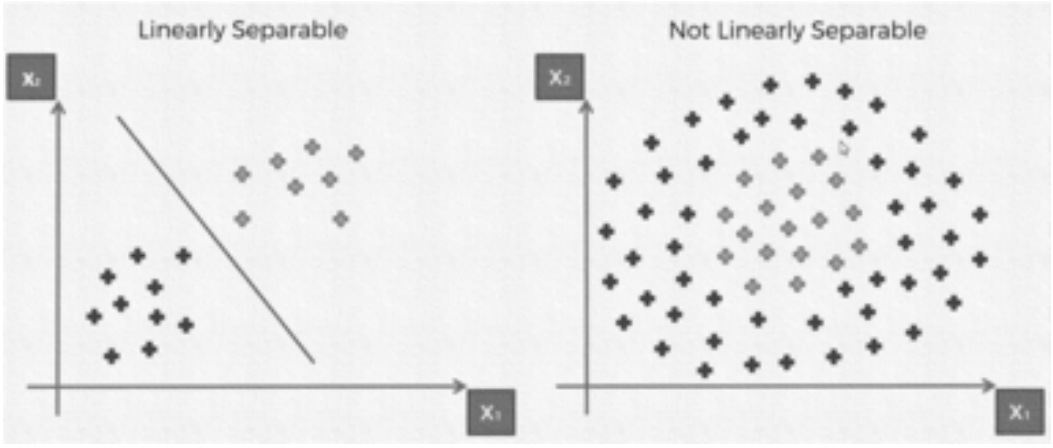
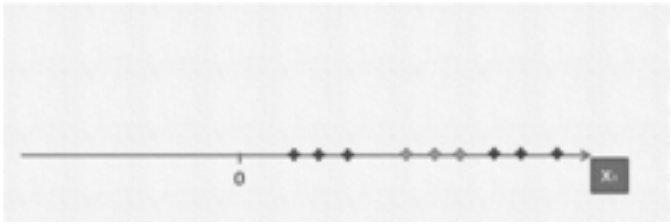
KERNEL SVM

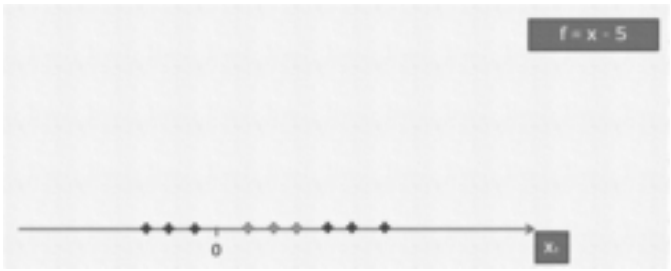
MOHAN M J

INTUITION

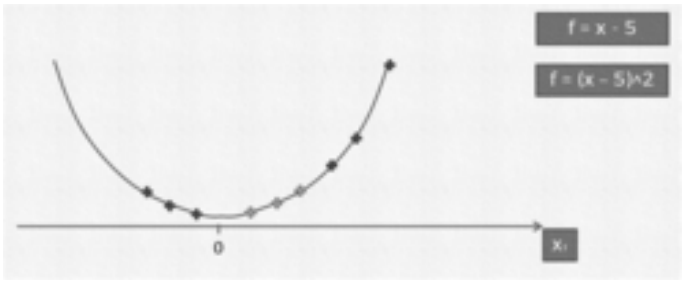


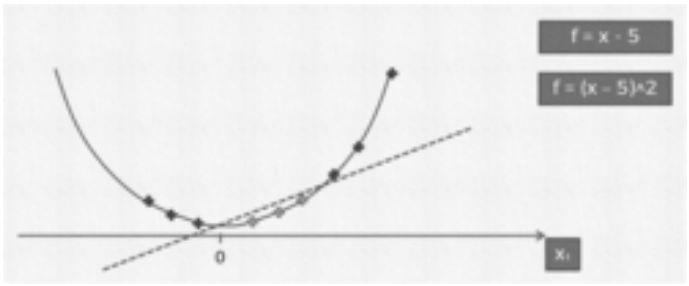
MAPPING TO HIGHER DIMENSION



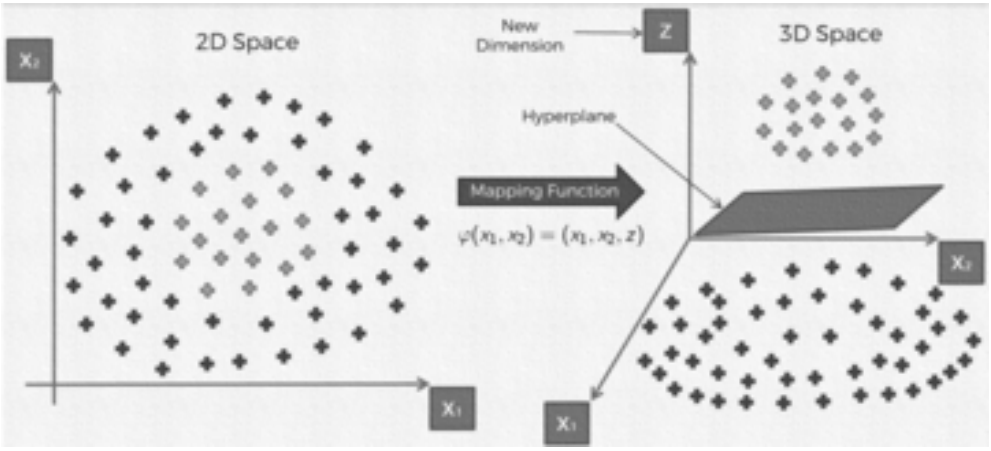


CONTD..

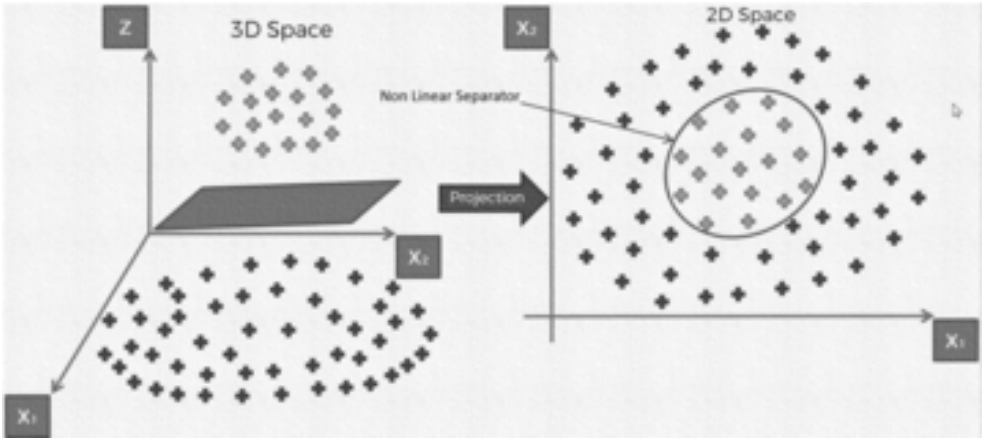




CONTD..

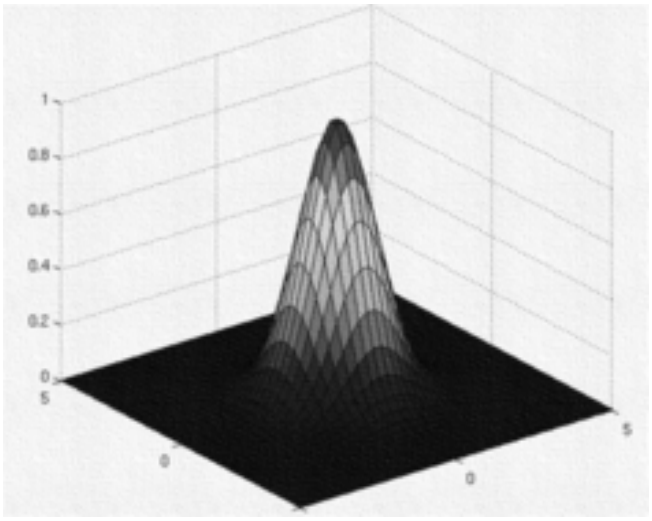

2D Space
New Dimension
Z
3D Space
Hyperplane
Mapping Function
$\varphi(x_1, x_2) = (x_1, x_2, z)$
X_2
X_1
X_3

CONTD..


Z
3D Space
X_3
2D Space
Non Linear Separator
Projection
X_2
X_1

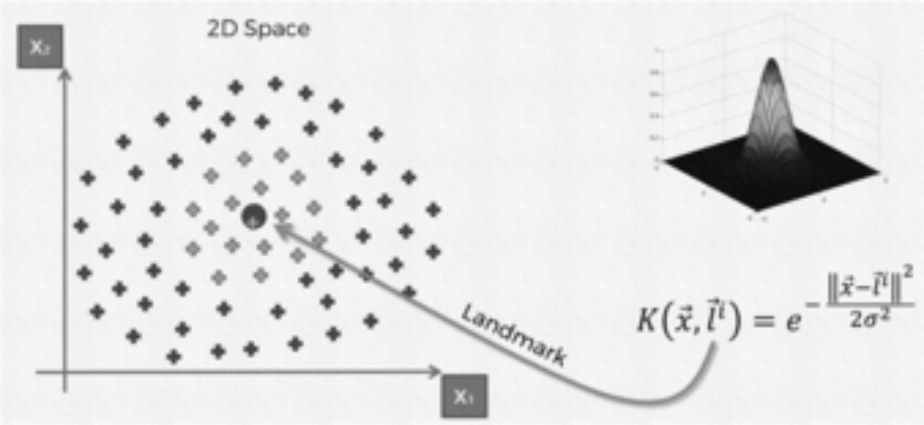
Mapping to higher dimensional space can be highly compute intensive

GAUSSIAN (RBF) KERNEL

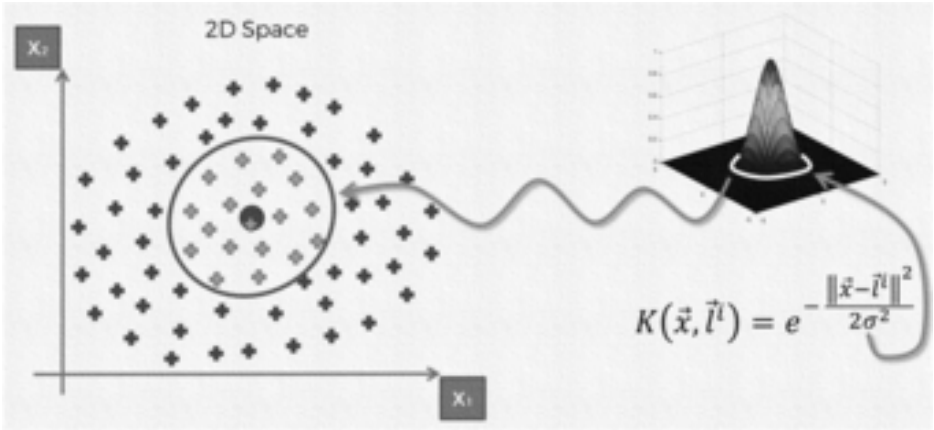


$$K(\vec{x}, \vec{l}^{i}) = e^{-\frac{\|\vec{x}-\vec{l}^{i}\|^2}{2\sigma^2}}$$

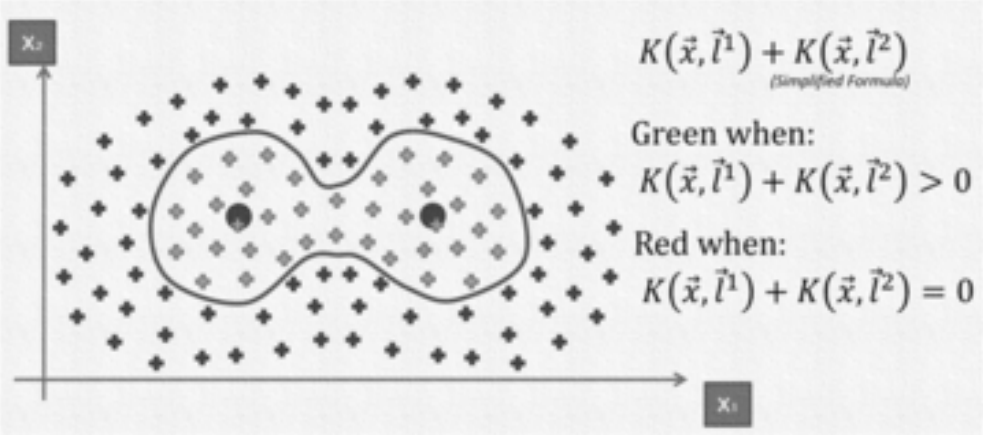
CONTD..


2D Space
X2
X1
Landmark
$K(\vec{x}, \vec{l}^{i}) = e^{-\frac{\|\vec{x}-\vec{l}^{i}\|^2}{2\sigma^2}}$

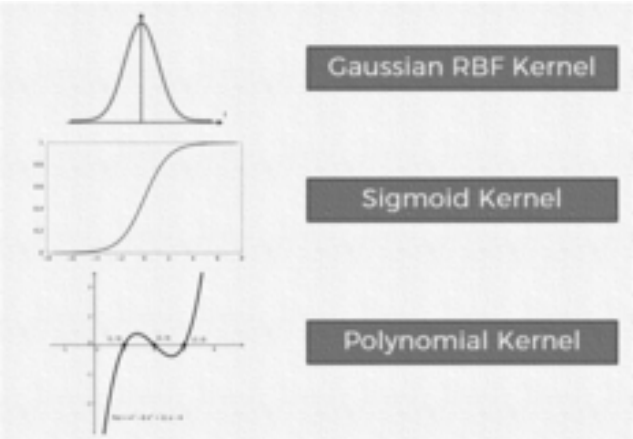
CONTD..


2D Space
X2
X1
$K(\vec{x}, \vec{l}^{i}) = e^{-\frac{\|\vec{x}-\vec{l}^{i}\|^2}{2\sigma^2}}$

CONTD..



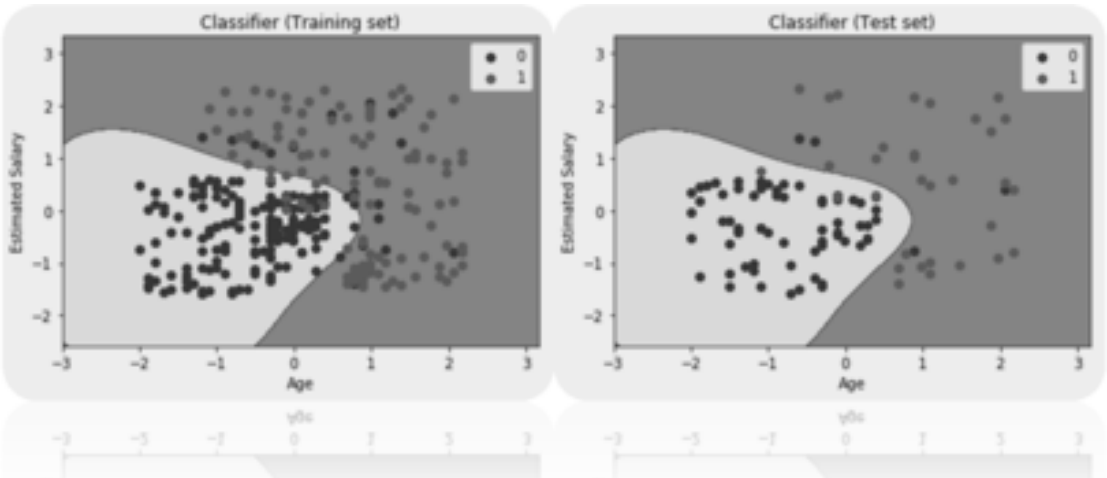
TYPES OF KERNEL FUNCTIONS



PYTHON CODE:

```
# Fitting classifier to the Training set
from sklearn.svm import SVC
classifier = SVC(kernel='rbf', random_state=0) #gaussian kernel
classifier.fit(X_train, y_train)
```

VISUALIZATION



THANK YOU