

21f1000886-notebook-t32023

January 7, 2024

```
[1]: # This Python 3 environment comes with many helpful analytics libraries
      ↵installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
      ↵docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list
      ↵all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that
      ↵gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved
      ↵outside of the current session
```

/kaggle/input/taxi-fare-guru-total-amount-prediction-challenge/sample.csv.csv
/kaggle/input/taxi-fare-guru-total-amount-prediction-challenge/train.csv
/kaggle/input/taxi-fare-guru-total-amount-prediction-challenge/test.csv

1 About Project

- **Name :** Taxi Fare Guru: Total Amount Prediction Challenge
- **Aim :** To build the most accurate model for predicting the `total_amount` paid by travelers for taxi rides.
- **Type :** Regression

2 Features & their significance

Columns	Significance
‘VendorID’	An identifier for taxi vendors.
‘tpep_pickup_datetime’	Timestamp indicating pickup time.
‘tpep_dropoff_datetime’	Timestamp indicating dropoff time.
‘passenger_count’	The number of passengers during the ride.
‘trip_distance’	The distance travelled during the trip.
‘RatecodeID’	Rate code for the ride (Set of rules which define how much they pay for what facilities).
‘store_and_fwd_flag’	A flag indicating whether the trip data was stored and forwarded.
‘PULocationID’	Pickup location identifier.
‘DOLocationID’	Drop off location identifier.
‘payment_type’	Payment type used for ride.
‘extra’	Extra charge for something.
‘tip_amount’	Tip amount given to vendor by passengers.
‘tolls_amount’	Amount paid on tolls during ride.
‘improvement_surcharge’	Extra amount for any kind of improvement.
‘total_amount’ (Target variable)	Total amount for ride.
‘congestion_surcharge’	Extra amount for driving a vehicle during charging hours.
‘Airport_fee’	Airport Fee.

3 Dummy Regressor - For Sample Submission

```
[2]: # Loading data
dummy_train_data = pd.read_csv("/kaggle/input/
                                ↪taxi-fare-guru-total-amount-prediction-challenge/train.csv")
dummy_test_data = pd.read_csv("/kaggle/input/
                                ↪taxi-fare-guru-total-amount-prediction-challenge/test.csv")
```

```
[3]: # Sample train data
dummy_train_data.head()
```

```
[3]: VendorID tpep_pickup_datetime tpep_dropoff_datetime passenger_count \
0 1 2023-06-28 17:20:21 2023-06-28 16:34:45 1.0
1 0 2023-06-29 23:05:01 2023-06-29 22:01:35 1.0
2 1 2023-06-30 10:19:31 2023-06-30 11:13:10 1.0
3 0 2023-06-29 13:23:09 2023-06-29 14:20:01 1.0
4 1 2023-06-29 22:03:32 2023-06-29 22:22:22 3.0

trip_distance RatecodeID store_and_fwd_flag PULocationID DOLocationID \
0 2.14 1.0 N 120 9
1 2.70 1.0 N 15 215
2 1.15 1.0 N 167 223
3 0.40 1.0 N 128 239
```

	4	1.10	1.0	N	203	52
0	Credit Card	2.5	7.165589	0.0	1.0	\
1	Credit Card	3.5	6.067401	0.0	1.0	
2	Credit Card	0.0	4.111547	0.0	1.0	
3	Credit Card	2.5	6.411079	0.0	1.0	
4	Credit Card	1.0	4.769377	0.0	1.0	
0		total_amount	congestion_surcharge	Airport_fee		
1		20.64	2.5	0.0		
2		25.55	2.5	0.0		
3		17.64	2.5	0.0		
4		12.80	2.5	0.0		
		18.00	2.5	0.0		

```
[4]: # train data columns
dummy_train_data.columns
```

```
[4]: Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount',
       'tolls_amount', 'improvement_surcharge', 'total_amount',
       'congestion_surcharge', 'Airport_fee'],
      dtype='object')
```

```
[5]: # Splitting features and target variables.
features = ['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
            'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
            'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount',
            'tolls_amount', 'improvement_surcharge',
            'congestion_surcharge', 'Airport_fee']
target = ['total_amount']
```

```
[6]: # Applying DummyRegressor Model
'''
from sklearn.dummy import DummyRegressor
dummy_rlf = DummyRegressor(strategy="mean")
dummy_rlf.fit(dummy_train_data[features], dummy_train_data[target])
dummy_prediction = dummy_rlf.predict(dummy_test_data)
'''
```

```
[6]: '\nfrom sklearn.dummy import DummyRegressor\ndummy_rlf =
DummyRegressor(strategy="mean")\ndummy_rlf.fit(dummy_train_data[features],
dummy_train_data[target])\ndummy_prediction =
dummy_rlf.predict(dummy_test_data)\n'
```

```
[7]: # Predicting and submitting
"""
dummy_len = len(dummy_prediction)
id = np.array([ i for i in range(1,dummy_len+1)])
dummy_sample = pd.DataFrame({"ID" : id, "total_amount" : dummy_prediction})
dummy_sample.to_csv("submission.csv", index=False)
#dummy_submission = pd.read_csv("/kaggle/working/submission.csv")
#dummy_submission.head()
"""

```

```
[7]: '\ndummy_len = len(dummy_prediction)\nid = np.array([ i for i in
range(1,dummy_len+1)])\ndummy_sample = pd.DataFrame({"ID" : id, "total_amount" :
dummy_prediction})\ndummy_sample.to_csv("submission.csv",
index=False)\n#dummy_submission =
pd.read_csv("/kaggle/working/submission.csv")\n#dummy_submission.head()\n'
```

4 Imports

```
[8]: import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, StandardScaler, MinMaxScaler, RobustScaler
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.model_selection import train_test_split, ShuffleSplit, cross_validate, cross_val_score, GridSearchCV, RandomizedSearchCV
from sklearn.dummy import DummyRegressor
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn import tree
from sklearn.tree import export_text
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor, GradientBoostingRegressor, AdaBoostRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import r2_score, mean_absolute_error
```

5 Used Important Functions

```
[9]: # Function 01 : For plotting Missing values
def plot_missing_values(train_data):
    """ For each column with missing values plot proportion that is missing."""
    data = [(col, train_data[col].isnull().sum() / len(train_data))]
```

```

        for col in train_data.columns if train_data[col].isnull().sum() > 0]
col_names = ['columns', 'percent_missing']
missing_data = pd.DataFrame(data, columns=col_names).
↪sort_values('percent_missing')
missing_data.plot(kind='barh', x='columns', y='percent_missing');
plt.title('Percent of missing values in columns');

# Function 02 : For applying label encoding on multiple columns.
class MultiColumnLabelEncoder:
    def __init__(self,columns = None):
        self.columns = columns

    def fit(self,X,y=None):
        return self # not relevant here

    def transform(self,X):
        """
        Transforming columns of X specified in self.columns using
        LabelEncoder(). If no columns specified, transforms all
        columns in X.
        """
        output = X.copy()
        if self.columns is not None:
            for col in self.columns:
                output[col] = LabelEncoder().fit_transform(output[col])
        else:
            for colname,col in output.iteritems():
                output[colname] = LabelEncoder().fit_transform(col)
        return output

    def fit_transform(self,X,y=None):
        return self.fit(X,y).transform(X)

# Function 03 : For plotting Actual vs Predicted
def act_vs_predict(act,pre):
    plt.scatter(act,pre,c='#BDB76B')
    plt.plot(act,act,'g-')
    plt.legend(['Predicted','Actual'])
    font1 = {'family':'serif','color':'black','size':20}
    font2 = {'family':'serif','color':'darkred','size':15}
    plt.title("Actual vs Predicted", fontdict=font1)
    plt.xlabel('Actual total_amount', fontdict=font2)
    plt.ylabel('Predicted total_amount', fontdict=font2)

# Function 04 : For determining what time of the day the ride was taken

```

```

def time_of_day(x):
    if x in range(6,12):
        return ('Morning')
    elif x in range(12,16):
        return ('Afternoon')
    elif x in range(16,22):
        return ('Evening')
    else:
        return ('Late night')

# Function 05 : For Detecting Outliers using the Inter Quantile Range(IQR)
def detect_outliers_iqr(data):
    outliers = []
    data = sorted(data)
    q1 = np.percentile(data, 25)
    q3 = np.percentile(data, 75)
    # print(q1, q3)
    IQR = q3-q1
    lwr_bound = q1-(1.5*IQR)
    upr_bound = q3+(1.5*IQR)
    # print(lwr_bound, upr_bound)
    for i in data:
        if (i<lwr_bound or i>upr_bound):
            outliers.append(i)
    return outliers# Driver code

```

6 Data Loading, Visualization and Preprocessing

sample.csv.csv : /kaggle/input/taxi-fare-guru-total-amount-prediction-challenge/sample.csv.csv
 train.csv : /kaggle/input/taxi-fare-guru-total-amount-prediction-challenge/train.csv
 test.csv : /kaggle/input/taxi-fare-guru-total-amount-prediction-challenge/test.csv

6.1 Data Loading

```
[10]: train_data = pd.read_csv("/kaggle/input/
                             ↵taxi-fare-guru-total-amount-prediction-challenge/train.csv")
test_data = pd.read_csv("/kaggle/input/
                         ↵taxi-fare-guru-total-amount-prediction-challenge/test.csv")
sample_data = pd.read_csv("/kaggle/input/
                           ↵taxi-fare-guru-total-amount-prediction-challenge/sample.csv.csv")
```

```
[11]: print("Shape of `train.csv` file :",train_data.shape)
```

Shape of `train.csv` file : (175000, 17)

```
[12]: print("Sample train data:")
train_data.head()
```

Sample train data:

```
[12]:   VendorID tpep_pickup_datetime tpep_dropoff_datetime passenger_count \
0           1 2023-06-28 17:20:21    2023-06-28 16:34:45          1.0
1           0 2023-06-29 23:05:01    2023-06-29 22:01:35          1.0
2           1 2023-06-30 10:19:31    2023-06-30 11:13:10          1.0
3           0 2023-06-29 13:23:09    2023-06-29 14:20:01          1.0
4           1 2023-06-29 22:03:32    2023-06-29 22:22:22          3.0

      trip_distance RatecodeID store_and_fwd_flag PULocationID DOLocationID \
0            2.14        1.0                 N         120             9
1            2.70        1.0                 N          15            215
2            1.15        1.0                 N         167            223
3            0.40        1.0                 N         128            239
4            1.10        1.0                 N         203            52

      payment_type extra tip_amount tolls_amount improvement_surcharge \
0  Credit Card    2.5    7.165589        0.0              1.0
1  Credit Card    3.5    6.067401        0.0              1.0
2  Credit Card    0.0    4.111547        0.0              1.0
3  Credit Card    2.5    6.411079        0.0              1.0
4  Credit Card    1.0    4.769377        0.0              1.0

      total_amount congestion_surcharge Airport_fee
0        20.64                  2.5        0.0
1        25.55                  2.5        0.0
2        17.64                  2.5        0.0
3        12.80                  2.5        0.0
4        18.00                  2.5        0.0
```

```
[13]: print("Shape of 'test.csv` file :",test_data.shape)
```

Shape of 'test.csv` file : (50000, 16)

```
[14]: print("Sample test data:")
test_data.head()
```

Sample test data:

```
[14]:   VendorID tpep_pickup_datetime tpep_dropoff_datetime passenger_count \
0           1 2023-06-29 00:21:20    2023-06-29 00:25:20          1.0
1           1 2023-06-30 17:44:43    2023-06-30 17:53:13          1.0
2           1 2023-06-29 18:17:04    2023-06-29 19:23:48          1.0
3           0 2023-06-30 21:33:53    2023-06-30 21:46:20          1.0
4           1 2023-06-29 14:53:54    2023-06-29 15:22:17          1.0
```

```

    trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID \
0           4.95          1.0                  N            20             3
1           2.10          1.0                  N             9            81
2           0.95          1.0                  N            92            90
3           0.80          1.0                  N            19           102
4           4.01          1.0                  N           131           229

    payment_type  extra  tip_amount  tolls_amount  improvement_surcharge \
0   Credit Card   1.0     6.067612          0.0              1.0
1   Credit Card   2.5     6.191269          0.0              1.0
2       Cash      2.5     3.983872          0.0              1.0
3   Credit Card   3.5     6.839341          0.0              1.0
4       Cash      0.0     1.468943          0.0              1.0

    congestion_surcharge  Airport_fee
0                  2.5          0.0
1                  2.5          0.0
2                  2.5          0.0
3                  2.5          0.0
4                  0.0          0.0

```

[15]: `print("Shape of 'sample.csv.csv' file :",sample_data.shape)`

```
Shape of 'sample.csv.csv' file : (1000, 2)
```

[16]: `print("Sample `submission.csv` file:")
sample_data.head()`

```
Sample `submission.csv` file:
```

[16]:

	ID	total_amount
0	1	24.456348
1	2	24.374058
2	3	19.878154
3	4	25.015569
4	5	22.252489

- Copying original data and storing it for future references.

[17]: `or_train_data = train_data.copy()
or_test_data = test_data.copy()`

6.2 Data Visualization & EDA-Exploratory data analysis

6.2.1 1. Overview

```
[18]: #shape
```

```
train_data.shape
```

```
[18]: (175000, 17)
```

```
[19]: #info
```

```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175000 entries, 0 to 174999
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   VendorID        175000 non-null   int64  
 1   tpep_pickup_datetime  175000 non-null   object  
 2   tpep_dropoff_datetime 175000 non-null   object  
 3   passenger_count    168923 non-null   float64 
 4   trip_distance     175000 non-null   float64 
 5   RatecodeID        168923 non-null   float64 
 6   store_and_fwd_flag 168923 non-null   object  
 7   PULocationID     175000 non-null   int64  
 8   DOLocationID     175000 non-null   int64  
 9   payment_type      175000 non-null   object  
 10  extra             175000 non-null   float64 
 11  tip_amount        175000 non-null   float64 
 12  tolls_amount      175000 non-null   float64 
 13  improvement_surcharge 175000 non-null   float64 
 14  total_amount      175000 non-null   float64 
 15  congestion_surcharge 168923 non-null   float64 
 16  Airport_fee       168923 non-null   float64 

dtypes: float64(10), int64(3), object(4)
memory usage: 22.7+ MB
```

```
[20]: # Numerical attribute statistics
```

```
train_data.describe()
```

```
VendorID  passenger_count  trip_distance  RatecodeID \
count    175000.000000    168923.000000  175000.000000  168923.000000
mean      0.728377        1.357678       5.145930     1.518307
std       0.445606        0.891283       394.971052    6.514678
min       0.000000        0.000000       0.000000     1.000000
25%      0.000000        1.000000       1.080000     1.000000
50%      1.000000        1.000000       1.840000     1.000000
75%      1.000000        1.000000       3.610000     1.000000
```

```

max           2.000000          9.000000  135182.060000      99.000000
              PULocationID    DOLocationID        extra     tip_amount \
count   175000.000000  175000.000000  175000.000000  175000.000000
mean    132.710349    132.701429    1.932143     6.127497
std     76.148799    76.192493    1.948497     4.610834
min     1.000000    1.000000    -7.500000    0.000079
25%    67.000000    67.000000    0.000000    3.473321
50%    133.000000   133.000000    1.000000    5.286217
75%    199.000000   199.000000    2.500000    7.502746
max    264.000000   264.000000   11.750000   484.876151

tolls_amount improvement_surcharge total_amount \
count   175000.000000          175000.000000  175000.000000
mean    0.646816                0.979689     29.633901
std     2.328274                0.198775     25.425206
min    -29.300000               -1.000000    -576.750000
25%    0.000000                1.000000     16.300000
50%    0.000000                1.000000     21.450000
75%    0.000000                1.000000     31.800000
max    80.000000                1.000000     587.250000

congestion_surcharge Airport_fee
count   168923.000000          168923.000000
mean    2.246971                0.158825
std     0.819216                0.511968
min    -2.500000               -1.750000
25%    2.500000                0.000000
50%    2.500000                0.000000
75%    2.500000                0.000000
max    2.500000                1.750000

```

```
[21]: # Categorical attribute statistics
train_data.describe(include='object')
```

```

[21]: tpep_pickup_datetime tpep_dropoff_datetime store_and_fwd_flag \
count           175000                  175000       168923
unique          109877                  109713         2
top            2023-06-28 18:11:16  2023-06-29 19:08:22       N
freq             8                      10      167729

payment_type
count           175000
unique            5
top            Credit Card
freq            135257

```

Observation

- There are 175000 rows (Observations) and 17 columns (variables).
- There are 10 columns having type `float64`, 3 columns having type `int64` and 4 columns having type `object`.
- Statistics for numerical attributes can be seen above.
- `store_and_fwd_flag` has two unique values. (most_frequent = 'N') i.e 'N' (No) & 'Y' (Yes)
- `payment_type` has 5 unique values. (most_frequent = 'Credit Card')

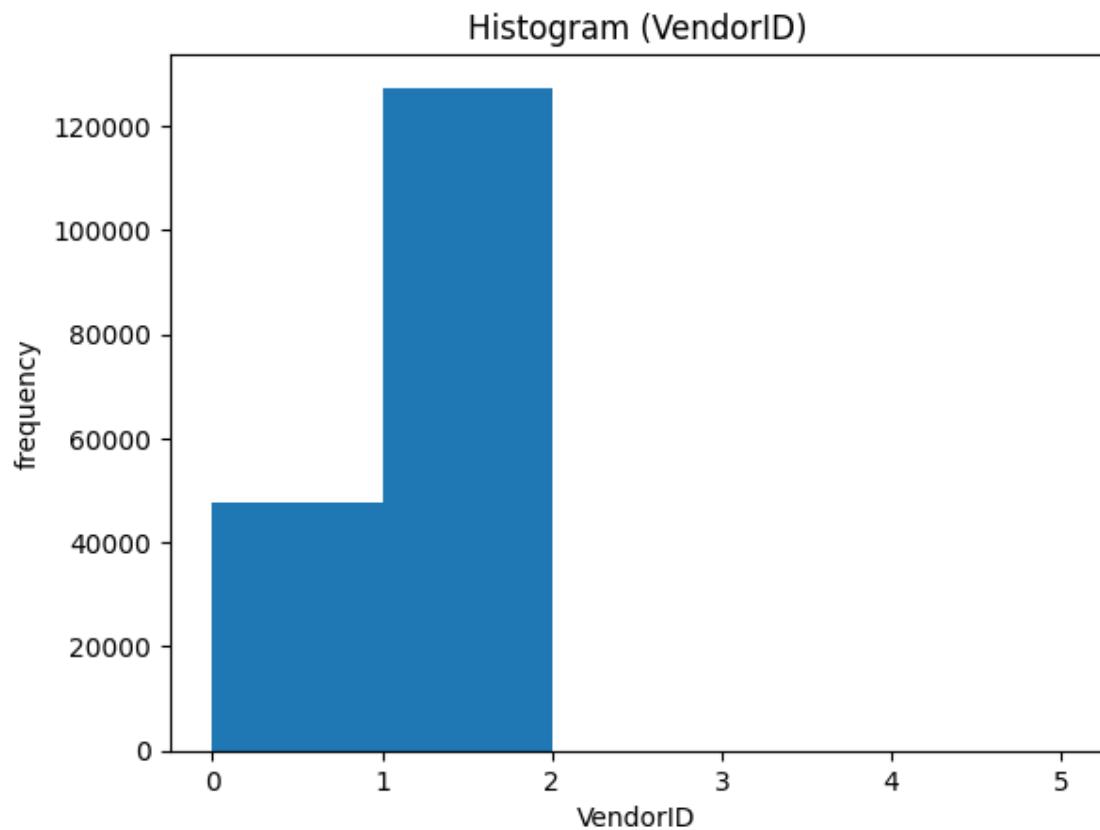
6.2.2 2. Columns/Attributes

1. VendorID

```
[22]: print("Unique values :", pd.unique(train_data['VendorID']))  
print("No. of distinct values :", len(pd.unique(train_data['VendorID'])))  
print("No. of missing values :", train_data['VendorID'].isnull().sum(),  
      ["","Percentage(%) :", (train_data['VendorID'].isnull().sum())*(100/  
      175000),"]")
```

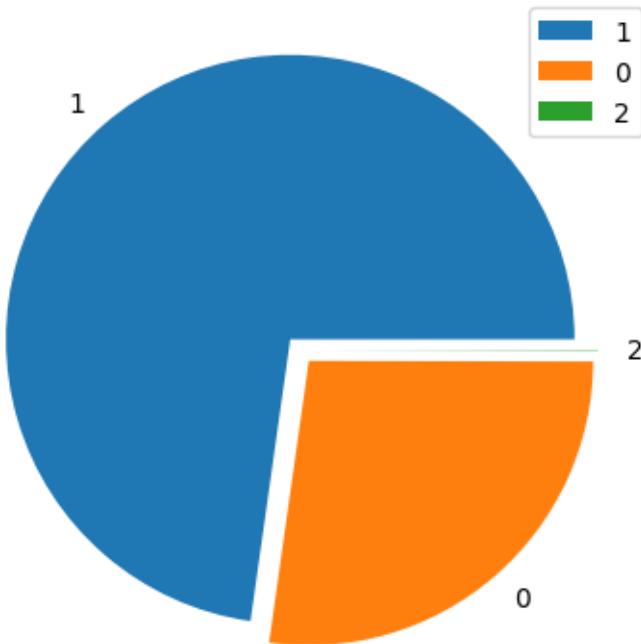
Unique values : [1 0 2]
No. of distinct values : 3
No. of missing values : 0 [Percentage(%) : 0.0]

```
[23]: plt.hist(train_data['VendorID'],bins=[0,1,2,3,4,5])  
plt.xlabel("VendorID")  
plt.ylabel("frequency")  
plt.title('Histogram (VendorID)')  
plt.show()
```



```
[24]: Unique_values = [1,0,2]
value_count = []
for i in Unique_values:
    value_count.append(train_data['VendorID'].value_counts()[i])
#print(value_count)
plt.pie(value_count,labels=Unique_values,explode=[0.05,0.05,0.05])
plt.title('Pie-chart (VendorID)')
plt.legend(Unique_values)
plt.show()
```

Pie-chart (VendorID)



Observations

- There are 3 distinct values.
- It doesn't contain any null value.
- Most frequent VendorID value is 1.

2. tpep_pickup_datetime

```
[25]: train_data['tpep_pickup_datetime'] = pd.  
       to_datetime(train_data['tpep_pickup_datetime'])
```

```
[26]: print("Maximum Value :",train_data['tpep_pickup_datetime'].max())  
      print("Minimum Value :",train_data['tpep_pickup_datetime'].min())  
      print("No. of missing values :",train_data['tpep_pickup_datetime'].isnull().  
            sum(), "[", "Percentage(%) :", (train_data['tpep_pickup_datetime'].isnull().  
            sum())*(100/175000), "]")
```

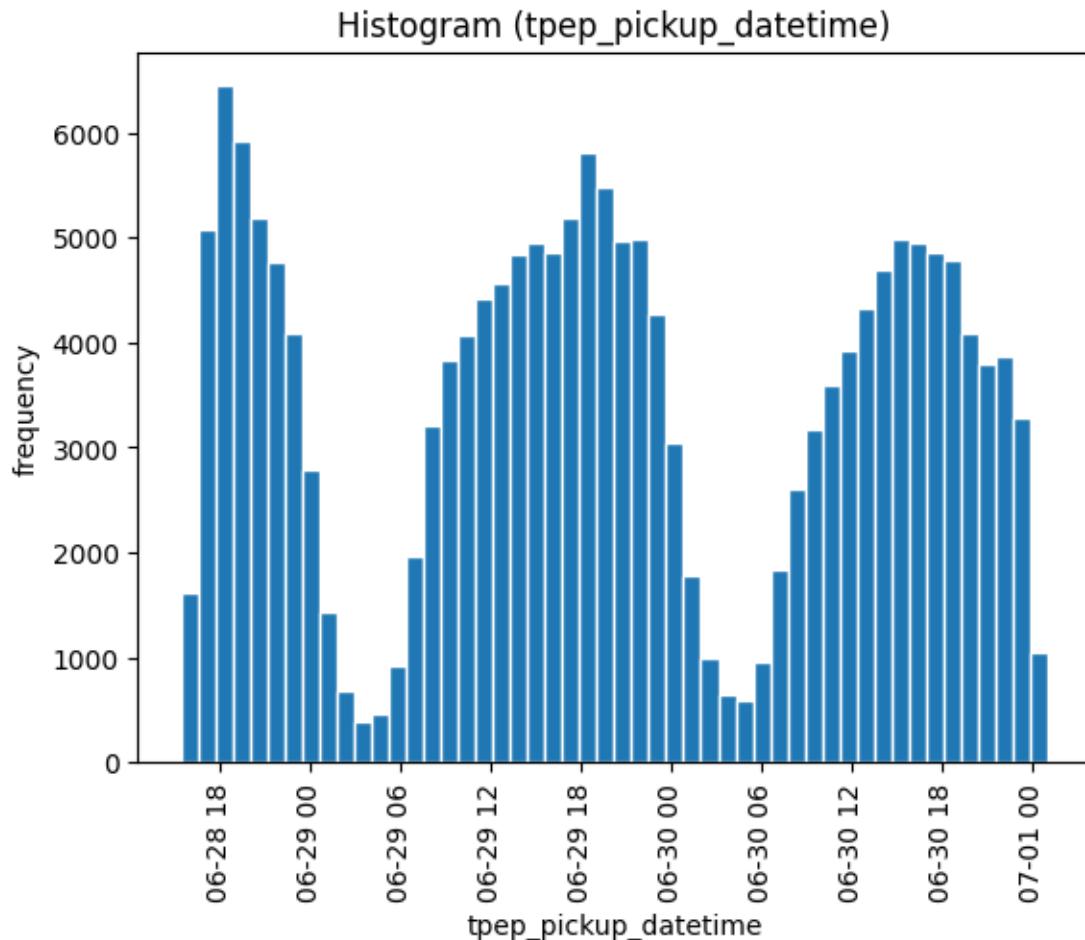
Maximum Value : 2023-07-01 00:58:11
Minimum Value : 2023-06-28 15:26:39
No. of missing values : 0 [Percentage(%) : 0.0]

```
[27]: plt.hist(train_data['tpep_pickup_datetime'],bins=50,ec='white')  
plt.xlabel("tpep_pickup_datetime")
```

```

plt.ylabel("frequency")
plt.title('Histogram (tpep_pickup_datetime)')
plt.xticks(rotation='vertical')
plt.show()

```



Observations

- There are no missing values.
- Maximum Value : 2023-07-01 00:58:11
- Minimum Value : 2023-06-28 15:26:39

3. tpep_dropoff_datetime

```
[28]: train_data['tpep_dropoff_datetime'] = pd.  
      to_datetime(train_data['tpep_dropoff_datetime'])
```

```
[29]: print("Maximum Value :",train_data['tpep_dropoff_datetime'].max())  
print("Minimum Value :",train_data['tpep_dropoff_datetime'].min())
```

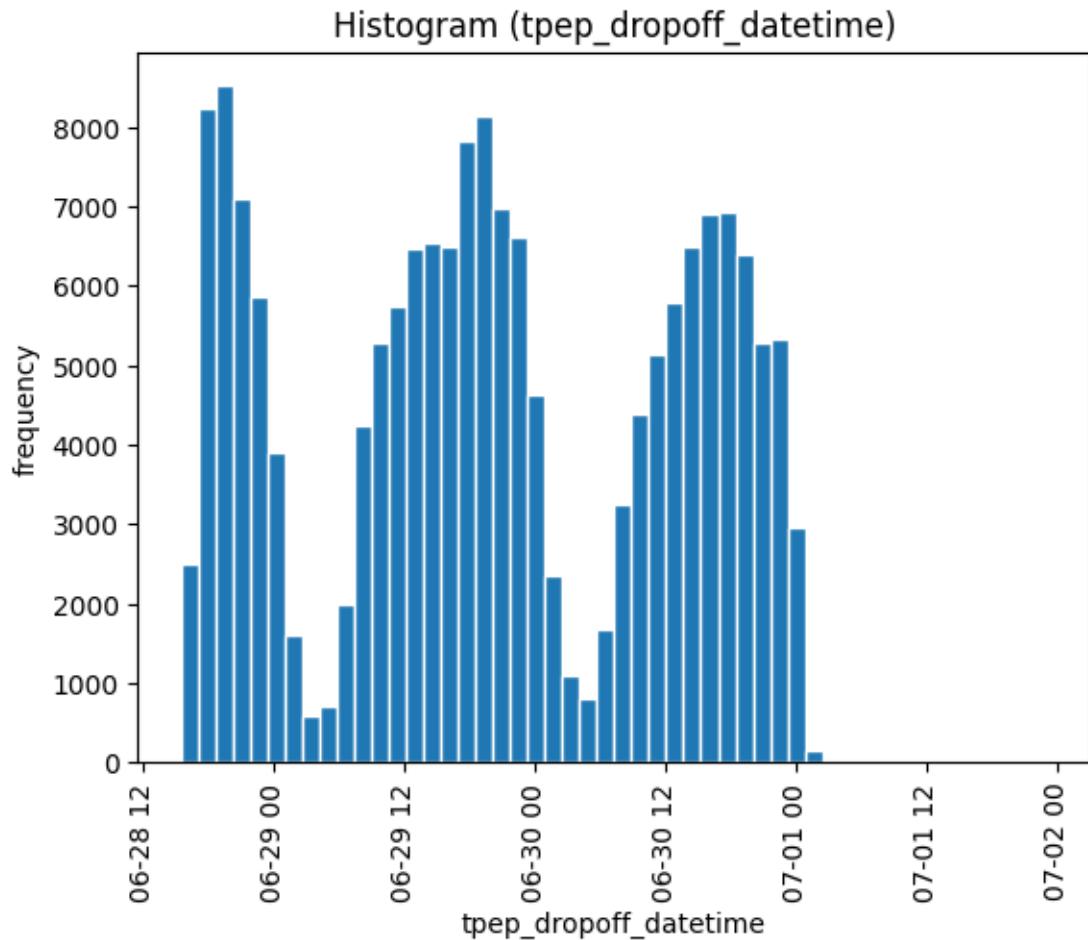
```

print("No. of missing values :",train_data['tpep_dropoff_datetime'].isnull().
    ↪sum(), "[", "Percentage(%) : ", (train_data['tpep_dropoff_datetime'].isnull().
    ↪sum())*(100/175000), "]")

```

Maximum Value : 2023-07-01 23:10:43
 Minimum Value : 2023-06-28 15:32:43
 No. of missing values : 0 [Percentage(%) : 0.0]

```
[30]: plt.hist(train_data['tpep_dropoff_datetime'],bins=50,ec='white')
plt.xlabel("tpep_dropoff_datetime")
plt.ylabel("frequency")
plt.title('Histogram (tpep_dropoff_datetime)')
plt.xticks(rotation='vertical')
plt.show()
```



Observations

- There are no missing values.

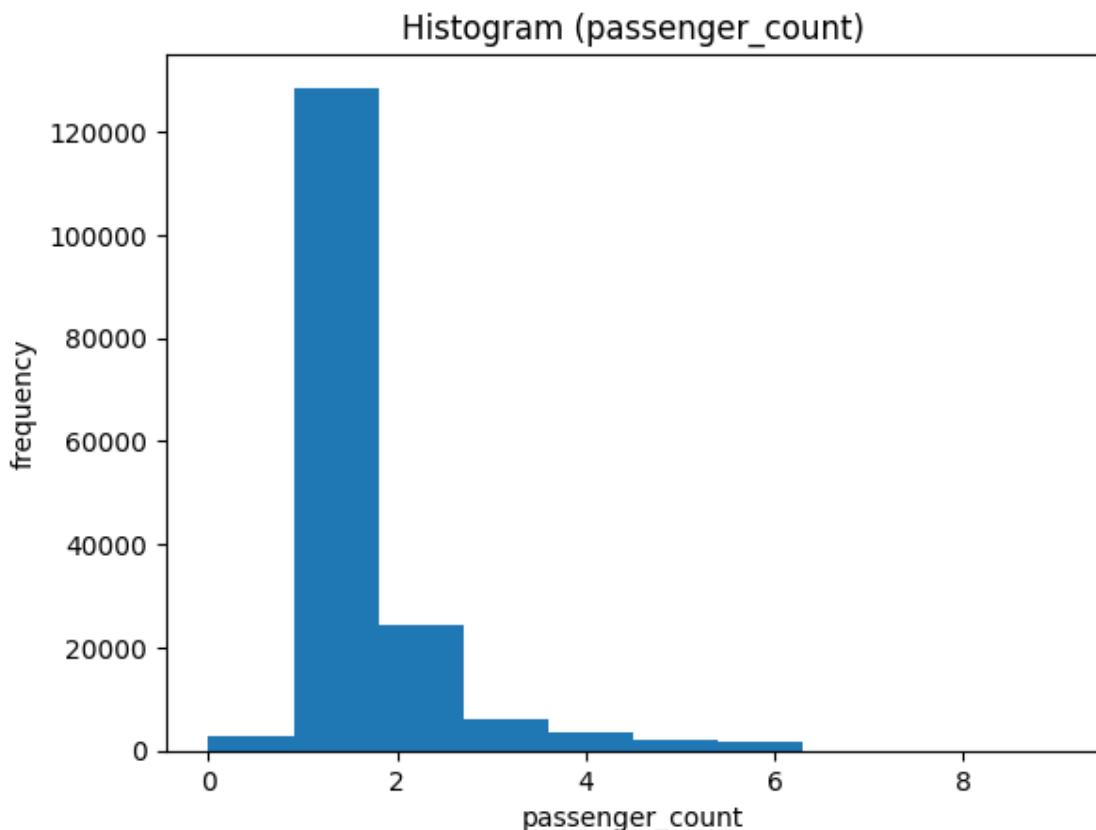
- Maximum Value : 2023-07-01 23:10:43
- Minimum Value : 2023-06-28 15:32:43

4. passenger_count

```
[31]: print("Unique values :", pd.unique(train_data['passenger_count']))
print("Value Counts :",train_data['passenger_count'].value_counts())
print("No. of distinct values :", len(pd.unique(train_data['passenger_count'])))
print("No. of missing values :",train_data['passenger_count'].isnull().sum(),u
    +" [", "Percentage(%) :", (train_data['passenger_count'].isnull().sum())*(100/
    +175000), "]")
print("No. of 0 values :
    +" ,len(train_data[train_data['passenger_count']==0]), "[", "Percentage(%) :
    +" ,len(train_data[train_data['passenger_count']==0])*(100/175000), "]")
print("No. of -ve values :
    +" ,len(train_data[train_data['passenger_count']<0]), "[", "Percentage(%) :
    +" ,len(train_data[train_data['passenger_count']<0])*(100/175000), "]")
print("Maximum Value :",train_data['passenger_count'].max())
print("Minimum Value :",train_data['passenger_count'].min())
```

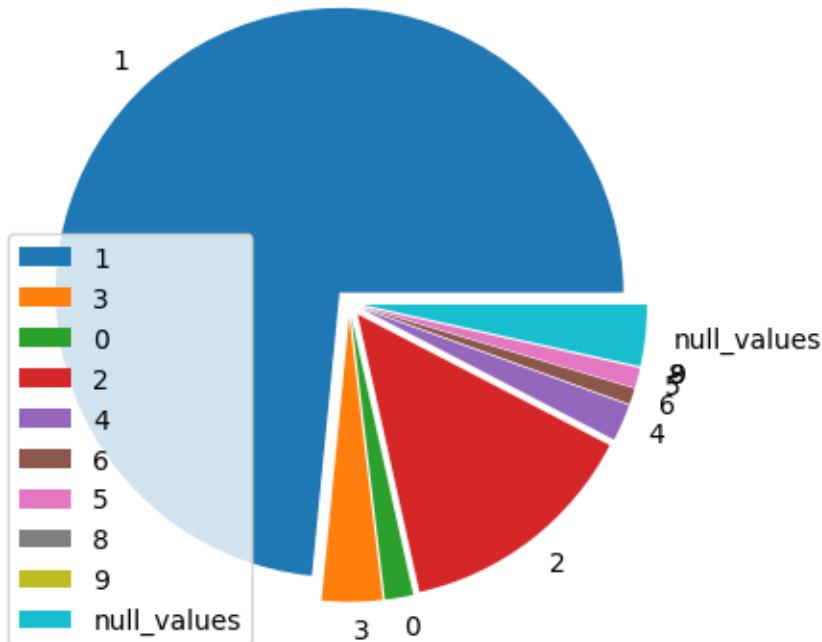
Unique values : [1. 3. 0. 2. nan 4. 6. 5. 8. 9.]
 Value Counts : passenger_count
 1.0 128534
 2.0 24316
 3.0 6018
 4.0 3668
 0.0 2818
 5.0 1970
 6.0 1596
 8.0 2
 9.0 1
 Name: count, dtype: int64
 No. of distinct values : 10
 No. of missing values : 6077 [Percentage(%) : 3.472571428571429]
 No. of 0 values : 2818 [Percentage(%) : 1.6102857142857143]
 No. of -ve values : 0 [Percentage(%) : 0.0]
 Maximum Value : 9.0
 Minimum Value : 0.0

```
[32]: plt.hist(train_data['passenger_count'])
plt.xlabel("passenger_count")
plt.ylabel("frequency")
plt.title('Histogram (passenger_count)')
plt.show()
```



```
[33]: Unique_values = [ 1,  3,  0,  2,  4,  6,  5,  8,  9]
value_count = []
for i in Unique_values:
    value_count.append(train_data['passenger_count'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(train_data['passenger_count'].isnull().sum())
#print(value_count)
plt.pie(value_count,labels=Unique_values,explode=[0.05,0.05,0.05,0.05,0.05,0.
    ↵05,0.05,0.05,0.05,0.05,])
plt.title('Pie-chart (passenger_count)')
plt.legend(Unique_values)
plt.show()
```

Pie-chart (passenger_count)



```
[34]: p_count_outliers = detect_outliers_iqr(train_data['passenger_count'])
print("Outliers :", p_count_outliers)
```

Outliers : []

Observations

- passenger_count contains 6077 missing values which is approx 3.5% of total number of values.
- passenger_count contains 2818 zero values which is approx 1.6% of total number of values.
- There are no negative values.
- There are 10 distinct values (including null values).
- Most Frequent value is 1.
- There are 2 with 8 & 1 with 9 passengers count.
- Maximum Value : 9.0
- Minimum Value : 0.0
- There is no outliers.

5. trip_distance

```
[35]: print("Unique values :", pd.unique(train_data['trip_distance']))
print("Value Counts :",train_data['trip_distance'].value_counts())
```

```

print("No. of missing values :",train_data['trip_distance'].isnull().sum(),["","Percentage(%) :", (train_data['trip_distance'].isnull().sum())*(100/175000),"]")
print("No. of 0 values :
      ,[len(train_data[train_data['trip_distance']==0]),"","Percentage(%) :",len(train_data[train_data['trip_distance']==0])*(100/175000),"]")
print("No. of -ve values :
      ,[len(train_data[train_data['trip_distance']<0]),"","Percentage(%) :",len(train_data[train_data['trip_distance']<0])*(100/175000),"]")
print("Maximum Value :",train_data['trip_distance'].max())
print("Minimum Value :",train_data['trip_distance'].min())
print("Value Counts (> 200) :",len(train_data[train_data['trip_distance']>200]))

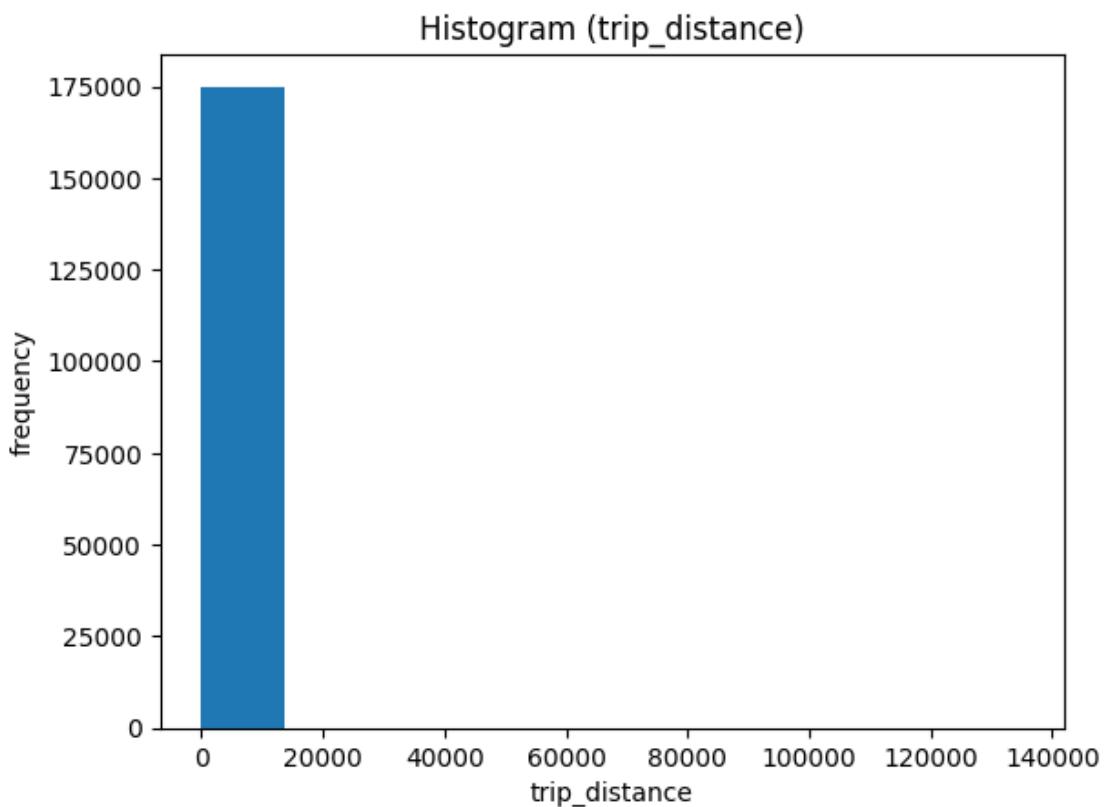
```

Unique values : [2.14 2.7 1.15 ... 22.34 26.12 15.17]
Value Counts : trip_distance

trip_distance	count
0.00	2632
1.00	2431
0.90	2383
1.20	2363
1.10	2297
..	
31.42	1
26.80	1
27.53	1
13.29	1
15.17	1

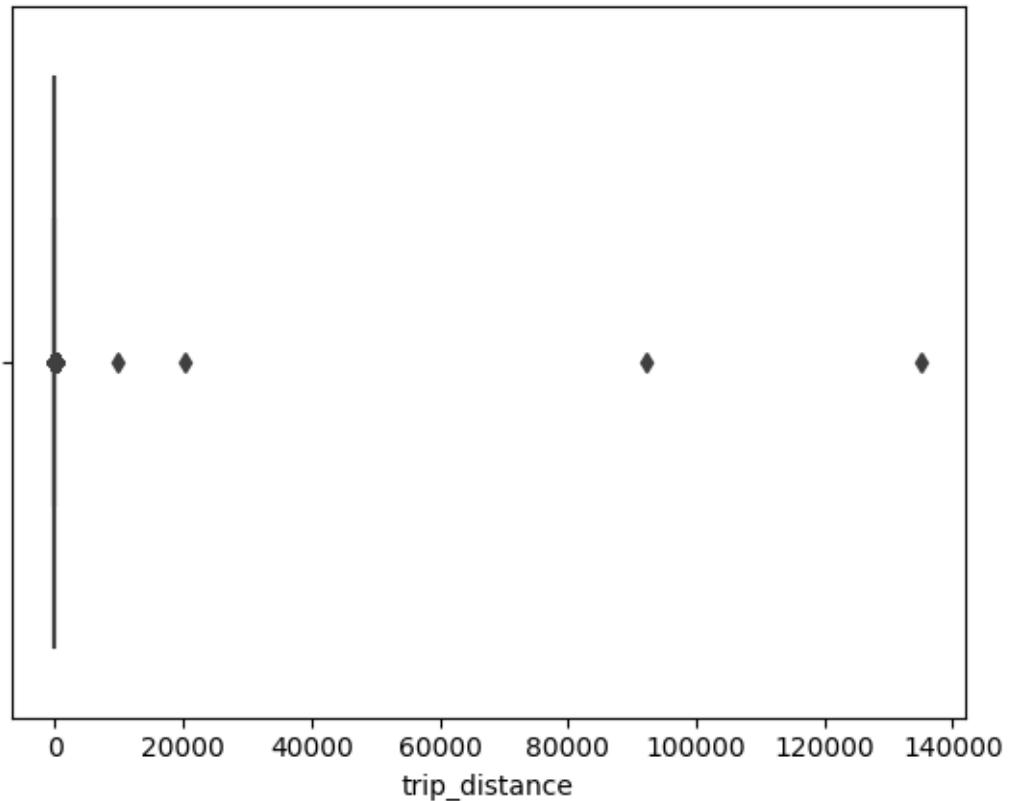
Name: count, Length: 2929, dtype: int64
No. of missing values : 0 [Percentage(%) : 0.0]
No. of 0 values : 2632 [Percentage(%) : 1.504]
No. of -ve values : 0 [Percentage(%) : 0.0]
Maximum Value : 135182.06
Minimum Value : 0.0
Value Counts (> 200) : 4

```
[36]: plt.hist(train_data['trip_distance'])
plt.xlabel("trip_distance")
plt.ylabel("frequency")
plt.title('Histogram (trip_distance)')
plt.show()
```



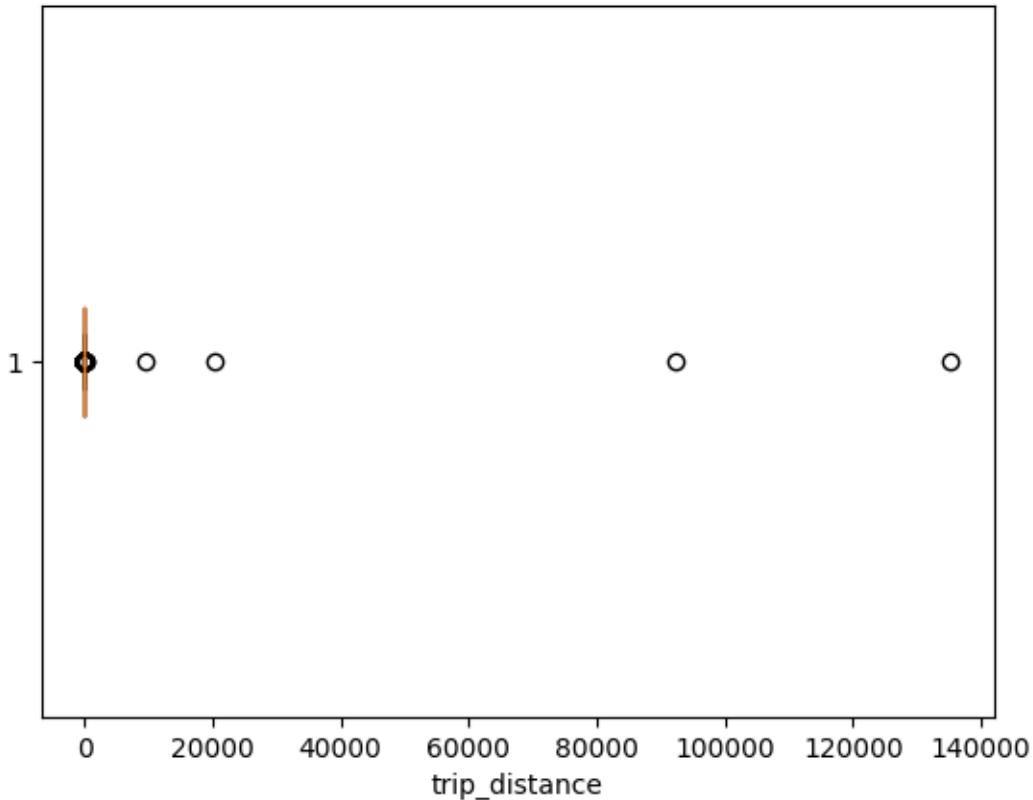
```
[37]: sns.boxplot(x='trip_distance', data=train_data)
```

```
[37]: <Axes: xlabel='trip_distance'>
```



```
[38]: plt.boxplot(train_data['trip_distance'], vert=False)
plt.title("Detecting outliers using Boxplot")
plt.xlabel('trip_distance')
plt.show()
```

Detecting outliers using Boxplot



```
[39]: sns.distplot(train_data['trip_distance'])
```

```
/tmp/ipykernel_20/1761663903.py:1: UserWarning:
```

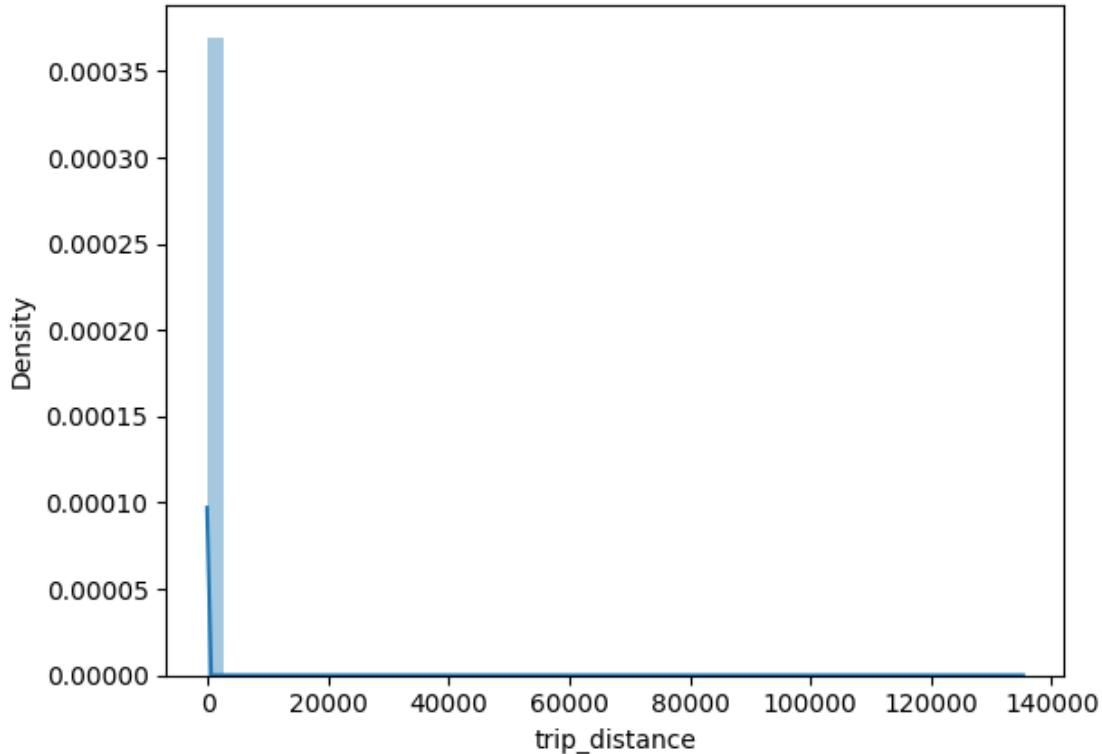
```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

```
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
```

```
For a guide to updating your code to use the new functions, please see  
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

```
sns.distplot(train_data['trip_distance'])
```

```
[39]: <Axes: xlabel='trip_distance', ylabel='Density'>
```



```
[40]: td_outliers = detect_outliers_iqr(train_data['trip_distance'])
print("Outliers Count :", len(td_outliers))
```

Outliers Count : 24133

Observations

- There are no missing values but it seems that there are 24133 outliers in it.
- `trip_distance` contains 2632 zero values which is approx 1.5% of total number of values.
- There are no negative values.
- Maximum Value : 135182.06
- Minimum Value : 0.0

6. RatecodeID

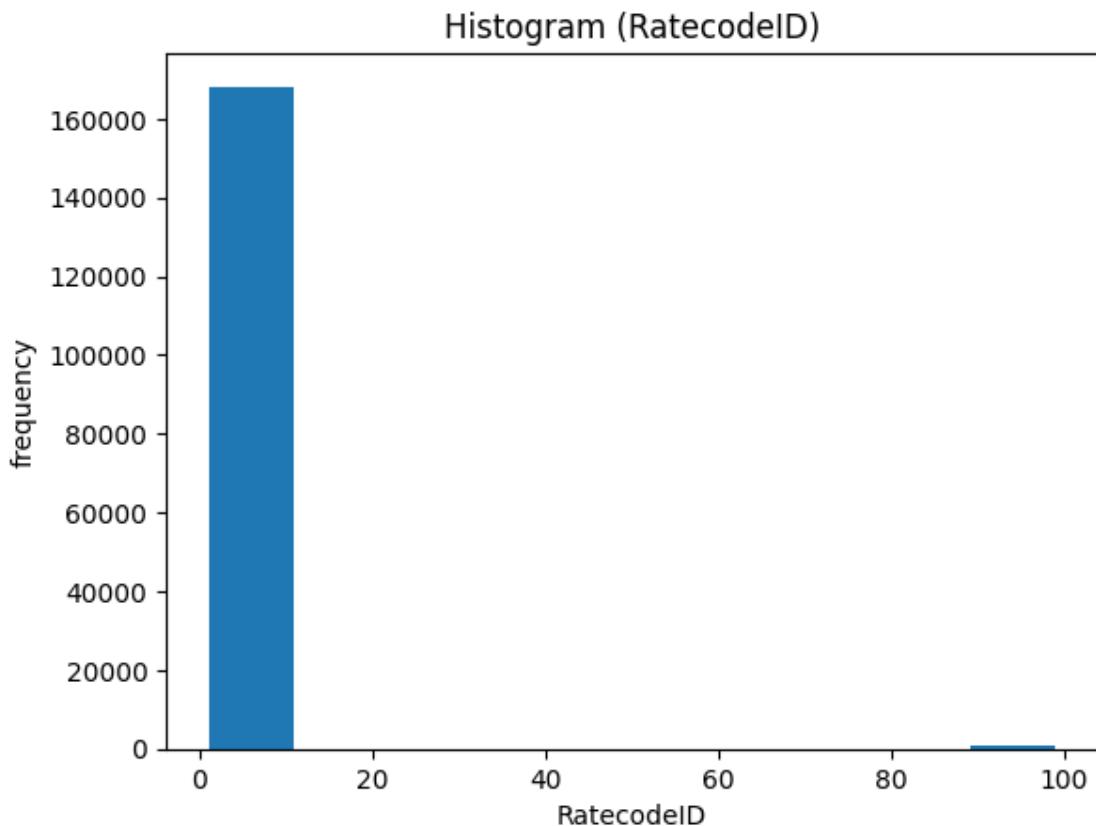
```
[41]: print("Unique values :", pd.unique(train_data['RatecodeID']))
print("No. of distinct values :", len(pd.unique(train_data['RatecodeID'])))
print("No. of missing values :", train_data['RatecodeID'].isnull().sum(), [
    " [", "Percentage(%)" : ", (train_data['RatecodeID'].isnull().sum())*(100/
    175000), "]"])
print("No. of 0 values :
    [", len(train_data[train_data['RatecodeID']==0]), " [", "Percentage(%)" : ",",
    len(train_data[train_data['RatecodeID']==0])*(100/175000), "]"])
```

```

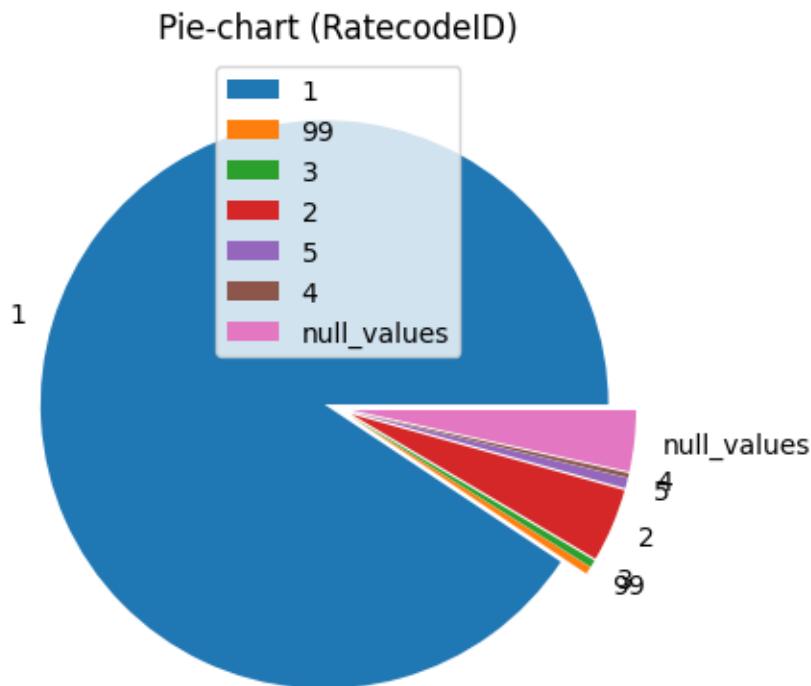
print("No. of -ve values :"
      ↵",len(train_data[train_data['RatecodeID']<0]), "[", "Percentage(%) :", ↵
      ↵len(train_data[train_data['RatecodeID']<0])*(100/175000), "]")"
print("Maximum Value :",train_data['RatecodeID'].max())
print("Minimum Value :",train_data['RatecodeID'].min())
print("Value Counts (=99) :",len(train_data[train_data['RatecodeID']==99])))
```

Unique values : [1. 99. 3. nan 2. 5. 4.]
 No. of distinct values : 7
 No. of missing values : 6077 [Percentage(%) : 3.472571428571429]
 No. of 0 values : 0 [Percentage(%) : 0.0]
 No. of -ve values : 0 [Percentage(%) : 0.0]
 Maximum Value : 99.0
 Minimum Value : 1.0
 Value Counts (=99) : 748

```
[42]: plt.hist(train_data['RatecodeID'])
plt.xlabel("RatecodeID")
plt.ylabel("frequency")
plt.title('Histogram (RatecodeID)')
plt.show()
```



```
[43]: Unique_values = [1, 99, 3, 2, 5, 4]
value_count = []
for i in Unique_values:
    value_count.append(train_data['RatecodeID'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(train_data['RatecodeID'].isnull().sum())
#print(value_count)
plt.pie(value_count, labels=Unique_values, explode=[0.05,0.05,0.05,0.05,0.05,0.05,0.05])
plt.title('Pie-chart (RatecodeID)')
plt.legend(Unique_values)
plt.show()
```



Observations

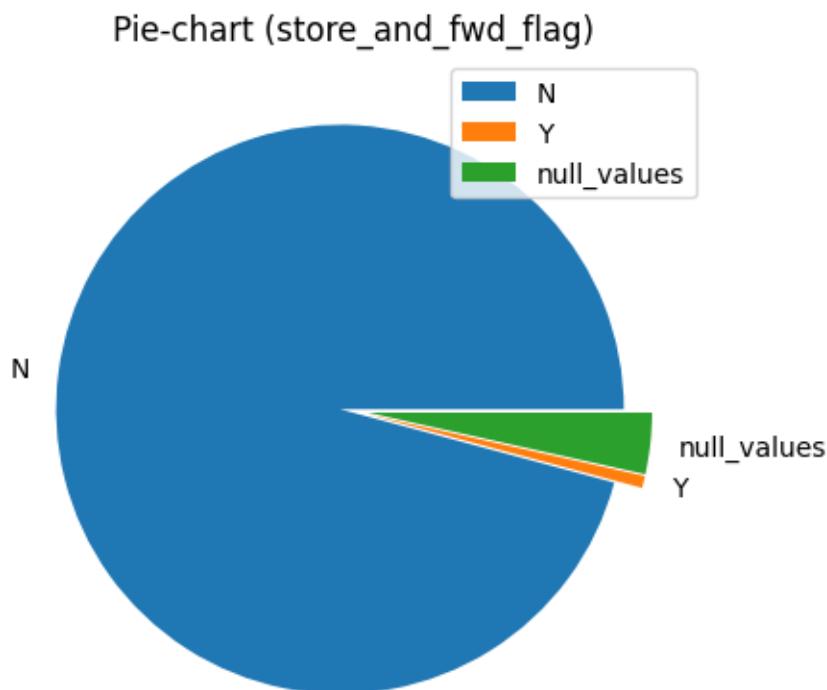
- RatecodeID contains 6077 missing values which is approx 3.5% of total number of values.
- There are no negative and zero values.
- There are 7 distinct values (including null values).
- Most Frequent value is 1.

7. store_and_fwd_flag

```
[44]: print("Unique values : ", pd.unique(train_data['store_and_fwd_flag']))
print("No. of distinct values : ", len(pd.
    ↪unique(train_data['store_and_fwd_flag'])))
print("No. of missing values : ", train_data['store_and_fwd_flag'].isnull().
    ↪sum(), "[", "Percentage(%) : ", (train_data['store_and_fwd_flag'].isnull().
    ↪sum())*(100/175000), "]")
```

Unique values : ['N' nan 'Y']
 No. of distinct values : 3
 No. of missing values : 6077 [Percentage(%) : 3.472571428571429]

```
[45]: Unique_values = ['N', 'Y']
value_count = []
for i in Unique_values:
    value_count.append(train_data['store_and_fwd_flag'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(train_data['store_and_fwd_flag'].isnull().sum())
#print(value_count)
plt.pie(value_count, labels=Unique_values, explode=[0.05, 0.05, 0.05])
plt.title('Pie-chart (store_and_fwd_flag)')
plt.legend(Unique_values)
plt.show()
```



Observations

- `store_and_fwd_flag` contains 6077 missing values which is approx 3.5% of total number of values.
- There are 3 distinct values (including null values).
- Most Frequent value is 'N'.

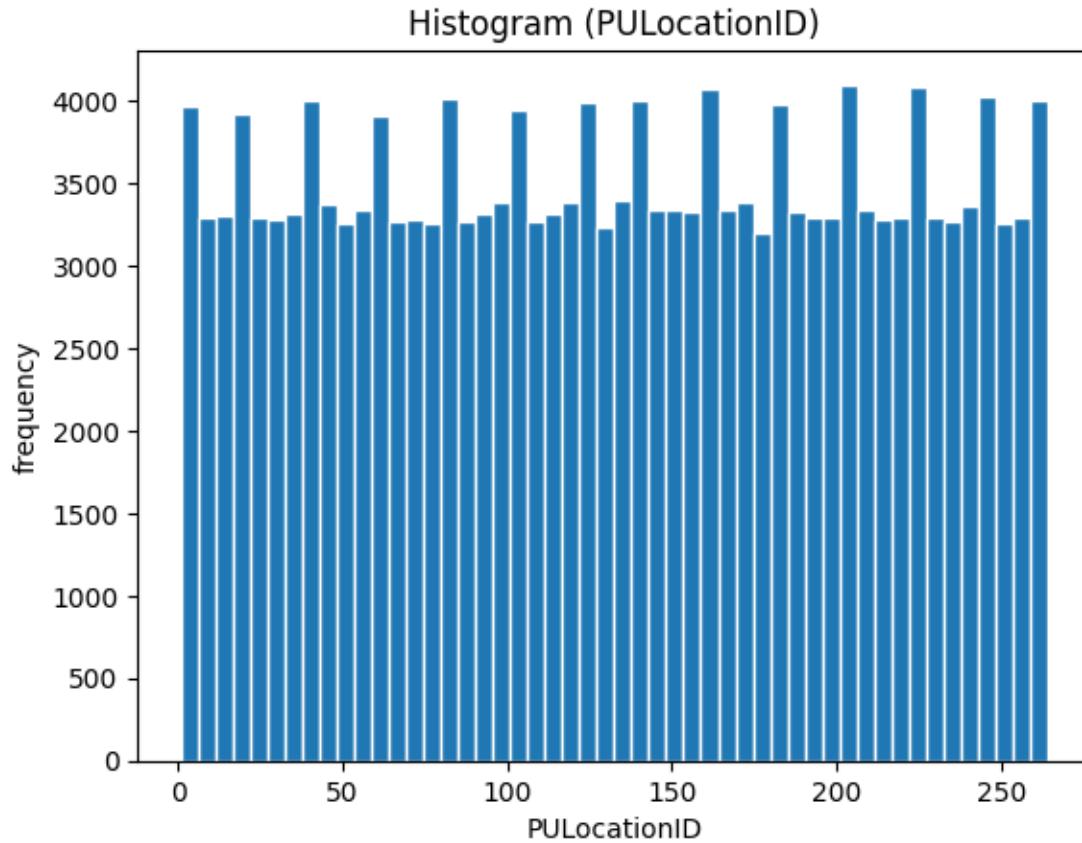
8. PULocationID

```
[46]: print("Unique values : ", pd.unique(train_data['PULocationID']))
print("No. of missing values : ", train_data['PULocationID'].isnull().sum(), [
    "[", "Percentage(%) : ", (train_data['PULocationID'].isnull().sum())*(100/175000), "]")
print("No. of 0 values :
    [", len(train_data[train_data['PULocationID']==0]), "[", "Percentage(%) : ",
    len(train_data[train_data['PULocationID']==0])*(100/175000), "]")
print("No. of -ve values :
    [", len(train_data[train_data['PULocationID']<0]), "[", "Percentage(%) : ",
    len(train_data[train_data['PULocationID']<0])*(100/175000), "]")
print("Maximum Value : ", train_data['PULocationID'].max())
print("Minimum Value : ", train_data['PULocationID'].min())
```

```
Unique values : [120 15 167 128 203 225 214 176 196 138 40 215 55 77 1 3
207 9
127 31 126 187 17 140 34 25 89 223 239 210 200 73 216 192 80 93
22 133 110 193 232 27 49 74 119 189 163 16 72 202 84 116 4 35
13 159 142 253 56 114 20 122 58 141 71 32 160 139 181 246 78 125
260 169 102 264 76 209 106 149 90 118 151 26 197 113 199 75 95 50
97 53 18 19 168 29 185 150 183 258 217 164 42 8 226 179 144 252
124 244 51 241 99 182 38 186 107 64 177 47 194 222 204 111 236 243
41 218 240 143 67 137 190 117 100 195 256 262 14 251 248 152 91 60
158 134 221 170 115 208 263 249 10 85 101 39 230 235 112 242 79 81
68 46 104 129 173 237 103 96 83 33 130 257 62 247 255 52 245 135
213 145 147 220 5 212 136 211 23 228 229 219 131 121 178 108 154 43
233 57 109 82 250 166 61 7 63 98 45 254 66 153 148 37 70 161
201 28 180 146 11 156 188 205 92 12 259 123 172 155 87 48 191 132
24 6 59 227 171 157 44 65 86 69 174 224 21 231 54 198 238 105
234 261 30 206 36 162 175 165 2 88 184 94]
No. of missing values : 0 [ Percentage(%) : 0.0 ]
No. of 0 values : 0 [ Percentage(%) : 0.0 ]
No. of -ve values : 0 [ Percentage(%) : 0.0 ]
Maximum Value : 264
Minimum Value : 1
```

```
[47]: plt.hist(train_data['PULocationID'], ec='white', bins=50)
plt.xlabel("PULocationID")
plt.ylabel("frequency")
plt.title('Histogram (PULocationID)')
```

```
plt.show()
```



Observations

- PULocationID doesn't contain any missing, zero or -ve values.
- Maximum Value : 264
- Minimum Value : 1

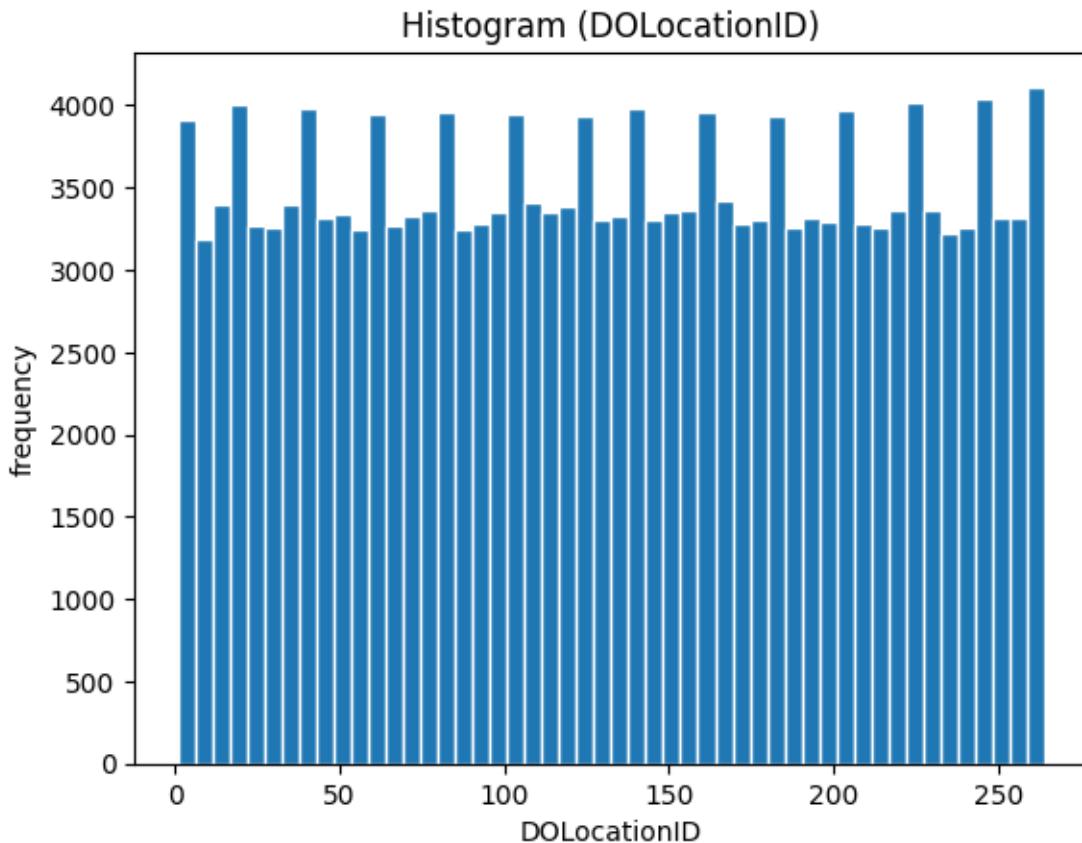
9. DOLocationID

```
[48]: print("Unique values :", pd.unique(train_data['DOLocationID']))
print("No. of missing values :",train_data['DOLocationID'].isnull().sum(),","
      ["","Percentage(%) :", (train_data['DOLocationID'].isnull().sum()*(100/
      175000)),"]")
print("No. of 0 values :
      [",len(train_data[train_data['DOLocationID']==0]),",","Percentage(%) :",,
      len(train_data[train_data['DOLocationID']==0])*(100/175000),"]")
print("No. of -ve values :
      [",len(train_data[train_data['DOLocationID']<0]),",","Percentage(%) :",,
      len(train_data[train_data['DOLocationID']<0])*(100/175000),"]")
```

```
print("Maximum Value :",train_data['DOLocationID'].max())
print("Minimum Value :",train_data['DOLocationID'].min())
```

Unique values : [9 215 223 239 52 256 240 227 139 196 153 125 64 27 181 53
40 111
37 257 151 225 36 152 224 222 47 158 203 59 21 113 220 14 254 124
97 13 182 206 148 65 248 236 221 192 241 128 147 7 263 217 68 160
185 30 106 29 218 80 232 22 184 180 229 137 150 260 242 16 15 117
70 109 183 73 48 231 159 91 189 207 11 179 255 35 23 84 154 165
50 135 243 45 247 249 104 191 112 172 43 176 108 149 102 170 136 61
34 210 230 127 5 85 264 118 92 233 2 156 208 94 107 261 100 81
33 10 134 155 93 245 119 115 89 20 163 1 173 145 175 51 237 202
262 75 19 130 204 123 169 228 200 90 238 253 79 121 72 252 258 212
74 246 178 174 162 105 17 164 197 186 86 216 4 101 26 122 54 219
63 98 44 103 38 31 18 3 157 193 28 141 209 190 116 226 166 24
142 143 66 140 250 55 42 57 138 129 96 99 168 39 194 132 46 131
171 78 244 195 214 133 77 41 177 56 120 146 114 76 110 8 6 49
211 88 25 83 82 95 12 251 205 259 58 161 32 201 235 67 62 199
69 167 187 213 234 188 60 144 71 87 198 126]
No. of missing values : 0 [Percentage(%) : 0.0]
No. of 0 values : 0 [Percentage(%) : 0.0]
No. of -ve values : 0 [Percentage(%) : 0.0]
Maximum Value : 264
Minimum Value : 1

```
[49]: plt.hist(train_data['DOLocationID'],ec='white',bins=50)
plt.xlabel("DOLocationID")
plt.ylabel("frequency")
plt.title('Histogram (DOLocationID)')
plt.show()
```



Observations

- DULocationID doesn't contain any missing, zero or -ve values.
- Maximum Value : 264
- Minimum Value : 1

10. payment_type

```
[50]: print("Unique values :", pd.unique(train_data['payment_type']))
print("Values Count :", train_data['payment_type'].value_counts())
print("No. of distinct values :", len(pd.unique(train_data['payment_type'])))
print("No. of missing values :", train_data['payment_type'].isnull().sum(), [
    " [", "Percentage(%) :", (train_data['payment_type'].isnull().sum())*(100/
    175000), "] ")
```

```
Unique values : ['Credit Card' 'Cash' 'Wallet' 'UPI' 'unknown']
Values Count : payment_type
Credit Card      135257
Cash            30141
Wallet          6077
unknown         2333
```

```

UPI           1192
Name: count, dtype: int64
No. of distinct values : 5
No. of missing values : 0 [ Percentage(%) : 0.0 ]

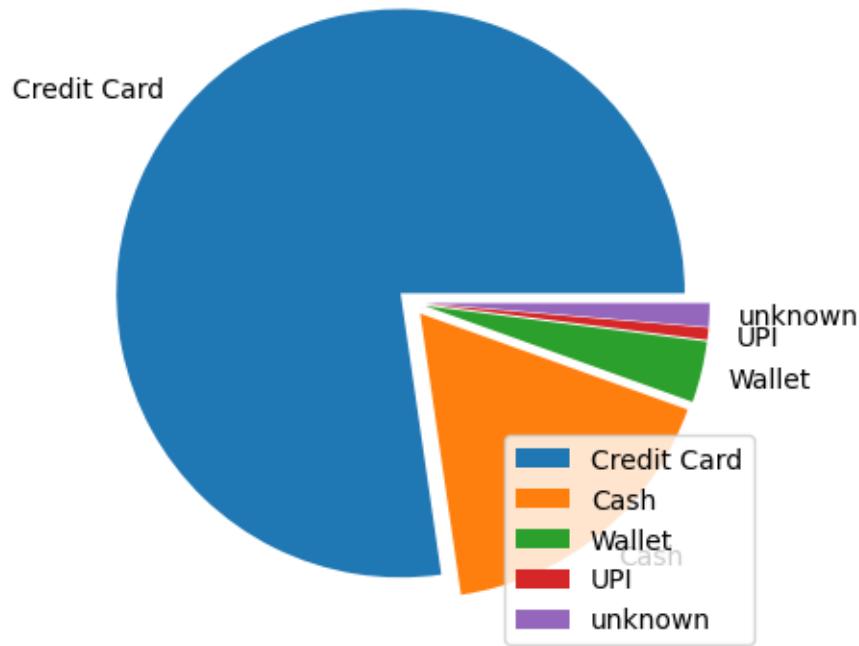
```

```

[51]: Unique_values = ['Credit Card', 'Cash', 'Wallet', 'UPI', 'unknown']
value_count = []
for i in Unique_values:
    value_count.append(train_data['payment_type'].value_counts()[i])
#Unique_values.append('null_values')
#value_count.append(train_data['store_and_fwd_flag'].isnull().sum())
#print(value_count)
plt.pie(value_count, labels=Unique_values, explode=[0.05,0.05,0.05,0.05,0.05])
plt.title('Pie-chart (payment_type)')
plt.legend(Unique_values)
plt.show()

```

Pie-chart (payment_type)



Observations

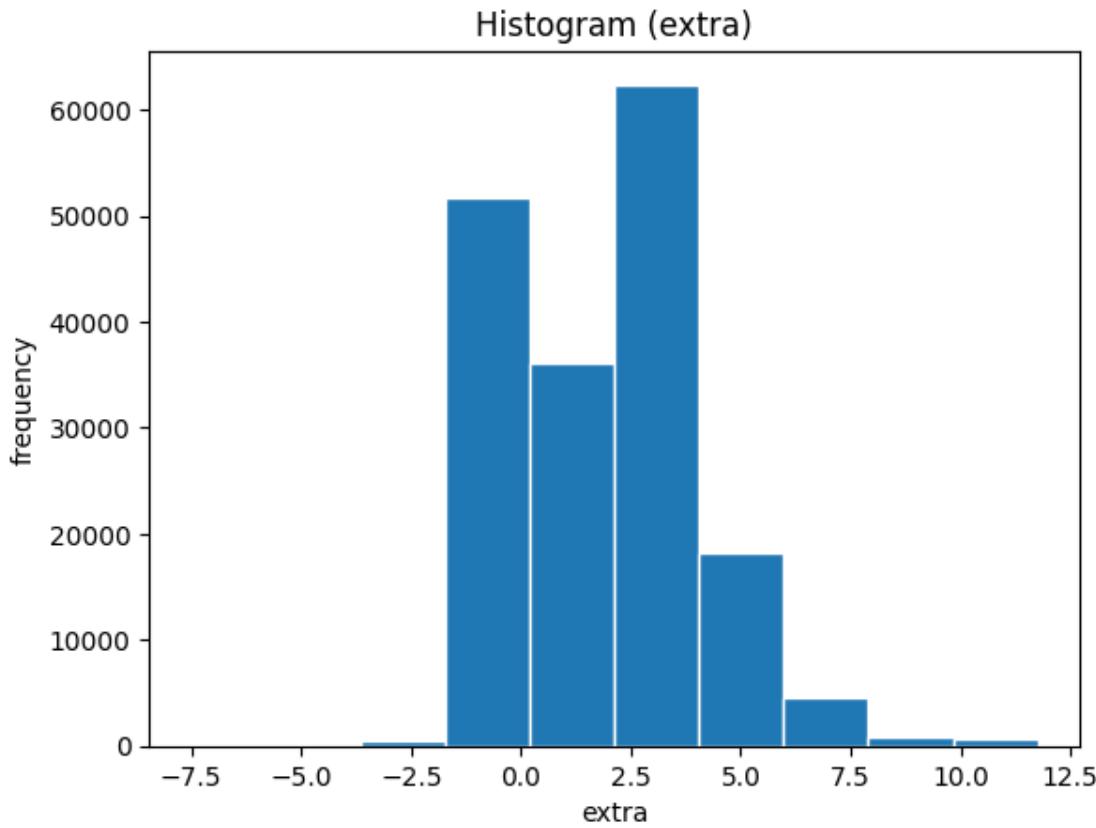
- There are no missing values.
- There are 5 distinct values which are 'Credit Card', 'Cash', 'Wallet', 'UPI', 'unknown'
- There are 2333 unknown values.

11. extra

```
[52]: print("Unique values : ", pd.unique(train_data['extra']))  
print("No. of missing values : ", train_data['extra'].isnull().sum(),  
     [" , "Percentage(%) : ", (train_data['extra'].isnull().sum())*(100/175000), "]")  
print("No. of 0 values :  
     [ , len(train_data[train_data['extra']==0]), [ , "Percentage(%) : ",  
     len(train_data[train_data['extra']==0])*(100/175000), "]")  
print("No. of -ve values :  
     [ , len(train_data[train_data['extra']<0]), [ , "Percentage(%) : ",  
     len(train_data[train_data['extra']<0])*(100/175000), "]")  
print("Maximum Value : ", train_data['extra'].max())  
print("Minimum Value : ", train_data['extra'].min())  
print("Mean Value : ", train_data['extra'].mean())
```

Unique values : [2.5 3.5 0. 1. 9.25 7.5 5. 4.25 6.75 -5. 6.
-2.5
7.75 -1. 10.25 2.75 1.75 10. 11.75 8.5 -7.5 -6. 0.25 0.11
5.25 0.75 1.5 3.25]
No. of missing values : 0 [Percentage(%) : 0.0]
No. of 0 values : 51247 [Percentage(%) : 29.284000000000002]
No. of -ve values : 1105 [Percentage(%) : 0.6314285714285715]
Maximum Value : 11.75
Minimum Value : -7.5
Mean Value : 1.9321434857142856

```
[53]: plt.hist(train_data['extra'], ec='white')  
plt.xlabel("extra")  
plt.ylabel("frequency")  
plt.title('Histogram (extra)')  
plt.show()
```



```
[54]: ex_outliers = detect_outliers_iqr(train_data['extra'])
print("Outliers Count :", len(ex_outliers))
```

Outliers Count : 4406

Observations

- extra contains no missing values.
- It has 4406 outliers.
- extra contains 51247 zero values which is approx 29.3% of total number of value.
- extra contains 1105 -ve values which is approx 0.6% of total number of value.
- Maximum Value : 11.75
- Minimum Value : -7.5
- Mean Value : 1.9321434857142856

12. tip_amount

```
[55]: print("Unique values :", pd.unique(train_data['tip_amount']))
print("Value Counts :", train_data['tip_amount'].value_counts())
```

```

print("No. of missing values :",train_data['tip_amount'].isnull().sum(),","
      ["","Percentage(%) :", (train_data['tip_amount'].isnull().sum())*(100/
      175000),"]")
print("No. of 0 values :
      [",len(train_data[train_data['tip_amount']==0]),",[", "Percentage(%) :",,
      len(train_data[train_data['tip_amount']==0])*(100/175000),"]]")
print("No. of -ve values :
      [",len(train_data[train_data['tip_amount']<0]),",[", "Percentage(%) :",,
      len(train_data[train_data['tip_amount']<0])*(100/175000),"]]")
print("Maximum Value :",train_data['tip_amount'].max())
print("Minimum Value :",train_data['tip_amount'].min())
print("Mean Value :",train_data['tip_amount'].mean())
print("Value Counts (> 180) :",len(train_data[train_data['tip_amount']>=180]))
print("Value Counts (> 400) :",len(train_data[train_data['tip_amount']>=400]))

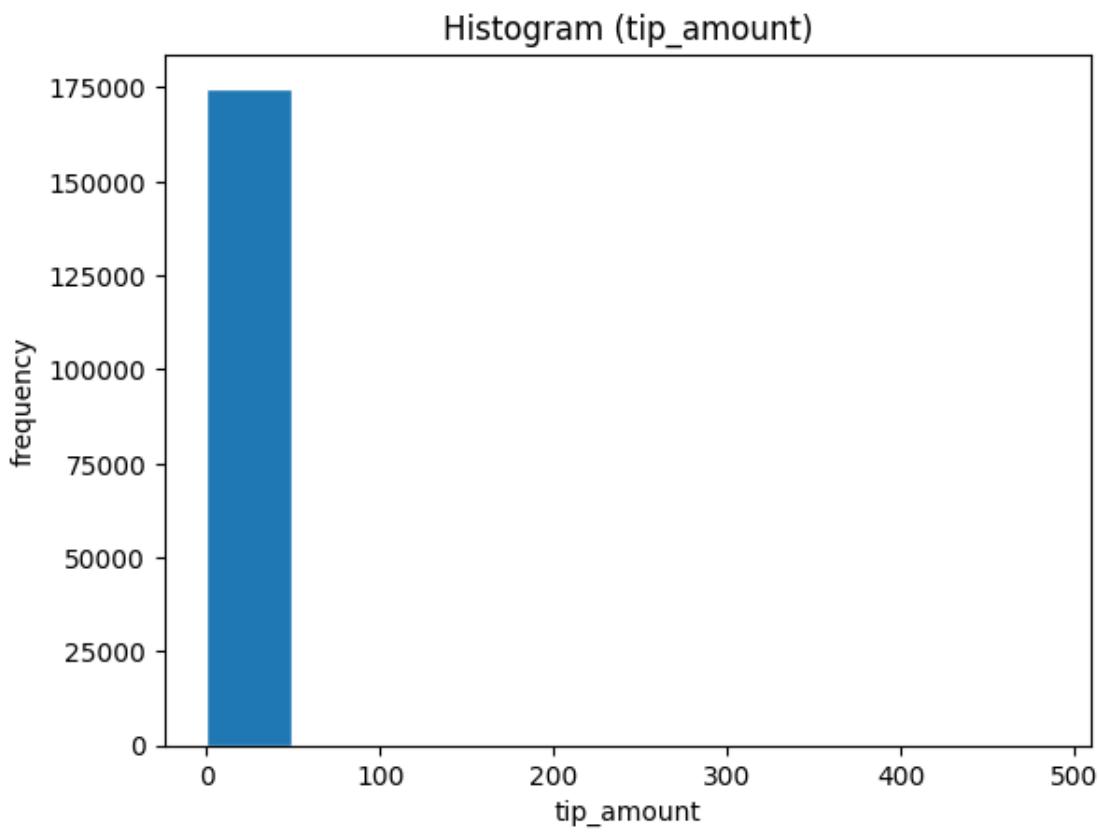
```

Unique values : [7.16558861 6.0674008 4.11154749 ... 4.24535387 10.47977632
6.54169878]
Value Counts : tip_amount

tip_amount	count
7.165589	1
3.850730	1
5.311822	1
9.137562	1
6.716744	1
..	
11.560123	1
3.256321	1
6.093614	1
1.099215	1
6.541699	1

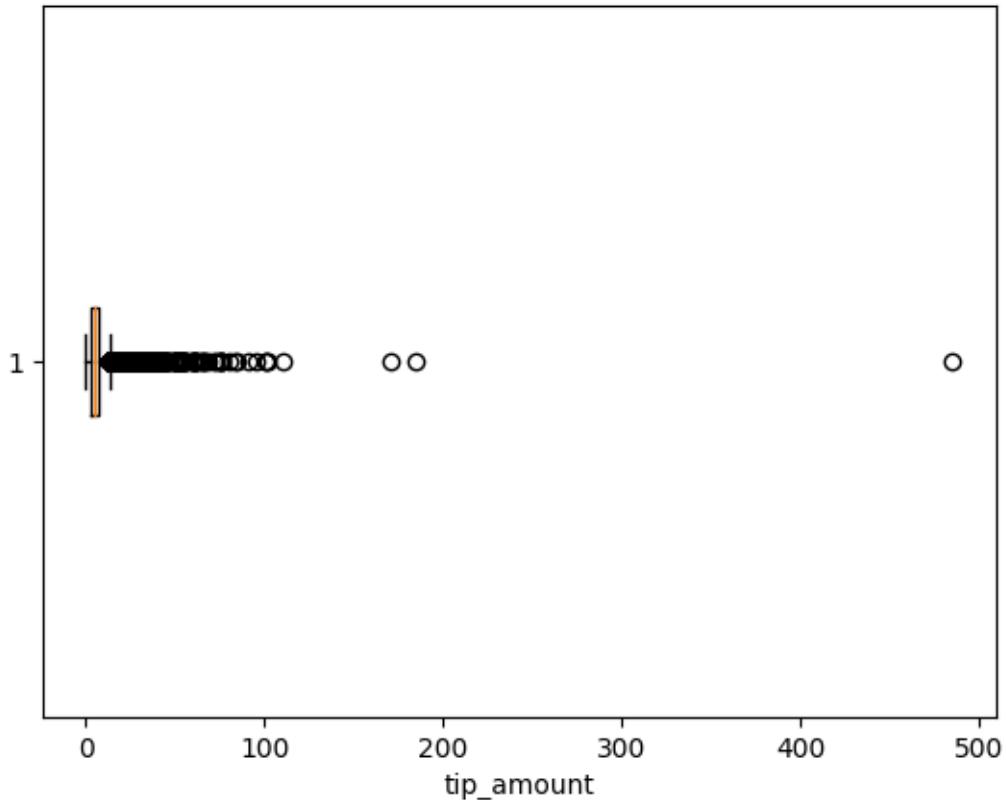
Name: count, Length: 175000, dtype: int64
No. of missing values : 0 [Percentage(%) : 0.0]
No. of 0 values : 0 [Percentage(%) : 0.0]
No. of -ve values : 0 [Percentage(%) : 0.0]
Maximum Value : 484.876150598094
Minimum Value : 7.907626361047804e-05
Mean Value : 6.127497228407633
Value Counts (> 180) : 2
Value Counts (> 400) : 1

```
[56]: plt.hist(train_data['tip_amount'],ec='white')
plt.xlabel("tip_amount")
plt.ylabel("frequency")
plt.title('Histogram (tip_amount)')
plt.show()
```



```
[57]: plt.boxplot(train_data['tip_amount'], vert=False)
plt.title("Detecting outliers using Boxplot")
plt.xlabel('tip_amount')
plt.show()
```

Detecting outliers using Boxplot



```
[58]: sns.distplot(train_data['tip_amount'])
```

```
/tmp/ipykernel_20/1792431322.py:1: UserWarning:
```

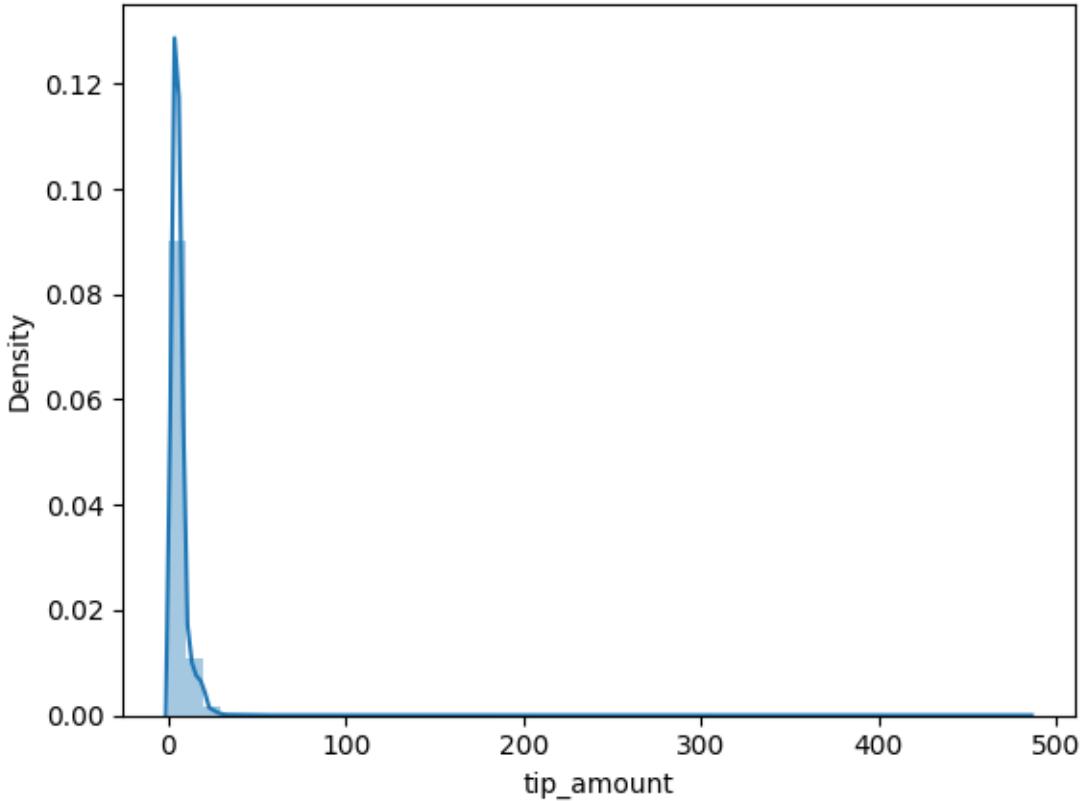
```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

```
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
```

```
For a guide to updating your code to use the new functions, please see  
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

```
sns.distplot(train_data['tip_amount'])
```

```
[58]: <Axes: xlabel='tip_amount', ylabel='Density'>
```



```
[59]: tip_outliers = detect_outliers_iqr(train_data['tip_amount'])
print("Outliers Count :", len(tip_outliers))
```

Outliers Count : 11218

Observations

- extra doesn't contain any missing, zero or -ve values.
- It has 11218 outliers.
- Maximum Value : 484.876150598094
- Minimum Value : 7.907626361047804e-05
- Mean Value : 6.127497228407633

13. tolls_amount

```
[60]: print("Unique values :", pd.unique(train_data['tolls_amount']))
print("No. of missing values :", train_data['tolls_amount'].isnull().sum(), [
    " [", "Percentage(%) :", (train_data['tolls_amount'].isnull().sum())*(100/
    175000), "] ")
print("No. of 0 values :
    [", len(train_data[train_data['tolls_amount']==0]), "[", "Percentage(%) :, "
    len(train_data[train_data['tolls_amount']==0])*(100/175000), "] ")
```

```

print("No. of -ve values :"
    ↪",len(train_data[train_data['tolls_amount']<0]),"[", "Percentage(%) :", ↪
    ↪len(train_data[train_data['tolls_amount']<0])*(100/175000),"]")"
print("Maximum Value :",train_data['tolls_amount'].max())
print("Minimum Value :",train_data['tolls_amount'].min())
print("Mean Value :",train_data['tolls_amount'].mean())

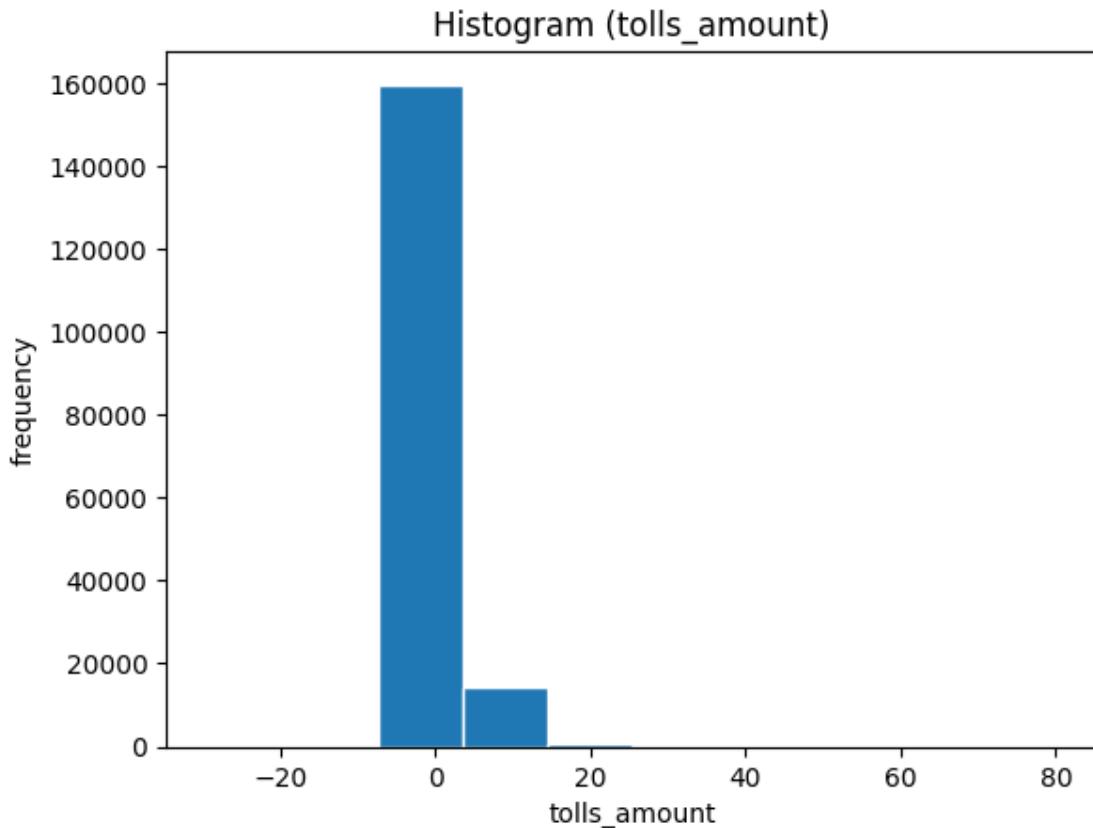
```

Unique values : [0.000e+00 6.550e+00 2.900e+01 1.275e+01 1.580e+01
-6.550e+00
2.175e+01 2.475e+01 1.930e+01 1.520e+01 1.475e+01 1.310e+01
2.450e+00 6.750e+00 3.000e+00 1.975e+01 2.025e+01 3.230e+01
1.965e+01 2.155e+01 9.550e+00 2.325e+01 3.200e+01 2.000e+01
1.675e+01 1.875e+01 1.305e+01 2.100e+01 1.550e+01 1.775e+01
2.130e+01 3.135e+01 8.550e+00 4.900e+00 1.500e+01 1.055e+01
2.075e+01 2.500e+01 1.155e+01 1.017e+01 3.585e+01 8.300e+00
9.050e+00 2.145e+01 5.300e+01 7.600e+01 1.585e+01 1.300e+01
5.000e+00 1.830e+01 2.275e+01 5.340e+00 2.011e+01 3.030e+01
2.455e+01 1.750e+00 1.375e+01 2.717e+01 2.255e+01 9.000e+00
1.855e+01 2.225e+01 1.795e+01 2.030e+01 -5.000e+00 3.053e+01
2.195e+01 8.360e+00 4.250e+00 1.575e+01 2.550e+01 -1.930e+01
2.110e+01 8.720e+00 1.650e+01 1.175e+01 2.400e+01 1.955e+01
1.000e+00 1.805e+01 2.200e+01 1.900e+01 1.970e+01 2.585e+01
1.785e+01 2.300e+01 1.780e+01 2.095e+01 2.760e+01 7.750e+00
1.765e+01 1.390e+01 8.210e+00 1.455e+01 2.125e+01 1.330e+01
2.573e+01 2.451e+01 3.000e+01 2.250e+01 2.600e+01 2.060e+01
2.000e+00 2.135e+01 7.000e+00 1.720e+01 2.050e+01 2.575e+01
1.510e+01 1.864e+01 6.300e+01 2.675e+01 2.465e+01 -2.130e+01
-8.300e+00 4.255e+01 1.700e+01 1.230e+01 -2.655e+01 -8.500e+00
2.930e+01 2.956e+01 1.825e+01 6.600e+00 3.605e+01 1.000e+01
2.330e+01 1.750e+01 1.625e+01 1.725e+01 2.950e+01 5.200e+00
1.355e+01 2.673e+01 1.050e+01 3.590e+01 2.500e+00 1.145e+01
3.205e+01 8.400e+00 -1.050e+01 2.775e+01 2.222e+01 1.925e+01
6.000e+00 2.230e+01 3.250e+01 1.810e+01 1.835e+01 1.850e+01
8.500e+00 -1.000e+01 2.630e+01 3.800e+01 2.085e+01 8.000e+01
-1.500e+01 8.460e+00 5.700e+00 1.080e+01 2.975e+01 2.340e+01
2.430e+01 1.565e+01 5.450e+00 2.020e+01 2.055e+01 -2.930e+01
1.200e+01 4.000e+00 2.985e+01 1.515e+01 4.492e+01 2.375e+01
-1.255e+01 4.725e+01 1.410e+01 1.783e+01 5.600e+01 1.030e+01
1.704e+01 2.525e+01 3.300e+01 1.615e+01 2.815e+01 1.280e+01
8.750e+00 4.200e+01 1.895e+01 1.600e+01 -8.550e+00 -1.475e+01
1.574e+01 1.311e+01 8.710e+00 2.150e+01 2.309e+01 -1.275e+01
2.264e+01 1.554e+01 -3.000e+00 4.000e+01 1.000e-02 3.825e+01
8.000e+00 4.515e+01 2.087e+01 1.915e+01 1.792e+01 2.730e+01
2.350e+01 1.405e+01 1.695e+01 1.499e+01]

No. of missing values : 0 [Percentage(%) : 0.0]
No. of 0 values : 159328 [Percentage(%) : 91.04457142857143]
No. of -ve values : 126 [Percentage(%) : 0.0720000000000001]

```
Maximum Value : 80.0
Minimum Value : -29.3
Mean Value : 0.6468162857142857
```

```
[61]: plt.hist(train_data['tolls_amount'], ec='white')
plt.xlabel("tolls_amount")
plt.ylabel("frequency")
plt.title('Histogram (tolls_amount)')
plt.show()
```



```
[62]: toll_outliers = detect_outliers_iqr(train_data['tolls_amount'])
print("Outliers Count :", len(toll_outliers))
```

```
Outliers Count : 15672
```

Observations

- `tolls_amount` contains no missing values.
- It has 15672 outliers.
- `tolls_amount` contains 159328 zero values which is approx 91.0% of total number of value.
- `tolls_amount` contains 126 -ve values which is approx 0.1% of total number of value.

- Maximum Value : 80.0
- Minimum Value : -29.3
- Mean Value : 0.6468162857142857

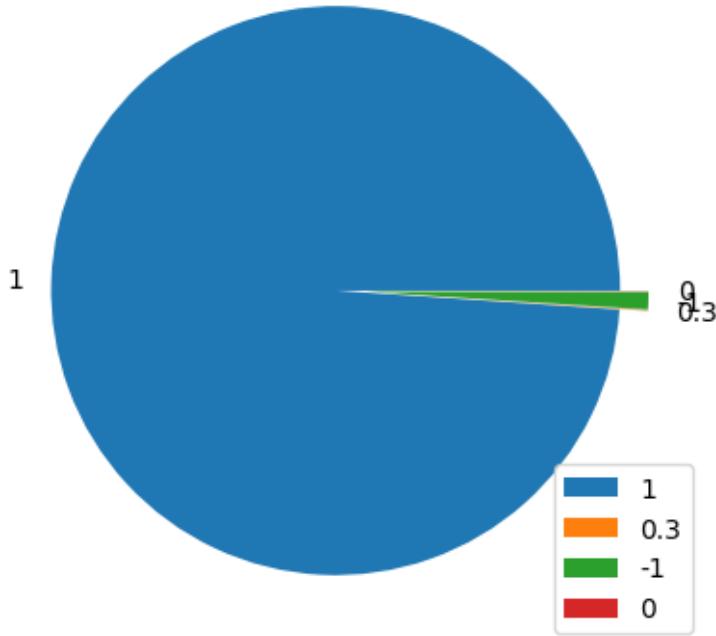
14. improvement_surcharge

```
[63]: print("Unique values :", pd.unique(train_data['improvement_surcharge']))
print("No. of distinct values :", len(pd.
    ↪unique(train_data['improvement_surcharge'])))
print("No. of missing values :", train_data['improvement_surcharge'].isnull().
    ↪sum(), "[", "Percentage(%) :", (train_data['improvement_surcharge'].isnull().
    ↪sum())*(100/175000), "]")
```

Unique values : [1. 0.3 -1. 0.]
 No. of distinct values : 4
 No. of missing values : 0 [Percentage(%) : 0.0]

```
[64]: Unique_values = [1, 0.3, -1, 0]
value_count = []
for i in Unique_values:
    value_count.append(train_data['improvement_surcharge'].value_counts()[i])
#Unique_values.append('null_values')
#value_count.append(train_data['store_and_fwd_flag'].isnull().sum())
#print(value_count)
plt.pie(value_count, labels=Unique_values, explode=[0.05,0.05,0.05,0.05])
plt.title('Pie-chart (improvement_surcharge)')
plt.legend(Unique_values)
plt.show()
```

Pie-chart (improvement_surcharge)



Observations

- There are no missing values.
- There are 4 distinct values.
- Most Frequent is 1.

15. total_amount (Target variable)

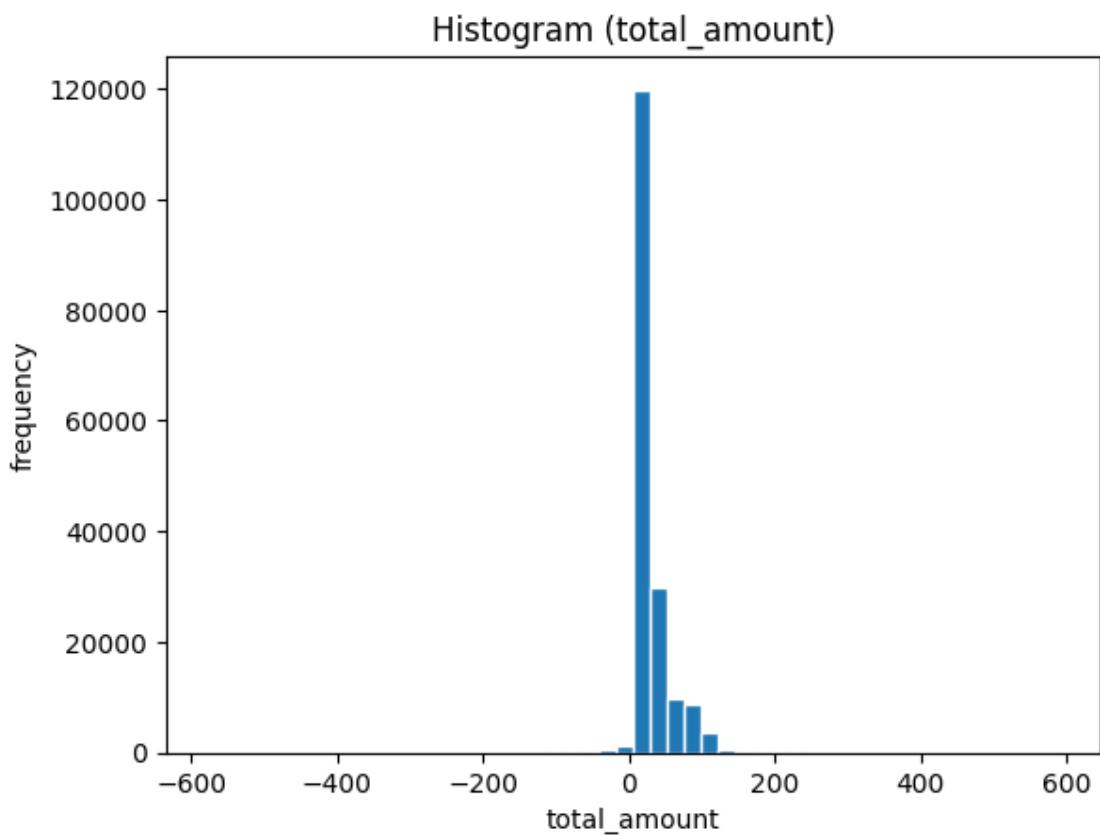
```
[65]: print("No. of missing values :",train_data['total_amount'].isnull().sum(),  
      ["","Percentage(%) :", (train_data['total_amount'].isnull().sum())*(100/  
      175000),"]")  
print("No. of 0 values :  
      ",len(train_data[train_data['total_amount']==0]),["","Percentage(%) :",  
      len(train_data[train_data['total_amount']==0])*(100/175000),"]")  
print("No. of -ve values :  
      ",len(train_data[train_data['total_amount']<0]),["","Percentage(%) :",  
      len(train_data[train_data['total_amount']<0])*(100/175000),"]")  
print("Maximum Value :",train_data['total_amount'].max())  
print("Minimum Value :",train_data['total_amount'].min())  
print("Mean Value :",train_data['total_amount'].mean())
```

No. of missing values : 0 [Percentage(%) : 0.0]

No. of 0 values : 22 [Percentage(%) : 0.012571428571428572]

```
No. of -ve values : 1725 [ Percentage(%) : 0.9857142857142858 ]
Maximum Value : 587.25
Minimum Value : -576.75
Mean Value : 29.633900971428567
```

```
[66]: plt.hist(train_data['total_amount'], ec='white', bins=50)
plt.xlabel("total_amount")
plt.ylabel("frequency")
plt.title('Histogram (total_amount)')
plt.show()
```



Observations

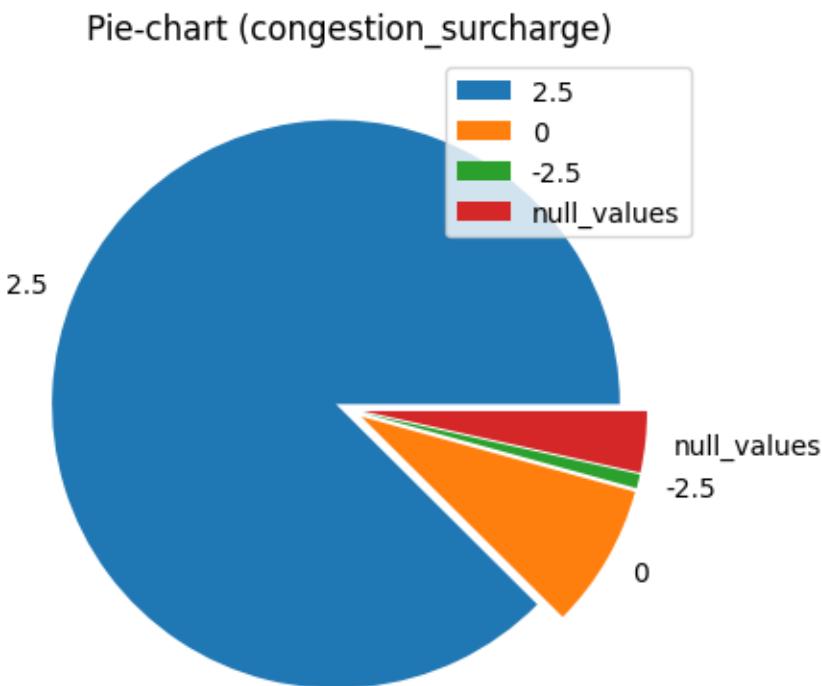
- `total_amount` doesn't contain any missing value.
- `total_amount` contain 22 zero values which is approx 0.1% of the total number of values.
- `total_amount` contain 1725 zero values which is approx 1.0% of the total number of values.
- Maximum Value : 587.25
- Minimum Value : -576.75
- Mean Value : 29.633900971428567

16. congestion_surcharge

```
[67]: print("Unique values : ", pd.unique(train_data['congestion_surcharge']))
print("No. of distinct values : ", len(pd.
    ↪unique(train_data['congestion_surcharge'])))
print("No. of missing values : ", train_data['congestion_surcharge'].isnull().
    ↪sum(), "[", "Percentage(%) : ", (train_data['congestion_surcharge'].isnull().
    ↪sum())*(100/175000), "]")
print("Mean Value : ", train_data['congestion_surcharge'].mean())
```

Unique values : [2.5 0. nan -2.5]
 No. of distinct values : 4
 No. of missing values : 6077 [Percentage(%) : 3.472571428571429]
 Mean Value : 2.246970513192401

```
[68]: Unique_values = [2.5, 0, -2.5]
value_count = []
for i in Unique_values:
    value_count.append(train_data['congestion_surcharge'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(train_data['congestion_surcharge'].isnull().sum())
#print(value_count)
plt.pie(value_count, labels=Unique_values, explode=[0.05,0.05,0.05,0.05])
plt.title('Pie-chart (congestion_surcharge)')
plt.legend(Unique_values)
plt.show()
```



Observations

- There are 4 distinct values (including null values as type).
- congestion_surcharge contains 6077 missing values which is approx 3.5% of total number of values.
- Most Frequent is 2.5
- Mean Value : 2.246970513192401

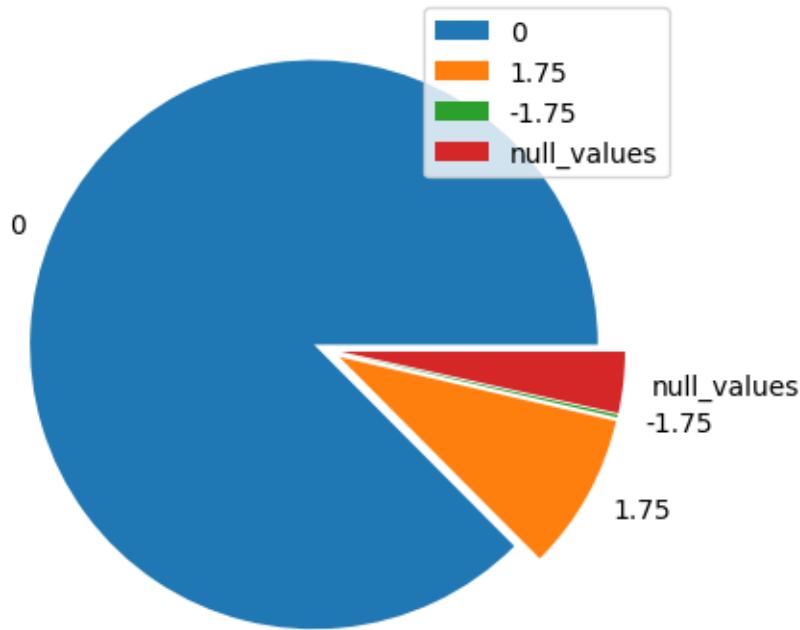
17. Airport_fee

```
[69]: print("Unique values :", pd.unique(train_data['Airport_fee']))
print("No. of distinct values :", len(pd.unique(train_data['Airport_fee'])))
print("No. of missing values :",train_data['Airport_fee'].isnull().sum(),","
      " [", "Percentage(%) :", (train_data['Airport_fee'].isnull().sum())*(100/
      175000), "]")
print("Mean Value :",train_data['Airport_fee'].mean())
```

```
Unique values : [ 0.    1.75   nan -1.75]
No. of distinct values : 4
No. of missing values : 6077 [ Percentage(%) : 3.472571428571429 ]
Mean Value : 0.15882532278020162
```

```
[70]: Unique_values = [0, 1.75, -1.75]
value_count = []
for i in Unique_values:
    value_count.append(train_data['Airport_fee'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(train_data['Airport_fee'].isnull().sum())
#print(value_count)
plt.pie(value_count,labels=Unique_values,explode=[0.05,0.05,0.05,0.05])
plt.title('Pie-chart (Airport_fee)')
plt.legend(Unique_values)
plt.show()
```

Pie-chart (Airport_fee)



Observations

- There are 4 distinct values (including null values as type).
- `Airport_fee` contains 6077 missing values which is approx 3.5% of total number of values.
- Most Frequent is 1.
- Mean Value : 0.15882532278020162

6.3 Overall Observations

- There are 5 attributes having missing values. (`passenger_count`, `RatecodeID`, `store_and_fwd_flag`, `congestion_surcharge`, `Airport_fee`)
 - These can be filled by the corresponding **most_frequent values**.
 - `Airport_fee` & `congestion_surcharge` can be checked by imputing their corresponding mean values.
- **Two attributes (`store_and_fwd_flag`, `payment_type`) are of Categorical type.** It can be encoded using Label Encoder. We will not use Ordinal Encoder because labels are not having some order.
- **We have also observed that some attributes have -ve value.** We will check our scores in both cases (by keeping and removing it) and compare them.
- `payment_type` has some unknown values.
- `passenger_count` & `trip_distance` has some 0 values.

- We have also two `datetime` type columns. We will drop it after creating new features from it.

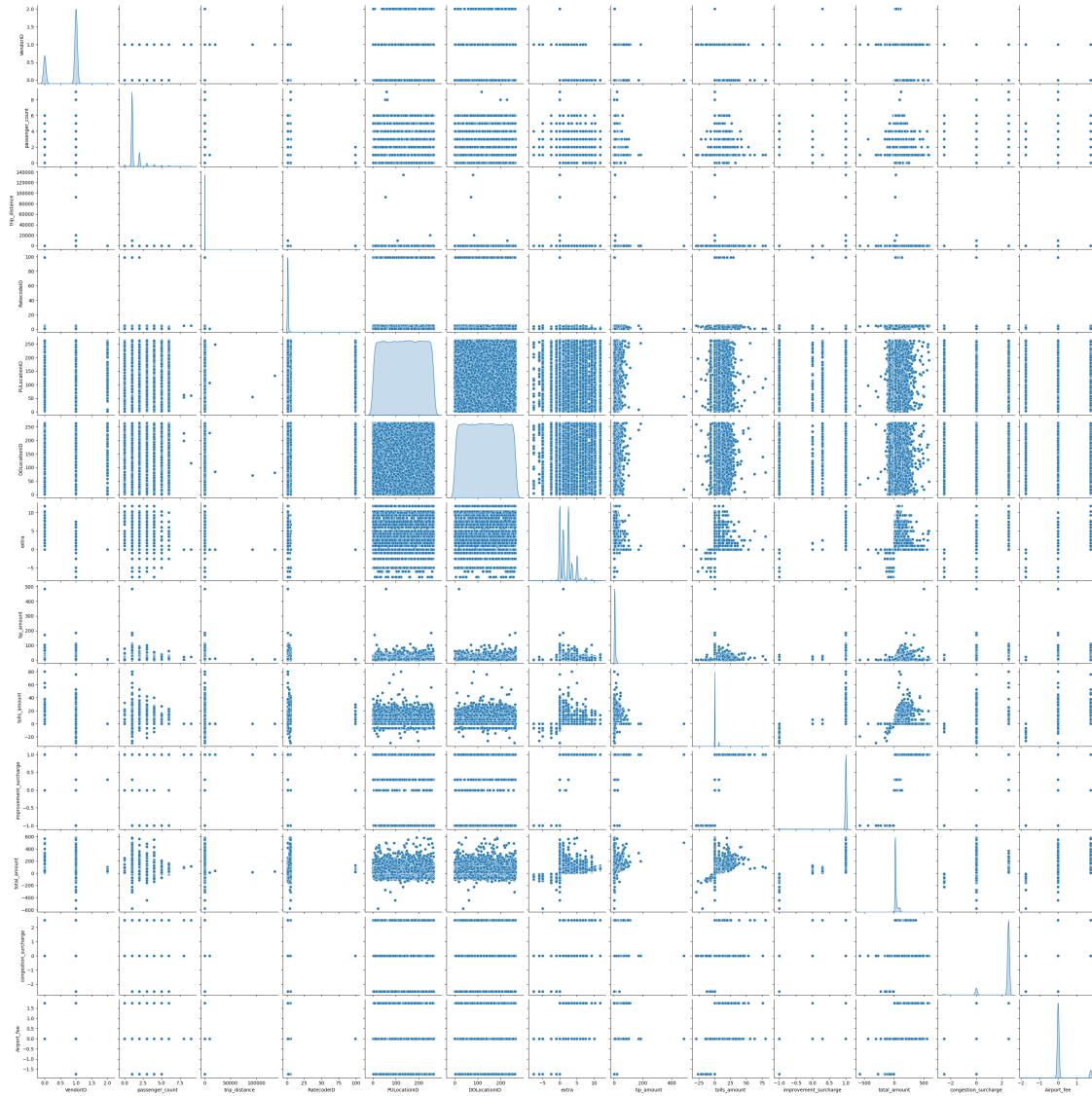
6.4 Bivariate Analysis

- Using `pairplot`

```
[71]: sns.pairplot(train_data, diag_kind='kde')
```

/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:
The figure layout has changed to tight
self._figure.tight_layout(*args, **kwargs)

```
[71]: <seaborn.axisgrid.PairGrid at 0x7d704390d8d0>
```



6.5 Data Preprocessing

Extract and creating new features from the `datetime` features

```
[72]: #train_data['pickup_day'] = train_data['tpep_pickup_datetime'].dt.day_name()
#train_data['dropoff_day'] = train_data['tpep_dropoff_datetime'].dt.day_name()
train_data['pickup_day_no'] = train_data['tpep_pickup_datetime'].dt.weekday
train_data['dropoff_day_no'] = train_data['tpep_dropoff_datetime'].dt.weekday
train_data['pickup_hour'] = train_data['tpep_pickup_datetime'].dt.hour
train_data['dropoff_hour'] = train_data['tpep_dropoff_datetime'].dt.hour
train_data['pickup_month'] = train_data['tpep_pickup_datetime'].dt.month
train_data['dropoff_month'] = train_data['tpep_dropoff_datetime'].dt.month
```

```
[73]: train_data['pickup_timeofday'] = train_data['pickup_hour'].apply(time_of_day)
train_data['dropoff_timeofday'] = train_data['dropoff_hour'].apply(time_of_day)
```

```
[74]: train_data.head()
```

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count		
0	1	2023-06-28 17:20:21	2023-06-28 16:34:45	1.0		
1	0	2023-06-29 23:05:01	2023-06-29 22:01:35	1.0		
2	1	2023-06-30 10:19:31	2023-06-30 11:13:10	1.0		
3	0	2023-06-29 13:23:09	2023-06-29 14:20:01	1.0		
4	1	2023-06-29 22:03:32	2023-06-29 22:22:22	3.0		
	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	
0	2.14	1.0	N	120	9	
1	2.70	1.0	N	15	215	
2	1.15	1.0	N	167	223	
3	0.40	1.0	N	128	239	
4	1.10	1.0	N	203	52	
	payment_type	...	congestion_surcharge	Airport_fee	pickup_day_no	
0	Credit Card	...	2.5	0.0	2	
1	Credit Card	...	2.5	0.0	3	
2	Credit Card	...	2.5	0.0	4	
3	Credit Card	...	2.5	0.0	3	
4	Credit Card	...	2.5	0.0	3	
	dropoff_day_no	pickup_hour	dropoff_hour	pickup_month	dropoff_month	
0	2	17	16	6	6	
1	3	23	22	6	6	
2	4	10	11	6	6	
3	3	13	14	6	6	
4	3	22	22	6	6	
	pickup_timeofday	dropoff_timeofday				
0	Evening	Evening				

```

1      Late night      Late night
2      Morning        Morning
3      Afternoon       Afternoon
4      Late night      Late night

```

[5 rows x 25 columns]

6.5.1 Handling Outliers

```

[75]: '''
# trip_distance
trip_percentile25 = train_data['trip_distance'].quantile(0.25)
trip_percentile75 = train_data['trip_distance'].quantile(0.75)
trip_iqr = trip_percentile75 - trip_percentile25

print("25th Percentile (Trip distance) :", trip_percentile25)
print("75th Percentile (Trip distance) :", trip_percentile75)
print("IQR (Trip distance) :", trip_iqr)

trip_upper_limit = trip_percentile75 + (trip_iqr*1.5)
trip_lower_limit = trip_percentile25 - (trip_iqr*1.5)

print("Upper Limit (Trip distance) :", trip_upper_limit)
print("Lower Limit (Trip distance) :", trip_lower_limit)

train_data['trip_distance']=np.where(
    train_data['trip_distance']>trip_upper_limit, trip_upper_limit,np.where(
        train_data['trip_distance']<trip_lower_limit,trip_lower_limit,
        train_data['trip_distance'])))

print("-----")

# tip_amount
tip_percentile25 = train_data['tip_amount'].quantile(0.25)
tip_percentile75 = train_data['tip_amount'].quantile(0.75)
tip_iqr = tip_percentile75 - tip_percentile25

print("25th Percentile (Tip Amount) :", tip_percentile25)
print("75th Percentile (Tip Amount) :", tip_percentile75)
print("IQR (Tip Amount) :", tip_iqr)

tip_upper_limit = tip_percentile75 + (tip_iqr*1.5)
tip_lower_limit = tip_percentile25 - (tip_iqr*1.5)

print("Upper Limit (Tip amount) :", tip_upper_limit)
print("Lower Limit (Tip amount) :", tip_lower_limit)

```

```

train_data['tip_amount']=np.where(
    train_data['tip_amount']>tip_upper_limit, tip_upper_limit,np.where(
        train_data['tip_amount']<tip_lower_limit,tip_lower_limit,
        ↪train_data['tip_amount']))
...

```

```

[75]: '\n# trip_distance\ntrip_percentile25 =
train_data[\'trip_distance\'].quantile(0.25)\ntrip_percentile75 =
train_data[\'trip_distance\'].quantile(0.75)\ntrip_iqr = trip_percentile75 -
trip_percentile25\n\nprint("25th Percentile (Trip distance) :",
trip_percentile25)\nprint("75th Percentile (Trip distance) :",
trip_percentile75)\nprint("IQR (Trip distance) :", trip_iqr)\n\ntrip_upper_limit =
trip_percentile75 + (trip_iqr*1.5)\ntrip_lower_limit = trip_percentile25 -
(trip_iqr*1.5)\n\nprint("Upper Limit (Trip distance) :",
trip_upper_limit)\nprint("Lower Limit (Trip distance) :", trip_lower_limit)\n\n
train_data[\'trip_distance\']=np.where(\ntrain_data[\'trip_distance\']>trip_upper_
_limit, trip_upper_limit,np.where(\ntrain_data[\'trip_distance\']<trip_lower_lim
it,trip_lower_limit, train_data[\'trip_distance\']))\n\nprint("-----"
-----")\n\n# tip_amount\ntrip_percentile25 =
train_data[\'tip_amount\'].quantile(0.25)\ntrip_percentile75 =
train_data[\'tip_amount\'].quantile(0.75)\ntrip_iqr = tip_percentile75 -
tip_percentile25\n\nprint("25th Percentile (Tip Amount) :",
tip_percentile25)\nprint("75th Percentile (Tip Amount) :",
tip_percentile75)\nprint("IQR (Tip Amount) :", tip_iqr)\n\ntrip_upper_limit =
tip_percentile75 + (tip_iqr*1.5)\ntrip_lower_limit = tip_percentile25 -
(tip_iqr*1.5)\n\nprint("Upper Limit (Tip amount) :",
tip_upper_limit)\nprint("Lower Limit (Tip amount) :", tip_lower_limit)\n\n
train_data[\'tip_amount\']=np.where(\ntrain_data[\'tip_amount\']>tip_upper_limit, tip_
upper_limit,np.where(\ntrain_data[\'tip_amount\']<tip_lower_limit,tip_lower_lim
it, train_data[\'tip_amount\']))\n'

```

```
[76]: sns.boxplot(train_data['trip_distance'])
```

```
[77]: sns.boxplot(train_data['tip_amount'])
```

```

[78]: index_pcount = train_data[(train_data['passenger_count']>=8)].index
train_data.drop(index_pcount , axis='index' , inplace=True)
#index_datecount =_
↪train_data[(train_data['tpep_pickup_datetime']==train_data['tpep_dropoff_datetime'])].
↪index
#train_data.drop(index_datecount , axis='index' , inplace=True)
train_data['extra'] = train_data['extra'].abs()
#train_data['tolls_amount'] = train_data['tolls_amount'].abs()
#toll_mean = train_data['tolls_amount'][train_data['tolls_amount']>0].mean()
train_data['tolls_amount'].mask(train_data['tolls_amount'] <0.0, 0.0,_
↪inplace=True)
#index_tripcount = train_data[(train_data['trip_distance']==0.0)].index

```

```

#train_data.drop(index_tripcount , axis='index', inplace=True)
#print("Most_frequent Value : ",train_data['trip_distance'].mode())
#index_p1count = train_data[(train_data['passenger_count']==0)].index
train_data['trip_distance'].mask(train_data['trip_distance'] == 0.0, 1.0, □
    ↵inplace=True)
train_data['Airport_fee'].mask(train_data['Airport_fee'] == -1.75, 1.75, □
    ↵inplace=True)
train_data['congestion_surcharge'].mask(train_data['congestion_surcharge'] == □
    ↵-2.5, 2.5, inplace=True)
train_data['passenger_count'].mask(train_data['passenger_count'] == 0, 1, □
    ↵inplace=True)
#train_data['passenger_count'].mask(train_data['passenger_count'] < 0, 1, □
    ↵inplace=True)
#tip_5th_per = np.percentile(train_data['tip_amount'], 5)
#tip_95th_per = np.percentile(train_data['tip_amount'], 95)
#train_data['tip_amount'].mask(train_data['tip_amount']<tip_5th_per, □
    ↵tip_5th_per, inplace=True)
#train_data['tip_amount'].mask(train_data['tip_amount']>tip_95th_per, □
    ↵tip_95th_per, inplace=True)
#index_tcount = train_data[(train_data['trip_distance']>200)].index
#index_ridcount = train_data[(train_data['RatecodeID']==99)].index
#index_tipcount = train_data[(train_data['tip_amount']>400)].index
#index_tollcount = train_data[(train_data['tolls_amount']<0)].index
#index_excount = train_data[(train_data['extra']<0)].index

#train_data.drop(index_p1count , axis='index', inplace=True)
#train_data.drop(index_ridcount , axis='index', inplace=True)
#train_data.drop(index_tcount , axis='index', inplace=True)
#train_data.drop(index_tipcount , axis='index', inplace=True)
#train_data.drop(index_tollcount , axis='index', inplace=True)
#train_data.drop(index_excount , axis='index', inplace=True)
train_data.reset_index()
train_data.info()

```

```

<class 'pandas.core.frame.DataFrame'>
Index: 174997 entries, 0 to 174999
Data columns (total 25 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   VendorID        174997 non-null   int64  
 1   tpep_pickup_datetime  174997 non-null   datetime64[ns]
 2   tpep_dropoff_datetime 174997 non-null   datetime64[ns]
 3   passenger_count     168920 non-null   float64 
 4   trip_distance       174997 non-null   float64 
 5   RatecodeID         168920 non-null   float64 
 6   store_and_fwd_flag  168920 non-null   object 

```

```

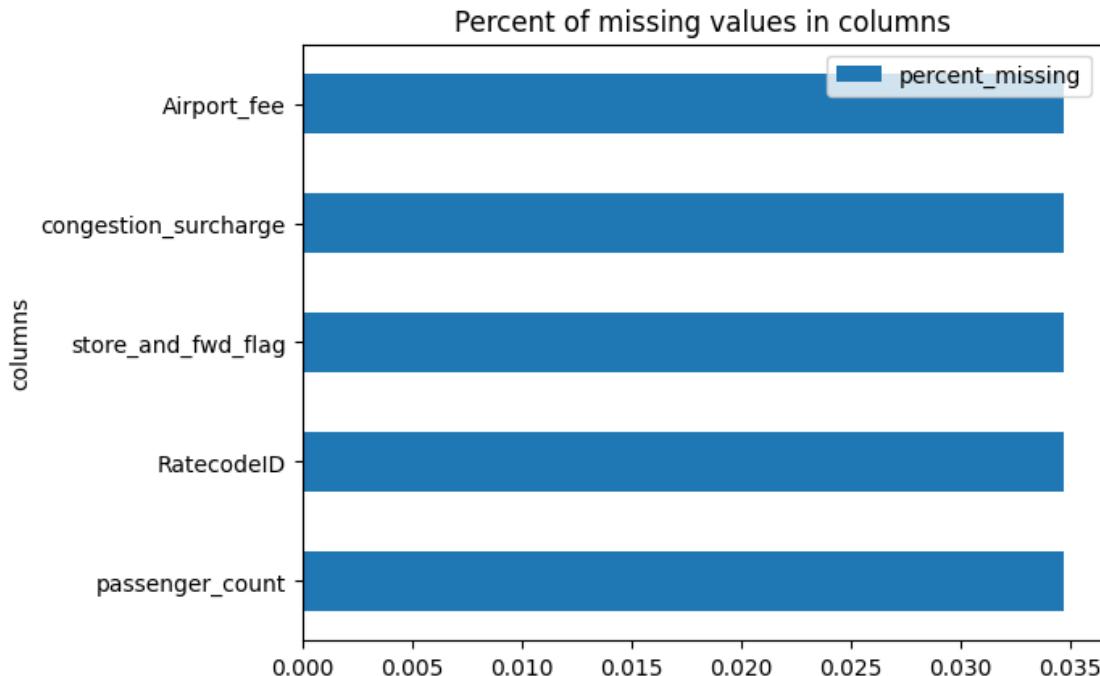
7   PULocationID           174997 non-null  int64
8   DOLocationID          174997 non-null  int64
9   payment_type           174997 non-null  object
10  extra                  174997 non-null  float64
11  tip_amount             174997 non-null  float64
12  tolls_amount           174997 non-null  float64
13  improvement_surcharge 174997 non-null  float64
14  total_amount            174997 non-null  float64
15  congestion_surcharge   168920 non-null  float64
16  Airport_fee             168920 non-null  float64
17  pickup_day_no          174997 non-null  int32
18  dropoff_day_no         174997 non-null  int32
19  pickup_hour             174997 non-null  int32
20  dropoff_hour            174997 non-null  int32
21  pickup_month            174997 non-null  int32
22  dropoff_month           174997 non-null  int32
23  pickup_timeofday        174997 non-null  object
24  dropoff_timeofday       174997 non-null  object
dtypes: datetime64[ns](2), float64(10), int32(6), int64(3), object(4)
memory usage: 30.7+ MB

```

6.5.2 Handling Missing Values

- Visualizing Missing Values

```
[79]: # Plotting missing value percentage for train data columns.
plot_missing_values(train_data)
```



```
[80]: mis_val_att = ["passenger_count", "RatecodeID", "store_and_fwd_flag", "congestion_surcharge", "Airport_fee"]
imp = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imp.fit(train_data)
train_data = pd.DataFrame(imp.transform(train_data), columns = train_data.columns)
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 174997 entries, 0 to 174996
Data columns (total 25 columns):
 #   Column           Non-Null Count  Dtype  
 ---  --  
 0   VendorID         174997 non-null   object  
 1   tpep_pickup_datetime  174997 non-null   datetime64[ns] 
 2   tpep_dropoff_datetime 174997 non-null   datetime64[ns] 
 3   passenger_count     174997 non-null   object  
 4   trip_distance       174997 non-null   object  
 5   RatecodeID          174997 non-null   object  
 6   store_and_fwd_flag   174997 non-null   object  
 7   PULocationID        174997 non-null   object  
 8   DOLocationID        174997 non-null   object  
 9   payment_type         174997 non-null   object  
 10  extra               174997 non-null   object  
 11  tip_amount          174997 non-null   object  
 12  tolls_amount         174997 non-null   object  
 13  improvement_surcharge 174997 non-null   object  
 14  total_amount         174997 non-null   object  
 15  congestion_surcharge 174997 non-null   object  
 16  Airport_fee          174997 non-null   object  
 17  pickup_day_no        174997 non-null   object  
 18  dropoff_day_no       174997 non-null   object  
 19  pickup_hour          174997 non-null   object  
 20  dropoff_hour         174997 non-null   object  
 21  pickup_month         174997 non-null   object  
 22  dropoff_month        174997 non-null   object  
 23  pickup_timeofday     174997 non-null   object  
 24  dropoff_timeofday    174997 non-null   object  
dtypes: datetime64[ns](2), object(23)
memory usage: 33.4+ MB
```

6.5.3 Handling Payment type unknown values

- Replacing it by cash value.

```
[81]: train_data['payment_type'].mask(train_data['payment_type'] == 'unknown',  
    ↪"Cash", inplace=True)
```

```
[82]: train_data['payment_type'].value_counts()
```

```
[82]: payment_type  
Credit Card      135254  
Cash            32474  
Wallet           6077  
UPI              1192  
Name: count, dtype: int64
```

6.5.4 Handling Categorical Variable

- Applying Label Encoding for attributes store_and_fwd_flag & payment_type

```
[83]: train_data = MultiColumnLabelEncoder(columns =  
    ↪['store_and_fwd_flag', 'payment_type', 'pickup_timeofday', 'dropoff_timeofday']).  
    ↪fit_transform(train_data)
```

```
[84]: train_data.head()
```

```
[84]:   VendorID tpep_pickup_datetime tpep_dropoff_datetime passenger_count \
0        1 2023-06-28 17:20:21    2023-06-28 16:34:45          1.0
1        0 2023-06-29 23:05:01    2023-06-29 22:01:35          1.0
2        1 2023-06-30 10:19:31    2023-06-30 11:13:10          1.0
3        0 2023-06-29 13:23:09    2023-06-29 14:20:01          1.0
4        1 2023-06-29 22:03:32    2023-06-29 22:22:22          3.0

   trip_distance RatecodeID  store_and_fwd_flag PULocationID DOLocationID \
0        2.14        1.0             0          120            9
1        2.7         1.0             0           15          215
2        1.15        1.0             0          167          223
3        0.4         1.0             0          128          239
4        1.1         1.0             0          203            52

   payment_type ... congestion_surcharge Airport_fee pickup_day_no \
0           1 ...                 2.5          0.0            2
1           1 ...                 2.5          0.0            3
2           1 ...                 2.5          0.0            4
3           1 ...                 2.5          0.0            3
4           1 ...                 2.5          0.0            3

   dropoff_day_no pickup_hour dropoff_hour pickup_month dropoff_month \
0             2          17          16            6            6
1             3          23          22            6            6
2             4          10          11            6            6
```

3	3	13	14	6	6
4	3	22	22	6	6
pickup_timeofday dropoff_timeofday					
0	1	1			
1	2	2			
2	3	3			
3	0	0			
4	2	2			

[5 rows x 25 columns]

6.5.5 Handling Negative Values

```
[85]: #print("No. of rows having -ve 'improvement_surcharge' value :  
#    ↪", train_data[train_data["improvement_surcharge"]<0].shape[0])  
#print("No. of rows having -ve 'total_amount' value :  
#    ↪", train_data[train_data["total_amount"]<0].shape[0])  
#print("No. of rows having -ve 'congestion_surcharge' value :  
#    ↪", train_data[train_data["congestion_surcharge"]<0].shape[0])  
#print("No. of rows having -ve 'extra' value :  
#    ↪", train_data[train_data["extra"]<0].shape[0])  
#print("No. of rows having -ve 'Airport_fee' value :  
#    ↪", train_data[train_data["Airport_fee"]<0].shape[0])  
#print("No. of rows having -ve 'tolls_amount' value :  
#    ↪", train_data[train_data["tolls_amount"]<0].shape[0])
```

- Removing rows having -ve improvement_surcharge value

```
[86]: #train_data.drop(train_data[train_data["improvement_surcharge"]<0].index, ↪  
#    ↪inplace=True)  
#train_data.shape
```

- Scores have been checked by keeping -ve values as it is as well as by removing it. Score after keeping it as given in dataset is good one.
- Now, Checking Negative values after running the above cell.

```
[87]: #print("No. of rows having -ve 'improvement_surcharge' value :  
#    ↪", train_data[train_data["improvement_surcharge"]<0].shape[0])  
#print("No. of rows having -ve 'total_amount' value :  
#    ↪", train_data[train_data["total_amount"]<0].shape[0])  
#print("No. of rows having -ve 'congestion_surcharge' value :  
#    ↪", train_data[train_data["congestion_surcharge"]<0].shape[0])  
#print("No. of rows having -ve 'extra' value :  
#    ↪", train_data[train_data["extra"]<0].shape[0])
```

```

#print("No. of rows having -ve 'Airport_fee' value : 
↪",train_data[train_data["Airport_fee"]<0].shape[0])
#print("No. of rows having -ve 'tolls_amount' value : 
↪",train_data[train_data["tolls_amount"]<0].shape[0])

```

6.5.6 Dropping tpep_pickup_datetime & tpep_dropoff_datetime columns

[88]: train_data = train_data.drop(['tpep_pickup_datetime', 'tpep_dropoff_datetime'],
axis=1)

[89]: train_data.info()

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 174997 entries, 0 to 174996
Data columns (total 23 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   VendorID        174997 non-null   object 
 1   passenger_count 174997 non-null   object 
 2   trip_distance    174997 non-null   object 
 3   RatecodeID       174997 non-null   object 
 4   store_and_fwd_flag 174997 non-null   int64  
 5   PULocationID    174997 non-null   object 
 6   DOLocationID    174997 non-null   object 
 7   payment_type     174997 non-null   int64  
 8   extra            174997 non-null   object 
 9   tip_amount       174997 non-null   object 
 10  tolls_amount     174997 non-null   object 
 11  improvement_surcharge 174997 non-null   object 
 12  total_amount     174997 non-null   object 
 13  congestion_surcharge 174997 non-null   object 
 14  Airport_fee      174997 non-null   object 
 15  pickup_day_no    174997 non-null   object 
 16  dropoff_day_no   174997 non-null   object 
 17  pickup_hour      174997 non-null   object 
 18  dropoff_hour     174997 non-null   object 
 19  pickup_month     174997 non-null   object 
 20  dropoff_month    174997 non-null   object 
 21  pickup_timeofday 174997 non-null   int64  
 22  dropoff_timeofday 174997 non-null   int64  
dtypes: int64(4), object(19)
memory usage: 30.7+ MB

```

6.5.7 Converting columns having type ‘object’ to ‘float64’ for further smooth processing.

```
[90]: train_data[['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID'] =  
    train_data[['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID'].  
    astype('float64')]
```

```
[91]: train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 174997 entries, 0 to 174996  
Data columns (total 23 columns):  
 #   Column           Non-Null Count  Dtype     
 ---  --  
 0   VendorID        174997 non-null   float64  
 1   passenger_count 174997 non-null   float64  
 2   trip_distance   174997 non-null   float64  
 3   RatecodeID      174997 non-null   float64  
 4   store_and_fwd_flag 174997 non-null   int64  
 5   PULocationID   174997 non-null   float64  
 6   DOLocationID   174997 non-null   float64  
 7   payment_type    174997 non-null   int64  
 8   extra           174997 non-null   float64  
 9   tip_amount      174997 non-null   float64  
 10  tolls_amount    174997 non-null   float64  
 11  improvement_surcharge 174997 non-null   float64  
 12  total_amount    174997 non-null   float64  
 13  congestion_surcharge 174997 non-null   float64  
 14  Airport_fee     174997 non-null   float64  
 15  pickup_day_no   174997 non-null   float64  
 16  dropoff_day_no  174997 non-null   float64  
 17  pickup_hour     174997 non-null   float64  
 18  dropoff_hour   174997 non-null   float64  
 19  pickup_month    174997 non-null   float64  
 20  dropoff_month   174997 non-null   float64  
 21  pickup_timeofday 174997 non-null   float64  
 22  dropoff_timeofday 174997 non-null   float64  
dtypes: float64(21), int64(2)  
memory usage: 30.7 MB
```

- At this point, We have train data having 23 Columns with no missing values. Also, Categorical variables have been label encoded.

7 Newly Added Features & their significance (After Preprocessing)

Newly added columns	Significance
pickup_day_no	Pickup day number.
dropoff_day_no	Dropoff day number.
pickup_hour	Pickup day hour.
dropoff_hour	Dropoff day hour.
pickup_month	Pickup month.
dropoff_month	Dropoff month.
pickup_timeofday	Pickup Time (Morning, Afternoon, Evening, Late night)
dropoff_timeofday	Dropoff Time (Morning, Afternoon, Evening, Late night)

[92]: train_data.head()

```
[92]:   VendorID  passenger_count  trip_distance  RatecodeID  store_and_fwd_flag \
0        1.0            1.0       2.14          1.0              0
1        0.0            1.0       2.70          1.0              0
2        1.0            1.0       1.15          1.0              0
3        0.0            1.0       0.40          1.0              0
4        1.0            3.0       1.10          1.0              0

      PULocationID  DOLocationID  payment_type  extra  tip_amount ... \
0         120.0        9.0             1     2.5    7.165589 ...
1         15.0        215.0            1     3.5    6.067401 ...
2         167.0        223.0            1     0.0    4.111547 ...
3         128.0        239.0            1     2.5    6.411079 ...
4         203.0        52.0             1     1.0    4.769377 ...

  congestion_surcharge  Airport_fee  pickup_day_no  dropoff_day_no \
0                2.5        0.0           2.0           2.0
1                2.5        0.0           3.0           3.0
2                2.5        0.0           4.0           4.0
3                2.5        0.0           3.0           3.0
4                2.5        0.0           3.0           3.0

  pickup_hour  dropoff_hour  pickup_month  dropoff_month  pickup_timeofday \
0        17.0        16.0          6.0          6.0            1.0
1        23.0        22.0          6.0          6.0            2.0
2        10.0        11.0          6.0          6.0            3.0
3        13.0        14.0          6.0          6.0            0.0
4        22.0        22.0          6.0          6.0            2.0

  dropoff_timeofday
0                 1.0
1                 2.0
2                 3.0
3                 0.0
4                 2.0
```

[5 rows x 23 columns]

7.1 Correlation

- Table

[93]: train_data.corr()

	VendorID	passenger_count	trip_distance	RatecodeID	\
VendorID	1.000000	0.066871	0.002844	-0.105156	
passenger_count	0.066871	1.000000	-0.000981	-0.023677	
trip_distance	0.002844	-0.000981	1.000000	0.000613	
RatecodeID	-0.105156	-0.023677	0.000613	1.000000	
store_and_fwd_flag	-0.126133	-0.007919	-0.000415	-0.004460	
PULocationID	-0.001305	-0.001053	-0.000958	-0.001102	
DOLocationID	-0.003953	-0.001017	-0.002497	-0.000644	
payment_type	0.012329	-0.084540	0.013834	0.010634	
extra	-0.529015	-0.009888	-0.001917	-0.068949	
tip_amount	0.043925	0.013730	0.005840	-0.031890	
tolls_amount	0.025171	0.037280	0.006894	0.061082	
improvement_surcharge	-0.063198	-0.002000	0.000434	0.002403	
total_amount	0.039668	0.047310	0.009915	0.054011	
congestion_surcharge	0.010394	-0.004634	-0.003366	-0.236278	
Airport_fee	0.040261	0.046014	0.006563	-0.003678	
pickup_day_no	-0.001655	0.029937	-0.000384	0.021791	
dropoff_day_no	-0.000171	0.031953	0.000137	0.021426	
pickup_hour	0.015398	0.026094	-0.006237	-0.046879	
dropoff_hour	0.012620	0.022100	-0.007443	-0.039506	
pickup_month	0.000609	0.009196	-0.000132	-0.002939	
dropoff_month	0.006810	0.016975	0.003445	-0.002302	
pickup_timeofday	-0.001298	-0.019541	0.002390	0.030660	
dropoff_timeofday	-0.001876	-0.019645	0.002523	0.028460	
	store_and_fwd_flag	PULocationID	DOLocationID	\	
VendorID	-0.126133	-0.001305	-0.003953		
passenger_count	-0.007919	-0.001053	-0.001017		
trip_distance	-0.000415	-0.000958	-0.002497		
RatecodeID	-0.004460	-0.001102	-0.000644		
store_and_fwd_flag	1.000000	0.000315	0.001457		
PULocationID	0.000315	1.000000	-0.000150		
DOLocationID	0.001457	-0.000150	1.000000		
payment_type	-0.019223	0.002478	0.000891		
extra	0.069603	0.001737	0.003519		
tip_amount	-0.013222	0.000781	-0.000253		
tolls_amount	-0.004787	-0.001246	-0.002177		
improvement_surcharge	0.006723	-0.000499	-0.002812		

total_amount	-0.007607	0.000763	-0.002980
congestion_surcharge	-0.005385	0.001212	0.002671
Airport_fee	-0.004629	-0.001367	-0.003778
pickup_day_no	-0.000769	0.002208	-0.000277
dropoff_day_no	-0.000907	0.001927	-0.000076
pickup_hour	-0.003078	-0.001890	0.001253
dropoff_hour	-0.002698	-0.001288	-0.000323
pickup_month	-0.003282	0.000909	-0.001634
dropoff_month	-0.003354	0.001804	0.001944
pickup_timeofday	-0.006747	0.002754	0.000346
dropoff_timeofday	-0.006335	0.003602	0.001102

	payment_type	extra	tip_amount	...	\
VendorID	0.012329	-0.529015	0.043925	...	
passenger_count	-0.084540	-0.009888	0.013730	...	
trip_distance	0.013834	-0.001917	0.005840	...	
RatecodeID	0.010634	-0.068949	-0.031890	...	
store_and_fwd_flag	-0.019223	0.069603	-0.013222	...	
PULocationID	0.002478	0.001737	0.000781	...	
DOLocationID	0.000891	0.003519	-0.000253	...	
payment_type	1.000000	-0.097800	0.257282	...	
extra	-0.097800	1.000000	0.152204	...	
tip_amount	0.257282	0.152204	1.000000	...	
tolls_amount	0.041060	0.195803	0.412287	...	
improvement_surcharge	0.094835	0.033142	0.076438	...	
total_amount	0.091613	0.202118	0.638644	...	
congestion_surcharge	0.098832	-0.036869	-0.112180	...	
Airport_fee	-0.076869	0.331879	0.322474	...	
pickup_day_no	-0.029555	-0.144289	-0.020564	...	
dropoff_day_no	-0.027878	-0.146177	-0.014274	...	
pickup_hour	0.003442	0.217579	0.012336	...	
dropoff_hour	0.000990	0.224008	0.011563	...	
pickup_month	-0.002437	-0.005252	-0.003099	...	
dropoff_month	0.000449	-0.010876	0.008753	...	
pickup_timeofday	0.029535	-0.134802	-0.016744	...	
dropoff_timeofday	0.033762	-0.122072	-0.011030	...	

	congestion_surcharge	Airport_fee	pickup_day_no	\
VendorID	0.010394	0.040261	-0.001655	
passenger_count	-0.004634	0.046014	0.029937	
trip_distance	-0.003366	0.006563	-0.000384	
RatecodeID	-0.236278	-0.003678	0.021791	
store_and_fwd_flag	-0.005385	-0.004629	-0.000769	
PULocationID	0.001212	-0.001367	0.002208	
DOLocationID	0.002671	-0.003778	-0.000277	
payment_type	0.098832	-0.076869	-0.029555	
extra	-0.036869	0.331879	-0.144289	

tip_amount	-0.112180	0.322474	-0.020564
tolls_amount	-0.178327	0.412501	0.021941
improvement_surcharge	0.044364	-0.019741	-0.008899
total_amount	-0.291446	0.551649	-0.005710
congestion_surcharge	1.000000	-0.451312	-0.019419
Airport_fee	-0.451312	1.000000	0.002588
pickup_day_no	-0.019419	0.002588	1.000000
dropoff_day_no	-0.023257	0.012691	0.971569
pickup_hour	0.029209	0.007696	-0.334416
dropoff_hour	0.031966	-0.003169	-0.257509
pickup_month	-0.000033	0.006310	0.158735
dropoff_month	-0.007200	0.023292	0.127287
pickup_timeofday	-0.008272	-0.007747	0.065932
dropoff_timeofday	-0.013903	-0.002283	0.054711

	dropoff_day_no	pickup_hour	dropoff_hour	\
VendorID	-0.000171	0.015398	0.012620	
passenger_count	0.031953	0.026094	0.022100	
trip_distance	0.000137	-0.006237	-0.007443	
RatecodeID	0.021426	-0.046879	-0.039506	
store_and_fwd_flag	-0.000907	-0.003078	-0.002698	
PULocationID	0.001927	-0.001890	-0.001288	
DOLocationID	-0.000076	0.001253	-0.000323	
payment_type	-0.027878	0.003442	0.000990	
extra	-0.146177	0.217579	0.224008	
tip_amount	-0.014274	0.012336	0.011563	
tolls_amount	0.027275	-0.040111	-0.033586	
improvement_surcharge	-0.008613	0.007047	0.007456	
total_amount	0.005944	-0.003871	-0.006740	
congestion_surcharge	-0.023257	0.029209	0.031966	
Airport_fee	0.012691	0.007696	-0.003169	
pickup_day_no	0.971569	-0.334416	-0.257509	
dropoff_day_no	1.000000	-0.261133	-0.346011	
pickup_hour	-0.261133	1.000000	0.752649	
dropoff_hour	-0.346011	0.752649	1.000000	
pickup_month	0.111536	-0.171130	-0.035032	
dropoff_month	0.211769	0.019072	-0.215792	
pickup_timeofday	0.076008	-0.354925	-0.379114	
dropoff_timeofday	0.065267	-0.321060	-0.346945	

	pickup_month	dropoff_month	pickup_timeofday	\
VendorID	0.000609	0.006810	-0.001298	
passenger_count	0.009196	0.016975	-0.019541	
trip_distance	-0.000132	0.003445	0.002390	
RatecodeID	-0.002939	-0.002302	0.030660	
store_and_fwd_flag	-0.003282	-0.003354	-0.006747	
PULocationID	0.000909	0.001804	0.002754	

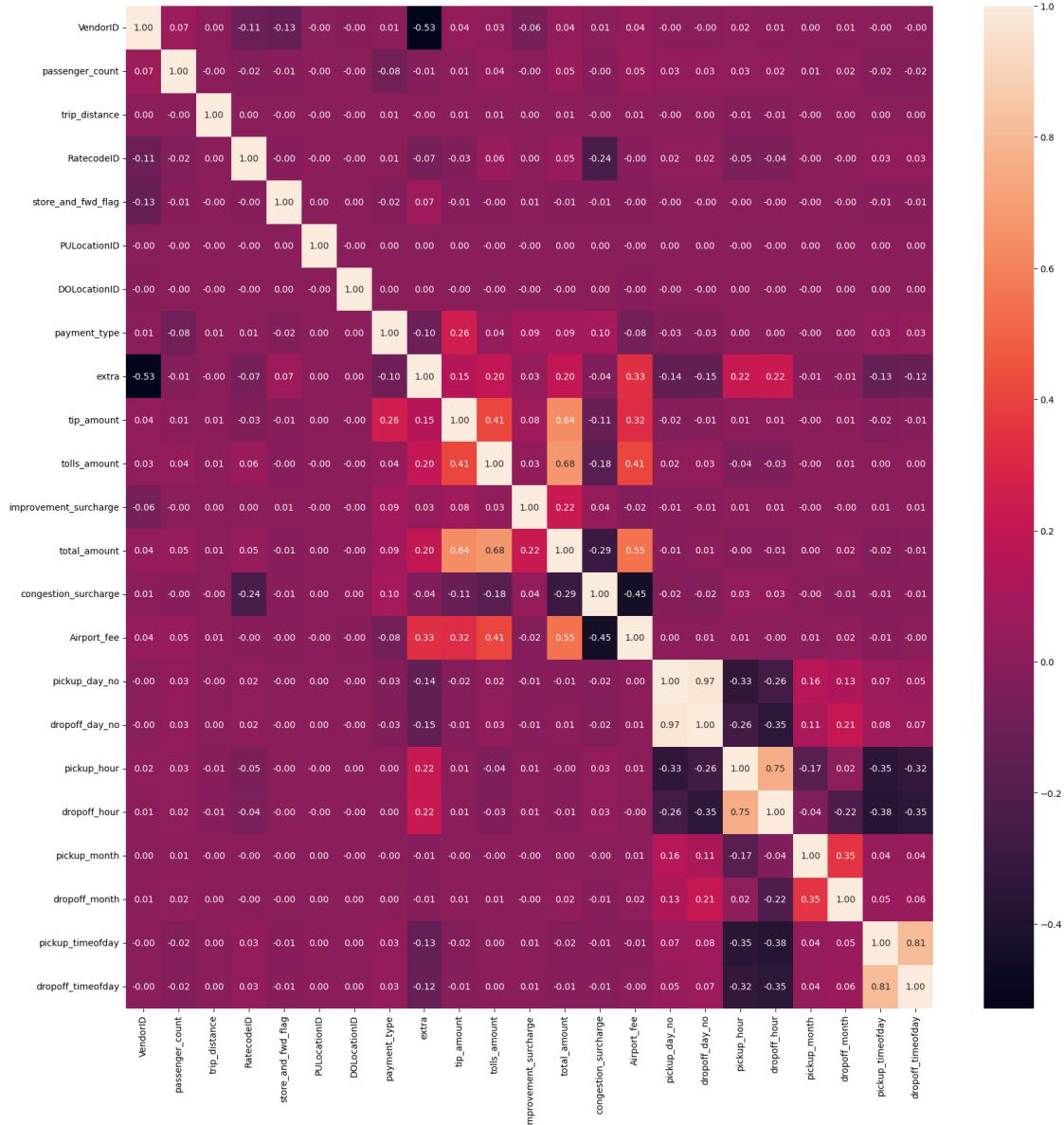
DOLocationID	-0.001634	0.001944	0.000346
payment_type	-0.002437	0.000449	0.029535
extra	-0.005252	-0.010876	-0.134802
tip_amount	-0.003099	0.008753	-0.016744
tolls_amount	-0.000327	0.008207	0.001027
improvement_surcharge	-0.000392	-0.000498	0.006804
total_amount	0.000915	0.022208	-0.020684
congestion_surcharge	-0.000033	-0.007200	-0.008272
Airport_fee	0.006310	0.023292	-0.007747
pickup_day_no	0.158735	0.127287	0.065932
dropoff_day_no	0.111536	0.211769	0.076008
pickup_hour	-0.171130	0.019072	-0.354925
dropoff_hour	-0.035032	-0.215792	-0.379114
pickup_month	1.000000	0.353202	0.042488
dropoff_month	0.353202	1.000000	0.054884
pickup_timeofday	0.042488	0.054884	1.000000
dropoff_timeofday	0.043180	0.056583	0.805571
dropoff_timeofday			
VendorID	-0.001876		
passenger_count	-0.019645		
trip_distance	0.002523		
RatecodeID	0.028460		
store_and_fwd_flag	-0.006335		
PULocationID	0.003602		
DOLocationID	0.001102		
payment_type	0.033762		
extra	-0.122072		
tip_amount	-0.011030		
tolls_amount	0.004301		
improvement_surcharge	0.005616		
total_amount	-0.013259		
congestion_surcharge	-0.013903		
Airport_fee	-0.002283		
pickup_day_no	0.054711		
dropoff_day_no	0.065267		
pickup_hour	-0.321060		
dropoff_hour	-0.346945		
pickup_month	0.043180		
dropoff_month	0.056583		
pickup_timeofday	0.805571		
dropoff_timeofday	1.000000		

[23 rows x 23 columns]

- Heatmap

```
[94]: plt.subplots(figsize=(20,20))
sns.heatmap(train_data.corr(), annot=True, fmt=".2f")
```

[94]: <Axes: >



Observation

- Attributes `store_and_fwd_flag`, `PULocationID`, `DOLocationID`, `payment_type` and `congestion_surcharge`, `pickup_day_no`, `dropoff_day_no`, `pickup_hour`, `dropff_hour`, `pickup_month`, `dropoff_month`, `pickup_timeofday`, `dropoff_timeofday` has negative value or very near to zero..

- Attributes `VendorID`, `passenger_count`, `trip_distance` and `RateCodeID` showing less value. (near to 0).
- Attributes `extra`, `tip_amount`, `tolls_amount`, `improvement_surcharge` and `Airport_fee` showing high value. (near to 1).

7.2 Visualizing whole Dataset at a time.

7.2.1 Using Histogram

```
[95]: train_data.hist(bins=50,figsize=(20,20),color='green')
# displaying histogram
plt.show()
```



7.3 Scaling

- Using StandardScaler()

```
[96]: train_data.head()
```

```
[96]:    VendorID  passenger_count  trip_distance  RatecodeID  store_and_fwd_flag \
0          1.0              1.0        2.14          1.0                  0
1          0.0              1.0        2.70          1.0                  0
2          1.0              1.0        1.15          1.0                  0
3          0.0              1.0        0.40          1.0                  0
4          1.0              3.0        1.10          1.0                  0

      PULocationID  DOLocationID  payment_type  extra  tip_amount ... \
0          120.0            9.0           1       2.5    7.165589 ...
1          15.0            215.0          1       3.5    6.067401 ...
2          167.0            223.0          1       0.0    4.111547 ...
3          128.0            239.0          1       2.5    6.411079 ...
4          203.0            52.0           1       1.0    4.769377 ...

  congestion_surcharge  Airport_fee  pickup_day_no  dropoff_day_no \
0                 2.5            0.0            2.0            2.0
1                 2.5            0.0            3.0            3.0
2                 2.5            0.0            4.0            4.0
3                 2.5            0.0            3.0            3.0
4                 2.5            0.0            3.0            3.0

  pickup_hour  dropoff_hour  pickup_month  dropoff_month  pickup_timeofday \
0          17.0            16.0            6.0            6.0            1.0
1          23.0            22.0            6.0            6.0            2.0
2          10.0            11.0            6.0            6.0            3.0
3          13.0            14.0            6.0            6.0            0.0
4          22.0            22.0            6.0            6.0            2.0

  dropoff_timeofday
0                 1.0
1                 2.0
2                 3.0
3                 0.0
4                 2.0

[5 rows x 23 columns]
```

```
[97]: scaler = StandardScaler()
scaler.
    ↪fit(train_data[['PULocationID', 'DOLocationID', 'trip_distance', 'extra', 'tip_amount', 'tolls_a
```

```

train_data[['PULocationID','DOLocationID','trip_distance','extra','tip_amount','tolls_amount'],
        ↵= pd.DataFrame(scaler.
        ↵transform(train_data[['PULocationID','DOLocationID','trip_distance','extra','tip_amount','t
        ↵columns = ↵
        ↵['PULocationID','DOLocationID','trip_distance','extra','tip_amount','tolls_amount','pickup_
train_data.head()

```

```
[97]:   VendorID  passenger_count  trip_distance  RatecodeID  store_and_fwd_flag \
0       1.0          1.0      -0.007649       1.0                  0
1       0.0          1.0      -0.006231       1.0                  0
2       1.0          1.0      -0.010155       1.0                  0
3       0.0          1.0      -0.012054       1.0                  0
4       1.0          3.0      -0.010282       1.0                  0

      PULocationID  DOLocationID  payment_type     extra  tip_amount ... \
0      -0.166932     -1.623529           1  0.281471  0.225187 ...
1      -1.545814     1.080152           1  0.801949 -0.013003 ...
2       0.450282     1.185149           1 -1.019723 -0.437214 ...
3      -0.061874     1.395144           1  0.281471  0.061539 ...
4       0.923042    -1.059168           1 -0.499245 -0.294535 ...

  congestion_surcharge  Airport_fee  pickup_day_no  dropoff_day_no \
0              2.5          0.0      -1.594167      -1.603084
1              2.5          0.0      -0.253021      -0.269033
2              2.5          0.0      1.088124      1.065018
3              2.5          0.0      -0.253021      -0.269033
4              2.5          0.0      -0.253021      -0.269033

  pickup_hour  dropoff_hour  pickup_month  dropoff_month  pickup_timeofday \
0      0.326177     0.150673     -0.065343     -0.088271      -0.363187
1      1.365637     1.158848     -0.065343     -0.088271      0.650232
2     -0.886528    -0.689473     -0.065343     -0.088271      1.663651
3     -0.366797    -0.185385     -0.065343     -0.088271     -1.376605
4      1.192394     1.158848     -0.065343     -0.088271      0.650232

  dropoff_timeofday
0      -0.369946
1       0.660823
2       1.691592
3      -1.400716
4       0.660823

[5 rows x 23 columns]
```

8 Features and Target (Train Data)

```
[98]: att = np.array(train_data.columns)
att
```

```
[98]: array(['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID',
       'store_and_fwd_flag', 'PULocationID', 'DOLocationID',
       'payment_type', 'extra', 'tip_amount', 'tolls_amount',
       'improvement_surcharge', 'total_amount', 'congestion_surcharge',
       'Airport_fee', 'pickup_day_no', 'dropoff_day_no', 'pickup_hour',
       'dropoff_hour', 'pickup_month', 'dropoff_month',
       'pickup_timeofday', 'dropoff_timeofday'], dtype=object)
```

```
[99]: features = np.concatenate((att[0:12],att[-10:]))
print("feature_variables : ",features)
```

```
feature_variables : ['VendorID' 'passenger_count' 'trip_distance' 'RatecodeID'
 'store_and_fwd_flag' 'PULocationID' 'DOLocationID' 'payment_type' 'extra'
 'tip_amount' 'tolls_amount' 'improvement_surcharge'
 'congestion_surcharge' 'Airport_fee' 'pickup_day_no' 'dropoff_day_no'
 'pickup_hour' 'dropoff_hour' 'pickup_month' 'dropoff_month'
 'pickup_timeofday' 'dropoff_timeofday']
```

```
[100]: target = att[-11]
print("target_variable : ",target)
```

```
target_variable : total_amount
```

```
[101]: X = train_data[features]
y = train_data[target]
```

8.0.1 splitting the dataset in training and validation sets with `train_test_split`

```
[102]: X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,random_state=42)
```

```
[103]: X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 139997 entries, 127124 to 121958
Data columns (total 22 columns):
 #   Column            Non-Null Count  Dtype  
 ---  -- 
 0   VendorID          139997 non-null  float64 
 1   passenger_count   139997 non-null  float64 
 2   trip_distance     139997 non-null  float64 
 3   RatecodeID        139997 non-null  float64
```

```

4   store_and_fwd_flag      139997 non-null  int64
5   PULocationID           139997 non-null  float64
6   DOLocationID           139997 non-null  float64
7   payment_type            139997 non-null  int64
8   extra                   139997 non-null  float64
9   tip_amount              139997 non-null  float64
10  tolls_amount            139997 non-null  float64
11  improvement_surcharge  139997 non-null  float64
12  congestion_surcharge   139997 non-null  float64
13  Airport_fee             139997 non-null  float64
14  pickup_day_no          139997 non-null  float64
15  dropoff_day_no         139997 non-null  float64
16  pickup_hour             139997 non-null  float64
17  dropoff_hour            139997 non-null  float64
18  pickup_month            139997 non-null  float64
19  dropoff_month           139997 non-null  float64
20  pickup_timeofday        139997 non-null  float64
21  dropoff_timeofday       139997 non-null  float64
dtypes: float64(20), int64(2)
memory usage: 24.6 MB

```

9 Building Baseline Model

9.1 Dummy Regressor

```
[104]: dummy=DummyRegressor()
dummy.fit(X_train,y_train)
dummy_predict = dummy.predict(X_val)
print(dummy_predict)
print("R2_Score (Dummy Regression) :",r2_score(y_val,dummy_predict))
```

[29.6158677 29.6158677 29.6158677 ... 29.6158677 29.6158677 29.6158677]
R2_Score (Dummy Regression) : -1.071278978659329e-05

10 Linear Regression

- Simple Multiple Linear Regeression

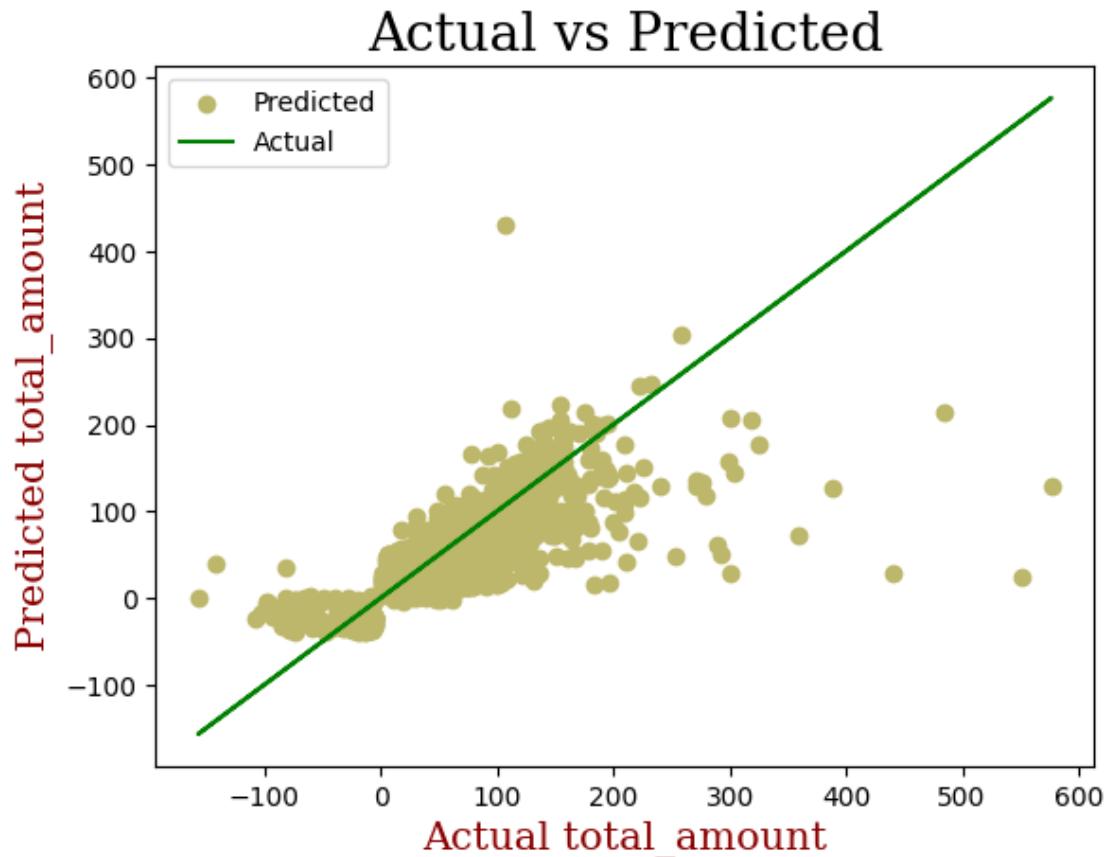
```
[105]: lin_reg = LinearRegression()
lin_reg.fit(X_train,y_train)
lin_predict = lin_reg.predict(X_val)
print(lin_predict)
lr_score = r2_score(y_val,lin_predict)
print("R2_Score (Multiple Linear Regression) :",lr_score)
```

[23.21419414 23.07504325 98.0870896 ... 18.368978 28.50271672
28.38644094]

R2_Score (Multiple Linear Regression) : 0.7170910000191486

- Plotting Actual vs Predicted

```
[106]: act_vs_predict(y_val,lin_predict)
```



10.1 LinearRegression with Cross Validation

```
[107]: shuffle_split_cv = ShuffleSplit(n_splits=10, test_size=0.2, random_state=0)
lin_reg_cv_results = cross_validate(LinearRegression(),
X_train,
y_train,
cv=shuffle_split_cv,
scoring="r2",
return_train_score=True,
return_estimator=True)

print(lin_reg_cv_results)
```

```
{'fit_time': array([0.19916511, 0.23253131, 0.23891759, 0.24089932, 0.23528385,
```

```
    0.23438215, 0.22892332, 0.23520708, 0.23659492, 0.2272234 ]),  
'score_time': array([0.01334071, 0.0130651 , 0.01314497, 0.01413488, 0.01970792,  
    0.01293159, 0.01337528, 0.01927209, 0.01322579, 0.01494288]),  
'estimator': [LinearRegression(), LinearRegression(), LinearRegression(),  
LinearRegression(), LinearRegression(), LinearRegression(), LinearRegression(),  
LinearRegression(), LinearRegression(), LinearRegression()], 'test_score':  
array([ 0.71016979,  0.70956151,  0.7091698 ,  0.71672728,  0.72148536,  
    0.7059929 ,  0.70930828,  0.67863734, -0.73687575,  0.7293165 ]),  
'train_score': array([0.71177755, 0.71167873, 0.71244755, 0.71019117,  
0.70942454,  
    0.71322688, 0.71196848, 0.72066845, 0.71212874, 0.70772944])}
```

```
[108]: lin_test_score = lin_reg_cv_results['test_score']  
lin_test_score
```

```
[108]: array([ 0.71016979,  0.70956151,  0.7091698 ,  0.71672728,  0.72148536,  
    0.7059929 ,  0.70930828,  0.67863734, -0.73687575,  0.7293165 ])
```

- Selecting best model

```
[109]: lin_best_model_index = np.argmax(lin_test_score)  
lin_selected_model = lin_reg_cv_results['estimator'][lin_best_model_index]  
lin_selected_model
```

```
[109]: LinearRegression()
```

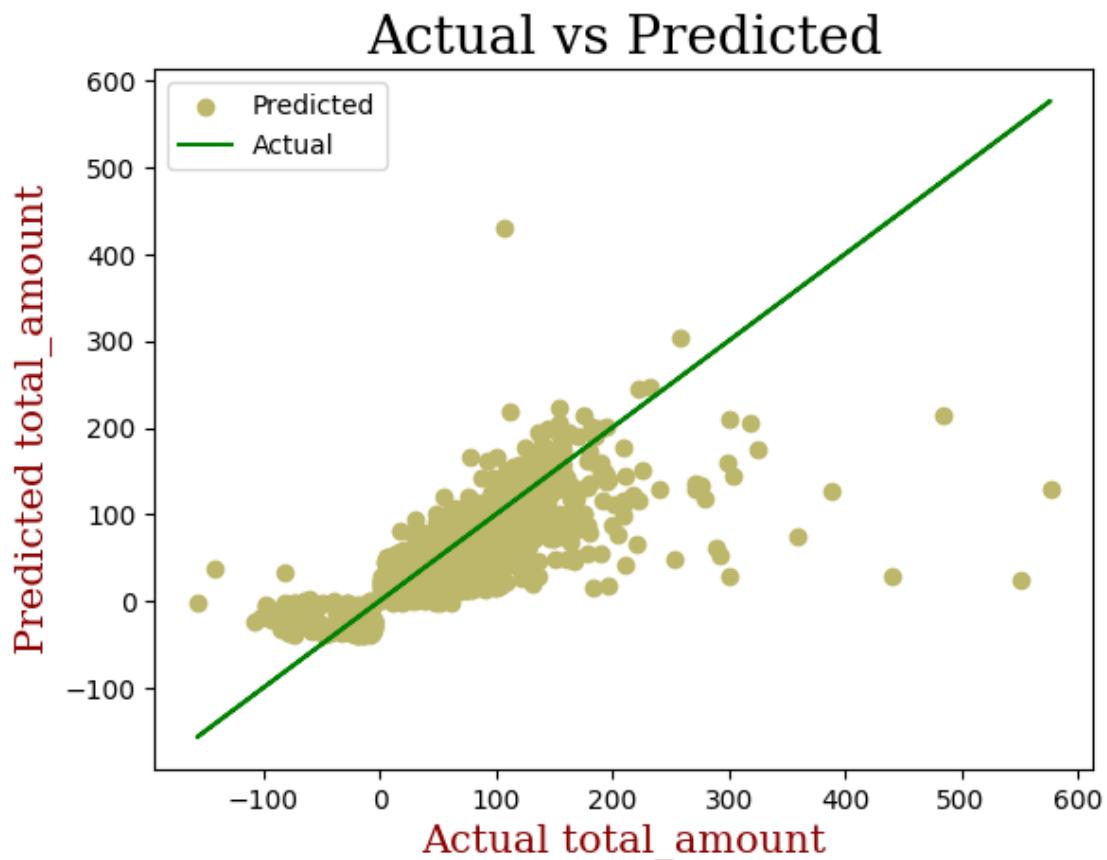
- Prediction

```
[110]: lin_cv_predict = lin_selected_model.predict(X_val)  
lin_cv_predict
```

```
[110]: array([23.2234771 , 23.15166472, 97.88447242, ..., 18.50375644,  
    28.45476118, 28.22431032])
```

- Plotting Actual vs Predicted

```
[111]: act_vs_predict(y_val,lin_cv_predict)
```



- R2 Score

```
[112]: lr_cv_score = r2_score(y_val,lin_cv_predict)
print("R2_Score (Multiple Linear Regression with Cross Validation) :
      ",lr_cv_score)
```

R2_Score (Multiple Linear Regression with Cross Validation) : 0.7170388309370268

11 Applying KNN and SVM Models

11.1 KNN (KNeighborsRegressor)

11.1.1 Simple KNeighborsRegressor

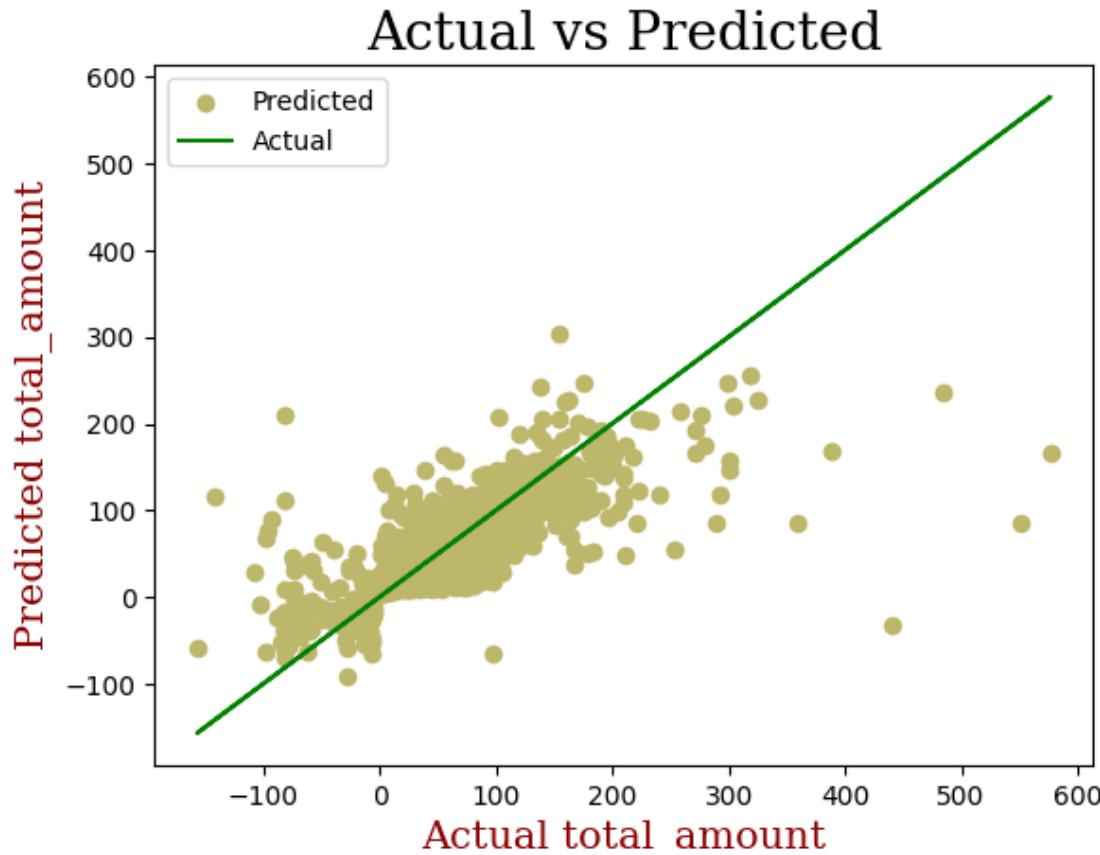
```
[113]: simp_KNN = KNeighborsRegressor()
simp_KNN.fit(X_train, y_train)
simp_KNN_predict = simp_KNN.predict(X_val)
print(simp_KNN_predict)
knn_score = r2_score(y_val,simp_KNN_predict)
print("R2_Score (KNN) :",knn_score)
```

```
[17.94 18.312 98.328 ... 17.16 22.224 26.29 ]
```

```
R2_Score (KNN) : 0.7629675702761719
```

- Plotting Actual vs Predicted

```
[114]: act_vs_predict(y_val,simp_KNN_predict)
```



11.1.2 Tuning Hyperparameters & Training as well as evaluating on the same.

- Using GridSearchCV

```
'''  
params = {'n_neighbors' : [i for i in range(1,31)]}  
gs = GridSearchCV(estimator=simp_KNN,  
                  param_grid=params,  
                  cv=10,  
                  n_jobs=-1)  
  
gs.fit(X_train,y_train)  
  
simp_KNN_gs = gs.best_estimator_
```

```
print("The best parameters using GridSearchCV is : ",simp_KNN_gs)
'''
```

```
[115]: '\nparams = {\\'n_neighbors\' : [i for i in range(1,31)]}\nngs =\nGridSearchCV(estimator=simp_KNN,\n                         param_grid=params,\n                         cv=10,\n                         n_jobs=-1)\nngs.fit(X_train,y_train)\nnsimp_KNN_gs =\ngs.best_estimator_\nprint("The best parameters using GridSearchCV is\n:",simp_KNN_gs)\n'
```

- Result
 - KNeighborsRegressor(n_neighbors=12)

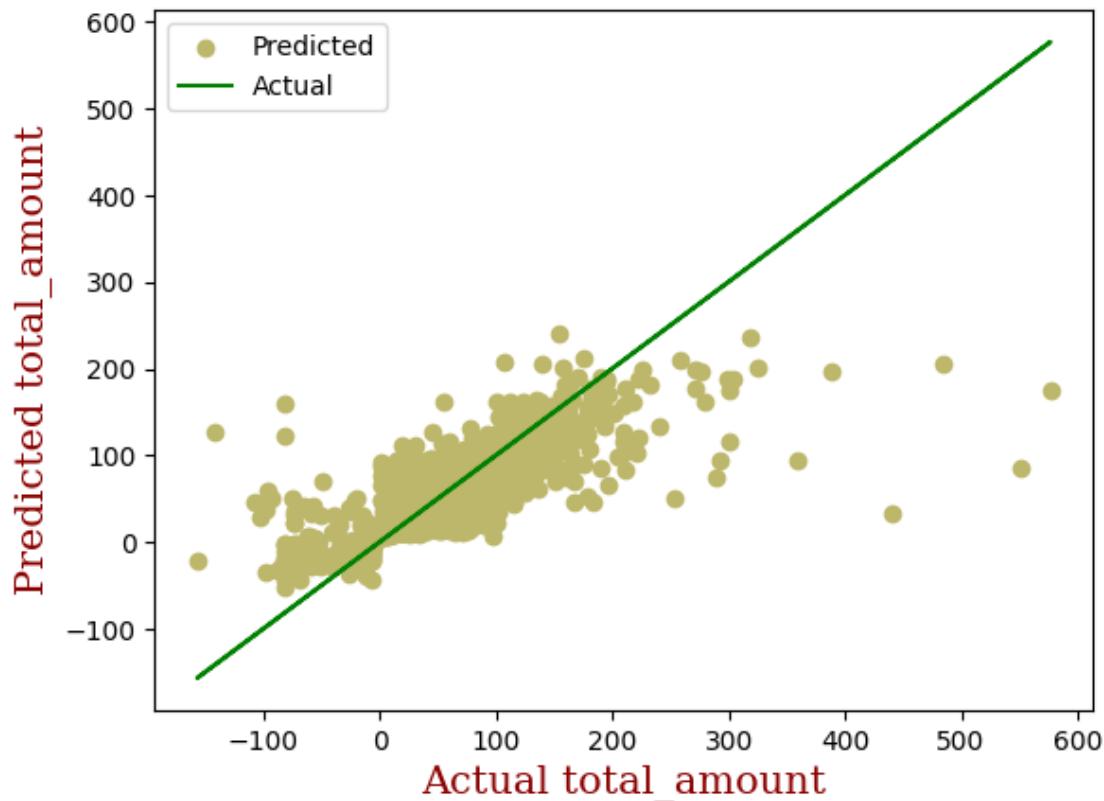
```
[116]: simp_KNN_gs = KNeighborsRegressor(n_neighbors=12)\nsimp_KNN_gs.fit(X_train, y_train)\nsimp_KNN_gs_predict = simp_KNN_gs.predict(X_val)\nprint(simp_KNN_gs_predict)\nknn_gs_score = r2_score(y_val,simp_KNN_gs_predict)\nprint("R2_Score (KNN_GridSearchCV) :",knn_gs_score)
```

```
[21.04583333 18.24583333 98.29666667 ... 16.585      20.84916667\n 26.98083333]\nR2_Score (KNN_GridSearchCV) : 0.7737493592887047
```

- Plotting Actual vs Predicted

```
[117]: act_vs_predict(y_val,simp_KNN_gs_predict)
```

Actual vs Predicted



- Using RandomizedSearchCV

```
[118]: '''
params = {'n_neighbors' : [i for i in range(1,31)]}
param_grid = params
rs = RandomizedSearchCV(simp_KNN,
                        param_grid,
                        cv=10,
                        n_jobs=-1)

rs.fit(X_train,y_train)

simp_KNN_rs = rs.best_estimator_
print("The best parameters using RandomizedSearchCV is :",simp_KNN_rs)
'''
```

```
[118]: '\nparams = {\\'n_neighbors\': [i for i in range(1,31)]}\nparam_grid =\nparams\nrs = RandomizedSearchCV(simp_KNN,\n                                param_grid,\n                                cv=10,\n                                n_jobs=-1)\n\nrs.fit(X_train,y_train)\n\nsimp_KNN_rs =\nrs.best_estimator_\nprint("The best parameters using RandomizedSearchCV is
```

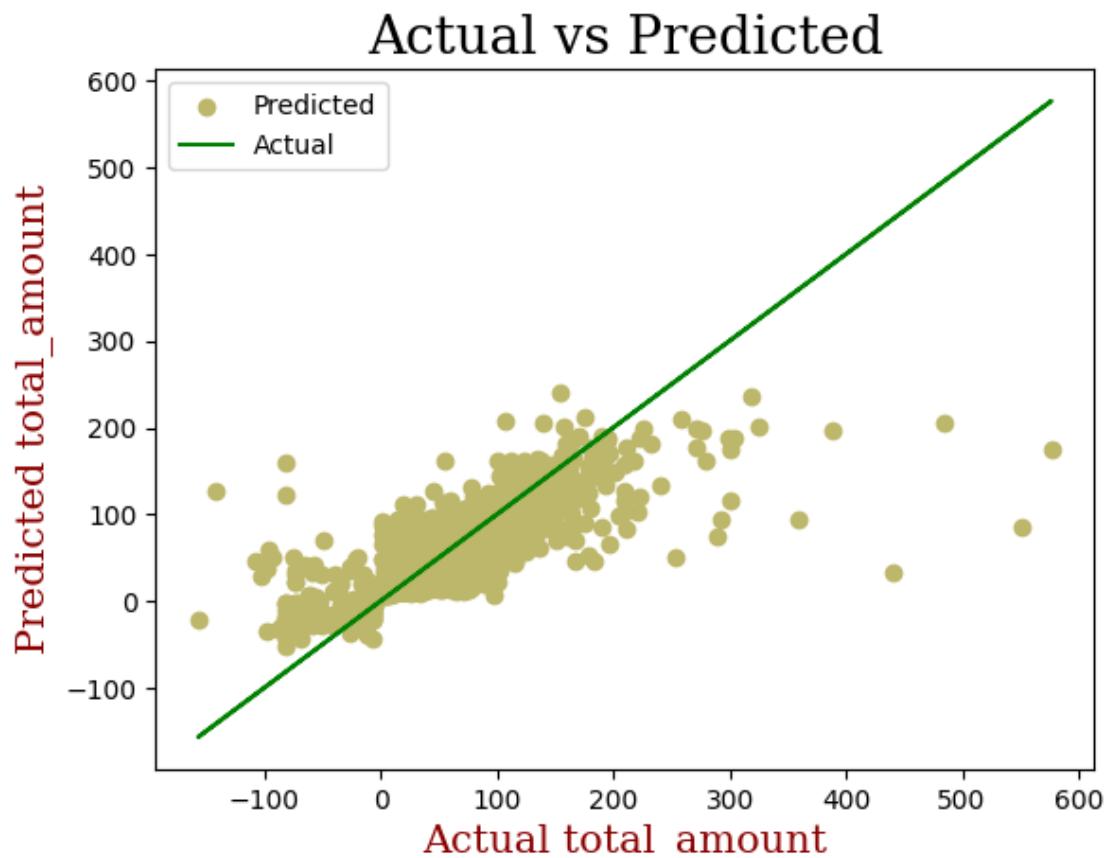
```
: ",simp_KNN_rs)\n'\n\n• Result\n– KNeighborsRegressor(n_neighbors=12)
```

```
[119]: simp_KNN_rs = KNeighborsRegressor(n_neighbors=12)\nsimp_KNN_rs.fit(X_train, y_train)\nsimp_KNN_rs_predict = simp_KNN_rs.predict(X_val)\nprint(simp_KNN_rs_predict)\nknn_rs_score = r2_score(y_val,simp_KNN_rs_predict)\nprint("R2_Score (KNN_RandomizedSearchCV) : ",knn_rs_score)
```

```
[21.04583333 18.24583333 98.29666667 ... 16.585      20.84916667\n26.98083333]\nR2_Score (KNN_RandomizedSearchCV) : 0.7737493592887047
```

- Plotting Actual vs Predicted

```
[120]: act_vs_predict(y_val,simp_KNN_rs_predict)
```



11.2 SVM (For Regression)

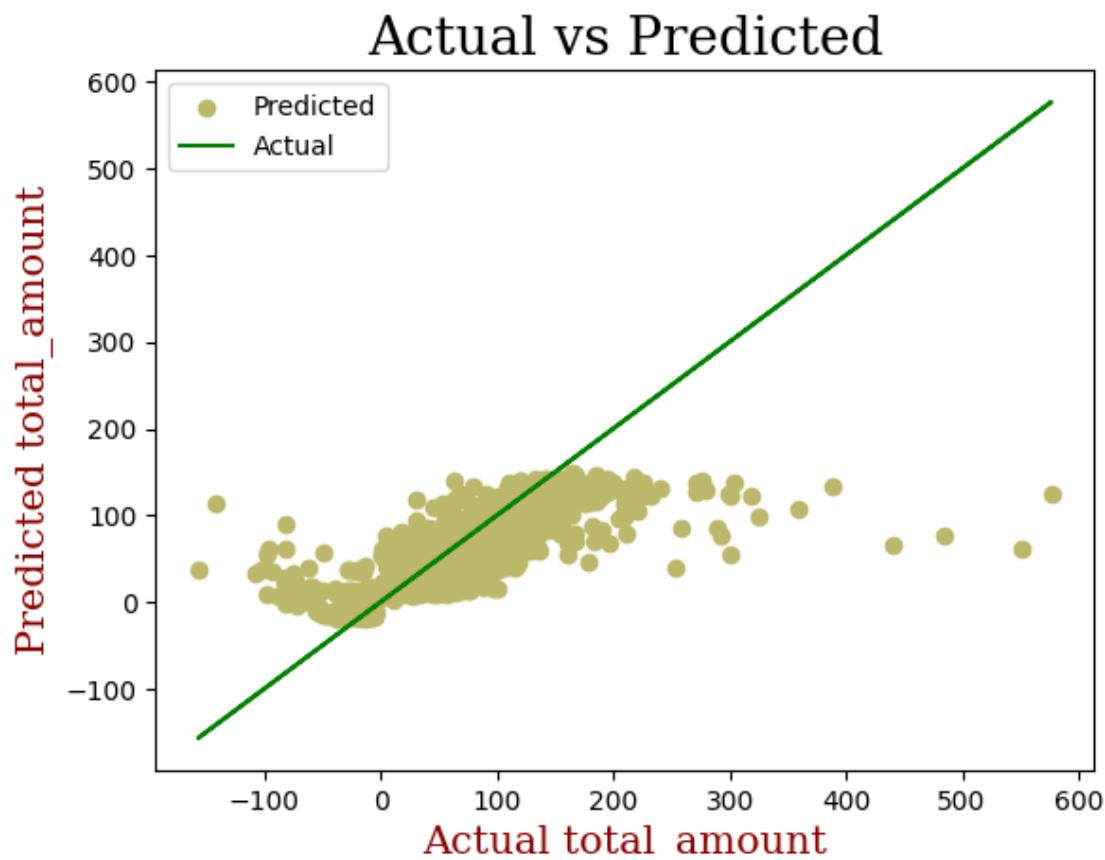
11.2.1 Simple SVR

```
[121]: simp_SVR = SVR()
simp_SVR.fit(X_train,y_train)
simp_SVR_predict = simp_SVR.predict(X_val)
print(simp_SVR_predict)
svr_score = r2_score(y_val,simp_SVR_predict)
print("R2_Score (SVR) :",svr_score)
```

```
[19.96743266 19.67240913 96.56888457 ... 14.76327008 24.04720859
 26.6116096 ]
R2_Score (SVR) : 0.7612822738273943
```

- Plotting Actual vs Predicted

```
[122]: act_vs_predict(y_val,simp_SVR_predict)
```



12 Applying CART, Bagging and Boosting, and MLP.

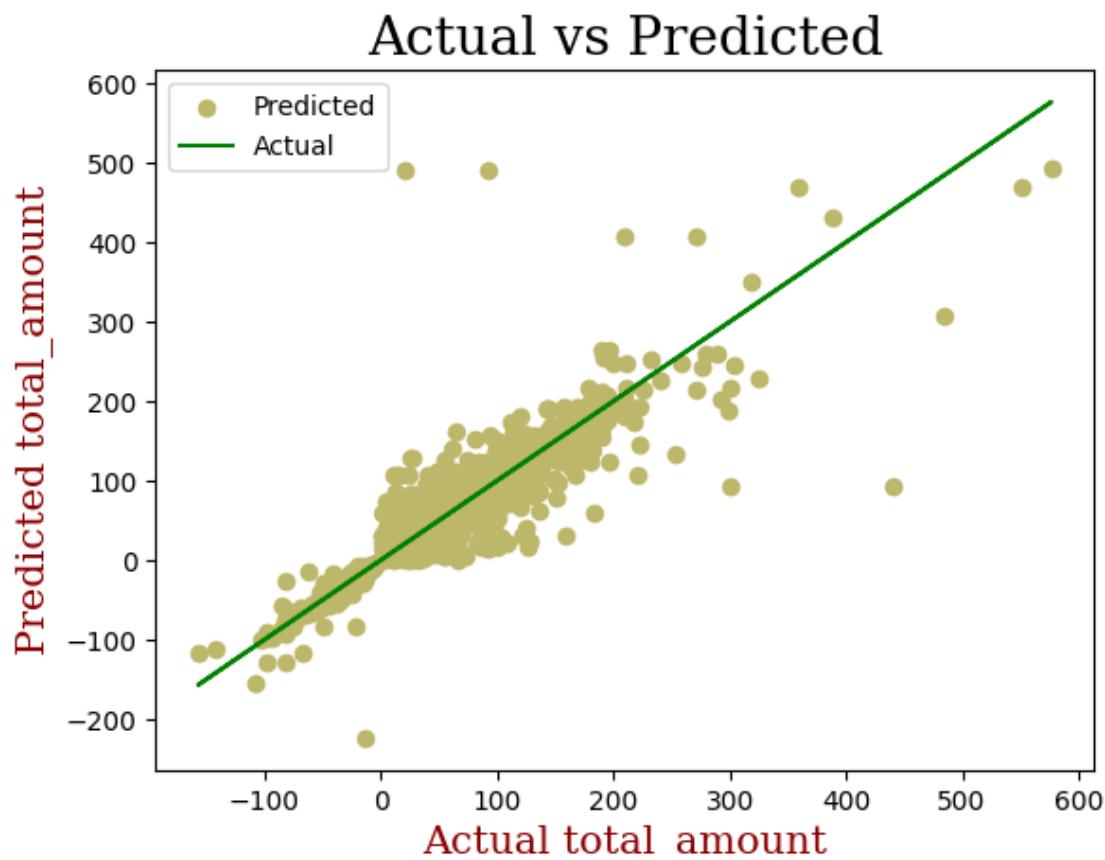
12.1 CART (DecisionTreeRegressor)

```
[123]: dt_reg = DecisionTreeRegressor()
dt_reg.fit(X_train,y_train)
dt_reg_predict = dt_reg.predict(X_val)
print(dt_reg_predict)
dt_score = r2_score(y_val,dt_reg_predict)
print("R2_Score (DecisionTreeRegressor) :",dt_score)
```

[49.5 21.6 97.3 ... 12.6 16.4 32.28]
R2_Score (DecisionTreeRegressor) : 0.9049938613771363

- Plotting Actual vs Predicted

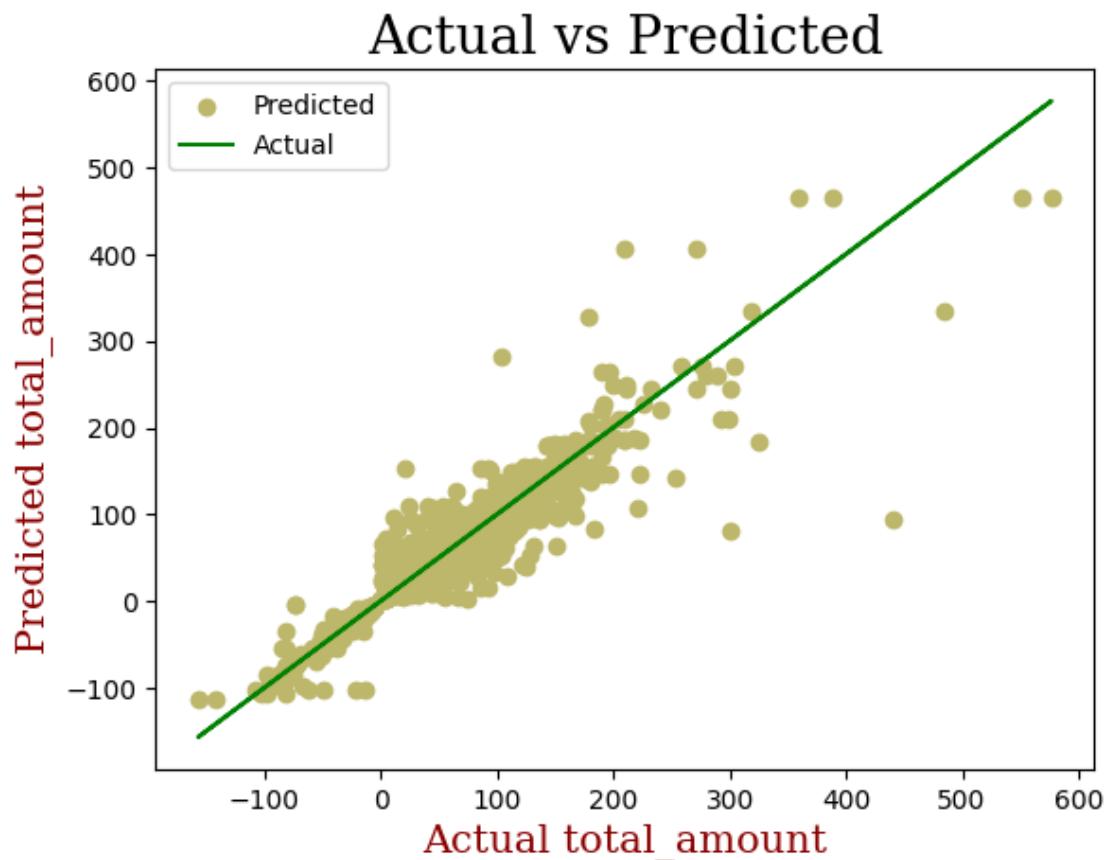
```
[124]: act_vs_predict(y_val,dt_reg_predict)
```



12.1.1 Tuning Hyperparameters & Training as well as evaluating on the same.

```
[125]: """
param_grid = {'max_depth': range(1, 20),
              'min_samples_split':range(2,17)}
dt_grid_search = GridSearchCV(DecisionTreeRegressor(),
                               param_grid=param_grid,
                               n_jobs=-1,
                               cv=10,
                               scoring="neg_mean_absolute_error",
                               return_train_score=True)
dt_grid_search.fit(X_train, y_train)
print ("The best parameter value is:", dt_grid_search.best_params_)
"""

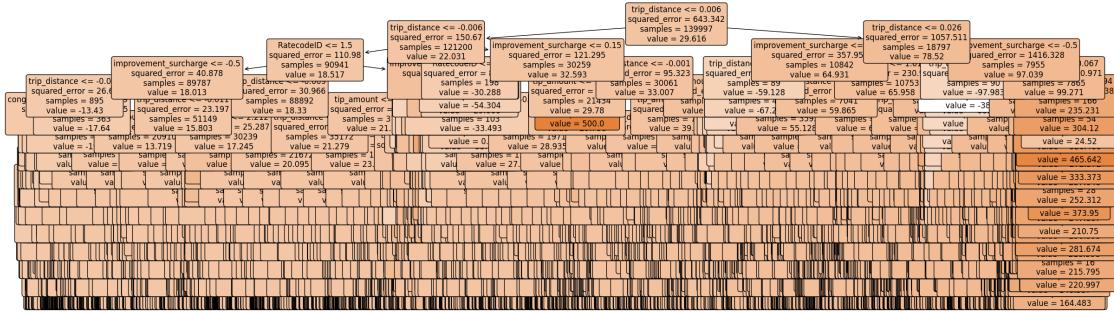
[125]: \nparam_grid = {'max_depth': range(1, 20),\n    'min_samples_split':range(2,17)}\ndt_grid_search =\nGridSearchCV(DecisionTreeRegressor(),\n    param_grid=param_grid,\n                           n_jobs=-1,\n                           cv=10,\n                           scoring="neg_mean_absolute_error",\n                           return_train_score=True)\ndt_grid_search.fit(X_train, y_train)\nprint ("The best\nparameter value is:", dt_grid_search.best_params_)\n\n    • Result\n        – The best parameter value is: {'max_depth': 15, 'min_samples_split': 16}\n\n[126]: dt_reg_gs = DecisionTreeRegressor(max_depth = 15, min_samples_split = 16)\ndt_reg_gs.fit(X_train,y_train)\ndt_reg_gs_predict = dt_reg_gs.predict(X_val)\nprint(dt_reg_gs_predict)\ndt_gs_score = r2_score(y_val,dt_reg_gs_predict)\nprint("R2_Score (DecisionTreeRegressor_GridSearchCV) :",dt_gs_score)\n\n[40.10333333 24.3855102 98.53263905 ... 11.90888889 17.68247093\n 33.87054913]\nR2_Score (DecisionTreeRegressor_GridSearchCV) : 0.9410002559982911\n\n    • Plotting Actual vs Predicted\n\n[127]: act_vs_predict(y_val,dt_reg_gs_predict)
```



12.2 Visualizing the tree

- As a tree diagram

```
[128]: plt.figure(figsize=(28,8), facecolor ='w')
# create the tree plot
a = tree.plot_tree(dt_reg_gs,
                    #use the feature names stored
                    feature_names = features,
                    rounded = True,
                    filled = True,
                    fontsize=12)
# show the plot
plt.show()
```



- Figure is very compact due to large number of depth and branches.
- As a text-based diagram

```
[129]: #export the decision rules
tree_rules = export_text(dt_reg)
#print the result
print(tree_rules)
```

```

|--- feature_2 <= 0.01
|   |--- feature_2 <= -0.01
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_11 <= -0.50
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |--- feature_8 <= 0.93
|   |   |   |   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |   |   |   |   |--- feature_8 <= -0.76
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |   |--- feature_8 > -0.76
|   |   |   |   |   |   |   |   |   |   |   |--- value: [-5.50]
|   |   |   |   |   |   |   |   |   |--- feature_13 > 0.88
|   |   |   |   |   |   |   |   |   |   |--- feature_8 <= -0.76
|   |   |   |   |   |   |   |   |   |   |   |--- feature_5 <= -0.23
|   |   |   |   |   |   |   |   |   |   |   |   |--- value: [-6.95]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_5 > -0.23
|   |   |   |   |   |   |   |   |   |   |   |   |--- value: [-6.25]
|   |   |   |   |   |   |   |   |   |   |--- feature_8 > -0.76
|   |   |   |   |   |   |   |   |   |   |--- feature_5 <= 1.22
|   |   |   |   |   |   |   |   |   |   |   |--- value: [-7.25]
```

```

|   |   |   |   |   |   |   |   |--- feature_5 >  1.22
|   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_8 >  -0.11
|   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |--- feature_16 <= 0.24
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_16 >  0.24
|   |   |   |   |--- feature_9 <= -0.44
|   |   |   |   |--- value: [-7.00]
|   |   |   |   |--- feature_9 >  -0.44
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |--- feature_6 <= 1.01
|   |   |   |   |--- value: [-8.75]
|   |   |   |   |--- feature_6 >  1.01
|   |   |   |   |--- value: [-10.85]
|--- feature_8 >  0.93
|   |--- feature_17 <= 0.15
|   |   |--- feature_6 <= 0.29
|   |   |--- value: [-11.25]
|   |   |--- feature_6 >  0.29
|   |   |--- value: [-9.50]
|   |--- feature_17 >  0.15
|   |   |--- feature_17 <= 0.99
|   |   |   |--- feature_5 <= 0.02
|   |   |   |--- value: [-13.65]
|   |   |   |--- feature_5 >  0.02
|   |   |   |--- value: [-13.75]
|   |--- feature_17 >  0.99
|   |   |--- value: [-12.25]
|--- feature_12 >  1.25
|--- feature_2 <= -0.01
|   |--- feature_8 <= -0.11
|   |   |--- feature_2 <= -0.01
|   |   |--- feature_8 <= -0.76
|   |   |   |--- feature_9 <= -1.17
|   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_9 >  -1.17
|   |   |   |--- truncated branch of depth 7
|   |   |   |--- feature_8 >  -0.76
|   |   |   |--- feature_9 <= -1.25
|   |   |   |--- value: [-8.70]
|   |   |   |--- feature_9 >  -1.25
|   |   |--- truncated branch of depth 5
|--- feature_2 >  -0.01

```

```

|   |   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- feature_16 <= 0.07
|   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |--- feature_16 >  0.07
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |--- feature_16 <= -0.80
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |--- feature_16 >  -0.80
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_8 >  -0.11
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |   |   |   |--- value: [-11.25]
|   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |--- feature_16 <= 0.41
|   |   |   |   |   |--- value: [-10.20]
|   |   |   |   |--- feature_16 >  0.41
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |--- feature_2 >  -0.01
|   |   |   |--- feature_9 <= -0.98
|   |   |   |   |--- feature_5 <= -0.10
|   |   |   |   |   |--- value: [-12.30]
|   |   |   |   |--- feature_5 >  -0.10
|   |   |   |   |   |--- value: [-11.60]
|   |   |   |   |--- feature_9 >  -0.98
|   |   |   |   |--- feature_9 <= -0.82
|   |   |   |   |   |--- value: [-13.00]
|   |   |   |   |--- feature_9 >  -0.82
|   |   |   |   |   |--- value: [-12.30]
|--- feature_2 >  -0.01
|   |--- feature_8 <= -0.11
|   |--- feature_5 <= -1.67
|   |   |--- feature_16 <= 0.15
|   |   |   |--- feature_6 <= -1.26
|   |   |   |   |--- value: [-18.20]
|   |   |   |--- feature_6 >  -1.26
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_16 >  0.15
|   |   |   |   |--- value: [-54.30]
|--- feature_5 >  -1.67
|   |--- feature_2 <= -0.01
|   |   |--- feature_2 <= -0.01
|   |   |   |--- truncated branch of depth 14
|   |   |--- feature_2 >  -0.01

```

```

| | | | | | | | | | | |--- truncated branch of depth 14
| | | | | | | | | | | |--- feature_2 > -0.01
| | | | | | | | | | | |--- feature_16 <= 0.50
| | | | | | | | | | | |--- truncated branch of depth 4
| | | | | | | | | | | |--- feature_16 > 0.50
| | | | | | | | | | | |--- truncated branch of depth 3
| | | | | | | | | | | |--- feature_8 > -0.11
| | | | | | | | | | | |--- feature_2 <= -0.01
| | | | | | | | | | | |--- feature_5 <= -1.16
| | | | | | | | | | | |--- feature_17 <= 0.40
| | | | | | | | | | | |--- truncated branch of depth 4
| | | | | | | | | | | |--- feature_17 > 0.40
| | | | | | | | | | | |--- truncated branch of depth 6
| | | | | | | | | | | |--- feature_5 > -1.16
| | | | | | | | | | | |--- feature_21 <= -0.89
| | | | | | | | | | | |--- truncated branch of depth 2
| | | | | | | | | | | |--- feature_21 > -0.89
| | | | | | | | | | | |--- truncated branch of depth 13
| | | | | | | | | | | |--- feature_2 > -0.01
| | | | | | | | | | | |--- feature_5 <= 1.68
| | | | | | | | | | | |--- feature_9 <= -0.42
| | | | | | | | | | | |--- truncated branch of depth 4
| | | | | | | | | | | |--- feature_9 > -0.42
| | | | | | | | | | | |--- truncated branch of depth 2
| | | | | | | | | | | |--- feature_5 > 1.68
| | | | | | | | | | | |--- value: [-16.50]
| | | | | |--- feature_2 > -0.01
| | | | | |--- feature_2 <= -0.01
| | | | | |--- feature_8 <= -0.11
| | | | | | | |--- feature_2 <= -0.01
| | | | | | | |--- feature_16 <= -0.80
| | | | | | | | |--- feature_9 <= -1.27
| | | | | | | | | |--- value: [-18.20]
| | | | | | | | | |--- feature_9 > -1.27
| | | | | | | | | |--- feature_6 <= 0.78
| | | | | | | | | | |--- truncated branch of depth 8
| | | | | | | | | |--- feature_6 > 0.78
| | | | | | | | | | |--- truncated branch of depth 5
| | | | | | | | | |--- feature_16 > -0.80
| | | | | | | | | |--- feature_6 <= 1.56
| | | | | | | | | |--- feature_2 <= -0.01
| | | | | | | | | | |--- truncated branch of depth 11
| | | | | | | | | |--- feature_2 > -0.01
| | | | | | | | | | |--- truncated branch of depth 12
| | | | | | | | | |--- feature_6 > 1.56
| | | | | | | | | | |--- feature_5 <= 0.95
| | | | | | | | | | |--- truncated branch of depth 3
| | | | | | | | | |--- feature_5 > 0.95

```

```

|   |   |   |   |   |   |   |   |--- value: [-28.70]
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- feature_17 <= -1.19
|   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- value: [-10.80]
|   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |   |--- feature_17 <= -1.95
|   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_17 > -1.95
|   |   |   |   |   |--- value: [-16.80]
|   |   |   |--- feature_17 > -1.19
|   |   |   |   |--- feature_21 <= -0.89
|   |   |   |   |   |--- feature_6 <= 0.34
|   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_6 > 0.34
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_21 > -0.89
|   |   |   |   |   |--- feature_6 <= -0.75
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_6 > -0.75
|   |   |   |   |--- truncated branch of depth 8
|--- feature_8 > -0.11
|   |--- feature_20 <= -0.87
|   |   |--- feature_15 <= -0.94
|   |   |   |--- value: [-22.80]
|   |   |--- feature_15 > -0.94
|   |   |   |--- value: [-33.30]
|--- feature_20 > -0.87
|   |--- feature_2 <= -0.01
|   |   |--- feature_9 <= -0.29
|   |   |   |--- feature_12 <= 1.25
|   |   |   |   |--- truncated branch of depth 2
|   |   |--- feature_12 > 1.25
|   |   |   |--- truncated branch of depth 10
|--- feature_9 > -0.29
|   |--- feature_6 <= 1.50
|   |   |--- truncated branch of depth 2
|   |--- feature_6 > 1.50
|   |   |--- value: [-10.80]
|--- feature_2 > -0.01
|   |--- feature_12 <= 1.25
|   |   |--- feature_5 <= 0.17
|   |   |   |--- value: [-15.19]
|   |   |--- feature_5 > 0.17
|   |   |--- truncated branch of depth 2
|--- feature_12 > 1.25
|   |--- feature_6 <= 0.96
|   |--- truncated branch of depth 10

```

```

|   |   |   |   |   |   |   |   |--- feature_6 >  0.96
|   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |--- feature_2 >  -0.01
|   |   |   |--- feature_21 <= 0.15
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- feature_17 <= -0.27
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- feature_16 <= -0.19
|   |   |   |   |   |   |--- value: [-16.10]
|   |   |   |   |   |   |--- feature_16 >  -0.19
|   |   |   |   |   |   |--- value: [-14.00]
|   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |--- feature_20 <= 0.14
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_20 >  0.14
|   |   |   |   |   |--- value: [-19.60]
|   |   |   |   |--- feature_17 >  -0.27
|   |   |   |   |--- feature_9 <= -1.27
|   |   |   |   |--- value: [-26.60]
|   |   |   |   |--- feature_9 >  -1.27
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |--- truncated branch of depth 9
|   |--- feature_2 >  -0.01
|   |--- feature_6 <= -0.74
|   |   |--- feature_5 <= -0.38
|   |   |--- feature_6 <= -1.32
|   |   |--- truncated branch of depth 2
|   |   |--- feature_6 >  -1.32
|   |   |--- truncated branch of depth 3
|   |   |--- feature_5 >  -0.38
|   |   |--- feature_6 <= -1.59
|   |   |--- value: [-17.80]
|   |   |--- feature_6 >  -1.59
|   |   |--- truncated branch of depth 4
|   |--- feature_6 >  -0.74
|   |   |--- feature_9 <= -1.12
|   |   |--- feature_9 <= -1.31
|   |   |--- value: [-25.60]
|   |   |--- feature_9 >  -1.31
|   |   |--- truncated branch of depth 3
|   |--- feature_9 >  -1.12
|   |   |--- feature_5 <= -1.38
|   |   |--- truncated branch of depth 4
|   |   |--- feature_5 >  -1.38
|   |   |--- truncated branch of depth 7
|--- feature_21 >  0.15

```

```

|   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- feature_9 <= -0.52
|   |   |   |   |   |   |--- feature_6 <= -0.48
|   |   |   |   |   |   |   |--- feature_6 <= -0.63
|   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |--- feature_6 > -0.63
|   |   |   |   |   |   |   |--- value: [-23.40]
|   |   |   |   |   |   |--- feature_6 > -0.48
|   |   |   |   |   |   |   |--- feature_17 <= -1.19
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |--- feature_17 > -1.19
|   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |--- feature_9 > -0.52
|   |   |   |   |   |--- feature_9 <= -0.40
|   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |   |   |--- value: [-15.70]
|   |   |   |   |   |--- feature_9 > -0.40
|   |   |   |   |   |--- feature_15 <= 0.40
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |--- feature_15 > 0.40
|   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |--- feature_2 > -0.01
|   |   |   |--- feature_5 <= -1.49
|   |   |   |   |--- feature_1 <= 1.50
|   |   |   |   |   |--- value: [-28.00]
|   |   |   |   |--- feature_1 > 1.50
|   |   |   |   |   |--- value: [-20.60]
|   |   |   |--- feature_5 > -1.49
|   |   |   |   |--- feature_5 <= -0.02
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_5 > -0.02
|   |   |   |   |   |--- feature_17 <= 0.23
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |--- feature_17 > 0.23
|   |   |   |   |   |   |--- value: [-22.00]
|--- feature_11 > -0.50
|--- feature_2 <= -0.01
|   |--- feature_2 <= -0.01
|   |--- feature_9 <= 0.27
|   |   |--- feature_7 <= 0.50
|   |   |   |--- feature_2 <= -0.01
|   |   |   |--- feature_8 <= 0.09
|   |   |   |   |--- feature_12 <= 1.25

```

```

|   |   |   |   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |   |   |   |   |--- feature_8 >  0.09
|   |   |   |   |   |   |   |   |--- feature_17 <= -0.10
|   |   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |   |   |   |--- feature_17 > -0.10
|   |   |   |   |   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |   |--- feature_17 <= -0.10
|   |   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |   |   |   |--- feature_17 > -0.10
|   |   |   |   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |   |   |   |--- truncated branch of depth 23
|   |   |   |   |   |   |   |--- feature_8 > -0.11
|   |   |   |   |   |   |   |--- truncated branch of depth 28
|   |   |   |   |   |--- feature_7 >  0.50
|   |   |   |   |   |--- feature_17 <= -0.10
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |--- truncated branch of depth 30
|   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |--- truncated branch of depth 35
|   |   |   |   |--- feature_17 > -0.10
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |--- truncated branch of depth 28
|   |   |   |   |--- feature_8 > -0.11
|   |   |   |   |--- truncated branch of depth 30
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |--- truncated branch of depth 29
|   |   |   |   |--- feature_8 > -0.11
|   |   |   |   |--- truncated branch of depth 27
|   |   |   |--- feature_9 >  0.27
|   |   |   |--- feature_9 <= 0.65
|   |   |   |--- feature_9 <= 0.40
|   |   |   |   |--- feature_16 <= -0.45
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- truncated branch of depth 9

```

```

|   |   |   |   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |   |   |   |   |--- feature_16 > -0.45
|   |   |   |   |   |   |   |   |--- feature_17 <= 0.57
|   |   |   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |   |   |   |--- feature_17 > 0.57
|   |   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_9 > 0.40
|   |   |   |   |   |   |--- feature_14 <= 0.42
|   |   |   |   |   |   |--- feature_9 <= 0.48
|   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_9 > 0.48
|   |   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |   |--- feature_14 > 0.42
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- value: [30.06]
|   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |--- feature_9 > 0.65
|   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |--- feature_9 <= 9.49
|   |   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_7 > 2.00
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_9 > 9.49
|   |   |   |   |   |   |--- value: [88.99]
|   |   |   |   |--- feature_10 > 1.13
|   |   |   |   |   |--- feature_20 <= 1.16
|   |   |   |   |   |   |--- value: [59.33]
|   |   |   |   |   |--- feature_20 > 1.16
|   |   |   |   |   |   |--- value: [84.84]
|--- feature_2 > -0.01
|   |--- feature_10 <= 2.21
|   |   |--- feature_9 <= 0.37
|   |   |--- feature_7 <= 0.50
|   |   |   |--- feature_12 <= 1.25
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |--- truncated branch of depth 32
|   |--- feature_7 > 0.50
|   |   |--- feature_21 <= 0.15

```

```

|   |   |   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 36
|   |   |   |   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |   |   |--- truncated branch of depth 38
|   |   |   |   |   |--- feature_21 > 0.15
|   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 33
|   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |--- truncated branch of depth 37
|   |   |   |--- feature_9 > 0.37
|   |   |--- feature_9 <= 0.80
|   |   |   |--- feature_9 <= 0.53
|   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |--- feature_21 > 0.15
|   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |--- feature_9 > 0.53
|   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |--- feature_7 > 2.00
|   |   |   |   |   |--- truncated branch of depth 5
|   |--- feature_9 > 0.80
|   |   |--- feature_9 <= 7.44
|   |   |   |--- feature_7 <= 2.00
|   |   |   |   |--- truncated branch of depth 18
|   |   |   |--- feature_7 > 2.00
|   |   |   |   |--- truncated branch of depth 10
|   |   |   |--- feature_9 > 7.44
|   |   |   |--- feature_9 <= 11.36
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_9 > 11.36
|   |   |   |   |--- truncated branch of depth 3
|--- feature_10 > 2.21
|   |--- feature_9 <= 2.25
|   |   |--- feature_10 <= 5.73
|   |   |--- feature_7 <= 0.50
|   |   |   |--- feature_5 <= -0.38
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_5 > -0.38
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |--- feature_7 > 0.50
|   |   |   |   |--- feature_16 <= 0.41
|   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |--- feature_16 > 0.41
|   |   |   |   |   |--- truncated branch of depth 8
|--- feature_10 > 5.73
|   |--- feature_20 <= 1.16
|   |   |--- feature_9 <= 1.92

```

```

|   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |--- feature_9 >  1.92
|   |   |   |   |   |   |   |   |   |--- value: [75.60]
|   |   |   |   |   |   |   |   |--- feature_20 >  1.16
|   |   |   |   |   |   |   |   |--- value: [42.92]
|   |   |   |   |   |--- feature_9 >  2.25
|   |   |   |   |   |--- feature_17 <= -0.19
|   |   |   |   |   |--- value: [171.91]
|   |   |   |   |   |--- feature_17 > -0.19
|   |   |   |   |   |--- feature_10 <= 4.32
|   |   |   |   |   |--- feature_8 <= -0.37
|   |   |   |   |   |--- value: [100.58]
|   |   |   |   |   |--- feature_8 > -0.37
|   |   |   |   |   |--- value: [102.26]
|   |   |   |   |   |--- feature_10 >  4.32
|   |   |   |   |   |--- value: [119.01]
|   |--- feature_2 > -0.01
|   |--- feature_9 <= 0.53
|   |   |--- feature_2 <= -0.01
|   |   |   |--- feature_9 <= -0.26
|   |   |   |--- feature_21 <= 0.15
|   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |--- feature_8 > -0.11
|   |   |   |   |--- feature_7 <= 0.50
|   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |--- feature_7 >  0.50
|   |   |   |   |--- truncated branch of depth 30
|   |   |   |--- feature_21 >  0.15
|   |   |   |--- feature_7 <= 0.50
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- truncated branch of depth 29
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |--- feature_7 >  0.50
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- truncated branch of depth 35
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- truncated branch of depth 28
|   |   |   |--- feature_9 > -0.26
|   |   |   |--- feature_21 <= 0.15
|   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |--- feature_8 > -0.11

```

```

|   |   |   |   |   |   |   |   |--- truncated branch of depth 28
|   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |--- feature_16 <= 0.76
|   |   |   |   |   |   |--- truncated branch of depth 26
|   |   |   |   |   |--- feature_16 > 0.76
|   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |--- feature_21 > 0.15
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- feature_17 <= -1.28
|   |   |   |   |   |   |--- truncated branch of depth 26
|   |   |   |   |   |--- feature_17 > -1.28
|   |   |   |   |   |--- truncated branch of depth 34
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |--- feature_17 <= -1.11
|   |   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |--- feature_17 > -1.11
|   |   |   |   |--- truncated branch of depth 24
|   |   |--- feature_2 > -0.01
|   |   |   |--- feature_9 <= -0.24
|   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- feature_7 <= 0.50
|   |   |   |   |   |--- feature_15 <= 0.40
|   |   |   |   |   |--- truncated branch of depth 25
|   |   |   |   |--- feature_15 > 0.40
|   |   |   |   |--- truncated branch of depth 23
|   |   |   |   |--- feature_7 > 0.50
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- truncated branch of depth 26
|   |   |--- feature_21 > 0.15
|   |   |   |--- feature_7 <= 0.50
|   |   |   |   |--- feature_17 <= -1.11
|   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |--- feature_17 > -1.11
|   |   |   |   |--- truncated branch of depth 24
|   |   |   |--- feature_7 > 0.50
|   |   |   |   |--- feature_9 <= -0.51
|   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |--- feature_9 > -0.51
|   |   |   |   |--- truncated branch of depth 24
|   |   |--- feature_9 > -0.24
|   |   |   |--- feature_21 <= 0.15
|   |   |   |   |--- feature_16 <= 0.76
|   |   |   |   |   |--- feature_14 <= 0.42
|   |   |   |   |   |--- truncated branch of depth 33
|   |   |   |   |   |--- feature_14 > 0.42
|   |   |   |   |   |--- truncated branch of depth 25

```

```

|   |   |   |   |   |   |   |--- feature_16 >  0.76
|   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 23
|   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |--- feature_17 <= -1.28
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |   |--- feature_17 >  -1.28
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |--- truncated branch of depth 22
|--- feature_9 >  0.53
|--- feature_9 <= 0.98
|   |--- feature_9 <= 0.71
|   |   |--- feature_2 <= -0.01
|   |   |   |--- feature_16 <= 0.76
|   |   |   |--- feature_15 <= 0.40
|   |   |   |   |--- truncated branch of depth 25
|   |   |   |--- feature_15 >  0.40
|   |   |   |   |--- truncated branch of depth 18
|   |   |   |--- feature_16 >  0.76
|   |   |   |   |--- feature_9 <= 0.60
|   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |--- feature_9 >  0.60
|   |   |   |   |   |--- truncated branch of depth 15
|--- feature_2 >  -0.01
|   |   |--- feature_16 <= 0.76
|   |   |--- feature_17 <= -0.94
|   |   |   |--- truncated branch of depth 12
|   |   |--- feature_17 >  -0.94
|   |   |   |--- truncated branch of depth 24
|   |--- feature_16 >  0.76
|   |   |--- feature_2 <= -0.01
|   |   |   |--- truncated branch of depth 13
|   |   |--- feature_2 >  -0.01
|   |   |   |--- truncated branch of depth 13
|--- feature_9 >  0.71
|   |--- feature_15 <= 0.40
|   |--- feature_16 <= 0.59
|   |   |--- feature_17 <= -0.77
|   |   |   |--- truncated branch of depth 12
|   |   |--- feature_17 >  -0.77
|   |   |   |--- truncated branch of depth 20

```

```

|   |   |   |   |   |   |   |--- feature_16 >  0.59
|   |   |   |   |   |   |--- feature_6 <= 1.67
|   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |   |   |--- feature_6 >  1.67
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_15 >  0.40
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- feature_9 <= 0.93
|   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_9 >  0.93
|   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |--- feature_9 <= 0.85
|   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |--- feature_9 >  0.85
|   |   |   |   |--- truncated branch of depth 12
|   |--- feature_9 >  0.98
|   |--- feature_9 <= 9.27
|   |--- feature_9 <= 1.92
|   |--- feature_15 <= 0.40
|   |--- feature_17 <= 0.74
|   |--- truncated branch of depth 19
|   |--- feature_17 >  0.74
|   |--- truncated branch of depth 7
|   |--- feature_15 >  0.40
|   |--- feature_2 <= -0.01
|   |--- truncated branch of depth 6
|   |--- feature_2 >  -0.01
|   |--- truncated branch of depth 10
|   |--- feature_9 >  1.92
|   |--- feature_5 <= 0.60
|   |--- feature_10 <= 2.90
|   |--- truncated branch of depth 10
|   |--- feature_10 >  2.90
|   |--- value: [82.27]
|   |--- feature_5 >  0.60
|   |--- feature_9 <= 2.00
|   |--- value: [75.90]
|   |--- feature_9 >  2.00
|   |--- truncated branch of depth 4
|   |--- feature_9 >  9.27
|   |--- feature_9 <= 14.83
|   |--- value: [94.50]
|   |--- feature_9 >  14.83
|   |--- value: [108.10]
|--- feature_3 >  1.50
|--- feature_11 <= -0.50
|   |--- feature_6 <= 0.33

```

```

|   |   |   |   |--- feature_3 <= 4.00
|   |   |   |   |--- feature_3 <= 2.50
|   |   |   |   |   |--- feature_5 <= 1.58
|   |   |   |   |   |   |--- feature_5 <= -1.30
|   |   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |   |--- feature_5 <= -1.39
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |--- feature_5 > -1.39
|   |   |   |   |   |   |   |--- value: [-4.00]
|   |   |   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |   |   |--- value: [-4.00]
|   |   |   |   |   |--- feature_5 > -1.30
|   |   |   |   |   |   |--- feature_8 <= 0.28
|   |   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |   |   |   |--- value: [-74.00]
|   |   |   |   |   |   |--- feature_8 > 0.28
|   |   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |   |   |   |--- value: [-79.00]
|   |   |   |   |--- feature_5 > 1.58
|   |   |   |   |--- value: [-4.00]
|--- feature_3 > 2.50
|   |--- feature_17 <= 0.23
|   |   |--- value: [-24.00]
|   |--- feature_17 > 0.23
|   |   |--- value: [-26.50]
|--- feature_3 > 4.00
|   |--- feature_21 <= 0.15
|   |   |--- feature_5 <= -0.51
|   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- value: [-13.12]
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- value: [-54.30]
|   |   |   |--- feature_5 > -0.51
|   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- value: [-441.00]
|   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |   |--- value: [-223.50]
|--- feature_21 > 0.15
|   |--- feature_5 <= 1.13
|   |   |--- feature_5 <= 0.05
|   |   |   |--- value: [-82.50]
|   |   |--- feature_5 > 0.05
|   |   |   |--- feature_16 <= -0.45
|   |   |   |   |--- feature_1 <= 2.50

```

```

|   |   |   |   |   |   |   |   |--- value: [-20.00]
|   |   |   |   |   |   |--- feature_1 >  2.50
|   |   |   |   |   |--- value: [-26.00]
|   |   |   |   |--- feature_16 > -0.45
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- value: [-34.00]
|   |   |   |--- feature_5 >  1.13
|   |   |--- value: [-153.50]
|--- feature_6 >  0.33
|--- feature_3 <= 2.50
|   |--- feature_2 <= -0.01
|   |   |--- feature_16 <= -2.45
|   |   |--- value: [-4.00]
|   |--- feature_16 > -2.45
|   |   |--- feature_9 <= -0.37
|   |   |   |--- feature_17 <= -1.95
|   |   |   |--- value: [-80.55]
|   |   |--- feature_17 > -1.95
|   |   |   |--- feature_8 <= 0.28
|   |   |   |--- truncated branch of depth 2
|   |   |--- feature_8 >  0.28
|   |   |   |--- truncated branch of depth 2
|--- feature_9 > -0.37
|   |--- feature_9 <= -0.34
|   |   |--- value: [-4.00]
|   |--- feature_9 > -0.34
|   |   |--- feature_8 <= 0.28
|   |   |   |--- value: [-74.00]
|   |--- feature_8 >  0.28
|   |   |--- truncated branch of depth 2
|--- feature_2 > -0.01
|--- value: [-3.25]
|--- feature_3 >  2.50
|--- feature_5 <= 1.51
|   |--- feature_17 <= -2.03
|   |   |--- feature_5 <= 0.45
|   |   |   |--- feature_9 <= 0.40
|   |   |   |--- value: [-43.50]
|   |   |--- feature_9 >  0.40
|   |   |   |--- value: [-44.80]
|   |--- feature_5 >  0.45
|   |--- value: [-66.50]
|--- feature_17 > -2.03
|   |--- feature_6 <= 1.62
|   |   |--- feature_9 <= -1.21
|   |   |--- value: [-13.30]

```

```

|   |   |   |   |   |   |   |--- feature_9 > -1.21
|   |   |   |   |   |   |--- feature_17 <= 0.65
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |--- feature_17 > 0.65
|   |   |   |   |   |   |--- value: [-20.50]
|   |   |   |   |   |--- feature_6 > 1.62
|   |   |   |   |   |--- value: [-12.66]
|   |   |   |--- feature_5 > 1.51
|   |   |   |   |--- feature_8 <= -0.37
|   |   |   |   |--- value: [-97.75]
|   |   |   |   |--- feature_8 > -0.37
|   |   |   |   |--- value: [-45.40]
|--- feature_11 > -0.50
|--- feature_9 <= 1.86
|   |--- feature_3 <= 52.00
|   |   |--- feature_10 <= 15.15
|   |   |--- feature_3 <= 2.50
|   |   |   |--- feature_11 <= 0.50
|   |   |   |--- value: [0.00]
|   |   |--- feature_11 > 0.50
|   |   |   |--- feature_10 <= 1.13
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_10 > 1.13
|   |   |   |   |--- feature_9 <= -0.25
|   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |--- feature_9 > -0.25
|   |   |   |   |--- truncated branch of depth 6
|   |   |--- feature_3 > 2.50
|   |   |--- feature_12 <= 1.25
|   |   |--- feature_3 <= 4.50
|   |   |   |--- feature_10 <= 2.47
|   |   |   |--- truncated branch of depth 11
|   |   |   |--- feature_10 > 2.47
|   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_3 > 4.50
|   |   |   |--- feature_2 <= -0.01
|   |   |   |--- truncated branch of depth 6
|   |   |   |--- feature_2 > -0.01
|   |   |   |--- truncated branch of depth 16
|   |   |--- feature_12 > 1.25
|   |   |--- feature_9 <= 0.75
|   |   |--- feature_9 <= -0.82
|   |   |   |--- truncated branch of depth 10
|   |   |   |--- feature_9 > -0.82
|   |   |   |--- truncated branch of depth 12

```

```

|   |   |   |   |   |   |   |--- feature_9 >  0.75
|   |   |   |   |   |   |--- feature_17 <= 0.40
|   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |   |--- feature_17 >  0.40
|   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |--- feature_10 >  15.15
|   |   |   |   |--- value: [431.00]
|   |   |--- feature_3 >  52.00
|   |   |   |--- feature_10 <= 1.13
|   |   |   |   |--- feature_11 <= 0.50
|   |   |   |   |   |--- feature_16 <= -0.45
|   |   |   |   |   |   |--- feature_5 <= -0.11
|   |   |   |   |   |   |--- value: [19.60]
|   |   |   |   |   |   |--- feature_5 >  -0.11
|   |   |   |   |   |   |--- value: [23.50]
|   |   |   |   |   |--- feature_16 >  -0.45
|   |   |   |   |   |--- value: [129.60]
|   |   |   |   |--- feature_11 >  0.50
|   |   |   |   |--- feature_6 <= 0.31
|   |   |   |   |   |--- feature_9 <= -0.42
|   |   |   |   |   |   |--- feature_17 <= 0.40
|   |   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |   |--- feature_17 >  0.40
|   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_9 >  -0.42
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |--- feature_6 >  0.31
|   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |--- feature_9 <= -0.55
|   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |--- feature_9 >  -0.55
|   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |--- feature_6 <= 0.34
|   |   |   |   |   |   |--- value: [48.00]
|   |   |   |   |   |--- feature_6 >  0.34
|   |   |   |   |   |--- truncated branch of depth 7
|--- feature_10 >  1.13
|   |--- feature_10 <= 8.05
|   |   |--- feature_16 <= 1.11
|   |   |   |--- feature_17 <= 1.07
|   |   |   |   |--- feature_16 <= 0.76
|   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |--- feature_16 >  0.76
|   |   |   |   |   |--- truncated branch of depth 3

```

```

|   |   |   |   |   |   |   |--- feature_17 >  1.07
|   |   |   |   |   |   |--- value: [40.55]
|   |   |   |   |   |--- feature_16 >  1.11
|   |   |   |   |   |--- feature_15 <= 0.40
|   |   |   |   |   |--- value: [75.25]
|   |   |   |   |   |--- feature_15 >  0.40
|   |   |   |   |   |--- value: [72.55]
|   |   |   |   |--- feature_10 >  8.05
|   |   |   |   |--- feature_9 <= -0.93
|   |   |   |   |--- value: [92.20]
|   |   |   |   |--- feature_9 >  -0.93
|   |   |   |   |--- value: [94.20]
|--- feature_9 >  1.86
|--- feature_9 <= 5.72
|   |--- feature_9 <= 3.46
|   |   |--- feature_9 <= 1.87
|   |   |--- value: [176.00]
|   |--- feature_9 >  1.87
|   |   |--- feature_9 <= 2.00
|   |   |   |--- feature_6 <= -0.91
|   |   |   |   |--- feature_9 <= 1.89
|   |   |   |   |--- value: [81.50]
|   |   |   |   |--- feature_9 >  1.89
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_6 >  -0.91
|   |   |   |   |--- feature_9 <= 1.89
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_9 >  1.89
|   |   |   |--- truncated branch of depth 3
|--- feature_9 >  2.00
|   |--- feature_16 <= 0.59
|   |   |--- feature_9 <= 2.07
|   |   |--- truncated branch of depth 2
|   |   |--- feature_9 >  2.07
|   |   |--- truncated branch of depth 16
|   |   |--- feature_16 >  0.59
|   |   |--- feature_9 <= 2.76
|   |   |   |--- truncated branch of depth 8
|   |   |   |--- feature_9 >  2.76
|   |   |   |--- truncated branch of depth 6
|--- feature_9 >  3.46
|   |--- feature_16 <= 1.28
|   |   |--- feature_2 <= -0.01
|   |   |--- feature_9 <= 4.84
|   |   |   |--- feature_16 <= -2.36
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |--- feature_16 >  -2.36
|   |   |   |--- truncated branch of depth 13

```

```

|   |   |   |   |   |   |   |--- feature_9 >  4.84
|   |   |   |   |   |   |--- feature_9 <= 5.58
|   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |--- feature_9 >  5.58
|   |   |   |   |   |   |--- value: [56.40]
|   |   |   |   |   |--- feature_2 > -0.01
|   |   |   |   |   |--- value: [27.51]
|   |   |   |   |--- feature_16 >  1.28
|   |   |   |   |--- value: [281.50]
|--- feature_9 >  5.72
|--- feature_6 <= 1.08
|   |--- feature_3 <= 4.00
|   |   |--- feature_16 <= 0.15
|   |   |--- value: [125.50]
|   |   |--- feature_16 >  0.15
|   |   |--- value: [76.50]
|   |--- feature_3 >  4.00
|   |   |--- feature_9 <= 6.58
|   |   |--- feature_6 <= 0.48
|   |   |   |--- feature_6 <= -0.21
|   |   |   |--- truncated branch of depth 3
|   |   |   |--- feature_6 > -0.21
|   |   |   |--- value: [192.66]
|   |   |--- feature_6 >  0.48
|   |   |--- value: [137.80]
|--- feature_9 >  6.58
|   |--- feature_13 <= 0.88
|   |   |--- feature_5 <= -0.44
|   |   |--- truncated branch of depth 2
|   |   |--- feature_5 > -0.44
|   |   |--- truncated branch of depth 3
|   |   |--- feature_13 >  0.88
|   |   |--- value: [175.95]
|--- feature_6 >  1.08
|   |--- feature_9 <= 10.18
|   |--- feature_14 <= -0.92
|   |   |--- value: [297.60]
|   |--- feature_14 > -0.92
|   |   |--- value: [216.25]
|--- feature_9 > 10.18
|   |--- feature_5 <= 0.93
|   |   |--- feature_17 <= 0.57
|   |   |   |--- feature_9 <= 23.26
|   |   |   |--- value: [331.20]
|   |   |   |--- feature_9 > 23.26
|   |   |   |--- value: [333.00]
|   |--- feature_17 >  0.57
|   |--- value: [364.20]

```

```

|   |   |   |   |   |   |   |--- feature_5 >  0.93
|   |   |   |   |   |   |--- value: [421.20]
|--- feature_2 > -0.01
|   |--- feature_11 <= 0.15
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_2 <= -0.00
|   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |   |--- feature_9 <= -1.28
|   |   |   |   |   |   |--- feature_2 <= -0.00
|   |   |   |   |   |   |--- value: [-21.30]
|   |   |   |   |   |   |--- feature_2 > -0.00
|   |   |   |   |   |   |--- value: [-4.00]
|   |   |   |   |--- feature_9 > -1.28
|   |   |   |   |   |--- feature_6 <= 1.63
|   |   |   |   |   |   |--- feature_8 <= -0.76
|   |   |   |   |   |   |   |--- feature_7 <= 1.00
|   |   |   |   |   |   |   |   |--- feature_6 <= 0.56
|   |   |   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |   |   |   |--- feature_6 >  0.56
|   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |--- feature_7 >  1.00
|   |   |   |   |   |   |   |   |--- feature_16 <= -0.80
|   |   |   |   |   |   |   |   |--- value: [-30.80]
|   |   |   |   |   |   |   |   |--- feature_16 > -0.80
|   |   |   |   |   |   |   |   |--- value: [-32.90]
|   |   |   |   |   |--- feature_8 > -0.76
|   |   |   |   |   |   |--- feature_2 <= -0.00
|   |   |   |   |   |   |   |--- feature_17 <= 0.74
|   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |--- feature_17 >  0.74
|   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |   |--- feature_2 > -0.00
|   |   |   |   |   |   |   |   |--- feature_17 <= -2.29
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |--- feature_17 > -2.29
|   |   |   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |--- feature_6 >  1.63
|   |   |   |   |   |   |--- feature_20 <= 0.14
|   |   |   |   |   |   |--- value: [-4.00]
|   |   |   |   |--- feature_20 >  0.14
|   |   |   |   |   |--- feature_5 <= -0.67
|   |   |   |   |   |   |--- value: [-22.40]
|   |   |   |   |   |--- feature_5 > -0.67
|   |   |   |   |   |--- value: [-22.70]
|--- feature_8 > -0.11
|   |--- feature_2 <= -0.00
|   |   |--- feature_12 <= 1.25
|   |   |   |--- value: [-20.65]

```

```

|   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |--- feature_1 <= 3.50
|   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |   |--- feature_16 <= 0.15
|   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |--- feature_16 >  0.15
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |   |   |   |--- feature_5 <= -1.20
|   |   |   |   |   |   |   |   |   |   |--- value: [-22.10]
|   |   |   |   |   |   |   |   |   |--- feature_5 >  -1.20
|   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |   |   |--- feature_1 >  3.50
|   |   |   |   |   |   |   |   |   |   |--- value: [-22.10]
|   |   |   |   |   |--- feature_2 >  -0.00
|   |   |   |   |   |   |--- feature_16 <= 0.41
|   |   |   |   |   |   |   |--- feature_15 <= -0.94
|   |   |   |   |   |   |   |   |--- value: [-27.70]
|   |   |   |   |   |   |   |--- feature_15 >  -0.94
|   |   |   |   |   |   |   |   |--- feature_9 <= -0.93
|   |   |   |   |   |   |   |   |   |--- feature_17 <= 0.32
|   |   |   |   |   |   |   |   |   |   |--- value: [-32.60]
|   |   |   |   |   |   |   |   |   |--- feature_17 >  0.32
|   |   |   |   |   |   |   |   |   |   |--- value: [-32.90]
|   |   |   |   |   |   |   |   |   |--- feature_9 >  -0.93
|   |   |   |   |   |   |   |   |   |--- feature_17 <= 0.23
|   |   |   |   |   |   |   |   |   |   |--- value: [-34.00]
|   |   |   |   |   |   |   |   |   |--- feature_17 >  0.23
|   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |--- feature_16 >  0.41
|   |   |   |   |   |   |   |--- feature_9 <= -1.19
|   |   |   |   |   |   |   |   |--- value: [-35.10]
|   |   |   |   |   |   |--- feature_9 >  -1.19
|   |   |   |   |   |   |   |--- feature_14 <= -0.25
|   |   |   |   |   |   |   |   |--- value: [-29.05]
|   |   |   |   |   |   |--- feature_14 >  -0.25
|   |   |   |   |   |   |   |--- feature_17 <= 0.57
|   |   |   |   |   |   |   |   |--- value: [-25.60]
|   |   |   |   |   |   |   |--- feature_17 >  0.57
|   |   |   |   |   |   |   |   |--- value: [-24.90]
|   |   |--- feature_2 >  -0.00
|   |   |   |--- feature_0 <= 0.50
|   |   |   |   |--- value: [0.00]
|   |   |--- feature_0 >  0.50
|   |   |   |--- feature_2 <= 0.00
|   |   |   |   |--- feature_16 <= -1.41
|   |   |   |   |   |--- feature_2 <= -0.00
|   |   |   |   |   |--- feature_16 <= -2.27

```

```

|   |   |   |   |   |   |   |   |--- feature_9 <= -0.47
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |--- feature_9 > -0.47
|   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |--- feature_16 > -2.27
|   |   |   |   |   |   |   |   |--- value: [-23.70]
|   |   |   |   |   |   |   |--- feature_2 > -0.00
|   |   |   |   |   |   |   |--- feature_6 <= -0.07
|   |   |   |   |   |   |   |--- value: [-32.55]
|   |   |   |   |   |   |   |--- feature_6 > -0.07
|   |   |   |   |   |   |   |--- value: [-29.40]
|   |   |   |   |   |--- feature_16 > -1.41
|   |   |   |   |   |--- feature_16 <= 0.59
|   |   |   |   |   |--- feature_6 <= 1.58
|   |   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |   |--- feature_13 > 0.88
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_6 > 1.58
|   |   |   |   |   |--- feature_20 <= 0.14
|   |   |   |   |   |--- value: [-39.40]
|   |   |   |   |   |--- feature_20 > 0.14
|   |   |   |   |   |--- value: [-49.00]
|   |   |   |   |--- feature_16 > 0.59
|   |   |   |   |--- feature_6 <= -0.01
|   |   |   |   |--- feature_5 <= -0.17
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_5 > -0.17
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_6 > -0.01
|   |   |   |   |--- feature_16 <= 1.28
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_16 > 1.28
|   |   |   |   |--- truncated branch of depth 2
|--- feature_2 > 0.00
|   |--- feature_8 <= -0.11
|   |   |--- feature_16 <= -0.71
|   |   |   |--- feature_17 <= -2.45
|   |   |   |   |--- value: [-41.85]
|   |   |   |   |--- feature_17 > -2.45
|   |   |   |   |--- feature_6 <= -0.77
|   |   |   |   |   |--- value: [-28.25]
|   |   |   |   |--- feature_6 > -0.77
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_16 > -0.71
|   |   |   |--- feature_14 <= -0.92
|   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |--- truncated branch of depth 5

```

```

|   |   |   |   |   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |   |   |   |   |--- value: [-27.55]
|   |   |   |   |   |   |   |--- feature_14 > -0.92
|   |   |   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |   |--- value: [-43.40]
|   |   |   |   |   |--- feature_8 > -0.11
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- feature_9 <= -1.02
|   |   |   |   |   |--- value: [-31.85]
|   |   |   |   |   |--- feature_9 > -1.02
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |--- feature_1 <= 3.50
|   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |--- feature_1 >  3.50
|   |   |   |   |   |--- value: [-34.70]
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- feature_15 <= 0.40
|   |   |   |   |--- feature_14 <= -0.92
|   |   |   |   |--- value: [-43.85]
|   |   |   |   |--- feature_14 > -0.92
|   |   |   |   |--- value: [-43.75]
|   |   |   |   |--- feature_15 >  0.40
|   |   |   |   |--- value: [-39.55]
|--- feature_3 >  1.50
|   |--- feature_17 <= -0.10
|   |   |--- value: [-4.77]
|   |--- feature_17 > -0.10
|   |   |--- feature_9 <= -0.59
|   |   |--- feature_6 <= -0.90
|   |   |   |--- value: [-55.55]
|   |   |--- feature_6 > -0.90
|   |   |   |--- value: [-52.40]
|   |   |--- feature_9 > -0.59
|   |   |--- feature_13 <= 0.88
|   |   |   |--- value: [-85.55]
|   |   |--- feature_13 >  0.88
|   |   |   |--- value: [-73.25]
|--- feature_11 >  0.15
|   |--- feature_2 <= -0.00
|   |   |--- feature_9 <= 71.24
|   |   |   |--- feature_9 <= 0.83
|   |   |   |--- feature_2 <= -0.00
|   |   |   |   |--- feature_9 <= -0.16
|   |   |   |   |--- feature_21 <= 0.15

```

```

|   |   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |   |--- feature_16 <= 0.76
|   |   |   |   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |   |   |   |--- feature_16 >  0.76
|   |   |   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |   |--- feature_16 <= 0.59
|   |   |   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |   |   |--- feature_16 >  0.59
|   |   |   |   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |   |--- feature_17 <= -1.28
|   |   |   |   |   |   |--- feature_3 <= 4.00
|   |   |   |   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |   |   |--- feature_3 >  4.00
|   |   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |   |--- feature_17 >  -1.28
|   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- truncated branch of depth 25
|   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |--- feature_9 >  -0.16
|   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- feature_16 <= 0.76
|   |   |   |   |   |   |--- feature_9 <= 0.19
|   |   |   |   |   |   |   |--- truncated branch of depth 28
|   |   |   |   |   |   |--- feature_9 >  0.19
|   |   |   |   |   |   |   |--- truncated branch of depth 30
|   |   |   |   |   |--- feature_16 >  0.76
|   |   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |--- feature_17 <= -1.28
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |   |--- feature_17 >  -1.28
|   |   |   |   |   |--- feature_2 <= -0.01
|   |   |   |   |   |   |--- truncated branch of depth 28
|   |   |   |   |   |   |--- feature_2 >  -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 26
|   |   |   |   |--- feature_2 >  -0.00
|   |   |   |   |--- feature_9 <= -0.06
|   |   |   |   |   |--- feature_16 <= -0.97
|   |   |   |   |   |   |--- feature_2 <= -0.00

```

```

|   |   |   |   |   |   |   |   |--- feature_9 <= -0.29
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |   |   |   |   |--- feature_9 > -0.29
|   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_2 > -0.00
|   |   |   |   |   |   |--- feature_10 <= 1.66
|   |   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |--- feature_10 > 1.66
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_16 > -0.97
|   |   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |   |--- feature_2 <= -0.00
|   |   |   |   |   |   |--- truncated branch of depth 23
|   |   |   |   |   |--- feature_2 > -0.00
|   |   |   |   |   |--- truncated branch of depth 28
|   |   |   |   |--- feature_3 > 1.50
|   |   |   |   |--- feature_5 <= 1.60
|   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |--- feature_5 > 1.60
|   |   |   |   |   |--- value: [491.00]
|   |--- feature_9 > -0.06
|   |   |--- feature_21 <= 0.15
|   |   |   |--- feature_2 <= -0.00
|   |   |   |   |--- feature_16 <= 0.76
|   |   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |--- feature_16 > 0.76
|   |   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |--- feature_2 > -0.00
|   |   |   |   |--- feature_16 <= 0.76
|   |   |   |   |   |--- truncated branch of depth 25
|   |   |   |   |--- feature_16 > 0.76
|   |   |   |   |--- truncated branch of depth 21
|   |--- feature_21 > 0.15
|   |   |--- feature_2 <= -0.00
|   |   |   |--- feature_16 <= -1.32
|   |   |   |   |--- truncated branch of depth 22
|   |   |   |--- feature_16 > -1.32
|   |   |   |   |--- truncated branch of depth 23
|   |   |   |--- feature_2 > -0.00
|   |   |   |--- feature_3 <= 3.00
|   |   |   |   |--- truncated branch of depth 31
|   |   |   |--- feature_3 > 3.00
|   |   |   |   |--- value: [69.00]
|--- feature_9 > 0.83
|   |--- feature_9 <= 1.82
|   |   |--- feature_9 <= 1.21
|   |   |   |--- feature_3 <= 1.50
|   |   |   |   |--- feature_2 <= -0.00

```

```

|   |   |   |   |   |   |   |   |--- feature_10 <= 3.88
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 27
|   |   |   |   |   |   |   |   |--- feature_10 >  3.88
|   |   |   |   |   |   |   |   |   |--- value: [84.66]
|   |   |   |   |   |   |   |--- feature_2 > -0.00
|   |   |   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |   |   |--- feature_3 <= 2.50
|   |   |   |   |   |   |--- feature_5 <= 0.27
|   |   |   |   |   |   |   |--- value: [90.55]
|   |   |   |   |   |   |--- feature_5 >  0.27
|   |   |   |   |   |   |   |--- value: [95.55]
|   |   |   |   |   |--- feature_3 >  2.50
|   |   |   |   |   |   |--- value: [48.96]
|   |   |   |--- feature_9 >  1.21
|   |   |   |--- feature_3 <= 1.50
|   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- feature_9 <= 1.46
|   |   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |--- feature_9 >  1.46
|   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |--- feature_17 <= -1.28
|   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |--- feature_17 > -1.28
|   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |--- feature_3 >  1.50
|   |   |   |   |--- feature_6 <= -1.24
|   |   |   |   |   |--- feature_0 <= 0.50
|   |   |   |   |   |   |--- value: [90.55]
|   |   |   |   |   |--- feature_0 >  0.50
|   |   |   |   |   |   |--- value: [88.48]
|   |   |   |   |--- feature_6 > -1.24
|   |   |   |   |   |--- feature_16 <= 0.24
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_16 >  0.24
|   |   |   |   |   |   |--- truncated branch of depth 2
|--- feature_9 >  1.82
|--- feature_9 <= 23.43
|   |--- feature_3 <= 1.50
|   |   |--- feature_14 <= 0.42
|   |   |   |--- feature_20 <= -0.87
|   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |--- feature_20 > -0.87
|   |   |   |   |   |--- truncated branch of depth 9

```

```

|   |   |   |   |   |   |   |--- feature_14 >  0.42
|   |   |   |   |   |   |--- feature_9 <= 4.32
|   |   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |   |--- feature_9 >  4.32
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |--- feature_10 <= 8.46
|   |   |   |   |--- feature_9 <= 2.83
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_9 >  2.83
|   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_10 >  8.46
|   |   |   |   |--- value: [154.60]
|   |   |   |--- feature_9 >  23.43
|   |   |   |--- value: [198.80]
|--- feature_9 >  71.24
|--- value: [500.00]
|--- feature_2 >  -0.00
|--- feature_9 <= 1.18
|   |--- feature_9 <= 0.33
|   |--- feature_2 <= 0.00
|   |   |--- feature_9 <= -0.24
|   |   |--- feature_20 <= 0.14
|   |   |   |--- feature_10 <= 4.32
|   |   |   |--- feature_12 <= 1.25
|   |   |   |   |--- truncated branch of depth 15
|   |   |   |--- feature_12 >  1.25
|   |   |   |   |--- truncated branch of depth 20
|   |   |   |--- feature_10 >  4.32
|   |   |   |--- feature_14 <= -0.25
|   |   |   |   |--- value: [61.55]
|   |   |   |--- feature_14 >  -0.25
|   |   |   |   |--- value: [84.70]
|--- feature_20 >  0.14
|   |--- feature_10 <= 1.13
|   |--- feature_12 <= 1.25
|   |   |--- truncated branch of depth 21
|   |--- feature_12 >  1.25
|   |   |--- truncated branch of depth 24
|--- feature_10 >  1.13
|   |--- feature_9 <= -1.25
|   |   |--- value: [62.85]
|   |--- feature_9 >  -1.25
|   |   |--- truncated branch of depth 8
|--- feature_9 >  -0.24
|   |--- feature_21 <= 0.15
|   |--- feature_2 <= 0.00
|   |   |--- feature_9 <= 0.07

```

```

|   |   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |   |   |   |   |--- feature_9 >  0.07
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |   |   |   |   |--- feature_16 <= 0.41
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |   |   |   |--- feature_16 >  0.41
|   |   |   |   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |   |   |--- feature_9 <= 0.16
|   |   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |   |   |--- feature_9 >  0.16
|   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |--- feature_10 <= 2.21
|   |   |   |   |--- feature_17 <= -0.44
|   |   |   |   |--- feature_9 <= -0.32
|   |   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |   |--- feature_9 >  -0.32
|   |   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |--- truncated branch of depth 18
|   |   |   |   |--- feature_17 >  -0.44
|   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |--- feature_9 <= -0.22
|   |   |   |   |   |--- truncated branch of depth 25
|   |   |   |   |   |--- feature_9 >  -0.22
|   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |--- feature_10 >  2.21
|   |   |   |--- feature_2 <= 0.01
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- feature_10 <= 3.93
|   |   |   |   |   |--- truncated branch of depth 12

```

```

|   |   |   |   |   |   |   |   |--- feature_10 >  3.93
|   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |--- value: [12.77]
|   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |--- feature_16 <= -2.36
|   |   |   |   |   |--- feature_3 <= 3.00
|   |   |   |   |   |--- value: [49.25]
|   |   |   |   |   |--- feature_3 >  3.00
|   |   |   |   |   |--- value: [13.75]
|   |   |   |   |   |--- feature_16 >  -2.36
|   |   |   |   |   |--- feature_3 <= 3.00
|   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |--- feature_3 >  3.00
|   |   |   |   |   |--- value: [97.55]
|--- feature_9 >  0.33
|   |--- feature_2 <= 0.00
|   |   |--- feature_21 <= 0.15
|   |   |--- feature_10 <= 1.78
|   |   |   |--- feature_16 <= 0.76
|   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |--- feature_16 >  0.76
|   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |--- truncated branch of depth 11
|   |   |   |--- feature_10 >  1.78
|   |   |   |   |--- feature_3 <= 3.00
|   |   |   |   |--- feature_6 <= 0.82
|   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |--- feature_6 >  0.82
|   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_3 >  3.00
|   |   |   |   |--- feature_9 <= 0.66
|   |   |   |   |--- value: [76.75]
|   |   |   |   |--- feature_9 >  0.66
|   |   |   |   |--- value: [75.63]
|   |--- feature_21 >  0.15
|   |   |--- feature_2 <= 0.00
|   |   |   |--- feature_16 <= -1.15
|   |   |   |--- feature_10 <= 1.13
|   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_16 >  -1.15

```

```

|   |   |   |   |   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 25
|   |   |   |   |   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |   |--- feature_16 <= -1.32
|   |   |   |   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |--- feature_16 >  -1.32
|   |   |   |   |   |   |--- feature_9 <= 1.13
|   |   |   |   |   |   |   |--- truncated branch of depth 18
|   |   |   |   |   |   |--- feature_9 >  1.13
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |--- feature_2 >  0.00
|   |   |   |--- feature_10 <= 0.37
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- feature_3 <= 4.50
|   |   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |   |   |--- truncated branch of depth 22
|   |   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |   |--- feature_3 >  4.50
|   |   |   |   |   |   |--- value: [86.00]
|   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- feature_3 <= 3.00
|   |   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_7 >  2.00
|   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |--- feature_3 >  3.00
|   |   |   |   |   |--- value: [80.00]
|   |--- feature_10 >  0.37
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_8 <= -0.11
|   |   |   |   |--- feature_9 <= 0.46
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_9 >  0.46
|   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |--- feature_8 >  -0.11
|   |   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |--- feature_3 >  1.50
|   |   |   |--- feature_5 <= -1.26
|   |   |   |   |--- value: [63.35]

```

```

|   |   |   |   |   |   |   |--- feature_5 > -1.26
|   |   |   |   |   |--- value: [92.30]
|   |   |--- feature_9 > 1.18
|   |   |--- feature_9 <= 1.94
|   |   |--- feature_10 <= 1.13
|   |   |   |--- feature_9 <= 1.41
|   |   |   |--- feature_2 <= 0.00
|   |   |   |--- feature_20 <= 0.14
|   |   |   |   |--- feature_6 <= -1.68
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_6 > -1.68
|   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |--- feature_20 > 0.14
|   |   |   |   |--- feature_9 <= 1.35
|   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |--- feature_9 > 1.35
|   |   |   |   |--- truncated branch of depth 9
|   |   |   |--- feature_2 > 0.00
|   |   |   |--- feature_20 <= 0.14
|   |   |   |--- feature_16 <= 0.41
|   |   |   |   |--- truncated branch of depth 11
|   |   |   |--- feature_16 > 0.41
|   |   |   |--- truncated branch of depth 13
|   |   |   |--- feature_20 > 0.14
|   |   |   |--- feature_5 <= 0.59
|   |   |   |--- truncated branch of depth 11
|   |   |   |--- feature_5 > 0.59
|   |   |   |--- truncated branch of depth 7
|   |   |--- feature_9 > 1.41
|   |   |--- feature_21 <= 0.15
|   |   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_9 <= 1.68
|   |   |   |--- truncated branch of depth 22
|   |   |   |--- feature_9 > 1.68
|   |   |   |--- truncated branch of depth 13
|   |   |--- feature_3 > 1.50
|   |   |--- value: [88.80]
|   |--- feature_21 > 0.15
|   |--- feature_2 <= 0.00
|   |   |--- feature_6 <= -0.96
|   |   |--- truncated branch of depth 11
|   |   |--- feature_6 > -0.96
|   |   |--- truncated branch of depth 10
|   |--- feature_2 > 0.00
|   |--- feature_16 <= -2.53
|   |--- truncated branch of depth 4
|   |--- feature_16 > -2.53
|   |--- truncated branch of depth 13

```

```

|   |   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |   |--- feature_17 <= -0.77
|   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |--- feature_17 >  -0.77
|   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |--- feature_6 <= -0.40
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |--- feature_6 >  -0.40
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_8 >  -0.11
|   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |--- feature_9 <= 1.61
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_9 >  1.61
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |--- feature_17 <= 0.74
|   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_17 >  0.74
|   |   |   |   |   |--- truncated branch of depth 8
|   |--- feature_3 >  1.50
|   |--- feature_6 <= 0.25
|   |   |--- feature_16 <= -1.23
|   |   |   |--- value: [88.05]
|   |   |--- feature_16 >  -1.23
|   |   |   |--- value: [100.55]
|   |--- feature_6 >  0.25
|   |   |--- value: [113.75]
|--- feature_9 >  1.94
|--- feature_3 <= 1.50
|   |--- feature_9 <= 2.54
|   |--- feature_16 <= 0.24
|   |   |--- feature_16 <= -0.28
|   |   |   |--- feature_8 <= 0.15
|   |   |   |   |--- truncated branch of depth 9
|   |   |   |--- feature_8 >  0.15
|   |   |   |   |--- truncated branch of depth 5
|   |   |   |--- feature_16 >  -0.28
|   |   |   |--- feature_5 <= 1.36
|   |   |   |   |--- truncated branch of depth 10
|   |   |--- feature_5 >  1.36
|   |   |   |   |--- truncated branch of depth 4
|   |--- feature_16 >  0.24
|   |   |--- feature_2 <= 0.00

```

```

|   |   |   |   |   |   |   |   |--- feature_9 <= 2.47
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |--- feature_9 >  2.47
|   |   |   |   |   |   |   |   |   |--- value: [56.03]
|   |   |   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |--- feature_9 >  2.54
|   |   |   |--- feature_8 <= 2.23
|   |   |   |   |--- feature_5 <= -0.02
|   |   |   |   |   |--- feature_8 <= -0.76
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_8 >  -0.76
|   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |--- feature_5 >  -0.02
|   |   |   |   |   |--- feature_6 <= -1.20
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |--- feature_6 >  -1.20
|   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |--- feature_8 >  2.23
|   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |--- value: [90.25]
|   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |--- value: [94.50]
|   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |   |--- value: [113.23]
|   |   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |   |--- value: [106.55]
|--- feature_3 >  1.50
|   |--- feature_6 <= -0.00
|   |   |--- feature_17 <= -1.61
|   |   |   |--- feature_6 <= -0.86
|   |   |   |--- value: [87.55]
|   |   |   |--- feature_6 >  -0.86
|   |   |   |--- value: [88.75]
|   |--- feature_17 >  -1.61
|   |   |--- feature_12 <= 1.25
|   |   |   |--- feature_9 <= 2.74
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_9 >  2.74
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_12 >  1.25
|   |   |   |--- feature_5 <= 0.35
|   |   |   |--- value: [98.70]

```

```

|   |   |   |   |   |   |   |   |--- feature_5 >  0.35
|   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_6 >  -0.00
|   |   |   |   |--- feature_2 <= 0.00
|   |   |   |   |--- feature_6 <= 0.84
|   |   |   |   |--- value: [68.95]
|   |   |   |   |--- feature_6 >  0.84
|   |   |   |   |--- value: [76.50]
|   |   |   |   |--- feature_2 >  0.00
|   |   |   |   |--- feature_16 <= -0.28
|   |   |   |   |--- value: [94.50]
|   |   |   |   |--- feature_16 >  -0.28
|   |   |   |   |--- value: [79.75]
--- feature_2 >  0.01
|--- feature_2 <= 0.03
|   |--- feature_11 <= -0.35
|   |--- feature_2 <= 0.01
|   |   |--- feature_8 <= -0.11
|   |   |--- feature_20 <= -0.87
|   |   |--- feature_16 <= -0.45
|   |   |   |--- feature_15 <= 0.40
|   |   |   |--- value: [-43.35]
|   |   |   |--- feature_15 >  0.40
|   |   |   |--- value: [-46.90]
|--- feature_16 >  -0.45
|   |--- feature_2 <= 0.01
|   |   |--- feature_9 <= -0.40
|   |   |   |--- feature_6 <= -0.12
|   |   |   |--- value: [-52.45]
|   |   |   |--- feature_6 >  -0.12
|   |   |   |--- value: [-51.40]
|   |   |   |--- feature_9 >  -0.40
|   |   |   |--- feature_15 <= 0.40
|   |   |   |--- value: [-55.25]
|   |   |   |--- feature_15 >  0.40
|   |   |   |--- value: [-53.90]
|   |--- feature_2 >  0.01
|   |--- value: [-63.00]
|--- feature_20 >  -0.87
|--- feature_9 <= 1.25
|   |--- feature_2 <= 0.01
|   |--- feature_21 <= 1.18
|   |   |--- feature_16 <= 1.11
|   |   |--- feature_16 <= -2.53
|   |   |--- value: [-41.60]
|   |   |--- feature_16 >  -2.53
|   |   |--- value: [-40.90]
|   |--- feature_16 >  1.11

```

```

|   |   |   |   |   |   |   |   |--- value: [-42.30]
|   |   |   |   |   |--- feature_21 >  1.18
|   |   |   |   |   |--- value: [-43.65]
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- feature_17 <= -2.12
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- value: [-51.35]
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- value: [-52.35]
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- feature_17 <= -2.45
|   |   |   |   |--- value: [-50.00]
|   |   |   |   |--- feature_17 >  -2.45
|   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_17 >  -2.12
|   |   |   |   |--- feature_16 <= -1.67
|   |   |   |   |   |--- feature_15 <= 0.40
|   |   |   |   |   |--- value: [-42.95]
|   |   |   |   |   |--- feature_15 >  0.40
|   |   |   |   |   |--- value: [-40.20]
|   |   |   |   |   |--- feature_16 >  -1.67
|   |   |   |   |   |--- feature_15 <= -0.94
|   |   |   |   |   |--- value: [-45.05]
|   |   |   |   |   |--- feature_15 >  -0.94
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_9 >  1.25
|   |   |   |   |--- value: [-33.55]
|--- feature_8 >  -0.11
|   |--- feature_17 <= -2.20
|   |   |--- feature_5 <= 0.63
|   |   |   |--- value: [-53.25]
|   |   |--- feature_5 >  0.63
|   |   |   |--- value: [-91.05]
|--- feature_17 >  -2.20
|   |--- feature_2 <= 0.01
|   |   |--- feature_5 <= -0.22
|   |   |   |--- value: [-41.65]
|   |   |--- feature_5 >  -0.22
|   |   |   |--- value: [-43.15]
|--- feature_2 >  0.01
|   |--- feature_20 <= -0.87
|   |   |--- feature_2 <= 0.01
|   |   |   |--- feature_7 <= 1.00
|   |   |   |   |--- value: [-61.20]
|   |   |   |--- feature_7 >  1.00
|   |   |   |   |--- value: [-61.05]
|--- feature_2 >  0.01

```

```

|   |   |   |   |   |   |   |--- value: [-69.30]
|   |   |   |   |--- feature_20 > -0.87
|   |   |   |   |--- feature_5 <= -1.43
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- value: [-42.35]
|   |   |   |   |   |--- feature_2 > 0.01
|   |   |   |   |   |--- value: [-52.85]
|   |   |   |   |--- feature_5 > -1.43
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- feature_16 <= 0.24
|   |   |   |   |   |   |--- value: [-64.10]
|   |   |   |   |   |--- feature_16 > 0.24
|   |   |   |   |   |   |--- value: [-55.70]
|   |   |   |   |--- feature_2 > 0.01
|   |   |   |   |   |--- feature_9 <= -0.35
|   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |--- feature_9 > -0.35
|   |   |   |   |   |--- value: [-60.85]
|--- feature_2 > 0.01
|--- feature_1 <= 2.50
|   |--- feature_3 <= 4.50
|   |--- feature_2 <= 0.02
|   |   |--- feature_16 <= 0.59
|   |   |--- feature_9 <= -0.77
|   |   |   |--- feature_6 <= -0.95
|   |   |   |--- feature_9 <= -1.09
|   |   |   |   |--- value: [-70.25]
|   |   |   |--- feature_9 > -1.09
|   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_6 > -0.95
|   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_2 > 0.02
|   |   |   |   |--- value: [-74.90]
|--- feature_9 > -0.77
|   |--- feature_2 <= 0.02
|   |--- feature_5 <= -1.09
|   |   |--- truncated branch of depth 2
|   |--- feature_5 > -1.09
|   |   |--- truncated branch of depth 4
|   |--- feature_2 > 0.02
|   |--- feature_8 <= -0.11
|   |   |--- truncated branch of depth 4
|   |--- feature_8 > -0.11
|   |   |--- truncated branch of depth 2
|--- feature_16 > 0.59
|--- feature_5 <= 1.07
|   |--- feature_16 <= 0.93

```

```

|   |   |   |   |   |   |   |   |--- feature_6 <= 0.50
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |--- feature_6 >  0.50
|   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |--- feature_16 >  0.93
|   |   |   |   |   |   |--- feature_14 <= -0.92
|   |   |   |   |   |   |   |--- value: [-56.95]
|   |   |   |   |   |   |--- feature_14 > -0.92
|   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |--- feature_5 >  1.07
|   |   |   |   |   |   |--- feature_9 <= -0.36
|   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |   |--- value: [-54.95]
|   |   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |   |--- value: [-58.40]
|   |   |   |   |   |--- feature_9 > -0.36
|   |   |   |   |   |   |--- value: [-48.55]
|   |   |   |--- feature_2 >  0.02
|   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |   |--- feature_17 <= 0.74
|   |   |   |   |   |   |--- feature_21 <= 0.66
|   |   |   |   |   |   |   |--- value: [-73.45]
|   |   |   |   |   |   |--- feature_21 >  0.66
|   |   |   |   |   |   |   |--- value: [-75.75]
|   |   |   |   |   |--- feature_17 >  0.74
|   |   |   |   |   |   |--- value: [-80.20]
|   |   |   |   |--- feature_2 >  0.03
|   |   |   |   |   |--- value: [-86.80]
|   |   |   |--- feature_3 >  4.50
|   |   |   |   |--- value: [-97.85]
|   |--- feature_1 >  2.50
|   |   |--- feature_14 <= -0.25
|   |   |   |--- value: [-78.25]
|   |   |--- feature_14 > -0.25
|   |   |   |--- value: [-117.55]
|--- feature_11 > -0.35
|   |--- feature_9 <= 1.61
|   |   |--- feature_2 <= 0.01
|   |   |   |--- feature_8 <= 1.39
|   |   |   |   |--- feature_9 <= 0.42
|   |   |   |   |   |--- feature_10 <= 0.89
|   |   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |--- feature_7 <= 1.50
|   |   |   |   |   |   |--- feature_3 <= 52.00
|   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |   |--- feature_3 >  52.00
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |--- feature_7 >  1.50

```

```

|   |   |   |   |   |   |   |   |--- feature_20 <= -0.87
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |   |   |--- feature_20 > -0.87
|   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_2 > 0.01
|   |   |   |   |   |--- feature_3 <= 51.50
|   |   |   |   |   |   |--- feature_7 <= 1.50
|   |   |   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |   |--- feature_7 > 1.50
|   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_3 > 51.50
|   |   |   |   |   |--- feature_17 <= -1.28
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |--- feature_17 > -1.28
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |--- feature_10 > 0.89
|   |   |   |   |--- feature_10 <= 4.75
|   |   |   |   |   |--- feature_7 <= 2.50
|   |   |   |   |   |   |--- feature_9 <= -0.26
|   |   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |   |--- feature_9 > -0.26
|   |   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |--- feature_7 > 2.50
|   |   |   |   |   |--- feature_6 <= -1.68
|   |   |   |   |   |   |--- value: [8.11]
|   |   |   |   |   |--- feature_6 > -1.68
|   |   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |--- feature_10 > 4.75
|   |   |   |   |--- feature_17 <= -1.70
|   |   |   |   |   |--- feature_6 <= 0.46
|   |   |   |   |   |   |--- value: [73.75]
|   |   |   |   |   |--- feature_6 > 0.46
|   |   |   |   |   |   |--- value: [66.25]
|   |   |   |   |--- feature_17 > -1.70
|   |   |   |   |   |--- value: [83.75]
|--- feature_9 > 0.42
|   |--- feature_10 <= 1.45
|   |   |--- feature_16 <= -0.28
|   |   |   |--- feature_7 <= 2.00
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_2 > 0.01
|   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |--- feature_7 > 2.00
|   |   |   |   |--- feature_9 <= 1.26
|   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |--- feature_9 > 1.26
|   |   |   |   |   |--- truncated branch of depth 4

```

```

|   |   |   |   |   |   |   |--- feature_16 > -0.28
|   |   |   |   |   |   |   |--- feature_3 <= 4.50
|   |   |   |   |   |   |   |   |--- feature_9 <= 1.26
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |   |   |   |   |--- feature_9 > 1.26
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |   |   |   |   |--- feature_3 > 4.50
|   |   |   |   |   |   |   |   |   |--- feature_6 <= -0.69
|   |   |   |   |   |   |   |   |   |   |--- value: [70.00]
|   |   |   |   |   |   |   |   |   |--- feature_6 > -0.69
|   |   |   |   |   |   |   |   |   |   |--- value: [90.00]
|   |   |   |   |   |--- feature_10 > 1.45
|   |   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |   |--- feature_3 <= 2.50
|   |   |   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |   |   |   |--- feature_2 > 0.01
|   |   |   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |   |   |--- feature_3 > 2.50
|   |   |   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |   |   |   |--- value: [90.81]
|   |   |   |   |   |   |   |--- feature_21 > 0.15
|   |   |   |   |   |   |   |   |--- value: [74.76]
|   |   |   |   |   |--- feature_7 > 2.00
|   |   |   |   |   |--- feature_17 <= -1.11
|   |   |   |   |   |   |--- feature_16 <= -2.45
|   |   |   |   |   |   |   |--- value: [60.34]
|   |   |   |   |   |   |--- feature_16 > -2.45
|   |   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |--- feature_17 > -1.11
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |--- feature_2 > 0.01
|   |   |   |   |   |   |--- truncated branch of depth 11
|--- feature_8 > 1.39
|--- feature_10 <= -0.07
|   |--- feature_9 <= -0.28
|   |   |--- feature_2 <= 0.01
|   |   |   |--- feature_5 <= 1.58
|   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |--- feature_5 > 1.58
|   |   |   |   |--- feature_9 <= -0.70
|   |   |   |   |   |--- value: [10.50]
|   |   |   |   |--- feature_9 > -0.70
|   |   |   |   |   |--- truncated branch of depth 4

```

```

|   |   |   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |   |   |   |   |   |--- value: [80.75]
|   |   |   |   |   |--- feature_9 >  -0.28
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |--- feature_9 <= 0.93
|   |   |   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |   |   |   |--- feature_9 >  0.93
|   |   |   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |   |   |--- feature_16 <= 0.41
|   |   |   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |   |   |--- feature_16 >  0.41
|   |   |   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |   |   |   |--- truncated branch of depth 7
|--- feature_10 >  -0.07
|   |--- feature_9 <= 1.00
|   |   |--- feature_2 <= 0.01
|   |   |   |--- feature_3 <= 1.50
|   |   |   |   |--- feature_9 <= 0.37
|   |   |   |   |   |--- truncated branch of depth 18
|   |   |   |   |   |--- feature_9 >  0.37
|   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |   |   |--- feature_9 <= -0.34
|   |   |   |   |   |   |--- value: [85.55]
|   |   |   |   |   |   |--- feature_9 >  -0.34
|   |   |   |   |   |   |--- value: [85.60]
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |--- truncated branch of depth 10

```

```

|   |   |   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |   |   |   |   |--- value: [88.05]
|   |   |   |   |   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |   |   |   |   |--- value: [87.30]
|   |   |   |   |--- feature_9 >  1.00
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- feature_17 <= -1.19
|   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |--- feature_17 > -1.19
|   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |--- feature_2 >  0.01
|   |   |   |--- feature_8 <= 2.30
|   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |--- feature_8 >  2.30
|   |   |   |   |--- feature_1 <= 2.50
|   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |--- feature_1 >  2.50
|   |   |   |   |--- truncated branch of depth 5
|--- feature_2 >  0.01
|   |--- feature_10 <= 1.86
|   |--- feature_2 <= 0.02
|   |   |--- feature_9 <= 0.81
|   |   |--- feature_8 <= 0.09
|   |   |--- feature_7 <= 2.50
|   |   |--- feature_3 <= 52.00
|   |   |   |--- truncated branch of depth 19
|   |   |--- feature_3 >  52.00
|   |   |   |--- truncated branch of depth 10
|   |   |--- feature_7 >  2.50
|   |   |--- feature_16 <= -1.49
|   |   |   |--- truncated branch of depth 10
|   |   |--- feature_16 > -1.49
|   |   |   |--- truncated branch of depth 12
|--- feature_8 >  0.09
|   |--- feature_9 <= -0.35
|   |--- feature_5 <= 1.72

```

```

|   |   |   |   |   |   |   |   |--- truncated branch of depth 18
|   |   |   |   |   |   |   |   |   |--- feature_5 >  1.72
|   |   |   |   |   |   |   |   |   |   |--- value: [100.95]
|   |   |   |   |   |   |   |   |--- feature_9 > -0.35
|   |   |   |   |   |   |   |   |--- feature_9 <= -0.35
|   |   |   |   |   |   |   |   |   |--- value: [93.25]
|   |   |   |   |   |   |   |   |--- feature_9 > -0.35
|   |   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |   |   |   |   |--- feature_9 >  0.81
|   |   |   |   |   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |   |   |   |--- feature_8 <= 1.39
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |   |   |   |   |   |--- feature_8 >  1.39
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |   |   |   |--- feature_8 <= 0.09
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |   |   |   |   |   |--- feature_8 >  0.09
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |   |   |   |   |--- feature_7 >  2.00
|   |   |   |   |   |   |   |   |   |--- feature_16 <= -0.89
|   |   |   |   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |--- feature_16 > -0.89
|   |   |   |   |   |   |   |   |   |--- feature_14 <= 0.42
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |   |   |--- feature_14 >  0.42
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|--- feature_2 >  0.02
|   |--- feature_3 <= 52.00
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_9 <= -0.25
|   |   |   |--- feature_2 <= 0.02
|   |   |   |--- truncated branch of depth 19
|   |   |   |--- feature_2 >  0.02
|   |   |   |--- truncated branch of depth 19
|   |   |   |--- feature_9 > -0.25
|   |   |   |--- feature_7 <= 2.00
|   |   |   |--- truncated branch of depth 16
|   |   |   |--- feature_7 >  2.00
|   |   |   |--- truncated branch of depth 12
|--- feature_3 >  1.50
|   |--- feature_3 <= 4.50
|   |   |--- feature_9 <= 1.02
|   |   |--- truncated branch of depth 11

```

```

|   |   |   |   |   |   |   |   |--- feature_9 >  1.02
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |--- feature_3 >  4.50
|   |   |   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_3 >  52.00
|   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |--- feature_6 <= 0.67
|   |   |   |   |--- feature_6 <= 0.19
|   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_6 >  0.19
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_6 >  0.67
|   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_2 >  0.02
|   |   |   |--- feature_6 <= 0.61
|   |   |   |--- feature_5 <= -0.63
|   |   |   |--- value: [57.00]
|   |   |   |--- feature_5 >  -0.63
|   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_6 >  0.61
|   |   |   |--- value: [64.00]
|--- feature_10 >  1.86
|   |--- feature_10 <= 4.75
|   |   |--- feature_7 <= 2.50
|   |   |--- feature_9 <= 0.23
|   |   |   |--- feature_2 <= 0.02
|   |   |   |--- feature_21 <= 0.15
|   |   |   |--- truncated branch of depth 19
|   |   |   |--- feature_21 >  0.15
|   |   |   |--- truncated branch of depth 17
|   |   |   |--- feature_2 >  0.02
|   |   |   |--- feature_3 <= 52.00
|   |   |   |--- truncated branch of depth 17
|   |   |   |--- feature_3 >  52.00
|   |   |   |--- truncated branch of depth 10
|   |   |--- feature_9 >  0.23
|   |   |   |--- feature_2 <= 0.02
|   |   |   |--- feature_21 <= 0.15
|   |   |   |--- truncated branch of depth 18
|   |   |   |--- feature_21 >  0.15
|   |   |   |--- truncated branch of depth 14
|   |   |--- feature_2 >  0.02

```

```

|   |   |   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |--- feature_7 >  2.50
|   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- value: [99.62]
|   |   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |--- feature_9 <= -1.17
|   |   |   |   |   |   |--- feature_17 <= -0.61
|   |   |   |   |   |   |--- value: [47.41]
|   |   |   |   |   |   |--- feature_17 >  -0.61
|   |   |   |   |   |   |--- value: [11.72]
|   |   |   |   |   |   |--- feature_9 >  -1.17
|   |   |   |   |   |   |--- feature_17 <= -1.45
|   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |--- feature_17 >  -1.45
|   |   |   |   |   |   |--- truncated branch of depth 11
|--- feature_10 >  4.75
|   |--- feature_2 <= 0.02
|   |--- feature_10 <= 5.83
|   |   |--- feature_6 <= 0.34
|   |   |   |--- feature_2 <= 0.02
|   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_2 >  0.02
|   |   |   |--- truncated branch of depth 3
|   |   |   |--- feature_6 >  0.34
|   |   |   |--- feature_13 <= 0.88
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |--- truncated branch of depth 3
|--- feature_10 >  5.83
|   |--- feature_2 <= 0.02
|   |   |--- feature_10 <= 7.14
|   |   |   |--- value: [84.25]
|   |   |   |--- feature_10 >  7.14
|   |   |   |   |--- value: [86.65]
|   |   |   |--- feature_2 >  0.02
|   |   |   |--- feature_14 <= -0.92

```

```

|   |   |   |   |   |   |   |   |--- value: [99.83]
|   |   |   |   |   |--- feature_14 > -0.92
|   |   |   |   |--- value: [116.00]
|   |   |   |--- feature_2 > 0.02
|   |   |   |--- feature_17 <= -1.95
|   |   |   |   |--- feature_16 <= -0.63
|   |   |   |   |--- value: [163.75]
|   |   |   |--- feature_16 > -0.63
|   |   |   |   |--- feature_6 <= 0.08
|   |   |   |   |--- value: [133.75]
|   |   |   |--- feature_6 > 0.08
|   |   |   |--- value: [122.32]
|   |   |--- feature_17 > -1.95
|   |   |--- feature_2 <= 0.02
|   |   |   |--- feature_2 <= 0.02
|   |   |   |--- value: [93.15]
|   |   |   |--- feature_2 > 0.02
|   |   |   |   |--- truncated branch of depth 2
|   |   |--- feature_2 > 0.02
|   |   |--- feature_1 <= 1.50
|   |   |   |--- truncated branch of depth 9
|   |   |--- feature_1 > 1.50
|   |   |   |--- truncated branch of depth 7
|--- feature_9 > 1.61
|   |--- feature_9 <= 2.61
|   |   |--- feature_2 <= 0.01
|   |   |--- feature_10 <= 1.78
|   |   |   |--- feature_9 <= 2.17
|   |   |   |--- feature_2 <= 0.01
|   |   |   |--- feature_9 <= 1.72
|   |   |   |--- feature_2 <= 0.01
|   |   |   |--- truncated branch of depth 5
|   |   |--- feature_2 > 0.01
|   |   |   |--- truncated branch of depth 11
|   |   |--- feature_9 > 1.72
|   |   |--- feature_9 <= 1.74
|   |   |   |--- truncated branch of depth 2
|   |   |--- feature_9 > 1.74
|   |   |   |--- truncated branch of depth 15
|   |--- feature_2 > 0.01
|   |   |--- feature_9 <= 1.62
|   |   |   |--- feature_9 <= 1.62
|   |   |   |--- truncated branch of depth 2
|   |   |--- feature_9 > 1.62
|   |   |--- value: [127.60]
|   |   |--- feature_9 > 1.62
|   |   |--- feature_8 <= 1.39
|   |   |--- truncated branch of depth 15

```

```

|   |   |   |   |   |   |   |   |--- feature_8 >  1.39
|   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |--- feature_9 >  2.17
|   |   |   |   |--- feature_17 <= 0.57
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |--- feature_5 <= -1.30
|   |   |   |   |--- value: [59.73]
|   |   |   |   |--- feature_5 >  -1.30
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |--- feature_17 >  0.57
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |--- feature_8 <= -0.76
|   |   |   |   |--- value: [70.80]
|   |   |   |   |--- feature_8 >  -0.76
|   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |--- feature_15 <= 0.40
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_15 >  0.40
|   |   |   |   |--- truncated branch of depth 5
|--- feature_10 >  1.78
|   |--- feature_9 <= 2.16
|   |   |--- feature_2 <= 0.01
|   |   |--- feature_10 <= 3.88
|   |   |   |--- feature_3 <= 1.50
|   |   |   |--- truncated branch of depth 18
|   |   |   |--- feature_3 >  1.50
|   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_10 >  3.88
|   |   |   |--- feature_17 <= 0.15
|   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_17 >  0.15
|   |   |   |--- value: [98.85]
|--- feature_2 >  0.01
|   |--- feature_8 <= 1.19
|   |   |--- feature_17 <= -0.94
|   |   |--- truncated branch of depth 8
|   |   |--- feature_17 >  -0.94
|   |   |--- truncated branch of depth 11
|   |   |--- feature_8 >  1.19
|   |   |--- feature_21 <= 0.15
|   |   |--- truncated branch of depth 16
|   |   |--- feature_21 >  0.15

```

```

|   |   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |--- feature_9 >  2.16
|   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |--- feature_1 <= 2.50
|   |   |   |   |--- feature_6 <= 0.61
|   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_6 >  0.61
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_1 >  2.50
|   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |--- value: [99.66]
|   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |--- value: [105.25]
|--- feature_2 >  0.01
|--- feature_9 <= 2.11
|   |--- feature_10 <= 2.19
|   |   |--- feature_2 <= 0.02
|   |   |--- feature_3 <= 1.50
|   |   |--- feature_8 <= 0.09
|   |   |--- truncated branch of depth 11
|   |   |--- feature_8 >  0.09
|   |   |--- truncated branch of depth 16
|   |   |--- feature_3 >  1.50
|   |   |--- feature_15 <= 0.40
|   |   |--- value: [78.19]
|   |   |--- feature_15 >  0.40
|   |   |--- truncated branch of depth 2
|--- feature_2 >  0.02
|--- feature_3 <= 1.50
|--- feature_2 <= 0.02
|--- truncated branch of depth 15
|--- feature_2 >  0.02
|--- truncated branch of depth 18
|--- feature_3 >  1.50
|--- feature_9 <= 1.76
|--- truncated branch of depth 3
|--- feature_9 >  1.76

```

```

|   |   |   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_10 >  2.19
|   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |--- feature_8 >  -0.11
|   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |--- feature_10 <= 5.73
|   |   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_10 >  5.73
|   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- value: [113.65]
|   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |--- value: [120.55]
|--- feature_9 >  2.11
|   |--- feature_2 <= 0.02
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_10 <= 1.78
|   |   |   |   |--- feature_20 <= 0.14
|   |   |   |   |   |--- truncated branch of depth 18
|   |   |   |   |--- feature_20 >  0.14
|   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |--- feature_10 >  1.78
|   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |--- truncated branch of depth 16
|--- feature_3 >  1.50
|   |--- feature_3 <= 4.50
|   |   |--- feature_16 <= 0.67
|   |   |   |--- truncated branch of depth 5
|   |   |   |--- feature_16 >  0.67
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_3 >  4.50
|   |   |   |   |--- value: [123.00]
|--- feature_2 >  0.02
|   |--- feature_10 <= 1.78
|   |   |--- feature_3 <= 1.50

```

```

|   |   |   |   |   |   |   |   |--- feature_9 <= 2.57
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |   |   |   |--- feature_9 >  2.57
|   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |   |--- feature_17 <= 0.07
|   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |--- feature_17 >  0.07
|   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_10 >  1.78
|   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- feature_10 <= 4.53
|   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |--- feature_10 >  4.53
|   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |--- feature_3 <= 2.50
|   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_3 >  2.50
|   |   |   |   |   |--- value: [106.98]
|--- feature_9 >  2.61
|   |--- feature_9 <= 4.10
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_2 <= 0.02
|   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- feature_14 <= 0.42
|   |   |   |   |   |   |--- feature_14 <= -0.92
|   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |--- feature_14 >  -0.92
|   |   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |--- feature_14 >  0.42
|   |   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |--- feature_21 >  0.15
|   |   |   |   |--- feature_2 <= 0.01
|   |   |   |   |   |--- feature_9 <= 2.92
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |--- feature_9 >  2.92
|   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |--- feature_2 >  0.01
|   |   |   |   |   |--- feature_0 <= 0.50
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_0 >  0.50
|   |   |   |   |   |   |--- truncated branch of depth 12
|   |   |   |--- feature_2 >  0.02
|   |   |   |--- feature_10 <= 1.78

```

```

|   |   |   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |   |   |--- feature_9 <= 2.97
|   |   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |--- feature_9 >  2.97
|   |   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |--- feature_10 >  1.78
|   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |--- feature_9 <= 3.09
|   |   |   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |   |--- feature_9 >  3.09
|   |   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |--- feature_3 >  1.50
|   |   |--- feature_10 <= 4.42
|   |   |   |--- feature_9 <= 3.19
|   |   |   |   |--- feature_5 <= 1.66
|   |   |   |   |   |--- feature_9 <= 2.64
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |--- feature_9 >  2.64
|   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |--- feature_5 >  1.66
|   |   |   |   |   |--- feature_2 <= 0.02
|   |   |   |   |   |   |--- value: [70.50]
|   |   |   |   |   |--- feature_2 >  0.02
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_9 >  3.19
|   |   |   |--- feature_13 <= 0.88
|   |   |   |   |--- feature_6 <= -0.55
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_6 >  -0.55
|   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |--- feature_6 <= 0.82
|   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_6 >  0.82
|   |   |   |   |   |--- truncated branch of depth 3
|   |   |--- feature_10 >  4.42
|   |   |--- feature_9 <= 3.79
|   |   |   |--- feature_2 <= 0.02

```

```

|   |   |   |   |   |   |   |   |--- feature_21 <= -0.89
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |--- feature_21 > -0.89
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |--- feature_2 > 0.02
|   |   |   |   |   |   |--- feature_16 <= -1.15
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |--- feature_16 > -1.15
|   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_9 > 3.79
|   |   |   |   |   |--- feature_3 <= 4.50
|   |   |   |   |   |   |--- feature_16 <= -0.80
|   |   |   |   |   |   |   |--- value: [120.19]
|   |   |   |   |   |   |--- feature_16 > -0.80
|   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |--- feature_3 > 4.50
|   |   |   |   |   |   |--- value: [160.05]
|--- feature_9 > 4.10
|--- feature_10 <= 8.90
|   |--- feature_3 <= 2.50
|   |   |--- feature_16 <= -2.53
|   |   |   |--- value: [204.00]
|   |   |--- feature_16 > -2.53
|   |   |   |--- feature_6 <= 1.61
|   |   |   |   |--- feature_8 <= 3.34
|   |   |   |   |   |--- truncated branch of depth 11
|   |   |   |   |--- feature_8 > 3.34
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |--- feature_6 > 1.61
|   |   |   |--- feature_15 <= 0.40
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |--- feature_15 > 0.40
|   |   |   |   |--- value: [102.85]
|--- feature_3 > 2.50
|--- feature_2 <= 0.02
|   |--- feature_5 <= -1.32
|   |   |--- value: [151.25]
|   |--- feature_5 > -1.32
|   |   |--- feature_2 <= 0.01
|   |   |   |--- value: [84.42]
|   |   |--- feature_2 > 0.01
|   |   |   |--- truncated branch of depth 4
|--- feature_2 > 0.02
|--- feature_3 <= 4.00
|   |--- feature_21 <= 0.66
|   |   |--- truncated branch of depth 6
|   |--- feature_21 > 0.66
|   |   |--- value: [117.70]

```

```

|   |   |   |   |   |   |   |--- feature_3 >  4.00
|   |   |   |   |   |   |--- feature_6 <= -0.57
|   |   |   |   |   |   |--- value: [175.94]
|   |   |   |   |   |   |--- feature_6 >  -0.57
|   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_10 >  8.90
|   |   |   |   |   |--- feature_17 <= 0.40
|   |   |   |   |   |--- feature_6 <= 0.91
|   |   |   |   |   |--- value: [214.05]
|   |   |   |   |   |--- feature_6 >  0.91
|   |   |   |   |   |--- value: [224.58]
|   |   |   |   |   |--- feature_17 >  0.40
|   |   |   |   |   |--- value: [144.78]
|--- feature_2 >  0.03
|   |--- feature_11 <= -0.50
|   |   |--- feature_2 <= 0.09
|   |   |--- feature_2 <= 0.05
|   |   |   |--- feature_3 <= 3.00
|   |   |   |--- feature_2 <= 0.04
|   |   |   |   |--- feature_8 <= 0.93
|   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |--- feature_17 <= 1.24
|   |   |   |   |--- feature_9 <= -1.05
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_9 >  -1.05
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_17 >  1.24
|   |   |   |   |--- value: [-68.85]
|   |   |   |--- feature_2 >  0.03
|   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |--- feature_2 >  0.03
|   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |--- feature_17 <= -1.70
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_17 >  -1.70
|   |   |   |   |--- truncated branch of depth 7
|   |   |   |--- feature_8 >  0.93
|   |   |   |--- feature_17 <= -0.27
|   |   |   |--- value: [-76.35]
|   |   |   |--- feature_17 >  -0.27
|   |   |   |--- feature_9 <= -0.36
|   |   |   |   |--- feature_8 <= 2.23
|   |   |   |   |--- truncated branch of depth 8
|   |   |   |--- feature_8 >  2.23
|   |   |   |--- value: [-91.70]

```

```

|   |   |   |   |   |   |   |--- feature_9 > -0.36
|   |   |   |   |   |--- value: [-79.00]
|   |   |   |--- feature_2 > 0.04
|   |   |   |   |--- feature_14 <= 0.42
|   |   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |--- feature_8 <= -0.76
|   |   |   |   |   |--- value: [-90.25]
|   |   |   |   |   |--- feature_8 > -0.76
|   |   |   |   |   |--- value: [-90.55]
|   |   |   |   |   |--- feature_3 > 1.50
|   |   |   |   |   |--- feature_8 <= 0.28
|   |   |   |   |   |--- value: [-82.30]
|   |   |   |   |   |--- feature_8 > 0.28
|   |   |   |   |   |--- feature_1 <= 3.00
|   |   |   |   |   |--- value: [-84.80]
|   |   |   |   |   |--- feature_1 > 3.00
|   |   |   |   |   |--- value: [-87.30]
|   |   |   |   |--- feature_14 > 0.42
|   |   |   |   |--- feature_5 <= 0.12
|   |   |   |   |   |--- feature_2 <= 0.04
|   |   |   |   |   |--- value: [-99.05]
|   |   |   |   |--- feature_2 > 0.04
|   |   |   |   |   |--- feature_9 <= -0.51
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |--- feature_9 > -0.51
|   |   |   |   |   |--- value: [-97.80]
|   |   |   |   |   |--- feature_5 > 0.12
|   |   |   |   |   |--- value: [-92.35]
|   |   |--- feature_3 > 3.00
|   |   |--- feature_8 <= 1.19
|   |   |   |--- feature_6 <= 1.03
|   |   |   |   |--- feature_6 <= 0.12
|   |   |   |   |--- value: [-99.75]
|   |   |   |   |--- feature_6 > 0.12
|   |   |   |   |--- value: [-91.25]
|   |   |   |   |--- feature_6 > 1.03
|   |   |   |   |--- feature_17 <= -0.86
|   |   |   |   |--- value: [-112.30]
|   |   |   |   |--- feature_17 > -0.86
|   |   |   |   |--- value: [-103.50]
|   |   |   |--- feature_8 > 1.19
|   |   |   |--- value: [-129.30]
|   |--- feature_2 > 0.05
|   |--- feature_2 <= 0.06
|   |   |--- feature_1 <= 1.50
|   |   |   |--- feature_5 <= -1.07
|   |   |   |   |--- feature_17 <= 0.57
|   |   |   |   |--- value: [-108.45]

```

```

|   |   |   |   |   |   |   |--- feature_17 >  0.57
|   |   |   |   |   |   |   |--- value: [-109.75]
|   |   |   |   |   |--- feature_5 >  -1.07
|   |   |   |   |   |--- feature_6 <= 0.32
|   |   |   |   |   |--- feature_16 <= 0.93
|   |   |   |   |   |   |--- feature_17 <= -0.35
|   |   |   |   |   |   |--- value: [-103.80]
|   |   |   |   |   |--- feature_17 >  -0.35
|   |   |   |   |   |--- value: [-103.15]
|   |   |   |   |   |--- feature_16 >  0.93
|   |   |   |   |   |--- value: [-106.05]
|   |   |   |   |--- feature_6 >  0.32
|   |   |   |   |--- value: [-100.60]
|   |   |--- feature_1 >  1.50
|   |   |   |--- feature_12 <= 1.25
|   |   |   |--- value: [-116.70]
|   |   |--- feature_12 >  1.25
|   |   |--- value: [-111.85]
|   |--- feature_2 >  0.06
|   |   |--- feature_5 <= 0.94
|   |   |--- value: [-124.20]
|   |--- feature_5 >  0.94
|   |--- value: [-139.55]
|--- feature_2 >  0.09
|   |--- feature_21 <= 1.18
|   |   |--- feature_15 <= 0.40
|   |   |--- value: [-273.25]
|   |--- feature_15 >  0.40
|   |--- value: [-305.30]
|   |--- feature_21 >  1.18
|   |--- value: [-576.75]
|--- feature_11 >  -0.50
|--- feature_2 <= 0.07
|   |--- feature_3 <= 2.50
|   |   |--- feature_9 <= 2.16
|   |   |--- feature_2 <= 0.04
|   |   |   |--- feature_9 <= 0.46
|   |   |   |--- feature_10 <= 2.43
|   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |--- feature_8 <= 1.39
|   |   |   |   |--- truncated branch of depth 13
|   |   |   |   |--- feature_8 >  1.39
|   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |--- feature_2 >  0.03
|   |   |   |   |--- feature_2 <= 0.04
|   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |--- feature_2 >  0.04
|   |   |   |--- truncated branch of depth 10

```

```

|   |   |   |   |   |   |   |--- feature_10 >  2.43
|   |   |   |   |   |   |   |--- feature_8 <= 1.39
|   |   |   |   |   |   |   |--- feature_10 <= 5.30
|   |   |   |   |   |   |   |   |--- truncated branch of depth 21
|   |   |   |   |   |   |   |--- feature_10 >  5.30
|   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |--- feature_8 >  1.39
|   |   |   |   |   |   |   |--- feature_10 <= 5.04
|   |   |   |   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |   |   |   |--- feature_10 >  5.04
|   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_9 >  0.46
|   |   |   |   |--- feature_10 <= 2.36
|   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |--- feature_2 >  0.03
|   |   |   |   |   |--- truncated branch of depth 19
|   |   |   |   |   |--- feature_7 >  2.00
|   |   |   |   |   |--- feature_8 <= -0.30
|   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |--- feature_8 >  -0.30
|   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_10 >  2.36
|   |   |   |   |--- feature_8 <= 1.39
|   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |   |   |--- feature_7 >  2.00
|   |   |   |   |   |--- truncated branch of depth 17
|   |   |   |   |   |--- feature_8 >  1.39
|   |   |   |   |   |--- feature_9 <= 1.48
|   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |--- feature_9 >  1.48
|   |   |   |   |   |--- truncated branch of depth 19
|--- feature_2 >  0.04
|   |--- feature_3 <= 1.50
|   |   |--- feature_2 <= 0.05
|   |   |   |--- feature_16 <= -2.36
|   |   |   |   |--- feature_9 <= -1.01
|   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_9 >  -1.01
|   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_16 >  -2.36
|   |   |   |   |--- feature_9 <= 1.05
|   |   |   |   |--- truncated branch of depth 12
|   |   |   |   |--- feature_9 >  1.05
|   |   |   |   |--- truncated branch of depth 6
|--- feature_2 >  0.05

```

```

|   |   |   |   |   |   |   |--- feature_10 <= 6.95
|   |   |   |   |   |   |   |--- feature_2 <= 0.06
|   |   |   |   |   |   |   |   |--- truncated branch of depth 16
|   |   |   |   |   |   |   |--- feature_2 >  0.06
|   |   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |--- feature_10 >  6.95
|   |   |   |   |   |   |   |--- feature_5 <= 0.06
|   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |--- feature_5 >  0.06
|   |   |   |   |   |   |   |   |--- value: [155.45]
|   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |--- feature_9 <= 0.71
|   |   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |   |--- feature_7 <= 0.50
|   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |--- feature_7 >  0.50
|   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |--- feature_9 <= -0.23
|   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_9 >  -0.23
|   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |--- feature_9 >  0.71
|   |   |   |   |--- feature_8 <= 1.39
|   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |--- feature_8 >  1.39
|   |   |   |   |--- feature_9 <= 1.71
|   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |--- feature_9 >  1.71
|   |   |   |   |   |--- truncated branch of depth 3
|--- feature_9 >  2.16
|--- feature_9 <= 3.30
|   |--- feature_10 <= 1.95
|   |--- feature_2 <= 0.04
|   |   |--- feature_9 <= 2.72
|   |   |   |--- feature_2 <= 0.03
|   |   |   |   |--- truncated branch of depth 13
|   |   |   |--- feature_2 >  0.03
|   |   |   |   |--- truncated branch of depth 16
|   |   |   |--- feature_9 >  2.72
|   |   |   |--- feature_2 <= 0.03
|   |   |   |   |--- truncated branch of depth 15
|   |   |   |--- feature_2 >  0.03
|   |   |   |   |--- truncated branch of depth 16
|--- feature_2 >  0.04

```

```

|   |   |   |   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |   |   |--- feature_5 <= 0.19
|   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |--- feature_5 >  0.19
|   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |--- feature_12 >  1.25
|   |   |   |   |   |   |   |--- feature_17 <= 0.32
|   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |--- feature_17 >  0.32
|   |   |   |   |   |   |   |--- value: [96.90]

|   |   |   |   |--- feature_10 >  1.95
|   |   |   |   |--- feature_8 <= 1.39
|   |   |   |   |   |--- feature_2 <= 0.06
|   |   |   |   |   |--- feature_10 <= 6.35
|   |   |   |   |   |   |--- truncated branch of depth 25
|   |   |   |   |   |--- feature_10 >  6.35
|   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_2 >  0.06
|   |   |   |   |--- feature_5 <= 1.11
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |--- feature_5 >  1.11
|   |   |   |   |   |--- value: [98.41]

|   |   |--- feature_8 >  1.39
|   |   |   |--- feature_2 <= 0.05
|   |   |   |--- feature_21 <= 0.15
|   |   |   |   |--- truncated branch of depth 24
|   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |--- truncated branch of depth 7
|   |   |   |--- feature_2 >  0.05
|   |   |   |--- feature_1 <= 1.50
|   |   |   |   |--- truncated branch of depth 3
|   |   |   |--- feature_1 >  1.50
|   |   |   |   |--- truncated branch of depth 2

|--- feature_9 >  3.30
|   |--- feature_2 <= 0.05
|   |--- feature_9 <= 6.23
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_2 <= 0.04
|   |   |   |   |--- truncated branch of depth 12
|   |   |   |--- feature_2 >  0.04
|   |   |   |   |--- truncated branch of depth 13
|   |   |   |--- feature_3 >  1.50
|   |   |   |   |--- feature_8 <= 1.39
|   |   |   |   |   |--- truncated branch of depth 20
|   |   |   |--- feature_8 >  1.39
|   |   |   |   |   |--- truncated branch of depth 15
|   |--- feature_9 >  6.23
|   |   |--- feature_9 <= 15.73

```

```

|   |   |   |   |   |   |   |   |--- feature_14 <= 0.42
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |--- feature_14 >  0.42
|   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |--- feature_9 >  15.73
|   |   |   |   |   |   |   |--- feature_6 <= 0.37
|   |   |   |   |   |   |   |   |--- value: [172.30]
|   |   |   |   |   |   |   |--- feature_6 >  0.37
|   |   |   |   |   |   |   |   |--- value: [185.75]
|   |   |   |   |   |--- feature_2 >  0.05
|   |   |   |   |--- feature_3 <= 1.50
|   |   |   |   |   |--- feature_9 <= 3.93
|   |   |   |   |   |   |--- feature_2 <= 0.06
|   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |   |--- feature_2 >  0.06
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |--- feature_9 >  3.93
|   |   |   |   |   |   |--- feature_9 <= 4.63
|   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |   |--- feature_9 >  4.63
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |--- feature_3 >  1.50
|   |   |   |   |--- feature_10 <= 6.95
|   |   |   |   |   |--- feature_9 <= 4.09
|   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |--- feature_9 >  4.09
|   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |--- feature_10 >  6.95
|   |   |   |   |   |--- value: [119.40]
|   |--- feature_3 >  2.50
|   |   |--- feature_3 <= 52.00
|   |   |--- feature_9 <= 4.89
|   |   |   |--- feature_2 <= 0.05
|   |   |   |   |--- feature_9 <= 3.46
|   |   |   |   |   |--- feature_10 <= 3.67
|   |   |   |   |   |--- feature_2 <= 0.04
|   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |--- feature_2 >  0.04
|   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |--- feature_10 >  3.67
|   |   |   |   |   |--- feature_2 <= 0.04
|   |   |   |   |   |--- truncated branch of depth 18
|   |   |   |   |   |--- feature_2 >  0.04
|   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |--- feature_9 >  3.46
|   |   |   |   |   |--- feature_9 <= 4.48
|   |   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |   |--- truncated branch of depth 11

```

```

|   |   |   |   |   |   |   |   |--- feature_2 >  0.03
|   |   |   |   |   |   |   |   |--- truncated branch of depth 14
|   |   |   |   |   |   |   |--- feature_9 >  4.48
|   |   |   |   |   |   |   |--- feature_5 <= -0.27
|   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |--- feature_5 >  -0.27
|   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |--- feature_2 >  0.05
|   |   |   |   |--- feature_7 <= 1.50
|   |   |   |   |--- feature_2 <= 0.05
|   |   |   |   |--- value: [287.26]
|   |   |   |   |--- feature_2 >  0.05
|   |   |   |   |--- feature_2 <= 0.06
|   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |--- feature_2 >  0.06
|   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |--- feature_7 >  1.50
|   |   |   |   |--- feature_6 <= 0.59
|   |   |   |   |--- value: [40.00]
|   |   |   |   |--- feature_6 >  0.59
|   |   |   |   |--- value: [41.00]
|--- feature_9 >  4.89
|   |--- feature_2 <= 0.04
|   |--- feature_9 <= 6.03
|   |   |--- feature_3 <= 3.50
|   |   |--- feature_2 <= 0.04
|   |   |--- truncated branch of depth 12
|   |   |--- feature_2 >  0.04
|   |   |--- truncated branch of depth 3
|   |   |--- feature_3 >  3.50
|   |   |--- feature_17 <= 0.23
|   |   |--- truncated branch of depth 4
|   |   |--- feature_17 >  0.23
|   |   |--- truncated branch of depth 4
|--- feature_9 >  6.03
|   |--- feature_3 <= 3.50
|   |--- feature_2 <= 0.03
|   |   |--- value: [191.15]
|   |--- feature_2 >  0.03
|   |--- truncated branch of depth 4
|   |--- feature_3 >  3.50
|   |--- feature_2 <= 0.04
|   |--- truncated branch of depth 3
|   |--- feature_2 >  0.04
|   |--- value: [180.05]
|--- feature_2 >  0.04
|   |--- feature_6 <= 1.55
|   |--- feature_9 <= 5.82

```

```

|   |   |   |   |   |   |   |   |--- feature_2 <= 0.05
|   |   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |   |   |--- feature_2 >  0.05
|   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |--- feature_9 >  5.82
|   |   |   |   |   |   |   |   |--- feature_2 <= 0.06
|   |   |   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |   |--- feature_2 >  0.06
|   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |--- feature_6 >  1.55
|   |   |   |   |   |--- feature_10 <= 7.07
|   |   |   |   |   |   |   |--- value: [284.65]
|   |   |   |   |   |--- feature_10 >  7.07
|   |   |   |   |   |   |   |--- value: [334.30]
|--- feature_3 >  52.00
|   |--- feature_10 <= 1.78
|   |   |--- feature_2 <= 0.03
|   |   |   |--- feature_5 <= 0.90
|   |   |   |   |--- feature_9 <= -0.56
|   |   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |   |   |--- value: [52.00]
|   |   |   |   |   |--- feature_2 >  0.03
|   |   |   |   |   |   |--- value: [50.00]
|   |   |   |   |   |--- feature_9 >  -0.56
|   |   |   |   |   |   |--- feature_10 <= 0.37
|   |   |   |   |   |   |--- value: [54.00]
|   |   |   |   |   |--- feature_10 >  0.37
|   |   |   |   |   |   |--- value: [55.00]
|   |   |   |   |--- feature_5 >  0.90
|   |   |   |   |   |--- feature_9 <= -0.54
|   |   |   |   |   |   |--- feature_20 <= -0.36
|   |   |   |   |   |   |--- value: [54.00]
|   |   |   |   |   |--- feature_20 >  -0.36
|   |   |   |   |   |   |--- value: [47.00]
|   |   |   |   |   |--- feature_9 >  -0.54
|   |   |   |   |   |   |--- feature_16 <= -0.45
|   |   |   |   |   |   |--- value: [38.00]
|   |   |   |   |   |--- feature_16 >  -0.45
|   |   |   |   |   |   |--- value: [25.70]
|   |   |   |--- feature_2 >  0.03
|   |   |   |   |--- feature_20 <= 0.14
|   |   |   |   |   |--- feature_20 <= -0.87
|   |   |   |   |   |   |--- feature_17 <= -0.19
|   |   |   |   |   |   |--- value: [51.45]
|   |   |   |   |   |   |--- feature_17 >  -0.19
|   |   |   |   |   |   |--- value: [52.45]
|   |   |   |   |--- feature_20 >  -0.87
|   |   |   |   |   |--- value: [45.00]

```

```

|   |   |   |   |   |   |   |--- feature_20 >  0.14
|   |   |   |   |   |   |   |--- feature_9 <= -1.02
|   |   |   |   |   |   |   |   |--- feature_5 <= -1.22
|   |   |   |   |   |   |   |   |   |--- value: [51.00]
|   |   |   |   |   |   |   |--- feature_5 >  -1.22
|   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |--- feature_9 >  -1.02
|   |   |   |   |   |   |   |--- feature_6 <= -0.01
|   |   |   |   |   |   |   |   |--- value: [65.45]
|   |   |   |   |   |   |   |--- feature_6 >  -0.01
|   |   |   |   |   |   |   |--- truncated branch of depth 2
|--- feature_10 >  1.78
|   |--- feature_10 <= 10.34
|   |   |--- feature_2 <= 0.04
|   |   |   |--- feature_17 <= -0.27
|   |   |   |   |--- feature_2 <= 0.03
|   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_2 >  0.03
|   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |--- feature_17 >  -0.27
|   |   |   |   |--- feature_9 <= -1.13
|   |   |   |   |   |--- value: [47.25]
|   |   |   |   |--- feature_9 >  -1.13
|   |   |   |   |--- truncated branch of depth 4
|--- feature_2 >  0.04
|   |--- feature_2 <= 0.05
|   |   |--- feature_16 <= 0.50
|   |   |--- truncated branch of depth 9
|   |   |--- feature_16 >  0.50
|   |   |--- truncated branch of depth 3
|   |   |--- feature_2 >  0.05
|   |   |--- feature_20 <= 1.16
|   |   |--- truncated branch of depth 2
|   |   |--- feature_20 >  1.16
|   |   |   |--- value: [75.25]
|   |   |--- feature_10 >  10.34
|   |   |   |--- value: [98.26]
|--- feature_2 >  0.07
|--- feature_2 <= 0.09
|   |--- feature_3 <= 2.50
|   |   |--- feature_3 <= 1.50
|   |   |   |--- feature_9 <= 3.47
|   |   |   |   |--- feature_2 <= 0.08
|   |   |   |   |--- feature_7 <= 2.00
|   |   |   |   |   |--- feature_17 <= -1.78
|   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |--- feature_17 >  -1.78
|   |   |   |--- truncated branch of depth 7

```

```

|   |   |   |   |   |   |   |--- feature_7 >  2.00
|   |   |   |   |   |   |   |--- feature_2 <= 0.07
|   |   |   |   |   |   |   |--- value: [103.92]
|   |   |   |   |   |   |   |--- feature_2 >  0.07
|   |   |   |   |   |   |   |--- value: [114.75]
|   |   |   |   |   |--- feature_2 >  0.08
|   |   |   |   |   |--- feature_8 <= 2.04
|   |   |   |   |   |--- feature_9 <= 2.41
|   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |--- feature_9 >  2.41
|   |   |   |   |   |   |--- value: [180.00]
|   |   |   |   |   |--- feature_8 >  2.04
|   |   |   |   |   |--- value: [196.60]
|   |   |   |--- feature_9 >  3.47
|   |   |   |--- feature_12 <= 1.25
|   |   |   |   |--- feature_6 <= 0.19
|   |   |   |   |--- feature_2 <= 0.09
|   |   |   |   |--- value: [194.75]
|   |   |   |   |--- feature_2 >  0.09
|   |   |   |   |--- value: [193.74]
|   |   |   |   |--- feature_6 >  0.19
|   |   |   |   |--- value: [197.70]
|   |   |   |--- feature_12 >  1.25
|   |   |   |   |--- feature_17 <= 0.15
|   |   |   |   |--- value: [175.80]
|   |   |   |   |--- feature_17 >  0.15
|   |   |   |   |--- value: [156.05]
|--- feature_3 >  1.50
|   |--- feature_10 <= 8.05
|   |   |--- feature_0 <= 0.50
|   |   |--- value: [74.00]
|   |   |--- feature_0 >  0.50
|   |   |--- feature_7 <= 0.50
|   |   |--- value: [80.55]
|   |   |--- feature_7 >  0.50
|   |   |--- value: [82.30]
|   |--- feature_10 >  8.05
|   |--- value: [120.30]
|--- feature_3 >  2.50
|--- feature_9 <= 7.82
|   |--- feature_2 <= 0.09
|   |   |--- feature_9 <= -1.17
|   |   |--- feature_5 <= 0.15
|   |   |--- feature_10 <= 8.77
|   |   |--- truncated branch of depth 2
|   |   |--- feature_10 >  8.77
|   |   |--- value: [208.39]
|   |--- feature_5 >  0.15

```

```

|   |   |   |   |   |   |   |   |--- feature_6 <= -0.09
|   |   |   |   |   |   |--- value: [143.05]
|   |   |   |   |   |--- feature_6 > -0.09
|   |   |   |   |   |--- value: [146.05]
|   |   |   |   |--- feature_9 > -1.17
|   |   |   |   |   |--- feature_17 <= -0.10
|   |   |   |   |   |--- feature_2 <= 0.08
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |--- feature_2 > 0.08
|   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |--- feature_17 > -0.10
|   |   |   |   |   |--- feature_10 <= 5.81
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |--- feature_10 > 5.81
|   |   |   |   |   |   |--- truncated branch of depth 9
|   |   |   |   |--- feature_2 > 0.09
|   |   |   |   |--- feature_5 <= -0.02
|   |   |   |   |   |--- feature_3 <= 4.50
|   |   |   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |   |   |--- value: [273.25]
|   |   |   |   |   |   |--- feature_8 > -0.11
|   |   |   |   |   |   |--- value: [274.25]
|   |   |   |   |   |--- feature_3 > 4.50
|   |   |   |   |   |--- value: [313.00]
|--- feature_5 > -0.02
|   |   |   |   |--- feature_12 <= 1.25
|   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |--- value: [236.00]
|   |   |   |   |   |--- feature_13 > 0.88
|   |   |   |   |   |--- value: [258.95]
|   |   |   |   |--- feature_12 > 1.25
|   |   |   |   |--- value: [211.10]
|--- feature_9 > 7.82
|   |   |--- feature_17 <= -2.03
|   |   |--- value: [334.62]
|--- feature_17 > -2.03
|   |   |--- feature_9 <= 8.73
|   |   |   |--- feature_6 <= -0.57
|   |   |   |   |--- feature_14 <= -0.92
|   |   |   |   |--- value: [256.08]
|   |   |   |   |--- feature_14 > -0.92
|   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |--- feature_6 > -0.57
|   |   |   |   |--- feature_15 <= -0.27
|   |   |   |   |--- value: [243.43]
|   |   |   |   |--- feature_15 > -0.27
|   |   |   |   |--- value: [243.07]
|--- feature_9 > 8.73

```

```

|   |   |   |   |   |   |   |--- feature_5 <= 1.38
|   |   |   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |--- feature_5 >  1.38
|   |   |   |   |   |   |--- value: [245.88]
|   |   |--- feature_2 >  0.09
|   |   |--- feature_2 <= 12.40
|   |   |   |--- feature_2 <= 0.14
|   |   |   |   |--- feature_9 <= 9.82
|   |   |   |   |   |--- feature_9 <= -1.21
|   |   |   |   |   |--- value: [407.05]
|   |   |   |   |   |--- feature_9 >  -1.21
|   |   |   |   |   |   |--- feature_8 <= 2.69
|   |   |   |   |   |   |--- feature_6 <= 0.85
|   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |   |--- feature_6 >  0.85
|   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |--- feature_8 >  2.69
|   |   |   |   |   |   |--- value: [373.95]
|   |   |   |   |--- feature_9 >  9.82
|   |   |   |   |--- feature_2 <= 0.11
|   |   |   |   |   |--- feature_17 <= 0.40
|   |   |   |   |   |   |--- feature_6 <= -0.43
|   |   |   |   |   |   |--- value: [358.27]
|   |   |   |   |   |   |--- feature_6 >  -0.43
|   |   |   |   |   |   |--- value: [351.31]
|   |   |   |   |   |--- feature_17 >  0.40
|   |   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |   |--- value: [332.76]
|   |   |   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |   |   |--- value: [340.98]
|   |   |   |--- feature_2 >  0.11
|   |   |   |   |--- feature_10 <= 4.53
|   |   |   |   |   |--- value: [307.62]
|   |   |   |   |--- feature_10 >  4.53
|   |   |   |   |   |--- feature_13 <= 0.88
|   |   |   |   |   |   |--- value: [320.10]
|   |   |   |   |   |--- feature_13 >  0.88
|   |   |   |   |   |   |--- value: [322.57]
|   |   |--- feature_2 >  0.14
|   |   |   |--- feature_2 <= 0.17
|   |   |   |   |--- feature_17 <= 1.24
|   |   |   |   |   |--- feature_10 <= 2.90
|   |   |   |   |   |   |--- feature_19 <= 5.62
|   |   |   |   |   |   |--- value: [461.95]
|   |   |   |   |   |   |--- feature_19 >  5.62

```

```

|   |   |   |   |   |   |   |   |   |   |   |--- value: [461.00]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_10 >  2.90
|   |   |   |   |   |   |   |   |   |   |   |--- feature_17 <= 0.99
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |   |   |--- feature_17 >  0.99
|   |   |   |   |   |   |   |   |   |   |   |--- value: [396.31]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_17 >  1.24
|   |   |   |   |   |   |   |   |   |   |   |--- value: [288.60]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_2 >  0.17
|   |   |   |   |   |   |   |   |   |   |   |--- feature_8 <= -0.11
|   |   |   |   |   |   |   |   |   |   |   |--- feature_14 <= 0.42
|   |   |   |   |   |   |   |   |   |   |   |--- feature_8 <= -0.76
|   |   |   |   |   |   |   |   |   |   |   |--- value: [470.30]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_8 >  -0.76
|   |   |   |   |   |   |   |   |   |   |   |--- value: [456.90]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_14 >  0.42
|   |   |   |   |   |   |   |   |   |   |   |--- value: [491.15]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_8 >  -0.11
|   |   |   |   |   |   |   |   |   |   |   |--- feature_10 <= 1.13
|   |   |   |   |   |   |   |   |   |   |   |--- feature_21 <= 0.15
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |   |   |--- feature_21 >  0.15
|   |   |   |   |   |   |   |   |   |   |   |--- value: [587.25]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_10 >  1.13
|   |   |   |   |   |   |   |   |   |   |   |--- value: [494.00]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_2 >  12.40
|   |   |   |   |   |   |   |   |   |   |   |--- feature_5 <= -0.17
|   |   |   |   |   |   |   |   |   |   |   |   |--- feature_5 <= -0.68
|   |   |   |   |   |   |   |   |   |   |   |   |--- value: [18.00]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_5 >  -0.68
|   |   |   |   |   |   |   |   |   |   |   |--- value: [9.60]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_5 >  -0.17
|   |   |   |   |   |   |   |   |   |   |   |--- feature_9 <= 0.36
|   |   |   |   |   |   |   |   |   |   |   |--- value: [27.92]
|   |   |   |   |   |   |   |   |   |   |   |--- feature_9 >  0.36
|   |   |   |   |   |   |   |   |   |   |   |--- value: [42.56]

```

12.3 Bagging and Boosting

Bagging: * `sklearn.ensemble.BaggingRegressor` * `sklearn.ensemble.RandomForestRegressor`
 Boosting: * `sklearn.ensemble.GradientBoostingRegressor` *
`sklearn.ensemble.AdaBoostRegressor`

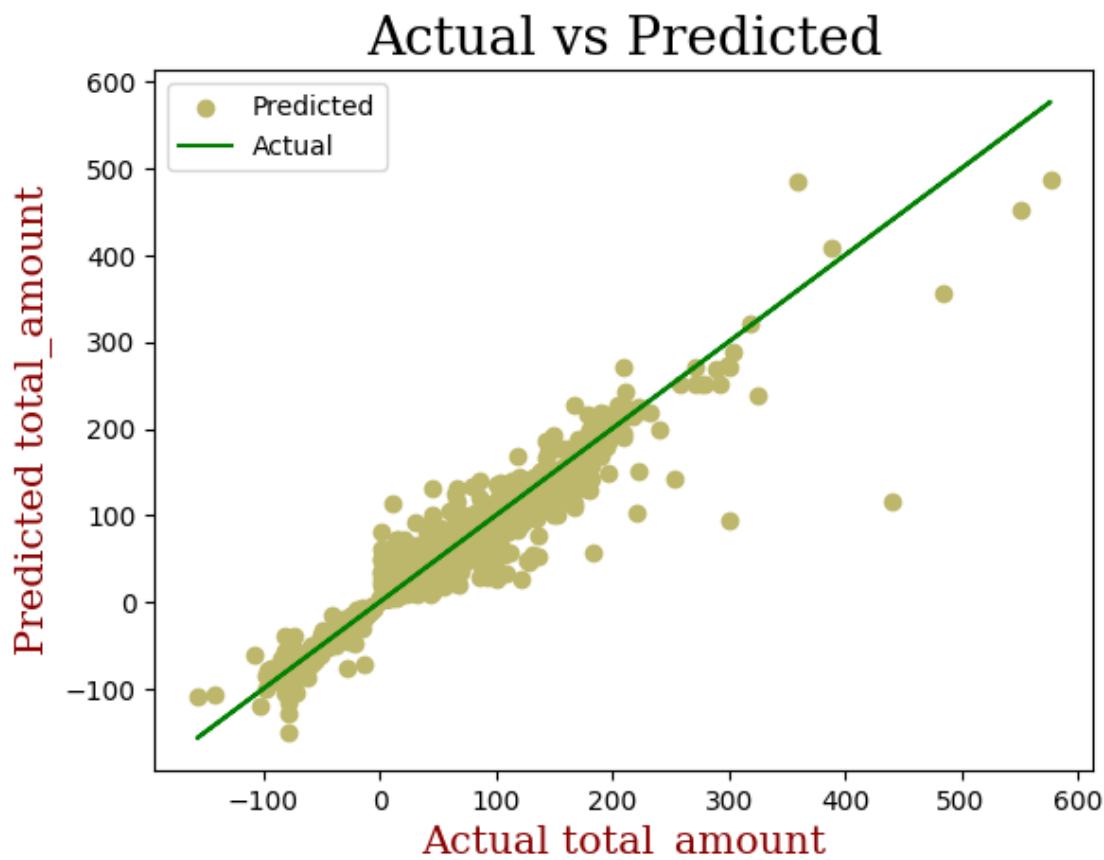
12.3.1 BaggingRegressor()

```
[130]: b1_reg = BaggingRegressor()  
b1_reg.fit(X_train, y_train)  
b1_reg_predict = b1_reg.predict(X_val)  
print(b1_reg_predict)  
b1_reg_score = r2_score(y_val,b1_reg_predict)  
print("R2_Score (BaggingRegressor) :" ,b1_reg_score)
```

[36.143 24.758 98.585 ... 11.259 17.898 33.04]
R2_Score (BaggingRegressor) : 0.953593491869053

- Plotting Actual vs Predicted

```
[131]: act_vs_predict(y_val,b1_reg_predict)
```



Tunning Hyperparameters & Training as well as evaluating on the same.

```
[132]: '''  
tuned_parameters = [{"n_estimators": [50, 100, 200],  
"max_features": [1, 2, 6, 8, 10, 12, 14],
```

```

        "max_samples": [0.5,0.1],
        "bootstrap": [True, False],
        "bootstrap_features": [True, False]}
]

Bag_model_GS = GridSearchCV(BaggingRegressor(), param_grid=tuned_parameters)
Bag_model_GS.fit(X_train,y_train)

print("The best parameter value is:", Bag_model_GS.best_params_)
'''

```

[132]: \ntuned_parameters = [{"n_estimators": [50,100,200],\n"max_features": [1,2,6,8,10,12,14],\n"max_samples": [0.5,0.1],\n"bootstrap": [True, False],\n"bootstrap_features": [True,\nFalse]}\n]\n\nBag_model_GS = GridSearchCV(BaggingRegressor(),\nparam_grid=tuned_parameters)\nBag_model_GS.fit(X_train,y_train)\n\nprint("The\nbest parameter value is:", Bag_model_GS.best_params_)\n'

- Result
 - The best parameter value is: {'bootstrap': False, 'bootstrap_features': False, 'max_features': 14, 'max_samples': 0.5, 'n_estimators': 200}

[133]: b2_reg = BaggingRegressor(bootstrap = **False**, bootstrap_features = **False**,\nmax_features = 14, max_samples = 0.5, n_estimators = 200)\nb2_reg.fit(X_train, y_train)\nb2_reg_predict = b2_reg.predict(X_val)\nprint(b2_reg_predict)\nb2_reg_score = r2_score(y_val,b2_reg_predict)\nprint("R2_Score (BaggingRegressor_GridSearchCV):",b2_reg_score)

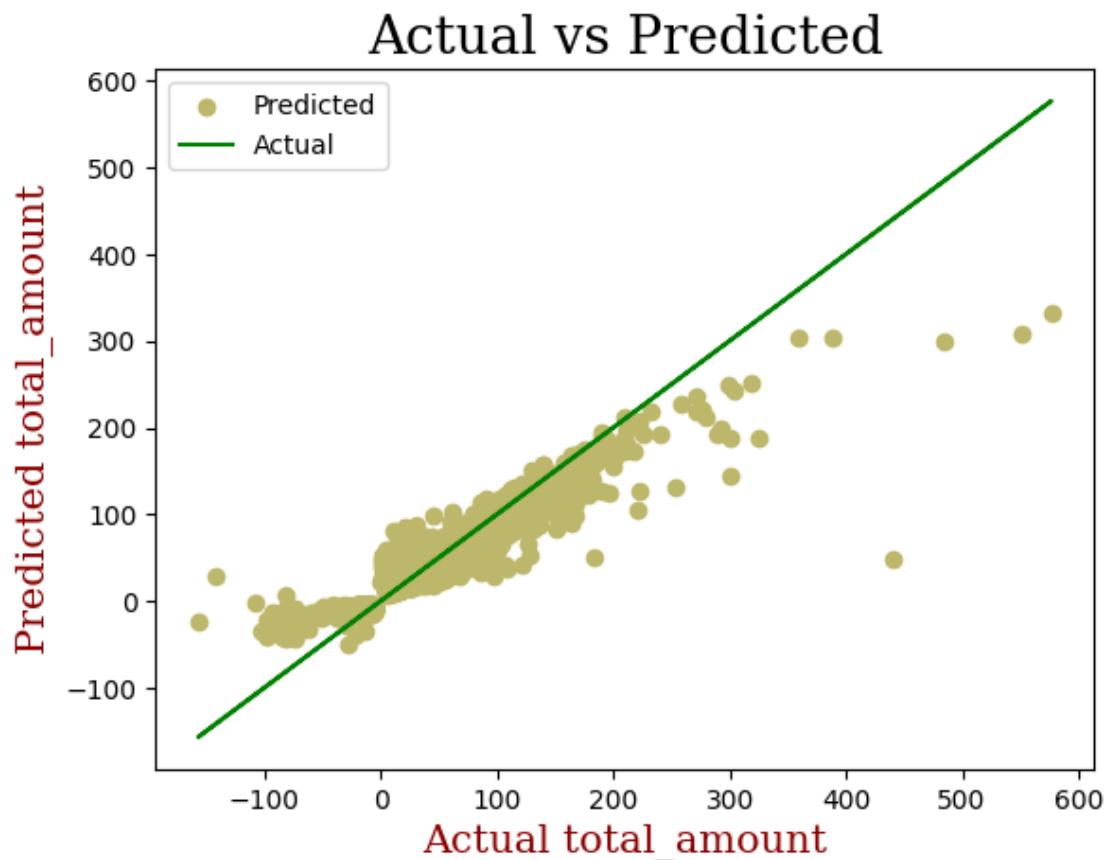
```

[32.25645333 23.41767869 96.9075985 ... 13.89428657 20.41377645
31.2600289 ]
R2_Score (BaggingRegressor_GridSearchCV): 0.9240647115132927

```

- Plotting Actual vs Predicted

[134]: act_vs_predict(y_val,b2_reg_predict)



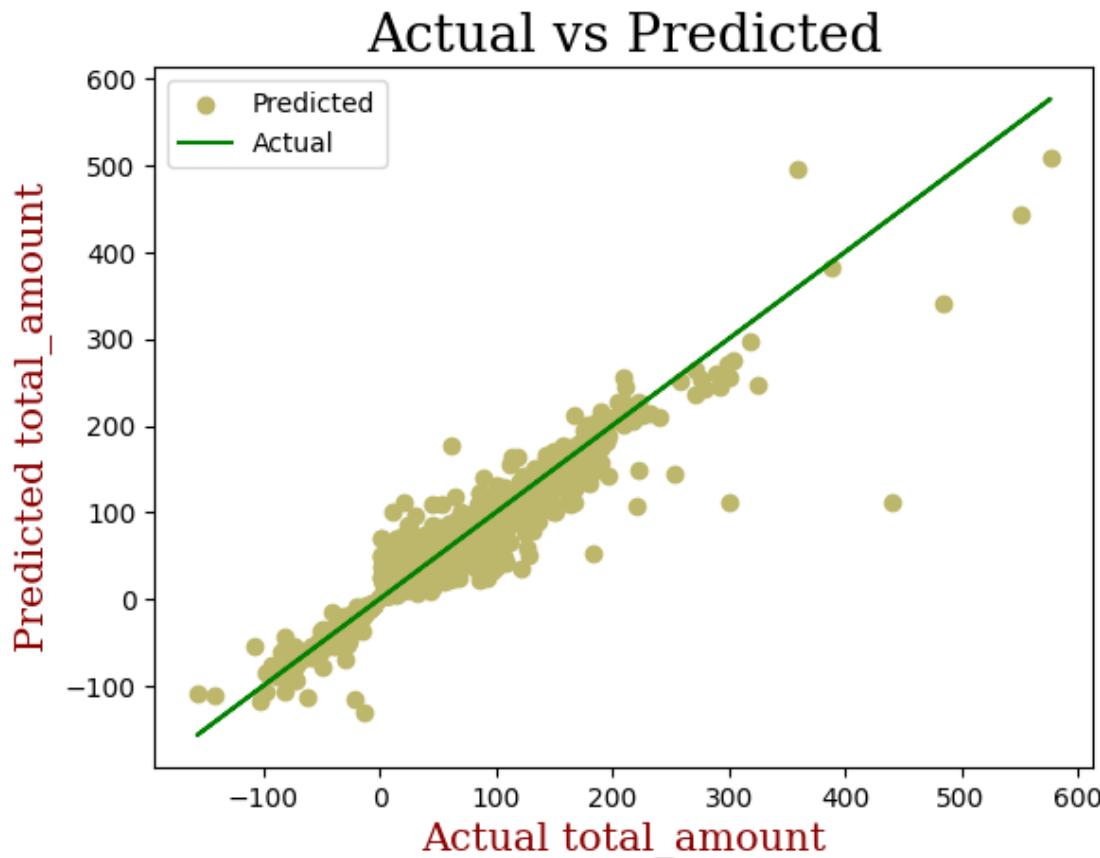
12.3.2 RandomForestRegressor()

```
[135]: rf_reg = RandomForestRegressor()
rf_reg.fit(X_train, y_train)
rf_reg_predict = rf_reg.predict(X_val)
print(rf_reg_predict)
rf_score = r2_score(y_val,rf_reg_predict)
print("R2_Score (RandomForestRegressor) :",rf_score)
```

[38.7645 24.0149 98.5336 ... 11.368 18.7129 34.1035]
R2_Score (RandomForestRegressor) : 0.9558003724642914

- Plotting Actual vs Predicted

```
[136]: act_vs_predict(y_val,rf_reg_predict)
```



Tunning Hyperparameters & Training as well as evaluating on the same.

```
[137]: '''
tuned_parameters = [{"n_estimators": [10,20,30,100],
                     "max_features" : ["sqrt", "log2"],
                     "min_samples_split" : [2,4,8,12,14],
                     "bootstrap": [True, False]}
]

RF_model_GS = GridSearchCV(RandomForestRegressor(), param_grid=tuned_parameters)
RF_model_GS.fit(X_train,y_train)

print ("The best parameter value is:",RF_model_GS.best_params_)
'''
```

```
[137]: '\ntuned_parameters = [{"n_estimators": [10,20,30,100],\n                     "max_features" : ["sqrt", "log2"],\n                     "min_samples_split" :\n                     [2,4,8,12,14],\n                     "bootstrap": [True, False]}\n]\n\nRF_model_GS =\nGridSearchCV(RandomForestRegressor(),\nparam_grid=tuned_parameters)\nRF_model_GS.fit(X_train,y_train)\n\nprint ("The
```

```
best parameter value is:",RF_model_GS.best_params_)\n'
```

- Result

- The best parameter value is: {'bootstrap': False, 'max_features': 'log2', 'min_samples_split': 12, 'n_estimators': 100}

```
[138]: rf_reg_gs = RandomForestRegressor(bootstrap= False, max_features = "log2",  
                                     min_samples_split = 12, n_estimators = 100)  
rf_reg_gs.fit(X_train, y_train)  
rf_reg_gs_predict = rf_reg_gs.predict(X_val)  
print(rf_reg_gs_predict)  
rf_gs_score = r2_score(y_val,rf_reg_gs_predict)  
print("R2_Score (RandomForestRegressor_GridSearchCV) :",rf_gs_score)
```

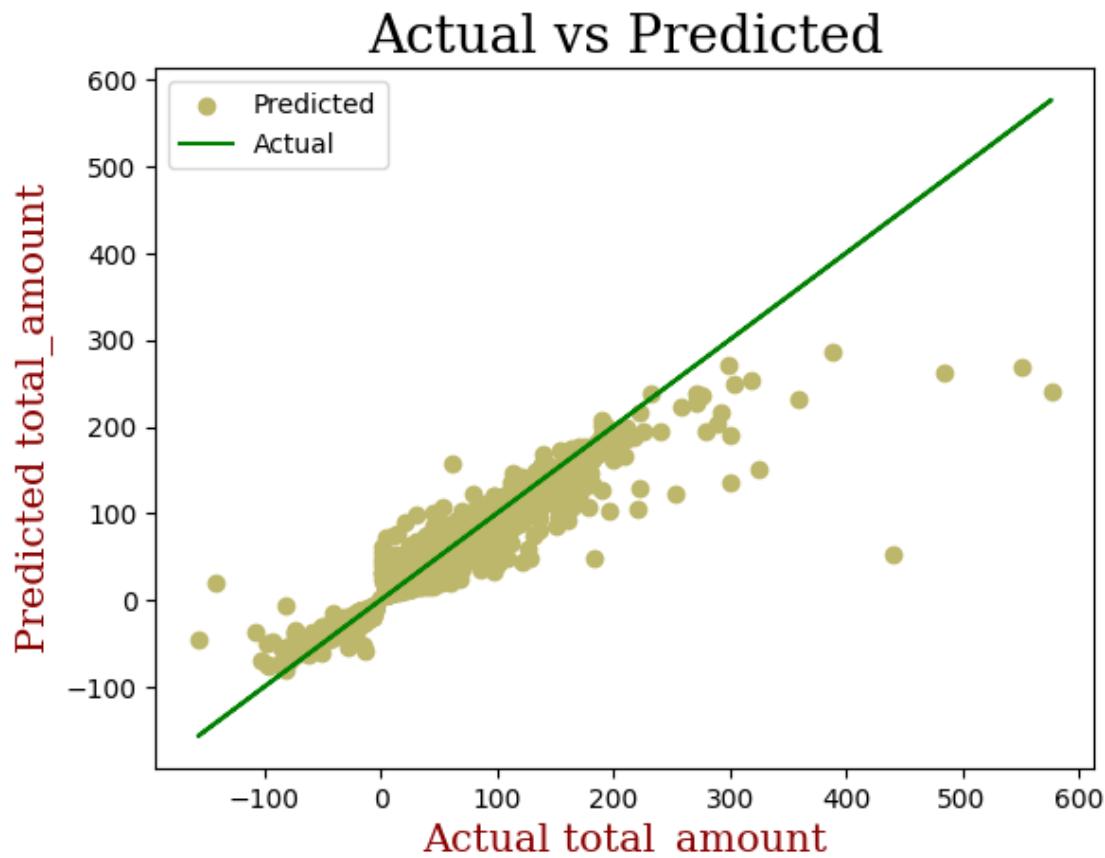
```
[35.85258519 25.19617547 98.40027754 ... 11.99899801 19.54522356
```

```
33.56592826]
```

```
R2_Score (RandomForestRegressor_GridSearchCV) : 0.9399512008533738
```

- Plotting Actual vs Predicted

```
[139]: act_vs_predict(y_val,rf_reg_gs_predict)
```



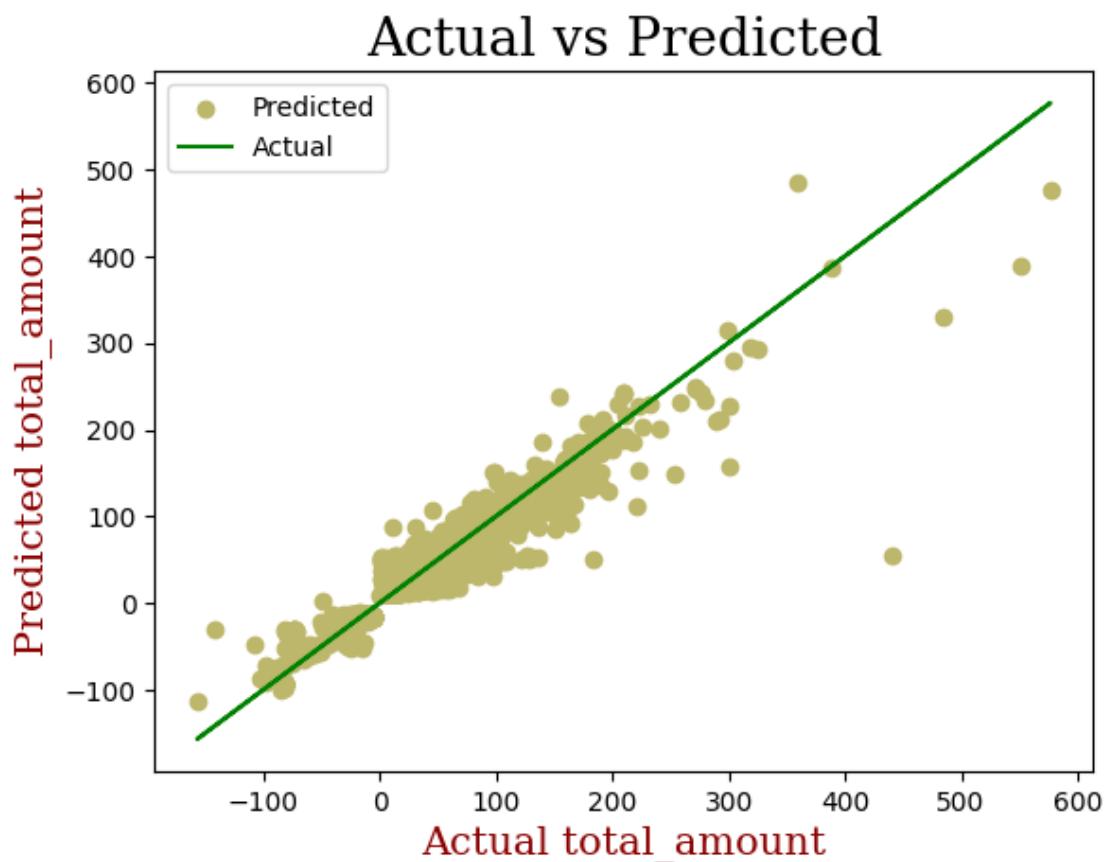
12.3.3 GradientBoostingRegressor()

```
[140]: gbr_reg = GradientBoostingRegressor()
gbr_reg.fit(X_train, y_train)
gbr_reg_predict = gbr_reg.predict(X_val)
print(gbr_reg_predict)
gbr_score = r2_score(y_val,gbr_reg_predict)
print("R2_Score (GradientBoostingRegressor) :",gbr_score)
```

```
[34.58479065 25.34970183 99.8001712 ... 12.13507249 19.51708466
32.66469827]
R2_Score (GradientBoostingRegressor) : 0.9450252139819497
```

- Plotting Actual vs Predicted

```
[141]: act_vs_predict(y_val,gbr_reg_predict)
```



Tunning Hyperparameters & Training as well as evaluating on the same.

```
[142]: '''
tuned_parameters = [ {'max_depth': [80, 100],
                     'max_features': [2, 3],
                     'min_samples_leaf': [3, 4],
                     'min_samples_split': [8, 10],
                     'n_estimators': [100, 200, 500]}
]

gb_model_gs = GridSearchCV(GradientBoostingRegressor(), param_grid = 
                           tuned_parameters)
gb_model_gs.fit(X_train,y_train)

print ("The best parameter value is:",gb_model_gs.best_params_)
'''
```

```
[142]: '\ntuned_parameters = [{\'max_depth\': [80, 100],\n    \'max_features\': [2,\n3],\n    \'min_samples_leaf\': [3, 4],\n    \'min_samples_split\': [8, 10],\n    \'n_estimators\': [100, 200, 500]}\n]\nngb_model_gs =\nGridSearchCV(GradientBoostingRegressor(), param_grid =\ntuned_parameters)\nngb_model_gs.fit(X_train,y_train)\n\nprint ("The best\nparameter value is:",gb_model_gs.best_params_)\n'
```

- Result

- The best parameter value is: {'max_depth': 80, 'max_features': 3, 'min_samples_leaf': 3, 'min_samples_split': 8, 'n_estimators': 500}

```
[143]: gbr_gs_reg = GradientBoostingRegressor(max_depth=80, max_features=3, 
                                             min_samples_leaf=3,
                                             min_samples_split=8, n_estimators=500)
gbr_gs_reg.fit(X_train, y_train)
gbr_gs_reg_predict = gbr_gs_reg.predict(X_val)
print(gbr_gs_reg_predict)
gbr_gs_score = r2_score(y_val,gbr_gs_reg_predict)
print("R2_Score (GradientBoostingRegressor) : ",gbr_gs_score)
```

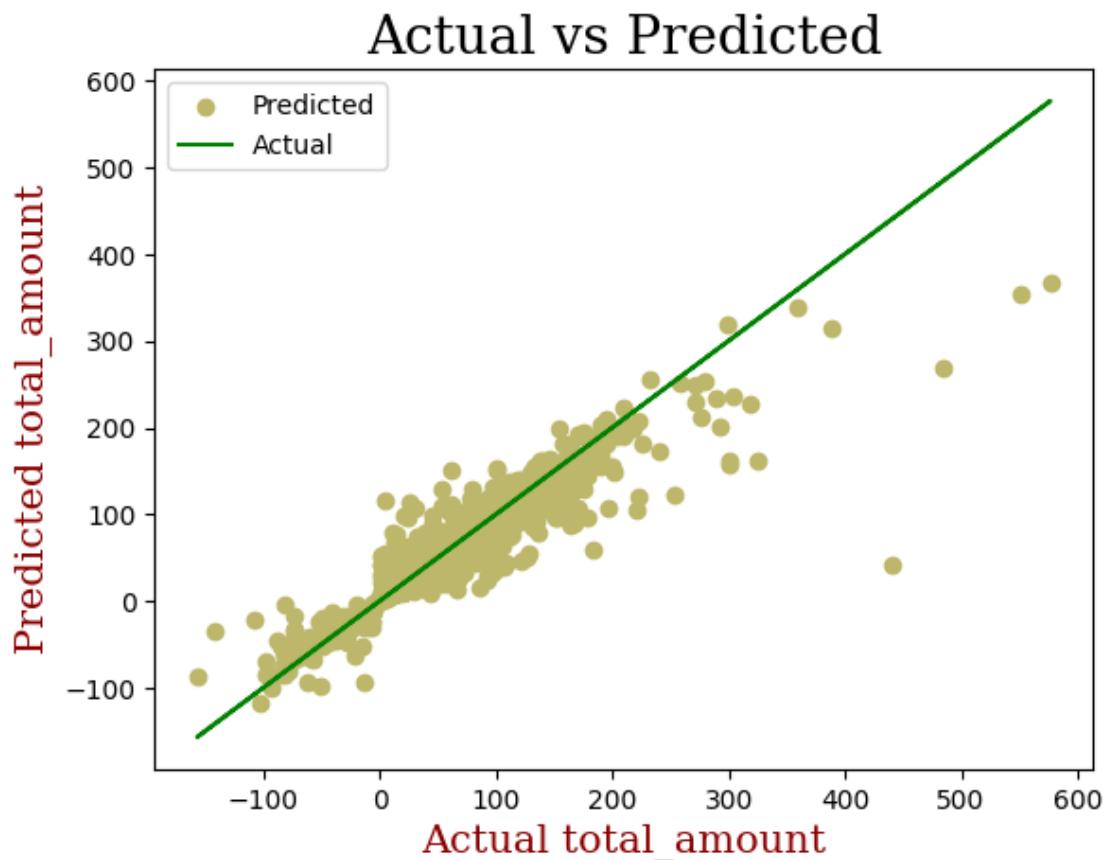
[35.56314981 23.93400861 98.7719081 ... 12.18134527 19.84103645

34.5502852]

R2_Score (GradientBoostingRegressor) : 0.9414157182291742

- Plotting Actual vs Predicted

```
[144]: act_vs_predict(y_val,gbr_gs_reg_predict)
```



12.3.4 AdaBoostRegressor()

```
[145]: abr_reg = AdaBoostRegressor()
abr_reg.fit(X_train, y_train)
abr_reg_predict = abr_reg.predict(X_val)
print(abr_reg_predict)
abr_score = r2_score(y_val,abr_reg_predict)
print("R2_Score (AdaBoostRegressor) :",abr_score)
```

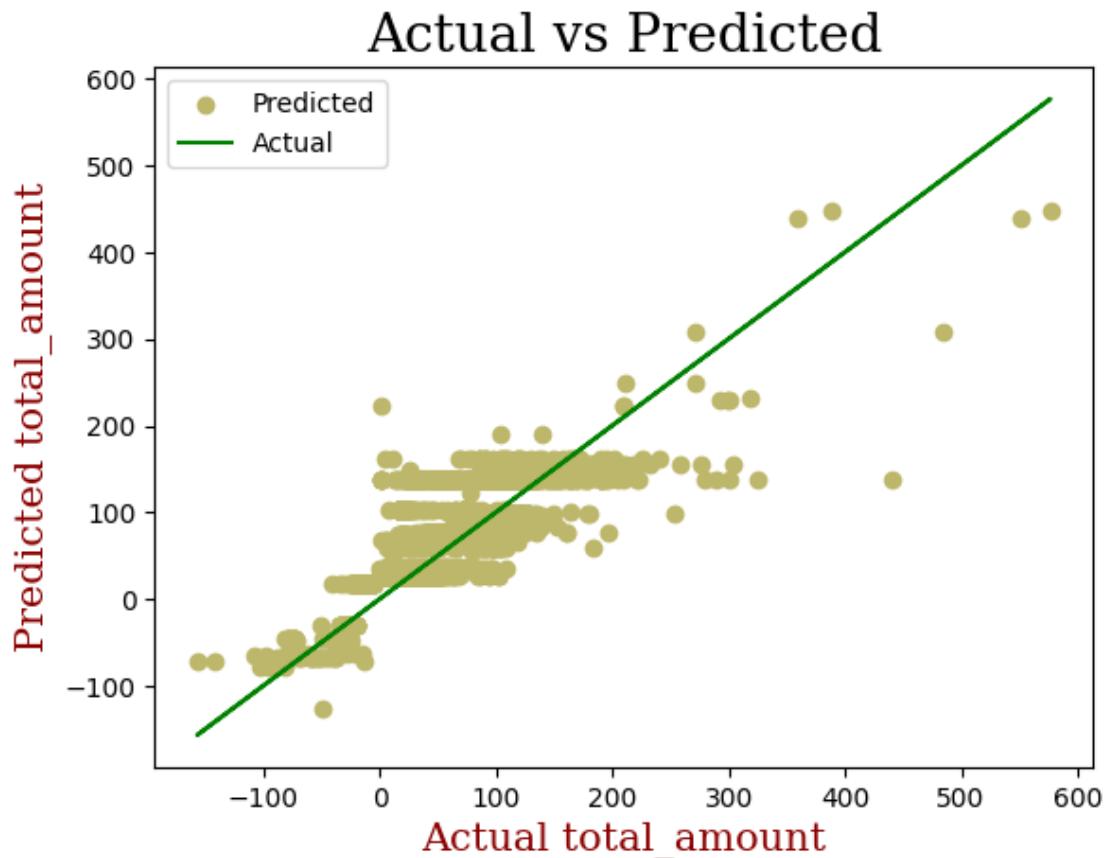
[33.01612259 27.81546549 95.34801327 ... 25.72434292 25.72434292

33.01612259]

R2_Score (AdaBoostRegressor) : 0.7029315901227482

- Plotting Actual vs Predicted

```
[146]: act_vs_predict(y_val,abr_reg_predict)
```



Tunning Hyperparameters & Training as well as evaluating on the same.

```
[147]: """
tuned_parameters = [{'n_estimators': [50, 100],
 'learning_rate' : [0.01, 0.05, 0.1, 0.5],
 'loss' : ['linear', 'square', 'exponential']}
]

ab_model_gs = GridSearchCV(AdaBoostRegressor(), param_grid=tuned_parameters)
ab_model_gs.fit(X_train,y_train)

print ("The best parameter value is:",ab_model_gs.best_params_)
"""

[147]: '\ntuned_parameters = [{\'n_estimators\': [50, 100],\n \'learning_rate\' :\n [0.01, 0.05, 0.1, 0.5],\n \'loss\' : [\'}linear\', \'}square\',\n \'}exponential\']}]\n\nab_model_gs = GridSearchCV(AdaBoostRegressor(),\n param_grid=tuned_parameters)\nab_model_gs.fit(X_train,y_train)\n\nprint ("The\nbest parameter value is:",ab_model_gs.best_params_)\n'
```

- Result

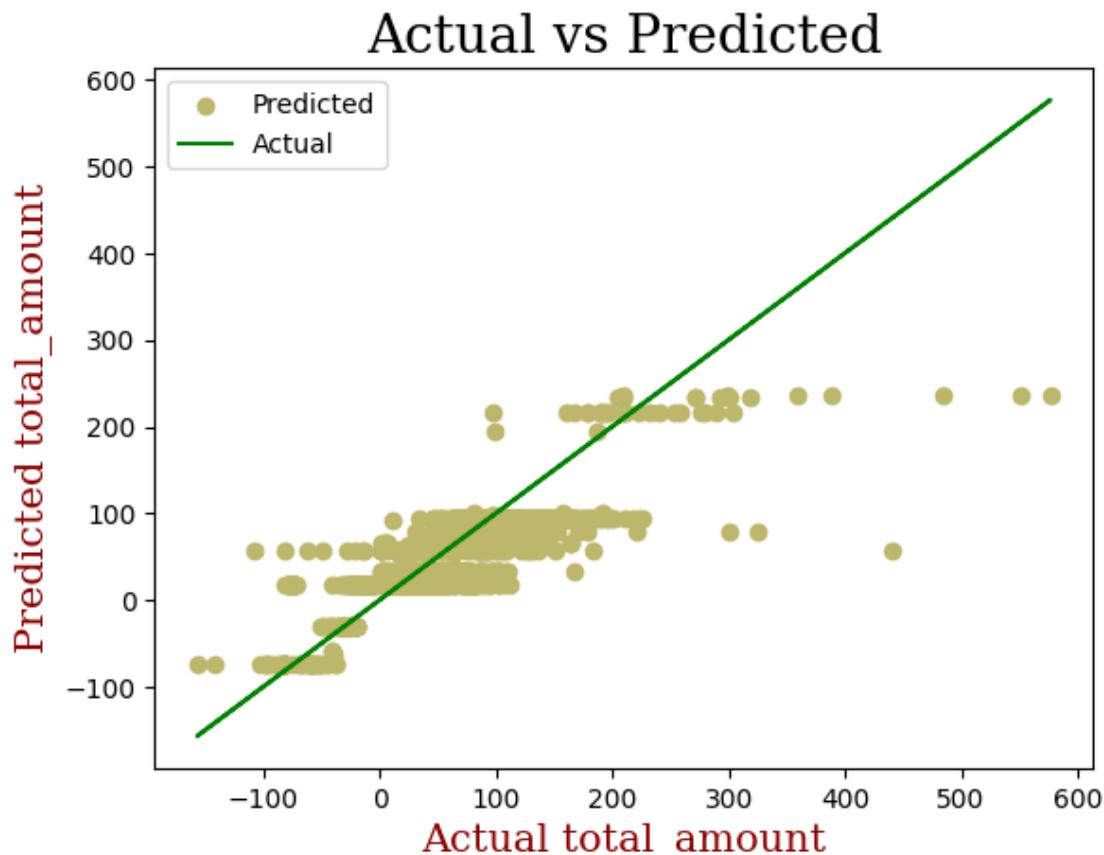
- The best parameter value is: {'learning_rate': 0.01, 'loss': 'exponential', 'n_estimators': 50}

```
[148]: abr_gs_reg = AdaBoostRegressor(learning_rate=0.01, loss='exponential', n_estimators=50)
        abr_gs_reg.fit(X_train, y_train)
        abr_gs_reg_predict = abr_gs_reg.predict(X_val)
        print(abr_gs_reg_predict)
        abr_gs_score = r2_score(y_val, abr_gs_reg_predict)
        print("R2_Score (AdaBoostRegressor) :", abr_gs_score)
```

[33.21667992 32.94129353 94.66289302 ... 18.15600922 18.15600922
32.94129353]
R2_Score (AdaBoostRegressor) : 0.8126664426526186

- Plotting Actual vs Predicted

```
[149]: act_vs_predict(y_val, abr_gs_reg_predict)
```



12.4 MLP (Multi-Layer Perceptron) Regressor

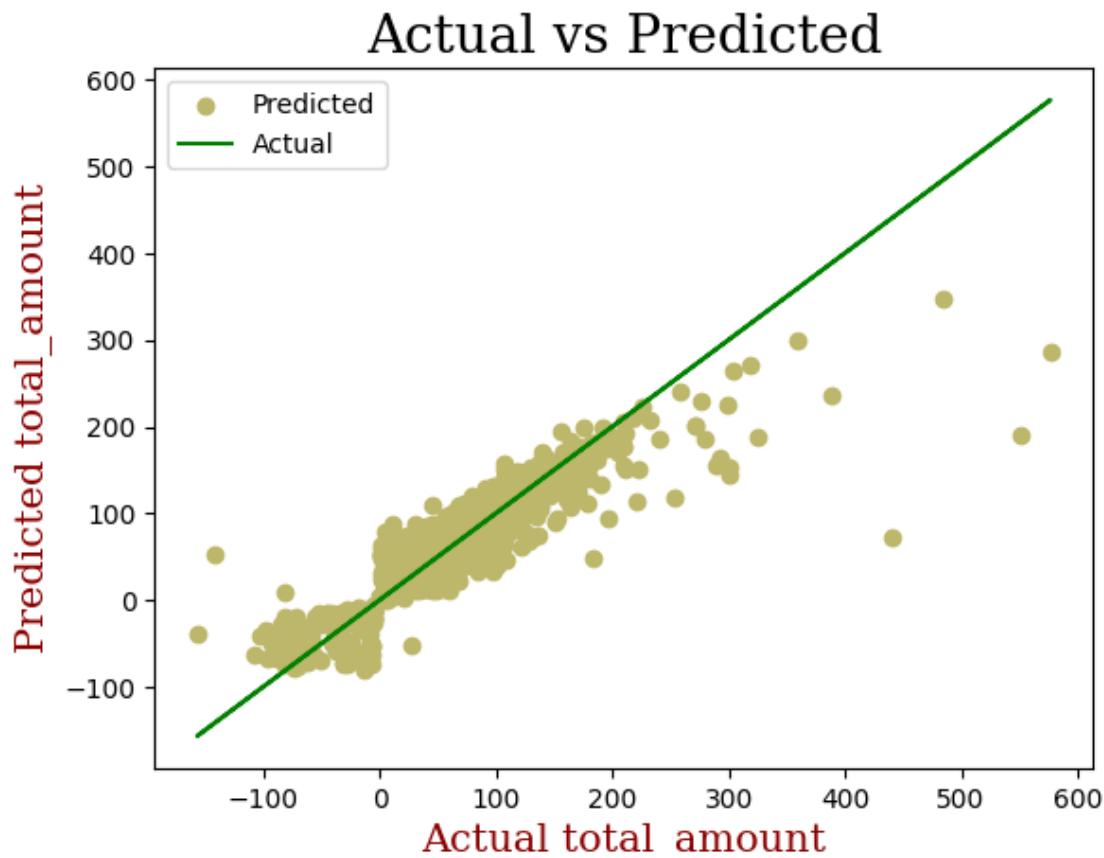
```
[150]: mlp_reg = MLPRegressor()
mlp_reg.fit(X_train, y_train)
mlp_reg_predict = mlp_reg.predict(X_val)
print(mlp_reg_predict)
mlp_score = r2_score(y_val, mlp_reg_predict)
print("R2_Score (MLPRegressor) :", mlp_score)
```

[36.73100112 25.93075791 96.41489588 ... 13.08092546 20.53488195
34.84404628]

R2_Score (MLPRegressor) : 0.9238723323787169

- Plotting Actual vs Predicted

```
[151]: act_vs_predict(y_val, mlp_reg_predict)
```



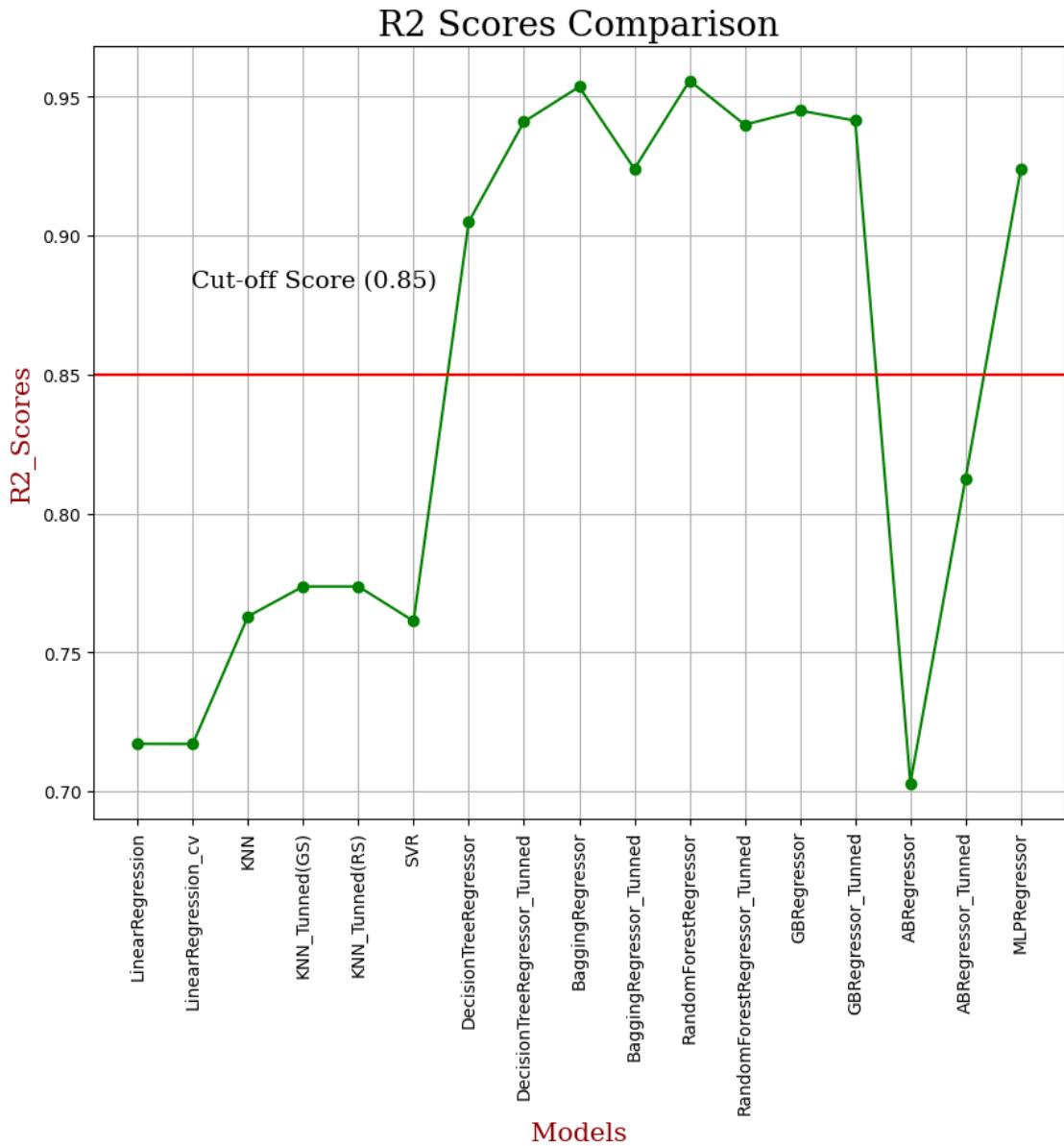
13 Comparison of R2 Scores (In case of different ML Models)

```
[152]: #Array having Name of Models
models = np.array(["LinearRegression", "LinearRegression_cv", "KNN",
                   "KNN_Tunned(GS)", "KNN_Tunned(RS)",
                   "SVR",
                   "DecisionTreeRegressor", "DecisionTreeRegressor_Tunned", "BaggingRegressor",
                   "BaggingRegressor_Tunned", "RandomForestRegressor",
                   "RandomForestRegressor_Tunned",
                   "GBRegressor", "GBRegressor_Tunned", "ABRegressor", "ABRegressor_Tunned",
                   "MLPRegressor"])

# Array having all R2 Scores
r2_scores = np.array([lr_score, lr_cv_score, knn_score, knn_gs_score,
                      knn_rs_score, svr_score, dt_score,
                      dt_gs_score, b1_reg_score, b2_reg_score, rf_score,
                      rf_gs_score, gbr_score, gbr_gs_score,
                      abr_score, abr_gs_score, mlp_score])

# Plotting
plt.figure( figsize = (10,8) )
ax=plt.subplot(111)
plt.plot(models, r2_scores, 'o-g')
plt.axhline(y = 0.85, color = 'r', linestyle = '-')
ax.text(0.1, 0.68, "Cut-off Score (0.85)",
        verticalalignment='bottom', horizontalalignment='left',
        transform=ax.transAxes,
        color='black', fontsize=14,family='serif')
font1 = {'family':'serif','color':'black','size':20}
font2 = {'family':'serif','color':'darkred','size':15}
plt.title("R2 Scores Comparison", fontdict=font1)
plt.xlabel("Models", fontdict=font2)
plt.ylabel("R2_Scores", fontdict=font2)
plt.grid()
plt.xticks(rotation = 90)

# Showing plot
plt.show()
```



13.0.1 Observations

- Models `LinearRegression`, `LinearRegression_cv`, `KNN`, `KNN_Tunned(GS)`, `KNN_Tunned(RS)`, `SVR`, `ABRegressor`, `ABRegressor_Tunned` are not passing the **cut-off score** after training on train data and validation on validation data.
- Models `DecisionTreeRegressor`, `DecisionTreeRegressor_Tunned`, `BaggingRegressor`, `BaggingRegressor_Tunned`, `RandomForestRegressor`, `RandomForestRegressor_Tunned`, `GBRegressor`, `GBRegressor_Tunned`, `MLPRegressor` are passing the **cut-off score** after training on train data and validation on validation data.
- `RandomForestRegressor` having default hyperparameters is giving the highest *R2 Score*.

- AdaBoostRegressor having default hyperparameters is giving the lowest *R2 Score*.

14 Applying same data preprocessing on test.csv

14.0.1 1. Overview

```
[153]: #shape
test_data.shape
```

[153]: (50000, 16)

```
[154]: #info
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   VendorID          50000 non-null   int64  
 1   tpep_pickup_datetime 50000 non-null   object  
 2   tpep_dropoff_datetime 50000 non-null   object  
 3   passenger_count      48221 non-null   float64 
 4   trip_distance        50000 non-null   float64 
 5   RatecodeID          48221 non-null   float64 
 6   store_and_fwd_flag    48221 non-null   object  
 7   PULocationID        50000 non-null   int64  
 8   DOLocationID        50000 non-null   int64  
 9   payment_type         50000 non-null   object  
 10  extra               50000 non-null   float64 
 11  tip_amount          50000 non-null   float64 
 12  tolls_amount         50000 non-null   float64 
 13  improvement_surcharge 50000 non-null   float64 
 14  congestion_surcharge 48221 non-null   float64 
 15  Airport_fee          48221 non-null   float64 
dtypes: float64(9), int64(3), object(4)
memory usage: 6.1+ MB
```

```
[155]: # Numerical attribute statistics
test_data.describe()
```

```
VendorID  passenger_count  trip_distance  RatecodeID \
count    50000.000000     48221.000000    50000.000000  48221.000000
mean      0.730280       1.358309      3.999013     1.567014
std       0.444584       0.879948      78.958759    6.875115
min       0.000000       0.000000      0.000000     1.000000
25%      0.000000       1.000000      1.090000     1.000000
```

50%	1.000000	1.000000	1.850000	1.000000	
75%	1.000000	1.000000	3.600000	1.000000	
max	2.000000	8.000000	17624.430000	99.000000	
	PULocationID	DOLocationID	extra	tip_amount	tolls_amount \
count	50000.000000	50000.000000	50000.000000	50000.000000	50000.000000
mean	132.208160	132.559300	1.918050	6.107765	0.615867
std	76.483766	76.410602	1.938568	4.408572	2.289421
min	1.000000	1.000000	-7.500000	0.000409	-23.000000
25%	66.000000	67.000000	0.000000	3.464018	0.000000
50%	132.000000	133.000000	1.000000	5.271687	0.000000
75%	199.000000	199.000000	2.500000	7.504048	0.000000
max	264.000000	264.000000	11.750000	96.551343	47.750000
	improvement_surcharge	congestion_surcharge	Airport_fee		
count	50000.000000	48221.000000	48221.000000		
mean	0.981354	2.255345	0.152133		
std	0.190203	0.803190	0.502866		
min	-1.000000	-2.500000	-1.750000		
25%	1.000000	2.500000	0.000000		
50%	1.000000	2.500000	0.000000		
75%	1.000000	2.500000	0.000000		
max	1.000000	2.500000	1.750000		

```
[156]: # Categorical attribute statistics
test_data.describe(include='object')
```

	tpep_pickup_datetime	tpep_dropoff_datetime	store_and_fwd_flag \	
count	50000	50000	48221	
unique	43216	43205	2	
top	2023-06-29 20:59:17	2023-06-29 22:46:33	N	
freq	6	5	47881	
	payment_type			
count	50000			
unique	5			
top	Credit Card			
freq	38672			

Observation

- There are 50000 rows (Observations) and 16 columns (variables).
- There are 9 columns having type `float64`, 3 columns having type `int64` and 4 columns having type `object`.
- Statistics for numerical attributes can be seen above.
- `store_and_fwd_flag` has two unique values. (most_frequent = 'N') i.e 'N' (No) & 'Y' (Yes)
- `payment_type` has 5 unique values. (most_frequent = 'Credit Card')

14.0.2 2. Columns/Attributes

1. VendorID

```
[157]: print("Unique values :", pd.unique(test_data['VendorID']))
print("No. of distinct values :", len(pd.unique(test_data['VendorID'])))
print("No. of missing values :", test_data['VendorID'].isnull().sum(), [
    " [", "Percentage(%) :", (test_data['VendorID'].isnull().sum())*(100/
    50000), "]"])
```

Unique values : [1 0 2]
No. of distinct values : 3
No. of missing values : 0 [Percentage(%) : 0.0]

Observations

- There are 3 distinct values.
- It doesn't contain any null value.
- Most frequent VendorID value is 1.

2. tpep_pickup_datetime

```
[158]: test_data['tpep_pickup_datetime'] = pd.
    to_datetime(test_data['tpep_pickup_datetime'])
```

```
[159]: print("Maximum Value :", test_data['tpep_pickup_datetime'].max())
print("Minimum Value :", test_data['tpep_pickup_datetime'].min())
print("No. of missing values :", test_data['tpep_pickup_datetime'].isnull().
    sum(), " [", "Percentage(%) :", (test_data['tpep_pickup_datetime'].isnull() .
    sum())*(100/50000), "]"])
```

Maximum Value : 2023-07-01 00:55:16
Minimum Value : 2023-06-28 15:31:06
No. of missing values : 0 [Percentage(%) : 0.0]

Observations

- There are no missing values.
- Maximum Value : 2023-07-01 00:55:16
- Minimum Value : 2023-06-28 15:31:06

3. tpep_dropoff_datetime

```
[160]: test_data['tpep_dropoff_datetime'] = pd.
    to_datetime(test_data['tpep_dropoff_datetime'])
```

```
[161]: print("Maximum Value :", test_data['tpep_dropoff_datetime'].max())
print("Minimum Value :", test_data['tpep_dropoff_datetime'].min())
print("No. of missing values :", test_data['tpep_dropoff_datetime'].isnull().
    sum(), " [", "Percentage(%) :", (test_data['tpep_dropoff_datetime'].isnull() .
    sum())*(100/50000), "]"])
```

```

Maximum Value : 2023-07-03 16:31:27
Minimum Value : 2023-06-28 15:41:05
No. of missing values : 0 [ Percentage(%) : 0.0 ]

```

Observations

- There are no missing values.
- Maximum Value : 2023-07-03 16:31:27
- Minimum Value : 2023-06-28 15:41:05

4. passenger_count

```
[162]: print("Unique values :", pd.unique(test_data['passenger_count']))
print("Values count :", test_data['passenger_count'].value_counts())
print("No. of distinct values :", len(pd.unique(test_data['passenger_count'])))
print("No. of missing values :", test_data['passenger_count'].isnull().sum(), [
    "[", "Percentage(%) :", (test_data['passenger_count'].isnull().sum())*(100/50000), "]"])
print("No. of 0 values :
    [", len(test_data[test_data['passenger_count']==0]), "[", "Percentage(%) :", [
        len(test_data[test_data['passenger_count']==0])*(100/50000), "]"])
print("No. of -ve values :
    [", len(test_data[test_data['passenger_count']<0]), "[", "Percentage(%) :", [
        len(test_data[test_data['passenger_count']<0])*(100/50000), "]"])
print("Maximum Value :", test_data['passenger_count'].max())
print("Minimum Value :", test_data['passenger_count'].min())
```

```

Unique values : [ 1.  2. nan  6.  4.  0.  3.  5.  8.]
Values count : passenger_count
1.0      36532
2.0      7155
3.0      1731
4.0      1062
0.0       781
5.0       546
6.0       413
8.0        1
Name: count, dtype: int64
No. of distinct values : 9
No. of missing values : 1779 [ Percentage(%) : 3.5580000000000003 ]
No. of 0 values : 781 [ Percentage(%) : 1.562 ]
No. of -ve values : 0 [ Percentage(%) : 0.0 ]
Maximum Value : 8.0
Minimum Value : 0.0

```

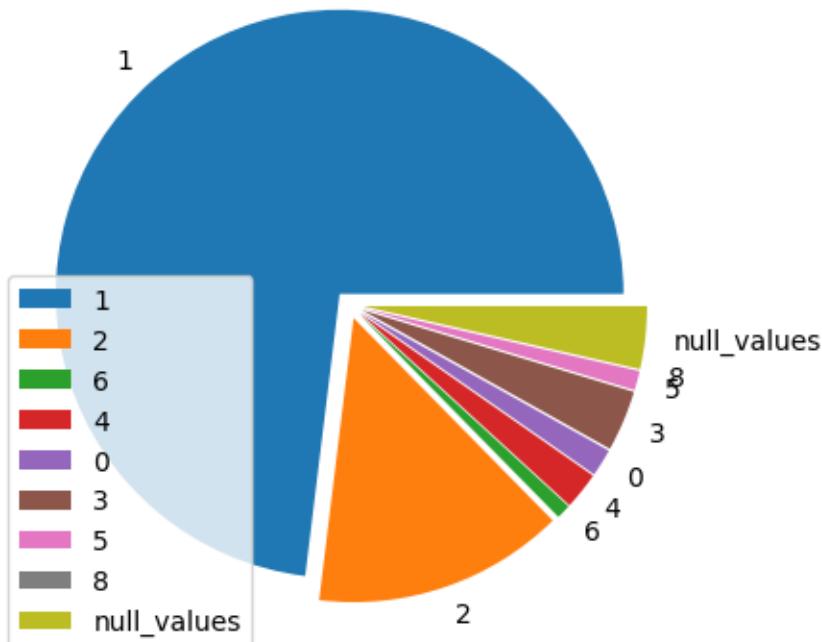
```
[163]: Unique_values = [ 1,  2,  6,  4,  0,  3,  5,  8]
value_count = []
for i in Unique_values:
```

```

    value_count.append(test_data['passenger_count'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(test_data['passenger_count'].isnull().sum())
#print(value_count)
plt.pie(value_count,labels=Unique_values,explode=[0.05,0.05,0.05,0.05,0.
    ↪05,0.05,0.05])
plt.title('Pie-chart (passenger_count)')
plt.legend(Unique_values)
plt.show()

```

Pie-chart (passenger_count)



Observations

- `passenger_count` contains 1779 missing values which is approx 3.6% of total number of values.
- `passenger_count` contains 781 zero values which is approx 1.6% of total number of values.
- There are no negative values.
- There are 9 distinct values (including null values).
- Most Frequent value is 1.
- Maximum Value : 8.0
- Minimum Value : 0.0

5. trip_distance

```
[164]: print("Unique values : ", pd.unique(test_data['trip_distance']))
print("No. of missing values : ", test_data['trip_distance'].isnull().sum(), "[", "Percentage(%) : ", (test_data['trip_distance'].isnull().sum())*(100/50000), "]")
print("No. of 0 values :
      [", len(test_data[test_data['trip_distance']==0]), "[", "Percentage(%) : ", (len(test_data[test_data['trip_distance']==0])*(100/50000)), "]")
print("No. of -ve values :
      [", len(test_data[test_data['trip_distance']<0]), "[", "Percentage(%) : ", (len(test_data[test_data['trip_distance']<0])*(100/50000)), "]")
print("Maximum Value : ", test_data['trip_distance'].max())
print("Minimum Value : ", test_data['trip_distance'].min())
print("Value Counts (> 200) : ", len(test_data[test_data['trip_distance']>200]))
```

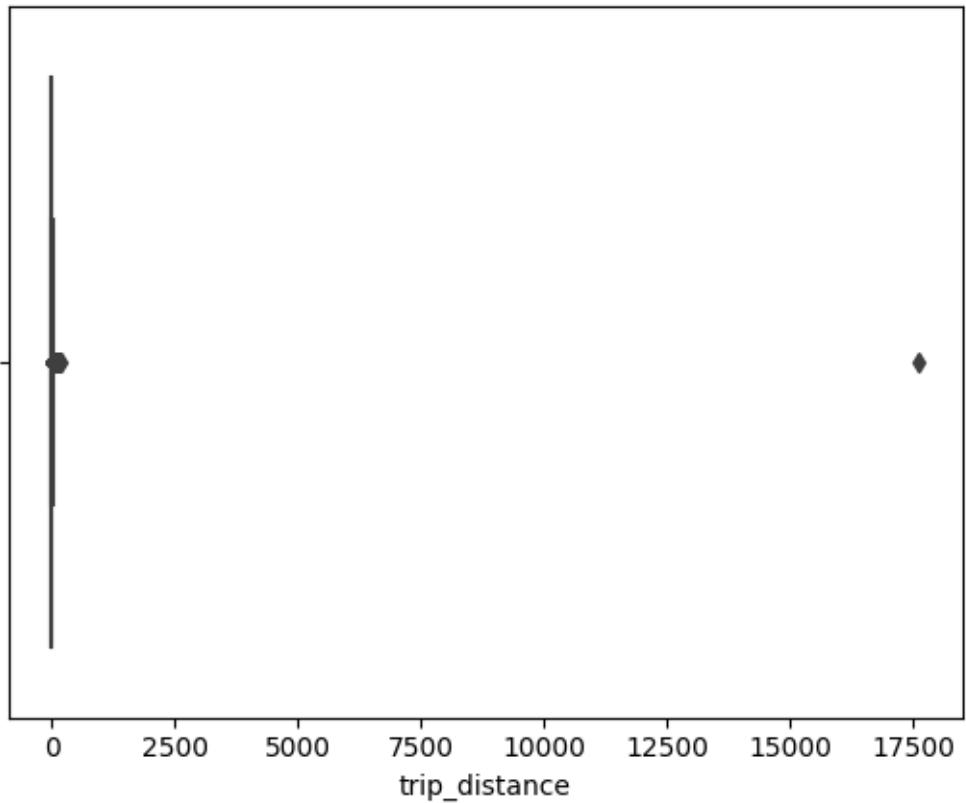
Unique values : [4.95 2.1 0.95 ... 20.9 30.7 29.09]
 No. of missing values : 0 [Percentage(%) : 0.0]
 No. of 0 values : 742 [Percentage(%) : 1.484]
 No. of -ve values : 0 [Percentage(%) : 0.0]
 Maximum Value : 17624.43
 Minimum Value : 0.0
 Value Counts (> 200) : 1

Observations

- There are no missing values.
- `trip_distance` contains 742 zero values which is approx 1.5% of total number of values.
- There are no negative values.
- Maximum Value : 17624.43
- Minimum Value : 0.0

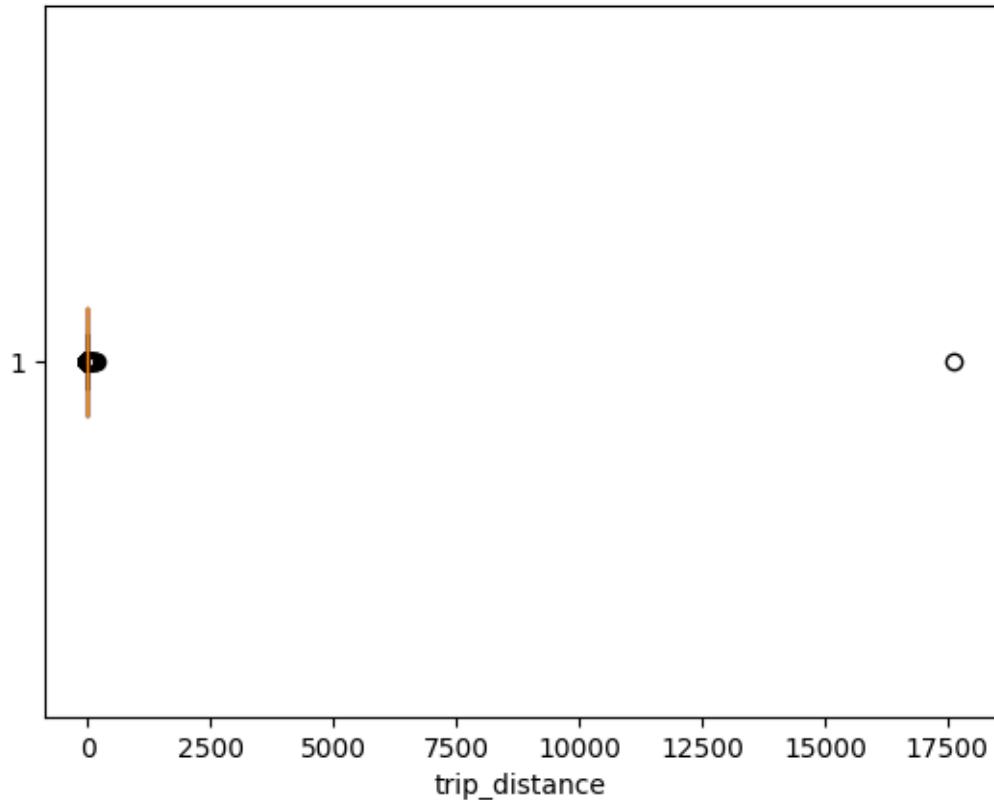
```
[165]: sns.boxplot(x='trip_distance', data=test_data)
# plt.boxplot(train_data['trip_distance'], vert=0, patch_artist = True)
# plt.xlabel("trip_distance")
# plt.title('Box_plot (trip_distance)')
# plt.show()
```

[165]: <Axes: xlabel='trip_distance'>



```
[166]: plt.boxplot(test_data['trip_distance'], vert=False)
plt.title("Detecting outliers using Boxplot")
plt.xlabel('trip_distance')
plt.show()
```

Detecting outliers using Boxplot



```
[167]: sns.distplot(test_data['trip_distance'])
```

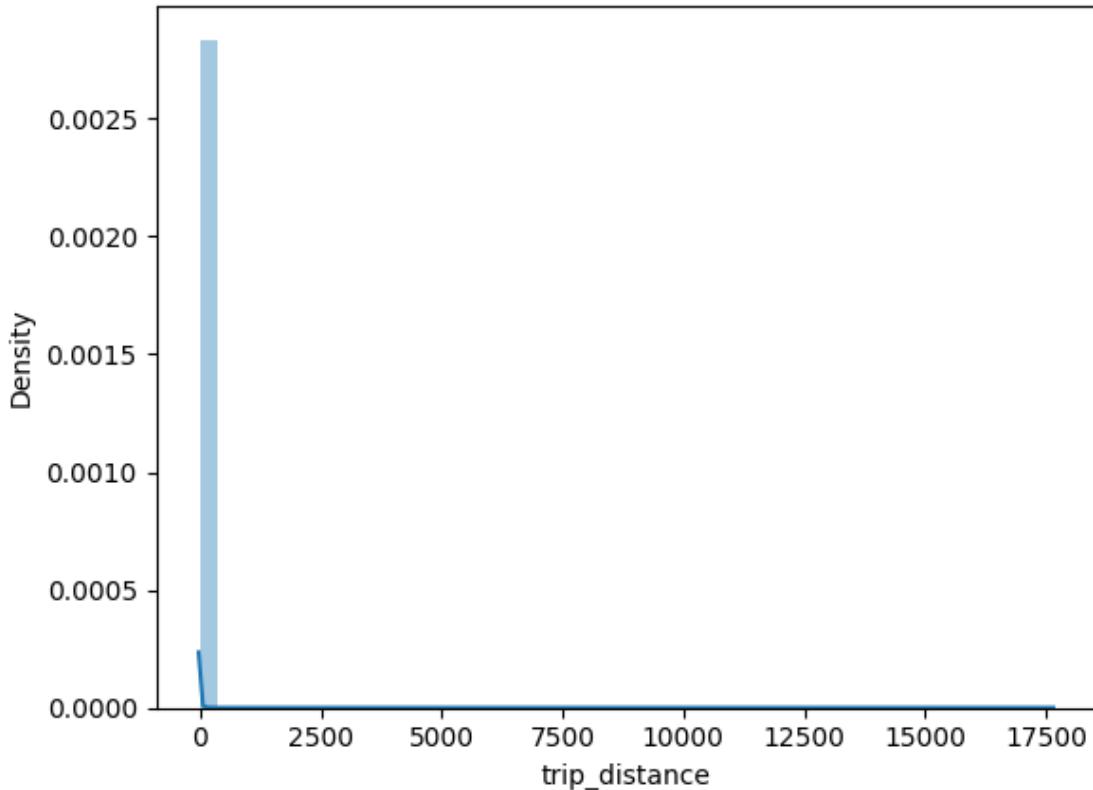
```
/tmp/ipykernel_20/2474477597.py:1: UserWarning:  
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
<https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(test_data['trip_distance'])
```

```
[167]: <Axes: xlabel='trip_distance', ylabel='Density'>
```



6. RatecodeID

```
[168]: print("Unique values : ", pd.unique(test_data['RatecodeID']))
print("No. of distinct values : ", len(pd.unique(test_data['RatecodeID'])))
print("No. of missing values : ", test_data['RatecodeID'].isnull().sum(), [
    " [", "Percentage(%) : ", (test_data['RatecodeID'].isnull().sum())*(100/50000), "]"])
print("No. of 0 values :
    [", len(test_data[test_data['RatecodeID']==0]), " [", "Percentage(%) : ",
    len(test_data[test_data['RatecodeID']==0])*(100/50000), "]"])
print("No. of -ve values :
    [", len(test_data[test_data['RatecodeID']<0]), " [", "Percentage(%) : ",
    len(test_data[test_data['RatecodeID']<0])*(100/50000), "]")
print("Maximum Value : ", test_data['RatecodeID'].max())
print("Minimum Value : ", test_data['RatecodeID'].min())
print("Value Counts (=99) : ", len(test_data[test_data['RatecodeID']==99]))
```

Unique values : [1. 4. 5. 2. nan 3. 99. 6.]

No. of distinct values : 8

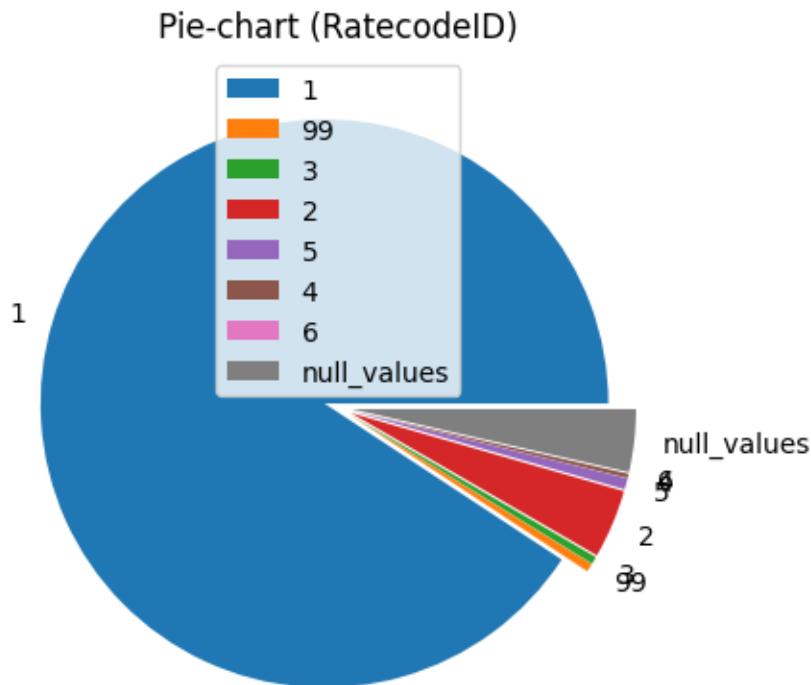
No. of missing values : 1779 [Percentage(%) : 3.5580000000000003]

No. of 0 values : 0 [Percentage(%) : 0.0]

No. of -ve values : 0 [Percentage(%) : 0.0]

```
Maximum Value : 99.0
Minimum Value : 1.0
Value Counts (=99) : 238
```

```
[169]: Unique_values = [1, 99, 3, 2, 5, 4, 6]
value_count = []
for i in Unique_values:
    value_count.append(test_data['RatecodeID'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(test_data['RatecodeID'].isnull().sum())
#print(value_count)
plt.pie(value_count, labels=Unique_values, explode=[0.05,0.05,0.05,0.05,0.05,0.
    ↪05,0.05])
plt.title('Pie-chart (RatecodeID)')
plt.legend(Unique_values)
plt.show()
```



Observations

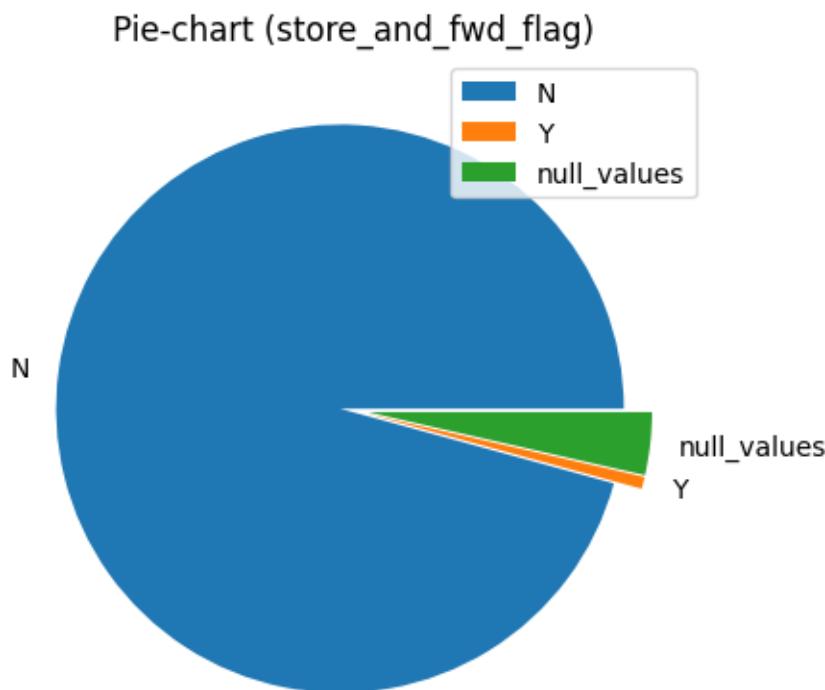
- RatecodeID contains 1779 missing values which is approx 3.6% of total number of values.
- There are no negative and zero values.
- There are 8 distinct values (including null values).
- Most Frequent value is 1.

7. store_and_fwd_flag

```
[170]: print("Unique values :", pd.unique(test_data['store_and_fwd_flag']))
print("No. of distinct values :", len(pd.
    ↪unique(test_data['store_and_fwd_flag'])))
print("No. of missing values :", test_data['store_and_fwd_flag'].isnull().sum(), [
    ↪"[", "Percentage(%) :", (test_data['store_and_fwd_flag'].isnull().sum())*(100/
    ↪50000), "]"])
```

```
Unique values : ['N' nan 'Y']
No. of distinct values : 3
No. of missing values : 1779 [ Percentage(%) : 3.5580000000000003 ]
```

```
[171]: Unique_values = ['N', 'Y']
value_count = []
for i in Unique_values:
    value_count.append(test_data['store_and_fwd_flag'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(test_data['store_and_fwd_flag'].isnull().sum())
#print(value_count)
plt.pie(value_count, labels=Unique_values, explode=[0.05, 0.05, 0.05])
plt.title('Pie-chart (store_and_fwd_flag)')
plt.legend(Unique_values)
plt.show()
```



Observations

- `store_and_fwd_flag` contains 1789 missing values which is approx 3.6% of total number of values.
- There are 3 distinct values (including null values).
- Most Frequent value is 'N'.

8. PULocationID

```
[172]: print("Unique values : ", pd.unique(test_data['PULocationID']))
print("No. of missing values : ", test_data['PULocationID'].isnull().sum(), [
    " [", "Percentage(%) : ", (test_data['PULocationID'].isnull().sum())*(100/50000), "]"])
print("No. of 0 values :
    [", len(test_data[test_data['PULocationID']==0]), " [", "Percentage(%) : ",
    len(test_data[test_data['PULocationID']==0])*(100/50000), "]"])
print("No. of -ve values :
    [", len(test_data[test_data['PULocationID']<0]), " [", "Percentage(%) : ",
    len(test_data[test_data['PULocationID']<0])*(100/50000), "]"])
print("Maximum Value : ", test_data['PULocationID'].max())
print("Minimum Value : ", test_data['PULocationID'].min())
```

```
Unique values : [ 20   9  92  19 131 194 163 146  45 254 170  81  31  17 171 224
220  11
197 221 249 199 104  64  54 144  84 212  56 192 158   2 244 105 246 253
156  16 125  27  24 258 123 106  77 102 241  12  98  91 160 263 256  49
211 174 201  44  28 166  95 132  21  69 172 200 130  99  23  52 190  22
196 195 115 150 162 181  74 202  83 136 234 121  47 103  38 245 185 193
127 117 231 209 262 145  15 110   7 157 178 155 251  55 148  13 112 176
   1 137  33  43 159 153 239 179 250  59 205 124  94 134 238  88 173  75
198 232  35 242  65 116  93 189 204  66 113 164  96 222 149 257   6 228
   78  61 259  48 139 207  76  85 138  25   8  29  79  63 161  32  68 180
111  89 188  80 147 240 218  39 252   5 216 118  70 248 186 237  58  51
167 210  57 203 243 227  34  60 214 225  40 235 129  30 177 233  82 219
126 107 187 114 140 217 168 109  53   3 223 165 247  41   4 260  46 122
182 135 141 183 100  71 143 264 169  37 151 215 206  42  14  26 128  87
   50  72 120 175  90  36 133 261 152  62 191 229 108 208 142 154  10 119
 213 255 236  97  73  18  67 101  86 230 184 226]
No. of missing values : 0 [ Percentage(%) : 0.0 ]
No. of 0 values : 0 [ Percentage(%) : 0.0 ]
No. of -ve values : 0 [ Percentage(%) : 0.0 ]
Maximum Value : 264
Minimum Value : 1
```

Observations

- `PULocationID` doesn't contain any missing, zero or -ve values.

- Maximum Value : 264
- Minimum Value : 1

9. DOLocationID

```
[173]: print("Unique values :", pd.unique(test_data['DOLocationID']))
print("No. of missing values :", test_data['DOLocationID'].isnull().sum(), "[", "Percentage(%) :", (test_data['DOLocationID'].isnull().sum())*(100/50000), "]")
print("No. of 0 values :
      [", len(test_data[test_data['DOLocationID']==0]), "[", "Percentage(%) :", len(test_data[test_data['DOLocationID']==0])*(100/50000), "]")
print("No. of -ve values :
      [", len(test_data[test_data['DOLocationID']<0]), "[", "Percentage(%) :", len(test_data[test_data['DOLocationID']<0])*(100/50000), "]")
print("Maximum Value :", test_data['DOLocationID'].max())
print("Minimum Value :", test_data['DOLocationID'].min())
```

```
Unique values : [ 3 81 90 102 229 154 26 192 232 238 73 68 100 124 173 136
99 213
144 184 159 237 58 82 67 217 40 89 44 9 153 106 113 203 196 254
125 163 33 50 181 35 78 210 155 171 187 182 84 105 162 56 219 200
221 151 123 16 176 199 4 201 209 31 257 119 103 249 91 126 207 52
42 74 240 18 179 36 86 88 129 93 134 253 45 51 10 145 60 185
261 239 189 5 22 263 54 180 178 235 174 46 17 143 25 216 168 170
260 204 109 227 256 205 101 262 14 167 37 198 87 117 8 231 1 172
223 23 69 24 108 20 234 252 112 128 63 246 157 226 236 138 259 183
12 211 247 242 114 158 193 55 150 139 160 11 195 57 148 34 64 97
95 190 191 135 27 215 165 77 70 111 188 212 132 83 28 149 197 66
76 65 43 245 228 142 222 146 116 243 75 85 225 186 175 21 137 214
224 79 107 7 248 39 29 13 38 6 127 94 59 147 166 220 230 233
255 133 96 120 104 19 131 15 244 140 30 118 122 218 47 71 251 258
49 41 98 48 177 250 53 202 208 130 194 62 61 264 161 72 32 152
169 121 241 156 164 80 92 2 110 141 206 115]
No. of missing values : 0 [ Percentage(%) : 0.0 ]
No. of 0 values : 0 [ Percentage(%) : 0.0 ]
No. of -ve values : 0 [ Percentage(%) : 0.0 ]
Maximum Value : 264
Minimum Value : 1
```

Observations

- DOLocationID doesn't contain any missing, zero or -ve values.
- Maximum Value : 264
- Minimum Value : 1

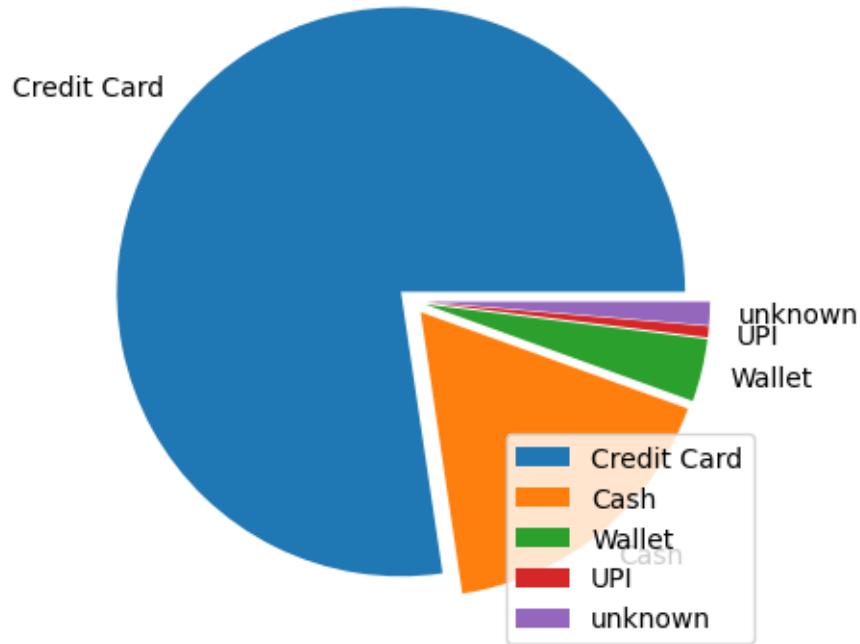
10. payment_type

```
[174]: print("Unique values :", pd.unique(test_data['payment_type']))
print("Values Count :", test_data['payment_type'].value_counts())
print("No. of distinct values :", len(pd.unique(test_data['payment_type'])))
print("No. of missing values :", test_data['payment_type'].isnull().sum(),",",
      "Percentage(%) :", (test_data['payment_type'].isnull().sum())*(100/
      50000),"]")
```

```
Unique values : ['Credit Card' 'Cash' 'UPI' 'unknown' 'Wallet']
Values Count : payment_type
Credit Card    38672
Cash          8571
Wallet         1779
unknown        665
UPI            313
Name: count, dtype: int64
No. of distinct values : 5
No. of missing values : 0 [ Percentage(%) : 0.0 ]
```

```
[175]: Unique_values = ['Credit Card', 'Cash', 'Wallet', 'UPI', 'unknown']
value_count = []
for i in Unique_values:
    value_count.append(test_data['payment_type'].value_counts()[i])
plt.pie(value_count, labels=Unique_values, explode=[0.05,0.05,0.05,0.05,0.05])
plt.title('Pie-chart (payment_type)')
plt.legend(Unique_values)
plt.show()
```

Pie-chart (payment_type)



Observations

- There are no missing values.
- There are 5 distinct values which are 'Credit Card', 'Cash', 'Wallet', 'UPI', 'unknown'
- Most frequent is Credit Card.
- There are some unknown values.

11. extra

```
[176]: print("Unique values :", pd.unique(test_data['extra']))
print("No. of missing values :", test_data['extra'].isnull().sum(), [
    "Percentage(%) :", (test_data['extra'].isnull().sum())*(100/50000), "]")
print("No. of 0 values :
    [", len(test_data[test_data['extra']==0]), "[", "Percentage(%) :", [
        len(test_data[test_data['extra']==0])*(100/50000), "]"])

print("No. of -ve values :
    [", len(test_data[test_data['extra']<0]), "[", "Percentage(%) :", [
        len(test_data[test_data['extra']<0])*(100/50000), "]"])

print("Maximum Value :", test_data['extra'].max())
print("Minimum Value :", test_data['extra'].min())
print("Mean Value :", test_data['extra'].mean())
```

```

Unique values : [ 1.      2.5     3.5     0.      5.      7.5     6.75   4.25   6.      7.75 10.
-1.
-2.5    1.75   9.25   2.75  -5.     11.75  10.25   8.5    -6.     0.03  -7.5    5.25
 3.2 ]
No. of missing values : 0 [ Percentage(%) : 0.0 ]
No. of 0 values : 14819 [ Percentage(%) : 29.638 ]
No. of -ve values : 289 [ Percentage(%) : 0.578 ]
Maximum Value : 11.75
Minimum Value : -7.5
Mean Value : 1.9180496

```

Observations

- extra contains no missing values.
- extra contains 14819 zero values which is approx 29.6% of total number of value.
- extra contains 289 -ve values which is approx 0.6% of total number of value.
- Maximum Value : 11.75
- Minimum Value : -7.5
- Mean Value : 1.9321434857142856

12. tip_amount

```
[177]: print("Unique values :", pd.unique(test_data['tip_amount']))
print("No. of missing values :", test_data['tip_amount'].isnull().sum(),",",
      ["","Percentage(%) :", (test_data['tip_amount'].isnull().sum())*(100/
      50000),"]")
print("No. of 0 values :
      ",len(test_data[test_data['tip_amount']==0]),"[", "Percentage(%) :",",
      len(test_data[test_data['tip_amount']==0])*(100/50000),"]")
print("No. of -ve values :
      ",len(test_data[test_data['tip_amount']<0]),"[", "Percentage(%) :",",
      len(test_data[test_data['tip_amount']<0])*(100/50000),"]")
print("Maximum Value :",test_data['tip_amount'].max())
print("Minimum Value :",test_data['tip_amount'].min())
print("Mean Value :",test_data['tip_amount'].mean())
```

```

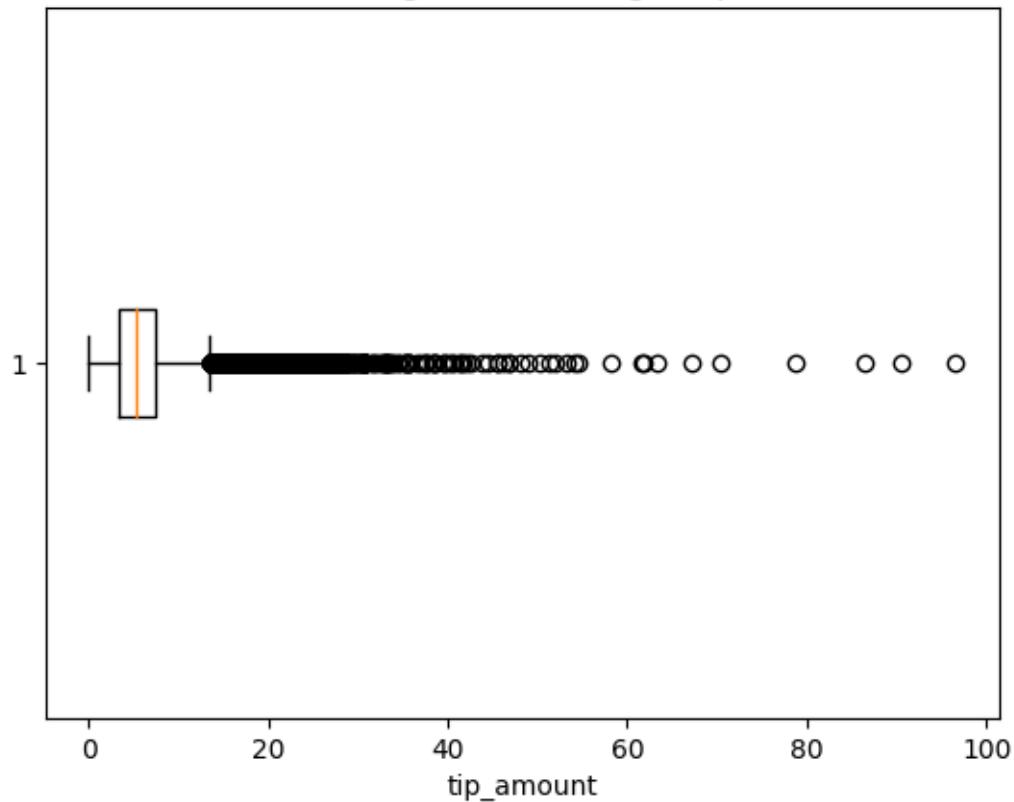
Unique values : [6.06761177 6.19126924 3.98387237 ... 5.63659038 7.29314367
1.96659215]
No. of missing values : 0 [ Percentage(%) : 0.0 ]
No. of 0 values : 0 [ Percentage(%) : 0.0 ]
No. of -ve values : 0 [ Percentage(%) : 0.0 ]
Maximum Value : 96.55134327894214
Minimum Value : 0.0004089398699957
Mean Value : 6.107764502747721

```

```
[178]: plt.boxplot(test_data['tip_amount'], vert=False)
plt.title("Detecting outliers using Boxplot")
plt.xlabel('tip_amount')
```

```
plt.show()
```

Detecting outliers using Boxplot

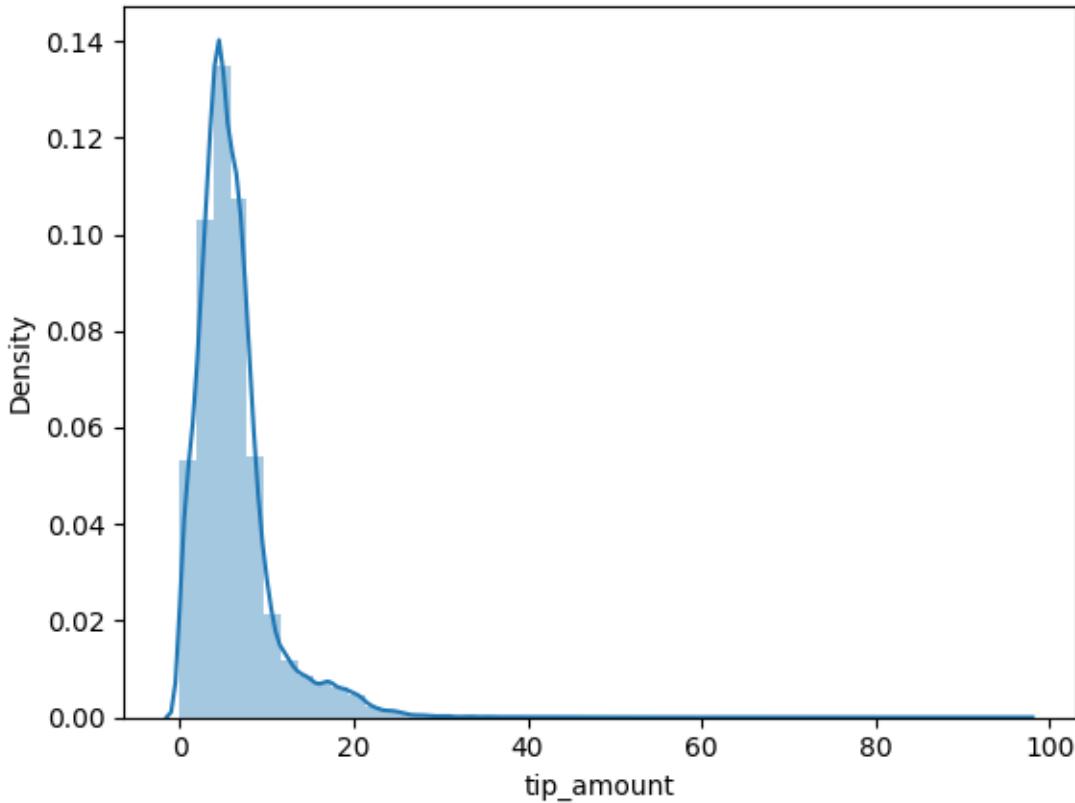


```
[179]: sns.distplot(test_data['tip_amount'])
```

```
/tmp/ipykernel_20/1311658211.py:1: UserWarning:  
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.  
Please adapt your code to use either `displot` (a figure-level function with  
similar flexibility) or `histplot` (an axes-level function for histograms).  
For a guide to updating your code to use the new functions, please see  
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

```
sns.distplot(test_data['tip_amount'])
```

```
[179]: <Axes: xlabel='tip_amount', ylabel='Density'>
```



Observations

- tip_amount doesn't contain any missing, zero or -ve values.
- Maximum Value : 96.55134327894214
- Minimum Value : 0.0004089398699957
- Mean Value : 6.107764502747721

13. tolls_amount

```
[180]: print("Unique values :", pd.unique(test_data['tolls_amount']))
print("No. of missing values :", test_data['tolls_amount'].isnull().sum(), [
    ["", "Percentage(%) :", (test_data['tolls_amount'].isnull().sum())*(100/50000), ""])
print("No. of 0 values :
    ", len(test_data[test_data['tolls_amount']==0]), [
        ["", "Percentage(%) :", (len(test_data[test_data['tolls_amount']==0])*(100/50000), "")]
    ])
print("No. of -ve values :
    ", len(test_data[test_data['tolls_amount']<0]), [
        ["", "Percentage(%) :", (len(test_data[test_data['tolls_amount']<0])*(100/50000), "")]
    ])
print("Maximum Value :", test_data['tolls_amount'].max())
print("Minimum Value :", test_data['tolls_amount'].min())
```

```
print("Mean Value :",test_data['tolls_amount'].mean())
```

```
Unique values : [ 0.       6.55   21.3    14.75   9.       12.75   10.      6.       19.75  
13.1  
19.3   18.75  21.     24.48  -6.55   20.75  14.55   8.55   20.25  13.75  
2.      3.      2.45   22.75  21.05  21.75  24.     -23.     29.      9.05  
24.3   27.3   22.     8.3     11.55  21.65  21.25  24.75  18.5    17.85  
25.5   12.     8.36   22.65  13.3    29.5    15.75  20.     9.55   17.75  
18.25  24.5   -15.75  6.45    5.      33.56  30.     7.      23.     17.25  
18.95  39.05  27.75  16.75  13.     11.75  29.3    26.3    34.05  -12.75  
39.3   -14.75 21.1    22.5    18.     26.75  19.     10.55  41.     7.74  
20.5   11.     25.3    27.8    8.      26.     19.95  34.     41.75  19.25  
21.45  41.3   25.25  18.3    12.55  14.65  -3.     19.65  15.2    20.55  
-8.5   47.75  1.      26.55  18.4    10.87  17.     23.25]  
No. of missing values : 0 [ Percentage(%) : 0.0 ]  
No. of 0 values : 45749 [ Percentage(%) : 91.498 ]  
No. of -ve values : 42 [ Percentage(%) : 0.084 ]  
Maximum Value : 47.75  
Minimum Value : -23.0  
Mean Value : 0.6158674
```

Observations

- tolls_amount contains no missing values.
- tolls_amount contains 45749 zero values which is approx 91.5% of total number of value.
- tolls_amount contains 42 -ve values which is approx 0.1% of total number of value.
- Maximum Value : 47.75
- Minimum Value : -23.0
- Mean Value : 0.6158674

14. improvement_surcharge

```
[181]: print("Unique values :", pd.unique(test_data['improvement_surcharge']))  
print("No. of distinct values :", len(pd.  
    ↪unique(test_data['improvement_surcharge'])))  
print("No. of missing values :", test_data['improvement_surcharge'].isnull().  
    ↪sum(), "[", "Percentage(%) :", (test_data['improvement_surcharge'].isnull().  
    ↪sum())*(100/50000), "]")
```

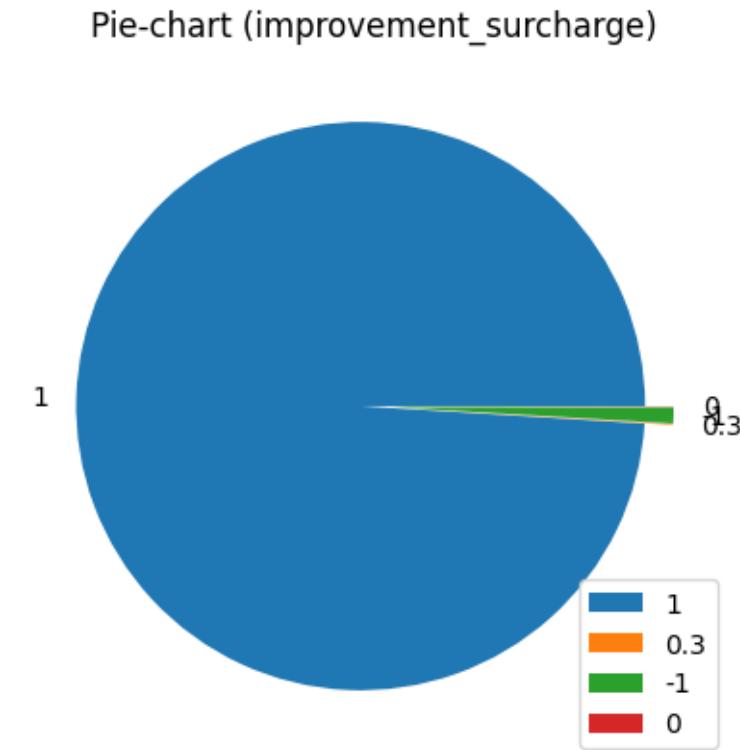
```
Unique values : [ 1.  -1.   0.3  0. ]  
No. of distinct values : 4  
No. of missing values : 0 [ Percentage(%) : 0.0 ]
```

```
[182]: Unique_values = [1, 0.3, -1, 0]  
value_count = []  
for i in Unique_values:  
    value_count.append(test_data['improvement_surcharge'].value_counts()[i])  
plt.pie(value_count, labels=Unique_values, explode=[0.05, 0.05, 0.05, 0.05])
```

```

plt.title('Pie-chart (improvement_surcharge)')
plt.legend(Unique_values)
plt.show()

```



Observations

- There are no missing values.
- There are 4 distinct values.
- Most Frequent is 1.

15. congestion_surcharge

```

[183]: print("Unique values :", pd.unique(test_data['congestion_surcharge']))
print("No. of distinct values :", len(pd.
    ↪unique(test_data['congestion_surcharge'])))
print("No. of missing values :", test_data['congestion_surcharge'].isnull().
    ↪sum(), "[", "Percentage(%) :", (test_data['congestion_surcharge'].isnull().
    ↪sum())*(100/50000), "]")
print("Mean Value :", test_data['congestion_surcharge'].mean())

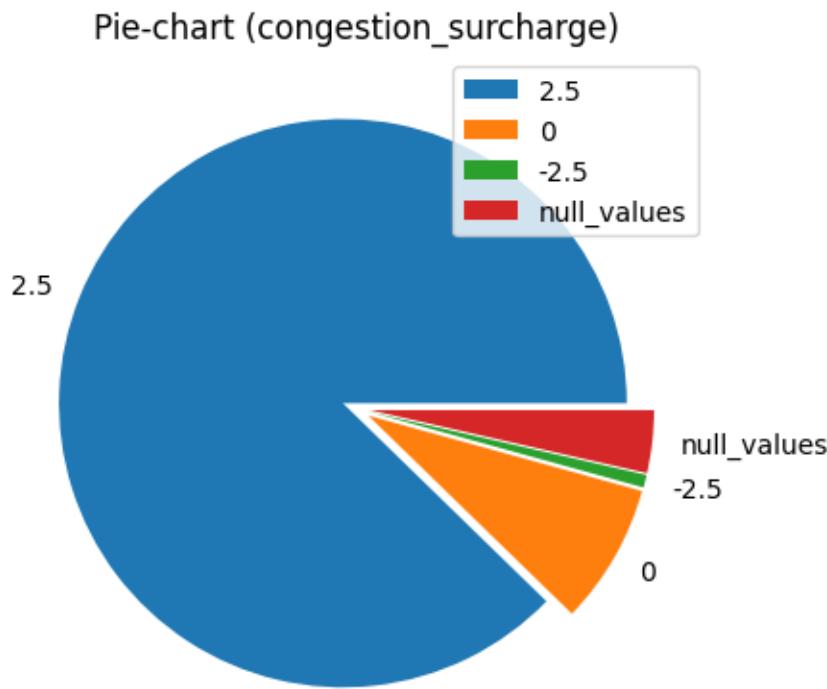
```

Unique values : [2.5 0. nan -2.5]

No. of distinct values : 4

```
No. of missing values : 1779 [ Percentage(%) : 3.5580000000000003 ]  
Mean Value : 2.2553451815599015
```

```
[184]: Unique_values = [2.5, 0, -2.5]  
value_count = []  
for i in Unique_values:  
    value_count.append(test_data['congestion_surcharge'].value_counts()[i])  
Unique_values.append('null_values')  
value_count.append(test_data['congestion_surcharge'].isnull().sum())  
#print(value_count)  
plt.pie(value_count, labels=Unique_values, explode=[0.05, 0.05, 0.05, 0.05])  
plt.title('Pie-chart (congestion_surcharge)')  
plt.legend(Unique_values)  
plt.show()
```



Observations

- There are 4 distinct values (including null values as type).
- `congestion_surcharge` contains 1779 missing values which is approx 01% of total number of values.
- Most Frequent is 2.5
- Mean Value : 2.2553451815599015

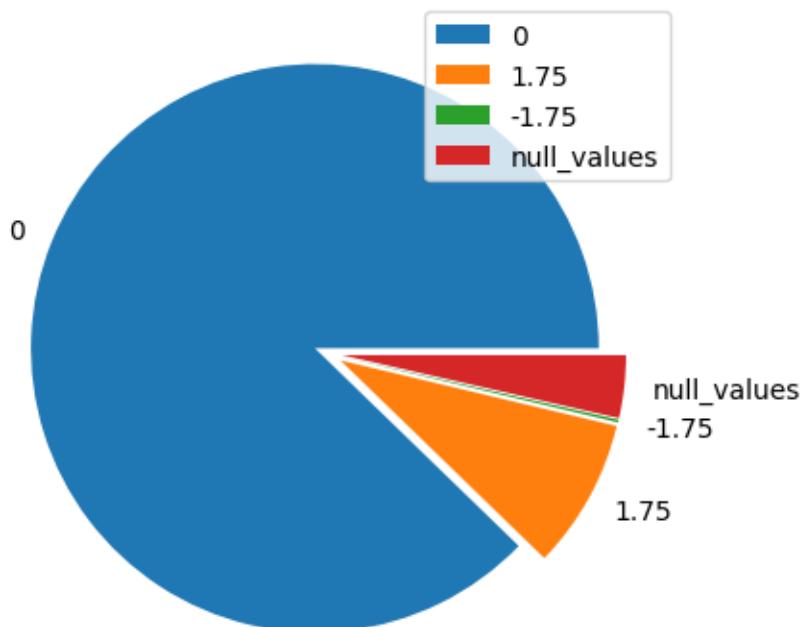
16. Airport_fee

```
[185]: print("Unique values :", pd.unique(test_data['Airport_fee']))
print("No. of distinct values :", len(pd.unique(test_data['Airport_fee'])))
print("No. of missing values :", test_data['Airport_fee'].isnull().sum(),",",
      "Percentage(%) :", (test_data['Airport_fee'].isnull().sum())*(100/
      50000),"]")
print("Mean Value :",test_data['Airport_fee'].mean())
```

```
Unique values : [ 0.    1.75   nan -1.75]
No. of distinct values : 4
No. of missing values : 1779 [ Percentage(%) : 3.5580000000000003 ]
Mean Value : 0.15213288816075984
```

```
[186]: Unique_values = [0, 1.75, -1.75]
value_count = []
for i in Unique_values:
    value_count.append(test_data['Airport_fee'].value_counts()[i])
Unique_values.append('null_values')
value_count.append(test_data['Airport_fee'].isnull().sum())
#print(value_count)
plt.pie(value_count,labels=Unique_values,explode=[0.05,0.05,0.05,0.05])
plt.title('Pie-chart (Airport_fee)')
plt.legend(Unique_values)
plt.show()
```

Pie-chart (Airport_fee)



Observations

- There are 4 distinct values (including null values as type).
- `Airport_fee` contains 6077 missing values which is approx 01% of total number of values.
- Most Frequent is 1.
- Mean Value : 0.15213288816075984

14.1 Overall Observations

- There are 5 attributes having missing values. (`passenger_count`, `RatecodeID`, `store_and_fwd_flag`, `congestion_surcharge`, `Airport_fee`)
- Two attributes (`store_and_fwd_flag`, `payment_type`) are of Categorical type. It can be encoded using Label Encoder. We will not use Ordinal Encoder because labels are not having some order.
- `payment_type` has some unknown values.
- `passenger_count` & `trip_distance` has some 0 values.

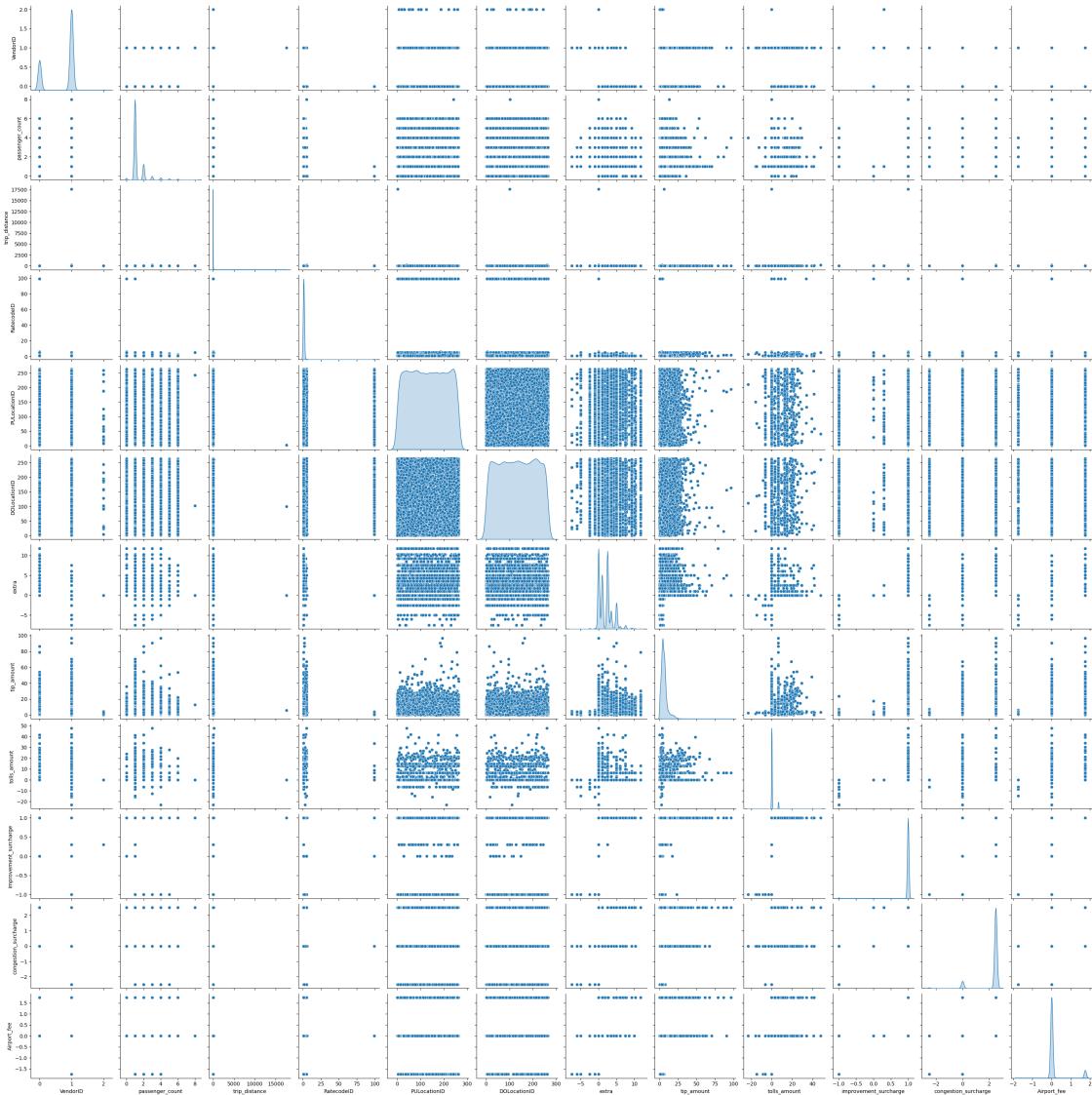
14.2 Bivariate Analysis

- Using `pairplot`

```
[187]: sns.pairplot(test_data, diag_kind='kde')
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserWarning:  
The figure layout has changed to tight  
self._figure.tight_layout(*args, **kwargs)
```

```
[187]: <seaborn.axisgrid.PairGrid at 0x7d702fec5fc0>
```



14.3 Test data preprocessing

14.3.1 Handling Outliers

[188]:

```
'''  
# trip_distance  
trip_percentile25 = test_data['trip_distance'].quantile(0.25)  
trip_percentile75 = test_data['trip_distance'].quantile(0.75)  
trip_iqr = trip_percentile75 - trip_percentile25  
  
print("25th Percentile (Trip distance) :", trip_percentile25)  
print("75th Percentile (Trip distance) :", trip_percentile75)  
print("IQR (Trip distance) :", trip_iqr)
```

```

trip_upper_limit = trip_percentile75 + (trip_iqr*1.5)
trip_lower_limit = trip_percentile25 - (trip_iqr*1.5)

print("Upper Limit (Trip distance) :", trip_upper_limit)
print("Lower Limit (Trip distance) :", trip_lower_limit)

test_data['trip_distance']=np.where(
test_data['trip_distance']>trip_upper_limit, trip_upper_limit,np.where(
test_data['trip_distance']<trip_lower_limit,trip_lower_limit,_
↪test_data['trip_distance']))

print("-----")

# tip_amount
tip_percentile25 = test_data['tip_amount'].quantile(0.25)
tip_percentile75 = test_data['tip_amount'].quantile(0.75)
tip_iqr = tip_percentile75 - tip_percentile25

print("25th Percentile (Tip Amount) :", tip_percentile25)
print("75th Percentile (Tip Amount) :", tip_percentile75)
print("IQR (Tip Amount) :", tip_iqr)

tip_upper_limit = tip_percentile75 + (tip_iqr*1.5)
tip_lower_limit = tip_percentile25 - (tip_iqr*1.5)

print("Upper Limit (Tip amount) :", tip_upper_limit)
print("Lower Limit (Tip amount) :", tip_lower_limit)

test_data['tip_amount']=np.where(
test_data['tip_amount']>tip_upper_limit, tip_upper_limit,np.where(
test_data['tip_amount']<tip_lower_limit,tip_lower_limit,_
↪test_data['tip_amount']))
'''


```

```

[188]: '\n# trip_distance\ntrip_percentile25 =
test_data[['trip_distance']].quantile(0.25)\ntrip_percentile75 =
test_data[['trip_distance']].quantile(0.75)\ntrip_iqr = trip_percentile75 -
trip_percentile25\n\nprint("25th Percentile (Trip distance) :",
trip_percentile25)\nprint("75th Percentile (Trip distance) :",
trip_percentile75)\nprint("IQR (Trip distance) :", trip_iqr)\n\ntrip_upper_limit =
trip_percentile75 + (trip_iqr*1.5)\ntrip_lower_limit = trip_percentile25 -
(trip_iqr*1.5)\n\nprint("Upper Limit (Trip distance) :",
trip_upper_limit)\nprint("Lower Limit (Trip distance) :", trip_lower_limit)\n\ntest_data[['trip_distance']] = np.where(\ntest_data[['trip_distance']]>trip_upper_limit,
trip_upper_limit,np.where(\ntest_data[['trip_distance']]<trip_lower_limit,
trip_lower_limit, test_data[['trip_distance']]))\n\nprint("-----"

```

```
-----")\n\n# tip_amount\ntip_percentile25 =  
test_data['tip_amount'].quantile(0.25)\ntip_percentile75 =  
test_data['tip_amount'].quantile(0.75)\n.tip_iqr = tip_percentile75 -  
tip_percentile25\n\nprint("25th Percentile (Tip Amount) :",  
tip_percentile25)\nprint("75th Percentile (Tip Amount) :",  
tip_percentile75)\nprint("IQR (Tip Amount) : ", .tip_iqr)\n\n.tip_upper_limit =  
tip_percentile75 + (.tip_iqr*1.5)\n.tip_lower_limit = tip_percentile25 -  
(.tip_iqr*1.5)\n\nprint("Upper Limit (Tip amount) :",  
tip_upper_limit)\nprint("Lower Limit (Tip amount) : ", .tip_lower_limit)\n\n\ntest_d  
ata['tip_amount']=np.where(\ntest_data['tip_amount']>tip_upper_limit, tip_up  
per_limit,np.where(\ntest_data['tip_amount']<tip_lower_limit,tip_lower_limit,  
test_data['tip_amount']))\n'
```

[189]: `#sns.boxplot(test_data['trip_distance'])`

[190]: `#sns.boxplot(test_data['tip_amount'])`

```
191]: test_data['trip_distance'].mask(test_data['trip_distance'] == 0.0, 1.0, □  
    ↳inplace=True)  
test_data['extra'] = test_data['extra'].abs()  
#test_data['improvement_surcharge'] = test_data['improvement_surcharge'].abs()  
#test_data['tolls_amount'] = test_data['tolls_amount'].abs()  
#toll_mean = test_data['tolls_amount'][test_data['tolls_amount']>0].mean()  
test_data['tolls_amount'].mask(test_data['tolls_amount'] <0.0, 0.0, □  
    ↳inplace=True)  
#tip_5th_per = np.percentile(test_data['tip_amount'], 5)  
#tip_95th_per = np.percentile(test_data['tip_amount'], 95)  
#test_data['tip_amount'].mask(test_data['tip_amount']<tip_5th_per, tip_5th_per, □  
    ↳inplace=True)  
#test_data['tip_amount'].mask(test_data['tip_amount']>tip_95th_per, □  
    ↳tip_95th_per, inplace=True)  
#test_data['trip_distance'].  
    ↳mask(test_data['trip_distance']>test_data['trip_distance'].median(), □  
        ↳test_data['trip_distance'].median(), inplace=True)  
test_data['Airport_fee'].mask(test_data['Airport_fee'] == -1.75, 1.75, □  
    ↳inplace=True)  
test_data['congestion_surcharge'].mask(test_data['congestion_surcharge'] == -2.  
    ↳5, 2.5, inplace=True)  
test_data['passenger_count'].mask(test_data['passenger_count'] == 0, 1, □  
    ↳inplace=True)  
#test_data['congestion_surcharge'].mask(test_data['congestion_surcharge'] < 0.  
    ↳0, 0.0, inplace=True)  
#test_data['improvement_surcharge'].mask(test_data['improvement_surcharge'] <  
    ↳-1, 1, inplace=True)  
#test_data['trip_distance'].mask(test_data['trip_distance']>15000, □  
    ↳train_data['trip_distance'].mean(), inplace=True)
```

```
#test_data['passenger_count'].mask(test_data['passenger_count'] == 8, 1, inplace=True)
```

Extract and creating new features from the datetime features

```
[192]: test_data['pickup_day'] = test_data['tpep_pickup_datetime'].dt.day_name()
test_data['dropoff_day'] = test_data['tpep_dropoff_datetime'].dt.day_name()
test_data['pickup_day_no'] = test_data['tpep_pickup_datetime'].dt.weekday
test_data['dropoff_day_no'] = test_data['tpep_dropoff_datetime'].dt.weekday
test_data['pickup_hour'] = test_data['tpep_pickup_datetime'].dt.hour
test_data['dropoff_hour'] = test_data['tpep_dropoff_datetime'].dt.hour
test_data['pickup_month'] = test_data['tpep_pickup_datetime'].dt.month
test_data['dropoff_month'] = test_data['tpep_dropoff_datetime'].dt.month
```

```
[193]: test_data['pickup_timeofday'] = test_data['pickup_hour'].apply(time_of_day)
test_data['dropoff_timeofday'] = test_data['dropoff_hour'].apply(time_of_day)
```

```
[194]: test_data.head()
```

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	
0	1	2023-06-29 00:21:20	2023-06-29 00:25:20		1.0
1	1	2023-06-30 17:44:43	2023-06-30 17:53:13		1.0
2	1	2023-06-29 18:17:04	2023-06-29 19:23:48		1.0
3	0	2023-06-30 21:33:53	2023-06-30 21:46:20		1.0
4	1	2023-06-29 14:53:54	2023-06-29 15:22:17		1.0

	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	
0	4.95	1.0		20		3
1	2.10	1.0		9		81
2	0.95	1.0		92		90
3	0.80	1.0		19		102
4	4.01	1.0		131		229

	payment_type	...	congestion_surcharge	Airport_fee	pickup_day_no	
0	Credit Card	...		2.5	0.0	3
1	Credit Card	...		2.5	0.0	4
2	Cash	...		2.5	0.0	3
3	Credit Card	...		2.5	0.0	4
4	Cash	...		0.0	0.0	3

	dropoff_day_no	pickup_hour	dropoff_hour	pickup_month	dropoff_month	
0	3	0	0	6		6
1	4	17	17	6		6
2	3	18	19	6		6
3	4	21	21	6		6
4	3	14	15	6		6

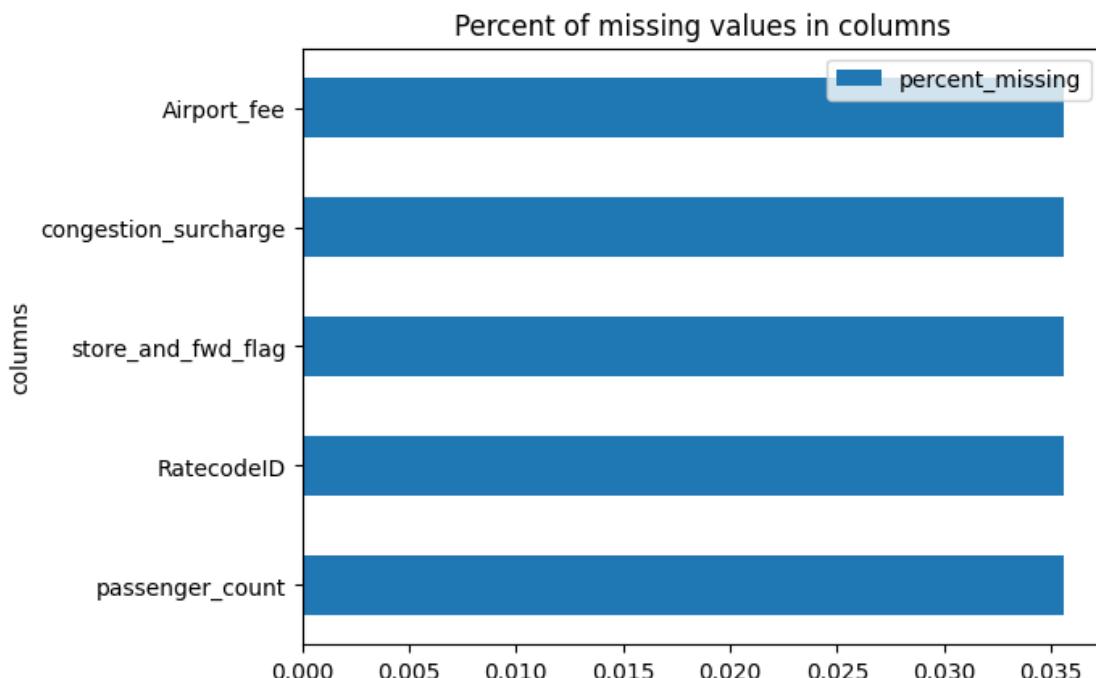
```

pickup_timeofday dropoff_timeofday
0      Late night      Late night
1        Evening       Evening
2        Evening       Evening
3        Evening       Evening
4   Afternoon       Afternoon
[5 rows x 24 columns]

```

14.3.2 Handling Missing Values

```
[195]: # Plotting Missing value percentage for test data
plot_missing_values(test_data)
```



```
[196]: imp = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
imp.fit(test_data)
test_data = pd.DataFrame(imp.transform(test_data), columns = test_data.columns)
train_data.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 174997 entries, 0 to 174996
Data columns (total 23 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   VendorID        174997 non-null  float64

```

```

1  passenger_count          174997 non-null float64
2  trip_distance            174997 non-null float64
3  RatecodeID               174997 non-null float64
4  store_and_fwd_flag        174997 non-null int64
5  PULocationID             174997 non-null float64
6  DOLocationID              174997 non-null float64
7  payment_type              174997 non-null int64
8  extra                      174997 non-null float64
9  tip_amount                174997 non-null float64
10 tolls_amount               174997 non-null float64
11 improvement_surcharge      174997 non-null float64
12 total_amount                174997 non-null float64
13 congestion_surcharge       174997 non-null float64
14 Airport_fee                 174997 non-null float64
15 pickup_day_no              174997 non-null float64
16 dropoff_day_no             174997 non-null float64
17 pickup_hour                  174997 non-null float64
18 dropoff_hour                 174997 non-null float64
19 pickup_month                 174997 non-null float64
20 dropoff_month                174997 non-null float64
21 pickup_timeofday             174997 non-null float64
22 dropoff_timeofday             174997 non-null float64
dtypes: float64(21), int64(2)
memory usage: 30.7 MB

```

14.3.3 Handling Payment type unknown values

- Replacing it by Cash

```
[197]: test_data['payment_type'].mask(test_data['payment_type'] == 'unknown', "Cash", ↴
    ↪inplace=True)
```

```
[198]: test_data['payment_type'].value_counts()
```

```
[198]: payment_type
Credit Card      38672
Cash             9236
Wallet           1779
UPI              313
Name: count, dtype: int64
```

14.3.4 Encoding Categorical Variable

```
[199]: test_data = MultiColumnLabelEncoder(columns = [
    ↪['store_and_fwd_flag', 'payment_type', 'pickup_timeofday', 'dropoff_timeofday']].
    ↪fit_transform(test_data))
```

14.3.5 Dropping tpep_pickup_datetime & tpep_dropoff_datetime columns

```
[200]: test_data = test_data.drop(['tpep_pickup_datetime', 'tpep_dropoff_datetime'],  
    ↪axis=1)
```

14.4 Coverting columns having type ‘object’ to ‘float64’ for further smooth processing.

```
[201]: test_data[['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID',  
    ↪=□  
    ↪test_data[['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID',  
    ↪astype('float64')]
```

14.5 Visualization of test data

```
[202]: test_data.hist(bins=50, figsize=(15,15), color='green')  
    # displaying histogram  
    plt.show()
```



14.6 Scaling

- Using same `StandardScaler()` as in case of train data.

```
[203]: test_data[['PUlocationID','DOlocationID','trip_distance','extra','tip_amount','tolls_amount',
             ↪= pd.DataFrame(scaler.
             ↪transform(test_data[['PUlocationID','DOlocationID','trip_distance','extra','tip_amount','tolls_amount',
             ↪columns = □
             ↪['PUlocationID','DOlocationID','trip_distance','extra','tip_amount','tolls_amount','pickup_'
test_data.head()
```

```
[203]:   VendorID  passenger_count  trip_distance  RatecodeID  store_and_fwd_flag \
0         1.0              1.0      -0.000534        1.0                  0
1         1.0              1.0      -0.007750        1.0                  0
```

```

2      1.0          1.0      -0.010661          1.0          0
3      0.0          1.0      -0.011041          1.0          0
4      1.0          1.0      -0.002914          1.0          0

   PULocationID  DOLocationID  payment_type     extra  tip_amount ... \
0      -1.480153      -1.702277           1  -0.499245  -0.012957 ...
1      -1.624608      -0.678553           1  0.281471  0.013863 ...
2      -0.534634      -0.560431           0  0.281471  -0.464906 ...
3      -1.493286      -0.402935           1  0.801949  0.154426 ...
4      -0.022477      1.263897           0 -1.019723 -1.010377 ...

  congestion_surcharge  Airport_fee  pickup_day_no  dropoff_day_no ...
0                  2.5          0.0      -0.253021      -0.269033
1                  2.5          0.0      1.088124      1.065018
2                  2.5          0.0      -0.253021      -0.269033
3                  2.5          0.0      1.088124      1.065018
4                  0.0          0.0      -0.253021      -0.269033

  pickup_hour  dropoff_hour  pickup_month  dropoff_month  pickup_timeofday ...
0      -2.618962      -2.537794      -0.065343      -0.088271      0.650232
1       0.326177       0.318702      -0.065343      -0.088271      -0.363187
2       0.499420       0.654760      -0.065343      -0.088271      -0.363187
3       1.019150       0.990819      -0.065343      -0.088271      -0.363187
4      -0.193554      -0.017356      -0.065343      -0.088271      -1.376605

  dropoff_timeofday
0            0.660823
1           -0.369946
2           -0.369946
3           -0.369946
4          -1.400716

[5 rows x 22 columns]

```

[204]: test_data.info()

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 22 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   VendorID        50000 non-null   float64
 1   passenger_count 50000 non-null   float64
 2   trip_distance   50000 non-null   float64
 3   RatecodeID      50000 non-null   float64
 4   store_and_fwd_flag 50000 non-null   int64  
 5   PULocationID   50000 non-null   float64

```

```

6   DOLocationID          50000 non-null float64
7   payment_type           50000 non-null int64
8   extra                  50000 non-null float64
9   tip_amount              50000 non-null float64
10  tolls_amount            50000 non-null float64
11  improvement_surcharge  50000 non-null float64
12  congestion_surcharge   50000 non-null float64
13  Airport_fee             50000 non-null float64
14  pickup_day_no           50000 non-null float64
15  dropoff_day_no          50000 non-null float64
16  pickup_hour              50000 non-null float64
17  dropoff_hour             50000 non-null float64
18  pickup_month              50000 non-null float64
19  dropoff_month             50000 non-null float64
20  pickup_timeofday         50000 non-null float64
21  dropoff_timeofday        50000 non-null float64
dtypes: float64(20), int64(2)
memory usage: 8.4 MB

```

[205]: test_data.head()

```

[205]:   VendorID  passenger_count  trip_distance  RatecodeID  store_and_fwd_flag \
0       1.0          1.0      -0.000534        1.0                 0
1       1.0          1.0      -0.007750        1.0                 0
2       1.0          1.0      -0.010661        1.0                 0
3       0.0          1.0      -0.011041        1.0                 0
4       1.0          1.0      -0.002914        1.0                 0

      PULocationID  DOLocationID  payment_type     extra  tip_amount ... \
0      -1.480153    -1.702277        1 -0.499245 -0.012957 ...
1      -1.624608    -0.678553        1  0.281471  0.013863 ...
2      -0.534634    -0.560431        0  0.281471 -0.464906 ...
3      -1.493286    -0.402935        1  0.801949  0.154426 ...
4      -0.022477    1.263897        0 -1.019723 -1.010377 ...

      congestion_surcharge  Airport_fee  pickup_day_no  dropoff_day_no \
0                  2.5          0.0      -0.253021      -0.269033
1                  2.5          0.0      1.088124      1.065018
2                  2.5          0.0      -0.253021      -0.269033
3                  2.5          0.0      1.088124      1.065018
4                  0.0          0.0      -0.253021      -0.269033

      pickup_hour  dropoff_hour  pickup_month  dropoff_month  pickup_timeofday \
0     -2.618962    -2.537794     -0.065343     -0.088271      0.650232
1      0.326177     0.318702     -0.065343     -0.088271     -0.363187
2      0.499420     0.654760     -0.065343     -0.088271     -0.363187
3      1.019150     0.990819     -0.065343     -0.088271     -0.363187

```

```

4      -0.193554      -0.017356      -0.065343      -0.088271      -1.376605

    dropoff_timeofday
0            0.660823
1           -0.369946
2           -0.369946
3           -0.369946
4          -1.400716

[5 rows x 22 columns]

```

```
[206]: #test_data = test_data.
     ↪drop(['pickup_timeofday', 'VendorID', 'pickup_day_no', 'dropoff_day_no', 'Airport_fee', 'store_a
     ↪axis=1)
```

15 Considering Correlation result

- From the above plotted heatmap, we can observe that 14 features are in good (+ve) correlation with target variable.
- And, The columns are : ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'Airport_fee', 'dropoff_day_no', 'pickup_month', 'dropoff_month']

15.0.1 Training and validating Random Forest Regressor on the above selected 14 features only.

```
[207]: corr_cols = ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', □
     ↪'PULocationID',
             'payment_type', 'extra', 'tip_amount', 'tolls_amount', □
     ↪'improvement_surcharge',
             'Airport_fee', 'dropoff_day_no', 'pickup_month', 'dropoff_month']

rf_reg_corr = RandomForestRegressor()
rf_reg_corr.fit(X_train[corr_cols], y_train)
rf_reg_corr_predict = rf_reg_corr.predict(X_val[corr_cols])
print("Predicted data :", rf_reg_corr_predict)
rf_corr_score = r2_score(y_val, rf_reg_corr_predict)
print("R2 Score (RF with selected columns only) :", rf_corr_score)
```

Predicted data : [38.5247 23.6207 98.3574 ... 11.4402 19.1987 32.9071]
R2 Score (RF with selected columns only) : 0.9520890858363609

16 Recursive feature elimination to select desired number of features.

Using Random Forest Regressor as estimator

```
[208]: '''
from sklearn.feature_selection import RFE

RF_Models = []
RF_r2_Scores = []

for i in range(5, 0, -1):
    rfe = RFE(estimator = RandomForestRegressor(), n_features_to_select=i)
    rfe.fit(X_train, y_train)
    sel_cols = []
    for j, col in zip(range(X_train.shape[1]), X_train.columns):
        if (rfe.ranking_[j] == 1):
            sel_cols.append(col)
    print("Total number of features :",i)
    RF_Models.append("RF_RFE_with_"+str(i)+"_+"+"Cols")
    print("Selected Columns are :",sel_cols)
    rf_rfe = RandomForestRegressor()
    rf_rfe.fit(X_train[sel_cols], y_train)
    rf_rfe_predict = rf_rfe.predict(X_val[sel_cols])
    print("Predicted values :",rf_rfe_predict)
    rf_rfe_score = r2_score(y_val,rf_rfe_predict)
    RF_r2_Scores.append(rf_rfe_score)
    print("R2_Score (RandomForestRegressor_RFE) :",rf_rfe_score)
    print()

print("RF_Models :", RF_Models)
print("RF_r2_Scores :", RF_r2_Scores)
'''
```

```
[208]: \nfrom sklearn.feature_selection import RFE\n\nRF_Models = []\nRF_r2_Scores = []\n\nfor i in range(5, 0, -1):\n    rfe = RFE(estimator =\n        RandomForestRegressor(), n_features_to_select=i)\n    rfe.fit(X_train,\n        y_train)\n    sel_cols = []\n    for j, col in zip(range(X_train.shape[1]),\n        X_train.columns):\n        if (rfe.ranking_[j] == 1):\n            sel_cols.append(col)\n    print("Total number of features :",i) \n\n    RF_Models.append("RF_RFE_with_"+str(i)+"_+"+"Cols")\n    print("Selected Columns are :",sel_cols)\n\n    rf_rfe = RandomForestRegressor()\n    rf_rfe.fit(X_train[sel_cols], y_train)\n    rf_rfe_predict =\n        rf_rfe.predict(X_val[sel_cols])\n    print("Predicted values :\n",rf_rfe_predict)\n\n    rf_rfe_score = r2_score(y_val,rf_rfe_predict)\n    RF_r2_Scores.append(rf_rfe_score)\n    print("R2_Score\n(RandomForestRegressor_RFE) :\n",rf_rfe_score)\n    print()\n\n
```

```
\nprint("RF_Models : ", RF_Models)\nprint("RF_r2_Scores : ", RF_r2_Scores)\n'
```

- **Result**

Total number of features : 22 Selected Columns are : ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'Airport_fee', 'pickup_day_no', 'dropoff_day_no', 'pickup_hour', 'dropoff_hour', 'pickup_month', 'dropoff_month', 'pickup_timeofday', 'dropoff_timeofday'] Predicted values : [37.9388 24.183 98.4436 ... 11.3555 18.4766 33.7393] R2_Score (RandomForestRegressor_RFE) : 0.9561782455655767

Total number of features : 21 Selected Columns are : ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'Airport_fee', 'pickup_day_no', 'dropoff_day_no', 'pickup_hour', 'dropoff_hour', 'dropoff_month', 'pickup_timeofday', 'dropoff_timeofday'] Predicted values : [37.2333 24.3653 98.4507 ... 11.2484 18.1649 34.0305] R2_Score (RandomForestRegressor_RFE) : 0.955722003641043

Total number of features : 20 Selected Columns are : ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'Airport_fee', 'pickup_day_no', 'dropoff_day_no', 'pickup_hour', 'dropoff_hour', 'pickup_timeofday', 'dropoff_timeofday'] Predicted values : [37.6167 23.7405 98.446 ... 11.2182 18.2508 34.3305] R2_Score (RandomForestRegressor_RFE) : 0.9565792143132187

Total number of features : 19 Selected Columns are : ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'Airport_fee', 'pickup_day_no', 'dropoff_day_no', 'pickup_hour', 'dropoff_hour', 'pickup_timeofday', 'dropoff_timeofday'] Predicted values : [37.8249 24.3703 98.4933 ... 11.1526 18.6497 34.065] R2_Score (RandomForestRegressor_RFE) : 0.9563181256783445

Total number of features : 18 Selected Columns are : ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'pickup_day_no', 'dropoff_day_no', 'pickup_hour', 'dropoff_hour', 'pickup_timeofday', 'dropoff_timeofday'] Predicted values : [37.4727 24.511 98.3318 ... 11.4249 17.9913 33.4051] R2_Score (RandomForestRegressor_RFE) : 0.9558156255813913

Total number of features : 17 Selected Columns are : ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'dropoff_day_no', 'pickup_hour', 'dropoff_hour', 'pickup_timeofday', 'dropoff_timeofday'] Predicted values : [38.2259 24.6048 98.2249 ... 11.4452 18.2079 33.8505] R2_Score (RandomForestRegressor_RFE) : 0.9558068344929752

Total number of features : 16 Selected Columns are : ['passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'pickup_day_no',

['pickup_hour', 'dropoff_hour', 'pickup_timeofday', 'dropoff_timeofday'] Predicted values : [38.8892 24.2139 98.2225 ... 11.4013 18.8612 33.5367] R2_Score (RandomForestRegressor_RFE) : 0.9558825814985351

Total number of features : 15 Selected Columns are : ['passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'pickup_day_no', 'pickup_hour', 'dropoff_hour', 'dropoff_timeofday'] Predicted values : [37.9604 24.2382 98.358 ... 11.2485 18.7239 33.9868] R2_Score (RandomForestRegressor_RFE) : 0.9566194990925527

Total number of features : 14 Selected Columns are : ['passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge', 'pickup_hour', 'dropoff_hour', 'dropoff_timeofday'] Predicted values : [37.3888 23.6099 98.4146 ... 11.3792 18.3575 33.3994] R2_Score (RandomForestRegressor_RFE) : 0.954943989095263

Total number of features : 13 Selected Columns are : ['passenger_count', 'trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'pickup_hour', 'dropoff_hour', 'dropoff_timeofday'] Predicted values : [38.0277 24.3484 97.9969 ... 11.4347 17.3264 33.7031] R2_Score (RandomForestRegressor_RFE) : 0.9534367345017617

Total number of features : 12 Selected Columns are : ['trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'pickup_hour', 'dropoff_hour', 'dropoff_timeofday'] Predicted values : [38.3127 24.2579 98.264 ... 11.4075 17.327 33.3825] R2_Score (RandomForestRegressor_RFE) : 0.9523303576455688

Total number of features : 11 Selected Columns are : ['trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'payment_type', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'pickup_hour', 'dropoff_hour'] Predicted values : [36.8941 23.8492 98.4767 ... 11.2561 18.0295 33.5922] R2_Score (RandomForestRegressor_RFE) : 0.9531813787266661

Total number of features : 10 Selected Columns are : ['trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'extra', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'pickup_hour', 'dropoff_hour'] Predicted values : [36.9642 23.8092 98.2655 ... 11.2049 17.6306 33.915] R2_Score (RandomForestRegressor_RFE) : 0.9514042995436127

Total number of features : 9 Selected Columns are : ['trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'pickup_hour', 'dropoff_hour'] Predicted values : [37.5386 23.8314 98.3854 ... 11.3616 19.1439 34.4214] R2_Score (RandomForestRegressor_RFE) : 0.9496425468171789

Total number of features : 8 Selected Columns are : ['trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'tip_amount', 'tolls_amount', 'improvement_surcharge', 'dropoff_hour'] Predicted values : [36.6395 24.6118 98.2832 ... 11.2789 18.971 33.7174] R2_Score (RandomForestRegressor_RFE) : 0.9488814727329483

Total number of features : 7 Selected Columns are : ['trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'tip_amount', 'tolls_amount', 'improvement_surcharge'] Predicted values : [38.9321 23.8824 98.7915 ... 12.3128 19.3548 36.9436] R2_Score (RandomForestRegressor_RFE) : 0.9429121641107724

Total number of features : 6 Selected Columns are : ['trip_distance', 'RatecodeID', 'PULocationID', 'DOLocationID', 'tip_amount', 'improvement_surcharge'] Predicted values : [39.0041 23.723 97.6006 ... 12.5613 19.4786 36.8866] R2_Score (RandomForestRegressor_RFE) : 0.9375039915951607

Total number of features : 5 Selected Columns are : ['trip_distance', 'RatecodeID', 'DOLocationID', 'tip_amount', 'improvement_surcharge'] Predicted values : [38.0591 25.7882 96.9694 ... 12.0177 19.4338 38.2195] R2_Score (RandomForestRegressor_RFE) : 0.9380819204870838

Total number of features : 4 Selected Columns are : ['trip_distance', 'RatecodeID', 'tip_amount', 'improvement_surcharge'] Predicted values : [39.6915 28.282 96.7877 ... 13.9734 21.3379 34.3977] R2_Score (RandomForestRegressor_RFE) : 0.9258540569625787

Total number of features : 3 Selected Columns are : ['trip_distance', 'tip_amount', 'improvement_surcharge'] Predicted values : [39.4993 28.8858 97.6198 ... 13.911 21.7446 34.5785] R2_Score (RandomForestRegressor_RFE) : 0.8922145364663899

Total number of features : 2 Selected Columns are : ['trip_distance', 'tip_amount'] Predicted values : [40.3389 27.6715 97.3886 ... 13.5038 21.6585 34.5027] R2_Score (RandomForestRegressor_RFE) : 0.7859565422966392

Total number of features : 1 Selected Columns are : ['trip_distance'] Predicted values : [39.39124297 26.1609182 96.54879884 ... 12.84366089 18.17438061 32.51282336] R2_Score (RandomForestRegressor_RFE) : 0.7372180184215582

RF_Models : ['RF_RFE_with_22_Cols', 'RF_RFE_with_21_Cols', 'RF_RFE_with_20_Cols', 'RF_RFE_with_19_Cols', 'RF_RFE_with_18_Cols', 'RF_RFE_with_17_Cols', 'RF_RFE_with_16_Cols', 'RF_RFE_with_15_Cols', 'RF_RFE_with_14_Cols', 'RF_RFE_with_13_Cols', 'RF_RFE_with_12_Cols', 'RF_RFE_with_11_Cols', 'RF_RFE_with_10_Cols', 'RF_RFE_with_9_Cols', 'RF_RFE_with_8_Cols', 'RF_RFE_with_7_Cols', 'RF_RFE_with_6_Cols', 'RF_RFE_with_5_Cols', 'RF_RFE_with_4_Cols', 'RF_RFE_with_3_Cols'] RF_r2_Scores : [0.9561782455655767, 0.955722003641043, 0.9565792143132187, 0.9563181256783445, 0.9558156255813913, 0.9558068344929752, 0.9558825814985351, 0.9566194990925527, 0.954943989095263, 0.9534367345017617, 0.9523303576455688, 0.9531813787266661, 0.9514042995436127, 0.9496425468171789, 0.9488814727329483, 0.9429121641107724, 0.9375039915951607, 0.9380819204870838, 0.9258540569625787, 0.8922145364663899, 0.7859565422966392, 0.7372180184215582]

```
[209]: RF_Models = ['RF_RFE_with_22_Cols', 'RF_RFE_with_21_Cols',  
    ↪ 'RF_RFE_with_20_Cols', 'RF_RFE_with_19_Cols',  
        ↪ 'RF_RFE_with_18_Cols', 'RF_RFE_with_17_Cols',  
            ↪ 'RF_RFE_with_16_Cols', 'RF_RFE_with_15_Cols',  
                ↪ 'RF_RFE_with_14_Cols', 'RF_RFE_with_13_Cols',  
                    ↪ 'RF_RFE_with_12_Cols', 'RF_RFE_with_11_Cols',  
                        ↪ 'RF_RFE_with_10_Cols', 'RF_RFE_with_9_Cols', 'RF_RFE_with_8_Cols',  
                            ↪ 'RF_RFE_with_7_Cols',  
                                ↪ 'RF_RFE_with_6_Cols', 'RF_RFE_with_5_Cols', 'RF_RFE_with_4_Cols',  
                                    ↪ 'RF_RFE_with_3_Cols',
```

```

'RF_RFE_with_2_Cols', 'RF_RFE_with_1_Cols']
RF_r2_Scores = [0.9561782455655767, 0.955722003641043, 0.9565792143132187, 0.
↳ 9563181256783445,
                0.9558156255813913, 0.9558068344929752, 0.9558825814985351, 0.
↳ 9566194990925527,
                0.954943989095263, 0.9534367345017617, 0.9523303576455688, 0.
↳ 9531813787266661,
                0.9514042995436127, 0.9496425468171789, 0.9488814727329483, 0.
↳ 9429121641107724,
                0.9375039915951607, 0.9380819204870838, 0.9258540569625787, 0.
↳ 8922145364663899,
                0.7859565422966392, 0.7372180184215582]

```

Plotting

```

plt.figure( figsize = (12,5) )
plt.plot(RF_Models, RF_r2_Scores, 'o-g')
font1 = {'family':'serif','color':'black','size':20}
font2 = {'family':'serif','color':'darkred','size':15}
plt.title("R2 Scores Comparison", fontdict=font1)
plt.xlabel("RF_Models", fontdict=font2)
plt.ylabel("RF_R2_Scores", fontdict=font2)
plt.grid()
plt.xticks(rotation = 90)

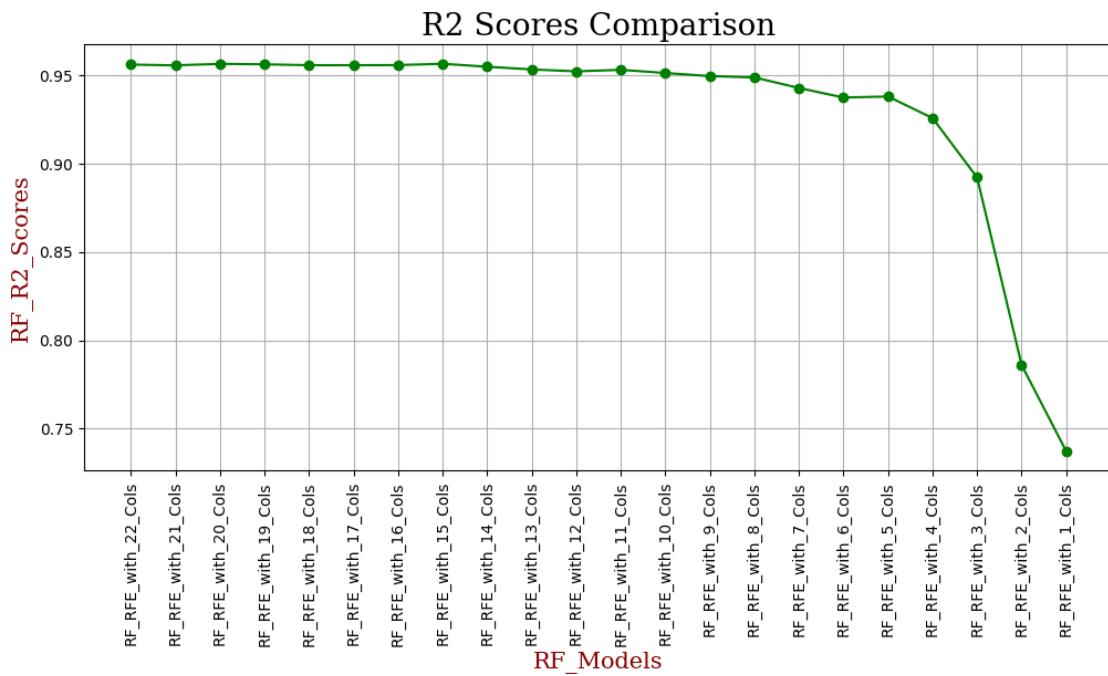
```

Showing plot

```

plt.show()

```



Note : From the above line plot, we can observe that we are getting the largest R2 scores in case of 20 columns and the columns are following:

```
-      ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID',
'store_and_fwd_flag', 'PULocationID', 'DOLocationID', 'payment_type', 'extra',
'tip_amount', 'tolls_amount', 'improvement_surcharge', 'congestion_surcharge',
'Airport_fee', 'pickup_day_no', 'dropoff_day_no', 'pickup_hour', 'dropoff_hour',
'pickup_timeofday', 'dropoff_timeofday']
```

16.0.1 Training and validating Random Forest Regressor on the above selected 20 features only.

```
[210]: rf_cols = ['VendorID', 'passenger_count', 'trip_distance', 'RatecodeID', □
    ↵ 'store_and_fwd_flag', 'PULocationID',
    'DOLocationID', 'payment_type', 'extra', 'tip_amount', □
    ↵ 'tolls_amount', 'improvement_surcharge',
    'congestion_surcharge', 'Airport_fee', 'pickup_day_no', □
    ↵ 'dropoff_day_no', 'pickup_hour',
    'dropoff_hour', 'pickup_timeofday', 'dropoff_timeofday']

rf_reg_rfe = RandomForestRegressor(n_estimators = 2000, n_jobs=-1)
rf_reg_rfe.fit(X_train[rf_cols], y_train)
rf_reg_rfe_predict = rf_reg_rfe.predict(X_val[rf_cols])
print("Predicted data : ", rf_reg_rfe_predict)
rf_rfe_score = r2_score(y_val, rf_reg_rfe_predict)
print("R2 Score (RF with selected columns only) : ", rf_rfe_score)
```

Predicted data : [37.82236 24.437365 98.46074 ... 11.286405 18.531895
33.955945]
R2 Score (RF with selected columns only) : 0.9562054562063217

```
[211]: '''
tuned_parameters = [{"n_estimators": [50,100, 150, 200, 250, 500],
    "max_features" : ["sqrt", "log2", None, 20],
    "max_samples" : [0.5, 0.6, 0.75, 1.0],
    "max_depth" : [2,6,8,10,12,16,20, None],
    "min_samples_split" : [2,4,8,12,14],
    "bootstrap": [True, False]}
]

RFE_model_RS = RandomizedSearchCV(RandomForestRegressor(), □
    ↵ param_distributions=tuned_parameters, n_jobs=-1, cv=5, verbose = 2)
RFE_model_RS.fit(X_train[rf_cols],y_train)

print ("The best parameter value is:",RFE_model_RS.best_params_)
'''
```

```
[211]: '\ntuned_parameters = [{"n_estimators": [50,100, 150, 200, 250, 500],\n    "max_features" : ["sqrt", "log2", None, 20],\n                                "max_samples" : [0.5,\n0.6, 0.75, 1.0],\n                                "max_depth" : [2,6,8,10,12,16,20, None],\n    "min_samples_split" : [2,4,8,12,14],\n                                "bootstrap": [True,\nFalse]}]\n\nRFE_model_RS = RandomizedSearchCV(RandomForestRegressor(),\nparam_distributions=tuned_parameters, n_jobs=-1, cv=5, verbose =\n2)\nRFE_model_RS.fit(X_train[rf_cols],y_train)\n\nprint ("The best parameter\nvalue is:",RFE_model_RS.best_params_)\n'
```

- Result Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=500; total time= 2.2min [CV] END bootstrap=True, max_depth=20, max_features=log2, max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 22.1s [CV] END bootstrap=True, max_depth=20, max_features=log2, max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 22.8s [CV] END bootstrap=True, max_depth=12, max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=150; total time= 22.1s [CV] END bootstrap=True, max_depth=2, max_features=log2, max_samples=1.0, min_samples_split=14, n_estimators=500; total time= 14.0s [CV] END bootstrap=True, max_depth=2, max_features=log2, max_samples=1.0, min_samples_split=14, n_estimators=500; total time= 14.1s [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 27.7s [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 27.1s [CV] END bootstrap=True, max_depth=None, max_features=None, max_samples=0.5, min_samples_split=12, n_estimators=500; total time= 5.2min

[CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=0.75, min_samples_split=12, n_estimators=150; total time= 31.8s [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=500; total time= 2.2min [CV] END bootstrap=True, max_depth=20, max_features=log2, max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 22.3s [CV] END bootstrap=True, max_depth=20, max_features=log2, max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 22.2s [CV] END bootstrap=True, max_depth=12, max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=150; total time= 21.8s [CV] END bootstrap=True, max_depth=12, max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=150; total time= 21.9s [CV] END bootstrap=True, max_depth=2, max_features=log2, max_samples=1.0, min_samples_split=14, n_estimators=500; total time= 14.0s [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 26.8s [CV] END bootstrap=True, max_depth=None, max_features=None, max_samples=0.5, min_samples_split=12, n_estimators=500; total time= 5.2min [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=0.75, min_samples_split=12, n_estimators=150; total time= 32.3s [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=0.75, min_samples_split=12, n_estimators=150; total time= 31.0s [CV] END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=500; total time= 2.2min [CV] END bootstrap=True, max_depth=20, max_features=log2,

```
max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 22.4s [CV] END
bootstrap=False, max_depth=2, max_features=20, max_samples=1.0, min_samples_split=2,
n_estimators=50; total time= 0.0s [CV] END bootstrap=False, max_depth=2, max_features=20,
max_samples=1.0, min_samples_split=2, n_estimators=50; total time= 0.0s [CV] END
bootstrap=False, max_depth=2, max_features=20, max_samples=1.0, min_samples_split=2,
n_estimators=50; total time= 0.0s [CV] END bootstrap=False, max_depth=2, max_features=20,
max_samples=1.0, min_samples_split=2, n_estimators=50; total time= 0.0s [CV] END boot-
strap=False, max_depth=2, max_features=20, max_samples=1.0, min_samples_split=2,
n_estimators=50; total time= 0.0s [CV] END bootstrap=True, max_depth=12,
max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=150; to-
tal time= 22.6s [CV] END bootstrap=True, max_depth=12, max_features=sqrt,
max_samples=1.0, min_samples_split=14, n_estimators=150; total time= 22.2s [CV] END
bootstrap=True, max_depth=2, max_features=log2, max_samples=1.0, min_samples_split=14,
n_estimators=500; total time= 14.3s [CV] END bootstrap=True, max_depth=2,
max_features=log2, max_samples=1.0, min_samples_split=14, n_estimators=500; to-
tal time= 14.5s [CV] END bootstrap=True, max_depth=None, max_features=sqrt,
max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 26.6s [CV] END boot-
strap=True, max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=8,
n_estimators=100; total time= 26.8s [CV] END bootstrap=True, max_depth=None,
max_features=None, max_samples=0.5, min_samples_split=12, n_estimators=500; to-
tal time= 5.2min [CV] END bootstrap=True, max_depth=None, max_features=sqrt,
max_samples=0.75, min_samples_split=12, n_estimators=150; total time= 32.7s [CV]
END bootstrap=True, max_depth=None, max_features=sqrt, max_samples=0.75,
min_samples_split=12, n_estimators=150; total time= 28.1s [CV] END bootstrap=True,
max_depth=None, max_features=sqrt, max_samples=1.0, min_samples_split=14,
n_estimators=500; total time= 2.2min [CV] END bootstrap=True, max_depth=None,
max_features=sqrt, max_samples=1.0, min_samples_split=14, n_estimators=500; to-
tal time= 2.1min [CV] END bootstrap=False, max_depth=10, max_features=None,
max_samples=1.0, min_samples_split=14, n_estimators=50; total time= 0.0s [CV] END boot-
strap=False, max_depth=10, max_features=None, max_samples=1.0, min_samples_split=14,
n_estimators=50; total time= 0.0s [CV] END bootstrap=False, max_depth=10,
max_features=None, max_samples=1.0, min_samples_split=14, n_estimators=50; to-
tal time= 0.0s [CV] END bootstrap=False, max_depth=10, max_features=None,
max_samples=1.0, min_samples_split=14, n_estimators=50; total time= 0.0s [CV] END boot-
strap=False, max_depth=10, max_features=None, max_samples=1.0, min_samples_split=14,
n_estimators=50; total time= 0.0s [CV] END bootstrap=False, max_depth=2,
max_features=sqrt, max_samples=1.0, min_samples_split=8, n_estimators=100; to-
tal time= 0.0s [CV] END bootstrap=False, max_depth=2, max_features=sqrt,
max_samples=1.0, min_samples_split=8, n_estimators=100; total time= 0.0s [CV] END
bootstrap=False, max_depth=2, max_features=sqrt, max_samples=1.0, min_samples_split=8,
n_estimators=100; total time= 0.0s [CV] END bootstrap=False, max_depth=2,
max_features=sqrt, max_samples=1.0, min_samples_split=8, n_estimators=100; total time=
0.0s [CV] END bootstrap=False, max_depth=2, max_features=sqrt, max_samples=1.0,
min_samples_split=8, n_estimators=100; total time= 0.0s [CV] END bootstrap=True,
max_depth=None, max_features=None, max_samples=0.5, min_samples_split=12,
n_estimators=500; total time= 5.2min [CV] END bootstrap=True, max_depth=None,
max_features=None, max_samples=0.5, min_samples_split=12, n_estimators=500; to-
tal time= 4.2min The best parameter value is: {'n_estimators': 500, 'min_samples_split': 12,
```

```
'max_samples': 0.5, 'max_features': None, 'max_depth': None, 'bootstrap': True}
```

```
[212]: rf_reg_rfe1 = RandomForestRegressor(n_jobs=-1,n_estimators = 500,  
    ↪min_samples_split = 12, max_samples=0.5, max_features = None, max_depth =  
    ↪None, bootstrap = True)  
rf_reg_rfe1.fit(X_train[rf_cols], y_train)  
rf_reg_rfe1_predict = rf_reg_rfe1.predict(X_val[rf_cols])  
print("Predicted data :", rf_reg_rfe1_predict)  
rf_rfe1_score = r2_score(y_val, rf_reg_rfe1_predict)  
print("R2 Score (RF with selected columns only) :", rf_rfe1_score)
```

```
Predicted data : [37.8324891  24.67483711  98.4699324 ... 11.37899214  
18.48546443  
33.9356232 ]  
R2 Score (RF with selected columns only) : 0.9570416333280967
```

17 Final Observation

- **Case 1 :** Among all Models, Random Forest Regressor is giving the best score.
- **Case 2 :** Training Random Forest Regressor using only positively correlated features also giving the good score.
-

17.1 Case 3 : After performing RFE using Random Forest Regressor, the subset of 20 features is giving good score.

Applying all the above cases on test data and observing the result below.

18 Final Submission (After Comparing model using R2 Scores and applying the best model on test.csv data)

```
[213]: #best_model_predict = rf_reg.predict(test_data)  
#best_model_predict = rf_reg_corr.predict(test_data[corr_cols])  
best_model_predict = rf_reg_rfe.predict(test_data[rf_cols])      # Giving the  
    ↪best score to the test data.  
#best_model_predict = rf_reg_rfe1.predict(test_data[rf_cols])  
best_model_predict
```

```
[213]: array([35.955 , 25.066395, 15.92205 , ..., 21.6817 , 35.880645,  
17.62315 ])
```

```
[214]: res_len = len(best_model_predict)  
id = np.array([ i for i in range(1,res_len+1)])  
result = pd.DataFrame({ "ID" : id, "total_amount" : best_model_predict})  
result.to_csv("submission.csv", index=False)
```

19 Conclusion

- `RandomForestRegressor()` having default hyperparameters with 20 selected columns after RFE is giving the best score.