Selection of Information Types Based on Personal Utility - a Testbed for Traffic Information Markets

Franziska Klügl
Dep. of Artificial Intelligence
University of Würzburg
Am Hubland
97074 Würzburg, Germany
kluegl@informatik.uni-wuerzburg.de

Ana L. C. Bazzan
Instituto de Informática,
UFRGS
Caixa Postal 15064
91.501-970 Porto Alegre, RS,
Brazil
bazzan@inf.ufrgs.br

Joachim Wahle
TrafGo GmbH
Grabenstr. 132
47057 Duisburg, Germany
wahle@traffgo.com

ABSTRACT
Traffic is an interesting research area for multi-agent systems, as the inter-dependence of actions leads to a high frequency of implicit coordination decisions among agents. The present work investigates the simulation of a market for traffic information. This market is implemented as a traffic centre where some measurements of the traffic conditions are evaluated. Simulated data generates information which is “sold” to drivers. Different levels of data aggregation, at different costs, are available. We simulate drivers buying this information and evaluating their utility. Based on their perception of this worthiness they will continue with their strategy of buying (or not) particular forms of information, or will abandon or change such a strategy. Our results are twofold. First, they corroborate previous studies from traffic engineers and traffic economists which i) question the presumption that information is necessarily beneficial for traffic as a whole, and ii) state that drivers who rely only on conventional information are likely to have an inaccurate knowledge of traffic conditions. Second, we show that not all types of simple information bring the same payoff to the informed drivers.

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Multagent systems, Coherence and coordination

General Terms
Economics

Keywords
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1. MOTIVATION
One of the challenges of Advanced Travel Information Systems (ATIS) is to achieve an adequate modelling and control of traffic flow. This becomes more and more important, for instance, for dynamic route guidance systems. To be effective, such systems have to make assumptions about the travel demand, and hence about travel choices and, especially, about the behaviour of people. It is clear that the decisions made in reaction to the information an ATIS provides alter the traffic situation and potentially make the predictions of the system obsolete. The problem is that currently drivers’ particular information demand and their reaction to it is neither registered nor considered in any forecast system.

Although a road user does not execute and reason about social actions in the narrow sense (e.g. [10]), traffic systems obviously exhibit social properties. The inter-dependence of actions leads to a high frequency of implicit coordination decisions. The more reliable the information that a driver gets about the current and future state of the traffic network, the more his actions — e.g. his/her route choice — depend on what s/he believes about the decisions of the other road users.

A commuting scenario is normally characterised by a driver facing a repeated situation regarding route selection. Especially interesting is the simulation of learning and self-organized coordination of route choice, without or with forecast, which we have been studying in [14, 15] respectively. In the former, we describe a basic model that involves microeconomics and artificial intelligence, which was validated against data from real laboratory experiments (with subjects playing the role of drivers). In the latter, we extend the previous work by integrating a forecast component. Every round consists of two phases: simulation of the traffic situation based on the information provided by drivers plus returning of a forecast, and actual driving based on a second decision of the drivers for which they receive some reward.

In these works we left open some questions to which we are now returning. One of them is the fact that although the abstraction of travel time on different routes into a simple formula for rewards is the standard basis for game-theoretic treatments, there are other forms of microscopic traffic simulations that have proved to reproduce the overall system behaviour. Thus we here replacing both steps of feedback generation by more realistic traffic simulations. A promising
candidate is the Nagel-Schreckenberg Model [18] we already used to study the effects of more or less up-to-date route information [24].

The other question left open is that it is not clear what kind of information is appropriate for a driver. Different forms of traffic information – with different associated costs – may be used to assess the future traffic situation for the selection of one route.

These two open issues are tackled in the present paper. We use the Nagel-Schreckenberg model to deal with the question: how different types of information, "sold" at different costs, can influence the performance of drivers in a commuting scenario.

In the next section, the microscopic model we employ is introduced, as well as some related work regarding approaches for modelling decision making in traffic scenarios, both with traditional and multiagent techniques. In sections 3 and 4 we present our model and discuss the results respectively.

2. MODELS FOR TRAFFIC SIMULATION

In their paper from 1994, Arnott and Small [3] mention the following figures: about one-third of all vehicular travels in metropolitan areas of the United States take place under congested conditions, causing a total delay in trips of about 6 billion vehicle-hours each year. Despite the fact that the figures are quite old, the situation has shown no significant improvement, if any. With costs of extending traffic networks skyrocketing, policy-makers have to carefully consider the behavioural aspects of the trips, i.e. the drivers behind the steering wheel. Fortunately, there is also a tendency of reducing that gap: several researchers are conducting simulations and/or proposing more realistic models which incorporate behavioural characteristics ([2, 7, 8, 17] among others).

There are two main approaches to the simulation of traffic: macroscopic and microscopic. The microscopic allows the description of each road user as detailed as desired (given computational restrictions), thus permitting a model of drivers’ behaviours. Travel and/or route choices may be considered. This is a key issue in simulating traffic, since those choices are becoming increasingly more complex, because more and more information is available. Multi-agent simulation is a promising technique for microscopic traffic models as the drivers’ behaviour can be described incorporating complex and individual decision-making.

Modelling traffic scenarios with multi-agent systems techniques is not new. However, the focus has been mainly on coarse-grained level regarding traffic problems as traffic agents monitoring problem areas (as in [19]). On the other hand, our long term work focuses on a fine-grained level or rather on traffic flow control. Currently, in order to make traffic simulations at the microscopic level, one may have to consider travel alternatives (and consequently an extensive search of information), joint and dynamic decision-making, contingency planning under uncertainty (e.g. due to congestion), and an increasing frequency of co-ordination decisions. This has consequences for the behavioural assumptions on which travel choice models needed to be grounded. At this level, there is now an increasing number of research studies. Among them, we can cite: [5, 4, 9, 12, 13, 22, 20, 24].

Burmeister and colleagues [9] tackle the deliberation level, although they do not address the problem of decision-making over route choice under social constraints. They model a so-called driver-vehicle-unit (DVU) as an agent, which has intentions, goals, resources and is able to behave (e.g. perception, negotiation). Their goal is to run a microscopic simulation based on a car-following model, which determines the behaviour of a driver as a function of the speed and space difference between its car and the vehicle in front of it. For each perceived situation, the DVU has a script that determines how to drive. However these scripts only tackle driving from the physical point of view (e.g. accelerate, brake), not considering psychological issues such as experience of the driver, its knowledge of the environment, its type (aggressive, defensive, etc.), or richer information sources (broadcast about congestion and road work) and expectations over other drivers.

However, we think there is a need to change the modelling paradigm of drivers in order to deal with both the cognitive as well as with the reactive tasks. In [6] a two-layer architecture for modelling drivers as agents in traffic is proposed, which uses a BDI formalism as well as a reactive model. BDI formalisation is also the topic in [21].

The reproduction of behaviour of drivers via multi layered architectures appears also in [20] where the authors discuss the viability of applying multi-agent simulation for unorganized traffic — which would consider the behavior of drivers (e.g. cautious, normal, and aggressive) ignoring traffic rules — and the construction of a simulator. Also the goal of the ARCHSIM model [13] is to generate realistic traffic situations by reproducing the behaviour of the drivers interacting in an artificial environment, and also permit the integration of a real driver in a driving simulator.

Therefore, it is easy to notice that the multiagent community is seeking to formalise the necessary combination of methods and techniques in order to tackle the complexity posed by simulating and anticipating traffic states. No matter the motivation behind (training of drivers, forecast, guidance to drivers, etc.), the approaches seem to converge.

Next, we describe some studies focussing on informed drivers’ decision making. We start with works from the traffic engineering and traffic economics communities. After, we review our previous results on iterated route choice. Finally, in the last subsection the microscopic model for simulation is introduced.

2.1 Information and its Effect

In Al-Deek and colleagues [1] the goal is to develop a framework for evaluating the effect of an ATIS. Three types of drivers are considered: those who are unequipped with electronic devices of any kind (i.e. they are able to get information only by observing congestion on site); those who only receive information via radio; and those equipped with an ATIS (only). The device in the latter case informs drivers about the shortest travel time route. Some drivers of the first type are completely unaware of the congestion event. In this case, they take their usual routes. Average travel time is measured and it is found that this time improves marginally with increased market penetration of the simulated ATIS. However, the benefits of the ATIS are marginal when there is more information available to travelers, especially through radio, but also through observation. These induce people to divert earlier to the alternative route.

In our work, we are also motivated by the need to investigate how drivers respond to an ATIS, and which factors affect travel decisions. Also we want to drop the “perfect
information” assumption (individuals having knowledge of all alternatives). This assumption is usually made because there is a gap between the engineering and behavioural models. Therefore, the traffic models do not account for the effect of information on the performance of the system, be it at overall level or at the individual one.

Of course, many aspects regarding the type of information as well as its contents or forms influence the behaviour of drivers. In our previous work we have dealt with these questions [14, 15]. We have investigated different scenarios in which different percentages of drivers are informed. The main conclusion is that providing different kinds of information may affect the performances (individual as well as overall), as it is detailed in the next subsection.

2.2 Scenarios for Iterated Route Choice

We use a well-known scenario for pre-trip planning. Every morning commuters try to get from their homes to their workplace on time. In modelling these scenarios it is possible to come close to reality, in which the participants have bounded rationality, social norms etc.

In many scenarios, for simplicity, it is assumed that there are two possible routes, A and B, connecting those places. Depending on the number of drivers that decide to take route A, route B might be faster. On the other hand, many drivers may think the same way and opt to select A. Their decisions depend on their beliefs about the environment and the behaviour of the other drivers, and how they develop their selection strategies.

2.2.1 Basic Decision Making

In [14] a scenario was simulated where N drivers have to decide to take one of the two routes in every round. At the end of the round, every driver gets a reward that is computed based on the number of drivers who selected the same route, in a game-theoretic fashion.

Regarding these drivers, we developed a simple model for the adaptive route choice based on their own relative success on that routes. As an agent has only qualitative information about the routes and its experiences with his own rewards, he cannot base his decisions on any sophisticated form of deliberation. The main result was that, under some circumstances, a route commitment emerges with the effect that not the individual drivers adapt to the optimal heuristic but the overall system evolves towards the equilibrium while most of the individual drivers learn to select a given route.

2.2.2 Reaction to Traffic Forecast

As mentioned earlier that simple scenario above was extended to test the effects of forecast. In this case the decision-making process consists of two phases. First, drivers make their initial route selection. Based on this information they receive a traffic forecast (travel time for that particular route). Then, they have a second chance to actually take their first choice or change it. Finally the actual driving is carried out. The experiences they make in their actual driving influences both their future selections of routes, and their future reactions to traffic forecasts.

2.3 The Microscopic Simulation Model

In the present paper, in order to generate dynamic information, a simple microscopic traffic flow model is employed.
Those four types of information are:

1. Boolean information about congestion: the driver is informed whether or not a route is jammed (a jam is defined by the existence of at least n driver with speed equal to zero. The number n depends on the route length – in our simulations we set n = 1% of route length); if both routes are congested, then the driver selects one at random.

2. TravelTime: we assume that a control system collects information on every vehicle: its travel time is registered; thus the system is able to compute the travel time for both routes; drivers buying this information would be able to take the faster one. This kind of "floating car" information was also used in [24]. For the calibration of the costs it is important to notice that this information must not be more expensive for the buyer than boolean jam information. It is quite easily collected (if the floating cars are not payed for their participation).

3. Mean Speed: a driver may also buy information about the current mean speed on both routes and take the one with the higher mean speed. Therefore the speed of every vehicle on the route has to be considered and aggregated into this information. Thus we assume that this information should be more expensive than the previous two.

4. Density: drivers get information about the current density (usually vehicles/km but in our case number of vehicles in relation to route length) on both routes; the lower the best. As this information integrates number of vehicles and route length with an additional computation step, we assumed it to be the most expensive one.

As already said, the higher the aggregate value, the more expensive. Thus, boolean information regarding jam (or not) costs less and density has the highest cost. Specifically, we have set values to: 1 for boolean information on traffic jam, as well as for information on travel time, 2 for information regarding speed, and 3 for information regarding density. A driver can also decide not to buy any information. Also, since they have a limited budget, they may go bankrupt and cannot afford to buy anything. These basic costs are modified using a weight that is also depending on the route length.

From now on when we refer to driver or agent, we actually mean an informed driver. The simulation scenario is enriched with a certain amount of noise drivers. They have a very simple behaviour: each selects its favourite route and this is initially assigned at random with 50%-50% distribution. When a driver decides not to buy any information, he exhibits the same behaviour. Informed drivers first choose the information they want to buy and then select the route that is currently the best one based on this information.

The information selection is based on an elaborated probability distribution which considers the types of information. Agents start with $1/(k+1)$ probability of choosing between one of the k information types. The $(k+1)$-th case is the decision of buying no information at all. This probability distribution changes within time depending on the rewards an agent gets, as it will be discussed later. The idea is to check whether the informed are better off regarding commuting time and reward which is computed by equation 1.

$$\text{Reward}(i) = (T_g - T_i) \times F_1 - \text{cost} \times F_2$$  \hspace{1cm} (1)$$

Here, $T_i$ is the travel time between A and B for driver $i$. $F_1$ and $F_2$ are two factors used for weighting possible success and information cost respectively. In these simulations they were both set to 1. $T_g$ is the current global averaged travel time - aggregated based on a certain window of the last drivers that arrived at the goal (10 in each route in this case). This number thus denotes something like a current mean travel time for both routes. This is due to the idea that drivers should not get a reward relative to some ideal but unrealistic travel time but in relation to the currently possible one. Since the computation of $T_g$ involves data from both routes, the consequence is that the drivers on the currently faster one get positive reward, whereas the drivers at the congested route receive a negative one.

### 3.2 Description of the Driver Agents

The dynamics and the movement on the selected route are simulated according to the Nagel-Schreckenberg rules as stated in Section 2.3. Table 1 shows some parameters used which relate to this basic model for driving, as well as to our extension regarding this particular scenario. In this table, only "static" parameters are shown (i.e. those which do not change during the simulation). The parameters which do change within time are: gap, current assigned route, last route selected, current speed, number of times the trip was made (number of turns), current travel time (last trip), overall travel time (sum of travel times over all trips), current probability distribution to select information, the last information type selected, current reward, and budget. These are all attributes of the individual agents. Budget is the balance each agent has after accounting its reward which also includes payment for the information (see Equation 1). In the
beginning of the simulation they have a budget of 100 units. If the budget decreases to zero, the drivers cannot afford any information and only select their favourite route until their budget is positive again. Although bankrupt drivers do not pay for information, they still receive feedback based on their travel decisions. Thus, the budget continues to change.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>max. speed</td>
<td>5</td>
</tr>
<tr>
<td>delay probability</td>
<td>25%</td>
</tr>
</tbody>
</table>
| favourite route     | 50%-50% prob.
| informed            | true or false |

Table 1: Relevant Model Parameters

Once drivers arrive at their destination (final point of that route for sake of simulation) they receive their individual reward according to the travel times (Equation 1).

Agents also go through an adaptation process in which the probability to select a kind of information (or no information) is computed based on the reward they received by using the specific information strategy. This process is detailed next.

Directly after receiving their individual reward, the amount according to that the probability for the information changes, is computed based on the following formula:

$$\Delta p_{k,i} = \frac{\text{rewards}_i}{T_g - T_{\text{min}}} \times \begin{cases} p_{k,i} : & \text{reward}_i < 0 \\ 1 - p_{k,i} : & \text{reward}_i > 0 \end{cases}$$

Where $p_{k,i}$ is hereby the probability that agent $i$ chooses information $k$. $T_g$ is as defined before, whereas $T_{\text{min}}$ denotes the minimum travel time (maximum flow, $T_{\text{min}} = \frac{\text{Route length}}{v_{\text{max}}}$).

The equation above consists of two parts. The left part is a relative evaluation of the reward – relative to the maximum reward that a driver could receive in the current situation. This part will always be lower or equal to 1. The right part of the formula functions as a kind of norm factor as it sets the delta value according to the current value.

In case there is a positive reward for agent $i$ using information $k$, the correspondent probability $p_{k,i}$ is increased while other probabilities decrease by equal shares. In case the reward is not positive (i.e. travel time actually increased by using that information), then the probability $p_{k,i}$ decreases and the others increase accordingly.

3.3 Multi Agent-based Simulation Environment

Multi-agent simulations can be very demanding to implement as the models have to consider particular instances of drivers, environment etc. Therefore, we use the general purpose multi-agent simulation environment SeSAm (Shell for Simulated Multi-Agent Systems), described in [16] and accessible on the web (www.simsesam.de). This is an environment for modelling and experimenting with agent systems. It provides a rule-based architecture with several possibilities for structuring. All actions of a SeSAm-agent are encapsulated in “activities” and “rules” which are selected using rules or some form of hierarchical structure. Due to the explicit representation and a visual interface for modelling and experimenting, SeSAm provides the possibility to directly translate specification graphs into running simulation code.

4. RESULTS

In this section we present our simulation results. In order to analyse them, the measurements we use are the reward the agents receive, and budget. All quantities are analysed along time (3000 simulation steps which means about 30 trips for each agent on average). For the analysis we ignored the initial 750 time steps due to the influence of starting conditions.

We perform the simulations with 120 agents (which is compatible with the length of the routes). Specifically, we have simulated a rate of informed to noise drivers of 1 to 2 because our previous tests indicated that this rate is closer to the system optimum. Thus, we have 40 informed and 80 noise drivers using both routes in the network. Remember that from the former 40, a percentage actually does not buy any information. We repeated all simulation runs 20 times.

4.1 Reward and Budget

We first undertook simulations considering each type of information isolated to better understand its effect. Figures 4 to 7 depict the development of the mean reward over all informed agents selecting density, overall travel time, boolean information, and speed respectively. In each case, the mean reward for the noise drivers is also plotted for comparison.
Notice that information has a cost and since the reward of informed accounts for it, in some cases the reward of noise drivers is higher than of those informed.

As expected, the type of information with higher aggregate value, like density, provided agents with high performance (see Figure 4). This happens in spite of the fact that this kind of information has the highest cost (3 units).

As for travel time (Figure 5), in this scenario, with a relatively short route length, travel time is the best information type. However for longer routes density is better, as the information about travel time becomes less up to date. Travel time information is – due to the route length – a delayed information as only when drivers arrive at the end of the route can they communicate their travel time.

Surprisingly, information on mean speed (Figure 6) brings the worst performance to the agents buying it. The fact that contributes to this situation is that speed information costs 2 units, which is high (even if it is not as high as the information on density). Another explanation for this result may be a fact which is intrinsic to the model: speed is a discrete quantity which takes only 6 values (from 0 to 5), i.e. the discretization of values is too coarse, so agents cannot really differentiate between the quantities as they all look more or less the same. Therefore, our assumption that speed would be a valuable information holds only if we consider standard measurements of speed (e.g., km/h) but not the range we use which comes from the discretization. On the other side it may also be an effect of the delay probability in the Nagel-Schreckenberg movement which reduces speed without relation to the actual traffic situation on the road.

In previous experiments we observed that the quality of boolean jam information was quite bad. Previously we defined jam as at least one vehicle with a speed equal to zero. That means jam information that most of the time an agent got the information that both routes were jammed. So the selection of a route was nearly random. This of course added too much noise to the network. After improving the definition of jam/no jam, also the performance of this kind of information had improved (Figure 7).

Another remarkable observation is that the variation in the development of the reward for informed drivers is noticeable higher than the changes in the reward for noise drivers. That means: if a driver uses information about the traffic state – i.e. information about what other drivers are currently doing – s/he may have more extreme benefit or loss depending on what the other drivers decide. Therefore one may really say traffic is a social phenomena.

To summarise the analysis regarding rewards, Table 2 shows the average of rewards during the time of the simulation. It is interesting to see how the decisions based on bad information support the success of noise drivers as happens in the scenario with mean speed information.

As for budget, since it is a function of the reward each agent gets, there is of course a strong correlation between these two quantities and the conclusions are similar: drivers selecting information on travel time and on density are better off. Figure 8 shows the change in budget for agents selecting the four types of information. One sees that, except for speed, the other three types of information do have
Table 2: Budgets and reward for different types of information averaged over time and 20 runs.

<table>
<thead>
<tr>
<th>Type of Information</th>
<th>Informed Budget</th>
<th>Informed Reward</th>
<th>Noise Budget</th>
<th>Noise Reward</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boolean jam</td>
<td>102.75</td>
<td>0.49</td>
<td>89.72</td>
<td>0.08</td>
</tr>
<tr>
<td>Travel time</td>
<td>111.73</td>
<td>1.44</td>
<td>85.91</td>
<td>0.53</td>
</tr>
<tr>
<td>Mean speed</td>
<td>20.03</td>
<td>-6.05</td>
<td>125.49</td>
<td>-0.39</td>
</tr>
<tr>
<td>Density</td>
<td>104.77</td>
<td>0.66</td>
<td>76.85</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Figure 8: Comparison of budgets characteristics for agents selecting each type of information.

Figure 9: General performance of informed drivers versus noise.

Figure 10: Mean rewards for informed and uninformed agents in a scenario without information cost.

4.2 Zero Cost Scenario

One may criticise that our setting of information cost is somewhat arbitrary. However, we tried to reflect actual effort put on producing this information. In additional simulation runs we tested the effect of alternative cost configuration. The results do not change significantly for other reasonable costs.

To illustrate this, we briefly give some results for simulation runs with zero costs for all kinds of information (Figure 10). It is quite clear that the formally more expensive types of information are now more attractive, however the general statements are the same as when costs are different. In the case all costs are set to zero, the mean reward over all time steps for informed drivers is 4.08, whereas for noise drivers it is −0.18.

The decrease in reward for informed drivers (as compared to the figures just given above when we discussed the case in which costs are different), is due to the fact that costs for information are now zero, so that the rewards are higher.

5. CONCLUSION AND OUTLOOK

The main issue tackled in this study is the question of what kind of information about current route state has an utility for a driver. This can be seen in the context of previous work about actual route choice. Here we add another dimension, namely the choice of information before making the actual decision. Therefore the impact of different information types on the individual utility and acceptance by a driver is studied using a simple model of an abstract route-choice scenario.

It is shown that the different types of information lead to different rewards. Some of these are not necessarily better than the rewards of noise drivers. Density and travel time turn out to be the best choices, whereas information about mean speed on a route leads to surprisingly bad performance. The study presented here also shows that information costs are acceptable, even relatively high ones, if the information is worth buying it.

There are some open questions that have to be answered before we can continue working on basic research about ATIS that integrate knowledge about drivers’ route decision dynamics. Firstly they are concerned with additional kinds of information not considered here. On one side, until now we did not use qualitative information types with different categories as possible values. On the other side more
sophisticated information types can be studied: Information about trends in density or travel time seems to be more relevant than the selective information available for specific times. As mentioned above, also the analysis of combinations of information types would be an interesting direction. In [15] we started to integrate traffic forecast into simple route choice models which turned out to stabilize the traffic system. This would be also an important extension to this study presented here.

Another interesting extension is the regulation of information prices based on the demand. Information that is requested more often should become more expensive, whereas the price of information that is not bought by the drivers can decrease. This could lead to a self-regulation of prices without any empirical setting of information cost and would improve the analogy to market mechanisms.

Finally, one can conclude that dealing with information in traffic scenarios is both demanding and fruitful: demanding, as agent models have to be found that capture the mechanisms of human decision-making on a appropriate level of abstraction, and fruitful, as even using simple scenarios can illuminate interesting feedback loops between individual informed decision making and resulting traffic situation.

6. REFERENCES


