Explain various types of Kernels with respect to the formula

Kernels are essential for SVMs because they enable the algorithm to efficiently work in high-dimensional feature spaces without explicitly computing the coordinates of the data points.

1. Linear Kernel:

   - Formula: (K(x, y) = x^T. y

   - The linear kernel represents a linear relationship between the input data points. It is the simplest kernel and is used when the data is linearly separable.

2. Polynomial Kernel:

   - Formula: K(x, y) = (x^T. y + c)^d

   - The polynomial kernel calculates the dot product of the input vectors in a higher-dimensional space using a polynomial function. The hyperparameters c and d control the degree of the polynomial and the bias, respectively.

3. Radial Basis Function (RBF) :

   - Formula: K(x, y) = exp(-gamma.|| x - y ||^2))

   - The RBF kernel maps the input vectors into an infinite-dimensional space by applying a Gaussian function. It measures the similarity between data points based on the Euclidean distance between them. The hyperparameter \(\gamma\) controls the width of the Gaussian distribution.

4. Sigmoid Kernel:

   - Formula: K(x, y) = tanh(alpha. x^T . y + c)

   - The sigmoid kernel computes the hyperbolic tangent of the dot product between input vectors, rescaled by the parameters \(c\) and \(\alpha\). It maps the input vectors into a higher-dimensional space and is suitable for non-linearly separable data.

5. Custom Kernels:

users can define custom kernels based on domain knowledge or specific requirements.