Mixed-integer linear programs for the SVR with feature and outlier detection

- Input: $(x^1, y_1), (x^2, y_2), \dots, (x^k, y_k) \in \mathbb{R}^d \times \mathbb{R}$
- User-chosen: d_0 and k_0 , nonzero naturals
- **Pre-processed** (from the input):

$$-R_1^U, R_2^U, \dots R_k^U \\ -W_1^L, W_2^L, \dots, W_d^L \\ -W_1^U, W_2^U, \dots, W_d^U$$

Basic model

$$\min \sum_{i=1}^{k} q_{i} \qquad (1)$$

$$q_{i} + y_{i} - ax^{i} - z - t_{i} \ge 0 \qquad \forall i = 1, 2, \dots, k \qquad (2)$$

$$-q_{i} + y_{i} - ax^{i} - z - t_{i} \le 0 \qquad \forall i = 1, 2, \dots, k \qquad (3)$$

$$t_{i} \ge -(1 - s_{i})R_{i}^{U} \qquad \forall i = 1, 2, \dots, k \qquad (4)$$

$$t_{i} \le (1 - s_{i})R_{i}^{U} \qquad \forall i = 1, 2, \dots, k \qquad (5)$$

$$a_{j} \ge W_{j}^{L} f_{j} \qquad \forall j = 1, 2, \dots, k \qquad (6)$$

$$a_{j} \le W_{j}^{U} f_{j} \qquad \forall j = 1, 2, \dots, k \qquad (7)$$

$$\sum_{j=1}^{d_{0}} f_{j} \le d_{0} \qquad (8)$$

$$\sum_{i=1}^{k_{0}} s_{j} \ge k_{0} \qquad (9)$$

$$a_{j} \in \mathbb{R} \qquad (11)$$

$$z \in \mathbb{R} \qquad (11)$$

$$f_{j} \in \{0, 1\} \qquad \forall j = 1, 2, \dots, d \qquad (12)$$

$$q_{i} \ge 0 \qquad \forall i = 1, 2, \dots, k \qquad (13)$$

$$t_{i} \in \mathbb{R} \qquad \forall i = 1, 2, \dots, k \qquad (14)$$

$$s_{i} \in \{0, 1\} \qquad \forall i = 1, 2, \dots, k \qquad (14)$$

Explanation.

- The pre-processed values R^U, W^L and W^U are such that an optimal solution (a^\star, z^\star) satisfies
 - $|y_i a^*x^i z^*| \le R_i^U$ for every $i = 1, 2, \dots, k$
 - $W_j^L \le a_j^* \le W_j^U$ for every $j = 1, 2, \dots, d$
 - they are difficult to compute exactly, so we will use *heuristics* (in this first phase I will provide them)
- $s_i = 0$ if and only if point (x^i, y_i) is to be considered an outlier
- constraints (2) and (3) together imply that $-q_i \leq y_i ax^i z t_i \leq q_i$, which is equivalent to $|y_i ax^i z t_i| \leq q_i$. That is, q_i is an upper-bound on the prediction error made by our solution (a, z) on the point (x^i, y_i) .
- from constraints (4) and (5) we obtain that $t_i = 0$ if and only if $s_i = 1$
- putting the last two observations together we obtain that if (x^i, y_i) is an outlier, then $s_i = 0$, then t_i can be nonzero and it can be used to "cancel" the error (using $t_i = y_i ax^i z$), thus $q_i \ge 0$. Since we minimize $\sum_{i=1}^k q_i$, $q_i = 0$ in an optimal solution for all outliers (it is never convenient to have a positive term when it can be zero!). So in an optimal solution we sum only the errors of the non-outliers.
- constraints (8) and (9) guarantee that no more than d_0 features are chosen, and no more than k_0 features are chosen.

Stronger model

$$\min \sum_{i=1}^{k} (p_i - (1 - s_i)R_i^U)$$

$$p_i \ge (1 - s_i)R_i^U$$

$$p_i \ge R_i^U$$

$$p_i + y_i - ax^i - z \ge 0$$

$$-p_i + y_i - ax^i - z \le 0$$

$$a_j \ge W_j^L f_j$$

$$a_j \le W_j^U f_j$$

$$\sum_{j=1}^{k_0} f_j \le d_0$$

$$\sum_{j=1}^{k_0} f_j \le d_0$$

$$\sum_{j=1}^{k_0} f_j \ge k_0$$

$$a_j \in \mathbb{R}$$

$$z \in \mathbb{R}$$

$$f_j \in \{0, 1\}$$

$$q_i \ge 0$$

$$s_i \in \{0, 1\}$$

$$f_i = 1, 2, ..., k$$

$$f_j = 1, 2, ..., k$$

$$f_j$$