Frame-Semantic Parsing with Softmax-Margin Segmental RNNs and a Syntactic Scaffold

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Task: Frame-semantic parsing

The goal is to parse sentences into FrameNet-style semantic graphs (Baker et. al., 1998).

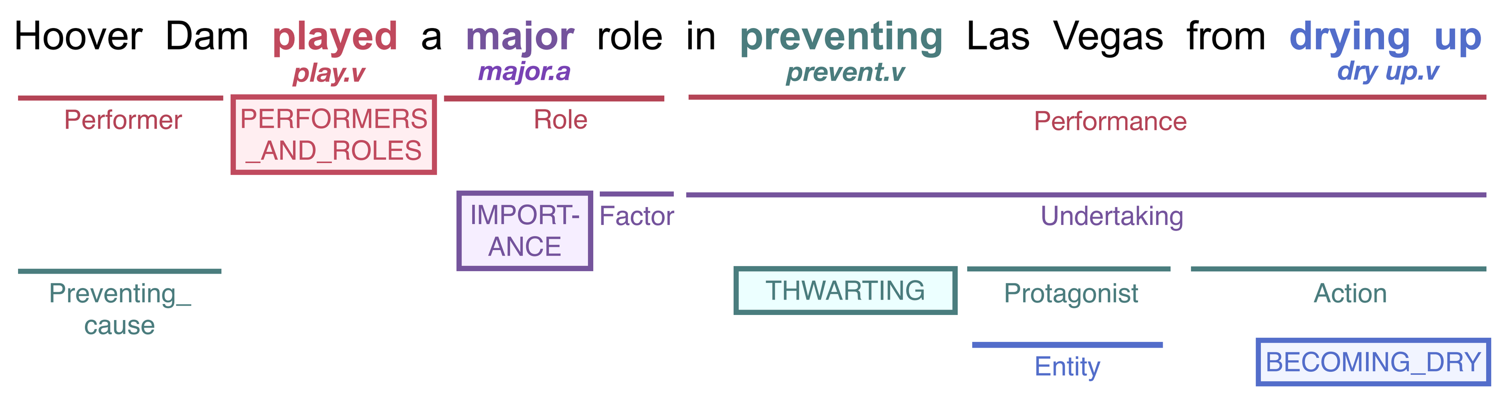


Figure: A FrameNet sentence with color-coded frame annotations below. Target words and phrases are highlighted, and their lexical units shown italicized below. Frames are shown in colored blocks, and frame-element segments are shown horizontally alongside the frame.

Focus: identifying and labeling argument spans.

Segmental Recurrent Neural Networks (Kong et. al., 2016)

- Variant of a semi-Markov conditional random field (Sarawagi and Kohen, 2004)
- Span representations are computed using bidirectional RNNs.
- Provide a generalization of BIO tagging schemes.
- Directly model an entire variable-length segment (rather than fixed-length label n-grams).
- Exact inference takes $O(nd\ell)$, n being the length of sentence, d maximum length of spans, and ℓ the number of labels.

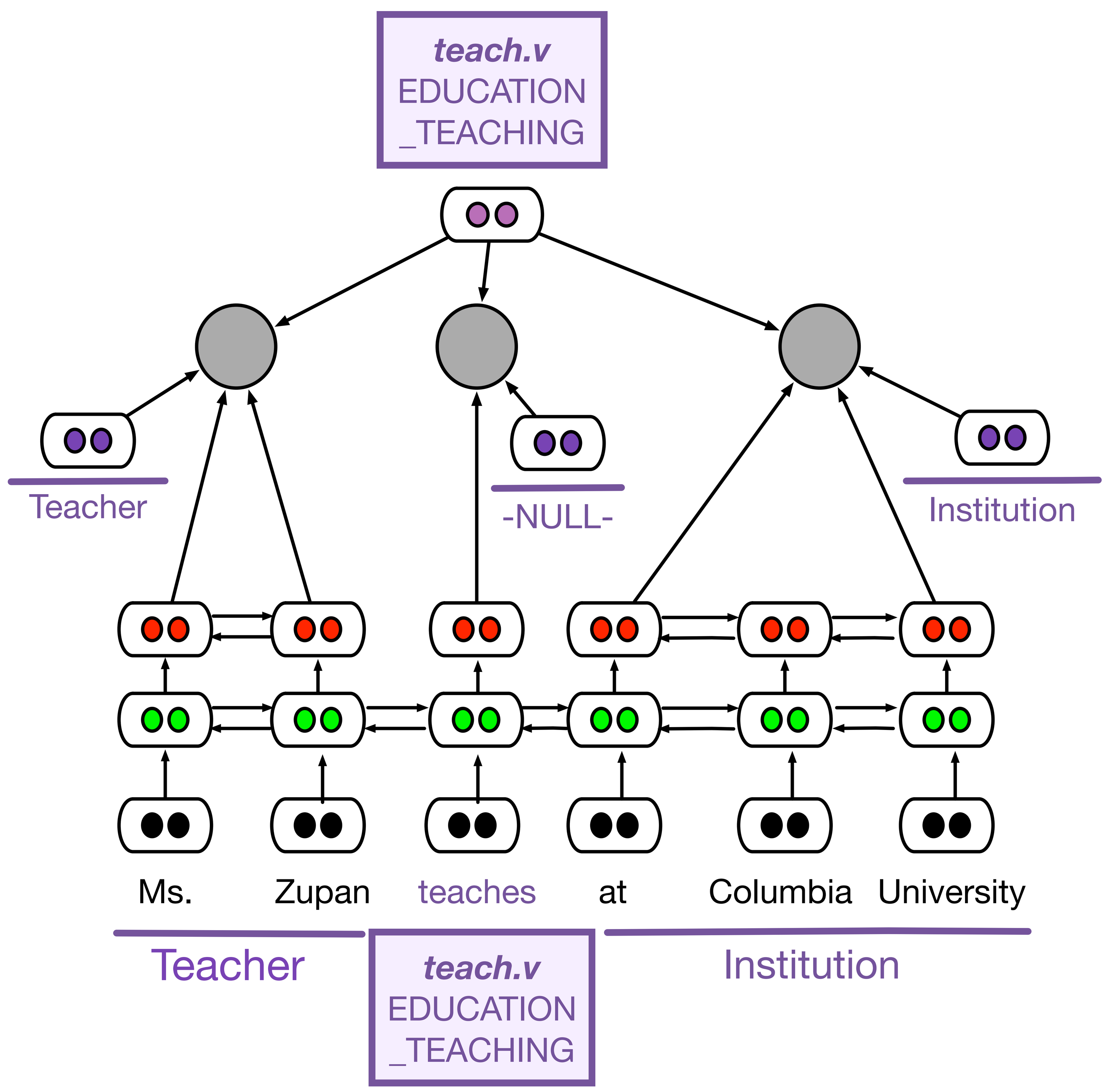


Figure: Illustration of the model architecture for an example sentence and its frame-semantic parse.s Black: input token embeddings. Purple: input frame and frame-element embeddings. Green: token biLSTM hidden states. Red: span embedding hidden states. Gray: segment factor.

Recall-oriented Softmax-Margin Segmental RNNs

A modified logloss objective that encourages recall over precision, by applying a cost function which penalizes false negatives by a factor α is used:

$$\text{loss}(\boldsymbol{x}, \boldsymbol{s}^*) = -\log \frac{\exp(\boldsymbol{s}^*, \boldsymbol{x})}{\sum_{\boldsymbol{s}} \exp\{(\boldsymbol{s}, \boldsymbol{x}) + \text{cost}(\boldsymbol{s}, \boldsymbol{s}^*)\}}, \quad (1)$$

$$\text{cost}(\boldsymbol{s}, \boldsymbol{s}^*) = \alpha \text{FN}(\boldsymbol{s}, \boldsymbol{s}^*) + \text{FP}(\boldsymbol{s}, \boldsymbol{s}^*), \quad (2)$$

This objective results in a boost in F1, primarily due to increase in recall.

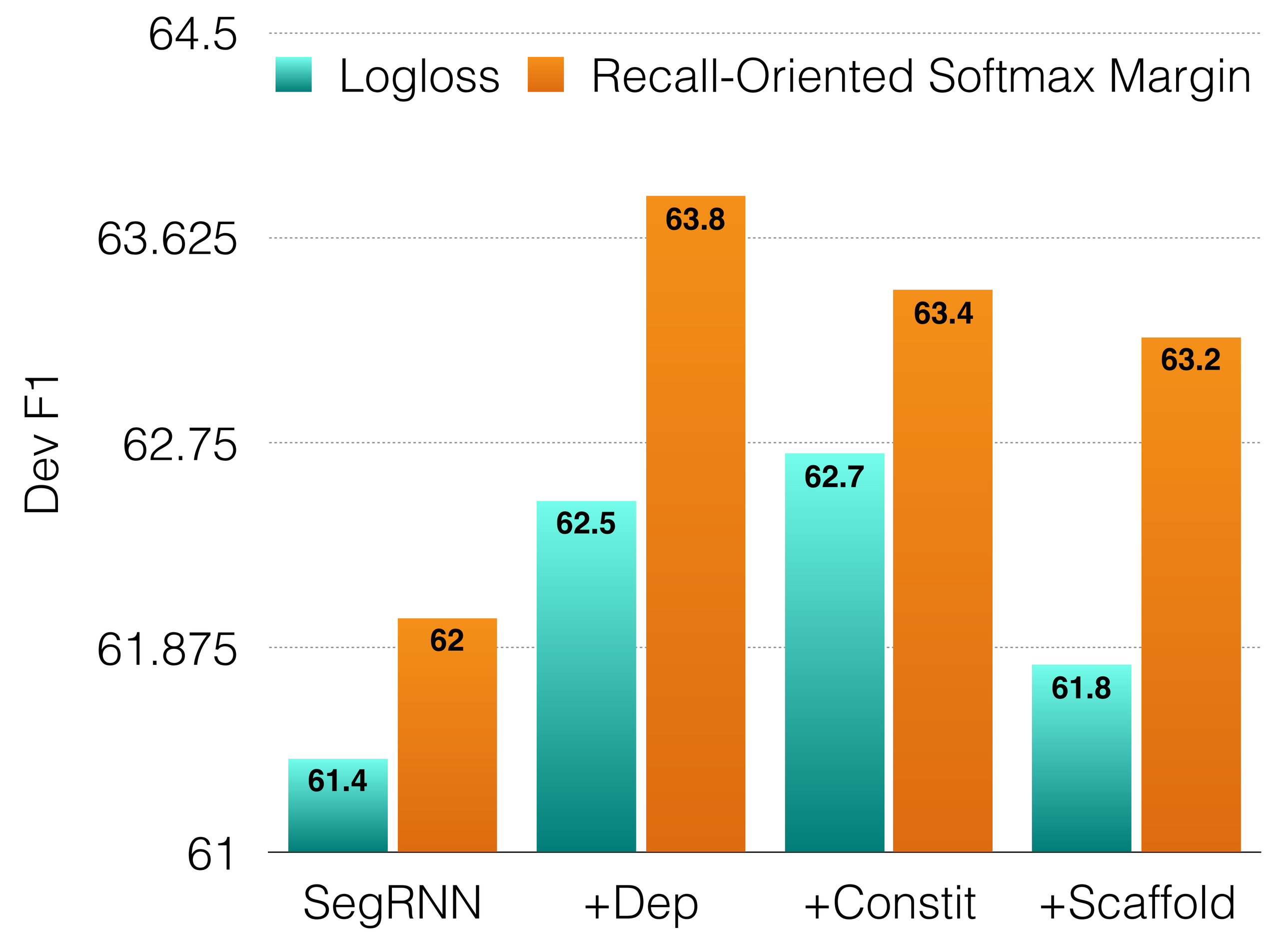


Figure: Log loss vs recall-oriented softmax margin loss

Incorporating Syntax I: Pipelining Syntactic Features

Constituency Features	Dependency Features
is_phrase	head_word
phrase_type	head_label
lca_type	out_#heads
constit_path_lstm	dep_path_lstm

Incorporating Syntax II: Syntactic Scaffolding

- Frame-semantic arguments are also syntactic constituents.
- Multi-task learning setup: simultaneously learn to predict syntactic constituents and frame-semantic arguments.
- Can exploit constituent span annotations from Penn Treebank.
- Bidirectional RNN parameters are shared between tasks.
- Scaffold is only needed at train time; usual test setup is followed.

Learning with a syntactic scaffold

A binary logistic regression loss is used to predict if a text span could be a constituent. $\text{loss}_{\text{scaffold}}(i, j, r^*, \boldsymbol{x}) =$

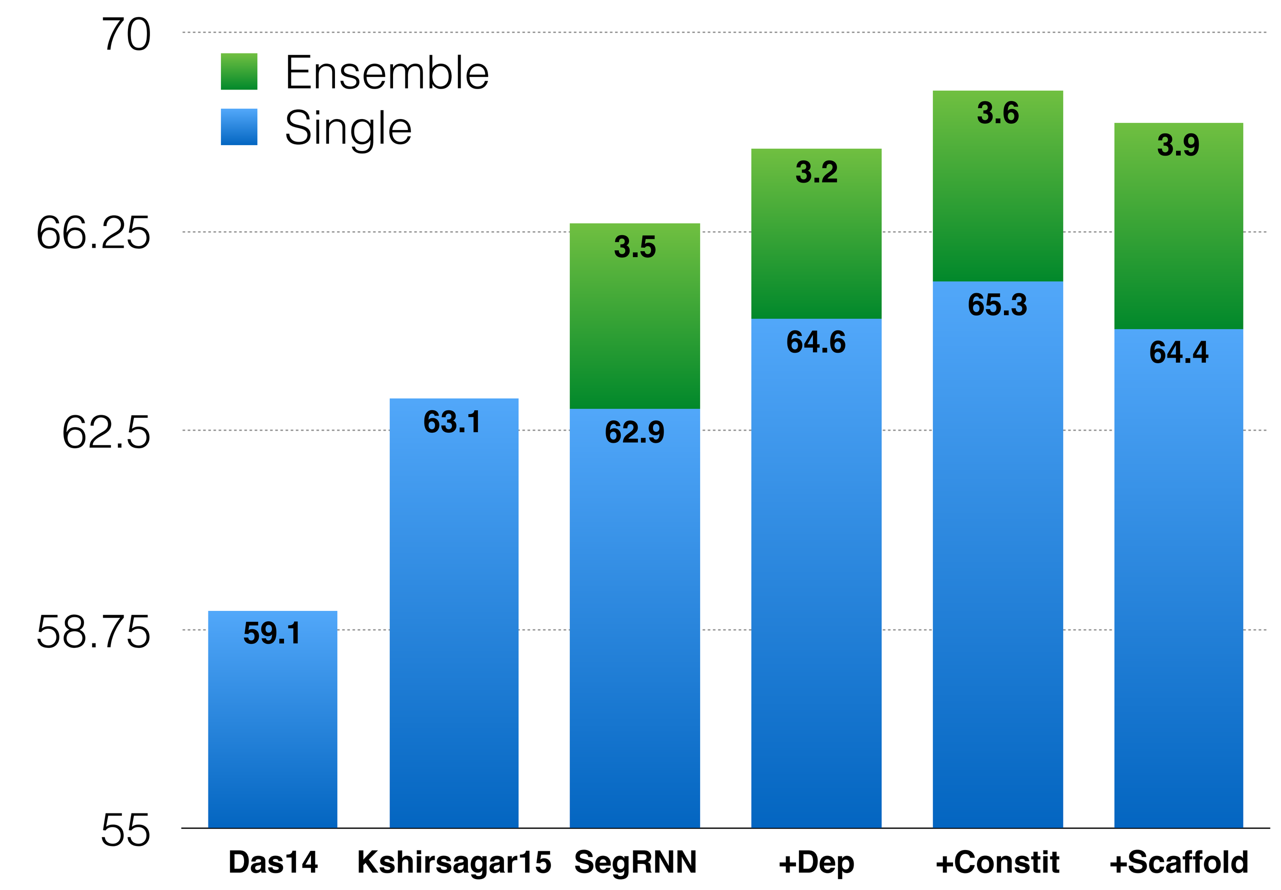
$$-\log \frac{\exp \psi(i, j, r^*, \boldsymbol{x})}{\sum_{r=\{0,1\}} \exp \psi(i, j, r, \boldsymbol{x})}. \quad (3)$$

The joint multi-task loss for a single sentence is:

$$\underbrace{\text{loss}(\boldsymbol{x}, \boldsymbol{s}^*)}_{\text{Eq. 1}} + \delta \sum_{\substack{1 \leqslant i \leqslant j \leqslant |\boldsymbol{x}| \\ j-i<D}} \text{loss}_{\text{scaffold}}(i, j, r^*, \boldsymbol{x}), \quad (4)$$

Argument Identification

Performance of argument identification only, using gold frames, on the FrameNet 1.5 test set.



Frame and Argument Identification

Parsing performance on the FrameNet 1.5 test set using a combined evaluation of frame identification and argument identification. The predicted frames are from FitzGerald et. al. (2015).