

Open Problem: Do Good Algorithms Necessarily Query Bad Points?

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Stochastic Approximation

Goal: Compute $w^* \in \operatorname{argmin}_w F(w) = \mathbb{E}_{\xi \sim D}[f(w; \xi)]$

- Approach: Use SGD [RM51]

$$w_{t+1} \leftarrow w_t - \eta_t \cdot \nabla f(w_t; \xi_t);$$

$$\mathbb{E}_{\xi_t}[\nabla f(w_t; \xi_t) | w_t, Z_{t-1}] = \nabla F(w_t)$$

- Iterate averaging [R88, PJ92, RSS11, JSB12, BM13]: anytime minimax optimal.
- SGD's final iterate (with fixed time horizon):
 - Non-smooth: [JNN19] optimal rates achievable.
 - Least Squares: [GKK19] near optimal (up to a $\log T$ factor).

The Infinite Horizon Case

- **Goal:** Understand query point behavior of SGD style methods in the limit.
- SGD's final iterate behavior (in an anytime sense):
 - Non-smooth case: [SZ12, HLPR18] sub-optimal by a $\log T$ factor.
 - Strongly Convex Least Squares: [GKKN19] sub-optimal by a condition number factor.
- Does **any*** stochastic gradient procedure have to query sub-optimal points infinitely often?

* Consider the following **non-adaptive** procedure:

Suppose an algorithm can query any iterate which is expressed as a fixed (potentially non-stationary) linear combination of all previous stochastic gradients, which is defined in advance at the start of the algorithm. That is,

$$\mathbf{w}_t = \alpha_0 \mathbf{w}_0 + \sum_{j < t} \alpha_j^{(t)} \nabla \mathbf{f}(\mathbf{w}_j; \xi_j), \alpha_j^{(t)} \in \mathbb{R} \ \forall \ j, t.$$

Our Question

- Does a **non-adaptive procedure** query sub-optimal iterates (beyond constant factors of the minimax rate) infinitely often?
- Special cases:
 - Non-smooth case: Can we bridge the $\log T$ factor indicated by [SZ12,HLPR18]
 - Smooth + Strongly convex case: Can we bridge the condition number factor indicated by [GKKN19]
 - Gradient norm: Can we achieve similar results as [A18].