KCD: Knowledge Walks and Textual Cues Enhanced Political Perspective Detection in News Media

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Political Perspective Detection

Political perspective detection aims to identify ideological stances of textual data such as social media posts and news articles.

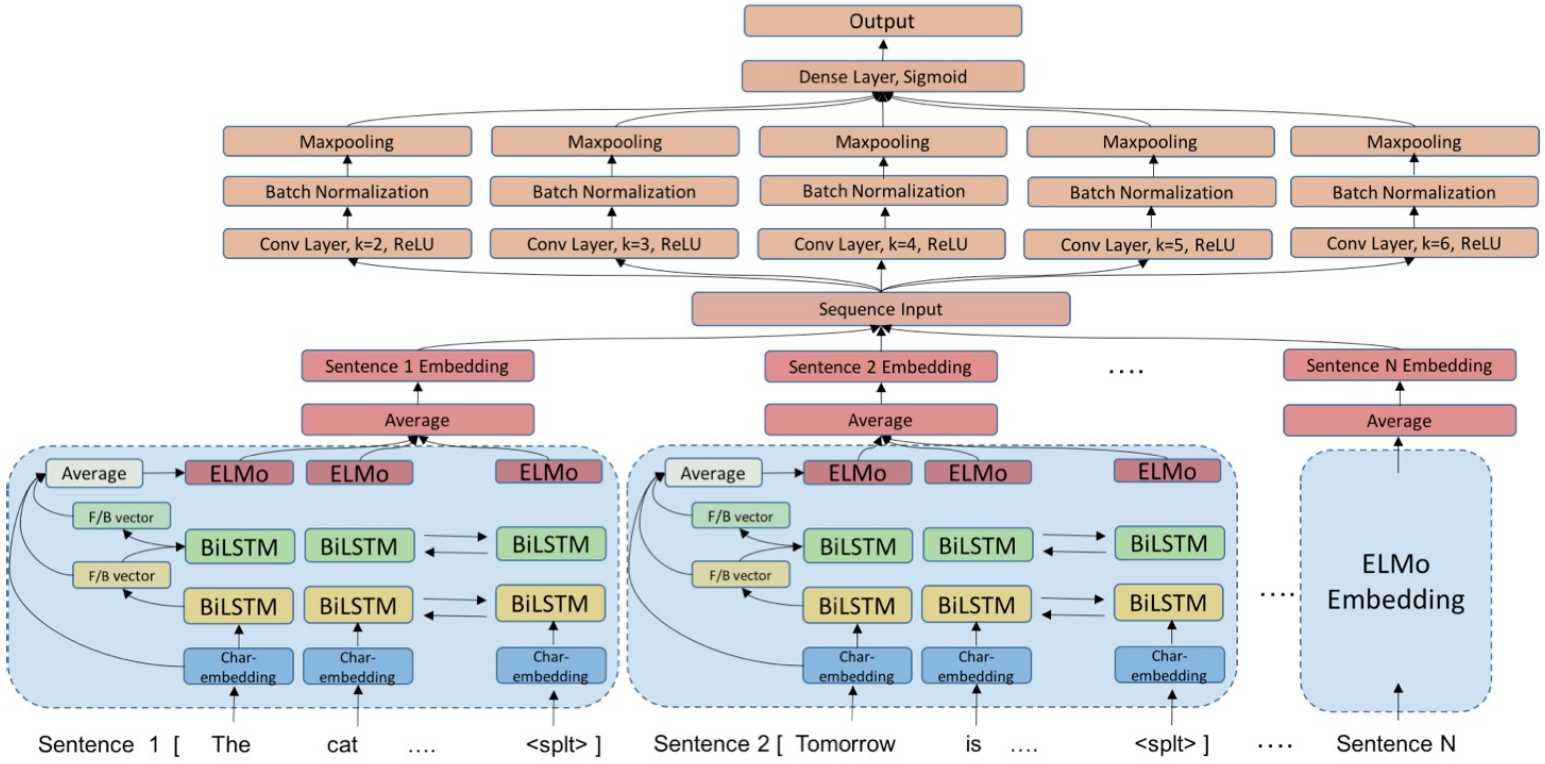
Source: Daily Kos Stance: Left

CNN *is reporting* that the ***Trump*** campaign were offered access to Wikileaks documents, including special access to a Wikileaks website, a month before Wikileaks began publishing ……
The email, which apparently *slipped* the memory of history's most forgetful campaign team, included a decryption key and address for documents stolen by Russian hackers and later ……
He *claimed* that …… "…… That means that the vast amount of stuff that we are publishing about ***Clinton*** will have a much higher impact, because it won't be perceived as coming from ……"
……

Existing Approach

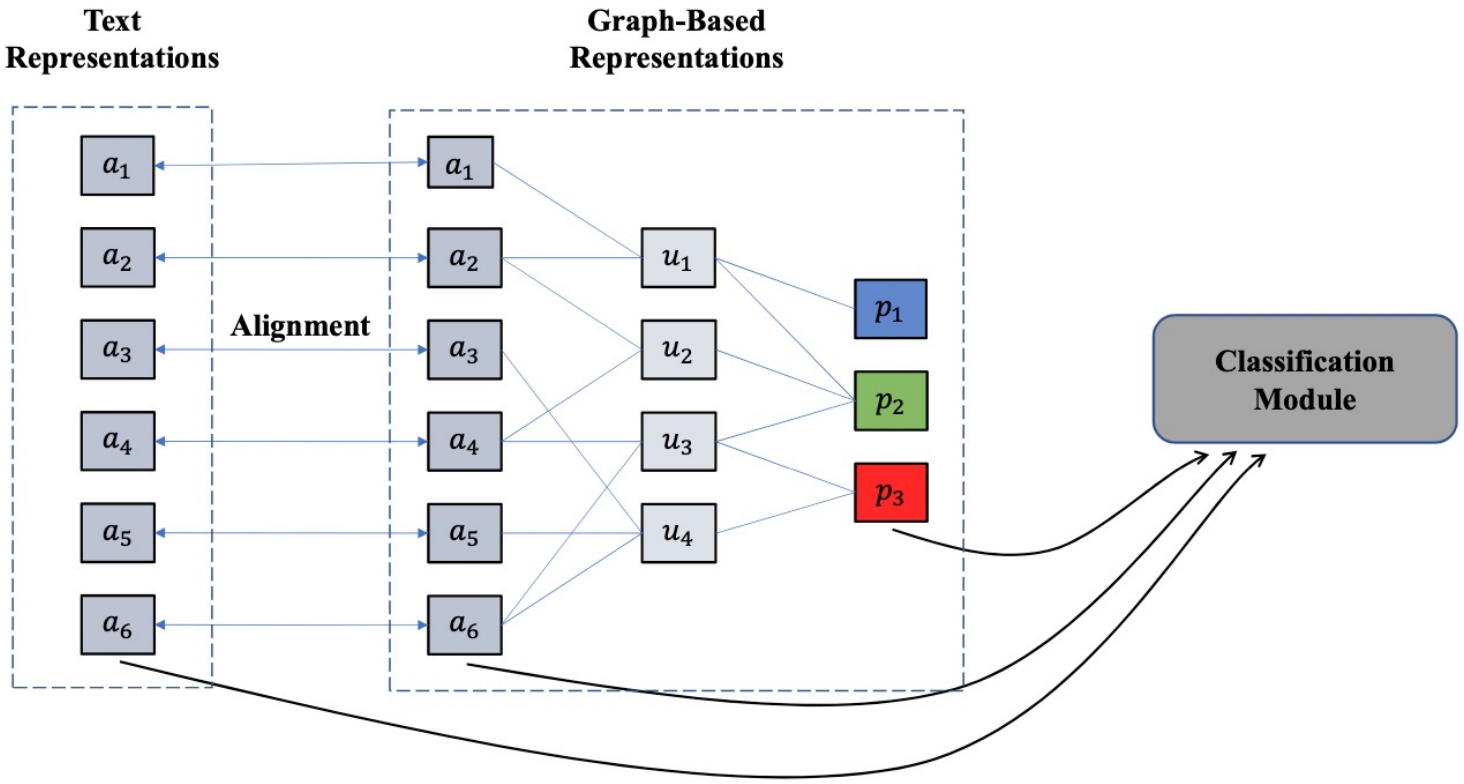
- Leveraging text analysis techniques for bias detection

  Jiang et al. , 2019



Existing Approach

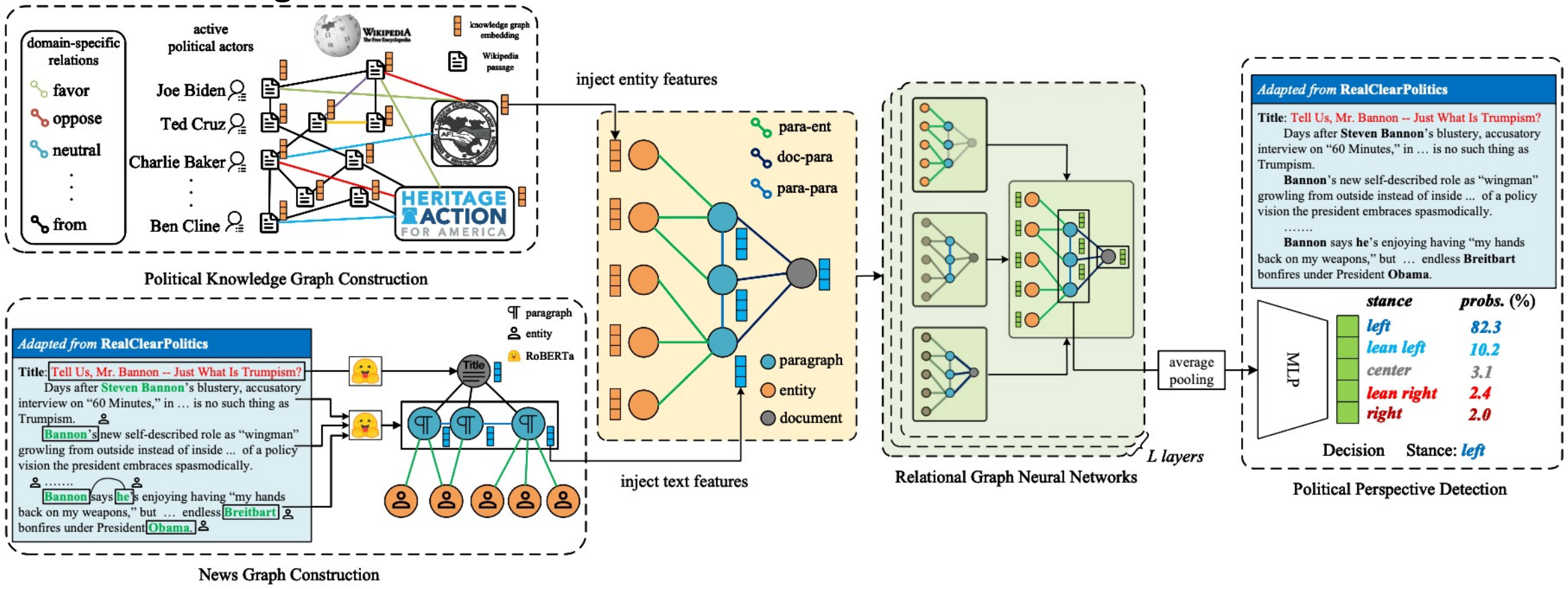
- Enriching text with the content and structure of social media
  Li and Goldwasser, 2019



Existing Approach

- Leveraging external knowledge graph

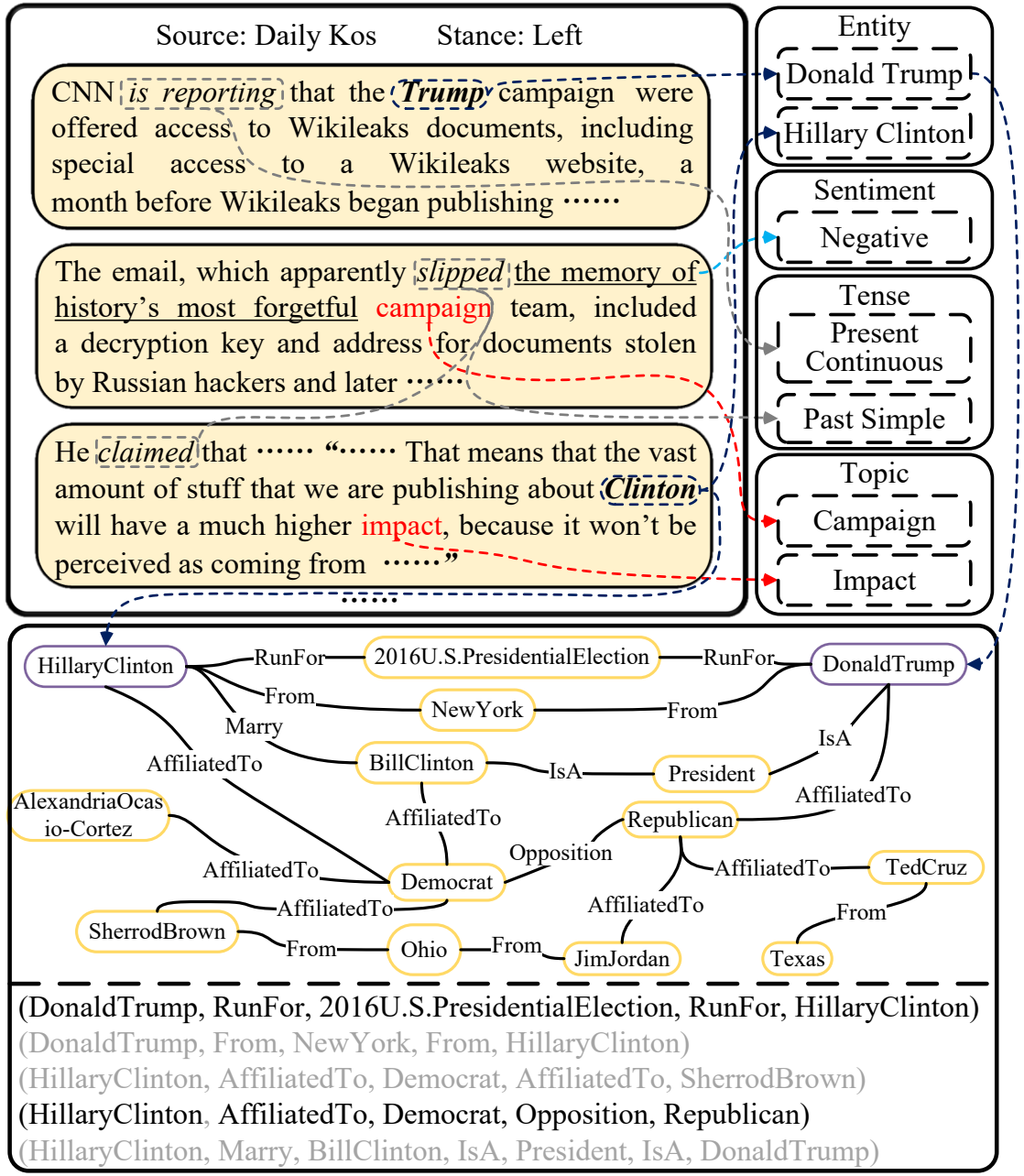
Feng et al. 2021



Motivation

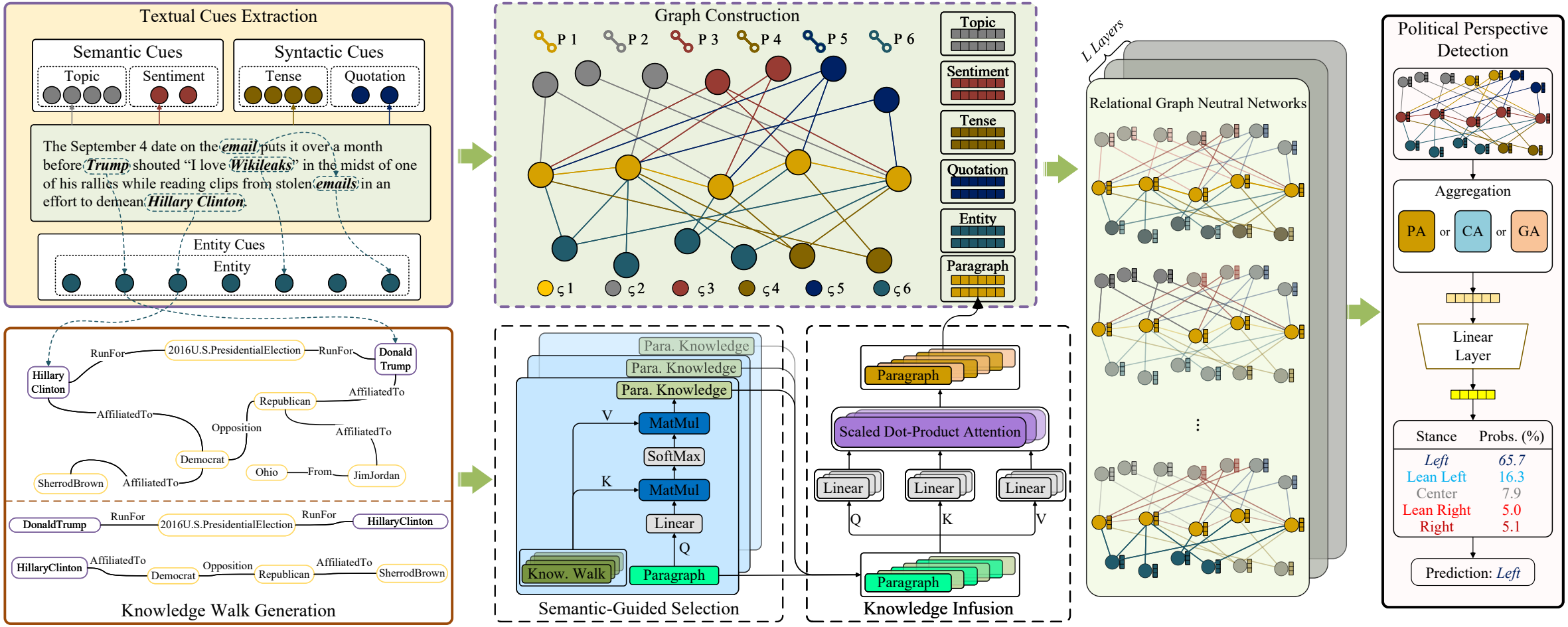
- Existing methods fail to leverage implicit semantic and syntactic indicators

- Existing methods fail to multi-hop reason with background knowledge



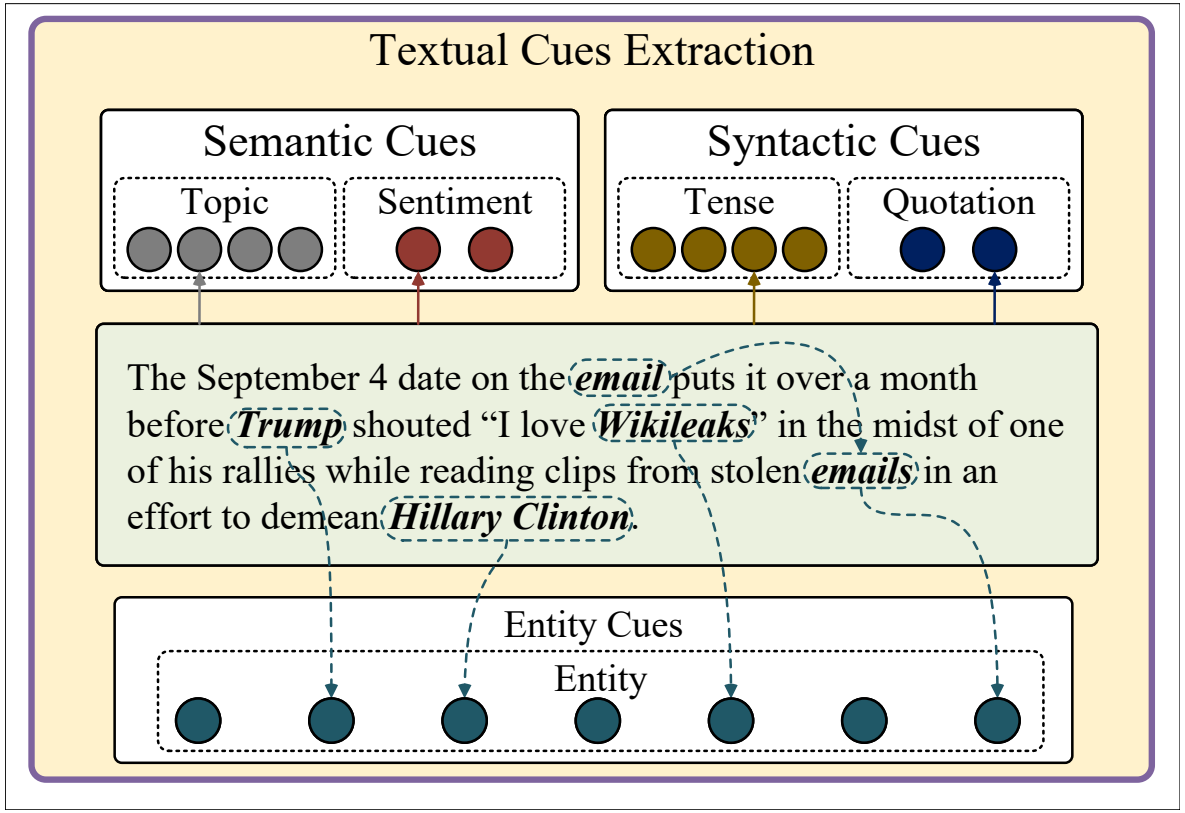
Methodology

Overview of our proposed framework KCD



Methodology

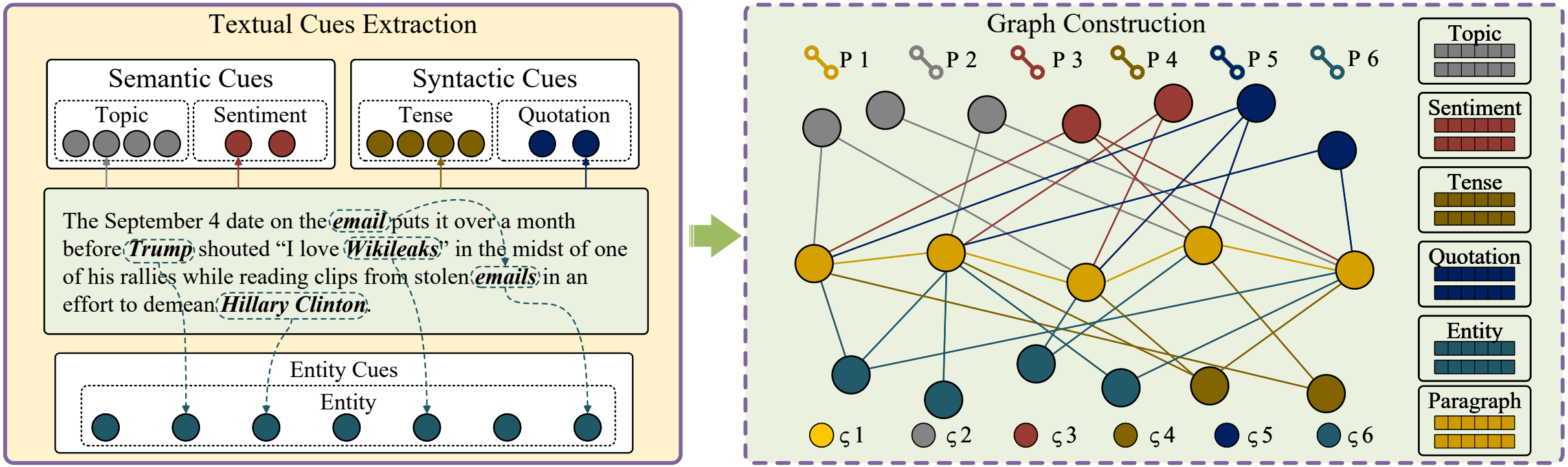
Textual Cues Extraction



- Topic Cues: Using BertTopic (Grootendorst, 2020) to mine the topics.
- Sentiment Cues: Using sentiment analysis API from Huggingface Transformers (Wolf et al., 2020).
- Tense Cues: Using NLTK (Bird et al., 2009) to extract the tense of news articles.
- Quotation Cues: Matching quotation marks.
- Entity Cues: Using TagMe (Ferragina and Scaiella, 2012) to align news articles with entities in the knowledge graph

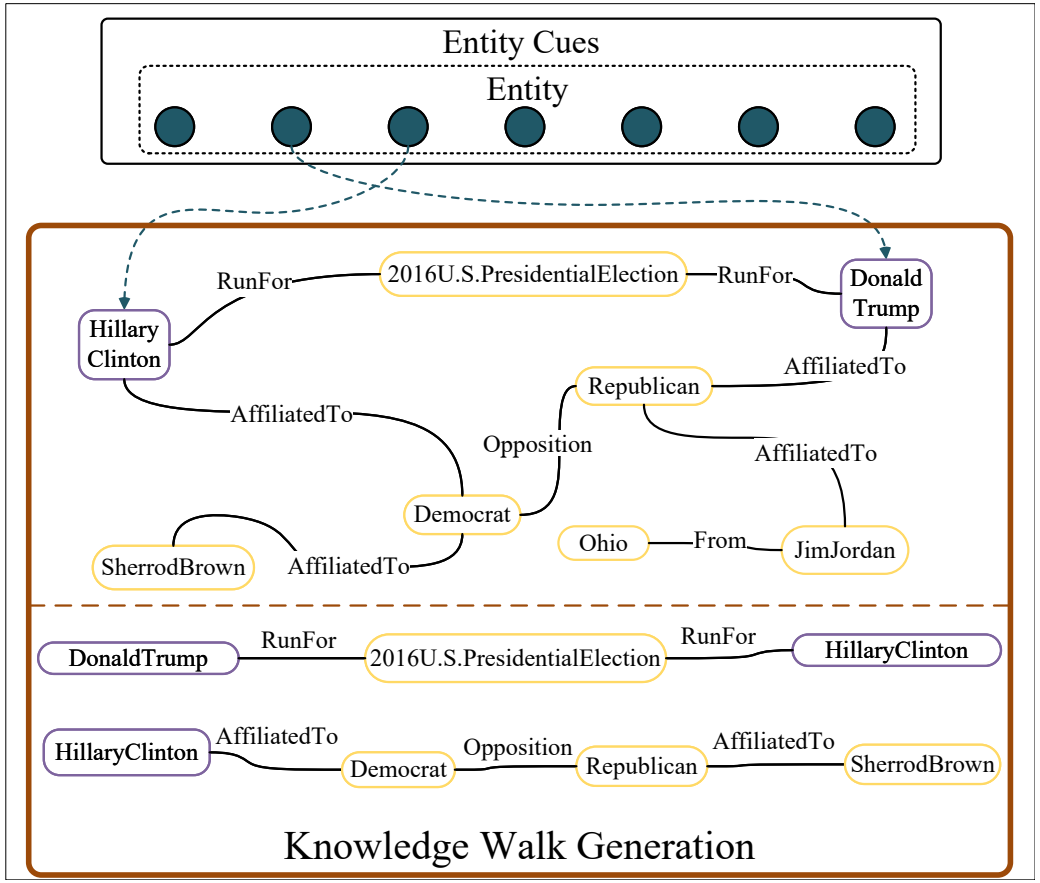
Methodology

News graph construction



Methodology

Knowledge Walk Generation



For *K*-hop knowledge walk:

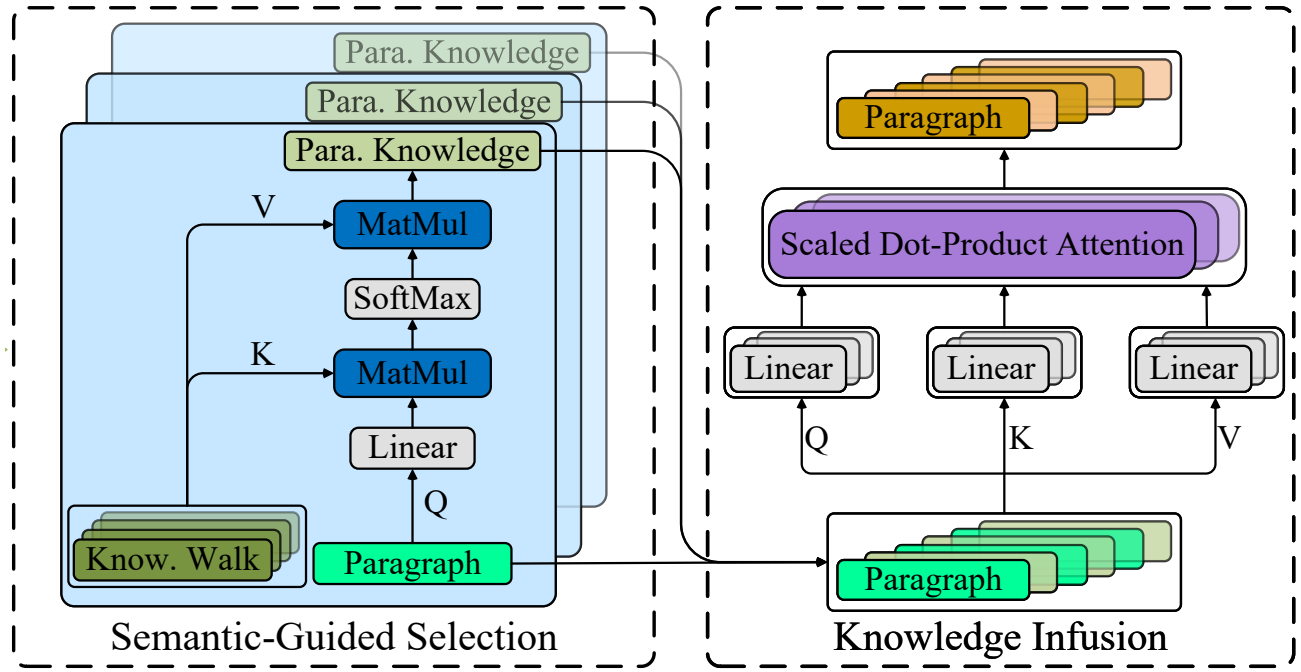
$$kw_i = \{e_{(0)}, r_{0,1}, e_{(1)}, \ldots, r_{K-1,K}, e_{(K)}\}$$

The conditional probability of entities hops:

$$P(e_{(i)}|e_{(i-1)}, r_{i-1,i}) = \frac{exp(p(r_{i-1,i}))}{\sum_{j=1}^{|N_r(i-1)|} exp(p(r_j))}$$

Methodology

Semantic-Guided Selection & Knowledge Infusion



Semantic-Guided Selection

Aggregate knowledge walks:

$$v_i^p = \sum_{j=1}^{m} \frac{exp(\alpha \cdot v_{i,j}^k)}{\sum_{q=1}^{m} exp(\alpha \cdot v_{i,q}^k)} v_{i,j}^k$$

Where α is:

$$\alpha = \phi(W_a v_i^s + b_a)$$

Infuse Knowledge and Text

Concatenate knowledge walk and text

$$T = concat([v_1^s, v_1^p, ..., v_n^s, v_n^p])$$

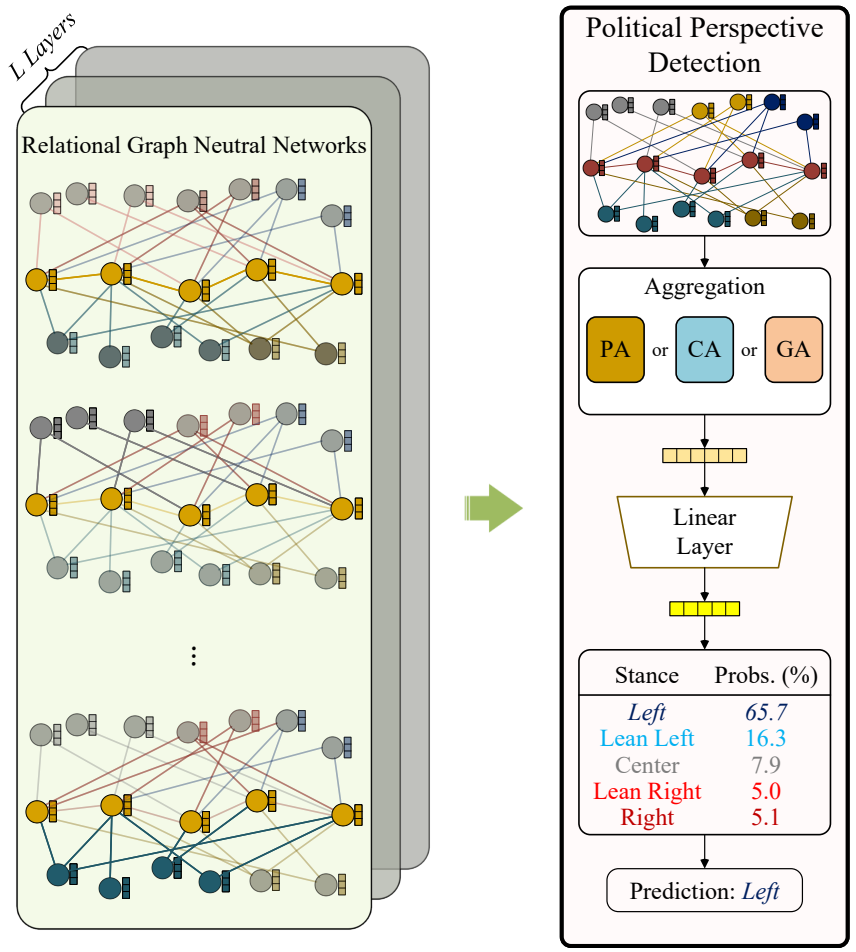
Infusing:

$$\tilde{T} = MultiHead(Q, K, V)$$

Where $Q = K = V = T$

Methodology

Learning and Optimization



Three aggregation strategies:

$$v_g = \begin{cases} \frac{1}{|\mathcal{V}1|} \sum_{v \in \mathcal{V}1} \overline{v} & \text{if Paragraph Average;} \\ \frac{1}{|\mathcal{V} - \mathcal{V}1|} \sum_{v \notin \mathcal{V}1} \overline{v} & \text{if Cue Average;} \\ \frac{1}{|\mathcal{V}|} \sum_{v \in \mathcal{V}} \overline{v} & \text{if Global Average.} \end{cases}$$

Classification:

$$\hat{y} = softmax(W_o \cdot v_g + b_o)$$

Datasets

Dataset	# Articles	# Class	Class Distribution
SemEval	645	2	407 / 238
Allsides	10,385	3	4,164 / 3,931 / 2,290

- We used the same dataset in previous works (Li and Goldwasser, 2019, 2021; Feng et al., 2021a)
- SemEval (Kiesel et al., 2019) is the training data set from the SemEval 2019 Task 4
- Allsides (Li and Goldwasser, 2019) is a larger and more diversified political perspective detection dataset

Baselines:

Text-based techniques

- **CNN** (Jiang et al., 2019)
- **HLSTM** (Yang et al., 2016)
- **HLSTM_Embed** and **HLSTM_Output** (Liand Goldwasser, 2021)

Language Model

- **Word2Vec** (Mikolov et al., 2013)
- **GloVe** (Pennington et al., 2014)
- **ELMo** (Peters et al., 2018), pre-trained
- **BERT** (Devlin et al., 2019)
- **RoBERTa** (Liu et al., 2019)

External knowledge enriched method

- **MAN** (Li and Goldwasser, 2021)
- **KGAP** (Feng et al., 2021a)

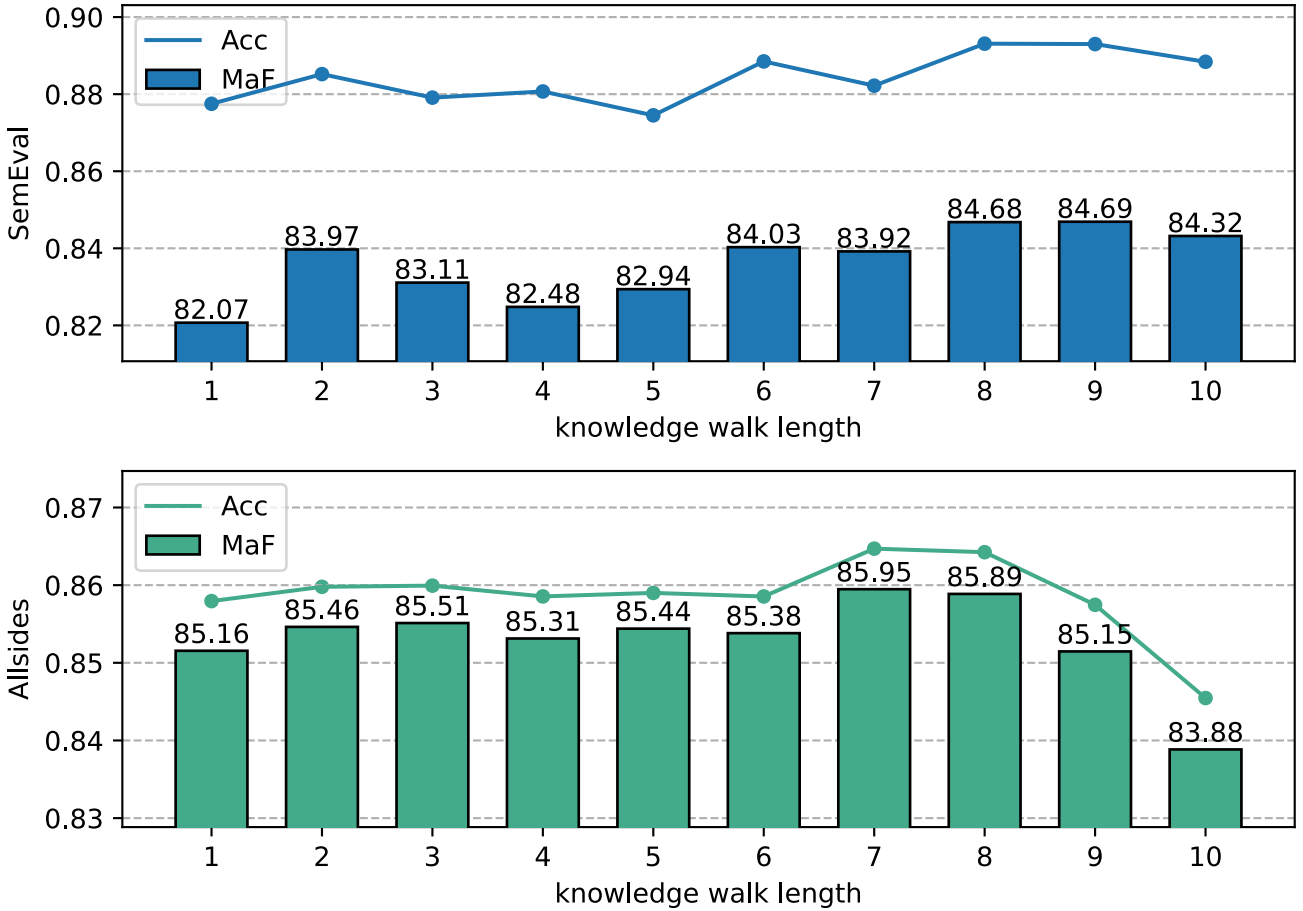
Experiment Result

Method	Setting	SemEval		AllSides	
		Acc	MaF	Acc	MaF
CNN	GloVe	79.63	N/A	N/A	N/A
	ELMo	84.04	N/A	N/A	N/A
HLSTM	GloVe	81.58	N/A	N/A	N/A
	ELMo	83.28	N/A	N/A	N/A
	Embed	81.71	N/A	76.45	74.95
	Output	81.25	N/A	76.66	75.39
Text Model	Word2Vec	70.27	39.37	48.58	34.33
	GloVe	80.71	63.64	71.01	69.81
	ELMo	86.78	80.46	81.97	81.15
	BERT	86.92	80.71	82.46	81.77
	RoBERTa	87.08	81.34	85.35	84.85
MAN	GloVe	81.58	79.29	78.29	76.96
	ELMo	84.66	83.09	81.41	80.44
	Ensemble	86.21	84.33	85.00	84.25
KGAP	GRGCN	89.56	84.94	86.02	85.52
KCD	GA	88.52	84.13	86.02	85.53
	CA	89.77	85.26	81.28	80.39
	PA	**90.87**	**87.87**	**87.38**	**87.14**
KCD (PA)	- w/o TC	88.22	83.53	86.08	85.58
	- w/o KW	87.29	81.77	85.51	85.00

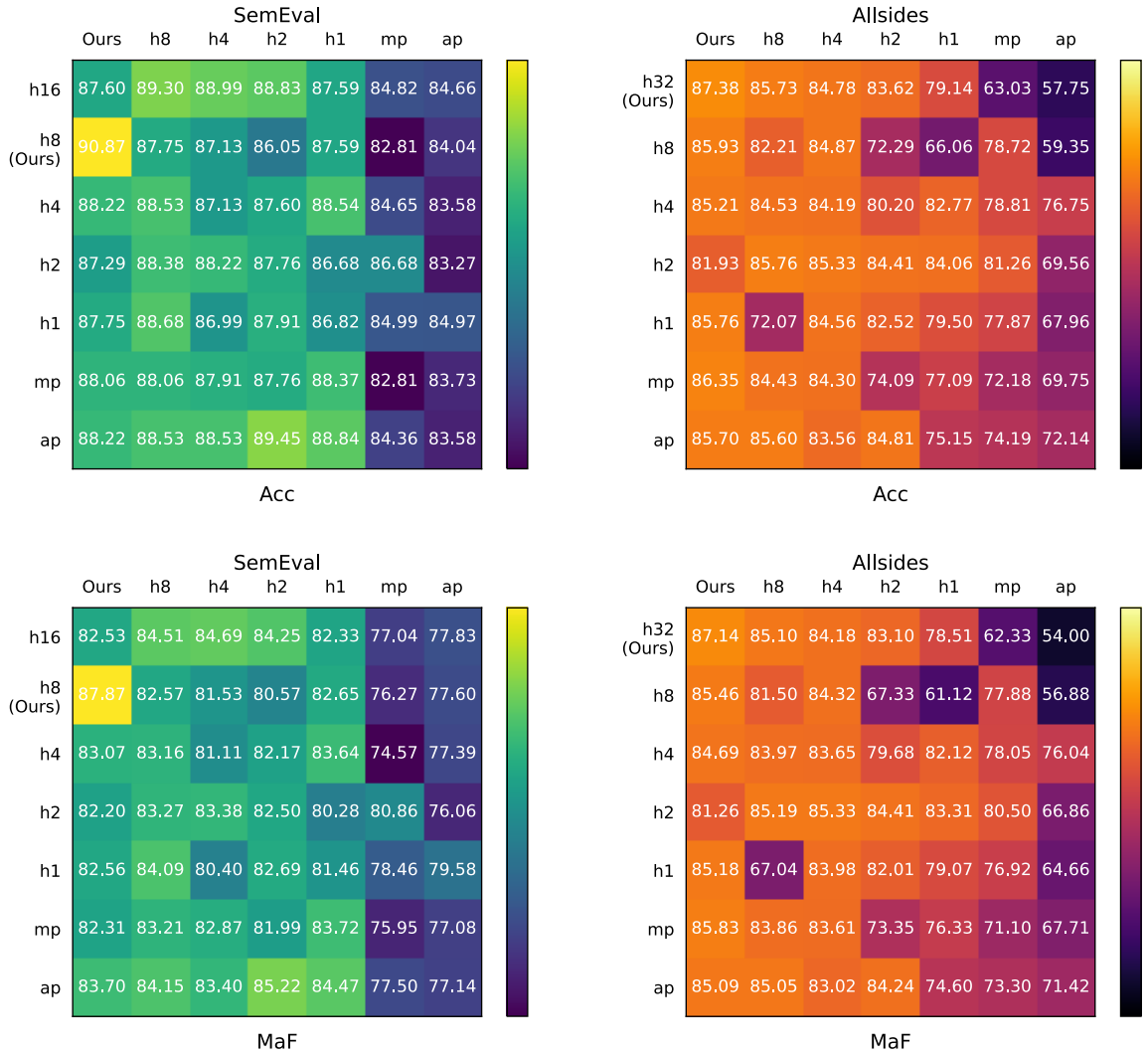
- KCD consistently outperforms state-of-the-art methods
- KCD and KGAP, the two method with knowledge graph outperform other baselines.
- PA outperforms CA and GA consistently.
- Removing textual cues and knowledge walks result in substantial performance drop.

Knowledge Walks Length Study

Our approach's performance when the maximum length of knowledge walk generation is specified from 1 to 10 knowledge graph triples



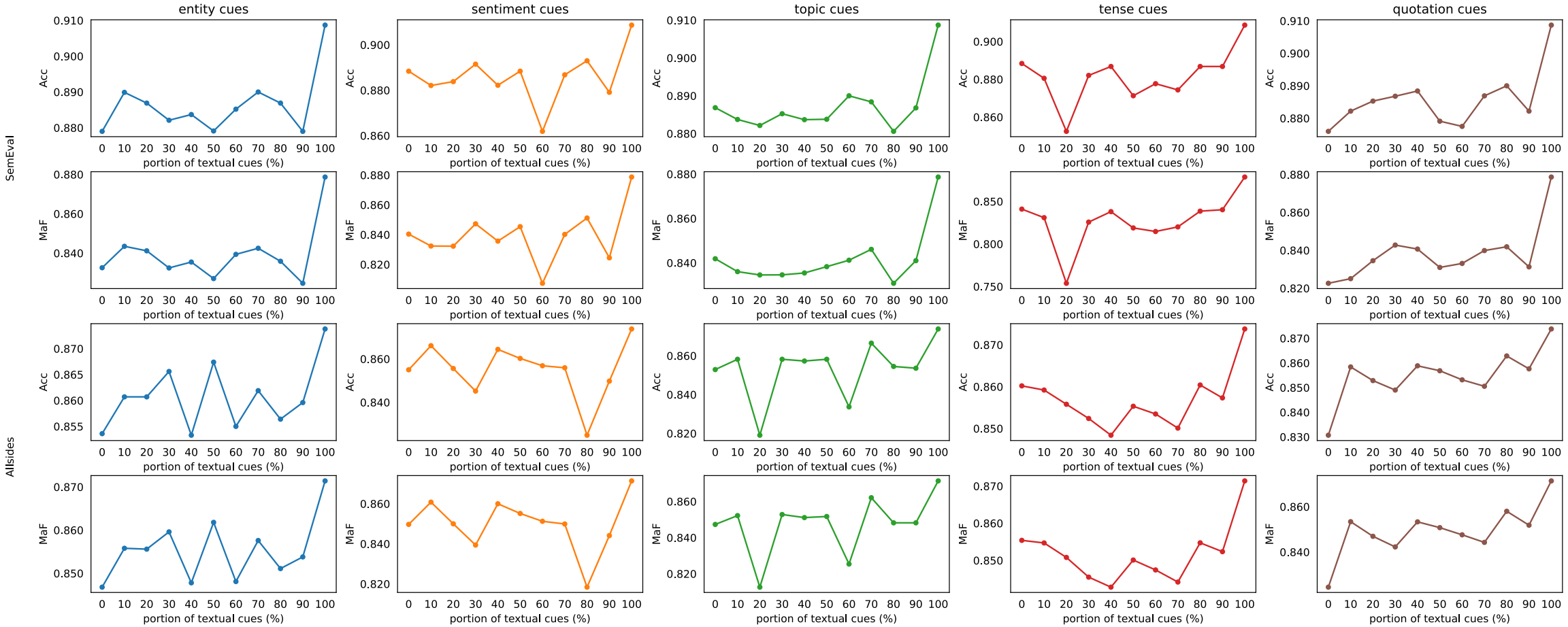
Knowledge Infusion Strategy Study



- Model performance with different knowledge infusion strategies at two aggregation steps.
- The horizontal and vertical axis represent the first and second aggregation. h_k denotes multi-head attention with k heads, mp and ap stand for max and average pooling.

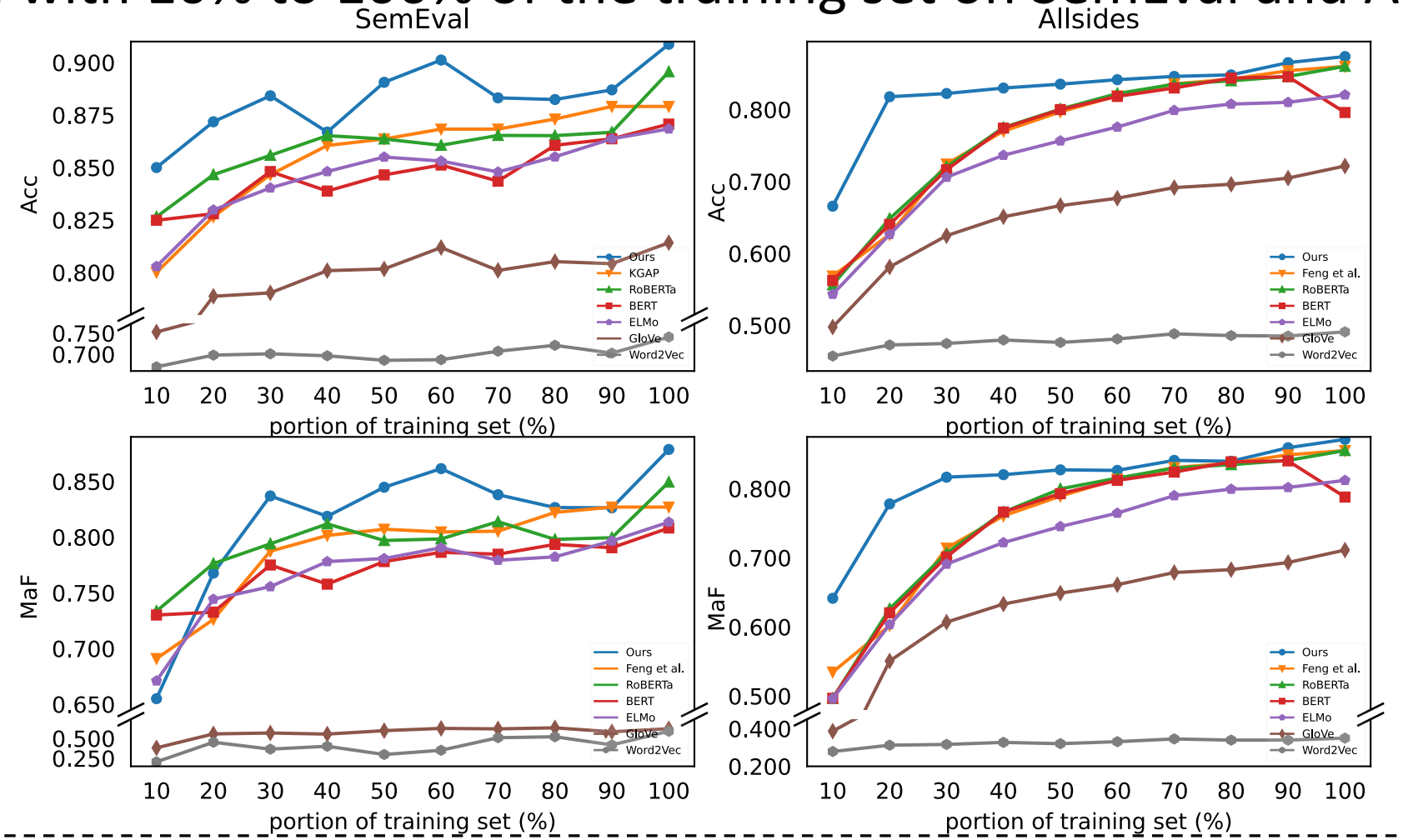
Textual Cues Study

Model performance when five different types of textual cues are gradually and randomly removed.



Data Efficiency Study

Model performance when KCD and various competitive baselines are trained with 10% to 100% of the training set on SemEval and Allsides.



Resources

We make the code and model of KCD available at:

- https://github.com/Wenqian-Zhang/KCD

The knowledge graph we used is available at:

- https://github.com/BunsenFeng/news_stance_detection

Q & A

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