A Deep Learning Alternative to Traditional Activity-Based Models: Learning Daily Travel Chains of Activities, Timing, and Modes

Sabya Mishra
Professor of Civil Engineering
University of Memphis

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Vice President, Travel Demand Analytics, Caliper Corporation

- Md Tawkir Ahmed

Doctoral Student, University of Memphis

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Motivation

- Travel choice forecasting guides planning decisions.
- Core of daily travel behavior includes:
  - Time of the Day: When the trip occurs?
  - Activity: Why trips are made?
  - Trip Chain: Sequence of trips in a day.

Widely used choice modeling includes:

- Discrete Choice Modeling (DCM)

  e.g, Multinomial/Nested Logit, Latent Class, Hybrid Choice Models

✓ Explainable

✓ Behaviorally grounded

✗ Hard to scale

- Many variables
- Lots of interactions
- Complex nesting

AI-Models

✓ High accuracy

✓ High-dimensional

✓ Nonlinear learning

✗ Harder to interpret

✗ Model design is hard

Can we get AI-level accuracy and DCM-level interpretability?

Objectives and Hypothesis

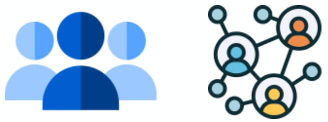
Objectives:

1. Build sequence aware multi-task TOD–Activity model.
2. Improve prediction accuracy.
3. Explore behavioral patterns while remaining policy-interpretable.

Benefits:

1. Planning level forecasts

2. Behavioral insights



3. Policy-relevant explanations

How can we develop such AI-DCM Model?

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Modeling Sequence

NL
(Baseline)
Interpretable baseline

→

NL+LSTM
(Controlled upgrade)
Same utility + sequence learning

→

AI-DCM
(Benchmark)
Flexible benchmark

Why NL as baseline model?

- When alternatives share common unobserved attributes.
- When shared factors create correlation among choices.

Aboutable, Ben-Akiva & Jaillet (2020)

<u>AI-Models:</u>

- GRU/LSTM: Sequence only
- CNN-LSTM: Patterns + sequence
- CNN-LSTM + Attn: Focus key steps
- Transformer: Strong attention interactions
- ST-GNN: Spatial + temporal context
- TasteNet: Heterogeneity
- TB-ResNet: Nonlinear cross-effects

What data and features feed the model to predict TOD and Activity?

Data

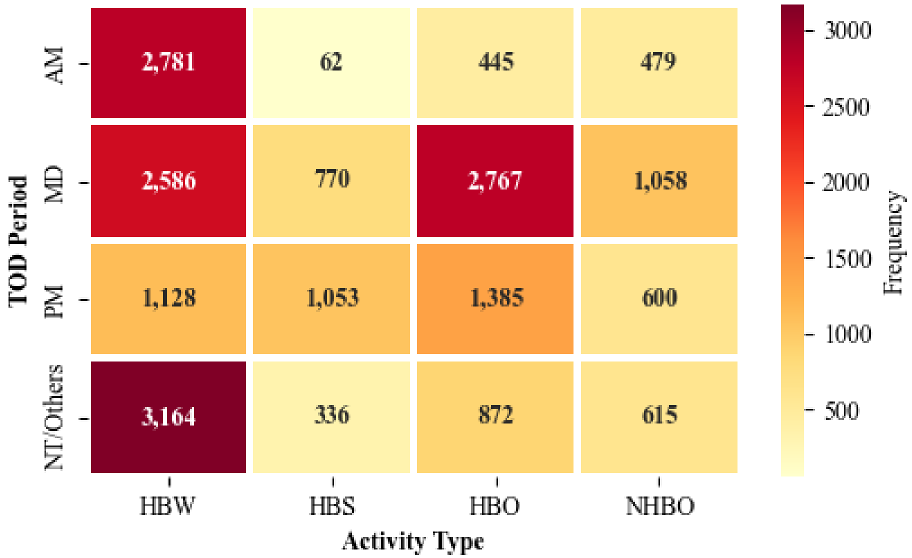
Study Area

Nevada, Reno Household Survey Data

- 2,000 households
- 4.5 months (January - June 2024)

Variables:

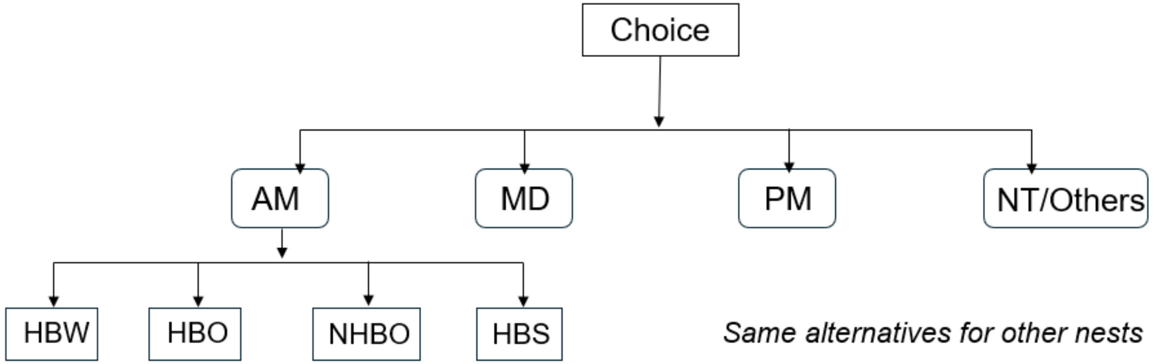
Variables: Demographics & Socioeconomic, Household & Vehicle Information Characteristics, Travel Characteristics, Trip location, etc.



Can the Baseline model serve our goal using the Data?

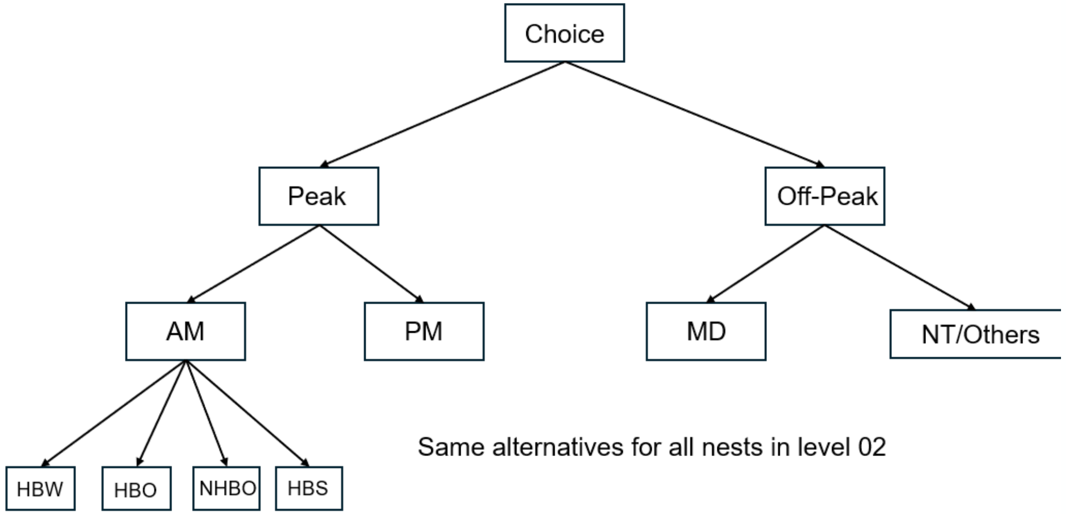
Statistical Model (Baseline)

Model 01



Same alternatives for other nests

Model 02



Same alternatives for all nests in level 02

Model fitness:

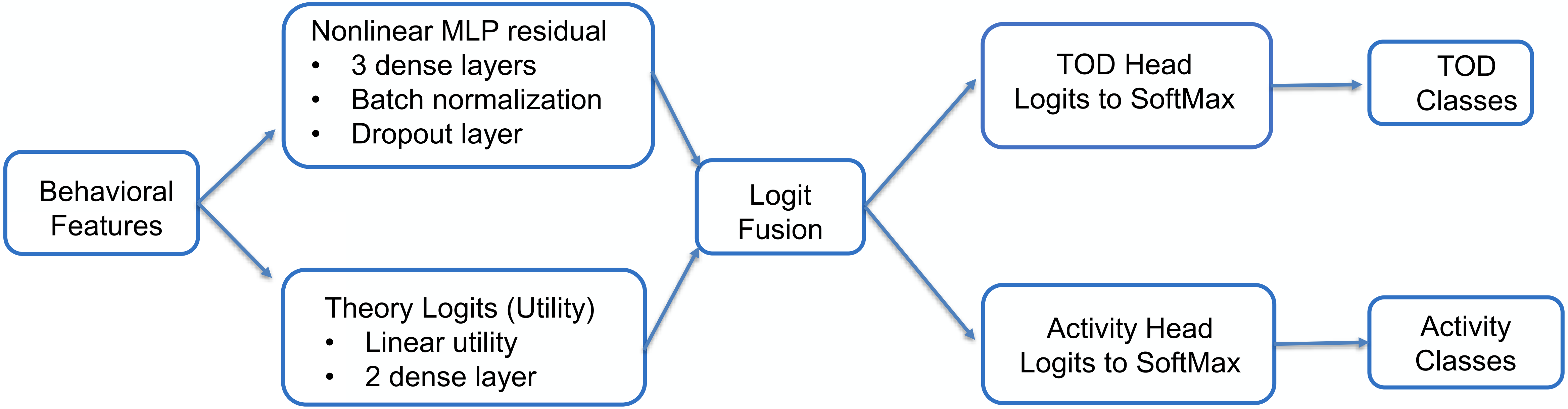
Model	Log likelihood	AIC	BIC	*Accuracy (%)
M01	-35,736.14	71,556.27	71,888.43	47.05
M02	-50,604.25	101,304.49	101,684.10	31.72

* Accuracy is the correct predictions over total predictions

Baseline NL structures struggle for prediction of TOD and activity

Modeling Framework of Hybrid AI-DCM

Proposed Multi-Task Prediction Modeling Framework



Benefit:

- AI learns flexible residual utility
- DCM logit keeps interpretability + accuracy

Which AI-DCM Models are More Accurate?

		TOD		Activity		Runtime
#	**Model**	**Train**	**Test**	**Train**	**Test**	**Minutes**
1	NL-LSTM	0.657	0.610	0.759	0.734	10.100
2	GRU	0.718	0.647	0.806	0.744	5.210
3	LSTM	0.718	0.634	0.809	0.733	7.960
4	CNN-LSTM + Attention	0.723	0.636	0.808	0.743	7.030
5	TasteNet	0.723	0.636	0.807	0.738	2.940
6	LSTM + Attention	0.736	0.653	0.816	0.734	7.140
7	CNN-LSTM	0.741	0.654	0.817	0.754	7.070
8	STGNN	0.759	0.628	0.838	0.712	6.810
9	Transformer	0.761	0.658	0.829	0.732	7.650
10	DEEP-U MLP	0.775	0.620	0.850	0.722	4.810
11	**TB-ResNet**	**0.789**	**0.658**	**0.843**	**0.739**	**2.860**

Best Model:

- TB-ResNet gives the strongest balanced performance
  - TOD Test = 0.658 and Activity Test = 0.739
  - low runtime (2.86 min)

Model Explainability

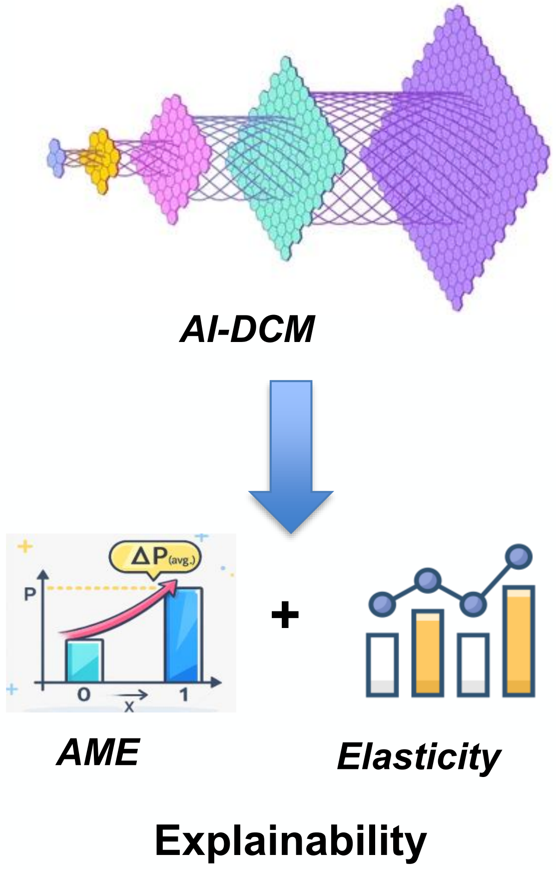
Model Output Comparison:

- Common ground: Both NL and AI-DCM output choice probabilities.

- Same metrics:

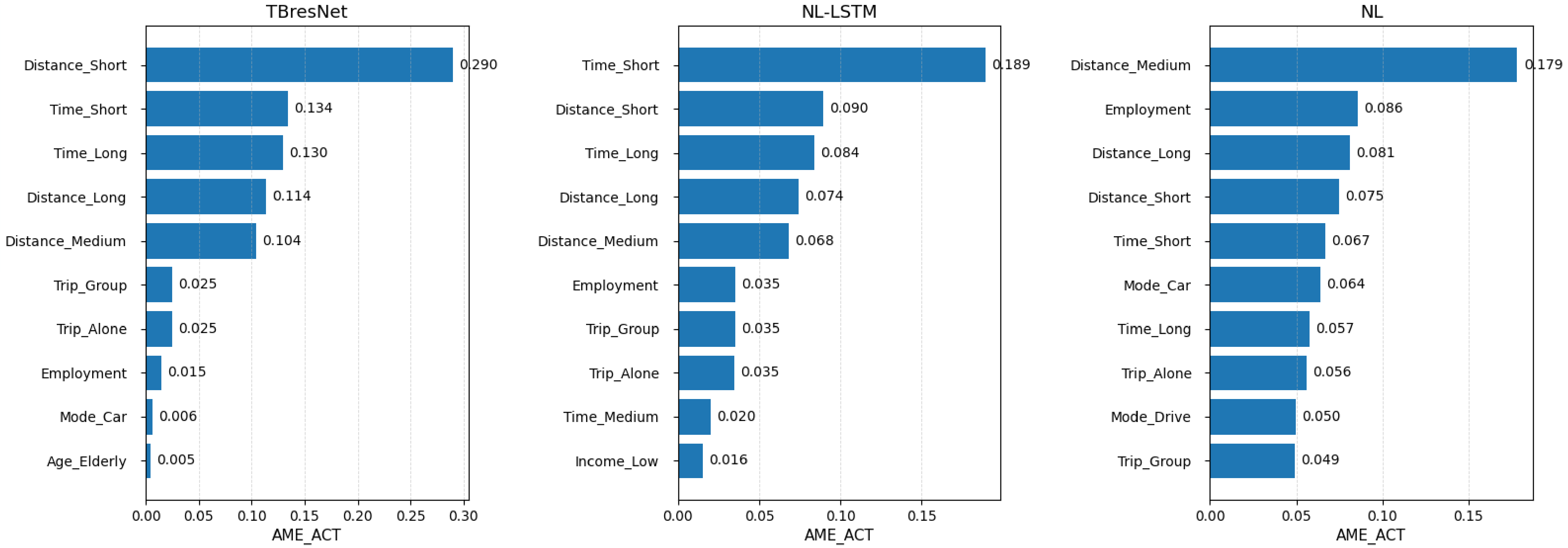
  1. Average Marginal Effect (AME) (Δ probability points)
     - AME: Average probability change after feature shift.

  2. Elasticity (% sensitivity) apply to both.
     - Percent probability change per percent feature change.



Global Feature Importance for Activity

Top 10 factors of each models

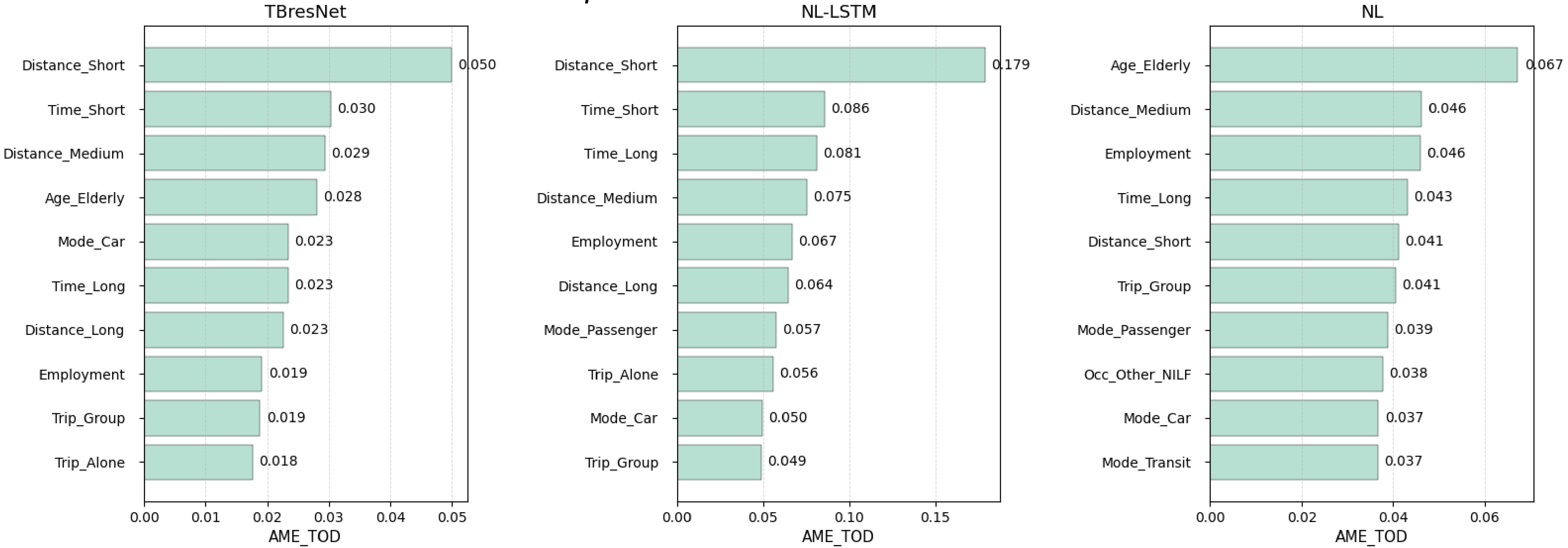


Distance & time dominate activity choice prediction.

- (HBW, HBS, HBO, NHBO) is driven mainly by travel impedance/feasibility.

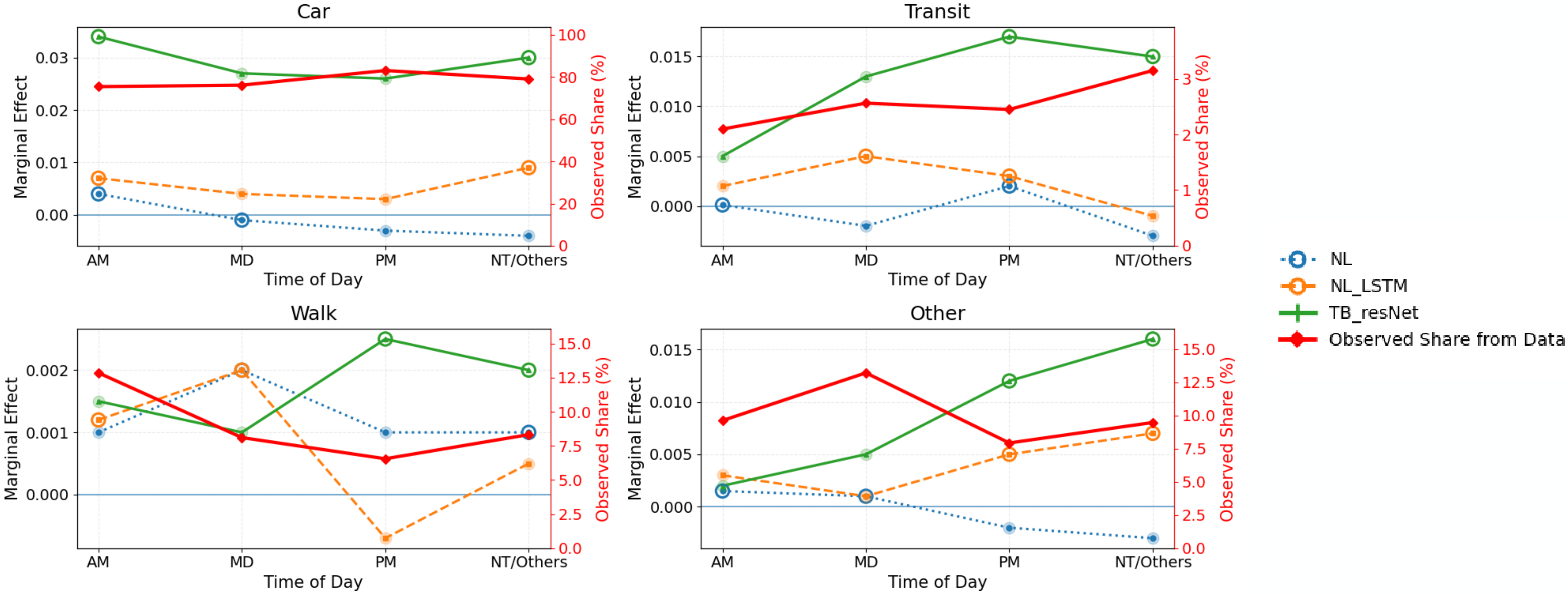
Global Feature Importance for Time of the Day

Top 10 factors of each models



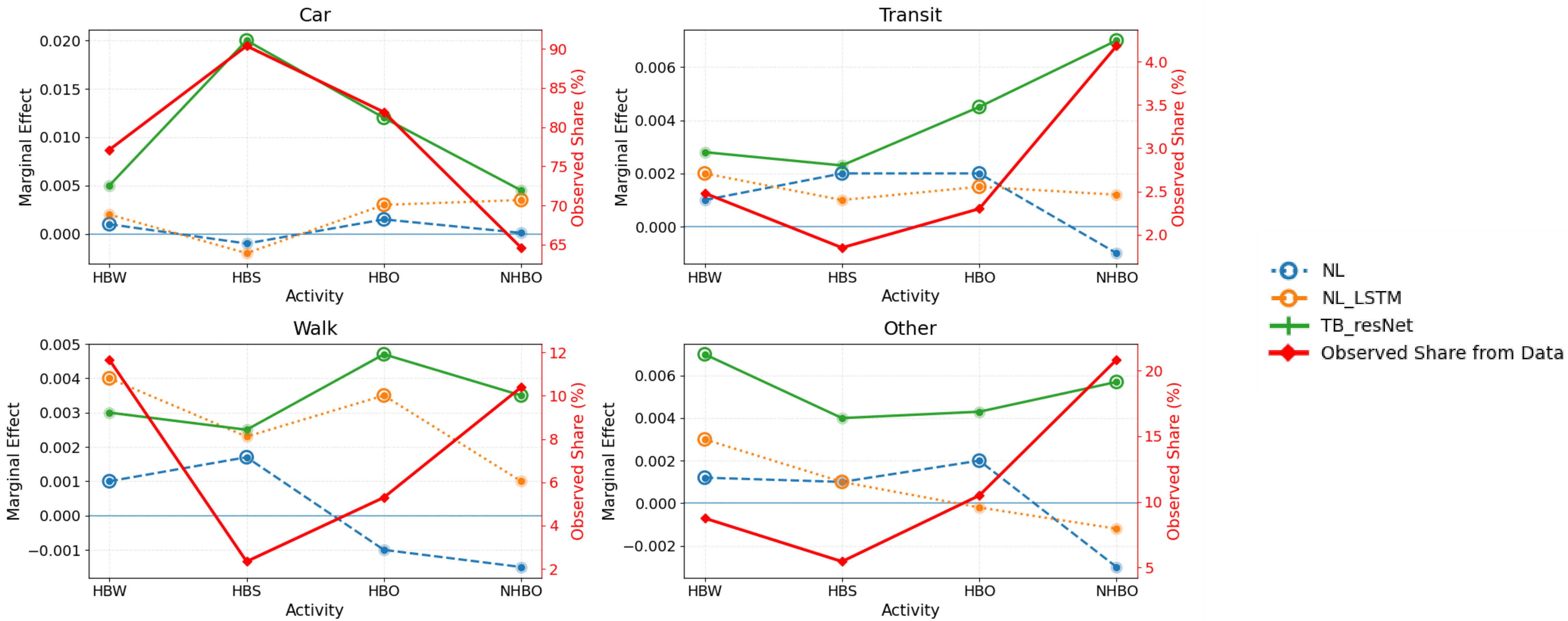
- TOD depends on constraints + schedules.
- Age/employment/mode refine timing choice.

TOD vs Model Marginal Effect



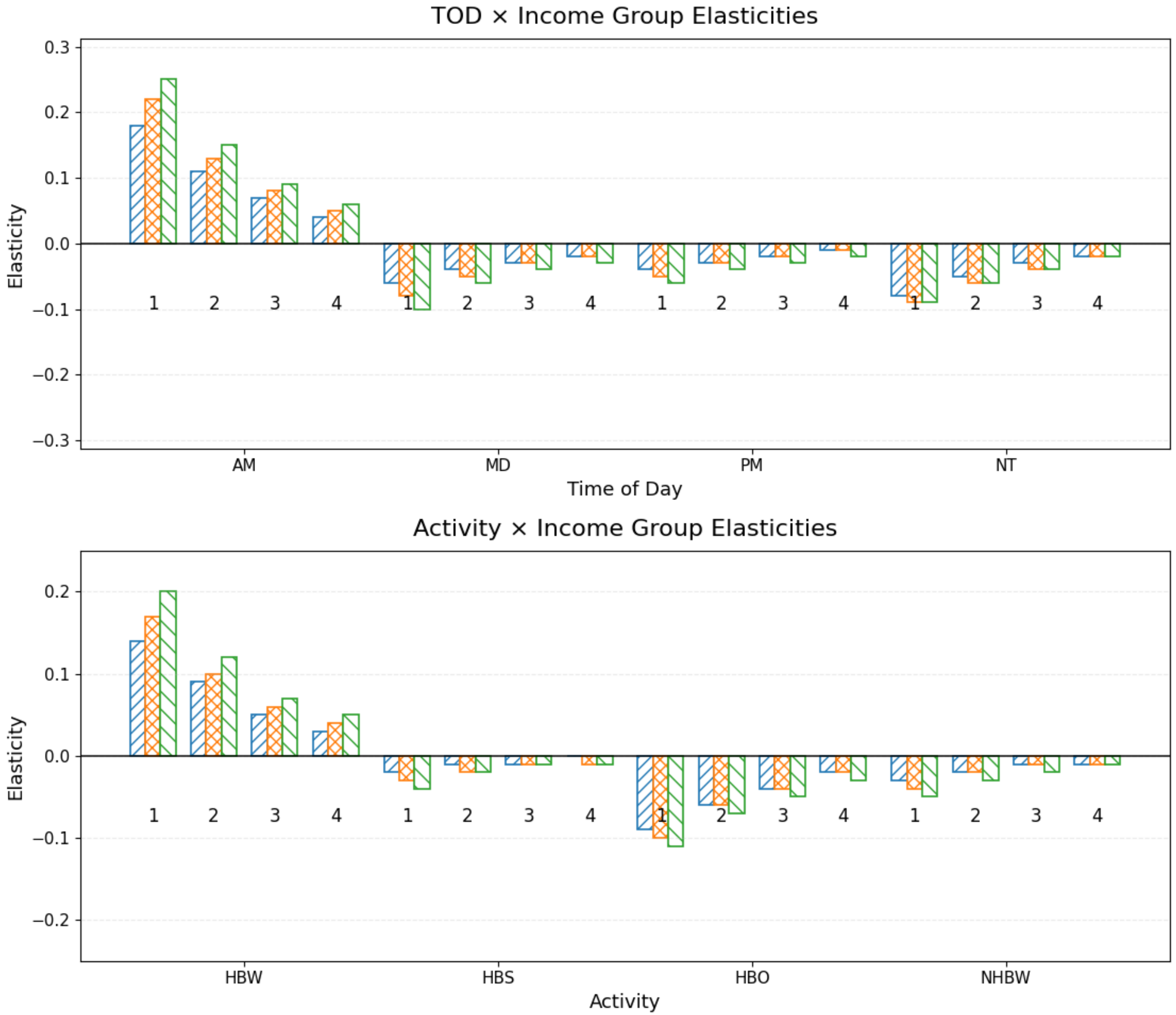
- TB-ResNet matches observed TOD mode shares overall.
- Captures expected peaks better than NL.

Activity vs Mode Marginal Effect



- TB_resNet best reproduces the observed activity–mode pattern
  e.g., high car share for HBS/HBO and lower car share for NHBO.

Elasticity Analysis of Income Group

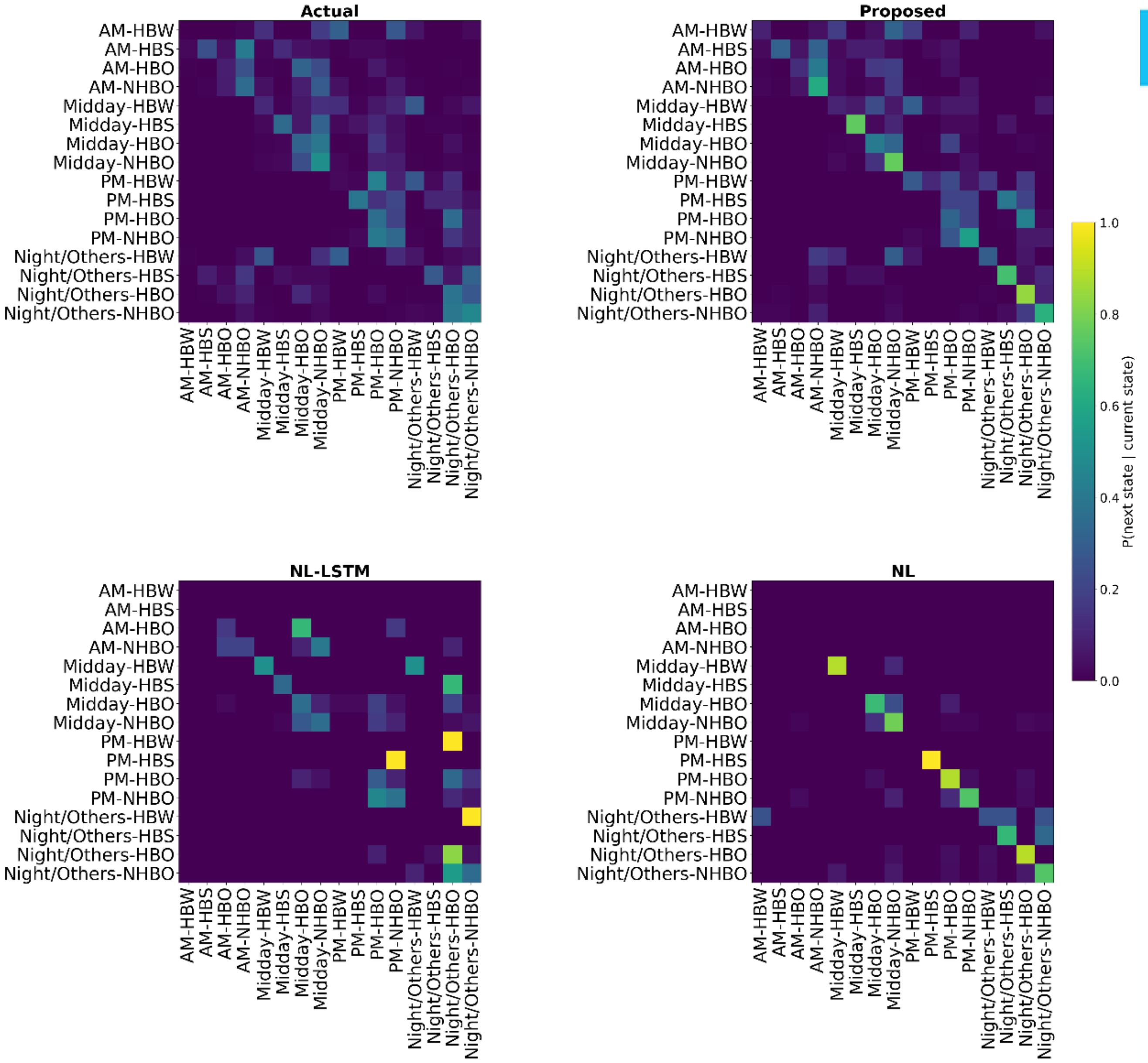


NL
NL_LSTM
TB_ResNet

1: Income_low
2: Income_LowMid
3: Income_HighMid
4: Income_High

Income gradient (most TODs/activities):
- effects are largest for Income_low.
- decline toward Income_High.

Trip Chain: TOD–Activity Transition Matrices - Nevada Data



Discussion

AI-DCM Model: (TB-ResNet)

The top features and AME magnitudes show similar patterns

- It means it can learn like DCM model e.g., global factors

It's learning effects consistent with traditional DCM.

- Features and AME magnitudes show similar patterns e.g., Mode vs TOD/Activity

It can capture strong detection heterogeneity.

- Higher magnitude indicates strong sensitively in groups (e.g., elasticities)

Conclusion

DCM

- Interpretable but weaker prediction.
- Perform weak in large data and variables.
- Interpretation is weak in multi-interaction.

Suitable for same size and less variable environment

AI-DCM

- Strong prediction and flexible.
- Captures nonlinearities and interactions.
- Supports DCM-style interpretation.
- Better practical/policy sensitivity insights

- Very deep nets are harder to explain
- Medium nets balance interpretability

Thank You!

Contact

Sabya Mishra
Email: smishra3@memphis.edu