traffic-accidents-analysis-and-ml

March 27, 2025

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
pd.set_option("display.max_columns",None)
pd.set_option('display.float_format', '{:.2f}'.format)
```

[2]:
```python
from sklearn.linear_model import Ridge, Lasso, ElasticNet , LinearRegression
from sklearn.model_selection import RandomizedSearchCV , cross_validate ,␣
↪train_test_split
from xgboost import XGBRegressor
from sklearn.metrics import r2_score , mean_squared_error
from keras.models import Sequential
from keras.layers import Dense
import tensorflow as tf
from catboost import CatBoostRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import BayesianRidge
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import VotingRegressor
```

[3]:
```python
data = pd.read_csv("traffic_accidents_dict new.csv")
df = data.copy()
df.head()
```

[3]:
```
   accidents  traffic_fine_amount  traffic_density  traffic_lights  \
0         20                 4.37             2.30          753.00
1         11                 9.56             3.28            5.45
2         19                 7.59             2.10            6.70
3         23                 6.39             4.92            9.41
4         23                 2.40             1.96            7.39
```

```
   pavement_quality  urban_area  average_speed  rain_intensity  vehicle_count  \
0              0.77           1         321.59            1.19         290.86
1              4.05           1         478.62            6.30         931.81
2            345.00           0         364.48            2.86         830.09
3              4.73           0          20.92            2.11         813.16
4              1.71           1          37.38            1.70           1.47

   time_of_day             Variable  \
0       160.43            accidents
1         8.91  traffic_fine_amount
2         5.57      traffic_density
3       131.45       traffic_lights
4         6.96     pavement_quality

                                         Description
0  Number of recorded accidents, as a positive in…
1  Traffic fine amount, expressed in thousands of…
2  Traffic density index, scale from 0 (low) to 1…
3  Proportion of traffic lights in the area (0 to…
4  Pavement quality, scale from 0 (very poor) to …
```

[4]:
```
def check_df(data,head=False):
    print("-------------------------- SHAPE --------------------------")
    print(data.shape)
    print("-------------------------- INFO --------------------------")
    print(data.info())
    print("-------------------------- ISNA --------------------------")
    print(data.isnull().sum().sort_values(ascending=False))
    print("-------------------------- NUNIQUE --------------------------")
    print(data.nunique().sort_values())
    print("-------------------------- DUPLICATED --------------------------")
    print(data.duplicated().sum())
    print("-------------------------- DESCRIBE --------------------------")
    display(data.describe().T)
    if head:
        print("-------------------------- HEAD --------------------------")
        display(data.head())
        print("-------------------------- TAIL --------------------------")
        display(data.tail())
```

[5]:
```
def col_types(data):
    cat_cols = [col for col in data.columns if data[col].dtypes=="O"]
    num_cols = [col for col in data.columns if data[col].dtypes!="O"]
    print(f"OBSERVISION : {data.shape[1]}")
    print(f"CAT COLS : {len(cat_cols)}")
    print(f"NUM COLS : {len(num_cols)}")
    return cat_cols , num_cols
```

[6]:

```
def box_plot(df,col):
    sns.boxplot(data=df,x=col,palette="inferno")
    plt.title(f"{col.upper()} boxplot")
    plt.tight_layout()
    plt.show()
```

[7]:

```
def outlier_thresholds(dataframe, col_name, q1=0.25, q3=0.75):
    quantile1 = dataframe[col_name].quantile(q1)
    quantile3 = dataframe[col_name].quantile(q3)
    interquantile_range = quantile3 - quantile1
    up_limit = quantile3 + 1.5 * interquantile_range
    low_limit = quantile1 - 1.5 * interquantile_range
    return low_limit, up_limit
```

[8]:

```
def check_outlier(dataframe, col_name):
    low_limit, up_limit = outlier_thresholds(dataframe, col_name)
    if dataframe[(dataframe[col_name] > up_limit) | (dataframe[col_name] <␣
↪low_limit)].any(axis=None):
        return True
    else:
        return False
```

[9]:

```
def replace_with_thresholds(dataframe, variable):
    low_limit, up_limit = outlier_thresholds(dataframe, variable)
    dataframe.loc[(dataframe[variable] < low_limit), variable] = low_limit
    dataframe.loc[(dataframe[variable] > up_limit), variable] = up_limit
```

[10]:

```
def cat_plot(df, col):
    plt.figure(figsize=(14,6))
    order = df[col].value_counts().index
    ax = sns.countplot(x=col, data=df, palette="viridis", order=order)
    total = len(df[col])
    for p in ax.patches:
        height = p.get_height()
        percentage = (height / total) * 100
        ax.text(p.get_x() + p.get_width() / 2, height + 1, f'{percentage:.2f}%',
                ha="center", va="bottom", fontsize=10)
    plt.title(col.upper())
    plt.ylabel(col.upper())
    plt.xticks(rotation=45)
    plt.xlabel("COUNT")
    plt.tight_layout()
    plt.show()
  ␣
↪print("---------------------------------------------------------------------------------
↪end="\n\n")
```

[11]:
```
def hist_plot(data, col):
    plt.figure(figsize=(10,6))
    sns.histplot(x=col,data=df,kde=True,bins=25,color="g")
    plt.title(col.upper())
    plt.ylabel("COUNT")
    plt.xlabel(col.upper())
    plt.tight_layout()
    plt.show()
   ␣
 ↪print("-----------------------------------------------------------------------------------
```

[12]:
```
def base_models(X,y,scoring="neg_mean_squared_error"):
  print("Base Models")
  regressions = [('Ridge',Ridge(alpha=1)),
                ('Lasso',Lasso(alpha=1)),
                ('ElasticNet',ElasticNet(alpha=1,l1_ratio=0.5)),
                ("Linear",LinearRegression()),
                ("Decision Tree",DecisionTreeRegressor()),
                ("Random Forest",RandomForestRegressor()),
                ('Gradient Boosting', GradientBoostingRegressor()),
                ("XGB",XGBRegressor(objective='reg:squarederror')),
                ('KNN', KNeighborsRegressor()),
                ('MLP', MLPRegressor()),
                ('Bayesian Ridge', BayesianRidge()),
                ("CatBoost",CatBoostRegressor(verbose=0))]
  for name,regression in regressions:
    cv_results = cross_validate(regression,X,y,cv=10,scoring=scoring)
    print(f"{scoring}: {round(cv_results['test_score'].mean(),4)} {name}")
```

[13]:
```
def hyperparameter_optimization_randomized(X, y, cv=5, scoring="r2",␣
 ↪n_iter=100):
    print("HYPERPARAMETER OPTIMIZATION WITH RANDOMIZEDSEARCH")
    best_models = {}


    regressors = [
        ('GradientBoosting', GradientBoostingRegressor(), gb_params),
        ('CatBoost', CatBoostRegressor(verbose=0), cat_params),
        ('XGBoost', XGBRegressor(objective='reg:squarederror'), xgb_params)
    ]

    for name, regressor, params in regressors:
        print(f"----------------- {name} -----------------")


        cv_results = cross_validate(regressor, X, y, cv=cv, scoring=scoring)
```

```
        print(f"{scoring} (Before): {round(cv_results['test_score'].mean(),␣
↪4)}")


        rs_best = RandomizedSearchCV(
            regressor,
            params,
            cv=cv,
            n_jobs=-1,
            verbose=False,
            n_iter=n_iter,
            random_state=42
        ).fit(X, y)


        final_model = regressor.set_params(**rs_best.best_params_)


        cv_results = cross_validate(final_model, X, y, cv=cv, scoring=scoring)
        print(f"{scoring} (After): {round(cv_results['test_score'].mean(), 4)}")
        print(f"{name} best params: {rs_best.best_params_}", end="\n\n")


        best_models[name] = final_model

    return best_models
```

[14]:
```
def voting_regressor(best_models, X, y, cv=5):
    print("Voting Regressor")

    voting_reg = VotingRegressor(estimators=[
        ("XGB", best_models['XGBoost']),
        ("GradientBoosting", best_models['GradientBoosting']),
        ("CatBoost",best_models["CatBoost"])
    ]).fit(X, y)


    cv_results = cross_validate(voting_reg, X, y, cv=cv,␣
↪scoring=["neg_mean_squared_error", "r2"])

    print(f"Neg MSE: {-cv_results['test_neg_mean_squared_error'].mean()}")
    print(f"R^2: {cv_results['test_r2'].mean()}")

    return voting_reg
```

[15]:
```
def plot_importance_ensemble(voting_reg, features):
    num=len(features)
```

```python
    feature_imp_df = pd.DataFrame(0, index=features.columns, columns=["Value"])


    for model in voting_reg.estimators_:
        if hasattr(model, 'feature_importances_'):

            feature_imp_df["Value"] += model.feature_importances_ /100


    feature_imp_df["Feature"] = features.columns
    feature_imp_df = feature_imp_df.sort_values(by="Value", ascending=False)


    plt.figure(figsize=(12, 7))
    sns.set(font_scale=1)
    ax = sns.barplot(x="Value", y="Feature", data=feature_imp_df[0:num])

    for p in ax.patches:
        ax.annotate(format(p.get_width(), '.4f'),
                    (p.get_width(), p.get_y() + p.get_height() / 2),
                    ha='left', va='center', fontsize=8)

    plt.title("Feature Importance - Voting Regressor")
    plt.tight_layout()
    plt.show()
```

[16]:

```python
check_df(df,True)
```

```
-------------------------- SHAPE --------------------------
(8756, 12)
-------------------------- INFO -------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8756 entries, 0 to 8755
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   accidents            8756 non-null   int64
 1   traffic_fine_amount  8756 non-null   float64
 2   traffic_density      8756 non-null   float64
 3   traffic_lights       8756 non-null   float64
 4   pavement_quality     8756 non-null   float64
 5   urban_area           8756 non-null   int64
 6   average_speed        8756 non-null   float64
 7   rain_intensity       8756 non-null   float64
 8   vehicle_count        8756 non-null   float64
 9   time_of_day          8756 non-null   float64
 10  Variable             8756 non-null   object
 11  Description          8756 non-null   object
```

```
dtypes: float64(8), int64(2), object(2)
memory usage: 821.0+ KB
None
-------------------------- ISNA --------------------------
accidents              0
traffic_fine_amount    0
traffic_density        0
traffic_lights         0
pavement_quality       0
urban_area             0
average_speed          0
rain_intensity         0
vehicle_count          0
time_of_day            0
Variable               0
Description            0
dtype: int64
-------------------------- NUNIQUE --------------------------
urban_area                2
Variable                 11
Description              12
accidents                31
traffic_lights         5600
rain_intensity         7416
pavement_quality       7892
traffic_fine_amount    8326
traffic_density        8330
time_of_day            8586
average_speed          8675
vehicle_count          8717
dtype: int64
-------------------------- DUPLICATED --------------------------
0
-------------------------- DESCRIBE --------------------------

                      count   mean    std  min    25%    50%    75%    max
accidents           8756.00  20.63   5.23 5.00  17.00  21.00  24.00  35.00
traffic_fine_amount 8756.00   5.45   2.60 1.00   3.20   5.43   7.68  10.00
traffic_density     8756.00  14.25  75.97 0.24   3.32   5.56   7.89 996.00
traffic_lights      8756.00  93.29 224.17 0.00   3.78   6.50   9.23 999.00
pavement_quality    8756.00  22.44 112.19 0.00   2.10   3.28   4.43 994.00
urban_area          8756.00   0.69   0.46 0.00   0.00   1.00   1.00   1.00
average_speed       8756.00 214.64 168.71 0.97  12.51 223.13 360.94 932.00
rain_intensity      8756.00  33.86 140.05 0.00   1.67   2.36   3.70 999.00
vehicle_count       8756.00 453.23 313.88 1.03 169.46 453.98 729.15 999.62
time_of_day         8756.00  83.65  97.82 0.12   6.51  12.18 174.78 999.00

-------------------------- HEAD --------------------------
```

```
   accidents  traffic_fine_amount  traffic_density  traffic_lights  \
0         20                 4.37             2.30          753.00   
1         11                 9.56             3.28            5.45   
2         19                 7.59             2.10            6.70   
3         23                 6.39             4.92            9.41   
4         23                 2.40             1.96            7.39   

   pavement_quality  urban_area  average_speed  rain_intensity  vehicle_count  \
0              0.77           1         321.59            1.19         290.86   
1              4.05           1         478.62            6.30         931.81   
2            345.00           0         364.48            2.86         830.09   
3              4.73           0          20.92            2.11         813.16   
4              1.71           1          37.38            1.70           1.47   

   time_of_day             Variable  \
0       160.43            accidents   
1         8.91  traffic_fine_amount   
2         5.57      traffic_density   
3       131.45       traffic_lights   
4         6.96     pavement_quality   

                                         Description  
0  Number of recorded accidents, as a positive in…  
1  Traffic fine amount, expressed in thousands of…  
2  Traffic density index, scale from 0 (low) to 1…  
3  Proportion of traffic lights in the area (0 to…  
4  Pavement quality, scale from 0 (very poor) to …  
-------------------------- TAIL --------------------------
      accidents  traffic_fine_amount  traffic_density  traffic_lights  \
8751         27                 2.77             6.94            6.60   
8752         18                 3.26             1.73          549.00   
8753         31                 2.56             8.53            2.78   
8754         10                 9.62             1.40            2.72   
8755         12                 8.69             4.20            5.39   

      pavement_quality  urban_area  average_speed  rain_intensity  \
8751              3.36           1         302.00            1.98   
8752              2.85           1           6.30            8.27   
8753              3.28           1         479.93            2.82   
8754              5.78           1         280.78            6.40   
8755              2.38           0         234.63            1.12   

      vehicle_count  time_of_day Variable Description  
8751         258.92        11.15        0           0  
8752         296.40        17.04        0           0  
8753         458.21       192.77        0           0  
8754         147.66         3.64        0           0  
```

```
8755          483.98         1.08        0           0
```

[17]:
```
cat_cols , num_cols = col_types(df)
```

```
OBSERVISION : 12
CAT COLS : 2
NUM COLS : 10
```

[18]:
```
df[cat_cols].head()
```

[18]:

	Variable	Description
0	accidents	Number of recorded accidents, as a positive in…
1	traffic_fine_amount	Traffic fine amount, expressed in thousands of…
2	traffic_density	Traffic density index, scale from 0 (low) to 1…
3	traffic_lights	Proportion of traffic lights in the area (0 to…
4	pavement_quality	Pavement quality, scale from 0 (very poor) to …

[19]:
```
df[num_cols].head()
```

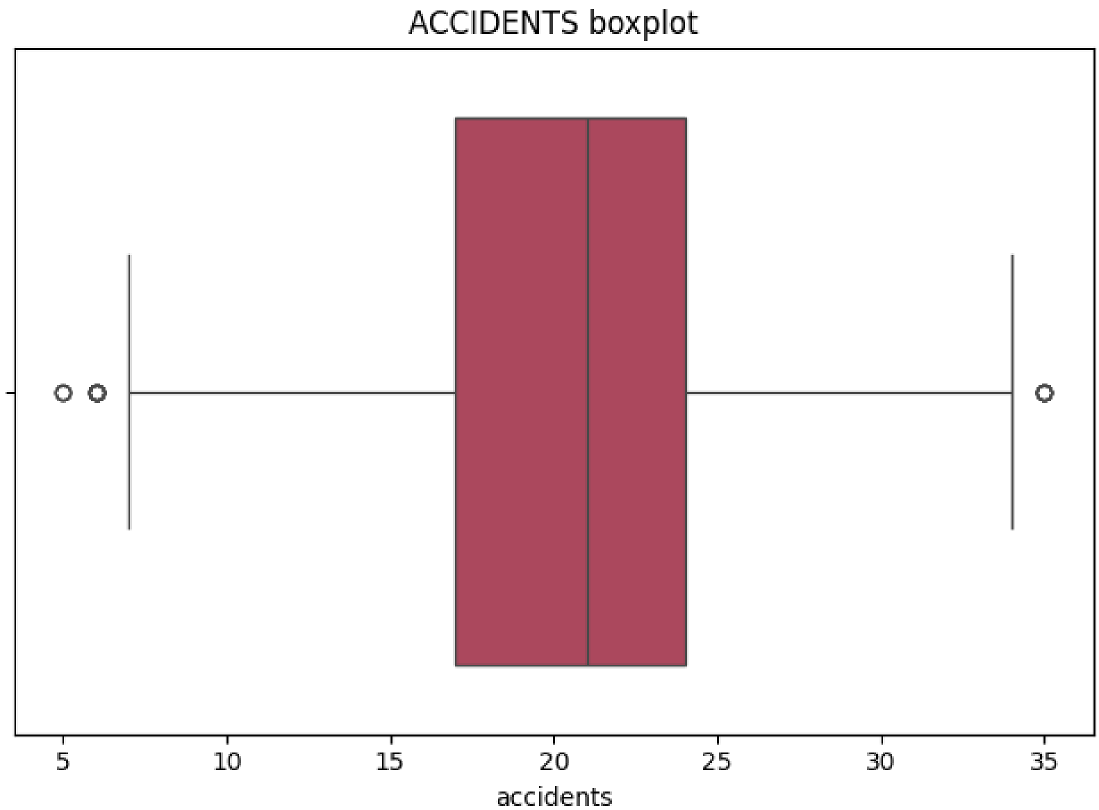
[19]:

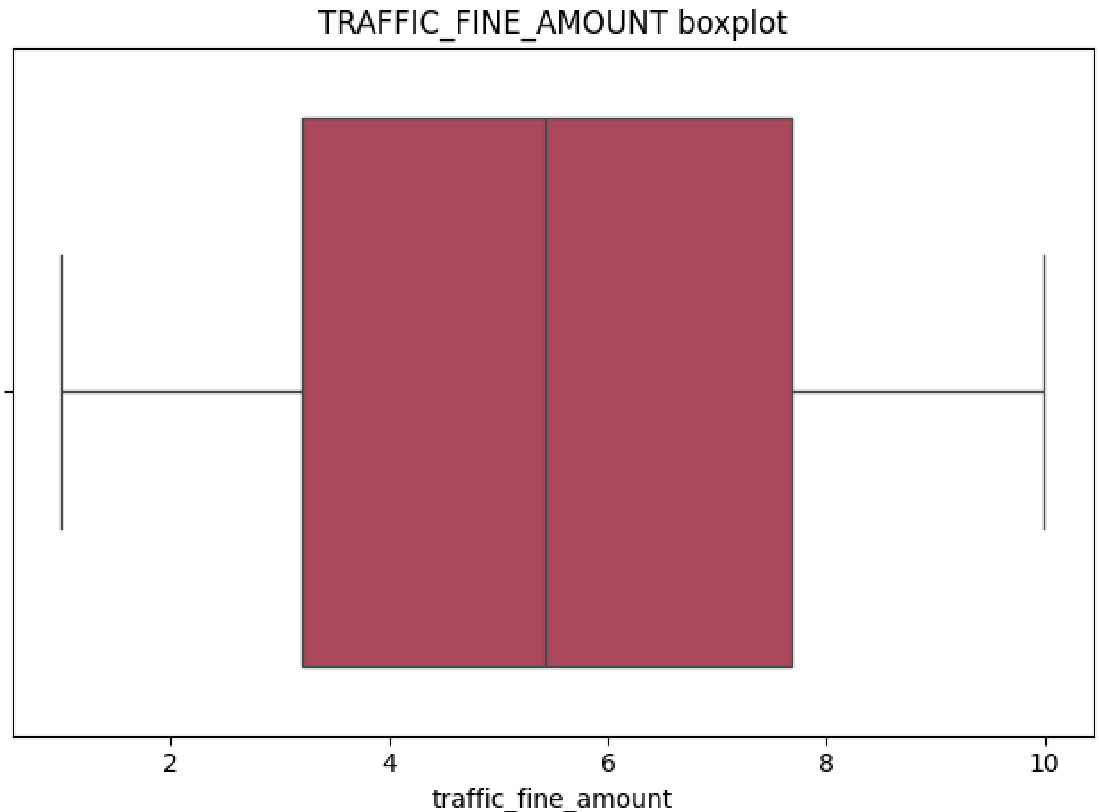
	accidents	traffic_fine_amount	traffic_density	traffic_lights	\
0	20	4.37	2.30	753.00	
1	11	9.56	3.28	5.45	
2	19	7.59	2.10	6.70	
3	23	6.39	4.92	9.41	
4	23	2.40	1.96	7.39	

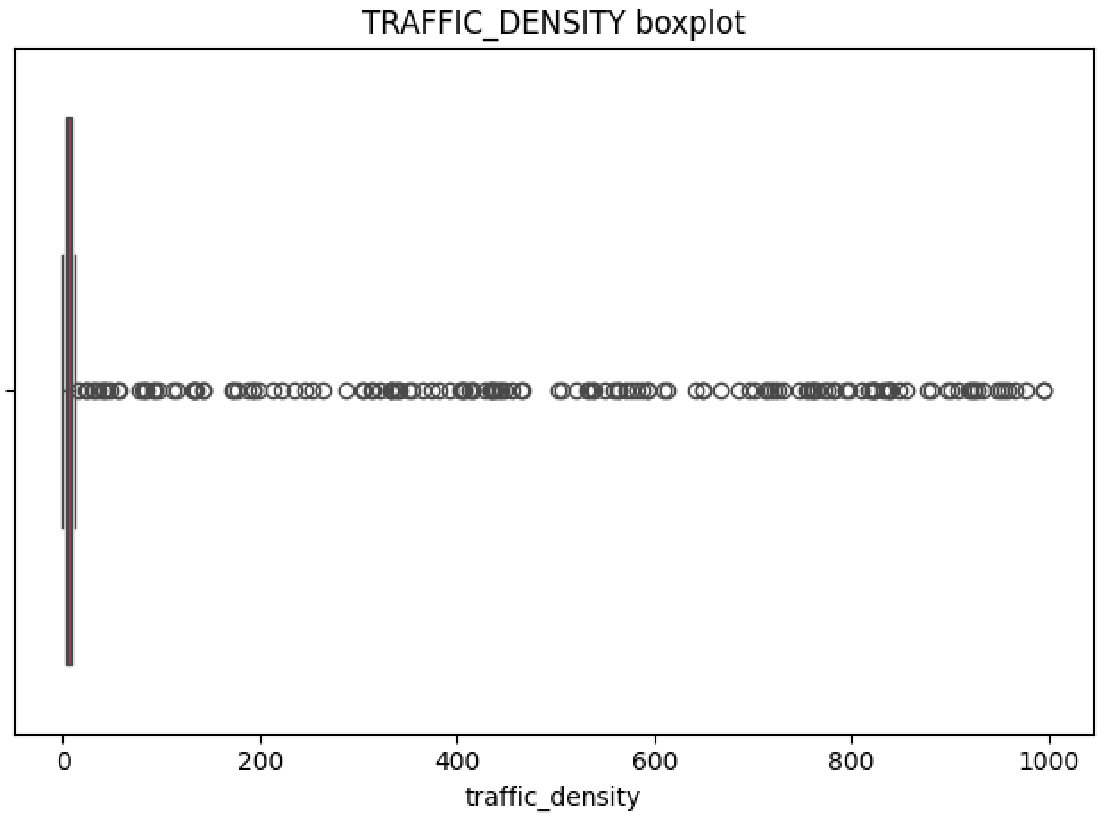
	pavement_quality	urban_area	average_speed	rain_intensity	vehicle_count	\
0	0.77	1	321.59	1.19	290.86	
1	4.05	1	478.62	6.30	931.81	
2	345.00	0	364.48	2.86	830.09	
3	4.73	0	20.92	2.11	813.16	
4	1.71	1	37.38	1.70	1.47	

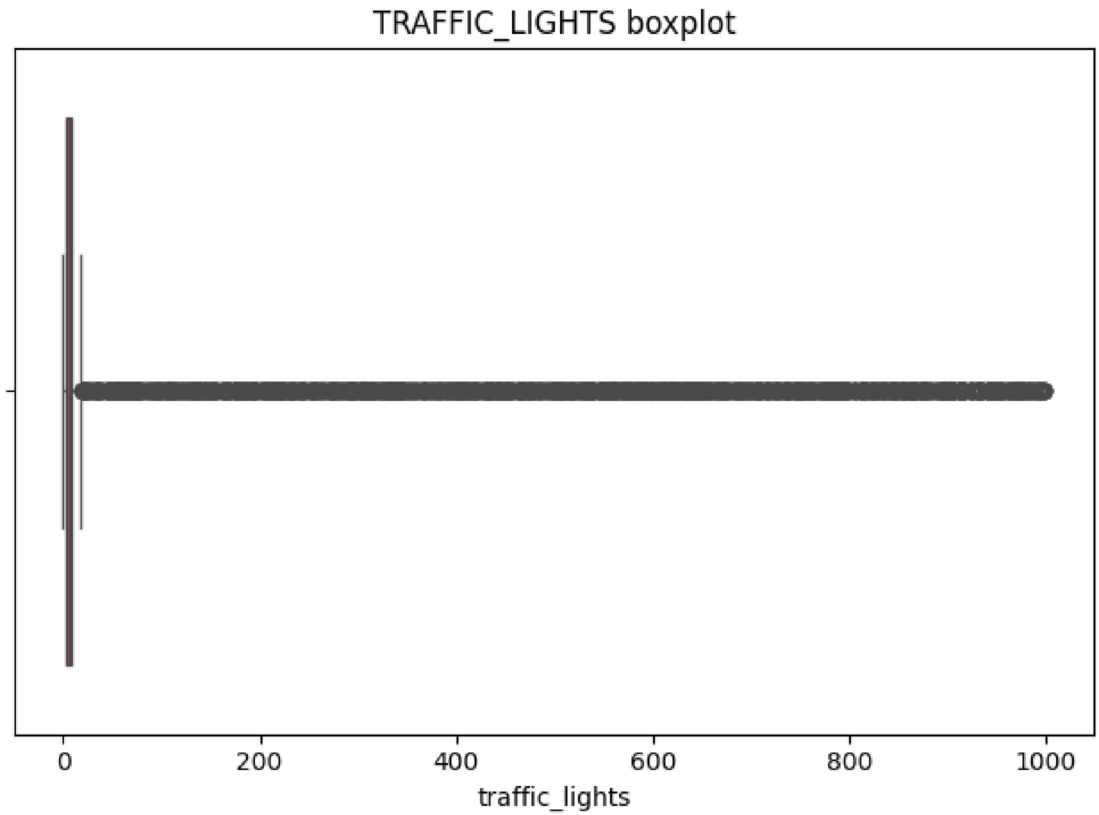
	time_of_day
0	160.43
1	8.91
2	5.57
3	131.45
4	6.96

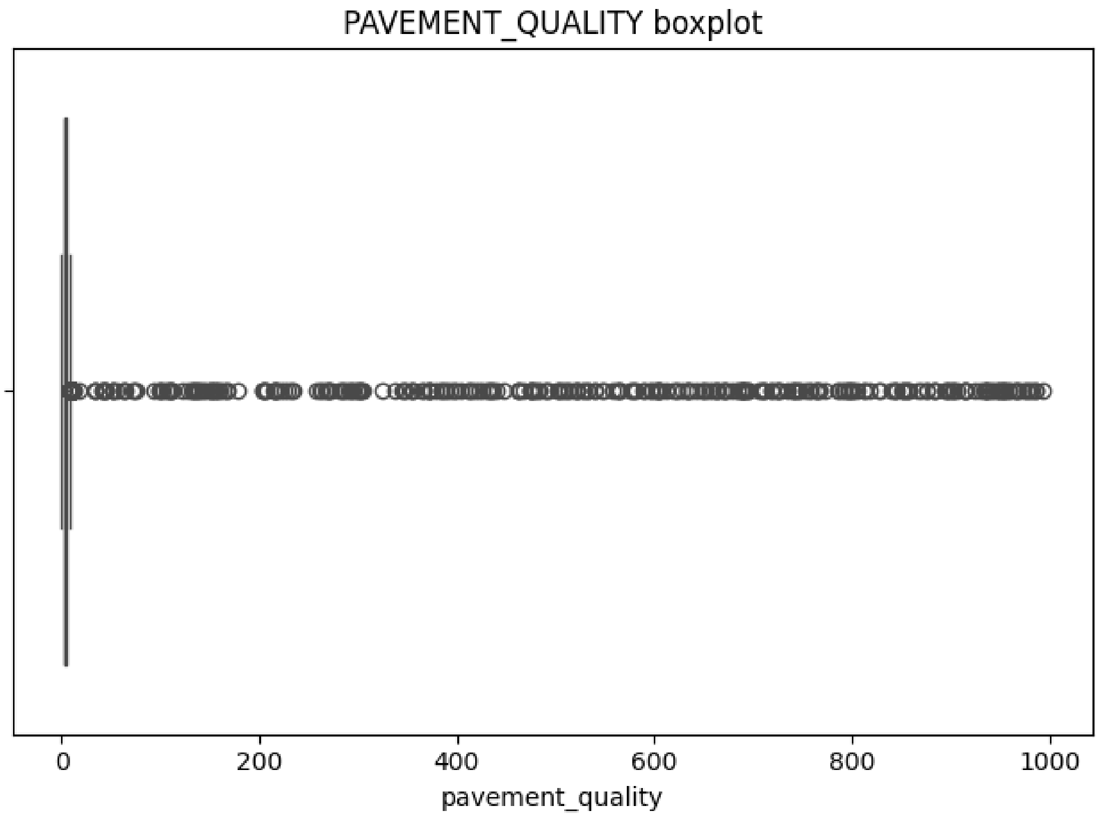
[20]:
```
for col in num_cols:
    box_plot(df,col)
```

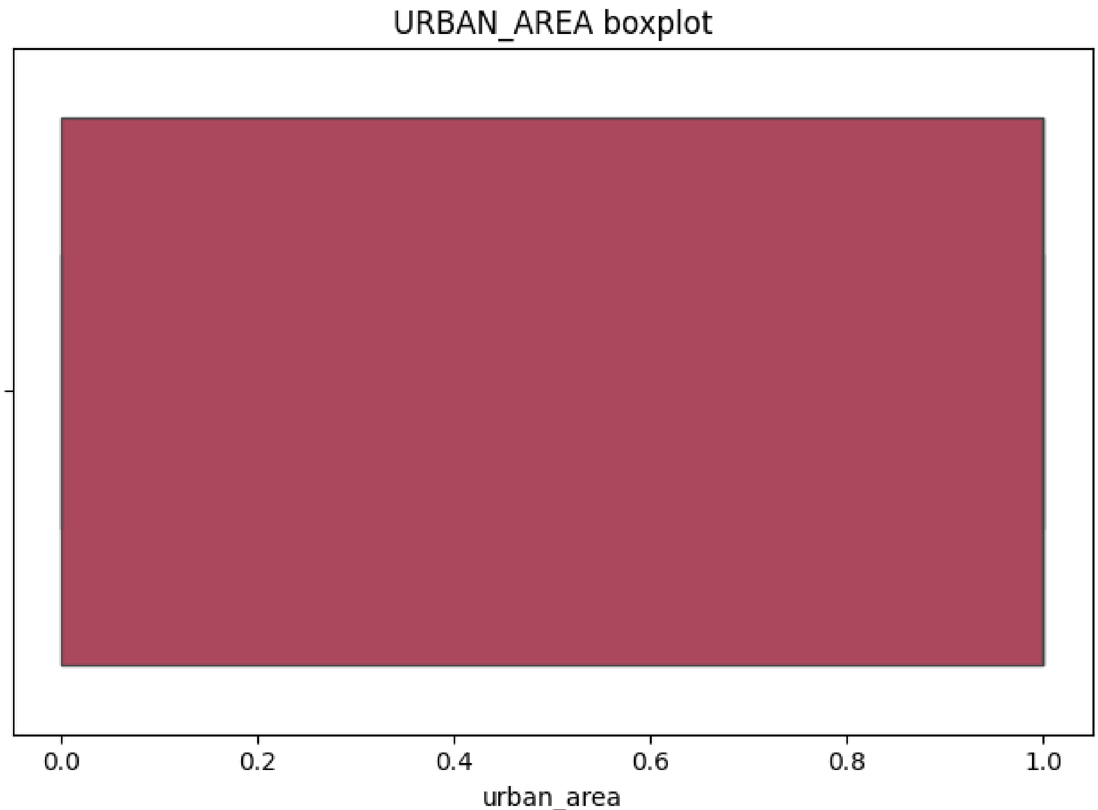

ACCIDENTS boxplot
5
10
15
20
25
30
35
accidents

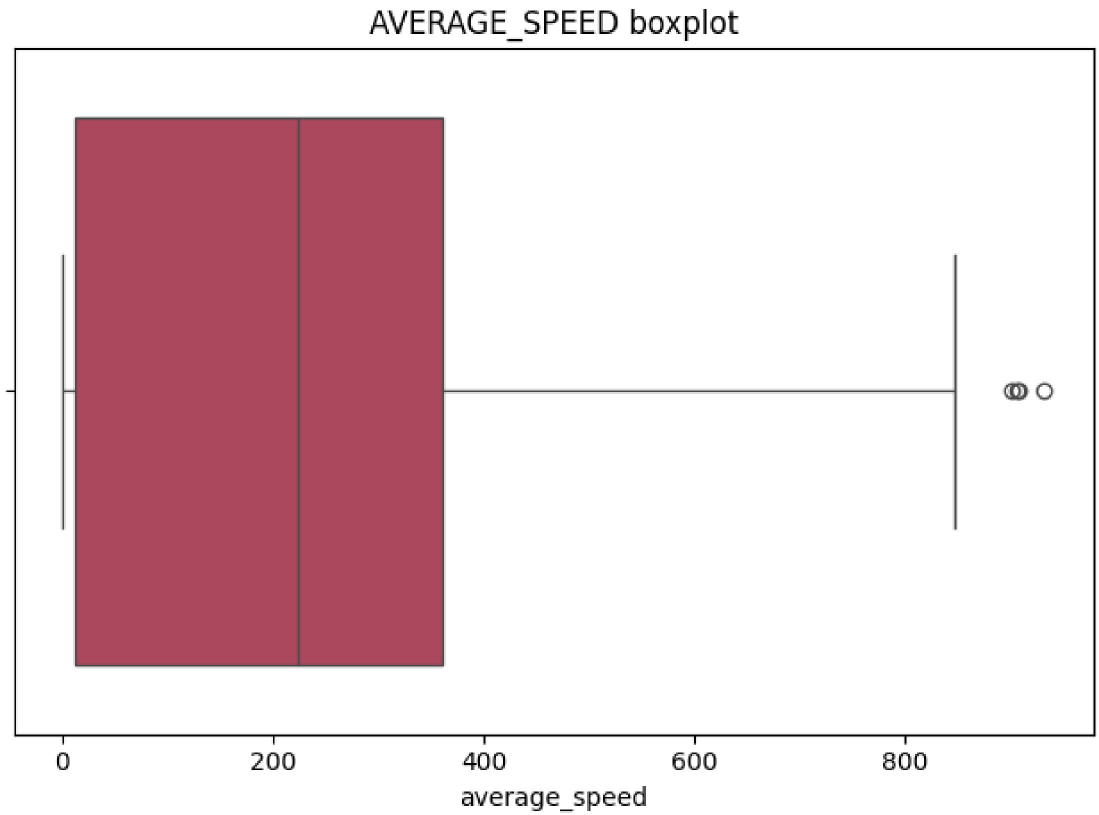

TRAFFIC_FINE_AMOUNT boxplot
2
4
6
8
10
traffic_fine_amount

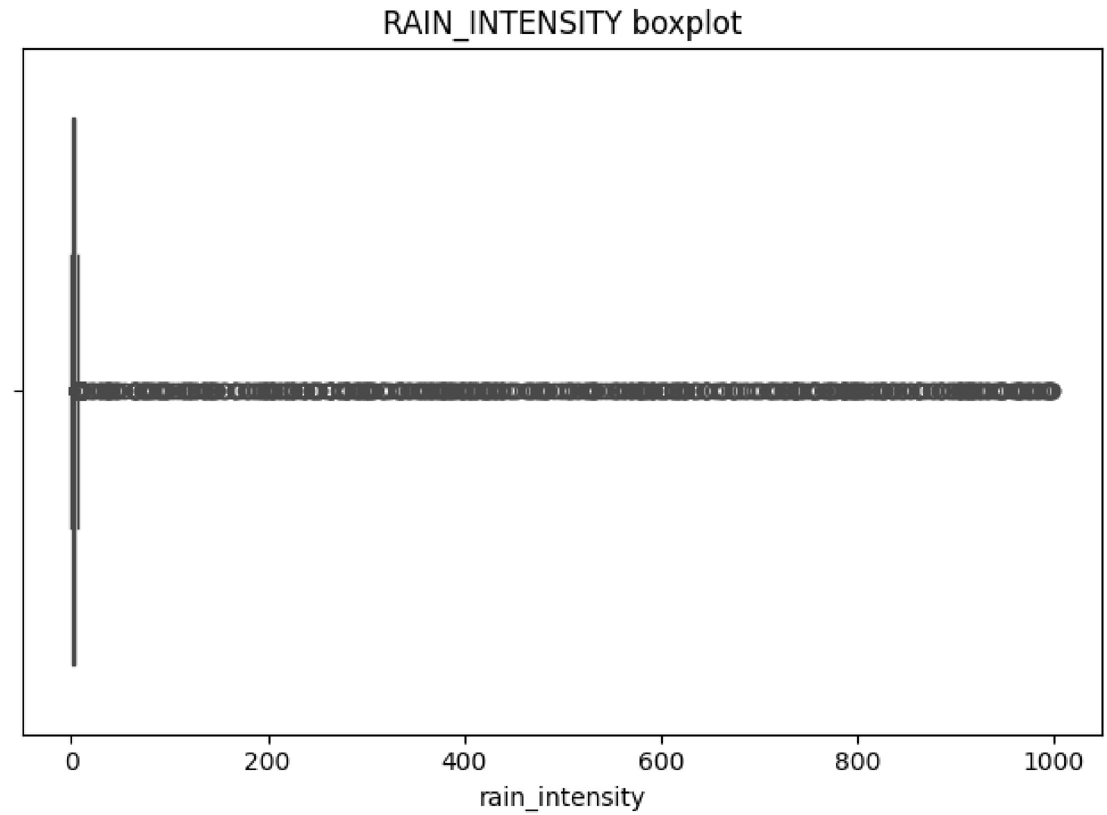

TRAFFIC_DENSITY boxplot
0
200
400
600
800
1000
traffic_density

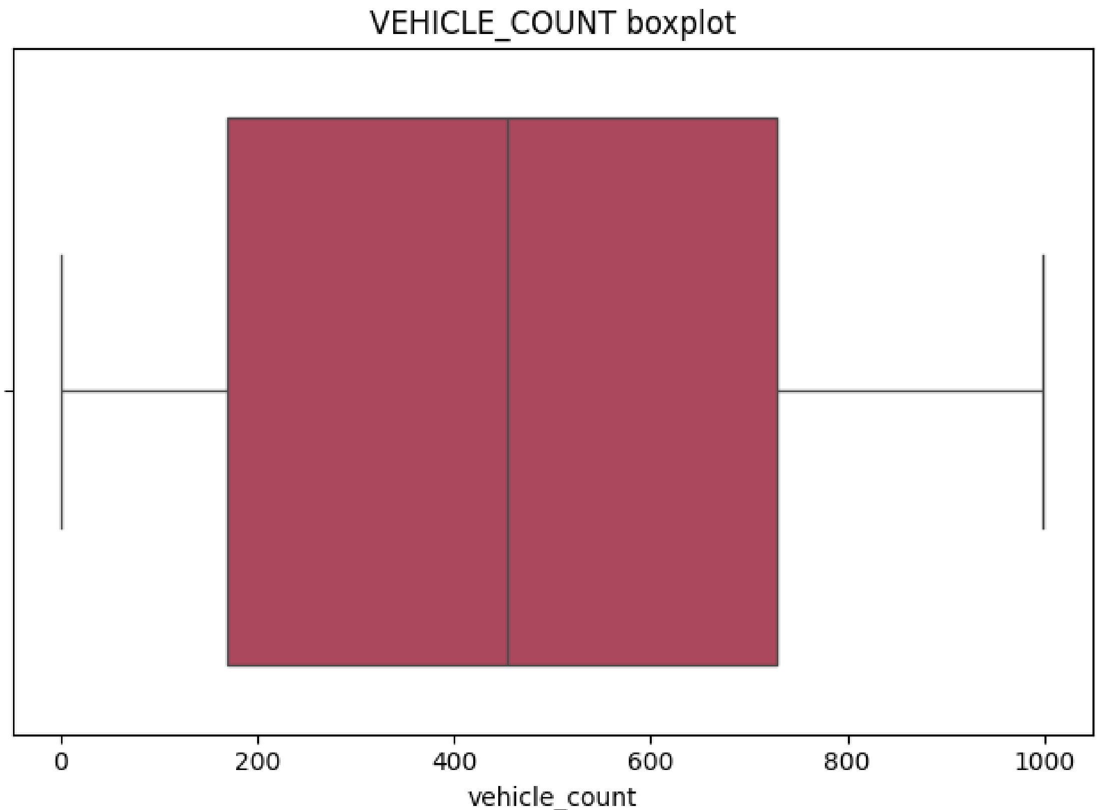

TRAFFIC_LIGHTS boxplot
0
200
400
600
800
1000
traffic_lights

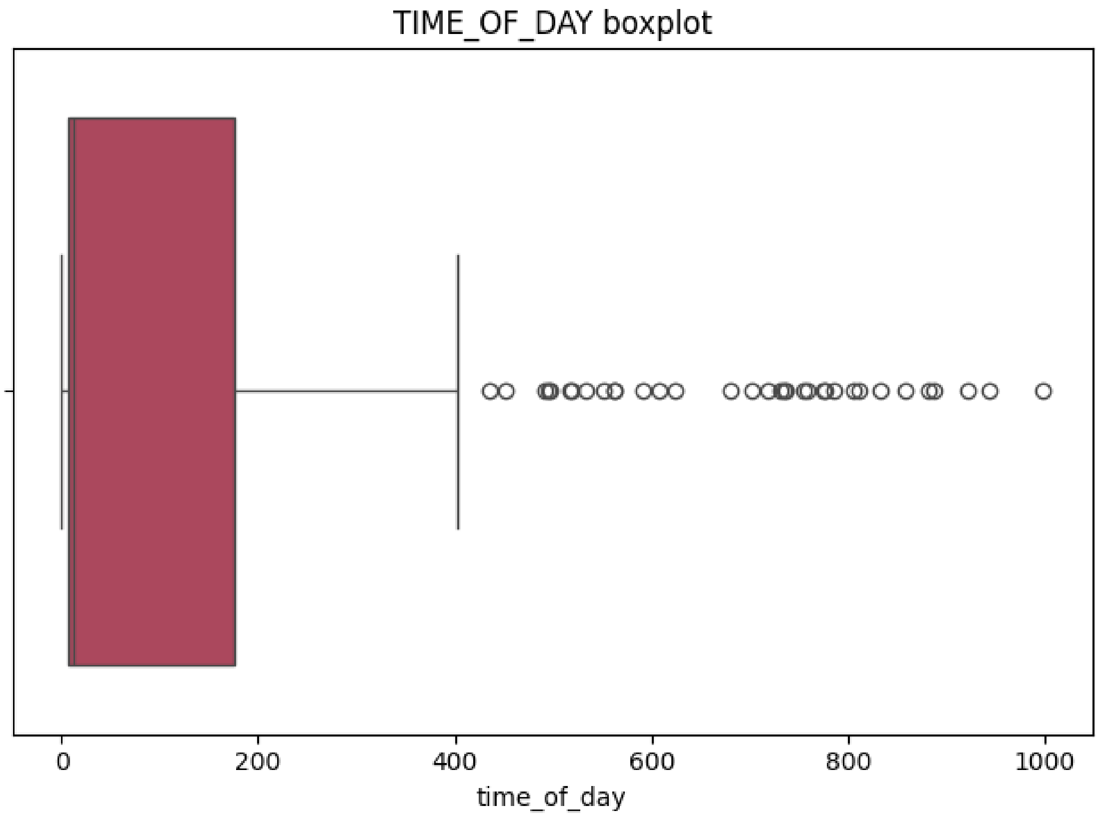

PAVEMENT_QUALITY boxplot
0
200
400
600
800
1000
pavement_quality


URBAN_AREA boxplot
0.0
0.2
0.4
0.6
0.8
1.0
urban_area


AVERAGE_SPEED boxplot
0
200
400
600
800
average_speed


RAIN_INTENSITY boxplot
0
200
400
600
800
1000
rain_intensity


VEHICLE_COUNT boxplot
0
200
400
600
800
1000
vehicle_count



[21]:
```
for col in num_cols:
    print(col.upper()," ",check_outlier(df,col))
```

```
ACCIDENTS   True
TRAFFIC_FINE_AMOUNT   False
TRAFFIC_DENSITY   True
TRAFFIC_LIGHTS   True
PAVEMENT_QUALITY   True
URBAN_AREA   False
AVERAGE_SPEED   True
RAIN_INTENSITY   True
VEHICLE_COUNT   False
TIME_OF_DAY   True
```

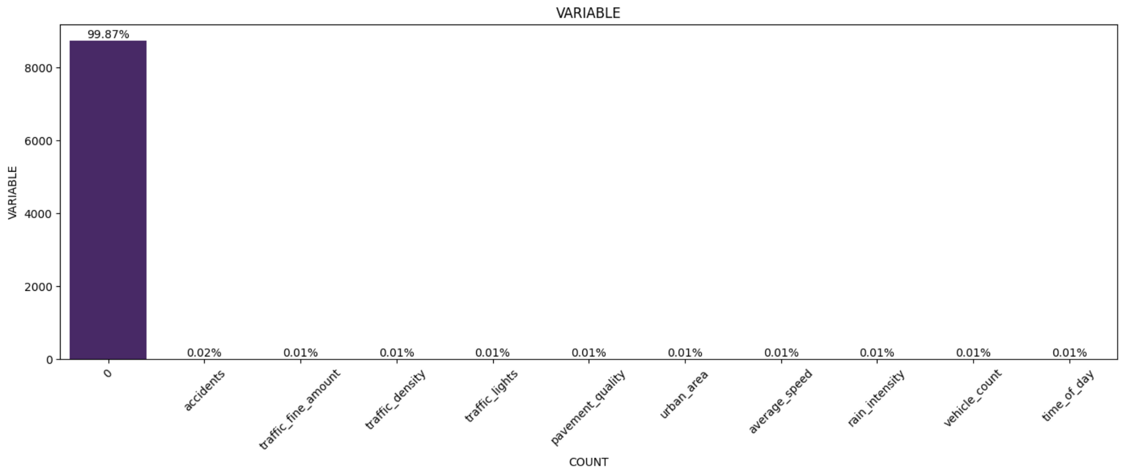
[22]:
```
for col in num_cols:
    replace_with_thresholds(df, col)
```

[23]:
```
for col in num_cols:
    print(col.upper()," ",check_outlier(df,col))
```

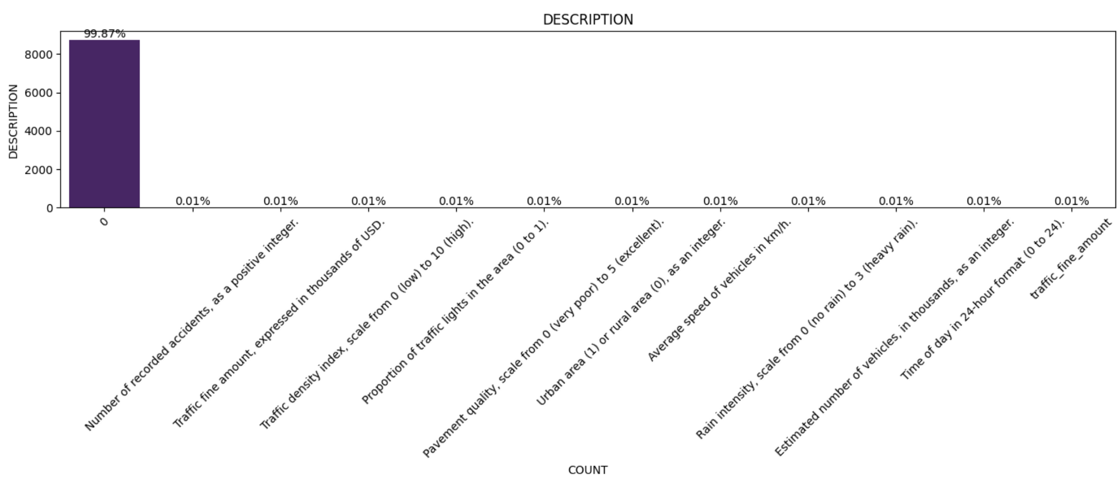
```
ACCIDENTS   False
TRAFFIC_FINE_AMOUNT   False
```

```
TRAFFIC_DENSITY   False
TRAFFIC_LIGHTS   False
PAVEMENT_QUALITY   False
URBAN_AREA   False
AVERAGE_SPEED   False
RAIN_INTENSITY   False
VEHICLE_COUNT   False
TIME_OF_DAY   False
```

[24]:
```
for col in cat_cols:
    cat_plot(df,col)
```



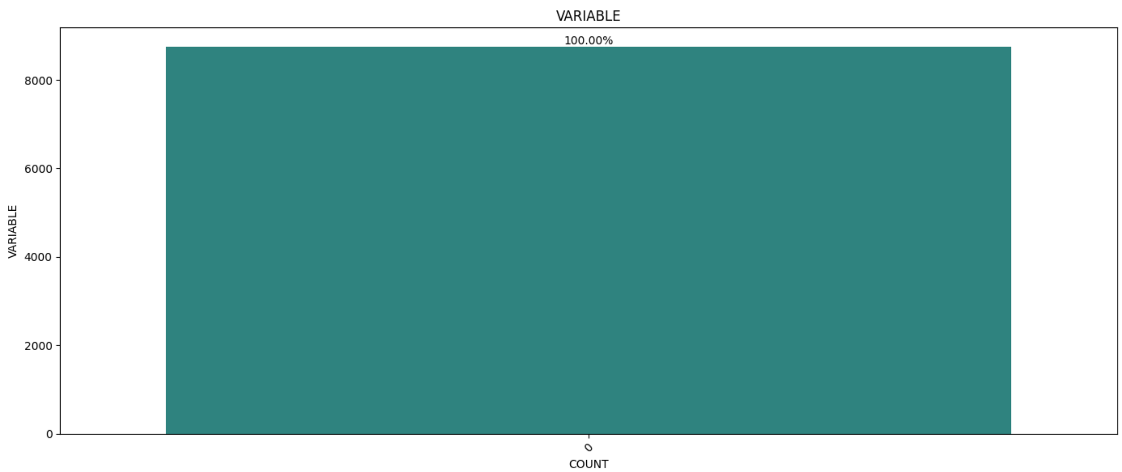

```
--------------------------------------------------------------------------------
----------------------------------
```

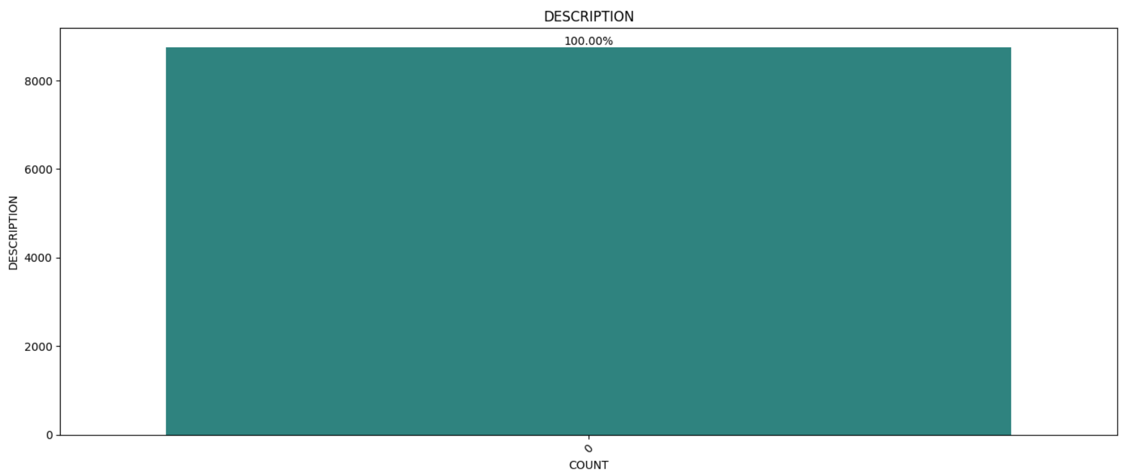


----

[25]:
```python
df = df[df["Variable"]=="0"]
```

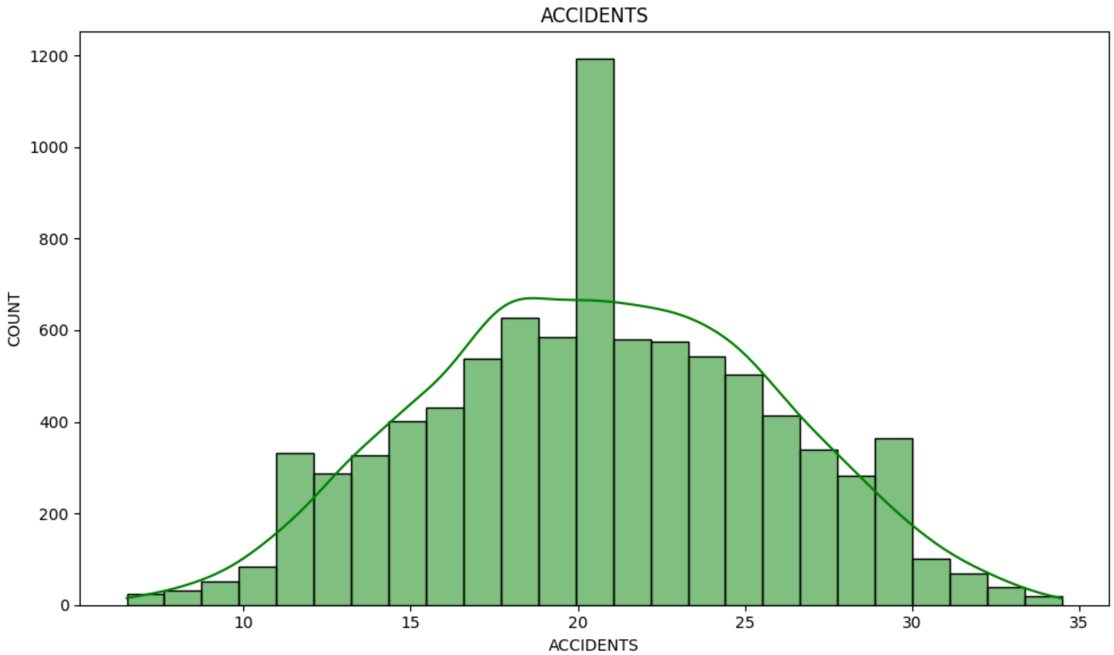
[26]:
```python
for col in cat_cols:
    cat_plot(df,col)
```



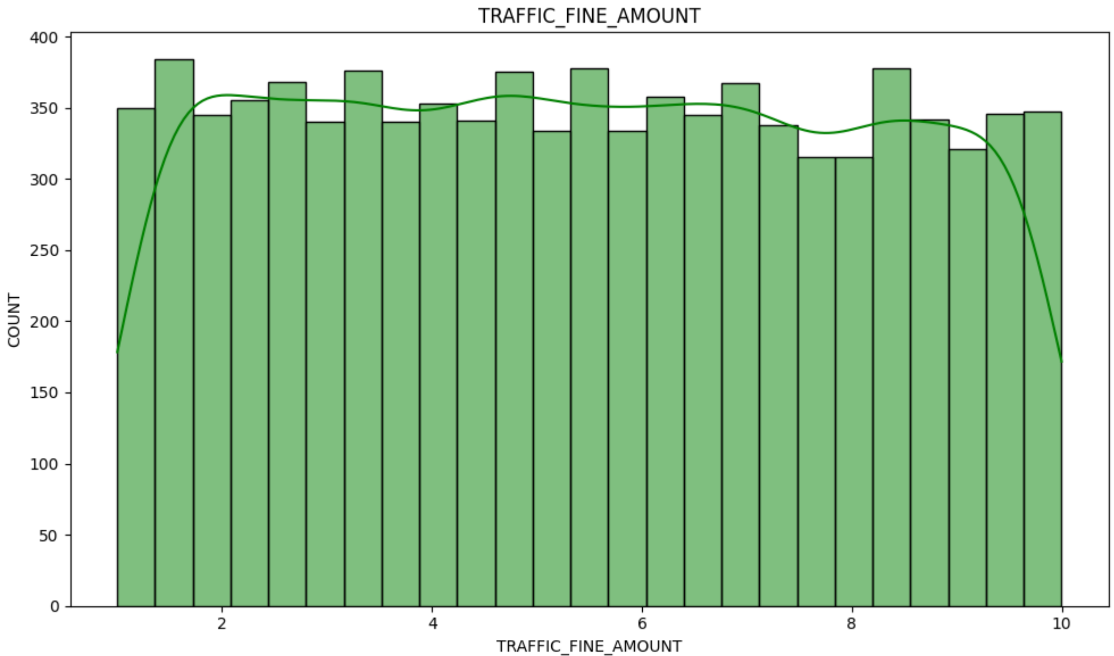


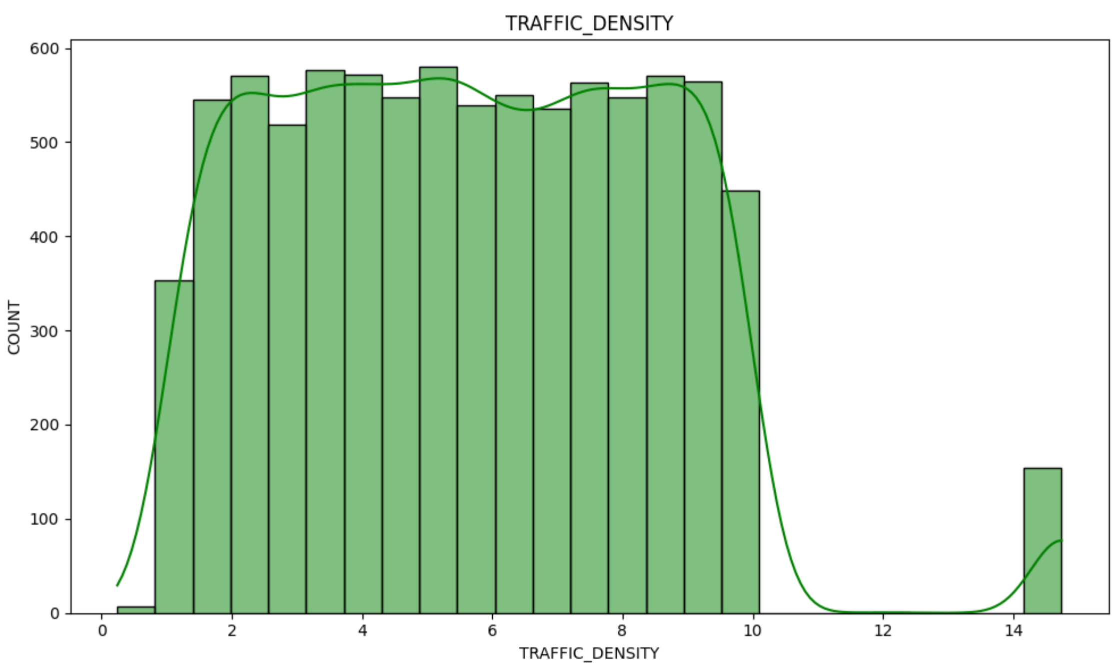
----

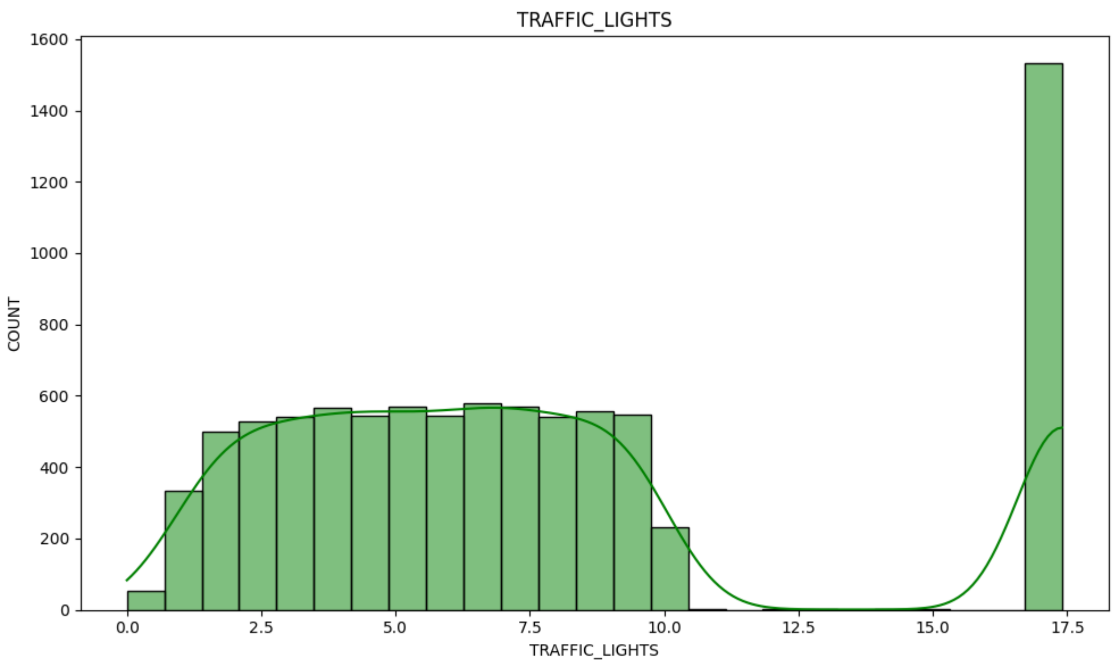
[27]:
```
for col in num_cols:
    hist_plot(df,col)
```

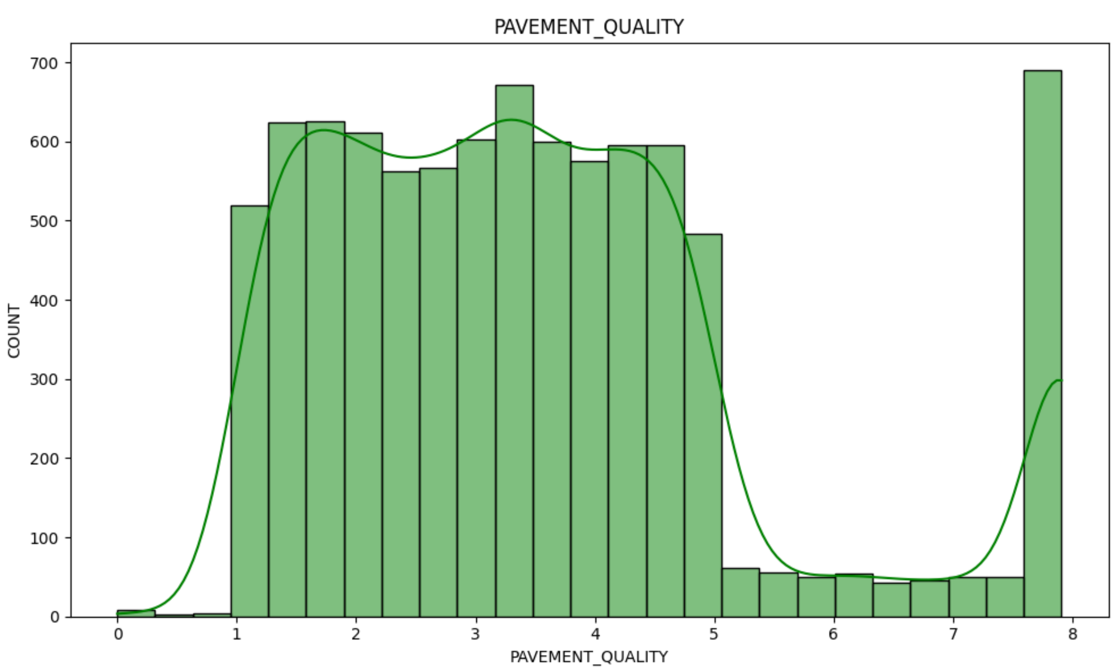


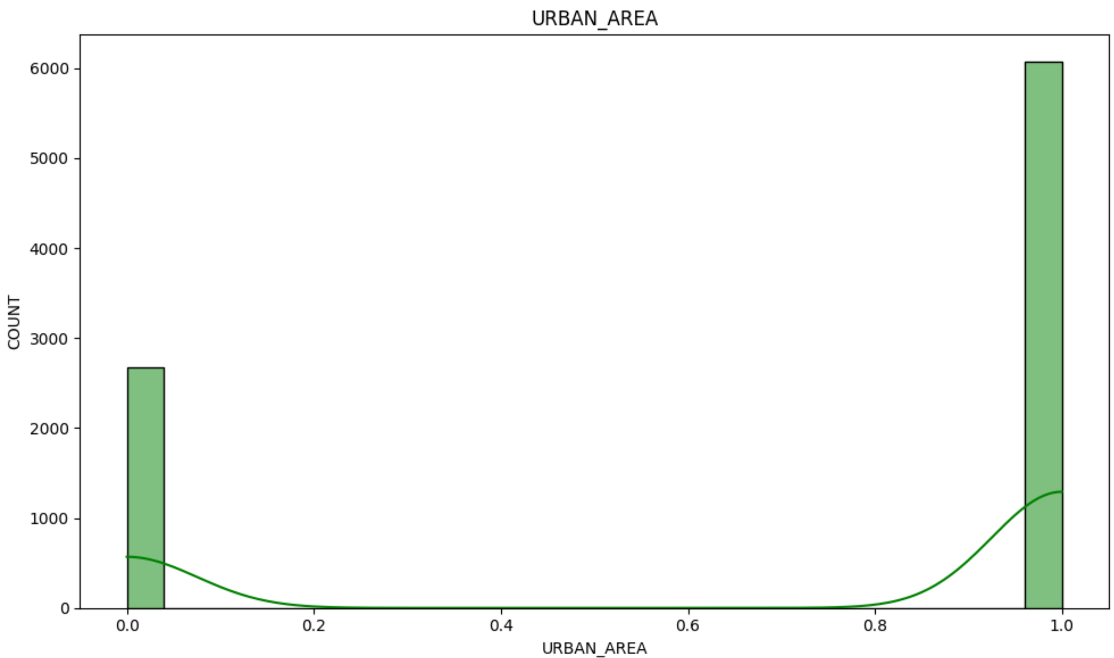

```
--------------------------------------------------------------------------------
--------
```

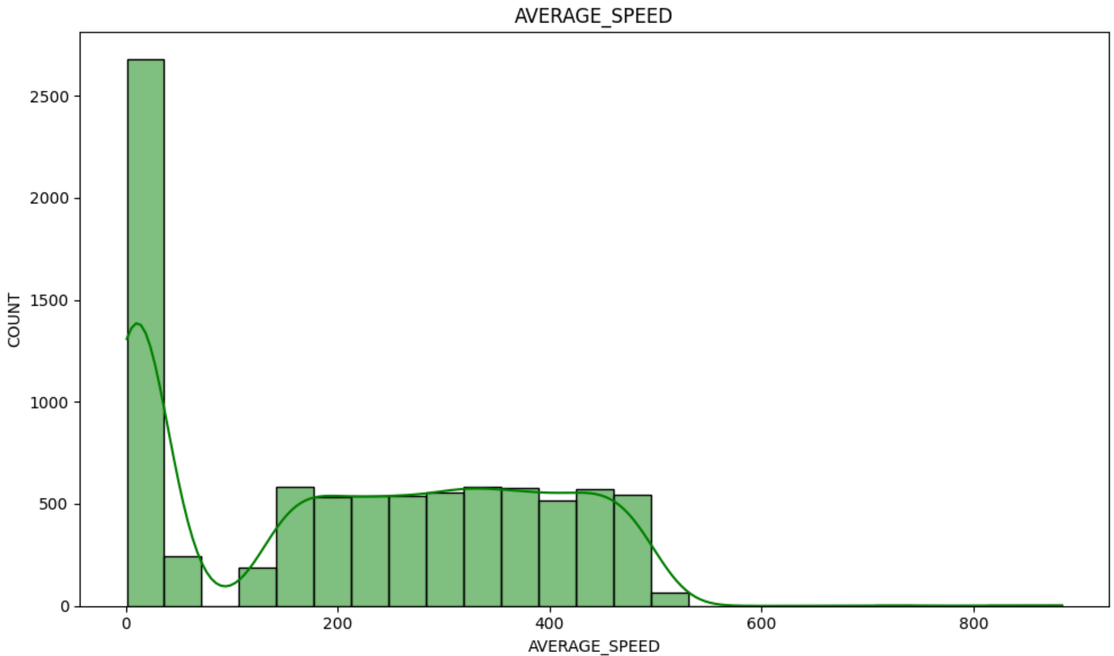

TRAFFIC_FINE_AMOUNT
COUNT
TRAFFIC_FINE_AMOUNT
0
50
100
150
200
250
300
350
400
2
4
6
8
10

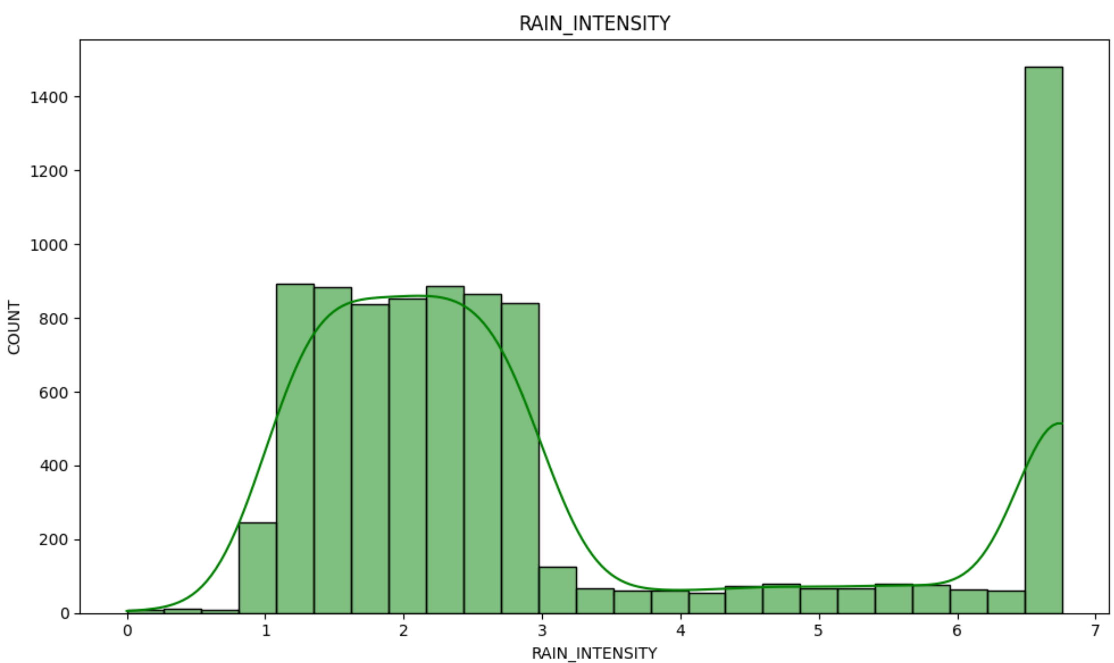

TRAFFIC_DENSITY
COUNT
TRAFFIC_DENSITY
0
100
200
300
400
500
600
0
2
4
6
8
10
12
14

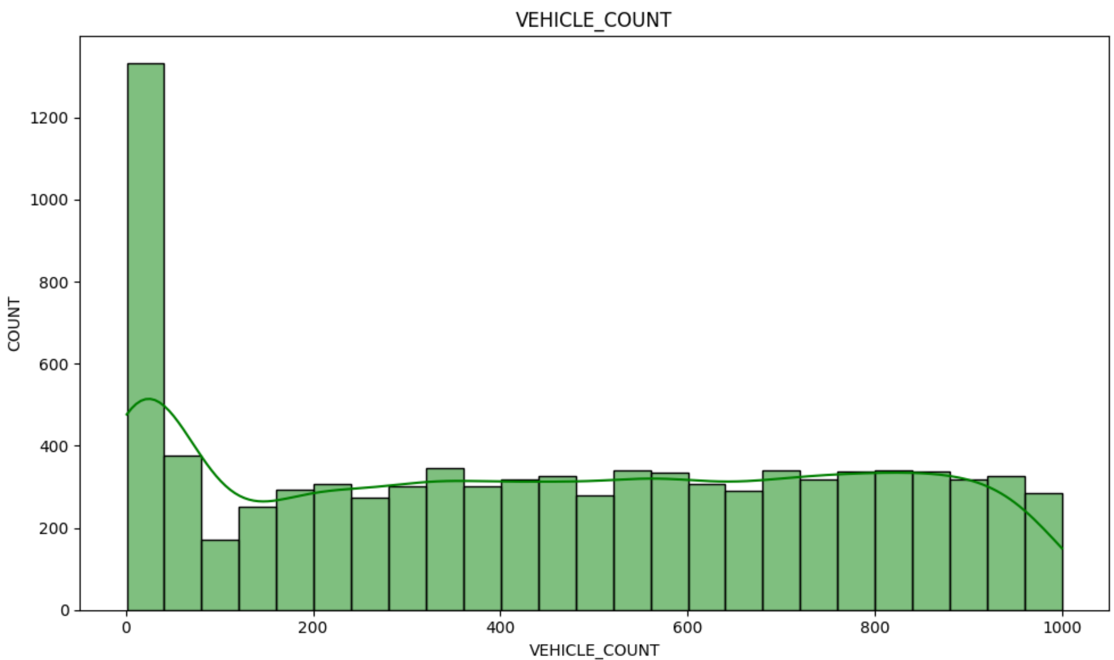

TRAFFIC_LIGHTS
COUNT
0
200
400
600
800
1000
1200
1400
1600
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
TRAFFIC_LIGHTS

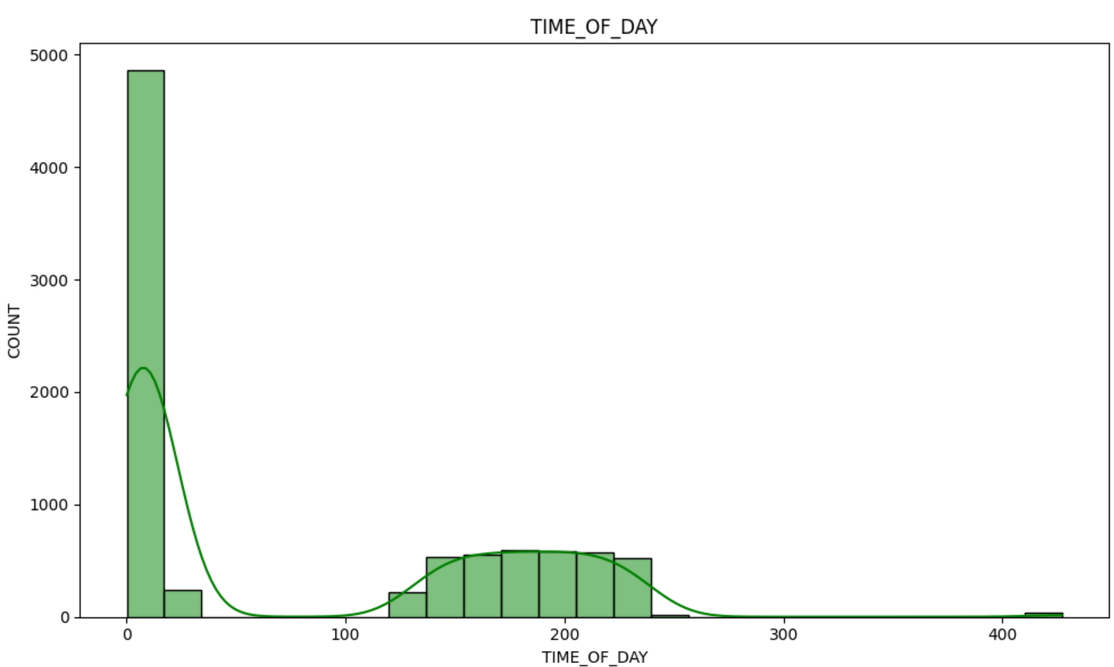

PAVEMENT_QUALITY
COUNT
0
100
200
300
400
500
600
700
0
1
2
3
4
5
6
7
8
PAVEMENT_QUALITY


URBAN_AREA
6000
5000
4000
3000
2000
1000
0
COUNT
0.0
0.2
0.4
0.6
0.8
1.0
URBAN_AREA


AVERAGE_SPEED
COUNT
2500
2000
1500
1000
500
0
0
200
400
600
800
AVERAGE_SPEED

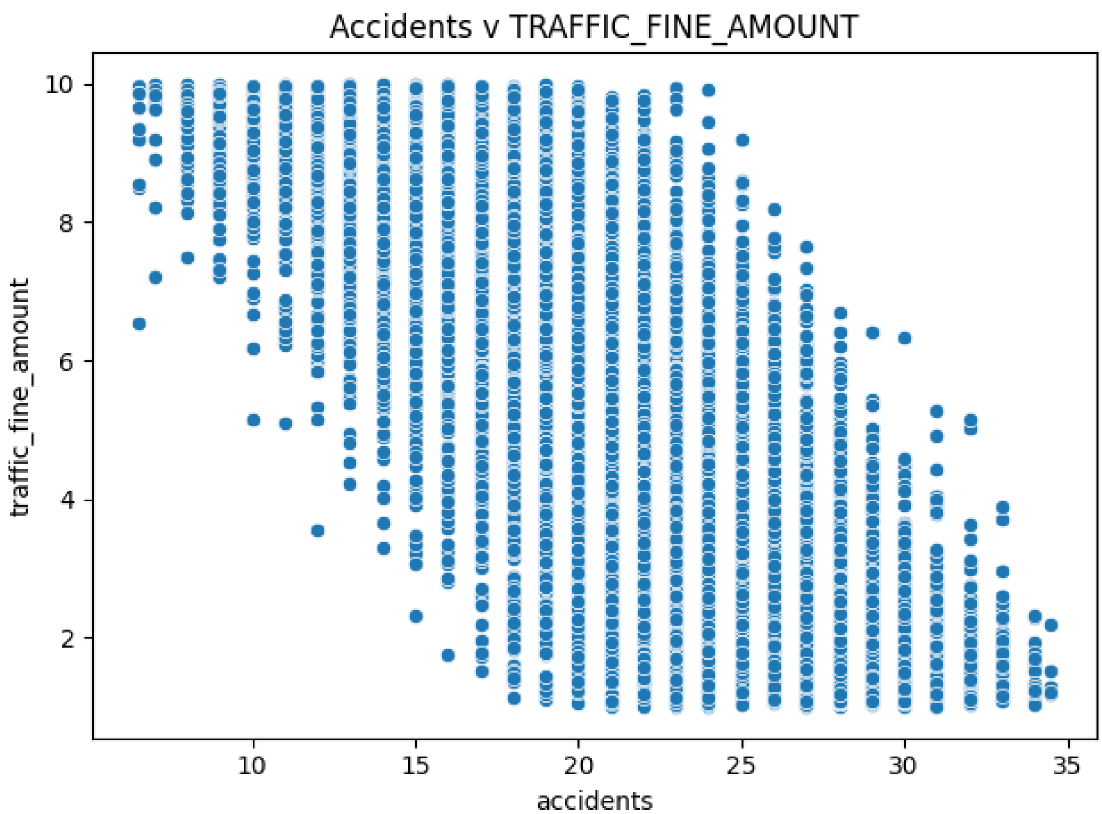

RAIN_INTENSITY
COUNT
1400
1200
1000
800
600
400
200
0
0
1
2
3
4
5
6
7
RAIN_INTENSITY

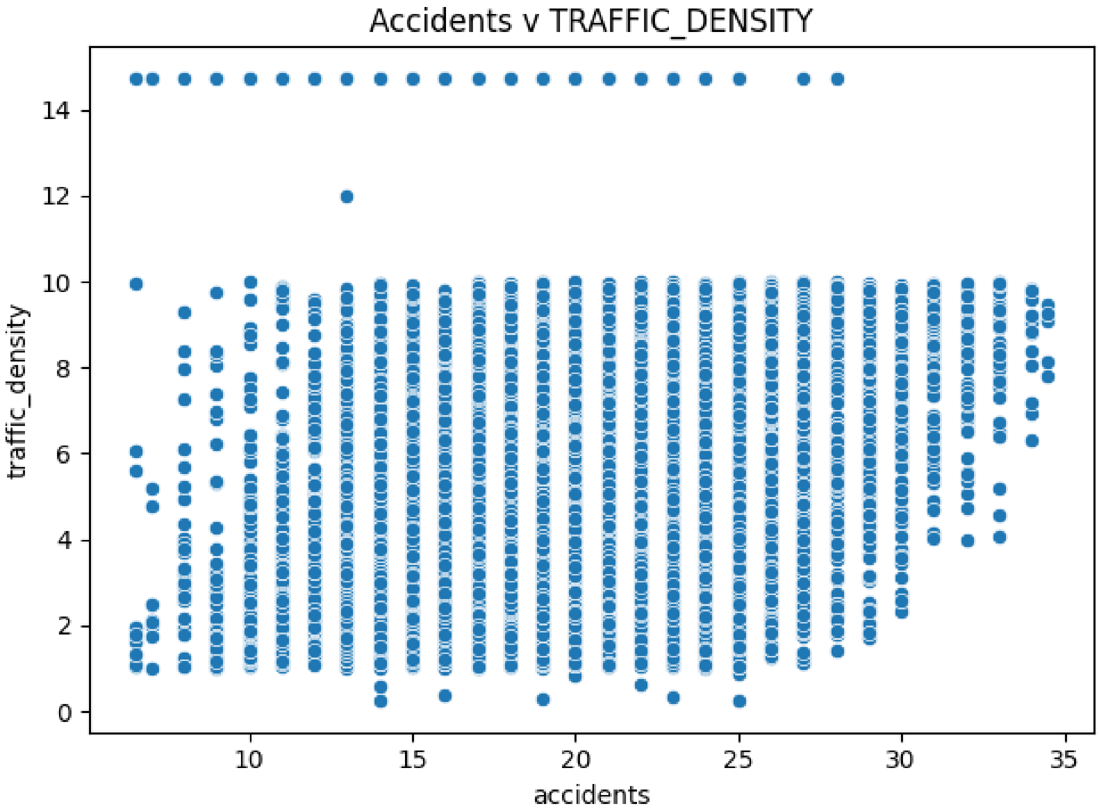

VEHICLE_COUNT
COUNT
VEHICLE_COUNT
0
200
400
600
800
1000
1200

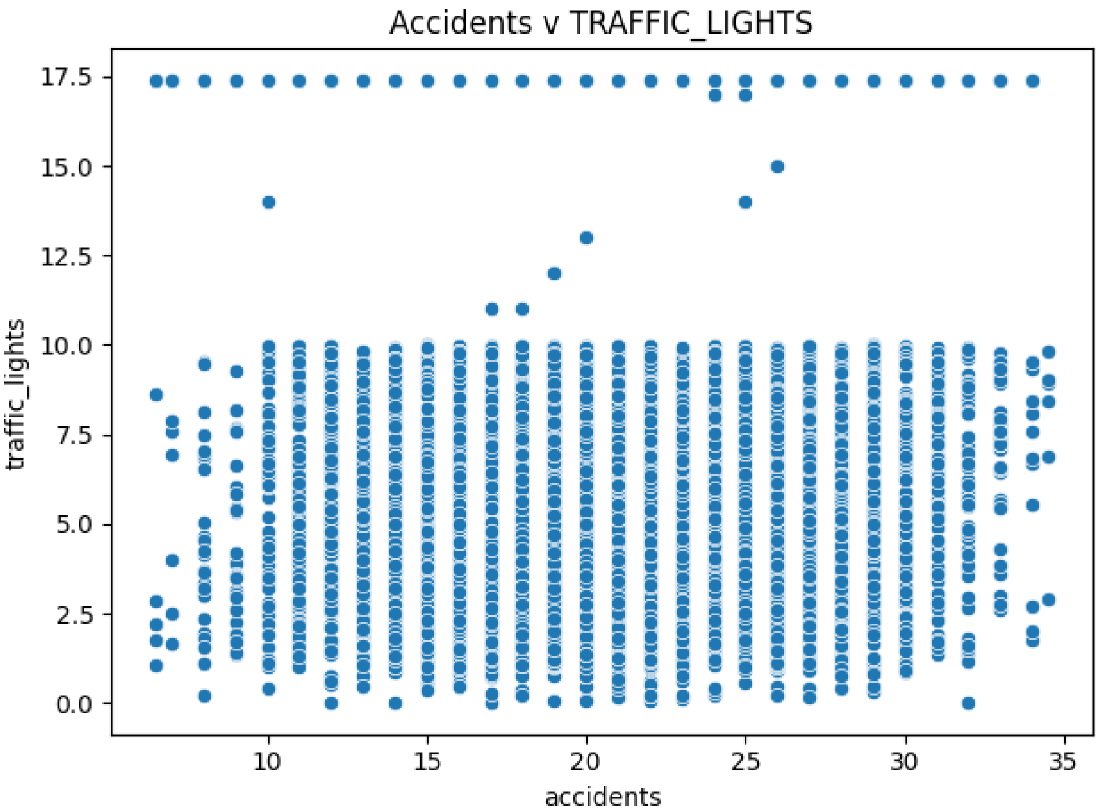

TIME_OF_DAY
COUNT
TIME_OF_DAY
0
100
200
300
400
1000
2000
3000
4000
5000

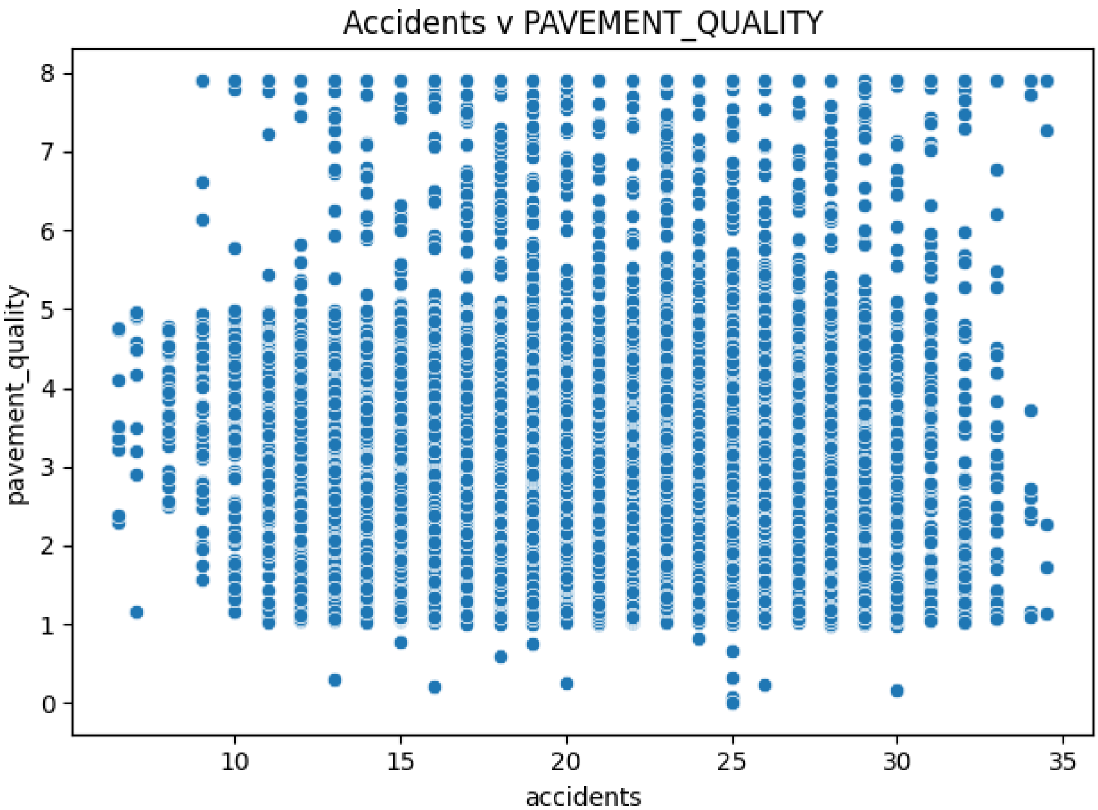
----

[28]:
```
nums = [col for col in num_cols if col not in "accidents"]
for col in nums:
    sns.scatterplot(data=df, x="accidents", y=col)
    plt.title(f"Accidents v {col.upper()}")
    plt.tight_layout()
    plt.show()
```

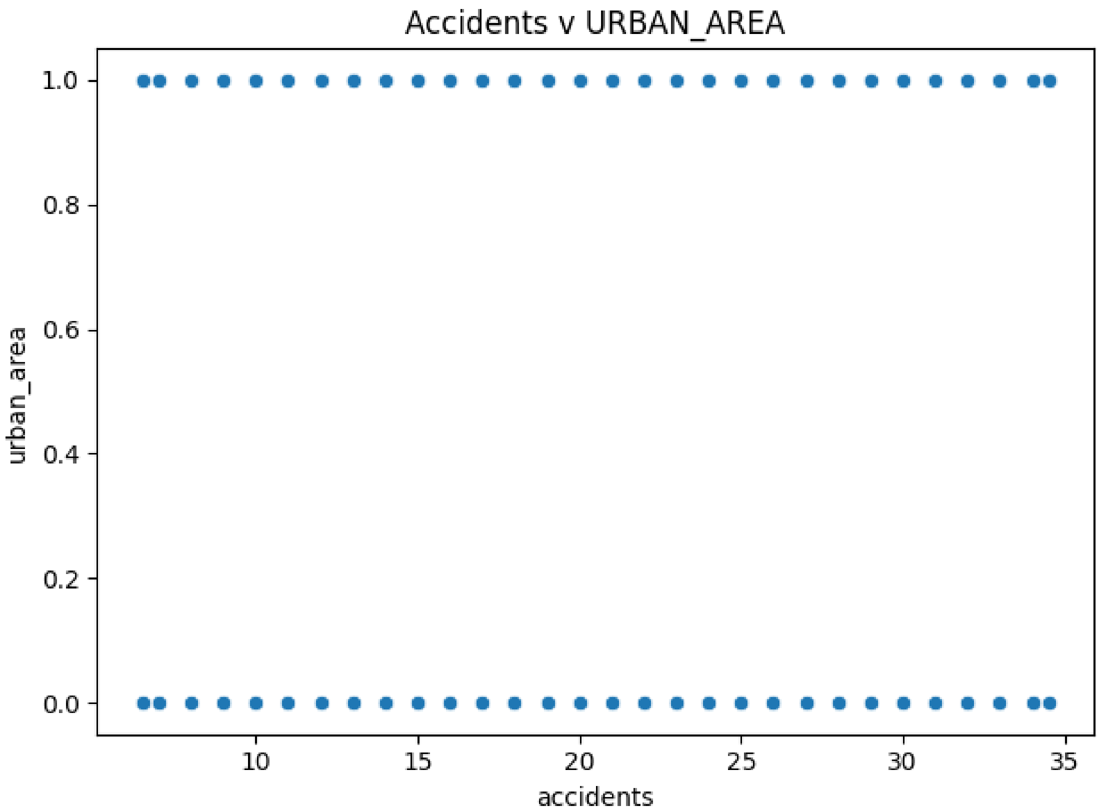


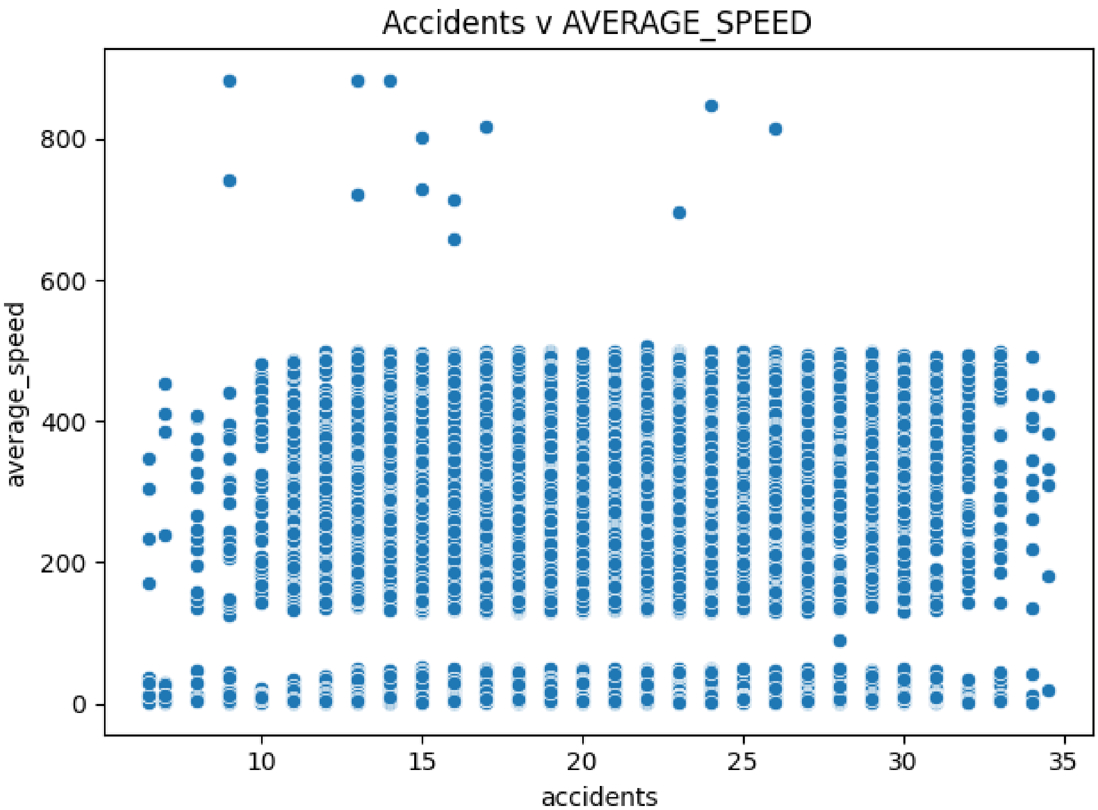

Accidents v TRAFFIC_DENSITY
traffic_density
accidents
0
2
4
6
8
10
12
14
10
15
20
25
30
35

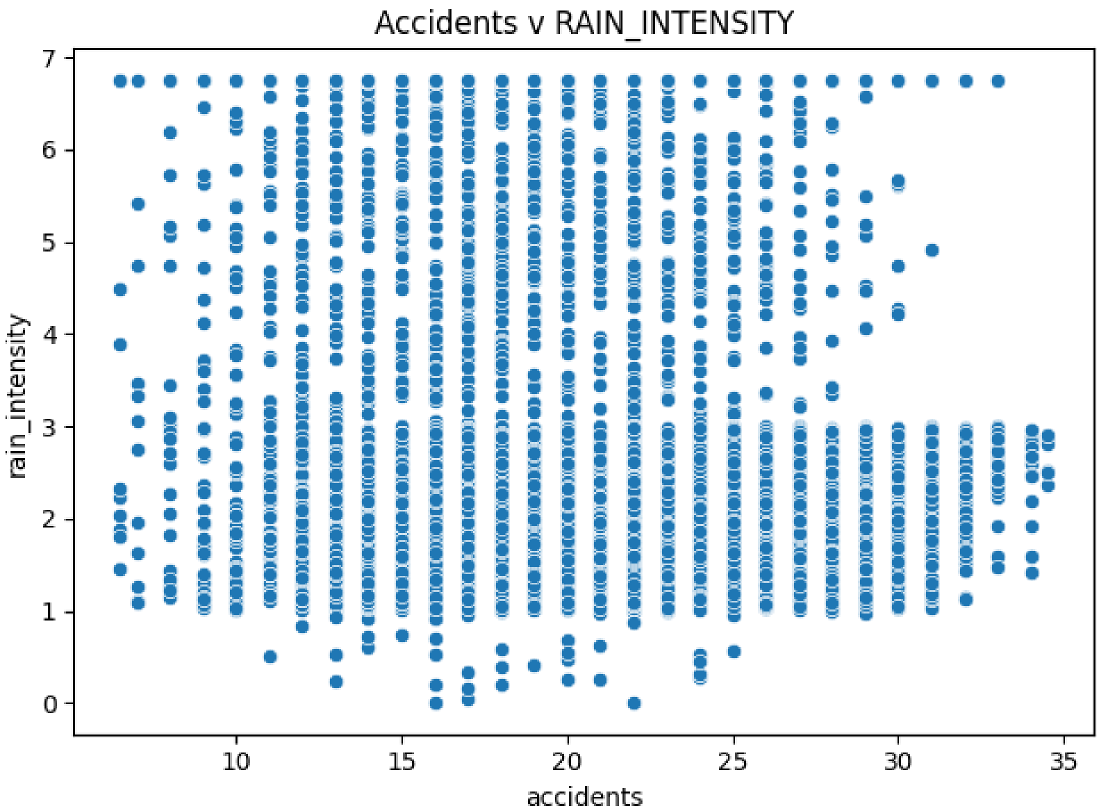

Accidents v TRAFFIC_LIGHTS
traffic_lights
accidents
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
10
15
20
25
30
35

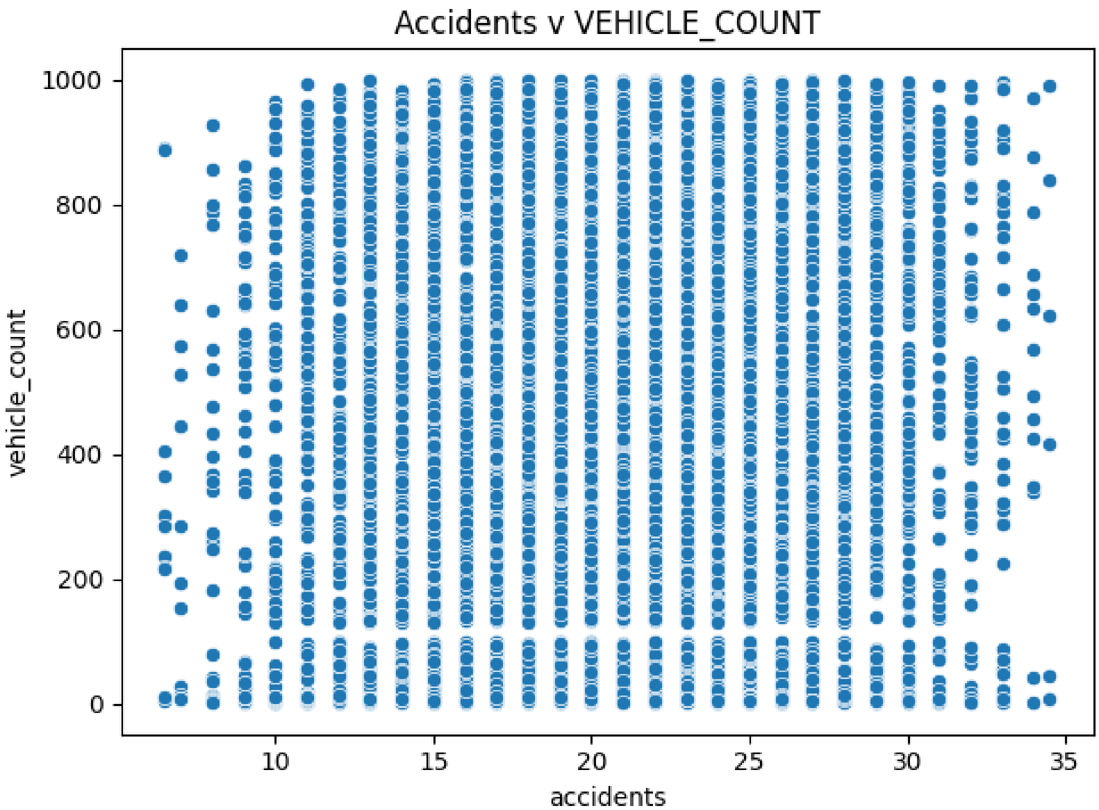


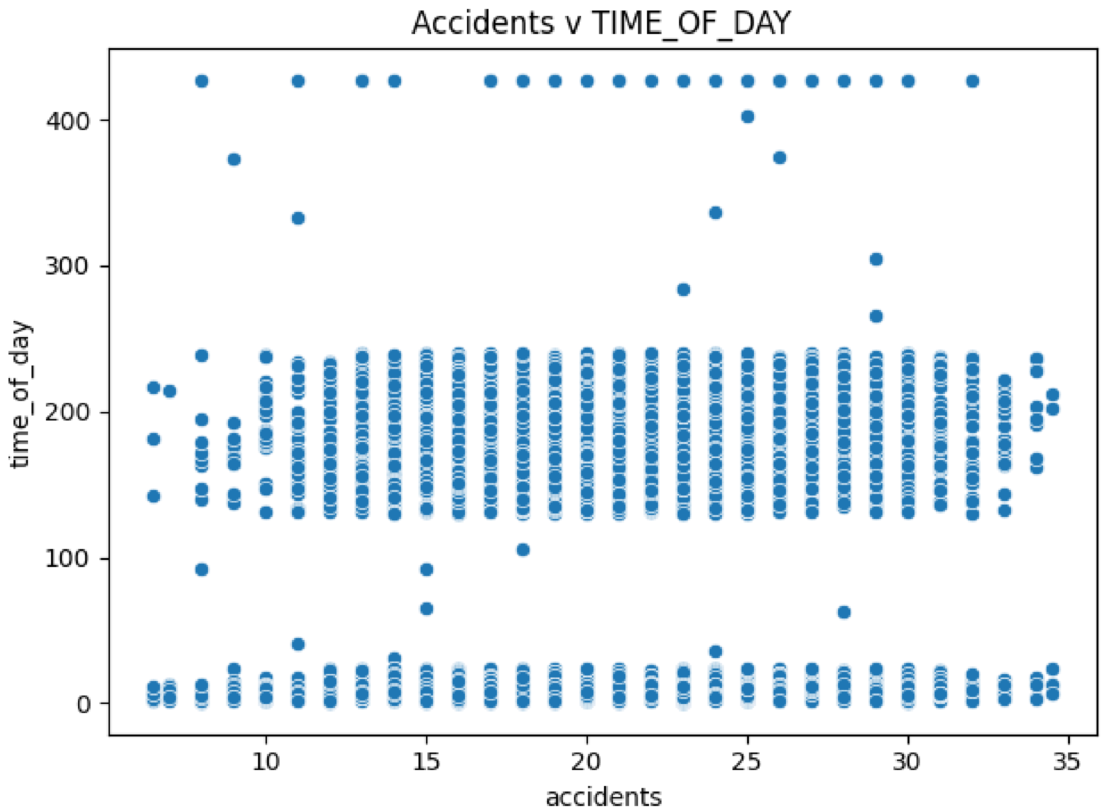
Accidents v PAVEMENT_QUALITY
pavement_quality
accidents
0
1
2
3
4
5
6
7
8
10
15
20
25
30
35


Accidents v URBAN_AREA
1.0
0.8
0.6
0.4
0.2
0.0
urban_area
10
15
20
25
30
35
accidents

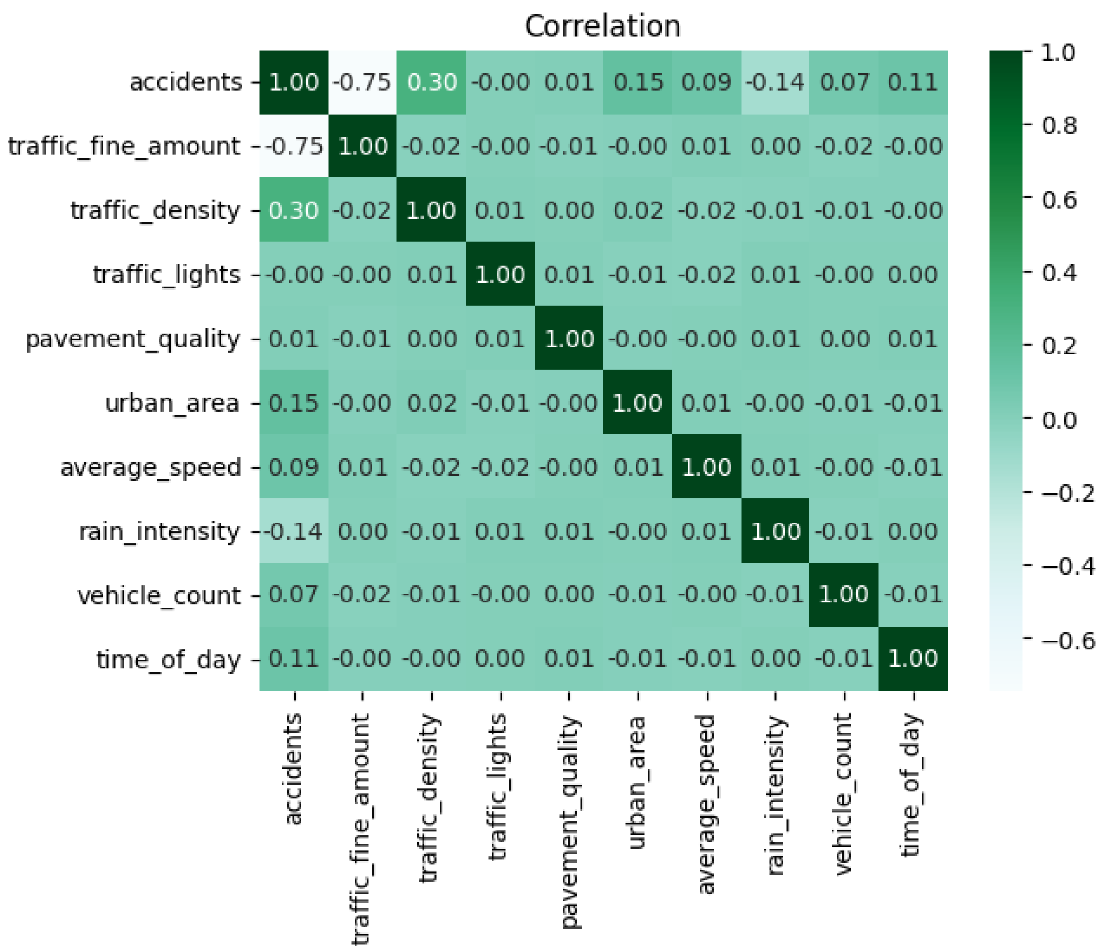

Accidents v AVERAGE_SPEED
average_speed
accidents
0
200
400
600
800
10
15
20
25
30
35


Accidents v RAIN_INTENSITY
rain_intensity
accidents
0
1
2
3
4
5
6
7
10
15
20
25
30
35


Accidents v VEHICLE_COUNT
vehicle_count
1000
800
600
400
200
0
10
15
20
25
30
35
accidents



[29]:
```
sns.heatmap(df[num_cols].corr(),annot=True,fmt=".2f",cmap="BuGn")
plt.title("Correlation",fontsize=12)
plt.show()
```




```
[30]: X = df.drop(["accidents","Variable","Description"],axis=1)
      y = df["accidents"]
```

```
[31]: X_train , X_test , y_train , y_test = train_test_split(X,y,test_size=0.
       ↪20,random_state=42)
```

```
[32]: scaler = MinMaxScaler()
```

```
[33]: X_train = scaler.fit_transform(X_train)
      X_test = scaler.fit_transform(X_test)
```

```
[34]: print(f"X Train Shape : {X_train.shape}\nX Test Shape : {X_test.shape}\nY Train␣
       ↪Shape : {y_train.shape}\nY Test Shape : {y_test.shape}")
```

```
X Train Shape : (6996, 9)
X Test Shape : (1749, 9)
Y Train Shape : (6996,)
Y Test Shape : (1749,)
```

[35]:
```
base_models(X_train,y_train,"r2")
```

```
Base Models
r2: 0.6958 Ridge
r2: 0.116 Lasso
r2: 0.0833 ElasticNet
r2: 0.6958 Linear
r2: 0.5707 Decision Tree
r2: 0.801 Random Forest
r2: 0.8352 Gradient Boosting
r2: 0.808 XGB
r2: 0.7134 KNN
r2: 0.7973 MLP
r2: 0.6958 Bayesian Ridge
r2: 0.8466 CatBoost
```

[36]:
```
cat_params = {
    'iterations': [100, 200, 300, 500],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'depth': [3, 5, 7, 10]
}

gb_params = {
    'n_estimators': [100, 200, 300, 500],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'max_depth': [3, 5, 7, 10]
}
xgb_params = {
    'n_estimators': [100, 200, 300, 500],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'max_depth': [3, 5, 7, 10]
}
```

[37]:
```
best_models = hyperparameter_optimization_randomized(X_train,y_train,n_iter=10)
```

```
HYPERPARAMETER OPTIMIZATION WITH RANDOMIZEDSEARCH
----------------- GradientBoosting -----------------
r2 (Before): 0.8361
r2 (After): 0.8389
GradientBoosting best params: {'n_estimators': 100, 'max_depth': 5,
'learning_rate': 0.1}

----------------- CatBoost -----------------
r2 (Before): 0.8457
r2 (After): 0.8488
CatBoost best params: {'learning_rate': 0.05, 'iterations': 300, 'depth': 5}

----------------- XGBoost -----------------
```

```
r2 (Before): 0.8068
r2 (After): 0.8309
XGBoost best params: {'n_estimators': 100, 'max_depth': 5, 'learning_rate': 0.1}
```

[38]:
```
voting_reg = voting_regressor(best_models,X_train,y_train)
```

```
Voting Regressor
Neg MSE: 4.272705632654722
R^2: 0.8442041169906338
```

[39]:
```
predict = voting_reg.predict(X_test)
```

[40]:
```
print(f"R2 Score: {r2_score(y_test, predict):.4f}")
print(f"MSE: {mean_squared_error(y_test, predict):.4f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test, predict)):.4f}")
```

```
R2 Score: 0.8453
MSE: 4.1274
RMSE: 2.0316
```

[41]:
```
plot_importance_ensemble(voting_reg,X)
```