Part 3 - Forecasting Regimes

June 24, 2020

1 Module 5: Regime Prediction with Machine Learning - Part 3

In this part we are going to predict economic regimes with machine learning algorithms using Pyhton's Scikit Learn package.

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1.2 1. Set Up Environment and Read Data

In [1]:
```
#load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn import model_selection
from sklearn import preprocessing
from sklearn.model_selection import TimeSeriesSplit
from sklearn.feature_selection import SelectFromModel

from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.tree import DecisionTreeClassifier
import xgboost as xgb

from matplotlib import pyplot as mp
import seaborn as sns
import os
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df=pd.read_csv('Dataset_Cleaned.csv')

Label = df["Regime"].apply(lambda regime: 1. if regime == 'Normal' else 0.)
df.insert(loc=2, column="Label", value=Label.values)

df.head()
```

Out[2]:
```
      Date     Regime  Label       RPI   W875RX1  DPCERA3M086SBEA  CMRMTSPLx  \
0   9/1/60  Recession    0.0 -0.277761 -0.295013        -0.212118   0.401363
1  10/1/60  Recession    0.0 -0.204460 -0.161434        -0.204519  -0.978339
2  11/1/60  Recession    0.0 -0.520186 -0.577658        -0.785798  -0.611700
3  12/1/60  Recession    0.0 -0.531320 -0.581530        -1.397470   0.071269
4   1/1/61     Normal    1.0  0.054513  0.096044        -0.375484  -1.608684

    RETAILx    INDPRO   IPFPNSS  ...  DTCTHFNM 3M lag  DTCTHFNM 6M lag  \
0 -0.321981 -0.764446 -0.632790  ...        -0.076853        -0.092745
1 -0.239615 -0.308591  0.059474  ...        -0.081327        -0.084890
2 -0.435990 -0.935469 -0.748034  ...        -0.084509        -0.087674
3 -0.375495 -1.163499 -0.921200  ...        -0.095048        -0.076637
4 -0.307555 -0.194576 -0.286457  ...        -0.103002        -0.081112

   DTCTHFNM 9M lag  DTCTHFNM 12M lag  DTCTHFNM 18M lag  INVEST 3M lag  \
0        -0.087114         -0.085455         -0.099002      -0.454463
1        -0.103429         -0.089335         -0.090643      -0.255545
2        -0.095868         -0.095503         -0.087956      -0.404823
3        -0.094476         -0.087146         -0.076214      -0.331993
4        -0.086616         -0.103462         -0.076910      -0.250758

   INVEST 6M lag  INVEST 9M lag  INVEST 12M lag  INVEST 18M lag
0      -0.566992      -0.395095       -0.450998       -0.089005
1      -0.415804      -0.483302       -0.473520        0.147174
2      -0.392308      -0.605015       -0.445070       -0.091651
3      -0.453979      -0.578110       -0.389378       -0.070555
4      -0.253854      -0.425585       -0.477942        0.167308

[5 rows x 711 columns]
```

In [3]:
```
df.tail()
```

Out[3]:
```
        Date  Regime  Label       RPI   W875RX1  DPCERA3M086SBEA  CMRMTSPLx  \
692   5/1/18  Normal    1.0 -0.158774 -0.087869         0.961837   0.428800
```

```
693  6/1/18  Normal    1.0  0.349410  0.372881         0.885853   0.063037
694  7/1/18  Normal    1.0  0.225752  0.198647         0.954238   0.150980
695  8/1/18  Normal    1.0  0.496621  0.504524         0.802270   0.788034
696  9/1/18  Normal    1.0 -0.077029 -0.231128        -0.561645   0.393889

      RETAILx    INDPRO   IPFPNSS  ...  DTCTHFNM 3M lag  DTCTHFNM 6M lag  \
692  2.458364 -2.071505 -3.897094  ...        -0.482484         0.035214
693  0.230187  1.119480  1.231754  ...        -0.658796        -0.179194
694  1.059808  0.675562 -0.051761  ...         0.108564        -0.311340
695 -0.474700  1.659097  0.954768  ...         0.104177        -0.482299
696 -0.817945  0.153438  0.379952  ...        -0.324269        -0.658623

     DTCTHFNM 9M lag  DTCTHFNM 12M lag  DTCTHFNM 18M lag  INVEST 3M lag  \
692        -0.213850          0.107884         -0.230363      -2.969053
693        -0.133821          0.236277         -0.197709      -1.758884
694        -0.144057         -0.120563         -0.293692      -1.727882
695         0.033552         -0.213885         -0.613278       0.143563
696        -0.180970         -0.133855         -0.085913       2.453857

     INVEST 6M lag  INVEST 9M lag  INVEST 12M lag  INVEST 18M lag
692       0.961673       0.029818        0.229887       -2.082950
693       2.236719       0.274491       -1.001393       -0.345305
694      -0.918590       0.481157       -0.256506        1.560538
695      -2.983834       0.964076        0.037260        0.000571
696      -1.766319       2.250399        0.282925       -0.081374

[5 rows x 711 columns]
```

1.3 2. Methodology

Our exercise will be based on classification problem. We have two binary outcomes that we want to predict with certain variables. Here we will summarize our approach to predict recessions with machine learning algorithms.

1. We will perform feature selection before making our forecasts. We will use L_1 regularized logistic regression for that purpose.
2. Separate dataset into training and validation datasets. Split based dataset based on time: the period over 1960-1996 is selected for training and the period over 1996-2018 is kept for validation
3. Evaluate performances of the machine learning algorithms on training dataset with cross validation (CV). Since we have time series structure we will use a special type of CV function in Python,`TimeSeriesSplit`. We will use Receiver operating characteristic (ROC) as scoring metric in our models. Related Python functions for this metric are `roc_auc_score` and `roc_curve`.
4. Select the best performing models based on average accuracy and standard deviation of the CV results. We will take logistic regression as a benchmark model since this is the traditional method has been used to approach this problem.

5. Then we make predictions on the validation dataset with selected models. First, we use `GridSearchCV` for selected model on training dataset to find best combination of parameters for the model. Then we evaluate the model on validation dataset and report accuracy metrics and feature importance results.

1.4 3. Feature Selection with L_1 Penalty

In [4]:
```
# Time Series Split
df_idx = df[df.Date == '12/1/96'].index[0]

df_targets=df['Label'].values
df_features=df.drop(['Regime','Date','Label'], axis=1)

df_training_features = df.iloc[:df_idx,:].drop(['Regime','Date','Label'], axis=1)
df_validation_features = df.iloc[df_idx:, :].drop(['Regime','Date','Label'], axis=1)

df_training_targets = df['Label'].values
df_training_targets=df_training_targets[:df_idx]

df_validation_targets = df['Label'].values
df_validation_targets=df_validation_targets[df_idx:]
```

In [5]:
```
print(len(df_training_features),len(df_training_targets),len(df_targets))
print(len(df_validation_features),len(df_validation_targets),len(df_features))
```

```
435 435 697
262 262 697
```

In [6]:
```
scoring="roc_auc"
kfold= model_selection.TimeSeriesSplit(n_splits=3)
seed=8

# Create regularization hyperparameter space
C = np.reciprocal([0.00000001, 0.00000005, 0.0000001, 0.0000005, 0.000001, 0.000005, 0
                         0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10,

# Create hyperparameter options
hyperparameters = dict(C=C)

model=LogisticRegression(max_iter=10000,penalty='l1')
LR_penalty=model_selection.GridSearchCV(estimator=model, param_grid= hyperparameters,
                                        cv=kfold, scoring=scoring).fit(X=df_features,
                                                                       y=df_targets).be

LR_penalty
```

Out[6]:
```
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=10000, multi_class='warn',
```

```
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

```
In [7]: X=df_features
        y=df_targets
        lr_l1 = LogisticRegression(C=0.1, max_iter=10000,penalty="l1").fit(X,y)
        model = SelectFromModel(lr_l1,prefit=True)
        feature_idx = model.get_support()
        feature_name = X.columns[feature_idx]
        X_new = model.transform(X)
        X_new.shape
```

```
Out[7]: (697, 35)
```

```
In [8]: feature_name
```

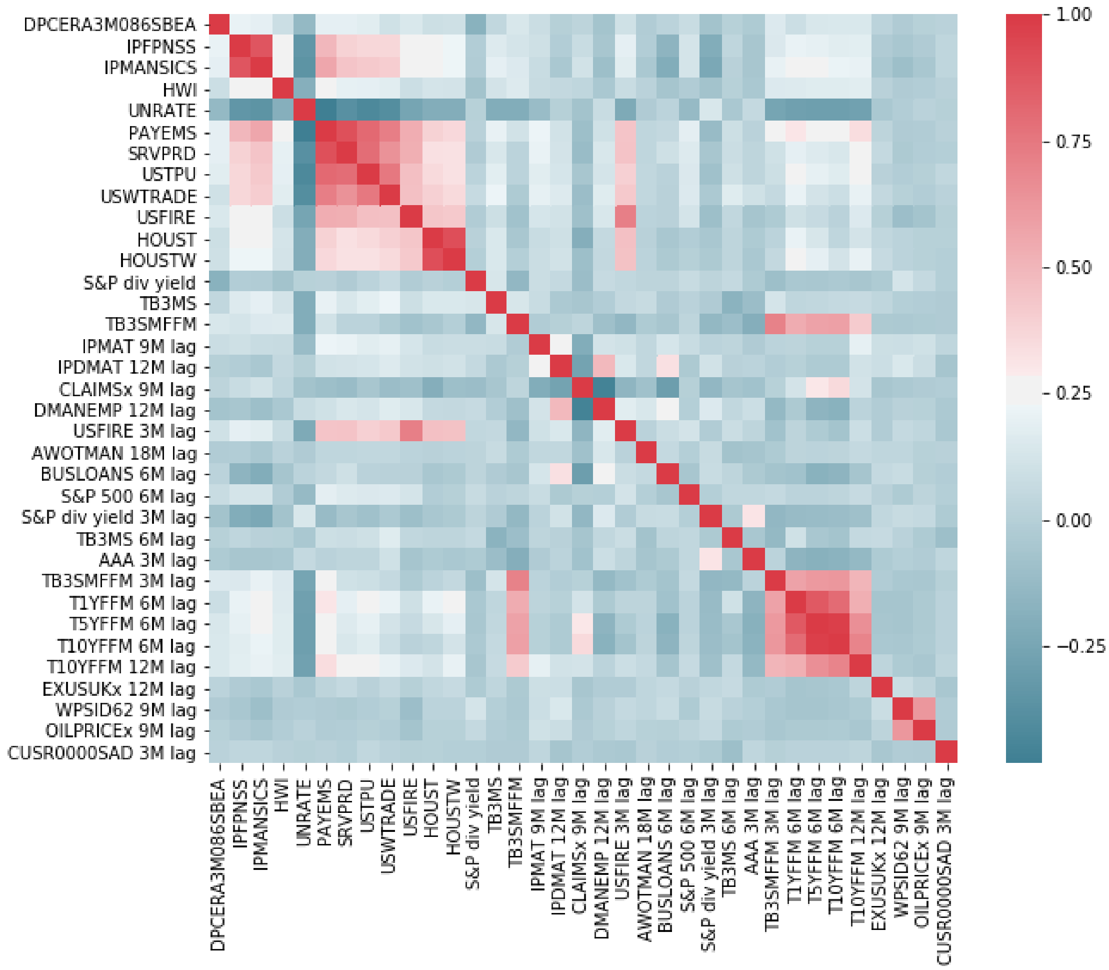
```
Out[8]: Index(['DPCERA3M086SBEA', 'IPFPNSS', 'IPMANSICS', 'HWI', 'UNRATE', 'PAYEMS',
               'SRVPRD', 'USTPU', 'USWTRADE', 'USFIRE', 'HOUST', 'HOUSTW',
               'S&P div yield', 'TB3MS', 'TB3SMFFM', 'IPMAT 9M lag', 'IPDMAT 12M lag',
               'CLAIMSx 9M lag', 'DMANEMP 12M lag', 'USFIRE 3M lag', 'AWOTMAN 18M lag',
               'BUSLOANS 6M lag', 'S&P 500 6M lag', 'S&P div yield 3M lag',
               'TB3MS 6M lag', 'AAA 3M lag', 'TB3SMFFM 3M lag', 'T1YFFM 6M lag',
               'T5YFFM 6M lag', 'T10YFFM 6M lag', 'T10YFFM 12M lag', 'EXUSUKx 12M lag',
               'WPSID62 9M lag', 'OILPRICEx 9M lag', 'CUSR0000SAD 3M lag'],
              dtype='object')
```

```
In [9]: df_2=df[feature_name]
        df_2.insert(loc=0, column="Date", value=df['Date'].values)
        df_2.insert(loc=1, column="Regime", value=df['Regime'].values)
        df_2.insert(loc=2, column="Label", value=df['Label'].values)

        df_2.head()
        df_2.shape
```

```
Out[9]: (697, 38)
```

```
In [10]: corr = df_2.drop(['Date','Regime','Label'],axis=1).corr()
         plt.figure(figsize=(10, 8))
         sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool),
                     cmap=sns.diverging_palette(220, 10, as_cmap=True), square=True)
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x10e77fb38>
```



1.5 4. Training Algorithms on Training Dataset

For a detail description of the machine learning algorithms you can check scikit-learn's documentation **here**.

```
In [11]: df=df_2
         df.shape
```

```
Out[11]: (697, 38)
```

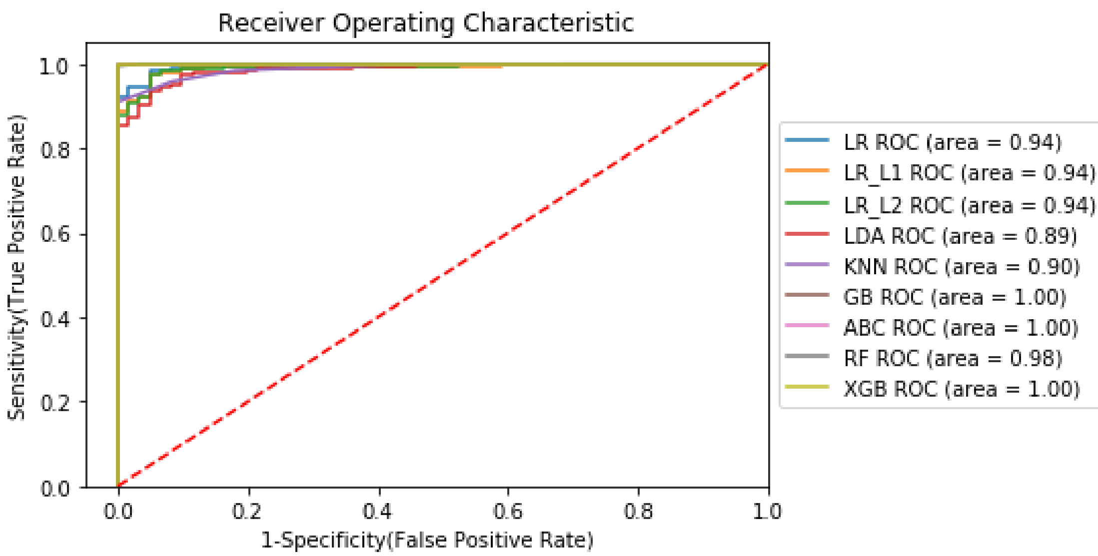
```
In [12]: # Time Series Split
         df_idx = df[df.Date == '12/1/96'].index[0]

         df_targets=df['Label'].values
         df_features=df.drop(['Regime','Date','Label'], axis=1)

         df_training_features = df.iloc[:df_idx,:].drop(['Regime','Date','Label'], axis=1)
```

```
df_validation_features = df.iloc[df_idx:, :].drop(['Regime','Date','Label'], axis=1)

df_training_targets = df['Label'].values
df_training_targets=df_training_targets[:df_idx]

df_validation_targets = df['Label'].values
df_validation_targets=df_validation_targets[df_idx:]
```

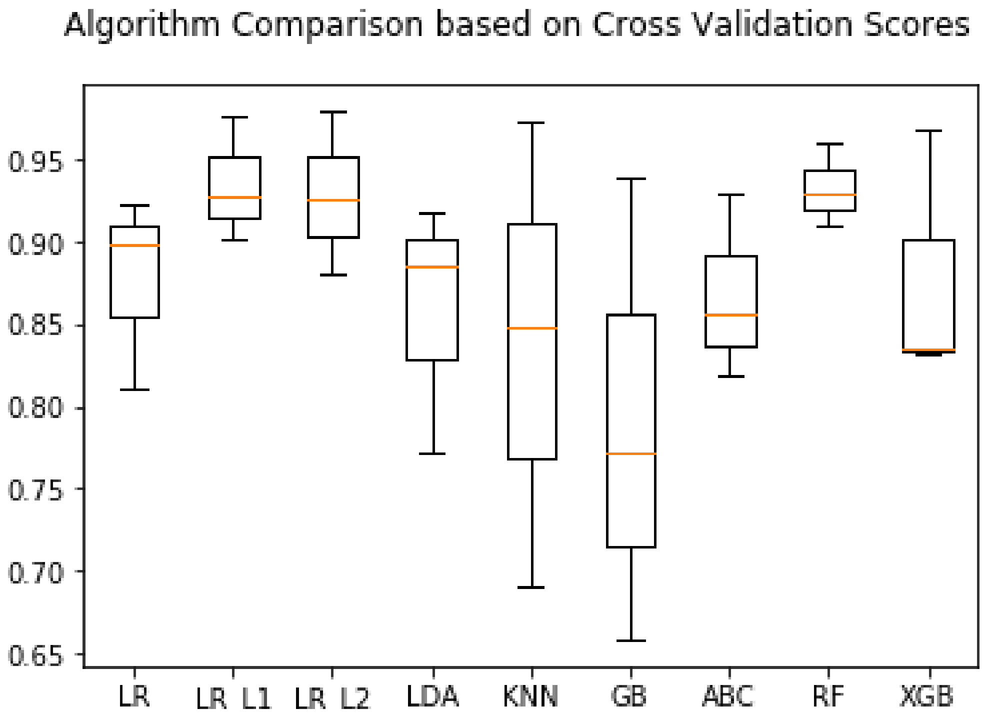
In [13]:
```
seed=8
scoring='roc_auc'
kfold = model_selection.TimeSeriesSplit(n_splits=3)
models = []

models.append(('LR', LogisticRegression(C=1e09)))
models.append(('LR_L1', LogisticRegression(penalty = 'l1')))
models.append(('LR_L2', LogisticRegression(penalty = 'l2')))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('GB', GradientBoostingClassifier()))
models.append(('ABC', AdaBoostClassifier()))
models.append(('RF', RandomForestClassifier()))
models.append(('XGB', xgb.XGBClassifier()))

results = []
names = []
lb = preprocessing.LabelBinarizer()

for name, model in models:
    cv_results = model_selection.cross_val_score(estimator = model, X = df_training_fe
                                                 y = lb.fit_transform(df_training_tar

    model.fit(df_training_features, df_training_targets) # train the model
    fpr, tpr, thresholds = metrics.roc_curve(df_training_targets, model.predict_proba
    auc = metrics.roc_auc_score(df_training_targets,model.predict(df_training_feature
    plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % (name, auc))
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)

plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.05, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic')
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.show()
```

```
warnings.filterwarnings('ignore')
```

```
LR: 0.877570 (0.047838)
LR_L1: 0.934921 (0.031076)
LR_L2: 0.928582 (0.040605)
LDA: 0.858740 (0.063361)
KNN: 0.837252 (0.115853)
GB: 0.790105 (0.115667)
ABC: 0.868133 (0.045829)
RF: 0.933246 (0.020609)
XGB: 0.878555 (0.063837)
```



In [14]:
```
fig = plt.figure()
fig.suptitle('Algorithm Comparison based on Cross Validation Scores')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



1.6 4. Evaluate Performances of the Algorithms on Validation Dataset

1.6.1 Logistic Regression

Logistic regression is the most commonly used statistical model for binary classification. It uses the logit model of relating log-odds of the dependent variable linearly with the predictor (explanatory) variables to learn a form of the following logistic function that is used to separate instances of the two different classes.

$Pr(y=1|x) = h_\beta(x) = \dfrac{1}{1+e^{-(\beta_0+\beta_1 x)}}$ where β_0 is the intercept and β is the vector of trained weights

The function returns a probability measure of which class a new instance is given its features, this measure is then used to make the final classification with some probability threshold, traditionally being 0.5.

The specific logistic function is learned through gradient descent which focuses on minimizing error calculated through some cost function. A typical approach is to use the following maximum-likelihood estimator to minimize error in predicted probabilities.

$$J(\beta) = -\frac{1}{N}\sum_{i=1}^{N} y_i log(h_\beta(x_i)) + (1-y_i) log(1-h_\beta(x_i))$$

where N is the number of observations, $h_\beta(x)$ is as defined above, and y_i is the predicted class

A regularization term

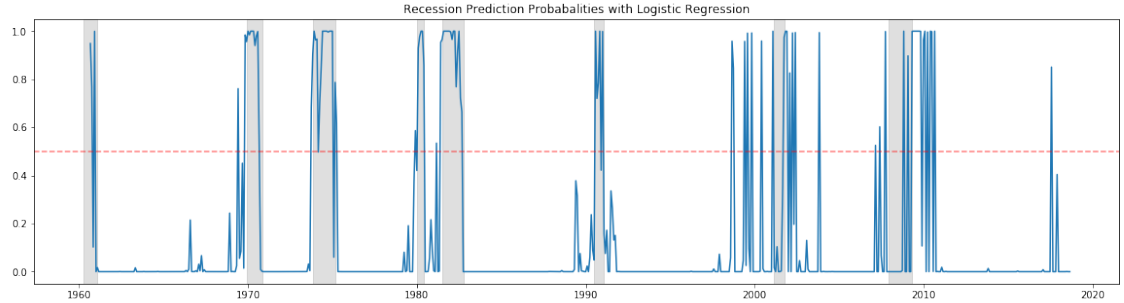
$$\lambda \sum_{i=1}^{N} |\beta_i| \text{ where } \lambda \text{ is a regularization parameter,}$$

is often added to the cost function to prevent overfitting by penalizing large coefficients. This regularization can be L1 or L2 penalty depending on the problem at hand.

```
In [15]: model=LogisticRegression(C=1e09) # high penalty
         LR=model.fit(df_training_features,df_training_targets)
         training_predictions=LR.predict(df_training_features)
         prob_predictions = LR.predict_proba(df_training_features)
         prob_predictions = np.append(prob_predictions, LR.predict_proba(df_validation_features
```

```
In [16]: import datetime
         # define periods of recession
         rec_spans = []
         #rec_spans.append([datetime.datetime(1957,8,1), datetime.datetime(1958,4,1)])
         rec_spans.append([datetime.datetime(1960,4,1), datetime.datetime(1961,2,1)])
         rec_spans.append([datetime.datetime(1969,12,1), datetime.datetime(1970,11,1)])
         rec_spans.append([datetime.datetime(1973,11,1), datetime.datetime(1975,3,1)])
         rec_spans.append([datetime.datetime(1980,1,1), datetime.datetime(1980,6,1)])
         rec_spans.append([datetime.datetime(1981,7,1), datetime.datetime(1982,10,1)])
         rec_spans.append([datetime.datetime(1990,7,1), datetime.datetime(1991,2,1)])
         rec_spans.append([datetime.datetime(2001,3,1), datetime.datetime(2001,10,1)])
         rec_spans.append([datetime.datetime(2007,12,1), datetime.datetime(2009,5,1)])
```

```
In [17]: sample_range = pd.date_range(start='9/1/1960', end='9/1/2018', freq='MS')

         plt.figure(figsize=(20,5))
         plt.plot(sample_range.to_series().values, prob_predictions[:,0])
         for i in range(len(rec_spans)):
             plt.axvspan(rec_spans[i][0], rec_spans[i][len(rec_spans[i]) - 1], alpha=0.25, colo
         plt.axhline(y=0.5, color='r', ls='dashed', alpha = 0.5)
         plt.title('Recession Prediction Probabalities with Logistic Regression')
         mp.savefig('plot1.png',  bbox_inches='tight')
         plt.show()
```

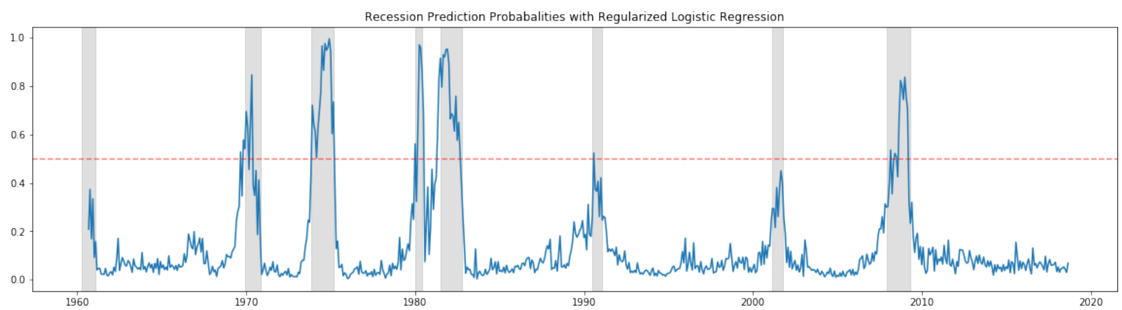


1.6.2 Logistic Regression with Regularization

In [18]:
```
# Create regularization penalty space
penalty = ['l1', 'l2']

# Create regularization hyperparameter space
C = np.reciprocal([0.00000001, 0.00000005, 0.0000001, 0.0000005, 0.000001, 0.000005, 0
                         0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10

# Create hyperparameter options
hyperparameters = dict(C=C, penalty=penalty)


model=LogisticRegression(max_iter=10000)
LR_penalty=model_selection.GridSearchCV(estimator=model, param_grid= hyperparameters,
                                        cv=kfold, scoring=scoring).fit(df_training_fea
                                                                       df_training_tar
training_predictions=LR_penalty.predict(df_training_features)
```

In [19]:
```
prob_predictions = LR_penalty.predict_proba(df_training_features)
prob_predictions = np.append(prob_predictions, LR_penalty.predict_proba(df_validation_
```

In [20]:
```
sample_range = pd.date_range(start='9/1/1960', end='9/1/2018', freq='MS')

plt.figure(figsize=(20,5))
plt.plot(sample_range.to_series().values, prob_predictions[:,0])
for i in range(len(rec_spans)):
    plt.axvspan(rec_spans[i][0], rec_spans[i][len(rec_spans[i]) - 1], alpha=0.25, colo
plt.axhline(y=0.5, color='r', ls='dashed', alpha = 0.5)
plt.title('Recession Prediction Probabalities with Regularized Logistic Regression')
mp.savefig('plot2.png',  bbox_inches='tight')
plt.show()
```



1.6.3 XGBoosting

In [21]:
```
xgboost = model_selection.GridSearchCV(estimator=xgb.XGBClassifier(),
                                       param_grid={'booster': ['gbtree']},
```

```
                                                scoring=scoring, cv=kfold).fit(df_training_fea
                                                                        lb.fit_transfor
        xgboost.fit(df_training_features, df_training_targets)
```

Out[21]:

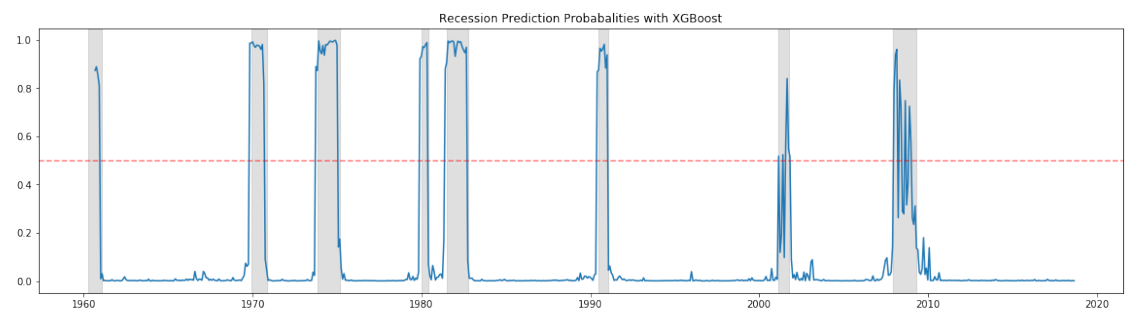
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

In [22]:

```
prob_predictions = xgboost.predict_proba(df_training_features)
prob_predictions = np.append(prob_predictions, xgboost.predict_proba(df_validation_fea
```

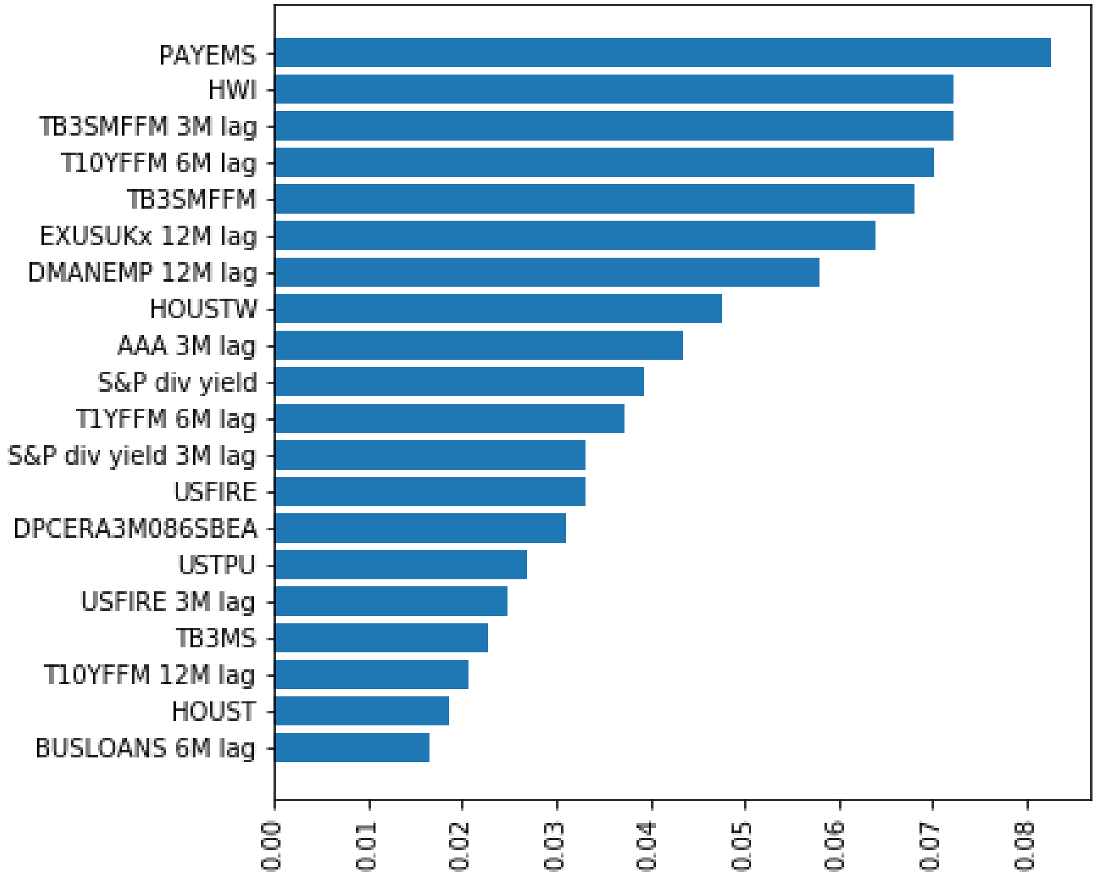
In [23]:

```
sample_range = pd.date_range(start='9/1/1960', end='9/1/2018', freq='MS')

plt.figure(figsize=(20,5))
plt.plot(sample_range.to_series().values, prob_predictions[:,0])
for i in range(len(rec_spans)):
    plt.axvspan(rec_spans[i][0], rec_spans[i][len(rec_spans[i]) - 1], alpha=0.25, colo
plt.axhline(y=0.5, color='r', ls='dashed', alpha = 0.5)
plt.title('Recession Prediction Probabalities with XGBoost')
mp.savefig('plot3.png',  bbox_inches='tight')
plt.show()
```



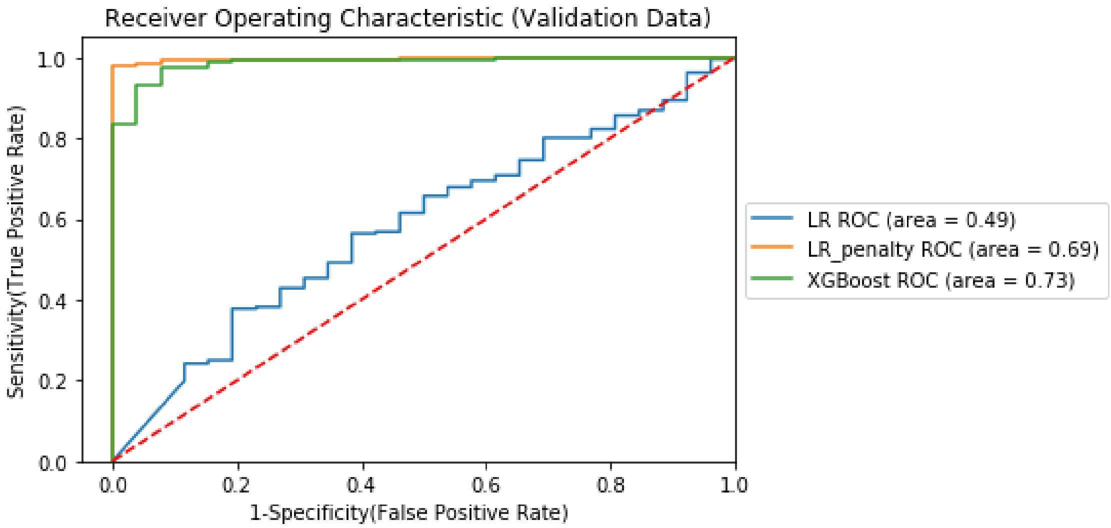
In [27]:

```
# find feature importances
headers = df.drop(['Regime','Label', 'Date'], axis=1).columns.values.tolist()
xgboost_importances = pd.DataFrame(xgboost.feature_importances_, index = headers, colu
_ = xgboost_importances.sort_values(by = ['Relative Importance'], ascending = False, i
xgboost_importances = xgboost_importances[xgboost_importances['Relative Importance']>(

# display importances in bar-chart and pie-chart
fig = plt.figure(figsize=(6,6))
plt.xticks(rotation='90')
plt.barh(y=np.arange(len(xgboost_importances)), width=xgboost_importances['Relative In
plt.gca().invert_yaxis()
mp.savefig('feature_importance.png',  bbox_inches='tight')
plt.show()
```

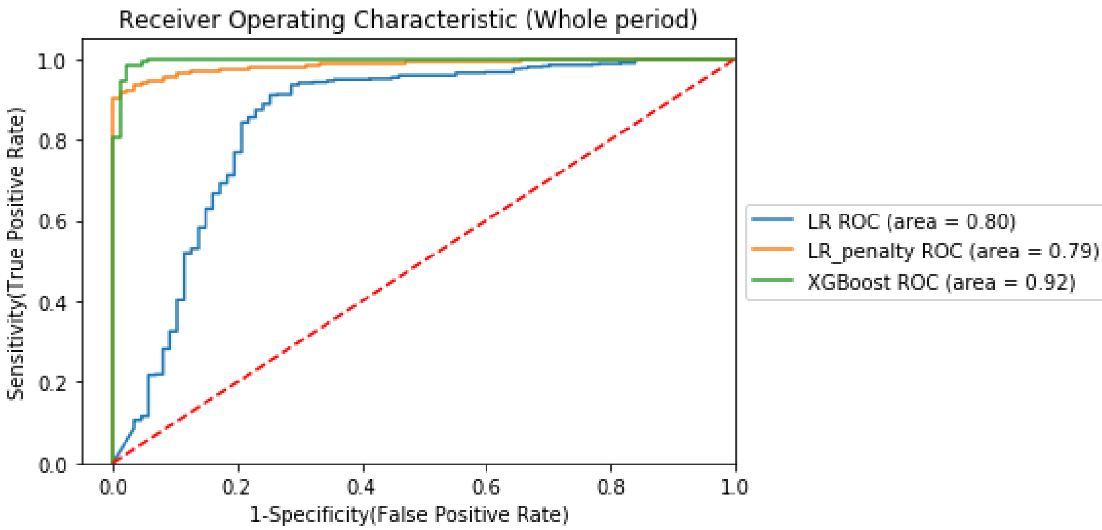


In [25]:
```
fpr, tpr, thresholds = metrics.roc_curve(df_validation_targets, LR.predict_proba(df_va
auc = metrics.roc_auc_score(df_validation_targets,LR.predict(df_validation_features))
plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % ('LR', auc))

fpr, tpr, thresholds = metrics.roc_curve(df_validation_targets, LR_penalty.predict_pro
auc = metrics.roc_auc_score(df_validation_targets,LR_penalty.predict(df_validation_fea
plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % ('LR_penalty', auc))

fpr, tpr, thresholds = metrics.roc_curve(df_validation_targets, xgboost.predict_proba
auc = metrics.roc_auc_score(df_validation_targets,xgboost.predict(df_validation_featur
plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % ('XGBoost', auc))

plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.05, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic (Validation Data)')
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
```

```
mp.savefig('ROC1.png',  bbox_inches='tight')
plt.show()
```



In [26]:
```
fpr, tpr, thresholds = metrics.roc_curve(df_targets, LR.predict_proba(df_features)[:,1
auc = metrics.roc_auc_score(df_targets,LR.predict(df_features))
plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % ('LR', auc))


fpr, tpr, thresholds = metrics.roc_curve(df_targets, LR_penalty.predict_proba(df_featu
auc = metrics.roc_auc_score(df_targets,LR_penalty.predict(df_features))
plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % ('LR_penalty', auc))

fpr, tpr, thresholds = metrics.roc_curve(df_targets, xgboost.predict_proba(df_features
auc = metrics.roc_auc_score(df_targets,xgboost.predict(df_features))
plt.plot(fpr, tpr, label='%s ROC (area = %0.2f)' % ('XGBoost', auc))

plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.05, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1-Specificity(False Positive Rate)')
plt.ylabel('Sensitivity(True Positive Rate)')
plt.title('Receiver Operating Characteristic (Whole period)')
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
mp.savefig('ROC2.png',  bbox_inches='tight')
plt.show()
```


Receiver Operating Characteristic (Whole period)
Sensitivity(True Positive Rate)
1-Specificity(False Positive Rate)
0.0
0.2
0.4
0.6
0.8
1.0
LR ROC (area = 0.80)
LR_penalty ROC (area = 0.79)
XGBoost ROC (area = 0.92)