Can we predict recessions or equity market downturns given publicly available macroeconomic data?

In [63]:
```
# Project Inspiration
# https://medium.com/@romanm111987/predicting-stock-market-crashes-with-statis
tical-machine-learning-techniques-and-neural-networks-b756d9b48497
# https://github.com/roman807/Predicting-Stock-Market-Crashes
```

Clean Data

In [64]:
```
%%javascript
IPython.OutputArea.prototype._should_scroll = function(lines) {
    return false;
}
```

Align Data

In [65]:
```
# First batch of data

import pandas as pd

SP500 = pd.read_csv('Data/SP500.csv')
T10T3 = pd.read_csv('Data/103.csv')
uRate = pd.read_csv('Data/Unrate.csv')
nfci = pd.read_csv('Data/nfci.csv')
GDP = pd.read_csv('Data/GDP.csv')

# Second batch of data
USDindex = pd.read_csv('Data/USDIndex.csv')
ManufacturingConfidence = pd.read_csv('Data/ManufacturingConfidence.csv')
HousePriceIndex = pd.read_csv('Data/HousePriceIndex.csv')
ConsumerSentiment = pd.read_csv('Data/ConsumerSentiment.csv')
PeopleOutputPerHour = pd.read_csv('Data/PeopleOutputPerHour.csv')
GS10 = pd.read_csv('Data/GS10.csv')
FEDFUNDS = pd.read_csv('Data/FEDFUNDS.csv')
USNIM = pd.read_csv('Data/USNIM.csv')
govtToGDP = pd.read_csv('Data/govtToGDP.csv')
CorporateProfits = pd.read_csv('Data/CorporateProfits.csv')
VIX = pd.read_csv('Data/VIX.csv')

# Annoying to integrate all these right now
#highYield = pd.read_csv('Data/highYield.csv')
#highYield = highYield.iloc[1:]
#BBB = pd.read_csv('Data/BBB.csv')
#BBB = BBB.iloc[1:]
#IG = pd.read_csv('Data/IG.csv')
#IG = IG.iloc[1:]

# Add these
# https://www.quandl.com/data/MULTPL/SHILLER_PE_RATIO_MONTH-Shiller-PE-Ratio-b
y-Month
# https://fred.stlouisfed.org/series/USREC
# https://fred.stlouisfed.org/series/M1
# https://fred.stlouisfed.org/series/M2
# https://fred.stlouisfed.org/series/MABMM301USM189S
# https://research.stlouisfed.org/
# https://fred.stlouisfed.org/series/CSUSHPISA
# https://fred.stlouisfed.org/series/USSLIND
# Add one year and three year performance to S&P
# https://fred.stlouisfed.org/series/TEDRATE
# https://fred.stlouisfed.org/series/CUSR0000SAC
#  https://fred.stlouisfed.org/series/DEXJPUS
# https://fred.stlouisfed.org/series/PERMIT
# https://fred.stlouisfed.org/series/T10YFFM
# https://www.quandl.com/data/FRED/NAPMPI-ISM-Manufacturing-Production-Index
# https://fred.stlouisfed.org/series/PAYEMS
# https://www.quandl.com/data/FRED/NAPM-ISM-Manufacturing-PMI-Composite-Index
```

In [66]:
```
ourData = [SP500, T10T3, uRate, nfci, GDP, USDindex,
          ManufacturingConfidence, HousePriceIndex, ConsumerSentiment,
          PeopleOutputPerHour, GS10, FEDFUNDS, USNIM, govtToGDP, CorporateProf
its, VIX]#, highYield, BBB, IG]
dataName = ['SP500', 'T10T3', 'uRate', 'nfci', 'GDP', 'USDIndex',
           'ManufacturingConfidence', 'HousePriceIndex', 'ConsumerSentiment',
          'PeopleOutputPerHour', 'GS10', 'FEDFUNDS', 'USNIM', 'govtToGDP', 'Co
rporateProfits', 'VIX']#, 'highYield', 'BBB', 'IG']
```

In [67]:
```
maxData = 0
maxDataType = 'xyz'
maxYear = 0
maxYearType = 'xyz'

for i in range(0, len(ourData)):
    start = '/'
    end = '/'

    date1 = ourData[i]['Date'][0]

    thisYear = int(date1[-4:])
    #print(thisYear, dataName[i])

    if thisYear > maxYear:
        maxYear = thisYear
        maxYearType = dataName[i]

    date2 = ourData[i]['Date'][1]
    #print(date2)
    #print('Month', date2.split('/')[0])
    #print((date2.split(start))[1].split(end)[0])
    #print(dataName[i], ":", int(date2.split('/')[0]) - int(date1.split('/')
[0]))
    if (int(date2.split('/')[0]) - int(date1.split('/')[0])) > maxData:
        maxData = int(date2.split('/')[0]) - int(date1.split('/')[0])
        maxDataType = dataName[i]
print(maxDataType, "data reporting is", maxData, "months")
print(maxYear, "is the last year in the data, and it is from", maxYearType)
```

```
GDP data reporting is 3 months
1990 is the last year in the data, and it is from VIX
```

In [68]:
```
# Create year column for all data

for i in range(0, len(ourData)):
    # Why can't we get year to match up to the column length
    yearList = [0] * len(ourData[i])
    #print(len(yearList))
    for j in range(0, len(yearList)):
        dateValue = ourData[i]['Date'][j]
        thisDate = int(dateValue[-4:])
        yearList[j] = thisDate
    ourData[i]['Year'] = yearList
```

In [69]:
```
# Filter data based on the max year

for i in range(0, len(ourData)):
    ourData[i]['Year'].astype(float)
    ourData[i]['Year'] = ourData[i][ourData[i]['Year'] >= maxYear]
```

In [70]:
```
# Drop nulls
for i in range(0, len(ourData)):
    ourData[i] = ourData[i].dropna()
```

In [72]:
```
# Check data outputs
# for i in range(0, len(ourData)):
    # print(ourData[i].head())
```

In [73]:
```
# We now need to filter out all data before 1982

SP500 = ourData[0]
T10T3 = ourData[1]
uRate = ourData[2]
nfci = ourData[3]
GDP = ourData[4]
USDindex = ourData[5]
ManufacturingConfidence = ourData[6]
HousePriceIndex = ourData[7]
ConsumerSentiment = ourData[8]
PeopleOutputPerHour = ourData[9]
GS10 = ourData[10]
FEDFUNDS = ourData[11]
USNIM = ourData[12]
govtToGDP = ourData[13]
CorporateProfits = ourData[14]
VIX = ourData[15]
#highYield = ourData[16]
#BBB = ourData[17]
#IG = ourData[18]
```

In [74]:
```
ourData = [SP500, T10T3, uRate, nfci, GDP, USDindex,
          ManufacturingConfidence, HousePriceIndex, ConsumerSentiment,
          PeopleOutputPerHour, GS10, FEDFUNDS, USNIM, govtToGDP, CorporateProf
its, VIX]#, highYield, BBB, IG]

dataName = ['SP500', 'T10T3', 'uRate', 'nfci', 'GDP', 'USDIndex',
           'ManufacturingConfidence', 'HousePriceIndex', 'ConsumerSentiment',
          'PeopleOutputPerHour', 'GS10', 'FEDFUNDS', 'USNIM', 'govtToGDP', 'Co
rporateProfits', 'VIX']#, 'highYield', 'BBB', 'IG']

smallestData = len(ourData[0])
smallestDataName = dataName[0]

for i in range(0, len(ourData)):
    # print(len(ourData[i]), dataName[i])
    if len(ourData[i]) < smallestData:
        smallestData = len(ourData[i])
        smallestDataName = dataName[i]
print(smallestData, smallestDataName)
```

```
116 GDP
```

In [75]:
```
# Get the dates lined up based on the smallest piece of data
#dataGathering = [0] * len(GDP)
w, h = 17, len(GDP); # This has to be based off the length of the shortest fil
e
results = [[0 for x in range(w)] for y in range(h)]

newData = [SP500, T10T3, uRate, nfci, USDindex,
          ManufacturingConfidence, HousePriceIndex, ConsumerSentiment,
          PeopleOutputPerHour, GS10, FEDFUNDS, USNIM, govtToGDP, CorporateProf
its, VIX]
```

In [76]:
```
# Results

# Need to add a new incrementer to position every time a new variable is added
to the test files.
position1 = 0
position2 = 0
position3 = 0
position4 = 0

position5 = 0
position6 = 0
position7 = 0
position8 = 0

position9 = 0
position10 = 0
position11 = 0
position12 = 0

position13 = 0
position14 = 0
position15 = 0

for i in range(0, len(GDP)): # This has to be based off the length of the shor
test file
    results[i][0] = GDP['Date'].iloc[i]
    results[i][1] = round(GDP['GDP'].iloc[i], 2)
    if GDP['Date'].iloc[i][:2] == newData[0]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[0]['Date'].iloc[i][-4:]:
        results[i][2] = round(newData[0]['SP500'].iloc[i], 2)
        # print(GDP['Date'].iloc[i])
        # print(newData[0]['Date'].iloc[i])
    else:
        while position1 <= len(newData[0]):
            if (GDP['Date'].iloc[i][:2] == newData[0]['Date'].iloc[position1]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[0]['Date'].iloc[position1][-4
:]):
                results[i][2] = round(newData[0]['SP500'].iloc[position1], 2)
                # print(GDP['Date'].iloc[i])
                # print(newData[0]['Date'].iloc[position1])
                break
            else:
                position1 = position1 + 1
    if GDP['Date'].iloc[i][:2] == newData[1]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[1]['Date'].iloc[i][-4:]:
        if newData[1]['T10Y3M'].iloc[position2] == 0:
                results[i][3] = round(newData[1]['T10Y3M'].iloc[position2 + 1
], 2)
                # print(GDP['Date'].iloc[i])
                # print(newData[1]['Date'].iloc[position2])
        else:
            results[i][3] = round(newData[1]['T10Y3M'].iloc[i], 2)
    else:
        while position2 <= len(newData[1]):
            if (GDP['Date'].iloc[i][:2] == newData[1]['Date'].iloc[position2]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[1]['Date'].iloc[position2][-4
```

```
:]):
                # Test if newData[1]['T10Y3M'].iloc[position2] == 0
                # if so, take the next one from it
                if newData[1]['T10Y3M'].iloc[position2] == 0:
                    results[i][3] = round(newData[1]['T10Y3M'].iloc[position2
+ 1], 2)
                    # print(GDP['Date'].iloc[i])
                    # print(newData[1]['Date'].iloc[position2])
                else:
                    results[i][3] = round(newData[1]['T10Y3M'].iloc[position2
], 2)
                    # print(GDP['Date'].iloc[i])
                    # print(newData[1]['Date'].iloc[position2])
                break
            else:
                position2 = position2 + 1
    if GDP['Date'].iloc[i][:2] == newData[2]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[2]['Date'].iloc[i][-4:]:
        results[i][4] = round(newData[2]['UNRATE'].iloc[i], 2)
    else:
        while position3 <= len(newData[2]):
            if (GDP['Date'].iloc[i][:2] == newData[2]['Date'].iloc[position3]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[2]['Date'].iloc[position3][-4
:]):
                results[i][4] = round(newData[2]['UNRATE'].iloc[position3], 2)
                # print(GDP['Date'].iloc[i])
                # print(newData[2]['Date'].iloc[position3])
                break
            else:
                position3 = position3 + 1
    if GDP['Date'].iloc[i][:2] == newData[3]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[3]['Date'].iloc[i][-4:]:
        results[i][5] = round(newData[3]['NFCI'].iloc[i], 2)
    else:
        while position4 <= len(newData[3]):
            if (GDP['Date'].iloc[i][:2] == newData[3]['Date'].iloc[position4]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[3]['Date'].iloc[position4][-4
:]):
                results[i][5] = round(newData[3]['NFCI'].iloc[position4], 2)
                # print(GDP['Date'].iloc[i])
                # print(newData[3]['Date'].iloc[position4])
                break
            else:
                position4 = position4 + 1
    if GDP['Date'].iloc[i][:2] == newData[4]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[4]['Date'].iloc[i][-4:]:
        if newData[4]['USDindex'].iloc[i] == '.':
            results[i][6] = newData[4]['USDindex'].iloc[position5 + 1]
            # print(GDP['Date'].iloc[i])
            # print(newData[4]['Date'].iloc[i])
        else:
            results[i][6] = newData[4]['USDindex'].iloc[position5]
    else:
        while position5 <= len(newData[4]):
            if (GDP['Date'].iloc[i][:2] == newData[4]['Date'].iloc[position5]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[4]['Date'].iloc[position5][-4
:]):
```

```
                # Test if newData[4]['USDindex'].iloc[position5] == '.'
                # if so, take the next one from it
                if newData[4]['USDindex'].iloc[position5] == '.':
                    results[i][6] = newData[4]['USDindex'].iloc[position5 + 1]
                else:
                    results[i][6] = newData[4]['USDindex'].iloc[position5]
                # print(GDP['Date'].iloc[i])
                # print(newData[4]['Date'].iloc[position5])
                break
            else:
                position5 = position5 + 1
    if GDP['Date'].iloc[i][:2] == newData[5]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[5]['Date'].iloc[i][-4:]:
        results[i][7] = round(newData[5]['ManufacturingConfidence'].iloc[i], 2
)
    else:
        while position6 <= len(newData[5]):
            if (GDP['Date'].iloc[i][:2] == newData[5]['Date'].iloc[position6]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[5]['Date'].iloc[position6][-4
:]):
                results[i][7] = round(newData[5]['ManufacturingConfidence'].il
oc[position6], 2)
                # print(GDP['Date'].iloc[i])
                # print(newData[5]['Date'].iloc[position6])
                break
            else:
                position6 = position6 + 1
    if GDP['Date'].iloc[i][:2] == newData[6]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[6]['Date'].iloc[i][-4:]:
        results[i][8] = round(newData[6]['HousePriceIndex'].iloc[i], 2)
    else:
        while position7 <= len(newData[6]):
            if (GDP['Date'].iloc[i][:2] == newData[6]['Date'].iloc[position7]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[6]['Date'].iloc[position7][-4
:]):
                results[i][8] = round(newData[6]['HousePriceIndex'].iloc[posit
ion7], 2)
                # print(GDP['Date'].iloc[i])
                # print(newData[6]['Date'].iloc[position7])
                break
            else:
                position7 = position7 + 1
    if GDP['Date'].iloc[i][:2] == newData[7]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[7]['Date'].iloc[i][-4:]:
        results[i][9] = newData[7]['ConsumerSentiment'].iloc[i]
    else:
        while position8 <= len(newData[7]):
            if (GDP['Date'].iloc[i][:2] == newData[7]['Date'].iloc[position8]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[7]['Date'].iloc[position8][-4
:]):
                results[i][9] = newData[7]['ConsumerSentiment'].iloc[position8
]
                # print(GDP['Date'].iloc[i])
                # print(newData[7]['Date'].iloc[position8])
                break
            else:
                position8 = position8 + 1
```

```
    if GDP['Date'].iloc[i][:2] == newData[8]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[8]['Date'].iloc[i][-4:]:
        results[i][10] = newData[8]['PeopleOutputPerHour'].iloc[i]
    else:
        while position9 <= len(newData[8]):
            if (GDP['Date'].iloc[i][:2] == newData[8]['Date'].iloc[position9]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[8]['Date'].iloc[position9][-4
:]):
                results[i][10] = newData[8]['PeopleOutputPerHour'].iloc[positi
on9]
                # print(GDP['Date'].iloc[i])
                # print(newData[8]['Date'].iloc[position9])
                break
            else:
                position9 = position9 + 1

    if GDP['Date'].iloc[i][:2] == newData[9]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[9]['Date'].iloc[i][-4:]:
        results[i][11] = newData[9]['GS10'].iloc[i]
    else:
        while position10 <= len(newData[9]):
            if (GDP['Date'].iloc[i][:2] == newData[9]['Date'].iloc[position10]
[:2]) and (GDP['Date'].iloc[i][-4:] == newData[9]['Date'].iloc[position10][-4
:]):
                results[i][11] = newData[9]['GS10'].iloc[position10]
                # print(GDP['Date'].iloc[i])
                # print(newData[9]['Date'].iloc[position10])
                break
            else:
                position10 = position10 + 1

    if GDP['Date'].iloc[i][:2] == newData[10]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[10]['Date'].iloc[i][-4:]:
        results[i][12] = newData[10]['FEDFUNDS'].iloc[i]
    else:
        while position11 <= len(newData[10]):
            if (GDP['Date'].iloc[i][:2] == newData[10]['Date'].iloc[position11
][:2]) and (GDP['Date'].iloc[i][-4:] == newData[10]['Date'].iloc[position11][-
4:]):
                results[i][12] = newData[10]['FEDFUNDS'].iloc[position11]
                # print(GDP['Date'].iloc[i])
                # print(newData[10]['Date'].iloc[position11])
                break
            else:
                position11 = position11 + 1

    if GDP['Date'].iloc[i][:2] == newData[11]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[11]['Date'].iloc[i][-4:]:
        results[i][13] = newData[11]['USNIM'].iloc[i]
    else:
        while position12 <= len(newData[11]):
            if (GDP['Date'].iloc[i][:2] == newData[11]['Date'].iloc[position12
][:2]) and (GDP['Date'].iloc[i][-4:] == newData[11]['Date'].iloc[position12][-
4:]):
                results[i][13] = newData[11]['USNIM'].iloc[position12]
                # print(GDP['Date'].iloc[i])
```

```
                # print(newData[11]['Date'].iloc[position12])
                break
            else:
                position12 = position12 + 1

    if GDP['Date'].iloc[i][:2] == newData[12]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[12]['Date'].iloc[i][-4:]:
        results[i][14] = newData[12]['GEXPND_GDP'].iloc[i]
    else:
        while position13 <= len(newData[12]):
            if (GDP['Date'].iloc[i][:2] == newData[12]['Date'].iloc[position13
][:2]) and (GDP['Date'].iloc[i][-4:] == newData[12]['Date'].iloc[position13][-
4:]):
                results[i][14] = newData[12]['GEXPND_GDP'].iloc[position13]
                # print(GDP['Date'].iloc[i])
                # print(newData[12]['Date'].iloc[position13])
                break
            else:
                position13 = position13 + 1

    if GDP['Date'].iloc[i][:2] == newData[13]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[13]['Date'].iloc[i][-4:]:
        results[i][15] = newData[13]['CorporateProfits'].iloc[i]
    else:
        while position14 <= len(newData[13]):
            if (GDP['Date'].iloc[i][:2] == newData[13]['Date'].iloc[position14
][:2]) and (GDP['Date'].iloc[i][-4:] == newData[13]['Date'].iloc[position14][-
4:]):
                results[i][15] = newData[13]['CorporateProfits'].iloc[position
14]
                # print(GDP['Date'].iloc[i])
                # print(newData[13]['Date'].iloc[position14])
                break
            else:
                position14 = position14 + 1

    if GDP['Date'].iloc[i][:2] == newData[14]['Date'].iloc[i][:2] and GDP['Dat
e'].iloc[i][-4:] == newData[14]['Date'].iloc[i][-4:]:
        results[i][16] = newData[14]['VIX'].iloc[i]
    else:
        while position15 <= len(newData[14]):
            if (GDP['Date'].iloc[i][:2] == newData[14]['Date'].iloc[position15
][:2]) and (GDP['Date'].iloc[i][-4:] == newData[14]['Date'].iloc[position15][-
4:]):
                if newData[14]['VIX'].iloc[position15] == '.':
                    results[i][16] = newData[14]['VIX'].iloc[position15 + 2]
                else:
                    results[i][16] = newData[14]['VIX'].iloc[position15]
                # print(GDP['Date'].iloc[i])
                # print(newData[14]['Date'].iloc[position15])
                break
            else:
                position15 = position15 + 1
```

In [78]:
```
# results
```

In [79]:
```
finalData = pd.DataFrame(results)
finalData.columns = ['Date', 'GDP', 'SP500', 'T10T3', 'uRate', 'nfci', 'USDIndex',
           'ManufacturingConfidence', 'HousePriceIndex', 'ConsumerSentiment',
          'PeopleOutputPerHour', 'GS10', 'FEDFUNDS', 'USNIM', 'govtToGDP', 'CorporateProfits', 'VIX']
```

In [80]:
```
# 20% or a larger drawdown from last stock market index top
# Using S&P 500 due to US market data ease of gathering. US around 50% of MSCI
indexes
# SP500

spDay = 0
spFirstDayOfQuarter = 0
spLastDayOfQuarter = 0
spMax = SP500['SP500'].iloc[0]
spMaxList = []
spNewMax = [] # 0 or 1
spBelowMax = [] # look at quarter end vs all time high
spQuarterReturn = []

spMaxQuarterDrawdown = []

# Something is still wrong with quarter max/min. Need to investigate
spQuarterMax = []
spQuarterMin = []
# need to figure out how to classify bear market

for i in range(1, len(finalData)):
    print(finalData['Date'].iloc[i])
    maxCheck = None
    while spDay <= len(SP500):
        if (finalData['Date'].iloc[i][:2] == SP500['Date'].iloc[spDay][:2]) an
d (finalData['Date'].iloc[i][-4:] == SP500['Date'].iloc[spDay][-4:]):
            print(SP500['SP500'].iloc[spDay])
            spMaxList.append(spMax)
            if maxCheck:
                spNewMax.append(1)
            else:
                spNewMax.append(0)
            #print((SP500['SP500'].iloc[spDay] / SP500['SP500'].iloc[spFirstDa
yOfQuarter]) - 1)
            spQuarterReturn.append(SP500['SP500'].iloc[spDay] / SP500['SP500']
.iloc[spFirstDayOfQuarter] - 1)
            quarterMax = SP500['SP500'].iloc[spFirstDayOfQuarter]
            quarterMin = SP500['SP500'].iloc[spFirstDayOfQuarter]
            checkValue = SP500['SP500'].iloc[spFirstDayOfQuarter]
            for j in range(spFirstDayOfQuarter, spDay):
                if SP500['SP500'].iloc[j] > quarterMax:
                    quarterMax = SP500['SP500'].iloc[j]
                if SP500['SP500'].iloc[j] < quarterMin:
                    quarterMin = SP500['SP500'].iloc[j]
                    checkValue = quarterMin / quarterMax - 1
            spQuarterMax.append(quarterMax)
            spQuarterMin.append(quarterMin)
            spMaxQuarterDrawdown.append(checkValue)
            spBelowMax.append((quarterMin / spMax) - 1)
            spFirstDayOfQuarter = spDay
            break
        else:
            spDay = spDay + 1
            if SP500['SP500'].iloc[spDay] > spMax:
                spMax = SP500['SP500'].iloc[spDay]
```

```
        maxCheck = True
    #spQuarterMaxDrawdown
```

```
4/1/1990
338.700012
7/1/1990
359.540009
10/1/1990
314.940002
1/1/1991
326.450012
4/1/1991
371.299988
7/1/1991
377.920013
10/1/1991
389.200012
1/1/1992
417.26001
4/1/1992
404.230011
7/1/1992
412.880005
10/1/1992
416.290009
1/1/1993
435.380005
4/1/1993
450.299988
7/1/1993
449.01998899999995
10/1/1993
461.27999900000003
1/1/1994
465.44000199999994
4/1/1994
438.920013
7/1/1994
446.200012
10/1/1994
461.73999000000003
1/1/1995
459.10998499999994
4/1/1995
501.85000599999995
7/1/1995
547.090027
10/1/1995
581.719971
1/1/1996
620.72998
4/1/1996
653.72998
7/1/1996
675.880005
10/1/1996
689.080017
1/1/1997
737.01001
4/1/1997
```

```
759.6400150000001
7/1/1997
891.0300289999999
10/1/1997
955.409973
1/1/1998
975.0399779999999
4/1/1998
1108.150024
7/1/1998
1148.560059
10/1/1998
986.3900150000001
1/1/1999
1228.099976
4/1/1999
1293.719971
7/1/1999
1380.959961
10/1/1999
1282.810059
1/1/2000
1455.219971
4/1/2000
1505.969971
7/1/2000
1469.540039
10/1/2000
1436.22998
1/1/2001
1283.27002
4/1/2001
1145.869995
7/1/2001
1236.719971
10/1/2001
1038.550049
1/1/2002
1154.670044
4/1/2002
1146.540039
7/1/2002
968.650024
10/1/2002
847.909973
1/1/2003
909.0300289999999
4/1/2003
858.4799800000001
7/1/2003
982.320007
10/1/2003
1018.2199710000001
1/1/2004
1108.47998
4/1/2004
1132.170044
```

```
7/1/2004
1128.939941
10/1/2004
1131.5
1/1/2005
1202.079956
4/1/2005
1172.920044
7/1/2005
1194.439941
10/1/2005
1226.699951
1/1/2006
1268.800049
4/1/2006
1297.810059
7/1/2006
1280.189941
10/1/2006
1331.319946
1/1/2007
1416.599976
4/1/2007
1424.550049
7/1/2007
1519.430054
10/1/2007
1547.040039
1/1/2008
1447.160034
4/1/2008
1370.180054
7/1/2008
1284.910034
10/1/2008
1161.060059
1/1/2009
931.7999880000001
4/1/2009
811.080017
7/1/2009
923.330017
10/1/2009
1029.849976
1/1/2010
1132.98999
4/1/2010
1178.099976
7/1/2010
1027.369995
10/1/2010
1146.23999
1/1/2011
1271.869995
4/1/2011
1332.410034
7/1/2011
```

```
1339.670044
10/1/2011
1099.22998
1/1/2012
1277.060059
4/1/2012
1419.040039
7/1/2012
1365.51001
10/1/2012
1444.48999
1/1/2013
1462.420044
4/1/2013
1562.170044
7/1/2013
1614.959961
10/1/2013
1695.0
1/1/2014
1831.97998
4/1/2014
1885.52002
7/1/2014
1973.319946
10/1/2014
1946.160034
1/1/2015
2058.199951
4/1/2015
2059.689941
7/1/2015
2077.419922
10/1/2015
1923.819946
1/1/2016
2012.660034
4/1/2016
2072.780029
7/1/2016
2102.949951
10/1/2016
2161.199951
1/1/2017
2257.830078
4/1/2017
2358.840088
7/1/2017
2429.01001
10/1/2017
2529.1201170000004
1/1/2018
2695.810059
4/1/2018
2581.8798829999996
7/1/2018
2726.709961
```

```
10/1/2018
2924.590088
```

In [81]:
```
finalData = finalData.iloc[1:]

finalData['spHistoricalMax'] = spMaxList
finalData['spMaxAchieved'] = spNewMax
finalData['spBelowMax'] = spBelowMax
finalData['spQuarterPerformance'] = spQuarterReturn
finalData['QuarterMax'] = spQuarterMax
finalData['QuarterMin'] = spQuarterMin
finalData['spMaxQuarterDrawdown'] = spMaxQuarterDrawdown
```

In [82]:
```
gdpMove = []
spMove = []
gdpMoveQoverQ = [] # did gdp grow from the last quarter to the next one
gdpMoveYoverY = [] # did gdp grow from last year's quarter to this year's quar
ter

for i in range(1, len(finalData)):
    #print(finalData['Date'].iloc[i], 'GDP', finalData['GDP'].iloc[i] - finalD
ata['GDP'].iloc[i - 1])
    if (finalData['GDP'].iloc[i] - finalData['GDP'].iloc[i - 1]) > 0.0:
        gdpMove.append(1)
    else:
        gdpMove.append(0)
    #print(finalData['Date'].iloc[i], 'SP500', finalData['SP500'].iloc[i] - fi
nalData['SP500'].iloc[i - 1])
    if (finalData['SP500'].iloc[i] - finalData['SP500'].iloc[i - 1]) > 0.0:
        spMove.append(1)
    else:
        spMove.append(0)
    if i >= 1:
        gdpMoveQoverQ.append((finalData['GDP'].iloc[i] / finalData['GDP'].iloc
[i - 1]) - 1)
    if i >= 4:
        gdpMoveYoverY.append((finalData['GDP'].iloc[i] / finalData['GDP'].iloc
[i - 4]) - 1)

finalData = finalData.iloc[1:]

#finalData['gdpMove'] = gdpMove
finalData['spMove'] = spMove
```

In [83]:
```
#finalData['GDP'].iloc[len(finalData) - 1] / (111.19 / 100)
gdpGrowth = pd.read_csv('Data/gdpGrowth.csv')
```

In [84]:
```
finalData['gdpGrowth'] = gdpGrowth['GDPgrowth']
finalData['gdpGrowth'].iloc[len(finalData) - 1] = 3.0
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:190: Settin
gWithCopyWarning:
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/indexing.html#indexing-view-versus-copy
  self._setitem_with_indexer(indexer, value)
```

In [85]:
```
finalData
```

Out[85]:

	Date	GDP	SP500	T10T3	uRate	nfci	USDIndex	ManufacturingConfidence	Ho
2	7/1/1990	6015.12	359.54	0.43	5.5	-0.23	91.5346	98.75	
3	10/1/1990	6004.73	314.94	1.34	5.9	0.25	86.2694	97.85	
4	1/1/1991	6035.18	326.45	1.31	6.4	0.37	84.878	97.13	
5	4/1/1991	6126.86	371.30	2.13	6.7	-0.20	90.2577	97.82	
6	7/1/1991	6205.94	377.92	2.50	6.8	-0.36	92.8816	99.58	
7	10/1/1991	6264.54	389.20	2.20	7.0	-0.49	88.2307	99.78	
8	1/1/1992	6363.10	417.26	2.82	7.3	-0.50	84.1381	99.11	
9	4/1/1992	6470.76	404.23	3.35	7.4	-0.62	89.7026	100.15	
10	7/1/1992	6566.64	412.88	3.47	7.7	-0.75	84.6773	100.05	
11	10/1/1992	6680.80	416.29	3.56	7.3	-0.56	84.284	99.62	
12	1/1/1993	6729.46	435.38	3.41	7.3	-0.74	92.1416	100.37	
13	4/1/1993	6808.94	450.30	3.10	7.1	-0.75	88.9357	99.64	
14	7/1/1993	6882.10	449.02	2.74	6.9	-0.88	89.6074	99.33	
15	10/1/1993	7013.74	461.28	2.36	6.8	-0.85	89.7271	99.91	
16	1/1/1994	7115.65	465.44	2.76	6.6	-0.88	92.4979	100.57	
17	4/1/1994	7246.93	438.92	3.34	6.4	-0.71	90.7396	100.90	
18	7/1/1994	7331.08	446.20	3.02	6.1	-0.69	87.3413	101.11	
19	10/1/1994	7455.29	461.74	2.61	5.8	-0.68	85.9581	101.21	
20	1/1/1995	7522.29	459.11	1.93	5.6	-0.52	87.466	100.67	
21	4/1/1995	7581.00	501.85	1.20	5.8	-0.65	81.3046	99.38	
22	7/1/1995	7683.12	547.09	0.53	5.7	-0.62	80.4226	98.93	
23	10/1/1995	7772.59	581.72	0.62	5.5	-0.65	84.1324	98.66	
24	1/1/1996	7868.47	620.73	0.40	5.6	-0.68	85.2252	98.43	
25	4/1/1996	8032.84	653.73	1.11	5.6	-0.62	86.7265	99.06	
26	7/1/1996	8131.41	675.88	1.47	5.5	-0.66	87.6481	99.55	
27	10/1/1996	8259.77	689.08	1.55	5.2	-0.69	87.9329	99.67	
28	1/1/1997	8362.66	737.01	1.35	5.3	-0.62	88.7042	100.13	
29	4/1/1997	8518.83	759.64	1.58	5.1	-0.67	93.0883	100.23	
30	7/1/1997	8662.82	891.03	1.27	4.9	-0.68	92.6502	100.65	
31	10/1/1997	8765.91	955.41	0.94	4.7	-0.62	94.6308	100.49	
...	...	...	...	...	...	...	...	...	
86	7/1/2011	15591.85	1339.67	3.20	9.0	-0.33	69.0975	100.07	
87	10/1/2011	15796.46	1099.23	1.78	8.8	0.12	73.3657	99.69	
88	1/1/2012	16019.76	1277.06	1.95	8.3	-0.06	72.9043	99.95	
89	4/1/2012	16152.26	1419.04	2.14	8.2	-0.33	72.5836	100.08	

	Date	GDP	SP500	T10T3	uRate	nfci	USDIndex	ManufacturingConfidence	Ho
90	7/1/2012	16257.15	1365.51	1.51	8.2	-0.24	74.7085	99.47	
91	10/1/2012	16358.86	1444.49	1.55	7.8	-0.45	72.7076	99.37	
92	1/1/2013	16569.59	1462.42	1.78	8.0	-0.54	73.3738	99.78	
93	4/1/2013	16637.93	1562.17	1.78	7.6	-0.61	76.1008	99.59	
94	7/1/2013	16848.75	1614.96	2.46	7.3	-0.57	77.4363	100.08	
95	10/1/2013	17083.14	1695.00	2.64	7.2	-0.63	75.2495	100.51	
96	1/1/2014	17102.93	1831.98	2.93	6.6	-0.75	76.426	100.18	
97	4/1/2014	17425.77	1885.52	2.73	6.2	-0.78	76.5809	100.42	
98	7/1/2014	17719.84	1973.32	2.56	6.2	-0.81	75.6811	100.62	
99	10/1/2014	17838.45	1946.16	2.40	5.7	-0.73	80.9928	100.78	
100	1/1/2015	17970.42	2058.20	2.10	5.7	-0.64	85.7577	100.18	
101	4/1/2015	18221.30	2059.69	1.84	5.4	-0.70	91.7881	99.81	
102	7/1/2015	18331.09	2077.42	2.42	5.2	-0.70	90.4411	99.73	
103	10/1/2015	18354.37	1923.82	2.05	5.0	-0.58	91.6013	99.15	
104	1/1/2016	18409.13	2012.66	2.02	4.9	-0.51	94.6663	99.03	
105	4/1/2016	18640.73	2072.78	1.56	5.0	-0.56	89.9376	99.59	
106	7/1/2016	18799.65	2102.95	1.18	4.8	-0.53	89.892	99.69	
107	10/1/2016	18979.24	2161.20	1.31	4.9	-0.54	90.2321	99.75	
108	1/1/2017	19162.55	2257.83	1.92	4.7	-0.68	96.4677	100.58	
109	4/1/2017	19359.12	2358.84	1.56	4.4	-0.69	94.2513	100.54	
110	7/1/2017	19588.07	2429.01	1.29	4.3	-0.79	90.8407	100.87	
111	10/1/2017	19831.83	2529.12	1.33	4.1	-0.81	88.3967	101.25	
112	1/1/2018	20041.05	2695.81	1.02	4.1	-0.83	87.2663	101.32	
113	4/1/2018	20411.92	2581.88	0.96	3.9	-0.73	86.4032	101.11	
114	7/1/2018	20658.20	2726.71	0.89	3.9	-0.77	90.4184	101.31	
115	10/1/2018	20865.14	2924.59	0.86	3.8	-0.83	90.1677	101.13	

114 rows × 26 columns

In [86]:
```
# Bear markets in this dataset
# March 2000 to October 2002 [41:52]
# October 2007 to March 2009 [71:77]

# Recessions in this dataset

bearMarket = []
recession = []

for i in range(0, len(finalData)):
    if (39 <= i <= 50) or (70 <= i <= 75):
        bearMarket.append(1)
    else:
        bearMarket.append(0)
finalData['bearMarket'] = bearMarket

for i in range(0, len(finalData)):
    if (0 <= i <= 2) or (42 <= i <= 44) or (69 <= i <= 75):
        recession.append(1)
    else:
        recession.append(0)
finalData['recession'] = recession
```

In [87]:
```
aggregatedData = finalData
```

In [88]:
```
bearMarket = finalData[finalData['bearMarket'] == 1]
bullMarket = finalData[finalData['bearMarket'] == 0]
```

The above work was data preparation, cleaning, and alignment, to allow for machine learning algorithms to properly work on the data at hand. The reason this had to be done was to match all the different data points on a quarterly basis.

Run Principal Compoment Analysis with Cleaned Aligned Data

In [103]:
```
# The below implemenation of principal component analysis is used to find the
 most relevant data points in our model using
# dimensionality reduction, which is the process of reducing the number of ran
dom variables under consideration, by
# obtaining a set of principal variables. This occurs by finding the eigenvect
ors and eigenvalues of the calculated
# covariance matrix to identify the principal components. Principal components
show the mamixmum amount of variance,
# to capture the most possible information out of each data point possible. Th
erefore, the greater the variance, the
# greater the amount of information contained within the data. Each principal
 component must be uncorrelated to the one
# prior to it. Eigenvectors are relevant in this case as eigenvectors of the c
ovariance matrix are actually the directions
# of the axes where there is the most variance. And eigenvalues are simply the
coefficients attached to eigenvectors,
# which give the amount of variance carried in each Principal Component, from
 which we can determine the amount of
# variance that is explained by each value.
```

In [25]:
```
keepColumns = ['T10T3', 'uRate', 'nfci', 'USDIndex',
       'ManufacturingConfidence', 'HousePriceIndex', 'ConsumerSentiment',
       'PeopleOutputPerHour', 'GS10', 'FEDFUNDS', 'USNIM', 'govtToGDP',
       'CorporateProfits', 'VIX']
dates = finalData['Date']
GrossDomesticProduct = finalData['GDP']
StandardandPoors = finalData['SP500']
```

In [26]:
```
# PCA overview

bearMarket = bearMarket[keepColumns]
bullMarket = bullMarket[keepColumns]

from sklearn.preprocessing import StandardScaler
pcaTestbearMarket = StandardScaler().fit_transform(bearMarket)
pcaTestbullMarket = StandardScaler().fit_transform(bullMarket)
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype float64, object were all convert
ed to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\User\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversion
Warning: Data with input dtype float64, object were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\User\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype float64, object were all convert
ed to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\User\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversion
Warning: Data with input dtype float64, object were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [27]:

```
# OR we can do this with one line of numpy:
import numpy as np
cov_matbearMarket = np.cov(pcaTestbearMarket.T)

print(cov_matbearMarket)

cov_matbullMarket = np.cov(pcaTestbullMarket.T)

print(cov_matbullMarket)
```

```
[[ 1.05882353  0.69768887  0.22768189 -0.07932444  0.02954967  0.37046228
  -0.54450791  0.43737624 -0.50782936 -0.94912303 -0.04537989  0.51114098
   0.14377941  0.23908947]
 [ 0.69768887  1.05882353  0.75855438 -0.41929593 -0.51984422  0.63673953
  -0.76045609  0.69211575 -0.86951742 -0.92815034 -0.49292726  0.89836907
   0.45974232  0.74584498]
 [ 0.22768189  0.75855438  1.05882353 -0.80748262 -0.76570516  0.81682564
  -0.82911497  0.7943465  -0.82254368 -0.55884893 -0.90120474  0.89928776
   0.63640437  0.75656443]
 [-0.07932444 -0.41929593 -0.80748262  1.05882353  0.30210455 -0.97032248
   0.80520708 -0.95199367  0.72440969  0.35690266  0.96935226 -0.80962035
  -0.95118899 -0.33067203]
 [ 0.02954967 -0.51984422 -0.76570516  0.30210455  1.05882353 -0.38154787
   0.56277545 -0.3112526   0.57820023  0.30034304  0.60117595 -0.53241567
  -0.15704261 -0.78333421]
 [ 0.37046228  0.63673953  0.81682564 -0.97032248 -0.38154787  1.05882353
  -0.94597302  1.04858661 -0.90531335 -0.63576439 -0.93912953  0.93759291
   0.9596426   0.41158702]
 [-0.54450791 -0.76045609 -0.82911497  0.80520708  0.56277545 -0.94597302
   1.05882353 -0.94172321  0.96545725  0.81742652  0.85017907 -0.96118983
  -0.7618609  -0.64485173]
 [ 0.43737624  0.69211575  0.7943465  -0.95199367 -0.3112526   1.04858661
  -0.94172321  1.05882353 -0.91967864 -0.6935149  -0.89771519  0.9574127
   0.96076699  0.42407772]
 [-0.50782936 -0.86951742 -0.82254368  0.72440969  0.57820023 -0.90531335
   0.96545725 -0.91967864  1.05882353  0.84883611  0.76229017 -0.96971628
  -0.77263883 -0.70977681]
 [-0.94912303 -0.92815034 -0.55884893  0.35690266  0.30034304 -0.63576439
   0.81742652 -0.6935149   0.84883611  1.05882353  0.37014633 -0.80705943
  -0.4133224  -0.56348998]
 [-0.04537989 -0.49292726 -0.90120474  0.96935226  0.60117595 -0.93912953
   0.85017907 -0.89771519  0.76229017  0.37014633  1.05882353 -0.84724689
  -0.84390555 -0.47335164]
 [ 0.51114098  0.89836907  0.89928776 -0.80962035 -0.53241567  0.93759291
  -0.96118983  0.9574127  -0.96971628 -0.80705943 -0.84724689  1.05882353
   0.83068603  0.63932351]
 [ 0.14377941  0.45974232  0.63640437 -0.95118899 -0.15704261  0.9596426
  -0.7618609   0.96076699 -0.77263883 -0.4133224  -0.84390555  0.83068603
   1.05882353  0.20127593]
 [ 0.23908947  0.74584498  0.75656443 -0.33067203 -0.78333421  0.41158702
  -0.64485173  0.42407772 -0.70977681 -0.56348998 -0.47335164  0.63932351
   0.20127593  1.05882353]]
[[ 1.01052632  0.69853505  0.07701569 -0.28183065  0.31670523 -0.1545143
  -0.46065555  0.01859534 -0.06567024 -0.55221037  0.13207131  0.61696312
  -0.05099668  0.01166102]
 [ 0.69853505  1.01052632  0.4811713  -0.6812171  -0.02873958 -0.14787444
  -0.81712956  0.11365159 -0.1272522  -0.45011823  0.09112244  0.88074074
   0.05127556  0.20616756]
 [ 0.07701569  0.4811713   1.01052632 -0.28475046 -0.39337327 -0.10671158
  -0.5128516   0.0318978   0.0427289   0.01273942 -0.01395908  0.36549413
  -0.05838368  0.68534649]
 [-0.28183065 -0.6812171  -0.28475046  1.01052632 -0.08078848 -0.3139511
   0.71830014 -0.48803686  0.36803851  0.44614112  0.33036401 -0.66196302
  -0.47863425  0.07347019]
 [ 0.31670523 -0.02873958 -0.39337327 -0.08078848  1.01052632  0.3738751
   0.25165431  0.36541951 -0.27600902 -0.40398407 -0.16090759 -0.0117603
   0.31777539 -0.23508225]
```

```
 [-0.1545143  -0.14787444 -0.10671158 -0.3139511   0.3738751   1.01052632
  -0.02198774  0.94522772 -0.83421932 -0.6291009  -0.91314607  0.0833474
   0.93804029 -0.19155186]
 [-0.46065555 -0.81712956 -0.5128516   0.71830014  0.25165431 -0.02198774
   1.01052632 -0.17655123  0.13760428  0.3412475   0.08732974 -0.78978443
  -0.16621842 -0.15476317]
 [ 0.01859534  0.11365159  0.0318978  -0.48803686  0.36541951  0.94522772
  -0.17655123  1.01052632 -0.93509882 -0.79222696 -0.92307745  0.27279176
   0.9786426  -0.06272675]
 [-0.06567024 -0.1272522   0.0427289   0.36803851 -0.27600902 -0.83421932
   0.13760428 -0.93509882  1.01052632  0.87594529  0.85801109 -0.28538546
  -0.92022707  0.03552648]
 [-0.55221037 -0.45011823  0.01273942  0.44614112 -0.40398407 -0.6291009
   0.3412475  -0.79222696  0.87594529  1.01052632  0.65220264 -0.54665173
  -0.74706172  0.03477606]
 [ 0.13207131  0.09112244 -0.01395908  0.33036401 -0.16090759 -0.91314607
   0.08732974 -0.92307745  0.85801109  0.65220264  1.01052632 -0.11603292
  -0.93417428  0.1109327 ]
 [ 0.61696312  0.88074074  0.36549413 -0.66196302 -0.0117603   0.0833474
  -0.78978443  0.27279176 -0.28538546 -0.54665173 -0.11603292  1.01052632
   0.27581438  0.03946212]
 [-0.05099668  0.05127556 -0.05838368 -0.47863425  0.31777539  0.93804029
  -0.16621842  0.9786426  -0.92022707 -0.74706172 -0.93417428  0.27581438
   1.01052632 -0.17000471]
 [ 0.01166102  0.20616756  0.68534649  0.07347019 -0.23508225 -0.19155186
  -0.15476317 -0.06272675  0.03552648  0.03477606  0.1109327   0.03946212
  -0.17000471  1.01052632]]
```

In [28]:

```python
# Compute the eigen values and vectors using numpy
eig_vals_bearMarket, eig_vecs_bearMarket = np.linalg.eig(cov_matbearMarket)

# Make a list of (eigenvalue, eigenvector) tuples
eig_pairs_bearMarket = [(np.abs(eig_vals_bearMarket[i]), eig_vecs_bearMarket
[:,i]) for i in range(len(eig_vals_bearMarket))]

# Sort the (eigenvalue, eigenvector) tuples from high to low
eig_pairs_bearMarket.sort(key=lambda x: x[0], reverse=True)

################################################################################
##################################################

eig_vals_bullMarket, eig_vecs_bullMarket = np.linalg.eig(cov_matbullMarket)

# Make a list of (eigenvalue, eigenvector) tuples
eig_pairs_bullMarket = [(np.abs(eig_vals_bullMarket[i]), eig_vecs_bullMarket
[:,i]) for i in range(len(eig_vals_bullMarket))]

# Sort the (eigenvalue, eigenvector) tuples from high to low
eig_pairs_bullMarket.sort(key=lambda x: x[0], reverse=True)
```

In [29]:
```
valSum_bullMarket = 0

for i in range(0, len(eig_vals_bullMarket)):
    valSum_bullMarket += eig_vals_bullMarket[i]
valSum_bullMarket
```

Out[29]: 14.147368421052633

In [30]:
```
# Principal component regression. Bull market

cumulativeVariance = 0
keepFeatures = []

for i in range(0, len(eig_vals_bullMarket)):
    print(bullMarket.columns[i], ":", eig_vals_bullMarket[i] / valSum_bullMark
et)
    cumulativeVariance = cumulativeVariance + (eig_vals_bullMarket[i] / valSum
_bullMarket)
    print(cumulativeVariance)
    if cumulativeVariance < .95:
        keepFeatures.append(bullMarket.columns[i])
keepFeatures
```

```
T10T3 : 0.42538101274934165
0.42538101274934165
uRate : 0.2684307248788796
0.6938117376282212
nfci : 0.12782853208788011
0.8216402697161014
USDIndex : 0.07566128941292843
0.8973015591290299
ManufacturingConfidence : 0.04070516222500826
0.9380067213540382
HousePriceIndex : 0.018857821123381344
0.9568645424774195
ConsumerSentiment : 0.014968138735846542
0.971832681213266
PeopleOutputPerHour : 0.012136748459461449
0.9839694296727275
GS10 : 0.006940353592395664
0.9909097832651231
FEDFUNDS : 0.00019739301805502438
0.9911071762831781
USNIM : 0.0004976084793488081
0.9916047847625269
govtToGDP : 0.001544380785334488
0.9931491655478614
CorporateProfits : 0.003855396957483967
0.9970045625053453
VIX : 0.0029954374946548116
1.0000000000000002
```

Out[30]: ['T10T3', 'uRate', 'nfci', 'USDIndex', 'ManufacturingConfidence']

This tells us in a bull market, the 10 Year to 3 Month Treasury spread, unemployment, the net financial conditions index, the USD Index, and manufacturing confidence explain around 95% of the variance in the data

In [31]:
```
valSum_bearMarket = 0

for i in range(0, len(eig_vals_bearMarket)):
    valSum_bearMarket += eig_vals_bearMarket[i]
valSum_bearMarket
```

Out[31]: 14.823529411764722

In [32]:
```
# Principal component regression. Bear market

cumulativeVariance = 0
keepFeatures = []

for i in range(0, len(eig_vals_bearMarket)):
    print(bearMarket.columns[i], ":", eig_vals_bearMarket[i] / valSum_bearMark
et)
    cumulativeVariance = cumulativeVariance + (eig_vals_bearMarket[i] / valSum
_bearMarket)
    print(cumulativeVariance)
    if cumulativeVariance < .95:
        keepFeatures.append(bearMarket.columns[i])
keepFeatures
```

```
T10T3 : 0.6764886000655195
0.6764886000655195
uRate : 0.14587588064102483
0.8223644807065443
nfci : 0.11318523361678383
0.9355497143233281
USDIndex : 0.020841481077244407
0.9563911954005725
ManufacturingConfidence : 0.016441855538251605
0.9728330509388241
HousePriceIndex : 0.014202927955721582
0.9870359788945456
ConsumerSentiment : 0.004636577337778211
0.9916725562323239
PeopleOutputPerHour : 0.003248823787082391
0.9949213800194062
GS10 : 0.0021174148713693753
0.9970387948907756
FEDFUNDS : 0.0013830061987347676
0.9984218010895104
USNIM : 0.0009058748192862953
0.9993276759087967
govtToGDP : 0.0005538114089430306
0.9998814873177397
CorporateProfits : 7.976701635998578e-05
0.9999612543340998
VIX : 3.874566590016237e-05
0.9999999999999999
```

Out[32]:
```
['T10T3', 'uRate', 'nfci']
```

This tells us in a bear market, the 10 Year to 3 Month Treasury spread, unemployment, the net financial conditions indexexplain around 95% of the variance in the data

In [33]:
```
finalDataPCA = finalData[keepColumns]

from sklearn.preprocessing import StandardScaler
pcaTestfinalDataPCA = StandardScaler().fit_transform(finalDataPCA)
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype float64, object were all convert
ed to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\User\Anaconda3\lib\site-packages\sklearn\base.py:464: DataConversion
Warning: Data with input dtype float64, object were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [34]:
```
# OR we can do this with one line of numpy:
import numpy as np
cov_mat_allData = np.cov(pcaTestfinalDataPCA.T)

print(cov_mat_allData)
```

```
[[ 1.00884956  0.68076192  0.0907866  -0.20768068  0.23023965 -0.09207856
  -0.46730652  0.05524655 -0.10435044 -0.60700722  0.10622832  0.57897957
  -0.0247804   0.04016726]
 [ 0.68076192  1.00884956  0.32442141 -0.58396471 -0.03162163 -0.08883385
  -0.75614042  0.14721712 -0.17293722 -0.50017185  0.04092456  0.86964335
   0.1046452   0.17912888]
 [ 0.0907866   0.32442141  1.00884956 -0.20501119 -0.62304585  0.07695894
  -0.56022306  0.11345595 -0.08512657 -0.10236316 -0.1653275   0.29503586
  -0.08218558  0.73762597]
 [-0.20768068 -0.58396471 -0.20501119  1.00884956 -0.1395028  -0.34178555
   0.62535969 -0.45052585  0.34291653  0.38104442  0.37328424 -0.69422625
  -0.51801252  0.14497254]
 [ 0.23023965 -0.03162163 -0.62304585 -0.1395028   1.00884956  0.22999029
   0.34181941  0.24945746 -0.15516216 -0.25683754 -0.04438355 -0.00443198
   0.32943528 -0.49830298]
 [-0.09207856 -0.08883385  0.07695894 -0.34178555  0.22999029  1.00884956
  -0.13000949  0.9451989  -0.83377719 -0.62033291 -0.90995065  0.15917983
   0.90298543 -0.09594262]
 [-0.46730652 -0.75614042 -0.56022306  0.62535969  0.34181941 -0.13000949
   1.00884956 -0.23737475  0.21228189  0.40920442  0.18497623 -0.76342922
  -0.1771486  -0.28661819]
 [ 0.05524655  0.14721712  0.11345595 -0.45052585  0.24945746  0.9451989
  -0.23737475  1.00884956 -0.93111196 -0.77046169 -0.91513493  0.31216131
   0.94742556 -0.01599085]
 [-0.10435044 -0.17293722 -0.08512657  0.34291653 -0.15516216 -0.83377719
   0.21228189 -0.93111196  1.00884956  0.85861131  0.84723822 -0.32691534
  -0.88476272 -0.03094769]
 [-0.60700722 -0.50017185 -0.10236316  0.38104442 -0.25683754 -0.62033291
   0.40920442 -0.77046169  0.85861131  1.00884956  0.61873563 -0.5707133
  -0.69657128 -0.03848442]
 [ 0.10622832  0.04092456 -0.1653275   0.37328424 -0.04438355 -0.90995065
   0.18497623 -0.91513493  0.84723822  0.61873563  1.00884956 -0.19112883
  -0.89420705  0.02779981]
 [ 0.57897957  0.86964335  0.29503586 -0.69422625 -0.00443198  0.15917983
  -0.76342922  0.31216131 -0.32691534 -0.5707133  -0.19112883  1.00884956
   0.34741576  0.02677733]
 [-0.0247804   0.1046452  -0.08218558 -0.51801252  0.32943528  0.90298543
  -0.1771486   0.94742556 -0.88476272 -0.69657128 -0.89420705  0.34741576
   1.00884956 -0.22603746]
 [ 0.04016726  0.17912888  0.73762597  0.14497254 -0.49830298 -0.09594262
  -0.28661819 -0.01599085 -0.03094769 -0.03848442  0.02779981  0.02677733
  -0.22603746  1.00884956]]
```

In [35]:
```
eig_vals_allData, eig_vecs_allData = np.linalg.eig(cov_mat_allData)

# Make a list of (eigenvalue, eigenvector) tuples
eig_pairs_allData = [(np.abs(eig_vals_allData[i]), eig_vecs_allData[:,i]) for
i in range(len(eig_vals_allData))]

# Sort the (eigenvalue, eigenvector) tuples from high to low
eig_pairs_allData.sort(key=lambda x: x[0], reverse=True)
```

In [36]:
```
valSum_allData = 0

for i in range(0, len(eig_vals_allData)):
    valSum_allData += eig_vals_allData[i]
valSum_allData
```

Out[36]:
```
14.123893805309724
```

In [37]:
```
cumulativeVariance = 0
keepFeatures = []

for i in range(0, len(eig_vals_allData)):
    print(finalDataPCA.columns[i], ":", eig_vals_allData[i] / valSum_allData)
    cumulativeVariance = cumulativeVariance + (eig_vals_allData[i] / valSum_al
lData)
    print(cumulativeVariance)
    if cumulativeVariance < .95:
        keepFeatures.append(finalDataPCA.columns[i])
keepFeatures
```

```
T10T3 : 0.42755808650771826
0.42755808650771826
uRate : 0.24453368073027412
0.6720917672379924
nfci : 0.15396052422110315
0.8260522914590955
USDIndex : 0.07489509084574118
0.9009473823048367
ManufacturingConfidence : 0.033685235229177164
0.9346326175340139
HousePriceIndex : 0.02197591637985096
0.9566085339138649
ConsumerSentiment : 0.012656023324236926
0.9692645572381018
PeopleOutputPerHour : 0.011174543980093753
0.9804391012181956
GS10 : 0.00022754754690922492
0.9806666487651048
FEDFUNDS : 0.0008397752853348407
0.9815064240504396
USNIM : 0.001640589632957301
0.983147013683397
govtToGDP : 0.0036748385477954107
0.9868218522311923
CorporateProfits : 0.0070612208658196425
0.993883073097012
VIX : 0.006116926902987989
1.0
```

Out[37]:
```
['T10T3', 'uRate', 'nfci', 'USDIndex', 'ManufacturingConfidence']
```

This tells us in all market data that has been collected, the 10 Year to 3 Month Treasury spread, unemployment, the net financial conditions index, the USD Index, and manufacturing confidence explain around 95% of the variance in the data

Neural Network model

In [105]:
```
# A multi-layer perceptron algorithm like the one used above is made up of man
y individual nuerons, which are simple
# computational units that have weighted input signals and produce an output s
ignal using an activation function. These
# activation functions can have a threshold, especially with a binary classifi
er, that decides whether 0 or 1 is output.
# In this case, data flows through an input layer, a hidden layer, and an outp
ut layer to predict whether there is a
# recession or not. In this case, input is a feature vector x multiplied by we
ights w and added to a bias b: y = w * x + b.

# Furthermore, the model operates by incorporating backpropagation, where the
 weights on each nuerons so as to minimize the
# difference between actual output and desired output. This is where it is cru
cial to split this into train and test data
# as well, so we can teach the model the characteristics of a recession.

# In this case, given the inputs we have, based on our prior models we can acc
urately predict a recession or market downturn
# in ~95% of cases, using a variety of different implementations.

# The output seen below is known as a confidence matrix, which tells us how of
ten we classified data properly, in this case
# regarding bear markets. a is a bull market properly classified as a bull mar
ket, b is a bear market incorrectly
# classified as a bull market, c is a bull market incorrrectly classified as a
bear market, and d is a bear market
# properly classified as a bear market.

# [[a  b]
# [c  d]]
```

In [90]:
```
# Fed Data
# https://www.kansascityfed.org/~/media/files/publicat/reswkpap/pdf/rwp17-11.p
df
```

In [91]:
```
nnColumns = ['GDP', 'SP500', 'T10T3', 'uRate', 'nfci', 'USDIndex',
       'ManufacturingConfidence', 'HousePriceIndex', 'ConsumerSentiment',
       'PeopleOutputPerHour', 'GS10', 'FEDFUNDS', 'USNIM', 'govtToGDP',
       'CorporateProfits', 'VIX', 'gdpGrowth', 'bearMarket']

nnData = finalData[nnColumns]
```

In [92]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(nnData.drop('bearMarket',
axis=1), nnData['bearMarket'], test_size = 0.25)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(max_iter=100)
parameter_space = {'hidden_layer_sizes': [(50,50,50), (100,100,100), (150,150,
150)], 'activation': ['tanh', 'relu'],
'solver': ['sgd', 'adam'], 'alpha': [0.0001, 0.05],'learning_rate': ['constan
t','adaptive'],}
from sklearn.model_selection import GridSearchCV
clf = GridSearchCV(mlp, parameter_space, n_jobs=-1, cv=3)
clf.fit(X_train, y_train.values.ravel())
predictions = clf.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test,predictions))
print(classification_report(y_test,predictions))
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype float64, object were all convert
ed to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: DataConver
sionWarning: Data with input dtype float64, object were all converted to floa
t64 by StandardScaler.

C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: DataConver
sionWarning: Data with input dtype float64, object were all converted to floa
t64 by StandardScaler.
  import sys

[[22  1]
 [ 1  5]]
              precision    recall  f1-score   support

           0       0.96      0.96      0.96        23
           1       0.83      0.83      0.83         6

   micro avg       0.93      0.93      0.93        29
   macro avg       0.89      0.89      0.89        29
weighted avg       0.93      0.93      0.93        29


C:\Users\User\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:
841: DeprecationWarning: The default of the `iid` parameter will change from
True to False in version 0.22 and will be removed in 0.24. This will change n
umeric results when test-set sizes are unequal.
  DeprecationWarning)
C:\Users\User\Anaconda3\lib\site-packages\sklearn\neural_network\multilayer_p
erceptron.py:562: ConvergenceWarning: Stochastic Optimizer: Maximum iteration
s (100) reached and the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

NN model with most predictive features

In [93]:
```
nnColumns = ['T10T3', 'uRate', 'nfci', 'USDIndex', 'ManufacturingConfidence',
'bearMarket']

nnData = finalData[nnColumns]
```

In [94]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(nnData.drop('bearMarket',
axis=1), nnData['bearMarket'], test_size = 0.33)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(max_iter=100)
parameter_space = {'hidden_layer_sizes': [(150,150,150), (200,200,200), (250,2
50,250)], 'activation': ['tanh', 'relu'],
'solver': ['sgd', 'adam'], 'alpha': [0.0001, 0.05],'learning_rate': ['constan
t','adaptive'],}
from sklearn.model_selection import GridSearchCV
clf = GridSearchCV(mlp, parameter_space, n_jobs=-1, cv=3)
clf.fit(X_train, y_train.values.ravel())
predictions = clf.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test,predictions))
print(classification_report(y_test,predictions))
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype float64, object were all convert
ed to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: DataConver
sionWarning: Data with input dtype float64, object were all converted to floa
t64 by StandardScaler.

C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: DataConver
sionWarning: Data with input dtype float64, object were all converted to floa
t64 by StandardScaler.
  import sys
C:\Users\User\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:
841: DeprecationWarning: The default of the `iid` parameter will change from
True to False in version 0.22 and will be removed in 0.24. This will change n
umeric results when test-set sizes are unequal.
  DeprecationWarning)

[[32  3]
 [ 1  2]]
              precision    recall  f1-score   support

           0       0.97      0.91      0.94        35
           1       0.40      0.67      0.50         3

   micro avg       0.89      0.89      0.89        38
   macro avg       0.68      0.79      0.72        38
weighted avg       0.92      0.89      0.91        38


C:\Users\User\Anaconda3\lib\site-packages\sklearn\neural_network\multilayer_p
erceptron.py:562: ConvergenceWarning: Stochastic Optimizer: Maximum iteration
s (100) reached and the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

In [95]:
```
keepColumns = ['Date', 'GDP', 'SP500', 'T10T3', 'uRate', 'nfci', 'USDIndex',
       'ManufacturingConfidence', 'HousePriceIndex', 'ConsumerSentiment',
       'PeopleOutputPerHour', 'GS10', 'FEDFUNDS', 'USNIM', 'govtToGDP',
       'CorporateProfits', 'VIX', 'gdpGrowth', 'bearMarket']
newData = finalData[keepColumns]
newData.head()
# finalData
```

Out[95]:

	Date	GDP	SP500	T10T3	uRate	nfci	USDIndex	ManufacturingConfidence	HouseP
2	7/1/1990	6015.12	359.54	0.43	5.5	-0.23	91.5346	98.75	
3	10/1/1990	6004.73	314.94	1.34	5.9	0.25	86.2694	97.85	
4	1/1/1991	6035.18	326.45	1.31	6.4	0.37	84.878	97.13	
5	4/1/1991	6126.86	371.30	2.13	6.7	-0.20	90.2577	97.82	
6	7/1/1991	6205.94	377.92	2.50	6.8	-0.36	92.8816	99.58	

In [96]:
```
newData.bearMarket = newData.bearMarket.shift(1)
newData.head()
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\generic.py:5096: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  self[name] = value
```

Out[96]:

	Date	GDP	SP500	T10T3	uRate	nfci	USDIndex	ManufacturingConfidence	HouseP
2	7/1/1990	6015.12	359.54	0.43	5.5	-0.23	91.5346	98.75	
3	10/1/1990	6004.73	314.94	1.34	5.9	0.25	86.2694	97.85	
4	1/1/1991	6035.18	326.45	1.31	6.4	0.37	84.878	97.13	
5	4/1/1991	6126.86	371.30	2.13	6.7	-0.20	90.2577	97.82	
6	7/1/1991	6205.94	377.92	2.50	6.8	-0.36	92.8816	99.58	

In [97]:
```
newData = newData.iloc[1:]
newData.head()
```

Out[97]:

	Date	GDP	SP500	T10T3	uRate	nfci	USDIndex	ManufacturingConfidence	HouseP
3	10/1/1990	6004.73	314.94	1.34	5.9	0.25	86.2694	97.85	
4	1/1/1991	6035.18	326.45	1.31	6.4	0.37	84.878	97.13	
5	4/1/1991	6126.86	371.30	2.13	6.7	-0.20	90.2577	97.82	
6	7/1/1991	6205.94	377.92	2.50	6.8	-0.36	92.8816	99.58	
7	10/1/1991	6264.54	389.20	2.20	7.0	-0.49	88.2307	99.78	

Lag Data by 3 months

In [1]:
```
# In this case, the data was lagged to allow for the values to have potentaial predictive ability a quarter ahead of time.
```

In [99]:
```
# Manually adjusted data to lag it
laggedData = pd.read_csv('newData.csv')
```

In [100]:
```
nnColumns = ['T10T3', 'uRate', 'nfci', 'USDIndex', 'ManufacturingConfidence', 'bearMarket']

nnData = laggedData[nnColumns]
```

In [101]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(nnData.drop('bearMarket',
axis=1), nnData['bearMarket'], test_size = 0.5)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(max_iter=150)
parameter_space = {'hidden_layer_sizes': [(150,150,150), (200,200,200), (250,2
50,250)], 'activation': ['tanh', 'relu'],
'solver': ['sgd', 'adam'], 'alpha': [0.00025, 0.05],'learning_rate': ['constan
t','adaptive'],}
from sklearn.model_selection import GridSearchCV
clf = GridSearchCV(mlp, parameter_space, n_jobs=-1, cv=3)
clf.fit(X_train, y_train.values.ravel())
predictions = clf.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test,predictions))
print(classification_report(y_test,predictions))
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:
841: DeprecationWarning: The default of the `iid` parameter will change from
True to False in version 0.22 and will be removed in 0.24. This will change n
umeric results when test-set sizes are unequal.
  DeprecationWarning)

[[46  0]
 [ 4  7]]
              precision    recall  f1-score   support

         0.0       0.92      1.00      0.96        46
         1.0       1.00      0.64      0.78        11

   micro avg       0.93      0.93      0.93        57
   macro avg       0.96      0.82      0.87        57
weighted avg       0.94      0.93      0.92        57
```

In [ ]:
```
# A multi-layer perceptron algorithm like the one used above is made up of man
y individual nuerons, which are simple
# computational units that have weighted input signals and produce an output s
ignal using an activation function. These
# activation functions can have a threshold, especially with a binary classifi
er, that decides whether zero or one is output.
#
```

Logistic Regression

In [ ]:
```
# A logistic regression works by classifying data based on the predict the lik
elihood occurrence of an event given
# the relationship between independent and dependent variables.
```

In [126]:
```
logitColumns = ['GDP', 'SP500', 'T10T3', 'uRate', 'nfci', 'USDIndex',
       'ManufacturingConfidence', 'HousePriceIndex', 'ConsumerSentiment',
       'PeopleOutputPerHour', 'GS10', 'FEDFUNDS', 'USNIM', 'govtToGDP',
       'CorporateProfits', 'VIX', 'gdpGrowth', 'bearMarket']

finalData = laggedData[logitColumns]

X = finalData.loc[:, finalData.columns != 'bearMarket']
y = finalData.loc[:, finalData.columns == 'bearMarket']
```

In [127]:
```
# Feature selection

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=0)

from sklearn.linear_model import LogisticRegression
from sklearn import metrics

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=0)
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:43
3: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify
a solver to silence this warning.
  FutureWarning)
C:\Users\User\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761: Da
taConversionWarning: A column-vector y was passed when a 1d array was expecte
d. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

Out[127]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [128]:
```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(
logreg.score(X_test, y_test)))
pd.options.display.float_format = '{:.2f}'.format
probac=logreg.predict_proba(X_test)
# print(probac)
probability = probac[:,0]
prob_df = pd.DataFrame(probability)
# print(prob_df)
```

```
Accuracy of logistic regression classifier on test set: 1.00
```

In [129]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[31  0]
 [ 0  3]]
```

In [130]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

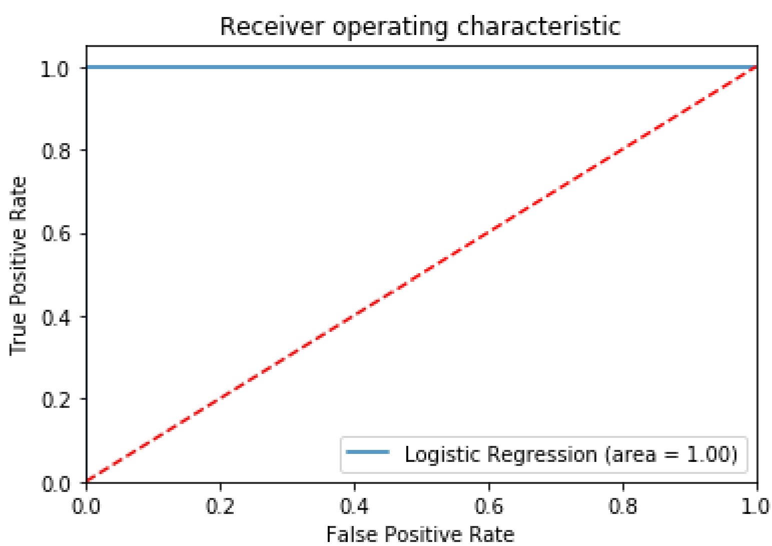
```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00        31
         1.0       1.00      1.00      1.00         3

   micro avg       1.00      1.00      1.00        34
   macro avg       1.00      1.00      1.00        34
weighted avg       1.00      1.00      1.00        34
```

In [131]:
```
%matplotlib inline

import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```



In [2]:
```
# Difference between probit model and logistic regression

# Basically both are linear models that have now been made nonlinear. For cate
gorical variables

# The logit model uses something called the cumulative distribution function o
f the logistic distribution.
# The probit model uses something called the cumulative distribution function
 of the standard normal distribution
# to define f (*). Both functions will take any number and rescale it to fall
 between 0 and 1. Hence, whatever α + βx
# equals, it can be transformed by the function to yield a predicted probabili
ty. Any function that would return a value
# between zero and one would do the trick, but there is a deeper theoretical m
odel underpinning logit and probit that
# requires the function to be based on a probability distribution. The logisti
c and standard normal cdfs turn out to be
# convenient mathematically and are programmed into just about any general pur
pose statistical package.
```

Random Forest Model

A random forest mode is made of decision trees that split the data in the most efficient way into the different potential outcomes. is the building block of a random forest and is an intuitive model. We can think of a decision tree as a series of yes/no questions asked about our data eventually leading to a predicted class (or continuous value in the case of regression). This is an interpretable model because it makes classifications much like we do: we ask a sequence of queries about the available data we have until we arrive at a decision (in an ideal world).

In [133]:
```
# Import train_test_split function
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=0)

# Import Random Forest Model
from sklearn.ensemble import RandomForestClassifier

# 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)

# Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

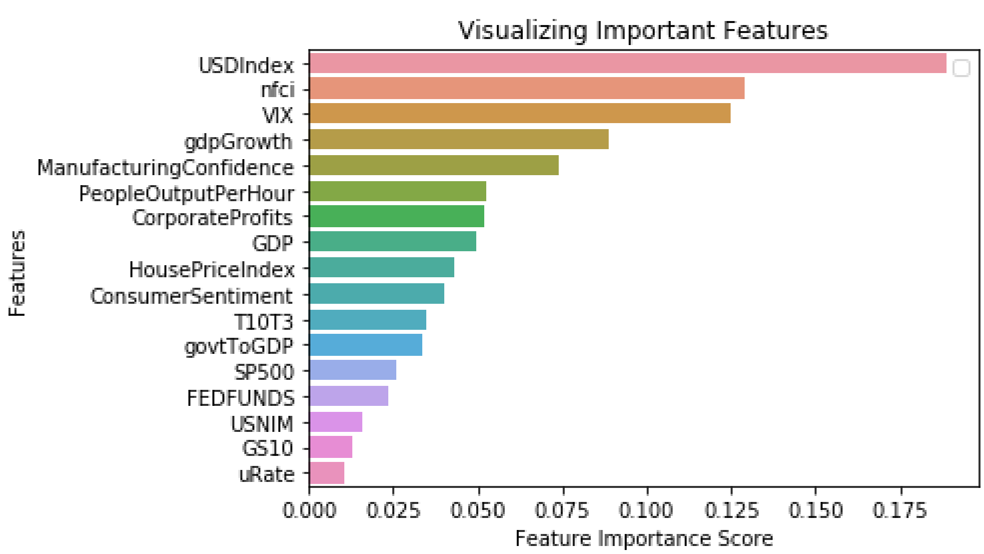
```
Accuracy: 1.0

C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: DataConve
rsionWarning: A column-vector y was passed when a 1d array was expected. Plea
se change the shape of y to (n_samples,), for example using ravel().
  # This is added back by InteractiveShellApp.init_path()
```

In [134]:
```
feature_imp = pd.Series(clf.feature_importances_,index=X_train.columns).sort_v
alues(ascending=False)
print(feature_imp)
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# Creating a bar plot
sns.barplot(x=feature_imp, y=feature_imp.index)
# 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.

USDIndex                  0.19
nfci                      0.13
VIX                       0.12
gdpGrowth                 0.09
ManufacturingConfidence   0.07
PeopleOutputPerHour       0.05
CorporateProfits          0.05
GDP                       0.05
HousePriceIndex           0.04
ConsumerSentiment         0.04
T10T3                     0.03
govtToGDP                 0.03
SP500                     0.03
FEDFUNDS                  0.02
USNIM                     0.02
GS10                      0.01
uRate                     0.01
dtype: float64
```



Within the random forest model, the most important features are the USDIndex, the net financial conditions index, and the VIX

KNN Algorithm

A KNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other. In this case, it would be the values on the two highest correlated features to bear markets. Given this, we can plot these two features on a graph, and classify whether we are in a bull market or a bear market. The "NN" within KNN stands for nearest neighbors, so we decide whether a new data point added to the graph is classified as a bear market or bull market based on the points around it.

In [92]:
```
dataCorrelations = nnData.corr().unstack().sort_values()
dataCorrelations['bearMarket']
```

Out[92]:
```
ManufacturingConfidence   -0.503642
uRate                     -0.029143
T10T3                      0.087757
USDIndex                   0.368988
nfci                       0.550893
bearMarket                 1.000000
dtype: float64
```

In [93]:
```
# Select the nfci and USDIndex since they are the highest correlated varibles
 to bear markets.
getData = ['nfci', 'USDIndex', 'bearMarket']

KNNdata = nnData[getData]
```

In [94]:
```
import numpy as np
from sklearn.metrics import confusion_matrix

def recallCalc(matrix):
    tp = matrix[1][1]
    fn = matrix[0][1]
    return(np.round(tp/(tp+fn), 5))

def precisionCalc(matrix):
    tp = matrix[1][1]
    fp = matrix[0][0]
    return(np.round(tp/(tp+fp), 5))

def fScore(precision, recall):
    return(np.round(2 * (precision * recall) / (precision + recall), 5))

def falsePositiveRate_(matrix):
    fp = matrix[0][1]
    tn = matrix[0][0]
    return(np.round(fp/(fp+tn), 5))

def truePositiveRate_(matrix):
    tp = matrix[1][1]
    fn = matrix[1][0]
    return(np.round(tp/(tp+fn), 5))

def accuracy(actual, pred):
    return(np.round(  (pred == actual).sum()/len(actual)  , 5))

def thresholdPredData(threshold, pred):
    predMal = pred
    for i in range(len(predMal)):
        if((threshold == 1.0) & (predMal[i].astype(float) == 1.0)):
            predMal[i] = 0.0
        elif((threshold == 0.0) & (predMal[i].astype(float) == 0.0)):
            predMal[i] = 1.0
        elif(predMal[i] > threshold):
            predMal[i] = 1
        else:
            predMal[i] = 0
    return(predMal.astype(int))
```

In [95]:
```
def analytics(fitModel, xv_test, yv_test):
    predMal = fitModel.predict_proba(xv_test)[:, 1]
    actual = yv_test
    w, h = 5, 11;
    additionalData = [[0 for x in range(w)] for y in range(h)]
    thresholds = np.round(np.linspace(0, 1, 11),6)
    fpr = []
    tpr = []
    for i in thresholds:
        predMal = fitModel.predict_proba(xv_test)[:, 1]
        pred = thresholdPredData(i, predMal)
        c_matrix = confusion_matrix(actual, pred)
        tpr.append(truePositiveRate_(c_matrix))
        fpr.append(falsePositiveRate_(c_matrix))
        additionalData[int(i * 10)][0] = i
        additionalData[int(i * 10)][1] = precisionCalc(c_matrix)
        additionalData[int(i * 10)][2] = recallCalc(c_matrix)
        additionalData[int(i * 10)][3] = accuracy(actual, pred)
        additionalData[int(i * 10)][4] = fScore(precisionCalc(c_matrix), recal
lCalc(c_matrix))
        print(c_matrix)
    additionalData = pd.DataFrame(data=additionalData, columns=['Threshold',
'Precision', 'Recall', 'Accuracy', 'fScore'])
    print(additionalData)
    df = pd.DataFrame({'threshold':thresholds, 'fpr':fpr, 'tpr':tpr})
    plt.plot(df.fpr, df.tpr)
    plt.plot([0, 90], [0, 90], '-')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])
    plt.show()
    print(df)
```

In [178]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
def predictions(train_features, test_features, train_outcome, test_outcome):
    w, h = 5, 1;
    KNNresults = [[0 for x in range(w)] for y in range(h)]
    KNNdatas = pd.DataFrame(KNNresults)
    KNNdatas.columns = ['a', 'b', 'c', 'd', 'e']

    for K in range(0, 5):
        K = K+1
        # ‘uniform’ : uniform weights. All points in each neighborhood are weighted equally.
        # ‘distance’ : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.
        for weights in ['uniform', 'distance']:
            # ‘ball_tree’ will use BallTree, ‘kd_tree’ will use KDTree, ‘brute’ will use a brute-force search.
            for algo in ['ball_tree', 'kd_tree', 'brute']:
            # manhattan_distance (l1), and euclidean_distance (l2) for p = 2.
                for powerDistance in [1,2]:
                    model = KNeighborsClassifier(n_neighbors = K, weights=weights, algorithm=algo, p=powerDistance)
                    model.fit(train_features, train_outcome)  #fit the model
                    pred=model.predict(test_features) #make prediction on test set
                    accuracy = accuracy_score(test_outcome, pred)
                    print([[K, weights, algo, powerDistance, accuracy]])
                    thisList=[[K, weights, algo, powerDistance, accuracy]]
                    KNNdatas = KNNdatas.append((thisList))
    KNNdatas.drop(KNNdatas.iloc[:, 1:5], inplace=True, axis=1)
    KNNdatas.drop(["a"], axis = 1, inplace = True)
    KNNdatas = KNNdatas.reset_index(drop=True)
    KNNdatas = KNNdatas.drop(KNNdatas.index[0])
    KNNdatas.columns = ['K', 'weights', 'algo', 'powerDistance', 'accuracy']
    print(KNNdatas)
    #print(KNNdatas['accuracy'].max())
    #print(KNNdatas['accuracy'].argmax())
    bestData = KNNdatas.iloc[KNNdatas['accuracy'].argmax() - 1]
    #print(bestData)
    from sklearn.metrics import confusion_matrix
    model = KNeighborsClassifier(n_neighbors = int(bestData.K), weights=bestData.weights, algorithm=bestData.algo, p=bestData.powerDistance)
    model.fit(train_features, train_outcome)  #fit the model
    # This is where we could do the threshold calculation
    analytics(model.fit(train_features, train_outcome), test_features, test_outcome)
    #gridshow(model, train_features, train_outcome, test_features, test_outcome, nGrid=100)
    pred=model.predict(test_features) #make prediction on test set
    #print(pred)
    accuracy = accuracy_score(test_outcome, pred)
    #print(accuracy)
    confusion_matrix(test_outcome, pred)
    return pred
```

In [179]:
```
from sklearn.model_selection import train_test_split
train_features, test_features, train_outcome, test_outcome = train_test_split(
KNNdata.drop(['bearMarket'], axis = 1),
    KNNdata['bearMarket'],
    test_size = .33,
    random_state = 7)
predictionsDataframe = pd.DataFrame(test_outcome)
predictionsDataframe['predictions'] = predictions(train_features, test_feature
s, train_outcome, test_outcome)
```

```
[[1, 'uniform', 'ball_tree', 1, 0.9473684210526315]]
[[1, 'uniform', 'ball_tree', 2, 0.9473684210526315]]
[[1, 'uniform', 'kd_tree', 1, 0.9473684210526315]]
[[1, 'uniform', 'kd_tree', 2, 0.9473684210526315]]
[[1, 'uniform', 'brute', 1, 0.9473684210526315]]
[[1, 'uniform', 'brute', 2, 0.9473684210526315]]
[[1, 'distance', 'ball_tree', 1, 0.9473684210526315]]
[[1, 'distance', 'ball_tree', 2, 0.9473684210526315]]
[[1, 'distance', 'kd_tree', 1, 0.9473684210526315]]
[[1, 'distance', 'kd_tree', 2, 0.9473684210526315]]
[[1, 'distance', 'brute', 1, 0.9473684210526315]]
[[1, 'distance', 'brute', 2, 0.9473684210526315]]
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
```

```
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)

[[2, 'uniform', 'ball_tree', 1, 0.8947368421052632]]
[[2, 'uniform', 'ball_tree', 2, 0.8947368421052632]]
[[2, 'uniform', 'kd_tree', 1, 0.8947368421052632]]
[[2, 'uniform', 'kd_tree', 2, 0.8947368421052632]]
[[2, 'uniform', 'brute', 1, 0.8947368421052632]]
[[2, 'uniform', 'brute', 2, 0.8947368421052632]]
[[2, 'distance', 'ball_tree', 1, 0.9473684210526315]]
[[2, 'distance', 'ball_tree', 2, 0.9473684210526315]]
[[2, 'distance', 'kd_tree', 1, 0.9473684210526315]]
[[2, 'distance', 'kd_tree', 2, 0.9473684210526315]]
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
```

```
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)

[[2, 'distance', 'brute', 1, 0.9473684210526315]]
[[2, 'distance', 'brute', 2, 0.9473684210526315]]
[[3, 'uniform', 'ball_tree', 1, 0.8947368421052632]]
[[3, 'uniform', 'ball_tree', 2, 0.8947368421052632]]
[[3, 'uniform', 'kd_tree', 1, 0.8947368421052632]]
[[3, 'uniform', 'kd_tree', 2, 0.8947368421052632]]
[[3, 'uniform', 'brute', 1, 0.8947368421052632]]
[[3, 'uniform', 'brute', 2, 0.8947368421052632]]
[[3, 'distance', 'ball_tree', 1, 0.9210526315789473]]
[[3, 'distance', 'ball_tree', 2, 0.9210526315789473]]
[[3, 'distance', 'kd_tree', 1, 0.9210526315789473]]
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
```

```
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)

[[3, 'distance', 'kd_tree', 2, 0.9210526315789473]]
[[3, 'distance', 'brute', 1, 0.9210526315789473]]
[[3, 'distance', 'brute', 2, 0.9210526315789473]]
[[4, 'uniform', 'ball_tree', 1, 0.8947368421052632]]
[[4, 'uniform', 'ball_tree', 2, 0.8947368421052632]]
[[4, 'uniform', 'kd_tree', 1, 0.8947368421052632]]
[[4, 'uniform', 'kd_tree', 2, 0.8947368421052632]]
[[4, 'uniform', 'brute', 1, 0.8947368421052632]]
[[4, 'uniform', 'brute', 2, 0.8947368421052632]]
[[4, 'distance', 'ball_tree', 1, 0.9210526315789473]]
[[4, 'distance', 'ball_tree', 2, 0.9210526315789473]]
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
```

```
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
```

```
[[4, 'distance', 'kd_tree', 1, 0.9210526315789473]]
[[4, 'distance', 'kd_tree', 2, 0.9210526315789473]]
[[4, 'distance', 'brute', 1, 0.9210526315789473]]
[[4, 'distance', 'brute', 2, 0.9210526315789473]]
[[5, 'uniform', 'ball_tree', 1, 0.8947368421052632]]
[[5, 'uniform', 'ball_tree', 2, 0.8947368421052632]]
[[5, 'uniform', 'kd_tree', 1, 0.8947368421052632]]
[[5, 'uniform', 'kd_tree', 2, 0.8947368421052632]]
[[5, 'uniform', 'brute', 1, 0.8947368421052632]]
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
```

```
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
```

```
[[5, 'uniform', 'brute', 2, 0.8947368421052632]]
[[5, 'distance', 'ball_tree', 1, 0.9210526315789473]]
[[5, 'distance', 'ball_tree', 2, 0.9210526315789473]]
[[5, 'distance', 'kd_tree', 1, 0.9210526315789473]]
[[5, 'distance', 'kd_tree', 2, 0.9210526315789473]]
[[5, 'distance', 'brute', 1, 0.9210526315789473]]
[[5, 'distance', 'brute', 2, 0.9210526315789473]]
      K   weights       algo  powerDistance  accuracy
1  1.00   uniform  ball_tree           1.00      0.95
2  1.00   uniform  ball_tree           2.00      0.95
3  1.00   uniform    kd_tree           1.00      0.95
4  1.00   uniform    kd_tree           2.00      0.95
5  1.00   uniform      brute           1.00      0.95
6  1.00   uniform      brute           2.00      0.95
7  1.00  distance  ball_tree           1.00      0.95
8  1.00  distance  ball_tree           2.00      0.95
9  1.00  distance    kd_tree           1.00      0.95
10 1.00  distance    kd_tree           2.00      0.95
11 1.00  distance      brute           1.00      0.95
12 1.00  distance      brute           2.00      0.95
13 2.00   uniform  ball_tree           1.00      0.89
14 2.00   uniform  ball_tree           2.00      0.89
15 2.00   uniform    kd_tree           1.00      0.89
16 2.00   uniform    kd_tree           2.00      0.89
17 2.00   uniform      brute           1.00      0.89
18 2.00   uniform      brute           2.00      0.89
19 2.00  distance  ball_tree           1.00      0.95
20 2.00  distance  ball_tree           2.00      0.95
21 2.00  distance    kd_tree           1.00      0.95
22 2.00  distance    kd_tree           2.00      0.95
23 2.00  distance      brute           1.00      0.95
24 2.00  distance      brute           2.00      0.95
25 3.00   uniform  ball_tree           1.00      0.89
26 3.00   uniform  ball_tree           2.00      0.89
27 3.00   uniform    kd_tree           1.00      0.89
28 3.00   uniform    kd_tree           2.00      0.89
29 3.00   uniform      brute           1.00      0.89
30 3.00   uniform      brute           2.00      0.89
31 3.00  distance  ball_tree           1.00      0.92
32 3.00  distance  ball_tree           2.00      0.92
33 3.00  distance    kd_tree           1.00      0.92
34 3.00  distance    kd_tree           2.00      0.92
35 3.00  distance      brute           1.00      0.92
36 3.00  distance      brute           2.00      0.92
37 4.00   uniform  ball_tree           1.00      0.89
38 4.00   uniform  ball_tree           2.00      0.89
39 4.00   uniform    kd_tree           1.00      0.89
40 4.00   uniform    kd_tree           2.00      0.89
41 4.00   uniform      brute           1.00      0.89
42 4.00   uniform      brute           2.00      0.89
43 4.00  distance  ball_tree           1.00      0.92
44 4.00  distance  ball_tree           2.00      0.92
45 4.00  distance    kd_tree           1.00      0.92
46 4.00  distance    kd_tree           2.00      0.92
47 4.00  distance      brute           1.00      0.92
48 4.00  distance      brute           2.00      0.92
49 5.00   uniform  ball_tree           1.00      0.89
```

```
50 5.00   uniform  ball_tree           2.00      0.89
51 5.00   uniform    kd_tree           1.00      0.89
52 5.00   uniform    kd_tree           2.00      0.89
53 5.00   uniform      brute           1.00      0.89
54 5.00   uniform      brute           2.00      0.89
55 5.00  distance  ball_tree           1.00      0.92
56 5.00  distance  ball_tree           2.00      0.92
57 5.00  distance    kd_tree           1.00      0.92
58 5.00  distance    kd_tree           2.00      0.92
59 5.00  distance      brute           1.00      0.92
60 5.00  distance      brute           2.00      0.92
[[ 0 32]
 [ 0  6]]
```

```
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
```

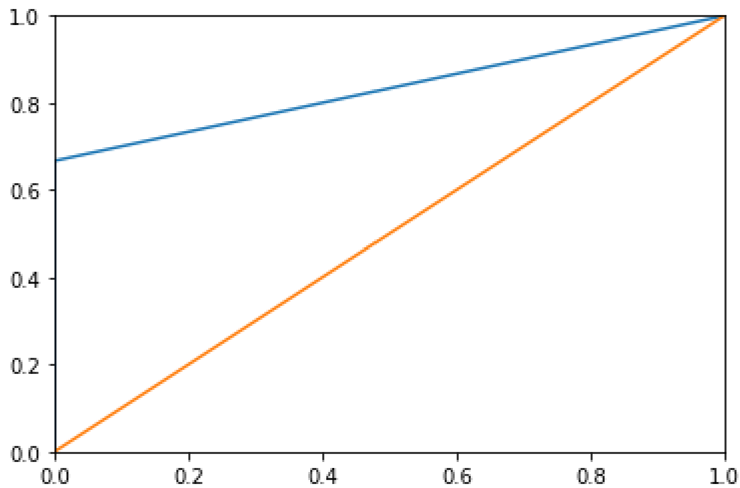
```
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\pandas\core\indexing.py:1494: Futur
eWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-rein
dex-listlike
  return self._getitem_tuple(key)
C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:33: FutureWar
ning:
The current behaviour of 'Series.argmax' is deprecated, use 'idxmax'
instead.
The behavior of 'argmax' will be corrected to return the positional
maximum in the future. For now, use 'series.values.argmax' or
'np.argmax(np.array(values))' to get the position of the maximum
row.

[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 2  4]]
[[32  0]
 [ 6  0]]
    Threshold  Precision  Recall  Accuracy  fScore
0        0.00       1.00    0.16      0.16    0.27
1        0.10       0.11    1.00      0.95    0.20
2        0.20       0.11    1.00      0.95    0.20
3        0.30       0.11    1.00      0.95    0.20
4        0.40       0.11    1.00      0.95    0.20
5        0.50       0.11    1.00      0.95    0.20
6        0.60       0.11    1.00      0.95    0.20
7        0.70       0.11    1.00      0.95    0.20
8        0.80       0.11    1.00      0.95    0.20
9        0.90       0.11    1.00      0.95    0.20
10       1.00       0.00     nan      0.84     nan
```

```
C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: RuntimeWar
ning: invalid value encountered in longlong_scalars
  import sys
```




```
    threshold  fpr  tpr
0        0.00 1.00 1.00
1        0.10 0.00 0.67
2        0.20 0.00 0.67
3        0.30 0.00 0.67
4        0.40 0.00 0.67
5        0.50 0.00 0.67
6        0.60 0.00 0.67
7        0.70 0.00 0.67
8        0.80 0.00 0.67
9        0.90 0.00 0.67
10       1.00 0.00 0.00
```

In this case on average, it seems that 1 neighbor was the most accurate classifier at ~95%