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

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

df.head()
```

```
   market_id  ... total_outstanding_orders
0        1.0  ...                     21.0
1        2.0  ...                      2.0
2        3.0  ...                      0.0
3        3.0  ...                      2.0
4        3.0  ...                      9.0

[5 rows x 14 columns]
```

Generic data about datasets

```python
df.shape
```

```
(197428, 14)
```

```python
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

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

```
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

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

```
        market_id  ... total_outstanding_orders
45            NaN  ...                    149.0
182           NaN  ...                     30.0
970           NaN  ...                     52.0
1126          NaN  ...                     72.0
1625          NaN  ...                     69.0
...           ...  ...                      ...
196027        NaN  ...                    232.0
196561        NaN  ...                     40.0
197170        NaN  ...                     64.0
197171        NaN  ...                     56.0
197259        NaN  ...                     20.0

[987 rows x 14 columns]
```

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

```
        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 x 2 columns]
```

```python
# df.loc[df['store_id']=='a914ecef9c12ffdb9bede64bb703d877']
[['market_id','store_id']].values[0]
[0],df.loc[df['store_id']=='a914ecef9c12ffdb9bede64bb703d877']
[['market_id','store_id']].values[0][1]

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
```

```
                                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 x 2 columns]
```

```python
store_id_market_id_mapping
```

```
                                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 x 2 columns]
```

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

```
='f0ade77b43923b38237db569b016ba25']

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

from tqdm import tqdm

# def get_store_and_market_id_mapping(store_ids):
#     store_id_and_market_id_mapping = {}
#     for store_id in tqdm(store_ids):
#         tmp_store_id =
store_id_market_id_mapping.loc[store_id_market_id_mapping['store_id']=
=store_id]
#         max_value_market_id = tmp_store_id.groupby('store_id')
['market_id'].apply(lambda x : x.mode().iloc[0]).iloc[0]
#         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

# get_store_and_market_id_mapping =
get_store_and_market_id_mapping(set(store_id_market_id_mapping['store_
id']))

# list(get_store_and_market_id_mapping.keys())

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

df_store_id_and_market_id_mapping
```

```
                              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 x 2 columns]
```

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

```
nan
```

```
df_store_id_and_market_id_mapping.loc[df_store_id_and_market_id_mappin
g['store_id']=='ea119a40c1592979f51819b0bd38d39d']
['market_id'].values[0]
```

```
4.0
```

Now Fixing the Missing Market_id

```
df.head()
```

```
   market_id  ... total_outstanding_orders
0        1.0  ...                     21.0
1        2.0  ...                      2.0
2        3.0  ...                      0.0
3        3.0  ...                      2.0
4        3.0  ...                      9.0

[5 rows x 14 columns]
```

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

```
        market_id  ... total_outstanding_orders
45            NaN  ...                    149.0
182           NaN  ...                     30.0
970           NaN  ...                     52.0
1126          NaN  ...                     72.0
1625          NaN  ...                     69.0
...           ...  ...                      ...
196027        NaN  ...                    232.0
196561        NaN  ...                     40.0
197170        NaN  ...                     64.0
197171        NaN  ...                     56.0
197259        NaN  ...                     20.0

[987 rows x 14 columns]
```

```
def get_new_market_id(market_id,store_id):
    """
    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
_mapping['store_id']==store_id]['market_id'].values)!=0):

new_market_id.append(df_store_id_and_market_id_mapping.loc[df_store_id
_and_market_id_mapping['store_id']==store_id]['market_id'].values[0])
```

```
            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))


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df['new_market_id'] = new_market_id

df['market_id'] = new_market_id

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

We have fixed market_id upto some extent

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

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

from sklearn.impute import SimpleImputer

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

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

df.head()
```

```
   market_id  ... total_outstanding_orders
0        1.0  ...                     21.0
1        2.0  ...                      2.0
2        3.0  ...                      0.0
3        3.0  ...                      2.0
4        3.0  ...                      9.0

[5 rows x 14 columns]
```

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

```
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
```

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

```
        market_id  ... total_outstanding_orders
109           3.0  ...                      4.0
7670          2.0  ...                    197.0
78511         4.0  ...                    167.0
115982        4.0  ...                    102.0
140635        2.0  ...                    176.0
158967        2.0  ...                    109.0
170416        5.0  ...                     31.0

[7 rows x 14 columns]
```

Fixing actual delivery time NAN Values

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

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

```
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
```

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

```
        market_id  ... total_outstanding_orders
2             3.0  ...                      0.0
3             3.0  ...                      2.0
4             3.0  ...                      9.0
5             3.0  ...                      2.0
6             3.0  ...                      9.0
...           ...  ...                      ...
197210        1.0  ...                     25.0
197211        1.0  ...                     24.0
197212        1.0  ...                     21.0
197259        5.0  ...                     20.0
197363        1.0  ...                     35.0

[4760 rows x 14 columns]
```

Fixing NAN value for store primary category

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

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)

store_id_and_store_primary_cate.head()
```

```
                              store_id store_primary_category
0   df263d996281d984952c07998dc54358               american
1   f0ade77b43923b38237db569b016ba25                mexican
8   f0ade77b43923b38237db569b016ba25                 indian
14  ef1e491a766ce3127556063d49bc2f98                italian
15  ef1e491a766ce3127556063d49bc2f98                italian
```

```
store_id_and_store_primary_cate.groupby(['store_id'])
['store_primary_category'].apply(lambda x : x.mode().iloc[0])
```

```
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
```

```
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_cate['s
tore_id']==store_id]
        max_value_market_id = tmp_store_id.groupby('store_id')
['store_primary_category'].apply(lambda x : x.mode().iloc[0]).iloc[0]
        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_mapping(set(store_id_and_store_pr
imary_cate['store_id']))
```

```
  0%|          | 0/6569 [00:00<?, ?it/s]

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

----------------------------------------------------------------------
-----
```

```
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_category_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_primary_cate['store_id']==store_id]
      9     max_value_market_id = tmp_store_id.groupby('store_id')['store_primary_category'].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:1191, 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:1413, 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:1210, 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: 
```

```
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_primary_category_mapping.keys())

get_store_and_store_primary_category_mapping_df['store_primary_categor
y'] = list(get_store_and_store_primary_category_mapping.values())

get_store_and_store_primary_category_mapping_df
```

```
                              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 x 2 columns]
```

```
df.head()
```

```
   market_id           created_at actual_delivery_time  \
0        1.0  2015-02-06 22:24:17  2015-02-06 23:27:16
1        2.0  2015-02-10 21:49:25  2015-02-10 22:56:29
2        3.0  2015-01-22 20:39:28  2015-01-22 21:09:09
3        3.0  2015-02-03 21:21:45  2015-02-03 22:13:00
4        3.0  2015-02-15 02:40:36  2015-02-15 03:20:26

                           store_id store_primary_category
order_protocol  \
0  df263d996281d984952c07998dc54358               american
1.0
1  f0ade77b43923b38237db569b016ba25                mexican
2.0
2  f0ade77b43923b38237db569b016ba25                    NaN
1.0
3  f0ade77b43923b38237db569b016ba25                    NaN
1.0
4  f0ade77b43923b38237db569b016ba25                    NaN
1.0

   total_items  subtotal  num_distinct_items  min_item_price
max_item_price  \
```

```
0             4      3441                    4              557
1239
1             1      1900                    1             1400
1400
2             1      1900                    1             1900
1900
3             6      6900                    5              600
1800
4             3      3900                    3             1100
1600

   total_onshift_partners  total_busy_partners
total_outstanding_orders
0                    33.0                 14.0
21.0
1                     1.0                  2.0
2.0
2                     1.0                  0.0
0.0
3                     1.0                  1.0
2.0
4                     6.0                  6.0
9.0

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_a
nd_store_primary_category_mapping_df['store_id']==store_id]
['store_primary_category'].values)!=0):

store_primary_category.append(get_store_and_store_primary_category_map
ping_df.loc[get_store_and_store_primary_category_mapping_df['store_id'
]==store_id]['store_primary_category'].values[0])
            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)

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```

```
df['get_new_store_primary_category'] = get_new_store_primary_category

df.isna().sum()

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

pd.DataFrame(df['get_new_store_primary_category'])

       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 x 1 columns]

valus =
SimpleImputer(missing_values=np.nan,strategy='most_frequent').fit_tran
sform(pd.DataFrame(df['get_new_store_primary_category']))

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)

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

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

```
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
```

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

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

                                store_id store_primary_category  \
160     45d38ce7f5231602e24a2103a0300ae6              breakfast
161     45d38ce7f5231602e24a2103a0300ae6              breakfast
162     45d38ce7f5231602e24a2103a0300ae6              breakfast
163     45d38ce7f5231602e24a2103a0300ae6              breakfast
164     45d38ce7f5231602e24a2103a0300ae6              breakfast
...                                  ...                    ...
197196  084afd913ab1e6ea58b8ca73f6cb41a6                 indian
197197  084afd913ab1e6ea58b8ca73f6cb41a6                 indian
197198  084afd913ab1e6ea58b8ca73f6cb41a6                 indian
197199  084afd913ab1e6ea58b8ca73f6cb41a6                 indian
197421  a914ecef9c12ffdb9bede64bb703d877                   fast

        order_protocol  total_items  subtotal  num_distinct_items  \
160                2.0            2       575                   2
161                2.0            5      1415                   3
162                2.0            1       650                   1
```

```
163                 2.0            5      1550                    5
164                 2.0            6      1110                    5
...                 ...          ...       ...                  ...
197196              2.0            3      1792                    3
197197              2.0            8      2923                    5
197198              2.0            3      3297                    3
197199              2.0            4      2776                    4
197421              4.0            2       979                    2

        min_item_price  max_item_price  total_onshift_partners  \
160                225             350                     NaN
161                185             675                     NaN
162                650             650                     NaN
163                225             700                     NaN
164                185             185                     NaN
...                ...             ...                     ...
197196             163            1177                     NaN
197197              50            1199                     NaN
197198             799            1299                     NaN
197199             179            1099                     NaN
197421             145             339                     NaN

        total_busy_partners  total_outstanding_orders
160                     NaN                       NaN
161                     NaN                       NaN
162                     NaN                       NaN
163                     NaN                       NaN
164                     NaN                       NaN
...                     ...                       ...
197196                  NaN                       NaN
197197                  NaN                       NaN
197198                  NaN                       NaN
197199                  NaN                       NaN
197421                  NaN                       NaN

[16262 rows x 14 columns]
```

```
df['total_onshift_partners'] =
SimpleImputer(missing_values=np.nan,strategy='median').fit_transform(p
d.DataFrame(df['total_onshift_partners']))
df['total_busy_partners'] =
SimpleImputer(missing_values=np.nan,strategy='median').fit_transform(p
d.DataFrame(df['total_busy_partners']))
df['total_outstanding_orders'] =
SimpleImputer(missing_values=np.nan,strategy='median').fit_transform(p
d.DataFrame(df['total_outstanding_orders']))

df.describe()
```

```
            market_id  order_protocol    total_items       subtotal  \
count  197428.000000   197428.000000  197428.000000  197428.000000
mean        2.978296        2.872865       3.196391    2682.331402
std         1.524646        1.505888       2.666546    1823.093688
min         1.000000        1.000000       1.000000       0.000000
25%         2.000000        1.000000       2.000000    1400.000000
50%         3.000000        3.000000       3.000000    2200.000000
75%         4.000000        4.000000       4.000000    3395.000000
max         6.000000        7.000000     411.000000   27100.000000

       num_distinct_items  min_item_price  max_item_price  \
count       197428.000000   197428.000000   197428.000000
mean             2.670791      686.218470     1159.588630
std              1.630255      522.038648      558.411377
min              1.000000      -86.000000        0.000000
25%              1.000000      299.000000      800.000000
50%              2.000000      595.000000     1095.000000
75%              3.000000      949.000000     1395.000000
max             20.000000    14700.000000    14700.000000

       total_onshift_partners  total_busy_partners
total_outstanding_orders
count           197428.000000        197428.000000
197428.000000
mean                44.164946            41.102230
56.645663
std                 33.143840            30.866801
50.663676
min                 -4.000000            -5.000000                  -
6.000000
25%                 19.000000            17.000000
19.000000
50%                 37.000000            34.000000
41.000000
75%                 62.000000            59.000000
80.000000
max                171.000000           154.000000
285.000000
```

Fixed all NAN value issues.

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

```
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
```

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

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

df.shape
```

```
(197421, 15)
```

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

```
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
```

```python
df
```

```
        market_id           created_at actual_delivery_time  \
0             1.0  2015-02-06 22:24:17  2015-02-06 23:27:16
1             2.0  2015-02-10 21:49:25  2015-02-10 22:56:29
2             3.0  2015-01-22 20:39:28  2015-01-22 21:09:09
3             3.0  2015-02-03 21:21:45  2015-02-03 22:13:00
4             3.0  2015-02-15 02:40:36  2015-02-15 03:20:26
...           ...                  ...                  ...
197416        1.0  2015-02-17 00:19:41  2015-02-17 01:24:48
197417        1.0  2015-02-13 00:01:59  2015-02-13 00:58:22
197418        1.0  2015-01-24 04:46:08  2015-01-24 05:36:16
```

```
197419       1.0  2015-02-01 18:18:15  2015-02-01 19:23:22
197420       1.0  2015-02-08 19:24:33  2015-02-08 20:01:41

                                store_id store_primary_category  \
0       df263d996281d984952c07998dc54358               american
1       f0ade77b43923b38237db569b016ba25                mexican
2       f0ade77b43923b38237db569b016ba25                 indian
3       f0ade77b43923b38237db569b016ba25                 indian
4       f0ade77b43923b38237db569b016ba25                 indian
...                                  ...                    ...
197416  a914ecef9c12ffdb9bede64bb703d877                   fast
197417  a914ecef9c12ffdb9bede64bb703d877                   fast
197418  a914ecef9c12ffdb9bede64bb703d877                   fast
197419  c81e155d85dae5430a8cee6f2242e82c               sandwich
197420  c81e155d85dae5430a8cee6f2242e82c               sandwich

        order_protocol  total_items  subtotal  num_distinct_items  \
0                  1.0            4      3441                   4
1                  2.0            1      1900                   1
2                  1.0            1      1900                   1
3                  1.0            6      6900                   5
4                  1.0            3      3900                   3
...                ...          ...       ...                 ...
197416             4.0            3      1389                   3
197417             4.0            6      3010                   4
197418             4.0            5      1836                   3
197419             1.0            1      1175                   1
197420             1.0            4      2605                   4

        min_item_price  max_item_price  total_onshift_partners  \
0                  557            1239                    33.0
1                 1400            1400                     1.0
2                 1900            1900                     1.0
3                  600            1800                     1.0
4                 1100            1600                     6.0
...                ...             ...                     ...
197416             345             649                    17.0
197417             405             825                    12.0
197418             300             399                    39.0
197419             535             535                     7.0
197420             425             750                    20.0

        total_busy_partners  total_outstanding_orders  \
0                      14.0                      21.0
1                       2.0                       2.0
2                       0.0                       0.0
3                       1.0                       2.0
4                       6.0                       9.0
...                     ...                       ...
197416                 17.0                      23.0
```

```
197417                11.0                         14.0
197418                41.0                         40.0
197419                 7.0                         12.0
197420                20.0                         23.0

        delivery_time_gt_created_at_check
0                                    True
1                                    True
2                                    True
3                                    True
4                                    True
...                                   ...
197416                               True
197417                               True
197418                               True
197419                               True
197420                               True

[197421 rows x 15 columns]
```

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

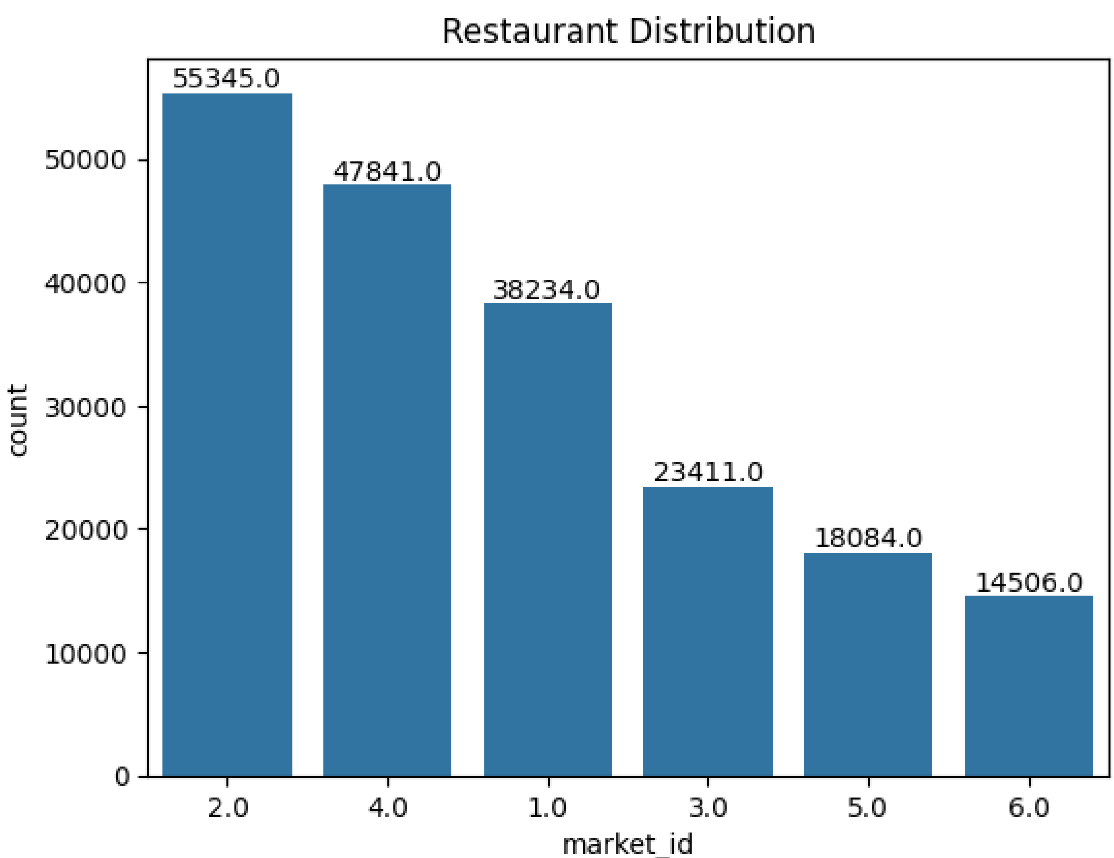
QC on created_at and actual_delivery_time

```
# df_created_at_and_actual_delivery_time =
df[['created_at','actual_delivery_time']]

# df_created_at_and_actual_delivery_time
# df_created_at_and_actual_delivery_time['check'] =
(df_created_at_and_actual_delivery_time['created_at']<=df_created_at_a
nd_actual_delivery_time['actual_delivery_time'])

# df_created_at_and_actual_delivery_time

# df_created_at_and_actual_delivery_time['check'].value_counts()

#
df_created_at_and_actual_delivery_time.loc[df_created_at_and_actual_de
livery_time['check']==False]

# df['delivery_time_gt_created_at_check'] =
(df['created_at']<=df['actual_delivery_time'])

# df = df.loc[df['delivery_time_gt_created_at_check']==True]

# df.to_csv('market.csv',index=False)

df.shape
```

```
(197421, 15)
```

Univariate Data Analysis

```python
# Create the countplot
ax =
sns.countplot(x=df['market_id'],order=df['market_id'].value_counts().i
ndex)

# 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()), ha='center', va='bottom')

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

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

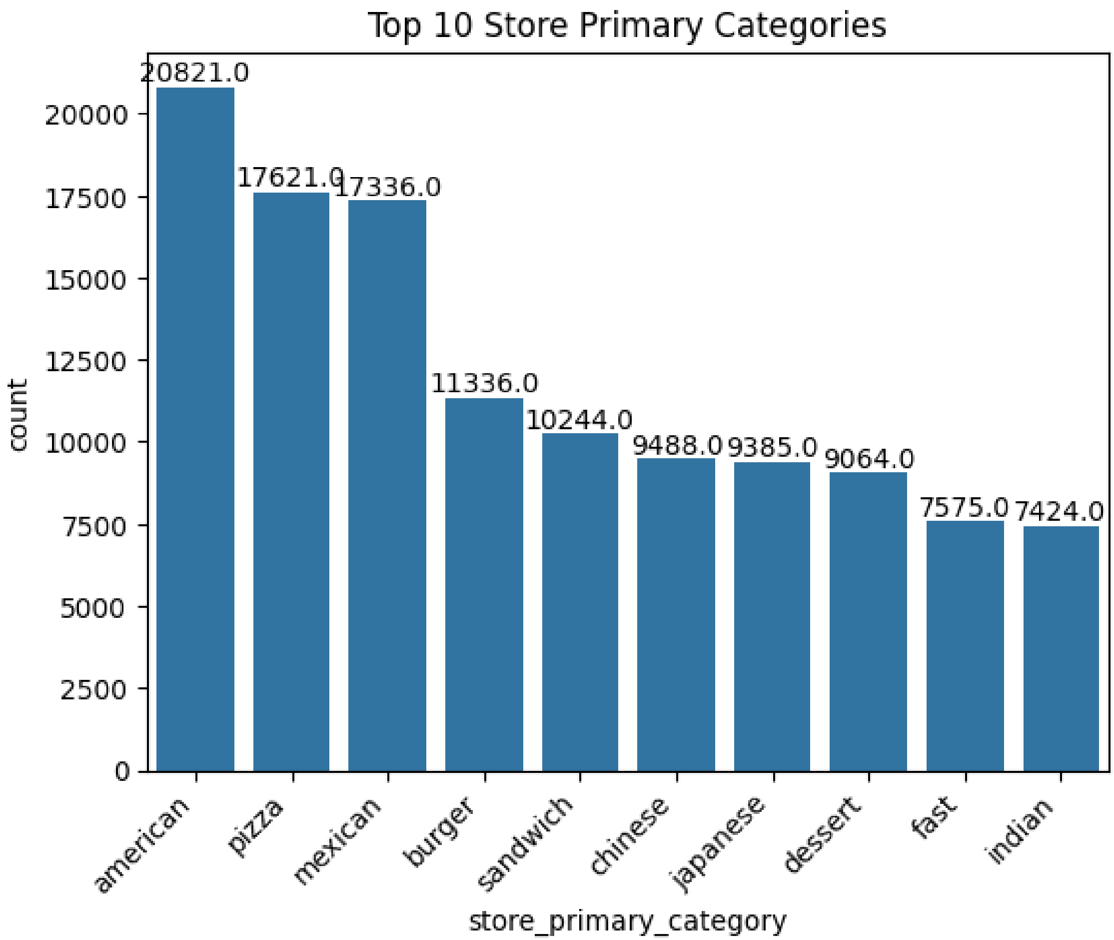



```
It is observed that most of the restaurants are located in market 2
```

Top 10 Store Primary Categories

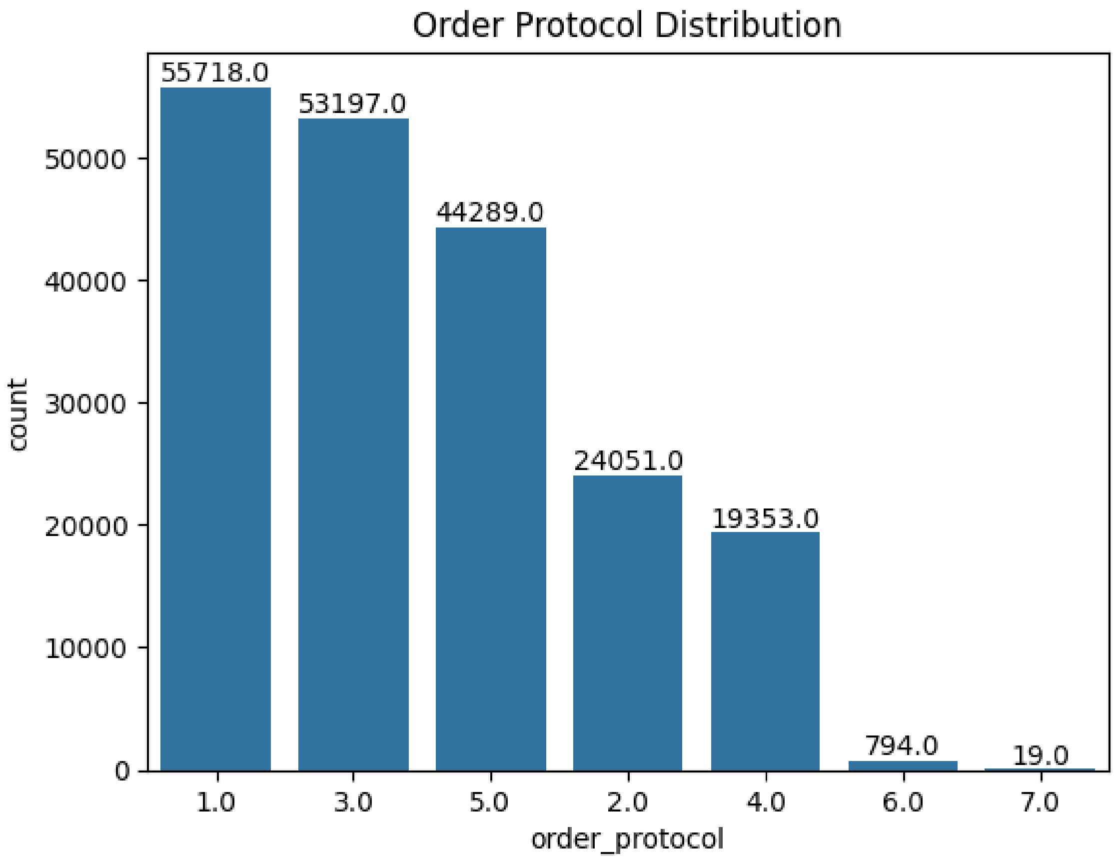
```
ax = sns.barplot(x=df['store_primary_category'].value_counts()
[:10].index,
                 y=df['store_primary_category'].value_counts()[:10])

# 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()), ha='center', va='bottom')

# 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_ticklabels() should only be used with a fixed number
of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
```



Order Protocol Distribution

```
# Create the countplot
ax =
sns.countplot(x=df['order_protocol'],order=df['order_protocol'].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()), ha='center', va='bottom')

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

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




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

```
df.head()

   market_id          created_at actual_delivery_time  \
0        1.0 2015-02-06 22:24:17  2015-02-06 23:27:16
1        2.0 2015-02-10 21:49:25  2015-02-10 22:56:29
2        3.0 2015-01-22 20:39:28  2015-01-22 21:09:09
3        3.0 2015-02-03 21:21:45  2015-02-03 22:13:00
4        3.0 2015-02-15 02:40:36  2015-02-15 03:20:26

                           store_id store_primary_category
order_protocol  \
0  df263d996281d984952c07998dc54358               american
1.0
1  f0ade77b43923b38237db569b016ba25                mexican
2.0
2  f0ade77b43923b38237db569b016ba25                 indian
1.0
3  f0ade77b43923b38237db569b016ba25                 indian
1.0
4  f0ade77b43923b38237db569b016ba25                 indian
1.0
```

```
   total_items  subtotal  num_distinct_items  min_item_price
max_item_price  \
0            4      3441                   4             557
1239
1            1      1900                   1            1400
1400
2            1      1900                   1            1900
1900
3            6      6900                   5             600
1800
4            3      3900                   3            1100
1600

   total_onshift_partners  total_busy_partners
total_outstanding_orders  \
0                    33.0                 14.0
21.0
1                     1.0                  2.0
2.0
2                     1.0                  0.0
0.0
3                     1.0                  1.0
2.0
4                     6.0                  6.0
9.0

   delivery_time_gt_created_at_check
0                                True
1                                True
2                                True
3                                True
4                                True
```

```
df['delivery_time_minutes'] = round((df['actual_delivery_time'] -
df['created_at']).dt.total_seconds()/60,2)

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

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_hour'])


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

```
df.head()

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

   order_protocol  total_items  subtotal  num_distinct_items
min_item_price  \
0             1.0            4      3441                   4
557
1             2.0            1      1900                   1
1400
2             1.0            1      1900                   1
1900
3             1.0            6      6900                   5
600
4             1.0            3      3900                   3
1100

   max_item_price  total_onshift_partners  total_busy_partners  \
0            1239                    33.0                 14.0
1            1400                     1.0                  2.0
2            1900                     1.0                  0.0
3            1800                     1.0                  1.0
4            1600                     6.0                  6.0

   total_outstanding_orders  delivery_time_minutes  day_of_week  \
0                      21.0                  62.98            4
1                       2.0                  67.07            1
2                       0.0                  29.68            3
3                       2.0                  51.25            1
4                       9.0                  39.83            6

   order_created_month  order_created_hour  order_delivery_hour  \
0                    2                  22                   23
1                    2                  21                   22
2                    1                  20                   21
3                    2                  21                   22
4                    2                   2                    3

   time_taken_to_delivery_hour
```

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

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

EDA for Numeric Columns

```
df.describe()
```

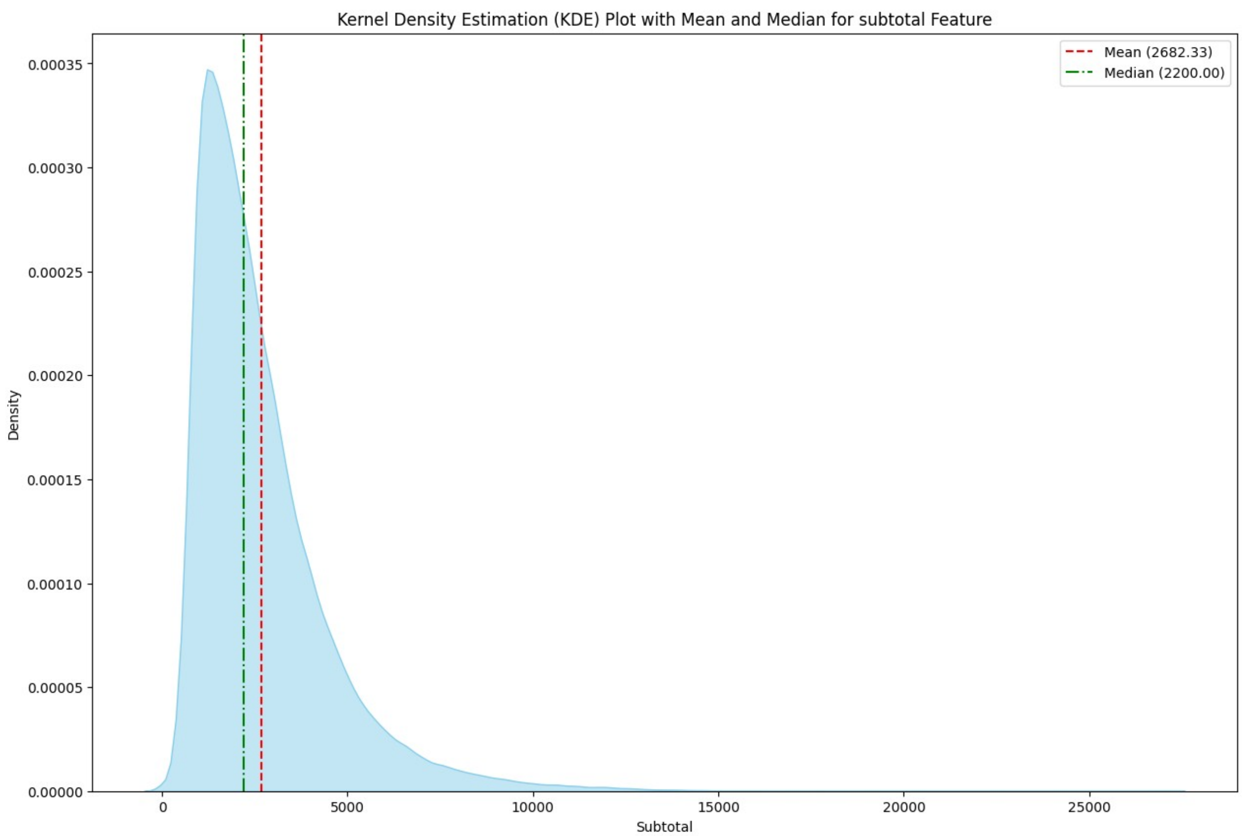
```
           market_id  order_protocol    total_items       subtotal  \
count  197421.000000   197421.000000  197421.000000  197421.000000
mean        2.978290        2.872871       3.196367    2682.326379
std         1.524658        1.505892       2.666552    1823.106256
min         1.000000        1.000000       1.000000       0.000000
25%         2.000000        1.000000       2.000000    1400.000000
50%         3.000000        3.000000       3.000000    2200.000000
75%         4.000000        4.000000       4.000000    3395.000000
max         6.000000        7.000000     411.000000   27100.000000

       num_distinct_items  min_item_price  max_item_price  \
count       197421.000000   197421.000000   197421.000000
mean             2.670780      686.224596     1159.590444
std              1.630261      522.044061      558.416236
min              1.000000      -86.000000        0.000000
25%              1.000000      299.000000      800.000000
50%              2.000000      595.000000     1095.000000
75%              3.000000      949.000000     1395.000000
max             20.000000    14700.000000    14700.000000

       total_onshift_partners  total_busy_partners
total_outstanding_orders  \
count           197421.000000        197421.000000
197421.000000
mean                44.163797            41.101327
56.643690
std                 33.142936            30.866192
50.661857
min                 -4.000000            -5.000000                  -
6.000000
25%                 19.000000            17.000000
19.000000
50%                 37.000000            34.000000
41.000000
75%                 62.000000            59.000000
80.000000
```

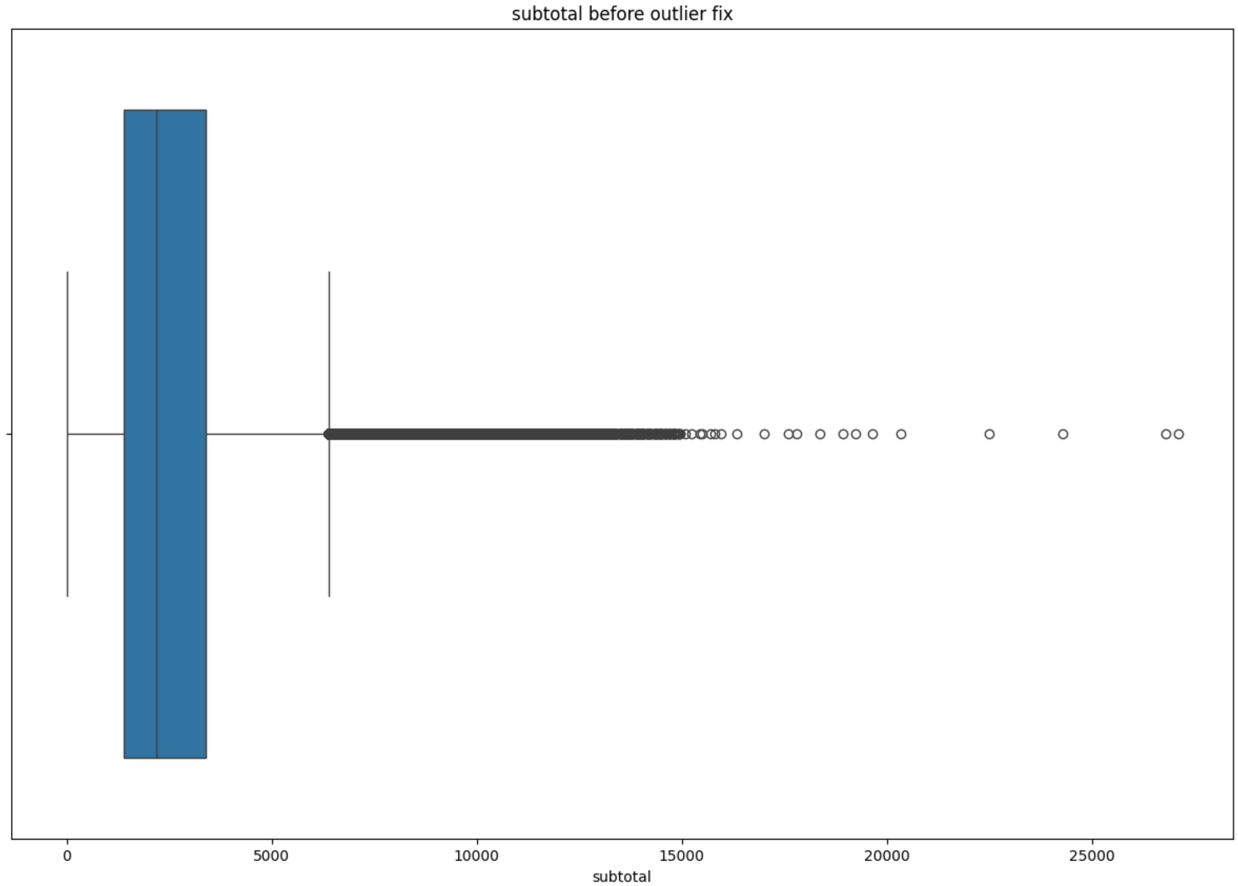
```
max                   171.000000           154.000000
285.000000

       delivery_time_minutes    day_of_week  order_created_month  \
count          197421.000000  197421.000000        197421.000000
mean               48.470949       3.218923             1.653157
std               320.493483       2.045759             0.476349
min                 1.680000       0.000000             1.000000
25%                35.070000       1.000000             1.000000
50%                44.330000       3.000000             2.000000
75%                56.350000       5.000000             2.000000
max            141947.650000       6.000000            10.000000

       order_created_hour  order_delivery_hour
time_taken_to_delivery_hour
count       197421.000000        197421.000000
197421.000000
mean             8.467362             8.539406
1.453650
std              8.658781             8.356449
3.817393
min              0.000000             0.000000
0.000000
25%              2.000000             2.000000
0.000000
50%              3.000000             4.000000
1.000000
75%             19.000000            19.000000
1.000000
max             23.000000            23.000000
23.000000
```

Skewness Analysis for Subtotal Feature

```
# 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})')
```

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

# 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()
```



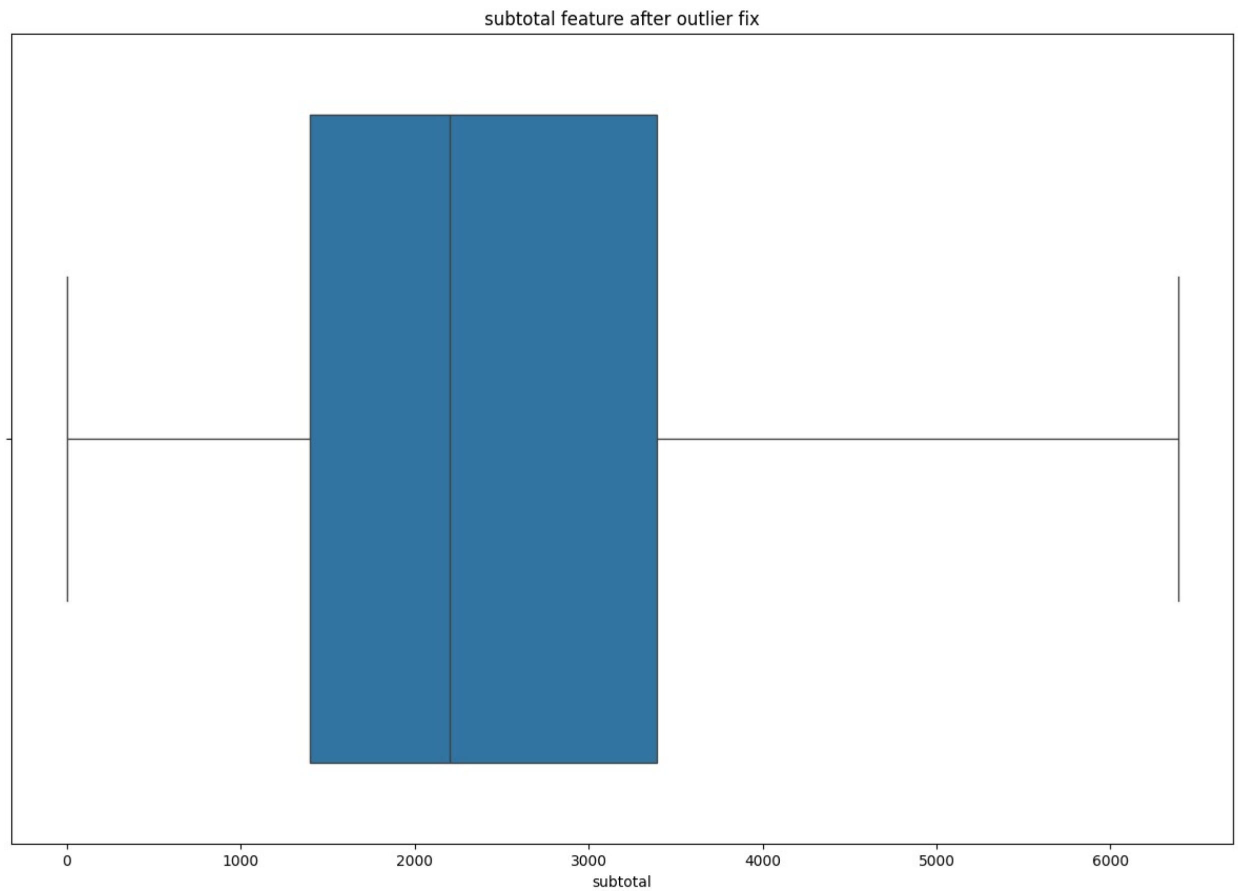


Using IQR Method to remove outliers

```
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)
```

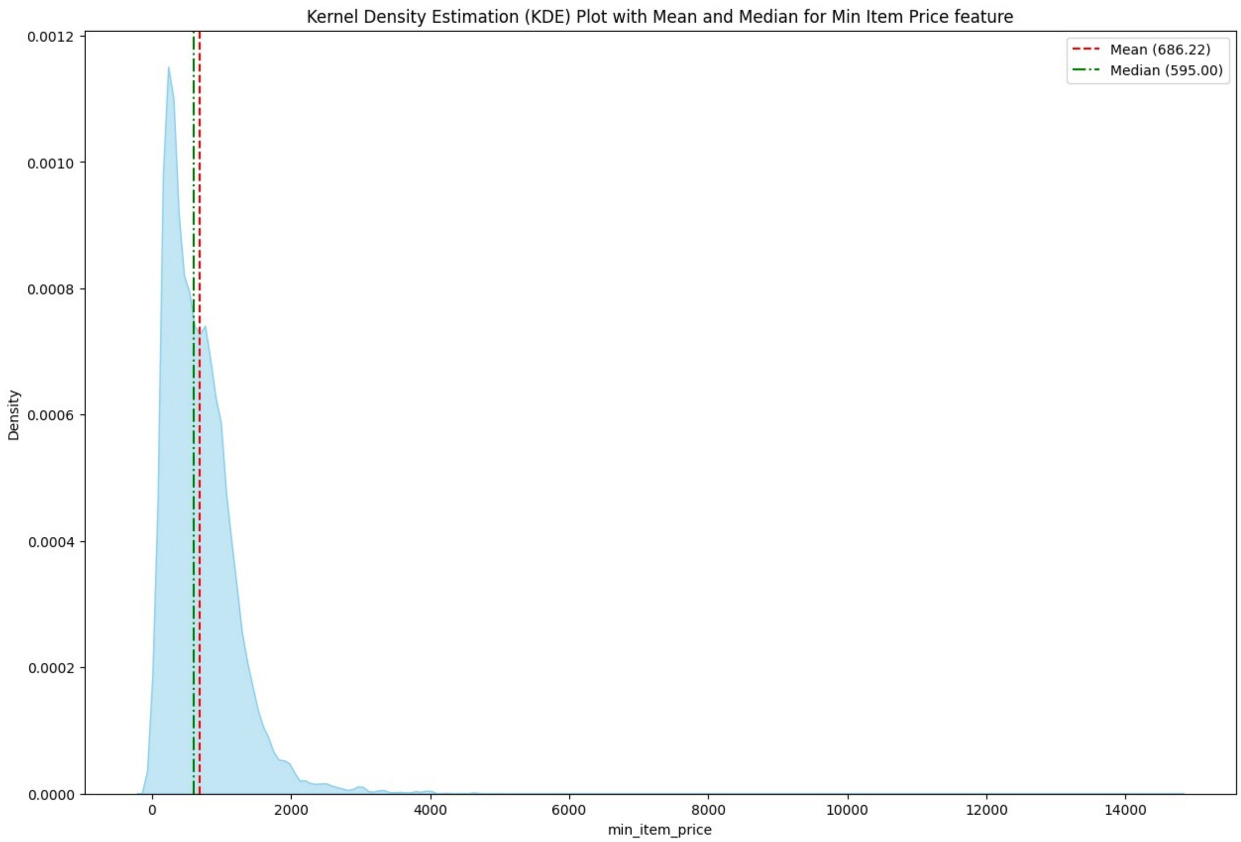
```
plt.figure(figsize=(15,10))
plt.title('subtotal feature after outlier fix')
sns.boxplot(x=df['subtotal'])
plt.show()
```

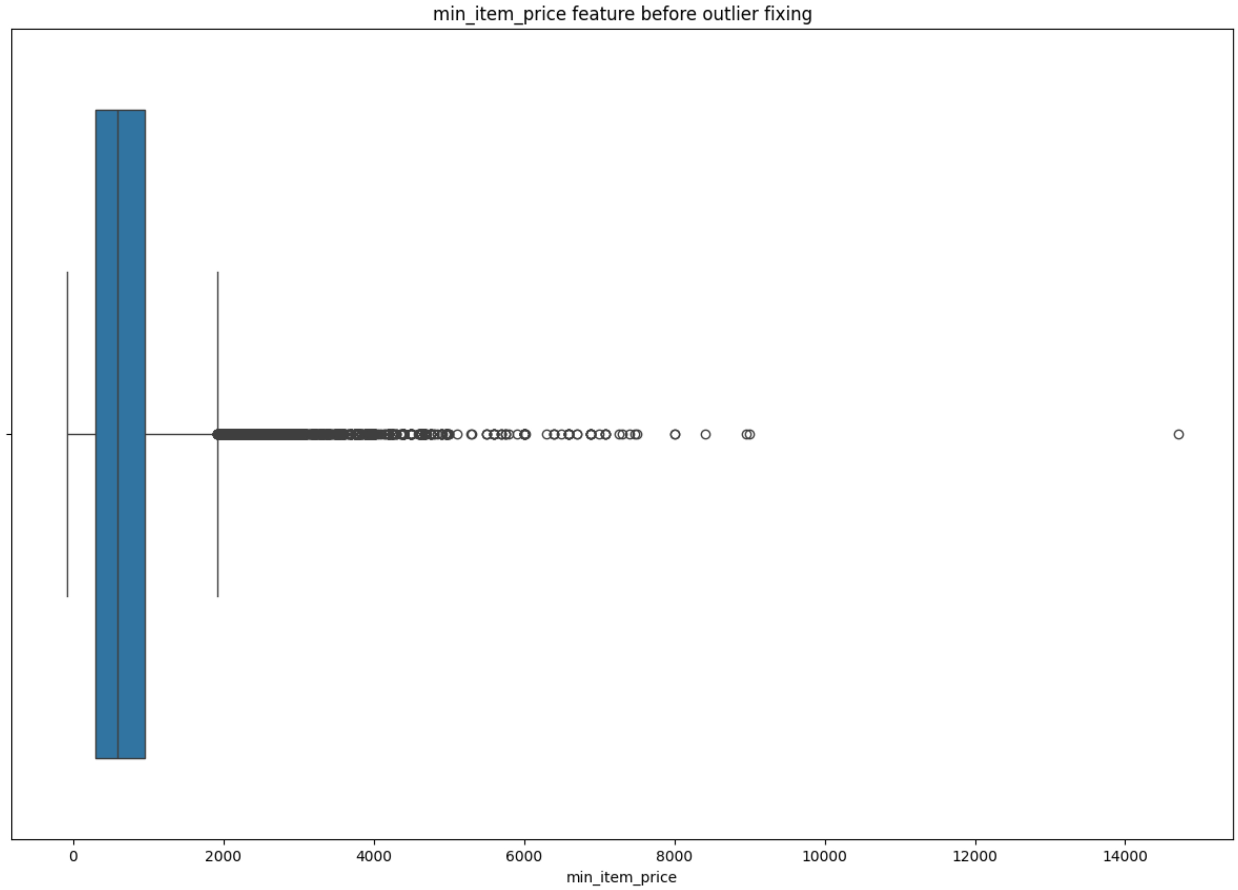


Skewness Analysis for Min Item Price Feature

```
# 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 feature')
```

```python
# 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()
```

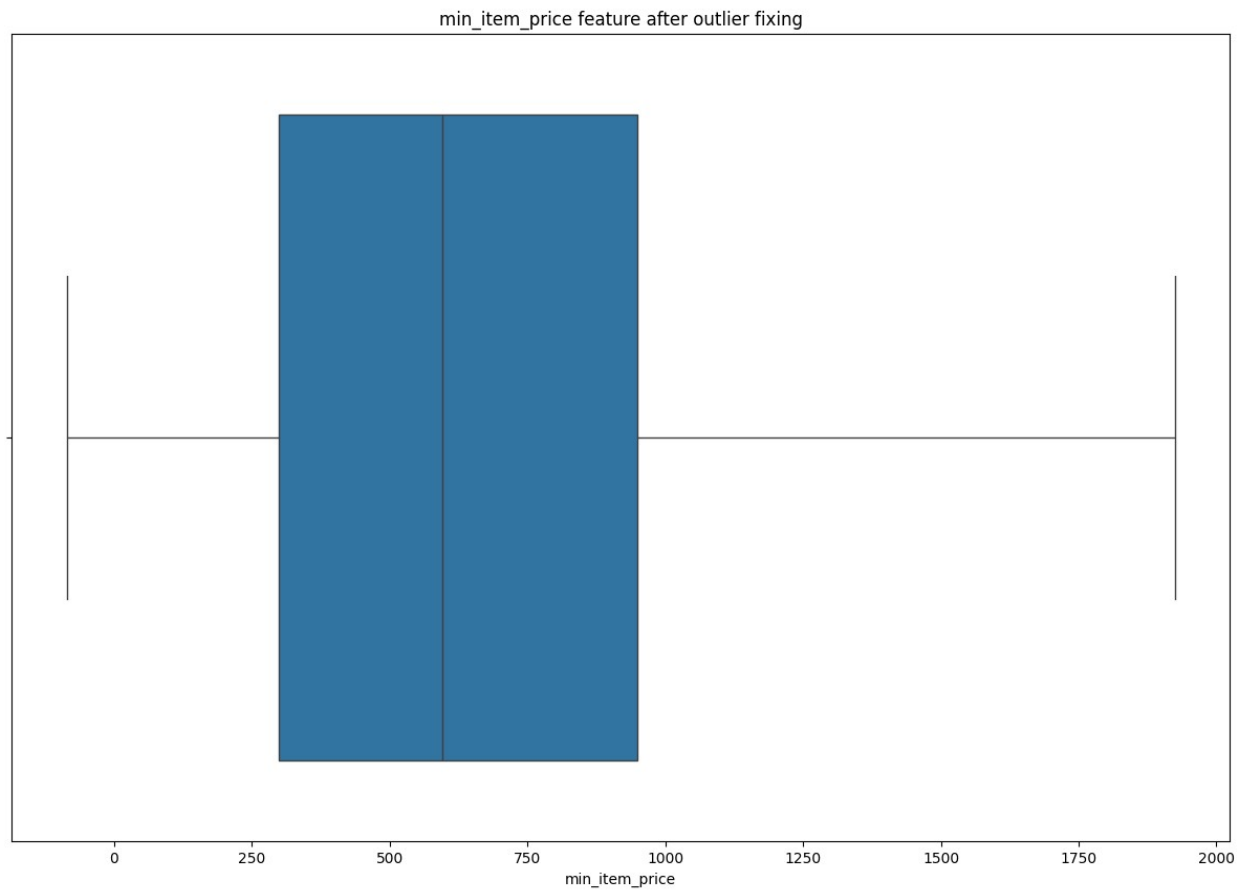





```
q1 = df['min_item_price'].quantile(0.25)
q3 = df['min_item_price'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['min_item_price'] =
np.where(df['min_item_price']>right_wisker,right_wisker,df['min_item_p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

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

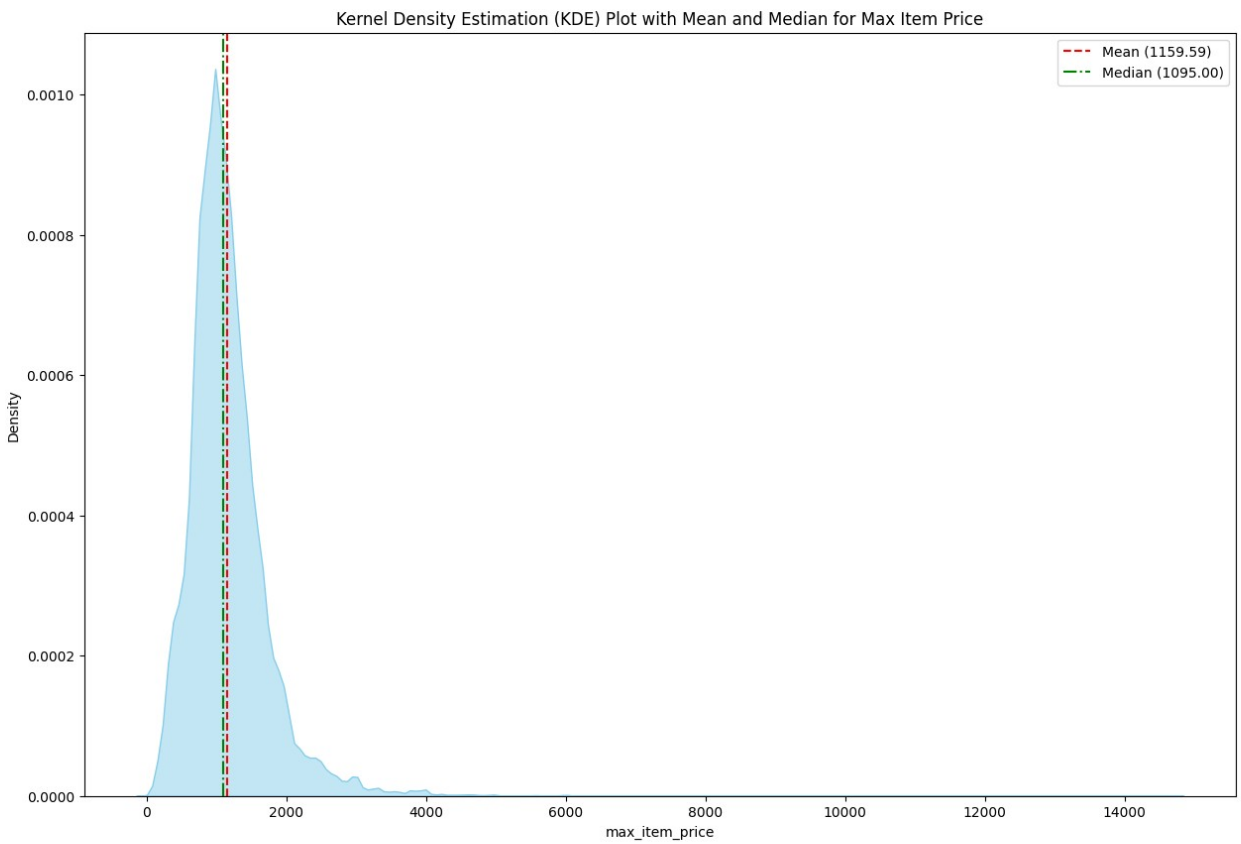
```
plt.figure(figsize=(15,10))
plt.title('min_item_price feature after outlier fixing')
sns.boxplot(x=df['min_item_price'])
plt.show()
```

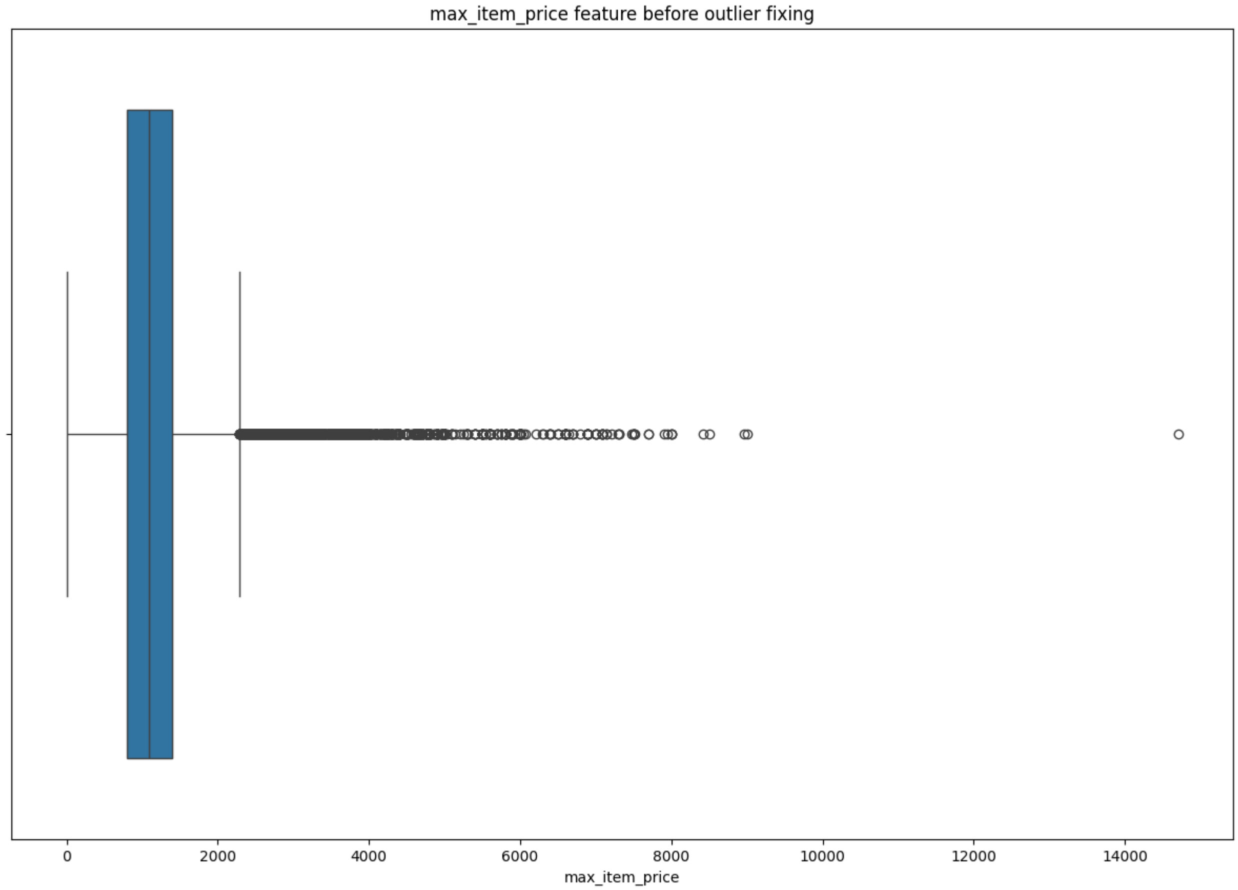


Skewness Analysis for Max Item Price Feature

```
# 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')
```

```
# Show legend
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()
```

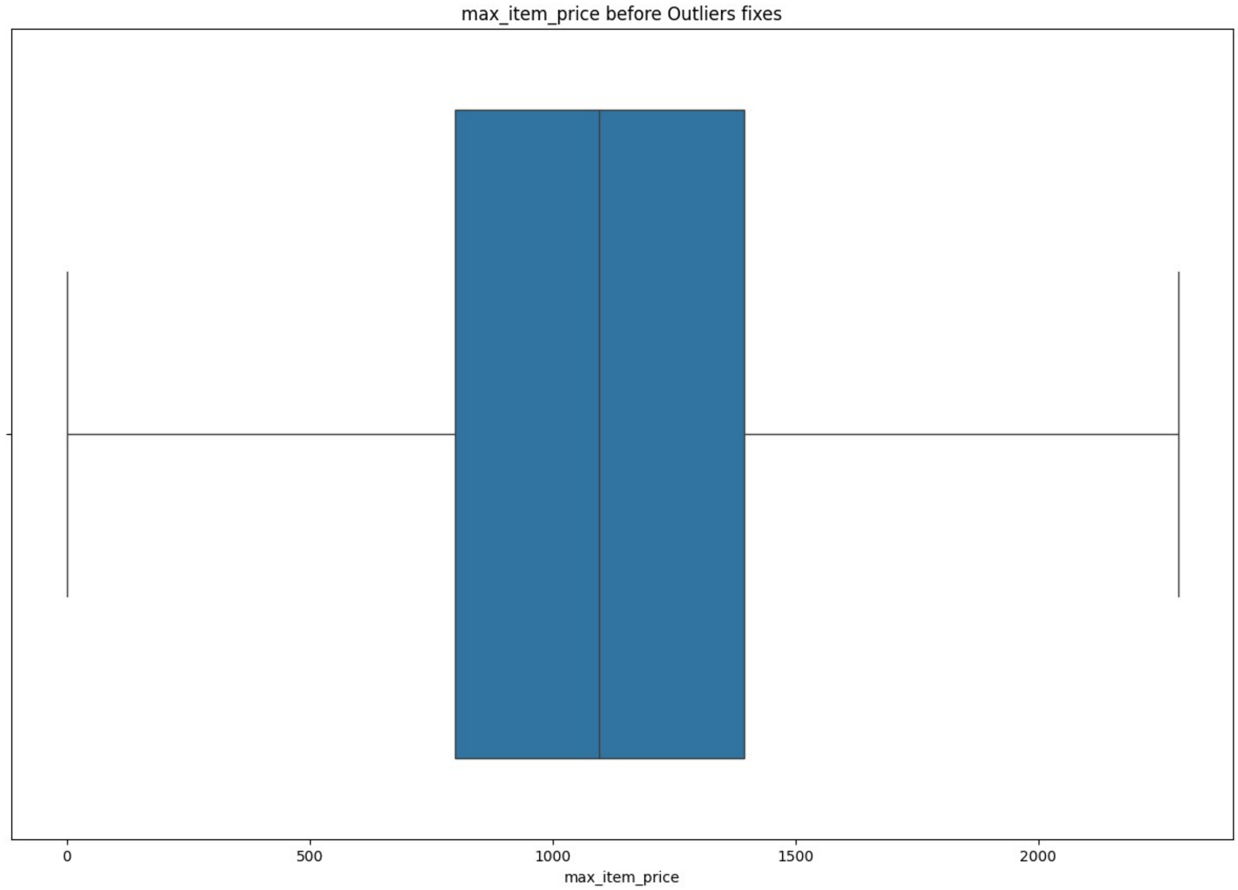





```
q1 = df['max_item_price'].quantile(0.25)
q3 = df['max_item_price'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['max_item_price'] =
np.where(df['max_item_price']>right_wisker,right_wisker,df['max_item_p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

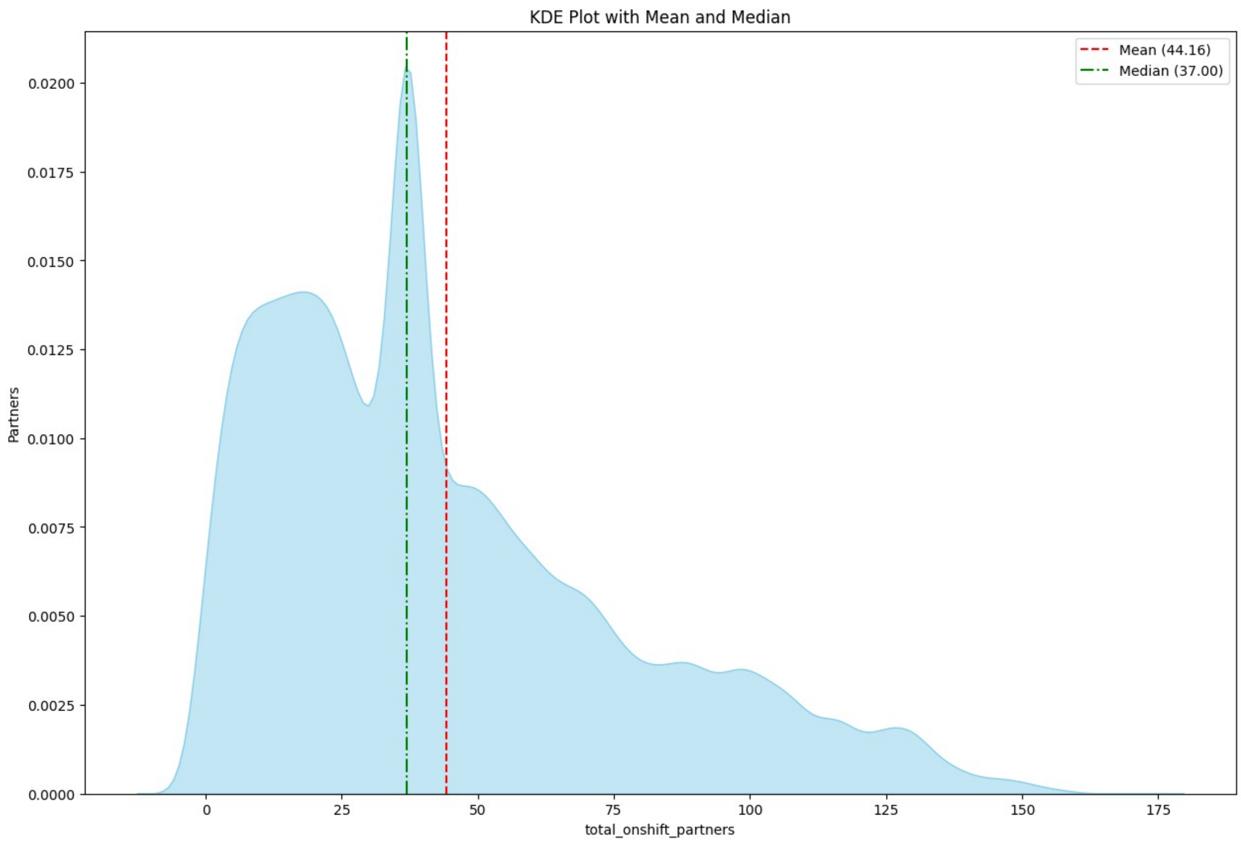
```
left, right wisker : (-92.5, 2287.5)
```

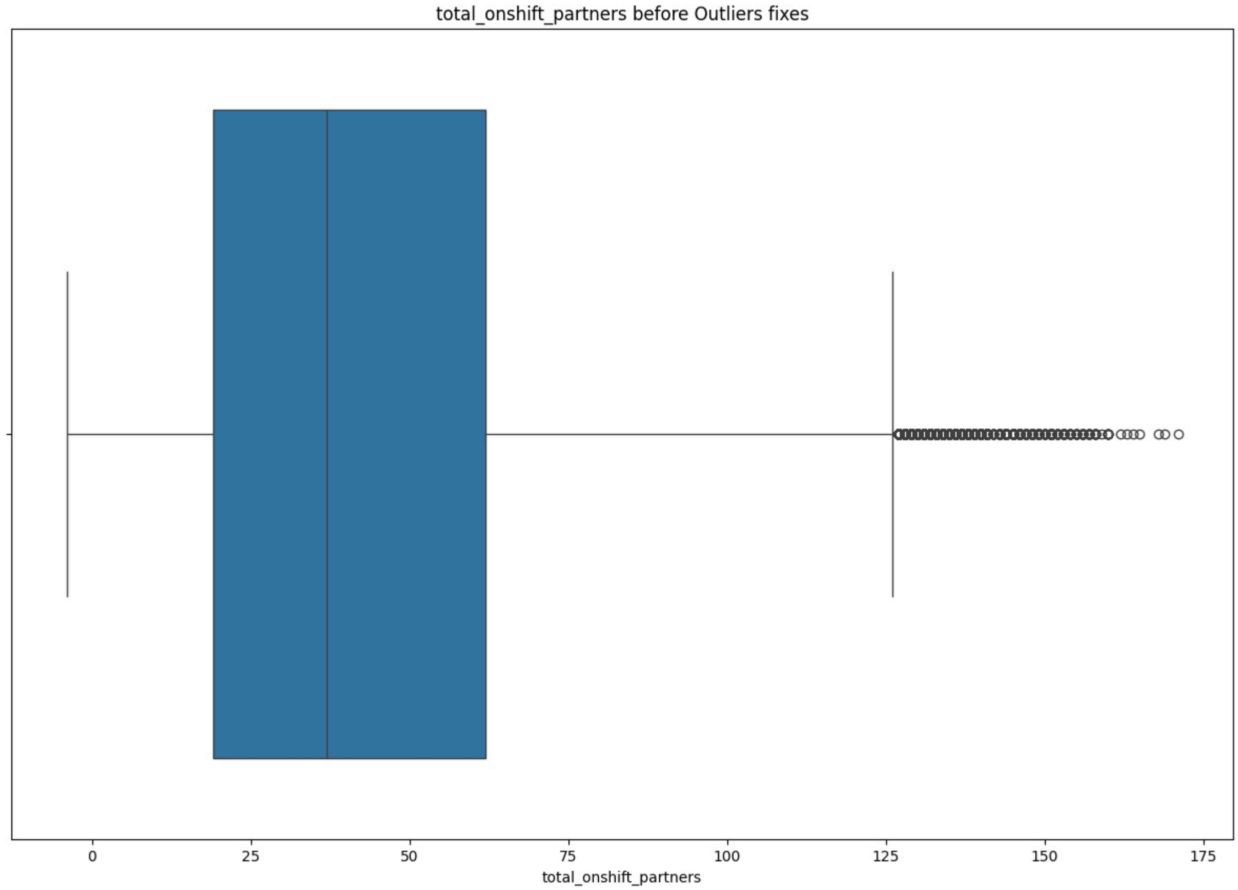
```
plt.figure(figsize=(15,10))
plt.title('max_item_price before Outliers fixes')
sns.boxplot(x=df['max_item_price'])
plt.show()
```




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

# 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()), ha='center', va='bottom')


# 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()
```

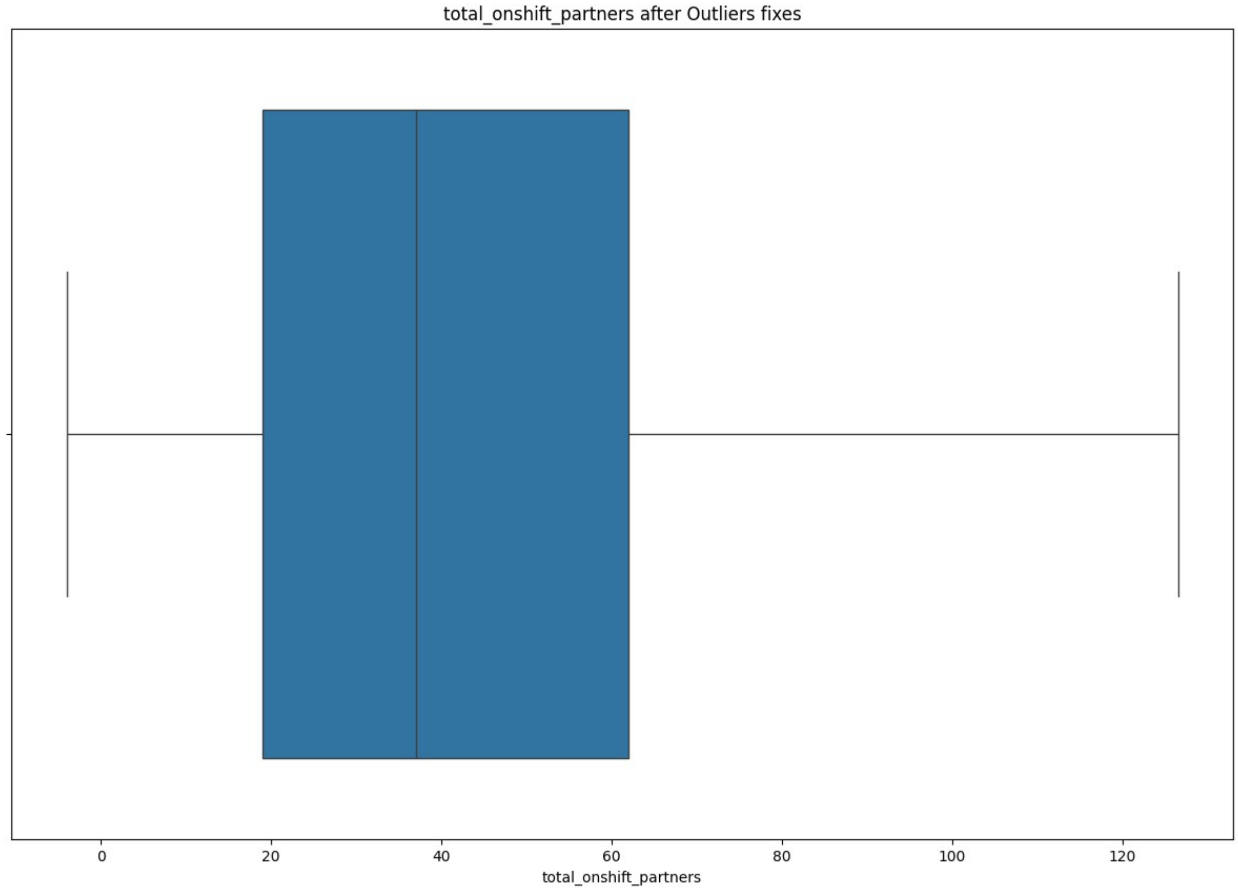





```
q1 = df['total_onshift_partners'].quantile(0.25)
q3 = df['total_onshift_partners'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['total_onshift_partners'] =
np.where(df['total_onshift_partners']>right_wisker,right_wisker,df['to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

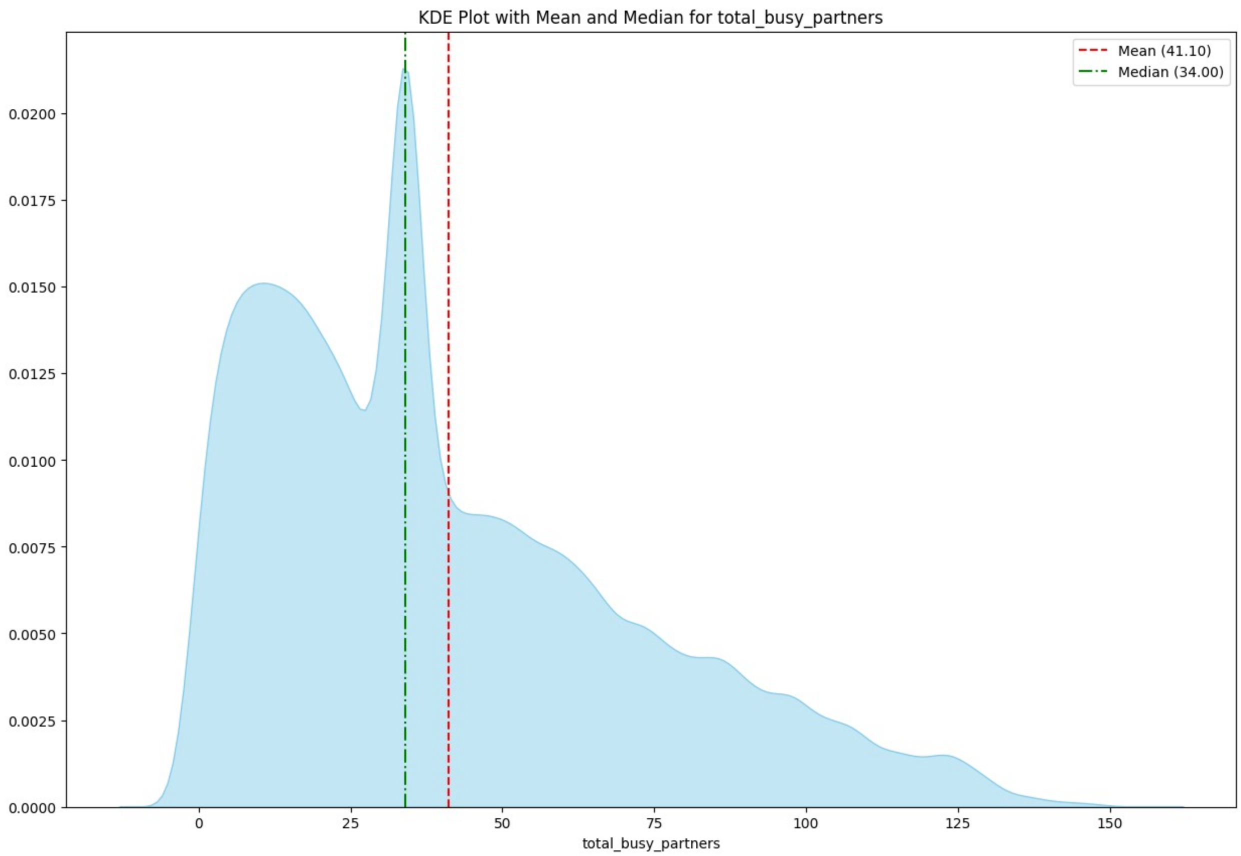
```
left, right wisker : (-45.5, 126.5)
```

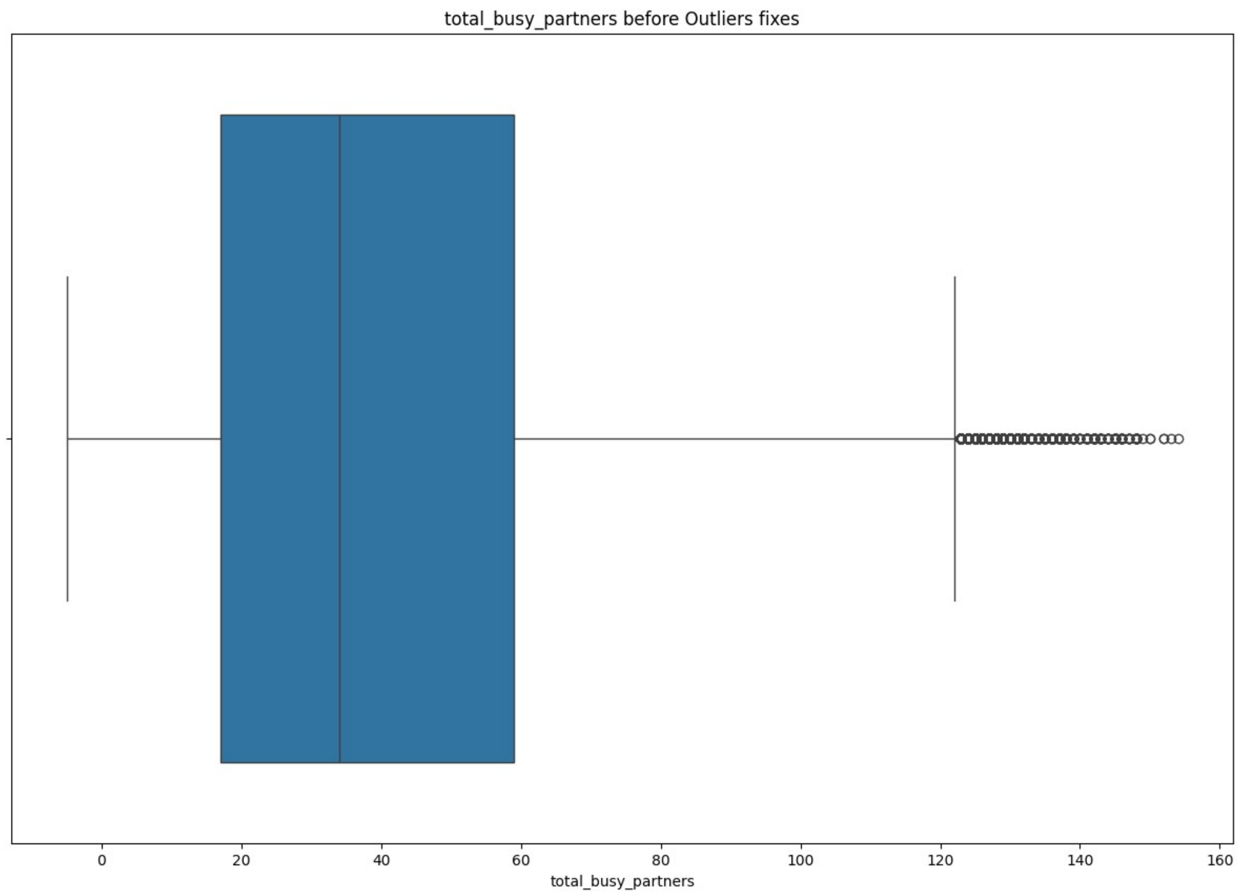
```
plt.figure(figsize=(15,10))
plt.title('total_onshift_partners after Outliers fixes')
sns.boxplot(x=df['total_onshift_partners'])
plt.show()
```




```
# 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()), ha='center', va='bottom')


# 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('')
```

```python
plt.title('KDE Plot with Mean and Median for total_busy_partners')

# 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()
```

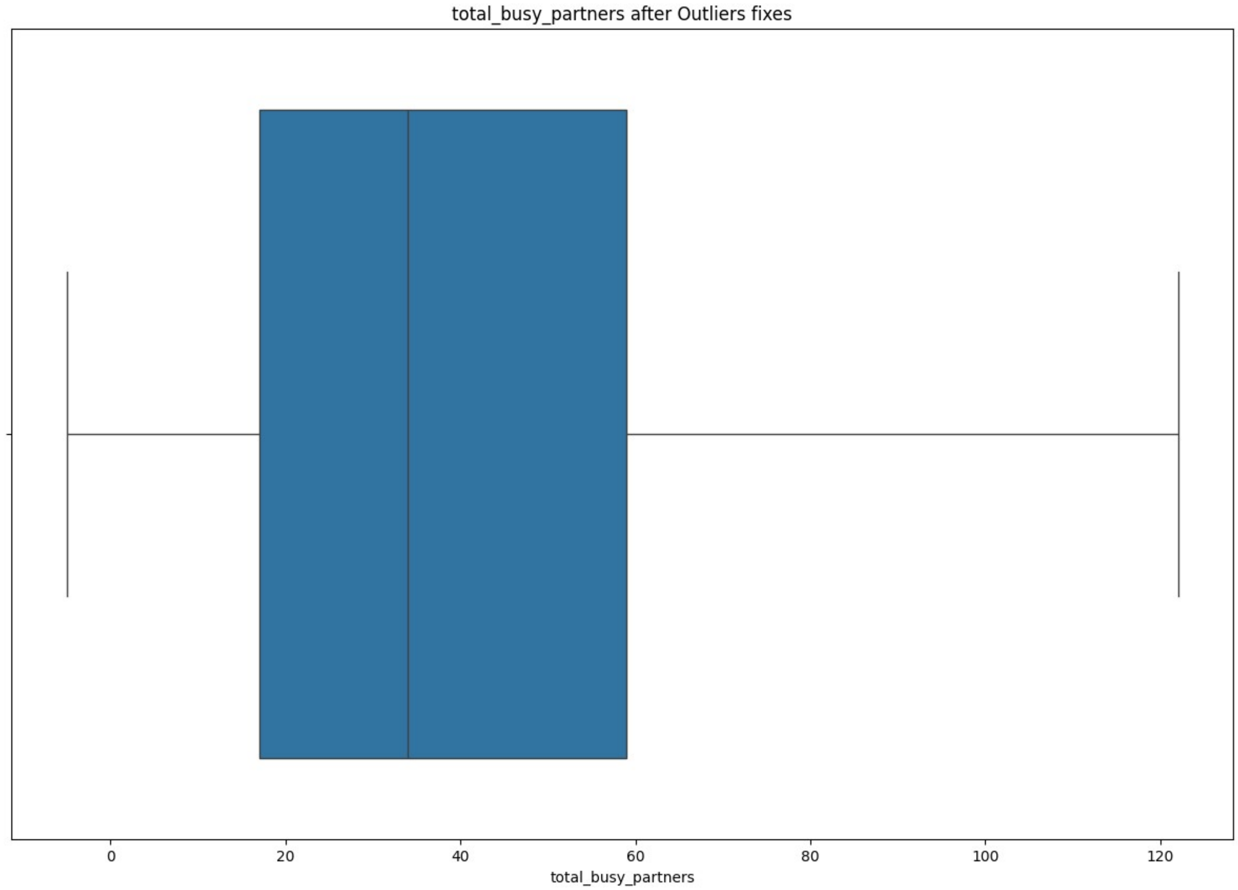





```
q1 = df['total_busy_partners'].quantile(0.25)
q3 = df['total_busy_partners'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['total_busy_partners'] =
np.where(df['total_busy_partners']>right_wisker,right_wisker,df['total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

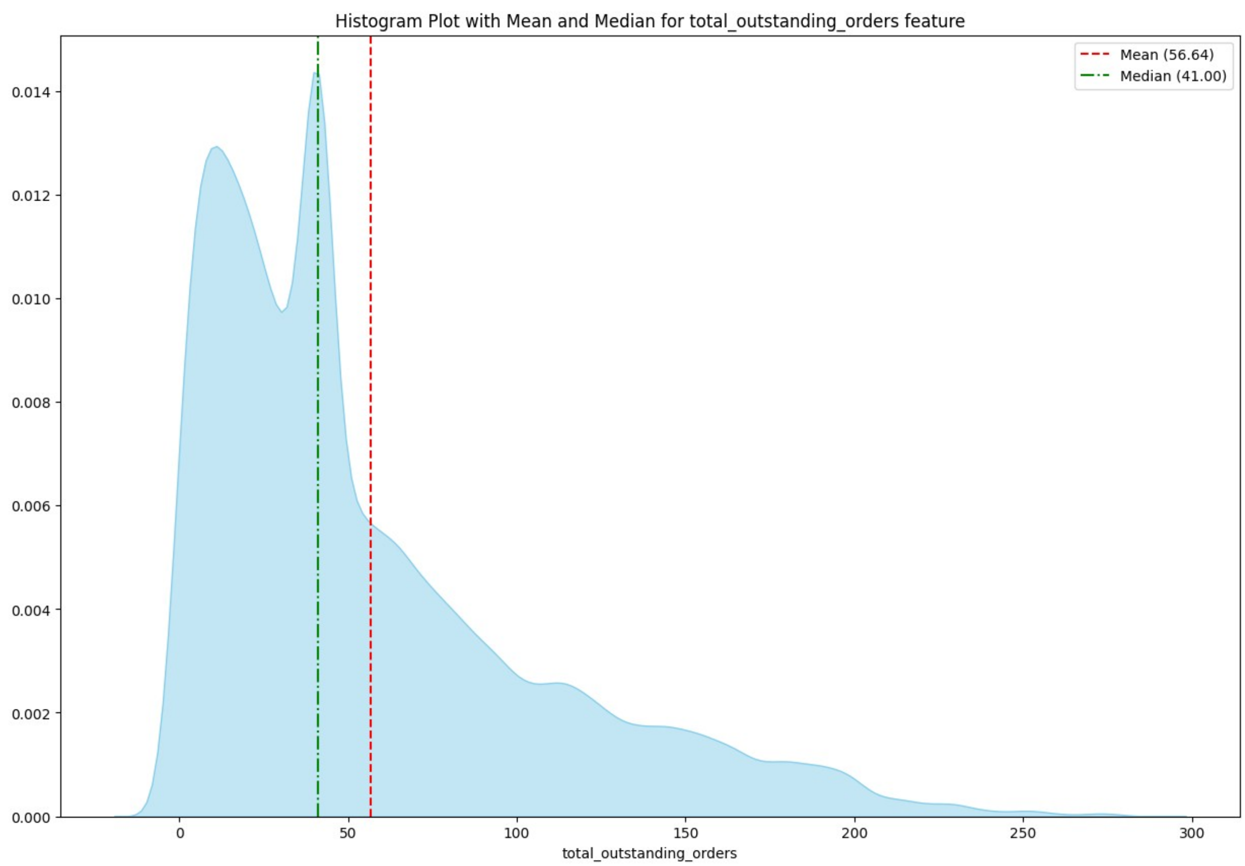
```
left, right wisker : (-46.0, 122.0)
```

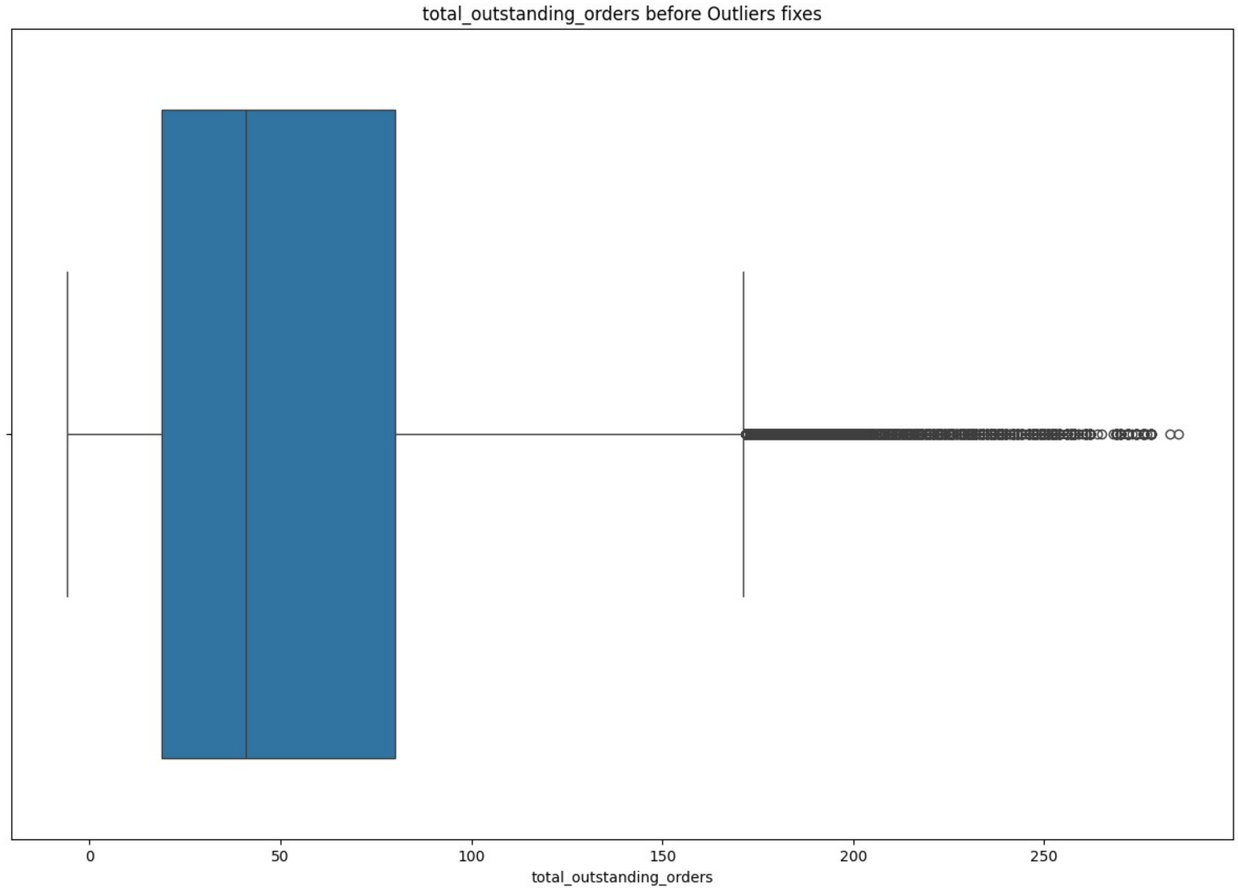
```
plt.figure(figsize=(15,10))
plt.title('total_busy_partners after Outliers fixes')
sns.boxplot(x=df['total_busy_partners'])
plt.show()
```




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

# 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()), ha='center', va='bottom')


# 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()
```

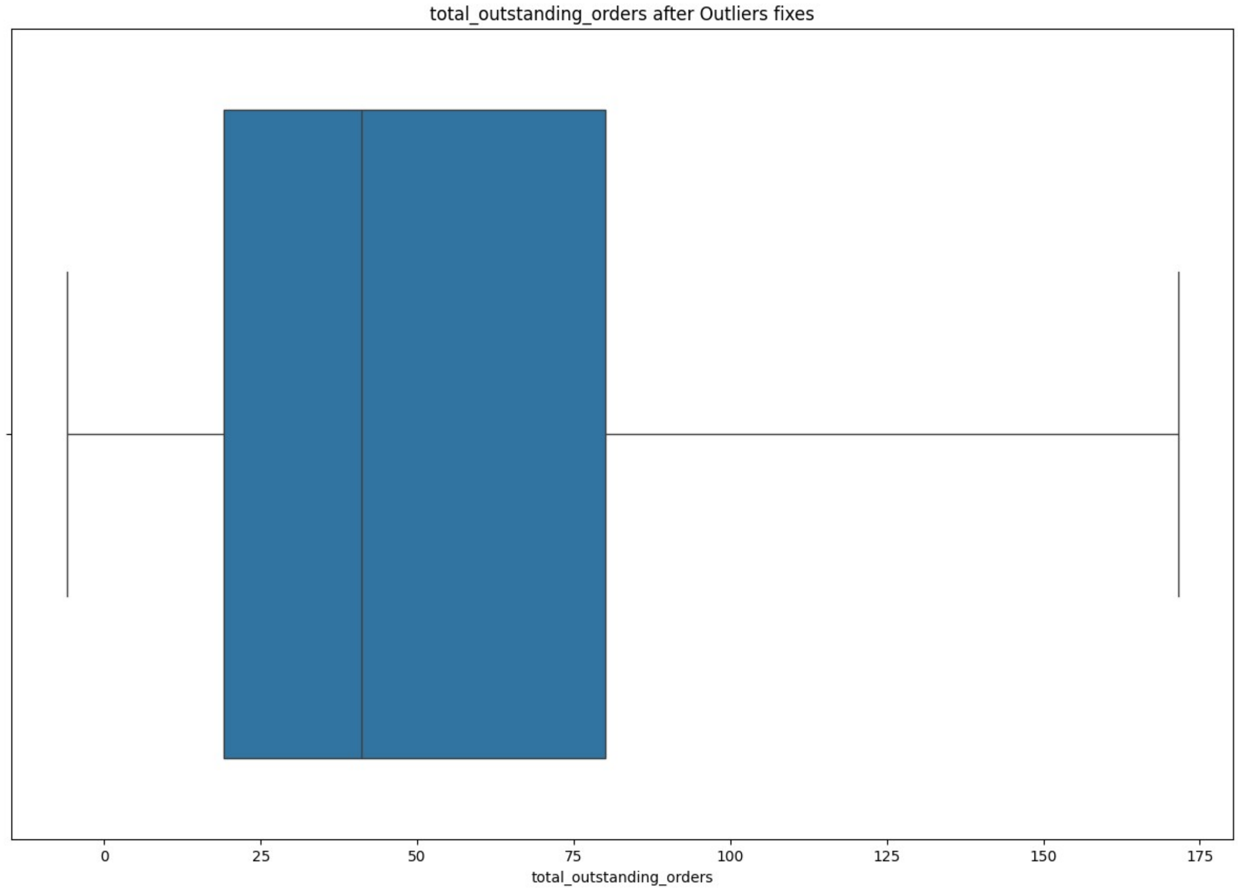





```
q1 = df['total_outstanding_orders'].quantile(0.25)
q3 = df['total_outstanding_orders'].quantile(0.75)
IQR = q3-q1
left_wisker = q1 - 1.5 * IQR
right_wisker = q3 + 1.5 * IQR
print(f'left, right wisker : {left_wisker,right_wisker}')
df['total_outstanding_orders'] =
np.where(df['total_outstanding_orders']>right_wisker,right_wisker,df['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

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

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

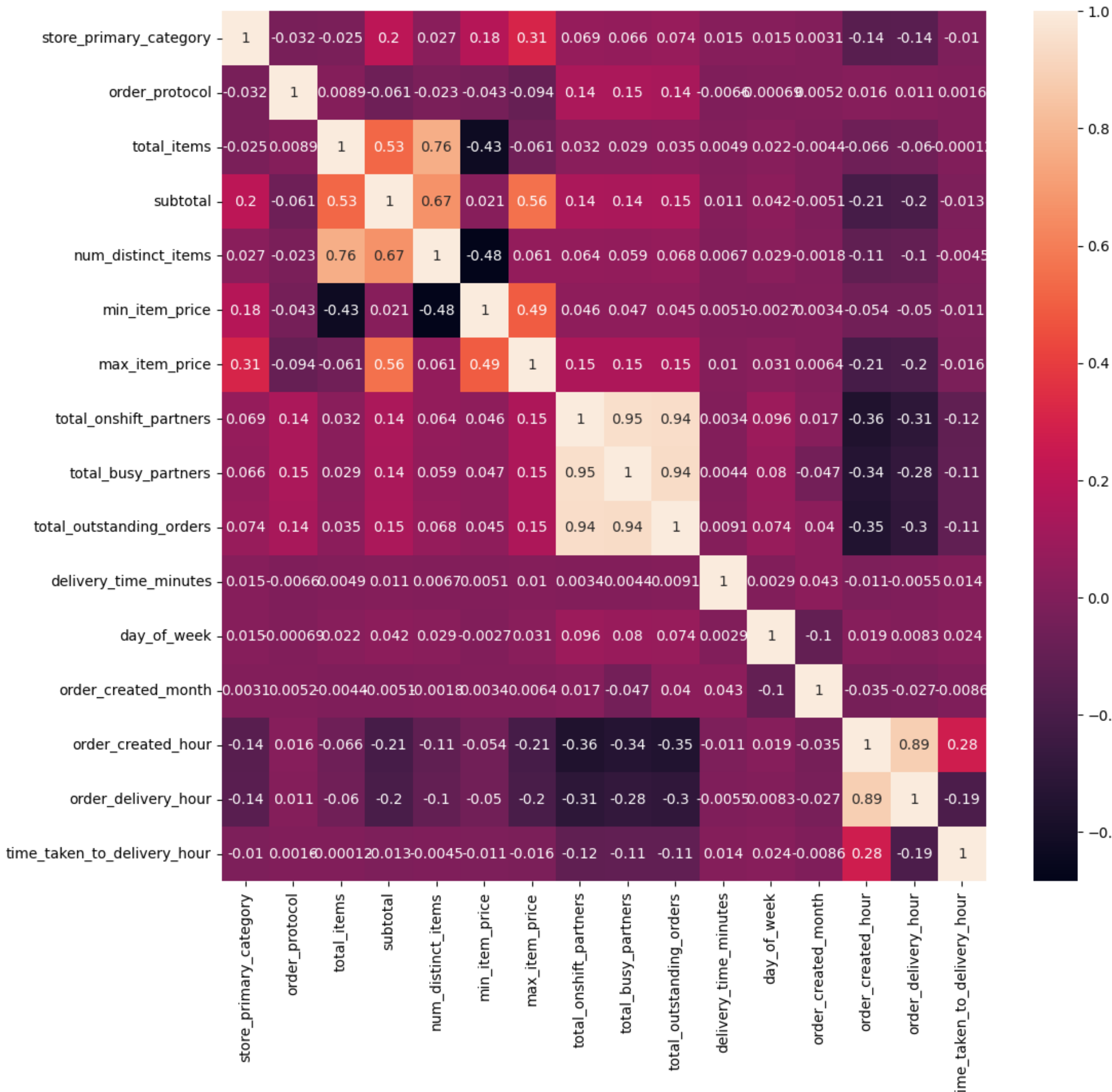



```
df.drop('market_id',axis=1, inplace=True)

from category_encoders import TargetEncoder

df['store_primary_category'] =
TargetEncoder().fit_transform(df['store_primary_category'],df['deliver
y_time_minutes'])

df.head()

   store_primary_category  order_protocol  total_items  subtotal  \
0               48.025105             1.0            4    3441.0
1               44.602766             2.0            1    1900.0
2               49.749557             1.0            1    1900.0
3               49.749557             1.0            6    6387.5
4               49.749557             1.0            3    3900.0

   num_distinct_items  min_item_price  max_item_price
total_onshift_partners  \
0                   4           557.0          1239.0
33.0
1                   1          1400.0          1400.0
1.0
```

```
2                    1         1900.0         1900.0
1.0
3                    5          600.0         1800.0
1.0
4                    3         1100.0         1600.0
6.0

   total_busy_partners  total_outstanding_orders
delivery_time_minutes  \
0                 14.0                      21.0
62.98
1                  2.0                       2.0
67.07
2                  0.0                       0.0
29.68
3                  1.0                       2.0
51.25
4                  6.0                       9.0
39.83

   day_of_week  order_created_month  order_created_hour
order_delivery_hour  \
0            4                    2                  22
23
1            1                    2                  21
22
2            3                    1                  20
21
3            1                    2                  21
22
4            6                    2                   2
3

   time_taken_to_delivery_hour
0                            1
1                            1
2                            1
3                            1
4                            1
```

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

```
<Axes: >
```




```
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(df.columns))]
    return vif_df,df
```

```
df_tmp = df.copy()

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

vif_df,df = check_vif(X)

vif_df
```

	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

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

vif_df,df = check_vif(df)

vif_df
```

	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

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

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

```
                        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
```

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

```
                        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
```

```
df.shape
```

```
(197421, 12)
```

```
df.head()
```

```
   store_primary_category  order_protocol  total_items  subtotal  \
0               -0.093025       -1.243699     0.301376  0.557004
1               -0.807830       -0.579639    -0.823675 -0.454813
2                0.267151       -1.243699    -0.823675 -0.454813
3                0.267151       -1.243699     1.051410  2.491669
4                0.267151       -1.243699    -0.073641  0.858383

   num_distinct_items  min_item_price  max_item_price
total_busy_partners  \
```

```
0          0.815344       -0.249754        0.226276             -
0.883125
1         -1.024857        1.625521        0.574103             -
1.275674
2         -1.024857        2.737784        1.654308             -
1.341098
3          1.428744       -0.154099        1.438267             -
1.308386
4          0.201944        0.958163        1.006185             -
1.144824

   day_of_week  order_created_month  order_delivery_hour  \
0     0.381804             0.728128             1.730476
1    -1.084648             0.728128             1.610807
2    -0.107013            -1.371177             1.491139
3    -1.084648             0.728128             1.610807
4     1.359439             0.728128            -0.662892

   time_taken_to_delivery_hour
0                    -0.118838
1                    -0.118838
2                    -0.118838
3                    -0.118838
4                    -0.118838
```

```
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)

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,)
```

```
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

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')

    ]


)

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
_________________________________________________________________
```

```
from tensorflow.keras.callbacks import EarlyStopping

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

hist =
model.fit(xtrain,ytrain,epochs=500,validation_data=(xval,yval),batch_s
ize=256,verbose=1,callbacks=[call_backs])
```

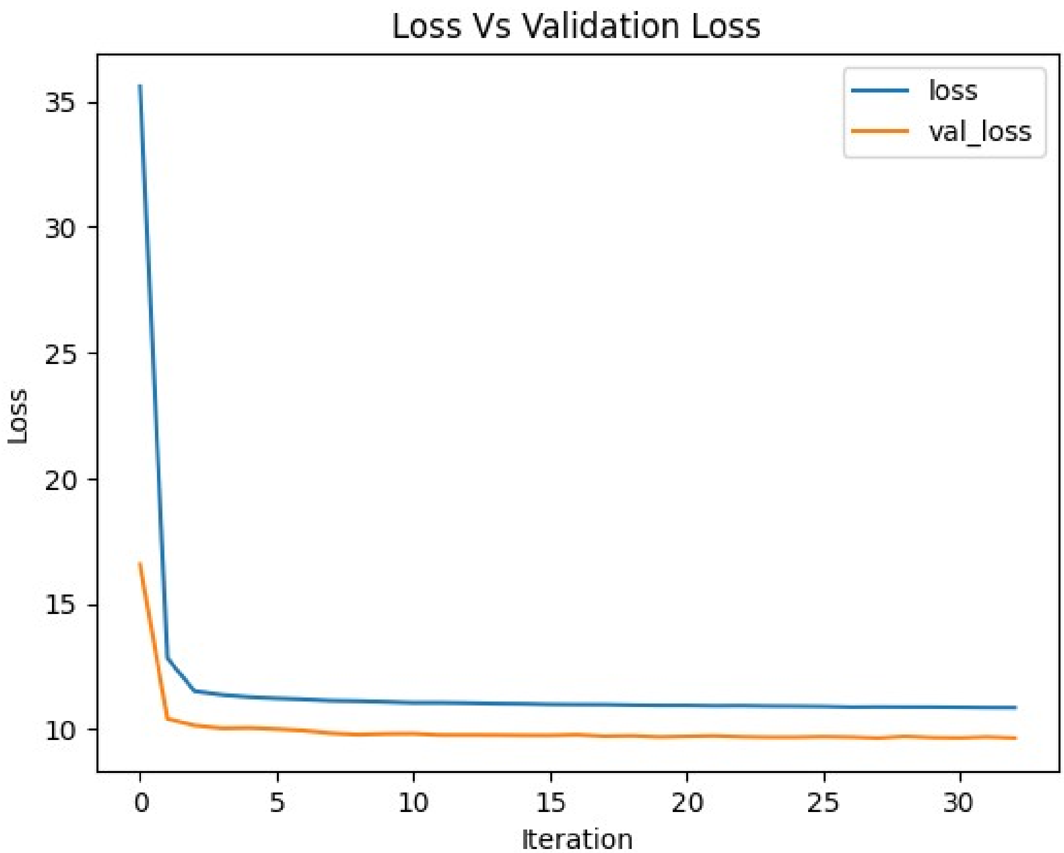
```
Epoch 1/500
```

```
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: 10.4252
Epoch 3/500
494/494 [==============================] - 9s 19ms/step - loss:
11.5161 - val_loss: 10.1553
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: 9.9561
Epoch 8/500
494/494 [==============================] - 10s 21ms/step - loss:
11.1483 - val_loss: 9.8490
Epoch 9/500
494/494 [==============================] - 10s 21ms/step - loss:
11.1309 - val_loss: 9.7985
Epoch 10/500
494/494 [==============================] - 10s 21ms/step - loss:
11.1017 - val_loss: 9.8280
Epoch 11/500
494/494 [==============================] - 10s 20ms/step - loss:
11.0665 - val_loss: 9.8350
Epoch 12/500
494/494 [==============================] - 10s 21ms/step - loss:
11.0672 - val_loss: 9.7831
Epoch 13/500
494/494 [==============================] - 10s 20ms/step - loss:
11.0540 - val_loss: 9.7841
Epoch 14/500
494/494 [==============================] - 10s 20ms/step - loss:
11.0332 - val_loss: 9.7803
Epoch 15/500
494/494 [==============================] - 10s 21ms/step - loss:
11.0242 - val_loss: 9.7706
Epoch 16/500
494/494 [==============================] - 9s 19ms/step - loss:
11.0011 - val_loss: 9.7674
Epoch 17/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9929 - val_loss: 9.7911
```

```
Epoch 18/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9898 - val_loss: 9.7304
Epoch 19/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9697 - val_loss: 9.7481
Epoch 20/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9562 - val_loss: 9.7005
Epoch 21/500
494/494 [==============================] - 10s 19ms/step - loss:
10.9561 - val_loss: 9.7243
Epoch 22/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9409 - val_loss: 9.7435
Epoch 23/500
494/494 [==============================] - 10s 20ms/step - loss:
10.9466 - val_loss: 9.7066
Epoch 24/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9313 - val_loss: 9.6902
Epoch 25/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9260 - val_loss: 9.6900
Epoch 26/500
494/494 [==============================] - 9s 19ms/step - loss:
10.9161 - val_loss: 9.7108
Epoch 27/500
494/494 [==============================] - 10s 19ms/step - loss:
10.8912 - val_loss: 9.6950
Epoch 28/500
494/494 [==============================] - 9s 19ms/step - loss:
10.8965 - val_loss: 9.6564
Epoch 29/500
494/494 [==============================] - 9s 19ms/step - loss:
10.8925 - val_loss: 9.7229
Epoch 30/500
494/494 [==============================] - 9s 19ms/step - loss:
10.8910 - val_loss: 9.6743
Epoch 31/500
494/494 [==============================] - 9s 19ms/step - loss:
10.8815 - val_loss: 9.6630
Epoch 32/500
494/494 [==============================] - 9s 19ms/step - loss:
10.8713 - val_loss: 9.6993
Epoch 33/500
494/494 [==============================] - 9s 19ms/step - loss:
10.8686 - val_loss: 9.6575

hist.history.keys()
```

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

```
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()
```




```
# model.save('proter_reg.h5')
```

```
model.evaluate(xtest,ytest)
```

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

```
9.569809913635254
```

```
y_pred = model.predict(xtest)
```

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

```
y_pred = y_pred.reshape(-1)
y_pred
```

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

```
from sklearn.metrics import r2_score,mean_squared_error,
mean_absolute_error,root_mean_squared_error
```

```
print(f' R2 Score : {r2_score(ytest,y_pred)}')
```

```
 R2 Score : 0.47361300590838007
```

```
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?

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.