



# KHAN: Knowledge-Aware Hierarchical Attention Networks for Accurate Political Stance Prediction

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code: <https://github.com/yy-ko/khan-www23>



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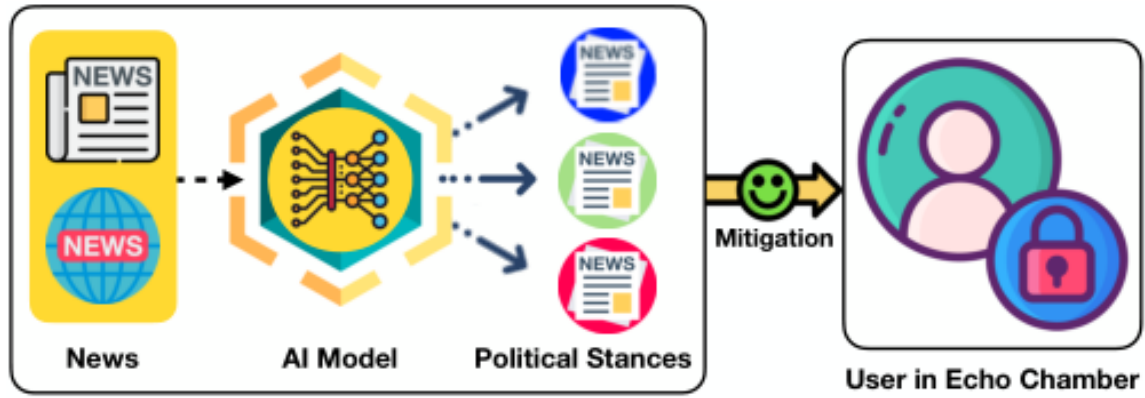
Reported by Zhaoze Gao



- 1. Introduction**
- 2. Approach**
- 3. Experiments**



# Introduction



The political stance prediction for news articles has been widely studied to mitigate the echo chamber effect – people fall into their thoughts and reinforce their pre-existing beliefs.

**Figure 1: Accurate provision of diverse political stances to mitigate the echo chamber effect.**

# Approach

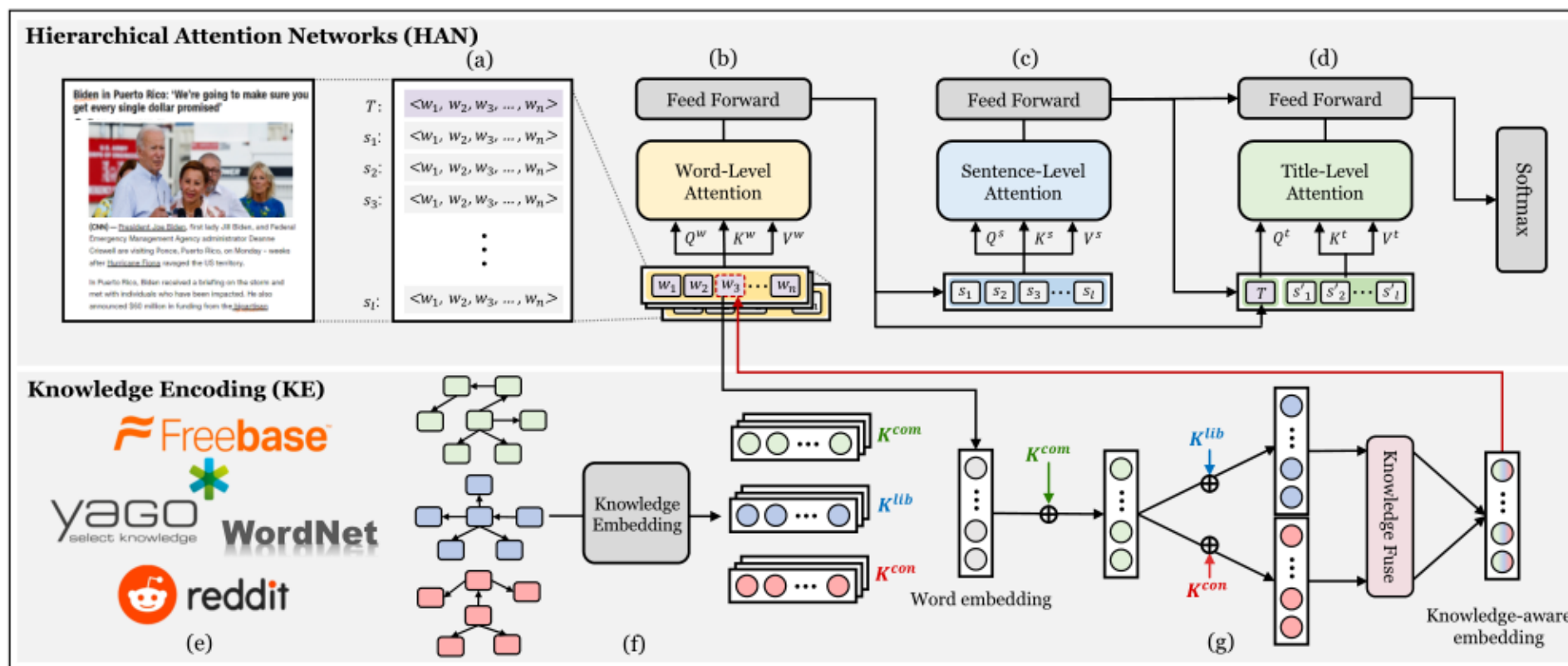


Figure 2: The overview of KHAN: hierarchical attention networks (upper) and knowledge encoding (lower).

# Approach

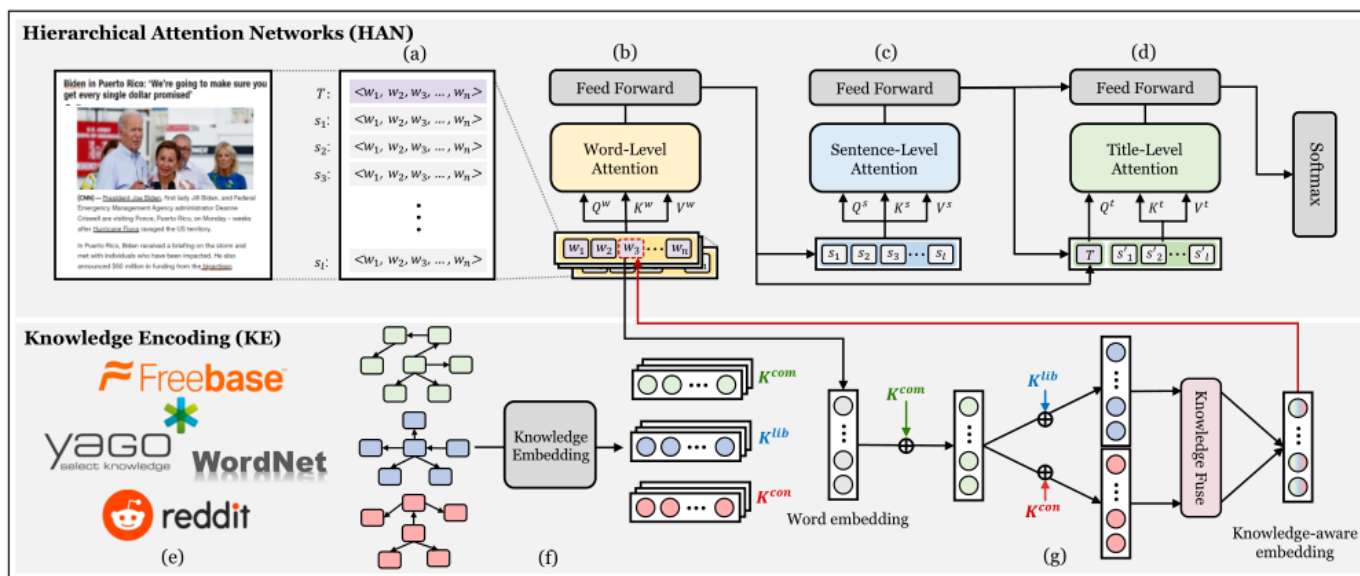


Figure 2: The overview of KHAN: hierarchical attention networks (upper) and knowledge encoding (lower).

Notation	Description
$W$	a set of word embeddings
$S$	a set of sentence embeddings
$T$	the title embedding
$w_i, s_j$	$i^{th}$ word embedding, $j^{th}$ sentence embedding
$d$	the embedding dimensionality
$N$	the total number of words in a dataset
$n$	the maximum number of words in a sentence
$l$	the maximum number of sentences in an article
$K^{com}$	a set of common knowledge embeddings
$K^{lib}$	a set of liberal knowledge embeddings
$K^{con}$	a set of conservative knowledge embeddings
$\alpha, \beta$	common and political knowledge factors
$A, a$	news article dataset and a news article
$X$	a set of learnable parameters
$F(\cdot)$	loss function (i.e., cross-entropy loss)
$\eta$	user-defined learning rate

$$S = \{s_1, s_2, \dots, s_l\}$$

# Approach

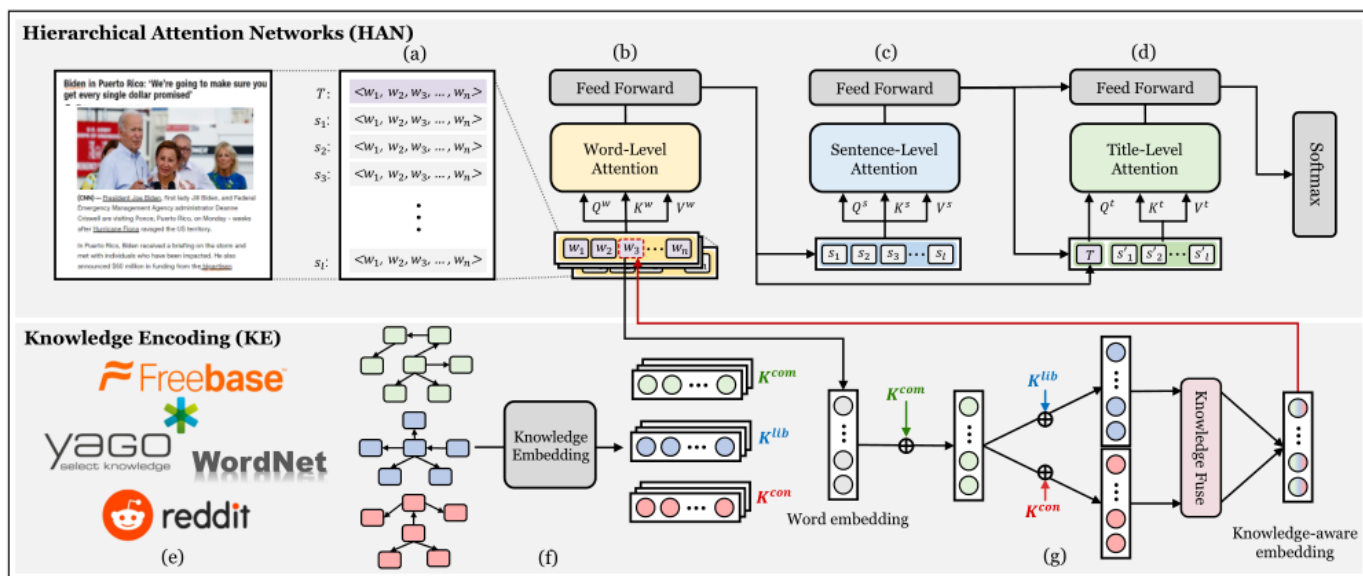


Figure 2: The overview of KHAN: hierarchical attention networks (upper) and knowledge encoding (lower).

$$\min_{w \in \mathbb{R}} \frac{1}{|A|} \sum_{a \in A} F(X, a) + \|X\|^2, \quad (1)$$

$$\tilde{W}_j = \text{MultiHead}(Q^w, K^w, V^w), \quad (2)$$

$$Q^w = K^w = V^w = W_j$$

$$s_j = \text{Avg}(\tilde{W}_j)$$

$$\tilde{S}_k = \text{MultiHead}(Q^s, K^s, V^s), \quad (3)$$

$$Q^s = K^s = V^s = S_k$$

# Approach

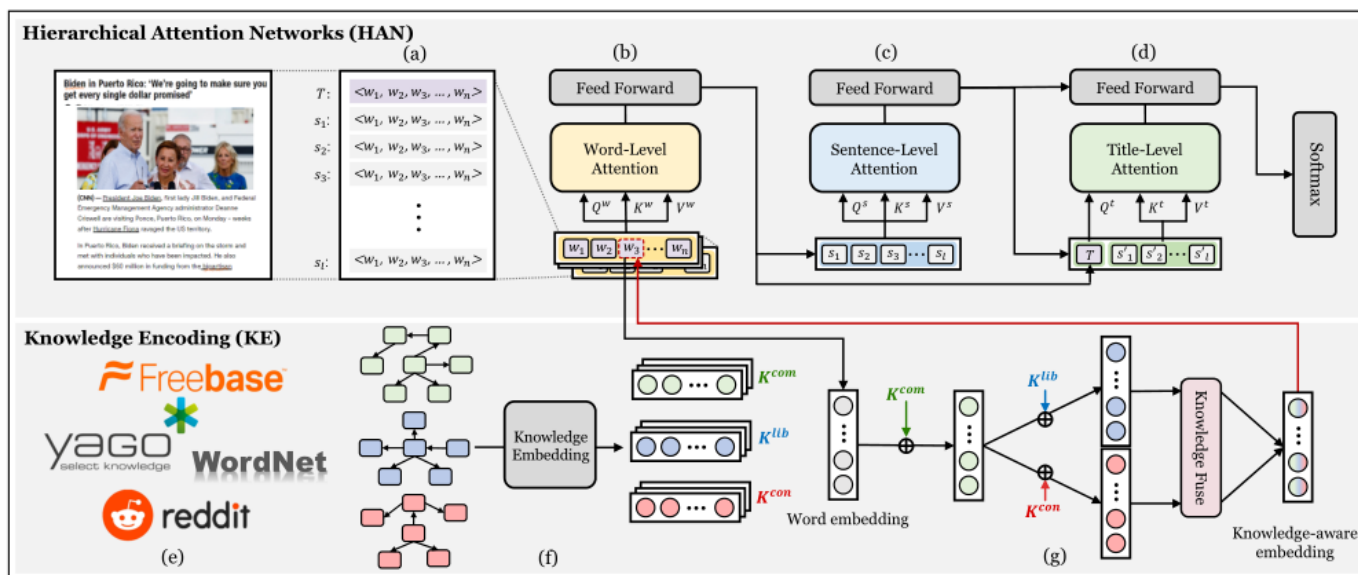


Figure 2: The overview of KHAN: hierarchical attention networks (upper) and knowledge encoding (lower).

$$\tilde{S}_k^T = \text{MultiHead}(Q^t, K^t, V^t), \quad (4)$$

$$\tilde{S}_k^* = \tilde{S}_k^T + \tilde{S}_k, \quad (5)$$

$$\hat{y} = \text{Predict}(a_k), \quad a_k = \text{Avg}(\tilde{S}_k^*), \quad (6)$$

# Approach

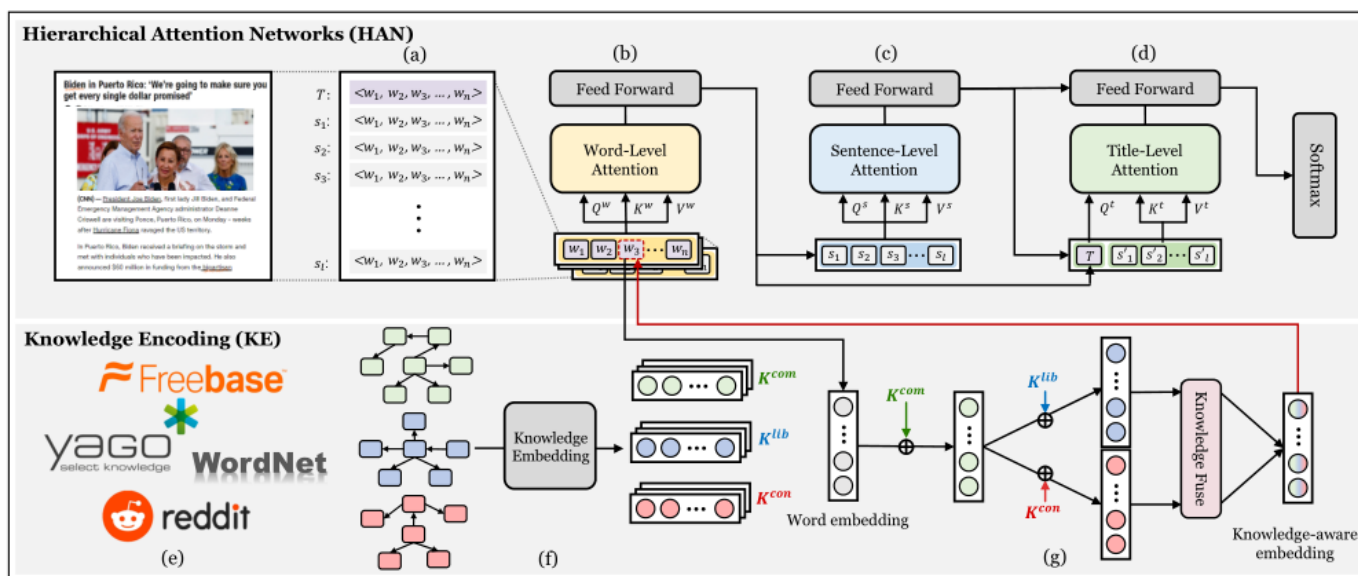


Figure 2: The overview of KHAN: hierarchical attention networks (upper) and knowledge encoding (lower).

$$\begin{aligned}
 e &\leftarrow W[i] \\
 e^{com} &\leftarrow (1 - \alpha) \cdot e \oplus \alpha \cdot K^{com}[i] \\
 e^{lib} &\leftarrow (1 - \beta) \cdot e^{com} \oplus \beta \cdot K^{lib}[i] \\
 e^{con} &\leftarrow (1 - \beta) \cdot e^{com} \oplus \beta \cdot K^{con}[i] \\
 W^*[i] &\leftarrow \text{Fuse}([e^{lib} || e^{con}]) \oplus e
 \end{aligned}$$

‘ $\oplus$ ’ means the element-wise addition





# Experiments

**Table 2: Statistics of political KGs.**

	KGAP [13]	KG-lib	KG-con
# of source posts	-	219,915	276,156
# of entities	1,071	5,581	6,316
# of relations	10,703	29,967	33,207
Political stances	Both	Liberal	Conservative

**Table 3: Statistics of political news article datasets.**

Dataset	# of articles	Class distribution
SemEval	645	407 / 238
AllSides-S	14.7k	6.6k / 4.6k / 3.5k
AllSides-L	719.2k	112.4k / 202.9k / 99.6k / 62.6k / 241.5k

# Experiments

Table 4: Comparison of the model accuracy on three real-world datasets (The bold font indicates the best results).

Method	Dataset		
	SemEval	AllSides-S	AllSides-L
<b>Word2Vec</b> [50]	0.7027	0.4858	0.4851
<b>GloVe</b> [55]	0.8071	0.7101	0.6354
<b>ELMo</b> [56]	0.8678	0.8197	0.7483
<b>BERT</b> [29]	0.8692	0.8246	0.7812
<b>RoBERTa</b> [48]	0.8708	0.8535	0.8222
<b>KGAP</b> [13]	0.8956	0.8602	N/A
<b>KCD</b> [69]	0.9087	0.8738	N/A
<b>KHAN-RotatE</b>	0.9426	0.9151	0.8584
<b>KHAN-HAKE</b>	0.9395	0.9216	0.8563
<b>KHAN-ModE</b>	<b>0.9521</b>	<b>0.9256</b>	<b>0.8617</b>

# Experiments

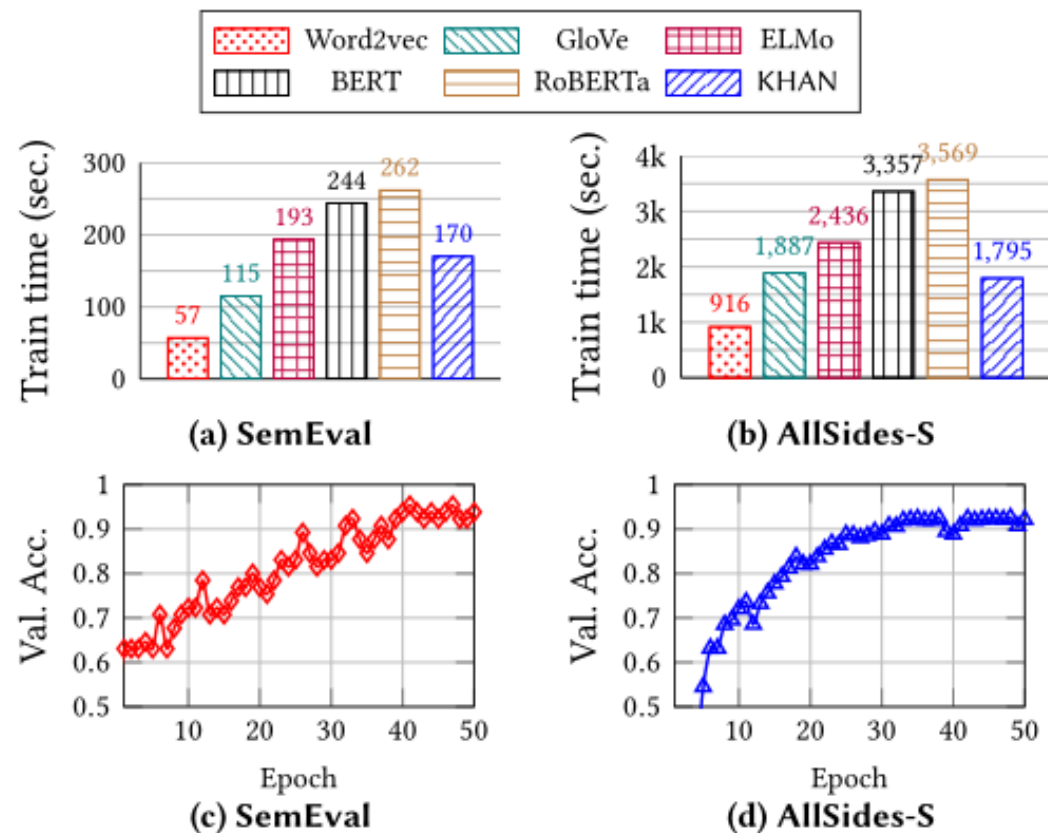


Figure 3: The training time and convergence rate with respect to training epochs on SemEval and AllSides-S.

# Experiments

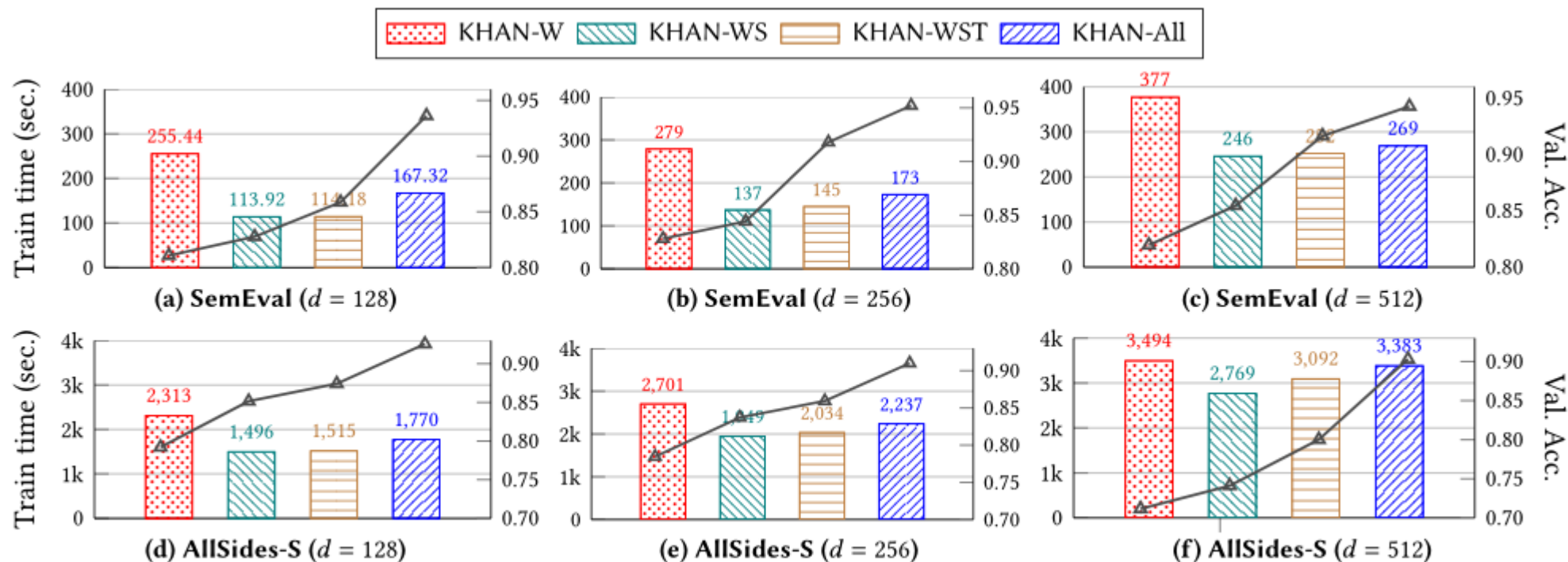


Figure 4: Effectiveness of the main components of KHAN in terms of the training time (bar) and model accuracy (line).

# Experiments

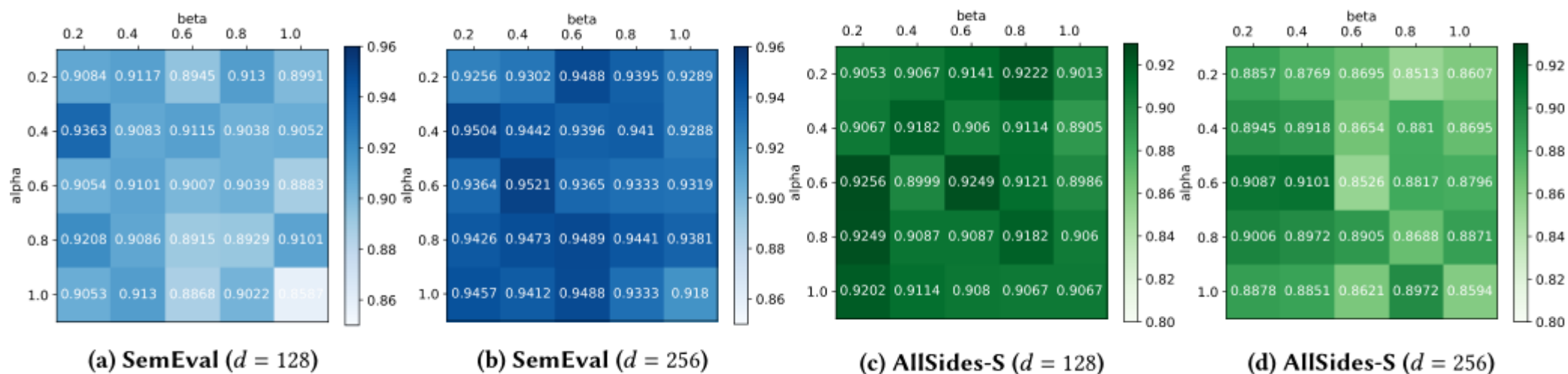


Figure 5: The impact of hyperparameters  $\alpha$  and  $\beta$  on the model accuracy of KHAN in political stance prediction.

# Experiments

**Table 5: Result of the user study: the top-5 factors in political stance predictions and their importance scores.**

Rank	Factor name	Importance score (1-5)
1	Context	$4.19 \pm 0.94$
2	Keyword	$4.01 \pm 0.88$
3	Person	$3.94 \pm 0.96$
4	Tone	$3.93 \pm 1.13$
5	Freq. used word	$3.35 \pm 1.07$

**Table 6: The knowledge graph (KG) completion accuracy of RotatE [62] on KG-lib and KG-con.**

RotatE						
Metric	KG-lib			KG-con		
	$d = 128$	$d = 256$	$d = 512$	$d = 128$	$d = 256$	$d = 512$
MR	632.69	573.84	567.85	728.78	654.26	640.45
MRR	0.1312	0.1700	0.1859	0.1079	0.1494	0.1633
HITS@1	0.0842	0.1089	0.1209	0.0692	0.0974	0.1093
HITS@3	0.1316	0.1801	0.1985	0.1059	0.1549	0.1693
HITS@10	0.2133	0.2859	0.3148	0.1743	0.2429	0.2625

# Experiments

Table 7: The knowledge graph (KG) completion accuracy of ModE [71] on KG-lib and KG-con.

ModE						
Metric	KG-lib			KG-con		
	$d = 128$	$d = 256$	$d = 512$	$d = 128$	$d = 256$	$d = 512$
MR	690.14	622.40	645.23	777.11	740.88	723.90
MRR	0.1312	0.1700	0.1859	0.1128	0.1354	0.1501
HITS@1	0.0842	0.1089	0.1209	0.0685	0.0801	0.0913
HITS@3	0.1316	0.1801	0.1985	0.1127	0.1404	0.1567
HITS@10	0.2133	0.2859	0.3148	0.1981	0.2458	0.2648

Table 8: The knowledge graph (KG) completion accuracy of HAKE [71] on KG-lib and KG-con.

HAKE						
Metric	KG-lib			KG-con		
	$d = 128$	$d = 256$	$d = 512$	$d = 128$	$d = 256$	$d = 512$
MR	593.76	597.58	606.03	694.30	684.55	685.92
MRR	0.1474	0.1688	0.1787	0.1311	0.1498	0.1639
HITS@1	0.0904	0.1102	0.1167	0.0831	0.0992	0.1120
HITS@3	0.1541	0.1761	0.1895	0.1348	0.1550	0.1704
HITS@10	0.2595	0.2844	0.3013	0.2205	0.2434	0.2612

# Experiments

Table 9: Comparison of our experimental results with the reported results [69] on SemEval (The bold font indicates the results better than the reported results).

Method	SemEval	
	Validation Acc.	Reported Acc.
<b>Word2Vec</b>	<b><math>0.7076 \pm 0.0104</math></b>	0.7027
<b>GloVe</b>	<b><math>0.8077 \pm 0.0251</math></b>	0.8071
ELMo	$0.8666 \pm 0.0197$	0.8678
<b>BERT</b>	<b><math>0.8769 \pm 0.0156</math></b>	0.8692
<b>RoBERTa</b>	<b><math>0.8923 \pm 0.0112</math></b>	0.8708
<b>KGAP</b>	N/A	0.8956
<b>KCD</b>	N/A	0.9087
<b>KHAN-RotatE</b>	$0.9426 \pm 0.0258$	N/A
<b>KHAN-HAKE</b>	$0.9395 \pm 0.0290$	N/A
<b>KHAN-ModE</b>	$0.9521 \pm 0.0183$	N/A

Table 10: Comparison of our experimental results with the reported results [69] on AllSides-S (The bold font indicates the results better than the reported results).

Method	AllSides-S	
	Validation Acc.	Reported Acc.
<b>Word2Vec</b>	<b><math>0.4977 \pm 0.0082</math></b>	0.4858
<b>GloVe</b>	$0.6978 \pm 0.0204$	0.7101
<b>ELMo</b>	$0.8085 \pm 0.0178$	0.8197
<b>BERT</b>	$0.8201 \pm 0.0101$	0.8246
<b>RoBERTa</b>	<b><math>0.8682 \pm 0.0081</math></b>	0.8535
<b>KGAP</b>	N/A	0.8602
<b>KCD</b>	N/A	0.8738
<b>KHAN-RotatE</b>	$0.9151 \pm 0.0105$	N/A
<b>KHAN-HAKE</b>	$0.9216 \pm 0.0041$	N/A
<b>KHAN-ModE</b>	$0.9256 \pm 0.0098$	N/A





**Thank you !**