Comparison of PCA and LDA

- Principal Component Analysis (PCA) identifies the combination of attributes (principal components, or directions in the feature space) that account for the most variance in the data.
- Linear Discriminant Analysis (LDA) tries to identify attributes that account for the most variance between classes. In particular, LDA, in contrast to PCA, is a supervised method, using known class labels.

In [1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd

from sklearn import datasets

from sklearn.decomposition import PCA

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
```

In [2]:
```
sns.set()
```

In [3]:
```
iris_df = sns.load_dataset('iris')
iris_df.head()
```

Out[3]:

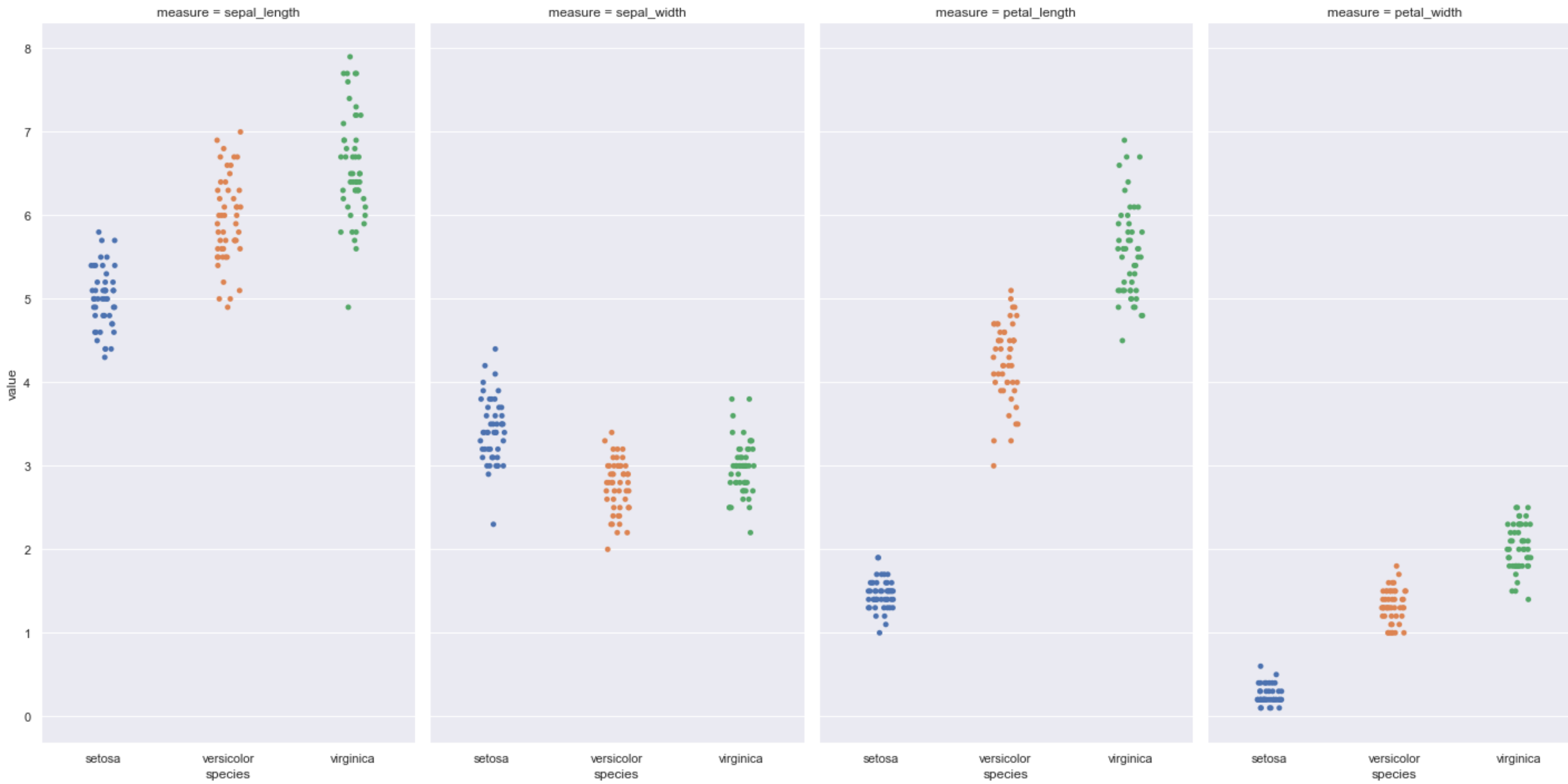
	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In [4]:
```
iris_long = pd.melt(iris_df, id_vars=['species'], var_name='measure', value_name='value')
iris_long.head()
```

Out[4]:

	species	measure	value
0	setosa	sepal_length	5.1
1	setosa	sepal_length	4.9
2	setosa	sepal_length	4.7
3	setosa	sepal_length	4.6
4	setosa	sepal_length	5.0

In [5]:
```
sns.catplot(x="species", y="value", hue="species", height=10, aspect=0.5,
                 col="measure", data=iris_long);
```



In [ ]:

In [ ]:

In [6]:
```
# Use the iris dataset from sklearn
```

In [7]:
```
iris = datasets.load_iris()

X = iris.data
y = iris.target
target_names = iris.target_names
feature_names = iris.feature_names
```

In [8]:
```
X[0:5]
```

Out[8]:
```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2]])
```

In [9]:
```
y[0:5]
```

Out[9]:
```
array([0, 0, 0, 0, 0])
```

In [10]:
```
target_names
```

Out[10]:
```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

In [11]:
```
feature_names
```

Out[11]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

PCA with 1 component

In [12]:
```
# PCA

pca = PCA(n_components=1)

X_r = pca.fit(X).transform(X)

X_r.shape
```

Out[12]:
```
(150, 1)
```

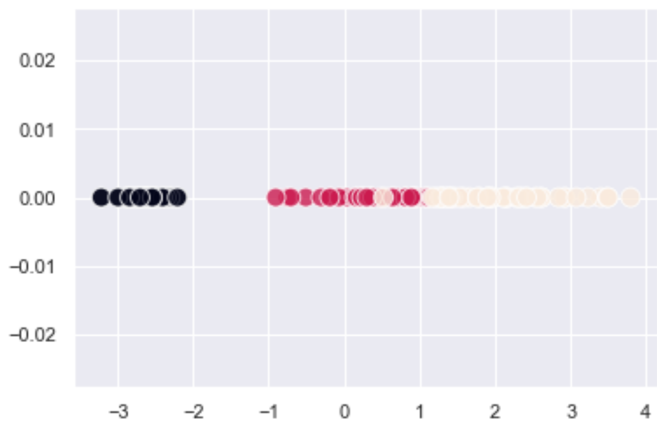
In [13]:
```
X_r[0:5]
```

Out[13]:
```
array([[-2.68412563],
       [-2.71414169],
       [-2.88899057],
       [-2.74534286],
       [-2.72871654]])
```

In [14]:
```
np.zeros(X_r.shape[0])
```

Out[14]:
```
array([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., 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.])
```

In [15]:
```
plt.scatter(X_r[:,0], np.zeros(X_r.shape[0]), c=iris.target,
            alpha=0.8, s=120,  marker='o', edgecolors='white');
```



In [16]:
```
print(pca.explained_variance_ratio_)
```

```
[0.92461872]
```

PCA with 2 components

In [17]:
```
#PCA

pca = PCA(n_components=2)

X_r = pca.fit(X).transform(X)

X_r.shape
```

Out[17]:
```
(150, 2)
```

In [18]:
```
X_r[0:5]
```

Out[18]:
```
array([[-2.68412563,  0.31939725],
       [-2.71414169, -0.17700123],
       [-2.88899057, -0.14494943],
       [-2.74534286, -0.31829898],
       [-2.72871654,  0.32675451]])
```

In [19]:
```
pca.inverse_transform(X_r)[0:5]
```

Out[19]:
```
array([[5.08303897, 3.51741393, 1.40321372, 0.21353169],
       [4.7462619 , 3.15749994, 1.46356177, 0.24024592],
       [4.70411871, 3.1956816 , 1.30821697, 0.17518015],
       [4.6422117 , 3.05696697, 1.46132981, 0.23973218],
       [5.07175511, 3.52655486, 1.36373845, 0.19699991]])
```

In [20]:
```
print(pca.explained_variance_ratio_)
```

```
[0.92461872 0.05306648]
```

LDA (fit based on class)

In [21]:
```
# LDA

lda = LinearDiscriminantAnalysis(n_components=2)

X_r2 = lda.fit(X, y).transform(X)
```

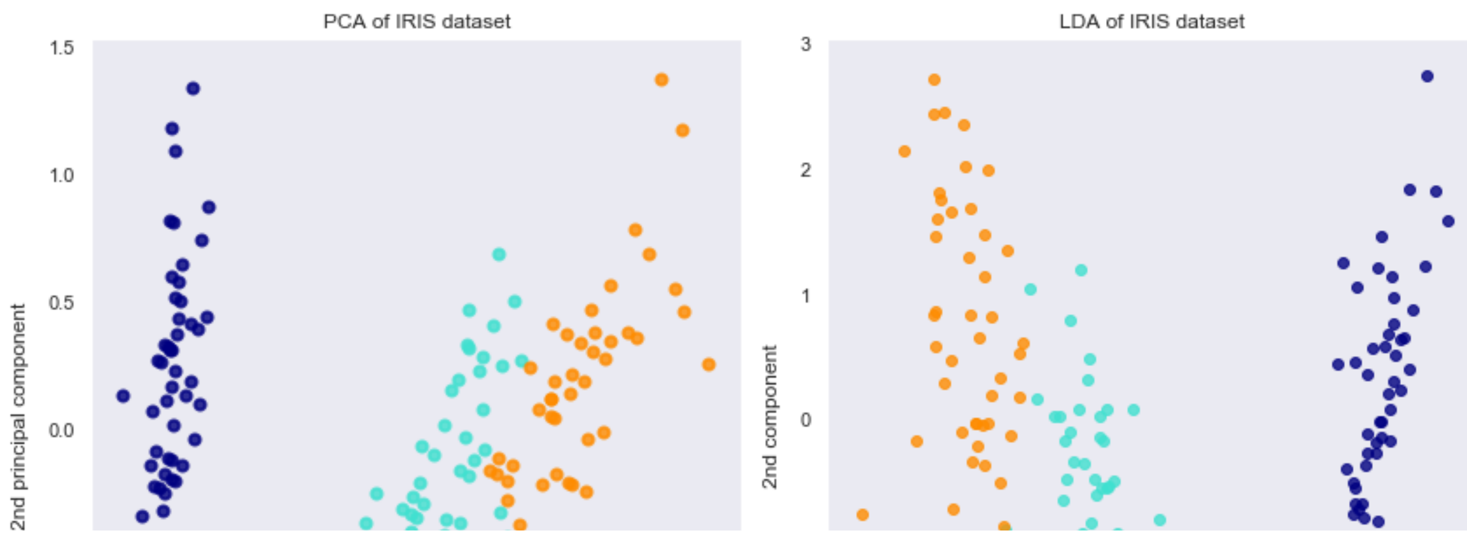
In [22]:
```
X_r2[0:5]
```

Out[22]:
```
array([[ 8.06179978,  0.30042062],
       [ 7.12868772, -0.78666043],
       [ 7.48982797, -0.26538449],
       [ 6.81320057, -0.67063107],
       [ 8.13230933,  0.51446253]])
```

In [23]:
```
print(lda.explained_variance_ratio_)
```

```
[0.9912126 0.0087874]
```

In [24]:
```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 7))

colors = ['navy', 'turquoise', 'darkorange']
lw = 2

for color, i, target_name in zip(colors, [0, 1, 2], target_names):
    ax1.scatter(X_r[y == i, 0], X_r[y == i, 1], color=color, alpha=.8, lw=lw,
                label=target_name)

for color, i, target_name in zip(colors, [0, 1, 2], target_names):
    ax2.scatter(X_r2[y == i, 0], X_r2[y == i, 1], alpha=.8, color=color,
                label=target_name)

ax1.set_title('PCA of IRIS dataset')
ax1.set_xlabel('1st principal component')
ax1.set_ylabel('2nd principal component')


ax2.set_title('LDA of IRIS dataset')
ax2.set_xlabel('1st component')
ax2.set_ylabel('2nd component')

for ax in (ax1, ax2):
    ax.legend(loc='best')
    ax.grid()

plt.tight_layout()
```



```
In [ ]:
```