Vehicle crashes dataset of New York City

Niha R Gali

Capstone Project-Data 606

About

Problem Statement

Understanding the vehicle crashes dataset of New York and develop a multiclass classifier to classify the contributing factor for those crashes

The Motor Vehicle Collisions vehicle table contains details on each vehicle involved in the crash. **Each row represents a motor vehicle involved in a crash.** The data in this table goes back to April 2016 when crash reporting switched to an electronic system.

Data Source

Dataset link:
https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Vehicles/bm4k-52h4

- Size : 114.4MB
- Rows : 3.7M
- Columns : 25
- Each row represents motor vehicle invloved in a crash.

Attributes

- UNIQUE_ID Unique record code generated by system.
- COLLISION_ID Crash identification code. Foreign Key, matches unique_id from the Crash table.
- CRASH_DATE Occurrence date of collision
- CRASH_TIME Occurrence time of collision
- VEHICLE_ID Vehicle identification code assigned by system
- STATE_REGISTRATION State where vehicle is registered.
- VEHICLE_TYPE Type of vehicle based on the selected vehicle category

Attributes

- VEHICLE_MAKE Vehicle make
- VEHICLE_MODEL Vehicle model
- VEHICLE_YEAR Year the vehicle was manufactured
- TRAVEL_DIRECTION Direction vehicle was traveling
- VEHICLE_OCCUPANTS Number of vehicle occupants
- DRIVER_SEX Gender of driver
- DRIVER_LICENSE_STATUS License, permit, unlicensed

Attributes

- DRIVER_LICENSE_JURISDICTION State where driver license was issued.
- PRE_CRASH Pre-crash action: Going straight, making right turn, passing, backing, etc.
- POINT_OF_IMPACT Location on the vehicle of the initial point of impact
- VEHICLE_DAMAGE Location on the vehicle where most of the damage occurred
- VEHICLE_DAMAGE_1 Additional damage locations on the vehicle
- VEHICLE_DAMAGE_2 Additional damage locations on the vehicle
- VEHICLE_DAMAGE_3 Additional damage locations on the vehicle

Attributes

- PUBLIC_PROPERTY_DAMAGE Public property damaged (Yes or No)
- PUBLIC_PROPERTY_DAMAGE_TYPE Type of public property damaged (ex. Sign, fence, light post, etc.)
- CONTRIBUTING_FACTOR_1 Factors contributing to the collision for designated vehicle
- CONTRIBUTING_FACTOR_2 Factors contributing to the collision for designated vehicle

Questions for analysis

- Understandig the contributing factor
- To find the extent of property damage
- What part of vehicle was damaged moslty ?
- What vehicles were involved in the accident ?
- Identify drivers license and sex distribution
- Accident distribution over time

Data Cleaning and Engineering

- There are very few rows like unique_id, collision_id, date and time with no missing data.
- Columns such as VEHICLE_MODEL, VEHICLE_DAMAGE_1, VEHICLE_DAMAGE_2, VEHICLE_DAMAGE_3, PUBLIC_PROPERTY_DAMAGE_TYPE have more than 65% of missing values.
- Reduced the number of rows with values 'Unspecified' by 49.8%.
- More than 90% of the data has 'No' that means in more than 90% of crashes there was no property damage.
- Most of the damages have occured at the front end of the car compared to other parts.
- A great portion of cars that were involved in an accident were either going straight or were parked.

Data Cleaning and Engineering

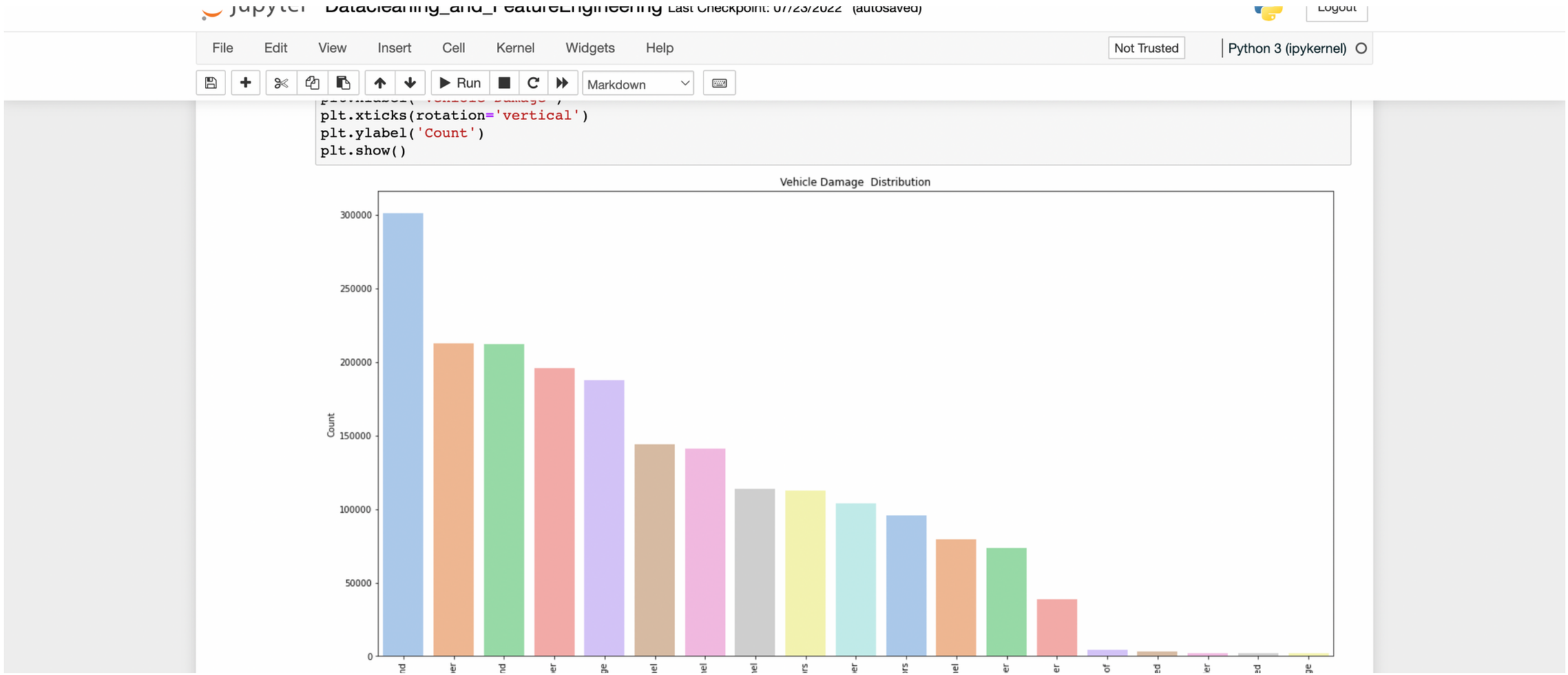
- About 95% of people who were involved in an accident are licensed.
- Majority of accidents were caused by Males.
- In 80% of the cases there is only one person in the vehicle which was involved in an accident.
- Dropping the unnecessary columns
  - UNIQUE_ID, COLLISION_ID, and VEHICLE_ID as they are unique and don't add value for this analysis.
  - CRASH_DATE, CRASH_TIME, VEHICLE_YEAR, CONTRIBUTING_FACTOR_2, and VEHICLE_MAKE as we extracted the main information from them.
  - VEHICLE_MODEL, PUBLIC_PROPERTY_DAMAGE, PUBLIC_PROPERTY_DAMAGE_TYPE as most of the data is missing.
  - STATE_REGISTRATION, DRIVER_LICENSE_STATUS, TRAVEL_DIRECTION, and DRIVER_LICENSE_JURISDICTION as data is highly skewed
  - VEHICLE_DAMAGE_cleaned as POINT_OF_IMPACT and VEHICLE_DAMAGE_cleaned very highly correlated.

Exploratory Data Analysis

Observations

- I observed that during the years 2017, 2018 there was an average of 175,000 accident.
- There is a decrease in the number of accidents in 2020 and 2021 due to the pandemic.
- I observed that their was a sudden spike in the number of accidents in the months of May and June.
- Contrast to common conception most of the accidents took place in the afternoon.
- Lack of attention was the major contributor for accidents followed by following too closely, not DUI or DWI.
- For the accidents having damages on the front end the driver was going straight.
- For the accidents having damages on the back end the driver was mostly backing the car.
- When there is only one person in the vehicle lack of attention and over speeding were the causes for accidents.
- Compared to females, men cause a lot of accidents due to distraction.

Exploratory Data Analysis



Exploratory Data Analysis

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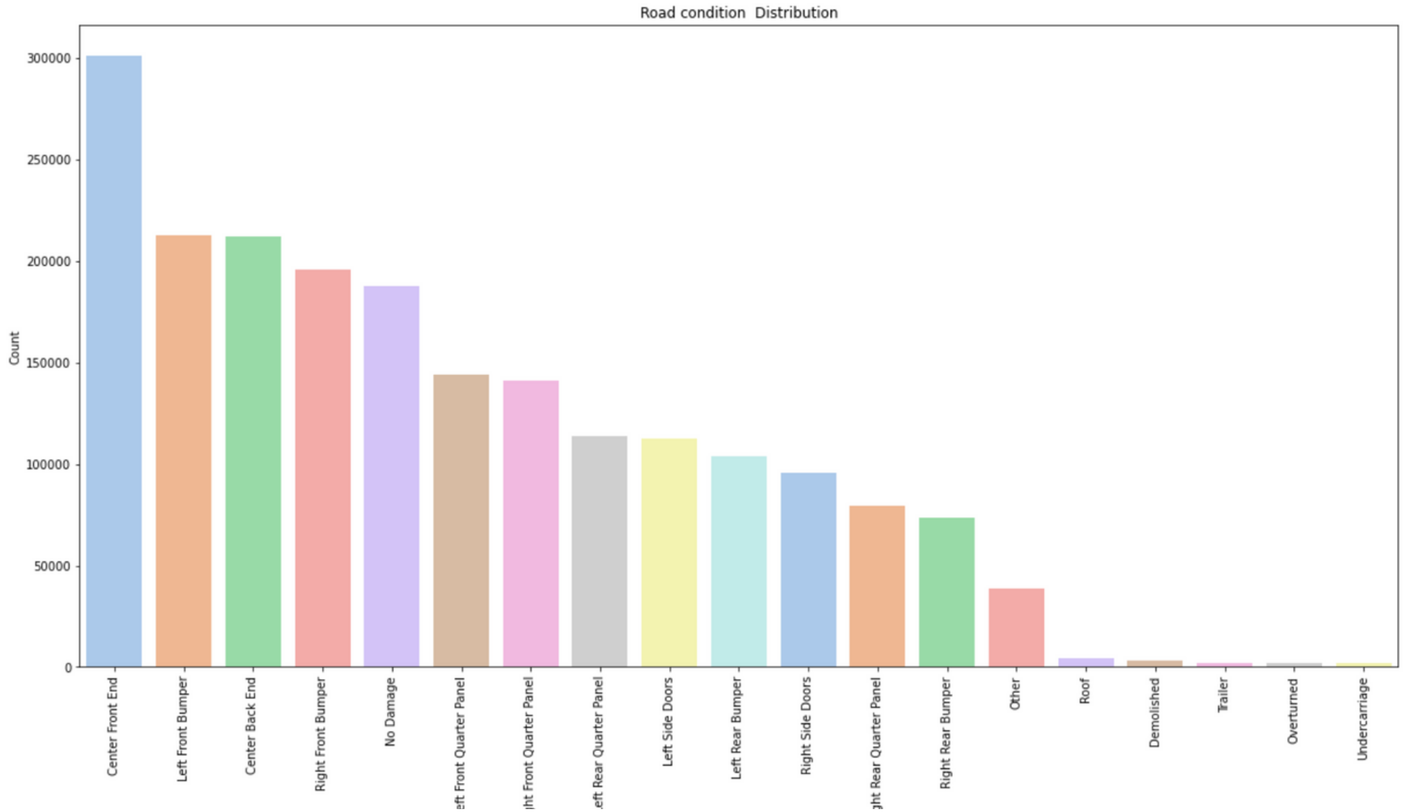
Run Markdown

```
print(dataset.VEHICLE_DAMAGE_cleaned.isnull().sum() * 100 / len(dataset))
```



Exploratory Data Analysis

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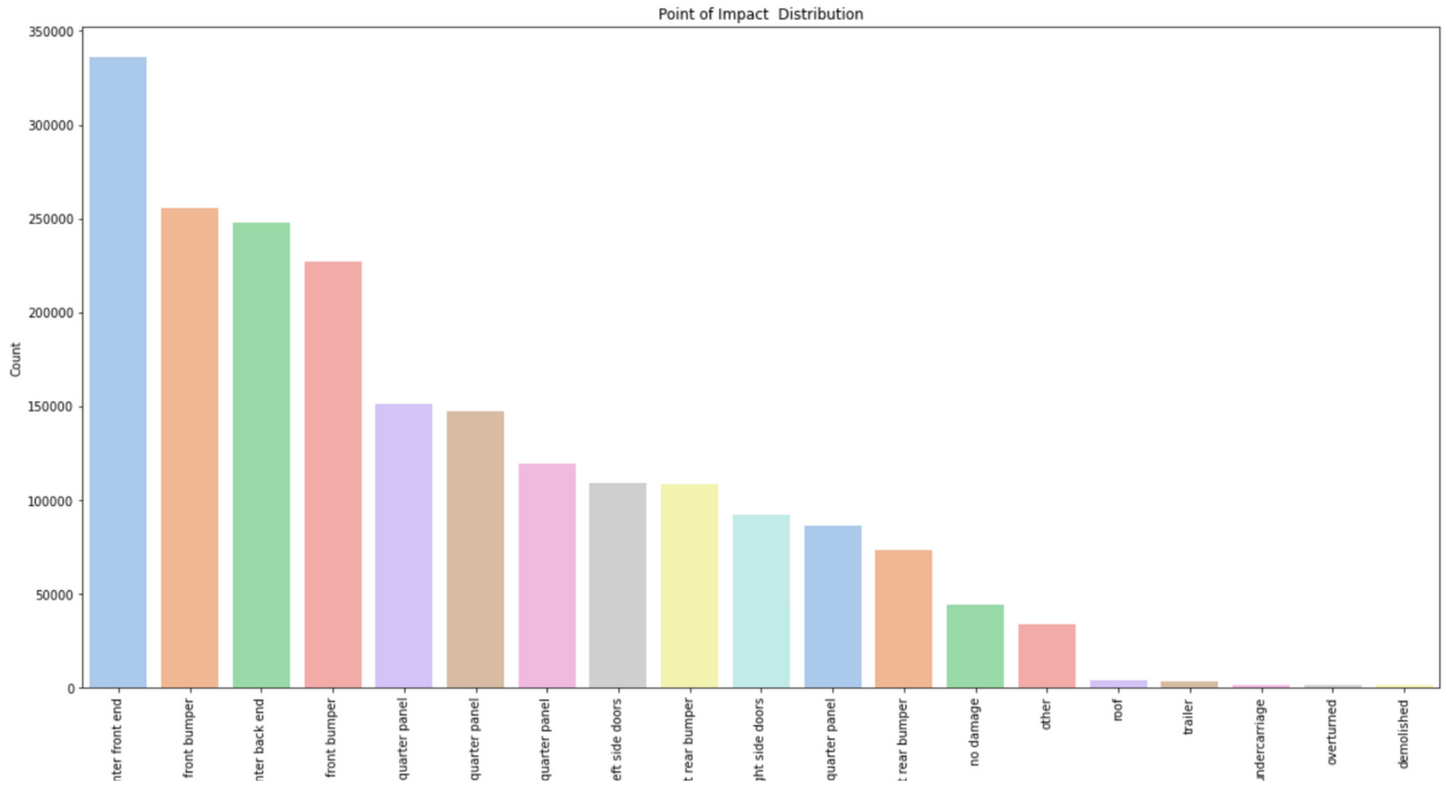
Run

Markdown

```
plt.show()
```



Exploratory Data Analysis

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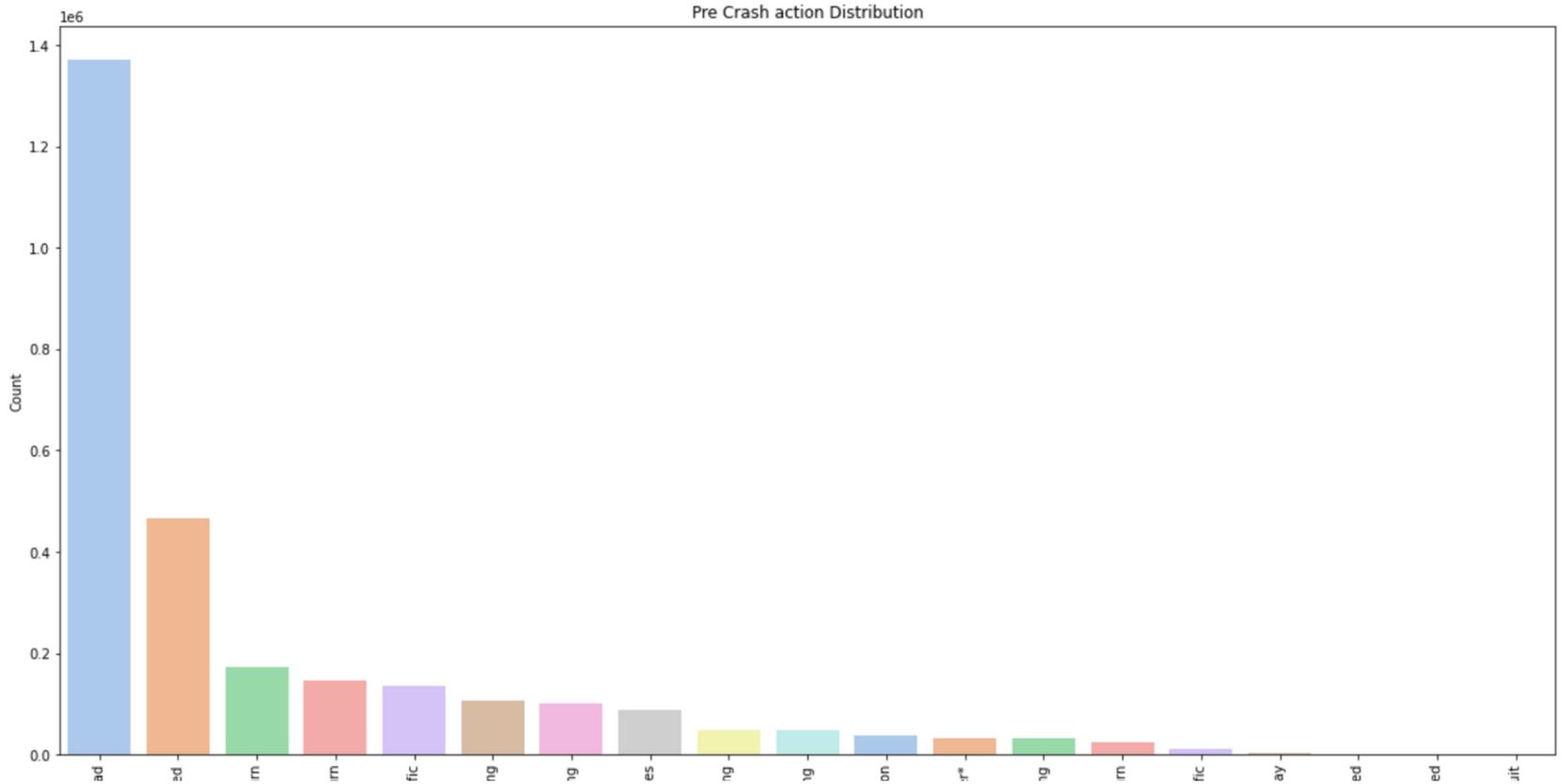
Run Markdown

```
plt.ylabel('Count')
plt.show()
```



Machine Learning

Categorical columns :

'VEHICLE_TYPE','DRIVER_SEX','POINT_OF_IMPACT','MAKE','Month','Week','Hour'

Numerical columns : 'how_old'

x(independentvariables)

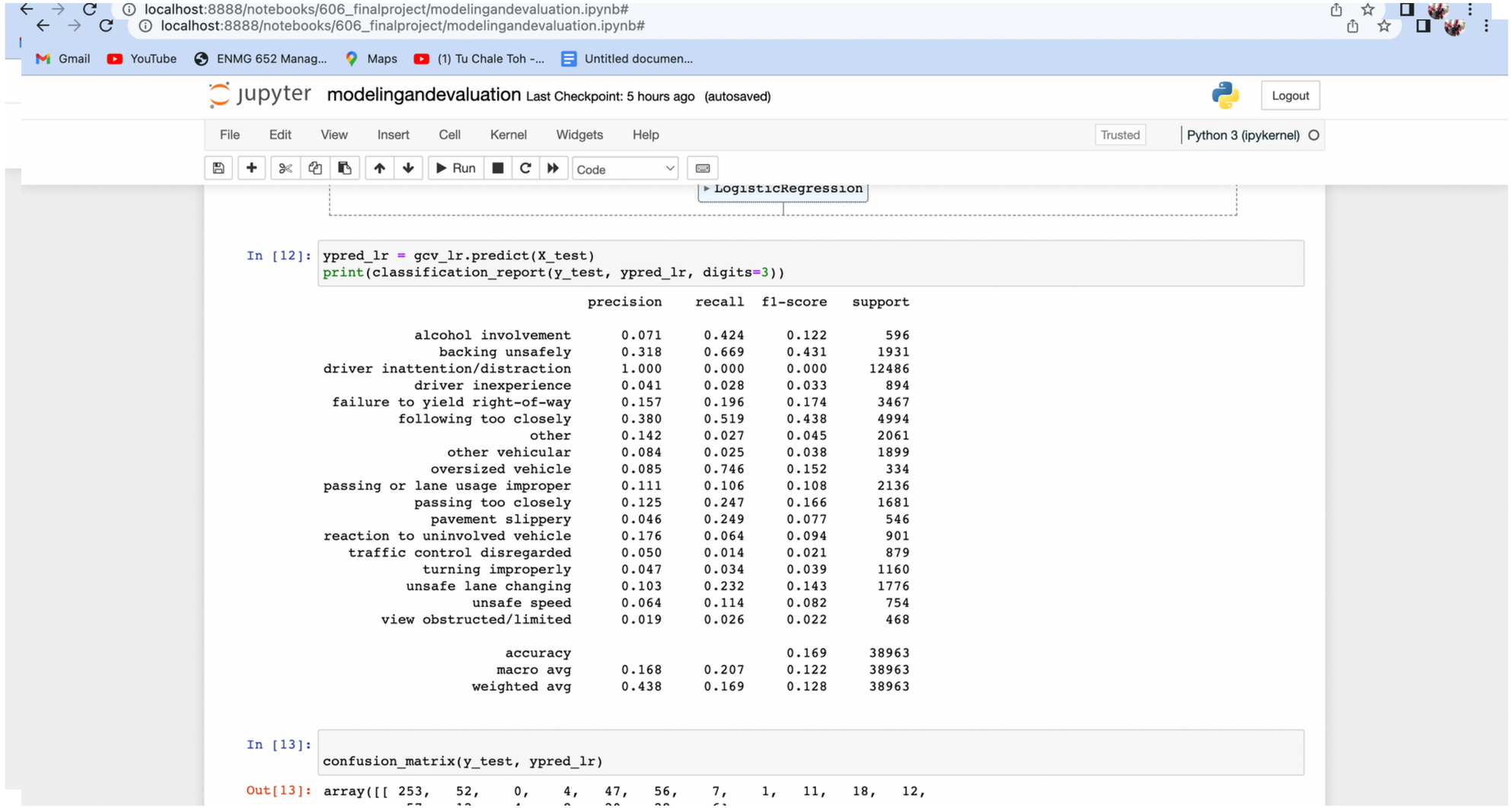
: 'VEHICLE_TYPE','DRIVER_SEX','POINT_OF_IMPACT','MAKE','Month','Week','Hour','how_old'

y(dependent variable) : 'CONTRIBUTING_FACTOR_1'

Models and Approach

- Logistic regression
- Decision tree
- Random forest
- Gradient Boosting Classifier
- Ada Boost Classifier

Logistic Regression



Observations

- When we use a logistic regression to classify the contributing factor we get a macro average of 0.312
- When it comes to driver's inattention the model has a 60% precision.
- When it comes to failure to yield right-of-way the model has a 21% precision.
- When it comes to following too closely the model has a 42.5% precision.
- When it comes to improper lane usage the model has a 15.7% precision.
- For others the model has a 16.7% precision.

Decision Tree Algorithm

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Run Markdown

In [16]:
```
ypred_tree = gcv_tree.predict(X_test)
print(classification_report(y_test, ypred_tree, digits=3))
```

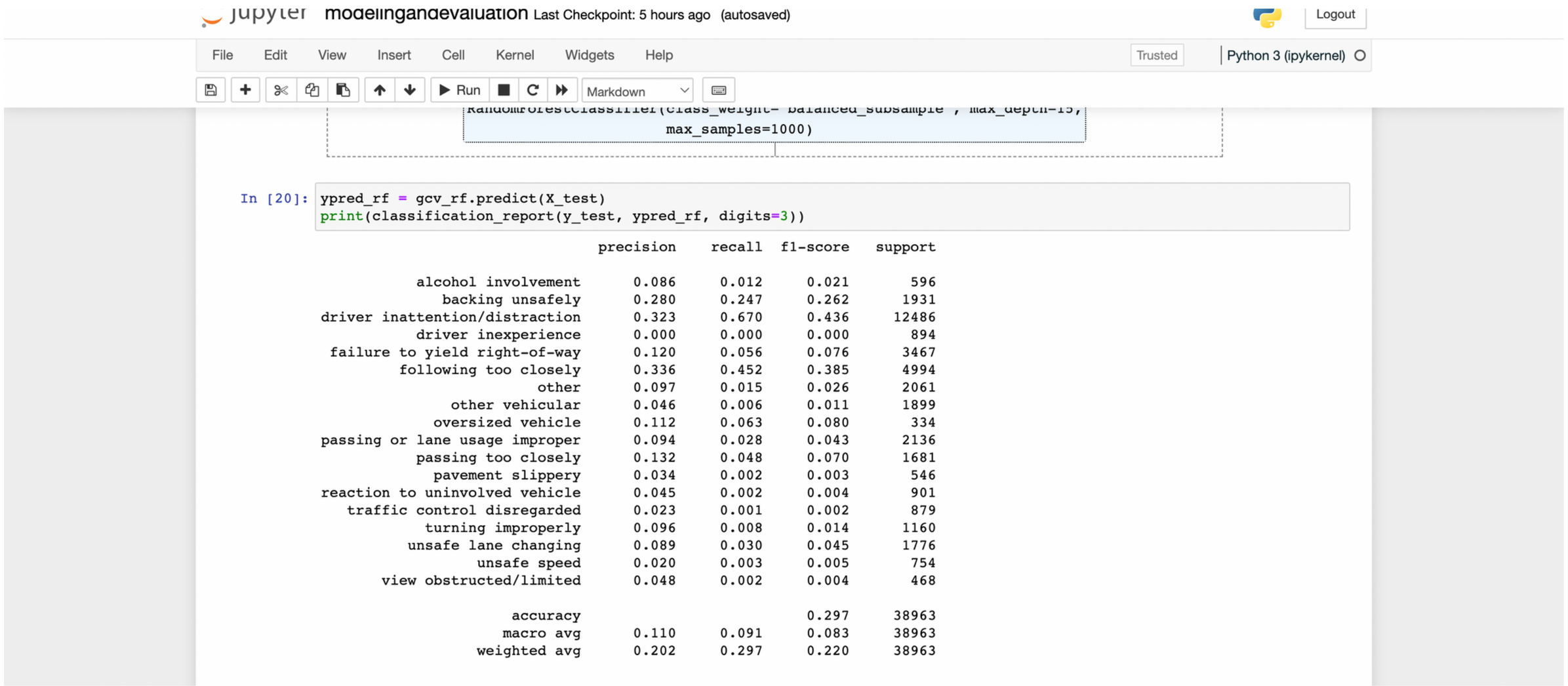
```
                                precision    recall  f1-score   support

            alcohol involvement      0.077     0.295     0.122       596
               backing unsafely      0.331     0.592     0.425      1931
driver inattention/distraction       0.000     0.000     0.000     12486
          driver inexperience        0.040     0.037     0.038       894
 failure to yield right-of-way       0.147     0.224     0.177      3467
        following too closely        0.372     0.459     0.411      4994
                         other       0.137     0.036     0.057      2061
               other vehicular       0.073     0.022     0.033      1899
             oversized vehicle       0.080     0.713     0.143       334
passing or lane usage improper       0.106     0.044     0.063      2136
           passing too closely       0.127     0.223     0.162      1681
             pavement slippery       0.042     0.165     0.067       546
reaction to uninvolved vehicle       0.104     0.131     0.116       901
   traffic control disregarded       0.038     0.046     0.041       879
            turning improperly       0.047     0.038     0.042      1160
          unsafe lane changing       0.096     0.231     0.136      1776
                   unsafe speed      0.046     0.159     0.071       754
      view obstructed/limited        0.017     0.030     0.022       468

                      accuracy                           0.156     38963
                     macro avg       0.104     0.191     0.118     38963
                  weighted avg       0.113     0.156     0.122     38963
```

In [17]:
```
confusion_matrix(y_test, ypred_tree)
```

Observations

- When we use a decision tree to classify the contributing factor we get a macro average of 0.295
- When it comes to driver's inattention the model has a 56% precision.
- When it comes to failure to yield right-of-way the model has a 21% precision.
- When it comes to following too closely the model has a 42% precision.
- When it comes to improper lane usage the model has a 15% precision.
- For others the model has a 13.8% precision.

Random Forest Algorithm



Observations

- When we use a Random Forest to classify the contributing factor we get a macro average of 0.329
- When it comes to driver's inattention the model has a 54% precision.
- When it comes to failure to yield right-of-way the model has a 21% precision.
- When it comes to following too closely the model has a 42% precision.
- When it comes to improper lane usage the model has a 16.6% precision.
- For others the model has a 31% precision

Gradient Booster Algorithm

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Run Markdown

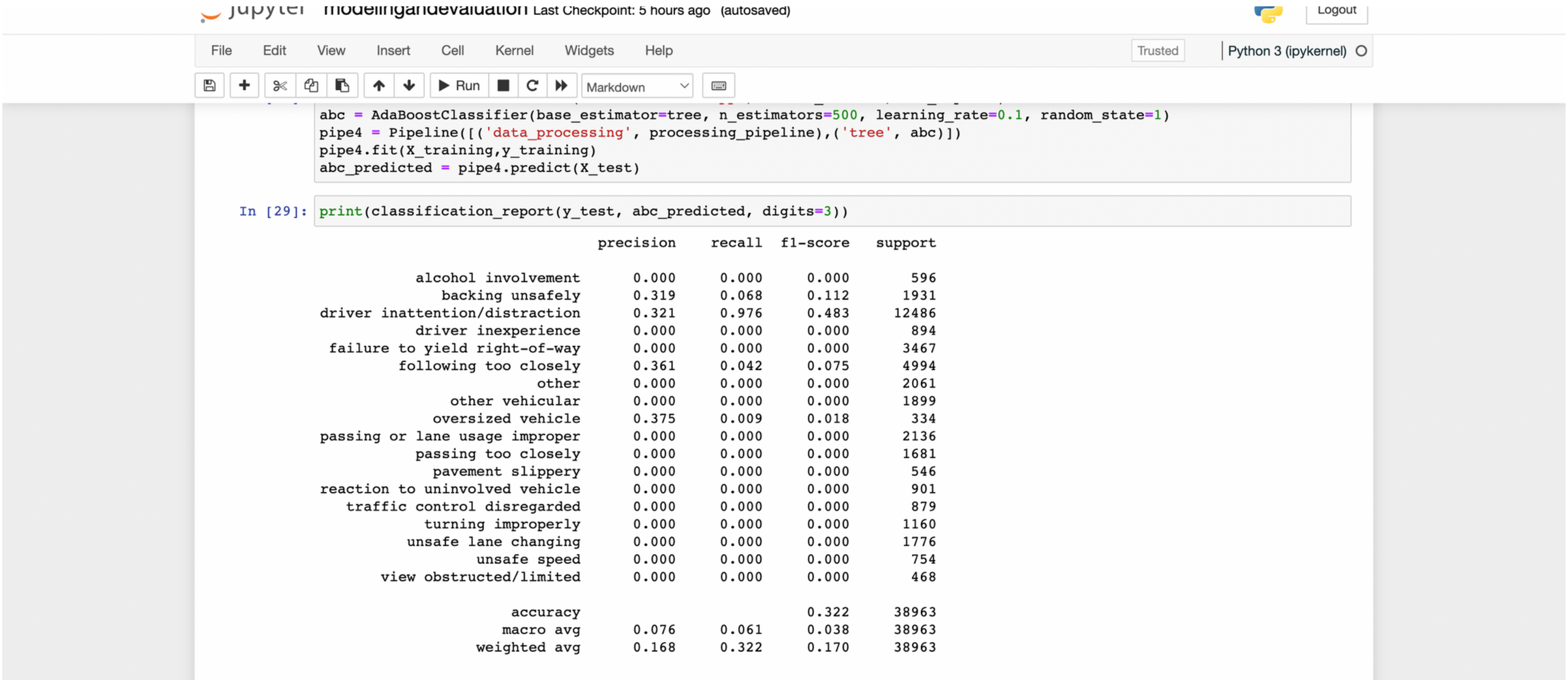
In [24]:
```
ypred_gb = gcv_gb.predict(X_test)
print(classification_report(y_test, ypred_gb, digits=3))
```

```
                                precision    recall  f1-score   support

            alcohol involvement      0.000     0.000     0.000       596
               backing unsafely      0.322     0.356     0.338      1931
driver inattention/distraction       0.325     0.873     0.474     12486
            driver inexperience      0.667     0.002     0.004       894
 failure to yield right-of-way       0.000     0.000     0.000      3467
         following too closely       0.396     0.263     0.316      4994
                          other       0.333     0.000     0.001      2061
                  other vehicular      0.000     0.000     0.000      1899
               oversized vehicle      0.182     0.006     0.012       334
passing or lane usage improper       0.000     0.000     0.000      2136
            passing too closely      0.000     0.000     0.000      1681
              pavement slippery      0.000     0.000     0.000       546
reaction to uninvolved vehicle       0.000     0.000     0.000       901
   traffic control disregarded       0.000     0.000     0.000       879
             turning improperly      0.000     0.000     0.000      1160
          unsafe lane changing       0.000     0.000     0.000      1776
                   unsafe speed      0.000     0.000     0.000       754
      view obstructed/limited        0.000     0.000     0.000       468

                      accuracy                           0.331     38963
                     macro avg      0.124     0.083     0.064     38963
                  weighted avg      0.205     0.331     0.209     38963
```

Observations

- When we use a gradient boosting to classify the contributing factor we get a macro average of 0.260
- When it comes to driver's inattention the model has a 51% precision.
- When it comes to failure to yield right-of-way the model has a 0% precision.
- When it comes to following too closely the model has a 45.4% precision.
- When it comes to improper lane usage the model has a 0% precision.
- For others the model has a 33.3% precision.

Ada Boost Classifier Algorithm



Observations

- When we use a Adaboosting classifier to classify the contributing factor we get a macro average of 0.192
- When it comes to driver's inattention the model has a 54% precision.
- When it comes to failure to yield right-of-way the model has a 0% precision.
- When it comes to following too closely the model has a 43.6% precision.
- When it comes to improper lane usage the model has a 0% precision.
- For others the model has a 0% precision.

Summary

I would use random forest or logistic regression as the final model. As both of these model identify the less frequently occuring classes more accurately compared to the complex algorithms like gradient boosting algortihm or adaboosting algorithm.

Future Scope

I would use the model that identifies the less frequently occuring classes more accurately compared to the complex algorithms.For the future of the project, I would like to identify various data sources that would help us look at a bigger picture of what the major contributing factors of the accident are and merge them with the existing dataset. Also, build machine learning models that could more accurately classify the contributing factor for an accident.