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A Plausible Logic Inference Engine

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November 4, 2011



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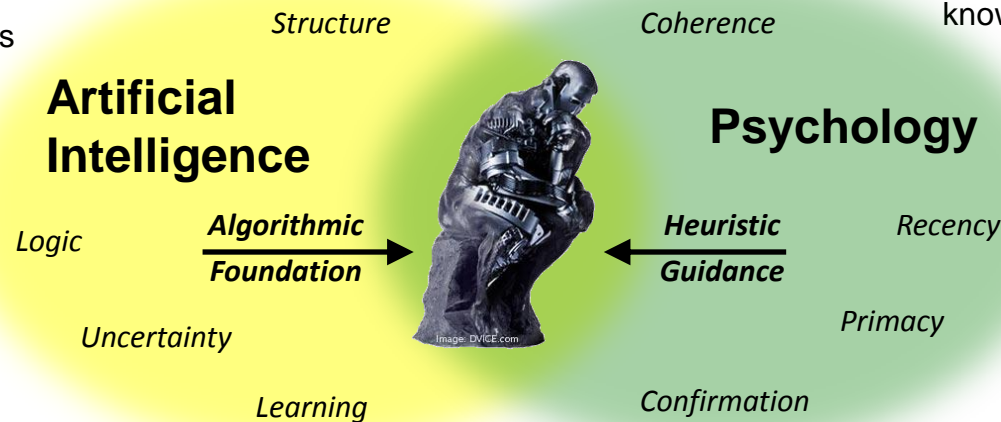
Overview

Background: Reasoning serves as a foundation for many high-level cognitive capabilities.

- Many AI approaches
 - Statistics and optimality
 - Logic and proof
- Several psychological theories
 - Concerned with source of error vs. source of power
 - Lacking in detail
- Both study different methods in isolation

Goals: Develop psychologically plausible methods for computational reasoning that reflect the strengths of human reasoning

- Flexible: nature and content of data
- Computationally efficient
- Pragmatic: useful absent optimality
- Self-sufficient: minimal reliance on knowledge engineers



Problem: Modern methods cannot emulate the flexibility, efficiency, or pragmatism of human reasoning.

- Reliant on brute-force computation
- Emphasis on proof and optimality
- Little connection to psychology/cognition literature

Approach:

- Start with a cognitive systems view
- Combine multiple reasoning techniques
- Drop notions of optimality and provability
- Incorporate known psychological biases
- Integrate learning ability

Knowledge Representation

The system has a foundation of first-order logic.

Predicates: represent conditions of the environment

$Neighbor(X, Y)$

Beliefs:

- Represent specific instances of a condition
- Stored in *working memory*
- Generated by inference or direct observation
- Include plausibility score

$$Neighbor(BOB, PETE) \stackrel{Pl=E^+ - E^-}{1.0=1.0-0.0}$$

$$-1 \leq Pl(b) \leq 1; \quad Pl(b) = -Pl(\neg b)$$

Rules:

- Represent generalized relationships among predicates
- Stored in *long-term memory*
- Use threshold logic
- Annotated with reliability factors

$$(v_0 + v_1 \times Pl(Alarm(X)) + v_2 \times Pl(Neighbor(X, Y)) > 0)$$

$$\stackrel{a=0.9}{\vdash} Alarm(X) \cup Neighbor(X, Y) \vdash Calls(Y, X)$$

$$\stackrel{b=0.1}{\vdash} (w_0 + w_1 \times Pl(Calls(Y, X)) > 0)$$

$$0 \leq a, b \leq 1$$

Key idea: Working memory structures are activations of long-term structures; consistent with Cowan's (1988) view that WM is an extension of LTM.

Inference Patterns and Evidence Propagation

Key idea: Logically unsound inference patterns are still useful for accumulating evidence about beliefs (Polya, 1954)

Example: Accepting the Consequent
(Abduction)

$$(v_0 + v_1 \times \text{Pl}(\text{Alarm}(X)) + v_2 \times \text{Pl}(\text{Neighbor}(X, Y)) > 0)$$

Given a rule

$$\bigoplus_{b=0.1}^{a=0.9} (w_0 + w_1 \times \text{Pl}(\text{Calls}(Y, X)) > 0)$$

And evidence

$$\text{Neighbor}(\text{BOB}, \text{PETE})^{\text{Pl}=1.0}, \quad \text{Calls}(\text{PETE}, \text{BOB})^{\text{Pl}=1.0}$$

Draw a conclusion

$$v_0 + v_1 \times \text{Pl}(\text{Alarm}(X)) + v_2 \times \text{Pl}(\text{Neighbor}(X, Y)) > 0$$

Generate a new belief

$$\text{Alarm}(\text{BOB})$$

Compute change
in evidence

$$DE^+(\text{Alarm}(\text{BOB})) = b \frac{\sum_{j \in S} w_j \text{Pl}(Q_j)}{\sum_{j \in S} |w_j|} \approx 0.1$$

Summary: Inference patterns govern the mechanics of combining beliefs with rules to derive new beliefs. Other patterns are similar.

Heuristics

Key idea: Many inferences are possible; apply known psychological biases as guidance heuristics.

Primacy & Recency
(evidence update):

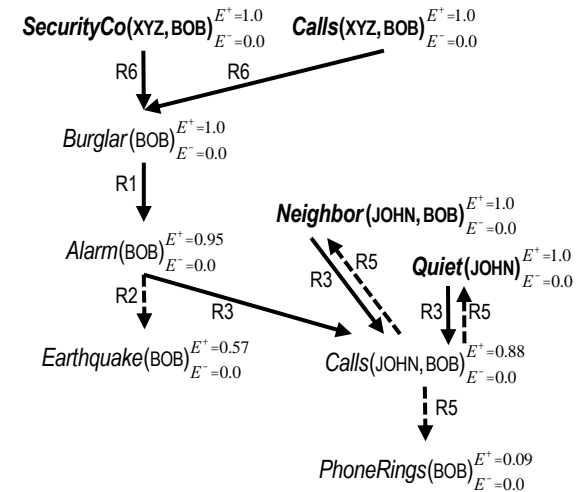
$$E_{t+1}(\text{Alarm}(\text{BOB})) = (1 - \nu_1)E_t(\text{Alarm}(\text{BOB})) + \nu_1 DE_t(\text{Alarm}(\text{BOB})) \\ \approx 0.03$$

Coherence
(working memory):

$$\text{coh}(b) = \frac{w_{b'} \text{rel}(b', b)}{d(b') + 1} \text{Pl}(b')$$

Confirmation
(plausibilities):

- Prefers rule applications with stronger evidence over weaker
- Ignores low-plausibility beliefs



Summary: Biases based on properties of beliefs. Aimed at reasoning along a small number of plausible trajectories.

Related and Future Work

Related work:

- Abductive Rationalizing Agents – Bridewell and Langley (2011)
- Extended Plausible Inference – Friedman (1981)
- Production Systems
- Markov Logic – Richardson and Domingos (2006)
- Bayesian Logic Programs – Kersting and DeRaedt (2005)

Future work:

- Agent goals – Adding and using goal information as a source of bias
- Analogical reasoning – Identifying and constructing analogies
- Learning – Acquiring and modifying rules and analogical mappings
- Metacognition – Adding to and modifying the inference patterns

Questions and Comments?

Extra Slides

Application: Plausible Reasoning to Support Analyst Decision Making

STATE OF THE ART

- Analysts review incoming data for “interesting situations”
- Increasingly overwhelmed by growth in data volume
- Modern computational inference techniques cannot emulate the flexibility, efficiency, or pragmatism of human reasoning
 - Computationally expensive
 - Questionable scalability
 - No connection to psychological literature or human capability

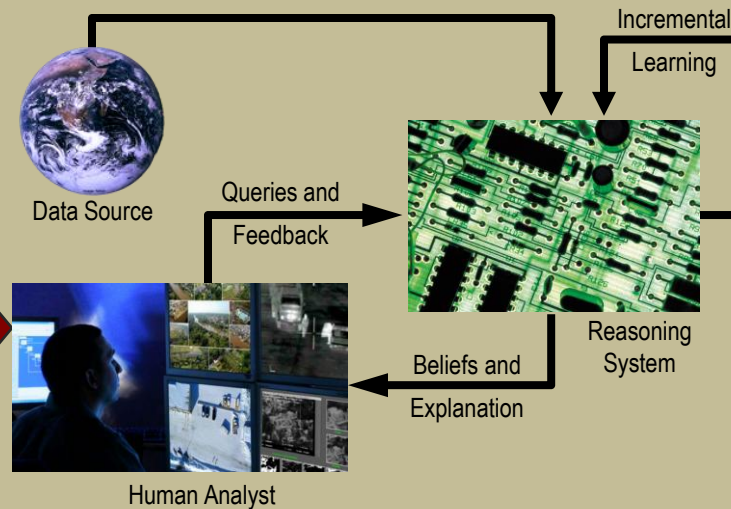
Integrate complimentary results from artificial intelligence and psychology to produce a flexible, efficient, and practical system.

- Combine logical, statistical, evidential reasoning techniques (each brings needed capability to bear)
- Integrate psychological biases (provide guidance to inference process)
- Integrate learning with inference (improve knowledge with experience)
- Keep the human in the loop (contrast to much work in AI)

Collaborative Data Analysis

Human analyst and computational reasoning system collaborate to:

- *Assess and explain data*
- *Expand knowledge about task and domain*
- *Improve speed and accuracy of assessments*
- *Improve outcomes associated with resulting decisions*



Reasoner provides computational power, but also constructs a model of analyst knowledge. This allows efficient, high level interactions, and provides a way to review analyst knowledge and methods.

GOALS

Create a psychologically plausible computational reasoning system that reflects the strengths of human reasoning and can help to develop insights into the fundamental mechanisms that guide human reasoning.

- Flexible (nature and content of data/information)
- Efficient (computation to produce results)
- Pragmatic (useful results absent optimality)

IMPACT

Approach leverages computational speed and human creative power to analyze large quantities of data.

Applications include:

- Situation assessment
- Cyber security
- Knowledge capture
- Foundation for realistic agent control (e.g. training simulators)

Current State of the Art

Artificial Intelligence

- Dominance of statistical inference and learning methods
(e.g. Bayes Nets and various generalizations, SAT-based methods)
 - Data intensive
 - Computationally expensive
 - Questionable scalability
- Logic-based approaches more efficient, but brittle
(e.g. rule engines, inductive logic)
 - Rely heavily on knowledge engineering
 - Do not capture uncertainty
 - Limited reasoning capacity
- Little or no connection to psychological literature

Psychology

- Multiple theories of human reasoning method and ability
- Frequently driven by attempts at accounting for errors
- Models tend to be theoretical and high-level
- Few detailed computational models of human reasoning

The learning engine monitors the stream of observations, beliefs, and rules to discover new or modify existing rules.

- Applies empirical evidence to expand and add nuance to long-term memory
- Engine runs in the background
- Changes occur incrementally



Pattern memory contains
inference, analogy, and
Examples: *Modus Ponens*

Inference Engine

Applied during
Antecedent

- Each pattern contains a statistical/numerical summary of the evidence
- Computationally simple to update with new beliefs, associations
- incremental incorporation of evidence (plausibility updates)

Analogy Engine

public part, and
constructing

Learning Engine

Key Points

- Simple
- Logic softened with degree of belief in the rule
- Nuanced with empirical experience

Pattern Memory