5.0.Log-Reg-Analyze

May 15, 2023

[148]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from scipy.stats import zscore
import warnings
warnings.filterwarnings("ignore")
```

[149]:
```
data=pd.read_csv('wdbc.data',header=None)
headers=['id','diagnosis','mean_radius','mean_texture','mean_perimeter','mean_area','mean_smoo
 ↪points','mean_symmetry','mean_fractal␣
 ↪dimension','SE_radius','SE_texture','SE_perimeter','SE_area','SE_smoothness','SE_compactnes
 ↪points','SE_symmetry','SE_fractal␣
 ↪dimension','worst_radius','worst_texture','worst_perimeter','worst_area','worst_smoothness'
 ↪points','worst_symmetry','worst_fractal dimension']
data.to_csv('labeledData.csv',header=headers,index=False)
data=pd.read_csv('labeledData.csv')
```

data.head()

[150]:
```
data.head()
```

[150]:

	id	diagnosis	mean_radius	mean_texture	mean_perimeter	mean_area	\
0	842302	M	17.99	10.38	122.80	1001.0	\
1	842517	M	20.57	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	M	11.42	20.38	77.58	386.1	
4	84358402	M	20.29	14.34	135.10	1297.0	

	mean_smoothness	mean_compactness	mean_concavity	mean_concave points	
0	0.11840	0.27760	0.3001	0.14710	\
1	0.08474	0.07864	0.0869	0.07017	
2	0.10960	0.15990	0.1974	0.12790	
3	0.14250	0.28390	0.2414	0.10520	
4	0.10030	0.13280	0.1980	0.10430	

```
   …  worst_radius  worst_texture  worst_perimeter  worst_area
0  …         25.38          17.33           184.60      2019.0  \
1  …         24.99          23.41           158.80      1956.0
2  …         23.57          25.53           152.50      1709.0
3  …         14.91          26.50            98.87       567.7
4  …         22.54          16.67           152.20      1575.0

   worst_smoothness  worst_compactness  worst_concavity  worst_concave points
0            0.1622             0.6656           0.7119                0.2654  \
1            0.1238             0.1866           0.2416                0.1860
2            0.1444             0.4245           0.4504                0.2430
3            0.2098             0.8663           0.6869                0.2575
4            0.1374             0.2050           0.4000                0.1625

   worst_symmetry  worst_fractal dimension
0          0.4601                  0.11890
1          0.2750                  0.08902
2          0.3613                  0.08758
3          0.6638                  0.17300
4          0.2364                  0.07678

[5 rows x 32 columns]
```

[151]:
```
def diag(z):
    if z=='M':
        return 1
    else:
        return 0
z=data['diagnosis'].apply(diag)
data.diagnosis=z
```

[152]:
```
df=pd.DataFrame(data=data)
df=df.drop('id',axis=1)
x=df.drop('diagnosis',axis=1)
y=df['diagnosis']
```

[153]:
```
x_scaled=x.apply(zscore)
x_scaled.describe()
```

[153]:
```
        mean_radius  mean_texture  mean_perimeter     mean_area
count  5.690000e+02  5.690000e+02    5.690000e+02  5.690000e+02  \
mean  -1.373633e-16  6.868164e-17   -1.248757e-16 -2.185325e-16
std    1.000880e+00  1.000880e+00    1.000880e+00  1.000880e+00
min   -2.029648e+00 -2.229249e+00   -1.984504e+00 -1.454443e+00
25%   -6.893853e-01 -7.259631e-01   -6.919555e-01 -6.671955e-01
50%   -2.150816e-01 -1.046362e-01   -2.359800e-01 -2.951869e-01
75%    4.693926e-01  5.841756e-01    4.996769e-01  3.635073e-01
```

```
max    3.971288e+00  4.651889e+00    3.976130e+00  5.250529e+00

       mean_smoothness  mean_compactness  mean_concavity  mean_concave points
count     5.690000e+02      5.690000e+02    5.690000e+02         5.690000e+02  \
mean     -8.366672e-16      1.873136e-16    4.995028e-17        -4.995028e-17
std       1.000880e+00      1.000880e+00    1.000880e+00         1.000880e+00
min      -3.112085e+00     -1.610136e+00   -1.114873e+00        -1.261820e+00
25%      -7.109628e-01     -7.470860e-01   -7.437479e-01        -7.379438e-01
50%      -3.489108e-02     -2.219405e-01   -3.422399e-01        -3.977212e-01
75%       6.361990e-01      4.938569e-01    5.260619e-01         6.469351e-01
max       4.770911e+00      4.568425e+00    4.243589e+00         3.927930e+00

       mean_symmetry  mean_fractal dimension  …  worst_radius
count   5.690000e+02            5.690000e+02  …  5.690000e+02  \
mean    1.748260e-16            4.745277e-16  … -8.241796e-16
std     1.000880e+00            1.000880e+00  …  1.000880e+00
min    -2.744117e+00           -1.819865e+00  … -1.726901e+00
25%    -7.032397e-01           -7.226392e-01  … -6.749213e-01
50%    -7.162650e-02           -1.782793e-01  … -2.690395e-01
75%     5.307792e-01            4.709834e-01  …  5.220158e-01
max     4.484751e+00            4.910919e+00  …  4.094189e+00

       worst_texture  worst_perimeter  worst_area  worst_smoothness
count   5.690000e+02     5.690000e+02  569.000000      5.690000e+02  \
mean    1.248757e-17    -3.746271e-16    0.000000     -2.372638e-16
std     1.000880e+00     1.000880e+00    1.000880      1.000880e+00
min    -2.223994e+00    -1.693361e+00   -1.222423     -2.682695e+00
25%    -7.486293e-01    -6.895783e-01   -0.642136     -6.912304e-01
50%    -4.351564e-02    -2.859802e-01   -0.341181     -4.684277e-02
75%     6.583411e-01     5.402790e-01    0.357589      5.975448e-01
max     3.885905e+00     4.287337e+00    5.930172      3.955374e+00

       worst_compactness  worst_concavity  worst_concave points
count       5.690000e+02     5.690000e+02          5.690000e+02  \
mean       -3.371644e-16     7.492542e-17          2.247763e-16
std         1.000880e+00     1.000880e+00          1.000880e+00
min        -1.443878e+00    -1.305831e+00         -1.745063e+00
25%        -6.810833e-01    -7.565142e-01         -7.563999e-01
50%        -2.695009e-01    -2.182321e-01         -2.234689e-01
75%         5.396688e-01     5.311411e-01          7.125100e-01
max         5.112877e+00     4.700669e+00          2.685877e+00

       worst_symmetry  worst_fractal dimension
count    5.690000e+02             5.690000e+02
mean     2.622390e-16            -5.744282e-16
std      1.000880e+00             1.000880e+00
min     -2.160960e+00            -1.601839e+00
```

```
25%     -6.418637e-01            -6.919118e-01
50%     -1.274095e-01            -2.164441e-01
75%      4.501382e-01             4.507624e-01
max      6.046041e+00             6.846856e+00

[8 rows x 30 columns]
```

[154]:
```
pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in
c:\users\sheel\appdata\local\programs\python\python311\lib\site-packages (1.2.2)
Requirement already satisfied: numpy>=1.17.3 in
c:\users\sheel\appdata\local\programs\python\python311\lib\site-packages (from
scikit-learn) (1.24.3)
Requirement already satisfied: scipy>=1.3.2 in
c:\users\sheel\appdata\local\programs\python\python311\lib\site-packages (from
scikit-learn) (1.10.1)
Requirement already satisfied: joblib>=1.1.1 in
c:\users\sheel\appdata\local\programs\python\python311\lib\site-packages (from
scikit-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
c:\users\sheel\appdata\local\programs\python\python311\lib\site-packages (from
scikit-learn) (3.1.0)
Note: you may need to restart the kernel to use updated packages.


[notice] A new release of pip available: 22.3.1 -> 23.1.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

[155]:
```
x_scaled.describe()
```

[155]:
```
        mean_radius  mean_texture  mean_perimeter     mean_area
count  5.690000e+02  5.690000e+02    5.690000e+02  5.690000e+02  \
mean  -1.373633e-16  6.868164e-17   -1.248757e-16 -2.185325e-16
std    1.000880e+00  1.000880e+00    1.000880e+00  1.000880e+00
min   -2.029648e+00 -2.229249e+00   -1.984504e+00 -1.454443e+00
25%   -6.893853e-01 -7.259631e-01   -6.919555e-01 -6.671955e-01
50%   -2.150816e-01 -1.046362e-01   -2.359800e-01 -2.951869e-01
75%    4.693926e-01  5.841756e-01    4.996769e-01  3.635073e-01
max    3.971288e+00  4.651889e+00    3.976130e+00  5.250529e+00

       mean_smoothness  mean_compactness  mean_concavity  mean_concave points
count     5.690000e+02      5.690000e+02    5.690000e+02         5.690000e+02  \
mean     -8.366672e-16      1.873136e-16    4.995028e-17        -4.995028e-17
std       1.000880e+00      1.000880e+00    1.000880e+00         1.000880e+00
min      -3.112085e+00     -1.610136e+00   -1.114873e+00        -1.261820e+00
25%      -7.109628e-01     -7.470860e-01   -7.437479e-01        -7.379438e-01
50%      -3.489108e-02     -2.219405e-01   -3.422399e-01        -3.977212e-01
```

```
75%       6.361990e-01      4.938569e-01    5.260619e-01         6.469351e-01
max       4.770911e+00      4.568425e+00    4.243589e+00         3.927930e+00

       mean_symmetry  mean_fractal dimension  …  worst_radius
count   5.690000e+02            5.690000e+02  …  5.690000e+02  \
mean    1.748260e-16            4.745277e-16  … -8.241796e-16
std     1.000880e+00            1.000880e+00  …  1.000880e+00
min    -2.744117e+00           -1.819865e+00  … -1.726901e+00
25%    -7.032397e-01           -7.226392e-01  … -6.749213e-01
50%    -7.162650e-02           -1.782793e-01  … -2.690395e-01
75%     5.307792e-01            4.709834e-01  …  5.220158e-01
max     4.484751e+00            4.910919e+00  …  4.094189e+00

       worst_texture  worst_perimeter  worst_area  worst_smoothness
count   5.690000e+02     5.690000e+02  569.000000      5.690000e+02  \
mean    1.248757e-17    -3.746271e-16    0.000000     -2.372638e-16
std     1.000880e+00     1.000880e+00    1.000880      1.000880e+00
min    -2.223994e+00    -1.693361e+00   -1.222423     -2.682695e+00
25%    -7.486293e-01    -6.895783e-01   -0.642136     -6.912304e-01
50%    -4.351564e-02    -2.859802e-01   -0.341181     -4.684277e-02
75%     6.583411e-01     5.402790e-01    0.357589      5.975448e-01
max     3.885905e+00     4.287337e+00    5.930172      3.955374e+00

       worst_compactness  worst_concavity  worst_concave points
count       5.690000e+02     5.690000e+02          5.690000e+02  \
mean       -3.371644e-16     7.492542e-17          2.247763e-16
std         1.000880e+00     1.000880e+00          1.000880e+00
min        -1.443878e+00    -1.305831e+00         -1.745063e+00
25%        -6.810833e-01    -7.565142e-01         -7.563999e-01
50%        -2.695009e-01    -2.182321e-01         -2.234689e-01
75%         5.396688e-01     5.311411e-01          7.125100e-01
max         5.112877e+00     4.700669e+00          2.685877e+00

       worst_symmetry  worst_fractal dimension
count    5.690000e+02             5.690000e+02
mean     2.622390e-16            -5.744282e-16
std      1.000880e+00             1.000880e+00
min     -2.160960e+00            -1.601839e+00
25%     -6.418637e-01            -6.919118e-01
50%     -1.274095e-01            -2.164441e-01
75%      4.501382e-01             4.507624e-01
max      6.046041e+00             6.846856e+00

[8 rows x 30 columns]
```

[156]:
```
from sklearn.decomposition import PCA
components=None
```

```
pca=PCA(n_components=components)
pca.fit(x_scaled)
```

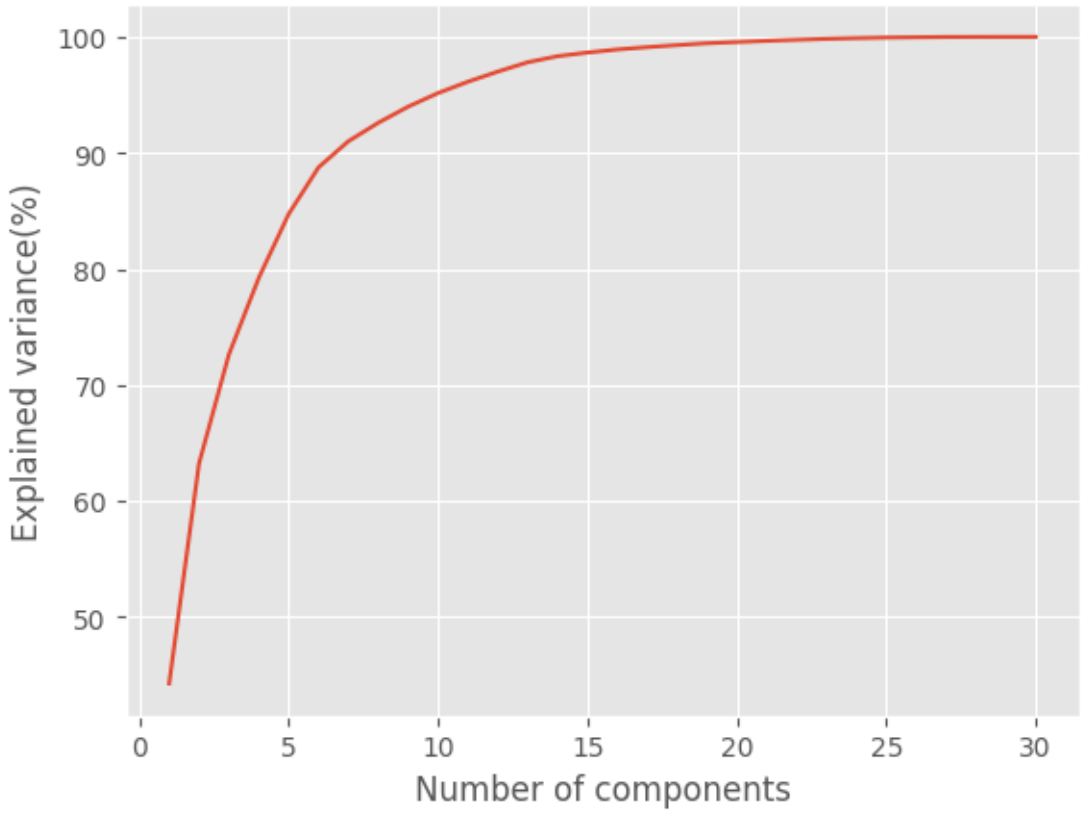
[156]:
```
PCA()
```

[157]:
```
print('Cumulative Variances Percentage:')
print(pca.explained_variance_ratio_.cumsum()*100)
```

```
Cumulative Variances Percentage:
[ 44.27202561  63.24320765  72.63637091  79.23850582  84.73427432
  88.75879636  91.00953007  92.59825387  93.98790324  95.15688143
  96.13660042  97.00713832  97.81166331  98.33502905  98.64881227
  98.91502161  99.1130184   99.28841435  99.45333965  99.55720433
  99.65711397  99.74857865  99.82971477  99.88989813  99.94150237
  99.96876117  99.99176271  99.99706051  99.99955652 100.        ]
```

[158]:
```
components=len(pca.explained_variance_ratio_)\
if components is None else components
plt.plot(range(1,components+1),
np.cumsum(pca.explained_variance_ratio_*100))
plt.xlabel('Number of components')
plt.ylabel('Explained variance(%)')
```

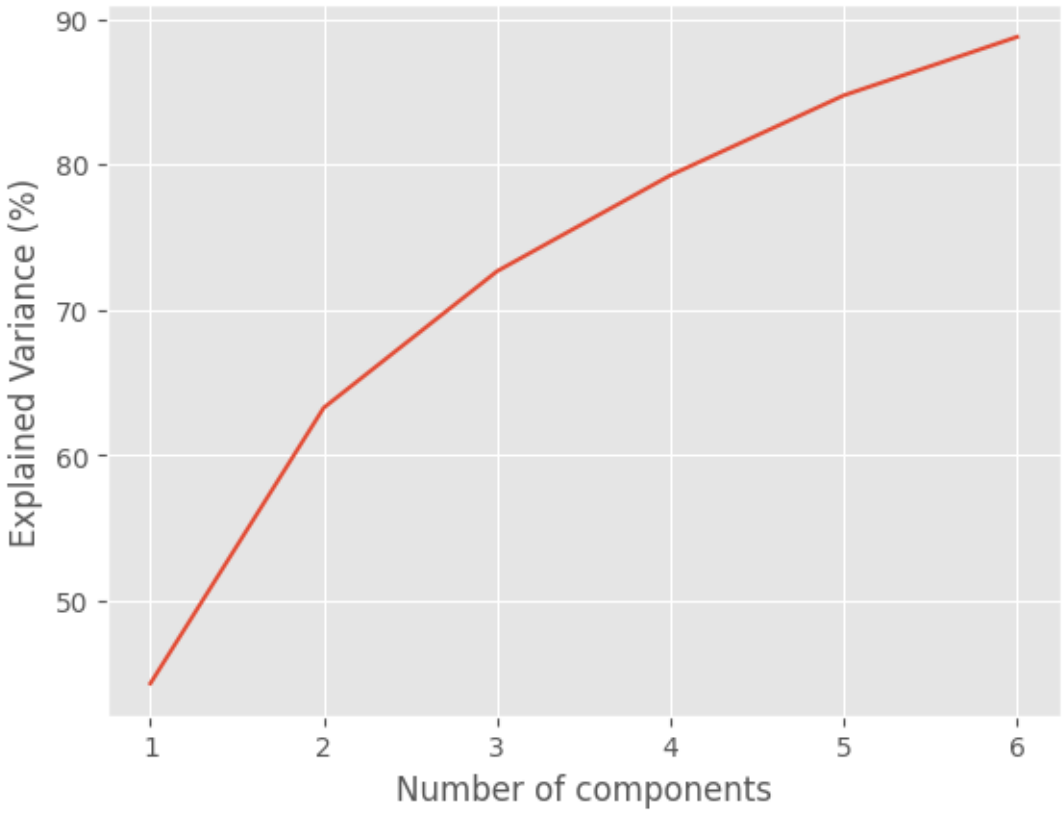
[158]:
```
Text(0, 0.5, 'Explained variance(%)')
```



[159]:
```
from sklearn.decomposition import PCA
pca=PCA(n_components=0.85)
pca.fit(x_scaled)
print('Cumulative Variances (Percentage):')
print(np.cumsum(pca.explained_variance_ratio_*100))
components=len(pca.explained_variance_ratio_)
print(f'Number of components:{components}')
plt.plot(range(1,components+1),
np.cumsum(pca.explained_variance_ratio_*100))
plt.xlabel('Number of components')
plt.ylabel('Explained Variance (%)')
```

```
Cumulative Variances (Percentage):
[44.27202561 63.24320765 72.63637091 79.23850582 84.73427432 88.75879636]
Number of components:6
```

[159]:
```
Text(0, 0.5, 'Explained Variance (%)')
```



[160]:
```
pca_components=abs(pca.components_)
print(pca_components)
```

```
[[2.18902444e-01 1.03724578e-01 2.27537293e-01 2.20994985e-01
  1.42589694e-01 2.39285354e-01 2.58400481e-01 2.60853758e-01
  1.38166959e-01 6.43633464e-02 2.05978776e-01 1.74280281e-02
  2.11325916e-01 2.02869635e-01 1.45314521e-02 1.70393451e-01
  1.53589790e-01 1.83417397e-01 4.24984216e-02 1.02568322e-01
  2.27996634e-01 1.04469325e-01 2.36639681e-01 2.24870533e-01
  1.27952561e-01 2.10095880e-01 2.28767533e-01 2.50885971e-01
  1.22904556e-01 1.31783943e-01]
 [2.33857132e-01 5.97060883e-02 2.15181361e-01 2.31076711e-01
  1.86113023e-01 1.51891610e-01 6.01653628e-02 3.47675005e-02
  1.90348770e-01 3.66575471e-01 1.05552152e-01 8.99796818e-02
  8.94572342e-02 1.52292628e-01 2.04430453e-01 2.32715896e-01
  1.97207283e-01 1.30321560e-01 1.83848000e-01 2.80092027e-01
  2.19866379e-01 4.54672983e-02 1.99878428e-01 2.19351858e-01
  1.72304352e-01 1.43593173e-01 9.79641143e-02 8.25723507e-03
  1.41883349e-01 2.75339469e-01]
 [8.53124284e-03 6.45499033e-02 9.31421972e-03 2.86995259e-02
  1.04291904e-01 7.40915709e-02 2.73383798e-03 2.55635406e-02
```

```
 4.02399363e-02 2.25740897e-02 2.68481387e-01 3.74633665e-01
 2.66645367e-01 2.16006528e-01 3.08838979e-01 1.54779718e-01
 1.76463743e-01 2.24657567e-01 2.88584292e-01 2.11503764e-01
 4.75069900e-02 4.22978228e-02 4.85465083e-02 1.19023182e-02
 2.59797613e-01 2.36075625e-01 1.73057335e-01 1.70344076e-01
 2.71312642e-01 2.32791313e-01]
[4.14089623e-02 6.03050001e-01 4.19830991e-02 5.34337955e-02
 1.59382765e-01 3.17945811e-02 1.91227535e-02 6.53359443e-02
 6.71249840e-02 4.85867649e-02 9.79412418e-02 3.59855528e-01
 8.89924146e-02 1.08205039e-01 4.46641797e-02 2.74693632e-02
 1.31687997e-03 7.40673350e-02 4.40733510e-02 1.53047496e-02
 1.54172396e-02 6.32807885e-01 1.38027944e-02 2.58947492e-02
 1.76522161e-02 9.13284153e-02 7.39511797e-02 6.00699571e-03
 3.62506947e-02 7.70534703e-02]
[3.77863538e-02 4.94688505e-02 3.73746632e-02 1.03312514e-02
 3.65088528e-01 1.17039713e-02 8.63754118e-02 4.38610252e-02
 3.05941428e-01 4.44243602e-02 1.54456496e-01 1.91650506e-01
 1.20990220e-01 1.27574432e-01 2.32065676e-01 2.79968156e-01
 3.53982091e-01 1.95548089e-01 2.52868765e-01 2.63297438e-01
 4.40659209e-03 9.28834001e-02 7.45415100e-03 2.73909030e-02
 3.24435445e-01 1.21804107e-01 1.88518727e-01 4.33320687e-02
 2.44558663e-01 9.44233510e-02]
[1.87407904e-02 3.21788366e-02 1.73084449e-02 1.88774796e-03
 2.86374497e-01 1.41309489e-02 9.34418089e-03 5.20499505e-02
 3.56458461e-01 1.19430668e-01 2.56032561e-02 2.87473145e-02
 1.81071500e-03 4.28639079e-02 3.42917393e-01 6.91975186e-02
 5.63432386e-02 3.12244482e-02 4.90245643e-01 5.31952674e-02
 2.90684919e-04 5.00080613e-02 8.50098715e-03 2.51643821e-02
 3.69255370e-01 4.77057929e-02 2.83792555e-02 3.08734498e-02
 4.98926784e-01 8.02235245e-02]]
```

[161]:
```
newdf=df.drop('diagnosis',axis=1)
print('Top 4 most important features in each component')

for row in range(pca_components.shape[0]):
    # get the indices of the top 6 values in each row
    temp = np.argpartition(-(pca_components[row]),4)

    # sort the indices in descending order
    indices = temp[np.argsort((-pca_components[row])[temp])][:4]

    # print the top 4 feature names

    print(f'Component {row}: {newdf.columns[indices].to_list()}')
```

```
Top 4 most important features in each component
Component 0: ['mean_concave points', 'mean_concavity', 'worst_concave points',
'mean_compactness']
```

```
Component 1: ['mean_fractal dimension', 'SE_fractal dimension', 'worst_fractal
dimension', 'mean_radius']
Component 2: ['SE_texture', 'SE_smoothness', 'SE_symmetry', 'worst_symmetry']
Component 3: ['worst_texture', 'mean_texture', 'SE_texture', 'mean_smoothness']
Component 4: ['mean_smoothness', 'SE_concavity', 'worst_smoothness',
'mean_symmetry']
Component 5: ['worst_symmetry', 'SE_symmetry', 'worst_smoothness',
'mean_symmetry']
```

[162]:
```
x_pca=pca.transform(x_scaled)
x_pca=pd.DataFrame(data=x_pca)
print(x_pca.shape)
print(x_pca)
```

```
(569, 6)
             0          1         2         3         4         5
0     9.192837   1.948583 -1.123166  3.633731 -1.195110  1.411424
1     2.387802  -3.768172 -0.529293  1.118264  0.621775  0.028656
2     5.733896  -1.075174 -0.551748  0.912083 -0.177086  0.541452
3     7.122953  10.275589 -3.232790  0.152547 -2.960878  3.053422
4     3.935302  -1.948072  1.389767  2.940639  0.546747 -1.226495
..         …         …         …         …         …         …
564   6.439315  -3.576817  2.459487  1.177314 -0.074824 -2.375193
565   3.793382  -3.584048  2.088476 -2.506028 -0.510723 -0.246710
566   1.256179  -1.902297  0.562731 -2.089227  1.809991 -0.534447
567  10.374794   1.672010 -1.877029 -2.356031 -0.033742  0.567936
568  -5.475243  -0.670637  1.490443 -2.299157 -0.184703  1.617837

[569 rows x 6 columns]
```

[163]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
random_state=42
x_train,x_test,y_train,y_test=\
train_test_split(x_scaled,y,test_size=0.
  ↪3,shuffle=True,random_state=random_state)
log_reg=LogisticRegression()
log_reg.fit(x_train,y_train)
log_reg.score(x_test,y_test)
```

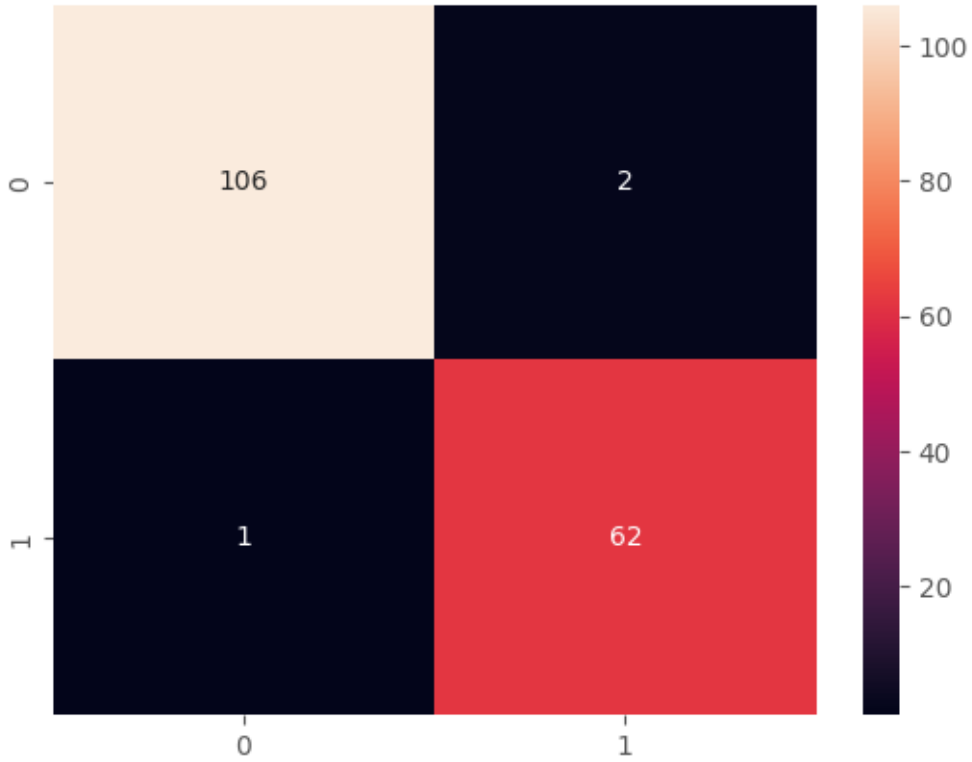
[163]:
```
0.9824561403508771
```

[164]:
```
from sklearn.metrics import f1_score,confusion_matrix
from sklearn.metrics import accuracy_score
acc=accuracy_score(y_test,log_reg.predict(x_test))
print('Accuracy is:',acc)
cm=confusion_matrix(y_test,log_reg.predict(x_test))
```

```
sns.heatmap(cm,annot=True,fmt='d')
```

```
Accuracy is: 0.9824561403508771
```

[164]: <Axes: >



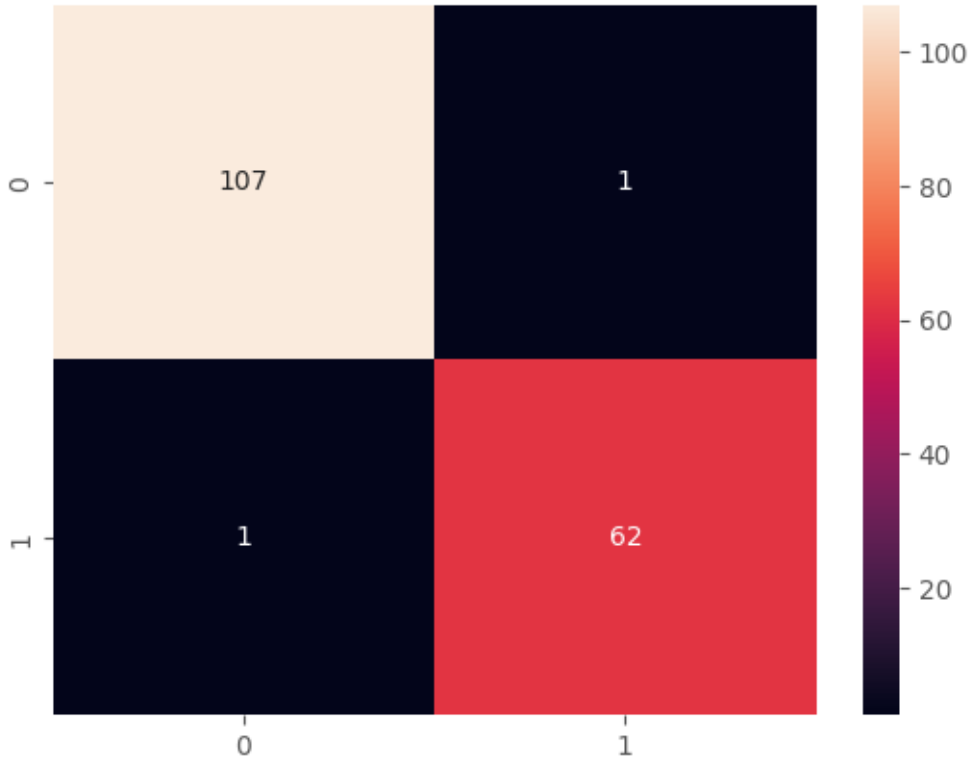
[165]:
```
random_state=42
x_pca_train,x_pca_test,y_pca_train,y_pca_test=\
train_test_split(x_pca,y,test_size=0.3,shuffle=True,random_state=random_state)
log_reg_pca=LogisticRegression()
log_reg_pca.fit(x_pca_train,y_pca_train)
y_pred=log_reg_pca.predict(x_pca_test)
log_reg_pca.score(x_pca_test,y_pca_test)
```

[165]: 0.9883040935672515

[166]:
```
from sklearn.metrics import f1_score,confusion_matrix
from sklearn.metrics import accuracy_score
acc_pca=accuracy_score(y_pca_test,log_reg_pca.predict(x_pca_test))
print('Accuracy is:',acc_pca)
cm=confusion_matrix(y_pca_test,log_reg_pca.predict(x_pca_test))
sns.heatmap(cm,annot=True,fmt='d')
```

```
Accuracy is: 0.9883040935672515
```

[166]: <Axes: >



[167]:
```
y_pred=log_reg_pca.predict(x_pca_test)
false_negatives=np.logical_and(y_pca_test!=y_pred,y_pred==0)
x_pca_test[false_negatives]
```

[167]:

	0	1	2	3	4	5
73	-0.361709	0.119739	-2.040956	1.058884	0.757109	-0.920448

[168]:
```
true_negatives=np.logical_and(y_pca_test==y_pred,y_pred==0)
x_pca_test[true_negatives]
```

[168]:

	0	1	2	3	4	5
204	-0.781190	0.652849	-0.643657	0.214468	-0.437680	-0.160489
431	-0.915804	2.479013	0.362607	0.261967	0.138472	-0.991236
540	-1.665475	2.389618	1.502249	0.875951	0.484546	-1.189518
81	1.167462	2.514516	-1.905719	0.638312	0.236181	0.138134
477	-3.172370	-2.089052	-0.978806	0.387097	1.419476	1.338365
..	…	…	…	…	…	…
426	-1.283187	2.550909	-0.083860	0.771512	0.556911	0.270002

```
69  -3.261279 -0.937838  0.205130  1.090072 -0.460350 -0.434329
542 -1.300930 -1.821415  0.373307 -1.848169  0.199627  0.765754
176  1.170898  7.014487  4.271862 -0.332640  2.909445 -0.389148
247  1.025901  2.361262 -1.616886  1.145963  4.144479 -0.207529

[107 rows x 6 columns]
```

[169]:
```
frames=[x_pca_test[false_negatives],x_pca_test[true_negatives]]
pred_neg=pd.concat(frames)
pred_neg
```

[169]:
```
            0         1         2         3         4         5
73  -0.361709  0.119739 -2.040956  1.058884  0.757109 -0.920448
204 -0.781190  0.652849 -0.643657  0.214468 -0.437680 -0.160489
431 -0.915804  2.479013  0.362607  0.261967  0.138472 -0.991236
540 -1.665475  2.389618  1.502249  0.875951  0.484546 -1.189518
81   1.167462  2.514516 -1.905719  0.638312  0.236181  0.138134
..        …         …         …         …         …         …
426 -1.283187  2.550909 -0.083860  0.771512  0.556911  0.270002
69  -3.261279 -0.937838  0.205130  1.090072 -0.460350 -0.434329
542 -1.300930 -1.821415  0.373307 -1.848169  0.199627  0.765754
176  1.170898  7.014487  4.271862 -0.332640  2.909445 -0.389148
247  1.025901  2.361262 -1.616886  1.145963  4.144479 -0.207529

[108 rows x 6 columns]
```

[170]:
```
stacks=[y_pca_test[false_negatives],y_pca_test[true_negatives]]
y_labels=np.hstack(stacks)
y_labels.shape
print(y_labels)
```

```
[1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

[171]:
```
new_df=pd.DataFrame(data=pred_neg)
new_df['diagnosis']=y_labels
new_df.shape
new_df.head()
```

[171]:
```
            0         1         2         3         4         5  diagnosis
73  -0.361709  0.119739 -2.040956  1.058884  0.757109 -0.920448          1
204 -0.781190  0.652849 -0.643657  0.214468 -0.437680 -0.160489          0
431 -0.915804  2.479013  0.362607  0.261967  0.138472 -0.991236          0
540 -1.665475  2.389618  1.502249  0.875951  0.484546 -1.189518          0
81   1.167462  2.514516 -1.905719  0.638312  0.236181  0.138134          0
```

[172]:
```
new_df['diagnosis'].value_counts()
```

[172]:
```
diagnosis
0    107
1      1
Name: count, dtype: int64
```

[191]:
```
new_df.head()
```

[191]:

	0	2	3	4	5	diagnosis
73	-0.361709	-2.040956	1.058884	0.757109	-0.920448	1
204	-0.781190	-0.643657	0.214468	-0.437680	-0.160489	0
431	-0.915804	0.362607	0.261967	0.138472	-0.991236	0
540	-1.665475	1.502249	0.875951	0.484546	-1.189518	0
81	1.167462	-1.905719	0.638312	0.236181	0.138134	0

[201]:
```
x_new=new_df.drop(['diagnosis'],axis=1)
y_new=new_df.diagnosis
y_new.value_counts()
```

[201]:
```
diagnosis
0    107
1      1
Name: count, dtype: int64
```

[202]:
```
x_new.head()
```

[202]:

	0	2	3	4	5
73	-0.361709	-2.040956	1.058884	0.757109	-0.920448
204	-0.781190	-0.643657	0.214468	-0.437680	-0.160489
431	-0.915804	0.362607	0.261967	0.138472	-0.991236
540	-1.665475	1.502249	0.875951	0.484546	-1.189518
81	1.167462	-1.905719	0.638312	0.236181	0.138134

[203]:
```
y_new.head()
```

[203]:
```
73     1
204    0
431    0
540    0
81     0
Name: diagnosis, dtype: int64
```

[204]:
```
new_df_corr=new_df.corr()['diagnosis'].abs().sort_values(ascending=False)
new_df_corr
```

[204]:
```
diagnosis    1.000000
2            0.144790
0            0.111248
5            0.103084
3            0.065245
4            0.054864
Name: diagnosis, dtype: float64
```

[205]:
```
features=new_df_corr[new_df_corr>0.1].index.to_list()[1:]
features
```

[205]:
```
[2, 0, 5]
```

[206]:
```
from sklearn.linear_model import LinearRegression
def calculate_vif(df, features):
    vif, tolerance = {}, {}
    # all the features that you want to examine
    for feature in features:
        # extract all the other features you will regress against
        x = [f for f in features if f != feature]
        x, y = df[x], df[feature]
        # extract r-squared from the fit
        r2 = LinearRegression().fit(x, y).score(x, y)

        # calculate tolerance
        tolerance[feature] = 1 - r2
        # calculate VIF
        vif[feature] = 1/(tolerance[feature])
    # return VIF DataFrame
    return pd.DataFrame({'VIF': vif, 'Tolerance': tolerance})
calculate_vif(new_df,features)
```

[206]:

	VIF	Tolerance
2	1.010225	0.989878
0	1.007177	0.992874
5	1.016517	0.983752

[208]:
```
x_train,x_test,y_train,y_test=train_test_split(x_new,y_new,test_size=0.
↪1,random_state=42)
log_reg_FN=LogisticRegression()
log_reg_FN=log_reg_FN.fit(x_train,y_train)
```

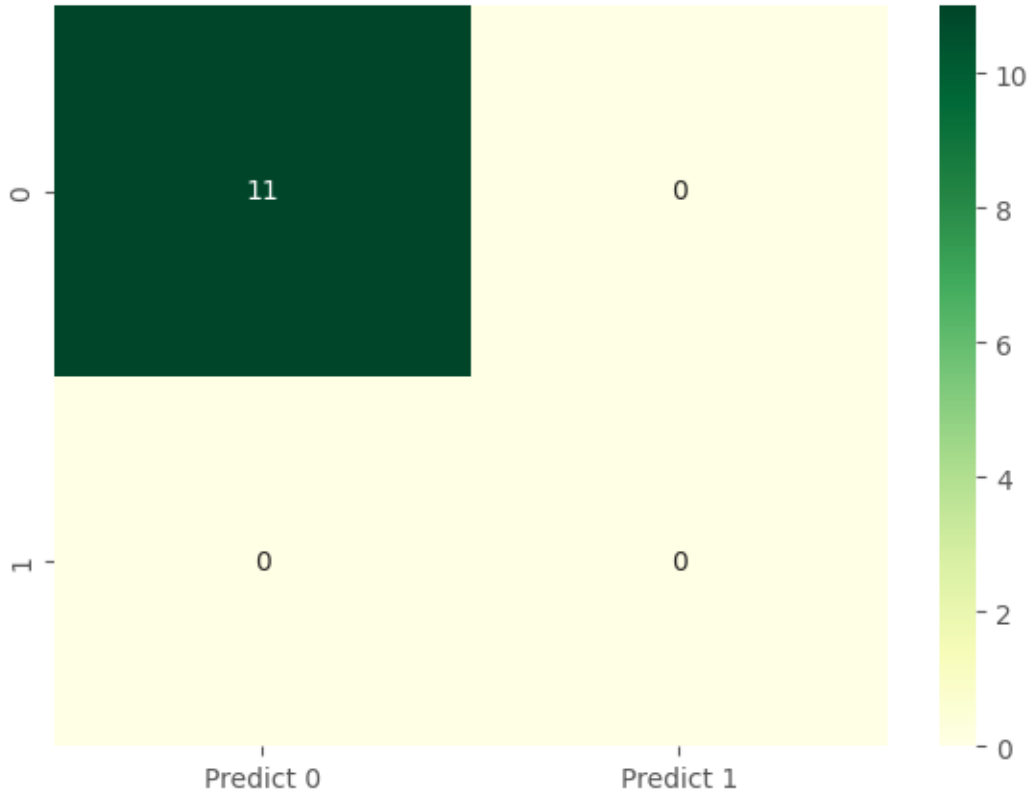
[209]:
```
log_reg_FN.score(x_test,y_test)
```

[209]:
```
1.0
```

[210]:
```
y_pred=log_reg_FN.predict(x_test)
from sklearn import metrics
print('Confusion Matrix')
cm=metrics.confusion_matrix(y_test,y_pred,labels=[0,1])
df_cm=pd.DataFrame(cm,index=[i for i in [0,1]],
                   columns=[i for i in ['Predict 0','Predict 1']])
plt.figure(figsize=(7,5))
sns.heatmap(df_cm,annot=True,fmt='.5g',cmap='YlGn')
```

```
Confusion Matrix
```

[210]: <Axes: >



[ ]: