In [1]:

```
# loading the dataset
from sklearn.datasets import load_breast_cancer
```

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

PREPROCESSING

In [3]:

```
breast_data = load_breast_cancer().data
print("Features:", breast_data.shape)   ### 569 rows and 30 columns expected

breast_labels = np.reshape(load_breast_cancer().target, (569,1))
print("Target:", breast_labels.shape) ### 569 rows and 1 target column expected
```

```
Features: (569, 30)
Target: (569, 1)
```

In [4]:

```
## Creating a Pandas dataframe for the dataset with the last column as the target variabl
e

final_breast_data = np.concatenate([breast_data,breast_labels],axis=1)
breast_dataset = pd.DataFrame(final_breast_data)

features = load_breast_cancer().feature_names
features_labels = np.append(features,'label')
breast_dataset.columns = features_labels
breast_dataset['label'] = breast_dataset['label'].astype(int)
breast_dataset.head()
```

Out[4]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	radius error	texture error
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	1.0950	0.9053
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	0.5435	0.7339
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	0.7456	0.7869
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	0.4956	1.1560
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	0.7572	0.7813

In [5]:

```
# Dividing the values into the features and labels
X = breast_dataset.iloc[:,:30].values
y = breast_dataset.iloc[:,30].values

print(np.shape(X), np.shape(y))
```

```
(569, 30) (569,)
```

VISUALISATION BEFORE DIMENTIONALITY REDUCTION

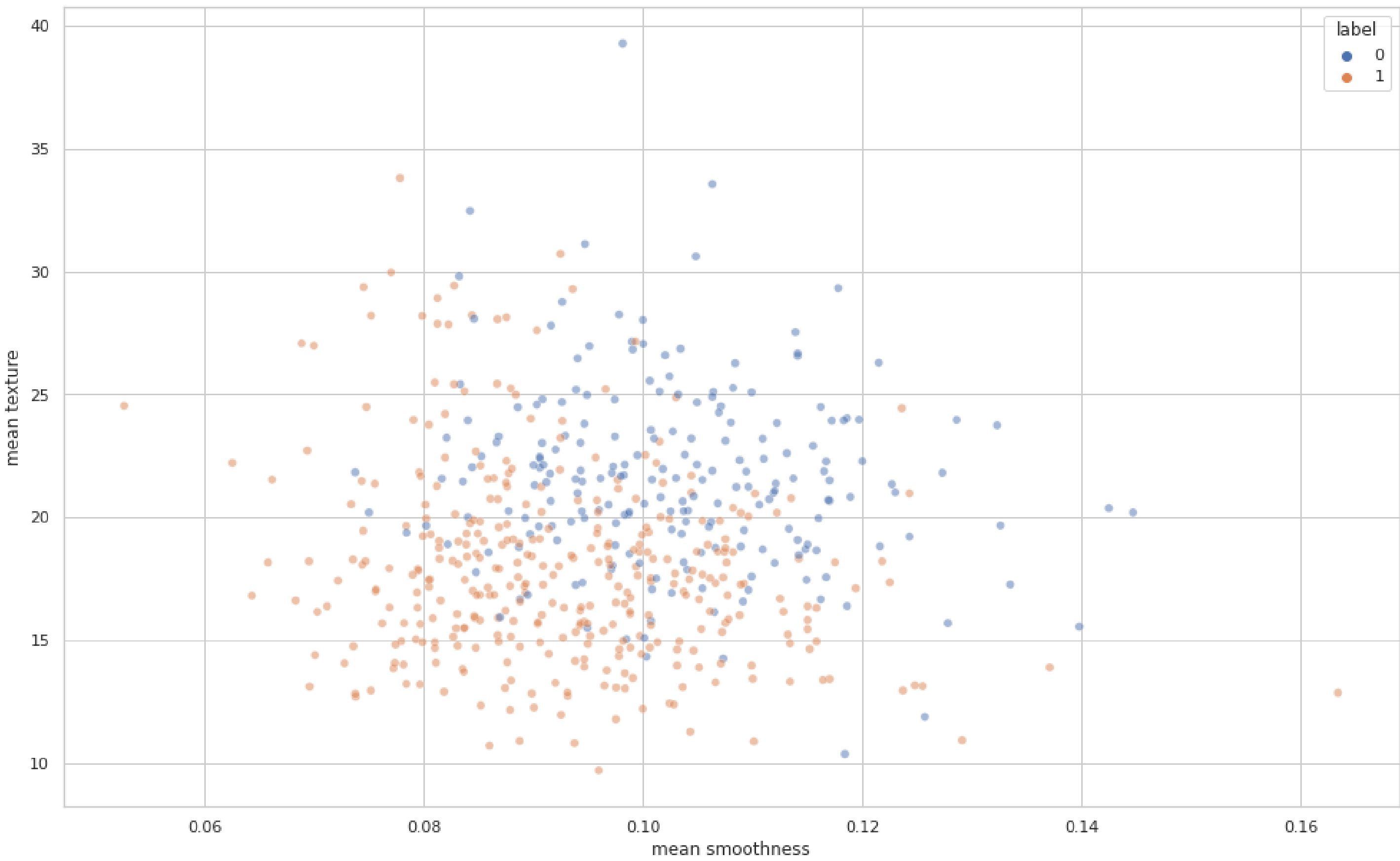
VISUALISATION BEFORE DIMENTIONALITY REDUCTION

In [6]:

```
sns.set(rc={'figure.figsize':(16.7,10.27)})
sns.set(style='whitegrid')
sns.scatterplot(x='mean smoothness', y='mean texture', data = breast_dataset, hue = 'label', alpha=0.5)
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8b844a07d0>
```

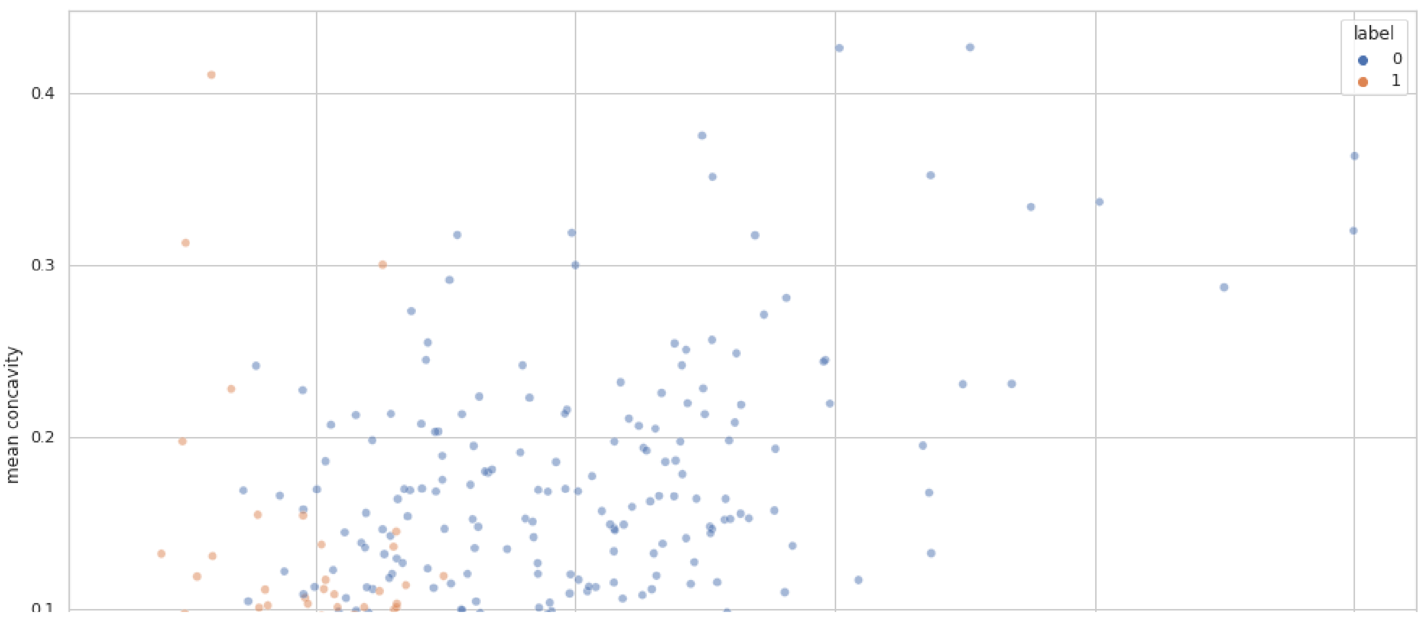


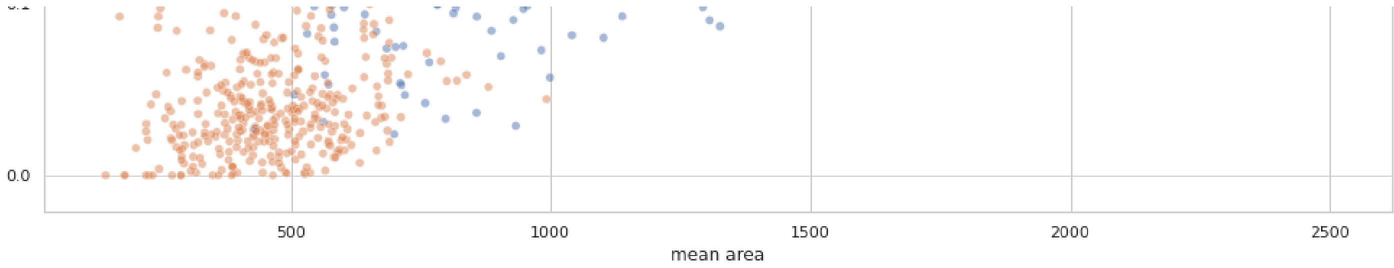
In [7]:

```
sns.set(rc={'figure.figsize':(16.7,10.27)})
sns.set(style='whitegrid')
sns.scatterplot(x='mean area', y='mean concavity', data = breast_dataset, hue = 'label',
alpha=0.5)
```

Out[7]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8b8158e710>
```





In [8]:

```
fig = px.scatter_3d(breast_dataset, x='mean area', y='mean concavity', z='mean texture',
color='label', title="3D Visualisation", opacity = 0.7, color_continuous_scale=px.colors
.sequential.Viridis)
fig.update_traces(marker=dict(size=6,))

fig.show(renderer = "colab")
```

USING PCA

1. Standardisation

In [9]:

```
from sklearn.preprocessing import StandardScaler
X_std = StandardScaler().fit_transform(X)
print("Mean: ",X_std.mean())
print("Standard Deviation: ",X_std.std())
```

```
Mean:  -6.826538293184326e-17
Standard Deviation:  1.0
```

2. Computing covariance matrix

2. Computing covariance matrix

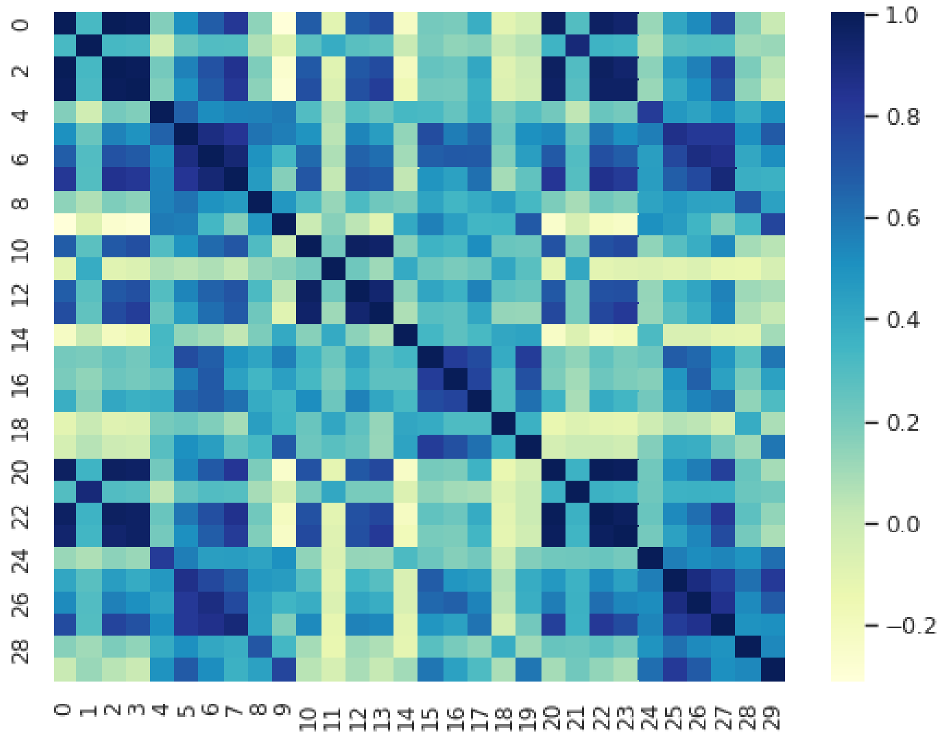
In [10]:

```
mean_vec = np.mean(X_std, axis=0) ## Computing feature wise means

cov_mat = 1/ (X_std.shape[0]-1) * (X_std - mean_vec).T.dot(X_std - mean_vec)

print('Covariance matrix first 5 rows and columns:\n', cov_mat[0:5, 0:5])
```

```
Covariance matrix first 5 rows and columns:
 [[ 1.00176056  0.32435193  0.99961207  0.98909547  0.17088151]
 [ 0.32435193  1.00176056  0.33011322  0.32165099 -0.02342969]
 [ 0.99961207  0.33011322  1.00176056  0.98824361  0.20764309]
 [ 0.98909547  0.32165099  0.98824361  1.00176056  0.17734005]
 [ 0.17088151 -0.02342969  0.20764309  0.17734005  1.00176056]]
```

In [11]:

```
from matplotlib.pyplot import figure
figure(figsize=(8, 6), dpi=80)
dataplot = sns.heatmap(cov_mat, cmap="YlGnBu")
plt.show()
```



In [12]:

```
cov_mat.shape
```

Out[12]:

```
(30, 30)
```

3. Calculating the eigenvectors and eigenvalues

Since the covariance matrix is square, we can calculate the eigenvectors and eigenvalues for this matrix.

In [13]:

```
eig_vals, eig_vecs = np.linalg.eig(cov_mat)
```

4. Computing the Principal Components

4. Computing the Principal Components

In [14]:

```
#Make a list of (eigenvalue, eigenvector) tuples
eig_pairs = []
for i in range(len(eig_vals)):
  eig_pairs.append( (np.abs(eig_vals[i]), eig_vecs[:,i]) )


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


# To visually confirm that the list is correctly sorted by decreasing eigenvalues
print('Top 10 Eigenvalues in descending order:')
for i in eig_pairs[:10]:
    print(i[0])
```

```
Top 10 Eigenvalues in descending order:
13.304990794374557
5.701374603726145
2.8229101550062268
1.984127517730196
1.6516332423301192
1.2094822398029743
0.6764088817009052
0.4774562546895081
0.417628782107817
0.3513108748817331
```

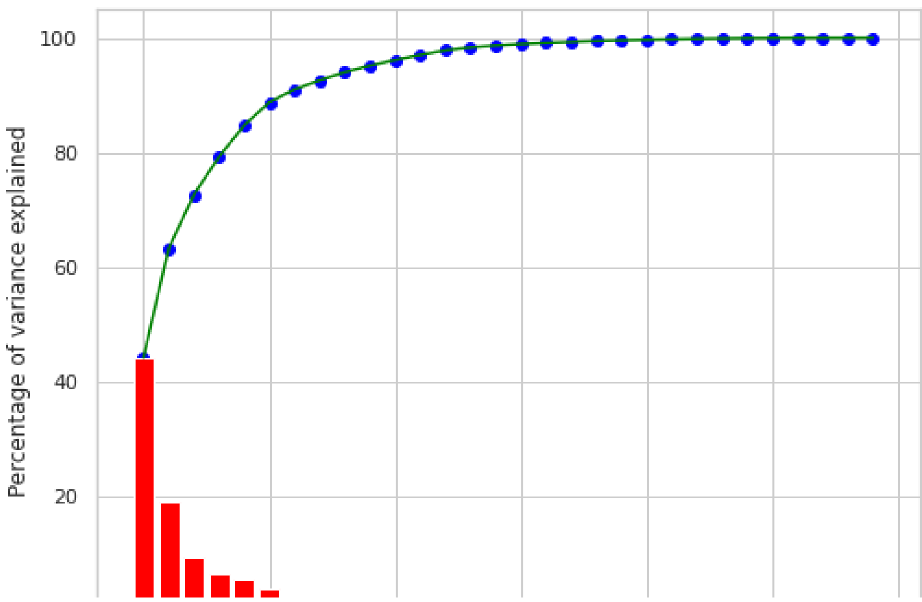
Plotting the variance explained and choosing the number of Principal components

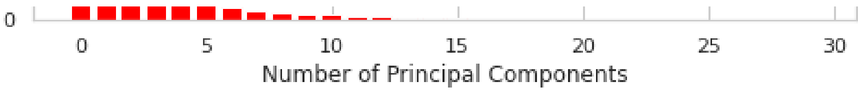
In [15]:

```
total = np.sum(eig_vals)
eig_val = 100 * eig_vals/total
eig_val = sorted(eig_val, reverse=True)


plt.figure(figsize = (8, 6))
plt.xlabel("Number of Principal Components")
plt.ylabel("Percentage of variance explained")
plt.bar(range(30), eig_val[:30], color = "red")
plt.plot(range(30), np.cumsum(eig_val[:30]), color = "green")
plt.scatter(range(30), np.cumsum(eig_val[:30]), color = "blue")
```

Out[15]:

```
<matplotlib.collections.PathCollection at 0x7f8b76276290>
```





5. Reducing the dimensions of the dataset

In [16]:

```
matrix_w = np.hstack((eig_pairs[0][1].reshape(30,1),
                      eig_pairs[1][1].reshape(30,1),
                      eig_pairs[2][1].reshape(30,1)))

Y_3PCs = X_std.dot(matrix_w)

print(Y_3PCs)
```

```
[[ 9.19283683  1.94858307 -1.12316616]
 [ 2.3878018  -3.76817174 -0.52929269]
 [ 5.73389628 -1.0751738  -0.55174759]
 ...
 [ 1.25617928 -1.90229671  0.56273053]
 [10.37479406  1.67201011 -1.87702933]
 [-5.4752433  -0.67063679  1.49044308]]
```

In [17]:

```
matrix_w = np.hstack((eig_pairs[0][1].reshape(30,1),
                      eig_pairs[1][1].reshape(30,1)))

Y_2PCs = X_std.dot(matrix_w)

print(Y_2PCs)
```

```
[[ 9.19283683  1.94858307]
 [ 2.3878018  -3.76817174]
 [ 5.73389628 -1.0751738 ]
 ...
 [ 1.25617928 -1.90229671]
 [10.37479406  1.67201011]
 [-5.4752433  -0.67063679]]
```

New datasets in 2 and 3 dimensions

In [18]:

```
final_df_2PCs = pd.DataFrame(columns=["PC1", "PC2", "Label"])

for i in range(len(Y_2PCs)):

    dicti = dict()

    dicti["PC1"] = Y_2PCs[i, 0]
    dicti["PC2"] = Y_2PCs[i, 1]
    if (int(breast_labels[i][0]) == 0):
      dicti["Label"] = "Benign"
    else:
      dicti["Label"] = "Malignant"

    final_df_2PCs = final_df_2PCs.append(dicti, ignore_index = True)

final_df_2PCs.head()
```

Out[18]:

	PC1	PC2	Label
0	9.192837	1.948583	Benign
1	2.387802	-3.768172	Benign
2	5.733896	-1.075174	Benign
3	7.122953	10.275589	Benign
4	3.935302	-1.948072	Benign

In [19]:

```
final_df_3PCs = pd.DataFrame(columns=["PC1", "PC2", "PC3","Label"])

for i in range(len(Y_3PCs)):

    dicti = dict()

    dicti["PC1"] = Y_3PCs[i, 0]
    dicti["PC2"] = Y_3PCs[i, 1]
    dicti["PC3"] = Y_3PCs[i, 1]
    if (int(breast_labels[i][0]) == 0):
      dicti["Label"] = "Benign"
    else:
      dicti["Label"] = "Malignant"

    final_df_3PCs = final_df_3PCs.append(dicti, ignore_index = True)

final_df_3PCs.head()
```

Out[19]:

	PC1	PC2	PC3	Label
0	9.192837	1.948583	1.948583	Benign
1	2.387802	-3.768172	-3.768172	Benign
2	5.733896	-1.075174	-1.075174	Benign
3	7.122953	10.275589	10.275589	Benign
4	3.935302	-1.948072	-1.948072	Benign

Visualisation

In [20]:

```
fig = px.scatter(final_df_2PCs, x='PC1', y='PC2', color='Label', title="Principal Compon
ent Axis")
fig.update_traces(marker=dict(size=6,))

fig.show(renderer = "colab")
```

In [21]:

```
fig = px.scatter_3d(final_df_3PCs, x='PC1', y='PC2', z='PC3', color='Label', title="Prin
cipal Component Axis")
fig.update_traces(marker=dict(size=6,))

fig.show(renderer = "colab")
```

USING SVD

1. Standardisation

In [22]:

```
from sklearn.preprocessing import StandardScaler
X_std = StandardScaler().fit_transform(X)
print("Mean: ",X_std.mean())
print("Standard Deviation: ",X_std.std())
```

```
Mean:  -6.826538293184326e-17
```

```
Mean:    6.820558295184520e-17
Standard Deviation:  1.0
```

In [23]:

```python
from numpy import array
from numpy import diag
from numpy import zeros
from scipy.linalg import svd
```

2. Calculating U, Sigma and V matrices

In [24]:

```python
def eigenvalue(A, v):
    val = A @ v / v
    return val[0]

def svd_dominant_eigen(A, epsilon=0.01):
    """returns dominant eigenvalue and dominant eigenvector of matrix A"""
    n, m = A.shape
    k=min(n,m)
    v = np.ones(k) / np.sqrt(k)
    if n > m:
        A = A.T @ A
    elif n < m:
        A = A @ A.T

    ev = eigenvalue(A, v)

    while True:
        Av = A@ v
        v_new = Av / np.linalg.norm(Av)
        ev_new = eigenvalue(A, v_new)
        if np.abs(ev - ev_new) < epsilon:
            break

        v = v_new
        ev = ev_new

    return ev_new, v_new

def svd(A, k=None, epsilon=1e-10):
    """returns k dominant eigenvalues and eigenvectors of matrix A"""
    A = np.array(A, dtype=float)
    n, m = A.shape

    svd_so_far = []
    if k is None:
      k = min(n, m)

    for i in range(k):
        matrix_for_1d = A.copy()

        for singular_value, u, v in svd_so_far[:i]:
            matrix_for_1d -= singular_value * np.outer(u, v)

        if n > m:
            _, v = svd_dominant_eigen(matrix_for_1d, epsilon=epsilon)  # next singular v
ector
            u_unnormalized = A @ v
            sigma = np.linalg.norm(u_unnormalized)  # next singular value
            u = u_unnormalized / sigma
        else:
            _, u = svd_dominant_eigen(matrix_for_1d, epsilon=epsilon)  # next singular v
ector
            v_unnormalized = A.T @ u
            sigma = np.linalg.norm(v_unnormalized)  # next singular value
```

```
            v = v_unnormalized / sigma

        svd_so_far.append((sigma, u, v))

    singular_values, us, vs = [np.array(x) for x in zip(*svd_so_far)]
    return singular_values, us.T, vs
```

In [25]:

```
s, u, v = svd(X_std)
```

3. Calculating the variance

In [26]:

```
var_explained = np.round(s**2/np.sum(s**2), decimals=3)
```

In [27]:

```
var_explained
```

Out[27]:

```
array([0.443, 0.19 , 0.094, 0.066, 0.055, 0.04 , 0.023, 0.016, 0.014,
       0.012, 0.01 , 0.009, 0.008, 0.005, 0.003, 0.003, 0.002, 0.002,
       0.002, 0.001, 0.001, 0.001, 0.001, 0.001, 0.001, 0.   , 0.   ,
       0.   , 0.   , 0.   ])
```

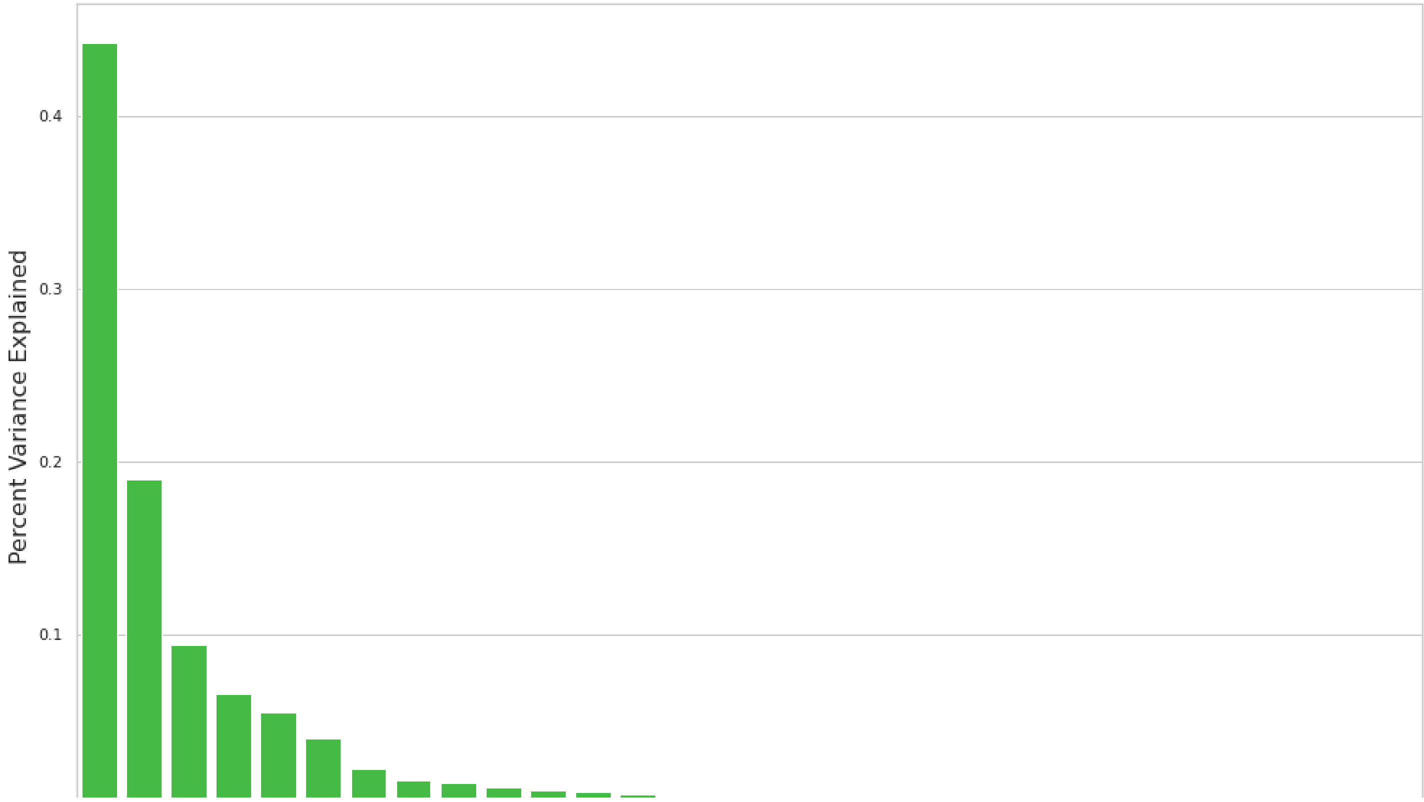
Reducing our dataset to 2 dimensions would preserve 63% of the variance and reducing it to 3 dimensions would preserve 72% of the variance

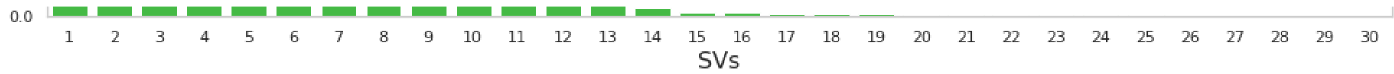
In [28]:

```
sns.barplot(x=list(range(1,len(var_explained)+1)),
            y=var_explained, color="limegreen")
plt.xlabel('SVs', fontsize=16)
plt.ylabel('Percent Variance Explained', fontsize=16)
```

Out[28]:

```
Text(0, 0.5, 'Percent Variance Explained')
```





Reducing dimensions of the dataset - New dataset in 2 and 3 dimensions

New dataset in 2 dimensions

In [29]:

```
final_df_2SVs = pd.DataFrame(columns=["SV1", "SV2", "Label"])

for i in range(len(u)):

    dicti = dict()

    dicti["SV1"] = u[i, 0]
    dicti["SV2"] = u[i, 1]
    if (int(breast_labels[i][0]) == 0):
      dicti["Label"] = "Benign"
    else:
      dicti["Label"] = "Malignant"

    final_df_2SVs = final_df_2SVs.append(dicti, ignore_index = True)

final_df_2SVs.head()
```

Out[29]:

	SV1	SV2	Label
0	0.105747	0.034242	Benign
1	0.027467	-0.066217	Benign
2	0.065958	-0.018894	Benign
3	0.081937	0.180569	Benign
4	0.045269	-0.034233	Benign

In [30]:

```
final_df_2SVs.shape
```

Out[30]:

```
(569, 3)
```

In [31]:

```
fig = px.scatter(final_df_2SVs, x='SV2', y='SV1', color='Label', title="Singular Value D
ecomposition")
fig.update_traces(marker=dict(size=6,))

fig.show(renderer = "colab")
```

New Dataset in 3 dimensions

In [32]:

```
final_df_3SVs = pd.DataFrame(columns=["SV1", "SV2", "SV3", "Label"])

for i in range(len(u)):

    dicti = dict()

    dicti["SV1"] = u[i, 0]
    dicti["SV2"] = u[i, 1]
    dicti["SV3"] = u[i, 2]
    if (int(breast_labels[i][0]) == 0):
      dicti["Label"] = "Benign"
    else:
      dicti["Label"] = "Malignant"

    final_df_3SVs = final_df_3SVs.append(dicti, ignore_index = True)

final_df_3SVs.head()
```

Out[32]:

	SV1	SV2	SV3	Label
0	0.105747	0.034242	-0.028049	Benign
1	0.027467	-0.066217	-0.013218	Benign
2	0.065958	-0.018894	-0.013779	Benign
3	0.081937	0.180569	-0.080734	Benign
4	0.045269	-0.034233	0.034707	Benign

In [33]:

```
fig = px.scatter_3d(final_df_3SVs, x='SV1', y='SV2', z='SV3', color='Label')
fig.update_traces(marker=dict(size=6,))

fig.show(renderer = "colab")
```