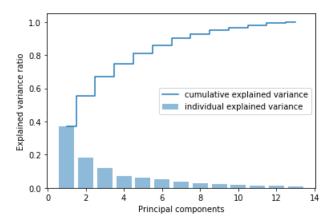
Machine Learning Workshop @ RGIT, Dec 2019

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```
In [0]: import numpy as np
         import pandas as pd
         import sklearn
         import sklearn.linear model as lm
         import sklearn.model_selection as cv
         import matplotlib.pyplot as plt
         %matplotlib inline
         from sklearn.decomposition import PCA
         from sklearn.decomposition import KernelPCA
In [0]: from google.colab import files
         uploaded = files.upload()
         Choose Files No file chosen
        Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
        Saving wine.data to wine (1).data
In [0]: import io
         wine = pd.read_csv(io.BytesIO(uploaded['wine.data']), header=None)
'Flavanoids', 'Nonflavanoid phenols', 'Proanthocyanins',
                            'Color intensity', 'Hue', 'OD280/OD315 of diluted wines',
                            'Proline']
        wine.head()
         # In this dataset, there are 3 possible class labels
Out[0]:
                                                                                                             C
           Class
                                                                             Nonflavanoid
                          Malic
                                    Alcalinity
                                                            Total
                                                                  Flavanoids
                                                                                          Proanthocyanins
                  Alcohol
                                Ash
                                              Magnesium
            label
                          acid
                                       of ash
                                                          phenols
                                                                                  phenols
                                                                                                           inter
         0
           1
                  14.23
                          1.71
                                2.43
                                    15.6
                                              127
                                                          2.80
                                                                  3.06
                                                                             0.28
                                                                                          2.29
                                                                                                           5.64
         1
           1
                                    11.2
                                              100
                                                          2.65
                                                                  2.76
                                                                             0.26
                                                                                          1.28
                  13.20
                          1.78
                               2.14
                                                                                                          4.38
         2
                                    18.6
                                              101
                                                                  3.24
                                                                                          2.81
           1
                  13.16
                          2.36
                               2.67
                                                         2.80
                                                                             0.30
                                                                                                          5.68
         3
           1
                  14.37
                          1.95
                               2.50
                                    16.8
                                              113
                                                         3.85
                                                                  3.49
                                                                             0.24
                                                                                          2.18
                                                                                                          7.80
         4
                                    21.0
                                                                  2.69
                  13.24
                          2.59
                               2.87
                                              118
                                                          2.80
                                                                             0.39
                                                                                          1.82
                                                                                                          4.32
                                                                                                            In [0]: wine.shape
Out[0]: (178, 14)
In [0]: wine_val = wine.values
        wine_val.shape
Out[0]: (178, 14)
In [0]: | np.unique(wine_val[:,0])
Out[0]: array([1., 2., 3.])
In [0]: X, y = wine_val[:,1:], wine_val[:,0]
```

```
In [0]: # Split the data into 70% training and 30% test subsets
        import sklearn.model_selection as cv
        X_train, X_test, y_train, y_test = cv.train_test_split(X, y,
                                                           test_size=0.3,
                                                           stratify=y,
                                                           random_state=0)
In [0]: # Standardize the data using StandardScaler
        # obtain X_train_std and X_test_std
        from sklearn.preprocessing import StandardScaler
        sc = StandardScaler()
        X_train_std = sc.fit_transform(X_train)
        X_test_std = sc.transform(X_test)
In [0]: print(X_train[:5,:5])
        print(X_train_std[:5,:5])
        [[ 13.62
                  4.95
                        2.35 20.
                 1.53
                        2.7
                              19.5 132.
          13.76
        [ 13.73
                  1.5
                        2.7
                              22.5 101.
        [ 13.51
                  1.8
                        2.65 19.
                                   110.
                                         ]
         [ 12.6
                  2.46
                        2.2
                              18.5
                                    94. ]]
        [ 0.88229214 -0.70457155 1.17533605 -0.09065504 2.34147876]
        [ 0.84585645 -0.73022996 1.17533605 0.81104754 0.13597904]
                                0.98882252 -0.24093881 0.77628541]
        [ 0.57866141 -0.4736459
         In [0]: | from sklearn.decomposition import PCA
        import matplotlib.pyplot as plt
        import numpy as np
        pca = PCA()
        X_train_pca = pca.fit_transform(X_train_std)
        print(pca.explained variance_ratio_)
        plt.bar(range(1, 14), pca.explained_variance_ratio_, alpha=0.5,
               align='center',label='individual explained variance')
        plt.step(range(1, 14), np.cumsum(pca.explained_variance_ratio_),
                where='mid',label='cumulative explained variance')
        plt.ylabel('Explained variance ratio')
        plt.xlabel('Principal components')
        plt.legend(loc='best')
        plt.show()
        [0.36951469 0.18434927 0.11815159 0.07334252 0.06422108 0.05051724
```

[0.36951469 0.18434927 0.11815159 0.07334252 0.06422108 0.05051724 0.03954654 0.02643918 0.02389319 0.01629614 0.01380021 0.01172226 0.00820609]

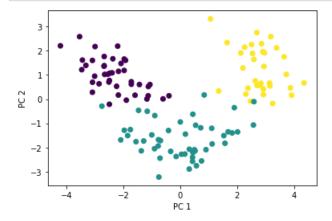


```
In [0]: # Apply PCA (2 components) on X_train_std
pca = PCA(n_components=2)

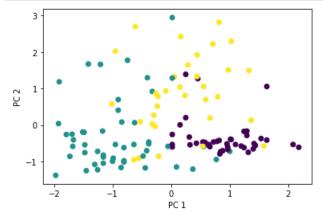
X_train_pca = pca.fit_transform(X_train_std)
```

```
In [0]: # Transform X_test_std using PCA
X_test_pca = pca.transform(X_test_std)
```

```
In [0]: # Do scatter plot of the transformed data
    plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1], c=y_train)
    plt.xlabel('PC 1')
    plt.ylabel('PC 2')
    plt.show()
```



In [0]: # Do scatter plot of the transformed data
plt.scatter(X_train_std[:, 0], X_train_std[:, 1], c=y_train)
plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.show()



```
In [0]: from matplotlib.colors import ListedColormap
         def plot_decision_regions(X, y, classifier, test_idx=None, resolution=0.02):
             # setup marker generator and color map
             markers = ('s', 'x', 'o', '^', 'v')
colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan')
             cmap = ListedColormap(colors[:len(np.unique(y))])
             # plot the decision surface
             x1_{min}, x1_{max} = X[:, 0].min() - 1, X[:, 0].max() + 1
             x2_{\min}, x2_{\max} = X[:, 1].min() - 1, X[:, 1].max() + 1
             xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution),
                                     np.arange(x2_min, x2_max, resolution))
             Z = classifier.predict(np.array([xx1.ravel(), xx2.ravel()]).T)
             Z = Z.reshape(xx1.shape)
             plt.contourf(xx1, xx2, Z, alpha=0.4, cmap=cmap)
             plt.xlim(xx1.min(), xx1.max())
             plt.ylim(xx2.min(), xx2.max())
             for idx, cl in enumerate(np.unique(y)):
                 plt.scatter(x=X[y == cl, 0], y=X[y == cl, 1],
                              alpha=0.8, c=cmap(idx),
                              marker=markers[idx], label=cl)
             # highlight test samples
             if test_idx:
                 # plot all samples
                 if not versiontuple(np. version ) >= versiontuple('1.9.0'):
                     X_test, y_test = X[list(test_idx), :], y[list(test_idx)]
                     warnings.warn('Please update to NumPy 1.9.0 or newer')
                 else:
                     X_test, y_test = X[test_idx, :], y[test_idx]
                 plt.scatter(X_test[:, 0],
                              X_test[:, 1],
                              c='',
                              alpha=1.0,
                              linewidths=1.
                              marker='o',
                              s=55, label='test set')
```

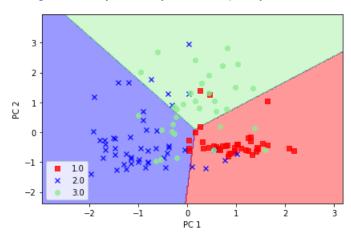
In [0]: # Train Logistic Regression classifier without using PCA

```
from sklearn.linear_model import LogisticRegression

lr_no_pca = LogisticRegression(solver='lbfgs', multi_class='ovr')
lr_no_pca = lr_no_pca.fit(X_train_std[:,:2], y_train)

plot_decision_regions(X_train_std[:,:2], y_train, classifier=lr_no_pca)
plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.legend(loc='lower left')
plt.tight_layout()
plt.show()
```

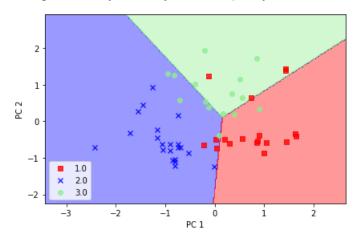
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-ma pping will have precedence in case its length matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.



```
In [0]: # Test the model
plot_decision_regions(X_test_std[:,:2], y_test, classifier=lr_no_pca)

plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.legend(loc='lower left')
plt.tight_layout()
plt.show()
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-ma pping will have precedence in case its length matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.



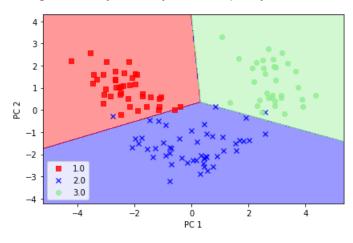
In [0]: # Train Logistic Regression classifier using the first 2 principal components

```
from sklearn.linear_model import LogisticRegression

lr_pca = LogisticRegression(solver='lbfgs', multi_class='ovr')
lr_pca = lr_pca.fit(X_train_pca, y_train)

plot_decision_regions(X_train_pca, y_train, classifier=lr_pca)
plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.legend(loc='lower left')
plt.tight_layout()
plt.show()
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-ma pping will have precedence in case its length matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.



```
In [0]: # Test the model
plot_decision_regions(X_test_pca, y_test, classifier=lr_pca)

plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.legend(loc='lower left')
plt.tight_layout()
plt.show()
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-ma pping will have precedence in case its length matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.

