BANEDANMARK

SORTEDmobility

DTU

Demand prediction and assignment for demand-oriented traffic management in rail

J. Victor Flensburg (MSc, PhD stud.) – jvfl@dtu.dk / jvfl@bane.dk
Carlos Lima Azevedo (Assoc. Prof.) – climaz@dtu.dk
Filipe Rodrigues (Assoc. Prof.) – rodr@dtu.dk

RailCPH 2023, 2023-05-22

ERA-NET Cofund Urban Accessibility and Connectivity

European Commission

URBAN EUROPE

Agenda

Agenda

- Background

Agenda

- Background
- Motivation

Agenda

- Background
- Motivation
- Framework overview

Agenda

- Background
- Motivation
- Framework overview
- Building blocks
  - Data
  - OD demand prediction
  - Arrival distributions
  - Path choice
  - Demand assignment

Agenda

- Background
- Motivation
- Framework overview
- Building blocks
    - Data
    - OD demand prediction
    - Arrival distributions
    - Path choice
    - Demand assignment
- Conclusion and perspectives

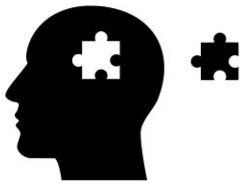
Background

The world of yesterday:

Background

The world of yesterday:

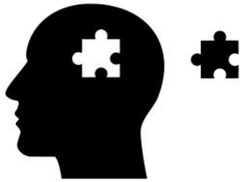
- Experiential decision making



Background

The world of yesterday:

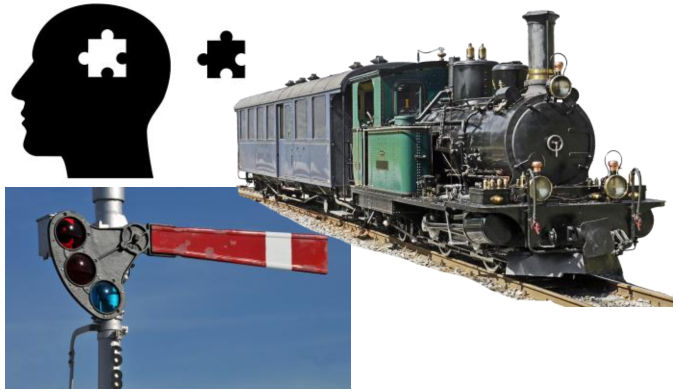
- Experiential decision making
- Analog signals



Background

The world of yesterday:

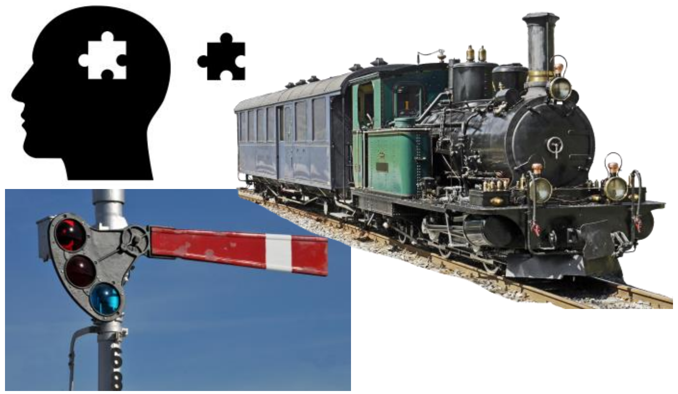
- Experiential decision making
- Analog signals
- Manual operation



Background

The world of yesterday:

- Experiential decision making
- Analog signals
- Manual operation
- Train-oriented management

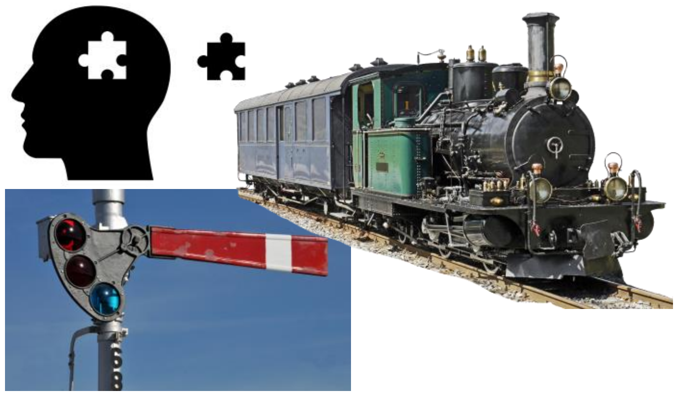


Background

The world of yesterday:

- Experiential decision making
- Analog signals
- Manual operation
- Train-oriented management

The world of tomorrow:



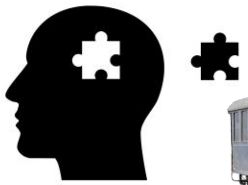
Background

The world of yesterday:

- Experiential decision making
- Analog signals
- Manual operation
- Train-oriented management

The world of tomorrow:

- Data-driven decision making

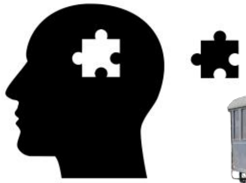

Background

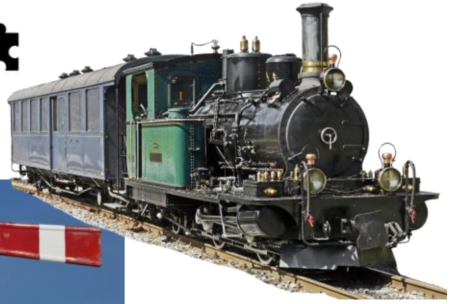
The world of yesterday:

- Experiential decision making
- Analog signals
- Manual operation
- Train-oriented management

The world of tomorrow:

- Data-driven decision making
- Digital signals



ertms

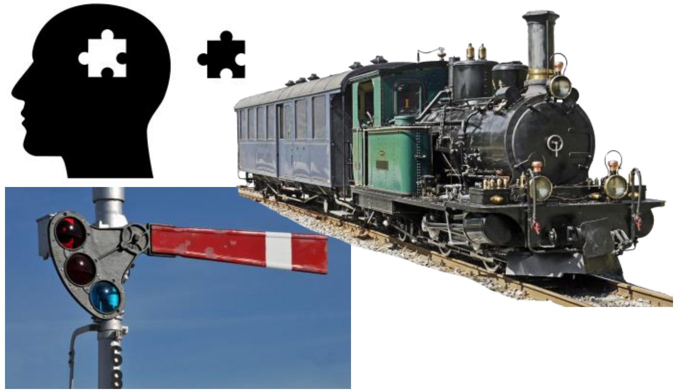
Background

The world of yesterday:

- Experiential decision making
- Analog signals
- Manual operation
- Train-oriented management

The world of tomorrow:

- Data-driven decision making
- Digital signals
- Automated operation

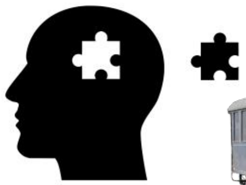
Background

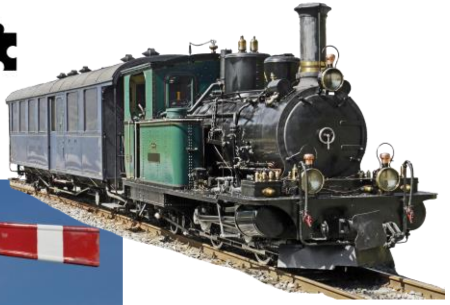
The world of yesterday:

- Experiential decision making
- Analog signals
- Manual operation
- Train-oriented management

The world of tomorrow:

- Data-driven decision making
- Digital signals
- Automated operation
- <u>Demand</u>-oriented management



Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

What we need to know:

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

What we need to know:

- Which trains to optimize?

Motivation

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

What we need to know:

- <u>Which</u> trains to optimize?
- <u>How</u> do people travel?

Motivation

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

What we need to know:

- Which trains to optimize?
- How do people travel?
- When do people travel?

Motivation

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

What we need to know:

- Which trains to optimize?
- How do people travel?
- When do people travel?
- Where do people travel?

Motivation

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

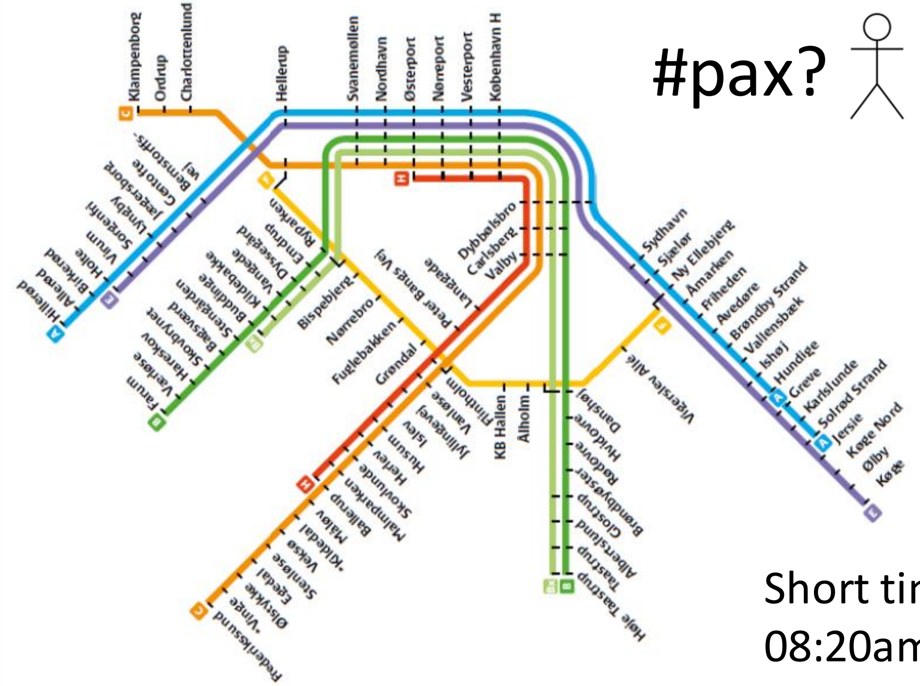
What we need to know:

- Which trains to optimize?
- How do people travel?
- When do people travel?
- Where do people travel?
- How many travellers?

Motivation

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).



#pax?

Short time interval, e.g., 08:20am to 08:40am

What we need to know:

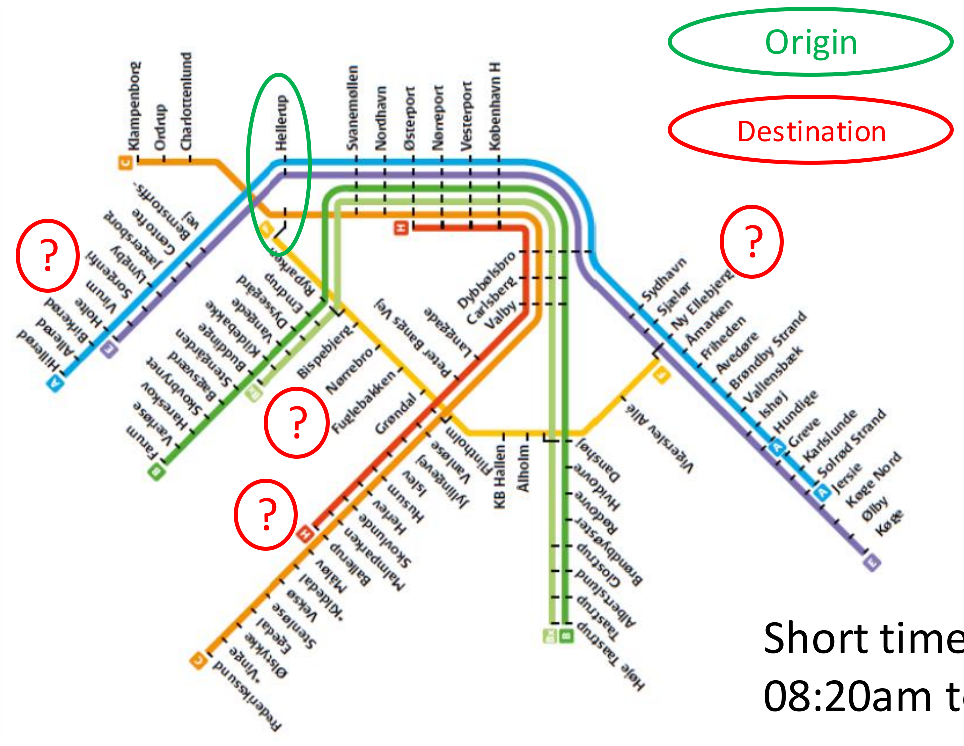
Motivation

- Which trains to optimize?
- How do people travel?
- When do people travel?
- Where do people travel?
- How many travellers?

Pipeline

Demand volume.

Motivation



Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

Short time interval, e.g., 08:20am to 08:40am

What we need to know:

Motivation

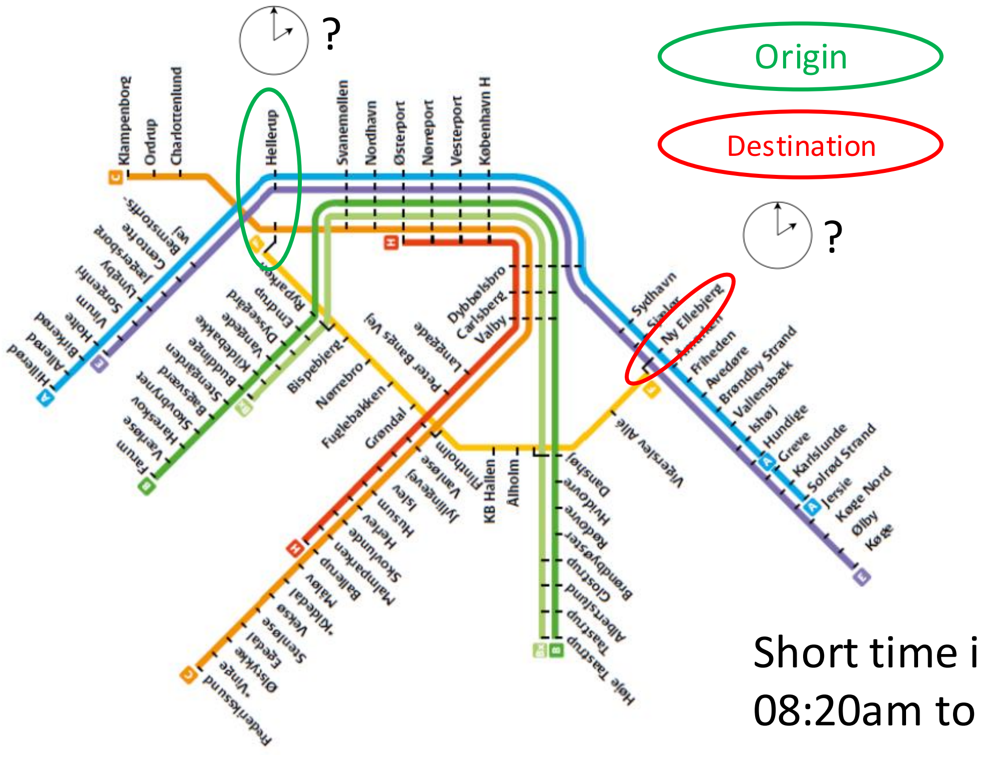
- <u>Which</u> trains to optimize?
- <u>How</u> do people travel?
- <u>When</u> do people travel?
- <u>Where</u> do people travel?
- <u>How many</u> travellers?

Pipeline

Spatial demand distribution.

Demand volume.

Motivation



Short time interval, e.g., 08:20am to 08:40am

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

What we need to know:

Motivation

- <u>Which</u> trains to optimize?
- <u>How</u> do people travel?
- <u>When</u> do people travel?
- <u>Where</u> do people travel?
- <u>How many</u> travellers?

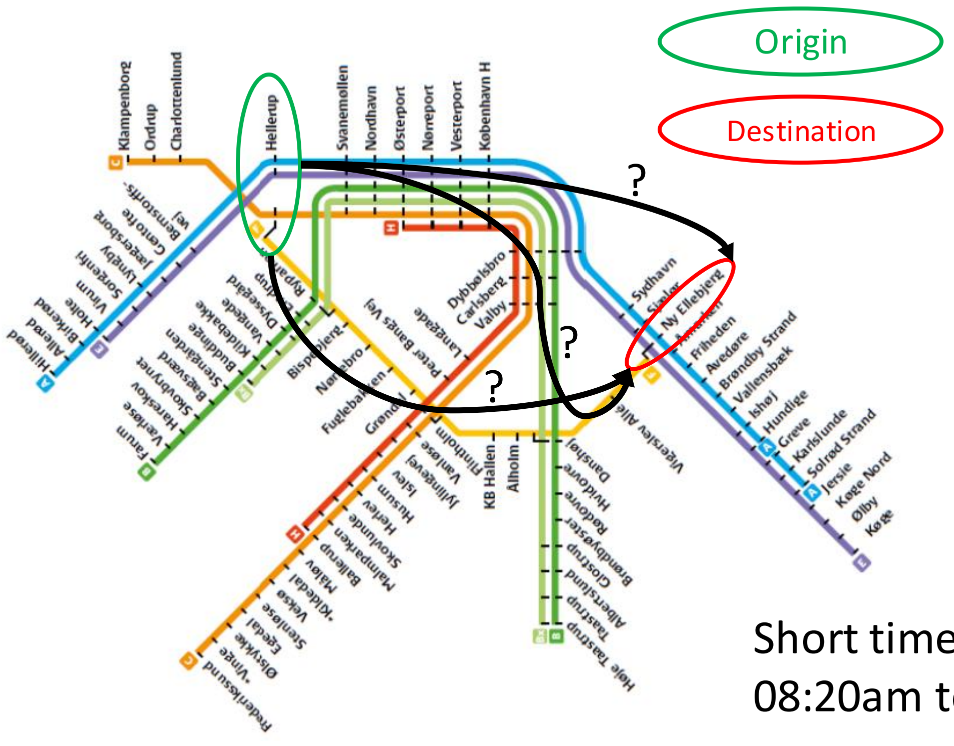
Pipeline

Temporal demand distribution.

Spatial demand distribution.

Demand volume.

Motivation



Short time interval, e.g., 08:20am to 08:40am

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).

What we need to know:

Motivation

- Which trains to optimize?
- How do people travel?
- When do people travel?
- Where do people travel?
- How many travellers?

Pipeline

Route/path choice.

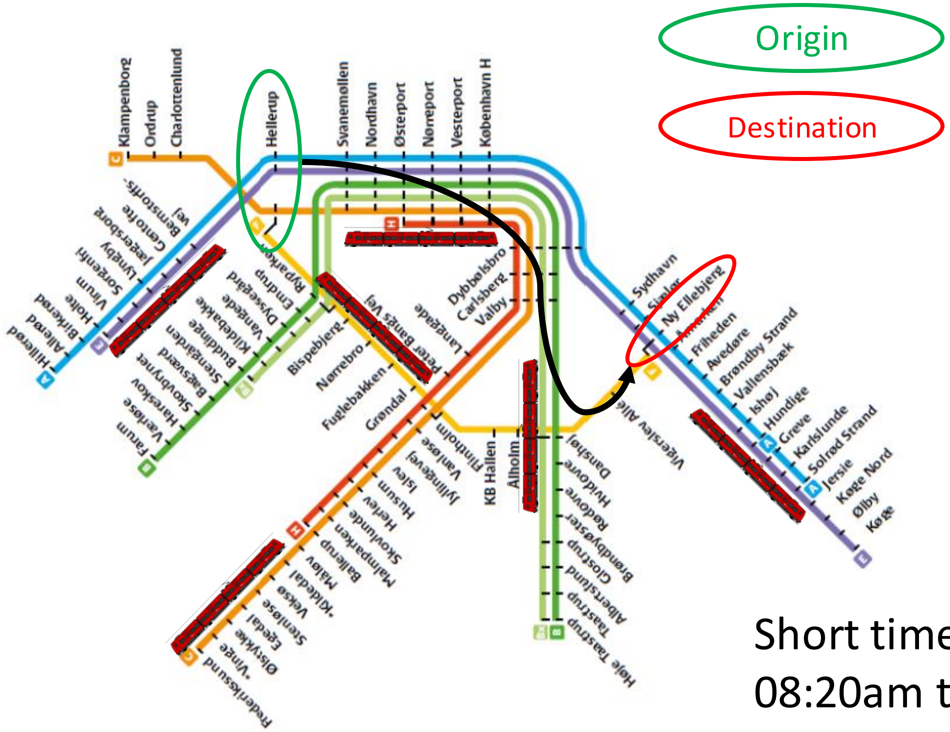
Temporal demand distribution.

Spatial demand distribution.

Demand volume.

Motivation

Goal: Manage rail traffic such that travel time of passengers is optimized in real-time (given an imperfect system).



Short time interval, e.g., 08:20am to 08:40am

What we need to know:

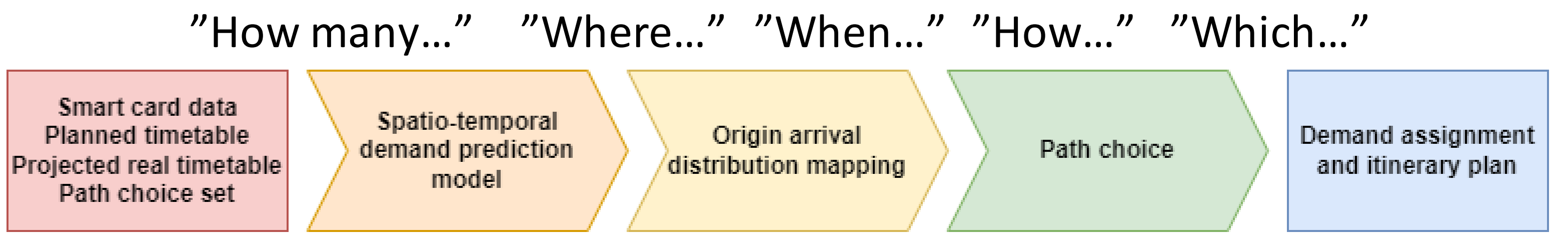
Motivation

- <u>Which</u> trains to optimize?
- <u>How</u> do people travel?
- <u>When</u> do people travel?
- <u>Where</u> do people travel?
- <u>How many</u> travellers?

Pipeline

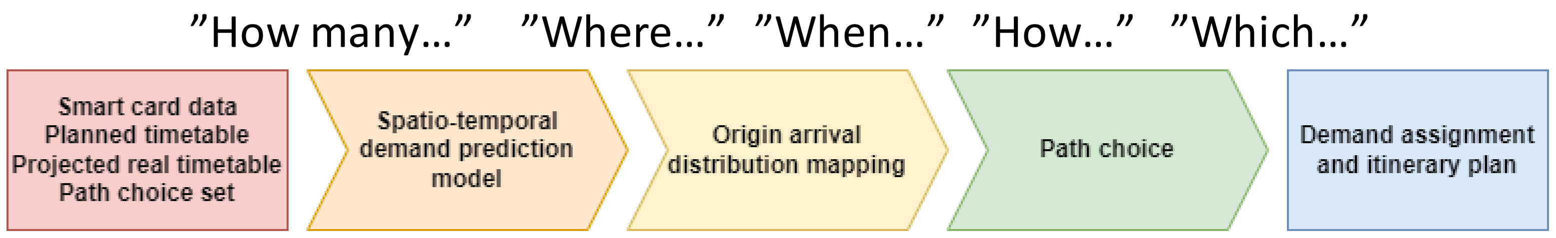
Demand assignment.
Route/path choice.
Temporal demand distribution.
Spatial demand distribution.
Demand volume.

Framework overview



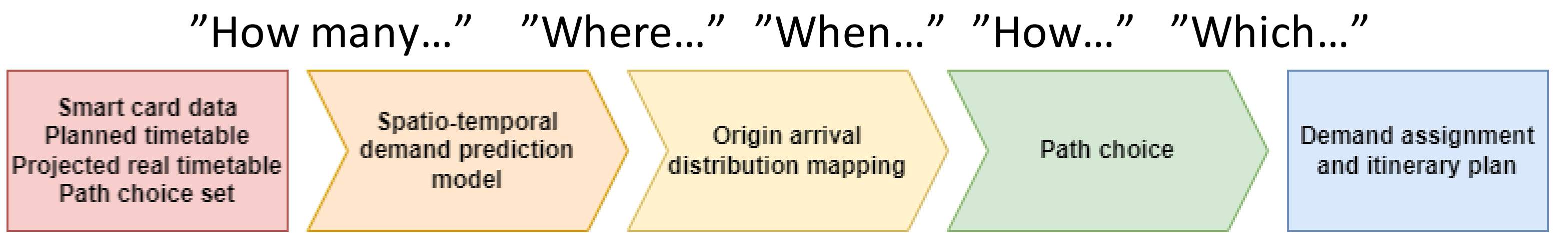
Framework overview

- Input – demand/supply/contextual data, planned/projected timetable, static path choice set, route choice parameters, …



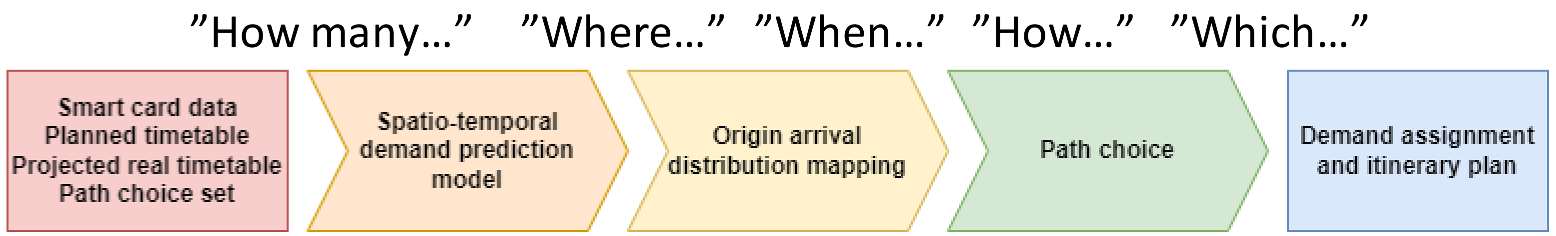
Framework overview

- Input – demand/supply/contextual data, planned/projected timetable, static path choice set, route choice parameters, …
- Model - Data-driven origin-destination (OD) demand prediction



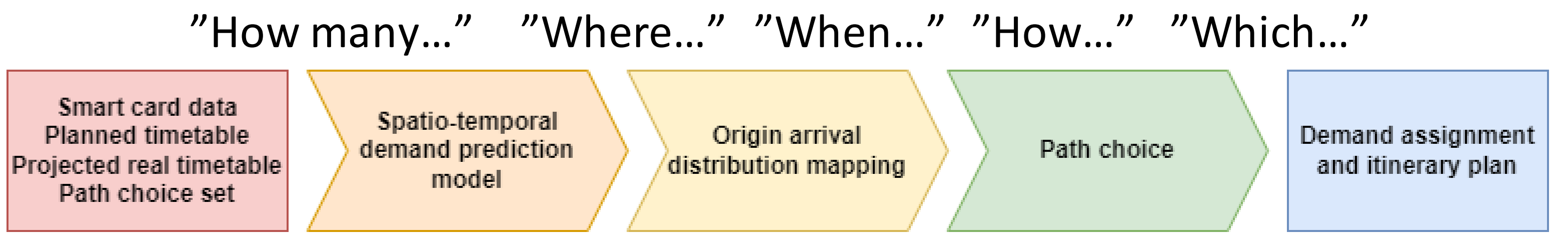
Framework overview

- Input – demand/supply/contextual data, planned/projected timetable, static path choice set, route choice parameters, …
- Model - Data-driven origin-destination (OD) demand prediction
- Model - Estimated origin arrival distributions



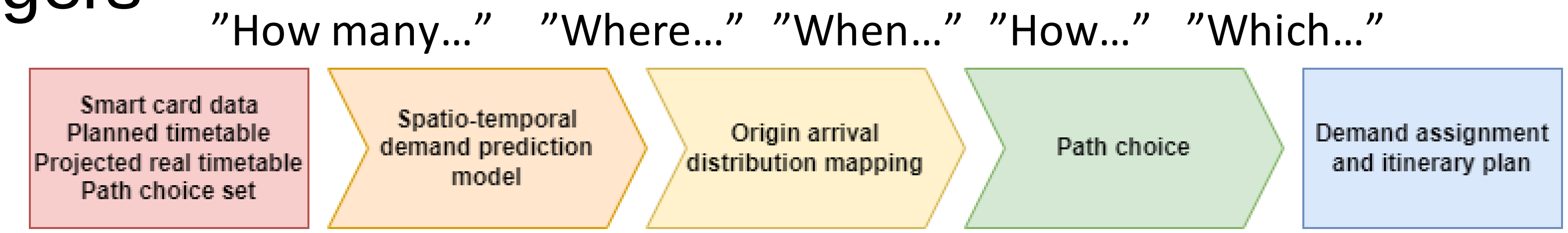
Framework overview

- Input – demand/supply/contextual data, planned/projected timetable, static path choice set, route choice parameters, …
- Model - Data-driven origin-destination (OD) demand prediction
- Model - Estimated origin arrival distributions
- Model – Train-specific path choice



Framework overview

- Input – demand/supply/contextual data, planned/projected timetable, static path choice set, route choice parameters, …
- Model - Data-driven origin-destination (OD) demand prediction
- Model - Estimated origin arrival distributions
- Model – Train-specific path choice
- Output – Expected train-specific itineraries of predicted passengers



Building blocks - Data

Building blocks - Data

- Smart card records (e.g., Rejsekort) – detailed multi-modal itineraries of passengers (assumed collected in real-time)

Building blocks - Data

- Smart card records (e.g., Rejsekort) – detailed multi-modal itineraries of passengers (assumed collected in real-time)
- Timetable (static) – planned timetable that trains ideally follow

Building blocks - Data

- Smart card records (e.g., Rejsekort) – detailed multi-modal itineraries of passengers (assumed collected in real-time)
- Timetable (static) – planned timetable that trains ideally follow
- Timetable (projected/realized) – projected trajectory of traffic, updated in real time

Building blocks - Data

- Smart card records (e.g., Rejsekort) – detailed multi-modal itineraries of passengers (assumed collected in real-time)
- Timetable (static) – planned timetable that trains ideally follow
- Timetable (projected/realized) – projected trajectory of traffic, updated in real time
- Static path choice set – estimated realistic (line-based) paths for each OD pair

Building blocks - Data

- Smart card records (e.g., Rejsekort) – detailed multi-modal itineraries of passengers (assumed collected in real-time)
- Timetable (static) – planned timetable that trains ideally follow
- Timetable (projected/realized) – projected trajectory of traffic, updated in real time
- Static path choice set – estimated realistic (line-based) paths for each OD pair
- Path choice preferences – estimated path choice model parameters for attributes like travel/waiting/walking time, transfers, etc.

Building blocks – OD demand prediction

- **Purpose:** At current time, predict demand distributed on OD pairs for next interval(s) of e.g., 10, 20, 30, 60 minutes

Building blocks – OD demand prediction

- **Purpose:** At current time, predict demand distributed on OD pairs for next interval(s) of e.g., 10, 20, 30, 60 minutes
- **Input:** Observable data that correlate with future demand distribution (observed OD matrices, recent supply/reliability variations, contextual data like weather,…)

REJSEKORT

DMI

Building blocks – OD demand prediction

- **Purpose:** At current time, predict demand distributed on OD pairs for next interval(s) of e.g., 10, 20, 30, 60 minutes
- **Input:** Observable data that correlate with future demand distribution (observed OD matrices, recent supply/reliability variations, contextual data like weather,…)
- **Model structures:** Linear regression, auto-regression, recurrent neural network, gated recurrent unit, graph NN, …

Building blocks – OD demand prediction

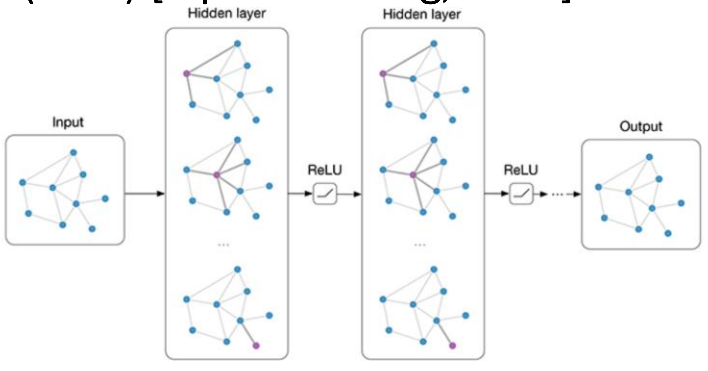
- **Purpose:** At current time, predict demand distributed on OD pairs for next interval(s) of e.g., 10, 20, 30, 60 minutes
- **Input:** Observable data that correlate with future demand distribution (observed OD matrices, recent supply/reliability variations, contextual data like weather,…)
- **Model structures:** Linear regression, auto-regression, recurrent neural network, gated recurrent unit, graph NN, …
- **Output:** OD matrix for each predicted interval (”how many”/”where”/”when”)

Building blocks – OD demand prediction

Considerations:

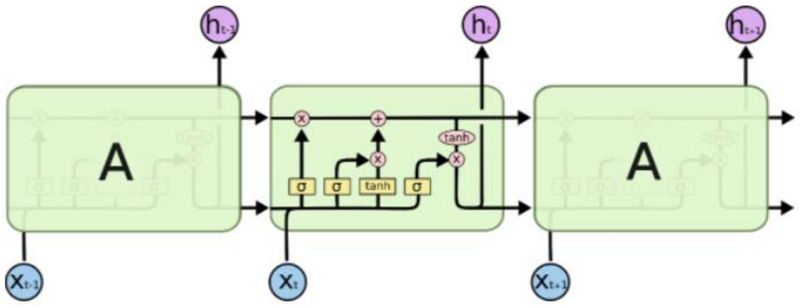
- High-dimensional sparse output – deep learning performs best, usually combination of ANNs tailored for sequential and spatial data, respectively

Graph Convolutional Network (GCN) [Kipf & Welling, 2017]

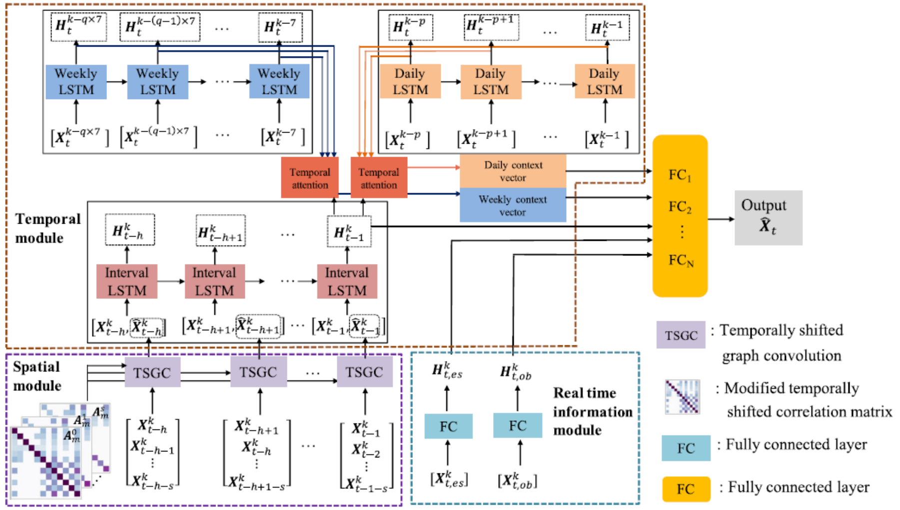


Figur: T. Kipf – https://tkipf.github.io/graph-convolutional-networks/

Long Short-Term Memory (LSTM) [Hochreiter & Schmidhuber, 1997]



Figur: http://colah.github.io/

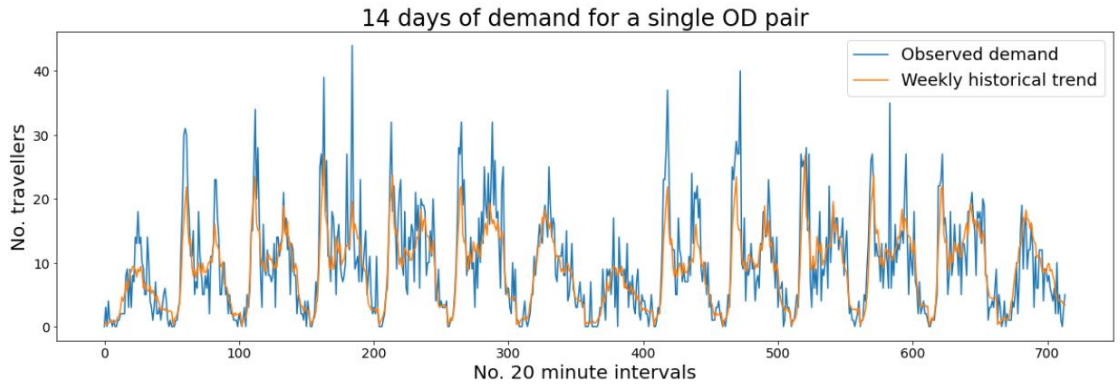


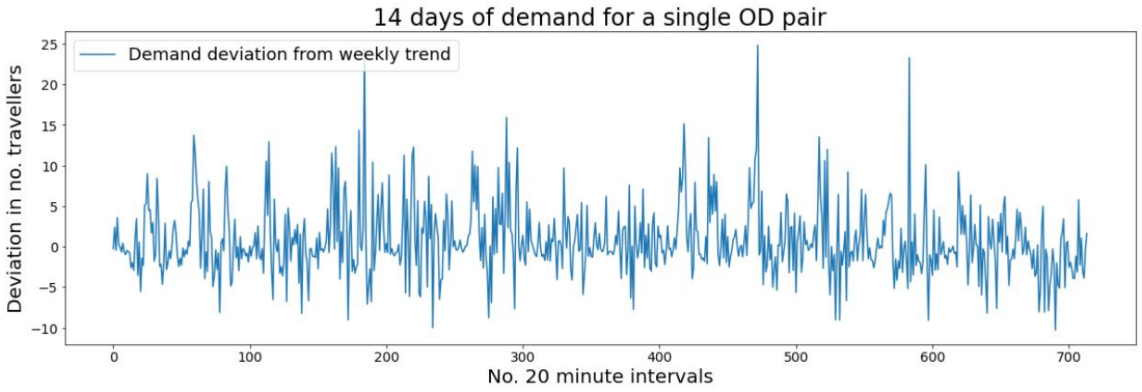
[1] Wenhua Jiang, Zhenliang Ma & Haris N. Koutsopoulos (2022). Deep learning for short-term origin–destination passenger flow prediction under partial observability in urban railway systems. *Neural Computing and Applications*, *34*, 4813-4830.

Building blocks – OD demand prediction

Considerations:

- High-dimensional sparse output – deep learning performs best, usually combination of ANNs tailored for sequential and spatial data, respectively
- Daily/weekly periodic behavior – periodic trend removed in input data and training/estimation target, only deviations predicted





Building blocks – OD demand prediction

Considerations:

- High-dimensional sparse output – deep learning performs best, usually combination of ANNs tailored for sequential and spatial data, respectively
- Daily/weekly periodic behavior – periodic trend removed in input data and training/estimation target, only deviations predicted
- Recent OD demand (i.e., last 1-2 hours) essential input features accounting for both spatial and temporal correlations

Building blocks – arrival distributions

- **Purpose:** Compute discretized traveller system entry time distribution at each station within predicted time intervals

Building blocks – arrival distributions

- **Purpose:** Compute discretized traveller system entry time distribution at each station within predicted time intervals
- **Input:** Type of distribution, estimated distribution parameters according to service headway

Building blocks – arrival distributions

- **Purpose:** Compute discretized traveller system entry time distribution at each station within predicted time intervals
- **Input:** Type of distribution, estimated distribution parameters according to service headway
- **Model structures:** Heuristic algorithm

Building blocks – arrival distributions

- **Purpose:** Compute discretized traveller system entry time distribution at each station within predicted time intervals
- **Input:** Type of distribution, estimated distribution parameters according to service headway
- **Model structures:** Heuristic algorithm
- **Output:** Normalized discrete distribution of passenger entry times at each station (e.g., in 30 second, 1 minute, 2 minute steps) (”when”)

Building blocks – arrival distributions

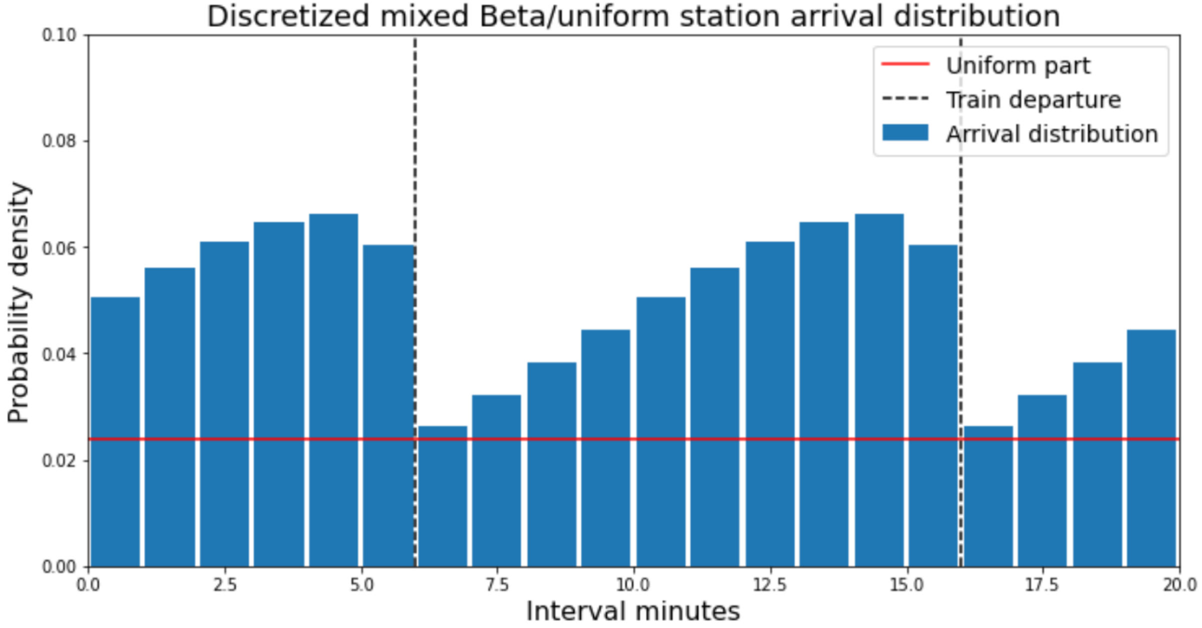
Considerations:

- Ingvardson et al., 2018 [1], estimate mixed Beta/Uniform distributions between train departures on Copenhagen S-bane, depending on headway

Building blocks – arrival distributions

Considerations:

- Ingvardson et al., 2018 [1], estimate mixed Beta/Uniform distributions between train departures on Copenhagen S-bane, depending on headway
- Arrival distribution for each departure based on static timetable, stacked and normalized



1) J. B. Ingvardson, O. A. Nielsen, S. Raveau, B. F. Nielsen, "Passenger arrival and waiting time distributions dependent on train service frequency and station characteristics: A smart card data analysis", Transportation Research Part C: Emerging Technologies, Volume 90, 2018, pp. 292-306

Building blocks – path choice

- **Purpose:** For each OD pair and origin arrival time, compute available paths, choice model attributes and probabilities

Building blocks – path choice

- **Purpose:** For each OD pair and origin arrival time, compute available paths, choice model attributes and probabilities
- **Input:** Projected timetable, path preferences, static pathset

Building blocks – path choice

- **Purpose:** For each OD pair and origin arrival time, compute available paths, choice model attributes and probabilities
- **Input:** Projected timetable, path preferences, static pathset
- **Model structures:** Heuristic for path generation, discrete choice model for probabilities, e.g., logit model

Building blocks – path choice

- **Purpose:** For each OD pair and origin arrival time, compute available paths, choice model attributes and probabilities
- **Input:** Projected timetable, path preferences, static pathset
- **Model structures:** Heuristic for path generation, discrete choice model for probabilities, e.g., logit model
- **Output:** Sets of train-based paths (”how”/”which”), and probability distributions for each set

Building blocks – path choice

Considerations:

- Train-based pathsets are here computed based on a pre-computed static line-based pathset per OD pair and assumptions on transfer time, etc.

Working timetable:

F Hellerup

↓		↑
02 12 22 32 42 52	Hellerup	24 34 44 54 04 14
04 14 24 34 44 54	Ryparken	21 31 41 51 01 11
06 16 26 36 46 56	Bispebjerg	19 29 39 49 59 09
07 17 27 37 47 57	Nørrebro	18 28 38 48 58 08
09 19 29 39 49 59	Fuglebakken	16 26 36 46 56 06
10 20 30 40 50 00	Grøndal	15 25 35 45 55 05
12 22 32 42 52 02	Flintholm	13 23 33 43 53 03
13 23 33 43 53 03	KB Hallen	12 22 32 42 52 02
15 25 35 45 55 05	Ålholm	10 20 30 40 50 00
16 26 36 46 56 06	Danshøj	09 19 29 39 49 59
17 27 37 47 57 07	Vigerslev Allé	08 18 28 38 48 58
20 30 40 50 00 10	Ny Ellebjerg	06 16 26 36 46 56

F Ny Ellebjerg

↓		↑
41 **51** 01 **11** 21 **31**	**København H**	27 **37** 47 **57** 07 **17**
43 **53** 03 **13** 23 **33**	Dybbølsbro	23 **33** 43 **53** 03 **13**
45 **55** 05 **15** 25 **35**	Carlsberg	21 **31** 41 **51** 01 **11**
48 **58** 08 **18** 28 **38**	Valby	19 **29** 39 **49** 59 **09**
50 **00** 10 **20** 30 **40**	Danshøj	17 **27** 37 **47** 57 **07**
51 **01** 11 **21** 31 **41**	Hvidovre	15 **25** 35 **45** 55 **05**
53 **03** 13 **23** 33 **43**	Rødovre	13 **23** 33 **43** 53 **03**
55 **05** 15 **25** 35 **45**	Brøndbyøster	11 **21** 31 **41** 51 **01**
58 **08** 18 **28** 38 **48**	Glostrup	08 **18** 28 **38** 48 **58**
01 **11** 21 **31** 41 **51**	Albertslund	06 **16** 26 **36** 46 **56**
04 **14** 24 **34** 44 **54**	Taastrup	02 **12** 22 **32** 42 **52**
07 **17** 27 **37** 47 **57**	Høje Taastrup	00 **10** 20 **30** 40 **50**

B Høje Taastrup

Line-based pathset:

Building blocks – path choice

Considerations:

- Train-based pathsets are here computed based on a pre-computed static line-based pathset per OD pair and assumptions on transfer time, etc.
- Path preferences can be homogenous or heterogenous

Building blocks – path choice

Considerations:

- Train-based pathsets are here computed based on a pre-computed static line-based pathset per OD pair and assumptions on transfer time, etc.
- Path preferences can be homogenous or heterogenous
- Core choice attributes are in-vehicle travel time, initial waiting time, transfer walking/waiting time, and number of transfers

Building blocks – path choice

Considerations:

- Train-based pathsets are here computed based on a pre-computed static line-based pathset per OD pair and assumptions on transfer time, etc.
- Path preferences can be homogenous or heterogenous
- Core choice attributes are in-vehicle travel time, initial waiting time, transfer walking/waiting time, and number of transfers
- Preferences estimated from domain-specific transport models

Building blocks – demand assignment

- Predict passenger <u>volume</u>, <u>arrival time</u> distribution, and <u>path choice</u>

Building blocks – demand assignment

- Predict passenger volume, arrival time distribution, and path choice
- Define passengers of each OD pair, origin arrival time, and path choice as a homogenous passenger group

Building blocks – demand assignment

- Predict passenger volume, arrival time distribution, and path choice
- Define passengers of each OD pair, origin arrival time, and path choice as a homogenous passenger group
- Collect and output all passenger groups and path itineraries

Building blocks – demand assignment

- Predict passenger volume, arrival time distribution, and path choice
- Define passengers of each OD pair, origin arrival time, and path choice as a homogenous passenger group
- Collect and output all passenger groups and path itineraries
- *Passenger assignment plan interpretable by demand-oriented traffic management module*

Conclusion and perspectives

Summary:

Conclusion and perspectives

Summary:

- Cutting-edge data-driven real-time OD demand prediction

Conclusion and perspectives

Summary:

- Cutting-edge data-driven real-time OD demand prediction
- Estimated arrival distributions based on timetable

Conclusion and perspectives

Summary:

- Cutting-edge data-driven real-time OD demand prediction
- Estimated arrival distributions based on timetable
- Train-based pathset generation

Conclusion and perspectives

Summary:

- Cutting-edge data-driven real-time OD demand prediction
- Estimated arrival distributions based on timetable
- Train-based pathset generation
- Train-specific path choice model

Conclusion and perspectives

Summary:

- Cutting-edge data-driven real-time OD demand prediction
- Estimated arrival distributions based on timetable
- Train-based pathset generation
- Train-specific path choice model
- Output passenger assignment interpretable by automated traffic management module to optimize passenger travel time

Conclusion and perspectives

Limitations:

Conclusion and perspectives

Limitations:

- Only rail considered and feeder services like buses ignored, weakening quality of assumptions

Conclusion and perspectives

Limitations:

- Only rail considered and feeder services like buses ignored, weakening quality of assumptions
- Real-time data availability assumption crucial for framework

Conclusion and perspectives

Limitations:

- Only rail considered and feeder services like buses ignored, weakening quality of assumptions
- Real-time data availability assumption crucial for framework
- Validation of path choice not always possible

Conclusion and perspectives

Limitations:

- Only rail considered and feeder services like buses ignored, weakening quality of assumptions
- Real-time data availability assumption crucial for framework
- Validation of path choice not always possible

Perspectives:

- Modular framework enables incremental improvement

Conclusion and perspectives

Limitations:

- Only rail considered and feeder services like buses ignored, weakening quality of assumptions
- Real-time data availability assumption crucial for framework
- Validation of path choice not always possible

Perspectives:

- Modular framework enables incremental improvement
- Framework in principle extendable to multimodal system (input/output dimensionality might increase a lot!)

Thank you for your attention!

J. Victor Flensburg – jvfl@dtu.dk / jvfl@bane.dk

Carlos M. Lima Azevedo – climaz@dtu.dk

Filipe Rodrigues – rodr@dtu.dk

This project is supported by the European Commission and funded under the Horizon 2020 ERA-NET Cofund scheme under grant agreement N° 875022

Innovationsfonden

This project is co-funded by Innovation Fund Denmark