

Learn over Past, Evolve for Future: Forecasting Temporal Trends for Fake News Detection

Beizhe Hu^{1,2}, Qiang Sheng^{1,2}, Juan Cao^{1,2}, Yongchun Zhu^{1,2}, Danding Wang¹, Zhengjia Wang^{1,2}, Zhiwei Jin³

¹Key Lab of Intelligent Information Processing, Institute of Computing Technology, Chinese Academy of Sciences

²University of Chinese Academy of Sciences

³ZhongKeRuijian Technology Co., Ltd

Presenter: Beizhe Hu





Media Synthesis &
Forensics Lab

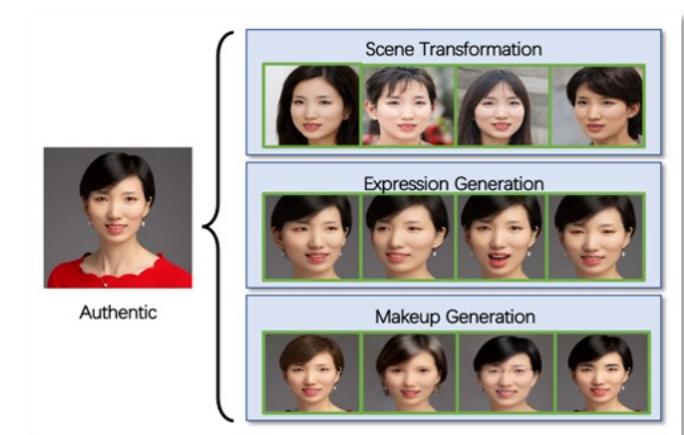
MAKE THE WORLD MORE CREDIBLE



Fake News Detection
Fact-Checking



Deep Synthesized Media
Detection & Attribution

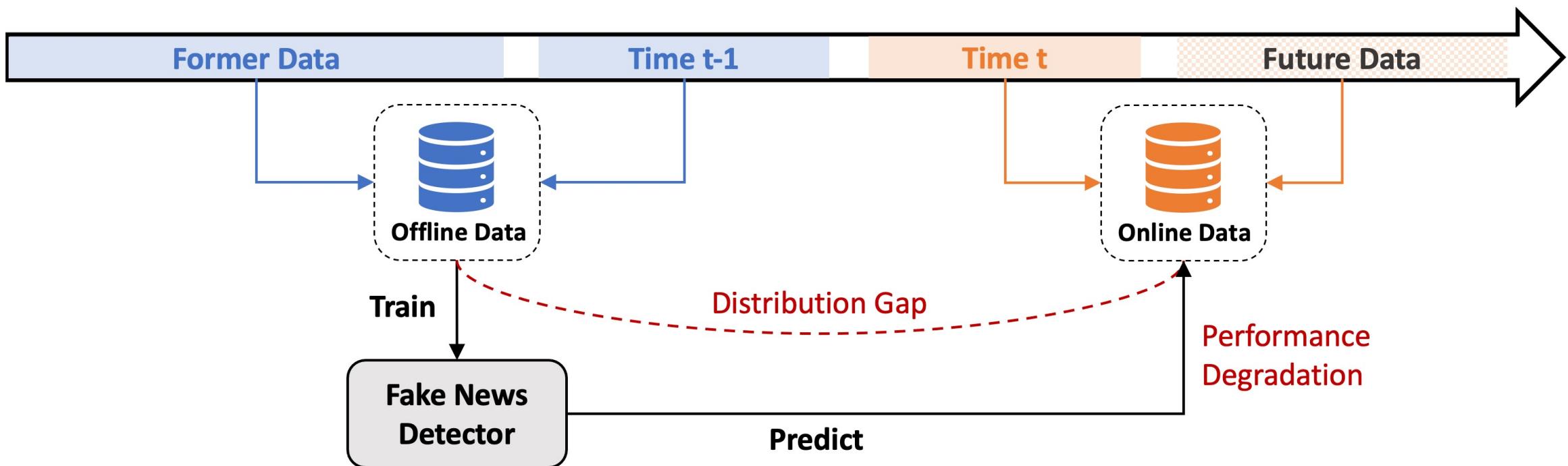


Attacking & Defense
for AI Safety

Introduction: Temporal shift in fake news detection



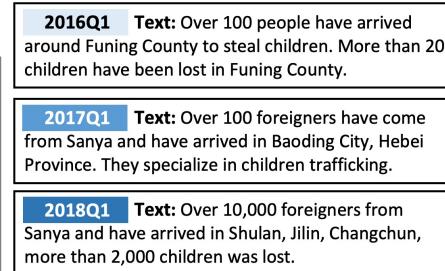
- The rapidly-evolving nature of news leads to the distributional difference between **offline** and **online** data, namely **temporal shift**
- **Temporal shift** causes significant **performance degradation** to the fake news detection model **trained on offline data** when **predicting on online data**



Introduction: Diverse topic-level temporal patterns

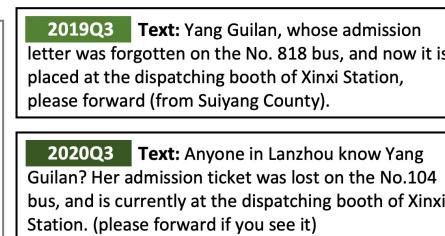
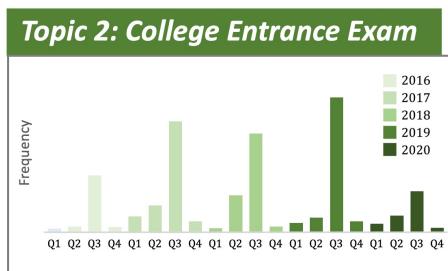


- The appearance of news events on the same **topic** presents **diverse temporal patterns**
- These temporal patterns indicate the **different importance** of news samples in the training set for detection **in future quarters**.



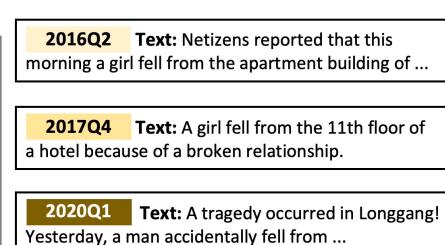
Topic 1: Child Trafficking
Long-standing rumors,
have been widely debunked

Decrease



Topic 2: College Entrance Exam
Experiencing periodic surges in a specific quarter annually

Periodicity



Topic 3: Falling Accident
No apparent temporal trend,
approximate stationarity

Stationary

Introduction: Diverse topic-level temporal patterns

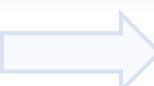


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Topic 1: Child Trafficking
Long-standing rumors,

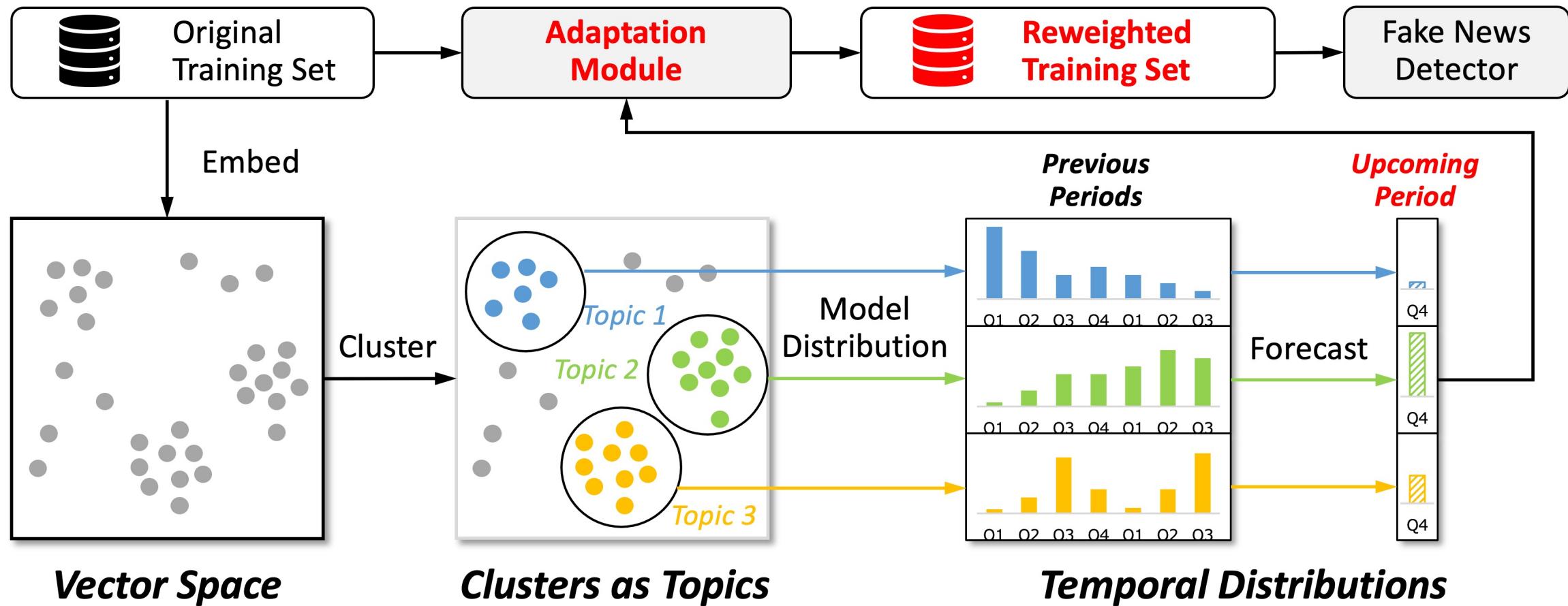
Can we model the temporal distribution patterns and forecast the topic-wise distribution in the upcoming time period for better temporal generalization?



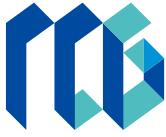
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Method: Forecasting Temporal Trends (FTT) Framework

- We propose a framework for Forecasting Temporal Trends (FTT) to guide the detector to fast adapt to future distribution.



Evaluation: Performance Comparison

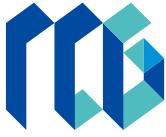


2020	Metric	Baseline	EANN _T	Same Period Reweighting	Prev. Period Reweighting	Combined Reweighting	FTT (Ours)
Q1	macF1	0.8344	0.8334	0.8297	0.8355	0.8312	0.8402
	Accuracy	0.8348	0.8348	0.8301	0.8359	0.8315	0.8409
	F1 _{fake}	0.8262	0.8181	0.8218	0.8274	0.8237	0.8295
	F1 _{real}	0.8425	0.8487	0.8377	0.8435	0.8387	0.8509
Q2	macF1	0.8940	0.8932	0.8900	0.9004	0.8964	0.9013
	Accuracy	0.8942	0.8934	0.8902	0.9006	0.8966	0.9014
	F1 _{fake}	0.8894	0.8887	0.8852	0.8953	0.8915	0.8981
	F1 _{real}	0.8986	0.8978	0.8949	0.9055	0.9013	0.9046
Q3	macF1	0.8771	0.8699	0.8753	0.8734	0.8697	0.8821
	Accuracy	0.8776	0.8707	0.8759	0.8741	0.8707	0.8827
	F1 _{fake}	0.8696	0.8593	0.8670	0.8640	0.8582	0.8743
	F1 _{real}	0.8846	0.8805	0.8836	0.8829	0.8812	0.8900
Q4	macF1	0.8464	0.8646	0.8464	0.8429	0.8412	0.8780
	Accuracy	0.8476	0.8647	0.8476	0.8442	0.8425	0.8784
	F1 _{fake}	0.8330	0.8602	0.8330	0.8286	0.8271	0.8707
	F1 _{real}	0.8598	0.8690	0.8598	0.8571	0.8553	0.8853
Average	macF1	0.8630	0.8653	0.8604	0.8631	0.8596	0.8754
	Accuracy	0.8636	0.8659	0.8610	0.8637	0.8603	0.8759
	F1 _{fake}	0.8546	0.8566	0.8518	0.8538	0.8501	0.8682
	F1 _{real}	0.8714	0.8740	0.8690	0.8723	0.8691	0.8827

- **Observations:**

- FTT outperforms the comparing methods **across all quarters**
- The average improvement of **F1 fake** is larger than that of **F1 real**

Evaluation: Performance Comparison



Break down the performance on the testing set according to the existence of their topics.

Subset of the test set	Metric	Baseline	FTT (Ours)
Existing Topics	macF1	0.8425	0.8658
	Accuracy	0.8589	0.8805
	F1 _{fake}	0.7997	0.8293
	F1 _{real}	0.8854	0.9023
New Topics	macF1	0.8728	0.8846
	Accuracy	0.8729	0.8846
	F1 _{fake}	0.8730	0.8849
	F1 _{real}	0.8727	0.8843

- **Observation:**

- FTT achieves performance improvements on **both** the **Existing Topics** and the **New Topics** subsets

Evaluation: Case Study



- **Objective:**

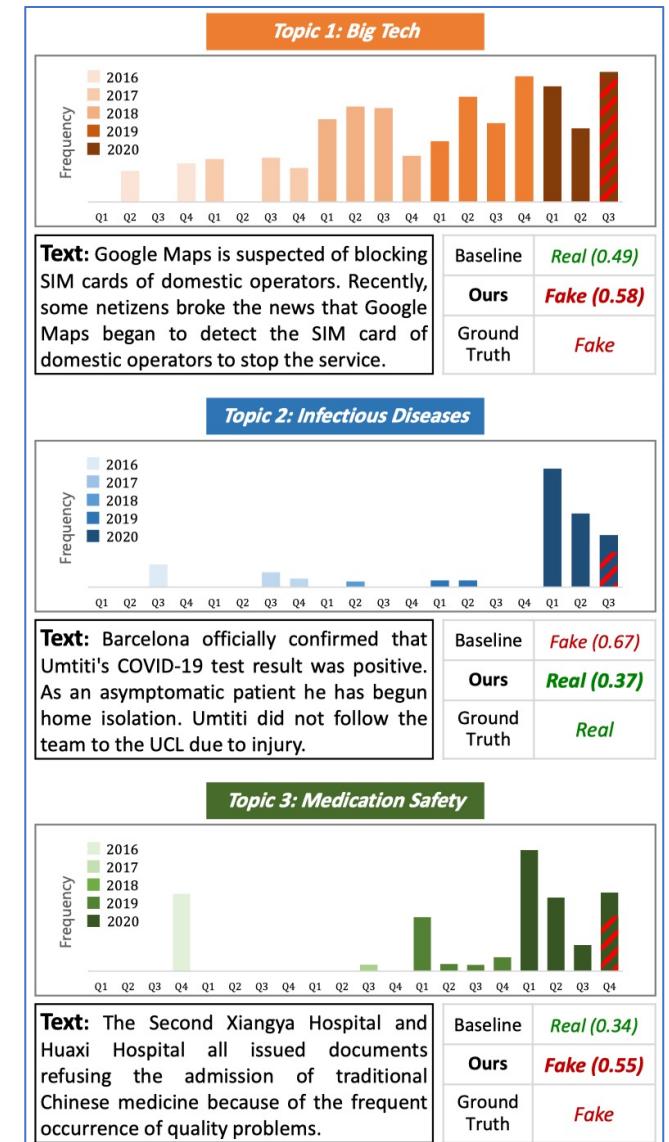
- Evaluation of FTT Framework

- **How to do:**

- Select topics assigned **positive weights** according to the forecasted results of the frequencies.

- **Results:**

- The detector **flips** its previously **incorrect predictions** in cases after training on the reweighted set





• Contributions

- **Problem:** To the best of our knowledge, we are the *first* to incorporate the characteristics of topic-level temporal patterns for fake news detection.
- **Method:** We propose a framework for **Forecasting Temporal Trends (FTT)** to tackle temporal generalization issue in fake news detection.
- **Industrial Value:** We experimentally show that our FTT overall outperforms five compared methods while maintaining good compatibility with any neural network-based fake news detector.



Project

THANKS.

Our code is available at <https://github.com/ICTMCG/FTT-ACL23>.

Feel free to contact Beizhe Hu (hubeizhe21s@ict.ac.cn) for any questions!



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