

Harmonized Cone for Feasible and Non-Conflict Directions in Training Physics-Informed Neural Networks

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*: Equal contribution

Optimization a Feasibility Problem

Find \mathbf{x}^* which satisfies following optimization problem 🙄

$$\begin{array}{ll} \min_{\mathbf{x}} & \mathbf{0}'\mathbf{x} \\ \text{Subject to} & g_i(\mathbf{x}) \leq b_i \quad \forall i \\ & h_j(\mathbf{x}) = b_j \quad \forall j \end{array}$$

Transforming Constraints into Optimization Objectives

$$\begin{array}{l} \min_{\mathbf{x}} \mathbf{0}'\mathbf{x} \\ \text{Subject to } \begin{array}{l} g_i(\mathbf{x}) \leq b_i \quad \forall i \\ h_j(\mathbf{x}) = b_j \quad \forall j \end{array} \end{array} = \begin{array}{l} \min_{\mathbf{x}} \mathbf{0}'\mathbf{x} \\ \text{Subject to } \begin{array}{l} (g_i(\mathbf{x}) - b_i) \leq 0 \quad \forall i \\ (h_j(\mathbf{x}) - b_j)^2 \leq 0 \quad \forall j \end{array} \end{array}$$

Lagrangian expression

$$\min_{\mathbf{x}} \max_{\lambda^g, \lambda^h} \sum_i \lambda_i^g (g_i(\mathbf{x}) - b_i) + \sum_j \lambda_j^h (h_j(\mathbf{x}) - b_j)^2$$

Transforming Constraints into Optimization Objectives

$$\begin{array}{ll} \min_{\mathbf{x}} & \mathbf{0}'\mathbf{x} \\ \text{Subject to} & g_i(\mathbf{x}) \leq b_i \quad \forall i \\ & h_j(\mathbf{x}) = b_j \quad \forall j \end{array}$$

=

$$\begin{array}{ll} \min_{\mathbf{x}} & \mathbf{0}'\mathbf{x} \\ \text{Subject to} & (g_i(\mathbf{x}) - b_i) \leq 0 \quad \forall i \\ & (h_j(\mathbf{x}) - b_j)^2 \leq 0 \quad \forall j \end{array}$$

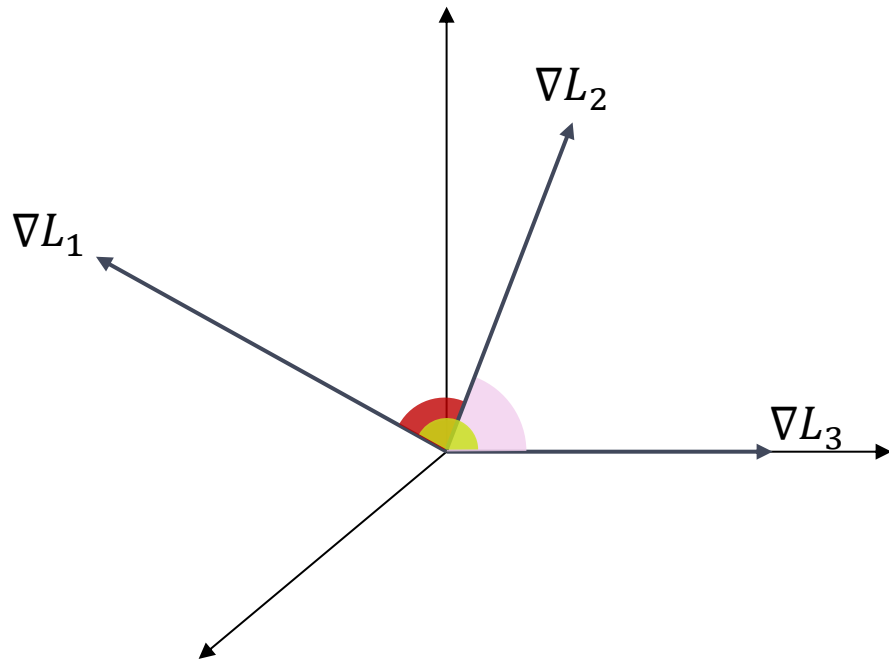


$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x}} \max_{\lambda} \sum_k \lambda_k L_k$$

Where Should the Gradient Move?

$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x}} \max_{\lambda} \sum_k \lambda_k L_k$$

Find the solution \mathbf{x}^* by **gradient descent**



.. Which direction should be chosen?

The region where the **conditions** required for **optimality** are satisfied!

Constraints Satisfaction as Multi-Objective Optimization

$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x}} \max_{\lambda} \sum_k \lambda_k L_k$$

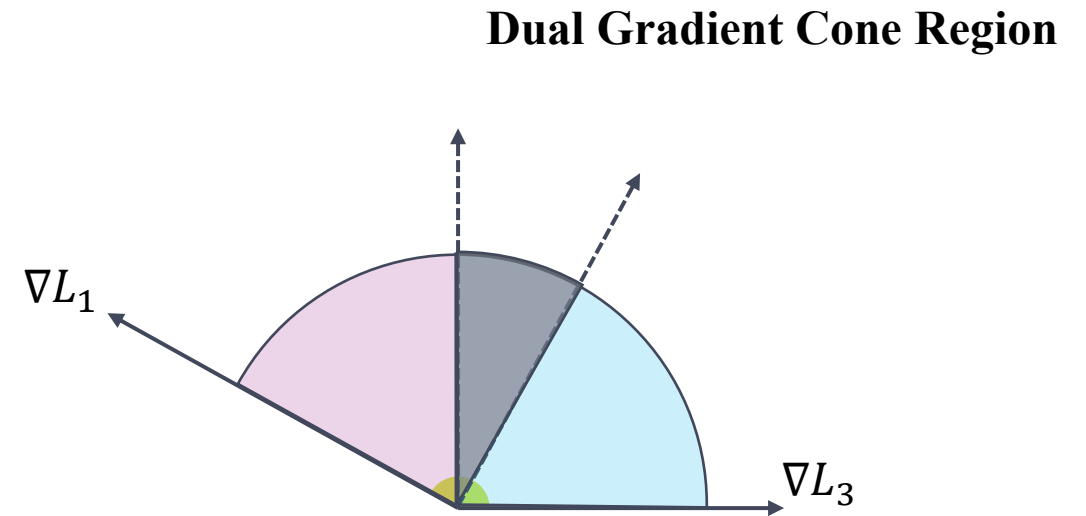
① Primal Feasibility

$$L_k \leq 0 \quad \forall k$$

$$\begin{array}{l} \min_{\mathbf{x}} \mathbf{0}'\mathbf{x} \\ \text{Subject to } L_k \leq 0 \quad \forall k \end{array}$$

Find a common optimal solution \mathbf{x}^* that satisfies all L_k

\therefore Multi-Objective Optimization



Non-negative Combination of Constraint Gradients

$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x}} \max_{\lambda} \sum_k \lambda_k L_k$$

② Dual Feasibility

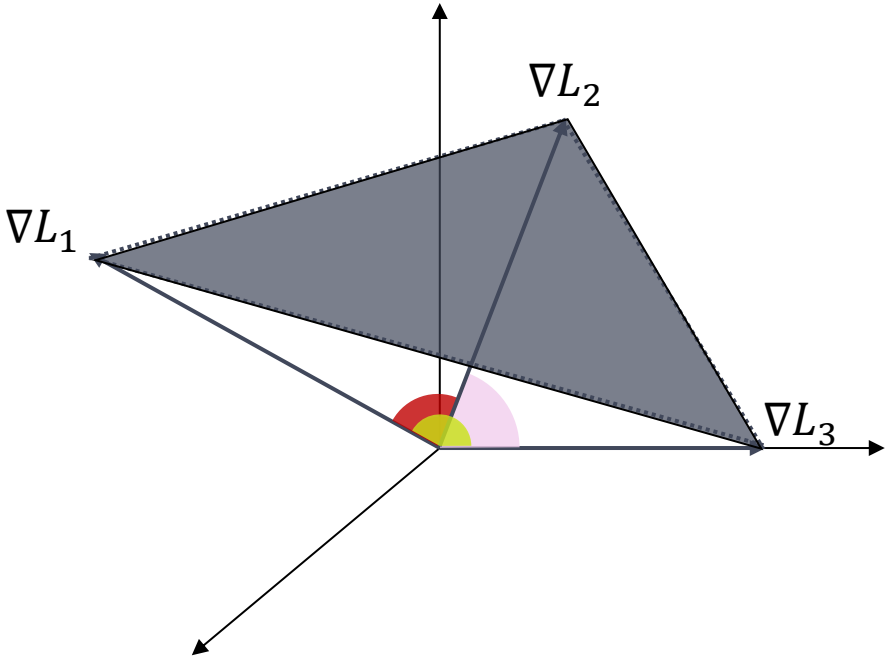
$$\lambda_k \geq 0 \quad \forall k$$

$$\begin{aligned} &\max_{\lambda} \lambda' L \\ &\text{Subject to } \lambda_k \geq 0 \quad \forall k \end{aligned}$$

Search within the space spanned by non-negative combination of L_k

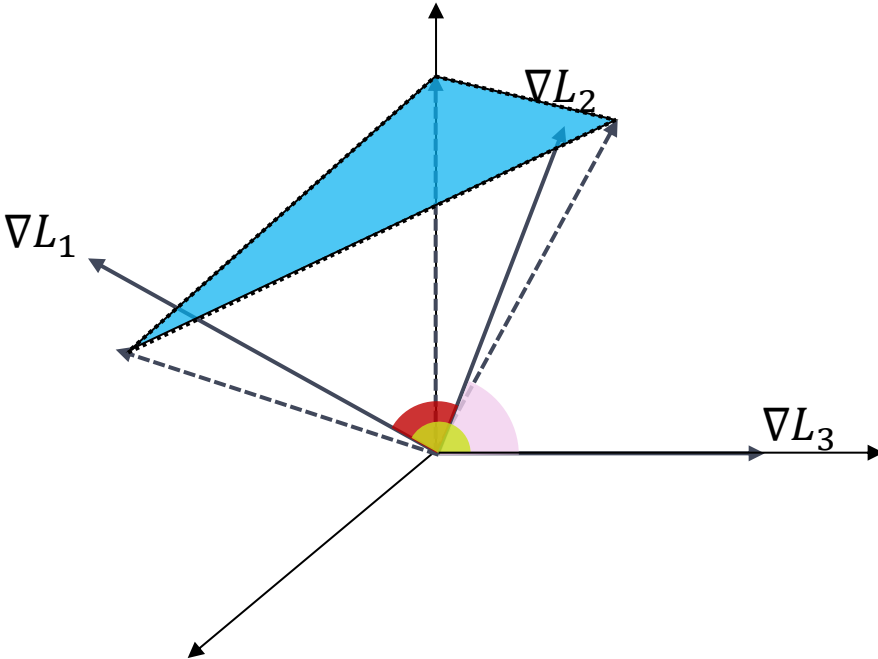
∴ Reweighting Methods

Primal Gradient Cone Region

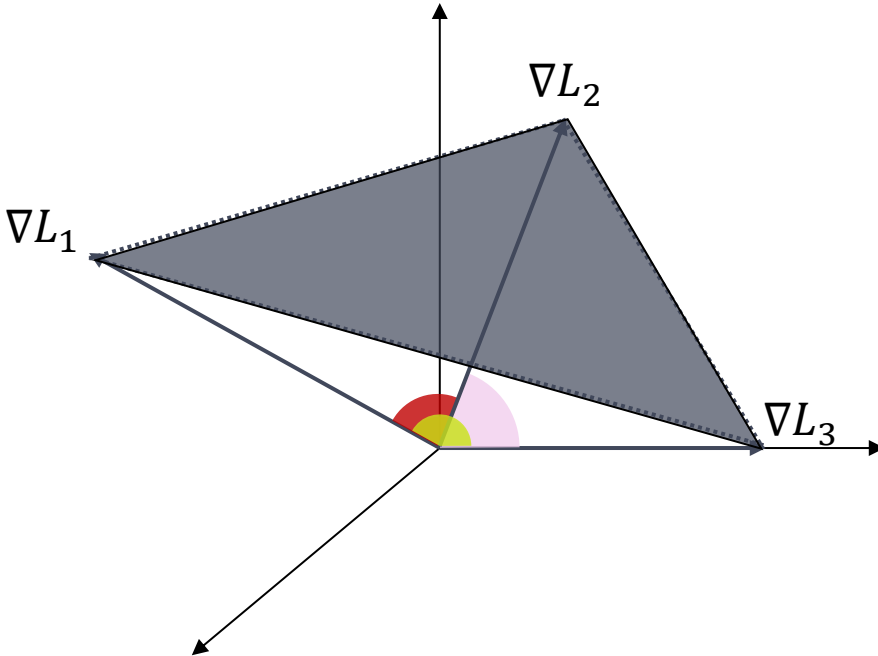


Harmonized Cone: Intersection of Primal and Dual Gradient Cone

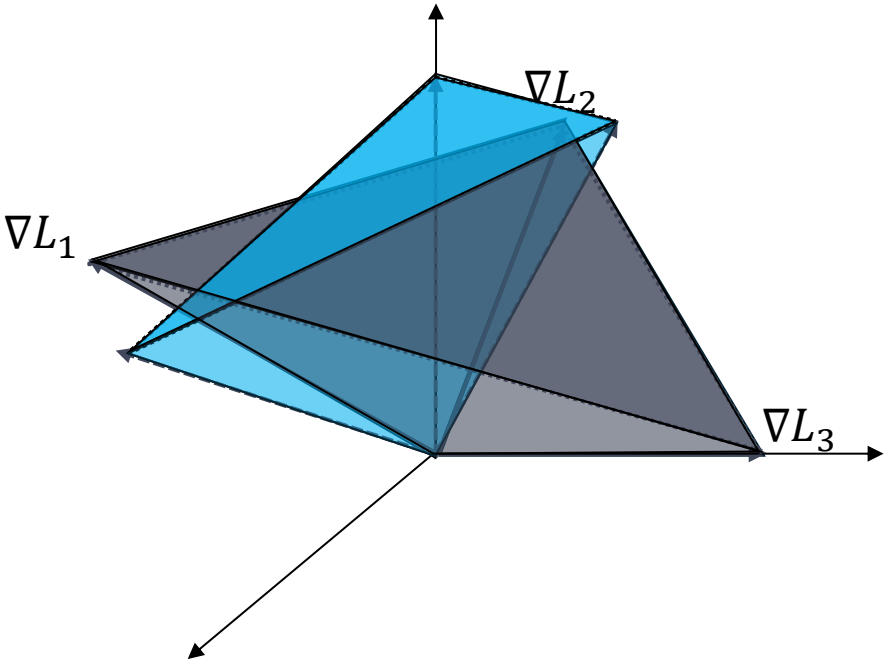
Dual Gradient Cone Region



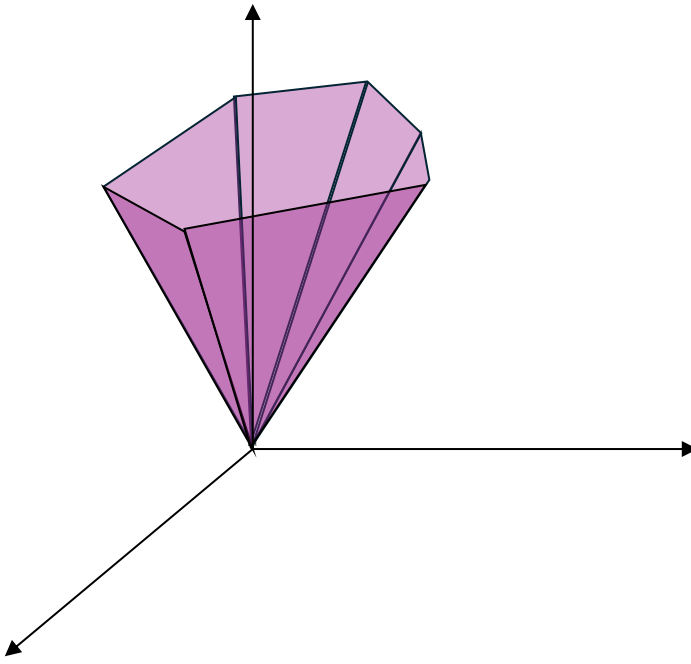
Primal Gradient Cone Region



Harmonized Cone: Intersection of Primal and Dual Gradient Cone



Harmonized Cone



Come check out our Harmonized Cone!

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