Robust Frame-Semantic Models with Lexical Unit Trees and Negative Samples

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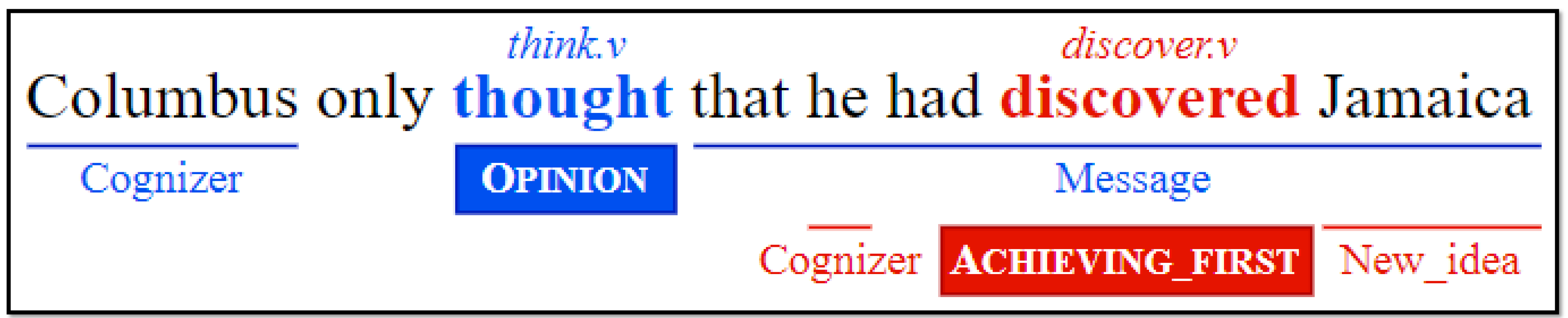
Frame-Semantic Parsing



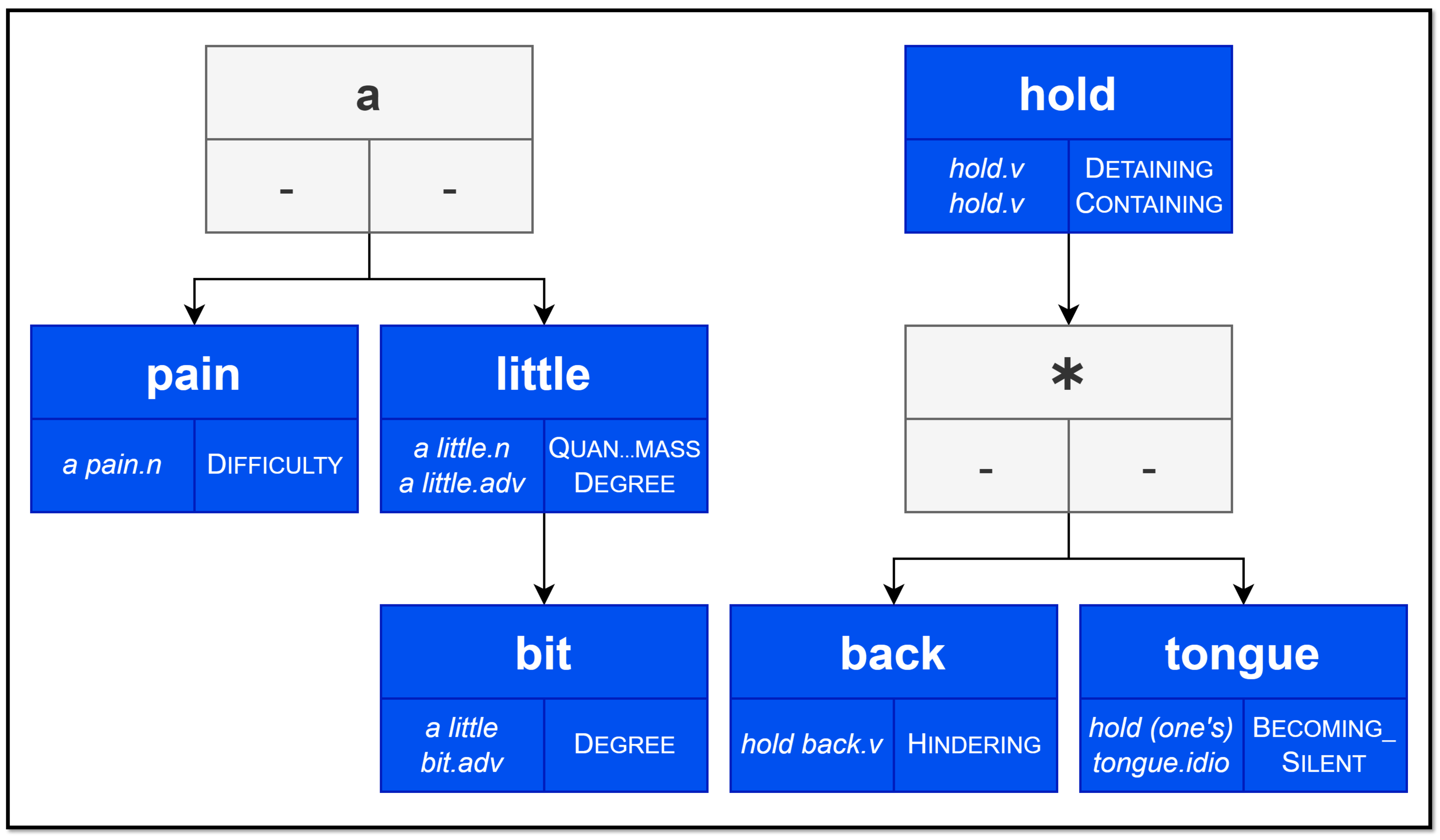
Terminology

- **Lexical Unit** – Pairing of a word and its meaning (*think.v*)
- **Frame** – Structures representing common situations (OPINION)
- **Target** – Words which evoke frames (**thought**)
- **Frame Element** – Key elements of a frame (Cognizer)

Dataset

- **FrameNet** – ~1,200 frames, ~6k sentences, ~19k targets
- **Test-1CF** – FrameNet samples with only 1 possible frame
- **Test-UU** – Test-1CF + 3 hard negative samples

Lexical Unit Tree



Candidate Target Generation

- Frames can only be evoked by certain words (Lexicon Filtering)
- Find frames for given word with lexical unit tree
- Wildcard supports disjoint lexical units using POS tags
- Covers **99.4%** of targets, **84.5%** false positive rate

Target Identification

Model	Acc	F1
Our model (candidate filter)	**0.788**	**0.775**
FIDO (Jiang and Riloff, 2021)	0.653	0.644
Our model	0.664	0.678

Model	FN1.5	FN1.7
Das et al. (2014)	0.454	-
Swayamdipta et al. (2017)	0.732	0.733
Bastianelli et al. (2020)	0.768	-
Lin et al. (2021)	0.769	0.763
Our model	**0.773**	**0.775**
Our model (manually filtered)	0.388	0.392

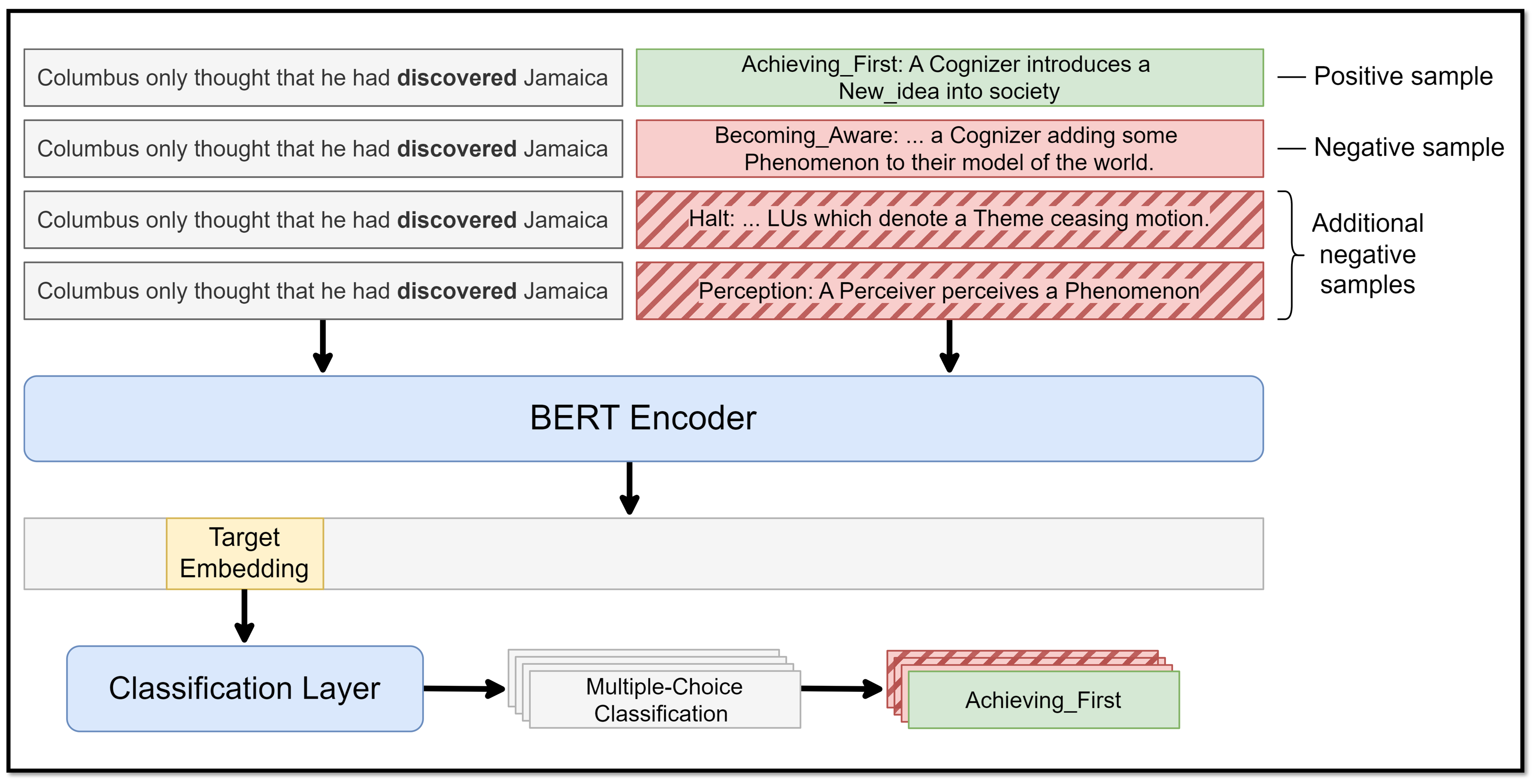
Frame Identification as Target Filtering (left)

- Can we directly replace target filtering with frame identification?
- **-9.7%** acc. vs target filter model, but **+3.4%** vs FIDO

Target Filtering (right)

- RoBERTa-based binary classification model
- **+1.2%** acc. vs SOTA model, **+38.3%** vs manual filtering

Frame Identification



K	# Frames	Our Model	FIDO	Δ
1	94	**0.781**	0.753	+0.028
3	235	**0.810**	0.778	+0.032
5	316	**0.853**	0.809	+0.044
10	426	**0.850**	0.826	+0.024

Model	Test-1CF	Test-UU
FIDO (Jiang and Riloff, 2021)	0.754	0.538
Our model	**0.893**	**0.603**

Additional Negative Sampling

- Improved performance on rare frames at all thresholds (left)
  - **+2.8%** acc. on 1-sample frames, **+4.4%** on 5-sample frames
- Enables learning on samples with only 1 possible frame
  - **+13.9%** acc. on Test-1CF, **+6.5%** on Test-UU
- Similar performance to best models while using less information
  - **+1.2%** acc. vs FIDO's frame-only model
  - **+0.2%** acc. vs full model
  - **-0.1%** acc. vs SOTA model

Model	FN1.5		FN1.7	
	All	Amb	All	Amb
Das et al. (2014)	0.836	0.692	-	-
Hermann et al. (2014)	0.887	0.737	-	-
Hartmann et al. (2017)	0.876	0.738	-	-
Yang and Mitchell (2017)	0.882	0.757	-	-
Swayamdipta et al. (2017)	0.864	-	0.866	-
Peng et al. (2018)	0.900	0.780	0.891	0.775
Bastianelli et al. (2020)	0.901	-	-	-
Lin et al. (2021)	0.906	-	0.906	-
Su et al. (2021)*	0.919	0.823	**0.924**	**0.844**
Tamburini (2022)*	**0.922**	**0.831**	0.922	0.843
Zheng et al. (2022a)	0.917	-	-	-
Jiang and Riloff (2021)	0.913	0.810	0.921	0.836
Jiang and Riloff (2021) (frame)	0.901	-	0.911	-
Our model (binary)	0.877	0.785	0.887	0.816
Our model	0.917	0.818	0.923	0.841

* Performance can not be verified due to private source code.

Contributions

- Novel lexical unit tree to enable support disjoint lexical units
- Developed bottom-up candidate target generation algorithm, leading to SOTA performance in target identification
- Evaluated effectiveness of language models for target filtering
- Enabled learning from single-frame targets in multiple-choice classification models
- Derived two new datasets from FrameNet for evaluating models on single-frame targets and similar lexical units

https://github.com/idirlab/frame

GitHub

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