Shortest Paths for Groups: Introducing a Predictive Memory for Cognitive Agents

Johannes Scholz

Institute of Geodesy, Graz University of Technology, Austria · johannes.scholz@tugraz.at

Short paper

Abstract

This paper elaborates on the effect of predictive memory on cognitive agents that are acting in selfish routing games. Selfish routing describes a situation, where agents are moving in a network with defined latency functions, and act in a strictly selfish manner. Under certain situations – i.e. specific definition of the network, associated latency functions, and agents acting strictly selfish – the Braess Paradox occurs. The Braess Paradox contradicts human intuition by the fact that adding a new low-latency edge to a given network does not reduce overall latency. By incorporating cognitive agents in the game theoretical approach, agents could overcome their strictly selfish behaviour, which in turn reduces overall latency. By incorporating a kind of predictive memory, each agent can learn from a number of personal experiences and alter their present behaviour accordingly, which can reduce overall latency.

1 Introduction

Any shortest path problem is well studied in literature, and is implemented in a number of GIS products and online services, such as Google Maps or Bing Maps. Routing and navigation is the foundation for numerous applications in GIS, mobile devices, satnavs to find the way in unfamiliar environments, or to manage logistics (SCHOLZ & BARTELME 2011).

According to MONTELLO (2005), navigation can be broken down into "wayfinding" (planning) and "locomotion" – the execution of the planned movements. Generally, navigation is the process of selecting a destination and a certain type of associated cost – e.g. time, distance, fuel cost. The costs are necessary to evaluate the possible routes to get from a starting point to the destination. Based on the selected cost a shortest path algorithm calculates the route with minimum cost from start to the destination point. Such a methodology – currently state-of-the-art – does not take into account that traffic is a dynamic system. The decisions of agents in the system directly affect the state of the network. Thus, any attributes of the network can be regarded as being time-dependent, which makes a deterministic prediction relatively hard. A number of shortest path algorithms under dynamic conditions have been published (KAMBUROWSKI 1985, KAUFMAN & SMITH 1993, ORDA & ROM 1991, ZILIASKOPOULOS & MAHMASSANI 1993, DING et al. 2008). The algorithms try to react to dynamic conditions in the traffic network, but end up with a solution for exactly one navigation agent. Hence, the decisions of other agents are not fully incurporated in the planning process of shortest paths.

GI_Forum – Journal for Geographic Information Science, 1-2015.

In order to “simulate” decisions of other agents in the traffic system, ROUGHGARDEN (2005) employs game theory. BRAESS (1968) elaborates on a problem called “Braess Paradox”. This paradox describes a situation where a group of agents tries to find the “best” route in a network with linear latency functions, by acting in a strictly selfish manner. By adding an extra high capacity edge, one would expect the average travel time to decrease, in comparison to the original network. In fact, average travel time increases due to the extra high capacity edge (BRAESS 1968, ROUGHGARDEN 2005).

The problem highlighted in this paper is to equip cognitive agents (SCHOLZ 2013) in a non-cooperative network game with a kind of predictive memory. The memory allows the users to learn from previous personal experiences and adapt their present behaviour accordingly. This paper is a theoretical paper that reviews concepts in the area of selfish routing. Numerical results are presented in a follow-up publication.

2 Cognitive Agents, Predictive Memory and Selfish Routing

This section elaborates on the principle of Selfish Routing and the resulting Braess Paradox. Subsequently, cognitive agents discussed as an option to overcome the strictly selfish behaviour, which can be equipped with a memory to learn from previous travel experiences.

2.1 Selfish Routing

A subfield of game theory is routing game theory (MYERSON 1991), which deals with routing decisions in a network. In an environment where each agent “plays” in a non-cooperative manner, each agent tries to increase its own benefit. Non-cooperation has a certain price – i.e. inefficiency – that is called the Price of Anarchy (PAPADIMITROU 2001).

By the example of the Braess Paradox, depicted in Figure 1, we would like to explain the term selfish routing. In a network with vertices, edges, and associated linear latency functions, a number of agents shall travel from vertex A to D. In this example there are 4000 agents traveling from A to D. The latency function of edges AB and CD are *x/100*, where *x* denotes the number of agents traversing the edge. The latency function of edges BD and AC equals *45*. The result of the routing game – i.e. the Nash equilibrium – in the original network is depicted in figure 1 (left), where 2000 agents are using AB→BD and 2000 agents are traversing AC→CD, with a total average travel time of 65 minutes per agent. In the amended network – with the high capacity edge BC with latency *1* – the Nash flow is at equilibrium when all 4000 agents use AB→BC→CD. A total average travel time of 81 minutes per agent is determined (ROUGHGARDEN 2005, ROUGHGARDEN & TARDOS 2002, BRAESS 1968 BECKMANN et al. 1956, WARDROP 1952). This example explains the Braess Paradox, where the introduction of an additional high capacity edge does not decrease the average travel time in the network.

2.2 Cognitive Agents and Predictive Memory

In contrast to the strictly non-cooperating agents presented in chapter 2.1, cognitive agents are capable of making their own – perhaps non-selfish – decisions based on their context.

Cognitive agents have been employed in wayfinding in built environments (RAUBAL & WORBOYS 1999, RAUBAL & EGENHOFER 1998). As agents traveling in a traffic network are not fully aware of the situation ahead of them, agents need to make decisions based on uncertain and incomplete information (SCHOLZ 2013). Predictive memory is a concept based on the recognition-prediction framework that induces constant learning from previous experiences (CLARK 2013, HAWKINS & BLAKESLEE 2007). Hence, any player in the system could overcome a strictly selfish behaviour by memorizing own actions and actions of other players, as well as the final result. When encountering a traffic situation where a decision is needed, which is "similar" to a memorized situation, the agent could act accordingly. E.g. an agent listens to a radio traffic service message saying that there is a traffic jam ahead and agents are advised to take a detour. The agent cannot evaluate the accuracy of the message and may only speculate about the behaviour of the other agents in the system. Thus, he may sense that all the other could take the detour and the traffic situation is clearing up, or the agent shall take the detour. Additionally, the traffic message could be outdated by the time the agent arrives at the reported location of the traffic jam, because in the meanwhile the tailback has disappeared.

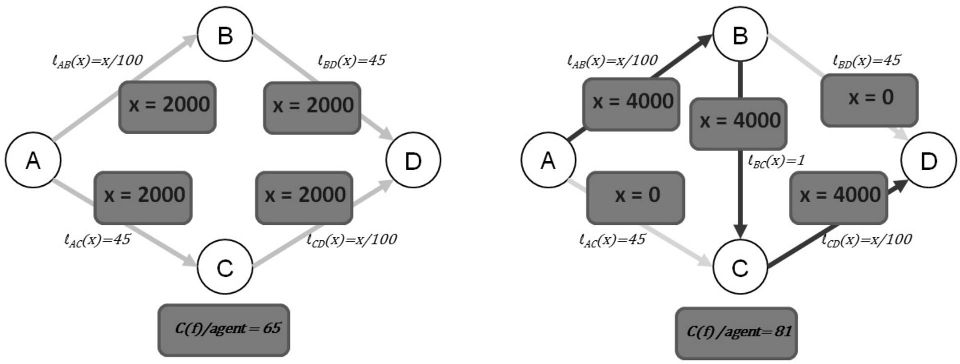

Fig. 1: Nash flow and corresponding cost per agent in the original network at equilibrium (left) and the Nash flow equilibrium after the new high capacity edge was included (right)

3 Conclusion and Outlook

The introduction of a predictive memory for cognitive agents in selfish routing games could contribute to GIScience and Intelligent Transportation Research. By modelling network flow with a certain degree of non-selfishness, by incorporating cognitive agents with a predictive memory, traffic situation could be predicted in a more accurate manner. This in turn could also be of interest to reduce the overall latency in traffic networks, by influencing the traffic flow. In literature, agents could be influenced by incentives for taking a certain detour or by personalized route suggestions similar to the concept of spatio-temporal Personal Information Management (ABDALLA & FRANK 2014).

References

ABDALLA, A. & FRANK, A. U. (2014), Designing Spatio-Temporal PIM Tools for Prospective Memory Support. In: Principle and Application Progress in Location-Based Services. Springer International Publishing, 227-242.

BECKMANN, M., MCGUIRE, C. B. & WINSTEN, C. B. (1956), Studies in the Economics of Transportation. Tech. rep.

BRAESS, D. (1968), Uber ein Paradoxon der Verkehrsplaning. Unternehmensforschung, 12, 258-268.

CLARK, A. (2013), Whatever next? Predictive brains, situated agents, and the future of cognitive science. Behavioral and Brain Sciences, 36 (3), 181-204.

DING, B., XU YU, J. & QIN, L. (2008), Finding time-dependent shortest paths over large graphs. In: Proceedings of the 11th international conference on Extending database technology: Advances in database technology. ACM, 205-216.

HAWKINS, J. & BLAKESLEE, S. (2007), On intelligence. Macmillan.

KAMBUROWSKI, J. (1985), A note on the stochastic shortest route problem. Operations Research, 33 (3), 696-698.

KAUFMAN, D. E. & SMITH, R. L. (1993), Fastest paths in time-dependent networks for ivhs application. IVHS Journal, 1, 1-11.

MONTELLO, D. R. (2005), Navigation. In: The Cambridge Handbook of Visuospatial Thinking. Ed. by P. Shah & A. Miyake. Cambridge University Press, 257-294.

MYERSON, R. B. (1991), Game Theory: Analysis of Conflict. Harvard University Press.

ORDA, A. & ROM, R. (1991), Minimum weight paths in time-dependent network. Networks, 21 (3), 295-320.

PAPADIMITRIOU, C. (2001), Algorithms, games, and the internet. In: Proceedings of the thirty-third annual ACM symposium on Theory of computing. ACM, 749-753.

RAUBAL, M. & EGENHOFER, M. J. (1998), Comparing the complexity of wayfinding tasks in built environments. Environment and planning, B 25, 895-914.

RAUBAL, M. & WORBOYS, M. (1999), A formal model of the process of wayfinding in built environments. In: Spatial information theory. Cognitive and computational foundations of geographic information science. Springer, 381-399.

ROUGHGARDEN, T. (2005), Selfish routing and the price of anarchy. The MIT Press.

ROUGHGARDEN, T. & TARDOS E. (2002), How bad is selfish routing? Journal of the ACM (JACM) 49 (2), 236-259.

SCHOLZ, J. & BARTELME, N. (2011), Decision Support for a Complex Spatial Scheduling Problem by a GIScience–Operations Research Approach: the case of VRPs with Pickup and Delivery and Time Windows. In: Geospatial Crossroads @ GI _Forum'11: Proceedings of the Geoinformatics Forum Salzburg, 91-100.

SCHOLZ, J. (2013), Shortest Paths from a Group Perspective-a Note on Selfish Routing Games with Cognitive Agents. In: Proceedings of ICA Workshop on Street Networks and Transport, Dresden, Germany. https://sites.google.com/site/icaworkshop2013/ (28-01-2015).

WARDROP, J. G. (1952), Road Paper. Some Theoretical aspects of road traffic research. In: ICE Proceedings: Engineering Divisions, Vol. 1.3. Ice Virtual Library, 325-362.

ZILIASKOPOULOS, A. & MAHMASSANI, H. S. (1993), Time-dependent shortest path algorithm for realtime intelligent vehicle highway system applications. Transportation Research Record, 1408, 295-320.