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Why NewsEnv? A Motivating Example

- **Assumption:** A news environment is an **important inspiration of the fabrication** of contemporary fake news, as fake news has to **grab attention** from it.

Let's observe the NewsEnv as a **fake news creator**!

The Syria-China football match seems **popular**. I can follow it by fabricating some **novel** (and fake) thing on this event!



A fake news creator

Syria beat China 2-1 in 2022 FIFA World Cup qualifier.

Syria announced a 48-hour ceasefire to celebrate the win over China Men's National Football Team. (FAKE)

A Zhang Linpeng's own goal gifted Syria a 2-1 win.

Wu Lei had a shot in the 29th minute of the first half.

Snow Dragon 2 sailed through 60°S for the first time.

Two pneumonic plague cases reported in Beijing.



A fake news creator

Horse-head statue of Old Summer Palace comes home.

Hong Kong has announced that all schools will be closed on Thursday.

News Environment (containing recent news items) in 2019/11/12~2019/11/14. Events are differentiated by colors.

Proposal: Perceive Popularity & Novelty from the NewsEnv

- **Popularity:** Fake news tends to emerge along with a **popular event**, to obtain great exposure and impacts.
- **Novelty:** Fake news often provide **novel side information** for a popular event, to catch audiences' attention and boost the spread.

Conventional $y = p(\text{Veracity}=\text{fake} \mid \text{Content})$

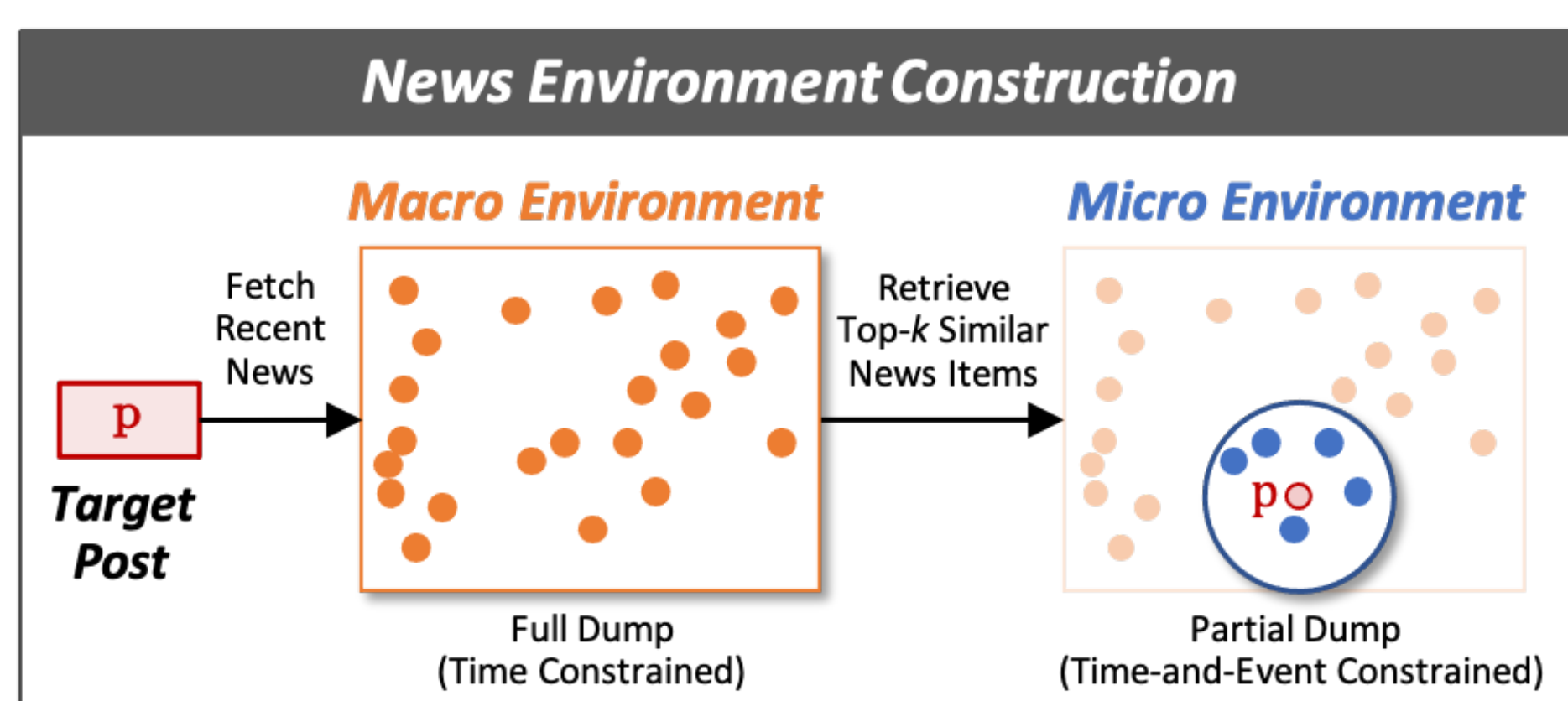
Ours (Theoretical) $y = p(\text{Veracity}=\text{fake} \mid \text{Content}, \text{NewsEnv})$

Ours (In Practice) $y = p(\text{Veracity}=\text{fake} \mid \text{Content}, \text{Popularity/Novelty in NewsEnv})$

NewsEnv Perception (NEP) Framework

Step 1: NewsEnv Construction

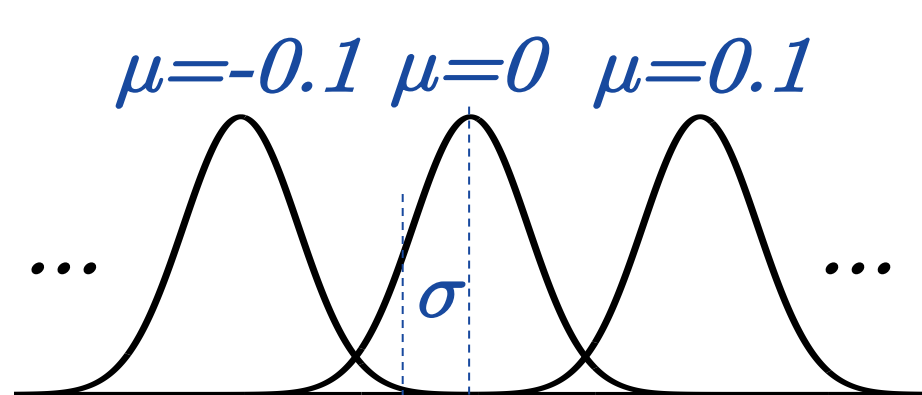
- **MacroEnv:** A full dump of **recent news items** (say, 3d) from selected outlets to reflect the represent distribution of mainstream focuses.
- **MicroEnv:** Retrieve **Top-k similar** news items to the target post p , to build a event-constrained environment.



Step 2: NewsEnv Perception

- ① **Representation and Similarity Calculation:** Use BERT to obtain vectors and *cosine* similarity to obtain the post-news item similarity.
- ② **Gaussian Kernel Pooling:** Transform the sim list into a fixed-dim vector.

- Determine the kernel distribution across $[-1,1]$



Soft Counting
when *cosine sim* $\rightarrow \mu$, output $\rightarrow 1$;
otherwise 0

- Calculate Gaussian outputs for each kernel. Sum, concat, & norm to obtain the Kernel Output.

$$K_k^i = \exp\left(-\frac{(s(p, e_i) - \mu_k)^2}{2\sigma_k^2}\right) \quad K_k(p, \mathcal{E}^{mac}) = \sum_{i=1}^{|\mathcal{E}^{mac}|} K_k^i \quad K(p, \mathcal{E}^{mac}) = \text{Norm}\left(\bigoplus_{k=1}^C K_k(p, \mathcal{E}^{mac})\right)$$

- **For Popularity-Oriented MacroEnv Perception:** Obtain the Kernel Output for $p-\mathcal{E}^{mac}$.

- **For Novelty-Oriented MicroEnv Perception:** Obtain the Kernel Output for $p-\mathcal{E}^{mic}$ & $m(\mathcal{E}^{mic})-\mathcal{E}^{mic}$ ($m(\mathcal{E}^{mic})$ is the center vector of MicroEnv).

③ Aggregation:

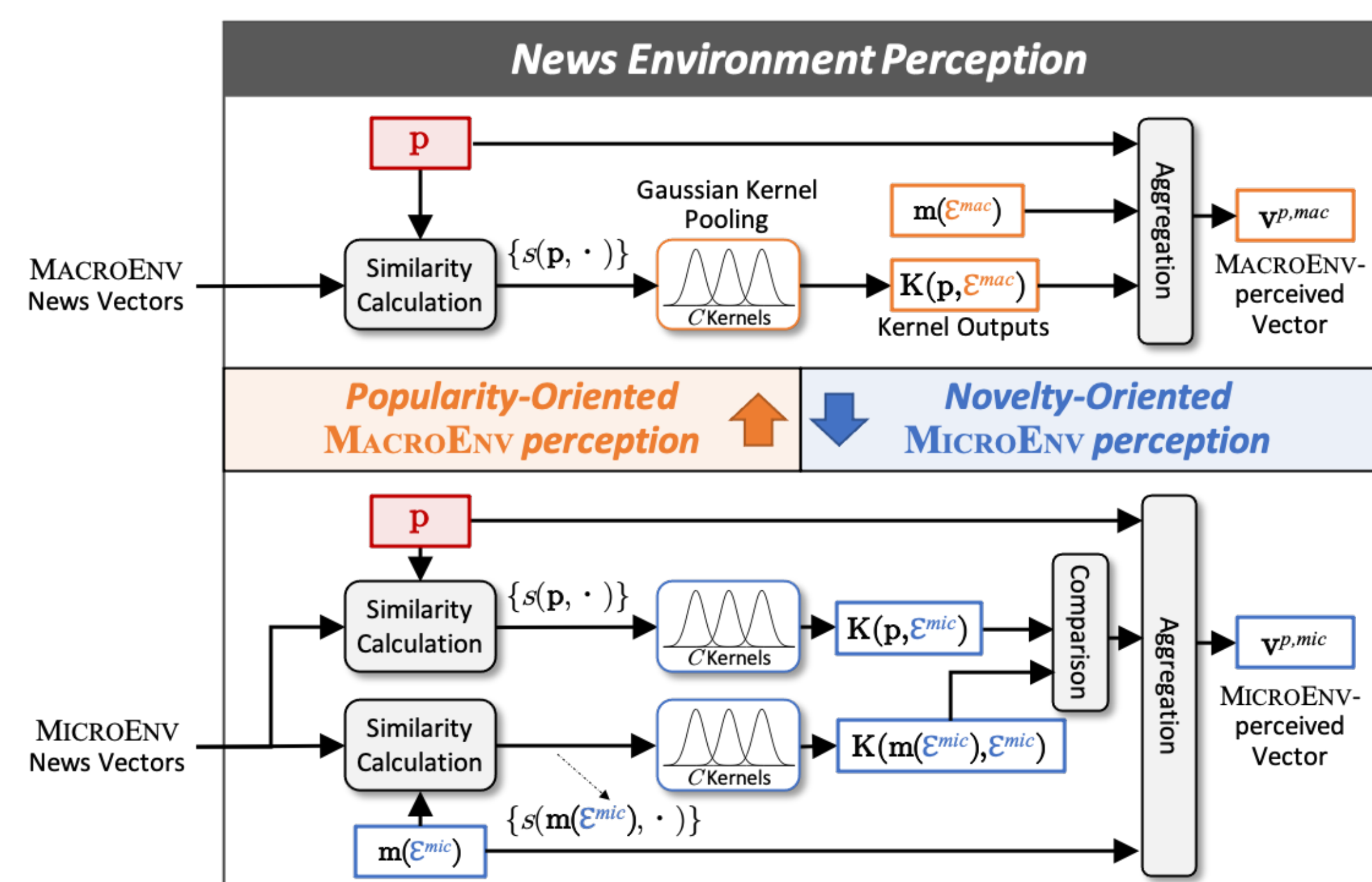
- **MacroEnv** $v^{p,mac} = \text{MLP}(p \oplus m(\mathcal{E}^{mac}) \oplus K(p, \mathcal{E}^{mac}))$

- **MicroEnv** $u^{sem} = \text{MLP}(p \oplus m(\mathcal{E}^{mic})),$

$$u^{sim} = \text{MLP}(g(K(p, \mathcal{E}^{mic}), K(m(\mathcal{E}^{mic}), \mathcal{E}^{mic})))$$

$$v^{p,mic} = \text{MLP}(u^{sem} \oplus u^{sim}),$$

where $g(x, y) = (x \odot y) \oplus (x - y)$.

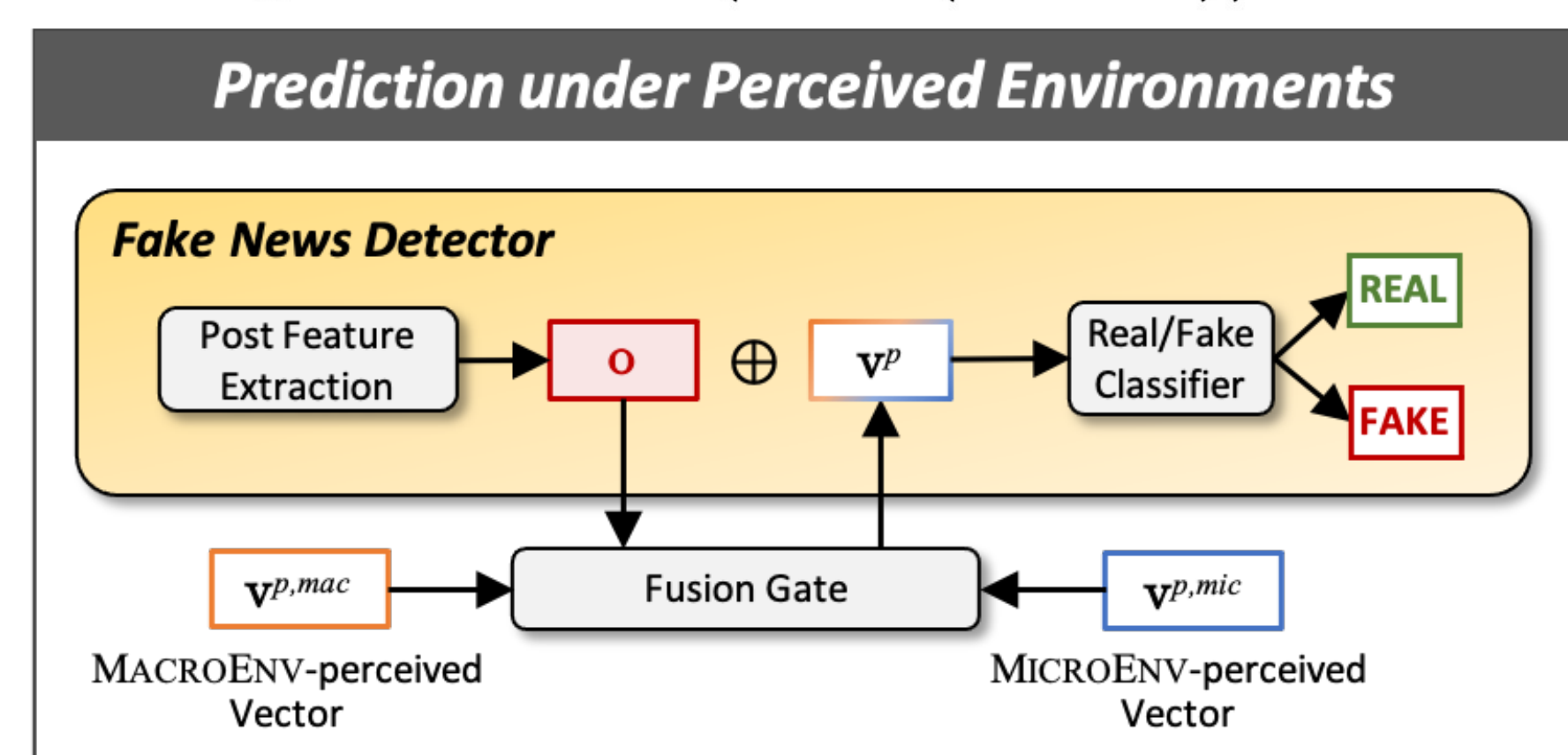


Step 3: Prediction under Perceived NewsEnv

- ① **Gate Fusion:** $v^p = g \odot v^{p,mac} + (1 - g) \odot v^{p,mic}$

$$g = \text{sigmoid}(\text{Linear}(o \oplus v^{p,mic}))$$

- ② **Final Prediction:** $\hat{y} = \text{softmax}(\text{MLP}(o \oplus v^p))$



Experiments on New 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

Model	Chinese				English			
	Acc.	macF1	F1 _{fake}	F1 _{real}	Acc.	macF1	F1 _{fake}	F1 _{real}
Post-Only	Bi-LSTM	0.727	0.713	0.652	0.775	0.705	0.704	0.689
	+NEP	0.776	0.771	0.739	0.803	0.718	0.718	0.720
	EANN _T	0.732	0.718	0.657	0.780	0.700	0.699	0.683
	+NEP	0.776	0.770	0.733	0.807	0.722	0.722	0.722
	BERT	0.792	0.785	0.744	0.825	0.709	0.709	0.701
	+NEP	0.810	0.805	0.772	0.837	0.718	0.718	0.720

Model	Chinese				English			
	Acc.	macF1	F1 _{fake}	F1 _{real}	Acc.	macF1	F1 _{fake}	F1 _{real}
"Zoom-In"	DeClarE	0.764	0.758	0.720	0.795	0.714	0.714	0.709
	+NEP	0.800	0.797	0.773	0.822	0.717	0.716	0.718
	MAC	0.755	0.751	0.717	0.784	0.706	0.705	0.701

Model	Chinese				English			
	Acc.	macF1	F1 _{fake}	F1 _{real}	Acc.	macF1	F1 _{fake}	F1 _{real}
"Zoom-In"	+NEP	0.764	0.760	0.732	0.789	0.716	0.716	0.716

News Outlet
Chinese People's Daily
Xinhua Agency
Xinhua Net
CCTV News
The Paper
Toutiao News
English Huffington Post
NPR
Daily Mail

Stats of News Outlets in NewsEnv

Performances

- All six base models see an improvement in terms of Acc. and macF1.

Conclusion

- **Problem:** To the best of our knowledge, we are the **first** to incorporate news environment perception in fake news detection.
- **Method:** We propose the **NEP framework** which exploits the perceived signals from the macro and micro news environments of the given post for fake news detection.
- **Data & Experiments:** We construct the **first** dataset that includes contemporary main-stream news data for fake news detection. Experiments on offline and online data show the effectiveness of NEP.



GitHub Repo