User-based representation of time-resolved multimodal public transportation networks

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Straightforward representation
Urban transportation network properties

spatially embedded  multimodal  time-resolved

Bus schedule
New representation including time information

Identify hidden patterns of privileged connections

Quantify overall efficiency for commuting flow

Overall aim: characterize different cities in the same framework
Urban transportation data

General Transit Feed Specification

geospatial information

&

schedule information
Transportation network representation

multi-edge & P-space
Public transportation vs car

Choice criteria:

1. total **travel time**
2. **variability** in the total travel time
3. number of **transfers**
Uncovering fast connections

Choice of a typical day: focus on commuting hours

Multi-edge P-space representation:

1. Weights: time spent in the transportation mean + waiting time

2. Penalties: transfer times
Uncovering efficient transportation connections

Adaptation of Dijkstra’s algorithm

→ Computation of the shortest path in time for any origin-destination pair

# of transfers limited
Shortest time paths

For each (origin, destination) commuting time vs geographical distance
Car commuting times

Extracted from the French national survey of transport and mobility 2007-2008

- distance travelled (1 Km resolution), by
- transportation mean used & trip duration (1 min resolution)

Typical time needed to commute a particular distance by car: median of the distribution of times over the entire sample
Travel time factors

For each distance:

- Public transportation commuting times
- Car commuting times
Privileged connections

The structural properties of the transportation network are geographically constrained.

Going beyond the geographical informations: the privileged connections are the results of the design of the transportation network.

How are these fast connections distributed in the city? At which extent are they linked to home-work commuting?
Analysis of the fast connections

Intuition: stations with similar connectivity patterns can exhibit some similarities

For instance:

1) we expect that some stops located in a residential neighborhood have similar connections with respect to the rest of the network, as some might be linked to stops located in the city center and in working areas

2) nearby stops having the same connectivity patterns can yield some resilience to the system
Detection of underlying patterns

Building of an adjacency matrix of the fast connections
Detection of underlying patterns

Non negative matrix factorization (NMF)

Given a non-negative matrix \( A \in \mathbb{R}^{m \times n}_+ \), a non-negative matrix factorization in \( K \) components is:

\[
A \approx WH
\]  \hspace{1cm} (1)

\[
a_{ij} = \sum_{k=1}^{K} w_{ik} h_{kj}
\]  \hspace{1cm} (2)

where \( W \in \mathbb{R}^{m \times K}_+ \) and \( H \in \mathbb{R}^{K \times n}_+ \)

\[\hat{W}, \hat{H} = \arg\min_{W,H \geq 0} D(A, WH)\]
Transportation network analysis

We run the method for different cities:

- 1) P-space **multiedge representation** of the transportation network

- 2) calculation of the **shortest paths**

- 3) **extraction of patterns** for different intervals of distances relevant for the city scale
Efficiency characterization

Percentage of commuters with access to good PT

- Nantes: 48% (107,495)
- Toulouse: 56% (167,216)
- Strasbourg: 45% (65,174)
- Paris area: 25% (274,057)
- Paris PC: 45% (157,1026)

- 61% (75,090)
- 70% (83,000)
Summary

- Representation taking into account:
  - spatial embeddedness
  - multimodality
  - time information
- Adapted Dijkstra’s algorithm
- Fingerprints of public transportation networks

Future work

- Integrating: bike sharing and car sharing
Thank you!

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http://rsos.royalsocietypublishing.org/content/3/7/160156

https://github.com/lalessan/user_basedPT
Shortest paths