



# Rationality in communication: from learning to planning and back

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# The story behind this talk

- Christos contacted me about work done a long time ago on learning argumentation strategies
- Remembering that line of work brought me back to question that's driven much of my later research, too
- In this talk I make an attempt to talk about the different pieces in the puzzle that I've tried to work on



# The Grand Challenge

- Understanding the principles of communication as rational action
    - *What should I say to whom to achieve my goals?*
  - A key problem in AI, philosophy, linguistics, widely studied in multiagent systems
    - Speech act theory
    - Signalling games
    - Dialog systems
    - Argumentation theory
- etc



# My Small Challenge

- Given what you have observed in previous communication and action, what is the best thing you should say from a bounded set of options?
- This involves:
  - calculating what one might say
  - tracking success/failure
  - generalising over instance experiences
- Problems:
  - observations are (mostly) statistical, language is (mostly) symbolic
  - semantic models (mostly) not very practical for computation, content languages (mostly) infinite
  - immediate vs long-term utility, “cheap talk”

# Learning communication strategies

- My PhD work was about *interaction frames* and reinforcement learning over them:

$$\begin{aligned}
 F = & \left\langle \overbrace{\left\langle \xrightarrow{5} \text{request}(A, B, X) \xrightarrow{3} \text{do}(B, X) \right\rangle}^T, \right. \\
 & \left\langle \overbrace{\{\text{can}(B, X)\}}^{\Theta_1}, \overbrace{\{\text{can}(B, \text{pay}(S))\}}^{\Theta_2} \right\rangle \\
 & \left\langle \overbrace{\xrightarrow{2} \langle [A/a], [B/b], [X/\text{pay}(\$100)] \rangle}^{C_1}, \right. \\
 & \left. \left. \overbrace{\xrightarrow{1} \langle [A/b], [B/a], [X/\text{pay}(S)] \rangle}^{C_2} \right\rangle \right\rangle
 \end{aligned}$$



# Learning communication strategies

- Mix of symbolic and numerical representation
- Problem: modelling communication state
  - what determines whether a communication choice is appropriate?
  - only domain-dependent solution provided, strategy value depending on goals
- Learning over finite sets of pre-defined options regarding speech acts and content
  - though some induction over patterns

# Learning communication strategies

`request(A, B, X) → accept(B, A, X) → confirm(A, B, X) → do(B, X)`

`request(A, B, X) → propose(B, A, Y) → accept(A, B, Y) → do(B, Y)`

`request(A, B, X) → propose-also(B, A, Y) → accept(A, B, Y) →  
do(B, X) → do(A, Y)`

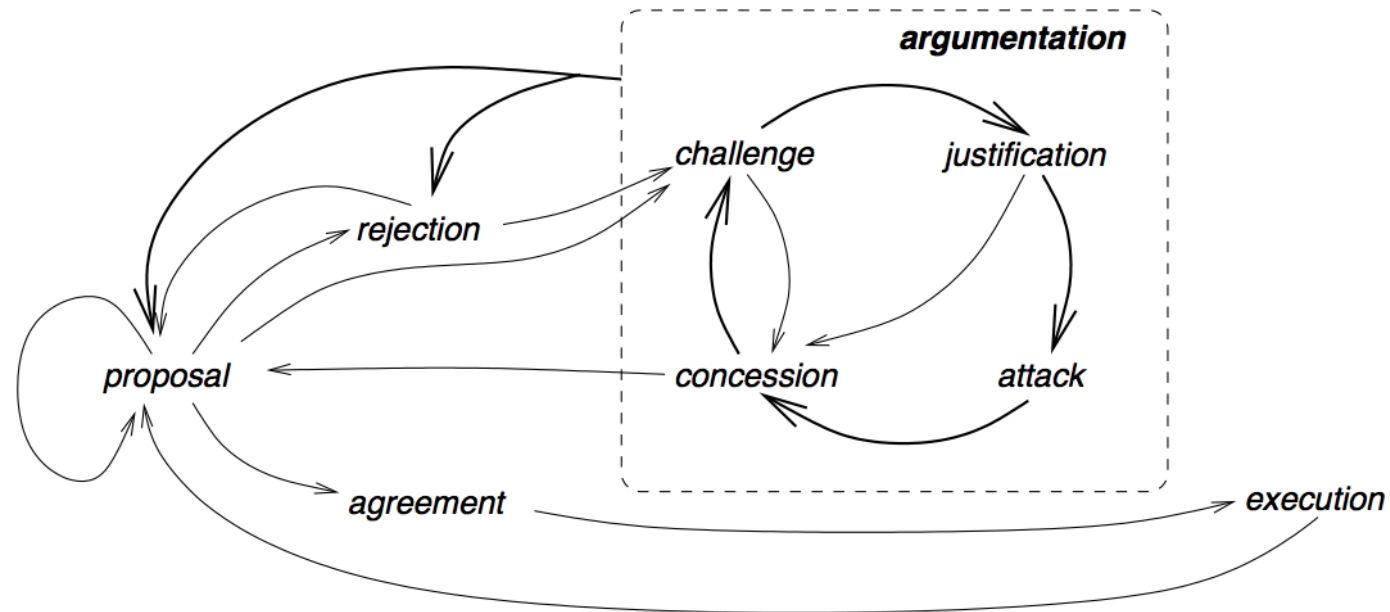
`request(A, B, X) → reject(B, A, X)`

`request(A, B, X) → propose(B, A, Y) → reject(B, A, Y)`

`request(A, B, X) → propose-also(B, A, Y) → reject(B, A, Y)`

# Learning argumentation strategies

- MR & Rahwan applied this to argumentation strategies based on model of interest-based negotiation





# Example: link exchange simulation

- Early example of social computing (now slightly outdated)

**Agent popularity**

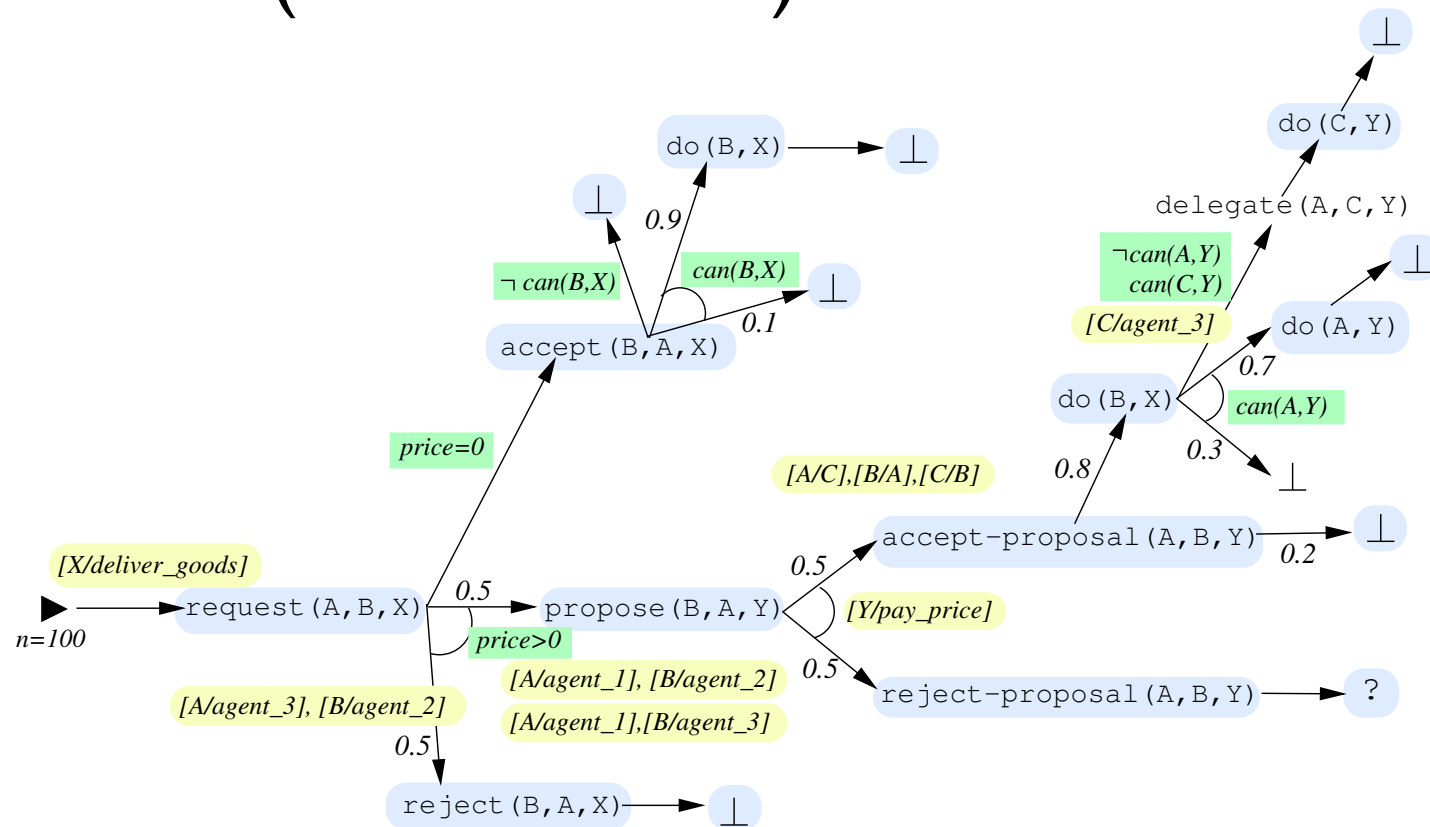
Agent	Popularity	Simple Popularity
g0:agent6	0.6111	0.2777
g0:agent5	0.1	0.1
g0:agent4	0.5908	0.1777
g0:agent3	0.5407	0.2444
g0:agent2	0.3116	0.1222
g0:agent1	0.1	0.1
g0:agent0	0.5987	0.2333
g0:agent9	0.5765	0.3555
g0:agent8	0.5101	0.1777
g0:agent7	0.6024	0.2888

```

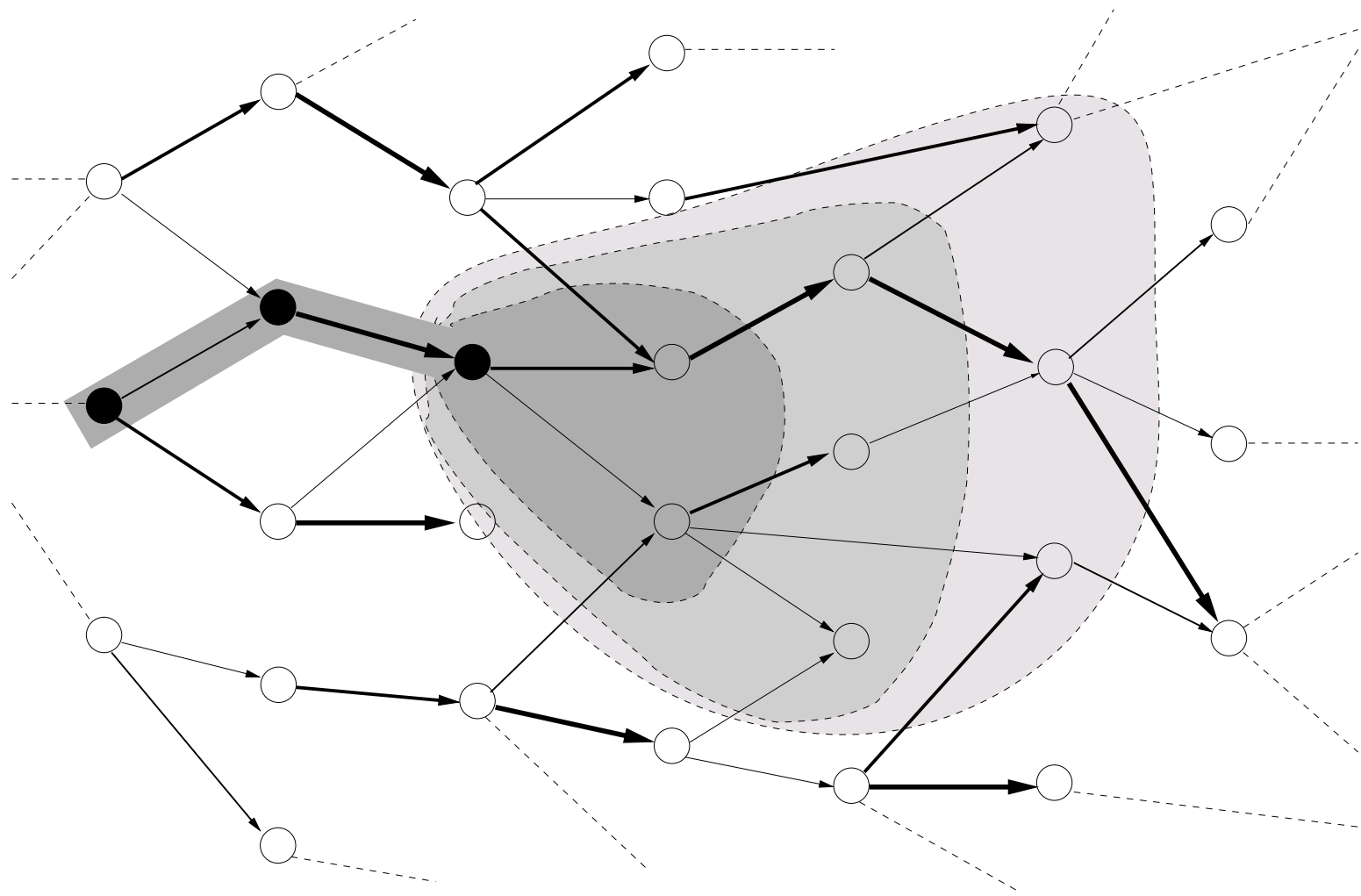
InFFra controller of "g0:agent1"
InFFra messages
(00:00:44): <END ENCOUNTER>
(00:00:50): <START ENCOUNTER>
(00:00:50): initiating message request(g0:agent1,g0:agent0,modifyRating(g0:agent0,g0:agent1,0))
(00:00:50): g0:agent1> perceived frame updated to
<frame(#15)/usg:[1]/step:0/bind:0>
{[request(g0:agent1,g0:agent0,modifyRating(g0:agent0,g0:agent1,0))]}
b[[]]
c[[]]
(00:00:51): received (as expected) accept(g0:agent0,g0:agent1,modifyRating(g0:agent0,g0:agent1,0))
(00:00:52): received accept(g0:agent0,g0:agent1,modifyRating(g0:agent0,g0:agent1,0))
(00:00:52): own turn initiated
(00:00:53): selected frame
<frame(#16)/usg:[3, 3, 2]/step:1/bind:0>
InFFra repository
<frame(#1)/usg:[8, 8, 8]/step:-1/bind:0>
{[request(V0,V1,V2), accept(V1,V0,V2), confirm(V0,V1,V2), do(V1,V2)]}
b[[]], [[V0, g0:agent1], [V1, g0:agent0], [V2, addLink(g0:agent0,g0:agent1,-2)]]; [[V0, g0:agent1], [V1, g0:agent0], [V2, number(-2)@3, other(V1)@3, can(V1,addLink(V1,V0,-2))@3, existsLink(V1,V0,-2)@4], [other(V1)@3, number(-2)@3, other(V1)@3, can(V1,addLink(V1,V0,-2))@3, existsLink(V1,V0,-2)@4]]
<frame(#29)/usg:[2]/step:-1/bind:0>
{[request(g0:agent0,g0:agent1,addLink(g0:agent1,g0:agent0,0))]}
b[[]]
c[[]]
<frame(#41)/usg:[1]/step:-1/bind:0>
{[request(g0:agent0,g0:agent1,addLink(g0:agent1,g0:agent0,-2))]}
b[[]]
c[[]]
    
```

# Expectation networks

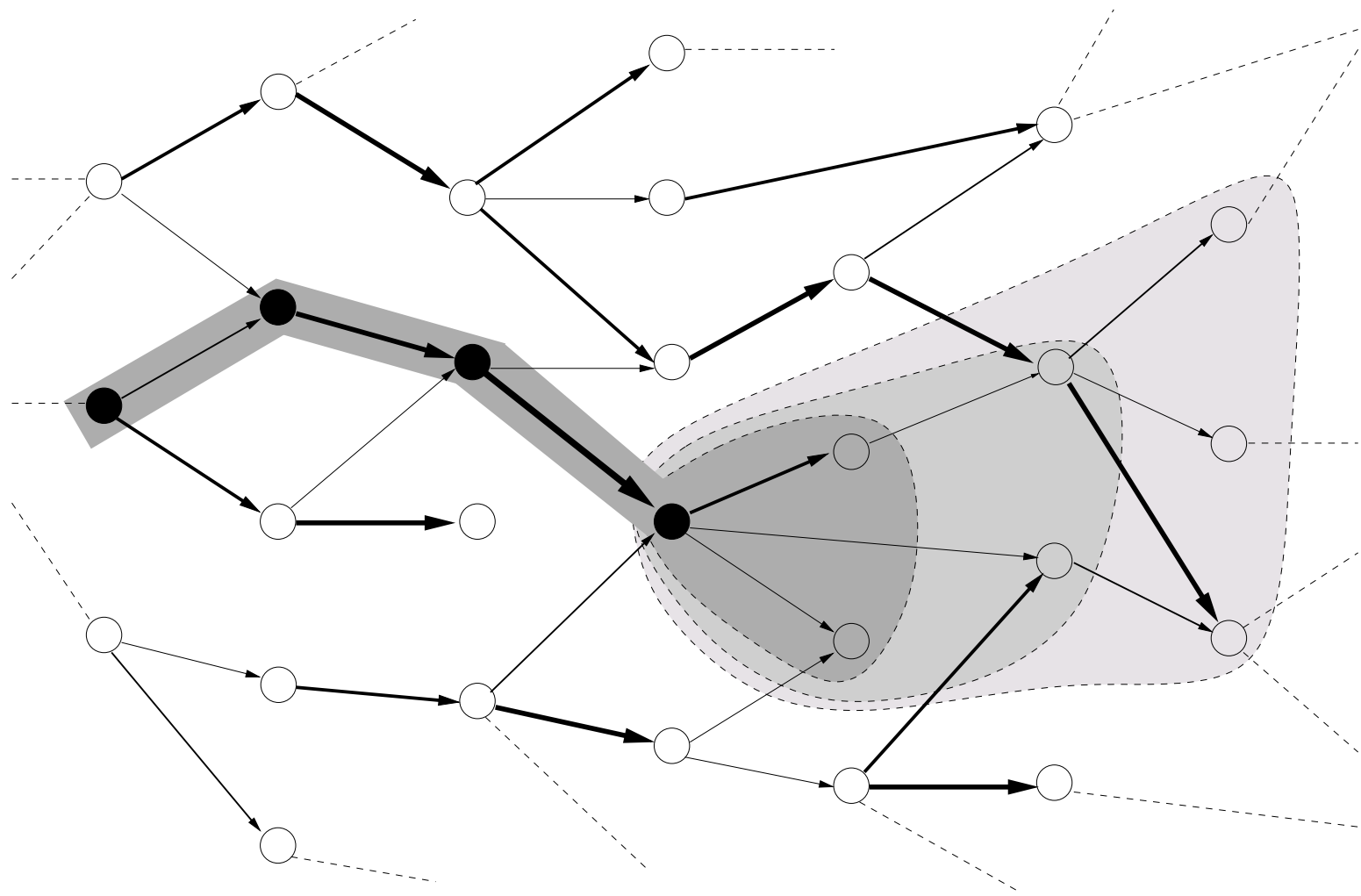
- Generalisation of the interaction frames idea (Nickles & MR)



# Prediction dynamics



# Prediction dynamics



## (Where) Did we go wrong?

- Novel in terms of modelling semantics in terms of experience and prediction
- But no account for generation of *what* is talked about
- Leads to thinking about what agents mostly talk about: *their own activities*
- Most expressive model for modelling complex activity (while remaining tractable): *planning*
- Tricky: how can you know know what to say when you first have to compute the things you might talk about?

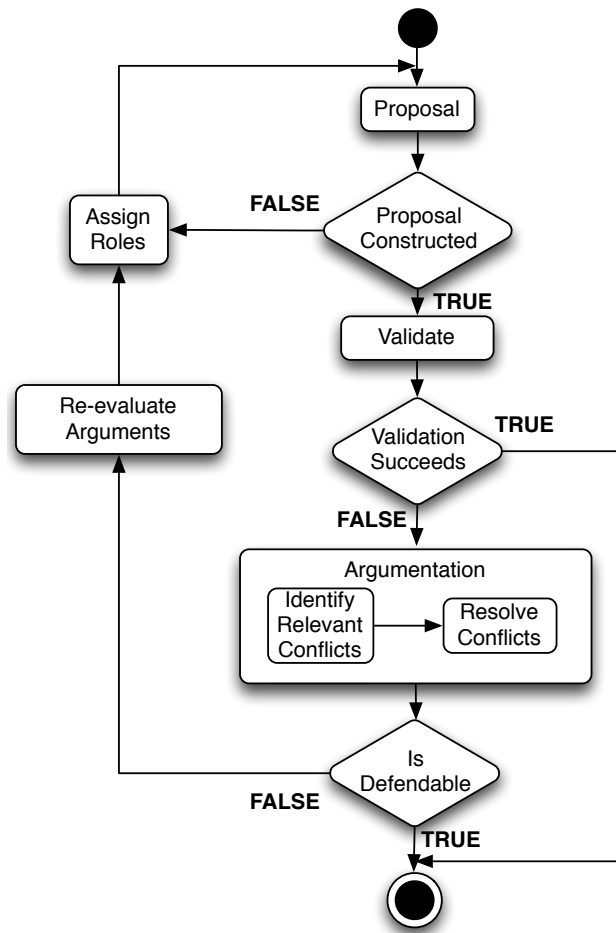
# The relevance of planning

- Classical planning problem  $P = \langle F, I, A, G \rangle$ , fluents  $F$ , initial state  $I$ , actions  $A$ , goal  $G$
- Extend the above framework (naively) to accommodate multiagent aspects
  - $P = \langle F, \{A_i\}, \{I_i\}, G \rangle$ : multi-perspective planning
  - $P = \langle F, A, I, \{G_i\} \rangle$ : multi-objective planning
  - $P = \langle \{F_i\}, \{A_i\}, I, G \rangle$ : multi-ontology planning
- Ignore concurrency, uncertainty, execution

# Multi-Perspective Planning

- Agents disagree about initial state and action definitions, but share goal:  $P_i = \langle F, \{A_i\}, \{I_i\}, G \rangle$
- Our work focuses on *acceptable plans*
  - $p$  is acceptable wrt  $KB_1$  and  $KB_2$  iff  
 $KB_1 \models p$  and  $KB_2 \models p$
- Belesiotis & MR developed argumentation-based method based on evaluating individual agents' proposals to compute defensible plan
- Scalability achieved by using off-the-shelf single-agent planners for sub-tasks in the process

# Argumentation-based conflict resolution in planning environments



- Plan proposal generated by single agent (with any planner)
- Dispute in case of disagreement, argumentation follows
- Ends in successful defence of initial proposal or rejection + belief revision



# Application: ArguDem

- A demonstrator for helping robots navigate:

The screenshot displays the ArguDem application interface. On the left, a 5x5 grid world is shown with columns labeled 0-4 and rows labeled 0-4. A robot icon is at (2,4), a goal icon is at (0,1), and black squares representing obstacles are at (0,2), (1,0), (1,4), (2,0), (2,2), (2,3), (3,2), and (3,3). A blue border highlights a path from (0,1) to (1,1), (1,2), (2,2), (3,2), and (3,3). A text box above the grid says "Cursor at: loc22". Below the grid are two circular icons: a refresh icon and a play icon.

**Human-Robot Dialog**

**Your options:**  
The goal is to help the robot reach its destination:  
Confirm the plan when you think its correct.  
**Black** squares are obstacles and the robot **cannot** pass through them!  
The robot **cannot** move diagonally.  
You can now ask the robot to come up with a plan.

**Robot says:**  
I believe that the following sequence of actions will take me to my destination:

- › Robot moves from loc24 to loc34
- › Robot moves from loc34 to loc33
- › Robot moves from loc33 to loc32
- › Robot moves from loc32 to loc22
- › Robot moves from loc22 to loc12
- › Robot moves from loc12 to loc11
- › Robot moves from loc11 to loc01

**Your options:**

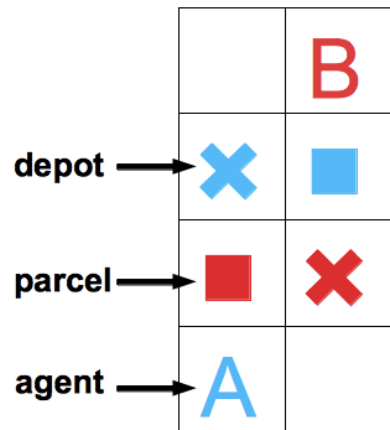
\* If you think that an action from the list above is not applicable click on it.

# Multi-Objective Planning

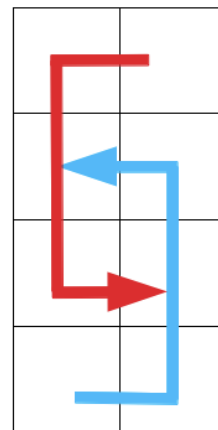
- Introduce independent goals:  $P = \langle F, A, I, \{G_i\} \rangle$
- Strategic problem, acceptability based on notions of stability and equilibrium
- Problem depends on whether contracts can be enforced and utility can be transferred
- Like concurrent planning with additional constraints on plan cost to individuals
- Hard to define meaningful solution concepts if goals incompatible or agents untrustworthy

# Example

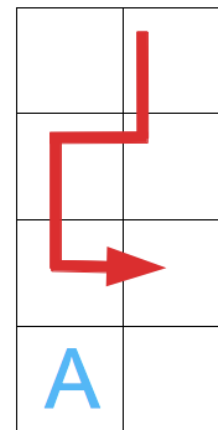
- Delivery domain



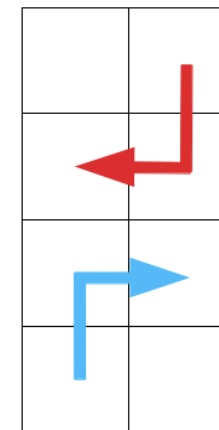
utility = reward - cost



“isolated”  
cost: 6/6  
*(inefficient)*



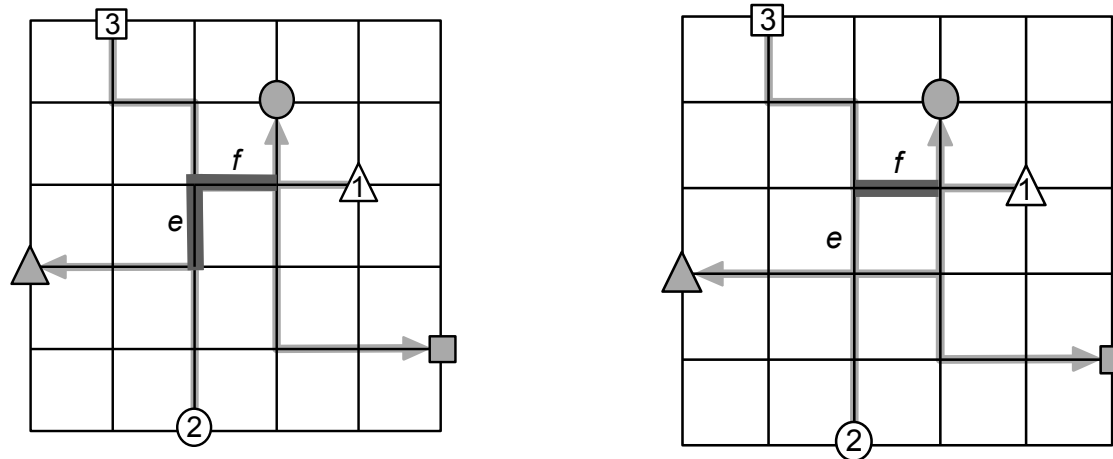
“selfish”  
cost: 0/8  
*(irrational)*



“cooperative”  
cost: 4/4  
*(stable)*

# Multi-Objective Planning

- Best-Response Planning (Jonsson & MR):
  - iterative method of optimising agents' individual plans without breaking others' plans
  - computes equilibrium plans fast in congestion games, restricted to interactions regarding cost
  - useful for plan optimisation in unrestricted domains
- Network routing example:



# Application: Trip Sharing

- Hrncir's system uses BRP to determine joint travel routes using real-world UK public transportation data (>200,000 connections)

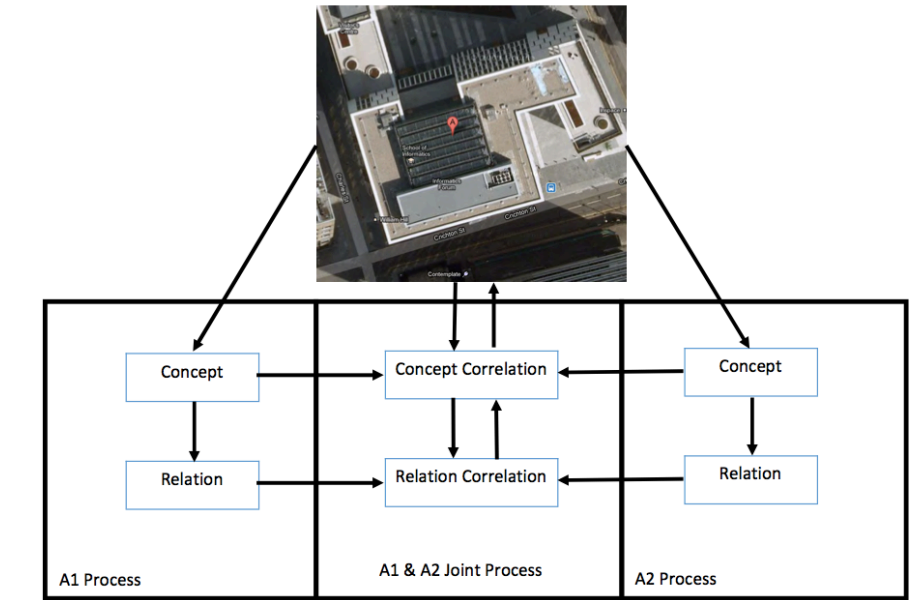


# Multi-Ontology Planning

- $P = \langle \{F_i\}, \{A_i\}, I, G \rangle$ : multi-ontology planning
- Systems like ORS (McNeill & Bundy) address the issue of creating plans under ontological disagreement
- But how does this relate to the data agents' local models come from?
- Moreover, even if we assume local models are initially known, how about change?
- These questions bring us back to thinking about data and symbol grounding

# Ontology evolution & language games

- Anslow's prototype of co-evolving concepts through mutual querying

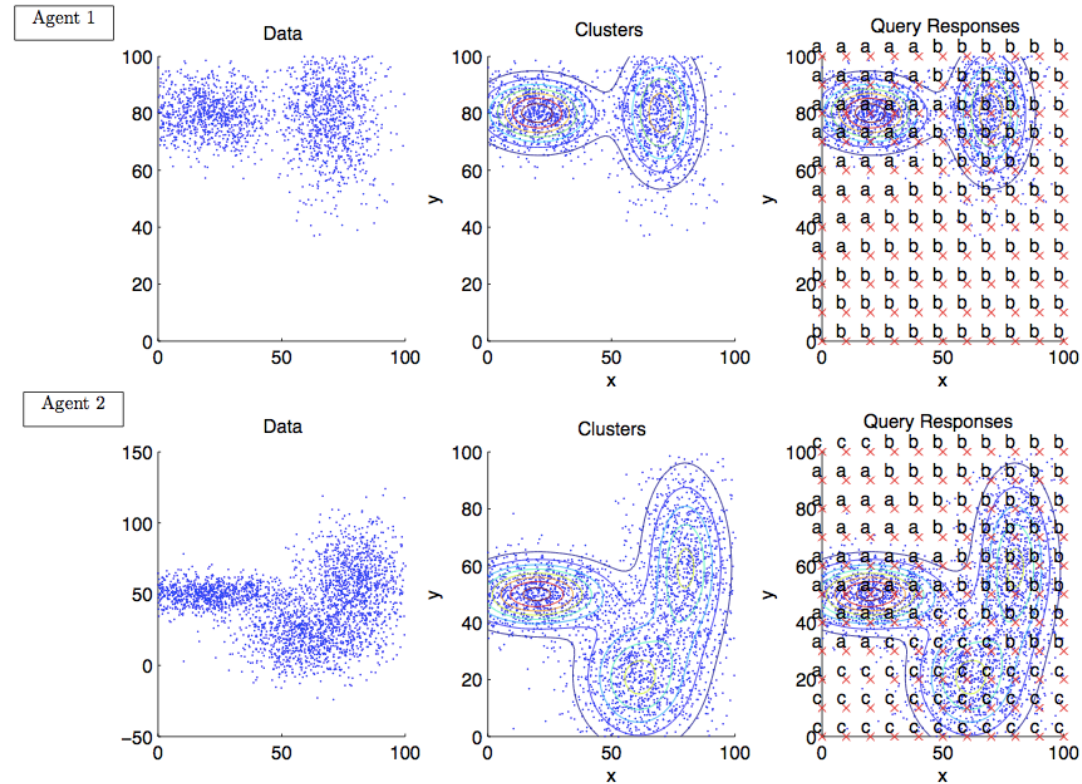


- Concept/relation correlation can be through symbolic ontologies



# Example: tracking objects/events

- Heterogeneous sensors clustering “interesting” events



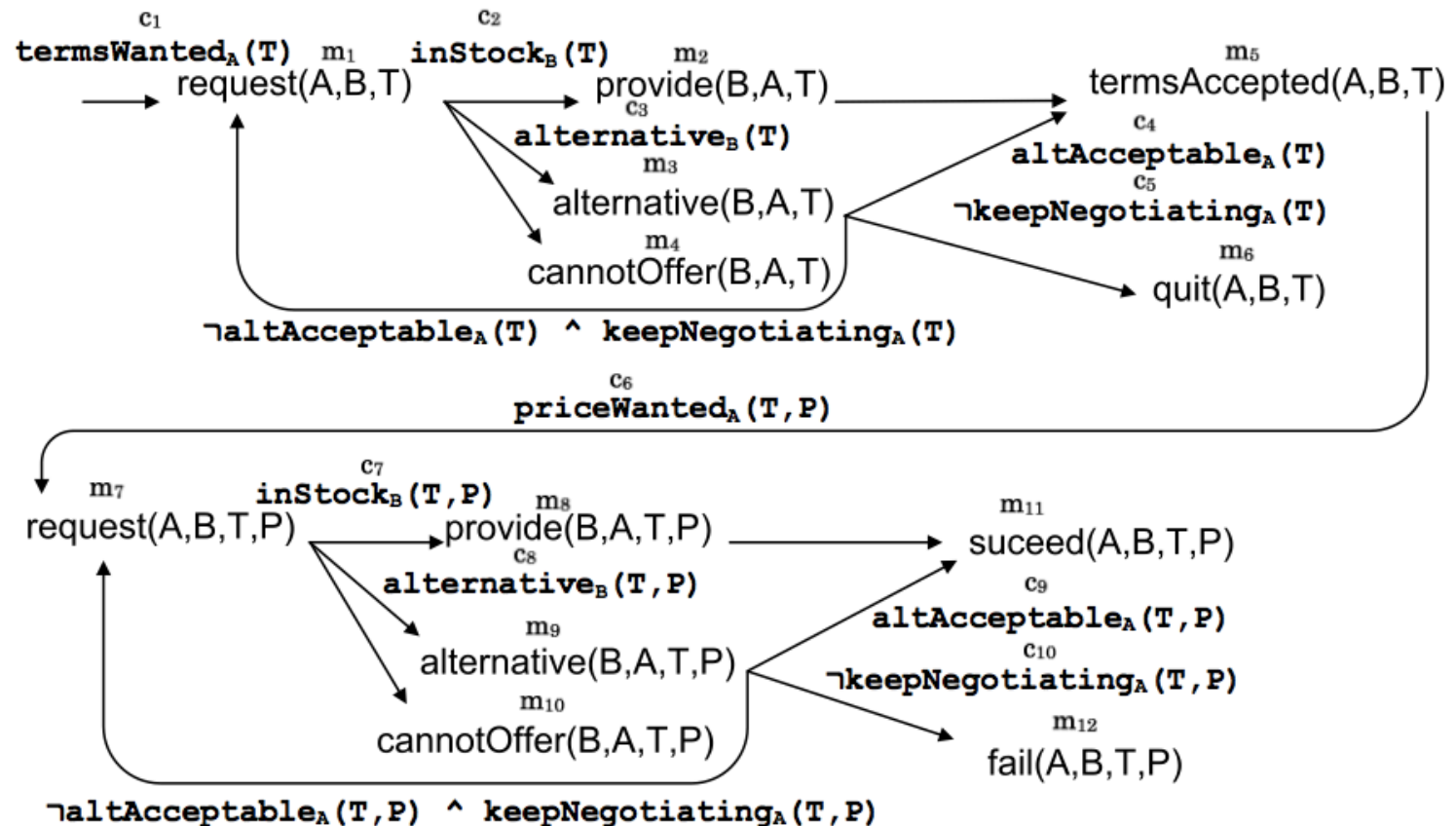




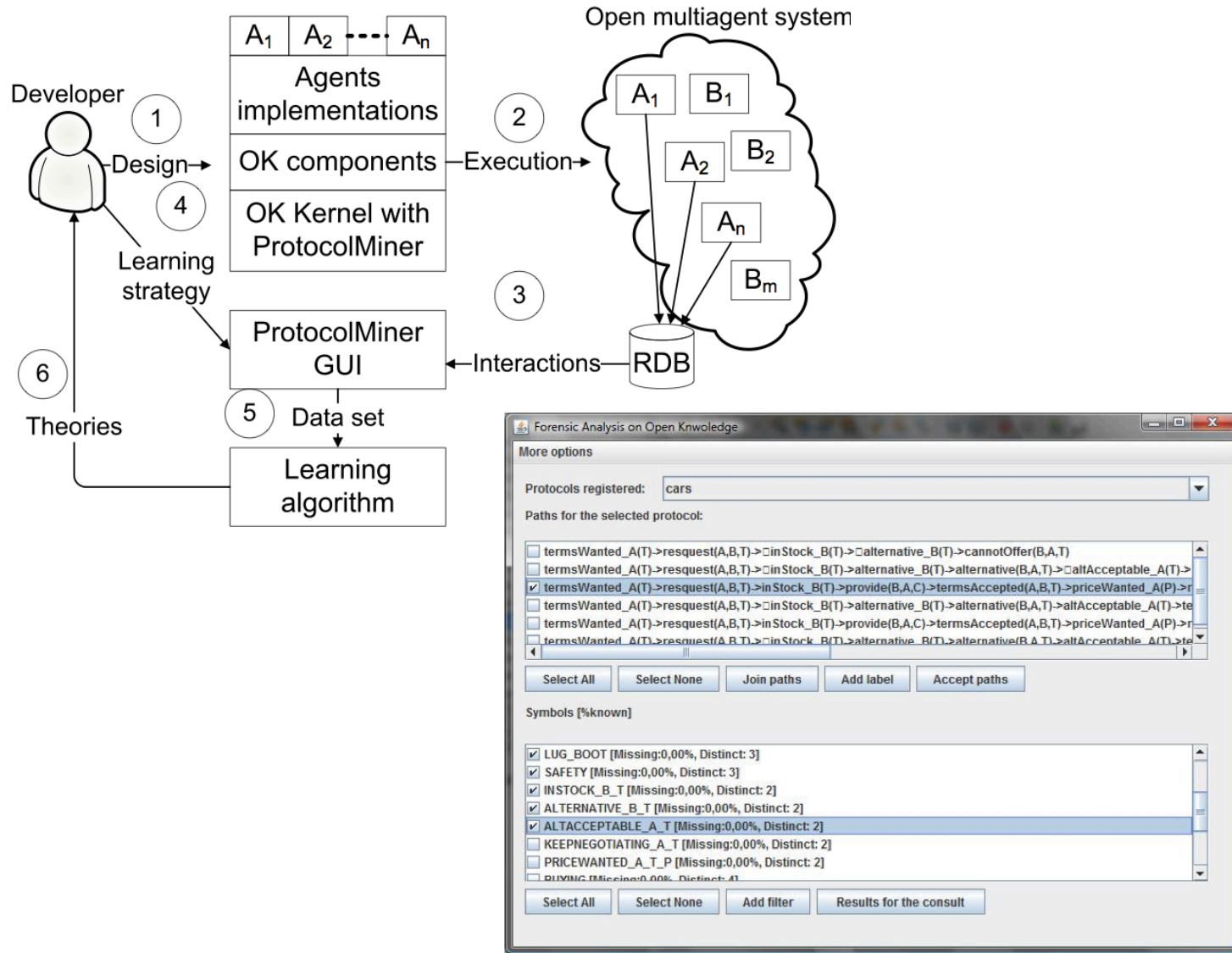
# Learning communication strategies revisited

- Qualitative context mining (Serrano&MR)
- Relate constraints in protocols to outcomes
- Can be used for
  - predicting outcomes and adjusting strategies
  - identifying misaligned constraint interpretations
  - deriving qualitative trust and reputation measures
- A much more generic, simpler view of interaction frames

# Qualitative context modelling



# ProtocolMiner



# Mining agent protocols

```
persons = 2: F (158)
persons = 4: F (158)
persons = more
|   lug_boot = small
|   |   doors = 2: F (8)
|   |   doors = 3: F (7)
|   |   doors = 4: F (8)
|   |   doors = 5-more: T (105)
|   lug_boot = med
|   |   doors = 2: F (13)
|   |   doors = 3: F (8)
|   |   doors = 4: F (13)
|   |   doors = 5-more: T (120)
|   lug_boot = big: T (402)
```



# The missing link

- Bottom-up data-driven methods enable us to build models of ontologies and strategies
- Top-down specification methods enable us to structure interaction space, “compute content”, limit search space
- How can we bring these two sides further together? **With the help of humans!**



# The way forward: Social Computation

- Imagine large-scale, hybrid, heterogeneous networks of humans and machines
- Crowdsourcing human intelligence where computational problem is too hard
- Conversely, support human users with automation for computation tasks
- Two major projects: SmartSociety and ESSENCE

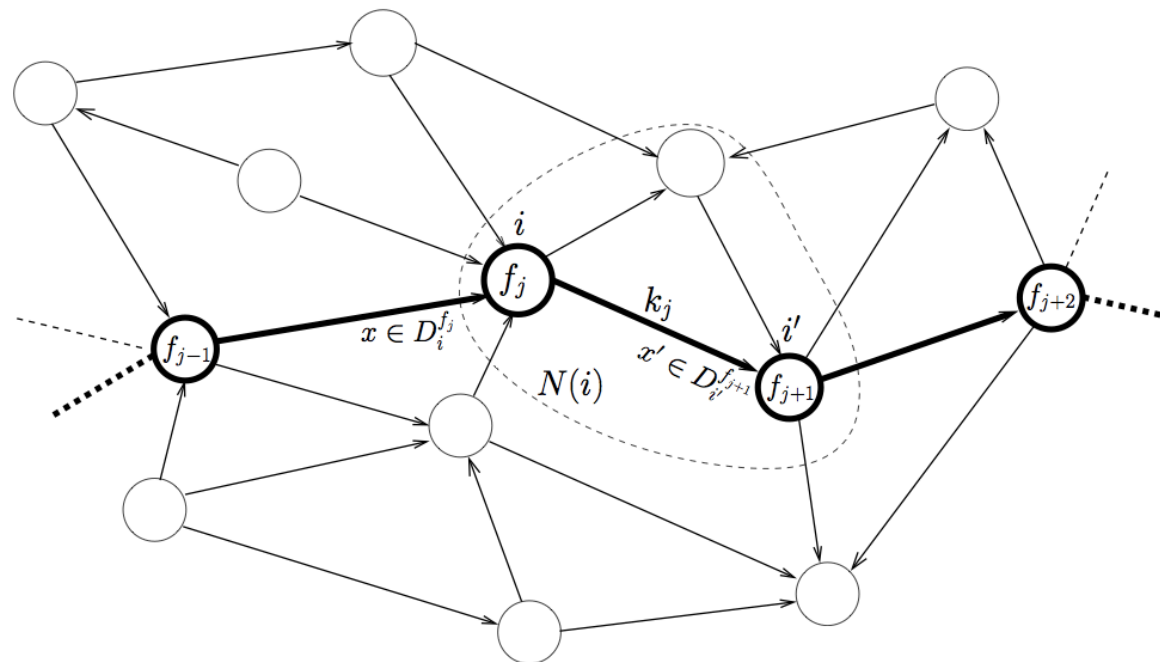
# SmartSociety



- 4-year €6.8M EU FP7 FET Integrated Project, co-ordinated by Trento
- Aim: building hybrid and diversity-aware collective adaptive systems to solve challenging societal problems
- Our focus: social orchestration of multi-level and overlapping concurrent computations + learning them from data
  - By the way, we're looking for a PhD student with machine learning/incentives background

# Lightweight social orchestration

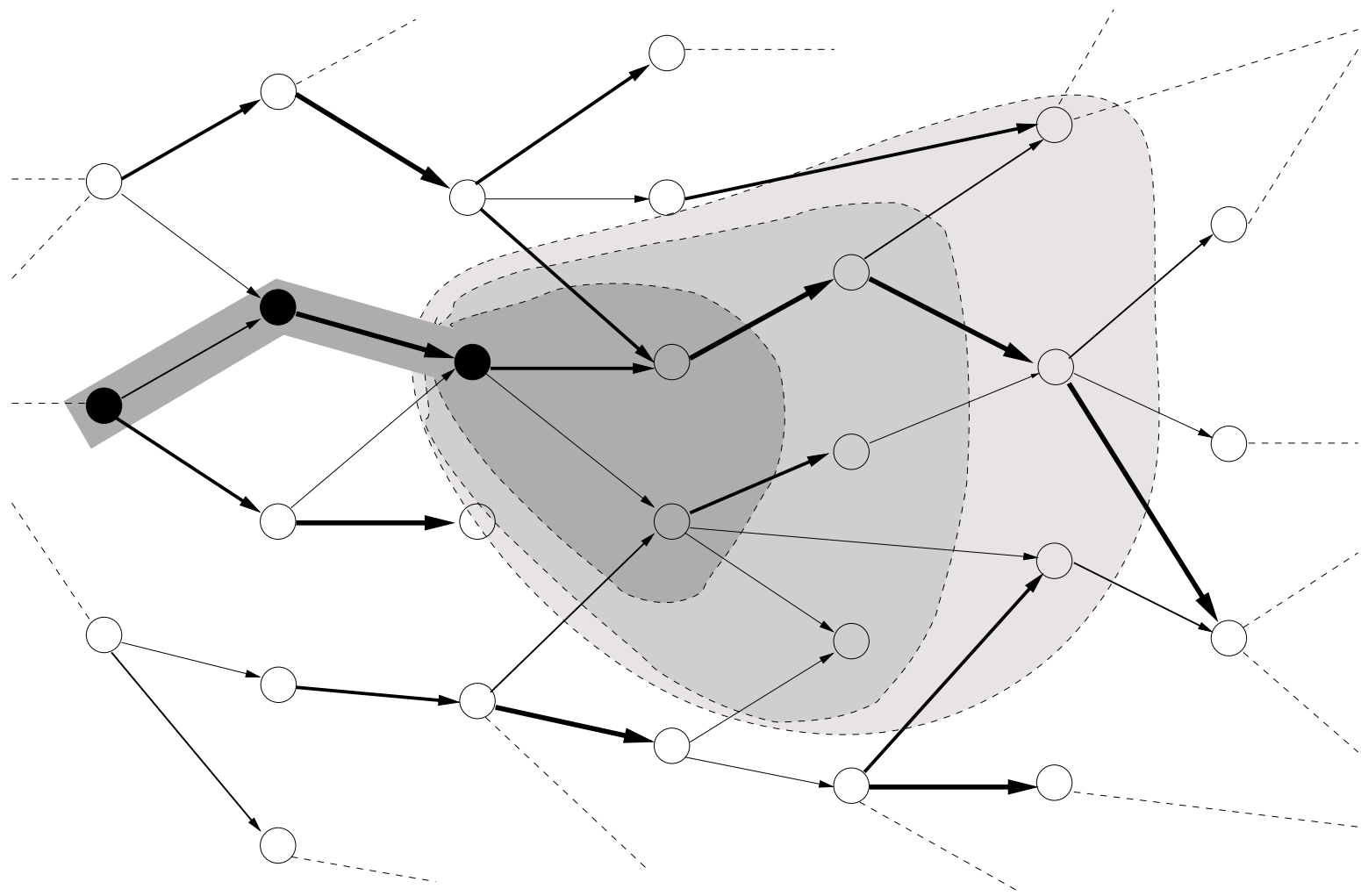
- Generalised planning and identification of emergent patterns in networks of computation



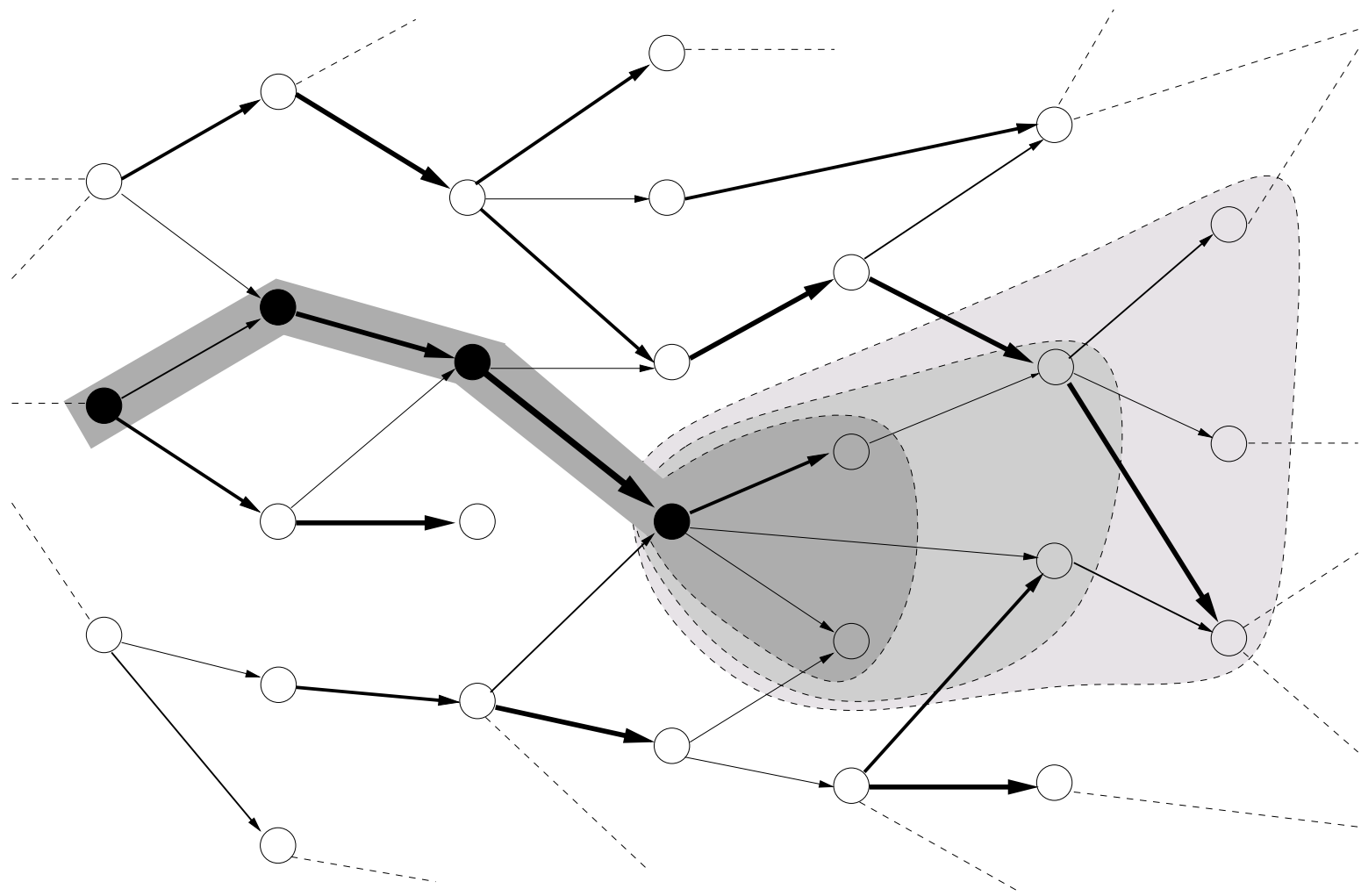
- Does this graph remind you of something?



# Prediction dynamics



# Prediction dynamics





# Evolution of Shared Semantics in Computational Environments

- 4-year, €4M Marie Curie Initial Training Network, co-ordinated by Edinburgh
- Aim: to exploit human methods for negotiating, sharing, and evolving meanings for computational systems
- Our focus: Communication planning from heterogeneous sensor data and ontology learning
  - By the way, we have funding for 11 PhD students and 4 post-docs (but you have to go abroad)



# Conclusions

- Presented a challenge but did not really propose a solution
- Described various methods for dealing with different parts of the problem
- Pervasive theme: tension between top-down and bottom-up methods
- The challenge lies in integrating them – new types of social computation systems may help