AI Planning for Autonomy

1. Plan & Goal Recognition

Contents of the Lecture

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Outline of the Lecture

1. Perceiving and Interpreting the Behavior of Others
2. Plan and Goal Recognition in AI
3. Plan and Goal Recognition and Classical Planning

The Heider-Simmel Experiment

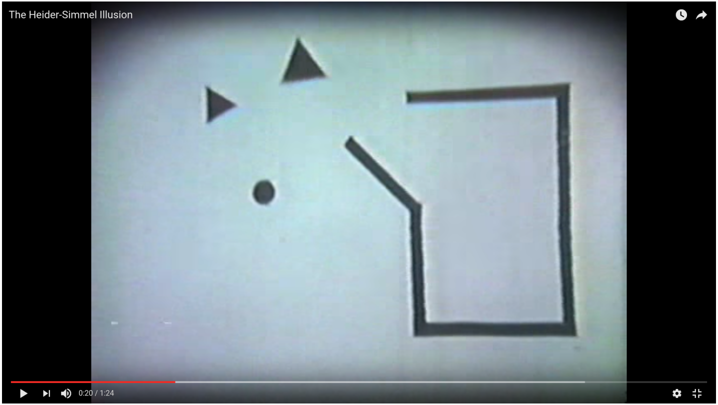


Figure: *An Experimental Study of Apparent Behavior*. F. Heider, M. Simmel. The American Journal of Psychology, Vol. 57, No. 2, April 1944

Link to video (YouTube)

Parsing the Big Triangle

Figure: The BIG triangle T.

PollEv.com/nirlipo

Question!

What kind of person is the Big Triangle?

(A): Aggressive, mean, angry. (B): Strong, powerful.
(C): (D): Ugly, sly.

→ (A): 97% of Heider & Simmel 1944 **experimental subjects** thought so.

→ (B): 14% thought the Big triangle was **a bully**.

→ (C): 8% didn't think T was very *bright*.

→ (D): And a 2% were perhaps letting their imagination go wild a bit too much.

what about the Smaller one...

Figure: The small triangle t.

PollEv.com/nirlipo

Question!

What kind of person is the Small Triangle?

(A): Fearless, defiant, cocky.
(B): Passive–aggressive.
(C): Clever, weak.
(D): Protective, loyal, devoted.

→ (A): 47% of the subjects chose words in this category.

→ (B): 11% found that t was a bit unpleasant.

→ (C): 53% had a lot of imagination.

→ (D): And 14% chose this one.

and about the circle...

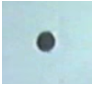


Figure: The circle c.

PollEv.com/nirlipo

Question!

What kind of person is the Circle?

(A): Frightened, fearful, helpless.
(B): Fidgety, playful, nervous.
(C): Clever, smart.
(D): Courageous.

→ (A): 75% of the subjects certainly *didn't think much* of c.

→ (B): And 61% found c a *bit of a handful*.

→ (C): 14% saw a *lot of nuance* in a black dot.

→ (D): And 11% found c to be *brave* (when T isn't around).

Significance of Heider & Simmel Results

Leaving aside issues with *priming* experimental subjects...

It does seem that

1. humans *tend* to **ascribe intentions** to *anything* that changes over time,
2. this rests on deeply rooted **assumptions**.

Heider & Simmel results are the *first* quantitative characterization of:

Folk Psychology

Human capacity to **explain** and **predict** behavior and mental state of others

. . . we're usually very good at it, but we fail often!

A Theory of Common Sense

The Intentional Stance, **Daniel Dennett** (1988)

1. **Decide** to consider the object being observed as *rational*.
2. Work out its **beliefs** and **goals** based on its *place* and *purpose* in the world.
3. Use **practical reasoning** to assess what the agent *ought to do* to pursue its **goals**.

The above provides a *systematic*, *reason–giving explanation* for actions, based on deeply embedded beliefs about the agent.

Plan and Goal Recognition in Artificial Intelligence

Key Idea: use generative models of behavior to predict actions.

Plan Recognition (PR) is Planning in reverse.

- Planning – we seek *plans* π to *achieve* goals G.
- PR: find goals G *accounting for* partially *observed* plan π.

Formalising GR as a Multi–Agent Task

Two possible *roles* for each agent:

- **Actor** – *performs* actions to change the state of the world.
- **Observer** – *perceives* actions and updates its beliefs on the **Actor** intentions.

and three possible *stances* for the **Actor**:

- *Adversarial* – obfuscates deliberately its goals.
- *Cooperative* – tries to tell the **Observer** what she is up to.
- *Indifferent* – does not care about the **Observer**.

Open Challenge→Stances could be *changing over time*

Components of Goal Recognition Task

Actions describe what the **Actor** does

- Walking from X to Y, opening a door, using a credit card...

Goals describe what the **Actor** wants

- To have breakfast, Park a car, Wreck a web service...

Plans describe how goals can be achieved

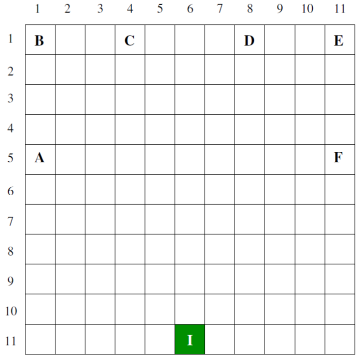
- Ordered sequences of actions
- These can be ranked according to **cost** or **efficiency**

Sensor Model describes what does the **Observer** perceives

- Does it always see every action done by the **Actor**?
- Are actions observed *directly*? Or only their *effects* are?
- Does it know exactly *where* in the world the **Actor** is?

Goal Recognition can be modeled using STRIPS

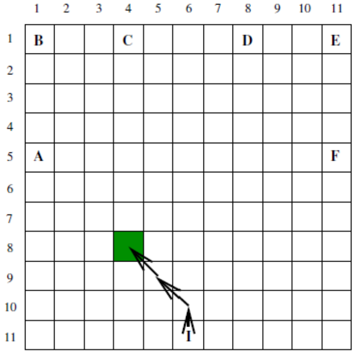
Example: Agent on a Grid World



- **starts** in "I", *may be* heading to "A", "B", . . ., "F".
- **moves along compass directions** *North*, etc. with cost 1 and *North West*, etc. with cost $\sqrt{2}$.

Example

Actor now at $(4,8)$ after going N once, and twice NW.



Question!

Assuming the Actor prefers CHEAPEST plans which goals are most likely?

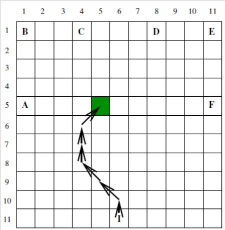
(A): A & B.
(B): C.
(C): D
(D): E & F

$\rightarrow$ (A) & (B): Cheapest plans for A, B, C **exist** with those **actions embedded**.

$\rightarrow$ (C) & (D): Cheapest plans for D, E & F **do not have** those actions.

Example

Actor now at $(5,5)$ after going N twice and once NE.



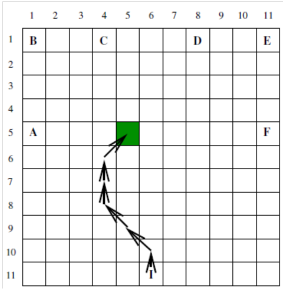
Question!

For which goal(s) observed actions are in a CHEAPEST plan?

(A): A & B.
(B): C.
(C): D, E & F
(D): None

$\rightarrow$(D) : Observed actions **are not** in any of the cheapest plans for **any** of the goals.

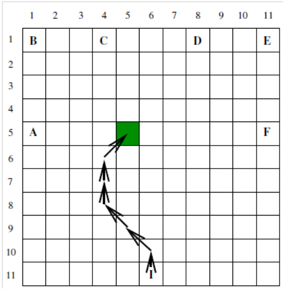
So Folk Psychology is Useless?



Remarks

- Verify obs *sufficient* for G Easy
- Determine to what degree obs *necessary* for G Hard

Folk Psychology with Counterfactual Reasoning

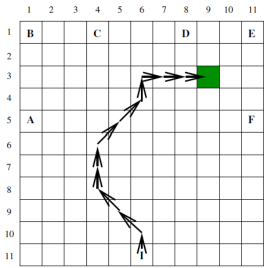


Counterfactual Reasoning (Pearl, 2001) to Establish Necessity

Compare **cost** of best plans that do not comply with observed actions, with best plans that do.

→ Then it follows B and C *more likely* than A or the rest.

Example



Question!

Actor at $(9, 3)$**, has gone** NE**,** N **and three times** E**, which are the most likely goals?**

- (A): A & B.
- (B): C & D.
- (C): E
- (D): F

→(C) : For E this difference is *minimal*.

Key Facts of the Model–Based Approach

1. $\diamond$ given **implicitly**, requires to **solve** $|\mathcal{G}|$ planning tasks
2. Plans "**extracted**" with **off–the–shelf** planning algorithms.
3. **Plausibility** of goals $\mathcal{G}$ given as a **probability distribution**
   - Goals are *plausible* when motivate plans *consistent* with O,
   - **and** when O is *necessary* to achieve goals *efficiently*.

Roadmap

1. Make off-the-shelf planners compute plans constrained w.r.t. O,
2. Derive $P(G|O)$ from best plans that comply with *and* work around O.

Pr as planning: Inferring the Goal Probabilities

Goal

Obtain **probability distribution** $P(G|O)$, $G \in \mathcal{G}$.

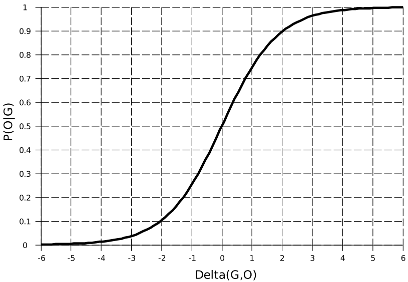
Outline of Approach

From **Bayes' Rule** $P(G|O) = \alpha\, P(O|G)\, Prob(G)$, where

- α norm. constant
- $Prob(G)$ given in problem specification
- $P(O|G)$ function of extra cost needed to not comply with O

$$P(O|G) = \text{function}(c^*(P'[G+\overline{O}])) - c^*(P'[G+O])) \quad (1)$$

Goals as Predictors for O (informally)



Properties

1. G predicts O badly when it would be more efficient to deviate from O.
2. G predicts O **perfectly** when G unfeasible if not doing O.

Demo: A Slightly More Interesting STRIPS Model

Fluents: *facts about the world*

- Locations of people
- State of appliances
- Locations of objects

Actions: *stuff people may do*

- Move across the place
- Interaction with objects & appliances

Goals: *why people do stuff*

- Cook some foodstuff
- Watch a movie
- Listen to a record
- Go to sleep
- Get ready to leave for work

Unitary action costs (to keep it simple)

GitHub Repo Pull Requests Welcome!

Anyone looking for a Masters' project? Thor 2 has been released!

Further Reading or Watching

Article *An Experimental Study of Apparent Behavior*. F. Heider, M. Simmel. The American Journal of Psychology, 57(2), 1944

A Probabilistic Plan Recognition Algorithm based on Plan Tree Grammars C. Geib, R. Goldman, Artificial Intelligence 173(11), 2009

Probabilistic Plan Recognition using off-the-shelf Classical Planners. M. Ramirez and H. Geffner. Proceedings AAAI, 2010.

Landmark-Based Heuristics for Goal Recognition. R. Pereira, N. Oren and F. Meneguzzi. Proceedings AAAI, 2017.

Heuristic Online Goal Recognition in Continuous Domains, M. Vered and G. Kaminka. Proceedings IJCAI, 2017.

Plan Recognition in Continuous Domains, G. Kaminka and M. Vered and N. Agmon, Proceedings AAAI, 2018.

Book Chapter 4, Section 4.3 *A Concise Introduction to Models and Methods for Automated Planning*. B. Bonet & H. Geffner, 2013.

Video Lecture *Engineering & Reverse-engineering Human Common Sense*, J. Tenenbaum, Allen Institute for AI, 2015.

Video Lecture *Steps towards Collaborative Dialogue*, P. Cohen, Monash University, 2018.