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

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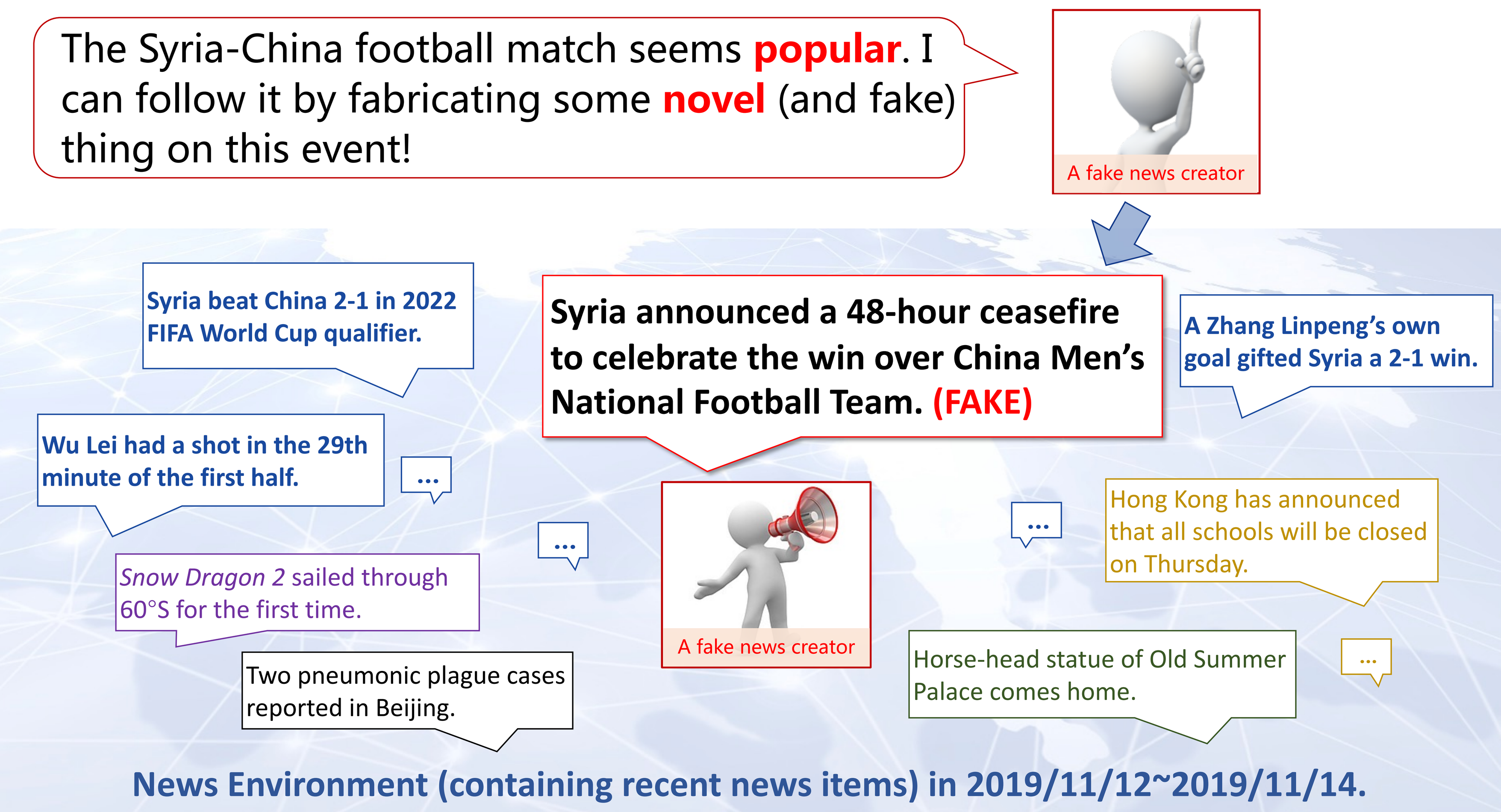
Why NewsEnv? A Motivating Example

- **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!



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

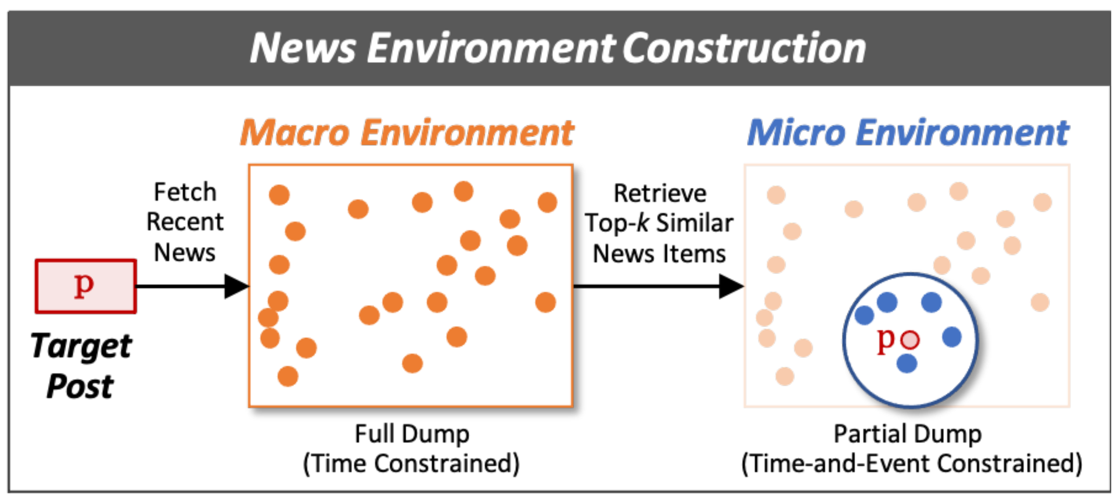
- **Popularity:** Fake news tends to emerge along with **a popular event**, to obtain great exposure and impacts.
- **Novelty:** Fake news often provides **novel side information** for a popular event, to catch audiences' attention and boost the spread.

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

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 an event-constrained environment.

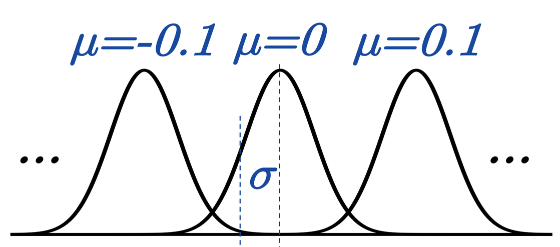


Step 2: NewsEnv Perception

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→μ, output → 1; otherwise 0

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

$$\mathbf{K}_k^i = \exp\left(-\frac{(s(\mathbf{p},\mathbf{e}_i)-\mu_k)^2}{2\sigma_k^2}\right) \qquad \mathbf{K}_k(\mathbf{p},\mathcal{E}^{mac}) = \sum_{i=1}^{|\mathcal{E}^{mac}|}\mathbf{K}_k^i \qquad \mathbf{K}(\mathbf{p},\mathcal{E}^{mac}) = \mathrm{Norm}\left(\bigoplus_{k=1}^{C}\mathbf{K}_k(\mathbf{p},\mathcal{E}^{mac})\right)$$

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

③ **Aggregation:**

- **MacroEnv**

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

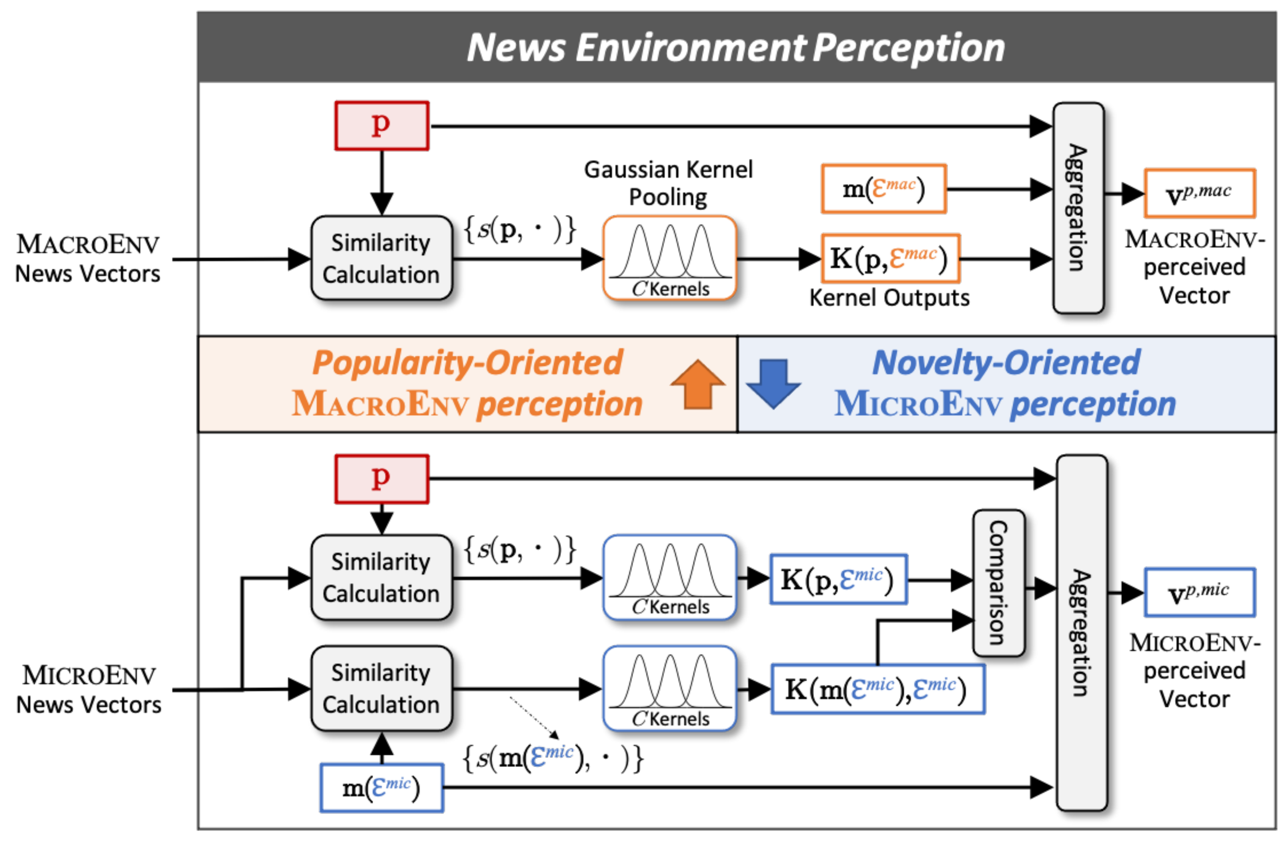
- **MicroEnv**

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

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

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

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



Step 3: Prediction under Perceived NewsEnv

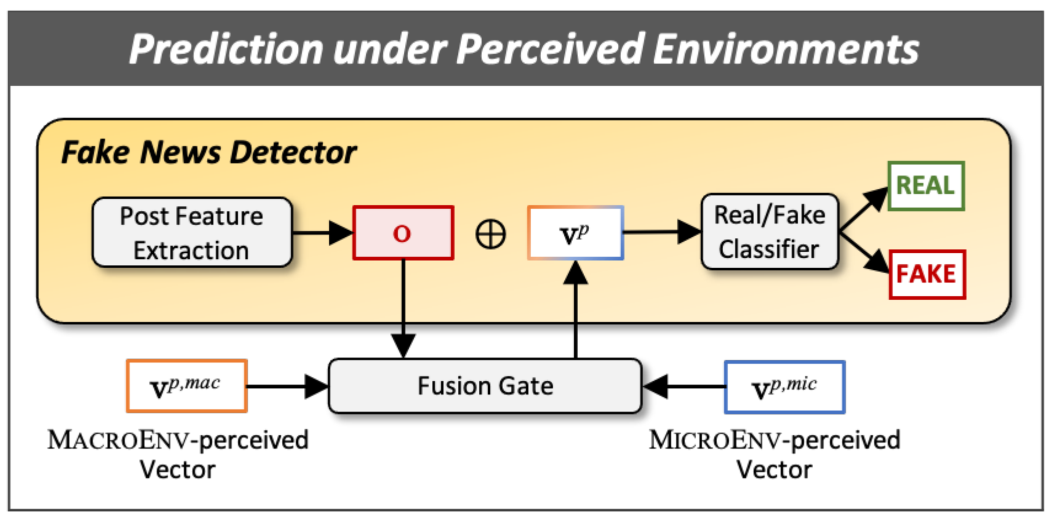
① **Gate Fusion:**

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

$$\mathbf{g} = \mathrm{sigmoid}\left(\mathrm{Linear}\left(\mathbf{o} \oplus \mathbf{v}^{p,mac}\right)\right)$$

② **Final Prediction:**

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



Experiments on New Datasets

Stats of 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		

News Outlets in NewsEnv

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

Performances

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

Model		Chinese Acc.	Chinese macF1	Chinese $\mathrm{F1}_{\mathrm{fake}}$	Chinese $\mathrm{F1}_{\mathrm{real}}$	English Acc.	English macF1	English $\mathrm{F1}_{\mathrm{fake}}$	English $\mathrm{F1}_{\mathrm{real}}$
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
	$\mathrm{EANN}_{\mathrm{T}}$	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**

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