

Optimization MTH702

Proximal GD, subGD, FWGD, CoordGD

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Projected Gradient Descent

- The constrained optimization forces the feasible set to be $X \subseteq \mathbb{R}^n$
- Projected Gradient Descent works well when the functions is convex and the feasible set as well (convex set have unique projection).
- **Idea** project every step $\Pi_X(y) := \operatorname{argmin}_{x \in X} \|x - y\|$.
- Projected GD step: $x_{t+1} = \Pi_X \left[x_t - \gamma \nabla f(x_t) \right]$
- Let $X \subseteq \mathbb{R}^d$ be closed and convex, $x \in X$, $y \in \mathbb{R}^d$. Then (i)
 $(x - \Pi_X(y))^T (y - \Pi_X(y)) \leq 0$
(ii) $\|x - \Pi_X(y)\|^2 + \|y - \Pi_X(y)\|^2 \leq \|x - y\|^2$

PGD Convergence Rate

- The same number of steps as gradient descent with same proofs but each step involves a projection onto X , may or may not be efficient(depends on the set).

Proximal Gradient Descent

Consider the objective function to be composed as:

$$f(x) := g(x) + h(x)$$

where g is nice function, but h is only simple (not differentiable) e.g. L1 norm or the indicator function.

- The classical GD step for minimizing g is:

$$x_{t+1} = \operatorname{argmin}_y g(x_t) + \nabla g(x_t)^T (y - x_t) + \frac{1}{2\gamma} \|y - x_t\|^2$$

For the step size $= 1/L$ it exactly minimizes the local quadratic model of g at our current iterate x_t , formed by the smoothness property with parameter L .

- Now for $f = g + h$, we do the exactly the same for g and h as it is:

$$x_{t+1} := \operatorname{argmin}_y g(x_t) + \nabla g(x_t)^T (y - x_t) + \frac{1}{2\gamma} \|y - x_t\|^2 + h(y)$$

$$x_{t+1} := \operatorname{argmin}_y \frac{1}{2\gamma} \|y - (x_t - \gamma \nabla g(x_t))\|^2 + h(y)$$

This is called proximal update (step).

Proximal Gradient Descent

- The proximal gradient step is also written as :

$$x_{t+1} := \text{Prox}_{h,\gamma}(x_t - \gamma \nabla g(x_t))$$

where the proximal operator for a a given function and parameter

$\gamma > 0$ is defined as: $\text{Prox}_{h,\gamma} := \underset{y}{\operatorname{argmin}} \left\{ \frac{1}{2\gamma} \|y - z\|^2 + h(y) \right\}$

- If $h(x) = 0$, we will have original GD.
- If $h = \Phi_x$ we will have projected GD.