LLM-ACTR: from Cognitive Models to LLMs in Manufacturing Solutions

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Agenda

Motivation and proposed solution

Formulate problems from business cases

Cognitive synthetic agent: VSM-ACTR

Data collection and analyze

LLM-ACTR: a developing knowledge transfer framework

Future work

References

Acknowledgement

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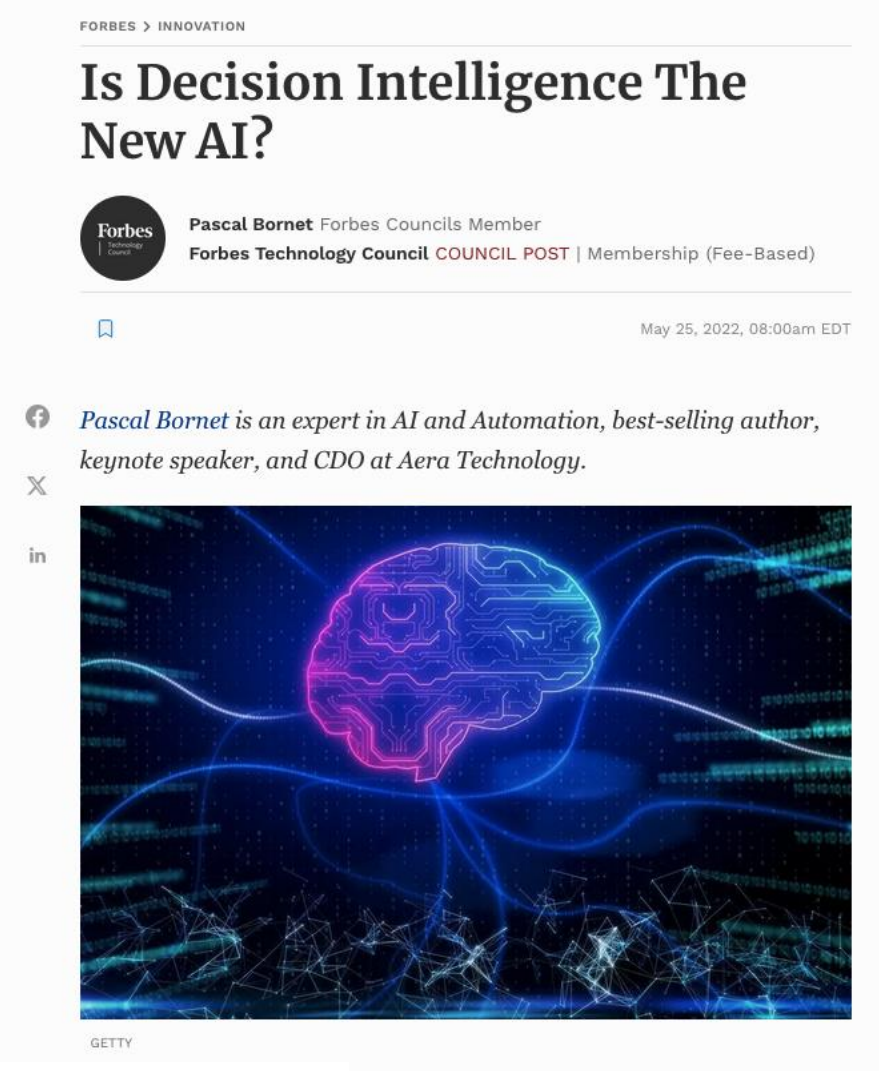
Introduction: motivation and proposed solution

Decision Intelligence



FORBES > INNOVATION

Is Decision Intelligence The New AI?

Pascal Bornet Forbes Councils Member
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GETTY

Decision Support

machines provide some basic tools to support human decision making

Decision Augmentation

machines play a larger and more proactive role in the decision process.

Decision Automation

machines perform both the decision step and the execution step autonomously.

Challenges for LLM-based Decision Making

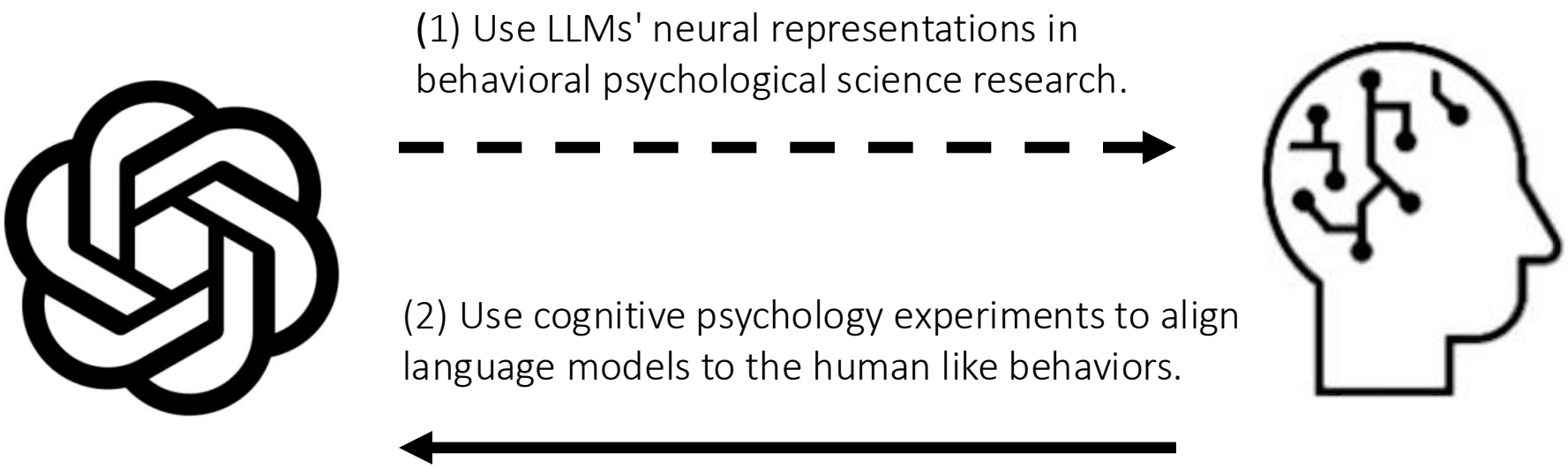
- Hallucinations
- Noisy inference behavior
- Lack of trust
- Bad predictions and increased risks

What If

Create an assisted AI decision-making tool **Cognitive-LLM**[1] that combines neural-symbolic representations to encode physical knowledge alongside machine learning models.

Cognitive-LLM aims to augment AI decision-making with human cognitive understanding and reflect how humans perceive and understand the world through cognition and knowledge.

Relating cognitive Psychology to Develop Human-Like Decision-Making Support Tool



Centaur^2

- Foundation model trained on larger-scale human subject data for psychological alignment.
- Data-expensive and computationally expensive experiment (160; 60,092)
- Lacks grounding in metacognition despite its size.
- This motivates us to support the development of human-like decision-making tools for companies such as Bosch LLC's, to fine-tune LLMs for domain-specific human like decision-making support tools.

Decision Intelligence *A Common Model of Cognition*

- ***Cognitive Architectures*** are computational frameworks that capture the invariant mechanisms of human cognition, including those underlying the functions of attention, control, learning, memory, adaptivity, perception and action
- A ***Cognitive Model*** is the software artifact resulting from using a Cognitive Architecture to model a human task
- The "***Common Model of Cognition***" is a recent development to consolidate four decades of research

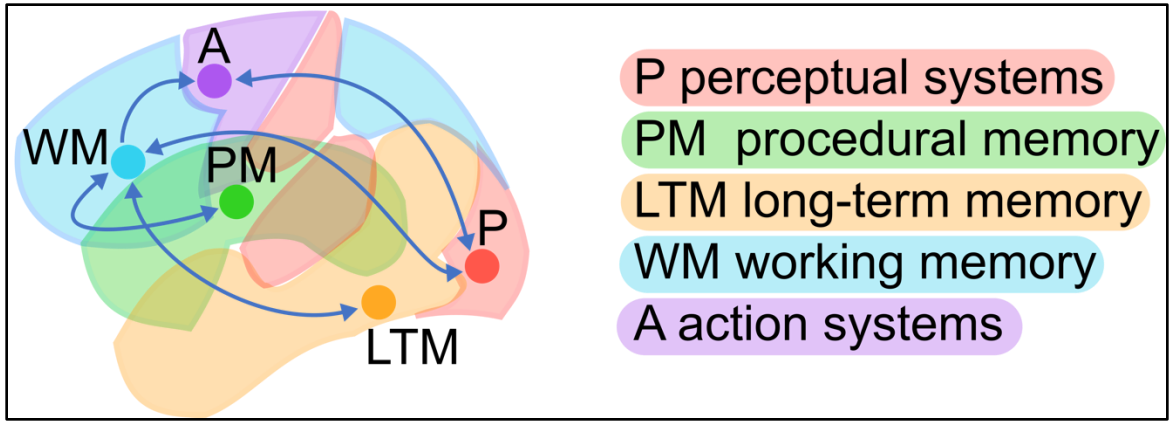
ELSEVIER

NeuroImage

Volume 235, 15 July 2021, 118035

Analysis of the human connectome data supports the notion of a "Common Model of Cognition" for human and human-like intelligence across domains

Andrea Stocco [a], Catherine Sibert [a], Zoe Steine-Hanson [b 1], Natalie Koh [c 2], John E. Laird [d], Christian J. Lebiere [e], Paul Rosenbloom [f]

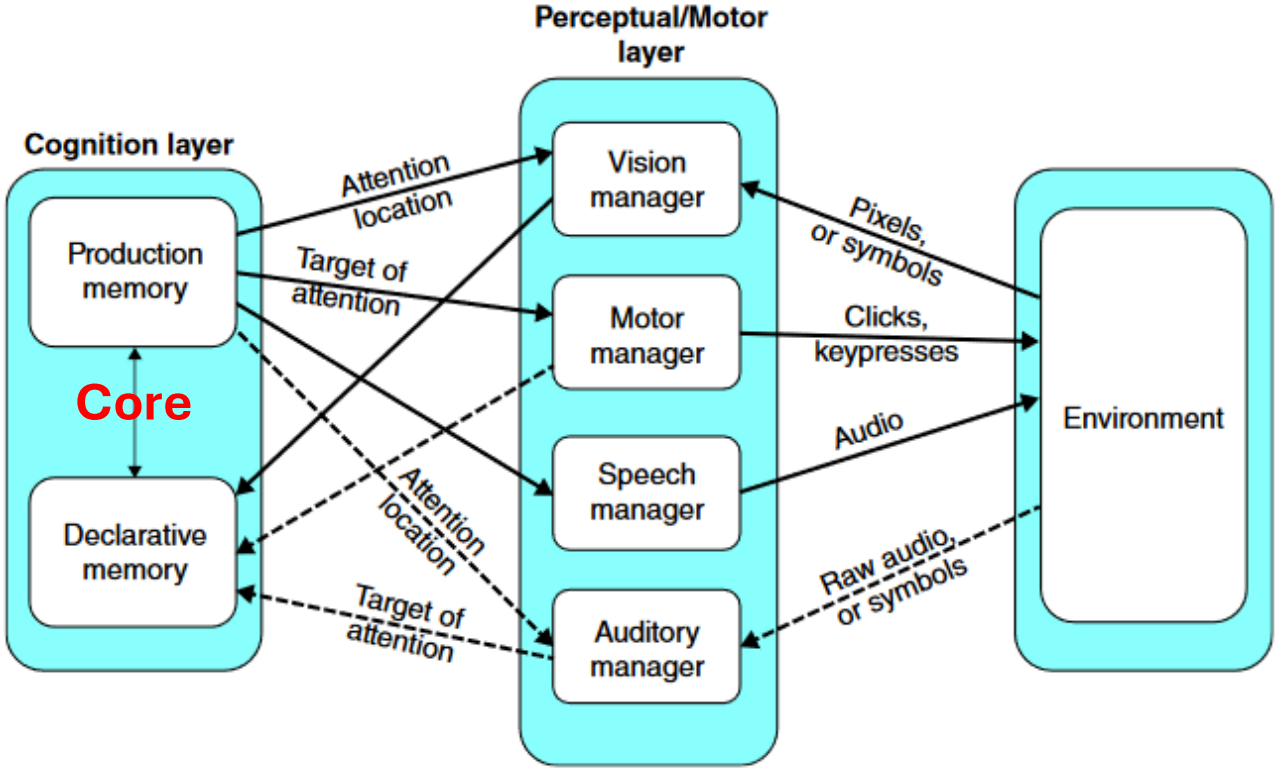


ACT-R^3: the Cognitive Architecture

- "Architecture" refers to the fundamental organizational principle of a complex cognition system.
- Modules to implement the fixed mechanisms of cognition

Productions,
if-then rules,
actionable memory

Chunks,
factual memory,
slot-value pairs



Proposed Solution *Cognitive LLMs*

1 2 3 4 5

Neuro-Symbolic Cognitive Method

Decision Making Problem

Synthetic cogAgent

Create a synthetic CogAgent on the task with human like reason, plan, and learning.

Knowledge curation

Cognitive model is used to run stochastic simulations of task at scale. Key semantic features are extracted.

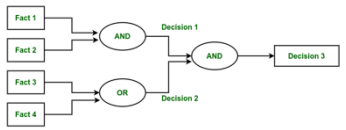
Knowledge transfer

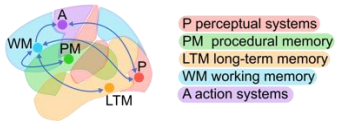
A knowledge transfer pipeline is used to calibrate LLM to perform decision augmentation for tasks in exercise

Cognitive LLMs

- A combination of different techniques like ontology-based formalization, NLP, psychometrics, are used to 1) model the symbolic components of the task, i.e., the declarative and procedural knowledge, and 2) set the sub-symbolic parameters (e.g., learning rate, similarity matching).
- Before running simulations at scale, tests are conducted on adequacy of symbolic and parametric representation

- Use mechanism of LLMs' next-token prediction and the cognitive decision-making knowledge representation





Cognitive LLMs Prototype

A production line consists of two sections with potential defect sources: pre-assembly and assembly

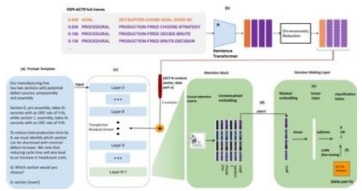
Pre-assembly takes 40 seconds with an Overall Equipment Effectiveness (OEE) rate of 88%

Assembly, on the other hand, takes 44 seconds but has a lower OEE rate of 80.1%

To achieve a total assembly time reduction of 4 seconds, we need to identify which section can be optimized with minimal impact on defect rate

It's important to note that reducing cycle time will also lead to an increase in **line headcount** cost

Cognitive LLM



Recommendations

A: I recommend reducing the time spent in the assembly section based on the following expert rationale:

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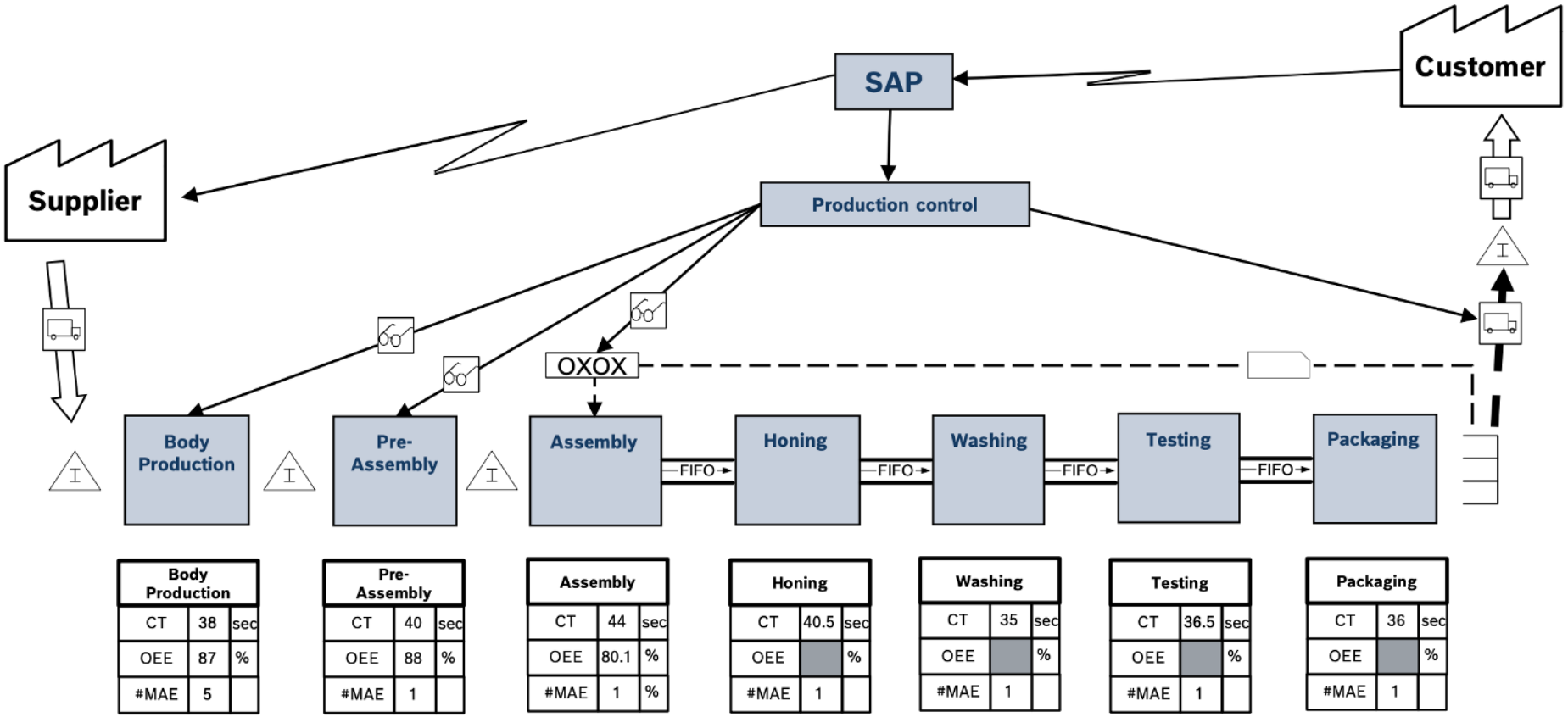
02

Formulate Problems from Business Cases

Production System Handbook, Value Stream Map



Body Production		
CT	38	sec
OEE	87	%
#MAE	5	

Pre-Assembly		
CT	40	sec
OEE	88	%
#MAE	1	

Assembly		
CT	44	sec
OEE	80.1	%
#MAE	1	%

Honing		
CT	40.5	sec
OEE		%
#MAE	1	

Washing		
CT	35	sec
OEE		%
#MAE	1	

Testing		
CT	36.5	sec
OEE		%
#MAE	1	

Packaging		
CT	36	sec
OEE		%
#MAE	1	

Define a Decision-Making Task

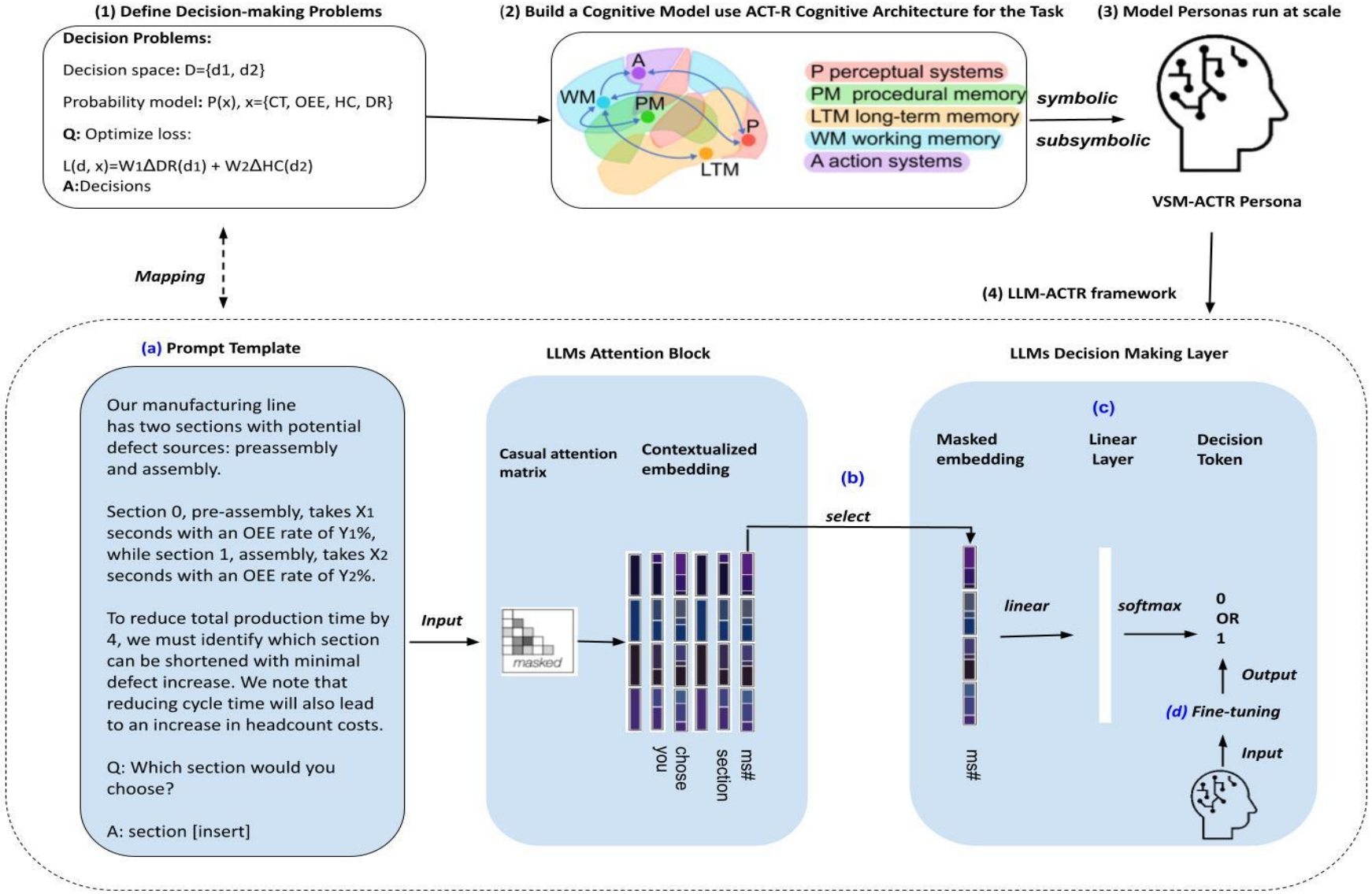
Decision space D={d1, d2}

Probability Model P(x), x={CT, OEE, HC, DR}

Loss function $L(d, x)=W_1 \cdot \Delta DR(d) + W_2 \cdot \Delta HC(d)$

Decisions $d^* = \arg\min_{d \in D} \mathbb{E}_{\mathbb{P}(X)}[L(d, X)]$

An exemplar of using Cognitive-LLM[1] in manufacturing decision making



03

Cognitive Synthetic Agent: VSM-ACTR

VSM-ACTR^4 model's Reason, Plan, and Learn

Reason Production rules for if-then actionable memory, each associated with utility; Declarative chunks for factual memory

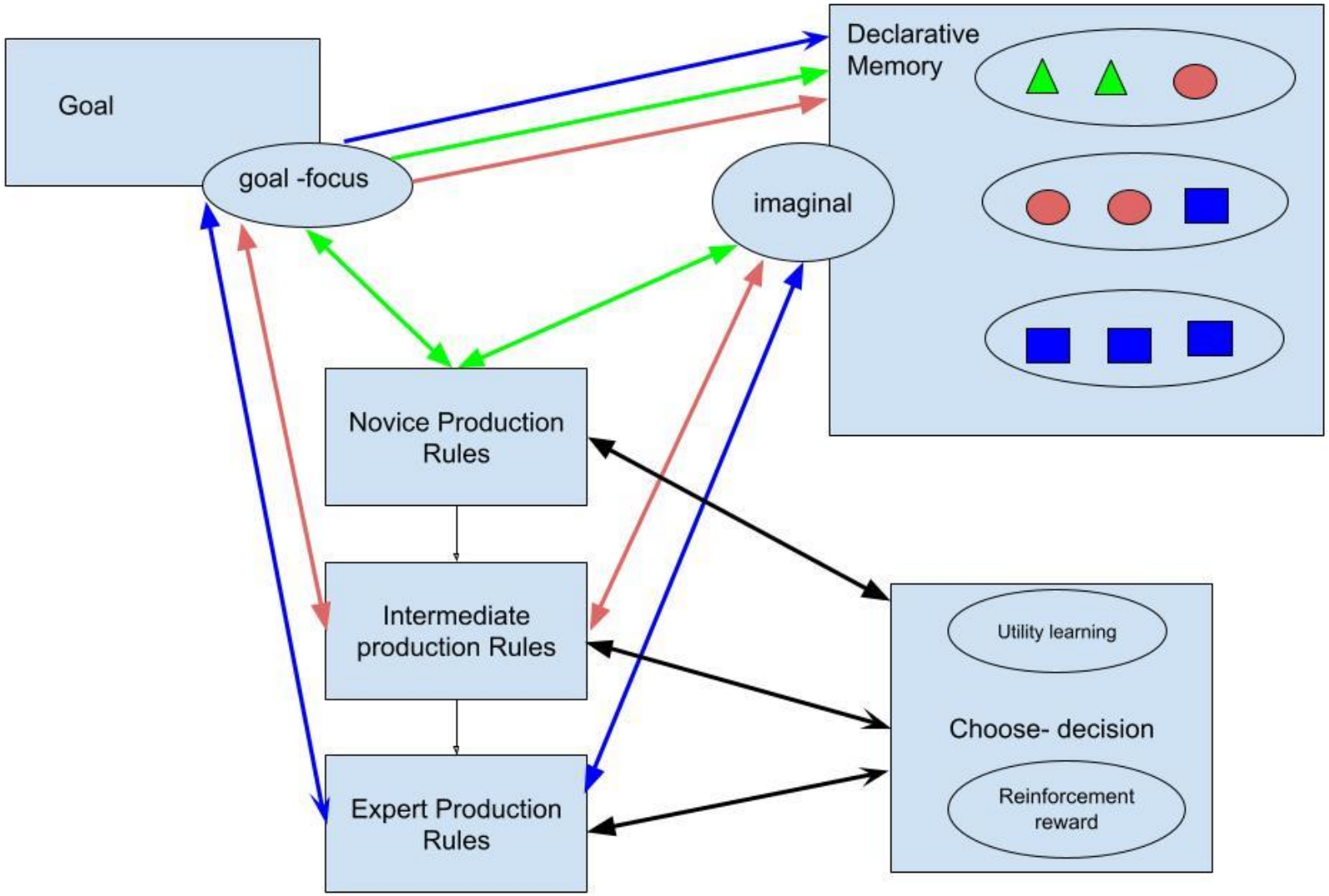
$$Eqn.1:\ U_i(n) = U_i(n-1) + \alpha\,[R_i(n) - U_i(n-1)]$$

Plan If multiple productions compete with expected utility values, the probability of selecting production is calculated use SoftMax function.

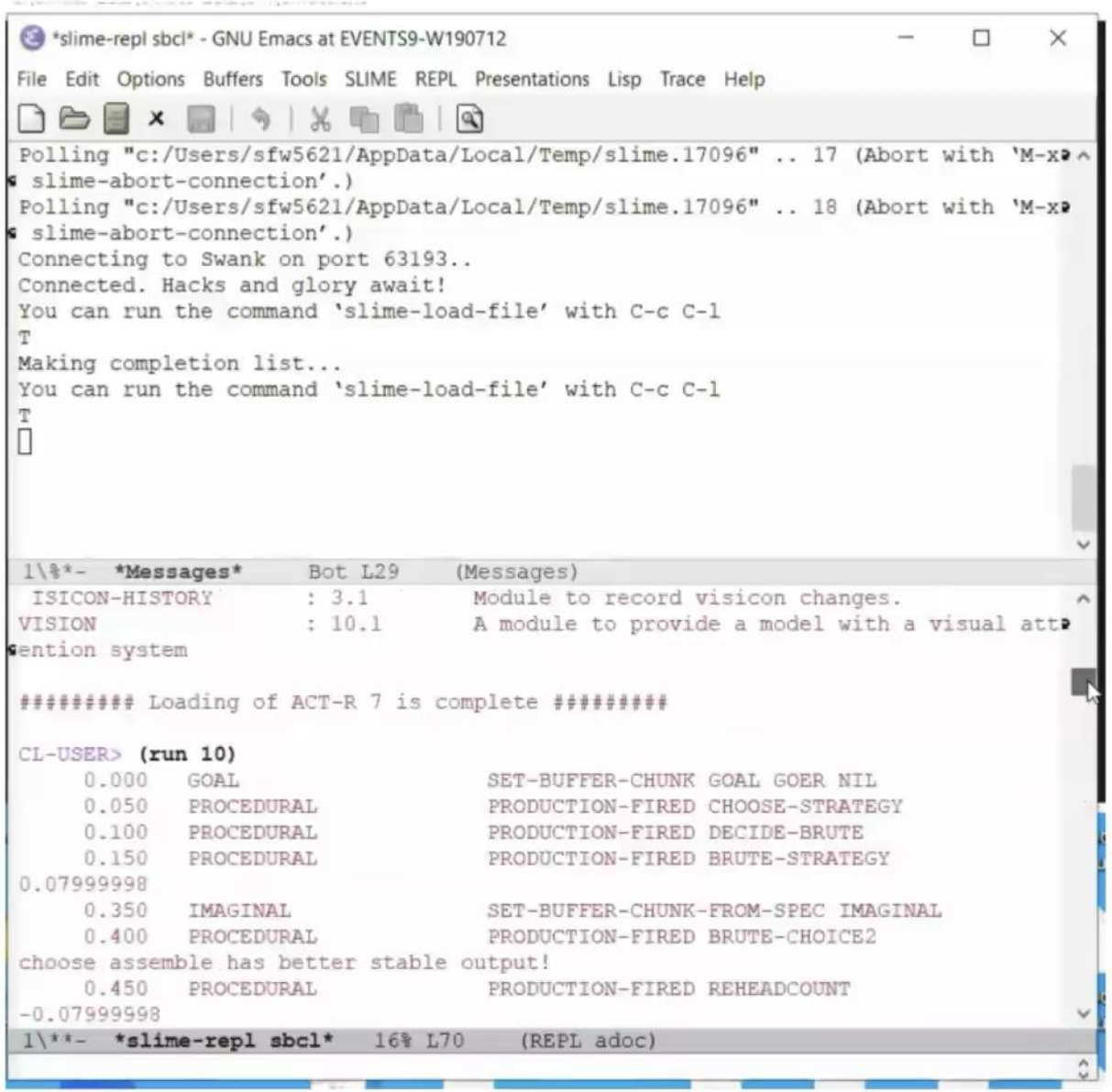
Reinforcement learning with metacognition

R is a reward function with customized incentives. e.g., rule-based, instance-based, or-hybrid. *VSM-ACTR use hybrid custom inventive where* $\boldsymbol{R(s, f(x))}$

Learning mechanism



start with beginner strategy



04

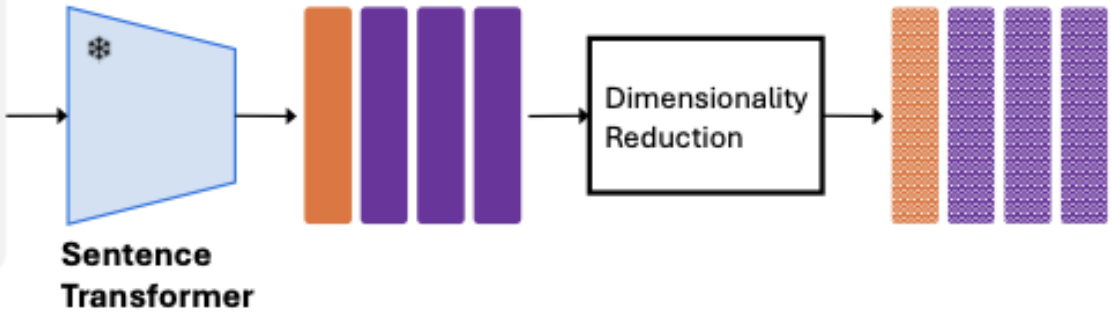
Data collection and analyze

Data Collection

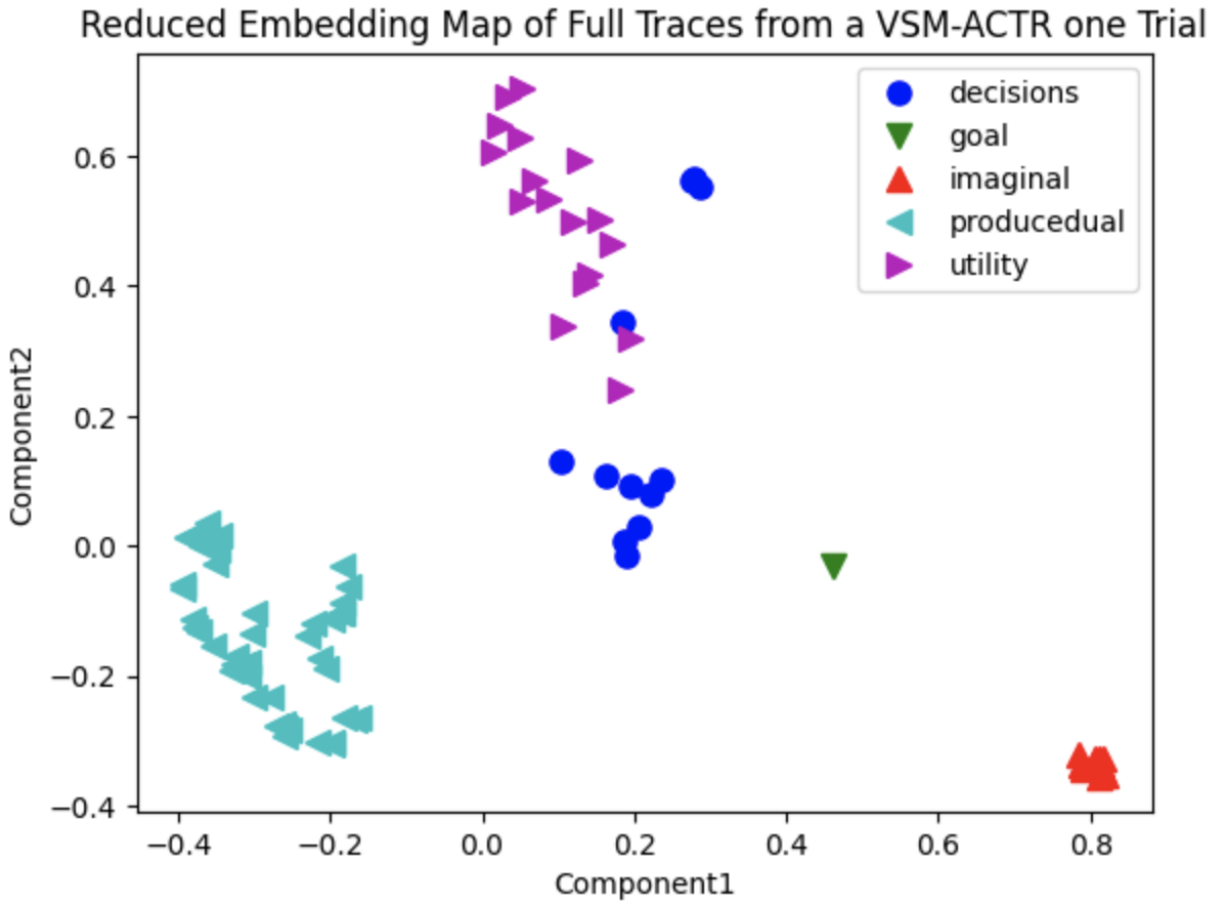
- VSM- ACTR's reasoning steps in real time using a concurrent protocol.
  - Data part a is a learned vector of decision-making steps.
  - Data part b consists of numerically encoded, reinforced decisions from VSM- ACTR

VSM-ACTR full traces

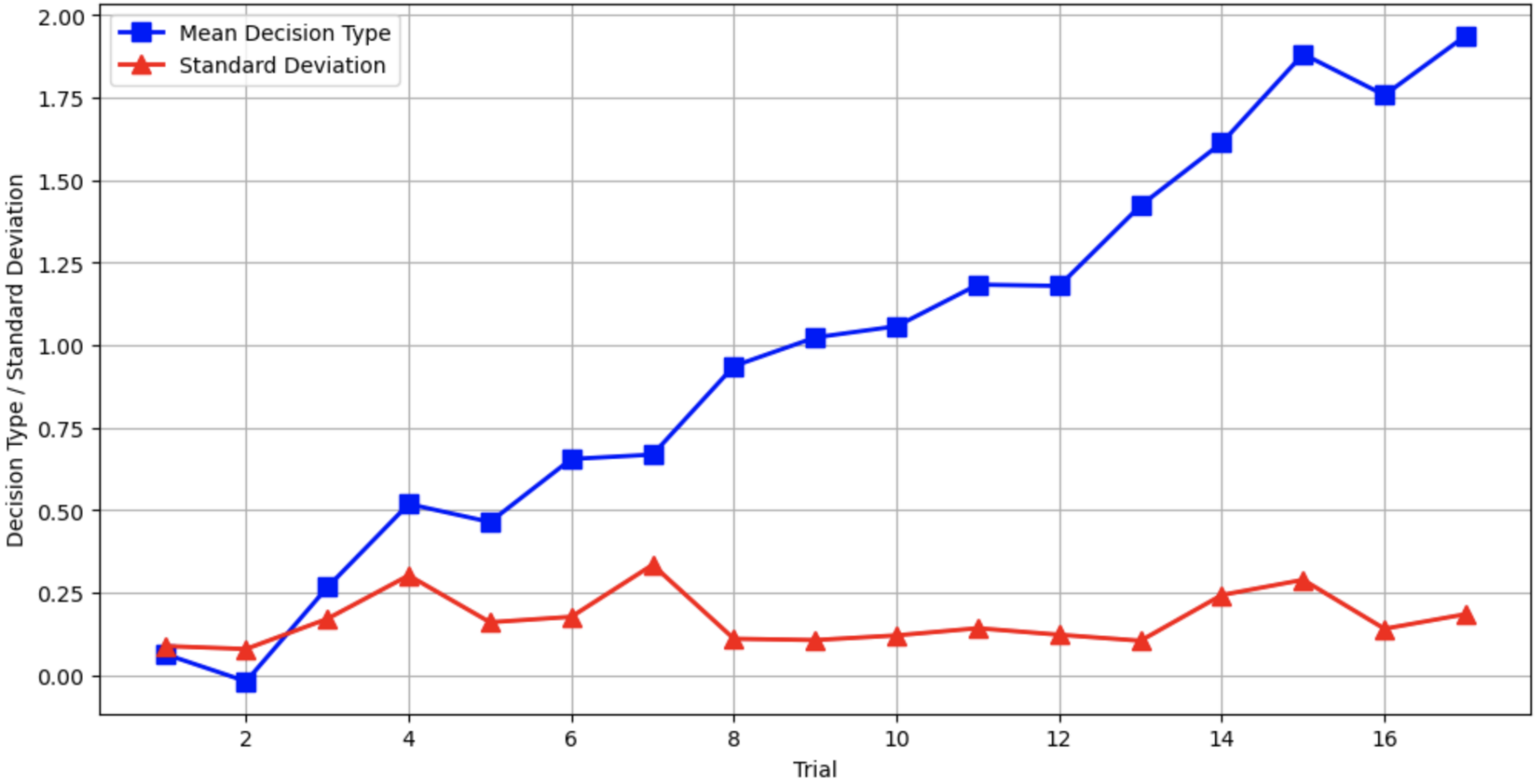
0.000	GOAL	SET-BUFFER-CHUNK GOAL GOER NIL
0.050	PROCEDURAL	PRODUCTION-FIRED CHOOSE-STRATEGY
0.100	PROCEDURAL	PRODUCTION-FIRED DECIDE-BRUTE
0.150	PROCEDURAL	PRODUCTION-FIRED BRUTE-DECISION
...		



Data analysis for learned VSM-ACTR vector



Data analysis for VSM-ACTR decisions



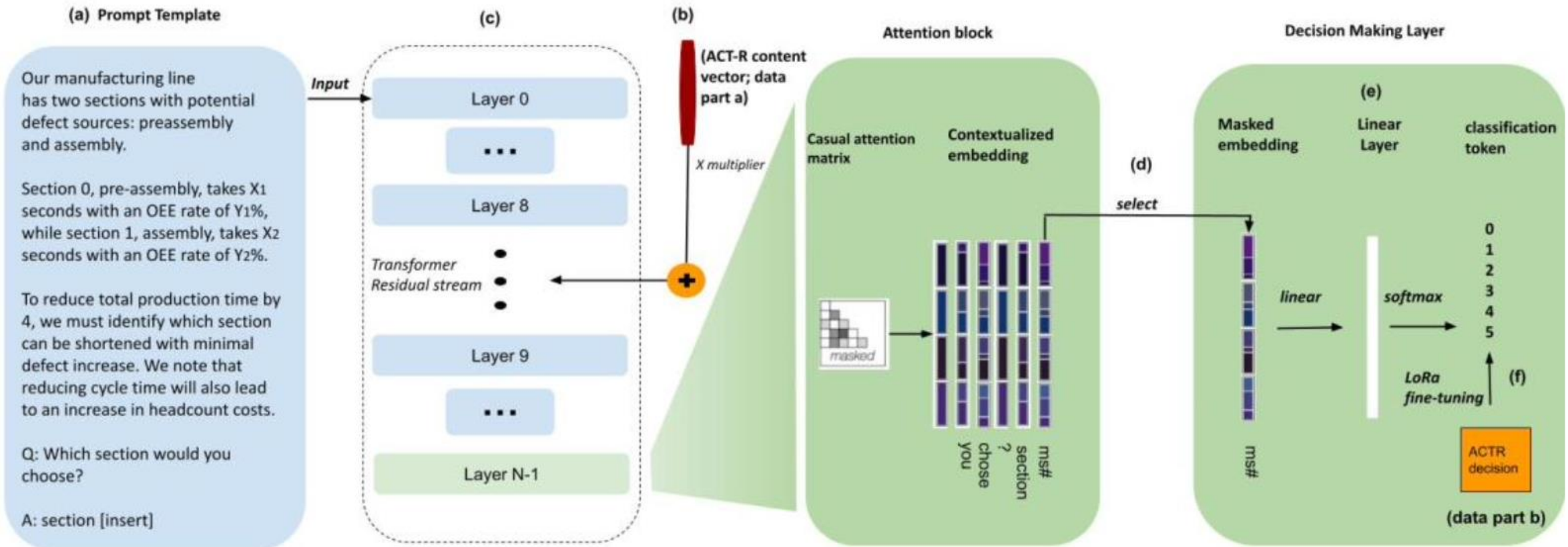
05

LLM-ACTR: A developing knowledge transfer framework

BOSCH

Research Question

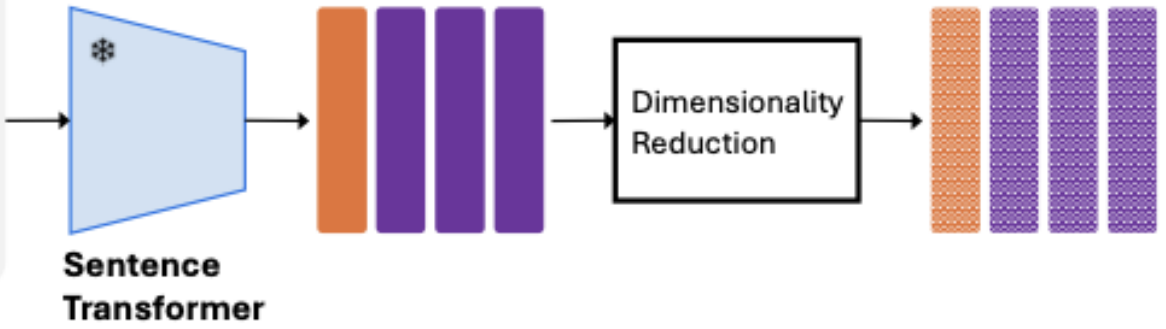
Can we transfer knowledge form cognitive models to LLMs to reflect how human understand the work through cognition and knowledge?


(a) Prompt Template
Our manufacturing line has two sections with potential defect sources: preassembly and assembly.
Section 0, pre-assembly, takes X1 seconds with an OEE rate of Y1%, while section 1, assembly, takes X2 seconds with an OEE rate of Y2%.
To reduce total production time by 4, we must identify which section can be shortened with minimal defect increase. We note that reducing cycle time will also lead to an increase in headcount costs.
Q: Which section would you choose?
A: section [insert]
Input
(c)
Layer 0
Layer 8
Transformer Residual stream
Layer 9
Layer N-1
(b)
(ACT-R content vector; data part a)
X multiplier
Attention block
Casual attention matrix
Contextualized embedding
masked
you
chose
?
section
ms#
(d)
select
Decision Making Layer
(e)
Masked embedding
Linear Layer
classification token
linear
softmax
0
1
2
3
4
5
LoRa fine-tuning
(f)
ms#
ACTR decision
(data part b)

Learning a cognitive decision-making vector

VSM-ACTR full traces

0.000	GOAL	SET-BUFFER-CHUNK GOAL GOER NIL
0.050	PROCEDURAL	PRODUCTION-FIRED CHOOSE-STRATEGY
0.100	PROCEDURAL	PRODUCTION-FIRED DECIDE-BRUTE
0.150	PROCEDURAL	PRODUCTION-FIRED BRUTE-DECISION
...		



Experiments

Baselines Pretrain, random guess, fine-tuned without a cognitive vector

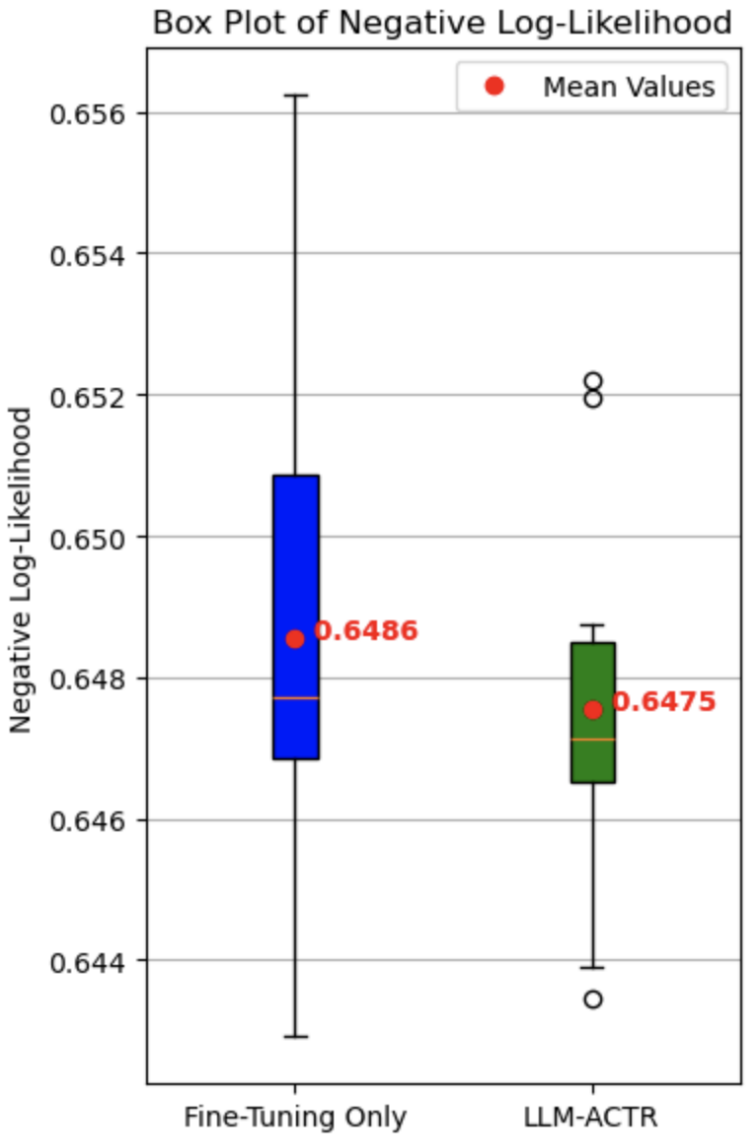
Dataset Decision-making trials simulated on a large scale; held-out data spared to assess performance on unseen problems.

Measurements Goodness of fit--Negative log likelihood and predictive accuracy

Results

Model	NLL	Accuracy
Chance-level	0.6931	0.4836
LlaMa	1.1330	0.3564
Cognitive-LLM	0.6534	0.6576

Results


Box Plot of Negative Log-Likelihood
Mean Values
0.656
0.654
0.652
0.650
0.648
0.646
0.644
Negative Log-Likelihood
0.6486
0.6475
Fine-Tuning Only
LLM-ACTR

Take away

It is possible to transfer human like decision knowledge from cognitive models to LLMs through activation engineering during the forward pass, and by fine-tuning LLMs with reinforcement decisions.

Summary

- Gold

This study extends previous research in applying large-scale cognitive psychology data to align human-like behaviors in language models. Demonstrates the feasibility of transferring knowledge from cognitive models to LLMs through the developing knowledge transfer framework *LLM-ACTR*.

- Coal
  - Trustworthiness of the cognitive synthetic agent.
  - Generalization.

Future Work *Out of Domain Generalization*

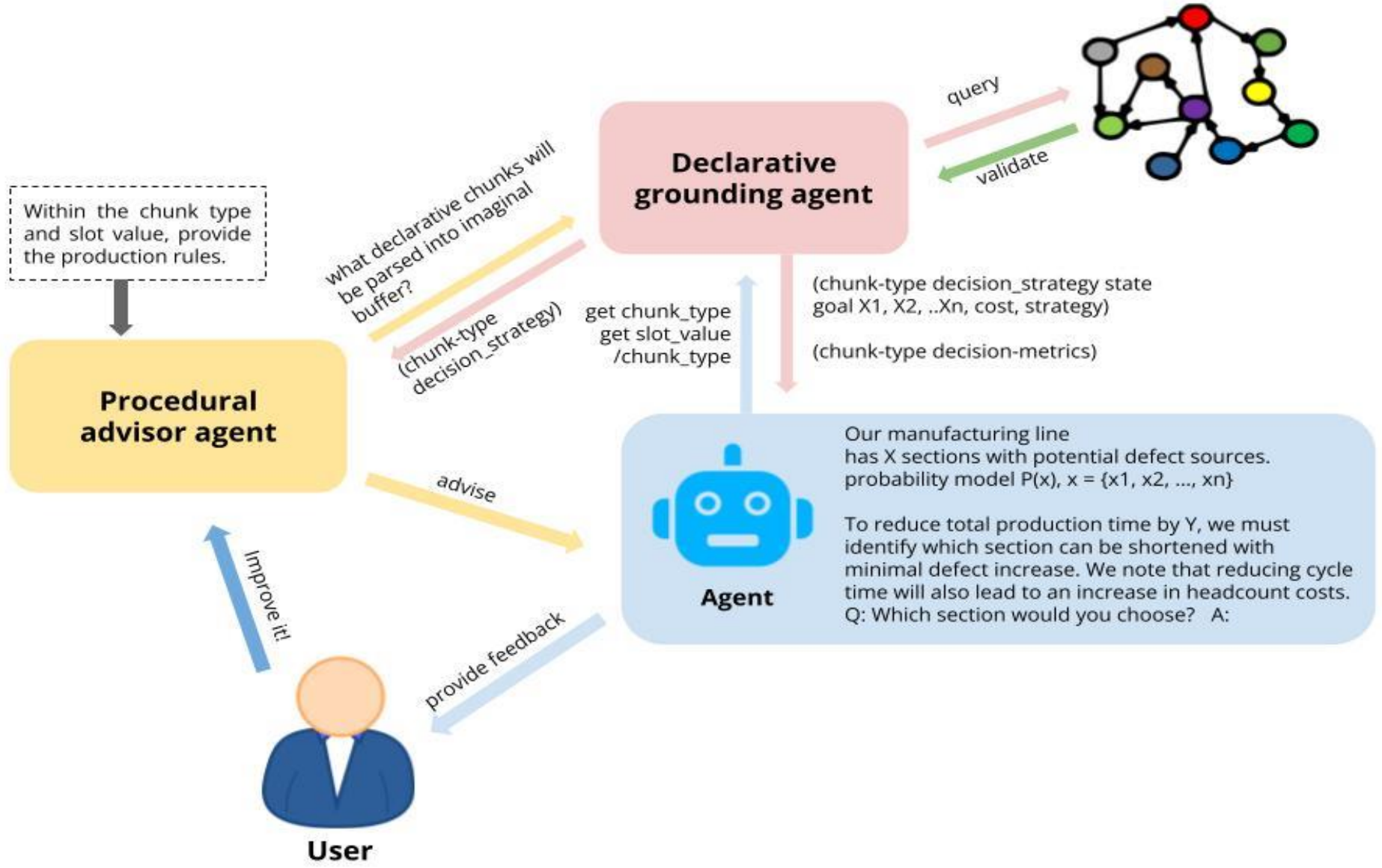
For

Expanded decision space $D = \{d_1, d_2, \ldots, d_n\}$

Complex probability model $P(x)$, $x = \{x_1, x_2, \ldots, x_n\}$?

Human like decisions ➔ guided perception, memory, and goal-setting

Cognitive multi-agent system[5] in decision support



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