SVM Kernels Indepth Intuition And Practical Explanation

```
In [1]:
            import numpy as np
            import matplotlib.pyplot as plt
         3
         4 x = np.linspace(-5.0, 5.0, 100) # ye line space -5 se 5 k bichme 100 point create krdega
         5 y = np.sqrt(10**2 - x**2)
In [2]:
Out[2]: array([-5.
                    . -4.8989899 . -4.7979798 . -4.6969697 . -4.5959596 .
           -4.49494949, -4.39393939, -4.29292929, -4.19191919, -4.09090909,
           -3.98989899, -3.888888889, -3.78787879, -3.68686869, -3.58585859,
           -3.48484848, -3.38383838, -3.28282828, -3.18181818, -3.08080808,
           -2.97979798, -2.87878788, -2.77777778, -2.67676768, -2.57575758,
           -2.47474747, -2.37373737, -2.27272727, -2.17171717, -2.07070707,
           -1.96969697, -1.86868687, -1.76767677, -1.666666667, -1.56565657,
           -1.46464646, -1.36363636, -1.26262626, -1.16161616, -1.06060606,
           -0.95959596, -0.85858586, -0.75757576, -0.65656566, -0.55555556,
           -0.45454545, -0.35353535, -0.25252525, -0.15151515, -0.05050505,
            0.05050505, 0.15151515, 0.25252525, 0.35353535, 0.45454545,
            0.5555556, 0.65656566, 0.75757576, 0.85858586, 0.95959596,
            1.06060606, 1.16161616, 1.26262626, 1.36363636, 1.46464646,
            1.56565657, 1.666666667, 1.76767677, 1.86868687, 1.96969697,
            2.07070707, 2.17171717, 2.27272727, 2.37373737, 2.47474747,
            2.57575758, 2.67676768, 2.77777778, 2.87878788, 2.97979798
            3.08080808, 3.18181818, 3.28282828, 3.38383838, 3.48484848
            3.58585859, 3.68686869, 3.78787879, 3.88888889, 3.98989899,
            4.09090909, 4.19191919, 4.29292929, 4.39393939, 4.49494949,
            4.5959596, 4.6969697, 4.7979798, 4.8989899, 5.
```

In [3]: 1 [x,-x]

```
Out[3]: [array([-5.
                     . -4.8989899 . -4.7979798 . -4.6969697 . -4.5959596 .
            -4.49494949, -4.39393939, -4.29292929, -4.19191919, -4.09090909,
            -3.98989899, -3.888888889, -3.78787879, -3.68686869, -3.58585859,
            -3.48484848, -3.38383838, -3.28282828, -3.18181818, -3.08080808,
            -2.97979798, -2.87878788, -2.77777778, -2.67676768, -2.57575758,
            -2.47474747, -2.37373737, -2.27272727, -2.17171717, -2.07070707,
            -1.96969697, -1.86868687, -1.76767677, -1.666666667, -1.56565657,
            -1.46464646, -1.36363636, -1.26262626, -1.16161616, -1.06060606,
            -0.95959596, -0.85858586, -0.75757576, -0.65656566, -0.55555556
            -0.45454545, -0.35353535, -0.25252525, -0.15151515, -0.05050505,
             0.05050505, 0.15151515, 0.25252525, 0.35353535, 0.45454545,
             0.5555556, 0.65656566, 0.75757576, 0.85858586, 0.95959596,
             1.06060606, 1.16161616, 1.26262626, 1.36363636, 1.46464646,
             1.56565657, 1.66666667, 1.76767677, 1.86868687, 1.96969697,
             2.07070707, 2.17171717, 2.27272727, 2.37373737, 2.47474747,
             2.57575758, 2.67676768, 2.77777778, 2.87878788, 2.97979798,
             3.08080808, 3.18181818, 3.28282828, 3.38383838, 3.48484848
             3.58585859, 3.68686869, 3.78787879, 3.888888889, 3.98989899
             4.09090909, 4.19191919, 4.29292929, 4.39393939, 4.49494949,
             4.5959596, 4.6969697, 4.7979798, 4.8989899, 5.
                     , 4.8989899 , 4.7979798 , 4.6969697 , 4.5959596 ,
             4.49494949, 4.39393939, 4.29292929, 4.19191919, 4.09090909,
             3.98989899, 3.888888889, 3.78787879, 3.68686869, 3.58585859,
             3.48484848, 3.38383838, 3.28282828, 3.18181818, 3.08080808,
             2.97979798, 2.87878788, 2.77777778, 2.67676768, 2.57575758,
             2.47474747, 2.37373737, 2.27272727, 2.17171717, 2.07070707,
             1.96969697, 1.86868687, 1.76767677, 1.66666667, 1.56565657,
             1.46464646, 1.36363636, 1.26262626, 1.16161616, 1.06060606,
             0.95959596, 0.85858586, 0.75757576, 0.65656566, 0.55555556,
             0.45454545, 0.35353535, 0.25252525, 0.15151515, 0.05050505,
            -0.05050505, -0.15151515, -0.25252525, -0.35353535, -0.45454545
            -0.55555556, -0.65656566, -0.75757576, -0.85858586, -0.95959596
            -1.06060606, -1.16161616, -1.26262626, -1.36363636, -1.46464646,
            -1.56565657, -1.666666667, -1.76767677, -1.86868687, -1.96969697,
            -2.07070707, -2.17171717, -2.27272727, -2.37373737, -2.47474747,
            -2.57575758, -2.67676768, -2.77777778, -2.87878788, -2.97979798
            -3.08080808, -3.18181818, -3.28282828, -3.38383838, -3.48484848,
            -3.58585859, -3.68686869, -3.78787879, -3.888888889, -3.98989899,
            -4.09090909, -4.19191919, -4.29292929, -4.39393939, -4.49494949
            -4.5959596, -4.6969697, -4.7979798, -4.8989899, -5.
```

In [4]: 1 y=np.hstack([y,-y]) 2 x=np.hstack([x,-x]) In [5]: 1 x

```
Out[5]: array([-5.
                    . -4.8989899 . -4.7979798 . -4.6969697 . -4.5959596 .
           -4.49494949, -4.39393939, -4.29292929, -4.19191919, -4.09090909,
           -3.98989899, -3.888888889, -3.78787879, -3.68686869, -3.58585859,
           -3.48484848, -3.38383838, -3.28282828, -3.18181818, -3.08080808,
           -2.97979798, -2.87878788, -2.77777778, -2.67676768, -2.57575758,
           -2.47474747, -2.37373737, -2.27272727, -2.17171717, -2.07070707,
           -1.96969697, -1.86868687, -1.76767677, -1.666666667, -1.56565657,
           -1.46464646, -1.36363636, -1.26262626, -1.16161616, -1.06060606,
           -0.95959596, -0.85858586, -0.75757576, -0.65656566, -0.55555556,
           -0.45454545, -0.35353535, -0.25252525, -0.15151515, -0.05050505,
            0.05050505, 0.15151515, 0.25252525, 0.35353535, 0.45454545
            0.5555556, 0.65656566, 0.75757576, 0.85858586, 0.95959596
            1.06060606, 1.16161616, 1.26262626, 1.36363636, 1.46464646
            1.56565657, 1.666666667, 1.76767677, 1.86868687, 1.96969697
            2.07070707, 2.17171717, 2.27272727, 2.37373737, 2.47474747,
            2.57575758, 2.67676768, 2.77777778, 2.87878788, 2.97979798
            3.08080808, 3.18181818, 3.28282828, 3.38383838, 3.48484848
            3.58585859, 3.68686869, 3.78787879, 3.888888889, 3.98989899
            4.09090909, 4.19191919, 4.29292929, 4.39393939, 4.49494949
            4.5959596, 4.6969697, 4.7979798, 4.8989899, 5.
                  , 4.8989899 , 4.7979798 , 4.6969697 , 4.5959596 ,
            4.49494949, 4.39393939, 4.29292929, 4.19191919, 4.09090909
            3.98989899, 3.888888889, 3.78787879, 3.68686869, 3.58585859
            3.48484848, 3.38383838, 3.28282828, 3.18181818, 3.08080808
            2.97979798, 2.87878788, 2.77777778, 2.67676768, 2.57575758
            2.47474747, 2.37373737, 2.27272727, 2.17171717, 2.07070707,
            1.96969697, 1.86868687, 1.76767677, 1.66666667, 1.56565657
            1.46464646, 1.36363636, 1.26262626, 1.16161616, 1.06060606
            0.95959596, 0.85858586, 0.75757576, 0.65656566, 0.55555556
            0.45454545, 0.35353535, 0.25252525, 0.15151515, 0.05050505,
           -0.05050505, -0.15151515, -0.25252525, -0.35353535, -0.45454545
           -0.5555556, -0.65656566, -0.75757576, -0.85858586, -0.95959596
           -1.06060606, -1.16161616, -1.26262626, -1.36363636, -1.46464646,
           -1.56565657, -1.666666667, -1.76767677, -1.86868687, -1.96969697,
           -2.07070707, -2.17171717, -2.27272727, -2.37373737, -2.47474747,
           -2.57575758, -2.67676768, -2.77777778, -2.87878788, -2.97979798,
           -3.08080808, -3.18181818, -3.28282828, -3.38383838, -3.48484848,
           -3.58585859, -3.68686869, -3.78787879, -3.888888889, -3.98989899,
           -4.09090909, -4.19191919, -4.29292929, -4.39393939, -4.49494949,
           -4.5959596, -4.6969697, -4.7979798, -4.8989899, -5.
```

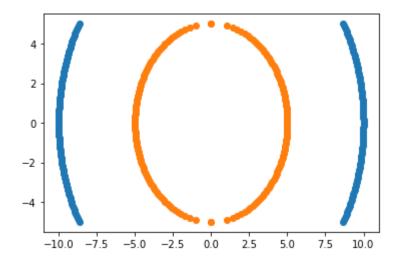
```
In [6]:

1  x1 = np.linspace(-5.0, 5.0, 100)
2  y1 = np.sqrt(5**2 - x1**2)
3  y1=np.hstack([y1,-y1])
4  x1=np.hstack([x1,-x1])
```

In [7]: 1 plt.scatter(y,x) #blue point

2 plt.scatter(y1,x1) #orange point inner one

Out[7]: <matplotlib.collections.PathCollection at 0x13fd9f9a550>



```
In [8]:
          1 np.vstack([y,x]).T
Out[8]: array([[ 8.66025404, -5.
            [8.71779204, -4.8989899],
            [8.77378994, -4.7979798],
            [8.82827705, -4.6969697],
            [8.88128118, -4.5959596],
            [8.93282873, -4.49494949],
            [8.98294476, -4.39393939],
            [ 9.03165312, -4.29292929],
            [9.07897646, -4.19191919],
            [ 9.12493632, -4.09090909],
            [ 9.16955321, -3.98989899],
            [ 9.21284664, -3.888888889],
            [ 9.25483518, -3.78787879],
            [ 9.29553652, -3.68686869],
            [ 9.3349675 , -3.58585859],
            [9.37314414, -3.48484848],
            [ 9.41008171, -3.38383838],
            [ 9.44579475, -3.28282828],
             9.4802971, -3.18181818],
            In [9]:
            import pandas as pd
            df1 =pd.DataFrame(np.vstack([y,x]).T,columns=['X1','X2'])
            df1['Y']=0
            df2 =pd.DataFrame(np.vstack([y1,x1]).T,columns=['X1','X2'])
            df2['Y']=1
         6 df = df1.append(df2)
         7 df.head(5)
Out[9]:
                 X1
                          X2 Y
         0 8.660254 -5.00000 0
           8.717792 -4.89899 0
           8.773790 -4.79798 0
           8.828277 -4.69697 0
         4 8.881281 -4.59596 0
```

```
1 df.tail()
In [10]:
Out[10]:
                     X1
                              X2 Y
          195 -1.969049 -4.59596 1
          196 -1.714198 -4.69697 1
          197 -1.406908 -4.79798 1
          198 -0.999949 -4.89899 1
          199 -0.000000 -5.00000 1
 In [11]:
           1 ### Independent and Dependent features
           2 X = df.iloc[:, :2]
           y = df.Y
In [12]:
          1 y
Out[12]: 0
             0
              0
             0
              0
         195
         196
         197 1
         198
               1
         199 1
         Name: Y, Length: 400, dtype: int64
In [13]:
           1 ## Split the dataset into train and test
           2 from sklearn.model selection import train test split
           3 X train,X test,y train,y test=train test split(X,y,test size=0.25,random state=0)
```

```
In [14]:
           1 y train
Out[14]: 50
         63
              0
         112 1
         159 0
         83
         192 0
         117 0
         47 0
         172 0
         Name: Y, Length: 300, dtype: int64
 In [15]:
           1 from sklearn.svm import SVC
           2 from sklearn.metrics import accuracy score
             classifier = SVC(kernel="linear")
             classifier.fit(X train, y train)
           5 y pred = classifier.predict(X test)
           6 accuracy score(y test, y pred)
Out[15]: 0.45
 In [16]:
           1 from sklearn.svm import SVC
           2 from sklearn.metrics import accuracy score
             classifier = SVC(kernel="poly")
              classifier.fit(X_train, y_train)
             y pred = classifier.predict(X test)
           6 accuracy score(y test, y pred)
Out[16]: 0.59
In [17]:
              from sklearn.svm import SVC
           2 from sklearn.metrics import accuracy score
             classifier = SVC(kernel="rbf")
              classifier.fit(X train, y train)
           5 y pred = classifier.predict(X test)
           6 accuracy score(y test, y pred)
Out[17]: 1.0
```

```
In [18]:
```

- 1 **from** sklearn.svm **import** SVC
- 2 from sklearn.metrics import accuracy_score
- 3 classifier = SVC(kernel="sigmoid")
- 4 classifier.fit(X_train, y_train)
- 5 y_pred = classifier.predict(X_test)
- 6 accuracy score(y test, y pred)

Out[18]: 0.51

accuracy before appying polynomial kernal

rbf has more accuracy, so for this circular type of data distribution use rbf automatically below thing will be executed by rbf

Polynomial Kernel

$$K(x,y) = (x^{\mathsf{T}}y + c)^d$$

In [19]:

- 1 # We need to find components for the Polynomical Kernel
- 2 #X1,X2,X1_square,X2_square,X1*X2
- 3 df['X1 Square']= df['X1']**2
- 4 df['X2_Square']= df['X2']**2
- 5 df['X1*X2'] = (df['X1'] *df['X2'])
- 6 df.head()

Out[19]:

	X1	X2	Υ	X1_Square	X2_Square	X1*X2
0	8.660254	-5.00000	0	75.000000	25.000000	-43.301270
1	8.717792	-4.89899	0	75.999898	24.000102	-42.708375
2	8.773790	-4.79798	0	76.979390	23.020610	-42.096467
3	8.828277	-4.69697	0	77.938476	22.061524	-41.466150
4	8.881281	-4.59596	0	78.877155	21.122845	-40.818009

```
In [20]:
           1 ### Independent and Dependent features
          2 X = df[['X1','X2','X1_Square','X2_Square','X1*X2']]
          y = df[Y]
In [21]:
         1 y
Out[21]: 0
             0
             0
             0
         195
         196
         197 1
         198 1
         199 1
         Name: Y, Length: 400, dtype: int64
  In [ ]:
In [22]:
             X_train, X_test, y_train, y_test = train_test_split(X, y,
           3
                                            test size = 0.25,
                                            random_state = 0)
           5
```

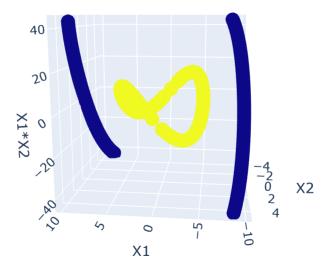
In [23]: 1 X train

Out[23]:

	X1	X2	X1_Square	X2_Square	X1*X2
50	4.999745	0.050505	24.997449	0.002551	0.252512
63	9.906589	1.363636	98.140496	1.859504	13.508984
112	-3.263736	3.787879	10.651974	14.348026	-12.362637
159	-9.953852	-0.959596	99.079176	0.920824	9.551676
83	3.680983	3.383838	13.549638	11.450362	12.455852
123	-4.223140	2.676768	17.834915	7.165085	-11.304366
192	-9.031653	-4.292929	81.570758	18.429242	38.772248
117	-9.445795	3.282828	89.223038	10.776962	-31.008922
47	9.996811	-0.252525	99.936231	0.063769	-2.524447
172	-9.738311	-2.272727	94.834711	5.165289	22.132526

300 rows × 5 columns

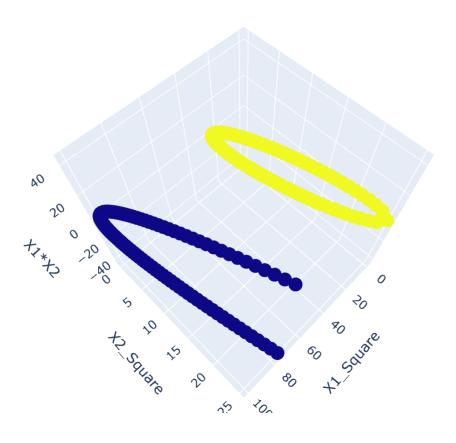
```
In [24]: 1 import plotly.express as px
2 3 fig = px.scatter_3d(df, x='X1', y='X2', z='X1*X2', color='Y')
5 fig.show()
```



In [25]:

ye upar wala graph jb apan ne normally data plot kr re hai tbka hai

- 2 # now isme dekh skte toh ye easily seprable nahi hai
- 3 # toh apan ne X1_square, X2_square nikala jissne niche wala graph bnra hai



In [27]:

data segregate krdiya pura

2 # ab niche wali accuracy sari 1 ari hai, kyoki seprate kr skte hai

```
In [28]:
              from sklearn.svm import SVC
           2 from sklearn.metrics import accuracy score
              classifier = SVC(kernel="linear")
              classifier.fit(X train, y train)
              y pred = classifier.predict(X test)
           6 accuracy score(y test, y pred)
Out[28]: 1.0
In [29]:
           1 from sklearn.svm import SVC
           2 from sklearn.metrics import accuracy score
              classifier = SVC(kernel="poly")
              classifier.fit(X train, y train)
             y pred = classifier.predict(X test)
           6 accuracy score(y test, y pred)
Out[29]: 1.0
In [30]:
              from sklearn.svm import SVC
           2 from sklearn.metrics import accuracy score
              classifier = SVC(kernel="rbf")
              classifier.fit(X train, y train)
           5 y pred = classifier.predict(X test)
           6 accuracy score(y test, y pred)
Out[30]: 1.0
In [31]:
           1 from sklearn.svm import SVC
           2 from sklearn.metrics import accuracy score
             classifier = SVC(kernel="sigmoid")
              classifier.fit(X train, y train)
           5 y pred = classifier.predict(X test)
           6 accuracy score(y test, y pred)
Out[31]: 1.0
In [32]:
           1 # yaha se ye nishkarsh nikalta hai ki
           2 # data ko split 3d me krdege toh accuracy nikal skti hai
           3 # toh uske liye apan ne polynomail kernal k formule lagaye or new data point create krdiye, jisse sari accuracy 1.0 agai
```

or rbf kernal jo hai vo usko automatically 3D me seprate krdega, bina polynomial lagye. jese line 17 and 30 me "rbf" apply kia hai