Data Driven Transport Planning – Hype or Asset ?

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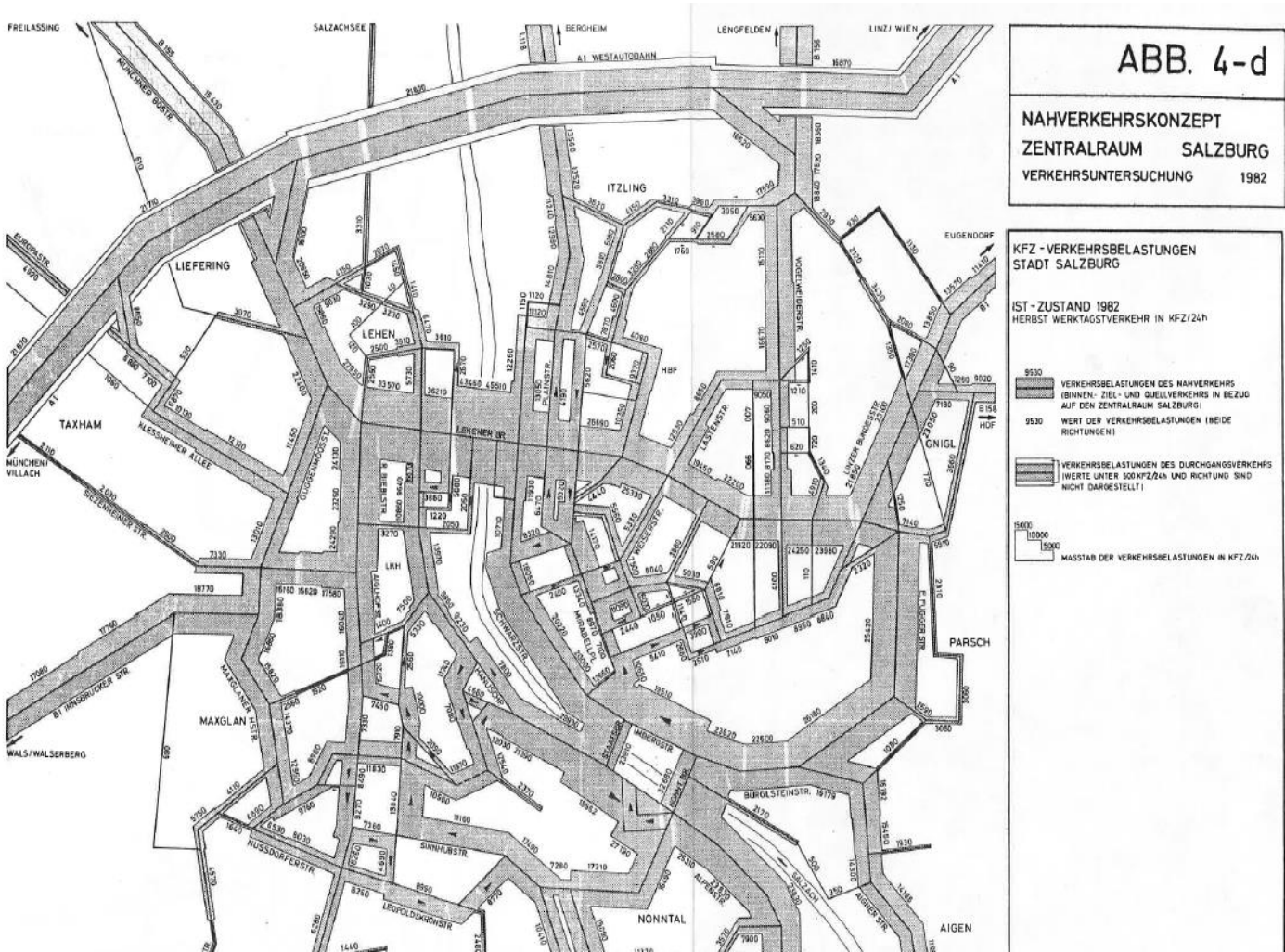
with support by Michael CIK

Transport Planning: Where do we go now?
Zürich, Dec. 8th, 2023

Data driven

Transport planning



Travel Demand Models require data

- Axhausen, K.W. (1989) Simulating activity chains: German approach, Journal of Transportation Engineering, 115 (3) 316–325.

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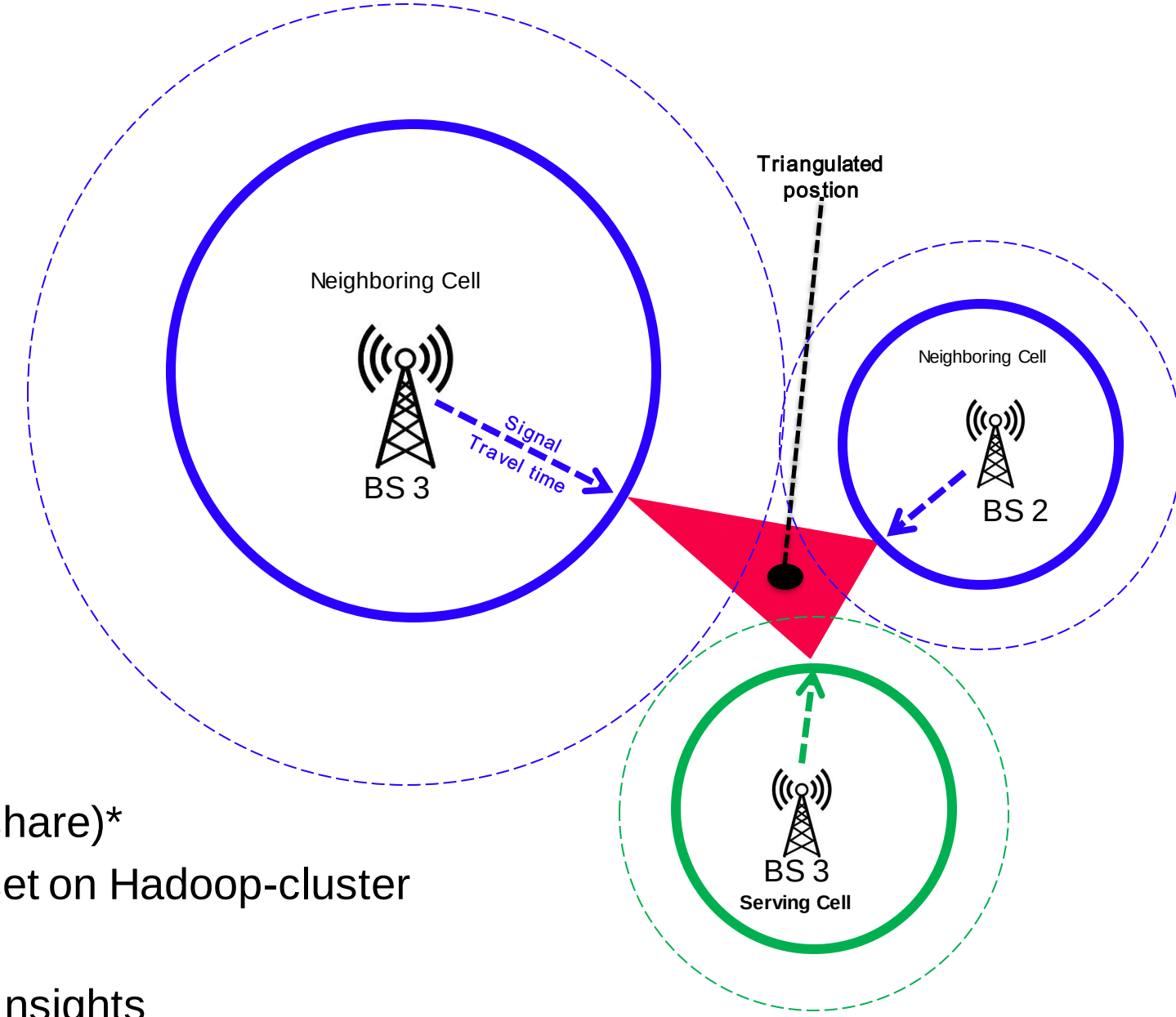
Mobile Phone Signaling Data (FPD (Floating Phone Data), CSD (Cellular Signaling Data))

Mobile Phone signaling Data (FPD, CSD)

- Location
  - estimated by triangulation
  - monitoring system of telecom
- Events of mobile device
  - IMSI → anonymized daily unique ID
  - Location (estimated)
  - Time, Event type, Home network
- ~ 1000 -2000 events/day per device (LTE by Austrian provider A1)
- A1 Austria:
  - 3.2 Mio mobile devices (38,2% market share)*
  - since 2019 ~80 GB/day, ~125 TB dataset on Hadoop-cluster
  - Development since 2013
  - TU Graz/KC – Start Up: Invenium Data Insights



*) RTR Telkom Monitor: Jahresbericht 2022

MPD – an appealing data source

- ☺ no additional device or application
- ☺ continuous data source everywhere
- ☺ data structure depends on telecom provider but not on region
- ☺ **observed NOT estimated OD matrices**

- data is fuzzy
- limited information per dataset

→ academics and start-ups

Literature on MPD & transportation

- Schlaich, Johannes; Otterstätter, Thomas; Friedrich, Markus (2010): Generating Trajectories from Mobile Phone Data. In: *TRB 89th Annual Meeting Compendium of Papers*.
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- Schulze, Gunnar; Horn, Christopher; Kern, Roman (2015): Map-Matching Cell Phone Trajectories of Low Spatial and Temporal Accuracy. In: *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, S. 2707–2714. DOI: 10.1109/ITSC.2015.435.
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- Chin, Kimberley; Huang, Haosheng; Horn, Christopher; Kasanicky, Ivan; Weibel, Robert (2019): Inferring fine-grained transport modes from mobile phone cellular signaling data. In: *Computers, Environment and Urban Systems* Vol 77, Artikel 101348. DOI: 10.1016/j.compenvurbsys.2019.101348.
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- Li, Mingxiao; Gao, Song; Lu, Feng; Zhang, Hengcai (2019): Reconstruction of human movement trajectories from large-scale low-frequency mobile phone data. In: *Computers, Environment and Urban Systems* 77, S. 101346. DOI: 10.1016/j.compenvurbsys.2019.101346.
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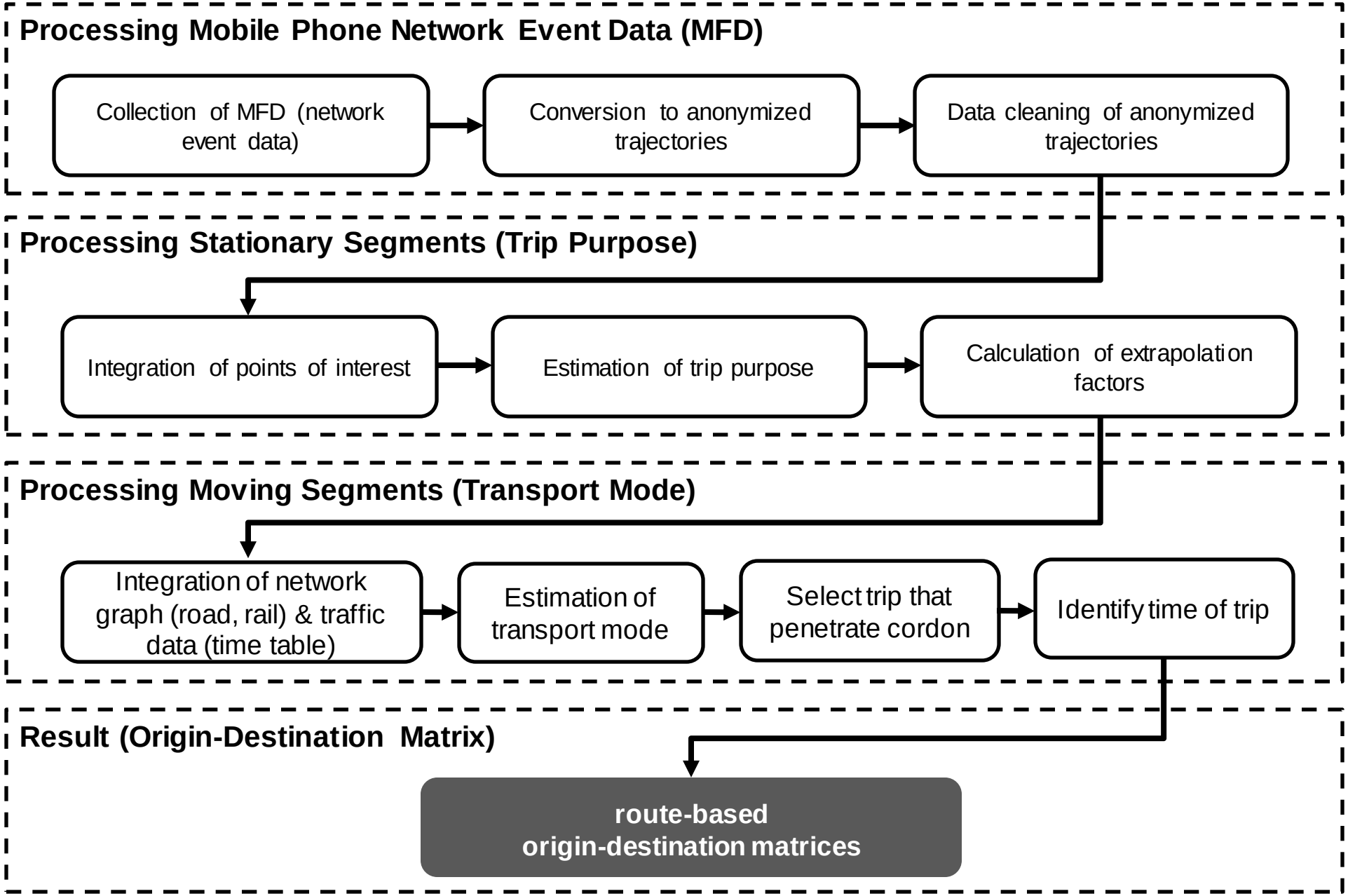
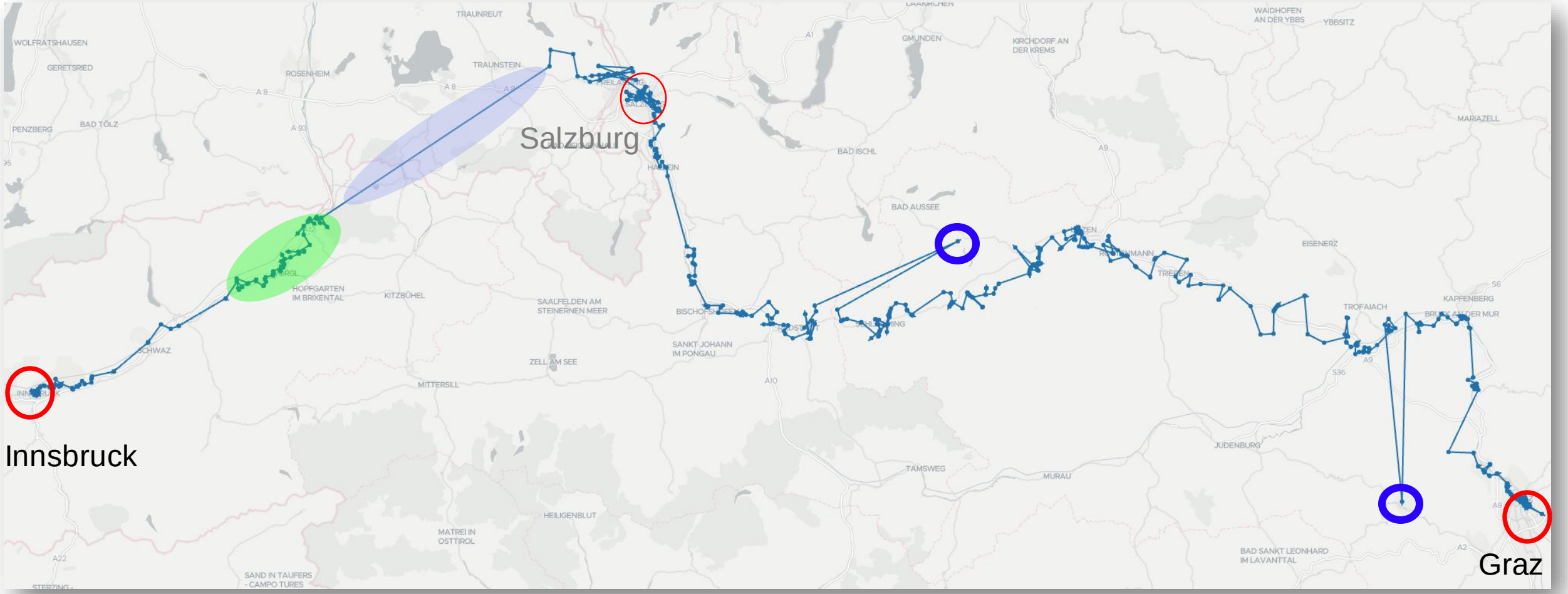
- Paipuri, Mahendra; Xu, Yanyan; González, Marta C.; Leclercq, Ludovic (2020): Estimating MFDs, trip lengths and path flow distributions in a multi-region setting using mobile phone data. In: Transportation Research Part C: Emerging Technologies 118, S. 102709. DOI: 10.1016/j.trc.2020.102709.
- Anda, Cuauhtemoc; Ordonez Medina, Sergio A.; Axhausen, Kay W. (2021): Synthesising digital twin travellers: Individual travel demand from aggregated mobile phone data. In: *Transportation Research Part C: Emerging Technologies* Vol 128, Artikel 103118. DOI: 10.1016/j.trc.2021.103118.
- Z. Li; G. Xiong; Z. Wei; Y. Zhang; M. Zheng; X. Liu et al. (2022): Trip Purposes Mining From Mobile Signaling Data. In: *IEEE Transactions on Intelligent Transportation Systems* 23 (8), S. 13190–13202. DOI: 10.1109/TITS.2021.3121551.
- Z Le Huang; Xia, Fan; Chen, Hui; Hu, Bowen; Zhou, Xiao; Li, Chunxiao et al. (2023): Reconstructing human activities via coupling mobile phone data with location-based social networks. In: *Travel Behaviour and Society* 33, S. 100606. DOI: 10.1016/j.tbs.2023.100606.
- Wischer, Thomas; Cik, Michael; Fellendorf, Martin (2023): Graph Supported Mode Detection within Mobile Phone Data Trajectories. In: Transportation Research Record 2677 (3), S. 18–32. DOI: 10.1177/03611981221150399.

General system architecture



Raw data: events and location

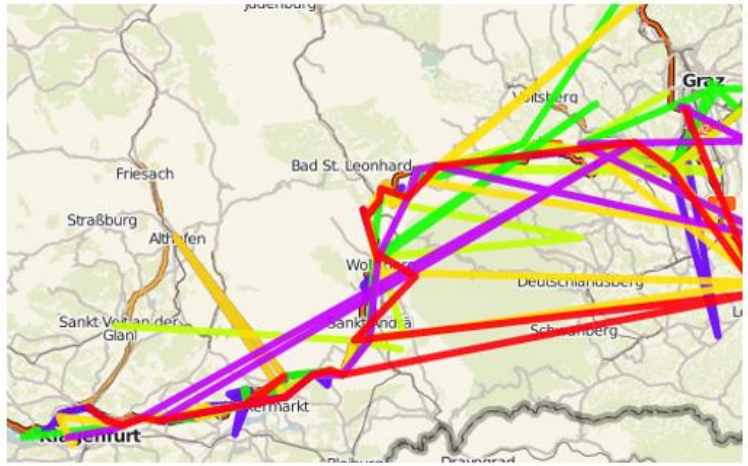
- 6 hour train ride with changing trains



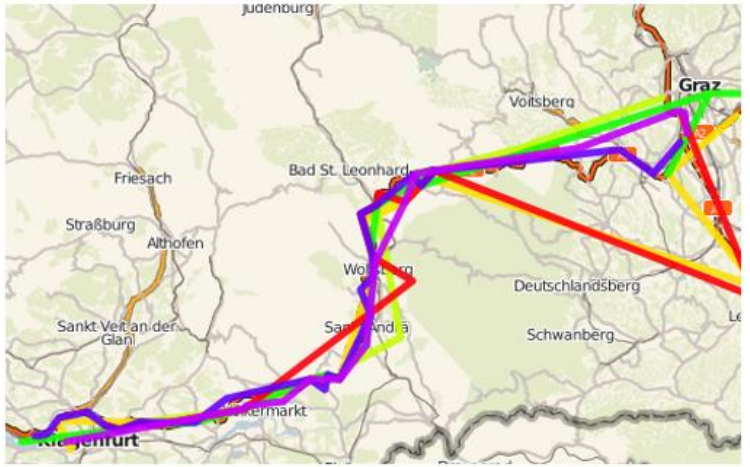
Raw data: eliminate outliers

- raw trajectories in (a) contain multiple outliers,
- removed by filters in (b), (c) and (d)

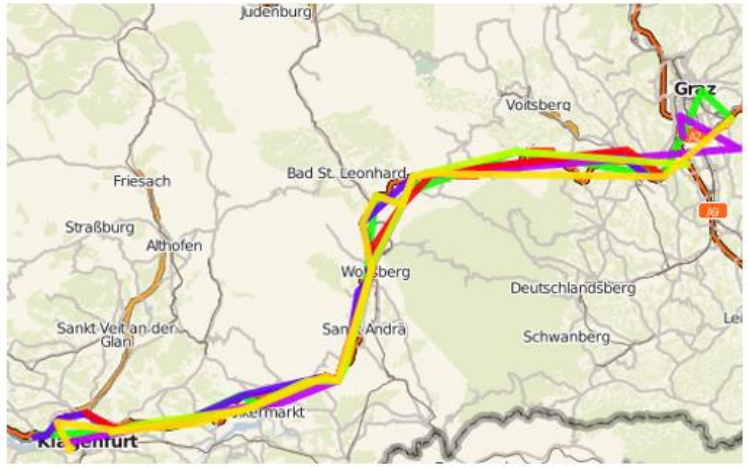
(a) No Filter



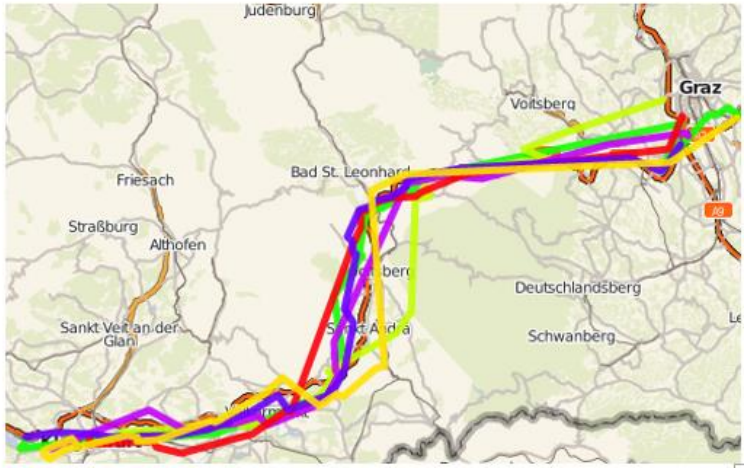
(b) Recursive Naive Filter



(c) Recursive Look-Ahead Filter

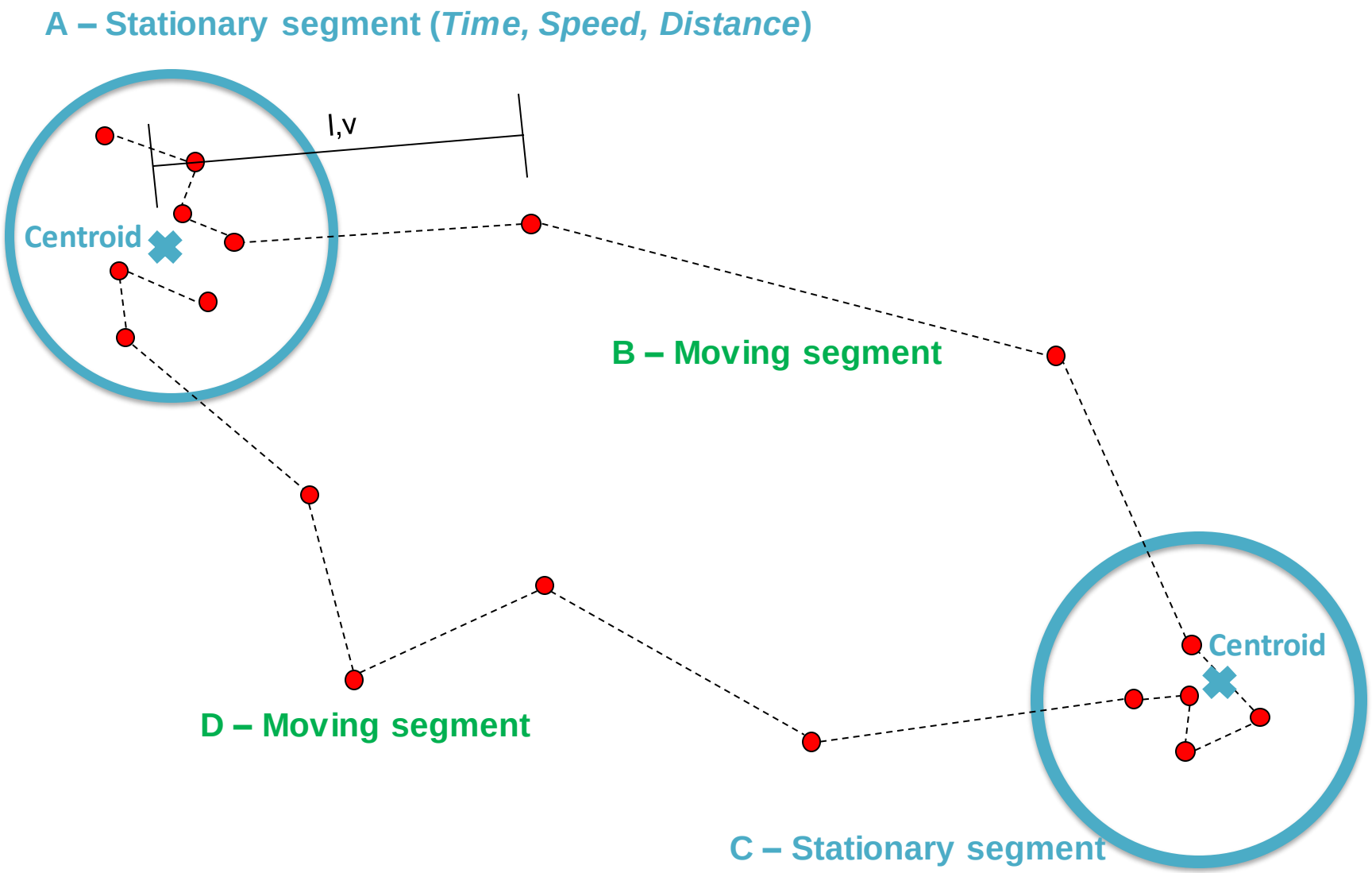


(d) Kalman Filter



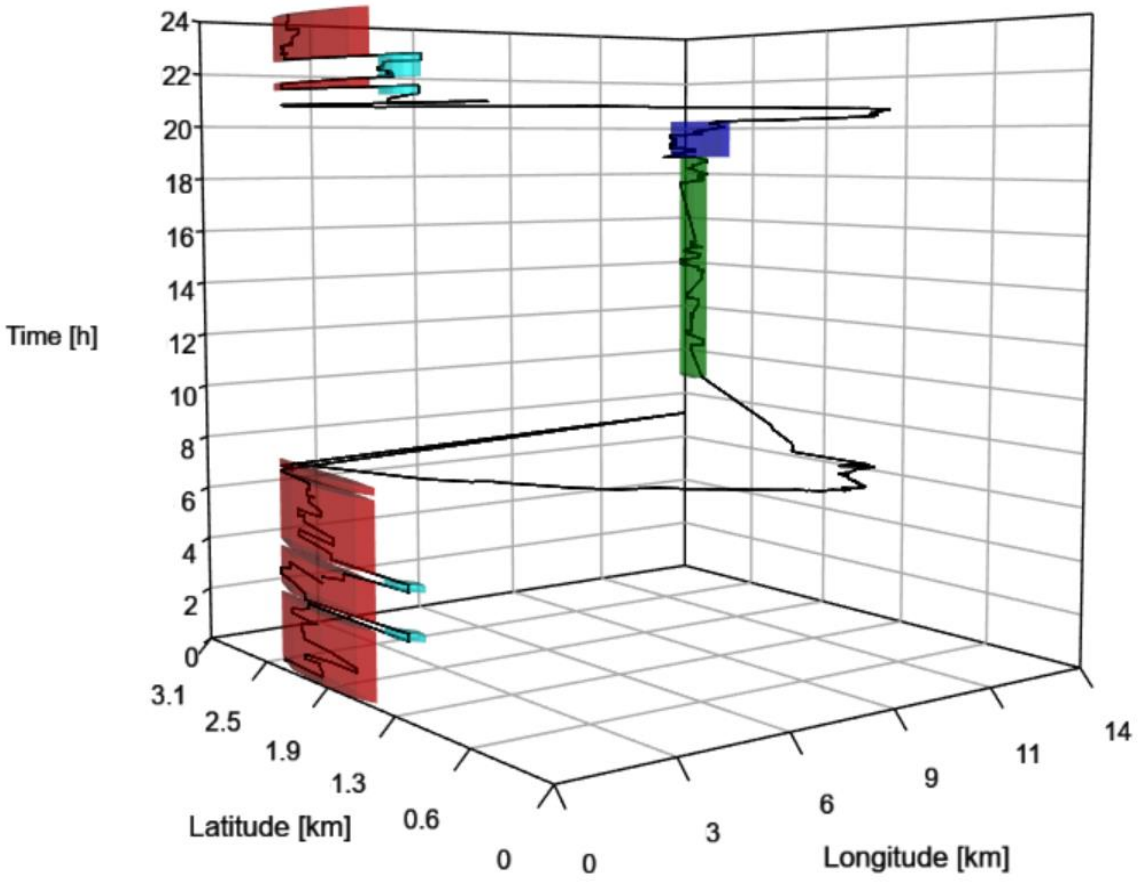
Horn, C., Klampfl, S., Cik, M., & Reiter, T. (2014). Detecting Outliers in Cell Phone Data: Correcting Trajectories to Improve Traffic Modeling. Transportation Research Record, 2405(1), 49-56. https://doi.org/10.3141/2405-07

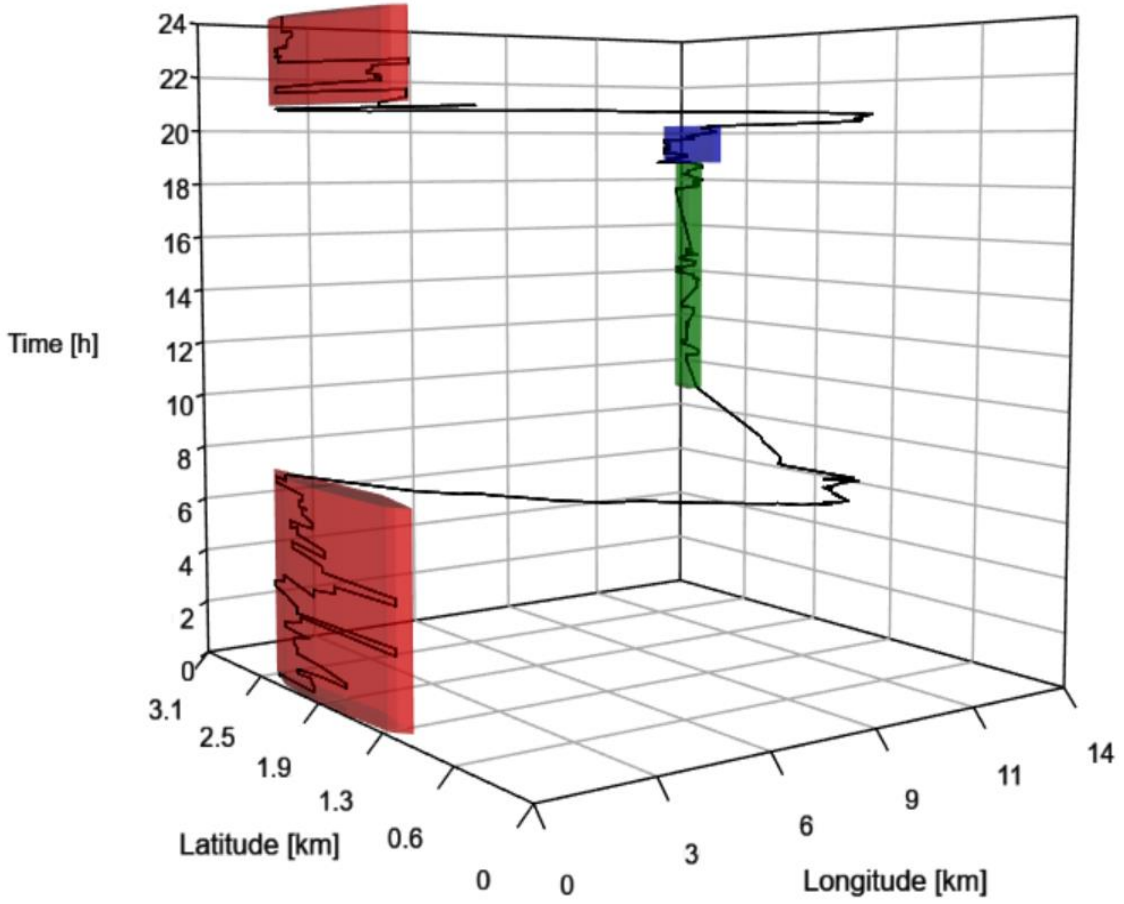
Data processing – identify stationary segments



Data processing - identify stationary segments

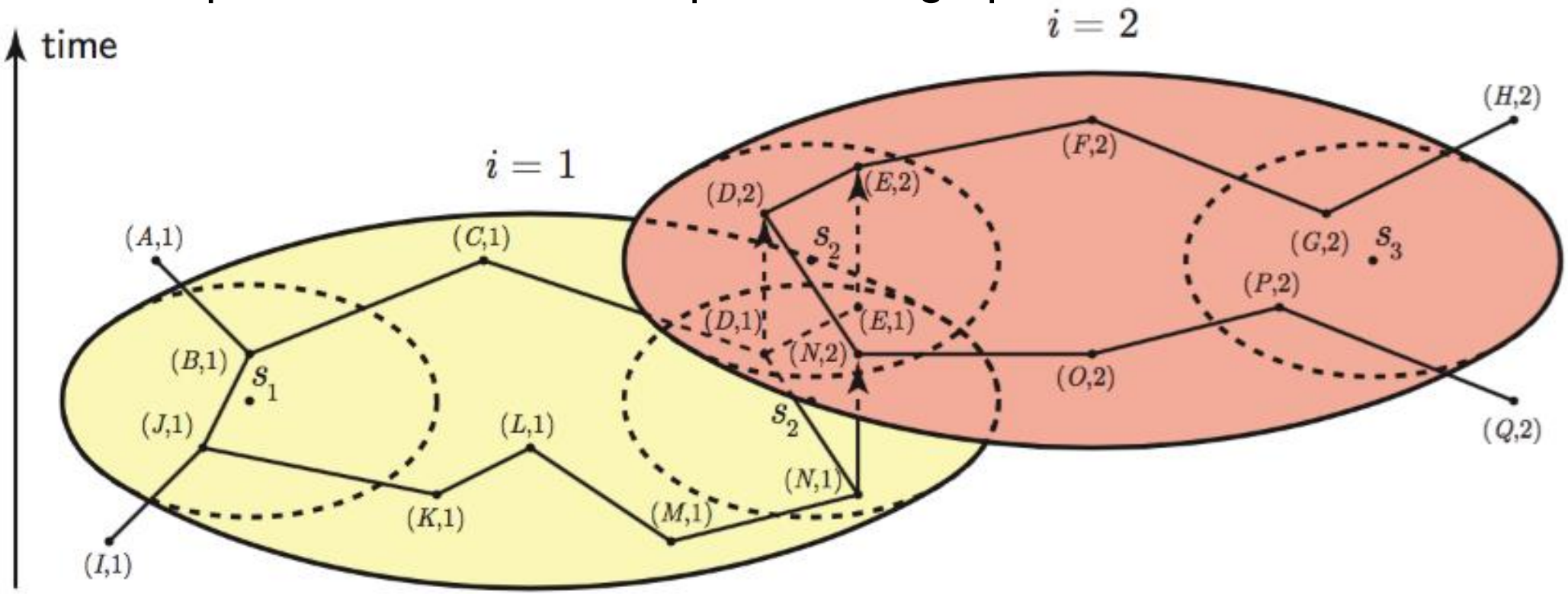
- Density based clustering and correction
- IMSI-location jumps (cyan outliers)
- Merge adjacent locations according to activity time (DBSCAN)





Data processing - Map-Matching

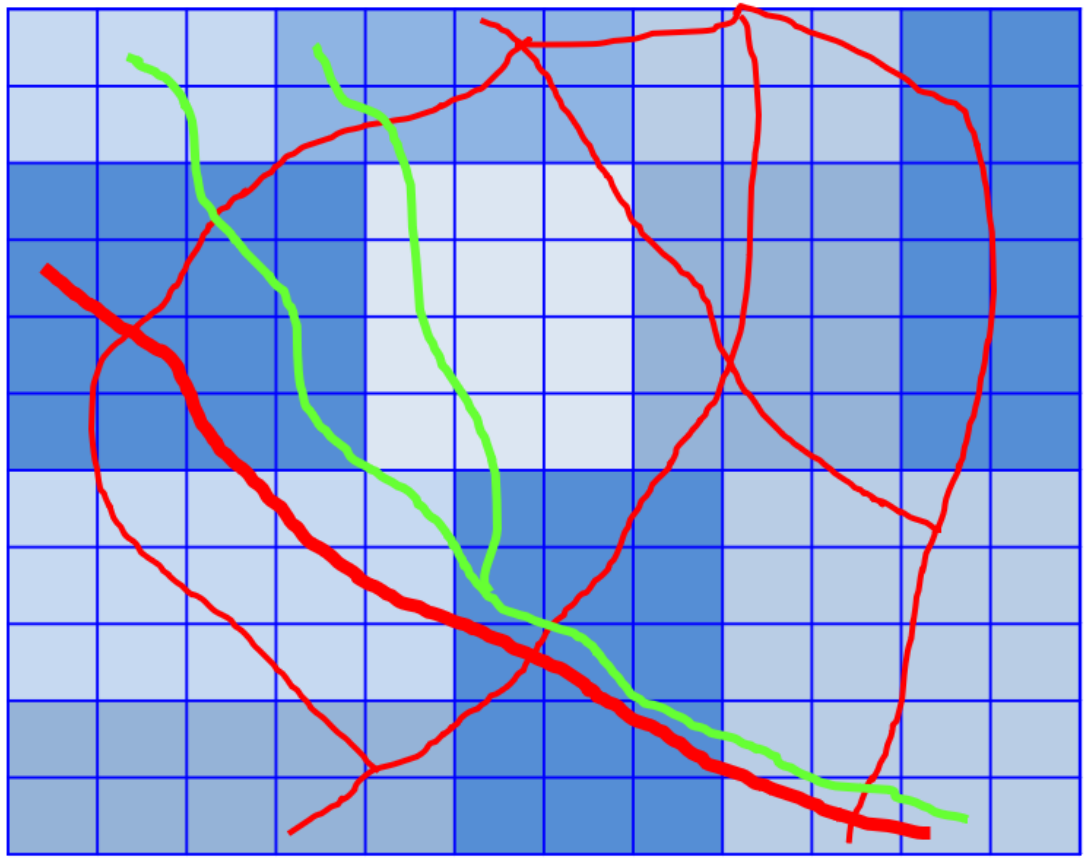
- Match trips on road or railway network
- Use real-time time-table of trains
- Subgraph-construction with buffer polygons
- Shortest path based on mode specific subgraphs



Schulze etal: IEEE, 2015 and Wischer etal: TRR, 2023

Match MPD-trajectory to Traffic Analysis Zone (TAZ)

- Mobile phone area not used directly
- Events of spur must be matched on rail tracks and roads
- Summation of all spurs to rail and road TAZ´s

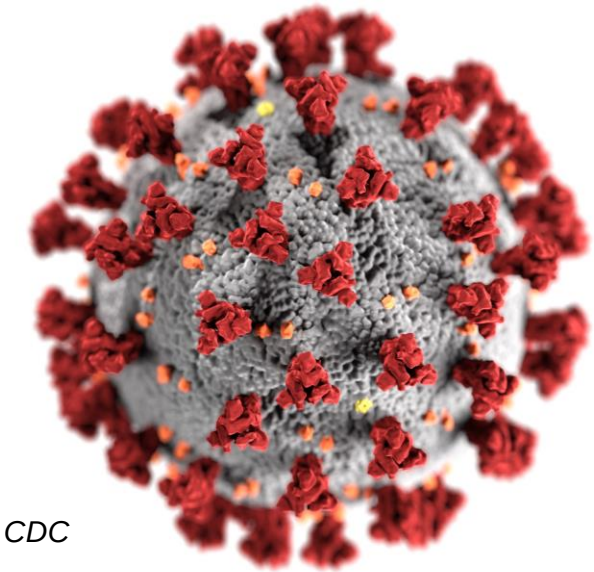


WHY ?

Passenger counts

Origin-Destination flows

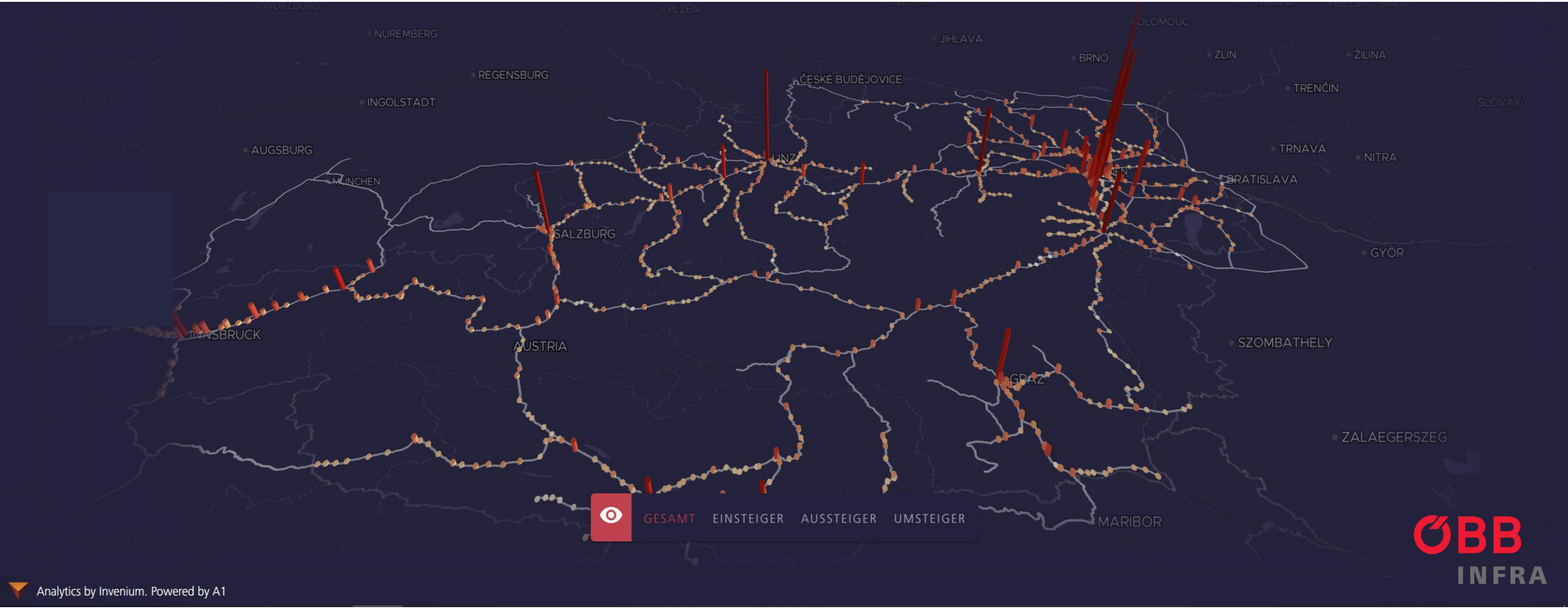
Renaissance of railways



© CDC

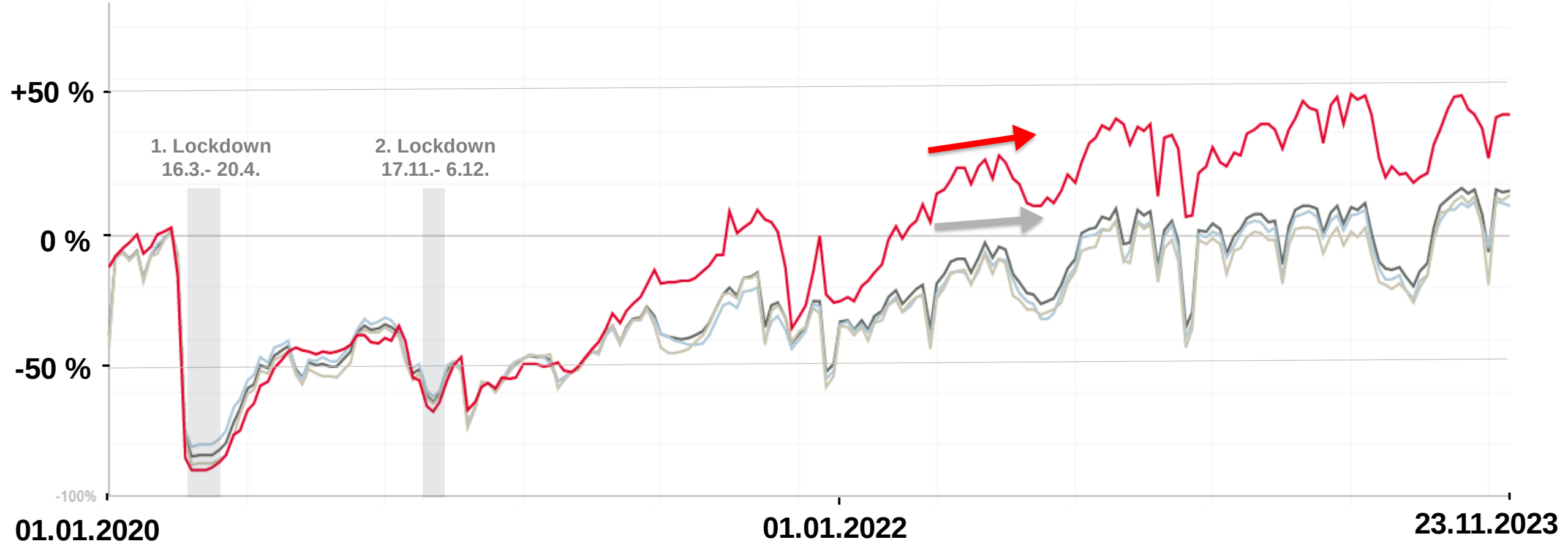
Passenger counts

- Continous passenger counts at every Austrain train station by day or hour and train type based on MPD
- Decision support system for railway network operator



Train Passengers in Austria 01/2020 – 11/2023

- Reference 100% avg. Weekday 22.2. – 11.3.2020

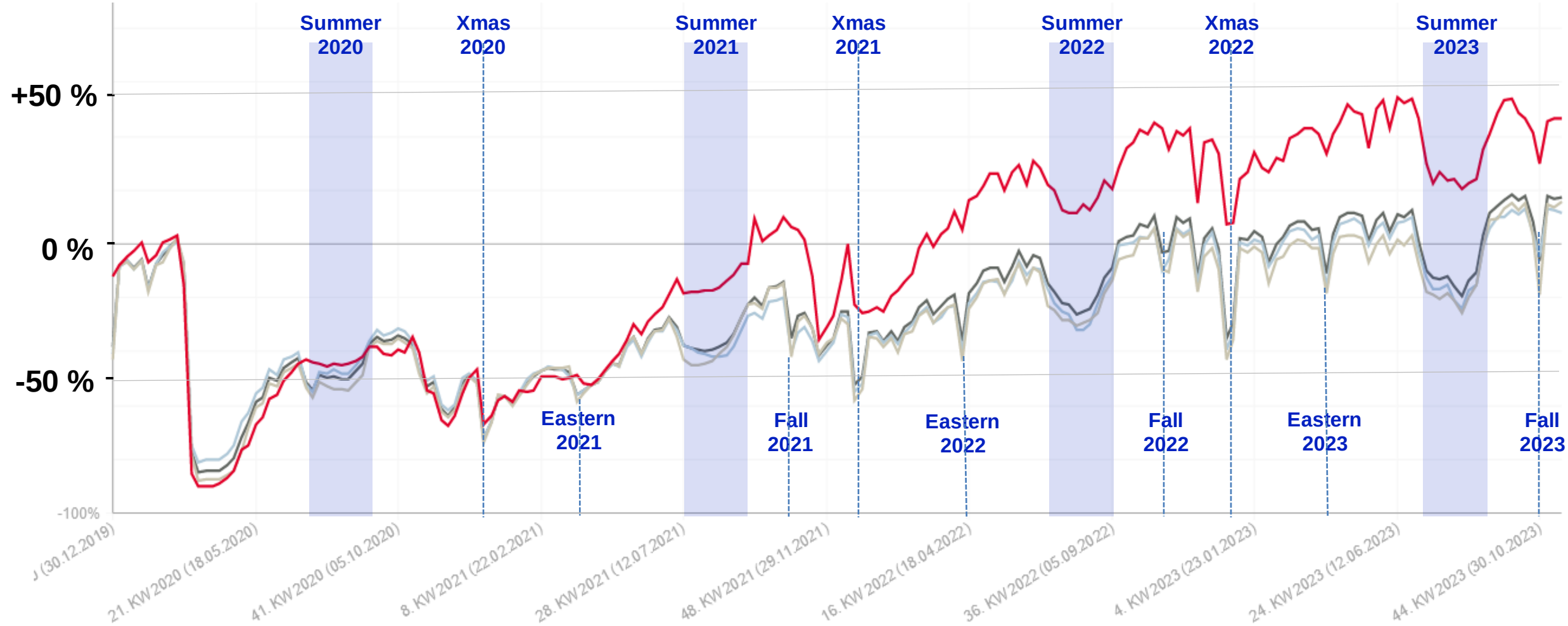


Data: Invenium Data Insights, 2023

total S-Bahn regional train long-distance train

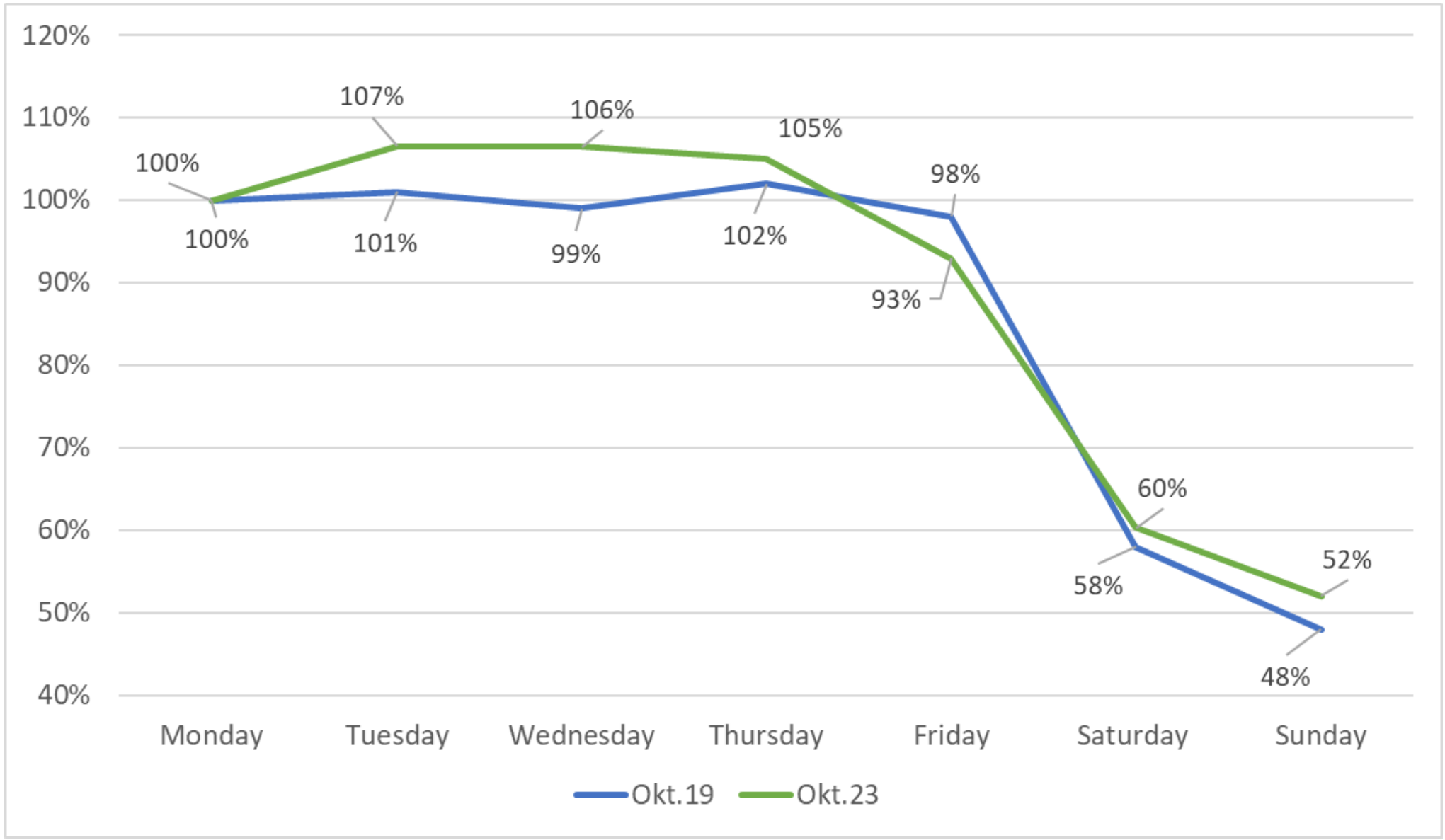
Train Passengers in Austria 01/2020 – 11/2023

- Reference 100% avg. Weekday 22.2. – 11.3.2020 (Lockdown 13.3.2020)

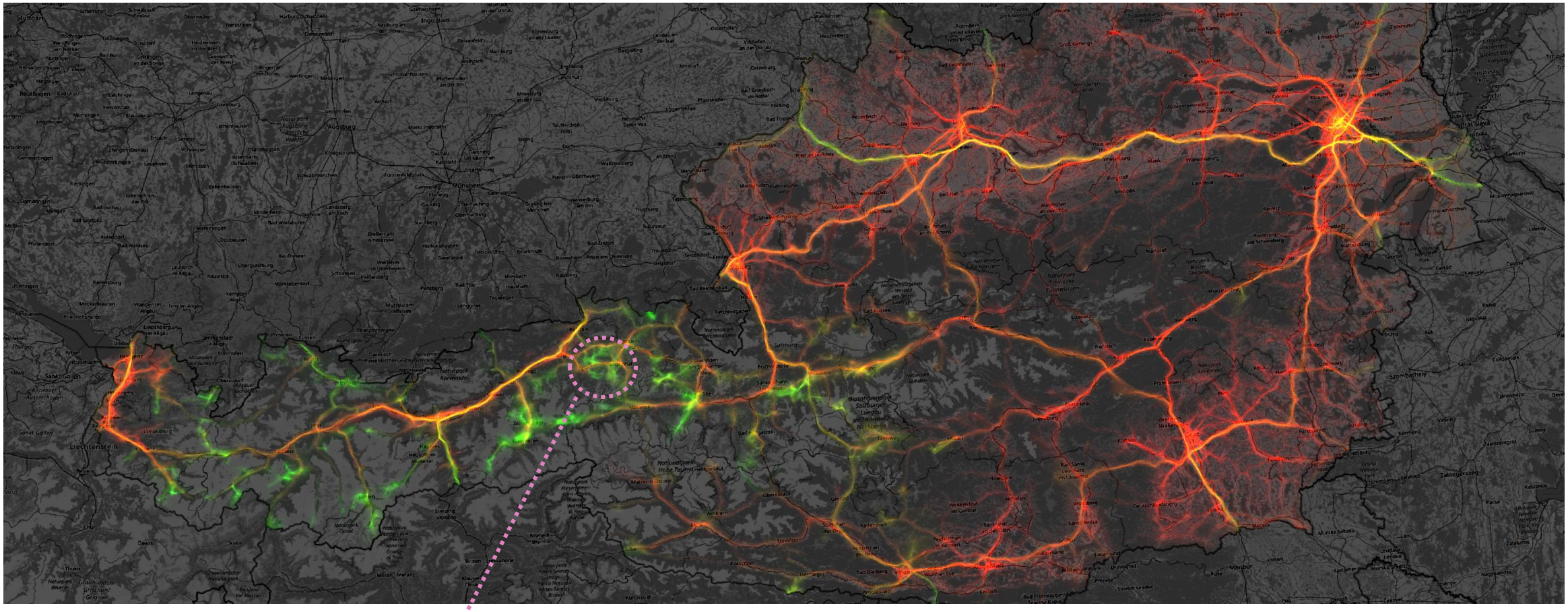


Passenger peaks changed to mid-week

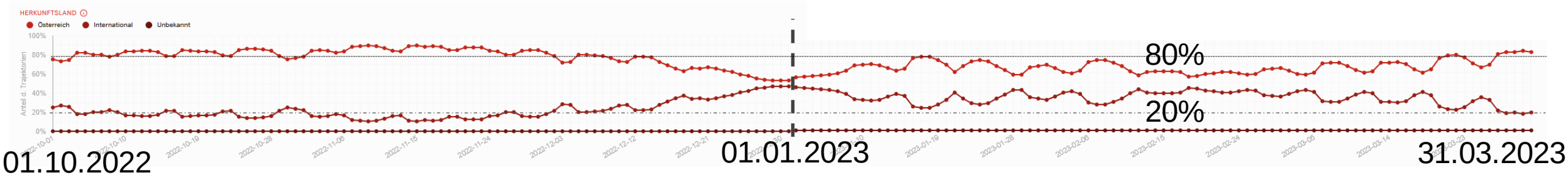
Variablitly of passenger demand at most heavy loaded Austrian train stop



National vs international travellers



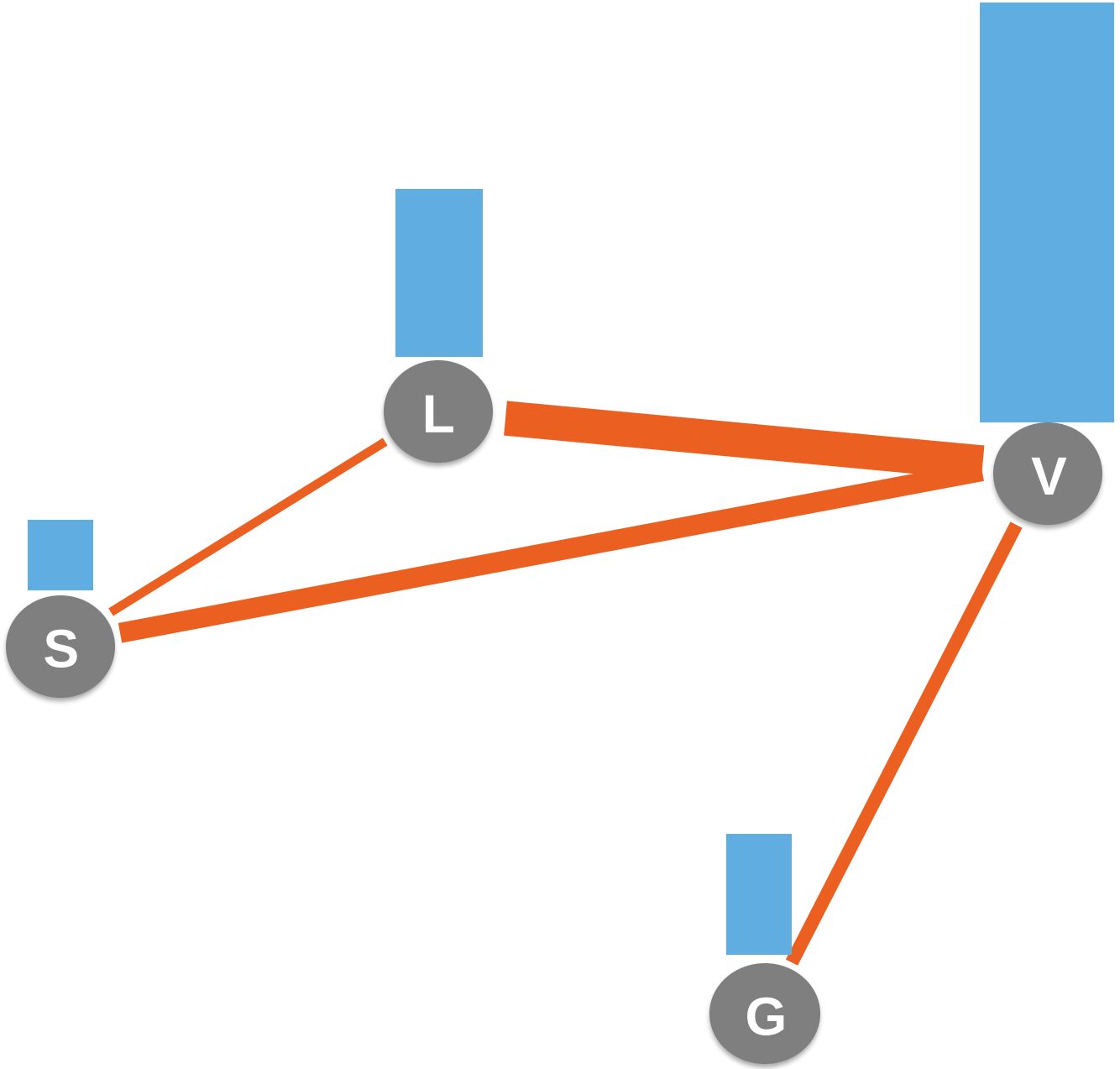
Trips in Kitzbüehl made by national and international residents



01.10.2022

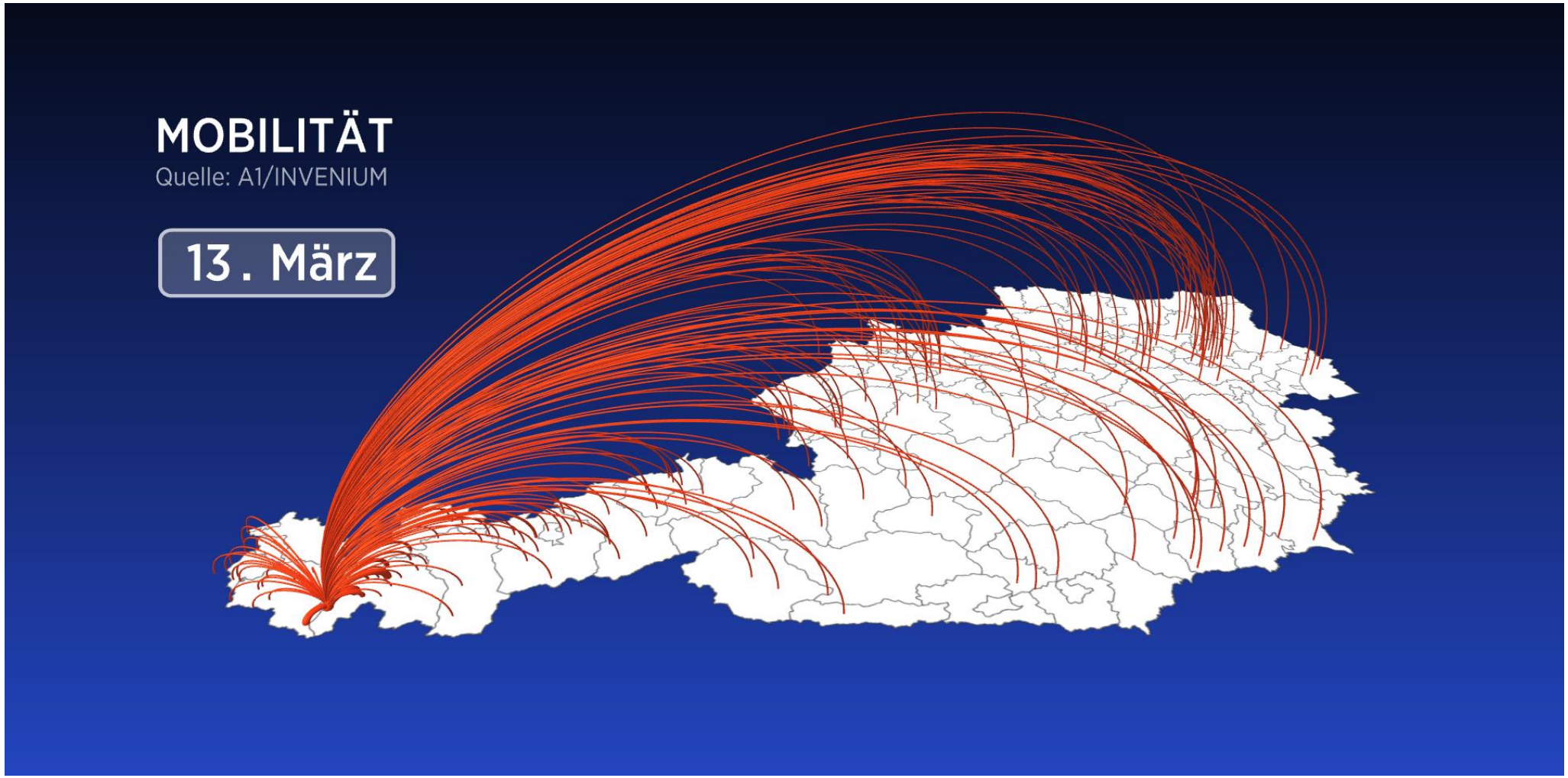
31.03.2023

Origin-Destination (OD) flows



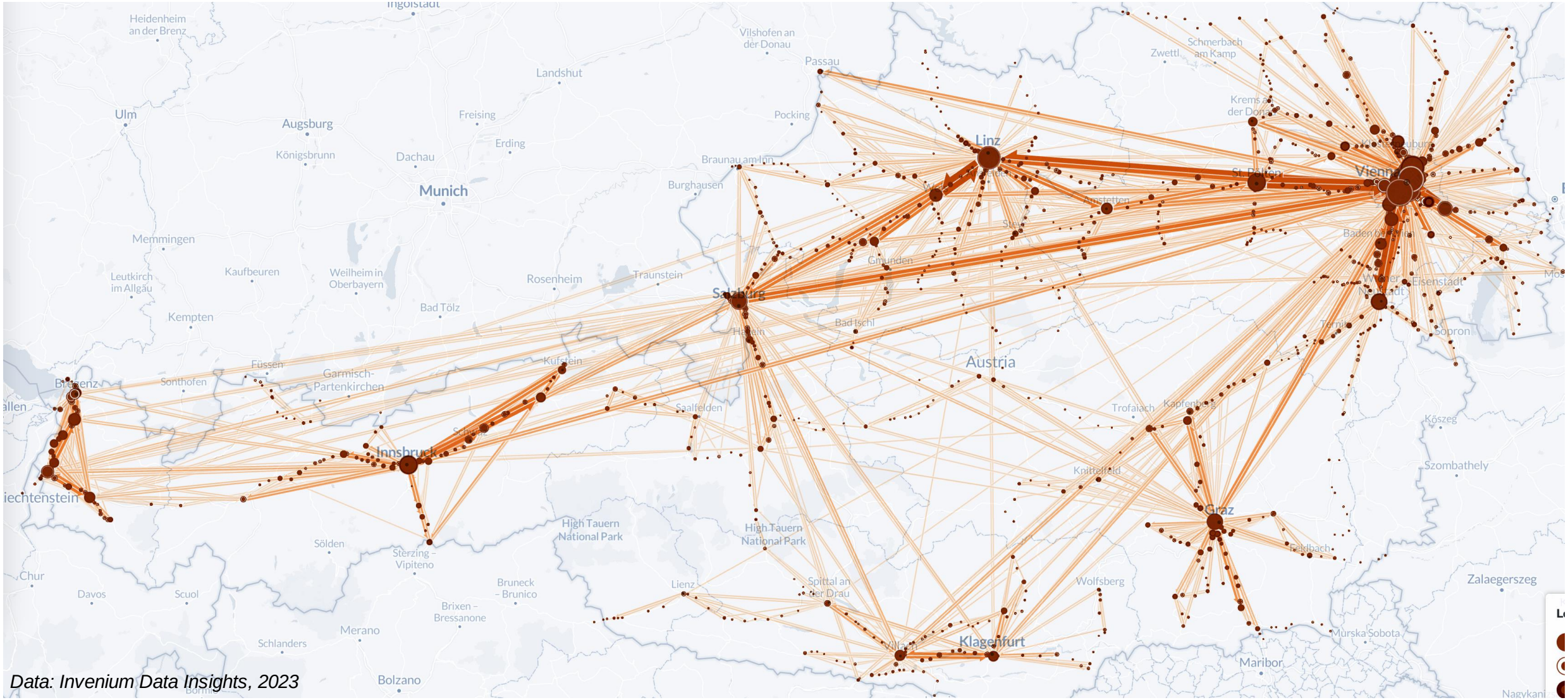
One origin – all destinations

- Departures by train from Ischgl after announcement of 1st lockdown



OD trips railway: **all trips**

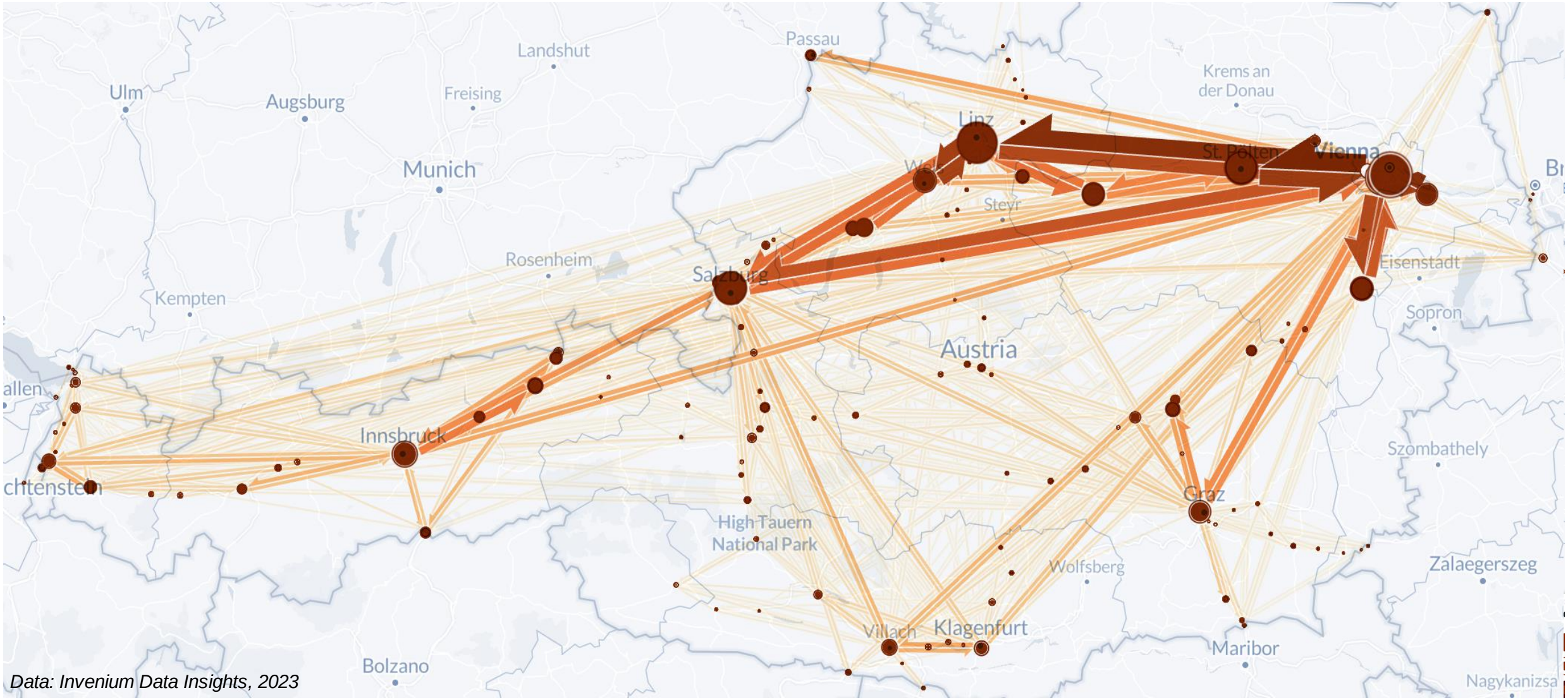
- Average working day Oktober 2022
- ~50km radius around metropolitan regions (except Vienna – Linz/Salzburg)



Data: Invenium Data Insights, 2023

OD trips railway: **long distance trips only**

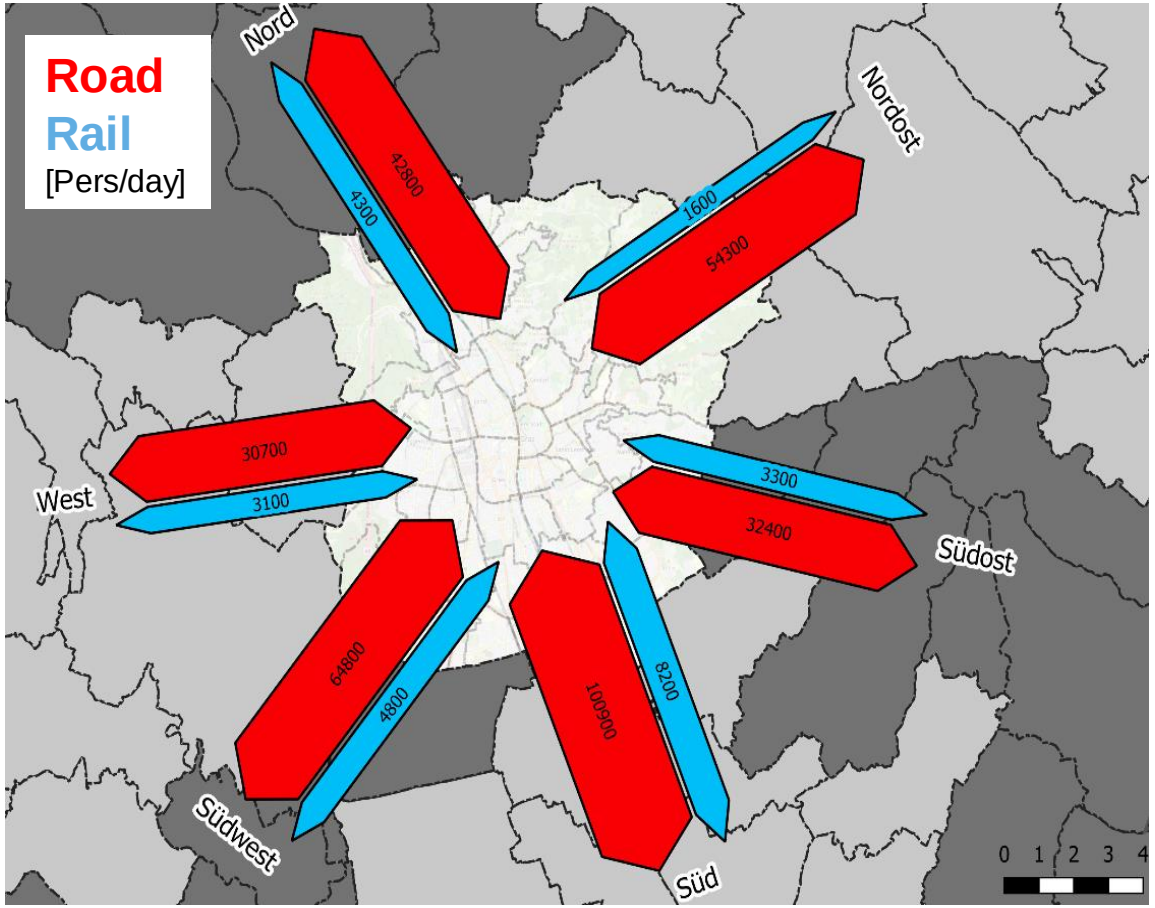
- Average working day October 2022
- Travel demand reflected by infrastructure supply (except Graz-Klagenfurt, Koralm 2025?)



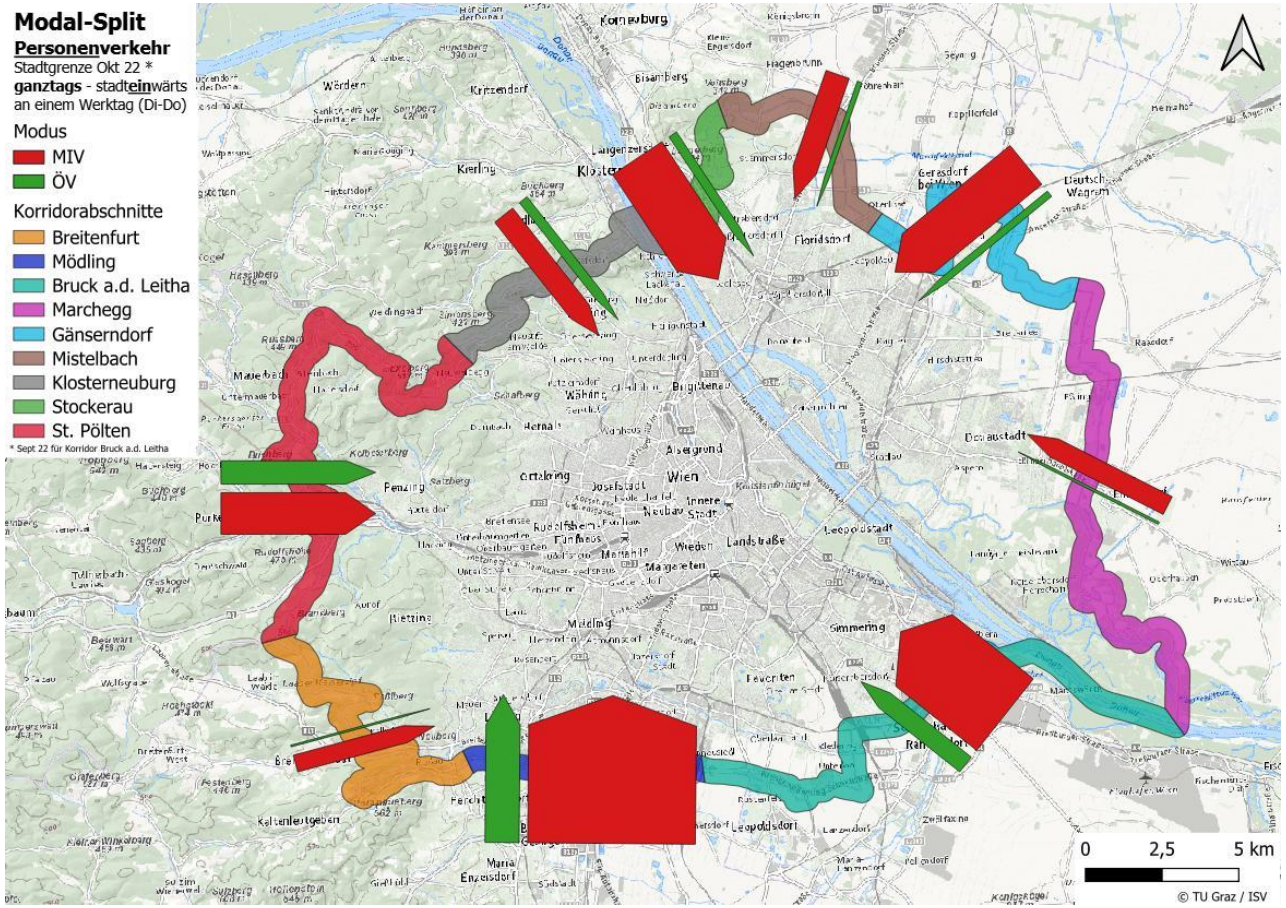
Data: Invenium Data Insights, 2023

Bimodal OD – flows: screenline analysis

- Trips from outer zone to inner zone via corridor based on FPD only (rail-road classification) for Graz
- Trips crossing corridor classified by car vs. public transport (train, tram, bus) for Vienna (right)



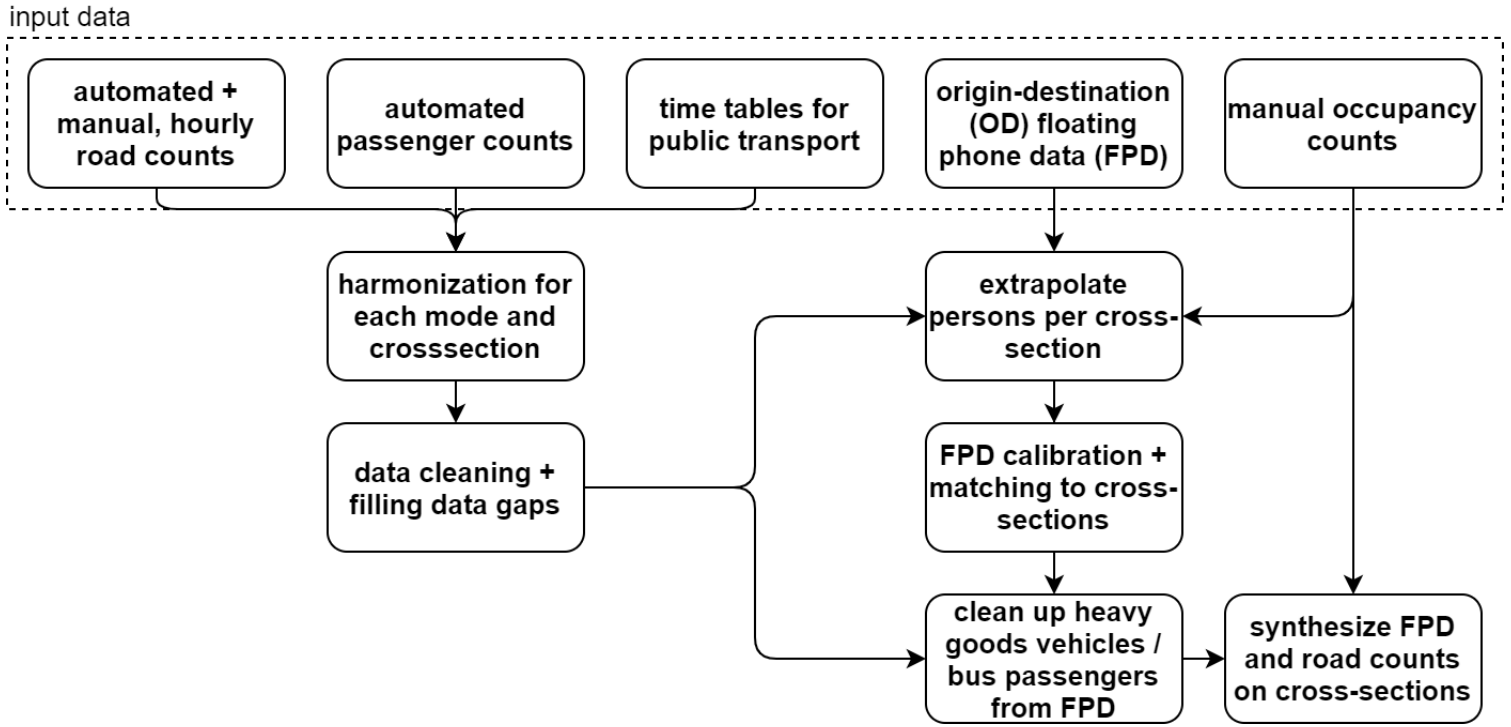
Cik etal: Grenzüberschreitender Verkehr Graz 2022, Land Steiermark u. Stadt Graz 2023

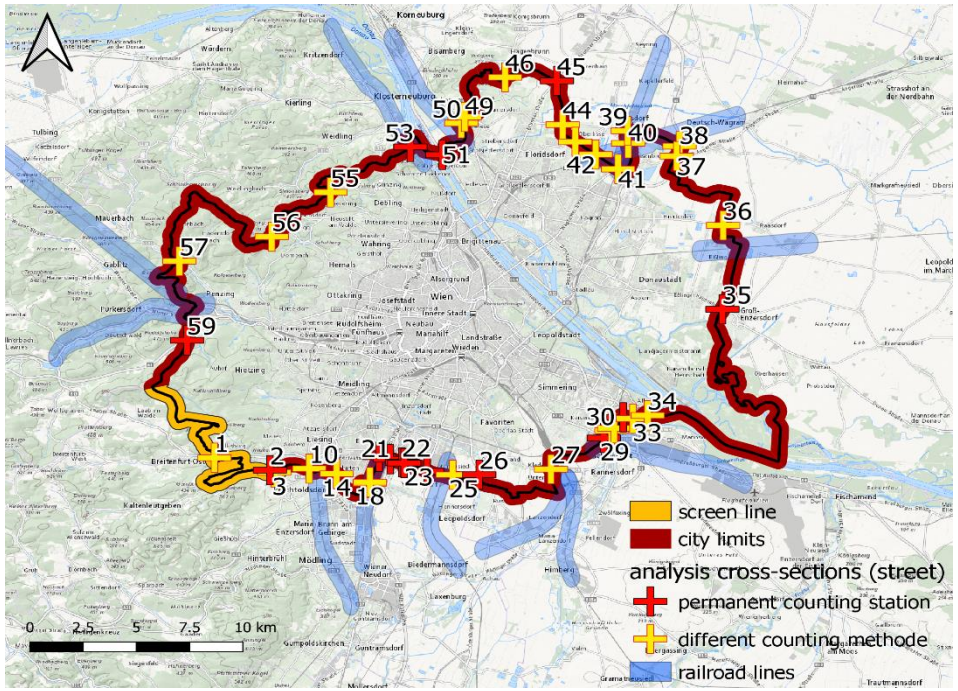


Fellendorf etal: Kordonerhebung Wien 2022, Magistrat Wien 2023

Mode classification requires additional data sources

- road traffic counters with car & HGV
- Manual vehicle occupancy counts
- 49 bus lines with passenger counts
- 13 railroad lines





Lammer etal.: Analysis of cross-border traffic for large cities using multiple data sources and new technologies, TRA 2022

Mode specific extrapolation and correction factors

- Telco market penetration by age group, sex and cell *i* (home location)

$$Trips_{total,i} = \sum_{group} \frac{Trips_{group,i}}{MarketShare_{group,i}}$$

- Bus passengers at corridor *l*
- Passenger car occupancy rate at corridor *l*

$$occupancy_{FPD,l} = \frac{persons_{FPD,l} - passengers_{bus,l} - vehicles_{>3,5t,l}}{vehicles_{\leq 3,5t,l}}$$

- HGV rate from traffic counts assigned relative to OD-pair

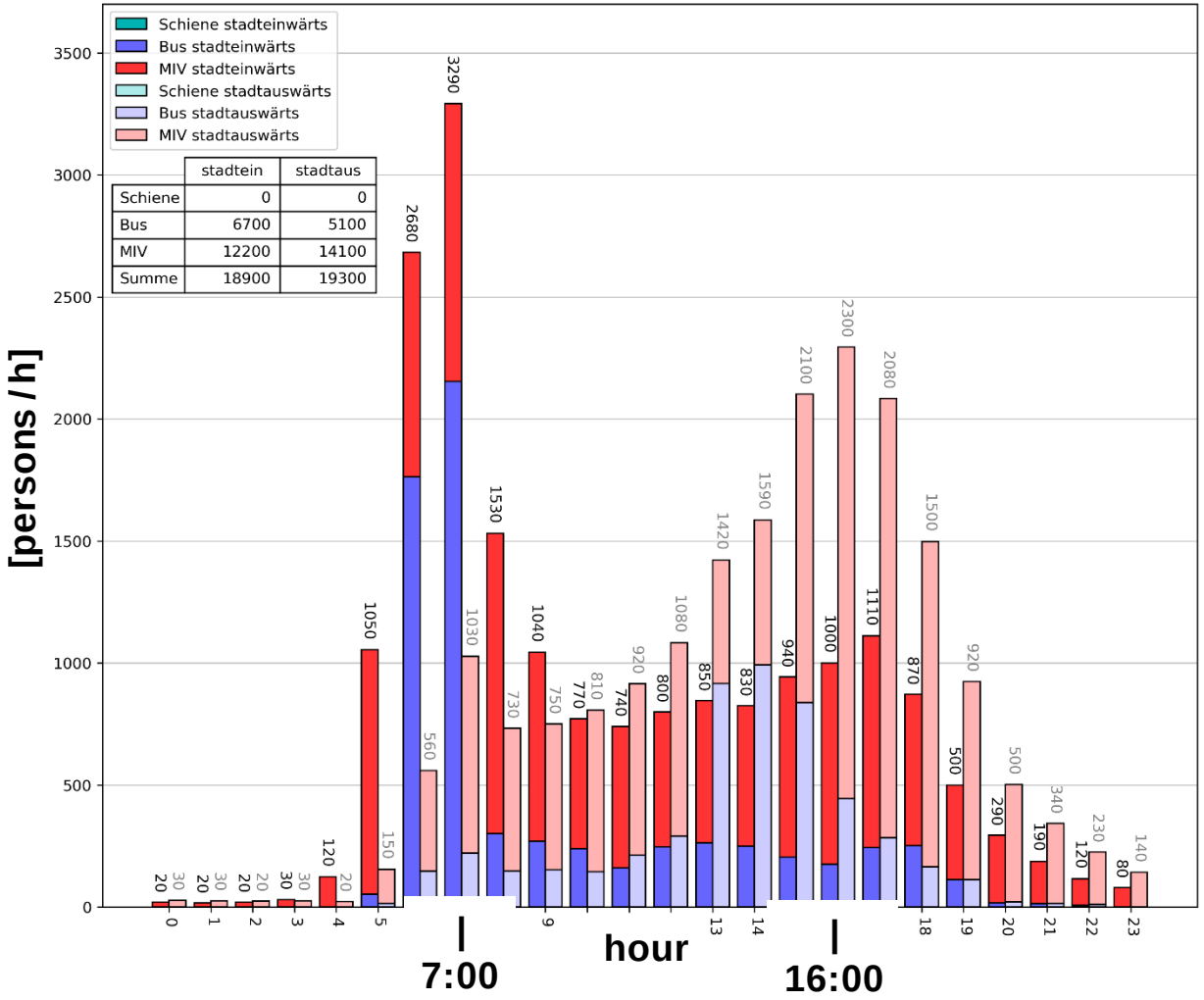
$$q_l = \sum_i \sum_j trips_{ij,l} = \sum_i \sum_j (trips_{FPD,ij,l} - vehicles_{>3,5t,l})$$

$$\sum_l trips_{persons,l} = \sum_l q_l$$

Hourly passenger profile

Graz corridor Northeast car & bus

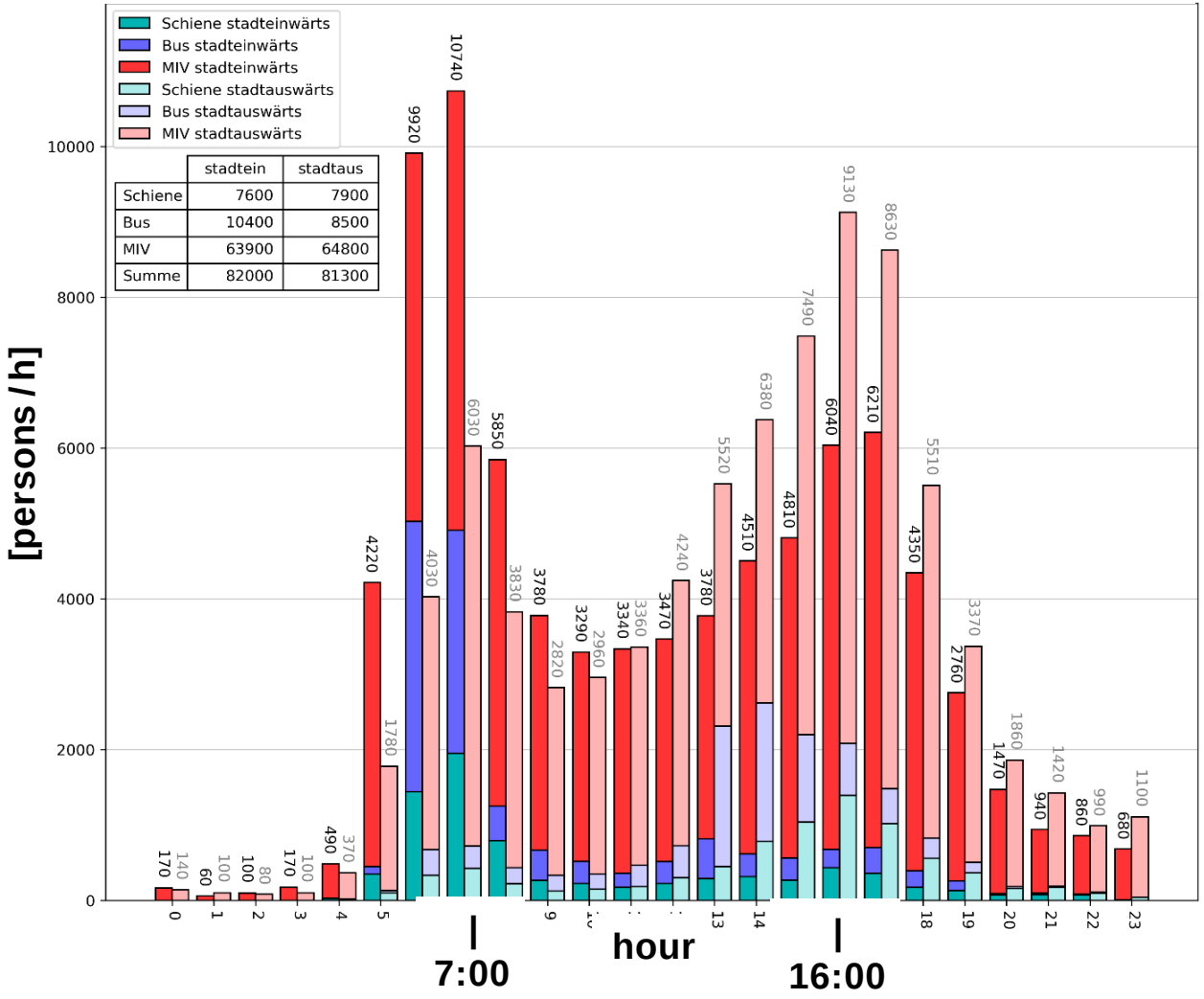
Passenger profile [Pers/h] crossing city boundary, inbound (dark); outbound (lightend)



	stadtein	stadtaus
Schiene	0	0
Bus	6700	5100
MIV	12200	14100
Summe	18900	19300

Graz corridor South with train

Passenger profile [Pers/h] crossing city boundary, inbound (dark); outbound (light)



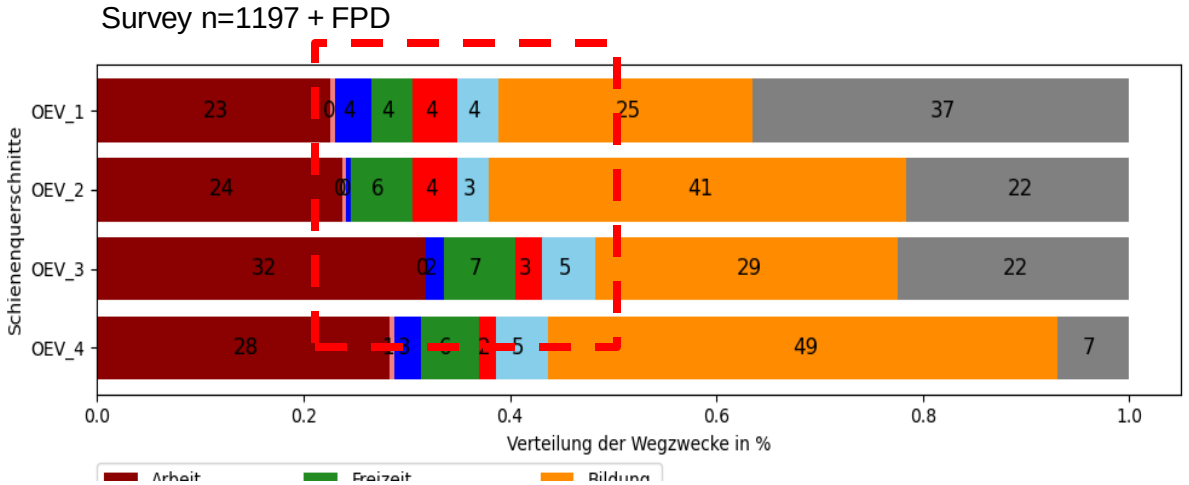
	stadtein	stadtaus
Schiene	7600	7900
Bus	10400	8500
MIV	63900	64800
Summe	82000	81300

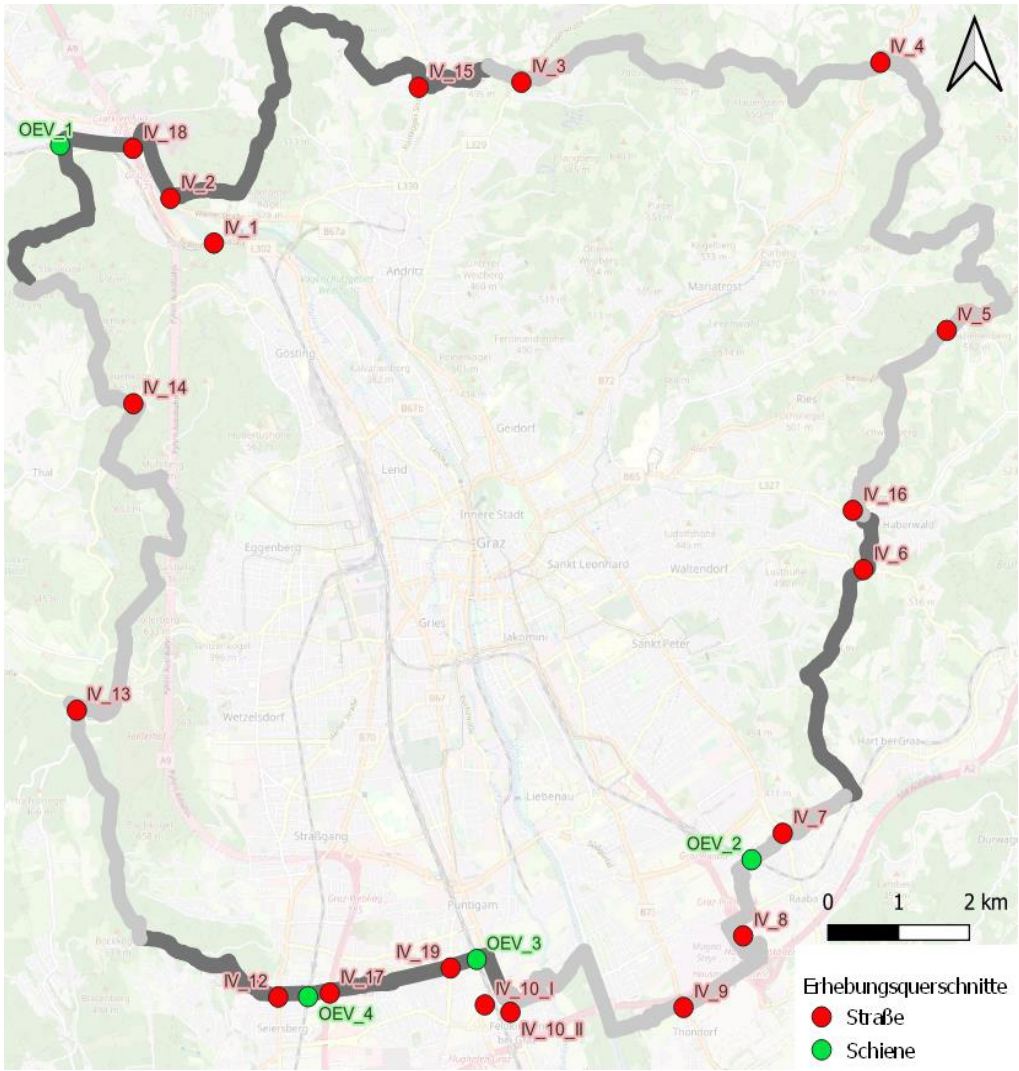
Cik etal: Grenzüberschreitender Verkehr Graz 2022, Land Steiermark u. Stadt Graz 2023

Activity identification

- Probability of activity at stationary segment
  - Home location (basically overnight adress)
  - Work (OSM and workplace census)
  - Education (OSM and school size)
  - Other

- trip purpose by in-vehicle passenger survey

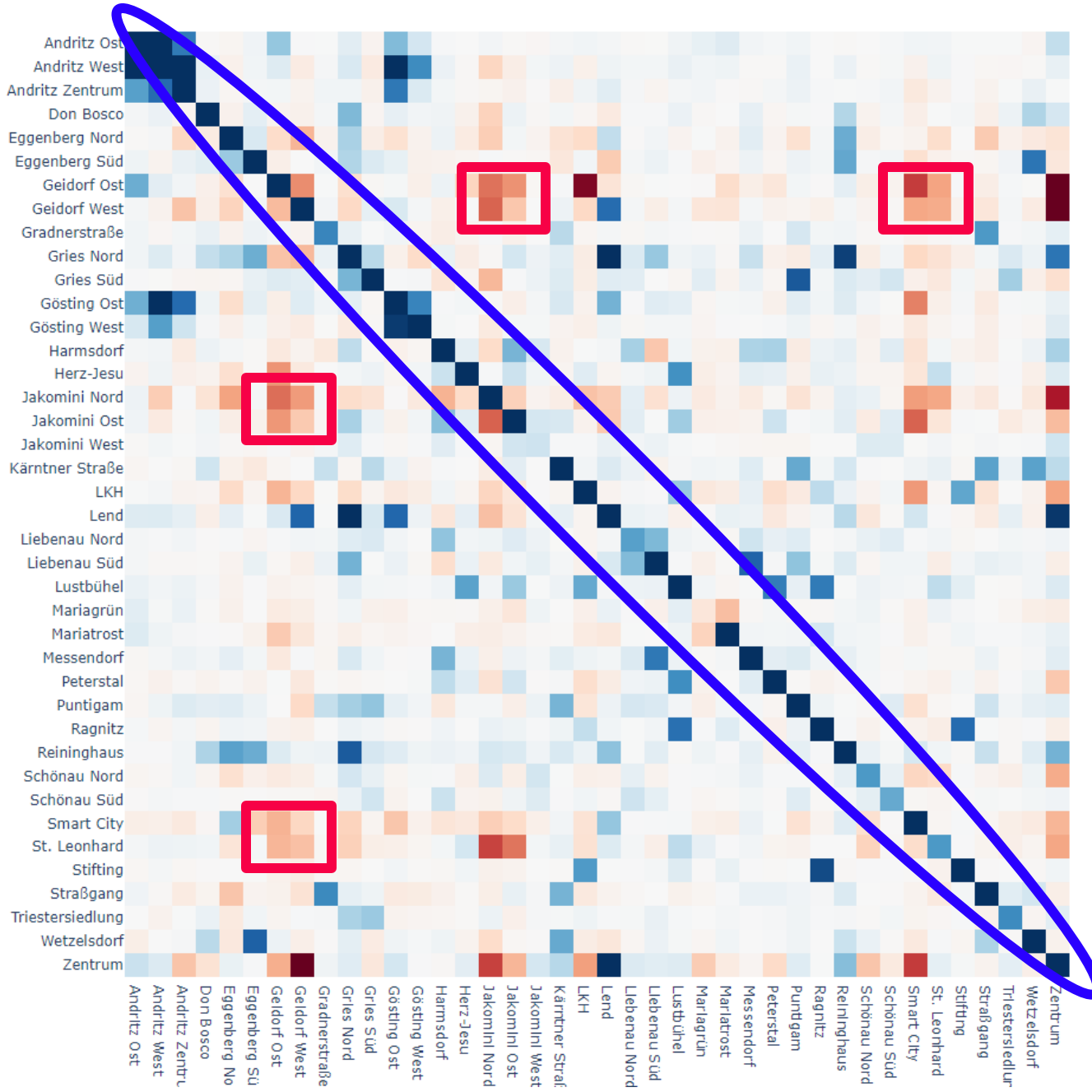




Comparison of OD-matrices (trips 2022 – trips 2020)

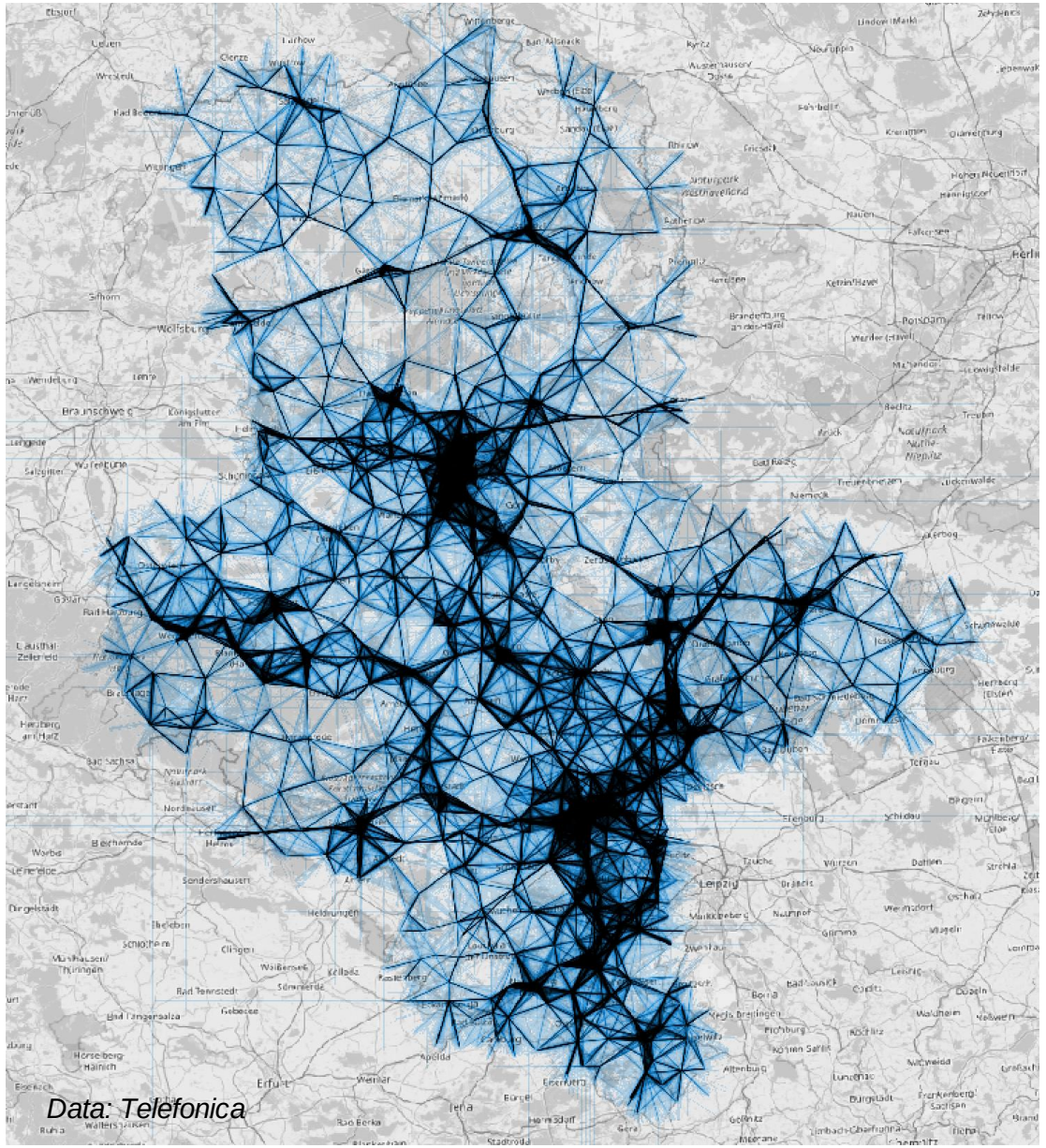
- Technique
  - Elementwise differences between two matrices (absolute, relative)
  - correlation single OD-pair and origin-row or destination-column

- Application
  - Two FPD-based OD‘s (days, saisonal, year,…)
  - Modelled vs measured OD
  - Volumes, trip-length, …



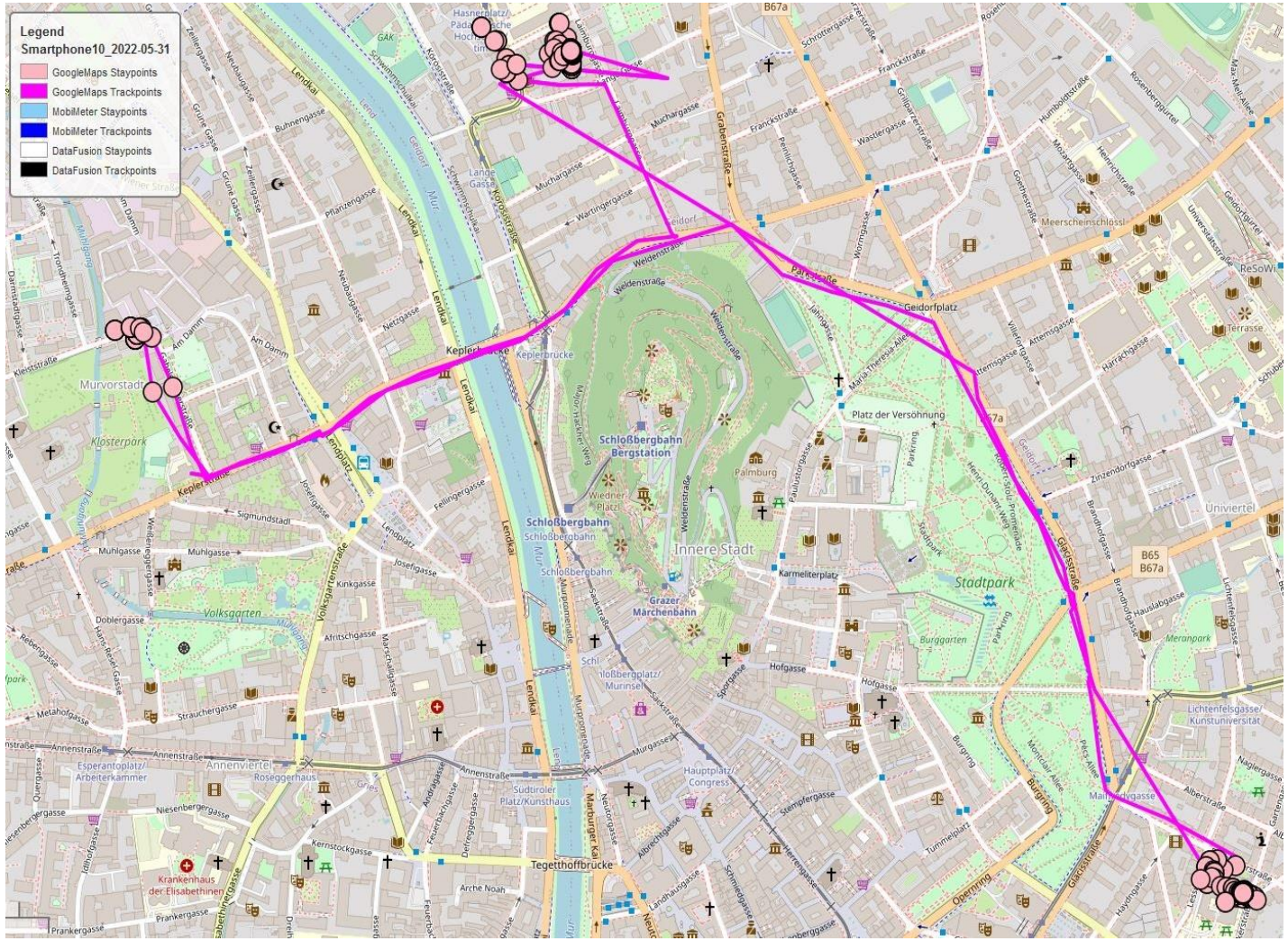
Fundamental KPI figures for transportation

- In Sachsen-Anhalt (workday 2023)
- 2,2 Millionen inhabitants generate
  - 7,145 Mio internal trips
  - 0,497 Mio originating trips
  - 0,492 Mio trips with destination in ST
  - ~160 Mio PersonKm
  - ~5 Mio h travel time



Further research: identify bicycle trips

- Database: 4.071 trips within Graz, 2.444 trips annotated and validated



Mode detection of bicycle trips

Data cleaning

Delete redundant data points

Recursive Look-Ahead Filter

Geometric filter

Segmentation

Density Based Clustering

(H) DBSCAN
ST-DBSCAN

or

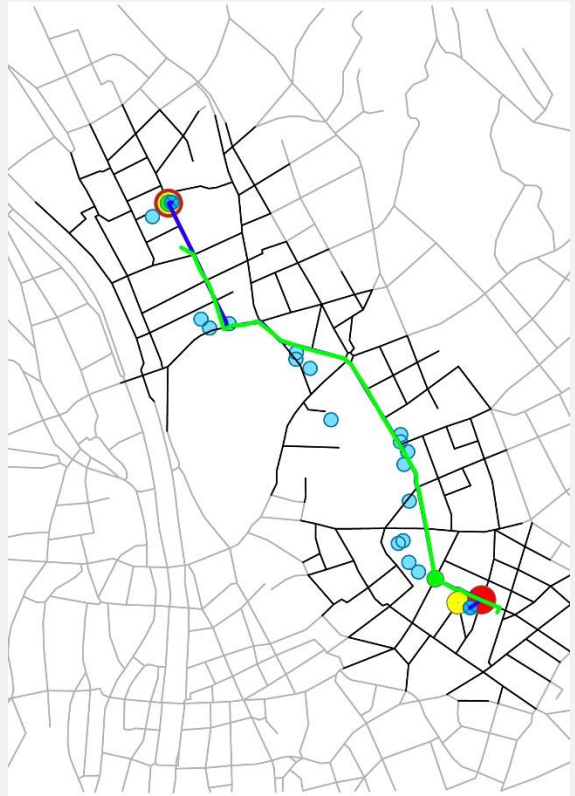
Time series analysis with machine learning

Time Series Forest

Support Vector Machines

(Recurrent) Neural Networks

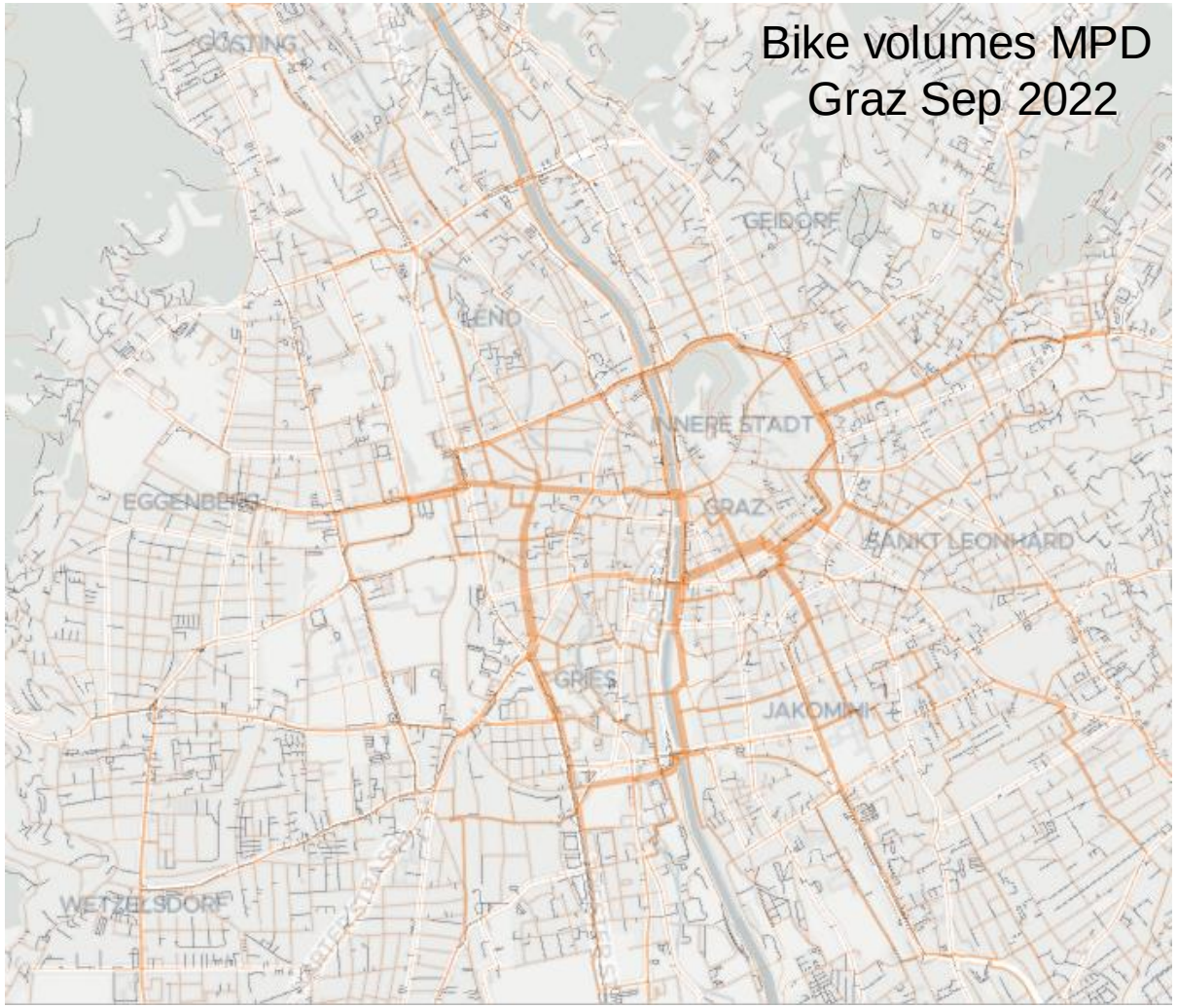
Map-matching

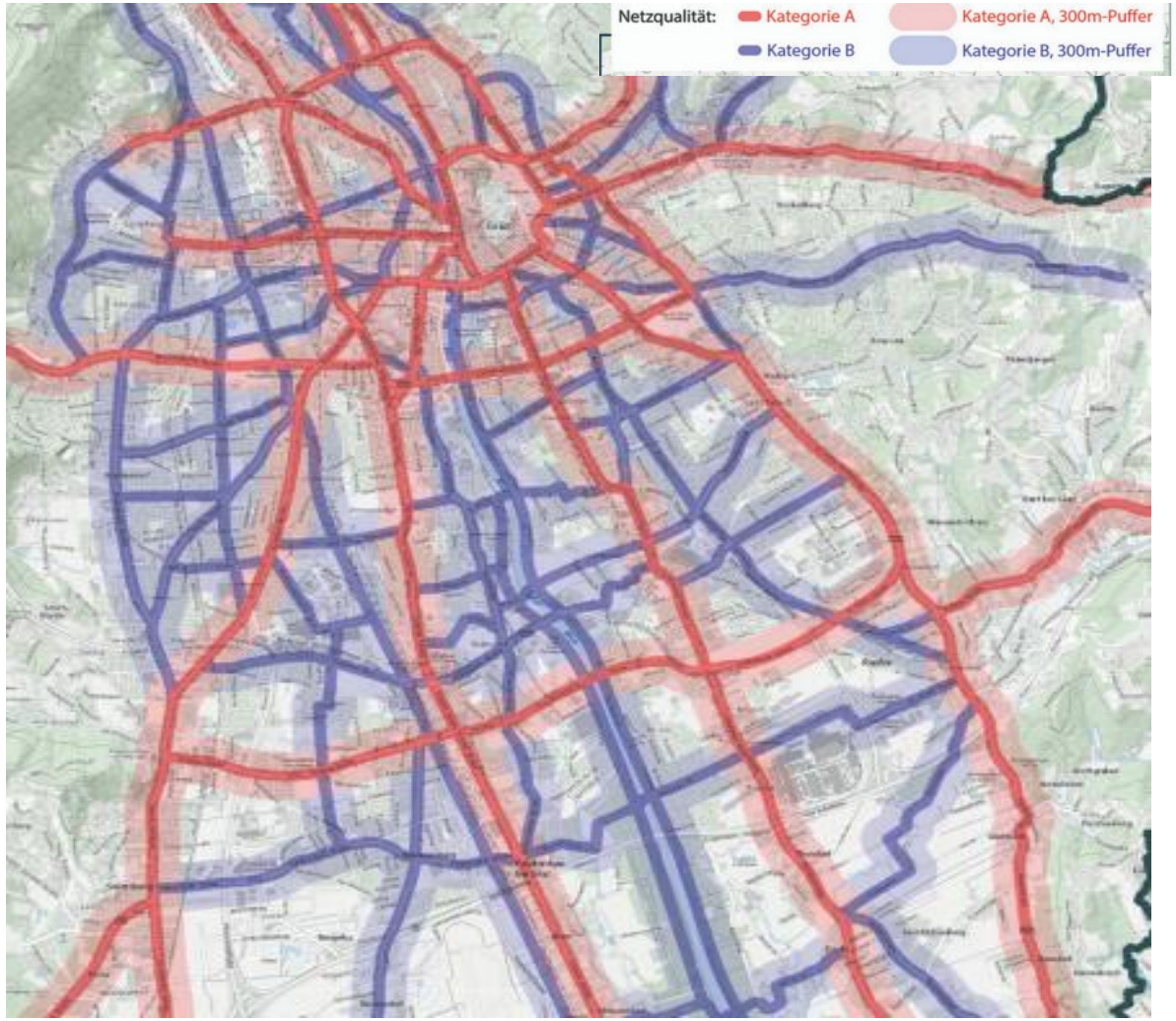


Wischer etal: TRR, 2023

Results: OD-matrices and link volumes

- Observed demand (left) appllied for bicycle infrastructure planning





Conclusion - Transport Planning: Where do we go now?

- Data driven transport planning (mobile phone data) an asset:
  - Continuity
  - Consistency
  - Survey independent
- OD-data for numerous
  - Urban
  - Regional
  - International
- Transport planning applications

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