APPLICATION OF ASYMPTOTIC LEARNING FOR COMMUNICATION AGENTS WITHIN SOCIAL NETWORK

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ABSTRACT

In this document a preview of asymptotic learning over Bayesian and Non-Bayesian model is presented. The conditions for establishment of asymptotic learning using two models and differences between two models are discussed. As result of that discussion, I present my approach for using Bayesian model for asymptotic learning in social network of connected agents for the braking of vehicles. Asymptotic learning in my approach is used for agent communication needed for making the best decision from single and multi agent's environment.

I. INTRODUCTION

The literature for application of asymptotic learning in social networks is divided using two models of learning: Non-Bayesian (Myopic, Naïve) learning and Bayesian learning.

Both models can be observed as heterogeneous environment of information and beliefs which depends from time in each moment. In heterogeneous environment of agents in Bayesian model all agents are observed from the point of view of all their history. In Non-Bayesian network belief is depending of the time needed two connected agents to change their belief.

In Bayesian model, agents receive noisy underlying signal about the world aggregated from the information of the individuals. This signal is sufficient for the society to learn "the true" state. Bayesian rules are used to determinate the highest probability from all past actions of individuals in the social network. Each individual chooses one of two possible actions depending on his posterior beliefs and the realized neighborhood. Asymptotic learning corresponds to individual decisions converging to the true action as the social network becomes large.

This paper presents my approach of usage of Bayesian model to introduce asymptotic learning for social network of vehicle agents that decide when the brakes on some road should be used.

The paper is organized as follows. Section 1 is introduction. Section 2 contains the comparison the models of asymptotic learning. Section 3 contains application of asymptotic learning in social network. Section 4 is analysis of the results, and Section 5 is conclusion.

II. COMPARISON THE MODELS OF ASYPTOTIC LERANING

There are lots of differences between two models of asymptotic learning. One of the main deference is the way network topologies are generated. In Bayesian model network topology is created trough stochastic process which determined each neighbor. In Non-Bayesian model, the network topology has to be stochastic because the noisy signal has stochastic weight.

The Non-Bayesian (Naïve) learning happens when agents are using some reasonable rules of thumb. The recent literature focus on the case where the underlying state is time-varying considered by following class of rules of thumb learning rules as 1)constant weights and 2)diminishing weight rules. They use Bayesian rules only to show change of posterior belief of agent [1]. In other literature is shown how rule of thumb learning can be used to show the action of the agent convergence to the true in some simple environments [2, 3]. The Non-Bayesian learning is studied over connected social network. When asymptotic learning is establishied the intuitive results which asymptotically must receive a payoff action of arbitrary individual in the social network are generated. Otherwise, individual could copy the behavior of other individual. They also study different but similar environments and derive results as consensus of connected individuals [4, 5, 6, 7]. The difference is that some of them

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preclude learning by royal family, i.e. the set of individuals is observed by everyone. In these environments an excessively influential group of individuals allow asymptotic learning because with Bayesian updating over a social network, individuals recognize who oversampled individuals or the royal family are and accordingly adjust the weight they give to their information [4, 5].

In the Bayesian model, agents receive noisy underlying signal about the world which aggregated the information in set of agents. In the literature, conditions for sufficient asymptotic learning by using Bayesian rules to achieve equilibrium for information in the agents are elaborated Each individual can be observed from all past actions and private beliefs are unbounded, and that information should be aggregated and the correct action should be chosen asymptotically [8]. In [9] Bayesian model with a countable number of agents that provide conditions under which asymptotic learning occurs is considered. In [10] there is a continuum of agents that focus on proportional sampling. The asymptotic learning is achieved under mild assumptions as long as the sample size is no smaller than two. Bayesian learning can be study when each individual observes his immediate predecessor where it is optimal to follow the actions of agents that deviate from past average behavior [11, 12].

There are two conditions which have to be sufficient for achieving asymptotic Bayesian learning. The first condition is that private beliefs have to be unbounded. Private beliefs are unbounded if the corresponding likelihood ratio is unbounded. The second condition is that social network has to have nonexpanding observations. A network topology has nonexpanding observations if there exists infinity many agents observing the actions of only a finite subset of agents. Nonexpanding observations do not allow asymptotic learning, since there exist infinity many agents who do not receive sufficiently many observations to be able to aggregate information.

The most essential deference between Bayesian and Non-Bayesian model of asymptotic learning models is uncertainty in connecting agents and their knowledge. In Bayesian model there is certainty in connecting in network where all agent have the same knowledge. In Non-Bayesian model there is uncertainty in connecting of agent in network which knowledge dynamically change in each moment of the time of generating the network.

The differences between the two discussed models are summarized in Table 1.

Table 1: Differences between two models

Bayesian model	**Non-Bayesian model**
Certainly connected agents	Uncertainly connected agents
Same knowledge	Non-Same knowledge
Past actions are observed	Active actions are observed
Non-Flexible Bayesian rules	Flexible Bayesian rules

III. Application

I use Bayesian model to introduce asymptotic learning for social network of vehicle agents. The vehicle agent should determine when to use break on the road. The social network of agents is formed using the criteria of current or the near past braking on the same road. The agent, which is acting at the moment on the road, receive noisy signal and connect to other agents in the social network to receive their past actions. Asymptotic learning is used to filtering the decision by the strongest connection i.e. connection by probability near to “1”. Deliberation is the time for comparison of interactions taken by simulating of data in agents. The vehicle agents use Bayesian network (Figure 1) created by nodes which are connecting by direct and indirect connections. Their knowledge and decision is modeled using variables that have few states.

When the vehicle agent receives noisy signal, it begins deceleration of the own speed. The deceleration is negative variable of acceleration and it has three states: small if deceleration is from $0 m/_{s^2}$ to $2 m/_{s^2}$, medium if deceleration is from $2\ m/_{s^2}$ to $4\ m/_{s^2}$ and big if deceleration is from $4\ m/_{s^2}$ to $6\ m/_{s^2}$. The medium deceleration is state for long and short distance to the obstacle depends from her driving speed, while small deceleration is the state when distance to the obstacle is long and driving speed is small.

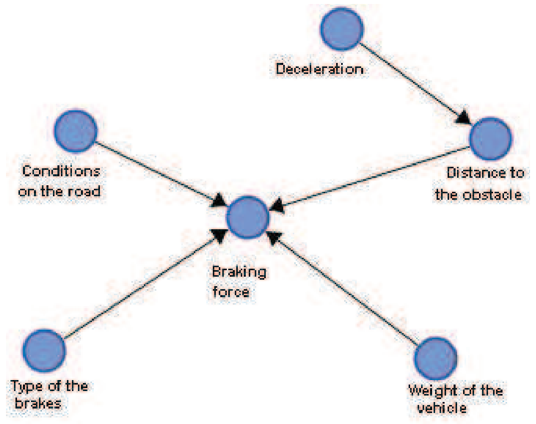

Figure 1: Bayesian network

Braking force is used to balance inertial momentums and resistances of the surface on the road. The agent receive information for intensity of application the braking force as surface on the road depends of the climate conditions on the road, the own weight, the distance to the obstacle and the type of brakes. The braking force of agent has three states: small if braking force is from 100N to 120N, big if braking force is from 140N to 160N and medium if braking force is from 120N to 140N. The agent receives noisy signal from the obstacle on the road which is on any distance from the vehicle. The distance to the obstacle has three states: short if distance to the obstacle is from 5m to 15m, medium if distance to the obstacle is from 15m to 25m, and long if distance to the obstacle is from 25m to 50m. The distance to the obstacle is changed by states of deceleration of vehicle. The braking force is affected of the surface on the road and the climate condition on the road. The condition on the road affect above coefficient of pasting of wheels to surface on the road - φ. The coefficient can be low if interval is from 0% to 0.40%, medium if interval if from 0.40% to 0.70% and high if interval is from 0.70% to 1.00%. The surface can be asphalt, concrete and macadam, while climate conditions on the road can be dry, dump and frozen. The braking force is big when road is dry, unlike when the road is dump or frozen. Each vehicle has own weight which can affect on the braking force. The weight of the vehicle has three states: easily if interval is from 7000N to 9000N, medium if interval is from 9000N to 12000N and heavily if interval is from 12000 to 16000. So, how much the vehicle is heavy, the braking force is bigger. The braking force depends of the type of brakes which can be: mechanical, hydraulic and pneumatic. The biggest braking force can be applied for mechanical, unlike hydraulic and pneumatic brakes where braking force is smaller. The state of some type of brakes is changeable of their efficiency as low if the interval if from 0% to 40%, medium if interval is from 40% to 80% and high efficiency interval is from 80 to 100%. The brakes have big efficiency if vehicle is new, while efficiency is decreased by age or when the brakes is not regularly maintain.

In my observing I use Bayesian model as more adequate to requirements of the system because it needs to observe past actions of agents as the past experience to get the highest payoff action form all. By receiving the noisy signal, the information for all agents became aggregated and Bayesian rules is used to determined probability for the states of the agent. The probabilities are determined by simulating data in Bayesian network for the four random chosen agents for the past braking on the same road. The most important decisions for agent are to determine the braking force and the distance to the obstacle. The result obtained from simulating data for braking force (by states small, medium and big) and distance to the obstacle (by states short, medium and long) are given in Table 2.

Table 2: Results from simulationg data from set of agents

Agent	**Braking force**	**Distance to the obstacle**
Agent 1	Small (18.18%)	Short (40.91%)
	Medium (54.55%)	Medium (27.27%)
	Big (27.27%)	Long (31.82%)
Agent 2	Small (14.29%)	Short (14.28%)
	Medium (60.71%)	Medium (71.43%)
	Big (25.00%)	Long (14.29%)
Agent 3	Small (69.23%)	Short (26.92%)
	Medium (23.08%)	Medium (23.08%)
	Big (7.69%)	Long (50.00%)
Agent 4	Small (8.82%)	Short (55.88%)
	Medium (20.59%)	Medium (20.59%)
	Big (70.59%)	Long (23.53%)

IV. ANALYSIS

Results from simulating data can be used in analysis of communication agents. Communication is gathered from the same type of agents i.e. agents for braking of vehicle.

Some of the most important characteristics of agent are autonomous and sociality. If agent is autonomous than agent doesn't need to communicate to other agents in social network, and it has active plan for getting the own action. According to asymptotic learning if agent behaves as a single agent by feature of autonomous it takes decision from its own history, or agent takes decision by high payoff probability which is approximation to "1". While if agent has feature to be social then agent communicates to other agents of social network and it has passive plan for its own action. By gathering communication from agents of social network it will get expert advice for acting according to final state of braking force and distance to the obstacle. The expert advice will be taken from multi agent system form by agents by strongest connection or probability which is approximation to "1". The simulation of data for set of four random agents and their features as "autonomous agent" and "social agents" the analysis for single and multi agent's environment is described below.

The first autonomous agent has the higher probability for medium braking force and short distance to the obstacle taking the probability from states as small and big braking force and long and short distance to the obstacle. This was launched to the equations (1) and (2).

$$P_{medium\ braking\ force}(54.55\%) > P_{big\ braking\ force}(27.27\%) > P_{small\ braking\ force}(18.18\%) \quad (1)$$

$$P_{short\ distance\ to\ the\ obstacle}\ (40.91\%) > P_{long\ distance\ to\ the\ obstacle}(31.82\%) > P_{medium\ distance\ to\ the\ obstacle}(27.27\%) \quad (2)$$

The emphatically braking force for safety braking is mean value determined from interval of medium braking force and short distance to the obstacle. Determined medium braking force has to be 123.15N for short distance of 13.23m.

The second autonomous agent has the higher probability for medium braking force and medium distance to the obstacle taking the probability from states as small and big braking force and long and short distance to obstacle. The second agent has the biggest probability for medium braking force that has to be 124.95N, for medium distance to the obstacle of 20.27m.

The third autonomous agent has the higher probability for small braking force and long distance to the obstacle taking the probability from states as medium and big braking force and medium and short distance to the obstacle. The third agent has the biggest probability for small braking force from 114.02N and long distance to the obstacle of 38.56m.

The fourth autonomous agent has the higher probability for big braking force and short distance to the obstacle taking the probability from states as small and medium braking force and long and medium distance to the obstacle. The fourth agent has the biggest probability for big braking force from 143.14N and short distance to the obstacle of 9.05m.

On the other hand, let assume that the first agent is "social" and receive signal for small braking force and long distance to the obstacle with probability of 18.18% for big braking force and probability of 31.82% for long distance to the obstacle. The first agent communicates in multi agent system (Figure 2). By comparison of probabilities of other agents it can be noticed that the third agent has the highest probability of 69.23% for small braking force and the highest probability for long distance to the obstacle of 50.00%. The third agent will give expert advice to the first agent for small braking force of 114.02N and long distance to the obstacle of 38.56m.

If the first agent is social and receive signal for big braking force and short distance to the obstacle and the agent has probability of 27.27% for big braking force and probability of 40.91%. That the first agent communicates in multi agent system (Figure 3). By comparison of probabilities of other agent we notice that the fourth agent has the highest probability from other of 70.59% for big braking force and state for short distance to the obstacle by the highest probability of 55.88%. That means the fourth agent will give expert advice to the first agent for big braking force of 143.14N for short distance to the obstacle from 9.05m.

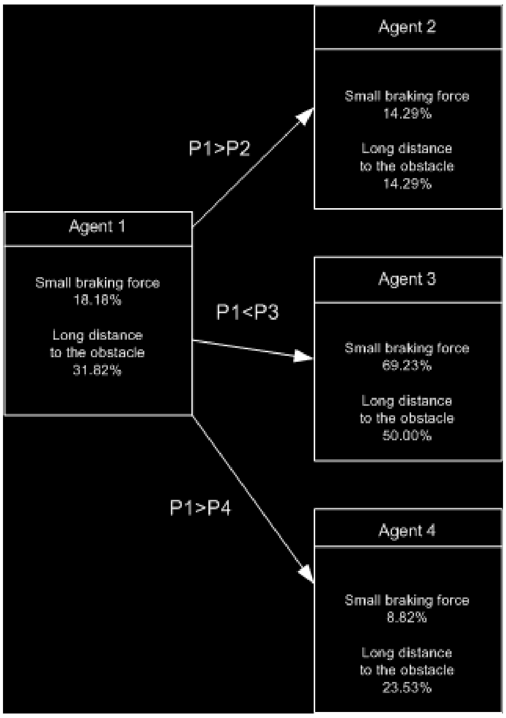

Figure 2: Communication in multi agent system

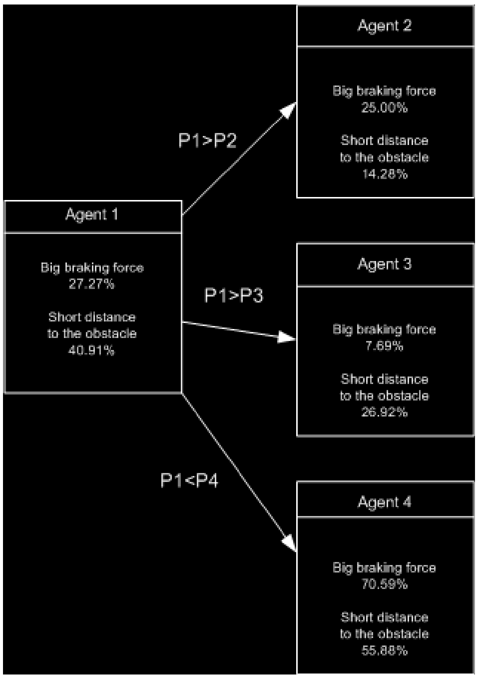

Figure 3: Communication in multi agent system

This similarity can be establish for other three agents in the social network if they receive noisy signal for some state of whom they haven't experience enough or generally they haven't any experience for braking of vehicle on the road.

V. CONCLUSION

In this work asymptotic learning and it using in social network of agents is elaborated. Asymptotic learning is condition for equilibrium from actions of set of agents whose information became aggregated when on them acting some noisy signal. The provided example scenario shows how asymptotic learning can improve the way of communication among agents by getting more precise action and underling state for safety braking on the road. In that way, asymptotic learning can be used as assistance of the decision of system, or entirely implemented system that will filtering decisions of agents. The system gives reasonable decision which will be useful for vehicle without drivers and for intelligent system build-in traditional vehicles that will assistance to drivers for safety braking on the road and adapting the action to conditions on the road. In the future work, I plan to adapt standard protocol for communication of agents by using asymptotic learning in ACL standardized by FIPA.

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