GradCraft: Elevating Multi-task Recommendations through Holistic Gradient Crafting

USTC & Kuaishou Technology

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KDD2024 BARCELONA, SPAIN

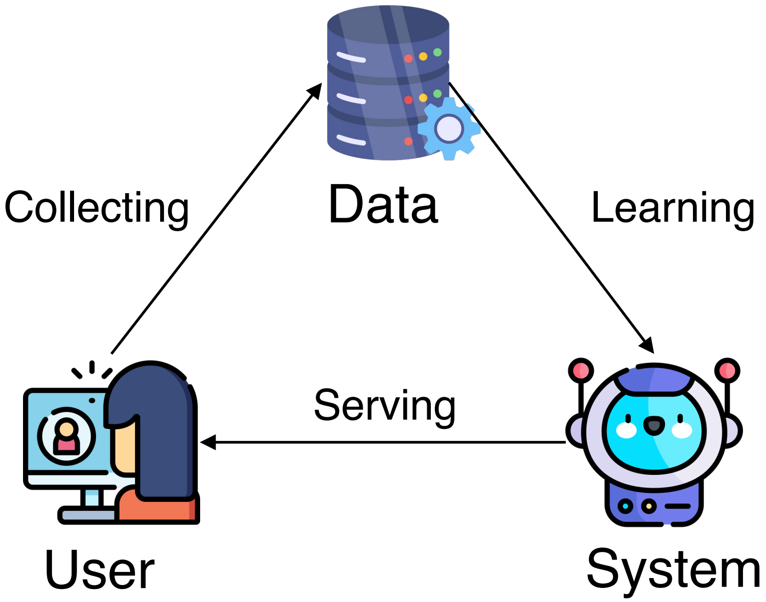
Outline

- Background
- Methodology
- Experiment
- Conclusion

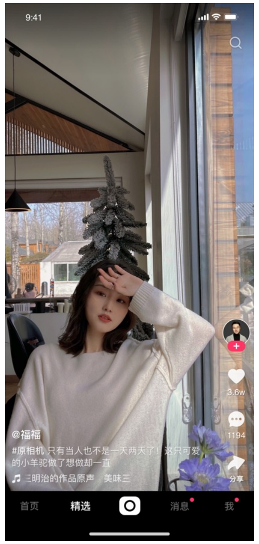
Background

➢ What is Multi-task Recommendation

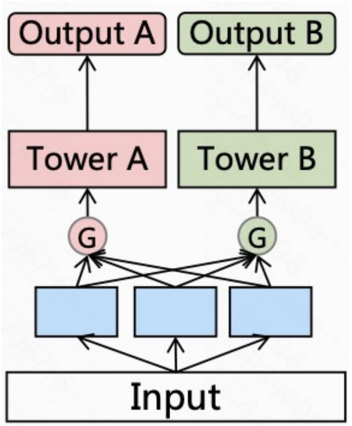
Feedback Loop



Why Muti-task Learning



- TaskA: long view
- TaskB: like
- TaskC: follow
- TaskD: forward
- …



$$\boldsymbol{Loss} = w_A * l_A + w_B * l_B + \ldots$$
$$\boldsymbol{Gradient} = w_A * g_A + w_B * g_B + \ldots$$

Background

➢ Challenge in Multi-task Recommendations

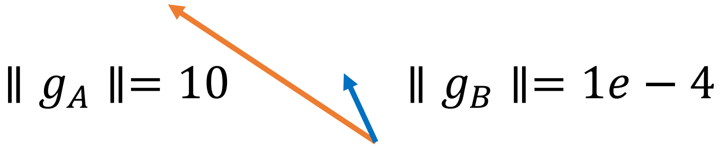
Task Heterogeneity

Viewing: long view

Engagement: like

Engagement behavior is **sparser** than viewing behavior

Gradient perspective: **gradient magnitudes** are different.



Task Cardinality

TaskA: long view

TaskB: like

TaskC: follow

…

Gradient perspective: **gradient directions** are different.

Conflicting task pairs (inner product < 0)

Methodology

➢ Gradient Magnitude Adjustment

- **Key:** ensure an appropriate level of magnitude balance
- **How:** align gradient norm with the maximum norm among tasks

For i in range(T): $\hat{g}_i = \tau \frac{\max_j \|g_j\|}{\|g_i\|} g_i + (1-\tau) g_i,$

Number of tasks

Hyper-parameter: control the proximity to the maximum norm

$\tau = 0$: keep the original magnitude

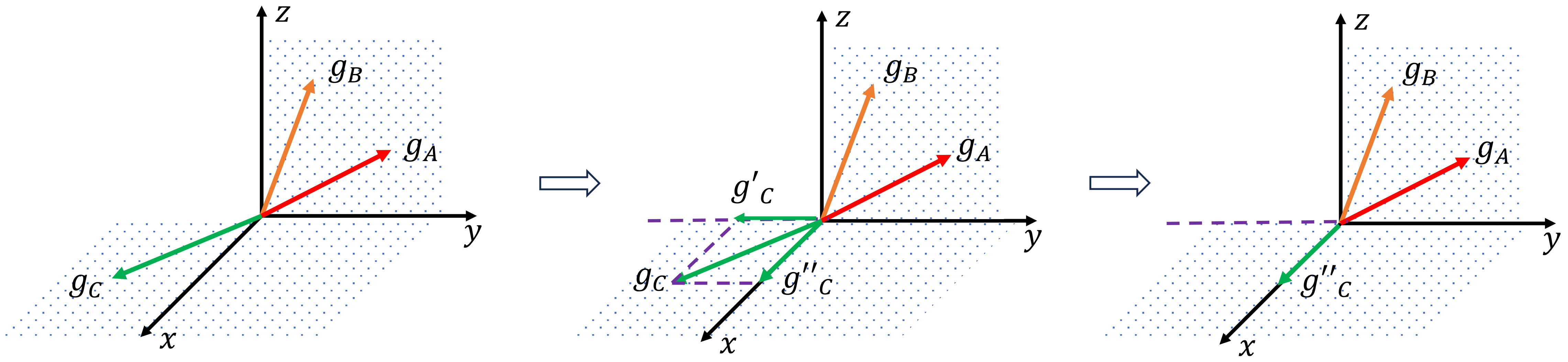
$\tau = 1$: equal the maximum norm

- Mitigate interference from magnitudes for subsequent manipulation

Methodology

➢ Gradient Direction Deconfliction

- ☐ **Key:** ensure task gradient does not conflict with other gradients
- ☐ **How:** global gradient projection



$$g_C g_A^T < 0$$
$$g_C g_B^T < 0$$

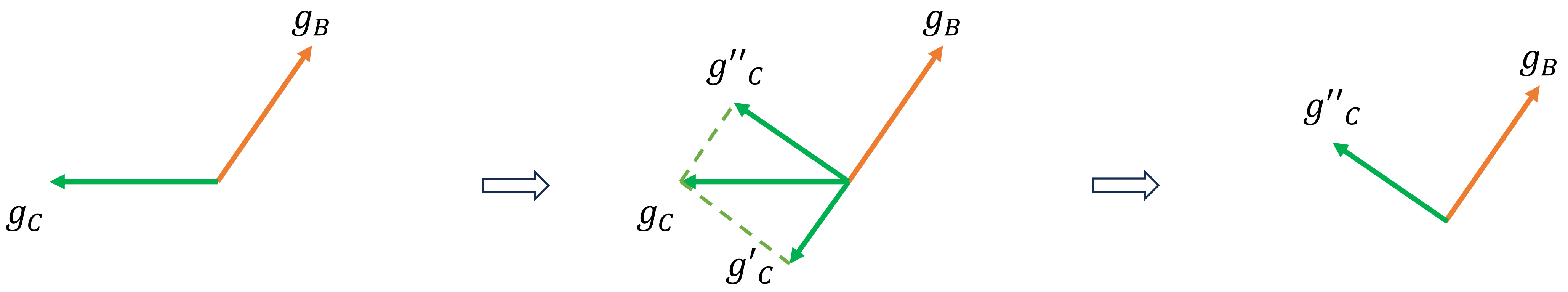
Global gradient projection

$$g''_C g_A^T = 0$$
$$g''_C g_B^T = 0$$

Methodology

➢ Gradient Direction Deconfliction

- For each task, our method **simultaneously** addresses all conflicting tasks
- Comparison: PCGrad [1] is **one vs one**, our projection method is **one vs all**
- When only **two tasks:** our projection method degrades to PCGrad



$g_C g_B^T < 0$ **PCGrad** $g''_C g_B^T = 0$

[1] Gradient Surgery for Multi-Task Learning. NeuralIPS 2020.

Methodology

➢ Gradient Direction Deconfliction

☐ Formulation of global gradient projection

✓ Stack all conflicting gradients	$G_i = [\hat{g}_{i_1}, \ldots, \hat{g}_{i_n}] \in \mathbb{R}^{n \times d},$
✓ Set the projection target	$G_i \tilde{g}_i^\top = \boldsymbol{z},$ $\boldsymbol{z} = [\epsilon \lVert \hat{g}_i \rVert \lVert \hat{g}_{i_1} \rVert, \ldots, \epsilon \lVert \hat{g}_i \rVert \lVert \hat{g}_{i_n} \rVert],$ Hyper-parameter: allow the positive inner product
✓ Give the projection to the space	$\tilde{g}_i = \hat{g}_i + \sum_{k=1}^{n} w_k \hat{g}_{i_k} = \hat{g}_i + \boldsymbol{w}^\top G_i,$
✓ Solve the weight vector	$\boldsymbol{w} = (G_i G_i^\top)^{-1}(-G_i \hat{g}_i^\top + \boldsymbol{z}).$

For i in range(T):

Input: $\hat{g}_i$

Output: $\tilde{g}_i$

Methodology

➢ Overall Framework of GradCraft

- 1. Compute all task losses, $[l_1, \dots, l_T]$
- 2. Obtain all task gradients, $[g_1, \dots, g_T]$
- 3. Gradient magnitude adjustment, $[\hat{g}_1, \dots, \hat{g}_T]$
- 4. Gradient direction deconfliction, $[\tilde{g}_1, \dots, \tilde{g}_T]$
- 5. Gradient combination, just average as $\frac{1}{T}\sum_{i=1}^{T} \tilde{g}_i$
- 6. Gradient update by the optimizer (shared parameters)

Experiment

➢ Offline Experiment Setting

- **Dataset:** Kuaishou (private), Wechat (public)
- **Task (Binary for simplicity):**
  - Viewing behavior: EffectiveView (EV), LongView (LV), CompleteView (CV)
  - Engagement behavior: Like, Follow, Forward
- **Evaluation:** average value of all tasks' AUC and GAUC
- **Baseline:**
  - Simple: Single, EqualWeighting
  - Other multi-task learning methods like Uncertainty and PCGrad
- **Backbone**: PLE [1]

[1] Progressive layered extraction (ple): A novel multi-task learning (mtl) model for personalized recommendations. RecSys 2020.

Experiment

➢ Offline Experiment Result

Method		Single	EW	UC	DWA	MGDA	Wechat PCGrad	PCGrad+	GradVac	CAGrad	IMTL	DBMTL	GradCraft
AUC	EV	0.7641	0.7641	0.7633	0.7646	0.7569	<u>0.7651</u>	0.7644	0.7648	0.7647	0.7629	0.7636	**0.7653**
	LV	0.8484	0.8484	0.8479	<u>0.8490</u>	0.8429	**0.8491**	0.8486	0.8489	0.8489	0.8478	0.8479	<u>0.8490</u>
	CV	0.7610	0.7604	0.7596	**0.7620**	0.7515	0.7614	0.7611	0.7613	0.7614	0.7589	0.7597	<u>0.7616</u>
	Like	0.8661	0.8664	<u>0.8671</u>	0.8656	0.8604	**0.8675**	0.8668	0.8665	0.8662	0.8669	0.8650	0.8661
	Fol	<u>0.8829</u>	0.8810	0.8763	0.8809	0.8803	0.8825	0.8827	0.8791	0.8801	0.8827	0.8750	**0.8888**
	For	0.8940	**0.9012**	0.9006	0.8983	0.8937	0.8968	0.9000	0.8991	0.9003	<u>0.9008</u>	0.8987	0.9001
	AV-A	0.8361	0.8369	0.8358	0.8367	0.8309	0.8371	<u>0.8373</u>	0.8366	0.8369	0.8367	0.8350	**0.8385**
	RI-A	0.000%	0.091%	-0.038%	0.078%	-0.639%	0.118%	<u>0.135%</u>	0.065%	0.099%	0.056%	-0.129%	**0.278%**
GAUC	EV	0.6207	0.6209	0.6194	0.6189	0.6055	**0.6226**	0.6195	0.6218	0.6200	0.6201	0.6178	<u>0.6221</u>
	LV	0.7731	0.7745	0.7740	0.7739	0.7684	<u>0.7754</u>	0.7736	**0.7755**	0.7743	0.7742	0.7732	0.7751
	CV	0.6499	0.6503	0.6489	0.6499	0.6345	<u>0.6515</u>	0.6493	0.6509	0.6491	0.6488	0.6464	**0.6518**
	Like	0.6324	0.6382	<u>0.6405</u>	0.6368	0.6328	**0.6422**	0.6380	0.6384	0.6390	0.6393	0.6385	0.6383
	Fol	0.6847	0.6820	<u>0.6962</u>	0.6915	0.6874	0.6899	0.6870	0.6721	0.6930	0.6894	0.6896	**0.7003**
	For	0.7012	0.7129	0.7154	0.7141	0.7021	<u>0.7164</u>	0.7140	0.7152	0.7135	0.7144	0.7124	**0.7176**
	AV-G	0.6770	0.6798	0.6824	0.6809	0.6718	<u>0.6830</u>	0.6802	0.6790	0.6815	0.6810	0.6796	**0.6842**
	RI-G	0.000%	0.413%	0.791%	0.559%	-0.809%	<u>0.887%</u>	0.472%	0.288%	0.653%	0.589%	0.380%	**1.056%**

Experiment

➢ Online Experiment on Kuaishou

- **Setting:**
  - Traffic: 1 week, 15 million users
  - Baseline: the SOTA multi-task learning method on our platform
  - Evaluation:
    - the average time users spend watching videos (WT)
    - the number of effective video viewing records (VV)
    - the instances of video sharing (Share)
- **Result:** WT **+0.505%**, VV **+0.950%**, Share **+1.746%**

Experiment

➢ In-depth Analysis

Ablation Study

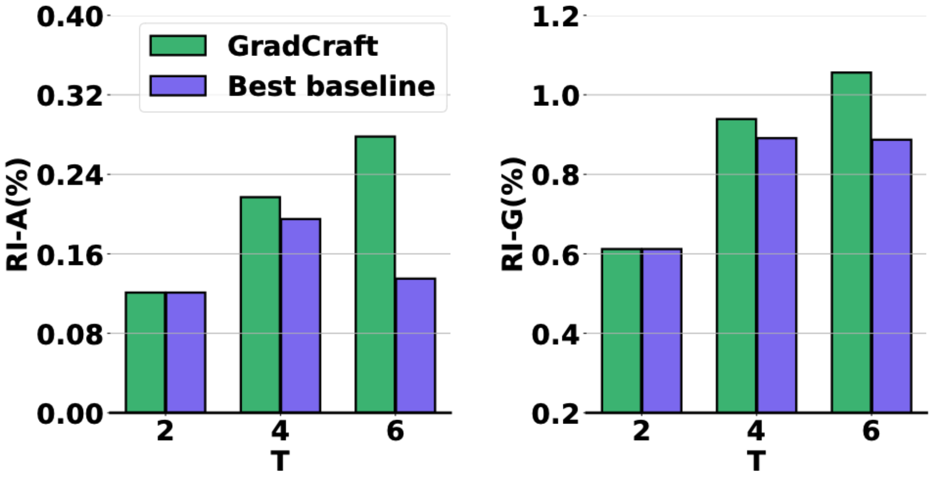
Magnitude: ✓ τ: control the proximity

Direction: ✓ ϵ: allow the positive inner product

✓ Projection: global (one vs all)

	Method	AV-A	RI-A	AV-G	RI-G
	GradCraft	0.8385	0.278%	0.6842	1.056%
$\epsilon = 0$	GradCraft-fix ϵ	0.8382	0.250%	0.6837	0.981%
$\tau = 1$	GradCraft-fix τ	0.8365	0.039%	0.6798	0.392%
$\tau = 0$	GradCraft-ori	0.8370	0.113%	0.6835	0.959%
one vs one	GradCraft-local	0.8371	0.118%	0.6830	0.887%

Effect of Task Number T



✓ GradCraft **scales up** effectively with the increasing complexity introduced by a growing number of tasks.

Conclusion

- Multi-task Learning in RecSys
  - **Challenge**: task heterogeneity and cardinality
  - **Motivation**: appropriate magnitude balance and global direction balance
  - **Methodology**:
    - Gradient magnitude adjustment
    - Gradient direction deconfliction
  - **Offline** experiment on real-world datasets
  - **Online** experiments on Kuaishou platform
  - **Future work**: apply to other domains and improve the efficiency

Thanks

The code has been released at
https://github.com/baiyimeng/GradCraft