

```

1 #import plotly.express as px
2 #df = px.data.iris()
3 #fig = px.scatter_3d(df, x='sepal_length', y='petal_length', z='petal_width',
4 #                    color='species')
5 #fig.show()

```

```

1 # USANDO PCA DE SCIKITLEARN

```

```

1 # Bibliotecas
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
5 # Datos
6 # https://archive.ics.uci.edu/ml/machine-learning-databases/wine/wine.data
7 df_wine = pd.read_csv('https://bit.ly/3L1ZZI4', header=None)
8 df_wine.shape

```

➡ (178, 14)

```

1 # Separar datos de entrenamiento y prueba
2 from sklearn.model_selection import train_test_split
3 X, y = df_wine.iloc[:,1:].values, df_wine.iloc[:,0].values
4 X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=42)
5 # estadarizamos
6 from sklearn.preprocessing import StandardScaler
7 sc = StandardScaler()
8 X_train_std = sc.fit_transform(X_train)
9 X_test_std = sc.transform(X_test)
10 X_train_std.shape, X_test_std.shape

```

➡ ((124, 13), (54, 13))

```

1 # Determinar número de componentes a conservar
2 from sklearn.decomposition import PCA
3 pca = PCA(n_components=13)
4 pca.fit(X_train_std)
5 pca.explained_variance_, pca.explained_variance_ratio_

```

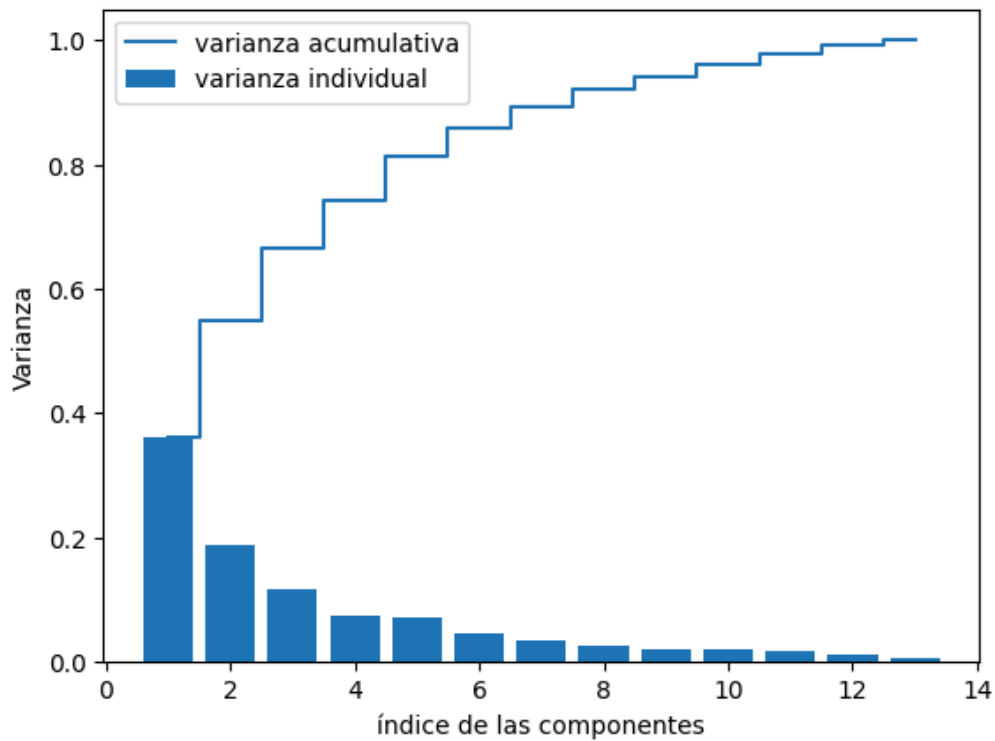
➡ (array([4.74376552, 2.45913372, 1.5276711 , 0.99327678, 0.92313257,
0.59663887, 0.46974164, 0.34681782, 0.28504118, 0.25665489,
0.23096439, 0.17349645, 0.09935613]),
array([0.36196226, 0.18763862, 0.11656548, 0.07578973, 0.07043753,
0.04552517, 0.03584257, 0.02646315, 0.02174942, 0.01958347,
0.01762321, 0.01323825, 0.00758114]))

```

1 # gráfica con los aportes de cada componente
2 import matplotlib.pyplot as plt
3 tot = sum(pca.explained_variance_ratio_)
4 var_exp = [ev/tot for ev in sorted(pca.explained_variance_ratio_,reverse=True)]
5 cum_var_exp = np.cumsum(var_exp)
6 plt.bar(range(1,14),var_exp,label='varianza individual',align='center')
7 plt.step(range(1,14),cum_var_exp,where='mid',label='varianza acumulativa')
8 plt.xlabel('índice de las componentes')
9 plt.ylabel('Varianza')

```

```
10 plt.legend(loc='best')
11 plt.show()
```



```
1 # Conservar 2 y revisar con regresión logística
2 from sklearn.linear_model import LogisticRegression
3 from sklearn.decomposition import PCA
4 pca = PCA(n_components=2)
5 lr = LogisticRegression()
```

```
1 # objetos de PCA y LR
2 # ajustar y transformar
3 X_train_pca = pca.fit_transform(X_train_std)
4 X_test_pca = pca.transform(X_test_std)
5 lr.fit(X_train_pca, y_train)
```

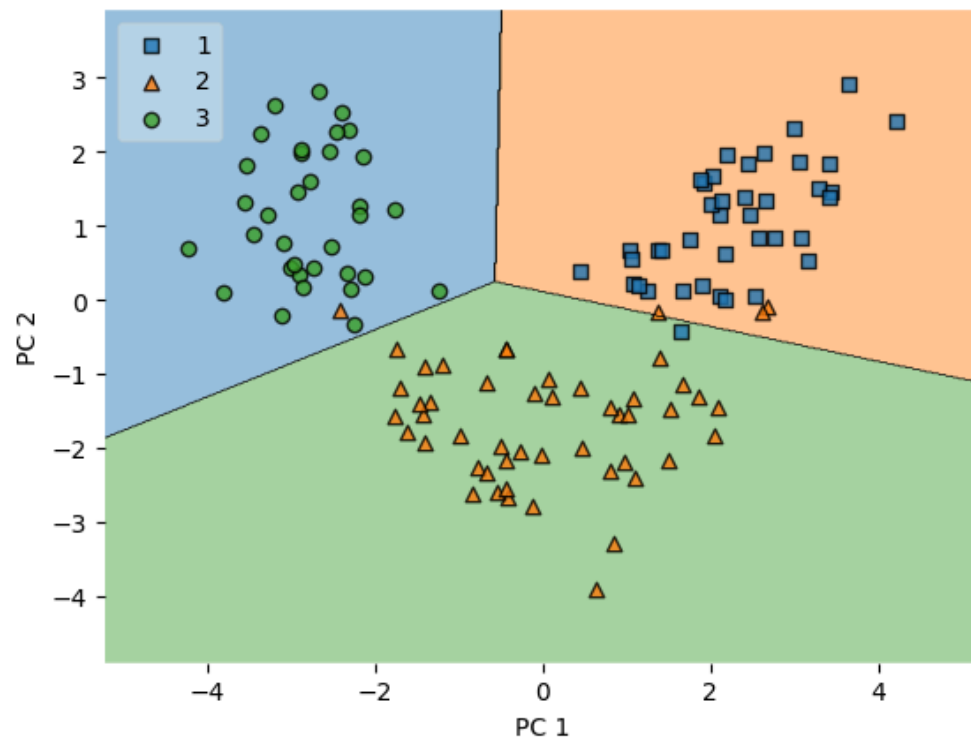


▼ **LogisticRegression** ⓘ ?

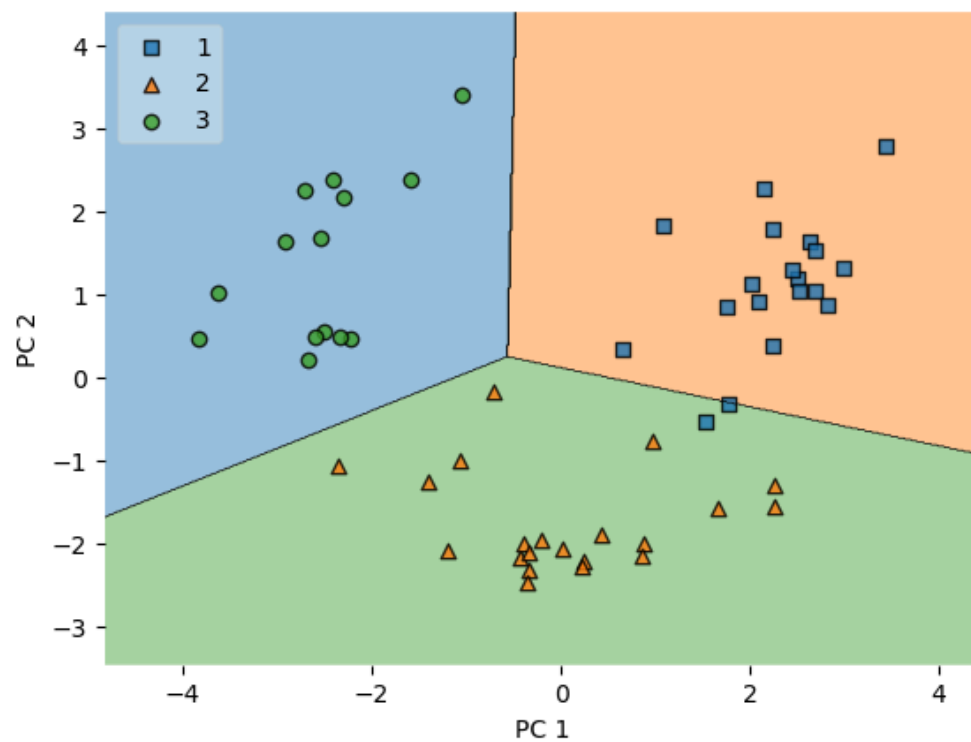
LogisticRegression()

```
1 #!pip install mlxtend
```

```
1 # Grafica del conjunto de entrenamiento
2 from mlxtend.plotting import plot_decision_regions
3 plot_decision_regions(X_train_pca, y_train, clf=lr, legend=2)
4 plt.xlabel('PC 1')
5 plt.ylabel('PC 2')
6 plt.show()
```



```
1 # Grafica del conjunto de prueba
2 plot_decision_regions(X_test_pca, y_test, clf=lr, legend=2)
3 plt.xlabel('PC 1')
4 plt.ylabel('PC 2')
5 plt.show()
```



1 # LDA CON PYTHON

```

1 # Bibliotecas
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
5 # Datos
6 df_wine = pd.read_csv('https://bit.ly/3L1ZZI4', header=None)

1 # Separar datos de entrenamiento y prueba
2 from sklearn.model_selection import train_test_split
3 X, y = df_wine.iloc[:,1:].values, df_wine.iloc[:,0].values
4 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
5 # estandarizamos
6 from sklearn.preprocessing import StandardScaler
7 sc = StandardScaler()
8 X_train_std = sc.fit_transform(X_train)
9 X_test_std = sc.transform(X_test)

1 # Revisar con regresión logística
2 from sklearn.linear_model import LogisticRegression
3 from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
4 # inicializar LDA y el modelo de RL
5 lda = LDA(n_components=2)
6 lr = LogisticRegression()
7 # Ajustar y transformar los datos
8 X_train_lda = lda.fit_transform(X_train_std, y_train)
9 lr.fit(X_train_lda, y_train)

```



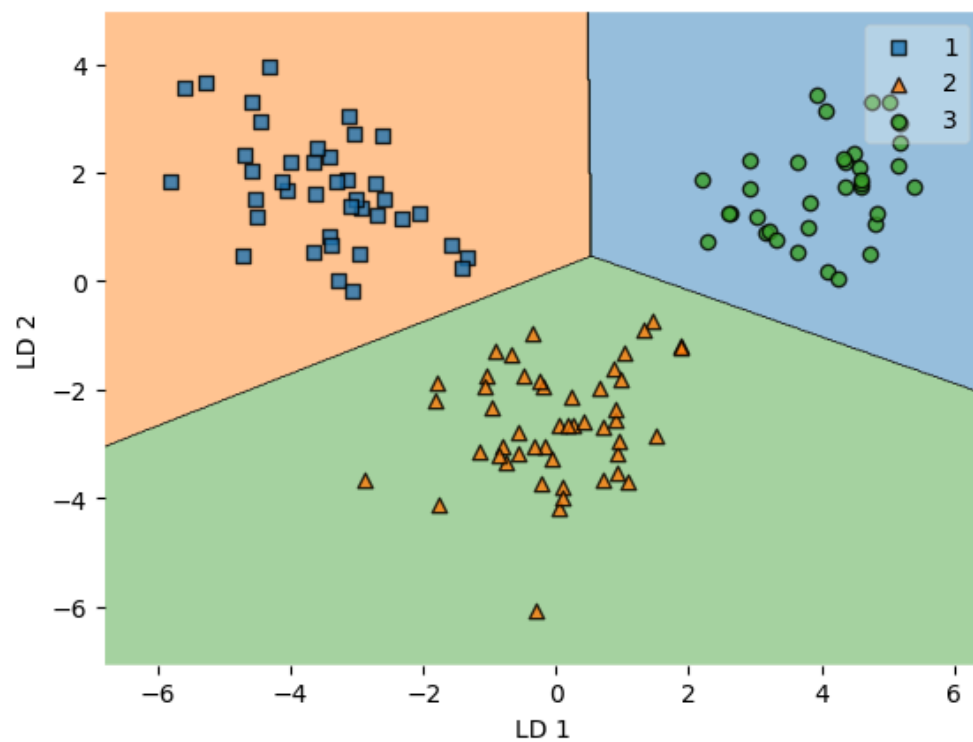
▼ **LogisticRegression** ⓘ ?

LogisticRegression()

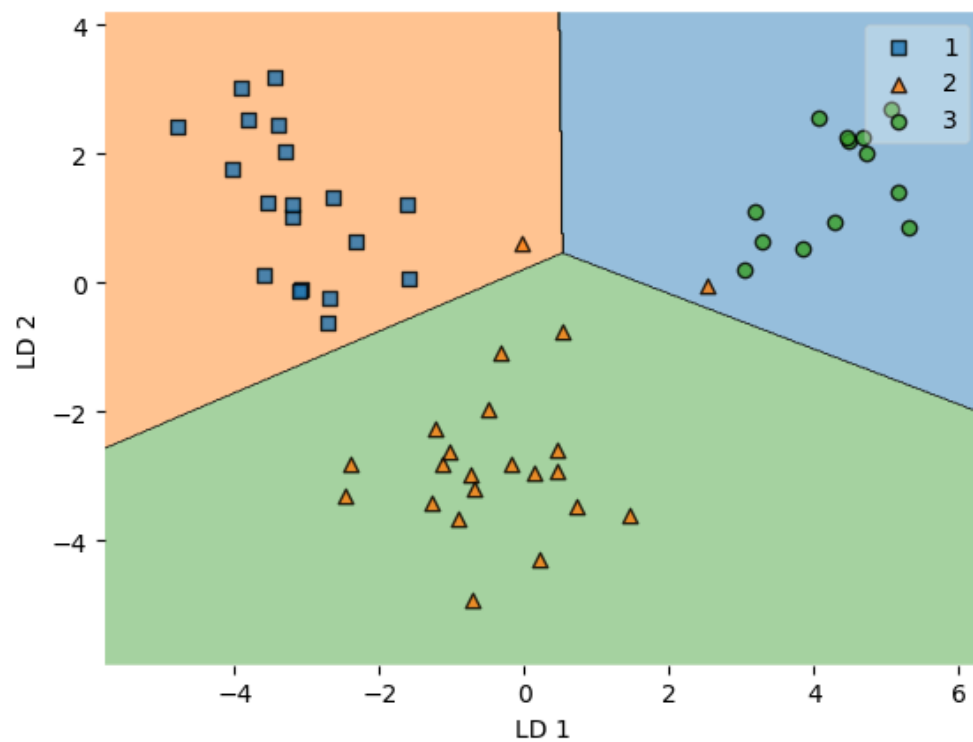
```

1 # Grafica del conjunto de entrenamiento
2 from mlxtend.plotting import plot_decision_regions
3 plot_decision_regions(X_train_lda, y_train, clf=lr)
4 plt.xlabel('LD 1')
5 plt.ylabel('LD 2')
6 plt.show()

```



```
1 # Grafica del conjunto de pruebas
2 X_test_lda = lda.transform(X_test_std)
3 plot_decision_regions(X_test_lda, y_test, clf=lr)
4 plt.xlabel('LD 1')
5 plt.ylabel('LD 2')
6 plt.show()
```

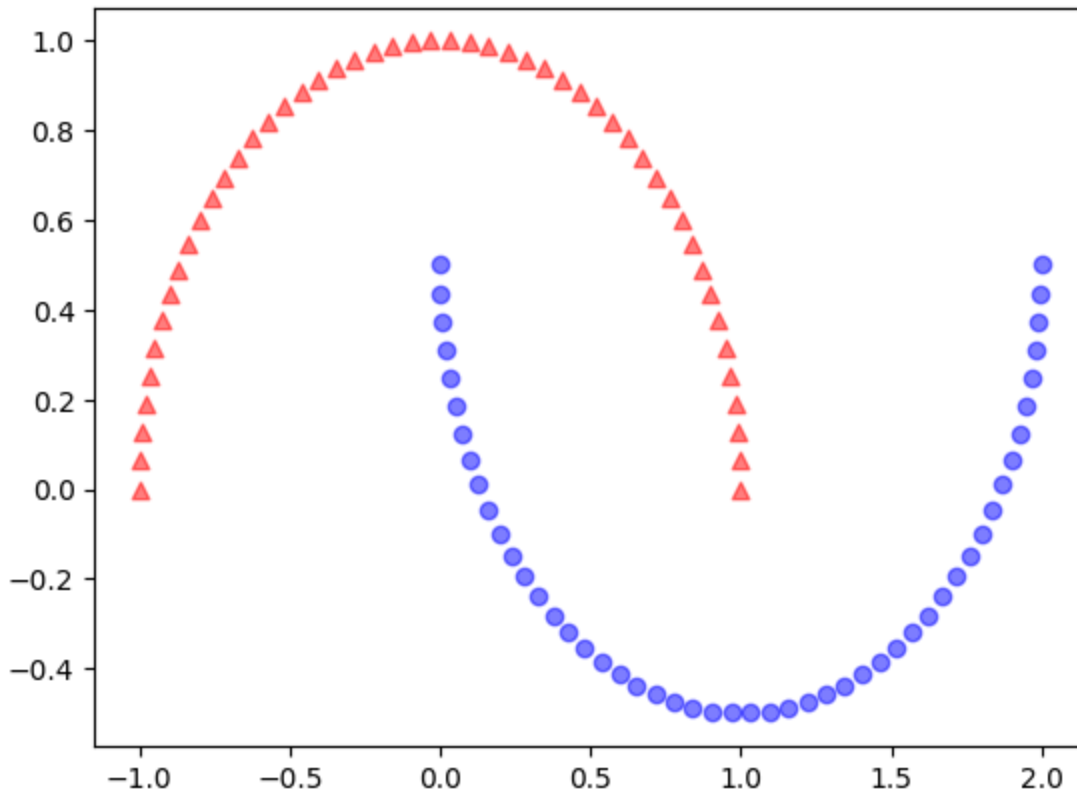


```

1 import numpy as np
2 import matplotlib.pyplot as plt

1 # Datos: Separar medias lunas
2 from sklearn.datasets import make_moons
3 X, y = make_moons(n_samples=100, random_state=123)
4 plt.scatter(X[y==0, 0], X[y==0, 1], color='red', marker='^', alpha=0.5)
5 plt.scatter(X[y==1, 0], X[y==1, 1], color='blue', marker='o', alpha=0.5)
6 plt.show()

```

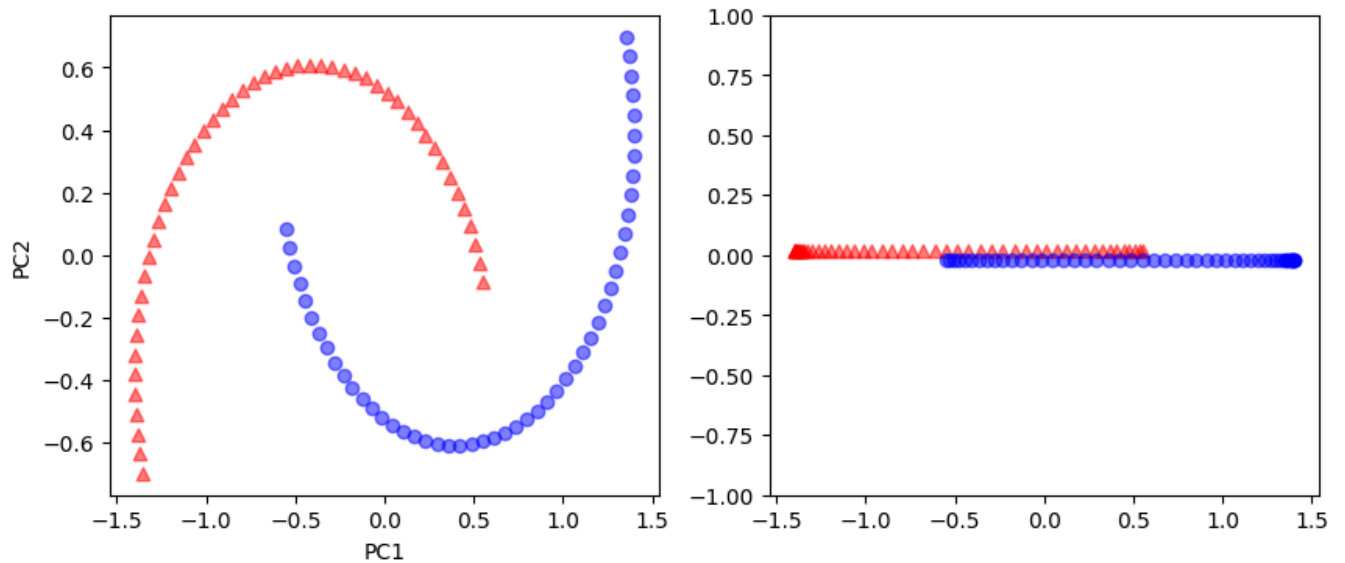


```

1 # Con PCA
2 from sklearn.decomposition import PCA
3 pca = PCA(n_components=2)
4 X_pca = pca.fit_transform(X)

1 fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,4))
2 ax[0].scatter(X_pca[y==0,0],X_pca[y==0,1],color='red',marker='^',alpha=0.5)
3 ax[0].scatter(X_pca[y==1,0],X_pca[y==1,1],color='blue',marker='o',alpha=0.5)
4 ax[1].scatter(X_pca[y==0,0],np.zeros((50,1))+0.02,color='red',marker='^',alpha=0.5)
5 ax[1].scatter(X_pca[y==1,0],np.zeros((50,1))-0.02,color='blue',marker='o',alpha=0.5)
6 ax[0].set_xlabel('PC1')
7 ax[0].set_ylabel('PC2')
8 ax[1].set_ylim([-1,1])
9 ax[0].set_xlabel('PC1')
10 plt.show()

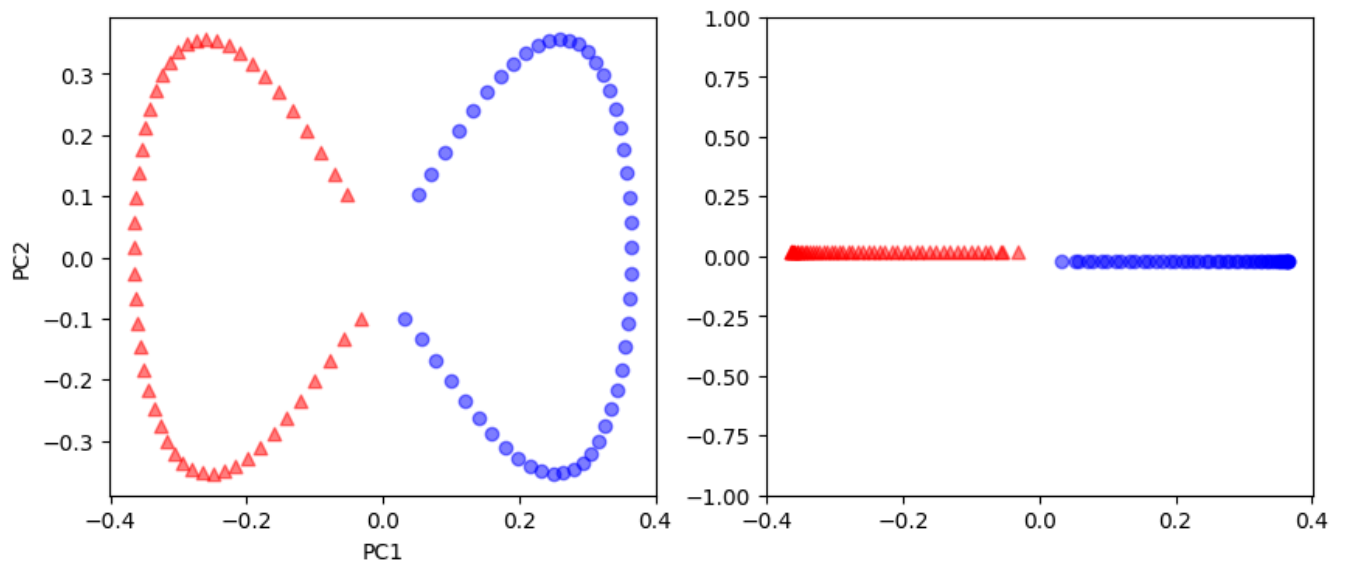
```



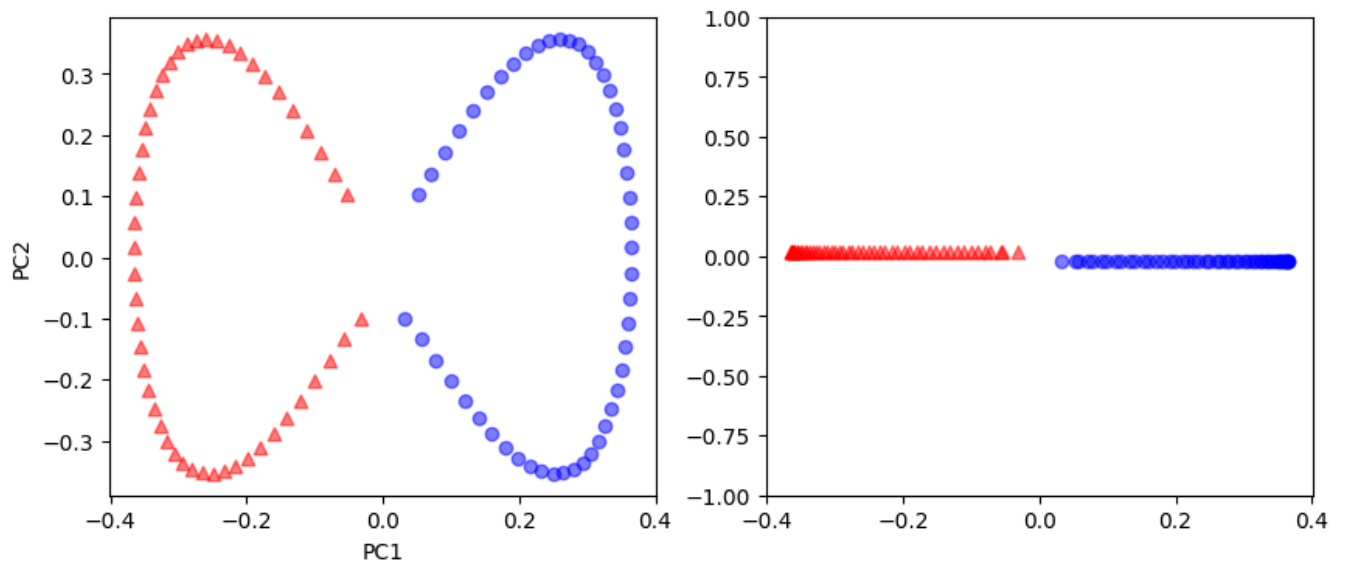
```
1 # Datos: Separar medias lunas
2 from sklearn.datasets import make_moons
3 X, y = make_moons(n_samples=100, random_state=123)
```

```
1 # Con KPCA de Python
2 from sklearn.decomposition import KernelPCA
3 kpca = KernelPCA(n_components=2, kernel='rbf', gamma=15)
4 X_kpca = kpca.fit_transform(X)
```

```
1 fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,4))
2 ax[0].scatter(X_kpca[y==0,0],X_kpca[y==0,1],color='red',marker='^',alpha=0.5)
3 ax[0].scatter(X_kpca[y==1,0],X_kpca[y==1,1],color='blue',marker='o',alpha=0.5)
4 ax[1].scatter(X_kpca[y==0,0],np.zeros((50,1))+0.02,color='red',marker='^',alpha=
5 ax[1].scatter(X_kpca[y==1,0],np.zeros((50,1))-0.02,color='blue',marker='o',alpha=
6 ax[0].set_xlabel('PC1')
7 ax[0].set_ylabel('PC2')
8 ax[1].set_ylim([-1,1])
9 ax[0].set_xlabel('PC1')
10 plt.show()
```

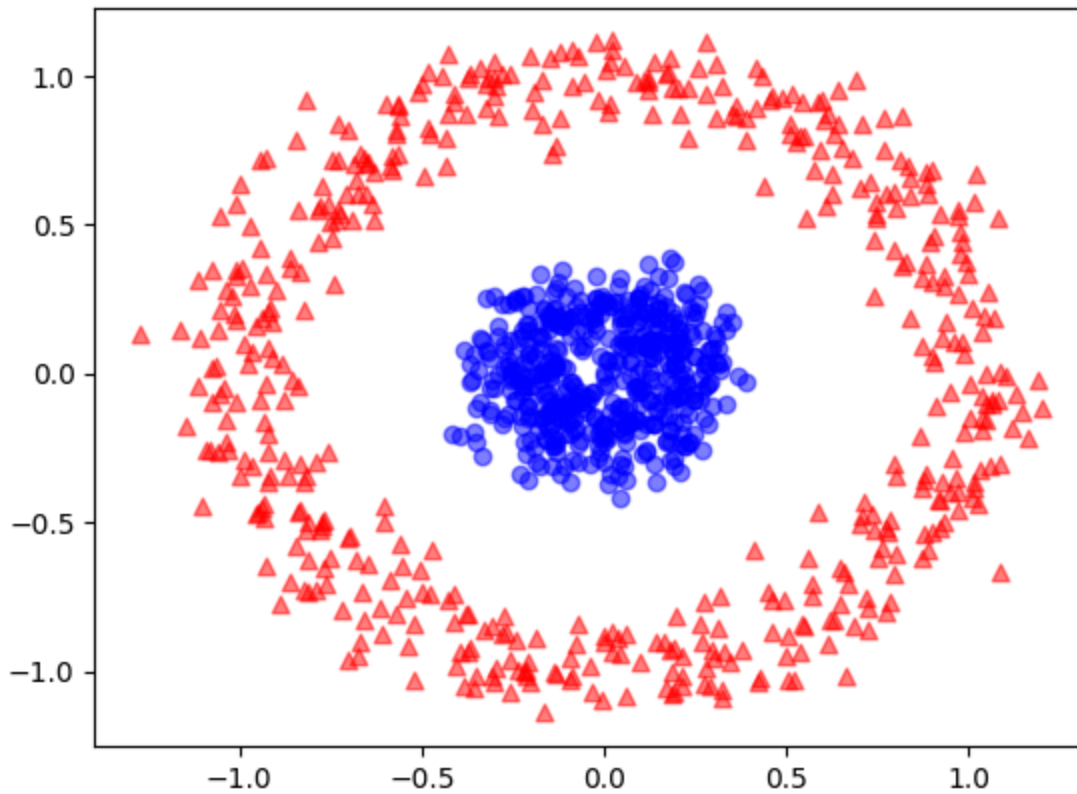


```
1 from sklearn.decomposition import KernelPCA
2 kpca = KernelPCA(n_components=2, kernel='rbf', gamma=15)
3 X_kpca = kpca.fit_transform(X)
4 fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,4))
5 ax[0].scatter(X_kpca[y==0,0],X_kpca[y==0,1],color='red',marker='^',alpha=0.5)
6 ax[0].scatter(X_kpca[y==1,0],X_kpca[y==1,1],color='blue',marker='o',alpha=0.5)
7 ax[1].scatter(X_kpca[y==0,0],np.zeros((50,1))+0.02,color='red',marker='^',alpha=
8 ax[1].scatter(X_kpca[y==1,0],np.zeros((50,1))-0.02,color='blue',marker='o',alpha
9 ax[0].set_xlabel('PC1')
10 ax[0].set_ylabel('PC2')
11 ax[1].set_ylim([-1,1])
12 ax[0].set_xlabel('PC1')
13 plt.show()
```

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```
1 # Datos: círculos concéntricos
2 from sklearn.datasets import make_circles
3 X, y = make_circles(n_samples=1000, random_state=123, noise=0.1, factor=0.2)
4 plt.scatter(X[y==0, 0], X[y==0, 1], color='red', marker='^', alpha=0.5)
5 plt.scatter(X[y==1, 0], X[y==1, 1], color='blue', marker='o', alpha=0.5)
6 plt.show()
```



```
1 # Intentar con PCA
2 from sklearn.decomposition import PCA
3 pca = PCA(n_components=2)
4 X_pca = pca.fit_transform(X)
```

```
1 fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,4))
2 # Código para graficar
3 plt.show()
```

```
1 # Con KPCA de Python
2 from sklearn.decomposition import KernelPCA
3 #kpca = KernelPCA()
4 #X_kpca = kpca.fit_transform(X)
```

```
1 fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,4))
2 # Código para graficar
3 plt.show()
```

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