Advances in Complex Systems

EMERGENCE OF A TRAFFIC FLOW CONVENTION IN A MULTI AGENT MODEL

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We study the emergence of self-organised traffic flow conventions in a multi-agent system. A transport system is modelled as a discrete grid, on which agents governed by a neural network can move with a velocity that depends on the number and directions of the agents occupying the site of the grid. We show that evolution leads to traffic flow conventions that depend on the transport system geometry. We also show that if we split the agents in different "species" that move simultaneously on the transport system but that cannot exchange genetic information, their mutual influence leads to the same traffic flow convention for all the species. Finally we develop a very simple evolutionary dynamic model (solvable in numerical and analytical way) that gives an interpretation of our results.

Keywords: evolutionary simulation, neural networks, traffic flow conventions, evolutionary game dynamics.

1. Introduction

The efficiency of a transport system can be enhanced by the introduction of traffic flow conventions. These conventions imply a restriction on the possible movements of the individuals, but result in an higher individual and collective benefit.
Examples of traffic flow conventions can be found both in human societies (for example for car traffic directionality, see [1], or in pedestrian flow, see [2] and [3]), and

between social insects [4].
These conventions can be viewed as a "symmetry breaking" phenomenon, since they usually imply a choice between a priori equivalent conventions.
In this work we show how a traffic flow convention can be developed under very general conditions in a adaptive multi-agent system. The purpose of this work is to obtain the convention as an emerging property [5, 6], and for this reason we will use agents regulated by "ecological neural networks" [7], in which the behaviour of the agents is developed through their unsupervised interaction with the environment (that includes the other agents). According to this philosophy the decision mechanism of the agents (the network) is optimised through a genetic algorithm, which can represent biological evolution but also the spreading of a winning strategy through communication (see [8] for this interpretation of genetic algorithms as a way to model the diffusion of ideas).
We also show that a common traffic flow convention can emerge even if we split the agents in different species that cannot exchange (genetic) information, i.e. that the evolutionary histories of the different species influence each other through a change of the environment.
We finally propose a very simple model in which agents can choose between a few strategies, some of them representing a traffic flow convention. We model the spreading of these strategies in the population using a system of differential (replicator) equations [9] that allow also an analytical analysis, and use the results to explain those of our multi-agent model.

2. The model

While studying how agents moving in a transport system could develop communication in order to avoid traffic jams [10], we noticed that in general agents developed also (and sometimes only) a traffic flow convention in order to solve the same problem. We thus assumed that under many different conditions agents had a tendency to develop some kind of traffic flow convention in order to optimise their movement, and decided to set up some kind of (simulated) experiment to check this behaviour. Since we wanted our experiment to be of a very general nature (and not tied to any specific actual transport system) we do not claim that the model can be of any practical use, if not (hopefully) in helping to understand some common feature of transport systems and of the ways "agents" move in them. At the same time our model has to include some of the features of a realistic system, i.e. its topological structure has to be simple but not trivial, and agents have to be able to choose between the largest possible number of strategies with a very reduced amount of constraints imposed by the modeller. (For us a transport system is an area in which a large number of agents move back and forth, and their movement has an effect on the movement of the others. The term agent can stand for a car driver, a pedestrian, an animal, a robot or just a simulated agent.)
To avoid any connection with a specific transport system (but also for computa-

tional economy) we use point like agents moving in discrete space, and the mutual influence of agents on each other's motion is introduced assuming that the more agents are located in the same portion of the system, the slower they move.

In our setup the transport system is a 2D Manhattan grid. Agents are located on the sites of this grid and at each time step they have a probability $0 \leq p \leq 1$ to perform an action, i.e. to use their decision mechanism and decide to move to one of the four neighbour sites (at Manhattan distance $d = 1$, where the distance between the points P_1 and P_2 is defined by $d(P_1, P_2) \equiv |x_1 - x_2| + |y_1 - y_2|$) or decide to rest. This means that with probability $1 - p$ they are forced to rest, and thus p stands for a discrete space-time version of what would be the agent's velocity in a continuum model, and has no relationship with the output of the decision system.

To introduce a traffic problem the probability p decreases with the number of agents located on a site. A very straightforward way to do that is, defining $n(i, j)$ as the number of agents on the site with coordinate (i, j), to use

$$p(n(i,j)) = \left(\frac{1}{n(i,j)}\right)^{\gamma} \tag{1}$$

(we name this setting "direction independent", because p does not depend on the directions the agents are moving in). $\gamma \geq 0$ is the "traffic factor" of our system, since traffic congestion grows with γ. From equation 1 follows that for $\gamma = 0$ we have $p = 1$ for any value of n, i.e. no traffic congestion can occur; while when $\gamma > 0$, $p = 1$ occurs only if $n = 1$, i.e. if the agent is alone on the site the velocity is maximal.

To study the influence of the motion of a group of agents on the evolution of another group, we need to introduce in p a dependence on the direction of the movement of agents. We thus define, identifying with the vector $\mathbf{n}(i, j) = \{n^k(i, j)\}$ the number of agents on site (i, j) coming from direction k ($k = 0, 1, 2, 3, 4$ stands for the last action performed by the agents, for example 0 could stand for standing still, 1 for going in the direction of growing xs, 2 for growing ys, etc.), the probability to act for an agent coming from direction l as

$$p^l(\mathbf{n}(i,j)) = \left(\frac{1}{1 + \frac{1}{2}(\sum_o n^o(i,j)) + n^c(i,j)}\right)^{\gamma} \tag{2}$$

where n^o is the number of agents coming from orthogonal directions or standing still and n^c the number of those coming from the opposite direction. From equation 2 follows that the probability to move in direction l is always 1 when $\gamma = 0$, while for $\gamma > 0$ it does not depend on n^l and is equal to 1 if all the agents have the same direction, assuming that agents moving in the same direction would not be an obstacle for the motion of the others. The agents moving in other directions slow the motion, and in particular we assume that agents moving in the opposite direction cause the strongest traffic effect (to force the emergence of the convention through the mechanism described in section 5).

Each agent is provided with a starting point (s_x, s_y) and goal point (g_x, g_y), which are randomly chosen and different for each agent (this introduces some complexity in an otherwise quite simple topology) . The decision mechanism of the agent consists in a neural network with a hidden layer composed of h neurons [11] that takes as 2 inputs the distances $\Delta_x = g_x - x$ and $\Delta_y = g_y - y$ to the goal from the point (x, y) on which the agent is located at a given time step, and gives 5 real outputs corresponding to the 5 possible moves (the move with the highest output is performed). Such a decision system allows for a very large number of possible strategies, even manifestly wrong ones as staying still or moving in the wrong direction.

The initial weights of the neural network are randomly chosen in a different way for each agent. This means that all the agents, which move simultaneously on the same grid, are in principle different. Furthermore we split the agents in n_f different "families" (or "species") that cannot exchange genetic information, i.e. have separated evolutionary histories (we use $n_f > 1$ when studying the effect of the behaviour of a given group of agents on the evolution of other agents with which they cannot exchange information).

The weights of the network evolve via genetic algorithm. Each generation consists of 20 tests, and in each test the agents have different and randomly chosen starting and goal points, in order to avoid any dependence of their behaviour on their particular position in a single test. The fitness of the agent is given by its average speed on all the tests, i.e. the average value of the ratio of the Manhattan distance from the start to the goal over the number of time steps needed to reach the goal t_g (t_g is, in each run, the time step at which the agent reaches the goal)

$$f = \frac{|g_x - s_x| + |g_y - s_y|}{t_g} \tag{3}$$

The dimension of the grid is set to 50×50 sites, while for each agent starting and goal points are required to be at least at Manhattan distance 35. The genetic algorithm [12] uses tournament selection (in order to create an agent in a generation, two agents are randomly chosen from the population of the previous generation, their fitness is compared and the characters of the agent with the higher fitness are deterministically passed to the new agent -we use deterministic tournament since the fitness function, depending on the behaviour of other agents, is not objective an introduces by itself a certain degree of stochasticity-), a mutation probability 0.05 and no cross over. For a neural network with h neurons in the hidden layer, the genes of the agents are the $(2 + 1) \times h + (h + 1) \times 5$ weights and biases of the the network [11], directly represented as real numbers. Initially the weights have values $-1 < w < 1$, and mutation acts as a Gaussian error with deviation 0.3. We used $h = 5$ for the experiments with a single species ($n_f = 1$), and $h = 5, 6, 7, 8$ for the experiments with $n_f = 4$.

Using evolvable neural networks is a common procedure in the field of evolutionary robotics [13], and a way to develop agents that can adapt spontaneously to their environment.

3. Clock wise and counter-clock wise behaviours

A similar experimental setting was used in [10] in order to study the emergence of a "pheromone" based communication system between agents in a transport system. We had unexpectedly found that the agents, besides developing a pheromone based traffic avoidance system, followed pheromone independent traffic flow conventions determined just by the geometrical structure of the system. In particular, since traffic jams occur easily in the middle of the grid, agents avoid this region introducing a clock wise or counter clock wise motion.

To study how this behaviour emerges, we defined a "good move" g as a move that lowers the Manhattan distance to the goal, and we split these moves as counter clock wise (or right-handed r) and clock wise (or left-handed l), corresponding to the different behaviours in figure 1 and table 1.

We thus characterise the system by the ratio of g, r and l moves over the total

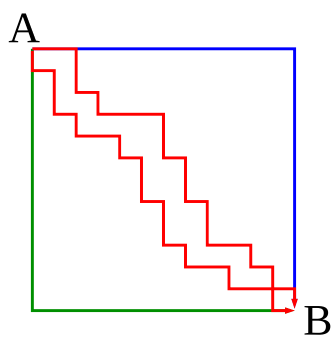

Fig. 1. Four "good" paths ($g = 1$) from point A to B. The red ones have almost an equal number of r and l moves, while the blue one is clock wise ($l = 1$, $r = 0.5$) and the green one counter clock wise ($r = 0.5$, $l = 1$).

number of moves (i.e. $g \equiv n_g/n$ where n is the number of moves performed and n_g the number of "good" moves), averaged over all the agents. Nevertheless we notice that agents use more information that the one shown in table 1, since they also know the magnitude of the distances to the goal, and thus in principle any path from the start to the goal is available (we can find a neural network that, given a starting and a goal point, will perform a given path).

4. Experimental results

4.1. *Evolution in absence of a traffic problem*

We first tested that for $\gamma = 0$ no traffic convention emerged. In this situation the optimal solutions are known, and correspond to perform a g move at each time step. Following figure 1 we expected solutions with an almost equal number of "left

Table 1. Definition of "good" (g), "left-handed" (l), "right-handed" (r) and "wrong" (w) moves on the basis of the sign of the distances to the goal. x++ means direction of growing xs, following the C programming language convention. Notice that the l and r sets overlap and thus $g \leq l + r$.

	x++	y++	x- -	y- -
$\Delta_x > 0\, \Delta_y > 0$	$g\ r$	$g\ l$	w	w
$\Delta_x > 0\, \Delta_y < 0$	$g\ l$	w	w	$g\ r$
$\Delta_x > 0\, \Delta_y = 0$	$g\ r\ l$	w	w	w
$\Delta_x < 0\, \Delta_y > 0$	w	$g\ r$	$g\ l$	w
$\Delta_x < 0\, \Delta_y < 0$	w	w	$g\ r$	$g\ l$
$\Delta_x < 0\, \Delta_y = 0$	w	w	$g\ r\ l$	w
$\Delta_x = 0\, \Delta_y < 0$	w	w	w	$g\ r\ l$
$\Delta_x = 0 \Delta_y > 0$	w	$g\ r\ l$	w	w

handed" and "right handed" moves to be more probable than those with "symmetry breaking", and actually evolution always led to an almost equal value of l and r, both for a single species with 4000 agents and for 4 different species composed each of 1000 agents. Every path with $g = 1$, regardless of the values of r and l, is equally good, but the ones with a value of r and g around 0.5 are more numerous and thus represent a kind of "thermodynamic equilibrium" of the evolutionary process in case $\gamma = 0$. The fitness (and thus the percentage of g moves) quickly reached a value next to 1, showing that the evolutionary process easily solves the problem.

4.2. *Evolution of one species in presence of a traffic problem*

We then studied the case with $\gamma > 0$, using a single species of 4000 agents, both in the "direction independent" and in the "collision" case.

In figure 2 we show the results of the evolutionary process in the $\gamma = 1$ "direction independent" case ("collision" is almost qualitatively identical). We can see that the two curves for the average values of l and r split during the evolutionary process, reaching in one case a value next to 1, while in the other a value next to 0. Since this is a symmetry breaking process, if we perform different evolutionary experiments, we observe with equal probability the emergence of a clock wise or counter clock wise motion.

In figure 3 we show the average values of l, r and g in the last 100 generations of the evolutionary process for different values of γ in the "direction independent" case, showing that both clock wise and counter clock wise behaviours emerge (once again "collision" does not present significant differences).

For low values of $\gamma > 0$ while the "winning" (most performed) move reaches a value next to 1, the "losing" one has a value around 0.5. This corresponds to a "perfect clock wise" or "perfect counter clock wise" behaviour according to table 1, as we have verified by observing the trajectories of the agents. For higher values of γ the

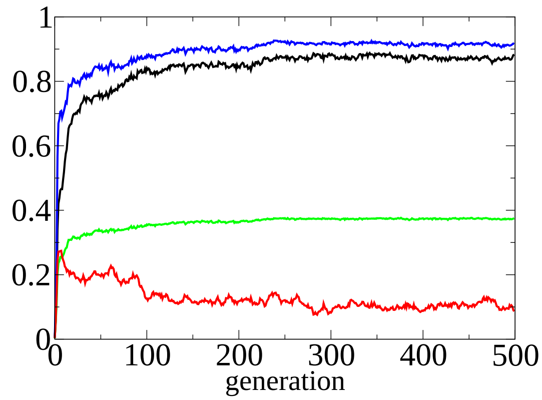

Fig. 2. Fitness (green line), g (blue line), l (red line) and r (black line) moves as a function of the generations for $\gamma = 1$ in the case of 1 species (direction independent).

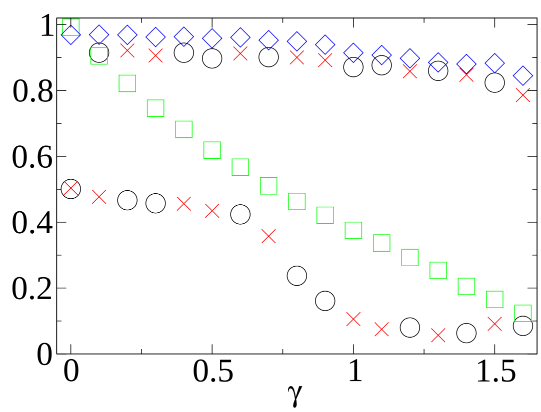

Fig. 3. Averages over the last 100 generations as a function of γ: fitness (green squares), g (blue diamonds), l (red crosses) and r (black circles) moves (one species, direction independent).

"losing" move assumes very low values, while the number of g moves is slightly lower. An analysis of the trajectories of the agents shows that they are always clock or counter clock wise (figure 4), but not in the sense of table 1, since also "wrong" moves are performed.

According to our interpretation of the results, since the starting and goal points of the agents are chosen to be far and thus probably located in opposite parts of the transportation system, the centre of the "town" is a critical traffic point for agents that perform an almost equal number of l and r moves, and thus evolution breaks the symmetry making the agents choose a path that avoids passing in the centre (figure 5). While for low values of γ this choice is performed between all the paths of

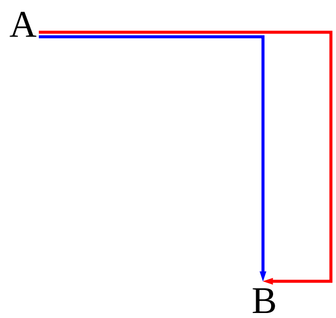

Fig. 4. The blue path corresponds to a perfect clock wise behaviour of minimum length $l = 1$, $r = 0.5$, while the red one has $l \approx 1$ and $r \approx 0$, is not of minimum length and is the path chosen by evolved agents for high values of γ.

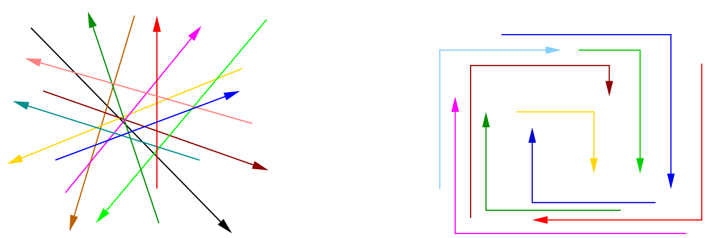

Fig. 5. The straight (i.e., with $r \approx l$) paths at left have a high probability to pass through the centre and can cause a traffic jam, while the clock wise paths at right avoid it.

minimum Manhattan length, for higher values of γ the agent chooses a longer (but quicker) path that allows it to stay distant from the centre. We remark that this result is obtained without any form of memory nor information about the position of the agent or of the centre, since the agents only know their distance to the goal.

4.3. *Evolution of different species in presence of a traffic problem*

In the experiments with a single family it was not completely clear how symmetry breaking arose. The process is surely due to the appearance of an agent that used a clock wise or counter clock wise path to reach the goal and, avoiding the centre, performs with a high fitness and passes its genes to the future generations. What is not clear is if this character (and thus a particular convention) simply invades all the population, or if the motion of the fitter agent (and of its offspring) influences the evolution of the others (forcing them to adopt its convention).
In order to test which hypothesis is right, we split the population in $n_f = 4$ different species, that could not exchange genetic information between them.
In the "direction independent" case the evolution seemed to be influenced only by the geometry of the system (the necessity to avoid the centre), and not by the

direction of the motion of the agents, and in general symmetry breaking arose only inside a single species, but not in the whole population (i.e., each family develops a convention, but these conventions can be different in different families). This result (i.e., the fact that the convention is developed simply to avoid the centre) shows that our agents, besides lacking any form of memory or information about their position, can acquire it from their evolutionary process.

The results for the "collision" case showed clearly the emergence of the same

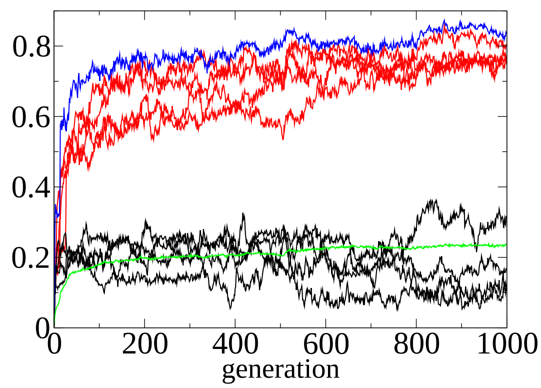

Fig. 6. Average fitness over species (green line), average values of g (blue line), l (red lines) and r (black lines) moves for all the species as a function of generations for $\gamma = 2$ in the "collision" case with 4 species.

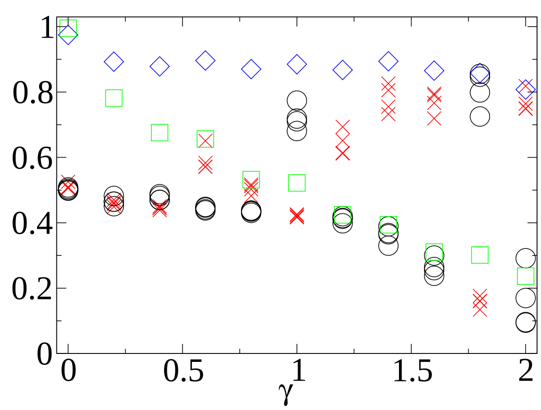

Fig. 7. Averages over the last 100 generations as a function of γ: fitness (green squares), g (blue diamonds), l (red crosses) and r (black circles) moves, in the "collision" case, 4 species. For $\gamma \geq 1$ circles and crosses are clearly distinct, i.e. a single convention as emerged in all the species.

global traffic flow convention in all the different species. In figure 6 we show the evolutionary process of all the species for $\gamma = 2$, while in figure 7 we show the γ dependence of the average values of all the moves and of the fitness for all the species in the last 100 generations. At least for large values of γ all the families adopt the same convention, as can be seen noticing that the values of the l and r averages are always clearly separated. We can thus assume that the agents following a traffic flow convention are able to influence the evolution of the other ones, even if they belong to different species. (We could say that the fact that a group of agents has developed a given convention, "imposes" the same convention also on the other groups, even without communication between the groups. By communication we actually mean genetic exchange, recalling that it can be also used as a metaphor for "spreading of ideas".)
Also in this case we notice two behaviours corresponding to different ranges of γ, the first (low values) corresponding to a traffic convention that follows a trajectory of minimal distance, while for higher values of γ a traffic convention that follows a longer path (we refer again to figure 3) emerges in all the species.
For low values of γ some of the simulations have not shown the emergence of a clear traffic flow convention in the first 1000 generations. Since the simulations with a single family lead to a traffic flow convention for the same values of γ, we can think that the absence of this convention in the 4 species case is due to a greater difficulty to develop it simultaneously for many families.

5. An evolutionary dynamics model

We also propose a very simple population dynamics model that should grasp the basic features of our multi-agent model. Let us suppose that a population of agents has to move between a location A and a location B (figure 8). In each generation the agents (roughly equally divided between the two locations) can choose between 3 paths to reach the goal, a straight one and two "detours". We can suppose that 4 strategies are present:

- strategy 0: taking the straight path
- strategy 1: taking a "clockwise detour"
- strategy 2: taking a "counter clockwise detour"
- strategy 3: taking a randomly chosen detour

(the last strategy could be obviously treated as a 1-2 mixed strategy, but we analyse it directly to stress more clearly how a specific traffic convention is developed in an evolutionary system).
We will assume that agents taking the straight path receive a fitness b, while those taking the detour receive fitness a, with $b \geq a$. Furthermore, they receive a negative fitness c/N for each agent that they meet moving opposite to their direction. It's easy to show that, in the limit of a large number of agents $N \gg 1$, the average fitness F_i of agents in population $x_i = N_i/N$ (depending on the population distribution

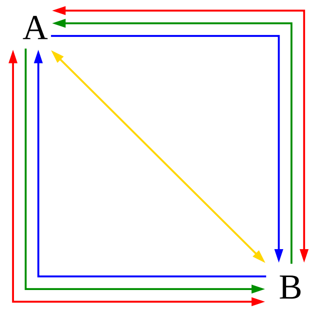

Fig. 8. Possible strategies of movement between locations A and B: yellow corresponds to strategy 0, blue to 1, green to 2 and red to 3 (the arrows point into the direction of the motion).

$\mathbf{x} = \{x_i\}$) is given by

$$F_0(\mathbf{x}) = b - \frac{c}{2}x_0 \tag{4}$$

$$F_1(\mathbf{x}) = a - \frac{c}{2}(x_2 + \frac{1}{2}x_3) \tag{5}$$

$$F_2(\mathbf{x}) = a - \frac{c}{2}(x_1 + \frac{1}{2}x_3) \tag{6}$$

$$F_3(\mathbf{x}) = a - \frac{c}{4}(x_1 + x_2 + x_3) \tag{7}$$

We can study the evolution of the populations assuming that they follow a replicator equation [9] as

$$\dot{x}_i(t) = x_i(F_i(\mathbf{x}) - \overline{F}(\mathbf{x})) \tag{8}$$

where the average fitness is given by

$$\overline{F}(\mathbf{x}) = \sum_i x_i F_i(\mathbf{x}) \tag{9}$$

Equations 8 are basically equivalent to an evolutionary algorithm using roulette wheel selection in the $N \gg 1$ limit (a few minor changes have to be done in the equation or in the usual definition of roulette wheel selection to obtain a complete equivalence, while mutation effects can be trivially included as exchange terms between the populations). Furthermore, if an equilibrium is found for equations 8, it should be an equilibrium for any evolutionary process using equations 4-7 as fitness functions, at least in the large N limit.

In order to study the behaviour of equations 8, let us assume that $x_1(0) > x_2(0)$. It follows that $F_1 > F_2$ and $F_1 > F_3$ $\forall t$, and thus $\frac{\dot{x}_1}{x_1} > \frac{\dot{x}_2}{x_2}$, $\frac{\dot{x}_1}{x_1} > \frac{\dot{x}_3}{x_3}$. From these conditions and $\sum_i x_i = 1$ follows that $\lim_{t\to\infty} x_2(t) = 0$, $\lim_{t\to\infty} x_3(t) = 0$. We can thus reduce ourselves to the system with the only x_0 and x_1 populations. It's straightforward to show that

$$x_0 = \frac{2(b-a)}{c} \tag{10}$$

$$x_1 = 1 - x_0 = \frac{c - 2(b-a)}{c} \tag{11}$$

is an attractor for any orbit with $x_0(0) > 0$, $x_1(0) > 0$ (the role of x_1 and x_2 is obviously exchanged if $x_2(0) > x_1(0)$). This evolutionary stable state ([9]), is an "user equilibrium", using the transport science terminology [14]. The "social optimum state" can be obtained searching the maximum of the overall fitness $\overline{F}(\mathbf{x})$ which is given by $x_0 = (b-a)/c$ and is not an equilibrium for the system defined by equations 8.
If $x_2(0) = x_1(0)$ it follows that $F_1 = F_2 = F_3$ $\forall t$ and thus we can treat these populations as a single one, $x_s = x_1 + x_2 + x_3$. Now the attractor for these initial conditions is

$$x_0 = \frac{4(b-a)+c}{3c} \tag{12}$$

$$x_s = 1 - x_0 = \frac{4}{3c}\left(a - b + \frac{c}{2}\right) \tag{13}$$

while the overall fitness would be maximised if $x_0 = (2(b-a)+c)/3c$.
Equations 10, 11 show that if $c > 0$ and $b = a$ the whole population is invaded by a given traffic flow convention, while for $b > a$, $c > 2(b-a)$ we have an equilibrium between agents going straight to the goal and following a traffic flow convention (x_1 invades the population if $c \gg b - a$). The equilibrium given by equations 12, 13 (that correspond to zero measure initial conditions) corresponds to equipartition between the 3 pure strategies ($x_0 = 1/3$, $x_s = 2/3$) if $c > 0$, $b = a$, while once again the we have $x_s > 0$ if $c > 2(b-a)$. (Since the x_i cannot assume negative values, in case $c < 2(b-a)$ the attractor is $x_0 = 1$ for any initial condition).
Introducing finite size (i.e. stochastic) effects and (low probability) mutation modifies only slightly the equilibrium states (for example allowing $\lim_{t\to\infty} x_i(t) > 0$ for dominated strategies) and removes the possible occurrence of the stable states of equations 12, 13 even for zero measure initial conditions. It is thus not surprising that we have a very good agreement between the results of equations 8 and their multi-agent representation (figure 9) (By multi-agent representation we mean a system with N individual agents moving between A and B and selected using a genetic algorithm).

6. Comparison between neural and differential models

Our neural network governed multi agent system should (roughly) correspond (in the collision case and for low values of $\gamma > 0$) to the system described by equations 8 with $b = a$, the main differences being that our agents are not just choosing between few strategies (the number of possible paths from start to goal is very high, furthermore a randomly created network is in general not able to reach the goal, as can be seen form figure 2 where for the first generation we have fitness $f \approx 0$) and that it is not so trivial to see that a traffic flow convention can optimise the transport system (since agents are simultaneously moving between randomly

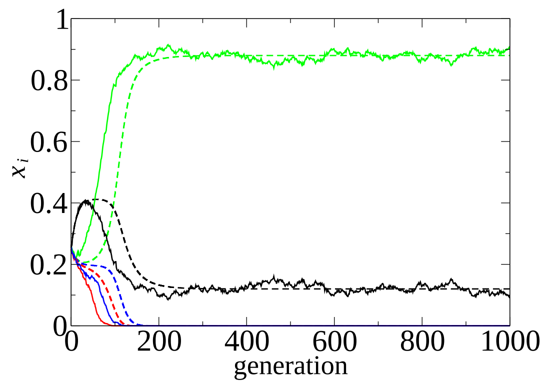

Fig. 9. Comparison between the evolution of equations 8 (dashed lines) and a single run of their multi agent representation (continuous lines, $N = 10^4$), for $b = 0.03$, $a = 0$ and $c = 0.5$. The asymptotic values obtained with the replicator equations are obviously in perfect agreement with equations 10, 11 (x_0 in black, x_1 in green, x_2 in red and x_3 in blue).

chosen and different points). Nevertheless, once a traffic flow convention has been found by the neural network system (and it was not a priori obvious that it would have been found), we should basically reduce to a situation equivalent to equilibrium 10, 11 with $a = b$ (the traffic flow convention follows a path of minimum length) and $c > 0$ (c has an obvious correspondence with γ), and thus to a system dominated by agents following the convention (in agreement with our results).
Once we pass to the high γ regime we gradually shift to a "detour" traffic flow convention (i.e., corresponding to $b > a$, as empirically verified in figures 3, 4) but the traffic congestion effect should be very high ($c \gg b - a$). For this reason, is not surprising that once again the whole system is dominated by agents following the convention. Our setting for the neural network model does not allow a reproduction of the $b > a$ low c regime which predicts the co-existence of different strategies. Nevertheless, it is not obvious that modifying the model in order to reproduce that regime (for example, assigning a slightly lower fitness to agents moving on the "periphery" of the grid) we would obtain a mixed strategy population. In a trivial model as that described by equations 8 is very easy to obtain an equilibrium between two strategies, since the number of allowed strategies is reduced, they are always both present and one can be obtained by direct mutation from the other. In a neural model two good strategies could be far away (in the space of neural weights) one from the other and thus it could be very difficult to reach an equilibrium.

7. Conclusions

We have shown that a traffic flow convention depending on the geometry of a transport system can emerge as the natural output of an evolutionary process. This

convention emerges as a "symmetry breaking" choice between paths of equal length when the occurrence of traffic jams is quite low, while it emerges as an actual choice of a longer but quicker path when the occurrence of traffic problems is very high.
We have also shown that, if the motion of the agents depends on the direction of the motion of the other agents located in the same site, the evolution of a group of agents, and thus their ability to develop a traffic flow convention, can influence the evolution of other agents even if there is no exchange of genetic information.
These results have been also explained with the aid of a simple replicator (evolutionary game) dynamic system, which allows an analytical treatment.
Even if the present formulation of our model was highly idealised, a future development could consist in using origin-destination models and travel time functions coming from traffic engineering literature, allowing a comparison with standard assignment results.

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