

Monte Carlo Semantics

Robust Inference and Logical Pattern Processing Based on
Integrated Deep and Shallow Semantics

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Why Inference?

- ▶ open-domain applications (QA, IE, IR, SUM)
- ▶ given two pieces of text T and H, find degree of logical
 - ▶ entailment $\llbracket BK \rightarrow (T \rightarrow H) \rrbracket$
 - ▶ or similarity $\llbracket BK \rightarrow (T \equiv H) \rrbracket$

Example

(BK) $\forall x : \text{tall}(x) \equiv \text{high}(x)$

(T) Including the 24m antenna,
the Eiffel Tower is 325m high.

\therefore (H) How tall is the Eiffel Tower?

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 - ▶ entailment $\llbracket \text{BK} \rightarrow (\text{T} \rightarrow \text{H}) \rrbracket$
 - ▶ or similarity $\llbracket \text{BK} \rightarrow (\text{T} \equiv \text{H}) \rrbracket$

Example

(BK) $\forall x, y : \text{acquire}(x, y) \rightarrow \text{owns}(x, y)$

(T) Yamaha had acquired the guitar brand Ibanez,
through its takeover of Hoshino Gakki Group,
earlier this week.

\therefore (H) $\text{owns}(\text{Yamaha}, \text{Ibanez})$

What is *Robust Inference*?

...in an ideal world, we would have either

▶ **(YES)**

$$\begin{aligned} &\vdash (\text{BK}_1 \rightarrow (\text{BK}_2 \rightarrow (\dots \rightarrow (\text{BK}_N \rightarrow (\text{T} \rightarrow \text{H}))))), \\ &\not\vdash (\text{BK}_1 \rightarrow (\text{BK}_2 \rightarrow (\dots \rightarrow (\text{BK}_N \rightarrow (\text{T} \rightarrow \neg\text{H}))))); \end{aligned}$$

▶ or **(NO)**

$$\begin{aligned} &\not\vdash (\text{BK}_1 \rightarrow (\text{BK}_2 \rightarrow (\dots \rightarrow (\text{BK}_N \rightarrow (\text{T} \rightarrow \text{H}))))), \\ &\vdash (\text{BK}_1 \rightarrow (\text{BK}_2 \rightarrow (\dots \rightarrow (\text{BK}_N \rightarrow (\text{T} \rightarrow \neg\text{H}))))). \end{aligned}$$

But if relevant knowledge is missing, say BK_1 , we could have

▶ **(DON'T KNOW)**

$$\begin{aligned} &\not\vdash (\text{BK}_2 \rightarrow (\dots \rightarrow (\text{BK}_N \rightarrow (\text{T} \rightarrow \text{H})))), \\ &\not\vdash (\text{BK}_2 \rightarrow (\dots \rightarrow (\text{BK}_N \rightarrow (\text{T} \rightarrow \neg\text{H})))). \end{aligned}$$

What is *Robust Inference*?

In the DON'T KNOW situation, where

$$\not\vdash \varphi \rightarrow \psi, \text{ while } \not\vdash \varphi \rightarrow \neg\psi,$$

we want to know whether or not

$$\llbracket \varphi \rightarrow \psi \rrbracket > \llbracket \varphi \rightarrow \neg\psi \rrbracket,$$

and, more generally, we want to know, whether for two candidate entailments $\varphi_1 \rightarrow \psi_1$ and $\varphi_2 \rightarrow \psi_2$, we have

$$\llbracket \varphi_1 \rightarrow \psi_1 \rrbracket > \llbracket \varphi_2 \rightarrow \psi_2 \rrbracket.$$

Outline

Problem Statement

Propositional Model Theory & Graded Validity

Shallow Inference: Bag-of-Words Encoding

Deep Inference: Syllogistic Encoding

Computation via the Monte Carlo Method

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Model Theory: Classical Bivalent Logic

Definition

- ▶ Let $\Lambda = \langle p_1, p_2, \dots, p_N \rangle$ be a propositional language.
- ▶ Let $w = [w_1, w_2, \dots, w_N]$ be a model.

The *truth value* $\| \cdot \|_w^\Lambda$ is:

$$\| \perp \|_w^\Lambda = 0;$$

$$\| p_i \|_w^\Lambda = w_i \text{ for all } i;$$

$$\| \varphi \rightarrow \psi \|_w^\Lambda = \begin{cases} 1 & \text{if } \|\varphi\|_w^\Lambda = 1 \text{ and } \|\psi\|_w^\Lambda = 1, \\ 0 & \text{if } \|\varphi\|_w^\Lambda = 1 \text{ and } \|\psi\|_w^\Lambda = 0, \\ 1 & \text{if } \|\varphi\|_w^\Lambda = 0 \text{ and } \|\psi\|_w^\Lambda = 1, \\ 1 & \text{if } \|\varphi\|_w^\Lambda = 0 \text{ and } \|\psi\|_w^\Lambda = 0; \end{cases}$$

for all formulae φ and ψ over Λ .

Model Theory: Satisfiability, Validity

Definition

- ▶ φ is *valid* iff $\|\varphi\|_w = 1$ for all $w \in \mathcal{W}$.
- ▶ φ is *satisfiable* iff $\|\varphi\|_w = 1$ for some $w \in \mathcal{W}$.

Definition

$$\llbracket \varphi \rrbracket_{\mathcal{W}} = \frac{1}{|\mathcal{W}|} \sum_{w \in \mathcal{W}} \|\varphi\|_w.$$

Corollary

- ▶ φ is *valid* iff $\llbracket \varphi \rrbracket_{\mathcal{W}} = 1$.
- ▶ φ is *satisfiable* iff $\llbracket \varphi \rrbracket_{\mathcal{W}} > 0$.

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Bag-of-Words Inference (1)

assume strictly bivalent models;

$$\Lambda = \{\text{socrates, is, a, man, every}\}, \quad |\mathcal{W}| = 2^5;$$

$$\frac{\text{(T) socrates} \wedge \text{is} \wedge \text{a} \wedge \text{man}}{\therefore \text{(H) every} \wedge \text{man} \wedge \text{is} \wedge \text{socrates}};$$

$$\Lambda_T = \{\text{a}\}, \quad |\mathcal{W}_T| = 2^1;$$

$$\Lambda_O = \{\text{socrates, is, man}\}, \quad |\mathcal{W}_O| = 2^3;$$

$$\Lambda_H = \{\text{every}\}, \quad |\mathcal{W}_H| = 2^1;$$

$$2^1 * 2^3 * 2^1 = 2^5;$$

Bag-of-Words Inference (2)

How to make this implication *false*?

- ▶ Choose the 1 out of 2^4 models from $\mathcal{W}_T \times \mathcal{W}_O$ which makes the antecedent true.
- ▶ Choose any of the $2^1 - 1$ models from \mathcal{W}_H which make the consequent false.

...now compute an expected value. Count zero for the $1 * (2^1 - 1) = 1$ model that makes this implication false. Count one, for the other $2^5 - 1$. Now

$$\llbracket T \rightarrow H \rrbracket_{\mathcal{W}} = 1 - \frac{1}{2^5} = 0.96875,$$

or, more generally,

$$\llbracket T \rightarrow H \rrbracket_{\mathcal{W}} = 1 - \frac{2^{|\Lambda_H|} - 1}{2^{|\Lambda_T| + |\Lambda_H| + |\Lambda_O|}}.$$

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Language: Syllogistic Syntax

Let

$$\Lambda = \{x_1, x_2, x_3, y_1, y_2, y_3\};$$

All X are $Y = (x_1 \rightarrow_G y_1) \wedge (x_2 \rightarrow_G y_2) \wedge (x_3 \rightarrow_G y_3)$

Some X are $Y = (x_1 \wedge y_1) \vee (x_2 \wedge y_2) \vee (x_3 \wedge y_3)$

All X are not $Y = \neg$ Some X are Y ,

Some X are not $Y = \neg$ All X are Y ,

where

$$\|\varphi \rightarrow_G \psi\| = \begin{cases} 1 & \text{if } \|\varphi\| \leq \|\psi\|, \\ \|\psi\| & \text{otherwise.} \end{cases}$$

Proof theory: A Modern Syllogism

$$\frac{}{\therefore \text{All } X \text{ are } X} \text{ (S}_1\text{),}$$
$$\frac{\text{Some } X \text{ are } Y}{\therefore \text{Some } X \text{ are } X} \text{ (S}_2\text{),}$$
$$\frac{\begin{array}{l} \text{All } Y \text{ are } Z \\ \text{All } X \text{ are } Y \end{array} \text{ (S}_3\text{),}}{\therefore \text{All } X \text{ are } Z}$$
$$\frac{\begin{array}{l} \text{All } Y \text{ are } Z \\ \text{Some } Y \text{ are } X \end{array} \text{ (S}_4\text{),}}{\therefore \text{Some } X \text{ are } Z}$$
$$\frac{\text{Some } X \text{ are } Y}{\therefore \text{Some } Y \text{ are } X} \text{ (S}_5\text{);}$$

Proof theory: “Natural Logic”

$$\frac{}{\therefore \text{All (red } X) \text{ are } X} \text{ (NL}_1\text{)},$$
$$\frac{\text{Some } X \text{ are (red } Y)}{\therefore \text{Some } X \text{ are } Y},$$
$$\frac{\text{Some (red } X) \text{ are } Y}{\therefore \text{Some } X \text{ are } Y},$$
$$\frac{\text{All } X \text{ are (red } Y)}{\therefore \text{All } X \text{ are } Y},$$
$$\frac{\text{All } X \text{ are } Y}{\therefore \text{All (red } X) \text{ are } Y},$$
$$\frac{}{\therefore \text{All cats are animals}} \text{ (NL}_2\text{)},$$
$$\frac{\text{Some } X \text{ are cats}}{\therefore \text{Some } X \text{ are animals}},$$
$$\frac{\text{Some cats are } Y}{\therefore \text{Some animals are } Y},$$
$$\frac{\text{All } X \text{ are cats}}{\therefore \text{All } X \text{ are animals}},$$
$$\frac{\text{All animals are } Y}{\therefore \text{All cats are } Y},$$

Natural Logic Robustness Properties

$$\frac{\text{Some } X \text{ are } Y}{\therefore \text{Some } X \text{ are (red } Y)} > \frac{\text{Some } X \text{ are } Y}{\therefore \text{Some } X \text{ are (big (red } Y))}$$

$$\frac{\text{Some } X \text{ are } Y}{\therefore \text{Some (red } X) \text{ are } Y} > \frac{\text{Some } X \text{ are } Y}{\therefore \text{Some (big (red } X)) \text{ are } Y}$$

$$\frac{\text{All } X \text{ are } Y}{\therefore \text{All } X \text{ are (red } Y)} > \frac{\text{All } X \text{ are } Y}{\therefore \text{All } X \text{ are (big (red } Y))}$$

$$\frac{\text{All (red } X) \text{ are } Y}{\therefore \text{All } X \text{ are } Y} > \frac{\text{All (big (red } X)) \text{ are } Y}{\therefore \text{All } X \text{ are } Y}$$

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Model Theory: Satisfiability, Validity, Expectation

Definition

$$\llbracket \varphi \rrbracket_{\mathcal{W}} = \frac{1}{|\mathcal{W}|} \sum_{w \in \mathcal{W}} \|\varphi\|_w.$$

How do we compute this in general?

Observation

- ▶ Draw w randomly from a uniform distribution over \mathcal{W} .
Now $\llbracket \varphi \rrbracket$ is the probability that φ is true in w .
- ▶ If $W \subseteq \mathcal{W}$ is a random sample over population \mathcal{W} , the sample mean $\llbracket \varphi \rrbracket_W$ approaches the population mean $\llbracket \varphi \rrbracket_{\mathcal{W}}$ as $|W|$ approaches \mathcal{W} .

Summary

This is work in progress, but could develop into a rich theoretic framework for robust textual inference and logical pattern processing.

- ▶ robust and practicable...
- ▶ ...in the worst case: does bag-of-words.

- ▶ justifiable from epistemology, logic, and linguistics;
- ▶ model theory enables inference via Monte Carlo method;
- ▶ proof theory is intuitive and well-understood;
is entailed in classical logic and entails natural logic.