

COLLECTIVE ENTITY DISAMBIGUATION

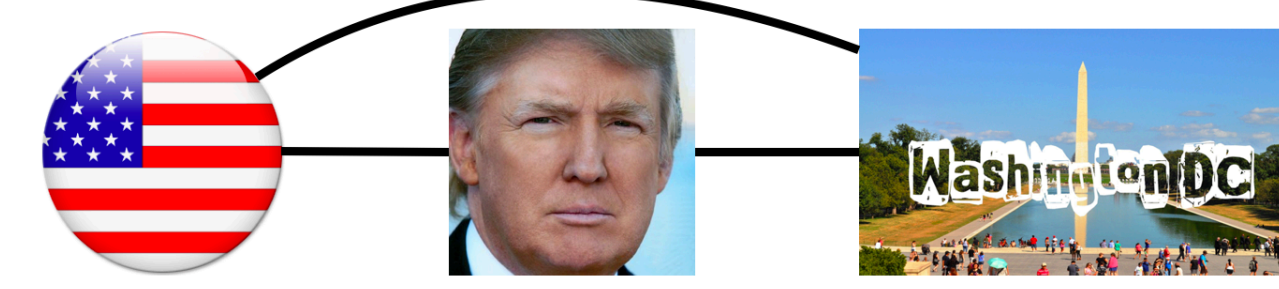
Entity mentions are ambiguous



- Local and global context for disambiguation

Structured prediction

- Entity dependencies:



- Inference: $\hat{\mathbf{y}} = \arg \max S(\mathbf{x}, \mathbf{y})$
- Learning:

$$\max S(\mathbf{x}, \text{US} + \text{Trump} + \text{Washington DC})$$

WHY GRADIENT TREE BOOSTING

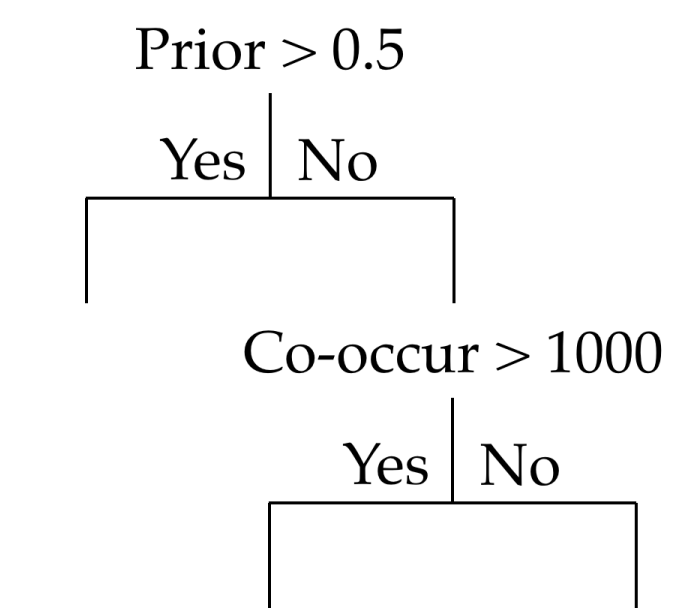
Heterogeneous features: $\phi(\mathbf{x}, \mathbf{y})$

Prior (| "Trump") $\in [0, 1]$

Co-occur (,) $\in \{0, 1, \dots, 10000, \dots\}$

- Ideal models can handle:
 - Categorical features and count data
 - Nonlinear relationships between features

Regression-tree-based models



Challenges

- Long-term dependencies between entities
- Approximate inference algorithms

MODEL

Structured Gradient Tree Boosting (SGTB)

$$S(\mathbf{x}, \mathbf{y}) = \sum_{t=1}^T F(\mathbf{x}, y_t, \mathbf{y}_{1:t-1})$$

$$p(\mathbf{y}|\mathbf{x}) = \frac{\exp\{\sum_{t=1}^T F(\mathbf{x}, y_t, \mathbf{y}_{1:t-1})\}}{Z(\mathbf{x})}$$

- Model F using Gradient Tree Boosting.
- Optimize with Functional gradient descent:

$$F_m(\mathbf{x}, y_t, \mathbf{y}_{1:t-1}) = F_{m-1}(\mathbf{x}, y_t, \mathbf{y}_{1:t-1}) - \eta_m g_m(\mathbf{x}, y_t, \mathbf{y}_{1:t-1})$$

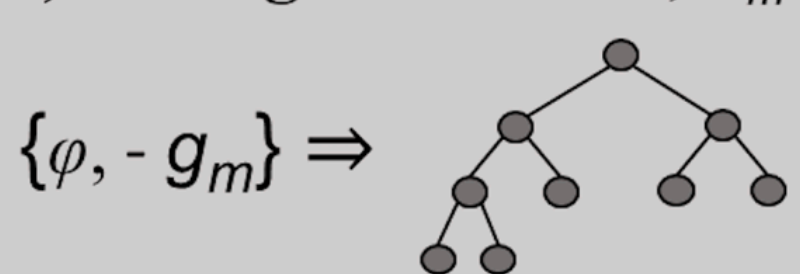
(i) Beam search using F_{m-1}

["United States", "Donald Trump", "Washington, D.C."]
["United States", "Donald Trump", "Washington (state)"]
["Us Weekly", "Trump, CO", "Washington, D.C."]
["Us (Novel)", "Trump University", "Washington (state)"]

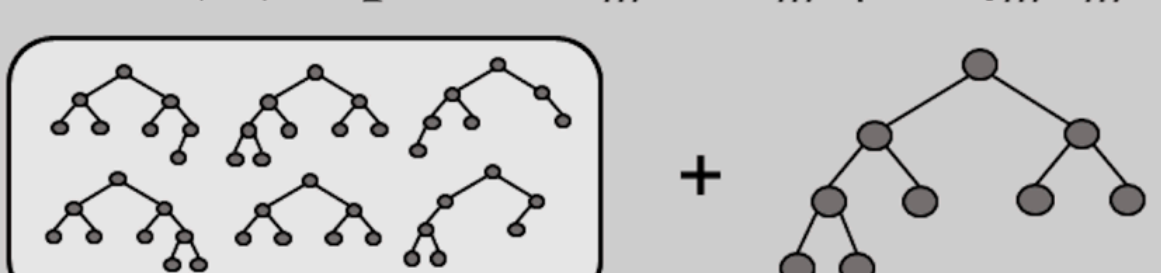
(ii) Compute functional gradient points, g_m

$g_m(\mathbf{x}, \text{"Washington, D.C."}, [\text{"United States"}, \text{"Donald Trump"}])$
 $g_m(\mathbf{x}, \text{"Washington (state)"}, [\text{"United States"}, \text{"Donald Trump"}])$
 $g_m(\mathbf{x}, \text{"Washington, D.C."}, [\text{"Us Weekly"}, \text{"Trump, CO"}])$
 $g_m(\mathbf{x}, \text{"Washington (state)"}, [\text{"Us (novel)"}, \text{"Trump University"}])$

(iii) Fit regression tree, h_m



(iv) Update $F_m = F_{m-1} + \eta_m h_m$



INFERENCE

Computing g_m requires inference

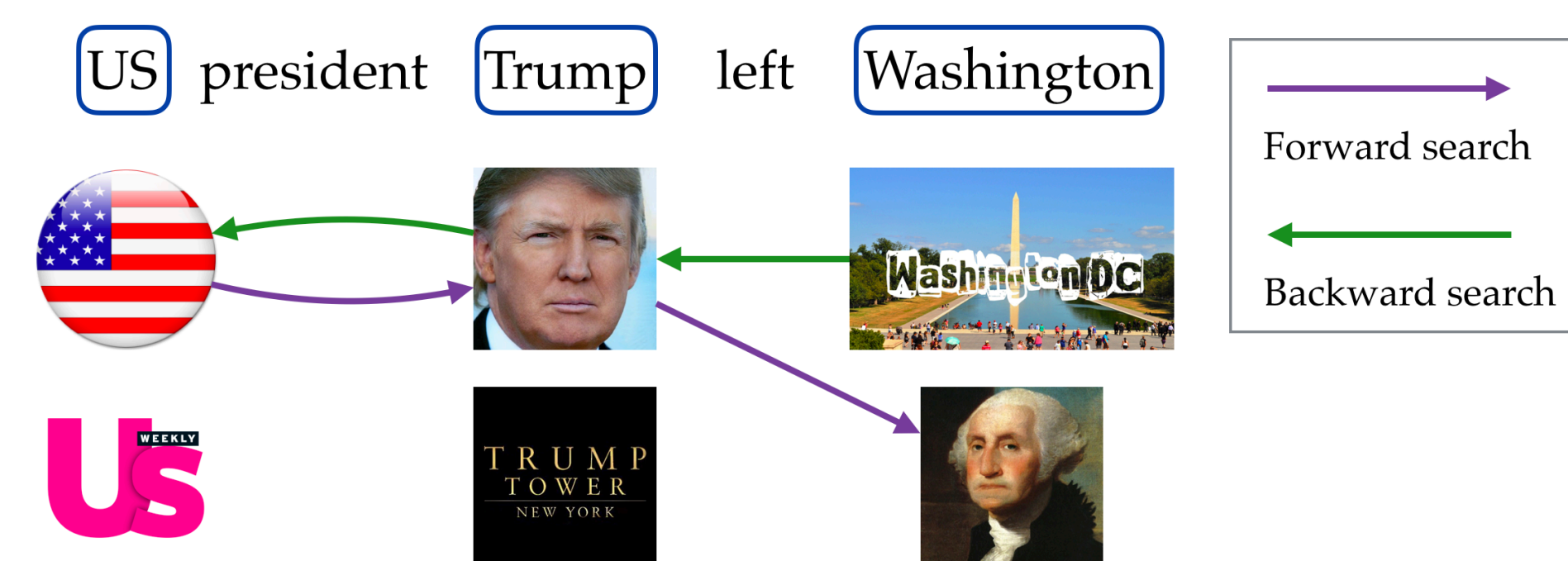
$$g_m(\mathbf{x}, y_t, \mathbf{y}_{1:t-1}) = \frac{\partial L(\mathbf{y}^*, S(\mathbf{x}, \mathbf{y}))}{\partial F(\mathbf{x}, y_t, \mathbf{y}_{1:t-1})}$$

$$= p(\mathbf{y}_{1:t}|\mathbf{x}) - \mathbf{1}[y_{1:t} = \mathbf{y}_{1:t}^*]$$

$$L(\mathbf{y}^*, S(\mathbf{x}, \mathbf{y})) = \log Z(\mathbf{x}) - S(\mathbf{x}, \mathbf{y}^*)$$

- Exact inference is intractable.
- Beam search is used to approximate $p(\mathbf{y}_{1:t}|\mathbf{x})$.

Bi-directional beam search



- New scoring function: $S(\mathbf{x}, \mathbf{y}) = (\vec{S} + \overleftarrow{S})/2$

Input : input document \mathbf{x} , candidate sequences $\{\mathbf{y}\}$, joint scoring function $S(\mathbf{x}, \mathbf{y}_{t_1:t_2})$

Output: beam sequence set C

$C \leftarrow \emptyset$

while not converged do

// forward beam search
for $t = 1, \dots, T$ **do**
 $C^{(F)} \leftarrow \text{top-B}_{\mathbf{y}_{1:t}}[S(\mathbf{x}, \mathbf{y}_{1:t}) + S(\mathbf{x}, \mathbf{y}_{T:t})]$
 // add gold subsequence
 $C^{(F)} \leftarrow C^{(F)} \cup \{\mathbf{y}_{1:t}^*\}$
 $C \leftarrow C \cup C^{(F)}$
end

end

// backward beam search
for $t = T, \dots, 1$ **do**
 $C^{(B)} \leftarrow \text{top-B}_{\mathbf{y}_{T:t}}[S(\mathbf{x}, \mathbf{y}_{T:t}) + S(\mathbf{x}, \mathbf{y}_{1:t})]$
 // add gold subsequence
 $C^{(B)} \leftarrow C^{(B)} \cup \{\mathbf{y}_{T:t}^*\}$
 $C \leftarrow C \cup C^{(B)}$
end

end

EXPERIMENTS

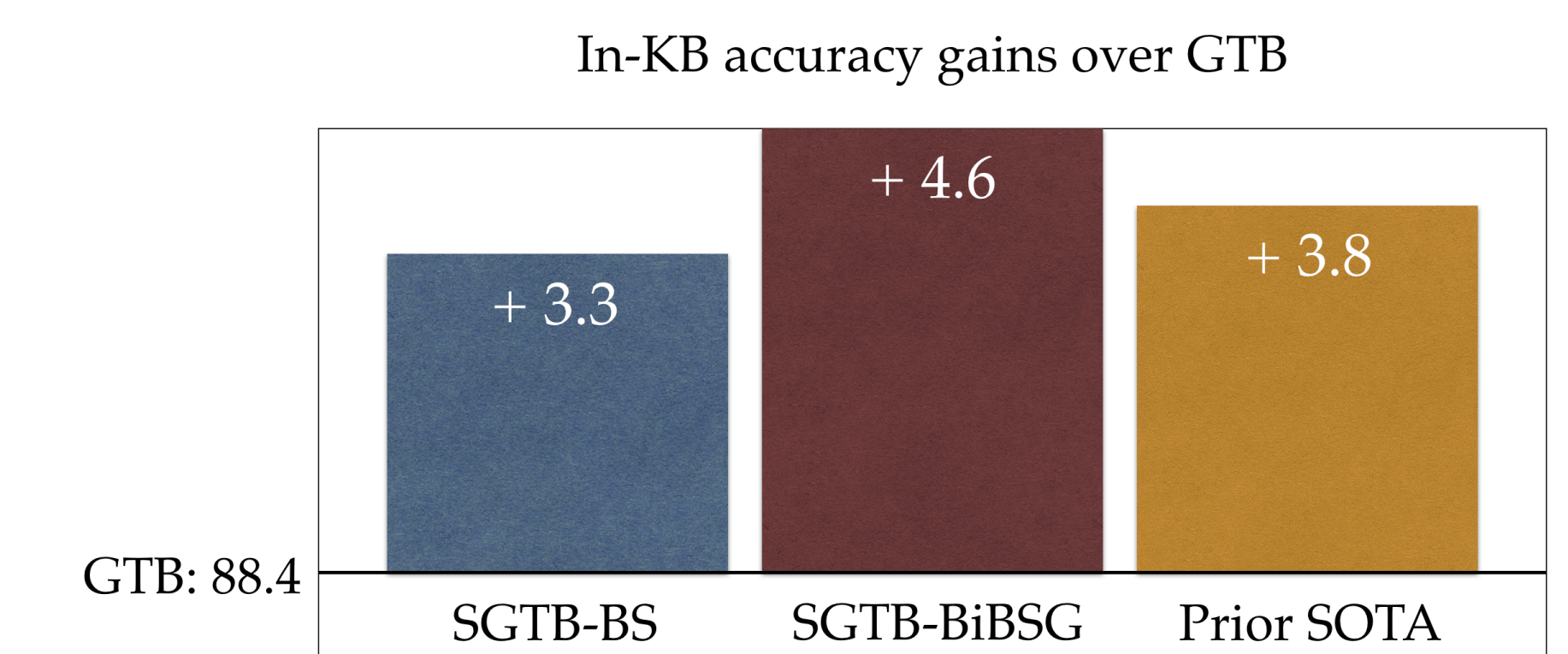
Data

Class	Dataset	# mention	# document	# mention per document
Training	AIDA-train	18,448	946	19.5
Validation	AIDA-dev	4,791	216	22.1
In-domain testing	AIDA-test	4,485	231	19.4
	AQUAINT	727	50	14.5
	MSNBC	656	20	32.8
Cross-domain testing	ACE	257	36	7.1
	CWEB	11,154	320	34.8
	WIKI	6,821	320	21.3

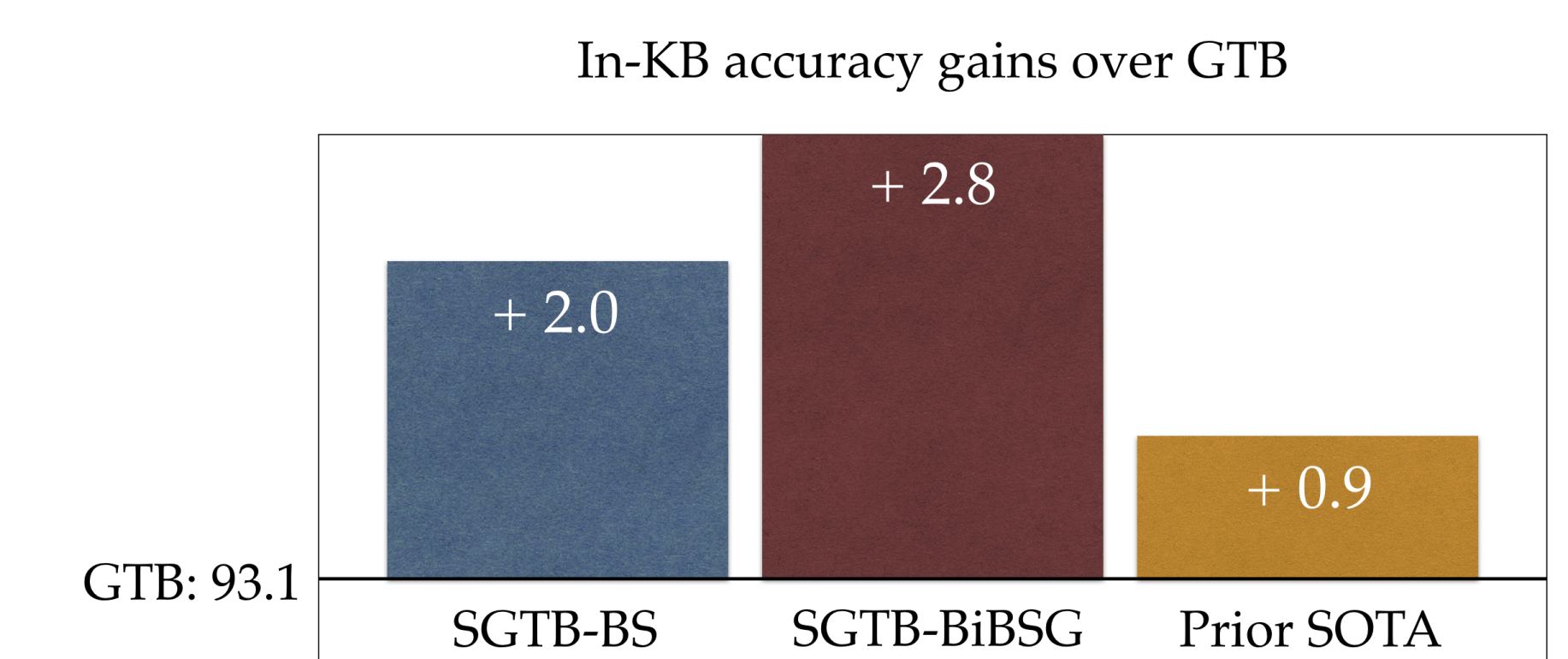
Setup

- Metrics
 - In-KB accuracy
 - Bag-of-Title (BoT) F1 score
- Competing systems
 - Gradient Tree Boosting (GTB)
 - SGTB with Beam search (SGTB-BS)
 - Bidir. BS using Gold path (SGTB-BiBSG)
 - Previous state-of-the-art (SOTA) systems

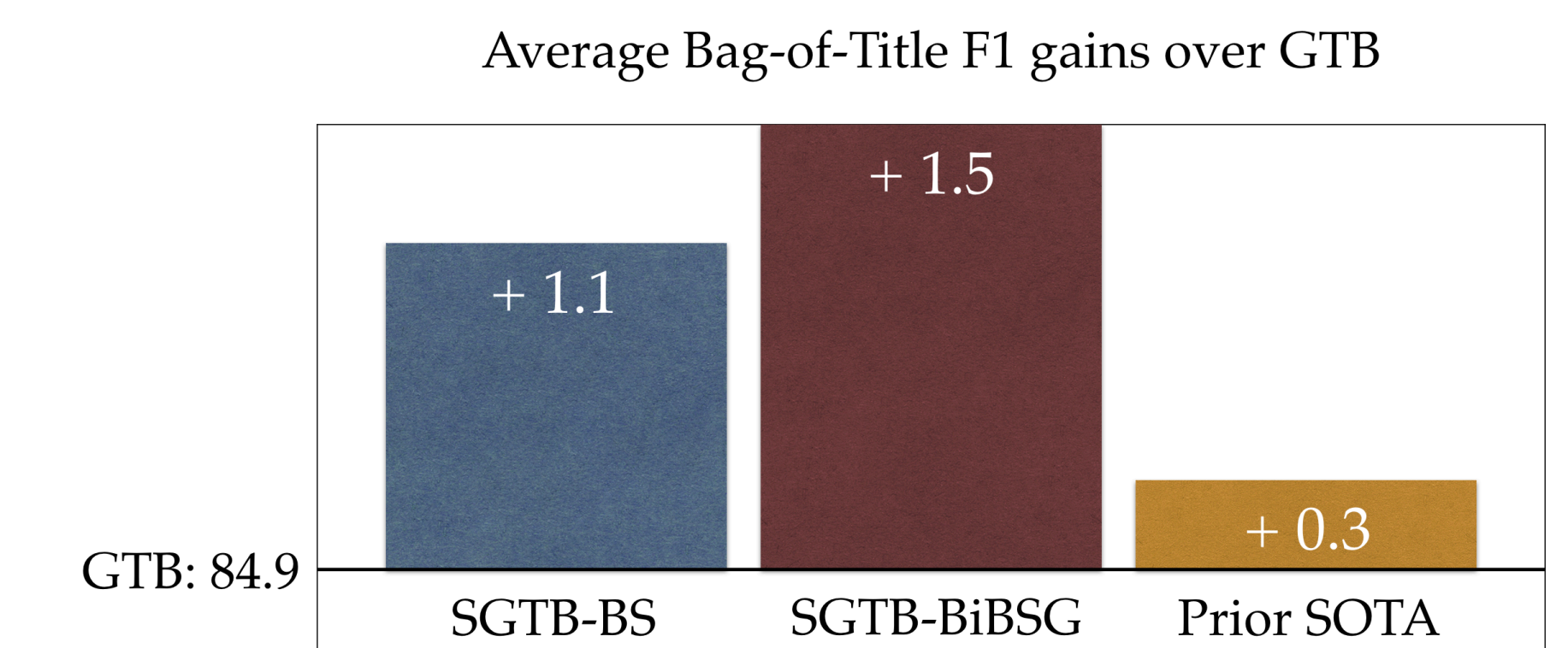
In-domain results



- Generate candidates with PPRforNED



Cross-domain results



SUMMARY

- We present a novel Structured Gradient Tree Boosting (SGTB) model for collectively disambiguating entities in a document.
- SGTB combines structured learning with Gradient Tree Boosting to produce globally optimal entity assignments for all the mentions.
- We present Bidirectional Beam Search with Gold path (BiBSG), an efficient approximate inference algorithm tailored for SGTB.
- SGTB achieves state-of-the-art (SOTA) results on popular entity disambiguation datasets of different domains.