Neurosymbolic AI for Advanced Air Mobility: Foundations, Technical Advances, and an Approach to Travel Demand Modeling

Kamal Acharya

University of Maryland, Baltimore County
Department of Information Systems

Tuesday, 20^{th} November , 2025

Outline

Outline

1. Neurosymbolic AI
2. Advanced Air Mobility
3. Neurosymbolic AI for Travel Demand Prediction

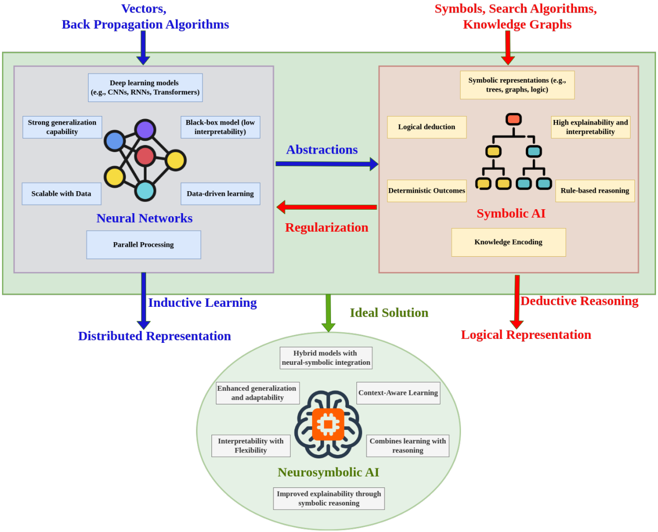
Introduction (1/4)

- Three waves of AI:
  - Symbolic (rules, logic)
  - Neural (learning, patterns)
  - Neurosymbolic (learning + reasoning)
- Limitations of Neural AI:
  - Black-box
  - No reasoning
  - Low interpretability
  - Weak robustness
- Limitations of Symbolic AI:
  - Cannot handle noise
  - Poor scalability
  - Manual rule creation
- Need for a hybrid approach.

Introduction (2/4)

- Neurosymbolic AI = neural perception + symbolic reasoning
- Key benefits:
  - Interpretability
  - Logical consistency
  - Safety and constraint handling
  - Data efficiency
- Ideal for high-stakes domains:
  - Robotics
  - Healthcare
  - Cybersecurity
  - Advanced Air Mobility (AAM)
- Foundation for trustworthy, explainable, rule-aligned AI.

Introduction (3/4)



Introduction (4/4)

Table: Comparing the Paradigms

Capability	Symbolic	Neural	Neurosymbolic
Robustness	Rule sensitive	Adversarially brittle	Symbolic guards improve resilience
Uncertainty quantification	Limited probabilistic logic	Adhoc confidence	Bayesian layers + logical guards
Intervenability	Editable rules	Opaque weights	Editable symbolic layer without re-training
Interpretability	Transparent rules	Opaque weights	Logic trace around learnt modules
Data Efficiency	Few examples	Large labelled sets	Prior knowledge + learning
Reasoning	Deductive, abductive	Limited compositional reasoning	Differentiable reasoning layers
Transfer/Fine-tuning	Brittle rule porting across domains	Fine tune with few examples	Combines frozen neural backbone with domain-specific rules
Scalability	State-space explosion	Handles high dimensional data	Neural front-end + symbolic back-end
Compute / carbon cost	Lightweight search	Energy-hungry training	Smaller models + priors

Classification by Sebastian and Pascal

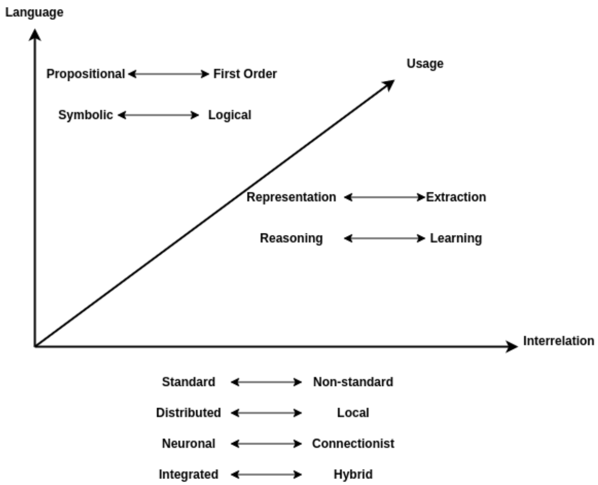


Figure: Classification by Sebastian and Pascal [1]

Classification by Kautz (1/7)

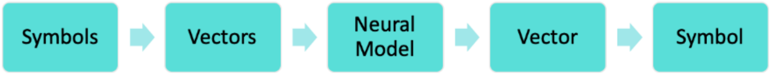
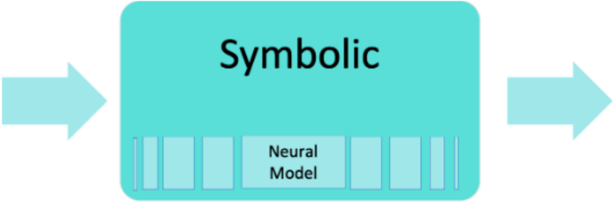


Figure: Symbolic Neuro symbolic

Classification by Kautz (2/7)



Symbolic[Neuro]

Classification by Kautz (3/7)

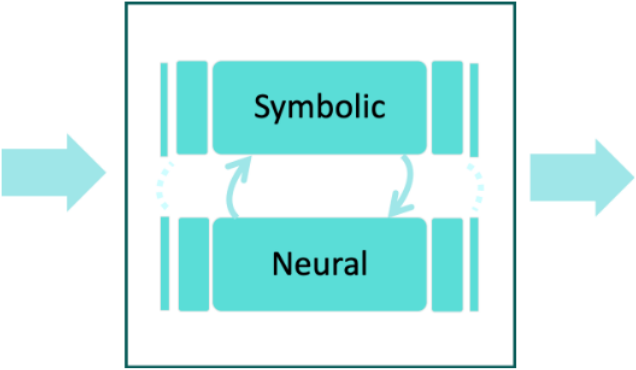
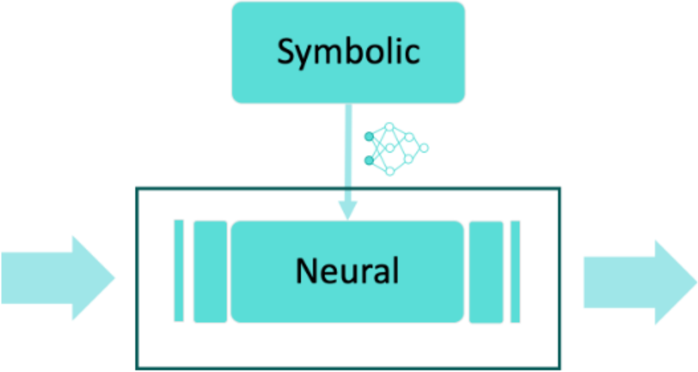


Figure: Neuro | Symbolic

Classification by Kautz (4/7)



Neuro:Symbolic → Neuro

Classification by Kautz (5/7)

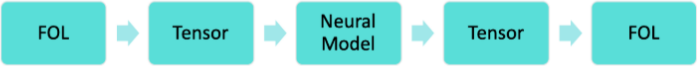
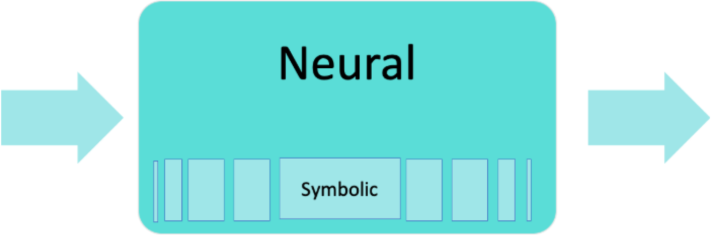


Figure: Neuro_{Symbolic}

Classification by Kautz (6/7)



Neuro[Symbolic]

Classification by Kautz (7/7)

Table: Classification by Henry Kautz [2]

Classification	Characteristic Features
Symbolic Neuro symbolic	Symbolic input is converted to feature vectors for the neural networks which give final results in the symbolic form
Symbolic[Neuro]	Neural pattern recognition subroutine within a symbolic problem solver
Neuro | Symbolic	A cascade from neural network into symbolic reasoner
Neuro: Symbolic $\rightarrow$ Neuro	Symbolic rules are input which are compiled so that their knowledge end up in the neural network
Neuro_{Symbolic}	Uses direct encodings of logical statements into neural structures
Neuro[Symbolic]	Embed symbolic reasoning inside neural engine to enable both superhuman and super combinatorial reasoning

Classification by Yu (1/4)

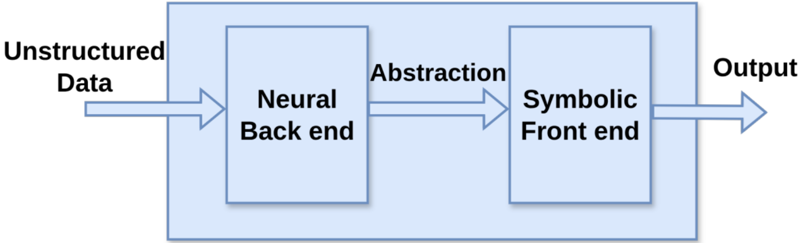


Figure: Learning for Reasoning

Classification by Yu (2/4)

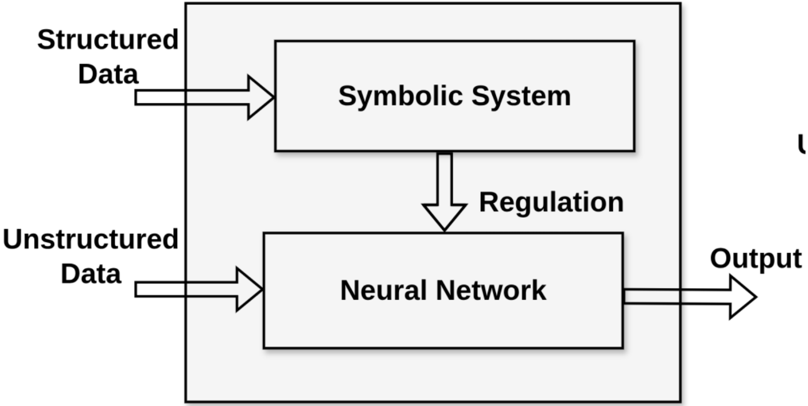


Figure: Reasoning for Learning

Classification by Yu (3/4)

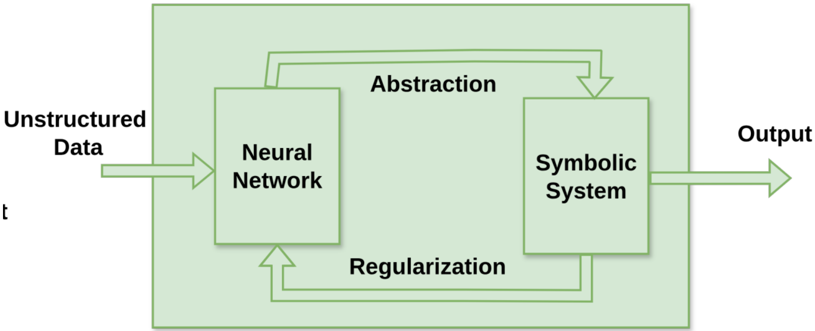


Figure: Learning-Reasoning

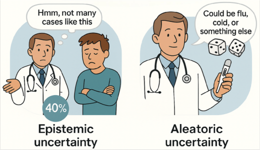
Classification by Yu (4/4)

Table: Classification by D. Yu and et al. [3]

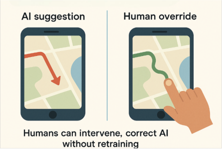
Classification	Characteristic Features
Learning for reasoning	Neural network play the role of the helper, it extracts the important symbols and information so that the search space of the symbolic system narrowed down
Reasoning for learning	Symbolic system act as a helper, it provides symbolic knowledge to the neural network from where the final decision is made
Learning-reasoning	Uses symbolic and neural systems as an alternate process. They both complement each other to give the final results

Three Pillars of Trustworthy AI

Stable Performance Under Varied Condition
Robustness



Measuring Confidence in Prediction
Uncertainty Quantification



Human Ability to Modify or Influence AI
Intervenability

Robustness (1/3)

- Ability of AI models to perform reliably under unexpected conditions.
- Goes beyond accuracy on clean training data.
- Ensures stable behavior with:
  - Noisy inputs
  - Missing or incomplete data
  - Distribution shifts
- Essential for trustworthy AI in safety-critical domains.

Robustness (2/3)

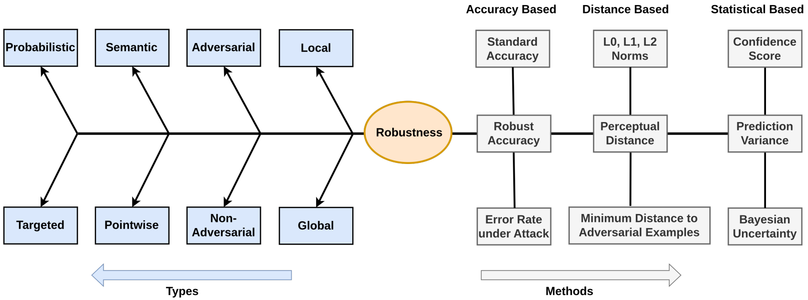


Figure: Various Categories of Robustness along with the Metrics of Measurement

Robustness (3/3)

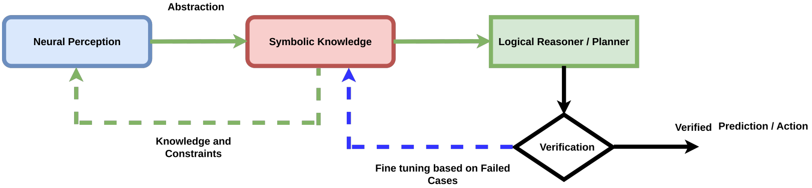


Figure: Neurosymbolic Robustness Pipeline

Uncertainty Quantification (1/3)

- UQ $=$ measuring how confident a model is in its predictions.
- ML models are data-driven $\rightarrow$ outputs always contain uncertainty.
- Sources of uncertainty:
  - Noisy or ambiguous data
  - Model limitations
  - Stochastic training (random initialization, SGD, shuffling)
- Needed to build reliable and trustworthy AI systems.

Uncertainty Quantification (2/3)

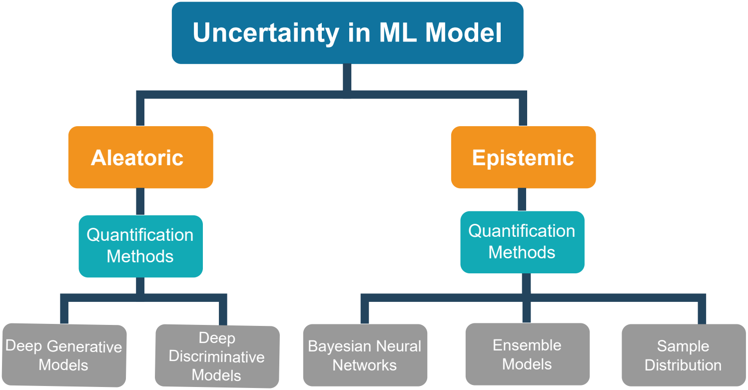


Figure: Various Categories of Uncertainty along with the Quantification Methods

Uncertainty Quantification (3/3)

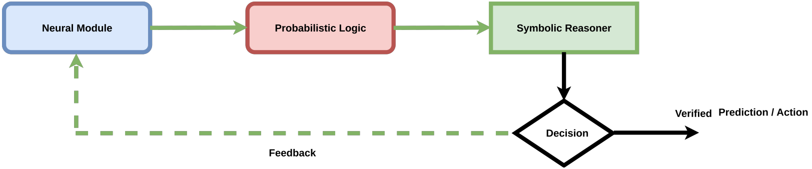


Figure: Neurosymbolic Uncertainty Quantification Pipeline

Intervenability (1/3)

- Intervenability = ability to modify or influence a model's internal process.
- Goes beyond interpretability (understanding) to active control.
- Enables targeted adjustments to:
  - Internal representations
  - Concept activations
  - Reasoning steps
- Allows humans to influence outputs in a predictable way.

Intervenability (2/3)

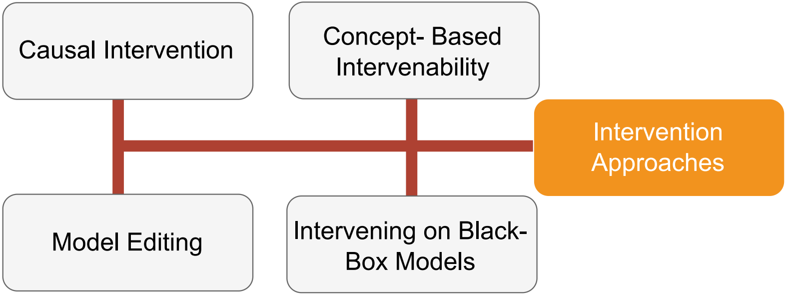


Figure: Various Approaches of Intervention of AI Models

Intervenability (2/3)

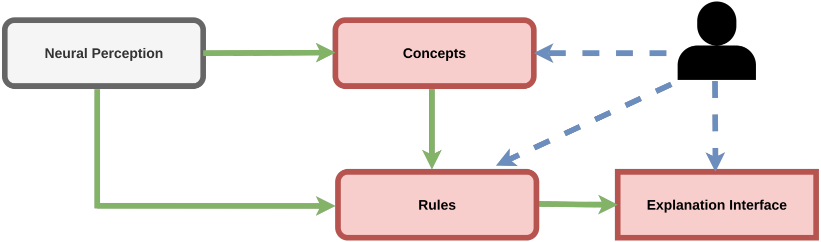


Figure: Human Intervention Pathways in a neurosymbolic Pipeline

Outline

1. Neurosymbolic AI
2. Advanced Air Mobility
3. Neurosymbolic AI for Travel Demand Prediction

Advanced Air Mobility (1/3)

- **What is Advanced Air Mobility (AAM)?**
  - A paradigm shift in air transportation.
  - Seamless integration of air mobility into daily life.
- **Key Components:**
  - Urban Air Mobility (UAM): Focused on intra-city air transport.
  - Regional Air Mobility (RAM): Expands beyond metropolitan areas.
- **Objective:**
  - Enable efficient, safe, and sustainable movement of people and goods.

Advanced Air Mobility (2/3)

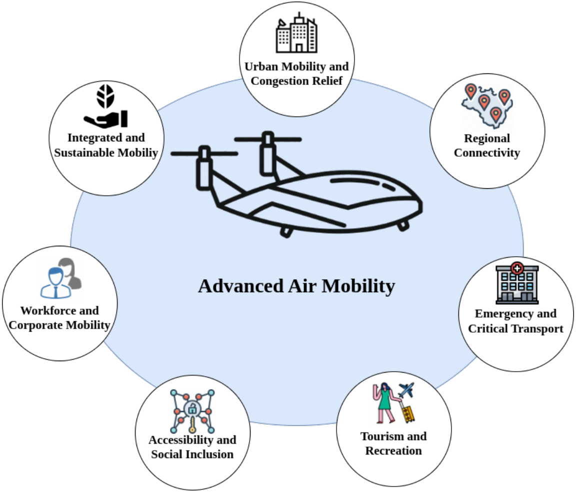
Transition to AAM

- Introduction of low-altitude airspace usage for short to medium-distance travel.
- Development of electric vertical take-off and landing (eVTOL) vehicles.

Key Differentiators from Conventional Aviation

- Autonomous Systems: Reduces human intervention.
- Advanced Air Traffic Management (ATM): Improves efficiency and accessibility.
- Sustainability Focus: Electric propulsion reduces carbon footprint.

Advanced Air Mobility (3/3)



Use Cases of Advanced Air Mobility

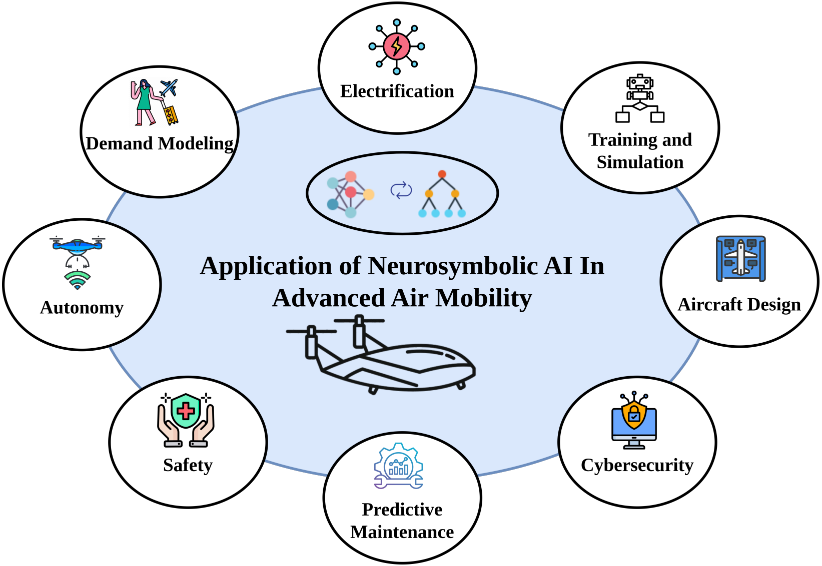


Figure: Applications of Neurosymbolic AI in AAM

Outline

Introduction (1/3)

- Accurate travel demand prediction is essential for transportation planning, congestion reduction, and infrastructure investment.
- Traditional models (e.g., statistical, time-series) struggle to capture nonlinear and multidimensional interactions in travel data.
- Neural Networks (NNs) offer high predictive power but lack interpretability, crucial for transportation decision-making.

Introduction (2/3)

- We propose a Neurosymbolic AI approach integrating Decision Tree (DT) rules with Neural Networks (NNs).
- DTs extract interpretable *if-then* rules, while NNs model complex travel demand patterns.
- Encoding DT rules as additional features in NNs bridges symbolic reasoning and deep learning.
- Our approach improves accuracy (MAE, R^2, CPC) while enhancing interpretability.

Introduction (3/3)

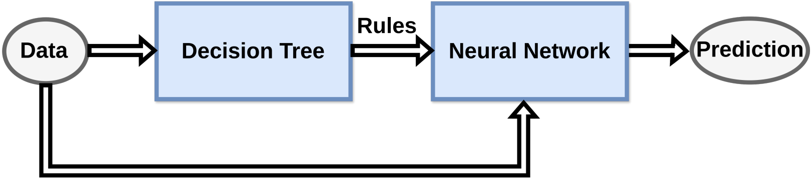


Figure: Neurosymbolic Approach Used in the Research

Methodology (1/4)

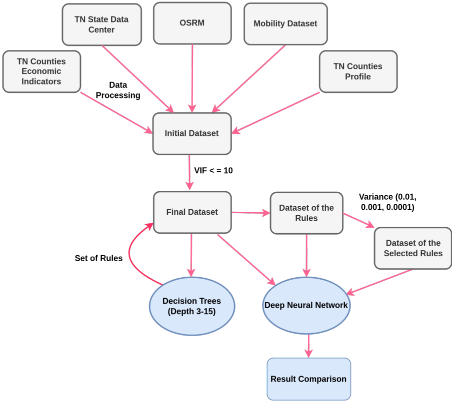


Figure: Research Process

Methodology (2/4)

Table: County-Level Features in Tennessee

Feature Category	Description
Land Use Counts	NaturalAreaCounts (forests, agriculture), PublicAreaCounts (residential, commercial, industrial)
Points of Interest (POI)	Counts of educational institutions, commercial areas, healthcare facilities, entertainment centers
Roads	MajorRoads (highways, expressways), OtherRoads (local, tertiary roads)
Transportation	Number of airports, railway stations, bus stations
Economic Features	Includes Unemployment Rate, Employed Population, and Sales Tax Revenue
Ranking	Overall ranking of counties based on health, economic well-being, and education
Population	Total population count for each county

Methodology (3/4)

Table: 8 Rules Extracted from Decision Tree of Depth 3

Conditions	Mean Value
distance_miles $\leq$ 46.08 AND POIs_Destination $>$ 323.0 AND POIs_Origin $>$ 307.0	31,867.81
distance_miles $\leq$ 46.08 AND POIs_Destination $>$ 323.0 AND POIs_Origin $\leq$ 307.0	9,709.81
distance_miles $\leq$ 46.08 AND 323.0 $\geq$ POIs_Destination $>$ 243.0	6,492.03
46.08 $<$ distance_miles $\leq$ 58.77 AND NaturalAreaCounts_Destination $>$ 935.5	2,728.70
distance_miles $\leq$ 46.08 AND POIs_Destination $\leq$ 243.0	1,648.22
distance_miles $>$ 58.77 AND POIs_Destination $>$ 773.5	544.09
46.08 $<$ distance_miles $\leq$ 58.77 AND NaturalAreaCounts_Destination $\leq$ 935.5	515.81
distance_miles $>$ 58.77 AND POIs_Destination $\leq$ 773.5	106.32

Methodology (4/4)

Table: Rules and Variance-Based Rules at Different Tree Depths

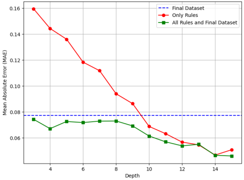
Depth	All Rules	Rules Selected by Variance		
		0.01	0.001	0.0001
3	8	6	8	8
4	16	7	14	16
5	32	11	24	32
6	64	15	32	58
7	116	18	46	101
8	202	20	60	163
9	324	20	83	251
10	505	23	103	374
11	753	20	128	531
12	1069	18	157	735
13	1485	14	164	992
14	2006	8	174	1278
15	2628	5	171	1595

Result (1/3)

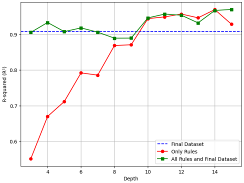
Table: Summary of Generated Dataset Configurations

Dataset Type	Description	Count	DT Depths
Final Dataset	Baseline dataset used for evaluation	1	-
Rule-Only Datasets	Extracted rules only	12	3–15
Rules + Final Dataset	Rules and baseline dataset	12	3–15
Rules (Variance 0.01) + Final	Rules filtered (variance $\leq$ 0.01) and combined with baseline	12	3–15
Rules (Variance 0.001) + Final	Rules filtered (variance $\leq$ 0.001) and combined with baseline	12	3–15
Rules (Variance 0.0001) + Final	Rules filtered (variance $\leq$ 0.0001) and combined with baseline	12	3–15

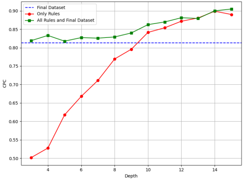
Result (2/3)



Mean Absolute Error



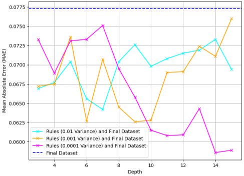
R^2



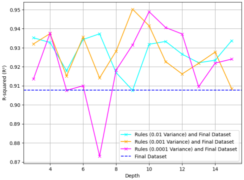
Common Part of Commuters

Figure: NN performance on Final, Rules and Combined dataset

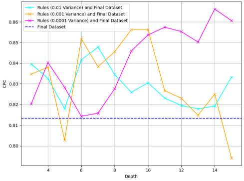
Result (3/3)



Mean Absolute Error



R^2



Common Part of Commuters

Figure: NN performance on various sets of rules selected on the basis of variances

Future Work

- **Dynamic rule selection**: Moving away from static predefined variance thresholds to more flexible approaches.
- **Exploring relevant dataset**: Including the features like weather which highly influenced the trip demand.

Publications

- **K. Acharya**, W. Raza, C. Dourado, A. Velasquez and H. H. Song, "**Neurosymbolic Reinforcement Learning and Planning: A Survey**," in IEEE Transactions on Artificial Intelligence, vol. 5, no. 5, pp. 1939-1953, May 2024, doi: 10.1109/TAI.2023.3311428. **IEEE Computational Intelligence Magazine's Publication Spotlight (Nov 2024)**
- **K. Acharya**, M. Lad, L. Sun and H. Song, "**Neurosymbolic Approach for Travel Demand Prediction: Integrating Decision Tree Rules into Neural Networks**," 2025 International Wireless Communications and Mobile Computing (IWCMC), Abu Dhabi, United Arab Emirates, 2025, pp. 600-605, doi: 10.1109/IWCMC65282.2025.11059465.
- **Acharya, K.**, Sharif, I., Lad, M., Sun, L. and Song, H., 2025, August. **Integrating neurosymbolic AI in advanced air mobility: a comprehensive survey**. In Proceedings of the Thirty-Fourth International Joint Conference on Artificial Intelligence (pp. 10362-10370).
- **K. Acharya** and H. H. Song, "**A Comprehensive Review of Neuro-symbolic AI for Robustness, Uncertainty Quantification, and Intervenability**," accepted in Arabian Journal for Science and Engineering, 2025.

Reference I

[1] Sebastian Bader and Pascal Hitzler. Dimensions of neural-symbolic integration-a structured survey. *arXiv preprint cs/0511042*, 2005.

[2] Henry Kautz. The third ai summer: Aaai robert s. engelmore memorial lecture. *AI Magazine*, 43(1):105–125, 2022.

[3] Dongran Yu, Bo Yang, Dayou Liu, Hui Wang, and Shirui Pan. A survey on neural-symbolic learning systems. *Neural Networks*, 166:105–126, 2023.

Thank You