06

Summary & Future directions

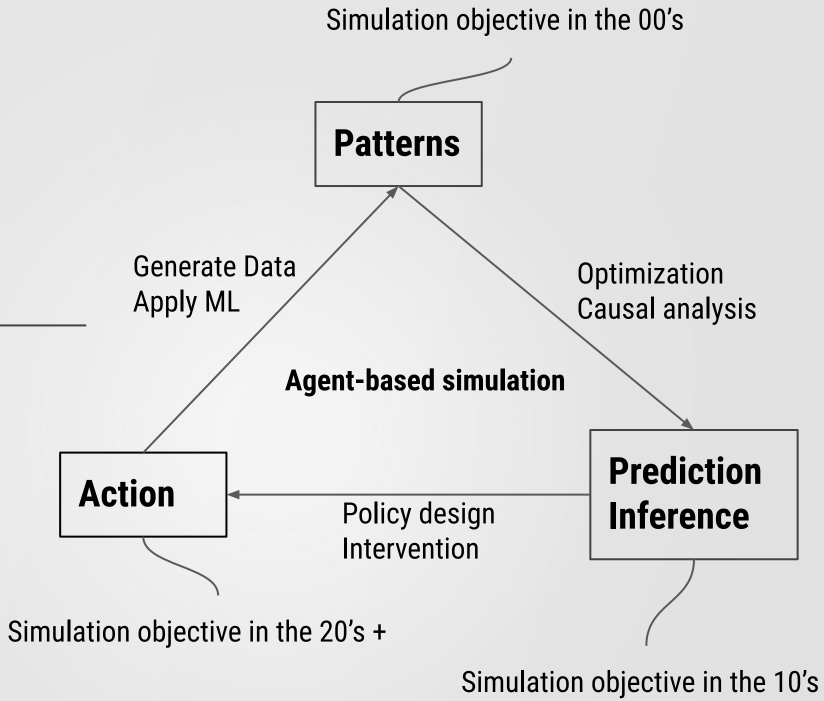
Complete the loop of **pattern**, **prediction & inference**, **action**
Interpretation and **evaluation**
Generative AI and **LLM**

Summary of Agent-based Simulation for Modern Web Applications

Complete the loop

Pattern Recognition, Prediction & Inference, and Action are the three pillars of modern web applications and perhaps artificial intelligence (AI).

Agent-based simulation is able to methodically integrating and summarizing concepts and solutions developed throughout history for each component across various problems.



Result Interpretation and evaluation for Agent-based Simulation

An agent has to serve a purpose, how to build an agent with the right amount of description or detail remains an **art** than **science**.

Natural systems have **soft factors** that are difficult to quantify, calibrate, or even justify.

One must not make decisions on the basis of the **quantitative outcome** of an agent-based simulation that are designed purely at the qualitative level

Outcome correlation with real-world experiments and testings

Reality faithfulness

Complexity of the assumption and hypothesis supported by visible mechanisms from the interventions

Assumption complexity
Intervention manipulability

What's Next for Agent-based Simulation?

Employ such as generative adversarial network (**GAN**) as a feature (or initial states) agent to produce **close-to-real** distributions

Large language models pre-trained on whole-web data exhibit remarkable capacity for in-context learning, enabling them to effectively tackle a diverse array of complex tasks with human-like proficiency. With appropriate set up and prompt engineering, LLM can serve as both **task-specific and generic agents**.

Can we imagine a simulation consists entirely of GenAI agents?

Real-world observations could be an agent itself (e.g. reward-model agent), leading to the potentially more **powerful** & **targeted** semi-synthetic analysis

Remark: considered as an alternative to the causal-structure-based simulation

Remark: although the directions presented in this slide have been explored to some extent, there remains much opportunities

Remark: naturally connects to learning from partial feedback with bandit or RL

Opening remark
Motivation, Introduction & Scope
01

Overview
Agent-based Simulation for
Modern Web Applications
02

For Information Retrieval
Web search engine
Conversation System
03

THANK YOU

Does anyone has any questions?

04
For Recommender System
Personalized Recommendation

05
For Marketing and Advertising
Bidding, Pricing, Ads Allocation

06
Summary and future directions
Landscape
Interpretation, evaluation
Generative AI, LLM

Slides and Recordings will be available on our webpage:
https://foundation4recsys.github.io/Tutorial-WWW23/

THANK YOU

Please feel free to contact us for follow-up and opportunities

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