ensemble-traffic-prediction-datase

April 1, 2024

**

Import Libraries

**

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import os
%matplotlib inline

import matplotlib.pyplot as plt
import matplotlib.pyplot as plotter
from sklearn.model_selection import cross_val_score
from sklearn import metrics
from sklearn.base import BaseEstimator, TransformerMixin, ClassifierMixin, clone
from sklearn.model_selection import KFold
from scipy import stats
from scipy.stats import norm, skew
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.feature_selection import SelectFromModel
import warnings
warnings.filterwarnings('ignore')
```

At first, we import nessesary python liblaries.

**

Read Dataset

**

[3]:
```
train = pd.read_csv('/kaggle/input/traffic-prediction-dataset/Traffic.csv')
train
```

[3]:
```
             Time  Date Day of the week  CarCount  BikeCount  BusCount  \
0     12:00:00 AM    10         Tuesday        31          0         4
1     12:15:00 AM    10         Tuesday        49          0         3
2     12:30:00 AM    10         Tuesday        46          0         3
```

```
3      12:45:00 AM    10         Tuesday        51          0         2
4       1:00:00 AM    10         Tuesday        57          6        15
…            …   …             …       …        …        …
2971   10:45:00 PM     9        Thursday        16          3         1
2972   11:00:00 PM     9        Thursday        11          0         1
2973   11:15:00 PM     9        Thursday        15          4         1
2974   11:30:00 PM     9        Thursday        16          5         0
2975   11:45:00 PM     9        Thursday        14          3         1

      TruckCount  Total Traffic Situation
0              4     39               low
1              3     55               low
2              6     55               low
3              5     58               low
4             16     94            normal
…           …     …             …
2971          36     56            normal
2972          30     42            normal
2973          25     45            normal
2974          27     48            normal
2975          15     33            normal

[2976 rows x 9 columns]
```

Here, we import data from a csv file, with pandas

[4]:
```
train, test = train_test_split(train,test_size=0.1,random_state=1992)
print("Shape of train: ",train.shape)
print("Shape of test",test.shape)
```

```
Shape of train:  (2678, 9)
Shape of test (298, 9)
```

before the data is processed ,Split train data and test data ,The accuracy of the final prediction is more realistic.

**

Visualization

**

[5]:
```
train.isnull().sum()
```

[5]:
```
Time                0
Date                0
Day of the week     0
CarCount            0
BikeCount           0
BusCount            0
```

```
TruckCount           0
Total                0
Traffic Situation    0
dtype: int64
```

[6]:
```
test.isnull().sum()
```

[6]:
```
Time                 0
Date                 0
Day of the week      0
CarCount             0
BikeCount            0
BusCount             0
TruckCount           0
Total                0
Traffic Situation    0
dtype: int64
```

train and test dataset is no Missing values in DataFrame.

[7]:
```
print('train')
display(train.info())
print('test')
display(test.info())
```

```
train
<class 'pandas.core.frame.DataFrame'>
Index: 2678 entries, 828 to 2313
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Time               2678 non-null   object
 1   Date               2678 non-null   int64 
 2   Day of the week    2678 non-null   object
 3   CarCount           2678 non-null   int64 
 4   BikeCount          2678 non-null   int64 
 5   BusCount           2678 non-null   int64 
 6   TruckCount         2678 non-null   int64 
 7   Total              2678 non-null   int64 
 8   Traffic Situation  2678 non-null   object
dtypes: int64(6), object(3)
memory usage: 209.2+ KB
```

```
None
```

```
test
<class 'pandas.core.frame.DataFrame'>
Index: 298 entries, 1338 to 896
Data columns (total 9 columns):
```

```
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Time               298 non-null    object
 1   Date               298 non-null    int64
 2   Day of the week    298 non-null    object
 3   CarCount           298 non-null    int64
 4   BikeCount          298 non-null    int64
 5   BusCount           298 non-null    int64
 6   TruckCount         298 non-null    int64
 7   Total              298 non-null    int64
 8   Traffic Situation  298 non-null    object
dtypes: int64(6), object(3)
memory usage: 23.3+ KB
```

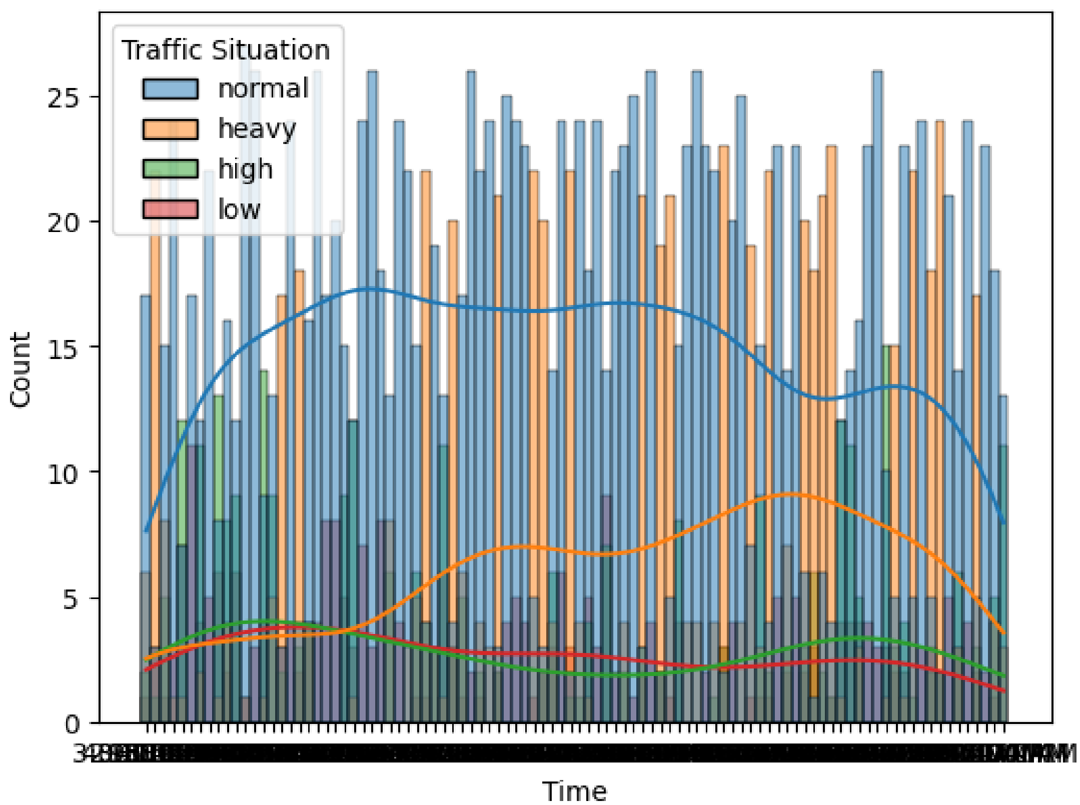
```
None
```

train and test dataset are no-null values.

We also can see that Time Day of the week Traffic Situation are object and must do the conversion.

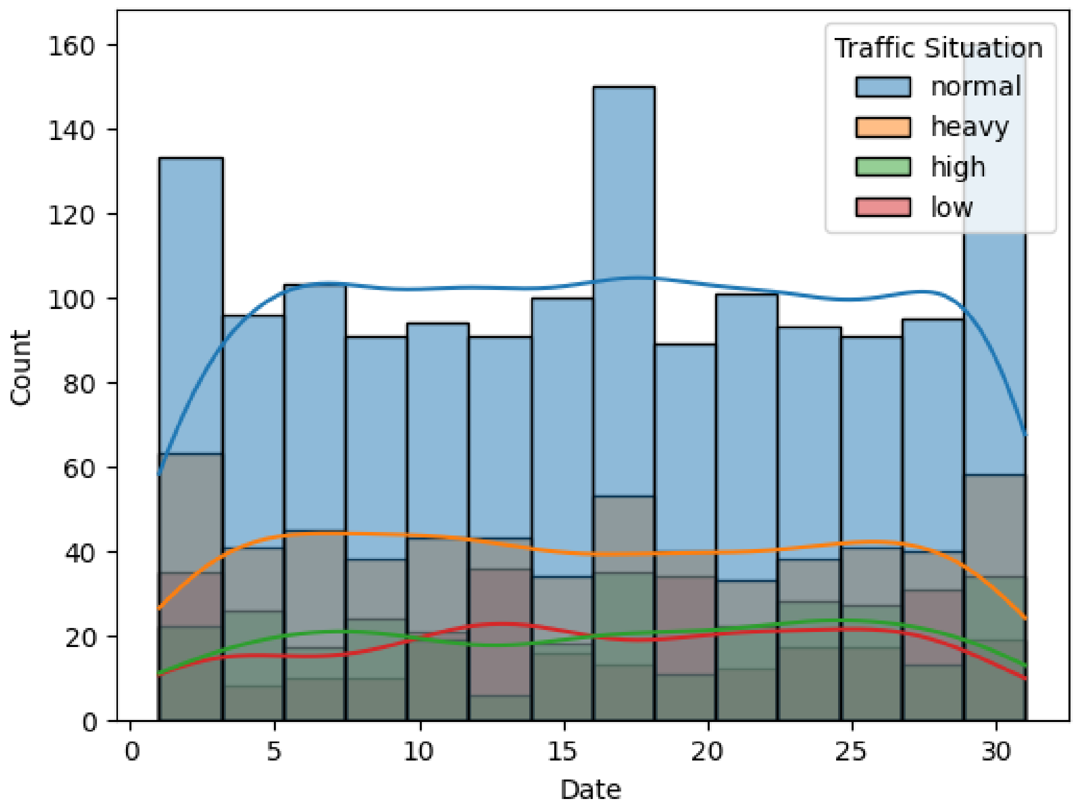
[9]:
```
sns.histplot(train,x='Time',hue='Traffic Situation',kde=True)
```

[9]: `<Axes: xlabel='Time', ylabel='Count'>`



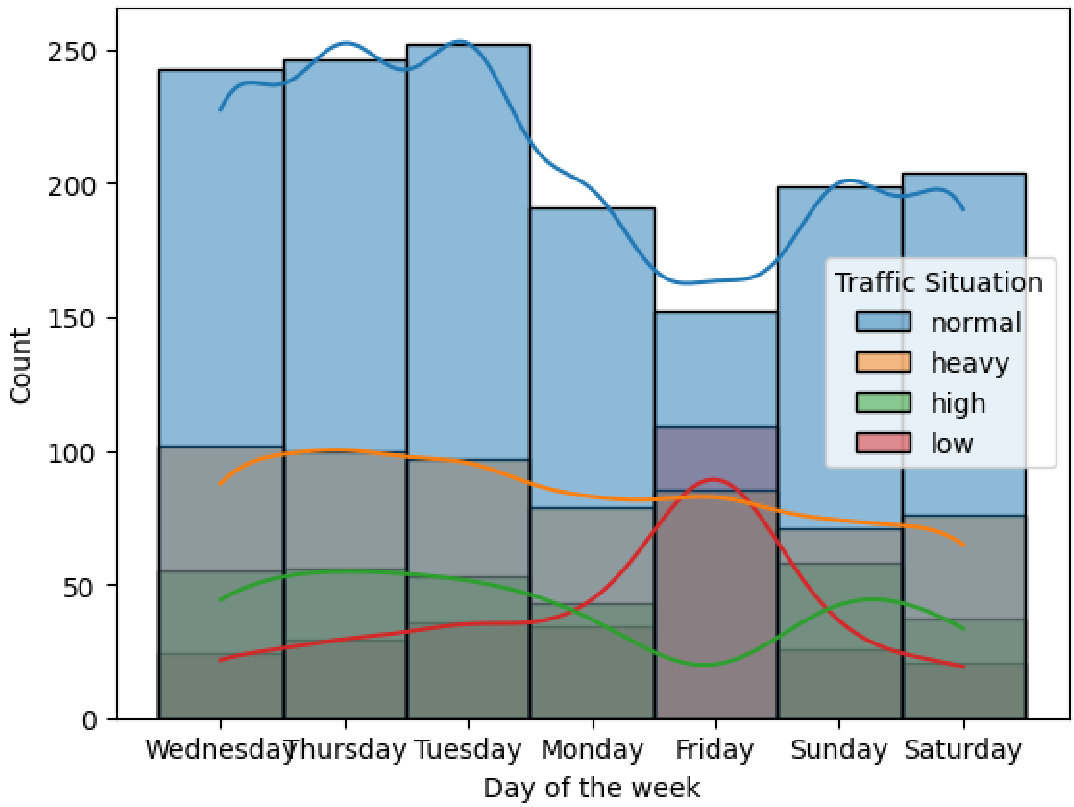
```python
[10]: sns.histplot(train,x='Date',hue='Traffic Situation',kde=True)
```

[10]: <Axes: xlabel='Date', ylabel='Count'>



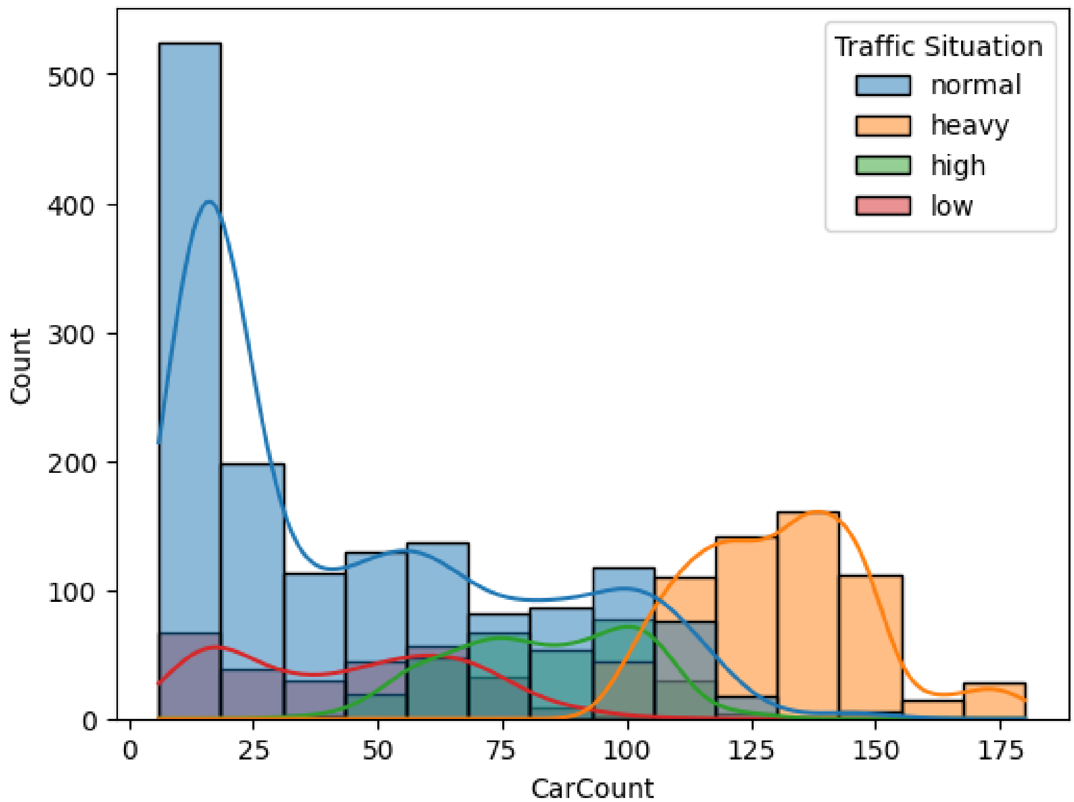

```python
[11]: sns.histplot(train,x='Day of the week',hue='Traffic Situation',kde=True)
```

[11]: <Axes: xlabel='Day of the week', ylabel='Count'>



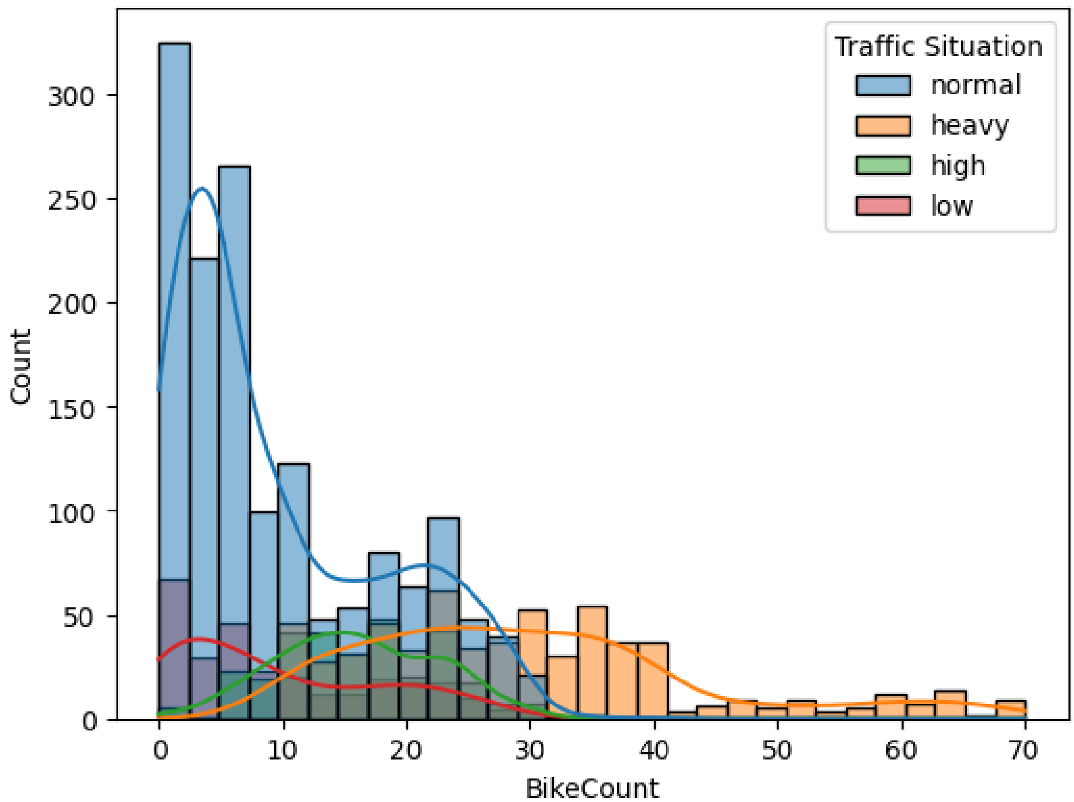
[12]:
```
sns.histplot(train,x='CarCount',hue='Traffic Situation',kde=True)
```

[12]: <Axes: xlabel='CarCount', ylabel='Count'>



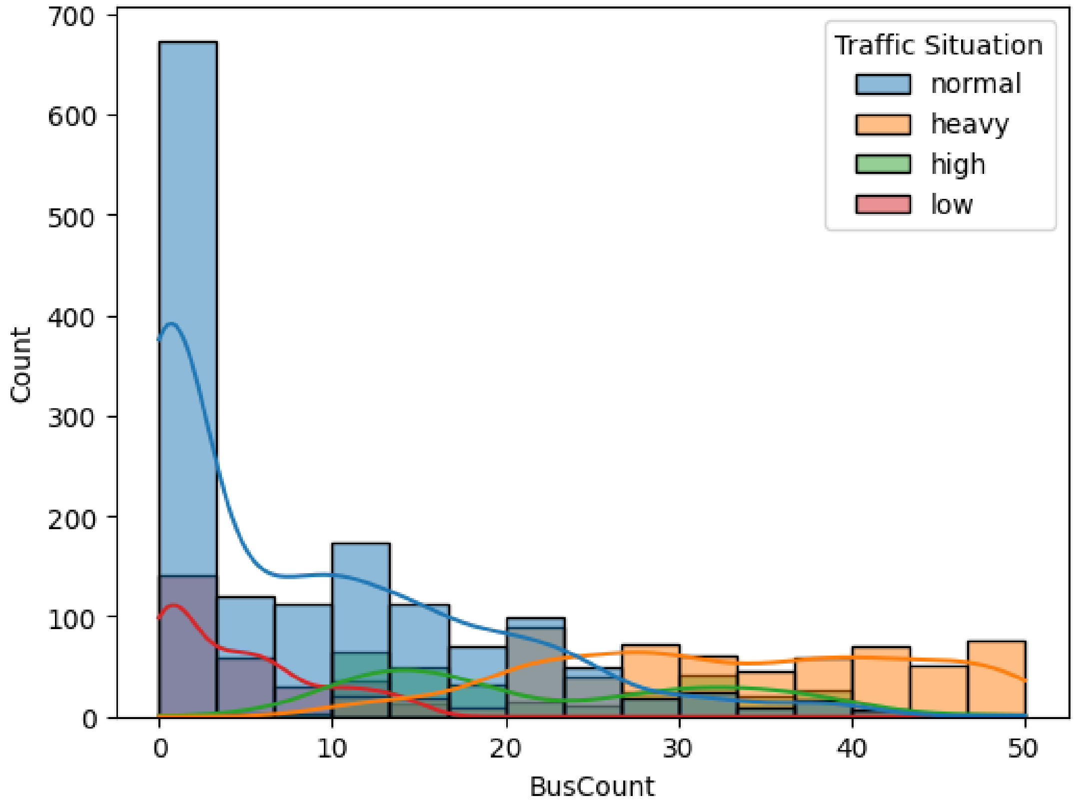
[13]:
```
sns.histplot(train,x='BikeCount',hue='Traffic Situation',kde=True)
```

[13]: <Axes: xlabel='BikeCount', ylabel='Count'>



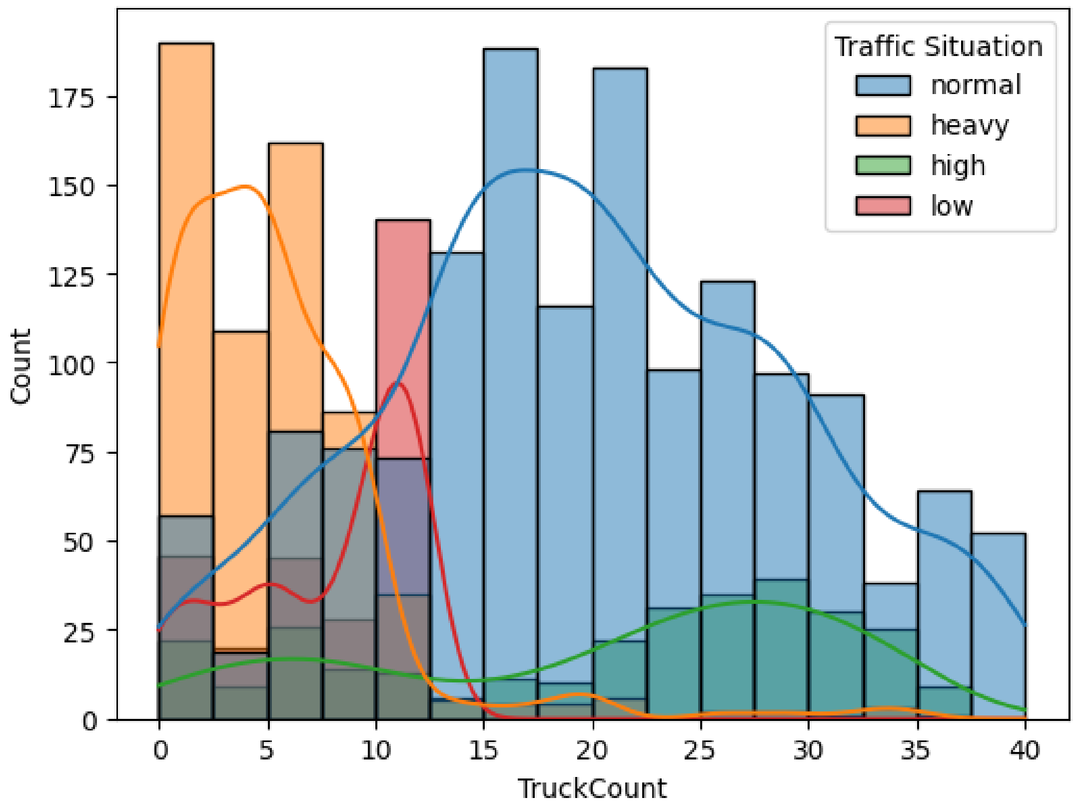
[14]:
```
sns.histplot(train,x='BusCount',hue='Traffic Situation',kde=True)
```

[14]: <Axes: xlabel='BusCount', ylabel='Count'>



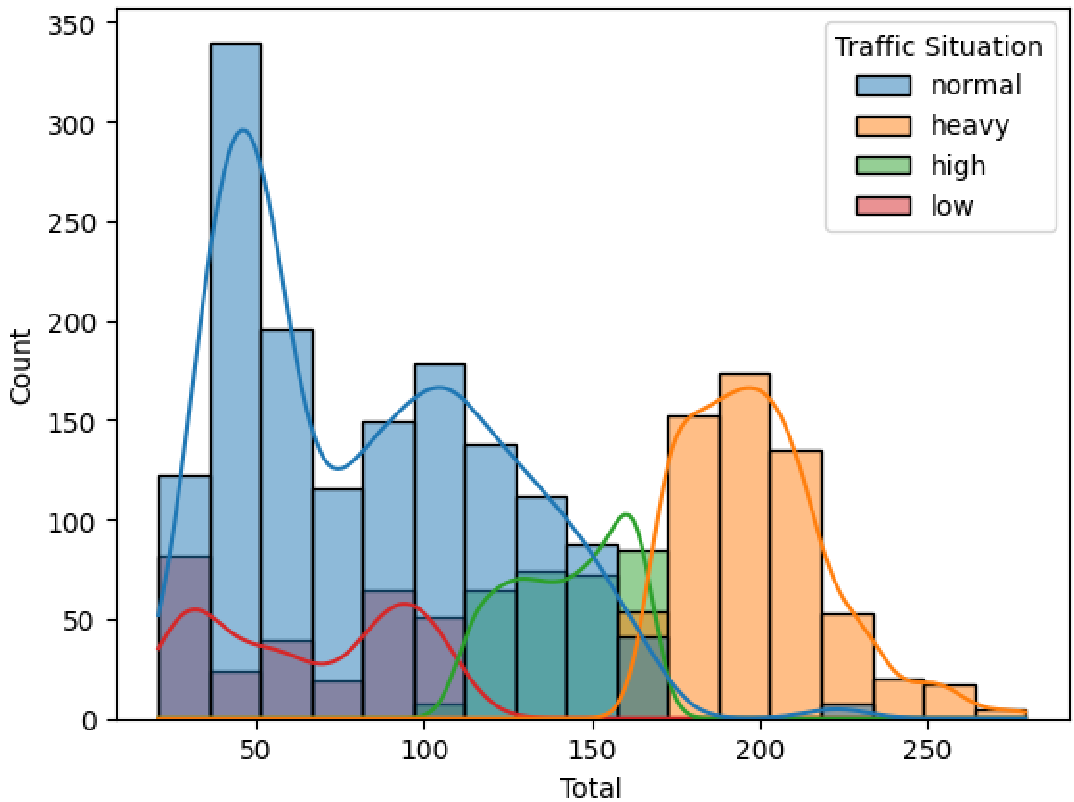

```
[15]: sns.histplot(train,x='TruckCount',hue='Traffic Situation',kde=True)
```

```
[15]: <Axes: xlabel='TruckCount', ylabel='Count'>
```




```
[16]: sns.histplot(train,x='Total',hue='Traffic Situation',kde=True)
```

```
[16]: <Axes: xlabel='Total', ylabel='Count'>
```



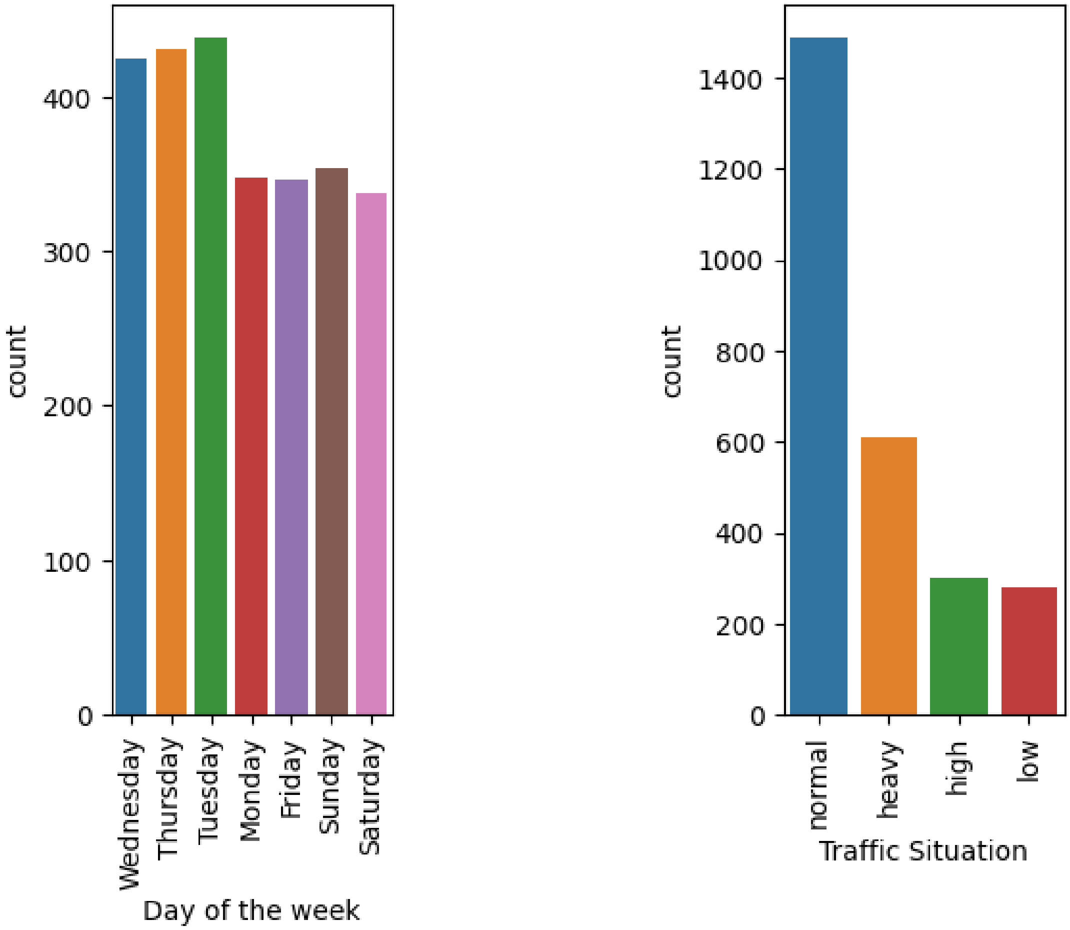
Visualize the relationship between each feature and target.

**

Preprocessing

**

[17]:
```
plt.subplot(1, 3, 1)
sns.countplot(x = train["Day of the week"])
plotter.xticks(rotation = 90);

plt.subplot(1, 3, 3)
sns.countplot(x = train["Traffic Situation"])
plotter.xticks(rotation = 90);
plt.show()
```



[18]:
```
df_temp=train
df_temp['Day of the week'] = df_temp['Day of the week'].replace({'Monday':
↪1,'Tuesday':2,'Wednesday':3,'Thursday':4,'Friday':5,'Saturday': 6,'Sunday':
↪7})
df_temp['Traffic Situation'] = df_temp['Traffic Situation'].replace({'low':␣
↪0,'normal': 1,'high': 2, 'heavy':3})
train=df_temp
train
```

[18]:
```
             Time  Date  Day of the week  CarCount  BikeCount  BusCount  \
828    3:00:00 PM    18                3        14         16         9
929    4:15:00 PM    19                4       104         31        37
2170   2:30:00 PM     1                3        91         22        34
2702   3:30:00 AM     7                2        18          2         1
2676   9:00:00 PM     6                1       105         14        13
…             …     …              …        …        …         …
1921  12:15:00 AM    30                1        19          2         0
```

```
229     9:15:00 AM     12                 4        24          18          37
1835    2:45:00 AM     29                 7        19           2           1
2216    2:00:00 AM      2                 4        12           3           0
2313    2:15:00 AM      3                 5        12           3           0

      TruckCount  Total  Traffic Situation
828           14     53                  1
929            6    178                  3
2170           8    155                  2
2702          27     48                  1
2676          32    164                  2
…            …     …                …
1921          22     43                  1
229           18     97                  1
1835          12     34                  0
2216          39     54                  1
2313          22     37                  1

[2678 rows x 9 columns]
```

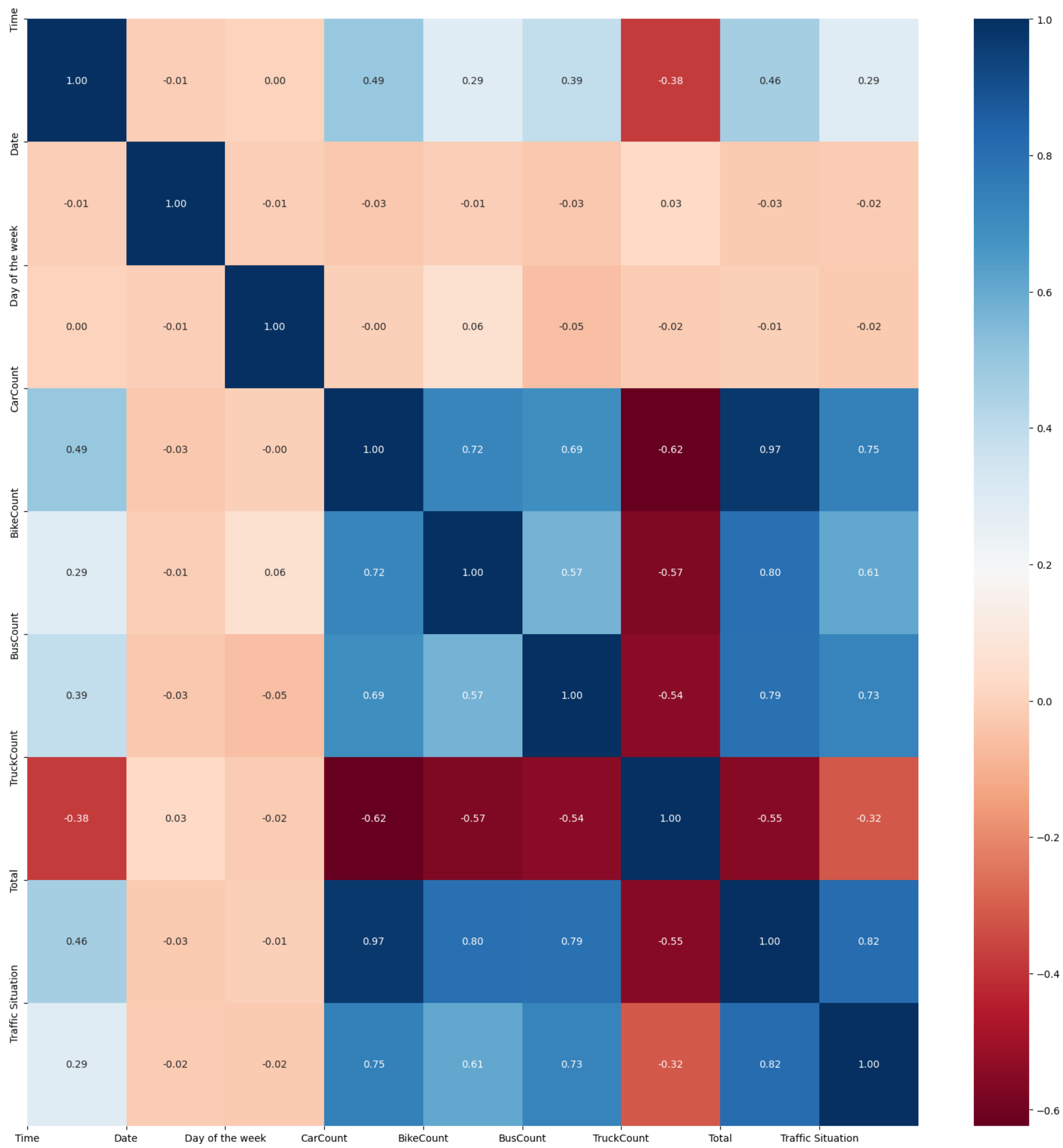
**

Feature Selection

**

[19]:

```
train_temp=train

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
train_temp['Time'] = le.fit_transform(train_temp['Time'])

corr = train_temp.corr(method='pearson')
fig, ax = plt.subplots(figsize=(20, 20))
sns.heatmap(corr, cmap='RdBu', annot=True, fmt=".2f")
plt.xticks(range(len(corr.columns)), corr.columns);
plt.yticks(range(len(corr.columns)), corr.columns)
plt.show()
```



We use Heatmap to find relations between features.

Most related features :

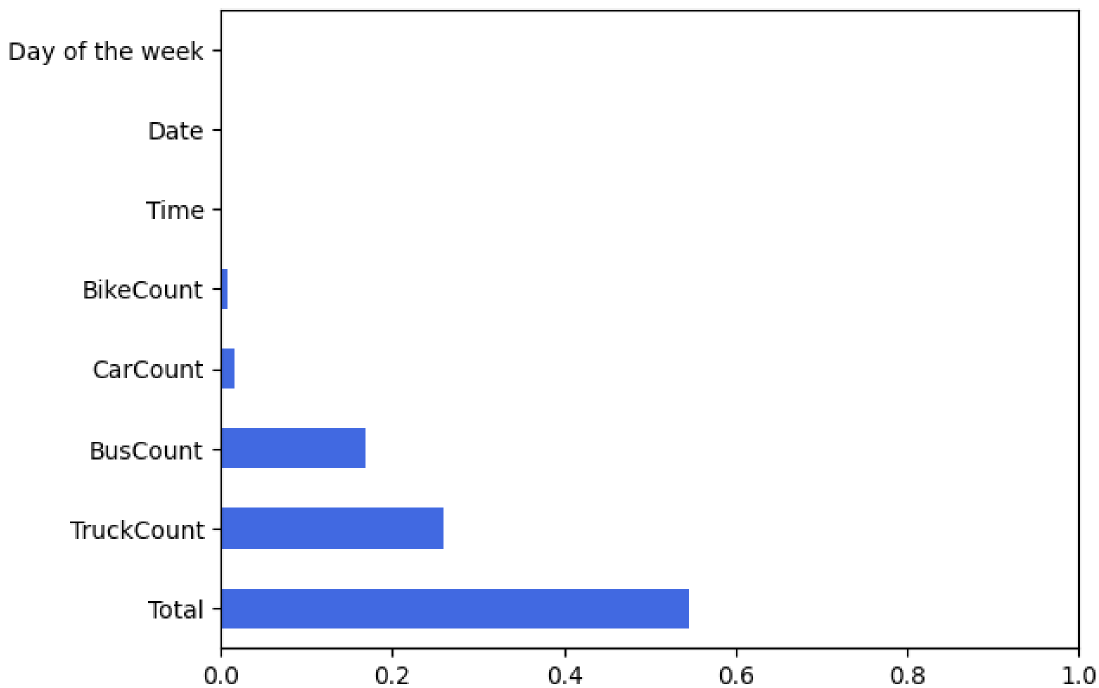
Total : 0.82

TruckCount : -0.32

[20]:
```
from xgboost import XGBClassifier
X_data_feature= train.drop(columns=['Traffic Situation'],axis=1)
y_data_feature= train['Traffic Situation']
```

```
model = [XGBClassifier()]

model = [model[i].fit(X_data_feature,y_data_feature) for i in range(len(model))]

num_chr = [12, 12, 10]

for i in range(len(model)):
    print(str(model[i])[:num_chr[i]] + ': \n',
          model[i].feature_importances_)
    feat_importances = pd.Series(model[i].feature_importances_,
                                 index=X_data_feature.columns)
    feat_importances.nlargest(10).plot(kind='barh', color='royalblue')
    plt.xlim(0, 1.0)
    plt.show()
```

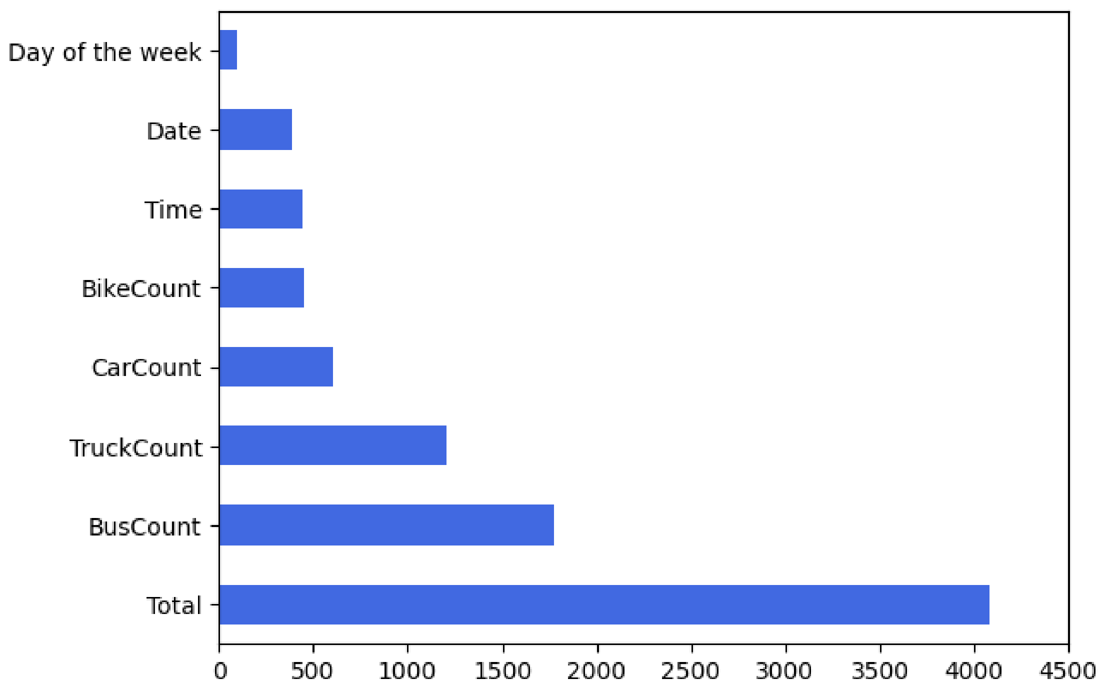
```
XGBClassifie:
 [1.8394163e-03 3.7277141e-04 1.7649922e-04 1.5505096e-02 7.1617216e-03
 1.6866037e-01 2.6005638e-01 5.4622775e-01]
```



[21]:
```
import lightgbm as lgb
from lightgbm import LGBMClassifier

model = [LGBMClassifier()]
```

```
model = [model[i].fit(X_data_feature,y_data_feature) for i in range(len(model))]

num_chr = [12, 12, 10]

for i in range(len(model)):
    print(str(model[i])[:num_chr[i]] + ': \n',
          model[i].feature_importances_)
    feat_importances = pd.Series(model[i].feature_importances_,
                                 index=X_data_feature.columns)
    feat_importances.nlargest(10).plot(kind='barh', color='royalblue')
    plt.xlim(0, 4500)
    plt.show()
```

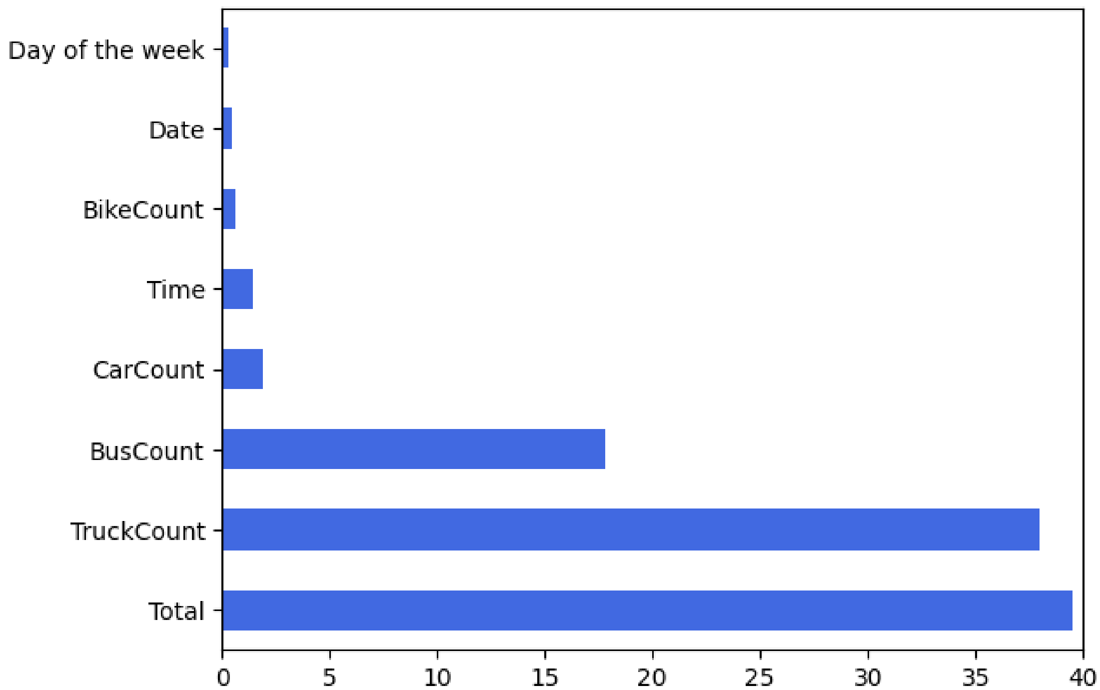
```
LGBMClassifi:
 [ 447  386   97  606  455 1779 1209 4081]
```



[22]:
```
from catboost import CatBoostClassifier

model = [CatBoostClassifier(logging_level='Silent')]

model = [model[i].fit(X_data_feature,y_data_feature) for i in range(len(model))]

num_chr = [12, 12, 10]
```

```
for i in range(len(model)):
    print(str(model[i])[:num_chr[i]] + ': \n',
          model[i].feature_importances_)
    feat_importances = pd.Series(model[i].feature_importances_,
                                 index=X_data_feature.columns)
    feat_importances.nlargest(10).plot(kind='barh', color='royalblue')
    plt.xlim(0, 40)
    plt.show()
```

```
<catboost.co:
 [ 1.46469851  0.43155772  0.31474545  1.92798683  0.63489931 17.78527162
 37.97612781 39.46471275]
```



To summarize the above three features important to judge, Day of the week and Date columns can be removed.

[23]:
```
train = train.drop(columns=["Day of the week","Date"],axis=1)
train
```

[23]:
```
      Time  CarCount  BikeCount  BusCount  TruckCount  Total  \
828     41        14         16         9          14     53
929     51       104         31        37           6    178
2170    37        91         22        34           8    155
2702    44        18          2         1          27     48
2676    89       105         14        13          32    164
```

```
…     …       …        …        …        …     …
1921     18        19        2        0         22      43
229      90        24       18       37         18      97
1835     38        19        2        1         12      34
2216     32        12        3        0         39      54
2313     34        12        3        0         22      37

      Traffic Situation
828                   1
929                   3
2170                  2
2702                  1
2676                  2
…                   …
1921                  1
229                   1
1835                  0
2216                  1
2313                  1

[2678 rows x 7 columns]
```

[26]:

```
X= train.drop(columns=["Traffic Situation"],axis=1)
y= train["Traffic Situation"]
```

[27]:

```
X_train=X
y_train=y

from sklearn.preprocessing import StandardScaler
StandardScaler = StandardScaler()
X_train = StandardScaler.fit_transform(X_train)
X_train = pd.DataFrame(X_train)
X_train
```

[27]:

```
             0         1         2         3         4         5
0    -0.248684 -1.200271  0.082850 -0.442325 -0.123578 -1.023389
1     0.113949  0.767295  1.253470  1.510645 -0.877003  1.056847
2    -0.393737  0.483091  0.551098  1.301398 -0.688647  0.674083
3    -0.139894 -1.112824 -1.009729 -1.000316  1.100737 -1.106598
4     1.491955  0.789157 -0.073233 -0.163329  1.571628  0.823860
…         …        …        …        …        …        …
2673 -1.082740 -1.090962 -1.009729 -1.070065  0.629847 -1.189808
2674  1.528218 -0.981653  0.238932  1.510645  0.253134 -0.291146
2675 -0.357474 -1.090962 -1.009729 -1.000316 -0.311934 -1.339584
2676 -0.575054 -1.243995 -0.931688 -1.070065  2.230875 -1.006747
2677 -0.502527 -1.243995 -0.931688 -1.070065  0.629847 -1.289659
```

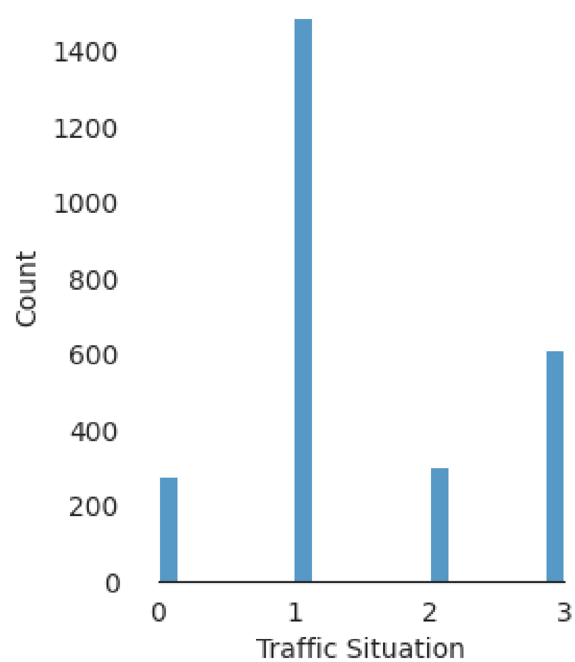
```
[2678 rows x 6 columns]
```

**

Target distribution

**

[28]:
```python
sns.set_style("white")
sns.set_color_codes(palette='deep')
f, ax = plt.subplots(figsize=(3, 4))
sns.histplot(y_train)
ax.xaxis.grid(False)

sns.despine(trim=True, left=True)
plt.show()

print("Skewness: %f" % y_train.skew())
print("Kurtosis: %f" % y_train.kurt())
```




```
Skewness: 0.527934
Kurtosis: -0.860804
```

Visualizing the distribution of targets.

**

Split Dataset

**

[29]:
```
from sklearn.model_selection import train_test_split
X_train, X_eval, y_train, y_eval = train_test_split(X_train,␣
↪y_train,test_size=0.2,random_state=2019)
print("Shape of X_train: ",X_train.shape)
print("Shape of X_eval: ", X_eval.shape)
print("Shape of y_train: ",y_train.shape)
print("Shape of y_eval",y_eval.shape)
```

```
Shape of X_train:  (2142, 6)
Shape of X_eval:  (536, 6)
Shape of y_train:  (2142,)
Shape of y_eval (536,)
```

[32]:
```
y_train =pd.DataFrame(y_train)
y_eval =pd.DataFrame(y_eval)
```

Splitting training and evaluation datasets.

**

VotingClassifier

**

[33]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import␣
↪LogisticRegression,SGDClassifier,RidgeClassifier
from sklearn.ensemble import␣
↪RandomForestClassifier,ExtraTreesClassifier,HistGradientBoostingClassifier,BaggingClassifie
from sklearn.ensemble import  AdaBoostClassifier, GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.dummy import DummyClassifier
from sklearn.svm import SVC
```

[34]:
```
from sklearn.ensemble import VotingClassifier
clf1 = AdaBoostClassifier()
clf2 = SGDClassifier()
clf3 = XGBClassifier()
clf4 = RandomForestClassifier()
clf5 = ExtraTreesClassifier()
clf6 = CatBoostClassifier(logging_level='Silent')
clf7 = KNeighborsClassifier()
clf8 = LogisticRegression()
clf9=  RidgeClassifier()
clf10= HistGradientBoostingClassifier()
clf11= BaggingClassifier()
clf12= GradientBoostingClassifier()
```

```
clf13= GaussianNB()
clf14= LGBMClassifier()
clf15= DummyClassifier()
clf16= SVC()

eclf = VotingClassifier(estimators=[('ADA', clf1), ('SGD', clf2), ('XGB',␣
↪clf3), ('RF', clf4), ('ET', clf5), ('CAT', clf6), ('KN', clf7),
                                   ('LG', clf8), ('RC', clf9), ('HBC', clf10),␣
↪('BC', clf11), ('GBC', clf12), ('GNB', clf13),
                                    ('LGBM', clf14),('DC', clf15),('SVC',␣
↪clf16)],voting='hard')

for clf, label in␣
↪zip([clf1,clf2,clf3,clf4,clf5,clf6,clf7,clf8,clf9,clf10,clf11,clf12,clf13,clf14,clf15,clf16
                      ['ADA',␣
↪'SGD','XGB','RF','ET','CAT','KN','LG','RC','HBC','BC','GBC','GNB','LGBM','DC','SVC']):
↪
    scores = cross_val_score(clf, X_train, y_train, scoring='accuracy', cv=5)
    print("Accuracy: %0.2f (+/- %0.2f) [%s]" % (scores.mean(), scores.std(),␣
↪label))
```

```
Accuracy: 0.55 (+/- 0.00) [ADA]
Accuracy: 0.86 (+/- 0.01) [SGD]
Accuracy: 1.00 (+/- 0.00) [XGB]
Accuracy: 1.00 (+/- 0.00) [RF]
Accuracy: 0.97 (+/- 0.00) [ET]
Accuracy: 1.00 (+/- 0.00) [CAT]
Accuracy: 0.93 (+/- 0.01) [KN]
Accuracy: 0.90 (+/- 0.02) [LG]
Accuracy: 0.77 (+/- 0.01) [RC]
Accuracy: 1.00 (+/- 0.00) [HBC]
Accuracy: 1.00 (+/- 0.00) [BC]
Accuracy: 1.00 (+/- 0.00) [GBC]
Accuracy: 0.81 (+/- 0.02) [GNB]
Accuracy: 1.00 (+/- 0.00) [LGBM]
Accuracy: 0.55 (+/- 0.00) [DC]
Accuracy: 0.94 (+/- 0.01) [SVC]
```

Just use the classification model (preset Parm) for testing , and remove some model with the low score .

remove ADA SGD KN LG RC GNB DC SVC , you also can remove the ET model , because it don't accuracy 100%.

**

StackingClassifier

**

I use VotingClassifier to select models and stackingclassifier for final prediction.

[35]:
```
class StackingAveragedModels(BaseEstimator, ClassifierMixin, TransformerMixin):
    def __init__(self, base_models, meta_model, n_folds=5):
        self.base_models = base_models
        self.meta_model = meta_model
        self.n_folds = n_folds

    def fit(self, X, y):
        self.base_models_ = [list() for x in self.base_models]
        self.meta_model_ = clone(self.meta_model)
        kfold = KFold(n_splits=self.n_folds, shuffle=True, random_state=156)

        # Train cloned base models then create out-of-fold predictions
        # that are needed to train the cloned meta-model
        out_of_fold_predictions = np.zeros((X.shape[0], len(self.base_models)))
        for i, model in enumerate(self.base_models):
            for train_index, holdout_index in kfold.split(X, y):
                instance = clone(model)
                self.base_models_[i].append(instance)
                instance.fit(X[train_index], y[train_index])
                y_pred = instance.predict(X[holdout_index])
                out_of_fold_predictions[holdout_index, i] = y_pred

        self.meta_model_.fit(out_of_fold_predictions, y)
        return self

    def predict(self, X):
        meta_features = np.column_stack([
            np.column_stack([model.predict(X) for model in base_models]).
 ↪mean(axis=1)
            for base_models in self.base_models_ ])
        return self.meta_model_.predict(meta_features)
```

[36]:
```
stacked_averaged_models = StackingAveragedModels(base_models =␣
 ↪(clf3,clf4,clf5,clf10,clf11,clf12,clf14),meta_model = clf6)
```

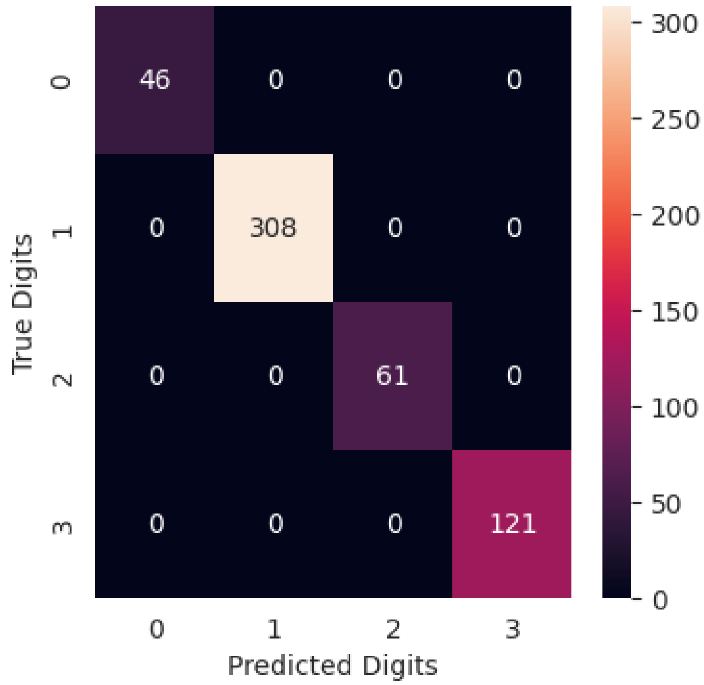
base model : XGB RF ET HBC BC GBC LGBM ; meta model : CAT

[37]:
```
stacking_model=stacked_averaged_models.fit(X_train.values, y_train.values)
```

[39]:
```
stacking_model.fit(X_train.values , y_train.values)
y_pred_stacking = stacking_model.predict(X_eval.values)
stacking_acc = accuracy_score(y_eval.values, y_pred_stacking)
print("stacking accuracy is: {0:.3f}%".format(stacking_acc * 100))
cm = confusion_matrix(y_eval, y_pred_stacking)
plt.figure(figsize=(4, 4))
sns.heatmap(cm, annot=True, fmt='.0f')
```

```
plt.xlabel("Predicted Digits")
plt.ylabel("True Digits")
plt.show()
```

```
stacking accuracy is: 100.000%
```



We obtained 100% accuracy on the evaluation dataset, but were unsure if there were any simulations that occurred before proceeding to the prediction test set.

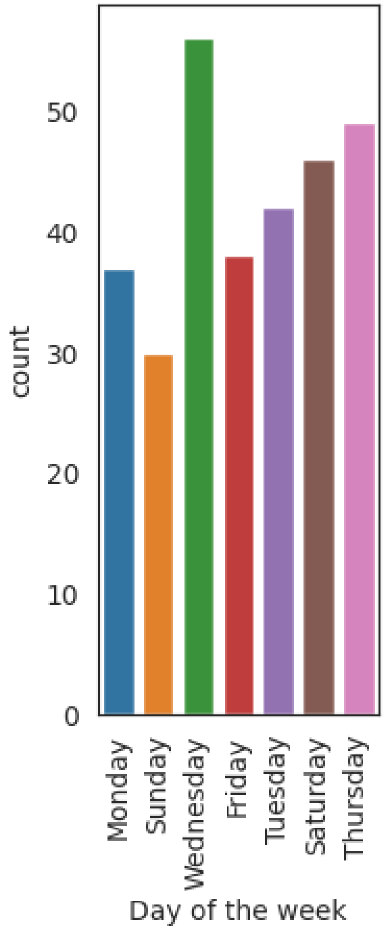
**

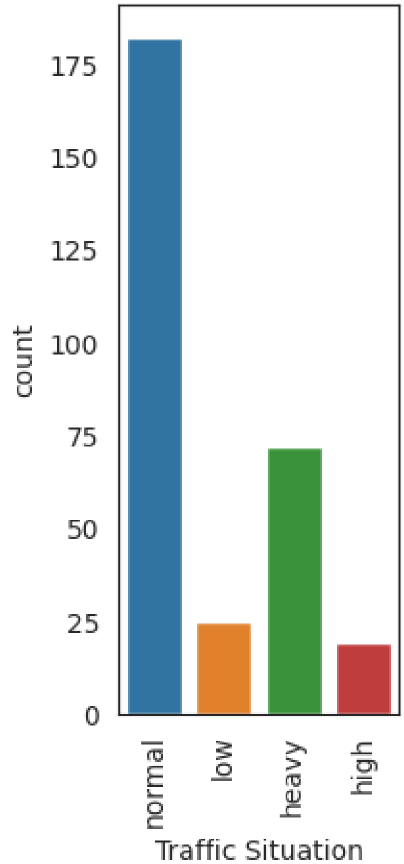
Predict test data

**

[40]:
```
test = test.reset_index(drop=True)
test_temp=test
```

[41]:
```
plt.subplot(1, 3, 1)
sns.countplot(x = test["Day of the week"])
plotter.xticks(rotation = 90);

plt.subplot(1, 3, 3)
sns.countplot(x = test["Traffic Situation"])
plotter.xticks(rotation = 90);
plt.show()
```





[42]:
```
df_temp=test_temp
df_temp['Day of the week'] = df_temp['Day of the week'].replace({'Monday':
 ↪1,'Tuesday':2,'Wednesday':3,'Thursday':4,'Friday':5,'Saturday': 6,'Sunday':
 ↪7})
df_temp['Traffic Situation'] = df_temp['Traffic Situation'].replace({'low':␣
 ↪0,'normal': 1,'high': 2, 'heavy':3})
test_temp=df_temp
test_temp
```

[42]:
```
            Time  Date  Day of the week  CarCount  BikeCount  BusCount  \
0    10:30:00 PM    23                1        12          0         0
1     9:30:00 AM    15                7        64         12        27
2    12:30:00 AM    18                3        20          5         0
3     5:00:00 AM    13                5        58         13         4
4     1:15:00 PM    20                5       161         50        10
..           …     …                …         …          …         …
293   5:00:00 AM    20                5        70          6         7
```

```
294  10:00:00 PM     9                4        17          4          1
295   9:45:00 PM    21                7        82         16         14
296   6:00:00 PM    29                7       112         13         37
297   8:00:00 AM    19                4       133         31         27

     TruckCount  Total  Traffic Situation
0            22     34                  1
1             8    111                  1
2            10     35                  0
3            15     90                  1
4             0    221                  3
..          …      …                  …
293          14     97                  1
294          20     42                  1
295          34    146                  2
296           6    168                  3
297           2    193                  3

[298 rows x 9 columns]
```

[43]:
```
test_temp = test_temp.drop(columns=['Traffic Situation'],axis=1)
test_temp
```

[43]:
```
            Time  Date  Day of the week  CarCount  BikeCount  BusCount  \
0    10:30:00 PM    23                1        12          0          0
1     9:30:00 AM    15                7        64         12         27
2    12:30:00 AM    18                3        20          5          0
3     5:00:00 AM    13                5        58         13          4
4     1:15:00 PM    20                5       161         50         10
..           …    …              …       …        …       …
293   5:00:00 AM    20                5        70          6          7
294  10:00:00 PM     9                4        17          4          1
295   9:45:00 PM    21                7        82         16         14
296   6:00:00 PM    29                7       112         13         37
297   8:00:00 AM    19                4       133         31         27

     TruckCount  Total
0            22     34
1             8    111
2            10     35
3            15     90
4             0    221
..          …      …
293          14     97
294          20     42
295          34    146
296           6    168
```

```
297           2    193

[298 rows x 8 columns]
```

[44]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
test_temp['Time'] = le.fit_transform(test_temp['Time'])
test_temp=test_temp.drop(columns=['Day of the week',"Date"],axis=1)
test_temp
```

[44]:

	Time	CarCount	BikeCount	BusCount	TruckCount	Total
0	5	12	0	0	22	34
1	87	64	12	27	8	111
2	20	20	5	0	10	35
3	55	58	13	4	15	90
4	27	161	50	10	0	221
..	…	…	…	…	…	…
293	55	70	6	7	14	97
294	1	17	4	1	20	42
295	90	82	16	14	34	146
296	63	112	13	37	6	168
297	77	133	31	27	2	193

[298 rows x 6 columns]

[45]:
```python
test_row = test_temp.shape[0]
test_row
```

[45]: 298

[46]:
```python
import_train = X.reset_index(drop=True)
import_train
```

[46]:

	Time	CarCount	BikeCount	BusCount	TruckCount	Total
0	41	14	16	9	14	53
1	51	104	31	37	6	178
2	37	91	22	34	8	155
3	44	18	2	1	27	48
4	89	105	14	13	32	164
…	…	…	…	…	…	…
2673	18	19	2	0	22	43
2674	90	24	18	37	18	97
2675	38	19	2	1	12	34
2676	32	12	3	0	39	54
2677	34	12	3	0	22	37

[2678 rows x 6 columns]

[47]:
```python
Row_Number=test_row
X_test_target1_df=import_train._append(test_temp,ignore_index=True)

from sklearn.preprocessing import StandardScaler
StandardScaler = StandardScaler()
X_test_target1_df = StandardScaler.fit_transform(X_test_target1_df)
test_pred_target0= pd.DataFrame(X_test_target1_df)
test_pred_target0 = pd.DataFrame(test_pred_target0).tail(Row_Number)#tail:
test_pred_target0 = test_pred_target0.reset_index(drop=True)
test_pred_target0
```

[47]:
```
            0         1         2         3         4         5
0   -1.536183 -1.236756 -1.161302 -1.065552  0.629601 -1.332963
1    1.437268 -0.102449 -0.227112  0.817348 -0.690898 -0.053479
2   -0.992259 -1.062247 -0.772056 -1.065552 -0.502255 -1.316347
3    0.276897 -0.233331 -0.149263 -0.786604 -0.030648 -0.402429
4   -0.738428  2.013469  2.731155 -0.368182 -1.445469  1.774355
..        …         …         …         …         …         …
293  0.276897  0.028432 -0.694207 -0.577393 -0.124969 -0.286113
294 -1.681229 -1.127688 -0.849905 -0.995815  0.440959 -1.200030
295  1.546052  0.290195  0.084284 -0.089233  1.761458  0.528104
296  0.566989  0.944603 -0.149263  1.514719 -0.879540  0.893671
297  1.074652  1.402688  1.252021  0.817348 -1.256826  1.309088

[298 rows x 6 columns]
```

[48]:
```python
test_pred_target0.isnull().sum()
```

[48]:
```
0    0
1    0
2    0
3    0
4    0
5    0
dtype: int64
```

[49]:
```python
Stacking_predict=stacking_model.predict(test_pred_target0.values)
```

[50]:
```python
#DataFrame
Stacking_predict_df=pd.DataFrame(Stacking_predict)

#rename lable
Stacking_predict_df=Stacking_predict_df.set_axis(axis=1,labels=['Stack_pred'])

#merge predict
test_pred=test.
 ↪merge(Stacking_predict_df,how='inner',left_index=True,right_index=True)
```

```
test_pred
```

[50]:

```
           Time  Date  Day of the week  CarCount  BikeCount  BusCount  \
0    10:30:00 PM    23                1        12          0         0
1     9:30:00 AM    15                7        64         12        27
2    12:30:00 AM    18                3        20          5         0
3     5:00:00 AM    13                5        58         13         4
4     1:15:00 PM    20                5       161         50        10
..           …     …              …       …          …         …
293   5:00:00 AM    20                5        70          6         7
294  10:00:00 PM     9                4        17          4         1
295   9:45:00 PM    21                7        82         16        14
296   6:00:00 PM    29                7       112         13        37
297   8:00:00 AM    19                4       133         31        27

     TruckCount  Total  Traffic Situation  Stack_pred
0            22     34                  1           1
1             8    111                  1           1
2            10     35                  0           0
3            15     90                  1           1
4             0    221                  3           3
..          …     …                …          …
293          14     97                  1           1
294          20     42                  1           1
295          34    146                  2           2
296           6    168                  3           3
297           2    193                  3           3

[298 rows x 10 columns]
```

**

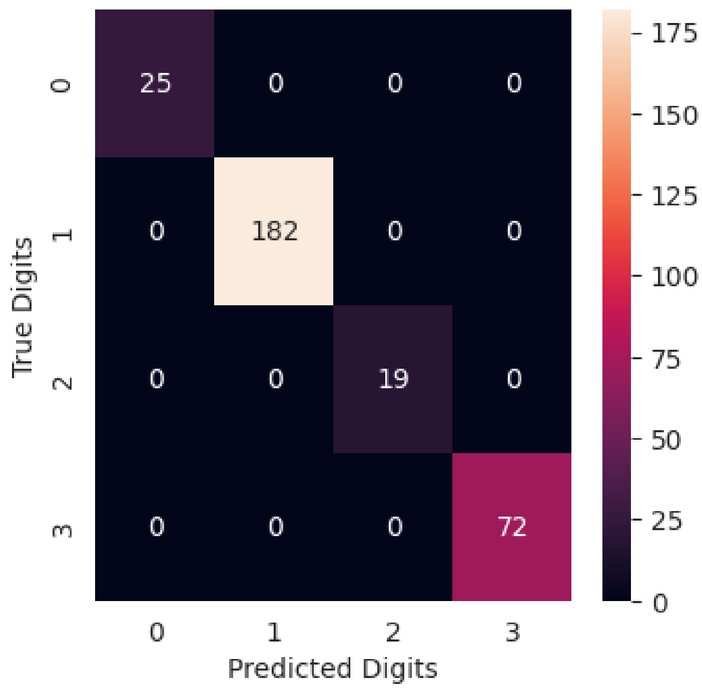
Accuracy

**

[51]:

```
stacking_acc = accuracy_score(test_pred['Traffic Situation'],␣
 ↪test_pred['Stack_pred'])
print("stacking accuracy is: {0:.3f}%".format(stacking_acc * 100))
cm = confusion_matrix(test_pred['Traffic Situation'], test_pred['Stack_pred'])
plt.figure(figsize=(4, 4))
sns.heatmap(cm, annot=True, fmt='.0f')
plt.xlabel("Predicted Digits")
plt.ylabel("True Digits")
plt.show()
```

```
stacking accuracy is: 100.000%
```



It's great. We obtained 100% accuracy on the evaluation test set.