

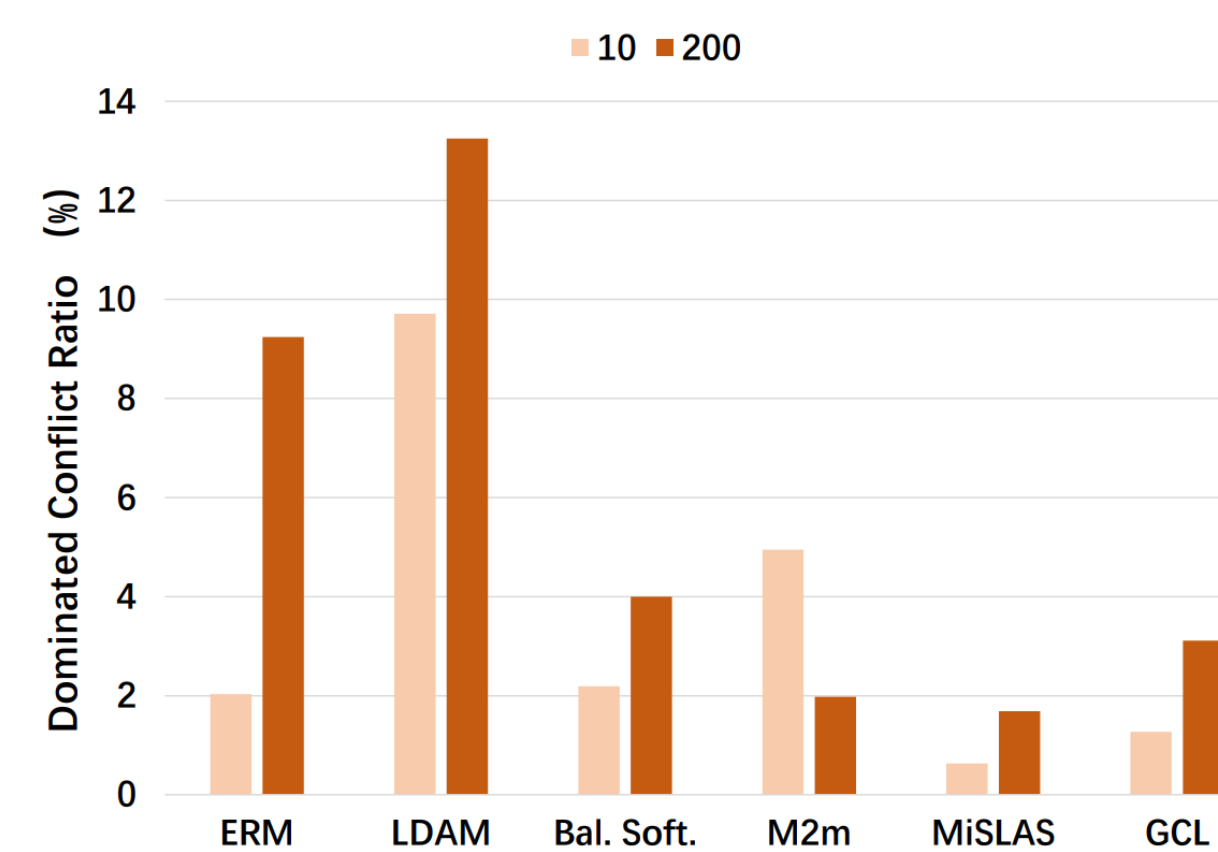
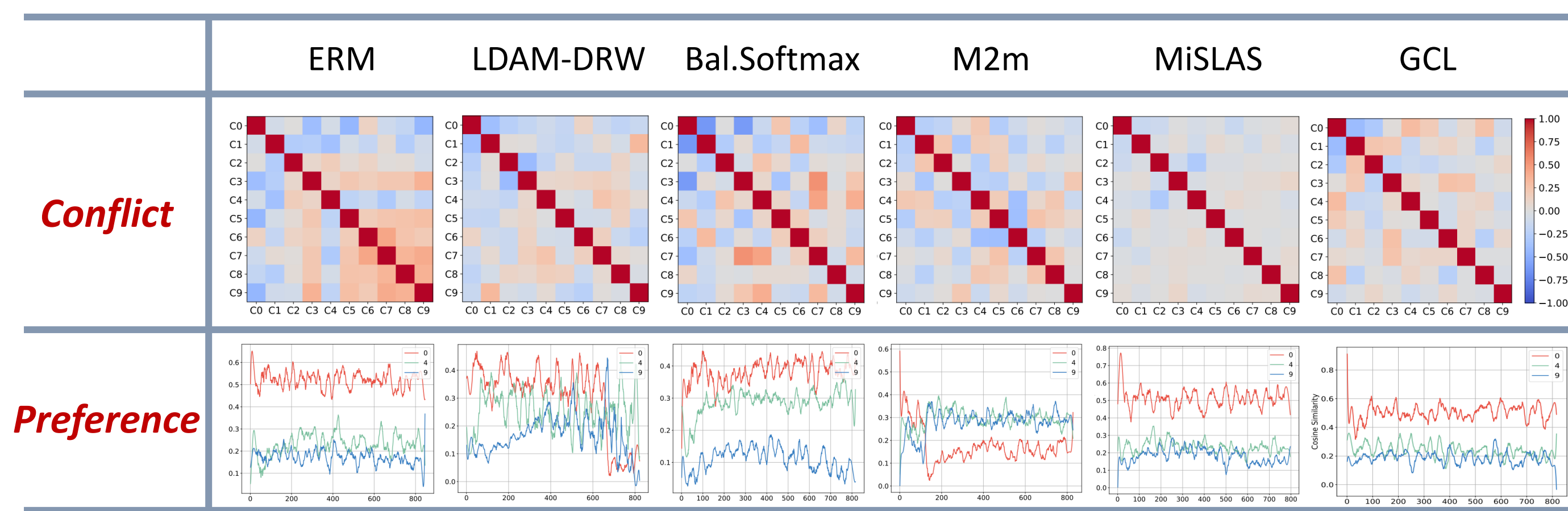
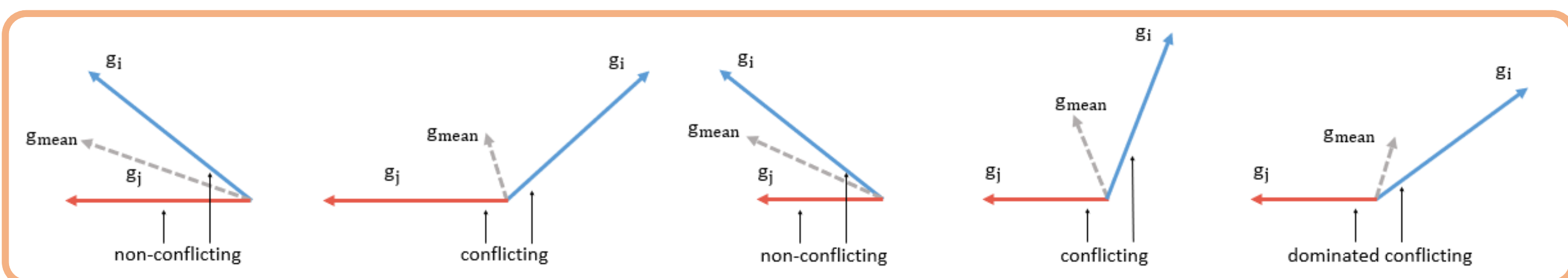


# Pareto Deep Long-Tailed Recognition: A Conflict-Averse Solution

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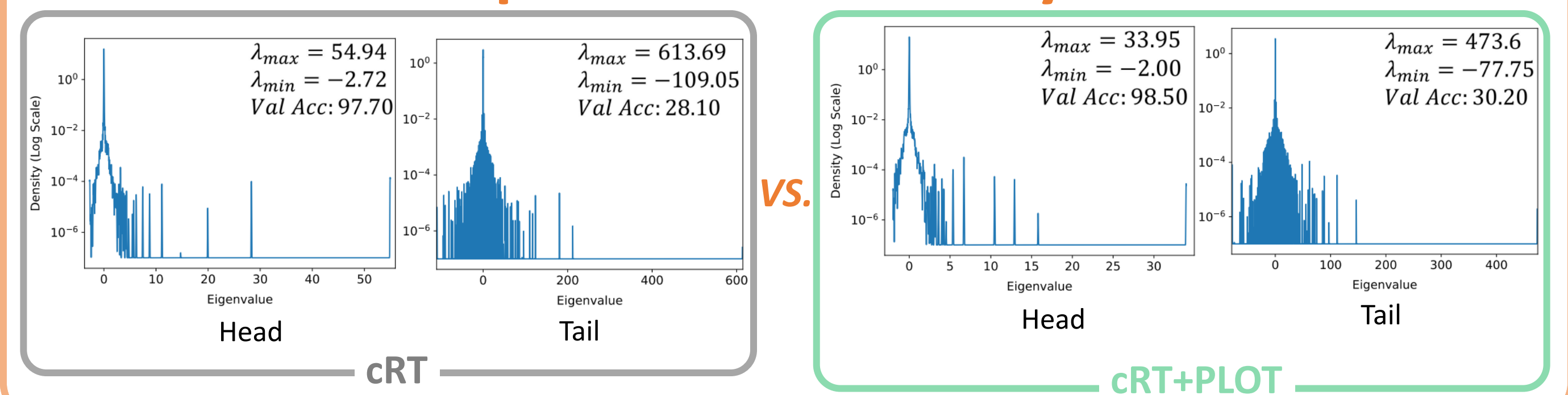


## Motivation

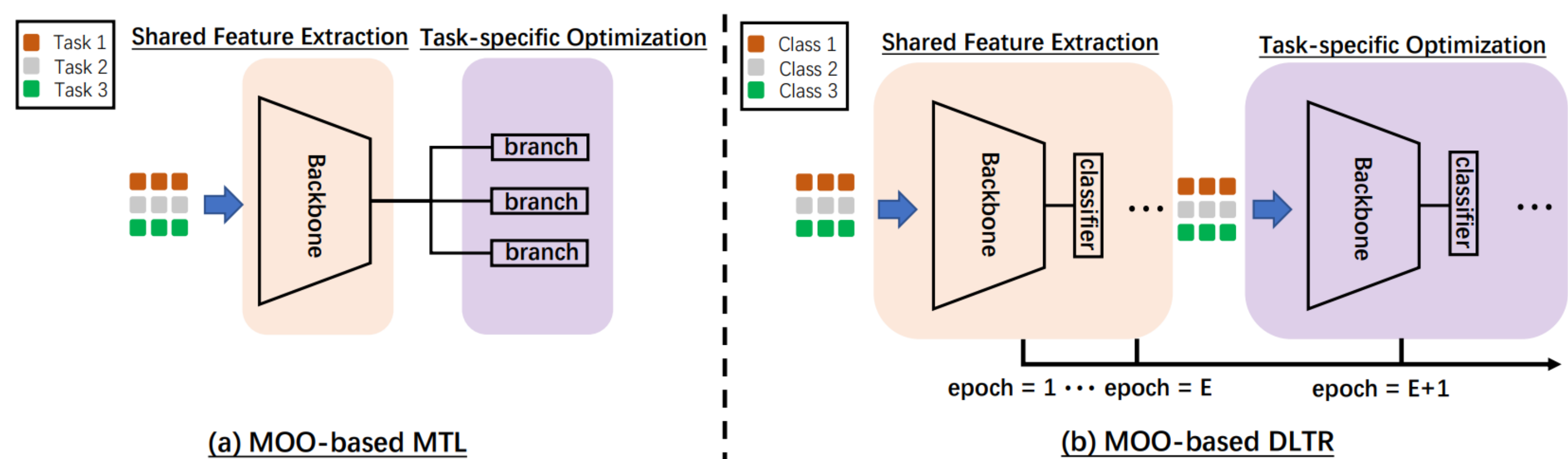


• There exist **conflict** and **preference** issues in LT models.  
• The issues are **exacerbated** in the LT setting.

## Representation Analysis



## MOO: From MTL to DLTR



Mitigate the conflict issue during representation learning

## Can MOO Benefit LT Models?

Imb.	cRT+Mixup				LDAM-DRW									
	Vanilla	w/ EPO	w/ MGDA	w/ CAGrad	Vanilla	w/ EPO	w/ MGDA	w/ CAGrad						
200	73.06	33.45	76.24▲	68.05	75.98▲	75.15	76.02▲	71.38	56.04	73.64▲	67.18	74.08▲	55.80	73.28▲
100	79.15	34.27	79.69▲	73.71	79.26▲	79.58	80.16▲	77.71	66.49	77.25▼	73.70	77.79▲	66.49	76.86▼
50	84.21	36.53	83.79▼	79.27	84.15▼	83.52	84.49▲	81.78	72.60	81.62▼	78.24	81.58▼	69.26	81.85▲

Imb.	Balanced Softmax				M2m									
	Vanilla	w/ EPO	w/ MGDA	w/ CAGrad	Vanilla	w/ EPO	w/ MGDA	w/ CAGrad						
200	81.33	45.37	81.40▲	74.13	80.90▼	79.20	80.93▼	73.43	51.90	73.07▼	57.14	72.63▼	70.95	73.84▲
100	84.90	44.33	85.30▲	79.06	85.10▲	83.77	85.40▲	77.55	57.89	76.57▼	52.37	76.48▼	76.24	77.95▲
50	89.17	41.43	88.97▼	79.43	88.90▼	88.00	89.27▲	80.94	42.07	81.19▲	46.38	80.66▼	78.19	81.11▲

Imb.	MiSLAS				GCL									
	Vanilla	w/ EPO	w/ MGDA	w/ CAGrad	Vanilla	w/ EPO	w/ MGDA	w/ CAGrad						
200	76.59	36.62	76.97▲	63.40	76.12▼	76.30	77.43▲	79.25	62.08	79.73▲	75.43	80.03▲	78.73	80.08▲
100	81.33	39.92	81.22▼	68.09	82.00▲	82.10	82.47▲	82.85	74.78	82.75▼	79.01	82.81▼	82.48	83.48▲
50	85.23	44.78	84.60▼	70.20	84.84▼	85.20	85.33▲	86.00	78.42	84.55▼	81.89	85.58▼	85.31	85.90▼

- Generally, applying MOO with our framework benefits LT models
- **CAGrad** shows a more **stable** performance compared to others

## Generalization Guarantee

**Theorem 1 (MOO-based DLTR Generalization Bound)**  
If the loss function  $l_k$  belonging to  $k_{th}$  category is  $M_k$ -Lipschitz, and  $\forall(x, y), (x', y') \in \mathcal{X} \times \mathcal{Y}, \forall h \in \mathcal{H}: \|[h(x), y] - [h(x'), y']\| \leq \mathcal{D}_{\mathcal{H}}$ , assume  $M_k \mathcal{D}_{\mathcal{H}}$  is bounded by  $M$ , then for any  $\epsilon > 0$  and  $\delta > 0$ , with probability at least  $1 - \delta$ , the following inequality holds for  $\forall h \in \mathcal{H}$  and  $\forall \omega \in \mathcal{W}$ :

$$\mathcal{L}_{\omega}(h) \leq \hat{\mathcal{L}}_{\omega}(h) + 2\mathfrak{R}_S(\mathcal{G}, \omega) + \sum_{k=1}^K \omega_k M \sqrt{\frac{\log \frac{1}{\delta}}{2}}$$

Derived Upper Bound

Variability Collapse Loss

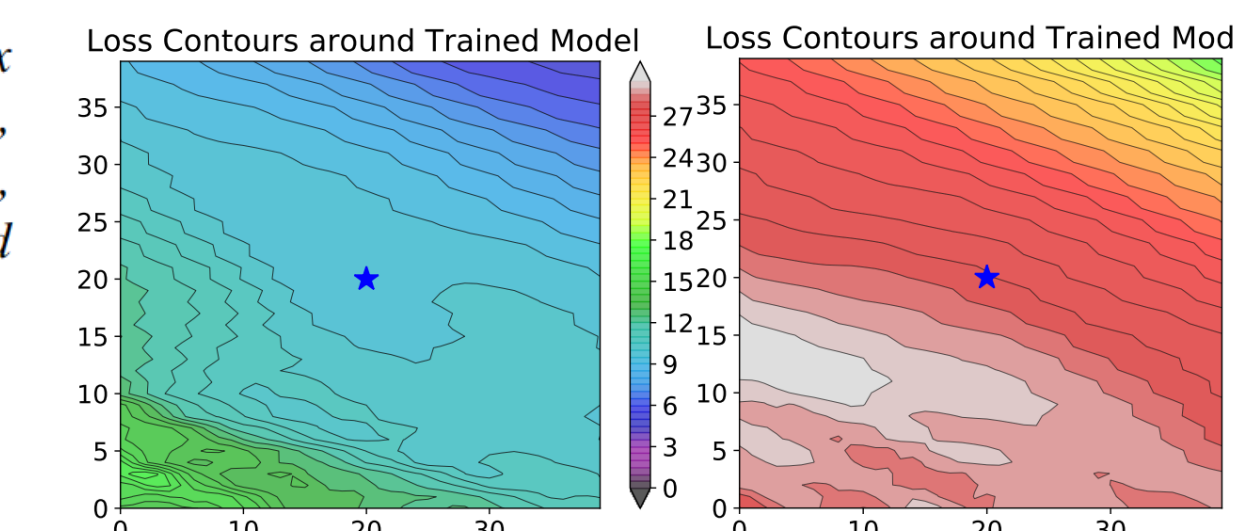
$$\mathcal{L}_{vc} = \frac{1}{K} \sum_{k=1}^K \text{Std}(\tilde{l}(x_*^k, y_*^k))$$

- Provide a theoretically derived design for generalization
- Happens to share the same formula with **Neural Collapse**

## Convergence Guarantee

**Theorem 2 (Convergence of CAGrad in DLTR)** With a fix step size  $\alpha$  and the assumption of  $H$ -Lipschitz on gradients, i.e.,  $\|\nabla \mathcal{L}_i(\theta) - \nabla \mathcal{L}_i(\theta')\| \leq H \|\theta - \theta'\|$  for  $i = 1, 2, \dots, K$ . Denote  $d^*(\theta_t)$  as the optimization direction of CAGrad at step  $t$ , then we have:

$$\mathcal{L}(\theta_{t+1}) - \mathcal{L}(\theta_t) \leq -\frac{\alpha}{2}(1 - c^2) \|g_0(\theta_t)\|^2 + \frac{\alpha}{2}(H\alpha - 1) \|d^*(\theta_t)\|^2,$$



**SAM:**  $\min_{\theta} \max_{\epsilon(\theta)} \mathcal{L}(\theta + \epsilon(\theta))$ , where  $\|\epsilon(\theta)\|_2 \leq \rho$ .

Provide convergence guarantee for **MOO in DLTR**  
See experimental results in our paper

Contact Us!

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Implementation: <https://github.com/zzpustc/PLOT>