



1. Yes, the points are linearly separable.

2. We know that the equation of the line is $y - y_1 = [(y_1 - y_2)/(x_1 - x_2)] * (x - x_1)$ where (x_1, y_1) & (x_2, y_2) are the midpoints of any two closest points of two different classes. Suppose we consider $(x_1, y_1) = (1, 0.5)$ [mid-point of $(0, 1)$ and $(1, 1)$] and $(x_2, y_2) = (1, 0)$ [the midpoint of $(1, 0)$ & $(2, 0)$], after simplification, the equation of the optimal hyperplane turns out to be $x + y - 1.5 = 0$. In this case, $(0, 1)$, $(1, 1)$, $(1, 0)$, and $(2, 0)$ become the support vectors as these vectors are the closest to the line from different classes. From the equation of the above line, we can see that the weight vector comes out to be $(1, 1)$ as the coefficients of x and y in the line.

3. As we can see, there are four support vectors. Each support vector is 0.5 units away from the hyperplane, and the margin becomes 1 unit as the distance between the nearest points is one unit. Suppose we remove $(1, 1)$ or $(1, 0)$ from the particular dataset. In that case, the margin will increase, while on the other hand, if we remove the other two, the optimal decision boundary will be as it is. There will be no change in the optimal hyperplane so that the margin will remain unchanged. We can verify the same by calculating the value of the distance from all the support vectors by the formula of the distance of a point from a line, i.e., $d = |Ax_1 + By_1 + C| / \sqrt{A^2 + B^2}$.

4. We get an optimal value at least as good as the previous one when we remove some constraints from a constrained maximization problem. This is because the set of candidates satisfying the initial (more robust) set of constraints is a subset of the candidates fulfilling the current (weaker) set of constraints. The old optimal solution is still available, and there may be better alternatives. In SVM, we maximize the margin while keeping the constraints imposed by training points in mind. Depending on the dataset, dropping any constraints can cause the margin to increase or remain the same. Generally, in the case of realistic datasets, it is expected that the margin will increase when we drop support vectors. But in this data, we saw that removing or keeping the support vectors can increase or preserve the margin unchanged, as we saw above.