Problem 1

A. Based on Mr. Kevin Murphy's definition for models: "non-parametric" models do have parameters but the number of their parameters is data-dependent, meaning it changes from dataset to dataset. The linear SVM, whose number of parameters is determined solely by the input dimension - and not the dataset size is parametric model. Nevertheless, Kernel SVM is non-parametric due to , a dataset of size $\boldsymbol{N}$ has an associated kernel matrix of size $\boldsymbol{N} * \boldsymbol{N}$.

B. No, because different kernels take the problem to different spaces with different dimensions. Therefore, the amount of margin obtained in different dimensions can not be a good criterion for comparing different models

C. the reason that SVMs tend to be resistant to over-fitting, even in cases where the number of attributes is greater than the number of observations, is that it uses regularization. They key to avoiding over-fitting lies in careful tuning of the regularization parameter, $\boldsymbol{C}$, and in the case of non-linear SVMs, careful choice of kernel and tuning of the kernel parameters.
The SVM is an approximate implementation of a bound on the generalization error, that depends on the margin (essentially the distance from the decision boundary to the nearest pattern from each class), but is independent of the dimensionality of the feature space (which is why using the kernel trick to map the data into a very high dimensional space isn't such a bad idea as it might seem). So in principle SVMs should be highly resistant to over-fitting, but in practice this depends on the careful choice of $\boldsymbol{C}$ and the kernel parameters. So SVM isn't always resistant to over-fitting, Unless the parameters are carefully selected

D. SVM ability to deal with noise depends on the noise strength and kernel used, for high-bias kernels such as linear or polynomial, noise should not the problem, for low-bias like RBF - it will affect classification. So Noise is not always ineffective for SVM accuracy.