



# Cognitively-Inspired Decision Intelligence for Manufacturing

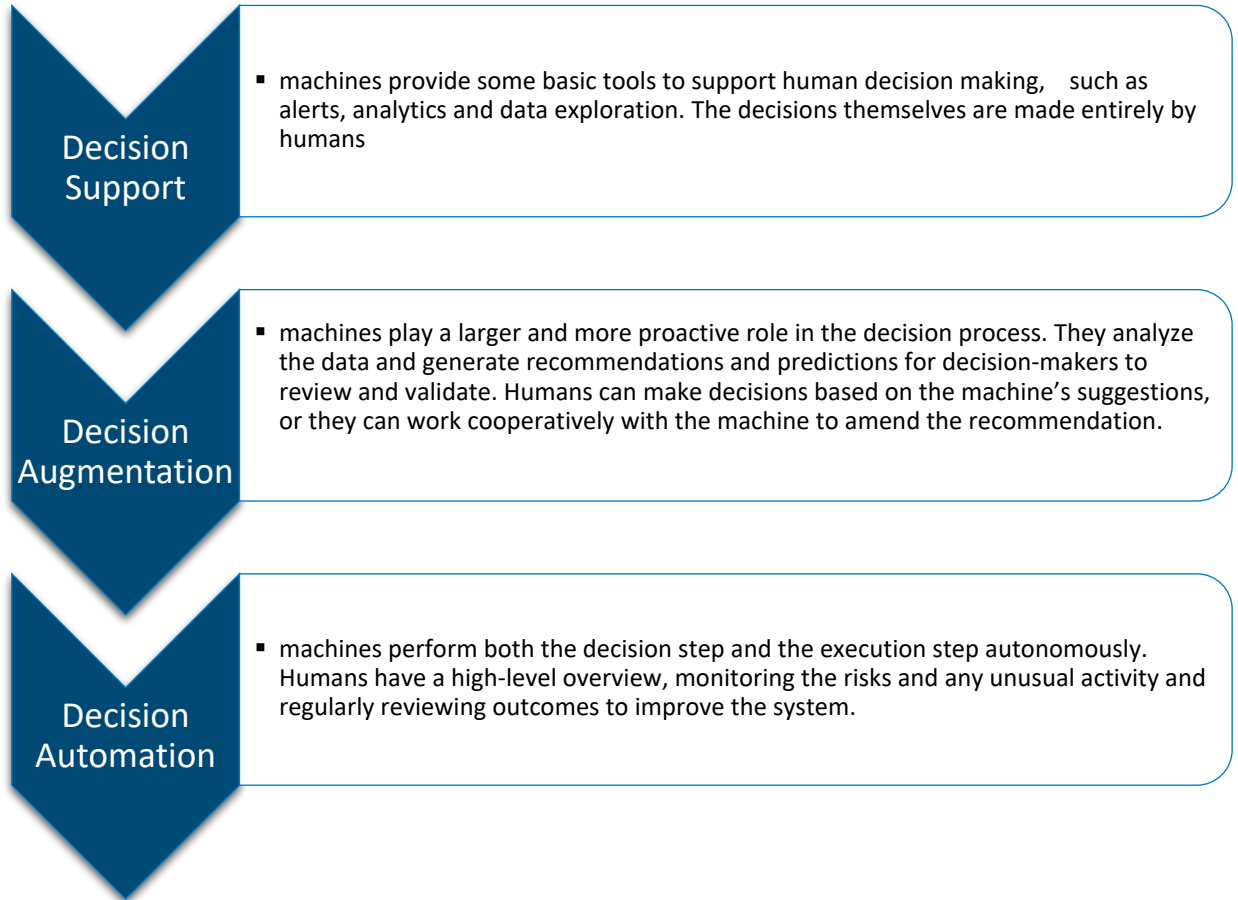
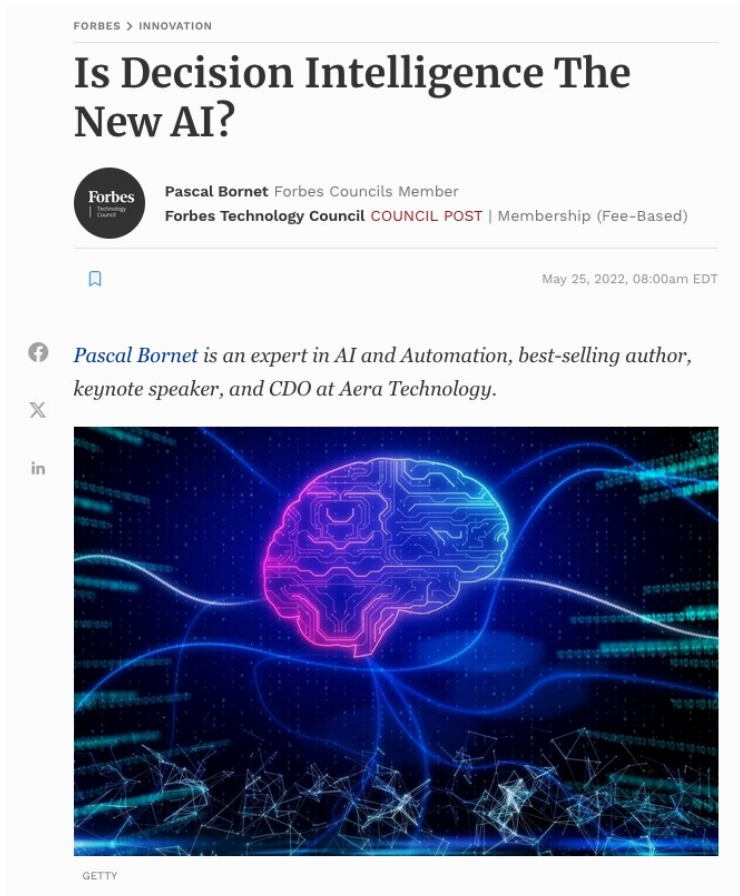
**Alessandro Oltramari<sup>1</sup> Siyu Wu<sup>1,2</sup>**

<sup>1</sup>Bosch Center for Artificial Intelligence  
Carnegie Bosch Institute  
Pittsburgh, USA

<sup>2</sup>Penn State University  
College of Information Science and Technology  
State College, USA

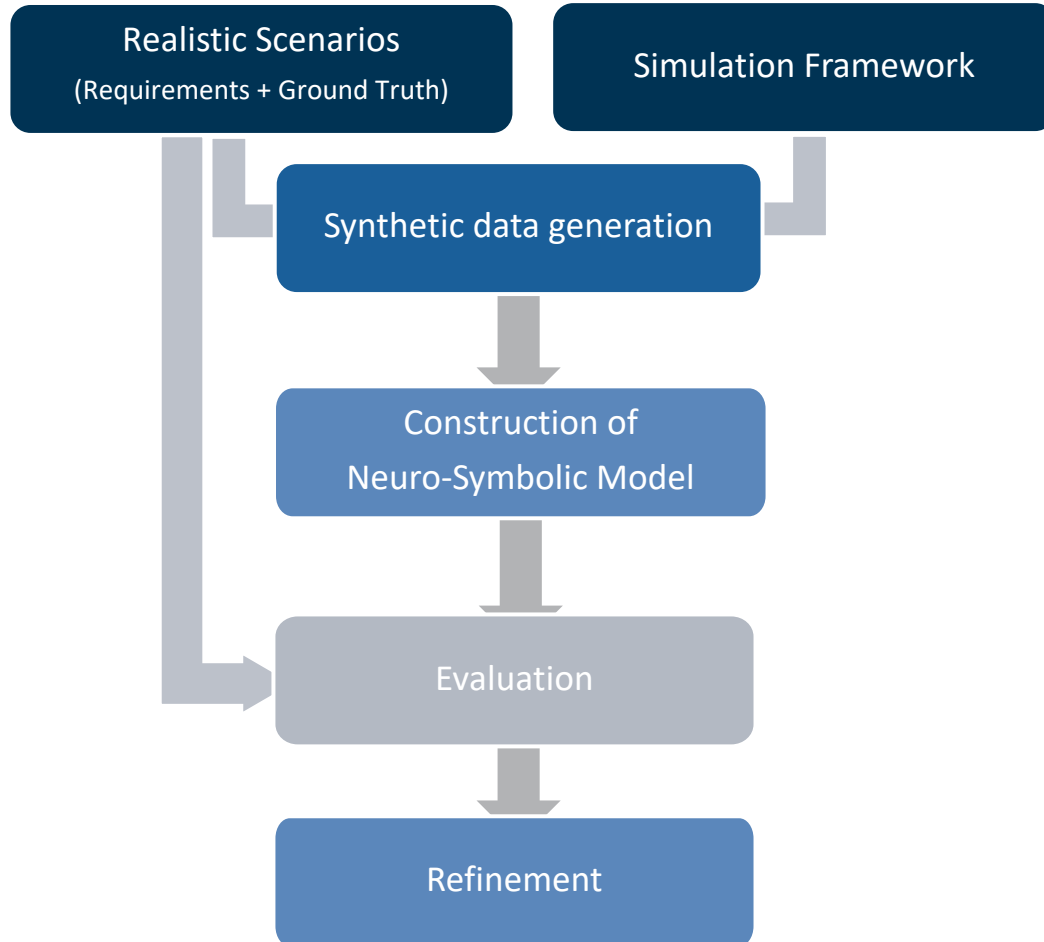
# Cognitively-Inspired Decision Intelligence for Manufacturing

## The Three Levels of Decision Intelligence



# Cognitively-Inspired Decision Intelligence for Manufacturing

## Our R&D Approach



- CADi projects adopt a unified methodological framework to tackle complex problems
  - **Simulation data** is often necessary within the manufacturing domain due to a lack of ground truth for learning; e.g. related to causal relations and decision processes
  - **Neuro-symbolic methods** are used to integrate prior domain knowledge with machine learning
- We use realistic scenarios to elicit requirements for generating synthetic data and evaluate neuro-symbolic models
- Our approach is iterative: after each evaluation stage we can refine the model and improve performance according to metrics of interest
  - **We use cognitive architectures to model decisions**

# Cognitively-Inspired Decision Intelligence for Manufacturing Landscape

- Logistic Optimization
- Demand Forecasting
- Supply Chain Decisions
- Causal Analysis
- Power System Simulation and Optimization
- Power and load forecasting
- Resource Scheduling
- O&M monitoring
- Production Scheduling
- Market Decision-Making
- Content Recommendation
- Inventory Pricing
- Sustainability
- Cybersecurity



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DECISION  
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NEUROSymbolic AI

IBM Operational Decision  
Manager

Discover, capture, analyze, automate and govern  
rules-based business decisions in the  
environment of your choice

**Cognitive Automation in Pricing,  
Promotions, and Forecasting**



## Decision Intelligence Lab

Our team specializes in researching and innovating technologies covering machine learning, mathematical modeling, optimization solving, time series prediction, causal analysis, interpretability of decision-making solutions, and decision-making assistance for intelligent systems, thus boosting operational efficiency and increasing profits while cutting costs. Our flagship products include the industry-leading MindOpt optimization solver, the intelligent power forecasting tool eForecaster, and the decision-making cloud platform. In addition, our innovative technologies are applicable to various scenarios, including power system simulation and optimization, power and load forecasting, content recommendation, resource scheduling, inventory pricing, O&M monitoring, production scheduling, marketing decision-making, and data intelligence analysis. Notably, our solutions have played a pivotal role in powering "Green Energy AI" projects in collaboration with major entities like the State Grid Corporation of China



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Decisions on Innovation



# Cognitively-Inspired Decision Intelligence for Manufacturing

## 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

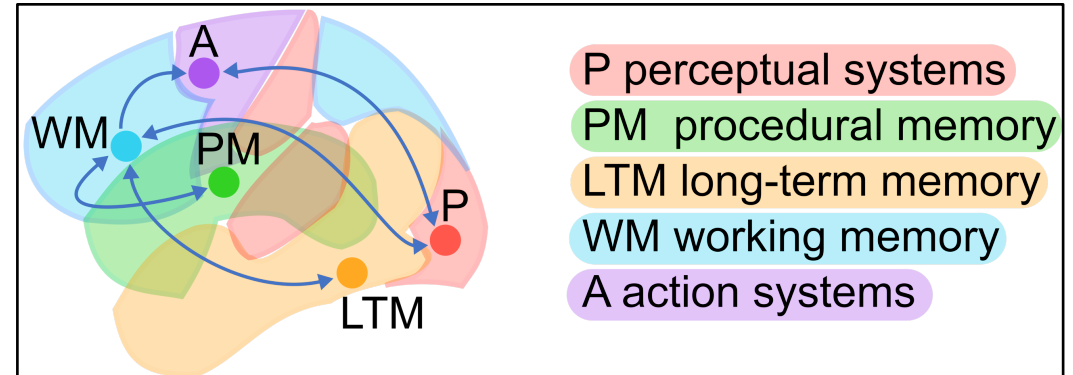


NeuroImage  
Volume 235, 15 July 2021, 118035



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<sup>a</sup>, Catherine Sibert<sup>a</sup>, Zoe Steine-Hanson<sup>b,1</sup>, Natalie Koh<sup>c,2</sup>, John E. Laird<sup>d</sup>, Christian J. Lebiere<sup>e</sup>, Paul Rosenbloom<sup>f</sup>



Stocco, Andrea, et al. "Analysis of the human connectome data supports the notion of a “Common Model of Cognition” for human and human-like intelligence across domains." *NeuroImage* 235 (2021).



Sibert, Catherine, Holly Sue Hake, and Andrea Stocco. "The structured mind at rest: low-frequency oscillations reflect interactive dynamics between spontaneous brain activity and a common architecture for task control." *Frontiers in Neuroscience* 16 (2022)



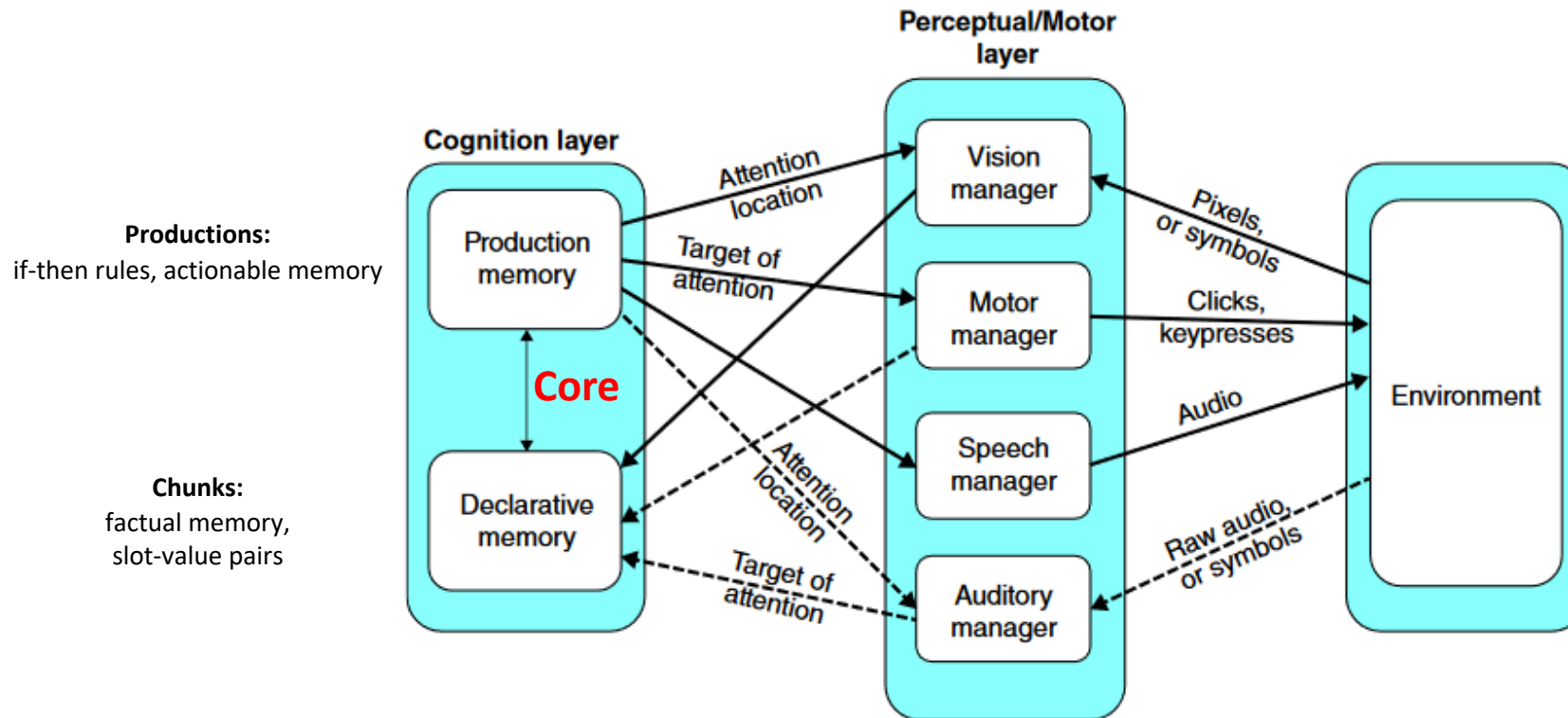
Kotseruba, Iuliia, and John K. Tsotsos. "40 years of cognitive architectures: core cognitive abilities and practical applications." *Artificial Intelligence Review* (2018): 1-78.



# Cognitively-Inspired Decision Intelligence for Manufacturing

## ACT-R: the Cognitive Architecture

- “Architecture” refers to the fundamental organizational principle of a complex cognition system.
- Modules are the sub-systems that implement the cognitive mechanisms of cognition (e.g. retrieval from memory)



# Cognitively-Inspired Decision Intelligence for Manufacturing

## Approach and Goals

- Integrating neural and symbolic levels within a genuinely-cognitive system framework can foster high-level reasoning typically required in complex decision scenarios
  - Looking back at decades of work in AI, our working hypothesis is that *the modes of neuro-symbolic integration are methodologically variegated and task-dependent*
- Our current effort revolves around a question in line with most recent literature in neuro-symbolic AI: **can we improve a large model by infusing contextual knowledge at scale? In particular, we are interested in infusing knowledge of the internal cognitive mechanisms underlying human decisions**
- We aim to answer to this question by empirically exploring various approaches
  - Fine-tuning LLAMA with cognitive model's behavior (predictions) and internal state outputs (also called “trace”), and evaluating performance against relevant baselines (e.g., off-the-shelf pretrained models, human ground truth) is the goal for the summer
    - Novel contributions: elicit relevant semantic features of decision steps extracted from computational cognitive model's behavior and replicate them into large models



# Cognitively-Inspired Decision Intelligence for Manufacturing

## Use Case: Continuous Improvement Process (CIP)

- Context: **Flexible manufacturing for optimizing production lines and layouts**
  - Dimensions: quantity, quality, time, cost
- Problem: how to optimize operations depends on temporal scales: *morning round* (every day) or *workshop* (every quarter)
  - *Morning rounds* are time-consuming
  - *Workshops* are affected by redundancy and scale in the volume of information, and absence thereof
- Approach: **Neuro-Symbolic Cognitive Architecture**
  - A solution that can support decision makers, especially at the macro-scale, improving their “situational awareness”
  - Cognitive models can replicate human decisions at different levels of expertise, and integrate learning algorithms with available knowledge
  - Integrated LLM
    - can be finetuned with synthetic data generated by cognitive model (**scalability**)
    - can bootstrap domain transfer of cognitive model (**generalizability**)
    - can be inspected for elicitation of decision steps (**explainability**)



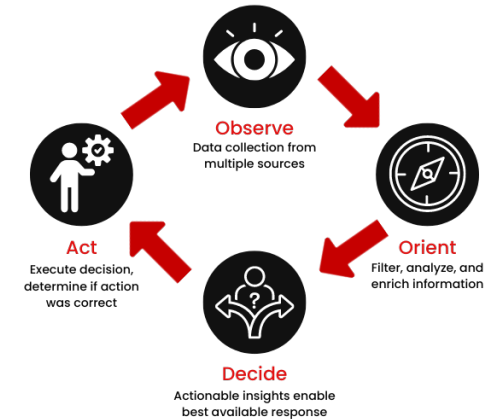


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### John Boyd's OODA Loop



# Cognitively-Inspired Decision Intelligence for Manufacturing

## The Task



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 rates.




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

# Cognitively-Inspired Decision Intelligence for Manufacturing

## CIP-ACT-R: Model Design (in collaboration with Siyu Wu, PSU)

- CIP-ACT-R: ACT-R model applied to Continuous Improvement Process in Bosch Production Systems
- Version 1.0
  - Rule-based model in decision making
  - Learning to distinguish novice, intermediate expert decision combinations depending on feedback
  - Testing of simple rules first and switching to more complex rules later
  - The model learns over the course of trials and exhibits individual differences. It demonstrates a human-like learning progression, showing a steep learning curve at the beginning and gradual improvements later on .
- Version 2.0
  - Incorporate metacognitive processes of reflecting and evaluating the progress of the selected approach
  - Implementing a reinforcement-learning mechanism in a production-system framework

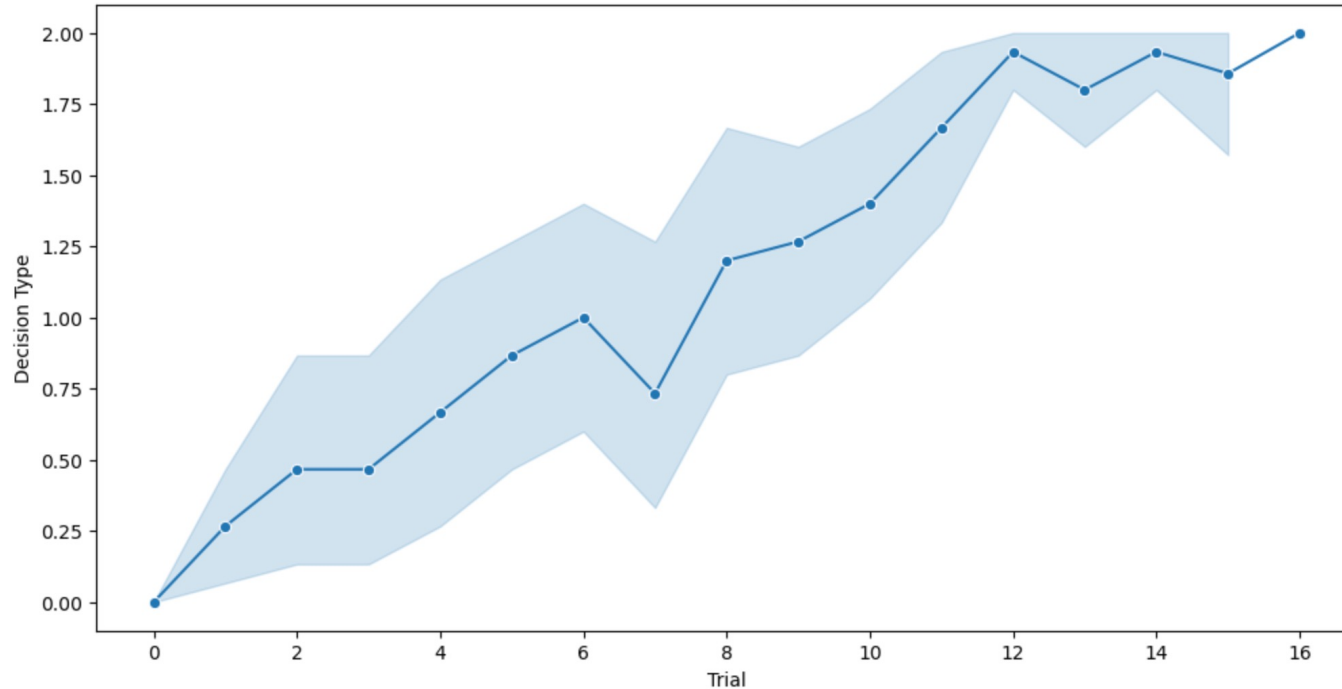
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 Siyu Wu, Alessandro Oltramari, Frank E Ritter. “Toward Using Cognitive Architecture For Manufacturing Solutions”.  
Submitted to *17th International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation (SBP-BRIMs)*

# Cognitively-Inspired Decision Intelligence for Manufacturing

## VSM-ACT 1.0

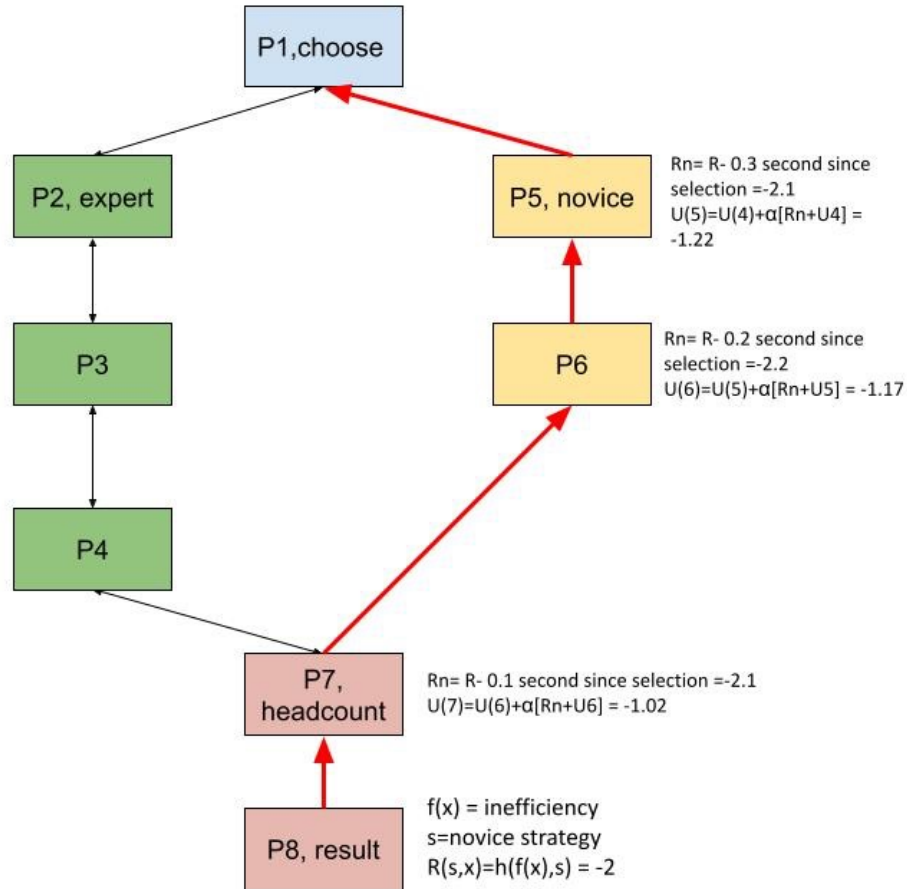
Overall Trend of Decision Types over Trials



- We run the model 15 times to better understand behavior, 15-16 trials per time
- We collected data with decision types encoded as 0, 1, and 2 for, respectively, novice, intermediate, and expert strategies
- Starting at approximately 0 in trial 0, the mean decision type rises to about 0.75 by trial 4 and reaches around 1.25 by trial 8. Despite slight fluctuations, the trend continues upward, with the mean decision type approaching 1.75 by trial 12 and around 1.9 by trial 16. The narrowing 95% confidence intervals, ranging from approximately 0.5 to 2.0 initially to 1.5 to 2.0 in later trials, indicate increasing consistency among participants' decision-making abilities.

# Cognitively-Inspired Decision Intelligence for Manufacturing

## VSM-ACT-R 2.0



- A penalty propagation for the novice strategy stems from head count cost inefficient decision
- A (not depicted) reward propagation for the expert strategy stems from head count cost efficient decision
- *We are still working on refining reward function in reinforcement learning algorithm*

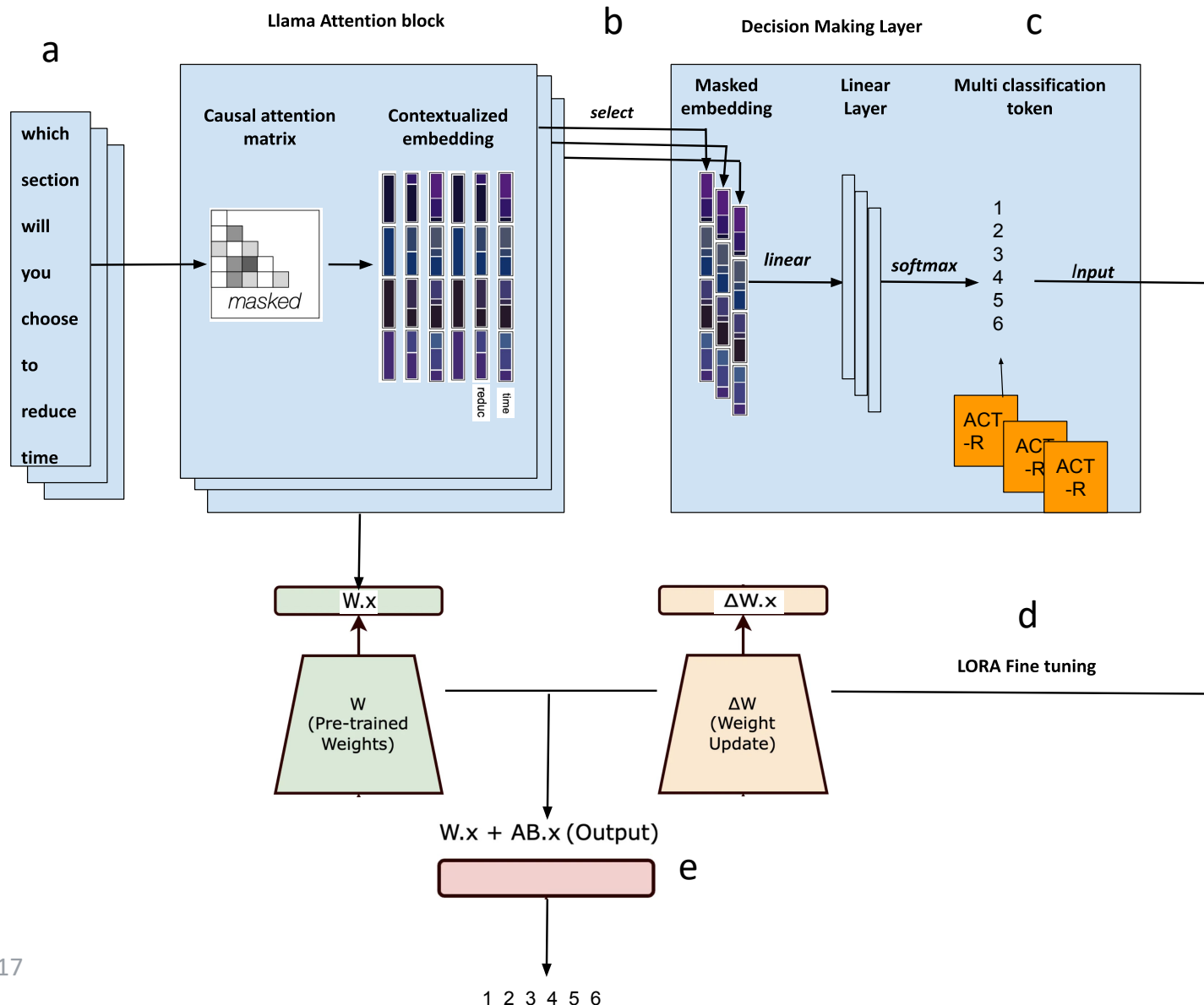
```
*slime-repl sbcl* - GNU Emacs at EVENTS9-W190712
File Edit Options Buffers Tools SLIME REPL Presentations Lisp Trace Help
Polling "c:/Users/sfw5621/AppData/Local/Temp/slime.17096" .. 17 (Abort with 'M-x ^
slime-abort-connection'.)
Polling "c:/Users/sfw5621/AppData/Local/Temp/slime.17096" .. 18 (Abort with 'M-x ^
slime-abort-connection'.)
Connecting to Swank on port 63193..
Connected. Hacks and glory await!
You can run the command 'slime-load-file' with C-c C-l
T
Making completion list...
You can run the command 'slime-load-file' with C-c C-l
T
[]

1\%- *Messages* Bot L29 (Messages)
ISICON-HISTORY : 3.1 Module to record visicon changes.
VISION : 10.1 A module to provide a model with a visual att
sention system

##### Loading of ACT-R 7 is complete #####

CL-USER> (run 10)
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-STRATEGY
0.07999998
0.350 IMAGINAL SET-BUFFER-CHUNK-FROM-SPEC IMAGINAL
0.400 PROCEDURAL PRODUCTION-FIRED BRUTE-CHOICE2
choose assemble has better stable output!
0.450 PROCEDURAL PRODUCTION-FIRED REHEADCOUNT
-0.07999998
1\%- *slime-repl sbcl* 16% L70 (REPL adoc)
```

start with beginner strategy

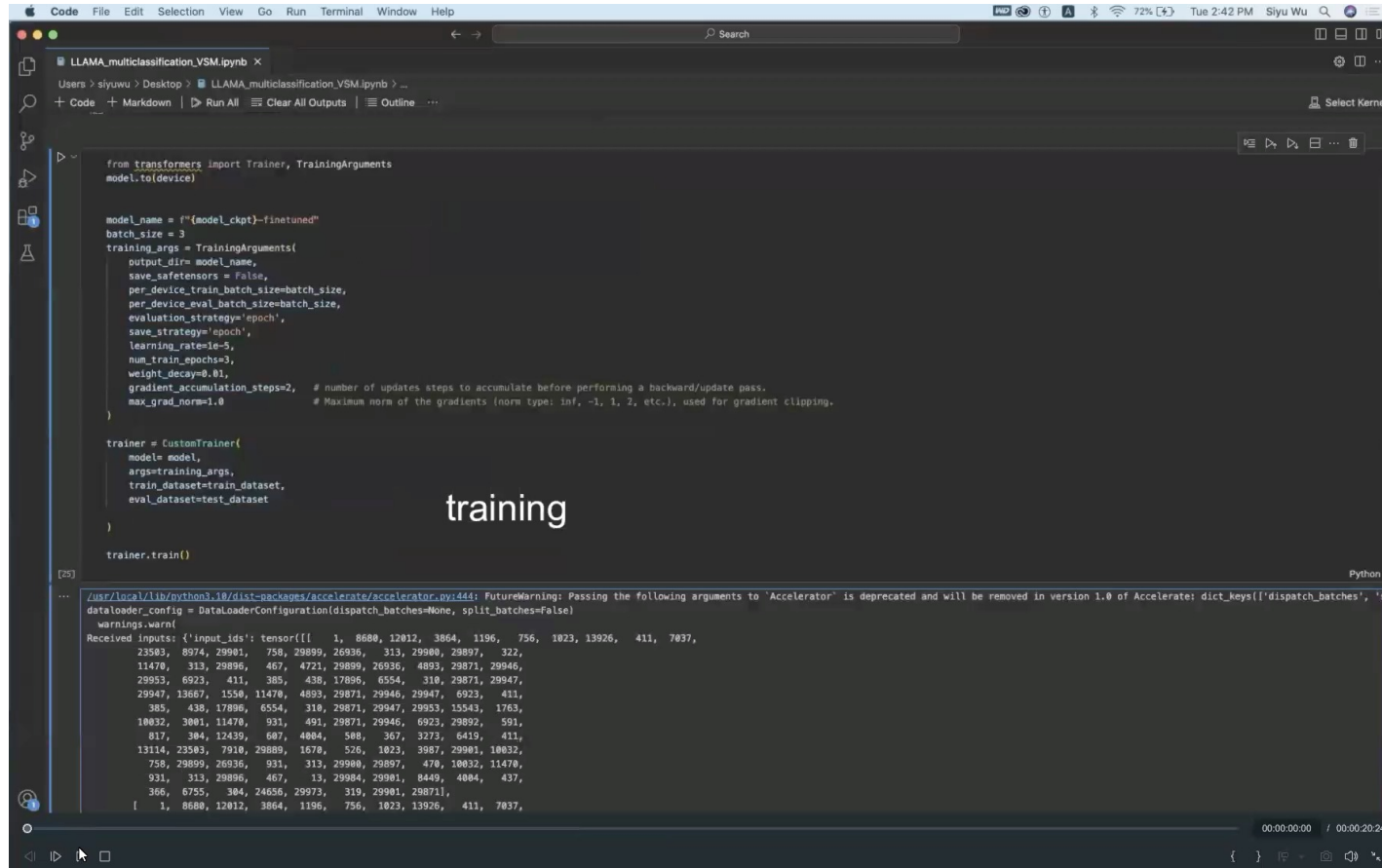


(a) We prompt the decision-making questions into Llama. (b) use Llama as the base model and get access to the last hidden layer for masked embeddings. (c) build a multi-classification layer upon the base model, using ACT-R decision-making strategy choices and results as the target classes and last hidden layer as features. (d) fine-tune the Llama model for multi-classification using LORA. (e) deploy the fine-tuned model in new inference tasks.



# Cognitively-Inspired Decision Intelligence for Manufacturing

## Fine-tuning LLAMA



```
from transformers import Trainer, TrainingArguments
model.to(device)

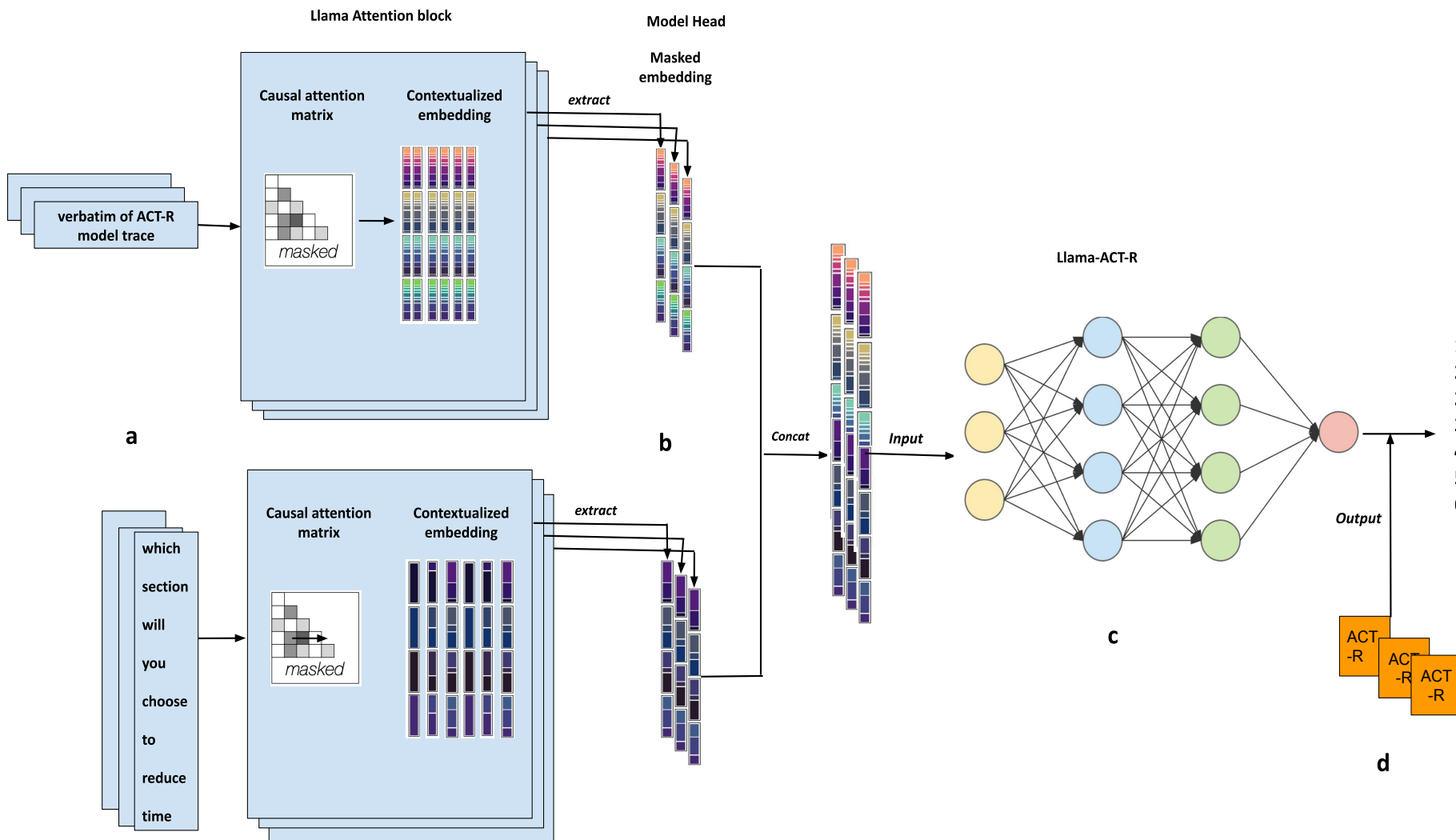
model_name = f"{model_ckpt}-finetuned"
batch_size = 3
training_args = TrainingArguments(
    output_dir=model_name,
    save_safetensors=False,
    per_device_train_batch_size=batch_size,
    per_device_eval_batch_size=batch_size,
    evaluation_strategy='epoch',
    save_strategy='epoch',
    learning_rate=1e-5,
    num_train_epochs=3,
    weight_decay=0.01,
    gradient_accumulation_steps=2, # number of updates steps to accumulate before performing a backward/update pass.
    max_grad_norm=1.0             # Maximum norm of the gradients (norm type: inf, -1, 1, 2, etc.), used for gradient clipping.
)

trainer = CustomTrainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=test_dataset
)

trainer.train()
```

training

```
... /usr/local/lib/python3.10/dist-packages/accelerate/accelerator.py:444: FutureWarning: Passing the following arguments to 'Accelerator' is deprecated and will be removed in version 1.0 of Accelerate: dict_keys(['dispatch_batches', '
data_loader_config = DataLoaderConfiguration(dispatch_batches=None, split_batches=False)
warnings.warnl
Received inputs: {'input_ids': tensor([[ 1, 8688, 12012, 3864, 1196, 756, 1023, 13926, 411, 7037,
23583, 8074, 29901, 758, 29899, 26836, 313, 29808, 29897, 322,
11470, 313, 29896, 467, 4721, 29899, 26936, 4893, 29871, 29946,
29953, 6923, 411, 385, 438, 17896, 6554, 310, 29871, 29947,
29947, 13667, 1550, 11478, 4893, 29871, 29946, 29947, 6923, 411,
385, 438, 17896, 6554, 310, 29871, 29947, 29953, 15543, 1763,
10032, 3001, 11478, 931, 491, 29871, 29946, 6923, 29892, 591,
817, 384, 12439, 687, 4884, 508, 367, 3273, 6419, 411,
13114, 23583, 7910, 29899, 1670, 576, 1023, 3087, 29901, 10032,
758, 29899, 26936, 931, 313, 29908, 29897, 476, 10032, 11478,
931, 313, 29896, 467, 13, 29904, 29901, 8449, 4884, 437,
366, 6755, 384, 24656, 29973, 319, 29901, 29871],
[ 1, 8688, 12012, 3864, 1196, 756, 1023, 13926, 411, 7037,
```



(a) We prompt the verbatim of the ACT-R model trace and the corresponding decision-making questions into LLaMA separately

(b) extract the last hidden layer for masked embeddings, concatenate the embeddings, and (

c) feed them into a multilayer neural network with softmax activation.

(d) Build and train the neural network model using ACT-R decision-making strategies and results as targets. We refer to the developed neural network model as LLaMA-ACT-R for decision making.

# Cognitively-Inspired Decision Intelligence for Manufacturing

## Recent Work

**AAAI-MAKE 2024:** Kaushik Roy, Alessandro Oltramari, Yuxin Zi, Chathurangi Shyalika, Vignesh Narayanan, Amit Sheth, "[Causal Event Graph-Guided Language-based Spatiotemporal Question Answering](#)". In Proceedings of AAAI Spring Symposia 2024, Stanford, March 25-27.



**AAAI LLM-CA 2023:** Alessandro Oltramari, "[Enabling High-Level Machine Reasoning with Cognitive Neuro-Symbolic Systems](#)". In *Proceedings of the AAAI Symposium Series*, vol. 2, no. 1, pp. 360-368. 2023.



**COLING 2022:** Ma, Ilievski, Francis, Nyberg, and Oltramari. "[Coalescing Global and Local Information for Procedural Text Understanding](#)". In Proceedings of the 29th International Conference on Computational Linguistics, pp. 1534-1545. 2022.



**AAAI 2021:** Ma, Kaixin, Filip Ilievski, Jonathan Francis, Yonatan Bisk, Eric Nyberg, and Alessandro Oltramari. "[Knowledge-driven Data Construction for Zero-shot Evaluation in Commonsense Question Answering](#)".



**AAAI-CSKG 2021:** Li, Yikang, Pulkit Goel, Varsha Kuppur Rajendra, Har Simrat Singh, Jonathan Francis, Kaixin Ma, Eric Nyberg, and Alessandro Oltramari. "[Lexically-constrained Text Generation through Commonsense Knowledge Extraction and Injection](#)".



**ACM SIGKDD 2023:** Zhang, Jiarui, Filip Ilievski, Kaixin Ma, Aravinda Kollaa, Jonathan Francis, and Alessandro Oltramari. "[A study of situational reasoning for traffic understanding](#)". In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 3262-3272. 2023.



**ACL-IJCNLP 2021:** Chen, Xi, Lin, Faner, Zhou, Yeju, Ma, Kaixin, Jonathan, Francis, Eric Nyberg, Alessandro Oltramari. "[Building Goal-oriented Document-grounded Dialogue Systems](#)".



**KBS Journal 2021:** Ilievski, Filip, Alessandro Oltramari, Kaixin Ma, Bin Zhang, Deborah L. McGuinness, and Pedro Szekely. "[Dimensions of commonsense knowledge](#)".



**IOS Press 2020:** Oltramari, A., Francis, J. Henson, C., Ma, K., and Wickramarachchi, R.. "[Neuro-Symbolic Architectures for Context Understanding](#)". In *Knowledge Graphs for eXplainable Artificial Intelligence: Foundations, Applications and Challenges*, pp. 143-160.



**EMNLP-COIN 2019:** Ma, Kaixin, Jonathan Francis, Quanyang Lu, Eric Nyberg, and Alessandro Oltramari. "[Towards generalizable neuro-symbolic systems for commonsense question answering](#)".



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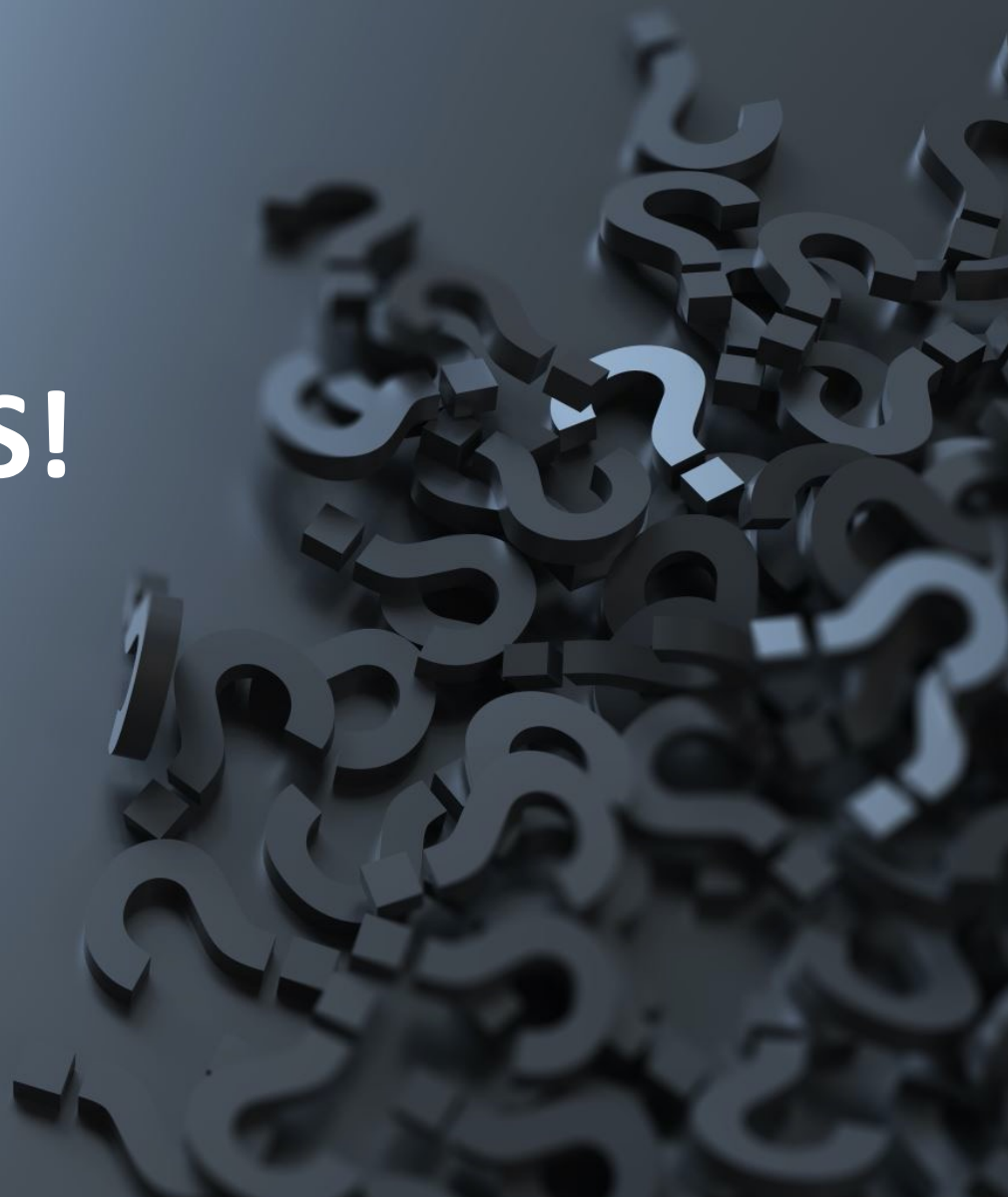
## Credits (Alphabetic Order)

Monireh Ebrahimi, Jon Francis, Cory Henson, Pascal Hitzler, Filip Ilievski, Christian Lebiere, Antonio Lieto, Kaixin Ma, Anees ul Mehdi, Eric Nyberg, Sarah Masud Preum, Ehsan Qasemi Frank Ritter, Kaushik Roy, Amit Seth, Siyu Wu

**Carnegie Mellon University**



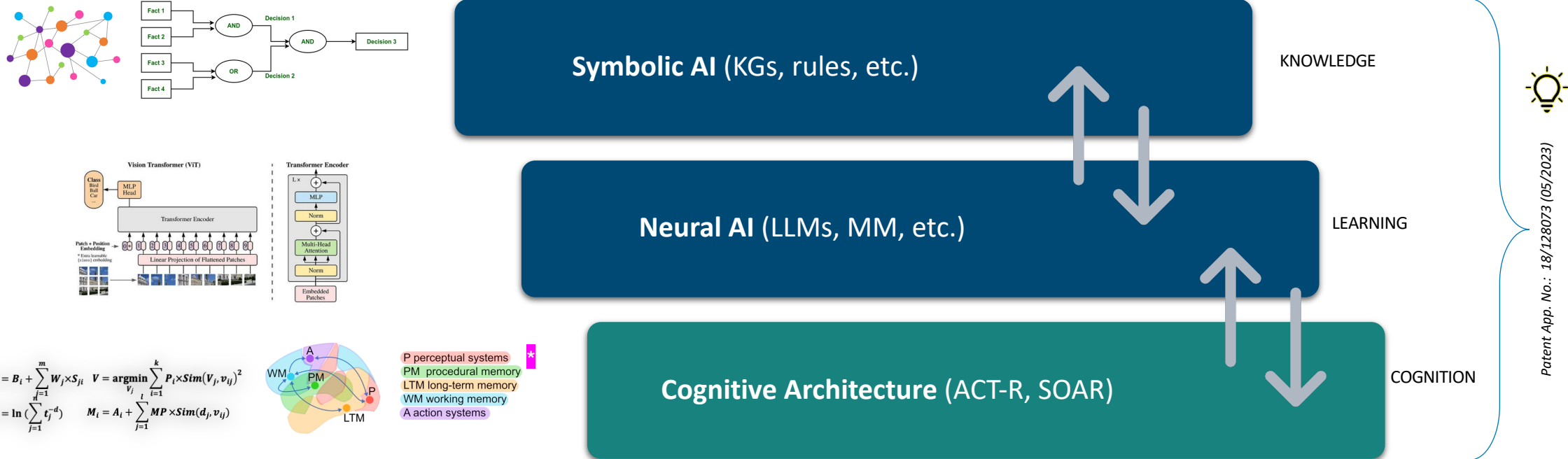
**THANKS!**



# LEFTOVERS

# Cognitively-Inspired Decision Intelligence for Manufacturing

## Our Solution: Integrating Cognitive Architectures & Neuro-Symbolic AI



AI SYSTEMS FOR  
DECISION INTELLIGENCE



# Cognitively-Inspired Decision Intelligence for Manufacturing

## Outline

- Our Group
- Motivations
- Use Case
- Approach and Methods
- Future Work



# Cognitively-Inspired Decision Intelligence for Manufacturing

## Bosch Research in North America



### North America

#### Research and Technology Center

Technology scouting in America and research in the areas of

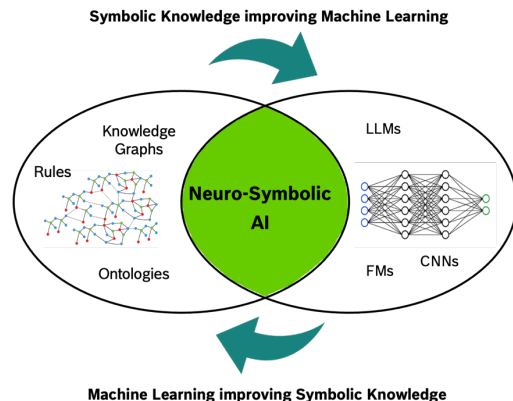
- ▶ Human-Machine Intelligence
- ▶ Modeling, Design and Control of Energy Systems and Materials
- ▶ Secure and Intelligent IoT
- ▶ Intelligent and Connected Sensors and Systems

# Cognitively-Inspired Decision Intelligence for Manufacturing

## The Causal Analysis and Decision Intelligence Group (CADI)

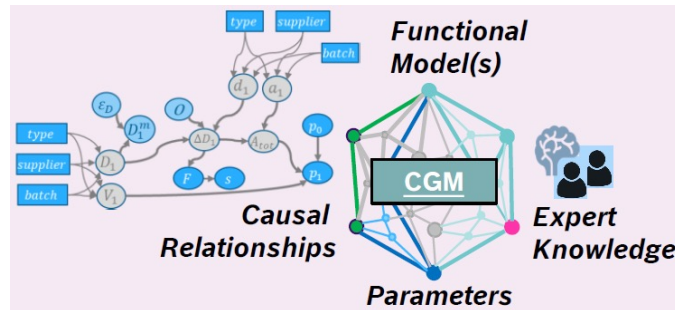
### NEURO-SYMBOLIC AI

- Bosch has vast amounts of **highly valuable data** and **rich domain expert knowledge**
- Neuro-Symbolic AI enables **automatic distillation of insights** from data and exploitation of expert knowledge for **causal analysis and decision intelligence**
- Current focus on cost savings and process optimization in manufacturing



### CAUSAL ANALYSIS

- **Causal AI** is a set of techniques for discovering causal relations and making inferences beyond mere correlation
- **Causal Neuro-Symbolic AI** is the integration of Causal AI with knowledge graphs and machine learning
- Applications in manufacturing
  - Finding root causes for anomalies
  - Predicting the quality of products
  - Optimizing process chains



\*CGM: Causal Graph Model

### DECISION INTELLIGENCE

- Decision intelligence (DI) aims to support, augment and automate human decisions by linking data with outcomes
- Contemporary DI is genuinely neuro-symbolic as it combines machine learning algorithms with knowledge graphs and rule-based systems
- Applications in manufacturing: Continuous Improvement Process (CIP)
  - Guide interventions during ramp-up phase of production line reconfiguration
  - Optimization of flexible manufacturing

