Self-Organizing Multi-Agent Systems (851-0585-49L)

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Assignment 1

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1 Agents

1.1 Scenario

In this assignment, a scenario for a multi-agent solution to the traffic problem in a big city, e.g. Zurich, will be investigated. The research aims at providing a strategy for the involved agents to behave such that the traffic flow between busy intersection points in a city will be improved. Think of avoiding busy intersections at certain moments of the day, and redirecting trips to use the available road capacity more optimally. The assignment does not consider micro-scale traffic phenomena, but only aims at modeling and improving the global task of distributing requested trips over the available road capacity in a clever manner. Most road users will want to minimize their own travel time, however perhaps this could result in delaying trips made by other agents. We are interested in finding an optimal strategy for all agents, hence globally seen, by taking into consideration agent preferences and fairness considerations. The scenario will be elaborated throughout the assignments when new aspects of the problem are introduced.

1.2 Hardware agents

The hardware agents involved in this problem is the set of all road users. In the city of Zurich, this concerns cars, buses, trams, pedestrians, cyclists and emergency vehicles like ambulances and police cars. In this work, it is assumed that cyclists do not change the traffic flow significantly. This is a reasonable assumption since the space occupied by a bicycle is virtually non-existing. Furthermore, other road users hardly experience any effects of the presence of cyclists in an urban environment. Pedestrians are disregarded for simplicity reasons.

1.3 Software Agents

Software agents involved in this problem are modern navigation systems with communication capabilities, like Google Maps and TomTom Live. Such systems gather real-time information about the traffic flow conditions and adapt their route proposal accordingly. Routes that infer a longer travel time due to e.g. traffic jams are avoided, and users are redirected to alternative routes to minimize travel time. Another software(-based) agent that could be used to influence the behavior of other agents are traffic lights. By cleverly controlling the traffic lights, traffic flow can be improved significantly; this is however beyond the scope of this work.

1.4 Interaction between agents

The urban environment is characterized by great complexity due to the interaction between a large number of agents. The focus on this work is put on macro-scale optimization of route planning between busy intersections based on real-time data regarding traffic density at the concerning locations. Traffic participants must obey to the signals given by traffic lights. We assume that road users do not violate the signals given by traffic lights. This implies that traffic lights can be used to regulate the traffic flow without further complications. On a larger scale, the behavior of agents in terms of route choice can be influenced by making use of dynamic navigation software. Furthermore, all agents are assumed to obey the directions given to them by their navigation systems. Although this is not perfectly realistic, disregarding directions given by these systems will be modeled later on by giving the agent's personal goals a higher priority than the collective goal thus making route deviations less likely. Lastly, these is interaction between all agents participating in traffic. For example, emergency vehicles will always have absolute priority over other vehicles, hence exerting a significant influence on the traffic flow. Trams have priority over all other agents provided that there are no traffic lights present. Note that these interactions have a dynamic nature: the time of the day influences the presence of certain agents on the road. Interactions between agents, the dynamic nature of the problem and possibly conflicting goals make the task of finding an optimal control strategy non-trivial.

1.5 Existing technology

As mentioned above, real-time data gathered by navigation software widely available. This makes it possible to determine a real-time control policy by proposing alternative routes. The software package that will be used to run simulations on in a later stage is MATSim. MATSim is an open source road traffic simulation package designed to handle large road networks.

2 Resources

The agents participating in the system have individual goals. For example they are aiming to reach a certain destination by using the shortest or fastest route, or get there with the lowest amount of fuel consumed. For most systems, these wishes cannot be fulfilled entirely for every individual, because the resources are limited and distributed between the agents. However, in order to maintain an efficient system, the available resources need to be handled in a clever way, so that every agent is satisfied for some extent and the distribution is not unfair. The goal of this assignment is to find a computational way to reach an optimal handling strategy or distribution of the available resources by also considering the individual goals of the agents.

2.1 Resources managed by the agents

In the described scenario, the agents are participating in a traffic environment. The most important resource therefore is the road network they use. Two cars cannot occupy the same spot on the same route at the same time, so this resource is by nature, distributed between the agents. Every road has a finite capacity for vehicles to get through in a given time period, hence traffic management is necessary. The optimal plan can be achieved via traffic control.

2.2 Handling resources

The road network is already available. The remaining task is to control the traffic via offering route plans to drivers in a way, that the overall throughput of the system is improved, the likelihood of traffic jams is reduced. We assume, that the car drivers use a route planning device in which they input their destination and preference (fastest, shortest, most economic). From real time data of the current traffic situation, a number of routes can be proposed to the driver to choose from. If an intersection gets too busy, alternative routes can make sure traffic jams get avoided by redirecting road users to less busy roads.

2.3 Problems or failure

The main consequences of bad traffic handling are traffic jams. Individual drivers will experience longer and unpredictable travel times. High traffic density at intersections can be resolved via alternative routes. However, in some cases even these methods cannot help in avoiding packed roads and long queues. The failure of traffic control can also arise from unexpected events such as accidents, break downs, fires or any technical malfunction. Ambulances, fire trucks and police cars can also be considered as disturbance of normal traffic flow, and can have an effect on the optimal route plans. In these cases most agents will experience a deterioration in their own goals.

2.4 Available datasets

By assuming that every driver uses route planning devices, information can be collected regarding the demand of using the given section of the traffic network. Every car has a starting point and a desired destination. The number of cars present in the network can be determined by making use of their GPS location. The offered routes can be calculated by looking at the current traffic situation and the start and desired destination locations.

In this assignment we rely on generated data. For creating individual plans, we intend to use the Multi-Agent Traffic Simulator (MATSim). The incoming or generated data needs to be transformed into a set of starting positions and desired destinations at certain points in time. This represents the demand, and can be used in simulated scenarios. We will also consider and compare rush hour and relatively low traffic situations during our simulation process.

3 Agents' Plans

3.1 Plan Generation

Every agent has a few preference parameters associated with it. These parameters express characteristics particular to that agent such as willingness to pay a toll charge to save time, willingness to take a path with a longer waiting time to minimize fuel usage, and so on. The inclusion of these parameters during plan generation is important because a user who does not mind taking a longer route should be assigned such a route during rush hours, rather than assigning it to someone who wants a shorter distance route. On the basis of these nuances, each agent generates four plans which are indicative of the agents' preferences. We generate four plans for each agent because our model assumes four costs parameters for each plan, as explained later in Section 4. In the worst case, each of these four plans will minimize exactly one of these costs.

As stated before, we will use the Multi-Agent Traffic Simulator (MATSim). We decided to use MATSIM because it is open source, has a very active online community, and also has maps of several major cities (such as Zurich and Berlin). At the beginning of each time interval, each agent will generate new plans from its current location to its destination. These plans will be fed to the EPOS algorithm. New plans are created at each time step because earlier made plans will not be able to account for any deviation from historical evidence such as the blocking of a road due to an accident.

3.2 Plan Representation

The plan for an agent is represented as vector of binary values. Each element of the vector is associated with a particular link in the network graph of the city. Consider the road network in Figure 1. A sample plan would be $[AB, BC, AD, BE, CF, DE, EF, DG, EH, FI, GH, HI]$, where each element is 1 if the current plan includes that link, otherwise it is 0. Links for cars going in opposite directions such as BA, CB, have been ignored for now just for convenience but will be included in the actual model.

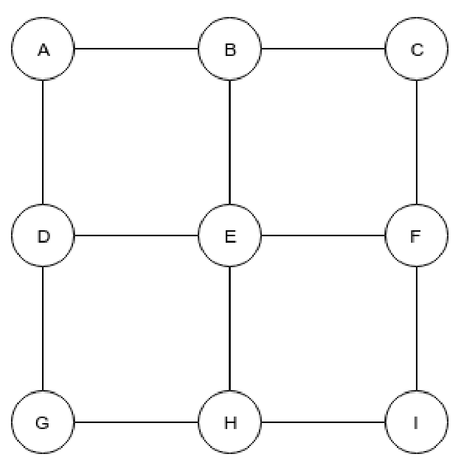

Figure 1: Sample Road Network.

Let us consider two cars C_1 and C_2. C_1 wants to go from node D to node I and generates plans $P_1^{C_1}$ and $P_2^{C_1}$. C_2, on the other hand wants to go from node B to node I and generates plans $P_1^{C_2}$ and $P_2^{C_2}$. All plans are generated with equal preference.

$$P_1^{C_1} = [0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0]$$
$$P_2^{C_1} = [0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1]$$
$$P_1^{C_2} = [0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0]$$
$$P_2^{C_2} = [0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1]$$

Case 1:
By choosing $P_1^{C_1}$ and $P_1^{C_2}$, the aggregate plan is: $[0, 0, 0, 1, 0, 1, 2, 0, 0, 2, 0, 0]$
Case 2:
By choosing $P_1^{C_1}$ and $P_2^{C_2}$, the aggregate plan is: $[0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1]$

The two other cases, $\{P_2^{C_1}, P_1^{C_2}\}$ and $\{P_2^{C_1}, P_2^{C_2}\}$, have been excluded from this discussion for brevity.

I-EPOS will be used to find out plans with minimum variance which would give Case 2 preference over Case 1. It is not difficult to see why generating plans with minimum variance will ensure proper traffic distribution. If the elements of the aggregated plan vector have lower variance, that would mean that traffic is distributed across all links as uniformly as possible thus avoiding traffic congestion.

However, there is one problem with the current representation. For longer routes, if links which the agent wants to take in the (far) future but not in the next time steps are set to 1, it affects the aggregate. This could force other agents, that want to use the link immediately, to change their plan and take other links. A solution to this problem is proposed by:

1. Modifying each plan to contain only the links which would be used in the next t intervals, with t to be chosen empirically, so that the links which they wish to use at a later stage are available for use by other agents immediately.

2. Updating the plans for each agent after each interval of time, where the new plan describes the route from its current position (instead of the starting position) to the destination. This ensures that all the links which have already been used by the agent are made available to other agents who might want to use them.

4 Local Agents' Objectives

Each plan has a cost vector associated with it, which provides the following information about the plan:

1. Estimated travel time - an estimate of the total time (including driving time and waiting time) it would take for the agent to reach its destination

2. Estimated waiting time - an estimate of the time the agent would have to wait at pedestrian crossings, traffic signs, etc.

3. Estimated fuel cost - an estimate of the fuel cost while driving from the agent's location to the destination.

4. Associated tolls - the total amount of money an agent would have to pay at toll booths to reach its destination.

This vector is represented as $[C_1, C_2, C_3, C_4]$. Each agent is asked to provide a preference measure for each of these costs - $[w_1, w_2, w_3, w_4]$, where w_1 is a measure of how much an agent dislikes long travel times. Each preference measure is in the range $[0, 1]$, where a value of 0 denotes that an agent is okay with the particular cost, and 1 denotes that he is very uncomfortable with it. The preference measures have been kept in the range $[0, 1]$ for the convenience of the agent. Note that the plan cost obtained by the dot product of the cost vector and the preference vector would not be justified. This is because it does not make sense to compare units of time (for travel and waiting times) with units of money (fuel and tolls) without appropriate scaling. Thus, each preference measure w_i would be multiplied with a scaling value α_i before being able to take the dot product. Hence, the cost for each plan can be represented as

$$C_{plan} = \sum_{n=1}^{4} \alpha_i w_i C_i$$

The scaling factors $\alpha_i, i = 1..4$, will be obtained empirically using MATSim.

5 Global system-wide objectives

The building blocks of global system behavior are the individual agent plans. Every agent affects the overall performance. The purpose of the global cost function is to map the aggregated plans of every agent to a "goodness" value. With a well-chosen global cost function, the different aggregated plans can be compared, and therefore optimized. The question remains: which objectives are important, which should be included in the global cost function, what makes a plan better than the other one?

5.1 Chosen global objectives

Under which circumstances can traffic be considered good? These objectives have already been discussed for individual agents, but it remains unclear what makes a control strategy good for the whole system? The low aggregated waiting time, travel time or overall fuel consumption among all cars could be good global objectives, but it is already included in our model as local objectives for agents. The agents will choose the plans with the lowest fuel consumption, travel or waiting time, if these are their personal preferences. In the global cost function we are aiming to make a plan with the best traffic distribution over the network. By offering several alternative routes to the agents, and choosing the aggregated plan in such a way, that the number of cars in each link are relatively evenly distributed, traffic jams at junctions can be avoided.

Consider the following example. Let P_1^A and P_2^A be two different aggregated plans in the system:

$$P_1^A = [0, 0, 4, 2, 1, 0, 2, 5, 3, 0] \longrightarrow Var\{P_1^A\} = 3.34444$$
$$P_2^A = [2, 1, 2, 2, 2, 0, 1, 2, 2, 3] \longrightarrow Var\{P_2^A\} = 0.67778$$

Every element stands for the number of cars going through that certain section of the road system in the next few minutes. By taking the variance of the plans, it is clear, that the plan with the lower variance is superior (P_2^A in this case), because the number of cars are closely evenly distributed in the section, therefore traffic jams are less likely to occur.

5.2 Alternative objectives

However minimizing the variance over road sections is a generally good approach to optimize the traffic flow, there are other objectives worth mentioning. Driving the algorithm towards a certain pattern of traffic distribution, for example keeping the number of cars as low as possible at a certain road section, can also be considered as a goal for I-EPOS. This scenario is especially important in case of unexpected events, traffic jams, accidents or ambulances entering the system. Image, that the agents notice, that an accident had occurred, and the whole control system keeps driving cars out of the way, creating a clear path for ambulances, police cars or fire trucks, and also preventing bigger traffic jams around the area of the accident.

5.3 Trade-off between local and global objectives

Imagine the following situation. Every car (C_1, C_2, C_3) can choose between two plans (P_1, P_2), with different route lengths (l_1, l_2). The route length is calculated by summing up the number of concerned road sections in an agents' individual plan. Longer route lengths are associated with longer travel time, which the agent might want to avoid depending on its preferences.

$$P_1^{C_1} = [1,0,1,0,0,0,1,0,0,0] \rightarrow l_1 = 3 \; or \; P_2^{C_1} = [1,0,0,1,1,0,1,0,0,1] \rightarrow l_1 = 5$$
$$P_1^{C_2} = [0,0,1,0,0,0,0,1,1,0] \rightarrow l_1 = 3 \; or \; P_2^{C_2} = [0,0,0,1,0,1,0,1,1,0] \rightarrow l_1 = 4$$
$$P_1^{C_3} = [0,0,1,0,0,0,1,0,0,1] \rightarrow l_1 = 3 \; or \; P_2^{C_3} = [0,1,1,0,0,0,1,0,0,1] \rightarrow l_1 = 4$$

As we can see below, if every agent were to choose its first plan, their travel time would be lower. However, on an aggregated level, the variance would be higher. The algorithm is likely to reject the agents' choices, and make them go on their second route in order to avoid traffic jams.

$$P_1^A = P_1^{C_1} + P_1^{C_2} + P_1^{C_3} = [1,0,3,0,0,0,2,1,1,1] \longrightarrow Var\{P_1^A\} = 0.988889$$
$$P_2^A = P_2^{C_1} + P_2^{C_2} + P_2^{C_3} = [1,1,1,2,1,1,2,1,1,2] \longrightarrow Var\{P_2^A\} = 0.233333$$

If the traffic density is very high, this might be a good strategy, but in some cases, for example in time periods with relatively low traffic, the aim of creating an evenly distributed traffic flow is not necessary, but overlooks the individual preferences. To avoid this effect, the λ (or α, β) parameter of the global cost function can be used to set the trade-off between agent and global objectives. In high traffic density situations, the global goal is highly important, however in low traffic density situations, agents are allowed to be more greedy.

5.4 Why global optimization is needed

In order to decide whether the chosen global objectives met the specifications of a combinatorial optimization problem, the conditions given in the assignment must be checked:

1. The overall goodness of a certain traffic situation only makes sense on an aggregated level. The goodness of the traffic flow in a whole section of a city can only be evaluated if we consider the movement of every car in that section and given time period. Therefore we sum up the plans of every individual agent, and apply the global cost function on this aggregated plan.

2. Every agent contributes to the outcome, however it is not possible to ensure, that if every agent chooses the best plan, the overall outcome is also going to be optimal (see the example above). The chosen global cost function is quadratic, it aims to minimize the variance of the number of cars over the examined road sections, hence it creates a relatively evenly distributed traffic flow. This global objective can only be achieved by coordination between agents. Therefore using I-EPOS for the optimization of the modelled problem is suitable.

6 Agents' Behavior

It is important to decide on the priority between local and global objectives. In several situations, agents are allowed to pursue their individual goals more greedily while in other cases the global objective is valued more. The overall cost C as a function of local cost L and global cost G can be modeled with a λ-parameter as follows:

$$C = (1-\lambda)G + \lambda L. \tag{1}$$

There are several situations that need to be considered for the proposed scenario.

From introductory texts in traffic flow phenomena we learn that the road capacity is dependent on the velocity of the vehicles using it. The higher the velocity, the bigger the gap between cars, hence the lower the road capacity. The maximum traffic density for a road section is therefore a function of the velocity of that section. Assume now that we know the theoretical maximum traffic density for each road segment i, $\rho_{i,max}$. Consider now three different scenarios:

1. $\rho_i < \rho_{i,max}$ for all road sections i (valley hours)
   All roads have a spare capacity with a safety factor δ (close to but smaller than 1), hence the traffic flow will not be influenced by additional vehicles on the road. Agents are now allowed to act perfectly greedily and only pursue their personal goal. Satisfying the global objective makes no sense as the road situation will not be affected. λ can be chosen large.

2. $\rho_i > \rho_{i,max}$ for all road sections i (peak hours)
   All roads are over their maximum capacity, hence traffic slow starts to become worse: vehicles start slowing down and eventually traffic jams will arise. λ should be chosen small to ensure that the global objective is pursued.

3. $\rho_i > \rho_{i,max}$ for some road sections i (imbalanced situation)
   This situation is clearly indicating an imbalance in the road capacity usage. The agents that have plans that include road sections for which the maximum capacity is surpassed should have a small λ. For agents with plans that do not include any of the busy road sections, λ can again be chosen large. Now notice that it does not matter how many road sections are over their capacity: as soon as the plan contains one road section that is over capacity, the value of λ should be chosen small.

If we want to account for some uncertainty in the road capacity, we can replace $\rho_{i,max}$ in the above by $\delta \, \rho_{i,max}$ with δ being a scaling factor close to but smaller than one.

In summary: as long as the set of possible plans of an agent does not contain any roads for which $\rho > \rho_{max}$, the λ parameter can be chosen large. The global objective becomes more and more important for busy roads. Hence, as soon as roads are over their capacity, the value of λ should be decreased. Note that in general we would like to avoid sudden discrete changes in the value of model parameter. To this end, a smooth transition from high to low λ values is constructed. The decrease of the value of λ starts at some fraction ϵ of ρ_{max} Figure 2 displays a possible trend that could be chosen.

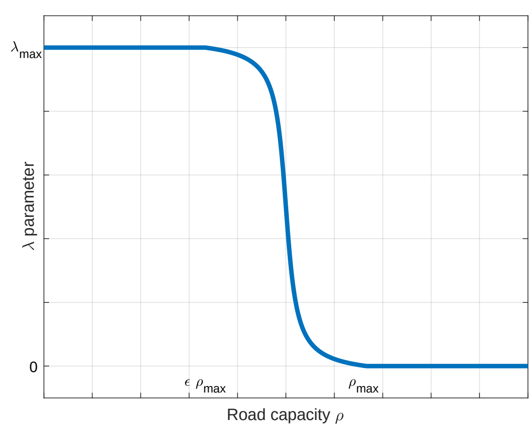

Figure 2: Possible value of λ parameter as a function of traffic density ρ.

Exceptions to the above stated rule are prioritized vehicles. For example an emergency vehicle, like an ambulance or a police car, will always have a large λ parameter, no matter the traffic density.

The above model to calculate the global cost can be altered to include an unfairness cost contribution U. The total cost is then given by

$$C = (1 - \alpha - \beta)G + \alpha U + \beta L, \tag{2}$$

with

$$\alpha + \beta \in [0, 1]. \tag{3}$$

Analogously to the discussion for λ, the different possible scenarios are discussed separately.

1. $\rho_i < \rho_{i,max}$ for all road sections i (valley hours)
   Agents are again allowed to act perfectly greedily and only pursue their personal goal. Satisfying the global objective makes no sense as the road situation will not be affected. β can be chosen close to 1.

2. $\rho_i > \rho_{i,max}$ for all road sections i (peak hours)
   All roads are over their maximum capacity, hence traffic slow starts to become worse: vehicles start slowing down and eventually traffic jams will arise. β should be chosen small to ensure that the global objective is pursued.

3. $\rho_i > \rho_{i,max}$ for some road sections i (imbalanced situation)
   Once more, the agents that have plans that include road sections for which the maximum capacity is surpassed should have a small β. For agents with plans that do not include any of the busy road sections, β can be chosen close to 1. Now notice that it does not matter how many road sections are over their capacity: as soon as the plan contains one road section that is over capacity, the value of β should be chosen small.

A good value for α is less obvious to determine without running some tests/simulations. Therefore, for now we will limit the discussion to indicating the allowed range of values for α, rather than providing concrete values.

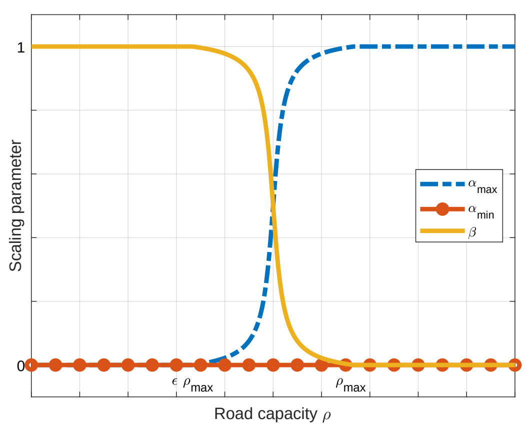

Figure 3: Possible value of α and β parameters as a function of traffic density ρ.

For completing the second assignment, the latter approach of using α and β is preferred over λ since this makes it possible to include fairness considerations in the generation of plans.