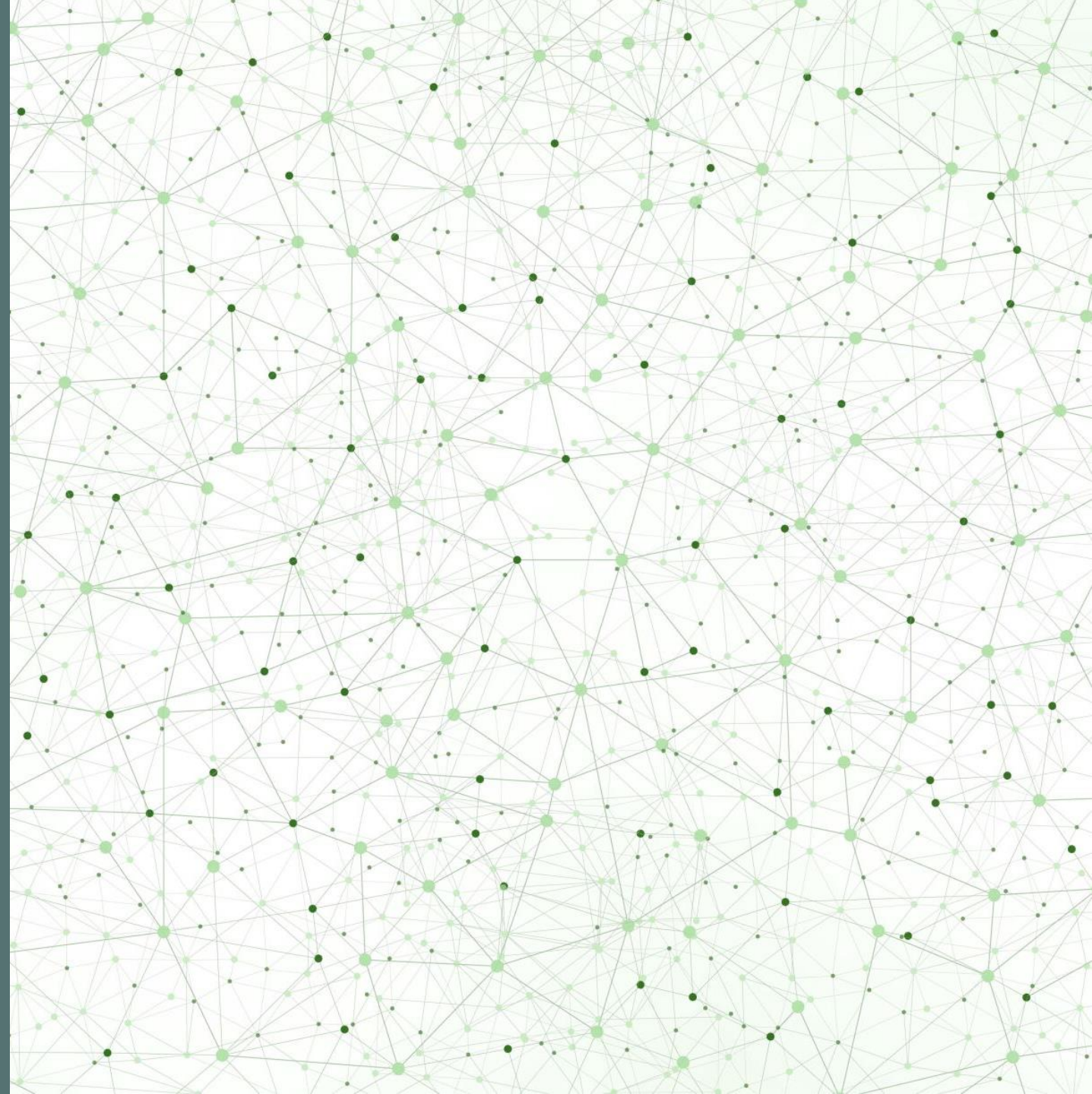# FTT: Forecasting Temporal Trends for Fake News Detection

Hu et al.

Diachronic LMs

By Amir Ghadanfar

PS (6 LP)
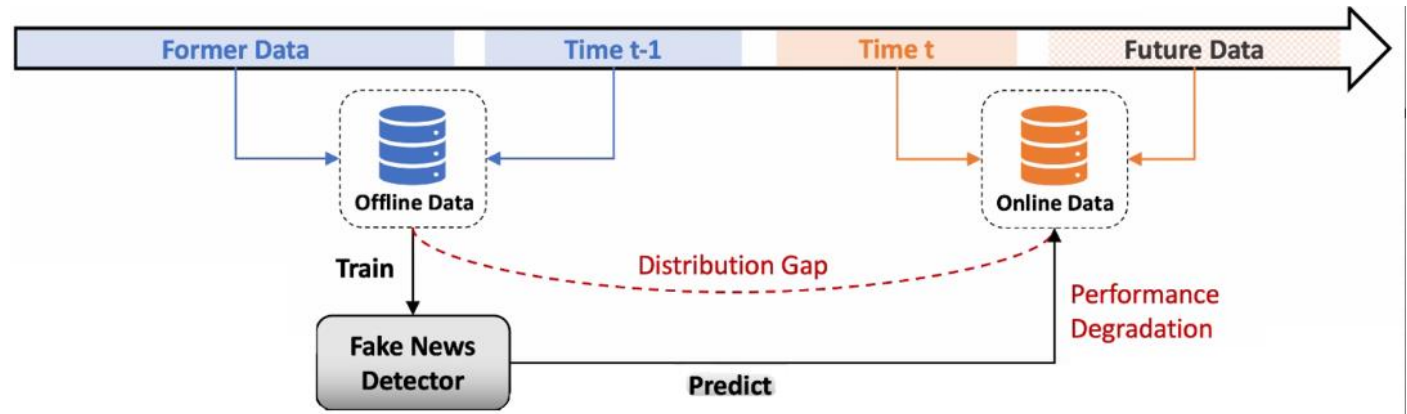
OVERVIEW

2/10/2024

2

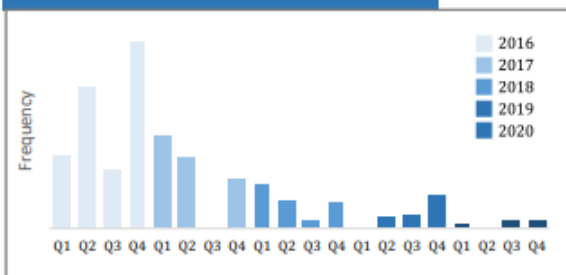# INTRODUCTION

Motivation

- Trust in news publication

- Importance of fake news detection

- Rapid evolution of news data

- Importance of temporal aspect

- Field of study is lacking

Challenging Data

- Temporal shift
- Offline vs. Online data
- Attributes of Consecutive data:
  - Temporal dependencies
  - No clear distributional boundaries
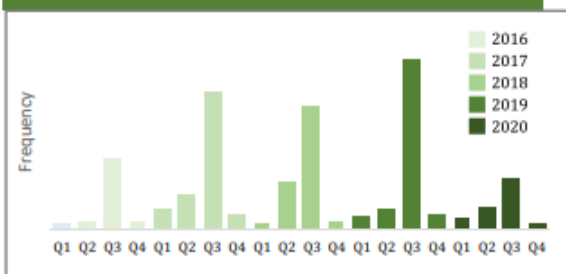- Models make faulty assumption

The "Solution"

- Temporal patterns in same-topic news data

- Improve generalization and adaptation

- Patterns in Figure:
  - Decrease
  - Periodicity
  - Approximate Stationary

FTT:
FORECAST TEMPORAL TRENDS

First look
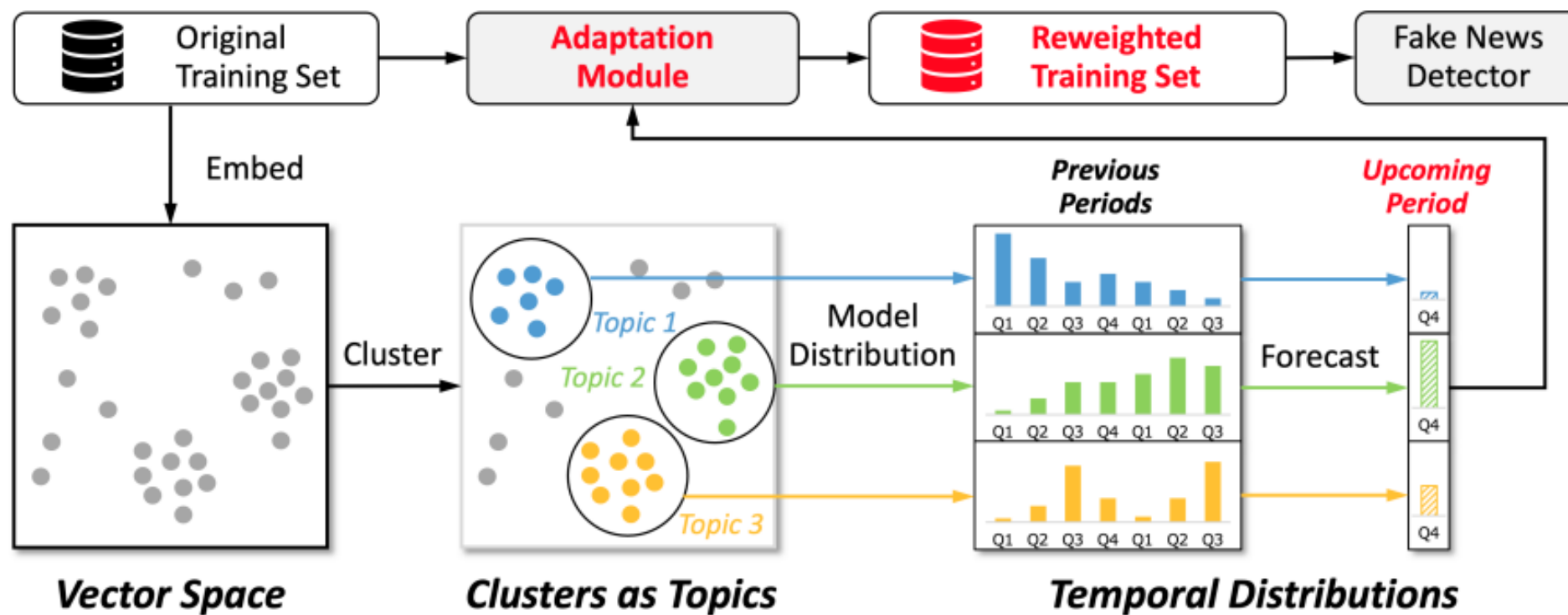
Data Representation

- Consecutive data

- Data representation in vector space

- Sentence BERT

- Single step incremental clustering

- Similarity threshold

Math notation:

$$D = \{D_q\}_{q=1}^{Q}$$

$$\theta_{similarity}$$

Temporal Distribution: Modeling

- Threshold for datapoints in a cluster

- Organize data for analysis

- Quarterly frequency sequence

- Break down time series

- Using decomposable time series model

Math notation:

$$\theta_{\text{count}}$$

$$f = \frac{N_{T,q}}{Nq}$$

Temporal Trends

- Non-periodic trends:
  - k = growth rate
  - m = offset
  - a, m = parameters
  - δ = Rate Adjustment Term
  - γ = Smoothing Term

- Periodic trend:
  - s = sum up of 4 regression models

- Trend modeling function: p

Math notation:

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

$$k_i = k + a(q)^T \delta$$

$$m_i = m + a(q)^T \gamma$$

$$s_i = (f_{i,q})$$

$$p_i(f) = g_i(f) + s_i(f)$$

Forecast Based Adaptation

- Fit model using forecast tool

- Create new train set with updated weights

- Mean absolute percentage error

- New weights correspond to forecast

Math notation:

$$\theta_{MAPE}$$

$$D_{Q'}$$

$$w_{i,Q} = Bound(\frac{p_i(f_{i,Q})}{\sum_{i=D_{Q'}} p_i(f_{i,\_Q})})$$

2/10/2024

Fake News Detection Training

- Incorporate framework into model

- Compatible with any NN

- Include weights in loss function

- Learn during backpropagation

Math notation:

$$\hat{y} = sigmoid(MLP(o_i))$$

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

EVALUATION

Dataset

- Data extracted from Chinese fake-news detection model

- Data from January 2016 – December 2020

  - Divided into 4 subsets pro year

- Imbalanced dataset

  - Under sampled every subset

- Testing on every subset from 2020

1. Experiment: Can FTT Help?

Comparison with 5 methods:

Baseline: instances weighted equally

EANN: neural network using adversarial training

Same period weighting

Previous period weighting

Combined weighting

1. Experiment: Can FTT Help?

| 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**

- FTT outperforms every other metric

- F1-fake higher on average than F1-real

- Heuristic methods are inconsistent

2. Experiment:
How Does FTT Help

- Cluster the Test-set

- Instances in same/new clusters = old/new topics

- FTT outperforms regarding both topic types

- Reweighting improves FTT:

  - Recognizing existing topics

  - Generalizing new 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**

CASE STUDY
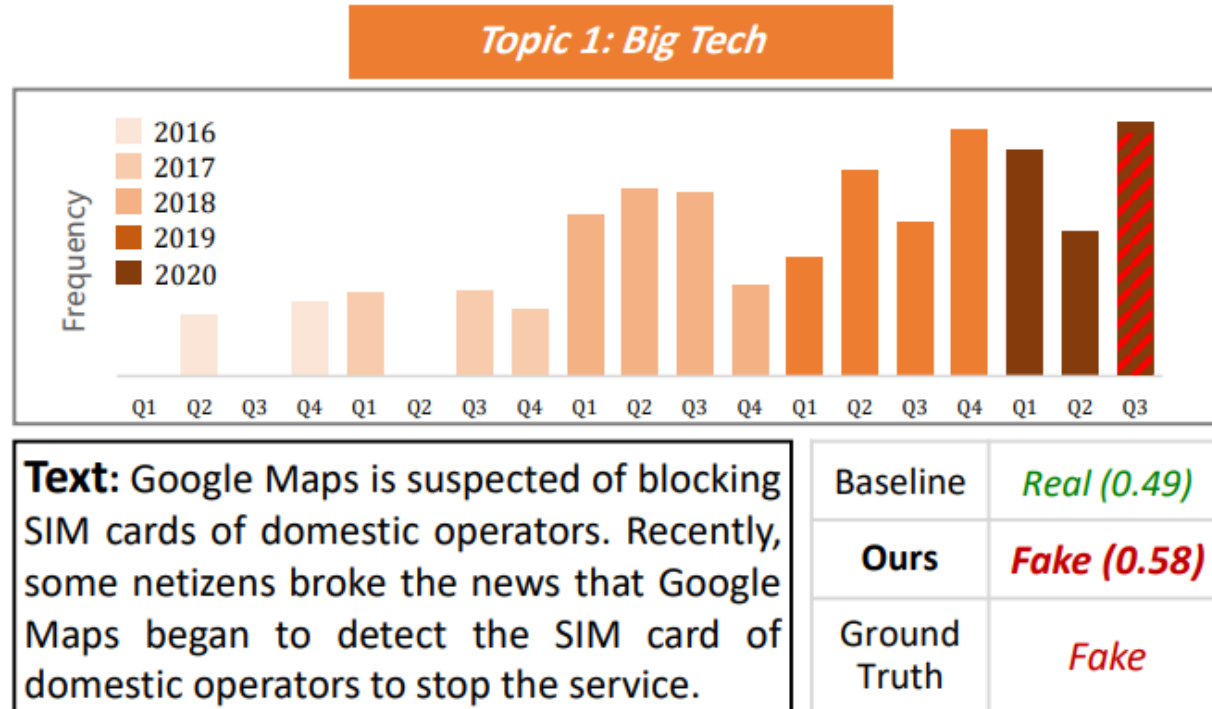
- Red dashed bars represents FTT forecast

- Texts are translated from Chinese

- FTT corrects model prediction

- Pattern of increase captured by FTT

CASE STUDY

Topic 2: Infectious Diseases
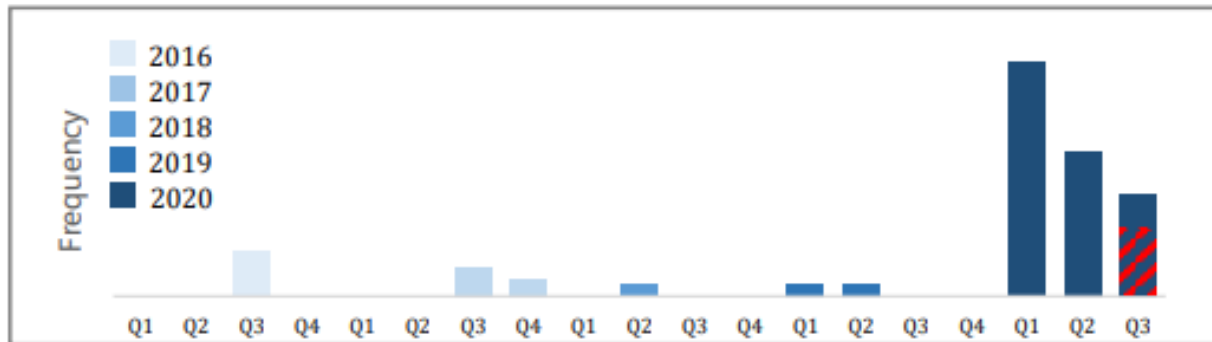
Text: Barcelona officially confirmed that Umtiti's COVID-19 test result was positive. As an asymptomatic patient he has begun home isolation. Umtiti did not follow the team to the UCL due to injury.

Baseline	Fake (0.67)
Ours	**Real (0.37)**
Ground Truth	Real

- FTT corrects model prediction
- Explosive trend fading over time
- Temporal pattern correctly forecasted

CASE STUDY
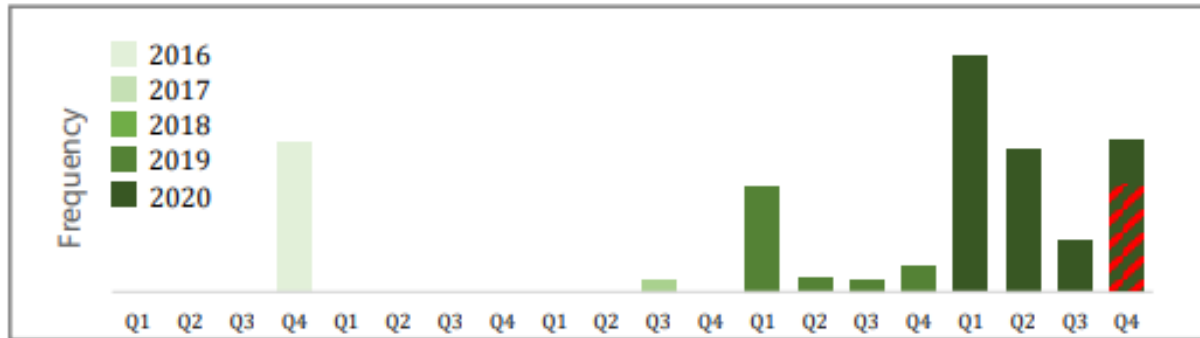
- FTT corrects model prediction
- "Smiling curve" pattern
- Successfully captured by framework

CONCLUSION

Sum-up

- Temporal shift as a common fake news detection challenge

- Modeling and forecasting temporal patterns as a solution

- Math behind FTT

- FTT outperforms other metrics

- Case study showcases the power of FTT

Limitations

Data:

- Only Chinese text data
- No details on how they got the data

In-topic prison:

- Difficulties on new topics

Scarce temporal patterns:

- Can't capture diverse temporal patterns

QUESTIONS ?