Zoom Out and Observe:
News Environment Perception for Fake News Detection

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code:https://github.com/ICTMCG/News-Environment-Perception

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Introduction

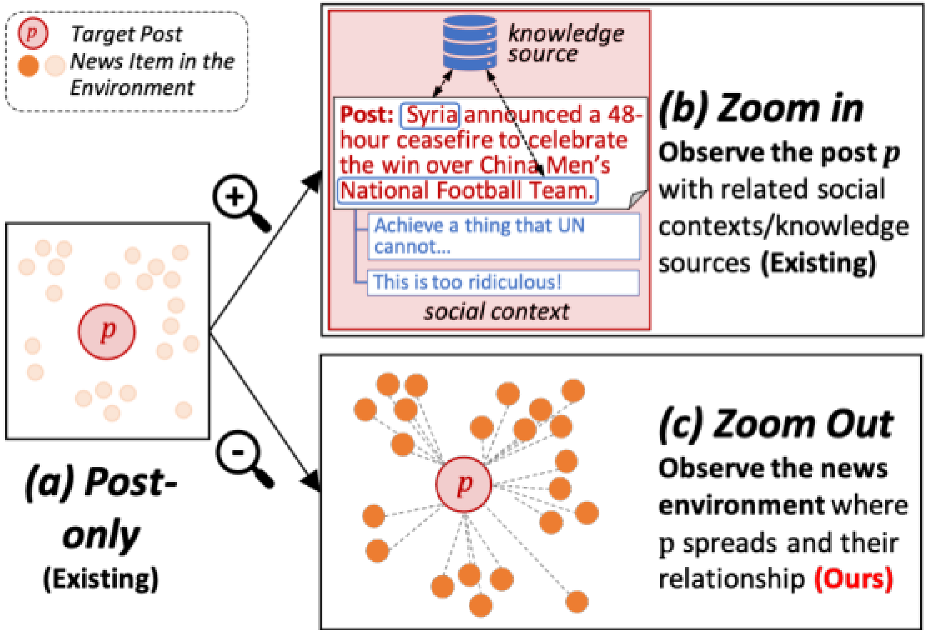


Figure 1: Existing methods for fake news detection rely on (a) the post content itself and (b) related post-level signals like social context and knowledge. Unlike (a) and (b), our method captures (c) signals from *news environments*.

Introduction

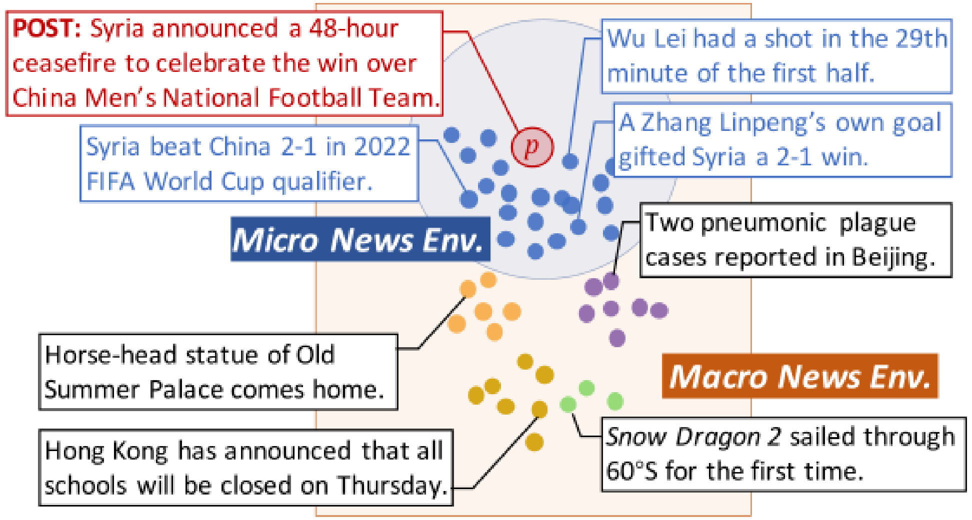


Figure 2: A fake news post p and its news environment containing recent news items in three days (2019/11/12 to 2019/11/14). Only the items in events that are reported multiple times (differentiated by dot colors) are displayed for brevity. We can see that p falls in a *popular* event on a Syria-China World Cup qualifier compared with other events and focuses on a *novel* aspect (unusual celebration in Syria).

events. We use a pretrained language model $\mathcal{M}$ (e.g., BERT (Devlin et al., 2019)) to obtain the post/news representation. For p or each item in the macro/micro environment e, the initial representation is the output of $\mathcal{M}$ for the [CLS] token:

$$\mathbf{p} = \mathcal{M}(p), \quad \mathbf{e} = \mathcal{M}(e). \tag{3}$$

Method

$$\mathbf{v}^p = \mathbf{g} \odot \mathbf{v}^{p,mac} + (\mathbf{1} - \mathbf{g}) \odot \mathbf{v}^{p,mic}, \tag{12}$$

where the gating vector $\mathbf{g} = \mathrm{sigmoid}(\mathrm{Linear}(\mathbf{o} \oplus \mathbf{v}^{p,mac}))$, sigmoid is to constrain the value of each element in $[0, 1]$, and $\mathbf{o}$ denotes the last-layer feature from a post-only detector.[3] $\mathbf{o}$ and $\mathbf{v}^p$ are further fed into an MLP and a softmax layer for final prediction:

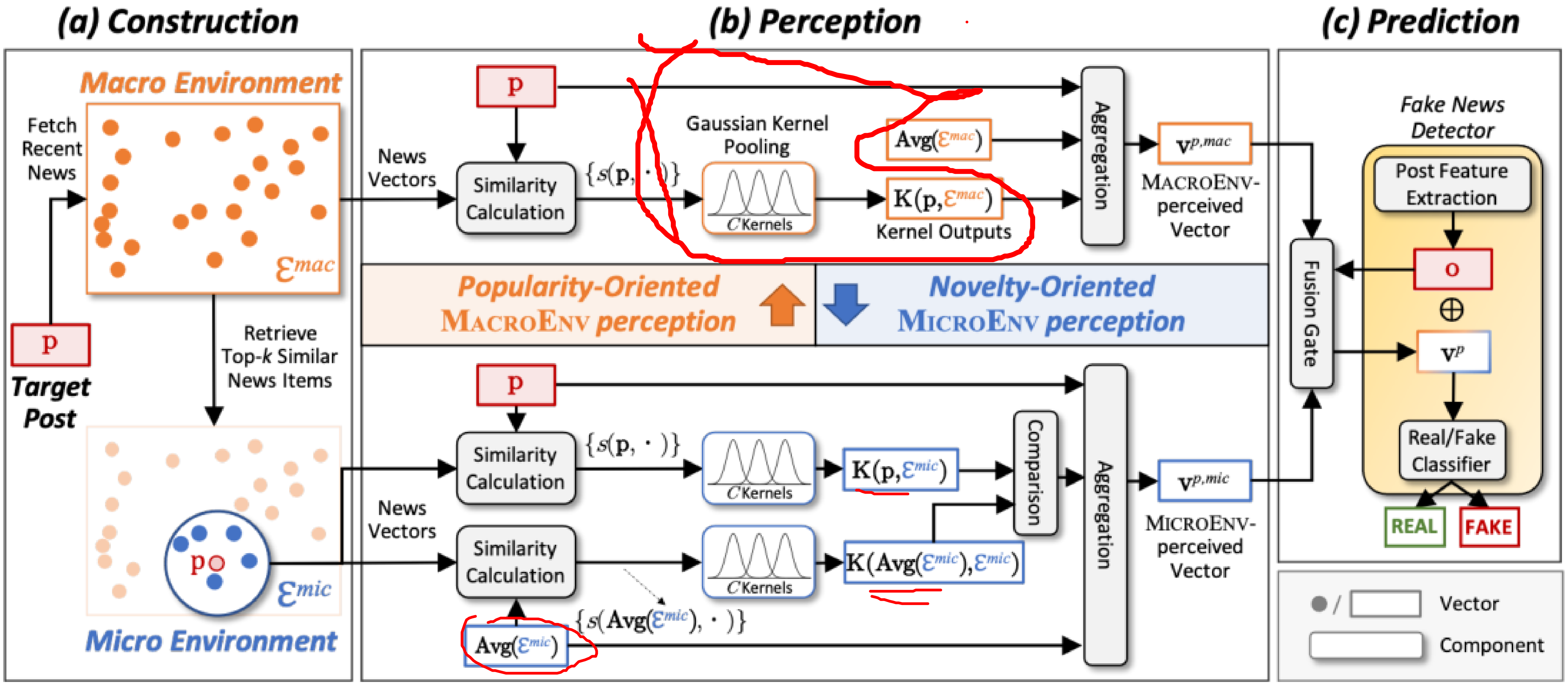
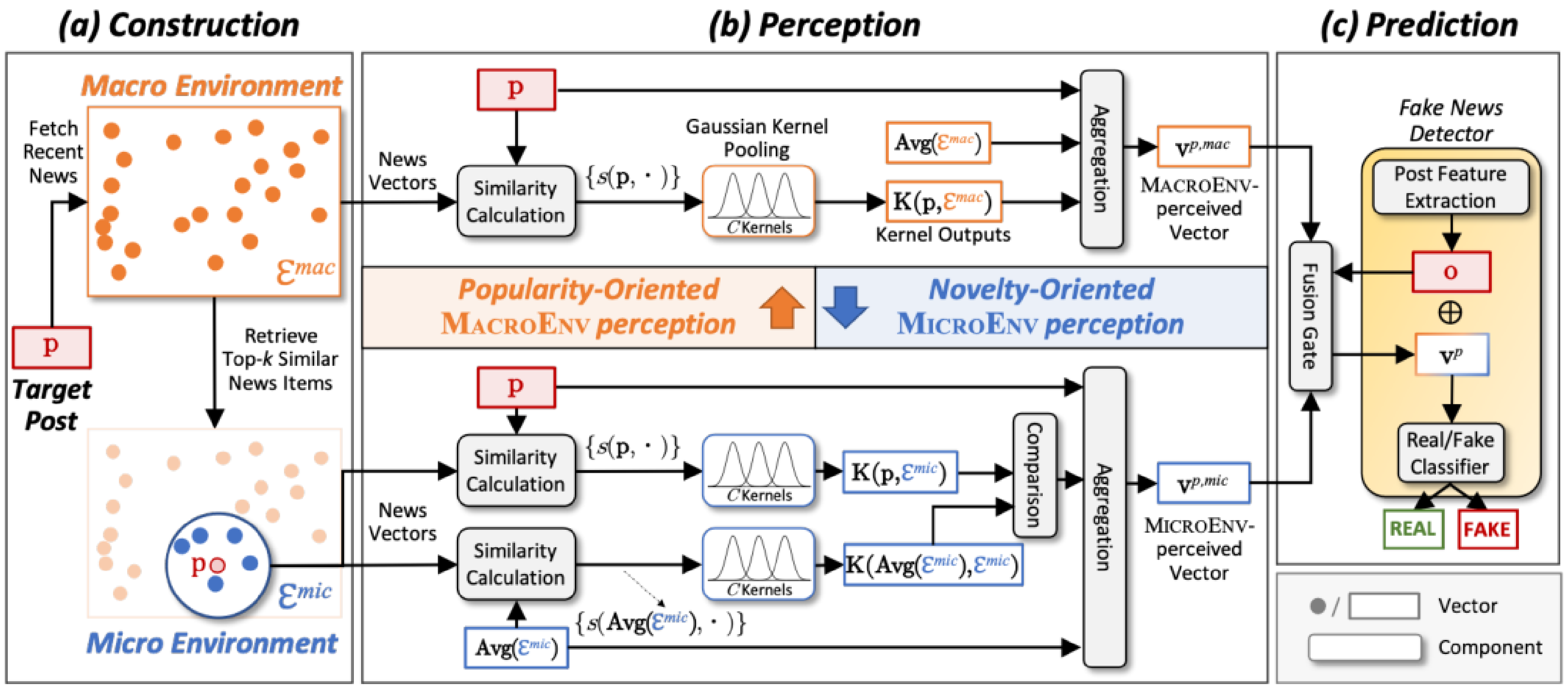


Figure 3: Architecture of the News Environment Perception Framework (NEP).

Method



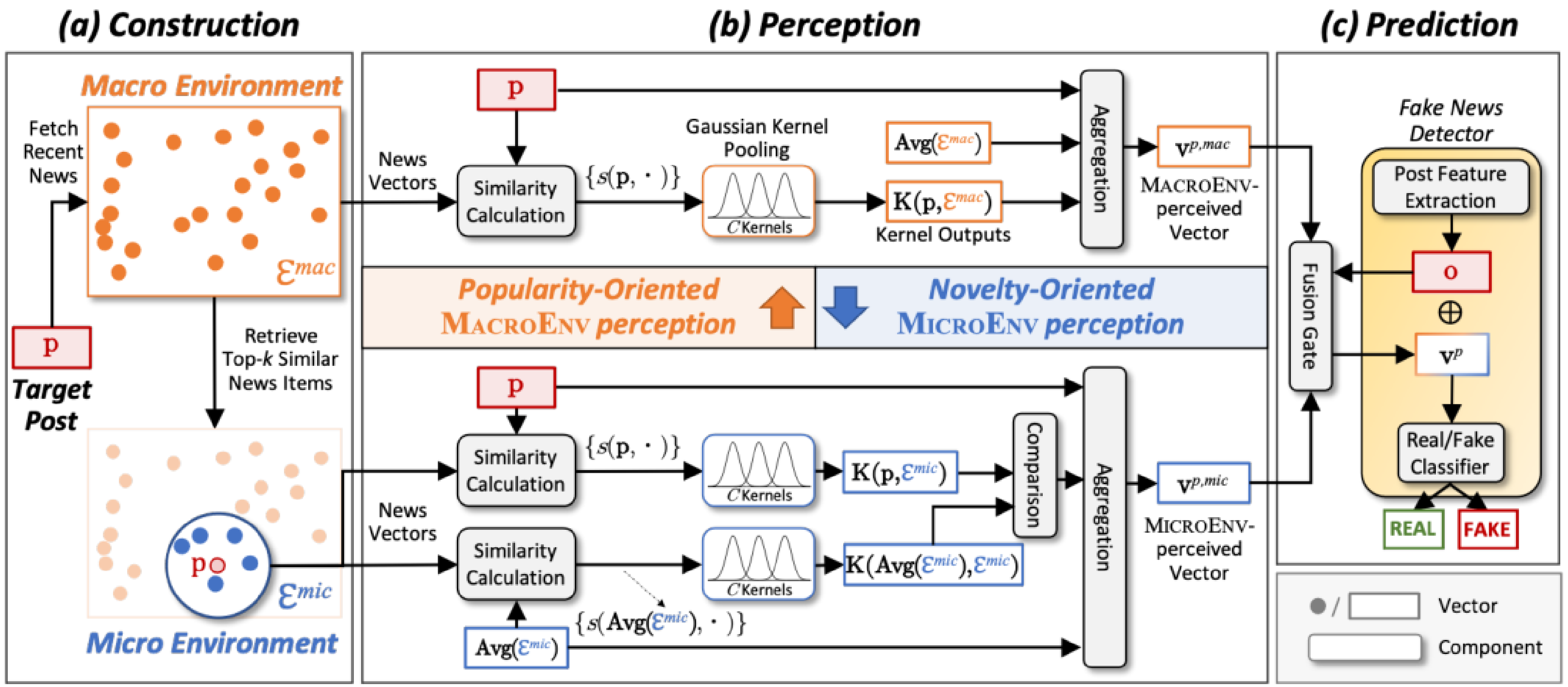
$$\mathcal{E}^{mac} = \{e : e \in \mathcal{E}, 0 < t_p - t_e \le T\} \quad (1)$$

$$\mathcal{E}^{mic} = \{e : e \in \mathrm{Topk}(p, \mathcal{E}^{mac})\} \quad (2)$$

$$\mathbf{p} = \mathcal{M}(p), \ \ \mathbf{e} = \mathcal{M}(e) \quad (3)$$

$$s(\mathbf{p}, \mathbf{e}_i) = \frac{\mathbf{p} \cdot \mathbf{e}_i}{\|\mathbf{p}\| \|\mathbf{e}_i\|} \quad (4)$$

Method



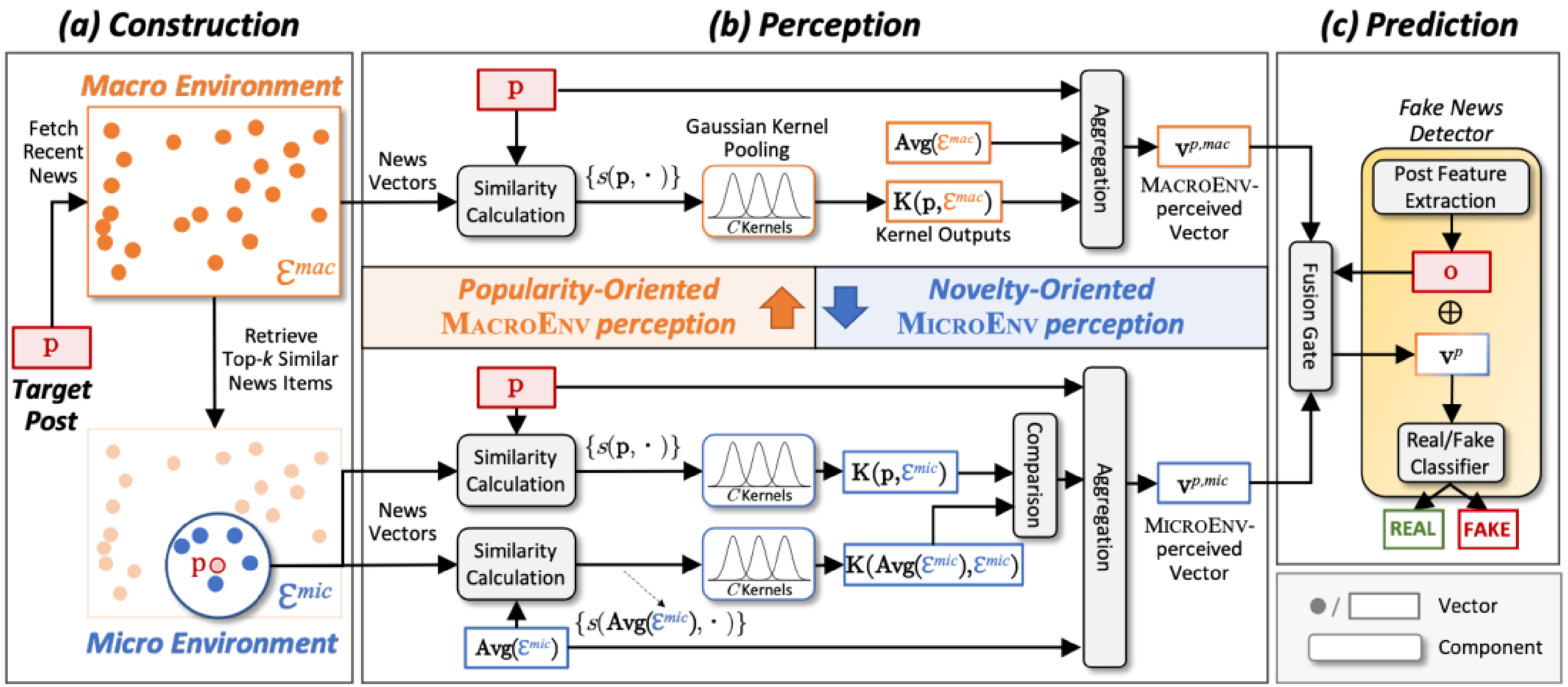
$$\mathbf{K}_k^i = \exp\left(-\frac{(s(\mathbf{p},\mathbf{e}_i)-\mu_k)^2}{2\sigma_k^2}\right) \quad (5)$$

$$\mathbf{K}_k(\mathbf{p},\mathcal{E}^{mac}) = \sum_{i=1}^{|\mathcal{E}^{mac}|} \mathbf{K}_k^i \quad (6)$$

$$\mathbf{K}(\mathbf{p},\mathcal{E}^{mac}) = \text{Norm}\left(\bigoplus_{k=1}^{C} \mathbf{K}_k(\mathbf{p},\mathcal{E}^{mac})\right) \quad (7)$$

$$\mathbf{v}^{p,mac} = \text{MLP}(\mathbf{p}\oplus\mathbf{m}(\mathcal{E}^{mac})\oplus\mathbf{K}(\mathbf{p},\mathcal{E}^{mac})) \quad (8)$$

Method



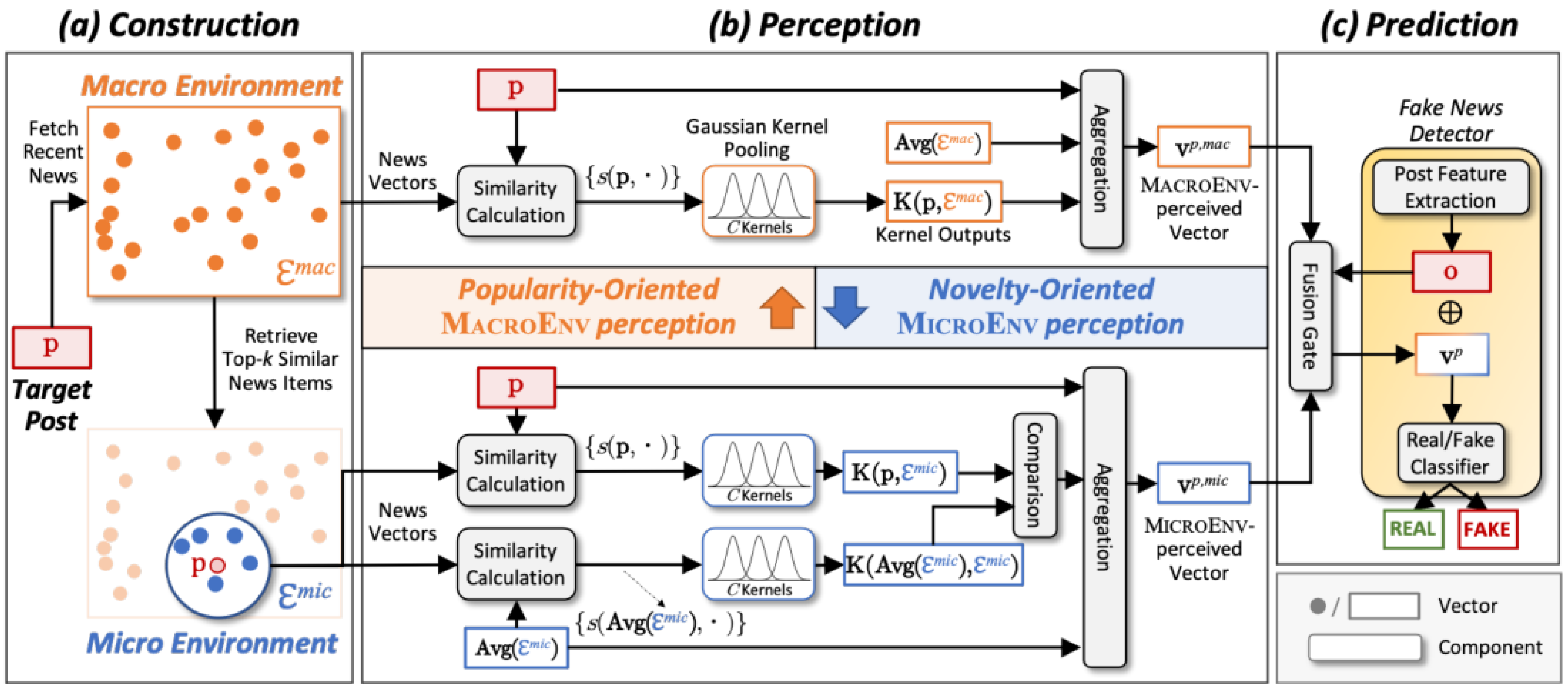
$$\mathbf{u}^{sem} = \mathrm{MLP}(\mathbf{p} \oplus \mathbf{m}(\mathcal{E}^{mic})) \quad (9)$$

$$\mathbf{v}^{p,mic} = \mathrm{MLP}(\mathbf{u}^{sem} \oplus \mathbf{u}^{sim}) \quad (11)$$

$$\mathbf{u}^{sim} = \mathrm{MLP}(\mathrm{g}(\mathbf{K}(\mathbf{p}, \mathcal{E}^{mic}), \mathbf{K}(\mathbf{m}(\mathcal{E}^{mic}), \mathcal{E}^{mic}))) \quad (10)$$

$$\mathrm{g}(\mathbf{x}, \mathbf{y}) = (\mathbf{x} \odot \mathbf{y}) \oplus (\mathbf{x} - \mathbf{y})$$

Method



$$\mathbf{v}^p = \mathbf{g} \odot \mathbf{v}^{p,mac} + (\mathbf{1} - \mathbf{g}) \odot \mathbf{v}^{p,mic} \quad (12)$$

$$\hat{\mathbf{y}} = \mathrm{softmax}(\mathrm{MLP}(\mathbf{o} \oplus \mathbf{v}^p)) \quad (13)$$

where the gating vector $\mathbf{g} = \mathrm{sigmoid}(\mathrm{Linear}(\mathbf{o} \oplus \mathbf{v}^{p,mac}))$, sigmoid is to constrain the value of each

Experiments

Table 1: Statistics of the datasets.

Dataset	Chinese			English		
	Train	Val	Test	Train	Val	Test
#Real	8,787	5,131	5,625	1,976	656	661
#Fake	8,992	4,923	5,608	1,924	638	628
Total	17,779	10,054	11,233	3,900	1,294	1,289
#News Items	583,208			1,003,646		
Min/Avg/Max of $\lvert\mathcal{E}^{mac}\rvert$ in 3 days	41 / 505 / 1,563			308 / 1,614 / 2,211		

Experiments

Table 2: Performance comparison of base models with and without the NEP. The better result in each group using the same base model are in **boldface**.

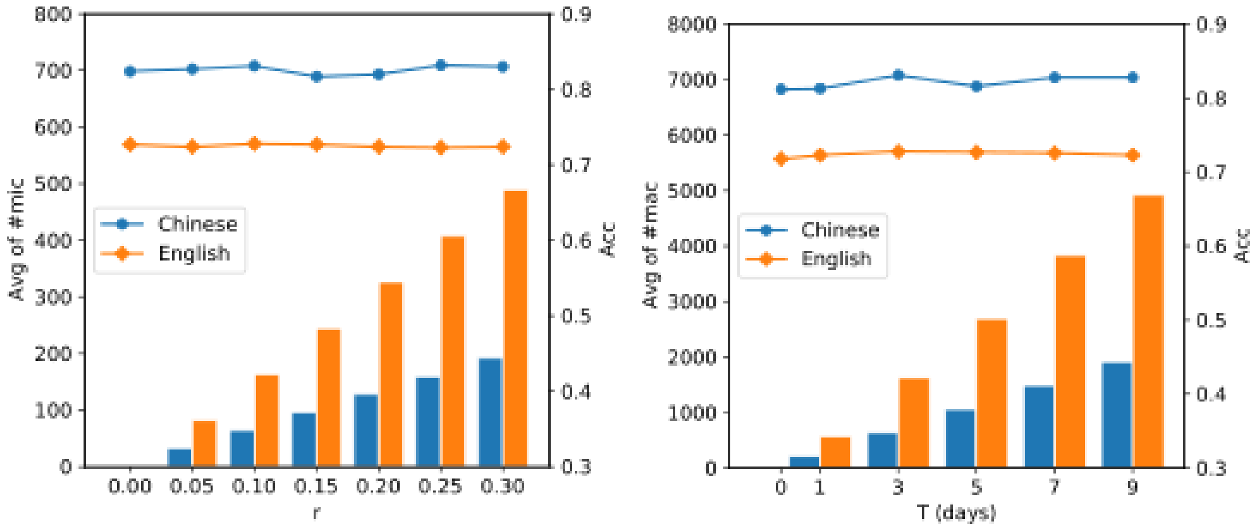
Model		Chinese Acc.	Chinese macF1	Chinese $F1_{fake}$	Chinese $F1_{real}$	English Acc.	English macF1	English $F1_{fake}$	English $F1_{real}$
Post-Only	Bi-LSTM	0.727	0.713	0.652	0.775	0.705	0.704	0.689	**0.719**
	+*NEP*	**0.776**	**0.771**	**0.739**	**0.803**	**0.718**	**0.718**	**0.720**	0.716
	$EANN_T$	0.732	0.718	0.657	0.780	0.700	0.699	0.683	0.714
	+*NEP*	**0.776**	**0.770**	**0.733**	**0.807**	**0.722**	**0.722**	**0.722**	**0.722**
	BERT	0.792	0.785	0.744	0.825	0.709	0.709	0.701	**0.716**
	+*NEP*	**0.810**	**0.805**	**0.772**	**0.837**	**0.718**	**0.718**	**0.720**	0.715
	BERT-Emo	0.812	0.807	0.776	0.838	0.718	0.718	0.719	0.718
	+*NEP*	**0.831**	**0.829**	**0.808**	**0.850**	**0.728**	**0.728**	**0.728**	**0.728**
"Zoom-In"	DeClarE	0.764	0.758	0.720	0.795	0.714	0.714	0.709	**0.718**
	+*NEP*	**0.800**	**0.797**	**0.773**	**0.822**	**0.717**	**0.716**	**0.718**	0.714
	MAC	0.755	0.751	0.717	0.784	0.706	0.705	0.708	0.701
	+*NEP*	**0.764**	**0.760**	**0.732**	**0.789**	**0.716**	**0.716**	**0.716**	**0.716**

Experiments

Table 3: Performance comparison of the NEP and its variants without the fake news detector or without the environment perception module. The best result in each group is in **boldface**.

Model	Chinese				English			
	Acc.	macF1	$F1_{fake}$	$F1_{real}$	Acc.	macF1	$F1_{fake}$	$F1_{real}$
MACROENV	0.689	0.659	0.557	0.761	0.693	0.693	**0.696**	0.689
MICROENV	0.666	0.626	0.503	0.748	0.695	0.695	0.694	0.696
MACROENV+MICROENV	**0.694**	**0.666**	**0.569**	**0.763**	**0.696**	**0.696**	0.694	**0.697**
BERT-Emo + *NEP*	**0.831**	**0.829**	**0.808**	**0.850**	**0.728**	**0.728**	**0.728**	0.728
w/o MACROENV	0.822	0.819	0.794	0.843	0.726	0.726	0.726	0.725
w/o MICROENV	0.824	0.820	0.795	0.845	0.723	0.723	0.715	**0.731**
DeClarE + *NEP*	**0.797**	**0.800**	**0.773**	**0.822**	**0.717**	**0.716**	0.718	**0.714**
w/o MACROENV	0.776	0.771	0.735	0.806	0.712	0.711	0.709	0.713
w/o MICROENV	0.778	0.773	0.736	0.809	0.709	0.709	**0.719**	0.698

Experiments



(a) Proportion Factor r (b) Day Difference T

Figure 4: Effects of (a) the proportion factor r and (b) the day difference T. Lines show the accuracies and bars show the average numbers of news items in the micro/macro environments.

Experiments

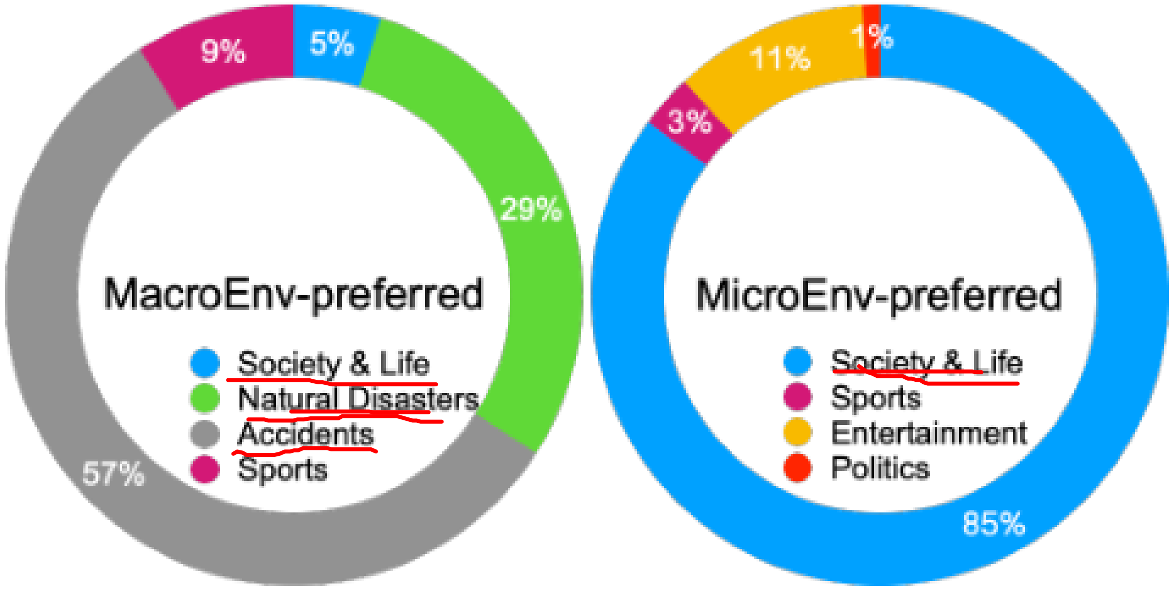


Figure 5: Categories of MACROENV- and MICROENV-preferred samples.

Experiments

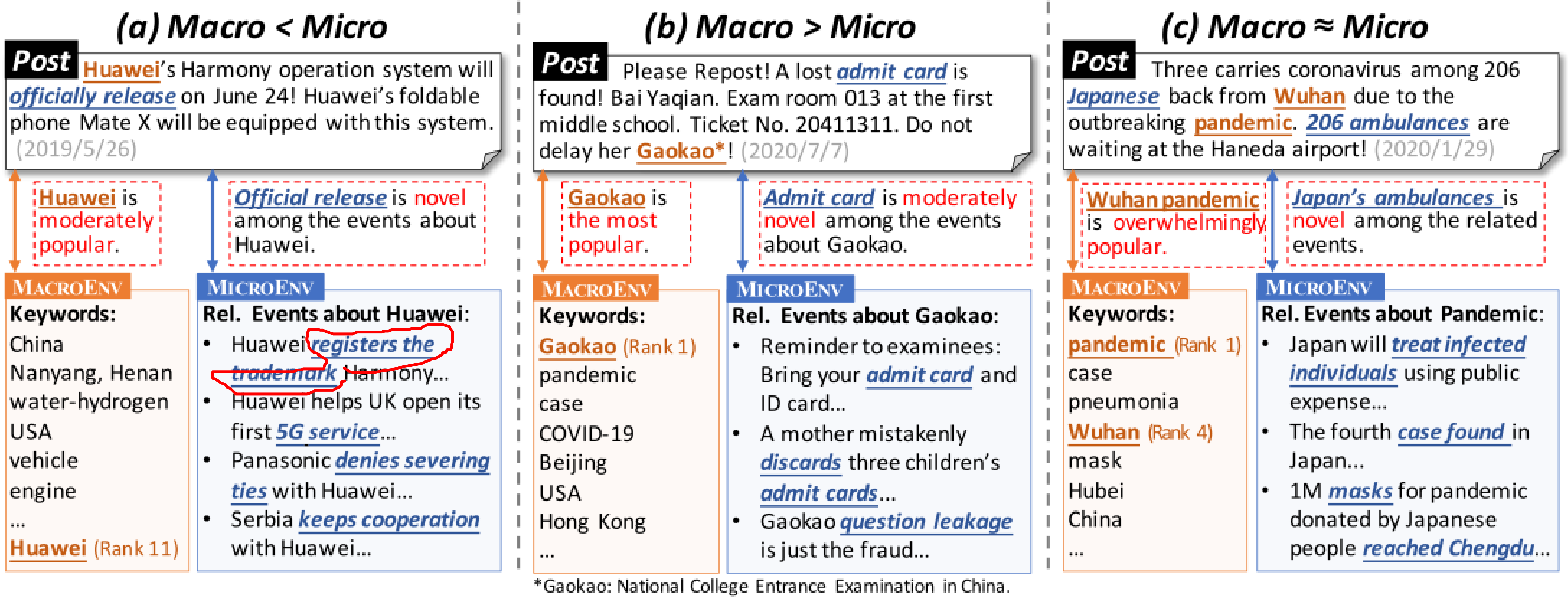


Figure 6: Three fake news cases with different preferences on environmental information. Underlined regular words hit the keywords in the MACROENV and *underlined italic* words are related to the MICROENV. Keywords are extracted using TextRank (Mihalcea and Tarau, 2004).

Experiments

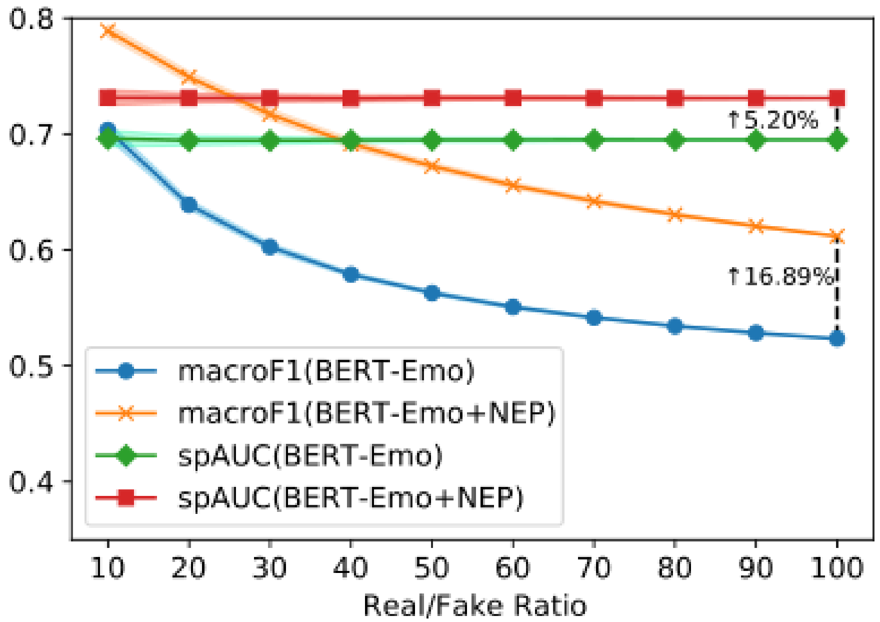


Figure 7: Macro F1s and spAUCs on the online data in different real/fake ratios. We sampled 100 times from the 100:1 set for each fo the first nine ratios. Shadows show the standard deviations. The percentages denote relative improvements using the NEP.

Thanks