Multiple-Participants Decision Making for Urban Traffic Control

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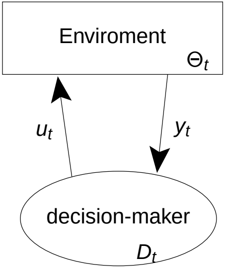
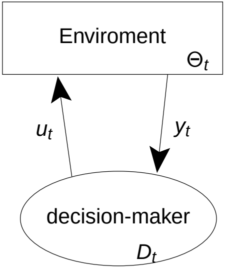
Outline

Bayesian Decision Making



1. System parameterization,
2. Model of consequences,
3. Description of aims (probabilistic).

Bayesian Decision Making



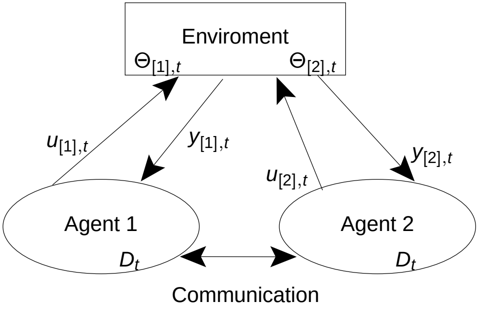
1. System parameterization,
2. Model of consequences,
3. Description of aims (probabilistic).

Outputs:

Learning: of changes of the enviroment (adaptivity),

Strategy: of decision making

Multiple-Participant Decision Making



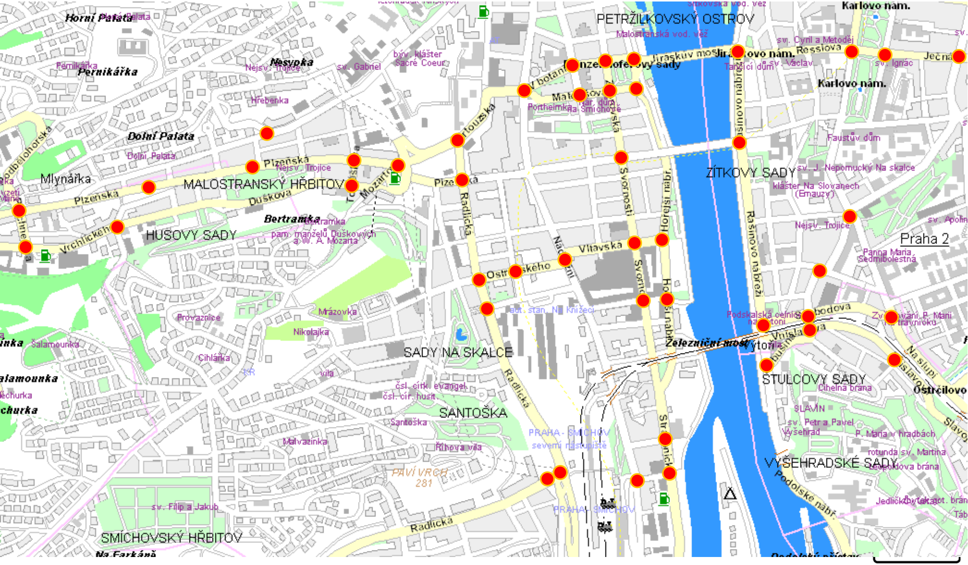
Agents act independently (autonomously). They have individual:

1. System parameterization,
2. Model of consequences,
3. Description of aims (probabilistic).

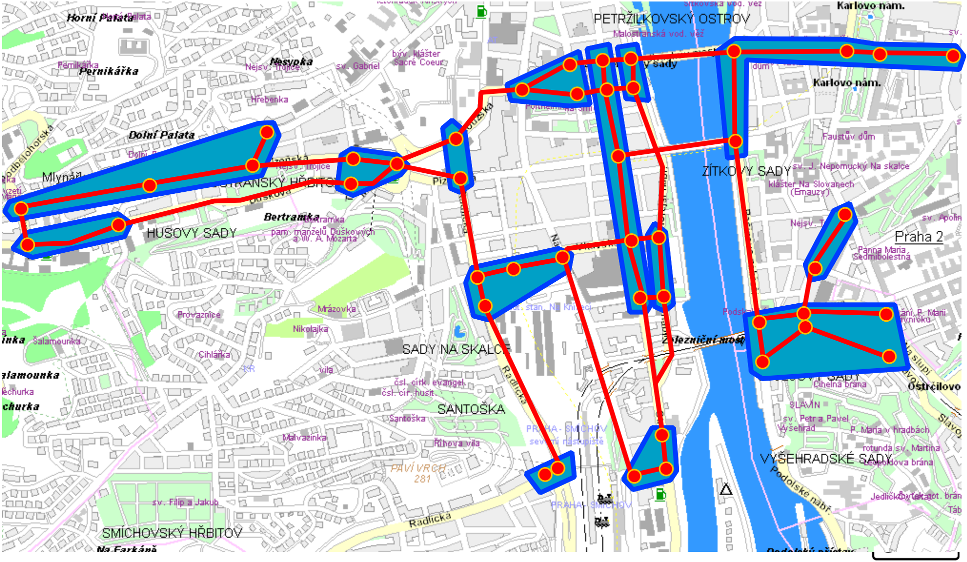
In order to cooperate:

4. Exchange and merging of experience and ideals.

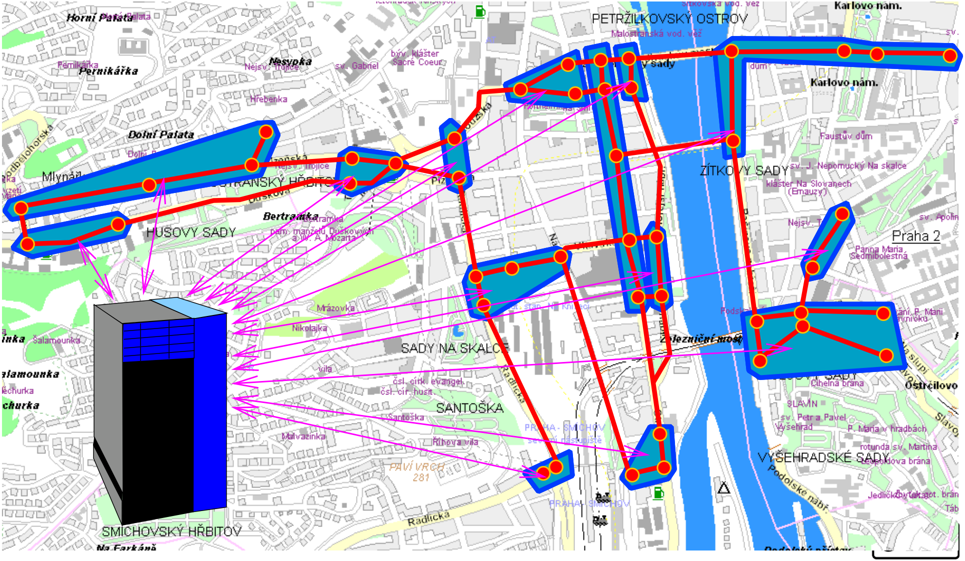
Urban Traffic Network



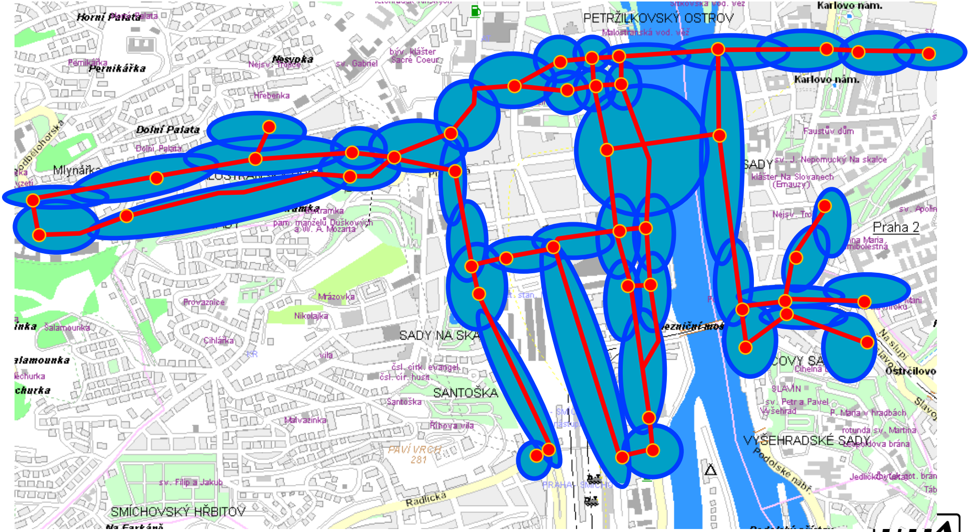
Hierarchical Control



Hierarchical Control



Multi-Agent Control



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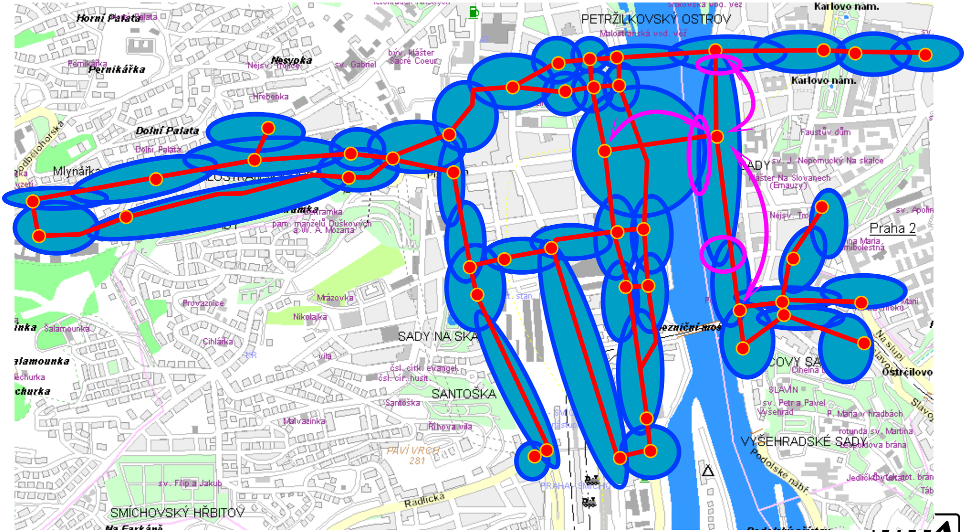
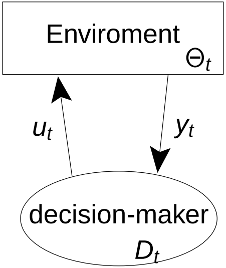
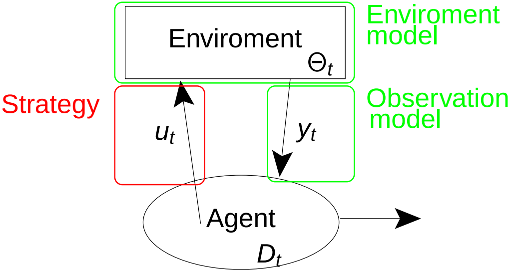


Design of a Single Agent



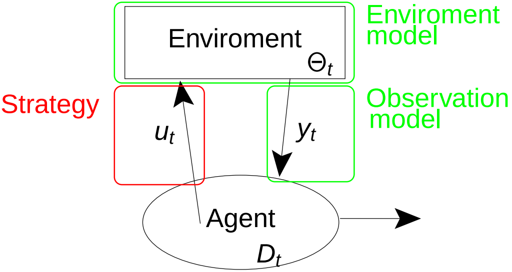
	Observations	Internals	Actions	Experience
Param.	y_t	Θ_t	u_t	D_{t-1}

Design of a Single Agent



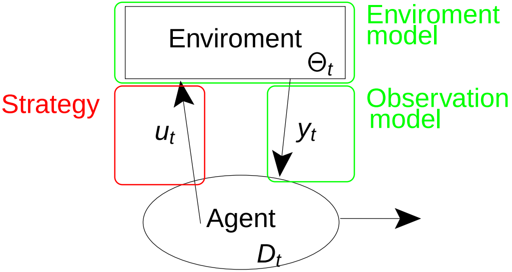
	Observations	Internals	Actions	Experience
Param.	y_t	Θ_t	u_t	D_{t-1}
Models	$f\left(y_t \middle| \Theta_t, D_{t-1}\right)$	$f\left(\Theta_t \middle| \Theta_{t-1}, u_t\right)$	$f\left(u_t \middle| D_{t-1}\right)$	$f\left(\Theta_t \middle| D_{t-1}\right)$

Design of a Single Agent



	Observations	Internals	Actions	Experience
Param.	y_t	Θ_t	u_t	D_{t-1}
Models	$f(y_t \mid \Theta_t, D_{t-1})$	$f(\Theta_t \mid \Theta_{t-1}, u_t)$	$f(u_t \mid D_{t-1})$	$f(\Theta_t \mid D_{t-1})$
Ideals	${}^{\lfloor I}f(y_t \mid \Theta_t, D_{t-1})$	${}^{\lfloor I}f(\Theta_t \mid \Theta_{t-1}, u_t)$	${}^{\lfloor I}f(u_t \mid D_{t-1})$	

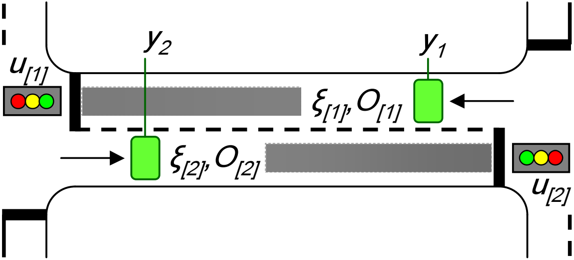
Design of a Single Agent



	Observations	Internals	Actions	Experience
Param.	y_t	Θ_t	u_t	D_{t-1}
Models	$f(y_t \mid \Theta_t, D_{t-1})$	$f(\Theta_t \mid \Theta_{t-1}, u_t)$	$f(u_t \mid D_{t-1})$	$f(\Theta_t \mid D_{t-1})$
Ideals	${}^{\lfloor I}f(y_t \mid \Theta_t, D_{t-1})$	${}^{\lfloor I}f(\Theta_t \mid \Theta_{t-1}, u_t)$	${}^{\lfloor I}f(u_t \mid D_{t-1})$	
Comm.	$f(y_t)$, ${}^{\lfloor I}f(y_t)$			

Step 1: Model Parameterization

Two junctions connected by one arm:

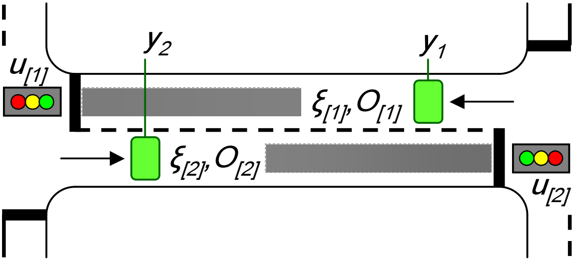


Parameterization:

Innovation: Intensity y_t [vehicles], Occupancy O [%].

Step 1: Model Parameterization

Two junctions connected by one arm:



Parameterization:

Innovation: Intensity y_t [vehicles], Occupancy O [%].
Ignorance: Queue length ξ [vehicles], Turning rate r [%].

Step 1: Model Parameterization

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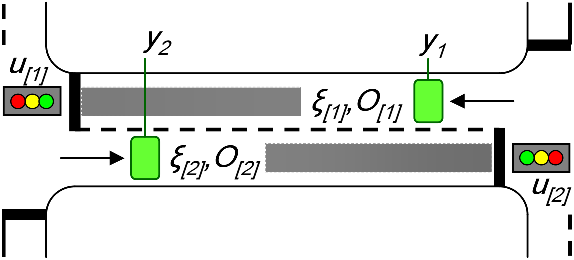
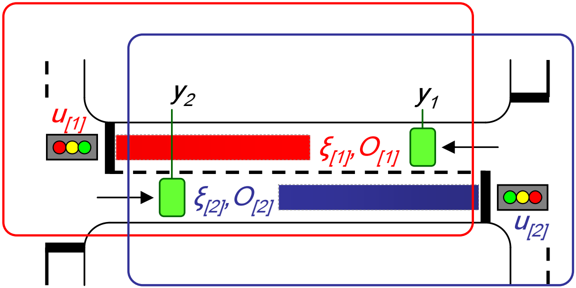


Parameterization:

Innovation: Intensity y_t [vehicles], Occupancy O [%].
Ignorance: Queue length ξ [vehicles], Turning rate r [%].
Actions : Relative green u [%].

Multi-Agent Scenario

Agents interaction over a single arm:



Parameterization:

	A1	A2
Observed:	y_1, y_2	y_1, y_2
Unobserved:	$\xi_{[1],t}, O_{[1],t}$	$\xi_{[2],t}, O_{[2],t}$
Controlled:	$u_{[1],t}$	$u_{[2],t}$

Step 2: Model of consequences

Internal model (without uncertainty):

$$\begin{bmatrix} \xi_t \\ O_t \end{bmatrix} = \mathbf{A} \begin{bmatrix} \xi_{t-1} \\ O_{t-1} \end{bmatrix} + \mathbf{B} u_{t-1} + \mathbf{F}$$

Observation model (without uncertainty):

$$\begin{bmatrix} \eta_t \\ O_t \end{bmatrix} = \mathbf{C} \begin{bmatrix} \xi_t \\ O_t \end{bmatrix} + \mathbf{G}$$

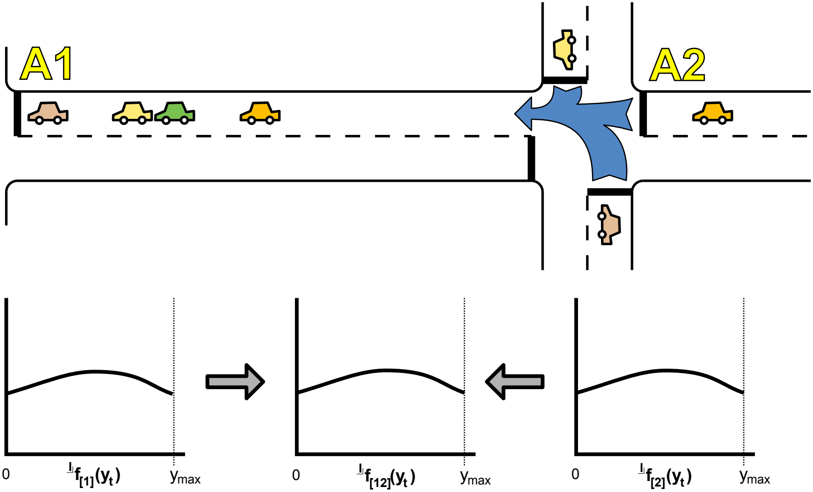
Adding uncertainty:

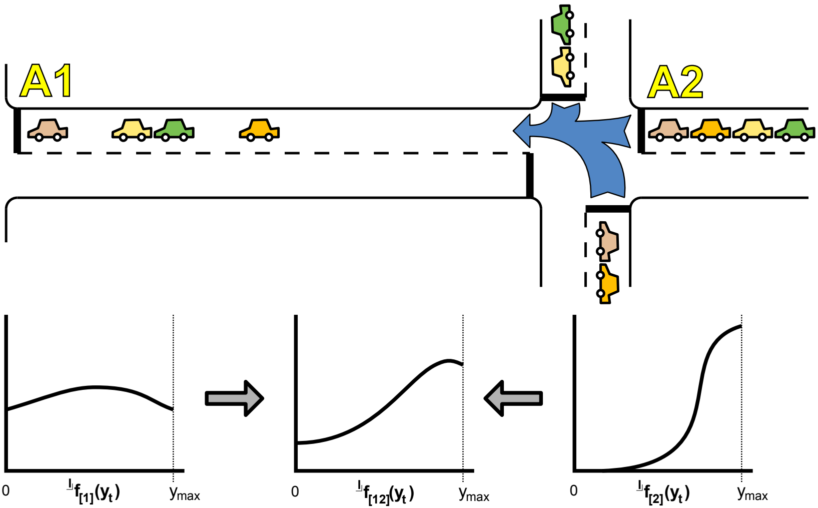
- Internal model: $f(\Theta_t|\Theta_{t-1}, u_{t-1}) = \mathcal{N}(\mathbf{A}\Theta_{t-1} + \mathbf{B}u_{t-1} + \mathbf{F}, \mathbf{Q})$
- Observation model: $f(y_t|\Theta_t) = \mathcal{N}(\mathbf{C}\Theta_t + \mathbf{G}, \mathbf{R})$
- $\mathcal{N}(\mu, \sigma)$ is a Gaussian pdf
- $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{F}, \mathbf{G}$ are matrices from deterministic system description
- matrices $\mathbf{Q}, \mathbf{R}$ describe allowed variance in the model description

Step 3: Ideal distributions

Every agent wants to:

- minimise its queue lengths:
  $^{\lfloor I}f(\xi_t) = tN(0, V_\xi, \langle 0, \xi_{\max}\rangle)$
- favours high intensities:
  $^{\lfloor I}f(y_t|\xi_t) = tN(\mu(\xi_t), V_y, \langle 0, y_{\max}\rangle)$


A1
A2
0
$^{I}f_{[1]}(y_t)$
y_{max}
0
$^{I}f_{[12]}(y_t)$
y_{max}
0
$^{I}f_{[2]}(y_t)$
y_{max}


A1
A2
0
$^{I}f_{[1]}(y_t)$
y_{max}
0
$^{I}f_{[12]}(y_t)$
y_{max}
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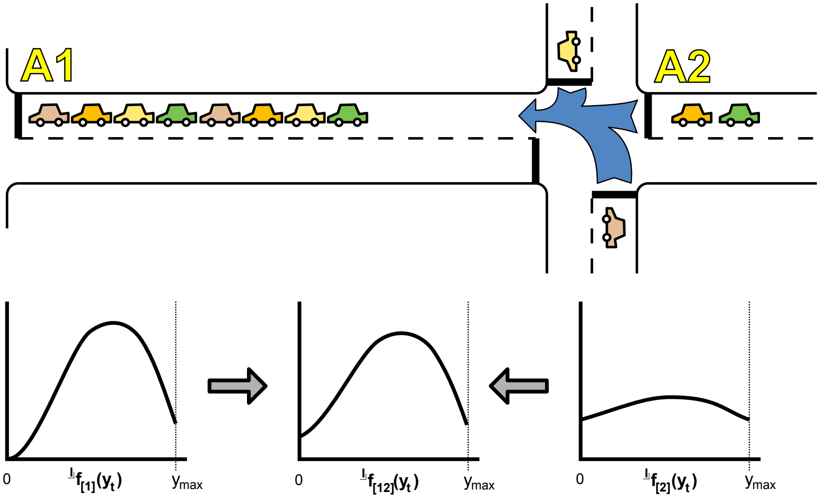
$^{I}f_{[2]}(y_t)$
y_{max}


A1
A2
0
$^I f_{[1]}(y_t)$
y_{max}
0
$^I f_{[12]}(y_t)$
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0
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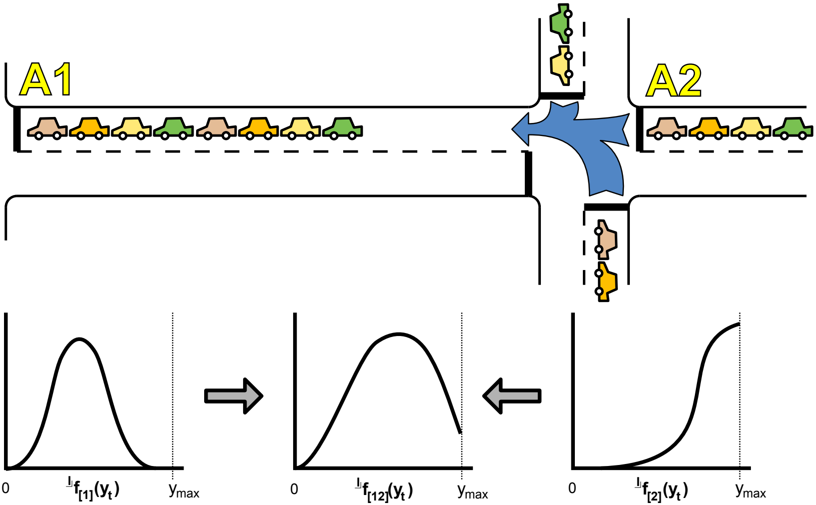
y_{max}


A1
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$^{I}f_{[1]}(y_t)$
y_{max}
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$^{I}f_{[12]}(y_t)$
y_{max}
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$^{I}f_{[2]}(y_t)$
y_{max}

Step 4: Communication

Since ξ_t is internal for each agent, we can exchange only marginal distributions:

$$^{\lfloor l}f(y_t|\xi_t) \rightarrow {}^{\lfloor l}f(y_t)$$

Since fully probabilistic design is a special case of dynamic programming, we need to communicate multi-step ahead predictions, i.e.

$$^{\lfloor l}f(y_t), {}^{\lfloor l}f(y_{t+1}), \ldots, {}^{\lfloor l}f(y_{t+h})$$

These are presented only to the neighbours, however, they influence the neighbours predictions, which are communicated further.

This is a gateway for long-distance communication.

Conclusion

Vision of Traffic Control in Urban Areas using Bayesian theory of Multiple Participant Decision-Making (Bayesian Agents)

Early stages of development.
Further work:

- Reliable software framework for testing,
- Double check of the traffic model,
- Experiments with merging algorithms,
- Understanding the role of the Ideal distributions.