DEVELOPING A NEW GENERATION OF REAL-TIME TRANSPORT TRIP PLANNERS

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Summary

✓ Limits of current route planners

✓ Next generations of real-time route planners:

  ➢ New methods for generation of suggested paths:
     • Average and individual utility-based approach
     • Descriptive and normative strategy-based approach

  ➢ Forecast of Vehicle Occupation Degree
Transit trip (route) planners

Current characteristics

✓ Input data: current position, destination, (eventually desired departure or arrival time, transport modes to be considered, path requirements (maximum values of some attributes), ...)

✓ Output data (Google Transit, Opentripplanner, Moovit, ..):

  ➢ (alternative) minimum travel time available path(s),
  ➢ Some (predictive) attributes: travel time, waiting time, ...
  ➢ Some external costs: CO2 emission, ...
  ➢ ....
Current transit route planners: a consideration

The contents of current route planners are fall short of:

- the requirements of **multimodal transit** networks
  - the **complex stochastic** networks
- the developments of **communication technology**
  - the opportunities of **open source data**
  - the potential of **computer science**
    (big data processing)
  - the **theoretic knowledge**
    in the public transport field
    (even if further developments have to be done)
Multi-modal Transit Traveller Support
(info+booking+ticketing): new requirements

- vehicles

- infrastructures

Control Center

New Methods of Trip Planning for Travellers of Advanced Transit Networks
Evolution of Traveller Communication: an opportunity

- Vehicles
- AVL systems
- Control center

Evolution of Traveller Communication:

- Stops
  - Static timetable
- User
  - Static timetable
  - Shared real-time info
  - Personal real-time info

Crowdsourcing info
City-wide Transit ITS Platform: an opportunity

*Integrated platform for smart cities to enable demand-adaptive transportation systems*
A new generation of trip planners:

✓ At prototype stage:

- new methods of path alternative generation for multiservice/multimodal networks: **Utility-based methods**
- Suggestion, in stochastic (unreliable) networks, of a path strategy
- providing of further travel attributes: **vehicle occupation degree**

✓ At concept stage:

- Suggestion, in stochastic (unreliable) networks, of a path strategy with a normative approach.
Generation methods of suggested paths

✓ rule-based (current trip planners):
  ➢ a set of filters is used to reduce the set of all feasible paths; such rules can be defined by the transport agency and/or by the traveller;
  ➢ identification of travel time best paths, eventually with weighted time components (access, waiting, transfer, on-board, and so on) (weights defined by the provider and/or by the traveller);

✓ utility-based (new trip planners):
  ➢ An utility function, tailored to travel purposes and average or personal preferences, is used to select the suggested alternative
Individual (Real-time) Traveller Information Systems: *path generation approaches*
**Multinomial logit average and individual parameters**

*Example of sub-urban path alternatives*

Frascati-Rome with Desired Arrival Time at 9:30 am
# Multinomial logit

average and individual parameters

*Estimated with 150 SP observations: sub-urban test case*

<table>
<thead>
<tr>
<th>USER</th>
<th>Model type</th>
<th>Waiting time (total)</th>
<th>On-board time (train)</th>
<th>On-board time (metro)</th>
<th>On-board time (bus)</th>
<th>Early and late arrival time</th>
<th>%-of-right (1&lt;sup&gt;st&lt;/sup&gt;)</th>
<th>%-of-right incl. 1&lt;sup&gt;st&lt;/sup&gt;+2&lt;sup&gt;nd&lt;/sup&gt; best</th>
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<tbody>
<tr>
<td>User A</td>
<td>logit ($\rho^2 = 0.71$)</td>
<td>$\beta_{\text{waiting}}$ = -0.44 $t = -4.06$</td>
<td>$\beta_{\text{railway}}$ = -0.08 $t = -1.3$</td>
<td>$\beta_{\text{metro}}$ = -0.34 $t = -1.64$</td>
<td>$\beta_{\text{bus}}$ = -0.43 $t = -3.24$</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -0.29 $t = -3.41$</td>
<td>84%</td>
<td>97%</td>
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<tr>
<td>User B</td>
<td>logit ($\rho^2 = 0.67$)</td>
<td>$\beta_{\text{waiting}}$ = -1.22 $t = -5.50$</td>
<td>$\beta_{\text{railway}}$ = -0.43 $t = -2.80$</td>
<td>$\beta_{\text{metro}}$ = -0.83 $t = -3.12$</td>
<td>$\beta_{\text{bus}}$ = -0.59 $t = -3.31$</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -0.57 $t = -3.27$</td>
<td>81%</td>
<td>98%</td>
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<tr>
<td>User C</td>
<td>Logit ($\rho^2 = 0.60$)</td>
<td>$\beta_{\text{waiting}}$ = -0.073 $t = -3.31$</td>
<td>-</td>
<td>-</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -0.265 $t = -6.81$</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -0.081 $t = -2.58$</td>
<td>64%</td>
<td>100%</td>
</tr>
<tr>
<td>User D</td>
<td>Logit ($\rho^2 = 0.90$)</td>
<td>$\beta_{\text{waiting}}$ = -0.773 $t = -3.65$</td>
<td>-</td>
<td>-</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -1.10 $t = -3.24$</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -0.074 $t = -0.67$</td>
<td>95%</td>
<td>100%</td>
</tr>
<tr>
<td>User E</td>
<td>Logit ($\rho^2 = 0.79$)</td>
<td>$\beta_{\text{waiting}}$ = -0.497 $t = -5.24$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -1.73 $t = -6.40$</td>
<td>88%</td>
<td>100%</td>
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<tr>
<td>User F</td>
<td>Logit ($\rho^2 = 0.69$)</td>
<td>$\beta_{\text{waiting}}$ = -0.105 $t = -1.71$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -0.169 $t = -2.90$</td>
<td>90%</td>
<td>96%</td>
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<td>Average</td>
<td>Logit ($\rho^2 = 0.51$)</td>
<td>$\beta_{\text{waiting}}$ = -0.219 $t = -11.59$</td>
<td>$\beta_{\text{railway}}$ = -0.062 $t = -3.96$</td>
<td>$\beta_{\text{metro}}$ = -0.08 $t = -1.58$</td>
<td>$\beta_{\text{bus}}$ = -0.18 $t = -6.29$</td>
<td>$\beta_{\Delta(\text{early/late})}$ = -0.036 $t = -2.29$</td>
<td>76%</td>
<td>90%</td>
</tr>
</tbody>
</table>
Average utility path definition

Example of application

The new App for getting around Rome and the Latium region.
Traveller’s individual utility function

In order to provide reliable path advices, a learning process of the individual utility function parameters of user $i$ with a two-step procedure, can be used (Arentze 2013; Nuzzolo et al., 2013):

1. utility function parameter initialisation
   (a first estimation of individual parameters)

2. updating of initial parameter
   (updating of individual parameters using revealed user’s choices during tool use)
Personal Traveller Advisor (Tor Vergata)

logical architecture

1. **AVL real-time**
2. **traffic real-time**
3. **road network**
4. **transit timetables**

- **user i multimodal path choice set identification**
- **user i multimodal path choice set**
- **user i path utility calculation and ranking**
- **user i information on alternative paths**

- **user i path choice**
  - **path k monitoring**
  - **tracking position X of user i on path k**
  - **reliable path advice**
    - **O, X, τ query**
    - **yes**
      - **user i en-route advice on path k**
    - **no**

- **O, D, r query**

- **registered user i**

- **user i preference learning**
  - **user i revealed paths**
    - **yes**
      - **user i en-route advice on path k**
    - **no**

- **user i initial personal parameters β_i**
  - **reliable path advice**
  - **no**

- **user i stated paths**
  - **user i SP survey**
  - **most common O^*, D^*, τ^***
  - **new user i**

**New Methods of Trip Planning for Travellers of Advanced Transit Networks**

Tor Vergata
University of Rome

ITSC 2015 – WS01 Toward the Next Generation of Urban Mobility
Individual path utility modelling in advanced Personal Trip Advisors

Open issues

✓ Very few works in individual path choice modelling
✓ Initialization of path utility function
  ▪ design of personal SP survey
  ▪ definition of efficient number of scenarios to propose to initial user
  ▪ identification of different specification according to different decision contexts (e.g. purpose of trip – work, pleasure; weather conditions)
  ▪ identification of functional form for taking into account the variations in tastes and preferences for the user over time
  ▪ parameters estimation for taking into account correlations among SP

✓ Updating of parameter estimations
  ▪ Batch approach (e.g. maximum likelihood methods)
  ▪ Bayesian approach

✓ Machine learning approach
Individual Utility Function: References


Complex Stochastic Networks

If the path attributes (e.g., travel time $t$) are random variables, the network is classified as stochastic.

Given an O-D pair of a stochastic network, let $SG$ the multimodal sub-graph including all the «considerable» paths connecting O-D.

If $SG$ includes (stop or pedestrian) diversion nodes and the unreliability (uncertainty) requires adaptive real-time choices of the diversion link, $SG$ is a stochastic complex sub-graph.

Example:
Example of stochastic transit network with diversion nodes and links

11 available hyper-paths:
- **hyper-path 1**: Origin - Stop A - Line 1 - Stop D - Destination
- **hyper-path 2**: Origin - Stop A - Line 2 - Line 3 - Stop D - Destination
- **hyper-path 3**: Origin - Stop A - Line 1 or Line 2 + Line 3 or Line 4 + Line 10 - Stop D - Destination
- …
Path advising for complex stochastic networks

✓ When travellers move on a stochastic complex network, even if an info system is available, **not a single path should be suggested but a dynamic optimal travel strategy should be used**

✓ A strategy is identified by:
  - a set of diversion nodes,
  - a set of diversion links for each diversion node and
  - a diversion rule of choice among diversion links

✓ Different strategies with different **set of diversion nodes** and different **diversion rules** can be applied

✓ The **strategy of max long run Expected Utility** should be used

✓ A sequence of successive recommended diversion nodes and links should be **dynamically** given, according the outcomes of random events

✓ A strategy can be topologically represented with an **hyper-path**, whit diversion nodes and links at decision points.
«Hyperpath» trip planner (SISTeMA, 2015)

✓ Hyperpath uses an hyperpath approach for path suggestion and the optimal hyperpath is found according to an adaptive-indifferent diversion rule, as proposed by Spiess and Florian: traveler boards the first arriving vehicle of a set of attractive lines (indifferent optimal strategy).

✓ This behavioral assumption is acceptable when no real-time predictive info is available, but at current stage of the information technology and telematics evolution, the suggestion could be given according to an adaptive-intelligent diversion rule, which uses also the available predictive information (intelligent optimal strategy).
Normative intelligent optimal strategy:

Search of optimal strategy

Given an unreliable service network connecting an Origin-Destination pair, which is the intelligent optimal strategy to be used in order to maximize the expected travel utility?

- As optimal policy in Automated Planning problem of Artificial Intelligence
- Markovian Decision Process
  - Existence and unicity conditions
- Reinforced learning approach, including predicted info and previous experiences
- Q learning algorithm
Normative intelligent adaptive strategy

Euristic sub-optimal sub-hyperpath search

✓ at diversion node $m$ and time $tau$ a basic hyperpath $Bkm$ is obtained through a non-compensatory approach

✓ the basic hyperpath $Bkm$ includes several inclusive sub-hyperpaths $TKml$, one for each diversion link $l$

✓ the $TKml$ of the different diversion links are compared in terms of anticipated utilities and the max anticipated utility total sub-hyperpath $TKm^*$ is found

$$AU_{Kml}^{τ_m} = α \cdot EU_{Kml}^{τ_m} + (1 - α) \cdot FU_{Kml}^{τ_m}$$

✓ the diversion link and the first next diversion node of the optimal $TKm^*$ are suggested.
Normative intelligent optimal strategy

At each time $\tau_m$, suggestions are provided according to the anticipated utility

$$AU_{K_{ml}}^{\tau_m} = \alpha \cdot EU_{K_{ml}}^{\tau_m} + (1 - \alpha) \cdot FU_{K_{ml}}^{\tau_m}$$

$EU_{K_{ml}}^{\tau_m}$ is the expected utility of hyperpath $K_{ml}$ computed at time $\tau_m$

$FU_{K_{ml}}^{\tau_m}$ is the utility of hyperpath $K_{ml}$ forecasted with predictive path attributes computed at time $\tau_m$

$H_q^z$ the path that has been experienced following the suggestions given by the info system at day $z$.
Normative intelligent adaptive strategy

Line 1 - travel time 15 mins - frequency: 6 buses/hour
Line 2 - travel time 4 mins - frequency: 15 buses/hour
Line 3 - travel time 3 mins - frequency: 12 buses/hour
Line 4 - travel time 3 mins - frequency: 15 buses/hour
Line 5 - travel time 6 mins - frequency: 12 buses/hour
Line 6 - travel time 5 mins - frequency: 9 buses/hour
Line 7 - travel time 3 mins - frequency: 6 buses/hour
Normative intelligent adaptive strategy

\textit{Euristic sub-optimal hyperpath search}

✓ For example the OD pair is connected by 5 paths composing a basic hyperpath with 5 diversion nodes (O, 10, 20, 40, 50).

✓ When the traveller is at origin, two diversion link are present: access link to stop 10 and access link to stop 20. If the total sub-hyperpath including stop 20 is the optimal, the path until this node is suggested.

✓ When the traveller arrives at node 20, each time a run of line 2 or 3 arrives at the stop, a new search of optimal sub-hyperpath until destination is carried out. If the indicated optimal sub-hyperpath includes node 40, when the traveller arrives in 40, a new sub-hyperpath search until destination is carried out.
Strategy advising:
new modelling challenges

- **Artificial Intelligence** approach development
- Dynamic real-time generation of the strategy choice set
- Dynamic real-time Utility computation for each strategy, accounting collective or individual preferences
Strategy choice: references

Real-time predictive information on occupation degree of vehicles

✓ From traveller point of view:
  ➢ Trade-off between waiting time and travel comfort.

✓ From operations control point of view
  ➢ Real-time applications of operations control strategies.
Occupation degree
short-term predicting methods

✓ Variables:
  - number of on-board passengers and at stop waiting travellers for each vehicle

✓ Statistical Aggregate (projection) methods:
  - Parameteric models (e.g. ARIMA)
  - Non parameteric models (e.g. Kalman filtering)
  - ......

✓ Real-time transit system simulation
  (e.g. real-time network models, O-D matrices and assignment models)
Simulation test

✓ on-board crowding info influences the departure time, increasing of the early schedule delay (14 -15 %), due to travellers departing earlier with respect their desired target time to anticipate crowding, with a relevant reduction (-26.0% and -24%) of the late schedule delay;

✓ in HIGH-crowding, on-board crowding info leads to a fail-to-board reduction of about 7%, which is also a side effect of anticipation of crowding additional;

✓ info on crowding allows increasing gains as crowding increases. For LOW-crowding 8.5% in waiting time and 14% in transfer time, which become 10 % and 15%, respectively, in the case of HIGH-crowding;

✓ the benefits in terms of total travel time are quite limited (1.7% in the best case scenario of HIGH-crowding), but the presence of information about on-board crowding reduces the average disutility of 4 % for LOW-crowding to 7% for HIGH-crowding
New transit modelling requirements

✓ Development of **real-time transit assignment** models
  ➢ Run (vehicle) oriented
  ➢ Simulation-based
  ➢ Demand and supply mesoscopic approach
  ➢ Taking into account crowding degree info
  ➢ Fixed point problem

✓ Use of more precise OD matrices and model parameters:
  ➢ **OD and path choice model parameters** upgrading based on real-time data collecting and **reverse assignment**
OD and path choice model parameters

upgrading: example of logical architecture
References

✓ Real-time transit assignment:
  ➢ TransITS Book of Cost Action (fortcaming)

✓ OD Matrix and model parameter updating and Reverse assignment:
Forthcoming (2016)

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IN THE CONTEXT OF ITS/ICT
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