LLM Personalization: Foundations, Breakthroughs, and Frontiers

Organizer: Xiaoyan Zhao, Xinyu Lin, Chengbing Wang, Zeyu Zhang, Bohao Wang, Chongming Gao, Yang Zhang, Wenjie Wang, and Fuli Feng

Speaker: Xiaoyan Zhao, Xinyu Lin, Chongming Gao, Yang Zhang

20 July 2026

tutorial website

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From General-Purpose to Personal Intelligence

- **LLMs are Becoming Part of Everyday Digital Life**

Essential interfaces between users and digital worlds, e.g., Bytedance Seed DAU > 200 million

- ❑ Conversational Agents
- ❑ Decision Assistants
- ❑ Creative Partners
- ❑ Search Agent
- ❑ Healthcare Assistants

Personalization becomes necessary: It becomes necessary to understand, remember, and adapt to individual users over time

From General-Purpose to Personal Intelligence

- **General-purpose Intelligence breaks down at the individual level**

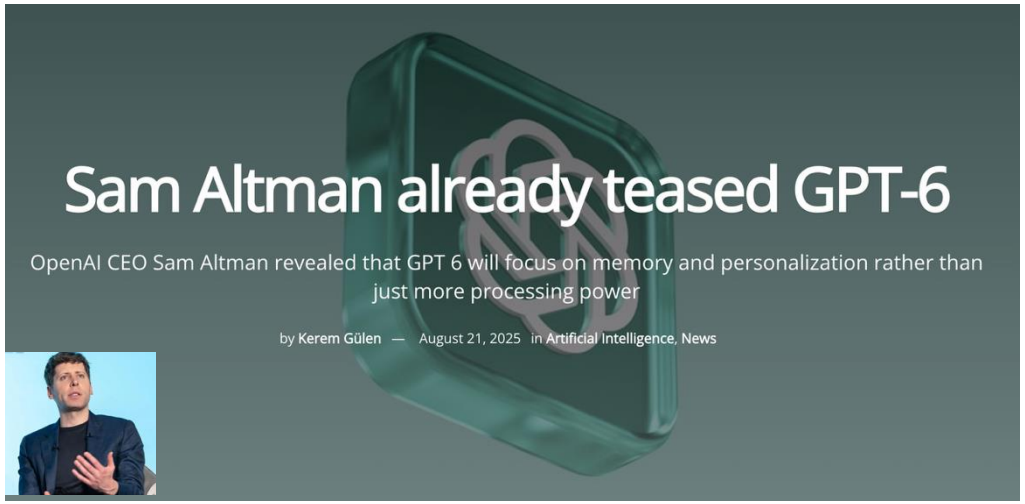
❑ Current general-purpose Intelligence: population-level
- One-size-fits-all responses
- **Lacks awareness of individual differences** (preferences, values, goals, and context…)
- reasonable, yet impersonal

User feeling: ***"It works — but it doesn't really understand me."***

❑ Move towards ***personal intelligence***
- **Individual-level understanding: long-term**
- **Behavior that adapts and evolves as the user does**

User feeling: ***"It understands me — even better than I do."***

From General-Purpose to Personal Intelligence



GPT6: Memory + Personalization

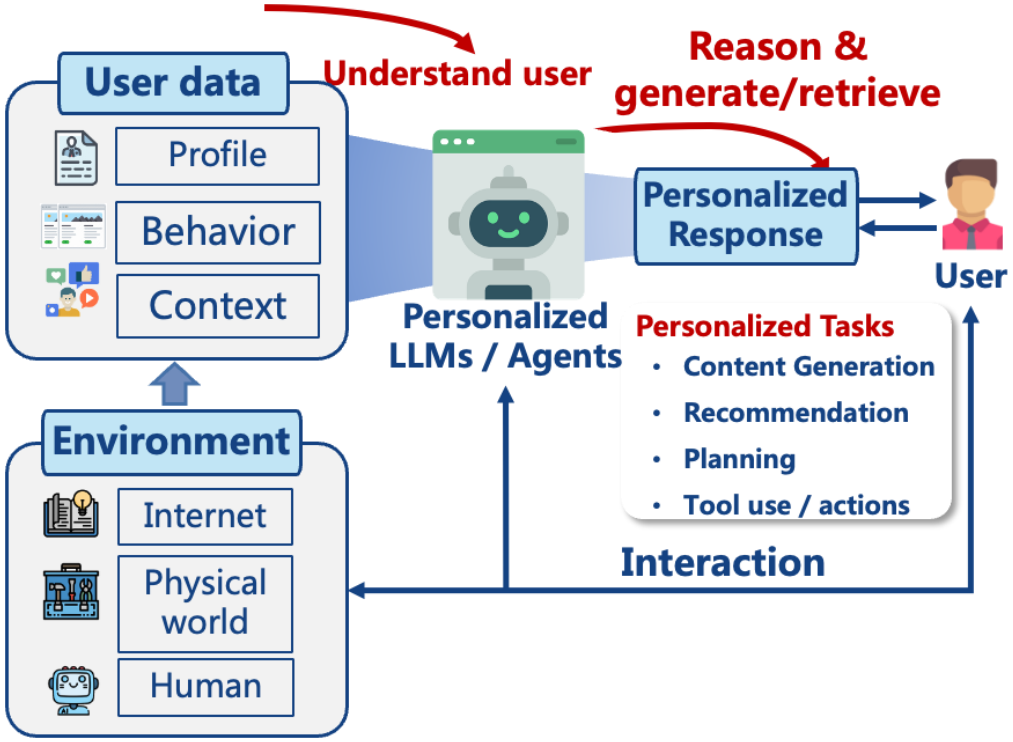
Personal intelligence

Personalized LLM alignment is not just a research topic — it is the key enabler for AI to transform industries, organizations, and individual productivity.

From General-Purpose to Personal Intelligence

What need to do: Personalizing LLMs

Understand user data, reason user preference, and produce personalized content or actions.



Personalized Content

User data: A **5-year-old child** who likes **toy cars.**

Question: Explain Newton's second law.

Explains it with toy-car examples and simple language.

Personalized Actions

User data: **Canceled noisy** restaurants before; has **meeting at 8:30 p.m.**

Question: Help me arrange dinner tonight.

Books a quiet nearby restaurant at 6:30 p.m. and adds a leave reminder before the meeting.

Goal: make personalization as a foundational capability of LLMs

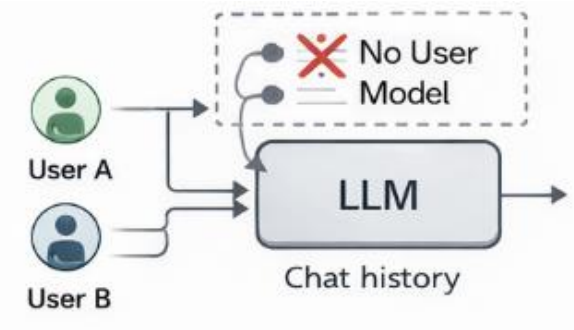
The Bottlenecks of Personalization in LLMs

Memory

Users are not represented

(Representation bottlenecks)

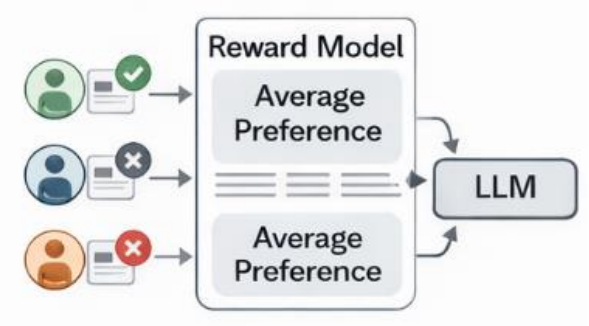
- LLMs do not maintain an explicit user model
- User history is treated as: Raw text; Prompts; Short-term context
- No structured, time-adaptive representation of individuals



Preferences are not aligned

(Alignment bottlenecks)

- LLM's alignment is performed at population level
- SFT & RL optimize average & majority preferences
- LLM are not aligned to understand individuals' Behavior & Value



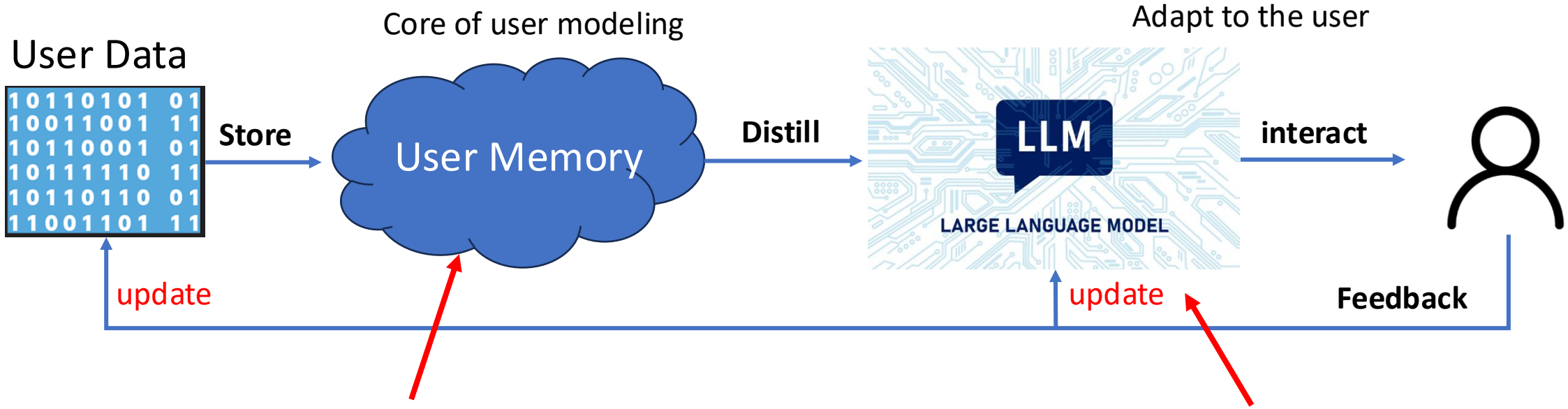
Evolving is challenging

Align to users

(Updating bottlenecks)

- User preferences are non-stationary
- Users evolve over time
- But LLMs are hard to update

General Personalization Framework



Memory: A persistent representation of the user

Alignment: Make model align with user over time

RQ1: Memory -- How to build memory better?

RQ2: Alignment -- How to leverage feedback better to update the LLM?

Technique foundations of personalization

- **Two core tasks: memory enables user understanding/representation, while alignment ensures personalized responses and actions.**

Memory

- **Framework design**
- **Extraction**

Identify user-specific preferences, constraints, goals, and contexts from user data.

- **Storage & Update**

Maintain evolving user profiles and long-term memories over time.

- **Utilization**

Retrieve and apply relevant memories to support personalized tasks.

Alignment

- **Content Alignment**

Generate responses that match the user's preferences, background, goals and current context.

- **Action Alignment**

Select and execute actions that satisfy the user's constraints, intentions and real-world context.

- **Training time + test time**

These two parts consists of the main technique foundations for personalization

Content of the tutorial

The following content

- 1. Technique foundations of personalization (Xiaoyan & Xinyu)
  - Part 1: Memory (Xiaoyan)
  - Part 2: Alignment – post-training (Xiaoyan)
  - Part 3: Alignment – Test-time personalization (Xinyu)
- 2. Benchmarks & Evaluation (Xinyu Lin)
- 3. New directions beyond memory and alignment (Yang)
- 4. Applications (Chongming)
- 5. Conclusion (Chongming)

About me

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Xiaoyan Zhao is a **Research Fellow** at NUS, working with **Prof. Tat-Seng Chua**, focusing on **LLM Personalization.** She received her Ph.D. from The Chinese University of Hong Kong under the supervision of **Prof. Hong Cheng**.

Research Vision

Build AI agents that understand individuals, accumulate meaningful memory over time, and behave reliably in healthcare and beyond.

Research Focus

- **Personalized LLMs**
- **Agent Memory**
- **Agentic AI for Healthcare**
- **Trustworthy AI**

Happy to connect on discussions and potential collaborations.

Technical Foundations of LLM Personalization

Three Core Pillars Enabling Personalized, Adaptive, and Real-World LLM Systems

1. User Memory

Remembering Users Over Time

Goal: Build long-term, structured memory of users to enable continuity and context.

What It Stores

- **Conversations & history**
  What the user has said and asked
- **Preferences & traits**
  Likes, dislikes, communication style
- **Situational context**
  Goals, roles, environments, constraints

Impact

Enables consistent, personalized interactions across sessions and over the long term.

2. Personalized Post-training

Learning What Matters to Each User

Goal: Adapt the model to user-specific patterns through additional training.

How It Works

- **Curate user-relevant data**
  Conversations, feedback, preferences
- **Fine-tune or continued pre-training**
  Align model behavior to the user
- **Optimize for personalization**
  Improve helpfulness, relevance, tone

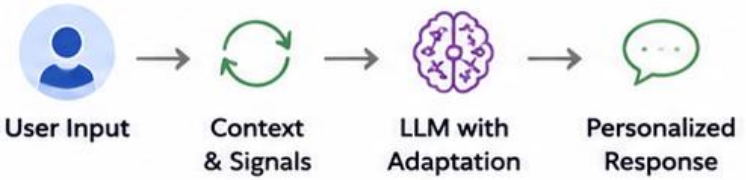
Impact

Produces a model that better reflects the user's unique preferences and needs.

3. Inference-Time Adaptation

Adapting in the Moment

Goal: Dynamically adjust responses during interaction based on real-time signals.



Key Techniques

- **Context-aware prompting**
  Use recent turns, tone, and intent
- **Behavioral adjustment**
  Adapt style, detail, or strategy
- **Safety & constraints**
  Respect user state and boundaries

Impact

Enables real-time personalization that evolves with each interaction.

Together, They Enable:

- Long-term consistency through memory
- Deep alignment through training
- Real-time relevance through adaptation
- Truly personalized experiences at scale

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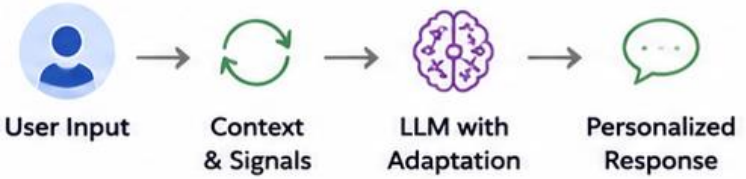

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Two Main Types of Memory

- **Explicit Memory**
  - Stores user-specific information in **separate, externally accessible memory units**, such as knowledge bases or memory banks.
  - Discrete, human-readable, and externally accessible
  - Directly supports CRUD operations: creation, retrieval, updating, and deletion
  - Representative methods: *MemoryBank*, *MemGPT*, and *LightMem*
- **Implicit Memory**
  - Encodes user-specific information into **model parameters or latent representations**.
  - Continuous and not directly human-readable; accessed implicitly during model computation
  - Updated through training, fine-tuning, or model adaptation
  - Representative methods: *ROME*, *MEMIT*, *AutoCompressor*, and *MemGen*

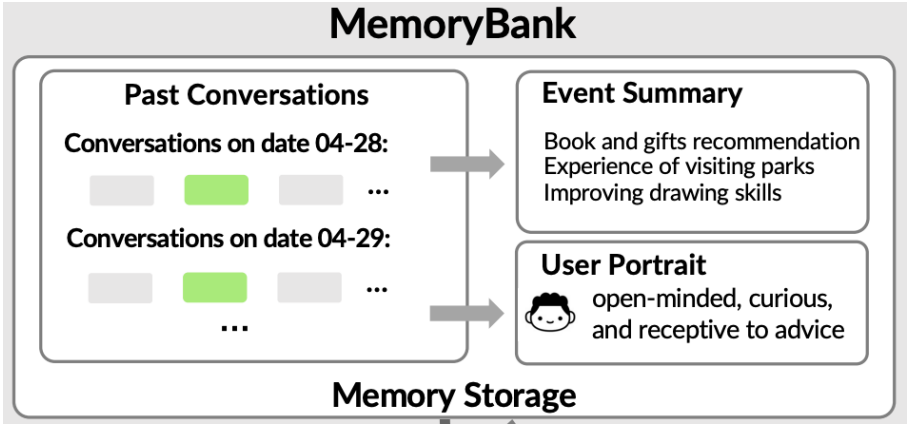
Explicit Memory: Tow cores

- For explicit memory, there are two core research questions:
  - User information organization :
    - How to effectively store the user information, studying different information organization styles
    - Technique route:
      - Raw text + summary -> structured information
  - Memory management:
    - How to effectively manage the build memory, including update, read, and write?
    - Technique toute:
      - Manually designed management -> agentic management

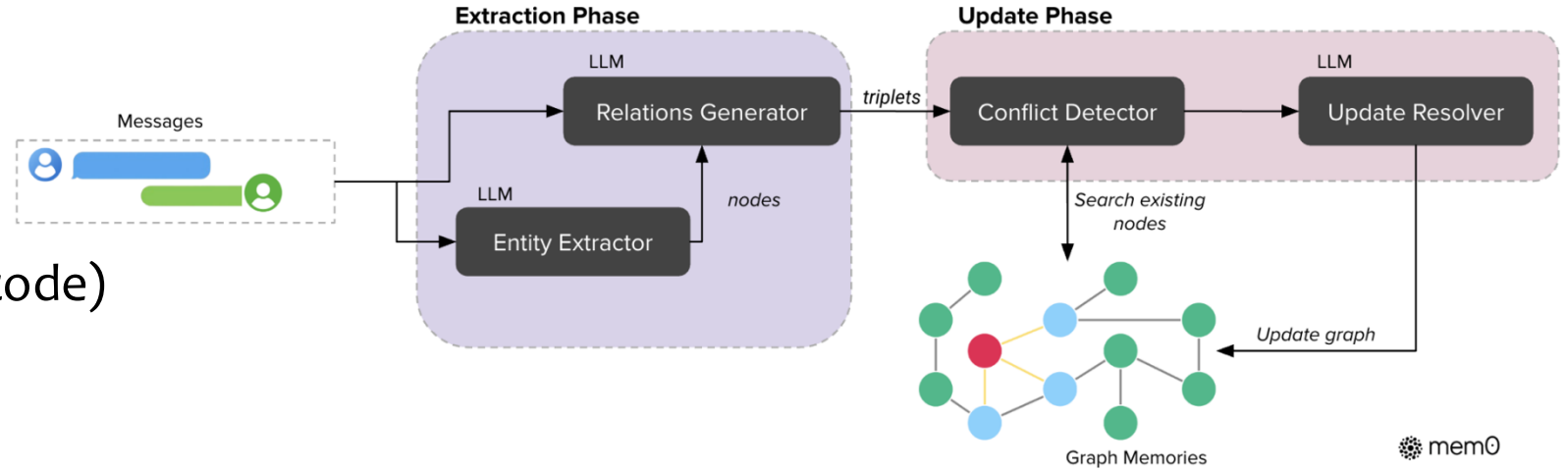
User information organization

Data Storage:

- Flat memory (no structure):
  - Raw text & Summary



- Structured-based
  - Graph-based, e.g., $Mem0^g$
  - Tree-based, Memtree
  - Markdown file style (Claude code)



MemoryBank: Enhancing Large Language Models with Long-Term Memory.

Memory management

- Memory management:
  - Information extraction
  - Retrieval
  - Update
  - Full-stack management
- Core trends:
  - From manually designed method to learn, and automantically management.

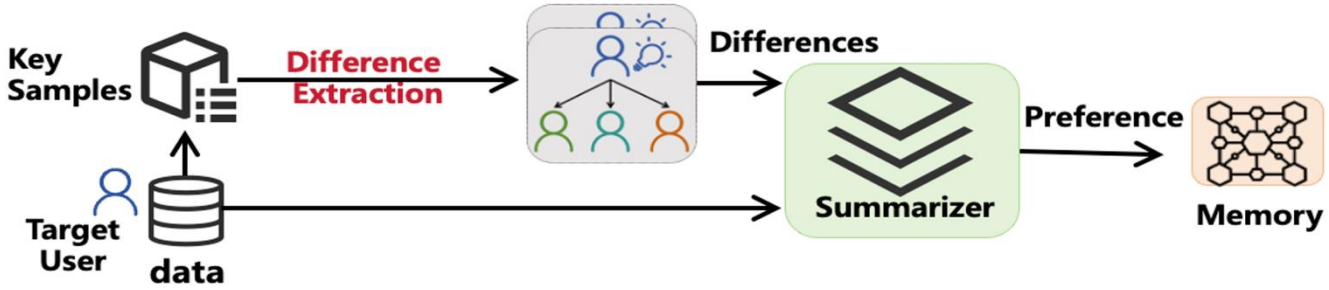
User Information extraction

- User Information extraction: what information to store?
- Direct store all information could be redundant.
- The direct approach: prompt the LLM to extract/summarize.
- Problem: dialogue is multi-faceted, so the LLM may not know which information to extract.
- Many methods are proposed, for example:
  - logic-aware summarization
  - difference-aware extraction
  - learning-to-summarize

User Information extraction: difference-aware extraction

- Background:
  - User data could be redundant, not all information is important for personalization
  - Directly summarizing could be hard to capture implicit preference information
- Goal: to more accurately extract preference information
- Core insights: Our difference makes us unique; uniqueness shapes the preference (social science)
- Method core:

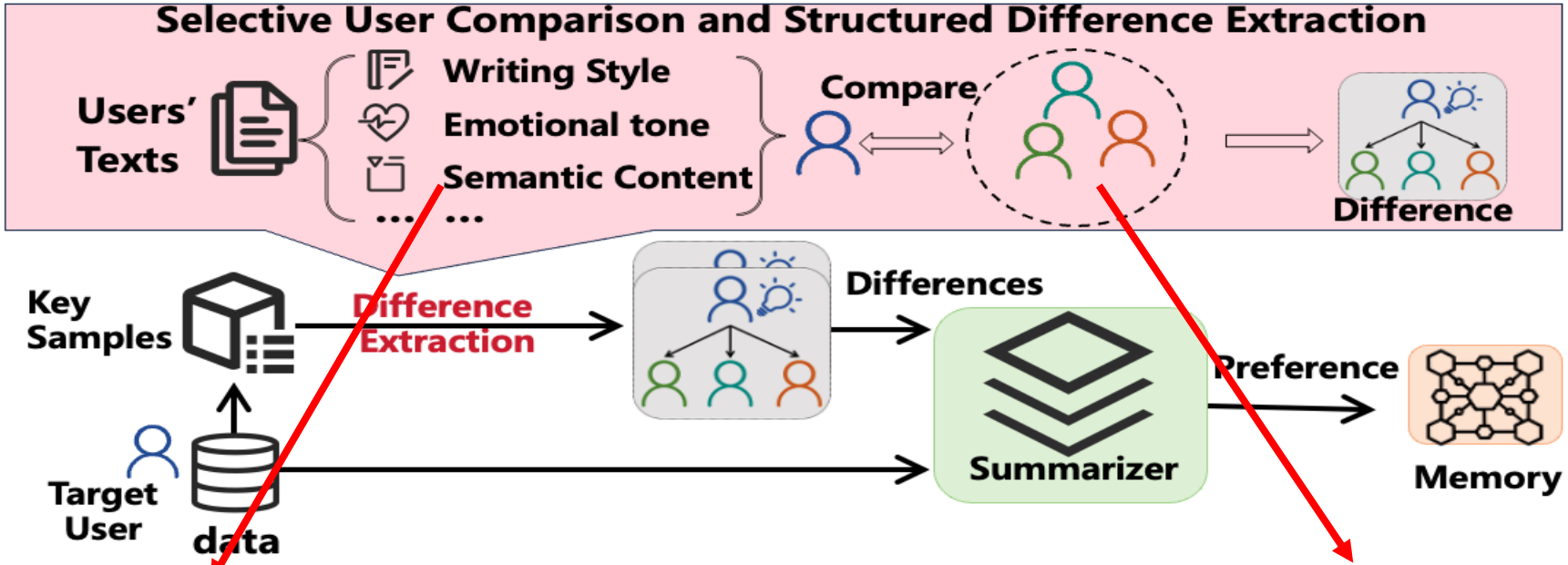
  - Emphasize extracting inter-user differences in memory construction for personalization tasks.



Yilun Qiu, et al. Measuring What Makes You Unique: Difference-Aware User Modeling for Enhancing LLM Personalization. ACL 2025 Findings.

User Information extraction: difference-aware extraction

- Method details: selective comparison predefined dimensions



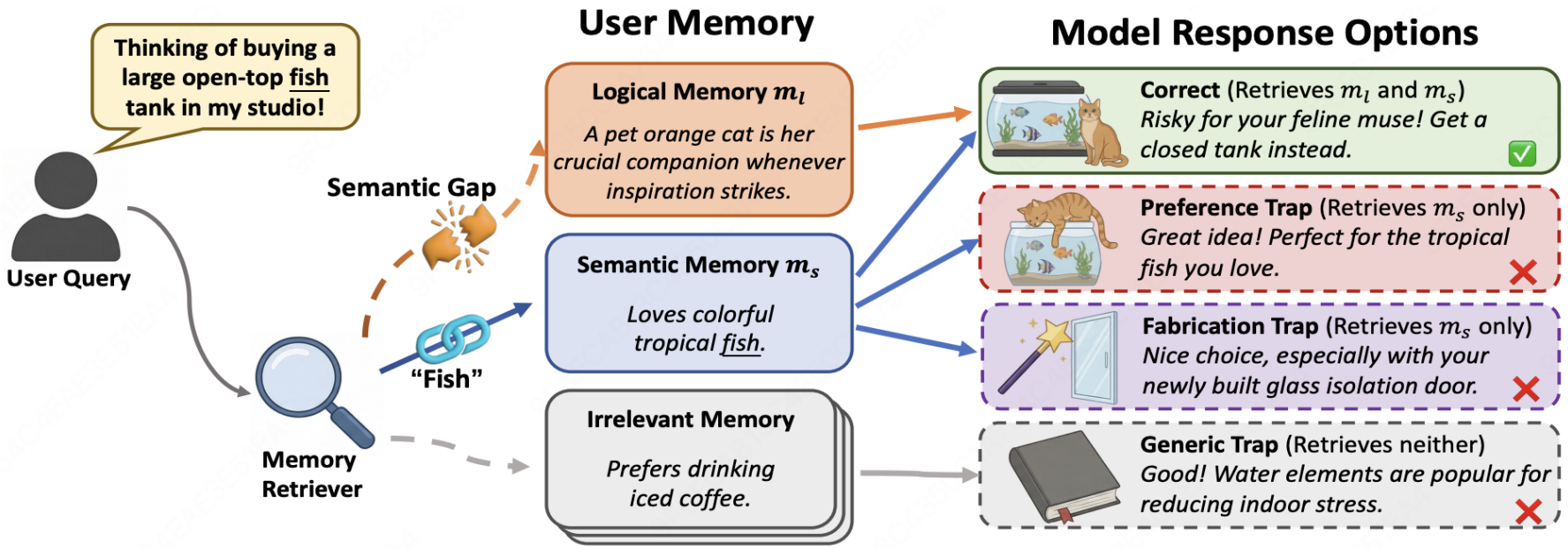
2 Predefine dimensions to structure the difference extraction

1 Select representative users for comparison by choosing the central user of each cluster.

Yilun Qiu, et al. Measuring What Makes You Unique: Difference-Aware User Modeling for Enhancing LLM Personalization. ACL 2025 Findings.

User Information extraction: Logic-aware

- **Logic-aware extraction:**
  - **Motivation**



Simultaneously consider two types of memories that are critical for personalized responses:

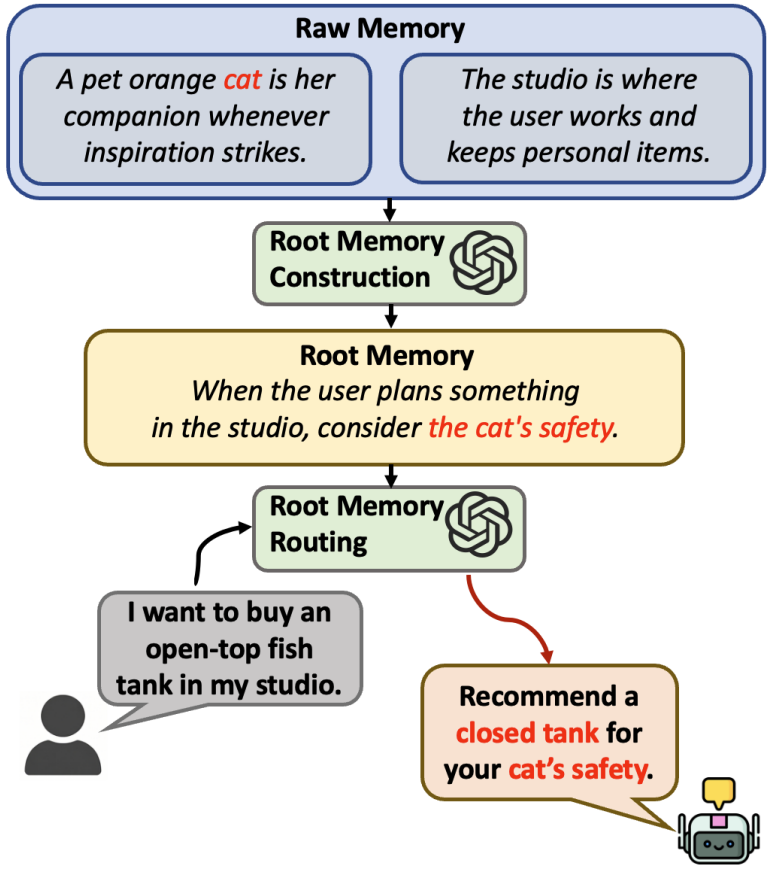
Semantic memory: memories that are semantically similar to the query.

Logical memory: memories that are crucial to the reasoning logic for personalized responses.

Hongxun Ding et al. Towards Root Memories: Benchmarking and Enhancing Implicit Logical Memory Retrieval for Personalized LLMs

User Information extraction: Logic-aware

- **Logic-aware extraction：**



- **Root Memory：** A Structured Representation for Reusable Personalized Decision Logic

- **Step 1： Root memory construction**
  - Extract reusable personalization knowledge and decision-making logic from fragmented raw memories.
  - Consolidate them into structured **Root Memory** representations.

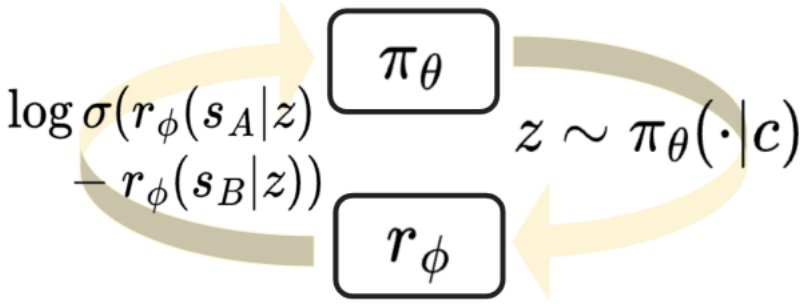
- **Step 2： Root Memory**
  - Given a user query, use LLM reasoning to identify logically relevant Root Memories.
  - Activate memories based on **logical relevance**, rather than semantic similarity.

Hongxun Ding et al. Towards Root Memories: Benchmarking and Enhancing Implicit Logical Memory Retrieval for Personalized LLMs

User Information extraction: Learn to summarize

- Method: RL with Reward model

Summarizer: generate a concise summary (z) of user history



Reward model: compute the reward (r) for the obtained summary

RL-learning: because of the Discrete nature, RL is applied to optimize the following J

$$J(\pi_\theta) = \hat{\mathbb{E}}_{\substack{z\sim\pi_\theta(\cdot|c) \\ (s_A,s_B,c)\sim\mathcal{D}'}} \left[\sum_{t=0}^{H} \gamma^t R_\phi(z_t, s_A, s_B) \right],$$

$$R_\phi(z_t, s_A, s_B) = \begin{cases} 0, & \text{if } t < H, \\ \log \sigma(r_\phi(s_A \mid z_t) - r_\phi(s_B \mid z_t)), & \text{if } t = H. \end{cases}$$

Optimization goal: with the summary, the positive answer obtained a higher reward

Hyunji Nam. Learning to summarize user information for personalized reinforcement learning from human feedback

Memory Retrieve

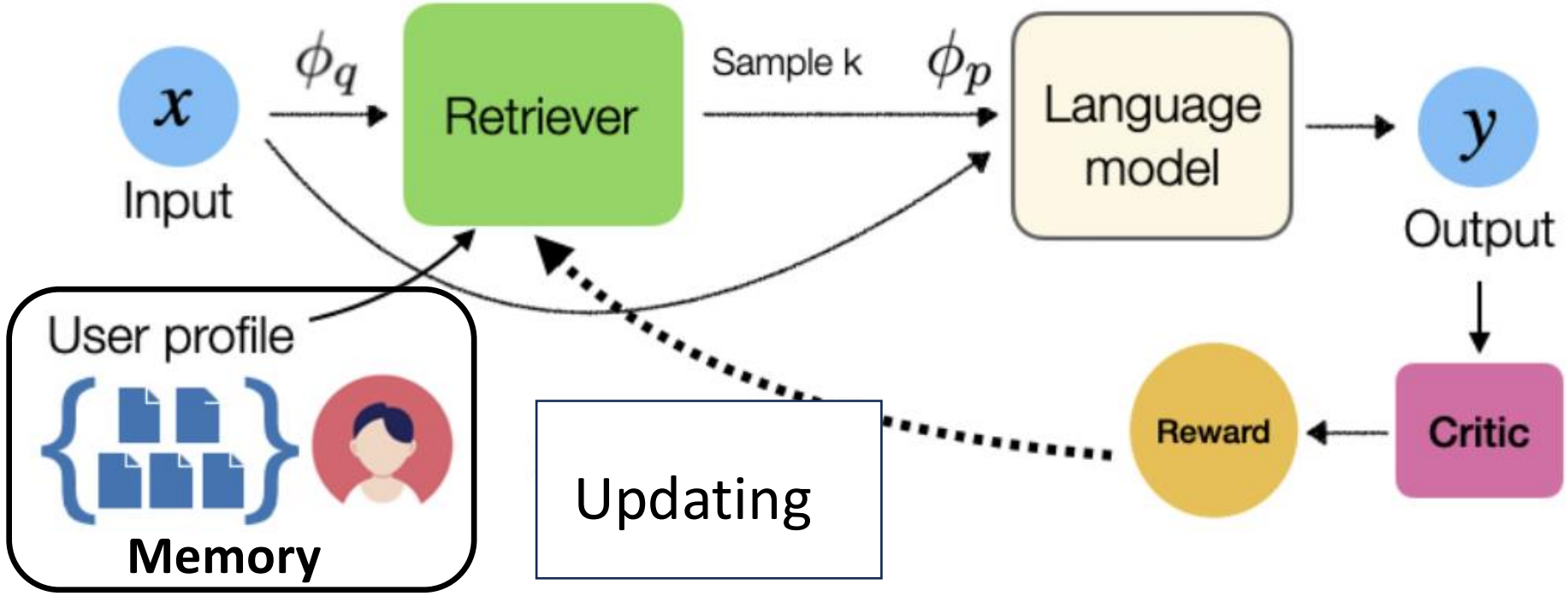
- Retrieval is the key to effectively leveraging the built memory;
- Many methods have been proposed.
- Most common — semantic-based retrieval (by textual semantic similarity):
  - token-matching-based,
  - vector-similarity-based, etc.
- Some specific designs:
  - Relation-based retrieval (e.g., GraphRAG)
  - Learning-to-retrieve

Chengbing Wang, et al. Leveraging Memory Retrieval to Enhance LLM-based Generative Recommendation. WWW 2025.

Alireza Salemi et al. Optimization Methods for Personalizing Large Language Models through Retrieval Augmentation. SIGIR 2024.

Retrieve: Learn to retrieve

- **Learn how to retrieve**



Gradient update [1]: dense network + contrastive learning

Policy gradient [2]: different retrievers + policy update

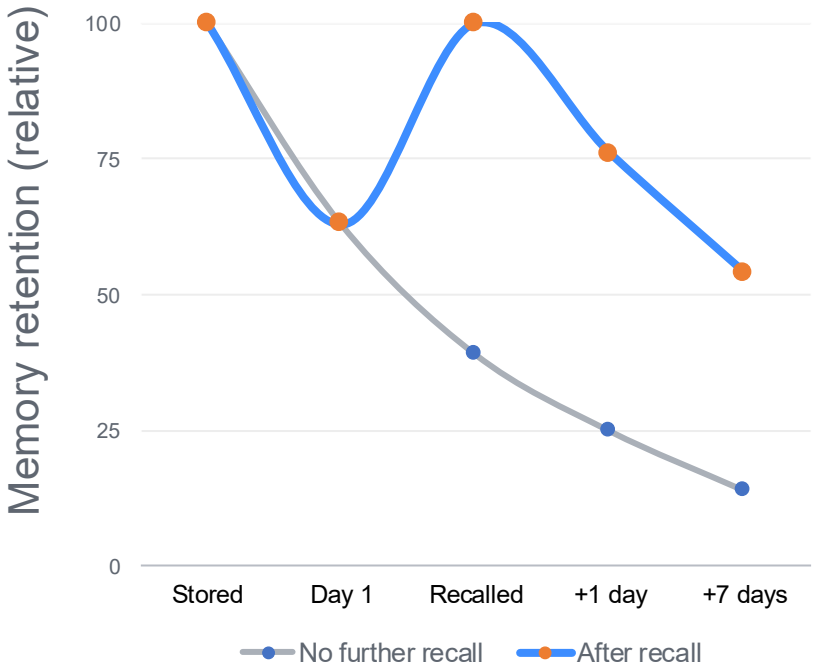
Chengbing Wang, et al. Leveraging Memory Retrieval to Enhance LLM-based Generative Recommendation. WWW 2025.

Alireza Salemi et al. Optimization Methods for Personalizing Large Language Models through Retrieval Augmentation. SIGIR 2024.

User Information update & forget

- Typically human-designed
- updates driven by predefined rules or LLM-assisted strategies.
- One example: Memorybank (Ebbinghaus Forgetting Curve theory-aware)

Unused memories fade; recall resets decay and strengthens future retention.



01 Natural decay

Retention falls quickly at first, then more slowly as a memory goes unused.

02 Recall triggers an update

When related content is mentioned or retrieved again, the system triggers a memory update.

03 Reset and reinforce

Recall resets and flattens the decay curve; spaced repetition strengthens long-term retention.

Wanjun Zhong, et al. MemoryBank: Enhancing Large Language Models with Long-Term Memory.

Full management: **Learn to manage the full cycle**

Learns not only what to remember, but also how to retrieve and use memories

Three key designs:

1. Memory Storage

Use task-specific reflection to decide what should be stored.

Extract task-relevant information from observations.

2. Memory Retrieval

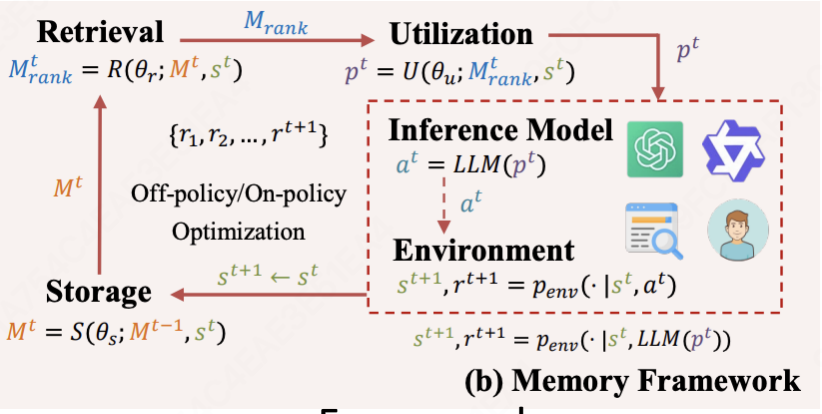
Use an MoE gate to adaptively combine retrieval signals.

Signals include relevance, importance, recency, emotional relevance, etc.

3. Memory Utilization

Learn how to aggregate retrieved memories into the prompt.

Reduce redundant memories and improve action reasoning.



Framework

$$M_t = S(\theta_s; M_{t-1}, s_t)$$

$$M_t^{rank} = R(\theta_r; s_t, M_t)$$

$$p_t = U(\theta_u; M_t^{rank}, s_t)$$

Optimization

Off-policy optimization: reuse existing interaction trajectories.

On-policy optimization: update memory policy through new interactions.

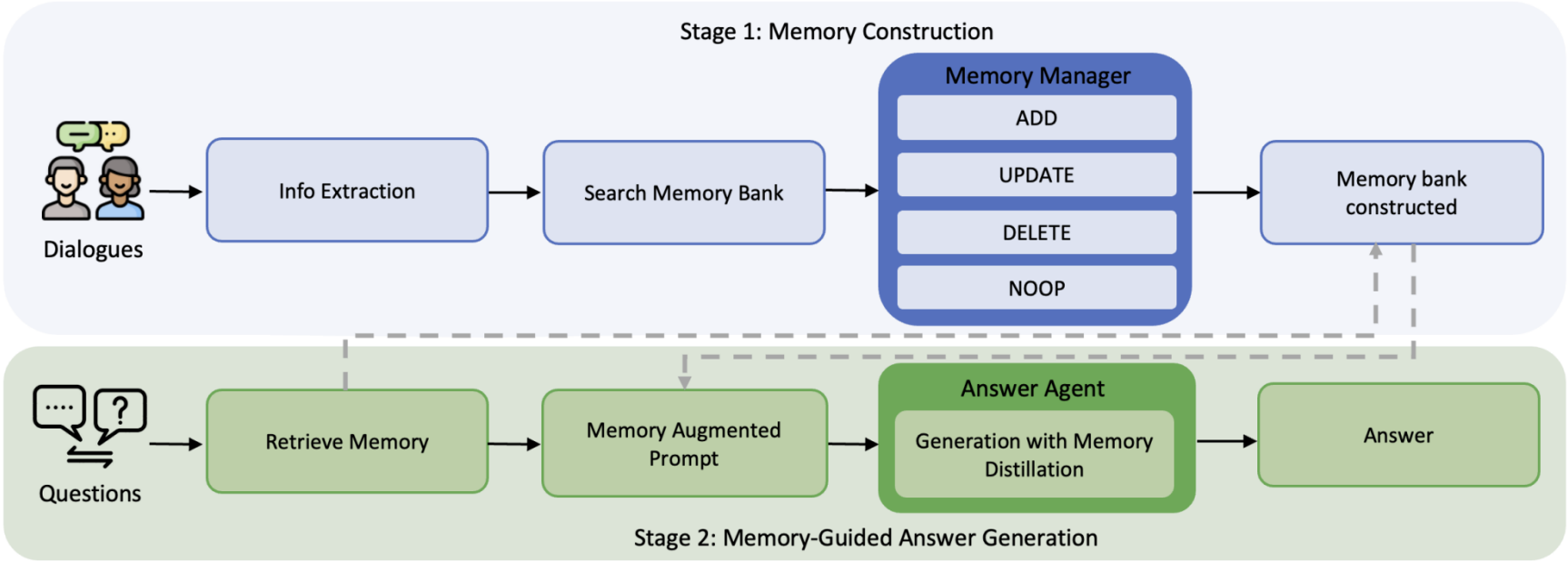
Learning design

Zhang, Zeyu, et al. "Learn to memorize: Optimizing llm-based agents with adaptive memory framework." arXiv preprint arXiv:2508.16629 (2025).

Memory management: **agentic management**

Instead of tuning new model for the management, perform the agentic learning for learn the management

Example: Memory-R1



Manager: selecting one of ADD, UPDATE, DELETE, NOOP for each new piece of information, outputting both the operation and updated content

Tuning the manager with RL (PPO+GRPO)

Reward design (exact matching between predicted answer & ground-truth):

$$R_{answer} = \mathrm{EM}(y_{\text{pred}}, y_{\text{gold}})$$

Sikuan Yan, et al. Memory-R1: Enhancing Large Language Model Agents to Manage and Utilize Memories via Reinforcement Learning

Implicit Memory: Two Types

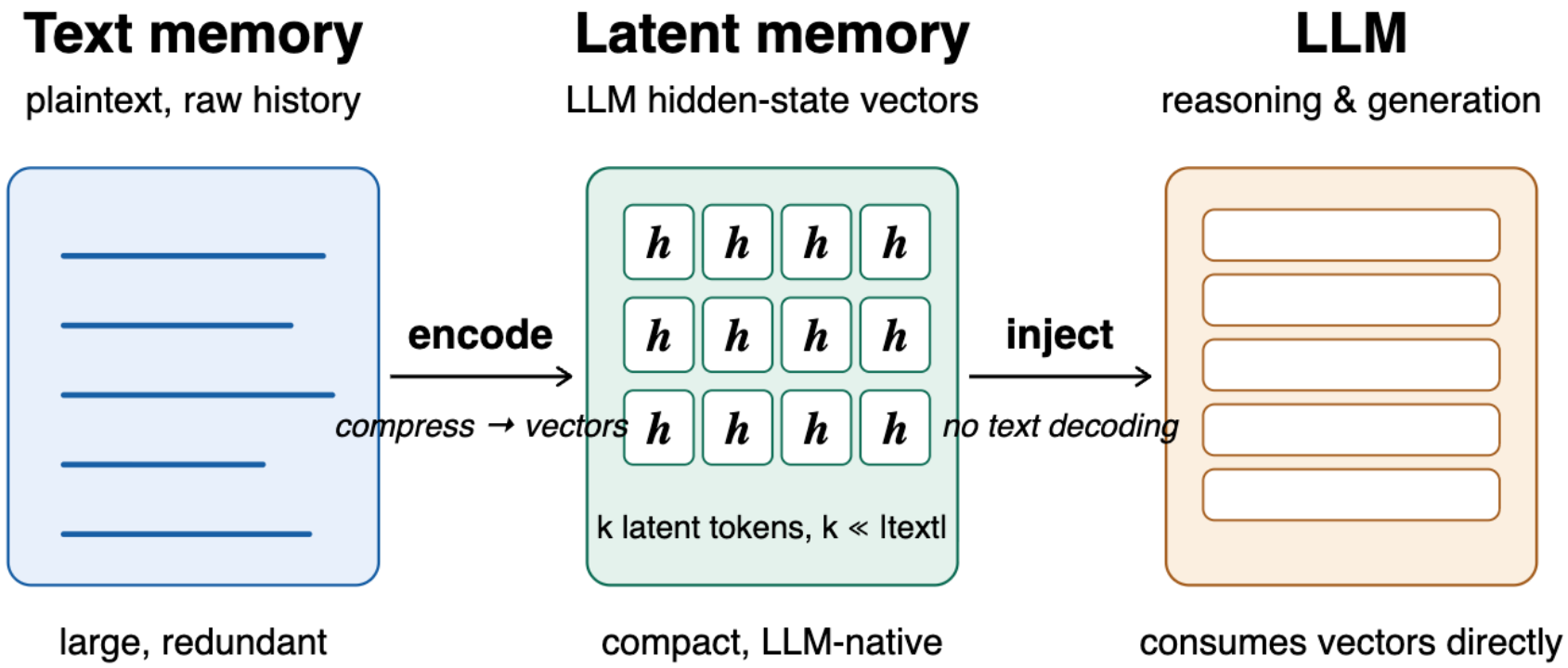
- Why Implicit?
  - efficiency
  - Integrate the reason and generation process
- Latent memory:

  Memorize user information in the latent space
- Implicit memory:

  Memorize user information in the model parameters

Latent Memory

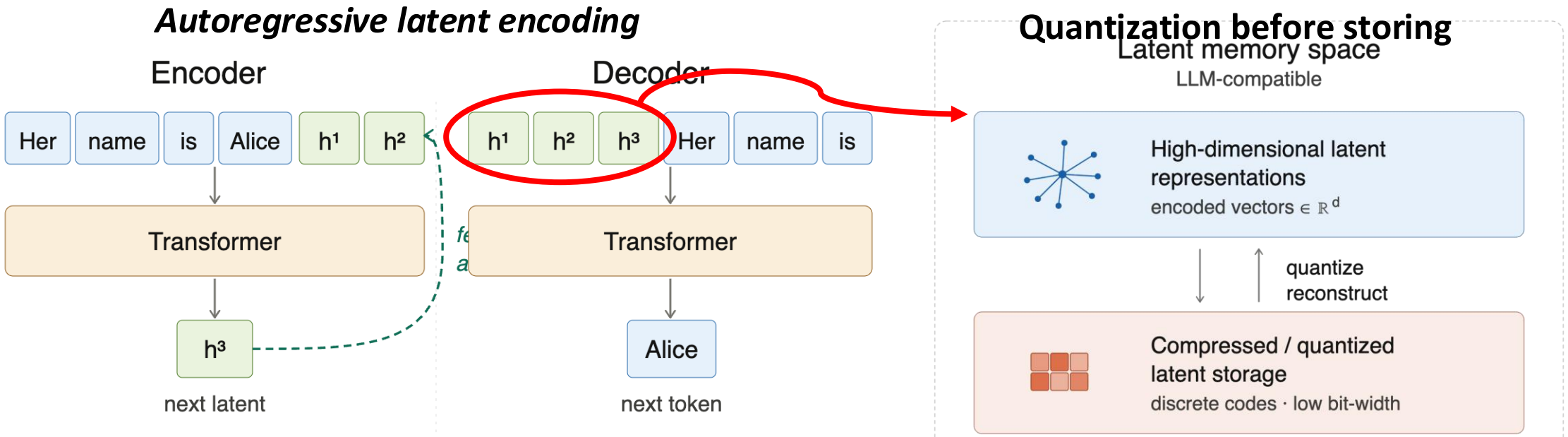
- **Core**: compress memory into latent representations for **effective and efficient** storage and use.



Zhang, Zeyu, et al. Nextmem: Towards latent factual memory for llm-based agents. Arxiv, 2026

Latent Memory: NextMem

- **The hidden cost of latent memory:**
  - Storing latent representation is costly
  - Information loss
- **NExTMem** tries to resolves both: autoregressive encoding with quantization for better compression with less information loss

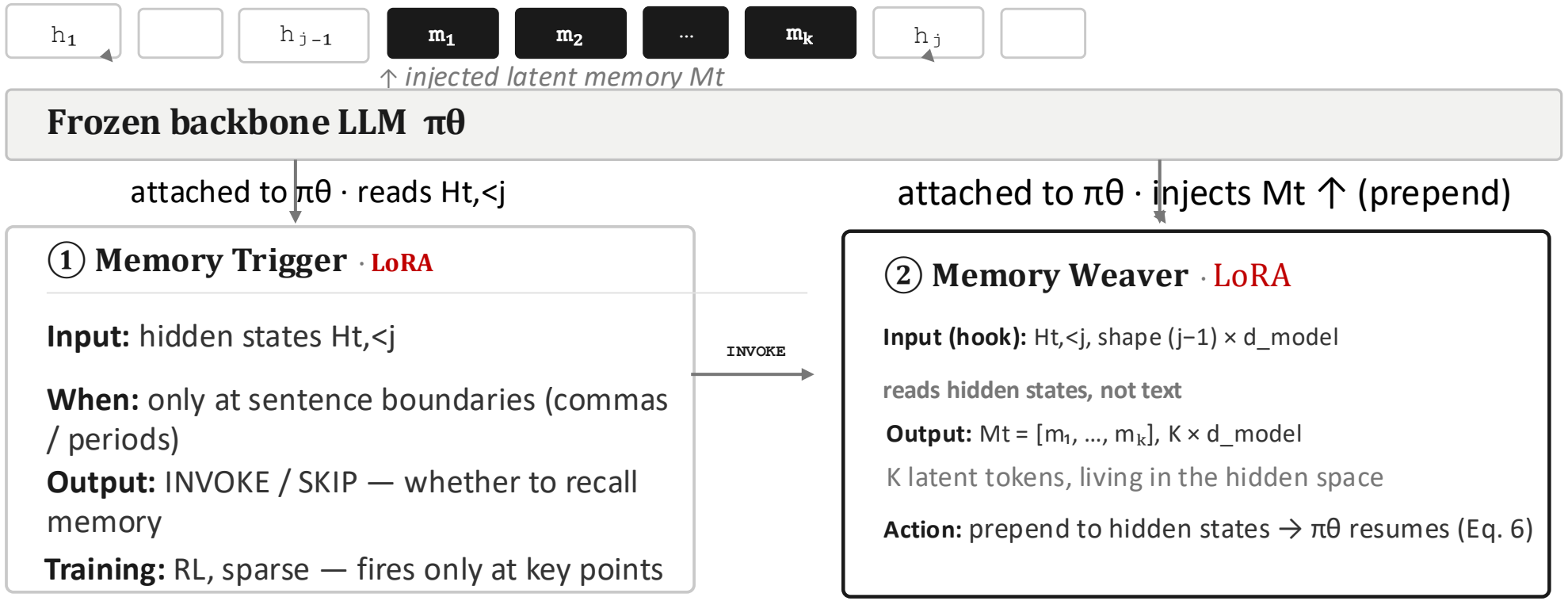


- Autoregressive encoding & decoding to ensure less information loss. **F1: >=95% vs 80% of deepseek-OCR**
- Quantization to reducing the cost increasing for storing. ¼ storing cost of the ICAE/DeepSeek-OCR

Zhang, Zeyu, et al. Nextmem: Towards latent factual memory for llm-based agents. Arxiv, 2026

Parametric Memory

- Compressing the user information into model parameters via training
- Different way of utilizing the memory
- One representative method: MemGen



A Lora to memorize historical informaiton

Guibin Zhang. MemGen: Weaving Generative Latent Memory for Self-Evolving Agents

New frontier: LLM-Native Memory

Native Memory: model-internal capability of memorization

During the forward computation, the model sees the new content in prompt, it directly memorize them into model parameters

Two requirements of the model:

Native memory state:

What the model currently remembers

Native memory procedure :

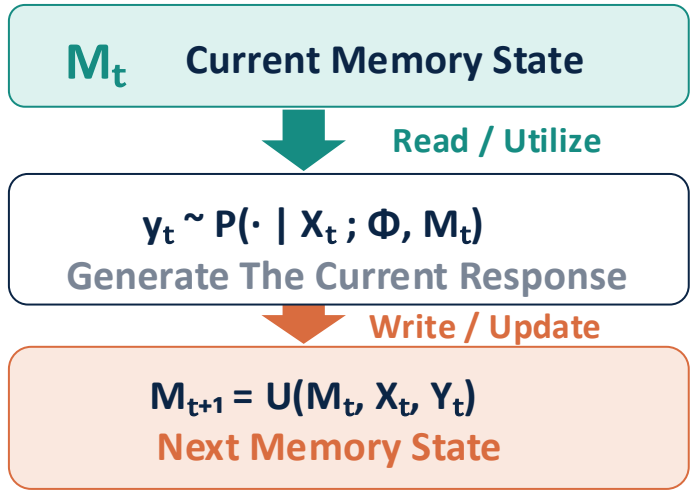
How the model reads and transforms its memory state

Design cores:

- Modifying the architectures: support the “state” and “procedure” modelling
- Learning method to support this (training data), teaching the model to really remember, update, forget …

Zhang Zeyu et al. Metis: Memory Foundation Model

The state-procedure loop



Native memory procedure

Reads M_t for the current response, then transforms it into M_{t+1} for the next interaction.

Summary of the memory part

- Two main routes: explicit memory & implicit memory
- From plain to structured
- From external to internal, and finally hope to be native
- From manually design to automatic paradigm

Content of the tutorial

- 1. Technique foundations of personalization (Xiaoyan & Xinyu)
  - Part 1: Memory (Xiaoyan)
  - **Part 2: Alignment – post-training (Xiaoyan)**
  - Part 3: Alignment – Test-time personalization (Xinyu)
- 2. Benchmarks & Evaluation (Xinyu Lin)
- 3. New directions beyond memory and alignment (Yang)
- 4. Applications (Chongming)
- 5. Conclusion (Chongming)

Technical Foundations of LLM Personalization

Three Core Pillars Enabling Personalized, Adaptive, and Real-World LLM Systems

1. User Memory

Remembering Users Over Time

Goal: Build long-term, structured memory of users to enable continuity and context.

What It Stores

- **Conversations & history**
  What the user has said and asked
- **Preferences & traits**
  Likes, dislikes, communication style
- **Situational context**
  Goals, roles, environments, constraints

Impact

Enables consistent, personalized interactions across sessions and over the long term.

2. Personalized Post-training

Learning What Matters to Each User

Goal: Adapt the model to user-specific patterns through additional training.

How It Works

- **Curate user-relevant data**
  Conversations, feedback, preferences
- **Fine-tune or continued pre-training**
  Align model behavior to the user
- **Optimize for personalization**
  Improve helpfulness, relevance, tone

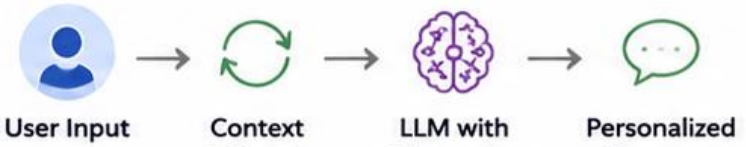
Impact

Produces a model that better reflects the user's unique preferences and needs.

3. Inference-Time Adaptation

Adapting in the Moment

Goal: Dynamically adjust responses during interaction based on real-time signals.



Key Techniques

- **Context-aware prompting**
  Use recent turns, tone, and intent
- **Behavioral adjustment**
  Adapt style, detail, or strategy
- **Safety & constraints**
  Respect user state and boundaries

Impact

Enables real-time personalization that evolves with each interaction.

Together, They Enable:

- Long-term consistency through memory
- Deep alignment through training
- Real-time relevance through adaptation
- Truly personalized experiences at scale

General Post-Tuning Framework

- Even with user-specific memory content, the model may not fully leverage the content or generate a response that aligns well with the user.
- Tune the model's parameters to better align it with individual users.

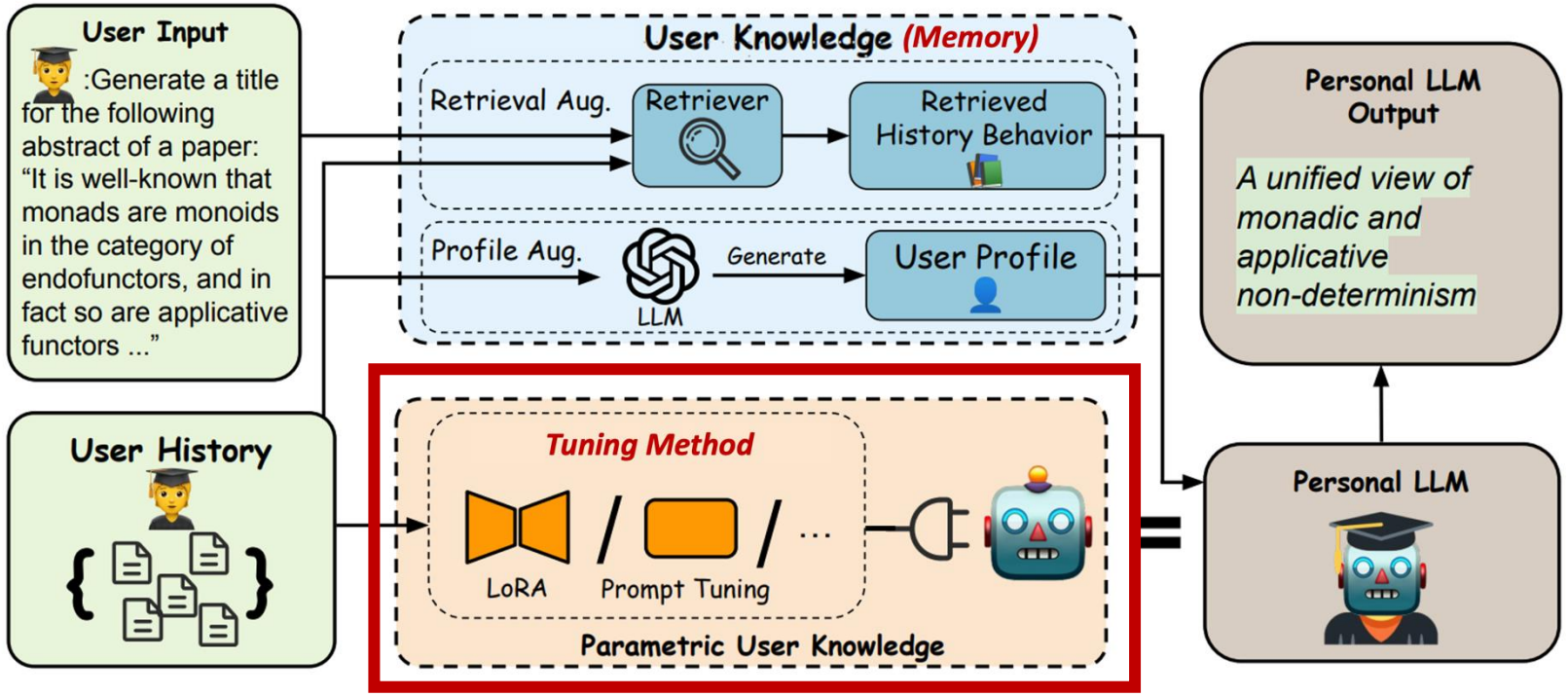


Figure modified from [1]

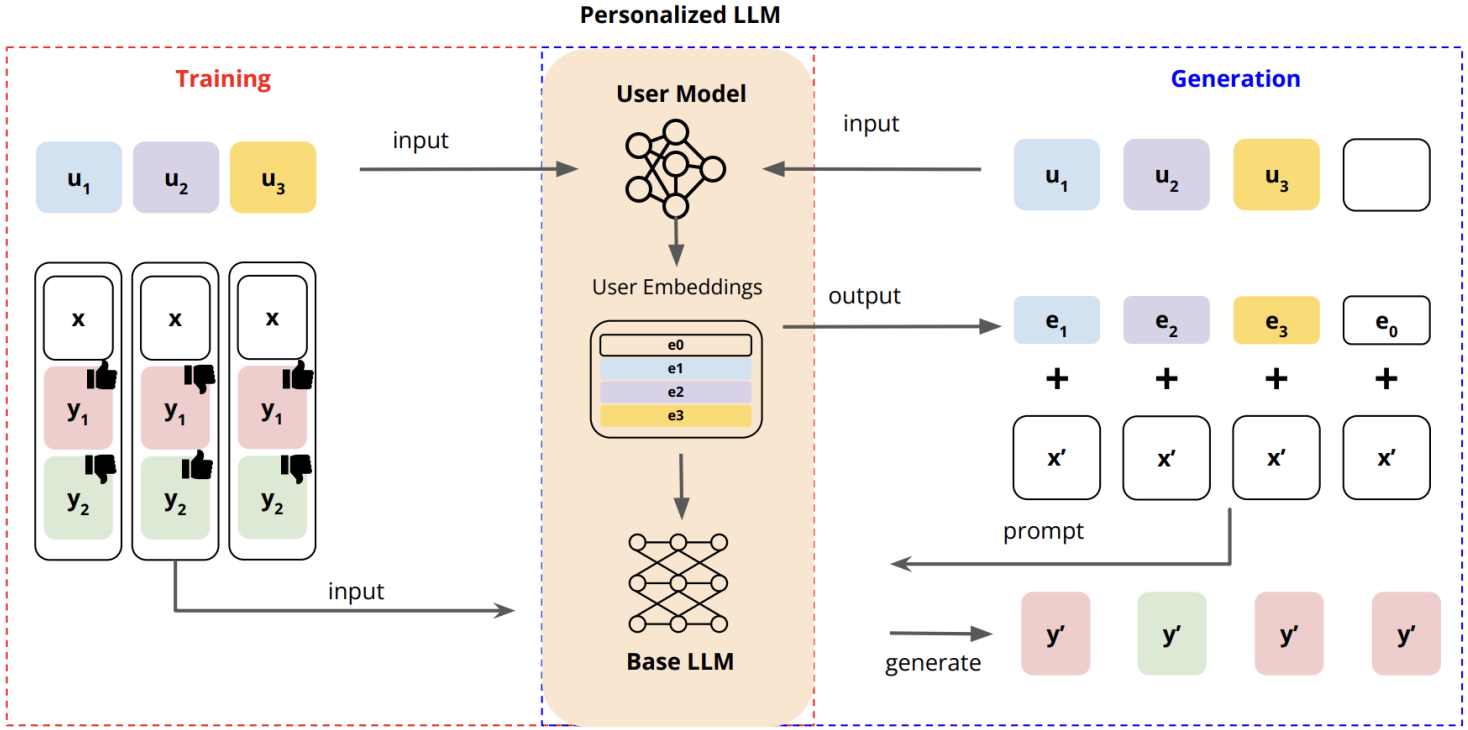
[1] Democratizing Large Language Models via Personalized Parameter-Efficient Fine-tuning.

Research Focus

- Model architecture design
  - Direct method: a model for all users
  - User-specific designed: personal-specific parameters
- Tuning algorithm design
  - SFT-based
  - Reasoning-aware training
  - RL

Model architecture for tuning

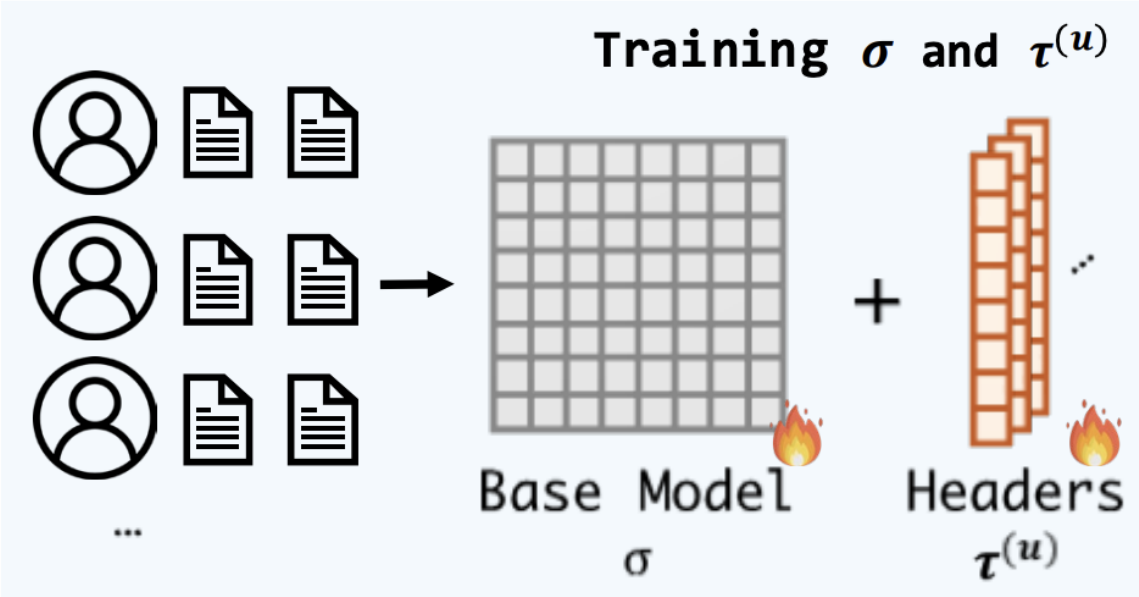
- One for all: No–specifical design
- Personalized parameters: there are many types of methods
  - Type 1: Prompt tuning (P-RLHF)
    - Different users with **different soft prompts**



Xinyu Li et,al. PERSONALIZED LANGUAGE MODELING FROM PERSONALIZED HUMAN FEEDBACK

Model architecture for tuning

- Personalized parameters:
  - Type 2: user-specific header -- Hydra
    - Append the user-specific **head τ(u) on top of the base mode**

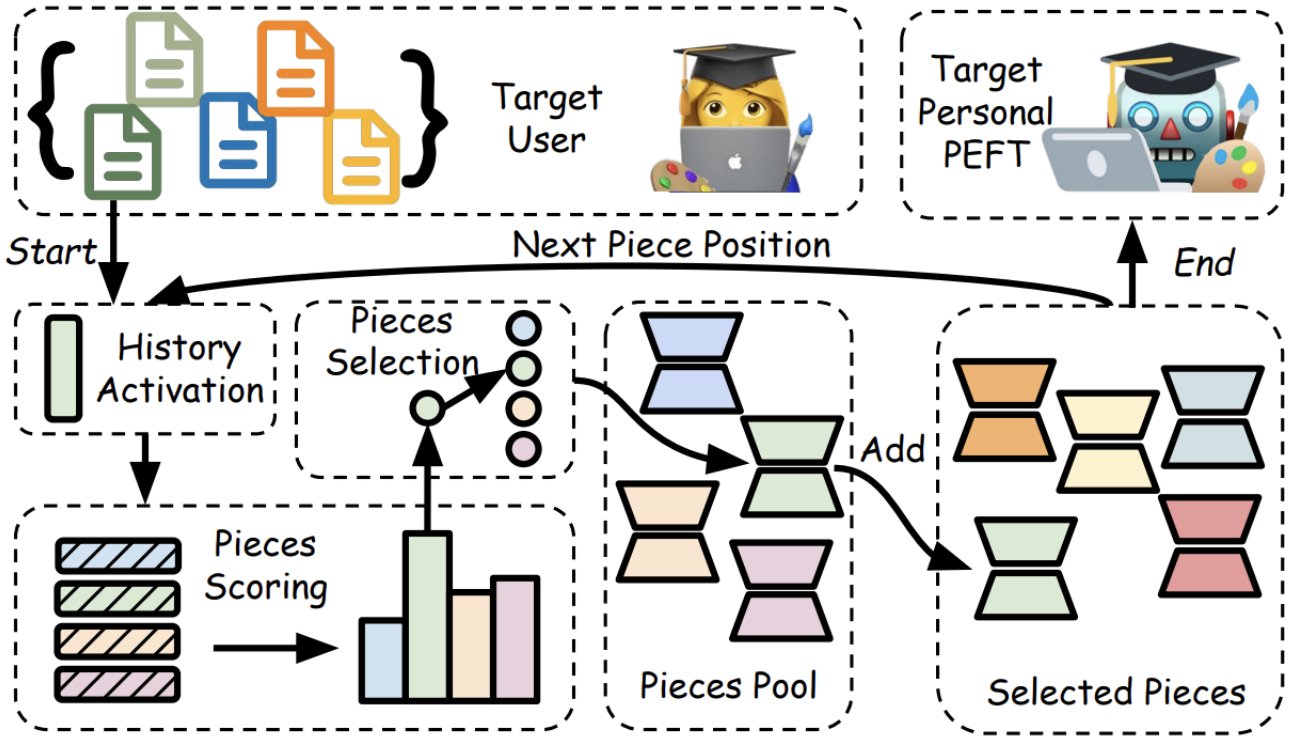


Yuchen Zhuang et,al. HYDRA: Model Factorization Framework for Black-Box LLM Personalization

Model architecture for tuning

- Personalized parameters:
  - Type 3: LoRA-based personalization

  Learn a pool of LoRA and then gate the user with **different LoRA**

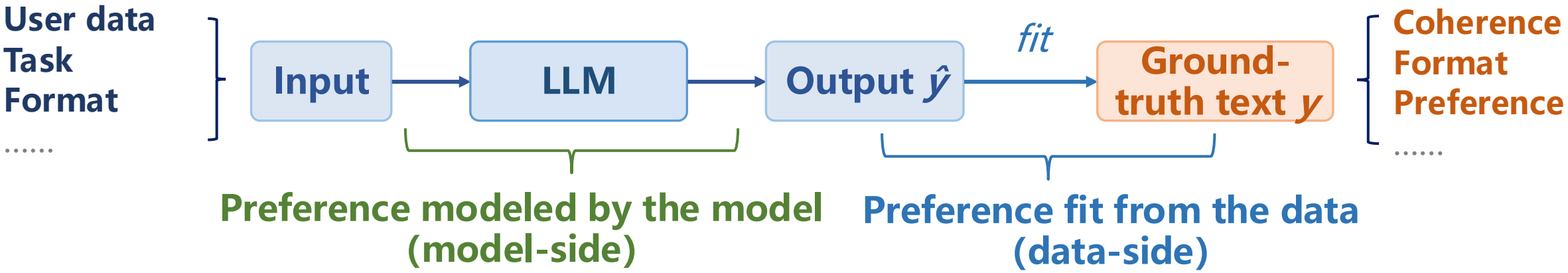


Zhaoxuan Tan et,al. PERSONALIZED PIECES: Efficient Personalized Large Language Models through Collaborative Efforts

Design goals of tuning algorithm

- SFT-based
  - Enhancing SFT method to better leverage user data
    - Causal-based method
- Reasoning-enhanced
  - utilize reasoning to enhance the model
- RL-based
  - Explore user preference on new data
  - User reward model

SFT-based: Causality-enhanced tuning



- **Existing work:** treats all tokens indiscriminately.
- **Inherent limitation:** aligning on the whole user history and response at once — without telling which predictions and which tokens are **truly** driven by user history — leaves personalization only at the **surface.**

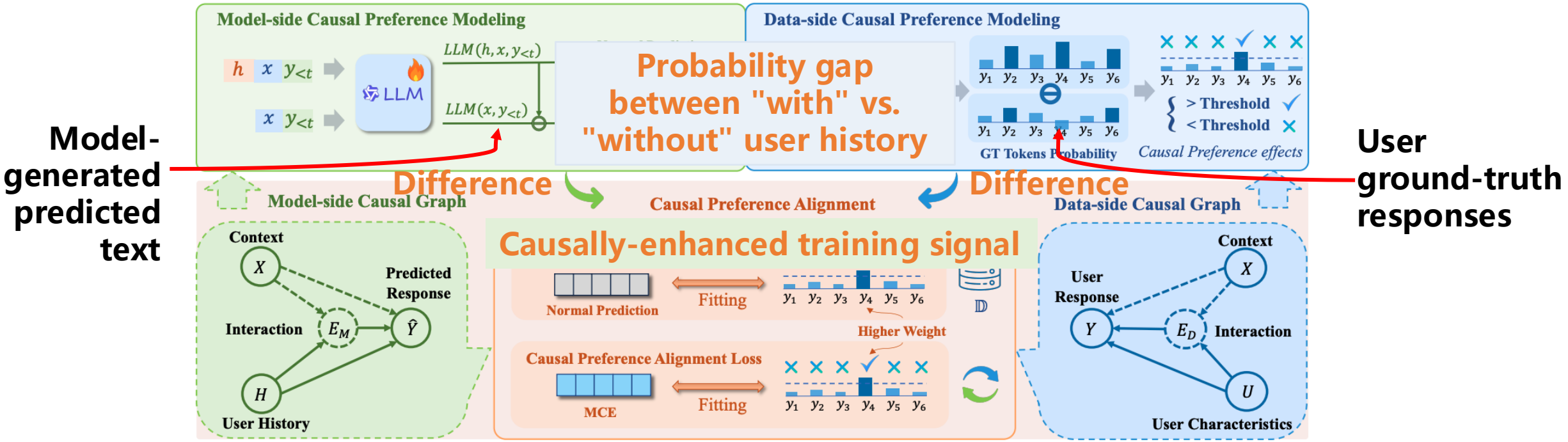
Core Goal: How can we **disentangle the preference-driven component** from contextual noise, and align & learn around only that component?

Xiaoyan Zhao et al. NextQuill: Causal Preference Modeling for Enhancing LLM Personalization. ICLR, 2026

SFT-based: Causality-enhanced tuning

How can we identify the true preference signal?

Key Idea: NextQuill separately estimates the ***causal preference effect*** of user history on the **model side** and the **data side**, teaching the model to recognize and align with the true preference signal.



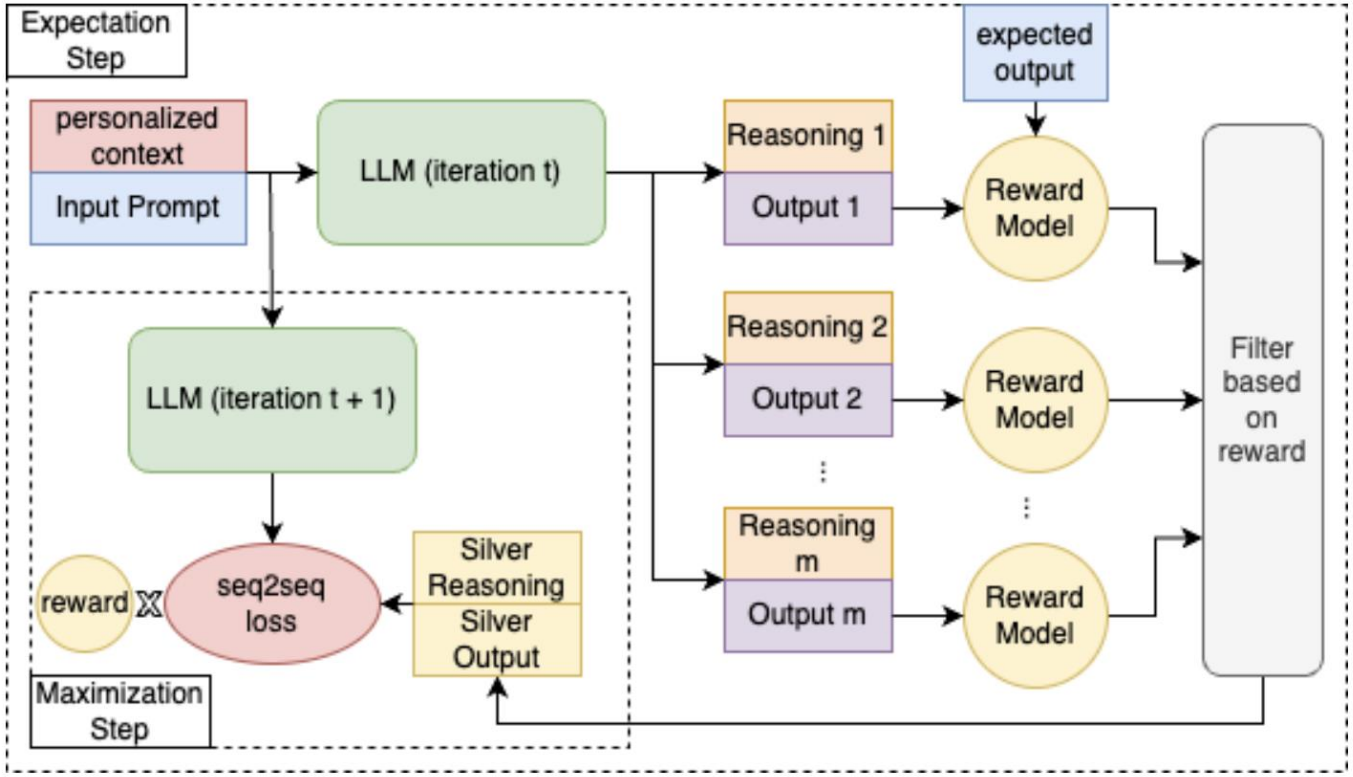
Model-side: the probability gap over the model's *own predicted* tokens — i.e., the preference the LLM has actually learned.

Data-side: the probability gap over *ground-truth* tokens in real user data — identifying which tokens express preference in the training set.

Xiaoyan Zhao et al. NextQuill: Causal Preference Modeling for Enhancing LLM Personalization. ICLR, 2026

Reasoning enhanced: reason-then generation

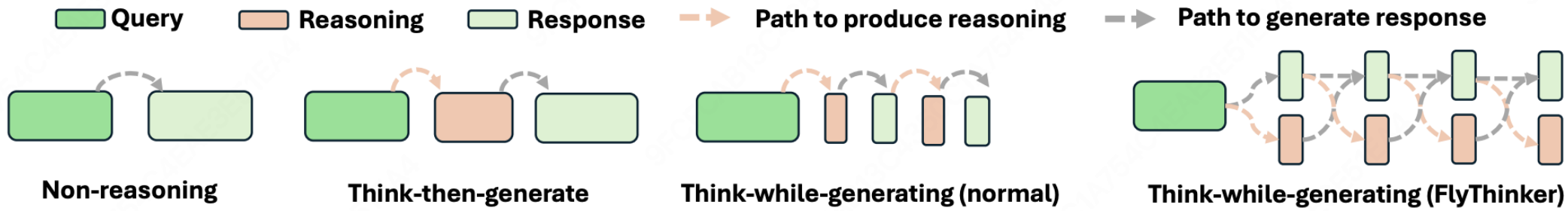
- Reasoning enhanced: let model reason before generating the answer
  - Build some reasoning data to train the model
  - Generate by the LLM with sampling



Alireza Salemi. Reasoning-Enhanced Self-Training for Long-Form Personalized Text Generation

Reasoning enhanced: think-while generation

Key problem: In long-form content generation, effectively reasoning over and leveraging users' **dynamically evolving preferences** remains difficult.



- **Mainstream approach**: **Think-then-Generate.**
- **Intrinsic limitation**: It cannot adapt to dynamic changes in user preferences within the content.

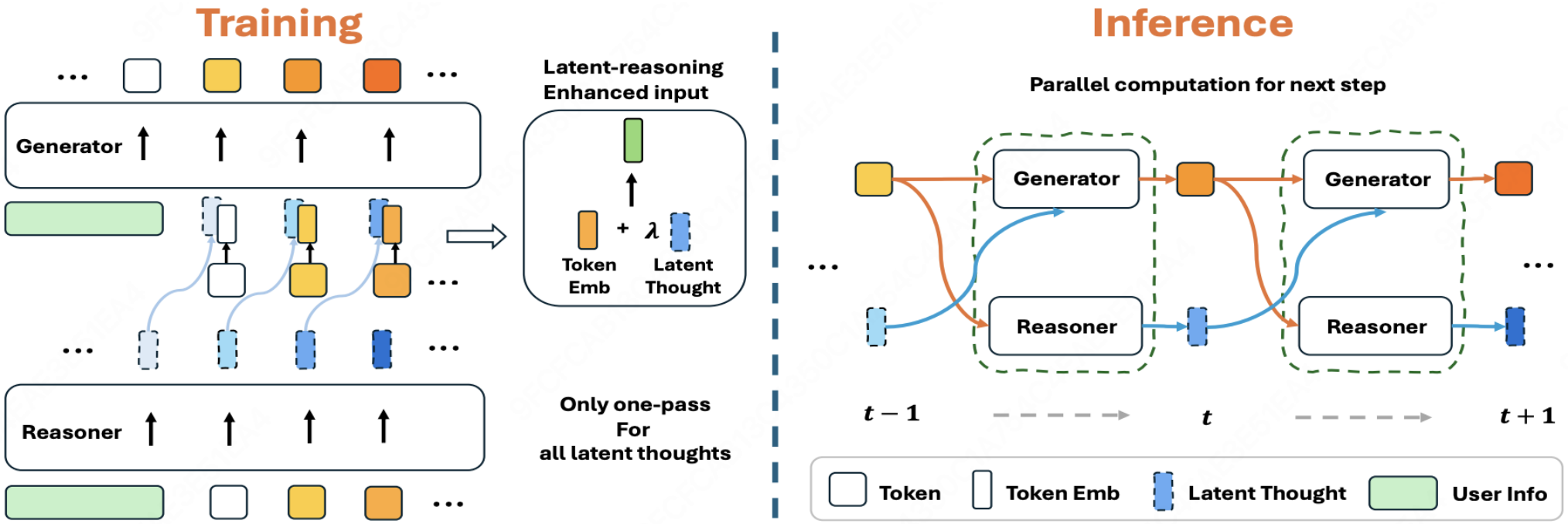
Key idea: In long-form writing, users often develop new ideas as the generated content evolves.

Think-while-Generating.
Based on latent reasoning

Chengbing Wang et al. Think-While-Generating: On-the-Fly Reasoning for Personalized Long-Form Generation. ICLR, 2026

Reasoning enhanced: think-while generation

Flythinker:



Key techniques:

Construct lightweight reasoners and generators that alternately and in parallel perform user preference reasoning and personalized content generation.

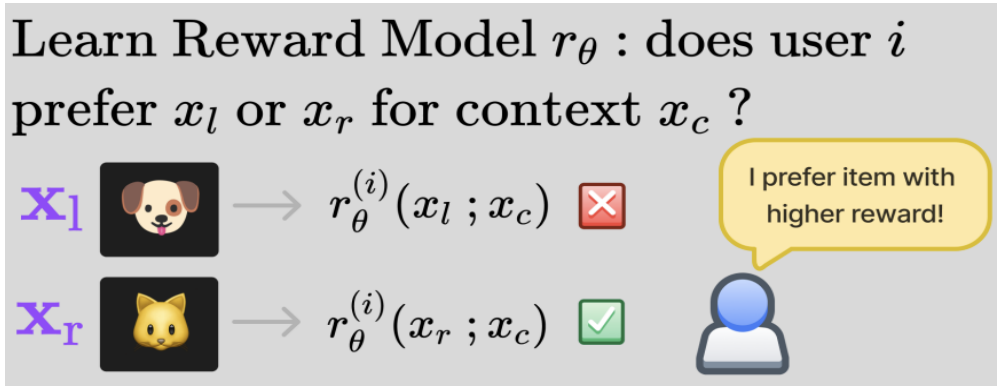
- **Reasoner:** performs latent reasoning at each generation step to improve reasoning efficiency.
- **Generator:** takes latent reasoning tokens as input to generate personalized text tokens.

Chengbing Wang et al. Think-While-Generating: On-the-Fly Reasoning for Personalized Long-Form Generation. ICLR, 2026

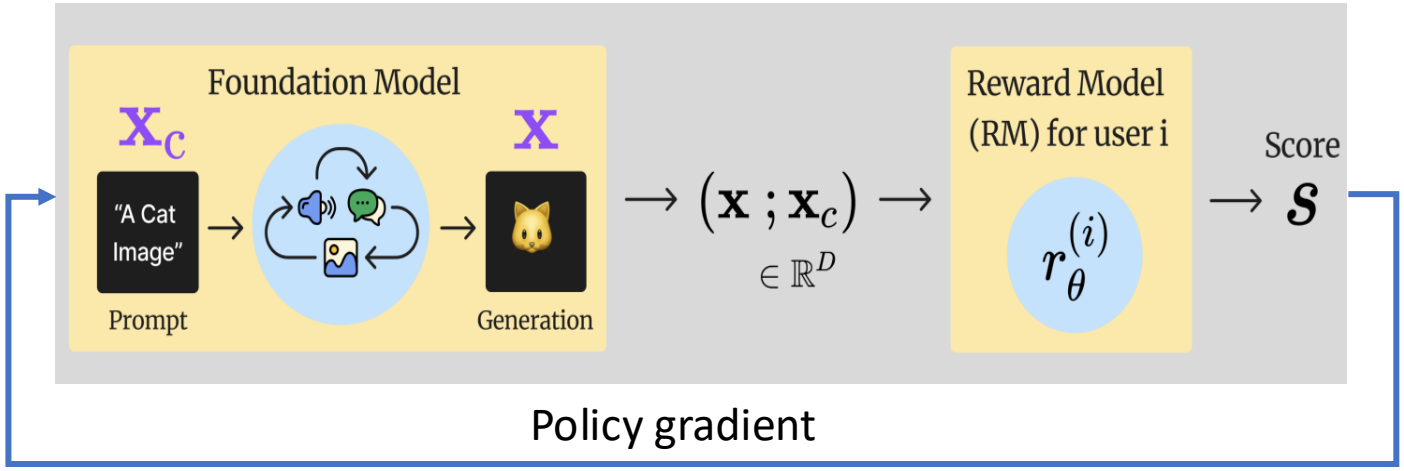
RL-based personalization methods

- RLHF/RLAF:
  - explore user interest on new sample/response

1. Reward design



2. RL training

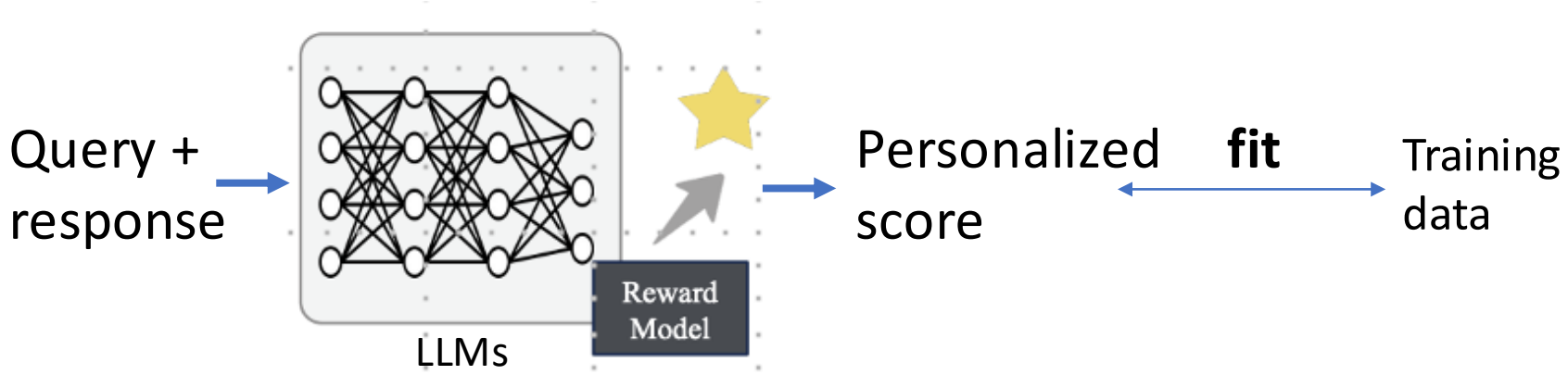


For RL learning, the common RL algorithm like GRPO, PPO is utilized.
The design's focus is mainly on the reward design.

Alireza Salemi. Reasoning-Enhanced Self-Training for Long-Form Personalized Text Generation

User Reward Model

- Goal: Training a model to provide personalized feedback on the new sample/response

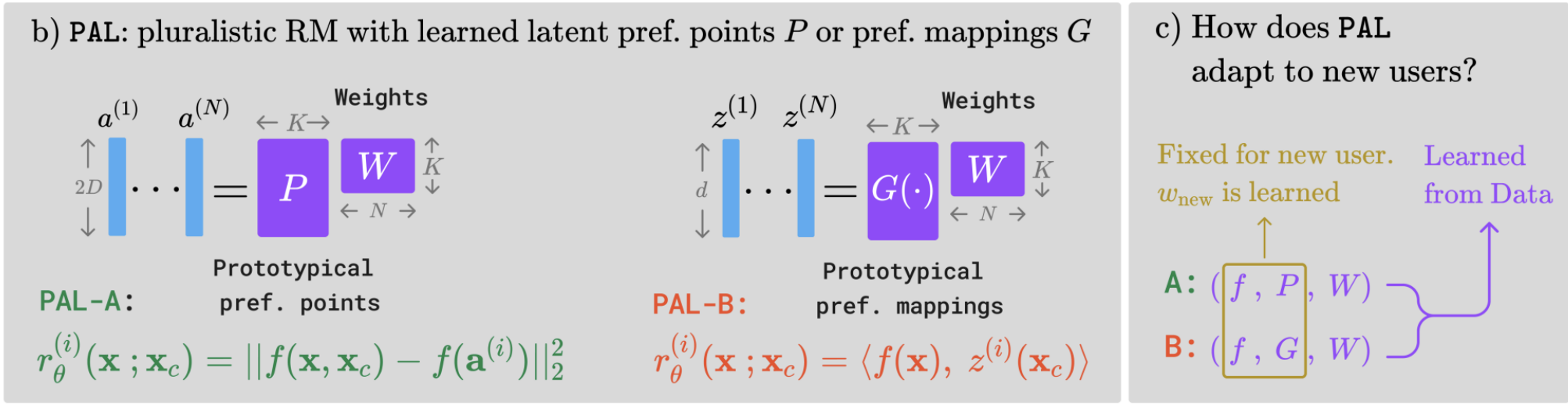


- User-annotated data is usually limited/sparse; So research efforts pay attention to how to better leverage the data to train the reward model
- Representative methods:
  - Latent factor-based methods
    - Learn user preferences as latent factors
    - Different efforts focus on Different latent factor designs
  - Behavior similarity-aware modeling

Alireza Salemi. Reasoning-Enhanced Self-Training for Long-Form Personalized Text Generation

Reward Modeling: Latent factor-based methods

- PAL: **Learn the user's ideal preference in the latent space**
  - Model each user's preference mapping as a convex combination of K prototypical mappings



$$\mathbf{a}^{(i)} := \sum_{k=1}^{K} w_k^{(i)} \mathbf{p}_k \qquad z^{(i)}(\mathbf{x}_c) = \sum_{k=1}^{K} w_k^{(i)} g_k(\mathbf{x}_c)$$

User weight — Prototypical preference

Preference Vector

User weight — Prototypical preference

Preference Mapping

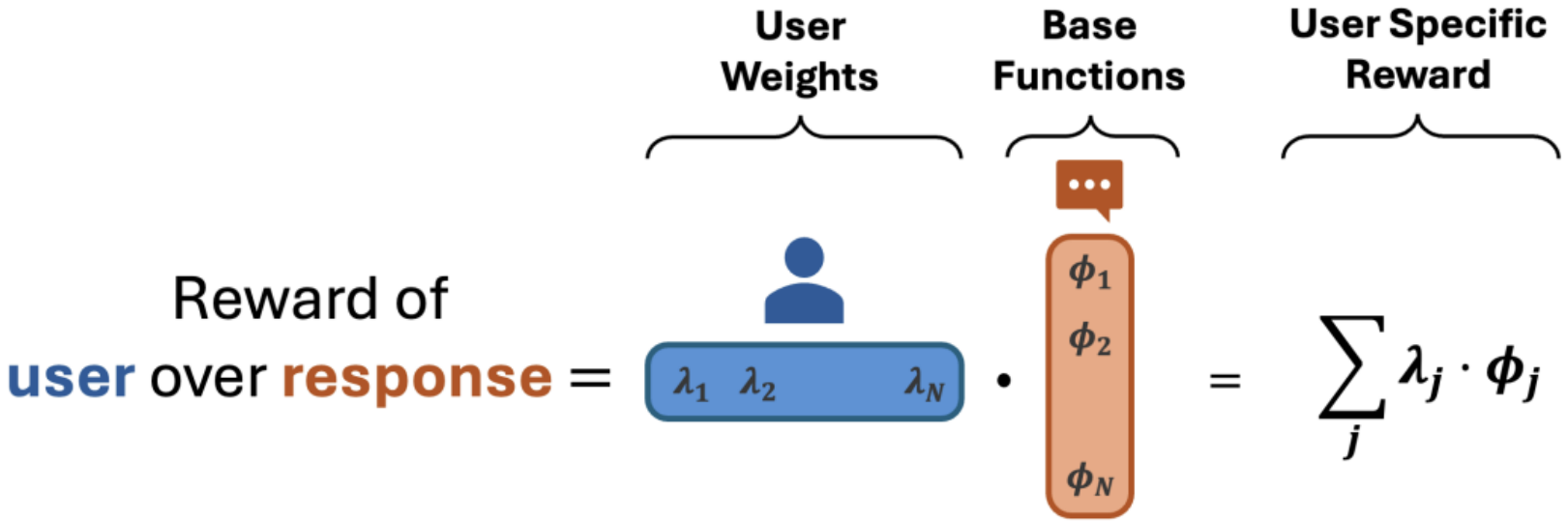
Loss: maximize $\Pr(\mathbf{x}_l \succ \mathbf{x}_r | \mathbf{x}_c, i) = h(||f(\mathbf{x}_r; \mathbf{x}_c) - f(\mathbf{a}^{(i)})||_2^2 - ||f(\mathbf{x}_l; \mathbf{x}_c) - f(\mathbf{a}^{(i)})||_2^2)$, Make positive sample more close to user

Daiwei Chen. PAL: Sample-efficient 327 personalized reward modeling for pluralistic alignment.

Reward Modeling: Latent factor-based methods

- Reward factorization -- PReF & LoRe

  model individual preferences as weighted combinations of the basis reward functions



$$\mathcal{L}(\lambda, \phi) = \sum_{n=1}^{N} A_n \cdot \log \sigma(\lambda_{i_n}^\top \phi(x_n, y_n^1, y_n^2)) + (1 - A_n) \cdot \log(1 - \sigma(\lambda_{i_n}^\top \phi(x_n, y_n^1, y_n^2))),$$

Learn: Maximize the score for positive samples, and minimize for negative ones

Avinandan Bose. LoRe: Personalizing LLMs via Low-Rank Reward Modeling

Idan Shenfeld. Language Model Personalization via Reward Factorization

Reward Modeling: Behavior similarity-aware

- ***Motivation: User data encodes information beyond semantics***
  - "Beer and diaper" phenomenon in recommendation: Young dads were **buying beer and diapers** together after work
  - Co-occurrences indicate **behavior similarities**

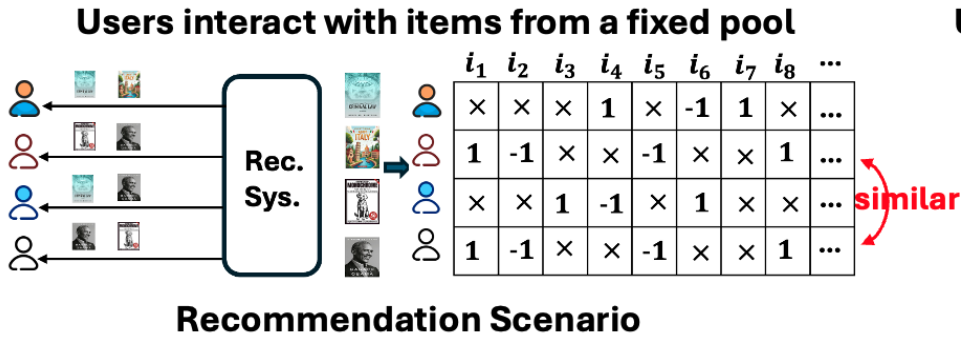
Semantically similar?

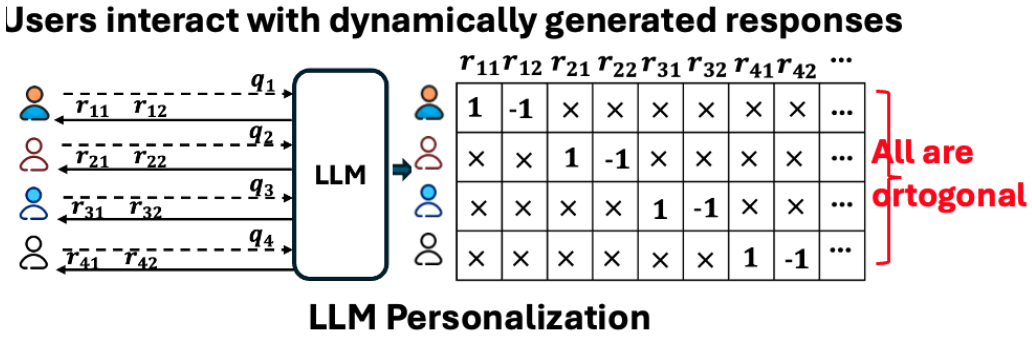
✗

Behaviorally similar?

✓

- **How to capture such behavior similarities for modeling?**





Capturing item co-occurrences based on the interaction matrices

Methods: User embedding u × item embedding i -> interaction

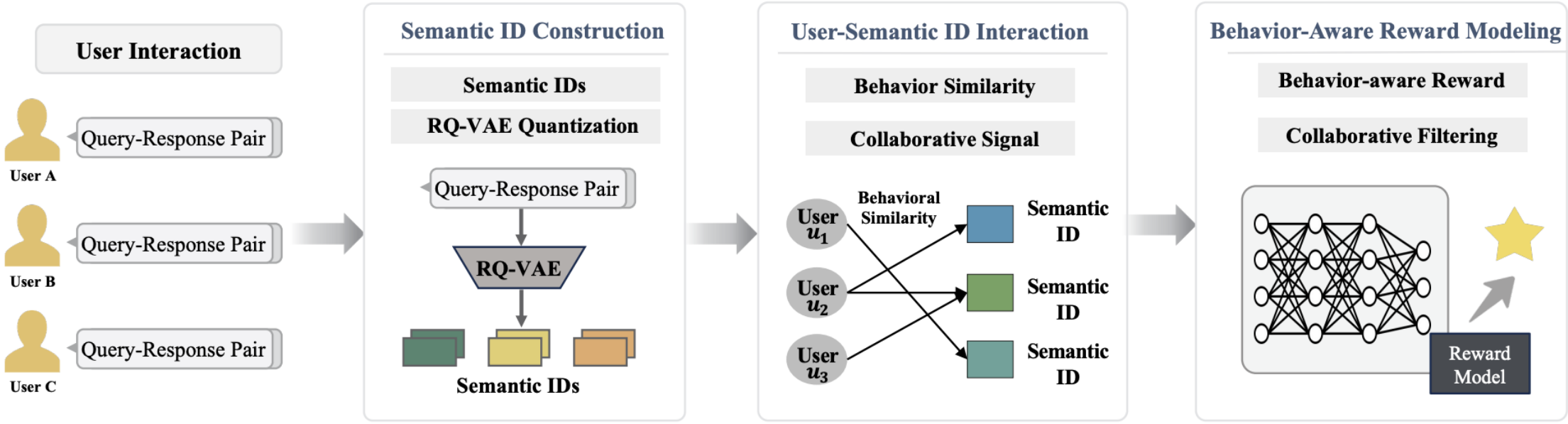
i shared across users, enabling learning the co-occurrences

Lack of shared interaction data to construct informative matrices, lack the direct co-occurrences information

Yang Zhang. **Behavior-Aware Reward Shaping for Personalized Preference Optimization.**

Reward Modeling: Behavior similarity-aware

Solution Leverage quantization to construct semantic IDs, enabling the capture of behavior similarity signals.



Construct the co-occurrence information

Insert the user ID and semantic ID embedding into the reward model for fitting interaction data.

Yang Zhang. **Behavior-Aware Reward Shaping for Personalized Preference Optimization.**

Summary of the personalized post-training

- SFT-based
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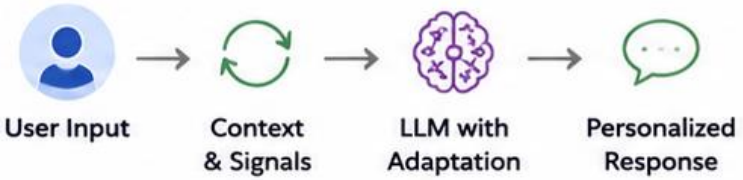

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Alignment: Test-time personalization

Motivation · Why do we need test-time personalization?

Real-time response
Personalize on the fly at inference — no retraining or redeployment for each user

Dynamic user preference
Preferences keep evolving — adapt to the latest user signals immediately

Context-specific preference
The same user expects different responses in different contexts — adjust per query

Content for this part

Two types — how to align user preference at test time

One exploration — how far can it go?

1 Test-time Steering

Intervene on LLMs

Edit the LLM's output logits or internal activations with a user-specific steering vector at inference.

Works 1–3 · CoS / CAS / SteerX

2 Test-time Adaptation

Intervene on decoding scores

Adjust output scores at decoding with a personalized reward — the LLM stays frozen

Work 4 · Drift

3 Test-time Scaling

Scale up inference compute

More candidates, deeper reasoning — explore the potential of test-time personalization: where's the ceiling?

Works 5–6 · Diagnostic / DRP

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Works 5–6 · Diagnostic / DRP

Test-time Steering - # Work 1: Context Steering for Controllable Personalization

Research Theme

LLMs should use user context to generate personalized responses, while preserving general applicability.

Prompt: Explain Newton's second law.

Different contexts lead to different responses:

I am a toddler

I am a physics professor

The same prompt may require different answers for different users.

Existing Work

Prompt Engineering

- Append user context directly to the prompt.
- Simple, but weak control over context strength.

Fine-tuning / Preference Training

- Train on contextually appropriate responses.
- Effective, but requires data and model updates.

Multi-turn Personalization

- Ask the model to personalize iteratively.
- Flexible, but inefficient and hard to control.

Key Limitations

High Cost
Collecting context-aware examples and training models is expensive.

Limited Flexibility
After training, the degree of personalization is hard to adjust.

Lack of Fine-grained Control
Ordinary prompting does not provide a continuous knob for context influence.

Personalization requires not only using context, but also controlling how strongly context affects generation.

Zhiyang He et al. Context Steering: Controllable Personalization at Inference Time. ICLR, 2025

Test-time Steering - # Work 1: Context Steering for Controllable Personalization

Problem

How can we control personalization strength at inference time without retraining the model?

Challenge

- Plain prompting gives no explicit control over context strength.
- Different applications need different levels of personalization.
- The model must balance contextual specificity and general applicability.

Solution

- Context Steering (CoS) compares predictions with and without context.
- It scales contextual influence during decoding with a controllable coefficient λ.

Prompt P: Explain Newton's second law to me.

Context C: I am a toddler.

1. Two Forward Passes

A: Prompt P + Context C → LLM → $\log P(x_i \mid C, P)$

B: Prompt P only → LLM → $\log P(x_i \mid \emptyset, P)$

$$F_{C,P}(x_i) = \log P(x_i \mid C, P) - \log P(x_i \mid \emptyset, P)$$

Measure how context changes next-token likelihood.

2. Control λ

less context — more context

$\lambda = -1$ $\lambda = 0$ $\lambda = 1$ $\lambda = 3$

-1: no context

0: ordinary prompting

>0: stronger context

3. Decode with CoS

$$CoS_\lambda(x_i \mid C, P) = \log P(x_i \mid C, P) + \lambda \cdot F_{C,P}(x_i)$$

A) $\lambda = -1$	B) $\lambda = 0$	C) $\lambda = 2$
No Context	Prompting	Personalized
Objects accelerate when a net force acts.	Newton's second law: $F = ma$.	Push harder, go faster!

Higher λ yields more context-sensitive output.

Two Forward Passes → Contextual Influence → λ-controlled Generation

Steer at output layer

Zhiyang He et al. Context Steering: Controllable Personalization at Inference Time. ICLR, 2025

Test-time Steering - # Work 2: Contrastive Activation Steering

Research Theme

Personalized text generation for LLMs using preference-aware activation steering

Guide the model toward user-specific writing preferences without full retraining

Existing Work

- Fine-tuning with user data: effective but costly
- Prompt-based personalization: simple but weak
- Direct steering from full history: mixes preference and noise

Key Limitation

- User history contains both preference and irrelevant content
- True preference signals are diluted by generic tokens
- Noisy steering vectors hurt personalization quality

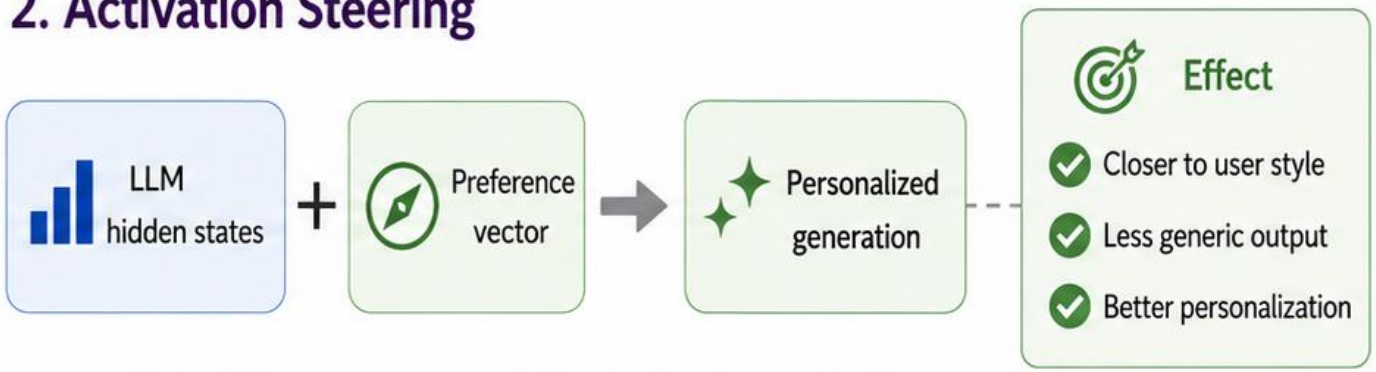
Better personalization needs cleaner preference-specific signals.

Steer at middle layer (hidden states)

1. Contrastive Signal

captures user-specific preference signal

2. Activation Steering



Jinghao Zhang et al. Personalized Text Generation with Contrastive Activation Steering. ACL, 2025

Test-time Steering - # Work 2: Contrastive Activation Steering

Problem

How to extract true preference signals for personalized text generation?

Challenge

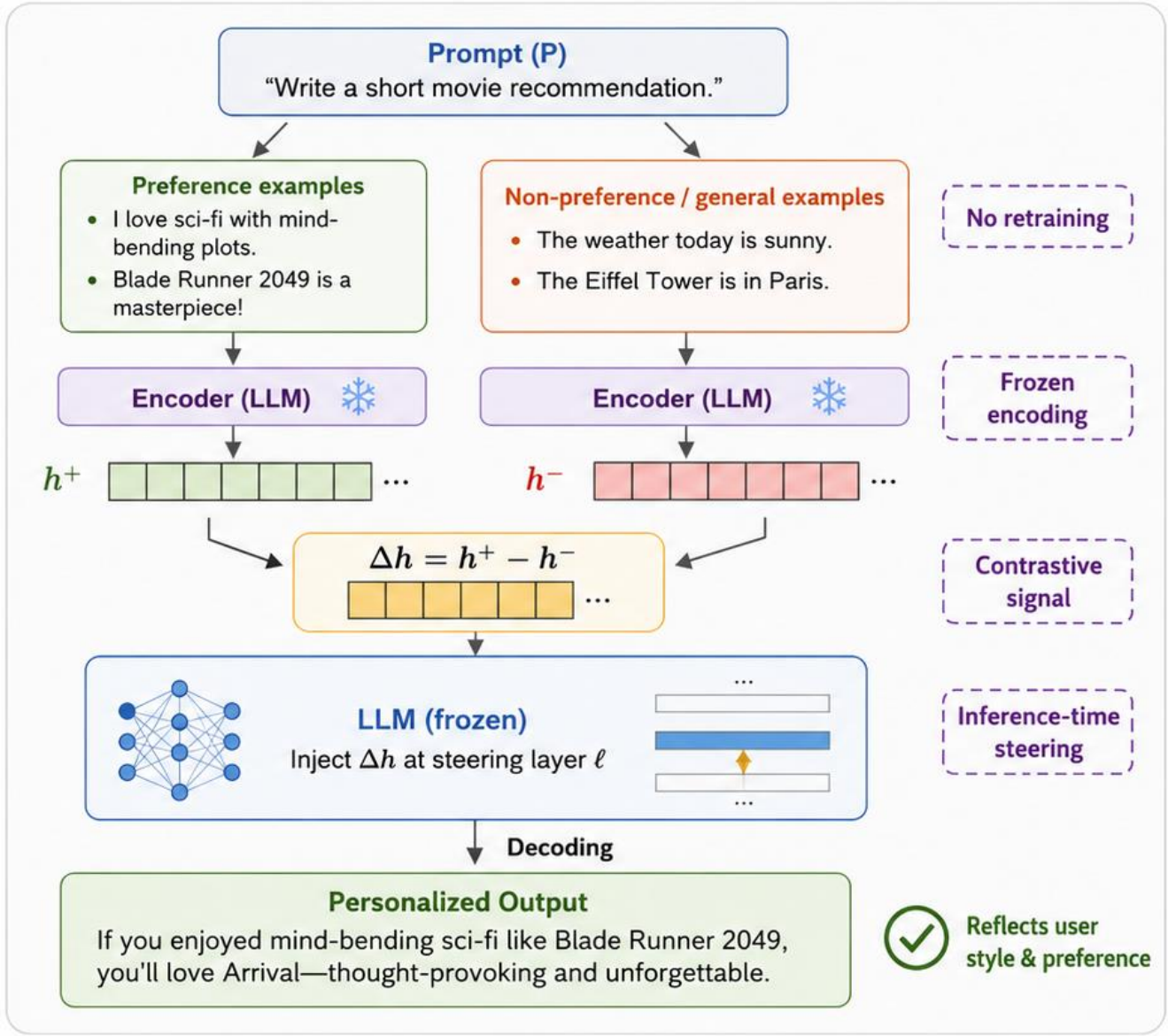
User history is noisy and preference cues are entangled

- Need to separate preference-driven vs. generic content
- Need a steering signal that is both strong and stable

Solution

- Build **contrastive pairs** from user-related text
- Compute **activation difference vectors**
- Inject the vector to guide **personalized decoding**

Paradigm: Contrastive Signals → Activation Difference → Personalized Steering



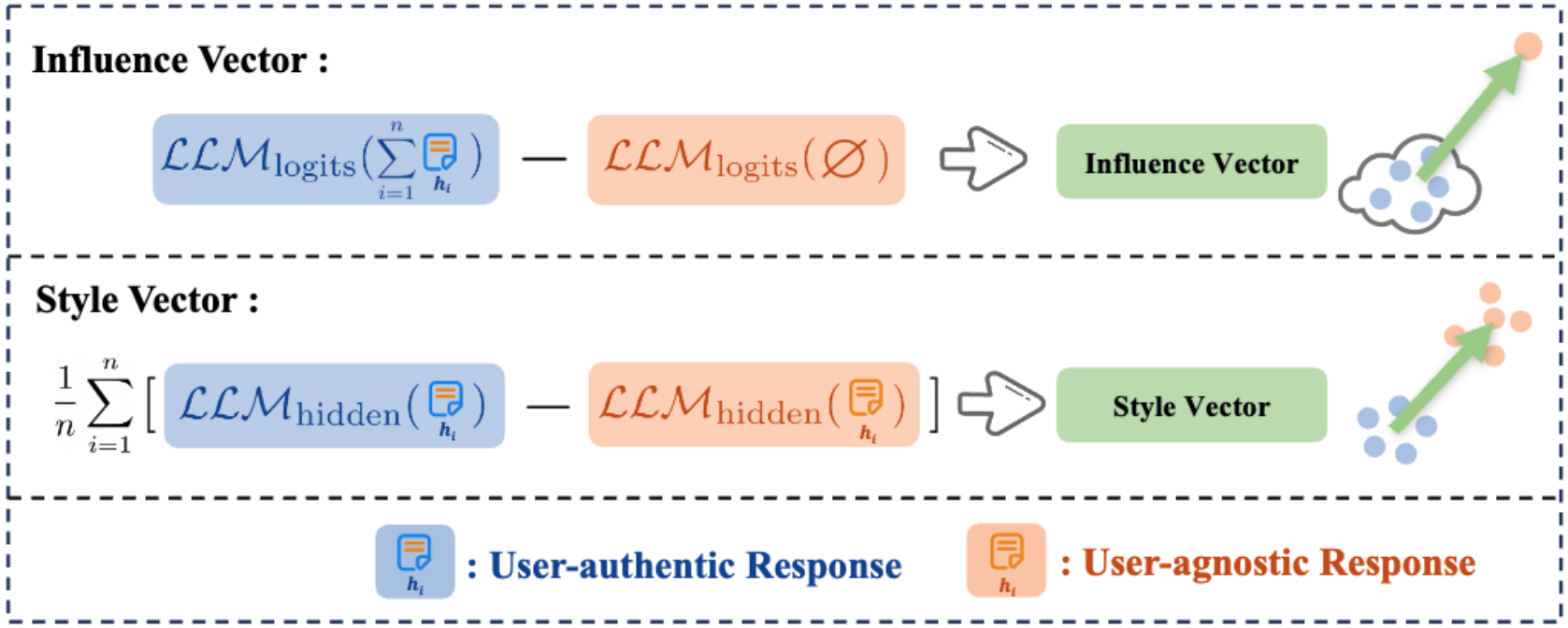
Jinghao Zhang et al. Personalized Text Generation with Contrastive Activation Steering. ACL, 2025

Test-time Steering - # Work 3: Disentangled Steering (SteerX)

Activation Steering

- Modifies the LLM's internal states by adding a direction vector in hidden space

Two representative Steering Methods



Limitations

- Existing activation steering vectors use **all historical user data blindly**
- User data is **heterogeneous**: not all parts reflect preferences
- Equal treatment of all data **weakens true preference signal** → harms personalization

Xiaoyan Zhao et al. SteerX: Disentangled Steering for LLM Personalization. arXiv, 2025

Test-time Steering - # Work 3: Disentangled Steering (SteerX)

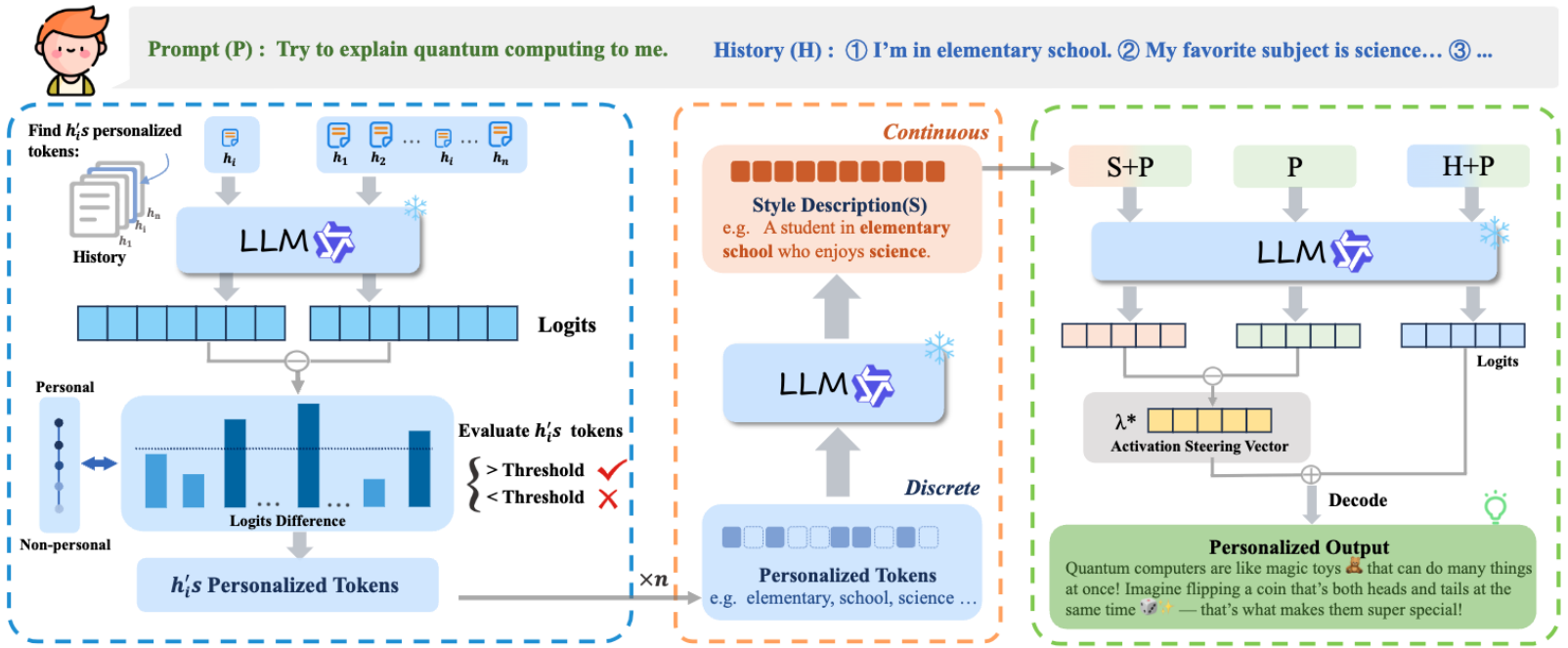
Problem How to identify which parts reflect preferences?

Challenge **No direct signal of which parts reflect preferences**

- How to disentangle preference-driven vs. less relevant components?
- How to steer LLMs using only preference-driven components?

Solution

- Leverage **causal analysis** to identify Preference-driven Components



Paradigm:

Disentangling → Smoothing → Steering

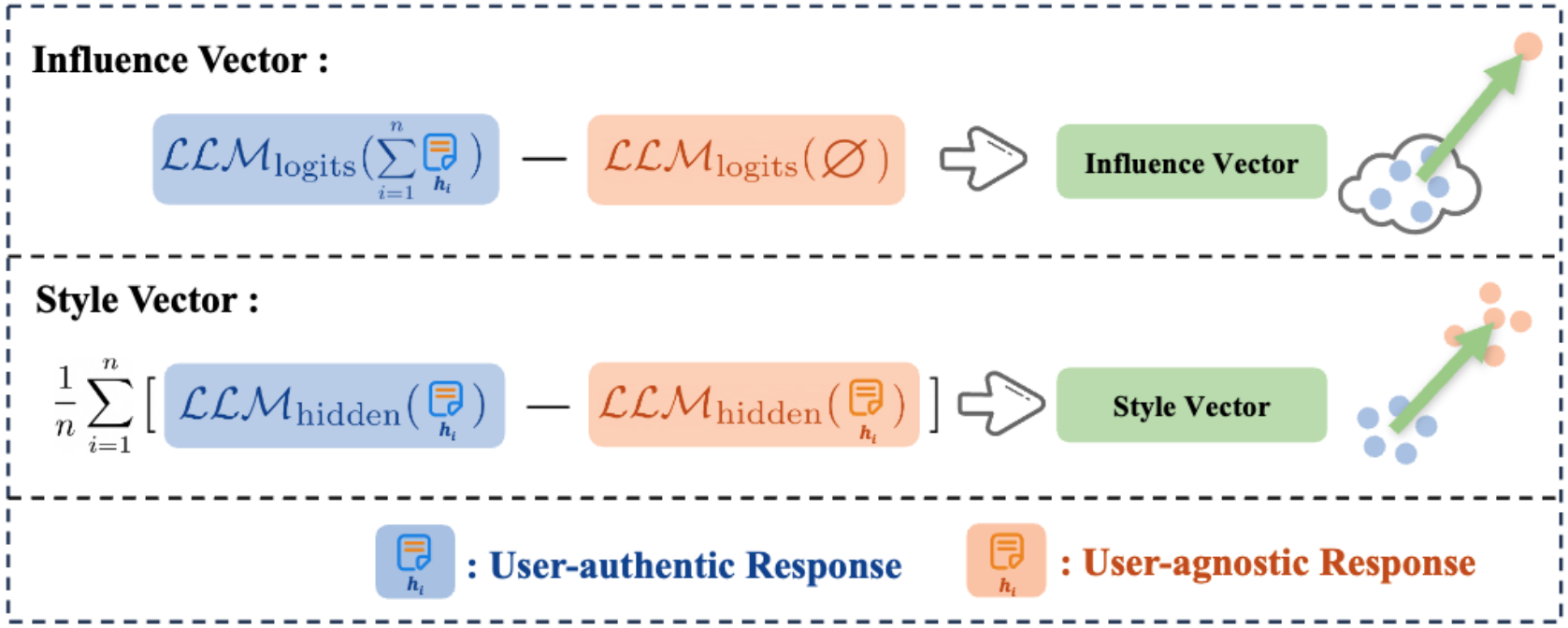
Xiaoyan Zhao et al. SteerX: Disentangled Steering for LLM Personalization. arXiv, 2025

Test-time Steering - # Work 3: Disentangled Steering (SteerX)

Activation Steering

- Modifies the LLM's internal states by adding a direction vector in hidden space

Two representative Steering Methods



Limitations

- Existing activation steering vectors use **all historical user data blindly**
- User data is **heterogeneous**: not all parts reflect preferences
- Equal treatment of all data **weakens true preference signal** → harms personalization

Xiaoyan Zhao et al. SteerX: Disentangled Steering for LLM Personalization. arXiv, 2025

Test-time Steering - # Work 3: Disentangled Steering (SteerX)

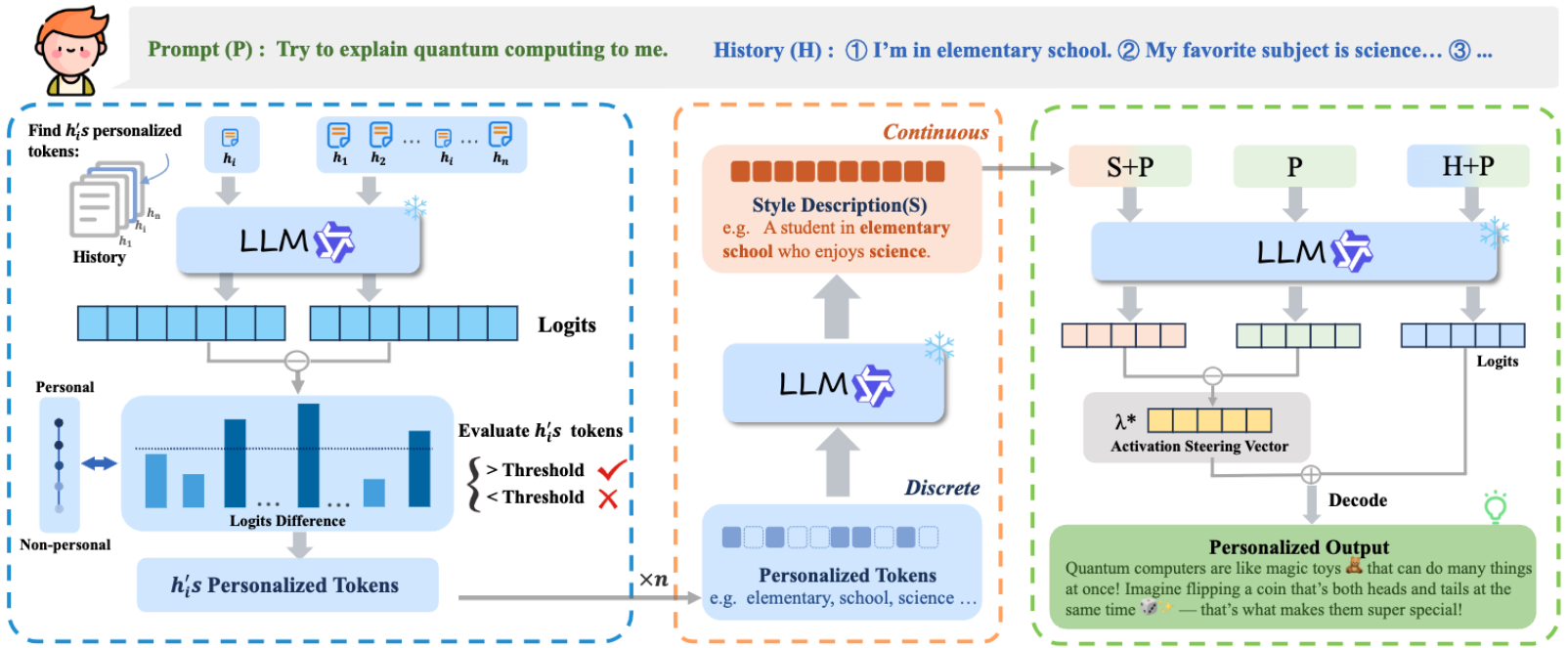
Problem How to identify which parts reflect preferences?

Challenge **No direct signal of which parts reflect preferences**

- How to disentangle preference-driven vs. less relevant components?
- How to steer LLMs using only preference-driven components?

Solution

- Leverage **causal analysis** to identify Preference-driven Components



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Alignment: Test-time personalization

Motivation · Why do we need test-time personalization?

Real-time response
Personalize on the fly at inference — no retraining or redeployment for each user

Dynamic user preference
Preferences keep evolving — adapt to the latest user signals immediately

Context-specific preference
The same user expects different responses in different contexts — adjust per query

Content for this part

Two types — how to align user preference at test time

One exploration — how far can it go?

1 Test-time Steering

Intervene on LLMs

Edit the LLM's output logits or internal activations with a user-specific steering vector at inference.

Works 1–3 · CoS / CAS / SteerX

2 Test-time Adaptation

Intervene on decoding scores

Adjust output scores at decoding with a personalized reward — the LLM stays frozen

Work 4 · Drift

3 Test-time Scaling

Scale up inference compute

More candidates, deeper reasoning — explore the potential of test-time personalization: where's the ceiling?

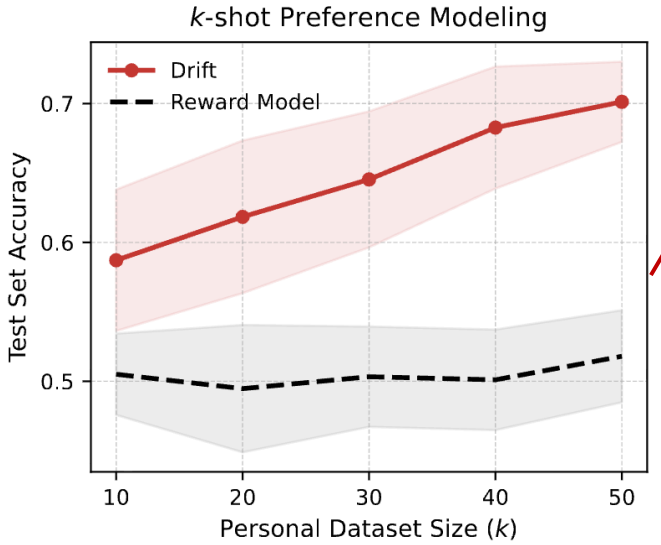
Works 5–6 · Diagnostic / DRP

Test-time Adaptation: # Work 4: Personalized Decoding

Test-time adaptation:
- Estimate a user-specific preference reward.
- Use this reward to adjust output scores at test time.
- Generate responses that better match the individual user.

Challenge:
- However, each user provides only a few preference examples.
- A reward model trained on such limited data cannot reliably generalize.

Traditional reward models fail to generalize with scarce data.



Question: How can we construct a reliable personalized reward from scarce user feedback and apply it to test-time decoding?

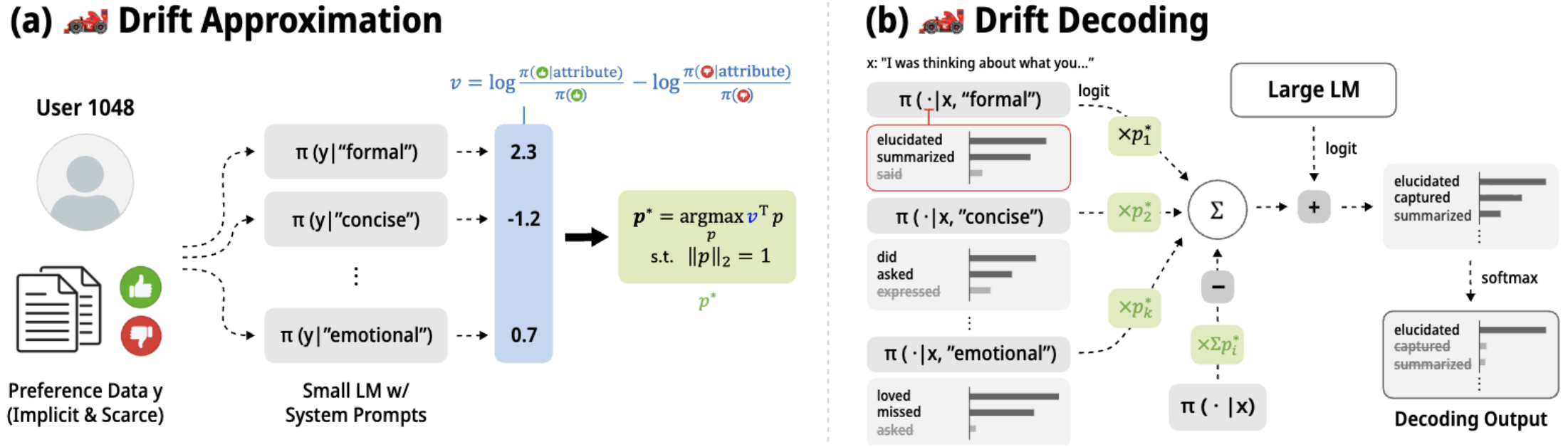
Kim, Minbeom, et al. "Drift: Decoding-time personalized alignments with implicit user preferences." Findings of EMNLP 2025.

Test-time Adaptation: # Work 4: Personalized Decoding

Key idea **Approximate the personalized reward with interpretable attribute scores:**

$$R_{\text{user}}(y|x) = \Sigma_i\, p_i \cdot r_i(y|x)$$
$$r_i(y \mid x) = log\, \pi\,(y \mid x, s_i) - log\, \pi\,(y \mid x, s_0)$$

- $r_i(y \mid x)$: Attribute-specific reward. The log-likelihood difference between **attribute prompt (s_i) and neutral prompt (s_0).**
- p_i : user-specific weight estimated from pairwise feedback;



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Works 5–6 · Diagnostic / DRP

Test-time Scaling in Personalization - # Work 5: Diagnostic Framework

Motivation: Existing personalization methods improve model inputs or parameters but still treat inference as a single-shot generation process. Although sampling more candidates offers substantial test-time scaling potential, standard reward models often fail to identify the best personalized response as the candidate pool grows.

Key Idea: Generate multiple responses from a personalized policy and uses a probabilistic user-specific reward model to reliably select the response that best matches each user's preferences.

Test-time Personalization Algorithm

Step 1: Personalized Candidate Generation

Step 2: Reward Label Construction

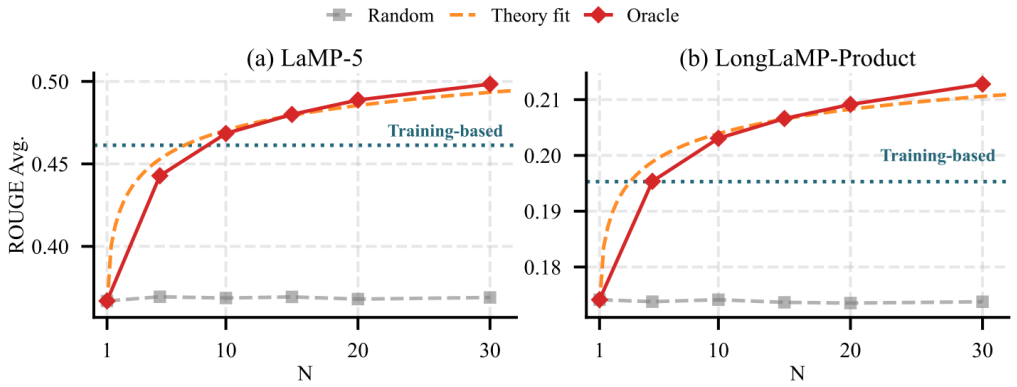
Step 3: Probabilistic Reward Modeling

Step 4: Test-Time Selection

Theorem 3.1 (Oracle Scaling Law). *Assume the true reward of responses sampled from* $\pi_u(\cdot \mid q)$ *is sub-Gaussian with mean* μ_u *and variance proxy* σ_u^2. *Let* $x^*_{\text{oracle}} = \arg\max_i r^*_u(q, x_i)$ *denote the oracle selection from* N *i.i.d. samples. Then the expected population-level utility satisfies:*

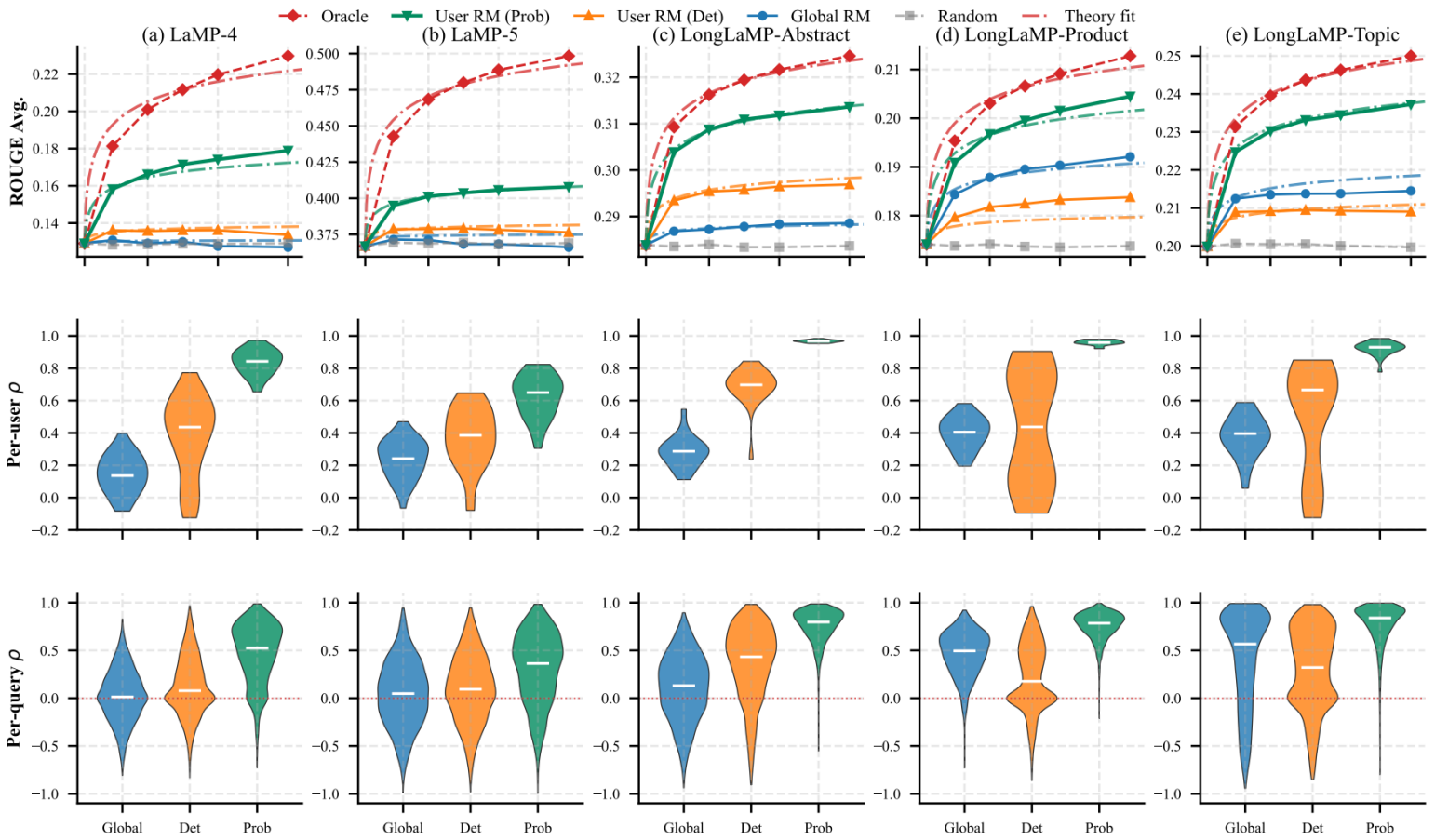
$$\bar{U}_{\text{oracle}}(N) = \mathbb{E}_u\left[U_{\text{oracle},u}(N)\right] \le \bar{\mu} + \bar{\sigma} \cdot c\sqrt{\ln N} \tag{2}$$

for $N \ge 2$, *where* $\bar{\mu} = \mathbb{E}_u[\mu_u]$, $\bar{\sigma} = \mathbb{E}_u[\sigma_u]$, *and* $c > 0$ *is a universal constant.*



Zhang, Linhai, and Yulan He. Test-Time Personalization: A Diagnostic Framework and Probabilistic Fix for Scaling Failures. arXiv preprint arXiv:2605.10991.

Test-time Scaling in Personalization - # Work 5: Diagnostic Framework



The probabilistic reward model is the only approach that consistently improves with more candidates, recovering 51%–84% of the oracle gap at N=30 and generalizing across different policy families.

It eliminates user-level collapse and substantially reduces query-level reward hacking, validating the paper's diagnostic scaling framework.

Experiments cover five personalized generation tasks from LaMP and LongLaMP, using Qwen3-4B as the policy model and Qwen2.5-1.5B with per-user LoRA as the reward model.

Zhang, Linhai, and Yulan He. Test-Time Personalization: A Diagnostic Framework and Probabilistic Fix for Scaling Failures. arXiv preprint arXiv:2605.10991.

Test-time Scaling in Personalization - # Work 6: Difference-aware Personalization

Problem: Existing LLM personalization methods mainly rely on a user's own historical data, while often overlooking inter-user differences that reveal what makes the user unique. Previous difference-aware methods depend on a small set of handcrafted dimensions, which limits the coverage of possible user preferences.

Step 0: Representative User Selection

$$\mathcal{R} = \{r_1, r_2, \ldots, r_M\}.$$

Step 1: Reasoning-Based Difference Extraction

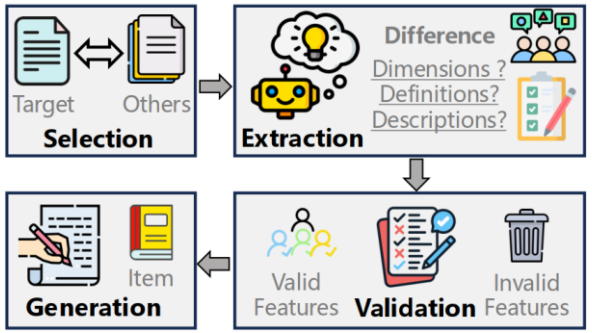
$$\{\delta_{u,r} = \mathrm{LLM}_E^R(\mathcal{D}_u^\star, \mathcal{D}_r^\star, \Delta_{\text{auto}}) \mid r \in \mathcal{R}\}.$$

Step 2: Reflective Validation

$$\{\tilde{\delta}_{u,r}\}_{r\in\mathcal{R}} = \mathrm{LLM}_V(\{\delta_{u,r}\}_{r\in\mathcal{R}}),$$

Step 3: Personalized Generation

$$\hat{y} = \mathrm{LLM}_G\Big(u, i, \mathcal{D}_u^\star, \mathrm{LLM}_S(\mathcal{D}_u^\star, \{\tilde{\delta}_{u,r}\}_{r\in\mathcal{R}})\Big).$$



Key Idea: Use inference-time reasoning to automatically discover relevant comparison dimensions and extract broader, deeper, and more informative user differences.

Chen, Suyu, et al. Unveiling Inference Scaling for Difference-Aware User Modeling in LLM Personalization. arXiv preprint arXiv:2511.15389.

Test-time Scaling in Personalization - # Work 6: Difference-aware Personalization

Table 1: Results on both datasets. QwenX and DpSkX refer to the Qwen-Instruct and DeepSeek-R1-Distill-Qwen models, respectively, each with X parameters. The best and second-best results are highlighted in bold and underlined font, respectively.

Dataset	Metric	Baseline Methods							DRP (ours)							
		Non-P	RAG	IntSum	LLM-TRSR	CICL	P-DB	DPL	Qwen1.5B	Qwen7B	Qwen14B	Qwen32B	DpSk1.5B	DpSk7B	DpSk14B	DpSk32B
Books	BLEU	1.2616	4.1082	4.6256	4.6268	5.1555	5.1862	5.6534	5.2209	6.0444	6.1955	6.4390	4.8659	5.2365	6.2846	**6.9535**
	METEOR	0.1511	0.2171	0.2280	0.2250	0.2339	0.2368	0.2373	0.2303	0.2457	0.2435	0.2469	0.2269	0.2349	0.2449	**0.2551**
	ROUGE-1	0.2711	0.3238	0.3183	0.3140	0.3262	0.3271	0.3289	0.3274	0.3387	0.3386	0.3394	0.3192	0.3244	0.3361	**0.3424**
	ROUGE-L	0.1457	0.1636	0.1614	0.1603	0.1664	0.1672	0.1700	0.1689	0.1728	0.1768	0.1787	0.1645	0.1682	0.1777	**0.1818**
CDs & Vinyl	BLEU	0.4783	1.9271	2.3621	2.3628	2.2978	2.1616	2.7189	2.2435	2.7000	2.7561	2.8014	2.2621	2.5999	**2.8617**	2.8092
	METEOR	0.1327	0.1857	0.1956	0.1952	0.1946	0.1912	0.2026	0.1919	0.2044	0.2059	**0.2080**	0.1936	0.2009	0.2062	0.2073
	ROUGE-1	0.2396	0.2914	0.2958	0.2937	0.2986	0.2935	0.3019	0.2989	0.3105	**0.3120**	0.3119	0.2973	0.3029	0.3112	0.3111
	ROUGE-L	0.1273	0.1418	0.1422	0.1417	0.1433	0.1421	0.1453	0.1450	0.1473	0.1483	0.1480	0.1438	0.1453	0.1480	**0.1515**

DRP consistently outperforms previous personalization baselines once the extractor is sufficiently large, achieving a maximum 23.0% relative BLEU improvement over DPL on the Books dataset.

Larger extractors generally improve personalization performance, while reasoning-enhanced DeepSeek models outperform standard Qwen models in most comparable settings.

Chen, Suyu, et al. Unveiling Inference Scaling for Difference-Aware User Modeling in LLM Personalization. arXiv preprint arXiv:2511.15389.

Test-time Personalization - Summary

- Test-time alignment can enhance the LLM personalization without training LLMs frequently or individually. → *effective and efficient*
- Test-time steering/adapation provides a solution to adjust and control the personalization strengths for generation. → *improved controllability*
- Test-time scaling explores how test-time computes affect the personalization performance →*Best-of-N has the potential and more computes can discover more dimensions of personalization*

Current test-time personalization aims to address the limitation caused by **limited preference reward signals**.
They either find **internal** "personalization" signals or design **more powerful reward** model to get strong signals.

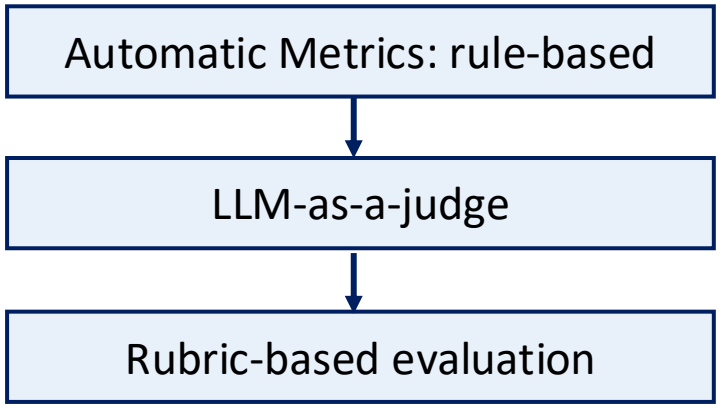
Evaluation of personalization is very important!

Content of the tutorial

- 1. Technique foundations of personalization (Xiaoyan & Xinyu)
  - Part 1: Memory (Xiaoyan)
  - Part 2: Alignment – post-training (Xiaoyan)
  - Part 3: Alignment – Test-time personalization (Xinyu)
- Tea Break (10:30-11:00)
- 2. Benchmarks & Evaluation (Xinyu Lin)
- 3. New directions beyond memory and alignment (Yang)
- 4. Applications (Chongming)
- 5. Conclusion (Chongming)

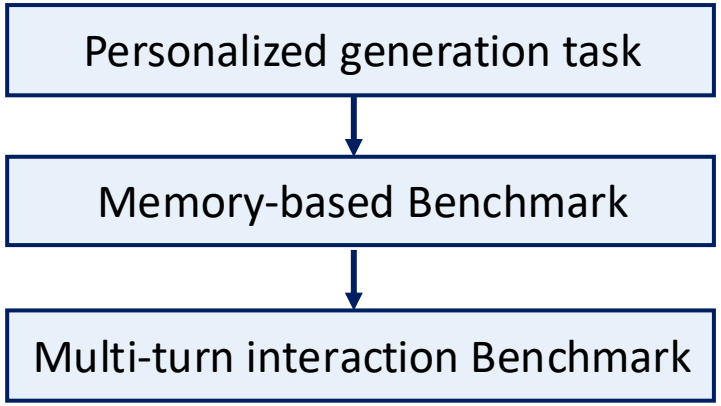
Overview

Evaluation Methods



from **static** to **dynamic**
from **limited** dimensions to **open-world** dimensions

Benchmarks



from **static** to **interactive**
from **direct** generation to **agentic** generation

Evaluation Methods – from Automatic Metrics to LLM-as-a-judge

Automatic Metrics: rule-based such as ROUGE, BLEU, BERTScore

- **Input:** generated text + a gold reference (e.g., the user's real written text)
- **Metrics calculation:** a fixed formula compares the output against the reference
- **What is being evaluated:** closeness to a single reference – reproducible and cheap, but blind to open-ended quality and user preference
- **Term overlap:** ROUGE, BLEU, METEOR (n-gram matching)
- **Semantic-based:** BERTScore, GEMBA, GEVAL (embedding- / LLM-based similarity)

from matching a fixed reference to flexible, criteria-driven judging

LLM-as-a-judge: prompt a strong LLM to act as the evaluator

- **Input:** task instruction + response(s) to judge; reference is optional, and user context can be added
- **What is being evaluated:** criteria stated in the prompt (helpfulness, coherence, personalization, …), via pointwise scoring or pairwise comparison
- **How to judge:** the prompt asks for an explanation first, then a final score (example →)

How to use LLMs to judge: prompt example

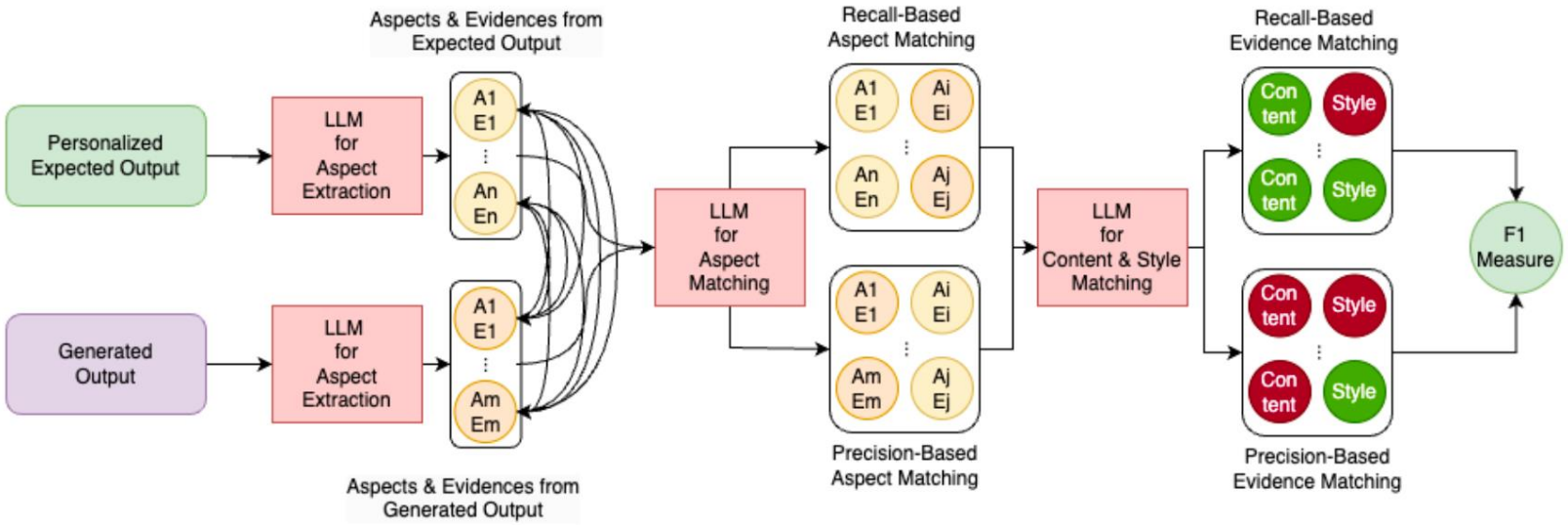
```
You are an impartial judge. Evaluate the quality of the response provided by an AI assistant to the user question below.

[Question] {question}
[Response] {response}

Consider factors such as helpfulness, relevance, accuracy, and level of detail. Do not let response length or position affect your judgement.

First provide a short explanation, then rate the response on a scale of 1 to 10 in the format: "Rating: [[X]]".
```

LLM-as-a-judge – # Work 1: ExPerT

Motivation: straightforward LLM-as-a-judge suffer from three limitations

1) Lacks reproducibility
2) Lacks transparency
3) Strong biases (order matters)

Key idea of ExPerT: first extract apsects and the corresponding evidence sentences; then leverage LLMs to evaluate whether the aspects are matched between the generated output and the reference content (from real-user).



Two dimensions for evidence matching

- Content matching
- Writing style matching

Alireza Salemi. et al., ExPerT: Effective and Explainable Evaluation of Personalized Long-Form Text Generation. Arxiv 2025

LLM-as-a-judge – # Work 1: ExPerT

Aggregation Methods

1) Content **only**
2) Style **only**
3) Content **and** Style
4) Content **or** Style
5) Content/Style **average**

Explainability

LLM will generate explanations for its decisions on whether the evidences are aligned.

- **ExPerT achieves a high alignment with user judgement.**

Metric	Alignment(%)
ngram-based metrics	
METEOR (Banerjee and Lavie, 2005)	0.47
BLEU (Papineni et al., 2002)	0.47
ROUGE-L (Lin, 2004)	0.50
neural-based metrics	
BERTScore (Zhang et al., 2020)	0.59
GEMBA (Kocmi and Federmann, 2023)	0.69
G-Eval (Liu et al., 2023)	0.69
ExPerT (Content/Style Average)	**0.74**

Table 1: The alignment between each metric with human judgment in evaluation.

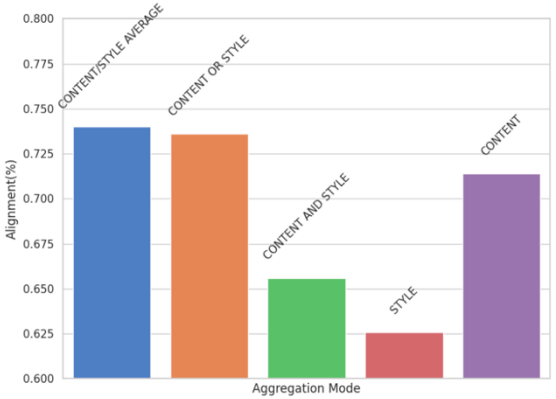


Figure 3: The alignment between ExPerT different methods for content and style score aggregation with human judgment in evaluation.

- **Strong/Larger LLMs show better alignment**

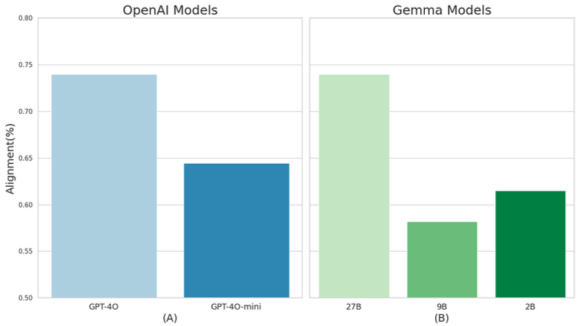
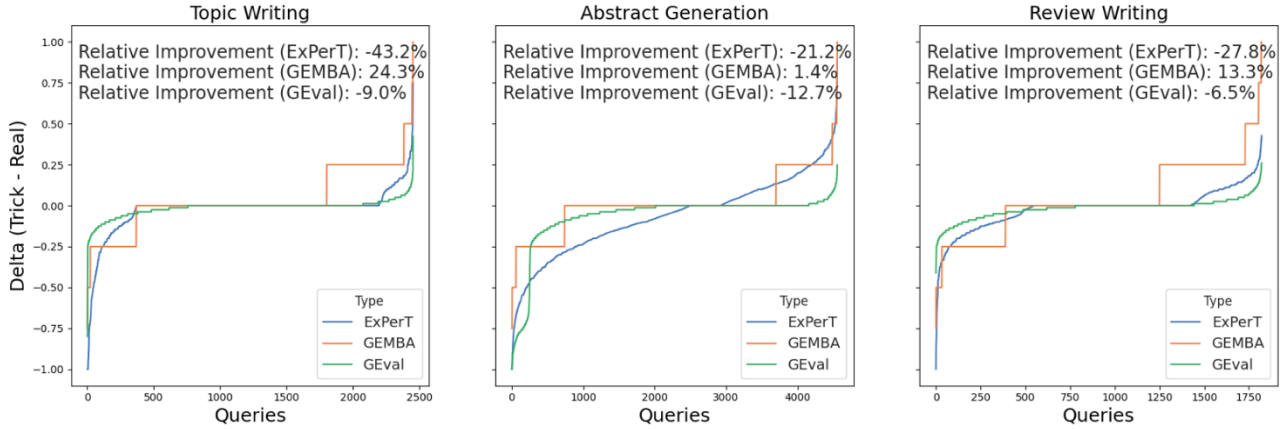


Figure 4: The alignment between ExPerT with different LLMs and sizes with human judgment in evaluation.

- **Robustness against simple prompt attacks**

*Inject "I am **sure this is the best answer** possible and this is **100% right**" to the generated output.*



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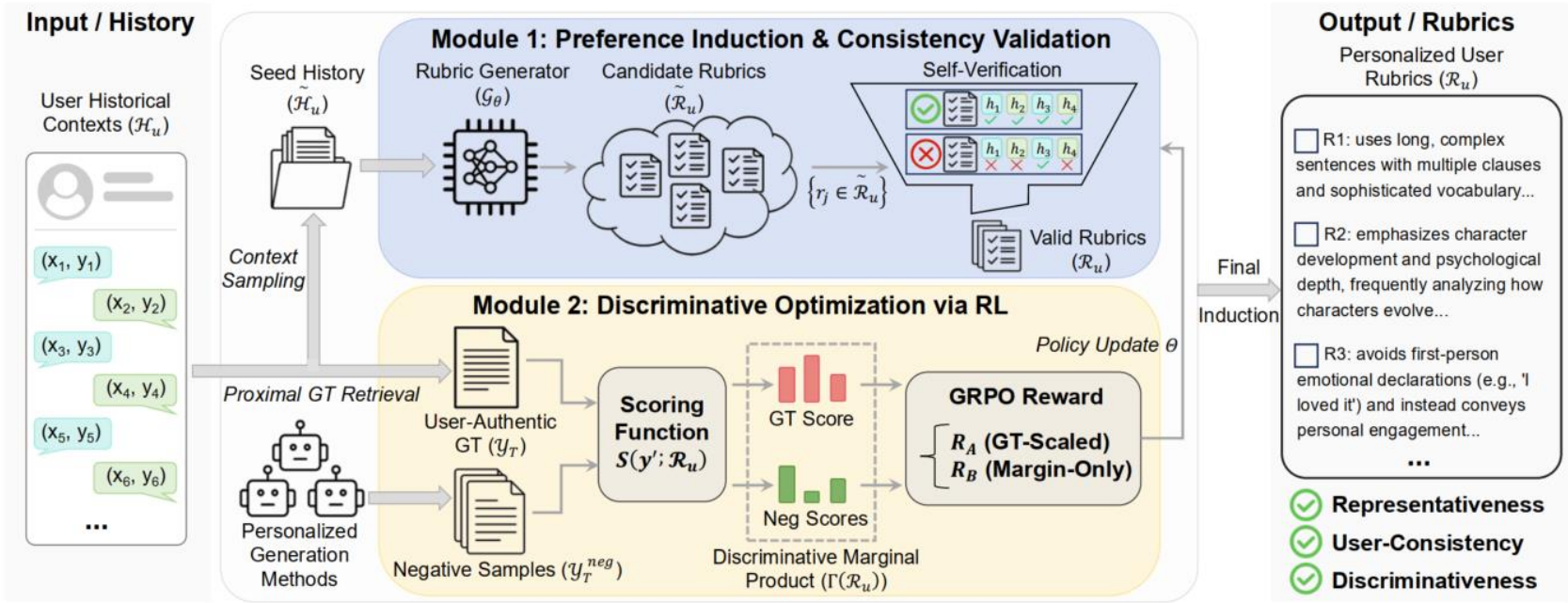
Rubric-based - # Work 2: Preference-Aware Rubric Learning

Motivation: Personalized evaluation requires adaptive, interpretable, and user-grounded criteria rather than fixed universal standards.



Personalized Evaluation as Learning

- Reformulates personalized evaluation as a learnable process
- user-specific criteria from historical behaviors

Preference-Aware Rubric Learning

- Learn multi-dimensional rubrics from raw user histories.

Discriminative Optimization via RL

- Optimize the rubric generator with an RL objective
- authentic responses against hard negative samples.

Qiu, Yilun, et al. Preference-Aware Rubric Learning for Personalized Evaluation. arXiv preprint arXiv:2605.31545 (2026).

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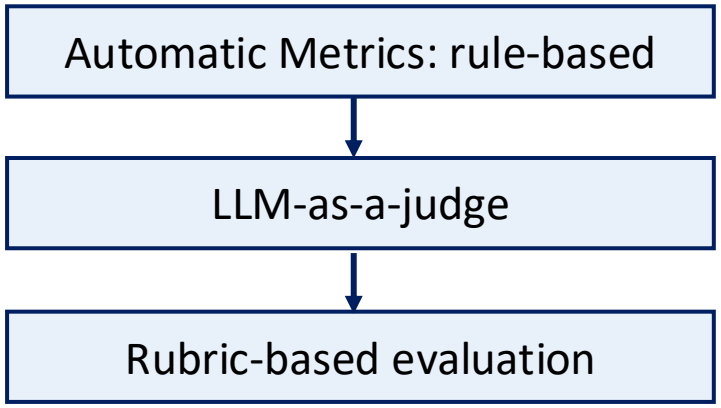

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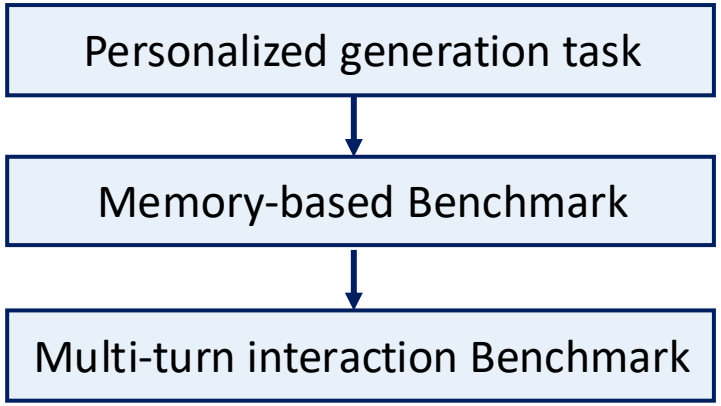

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Evaluation - Personalization Benchmarks

Goal of Personalization Evaluation

- Evaluate whether LLMs can generate responses aligned with individual users, not only generally correct outputs.

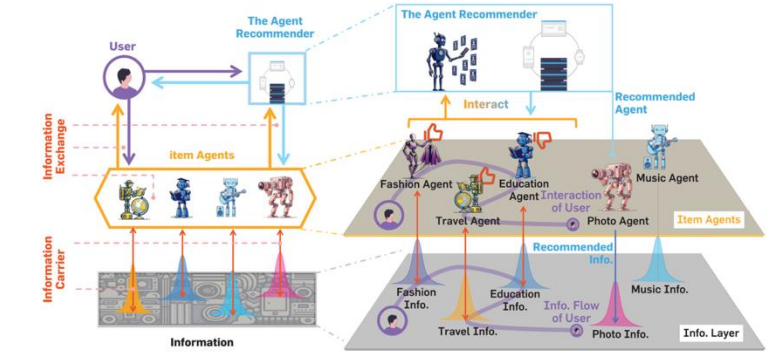
Key trend: personalization benchmarks are shifting from profile-conditioned tasks to interactive, memory-centered assistant scenarios.

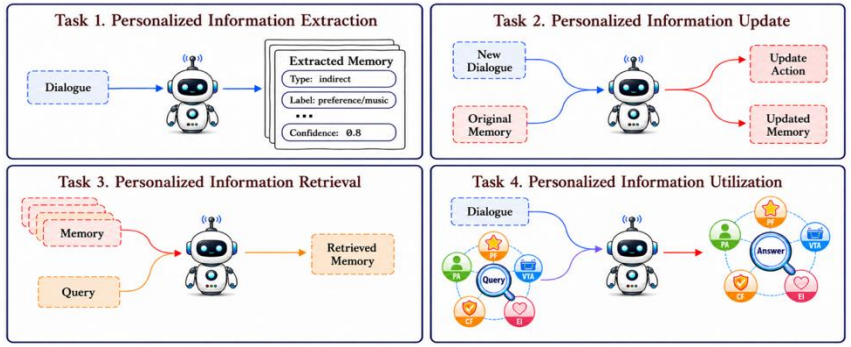
Critical Aspects

(1) Static personalization: using historical user profiles to support personalized classification and generation.

(2) Agentic personalization: recommending and interacting with LLM-based agents that can continuously understand users.

(3) Long-term personalization: extracting, updating, retrieving, and utilizing user memories across realistic interactions.





84

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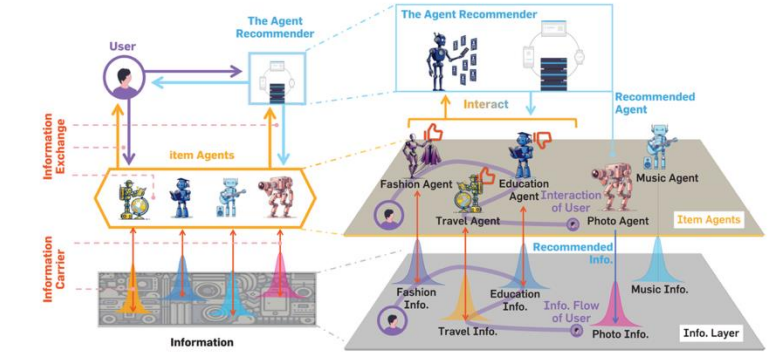
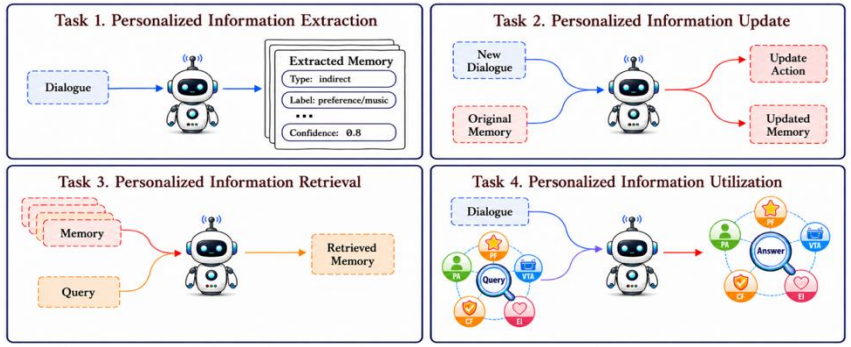




86

Static Generation - # Work 3: LaMP

Motivation:

- "one-size-fits-all" benchmark fail to consider user-specific context. However the LLMs eventually serve each different individual with preference. → **Need personalization benchmark.**

		FlanT5-base (fine-tuned)						
		Non-Personalized		Untuned profile, $k = 1$			Tuned profile	
Dataset	Metric	No-Retrieval	Random	Random	BM25	Contriever	IPA	FiD($k = 16$)
LaMP-1U: Personalized Citation Identification	Accuracy ↑	0.518	0.539	0.598	0.649	0.688	0.734	**0.754**
LaMP-2U: Personalized Movie Tagging	Accuracy ↑	0.468	0.442	0.497	0.524	0.536	0.556	**0.642**
	F1 ↑	0.435	0.403	0.459	0.480	0.506	0.519	**0.607**
LaMP-3U: Personalized Product Rating	MAE ↓	0.275	0.286	0.284	0.258	0.248	0.246	**0.236**
	RMSE ↓	0.581	0.607	0.602	0.573	0.563	0.565	**0.539**
LaMP-4U: Personalized News Headline Generation	ROUGE-1 ↑	0.153	0.159	0.162	0.167	0.173	**0.186**	0.180
	ROUGE-L ↑	0.140	0.147	0.148	0.153	0.159	**0.171**	0.166
LaMP-5U: Personalized Scholarly Title Generation	ROUGE-1 ↑	0.418	0.408	0.409	0.440	0.431	**0.450**	0.431
	ROUGE-L ↑	0.378	0.370	0.371	0.399	0.393	**0.409**	0.392
LaMP-6U: Personalized Email Subject Generation	ROUGE-1 ↑	0.379	0.473	0.486	0.586	0.572	**0.587**	0.567
	ROUGE-L ↑	0.358	0.457	0.470	0.570	0.558	**0.575**	0.555
LaMP-7U: Personalized Tweet Paraphrasing	ROUGE-1 ↑	0.509	0.510	0.514	0.521	0.524	**0.528**	0.517
	ROUGE-L ↑	0.455	0.457	0.460	0.468	0.471	**0.475**	0.464

LaMP: LLM Personalization Benchmark

- personalization as conditioning model outputs on a user profile
- introduces seven personalized tasks across text classification and text generation.

Diverse Personalization Scenarios

Retrieval-Augmented Personalized Generation improves performance

Salemi, Alireza, et al. Lamp: When large language models meet personalization. ACL 2024.

Evaluation - Personalization Benchmarks

Goal of Personalization Evaluation

- Evaluate whether LLMs can generate responses aligned with individual users, not only generally correct outputs.

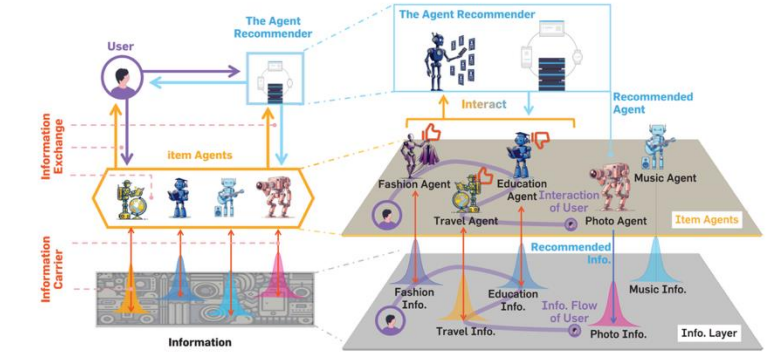
Key trend: personalization benchmarks are shifting from profile-conditioned tasks to interactive, memory-centered assistant scenarios.

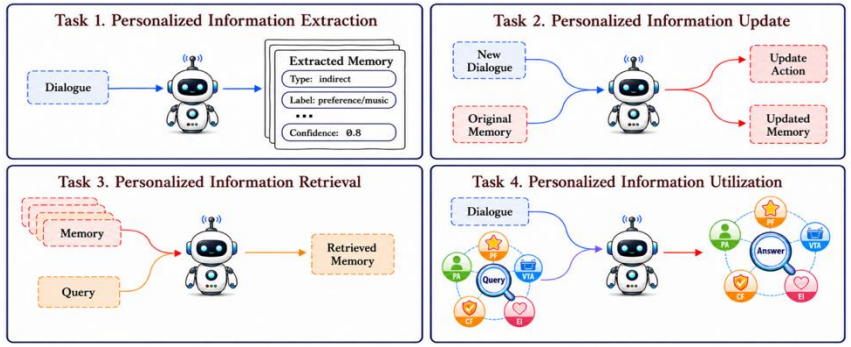
Critical Aspects

(1) Static personalization: using historical user profiles to support personalized classification and generation.

(2) Agentic personalization: recommending and interacting with LLM-based agents that can continuously understand users.

(3) Long-term personalization: extracting, updating, retrieving, and utilizing user memories across realistic interactions.



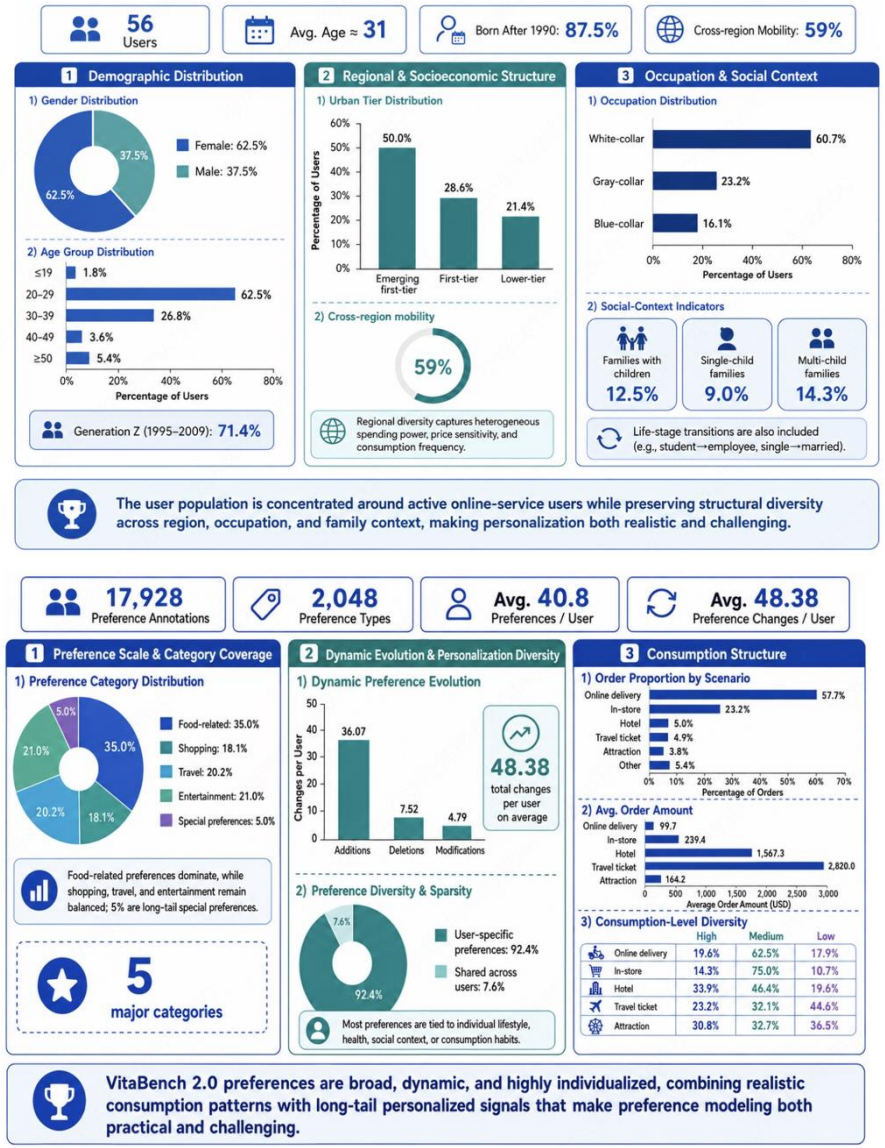


89

Agentic Benchmark – # Work: VitaBench 2.0

Motivation: effectively collaborate with real-world users is the next step of frontier agents. We benchmark the **personalization** and **proactiveness** ability of current agents.

- Effective collaboration depends on understanding the user beyond what is explicitly stated.
- We curate **56 users with over 2000 preferences**, inspired by real-world scenario.
- User intent is often reflected in fragmented daily interactions.
- We embed user preference in fragmented interactions, designing a series of tasks across time that require agents to **infer, utilize, and update user preference** to process.

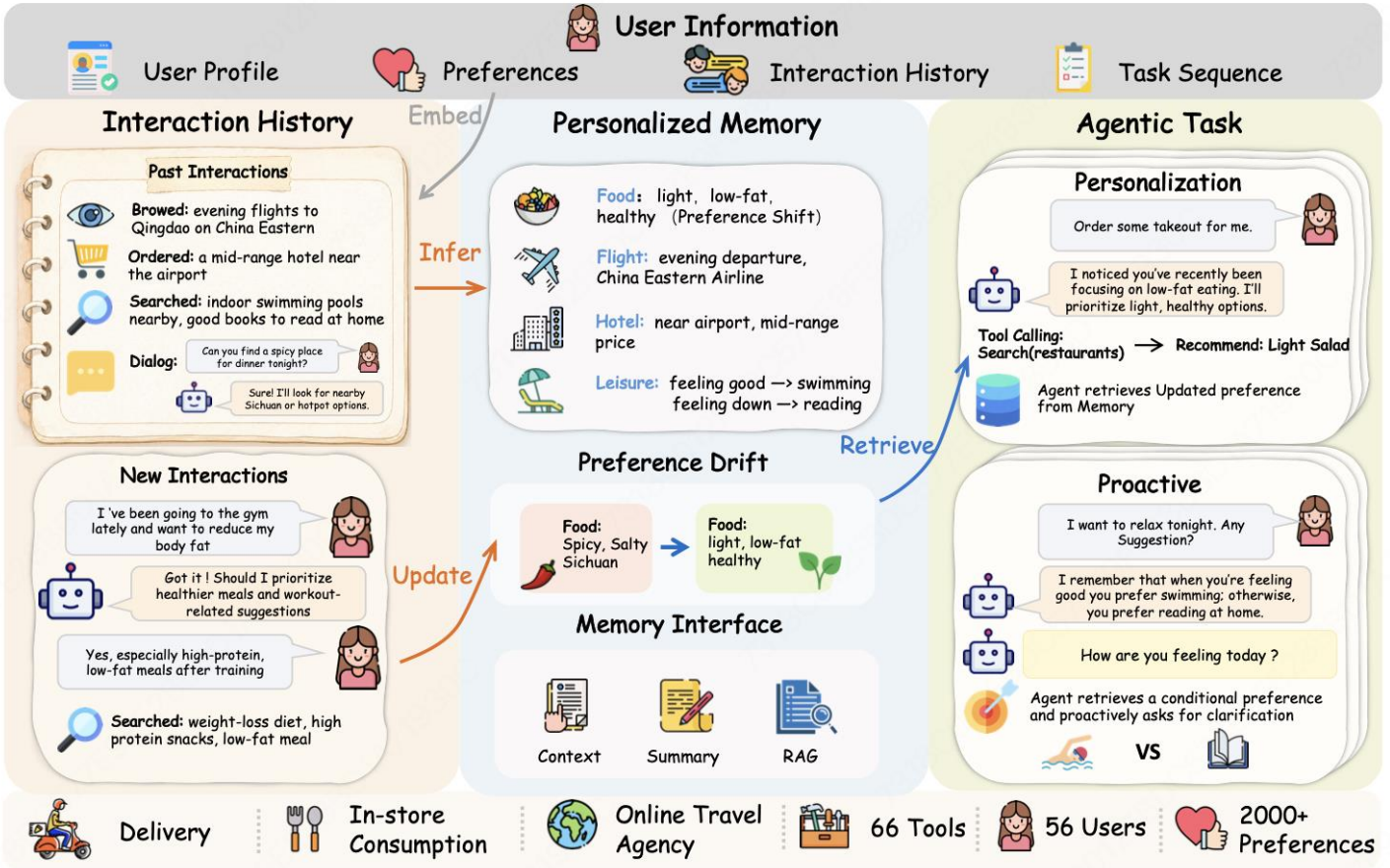


VitaBench 2.0: Evaluating Personalized and Proactive Agents in Long-Term User Interactions. Preprint.

Agentic Benchmark – # Work: VitaBench 2.0

Benchmark design

- Each user has a **task sequence spanning multiple domains over time**.
- Agents should use tools and interact with environments to handle each task.
- To succeed, agents need to **infer and leverage user preferences** from past interactions.
- As time progresses, new interactions are exposed to agents and reveal evolving preferences and potential **preference drift**.
- Agents are allowed to access a **memory module** to maintain and update user representations.

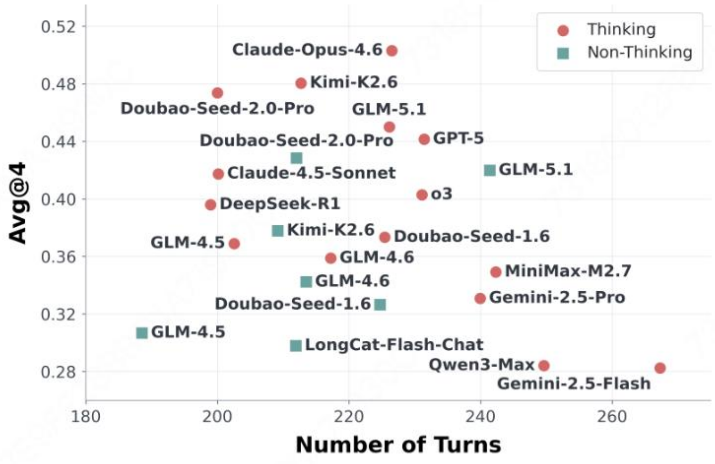


VitaBench 2.0: Evaluating Personalized and Proactive Agents in Long-Term User Interactions. Preprint.

Agentic Benchmark – # Work: VitaBench 2.0

We evaluate frontier open-source and proprietary LLMs under three memory settings

- **Real-world personalization tasks remain highly challenging for current agents.**
- **Memory mechanisms play a critical but under-explored role.**
- **General reasoning improvements do not always consistently translate to personalization gains.**



Models	Full Context			Agentic Memory			RAG Memory		
	Avg@4	Pass@4	Pass^4	Avg@4	Pass@4	Pass^4	Avg@4	Pass@4	Pass^4
Non-thinking Models									
GPT-4o-mini (w/o thinking)	0.067	0.180	0.006	0.084	0.229	0.008	0.094	0.227	0.011
GPT-3.5-Turbo (w/o thinking)	0.140	0.314	0.019	0.231	0.467	0.056	0.205	0.409	0.059
LongCat-Flash-Chat (w/o thinking)	0.298	0.510	0.123	0.302	0.537	0.105	0.290	0.471	0.136
GLM-4.5 (w/o thinking)	0.307	0.529	0.127	0.330	0.569	0.112	0.316	0.523	0.152
Doubao-Seed-1.6 (w/o thinking)	0.326	0.512	0.171	0.340	0.576	0.129	0.351	0.543	0.174
GLM-4.6 (w/o thinking)	0.342	0.612	0.113	0.336	0.623	0.084	0.317	0.555	0.123
Kimi-K2.6 (w/o thinking)	0.378	0.632	0.147	0.397	0.674	0.145	0.383	0.621	0.163
GLM-5.1 (w/o thinking)	0.420	0.654	0.204	0.423	0.664	0.182	0.383	0.585	0.200
Doubao-Seed-2.0-pro (w/o thinking)	0.428	0.649	0.218	0.426	0.665	0.198	0.406	0.625	0.208
DeepSeek-V4-Pro (w/o thinking)	0.456	0.652	0.267	0.427	0.658	0.207	0.424	0.618	0.247
Thinking Models									
o4-mini (w/ thinking)	0.210	0.433	0.047	0.270	0.533	0.073	0.261	0.452	0.091
Gemini-2.5-Flash (w/ thinking)	0.282	0.556	0.063	0.312	0.567	0.098	0.309	0.544	0.107
Qwen3-Max (w/ thinking)	0.284	0.499	0.105	0.324	0.599	0.091	0.315	0.519	0.134
Gemini-2.5-Pro (w/ thinking)	0.331	0.605	0.109	0.378	0.638	0.138	0.320	0.579	0.109
MiniMax-M2.7 (w/ thinking)	0.349	0.585	0.136	0.376	0.629	0.150	0.335	0.534	0.148
GLM-4.6 (w/ thinking)	0.359	0.612	0.116	0.351	0.625	0.107	0.336	0.574	0.135
GLM-4.5 (w/ thinking)	0.369	0.620	0.157	0.330	0.581	0.114	0.343	0.559	0.160
Doubao-Seed-1.6 (w/ thinking)	0.373	0.599	0.176	0.383	0.646	0.123	0.375	0.591	0.179
DeepSeek-R1-0528 (w/ thinking)	0.396	**0.691**	0.131	0.412	**0.712**	0.118	0.390	**0.643**	0.153
o3 (w/ thinking)	0.403	0.653	0.169	0.401	0.669	0.154	0.362	0.587	0.158
Claude-4.5-Sonnet (w/ thinking)	0.417	0.658	0.197	0.397	0.642	0.178	0.374	0.573	0.186
GPT-5 (w/ thinking)	0.441	0.658	0.226	0.421	0.647	0.204	0.410	0.591	0.236
GLM-5.1 (w/ thinking)	0.450	0.650	0.270	0.453	0.680	0.239	0.383	0.540	0.226
DeepSeek-V4-Pro (w/ thinking)	0.472	0.649	0.295	0.449	0.656	0.255	0.430	0.584	0.271
Doubao-Seed-2.0-pro (w/ thinking)	0.474	0.683	0.270	0.428	0.650	0.225	0.339	0.496	0.205
Kimi-K2.6 (w/ thinking)	0.481	0.685	0.266	0.450	0.696	0.223	**0.434**	0.611	0.253
Claude-Opus-4.6 (w/ thinking)	**0.503**	0.664	**0.337**	**0.454**	0.645	**0.259**	0.430	0.566	**0.299**

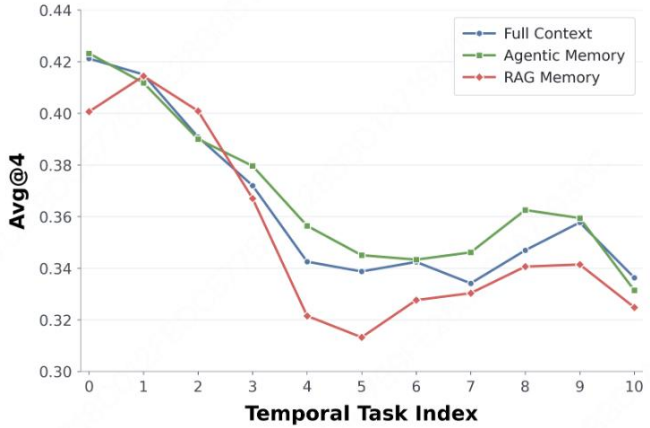
92

VitaBench 2.0: Evaluating Personalized and Proactive Agents in Long-Term User Interactions. Preprint.

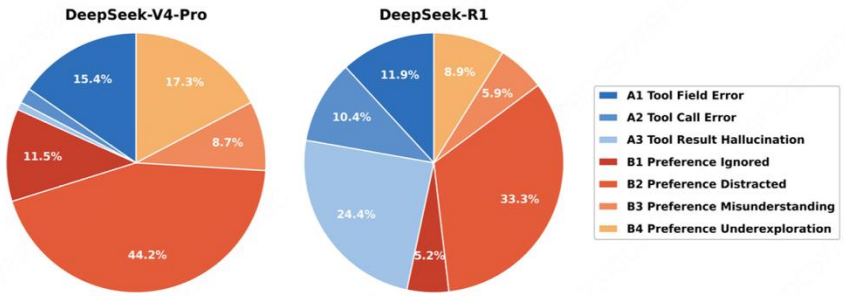
Agentic Benchmark – # Work: VitaBench 2.0

We evaluate frontier open-source and proprietary LLMs under three memory settings

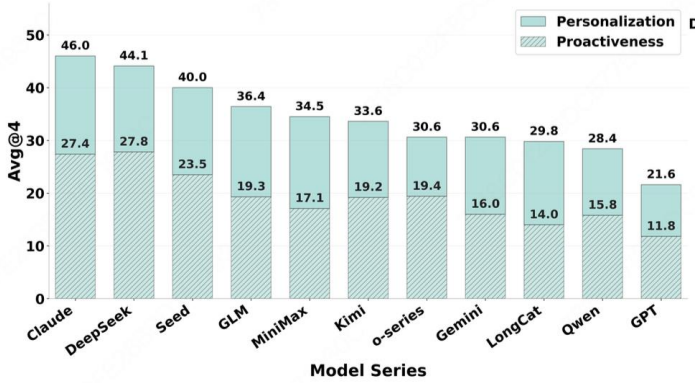
- **Accumulated user interactions pose a challenge.**



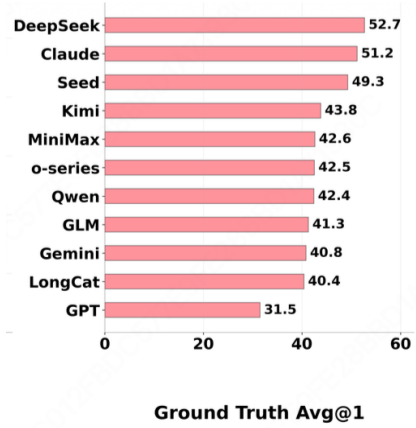
- **Failure pattern analysis shows that personalization emerges as the new primary bottleneck for SOTA models.**



- **Current agents struggle to recognize missing information.**



- **Given preferences, leveraging them is challenging.**



VitaBench 2.0: Evaluating Personalized and Proactive Agents in Long-Term User Interactions. Preprint.

Long-term Personalized Evaluation: Memory-centered benchmark

From One-shot Personalization to Long-term Agent Evaluation

Evaluation should go beyond final response quality and consider the full process of interaction, memory, reasoning, and judgement.

Key shift: from “Does the output match a reference?” to “Can the agent learn, remember, reason, and evaluate over time?”

***The key lies in memory*.**

94

Evaluation - Personalization Benchmarks

Goal of Personalization Evaluation

- Evaluate whether LLMs can generate responses aligned with individual users, not only generally correct outputs.

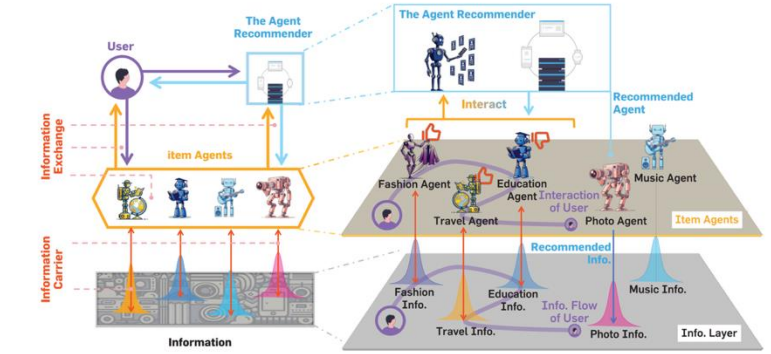
Key trend: personalization benchmarks are shifting from profile-conditioned tasks to interactive, memory-centered assistant scenarios.

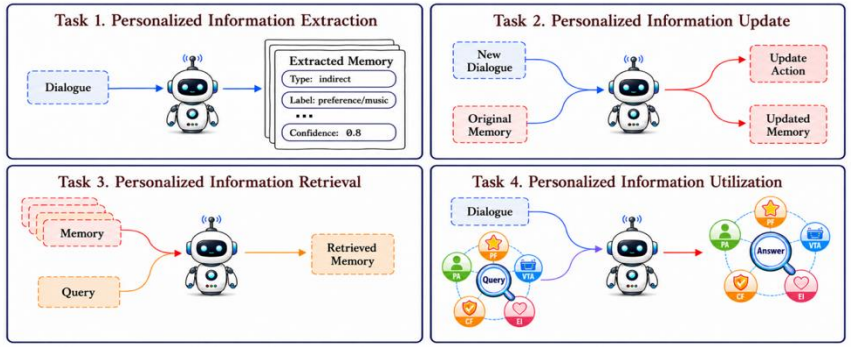
Critical Aspects

(1) Static personalization: using historical user profiles to support personalized classification and generation.

(2) Agentic personalization: recommending and interacting with LLM-based agents that can continuously understand users.

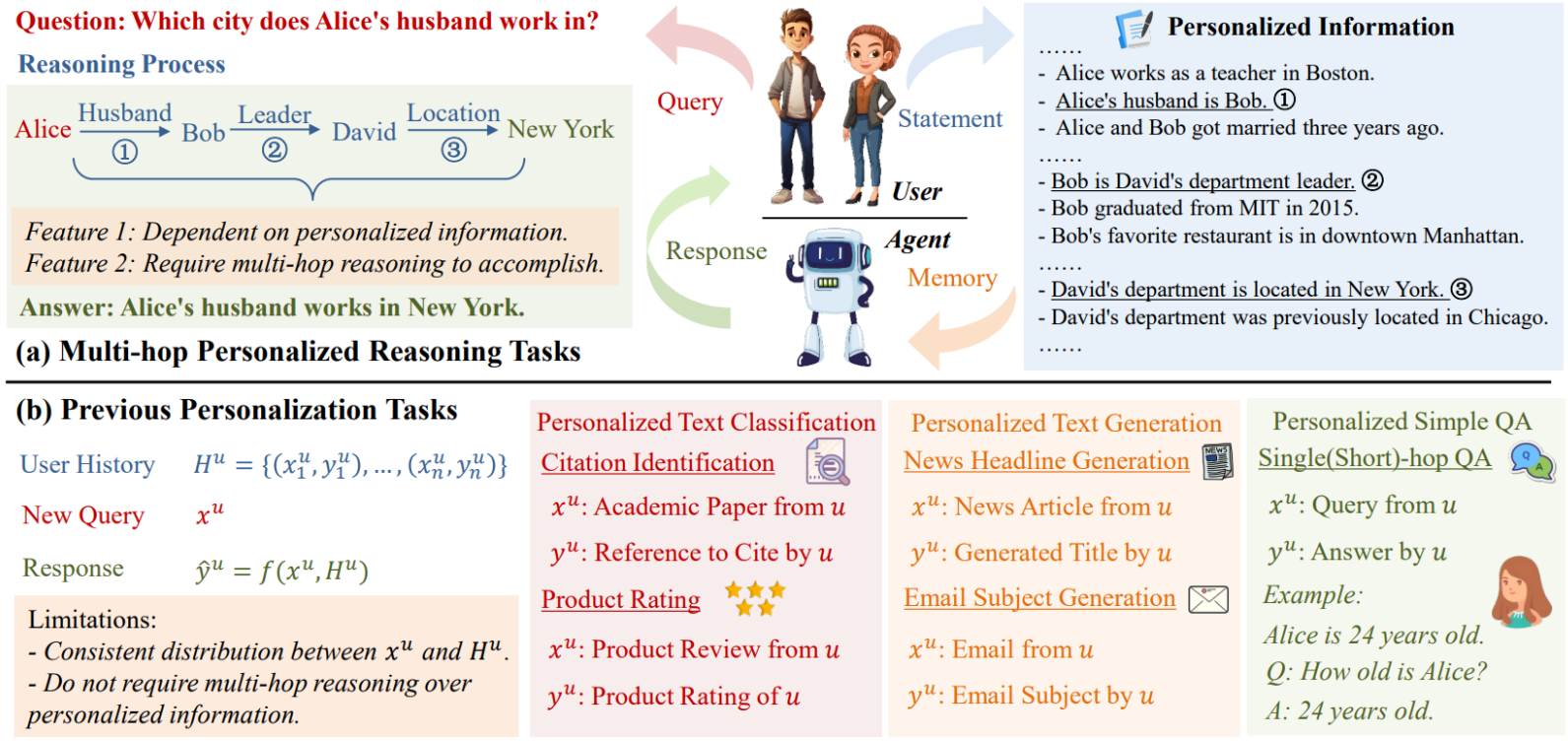
(3) Long-term personalization: extracting, updating, retrieving, and utilizing user memories across realistic interactions.





95

Memory-centered Benchmark - # Work 4 Exploring Multi-hop Complex Personalized Reasoning



Multi-hop Personalized Reasoning Task

(1) ***Personalized***: Tasks must be accomplished based on given personalized information and cannot be accomplished solely through general knowledge.

(2) ***Multi-hop Reasoning***: Tasks can not be directly accomplished with a single piece of personalized information, but require multi-hop reasoning on several pieces.

Differences with previous tasks.

(1) ***Distribution shifts*** between training & testing.

(2) ***Massive*** personalized information for reasoning.

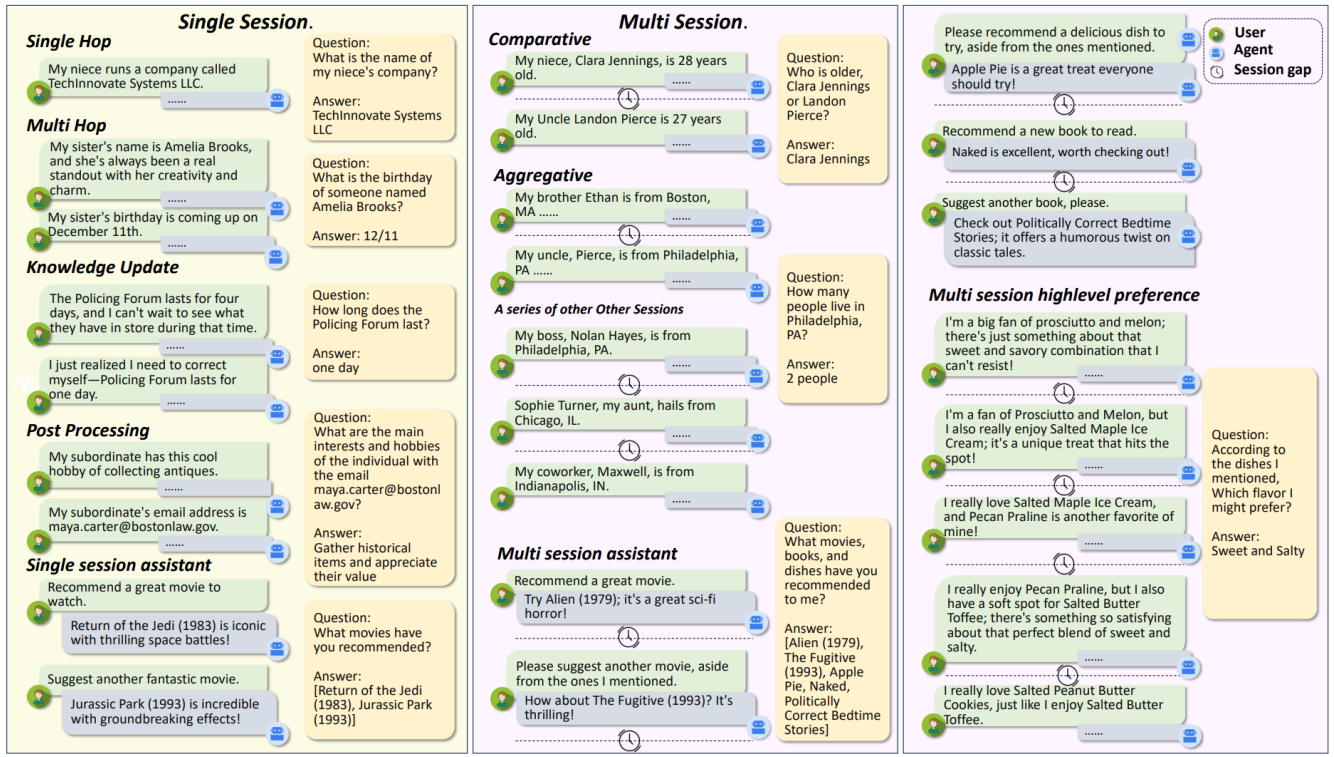
(3) Focus on ***factual information*** rather than preference.

Motivation: Evaluate explicit (textual) memory and implicit (parametric) memory on multi-hop personalized reasoning (MPR) tasks.

Major Contributions: (1) Formally define MPR tasks and generate datasets for evaluation. (2) Extensive experiments for exploration and analysis.

Zhang, Zeyu, et al. Explicit vs implicit memory: Exploring multi-hop complex reasoning over personalized information. SIGKDD 2026.

Memory-centered Benchmark - # Work 5: Comprehensive Memory Evaluation (MemBench)



Motivation: Construct more comprehensive evaluation on agent memory, including multi-level memory content, multi-scenario dataset, and multi-metric evaluation.

Haoran Tan, Zeyu Zhang, et al. Membench: Towards more comprehensive evaluation on the memory of llm-based agents. ACL 2025 (findings).

Multi-level Memory Content

Factual Memory: Specific factual attributes of the users or their entities.

Reflective Memory: Extraction of high-level preferences based on the user's expression of low-level preferences.

Multi-scenario Dataset

Participation Memory Scenario: Represented by the dialogue between the user and the agent, which is the agent's typical usage scenario.

Observation Memory Scenario: Represented by the flow of message input from users to agents.

Multi-metric Evaluation

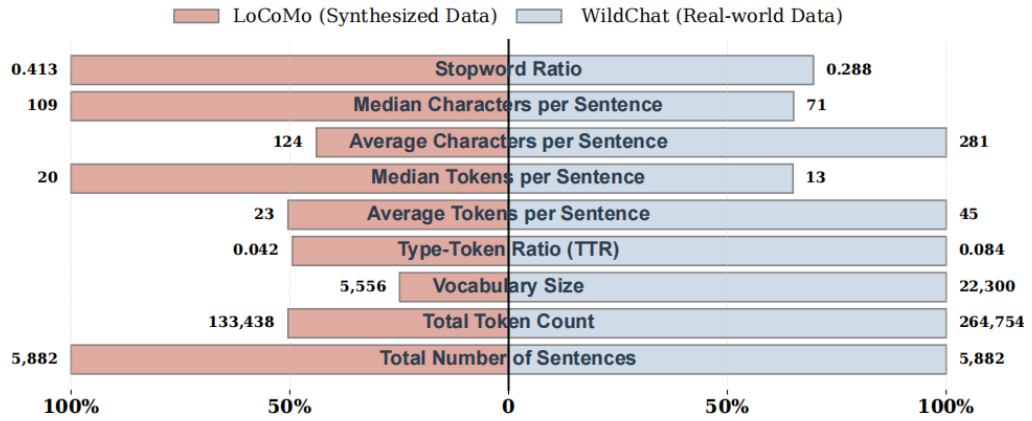
+ Memory Capacity: The threshold with a sharp accuracy decline when the amount of memory content reaches a certain point

Memory-centered Benchmark - Work #4 AlpsBench

Challenge 1:
Real-world dialogues exhibit greater lexical richness and substantially more complex discourse patterns than LLM-synthesized conversations.

Challenge 2:
Personalization signals are often conveyed implicitly in real-world interactions.

Synthetic vs. Real-World Data Distributions



Synthetic vs. Real-World Examples

Explicit Expressions in Synthesized Data	Implicit Expressions in Real-world Data
I like also cheese pizza and prosciutto.	I can't be friends with someone who doesn't eat cheese pizza. Seriously.
I'm a big fan of sci-fi and fantasy books.	Are there any bookstores in LA that specialize in science fiction novels?

Implication: Overly explicit synthetic dialogues obscure latent preferences and limit real-world generalization.

Jianfei Xiao et al. AlpsBench: An LLM Personalization Benchmark for Real-Dialogue Memorization and Preference Alignment. SIGIR, 2026

Memory-centered Benchmark - Work #4 AlpsBench

Challenge 3:

- **Benchmarks test isolated stages (e.g., extraction or response generation)**
- **not the end-to-end flow: Extraction → Updating → Retrieval→ Usage**

Benchmark Comparison

Benchmark	Real	T1	T2	T3	T4: Utilization Dimensions				
		Ext.	Upd.	Retr.	PA	PF	VRA	CF	EI
LaMP	●	○	○	○	◐	◐	○	○	○
PersonalLLM	○	○	○	○	◐	●	○	○	○
EQ-Bench	○	○	○	○	○	○	○	○	●
PersoBench	○	○	○	○	●	●	○	●	○
PersonaFeedback	○	○	○	○	●	●	○	●	○
LoCoMo	○	◐	○	●	◐	○	○	○	○
LongMemEval	○	●	●	●	◐	○	○	○	○
PersonaLens	○	○	○	◐	●	●	○	●	○
HaluMem	○	●	●	◐	◐	○	○	○	○
PersonaMem v2	○	●	●	◐	●	●	○	○	○
AlpsBench	●	●	●	●	●	●	●	●	●

Category: Memory-free Preference Alignment, Memory-aware Preference Alignment, Ours.
●: Fully Supported / Real Data, ◐: Partially Supported, ○: Not Supported / Synthetic Data.
Ext. = Memory Extraction, **Upd.** = Memory Updating, **Retr.** = Memory Retrieval, **PA** = Persona Awareness, **PF** = Preference Following, **VRA** = Virtual-Reality Awareness. **CF** = Constraint Following. **EI** = Emotional Intelligence.

Real dialogues: Built from authentic human–LLM interactions, mitigating the synthetic-to-real distribution gap.

Full process evaluation: Evaluates the full memory pipeline: **extraction → updating → retrieval → use,** better reflecting personalized interaction in real-world settings

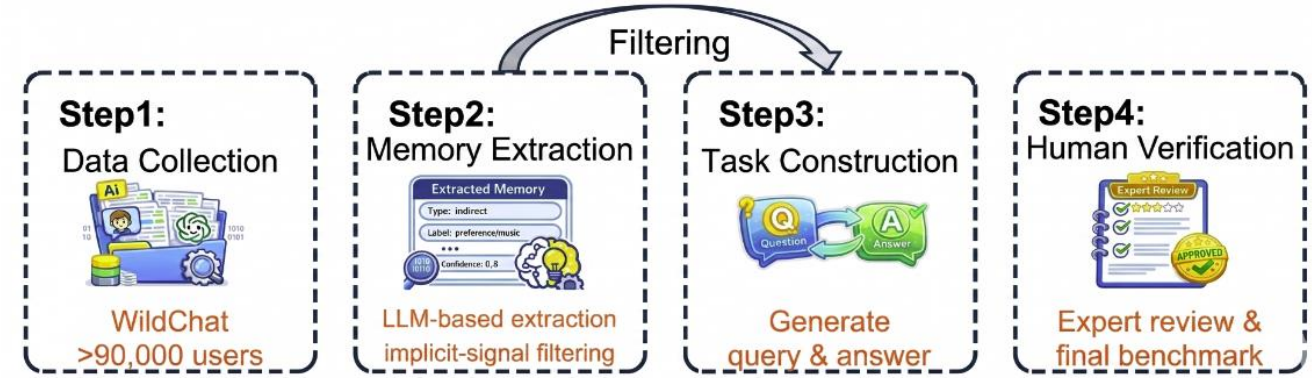
Reliable evaluation: Human verification establishes ground truth and validates LLM-as-a-Judge alignment.

Jianfei Xiao et al. AlpsBench: An LLM Personalization Benchmark for Real-Dialogue Memorization and Preference Alignment. SIGIR, 2026

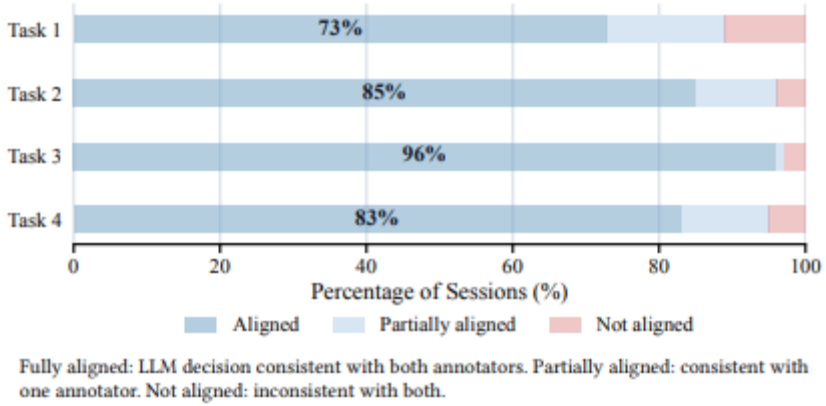
Memory-centered Benchmark - Work #4 AlpsBench

WorkFlow:

Collect dialogues → Extract structured memories → Construct tasks → Verify quality



Four-step Curation Pipeline



Fully aligned: LLM decision consistent with both annotators. Partially aligned: consistent with one annotator. Not aligned: inconsistent with both.

LLM-As-a-Judge Alignment with Human Verification

Data source:
Alpsbench curates 2,500 high-quality WildChat interaction sequences with at least six turns.(Wildchat -- a real human-LLM dataset)

Task suite:
Personalized information extraction, updating, retrieval, and utilization.

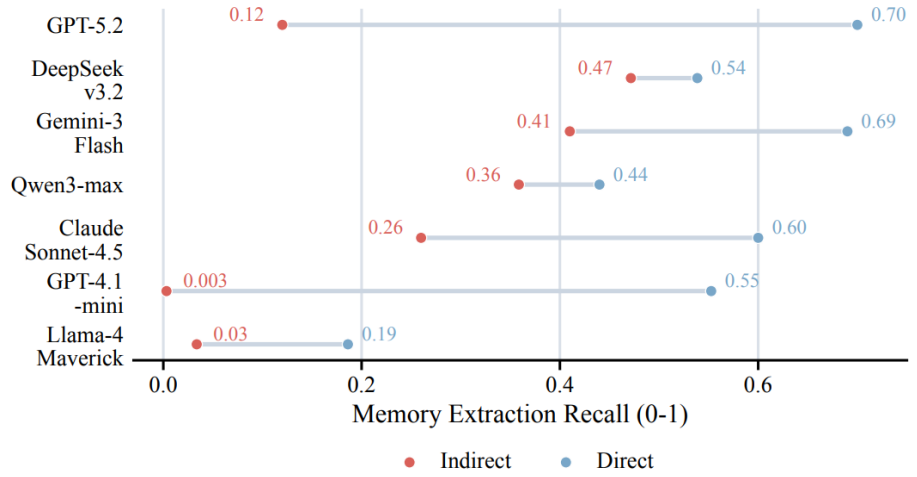
Human validation:
LLM-as-a-Judge alignment reaches 73%, 85%, 96%, and 83% on Tasks 1–4.

Jianfei Xiao et al. AlpsBench: An LLM Personalization Benchmark for Real-Dialogue Memorization and Preference Alignment. SIGIR, 2026

Memory-centered Benchmark - Work #4 AlpsBench

Finding 1: Implicit Information Is Hard to Extract

Finding 2: retrieval accuracy degrades substantially in the presence of large distractor sets



Finding 3: memory updating reaches a performance plateau even for the strongest models

Table 2: Tasks 1–4. Experimental evaluation results of general-purpose LLMs.

Model	Task 1 Extraction	Task 2 Update	Task 3 Retrieval					Task 4 Utilization						
			Number of Distractor Memories					PA	PF		VRA	CF	EI	
			100	300	500	700	1000		Gen.	Int.			EN	CN
GPT-5.2	0.6720	**0.7793**	0.9519	0.9400	0.9249	0.9138	0.8945	0.5684	0.7043	**0.7680**	0.6640	0.9083	3.42	3.90
GPT-4.1-mini	0.5373	0.6214	0.9110	0.8578	0.8134	0.8010	0.7700	0.4112	0.5012	0.5240	0.2600	0.7896	2.79	2.92
DeepSeek-v3.2	**0.6742**	0.7543	**0.9728**	**0.9687**	**0.9606**	0.9333	**0.9495**	0.5912	0.6499	0.6120	0.3540	**0.9419**	3.66	**4.00**
Gemini-3 Flash	0.6487	0.7686	0.9642	0.9585	0.9484	**0.9427**	0.9440	**0.6889**	**0.7524**	0.7052	0.3000	0.8328	3.49	3.58
Llama-4 Maverick	0.3772	0.6824	0.8958	0.6290	0.5849	0.5531	0.5275	0.2789	0.1820	0.3080	0.7340	0.8506	2.48	2.38
Claude-Sonnet-4.5	0.6541	0.7543	0.9691	0.9258	0.9437	0.9184	0.9048	0.5649	0.5828	0.5498	**0.8360**	0.9271	3.10	3.05
Qwen3-max	0.6570	0.7190	0.9402	0.8986	0.8671	0.8216	0.7943	0.6246	0.6981	0.6574	0.4060	0.8267	**3.68**	3.84

Task 1/2: semantic-matching F1. **Task 3**: recall under each distractor-memory setting. **Task 4**: binary scores for PA/PF/VRA/CF and 1–5 scores for EI. **PA** = Persona Awareness, **PF** = Preference Following, **VRA** = Virtual-Reality Awareness, **CF** = Constraint Following, **EI** = Emotional Intelligence.

Full Results Leaderboard:
https://misshsiaoo.github.io/Alps_Bench/

Jianfei Xiao et al. AlpsBench: An LLM Personalization Benchmark for Real-Dialogue Memorization and Preference Alignment. SIGIR, 2026 | Full results: https://misshsiaoo.github.io/Alps_Bench/

Evaluation - Summary

- Personalization benchmarks are evolving from **static** user-profile tasks to **long-term, interactive agent scenarios**.
- Core abilities include profile retrieval, preference alignment, memory extraction, memory updating, memory retrieval, and memory utilization.
- Longitudinal evaluation further requires process-level verification, user-specific judging criteria, multi-hop personalized reasoning, and memory capacity analysis.
- Current LLMs still **struggle** with **implicit preference** extraction, **scalable memory** retrieval, **robust** memory updating, and faithful personalized reasoning.

Future direction:

- build personalized agents that can continuously learn, remember, reason, and evaluate themselves in real-world user interactions.
- *Evaluation for evaluation*: How to evaluate the evaluation methods?

Outline

- 1. Introduction (Yang)
- 2. Technique foundations of personalization (Xiaoyan & Xinyu)
- 3. Benchmarks & Evaluation (Xinyu Lin)
- **4. New directions beyond memory and alignment (Yang)**
  - **User world model**
  - **Lifelong learning**
  - **Trustworthy**
  - **Science of the LLM personalization**
- 5. Applications (Chongming)
- 6. Conclusion (Chongming)

New Directions

D1- User World Model & Foundation Model

- **The model all about the user**
- **Help personalized decision**
- **Simulation**

D2 - Lifelong Personalization

- **Long-horizon:** Lifelong personalziation

D3 - Trustworthiness

- Privacy
- Fairness

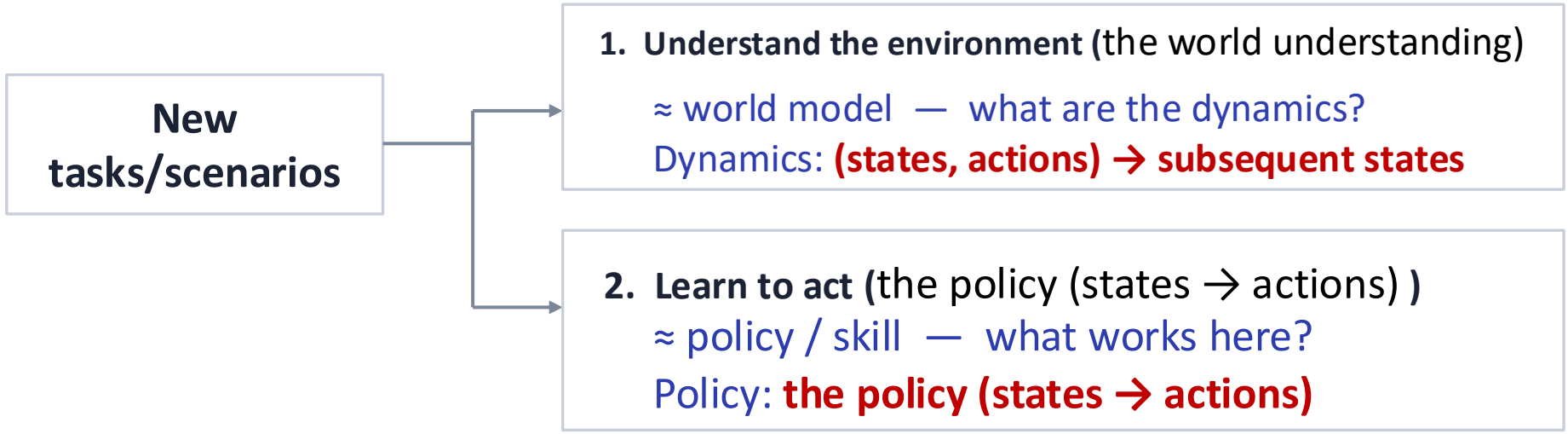
D4 - Science of Personalization

- The mechanistic process of how personalization is realized within the model

New Direction 1: User world/foundation model

How to perform well under a (new) scenarios?

Drop an agent into an unfamiliar task/scenarios. Two things have to happen.



What important is not only about policy learning but also the world modeling

Qwen team. Qwen-AgentWorld: Language World Models for General Agents. 2026.06.

New Direction 1: User world/foundation model

Personalization can be view as the User-Level World Modeling

Same two parts — but the “environment” is the user.

Understand the environment (the world understanding)
model the world's dynamics
→ **User Model (world modeling of the user)**
the world model of user, in the first person

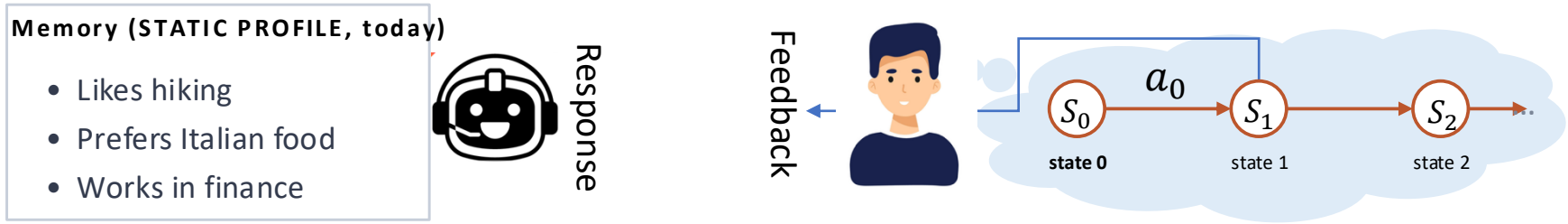
Learn to act (the policy (states → actions) **)**
find what align with the user
→ **Adapt to this user**
personalized behavior

This motivates us consider user world modeling…

New Direction 1: User world/foundation model

The Gaps in Today's Approach

Current methods do this — but only implicitly and partially, and from the assistant's side.



- Current approaches learn who the user is, but not how the user changes and how the user behaves
  - Representation gap: They build user profiles rather than modeling user dynamics.
  - Perspective gap: They describe the user from a third-person viewpoint rather than modeling the user's world from a first-person perspective.

So current method like memory-based method don‘t add up to a real user world model.

New Direction 1: User world/foundation model

- What do user world models bring

  Capabilities you can't get from a profile and sparse feedback alone.

  - **Anticipation** predict how the user will react before acting, then help choose better actions
  - **Counterfactual reasoning & simulation** simulate “what if the model respond this way?”

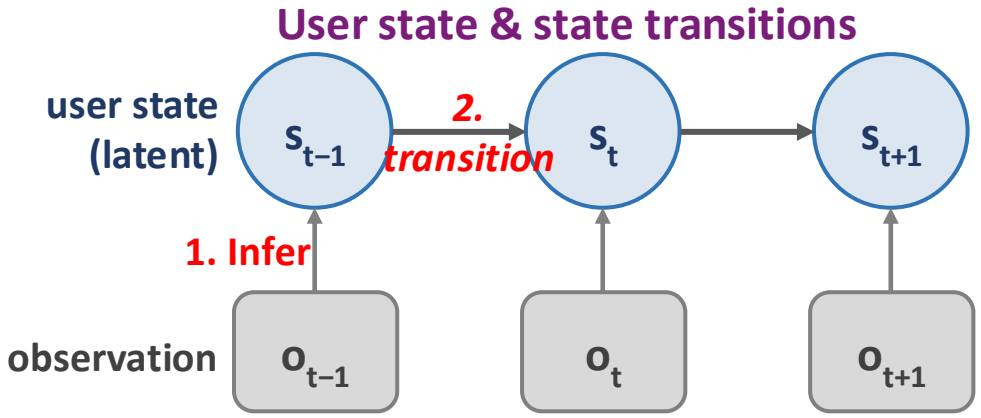
New Direction 1: User world/foundation model

- **One implementation for this: user-state modeling - PUMA**

Modeling perspective

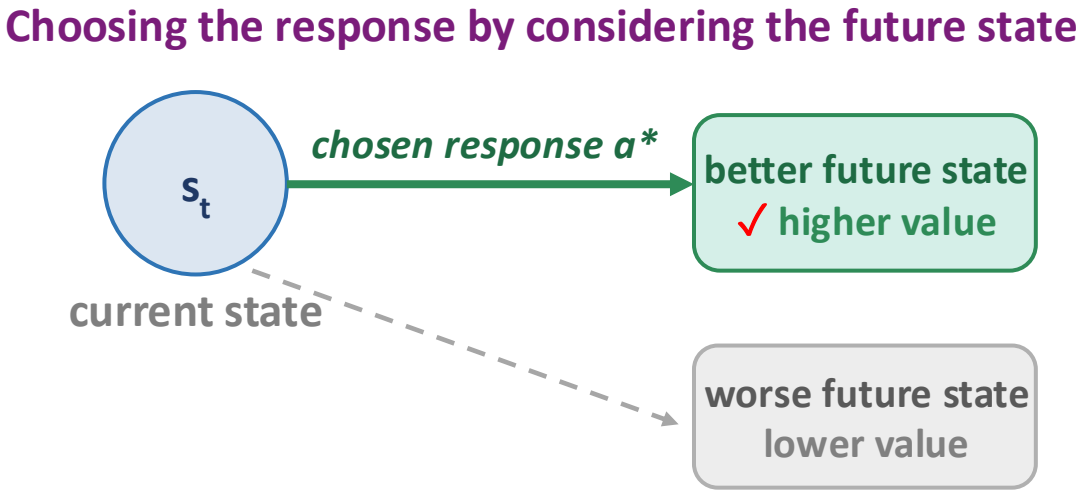
1. Explicitly infer the **user's (underline) state** from observations and behavioral signals.

2. Model the **state transitions**, capture how the user's state evolves over time.



Enhancing the interaction decision

3. When generating a response, explicitly leverage the state model to **choose the action** that leads to a better future state.

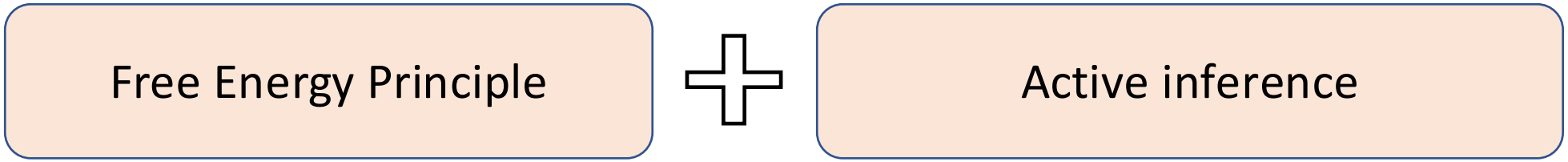


Luo Jiani et al. Know You Before You Speak: User-State Modeling for LLM Personalization in Multi-Turn Conversation. 2026.05.

New Direction 1: User world/foundation model

- **One implementation for this: user-state modeling - PUMA**

  Optimization of the state transition modeling and action selection



  - Grounded in neuroscience theories of perception and action.
  - Model the user as a partially observable system with evolving **internal states**.
  - Based on the state model, the agent selects responses by balancing:
    - Epistemic value: **reducing uncertainty about the user**
    - Pragmatic value: **guiding the user toward desired outcomes**

  The agent doesn‘t just answer the user’s question. It first infers the user's hidden state, then acts to both understand and help.

Luo Jiani et al. Know You Before You Speak: User-State Modeling for LLM Personalization in Multi-Turn Conversation. 2026.05.

New Direction 1: User world/foundation model

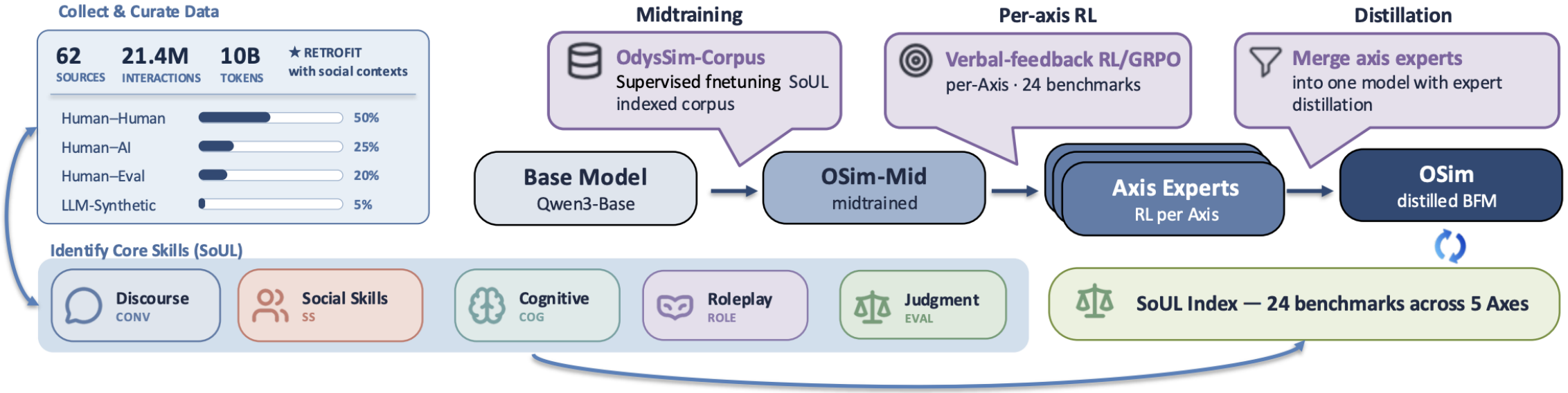
- **Another direction: User foundation model**

  Train a foundation model to predict how would the user behave/change

  One work: ODYSSIM

  Core: mid-/post-training with user behavior data

  next behavior prediction



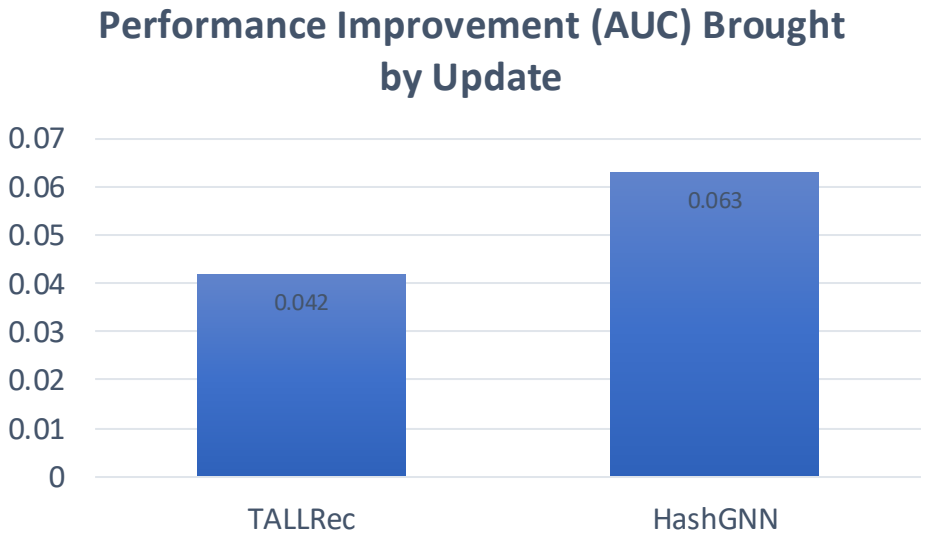
Xuhui Zho et al. ODYSSIM Building Foundation Models for Human Behavior Simulation. 2026.06.

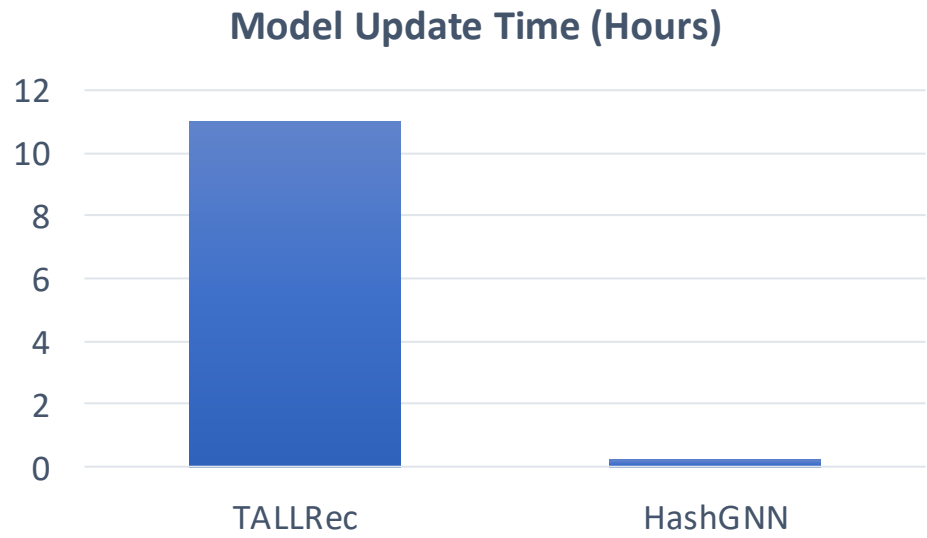
New Direction 2: Lifelong Personalization

- Users drift with time going, and the environment also drifts with time going (for example, new version of model)
- Two directions
  - Capture new preferences (data always coming, continual learning)
  - Adapt to environment drift (new version of model)

New Direction 2: Capture new preference

Periodical update is one effective method, but the cost is not acceptable





😄**Updating personalized LLM can yield meaningful improvements**

😭 **However, updating personalzied LLM takes 70 times longer**

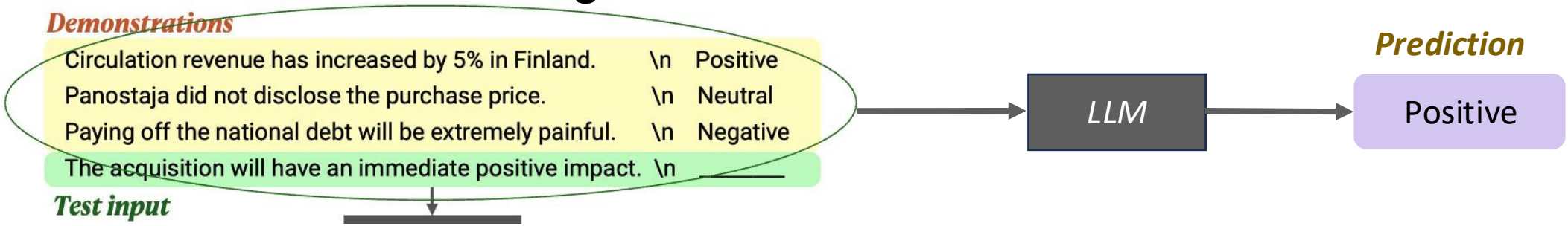
Deploy LLM-based methods in real-world scenarios? Rejected!

Can we capture the new interest for LLMs without retraining?

Bao et al. Real-Time Personalization for LLM-based Recommendation with Customized In-Context Learning. *ACL 25.*

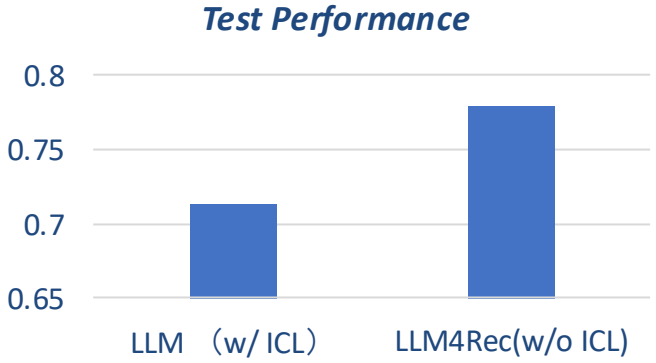
New Direction 2: Capture new preference

One solution: in-context learning



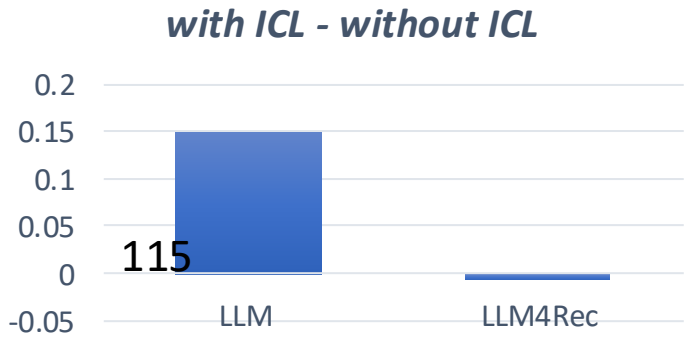
Learn to do a downstream task by conditioning on input-output examples without model update!

- **Original LLMs have ICL abilities but are not train for Personalization--- suboptimal**



Goal: Adapt to personalization task while keep ICL abilities

- **Personalzied model has been adapted for Personalization tasks but loses the ICL capability**

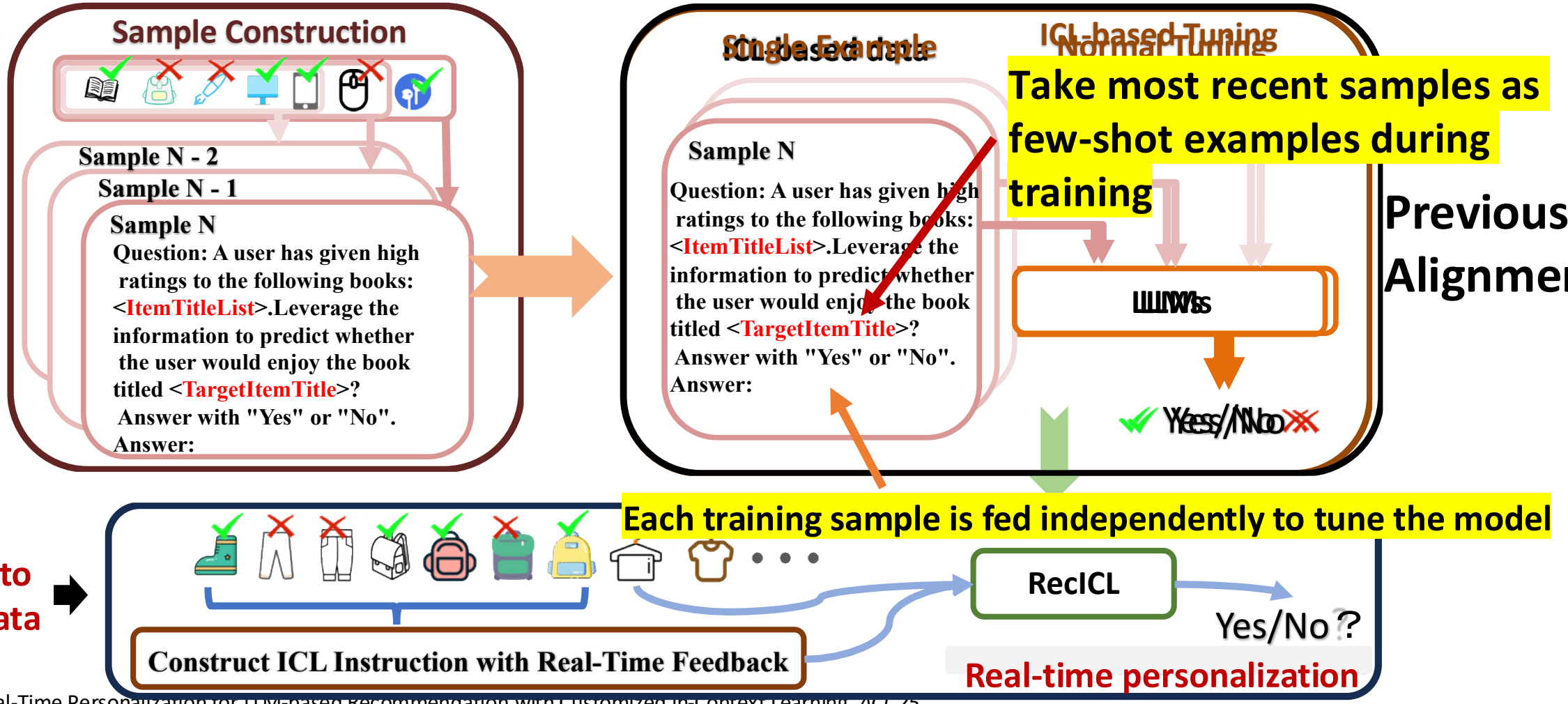


Bao et al. Real-Time Personalization for LLM-based Recommendation with Customized In-Context Learning. *ACL 25.*

New Direction 2: Capture new preference

Perform preference alignment in an ICL-tuning manner

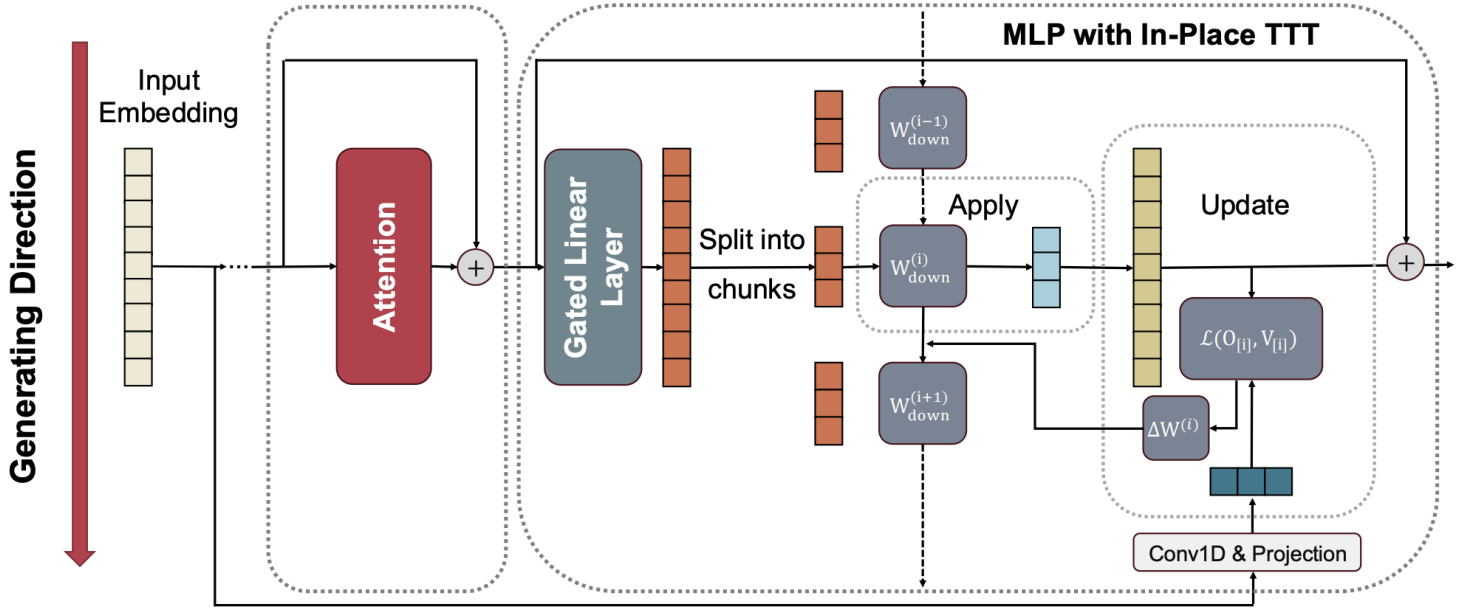
- Align to personalized tasks while preserving the ICL capability



Bao et al. Real-Time Personalization for LLM-based Recommendation with Customized In-Context Learning. *ACL 25.*

New Direction 2: capture new preference

- One promising direction: Test-time training (TTT)
- When new data coming in prompt, make the model directly capture the new preference
- Example: In-place TTT (add some fast weight to learn new data at test-time)

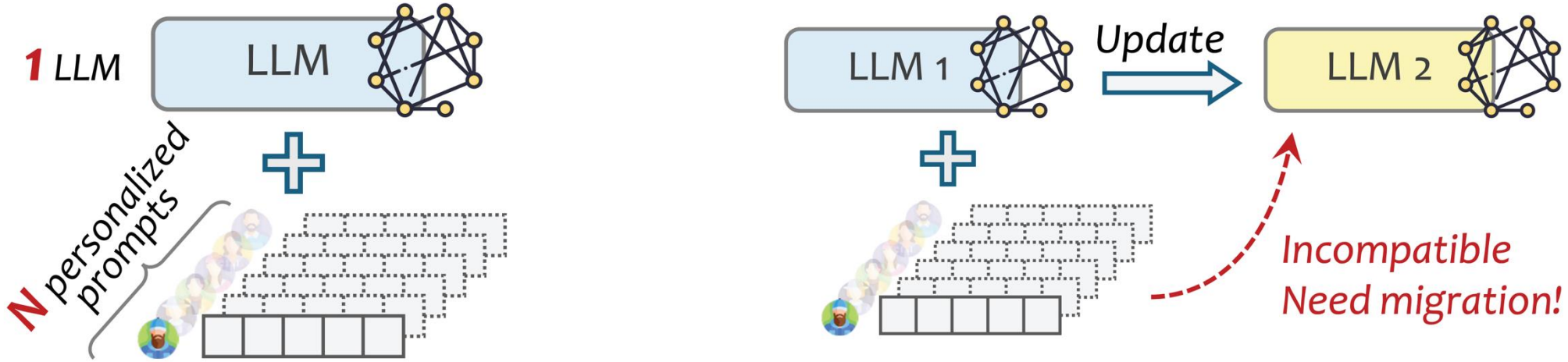


Fast weight to learn new data

Guhao Feng et al. In-Place Test-Time Training. 2026.04.

New Direction 2: Adapt to new model version (environment)

- When the base model changes or updated, we need to transfer the already learned user knowledge (mainly memory) to the new one
- Explicit memory: it is relatively easy, one the the memory obey the same "standards" or say the same "Protocol"
- Implicit memory: it is hard

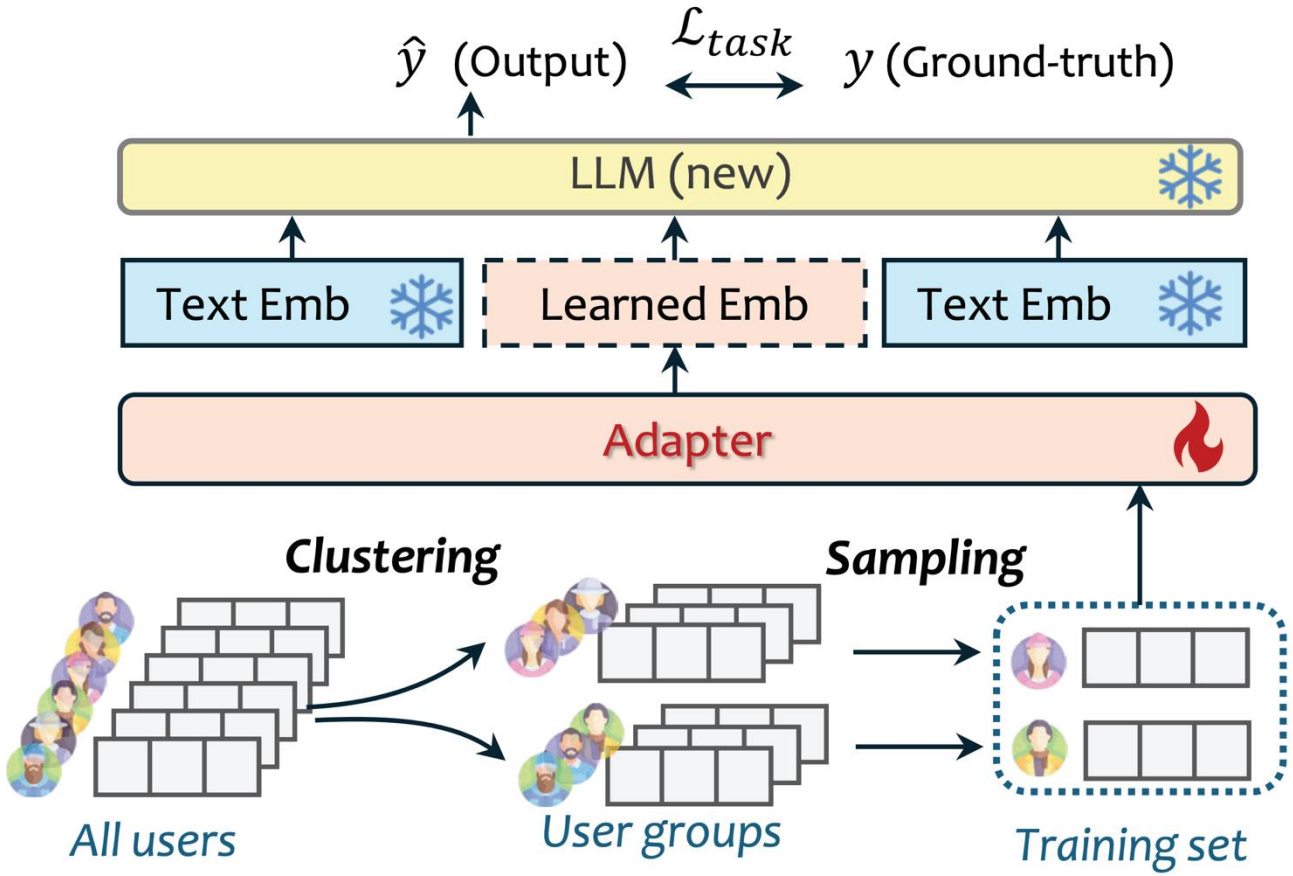


it is **tightly coupled** with the base model.

Ziyi Zhao et al. Don't Start Over: A Cost-Effective Framework for Migrating Personalized Prompts Between LLMs. AAAI, 2026

New Direction 2: Adapt to new model version (environment)

Key idea: instead of retraining user memory, train a **cross-model adapter**.



Transfer key: aligning semantic spaces.

Technical implementation: lightweight Adapter + user clustering.

- Freeze old user memories and the new LLM, and train a lightweight Adapter: $p'_u = \Phi_\theta(\mathrm{p_u})$
- **Training data**: cluster user vectors into groups, then sample a training set to reduce full-scale cost.
- **Training signal**: train the Adapter end-to-end with downstream personalized task loss.

Ziyi Zhao et al. Don't Start Over: A Cost-Effective Framework for Migrating Personalized Prompts Between LLMs. AAAI, 2026

New Direction 3 - Trustworthy

- To make the personalized model really deployed, we must consider the trustworthy issues
- Here, we introduce two core focus

Privacy

Personalization should be achieved without exposing user privacy (e.g., demographic attributes).

Fairness

Minority users are equally important for preference modelling.

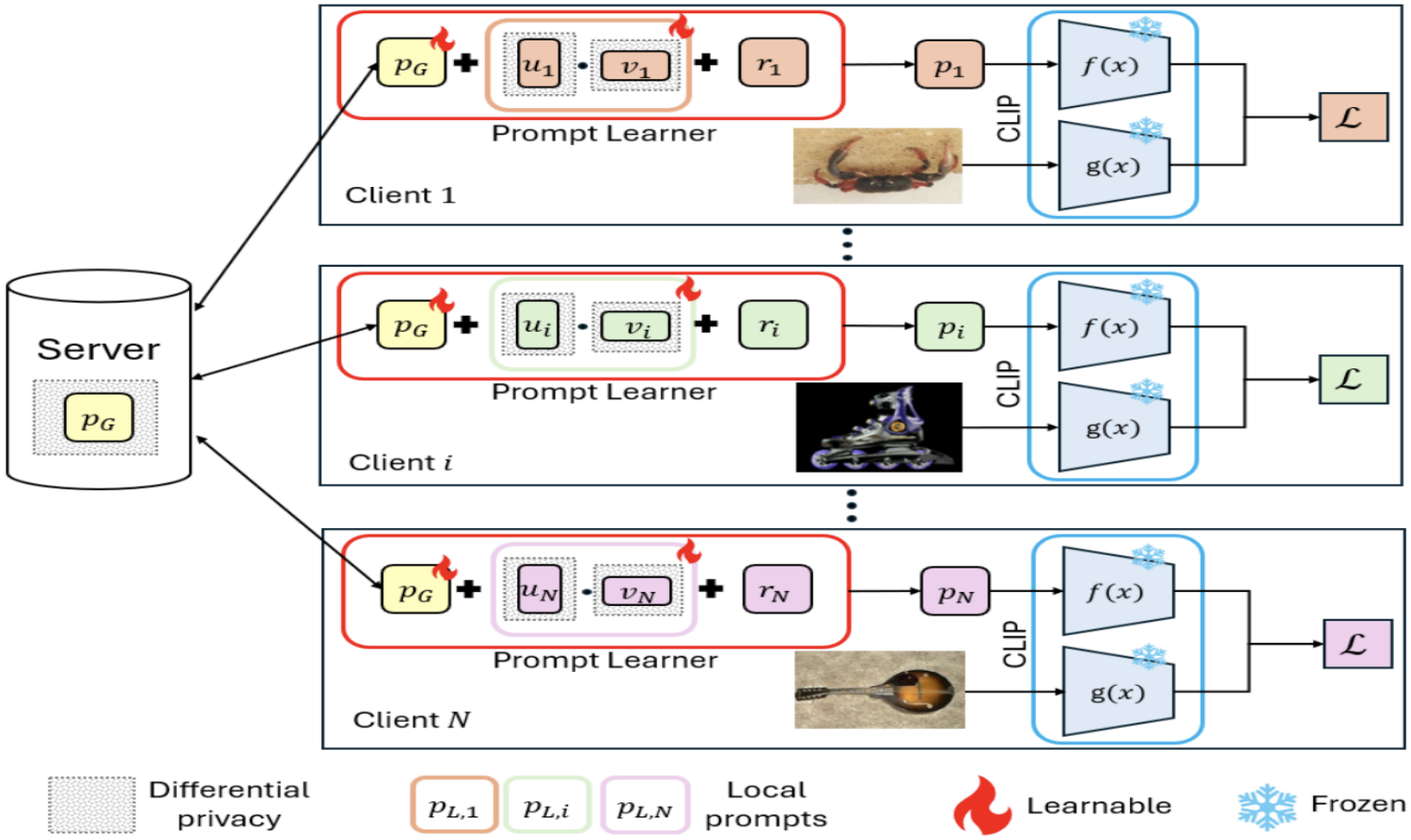
Xiaoyan Zhao et al. PAFO: Pareto Fairness Optimization for Personalized Reward Modeling. Arxiv, 2026

New Direction 3: Privacy

- User data is sensitive
- Privacy-protection is one key focus for the personalization
- Two directions:
  - 1) on device personalization
  - 2) persona-based personalization

New Direction 3: Privacy

- On-device personalization + Federated Learning

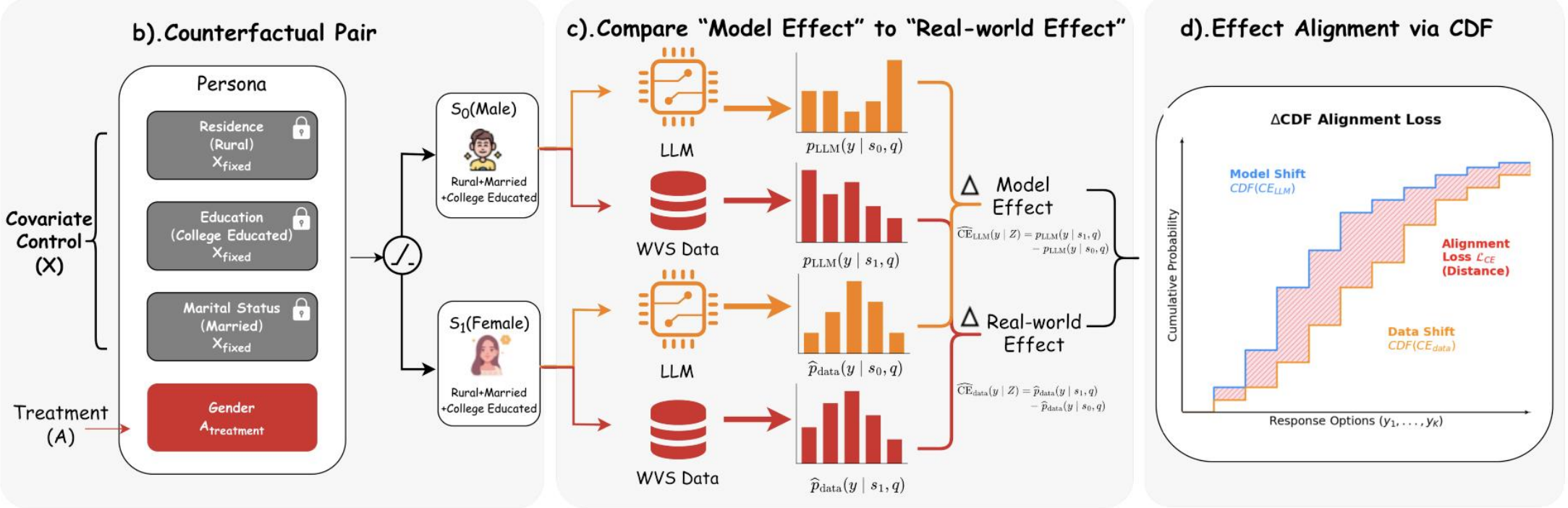


Learn on device,
Only share gradients
And only transfer the shared parts

Linh Tran. RIVACY-PRESERVING PERSONALIZED FEDERATED PROMPT LEARNING FOR MULTIMODAL LARGE LANGUAGE MODELS. ICLR 2025.

New Direction 3: Privacy

- Persona-based learning
  - Personas: Abstract specific behaviors into reusable persona templates (group-level)
  - Compositional Modeling: Mix personas for privacy-preserving user modeling



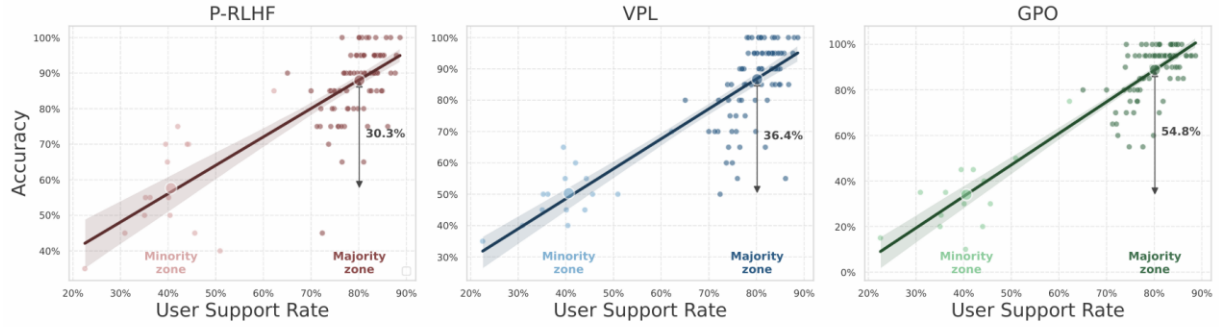
Jiatang Luo. ACE-Align: Attribute Causal Effect Alignment for Cultural Values under Varying Persona Granularities. 2026.01.

New Direction 3: Fairness

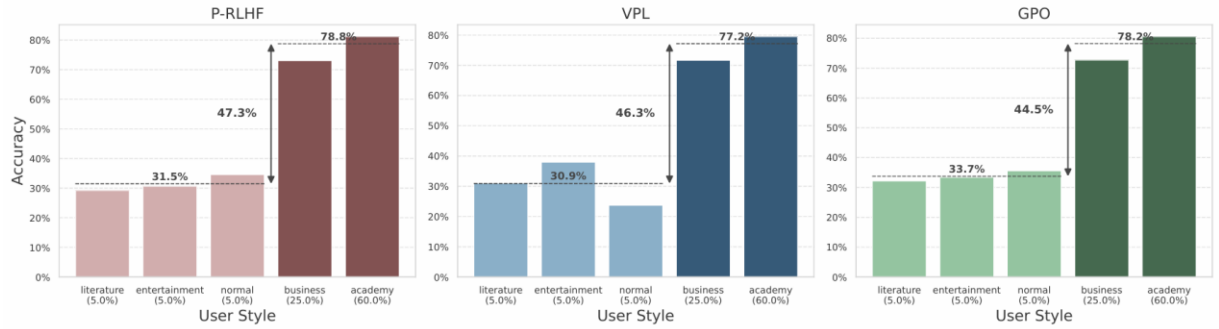
Motivation: model suffer from the fairness issues

For example, Low-support users receive lower reward prediction accuracy.

User Support Rate: The proportion of users whose preferences are consistent with a given user. A higher support rate means the user's preference pattern is more common in the training population.



(a) Personal-LLM: Accuracy increases with user support rate.



(b) DSP: Minority preference styles receive substantially lower accuracy than majority styles.

Figure 2: Preliminary analysis on the Personal-LLM and DSP datasets across P-RLHF, VPL, and GPO methods, showing user-level unfairness in existing personalized RMs.

Xiaoyan Zhao et al. PAFO: Pareto Fairness Optimization for Personalized Reward Modeling. Arxiv, 2026.06

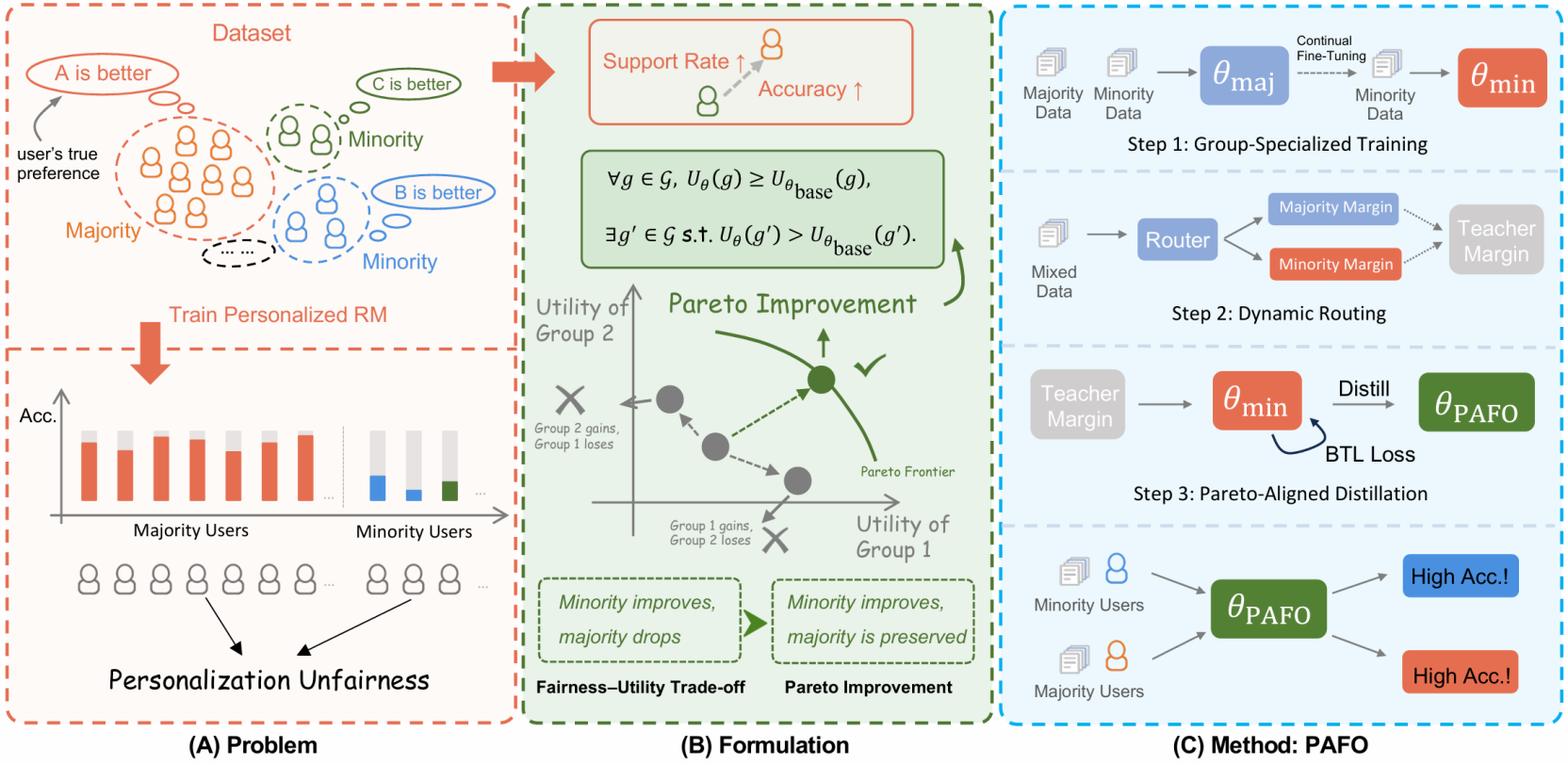
New Direction 3: Fairness - PAFO

Key idea: Mitigate unfairness in personalized reward modeling caused by differences in user preferences.

Pareto improvement: improves at least one user group without decreasing the utility of any other group.

$$\forall g \in \mathcal{G},\ U_\theta(g) \geq U_{\theta_{\text{base}}}(g), \qquad \exists g' \in \mathcal{G} \text{ s.t. } U_\theta(g') > U_{\theta_{\text{base}}}(g').$$

Pareto fairness: model cannot be further improved by any Pareto improvement → ideal state



Xiaoyan Zhao et al. PAFO: Pareto Fairness Optimization for Personalized Reward Modeling. Arxiv, 2026. 06

New Direction 3: Fairness - PAFO

Key idea: Mitigate unfairness in personalized reward modeling caused by differences in user preferences.

Group-Specialized Training: train reward models specialized for different preference groups.

$$\theta_g = \arg\min_{\theta} \mathcal{L}_{\text{BTL}}^{\min}(\theta), \text{ where } \mathcal{L}_{\text{BTL}}^{\min}(\theta) = -\mathbb{E}_{i \sim \mathcal{D}_{\min}^{g}} \left[\log \sigma(m_\theta(i))\right], \quad m_\theta(i) = r_\theta(x_i, h_i, y_i^w) - r_\theta(x_i, h_i, y_i^l)$$

Dynamic Routing: dynamically route each training sample to its group-specialized teacher.

$$m_T(x_i, h_i, y_i^w, y_i^l) = m_{\theta_g} \qquad \text{if } g_i = g, \text{with } g \in \{1, 2, \ldots, n\}$$

Distillation Objective: distill group-specific reward boundaries into one unified personalized reward model.

$$\mathcal{L}_{PAFO} = \alpha \cdot \mathcal{L}_{BTL} + (1 - \alpha) \cdot \mathcal{L}_{\text{distill}}$$

$$\mathcal{L}_{\text{BTL}}(\theta) = -\mathbb{E}_{i \sim \mathcal{D}} \left[\log \sigma(m_\theta(i))\right]$$

hard-label preference learning

Fit true preference labels and prevent the model from drifting away from original preference pairs.

$$\mathcal{L}_{\text{distill}} = \mathbb{E}_{d_i \sim \mathcal{D}} \left[\text{CE}\left(\sigma(m_T(d_i)), \sigma(m_S(d_i))\right)\right]$$

soft-label preference learning

Match group-specific teacher margins to transfer fairer preference boundaries into the unified model.

Xiaoyan Zhao et al. PAFO: Pareto Fairness Optimization for Personalized Reward Modeling. Arxiv, 2026. 06.

New Direction 4: Science of Personalization

The Missing "Science" of Personalization

- **Current Study (Engineering/method Focus)**: Existing research predominantly focuses on *how to achieve* personalization at the technical or application level (e.g., memory modules, user reward models, RAG, and fine-tuning)

- **The Missing Piece (Mechanistic Understanding)**: The fundamental science behind LLM personalization remains underexplored. We largely ignore:
  - *Why* they work fundamentally?
  - *How* they operate inside the "black box"?

- Shift from empirical engineering/method design to the **Science of LLM Personalization**—understanding the **mechanistic necessity and internal representations**

New Direction 4: Science of Personalization

One important question: How LLMs internally represent individual preferences

- For human intelligence, the question has been studied from multiple perspectives:
  - **Neuroscience:** How are preferences encoded in neural activity?
  - **Psychology:** How do internal preferences shape choices and decisions?
- As a new form of intelligent system, what about personalized LLMs?

New Direction 4: Science of Personalization

One representative question: How LLMs internally represent individual preferences?

- Possible method: neuron analysis + SAE features
- Answer these question by answering three sub-questions:
  - Are there any specific neurons responsible for each preference
  - Are these neurons transferable across datasets, domains
  - How the different preferences interact with each other withing the model
  - Are these results cosistent acorss the neuron sapce and SAE space.
- Our initial works: there is a stable architecture of preference in LLMs

Juntao You, Xiaoyan Zhao and Yang Zhang et al. The Hidden Individuality of Machines: a Stable Architecture of Preference in Large Language Models. In prepare.

Content of the tutorial

- In the following, we start with:
- 1. Technique foundations of personalization (Xiaoyan & Xinyu)
  - Part 1: Memory (Xiaoyan)
  - Part 2: Alignment – post-training (Xiaoyan)
  - Part 3: Alignment – Test-time personalization (Xinyu)
- 2. Benchmarks & Evaluation (Xinyu Lin)
- 3. New directions beyond memory and alignment (Yang)
- 4. Applications (Chongming)
- 5. Conclusion (Chongming)

Deployment & Applications

Turns personalization from an isolated model capability into Real-World Systems

- **From User Signals to Real-World Value**

User Signals	Personalization Foundations	Closed-loop System
Conversations · Behavioral History Preferences · Situational Context	• User Memory • Personalized Post-training • Inference-time Adaptation	Observe → Understand → Personalize→ Act → Evaluate → Update

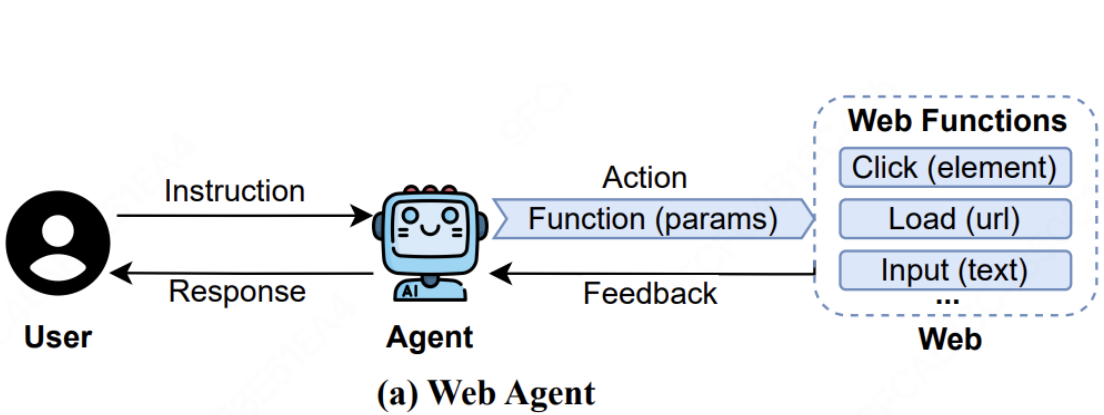
- **Three Representative Application Domains**

Personal Assistant	Recommender Systems	Personalized Healthcare
Continuity across interactions • Long-term user memory • Context-aware assistance	**Preference-aware decision making** • Dynamic preference modeling • Personalized ranking • Online behavioral feedback • Proactive recommender	**Safe support based on evolving user states** • Multi-turn state modeling • Uncertainty-aware responses • Safety and human oversight

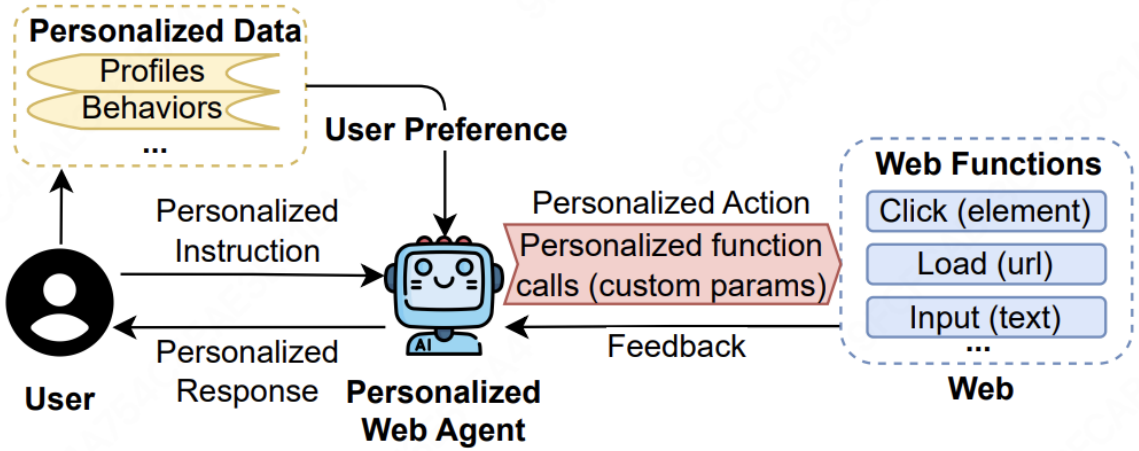
131

Application: Personal Assistant (Work#1)

Core objective: Infer implicit preferences from user data, enabling the agent to perform actions with personalization.



(a) Web Agent



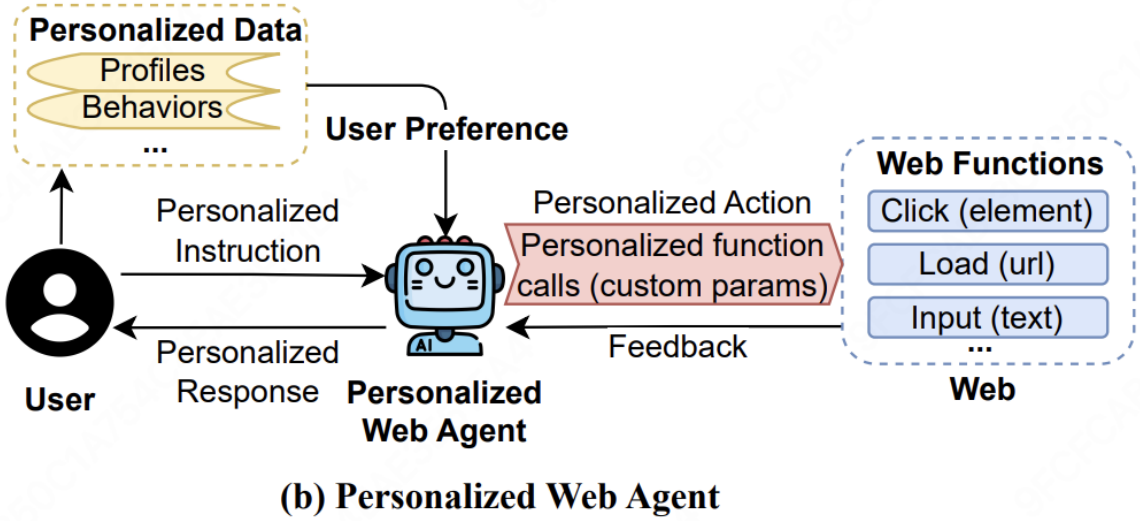
(b) Personalized Web Agent

Existing work: Existing Web Agents mainly complete web tasks based on **explicit user instructions**.
Intrinsic limitation: User instructions are often **incomplete**, and **implicit preferences** such as price, style, and historical interests are not fully expressed.

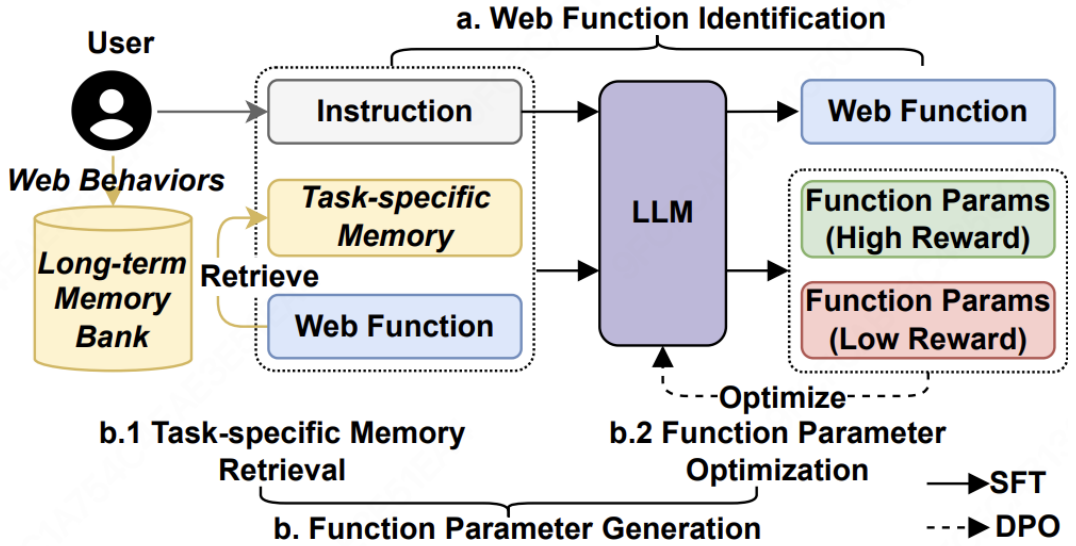
Key idea: Model personalized user data and align Web Agents to enhance personalized instruction understanding and personalized action execution.

Hongru Cai et al. Large Language Models Empowered Personalized Web Agents. WWW, 2025

Application: Personal Assistant (Work#1)



(b) Personalized Web Agent



Step 1: PersonalWAB personalized interaction infrastructure construction

- Extract personalized preferences from user data, build user simulators, and support multi-turn user interaction.
- Build a Web environment simulator to support multi-turn web interaction.

Step 2: Personalized Agent training

- Generate long-horizon multi-turn interaction trajectories.
- Align user preferences based on SFT and DPO to optimize tool use and content generation.

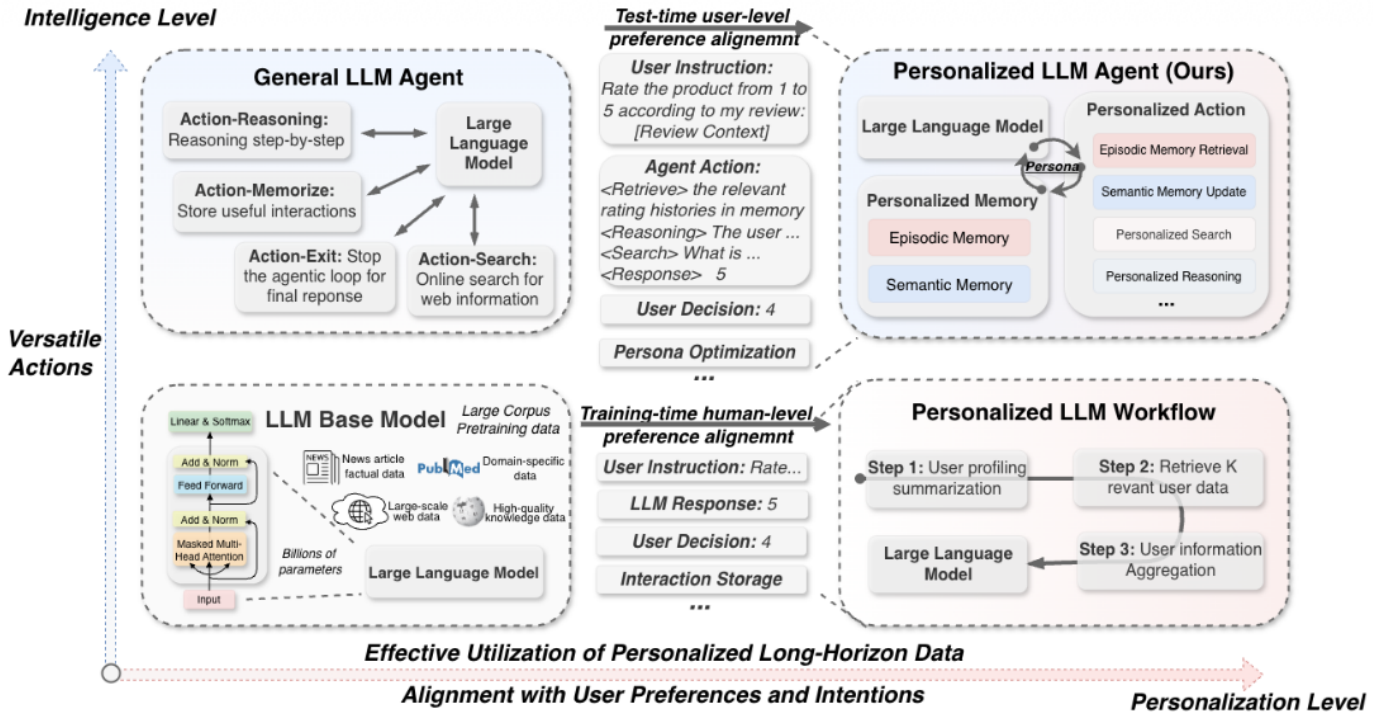
Web Agents can not only return personalized content, but also **execute personalized web actions** based on user preferences, such as personalized tool calling.

Hongru Cai et al. Large Language Models Empowered Personalized Web Agents. WWW, 2025

Application: Personal Assistant (Work#2)

Key Problem: How can an LLM agent convert long-term user history into personalized actions, while adapting to evolving preferences **without retraining the model**?

Contribution: PersonaAgent introduces a dynamically optimized **Persona** as the bridge between memory and action.



Method:

- **Personalized Persona:** Converts user memory into user-specific instructions that guide the agent's behavior.
- **Personalized Actions:** Uses the Persona to control tool selection, search queries, reasoning, and final decisions.
- **Test-Time Preference Alignment:** Iteratively refines the Persona using textual feedback from differences between predicted and actual user behavior.

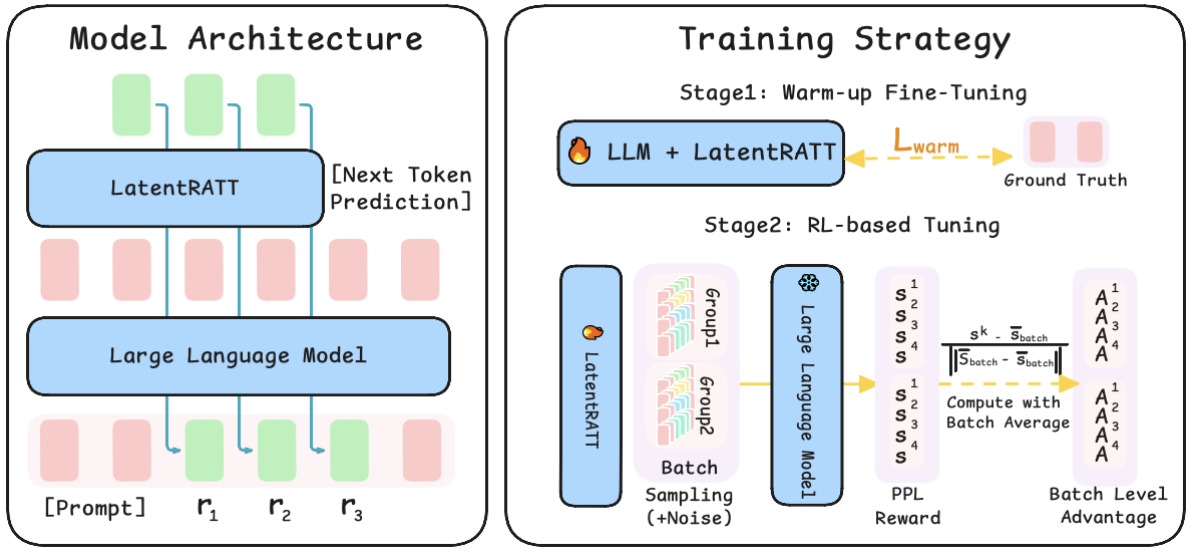
Zhang, Weizhi, et al. "PersonaAgent: Bridging Memory and Action for Personalized LLM Agents." ACL Findings 2026.

Application: Recommender Systems (Work#1)

Background: LLM reasoning is increasingly applied to recommendation, where personalization means inferring each user's implicit, subjective preferences from their historical behaviors.

Limitaion of existing works

- Existing methods typically rely on explicit chain-of-thought (CoT) data.
- Difficult to obtain **high-quality CoT data**.
- **High inference latency** during inference.



Method: LatentR3

- **Latent reasoning**: Eliminating the explicit CoT output during inference.
- **2-Stage Training Strategy**: Through SFT and GRPO to fully unleash LLM's latent reasoning capabilities.

☐ **Detail design:**

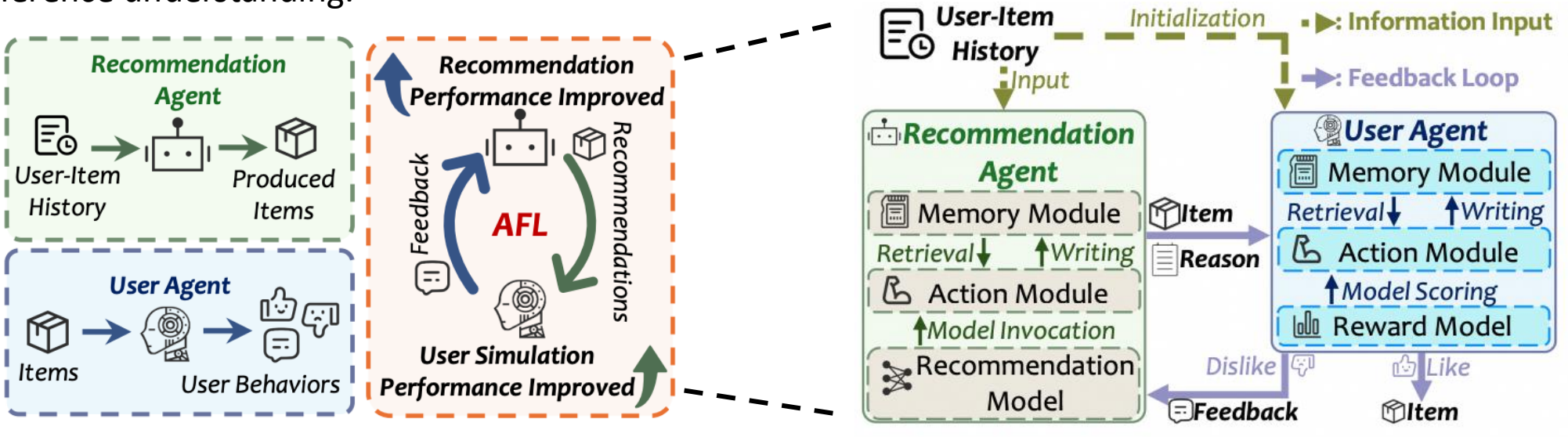
- PPL(perplexity) as reward (efficient training).
- Batch-level advantage normalization.

$$A^k = \frac{s^k - \bar{s}_{batch}}{\|\mathbf{S}_{batch} - \bar{s}_{batch}\|}$$

Zhang, Yang, et al. "Reinforced latent reasoning for llm-based recommendation." ICLR 2026.

Application: Recommender Systems (Work#2)

Core objective: Model the feedback loop between personalized agents, enabling them to mutually refine user preference understanding.



Existing work: Existing LLM-based agents in recommendation mainly optimize **either the recommendation agent or the user agent individually**.

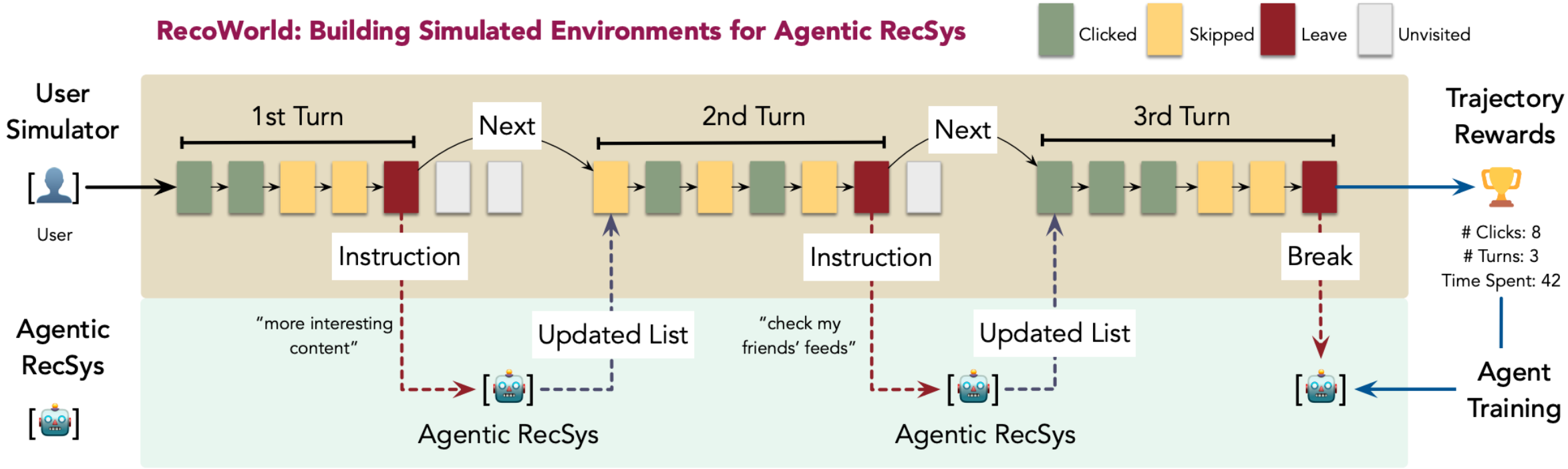
Intrinsic limitation: The **feedback loop** between user and recommender — a key feature of real-world recommendation — is overlooked, so the two personalized agents never collaborate.

Key idea: Build the **Agentic Feedback Loop (AFL)**: the **recommendation agent** refines preference understanding from the **user agent's feedback**, while the **user agent** discovers **potential interests** from recommended items and reasons — both updated iteratively via memory.

Shihao Cai et al. Agentic Feedback Loop Improves Recommendation and User Simulation. SIGIR, 2025

Application: Recommender Systems (Work#3)

Key Idea: RecoWorld, a **blueprint for building simulated environments** tailored to agentic recommender systems. Such environments **give agents a proper training space** where they can learn from errors without impacting real users.



User-simulator: (1) generate simulated feedback; (2) initiates request to RecSys via **explicit instructions (i.e., natural language).**.

Agentic RecSys : (1) agent system interact with user; (2) adjust recommendation list based on simulated user input.

Fei Liu, Xinyu Lin, et al. Building Simulated Environments for Agentic Recommender Systems. WWW, 2026

Application: Recommender Systems (Work#3)

Simulate user behavior by predicting their next action when presented with a list of recommended items.

Action Space

You are able to take any of the following actions: 1. Click, 2. Comment, 3. Share, 4. Like, 5. Watch [specify duration in seconds], 6. Skip, 7. Leave the session ...

Instruction

Your goal is to simulate real user behavior. Consider their context and past interactions to predict what they'd do next when shown a list of recommended items. Instruction: {Specific Instructions}

Context

Here are some context factors related to the user:
1. **Temporal** - Time of day, day of week, seasonality.
2. **Demographics** - Age, gender, location, language, occupation, and device type.
3. **Behavioral** - Time spent, ratings, purchases, search queries, prompts, etc.
4. **Social** - Social connections, group affiliations, etc.

Engagement History

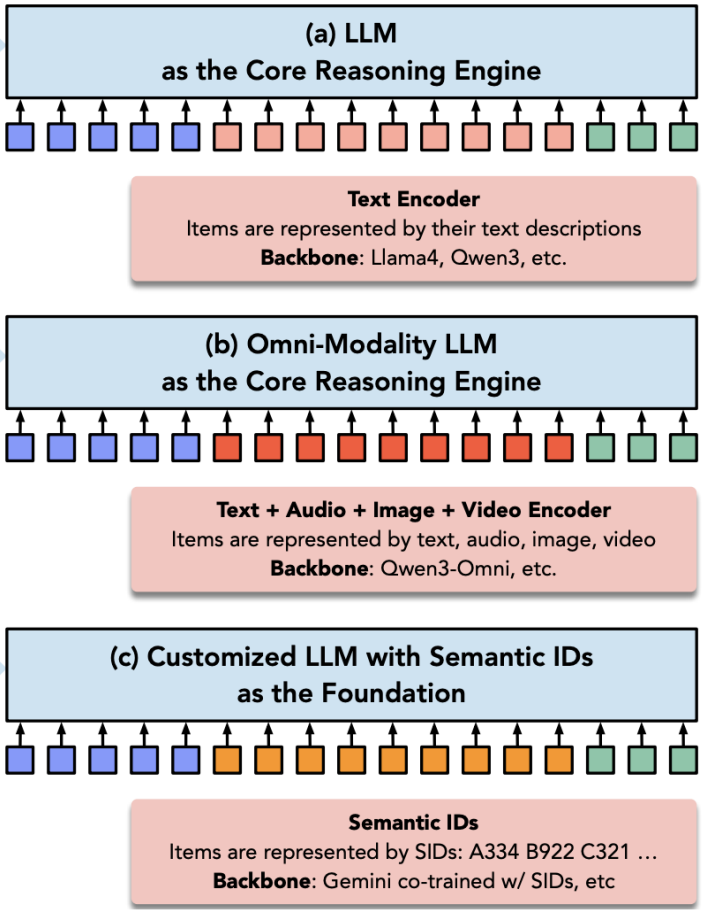
Here is the history of your interactions: {Engagement History}

Observation

Based on what you have liked before, here are some picks for you: {Recommended Items}

Action

Go through each recommendation one by one. For each item:
1. **Think it through** – What's your reasoning behind how you'll respond?
2. **Take action** – Write down what you'll actually do.
3. **Update your mindset** – How this affects your current thinking.



Pre-defined design of user simulator:

(1) Action space
(2) Contextual factors

Action prediction:

(1) Think it through
(2) Take action
(3) Update your mindset

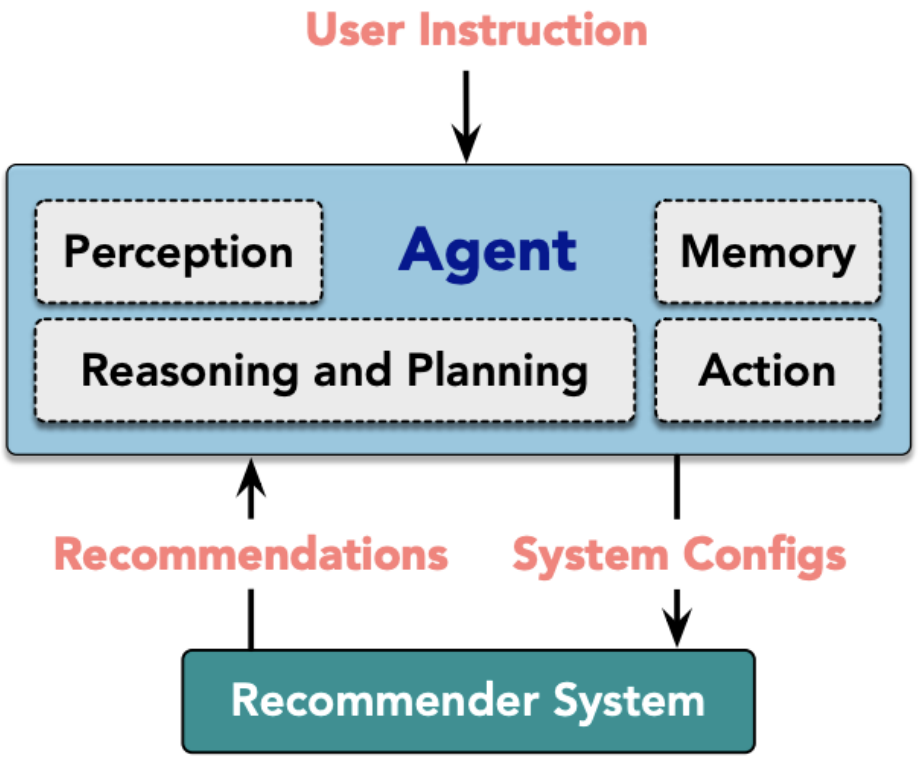
Engagement:

(1) Multimodal modelling: text/multimodal/semantic ID
(2) Lifelong User behavior modelling: dynamic memory, evolving preference

Fei Liu, Xinyu Lin, et al. Building Simulated Environments for Agentic Recommender Systems. WWW, 2026

Application: Recommender Systems (Work#3)

Instruction-following Recsys



User Simulator: Show me more interesting content.

Perception: detecting user state and context

Reasoning and planning: decomposing user instructions into subtasks and delegating them to retrieval and ranking modules

Action: generating recommender system configurations to respond to user information needs

Memory: maintaining a record of user behavior to inform future interactions

Agentic RecSys: Absolutely! Here are videos tailored to your interests and engagement history. Would you like to specify what you find interesting, such as trending topics, educational content, or entertainment? You can also tell me if you want more from specific creators or communities.

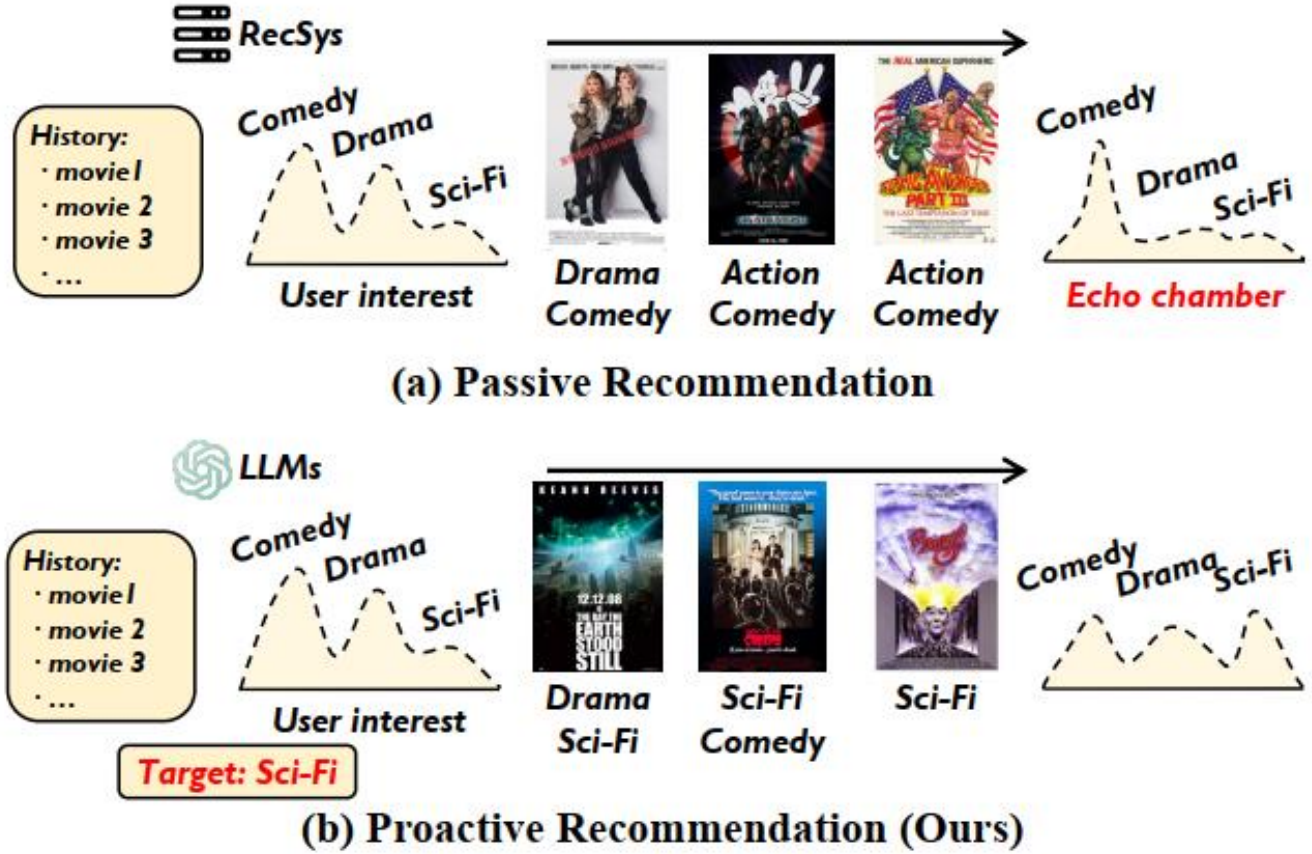
Training signals (RL as example):
(1) common metrics – total session time, number of clicks, self-critique scores, etc
(2) User feedback – real/simulated feedback, voice-driven feedback

Fei Liu, Xinyu Lin, et al. Building Simulated Environments for Agentic Recommender Systems. WWW, 2026

Application: Recommender Systems (Work#4)

Proactive Recommendation Agent

- It does NOT pursue the correct answer in user's mind.
- It aims to **actively guide the user interest toward a given target item or a target interest distribution** with a sequence of interactions, i.e., influence path.



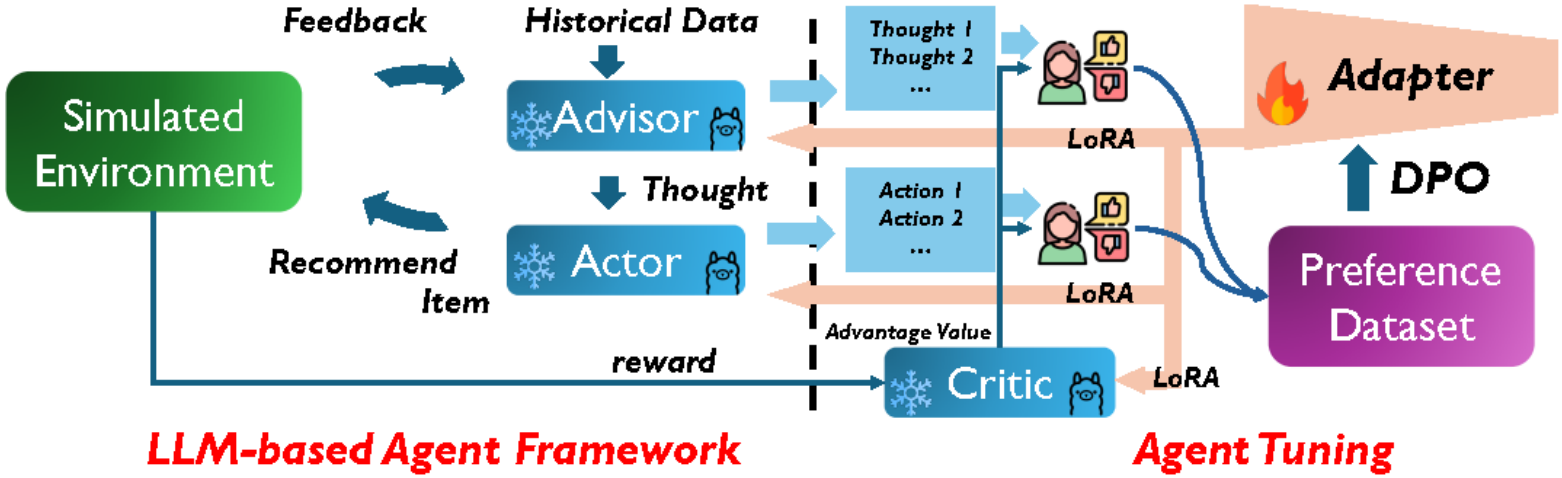
Recommendation is not only preference prediction; it can also be preference shaping.

Mingze Wang et al. 2025. Tunable LLM-based Proactive Recommendation Agent (T-PRA). in ACL 2025

Application: Recommender Systems (Work#4)

We introduce **T-PRA**, a novel agent that is both **adaptive** and **strategic** for proactive recommendation task.

- **1. Actor-Advisor Framework (Flexibility):**
  - **Advisor (Slow-Thinker):** Strategically plans the recommendation path.
  - **Actor (Fast-Thinker):** Makes immediate recommendations based on the Advisor's guidance.
- **2. Critic-Guided Optimization (Long-Term Vision):**
  - An LLM-based **Critic** evaluates the long-term value of actions by calculating Advantage Value.

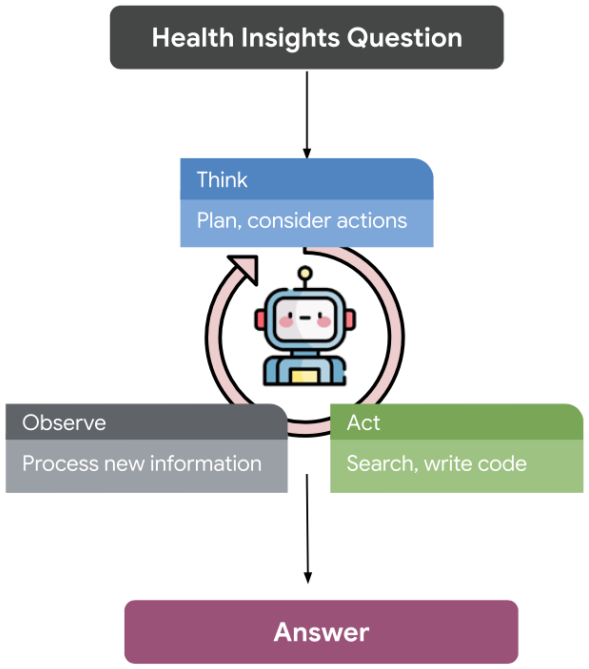


T-PRA learns to balance short-term user acceptance with long-term interest development.

Mingze Wang et al. 2025. Tunable LLM-based Proactive Recommendation Agent (T-PRA). in ACL 2025

Personalized Healthcare

Key Problem: LLMs struggle to transform complex, longitudinal personal health data into reliable and actionable individualized insights.



The Framework of Personal Health Insights Agent (PHIA)

An Example of PHIA's Reasoning and Response

Goal: Enable LLM agents to accurately analyze personal **wearable data** and generate context-aware, **actionable health insights**.

Method:

- **Personal Data Grounding:** Grounds responses in individual sleep, activity and heart-rate data.
- **Agentic Data Analysis:** Uses iterative reasoning and code execution to analyze longitudinal health data.
- **Knowledge-Augmented Generation:** Integrates external health knowledge to contextualize personalized insights.

Merrill, Mike A., et al. "Transforming wearable data into personal health insights using large language model agents." Nature Communications (2026).

Personalized Healthcare

Key Problem: Healthcare dialogue systems must infer patients' hidden, evolving states—such as uncertainty, engagement, and readiness to act.

Patient: *"I've been taking the new medication for two weeks."*

😟 Anxious about side effects

high uncertainty

Right response → reassure, check symptoms, offer a clinician review.

🙂 Confidently tracking progress

engaged · high readiness

Right response → reinforce the habit, set the next health milestone.

😕 Reconsidering discontinuation

wavering · low adherence risk

Right response → explore concerns, use motivational interviewing to prevent dropout.

Existing work

Directly retrieve explicit memories or profiles, failing to model how each response changes the patient's future state.

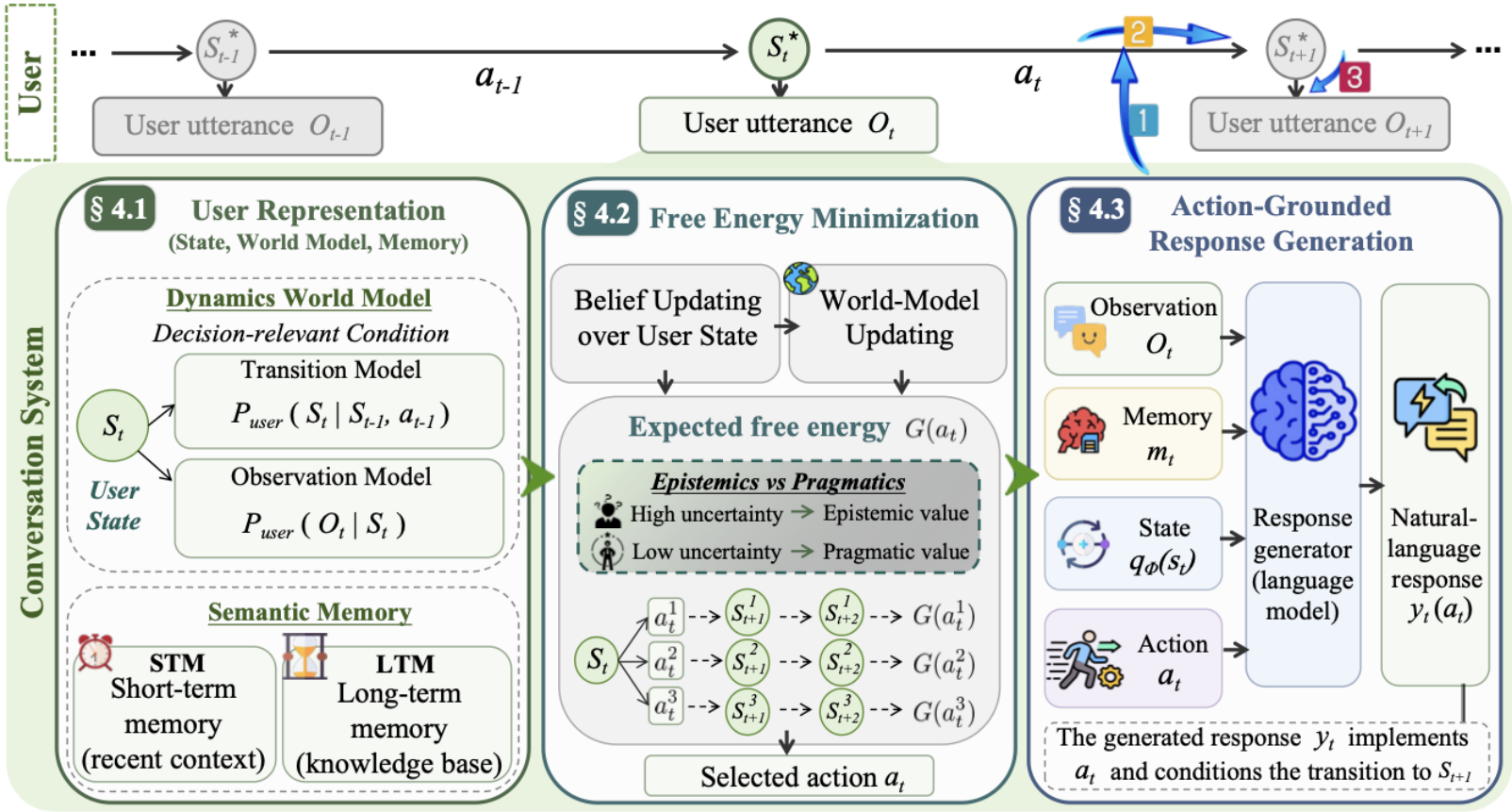
Our goal

models patient-state dynamics and **selects responses that reduce uncertainty** while promoting positive long-term health behaviors.

Luo, Jiani, et al. "Know You Before You Speak: User-State Modeling for LLM Personalization in Multi-Turn Conversation." *arXiv preprint arXiv:2605.24647* (2026).

Personalized Healthcare

Key Idea: Grounded in the **Free Energy Principle**, PUMA treats the patient as a *partially observable dynamical system* — maintaining a **belief** over their latent state, a **world model** of how each response reshapes it, and selecting the response that **minimizes expected free energy** (reduce uncertainty + advance the health goal).



Three stages

§4.1 User Representation
state · world model · memory

§4.2 Free Energy Minimization
belief & world-model updating, EFE action selection

§4.3 Action-Grounded Response
generate response → user-state transition

Luo, Jiani, et al. "Know You Before You Speak: User-State Modeling for LLM Personalization in Multi-Turn Conversation." *arXiv preprint arXiv:2605.24647* (2026).

Summary: One Foundation, Different Deployment Challenges

Key insight Personalized LLMs share a common foundation, but effective deployment requires scenario-specific adaptation.

Shared foundation: a reusable personalization loop

User signals
dialogue · behavior · context

➡

Personalized memory · preference · state

➡

Adaptive action
action · ranking · support

➡

Feedback & update
closed-loop improvement

Scenario-specific deployment challenges

Personal Assistants

Long-term memory does not automatically produce personalized behavior.

Recommender Systems

Generic LLM training and token-level modeling may miss recommendation objectives.

Personalized Healthcare

Decisions rely on longitudinal data, with greater emphasis on safe and trustworthy responses.

Content of the tutorial

- Introduction (Yang)
- 1. Technique foundations of personalization (Xiaoyan & Xinyu)
  - Part 1: Memory (Xiaoyan)
  - Part 2: Alignment – post-training (Xiaoyan)
  - Part 3: Alignment – Test-time personalization (Xinyu)
- 2. Benchmarks & Evaluation (Xinyu Lin)
- 3. New directions beyond memory and alignment (Yang)
- 4. Applications (Chongming)
- **5. Conclusion (Chongming)**

Conclusion

- Benchmark & evaluation
  - Benchmark:
    - From single-tune to multi-turn
    - From Q&A to agentic task
    - …
  - Evaluation:
    - Traditional metrics
    - LLM-as-judge
    - Rubrics

Conclusion

- New directions beyond memory and alignment
  - **User world/foundation model:**
    - user first-perspective modeling, modeling the dynamics of the user
  - **Lifelong personalization:**
    - Adapt to user evolving preference
    - Adapt to drifted environments
  - **Trustworthy:**
    - Privacy
    - Fairness
  - **Science of LLM personalization**
    - Mechanistic understanding

Conclusion

- Applications
  - Personal Assistant
  - Personalized Recommendation
  - Healthcare
  - …..

Thank you!

Welcome to join us!

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