Foundation Models-O1

Ruibo Tu, 2024 Sep. 23rd

Ruibo's blog for the talk

Foundation Models

“Gigantic pre-trained models
Trained on enormous data
Used in a few-/zero-shot manner”

Next token prediction

Language

- GPT-4
- Gemini2
- LLaMA3
- …

Masked prediction

Vision

- SAM
- MAE
- Dino2
- …

Bi-modal

- GPT-4V
- CLIP
- …

Limitations of FMs

- **Not world models**: (Mechanisms, states)
  - Observational data (*no interventional data, experimentation*)
  - Hallucination: confidently wrong results, sounds well but wrong

- **GPT limitation**:
  - Cannot modify autoregressively generated results (*OpenAI-o1*)
  - Small working memory (*CoT: More computation for relaxing the constraint*)

- **Challenges**:
  1. **Reasoning**: No aware of structural/causal dependencies among factors
  2. **Planning**: Incremental planning✅, no hierarchical / long-term planning❌

“Predicting consequences of actions requires to capturing causal relationships correctly”

***Unknown: FMs*.**

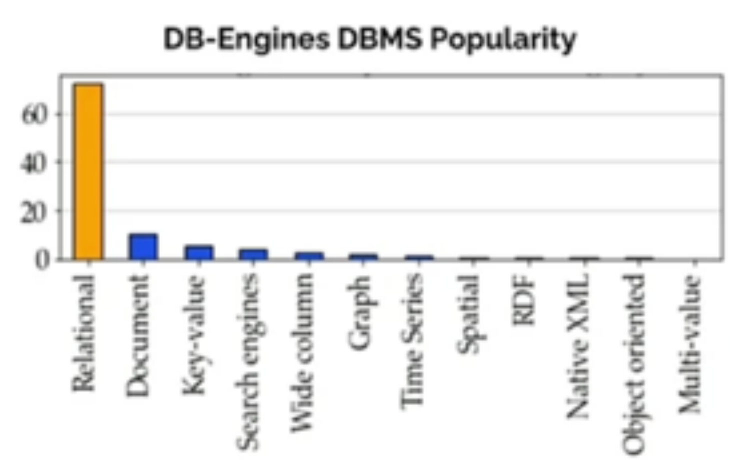
“Many tasks are based on table understanding”

Under-explored: FMs.

Data are very likely in the form of tables

Tables are **everywhere**

Spreadsheets, documents, web (pages), databases, ...



Goal: Building a foundation model for data scientists and ML engineers

Tabular data

	C1	C2	C3
R1		1.68	
R2	Healthy	1.75	Very Satisfied
R3	NULL	1.98	
R4		2.01	

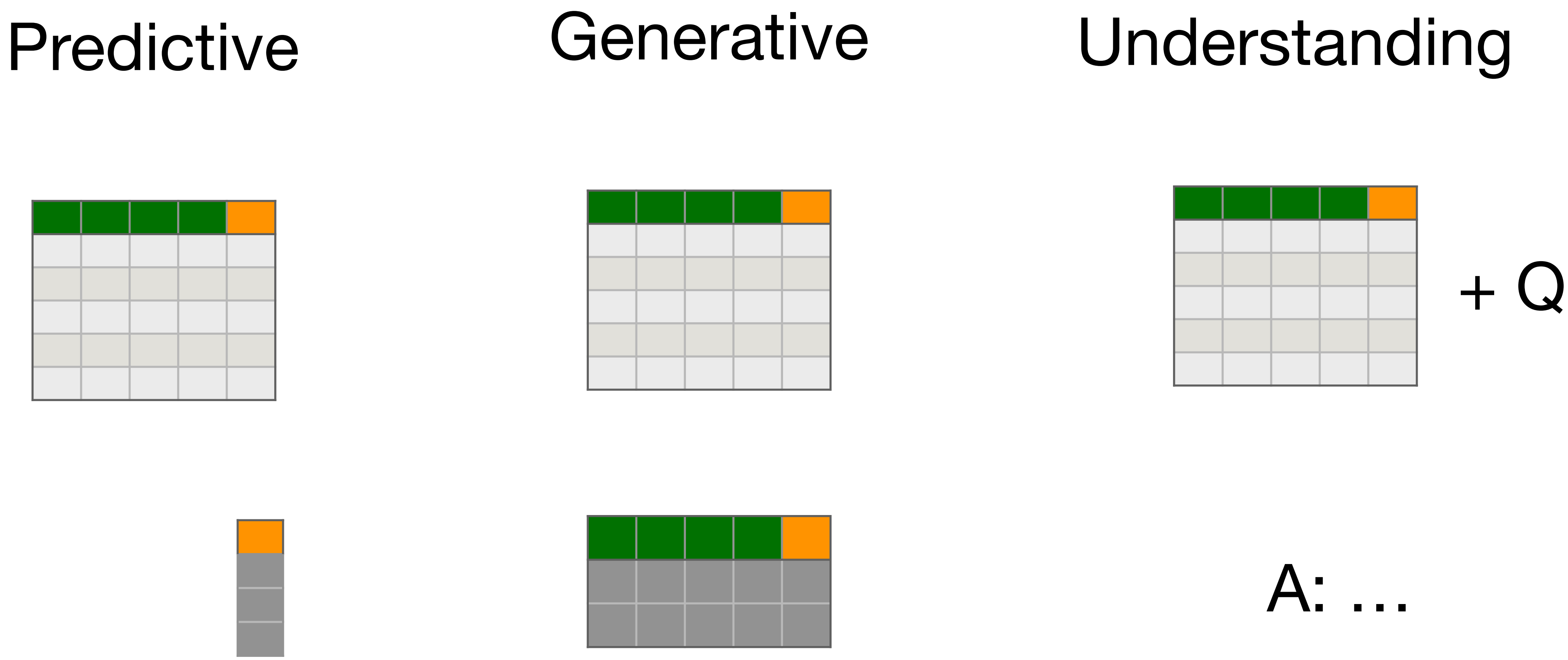
	C1	C2	C3
R5	Sick	1.56	NULL
R6		1.75	Less Satisfied
R7		1.88	

	C2	C3	C4
R1	1.68		
R2	1.75	Very Satisfied	Male
R3	1.98		
R4	2.01		

	C2	C5	C6
R1	1.68		
R2	1.75	9.9	Rare
R3	1.98		
R4	NULL	NULL	NULL
R5	NULL	NULL	NULL
R6	NULL	NULL	NULL
R7	1.88	10.1	Medium

- Missing data imputation
- Feature selection
- Root cause analysis
- A/B testing
- Anomaly detection
- ML-based Predictive analysis
- Causal discovery
- Potential outcome prediction

SOTA Tabular Tasks



SOTA Tabular Methods

Encoder-Decoder: Generic representation learning

- Self-supervised learning, contrastive learning
- BERT

Only-**Decoder**: Generative tasks as the general objective

- Predict next token
- GPT
- Diffusion models

Challenges

	C1	C2	C3
R1		1.68	
R2	Healthy	1.75	Very Satisfied
R3	NULL	1.98	
R4		2.01	

	C1	C2	C3
R1		3.01	
R2	Sick	2.22	Satisfied
R3	NULL	2.01	
R4		2.91	

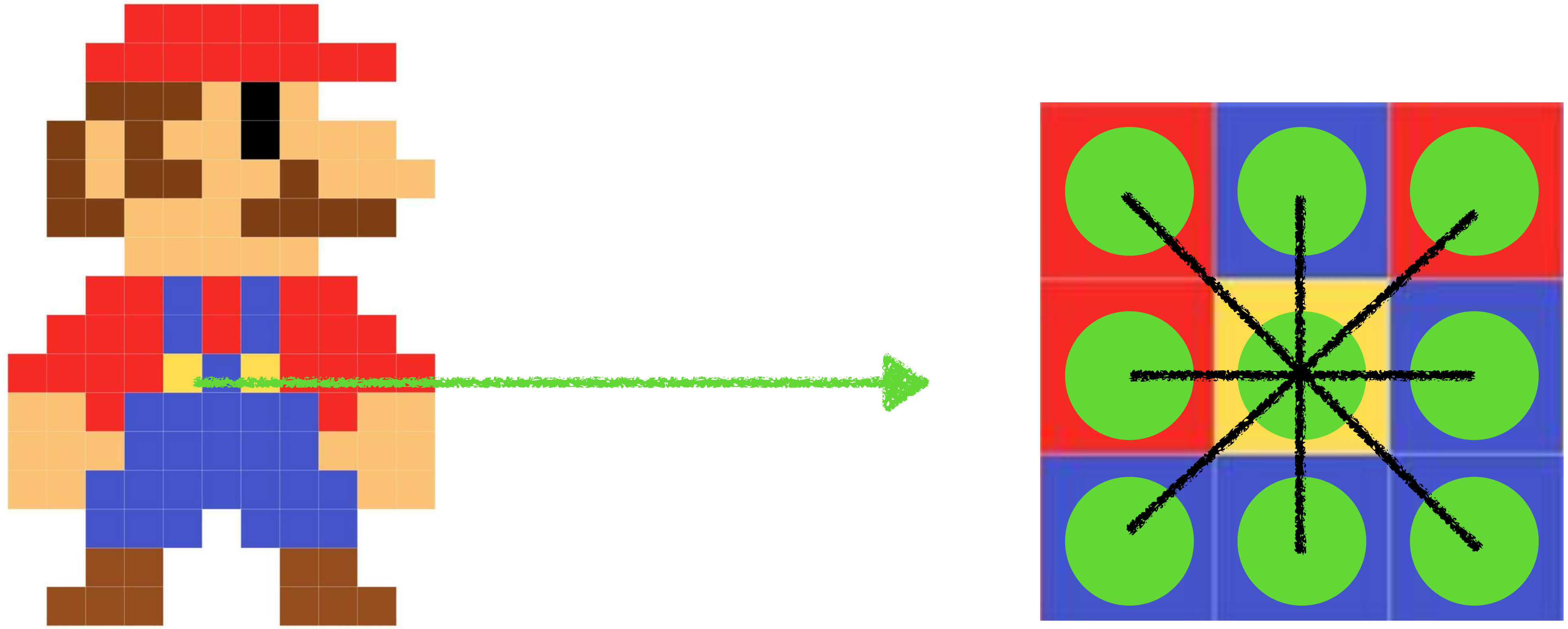
	C2	C3	C4
R1	1.68		
R2	1.75	Very Satisfied	Male
R3	1.98		
R4	2.01		

1. Practical challenges
   - Transformer structure
   - Mixed data type
   - Missing values
2. Structural dependencies
   - Prior: Causal relationships
   - Domain / Distribution shift
   - Cross-table reasoning

Open problems

“How to enable FMs to
capture (causal) structural information”

Order of an image



Order of an sentence

Order of a table

Col. order

Row. order

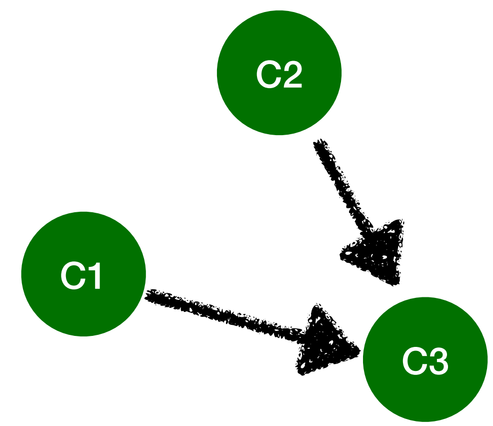
	C1	C2	C3
R1		1.68	
R2	Healthy	1.75	Very Satisfied
R3	NULL	1.98	
R4		2.01	

	C1	C3	C2
R1			1.68
R2	Healthy	Very Satisfied	1.75
R3	NULL		1.98
R4			2.01

	C1	C2	C3
R1		1.68	
R2	Healthy	1.75	Very Satisfied
R4		2.01	
R3	NULL	1.98	

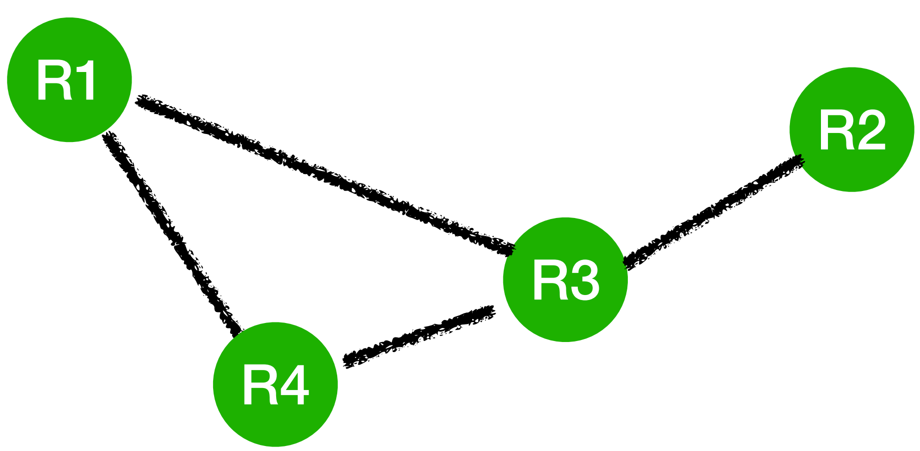
The same table

Graph + Table



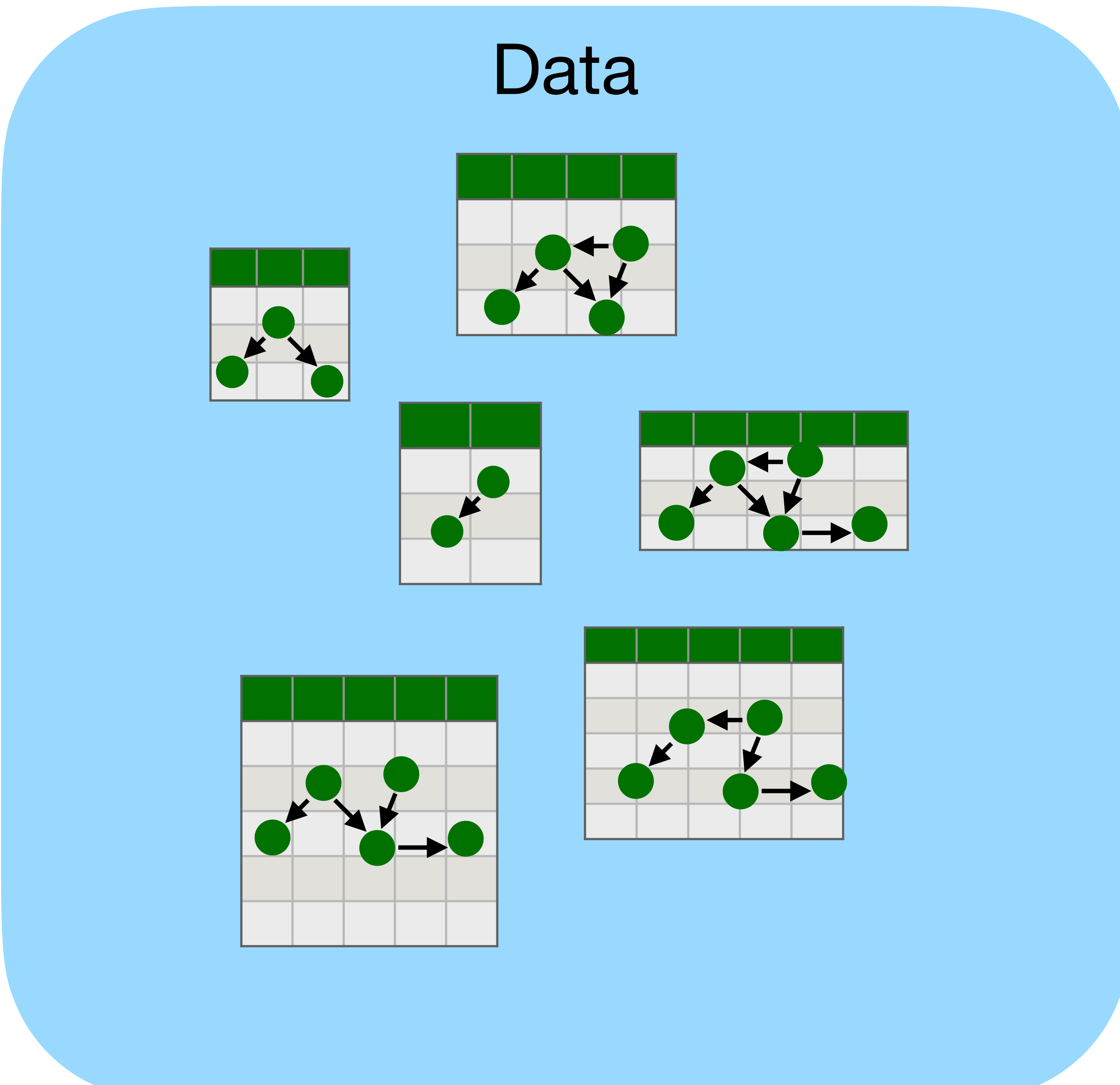
Causal graph

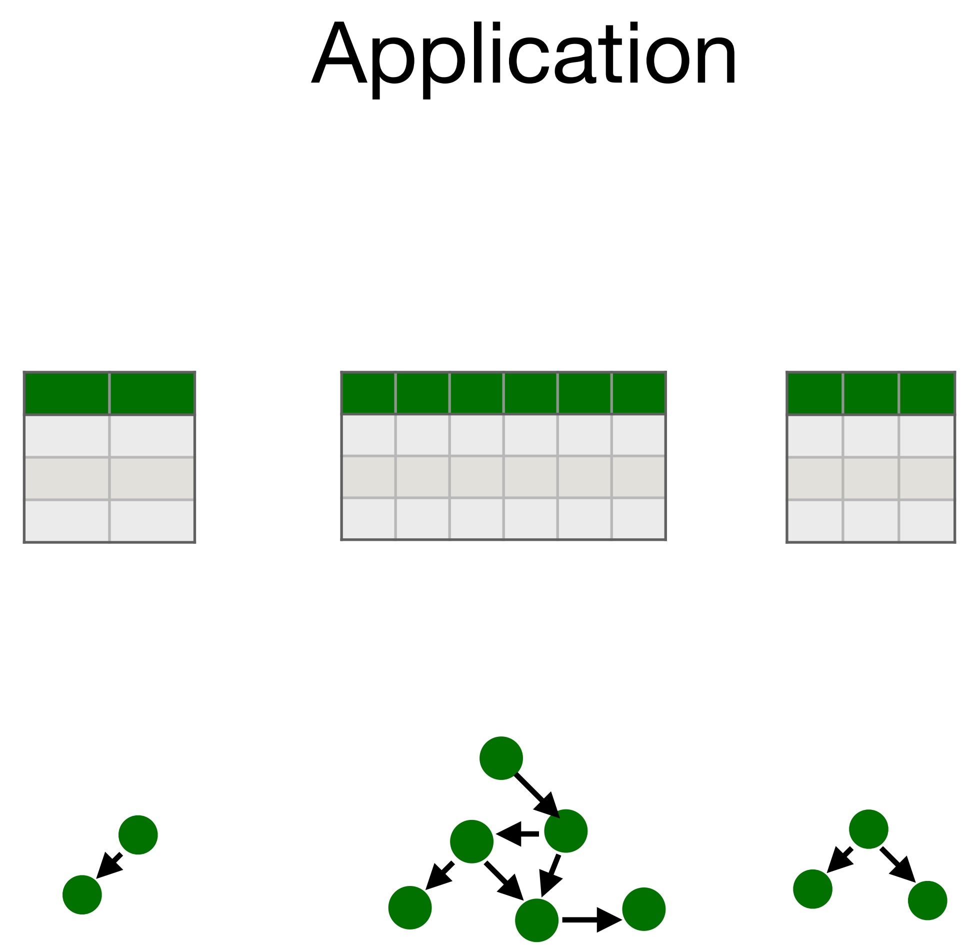
	C1	C2	C3
R1		1.68	
R2	Healthy	1.75	Very Satisfied
R3	**NULL**	1.98	
R4		2.01	



Social-Network graph

(Causal) Structure-Aware Foundation Models





“Our benchmarks
For LLMs and other generative models”

LLM Benchmarks

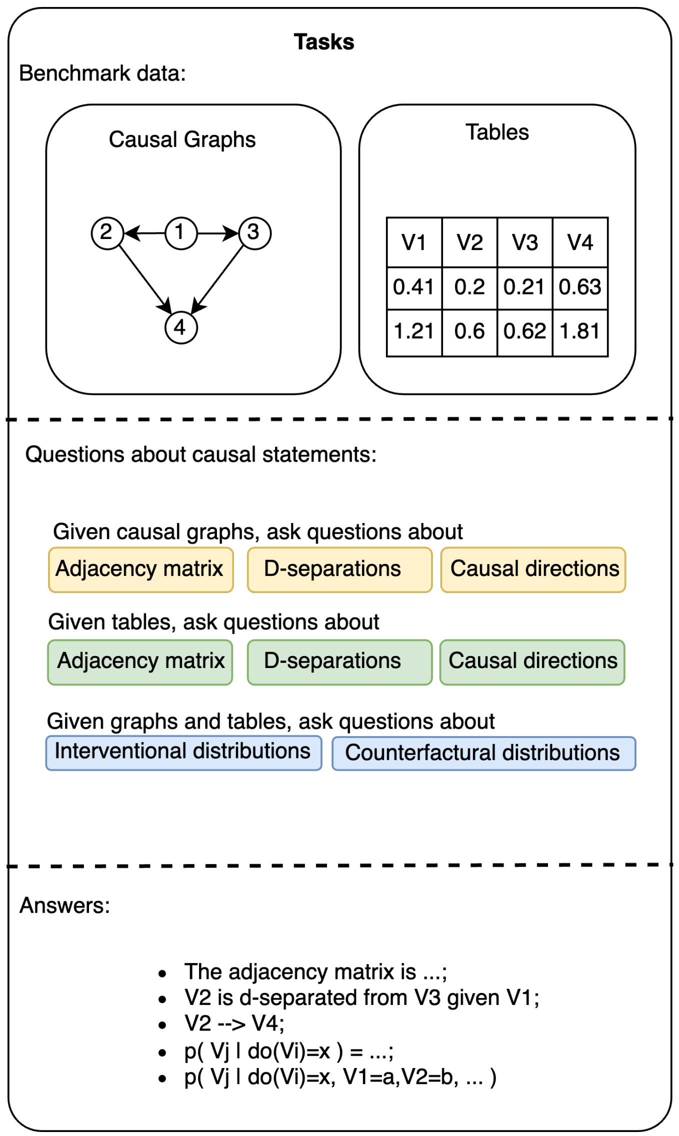
1. Common Benchmarks: well regularized
    - Conversational, arithmetic math, competition coding tests
2. Tuned for a better number
    - Skills in real-world applications?

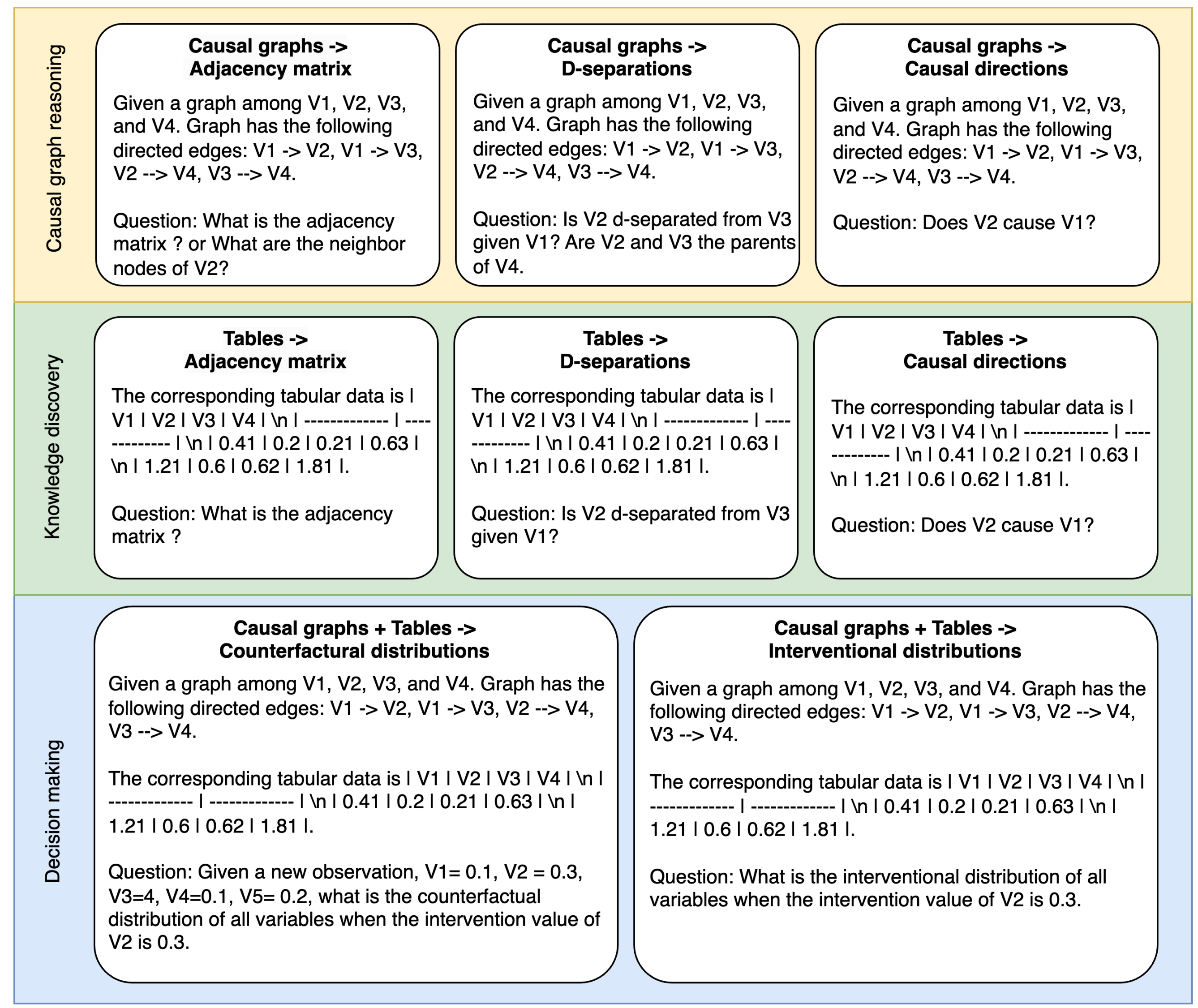
A benchmark for causal reasoning and decision making

Causal reasoning ability is the **core** for *Reasoning* and *Decision-making*

- Numerical and mathematical reasoning
- Applications:
    - Agent, Healthcare, Education …

Work 1: A benchmark for causal reasoning and decision-making





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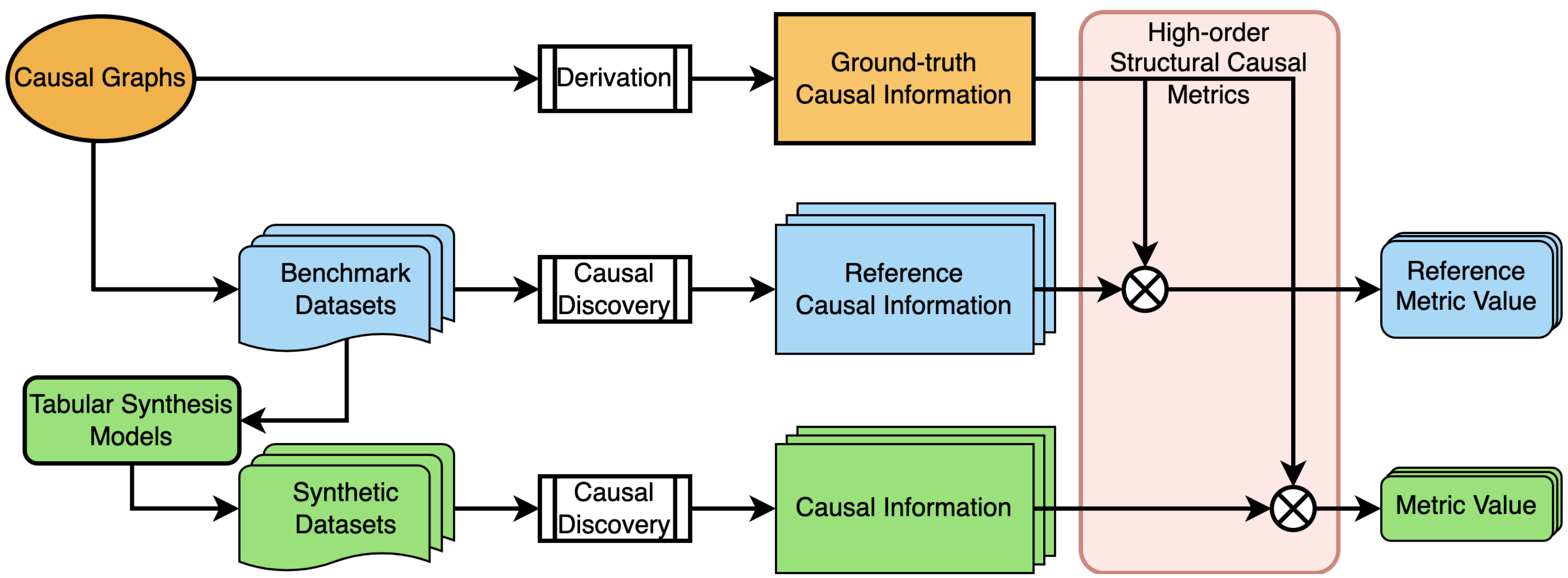
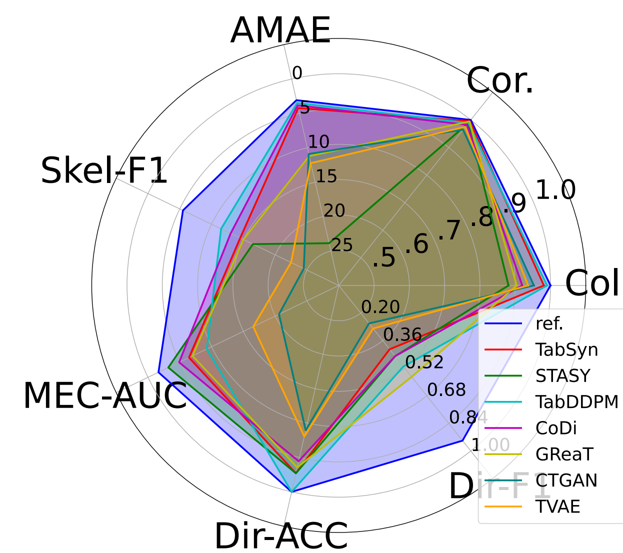
Meta

Work 2: A benchmark for evaluating tabular synthesis model capability for preserving causal information



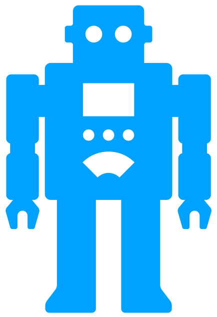
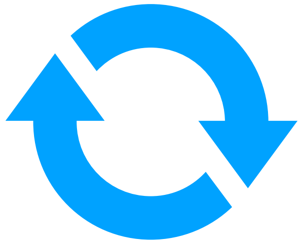


- Diffusion-based
- LLM-based

Part 2

“Decision-making of FMs (agents)”

Agents (RL)

Agents	Interactions	Environments
		
Dialogue Agent	QA, conversation	Human
Game Agent	APIs	Text, Video Games

Goal: Robust agents learn causal world models

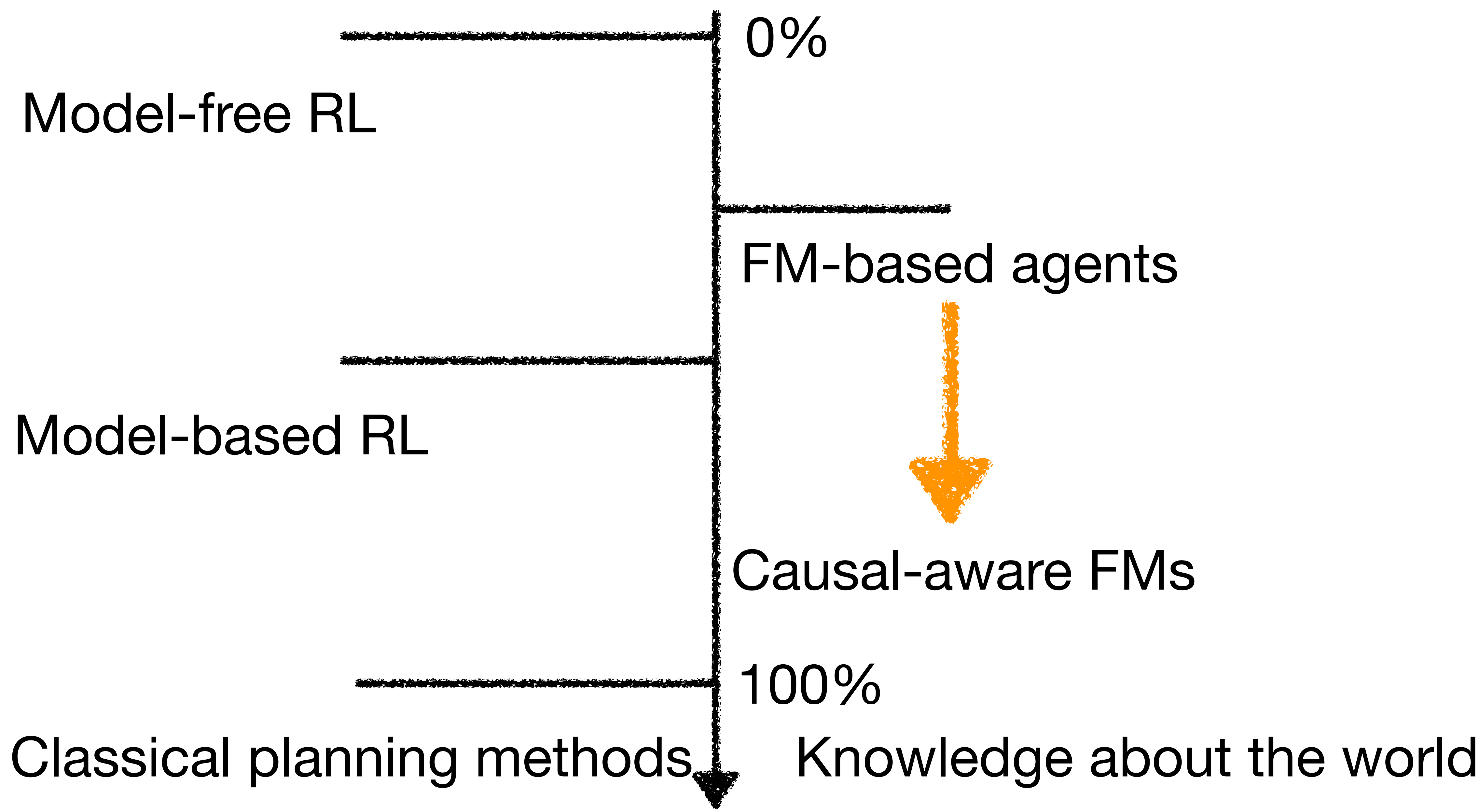
"Predict consequences of actions"

Minimum requirement for generalization
- Efficiency: Sample quality and efficiency
- Effectiveness: generalization

"Only interacting with the world and causal discovery can get causal information."

Richens, J. and Everitt, T., 2024. Robust agents learn causal world models. *Honorable mention of ICLR2024*

Knowledge about the world

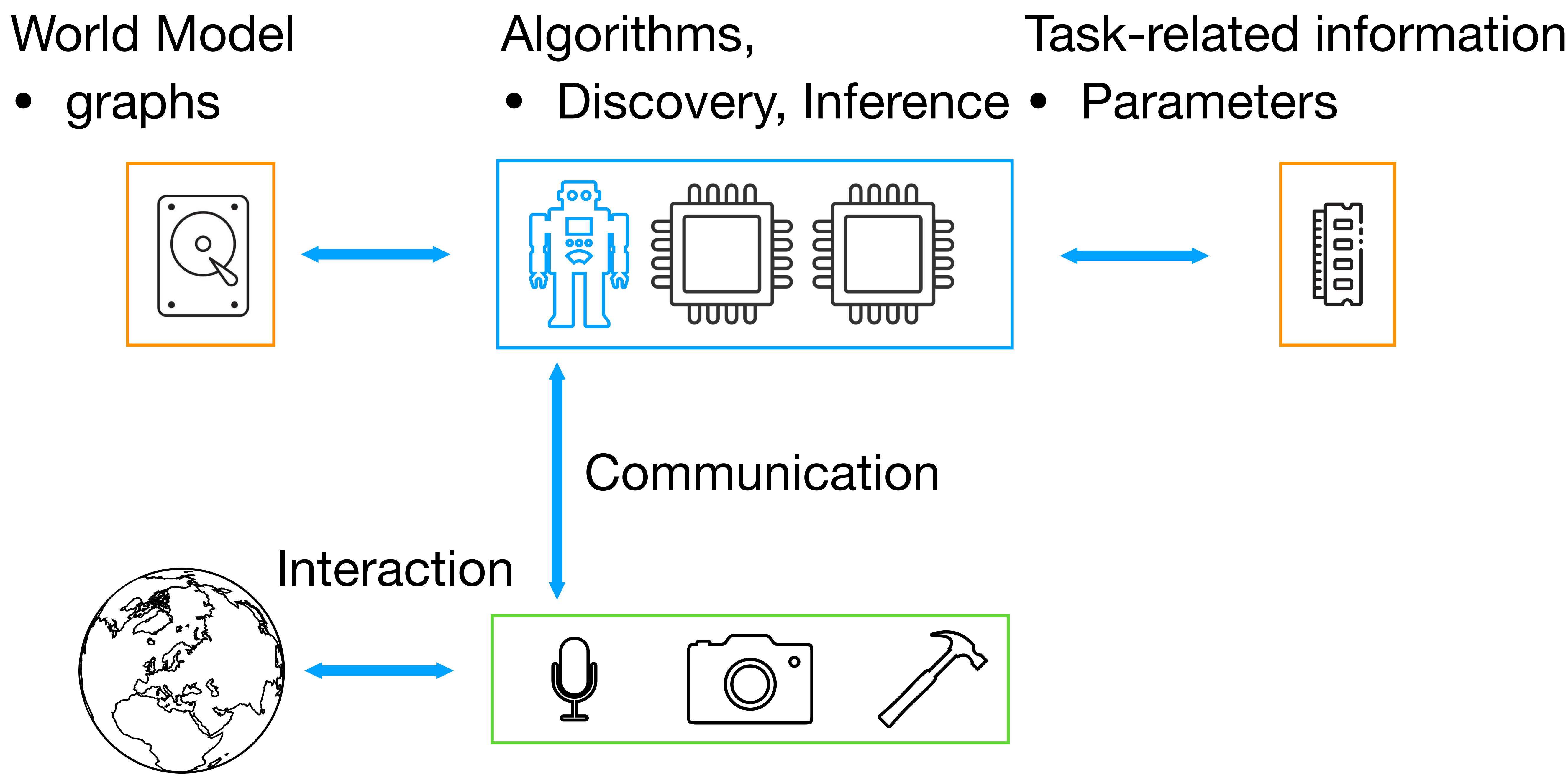


Agents with a causal world model

Model-based RL

Causal (SCM)-based

Causal-aware FM agents



Non-causal FM agents

1. Augmenting memories and hard drives
2. Iterative prompts with in/external feedbacks
3. Combine with planning methods
4. On/offline fine-tuning

Wang, G., Xie, Y., Jiang, Y., Mandlekar, A., Xiao, C., Zhu, Y., ... & Anandkumar, A. (2023). Voyager: An open-ended embodied agent with large language models. arXiv preprint arXiv:2305.16291.
Li, Shuang, Xavier Puig, Chris Paxton, Yilun Du, Clinton Wang, Linxi Fan, Tao Chen et al. "Pre-trained language models for interactive decision-making." Advances in Neural Information Processing Systems 35 (2022): 31199-31212.
Yoneda, T., Fang, J., Li, P., Zhang, H., Jiang, T., Lin, S., Picker, B., Yunis, D., Mei, H. and Walter, M.R., 2023. Statler: State-maintaining language models for embodied reasoning. arXiv preprint arXiv:2306.17840.
Hao, S., Gu, Y., Ma, H., Hong, J.J., Wang, Z., Wang, D.Z. and Hu, Z., 2023. Reasoning with language model is planning with world model. arXiv preprint arXiv:2305.14992.
Pouplin, T., Sun, H., Holt, S. and Van der Schaar, M., 2024. Retrieval-Augmented Thought Process as Sequential Decision Making. arXiv preprint arXiv:2402.07812.

“Causal-aware FMs for
Reasoning and decision-making”

Thank you for listening!

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