

# 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 how you labeled this...

“Bob and his wife Alice visited Stanford University last Thursday.”

Do you think Bob and Alice are married?

☒ Yes  
☐ No

Why?

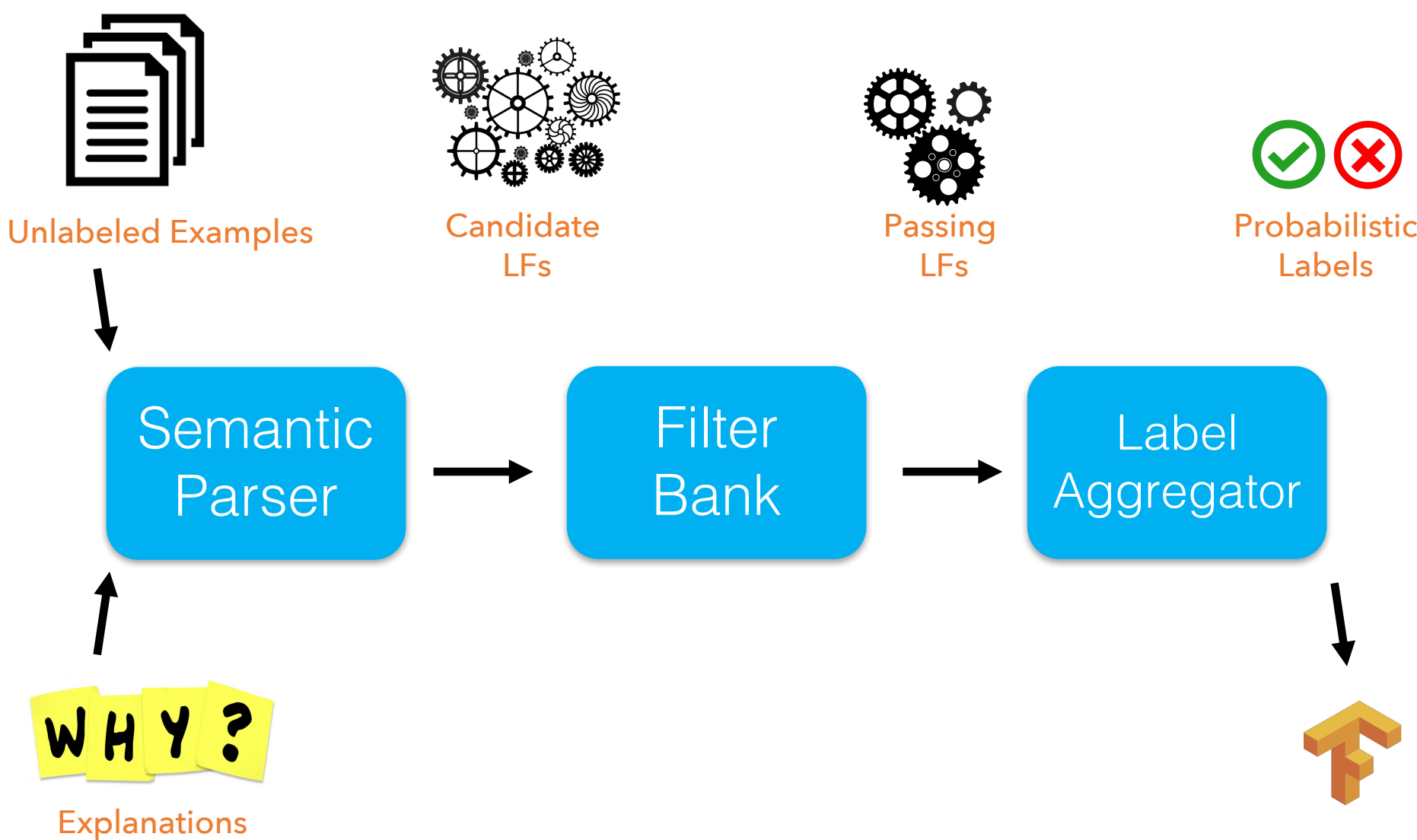
Because the words ‘his wife’ are immediately to the left of Alice.

### 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

**Key Idea:** Use natural language explanations to programmatically label large training sets. Use filters and noise modeling to address the ambiguity introduced by using natural language.



## 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 ●●●●●●●●●●●●●●●● ●●●●●●●●●●●●●●●● = ●

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.

	Accessibility	
	Low	High
Scalability	Low	Manual Labeling
	High	Babble Labble

## Semantic Parser

### Example X:

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

### Explanation Y:

“‘wife’ precedes Michelle in the sentence”

### Normalized Explanation:

“‘wife’ precedes B in the sentence”

### Candidate Programs:

#	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”

