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Cognitive stances in urban mobility: a simulation experiment

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Premises

This paper reports about a model application which is being carried out at Ires for getting insights into the decision-making process underlying individuals' mobility in urban contexts (Occelli 2004; Occelli and Staricco 2005). More specifically, the model, which has been called CogMob, makes an effort to extend the cognitive abilities conventionally attributed to urban agents in describing their mobility behavior.

In most mobility models, cognitive abilities are based on the unquestioned assumption that agents' reasoning possesses an unlimited capacity (Occelli 2004; Occelli and Bellomo 2003). Reasoning plays a major role in discrete choice models, which since the mid 1970s have become the dominant modelling approach in transportation analysis. In these models, an agent is supposed to be able to evaluate all possible choice alternatives and select the one which maximizes his utility. The hypothesis has turned out to be very unrealistic: if an agent had to choose among n destinations, p modes and q departure times for a single trip, he should evaluate n x p x q alternatives. Even if he had to consider the sequence order of activities in activity schedules, for a list of ten activities there are almost ten million possible solutions (Charypar and Nagel 2005).

A recurrent finding supporting the principle of bounded rationality is that people use heuristic decision rules that circumvent their information-processing limits and simplify the decision task (Gärling 2004). Individuals, therefore, can be viewed as agents whose decision process is structured according to a hierarchy of

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IRES-Istituto di Ricerche Economico Sociali del Piemonte, Torino, Italy e-mail: occelli@ires.piemonte.it *if-then* rules, akin to those performed by classifier systems in complex adaptive systems (Balmer et al. 2004).

Building upon the arguments put forward in the cognitive science literature (Hutchins 1999; Fauconnier and Turner 2002), in the CogMob model agents are endowed with a set of so-called cognitive stances which can be differentially applied in their mobility choices. These are identified by articulating a knowledge and a reflexivity dimension, and are defined as:

- *Habitual behavior*: The agent chooses the route he is most familiar with, without considering alternatives and evaluating its performance.
- *Learning by instruction*: The agent chooses the route he got information about. This is provided either by those agents he usually meets at his residence or workplaces, or by a system whisper, i.e. an Internet router that suggests the path with the lowest expected travel time.
- *Reasoning*: The agent chooses among the travel paths he has already run through in the past, which is the most convenient one.
- *Visioning*: The agent explores a novel travel path, never undertook before, by selecting a route at random.

The adoption of a cognitive stance depends on agent's personality, i.e. proneness to habitual versus deliberative behaviour, exploration versus exploitation.

In addition, a claim is made that cognitive stances are related to both syntactic and semantic components of agents' mental worlds. A same cognitive stance can be applied in different choice contexts, i.e. reasoning can be used in route choice for minimizing personal monetary disutility, maximizing time savings, minimizing safety risks, etc.

The semantic component accounts for the set of values referred to by agents in interpreting the world and gives



sense to the resulting mental representations: monetary utility, sustainability, aesthetics, time saving, safety, etc. These values can belong to an agent's internal world, being driven by his/her beliefs and desires, and external world, being entrenched in the norms, rules, social obligations constituting the individual's cultural world. Semantic values may influence the adoption of certain cognitive stances. In addition, they can be modified as a consequence of transport policies (i.e. campaigns promoting safety or the use of public transport, and so on) or as a result of interactions with other agents having different values (Chavalarias 2004).

Simulation experiments

CogMob is a multi-agent model implemented on a SWARM simulation platform.

In the current version of the model, n agents have to choose their travel path from s residences to t workplaces and back. They are supposed to move on a spatial network (a grid) of x nodes and repeat their moves for a certain time period (consisting of y days). n, s, t, x and y are parameters which are specified in each simulation experiment. Each agent has his own personality, defined by means of four parameters, *hab, expl, reas* and *learn*, reflecting his aptitude to adopt each of the four cognitive stances. Every day, agents choose their travel path by applying the following selection function:

```
selectionFunction() {
  random n;
  if(n<hab) {
    habitualBehaviour();
  }
  else if(n<(hab+expl)) {
    explorativeBehaviour();
  }
  else if(n<(hab+expl+reas)) {
    reasoningBehaviour();
  }
  else if(n<(hab+expl+reas+learn)) {
    learningBehaviour();
  }
}</pre>
```

where *n*, *hab*, *expl*, *reas* and *learn* are number between 0 and 1, and (hab + expl + reas + learn) = 1.

In the simulation experiments carried out so far, there are 990 agents located in 100 residences and 2 workplaces. The spatial network has 100 nodes and the simulation period lasts for 50 days.

Table 1

	Probability of adopting:			
Kind of agent	habitual behaviour (norm) %	exploration (expl) %	reasoning (reas) %	learning by instruction (learn) %
habitual	80.0	6.7	6.7	6.7
explorative	6.7	80.0	6.7	6.7
reasoning	6.7	6.7	80.0	6.7
instructed	6.7	6.7	6.7	80.0
balanced	25.0	25.0	25.0	25.0
explorative reasoning instructed	6.7 6.7 6.7	80.0 6.7 6.7	6.7 80.0 6.7	6.7 80.0

We considered five types of agents, defined according to varying probabilities of adopting a certain cognitive stance, i.e. different values of the *hab*, *expl*, *reas* and *learn* parameters (Table 1).

Two ideal spatial configurations are explored, i.e. all workplaces are located either in the centre or in the periphery. Three different spatial networks are also considered: (a) a grid network, where all links have a same maximum speed; (b) a heterogeneous network in which there is suburban high-speed ring around the core area and (c) a heterogeneous network where there are two high-speed radial axes.

Time saving is the principal semantic reference underlying the agents' goal. Agents, therefore, are motivated to reach their workplace and go back home by selecting the route with the lowest travel times.

Main results

A few results of the simulation experiments can be summarized as follows.

Apart from slight variations due to the presence of a random function, on the average, reasoning agents (those with a 80% reasoning in their cognitive stances) obtain better results (have lower travel times) than agents who adopt each of the four cognitive stances with the same probabilities. These on their turn have better results than agents who take up an explorative cognitive stance, exploring new travel paths at random. Explorative agents, finally, perform better than those who tend to undertake the same route, with a probability of 80%. This ranking is independent of the spatial configuration. Some differences in time savings are observed depending on the type of spatial network, they are lowest in a uniform undifferentiated network (mean deviation from the average is between -0.3 and -0.7% for reasoning agents, +1.0% for habitual agents); they are highest in non-homogenous spatial structures (between -1.5 and -1.9% for reasoning agents, +1.7% for habitual agents).

The performance of those agents who are supposed to learn by instruction shows a greater variability. First, it is very sensitive to the type of spatial network. Instructed agents are the best in undifferentiated networks, while they behave worse than reasoning and balanced agents in heterogeneous networks (probably because in this case the whisper suggests them to use the same high-speed links, thus causing congestion). In addition, they obtain better results in journeys-to-work (i.e. from many dispersed residential locations to few concentrated workplaces) than in journeys-to-home. The other types of agents do not show this difference. Finally, agents who get information from neighbours perform significantly better than agents instructed by the whisper: the latter, in fact, does not provide detailed information about



congestion levels and agents tend to underestimate travel times. On the contrary, the information given by neighbours who daily commute does reflect travel times more realistically.

Although far from being definitive, two main policy suggestions can be drawn from the above results:

- First, they show how tailoring policy measures according to agents' different personalities can improve the effectiveness of mobility policies. For example, for habitual agents it might be convenient to make them experiencing alternative ways of moving, while for explorative agents measures aimed at giving more detailed information about travel times on alternative routes might prove themselves more effective.
- Second, they point out that agents' behaviours can evolve as a consequence of a learning process, whose deployment is based on both syntactic and semantic component. In so far as the latter should raise sustainability reference values, soft transport policies where the semantic component plays a central role turn out to be as much important as hard ones.

The following aspects will be dealt with in next simulation experiments:

- The introduction of a wider palette of semantic reference values, i.e. agents might choose their travel path not only depending on maximum time savings, but also considering monetary disutility, congestion discomfort and scenery and landscape aesthetics of a certain route.
- The possibility to make endogenous the interaction between syntactic and semantic components. This means that agents would modify the probability of

adopting certain cognitive stances, according to the success of their previous choices or their willingness to comply with certain policy prescriptions.

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