On the adaptive fitness of the social sense: lessons from Bayesian Decision Theory

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Dr. Marie Devaine
Theory of Mind: the “false belief” test

Wimmer & Perner, 1983
Lifespan dynamics of Theory of Mind

false belief test
(n = 8884)

Frith-Happé animations
(n = 6098)

hide-and-seek
(n = 5926)
What computational problem does ToM solve?

1) ToM = *inverse* Bayesian Decision Theory?

2) ToM sophistication = depth of recursive beliefs?

[Denett 1987]
playing without ToM ($0$-ToM)

« I believe that you will hide behind the tree »
playing with ToM: recursive beliefs ($1$-ToM)

« I believe that you believe that I will hide behind the tree »
playing with ToM: recursive beliefs (2-ToM)

« I believe that you believe that I believe ... »
Overview of the talk

✓ Does ToM make a difference when we learn?

✓ Limited ToM sophistication: did evolution fool us?

✓ Playing *hide-and-seek* with non-human primates

✓ What about people with autism spectrum disorder?

✓ A short lesson from fMRI
Overview of the talk

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**k-ToM**: recursive meta-Bayesian modelling

- **k-ToM** learns how the other learns and her ToM sophistication level:

  \[ \lambda^{(k)}_r = f \left( \lambda^{(k)}_{r-1}, a_r, \theta^{(k)}_1 \right) \]

- **k-ToM** acts according to her beliefs and preferences:

  \[ p \left( a_{1,r+1} \mid \theta^{(k)} \right) \propto \exp - \rho \left( \lambda^{(k)}_{r+1}, a_{1,r+1} \right) / \theta^{(k)}_2 \]

- This induces a likelihood for a [k+1]-ToM observer:

  \[ p \left( a_{1,r} \mid \theta^{(1,...,k)}, \kappa, m_{k+1} \right) = \prod_{k'=0}^{k} \prod_{\tau'=1}^{\tau} p \left( a_{1,\tau'} \mid \theta^{(k)} \right)^{\xi_{k'}(\kappa)} \]

- Nulling the ensuing Free-Energy derivative yields the [k+1]-ToM learning rule:

  \[ \lambda^{(k+1)}_{r+1} = f \left( \lambda^{(k+1)}_r, a_r, \theta^{(k+1)}_1 \right) \]

  \[ f : \lambda^{(k+1)}_r \rightarrow \arg \max F^{(k+1)}_r \]

  \[ F^{(k+1)}_r = \left\langle \ln p \left( a_{1,r} \mid \theta^{(1,...,k)}, \kappa, m_{k+1} \right) \right\rangle + \left\langle \ln p \left( \theta^{(1,...,k)}, \kappa \mid m_{k+1} \right) \right\rangle - \left\langle \ln q_r \left( \theta^{(1,...,k)}, \kappa \right) \right\rangle \]
**k-ToM: VB belief update rule**

\[ p_{t_{op}}^{} = \sum_{l<\kappa} \lambda_{t}^{k,\kappa} \ p_{t_{op}}^{op,\kappa} \]

\[ p_{t_{op}}^{op,\kappa} \approx s \circ \tilde{v}_{t_{op}}^{\kappa} \left( \mu_{t-1}^{k,\kappa}, \Sigma_{t-1}^{k,\kappa} \right) \]

\[ \lambda_{t}^{k,\kappa} \approx \left[ \frac{\lambda_{t-1}^{k,\kappa} \ p_{t_{op}}^{op,\kappa}}{\sum_{\kappa' \ < \ k} \lambda_{t-1}^{k,\kappa'} \ p_{t_{op}}^{op,\kappa'}} \right] ^{a_{t_{op}}^{op}} \left[ \frac{\lambda_{t-1}^{k,\kappa} \left( 1 - p_{t_{op}}^{op,\kappa} \right)}{\sum_{\kappa' \ < \ k} \lambda_{t-1}^{k,\kappa'} \left( 1 - p_{t_{op}}^{op,\kappa'} \right)} \right] ^{1-a_{t_{op}}^{op}} \]

\[ \mu_{t}^{k,\kappa} \approx \mu_{t-1}^{k,\kappa} + \lambda_{t}^{k,\kappa} \Sigma_{t}^{k,\kappa} \ W_{t-1}^{\kappa} \left( a_{t_{op}}^{op} - s \circ v_{t_{op}}^{\kappa} \left( \mu_{t-1}^{k,\kappa} \right) \right) \]

\[ \Sigma_{t}^{k,\kappa} \approx \left[ \left( \Sigma_{t-1}^{k,\kappa} + \sigma_{k}^{\kappa} \right)^{-1} + s \circ v_{t_{op}}^{\kappa} \left( \mu_{t-1}^{k,\kappa} \right) \lambda_{t}^{k,\kappa} \ W_{t-1}^{\kappa} W_{t-1}^{\kappa \ T} \right] ^{-1} \]

\[ v_{t_{op}}^{1}(x_{t_{op}}^{1}) = \frac{p_{t_{op}}^{self} \Delta U_{t_{op}}^{1} + \left( 1 - p_{t_{op}}^{self} \right) \Delta U_{t_{op}}^{0}}{\beta_{t}} \]
**k-ToM’s learning rule in competitive games**

1st-order Volterra decomposition:

\[
p(a_{i}^{\text{self}} = 1 \mid \omega) = s \left( \omega^{0} + \sum_{\tau} \omega_{\tau}^{\text{op}} a_{i-\tau}^{\text{op}} + \sum_{\tau} \omega_{\tau}^{\text{self}} a_{i-\tau}^{\text{self}} \right)
\]

![Graphs showing own action and opponent's action weights with different ToM levels and accuracy rates.]
**$k$-ToM’s performance in competitive games**

**payoff table**
(« hide and seek »)

<table>
<thead>
<tr>
<th></th>
<th>hider: $a_1 = 1$</th>
<th>hider: $a_1 = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>seeker: $a_2 = 1$</td>
<td>-1, 1</td>
<td>1, -1</td>
</tr>
<tr>
<td>seeker: $a_2 = 0$</td>
<td>1, -1</td>
<td>-1, 1</td>
</tr>
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**simulated behavioural performance**
(#wins/trial)

$\tau = 512$
Everybody is somebody’s fool

1-ToM predicts 0-ToM

0-ToM predicts 1-ToM
**Behavioural task design**

**social framing** (game « hide and seek »)

You are playing against Player 1

alternative options (1.2 sec)

subject's choice

feedback (1 sec)

You win!

non-social framing (casino gambling task)

Session 1

1 2

You win!
Behavourial performances (N=26)

Devaine et al. (2014a)
Learning style: similarity to best $k$-ToM response

ANOVA:
- **Framing** ($p=0.02$), **op** ($p=0.0001$), 0 framingXop
- 0 age, 0 sex

SOBEL:
- **mediation of framing** ($p=0.010$), **mediation of op** ($p=0.013$)

Devaine et al. (2014a)
Trial-by-trial choice sequences: learning styles

- **RB**: Nash strategy (random)
- **WS**: Win-Stay Loose -switch (heuristic)
- **RL**: trial-and-error learning
- **0-ToM**: Bayes. learning
- **BSL**: Bayes. sequence learning
- **HGF**: Bayes. volatility learning
- **Inf**: influence learning
- **1-ToM**: meta-Bayes. learning
- **2-ToM**: meta-Bayes. learning
- **k-ToM**: meta-Bayes. learning

Devaine et al. (2014a)
Analysis of trial-by-trial choice sequences

Devaine et al. (2014a)
Variability of human ToM sophistication

Devaine et al. (2014a)
Overview of the talk

- Does ToM make a difference when we learn?
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- Playing *hide-and-seek* with non-human primates
- What about people with autism spectrum disorder?
- A short lesson from fMRI
# Competitive versus cooperative games

« hide and seek »

<table>
<thead>
<tr>
<th></th>
<th>P1: $a_1 = 1$</th>
<th>P1: $a_1 = 0$</th>
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<tbody>
<tr>
<td>P2: $a_2 = 1$</td>
<td>-1, 1</td>
<td>1, -1</td>
</tr>
<tr>
<td>P2: $a_2 = 0$</td>
<td>1, -1</td>
<td>-1, 1</td>
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« battle of the sexes »

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<th>P1: $a_1 = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>P2: $a_2 = 1$</td>
<td>2, 0</td>
<td>-1, -1</td>
</tr>
<tr>
<td>P2: $a_2 = 0$</td>
<td>-1, -1</td>
<td>0, 2</td>
</tr>
</tbody>
</table>

Devaine et al. (2014b)
Being right is as good as being smart

« hide and seek »

« battle of the sexes »

Devaine et al. (2014b)
Evolutionary game theory

Can we explain the emergence of the natural bound on ToM sophistication?

→ Average adaptive fitness:
  
  • is a function of the behavioural performance, relative to other phenotypes
  • depends upon the frequency of other phenotypes within the population

\[ s_k \text{ frequency of phenotype } k \text{ within the population} \]

\[ \omega_i \text{ frequency of game } i \]

\[ Q^{(i)}(\tau) \text{ expected payoff matrix of game } i \text{ at round } \tau \]

→ Replicator dynamics [Maynard-Smith 1982, Hofbauer 1998]:

\[ \frac{ds}{dt} = \text{Diag} (s) \left( \sum_i \omega_i Q^{(i)}(\tau) s - \sum_i \omega_i s^T Q^{(i)}(\tau) s \right) \]

evolutionary stable states: \[ s_\infty \equiv \lim_{t \to \infty} s(t) \]
Replicator dynamics and ESS

« hide and seek »

« battle of the sexes »
ESS: phase portrait

Devaine et al. (2014b)
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The main confound in primates’ ToM assessment

You’re competing for the food. Where should you approach the food from?

[Hare 2006]
Evolutionary pressure on ToM sophistication

Machiavellian intelligence hypothesis [Whitten 1996]

Cognitive scaffolding hypothesis [Dunbar 1998]

\[ r = -0.28, p = 0.54 \]
Playing “hide and seek“ with primates

• **Subjects (n=39):**
  Macaques (4+5), Orangutans (7), Chimps (6), Gorillas (5), Mangabeys (8), Lemurs (4)

• **Experimental paradigm:**
  ✓ habituation/training sessions (rule learning)
  ✓ 3 opponent types (RB, 0-ToM, 1-ToM) X 4 sessions
  ✓ control task (behavioural perseveration)

Devaine et al. (submitted)
Behavioural performances

Devaine et al. (submitted)
(brain) size matters

Devaine et al. (submitted)
Variability of non-human ToM sophistication

Devaine et al. (submitted)
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ASD: ToM deficit hypothesis

[Baron-Cohen et al., 1985]
ASD patients: summary statistics

- High functioning autistic patients (N=24)
- Neurotypical participants (N=24)
  matched for age, IQ, sex (21 males)

<table>
<thead>
<tr>
<th>Group</th>
<th>ASD</th>
<th>NT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>25.5 (5.7)</td>
<td>27.9 (8.6)</td>
</tr>
<tr>
<td>IQ</td>
<td>104 (17)</td>
<td>106 (14)</td>
</tr>
<tr>
<td>Social anhedonia</td>
<td>14.8 (8.4)</td>
<td>9.7 (4.2)</td>
</tr>
</tbody>
</table>

deceptive framing manipulation:  
sanity check

Devaine et al. (2015)
Behavioural performances (relative to RB)

Opponent x framing

NT

NO EFFECT OF FRAMING

ASD

NO EFFECT OF FRAMING
Model-based analysis: ToM sophistication

ToM sophistication: \( E[k \mid y] = \sum_{k=0}^{3} k \ p(k \mid y) \)

**NS framing**

\( p=0.13 \)

**Soc framing**

\( p=0.01 \)
Model-based analysis: learning style rigidity

Model stability: $P(m_1 = m_2 \mid y) = \sum_m P(m_1 = m \mid y_1) P(m_2 = m \mid y_2)$

across framings: $p < 10^{-4}$

across repetitions: $p = 0.02$
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(embarrassingly preliminary) fMRI results

- 2 framings (social VS non-social)
- 2 types of complexity (sequence VS 1-ToM)

Hill et al. (not even in prep.)
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Summary

• Does mentalizing make a difference when we learn?
  - social framing effect ("mentalize or be fooled")
  - distribution of ToM sophistication = mixed

• Evolution of ToM:
  - cooperation+learning → natural bounds to ToM sophistication
    ("being right is as good as being smart")
  - non-human primates → (brain) size matters

• Autism:
  - ToM sophistication: ASD < NT
  - Learning style rigidity: ASD > NT

• fMRI:
  - rTPJ: automatically detects intentional behaviour?
References and acknowledgements

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Dealing with uncertain motives: advice taking task

probabilistic cue

informed advice

player’s decision

outcome

progress bar

Gold target = 20 CHF
Silver target = 10 CHF

[Diaconescu et al., 2014]
Dealing with uncertain motives: results (N=16)

2-ToM: worst subject

2-ToM: best subject

model attributions

exceedance probabilities