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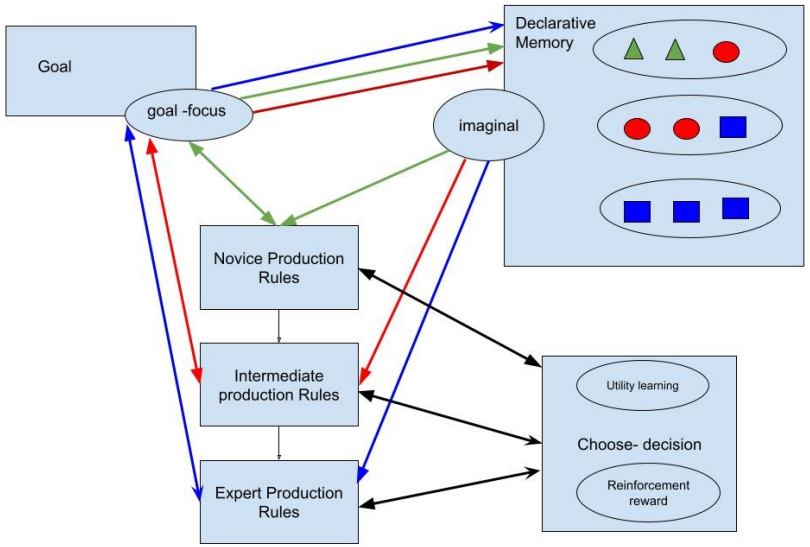
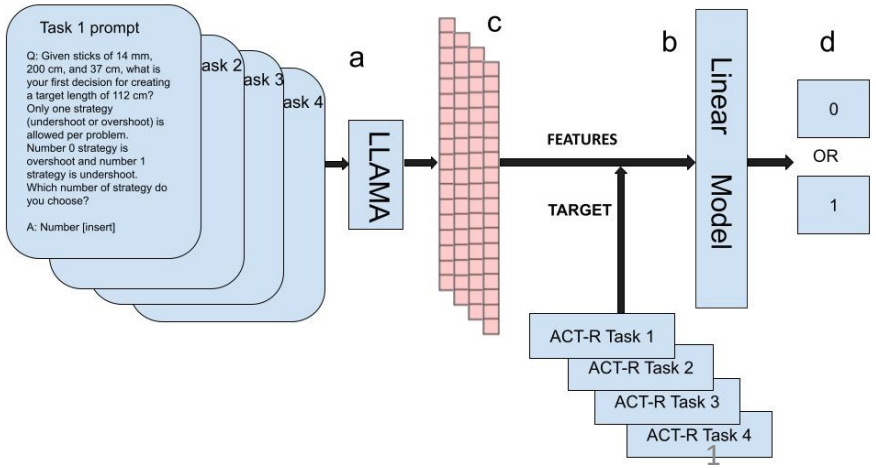
LLAMA-ACT-R: Use Neuro-Symbolic Architecture (ACT-R) for LLM Decision Making in Manufacturing



Siyu Wu

Soar Workshop 2024



Reference

Binz, M., & Schulz, E.(2024) Turning large language models into cognitive models, ICLR.

Ritter, F. E., Tehranchi, F., & Oury, J. D. (2019). ACT-R: A cognitive architecture for modeling cognition. *Wiley Interdisciplinary Reviews: Cognitive Science*, 10(3), Paper e1488.

Wu, S., Bagherzadeh, A., Ritter, F., Tehranchi, F. (2023, Sep) Cognition Models Bake-off: Lessons Learned from Creating Long-Running Cognitive Models. *Poster in proceedings 16th International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation (SBP-BRIMs)*

Wu, S., Giles, C. L., & Ritter, F. E.(2024) LLAMA-ACT-R, a neuro-symbolic architecture (ACT-R) for LLM decision making. In Poster presented in Annual Ethical AI Symposium. University of Michigan Institute for Data Science.

Introduction

1. LLMs tend to use shortcuts and cannot remember past interactions. Limit their ability to improve over time unlike humans
2. Decision-Making in the Era of Industry 4.0: Complex and Challenging
3. Language models in domain-specific decision-making Q&A suffer from:
   - Inaccurate and irrelevant context.
   - No memory, leading to inconsistent and unhuman like responses trajectory

Proposed Solution

1. Using Cognitive Architecture to Model Levels of Human Decision-Making Behaviors for Enhanced Production Efficiency

2. LLAMA-ACT-R Framework: Employing Neuro-Symbolic Architecture for LLM Decision-Making

Related Work

Use ACT-R model to simulate human behavior, behavior variance, learning, and error-making.

📘 Wu, S., Bagherzadeh, A., Ritter, F., Tehranchi, F. (2023, Sep) Cognition Models Bake-off: Lessons Learned from Creating Long-Running Cognitive Models. *Poster in proceedings 16th International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation (SBP-BRIMs)*

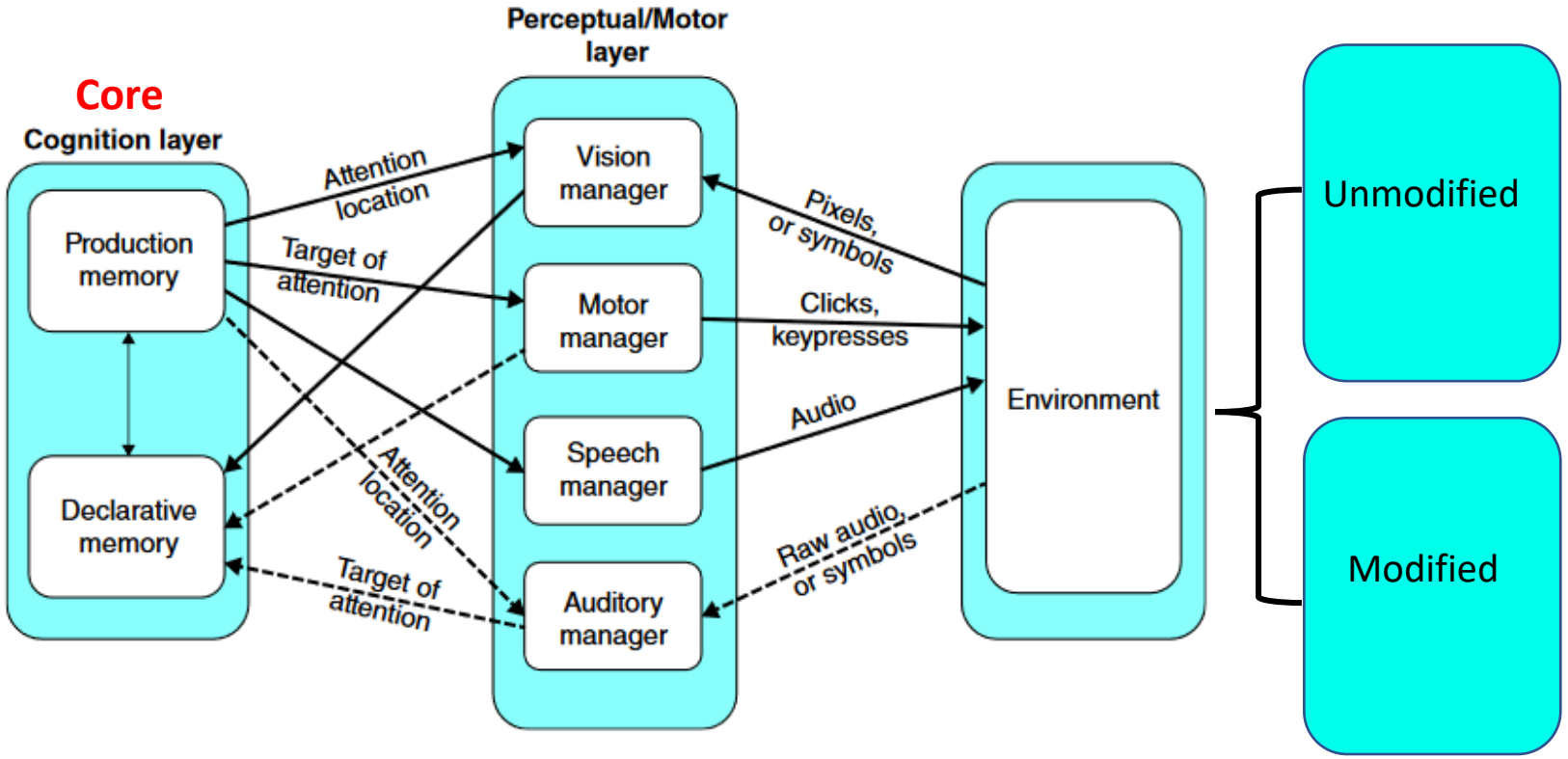
Image adapted from: Ritter, F. E., Tehranchi, F., & Oury, J. D. (2019). ACT-R: A cognitive architecture for modeling cognition. Wiley Interdisciplinary Reviews: Cognitive Science, 10(3), Paper e1488. http://acs.ist.psu.edu/papers/ritterTOip.pdf

ACT-R

- Cognitive architecture
- Modules to implement the fixed mechanisms of cognition

Productions,
if-then rules,
actionable memory

Chunks,
factual memory,
slot-value pairs



Feature Extraction of Open-source Large Language Models for Behavioral Science

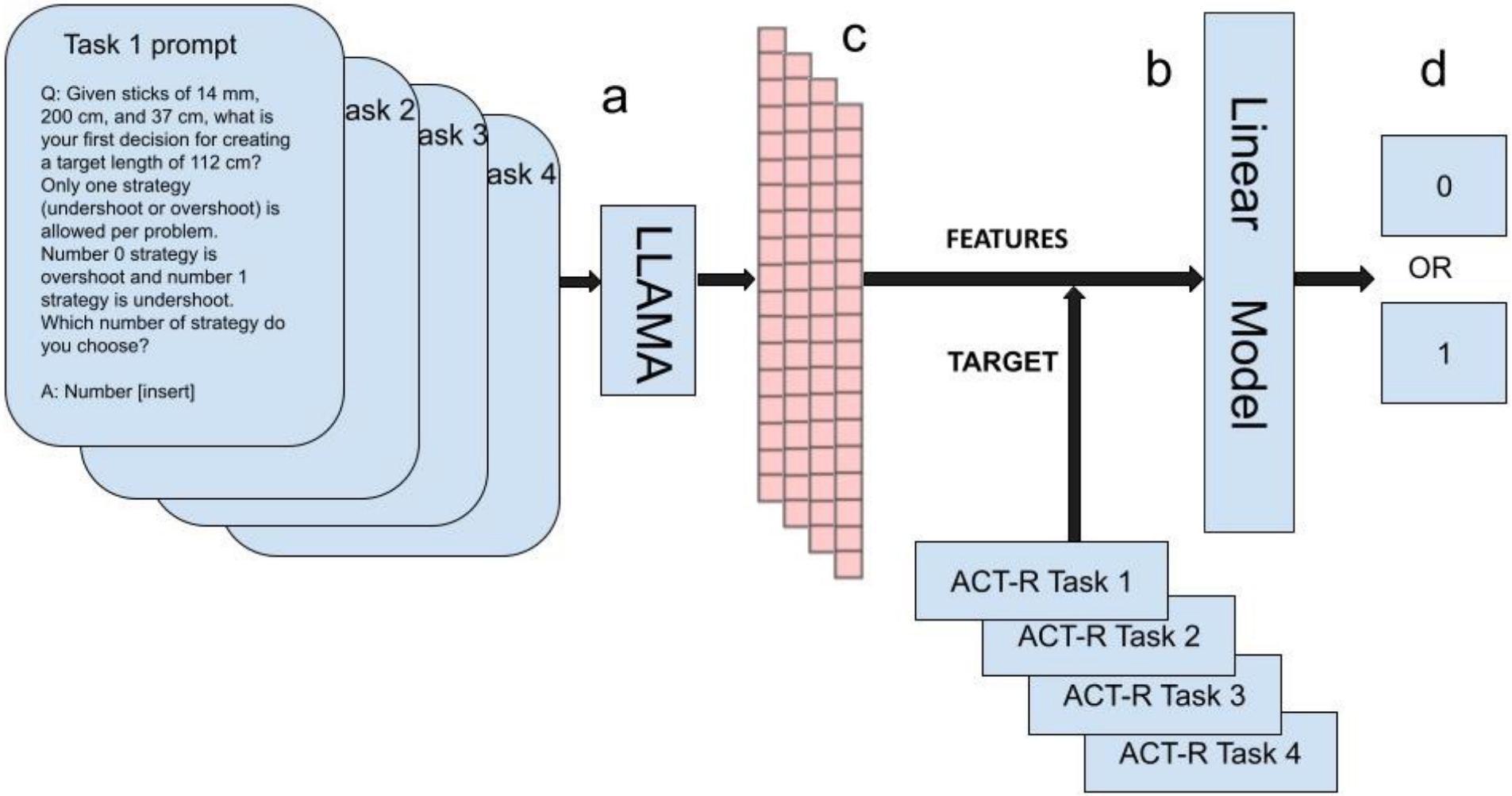
Passing text input through an openly accessible LLM and capturing the resulting final embeddings. These embeddings capture both the content and context within the prompts, offering the least information loss for further analysis.

Binz, M., & Schulz, E. (2024) Turning large language models into cognitive models, ICLR.

Schema of LLAMA-ACT-R

1. ACT-R Model Create and Setup
2. LLAMA-ACT-R

Schema of LLAMA-ACT-R



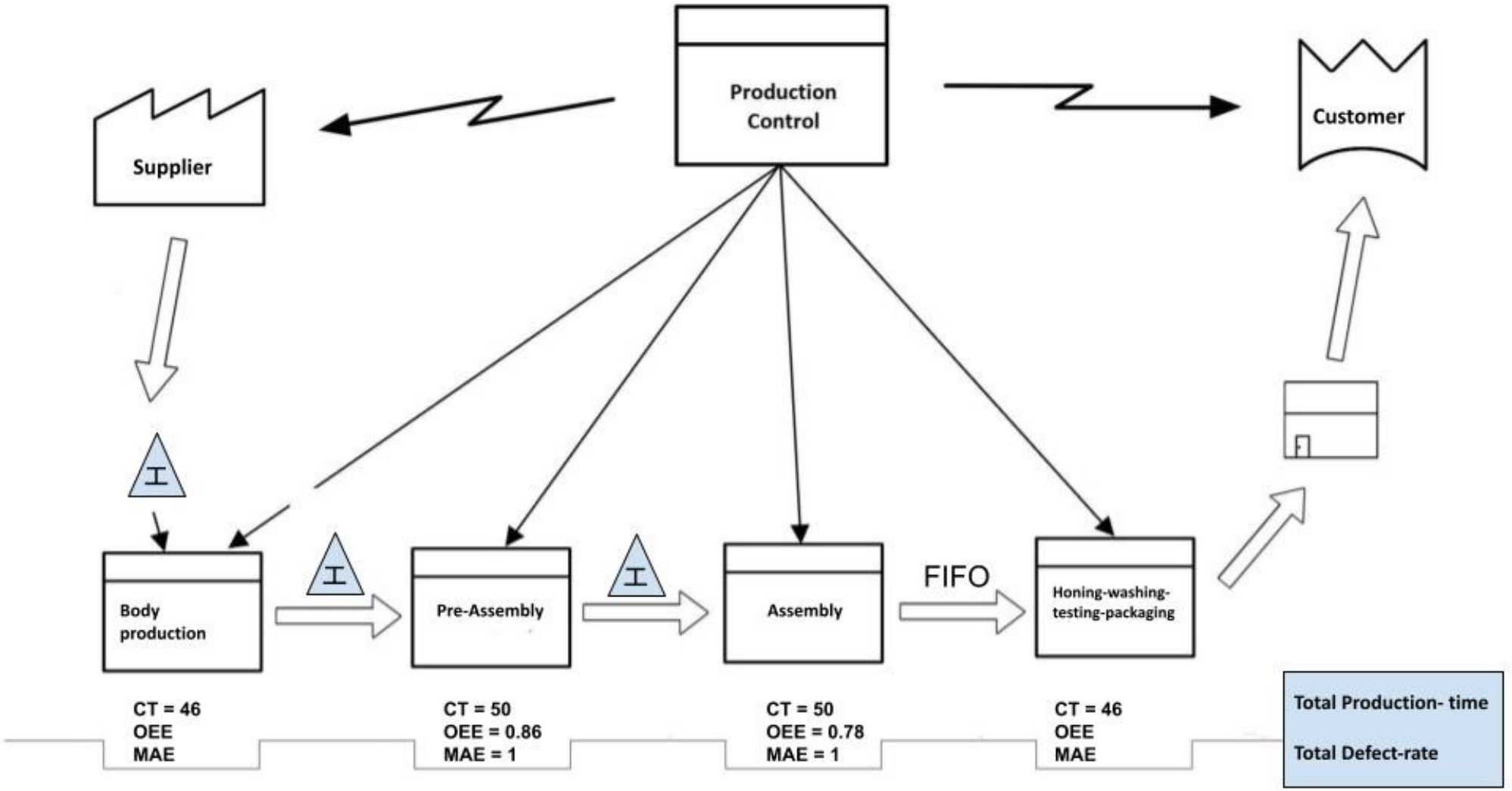
Proposed Contribution

Fine-tuned language model predicts human decisions and offers learning insights, overcoming limitations of previous work by Binz & Schulz (2024) for broader task application.

A USE CASE: VSM-ACT-R

1. **Using Cognitive Architecture to Model Levels of Human Decision-Making Behaviors for Enhanced Production Efficiency**: This approach integrates CAs to simulate and model levels of decision-making processes in manufacturing (production line), encompassing error generation, learning, and strategy optimization.

Value Stream Map



Process

1. Defining divisions of efficiency sectors using Value Stream Map.
2. Establishing constraints on production line efficiency and abstract domain centered decision-making problem.
3. Employing a human-centered approach to model various levels of decision-making using ACT-R.
4. Testing and tuning the model to mimic human learning and error-making for novice, intermediate and expert.

Decision-making problem abstraction and formulation

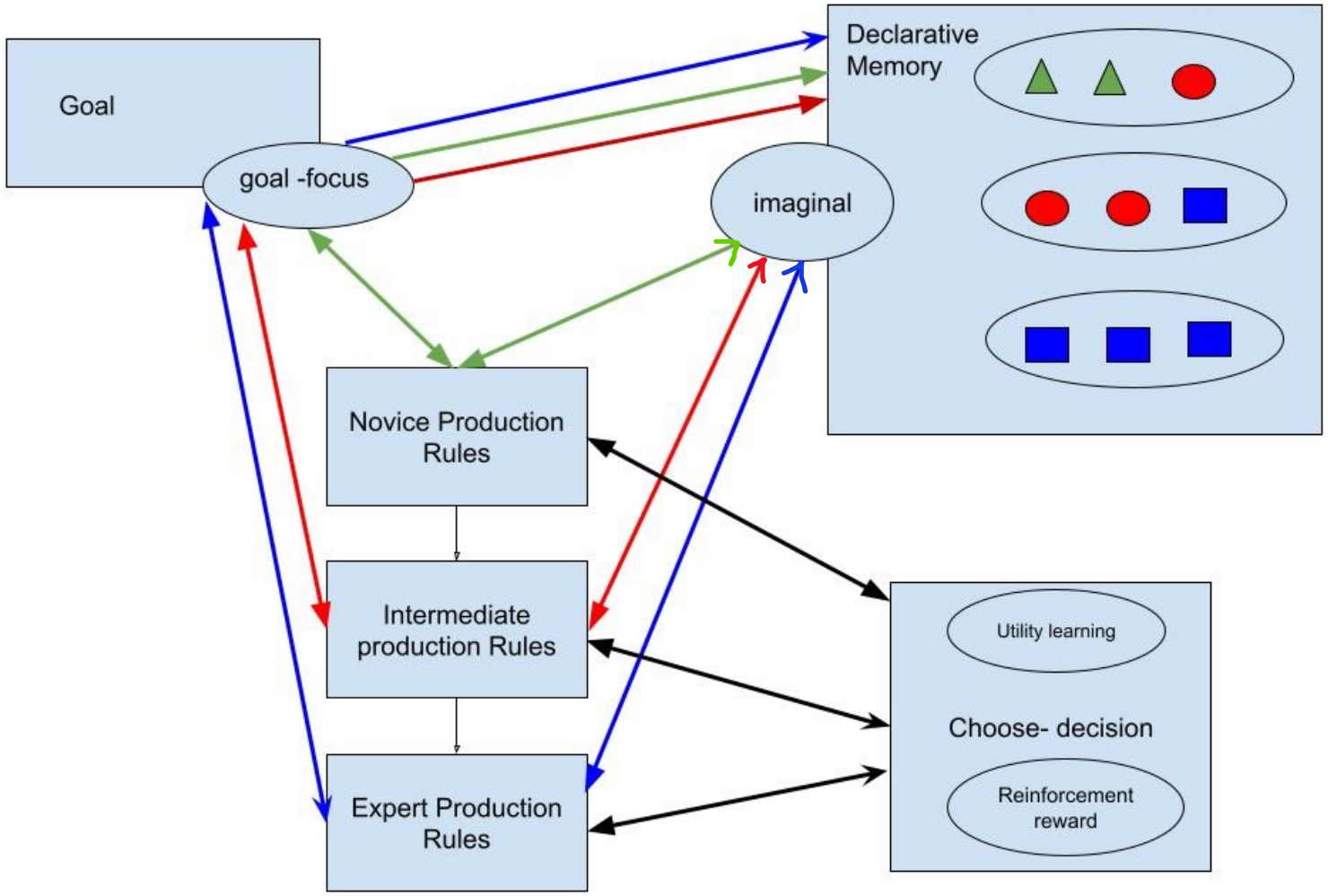
With a focus on maintaining stable output as the target for the Bosch plant and by examining the structure of the Value Stream Map (VSM), we develop a decision-making problem that balances increasing time efficiency on the assembly line with maintaining stable output.

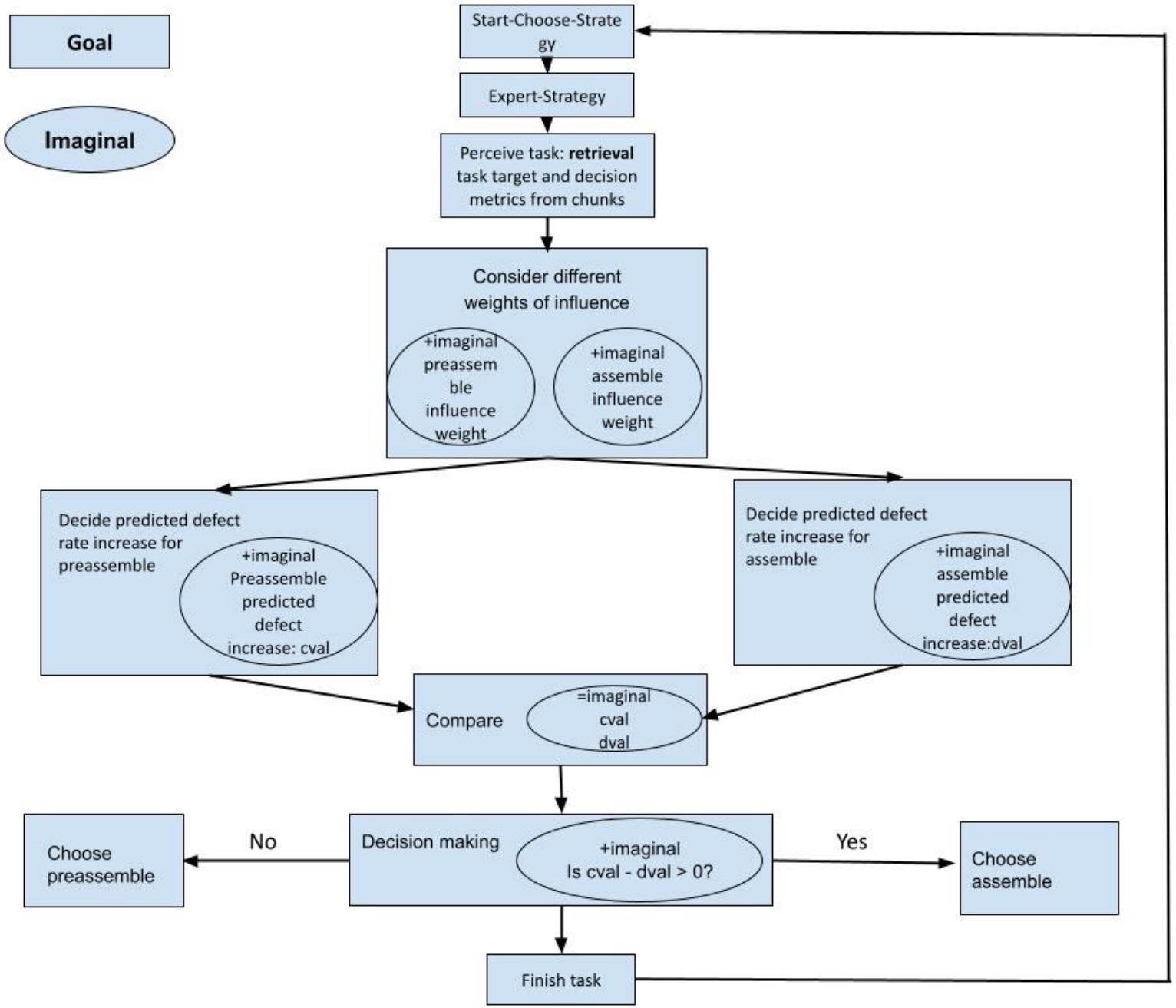
"Our manufacturing line has two sections with potential defect sources: pre-assembly and assembly. Pre-assembly takes 40 seconds with an OEE (Overall Equipment Effectiveness) rate of 88%, while assembly takes 44 seconds with an OEE rate of 80.1%. To reduce total assembly time by 4 seconds, we need to identify which section can be shortened with minimal defect increase. There are two options: reduce pre-assembly time or reduce assembly time."

Used human-centered approach to develop different expertise levels of decision-making

1. The process begins by interviewing plant managers at Bosch USA to understand the complex decision-making challenges they face daily.
2. Their insights, combined with a VSM tailored to their specific plant system, are used to enhance production time efficiency at a Bosch plant.
3. The model possesses capabilities across a variety of production efficiency decision-making rationales. It can perform tasks using decision-making algorithms observed from human subjects and incorporate personas representing a range of expertise levels, from novice to expert.

Level of Expertise Mechanism in VSM-ACT-R



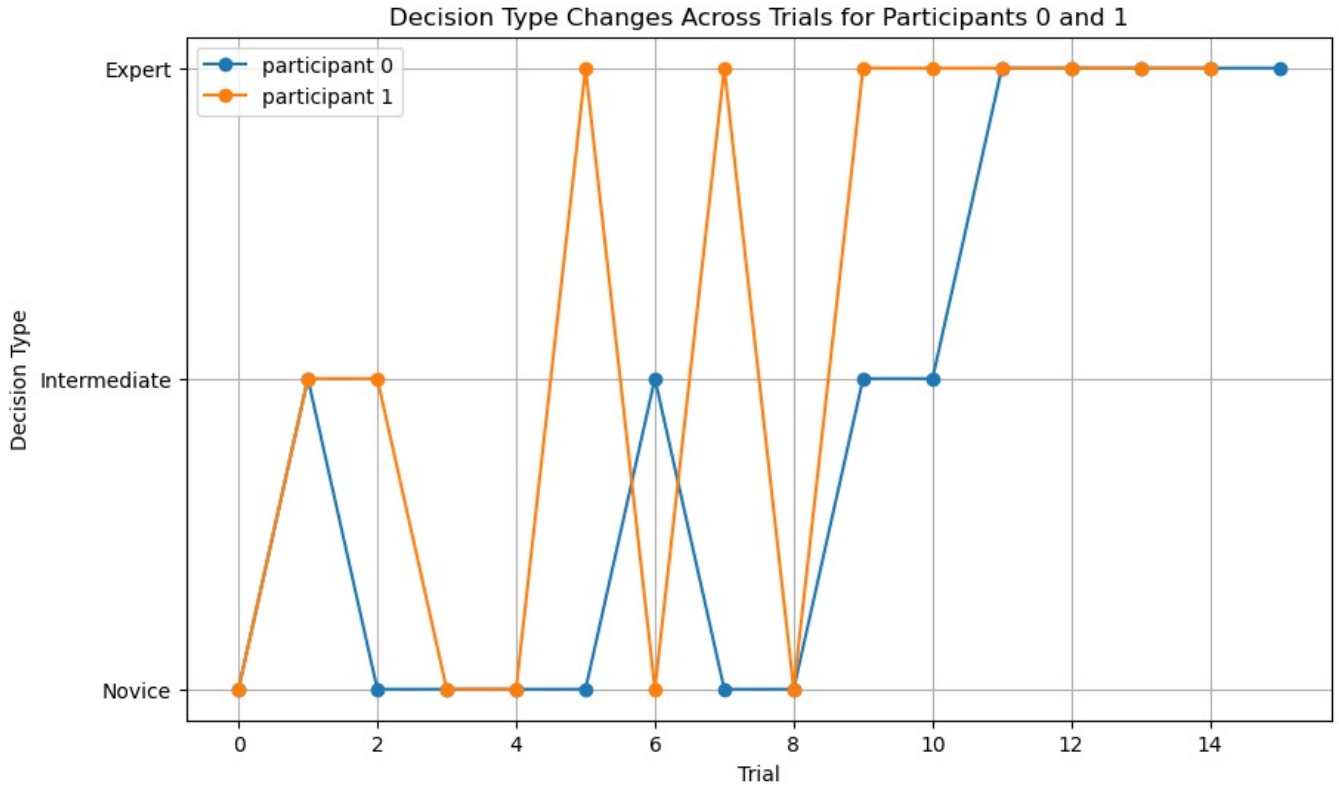


https://github.com/SiyuWu528/VSM-ACT-R

Output

```
     0.450   PROCEDURAL              PRODUCTION-FIRED NAIVE-DECISION
assebly is always the right place to reduce time!
 Utility updates with Reward = 0.0   alpha = 0.2
  Updating utility of production CHOOSE-STRATEGY
   U(n-1) = -0.054000005   R(n) = -0.15 [0.0 - 0.15 seconds since selection]
   U(n) = -0.0732
  Updating utility of production NAIVE-CHOICE
   U(n-1) = 6.3639994   R(n) = -0.1 [0.0 - 0.1 seconds since selection]
   U(n) = 5.0711994
  Updating utility of production NAIVE-DECISION
   U(n-1) = -0.018000001   R(n) = -0.05 [0.0 - 0.05 seconds since selection]
   U(n) = -0.024400001
     0.500   PROCEDURAL              PRODUCTION-FIRED CHOOSE-STRATEGY
     0.550   PROCEDURAL              PRODUCTION-FIRED EXPERT-STRATEGY
     0.600   PROCEDURAL              PRODUCTION-FIRED PERCEIVE
     0.650   PROCEDURAL              PRODUCTION-FIRED PREASSEMBLE-WEIGHT
0.5
caculate the preassemble defect decision weight
```

Learning Rate



Individual Difference

Mixed Linear Model Regression Results

Model:	MixedLM	Dependent Variable:	decision_type
No. Observations:	166	Method:	REML
No. Groups:	11	Scale:	0.4305
Min. group size:	15	Log-Likelihood:	-177.8519
Max. group size:	16	Converged:	Yes
Mean group size:	15.1		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	0.210	0.143	1.464	0.143	-0.071	0.490
trial	0.123	0.012	10.504	0.000	0.100	0.146
Group Var	0.104	0.093				

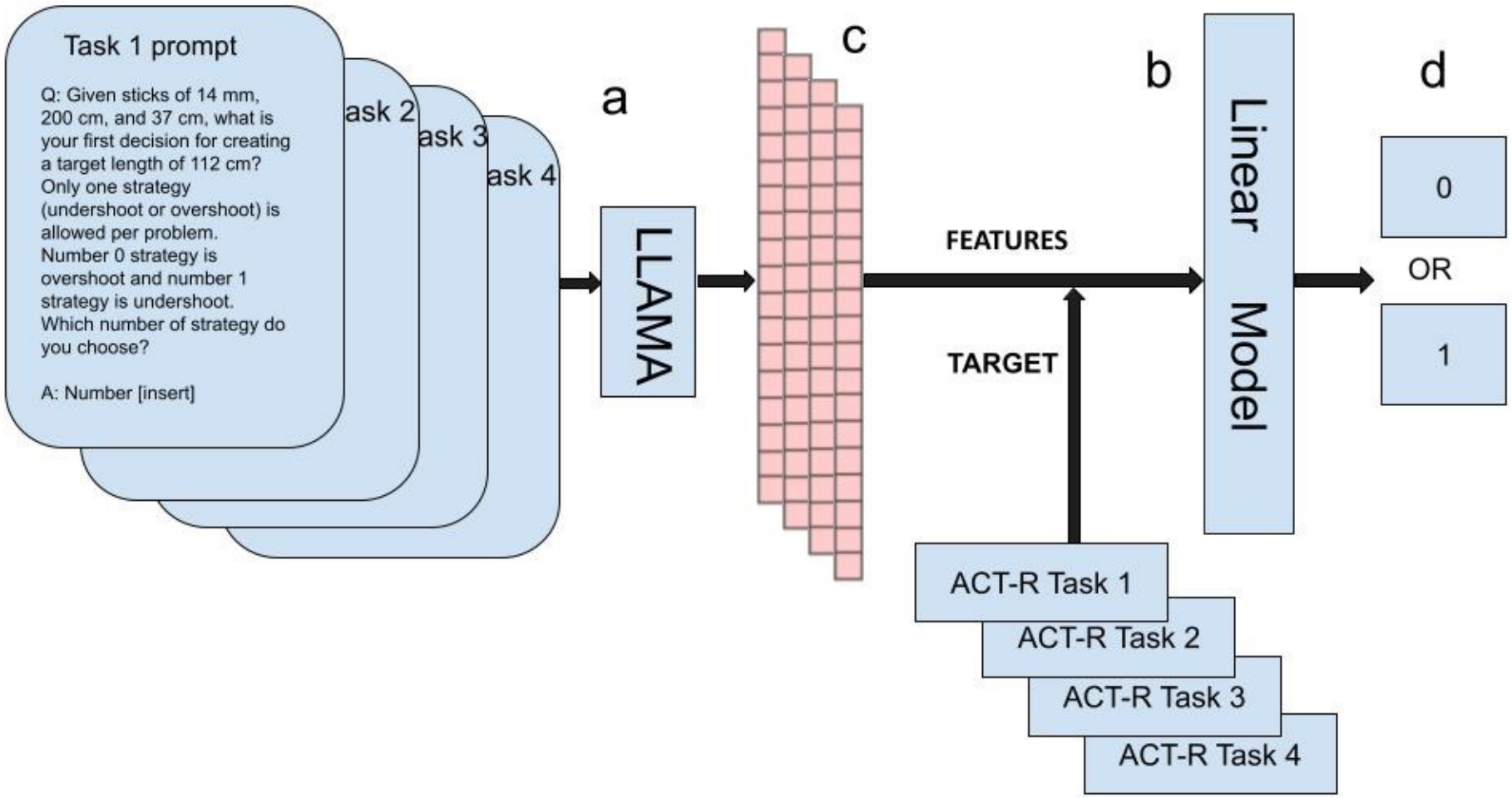
Learning progress

OrderedModel Results

Dep. Variable:	decision_type	Log-Likelihood:	-133.42
Model:	OrderedModel	AIC:	272.8
Method:	Maximum Likelihood	BIC:	282.2
Date:	Tue, 28 May 2024		
Time:	18:39:14		
No. Observations:	166		
Df Residuals:	163		
Df Model:	1		

	coef	std err	z	P>|z|	[0.025	0.975]
trial	0.3252	0.046	7.103	0.000	0.236	0.415
0/1	1.5651	0.358	4.371	0.000	0.863	2.267
1/2	-0.0199	0.180	-0.110	0.912	-0.373	0.333

What's next


Task 1 prompt
Q: Given sticks of 14 mm, 200 cm, and 37 cm, what is your first decision for creating a target length of 112 cm? Only one strategy (undershoot or overshoot) is allowed per problem. Number 0 strategy is overshoot and number 1 strategy is undershoot. Which number of strategy do you choose?
A: Number [insert]
ask 2
ask 3
ask 4
a
LLAMA
c
FEATURES
TARGET
b
Linear Model
d
0
OR
1
ACT-R Task 1
ACT-R Task 2
ACT-R Task 3
ACT-R Task 4

Contribution

- The VSM-ACT-R model is a neural-symbolic cognitive model designed to optimize time reduction in the assembly sectors of the production line.
- The deployment of LLAMA-ACT-R enables LLMs to become a customized tool for plant decision-makers to request decision-making assistance, as well as a learning tool that mimics the observed learning and error-making in the same domain.

Completed

- VSM-ACT-R built

Nuggets

- Leverage CAs strength to build better LLMs through a novel integration strategy.

Further work

- Data collection
- Fine tune Llama

Coal

- No funding after summer

Thank you

- Dan Bothell for VSM-ACT-R help
- Thank my collaborators and mentors Frank E Ritter, C Lee Giles, Alessandro Oltramari from PSU and Bosch