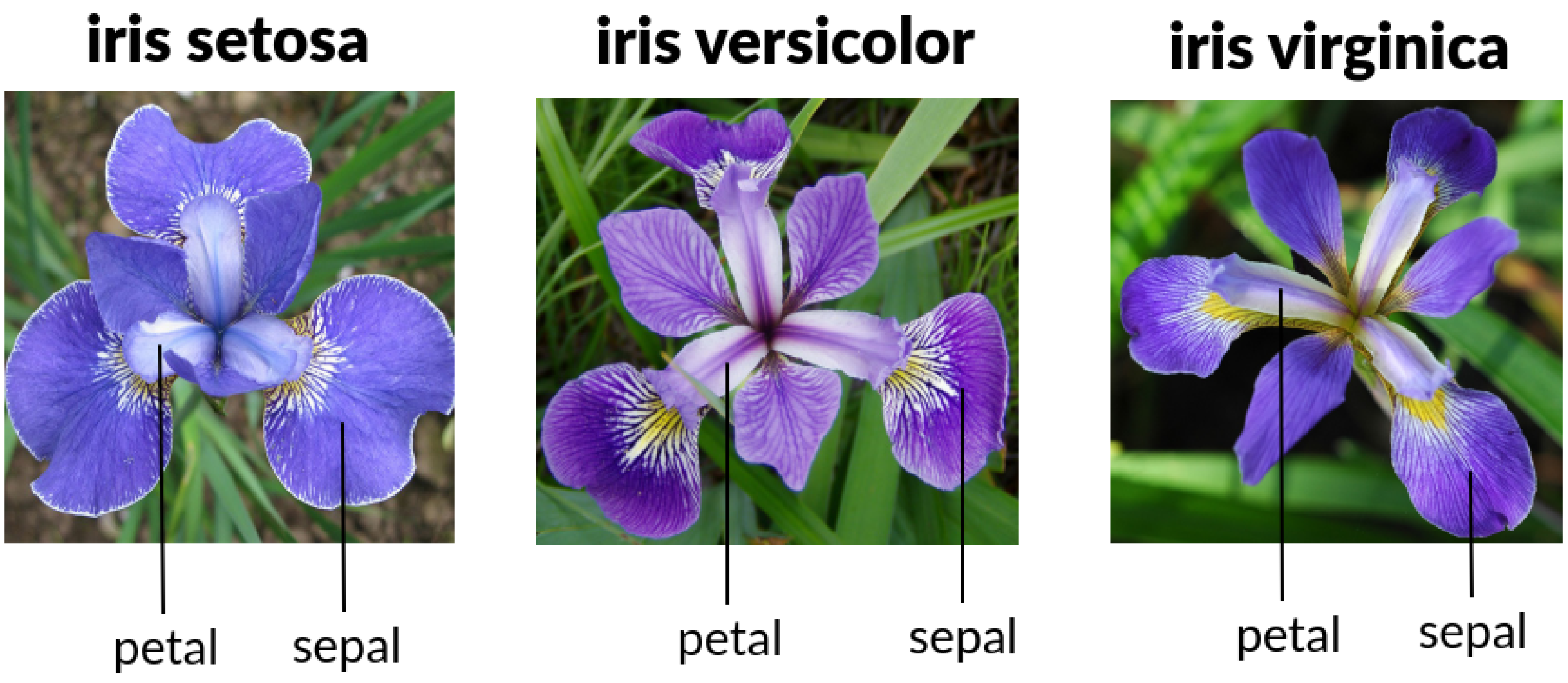
Demo 4: A demo project for IRIS Flower Classification

(Refer to:[https://ai.plainenglish.io/iris-flower-classification-step-by-step-tutorial-c8728300dc9e (https://ai.plainenglish.io/iris-flower-classification-step-by-step-tutorial-c8728300dc9e)](https://ai.plainenglish.io/iris-flower-classification-step-by-step-tutorial-c8728300dc9e))

1 Introduction

1.1 What is IRIS ?

IRIS Dataset is a dataset containing of 3 different types of irises' (Setosa, Versicolour, and Virginica) with measured petal and sepal length.



1.2 Aims

In this demo, we aim to

1. analyze the data composition of IRIS,
2. data distribution and visulation
3. use traditional machine learning algrothims for classification, etc.

2 Dataset Loading

In this section, we illustrate how to use Pandas lib to load a dataset and list its items.

In [1]:

```
# import the required library
import numpy as np
import pandas as pd
import seaborn as sns
sns.set_palette('husl')
import matplotlib.pyplot as plt
import matplotlib.style as style
style.use('seaborn-deep')
import sklearn


# dataset_soruce = 'https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv'
dataset_source = './iris.csv'
col_name = ['sepal-length','sepal-width','petal-length','petal-width','class']
dataset = pd.read_csv(dataset_source, names=col_name)
```

executed in 1.45s, finished 23:30:22 2021-03-24

In [2]:
```
# List some items at the beginning and the end
dataset
```
executed in 21ms, finished 23:30:22 2021-03-24

Out[2]:

	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
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

In [3]:

```
# List only the top 10 items
dataset.head(10)
```

executed in 9ms, finished 23:30:22 2021-03-24

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
5	5.4	3.9	1.7	0.4	Iris-setosa
6	4.6	3.4	1.4	0.3	Iris-setosa
7	5.0	3.4	1.5	0.2	Iris-setosa
8	4.4	2.9	1.4	0.2	Iris-setosa
9	4.9	3.1	1.5	0.1	Iris-setosa

In [4]:

```
# Show the summary of the dataset
dataset.info()
```

executed in 5ms, finished 23:30:22 2021-03-24

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
sepal-length    150 non-null float64
sepal-width     150 non-null float64
petal-length    150 non-null float64
petal-width     150 non-null float64
class           150 non-null object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [5]:
```
# How many classes it has?
dataset['class'].value_counts()
```
executed in 6ms, finished 23:30:22 2021-03-24

Out[5]:
```
Iris-versicolor    50
Iris-virginica     50
Iris-setosa        50
Name: class, dtype: int64
```

Indicating we are going to the 3-class classification!

In [6]:
```
dataset.describe()
```
executed in 22ms, finished 23:30:22 2021-03-24

Out[6]:

	sepal-length	sepal-width	petal-length	petal-width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

3 Dataset Analysis

3.1 Dataset Discription

In [7]:
```
dataset.describe()
```
executed in 22ms, finished 23:30:22 2021-03-24

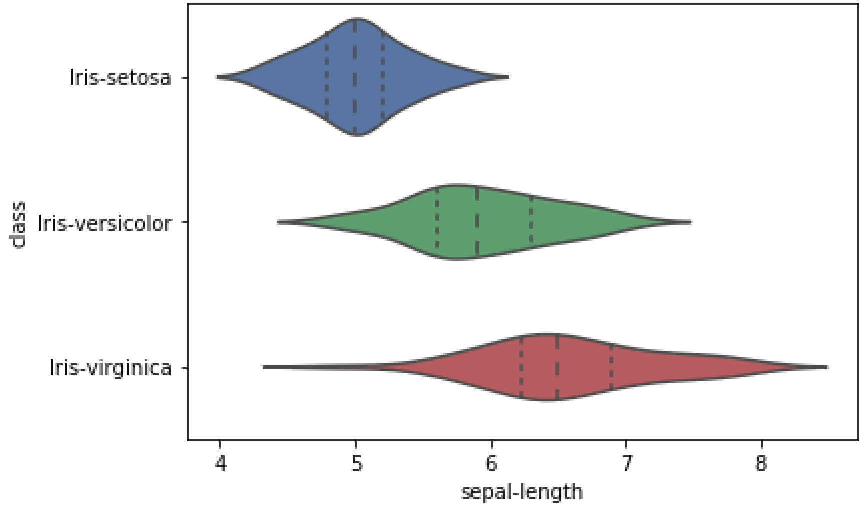
Out[7]:

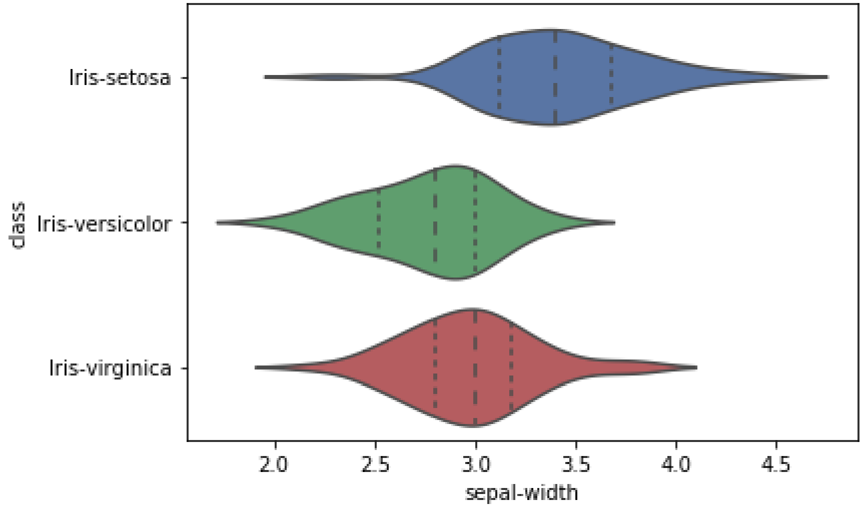
	sepal-length	sepal-width	petal-length	petal-width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

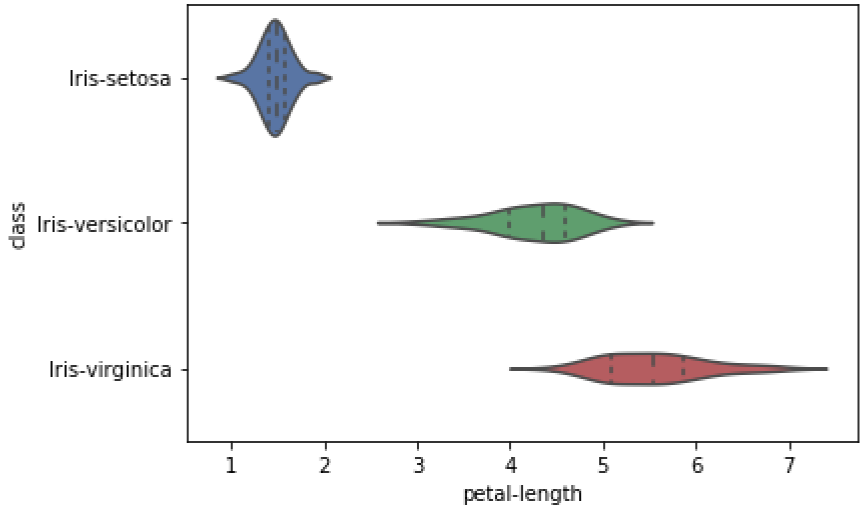
3.2 Characteristic Distribution

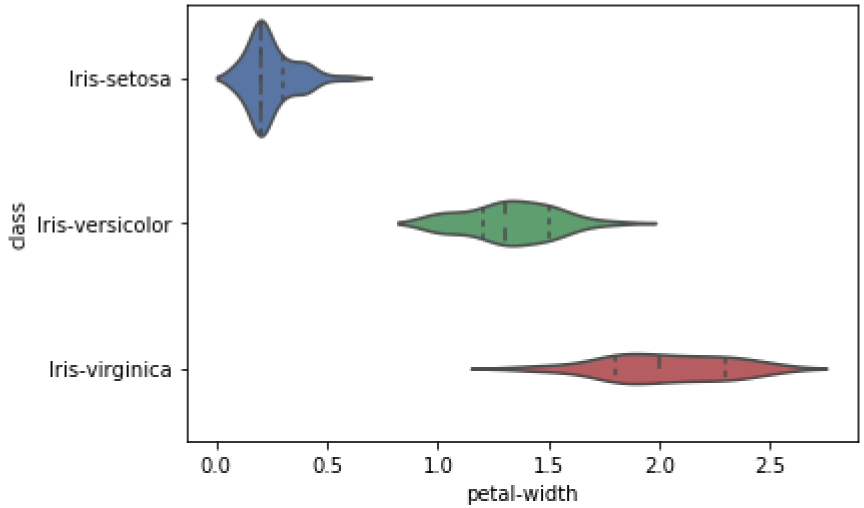
In [8]:
```
sns.violinplot(y='class', x='sepal-length', data=dataset, inner='quartile')
plt.show()
sns.violinplot(y='class', x='sepal-width', data=dataset, inner='quartile')
plt.show()
sns.violinplot(y='class', x='petal-length', data=dataset, inner='quartile')
plt.show()
sns.violinplot(y='class', x='petal-width', data=dataset, inner='quartile')
plt.show()
```

executed in 725ms, finished 23:30:23 2021-03-24





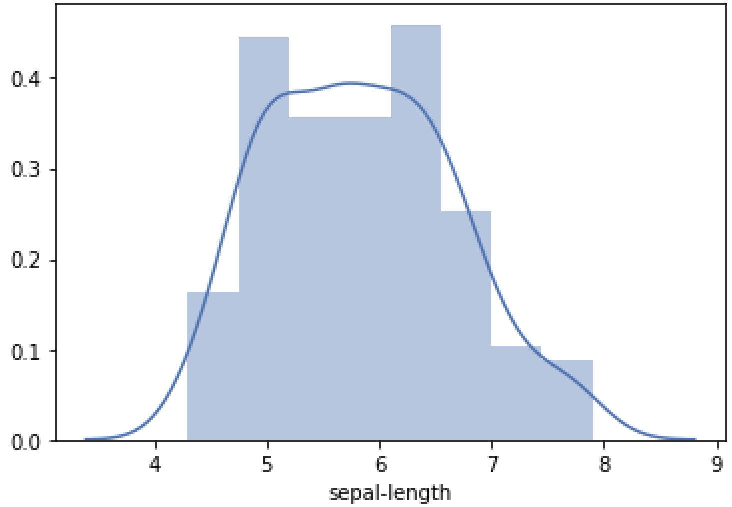

Iris-setosa
Iris-versicolor
Iris-virginica
class
1
2
3
4
5
6
7
petal-length

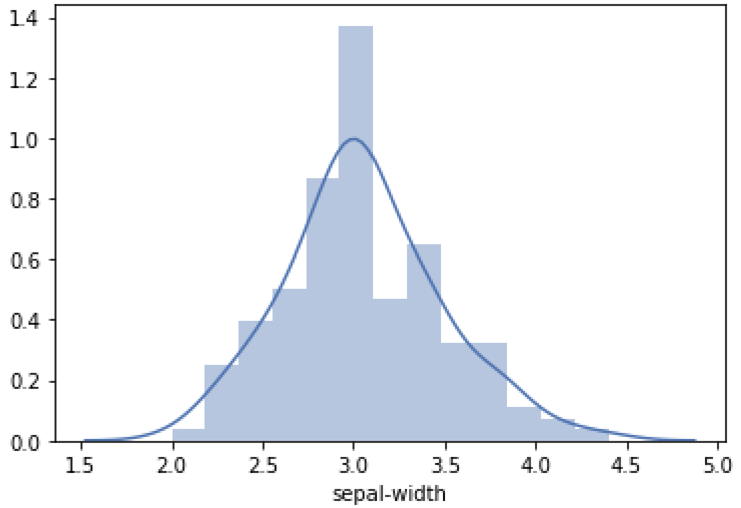

Iris-setosa
Iris-versicolor
Iris-virginica
class
0.0
0.5
1.0
1.5
2.0
2.5
petal-width

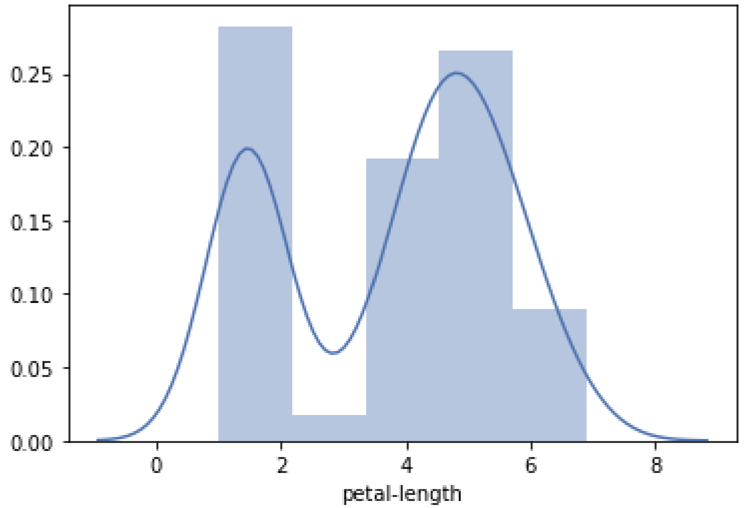
In [9]:

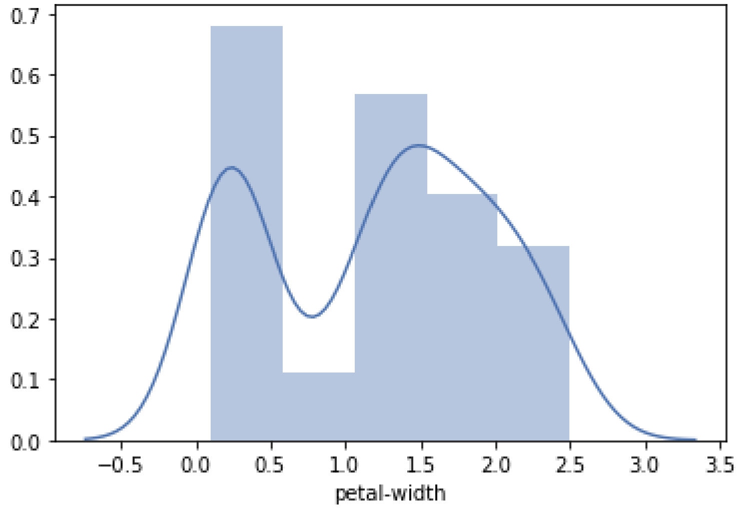
```
# Using another plot style
sns.distplot(dataset["sepal-length"], rug=False, hist=True); plt.show();
sns.distplot(dataset["sepal-width"], rug=False, hist=True); plt.show();
sns.distplot(dataset["petal-length"], rug=False, hist=True); plt.show();
sns.distplot(dataset["petal-width"], rug=False, hist=True); plt.show();
```

executed in 624ms, finished 23:30:23 2021-03-24




1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
sepal-width

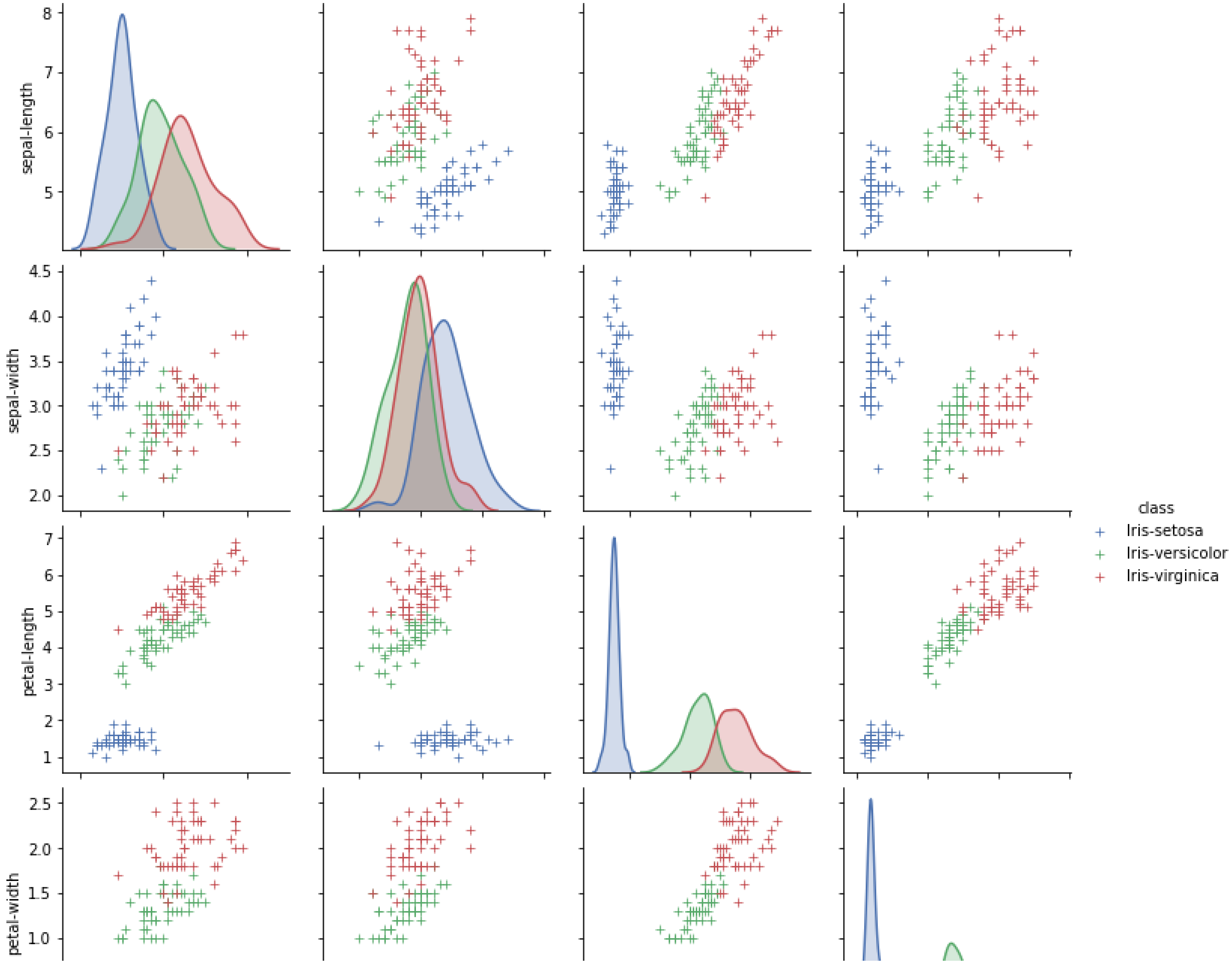

0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
petal-length

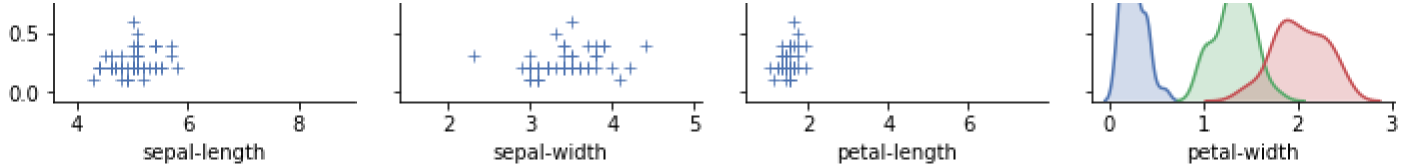


3.3 Pair-wise Characteris Analysis

In [10]:
```
sns.pairplot(dataset, hue='class', markers='+')
plt.show()
```

executed in 3.82s, finished 23:30:27 2021-03-24





Finding: Different classes show various pair-wise characteristic relationships, meaning they can be separable.

3.4 Principle Component Analysis (PCA)

In [11]:
```
# Convert the dataset from Dataframe to Numpy array for PCA using sklearn
dataset_np = dataset.to_numpy()
X = dataset_np[:, :-1]
Y = dataset_np[:, -1]

from sklearn.decomposition import PCA

# Reduce the data dimension to 2
pca = PCA(n_components=2)
X_transform = pca.fit(X).transform(X)

# Percentage of variance explained for each components
print('explained variance ratio (first two components): %s'
      % str(pca.explained_variance_ratio_))
```

executed in 76ms, finished 23:30:27 2021-03-24

```
explained variance ratio (first two components): [ 0.92461621  0.05301557]
```

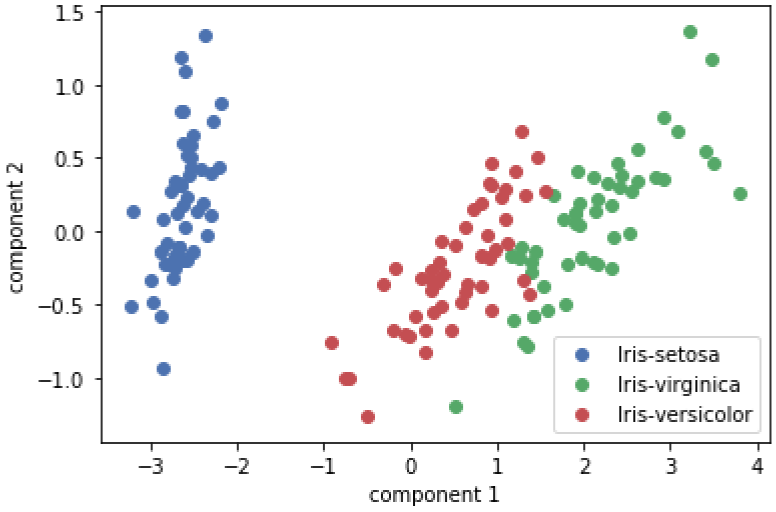
In [12]:

```
plt.figure(1)
for cls in set(dataset['class']):
    idx = np.where(Y == cls)[0]
    plt.scatter(X_transform[idx, 0], X_transform[idx, 1])

plt.xlabel('component 1')
plt.ylabel('component 2')
plt.legend(list(set(dataset['class'])))
```

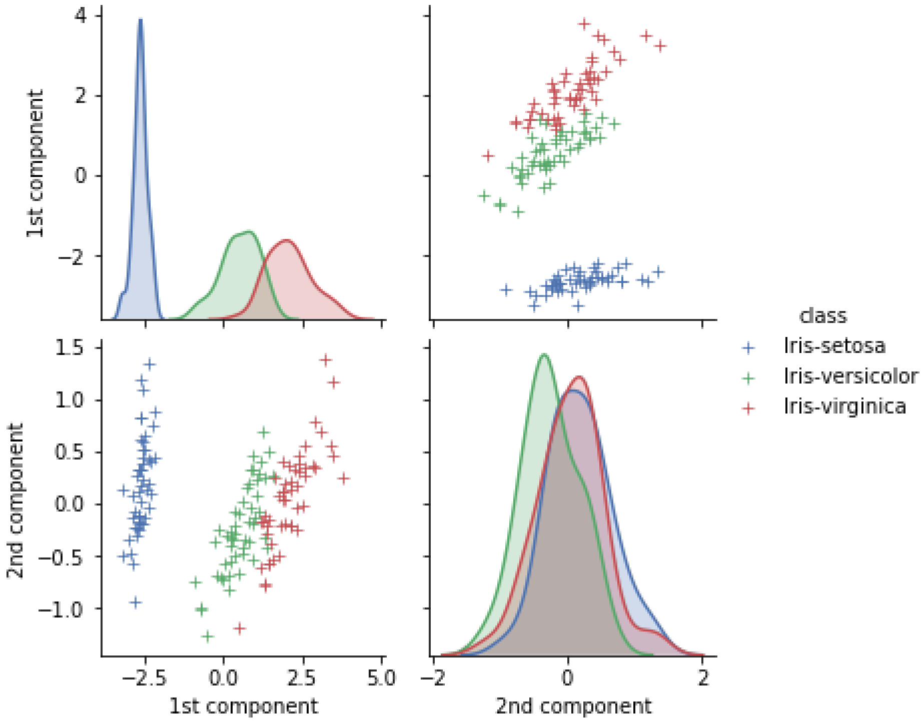
executed in 214ms, finished 23:30:27 2021-03-24

Out[12]: <matplotlib.legend.Legend at 0x13993cbe0>



In [13]:
```
X_Y = np.concatenate((X_transform, Y[:, np.newaxis]), axis=1)
X_Y = pd.DataFrame(X_Y, columns=['1st component', '2nd component', 'class'])
sns.pairplot(X_Y, hue='class', markers='+')
```
executed in 990ms, finished 23:30:28 2021-03-24

Out[13]: <seaborn.axisgrid.PairGrid at 0x13a8c6588>



The 1st main component can nearly separate the data.

4 Machine Learning Methods for IRIS Classification

4.1 Classification and Results

In [14]:

```
# import the required libs
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

executed in 24ms, finished 23:30:28 2021-03-24

In [15]:

```
# Split the dataset according to the train-test ratio 8:2
X, Y = dataset.drop(['class'], axis=1),  dataset['class']
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20, random_state=1)
```

executed in 5ms, finished 23:30:28 2021-03-24

In [16]:

```
# Classify the IRIS dataset, using 10-fold validation.

import warnings
warnings.filterwarnings('ignore')

models = {
    'LR': LogisticRegression,
    'LDA': LinearDiscriminantAnalysis,
    'KNN': KNeighborsClassifier,
    'CART': DecisionTreeClassifier,
    'NB': GaussianNB,
    'SVC': SVC
}

results = []
for model_name in models:
    kfold = StratifiedKFold(n_splits=10, random_state=1, shuffle=True)
    model = models[model_name]()
    cv_results = cross_val_score(model, X_train, y_train, cv=kfold, scoring='accuracy')
    for r in cv_results:
        results.append([float(r), model_name])
    mean, std = cv_results.mean(), cv_results.std()

    print('%s: %f (%f)' % (model_name, cv_results.mean(), cv_results.std()))
```

executed in 341ms, finished 23:30:29 2021-03-24

```
LR: 0.966667 (0.040825)
LDA: 0.975000 (0.038188)
KNN: 0.958333 (0.041667)
CART: 0.941667 (0.053359)
NB: 0.950000 (0.055277)
SVC: 0.966667 (0.040825)
```

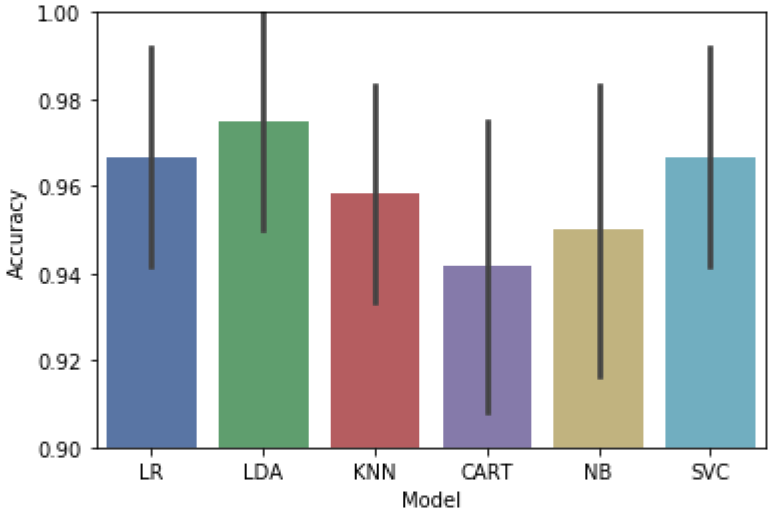
4.2 Comparson and Visualization

In [18]:

```
# Convert from python list to numpy array
results = np.array(results)
result_df = pd.DataFrame(results, columns=['Accuracy', 'Model'])
result_df = result_df.astype({'Accuracy': 'float32'})

sns.barplot(x="Model", y="Accuracy", data=result_df)
plt.ylim([0.9, 1.])
plt.show()
```

executed in 198ms, finished 23:31:08 2021-03-24



5 Conclusion

All the employed traditional machine learning methods work well, achieving over 90% classification accuracy.

The best model in this experiment is Linear Discriminant Analysis (LDA).

In [ ]: