0mfog7c5q

June 22, 2025

##BUSINESS CASE - PORTER

Porter is India's Largest Marketplace for Intra-City Logistics. Leader in the country's $40 billion intra-city logistics market, Porter strives to improve the lives of 1,50,000+ driver-partners by providing them with consistent earning & independence. Currently, the company has serviced 5+ million customers.

Porter works with a wide range of restaurants for delivering their items directly to the people.

Porter has a number of delivery partners available for delivering the food, from various restaurants and wants to get an estimated delivery time that it can provide the customers on the basis of what they are ordering, from where and also the delivery partners.

This dataset has the required data to train a neural network model that will do the delivery time estimation, based on all those features.

###Defining problem statement, importing the data and data structure analysis

[4]:
```
#IMPORTING IMPORTANT LIBRARIES
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[5]:
```
#downloading the dataset
!gdown 1kkgBGldeswHBgVKEJiqqG7VZvqZNMc-5
```

```
Downloading…
From: https://drive.google.com/uc?id=1kkgBGldeswHBgVKEJiqqG7VZvqZNMc-5
To: /content/data_2.csv
100% 15.7M/15.7M [00:00<00:00, 46.0MB/s]
```

[6]:
```
#reading the data to dataframe
df=pd.read_csv('data_2.csv')
```

[7]:
```
df
```

[7]:

	market_id	created_at	actual_delivery_time	\
0	1.0	2015-02-06 22:24:17	2015-02-06 23:11:17	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:33:25	
2	2.0	2015-02-16 00:11:35	2015-02-16 01:06:35	
3	1.0	2015-02-12 03:36:46	2015-02-12 04:35:46	
4	1.0	2015-01-27 02:12:36	2015-01-27 02:58:36	
…	…	…	…	
175772	1.0	2015-02-17 00:19:41	2015-02-17 01:02:41	
175773	1.0	2015-02-13 00:01:59	2015-02-13 01:03:59	
175774	1.0	2015-01-24 04:46:08	2015-01-24 05:32:08	
175775	1.0	2015-02-01 18:18:15	2015-02-01 19:03:15	
175776	1.0	2015-02-08 19:24:33	2015-02-08 20:01:33	

	store_primary_category	order_protocol	total_items	subtotal	\
0	4	1.0	4	3441	
1	46	2.0	1	1900	
2	36	3.0	4	4771	
3	38	1.0	1	1525	
4	38	1.0	2	3620	
…	…	…	…	…	
175772	28	4.0	3	1389	
175773	28	4.0	6	3010	
175774	28	4.0	5	1836	
175775	58	1.0	1	1175	
175776	58	1.0	4	2605	

	num_distinct_items	min_item_price	max_item_price	\
0	4	557	1239	
1	1	1400	1400	
2	3	820	1604	
3	1	1525	1525	
4	2	1425	2195	
…	…	…	…	
175772	3	345	649	
175773	4	405	825	
175774	3	300	399	
175775	1	535	535	
175776	4	425	750	

	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	\
0	33.0	14.0	21.0	
1	1.0	2.0	2.0	
2	8.0	6.0	18.0	
3	5.0	6.0	8.0	
4	5.0	5.0	7.0	
…	…	…	…	
175772	17.0	17.0	23.0	

```
175773                  12.0                 11.0                  14.0
175774                  39.0                 41.0                  40.0
175775                   7.0                  7.0                  12.0
175776                  20.0                 20.0                  23.0

        estimated_store_to_consumer_driving_duration
0                                              861.0
1                                              690.0
2                                              289.0
3                                              795.0
4                                              205.0
…                                                …
175772                                         331.0
175773                                         915.0
175774                                         795.0
175775                                         384.0
175776                                         134.0

[175777 rows x 14 columns]
```

Data Dictionary

Each row in this file corresponds to one unique delivery. Each column corresponds to a feature as explained below.

1. market_id : integer id for the market where the restaurant lies
2. created_at : the timestamp at which the order was placed
3. actual_delivery_time : the timestamp when the order was delivered
4. store_primary_category : category for the restaurant
5. order_protocol : integer code value for order protocol(how the order was placed ie: through porter, call to restaurant, pre booked, third part etc)
6. total_items subtotal : final price of the order
7. num_distinct_items : the number of distinct items in the order
8. min_item_price : price of the cheapest item in the order
9. max_item_price : price of the costliest item in order
10. total_onshift_partners : number of delivery partners on duty at the time order was placed
11. total_busy_partners : number of delivery partners attending to other tasks
12. total_outstanding_orders : total number of orders to be fulfilled at the moment
13. estimated_store_to_consumer_driving_duration : approximate travel time from restaurant to customer

[8]:
```
#shape of the data
df.shape
```

[8]:
```
(175777, 14)
```

[9]:
```
#data types of columns
df.dtypes
```

[9]:
```
market_id                                             float64
created_at                                             object
actual_delivery_time                                   object
store_primary_category                                  int64
order_protocol                                        float64
total_items                                             int64
subtotal                                                int64
num_distinct_items                                      int64
min_item_price                                          int64
max_item_price                                          int64
total_onshift_dashers                                 float64
total_busy_dashers                                    float64
total_outstanding_orders                              float64
estimated_store_to_consumer_driving_duration          float64
dtype: object
```

[10]:
```
#converting the datetime columns into datetime
df['created_at']=pd.to_datetime(df['created_at'])
```

[11]:
```
df['actual_delivery_time']=pd.to_datetime(df['actual_delivery_time'])
```

[12]:
```
#null values
df.isnull().sum()
```

[12]:
```
market_id                                             0
created_at                                            0
actual_delivery_time                                  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_dashers                                 0
total_busy_dashers                                    0
total_outstanding_orders                              0
estimated_store_to_consumer_driving_duration          0
dtype: int64
```

###Data preprocessing and feature engineering

[13]:
```
#Creating day of week column from created at timestamp
df['day_of_week']=df['created_at'].dt.day_name()
```

[14]:
```
#creating hour of day column from created at timestamp
df['time_of_day']=df['created_at'].dt.hour
```

[15]:
```
df
```

[15]:

```
        market_id          created_at actual_delivery_time  \
0             1.0 2015-02-06 22:24:17  2015-02-06 23:11:17
1             2.0 2015-02-10 21:49:25  2015-02-10 22:33:25
2             2.0 2015-02-16 00:11:35  2015-02-16 01:06:35
3             1.0 2015-02-12 03:36:46  2015-02-12 04:35:46
4             1.0 2015-01-27 02:12:36  2015-01-27 02:58:36
…             …                   …                   …
175772        1.0 2015-02-17 00:19:41  2015-02-17 01:02:41
175773        1.0 2015-02-13 00:01:59  2015-02-13 01:03:59
175774        1.0 2015-01-24 04:46:08  2015-01-24 05:32:08
175775        1.0 2015-02-01 18:18:15  2015-02-01 19:03:15
175776        1.0 2015-02-08 19:24:33  2015-02-08 20:01:33

        store_primary_category  order_protocol  total_items  subtotal  \
0                            4             1.0            4      3441
1                           46             2.0            1      1900
2                           36             3.0            4      4771
3                           38             1.0            1      1525
4                           38             1.0            2      3620
…                           …               …          …       …
175772                      28             4.0            3      1389
175773                      28             4.0            6      3010
175774                      28             4.0            5      1836
175775                      58             1.0            1      1175
175776                      58             1.0            4      2605

        num_distinct_items  min_item_price  max_item_price  \
0                        4             557            1239
1                        1            1400            1400
2                        3             820            1604
3                        1            1525            1525
4                        2            1425            2195
…                      …               …               …
175772                   3             345             649
175773                   4             405             825
175774                   3             300             399
175775                   1             535             535
175776                   4             425             750

        total_onshift_dashers  total_busy_dashers  total_outstanding_orders  \
0                        33.0                14.0                      21.0
1                         1.0                 2.0                       2.0
2                         8.0                 6.0                      18.0
3                         5.0                 6.0                       8.0
4                         5.0                 5.0                       7.0
```

```
…                       …                   …                       …
175772                  17.0                17.0                    23.0
175773                  12.0                11.0                    14.0
175774                  39.0                41.0                    40.0
175775                   7.0                 7.0                    12.0
175776                  20.0                20.0                    23.0

        estimated_store_to_consumer_driving_duration day_of_week  time_of_day
0                                              861.0      Friday           22
1                                              690.0     Tuesday           21
2                                              289.0      Monday            0
3                                              795.0    Thursday            3
4                                              205.0     Tuesday            2
…                                                …           …          …
175772                                         331.0     Tuesday            0
175773                                         915.0      Friday            0
175774                                         795.0    Saturday            4
175775                                         384.0      Sunday           18
175776                                         134.0      Sunday           19

[175777 rows x 16 columns]
```

[16]:
```
#creating target column
df['delivery_time']=(df['actual_delivery_time']-df['created_at']).dt.
 ↪total_seconds()
```

[17]:
```
df
```

[17]:
```
        market_id          created_at actual_delivery_time  \
0             1.0 2015-02-06 22:24:17  2015-02-06 23:11:17
1             2.0 2015-02-10 21:49:25  2015-02-10 22:33:25
2             2.0 2015-02-16 00:11:35  2015-02-16 01:06:35
3             1.0 2015-02-12 03:36:46  2015-02-12 04:35:46
4             1.0 2015-01-27 02:12:36  2015-01-27 02:58:36
…             …                   …                   …
175772        1.0 2015-02-17 00:19:41  2015-02-17 01:02:41
175773        1.0 2015-02-13 00:01:59  2015-02-13 01:03:59
175774        1.0 2015-01-24 04:46:08  2015-01-24 05:32:08
175775        1.0 2015-02-01 18:18:15  2015-02-01 19:03:15
175776        1.0 2015-02-08 19:24:33  2015-02-08 20:01:33

        store_primary_category  order_protocol  total_items  subtotal  \
0                            4             1.0            4      3441
1                           46             2.0            1      1900
2                           36             3.0            4      4771
3                           38             1.0            1      1525
4                           38             1.0            2      3620
```

```
…                        …              …          …       …
175772                      28            4.0          3      1389
175773                      28            4.0          6      3010
175774                      28            4.0          5      1836
175775                      58            1.0          1      1175
175776                      58            1.0          4      2605

        num_distinct_items  min_item_price  max_item_price  \
0                        4             557            1239
1                        1            1400            1400
2                        3             820            1604
3                        1            1525            1525
4                        2            1425            2195
…                      …              …               …
175772                   3             345             649
175773                   4             405             825
175774                   3             300             399
175775                   1             535             535
175776                   4             425             750

        total_onshift_dashers  total_busy_dashers  total_outstanding_orders  \
0                        33.0                14.0                      21.0
1                         1.0                 2.0                       2.0
2                         8.0                 6.0                      18.0
3                         5.0                 6.0                       8.0
4                         5.0                 5.0                       7.0
…                       …                   …                         …
175772                   17.0                17.0                      23.0
175773                   12.0                11.0                      14.0
175774                   39.0                41.0                      40.0
175775                    7.0                 7.0                      12.0
175776                   20.0                20.0                      23.0

        estimated_store_to_consumer_driving_duration day_of_week  time_of_day  \
0                                              861.0      Friday           22
1                                              690.0     Tuesday           21
2                                              289.0      Monday            0
3                                              795.0    Thursday            3
4                                              205.0     Tuesday            2
…                                              …         …          …
175772                                         331.0     Tuesday            0
175773                                         915.0      Friday            0
175774                                         795.0    Saturday            4
175775                                         384.0      Sunday           18
175776                                         134.0      Sunday           19

        delivery_time
```

```
0              2820.0
1              2640.0
2              3300.0
3              3540.0
4              2760.0
…               …
175772         2580.0
175773         3720.0
175774         2760.0
175775         2700.0
175776         2220.0

[175777 rows x 17 columns]
```

[18]:
```
#identifying categorical columns
categorical=['market_id','store_primary_category','order_protocol','day_of_week','time_of_day'
```

[19]:
```
#creating a copy of data for visualisation
data=df.copy()
```

For avoiding higher dimentionality and misleading arbitrary order, target encoding is used.

[20]:
```
#target encoding using mean
for col in categorical:
  mean_encoded=df.groupby(col)['delivery_time'].mean()
  df[col]=df[col].map(mean_encoded)
```

[21]:
```
df
```

[21]:
```
          market_id          created_at actual_delivery_time  \
0       2947.476761 2015-02-06 22:24:17  2015-02-06 23:11:17
1       2692.524266 2015-02-10 21:49:25  2015-02-10 22:33:25
2       2692.524266 2015-02-16 00:11:35  2015-02-16 01:06:35
3       2947.476761 2015-02-12 03:36:46  2015-02-12 04:35:46
4       2947.476761 2015-01-27 02:12:36  2015-01-27 02:58:36
…             …                 …                   …
175772  2947.476761 2015-02-17 00:19:41  2015-02-17 01:02:41
175773  2947.476761 2015-02-13 00:01:59  2015-02-13 01:03:59
175774  2947.476761 2015-01-24 04:46:08  2015-01-24 05:32:08
175775  2947.476761 2015-02-01 18:18:15  2015-02-01 19:03:15
175776  2947.476761 2015-02-08 19:24:33  2015-02-08 20:01:33

        store_primary_category  order_protocol  total_items  subtotal  \
0                  2758.033328     2870.586728            4      3441
1                  2673.125882     2801.758736            1      1900
2                  2883.443086     2798.771777            4      4771
3                  2946.986484     2870.586728            1      1525
```

```
4                  2946.986484     2870.586728            2      3620
…                         …            …          …       …
175772             2560.711316     2593.749275            3      1389
175773             2560.711316     2593.749275            6      3010
175774             2560.711316     2593.749275            5      1836
175775             2572.709283     2870.586728            1      1175
175776             2572.709283     2870.586728            4      2605

        num_distinct_items  min_item_price  max_item_price  \
0                        4             557            1239
1                        1            1400            1400
2                        3             820            1604
3                        1            1525            1525
4                        2            1425            2195
…                      …              …               …
175772                   3             345             649
175773                   4             405             825
175774                   3             300             399
175775                   1             535             535
175776                   4             425             750

        total_onshift_dashers  total_busy_dashers  total_outstanding_orders  \
0                        33.0                14.0                      21.0
1                         1.0                 2.0                       2.0
2                         8.0                 6.0                      18.0
3                         5.0                 6.0                       8.0
4                         5.0                 5.0                       7.0
…                         …                   …                         …
175772                   17.0                17.0                      23.0
175773                   12.0                11.0                      14.0
175774                   39.0                41.0                      40.0
175775                    7.0                 7.0                      12.0
175776                   20.0                20.0                      23.0

        estimated_store_to_consumer_driving_duration  day_of_week  \
0                                              861.0  2664.641657
1                                              690.0  2672.489876
2                                              289.0  2918.748864
3                                              795.0  2694.468650
4                                              205.0  2672.489876
…                                              …            …
175772                                         331.0  2672.489876
175773                                         915.0  2664.641657
175774                                         795.0  2908.850865
175775                                         384.0  2844.587696
175776                                         134.0  2844.587696
```

```
        time_of_day  delivery_time
0       2442.118095         2820.0
1       2408.842352         2640.0
2       2781.709700         3300.0
3       3010.686701         3540.0
4       3041.410506         2760.0
…             …             …
175772  2781.709700         2580.0
175773  2781.709700         3720.0
175774  2757.554348         2760.0
175775  2544.297740         2700.0
175776  2611.963916         2220.0

[175777 rows x 17 columns]
```

###Data visualization and cleaning

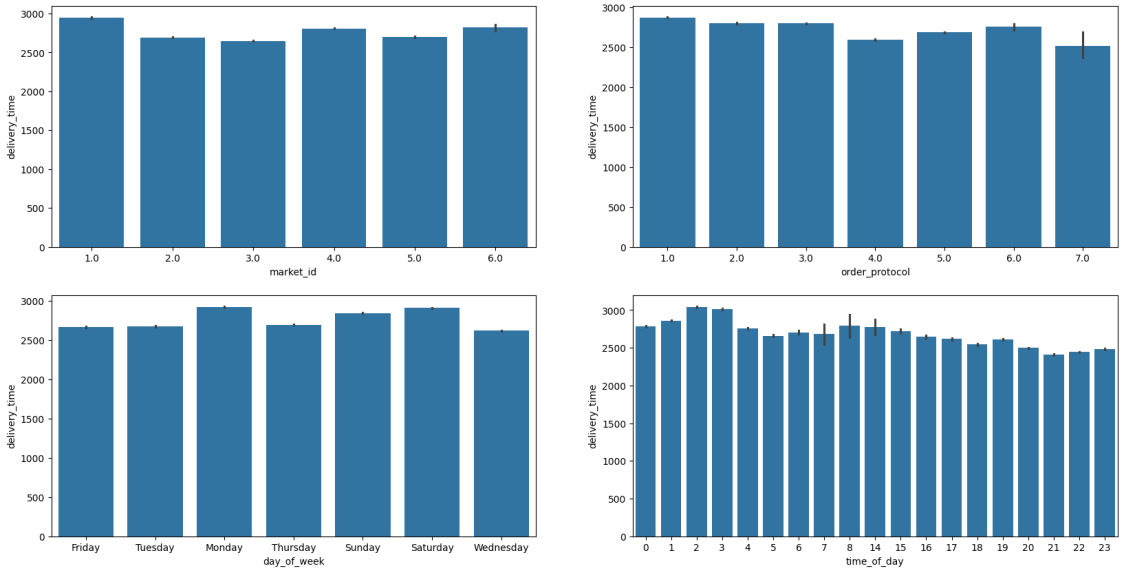
[22]:
```
data
```

[22]:
```
        market_id          created_at actual_delivery_time  \
0             1.0 2015-02-06 22:24:17  2015-02-06 23:11:17
1             2.0 2015-02-10 21:49:25  2015-02-10 22:33:25
2             2.0 2015-02-16 00:11:35  2015-02-16 01:06:35
3             1.0 2015-02-12 03:36:46  2015-02-12 04:35:46
4             1.0 2015-01-27 02:12:36  2015-01-27 02:58:36
…             …                   …                   …
175772        1.0 2015-02-17 00:19:41  2015-02-17 01:02:41
175773        1.0 2015-02-13 00:01:59  2015-02-13 01:03:59
175774        1.0 2015-01-24 04:46:08  2015-01-24 05:32:08
175775        1.0 2015-02-01 18:18:15  2015-02-01 19:03:15
175776        1.0 2015-02-08 19:24:33  2015-02-08 20:01:33

        store_primary_category  order_protocol  total_items  subtotal  \
0                            4             1.0            4      3441
1                           46             2.0            1      1900
2                           36             3.0            4      4771
3                           38             1.0            1      1525
4                           38             1.0            2      3620
…                          …               …          …       …
175772                      28             4.0            3      1389
175773                      28             4.0            6      3010
175774                      28             4.0            5      1836
175775                      58             1.0            1      1175
175776                      58             1.0            4      2605

        num_distinct_items  min_item_price  max_item_price  \
0                        4             557            1239
```

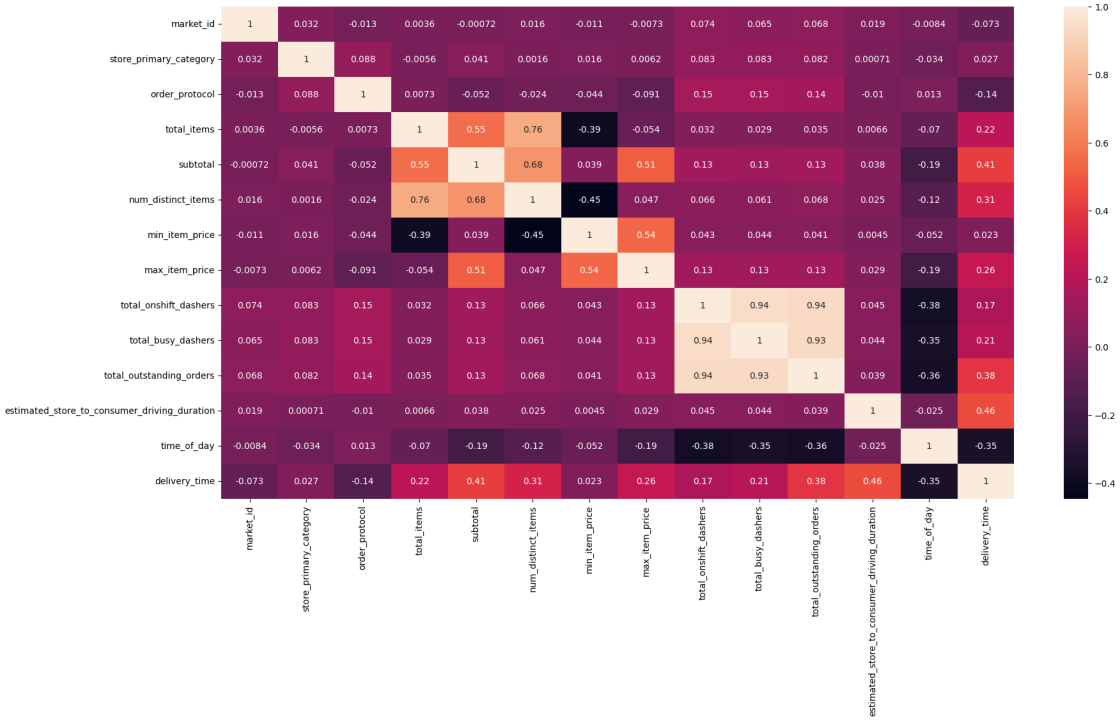
```
1                        1            1400            1400
2                        3             820            1604
3                        1            1525            1525
4                        2            1425            2195
…                      …              …               …
175772                   3             345             649
175773                   4             405             825
175774                   3             300             399
175775                   1             535             535
175776                   4             425             750

        total_onshift_dashers  total_busy_dashers  total_outstanding_orders  \
0                        33.0                14.0                      21.0
1                         1.0                 2.0                       2.0
2                         8.0                 6.0                      18.0
3                         5.0                 6.0                       8.0
4                         5.0                 5.0                       7.0
…                        …                   …                        …
175772                   17.0                17.0                      23.0
175773                   12.0                11.0                      14.0
175774                   39.0                41.0                      40.0
175775                    7.0                 7.0                      12.0
175776                   20.0                20.0                      23.0

        estimated_store_to_consumer_driving_duration day_of_week  time_of_day  \
0                                              861.0      Friday           22
1                                              690.0     Tuesday           21
2                                              289.0      Monday            0
3                                              795.0    Thursday            3
4                                              205.0     Tuesday            2
…                                              …         …              …
175772                                         331.0     Tuesday            0
175773                                         915.0      Friday            0
175774                                         795.0    Saturday            4
175775                                         384.0      Sunday           18
175776                                         134.0      Sunday           19

        delivery_time
0              2820.0
1              2640.0
2              3300.0
3              3540.0
4              2760.0
…               …
175772         2580.0
175773         3720.0
175774         2760.0
```

```
175775          2700.0
175776          2220.0

[175777 rows x 17 columns]
```

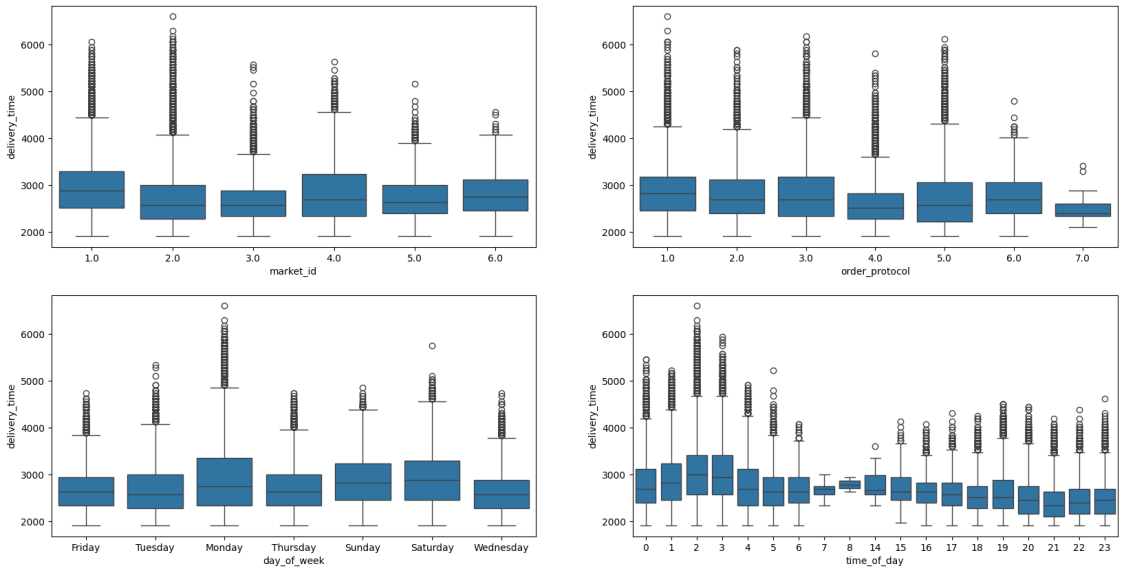
[23]:
```
#distribution of delivery time with respect to categorical variables
plt.figure(figsize=(20,10))
plt.subplot(2,2,1)
sns.barplot(data=data,x='market_id',y='delivery_time')
plt.subplot(2,2,2)
sns.barplot(data=data,x='order_protocol',y='delivery_time')
plt.subplot(2,2,3)
sns.barplot(data=data,x='day_of_week',y='delivery_time')
plt.subplot(2,2,4)
sns.barplot(data=data,x='time_of_day',y='delivery_time')
plt.show()
```



[24]:
```
#correlation between numeric variables
plt.figure(figsize=(20,10))
sns.heatmap(data.corr(numeric_only=True),annot=True)
plt.show()
```

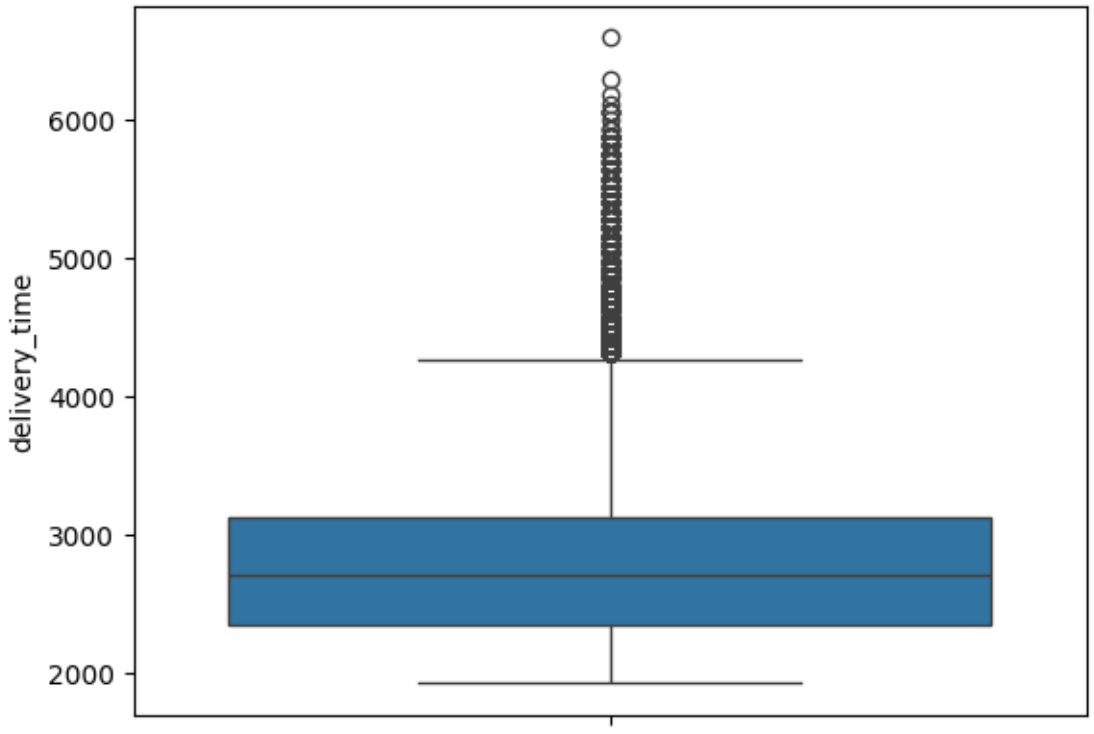


[25]:
```
#boxplot of delivery time with respect to categorical variables
plt.figure(figsize=(20,10))
plt.subplot(2,2,1)
sns.boxplot(data=data,x='market_id',y='delivery_time')
plt.subplot(2,2,2)
sns.boxplot(data=data,x='order_protocol',y='delivery_time')
plt.subplot(2,2,3)
sns.boxplot(data=data,x='day_of_week',y='delivery_time')
plt.subplot(2,2,4)
sns.boxplot(data=data,x='time_of_day',y='delivery_time')
plt.show()
```



[26]:
```
sns.boxplot(data=df,y='delivery_time')
```

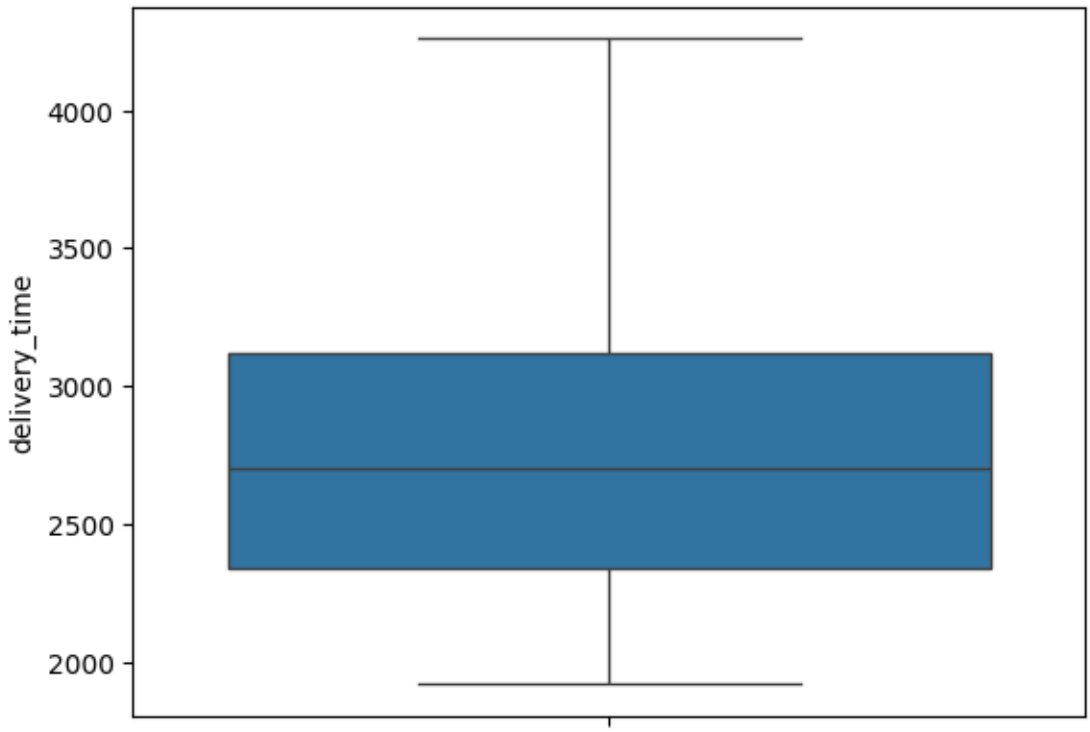
[26]: <Axes: ylabel='delivery_time'>



[27]:
```
#removing outliers using IQR method
Q1 = df['delivery_time'].quantile(0.25)
Q3 = df['delivery_time'].quantile(0.75)
IQR = Q3 - Q1
df = df[(df['delivery_time'] >= Q1 - 1.5 * IQR) & (df['delivery_time'] <= Q3 +␣
↪1.5 * IQR)]
```

[28]:
```
sns.boxplot(data=df,y='delivery_time')
```

[28]:
```
<Axes: ylabel='delivery_time'>
```



###Regression with neural networks

[29]:
```
#removing unnecessary columns
df.drop(['created_at','actual_delivery_time'],axis=1,inplace=True)
```

```
<ipython-input-29-1542807485>:2: 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
  df.drop(['created_at','actual_delivery_time'],axis=1,inplace=True)
```

[30]:
```
df
```

[30]:

	market_id	store_primary_category	order_protocol	total_items	subtotal	num_distinct_items	min_item_price	max_item_price	total_onshift_dashers	total_busy_dashers	total_outstanding_orders	estimated_store_to_consumer_driving_duration	day_of_week
0	2947.476761	2758.033328	2870.586728	4	3441	4	557	1239	33.0	14.0	21.0	861.0	2664.641657
1	2692.524266	2673.125882	2801.758736	1	1900	1	1400	1400	1.0	2.0	2.0	690.0	2672.489876
2	2692.524266	2883.443086	2798.771777	4	4771	3	820	1604	8.0	6.0	18.0	289.0	2918.748864
3	2947.476761	2946.986484	2870.586728	1	1525	1	1525	1525	5.0	6.0	8.0	795.0	2694.468650
4	2947.476761	2946.986484	2870.586728	2	3620	2	1425	2195	5.0	5.0	7.0	205.0	2672.489876
…	…	…	…	…	…	…	…	…	…	…	…	…	…
175772	2947.476761	2560.711316	2593.749275	3	1389	3	345	649	17.0	17.0	23.0		
175773	2947.476761	2560.711316	2593.749275	6	3010	4	405	825	12.0	11.0	14.0		
175774	2947.476761	2560.711316	2593.749275	5	1836	3	300	399	39.0	41.0	40.0		
175775	2947.476761	2572.709283	2870.586728	1	1175	1	535	535	7.0	7.0	12.0		
175776	2947.476761	2572.709283	2870.586728	4	2605	4	425	750	20.0	20.0	23.0		

```
…                                                …          …
175772                                           331.0  2672.489876
175773                                           915.0  2664.641657
175774                                           795.0  2908.850865
175775                                           384.0  2844.587696
175776                                           134.0  2844.587696

        time_of_day  delivery_time
0       2442.118095         2820.0
1       2408.842352         2640.0
2       2781.709700         3300.0
3       3010.686701         3540.0
4       3041.410506         2760.0
…               …              …
175772  2781.709700         2580.0
175773  2781.709700         3720.0
175774  2757.554348         2760.0
175775  2544.297740         2700.0
175776  2611.963916         2220.0

[174028 rows x 15 columns]
```

[31]:
```
X=df.drop('delivery_time',axis=1)
y=df['delivery_time']
```

[32]:
```
#standard scaling the features
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
for col in X.columns:
  X[col]=sc.fit_transform(X[[col]])
y=sc.fit_transform(y.values.reshape(-1,1))
```

[33]:
```
#train-test split
from sklearn.model_selection import train_test_split

X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.
 ↪1, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
 ↪test_size=0.1, random_state=42)

print('Train : ', X_train.shape, y_train.shape)
print('Validation:', X_val.shape, y_val.shape)
print('Test  : ', X_test.shape, y_test.shape)
```

```
Train :  (140962, 14) (140962, 1)
Validation: (15663, 14) (15663, 1)
Test  :  (17403, 14) (17403, 1)
```

[34]:
```
#importing tensorflow and keras
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
```

[37]:
```
from tensorflow.keras.layers import Dropout
```

[31]:
```
#creating a baseline model
def create_baseline():

  model = Sequential([
                    Dense(14,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                    Dense(64,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                    Dense(32,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                    Dense(1,)])
  return model
```

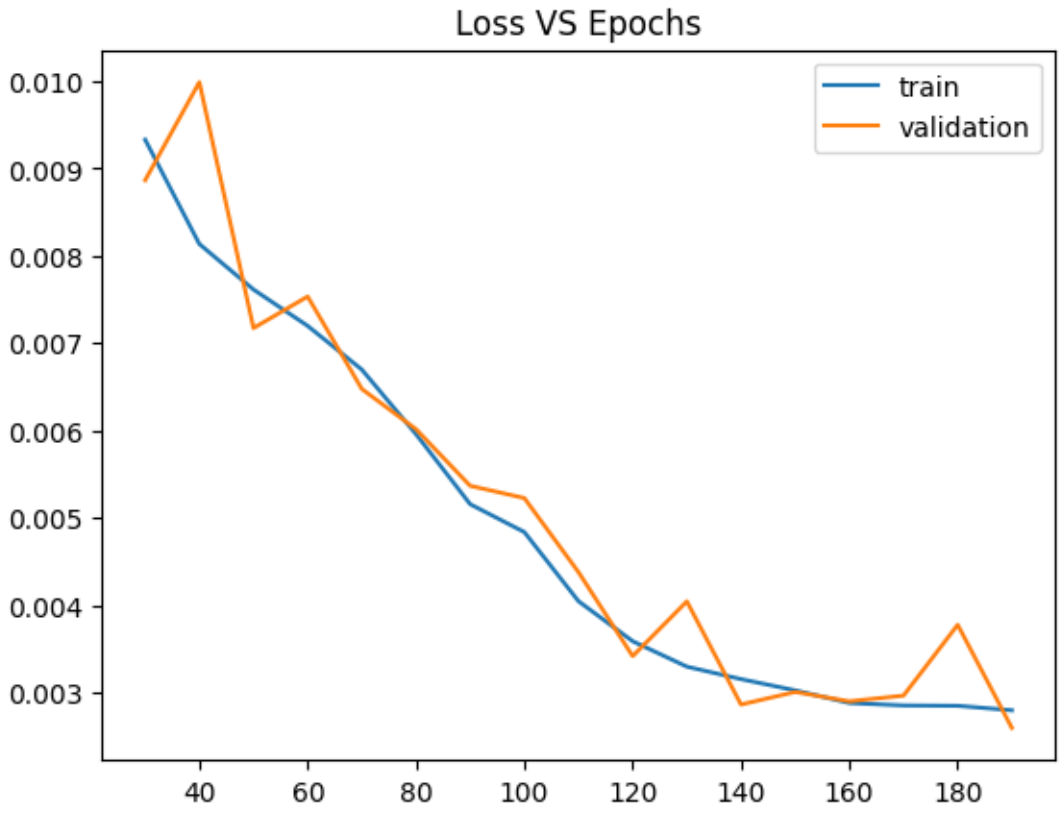
[32]:
```
model = create_baseline()
```

[33]:
```
model.compile(optimizer = tf.keras.optimizers.Adam(),loss = tf.keras.losses.MSE␣
 ↪)
```

[ ]:
```
history = model.fit(X_train, y_train, validation_data = (X_val, y_val), ␣
 ↪epochs=200, verbose = 0)
epochs = history.epoch
loss = history.history["loss"]
val_loss = history.history["val_loss"]


plt.plot(epochs, loss, label="train")
plt.plot(epochs, val_loss, label="validation")

plt.legend()
plt.title("Loss VS Epochs")

plt.show()
```

[35]:
```
epochs = history.epoch[30::10]
loss = history.history["loss"][30::10]
val_loss = history.history["val_loss"][30::10]


plt.plot(epochs, loss, label="train")
plt.plot(epochs, val_loss, label="validation")
```

```
plt.legend()
plt.title("Loss VS Epochs")

plt.show()
```



Applying LR decay

[41]:
```
from tensorflow.keras.callbacks import LearningRateScheduler
```

[42]:
```
def scheduler(epoch, lr):
  r_0 = 0.01
  lr = (1/(1+r_0*epoch))*lr

  return lr
```

[43]:
```
LRdecay = LearningRateScheduler(scheduler)
```

Applying drop out with changes in NN

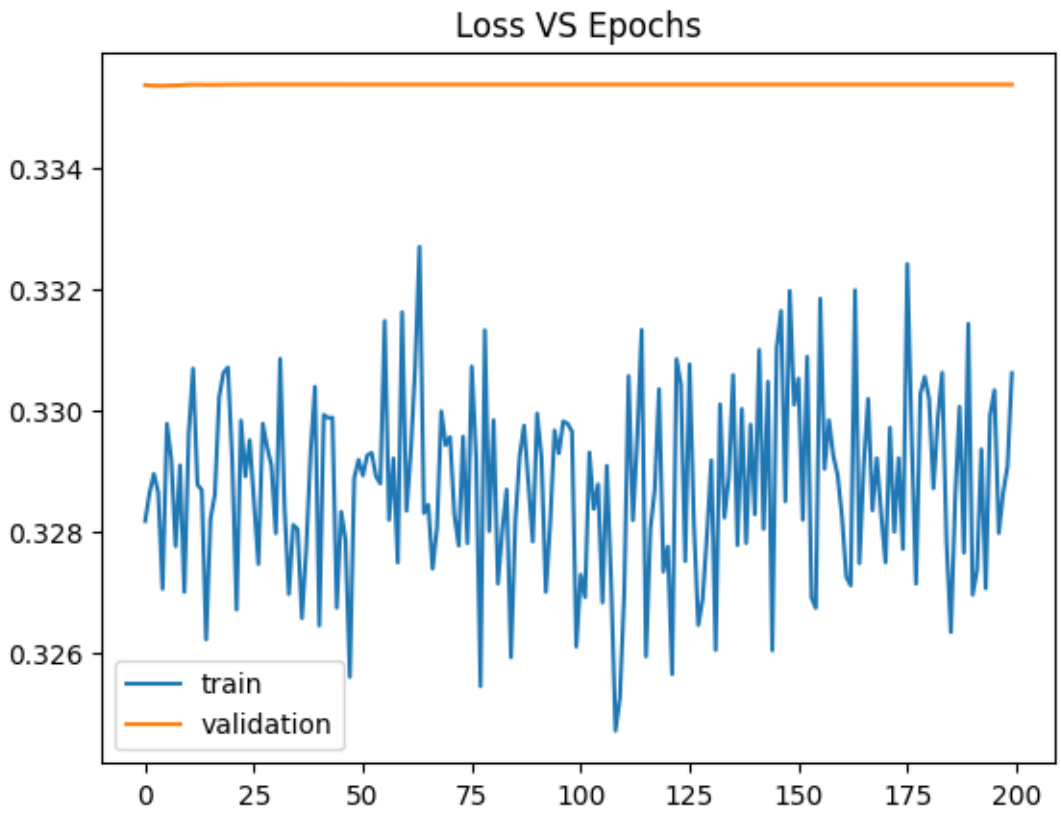
[56]:
```
def create_dropout():

  model = Sequential([
                      Dense(14,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                      Dropout(0.3),
                      Dense(64,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                      Dropout(0.3),
                      Dense(32,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                      Dropout(0.3),
                      Dense(16,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                      Dropout(0.3),
                      Dense(8,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                      Dropout(0.3),
                      Dense(4,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                      Dropout(0.3),
                      Dense(1,)])
  return model
```

[57]:
```
model = create_dropout()
```

[58]:
```
model.compile(optimizer = tf.keras.optimizers.Adam(beta_1 = 0.9, beta_2 = 0.999␣
 ↪),
                loss = tf.keras.losses.MSE,metrics = ["MAPE"])
```

[63]:
```
history = model.fit(X_train, y_train, validation_data = (X_val, y_val), ␣
 ↪epochs=200, batch_size=128,callbacks=[LRdecay], verbose = 0)
```

[64]:
```
epochs = history.epoch
loss = history.history["loss"]
val_loss = history.history["val_loss"]



plt.plot(epochs, loss, label="train")
plt.plot(epochs, val_loss, label="validation")

plt.legend()
plt.title("Loss VS Epochs")

plt.show()
```



[65]:
```
model.evaluate(X_test,y_test)
```

```
544/544              2s 3ms/step -
MAPE: 77.4895 - loss: 0.3437
```

[65]:
```
[0.3389817476272583, 76.8361587524414]
```

[35]:
```
def create_dropout2():

  model = Sequential([
                    Dense(14,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                    Dropout(0.3),
                    Dense(32,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                    Dropout(0.3),
                    Dense(16,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
                    Dropout(0.3),
                    Dense(8,␣
 ↪activation="relu",kernel_initializer='glorot_uniform'),
```

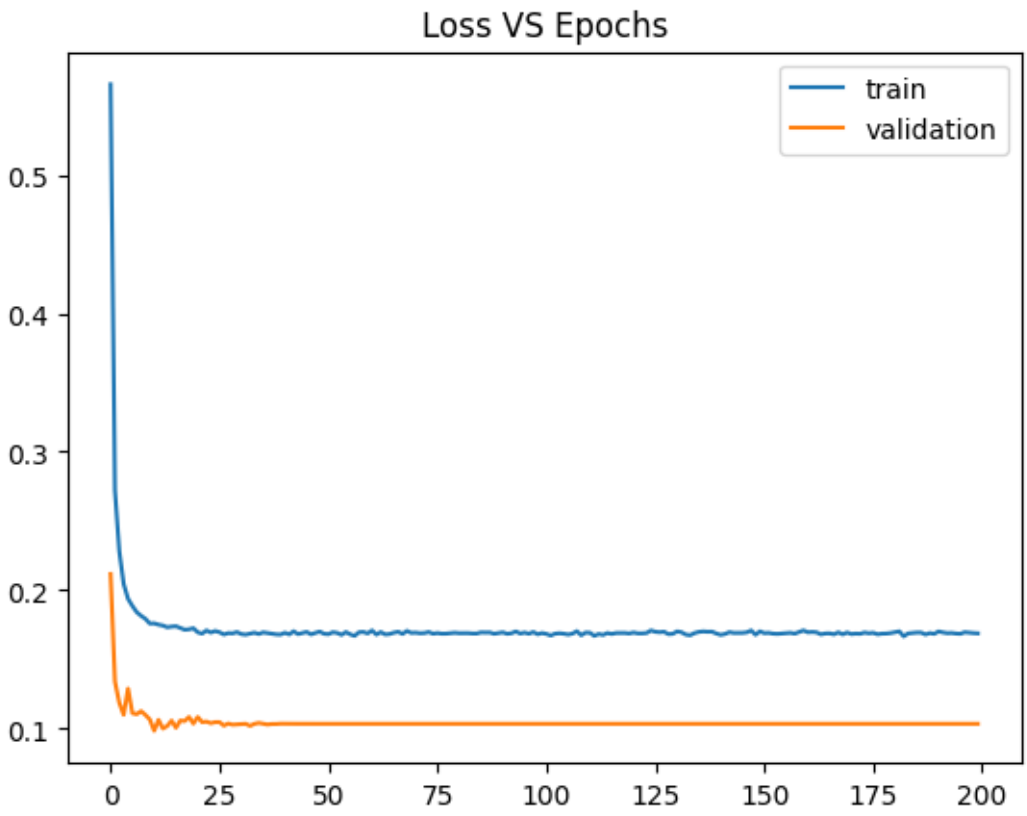
```
                    Dropout(0.3),
                    Dense(1,)])
  return model
```

[38]:
```
model = create_dropout2()
```

[39]:
```
model.compile(optimizer = tf.keras.optimizers.Adam(beta_1 = 0.9, beta_2 = 0.999␣
 ↪),
                loss = tf.keras.losses.MSE,metrics = ["MAPE"])
```

[44]:
```
history = model.fit(X_train, y_train, validation_data = (X_val, y_val), ␣
 ↪epochs=200, batch_size=128,callbacks=[LRdecay], verbose = 0)
```

[45]:
```
epochs = history.epoch
loss = history.history["loss"]
val_loss = history.history["val_loss"]



plt.plot(epochs, loss, label="train")
plt.plot(epochs, val_loss, label="validation")

plt.legend()
plt.title("Loss VS Epochs")

plt.show()
```



[46]:
```
model.evaluate(X_test,y_test)
```

```
544/544              2s 3ms/step -
MAPE: 70.0924 - loss: 0.1056
```

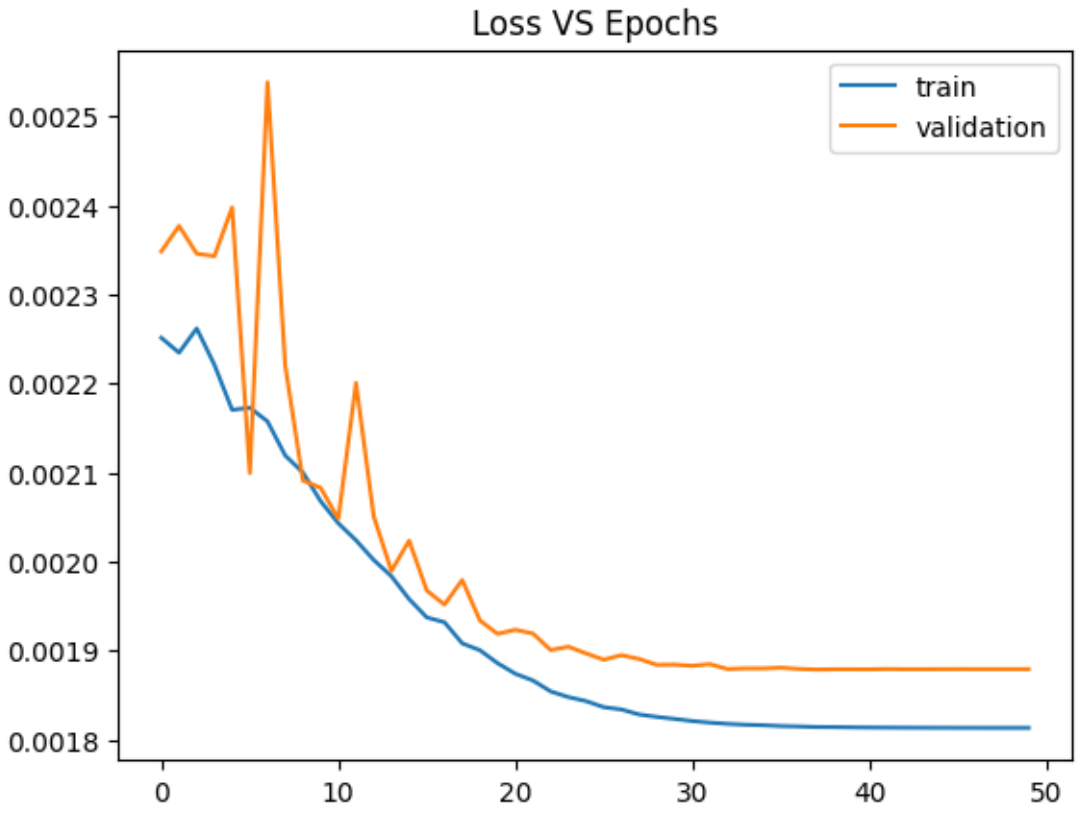
[46]:
```
[0.10365075618028641, 69.6887435913086]
```

[41]:
```
model.compile(optimizer = tf.keras.optimizers.Adam(beta_1 = 0.9, beta_2 = 0.999␣
 ↪),
                loss = tf.keras.losses.MSE,metrics = ["MAPE"])
```

[51]:
```
history = model.fit(X_train, y_train, validation_data = (X_val, y_val), ␣
 ↪epochs=50, batch_size=128,callbacks=[LRdecay], verbose = 0)
```

[52]:
```
epochs = history.epoch
loss = history.history["loss"]
val_loss = history.history["val_loss"]


plt.plot(epochs, loss, label="train")
plt.plot(epochs, val_loss, label="validation")
```

```
plt.legend()
plt.title("Loss VS Epochs")

plt.show()
```



[53]:
```
model.evaluate(X_test,y_test)
```

```
544/544             3s 5ms/step -
MAPE: 19.0628 - loss: 0.0019
```

[53]: [0.0018848837353289127, 18.70368003845215]