1. Dimensionality Reduction

1. Principal Component Analysis (PCA)

Load Required Libraries

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from IPython.display import display_html
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Configure visual display properties
sns.set_theme(style="whitegrid")
sns.set(rc={'figure.figsize':(20,10)})
```

Load data

In [3]:
```
iris_df=pd.read_csv('iris.csv')
iris_df.head()
```

Out[3]:

	sepal_length	sepal_width	petal_length	petal_width	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

Standarddize data first

PCA requires us to standardize the data first to a unit scale with mean 0 and variance 1

In [4]:
```
features=iris_df[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']] # features
y=iris_df['class'] #target

X=StandardScaler().fit_transform(features) # scale the data
X_scaled=pd.DataFrame(X, columns=['sepal_length', 'sepal_width', 'petal_length', 'petal_width']) # create dataframe of scaled data
scaled_df=pd.concat([X_scaled,y],axis=1) # join scaled dataframe with target variable

# Display the two dataframes side by side
iris_df = iris_df.head().style.set_table_attributes("style='display:inline'").set_caption('Original DataFrame')
scaled_df = scaled_df.head().style.set_table_attributes("style='display:inline'").set_caption('Scaled DtaFrame')

display_html(iris_df._repr_html_()+"     "+scaled_df._repr_html_(), raw=True)
```

Original DataFrame

	sepal_length	sepal_width	petal_length	petal_width	class
0	5.100000	3.500000	1.400000	0.200000	Iris-setosa
1	4.900000	3.000000	1.400000	0.200000	Iris-setosa
2	4.700000	3.200000	1.300000	0.200000	Iris-setosa
3	4.600000	3.100000	1.500000	0.200000	Iris-setosa
4	5.000000	3.600000	1.400000	0.200000	Iris-setosa

Scaled DtaFrame

	sepal_length	sepal_width	petal_length	petal_width	class
0	-0.900681	1.032057	-1.341272	-1.312977	Iris-setosa
1	-1.143017	-0.124958	-1.341272	-1.312977	Iris-setosa
2	-1.385353	0.337848	-1.398138	-1.312977	Iris-setosa
3	-1.506521	0.106445	-1.284407	-1.312977	Iris-setosa
4	-1.021849	1.263460	-1.341272	-1.312977	Iris-setosa

Perform PCA with 2 components

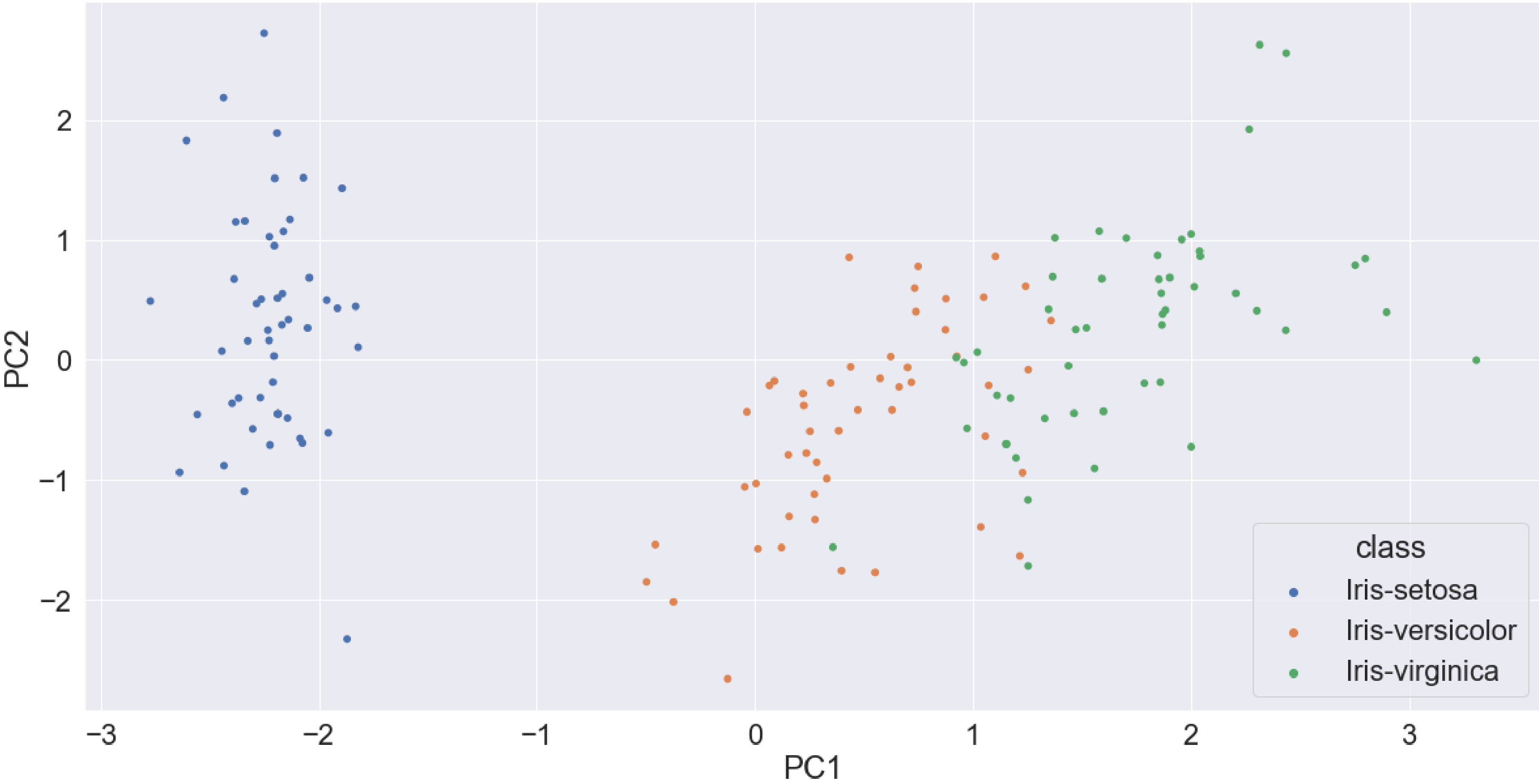
In [5]:
```
pca=PCA(n_components=2)
pca_fit=pca.fit_transform(X_scaled) # fit and transform data with 2 Components
pca_df=pd.DataFrame(pca_fit,columns=['PC1','PC2']) # Create PCA dataframe
pca_df=pd.concat([pca_df,y],axis=1) # join pca dataframe with target variable
pca_df.head()
```

Out[5]:

	PC1	PC2	class
0	-2.264542	0.505704	Iris-setosa
1	-2.086426	-0.655405	Iris-setosa
2	-2.367950	-0.318477	Iris-setosa
3	-2.304197	-0.575368	Iris-setosa
4	-2.388777	0.674767	Iris-setosa

Visualize PCA

In [6]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
sns.scatterplot(x="PC1", y="PC2", sizes=(1, 8), linewidth=0,data=pca_df,hue='class')
plt.show()
```



Explained Variance

Explained Variance tells us the variation in each principal component and how much information we have lost when reducing the dimensionality of the data from high-space (4 features) to low-space (2 features). Variance for teh first and second principal components

In [7]:
```
(pca.explained_variance_ratio_)*100
```
Out[7]:
```
array([72.77045209, 23.03052327])
```

Total variance after dimensionality reduction

In [8]:
```
sum(pca.explained_variance_ratio_)*100
```
Out[8]:
```
95.80097536148199
```

2. Independent Component Analysis

In [9]:
```
from sklearn.decomposition import FastICA
```

In [10]:
```
ica=FastICA(n_components=2,random_state=0)
ica_fit=ica.fit_transform(X_scaled)
ica_df=pd.DataFrame(ica_fit,columns=['IC1','IC2'])
ica_df=pd.concat([ica_df,y],axis=1)
ica_df.head()
```
Out[10]:

	IC1	IC2	class
0	0.106742	-0.046924	Iris-setosa
1	0.101808	0.052094	Iris-setosa
2	0.114232	0.022962	Iris-setosa
3	0.111976	0.044912	Iris-setosa
4	0.112162	-0.061513	Iris-setosa

Visualize Independet Component Analysis

In [11]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
sns.scatterplot(x="IC1", y="IC2", sizes=(1, 8), linewidth=0,data=ica_df,hue='class')
plt.show()
```

3. Random Forest

Get feature importance with RandomForest

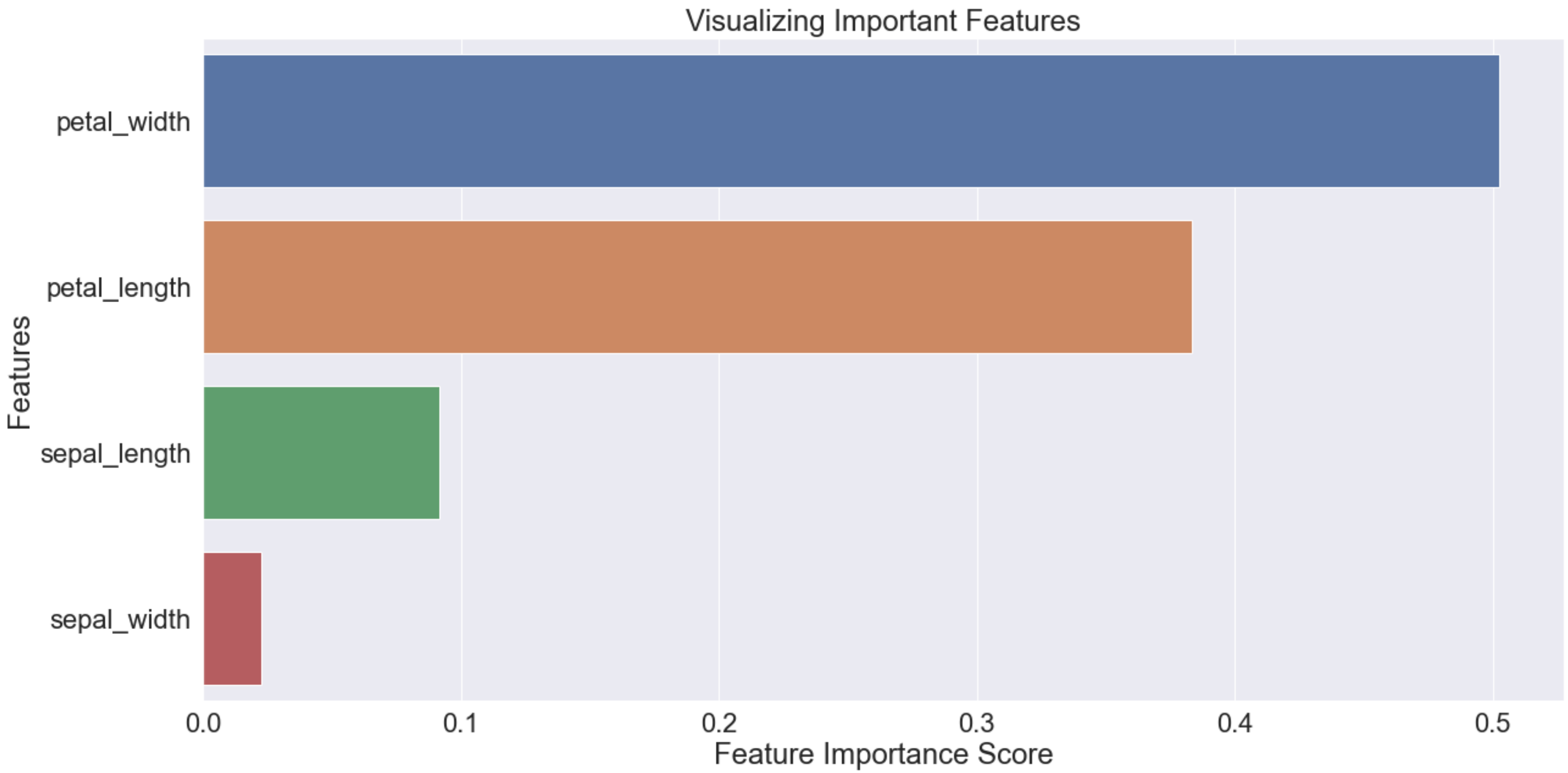
In [12]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [13]:
```
rf_clf=RandomForestClassifier(n_estimators=100)
rf_clf.fit(X_scaled,y) # train the model

feature_imp = pd.Series(rf_clf.feature_importances_,index=X_scaled.columns).sort_values(ascending=False)
feature_imp
```

Out[13]:
```
petal_width     0.502619
petal_length    0.383139
sepal_length    0.091559
sepal_width     0.022683
dtype: float64
```

Visualize Feature Importance

In [14]:
```
sns.barplot(y=feature_imp.index, x=feature_imp)
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.show()
```



4. Factor Analysis

In [15]:
```
from sklearn.decomposition import FactorAnalysis
```

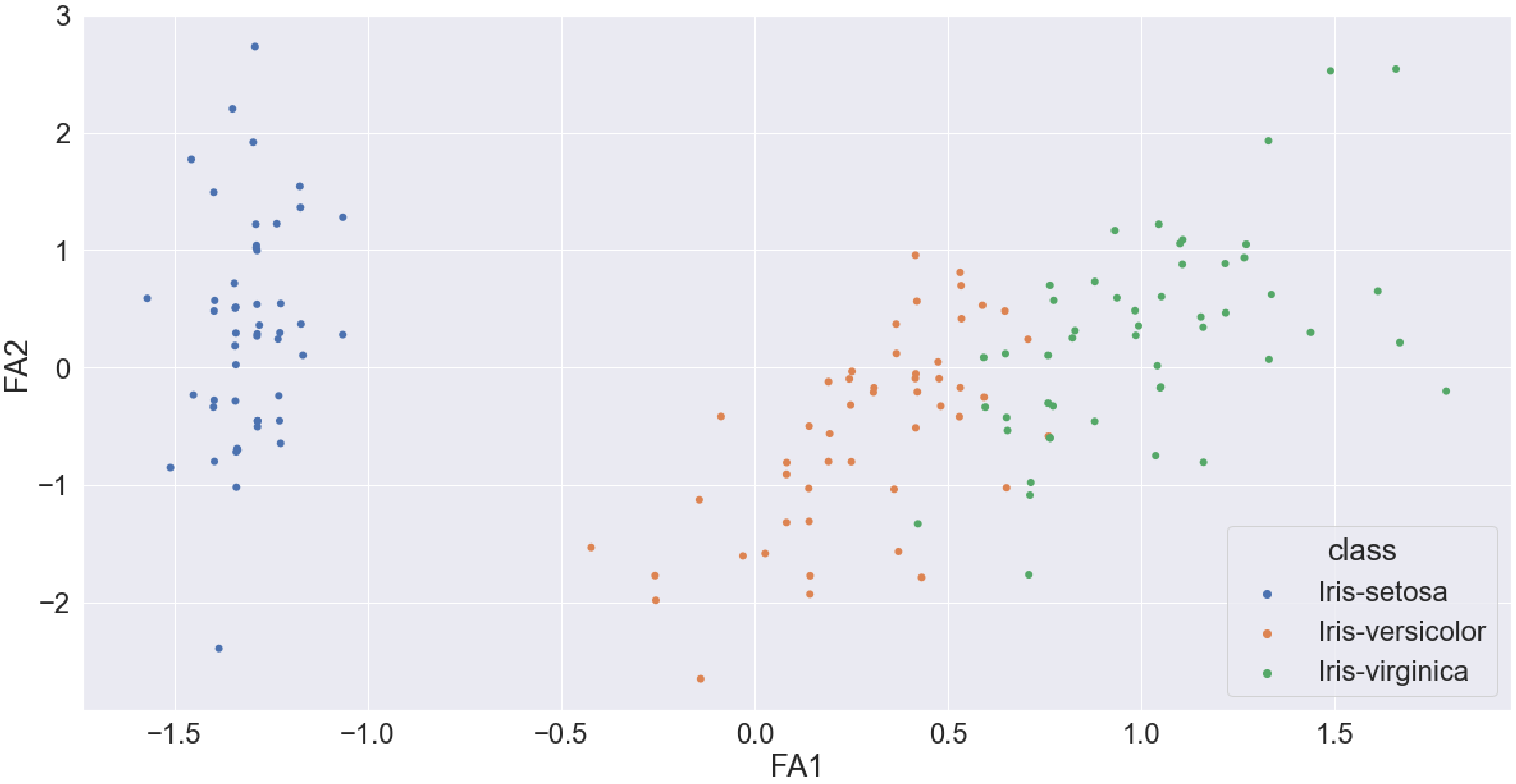
In [16]:
```
fa=FactorAnalysis(n_components=2,random_state=0)
fa_transform=fa.fit_transform(X_scaled)
fa_df=pd.DataFrame(fa_transform,columns=['FA1','FA2'])
fa_df=pd.concat([fa_df,y],axis=1)
fa_df.head()
```

Out[16]:

	FA1	FA2	class
0	-1.342095	0.505984	Iris-setosa
1	-1.336775	-0.689392	Iris-setosa
2	-1.396478	-0.278447	Iris-setosa
3	-1.284444	-0.503736	Iris-setosa
4	-1.344103	0.717821	Iris-setosa

Visualize Factor Analysis output

In [17]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
sns.scatterplot(x="FA1", y="FA2", sizes=(1, 8), linewidth=0,data=fa_df,hue='class')
plt.show()
```



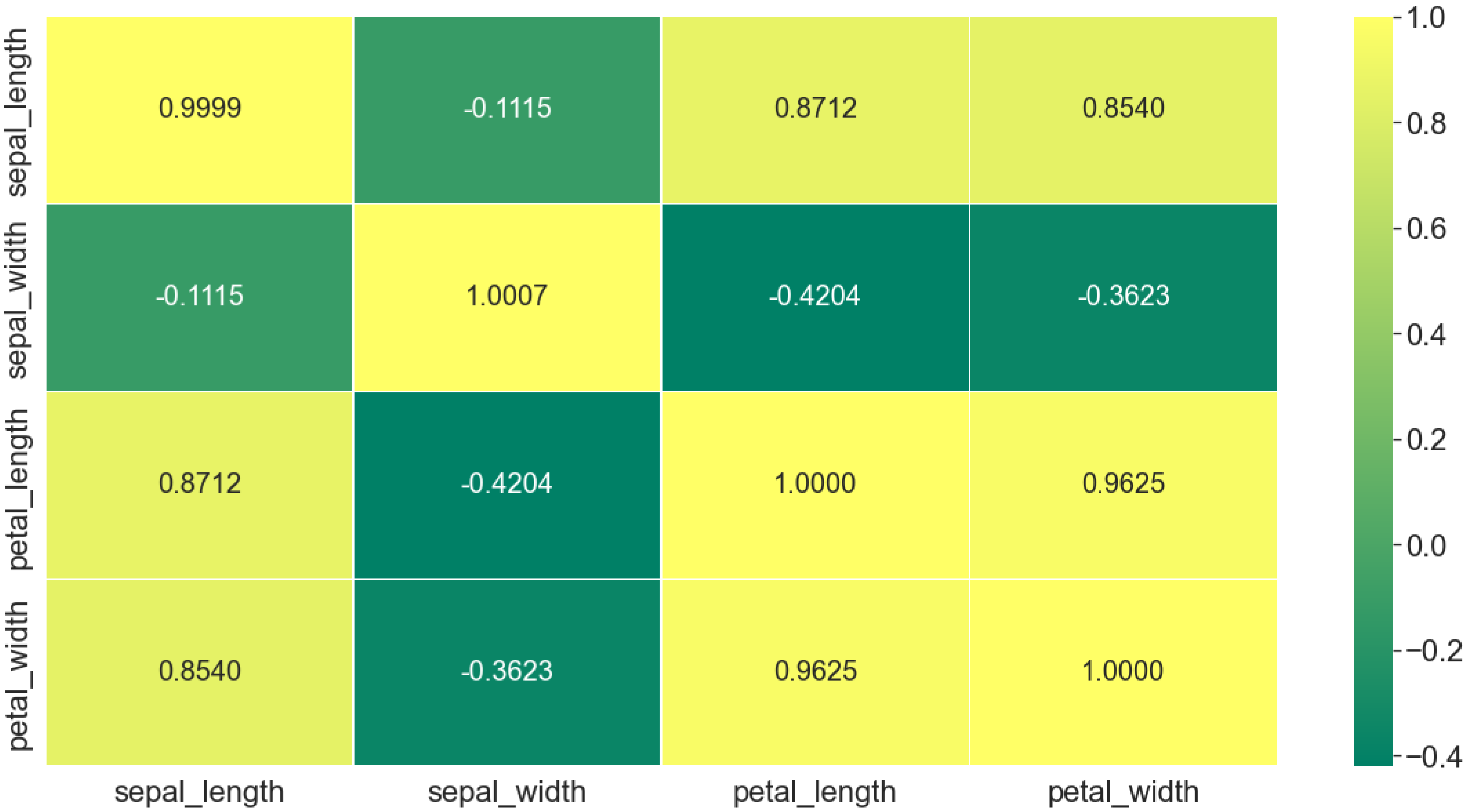
Compute Features Covariance

In [18]:
```
fa_cov=pd.DataFrame(fa.get_covariance(),columns=X_scaled.columns,index=X_scaled.columns)
fa_cov
```

Out[18]:

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	0.999936	-0.111460	0.871248	0.853953
sepal_width	-0.111460	1.000667	-0.420422	-0.362274
petal_length	0.871248	-0.420422	1.000007	0.962519
petal_width	0.853953	-0.362274	0.962519	1.000002

In [19]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
plt.rcParams['text.color'] = 'blue'
plt.rcParams['font.size'] = 20
sns.heatmap(fa_cov, annot=True, fmt=".4f", linewidths=.5,cmap='summer')
plt.show()
```



5. Low Variance filter

In [20]:
```
from sklearn.feature_selection import VarianceThreshold
```

In [21]:
```
threshold_value=0.5
vt=VarianceThreshold(threshold=threshold_value)
vt_fit=vt.fit_transform(features)
```

Get variances for each feature

In [22]:
```
print(vt.variances_) # actual variance values
print(vt.get_support()) # True has high variance False has low variance than the threshold
```

```
[0.68112222 0.18675067 3.09242489 0.57853156]
[ True False  True  True]
```

Get columns with low variance based on 0.05 threshold i.e value with similarity of 50%

In [23]:
```
low_var_=[column for column in features.columns if column not in features.columns[vt.get_support()]]
low_var_
```

Out[23]:
```
['sepal_width']
```

In [24]:
```
remove_low_vars_=features.drop(low_var_,axis=1)

# Drop features with variance less than 50%
iris_df = features.head().style.set_table_attributes("style='display:inline'").set_caption('Original Data')
low_vars_df_ = remove_low_vars_.head().style.set_table_attributes("style='display:inline'").set_caption('After Removin
g Low Variance Features')

display_html(iris_df._repr_html_()+"     "+low_vars_df_._repr_html_(), raw=True)
```

Original Data

	sepal_length	sepal_width	petal_length	petal_width
0	5.100000	3.500000	1.400000	0.200000
1	4.900000	3.000000	1.400000	0.200000
2	4.700000	3.200000	1.300000	0.200000
3	4.600000	3.100000	1.500000	0.200000
4	5.000000	3.600000	1.400000	0.200000

After Removing Low Variance Features

	sepal_length	petal_length	petal_width
0	5.100000	1.400000	0.200000
1	4.900000	1.400000	0.200000
2	4.700000	1.300000	0.200000
3	4.600000	1.500000	0.200000
4	5.000000	1.400000	0.200000

Option 2 Get features with variance < 50%

In [25]:
```
variance=features.var()
variance
```

Out[25]:
```
sepal_length    0.685694
sepal_width     0.188004
petal_length    3.113179
petal_width     0.582414
dtype: float64
```

In [26]:
```python
low_var_features = [ ]

for i in range(0,len(variance)):
    if variance[i]<=0.50:
        low_var_features.append(features.columns[i])

low_var_features
```

Out[26]: ['sepal_width']

In [27]:
```python
remove_low_var_features=features.drop(low_var_features,axis=1)
remove_low_var_features.head()
```

Out[27]:

	sepal_length	petal_length	petal_width
0	5.1	1.4	0.2
1	4.9	1.4	0.2
2	4.7	1.3	0.2
3	4.6	1.5	0.2
4	5.0	1.4	0.2

In [28]:
```
# Drop features with variance less than 50%
iris_df = features.head().style.set_table_attributes("style='display:inline'").set_caption('Original Data')
low_var_features_df = remove_low_var_features.head().style.set_table_attributes("style='display:inline'").set_caption(
'After Removing Low Variance Features')

display_html(iris_df._repr_html_()+"     "+low_var_features_df._repr_html_(), raw=True)
```

Original Data

	sepal_length	sepal_width	petal_length	petal_width
0	5.100000	3.500000	1.400000	0.200000
1	4.900000	3.000000	1.400000	0.200000
2	4.700000	3.200000	1.300000	0.200000
3	4.600000	3.100000	1.500000	0.200000
4	5.000000	3.600000	1.400000	0.200000

After Removing Low Variance Features

	sepal_length	petal_length	petal_width
0	5.100000	1.400000	0.200000
1	4.900000	1.400000	0.200000
2	4.700000	1.300000	0.200000
3	4.600000	1.500000	0.200000
4	5.000000	1.400000	0.200000

6. High Correlation Filter

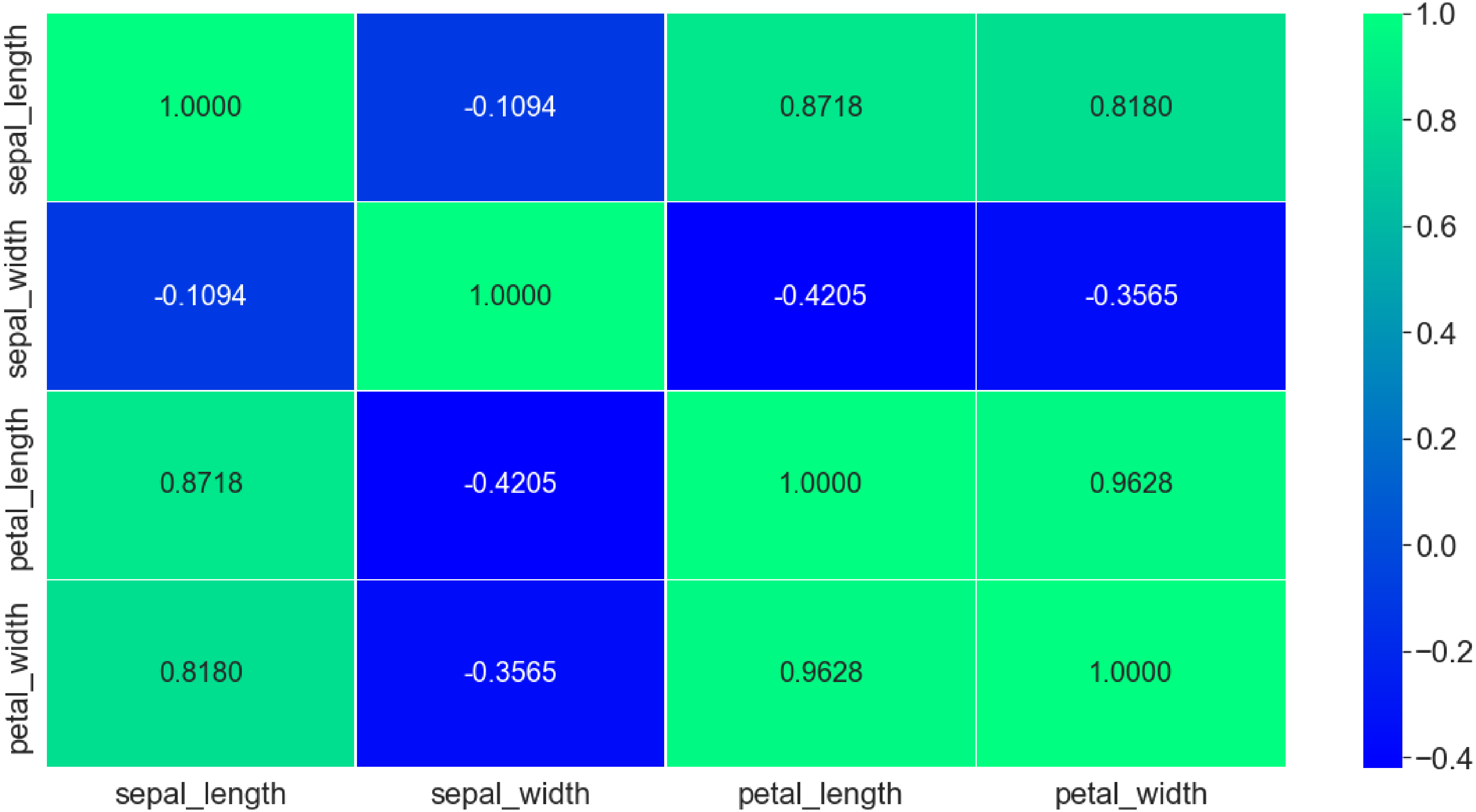
Get the correlation matrix first

In [29]:
```
cor_matrix=features.corr()
cor_matrix
```

Out[29]:

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.109369	0.871754	0.817954
sepal_width	-0.109369	1.000000	-0.420516	-0.356544
petal_length	0.871754	-0.420516	1.000000	0.962757
petal_width	0.817954	-0.356544	0.962757	1.000000

In [30]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
plt.rcParams['text.color'] = 'blue'
plt.rcParams['font.size'] = 20
sns.heatmap(cor_matrix, annot=True, fmt=".4f", linewidths=.5,cmap='winter')
plt.show()
```



Remove correlated features that are duplicates

In [31]:
```
cor_matrix.unstack().sort_values()
```

Out[31]:
```
sepal_width   petal_length   -0.420516
petal_length  sepal_width    -0.420516
sepal_width   petal_width    -0.356544
petal_width   sepal_width    -0.356544
sepal_length  sepal_width    -0.109369
sepal_width   sepal_length   -0.109369
sepal_length  petal_width     0.817954
petal_width   sepal_length    0.817954
sepal_length  petal_length    0.871754
petal_length  sepal_length    0.871754
              petal_width     0.962757
petal_width   petal_length    0.962757
sepal_length  sepal_length    1.000000
sepal_width   sepal_width     1.000000
petal_length  petal_length    1.000000
petal_width   petal_width     1.000000
dtype: float64
```

In [32]:
```
cor_matrix.unstack().sort_values().drop_duplicates() # drop duplicates features
```

Out[32]:
```
sepal_width   petal_length   -0.420516
              petal_width    -0.356544
sepal_length  sepal_width    -0.109369
              petal_width     0.817954
              petal_length    0.871754
petal_length  petal_width     0.962757
sepal_length  sepal_length    1.000000
dtype: float64
```

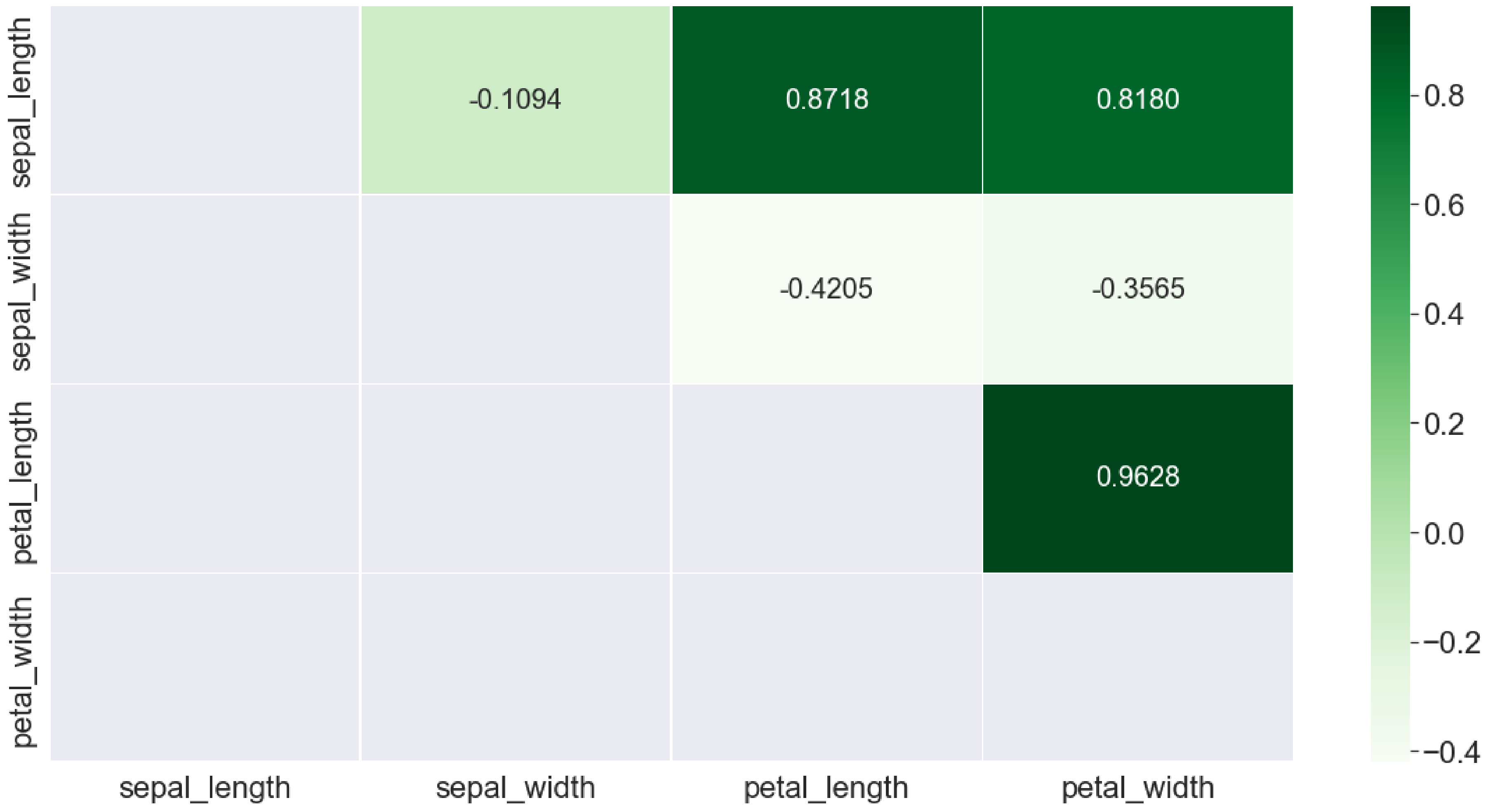
Remove correlated features based on defined correlation threshold

In [33]:
```
# Create an upper triangle matrix with np.triu
upper_triangle_martix = cor_matrix.where(np.triu(np.ones(cor_matrix.shape),k=1).astype(np.bool))
upper_triangle_martix
```

Out[33]:

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	NaN	-0.109369	0.871754	0.817954
sepal_width	NaN	NaN	-0.420516	-0.356544
petal_length	NaN	NaN	NaN	0.962757
petal_width	NaN	NaN	NaN	NaN

In [34]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
plt.rcParams['font.size'] = 20
sns.heatmap(upper_triangle_martix, annot=True, fmt=".4f", linewidths=.5,cmap='Greens')
plt.show()
```



In [35]:
```
correlated_features=[column for column in upper_triangle_martix.columns if any(upper_triangle_martix[column] > 0.90)]
correlated_features
```

Out[35]:
```
['petal_width']
```

In [36]:
```
remove_correlated_features=features.drop(correlated_features,axis=1)
remove_correlated_features.head()
```

Out[36]:

	sepal_length	sepal_width	petal_length
0	5.1	3.5	1.4
1	4.9	3.0	1.4
2	4.7	3.2	1.3
3	4.6	3.1	1.5
4	5.0	3.6	1.4

In [37]:
```
# Display the two dataframes side by side
iris_df = features.head().style.set_table_attributes("style='display:inline'").set_caption('Original Data')
uncorrelated_df = remove_correlated_features.head().style.set_table_attributes("style='display:inline'").set_caption(
'After Removing Correlated Features')

display_html(iris_df._repr_html_()+"     "+uncorrelated_df._repr_html_(), raw=True)
```

Original Data

	sepal_length	sepal_width	petal_length	petal_width
0	5.100000	3.500000	1.400000	0.200000
1	4.900000	3.000000	1.400000	0.200000
2	4.700000	3.200000	1.300000	0.200000
3	4.600000	3.100000	1.500000	0.200000
4	5.000000	3.600000	1.400000	0.200000

After Removing Correlated Features

	sepal_length	sepal_width	petal_length
0	5.100000	3.500000	1.400000
1	4.900000	3.000000	1.400000
2	4.700000	3.200000	1.300000
3	4.600000	3.100000	1.500000
4	5.000000	3.600000	1.400000

7. t-Distributed Stochastic Neighbor Embedding (t-SNE)

In [38]:
```
from sklearn.manifold import TSNE
```

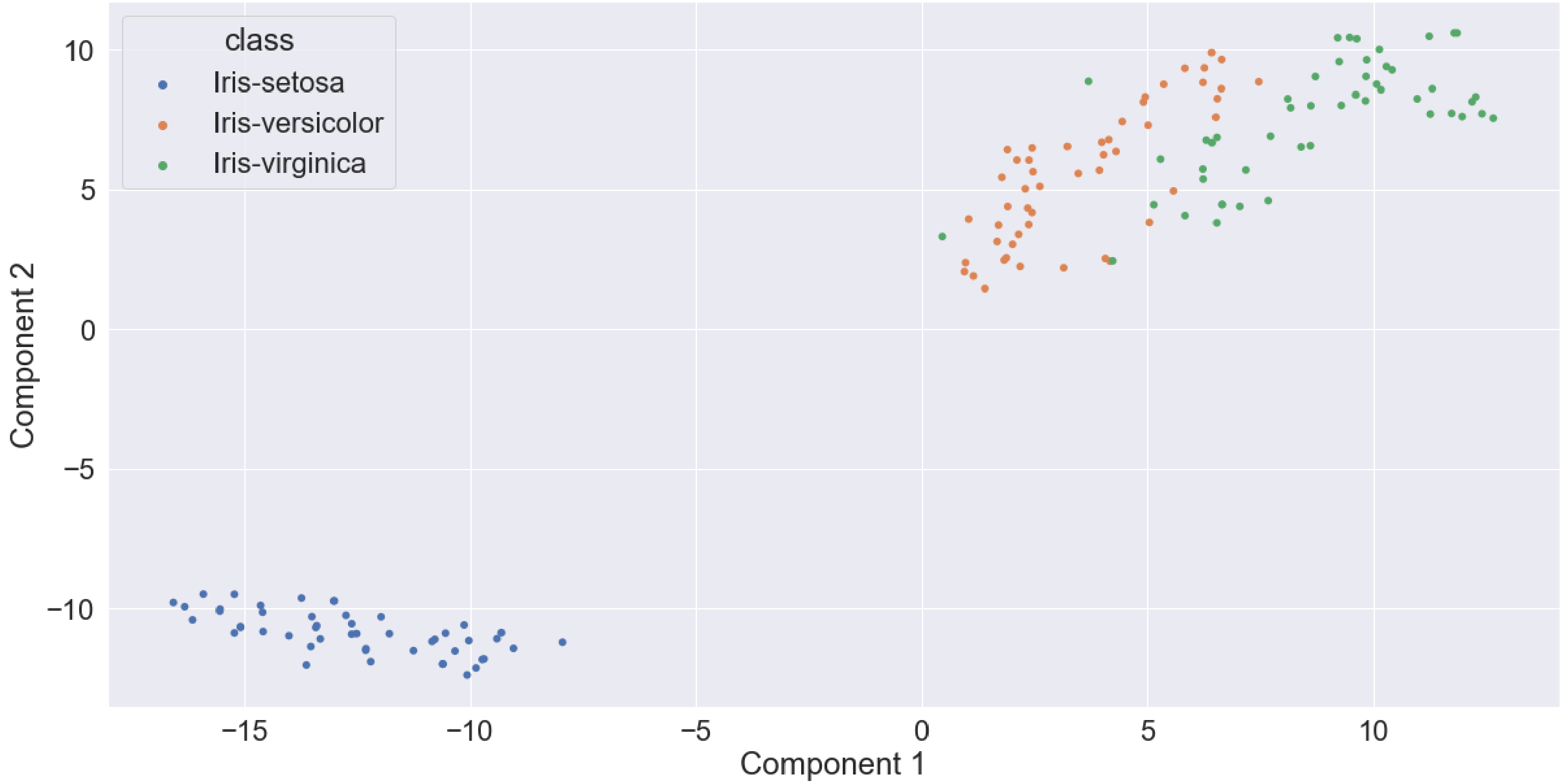
In [39]:
```
tsne=TSNE(n_components=2,init='random',random_state=0)
tsne_fit=tsne.fit_transform(X_scaled)
tsne_df=pd.DataFrame(tsne_fit,columns=['Component 1','Component 2'])
tsne_df=pd.concat([tsne_df,y],axis=1)
tsne_df.head()
```

Out[39]:

	Component 1	Component 2	class
0	-13.393528	-10.616657	Iris-setosa
1	-9.864830	-12.134668	Iris-setosa
2	-10.778847	-11.105656	Iris-setosa
3	-10.024701	-11.151320	Iris-setosa
4	-14.010548	-10.978813	Iris-setosa

Visualize tsne

In [40]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
sns.scatterplot(x="Component 1", y="Component 2", sizes=(1, 8), linewidth=0,data=tsne_df,hue='class')
plt.show()
```



2. Feature Selection

1. Univariate Feature Selection

i. Univariate Feature Selection using SelectKBest
We use chi2 as our score function because the input features are non-negative and the output is categorical. For categorical output variable we use f_classif scoring function. For numerical output variable we use r_regression scoring function.

In [41]:
```
from sklearn.feature_selection import SelectKBest,chi2
```

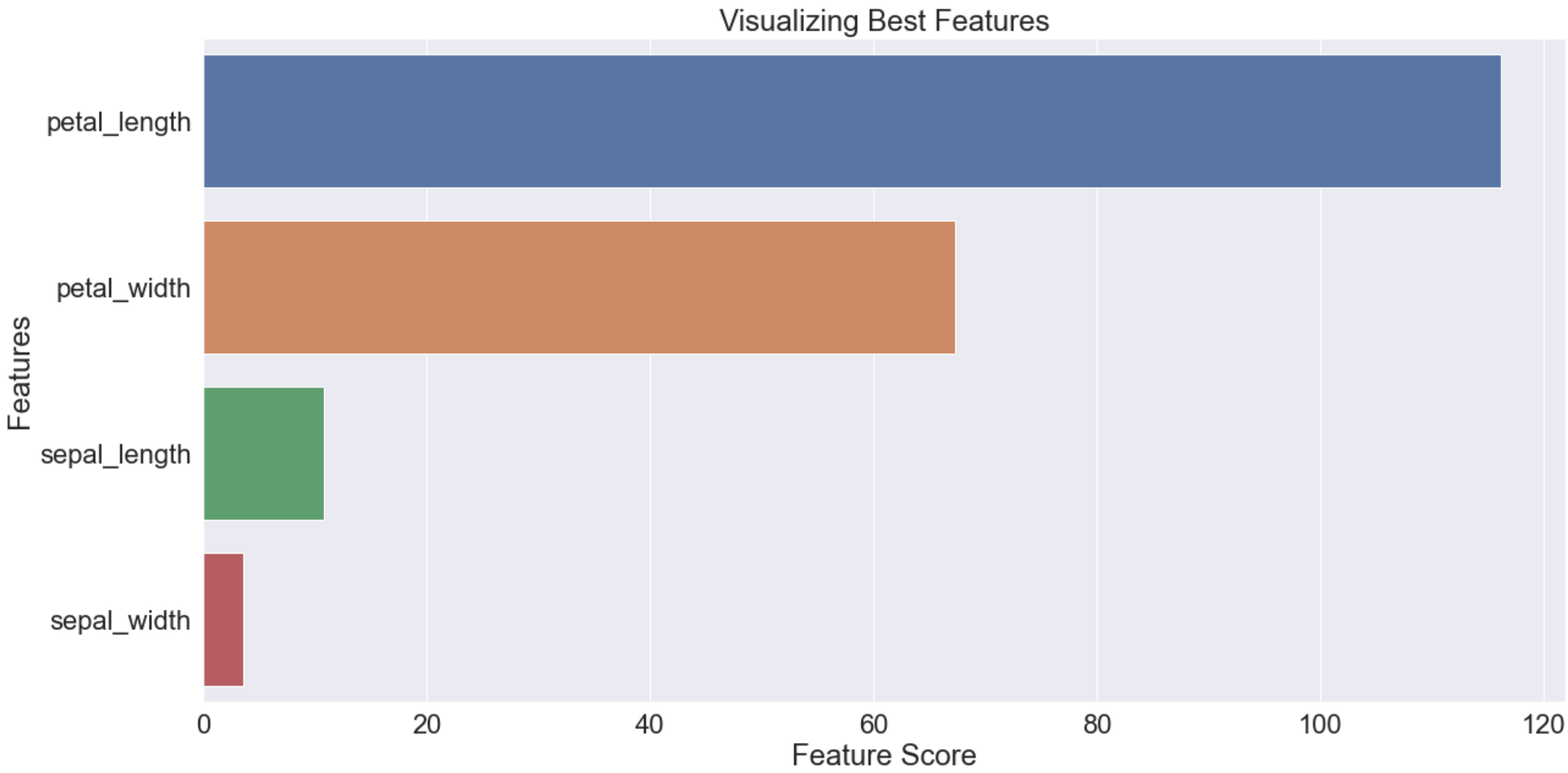
In [52]:
```
select_k_best=SelectKBest(chi2,k=3)
select_k_best_fit=select_k_best.fit(features,y)
k_best=pd.DataFrame(select_k_best_fit.scores_,columns=['Score'],index=features.columns).sort_values(by='Score',ascendi
ng=False)
k_best
```

Out[52]:

	Score
petal_length	116.169847
petal_width	67.244828
sepal_length	10.817821
sepal_width	3.594499

Visualize k best features

In [54]:
```
sns.barplot(y=k_best.index, x=k_best.Score)
plt.xlabel('Feature Score')
plt.ylabel('Features')
plt.title("Visualizing Best Features")
plt.show()
```



Select 3 best features

In [43]:
```
print(k_best.nlargest(3,'Score'))
```

```
petal_length    116.169847
petal_width      67.244828
sepal_length     10.817821
dtype: float64
```

ii. Univariate Feature Selection using SelectPercentile

We use chi2 as our score function because the input features are non-negative and the output is categorical. For categorical output variable we use f_classif scoring function. For numerical output variable we use r_regression scoring function.

In [44]:
```
from sklearn.feature_selection import SelectPercentile, chi2
```

In [48]:
```
select_p_best=SelectPercentile(chi2,percentile=10)
select_p_best_fit=select_p_best.fit(features,y)
p_best=pd.DataFrame(select_p_best_fit.scores_,columns=['Score'],index=features.columns).sort_values(by='Score',ascendi
ng=False)
p_best
```

Out[48]:

	Score
petal_length	116.169847
petal_width	67.244828
sepal_length	10.817821
sepal_width	3.594499

Select best 3 features

In [55]:
```
print(p_best['Score'].nlargest(3))
```

```
petal_length    116.169847
petal_width      67.244828
sepal_length     10.817821
Name: Score, dtype: float64
```

2. Feature importance with Random Forest

In [56]:
```
from sklearn.ensemble import RandomForestClassifier
```

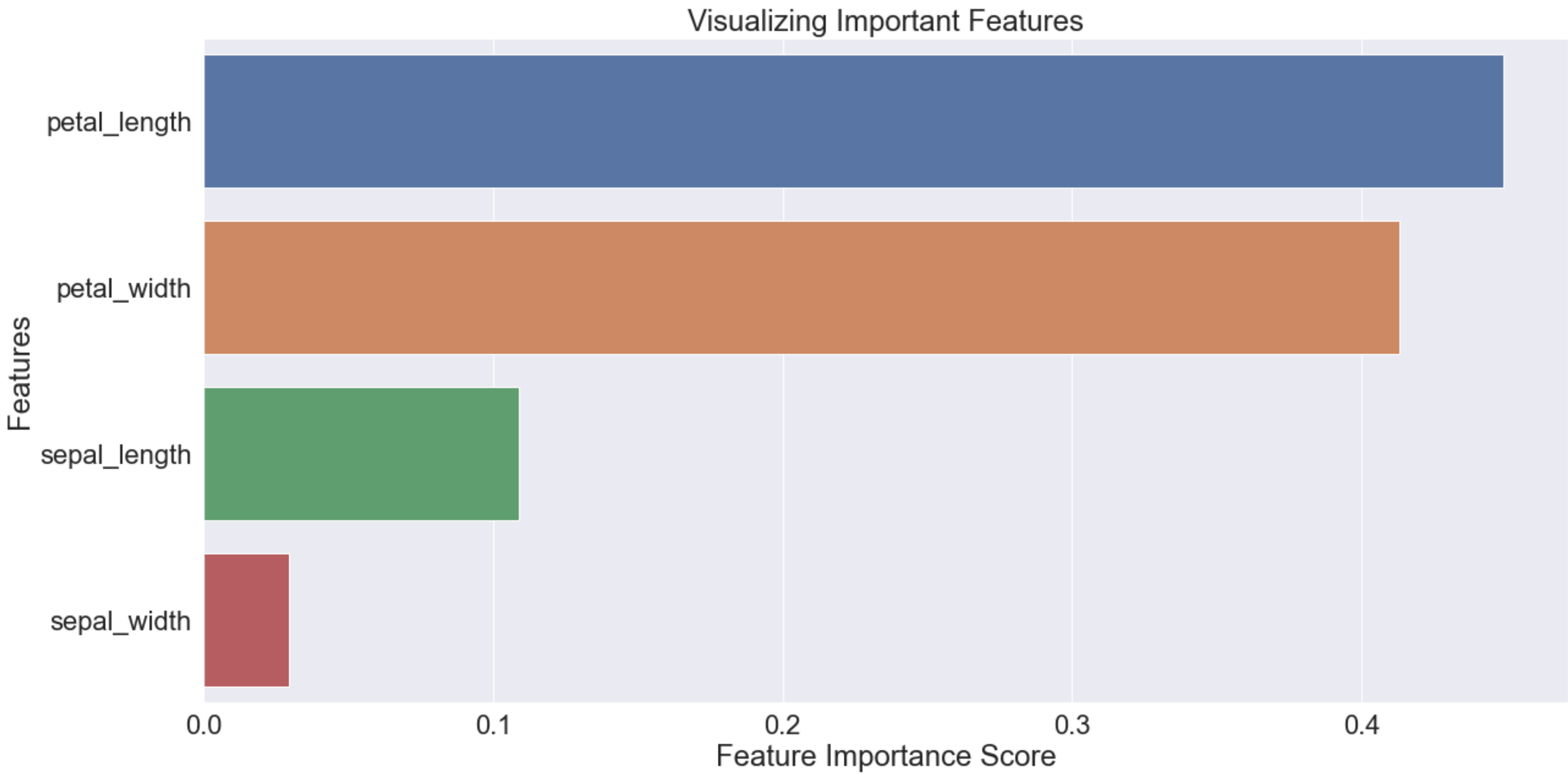
In [63]:
```
rf_clf=RandomForestClassifier(n_estimators=100)
rf_clf.fit(X_scaled,y) # train the model

feature_imp = pd.DataFrame(rf_clf.feature_importances_,columns=['Score'],index=features.columns).sort_values(by='Scor
e',ascending=False)
feature_imp
```

Out[63]:

	Score
petal_length	0.449096
petal_width	0.412924
sepal_length	0.108745
sepal_width	0.029235

Visualize Feature importance

In [66]:
```
sns.barplot(y=feature_imp.index, x=feature_imp['Score'])
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.show()
```



Select 3 best features

In [67]:
```
print(feature_imp['Score'].nlargest(3))
```

```
petal_length    0.449096
petal_width     0.412924
sepal_length    0.108745
Name: Score, dtype: float64
```

3. Low Variance Filter

1. Low Variance filter using sklearn VarianceThreshold

In [68]:
```
from sklearn.feature_selection import VarianceThreshold
```

In [69]:
```
threshold_value=0.5
vt=VarianceThreshold(threshold=threshold_value)
vt_fit=vt.fit_transform(features)
```

Get variance for each feature

In [159]:
```
print(vt.variances_) # actual variance values
```

```
[0.68112222 0.18675067 3.09242489 0.57853156]
```

i. Get features with high variance

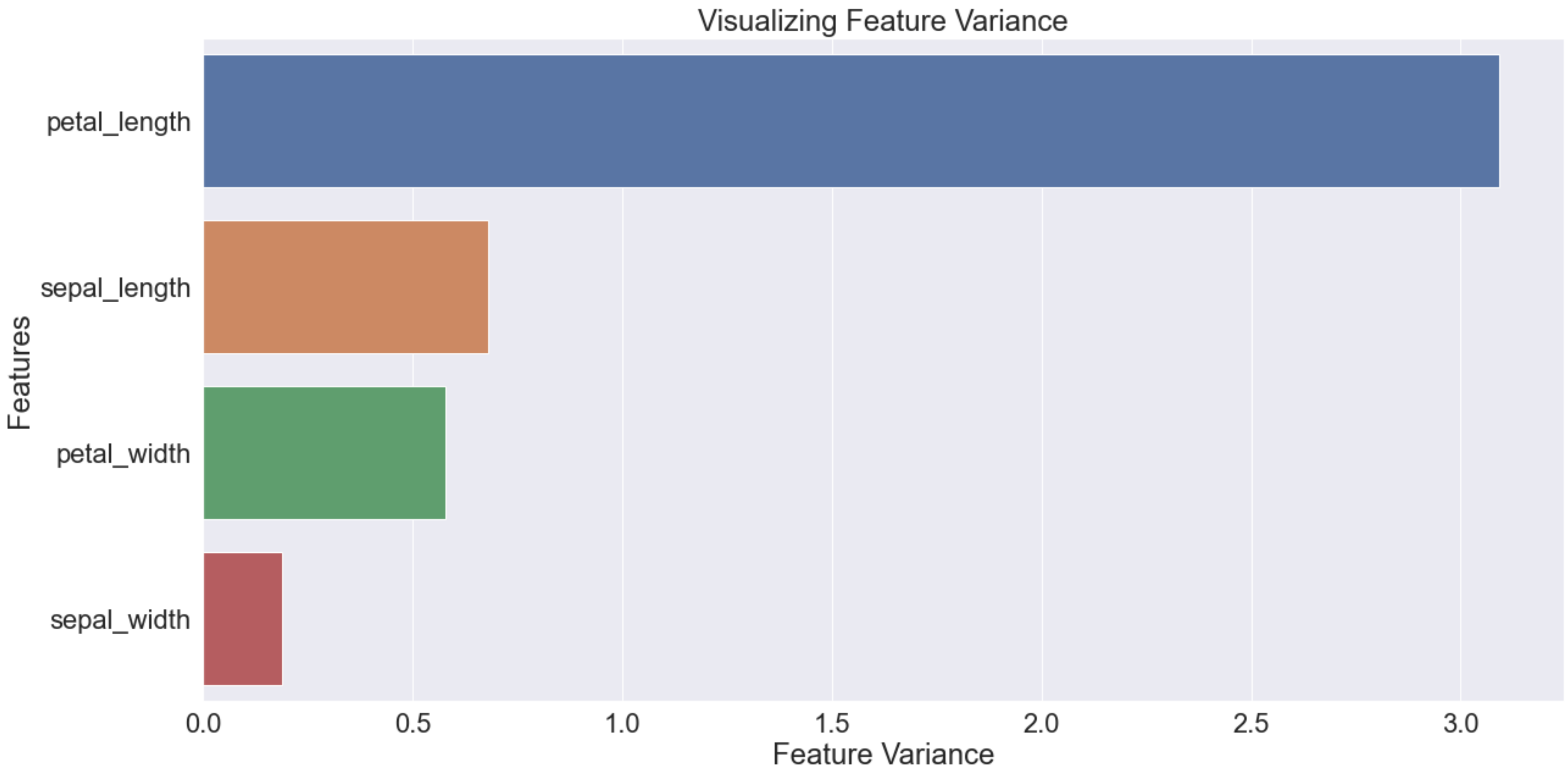
In [73]:
```
feature_variance=pd.DataFrame(vt.variances_,columns=['Score'],index=features.columns).sort_values(by='Score',ascending
=False)
feature_variance
```

Out[73]:

	Score
petal_length	3.092425
sepal_length	0.681122
petal_width	0.578532
sepal_width	0.186751

Visualize Feature Variance

In [75]:
```
sns.barplot(y=feature_variance.index, x=feature_variance['Score'])
plt.xlabel('Feature Variance')
plt.ylabel('Features')
plt.title("Visualizing Feature Variance")
plt.show()
```



In [74]:
```
print(feature_variance['Score'].nlargest(3))
```

```
petal_length    3.092425
sepal_length    0.681122
petal_width     0.578532
Name: Score, dtype: float64
```

ii. Get columns with low variance based on 0.05 threshold i.e value with similarity of 50%

In [78]:
```
print(vt.variances_) # actual variance values
print(vt.get_support()) # True has high variance False has low variance than the threshold

low_var_=[column for column in features.columns if column not in features.columns[vt.get_support()]]
low_var_
```

```
[0.68112222 0.18675067 3.09242489 0.57853156]
[ True False  True  True]
```

Out[78]: ['sepal_width']

In [76]:
```
remove_low_vars_=features.drop(low_var_,axis=1)

# Drop features with variance less than 50%
iris_df = features.head().style.set_table_attributes("style='display:inline'").set_caption('Original Data')
low_vars_df_ = remove_low_vars_.head().style.set_table_attributes("style='display:inline'").set_caption('After Removin
g Low Variance Features')

display_html(iris_df._repr_html_()+"     "+low_vars_df_._repr_html_(), raw=True)
```

Original Data

	sepal_length	sepal_width	petal_length	petal_width
0	5.100000	3.500000	1.400000	0.200000
1	4.900000	3.000000	1.400000	0.200000
2	4.700000	3.200000	1.300000	0.200000
3	4.600000	3.100000	1.500000	0.200000
4	5.000000	3.600000	1.400000	0.200000

After Removing Low Variance Features

	sepal_length	petal_length	petal_width
0	5.100000	1.400000	0.200000
1	4.900000	1.400000	0.200000
2	4.700000	1.300000	0.200000
3	4.600000	1.500000	0.200000
4	5.000000	1.400000	0.200000

iii. Get Feature Variance from DataFrame

In [79]:
```
variance=features.var()
variance
```

Out[79]:
```
sepal_length    0.685694
sepal_width     0.188004
petal_length    3.113179
petal_width     0.582414
dtype: float64
```

In [80]:
```
low_var_features = [ ]

for i in range(0,len(variance)):
    if variance[i]<=0.50:
        low_var_features.append(features.columns[i])

low_var_features
```

Out[80]:
```
['sepal_width']
```

In [81]:
```
remove_low_var_features=features.drop(low_var_features,axis=1)
remove_low_var_features.head()
```

Out[81]:

	sepal_length	petal_length	petal_width
0	5.1	1.4	0.2
1	4.9	1.4	0.2
2	4.7	1.3	0.2
3	4.6	1.5	0.2
4	5.0	1.4	0.2

In [83]:
```
# Drop features with variance less than 50%
iris_df = features.head().style.set_table_attributes("style='display:inline'").set_caption('Original Data')
low_var_features_df = remove_low_var_features.head().style.set_table_attributes("style='display:inline'").set_caption(
'After Removing Low Variance Features')

display_html(iris_df._repr_html_()+"     "+low_var_features_df._repr_html_(), raw=True)
```

Original Data

	sepal_length	sepal_width	petal_length	petal_width
0	5.100000	3.500000	1.400000	0.200000
1	4.900000	3.000000	1.400000	0.200000
2	4.700000	3.200000	1.300000	0.200000
3	4.600000	3.100000	1.500000	0.200000
4	5.000000	3.600000	1.400000	0.200000

After Removing Low Variance Features

	sepal_length	petal_length	petal_width
0	5.100000	1.400000	0.200000
1	4.900000	1.400000	0.200000
2	4.700000	1.300000	0.200000
3	4.600000	1.500000	0.200000
4	5.000000	1.400000	0.200000

4. High Correlation Filter

Refere to Section 6. High Correlation Filter on the Dimensionality Reduction in this notebook

5. L1 Regularization

In [88]:
```
from sklearn.linear_model import Lasso, LogisticRegression
from sklearn.feature_selection import SelectFromModel
```

In [147]:
```
model=LogisticRegression(C=1,solver='liblinear', penalty='l1')
select_model=SelectFromModel(model,threshold=1.0)
select_model.fit(X_scaled,y)
```

Out[147]:
```
SelectFromModel(estimator=LogisticRegression(C=1, penalty='l1',
                                             solver='liblinear'),
                threshold=1.0)
```

Features with 0 coefficients

In [156]:
```
np.round(select_model.estimator_.coef_,1)
```

Out[156]:
```
array([[ 0. ,  1.2, -4.4,  0. ],
       [ 0. , -1.2,  0.8, -0.8],
       [ 0. , -0.5,  2.7,  4.6]])
```

In [157]:
```
select_model.get_support()
```

Out[157]:
```
array([False,  True,  True,  True])
```

In [150]:
```
select_model.threshold_
```

Out[150]:
```
1.0
```

In [158]:
```
X_scaled.columns[(select_model.get_support())]
```

Out[158]:
```
Index(['sepal_width', 'petal_length', 'petal_width'], dtype='object')
```