

# 1 Knapsack Problem

After the previous formalization the optimization problem is the following

$$\begin{aligned}
\max_{\beta_i} & -\frac{1}{2} \sum_i \sum_j \beta_i \beta_j K(x_i, x_j) \\
& - \varepsilon \sum_i |\beta_i| \\
& + \sum_i y_i \beta_i
\end{aligned} \tag{1}$$

$$\text{With the constraints} \quad \begin{cases} \sum_i \beta_i = 0 \\ \beta_i \in [-C, C] \end{cases}$$

The problem of maximization can be substituted by a minimization obtaining a formulation that recalls the one of a Convex Separable Knapsack problem.

$$\begin{aligned}
\min_{\beta_i} & \frac{1}{2} \sum_i \sum_j \beta_i \beta_j K(x_i, x_j) \\
& + \varepsilon \sum_i |\beta_i| \\
& - \sum_i y_i \beta_i
\end{aligned} \tag{2}$$

$$\text{With the constraints} \quad \begin{cases} \sum_i \beta_i = 0 \\ \beta_i \in [-C, C] \end{cases}$$

We define the Lagrangian Relaxation:

$$\begin{aligned}
\mathcal{L}(\mu) = & \frac{1}{2} \sum_i \sum_j \beta_i \beta_j K(x_i, x_j) \\
& + \varepsilon \sum_i |\beta_i| \\
& - \sum_i y_i \beta_i \\
& + \mu \left( \sum_i \beta_i - 0 \right)
\end{aligned} \tag{3}$$

$$\text{With the constraints} \quad \beta_i \in [-C, C]$$

The objective is to minimize  $\beta$  and to do so we calculate  $\frac{\partial \mathcal{L}}{\partial \beta_i} = 0$

$$\frac{\partial \mathcal{L}}{\partial \beta_i} \longrightarrow \beta_i K(x_i, x_i) + \varepsilon \text{sgn}(\beta_i) - y_i + \mu \quad (4)$$

At this point we can define the two breakpoints for each  $\beta_i$ , which represent the upper and lower bound of the Lagrangian multiplier  $\mu$ .

*Remark:* upper and lower bound for each  $\beta_i$  is the same  $(-C; C)$ .

$$\begin{aligned} \mu_i^l &= -(-C * K(x_i, x_i)) - \varepsilon \text{sgn}(-C) + y_i \\ \mu_i^u &= -(C * K(x_i, x_i)) - \varepsilon \text{sgn}(C) + y_i \\ \text{where } \forall_i \quad \mu_i^u &< \mu_i^l \end{aligned} \quad (5)$$

Each  $\beta_i$  can be defined wrt to  $\mu$

$$\beta_i(\mu) = \begin{cases} C & \text{if } \mu < \mu_i^u \\ \frac{y_i - \varepsilon \text{sgn}(\beta_i) - \mu}{K(x_i, x_i)} & \text{if } \mu_i^u \leq \mu \leq \mu_i^l \\ -C & \text{if } \mu > \mu_i^l \end{cases} \quad (6)$$

At this point using for example *Algorithm 3.1* of [1], we can compute the value of  $\mu^*$  that implies how to find the correct values of  $\beta_i$  that satisfy the constraints.

## 2 How to use it

Now that we have given a formulation for the resolution of the Knapsack problem, the focus shifts towards how we can use it in our minimization problem that needs to be solved using a deflected subgradient method.

At each step we compute the values of  $\beta$  and we want to make sure that their values satisfy the linear and box constraints imposed by the problem.

Here a pseudocode that summarize the steps.

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**Algorithm 1:** Compute  $\beta$

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1 while optima criteria are not satisfied do
2    $v \leftarrow f(\beta)$ 
3    $g \leftarrow \nabla f(\beta)$ 
4   check if a better solution was found
5    $d \leftarrow \gamma g + (1 - \gamma)d_{prev}$ 
6    $stepsize \leftarrow \frac{\psi(v - f_{ref} + \delta)}{\|d\|^2}$ 
7    $\beta \leftarrow \beta - stepsize \cdot d$ 
8   project  $\beta$  by solving the KP
9 end
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A probably trivial point, related to the computation of the direction, makes our approach incorrect. As we can see the current direction depends on the previous direction, but if we take a closer look at the execution flow, it does not.

What algorithm 1 does at every iteration is a lot of calculations to find a direction, a stepsize and therefore a new  $\beta$  which then gets projected in the feasible region to satisfy the constraints. The projection, as shown in *algorithm 3.1* of [1], is based uniquely on the use of breakpoints, created using the upper and lower bound of the  $\beta_i$  variable. Therefore the actual computed values of  $\beta_i$  before the projection are not taken into consideration. This leads to a deterministic computation of  $\beta_i$  values which depends only on the solution of the knapsack problem, giving zero weight to the deflection

applied before. We are stunned (and not in a good way): we have a clearer understanding of how deflection works and also of how a knapsack problem can be solved. We find ourselves in a *saddle point* trying to figure out how to merge the two.

### 3 Reference

1. Breakpoint searching algorithms for the continuous quadratic knapsack problem - Krzysztof C. Kiwiel