**Explain various types of Kernels with respect to the formula**

In Support Vector Machines (SVM), kernels are functions used to map the input data into a higher-dimensional feature space. This transformation enables SVM to find a linear decision boundary in the higher-dimensional space, even when the original data may not be linearly separable in the input space. The kernel trick allows SVM to efficiently compute the dot product between feature vectors in the higher-dimensional space without explicitly computing the transformation.

**Linear Kernel:**

**Formula**: *K*(*xi*​,*xj*​)=*xiT*​*xj*​

**Description**: The linear kernel represents a linear decision boundary. It is the simplest kernel and is effective when the data is linearly separable or has a large number of features.

***Polynomial Kernel:***

**Formula**: *K*(*xi*​,*xj*​)=(*γxiT*​*xj*​+*r*)*d*

**Description**: The polynomial kernel computes the dot product of the input vectors raised to a certain power d, optionally adding a constant term r. It captures higher-order relationships between features.

***Radial Basis Function (RBF) Kernel:***

**Formula**: *K*(*xi*​,*xj*​)=exp(−*γ*∣∣*xi*​−*xj*​∣∣2)

**Description**: The RBF kernel (also known as Gaussian kernel) measures the similarity between two samples in the feature space. It is based on the distance between the samples and is controlled by the parameter *γ*. It is highly flexible and can capture complex decision boundaries.

**Sigmoid Kernel:**

**Formula**: *K*(*xi*​,*xj*​)=tanh(*γxiT*​*xj*​+*r*)

**Description**: The sigmoid kernel maps the input data into a feature space using the hyperbolic tangent function. It can be useful when dealing with non-linearly separable data, but it is less commonly used compared to linear, polynomial, and RBF kernels.