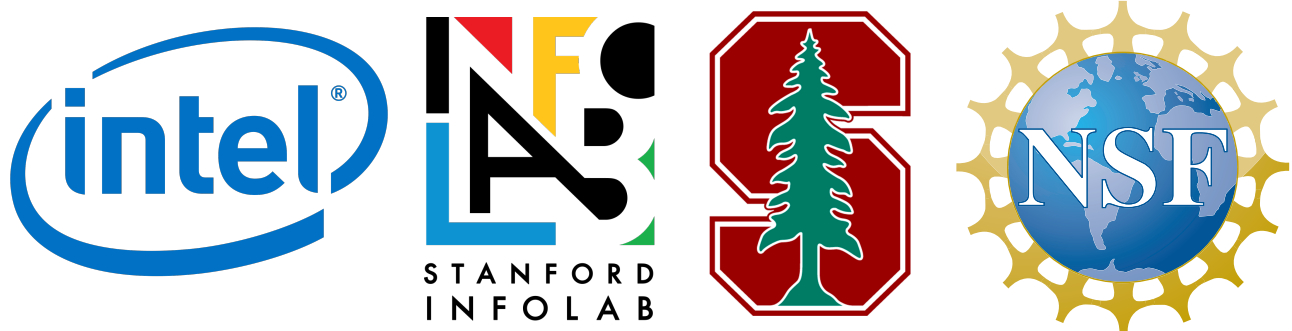


Babble Labble: Learning from Natural Language Explanations

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Big Idea: Explain Yourself!

- Collecting supervision one bit (one binary label) at a time is tedious, slow, expensive, and not very scalable.
- Explanations describing why certain labels were given can be used to vicariously label large amounts of unlabeled data.
- The potentially overlapping/conflicting labels can be resolved statistically to generate probabilistic “noise-aware” labels for downstream discriminative models.

Explain why you labeled this...

Example

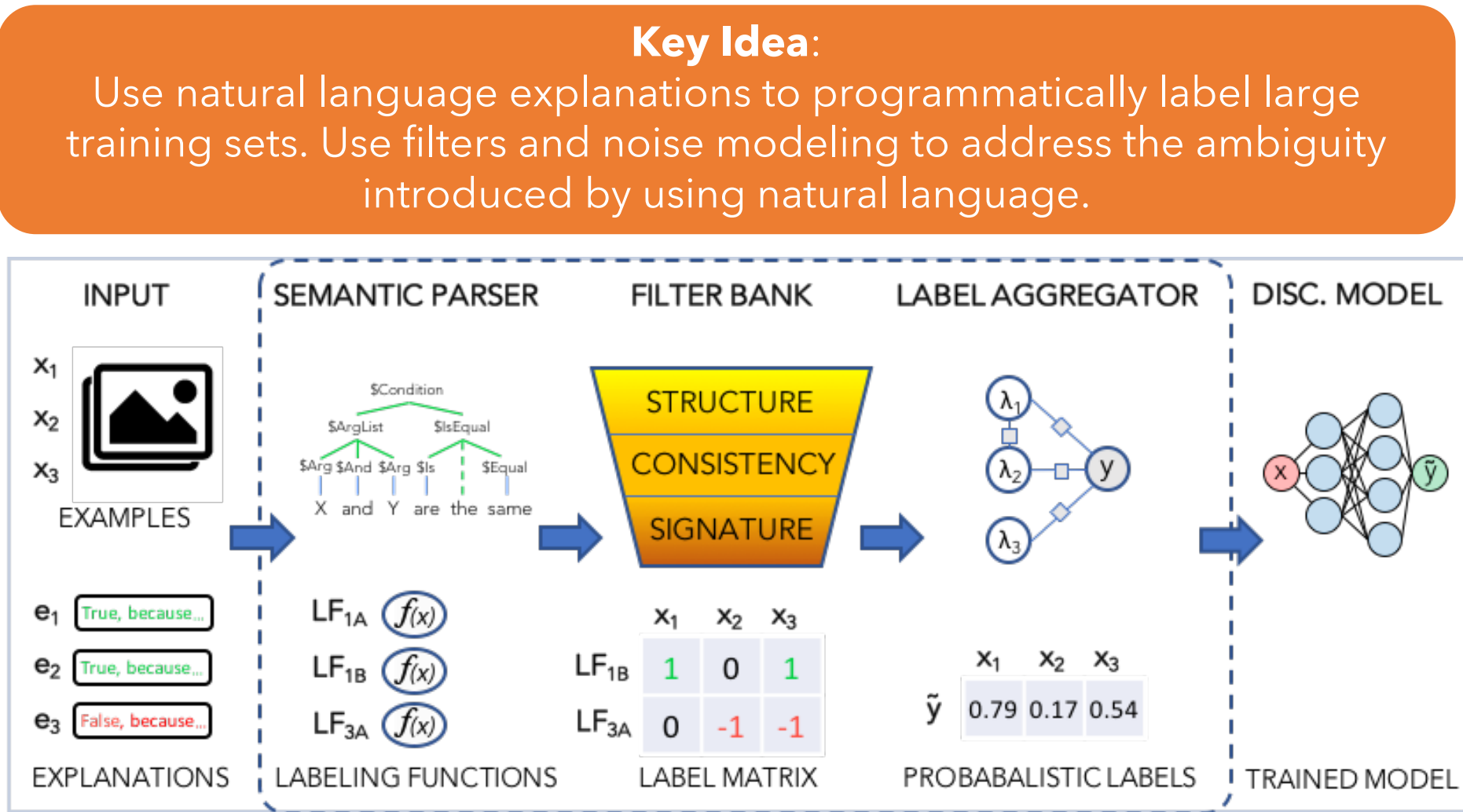
Label ☐ Is X married to Y?

Explanation

And get supervision on these for free...

- ✓ “Barack batted back tears as he thanked his wife, Michelle, for all her help.”
- ✓ “Both Bill and his wife Hillary smiled and waved at reporters as they rode by.”
- ✓ “George attended the event with his wife, Laura, and their two daughters.”

The Babble Labble Framework



Inputs: -Unlabeled Data -Explanations

Babble Labble: -Runs automatically -Requires no training

Outputs: -Labeled Dataset -Trained Model

Filter Bank & Label Aggregator

Filters

Consistency (Bad information)
Input: X has label ● because Y
Evaluate: $LF_Y(X) = \text{red} \neq \text{green}$

Uniform Signature (No information)
LF 1: ●●●●●●●●●●●●●●●●

Redundant Signature (No new information)
LF 1: ●●●●●●●●●●●●●●●●
LF 2: ●●●●●●●●●●●●●●●●

Label Aggregation

Model LF accuracies
*high disagreement = low assumed accuracy

LF 1: ●●●●●●●●●●●●●●●●
LF 2: ●●●●●●●●●●●●●●●●
LF 3: ●●●●●●●●●●●●●●●●
*LF 4: ●●●●●●●●●●●●●●●●

Model LF dependencies (Structure learning)
VS

●●●●●●●●●●●●●●●● = ●
●●●●●●●●●●●●●●●● VS ●●●●●●●●●●●●●●●● = ●
Exp 1 Exp 2 Exp 3 Exp 4

Motivation

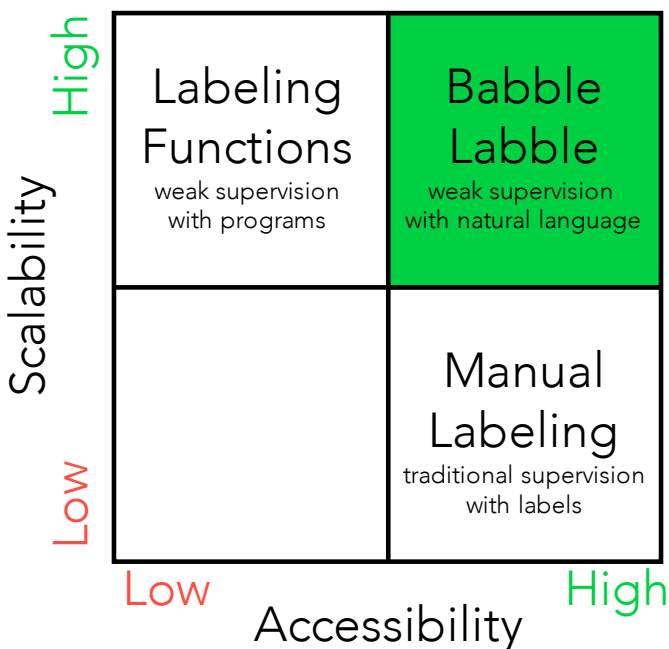
Why supervise with natural language instead of formal programs?

- 1) Ease of Use:**
Conversational interfaces are the new normal!



- 2) Faster supervision:**
No need to look up syntax or find missing semicolons!

- 3) More sources of supervision:**
Not everyone can program.
Everyone can explain.



Semantic Parser

Example X:
A Barack and his wife Michelle live in the White House.
B

Explanation Y:
“wife’ precedes Michelle in the sentence”

Normalized Explanation:
“wife’ precedes B in the sentence”

#	Program	Observations
1	Before(‘wife’, B)	Correct
2	Before(B, ‘wife’)	False for X
3	In(B, Sentence)	Trivially True for all examples
4	After(B, ‘wife’)	Correct, but redundant with #1

Traditional approach: use labeled examples to learn to rank candidate programs
Our approach: handle parsing ambiguity downstream with filters and modeling

Experimental Results: Chemical-Disease Relations

Task: Identify mentions of chemicals causing diseases in PubMed.

True - “because ‘induced by’, ‘caused by’, or ‘due to’ is between the disease and the chemical”

False - “because a treatment word is between the chemical and the disease and the chemical is within 100 characters to the left of the disease”

False - “because the pair of canonical IDs of the chemical and the disease is in the therapeutic combinations dictionary”

