How you can drive safely in 2020

Use LR/KNN/Decision Tree/Random Forest classification algorithms from sklearn to predict the accident severity

Due to the limit of computer capacity, I am focusing on the State of California. I will only select a few features I believe are more relavant to severity. Categorical data will be treated with Pandas get_dummies method. Rows with missing values will be dropped.

Data source

https://www.kaggle.com/sobhanmoosavi/us-accidents (https://www.kaggle.com/sobhanmoosavi/us-accidents)

Acknowledgements

Moosavi, Sobhan, Mohammad Hossein Samavatian, Srinivasan Parthasarathy, and Rajiv Ramnath. “A Countrywide Traffic Accident Dataset.”, 2019.

Moosavi, Sobhan, Mohammad Hossein Samavatian, Srinivasan Parthasarathy, Radu Teodorescu, and Rajiv Ramnath. "Accident Risk Prediction based on Heterogeneous Sparse Data: New Dataset and Insights." In proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ACM, 2019.

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Step 1. Import libraries

In [1]:
```
# Import numpy, pandas, matpltlib.pyplot, sklearn modules and seaborn
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.set_option('display.max_rows', 200)
pd.set_option('display.max_columns', 200)
plt.style.use('ggplot')

# Import KNeighborsClassifier from sklearn.neighbors
from sklearn.neighbors import KNeighborsClassifier

# Import DecisionTreeClassifier from sklearn.tree
from sklearn.tree import DecisionTreeClassifier

# Import RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier

# Import LogisticRegression
from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve, auc
```

Step 2. Import the dataset

In [2]:
```
# Import the data
df = pd.read_csv('./US_Accidents_May19.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2243939 entries, 0 to 2243938
Data columns (total 49 columns):
ID                       object
Source                   object
TMC                      float64
Severity                 int64
Start_Time               object
End_Time                 object
Start_Lat                float64
Start_Lng                float64
End_Lat                  float64
End_Lng                  float64
Distance(mi)             float64
Description              object
Number                   float64
Street                   object
Side                     object
City                     object
County                   object
State                    object
Zipcode                  object
Country                  object
Timezone                 object
Airport_Code             object
Weather_Timestamp        object
Temperature(F)           float64
Wind_Chill(F)            float64
Humidity(%)              float64
Pressure(in)             float64
Visibility(mi)           float64
Wind_Direction           object
Wind_Speed(mph)          float64
Precipitation(in)        float64
Weather_Condition        object
Amenity                  bool
Bump                     bool
Crossing                 bool
Give_Way                 bool
Junction                 bool
No_Exit                  bool
Railway                  bool
Roundabout               bool
Station                  bool
Stop                     bool
Traffic_Calming          bool
Traffic_Signal           bool
Turning_Loop             bool
Sunrise_Sunset           object
Civil_Twilight           object
Nautical_Twilight        object
Astronomical_Twilight    object
dtypes: bool(13), float64(14), int64(1), object(21)
memory usage: 644.1+ MB
```

Step 3. Extract year, month, day, hour, weekday, and time to clear accidents

In [3]:
```
# Convert Start_Time and End_Time to datetypes
df['Start_Time'] = pd.to_datetime(df['Start_Time'], errors='coerce')
df['End_Time'] = pd.to_datetime(df['End_Time'], errors='coerce')

# Extract year, month, day, hour and weekday
df['Year']=df['Start_Time'].dt.year
df['Month']=df['Start_Time'].dt.strftime('%b')
df['Day']=df['Start_Time'].dt.day
df['Hour']=df['Start_Time'].dt.hour
df['Weekday']=df['Start_Time'].dt.strftime('%a')

# Extract the amount of time in the unit of minutes for each accident, round t
o the nearest integer
td='Time_Duration(min)'
df[td]=round((df['End_Time']-df['Start_Time'])/np.timedelta64(1,'m'))
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2243939 entries, 0 to 2243938
Data columns (total 55 columns):
ID                       object
Source                   object
TMC                      float64
Severity                 int64
Start_Time               datetime64[ns]
End_Time                 datetime64[ns]
Start_Lat                float64
Start_Lng                float64
End_Lat                  float64
End_Lng                  float64
Distance(mi)             float64
Description              object
Number                   float64
Street                   object
Side                     object
City                     object
County                   object
State                    object
Zipcode                  object
Country                  object
Timezone                 object
Airport_Code             object
Weather_Timestamp        object
Temperature(F)           float64
Wind_Chill(F)            float64
Humidity(%)              float64
Pressure(in)             float64
Visibility(mi)           float64
Wind_Direction           object
Wind_Speed(mph)          float64
Precipitation(in)        float64
Weather_Condition        object
Amenity                  bool
Bump                     bool
Crossing                 bool
Give_Way                 bool
Junction                 bool
No_Exit                  bool
Railway                  bool
Roundabout               bool
Station                  bool
Stop                     bool
Traffic_Calming          bool
Traffic_Signal           bool
Turning_Loop             bool
Sunrise_Sunset           object
Civil_Twilight           object
Nautical_Twilight        object
Astronomical_Twilight    object
Year                     int64
Month                    object
Day                      int64
Hour                     int64
Weekday                  object
```

```
Time_Duration(min)       float64
dtypes: bool(13), datetime64[ns](2), float64(15), int64(4), object(21)
memory usage: 746.9+ MB
```

Step 4. Deal with outliers

A. Drop rows with negative time_duration

In [4]:
```
# Check if there is any negative time_duration values
df[td][df[td]<=0]
```

Out[4]:
```
69720      -0.0
69721      -0.0
69722      -0.0
69723      -1.0
69724      -1.0
309389    -30.0
309390    -30.0
746173    -30.0
746174    -31.0
1482940   -30.0
1483025   -30.0
1483026   -31.0
2038017   -31.0
Name: Time_Duration(min), dtype: float64
```

In [5]:
```
# Drop the rows with td<0

neg_outliers=df[td]<=0

# Set outliers to NAN
df[neg_outliers] = np.nan

# Drop rows with negative td
df.dropna(subset=[td],axis=0,inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2243926 entries, 0 to 2243938
Data columns (total 55 columns):
ID                       object
Source                   object
TMC                      float64
Severity                 float64
Start_Time               datetime64[ns]
End_Time                 datetime64[ns]
Start_Lat                float64
Start_Lng                float64
End_Lat                  float64
End_Lng                  float64
Distance(mi)             float64
Description              object
Number                   float64
Street                   object
Side                     object
City                     object
County                   object
State                    object
Zipcode                  object
Country                  object
Timezone                 object
Airport_Code             object
Weather_Timestamp        object
Temperature(F)           float64
Wind_Chill(F)            float64
Humidity(%)              float64
Pressure(in)             float64
Visibility(mi)           float64
Wind_Direction           object
Wind_Speed(mph)          float64
Precipitation(in)        float64
Weather_Condition        object
Amenity                  float64
Bump                     float64
Crossing                 float64
Give_Way                 float64
Junction                 float64
No_Exit                  float64
Railway                  float64
Roundabout               float64
Station                  float64
Stop                     float64
Traffic_Calming          float64
Traffic_Signal           float64
Turning_Loop             float64
Sunrise_Sunset           object
Civil_Twilight           object
Nautical_Twilight        object
Astronomical_Twilight    object
Year                     float64
Month                    object
Day                      float64
Hour                     float64
Weekday                  object
```

```
Time_Duration(min)       float64
dtypes: datetime64[ns](2), float64(32), object(21)
memory usage: 958.7+ MB
```

In [6]:
```
# Double check to make sure no more negative td
df[td][df[td]<=0]
```

Out[6]:
```
Series([], Name: Time_Duration(min), dtype: float64)
```

Step 4. Deal with outliers

B. Fill outliers with median values

In [7]:

```
# Remove outliers for Time_Duration(min): n * standard_deviation (n=3), backfi
ll with median

n=3

median = df[td].median()
std = df[td].std()
outliers = (df[td] - median).abs() > std*n

# Set outliers to NAN
df[outliers] = np.nan

# Fill NAN with median
df[td].fillna(median, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2243926 entries, 0 to 2243938
Data columns (total 55 columns):
ID                       object
Source                   object
TMC                      float64
Severity                 float64
Start_Time               datetime64[ns]
End_Time                 datetime64[ns]
Start_Lat                float64
Start_Lng                float64
End_Lat                  float64
End_Lng                  float64
Distance(mi)             float64
Description              object
Number                   float64
Street                   object
Side                     object
City                     object
County                   object
State                    object
Zipcode                  object
Country                  object
Timezone                 object
Airport_Code             object
Weather_Timestamp        object
Temperature(F)           float64
Wind_Chill(F)            float64
Humidity(%)              float64
Pressure(in)             float64
Visibility(mi)           float64
Wind_Direction           object
Wind_Speed(mph)          float64
Precipitation(in)        float64
Weather_Condition        object
Amenity                  float64
Bump                     float64
Crossing                 float64
Give_Way                 float64
Junction                 float64
No_Exit                  float64
Railway                  float64
Roundabout               float64
Station                  float64
Stop                     float64
Traffic_Calming          float64
Traffic_Signal           float64
Turning_Loop             float64
Sunrise_Sunset           object
Civil_Twilight           object
Nautical_Twilight        object
Astronomical_Twilight    object
Year                     float64
Month                    object
Day                      float64
Hour                     float64
Weekday                  object
```

```
Time_Duration(min)       float64
dtypes: datetime64[ns](2), float64(32), object(21)
memory usage: 958.7+ MB
```

In [8]:
```
# Print time_duration information
print('Max time to clear an accident: {} minutes or {} hours or {} days; Min t
o clear an accident td: {} minutes.'.format(df[td].max(),round(df[td].max()/60
), round(df[td].max()/60/24), df[td].min()))
```

```
Max time to clear an accident: 12424.0 minutes or 207 hours or 9 days; Min to
clear an accident td: 1.0 minutes.
```

In [9]:
```
# Export the data
# df.to_csv('./US_Accidents_May19_clean.csv',index=False)
```

Step 5. Select a list of features for machine learning algorithms

Only select relavant columns without overwhelming the computer

In [10]:
```
# Set the list of features to include in Machine Learning
feature_lst=['Source','TMC','Severity','Start_Lng','Start_Lat','Distance(mi)',
'Side','City','County','State','Timezone','Temperature(F)','Humidity(%)','Pres
sure(in)', 'Visibility(mi)', 'Wind_Direction','Weather_Condition','Amenity','B
ump','Crossing','Give_Way','Junction','No_Exit','Railway','Roundabout','Statio
n','Stop','Traffic_Calming','Traffic_Signal','Turning_Loop','Sunrise_Sunset',
'Hour','Weekday', 'Time_Duration(min)']
```

In [11]:
```
# Select the dataset to include only the selected features
df_sel=df[feature_lst].copy()
df_sel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2243926 entries, 0 to 2243938
Data columns (total 34 columns):
Source                  object
TMC                     float64
Severity                float64
Start_Lng               float64
Start_Lat               float64
Distance(mi)            float64
Side                    object
City                    object
County                  object
State                   object
Timezone                object
Temperature(F)          float64
Humidity(%)             float64
Pressure(in)            float64
Visibility(mi)          float64
Wind_Direction          object
Weather_Condition       object
Amenity                 float64
Bump                    float64
Crossing                float64
Give_Way                float64
Junction                float64
No_Exit                 float64
Railway                 float64
Roundabout              float64
Station                 float64
Stop                    float64
Traffic_Calming         float64
Traffic_Signal          float64
Turning_Loop            float64
Sunrise_Sunset          object
Hour                    float64
Weekday                 object
Time_Duration(min)      float64
dtypes: float64(24), object(10)
memory usage: 599.2+ MB
```

In [12]:
```
# Export the data with selected features
# df_sel.to_csv('./US_Accidents_May19_clean_sel.csv',index=False)
```

Step 6. Drop rows with missing values

In [13]:
```
# Check missing values
df_sel.isnull().mean()
```

Out[13]:
```
Source                0.000217
TMC                   0.230302
Severity              0.000217
Start_Lng             0.000217
Start_Lat             0.000217
Distance(mi)          0.000217
Side                  0.000217
City                  0.000248
County                0.000217
State                 0.000217
Timezone              0.001172
Temperature(F)        0.027943
Humidity(%)           0.028925
Pressure(in)          0.025724
Visibility(mi)        0.031997
Wind_Direction        0.021230
Weather_Condition     0.032285
Amenity               0.000217
Bump                  0.000217
Crossing              0.000217
Give_Way              0.000217
Junction              0.000217
No_Exit               0.000217
Railway               0.000217
Roundabout            0.000217
Station               0.000217
Stop                  0.000217
Traffic_Calming       0.000217
Traffic_Signal        0.000217
Turning_Loop          0.000217
Sunrise_Sunset        0.000252
Hour                  0.000217
Weekday               0.000217
Time_Duration(min)    0.000000
dtype: float64
```

In [14]:
```
df_sel.dropna(subset=df_sel.columns[df_sel.isnull().mean()!=0], how='any', axi
s=0, inplace=True)
df_sel.shape
```

Out[14]:
```
(1663631, 34)
```

In [15]:
```
# Export the data with selected features
# df_sel.to_csv('./US_Accidents_May19_clean_sel_dropna.csv',index=False)
```

Step 7. Select the state of interest: CA

Due to the limitation of personal laptop, the whole US dataset is too big to handle

In [16]:
```
# Import data if it was already exported based on previous work
# df_sel=pd.read_csv('./US_Accidents_May19_clean_sel_dropna.csv')
```

In [17]:
```
# Set state
state='CA'

# Select the state of Pennsylvania
df_state=df_sel.loc[df_sel.State==state]
df_state.drop('State',axis=1, inplace=True)
df_state.info()
```

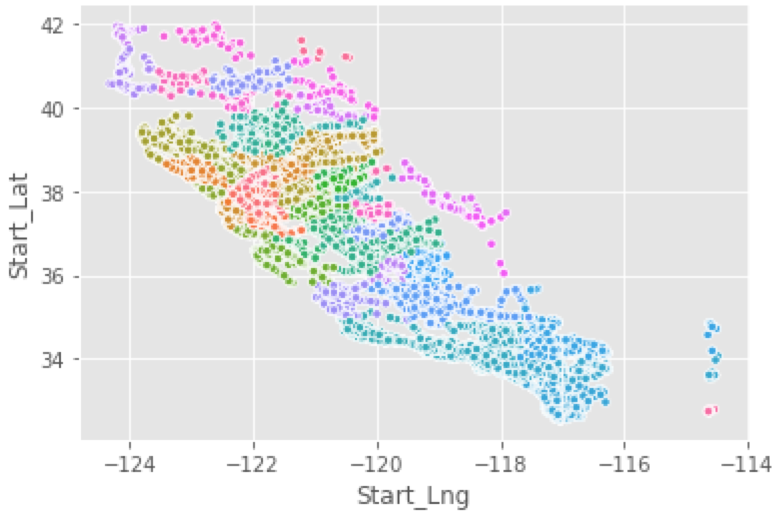
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 354854 entries, 728 to 1727176
Data columns (total 33 columns):
Source                354854 non-null object
TMC                   354854 non-null float64
Severity              354854 non-null float64
Start_Lng             354854 non-null float64
Start_Lat             354854 non-null float64
Distance(mi)          354854 non-null float64
Side                  354854 non-null object
City                  354854 non-null object
County                354854 non-null object
Timezone              354854 non-null object
Temperature(F)        354854 non-null float64
Humidity(%)           354854 non-null float64
Pressure(in)          354854 non-null float64
Visibility(mi)        354854 non-null float64
Wind_Direction        354854 non-null object
Weather_Condition     354854 non-null object
Amenity               354854 non-null float64
Bump                  354854 non-null float64
Crossing              354854 non-null float64
Give_Way              354854 non-null float64
Junction              354854 non-null float64
No_Exit               354854 non-null float64
Railway               354854 non-null float64
Roundabout            354854 non-null float64
Station               354854 non-null float64
Stop                  354854 non-null float64
Traffic_Calming       354854 non-null float64
Traffic_Signal        354854 non-null float64
Turning_Loop          354854 non-null float64
Sunrise_Sunset        354854 non-null object
Hour                  354854 non-null float64
Weekday               354854 non-null object
Time_Duration(min)    354854 non-null float64
dtypes: float64(24), object(9)
memory usage: 92.0+ MB

C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\frame.py:4102: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

In [18]:
```
# Map of accidents, color code by county

sns.scatterplot(x='Start_Lng', y='Start_Lat', data=df_state, hue='County', leg
end=False, s=20)
plt.show()
```



Step 8. Deal with categorical data: pd.get_dummies()

In [19]:
```
# Generate dummies for categorical data
df_state_dummy = pd.get_dummies(df_state,drop_first=True)

# Export data
df_state_dummy.to_csv('./US_Accidents_May19_{}_dummy.csv'.format(state),index=
False)

df_state_dummy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 354854 entries, 728 to 1727176
Columns: 1162 entries, TMC to Weekday_Wed
dtypes: float64(24), uint8(1138)
memory usage: 452.8 MB
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

Data preparation: train_test_split

In [20]:
```
# Assign the data
df=df_state_dummy


# Set the target for the prediction
target='Severity'



# Create arrays for the features and the response variable

# set X and y
y = df[target]
X = df.drop(target, axis=1)

# Split the data set into training and testing data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
m_state=21, stratify=y)
```

In [21]:
```
# List of classification algorithms
algo_lst=['Logistic Regression',' K-Nearest Neighbors','Decision Trees','Rando
m Forest']

# Initialize an empty list for the accuracy for each algorithm
accuracy_lst=[]
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

Algorithm A. Logistic regression

In [22]:
```
# Logistic regression
lr = LogisticRegression(random_state=0)
lr.fit(X_train,y_train)
y_pred=lr.predict(X_test)

# Get the accuracy score
acc=accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

print("[Logistic regression algorithm] accuracy_score: {:.3f}.".format(acc))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
32: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify
a solver to silence this warning.
  FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
69: FutureWarning: Default multi_class will be changed to 'auto' in 0.22. Spe
cify the multi_class option to silence this warning.
  "this warning.", FutureWarning)

[Logistic regression algorithm] accuracy_score: 0.809.
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

Algorithm B. The K-Nearest Neighbors (KNN) algorithm

KNN with 6 neighors

In [23]:
```
# Create a k-NN classifier with 6 neighbors
knn = KNeighborsClassifier(n_neighbors=6)

# Fit the classifier to the data
knn.fit(X_train,y_train)

# Predict the labels for the training data X
y_pred = knn.predict(X_test)

# Get the accuracy score
acc=accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

print('[K-Nearest Neighbors (KNN)] knn.score: {:.3f}.'.format(knn.score(X_test
, y_test)))
print('[K-Nearest Neighbors (KNN)] accuracy_score: {:.3f}.'.format(acc))
```

```
[K-Nearest Neighbors (KNN)] knn.score: 0.604.
[K-Nearest Neighbors (KNN)] accuracy_score: 0.604.
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

Algorithm B. The K-Nearest Neighbors (KNN) algorithm

Optmize the number of neighors: plot the accuracy versus number of neighbors

It took too much time, skip this part.

Setup arrays to store train and test accuracies

neighbors = np.arange(1, 9) train_accuracy = np.empty(len(neighbors)) test_accuracy = np.empty(len(neighbors))

Loop over different values of k

for i, n_neighbor in enumerate(neighbors):

```
# Setup a k-NN Classifier with n_neighbor
knn = KNeighborsClassifier(n_neighbors=n_neighbor)

# Fit the classifier to the training data
knn.fit(X_train,y_train)

#Compute accuracy on the training set
train_accuracy[i] = knn.score(X_train, y_train)

#Compute accuracy on the testing set
test_accuracy[i] = knn.score(X_test, y_test)
```

Generate plot

plt.title('k-NN: Varying Number of Neighbors') plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy') plt.plot(neighbors, train_accuracy, label = 'Training Accuracy') plt.legend() plt.xlabel('Number of Neighbors') plt.ylabel('Accuracy') plt.show()

Step 9. Predict the accident severity with various supervised machine learning algorithms

Algorithm C. Decision Tree

In [24]:
```
# Decision tree algorithm

# Instantiate dt_entropy, set 'entropy' as the information criterion
dt_entropy = DecisionTreeClassifier(max_depth=8, criterion='entropy', random_s
tate=1)


# Fit dt_entropy to the training set
dt_entropy.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred= dt_entropy.predict(X_test)

# Evaluate accuracy_entropy
accuracy_entropy = accuracy_score(y_test, y_pred)


# Print accuracy_entropy
print('[Decision Tree -- entropy] accuracy_score: {:.3f}.'.format(accuracy_ent
ropy))



# Instantiate dt_gini, set 'gini' as the information criterion
dt_gini = DecisionTreeClassifier(max_depth=8, criterion='gini', random_state=1
)


# Fit dt_entropy to the training set
dt_gini.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred= dt_gini.predict(X_test)

# Evaluate accuracy_entropy
accuracy_gini = accuracy_score(y_test, y_pred)

# Append to the accuracy list
acc=accuracy_gini
accuracy_lst.append(acc)

# Print accuracy_gini
print('[Decision Tree -- gini] accuracy_score: {:.3f}.'.format(accuracy_gini))
```

```
[Decision Tree -- entropy] accuracy_score: 0.743.
[Decision Tree -- gini] accuracy_score: 0.751.
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

Algorithm D. Random Forest

n_estimators=100

In [25]:
```
# Random Forest algorithm

#Create a Gaussian Classifier
clf=RandomForestClassifier(n_estimators=100)

#Train the model using the training sets y_pred=clf.predict(X_test)
clf.fit(X_train,y_train)

y_pred=clf.predict(X_test)


# Get the accuracy score
acc=accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)


# Model Accuracy, how often is the classifier correct?
print("[Randon forest algorithm] accuracy_score: {:.3f}.".format(acc))
```

```
[Randon forest algorithm] accuracy_score: 0.892.
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

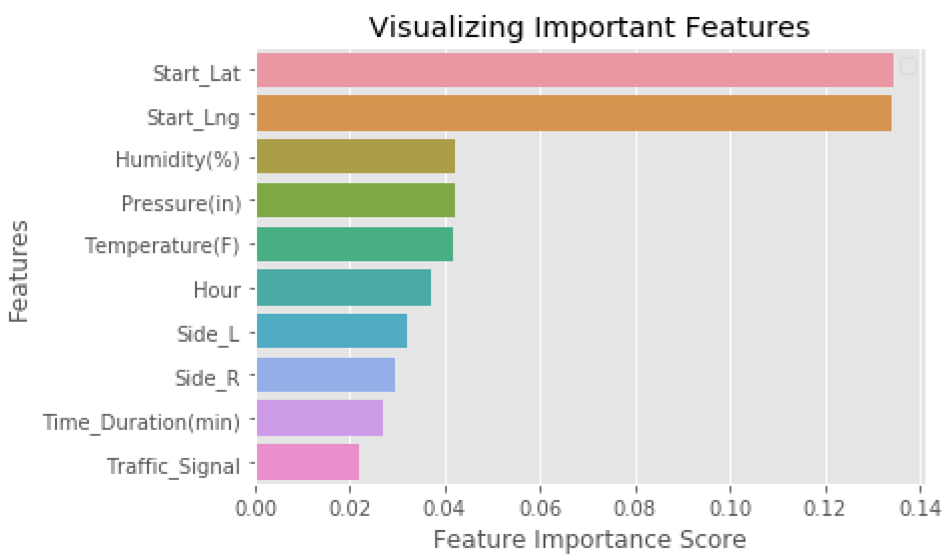
Algorithm D. Random Forest

Visualize important features

In [26]:
```
feature_imp = pd.Series(clf.feature_importances_,index=X.columns).sort_values(
ascending=False)

# Creating a bar plot, displaying only the top k features
k=10
sns.barplot(x=feature_imp[:10], y=feature_imp.index[:k])
# Add labels to your graph
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```



In [27]:
```
# List top k important features
k=20
feature_imp.sort_values(ascending=False)[:k]
```

Out[27]:
```
Start_Lat                  0.134451
Start_Lng                  0.134298
Humidity(%)                0.042199
Pressure(in)               0.042120
Temperature(F)             0.041817
Hour                       0.037062
Side_L                     0.032037
Side_R                     0.029736
Time_Duration(min)         0.026945
Traffic_Signal             0.021809
Distance(mi)               0.014331
Visibility(mi)             0.012959
TMC                        0.010856
Junction                   0.007621
Sunrise_Sunset_Night       0.007340
County_Los Angeles         0.007255
County_Sonoma              0.005987
City_Oakland               0.005886
Weather_Condition_Clear    0.005804
Weekday_Wed                0.005721
dtype: float64
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

Algorithm D. Random Forest

Select the top important features, set the threshold

In [28]:
```
# Create a selector object that will use the random forest classifier to ident
ify
# features that have an importance of more than 0.03
sfm = SelectFromModel(clf, threshold=0.03)

# Train the selector
sfm.fit(X_train, y_train)

feat_labels=X.columns

# Print the names of the most important features
for feature_list_index in sfm.get_support(indices=True):
    print(feat_labels[feature_list_index])
```

```
Start_Lng
Start_Lat
Temperature(F)
Humidity(%)
Pressure(in)
Hour
Side_R
```

In [29]:
```
# Transform the data to create a new dataset containing only the most importan
t features
# Note: We have to apply the transform to both the training X and test X data.
X_important_train = sfm.transform(X_train)
X_important_test = sfm.transform(X_test)

# Create a new random forest classifier for the most important features
clf_important = RandomForestClassifier(n_estimators=100, random_state=0, n_job
s=-1)

# Train the new classifier on the new dataset containing the most important fe
atures
clf_important.fit(X_important_train, y_train)
```

Out[29]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=No
ne,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=-1, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

In [30]:
```
# Apply The Full Featured Classifier To The Test Data
y_pred = clf.predict(X_test)

# View The Accuracy Of Our Full Feature Model
print('[Randon forest algorithm -- Full feature] accuracy_score: {:.3f}.'.form
at(accuracy_score(y_test, y_pred)))

# Apply The Full Featured Classifier To The Test Data
y_important_pred = clf_important.predict(X_important_test)

# View The Accuracy Of Our Limited Feature Model
print('[Randon forest algorithm -- Limited feature] accuracy_score: {:.3f}.'.f
ormat(accuracy_score(y_test, y_important_pred)))
```

```
[Randon forest algorithm -- Full feature] accuracy_score: 0.892.
[Randon forest algorithm -- Limited feature] accuracy_score: 0.911.
```

Step 9. Predict the accident severity with various supervised machine learning algorithms

Plot the accuracy score versus algorithm

In [31]:

```
# Make a plot of the accuracy scores for different algorithms

# Generate a list of ticks for y-axis
y_ticks=np.arange(len(algo_lst))

# Combine the list of algorithms and list of accuracy scores into a dataframe,
sort the value based on accuracy score
df_acc=pd.DataFrame(list(zip(algo_lst, accuracy_lst)), columns=['Algorithm','A
ccuracy_Score']).sort_values(by=['Accuracy_Score'],ascending = True)

# Export to a file
df_acc.to_csv('./Accuracy_scores_algorithms_{}.csv'.format(state),index=False)

# Make a plot
ax=df_acc.plot.barh('Algorithm', 'Accuracy_Score', align='center',legend=False
,color='0.5')

# Add the data label on to the plot
for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_width()+0.02, i.get_y()+0.2, str(round(i.get_width(),2)), fo
ntsize=10)

# Set the limit, lables, ticks and title
plt.xlim(0,1.05)
plt.xlabel('Accuracy Score')
plt.yticks(y_ticks, df_acc['Algorithm'], rotation=0)
plt.title('[{}] Which algorithm is better?'.format(state))

plt.show()
```