Phase 3 Project:
Using Machine Learning for determining Car Accidents causes ¶

OVERVIEW

The objective of the project :

Using traffic accident data published on Chicago Data portal to determine if an accident was caused by a driver

DATA

The row data consists of 3 datasets:

Crashes (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if)

Crash data shows information about each traffic crash on city streets within the City of Chicago limits

People (https://data.cityofchicago.org/Transportation/Traffic-Crashes-People/u6pd-qa9d)

This data contains information about people involved in a crash and if any injuries were sustained.

Vehicles (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Vehicles/68nd-jvt3)

This dataset contains information about vehicles involved in a traffic crash.

- All three datasets are gziped and saved in data/raw folder

DATA PREPARATION

- People and Vehicles datasets were joined using VEHICLE_ID and CRASH_RECORD_ID
- Crashes dataset was joined with People/Vehicles using CRASH_RECORD_ID
- Datasets were filtered to consider only Drivers (passengers, pedestrians, etc were excluded)
- Data was cleaned (Rows with unknown or missing data were removed)
- Target variable was bined into two categories: "AT_FAULT" and "NOT_AT_FAULT'

All the steps for Data preparation and cleaning were put into: "initial_prep.py" script

The processed data was generated by initial_prep.py as "crashes.gz" and placed into data/processed folder

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MODELING

We considered the following models:

- Logistic Regression
- Decision Tree
- Extra Tree
- Nearest Neighbor (KNN)
- Random Forest
- Bayesian
- GXBoost

We also tried "bagging" and "voting" Ensembles of the models above

Features Selection

- We started with 20 features and filtered them one by one until we end up with only 5.

RESULTS

GXBoost model was chosen as marginally better model (close second and third were Random Forest and Logistic Regression)

In [10]:
```
# Uncomment only if you want to reprocess the raw data using initial_prep.p
# The script will re-create crashes.gz, comma separated gzipped file in ../

## %run src/preprocessing/initial_prep.py
```

In [11]:
```
# Import required sklearn, pandas, numpy and other libraries:

%run src/import_libraries.py

%matplotlib inline
```

Loading processed data

In [12]:
```
full_df=pd.read_csv('data/processed/crashes.gz', compression='gzip', low_me
full_df.shape
```

Out[12]:
```
(348442, 154)
```

Defining Training and testing sets

In [13]:
```
#sample_df=full_df.sample(100000, random_state=100)
sample_df=full_df.copy()

y = sample_df['GUILTY']
x = sample_df.drop(['GUILTY'],axis=1)

X_train, X_test, y_train, y_test = train_test_split(x, y, random_state=100,

nominal_columns = [ 'FIRST_CRASH_TYPE', 'FIRST_CONTACT_POINT', 'MANEUVER',
                    'TRAFFIC_CONTROL_DEVICE', 'VEHICLE_DEFECT']

X_train = X_train[nominal_columns]
X_test = X_test[nominal_columns]
```

Defining a pipeline

In [14]:
```
from sklearn.base import BaseEstimator, TransformerMixin


cat_pipeline = Pipeline([
        ('cat_encoder', OneHotEncoder(sparse=False, handle_unknown =  'igno
         ('std_scaler', StandardScaler()),
    ])
```

In [15]:
```
XGB_pipeline = Pipeline([ ( "cat_pipeline", cat_pipeline ),
                  ('boost', XGBClassifier(use_label_encoder=False,
                                          eval_metric='auc',  n_estimators=
                 ])



pipe_grid={}

gs_pipe = GridSearchCV(estimator=XGB_pipeline, param_grid=pipe_grid,  cv=3,
```

Training and Predicting

In [16]:
```
gs_pipe.fit(X_train, y_train)
y_pred_train=gs_pipe.predict(X_train)
y_pred_test=gs_pipe.predict(X_test)
```

EVALUATION

In [17]:
```
#print(XGB_pipeline.score(X_train, y_train ))
print(gs_pipe.score(X_train, y_train ))
print(classification_report(y_train, y_pred_train))
print('------------')
print(classification_report(y_test, y_pred_test))
```

```
0.8606039887951131
              precision    recall  f1-score   support

           0       0.83      0.87      0.85    145500
           1       0.74      0.68      0.71     80987

    accuracy                           0.80    226487
   macro avg       0.78      0.77      0.78    226487
weighted avg       0.80      0.80      0.80    226487

------------
              precision    recall  f1-score   support

           0       0.83      0.86      0.84     78346
           1       0.73      0.67      0.70     43609

    accuracy                           0.79    121955
   macro avg       0.78      0.77      0.77    121955
weighted avg       0.79      0.79      0.79    121955
```

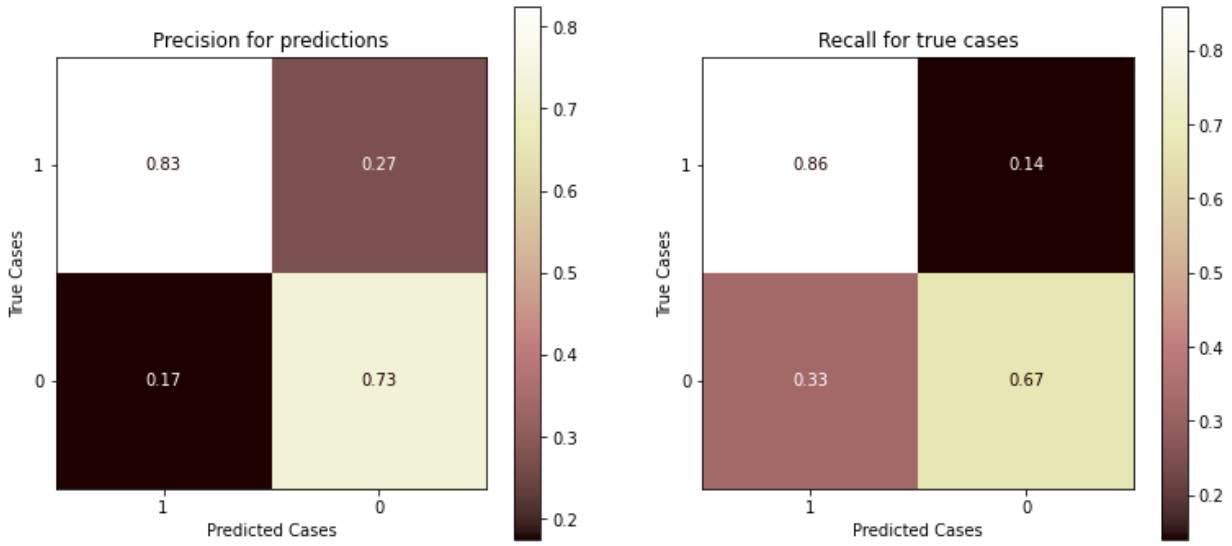
In [18]:
```
fig, ax = plt.subplots(figsize=(13,6), ncols=2)

ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test, normalize='pre
                                        display_labels=[1,0],cmap='pink', a


ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test, normalize='tru
                                        display_labels=[1,0],cmap='pink', a

ax[0].set_title("Precision for predictions")
ax[1].set_title("Recall for true cases")

ax[0].set_xlabel('Predicted Cases')
ax[0].set_ylabel('True Cases')
ax[1].set_xlabel('Predicted Cases')
ax[1].set_ylabel('True Cases');
```



Our model is much better in determining not_at_fault (1) class than "at_fault" (0).
Still it can be helpful for Legal and Insurance Companies and lawyers investigating traffic accidents