# pca-cancer-dataset

December 19, 2023

[106]:
```python
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

[107]:
```python
df=pd.read_csv("/kaggle/input/breast-cancer-wisconsin-data/data.csv")
df.head()
```

[107]:
```
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
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

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
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

   …  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0  …          17.33           184.60      2019.0            0.1622
1  …          23.41           158.80      1956.0            0.1238
2  …          25.53           152.50      1709.0            0.1444
3  …          26.50            98.87       567.7            0.2098
4  …          16.67           152.20      1575.0            0.1374

   compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
```

```
4             0.2050          0.4000                0.1625          0.2364

   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN

[5 rows x 33 columns]
```

[108]:
```
df.shape
```

[108]:
```
(569, 33)
```

[109]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       569 non-null    int64
 1   diagnosis                569 non-null    object
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
 32  Unnamed: 32              0 non-null      float64
dtypes: float64(31), int64(1), object(1)
memory usage: 146.8+ KB
```

[110]:

```python
# Drop unnecessary columns
df.drop(["Unnamed: 32","id"],axis=1,inplace=True)
df.head()
```

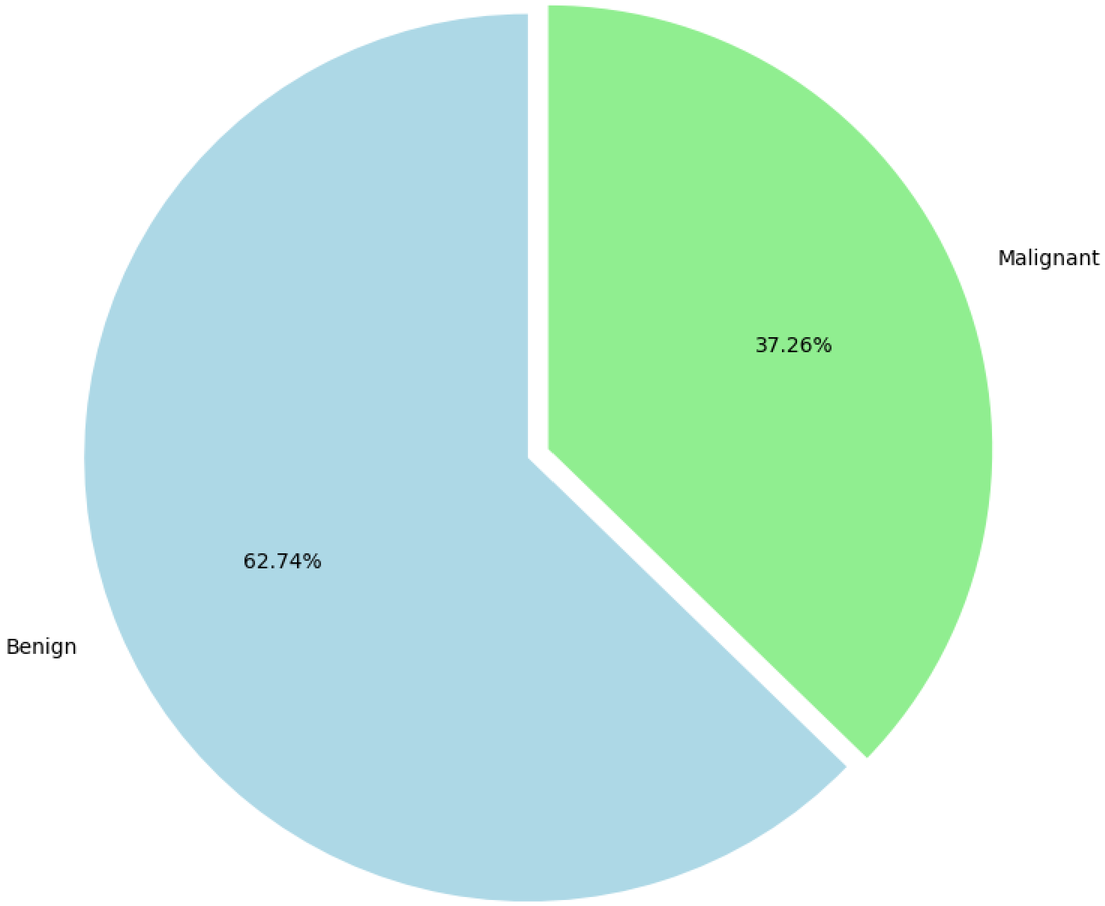
[110]:

```
  diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0         M        17.99         10.38          122.80     1001.0
1         M        20.57         17.77          132.90     1326.0
2         M        19.69         21.25          130.00     1203.0
3         M        11.42         20.38           77.58      386.1
4         M        20.29         14.34          135.10     1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
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

   symmetry_mean  …  radius_worst  texture_worst  perimeter_worst  \
0         0.2419  …         25.38          17.33           184.60
1         0.1812  …         24.99          23.41           158.80
2         0.2069  …         23.57          25.53           152.50
3         0.2597  …         14.91          26.50            98.87
4         0.1809  …         22.54          16.67           152.20

   area_worst  smoothness_worst  compactness_worst  concavity_worst  \
0      2019.0            0.1622             0.6656           0.7119
1      1956.0            0.1238             0.1866           0.2416
2      1709.0            0.1444             0.4245           0.4504
3       567.7            0.2098             0.8663           0.6869
4      1575.0            0.1374             0.2050           0.4000

   concave points_worst  symmetry_worst  fractal_dimension_worst
0                0.2654          0.4601                  0.11890
1                0.1860          0.2750                  0.08902
2                0.2430          0.3613                  0.08758
```

```
3                 0.2575          0.6638                    0.17300
4                 0.1625          0.2364                    0.07678

[5 rows x 31 columns]
```

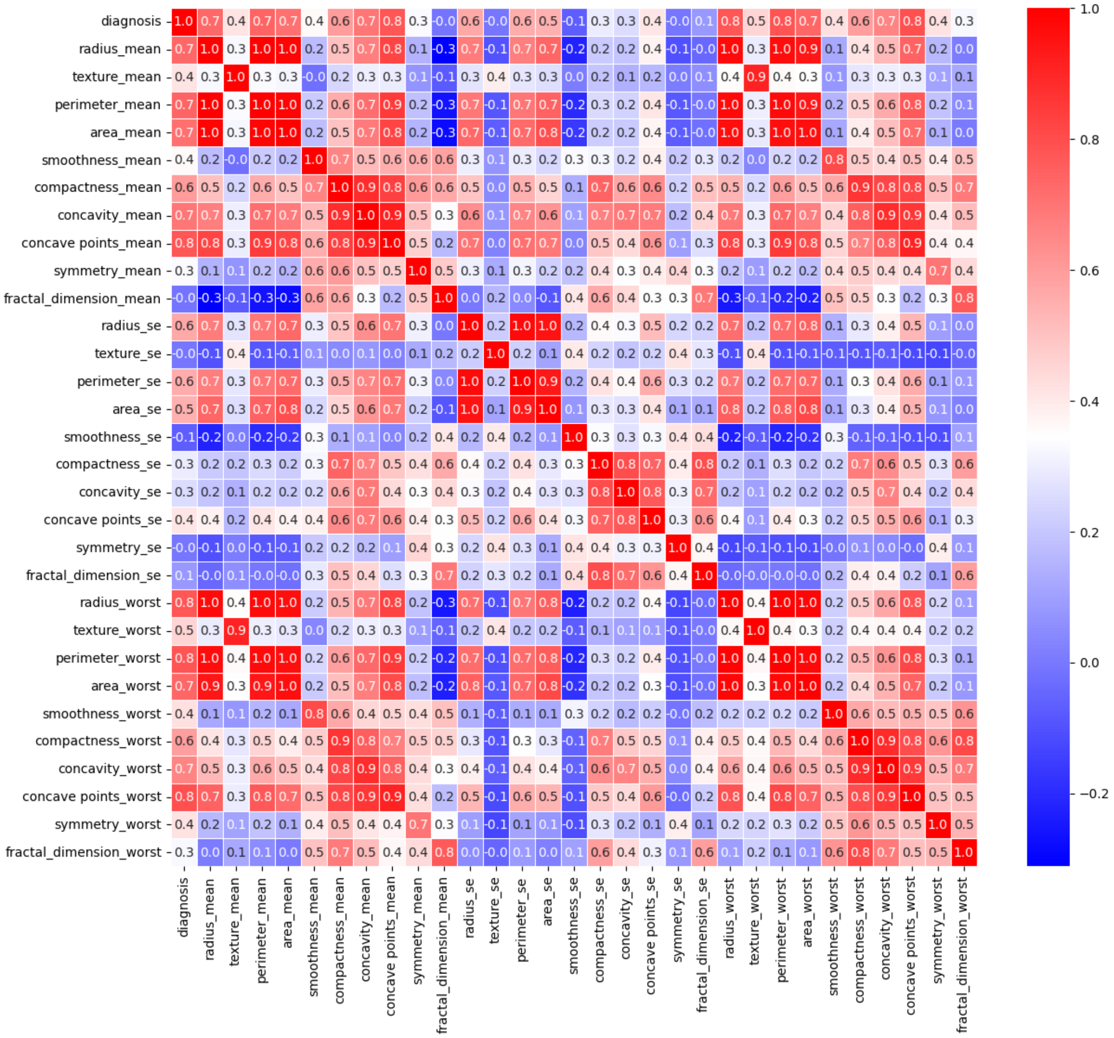
[111]:
```
# Categorical data convert to numeric data
df["diagnosis"] = [
    1 if item == "M"
    else 0  for item in df["diagnosis"]]
```

[112]:
```
# Pie chart
plt.pie(df.diagnosis.value_counts(), startangle=90, explode=[0.05, 0.05],␣
 ↪autopct='%0.2f%%',
        labels=['Benign', 'Malignant'], colors=['#add8e6', '#90ee90'], radius=2)
plt.show()
```



## Correlation Matrix

[113]:
```
import seaborn as sns
f,ax = plt.subplots(figsize=(14,12))
sns.heatmap(df.corr(), cmap="bwr", annot=True, linewidths=0.5, fmt= '.1f',ax=ax)
plt.show()
```



## PCA (Principal Component Analysis)

[114]:
```
from sklearn.preprocessing import StandardScaler
Y = df["diagnosis"]
X = df.drop('diagnosis', axis=1)
```

[115]:
```
sc = StandardScaler()
X = sc.fit_transform(X)
X.shape
```

[115]:

```
(569, 30)
```

[116]:

```
#PCA
from sklearn.decomposition import PCA
n_components = 3
pca = PCA(n_components=n_components)
pca.fit(X)
components = pca.transform(X)
X.shape
```

[116]:

```
(569, 30)
```

[117]:

```
components.shape
```

[117]:

```
(569, 3)
```

[118]:

```
pca.explained_variance_ratio_
np.cumsum(pca.explained_variance_ratio_)
```

[118]:

```
array([0.44272026, 0.63243208, 0.72636371])
```

[119]:

```
df_pca=pd.DataFrame({"PC":["PC1","PC2","PC3"],
                     "var": np.cumsum(pca.explained_variance_ratio_)})

df_pca
```

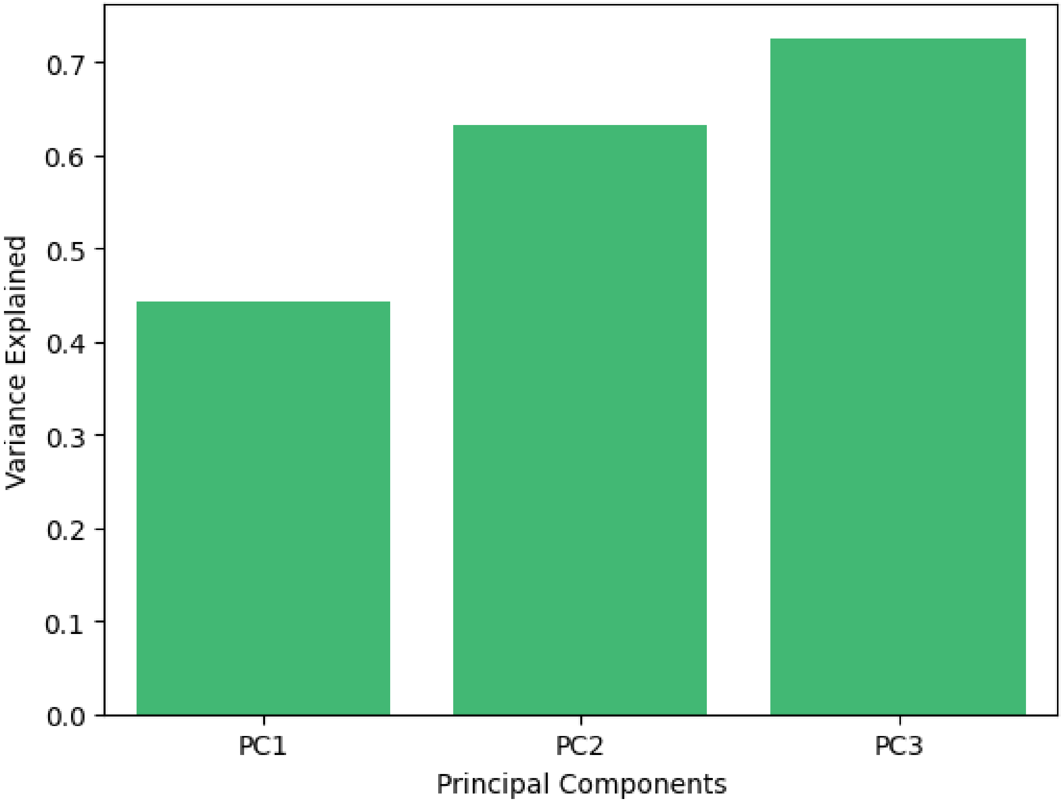
[119]:

```
    PC       var
0  PC1  0.442720
1  PC2  0.632432
2  PC3  0.726364
```

### PCA Visualization

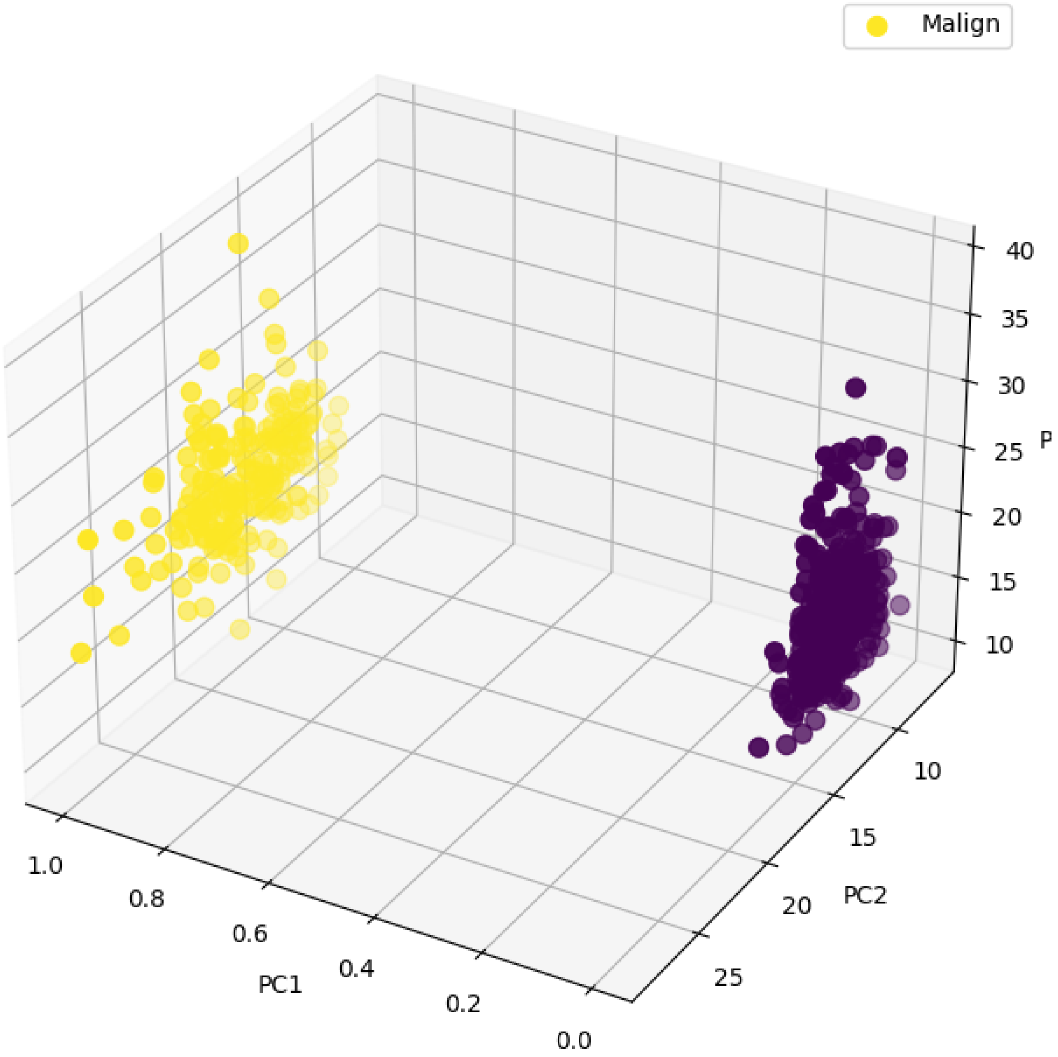
[120]:

```
sns.barplot(x="PC", y="var", data=df_pca, color="#2ecc71")
plt.ylabel("Variance Explained")
plt.xlabel("Principal Components")
plt.show()
```

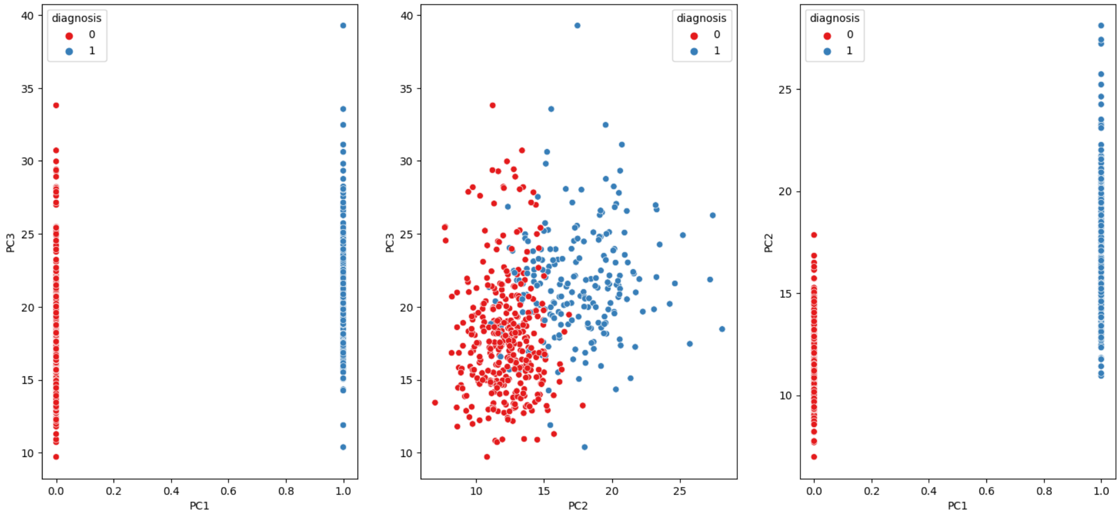


[121]:

```
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure(figsize=(15, 8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df.iloc[:, 0], df.iloc[:, 1], df.iloc[:, 2], c=df['diagnosis'], s=60)
ax.legend(['Malign'])
ax.set_xlabel('PC1')
ax.set_ylabel('PC2')
ax.set_zlabel('PC3')
ax.view_init(30, 120)
```



```
[122]: # First subplot
       plt.figure(figsize=(18, 8))
       plt.subplot(1, 3, 1)
       sns.scatterplot(x=df.iloc[:, 0], y=df.iloc[:, 2], hue=df['diagnosis'],␣
        ↪palette='Set1')
       plt.xlabel('PC1')
       plt.ylabel('PC3')

       # Second subplot
       plt.subplot(1, 3, 2)
       sns.scatterplot(x=df.iloc[:, 1], y=df.iloc[:, 2], hue=df['diagnosis'],␣
        ↪palette='Set1')
       plt.xlabel('PC2')
       plt.ylabel('PC3')


       # 3rd subplot
       plt.subplot(1, 3, 3)
       sns.scatterplot(x=df.iloc[:, 0], y=df.iloc[:, 1], hue=df['diagnosis'],␣
        ↪palette='Set1')
       plt.xlabel('PC1')
       plt.ylabel('PC2')

       plt.show()
```



[123]:
```
pca = PCA(n_components=3)  # Set the appropriate number of components
pca.fit(df)

# Create a DataFrame for principal components
df_pc = pd.DataFrame(pca.components_, columns=df.columns)

# Display the DataFrame
df_pc
```

[123]:
```
   diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0   0.000532     0.005086      0.002197        0.035076   0.516826
1  -0.000220     0.009287     -0.002882        0.062748   0.851824
2  -0.001755    -0.012343     -0.006356       -0.071671  -0.027894

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0         0.000004          0.000041        0.000082             0.000048
1        -0.000015         -0.000003        0.000075             0.000046
```

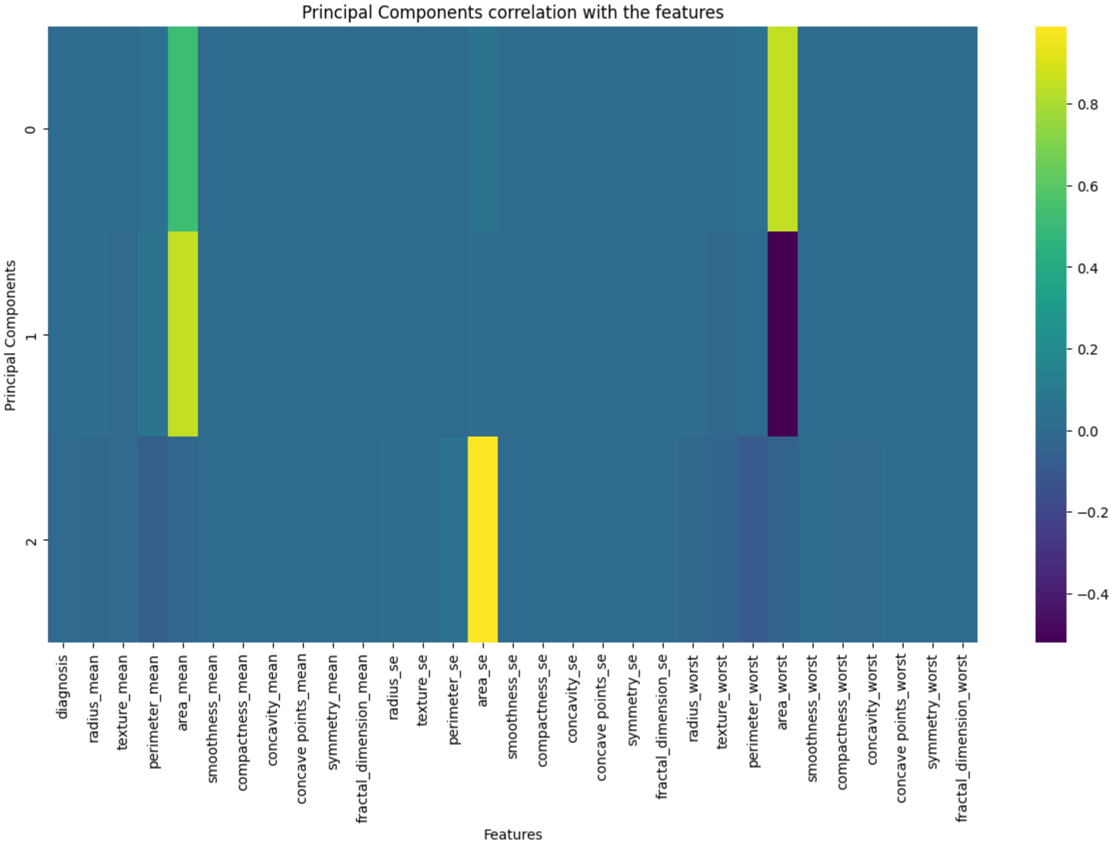
```
2         0.000073           0.000102        0.000266             0.000036

   symmetry_mean  …    radius_worst  texture_worst  perimeter_worst  \
0       0.000007  …        0.007155       0.003067         0.049458   
1      -0.000025  …       -0.000569      -0.013215        -0.000186   
2       0.000141  …       -0.015566      -0.031546        -0.092316   

   area_worst  smoothness_worst  compactness_worst  concavity_worst  \
0    0.852063          0.000006           0.000101         0.000169   
1   -0.519742         -0.000077          -0.000256        -0.000175   
2   -0.039317         -0.000042          -0.000765        -0.000847   

   concave points_worst  symmetry_worst  fractal_dimension_worst  
0              0.000074        0.000018                 0.000002  
1             -0.000031       -0.000157                -0.000055  
2             -0.000334       -0.000350                -0.000041  

[3 rows x 31 columns]
```

[124]:

```
plt.figure(figsize=(15, 8))
sns.heatmap(df_pc, cmap='viridis')
plt.title('Principal Components correlation with the features')
plt.xlabel('Features')
plt.ylabel('Principal Components')
```

[124]:

```
Text(158.22222222222223, 0.5, 'Principal Components')
```


Principal Components correlation with the features
Principal Components
0
1
2
Features
diagnosis
radius_mean
texture_mean
perimeter_mean
area_mean
smoothness_mean
compactness_mean
concavity_mean
concave points_mean
symmetry_mean
fractal_dimension_mean
radius_se
texture_se
perimeter_se
area_se
smoothness_se
compactness_se
concavity_se
concave points_se
symmetry_se
fractal_dimension_se
radius_worst
texture_worst
perimeter_worst
area_worst
smoothness_worst
compactness_worst
concavity_worst
concave points_worst
symmetry_worst
fractal_dimension_worst
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4