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

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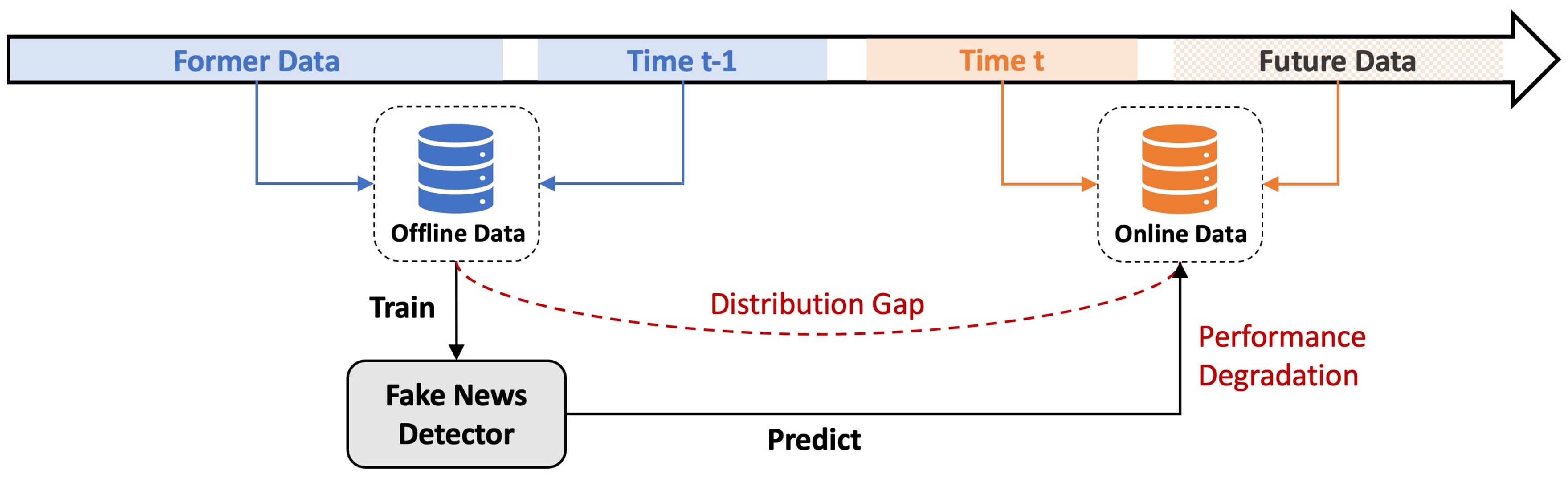
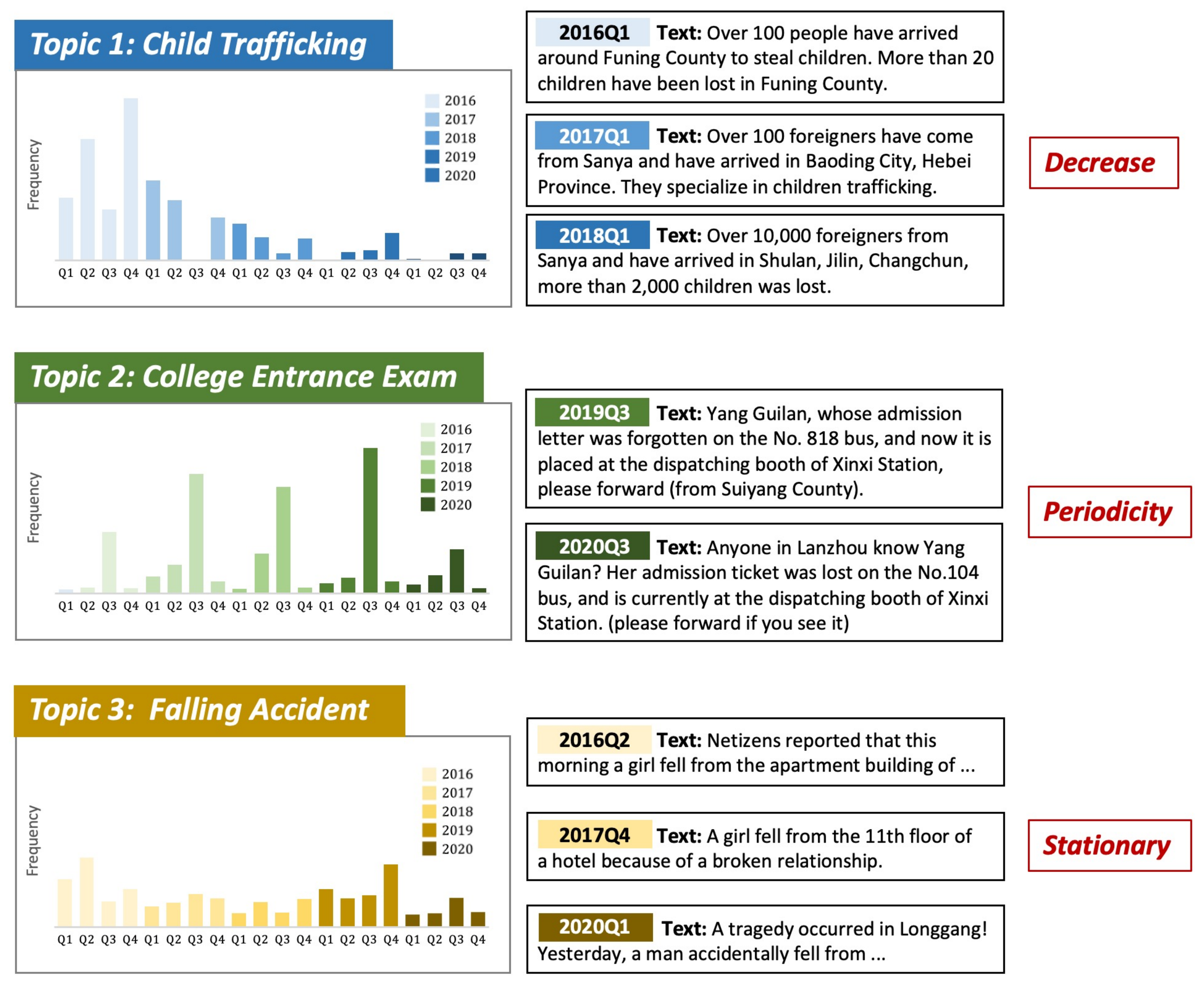
Introduction

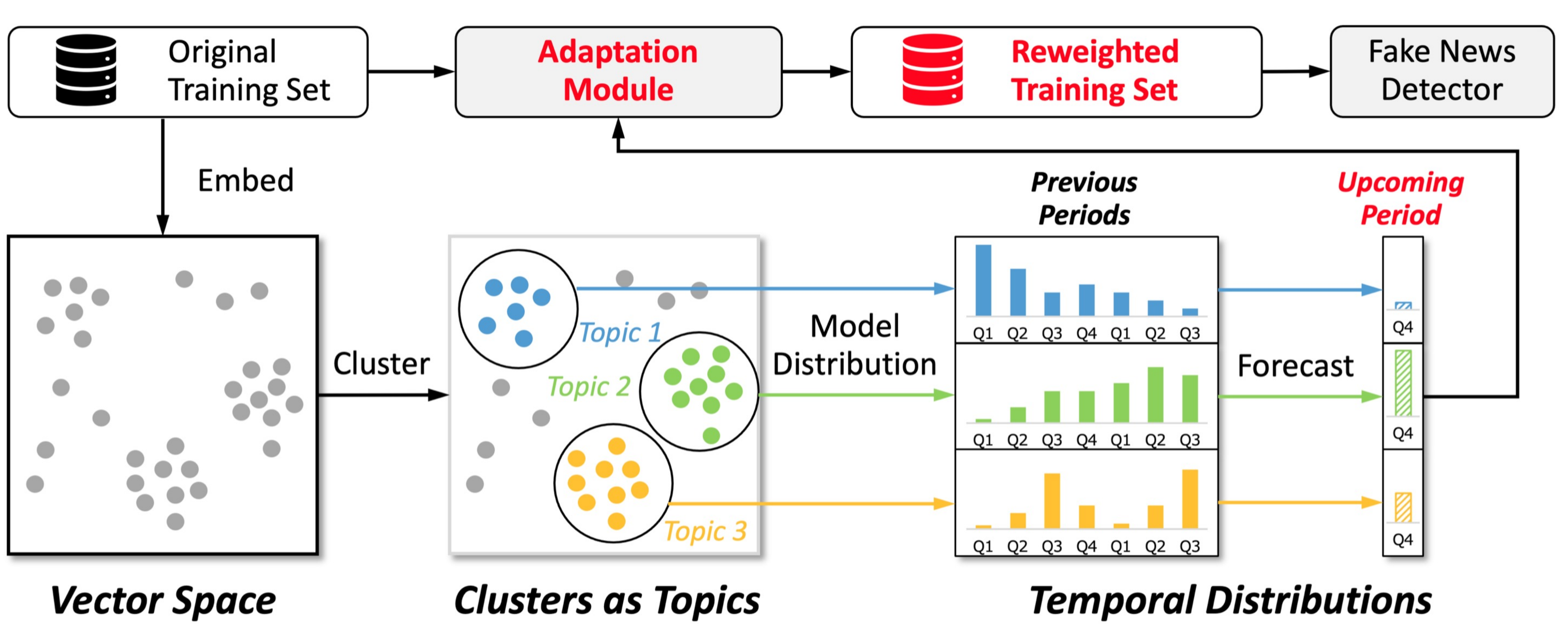
➢ ***Temporal shift*** **in real-world fake news detection scenarios:**
The rapidly-evolving nature of news leads to the distributional difference between offline and online data, namely temporal shift, which causes significant performance degradation to the fake news detection model.



➢ **Observation:** The appearance of news events on the same topic presents diverse temporal patterns, which indicate the different importance of news samples in the training set for detection in future quarters.



Our Method: Forecasting Temporal Trends (FTT) Framework



Step 1: News Representation

➢ Transform the news content into a vector space to obtain its representation

Step 2: Topic Discovery

➢ Perform clustering on news items to group news items into distinct clusters which correspond to topics

Step 3: Temporal Distribution Modeling and Forecasting

① **Modeling:** To model the temporal distribution, we adopt a decomposable time series model on the quarterly sequences and consider the following two trends:

➢ **General Trend** A topic may increase, decrease, or have a small fluctuation in terms of a general non-periodic trend. To fit the data points, we use a piecewise linear function:

$$g_i(f_{i,q}) = k_i f_{i,q} + m_i$$

➢ **Quarterly Trend** For topics having quarterly periodic, we add four extra binary regressors corresponding to Q1~Q4, obtain the quarterly seasonality function $s_i(f_{i,q})$ by summing the four regression models.

② **Focasting:** To forecast the trend of Topic i in the upcoming Quarter Q, we sum up the two trend modeling functions:

$$p_i(f_{i,Q}) = g_i(f_{i,Q}) + s_i(f_{i,Q})$$

Step 4: Forecast-Based Adaptation

➢ Based on the topic-wise forecasts of frequency distribution in Quarter Q, we apply instance reweighting to the training set.

➢ We calculate and then normalize the ratio between the forecasted frequency of Topic i and the sum of all forecasted frequencies of the preserved topics:

$$w_{i,Q} = \mathrm{Bound}\left(\frac{p_i(f_{i,Q})}{\sum_{i \in Q'} p_i(f_{i,Q})}\right)$$

Step 5: Fake News Detector Training

➢ We use the new weights based on the forecasted temporal distribution to increase or decrease the impact of instances during the training process:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} w_{i,Q}\mathrm{CrossEntropy}(y_i, \hat{y}_i)$$

Experiments & Case Study

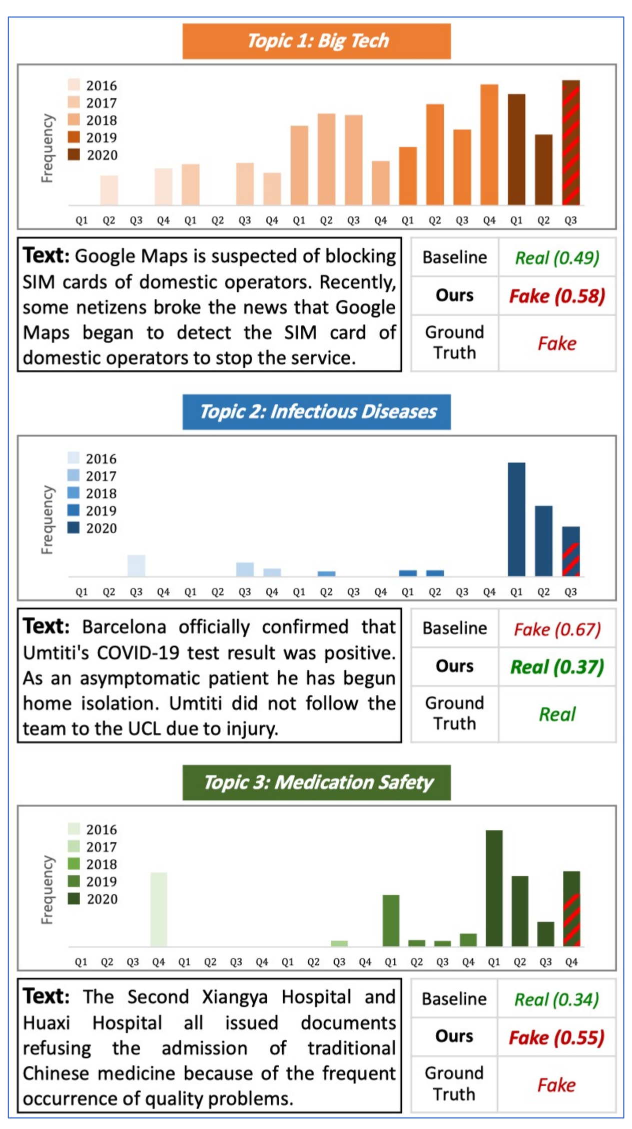
2020	Metric	Baseline	EANN_T	Same Period Reweighting	Prev. Period Reweighting	Combined Reweighting	FTT (Ours)
Q1	macF1	0.8344	0.8334	0.8297	0.8355	0.8312	**0.8402**
	Accuracy	0.8348	0.8348	0.8301	0.8359	0.8315	**0.8409**
	$\mathrm{F1}_{\mathrm{fake}}$	0.8262	0.8181	0.8218	0.8274	0.8237	**0.8295**
	$\mathrm{F1}_{\mathrm{real}}$	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**
	$\mathrm{F1}_{\mathrm{fake}}$	0.8894	0.8887	0.8852	0.8953	0.8915	**0.8981**
	$\mathrm{F1}_{\mathrm{real}}$	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**
	$\mathrm{F1}_{\mathrm{fake}}$	0.8696	0.8593	0.8670	0.8640	0.8582	**0.8743**
	$\mathrm{F1}_{\mathrm{real}}$	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**
	$\mathrm{F1}_{\mathrm{fake}}$	0.8330	0.8602	0.8330	0.8286	0.8271	**0.8707**
	$\mathrm{F1}_{\mathrm{real}}$	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**
	$\mathrm{F1}_{\mathrm{fake}}$	0.8546	0.8566	0.8518	0.8538	0.8501	**0.8682**
	$\mathrm{F1}_{\mathrm{real}}$	0.8714	0.8740	0.8690	0.8723	0.8691	**0.8827**

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

↑ FTT outperforms the baseline and four other methods across all quarters in terms of most of the metrics

↗ Our design makes the model not only more familiar with news items in existing topics but also more generalizable to news items in new topics.

→ After training on the reweighted set, the detector flips its previously incorrect predictions.



Conclusion

➢ **Problem:** To the best of our knowledge, we are the ***first*** to incorporate the feature of topic-level temporal patterns for fake news detection.

➢ **Method:** We propose the FTT framework which forecasts temporal trends to tackle temporal generalization issue in fake news detection.

➢ **Industrial Value:** We experimentally show that our FTT overall outperforms compared methods while maintaining good compatibility with any neural network-based fake news detector.

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