Predicting for the adaptive transport system

...and other necessary ingredients for resilient urban mobility

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DTU

Some “future mobility” visions...

Dynamic
Public Transport

Mobility as
a Service (MaaS)

Shared
modes

Dynamic
pricing

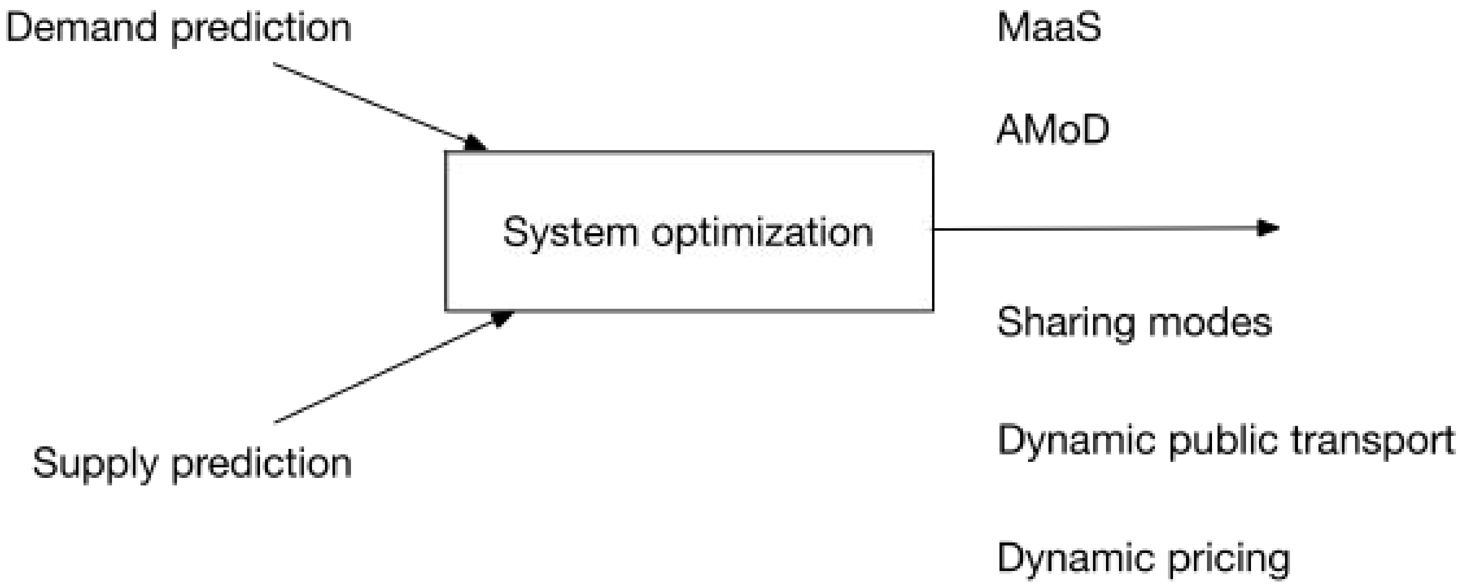
Autonomous Mobility on
Demand (AMoD)

Some “future mobility” visions…

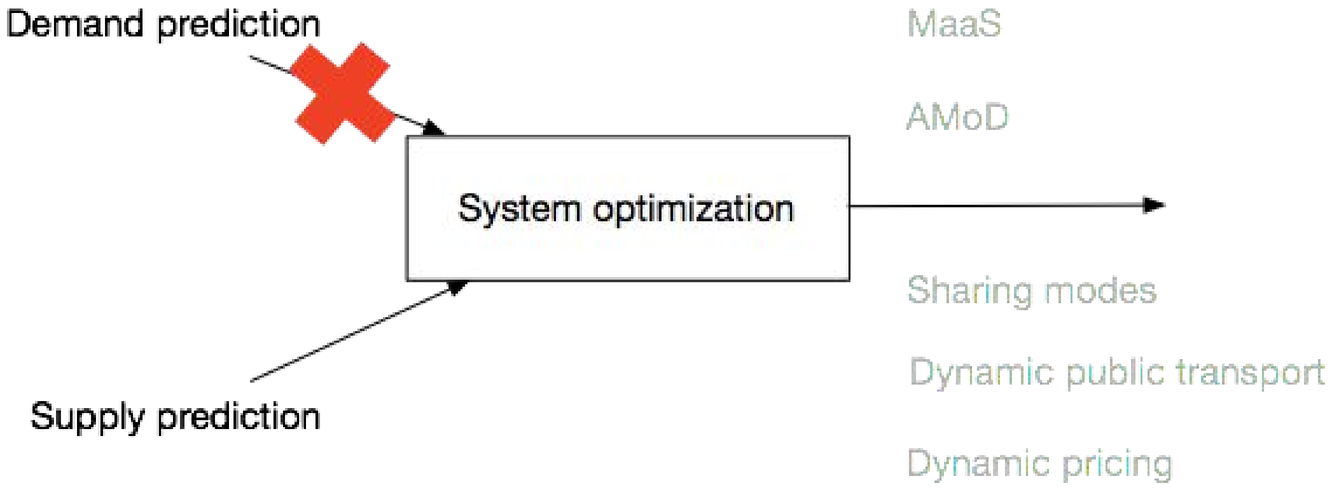
And some possible nightmares...

And some possible nightmares...

The prediction-optimization pipeline

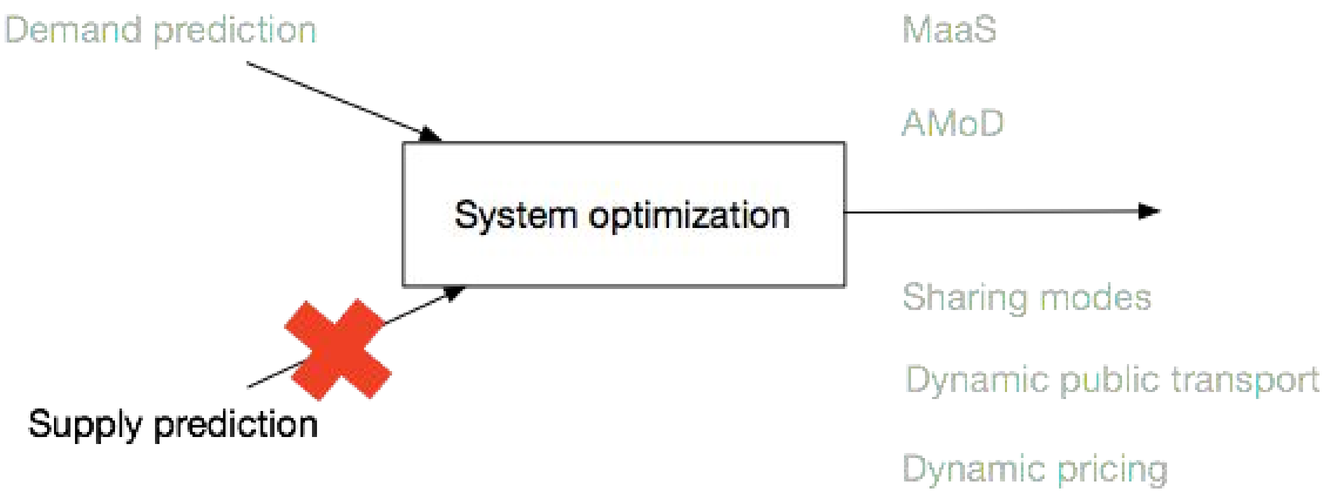


In non-recurrent conditions...



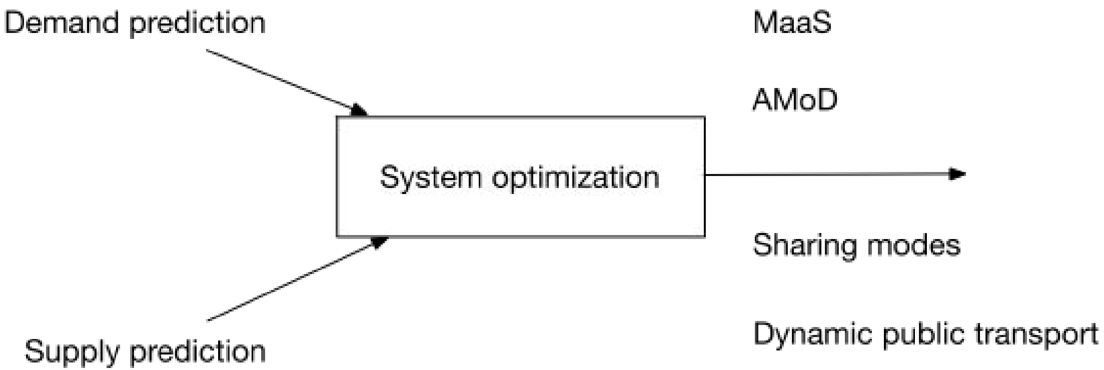
Wrong balancing
Wrong pricing

In non-recurrent conditions...



Wrong routing
Wrong scheduling

Transport services of the (near!) future



Attention to stress scenarios!!

Large events

Incidents

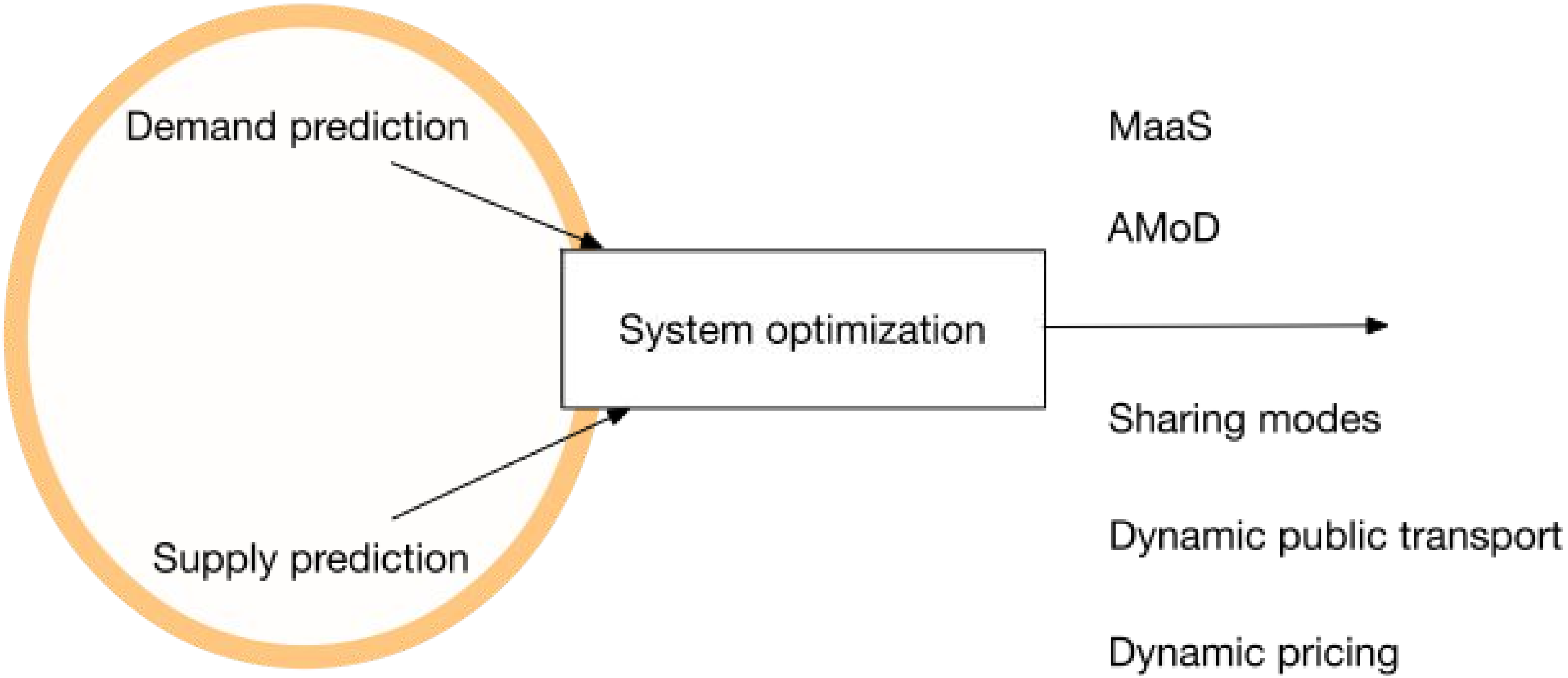
System breakdowns

...

No “future mobility” will be adaptive without VERY robust prediction capability…

…especially in non-recurrent conditions!

Focus of this talk



Non-recurrent scenarios

Demand	Supply	
		Expectable
		Unexpectable

Non-recurrent scenarios

	Demand	Supply
Expectable	special events, demonstrations, holidays	
Unexpectable		

Non-recurrent scenarios

	Demand	Supply
Expectable	special events, demonstrations, holidays	road works, closures, mega events
Unexpectable		

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Non-recurrent scenarios

	Demand	Supply
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Expectable demand

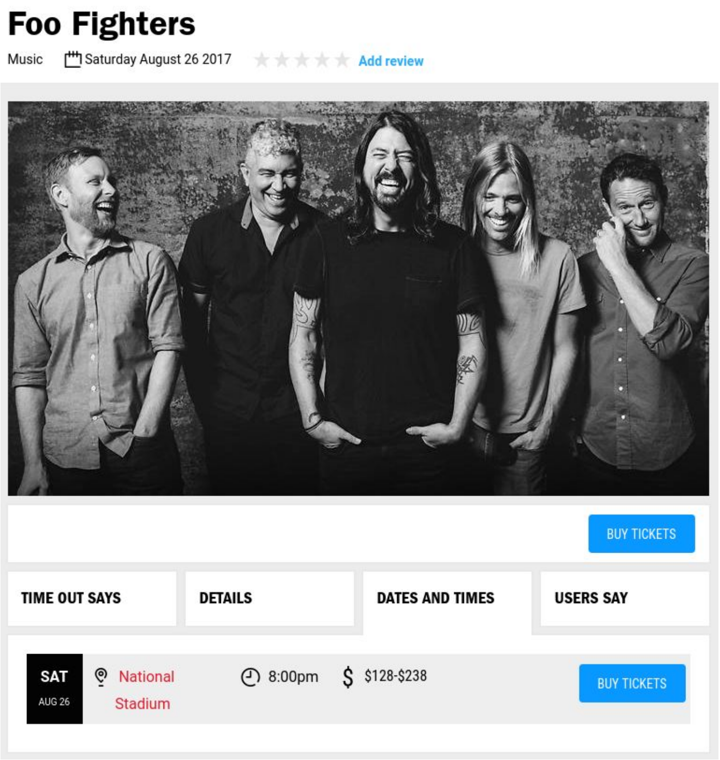
Event information is usually online

- Event homepages
- Event listings
- Social media (e.g. twitter, facebook)
- News feeds

...

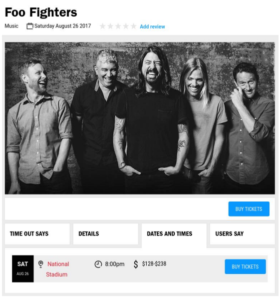
Lots of potential sources, but a lot in free form text

Accounting for event information



natural language processing → Machine-interpretable features

Accounting for event information

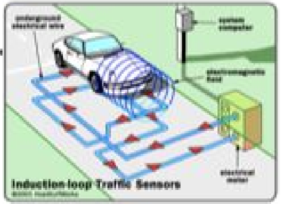


Topic modeling

Bayesian additive model (BAM)

Demand prediction

INRIX REJSEKORT



Data preparation

Rodrigues, F., Borysov, S., Ribeiro, B. and Pereira, F., 2016. A Bayesian additive model for understanding public transport usage in special events. *IEEE transactions on pattern analysis and machine intelligence*

Bayesian additive model

$$y = f_r(\mathbf{x}_r) + \sum_{k=1}^{K} f_e(\mathbf{x}_{e_k}) + \epsilon$$

Gaussian process that models routine component

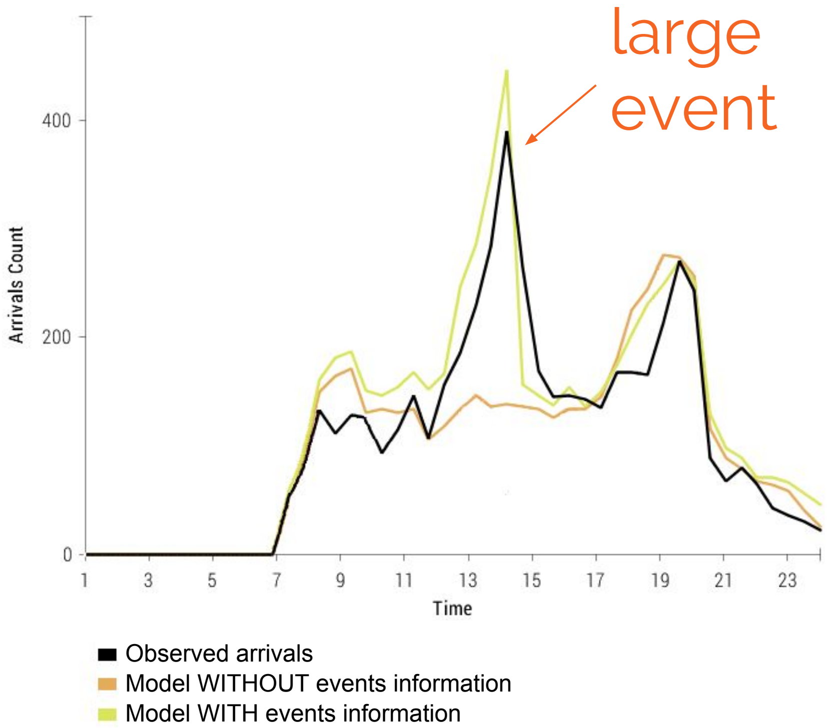
Gaussian process that models the effect of events

Public transport arrivals in Singapore

Data:

- 5 months of smartcard data (bus, metro, light rail)
- 2 study areas
  - Singapore Indoor Stadium
  - Singapore Expo

An example

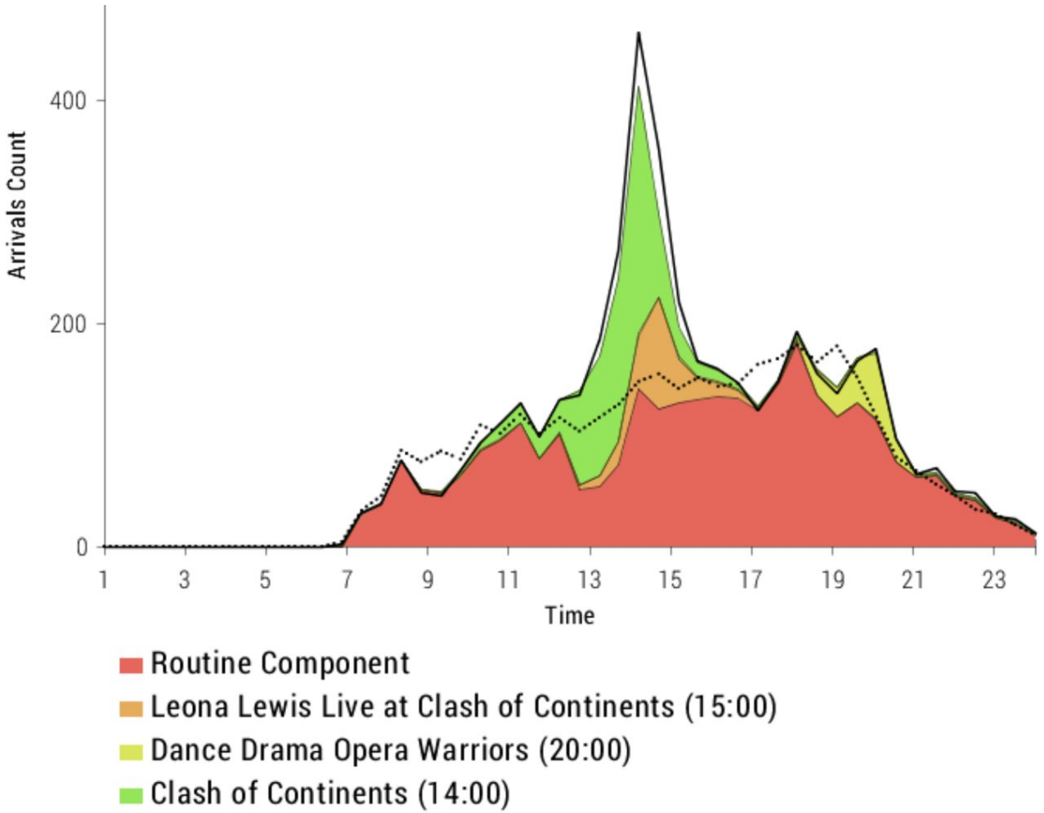

large
event
Arrivals Count
400
200
0
1
3
5
7
9
11
13
15
17
19
21
23
Time
Observed arrivals
Model WITHOUT events information
Model WITH events information

Public transport arrivals in Singapore

		Evaluation: event periods only		
Area	Model	RAE	CorrCoef	R^2
Stadium	Linear Reg. (routine only)	66.817 (8.322)	0.783 (0.065)	0.457 (0.108)
	Linear Reg. (routine + events)	55.493 (7.710)	0.864 (0.025)	0.627 (0.057)
	GP (routine only)	62.069 (8.584)	0.801 (0.066)	0.409 (0.105)
	GP (routine + events)	59.761 (9.876)	0.802 (0.080)	0.625 (0.056)
	BAM-GP (truncated)	**42.338 (6.172)**	**0.907 (0.022)**	**0.789 (0.034)**
Expo	Linear Reg. (routine only)	82.999 (6.354)	0.537 (0.056)	0.323 (0.051)
	Linear Reg. (routine + events)	81.029 (5.749)	0.620 (0.052)	0.370 (0.048)
	GP (routine only)	56.473 (6.638)	0.843 (0.038)	0.698 (0.046)
	GP (routine + events)	54.743 (4.034)	0.798 (0.037)	0.576 (0.074)
	BAM-GP (truncated)	**46.033 (4.569)**	**0.884 (0.032)**	**0.720 (0.077)**

RAE: relative absolute error
CorrCoef: correlation coefficient
R2: coefficient of determination

Exploiting the model's additive structure



Predicting taxi demand in event areas

Goal: Given the taxi demand in the last L days, predict taxi demand for the next day

Focus: special event areas

A deep learning approach

Recent work currently under review!

Predicting taxi demand in NYC

Data:

- All taxi trips from 2013 to 2016
- 2 study areas
  - Barclays Center
  - Terminal 5

Predicting taxi demand in NYC

Method	MAE	RMSE	MAPE
SVR L	186.7 ($\pm$0.0)	252.2 ($\pm$0.0)	20.4 ($\pm$0.0)
SVR L+W	185.3 ($\pm$0.0)	251.6 ($\pm$0.0)	20.2 ($\pm$0.0)
SVR L+W+E	177.0 ($\pm$0.0)	244.4 ($\pm$0.0)	19.1 ($\pm$0.0)
GP L	204.5 ($\pm$0.0)	264.6 ($\pm$0.0)	22.5 ($\pm$0.0)
GP L+W	204.2 ($\pm$0.0)	264.8 ($\pm$0.0)	22.5 ($\pm$0.0)
GP L+W+E	184.4 ($\pm$0.0)	250.3 ($\pm$0.0)	20.3 ($\pm$0.0)
DL-FC L	181.4 ($\pm$2.5)	250.0 ($\pm$1.6)	19.7 ($\pm$0.3)
DL-FC L+W	180.7 ($\pm$2.1)	250.1 ($\pm$1.3)	19.6 ($\pm$0.3)
DL-FC L+W+E	168.1 ($\pm$2.8)	242.7 ($\pm$1.9)	18.1 ($\pm$0.3)
DL-FC L+W+E+T	**158.1** ($\pm$3.4)	236.2 ($\pm$2.3)	**16.8** ($\pm$0.5)

L = time-series lags only
W = weather
E = event information
T = event text

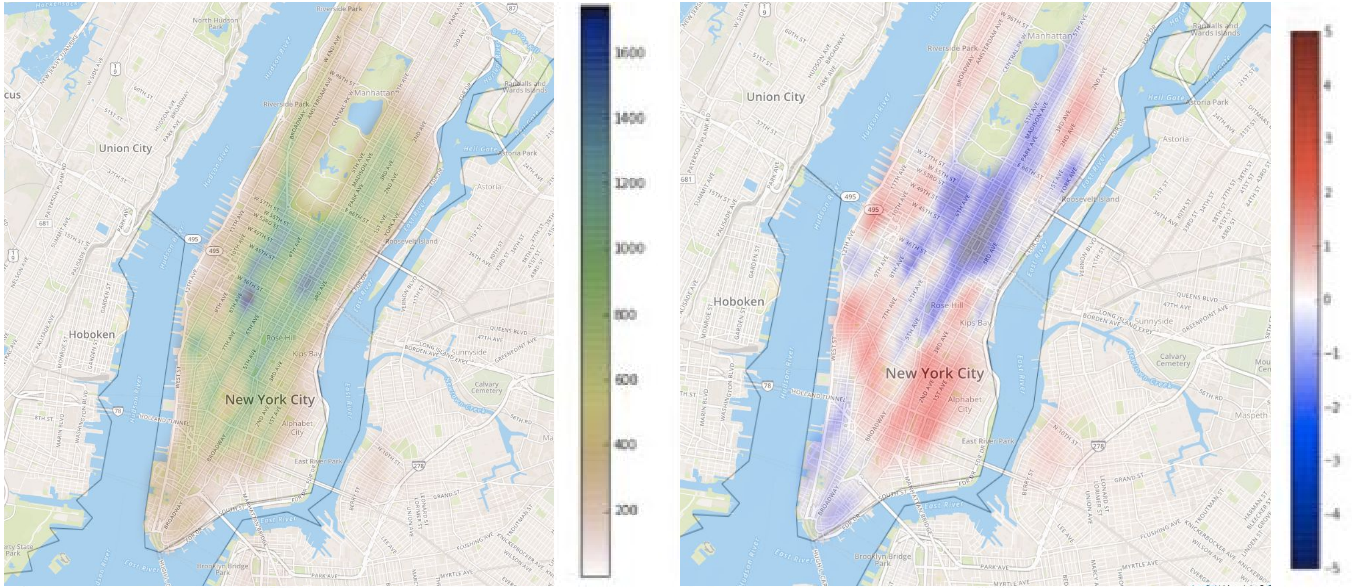
MAE: mean absolute error
RMSE: root mean sq. error
MAPE: mean absolute percentage error

Non-recurrent scenarios

	Demand	Supply
Expectable	special events, demonstrations, holidays	road works, closures, mega events
Unexpectable	crisis situations, unknown high fluctuations	incidents, weather, crisis situations

Unexpectable demand

Step 1: anomaly detection

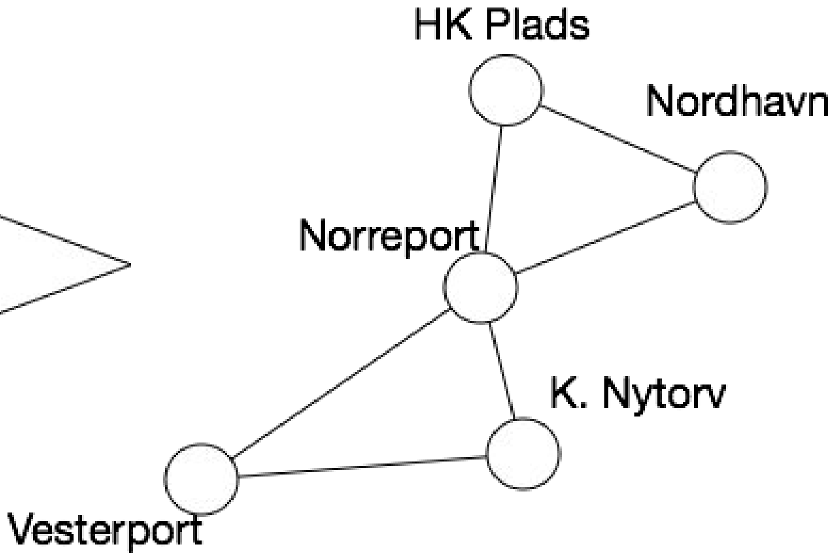


(a) (b)

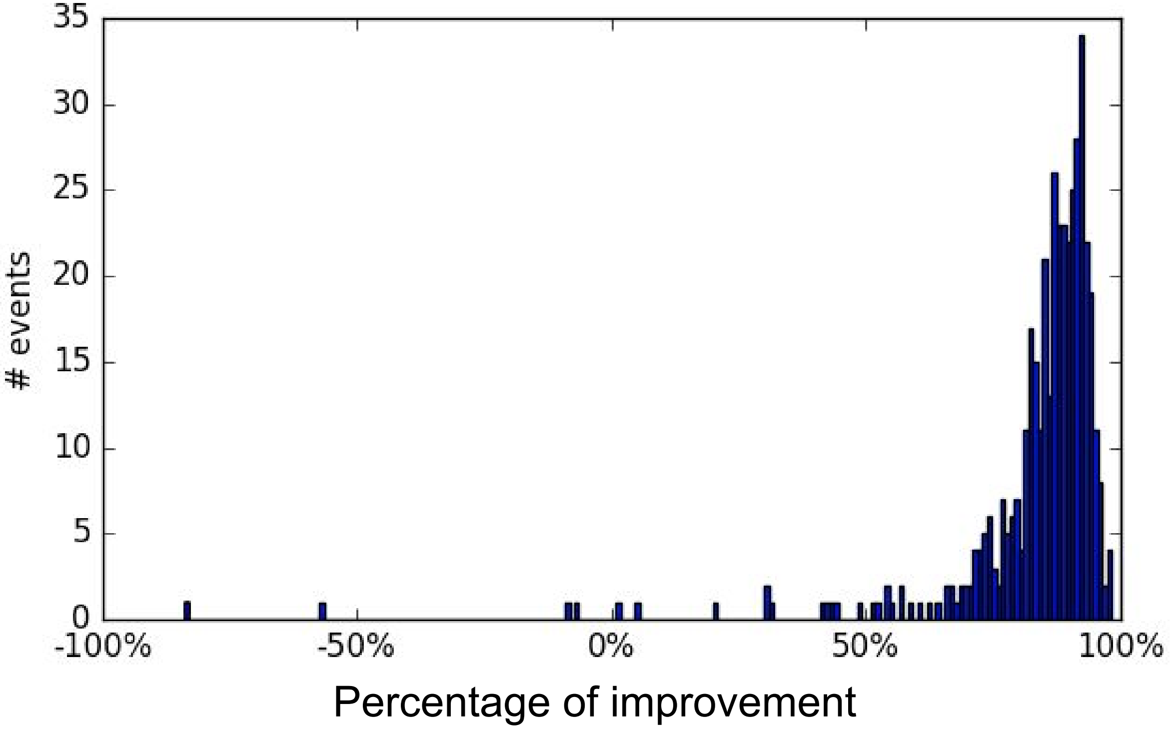
Markou, I., Rodrigues, F. and Pereira, F.C., 2017. Use of Taxi-Trip Data in Analysis of Demand Patterns for Detection and Explanation of Anomalies. Transportation Research Record: Journal of the Transportation Research Board

Step 2: propagating information

Correlated models



Preliminary results

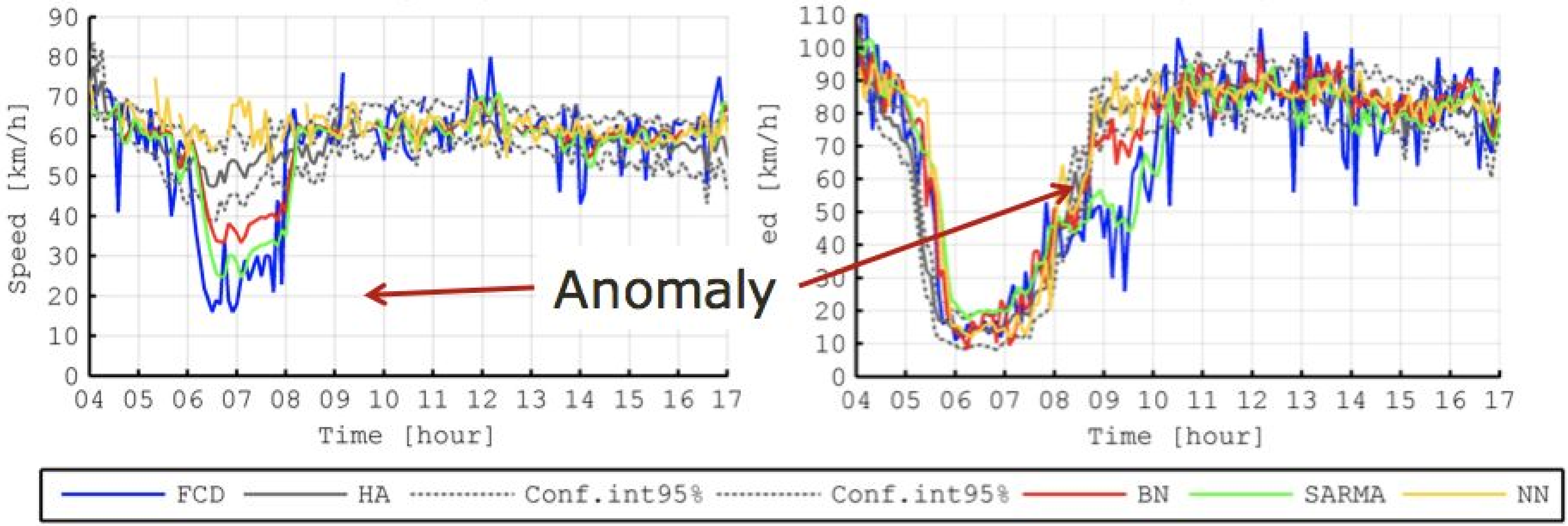


Non-recurrent scenarios

	Demand	Supply
Expectable	special events, demonstrations, holidays	road works, closures, mega events
Unexpectable	crisis situations, unknown high fluctuations	incidents, weather, crisis situations

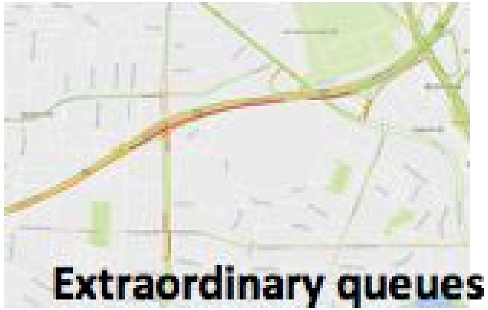
Unexpectable supply

Step 1: anomaly detection



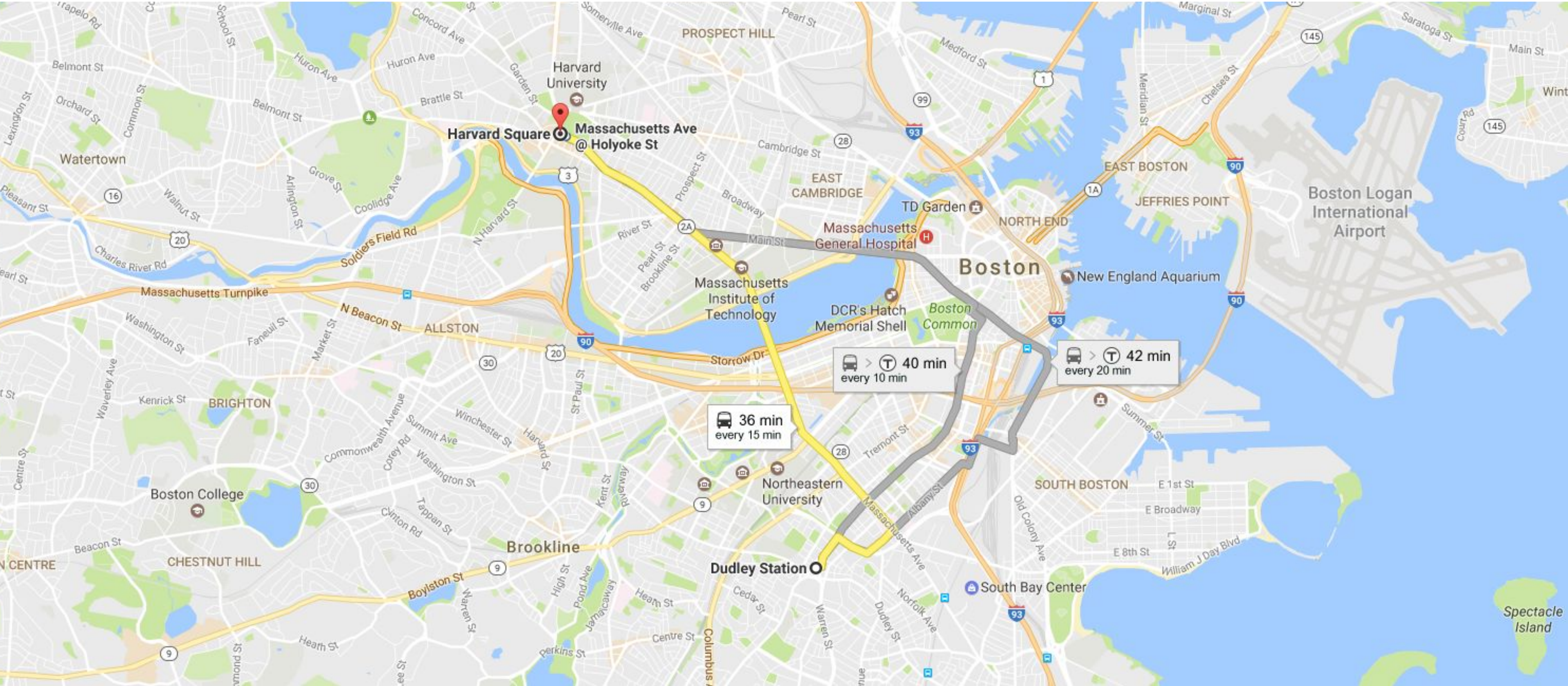
Running application in Denmark

Extraordinary queueing with Inrix data



Step 2: robust prediction

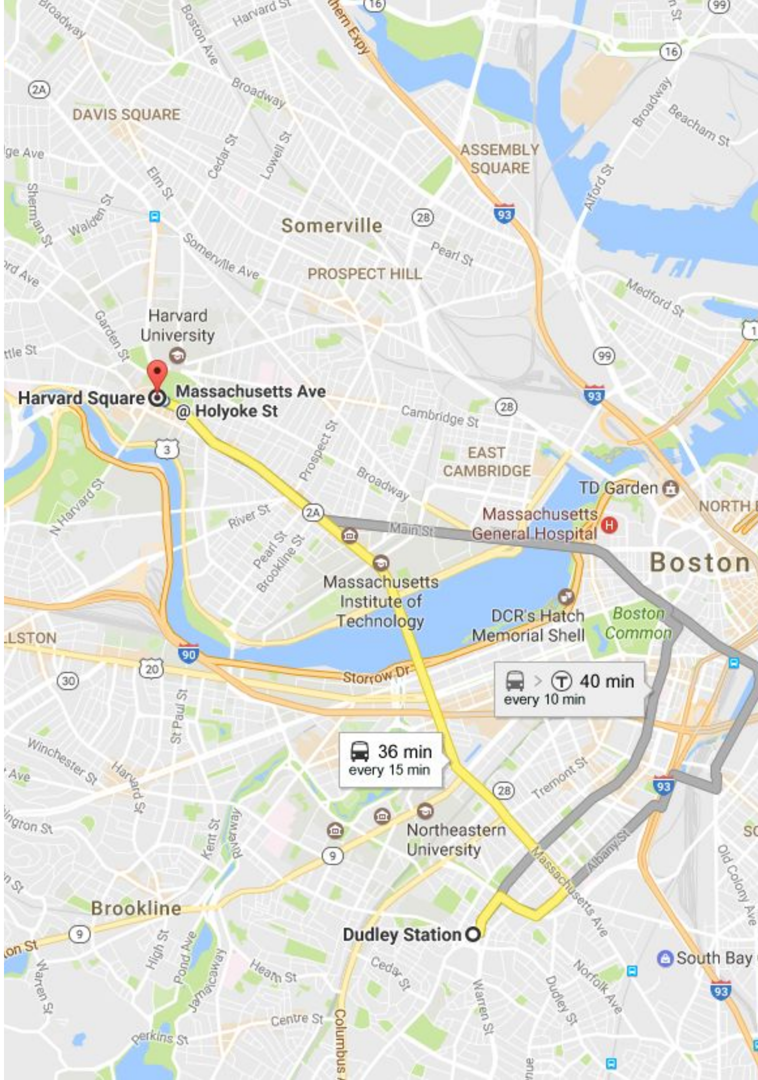
Step 2: robust prediction



Accounting for uncertainty

Why should we care?

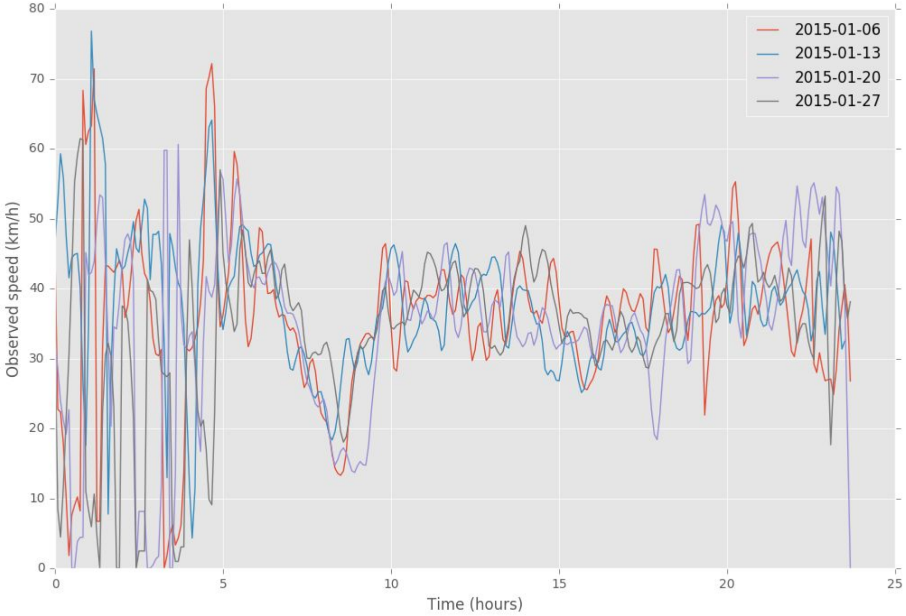
- We use prediction models to make decisions!



Accounting for uncertainty

Heteroscedastic models

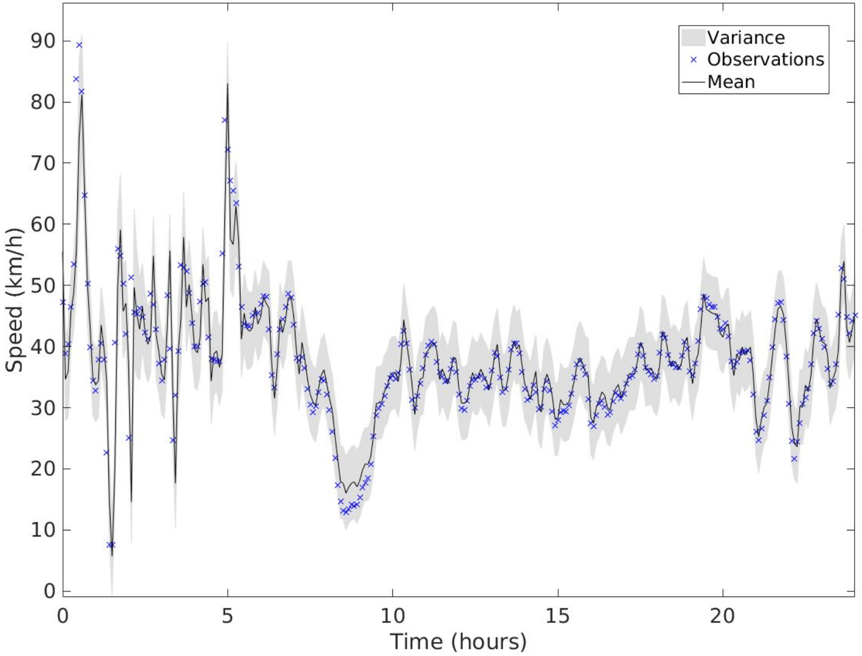
- Observation noise is non-constant (e.g. time-dependent)
- Jointly model signal mean and variance



Accounting for uncertainty

Heteroscedastic Gaussian processes (GPs)

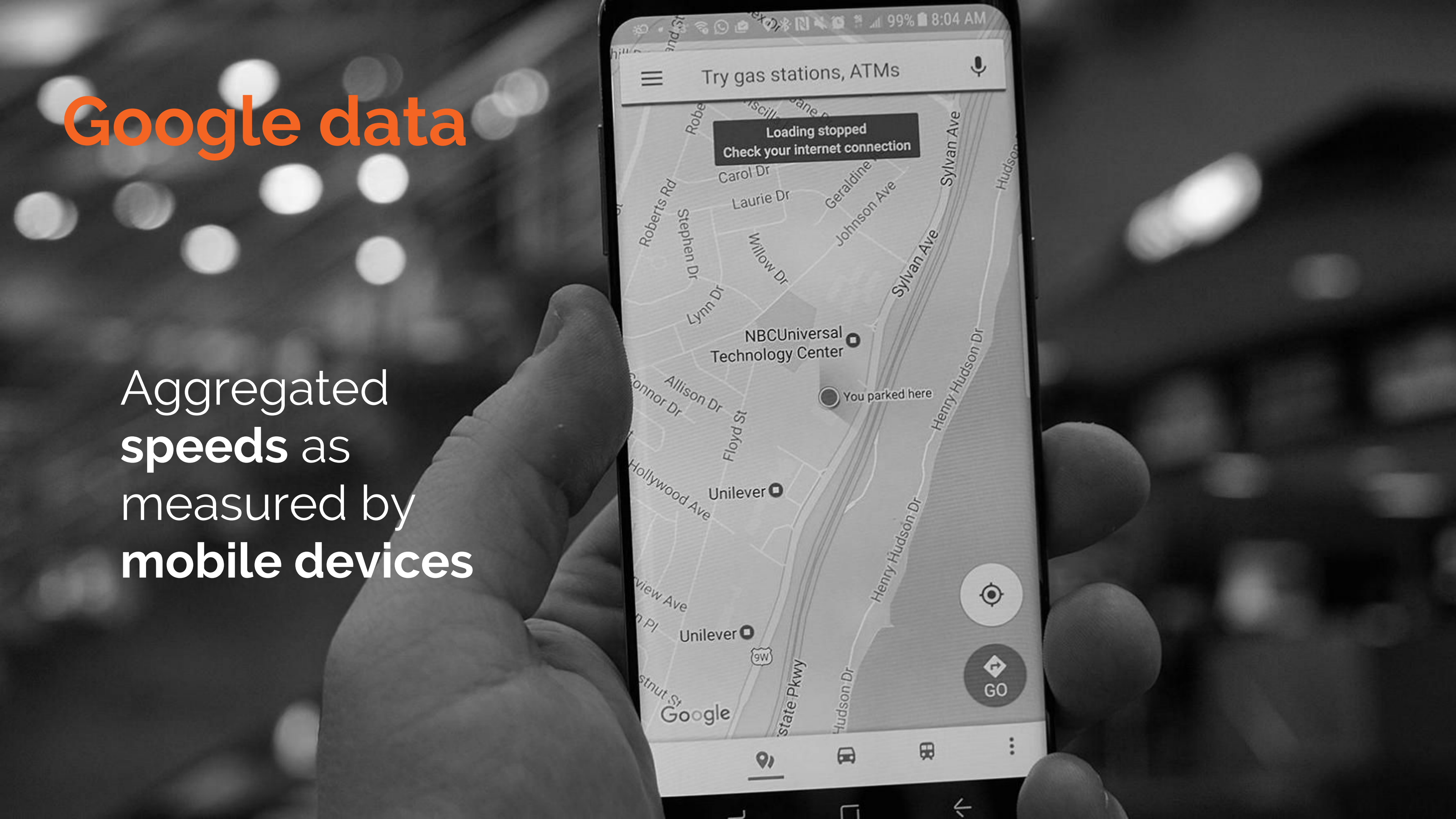
- GP models the mean of the signal
- Another GP models the variance of the signal

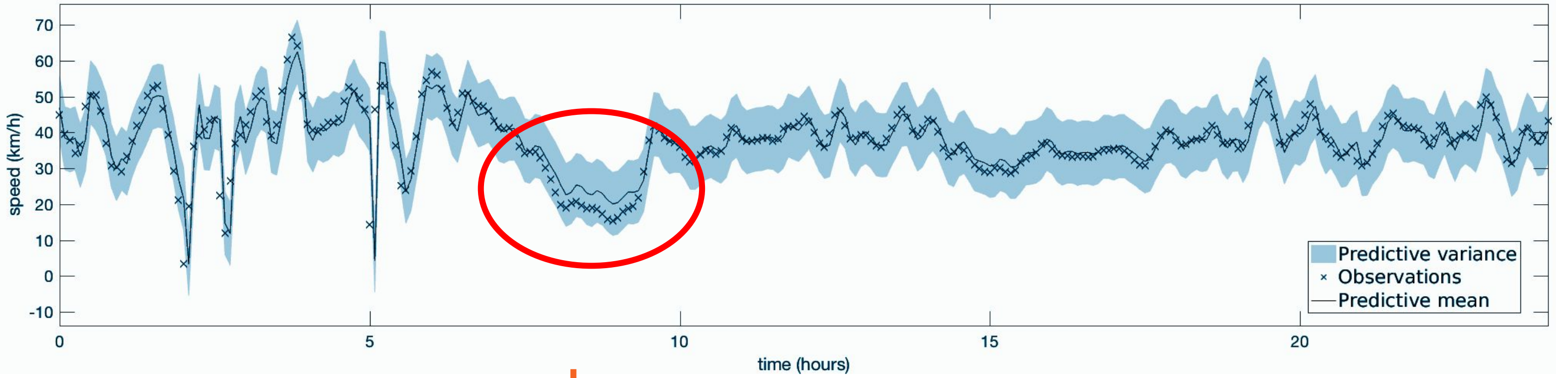


Recent work currently under review!

Google data

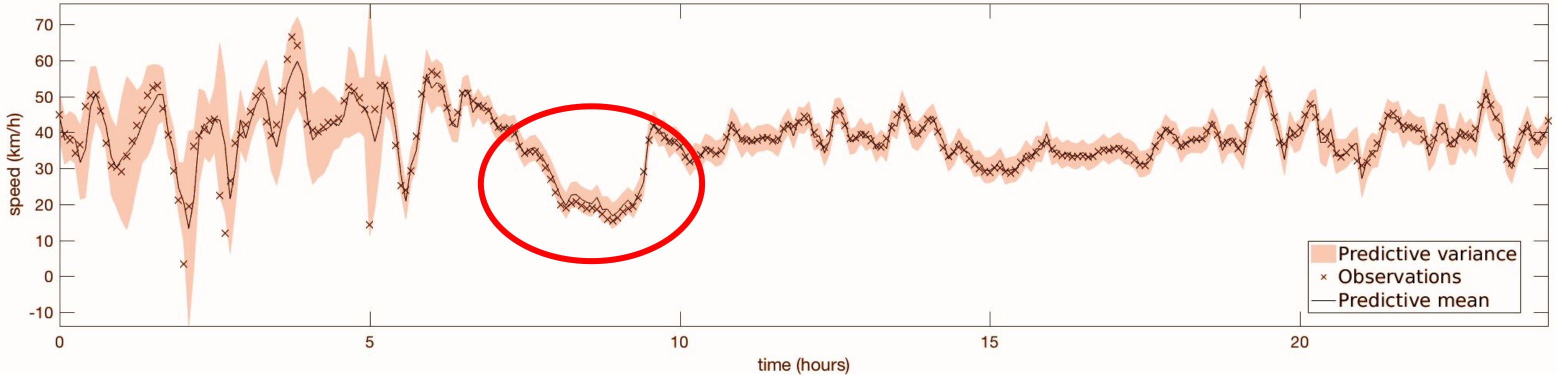
Aggregated **speeds** as measured by **mobile devices**



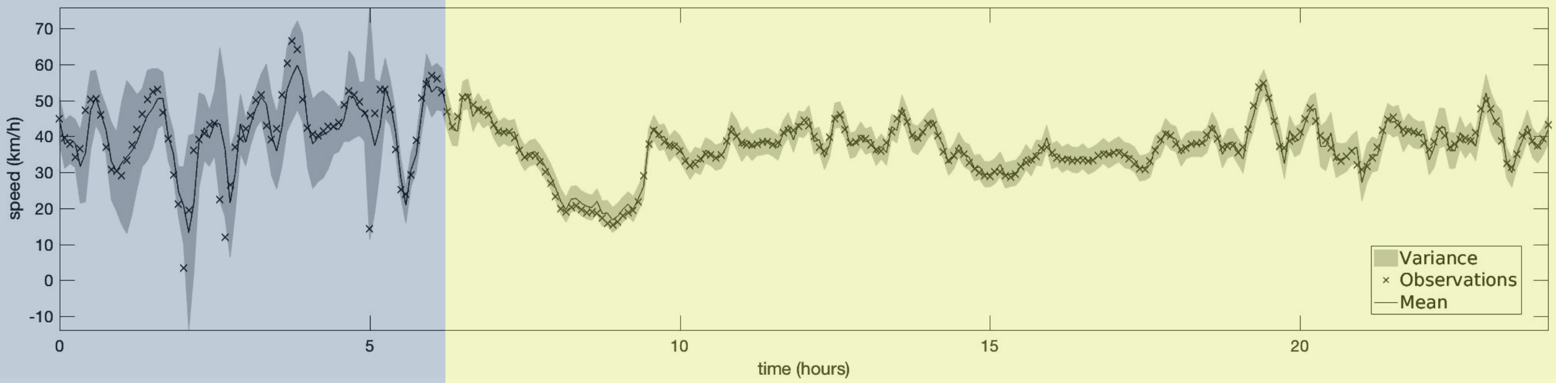


Heteroscedastic

More accurate predictions and more precise confidence intervals!



Properly handling uncertainty



More **uncertain**
during night periods

More **confident**
during day periods

Some results

Evaluation of the prediction means

MAE: mean absolute error
RAE: relative absolute error
R2: coeff. of determination

ID	Method	Eval: all periods			Eval: day periods		
		MAE	RAE	R^2	MAE	RAE	R^2
1	ARIMA	2.845	40.830	0.718	1.780	33.467	0.878
	GP	2.639	38.180	0.765	1.767	33.210	0.884
	HGP	2.396	34.368	0.778	1.467	27.576	0.913
	FC-HGP	**2.296**	**33.114**	**0.779**	**1.270**	**23.880**	**0.934**
4	ARIMA	2.933	43.471	0.717	1.812	36.219	0.863
	GP	2.595	38.463	0.770	1.637	32.724	0.886
	HGP	2.294	34.008	0.770	1.283	25.636	0.921
	FC-HGP	**2.272**	**33.678**	**0.783**	**1.202**	**24.019**	**0.933**
5	ARIMA	2.748	39.560	0.732	1.712	32.823	0.885
	GP	2.555	36.764	0.779	1.662	31.829	0.895
	HGP	2.342	33.696	**0.791**	1.423	27.235	0.918
	FC-HGP	**2.254**	**32.423**	0.785	**1.229**	**23.522**	**0.938**

Some results

Evaluation of the prediction intervals

NLPD: negative log predictive density
ICP: interval coverage percentage
MIL: mean interval length

Place ID	Method	NLPD	ICP	MIL
1	ARIMA	0.796	0.949	18.257
	GP	0.679	0.961	18.193
	HGP	0.453	0.950	14.987
	FC-HGP	**0.040**	0.959	11.540
4	ARIMA	0.783	0.942	18.017
	GP	0.728	0.960	18.114
	HGP	0.658	0.929	11.899
	FC-HGP	**0.019**	0.957	11.100
5	ARIMA	0.766	0.946	17.458
	GP	0.646	0.959	17.293
	HGP	0.418	0.953	14.514
	FC-HGP	**0.024**	0.958	11.176

Bus travel time prediction

We can exploit the network structure and spatio-temporal correlations to get robust joint prediction models!

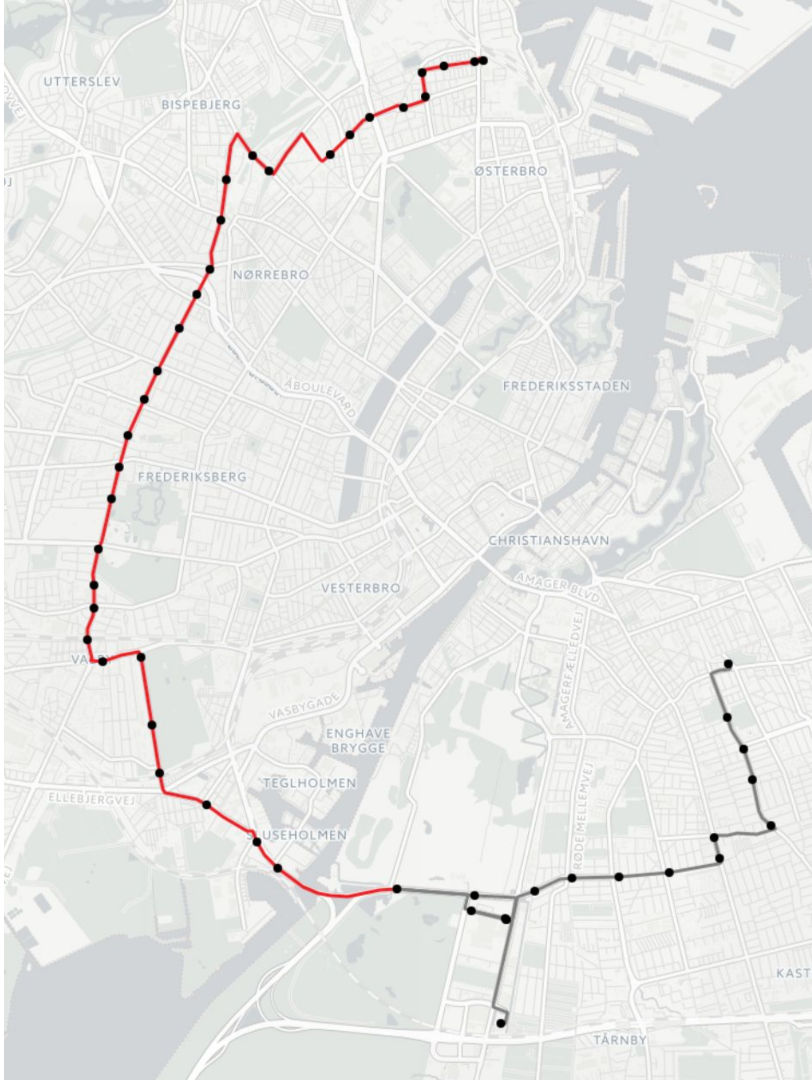
Robust bus travel time prediction

Deep learning architecture

Recent work currently under review!

Movia data

- Real-time AVL-system
- 1,2M travel time observations
- 4A bus line in Copenhagen
- May to October 2017



Results

Model	Time ahead	RMSE (min)	MAE (min)	MAPE (%)
Historical average		4.35	3.23	6.51 %
Current model	t + 1 (15 min)	4.92	3.90	8.05 %
	t + 2 (30 min)	4.91	3.46	6.82 %
	t + 3 (45 min)	5.47	4.15	8.68 %
Pure LSTM	t + 1 (15 min)	3.48	2.48	5.02 %
	t + 2 (30 min)	3.56	2.51	5.08 %
	t + 3 (45 min)	3.68	2.62	5.34 %
Google Traffic	t + 1 (15 min)	3.67	2.96	6.32 %
ConvLSTM	t + 1 (15 min)	2.66	1.99	4.19 %
	t + 2 (30 min)	2.89	2.11	4.44 %
	t + 3 (45 min)	3.11	2.27	4.75 %

RMSE: root mean squared error
MAE: mean absolute error
MAPE: mean absolute percentage error

Summary

- Accounting for the effect of external factors
  - E.g. events, weather, etc.
- Anomaly detection
- Properly handling uncertainty
  - Account for observation noise
  - Produce confidence intervals for predictions
- Robust joint prediction models
  - Exploit spatio-temporal correlations

Predicting for the adaptive transport system

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