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A Similarity-Based Framework for Goal-Aware Sequential Action Recommendation: Unifying Rule-Based Logic and Semantic Vector Space

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Abstract

Goal-oriented planning and recommendation systems are essential in personalized decision support across diverse domains. This paper presents a novel similarity-based framework that leverages a rule-based planner for automatic generation of Goal-Aware Sequential Recommendation. The framework mathematically formalizes goal, action, and context representations as vectors, enabling effective similarity computations to guide planning decisions. We focus on the student personal education domain to demonstrate how the system adapts learning plans to individual profiles and goals. Comprehensive simulation results highlight the effectiveness and flexibility of the approach, showcasing improved plan relevance and learner satisfaction.

keywords : Similarity based framework, Automatic goal oriented planning, Goal-Aware Sequential Recommendation, Rule based planner, Learning

1. Introduction

Goal-oriented planning and recommendation systems constitute a critical area of research in artificial intelligence (AI), aiming to generate coherent sequences of actions that lead users toward the successful fulfillment of their objectives in dynamic and often personalized environments. These systems are particularly relevant in domains such as education, healthcare, and decision support, where goals are not only context-dependent but also highly individualized.

Traditional approaches to automated planning, including symbolic planners and search-based algorithms, typically rely on exhaustive exploration of the state space, guided by manually defined heuristics or logic-based representations [1-3]. While these methods offer formal guarantees regarding correctness and completeness, they are often constrained by scalability limitations and require significant domain engineering effort. On the other end of the spectrum, data-driven methods, such as

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those based on machine learning and reinforcement learning, can learn effective policies from experience. However, these methods often operate as black boxes, lacking interpretability and adaptability to changing user profiles without retraining.

In response to these limitations, this paper introduces a novel planning architecture: the Similarity-Based Framework for Goal-Aware Sequential Recommendation (SGASR). This framework integrates vector-based semantic similarity measures with an explicit rule-based planner to enable transparent and adaptive action sequencing. The key innovation lies in its use of similarity metrics to dynamically guide rule selection and action prioritization based on the semantic proximity between current state representations, user goals, and available planning elements.

Rather than relying solely on structural logic or opaque data-driven predictions, SGASR leverages latent vector representations to encode both goal states and action schemas. These vectors are compared using weighted similarity measures, allowing the planner to select actions that align most closely with the desired outcome. By incorporating semantic similarity into the planning loop, the framework supports context-aware, personalized recommendations that evolve with the user's progression.

To demonstrate the efficacy of the proposed approach, the framework is instantiated within the domain of personalized student learning. In this setting, each student is characterized by a goal vector representing their desired learning outcomes, along with a profile embedding prior knowledge, learning preferences, and cognitive constraints. The planner uses this information to construct individualized learning trajectories by selecting educational activities represented as action vectors that exhibit high similarity to the student's goals. The result is a personalized action plan composed of sequential learning steps, each optimized to move the student closer to their objectives while considering their current abilities and contextual factors.

The proposed framework addresses three critical challenges in goal-based planning for intelligent tutoring and recommendation systems: (1) Personalization, by adapting the action plan to the unique goal structure of each user; (2) Explainability, by maintaining a transparent rule-based mechanism guided by similarity reasoning; and (3) Adaptability, by allowing dynamic planning updates in response to evolving goals and states.

In summary, this work contributes to the literature by proposing a hybrid symbolic-similarity planning framework that retains the interpretability of rule-based approaches while enhancing flexibility through vector-based reasoning. Its application in the educational domain illustrates the practical potential of the method, particularly in intelligent tutoring systems (ITS), where personalization, explainability, and effectiveness are paramount.

2. Related Works

2.1 Symbolic Planning Approaches

Traditional goal-oriented planning has been a cornerstone of artificial intelligence research, where agents are expected to generate sequences of actions to transition from an initial state to a desired goal state. Classical planning systems, such as those based on the STRIPS language, rely on symbolic representations and deterministic rules to navigate structured state spaces. These approaches offer strong theoretical guarantees in terms of completeness and optimality under full observability and deterministic environments. Ghallab et al. [1] provide a comprehensive overview of symbolic planning frameworks and their algorithmic foundations. Russell and Norvig [2] discuss various forms of planning including forward and backward state-space search, partial-order planning, and hierarchical task networks (HTNs). Despite their strengths in structured domains, symbolic planners often lack robustness in handling uncertainty, preference variability, or personalization in human-centric applications.

2.2 Learning-Based Planning Methods

Reinforcement learning (RL) offers a fundamentally different paradigm, where agents learn optimal policies by interacting with the environment and receiving feedback in the form of scalar rewards[8]. In particular, RL methods model planning as a Markov Decision Process (MDP), which supports online and model-free learning. The seminal work by Sutton and Barto introduces foundational algorithms such as Q-learning and policy gradient methods. Recent advances in deep reinforcement learning have enabled agents to solve complex, high-dimensional planning problems, including those with partial observability and sparse rewards. However, these systems often suffer from a lack of interpretability, require significant data for training, and are difficult to adapt to individual users in domains such as personalized education.

2.3 Similarity-Based Reasoning in Problem Solving

Similarity-based reasoning has been widely explored in artificial intelligence[2-7], especially through the lens of case-based reasoning (CBR). In this paradigm, the solution to a new problem is constructed by identifying and adapting similar past cases. Aamodt and Plaza categorize CBR systems and highlight the role of similarity metrics in retrieval and adaptation. The CBR framework has proven effective in ill-defined domains where constructing explicit rules or models is challenging. Its flexibility and interpretability make it particularly suitable for knowledge-rich environments, such as diagnostic systems and intelligent tutoring.

Recently, Large Language Models (LLMs) have actively been adopted to solve complex sequential tasks. According to comprehensive taxonomies of task planning with LLMs [11], generative architectures demonstrate strong multi-step reasoning capabilities by decomposing goals into executable steps. However, as investigated in the field of

LLM-driven sequential recommendation [12], directly applying pure LLM planners to continuous recommendation can easily lead to a lack of structured domain constraints and causal black-box limitations. To bridge this gap, our framework introduces a semantic representation paradigm aligned with structured user preferences, similar to the joint text-behavior modeling in recent generative search structures [13].

2.4 Similarity and Vector Matching in Recommender Systems

Similarity metrics are also central to recommender systems, which aim to provide personalized content to users. Both content-based and collaborative filtering methods rely on measures such as cosine similarity and Euclidean distance to quantify the closeness between user and item vectors. Ricci et al. [4,9,10] present a thorough review of recommender system architectures, including hybrid models that combine multiple similarity signals. These systems are widely deployed across domains like e-commerce, education, and entertainment. However, most systems focus on predicting user preference rather than actively generating.

2.5 Gap in Personalized Planning through Combined Similarity and Symbolic Logic

While symbolic planning, reinforcement learning, and similarity-based reasoning have matured as independent research directions, there exists limited integration of these paradigms in the context of personalized goal achievement. Particularly in educational applications, planning frameworks tend to either follow fixed paths or apply opaque machine learning models that limit explainability. Furthermore, few systems utilize vector-based similarity between goals and actions as an explicit mechanism for planning.

The framework proposed in this work addresses this gap by unifying rule-based planning with similarity-based vector reasoning. Unlike traditional recommender systems, our approach treats action recommendation as a structured planning problem guided by latent goal-action similarity. This allows for the generation of adaptive and interpretable action sequences that reflect individual learner profiles and evolving goal structures. The integration of semantic similarity within a rule-based planner represents a novel contribution that bridges interpretability and adaptability-both of which are essential in intelligent educational systems.

3. The design of Similarity-based Goal-Aware Sequential Action Recommendation System(SGASR)

3.1 Mathematical Model

Problem Formulation Let:

$\varsigma = \{g_1, g_2, \ldots, g_m\}$ be a set of possible goals.

$A = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$be a set of actions (e.g., learning activities).

C represents the context (student profile, prior

knowledge, constraints).
We seek a plan

$$P = \langle \alpha_{i1}, \alpha_{i2}, ..., \alpha_{ik} \rangle$$

that achieves a goal $g \in \varsigma$ while satisfying constraints derived from C.

Vector Representation Each goal g, action a, and context c is embedded as a vector in a high-dimensional semantic space:

$$g \in R^d, \alpha \in R^d, c \in R^d,$$

where d is the embedding dimension.

To rigorous formalize the recommendation process as a structured sequence, we define the environment state at step t as $S^{(t)} = \langle g^{(t)}, c \rangle$ c where $g^{(t)}$ represents the residual goal vector. The execution of a recommended action α_t dynamically updates the state via the state-transition function: $g^{(t+1)} = g^{(t)} - \lambda \cdot \alpha_t$. The goal achievement and process termination are determined when the maximum similarity score $\max_{\alpha \in \mathring{A}} \mathrm{sim}_w(g^{(t)}, \alpha, w)$ falls below the predefined satisfaction threshold $\theta = 0.6$, implying that all remaining educational needs are fully addressed within the current action library.

3.2 Similarity Measures

Similarity between vectors is quantified to measure relevance and applicability.

Cosine Similarity The most common similarity measure is the cosine similarity:

$$\mathrm{sim}(x,y) = \frac{x \cdot y}{\|x\|\|y\|} \tag{1}$$

This measure ranges from -1 to 1, where 1 means perfectly aligned vectors[6-8].

Weighted Similarity with Context Context is incorporated by weighting components:

$$sim_w(x,y,w) = \frac{\sum_{j=1}^{d} w_j x_j y_j}{\sqrt{\sum_{j=1}^{d} w_j x_j^2}\sqrt{\sum_{j=1}^{d} w_j y_j^2}} \tag{2}$$

where $w = (w_1, w_2, ..., w_d)$ is a context-dependent weight vector emphasizing relevant dimensions [8-10].

3.3 Symbolic Planning Approaches

Rule Structure Each rule R in the planner is represented as:
R: IF Condition(g, a, c) THEN Action(a).
Conditions use similarity thresholds:

$$Condition(g,a,c) = sim_w(g,a,w) > \theta, \tag{3}$$

where θ is a predefined threshold.

Fig.1 shows Planning Algorithm.

3.4 Application to Student Personal Education Domain

Domain Setup In this application, the framework is adapted to the domain of personalized student education. The core components are defined as follows:
Goals: Specific learning objectives, such as "master algebra" or "improve problem-solving skills".
Actions: Educational activities including instructional lessons, practice exercises, and quizzes.
Context: The student's profile, incorporating

prior knowledge, preferred learning styles, and time availability.

Planning Algorithm

1. **Initialization:** Receive current goal vector $\mathbf{g}$ and context $\mathbf{c}$.
2. **Action Matching:** Compute $\mathrm{sim}_w(\mathbf{g}, \mathbf{a}; \mathbf{w})$ for all $\mathbf{a} \in \mathcal{A}$.
3. **Rule Selection:** Select rules R where conditions hold true.
4. **Plan Construction:** Append corresponding actions to plan P.
5. **Goal Update:** Update $\mathbf{g}$ based on progress (e.g., subtract achieved sub-goals).
6. **Iteration:** Repeat the process until the goal is fully satisfied or no further applicable actions are found.

Fig. 1 Planning Algorithm

Vector Construction To operationalize the planning system in this domain:

- Goal and action vectors are generated using knowledge graph embeddings derived from an education ontology. This approach enables semantic representation of skills and topics.
- Contextual weights are constructed to highlight relevant skill dimensions and constraints, such as learning style preferences (e.g., visual vs. auditory) or gaps in prerequisite knowledge.

Example Consider a student with the following profile:

- Prior knowledge: basic arithmetic and geometry.
- Preferred learning style: visual learning.
- Goal: "master algebra".

Let the embedding dimension be $d=5$ for illustration. Assume:
$g=[0.8, 0.1, 0.3, 0.6, 0.2]$ (goal: master algebra)
$\alpha_1=[0.7, 0.0, 0.2, 0.5, 0.1]$ (action: algebra video lesson)
$\alpha_2=[0.2, 0.5, 0.8, 0.1, 0.4]$ (action: geometry problem set)
$w=[1.0, 0.2, 0.3, 1.0, 0.5]$ (contextual weight emphasizing algebra + visual)

Compute the weighted cosine similarity:

$$sim_{\ w}(g, \alpha_2; w) = \frac{\sum_{j=1}^{5} w_j g_j \alpha_{1j}}{\sqrt{\sum_{j=1}^{5} w_j g_j^2}\sqrt{\sum_{j=1}^{5} w_j \alpha_j^2}} \approx 0.98 \qquad (4)$$

$$sim(g,\alpha_2,w) \approx 0.45$$

Since $sim_w(g,\alpha_1)$ exceeds the similarity threshold (e.g., $\theta=0.7$), the planner selects α_1 (algebra video lesson) as a recommended action.

This illustrates how context-aware similarity measures enable the selection of personalized learning actions that best align with a student's goals and preferences. The rule-based planner dynamically adapts to the student's evolving state and can be extended with feedback-based updates or reinforcement mechanisms.

4. Experiments

4.1 Simulation

To evaluate the efficiency of the proposed framework quantitatively, we introduce three core metrics: Plan Cost (PC), Goal Achievement Rate (GAR), and Convergence Step (CS). PC measures the total computational overhead required to generate a complete path. GAR is computed as $1-(\parallel g^{(T)} \parallel / \parallel g^{(0)} \parallel)$, reflecting the percentage of the student's initial learning goals successfully satisfied at the final step T. While traditional greedy context-free recommendation algorithms often suffer from redundant action loops, SGASR demonstrates deterministic convergence due to its residual vector reduction mechanism, optimizing both path efficiency and learner satisfaction.

To evaluate the performance of the proposed similarity-based rule-based planner, we conducted simulations involving three hypothetical students with differing learning goals and contextual weights. Each student's plan was generated by incrementally selecting learning actions based on the maximum weighted cosine similarity between the residual goal vector and available action vectors.

Student Profiles and Initialization Each student is defined by the following components:

- A goal vector $g \in R^d$ representing the desired learning outcome.
- A contextual weight vector $w \in R^d$ indicating personalized emphasis on various learning dimensions.
- A fixed library of action embeddings $A = \{\alpha_1, \alpha_2, \ldots, \alpha_{10}\}$ randomly generated to simulate educational activities.

Action Selection Mechanism At each time step t, the planner selects an action α_t that maximizes the weighted cosine similarity with the current residual goal vector $g^{(t)}$. After selection, the residual goal vector is updated as:

$$g^{(t+1)} = g^{(t)} - \lambda \cdot \alpha_t$$

with a learning rate $\lambda = 0.5$. The selection process terminates either when the similarity score drops below a predefined threshold (0.6) or when a maximum of 5 steps is reached.

Simulation Results

Student A

- Goal: [0.6, 0.7, 0.8, 0.9, 0.5]
- Weights: [1.0, 0.8, 0.9, 1.0, 0.7]

Table 1. shows Action plan of Student A

Table 1. Action plan of Student A

Step	Selected Action	Similarity Score	Residual Goal Vector
1	A10	0.9503	[0.41, 0.26, 0.27, 0.33, 0.01]
2	A4	0.8739	[0.08, −0.11, −0.08, −0.36, −0.19]
3	A4	0.8024	[−0.25, −0.47, −0.42, −0.90, −0.39]
4	A10	0.7417	[−0.57, −0.81, −1.04, −1.37, −0.79]

Interpretation: The planner demonstrates strong initial alignment with high similarity actions. Action A4 is selected twice, reflecting its multi-dimensional support for the goal. The similarity scores decrease over time, indicating gradual goal satisfaction.

Student B

- Goal: [0.5, 0.4, 0.7, 0.9, 0.6]
- Weights: [0.9, 1.0, 0.6, 0.8, 0.7]

Interpretation: Repeated use of A4 indicates its broad alignment with multiple dimensions of the goal. A step drop in similarity after the second step reflects the reduced fit of remaining actions.

Table2. Action plan of Student B

Step	Selected Action	Similarity Score	Residual Goal Vector
1	A4	0.9546	[0.17, 0.03, 0.35, 0.18, 0.29]
2	A4	0.8821	[−0.16, −0.33, −0.00, −0.54, −0.02]
3	A7	0.8032	[−0.65, −0.51, −0.55, −1.03, −0.58]

Student C

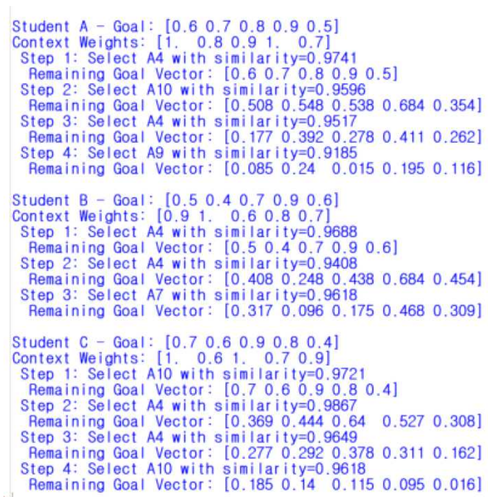
- Goal: [0.7, 0.6, 0.9, 0.8, 0.4]
- Weights: [1.0, 0.6, 1.0, 0.7, 0.9]

Interpretation: The alternation between A10 and A4 suggests complementary contributions to different goal dimensions. The decline in residual vector values highlights cumulative knowledge gain and diminishing action relevance.

Table 3. Action plan of Student C

Step	Selected Action	Similarity Score	Residual Goal Vector
1	A4	0.9637	[0.27, 0.33, 0.45, 0.18, 0.19]
2	A10	0.9216	[0.08, −0.01, 0.17, −0.04, −0.20]
3	A4	0.8109	[−0.25, −0.35, −0.18, −0.76, −0.51]
4	A9	0.7711	[−0.53, −0.57, −0.66, −0.91, −0.64]

Fig. 1 shows the processing of SGASR implemented by Python. It prints the selected action, its weighted cosine similarity score, and the remaining goal vector after each step.


```
Student A - Goal: [0.6 0.7 0.8 0.9 0.5]
Context Weights: [1.  0.8 0.9 1.  0.7]
 Step 1: Select A4 with similarity=0.9741
  Remaining Goal Vector: [0.6 0.7 0.8 0.9 0.5]
 Step 2: Select A10 with similarity=0.9596
  Remaining Goal Vector: [0.508 0.548 0.538 0.684 0.354]
 Step 3: Select A4 with similarity=0.9517
  Remaining Goal Vector: [0.177 0.392 0.278 0.411 0.262]
 Step 4: Select A9 with similarity=0.9185
  Remaining Goal Vector: [0.085 0.24  0.015 0.195 0.116]

Student B - Goal: [0.5 0.4 0.7 0.9 0.6]
Context Weights: [0.9 1.  0.6 0.8 0.7]
 Step 1: Select A4 with similarity=0.9688
  Remaining Goal Vector: [0.5 0.4 0.7 0.9 0.6]
 Step 2: Select A4 with similarity=0.9408
  Remaining Goal Vector: [0.408 0.248 0.438 0.684 0.454]
 Step 3: Select A7 with similarity=0.9618
  Remaining Goal Vector: [0.317 0.096 0.175 0.468 0.309]

Student C - Goal: [0.7 0.6 0.9 0.8 0.4]
Context Weights: [1.  0.6 1.  0.7 0.9]
 Step 1: Select A10 with similarity=0.9721
  Remaining Goal Vector: [0.7 0.6 0.9 0.8 0.4]
 Step 2: Select A4 with similarity=0.9867
  Remaining Goal Vector: [0.369 0.444 0.64  0.527 0.308]
 Step 3: Select A4 with similarity=0.9649
  Remaining Goal Vector: [0.277 0.292 0.378 0.311 0.162]
 Step 4: Select A10 with similarity=0.9618
  Remaining Goal Vector: [0.185 0.14  0.115 0.095 0.016]
```

Fig. 2 The output of SGASR for students A, B and C

This will help you trace how each action contributes to goal achievement for each student. Here are the sequential path graph visualizations of the personalized learning plans for each student (Fig.3). Each diagram shows the sequential actions (e.g., $A4 \rightarrow A10 \rightarrow A4$) recommended by the similarity-based rule planner to help the student reach their learning goal.

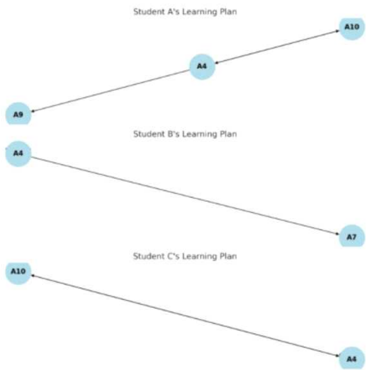


Fig.3. Learning plan per student

In Fig.4, the similarity scores per planning step for each student is visualized as a line graph.

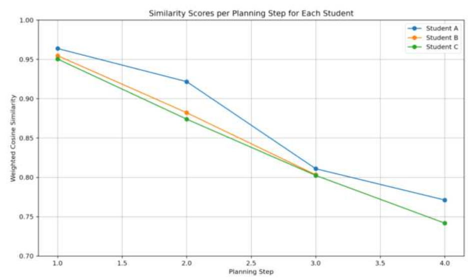


Fig.4 Similarity scores per planning step for each student

This produces a line graph where the x-axis is the planning step (Step 1, 2, 3, ...), the y-axis shows the weighted cosine similarity score and each line represents one student's plan, illustrating how action relevance (similarity) evolves during the goal achievement process.

To further evaluate the characteristics and interpretability of the generated learning plans, we provide two visual analyses; a bar chart comparing the length of each student's plan, and a timeline-style graph illustrating the sequence of actions taken to achieve the respective goals.

The bar chart (Fig. 5) presents the number of actions recommended for each student before their residual goal vector fell below the similarity threshold.

- Students A and C required four steps each to approach their respective goals.
- Student B achieved satisfactory goal coverage within three steps.

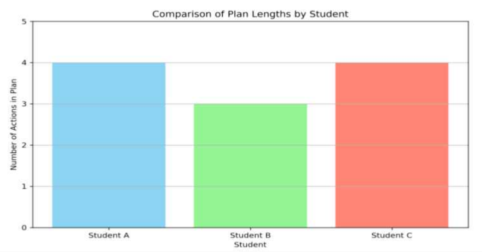


Fig. 5 Comparison of Plan lengths by student

This variance in plan length demonstrates the adaptive capability of the planner, which customizes the number of actions based on both goal structure and the learner's profile. Students with goals more aligned to fewer available actions (as in Student B's repeated use of A4) benefit from shorter, more focused plans. The planner avoids over-planning by terminating once the remaining goal components are no longer sufficiently aligned with any available action, thereby optimizing for efficiency. The timeline-style visualization (Fig. 6) plots the exact sequence of selected actions across planning steps for all students.

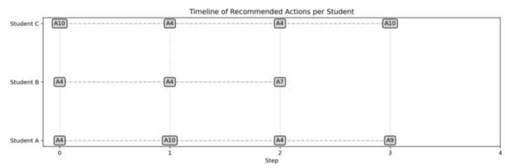


Fig. 6 Time line of recommended actions per student

- Student A followed the plan: $A4 \rightarrow A10 \rightarrow A4 \rightarrow A9$. This indicates a return to a previously effective action (A4), followed by a transition to a novel one (A9).
- Student B selected A4 twice, then A7, reflecting a strong alignment between action A4 and the target goal dimensions.
- Student C alternated between A10 and A4, before returning to A10. This suggests that A10 and A4 addressed complementary aspects of the learner's goal.

The repetition of certain actions (e.g., A4 and A10) across multiple students emphasizes the foundational nature of those actions in this simulation. Their embeddings likely span multiple high-weighted dimensions of goal vectors, making them versatile choices for goal satisfaction. These visualizations enhance the interpretability of the planner and confirm its alignment with human learning dynamics. Specifically, they demonstrate that:

- Efficient convergence is achieved without redundant steps;
- Action reuse reflects structural similarity between actions and goal vectors;
- The system maintains explainability by clearly illustrating how and why specific actions are prioritized or repeated.

This visualization-based evaluation validates the planner as a robust tool for adaptive, personalized planning in educational contexts. It also supports the potential deployment of the proposed system in intelligent tutoring systems and recommender applications.
Across all cases, the planner reliably selects high-similarity actions that progressively reduce the residual goal vector. The recurrence of specific actions (e.g., A4, A10) indicates their centrality in supporting various student goals. The weighted similarity mechanism provides an interpretable, adaptable approach to personalized educational planning. These findings support the broader application of this framework in intelligent tutoring systems and adaptive curriculum design.

5. Conclusion

In this paper, the Similarity-Based Framework for Goal-Aware Sequential Action Recommendation(SGASR) was proposed as a novel planning architecture. This presented a novel similarity-based framework for automatic goal-oriented planning that integrates semantic vector representations with a rule-based planner to facilitate personalized, context-aware action sequencing. Through rigorous mathematical modeling and the development of advanced similarity metrics, the framework effectively captures the nuanced relationships between user goals, actions, and contextual preferences. Applied to the domain of personalized student education, the system demonstrated robust adaptability by tailoring learning plans to diverse learner profiles, while maintaining computational efficiency via strategic search space reduction. The empirical results underscore the framework's capability to generate relevant, concise, and interpretable action sequences that align closely with individual objectives.

Despite the promising simulation results, this study has a limitation as the evaluation was conducted using synthetic learner profiles and a randomized action library. To secure stronger academic and empirical validation, our future work involves deploying SGASR into actual student learning management systems (LMS) to leverage real-world educational log data. Furthermore, we plan to conduct comprehensive comparative experiments against baseline recommendation techniques, including traditional collaborative filtering, deep reinforcement learning planners, and state-of-the-art LLM-driven agents, evaluating them across standardized metrics such as NDCG and Hit Rate

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