Machine learning Homework- Constrained Optimisation & SVM

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Problem 1:

We construct the Lagrangian function as $\mathcal{L}(\theta, \alpha) = f_0(\theta) + \alpha f_1(\theta)$
forcing $\nabla_\theta \mathcal{L} = 0$. We get $\theta_1 = -\frac{1}{2\alpha}$ and $\theta_2 = \frac{\sqrt{3}}{2\alpha}$
substituting back the θ in the Lagrangian function and minimising with respect to α, we get $\alpha = \pm\frac{1}{2}$ we take only the positive values of $\alpha = 1/2$.
Therefore $\theta_1 = -1$
$\theta_2 = \sqrt{3}$

Problem 2:

Solved in a Jupyter Notebook attached at the end of problem of Problem 5.

Problem 3:

- Both use hyperplane for classification
- SVM have margins and perceptrons do not have them

Problem 4:

Problem 5:

1. from $g(\alpha)$ we know that $\alpha Q \alpha^T$ is equivalent to $-\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j \alpha_i \alpha_j \mathbf{x}_i \mathbf{x}_j$. By rearranging the scalars we get,$-\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i y_i y_j \mathbf{x}_i \mathbf{x}_j \alpha_j$.
   Therefore $Q = (-yy^T(hadamard)XX^T)$
2. We know that $Q = -p^T p$ and also we know that $p^T p$ is positive semi definite due to its symmetric nature. So $a^t(p^T p)a \geq 0$ but we negative sign also. Therefore, Q is negative semi definite.
3. The negative semi definiteness allows the concave optimisation to be a maximisation problem.