From data poor to data rich: using AI and why traffic engineers should not forget to think

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based on joint work with Guopeng Li
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TU Delft

TU Delft Transport

- Education and research
- Top ranked for traffic engineering
- Various disciplines, all within the Transport Institute Delft
- Automated vehicles, Data & computing, Rail, Observations, Road traffic

ACADEMIC RANKING OF WORLD UNIVERSITIES SINCE 2003

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Home>> Global Ranking of Academic Subjects 2019>> Transportation Science & Technology

ShanghaiRanking's Global Ranking of Academic Subjects 2019 - Transportation Science & Technology 2019

Field: Engineering **Subject:** Transportation Science & Technology **Methodology**

World Rank	Institution*	Country/Region	Total Score	Score on PUB
1	Beijing Jiaotong University		290.4	95.4
2	Tsinghua University		282.1	85.2
3	Delft University of Technology		272.2	100.0
4	Southeast University		265.5	84.4
5	University of Sydney		239.1	76.7
6	Tongji University		238.1	83.8
7	Massachusetts Institute of Technology (MIT)		235.0	71.0
8	University of British Columbia		232.7	68.3
9	University of California, Berkeley		232.5	76.6
10	Shanghai Jiao Tong University		232.2	71.0

Traffic Dynamics Modelling & Control

- Taking care of earth resources
- Quality of life (reduce emissions, travel time, ease of travel)
- Quick, safe, and predictable travels

About me

- Background as physicist in flows (MSc)
- Since 2004 in traffic engineering
- Associate professor at TU Delft
- Director of lab on
  traffic dynamics modelling and control

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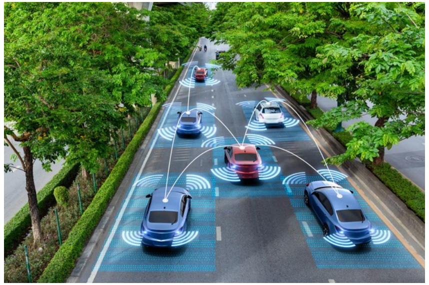
From data poor to data rich

- When I started:
  “Our field is data poor and assumption rich”
- This has changed in the meantime...
- All traffic is observed by loop detectors or cameras
- Vehicles share their position (and speed)
- Vehicles sense their surroundings



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The role of traffic predictions

- Informing people on the traffic state is useful
- Different compared to weather predictions: the weather is not influenced by the predictions
- Predictions can be used to
  - Advise travellers on postponing/cancelling trip
  - route traffic
  - Advise drivers on unsafe situations
  - Advise drivers to actively do something (e.g., change lanes)
  - Intervene in automated vehicle (predictions on a different scale?)

Common traffic prediction

- Up to 15 years ago: traffic model
- Since then: data-driven methods
- E.g., train a neural network
  (because it can do anything)
  - Problem: it learns what we already knew
  - Or if designed poorly, it does worse

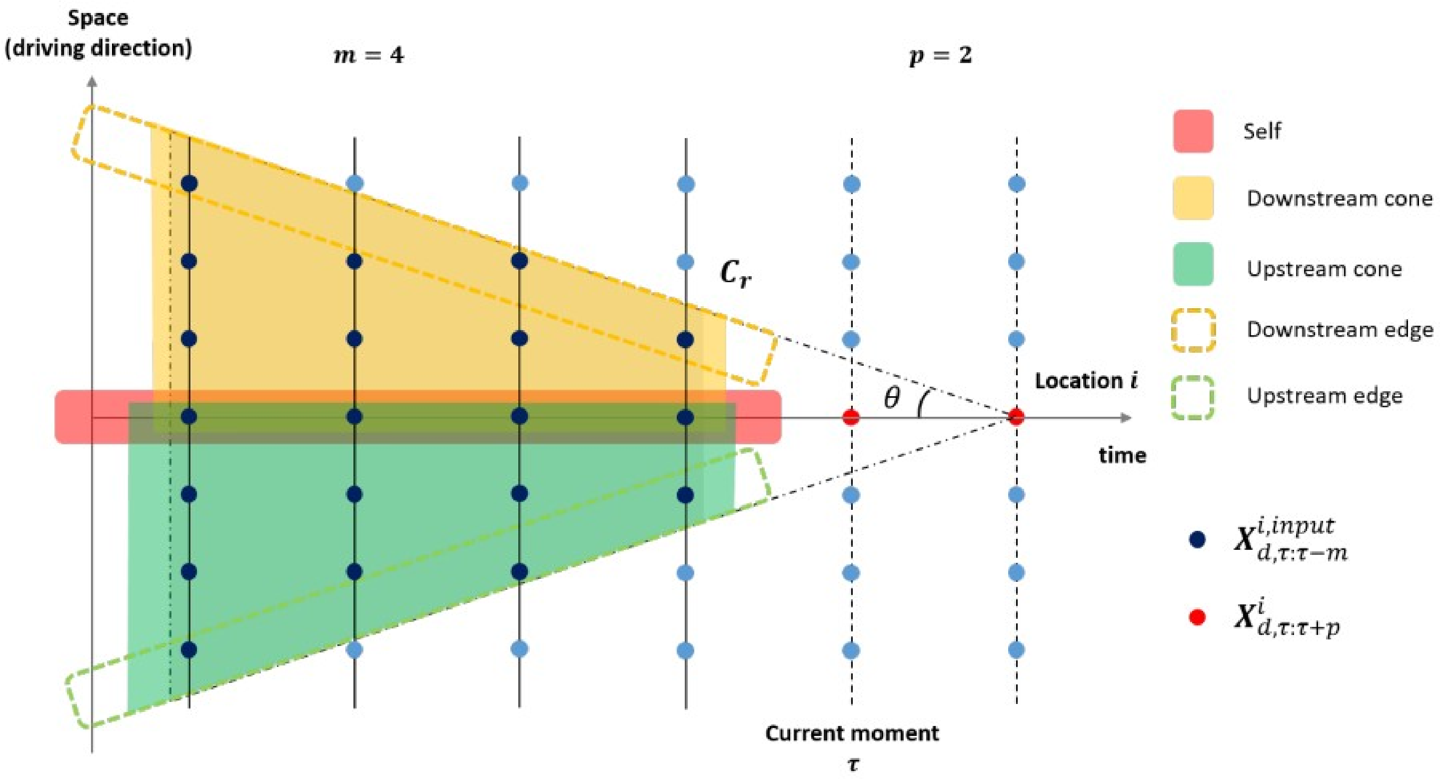
Example

- Traffic data is much available
- Learn how the traffic states evolves from one state to the next
- Long training times
- limit influence to next neighbor detectors
- *Traffic information goes upstream and downstream*
- That should be included, if not, predictions are bad
- Limit to next neighbor at each side:
  back at cell transmission model which was already known

Which information to include

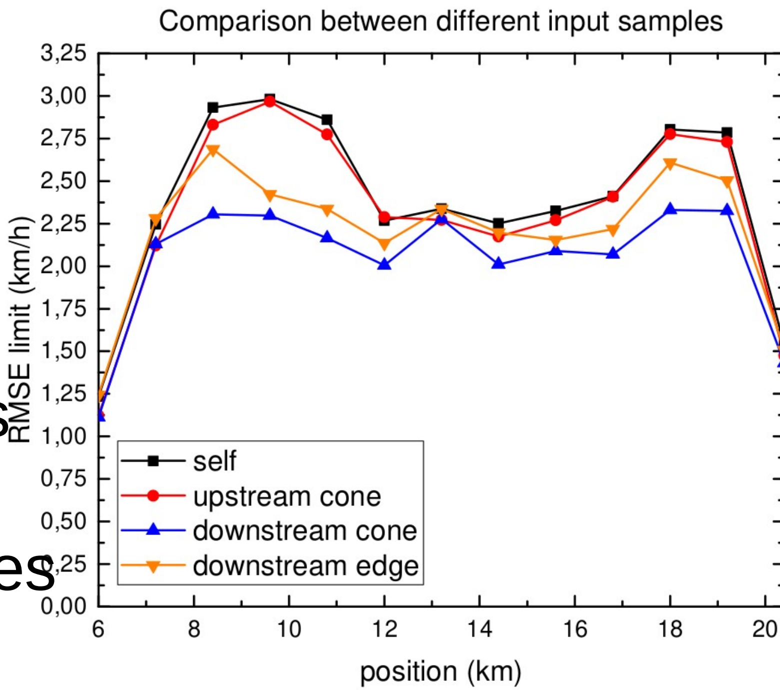
- Speed of information is limited, we know from decades of traffic flow theory
- No need to include all observations:
  limit in space and time

5 different inclusion possibilities



Results

- Self is worst (least information)
- congestion travels upstream, so:
  - Upstream hardly gives information
  - Downstream cone gives more information than just the edge (so different speeds)



Limits to predictability

Errors and unknowns

- Every deviation from our prediction is an error
- Deterministic view: improve prediction further and you’ll end up without an error
- Traffic engineering mind: collect more data, fit more refined models and improve
- At first: limit in predicting traffic state more than ~30 mins ahead
- Natural limit: length of the trip

Errors due to model or in process

- Consider a dice: that is hard to predict well
- The process itself is stochastic, and no model can make a good prediction
- Question: are errors in traffic of the nature of dices or because of badly chosen models?

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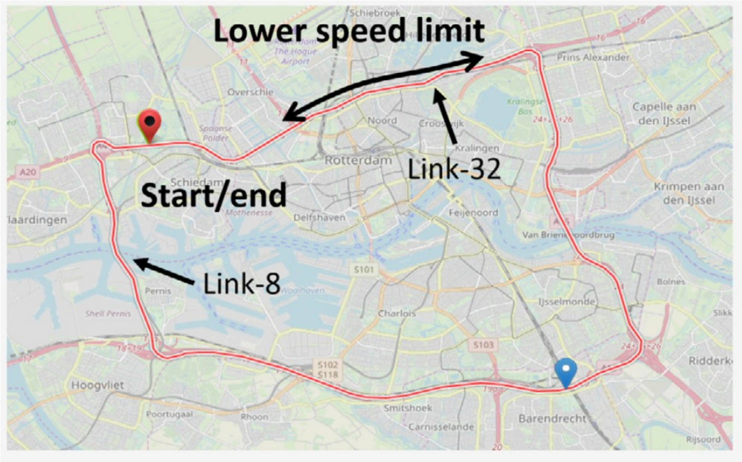
Lower bound of model error

- Regardless of model, check the uncertainty in the data
- Possible due to the amounts of data available
- Use entropy to find this:
  - Find similar traffic states
  - Check how the future diverges
- Compare the minimum with the best models
- Do so for
  - Deterministic models (= predicting one value)
  - Stochastic models (=probabilistic models)

Lower bound of model error

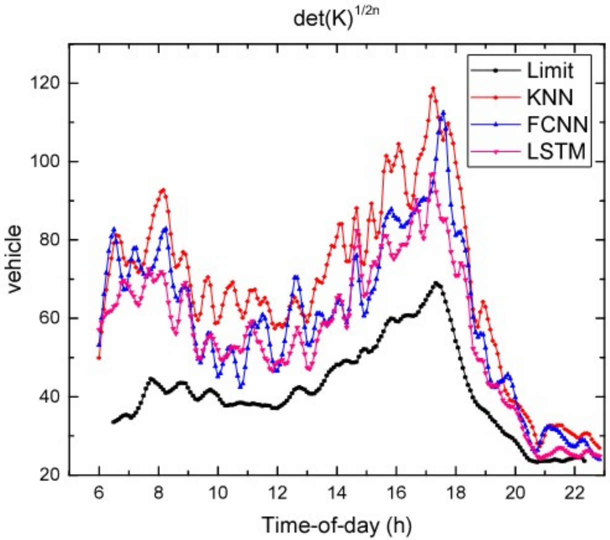
- Network:
  Rotterdam
  ca 500,000 inhabitants
  ~3-4 lane freeway
  ca 10x10 km

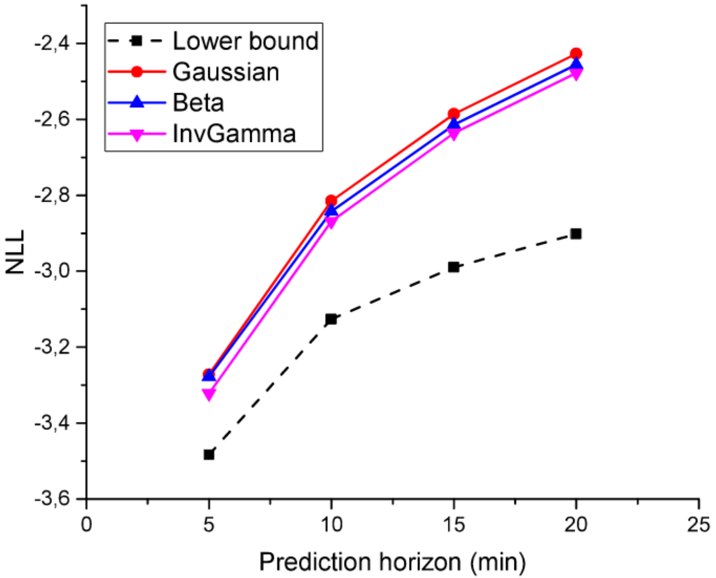


- 2 test cases:
  - Nr of vehicles in the full network (1 dimension)
  - Speeds at all locations (35 dimensions)

Lower bound of single variate

- For stochastic models, the assumed distribution matters…but has little effect
- Close to lower bound with current approaches





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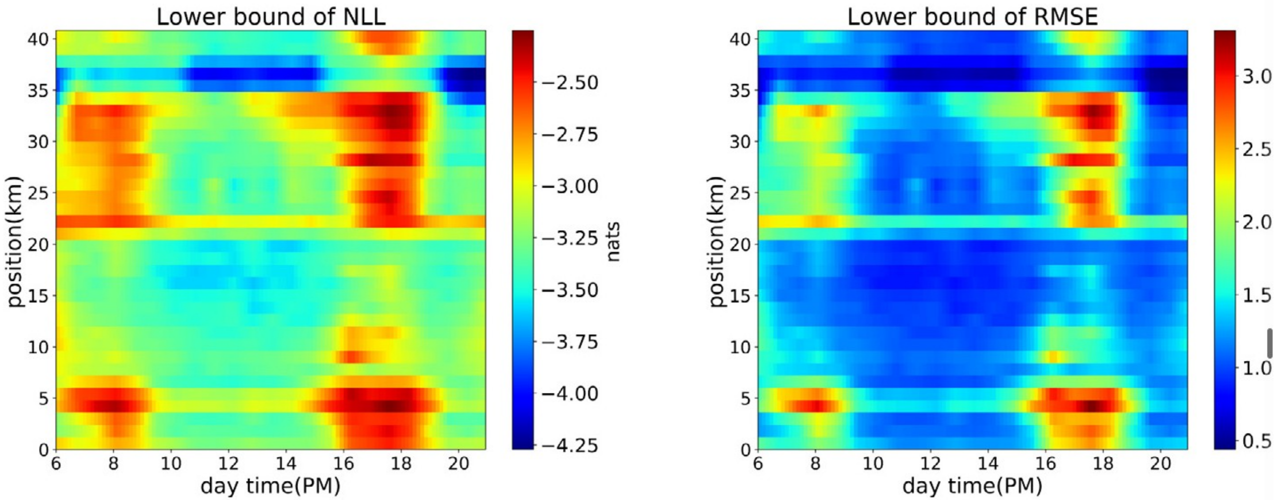
Lower bound multi-variate model

- Speed at all locations
- Lower bound depends on traffic state: sometimes (in peak periods) states are uncertain (mostly near traffic breakdown)



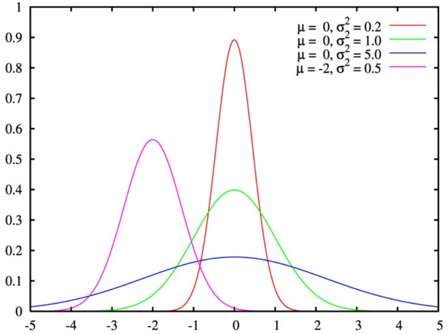
Prediction should be a distribution

- Up to now: next speed(s) have been predicted
- Error as a value or a likelihood in a pdf that the right value has been predicted
- We know now that traffic predictions are inherently stochastic
- Therefore, let's predict the probabilities for a single prediction

Example: current state

1
2
5
7

output

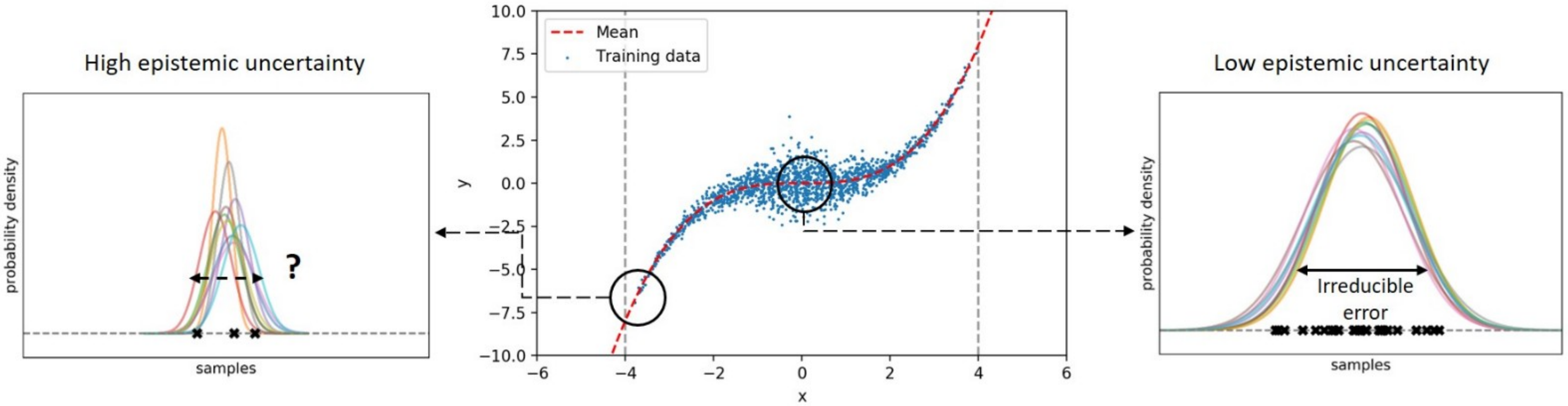


Two types of uncertainty

- Aleatoric – process is random (from alea, die)
  Even rolling many, many times,
  we can never predict dice

- Epistemic – we do not know enough
  One (or zero) observations of an unknown case
  gives not sufficient information

Example

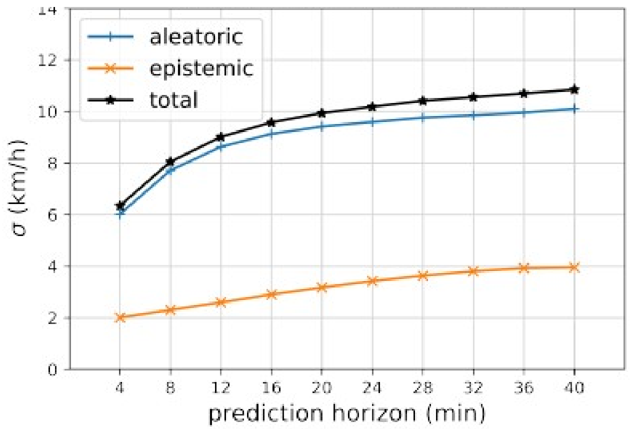


- Many observations around x=0,
  but unknown process, so uncertain (aleatoric)
- Few observations at boundary,
  so uncertain (epistemic)

How does this work for traffic prediction

- Quantify the sources of uncertainty due to each cause
- Test on speed prediction for ringways around Amsterdam
  - 193 links
  - Network
  - 2x 1 month of data
  - 1 minute aggregate
  - Prediction: 4-20 minutes ahead

Resulting uncertainties



- Uncertainties increase with increasing time horizon (as expected)
- Total uncertainty almost fully caused by aleatoric uncertainty (very interesting new finding)

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More data?

- Some very rare cases contribute to uncertainty
- 4 cases in 2022, 7 cases in 2019
- These are very rare events; more data of these, whatever they are, would be useful
- Typically, rare events happen not often
  (that information actually contains information :)

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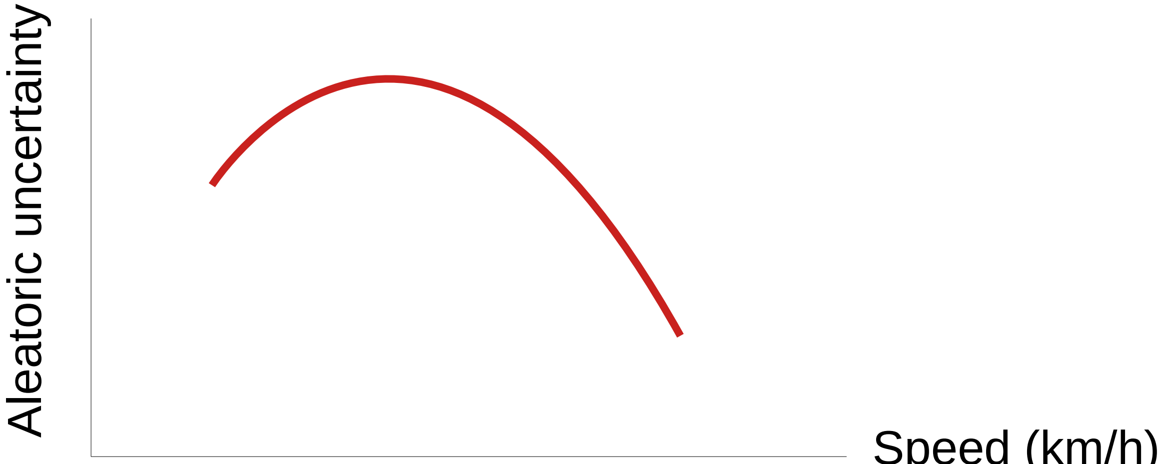
How do they depend on speed?



- For high speeds: certain (speeds will remain high)
- For low speeds: certain (speeds will remain low)
- Near critical speed: highest uncertainty (might go into breakdown)

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How do they depend on location?

- We tracked all links and considered where the highest uncertainty came from
- Highest uncertainty near onramps causing jams (another indication that the start of a traffic jam gives highest uncertainty)

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Conclusions

- Traffic prediction can in many cases be predicted by a data driven model
- Training it can take time; adding information on knowledge of traffic
  - simplifies the model
  - Makes predictions more reliable
  - Speeds up computation
- Traffic evolves with inherent uncertainty
- Sufficient data is generally available (no need for more data)
- Rare events are rare

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References

- Li, G, Knoop, V.L., and Van Lint, H. (2022) Estimate the limit of predictability in short-term traffic forecasting: An entropy-based approach. Transportation Research part C, Vol 138, 103607
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