(1.) For RBF or gaussian kernels, one has to note that it doesn't map lower dimension points to higher or infinite dimension. However, it gives a way to calculate the dot-product between the points, if they had been mapped to higher dimensional points.

The kernel is defined as :

$$K(\bar{x}_i, \bar{x}_j) = e^{-\frac{\|\bar{x}_i - \bar{x}_j\|^2}{2\sigma^2}}$$

where $\bar{x}_i, \bar{x}_j$ are the points in the lower dimension.

Now, if we use power series expansion for the exponential, we get,

$$K'(\bar{x}_i, \bar{x}_j) = \sum_{n=0}^{+\infty} \frac{(\bar{x}_i \cdot \bar{x}_j)^n}{\sigma^n n!}$$

This expression is nothing but a polynomial kernel of n degree. $\therefore$ RBF kernel is a combination of all polynomial kernels with degree $n \geq 0$. Since polynomial kernel projects vectors into space with higher number of dimensions and this polynomial kernel is of infinite degree, we say that RBF kernel deals with infinite dimensions. Hence, RBF doesn't really map each point to a new dimension, and overfitting doesn't happen.

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(3.) Graphically it can be seen that decision boundary lies ~~at~~ between $x=2$ and $x=5$ with X3, X5, X7, as support vectors. Since these are independent of y, we can directly write the width of margin as $(5-2) = \underline{\underline{3}}$

When we remove X7, our support vectors will change to X1, X3 on -ve side & X5, X8 on +ve side.

Now the width equals the distance between the lines formed by points (X3, X1) & (X5, X8).

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4. XOR operator can be modeled using SVM only if a Kernel is used to convert the points in the XOR funtion to a higher dimension to make ~~it~~ them linearly seperable by a hyperplane.

Using linear /simple SVM, XOR funtion can't be modeled.