

# Learning to Distinguish Between Belief and Truth

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Stefano V. Albrecht

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Department of Computer Science  
The University of Texas at Austin

Introduction

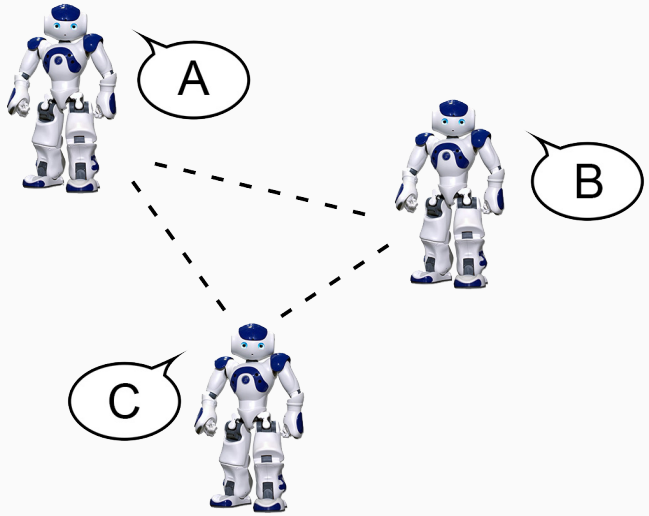
Behavioural Hypothesis Testing

The Future

# Introduction

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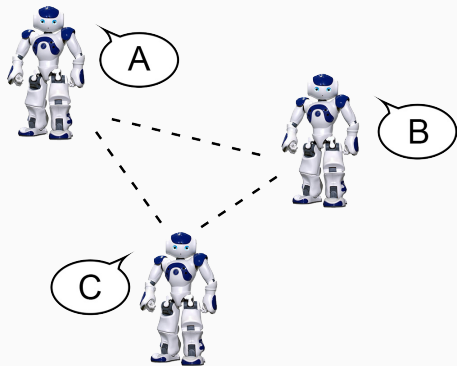
# Multi-Agent Systems



# Multi-Agent Systems

Sources of uncertainty:

- states
- actions
- **behaviour**



Model-free methods:

- E.g. regret, policy gradient, model-free RL
- *Does not address behaviour uncertainty*

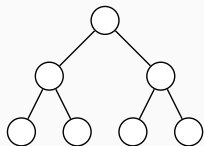
# Agent Modelling

Model-free methods:

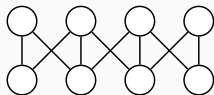
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Model-based methods:

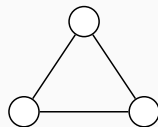
- Learn model of agent behaviour during interaction, e.g.



Decision tree



Neural network



State machine

- Use model to plan own actions

Why agent modelling?

- Generalise observations to unseen situations
- Plan into the future (e.g. guided exploration, risk control)
- But...



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- Generalise observations to unseen situations
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**Problem: no model criticism**

Does not check validity of model during interaction

May use *incorrect model* without ever realising it

# Agent Modelling – Example

Simple example:

- Rock-Paper-Scissors
- Human plays R-P-S-R-P-S-...

Model human as fixed distribution:

- Limit model is  $\langle \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \rangle$
- Expected payoff with correct model is 1
- Expected payoff with learned model is 0

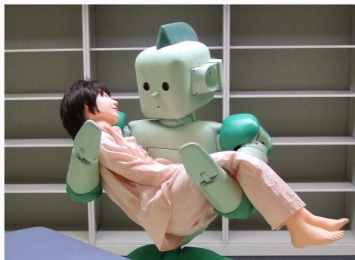
Robot never realises that model is wrong!



# Agent Modelling – Example

Complex examples:

- elderly support
- user interfaces
- electronic markets



What can go wrong?

- In general, **anything**
- Wrong models can make wrong predictions
- Wrong predictions can lead to **bad actions**


# Belief and Truth

Model is effective **hypothesis** (*belief*) of agent

- Hypothesis can be **false**
- But: model not treated as hypothesis

**Idea:** learn beliefs over multiple models

$\theta_1$	$\theta_1$	...	$\theta_n$
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 $\Pr(\theta_x|H^t)$

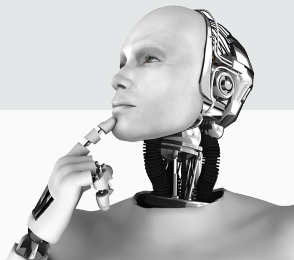
**Same problem:**

- $\Pr(\theta_x|H^t)$  is relative likelihood, not absolute truth
- Models may still be **wrong**

# Belief and Truth

We need agent to do both:

- Construct hypothesis of behaviour
- Contemplate **truth** of hypothesis



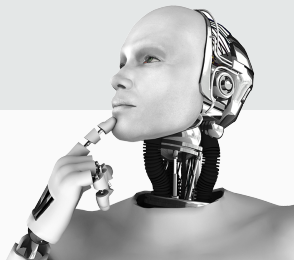
# Belief and Truth

We need agent to do both:

- Construct hypothesis of behaviour
- Contemplate **truth** of hypothesis

Allows agent to...

- Reject model
- Change assumptions
- Change modelling method
- Get **better model**
  - or –
- Resort to **safe policy** with no/minimal model



# Behavioural Hypothesis Testing

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# Behavioural Hypothesis Testing

Model is hypothesis because:

- true or false
- testable

**Natural question:**

Given hypothesis  $\pi_j^*$  for agent  $j$  and history  $H^t$ ,  
does  $j$  really behave according to  $\pi_j^*$ ?



## Behavioural Hypothesis Testing – Example

$t$	$(a_1^t, a_2^t)$	$\pi_2^*$
1	$(R, P)$	$\langle .3, .1, .6 \rangle$
2	$(S, R)$	$\langle .2, .3, .5 \rangle$
3	$(P, S)$	$\langle .7, .1, .2 \rangle$
4	$(P, S)$	$\langle .0, .4, .6 \rangle$
5	$(R, P)$	$\langle .4, .2, .4 \rangle$

# Behavioural Hypothesis Testing

Natural to compute some **score** from table:

- e.g. empirical frequency  
(Conitzer and Sandholm, 2007; Foster and Young, 2003)
- **But:** when is scoring scheme sufficient?
- **But:** how to choose threshold parameter for score?

# Behavioural Hypothesis Testing

Natural to compute some **score** from table:

- e.g. empirical frequency  
(Conitzer and Sandholm, 2007; Foster and Young, 2003)
- **But:** when is scoring scheme sufficient?
- **But:** how to choose threshold parameter for score?

Proposed solution: **Frequentist hypothesis test** ( $p$ -value)

- Allow for multiple scoring criteria in test statistic
- Significance level  $\alpha$  invariant of scoring scheme

# Preliminaries

Each agent  $i$  has **behaviour**  $\pi_i \in \Pi_i$

- $\pi_i(H^t) \in \Delta(A_i)$
- $A_i$  is action space for agent  $i$
- $H^t = (s^0, a^0, s^1, a^1, \dots, s^t)$  is history
- $s^\tau$  is signal/state observed at time  $\tau$
- $a^\tau = (a_1^\tau, \dots, a_m^\tau)$  is tuple of actions taken at time  $\tau$

## Two-Sample Problem

We control  $i$  and observe  $j$

- $\pi_j$  is **true** behaviour of  $j$
- $\pi_j^*$  is **hypothesised** behaviour of  $j$
- Question:  $\pi_j^* = \pi_j$ ?

# Two-Sample Problem

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- Question:  $\pi_j^* = \pi_j$ ?

Cannot answer directly since  $\pi_j$  unknown, but

- We know  $\mathbf{a}_j^t = (a_j^0, \dots, a_j^{t-1})$  from  $H^t$
- Can generate  $\hat{\mathbf{a}}_j^t = (\hat{a}_j^0, \dots, \hat{a}_j^{t-1})$  using  $\pi_j^*$
- **Two-sample problem:** were  $\mathbf{a}_j^t$  and  $\hat{\mathbf{a}}_j^t$  generated by  $\pi_j^*$ ?

# Frequentist Hypothesis Test

Compute  $p$ -value:

$$p = P \left( |T(\tilde{\mathbf{a}}_j^t, \hat{\mathbf{a}}_j^t)| \geq |T(\mathbf{a}_j^t, \hat{\mathbf{a}}_j^t)| \right)$$

$$\tilde{\mathbf{a}}_j^t \sim \left( \pi_j^*(H^0), \dots, \pi_j^*(H^{t-1}) \right)$$

Null-assumption:  $\pi_j^* = \pi_j$

Reject  $\pi_j^*$  if  $p$  below some *significance level*  $\alpha \in [0, 1]$

# Test Statistic

Test statistic:

$$T(\tilde{\mathbf{a}}_j^t, \hat{\mathbf{a}}_j^t) = \frac{1}{t} \sum_{\tau=1}^t T_{\tau}(\tilde{\mathbf{a}}_j^{\tau}, \hat{\mathbf{a}}_j^{\tau})$$

$$T_{\tau}(\tilde{\mathbf{a}}_j^{\tau}, \hat{\mathbf{a}}_j^{\tau}) = \sum_{k=1}^K w_k \left( z_k(\tilde{\mathbf{a}}_j^{\tau}, \pi_j^*) - z_k(\hat{\mathbf{a}}_j^{\tau}, \pi_j^*) \right)$$

$w_k \in \mathbb{R}$  is weight for *score function*  $z_k \in Z$

Intuition:  $z_k(\tilde{\mathbf{a}}_j^{\tau}, \pi_j^*)$  *likelihood* that  $\pi_j^*$  produced  $\tilde{\mathbf{a}}_j^{\tau}$



## Example Score Functions

$$z_1(\mathbf{a}_j^t, \pi_j^*) = \frac{1}{t} \sum_{\tau=0}^{t-1} \frac{\pi_j^*(H^\tau)[a_j^\tau]}{\max_{a_j} \pi_j^*(H^\tau)[a_j]}$$

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$$z_2(\mathbf{a}_j^t, \pi_j^*) = \frac{1}{t} \sum_{\tau=0}^{t-1} 1 - \mathbb{E}_{a_j \sim \pi_j^*(H^\tau)} \left| \pi_j^*(H^\tau)[a_j^\tau] - \pi_j^*(H^\tau)[a_j] \right|$$

## Example Score Functions

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$$z_3(\mathbf{a}_j^t, \pi_j^*) = \sum_{a_j \in A_j} \min \left[ \frac{1}{t} \sum_{\tau=0}^{t-1} [a_j^\tau = a_j]_1, \frac{1}{t} \sum_{\tau=0}^{t-1} \pi_j^*(H^\tau)[a_j] \right]$$

# Learning the Test Distribution

Can show that test statistic eventually normal, but:

- shaped gradually over time
- initially **skewed**

Need special distribution to capture dynamics:

- **Skew-normal distribution** (Azzalini, 1985)

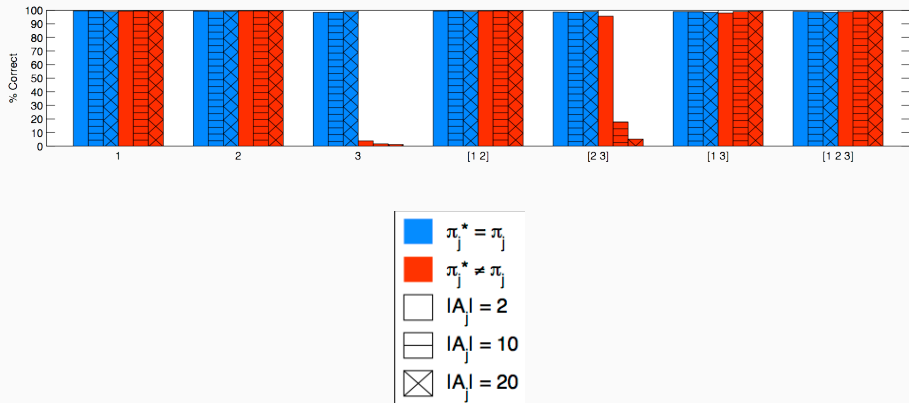
$$f(x | \xi, \omega, \beta) = \frac{2}{\omega} \phi\left(\frac{x - \xi}{\omega}\right) \Phi\left(\beta \left(\frac{x - \xi}{\omega}\right)\right)$$

- $\phi$  and  $\Phi$  are standard normal PDF and CDF
- Learn parameters  $\xi, \omega, \beta$  during interaction

# Experiments: Random Behaviours

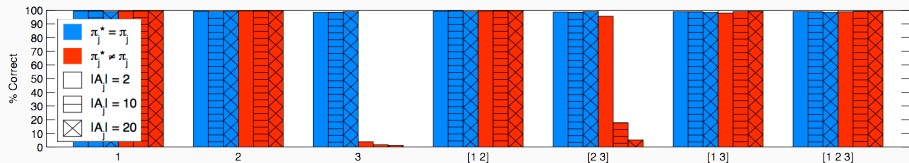
$\pi_i, \pi_j, \pi_j^*$ : random action distribution in each time step

Tested all combinations of score functions  $z_1, z_2, z_3$

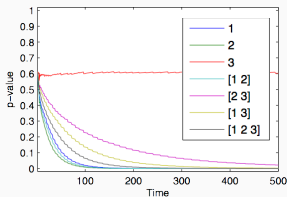


# Experiments: Random Behaviours

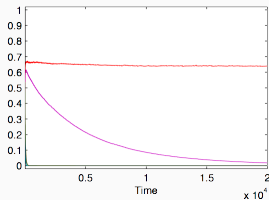
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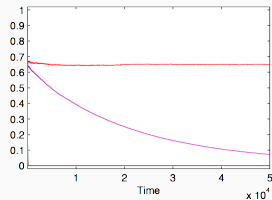
Score combination can “heal” convergence:



$$|A_j| = 2$$



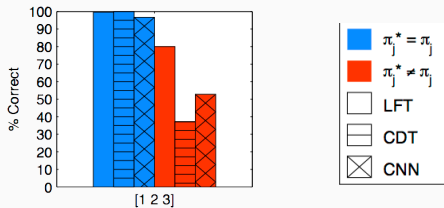
$$|A_j| = 10$$



$$|A_j| = 20$$

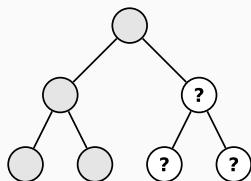
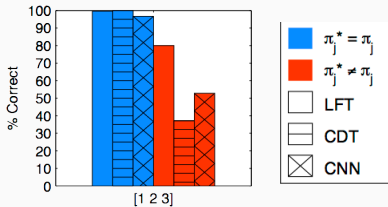
# Experiments: Adaptive Behaviours

$\pi_i, \pi_j, \pi_j^*$ : behaviour from same adaptive class (LFT, CDT, CNN)



# Experiments: Adaptive Behaviours

$\pi_i, \pi_j, \pi_j^*$ : behaviour from same adaptive class (LFT, CDT, CNN)



## Limitation:

Does not probe specific aspects of hypothesis!





S. Albrecht, J. Crandall, and S. Ramamoorthy.  
**Belief and truth in hypothesised behaviours.**  
*Artificial Intelligence*, 235:63–94, 2016.



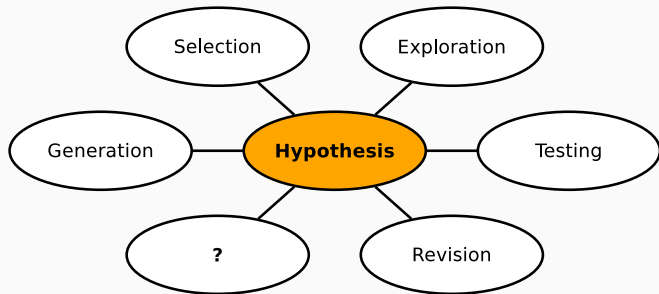
S. Albrecht and S. Ramamoorthy.  
**Are you doing what I think you are doing? Criticising uncertain agent models.**  
*In 31st Conference on Uncertainty in Artificial Intelligence*,  
pages 52–61, 2015.

## The Future

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Testing is only part of bigger picture...

- Need **hypothesis** “*contemplation*”



# The Future

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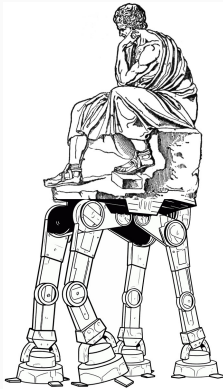
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# The Future

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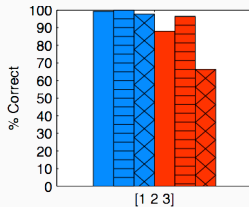
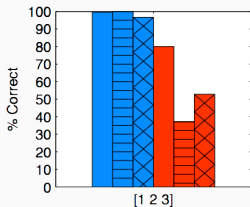
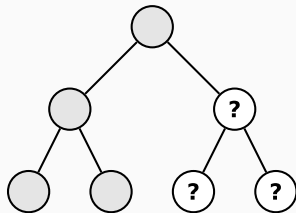
- Need *hypothesis* “*contemplation*”



# The Future

## Exploration:

- How and when to explore aspects of hypothesis?



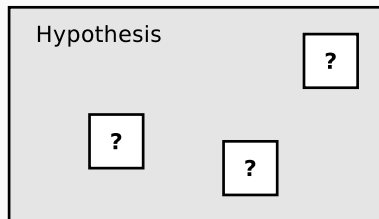
using random exploration

## Revision:

- How to revise and improve aspects of hypothesis?

## Example:

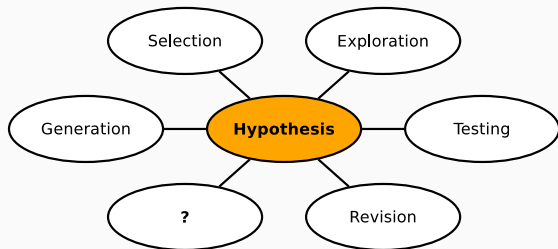
- Hypothesis is reinforcement learner
- How to revise
  - ... *learning rate*?
  - ... *exploration rate*?
  - ... *discount rate*?



# The Future

Individual pieces of puzzle exist

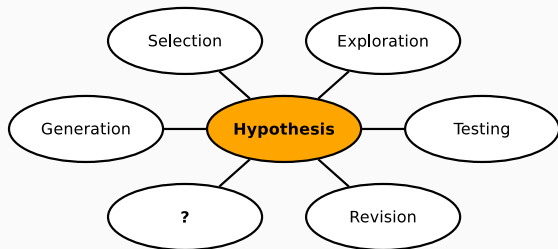
- Need integration into complete solution
- Important, feasible, and timely
- Relevant in all areas of AI





## Challenges:

- Complexity, soundness, completeness, etc.
- Contemplate **usefulness**, not just correctness
- Can agent **learn on its own** how to contemplate?



Thank you