SVM Kernels Indepth Intuition And Practical Explanation

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt

x = np.linspace(-5.0, 5.0, 100)
y = np.sqrt(10**2 - x**2)
y=np.hstack([y,-y])
```

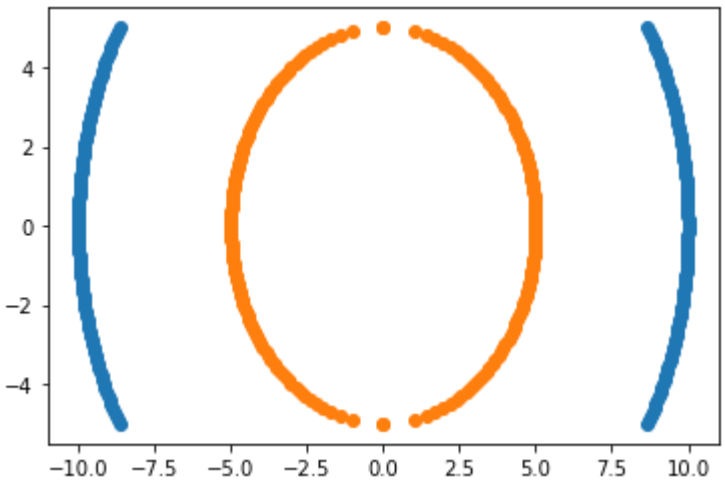
In [39]:

Out[39]:
```
array([ 8.66025404,  8.71779204,  8.77378994,  8.82827705,  8.88128118,
        8.93282873,  8.98294476,  9.03165312,  9.07897646,  9.12493632,
        9.16955321,  9.21284664,  9.25483518,  9.29553652,  9.3349675 ,
        9.37314414,  9.41008171,  9.44579475,  9.4802971 ,  9.51360192,
        9.54572176,  9.57666854,  9.60645359,  9.63508769,  9.66258107,
        9.68894344,  9.714184  ,  9.73831149,  9.76133416,  9.7832598 ,
        9.80409577,  9.82384901,  9.84252604,  9.86013297,  9.87667553,
        9.89215905,  9.90658851,  9.91996849,  9.93230325,  9.94359667,
        9.9538523 ,  9.96307334,  9.97126266,  9.9784228 ,  9.98455598,
        9.98966408,  9.99374868,  9.99681104,  9.99885209,  9.99987246,
        9.99987246,  9.99885209,  9.99681104,  9.99374868,  9.98966408,
        9.98455598,  9.9784228 ,  9.97126266,  9.96307334,  9.9538523 ,
        9.94359667,  9.93230325,  9.91996849,  9.90658851,  9.89215905,
        9.87667553,  9.86013297,  9.84252604,  9.82384901,  9.80409577,
        9.7832598 ,  9.76133416,  9.73831149,  9.714184  ,  9.68894344,
        9.66258107,  9.63508769,  9.60645359,  9.57666854,  9.54572176,
        9.51360192,  9.4802971 ,  9.44579475,  9.41008171,  9.37314414,
        9.3349675 ,  9.29553652,  9.25483518,  9.21284664,  9.16955321,
        9.12493632,  9.07897646,  9.03165312,  8.98294476,  8.93282873,
        8.88128118,  8.82827705,  8.77378994,  8.71779204,  8.66025404,
       -8.66025404, -8.71779204, -8.77378994, -8.82827705, -8.88128118,
       -8.93282873, -8.98294476, -9.03165312, -9.07897646, -9.12493632,
       -9.16955321, -9.21284664, -9.25483518, -9.29553652, -9.3349675 ,
       -9.37314414, -9.41008171, -9.44579475, -9.4802971 , -9.51360192,
       -9.54572176, -9.57666854, -9.60645359, -9.63508769, -9.66258107,
       -9.68894344, -9.714184  , -9.73831149, -9.76133416, -9.7832598 ,
       -9.80409577, -9.82384901, -9.84252604, -9.86013297, -9.87667553,
       -9.89215905, -9.90658851, -9.91996849, -9.93230325, -9.94359667,
       -9.9538523 , -9.96307334, -9.97126266, -9.9784228 , -9.98455598,
       -9.98966408, -9.99374868, -9.99681104, -9.99885209, -9.99987246,
       -9.99987246, -9.99885209, -9.99681104, -9.99374868, -9.98966408,
       -9.98455598, -9.9784228 , -9.97126266, -9.96307334, -9.9538523 ,
       -9.94359667, -9.93230325, -9.91996849, -9.90658851, -9.89215905,
       -9.87667553, -9.86013297, -9.84252604, -9.82384901, -9.80409577,
       -9.7832598 , -9.76133416, -9.73831149, -9.714184  , -9.68894344,
       -9.66258107, -9.63508769, -9.60645359, -9.57666854, -9.54572176,
       -9.51360192, -9.4802971 , -9.44579475, -9.41008171, -9.37314414,
       -9.3349675 , -9.29553652, -9.25483518, -9.21284664, -9.16955321,
       -9.12493632, -9.07897646, -9.03165312, -8.98294476, -8.93282873,
       -8.88128118, -8.82827705, -8.77378994, -8.71779204, -8.66025404])
```

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

In [5]:
```
plt.scatter(y,x)
```

Out[5]:
```
<matplotlib.collections.PathCollection at 0x229ae0785e0>
```



In [6]:

Out[6]:
```
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, -3.88888889],
       [ 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 [7]:
```
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
df = df1.append(df2)
```

Out[7]:

	X1	X2	Y
0	8.660254	-5.00000	0
1	8.717792	-4.89899	0
2	8.773790	-4.79798	0
3	8.828277	-4.69697	0
4	8.881281	-4.59596	0

In [8]:

Out[8]:

	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 [9]:
```
### Independent and Dependent features
X = df.iloc[:, :2]
```

In [10]:

Out[10]:
```
0      0
1      0
2      0
3      0
4      0
      ..
195    1
196    1
197    1
198    1
199    1
Name: Y, Length: 400, dtype: int64
```

In [11]:
```
## Split the dataset into train and test
from sklearn.model_selection import train_test_split
```

In [12]:

Out[12]:

	X1	X2
50	4.999745	0.050505
63	9.906589	1.363636
112	-3.263736	3.787879
159	-9.953852	-0.959596
83	3.680983	3.383838
...	...	...
123	-4.223140	2.676768
192	-9.031653	-4.292929
117	-9.445795	3.282828
47	9.996811	-0.252525
172	-9.738311	-2.272727

300 rows × 2 columns

Polynomial Kernel

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

In [14]:
```
# We need to find components for the Polynomical Kernel
#X1,X2,X1_square,X2_square,X1*X2

df['X1_Square']= df['X1']**2

df['X2_Square']= df['X2']**2
df['X1*X2'] = (df['X1'] *df['X2'])
```

Out[14]:

	X1	X2	Y	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 [15]:
```
### Independent and Dependent features
X = df[['X1','X2','X1_Square','X2_Square','X1*X2']]
```

In [16]:

Out[16]:
```
0      0
1      0
2      0
3      0
4      0
      ..
195    1
196    1
197    1
198    1
199    1
Name: Y, Length: 400, dtype: int64
```

In [ ]:

In [17]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,  r
```

In [18]:

Out[18]:

	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 [ ]:

In [19]:
```
import plotly.express as px

fig = px.scatter_3d(df, x='X1', y='X2', z='X1*X2',
                    color='Y')
```

In [20]:
```
fig = px.scatter_3d(df, x='X1_Square', y='X1_Square', z='X1*X2',
                    color='Y')
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [51]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
classifier = SVC(kernel="linear")
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
```

Out[51]: 0.45

In [52]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
classifier = SVC(kernel="poly")
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
```

Out[52]: 0.59

In [53]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
classifier = SVC(kernel="rbf")
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
```

Out[53]: 1.0

In [54]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
classifier = SVC(kernel="sigmoid")
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
```

Out[54]: 0.51

In [ ]: