Experimental and causal view on information integration in autonomous agents

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Slides available on pgeiger.org
Introduction

Internet of things, self-driving cars, etc.: many trends that increase the number of connected intelligent agents (sensors and actuators)
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Problem statement:

How can an agent autonomously integrate as much relevant data (or higher level information) as possible from others to inform causal model/ actions?
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Problem statement:

How can an agent autonomously integrate as much relevant data (or higher level information) as possible from others to inform causal model/ actions?

Examples:

- Road experience transfer between different self-driving cars
- Path descriptions based on landmarks or maps
Previous work

Various approaches to various versions of this problem:

- Reinforcement learning (RL)
- Learning from demonstrations (LfD)
- Transfer learning for agents (TLA)
- Multi-agent systems (MAS)
- Knowledge representation
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(Inaccurate? Missing something?)
Our two perspectives on this problem:

1. Simulated experiments – to obtain better understanding
2. Causal models – e.g. for transfer across different agent hardware
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Structure for both:
- introduce toy instance of the problem
- illustrate approach
Experimental view on information integration in autonomous agents

Problem instance: navigation from video in ‘Malmo’

Background: AI experimentation platform ‘Malmo’: library for programming agents for ‘Minecraft’ (computer game) [Bignell2016]
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Task: unknown landscape; navigate to visually recognizable goal
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Task: unknown landscape; navigate to visually recognizable goal

Available heterogeneous information:
- agent’s own sensors (position $q$, image $y$) and action (move left/right/forward/backward) at each time $t$
- “local controller” (past experience on “local physical laws”)
- video $y_{0:L}^*$ of a different (“source”) agent that gets to the goal

NB: no actions given! – allows e.g. for differing action spaces
A simple integrating agent algorithm

(Given: local controller $ctl$, source agent’s video $y_{1:L}^*$)
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A simple integrating agent algorithm

(Given: local controller $ctl$, source agent’s video $y^*_{1:L}$)

For $i = 1, \ldots, L$

1. Use $ctl$ and interaction with environment to search locally around position $q_{i-1}$ for position $q_i$ with image $y$ most similar to $y^*_i$

   (formally: $q_i := \arg \min_q \| Gauss \ast (y^*_i - \mathbb{E}(Y|Q = q)) \|_2$)

2. Use $ctl$ to go to $q_i$
A simple integrating agent algorithm

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Proof-of-concept implementation - evaluation on next slide

- $ctl :=$ proportional controller based on previous experience
- uses teleportation in search for $q_i$
Experimental view on information integration in autonomous agents

Evaluation on “Malmo”
Experimental view on information integration in autonomous agents

Evaluation on “Malmo”

Source agents trajectory (blue) and integration method (red):
1. Introduction

2. Experimental view on information integration in autonomous agents

3. Causal view on information integration in autonomous agents

4. Conclusions
Causal view on information integration in autonomous agents

Problem instance: experience transfer between cars

Setup: two (or more) self-driving cars with different hardware
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Task – w.l.o.g. for car 1: safely follow some trajectory (e.g. road)
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Task – w.l.o.g. for car 1: safely follow some trajectory (e.g. road)

Available heterogeneous information:

- hardware specifications of all cars (e.g. table with HP, ...)
- past experiences (actions/observations) of all cars
- influence structure between relevant variables (“causal DAG”, see next slide)
Causal view on information integration in autonomous agents

Background: causal models & transportability

**Def.**: diagram (DAG) plus factorizing distribution over set of random variables [Pearl2000]
Causal view on information integration in autonomous agents

Background: causal models & transportability

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Reason about (identifiability of) outcomes of manipulations of the underlying system
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Reason about (identifiability of) outcomes of manipulations of the underlying system

Main example: “X causes Y” := “intervening on X changes Y”
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Reason about (identifiability of) *outcomes of manipulations* of the underlying system

Main example: “X causes Y” := “intervening on X changes Y”

But useful for reasoning about related systems in general - example:

```
X → Z ← Y
```

\[ P(z, y|x) = P(z|x)P(y) \]

\[ \Rightarrow \text{system } P(z, y|x_1) \text{ contains information } P(y) \]

about modified system \( P(z, y|x_2) \) [Pearl2011]
Causal view on information integration in autonomous agents

Causal reasoning for toy scenario

\[ y(t) \]
\[ F(t) \]
\[ G(t) \]
\[ \dot{y}(t) \]
\[ u(t) \]

- \( u(t) \): control signal
- \( y(t) \): position
- \( F(t) \): force from engine
- \( G(t) \): other forces (friction etc.)
- \( HP \): horse powers

1. Assume two cars only differ in \( HP = hp_1, hp_2 \)
2. causal DAG \( \Rightarrow \) car 2’s experience about mechanism \( p(G | y) \) transferable to car 1.
3. Additivity of \( y \) & knowing \( p(F | u, hp_1) \) \( \Rightarrow \) identify dynamics of car 1
   - E.g.: Car 1 avoids slipping on oil spill at position not visited before
Causal view on information integration in autonomous agents

Causal reasoning for toy scenario

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\[ \downarrow \quad \downarrow \]
\[ F(t) \quad G(t) \]
\[ HP \quad \rightarrow \]
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\[ y: \text{position} \]
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Experimental view

Simple “integrating agent” partially succeeded in toy navigation task on “Malmo”

Important: take several measurements then averaging; problem: repetitive structures

NB: Other AI platforms exist, such as “OpenAI Gym”

Causal view

▶ encode mechanics and reason about transferability

Unclear: can this be done by classical say Bayes nets?

Future directions

▶ Use machine learning to infer “integration mapping”

“Universal representation” ⇝ $n$ instead of $n^2$ mappings
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References

- [Geiger2016] Philipp Geiger, Katja Hofmann, Bernhard Schoelkopf: Experimental and causal view on autonomous information integration in agents.

- [Bignell2016] David Bignell, Katja Hofmann, Tim Hutton, and Matthew Johnson, ‘The Malmo platform for artificial intelligence experimentation’, in IJCAI, (2016).

- [Pearl2011] Judea Pearl and Elias Bareinboim: Transportability of causal and statistical relations: A formal approach. AAAI 2011.

- [Pearl2000] Judea Pearl: Causality. Cambridge University Press, 2000.

- https://philippgeiger.org

- https://ei.is.tuebingen.mpg.de/research_groups/causal-inference-group