1. While a Hilbert space is a real or complex vector equipped with a norm induced from an inner product under which it is a complete metric space, a reproducing Hilbert space is one in which the evaluation operator $L_x : f \to f(x)$ is a bounded operator. I honestly can't think of a counterexample, i.e. a Hilbert space that is not reproducing.

2. *Shattering* is an amazing description. Given the intersection of a set collection $\mathcal{H}$ and a set C, $\mathcal{H}$ shatters C is $\mathcal{H} \cap C$ contains all the subsets of C, i.e. $|\mathcal{H} \cap C| = 2^{|C|}$. The Vapnik-Cherenkov dimension is $\mathcal{H}$ is the largest of a set such that it is shattered by $\mathcal{H}$.

3. The inner product of vectors u and v is $\langle u, v \rangle = u^T v$.

4. SVM arises because we might need non-linear decision boundaries and we don't want to deal with an enlarged feature space.

5. While the linear SVC can be represented as $f(x) = \beta_0 + \sum_{i=1}^{n} \alpha_i \langle x, x_i \rangle$, using kernels we aim to represent different SVMs as $f(x) = \beta_0 + \sum_{i \in \mathcal{S}} \alpha_i K(x, x_i)$ where the different kernels $K(x, x_i)$ are as follows.

6. An SVC is an SVM which uses the linear kernel, $K(x_i, x_i') = \sum_{j=1}^{p} x_{ij} x_{i'j}$

7. A polynomial kernel of degree d is one where the kernel has the form $K(x_i, x_{i'}) = (1 + \sum_{j=1}^{p} x_{ij} x_{i'j})^d$.

8. A radial kernel has the form $K(x_i, x_{i'}) = \exp(-\gamma \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2)$.

9. Kernels are necessary because they simplify calculations, instead of calculating using an enlarged feature space.

10. SVM's can be generalized to have more than two classes.