Data Science Masters :Assignment 30

Problem:

Using PCA (Principal Component Analysis) , to transform iris data into 3 dimensions and plot a 3d chart with transformed dimensions and color each data point with specific class

Solution:

Importing Libraries...

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
%matplotlib inline

# modules for Machine Learning
from sklearn.decomposition  import PCA  as sklearnPCA
from sklearn import datasets
from sklearn.preprocessing import StandardScaler
from matplotlib.cm import register_cmap
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score , confusion_matrix
```

In [2]:

```
# Load Dataset
iris_dataset = datasets.load_iris()
```

In [5]:

```
# Description of Dataset
iris_dataset.DESCR
```

Out[5]:

```
'Iris Plants Database\n====================\n\nNotes\n-----\nData Set Charac
teristics:\n    :Number of Instances: 150 (50 in each of three classes)\n
:Number of Attributes: 4 numeric, predictive attributes and the class\n    :
Attribute Information:\n        - sepal length in cm\n        - sepal width
in cm\n        - petal length in cm\n        - petal width in cm\n        -
class:\n                - Iris-Setosa\n                - Iris-Versicolour\n
               - Iris-Virginica\n    :Summary Statistics:\n\n    ===========
=== ==== ==== ======= ===== ====================\n                    Min  M
ax   Mean    SD   Class Correlation\n    ============== ==== ==== ======= ==
=== ====================\n    sepal length:   4.3  7.9   5.84   0.83    0.78
26\n    sepal width:    2.0  4.4   3.05   0.43   -0.4194\n    petal length:
  1.0  6.9   3.76   1.76    0.9490  (high!)\n    petal width:    0.1  2.5
1.20  0.76     0.9565  (high!)\n    ============== ==== ==== ======= ===== =
===================\n\n    :Missing Attribute Values: None\n    :Class Distr
ibution: 33.3% for each of 3 classes.\n    :Creator: R.A. Fisher\n    :Dono
r: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n    :Date: July, 1988\n
\nThis is a copy of UCI ML iris datasets.\nhttp://archive.ics.uci.edu/ml/dat
asets/Iris\n\nThe famous Iris database, first used by Sir R.A Fisher\n\nThis
is perhaps the best known database to be found in the\npattern recognition l
iterature.  Fisher\'s paper is a classic in the field and\nis referenced fre
quently to this day.  (See Duda & Hart, for example.)  The\ndata set contain
s 3 classes of 50 instances each, where each class refers to a\ntype of iris
plant.  One class is linearly separable from the other 2; the\nlatter are NO
T linearly separable from each other.\n\nReferences\n----------\n   - Fishe
r,R.A. "The use of multiple measurements in taxonomic problems"\n     Annual
Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to\n     Mathem
atical Statistics" (John Wiley, NY, 1950).\n   - Duda,R.O., & Hart,P.E. (197
3) Pattern Classification and Scene Analysis.\n     (Q327.D83) John Wiley &
Sons.  ISBN 0-471-22361-1.  See page 218.\n   - Dasarathy, B.V. (1980) "Nosi
ng Around the Neighborhood: A New System\n     Structure and Classification
Rule for Recognition in Partially Exposed\n     Environments".  IEEE Transac
tions on Pattern Analysis and Machine\n     Intelligence, Vol. PAMI-2, No.
1, 67-71.\n   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEE
E Transactions\n     on Information Theory, May 1972, 431-433.\n   - See als
o: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II\n     concep
tual clustering system finds 3 classes in the data.\n   - Many, many more
...\n'
```

In [6]:

```
# Iris feature names
iris_features = iris_dataset.feature_names
iris_features
```

Out[6]:

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

In [7]:

```
# Target Variable
iris_target= iris_dataset.target
iris_target
```

Out[7]:

```
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, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [8]:

```
# Feature data  from Iris dataset
iris_data= iris_dataset.data
iris_data
```

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],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
```

In [11]:

```
# Creating DataFrame
df_IrisData = pd.DataFrame(data= iris_data , columns= iris_features)
df_IrisData['target'] = iris_target
df_IrisData.head(2)
```

Out[11]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0

Exploratory data analysis

In [12]:

```
# Check whether data set conins null /NA
df_IrisData.isnull().sum()
```

Out[12]:

```
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
target               0
dtype: int64
```

In [14]:

```
# Statistical analysis
df_IrisData.iloc[:,0:4].describe()
```

Out[14]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
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

In [15]:

```
# Unique data
df_IrisData['target'].unique()
```

Out[15]:

```
array([0, 1, 2], dtype=int64)
```

Data Visualization

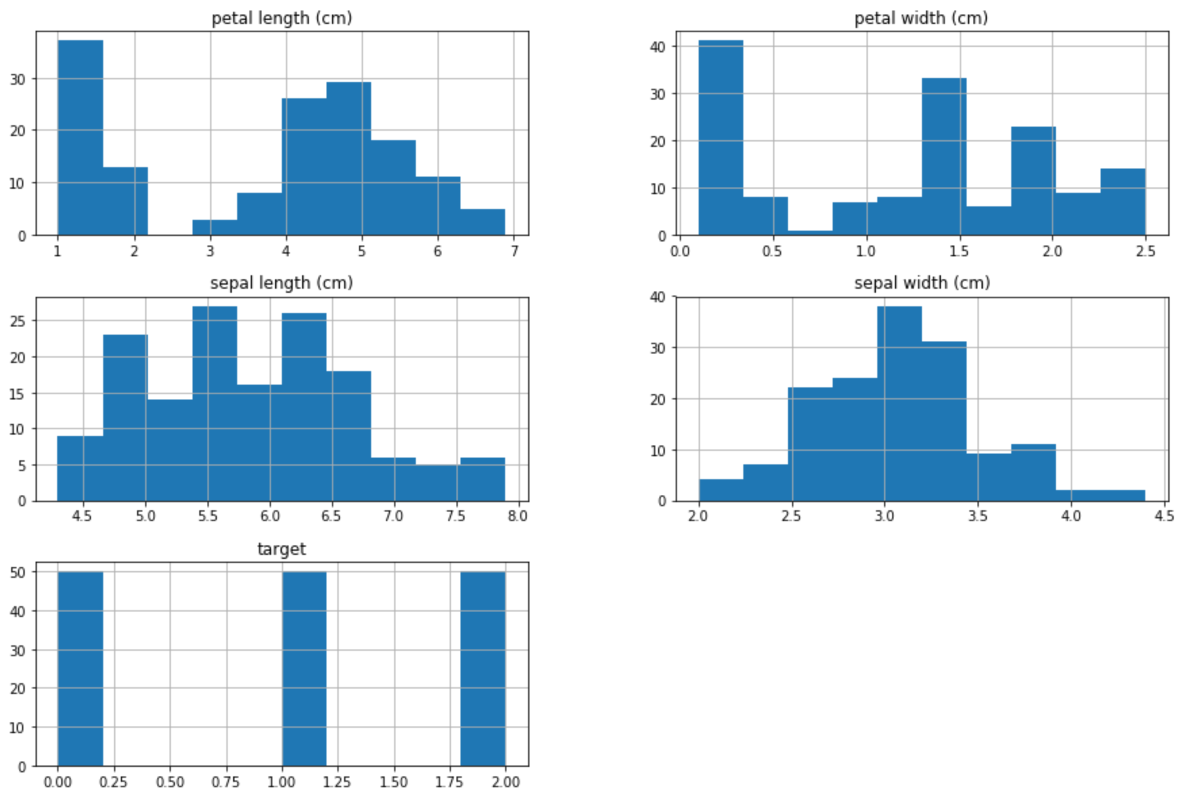
In [16]:

```
# Distribution of features of iris data
plt.figure(figsize=(15,10))
df_IrisData.hist(figsize=(15,10))
```

Out[16]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000188B3410F60
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000188B36F76A0
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000188B37249B0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000188B374CCC0
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000188B3774F60
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000188B3774F98
>]],
      dtype=object)
```

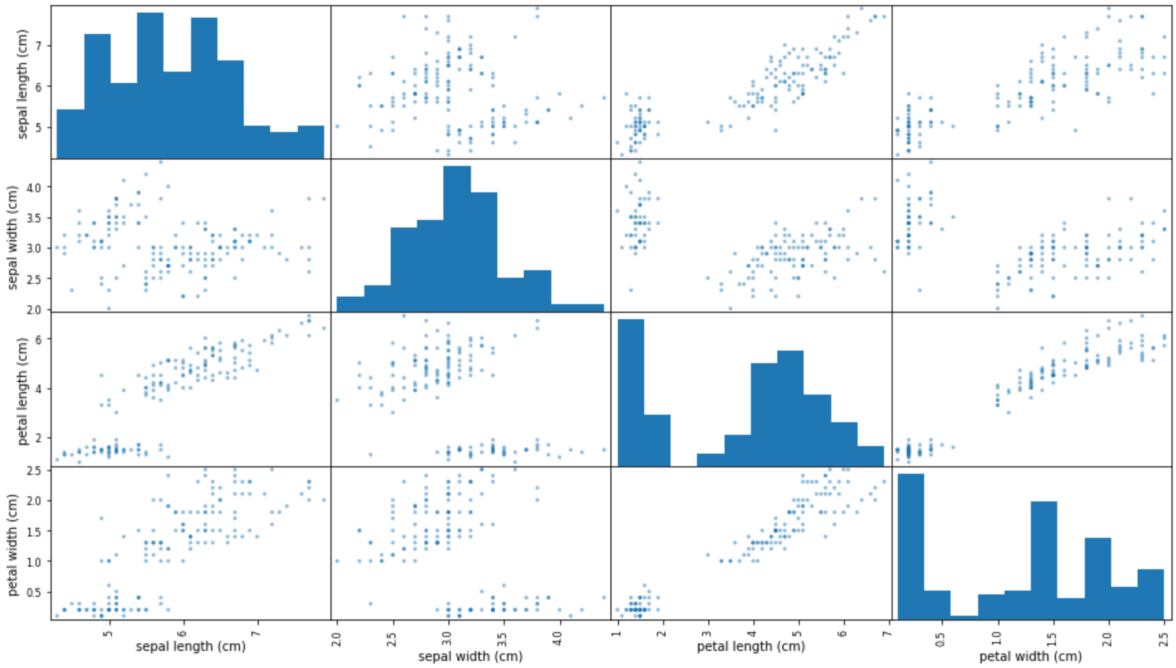
```
<Figure size 1080x720 with 0 Axes>
```



In [17]:

```
# Scatter plot between features

from pandas.plotting import scatter_matrix
scatter_matrix(frame=df_IrisData.iloc[:,0:4] , figsize=(16,9))
plt.show()
```



In [18]:

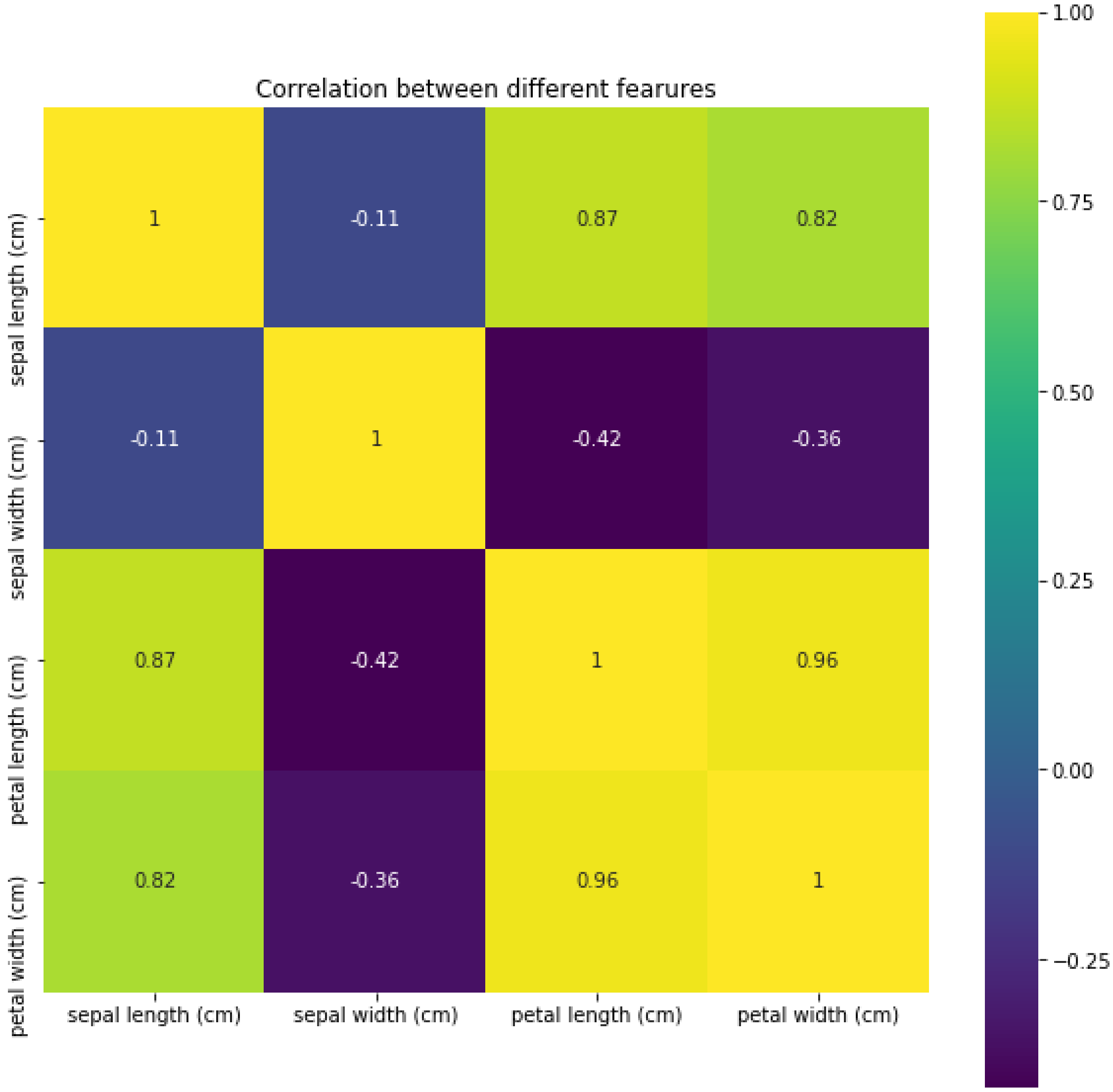
```
#Correlation map between features

correlation = df_IrisData.iloc[:,0:4].corr()
plt.figure(figsize=(10,10))
sns.heatmap(correlation, vmax=1, square=True,annot=True,cmap='viridis')

plt.title('Correlation between different fearures')
```

Out[18]:

```
Text(0.5,1,'Correlation between different fearures')
```



Data Prepration

In [19]:

```
# Selection of feature and target data

df_Feature = df_IrisData.iloc[:,0:4]
df_target = df_IrisData.iloc[:,-1:]
```

In [20]:

```
# Standardizing the data
# Scale the data to be between -1 and 1
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_std=scaler.fit_transform(df_Feature)
X_std[0:10]
```

Out[20]:

```
array([[-0.90068117,  1.03205722, -1.3412724 , -1.31297673],
       [-1.14301691, -0.1249576 , -1.3412724 , -1.31297673],
       [-1.38535265,  0.33784833, -1.39813811, -1.31297673],
       [-1.50652052,  0.10644536, -1.2844067 , -1.31297673],
       [-1.02184904,  1.26346019, -1.3412724 , -1.31297673],
       [-0.53717756,  1.95766909, -1.17067529, -1.05003079],
       [-1.50652052,  0.80065426, -1.3412724 , -1.18150376],
       [-1.02184904,  0.80065426, -1.2844067 , -1.31297673],
       [-1.74885626, -0.35636057, -1.3412724 , -1.31297673],
       [-1.14301691,  0.10644536, -1.2844067 , -1.4444497 ]])
```

Apply PCA Algorithm

In [23]:

```
# PCA algorithm from sklearn.decomposition
from sklearn.decomposition import PCA

sklearnPCA = PCA(n_components= 3)    # n_compenets : defines no. of principal components to
Y_sklearn = sklearnPCA.fit_transform(X_std)  # Applying normalize data into PCA
Y_sklearn
```

Out[23]:

```
array([[-2.26454173e+00,  5.05703903e-01, -1.21943348e-01],
       [-2.08642550e+00, -6.55404729e-01, -2.27250832e-01],
       [-2.36795045e+00, -3.18477311e-01,  5.14796236e-02],
       [-2.30419716e+00, -5.75367713e-01,  9.88604444e-02],
       [-2.38877749e+00,  6.74767397e-01,  2.14278490e-02],
       [-2.07053681e+00,  1.51854856e+00,  3.06842583e-02],
       [-2.44571134e+00,  7.45626750e-02,  3.42197636e-01],
       [-2.23384186e+00,  2.47613932e-01, -8.25744645e-02],
       [-2.34195768e+00, -1.09514636e+00,  1.53562399e-01],
       [-2.18867576e+00, -4.48629048e-01, -2.46559522e-01],
       [-2.16348656e+00,  1.07059558e+00, -2.64009373e-01],
       [-2.32737775e+00,  1.58587455e-01,  1.00165616e-01],
       [-2.22408272e+00, -7.09118158e-01, -2.23214514e-01],
       [-2.63971626e+00, -9.38281982e-01,  1.89570030e-01],
       [-2.19229151e+00,  1.88997851e+00, -4.69480095e-01],
       [-2.25146521e+00,  2.72237108e+00,  3.26037967e-02],
       [-2.20275048e+00,  1.51375028e+00, -1.36349158e-03],
       [-2.19017916e+00,  5.14304308e-01, -3.86155949e-02],
```

In [24]:

```
# Trasaforming Principle components returned by PCA model with traget variable into datafra
df_Compenets = pd.DataFrame(data = Y_sklearn, columns = ['principal component 1', 'principa
df_Compenets = pd.concat([df_Compenets,df_target[['target']]], axis=1)
df_Compenets.head()
```

Out[24]:

	principal component 1	principal component 2	principal component 3	target
0	-2.264542	0.505704	-0.121943	0
1	-2.086426	-0.655405	-0.227251	0
2	-2.367950	-0.318477	0.051480	0
3	-2.304197	-0.575368	0.098860	0
4	-2.388777	0.674767	0.021428	0

In [25]:

```
print(f"components_ in the data transformed to 3D : \n{sklearnPCA.components_}\n")
print(f"explained_variance_ in the data transformed to 3D : \n{sklearnPCA.explained_varianc
print(f"score in the data transformed to 3D : \n{sklearnPCA.score(X_std)}")
```

```
components_ in the data transformed to 3D :
[[ 0.52237162 -0.26335492  0.58125401  0.56561105]
 [ 0.37231836  0.92555649  0.02109478  0.06541577]
 [-0.72101681  0.24203288  0.14089226  0.6338014 ]]

explained_variance_ in the data transformed to 3D :
[2.93035378 0.92740362 0.14834223]

score in the data transformed to 3D :
-3.270481937196946
```

3-D Viasualisation of principal components

In [26]:

```
# Transforming iris data target variable classes into tuple

class_var = list(range(3)) # 3 classes 0,1,2
class_var_desc = list(iris_dataset.target_names)
class_variable = tuple(zip(class_var_desc,class_var))
print("iris data class :", class_variable)
list(class_variable)
```

```
iris data class : (('setosa', 0), ('versicolor', 1), ('virginica', 2))
```

Out[26]:

```
[('setosa', 0), ('versicolor', 1), ('virginica', 2)]
```

In [27]:

```python
# 3D plot
from mpl_toolkits.mplot3d import Axes3D


figure = plt.figure(1, figsize=(15, 10))
plt.clf()
ax = Axes3D( fig= figure , rect=[0, 0, .95, 1], elev=48, azim=134)
plt.cla()

# Assigning lables to axis of graph
for name, label in list(class_variable):
    ax.text3D(
        Y_sklearn[iris_target == label, 0].mean(),
        Y_sklearn[iris_target == label, 1].mean() + 1.5,
        Y_sklearn[iris_target == label, 2].mean(), name,
        horizontalalignment='center',  verticalalignment='center',
        bbox=dict(alpha=.5, edgecolor='r', facecolor='w'))

# Setting up data points on graph
ax.scatter(Y_sklearn[:, 0], Y_sklearn[:, 1], Y_sklearn[:, 2], c=iris_target, cmap=plt.cm.Se
ax.set_title("3D visualisation of  PCA directions of transformed iris data")
ax.w_xaxis.set_ticklabels(['principal component 1'])
ax.w_yaxis.set_ticklabels(['principal component 2'])
ax.w_zaxis.set_ticklabels(['principal component 3'])
plt.show()
```