1. You might have read the notes on Kernels and SVMs at:
   `https://www.dropbox.com/s/qryziuo3u143q5e/KERNEL-REVIEW.pdf?dl=0`
   See the Sec 3.3 (equations)
   Why is $a \in R^+$ written there?
   1.1 It could have been $a \in R^-$
   1.2 a negative does not lead to K being PSD
   1.3 It is a typo.

   Ans: B

2. You might have read the notes on Kernels and SVMs at:
   `https://www.dropbox.com/s/qryziuo3u143q5e/KERNEL-REVIEW.pdf?dl=0`
   See the Sec 3.3. Assume $\alpha_i \in R^+$; $\beta_i \in R^+$; $\kappa_i(\mathbf{p}, \mathbf{q})$ being a valid kernel. Also K and L are some positive integers.
   Then a new kernel $\kappa(\cdot, \cdot) =$
   2.1 $\sum_{i=1}^{K} \kappa_i(\mathbf{p}, \mathbf{q})$ is a valid kernel.
   2.2 $\prod_{i=1}^{L} \kappa_i(\mathbf{p}, \mathbf{q})$ is a valid kernel.
   2.3 $\sum_{i=1}^{K} \alpha_i \kappa_i(\mathbf{p}, \mathbf{q})$ is a valid kernel.
   2.4 $\prod_{i=1}^{L} \beta_i \kappa_i(\mathbf{p}, \mathbf{q})$ is a valid kernel.

2.5 $\sum_{i=1}^{K} \alpha_i \kappa_i(\mathbf{p}, \mathbf{q}) + \prod_{i=1}^{L} \beta_i \kappa_i(\mathbf{p}, \mathbf{q})$ is a valid kernel

Ans: ABCDE

3. You might have read the notes on Kernels and SVMs at:
`https://www.dropbox.com/s/qryziuo3u143q5e/KERNEL-REVIEW.pdf?dl=0`
See the pseudo-code for Kernel Perceptron (Algorithm 3).
Assime the kernel to be $(\mathbf{x}^T \mathbf{y})^2$
   3.1 The initialization $\alpha_i = 0$ is a must. With no other initialization, this algorithm will not work (say will not converge)
   3.2 Step of computing Kernel Matrix (step 2) should have been in side the loop (repeat structure).
   3.3 Since this is now Kernelized, with any data (irrespective of whether the data is linearly separable or not), this algorithm will converge.
   3.4 For data that is linearly separable, this algorithm will give you a linear decision boundary.
   3.5 None of the above.

   Ans: E

4. You might have read the notes on Kernels and SVMs at:
`https://www.dropbox.com/s/qryziuo3u143q5e/`

KERNEL-REVIEW.pdf?dl=0

Look at the equation (94) related to the objective function:

4.1 This is an L1 softmargin SVM

4.2 This is an L2 softmargin SVM

4.3 There is a typo. ξ_i should be replaced as ξ_i^2

4.4 There is a typo. LHS will have to be $j(\mathbf{w}\xi)$, since ξ is another variable that we need to optimize.

4.5 None of the above.

Ans: A

5. You might have read the notes on Kernels and SVMs at: https://www.dropbox.com/s/qryziuo3u143q5e/KERNEL-REVIEW.pdf?dl=0

Consider the decision making rule. “one side of a line (in 2D) is +ve class and other side of a line is -ve class” Figure 7 shows that VC dimension of a class of functions (lines) in 2D is 3.

What is the VC dimension in 1D for a function class. If $x > \theta$, positive, else negative.

Write your answer in the space provided.

(Sample answer (possibly incorrect): 1)
FIB Ans: 2 Can shatter every set of 2 points (though needs to shatter only one) but cannot shatter any set of 3 points