

# **Bayesian learning for agent cooperation**

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• An agent may need to work with others to achieve its individual goals

If others are not cooperative, the agent must do its best to

fit in with how others are behaving

Some tasks require cooperation

- Even if the others are cooperative, if the situation is complex, computing optimal behaviour may be not be possible in a timely fashion
- Especially as time or bandwidth constraints may

- Other agents will act according to:
- their strategy, and
- their view of the situation

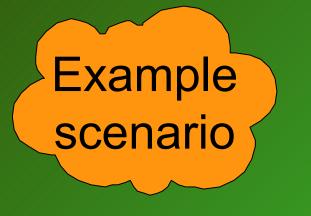
Cooperating in uncertain environments means guessing what others are thinking

- If an agent is not aware of a disaster victim, it will not move to the rescue, even if the victim is close by and in critical condition
- We must model other agents' beliefs about the situation, as

#### limit communication

After an earthquake, the state of the world is uncertain Aftershocks, fire and wind may change the world very rapidly Victims are buried under rubble and must be found quickly,

dug out and treated





Communications networks may be down or congested

Earthquake in San Francisco Rescuers from all areas and all directions must

try and coordinate to discover and rescue the victims

### Internal states of a finite state machine

- (fsm) determine the immediate action
- The subsequent observations determine the next internal state

• But this is unnecessary: look a few steps ahead, approximate

the rest with a simple heuristic: finite-horizon best response

well as their strategies.

#### •Agents can use **Bayes' rule** to update their beliefs about:

• The state of the world s

• The strategies of the others  $\sigma_i$ 

• The world dynamics  $\theta$ 

 $P(Model \mid observations) \propto$ P(observations | Model) P(model)

Bayes' rule

• The observations and thus beliefs of the others  $o_i$ ,  $b_i$ 

• The agent maintains a **belief state** *P(M)* over the model  $M=(s, \theta, \{\sigma_i\}, \{o_i, b_i\})$ 

## Guessing what other people are thinking is hard

Recursive Bellman equations compute the best response action

to a belief state, taking into account the effect on future states

•For large problems, the Bayesian update to M, and the best

response, are intractable

**Bellman equations**  $Q(b, a) = \sum_{x} P(x \mid b) \sum P(s' \mid x, a) [R(s') + \gamma V(b')]$  $V(b') = \max_{a} Q(b', a)$ 

x : unknowns in model M Terms *R(s) :* immediate **reward** of world state *s V(b) :* long-term **value** of belief state *b* Q(b, a) : value of action a in belief state b

Success!

with five agents

null —•

- *n x n* gridworld, with *k* ambulance agents
- Buried victims continuously arriving across the grid
- **16**<sup>n</sup> possible states: 4096 for n = 3, many millions for n > 7.

• Maintaining beliefs over s, o, and a set of fsms F, is tractable • Agents can move  $(r \rightarrow, I \leftarrow, u^{\uparrow}, d^{\downarrow})$  or dig • 5<sup>\*</sup> joint actions: 125 for k = 3, 78,000 for k = 7Approximate others, using finite state machines smart —— null —• pest response — Finite-horizon best response (modified Bellman) Increasing the grid size to 12x12 Increasing the number of Best response is still not  $Q_{k+1}(b, a) = \sum_{x} P(x|b) \sum P(s'|x,a) [R(s') + \gamma W_{k}(b')]$ agents on a 7x7 grid  $V_k(b') = \max_a Q_k(b', a)$  and  $V_0(b') = heuristic(b')$ tractable, because it iterates over all possible belief-states

Better than hand designed policy at capitalising on num. agents

Better than hand designed policy as grid size increases

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autonomous learning agents for decentralised data and information networks