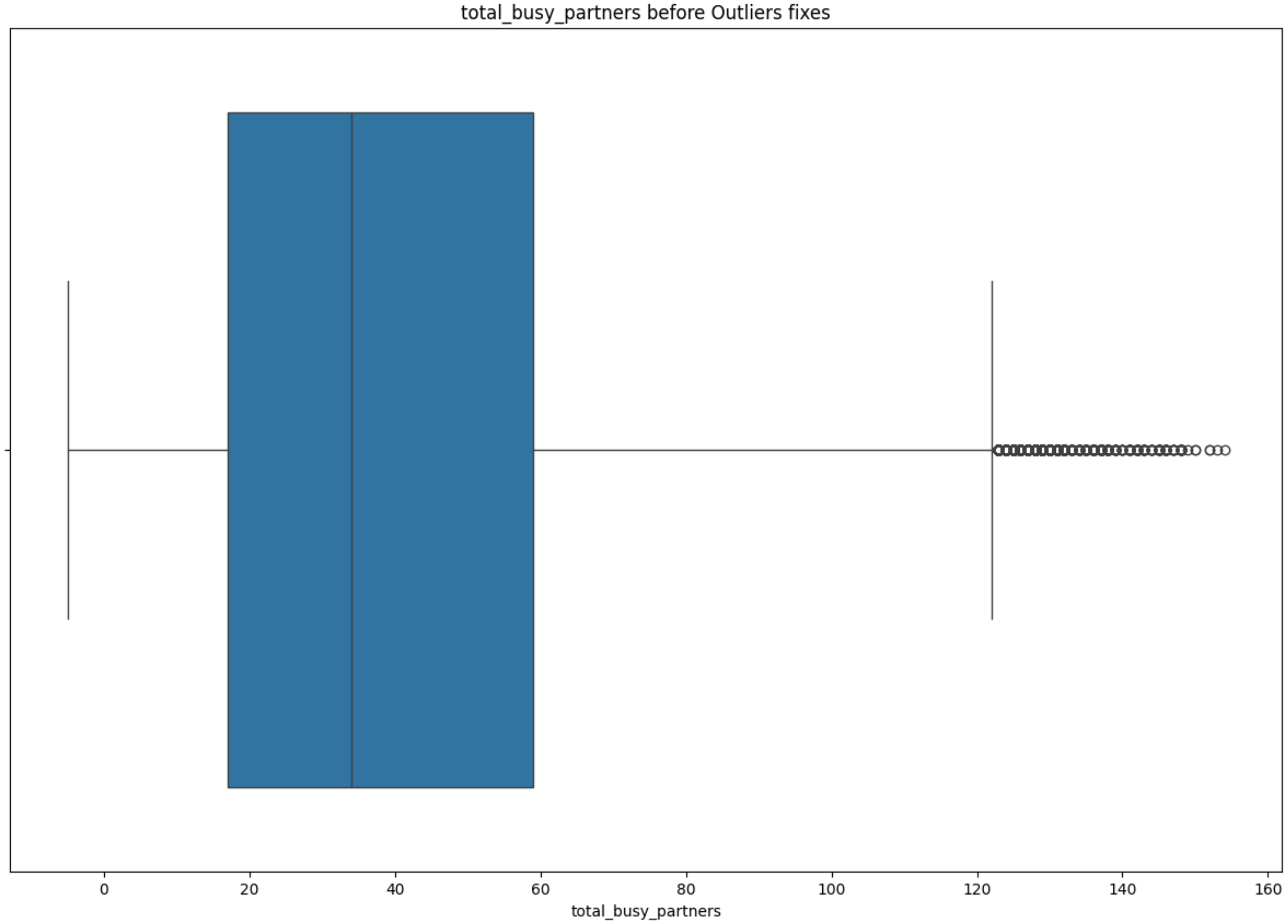
```
# Create the KDE plot
plt.figure(figsize=(15,10))
ax = sns.kdeplot(data=df, x='total_busy_partners', fill=True, color='skyblue', alpha=0.5

# Calculate mean and median
mean_val = np.mean(df['total_busy_partners'])
median_val = np.median(df['total_busy_partners'])

for p in ax.patches:
    ax.annotate(f"{p.get_height()}", (p.get_x() + p.get_width() / 2.0, p.get_height()),


# Add vertical lines for mean and median
ax.axvline(mean_val, color='red', linestyle='--', label=f'Mean ({mean_val:.2f})')
ax.axvline(median_val, color='green', linestyle='-.', label=f'Median ({median_val:.2f})'

# Set labels and title
plt.xlabel('total_busy_partners')
plt.ylabel('')
plt.title('KDE Plot with Mean and Median for total_busy_partners')
```

Loading [MathJax]/extensions/Safe.js

```
# Show legend
plt.legend()

# Show the plot
plt.show()

plt.figure(figsize=(15,10))
plt.title('total_busy_partners before Outliers fixes')
sns.boxplot(x=df['total_busy_partners'])
plt.show()
```



Loading [MathJax]/extensions/Safe.js



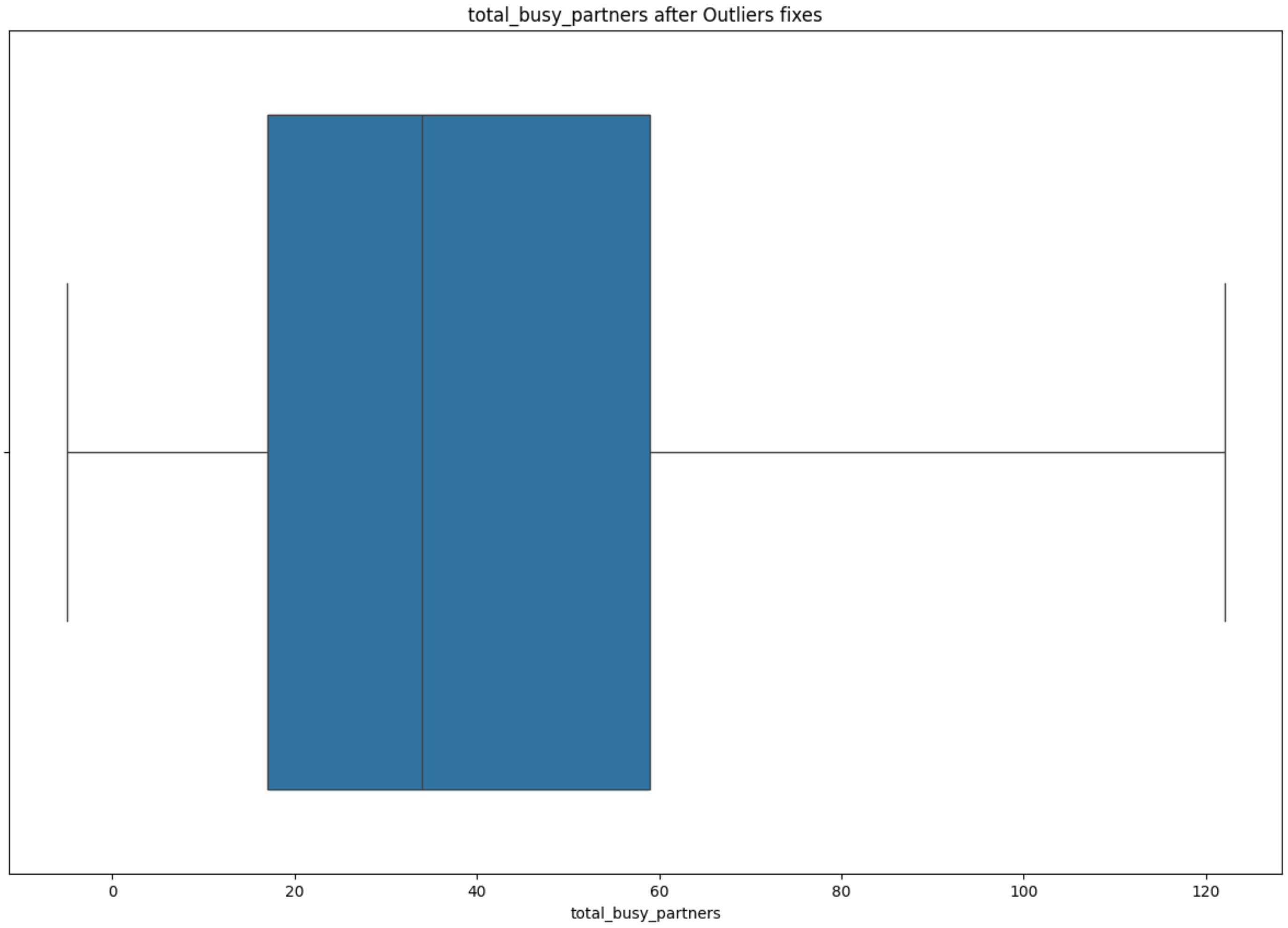
In [625…

```
q1 = df['total_busy_partners'].quantile(0.25)
q3 = df['total_busy_partners'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['total_busy_partners'] = np.where(df['total_busy_partners']>right_wisker,right_wisker
```

```
left, right wisker : (-46.0, 122.0)
```

In [626…

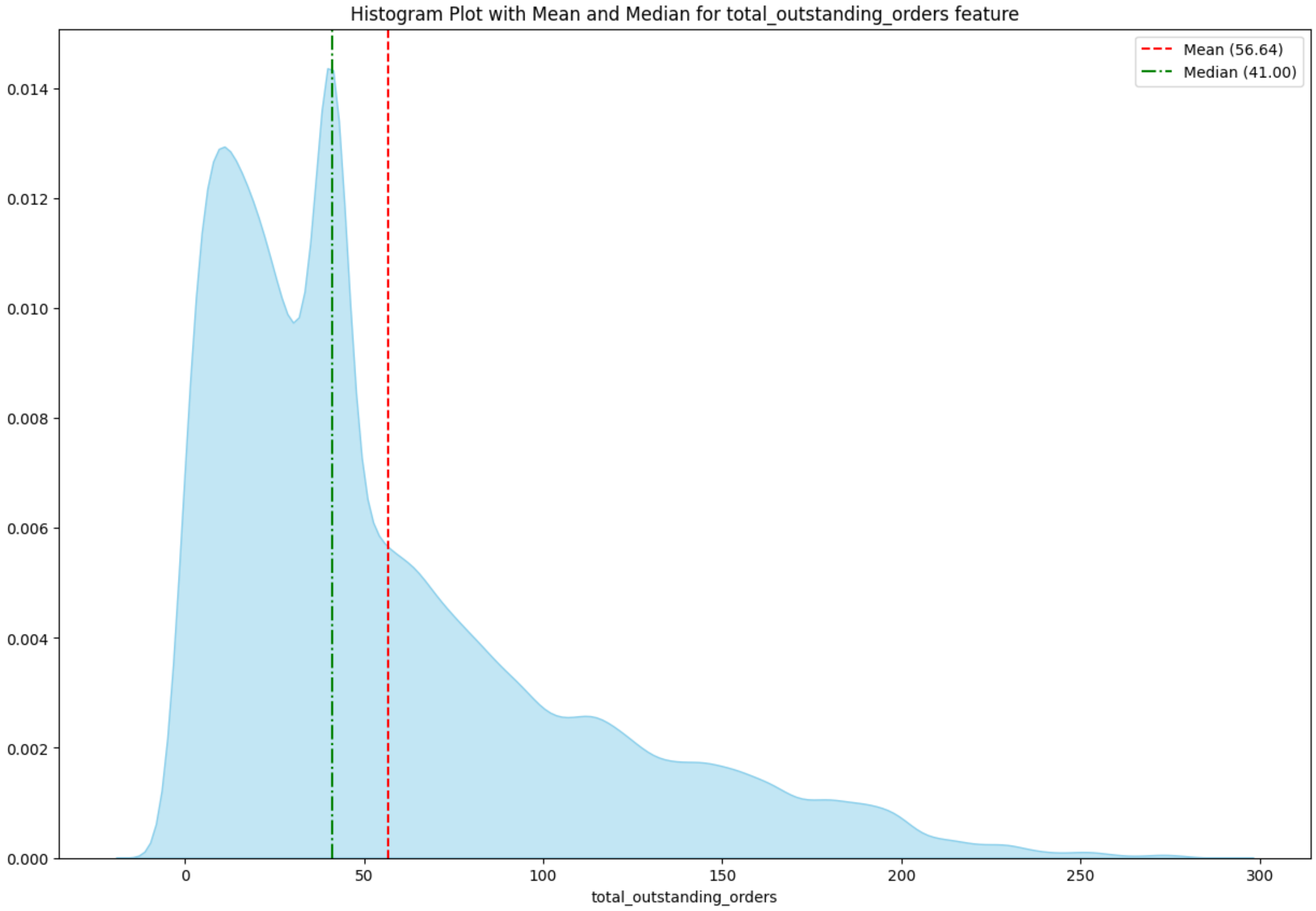
```
plt.figure(figsize=(15,10))
plt.title('total_busy_partners after Outliers fixes')
sns.boxplot(x=df['total_busy_partners'])
plt.show()
```

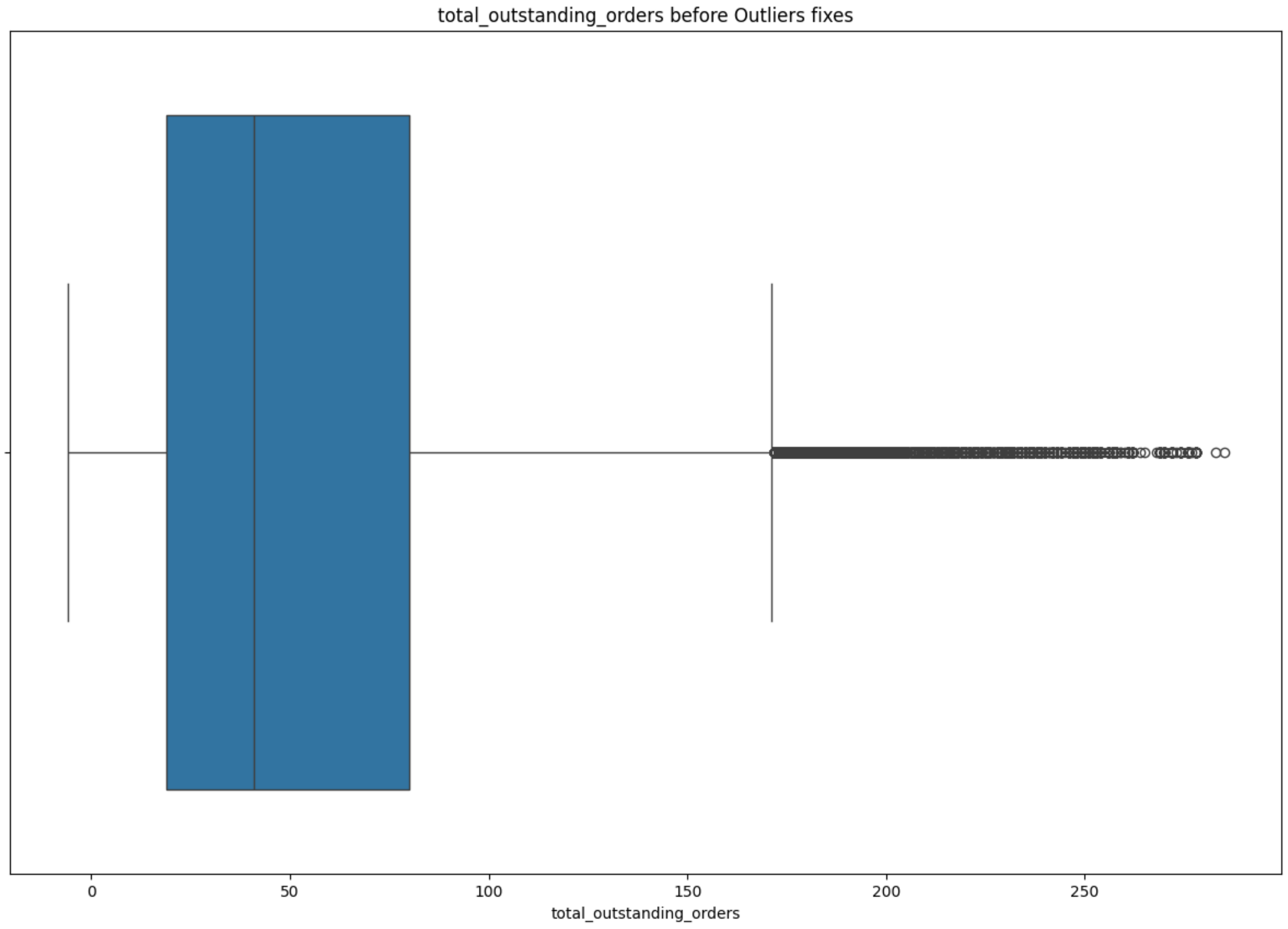


In [627…

```
# Create the KDE plot
plt.figure(figsize=(15,10))
ax = sns.kdeplot(data=df, x='total_outstanding_orders', fill=True, color='skyblue', alph

# Calculate mean and median
mean_val = np.mean(df['total_outstanding_orders'])
median_val = np.median(df['total_outstanding_orders'])

for p in ax.patches:
    ax.annotate(f"{p.get_height()}", (p.get_x() + p.get_width() / 2.0, p.get_height()),


# Add vertical lines for mean and median
ax.axvline(mean_val, color='red', linestyle='--', label=f'Mean ({mean_val:.2f})')
ax.axvline(median_val, color='green', linestyle='-.', label=f'Median ({median_val:.2f})'

# Set labels and title
plt.xlabel('total_outstanding_orders')
plt.ylabel('')
plt.title('Histogram Plot with Mean and Median for total_outstanding_orders feature')

# Show legend
plt.legend()

# Show the plot
plt.show()
plt.figure(figsize=(15,10))
plt.title('total_outstanding_orders before Outliers fixes')
sns.boxplot(x = df['total_outstanding_orders'])
plt.show()
```

Loading [MathJax]/extensions/Safe.js





In [628…

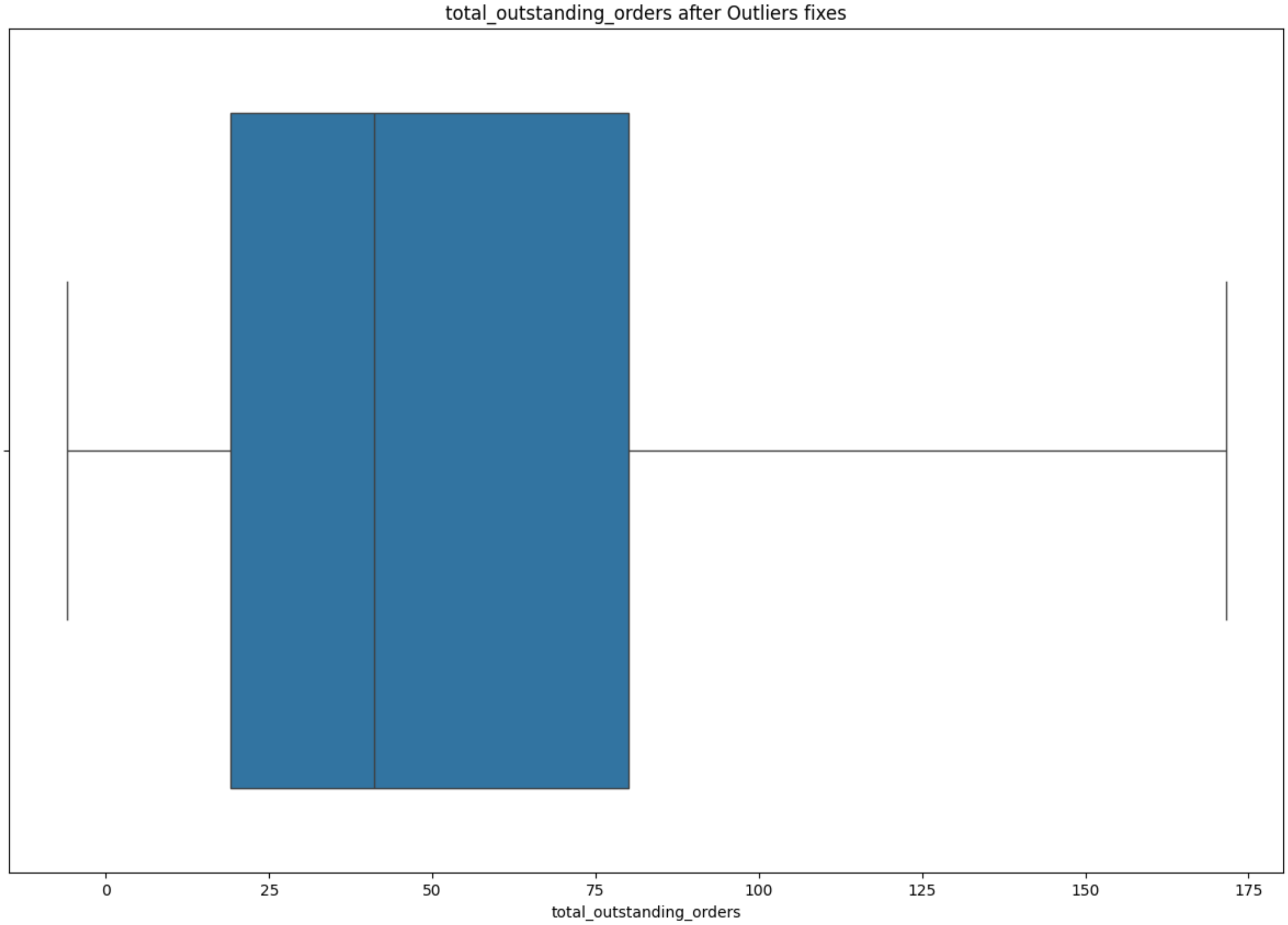
```
q1 = df['total_outstanding_orders'].quantile(0.25)
q3 = df['total_outstanding_orders'].quantile(0.75)
```

```
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['total_outstanding_orders'] = np.where(df['total_outstanding_orders']>right_wisker,ri
```

```
left, right wisker : (-72.5, 171.5)
```

In [629…

```
plt.figure(figsize=(15,10))
plt.title('total_outstanding_orders after Outliers fixes')
sns.boxplot(x = df['total_outstanding_orders'])
plt.show()
```



In [520…

```
df.drop('market_id',axis=1, inplace=True)
```

In [521…

```
from category_encoders import TargetEncoder
```

In [522…

```
df['store_primary_category'] = TargetEncoder().fit_transform(df['store_primary_category'
```

In [523…

```
df.head()
```

Out[523]:

| | store_primary_category | order_protocol | total_items | subtotal | num_distinct_items | min_item_price | max_item_ |
|---|---|---|---|---|---|---|---|
| **0** | 48.025105 | 1.0 | 4 | 3441.0 | 4 | 557.0 | 1 |
| **1** | 44.602766 | 2.0 | 1 | 1900.0 | 1 | 1400.0 | 1 |
| **2** | 49.749557 | 1.0 | 1 | 1900.0 | 1 | 1900.0 | 1 |
| **3** | 49.749557 | 1.0 | 6 | 6387.5 | 5 | 600.0 | 1 |
| **4** | 49.749557 | 1.0 | 3 | 3900.0 | 3 | 1100.0 | 1 |

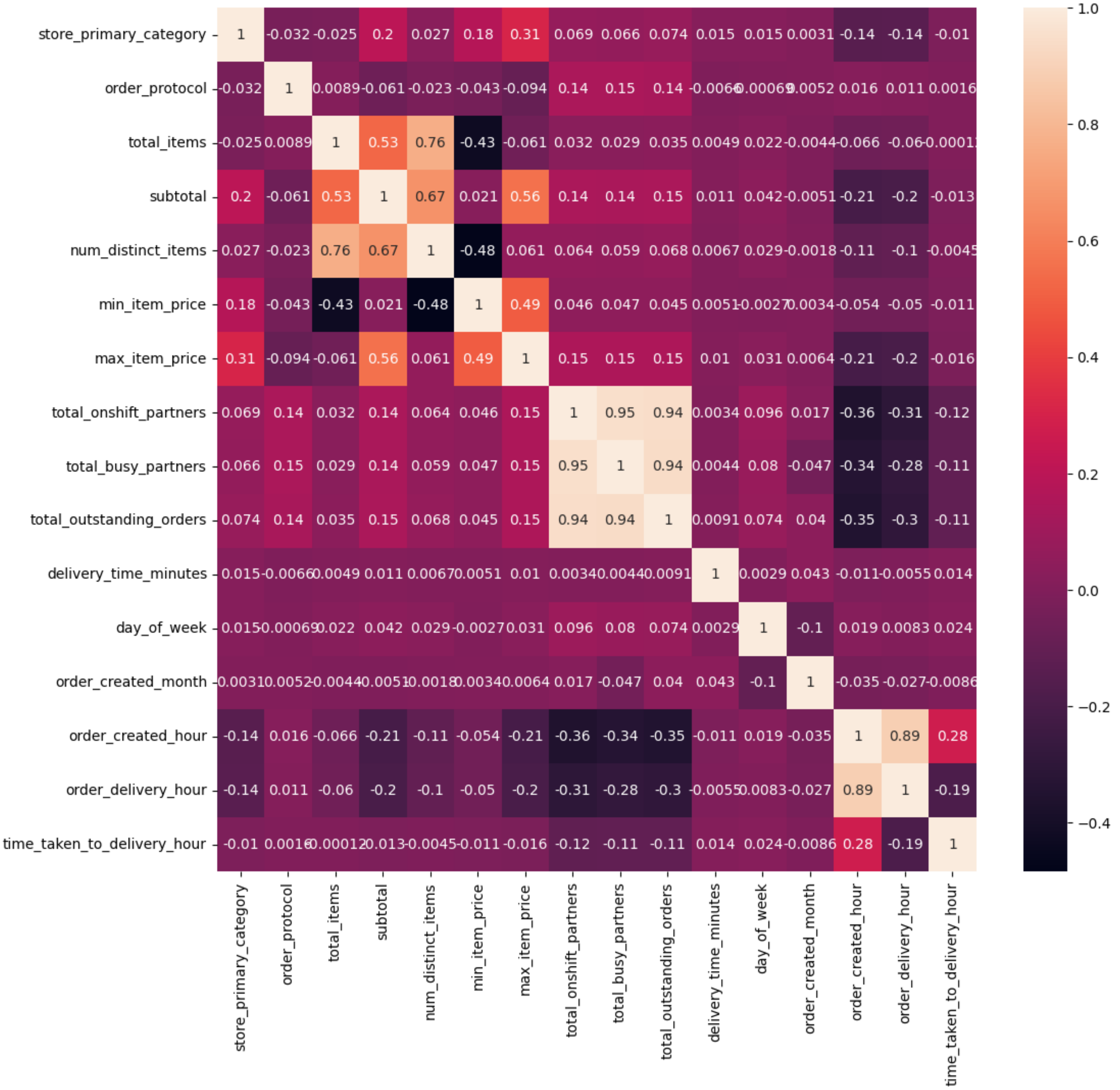
Loading [MathJax]/extensions/Safe.js

In [524…

```
plt.figure(figsize=(12,11))
sns.heatmap(df.corr(),annot=True)
```

Out[524]:

```
<Axes: >
```



In [525…

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.preprocessing import StandardScaler
def check_vif(df):
    tmp = df.columns
    df = StandardScaler().fit_transform(df)
    df = pd.DataFrame(df,columns=tmp)
    vif_df = pd.DataFrame()
    vif_df['Features'] = df.columns
    vif_df["VIF"] = [round(variance_inflation_factor(df.values, i),2) for i in range(len
    return vif_df,df
```

In [526…

```
df_tmp = df.copy()
```

In [527…

```
X = df.drop('delivery_time_minutes',axis=1)
Y = df['delivery_time_minutes']
```

Loading [MathJax]/extensions/Safe.js

In [528…

```
vif_df,df = check_vif(X)
```

In [529…

```
vif_df
```

Out[529]:

|  | Features | VIF |
|---|---|---|
| **0** | store_primary_category | 1.12 |
| **1** | order_protocol | 1.04 |
| **2** | total_items | 2.61 |
| **3** | subtotal | 3.81 |
| **4** | num_distinct_items | 4.23 |
| **5** | min_item_price | 2.13 |
| **6** | max_item_price | 2.48 |
| **7** | total_onshift_partners | 13.59 |
| **8** | total_busy_partners | 12.87 |
| **9** | total_outstanding_orders | 11.73 |
| **10** | day_of_week | 1.03 |
| **11** | order_created_month | 1.09 |
| **12** | order_created_hour | 68.70 |
| **13** | order_delivery_hour | 65.05 |
| **14** | time_taken_to_delivery_hour | 15.22 |

In [530…

```
df.drop('total_onshift_partners',axis=1,inplace=True)
```

In [531…

```
vif_df,df = check_vif(df)
```

In [532…

```
vif_df
```

Out[532]:

|  | Features | VIF |
|---|---|---|
| **0** | store_primary_category | 1.12 |
| **1** | order_protocol | 1.04 |
| **2** | total_items | 2.61 |
| **3** | subtotal | 3.81 |
| **4** | num_distinct_items | 4.23 |
| **5** | min_item_price | 2.13 |
| **6** | max_item_price | 2.48 |
| **7** | total_busy_partners | 9.05 |
| **8** | total_outstanding_orders | 9.16 |
| **9** | day_of_week | 1.02 |
| **10** | order_created_month | 1.08 |
| **11** | order_created_hour | 67.78 |
| **12** | order_delivery_hour | 63.95 |
| **13** | time_taken_to_delivery_hour | 14.97 |

In [533…

```
df.drop('total_outstanding_orders',axis=1,inplace=True)
```

In [534…

```
vif_df,df = check_vif(df)
vif_df
```

Out[534]:

| | Features | VIF |
|---|---|---|
| **0** | store_primary_category | 1.12 |
| **1** | order_protocol | 1.04 |
| **2** | total_items | 2.61 |
| **3** | subtotal | 3.80 |
| **4** | num_distinct_items | 4.23 |
| **5** | min_item_price | 2.13 |
| **6** | max_item_price | 2.48 |
| **7** | total_busy_partners | 1.19 |
| **8** | day_of_week | 1.02 |
| **9** | order_created_month | 1.02 |
| **10** | order_created_hour | 66.31 |
| **11** | order_delivery_hour | 62.78 |
| **12** | time_taken_to_delivery_hour | 14.70 |

In [535…

```
df.drop('order_created_hour',axis=1,inplace=True)
vif_df,df = check_vif(df)
vif_df
```

Out[535]:

| | Features | VIF |
|---|---|---|
| **0** | store_primary_category | 1.12 |
| **1** | order_protocol | 1.04 |
| **2** | total_items | 2.61 |
| **3** | subtotal | 3.80 |
| **4** | num_distinct_items | 4.23 |
| **5** | min_item_price | 2.13 |
| **6** | max_item_price | 2.48 |
| **7** | total_busy_partners | 1.18 |
| **8** | day_of_week | 1.02 |
| **9** | order_created_month | 1.01 |
| **10** | order_delivery_hour | 1.21 |
| **11** | time_taken_to_delivery_hour | 1.07 |

In [536…

```
df.shape
```

Out[536]:

```
(197421, 12)
```

In [537…

```
df.head()
```

Out[537]:

| | store_primary_category | order_protocol | total_items | subtotal | num_distinct_items | min_item_price | max_iten |
|---|---|---|---|---|---|---|---|
| **0** | -0.093025 | -1.243699 | 0.301376 | 0.557004 | 0.815344 | -0.249754 | 0. |
| **1** | -0.807830 | -0.579639 | -0.823675 | -0.454813 | -1.024857 | 1.625521 | 0. |
| **2** | 0.267151 | -1.243699 | -0.823675 | -0.454813 | -1.024857 | 2.737784 | 1. |
| **3** | 0.267151 | -1.243699 | 1.051410 | 2.491669 | 1.428744 | -0.154099 | 1. |
| **4** | 0.267151 | -1.243699 | -0.073641 | 0.858383 | 0.201944 | 0.958163 | 1. |

In [538…

```
from sklearn.model_selection import train_test_split as tts
xtrain_val,xval,ytrain_val,yval = tts(df,Y,test_size=0.2,random_state=42)

xtrain,xtest,ytrain,ytest = tts(xtrain_val,ytrain_val,test_size=0.2,random_state=42)
```

In [539…

```
print(f'train shape : {xtrain.shape},{ytrain.shape}')
print(f'test shape : {xtest.shape},{ytest.shape}')
print(f'val shape : {xval.shape},{yval.shape}')
```

```
train shape : (126348, 12),(126348,)
test shape : (31588, 12),(31588,)
val shape : (39485, 12),(39485,)
```

In [540…

```
from tensorflow.keras.layers import Dense,Activation, BatchNormalization, Dropout
from tensorflow.keras.optimizers import Nadam
from tensorflow.keras.models import Sequential
from tensorflow.keras.activations import relu
```

In [570…

```
L2reg = tf.keras.regularizers.L2(l2=1e-6)
model = Sequential(
    [

        Dense(256,input_shape=(xtrain.shape[1],)),
        BatchNormalization(),
        Activation(relu),
        Dropout(0.2),

        Dense(128,kernel_regularizer=L2reg),
        BatchNormalization(),
        Activation(relu),
        Dropout(0.3),

        Dense(64,kernel_regularizer=L2reg),
        BatchNormalization(),
        Activation(relu),
        Dropout(0.1),

        Dense(32,kernel_regularizer=L2reg),
        BatchNormalization(),
        Activation(relu),
        Dropout(0.1),

        Dense(64,kernel_regularizer=L2reg),
        BatchNormalization(),
        Activation(relu),

        Dense(1,activation='linear')

    ]


)
```

Loading [MathJax]/extensions/Safe.js

In [571…

```
model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_17 (Dense)            (None, 256)               3328      
                                                                 
 batch_normalization_13 (Bat  (None, 256)              1024      
 chNormalization)                                                
                                                                 
 activation_13 (Activation)  (None, 256)               0         
                                                                 
 dropout_12 (Dropout)        (None, 256)               0         
                                                                 
 dense_18 (Dense)            (None, 128)               32896     
                                                                 
 batch_normalization_14 (Bat  (None, 128)              512       
 chNormalization)                                                
                                                                 
 activation_14 (Activation)  (None, 128)               0         
                                                                 
 dropout_13 (Dropout)        (None, 128)               0         
                                                                 
 dense_19 (Dense)            (None, 64)                8256      
                                                                 
 batch_normalization_15 (Bat  (None, 64)               256       
 chNormalization)                                                
                                                                 
 activation_15 (Activation)  (None, 64)                0         
                                                                 
 dropout_14 (Dropout)        (None, 64)                0         
                                                                 
 dense_20 (Dense)            (None, 32)                2080      
                                                                 
 batch_normalization_16 (Bat  (None, 32)               128       
 chNormalization)                                                
                                                                 
 activation_16 (Activation)  (None, 32)                0         
                                                                 
 dropout_15 (Dropout)        (None, 32)                0         
                                                                 
 dense_21 (Dense)            (None, 64)                2112      
                                                                 
 batch_normalization_17 (Bat  (None, 64)               256       
 chNormalization)                                                
                                                                 
 activation_17 (Activation)  (None, 64)                0         
                                                                 
 dense_22 (Dense)            (None, 1)                 65        
                                                                 
=================================================================
Total params: 50,913
Trainable params: 49,825
Non-trainable params: 1,088
_________________________________________________________________
```

In [572…

```
from tensorflow.keras.callbacks import EarlyStopping
```

In [573…

```
optimizers = Nadam()
loss = tf.keras.losses.Huber()
call_backs = EarlyStopping(monitor="val_loss",patience=5)
model.compile(optimizer=optimizers,loss=loss)
```

In [574…

```
hist = model.fit(xtrain,ytrain,epochs=500,validation_data=(xval,yval),batch_size=256,ver
```

Loading [MathJax]/extensions/Safe.js

```
Epoch 1/500
494/494 [==============================] - 14s 20ms/step - loss: 35.5876 - val_loss: 16.
5625
Epoch 2/500
494/494 [==============================] - 9s 19ms/step - loss: 12.8314 - val_loss: 10.4
252
Epoch 3/500
494/494 [==============================] - 9s 19ms/step - loss: 11.5161 - val_loss: 10.1
553
Epoch 4/500
494/494 [==============================] - 10s 20ms/step - loss: 11.3749 - val_loss: 10.
0455
Epoch 5/500
494/494 [==============================] - 11s 22ms/step - loss: 11.2871 - val_loss: 10.
0611
Epoch 6/500
494/494 [==============================] - 10s 21ms/step - loss: 11.2374 - val_loss: 10.
0143
Epoch 7/500
494/494 [==============================] - 10s 21ms/step - loss: 11.1992 - val_loss: 9.9
561
Epoch 8/500
494/494 [==============================] - 10s 21ms/step - loss: 11.1483 - val_loss: 9.8
490
Epoch 9/500
494/494 [==============================] - 10s 21ms/step - loss: 11.1309 - val_loss: 9.7
985
Epoch 10/500
494/494 [==============================] - 10s 21ms/step - loss: 11.1017 - val_loss: 9.8
280
Epoch 11/500
494/494 [==============================] - 10s 20ms/step - loss: 11.0665 - val_loss: 9.8
350
Epoch 12/500
494/494 [==============================] - 10s 21ms/step - loss: 11.0672 - val_loss: 9.7
831
Epoch 13/500
494/494 [==============================] - 10s 20ms/step - loss: 11.0540 - val_loss: 9.7
841
Epoch 14/500
494/494 [==============================] - 10s 20ms/step - loss: 11.0332 - val_loss: 9.7
803
Epoch 15/500
494/494 [==============================] - 10s 21ms/step - loss: 11.0242 - val_loss: 9.7
706
Epoch 16/500
494/494 [==============================] - 9s 19ms/step - loss: 11.0011 - val_loss: 9.76
74
Epoch 17/500
494/494 [==============================] - 9s 19ms/step - loss: 10.9929 - val_loss: 9.79
11
Epoch 18/500
494/494 [==============================] - 9s 19ms/step - loss: 10.9898 - val_loss: 9.73
04
Epoch 19/500
494/494 [==============================] - 9s 19ms/step - loss: 10.9697 - val_loss: 9.74
81
Epoch 20/500
494/494 [==============================] - 9s 19ms/step - loss: 10.9562 - val_loss: 9.70
05
Epoch 21/500
494/494 [==============================] - 10s 19ms/step - loss: 10.9561 - val_loss: 9.7
243
Epoch 22/500
```

Loading [MathJax]/extensions/Safe.js

```
494/494 [==============================] - 9s 19ms/step - loss: 10.9409 - val_loss: 9.74
35
Epoch 23/500
494/494 [==============================] - 10s 20ms/step - loss: 10.9466 - val_loss: 9.7
066
Epoch 24/500
494/494 [==============================] - 9s 19ms/step - loss: 10.9313 - val_loss: 9.69
02
Epoch 25/500
494/494 [==============================] - 9s 19ms/step - loss: 10.9260 - val_loss: 9.69
00
Epoch 26/500
494/494 [==============================] - 9s 19ms/step - loss: 10.9161 - val_loss: 9.71
08
Epoch 27/500
494/494 [==============================] - 10s 19ms/step - loss: 10.8912 - val_loss: 9.6
950
Epoch 28/500
494/494 [==============================] - 9s 19ms/step - loss: 10.8965 - val_loss: 9.65
64
Epoch 29/500
494/494 [==============================] - 9s 19ms/step - loss: 10.8925 - val_loss: 9.72
29
Epoch 30/500
494/494 [==============================] - 9s 19ms/step - loss: 10.8910 - val_loss: 9.67
43
Epoch 31/500
494/494 [==============================] - 9s 19ms/step - loss: 10.8815 - val_loss: 9.66
30
Epoch 32/500
494/494 [==============================] - 9s 19ms/step - loss: 10.8713 - val_loss: 9.69
93
Epoch 33/500
494/494 [==============================] - 9s 19ms/step - loss: 10.8686 - val_loss: 9.65
75
```

In [575…

```
hist.history.keys()
```

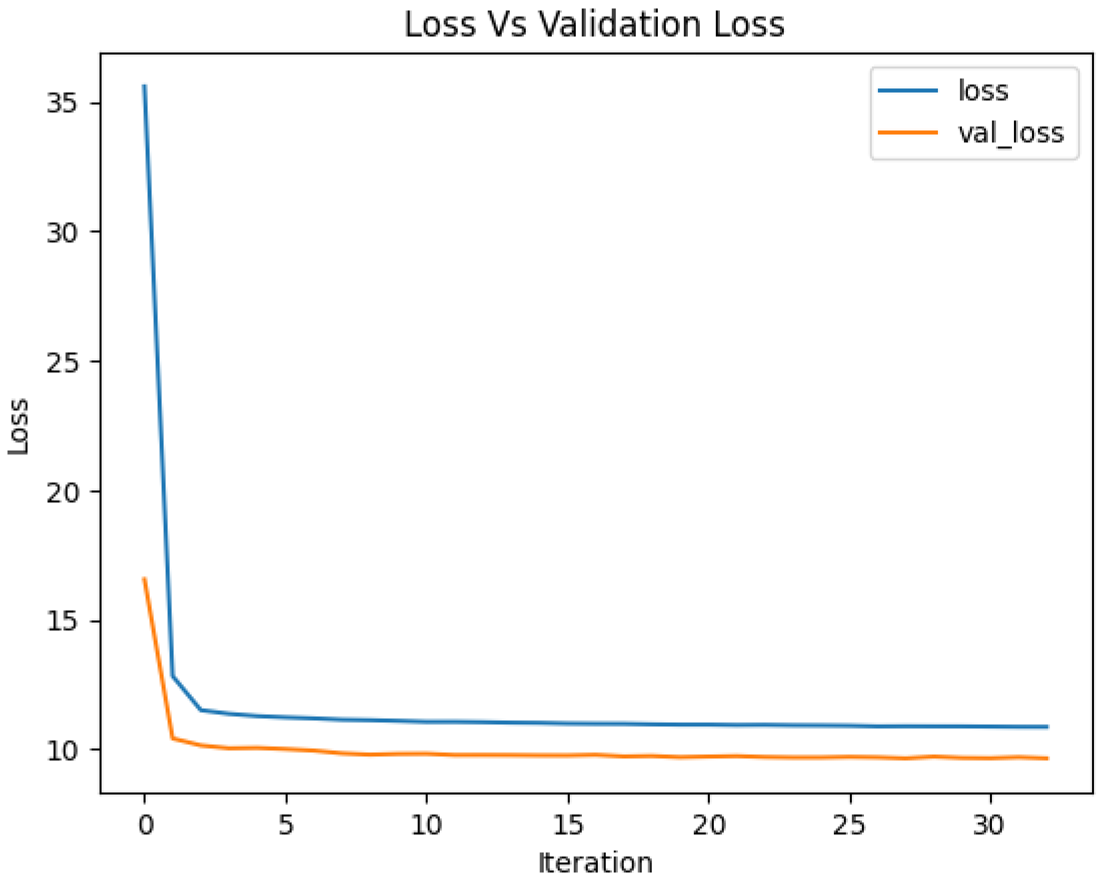
Out[575]:

```
dict_keys(['loss', 'val_loss'])
```

In [576…

```
loss = hist.history['loss']
val_loss = hist.history['val_loss']
plt.plot(loss,label='loss')
plt.plot(val_loss,label='val_loss')
plt.title('Loss Vs Validation Loss')
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

Loading [MathJax]/extensions/Safe.js



```
In [585…  # model.save('proter_reg.h5')
```

```
In [577…  model.evaluate(xtest,ytest)
```

```
          988/988 [==============================] - 4s 4ms/step - loss: 9.5698
Out[577]:  9.569809913635254
```

```
In [578…  y_pred = model.predict(xtest)
```

```
          988/988 [==============================] - 4s 4ms/step
```

```
In [579…  y_pred = y_pred.reshape(-1)
          y_pred
```

```
Out[579]:  array([44.809242, 61.13754 , 45.460415, ..., 32.036903, 47.99863 ,
                  40.375557], dtype=float32)
```

```
In [580…  from sklearn.metrics import r2_score,mean_squared_error, mean_absolute_error,root_mean_s
```

```
In [581…  print(f' R2 Score : {r2_score(ytest,y_pred)}')
```

```
           R2 Score : 0.47361300590838007
```

```
In [582…  print(f'MSE : {mean_squared_error(ytest,y_pred)}')
          print(f'MAE : {mean_absolute_error(ytest,y_pred)}')
          print(f'RMSE : {root_mean_squared_error(ytest,y_pred)}')
```

```
          MSE : 202.07368125973795
          MAE : 10.05683023617481
          RMSE : 14.215262264894656
```

# Questions

`1. Defining the problem statements and where can this and modifications of this be used?`

Ans : This modification can we used in giving tentative time line for all users.

`2. List 3 functions the pandas datetime provides with one line explanation?`

Ans :

1. pd.to_datetime() -> this helps to convert the data in datetime so that we can pull relvant information from timestamp data.
2. pd.series.dt.month() -> This function is used to pull month from timestamp data

3. pd.series.dt.year() -> This function is used to pull year from timestamp

`3. Why do we need to check for outliers in our data?`

ans : It is important to check for outliers in data because it hampers the model tranining.

`4. Name 3 outlier removal methods?`

Ans :

1. IQR method -> this method is used to find outlier using quartile calculation.
2. Z-score method -> this method is used to replace outliers with zscore.
3. Median imputation method -> this method is used to replace outliers with median of data.

`5. What classical machine learning methods can we use for this problem?`

Ans : Since this problem is all about predicting delivery time as per features, so here we can utlize Linear Regression algorithm.

`6. Why is scaling required for neural networks?`

Ans : Scaling is important because if we don't have scale data then weight update may get hamper and due to that learning for model can go wrong.

`7 .Briefly explain your choice of optimizer?`

Ans : For training model I have utilized NADAM algo, because it helps model to coverge faster by choosing less deviated vector and due to this enhancement model converge faster than any other algorithm.

`8. Which activation function did you use and why?`

Ans : I have utilized RELU activation function, because of following points

```
    1. This is non-linear function which helps model to learn different
features by creating different combination by its own.

    2. It helps in penalizing -ve values which helps model to learn
effectively all features.
```

1. Why does a neural network perform well on a large dataset?

Loading [MathJax]/extensions/Safe.js

Ans : The computational efficiency of a neural network is higher than any ML algorithm, due to this feature Neural network performs well on a large dataset.

```
In [ ]:
```