PataLLM: Personalized Automated Test Assembly with Educational Knowledge Graphs via Reinforcement Learning Induced Large Language Models

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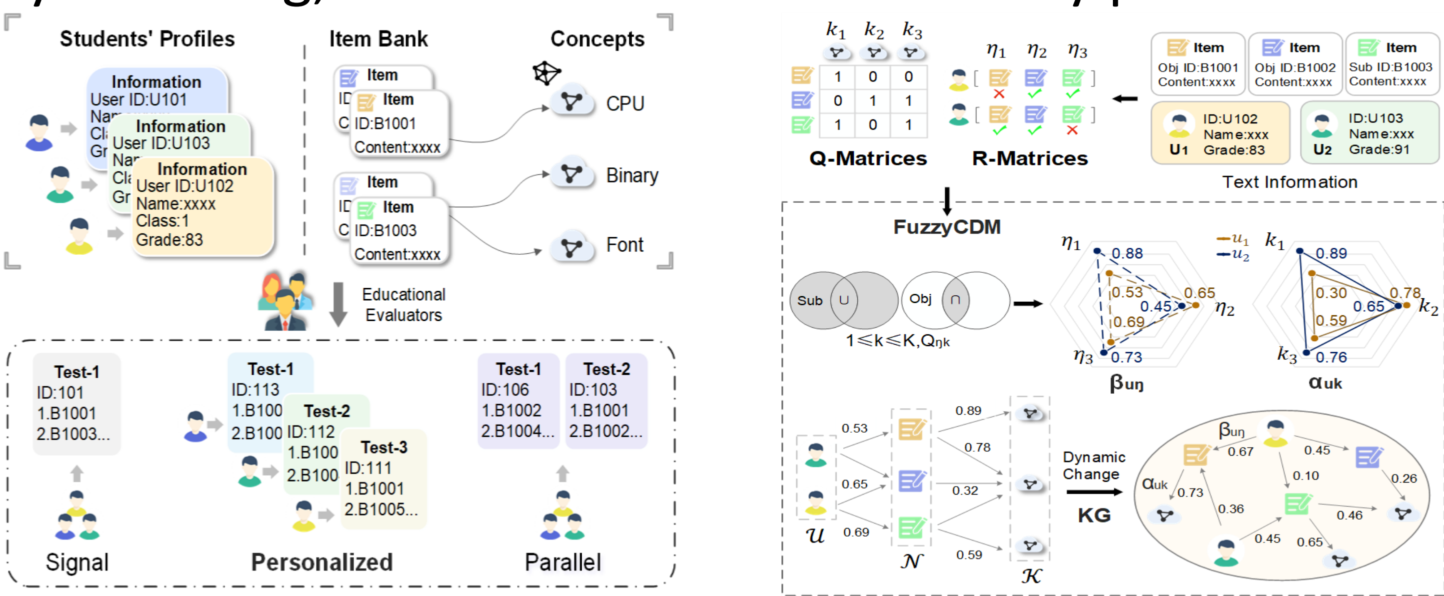
Problems & Ideas

- Problems of Automated test assembly approaches:
  - The traditional single and parallel tests approaches are static and fail to account for individual differences, often compromising fairness.
  - Heuristic algorithms depend on predefined rules, underutilize heterogeneous data, and cannot dynamically adapt to learners' evolving abilities.
- Ideas: Leverages LLMs as decision agents, integrates multi-source data into knowledge graph, incorporates FuzzyCDM for fine-grained ability modeling, and formulates the assembly process as a RL task.



Left: Three forms of automated test assembly. Right: FuzzyCDM completes students' mastery of items and concepts, and dynamically constructs the educational knowledge graph.

Main Contributions

- Contributions:
  - LLM-driven framework that personalizes test generation based on students’ knowledge attribute states.
  - Integrate multi-source data and FuzzyCDM into a unified knowledge graph to enhance students’ cognitive representation.
  - RL optimization process, achieving dynamic adaptation and significant performance gains on three years of real-world data.

Setting	2021 Bank						2022 Bank						2023 Bank					
	CDI (↑)			ADI (↑)			CDI (↑)			ADI (↑)			CDI (↑)			ADI (↑)		
	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3	C1	C2	C3
Platform	0.356	0.361	0.338	0.241	0.255	0.228	0.388	0.351	0.380	0.231	0.256	0.229	0.320	0.322	0.309	0.241	0.229	0.241
P-CDI	0.446	0.253	0.416	0.135	0.327	0.185	0.463	0.309	0.455	0.188	0.335	0.186	0.403	0.276	0.385	0.197	0.301	0.195
S-MOPSO/D	0.414	0.417	0.376	0.258	0.286	0.262	0.424	0.383	0.413	0.262	0.295	0.265	0.346	0.350	0.339	0.273	0.259	0.272
NSGA-II	0.427	0.431	0.388	0.268	0.297	0.272	0.440	0.393	0.421	0.273	0.304	0.277	0.353	0.358	0.348	0.282	0.267	0.281
LP	0.398	0.403	0.364	0.263	0.277	0.250	0.417	0.375	0.407	0.259	0.283	0.257	0.340	0.342	0.332	0.266	0.249	0.264
DQN	0.442	0.447	0.397	0.277	0.309	0.283	0.453	0.405	0.435	0.283	0.315	0.288	0.362	0.369	0.355	0.290	0.278	0.292
PataLLM																		
LLaMA-2-7B	0.473	0.476	0.417	0.291	0.328	0.308	0.483	0.426	0.454	0.307	0.338	0.311	0.381	0.385	0.373	0.312	0.296	0.312
Vicuna-7B	0.489	0.492	0.429	0.305	0.340	0.322	0.498	0.440	0.466	0.320	0.353	0.324	0.389	0.396	0.384	0.325	0.307	0.325
LLaMA-3-8B	0.503	0.506	0.439	0.315	0.357	0.338	0.512	0.459	0.481	0.336	0.371	0.340	0.401	0.411	0.396	0.340	0.319	0.338
GPT-3.5	0.542	0.554	0.514	0.391	0.420	0.404	0.592	0.527	0.554	0.401	0.434	0.419	0.474	0.477	0.477	0.412	0.395	0.418
GPT-4o	**0.551**	**0.560**	**0.522**	**0.413**	**0.437**	**0.436**	**0.614**	**0.541**	**0.562**	**0.435**	**0.445**	**0.449**	**0.484**	**0.489**	**0.492**	**0.431**	**0.435**	**0.432**

PataLLM consistently outperforms all baselines across three cohorts, achieving higher CDI and ADI. Larger LLM capacity further improves decision quality, and performance remains robust across different academic tracks and years.