Minority-Aware Satisfaction Estimation in Dialogue Systems via Preference-Adaptive Reinforcement Learning

Yahui Fu, Zi Haur Pang, Tatsuya Kawahara

京都大学



Why Model User Satisfaction Beyond the Majority?

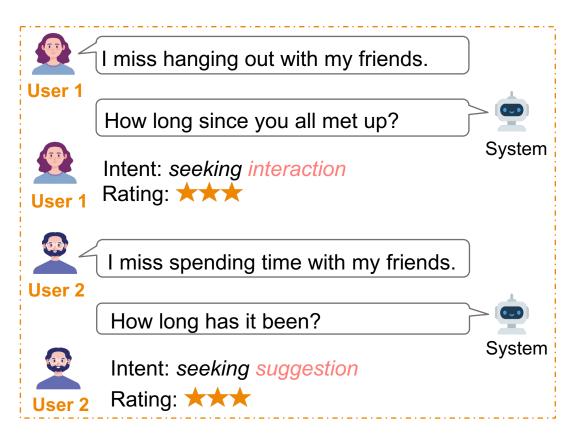
Why Model User Satisfaction Beyond the Majority?

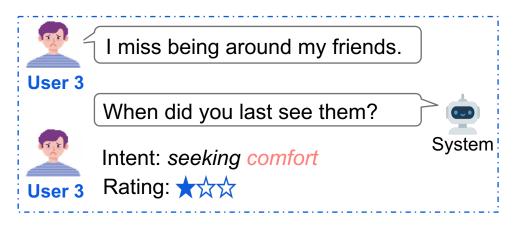
💡 Motivation: User satisfaction is subjective 🗣

→ same response strategy ≠ same satisfaction

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→ majority voting suppresses minority preferences



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© Goal: Build a satisfaction estimator that adapts to both majority and

minority users.





Method: User-specific Reasoning

Understanding users' intents

- What do they need?
- How do they feel?



Appropriate response strategy

- Questioning, reflecting, suggesting...
- Tailored, not one-size-fits-all





High satisfaction across diverse users



Method: User-specific Reasoning

Step1: User-specific Chain-of-Personalized-Reasoning (CoPeR) Synthesis

Context c:

[user] I am feeling quite sad. I miss hanging out with my friends in person. [supporter] It looks like you are missing your friends a lot, am I right?

Satisfaction y: not so helpful (score 3)

Reasoning:

Step1: What is the user's intent...

Step2: Identify the strategy of supporter

◆ Step3: Did the support <u>match</u> the user's intent...

Step4: <u>Explain</u> why the user gave a satisfaction score of 3...consider empathy, relevance...



Output r_{coper} :

 $r_{
m intent}$: To <u>express their sadness</u> regarding missing inperson interactions with friends...

 $r_{
m strategy}$: <u>Reflection of feelings</u>...

 $r_{
m match}$: <u>Partially aligned</u> by...

 $r_{
m reason}$: The user gave a satisfaction score of <u>3</u> because, while their feelings were acknowledged, they likely

expected more practical support to address their sadness...

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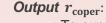
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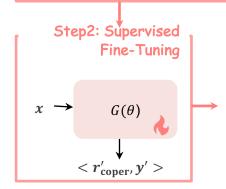
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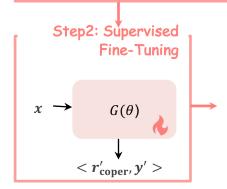
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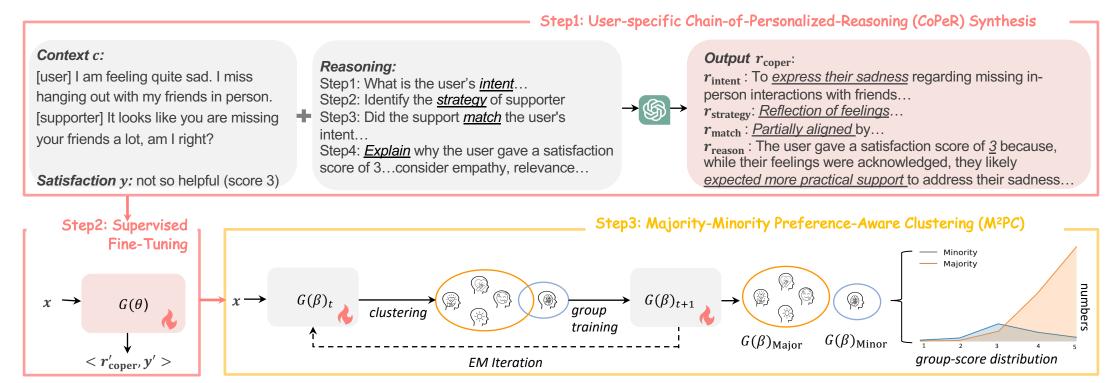
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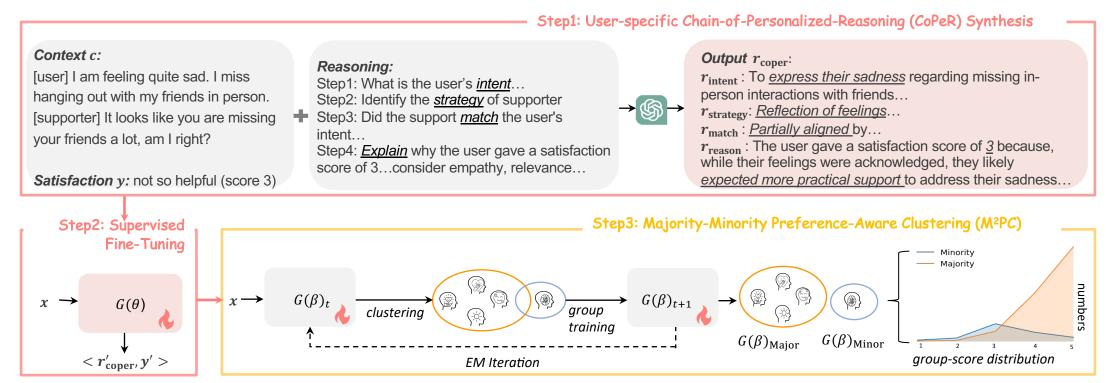
SFT still mixes all users → minority preferences get **suppressed**.

Real systems lack group labels → supervised separate training is **impossible**.

Method: Majority-Minority Preference-Aware Clustering (M²PC)



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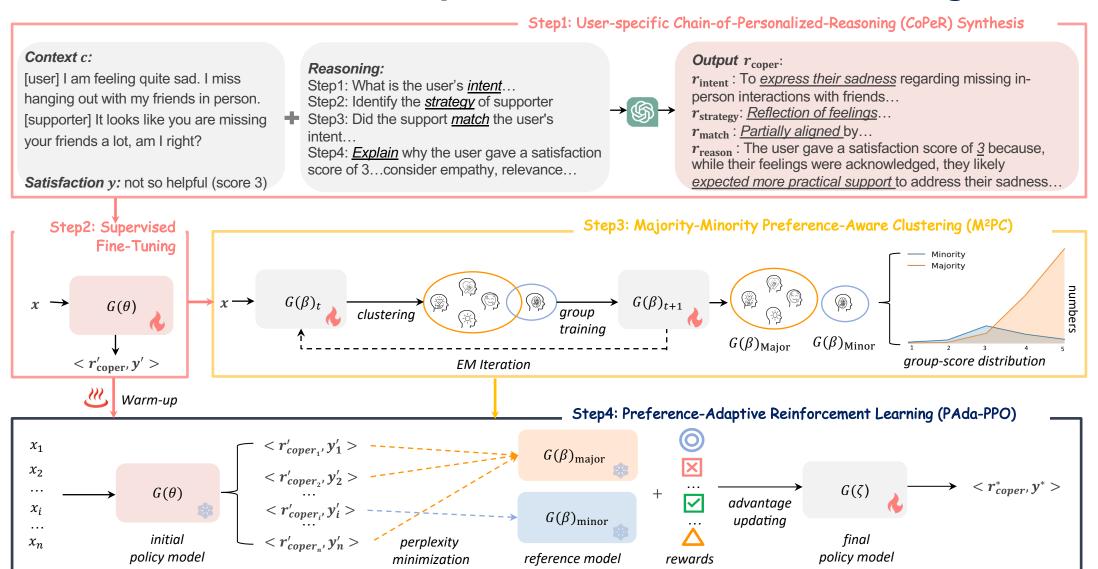




Reference model inherits majority bias → RL cannot adapt well.

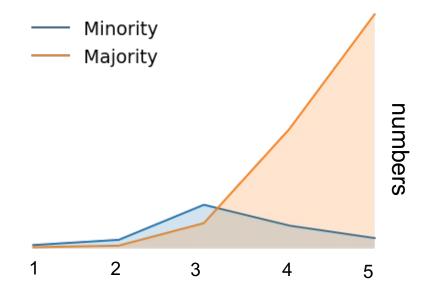
M²PC learns majority/minority references → RL adapts to each group.

Method: Preference-Adaptive Reinforcement Learning



Experiment

- □ Dataset: Emotional Support Conversation
- ☐ User Groups
- Majority (81.4%): >60% high-satisfaction scores per dialogue
- Minority (18.6%): ≤60% high-satisfaction scores
- ☐ Group-Satisfaction score Distribution



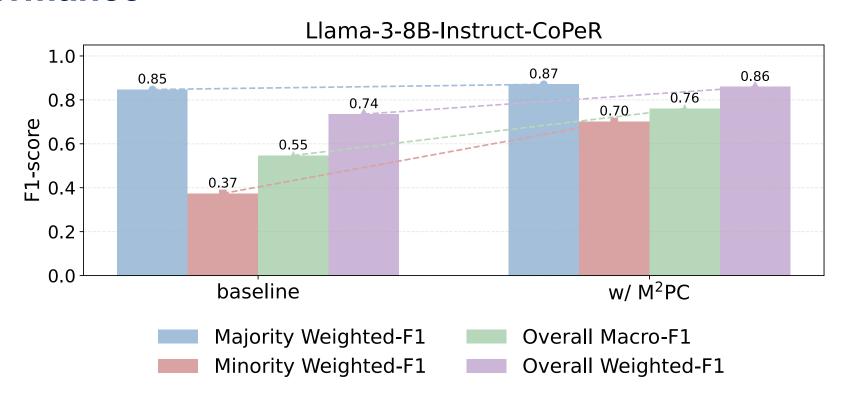
User-Specific Reasoning Enhances Overall Performance

Systems	F1 _{low}	F1 _{high}	F1 _{weight}	F1 _{macro}
Llama-3-8B-Instruct	0.24	0.82	0.71	0.53
+User-specific	0.27	0.86	0.75	0.56

□ Performance improved on both classes:

Low-F1 \uparrow 0.24 \rightarrow 0.27 (+13%), High-F1 \uparrow 0.82 \rightarrow 0.86 (+5%)

M²PC Achieves Substantial Minority Gains with Balanced Performance



- ☐ Significant improvements on the validation set:
 - Minority Weighted-F1 ↑ 0.37 → 0.70 (+89%)
 - Overall Macro-F1 ↑ 0.55 → 0.76 (+38%)

Preference-Adaptive RL Enhances Minority Predictions

Systems	F1 _{low}	F1 _{high}	F1 _{weight}	F1 _{macro}
Llama-3-8B-Instruct	0.24	0.82	0.71	0.53
+User-specific	0.27	0.86	0.75	0.56
RL with PPO	0.22	0.88	0.76	0.55
RL with PAda-PPO	0.36	0.86	0.77	0.61

☐ Performances improved on each class:

Low- $F_1 \uparrow 0.24 \rightarrow 0.27 \ (+13\%), \ High-F_1 \uparrow 0.82 \rightarrow 0.86 \ (+5\%),$

□ RL with PAda-PPO further improves the low-satisfaction class:

Low-F1 \uparrow 0.22 \rightarrow 0.36 (+64%).

Does Our Method Support Smaller Subgroups?

- ☐ Method: Cluster subgroups by k-means++ on last hidden states.
- ☐ Optimal is by silhouette score.

Accounts for Smaller Yet Distinct Subgroups

Groups	1	2	3	4	5	6	7	•••
Maj.	0.71 (134)	0.79(105)	0.93 (56)	0.85 (48)	0.94(44)	0.94(39)	0.90(30)	
Min.	0.70(22)	0.61(21)	0.67(7)	0.91(6)	0.67(6)	1.00(5)	0.80(5)	•••
Gropus	13	14	15	16	17	18	19	20
Maj.	0.90 (19)	0.96 (14)	1.00 (9)	1.00(8)	1.00(8)	1.00(7)	1.00(4)	-
Min.	0.67(3)	0.53(3)	0.53(3)	0.67(3)	1.00(3)	0.67(2)	1.00(2)	1.00(2)

Note: Each cell shows "weighted-F1 (number of users)"

Majority (17/17)/ Minority (12/18): Smaller outperform largest

→ Captures diverse characteristics rather than overfitting to frequent patterns.

Takeaways

- ☐ We address the often-overlooked preferences of minority users.
- ☐ User satisfaction is inherently subjective; reasoning enables *personalization*.
- ☐ M²PC uncovers diverse user clusters, while PAda-PPO *aligns rewards* with subgroup preferences.
- ☐ Our framework achieves significant *improvements for minority users* while preserving majority performance.

Thank you for your attention!



Paper



Code



Contact



