homework9

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SECTION: C S-5970-995
CS 5970: Machine Learning Practices

1 Homework 9: Decision

1.1 Assignment Overview

Follow the TODOs and read through and understand any provided code. Post any questions you might have to the Canvas discussion. For all plots, make sure all necessary axes and curves are clearly and accurately labeled. Include figure/plot titles appropriately as well.

1.1.1 Task

For this assignment you will be exploring Decision Tree Classifiers.

1.1.2 Data set

The data file can be found on Canvas under Files/Homework Solutions, and on git and the server under datasets/fraud_detection/health_provider_fraud.csv.

These data were re-configured from a dataset collected for the purpose of detecting Health care Provider Fraud. Total Medicare spending increases exponentially due to frauds in Medicare claims. Healthcare fraud involves health care providers, physicians, patients, and beneficiaries acting in-tandum to construct fraudulent claims.

The goal is to "predict potentially fraudulent providers" from summary statistics of their filed healthcare claims.

Features
The features are aggregate statistics computed as either the mean or the sum. For the following features, the column is indicative of the average value for the provider's claims:
* InscClaimAmtReimbursed
* DeductibleAmtPaid * NoOfMonths_PartACov * NoOfMonths_PartBCov * IPAnnualReimbursementAmt * IPAnnualDeductibleAmt * OPAnnualReimbursementAmt * OPAnnualDeductibleAmt * NumPhysiciansSeen * NumProcedures * NumDiagnosisClaims * Age

For the following features, the column is indicative of the total number among the provider's claims:
* ChronicCond_Alzheimer
* ChronicCond_Heartfailure
* ChronicCond_KidneyDisease
* ChronicCond_Cancer
* ChronicCond_ObstrPulmonary
* ChronicCond_Depression
* ChronicCond_Diabetes
* ChronicCond_IschemicHeart
* ChronicCond_Osteoporasis
* ChronicCond_rheumatoidarthritis
* ChronicCond_stroke
* RenalDiseaseIndicator

These data were amalagmated from the HEALTHCARE PROVIDER FRAUD DETECTION ANALYSIS data set on Kaggle.

1.1.3 Objectives

- Introduction to Decision Trees

1.1.4 Notes

- Do not save work within the ml_practices folder

1.1.5 General References

- Guide to Jupyter
- Python Built-in Functions
- Python Data Structures
- Numpy Reference
- Numpy Cheat Sheet
- Summary of matplotlib
- DataCamp: Matplotlib
- Pandas DataFrames
- Sci-kit Learn Linear Models
- Sci-kit Learn Ensemble Models
- Sci-kit Learn Metrics
- Sci-kit Learn Model Selection
- Sci-kit Learn Pipelines
- Sci-kit Learn Preprocessing

[2]:
```
# THESE FIRST 3 IMPORTS ARE FROM FILES IN THE ML_PRACTICES FOLDER UNDER HW9
# Use the versions found in the hw9 folder as some changes were made
import visualize
import metrics_plots
```

```python
from pipeline_components import DataSampleDropper, DataFrameSelector, DataScaler

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import re, os, pathlib
import time as timelib

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, RobustScaler
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, roc_curve, auc
from sklearn.metrics import log_loss, f1_score
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.linear_model import SGDClassifier, LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import DecisionTreeRegressor, export_graphviz
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, OrdinalEncoder
from sklearn.externals import joblib
import pickle as pkl

FIGW = 5
FIGH = 5
FONTSIZE = 12

plt.rcParams['figure.figsize'] = (FIGW, FIGH)
plt.rcParams['font.size'] = FONTSIZE

plt.rcParams['xtick.labelsize'] = FONTSIZE
plt.rcParams['ytick.labelsize'] = FONTSIZE

%matplotlib inline
plt.style.use('ggplot')
```

[3]:
```python
""" PROVIDED
Display current working directory of this notebook. If you are using
relative paths for your data, then it needs to be relative to the CWD.
"""
HOME_DIR = pathlib.Path.home()
pathlib.Path.cwd()
```

[3]: PosixPath('/home/jovyan/homework/hw9')

2 LOAD DATA

[4]:
```
# TODO: set path appropriately.
# data file can be found on canvas under Files/Homework Solutions, and on git
# and the server under datasets/fraud_detection/
fname = "health_provider_fraud.csv"
claims_data = pd.read_csv(fname)
claims_data.shape
```

[4]:
```
(5410, 25)
```

[5]:
```
""" PROVIDED
Display data info
"""
claims_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5410 entries, 0 to 5409
Data columns (total 25 columns):
Provider                           5410 non-null object
PotentialFraud                     5410 non-null bool
Age                                5410 non-null float64
NumPhysiciansSeen                  5410 non-null float64
NumProcedures                      5410 non-null float64
NumDiagnosisClaims                 5410 non-null float64
InscClaimAmtReimbursed             5410 non-null float64
DeductibleAmtPaid                  5409 non-null float64
NoOfMonths_PartACov                5410 non-null float64
NoOfMonths_PartBCov                5410 non-null float64
IPAnnualReimbursementAmt           5410 non-null float64
IPAnnualDeductibleAmt              5410 non-null float64
OPAnnualReimbursementAmt           5410 non-null float64
OPAnnualDeductibleAmt              5410 non-null float64
ChronicCond_Alzheimer              5410 non-null int64
ChronicCond_Heartfailure           5410 non-null int64
ChronicCond_KidneyDisease          5410 non-null int64
ChronicCond_Cancer                 5410 non-null int64
ChronicCond_ObstrPulmonary         5410 non-null int64
ChronicCond_Depression             5410 non-null int64
ChronicCond_Diabetes               5410 non-null int64
ChronicCond_IschemicHeart          5410 non-null int64
ChronicCond_Osteoporasis           5410 non-null int64
ChronicCond_rheumatoidarthritis    5410 non-null int64
ChronicCond_stroke                 5410 non-null int64
dtypes: bool(1), float64(12), int64(11), object(1)
memory usage: 1019.7+ KB
```

[6]:
```python
""" PROVIDED
Display the head of the data
"""
claims_data.head()
```

[6]:
```
   Provider  PotentialFraud        Age  NumPhysiciansSeen  NumProcedures  \
0  PRV51001           False  78.840000           1.280000       0.120000
1  PRV51003            True  70.022727           1.181818       0.363636
2  PRV51004           False  72.161074           1.322148       0.000000
3  PRV51005            True  70.475536           1.209442       0.000000
4  PRV51007           False  69.291667           1.125000       0.013889

   NumDiagnosisClaims  InscClaimAmtReimbursed  DeductibleAmtPaid  \
0            3.640000             4185.600000         213.600000
1            5.765152             4588.409091         502.166667
2            2.751678              350.134228           2.080537
3            2.786266              241.124464           3.175966
4            3.208333              468.194444          45.333333

   NoOfMonths_PartACov  NoOfMonths_PartBCov  …  ChronicCond_Heartfailure  \
0            12.000000            12.000000  …                        19
1            11.818182            11.871212  …                        80
2            11.865772            11.959732  …                        88
3            11.907296            11.939914  …                       680
4            11.833333            11.833333  …                        40

   ChronicCond_KidneyDisease  ChronicCond_Cancer  ChronicCond_ObstrPulmonary  \
0                         17                   5                          10
1                         64                  10                          41
2                         50                  16                          41
3                        507                 165                         295
4                         22                  12                          16

   ChronicCond_Depression  ChronicCond_Diabetes  ChronicCond_IschemicHeart  \
0                       9                    21                         23
1                      54                   100                        112
2                      63                   105                        108
3                     485                   799                        895
4                      29                    49                         51

   ChronicCond_Osteoporasis  ChronicCond_rheumatoidarthritis  \
0                         6                                8
1                        33                               38
2                        49                               46
3                       344                              331
4                        21                               22
```

```
   ChronicCond_stroke
0                   6
1                  12
2                  17
3                 124
4                  12

[5 rows x 25 columns]
```

[7]:
```
""" PROVIDED
Display the summary statistics
Make sure you skim this
"""
claims_data.describe()
```

[7]:
```
               Age  NumPhysiciansSeen  NumProcedures  NumDiagnosisClaims  \
count  5410.000000        5410.000000    5410.000000         5410.000000
mean     73.731027           1.227410       0.108011            3.676631
std       4.712307           0.220822       0.246305            1.882603
min      34.000000           0.500000       0.000000            0.000000
25%      71.768368           1.000000       0.000000            2.696134
50%      73.863636           1.200000       0.000000            3.000000
75%      75.760000           1.375000       0.083333            3.847902
max     101.000000           3.000000       3.000000           11.000000

       InscClaimAmtReimbursed  DeductibleAmtPaid  NoOfMonths_PartACov  \
count             5410.000000        5409.000000          5410.000000
mean              1740.679369         155.643175            11.919716
std               3484.473124         306.489453             0.395682
min                  0.000000           0.000000             0.000000
25%                232.394593           0.312500            11.994207
50%                356.085106           4.285714            12.000000
75%               1490.154301         137.418605            12.000000
max              57000.000000        1068.000000            12.000000

       NoOfMonths_PartBCov  IPAnnualReimbursementAmt  IPAnnualDeductibleAmt  \
count          5410.000000               5410.000000            5410.000000
mean             11.930647               6166.692586             666.980865
std               0.310612               6203.422910             623.108956
min               0.000000                  0.000000               0.000000
25%              11.965836               2902.238095             356.000000
50%              12.000000               4729.047927             527.580008
75%              12.000000               7336.173195             801.000000
max              12.000000             103000.000000           12068.000000

       …  ChronicCond_Heartfailure  ChronicCond_KidneyDisease  \
count  …               5410.000000                5410.000000
```

mean	…	60.921072	42.510906
std	…	158.698296	110.048136
min	…	0.000000	0.000000
25%	…	6.000000	4.000000
50%	…	18.000000	13.000000
75%	…	52.750000	37.000000
max	…	4638.000000	3111.000000

	ChronicCond_Cancer	ChronicCond_ObstrPulmonary	ChronicCond_Depression \
count	5410.000000	5410.000000	5410.000000
mean	15.620148	32.288540	44.863956
std	41.558020	82.958866	117.563035
min	0.000000	0.000000	0.000000
25%	1.000000	3.000000	4.000000
50%	5.000000	10.000000	13.000000
75%	13.000000	29.000000	39.000000
max	1238.000000	2312.000000	3592.000000

	ChronicCond_Diabetes	ChronicCond_IschemicHeart \
count	5410.000000	5410.000000
mean	72.783549	78.341959
std	190.919202	205.233787
min	0.000000	0.000000
25%	7.000000	7.000000
50%	22.000000	23.000000
75%	62.750000	67.000000
max	5784.000000	6074.000000

	ChronicCond_Osteoporasis	ChronicCond_rheumatoidarthritis \
count	5410.000000	5410.000000
mean	32.775231	32.107024
std	85.862305	84.497824
min	0.000000	0.000000
25%	3.000000	3.000000
50%	10.000000	9.000000
75%	28.000000	28.000000
max	2531.000000	2511.000000

	ChronicCond_stroke
count	5410.000000
mean	10.495564
std	27.171512
min	0.000000
25%	1.000000
50%	3.000000
75%	9.000000
max	810.000000

```
[8 rows x 23 columns]
```

3 PRE-PROCESS DATA

[8]:
```python
""" PROVIDED
Construct preprocessing pipeline
"""
selected_features = claims_data.columns
scaled_features = ['InscClaimAmtReimbursed', 'DeductibleAmtPaid',
                   'IPAnnualReimbursementAmt', 'IPAnnualDeductibleAmt',
                   'OPAnnualReimbursementAmt', 'OPAnnualDeductibleAmt']

pipe = Pipeline([
    ('RowDropper', DataSampleDropper()),
    ('FeatureSelector', DataFrameSelector(selected_features)),
    ('Scale', DataScaler(scaled_features))
])
```

[9]:
```python
""" TODO
Pre-process the data using the defined pipeline
"""
processed_data = pipe.fit_transform(claims_data)
processed_data.shape
```

[9]:
```
(5409, 25)
```

[10]:
```python
""" TODO
Verify all NaNs removed
"""
np.any(np.isnan(processed_data.drop(['Provider'], axis=1).astype('float64')))
```

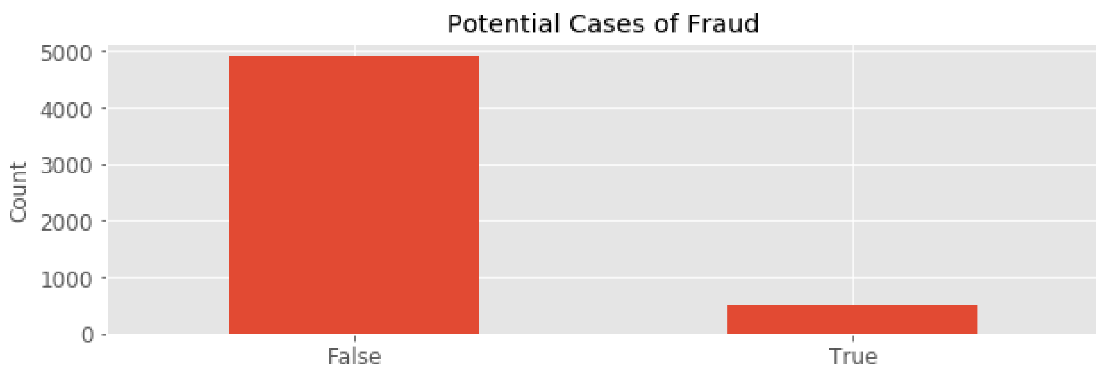
[10]:
```
False
```

4 VISUALIZE DATA

[11]:
```python
""" PROVIDED
Plot the class distributions for no potential fraud and potential fraud
"""
class_counts = pd.value_counts(processed_data['PotentialFraud'])
class_counts.plot(kind='bar', rot=0, figsize=(10,3))
plt.title("Potential Cases of Fraud")
plt.ylabel("Count")
```

```python
# Display the class fractions
nsamples, nfeatures = processed_data.shape
class_counts / nsamples
```

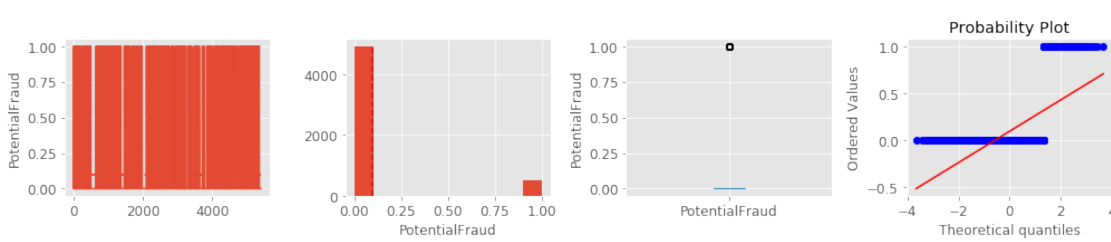
[11]:
```
False    0.906452
True     0.093548
Name: PotentialFraud, dtype: float64
```



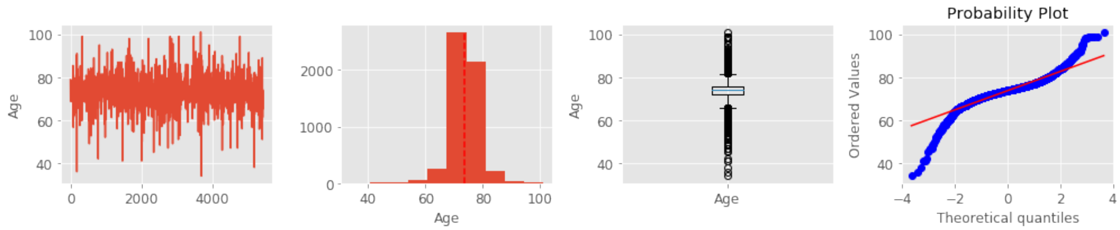
[12]:
```python
""" PROVIDED
Extract positions of the postive and negative cases
"""
pos = processed_data['PotentialFraud'] == 1
neg = processed_data['PotentialFraud'] == 0
```

[13]:
```python
""" PROVIDED
Visualize the data using visualize.featureplots
"""
# Drop the provider name from the visualized data since it is not numeric
cdata = processed_data.drop(['Provider'], axis=1).astype('float64')
visualize.featureplots(cdata.values, cdata.columns)
```

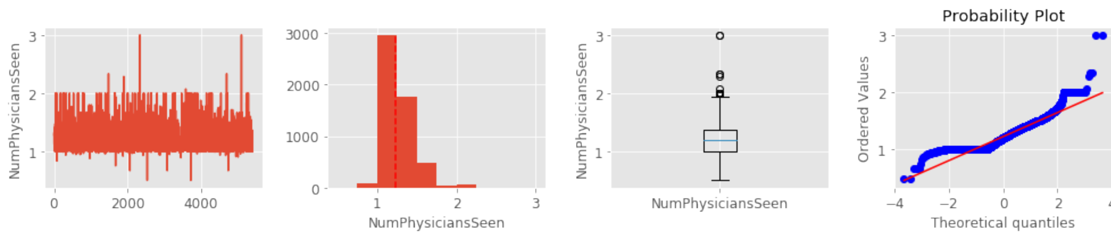
```
FEATURE: PotentialFraud
```



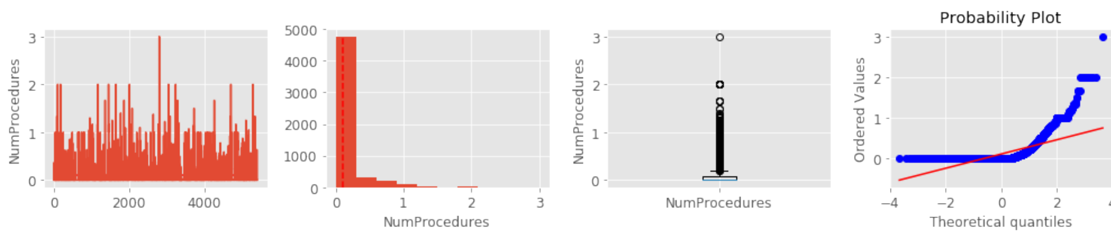
FEATURE: Age



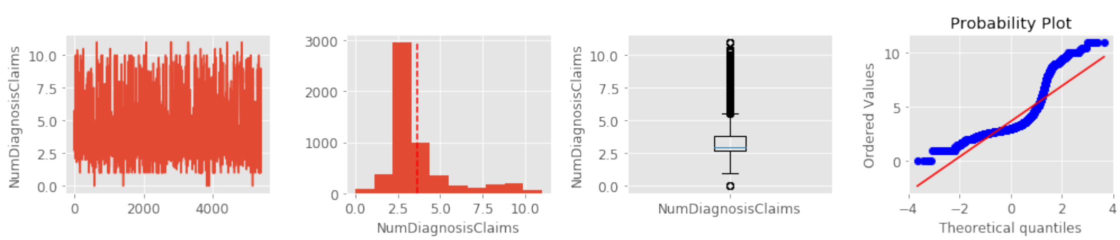
FEATURE: NumPhysiciansSeen



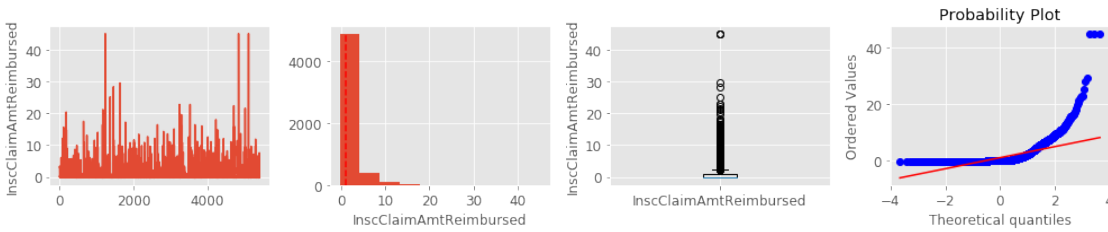
FEATURE: NumProcedures



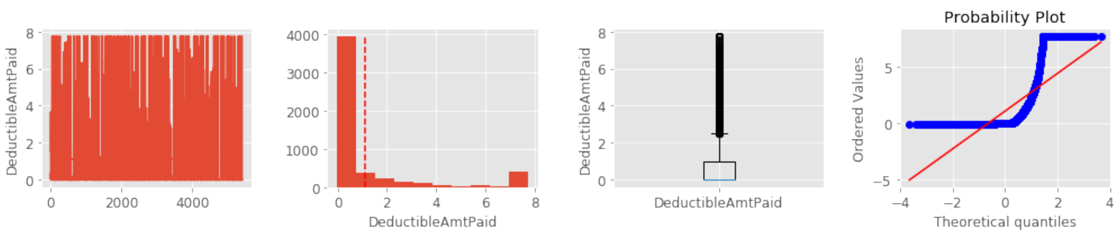
FEATURE: NumDiagnosisClaims



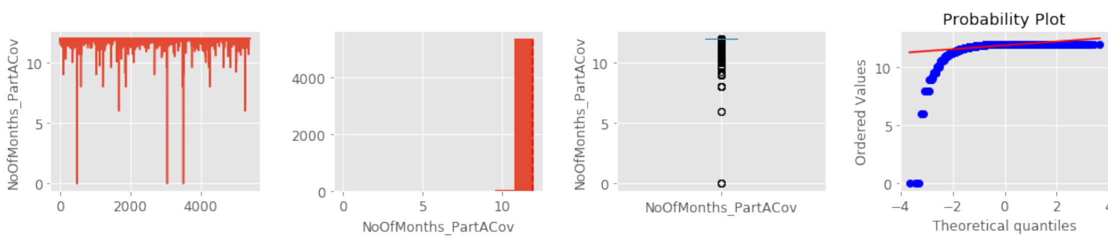
FEATURE: InscClaimAmtReimbursed



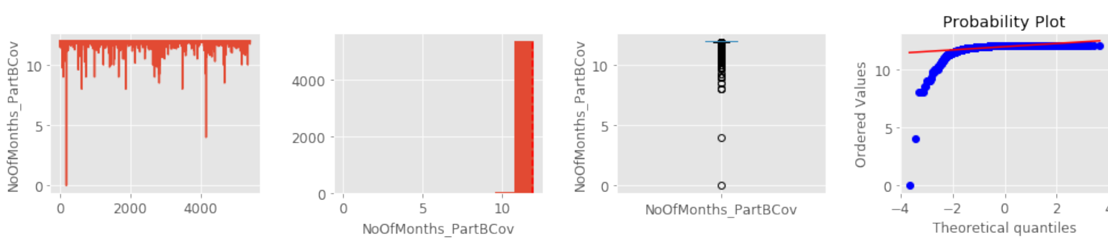
FEATURE: DeductibleAmtPaid



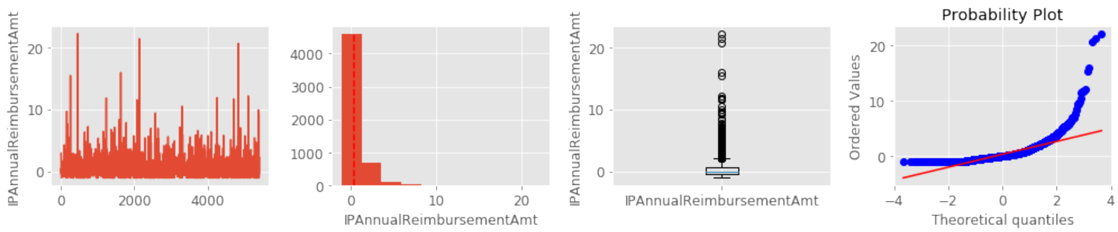
FEATURE: NoOfMonths_PartACov



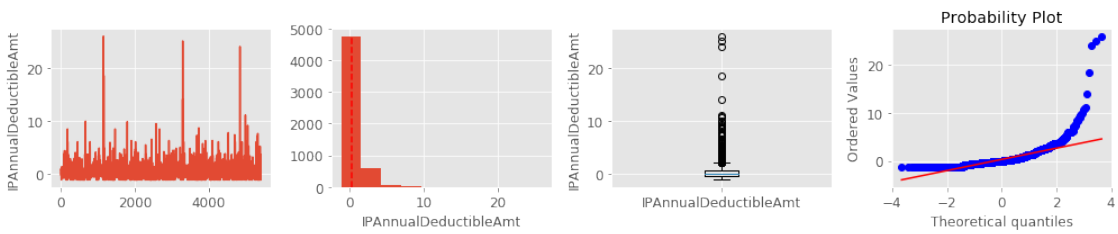
FEATURE: NoOfMonths_PartBCov



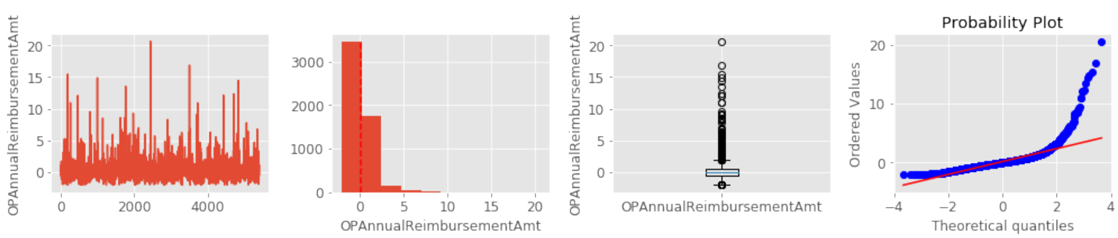
FEATURE: IPAnnualReimbursementAmt



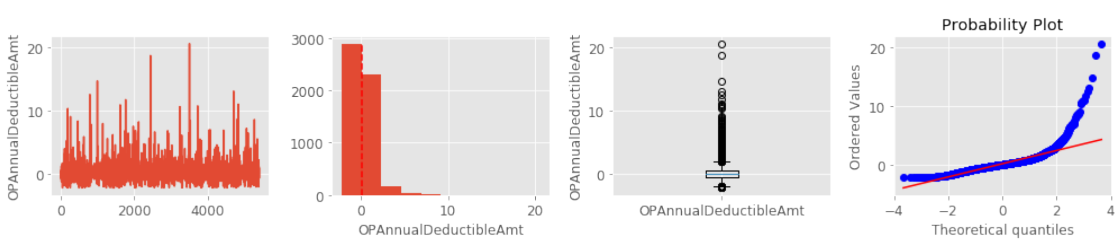
FEATURE: IPAnnualDeductibleAmt



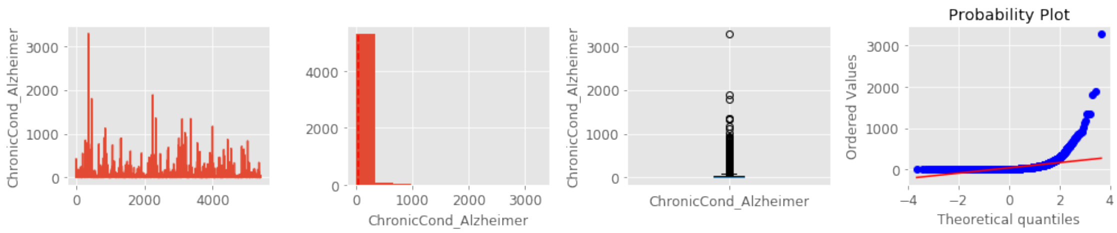
FEATURE: OPAnnualReimbursementAmt



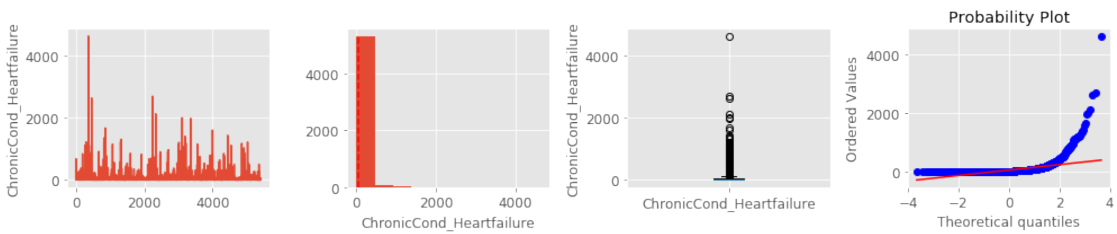
FEATURE: OPAnnualDeductibleAmt



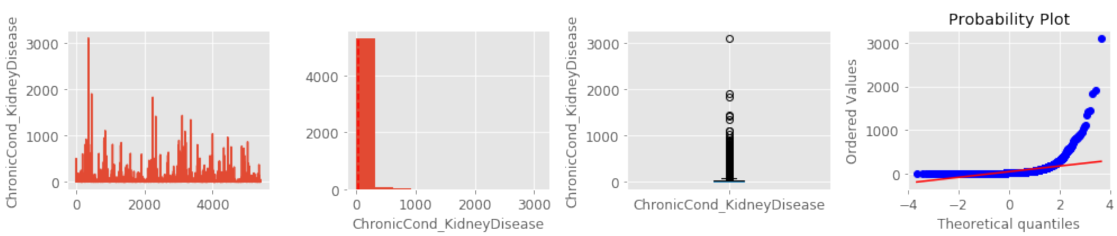
FEATURE: ChronicCond_Alzheimer



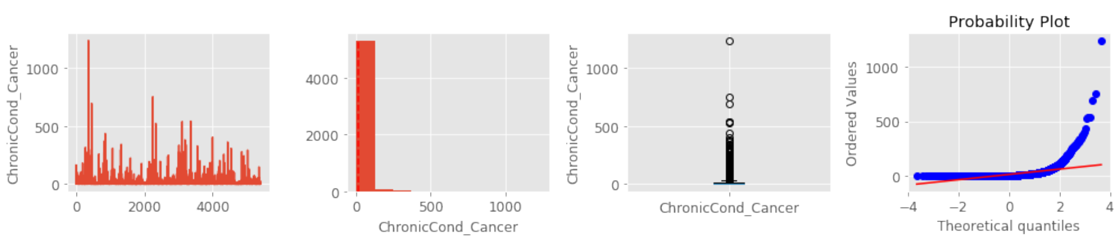
FEATURE: ChronicCond_Heartfailure



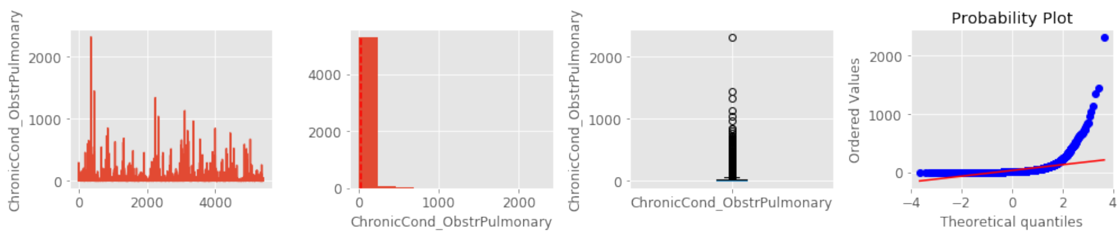
FEATURE: ChronicCond_KidneyDisease



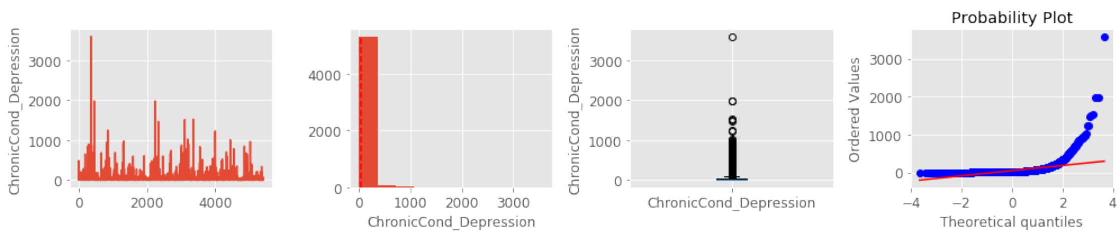
FEATURE: ChronicCond_Cancer



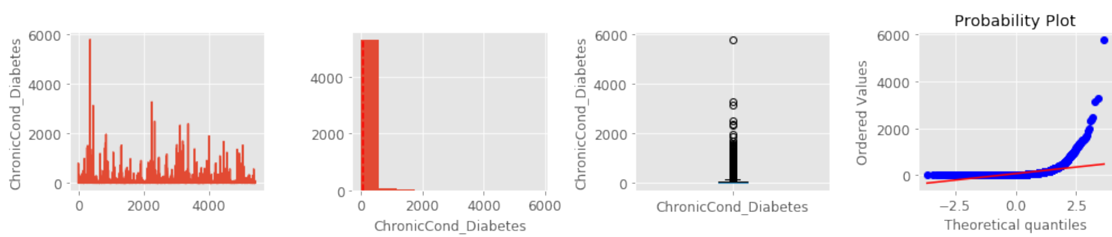
FEATURE: ChronicCond_ObstrPulmonary



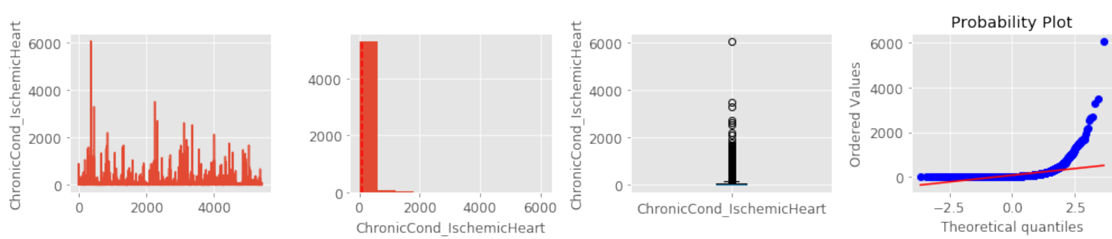
FEATURE: ChronicCond_Depression



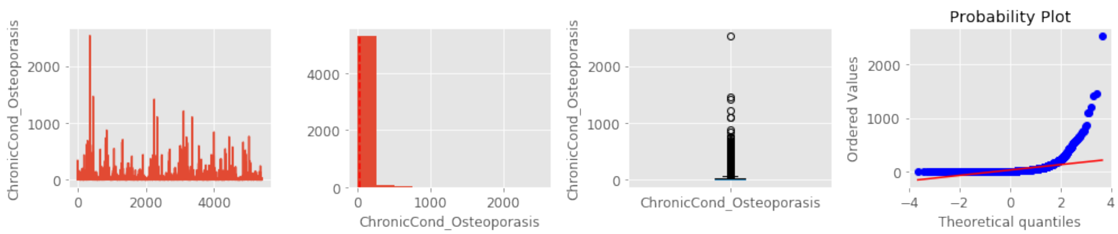
FEATURE: ChronicCond_Diabetes



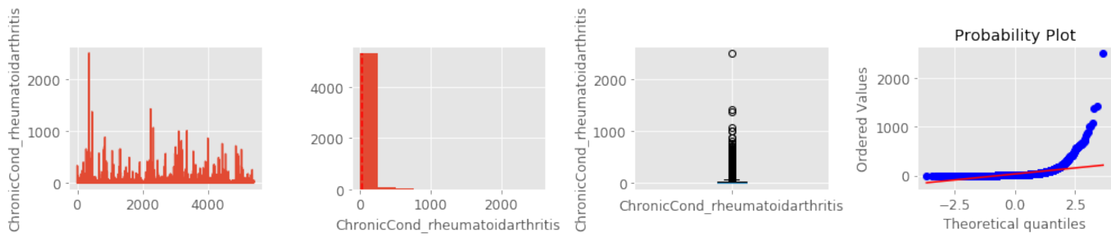
FEATURE: ChronicCond_IschemicHeart



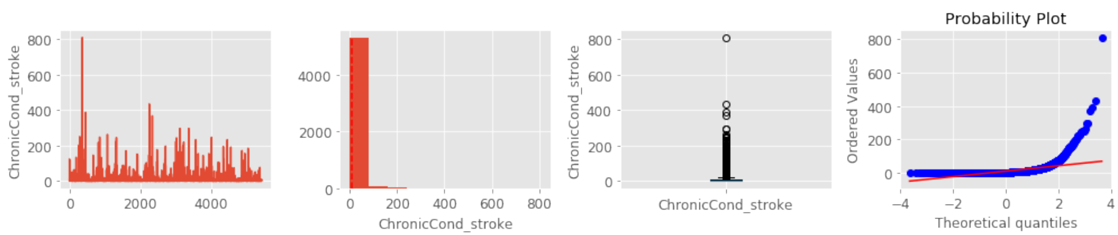
FEATURE: ChronicCond_Osteoporasis



FEATURE: ChronicCond_rheumatoidarthritis



FEATURE: ChronicCond_stroke



5 Decision Tree Classifiers

5.0.1 Model Exploration

[14]:
```
""" TODO
Split data into X (the inputs) and y (the outputs)

Hold out a subset of the data, before training and cross validation
using train_test_split, with stratify NOT equal to None, and a test_size
fraction of .2.

For this exploratory section, the held out set of data is a validation set.
For the GridSearch section, the held out set of data is a test set.
```

```
"""
targetnames = ['NonFraud', 'Fraud'] #set to nonfraud if not fraud

# TODO: Separate the data into X and y
X = cdata.drop('PotentialFraud', axis=1)
y = cdata['PotentialFraud']

# TODO: Split data into train and test sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
 ↪stratify= y)
X_train.head()
```

[14]:

```
            Age  NumPhysiciansSeen  NumProcedures  NumDiagnosisClaims  \
4509  47.000000           1.000000       0.000000            2.000000
1131  72.652174           1.000000       0.000000            2.652174
5253  74.000000           1.189655       0.000000            2.534483
2142  72.692308           1.307692       0.000000            3.769231
4960  69.545455           0.909091       0.363636            7.363636

      InscClaimAmtReimbursed  DeductibleAmtPaid  NoOfMonths_PartACov  \
4509               -0.203529          -0.031258            12.000000
1131               -0.006412           0.002039            11.869565
5253               -0.013817          -0.007365            12.000000
2142               -0.023117          -0.025648            11.076923
4960                3.256315           5.421453            12.000000

      NoOfMonths_PartBCov  IPAnnualReimbursementAmt  IPAnnualDeductibleAmt  \
4509            12.000000                 -0.164503               1.214458
1131            12.000000                 -0.129817               0.027452
5253            11.965517                 -0.349052              -0.164233
2142            10.153846                  0.381115               0.660612
4960            12.000000                  2.140070               3.396276

      …  ChronicCond_Heartfailure  ChronicCond_KidneyDisease  \
4509  …                       0.0                        1.0
1131  …                      45.0                       37.0
5253  …                      34.0                       20.0
2142  …                       6.0                        2.0
4960  …                      10.0                        6.0

      ChronicCond_Cancer  ChronicCond_ObstrPulmonary  ChronicCond_Depression  \
4509                 1.0                         1.0                     0.0
1131                12.0                        22.0                    37.0
5253                 8.0                        10.0                    28.0
2142                 2.0                         3.0                     5.0
4960                 6.0                         6.0                     4.0
```

```
       ChronicCond_Diabetes  ChronicCond_IschemicHeart  \
4509                    0.0                        1.0
1131                   68.0                       66.0
5253                   40.0                       40.0
2142                    8.0                       12.0
4960                   10.0                        8.0

       ChronicCond_Osteoporasis  ChronicCond_rheumatoidarthritis  \
4509                        1.0                              0.0
1131                       42.0                             31.0
5253                       13.0                             13.0
2142                        4.0                              5.0
4960                        3.0                              6.0

       ChronicCond_stroke
4509                  0.0
1131                 16.0
5253                  4.0
2142                  0.0
4960                  3.0

[5 rows x 23 columns]
```

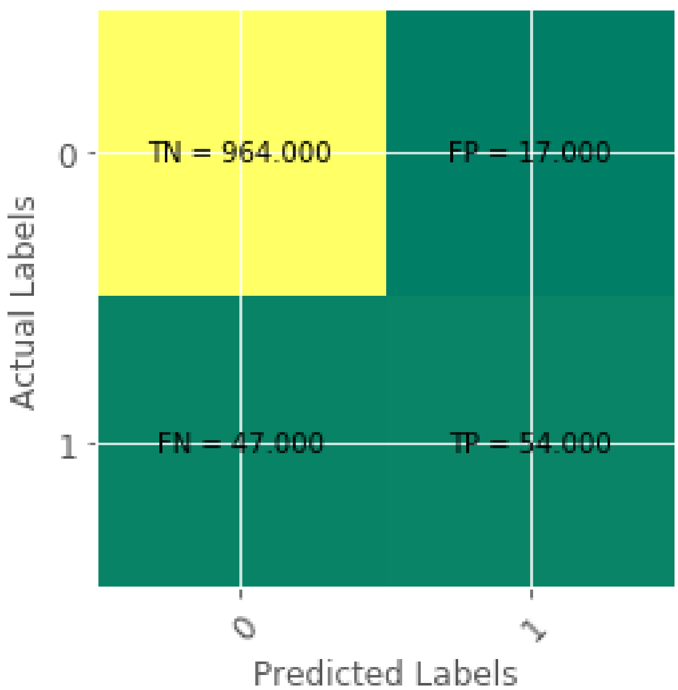
[15]:

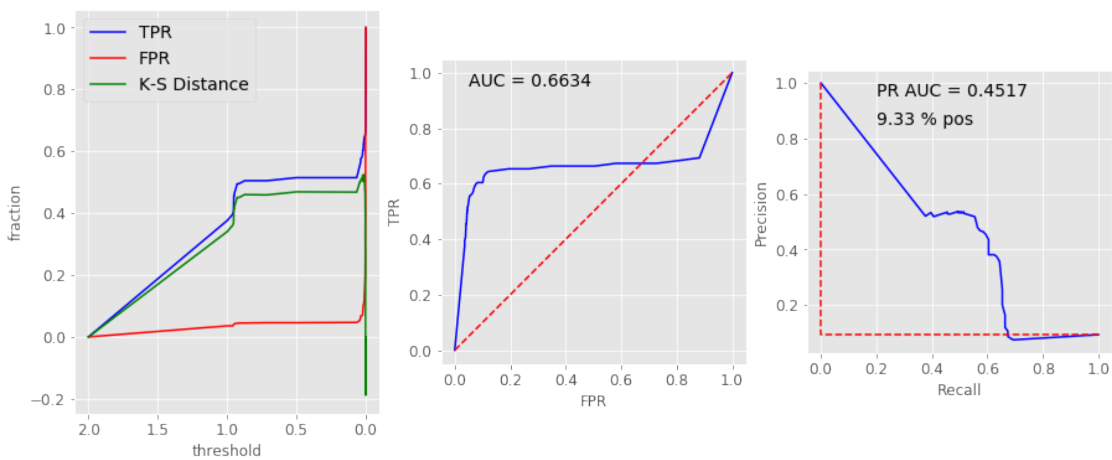
```
""" TODO
Play around with the hyper-parameters. Pick your favorite model to leave with␣
 ↪in
your submitted report.
"""
# TODO: Create and fit the model
classifier = DecisionTreeClassifier(max_depth = 200, max_leaf_nodes = 40)
classifier.fit(X_train, y_train)

# TODO: Predict with the model on the validation set
preds_val = classifier.predict(X_val)


# TODO: Obtain prediction probabilities for the validation set, using
# cross_val_predict with cv=10 and method='predict_proba'
proba_val = cross_val_predict(classifier, X_val, y_val, cv=10,␣
 ↪method='predict_proba')


# TODO: The mean CV accuracy on the given validation data and labels, using
# cross_val_score and cv=10

scorescv = cross_val_score(classifier, X_val, y_val, cv=10)
np.mean(scorescv)
```

[15]: 0.9140067340067338

[16]:
```
""" TODO
Display the confusion matrix, KS plot, ROC curve, and PR curve for the␣
↪validation set
using metrics_plots.ks_roc_prc_plot

The red dashed line in the PRC is indicative of a the expected performance for␣
↪a random
classifier, which would predict predict postives at the rate of occurance␣
↪within the data set
"""
# TODO: Confusion Matrix
confusion = confusion_matrix(y_val, preds_val)
metrics_plots.confusion_mtx_colormap(confusion, [0,1],[0,1])


# TODO: Curves
# Note, you'll want the probability class predictions for the class label 1
# See the API page for the DecisionTreeClassifier predict_proba; proba_val[:,1]
metrics_plots.ks_roc_prc_plot(y_val, proba_val[:,1])


# Obtain the PSS and F1 Score
pss_val = metrics_plots.skillScore(y_val, preds_val)
f1_val = f1_score(y_val, preds_val)
print("PSS: %.4f" % pss_val[0])
print("F1 Score %.4f" % f1_val)
```

```
ROC AUC: 0.6633764293860578
PRC AUC: 0.4516731565973817
PSS: 0.5173
F1 Score 0.6279
```





[17]:
```
""" TODO
Export the image of the tree model
use export_graphviz
"""
export_graphviz(classifier, out_file='model.dot', filled=True, rounded=True)
```

6 GRID SEARCH CV

[18]:
```python
""" TODO
Estimated time: <10 min on mlserver
Set up and run the grid search using GridSearchCV and the following
settings:
* The below scoring dictionary for scoring,
* refit set to 'f1' as the optimized metric
* Twenty for the number of cv folds,
* n_jobs=3,
* verbose=2,
* return_train_score=True
"""
# Optimized metric
opt_metric = 'f1'
scoring = {opt_metric:opt_metric}

# Flag to re-load previous run regardless of whether the file exists
force = True
# File previous run is saved to
srchfname = "hw9_search_" + opt_metric + ".pkl"

# SETUP EXPERIMENT HYPERPARAMETERS
max_depths = [None, 200, 100, 10, 8, 6, 4]
max_leaf_nodes = [None, 10, 5, 2]

ndepths = len(max_depths)
nleaves = len(max_leaf_nodes)

# TODO: Create the dictionary of hyper-parameters to try
hyperparams = {'max_depth':max_depths, 'max_leaf_nodes':max_leaf_nodes,
               'class_weight':[None, 'balanced']}

# RUN EXPERIMENT
time0 = timelib.time()
search = None
if force or (not os.path.exists(srchfname)):
    # TODO: Create the GridSearchCV object
    search = GridSearchCV(DecisionTreeClassifier(), param_grid=hyperparams,␣
↪scoring=scoring,
                          refit=opt_metric, cv=20, n_jobs=3,
                          verbose=2, return_train_score=True)

    # TODO: Execute the grid search by calling fit using the training data
    search.fit(X_train, y_train)

    # TODO: Save the grid search object
```

```
    joblib.dump(search, srchfname)

    print("Saved %s" % srchfname)
else:
    # TODO: Re-load the grid search object
    search = joblib.load(srchfname)
    print("Loaded %s" % srchfname)

time1 = timelib.time()
duration = time1 - time0
print("Elapsed Time: %.2f min" % (duration / 60))

search
```

```
Fitting 20 folds for each of 56 candidates, totalling 1120 fits

[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  71 tasks      | elapsed:    1.7s

Saved hw9_search_f1.pkl
Elapsed Time: 0.21 min

[Parallel(n_jobs=3)]: Done 1120 out of 1120 | elapsed:   12.6s finished
```

[18]:
```
GridSearchCV(cv=20, error_score='raise-deprecating',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='gini',
max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best'),
       fit_params=None, iid='warn', n_jobs=3,
       param_grid={'max_depth': [None, 200, 100, 10, 8, 6, 4], 'max_leaf_nodes':
[None, 10, 5, 2], 'class_weight': [None, 'balanced']},
       pre_dispatch='2*n_jobs', refit='f1', return_train_score=True,
       scoring={'f1': 'f1'}, verbose=2)
```

7 RESULTS

[19]:
```
""" PROVIDED
Display the head of the results for the grid search
See the cv_results_ attribute
"""
all_results = search.cv_results_
df_res = pd.DataFrame(all_results)
df_res.head(3)
```

```
[19]:    mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
      0       0.055057      0.007881         0.001549        0.000282
      1       0.023269      0.003426         0.001456        0.000294
      2       0.019504      0.003028         0.001401        0.000314

        param_class_weight param_max_depth param_max_leaf_nodes  \
      0               None            None                 None
      1               None            None                   10
      2               None            None                    5

                                                   params  split0_test_f1  \
      0  {'class_weight': None, 'max_depth': None, 'max…        0.500000
      1  {'class_weight': None, 'max_depth': None, 'max…        0.484848
      2  {'class_weight': None, 'max_depth': None, 'max…        0.466667

         split1_test_f1  …  split12_train_f1  split13_train_f1  split14_train_f1  \
      0        0.488889  …          1.000000          1.000000          1.000000
      1        0.437500  …          0.595200          0.628571          0.632624
      2        0.424242  …          0.499096          0.497278          0.490909

         split15_train_f1  split16_train_f1  split17_train_f1  split18_train_f1  \
      0          1.000000          1.000000          1.000000          1.000000
      1          0.631579          0.637016          0.617284          0.617054
      2          0.450098          0.496377          0.375479          0.490909

         split19_train_f1  mean_train_f1  std_train_f1
      0          1.000000       1.000000      0.000000
      1          0.632948       0.620993      0.014757
      2          0.490909       0.492403      0.034335

      [3 rows x 53 columns]
```

```
[20]: """ TODO
      Obtain the best model from the grid search and
      fit it to the full training data
      """
      classifier_best = DecisionTreeClassifier(max_depth = search.
       ↪best_params_['max_depth'], max_leaf_nodes = search.
       ↪best_params_['max_leaf_nodes'],
                                               class_weight=search.
       ↪best_params_['class_weight'])

      classifier_best.fit(X_train, y_train)
```

```
[20]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=4,
                  max_features=None, max_leaf_nodes=10,
                  min_impurity_decrease=0.0, min_impurity_split=None,
```

```
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

[21]:
```
""" TODO
Export the image of the best model
use export_graphviz
"""
export_graphviz(classifier_best, out_file='model2.dot', filled=True,␣
 ↪rounded=True)
```

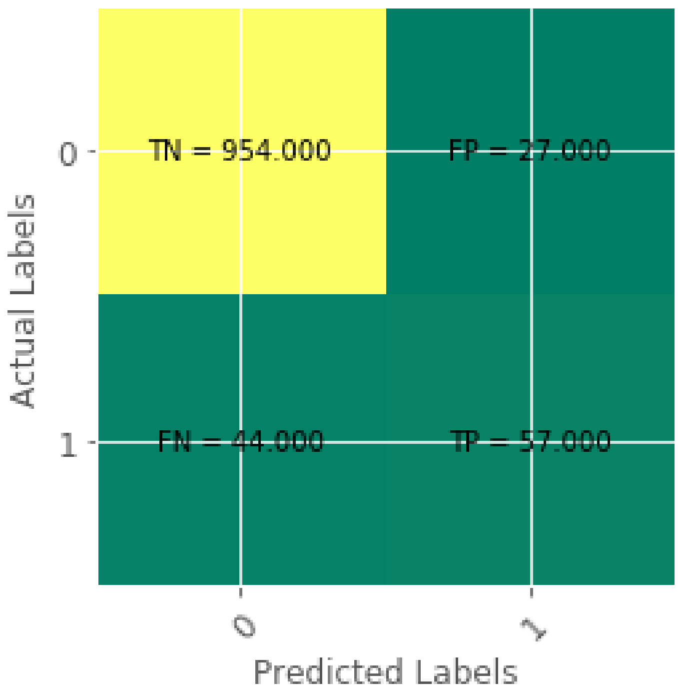
[24]:
```
search.best_params_
```

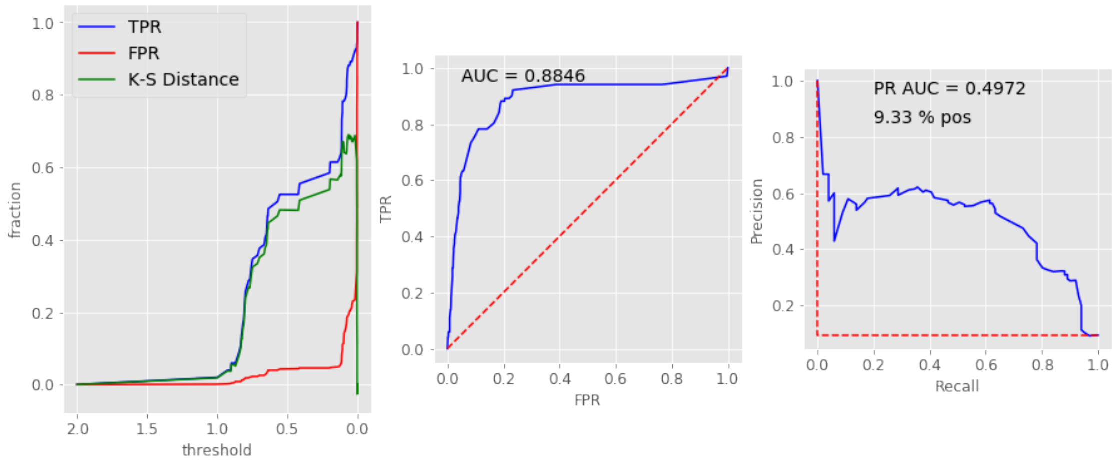
[24]:
```
{'class_weight': None, 'max_depth': 4, 'max_leaf_nodes': 10}
```

[22]:
```
""" TODO
Display the confusion matrix, KS plot, ROC curve, and PR curve for the test
set using metrics_plots.ks_roc_prc_plot

The red dashed line in the PRC is indicative of a the expected performance for
a random classifier, which would predict predict postives at the rate of
occurance within the data set
"""
# TODO: Predict with the best model on the test set
preds_best = classifier_best.predict(X_val)


# TODO: Obtain prediction probabilities for the test set using cross_val_predict
# 'predict_proba' as the method
proba_test = cross_val_predict(classifier_best, X_val, y_val, cv=10,␣
 ↪method='predict_proba')


# TODO: Compute mean accuracy (using cross_val_score) on the given test data␣
 ↪and labels
scorescv = cross_val_score(classifier_best, X_val, y_val, cv=10)


# TODO: Confusion Matrix
confusion = confusion_matrix(y_val, preds_best)
metrics_plots.confusion_mtx_colormap(confusion, [0,1],[0,1])


# TODO: Curves (i.e. ROC, PRC, etc) use metrics_plots.ks_roc_prc_plot and the
# the probabilities for the class label of 1
metrics_plots.ks_roc_prc_plot(y_val, proba_test[:,1])
```

```
# Obtain the PSS and F1 Score
pss_test = metrics_plots.skillScore(y_val, preds_best)
f1_test = f1_score(y_val, preds_best)
print("PSS: %.4f" % pss_test[0])
print("F1 Score %.4f" % f1_test)
```

```
ROC AUC: 0.8846347937546049
PRC AUC: 0.49717844809924244
PSS: 0.5368
F1 Score 0.6162
```

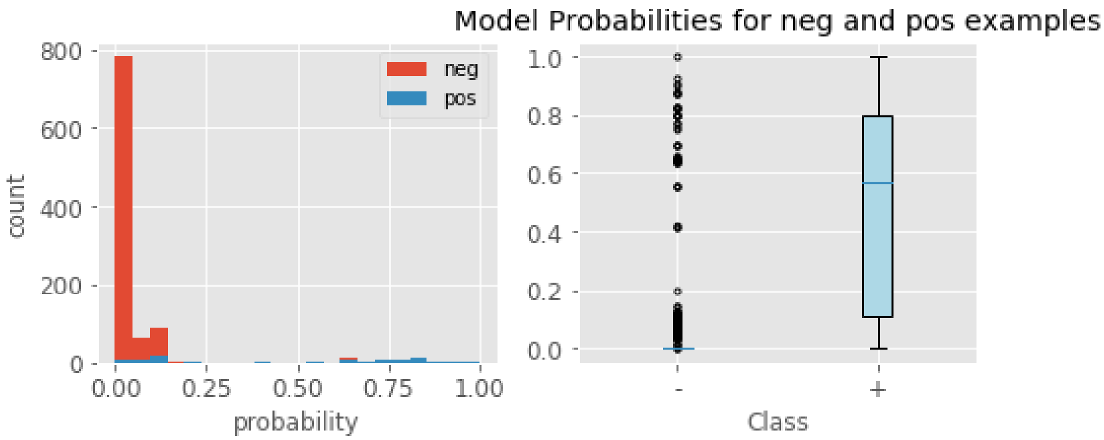




[23]:
```python
""" PROVIDED
Plot a histogram of the test scores from the best model.
Compare the distribution of scores for positive and negative examples
using boxplots.

Create one subplot of the distribution of all the scores, with a histogram.
Create a second subplot comparing the distribution of the scores of the
positive examples with the distribution of the negative examples, with boxplots.
"""
# Obtain the pos and neg indices
pos_inds = np.where(y_val)[0]
neg_inds = np.where(y_val == 0)[0]

# Separate the scores for the pos and neg examples
proba_pos = proba_test[pos_inds, 1]
proba_neg = proba_test[neg_inds, 1]

# Plot the distribution of all scores
nbins = 21
plt.figure(figsize=(8,3))
plt.subplot(1,2,1)
plt.hist(proba_neg, bins=nbins)
plt.hist(proba_pos, bins=nbins)
plt.xlabel('probability', fontsize=FONTSIZE)
plt.ylabel('count', fontsize=FONTSIZE)
plt.legend(['neg', 'pos'])

# Plot the boxplots of the pos and neg examples
plt.subplot(1,2,2)
boxplot = plt.boxplot([proba_neg, proba_pos], patch_artist=True, sym='.')
boxplot['boxes'][0].set_facecolor('pink')
```

```
boxplot['boxes'][1].set_facecolor('lightblue')
plt.xticks(ticks=[1, 2], labels=['-', '+'])
plt.xlabel("Class")
plt.title("Model Probabilities for neg and pos examples")
```

[23]: Text(0.5, 1.0, 'Model Probabilities for neg and pos examples')



8 Discussion

In 3 to 4 paragraphs, discuss and interpret the test results for the best model. Include a brief discussion of the histogram and boxplots of the scores. Compare the best model from the grid search to the one you chose in the exploration section. Additionally, embed the image of the best tree model into the notebook using:
`<center><img src="path_to_model.png"  style="width:100%;height:100%">`

The best model from the result test found that the best parameters given into gridsearch in order to optimize a DecisionTree on the data we are experimenting with are the parameters class_weight: None, max_depth: 4, and max_leaf_nodes: 10. These parameters mean that when we create a DecisionTreeClassifier, we should create a model that has a maximum depth on the tree of 4, weight one on classes, and 10 max leaf nodes in best-first fashion. This model on the testing data led to results of ROC AUC: 0.8846, PRC AUC: 0.4972, PSS 0.5368, and F1 Score 0.6162. This score is not great but could almost certainly be improved through the use of RandomForest or another classification model like SVM. A decision tree is meant to be light-weight, so the trade off for its efficiency is a weaker accuracy. If we stacked up our decision tree with RandomForest, then the efficiency to create a best fit model would decrease, but its accuracy would likely increase.

The scores returned to my test model can be interpreted as follows. The ROC AUC of 0.8846 shows that the ratio between true positive rate and false positive rate is good. We are not making false positives at a rate high enough to decrease my ROC AUC any lower. A score of one here would lead to all true positives. This is not the case, though, because my model does not get every positive correct. My PRC AUC is not great because the recall is so high. At 0.4971, this number could be higher. But because my model is having to recall at such a high percent, my recall perfect is so middling. This could against be improved by a model that better classifies than does my DecisionTreeClassifier. My PSS score is 0.5368. The PSS is a precision measurement score that is calculated by examining the false positive to true positive ratio. My F1 Score is 0.6162. This F1 Score is harmonic mean that helps to consider the tradeoff in importance between recall and precision.

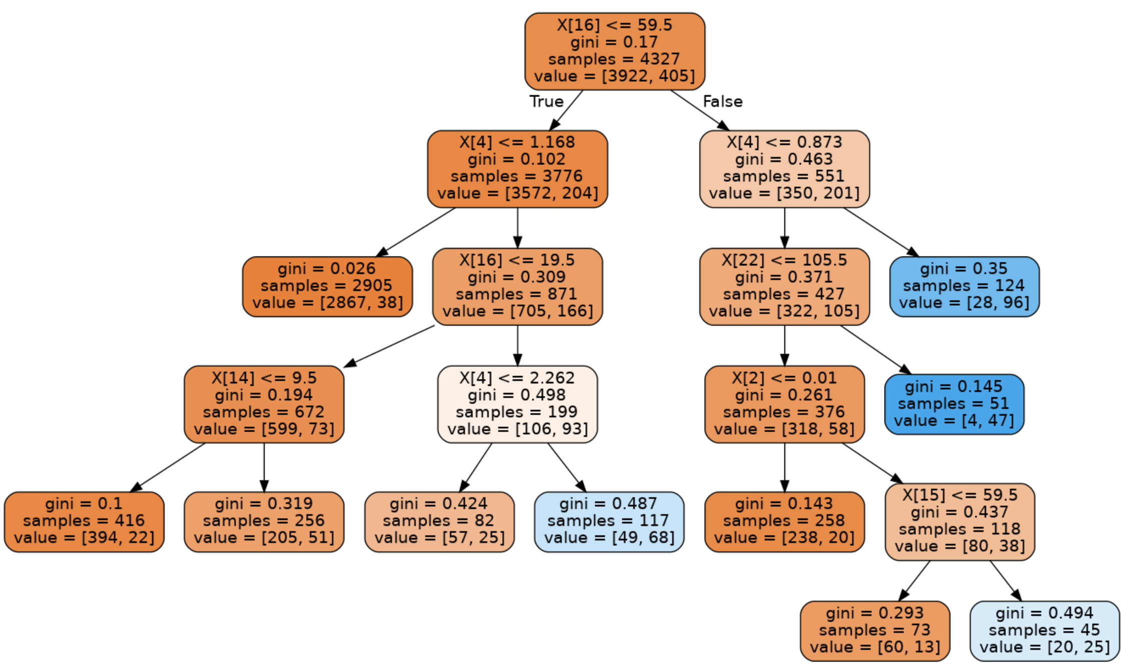
The model probabilities for negative and positive examples shows how probability impacts the negative and positive scoringg. We can see that a low probability is where our Nonfraudulent charges usually find themselves, whereas a higher probability is where positive for Fraudulent charges often are. More interesting insights can also be seen when examining this distribution in a boxplot. The negative values are polarized towards in polar ends of 0 and 1 such that they are largely concentrated towards those ends. We see, though, that positives fall largely in-between the negative distribution. These two graphs help us visually gain insight into how the classifier is able to determine the differences between positives and negatives on classification.

The best model from grid search is an improvement over the exploration model I built. For exploration I just randomly guessed at parameters to best fit my model. I came to choose these parameters based off of reading the documentation for the DecisionTreeClassifier. So I chose max_depth = 200 and max_leaf_nodes = 40. This gave me the following precision scores. ROC AUC: 0.6634, PRC AUC: 0.4517, PSS: 0.5173, and F1 Score: 0.6279. This was worse than my optimized grid-search parameters which gave me best fit parameters of class_weight: None, max_depth = 4, and max_leaf_nodes = 10. These parameters gave me precision scores of ROC AUC: 0.8846, PRC AUC: 0.4971, PSS: 0.5368, and F1 Score: 0.6162. My optimized F1 score is lower than the exploration F1 score, but all other metrics are improved on my optimized model.

My best model tree diagram is actually more simple to view than my exploration model because of the parameters passed into the initializer. The model is less deep because max_depth is smaller. And we can see the frequency at which test data flows through the diagram through coloration. DecisionTrees work by literally creating a tree by which independent data flows to reach its dependent conclusion. We can see how DecisionTreeClassifier has concluded by examining the tree.

Exploration Model

BEST MODEL!


X[16] <= 59.5
gini = 0.17
samples = 4327
value = [3922, 405]
True
False
X[4] <= 1.168
gini = 0.102
samples = 3776
value = [3572, 204]
X[4] <= 0.873
gini = 0.463
samples = 551
value = [350, 201]
gini = 0.026
samples = 2905
value = [2867, 38]
X[16] <= 19.5
gini = 0.309
samples = 871
value = [705, 166]
X[22] <= 105.5
gini = 0.371
samples = 427
value = [322, 105]
gini = 0.35
samples = 124
value = [28, 96]
X[14] <= 9.5
gini = 0.194
samples = 672
value = [599, 73]
X[4] <= 2.262
gini = 0.498
samples = 199
value = [106, 93]
X[2] <= 0.01
gini = 0.261
samples = 376
value = [318, 58]
gini = 0.145
samples = 51
value = [4, 47]
gini = 0.1
samples = 416
value = [394, 22]
gini = 0.319
samples = 256
value = [205, 51]
gini = 0.424
samples = 82
value = [57, 25]
gini = 0.487
samples = 117
value = [49, 68]
gini = 0.143
samples = 258
value = [238, 20]
X[15] <= 59.5
gini = 0.437
samples = 118
value = [80, 38]
gini = 0.293
samples = 73
value = [60, 13]
gini = 0.494
samples = 45
value = [20, 25]

```
[ ]:
```