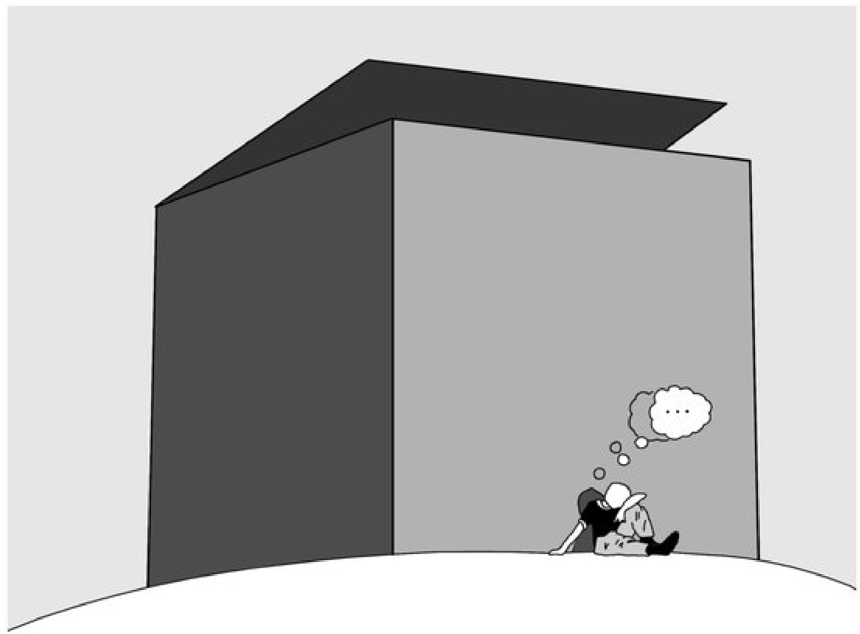
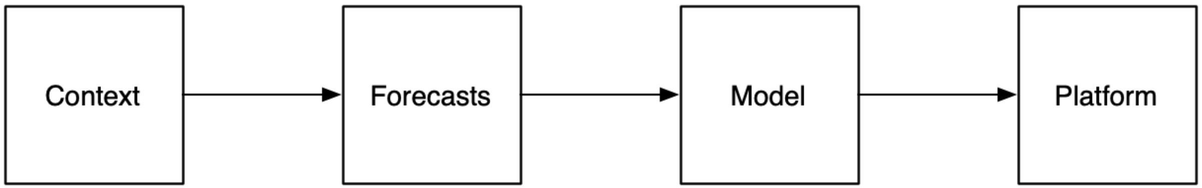
Rediscovering the lost art of travel forecasting



Rick Donnelly | TUM Activity-Based Model Symposium 2022 | 12-Sep-2022

Davidson diagram



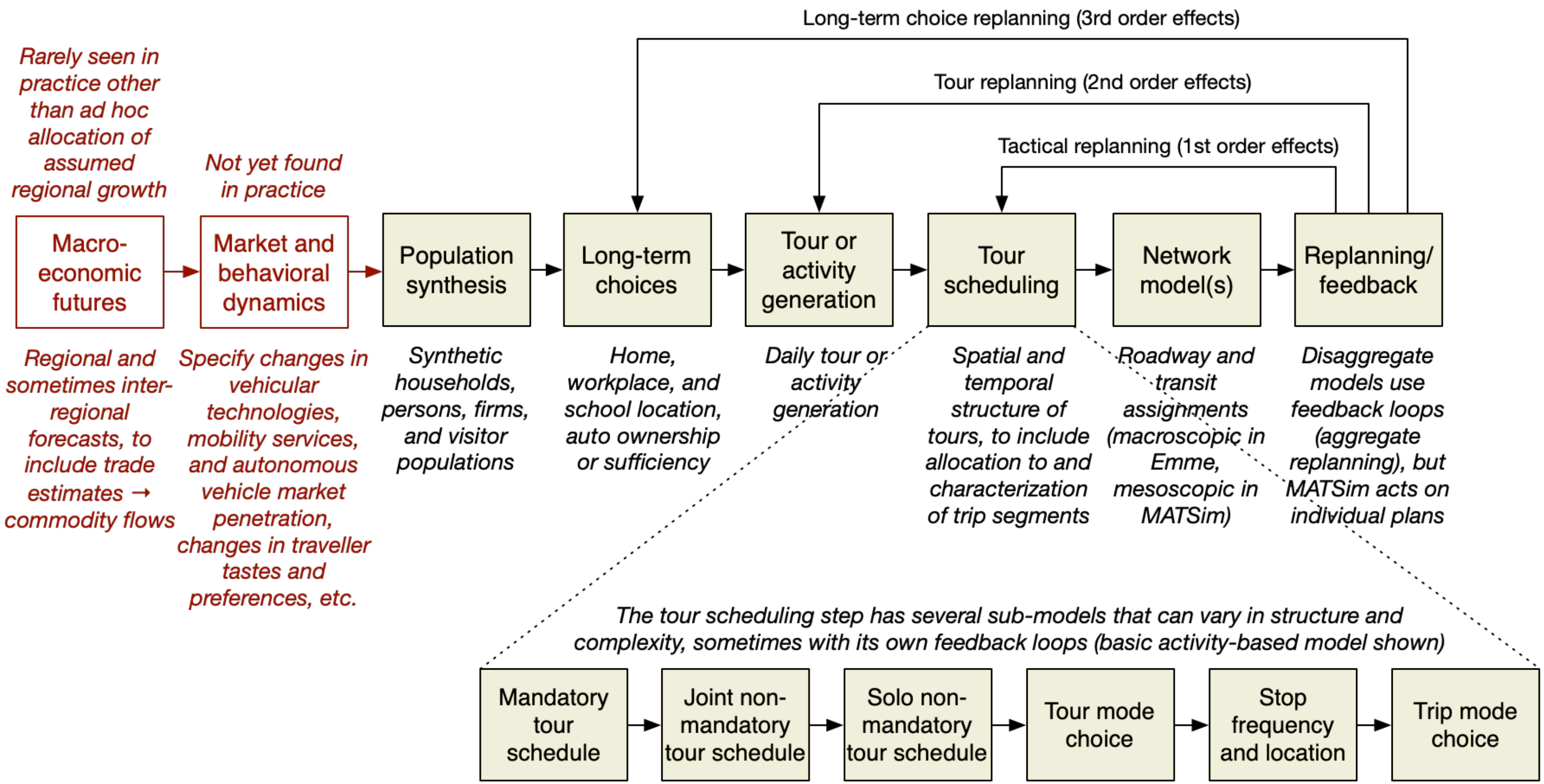
We build forecasting models to inform public policy and investment decisions. What story are we trying to tell, and who is the audience? What are relevant performance measures?

We are most often engaged to develop forecasts of future conditions. What range of assumptions and what properties of the modelled system are being tested?

We can decide on the most appropriate modelling approaches and methods once we have the larger context defined.

Once we understand the context, analytical requirements, and most appropriate model(s) we can decide upon the best data, software, and hardware solutions.

Ideal framework?



The case for activity and tour-based models

Where advanced models are superior to traditional models:

1. Pricing studies
2. Equity analyses
3. Analyses of complex public transport choices
4. Multi-scale modeling
5. Incorporating network reliability
6. Dynamic network modeling
7. New transport modes
8. Data mining opportunities

Architectures and artifacts

Modeling systems
Macroeconomic Population synthesis Resident travel Visitor model(s) Commercial vehicles Network assignment Evaluation

Sketch planning models
Trip-based models
Activity-based models
Data-driven models
Probabilistic models
Generative models
Machine learning
System dynamic models
Random numbers
Group consensus

Markets
Households and persons Residents making local trips Residents making long-distance trips Visitors Firms and economic sectors Commodities by mode of travel Imports and exports Long-distance trucks Urban trucks …

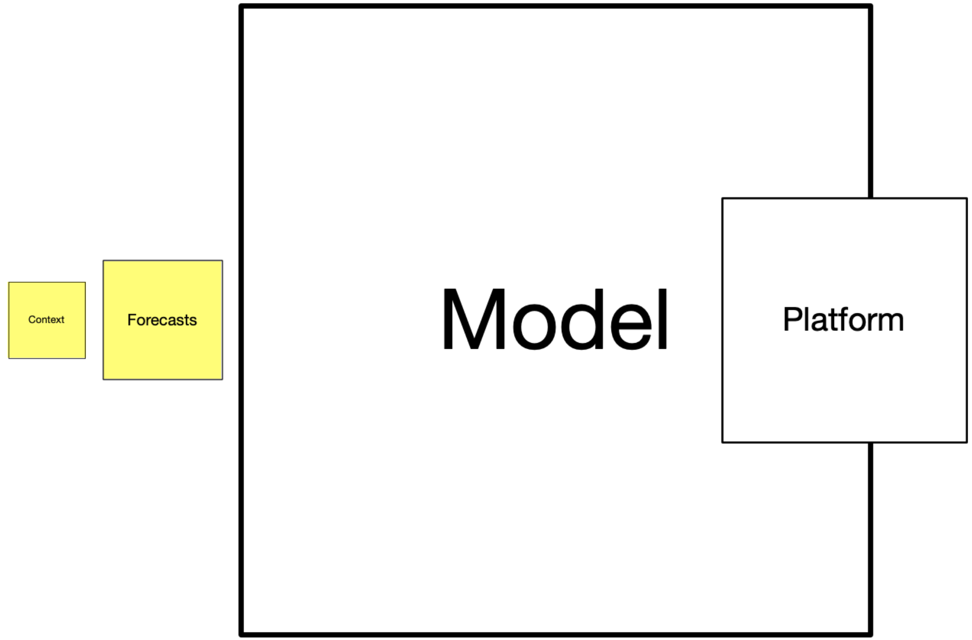
Traditional metrics	Emerging metrics
Aggregate network statistics (VKT, VHT, …) Travel times and reliability Per-capita change in VKT, non-auto travel, … Wide economic benefits Degree and extent of congestion Public transport and pricing revenues Environmental impacts Network level of service Cost-benefit analyses	Empty kilometres of travel (CVs) Aggregate accessibility measures Consumer surplus or user benefits Network reliability and resilience Social welfare statistics Pricing revenues and equity Risk and uncertainty analyses

Topologies
Global State Places (polygons) Places (points) **Agents** **Objects**

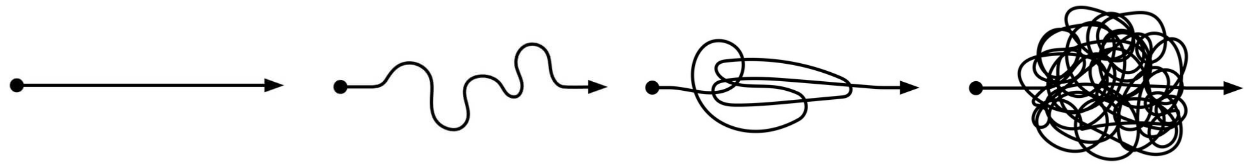
Agents	Agent properties
Persons Households Vehicles Roadways Intersections Mobility service providers Public transport operators Jurisdictions Firms Establishments Buildings Gateways	Preferences Budgets Choices Activities Tours Trips Routes

Objects
Buildings Facilities Vehicles Signals Sensors Roadways Junctions (intersections) Transit lines

Distortion field



What could go wrong?



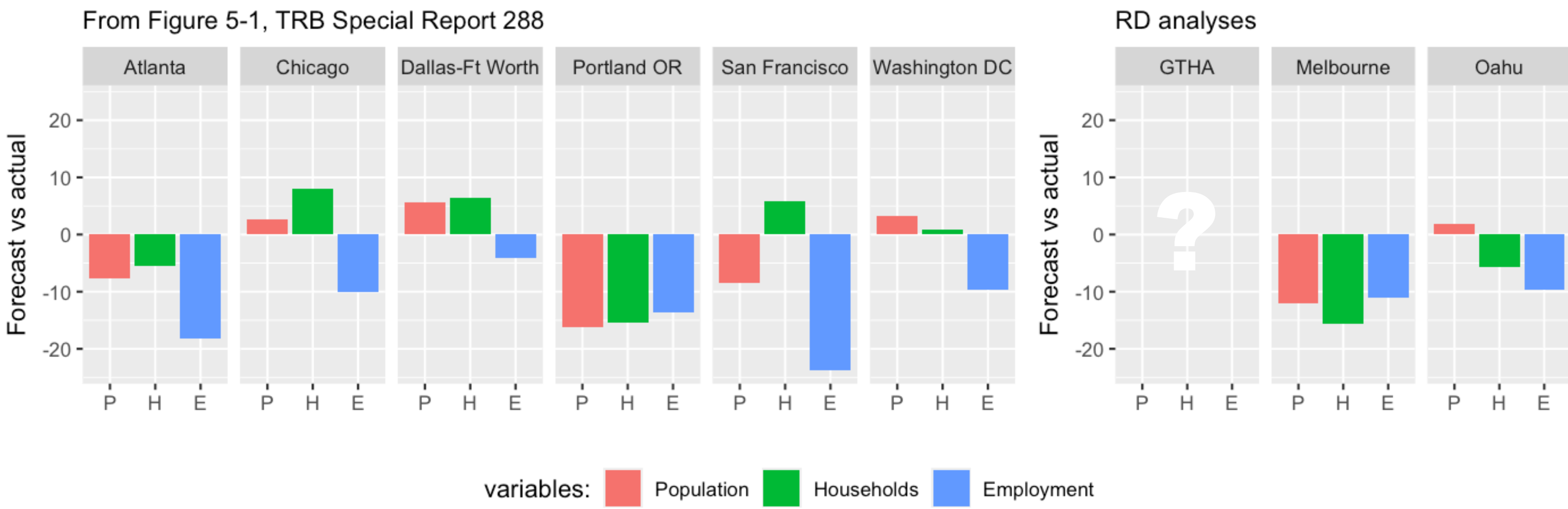
Internal

- Creeping complexity and compli-catedness
- Overfit models
- Increasing computational burdens
- Noise vs signal
- Parameter storm
- Outdated assumptions
- Inaccurate forecasts
- Lack of resources

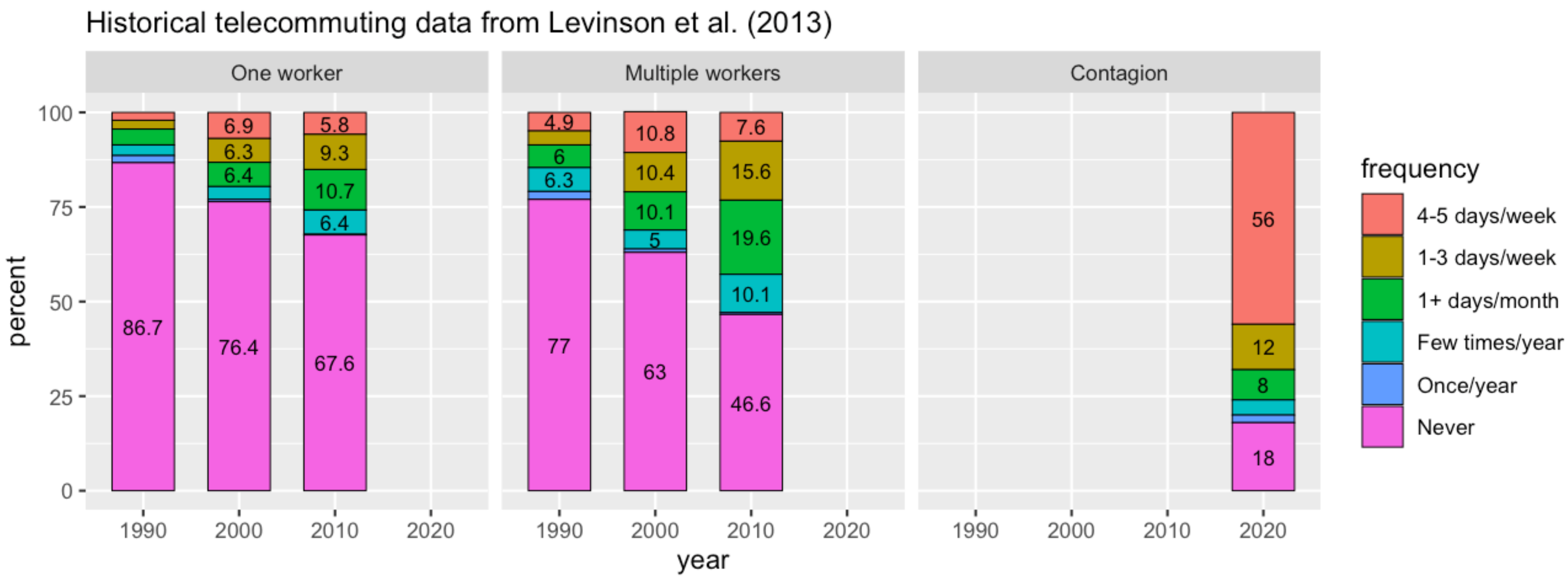
External

- Uncertainty
- Issue evolves faster than models
- Accelerating social, behavior, and technological changes
- Uncertainty
- Ransomware infections
- Loss of confidence
- Irrelevance to policymaking
- Lack of time

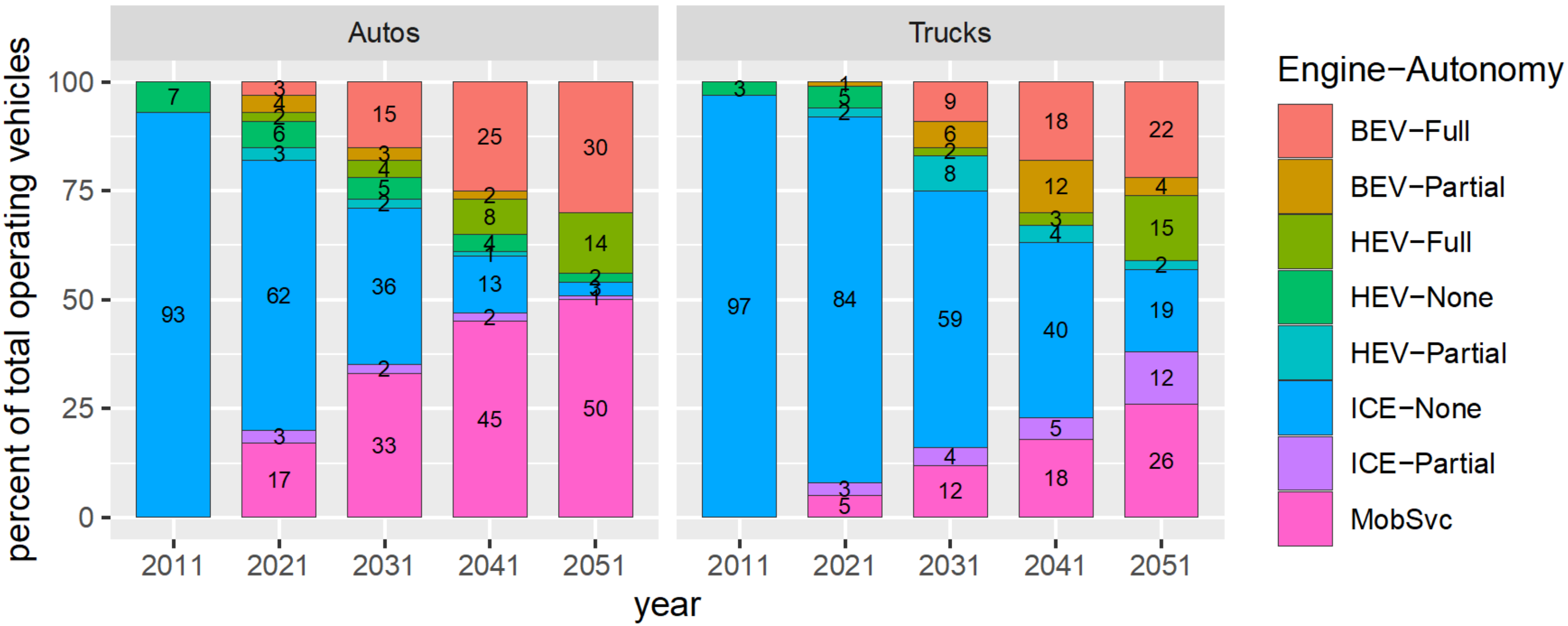
Forecasts vs reality



Telecommuting trends over time

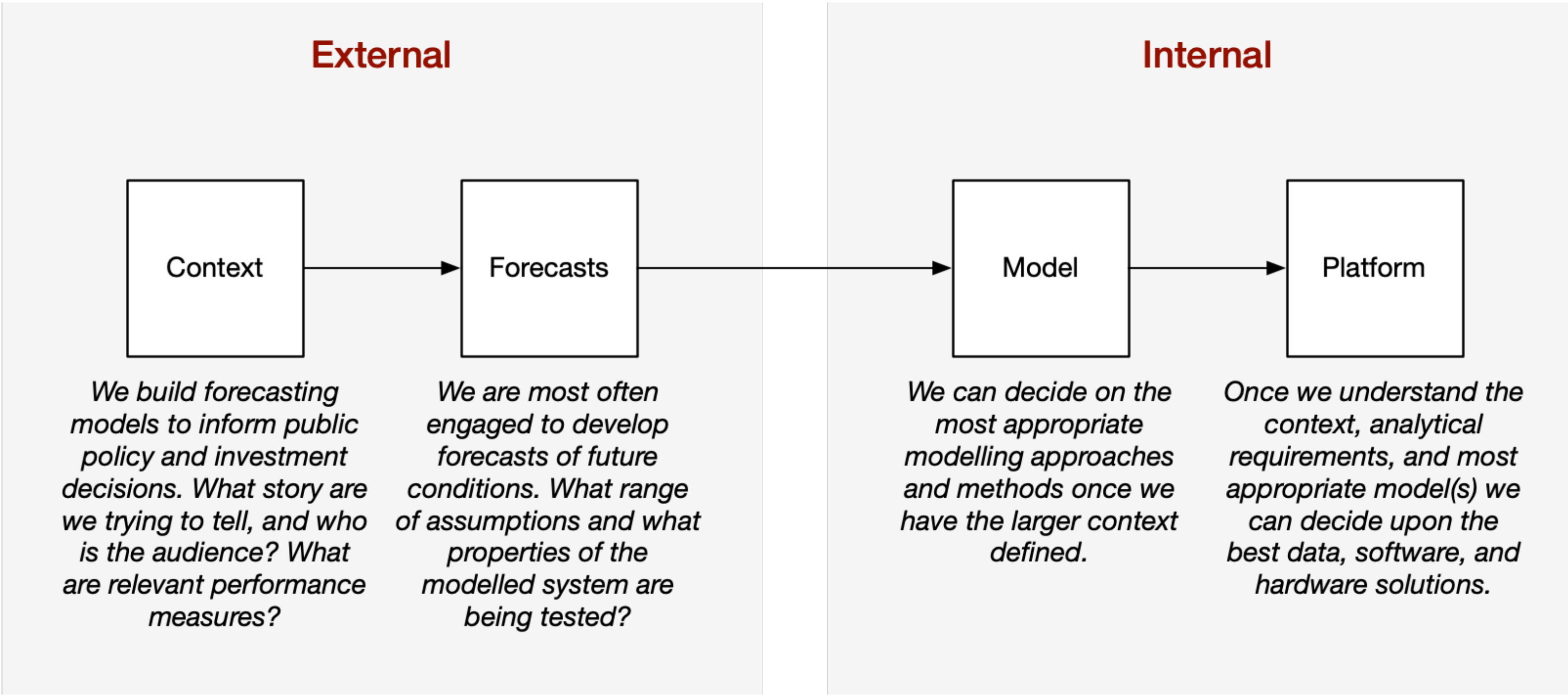


Changes in vehicle fleet



Engines: BEV = battery electric vehicle, HEV = hybrid electric vehicle, ICE = internal combustion engine, MobSvc = mobility services

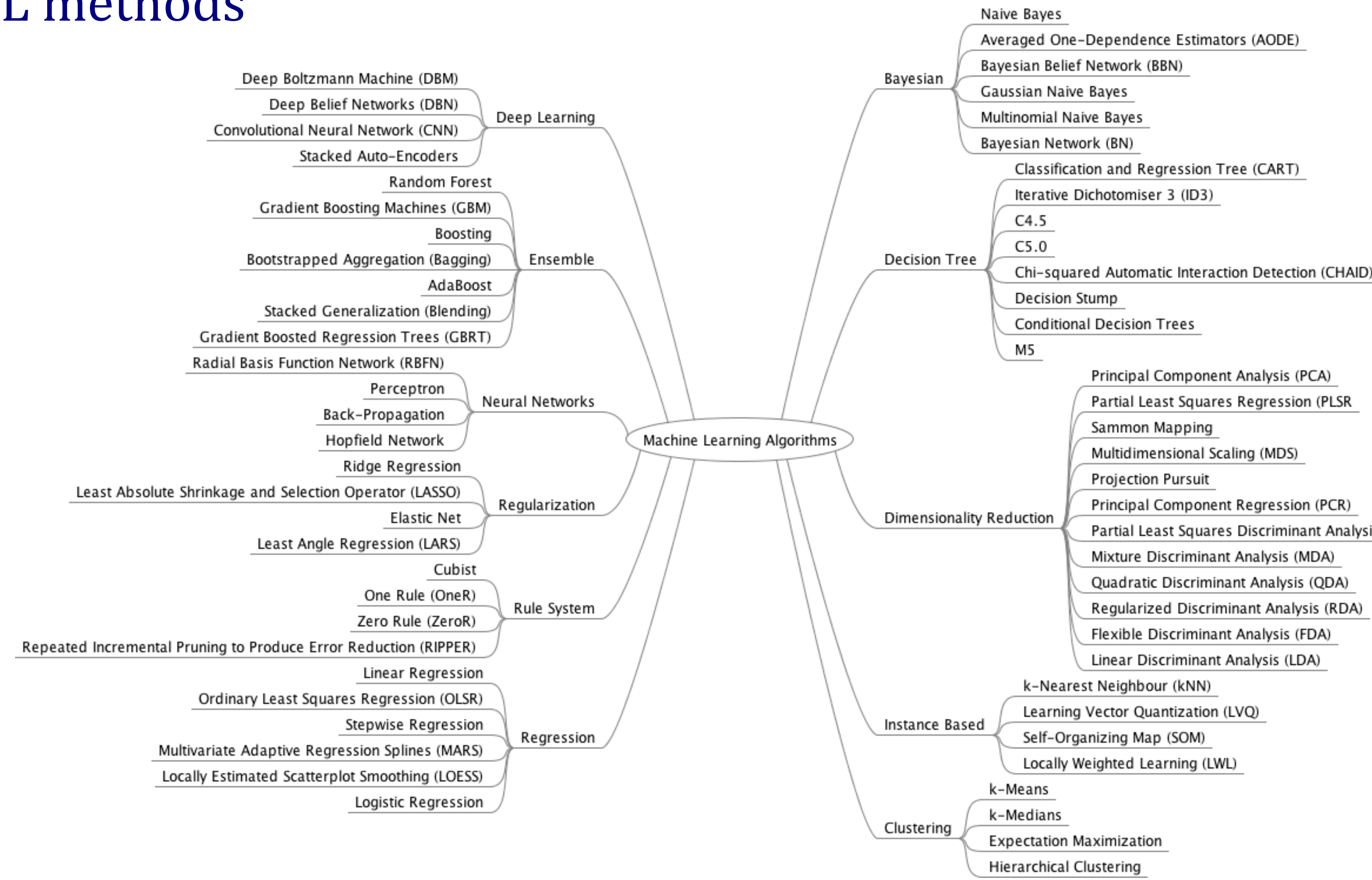
Davidson diagram



Change how I use them

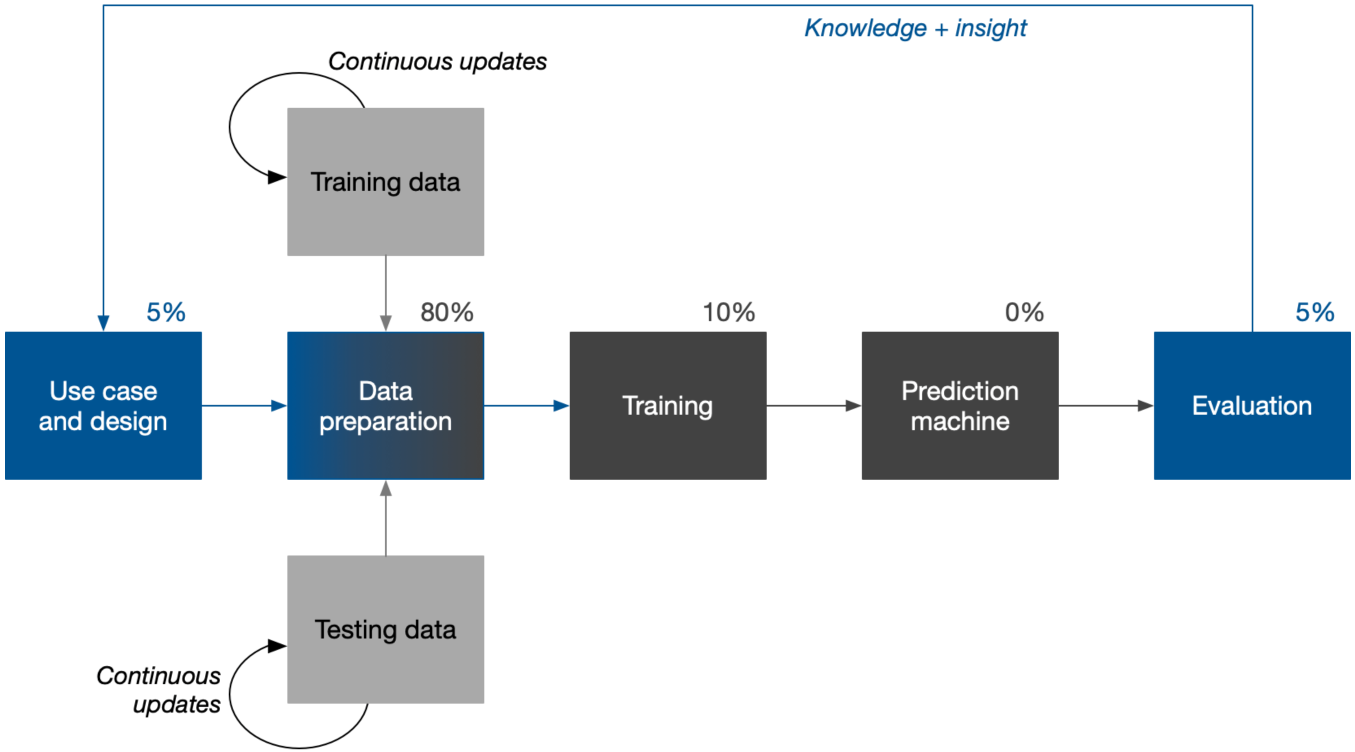
Improve and expand our tools

ML methods



Source: https://eulertech.wordpress.com/2017/10/03/machine-learning-algorithms-in-one-map/

ML in a nutshell



Quick intercity mode choice example

Table 5.4: Long-distance travel surveys

Category	Attribute	NHTS	TSRC
Extents	Years included	2002	2012-14
	Total usable observations	45,118	167,481
Variables	Mode (of travel)	✓	✓
	Age group	✓	✓
	Gender	✓	✓
	Education	✓	✓
	Employment status	✓	✓
	Occupation	✓	
	Household income	✓	✓
	Travel party size	✓	✓
	Trip purpose	✓	✓
	Nights away	✓	✓
	Distance (one-way)	✓	✓
	Year	✓	✓
	Percent personally paid	✓	✓
	Annual frequency	✓	

Perfect case study in imbalanced data

Table 5.5: Number of observations by intercity mode of travel

	NHTS		TSRC	
Mode	Records	Percent	Records	Percent
Air	3,347	7.4	7,994	4.8
Auto	40,333	89.3	150,456	89.8
Bus	993	2.1	3,513	2.1
Other	77	0.2	3,427	2.0
Rail	392	0.9	1,268	0.8
Ship	36	0.1	823	0.5
Total	45,118	100.0	167,481	100.0

Starting position

Percent incorrect predictions

Mode	Logit model	Random guess
Air	15.1	95.6
Auto	4.2	10.3
Bus	69.7	98.2
Other	—	97.9
Rail	51.8	99.2
Ship	100.0	99.8

Console Terminal × Jobs ×

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```
> combined$guess <- sample(observed_shares$mode, nrow(combined), r
+   prob = observed_shares$share)
> result <- xtabs(~mode + guess, data = combined, na.action = na.p
L)
> noquote(result)
        guess
mode       Air   Auto    Bus  Other   Rail   Ship
  Air      383   7209    155    161     49     37
  Auto    7282 134980   3141   3057   1212    784
  Bus      164   3150     81     74     27     17
  Other    181   3061     78     70     28      9
  Rail      69   1132     26     25     10      6
  Ship      53    732     20     12      3      3
> noquote(paste("Random guess accuracy = ", accuracy(result)))
[1] Random guess accuracy =  0.81
> modal_accuracy(combined, combined$guess)
   mode Correct Incorrect pctIncorrect
1   Air     383      7611         95.2
2  Auto  134980     15476         10.3
3   Bus      81      3432         97.7
4 Other      70      3357         98.0
5  Rail      10      1258         99.2
6  Ship       3       820         99.6
> |
```

Simple decision tree

Console　Terminal　Jobs

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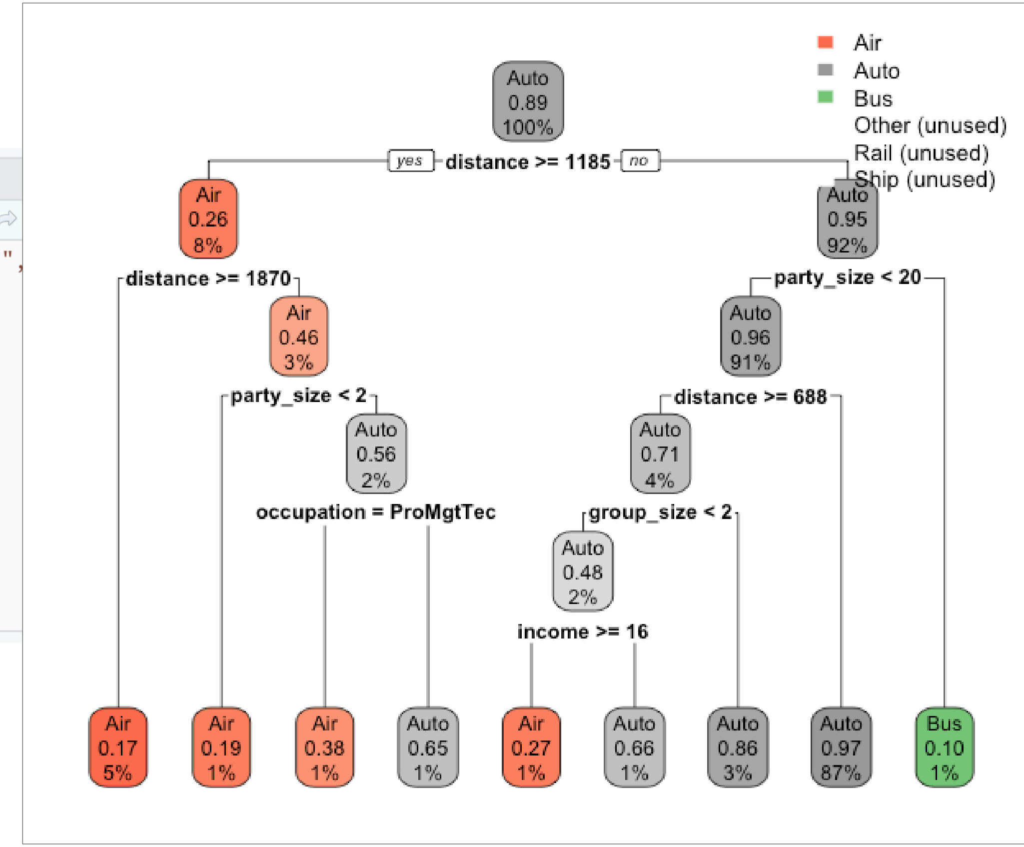
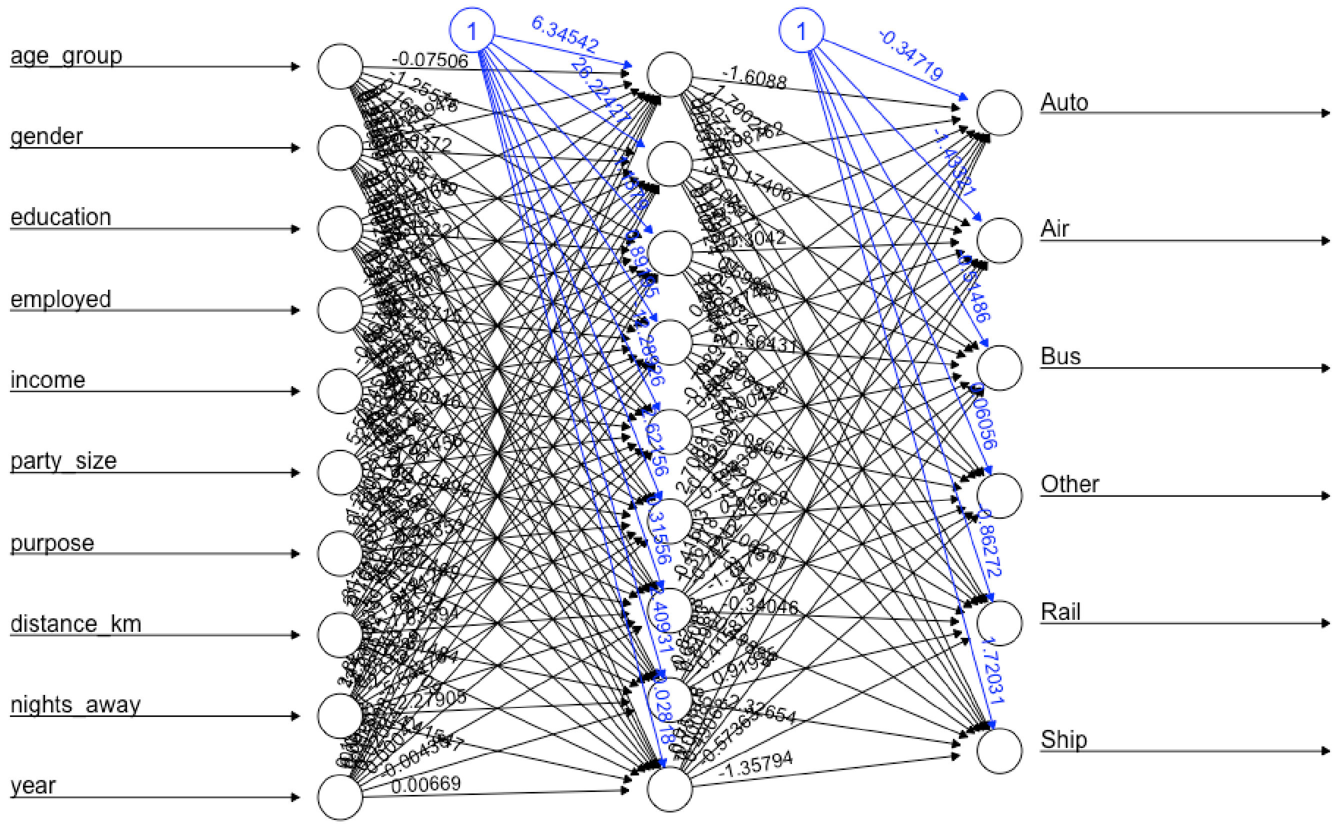
```
> noquote(paste("All modes: decision tree accuracy = ",
[1] All modes: decision tree accuracy =  0.94
> source("./feature_accuracy.R")
> noquote(feature_accuracy(df_test, mode, pred))
   mode .groups Correct Incorrect pctIncorrect
1   Air    drop     517       180         25.8
2  Auto    drop    7936       138          1.7
3   Bus    drop      54       107         66.5
4 Other    drop       0        10        100.0
5  Rail    drop       0        72        100.0
6  Ship    drop       0        10        100.0
> 
```



Maybe neural net



Results

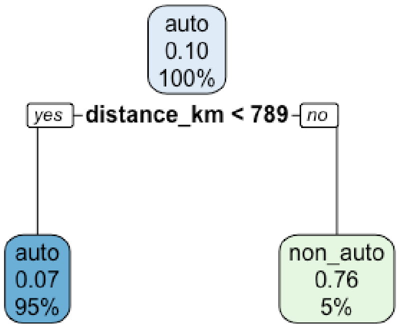
Percent **incorrect** predictions

Mode	Logit model	Random guess	Decision tree	Bagged tree	Neural net (h=24)	SEDO bagged tree	SEDO + random
Air	15.1	95.6	41.7	29.2	10.1	**9.5**	**9.5**
Auto	4.2	10.3	**0.5**	1.4	7.4	0.8	0.8
Bus	79.7	98.2	100.0	91.1	24.8	26.9	**21.8**
Other	—	97.9	100.0	94.9	77.5	36.5	**29.3**
Rail	81.8	99.2	100.0	93.4	40.0	77.4	**37.9**
Ship	100.0	99.8	100.0	96.8	63.3	64.4	**60.3**

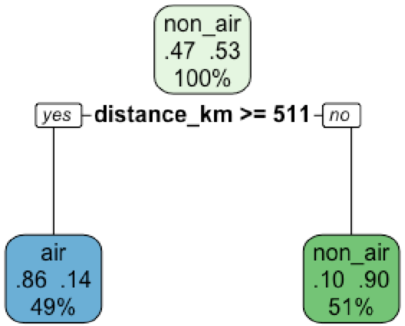
Notes:
(a) Shaded cells indicate acceptable levels of predictive accuracy
(b) Values in bolded red indicate prediction with least error for each mode of travel

SEDO (3 levels)

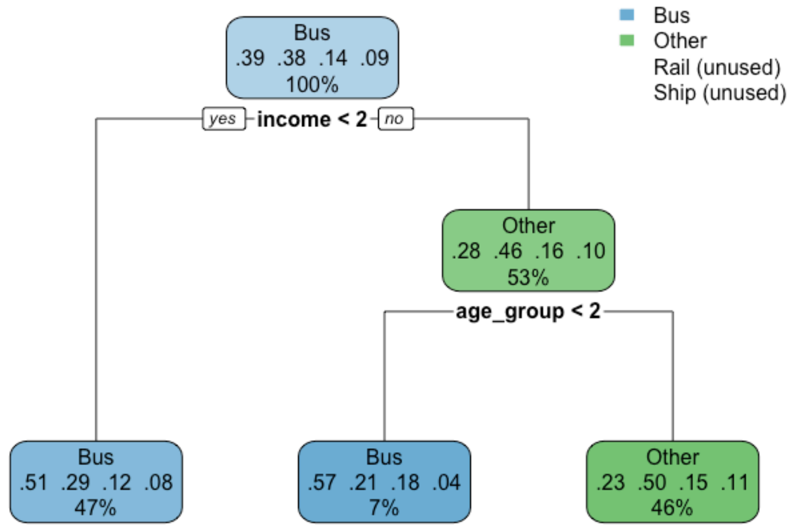
L1
(auto vs. non-auto)



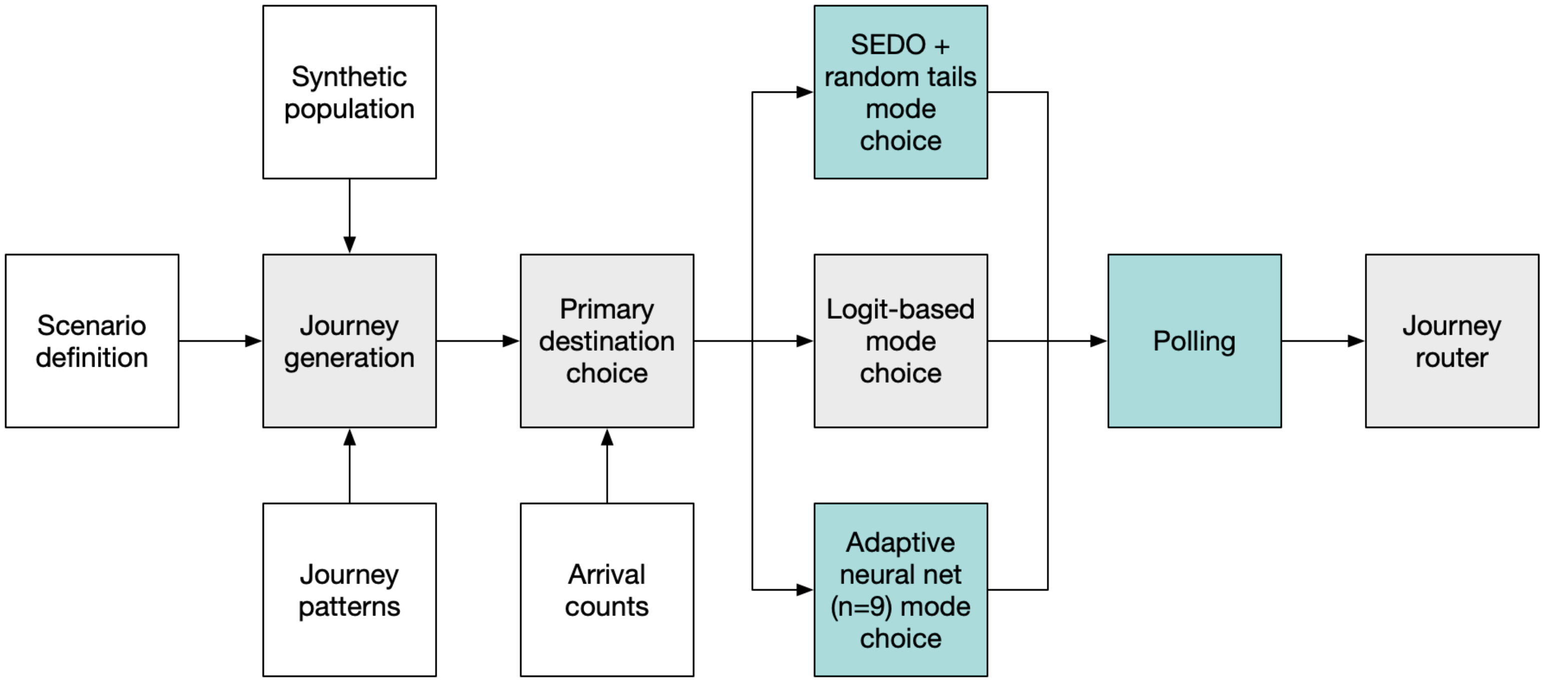
L2
(air vs. non-air)



L3
(remaining modes)



Final modeling system



My view

How can we build evidence-based planning models that overcome:

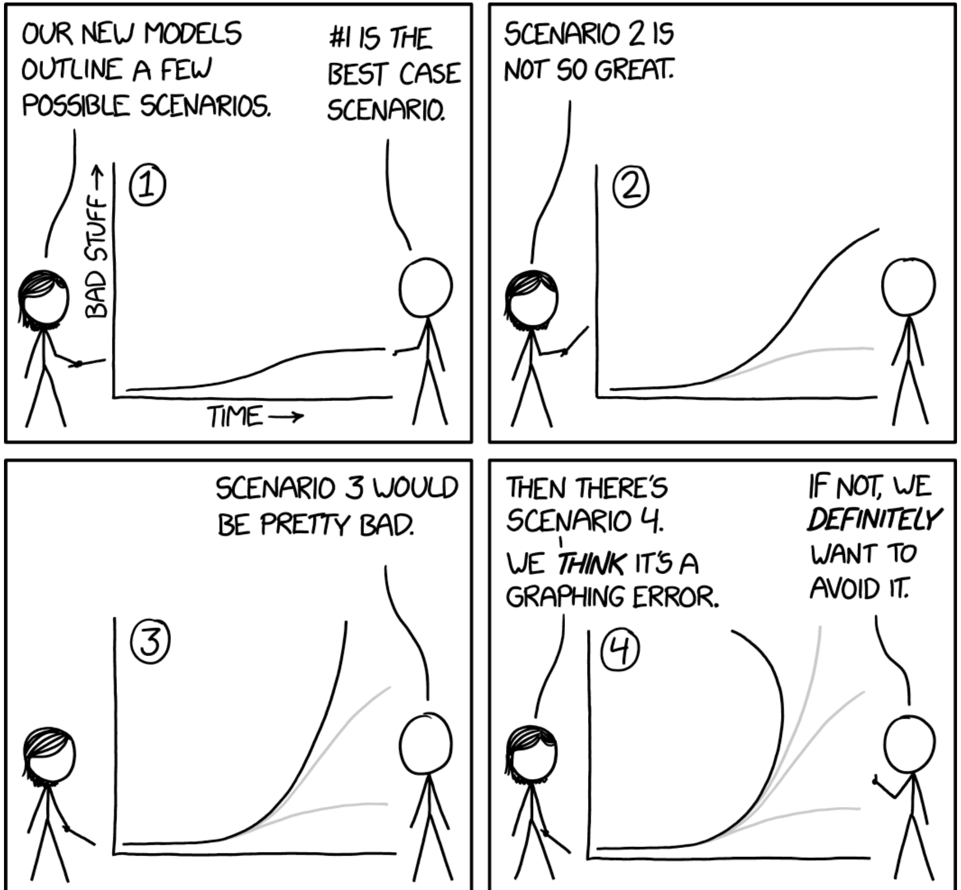
ML limitations

- Doesn’t comprehend larger context
- Data limitations (quality, quantity, stationarity, …)
- Data silos
- Stochastic
- Lack of interpretability
- P-hacking
- AI solutionism
- Ethical concerns

Human limitations

- Biases and prejudices
- Linear thinking
- Mistakes
- Agendas
- Replication mindset
- Misinterpreting results
- Difficulty comprehending multi-dimensional interactions

Scenario thinking example

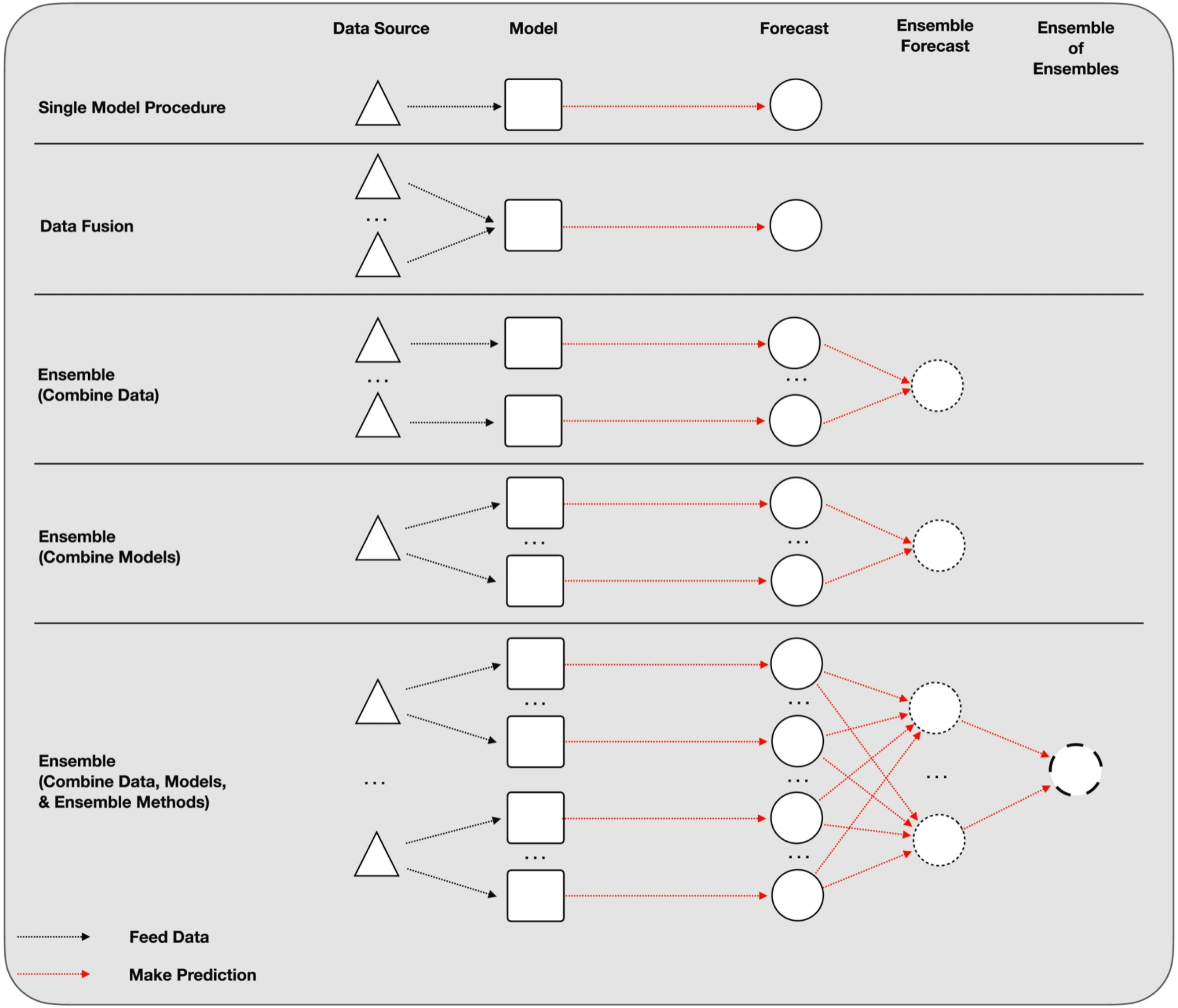


Scenario thinking

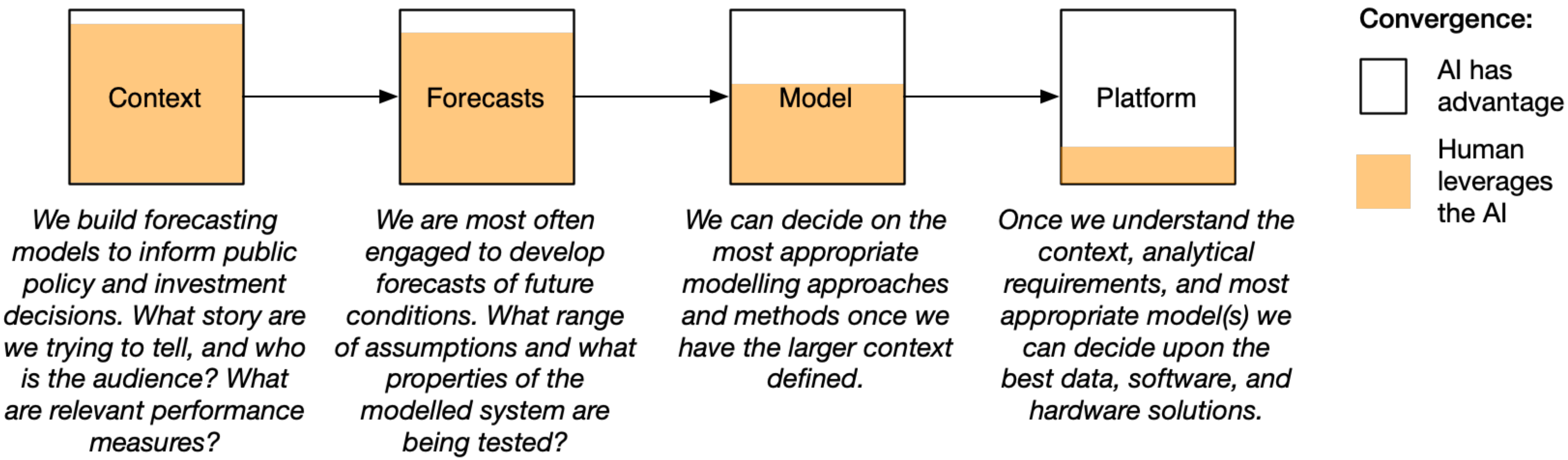
Contagions	Future of work	Automation + AI	Autonomous vehicles	Military presence
1. Return to 2019 2. Rolling sheltering and isolation 3. Relative calm between cyclical pandemics 4. Rolling pandemics the new normal 5. A universal vaccine or cure emerges	1. Return to 2019 2. Increased telework and hybrid office-remote work 3. Sustained shift towards remote work	1. AI winter 2. Second Machine Age scenario with higher unemploy-ment 3. Automation trends plateau 4. AI dominance	1. Bureaucratic and regulatory inertia 2. AVs remain niche products 3. Widespread adoption of AVs 4. Level 5 automation dominates travel	1. Remain at current levels 2. Digital warfare focus reduces traditional forces 3. Stronger Pacific presence to deter Chinese expansion 4. Drones replace human warriors

“Methods of combining data and models” (Figure 2.1)

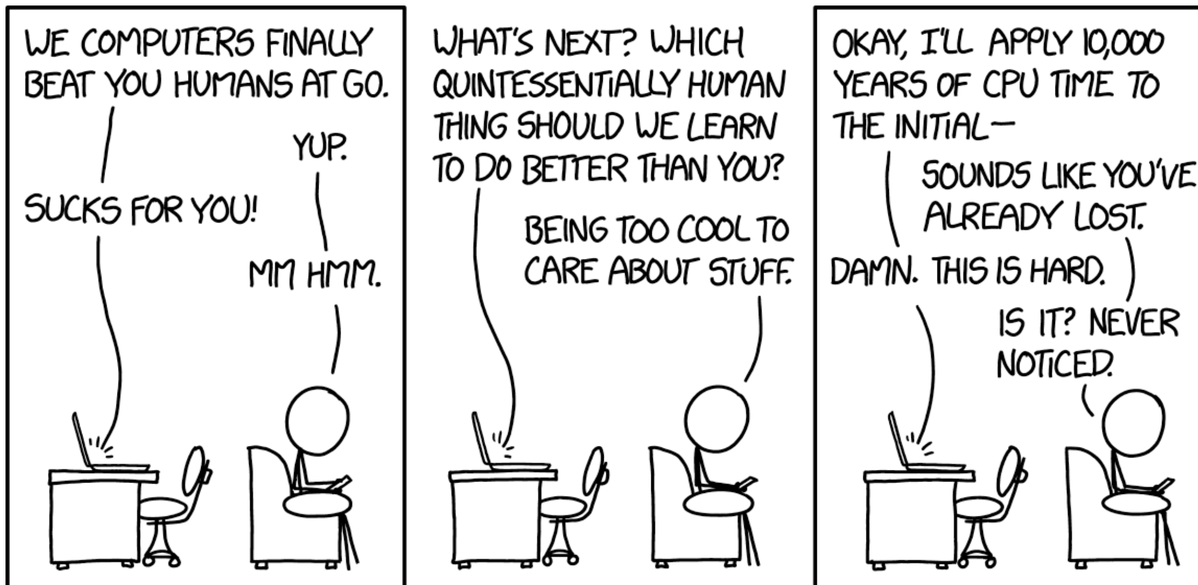
From H. Wu (2021), Theory of ensemble forecasting – with applications to transport modeling, Unpublished PhD thesis, The University of Sydney



Davidson diagram redux



Tear it apart?



Highly recommended

- H. Wu (2021), Theory of ensemble forecasting – with applications to transport modeling, Unpublished PhD thesis, The University of Sydney.
  https://ses.library.usyd.edu.au/handle/2123/26252
- W. Li & K. M. Kockelman (2021), "How does machine learning compare to conventional econometrics for transport data sets? A test of ML versus MLE", *Growth and Change,* in press.
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  https://www.coursera.org/learn/machine-learning
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