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## Exercise Sheet 13

## Exercise 1: Weighting the Data (70 P)

We consider the following three two-dimensional binary classification datasets composed of 16 samples each:

$\overset{X_1}{\bullet}$	<b>x</b> <sub>2</sub> ●	<b>x</b> <sub>3</sub>					<b>x</b> <sub>2</sub> ●	<b>x</b> <sub>3</sub>	-	$\overset{X_1}{\bullet}$	<b>x</b> <sub>2</sub> ●	-	-
<b>X</b> <sub>5</sub> ●	<b>x</b> <sub>6</sub> ●	x <sub>7</sub>					<b>x</b> <sub>6</sub> ●	x <sub>7</sub>		X <sub>5</sub> ●	<b>x</b> <sub>6</sub> ●		
X <sub>9</sub> ●	x <sub>10</sub> ●	<b>X</b> <sub>11</sub> ●				X <sub>9</sub> ●		<b>x</b> <sub>11</sub> ●		X <sub>9</sub> ●		<b>x</b> <sub>11</sub> ●	
X <sub>13</sub> ●	X <sub>14</sub> ●	x <sub>15</sub> ●				X <sub>13</sub> ●		x <sub>15</sub> ●		x <sub>13</sub>		x <sub>15</sub> ●	
(i)					(ii)					(iii)			

Black circles denote the first class (-1) and white circles denote the second class (+1). We decide to use a boosted classifier with a linear soft-margin SVM as weak learner. The boosted classifier is given by the discriminant function

$$f(x) = \alpha_0 + \sum_{t=1}^{T} \alpha_t h_t(x)$$

where  $\alpha_0, \ldots, \alpha_T \in \mathbb{R}$ , and where the function

$$h_t(x) = \operatorname{sign}(w_t^{\top} x_i + b_t)$$

returns the classification result (-1 or +1) of the tth weak classifier. It is trained, under the weighting of the data  $p_{t,1}, \ldots, p_{t,16}$ , to minimize the SVM objective

$$\min_{w_t, \xi_t, b_t} \frac{1}{2} \|w_t\|^2 + C \sum_{i=1}^{16} p_{t,i} \, \xi_{t,i}$$

under the constraints

$$\forall_{i=1}^{16} : y_i(w_t^\top x_i + b_t) \ge 1 - \xi_{t,i}, \quad \xi_{t,i} \ge 0.$$

We also assume the parameter C to be large (e.g. C=100).

Determine at hand and for each dataset a possible boosted classifier that classifies the data perfectly. Draw the decision boundary learned by each individual weak learner, and the final decision boundary. Write down the coefficients  $\alpha_0, \ldots, \alpha_T$ , and the weighting terms  $p_{t,i}$  for each weak learner  $1 \le t \le T$  and data point  $1 \le i \le 16$ .

## Exercise 2: Boosted Regressors (30 P)

We consider the boosted regressor

$$f(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$$

where  $h_t(x) = w_t^{\top} x$  is the real-valued prediction produced by the tth weak regressor and  $x \in \mathbb{R}^d$ . Assuming a labeled dataset  $\{(x_1, y_1), \dots, (x_n, y_n)\}$ , the boosted regressor is trained to minimize the mean squared error

$$\sum_{i=1}^{n} \left( y_i - f(x_i) \right)^2, \tag{1}$$

where each weak regressor minimizes the following weighted objective function

$$\sum_{i=1}^{n} p_{t,i} (y_i - h_t(x_i))^2.$$

Show that a single weak regressor can be made as accurate as the boosted regressor when using an appropriate weighting  $\{p_1, \ldots, p_n\}$ . Write down one possible weighting for the single regressor that leads to the same accuracy as the optimal regressor in the sense of Equation (1).