IMPROVING DESTINATION CHOICE WITH AI

Caliper

Transportation & Mapping Solutions

Maptitude • TransCAD • TransModeler

CONTEXT

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CONTEXT OF FHWA TMIP PROJECT

- Acknowledgement and thanks for FHWA sponsorship of this important work

- Part of larger project to improve travel forecasting through the use of **big data** and **AI**
  - ***Review of literature and practice***
  - Testing new methods
  - Implementation pilot projects with case studies
  - “Playbook” for incorporating AI in travel models
  - TMIP webinars to promote Playbook methods

CALIPER TEAM

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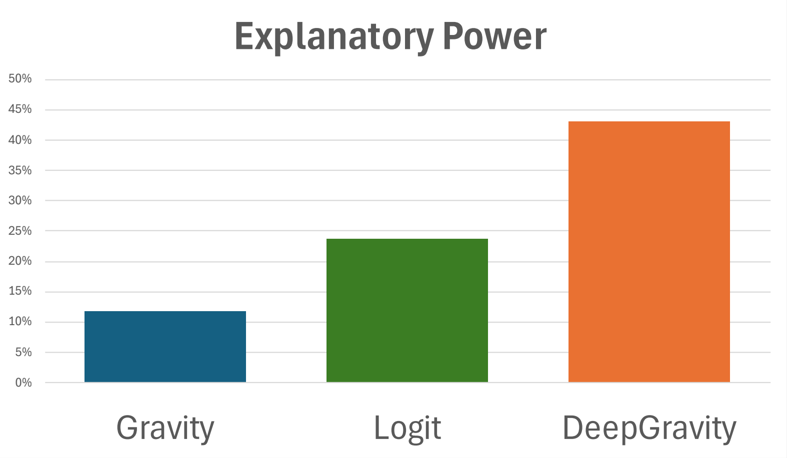
PROJECT FOCUS

- Focus on AI
  - References to TMIP resources on big data
- Focus on Practical Improvements for the Near- to Mid-Term
  - Methods to improve/replace individual model components
  - AI-DCMs
  - Primary focus on Destination Choice
    - Largest source of error in existing models – largest opportunity for improvement



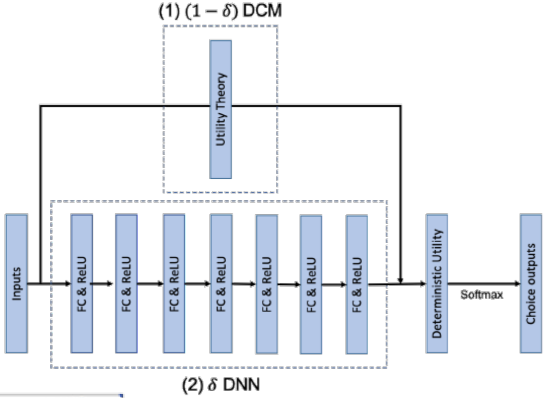
AI-DCM MODELS

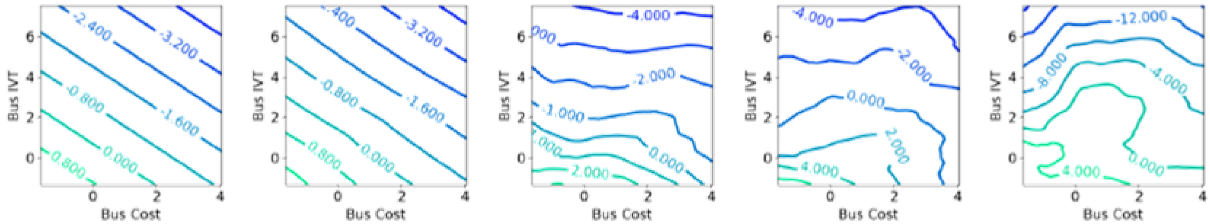
- Artificial Intelligence – Discrete Choice Models
- Combine neural networks and logit models
- Attempt to combine the best of both traditional and newer methods
  - Theoretical basis and interpretability of traditional models
  - Explanatory power and accuracy of AI
- Six types proposed so far
  - L-MNL
  - ResLogit
  - TB-ResNet
  - TasteNet
  - RUMnets
  - e-Logit

TB-RESNETS

- Ensemble of Logit and Deep NN
- Interpretable as a logit or DNN
- Utilities weighted average of logit and DNN
- Weight estimable from data

Fig. 1. Architecture of TB-ResNet. Both DCM and DNN are flexible





(a) MNL (50.6%) (b) MNL-ResNet ($\delta = 10^{-5}$; 53.1%) (c) MNL-ResNet ($\delta = 0.008$; 57.0%) (d) MNL-ResNet ($\delta = 0.05$; 56.1%) (e) DNN (55.8%)

Fig. 2. Utility functions of MNL-ResNets, MNL, and DNNs. Upper row: visualization of 2D utility functions, and percentages in the parentheses represent the prediction accuracy. Lower row:

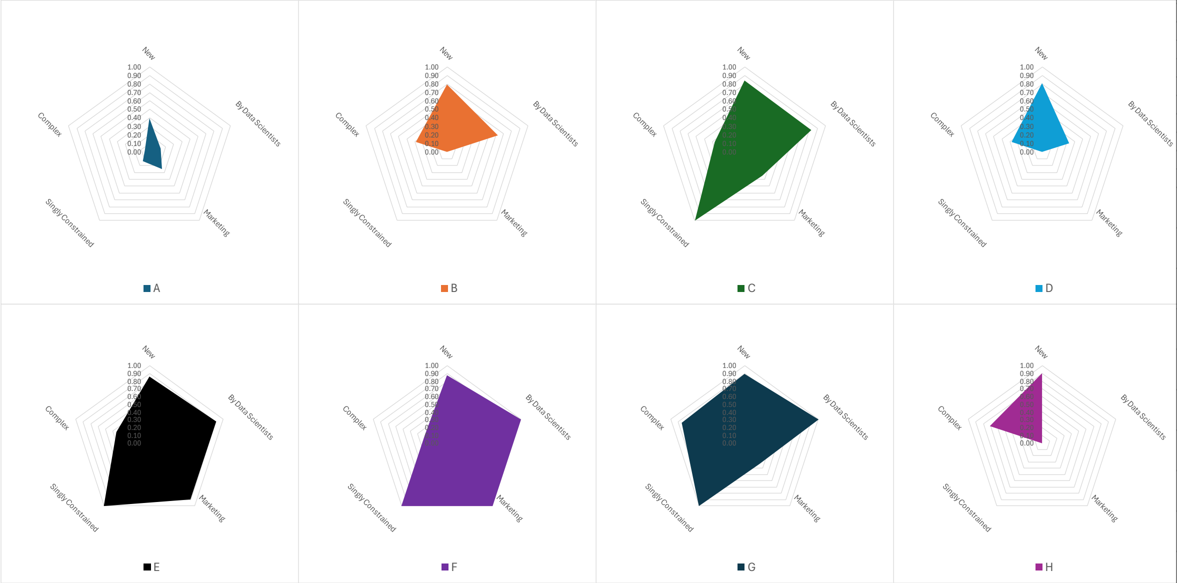
LITERATURE REVIEW

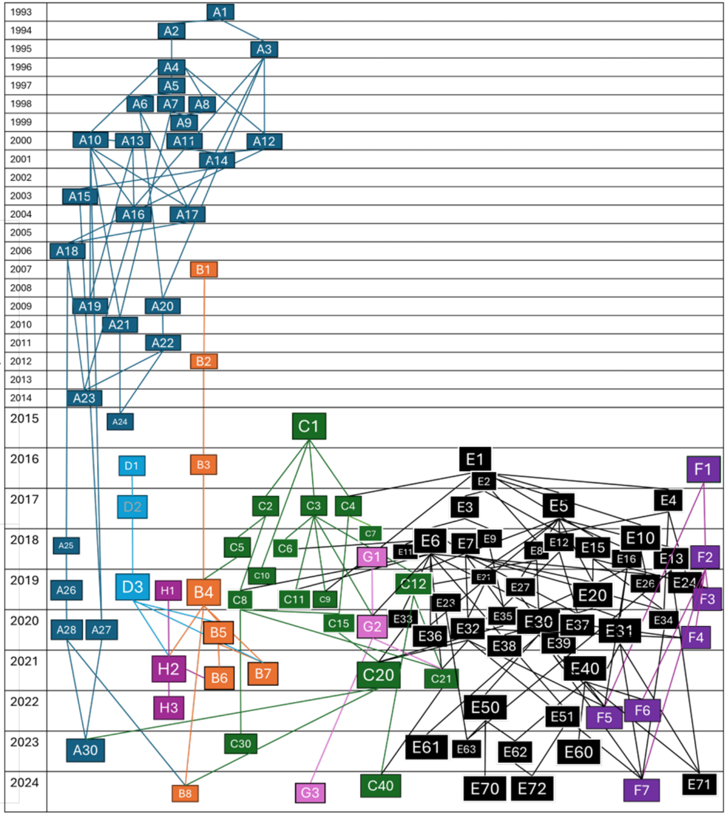
LITERATURE REVIEW

- Identified 354 papers from 1993 to present
- Explosion of papers from 2016, peaking in 2020, stabilized around 2018-19 levels
- Needed to prioritize, mostly based on citation rates
- Cursory review of 123 papers and 18 surveys/reviews
- Report summarizes 34 papers
  - Plus, a brief overview of 15 early papers
  - And appendix with 13 paper summaries
- Identified 8 branches of the literature

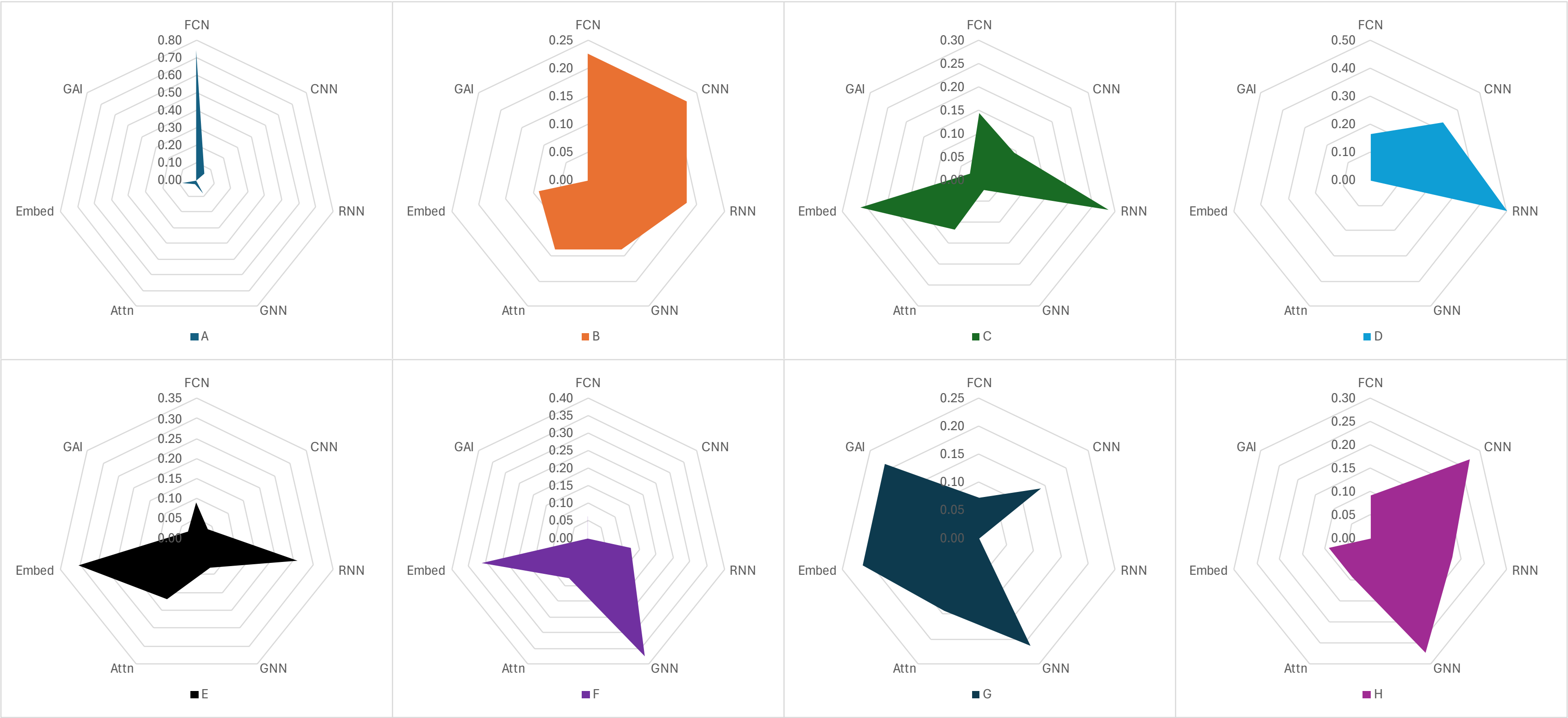
BRANCHES OF THE LITERATURE

- Eight branches of the literature
  - Based on citations, but vary across many dimensions





BRANCHES METHODOLOGICAL FOCUS



MODEL-BASED META-ANALYSIS

HOW TO COMPARE MODELS?

- 22 different metrics reported
  - 14 goodness-of-fit metrics
  - 8 error metrics
- Assumption:
  - **Relative** improvement in fit or decrease in error are comparable, though not identical, regardless of fit / error metric used
- Approach:
  - Model a latent generic fitness measure which minimizes squared error between modeled and published relative comparisons

Metric	Type	Normalized	% Papers Reporting
RMSE	Error	No	26.6%
k-Recall / HR	Fit	Yes	21.1%
k-Accuracy	Fit	Yes	20.2%
MAE	Error	No	13.8%
R2	Fit	Yes	12.8%
k-MAP	Fit	Yes	11.0%
k-Precision	Fit	Yes	10.1%
k-NDCG	Fit	Yes	8.3%
F1 / DSC	Error	Yes	9.2%
MAPE	Error	Yes	7.3%
MSE	Error	No	7.3%
MRR	Fit	Yes	7.3%
AUC	Fit	Yes	6.4%
ARV	Error	No	6.4%
Distance	Fit	Yes	5.5%
JSD	Fit	Yes	3.7%
sMAPE	Fit	Yes	3.7%
SRMSE	Fit	Yes	2.8%
LL	Error	Yes	1.8%
k-Top	Fit	Yes	0.9%
WMAPE	Error	Yes	0.9%
k-DCG	Fit	No	0.9%

LATENT FITNESS MODEL

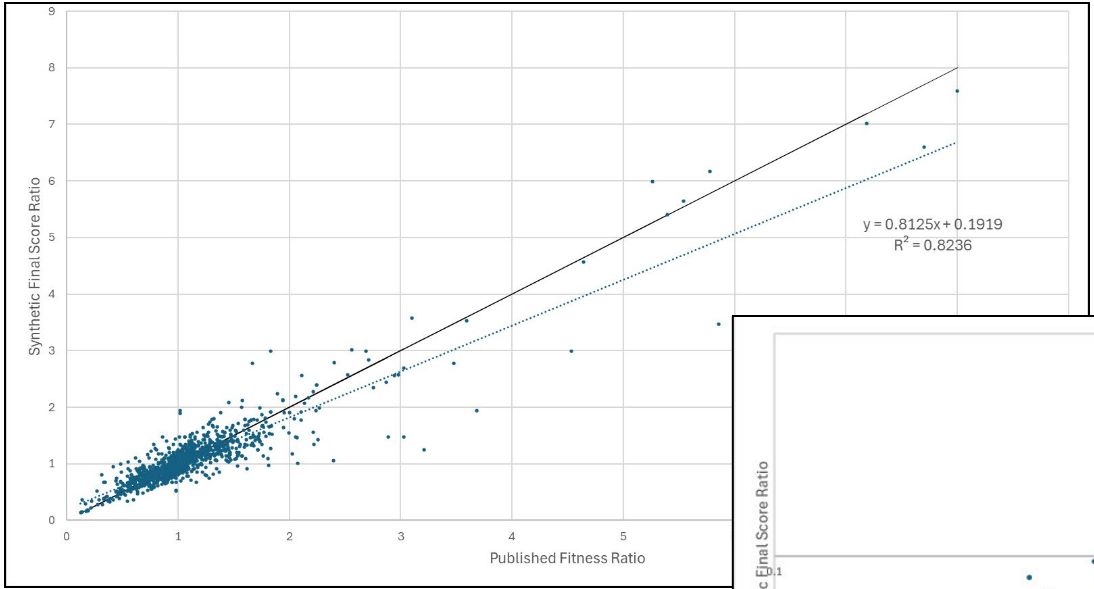
- Latent fitness score defined on unit interval [0,1]
- Binary logit model
  - Model specific constant
  - 10 methodological dummy variables
    - FCN
    - RNN
    - CNN
    - GNN
    - GCN
    - Attention
    - Embeddings
    - SSL
    - LLM
    - GAN
- LSE with regularization term
  - (squared difference from initial score calculated as normalized average of ratio of model's goodness-of-fit to other models)

DATA CONSTRUCT

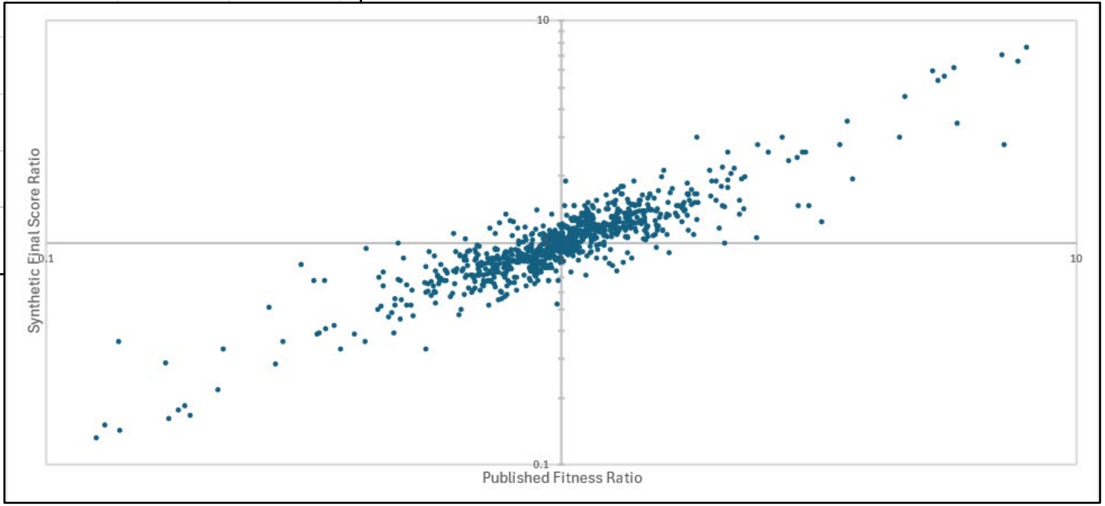
- 12 metrics used in meta-analysis
- Preference for normalized
  - 78% normalized used in meta-analysis
  - Highest preference for metrics normalized on the unit interval
- Observed Data:
  - 629 relative comparisons
  - Published in 81 papers
  - Which used 176 datasets

Metric	Type	Normalized	% Papers Reporting	% Comparisons in Meta-Analysis
RMSE	Error	No	26.6%	9.4%
k-Recall / HR	Fit	Yes	21.1%	12.7%
k-Accuracy	Fit	Yes	20.2%	21.8%
MAE	Error	No	13.8%	0.0%
R2	Fit	Yes	12.8%	2.4%
k-MAP	Fit	Yes	11.0%	0.0%
k-Precision	Fit	Yes	10.1%	2.4%
k-NDCG	Fit	Yes	8.3%	0.0%
F1 / DSC	Error	Yes	9.2%	16.5%
MAPE	Error	Yes	7.3%	8.0%
MSE	Error	No	7.3%	0.0%
MRR	Fit	Yes	7.3%	0.0%
AUC	Fit	Yes	6.4%	4.1%
ARV	Error	No	6.4%	0.0%
Distance	Fit	Yes	5.5%	2.2%
JSD	Fit	Yes	3.7%	3.7%
sMAPE	Fit	Yes	3.7%	3.3%
SRMSE	Fit	Yes	2.8%	0.8%
LL	Error	Yes	1.8%	0.0%
k-Top	Fit	Yes	0.9%	0.0%
WMAPE	Error	Yes	0.9%	0.0%
k-DCG	Fit	No	0.9%	0.0%

MODELED SCORE RATIOS VS. PUBLISHED



$r^2 = 0.824$



META-ANALYSIS RESULTS

- Best methods
  - GAI
    - GAN
    - LLM
  - SSL
  - GCN
- Small Sample Size for best
  - GAI (8)
  - SSL (6)
  - LLM (3)

	Utility Coefficient	Factor	Avg. Score
FCN	-0.111	0.89	0.37
RNN	-0.250	0.78	0.35
CNN	0.014	1.01	0.41
GNN	0.046	1.05	0.39
GCN	0.066	1.07	0.44
Attention	-0.155	0.86	0.45
Embeddings	-0.162	0.85	0.41
SSL	0.110	1.12	0.43
GAN	1.790	5.99	0.79
LLM	0.518	1.68	0.66

RECOMMENDATIONS FOR NEXT PHASE

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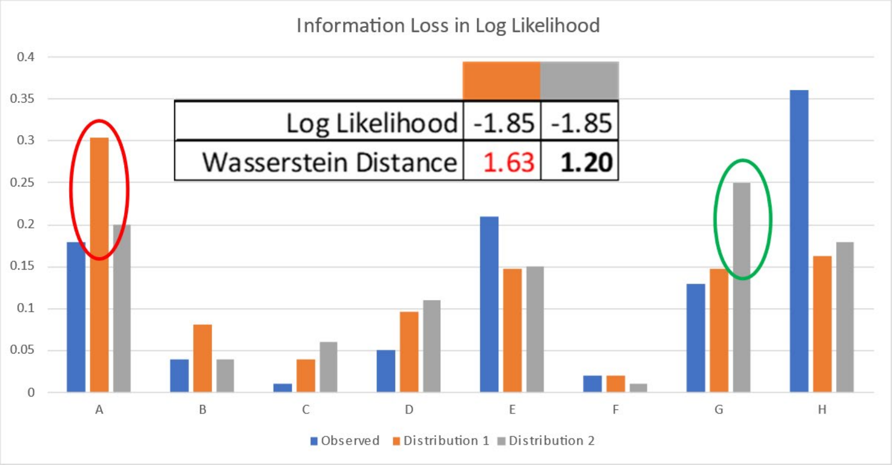
PERFORMANCE MEASUREMENT

- Importance of Out-of-Sample (Holdout Sample) Validation
  - Standard practice of good data science
  - Extremely rare in travel forecasting practice
  - Key opportunity to improve the practice
- Choice of Metric
  - Huge variety of error / goodness-of-fit metrics
  - Minimum Wasserstein distance
    - Powerful in computer vision, with CNNs
    - Gives credit for getting close



NOW TESTING

- Recommended models for testing in AI-DCMs
  - GAN: MoveSim/TrajGAN, highest scores
  - SSL GCN: STHGCN, #7 highest score, highest non-GAI, high confidence
  - MLP/FCN: DeepGravity, reference, average performance with minimal complexity

Rank	Model	Paper	Final Score	FCN	RNN	CNN	GNN	Attention	Embeddings	SSL	GAN	LLM
1	MoveSim	Feng et al. (2020a)	0.983	0	0	1	0	1	1	0	1	0
2	TrajGAN	Ouyang et al. (2018)	0.979	0	0	1	1	0	1	0	1	0
3	COLA	Wang et al. (2024)	0.950	1	0	0	0	1	1	0	1	0
4	LLM4POI	Li et al. (2024)	0.851	0	0	0	0	0	1	0	0	1
5	Geo-ALM	Liu et al. (2019b)	0.788	0	0	0	0	0	0	0	1	0
6	LLMove	Feng et al. (2024)	0.697	0	0	0	0	0	1	0	0	1
7	STHGCN	Yan et al. (2023)	0.675	1	0	1	1	0	1	1	0	0
8	CatDM	Yu et al. (2020)	0.669	0	1	0	0	0	1	0	0	0
9	EEDN	Wang et al. (2023b)	0.587	0	0	1	1	1	1	1	0	0
10	DRAN	Wang et al. (2022b)	0.551	0	0	0	1	1	1	0	0	0
43	DeepGravity	Simini et al. (2021)	0.412	1	0	0	0	0	0	0	0	0

CONTACTS

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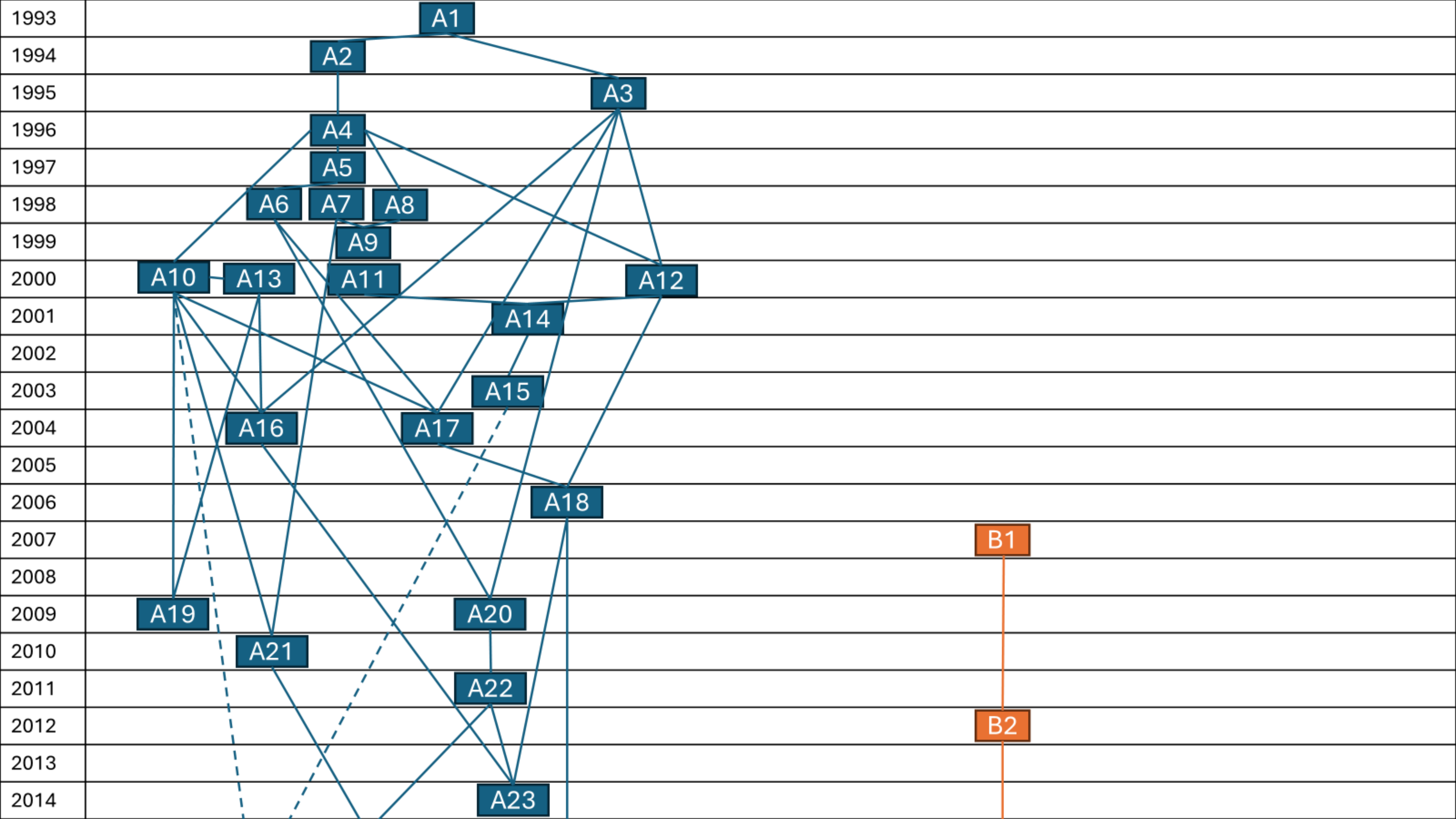
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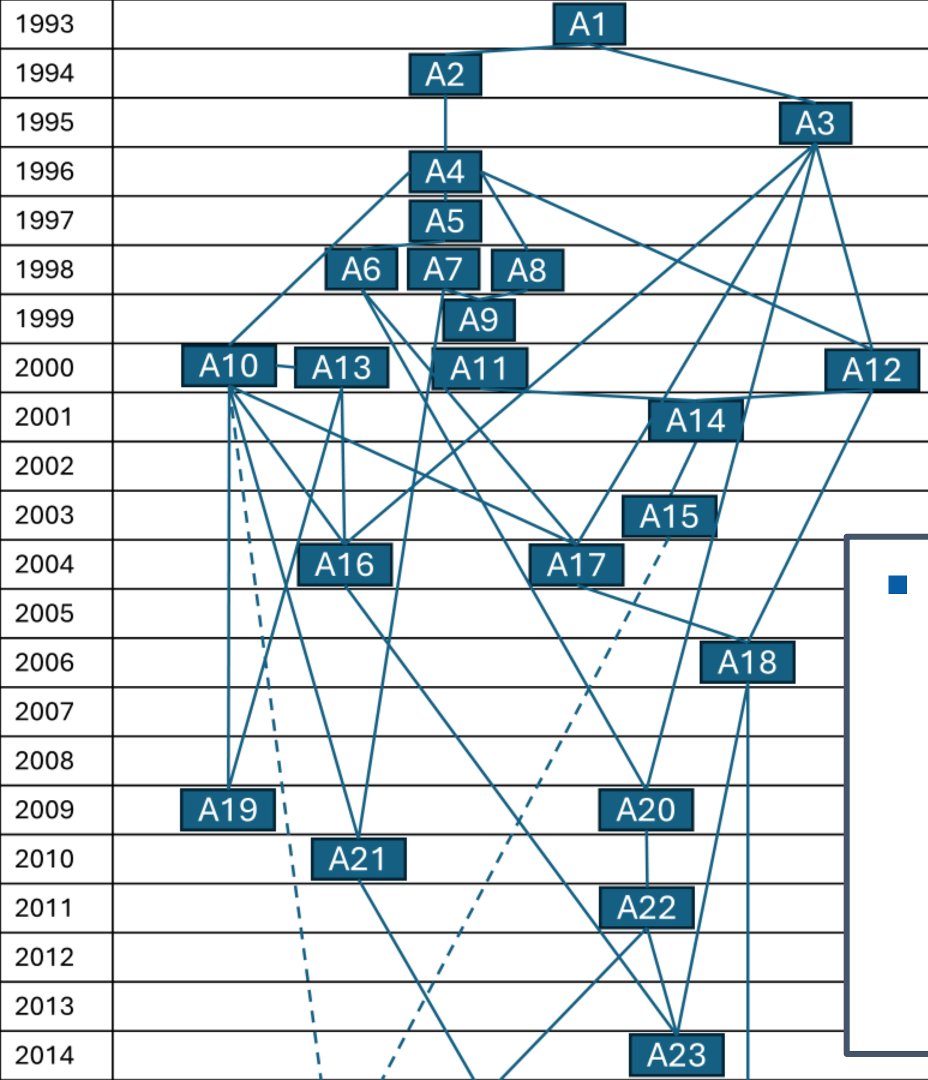
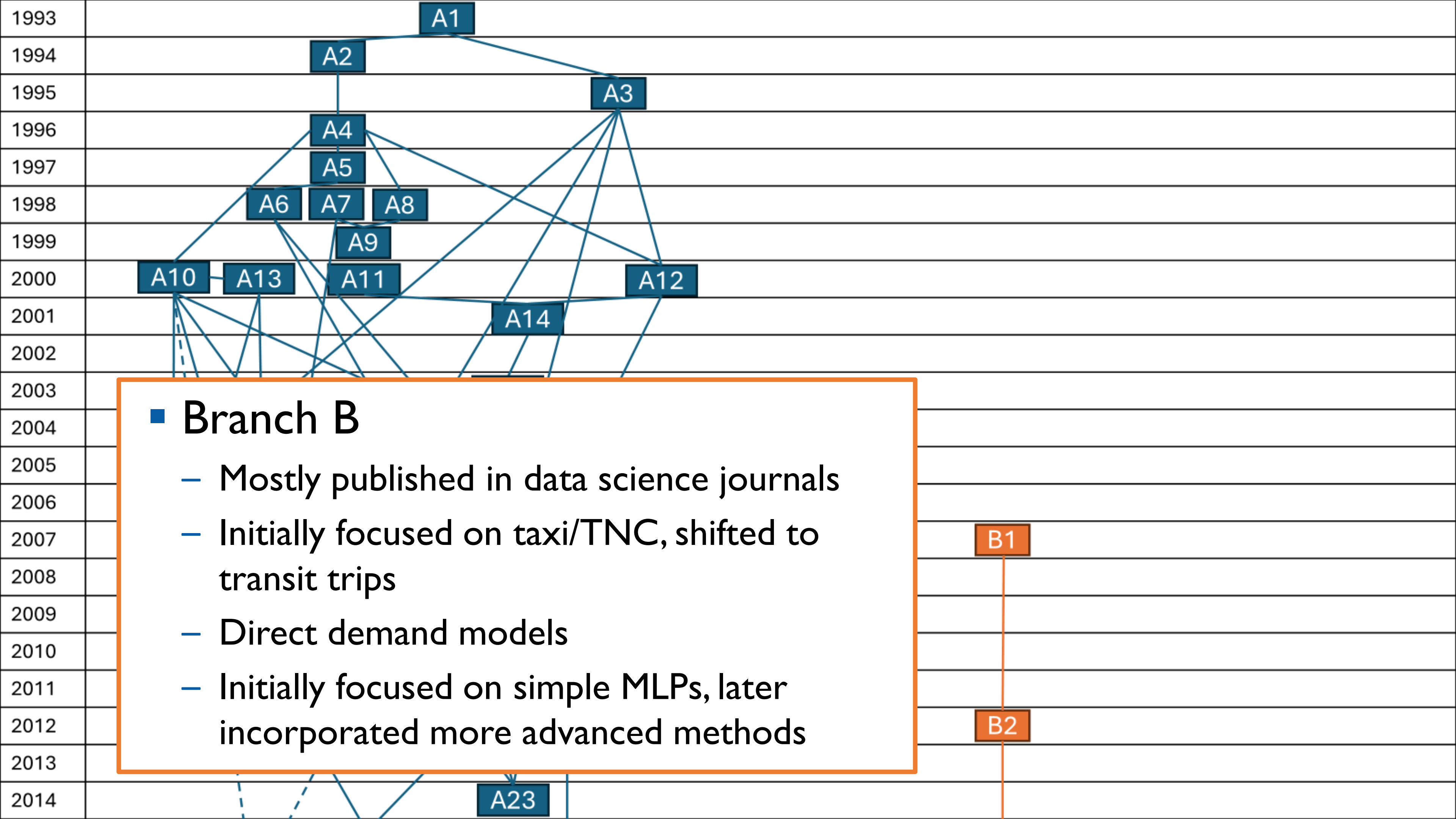
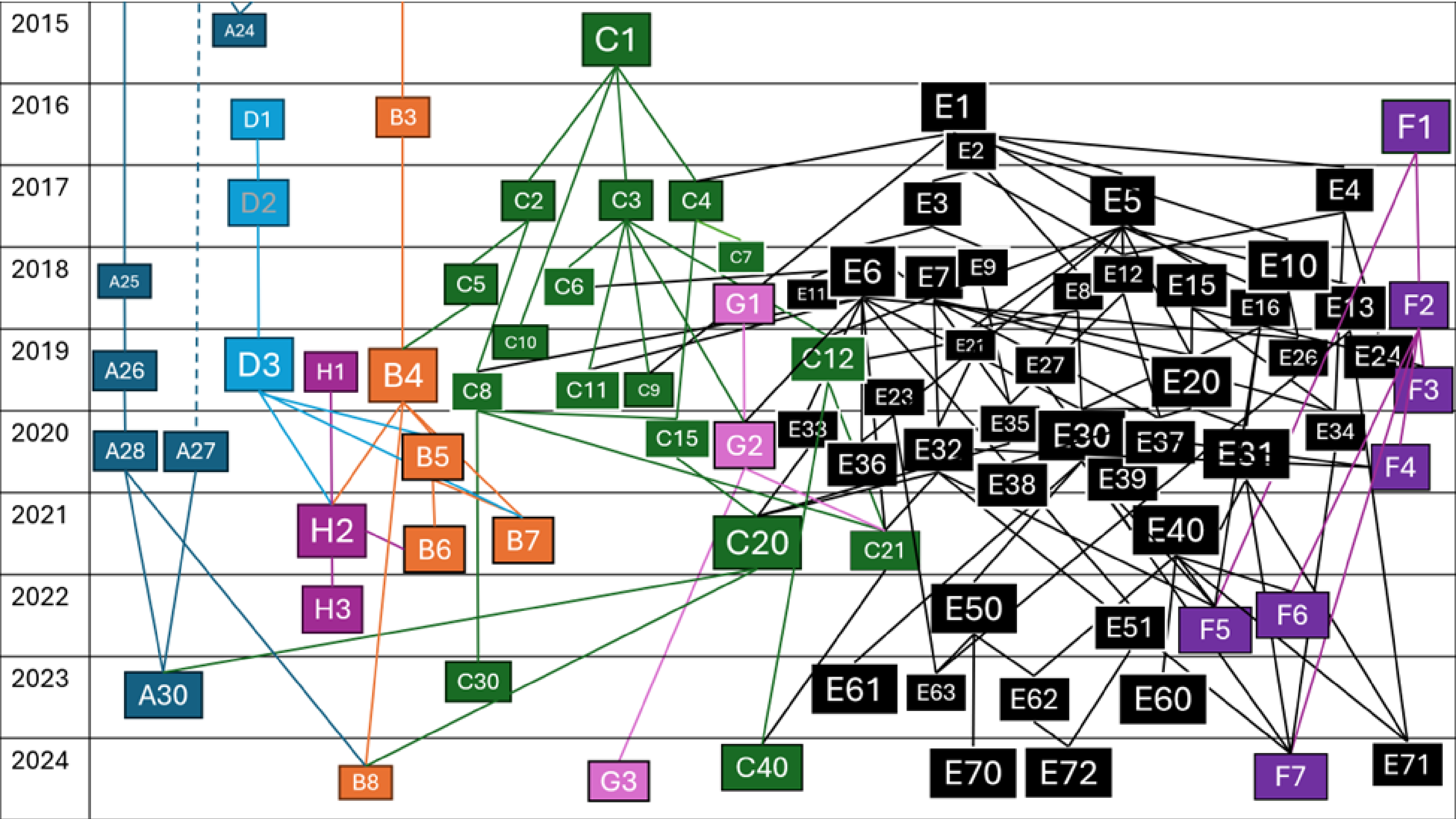


- Branch A
  - Mostly published in geography/GIS and transportation journals
  - Initially focused on commuting, later various applications
  - Direct demand models
  - Mostly focused on simple MLPs



- Branch B
  - Mostly published in data science journals
  - Initially focused on taxi/TNC, shifted to transit trips
  - Direct demand models
  - Initially focused on simple MLPs, later incorporated more advanced methods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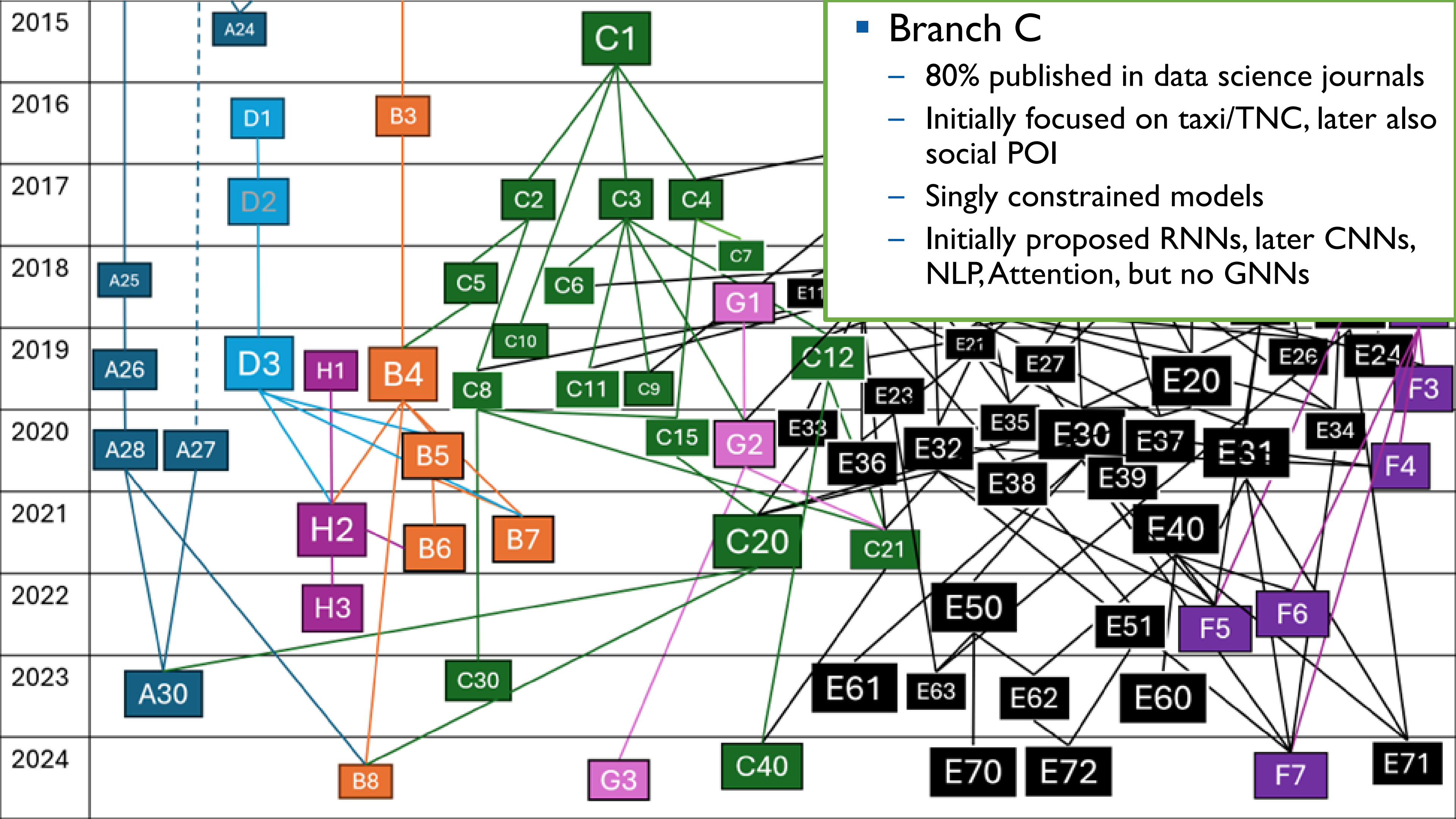
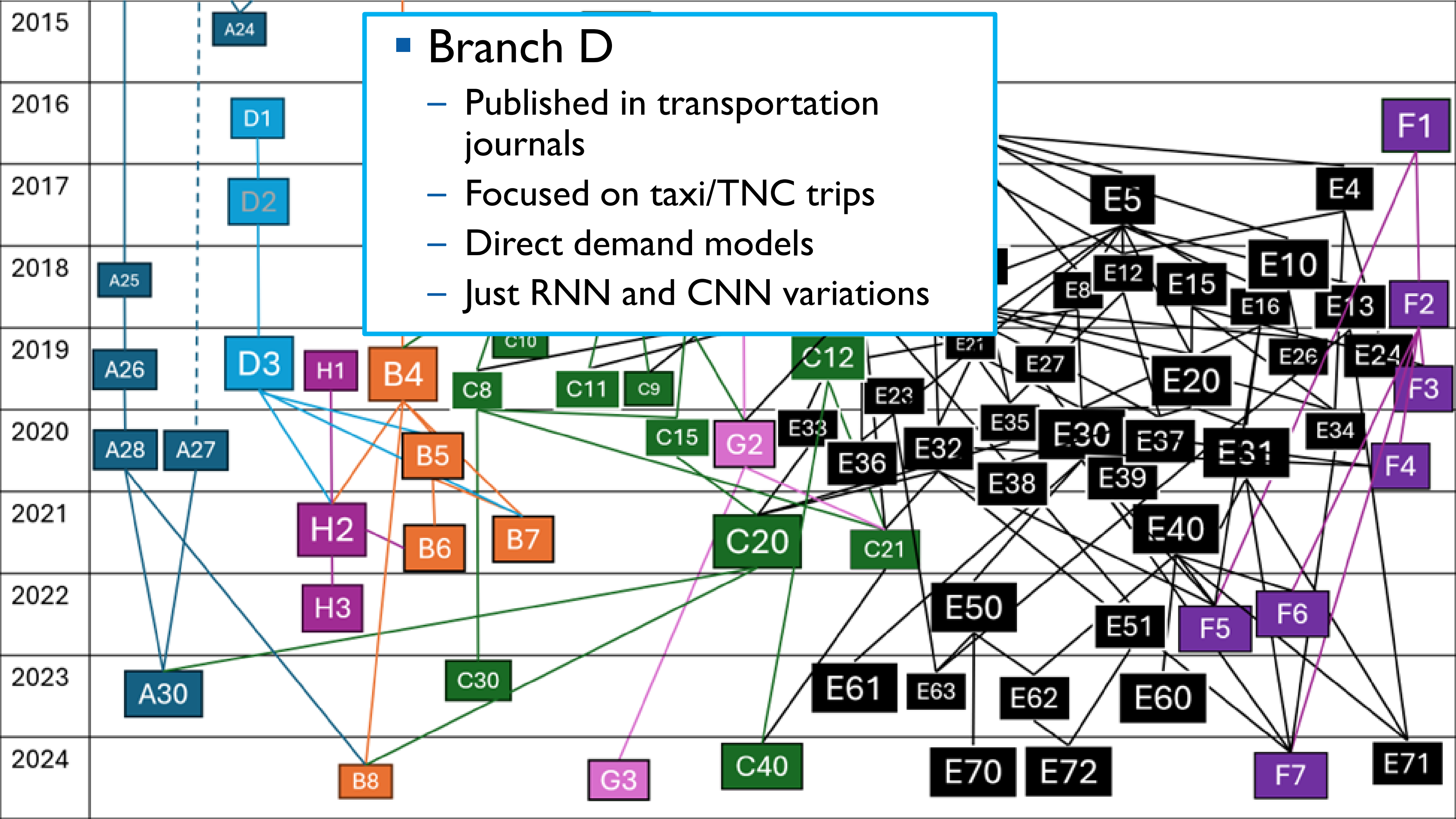
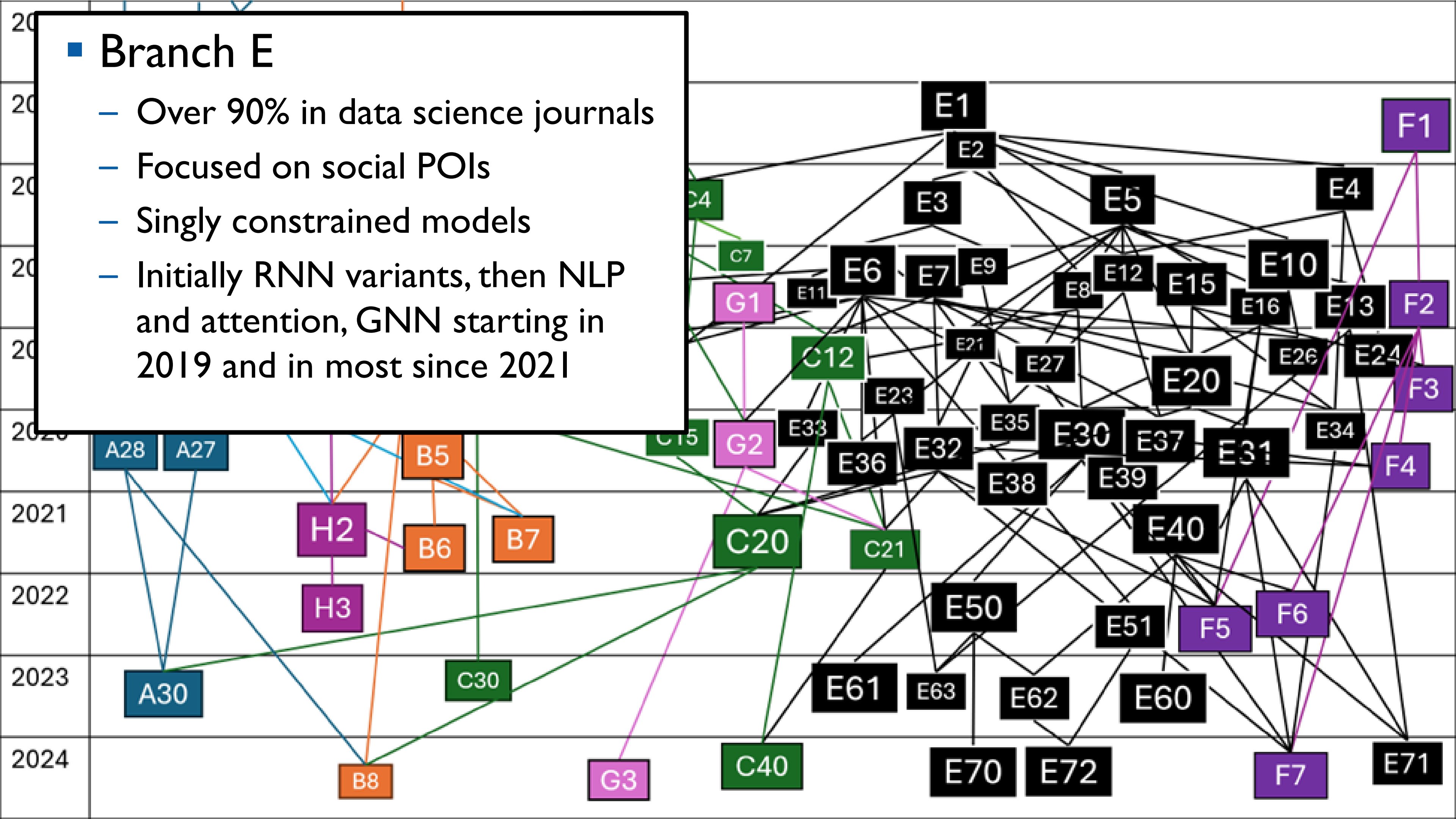


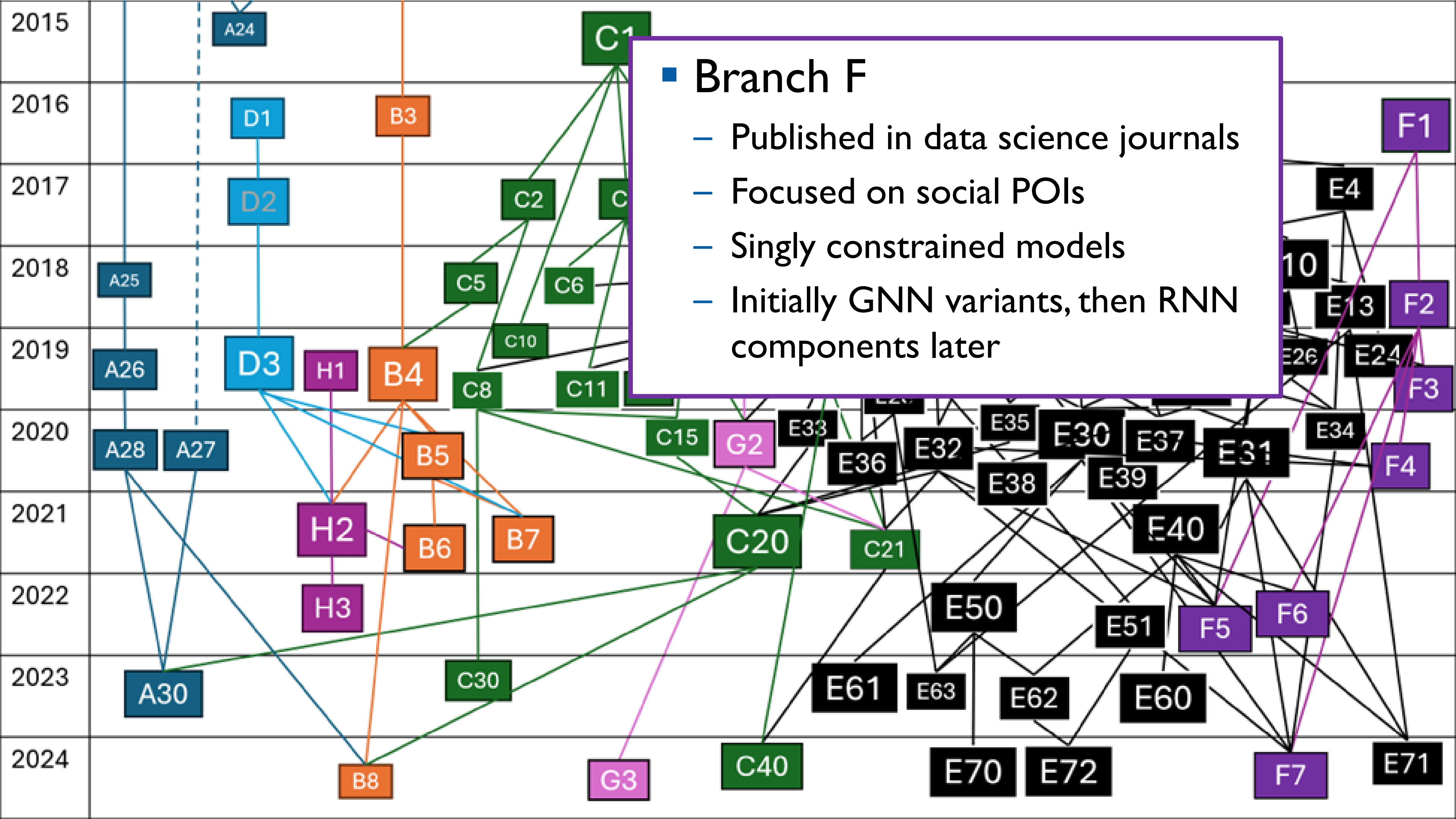
- Branch C
  - 80% published in data science journals
  - Initially focused on taxi/TNC, later also social POI
  - Singly constrained models
  - Initially proposed RNNs, later CNNs, NLP, Attention, but no GNNs

- Branch D
  - Published in transportation journals
  - Focused on taxi/TNC trips
  - Direct demand models
  - Just RNN and CNN variations

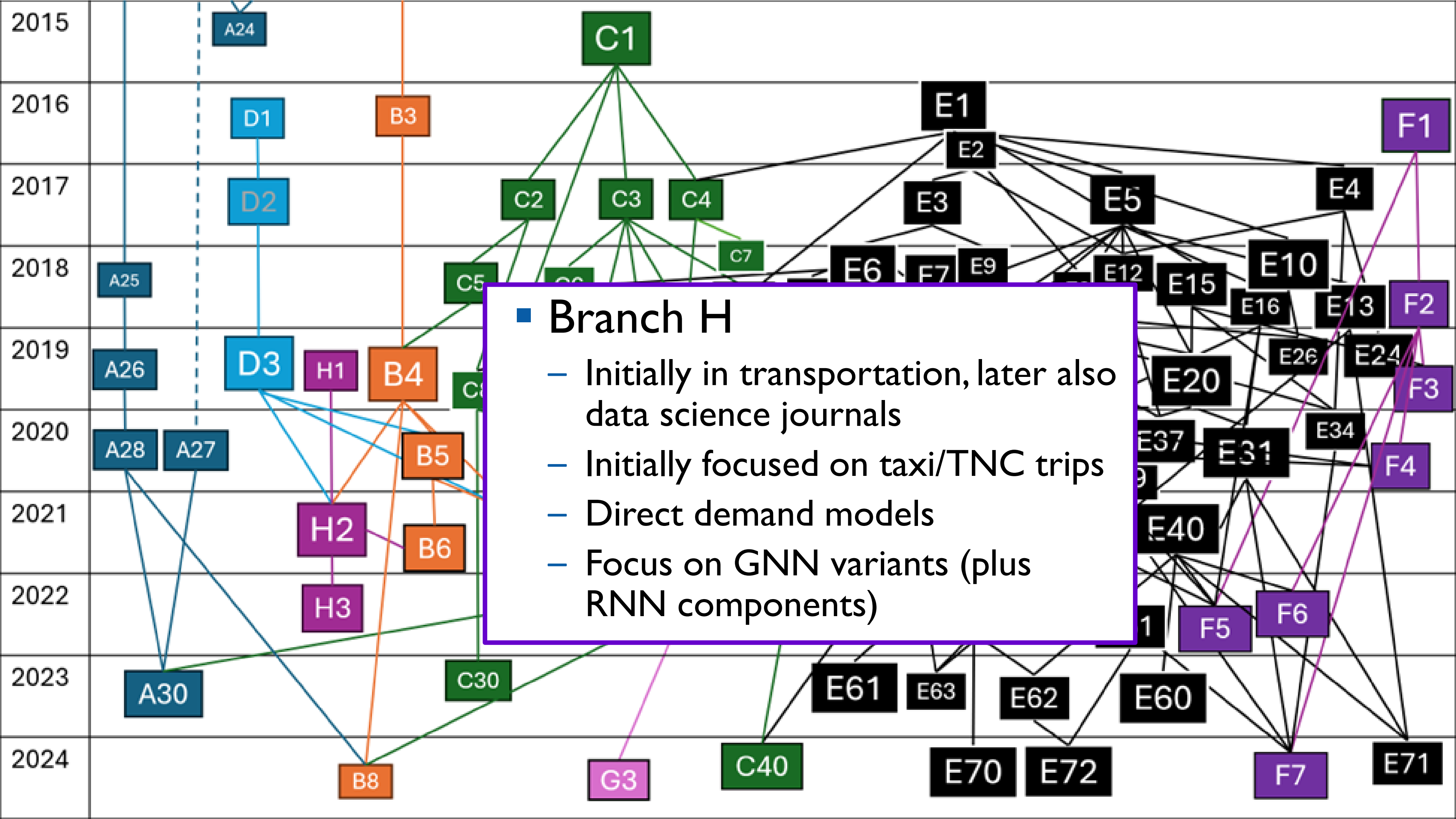


- Branch E
  - Over 90% in data science journals
  - Focused on social POIs
  - Singly constrained models
  - Initially RNN variants, then NLP and attention, GNN starting in 2019 and in most since 2021





- Branch F
  - Published in data science journals
  - Focused on social POIs
  - Singly constrained models
  - Initially GNN variants, then RNN components later



Branch H

- Initially in transportation, later also data science journals
- Initially focused on taxi/TNC trips
- Direct demand models
- Focus on GNN variants (plus RNN components)