Predictions for At Fault Drivers- Phase 3 Project

Angela Joseph-Pauline

Overview

Using Logistic Modeling and DecisionTreeRegression to predict the possibility of a driver being at fault for car crashes i the Chicargo, IL area. The Data was provided by the Chicago, IL police department.

In [20]:

```
#imports
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

#this allows plotsto appear directly in the notebook
%matplotlib inline

from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.dummy import DummyClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import load_iris
from sklearn import svm, datasets
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import plot_roc_curve, roc_curve, auc
from sklearn.base import BaseEstimator
```

import DataFrame and clean data

In [21]:

```python
df = pd.read_csv("Traffic_Crashes_-_Crashes.csv")
df.head()
```

Out[21]:

	CRASH_RECORD_ID	RD_NO	CRASH_DATE_EST_I	CRAS
0	4fd0a3e0897b3335b94cd8d5b2d2b350eb691add56c62d...	JC343143	NaN	07. 05:5
1	009e9e67203442370272e1a13d6ee51a4155dac65e583d...	JA329216	NaN	06. 04:0
2	ee9283eff3a55ac50ee58f3d9528ce1d689b1c4180b4c4...	JD292400	NaN	07. 10:2
3	f8960f698e870ebdc60b521b2a141a5395556bc3704191...	JD293602	NaN	07 01:0
4	8eaa2678d1a127804ee9b8c35ddf7d63d913c14eda61d6...	JD290451	NaN	07. 02:0

5 rows × 49 columns

In [22]:

```python
#examine data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 496491 entries, 0 to 496490
Data columns (total 49 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   CRASH_RECORD_ID                496491 non-null  object
 1   RD_NO                          492845 non-null  object
 2   CRASH_DATE_EST_I               37328 non-null   object
 3   CRASH_DATE                     496491 non-null  object
 4   POSTED_SPEED_LIMIT             496491 non-null  int64
 5   TRAFFIC_CONTROL_DEVICE         496491 non-null  object
 6   DEVICE_CONDITION               496491 non-null  object
 7   WEATHER_CONDITION              496491 non-null  object
 8   LIGHTING_CONDITION             496491 non-null  object
 9   FIRST_CRASH_TYPE               496491 non-null  object
 10  TRAFFICWAY_TYPE                496491 non-null  object
 11  LANE_CNT                       198965 non-null  float64
 12  ALIGNMENT                      496491 non-null  object
 13  ROADWAY_SURFACE_COND           496491 non-null  object
 14  ROAD_DEFECT                    496491 non-null  object
```

In [23]:

```
#change all column names to lower case
df.columns = [x.lower() for x in df.columns]
df.head()
```

Out[23]:

	crash_record_id	rd_no	crash_date_est_i	crash_dat
0	4fd0a3e0897b3335b94cd8d5b2d2b350eb691add56c62d...	JC343143	NaN	07/10/201 05:56:0 PM
1	009e9e67203442370272e1a13d6ee51a4155dac65e583d...	JA329216	NaN	06/30/201 04:00:0 PM
2	ee9283eff3a55ac50ee58f3d9528ce1d689b1c4180b4c4...	JD292400	NaN	07/10/202 10:25:0 AM
3	f8960f698e870ebdc60b521b2a141a5395556bc3704191...	JD293602	NaN	07/11/202 01:00:0 AM
4	8eaa2678d1a127804ee9b8c35ddf7d63d913c14eda61d6...	JD290451	NaN	07/08/202 02:00:0 PM

5 rows × 49 columns

In [24]:
```
#Check for null values
print(df.isnull().sum())
```

```
crash_record_id                      0
rd_no                             3646
crash_date_est_i                459163
crash_date                           0
posted_speed_limit                   0
traffic_control_device               0
device_condition                     0
weather_condition                    0
lighting_condition                   0
first_crash_type                     0
trafficway_type                      0
lane_cnt                        297526
alignment                            0
roadway_surface_cond                 0
road_defect                          0
report_type                      12156
crash_type                           0
intersection_related_i          384435
not_right_of_way_i              473049
hit_and_run_i                   349519
damage                               0
date_police_notified                 0
prim_contributory_cause              0
sec_contributory_cause               0
street_no                            0
street_direction                     3
street_name                          1
beat_of_occurrence                   5
photos_taken_i                  490267
statements_taken_i              486457
dooring_i                       494915
work_zone_i                     493312
work_zone_type                  493984
workers_present_i               495725
num_units                            0
most_severe_injury                1015
injuries_total                    1004
injuries_fatal                    1004
injuries_incapacitating           1004
injuries_non_incapacitating       1004
injuries_reported_not_evident     1004
injuries_no_indication            1004
injuries_unknown                  1004
crash_hour                           0
crash_day_of_week                    0
crash_month                          0
latitude                          2770
longitude                         2770
location                          2770
dtype: int64
```

In [25]:
```
#Drop null values
df=df.dropna(axis=1)
```

In [26]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 496491 entries, 0 to 496490
Data columns (total 22 columns):
 #   Column                   Non-Null Count   Dtype 
---  ------                   --------------   ----- 
 0   crash_record_id          496491 non-null  object
 1   crash_date               496491 non-null  object
 2   posted_speed_limit       496491 non-null  int64 
 3   traffic_control_device   496491 non-null  object
 4   device_condition         496491 non-null  object
 5   weather_condition        496491 non-null  object
 6   lighting_condition       496491 non-null  object
 7   first_crash_type         496491 non-null  object
 8   trafficway_type          496491 non-null  object
 9   alignment                496491 non-null  object
 10  roadway_surface_cond     496491 non-null  object
 11  road_defect              496491 non-null  object
 12  crash_type               496491 non-null  object
 13  damage                   496491 non-null  object
 14  date_police_notified     496491 non-null  object
 15  prim_contributory_cause  496491 non-null  object
 16  sec_contributory_cause   496491 non-null  object
 17  street_no                496491 non-null  int64 
 18  num_units                496491 non-null  int64 
 19  crash_hour               496491 non-null  int64 
 20  crash_day_of_week        496491 non-null  int64 
 21  crash_month              496491 non-null  int64 
dtypes: int64(6), object(16)
memory usage: 83.3+ MB
```

In [27]:

```
#Confirm nulls have been dropped
print(df.isnull().sum())
```

```
crash_record_id            0
crash_date                 0
posted_speed_limit         0
traffic_control_device     0
device_condition           0
weather_condition          0
lighting_condition         0
first_crash_type           0
trafficway_type            0
alignment                  0
roadway_surface_cond       0
road_defect                0
crash_type                 0
damage                     0
date_police_notified       0
prim_contributory_cause    0
sec_contributory_cause     0
street_no                  0
num_units                  0
crash_hour                 0
crash_day_of_week          0
crash_month                0
dtype: int64
```

Assign Driver responsibility

Assign values in columns prim_contributory_cause in order to determine if Driver is at fault.

Driver at fault = 1

Outside circumstances= 0

In [28]:

```
#check value count
df['prim_contributory_cause'].value_counts().to_dict()
```

Out[28]:

```
{'UNABLE TO DETERMINE': 184177,
 'FAILING TO YIELD RIGHT-OF-WAY': 54473,
 'FOLLOWING TOO CLOSELY': 52427,
 'NOT APPLICABLE': 26650,
 'IMPROPER OVERTAKING/PASSING': 23572,
 'IMPROPER BACKING': 21669,
 'FAILING TO REDUCE SPEED TO AVOID CRASH': 21422,
 'IMPROPER LANE USAGE': 19136,
 'IMPROPER TURNING/NO SIGNAL': 16439,
 'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE': 15567,
 'DISREGARDING TRAFFIC SIGNALS': 9036,
 'WEATHER': 8529,
 'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE
MANNER': 6205,
 'DISREGARDING STOP SIGN': 5500,
 'DISTRACTION - FROM INSIDE VEHICLE': 3640,
 'EQUIPMENT - VEHICLE CONDITION': 3121,
 'PHYSICAL CONDITION OF DRIVER': 2915,
 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)': 2911,
 'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)': 264
7,
 'DRIVING ON WRONG SIDE/WRONG WAY': 2346,
 'DISTRACTION - FROM OUTSIDE VEHICLE': 2185,
 'EXCEEDING AUTHORIZED SPEED LIMIT': 1982,
 'EXCEEDING SAFE SPEED FOR CONDITIONS': 1684,
 'ROAD ENGINEERING/SURFACE/MARKING DEFECTS': 1390,
 'ROAD CONSTRUCTION/MAINTENANCE': 1197,
 'DISREGARDING OTHER TRAFFIC SIGNS': 1068,
 'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST': 926,
 'CELL PHONE USE OTHER THAN TEXTING': 697,
 'DISREGARDING ROAD MARKINGS': 677,
 'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)': 551,
 'ANIMAL': 416,
 'TURNING RIGHT ON RED': 349,
 'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ET
C.)': 235,
 'TEXTING': 215,
 'DISREGARDING YIELD SIGN': 187,
 'RELATED TO BUS STOP': 168,
 'BICYCLE ADVANCING LEGALLY ON RED LIGHT': 66,
 'PASSING STOPPED SCHOOL BUS': 64,
 'OBSTRUCTED CROSSWALKS': 33,
 'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT': 19}
```

In [29]:
```
#assigning values
num= {'UNABLE TO DETERMINE': 0,
 'FAILING TO YIELD RIGHT-OF-WAY': 1,
 'FOLLOWING TOO CLOSELY': 1,
 'NOT APPLICABLE': 0,
 'IMPROPER OVERTAKING/PASSING': 23572,
 'IMPROPER BACKING': 21669,
 'FAILING TO REDUCE SPEED TO AVOID CRASH': 21422,
 'IMPROPER LANE USAGE': 19136,
 'IMPROPER TURNING/NO SIGNAL': 16439,
 'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE': 15567,
 'DISREGARDING TRAFFIC SIGNALS': 9036,
 'WEATHER': 0,
 'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE M
 'DISREGARDING STOP SIGN': 5500,
 'DISTRACTION - FROM INSIDE VEHICLE': 3640,
 'EQUIPMENT - VEHICLE CONDITION': 0,
 'PHYSICAL CONDITION OF DRIVER': 2915,
 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)': 0,
 'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)': 2647,
 'DRIVING ON WRONG SIDE/WRONG WAY': 2346,
 'DISTRACTION - FROM OUTSIDE VEHICLE': 2185,
 'EXCEEDING AUTHORIZED SPEED LIMIT': 1982,
 'EXCEEDING SAFE SPEED FOR CONDITIONS': 1684,
 'ROAD ENGINEERING/SURFACE/MARKING DEFECTS': 0,
 'ROAD CONSTRUCTION/MAINTENANCE': 0,
 'DISREGARDING OTHER TRAFFIC SIGNS': 1068,
 'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST': 0,
 'CELL PHONE USE OTHER THAN TEXTING': 697,
 'DISREGARDING ROAD MARKINGS': 677,
 'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)': 551,
 'ANIMAL': 0,
 'TURNING RIGHT ON RED': 349,
 'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ETC.)
 'TEXTING': 215,
 'DISREGARDING YIELD SIGN': 187,
 'RELATED TO BUS STOP': 168,
 'BICYCLE ADVANCING LEGALLY ON RED LIGHT': 66,
 'PASSING STOPPED SCHOOL BUS': 64,
 'OBSTRUCTED CROSSWALKS': 33,
 'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT': 19}
```

In [30]:
```
#assign 1- to driver responsibility
for key in num.keys():
    if num[key]:
        num[key]=1
```

In [31]:
```
num
```

Out[31]:
```
{'UNABLE TO DETERMINE': 0,
 'FAILING TO YIELD RIGHT-OF-WAY': 1,
 'FOLLOWING TOO CLOSELY': 1,
 'NOT APPLICABLE': 0,
 'IMPROPER OVERTAKING/PASSING': 1,
 'IMPROPER BACKING': 1,
 'FAILING TO REDUCE SPEED TO AVOID CRASH': 1,
 'IMPROPER LANE USAGE': 1,
 'IMPROPER TURNING/NO SIGNAL': 1,
 'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE': 1,
 'DISREGARDING TRAFFIC SIGNALS': 1,
 'WEATHER': 0,
 'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE
MANNER': 1,
 'DISREGARDING STOP SIGN': 1,
 'DISTRACTION - FROM INSIDE VEHICLE': 1,
 'EQUIPMENT - VEHICLE CONDITION': 0,
 'PHYSICAL CONDITION OF DRIVER': 1,
 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)': 0,
 'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)': 1,
 'DRIVING ON WRONG SIDE/WRONG WAY': 1,
 'DISTRACTION - FROM OUTSIDE VEHICLE': 1,
 'EXCEEDING AUTHORIZED SPEED LIMIT': 1,
 'EXCEEDING SAFE SPEED FOR CONDITIONS': 1,
 'ROAD ENGINEERING/SURFACE/MARKING DEFECTS': 0,
 'ROAD CONSTRUCTION/MAINTENANCE': 0,
 'DISREGARDING OTHER TRAFFIC SIGNS': 1,
 'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST': 0,
 'CELL PHONE USE OTHER THAN TEXTING': 1,
 'DISREGARDING ROAD MARKINGS': 1,
 'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)': 1,
 'ANIMAL': 0,
 'TURNING RIGHT ON RED': 1,
 'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ET
C.)': 1,
 'TEXTING': 1,
 'DISREGARDING YIELD SIGN': 1,
 'RELATED TO BUS STOP': 1,
 'BICYCLE ADVANCING LEGALLY ON RED LIGHT': 1,
 'PASSING STOPPED SCHOOL BUS': 1,
 'OBSTRUCTED CROSSWALKS': 1,
 'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT': 1}
```

In [32]:
```
##apply new column to DataFrame
df['target']= df.prim_contributory_cause.map(num)
```

In [33]:
```
#check that it is in the DataFrame
df.head()
```

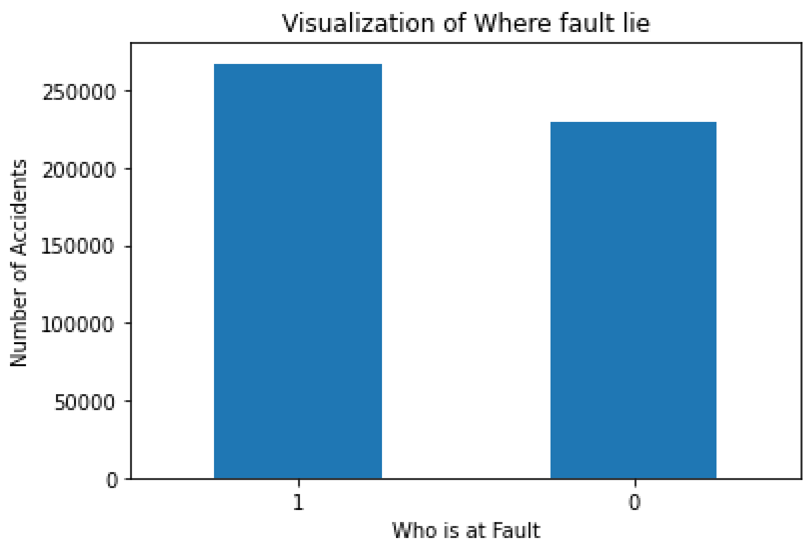
Out[33]:

	crash_record_id	crash_date	posted_speed_limit	traffic_
0	4fd0a3e0897b3335b94cd8d5b2d2b350eb691add56c62d...	07/10/2019 05:56:00 PM	35	
1	009e9e67203442370272e1a13d6ee51a4155dac65e583d...	06/30/2017 04:00:00 PM	35	STOP
2	ee9283eff3a55ac50ee58f3d9528ce1d689b1c4180b4c4...	07/10/2020 10:25:00 AM	30	TI
3	f8960f698e870ebdc60b521b2a141a5395556bc3704191...	07/11/2020 01:00:00 AM	30	
4	8eaa2678d1a127804ee9b8c35ddf7d63d913c14eda61d6...	07/08/2020 02:00:00 PM	20	

5 rows × 23 columns

Check Class balance of Target Data

In [34]:
```
#Build a graph to visualize the data differnce between Drivers fault and Driv

count_classes = pd.value_counts(df['target'], sort = True)

count_classes.plot(kind = 'bar', rot=0)

plt.title("Visualization of Where fault lie")

plt.xticks(range(2))

plt.xlabel("Who is at Fault")

plt.ylabel("Number of Accidents")
plt.savefig('class_balance', dpi=300)
```



In [35]:
```
#Assign variables names to Target values

not_fault = df[df['target']==1]

fault = df[df['target']==0]
```

In [36]:
```
print(not_fault.shape, fault.shape)
```

```
(267174, 23) (229317, 23)
```

The Dataset shows that the dataset is pretty evenly distributed with a small bias to false positives. The difference between the Driver at fault, fault, and outside circumstances, not_fault, is 37,857.

Train and Model data

Train the data and apply the X values to the DataFrame's numeric values then check cross validation.

In [37]:
```
#Check that data is uniform
df.dtypes
```

Out[37]:
```
crash_record_id            object
crash_date                 object
posted_speed_limit          int64
traffic_control_device     object
device_condition           object
weather_condition          object
lighting_condition         object
first_crash_type           object
trafficway_type            object
alignment                  object
roadway_surface_cond       object
road_defect                object
crash_type                 object
damage                     object
date_police_notified       object
prim_contributory_cause    object
sec_contributory_cause     object
street_no                   int64
num_units                   int64
crash_hour                  int64
crash_day_of_week           int64
crash_month                 int64
target                      int64
dtype: object
```

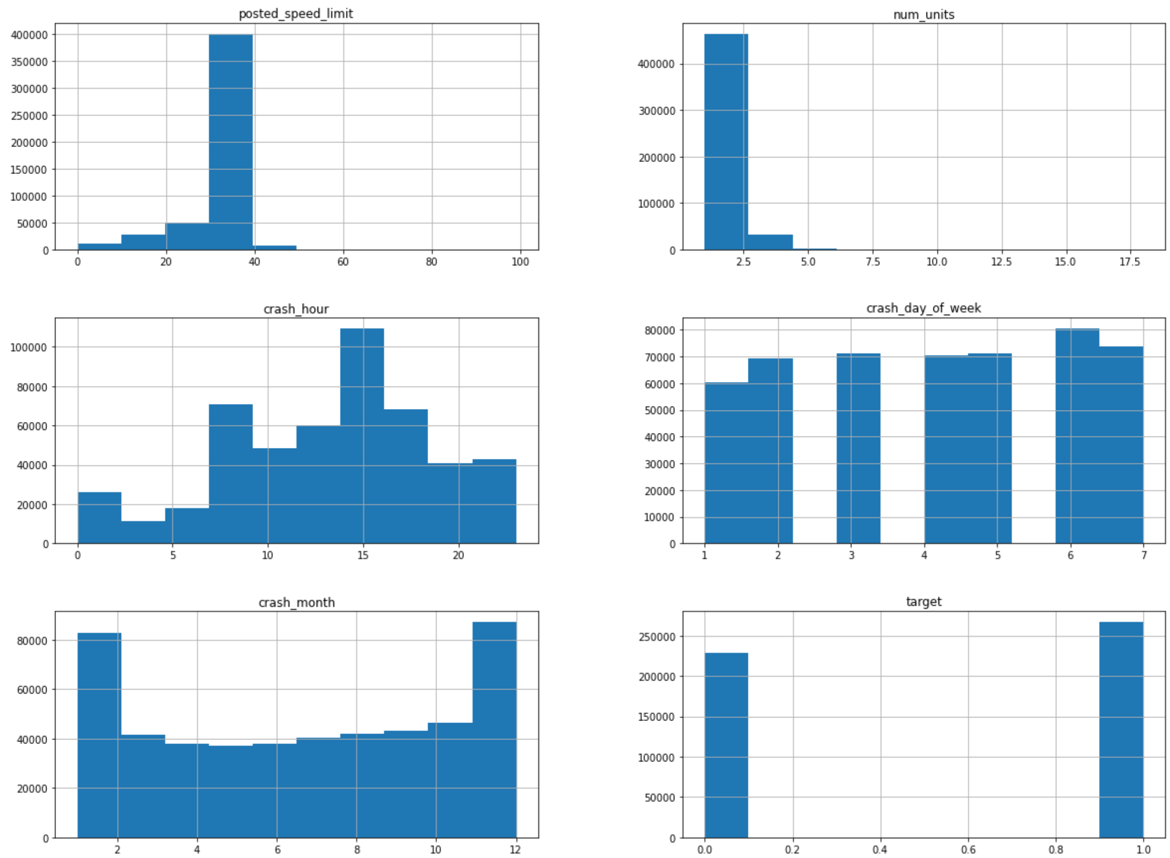
In [38]:
```
#drop unneeded columns
drop= ['crash_record_id',
'crash_date',
'first_crash_type',
'crash_type',
'date_police_notified',
'prim_contributory_cause',
'sec_contributory_cause',
'street_no']
df= df.drop(drop, axis=1)
```

In [39]:
```
#train data
X = df.drop('target', axis=1)
y = df['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

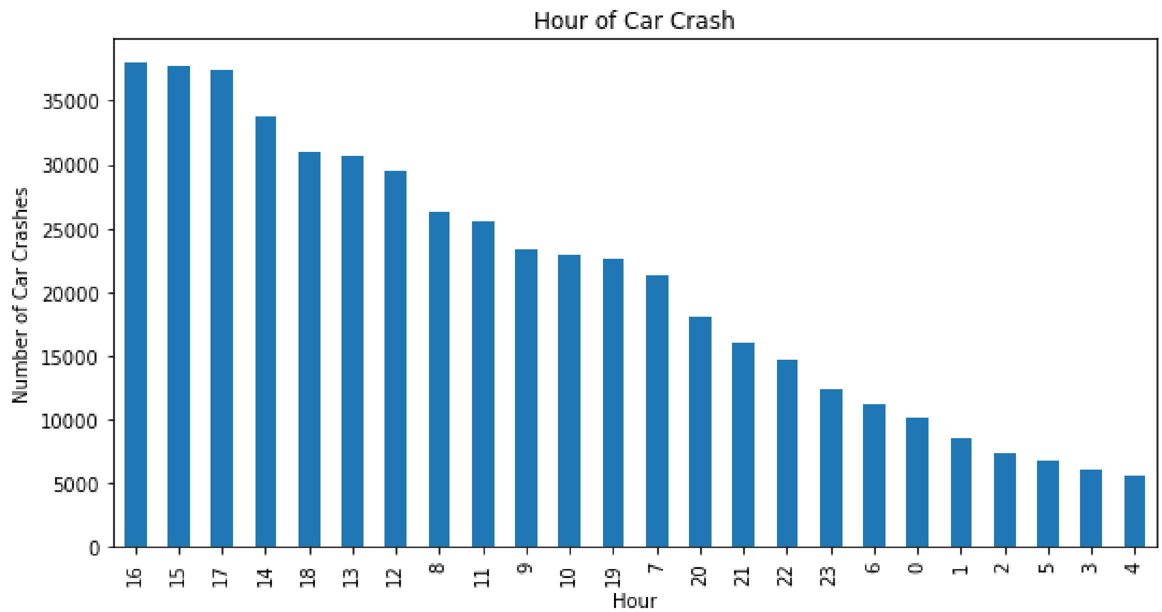
In [40]:
```
#seporate numerical features
num_feats = DummyClassifier(strategy= 'most_frequent')
X_train_numeric = X_train[['posted_speed_limit',
                           'num_units',
                             'crash_hour',
                           'crash_day_of_week', 'crash_month', ]].copy()
```

In [41]:
```
num_feats = DummyClassifier(strategy= 'most_frequent')
X_test_numeric = X_test[['posted_speed_limit',
                           'num_units',
                             'crash_hour',
                           'crash_day_of_week', 'crash_month', ]].copy()
```

In [87]:
```
#visualisation of the numeric values
df.hist(figsize=(20,15));
plt.savefig('num_hist', dpi=300)
```



In [88]:
```
df['crash_hour'].value_counts().plot(kind='bar', figsize=(10,5))
plt.title('Hour of Car Crash')
plt.ylabel('Number of Car Crashes')
plt.xlabel('Hour')
plt.savefig('Hours_of_crash', dpi=300)
```



In [42]:
```
#check cross validation score of numerical features
num_cross_val_score = cross_val_score(num_feats, X_train_numeric, y_train, cv
num_cross_val_score
```

Out[42]:
```
array([0.53746274, 0.53746274, 0.53744931, 0.53745653, 0.53745653])
```

Scaling Data

Scale data then model the data to preform a logistic Regression model. Finally, check the predictivity score of the model.

In [43]:
```
log_reg_model = LogisticRegression()
```

In [44]:
```
#fit and transform trained data into scaled data.
scaler= StandardScaler()
X_train_scaled=X_train_numeric.copy()
scaler.fit(X_train_scaled)
X_train_scaled=scaler.transform(X_train_scaled)
```

In [45]:
```
#scaled logestical regession model
num_cross_val_score = cross_val_score(log_reg_model, X_train_scaled, y_train,
num_cross_val_score
```

Out[45]:
```
array([0.56822515, 0.56657357, 0.56857427, 0.5686759 , 0.56903844])
```

In [46]:
```
log_reg_model= LogisticRegression(random_state=0).fit(X_train_scaled, y_trair
```

In [47]:
```
log_reg_model.predict_proba(X_train_scaled)
```

Out[47]:
```
array([[0.45827858, 0.54172142],
       [0.46637025, 0.53362975],
       [0.55293695, 0.44706305],
       ...,
       [0.47047336, 0.52952664],
       [0.48431316, 0.51568684],
       [0.41606071, 0.58393929]])
```

In [48]:
```
log_reg_model.score(X_train_scaled, y_train)
```

Out[48]:
```
0.5682040347183431
```

The accuracy score shows that this model is predictive up to about 56%. The use of the numerical features allow us to predict the probability of a Driver at fault by more than half. The next steps is to add the categorical features to see if they will increase the odds ratio.

OneHotEncode Categorical Data for logistical Regression

In [49]:
```
#find the Categorical Data
X_train.dtypes
```

Out[49]:
```
posted_speed_limit         int64
traffic_control_device    object
device_condition          object
weather_condition         object
lighting_condition        object
trafficway_type           object
alignment                 object
roadway_surface_cond      object
road_defect               object
damage                    object
num_units                  int64
crash_hour                 int64
crash_day_of_week          int64
crash_month                int64
dtype: object
```

In [50]:
```
#fit and transform categoricals
categoricals = X_train.select_dtypes('object')
categorical_names = categoricals.columns
ohe = OneHotEncoder(sparse= False)
ohe.fit(categoricals)
categorical_ohe= ohe.transform(categoricals)

categorical_ohe=pd.DataFrame(categorical_ohe, columns= ohe.get_feature_names(
```

In [51]:
```
#drop and concat categorical data
X_train= X_train.reset_index()
X_train= X_train.drop(categorical_names, axis= 1)
X_train_ohe= pd.concat([X_train, categorical_ohe], axis= 1)
```

In [52]:
```
#confirm it worked
X_train_ohe.head()
```

Out[52]:

	index	posted_speed_limit	num_units	crash_hour	crash_day_of_week	crash_month	x0_I CF
0	45171	35	2	8	2	1	
1	198424	30	2	7	2	12	
2	231653	10	2	13	7	10	
3	19472	30	2	19	6	3	
4	390007	30	2	5	4	6	

5 rows × 94 columns

In [53]:
```
#Preform a logistical model with ohe
log_model = LogisticRegression()

print("Old:", num_cross_val_score)
print("New:", cross_val_score(log_model, X_train_ohe, y_train, cv=5))
```

```
Old: [0.56822515 0.56657357 0.56857427 0.5686759  0.56903844]
New: [0.53746274 0.53746274 0.53744931 0.53745653 0.53745653]
```

In [54]:
```
log_model= LogisticRegression(random_state=0).fit(X_train_ohe, y_train)
```

In [55]:
```
log_model.predict_proba(X_train_ohe)
```

Out[55]:
```
array([[0.4942098 , 0.5057902 ],
       [0.47458601, 0.52541399],
       [0.47033934, 0.52966066],
       ...,
       [0.48309412, 0.51690588],
       [0.48118206, 0.51881794],
       [0.48437133, 0.51562867]])
```

In [56]:
```
log_model.score(X_train_ohe, y_train)
```

Out[56]:
```
0.537457568856615
```

The addition of the categorical feature did not help the model as expected. The accurscry score fell by about 3%. We will try a different predictive model to see if that will help or accuracy score. We will use the Decision Tree Regression Model.

DecisionTreeClassifier Model

In [57]:
```
clf = DecisionTreeClassifier(random_state=0)
iris = load_iris()


print("Old:", num_cross_val_score)
print("New:", cross_val_score(clf, X_train_ohe, y_train, cv=5))
```

```
Old: [0.56822515 0.56657357 0.56857427 0.5686759  0.56903844]
New: [0.55166904 0.5491581  0.5510648  0.5524284  0.55037396]
```

In [59]:
```
clf_model= clf.fit(X_train_ohe, y_train, sample_weight=None, check_input=True
```

In [60]:
```
clf.score(X_train_ohe, y_train, sample_weight=None)
```

Out[60]:
```
1.0
```

In [61]:
```
clf.predict_proba(X_train_ohe, check_input=True)
```

Out[61]:
```
array([[0., 1.],
       [1., 0.],
       [1., 0.],
       ...,
       [1., 0.],
       [1., 0.],
       [0., 1.]])
```

The DecisionTreeRegressor Model provided an accuracy score of about 55%. This is about 1% less from the original model but better then the model that included the categoricals.

Conclusion

In conclusion, the best features for predicting the fault of Drivers in car crashes in Chicargo, IL were the numerical features. The features such as speed limit and time of day, had an accurancy of about 57% . Categorical features could predict a crash more then half the time but it is still less then that of the numerical features, categorical features can predict the crashes about 54% of the time. Furthermore, The DecisionTreeRegressor model was a better indicator then the logistical model that included the categoricals but it was still about 1% less then the original logistical model that only included that numerical model.