# Predicting Severity of Car Accidents

## A Project Report Submitted for the IBM Data Science Capstone Project

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## 1. Problem description

This capstone project addresses car accidents and the prediction of their severities given historical data on car accidents collected over many years. Predicting the severity of a car accident will help dispatching the appropriate emergency services to the accident scene. Ultimately, this will make an effective use of resources and help save more lives. In addition to predicting severity, the exploration of collected data can help pinpointing other problems that can be identified and addressed. Road quality and conditions can be improved again leading to the well being and safety of the population.

Car accident data that can be useful for predicting the severity of accidents and for developing policies and making decisions that can improve the safety conditions and make efficient use of financial and other resources should include for each reported accident, among other things: the time (hour, minute) of the accident, the day of the accident, the location of the accident and its severity, the number of people involved, the road conditions and the weather condition during the accident. Once an accident is reported, this system would predict the severity of the reported accident based on the learning from the historical data. Based on the prediction, appropriate actions can be performed.

This system can be used by various government departments and authorities to deal in an efficient and effective way with the accident itself. In addition, improvements and new policies and guidelines can be developed based on the analysis of the collected data. Departments and authorities that can be involved and can benefit from this system include the police department, the fire department, hospitals, civil defense, traffic and transport department and public works.

## 2. Data description

The data on car accidents that we have used in this project was obtained from Kaggle.com (https://www.kaggle.com/ahmedlahlou/accidents-in-france-from-2005-to-2016). It consists of five different excel sheets recording information collected about car accidents in France from 2005 to 2016. Fortunately, I know French so it was easy for me to understand the data and I renamed most of the features to the English language.

The five files that we have downloaded from Kaggle.com are:

1. The characteristics.csv file which contains data related to the characteristics of each accident recorded. The file contains 16 columns and 839985 rows. The columns include the accident number, date and time of the accident, the address, the lighting condition and other information.

2. The places.csv file which contains data related to the places where each accident has occurred. The file contains 18 columns and 839985 rows. The columns include the accident number, the lane and other information.
3. The users.csv file which contains data related to the people involved in each accident recorded. The file contains 12 columns and 1876005 rows. The columns include the accident number, the year of birth, the gravity of the injury, the gender and other information.
4. The characteristics.csv file which contains data related to the characteristics of each accident recorded. The file contains 9 columns and 1433389 rows. The columns include the accident number, the type of vehicle and other information about the vehicles involved.
5. The holidays.csv file which contains data related to the dates of holidays in France during 2005-2016. The file contains 2 columns and 132 rows. The columns include the date of the holiday and the holiday name.

Below we provide the python code that gives information about the five files that will be used in our project.

The characteristics file:

```
# First the characteristics file
dataframe_characteristics = pd.read_csv('caracteristics.csv', encoding = 'latin-1', low_memory = False)
dataframe_characteristics.head(5)
```

| | Num_Acc | an | mois | jour | hrmn | lum | agg | int | atm | col | com | adr | gps | lat | long | dep |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 201600000001 | 16 | 2 | 1 | 1445 | 1 | 2 | 1 | 8.0 | 3.0 | 5.0 | 46, rue Sonneville | M | 0.0 | 0 | 590 |
| 1 | 201600000002 | 16 | 3 | 16 | 1800 | 1 | 2 | 6 | 1.0 | 6.0 | 5.0 | 1a rue du cimetière | M | 0.0 | 0 | 590 |
| 2 | 201600000003 | 16 | 7 | 13 | 1900 | 1 | 1 | 1 | 1.0 | 6.0 | 11.0 | NaN | M | 0.0 | 0 | 590 |
| 3 | 201600000004 | 16 | 8 | 15 | 1930 | 2 | 2 | 1 | 7.0 | 3.0 | 477.0 | 52 rue victor hugo | M | 0.0 | 0 | 590 |
| 4 | 201600000005 | 16 | 12 | 23 | 1100 | 1 | 2 | 3 | 1.0 | 3.0 | 11.0 | rue Joliot curie | M | 0.0 | 0 | 590 |

```
# column names in the data frame for characteristics
dataframe_characteristics.columns
```

```
Index(['Num_Acc', 'an', 'mois', 'jour', 'hrmn', 'lum', 'agg', 'int', 'atm',
       'col', 'com', 'adr', 'gps', 'lat', 'long', 'dep'],
      dtype='object')
```

```
# number of rows and columns in the data frame for characteristics
dataframe_characteristics.shape
```

```
(839985, 16)
```

The places file:

```
# Second -  the places file
dataframe_places = pd.read_csv('places.csv', encoding = 'latin-1', low_memory = False)
dataframe_places.head(5)
```

| | Num_Acc | catr | voie | v1 | v2 | circ | nbv | pr | pr1 | vosp | prof | plan | lartpc | larrout | surf | infra | situ | env1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 201600000001 | 3.0 | 39 | NaN | NaN | 2.0 | 0.0 | NaN | NaN | 0.0 | 1.0 | 3.0 | 0.0 | 0.0 | 1.0 | 0.0 | 1.0 | 0.0 |
| 1 | 201600000002 | 3.0 | 39 | NaN | NaN | 1.0 | 0.0 | NaN | NaN | 0.0 | 1.0 | 2.0 | 0.0 | 58.0 | 1.0 | 0.0 | 1.0 | 0.0 |
| 2 | 201600000003 | 3.0 | 1 | NaN | NaN | 2.0 | 2.0 | NaN | NaN | 0.0 | 1.0 | 3.0 | 0.0 | 68.0 | 2.0 | 0.0 | 3.0 | 99.0 |
| 3 | 201600000004 | 4.0 | 0 | NaN | NaN | 2.0 | 0.0 | NaN | NaN | 0.0 | 1.0 | 1.0 | 0.0 | 0.0 | 1.0 | 0.0 | 1.0 | 99.0 |
| 4 | 201600000005 | 4.0 | 0 | NaN | NaN | 0.0 | 0.0 | NaN | NaN | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 1.0 | 0.0 | 1.0 | 3.0 |

```
# column names in the data frame for places
dataframe_places.columns
```

```
Index(['Num_Acc', 'catr', 'voie', 'v1', 'v2', 'circ', 'nbv', 'pr', 'pr1',
       'vosp', 'prof', 'plan', 'lartpc', 'larrout', 'surf', 'infra', 'situ',
       'env1'],
      dtype='object')
```

```
# number of rows and columns in the data frame for places
dataframe_places.shape
```

```
(839985, 18)
```

The users file:

```
# Third -  the users file
dataframe_users = pd.read_csv('users.csv', encoding = 'latin-1', low_memory = False)
dataframe_users.head(5)
```

| | Num_Acc | place | catu | grav | sexe | trajet | secu | locp | actp | etatp | an_nais | num_veh |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 201600000001 | 1.0 | 1 | 1 | 2 | 0.0 | 11.0 | 0.0 | 0.0 | 0.0 | 1983.0 | B02 |
| 1 | 201600000001 | 1.0 | 1 | 3 | 1 | 9.0 | 21.0 | 0.0 | 0.0 | 0.0 | 2001.0 | A01 |
| 2 | 201600000002 | 1.0 | 1 | 3 | 1 | 5.0 | 11.0 | 0.0 | 0.0 | 0.0 | 1960.0 | A01 |
| 3 | 201600000002 | 2.0 | 2 | 3 | 1 | 0.0 | 11.0 | 0.0 | 0.0 | 0.0 | 2000.0 | A01 |
| 4 | 201600000002 | 3.0 | 2 | 3 | 2 | 0.0 | 11.0 | 0.0 | 0.0 | 0.0 | 1962.0 | A01 |

```
# column names in the data frame for users
dataframe_users.columns
```

```
Index(['Num_Acc', 'place', 'catu', 'grav', 'sexe', 'trajet', 'secu', 'locp',
       'actp', 'etatp', 'an_nais', 'num_veh'],
      dtype='object')
```

```
# number of rows and columns in the data frame for users
dataframe_users.shape
```

```
(1876005, 12)
```

The vehicles file:

```
# Fourth -  the vehicles file
dataframe_vehicles = pd.read_csv('vehicles.csv', encoding = 'latin-1', low_memory = False)
dataframe_vehicles.head(5)
```

| | Num_Acc | senc | catv | occutc | obs | obsm | choc | manv | num_veh |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 201600000001 | 0.0 | 7 | 0 | 0.0 | 0.0 | 1.0 | 1.0 | B02 |
| 1 | 201600000001 | 0.0 | 2 | 0 | 0.0 | 0.0 | 7.0 | 15.0 | A01 |
| 2 | 201600000002 | 0.0 | 7 | 0 | 6.0 | 0.0 | 1.0 | 1.0 | A01 |
| 3 | 201600000003 | 0.0 | 7 | 0 | 0.0 | 1.0 | 6.0 | 1.0 | A01 |
| 4 | 201600000004 | 0.0 | 32 | 0 | 0.0 | 0.0 | 1.0 | 1.0 | B02 |

```
# column names in the data frame for vehicles
dataframe_vehicles.columns
```

```
Index(['Num_Acc', 'senc', 'catv', 'occutc', 'obs', 'obsm', 'choc', 'manv',
       'num_veh'],
      dtype='object')
```

```
# number of rows and columns in the data frame for vehicles
dataframe_vehicles.shape
```

```
(1433389, 9)
```

The holidays file:

```
# Fifth -  the holidays file
dataframe_holidays = pd.read_csv('holidays.csv', encoding = 'latin-1', low_memory = False)
dataframe_holidays.head(5)
```

| | ds | holiday |
|---|---|---|
| 0 | 2005-01-01 | New year |
| 1 | 2005-03-28 | Easter Monday |
| 2 | 2005-05-01 | Labour Day |
| 3 | 2005-05-05 | Ascension Thursday |
| 4 | 2005-05-08 | Victory in Europe Day |

```
# column names in the data frame for holidays
dataframe_holidays.columns
```

```
Index(['ds', 'holiday'], dtype='object')
```

```
# number of rows and columns in the data frame for holidays
dataframe_holidays.shape
```

```
(132, 2)
```

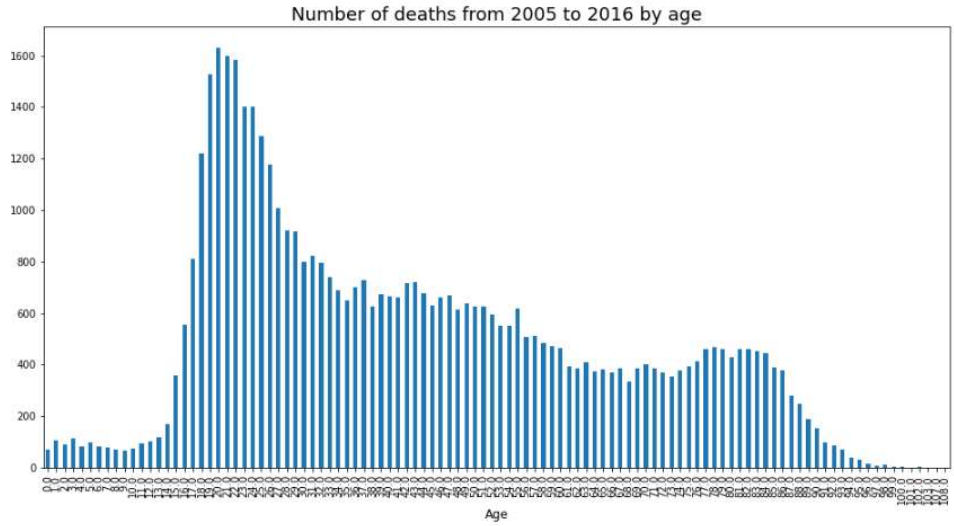
## 3. Data cleaning

After checking the data file contents, we can see there are a lot of data that are either not available or seem abnormal. Also, many features are not needed or useful for the analysis and can be dropped from the data sets. After cleaning the data from the five data files, we joined them in one single data frame.

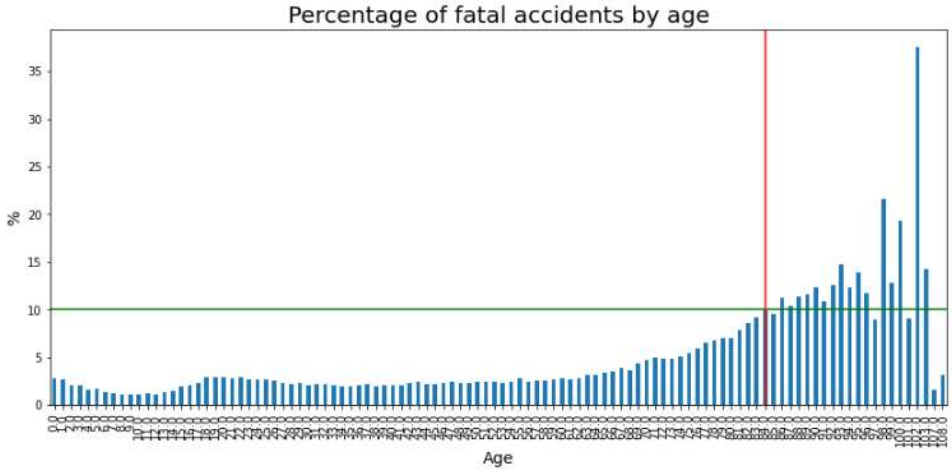
## 4. Exploratory data analysis

Before building the prediction models, we decided to explore the data we loaded about accidents recorded in France from 2005 to 2016. The aim of this exploratory data analysis is to gain more information about the data and get more insight of its content and the relationship among its data features. For each of the finding, we plotted the graph to show the relationships among features. The following are some of the interesting findings about the data set.

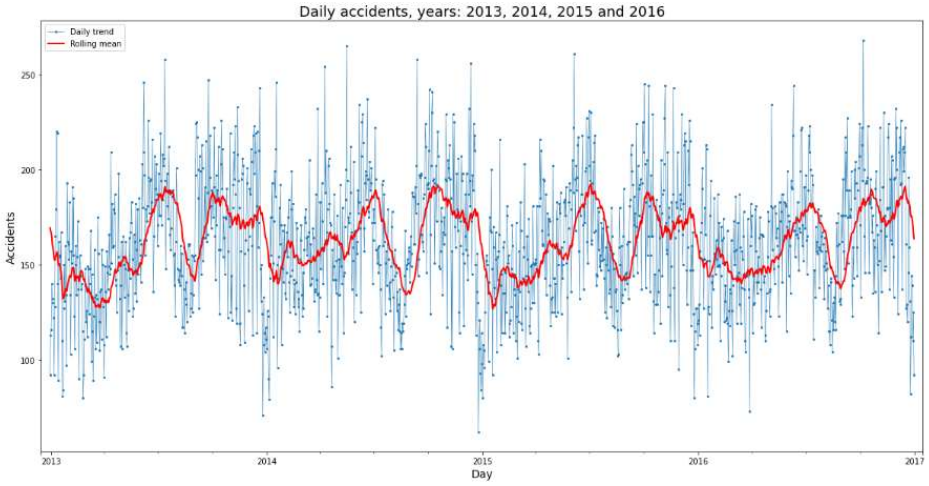
The number of dead persons by age as plotted below shows one peak for young ages between 20 and 30, and another peak among old age people (around 83 years old).



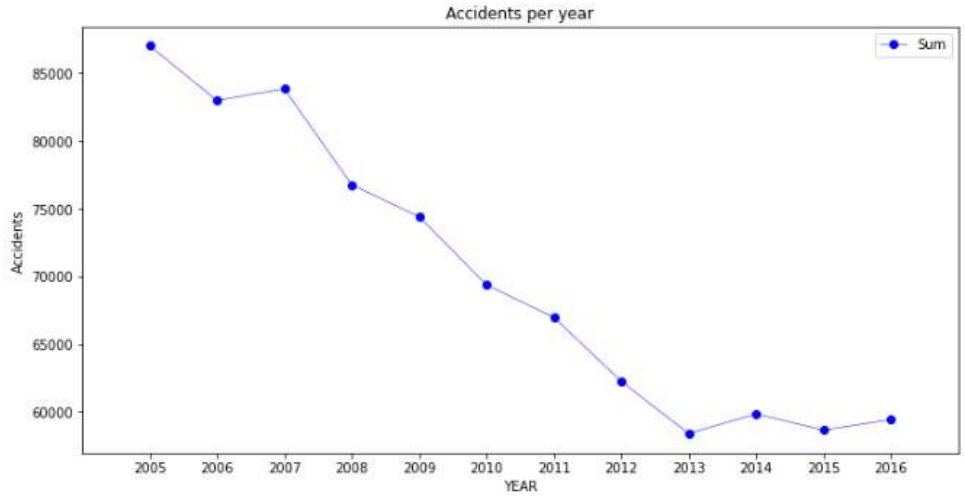
The percentage of fatal accidents by age as plotted below shows that most fatal accidents involved old age persons.



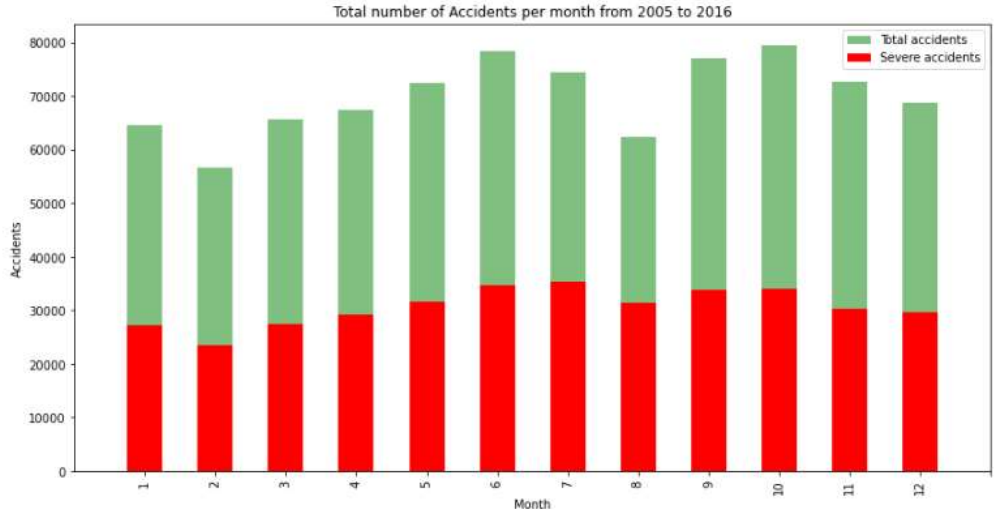

The number of daily accidents for the last four years (2013-2016) plotted below shows a fluctuation around 250 accidents per day.



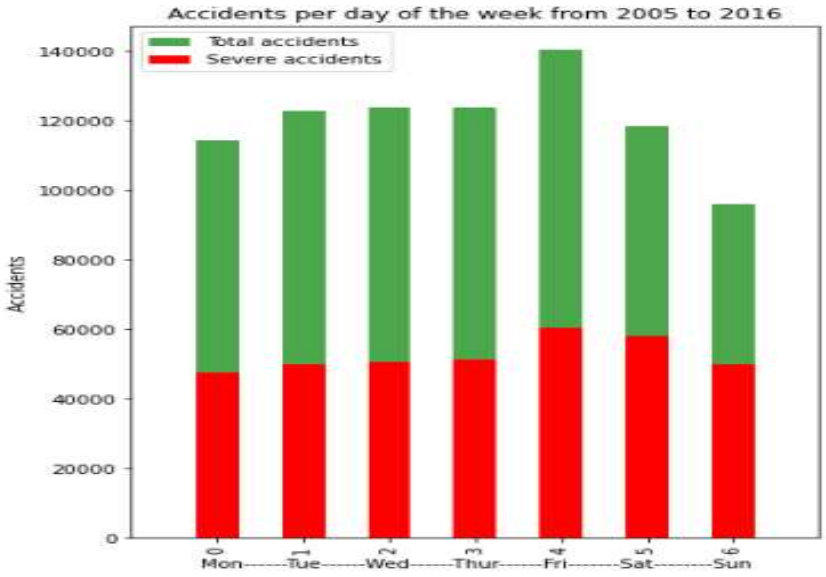
The number of accidents per year plotted below shows a decrease of the number of accidents from around 85000 to 60000 accidents per year. This shows a positive trend that need to be investigated in terms of the changes that were made to make this decrease happen.



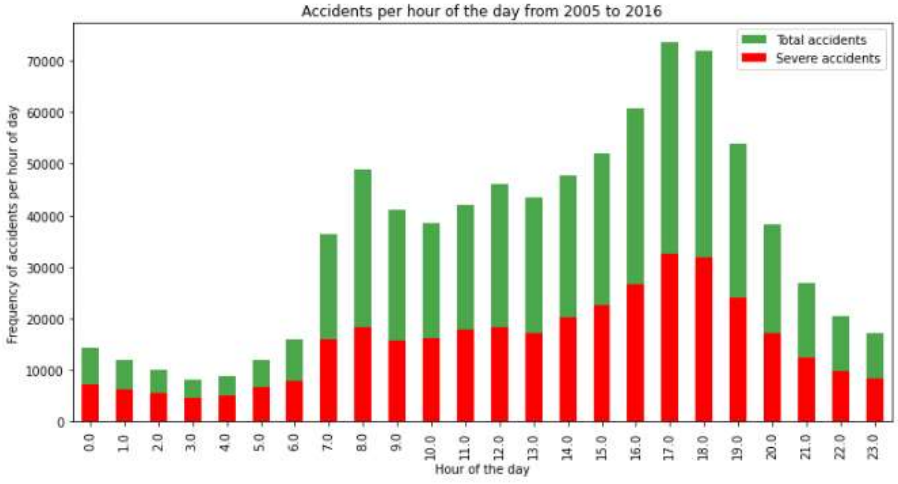

The number of accidents per month plotted below shows that June and October have slightly more accidents than other months. This may be related to travel for summer vacation.



The number of accidents per day of the week plotted below shows that Friday is the day where more accidents than any other day happened. This can be explained by accidents due to the rush for the weekend!




The number of fatal and severe accidents per the hour of the day as plotted below shows that during the 8-9 am and 5-6 pm the number of accidents peak. This is explained by the morning and evening rush hours when people travel to and from work.



## 5. Data preparation

In this step some more data cleaning and dropping of unimportant features were performed. In addition, we have decided on the split of the data set into training and test tests that will be used when the models developed in the next section were tested.

```
#Some feature's values range from 1 to 9 while others just go either for 1 or 2,
#Normalizing the data makes that any feature has more influence in the result than others.

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

xtrain, xtest, ytrain, ytest = train_test_split(dataframe.drop('SEVERITY', axis=1), dataframe['SEVERITY'], test_size=0.2, random
xtrain, xval, ytrain, yval = train_test_split(xtrain, ytrain, test_size=0.2)

print('Size of training set:', xtrain.shape[0],'\n'
      'Size of test set:',xtest.shape[0],'\n'
      'Size of evaluation set:', xval.shape[0])
```

```
Size of training set: 537590
Size of test set: 167997
Size of evaluation set: 134398
```

## 6. Model development

We have built various models using four different machine learning techniques, namely, the decision tree model, the logistic regression model, the k-nearest neighbor model and the support vector machine model.

In the following, we show each model and its parameters along with its performance and accuracy.

### 6.1. Decision tree (DT) and random forest (RF) model

We first built a decision tree classifier model which had an accuracy of 0.63. We then built four random forest classifier model with different parameters to check which leads to the best accuracy.

We found that the best accuracy was obtained for the random forest model with 10 decision trees and a maximum of 8 features among the 23 features of the data frame.

```
#number of decision trees reduced from 50 to 10
#Limiting the number of features to look at when creating the next split to 8
#Limiting the max depth of the tree to 12


t0=time.time()
model_randomForest = RandomForestClassifier(n_estimators=10, max_features=8, max_depth =12,criterion='entropy',random_state=0, n
model_randomForest.fit(xtrain,ytrain)
print('Time taken :' , time.time()-t0)
yhat = model_randomForest.predict(xval)
score_randomForest = accuracy_score(yval,yhat)
print('Accuracy :',score_randomForest)
```

```
Time taken : 8.156516551971436
Accuracy : 0.7214988318278546
```

## 6.2. Logistic regression (LR) model

To use the logistic regression model, we first have to find the best regularization coefficient, the one that leads to the highest accuracy. As shown below, the best coefficient is 0.001.

```
accuracy = np.zeros(6)
i=0
for c in [0.5, 0.1, 0.01, 0.001, 10, 100]:
    logisticRegression = LogisticRegression(C=c, solver='liblinear').fit(xtrain, ytrain)
    yhat = logisticRegression.predict(xval)
    accuracy[i] = accuracy_score(yval,yhat)
    i+=1
accuracy
```

```
array([0.65830593, 0.65831337, 0.65857379, 0.65904255, 0.65832825,
       0.65832825])
```

We then use this coefficient to build the model and

```
t0=time.time()
logisticRegression = LogisticRegression(C=0.001, solver='liblinear').fit(xtrain, ytrain)
t_logisticRegression = time.time()-t0
print('Time taken :' , t_logisticRegression)
yhat = logisticRegression.predict(xtest)
jaccard_logisticRegression = jaccard_score(ytest,yhat)
c_logisticRegression = classification_report(ytest,yhat)
prec_logisticRegression = precision_score(ytest, yhat)
rec_logisticRegression = recall_score(ytest, yhat)
print('Jaccard :',jaccard_logisticRegression,'\n',   c_logisticRegression)
```

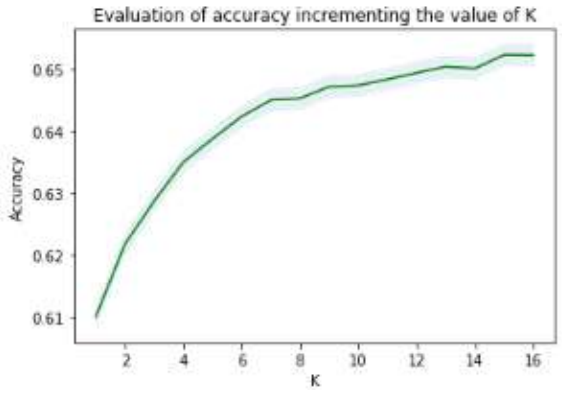
```
Time taken : 4.526005029678345
Jaccard : 0.3717329026977403
              precision    recall  f1-score   support

           0       0.66      0.82      0.73     94297
           1       0.67      0.46      0.54     73700

    accuracy                           0.66    167997
   macro avg       0.66      0.64      0.64    167997
weighted avg       0.66      0.66      0.65    167997
```

### 6.3. K-nearest neighbor (KNN) model

To use this model, we needed first to find the best value for k (the number of nearest neighbors) that lead to the best model accuracy. We found that K = 15 is the best value as plotted in the graph below.

```
tt = xtrain.shape[0]
tv = xval.shape[0]

xtrain[int(tt*0.5):].shape[0], xval[int(tv*0.5):].shape[0]

ks = 17
mean_accuracy = np.zeros(ks-1)
std_accuracy = np.zeros(ks-1)

for n in range(1,ks):
    neigh = KNeighborsClassifier(n_neighbors = n).fit(xtrain[int(tt*0.5):],ytrain[int(tt*0.5):])
    yhat = neigh.predict(xval[int(tv*0.5):])
    mean_accuracy[n-1] = accuracy_score(yval[int(tv*0.5):],yhat)
    std_accuracy[n-1] = np.std(yhat==yval[int(tv*0.5):])/np.sqrt(yhat.shape[0])
print('Best performing K is '+ str(mean_accuracy.argmax()+1) + ' with an accuracy of ' +str(mean_accuracy.max()))

plt.plot(range(1,ks),mean_accuracy,'g')
plt.xlabel('K')
plt.ylabel('Accuracy')
plt.title('Evaluation of accuracy incrementing the value of K')
plt.fill_between(range(1,ks), mean_accuracy -1 * std_accuracy , mean_accuracy + 1 * std_accuracy, alpha=0.1)
```

```
Best performing K is 15 with an accuracy of 0.6523906605753061

<matplotlib.collections.PolyCollection at 0x2a1aaedcac0>
```



Then we build the KNN model and compute the jaccard precision score.

```
t0=time.time()
model_KNN = KNeighborsClassifier(n_neighbors = 16, n_jobs=-1)
model_KNN.fit(xtrain,ytrain)
t_KNN = time.time()-t0
print('Time taken :' , t_KNN)
yhat = model_KNN.predict(xtest)
jaccard_KNN = jaccard_score(ytest,yhat)
c_KNN = classification_report(ytest,yhat)
prec_KNN = precision_score(ytest, yhat)
rec_KNN = recall_score(ytest, yhat)
print('Jaccard :',jaccard_KNN,'\n',  c_KNN)
```

```
Time taken : 189.3194124698639
Jaccard : 0.39912135367118107
              precision    recall  f1-score   support

           0       0.67      0.79      0.73     94297
           1       0.65      0.51      0.57     73700

    accuracy                           0.67    167997
   macro avg       0.66      0.65      0.65    167997
weighted avg       0.66      0.67      0.66    167997
```

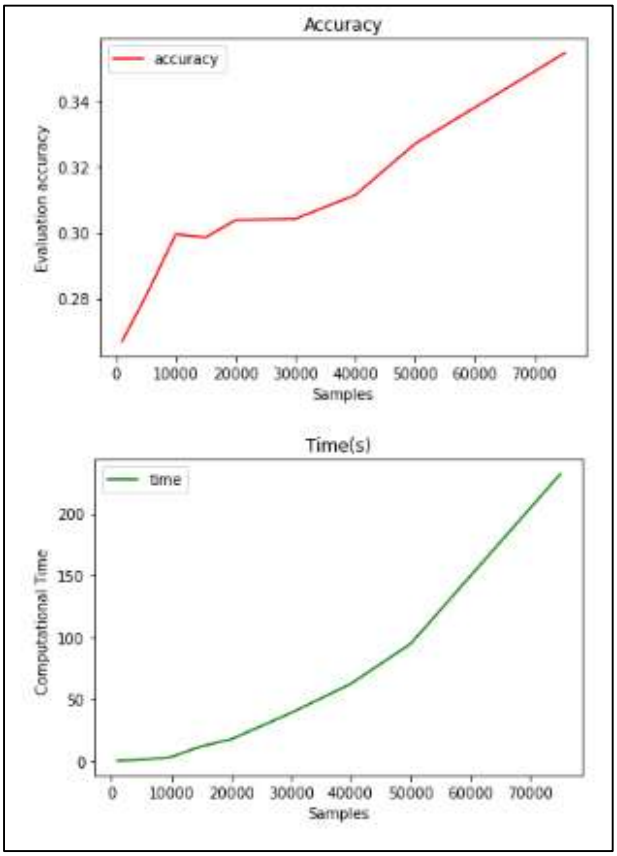
### 6.4. Support vector machine (SVM) model

For this model, we have used 9 samples of different sample sizes. We then plotted the accuracy of the model for each of the different samples.

```
size = [1000,5000,10000,15000,20000,30000,40000,50000,75000]
accuracy = []
t = []
for s in size:
    t0=time.time()
    sv = SVC().fit(xtrain[:s],ytrain[:s])
    t.append(time.time()-t0)
    yhat = sv.predict(xval[:s])
    accuracy.append(jaccard_score(yval[:s],yhat))

performance = pd.DataFrame({'acc':accuracy, 'time':t}, index=size)
performance
```

```
Time taken : 238.07018876075745
Jaccard : 0.3717329026977403
              precision    recall  f1-score   support

           0       0.66      0.82      0.73     94297
           1       0.67      0.46      0.54     73700

    accuracy                           0.66    167997
   macro avg       0.66      0.64      0.64    167997
weighted avg       0.66      0.66      0.65    167997
```

Clearly, the larger the sample is, the more accurate the model is. But evidently, increasing the sample size will require longer execution size. The execution time is not linear with the sample size as shown in the plots below.



## 7. Results and analysis

The table below summarizes the performance of each of the four models we built and tested in the above section. For each of the four models, we have used the parameters that lead to the best accuracy of the model as discussed before.

| Algorithm | Jaccard | f1-score | Precision | Recall |
|---|---|---|---|---|
| Random Forest | 0.488 | 0.72 | 0.722 | 0.601 |
| Logistic Regression | 0.371 | 0.667 | 0.667 | 0.456 |
| KNN | 0.399 | 0.652 | 0.652 | 0.506 |
| SVM | 0.358 | 0.688 | 0.660 | 0.427 |

The following are some of the observations we can make on the four models and their accuracy and performance.

- Precision means the percentage of predicted severe accidents that were truly severe.
- Recall is the percentage of truly severe accidents that were correctly predicted.
- Recall is more important than the precision as a high recall means that all required resources will be equipped up to the severity of the accident.
- LR, KNN and SVM models have similar accuracy.
- RF model is the best model since it has the highest accuracy and highest recall.
- The best model with the highest precision is the Random Forest Decision Tree model with a precision of 0.72 and a recall of 0.59