

Mixed Integer Programming

Mixed Integer Programming

Zero order methods. Gradient free optimization. Global optimization

- [Шпаргалка по результатам в безградиентной оптимизации](#)
- [RL и эволюционные алгоритмы](#)

 Open in Colab

- Global optimization illustration

 Open in Colab

- Nevergrad library

 Open in Colab

- Optuna quickstart

- [Демонстрация медленности методов нулевого порядка](#)

 Open in Colab

- Подбор гиперпараметров модели машинного обучения в Keras с помощью Optuna
- [A Tutorial on Zero-Order Optimization](#)

Case 1: 2-Point & Multi-Point Estimators

- A naïve approach:

$$G_f^{2n}(x; u) = \sum_{i=1}^n \frac{f(x + ue_i) - f(x - ue_i)}{2u} e_i$$

- When f is L -smooth, we have

$$\|G_f^{2n}(x; u) - \nabla f(x)\| \leq \frac{1}{2} u L \sqrt{n}$$

where $f^u(x) = \mathbb{E}_{y \sim \lambda}[f(x + uy)]$ is a smooth version of f

$\lambda = \text{Uni}(\mathbb{B}_n)$

Case 1: 2-Point & Multi-Point Estimators

- 2-point gradient estimator:

$$G_f^{(2)}(x; u, z) = n \frac{f(x + uz) - f(x - uz)}{2u} z \quad z \sim \lambda$$

where λ is spherically symmetric with $\mathbb{E}_{z \sim \lambda}[\|z\|^2] = 1$

$$f^u = \mathbb{E}_z G_f^{(2)}$$

- Some facts for L -smooth / convex / μ -strongly convex function f :

- f^u is L -smooth / convex / μ -strongly convex

$$|f^u(x) - f(x)| \leq \frac{1}{2} u^2 L \cdot \frac{n}{n+2} \mathbb{E}_{z \sim \lambda}[\|z\|^4]$$

$$\|\nabla f^u(x) - \nabla f(x)\| \leq uL \cdot \frac{n}{n+1} \mathbb{E}_{z \sim \lambda}[\|z\|^3]$$

$$\begin{aligned} & \mathbb{E}_{z \sim \lambda}[\|G_f^{(2)}(x; u, z)\|^2] \\ & \leq (1 + \kappa) \mathbb{E}_{z \sim \lambda}[\|z\|^4] \cdot n \|\nabla f(x)\|^2 \\ & \quad + \frac{1 + \kappa}{4\kappa} \mathbb{E}_{z \sim \lambda}[\|z\|^6] \cdot n^2 u^2 L^2 \end{aligned}$$