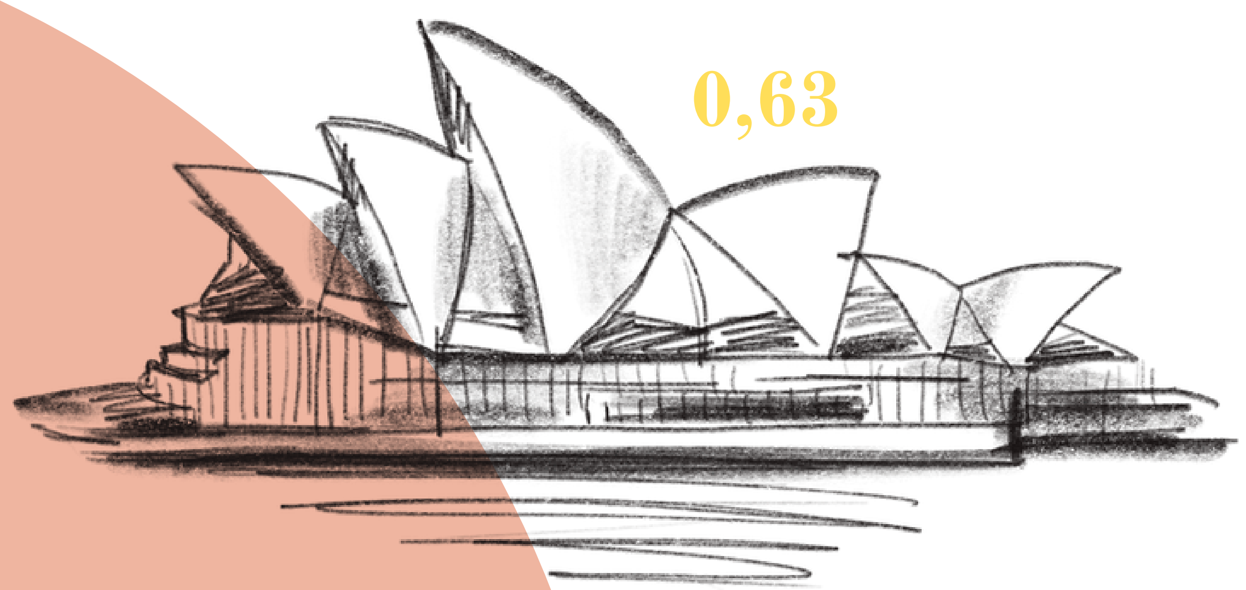
0,45

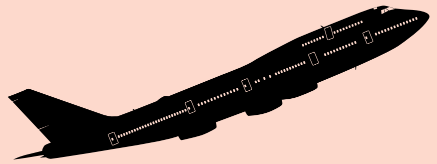
0,63



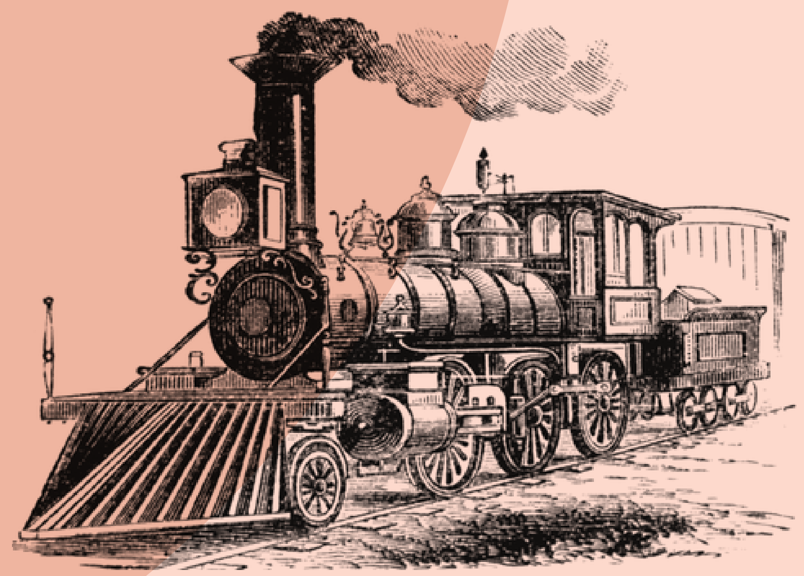
Urban Mood Forecaster

Time Series Analysis and Forecasting of Global Sentiment

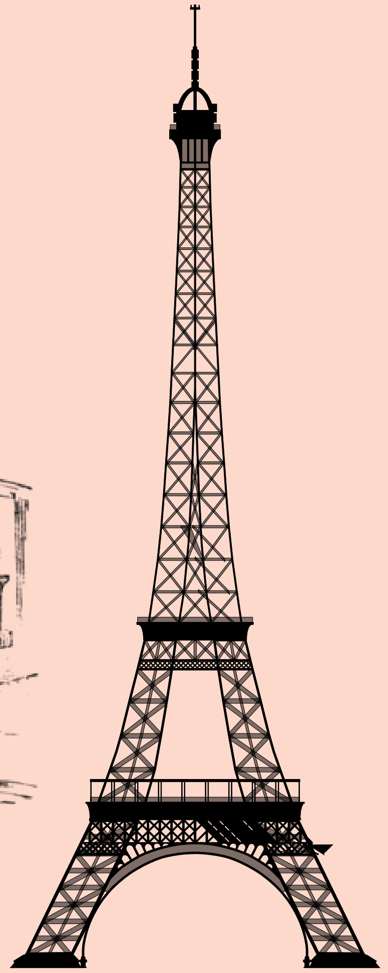
0,78



Team Members:
Shushan Meyroyan, Shushan Gevorgyan,
Armen Madoyan, Davit Sargsyan



0,75

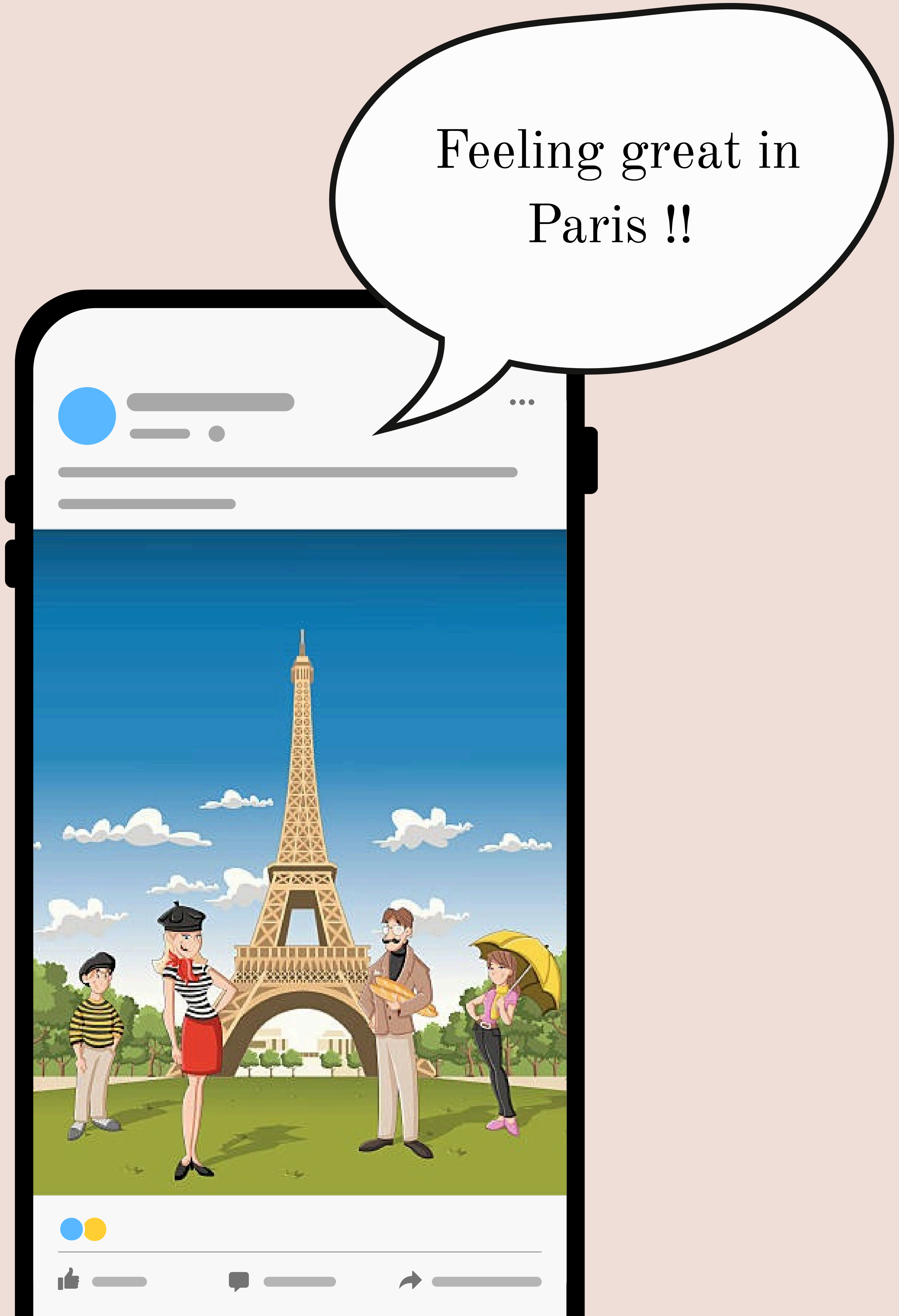


Motivation: Why do we care about mood?

- UN Sustainable Development Goals include subjective well-being.
- Traditional indicators like GDP and unemployment miss how people actually feel.

Your paragraph text

- Social media (Twitter/X) provides high-frequency, geo-tagged signals of public mood.
- Question: Can we turn these signals into a systematic “urban mood” monitor and forecaster?



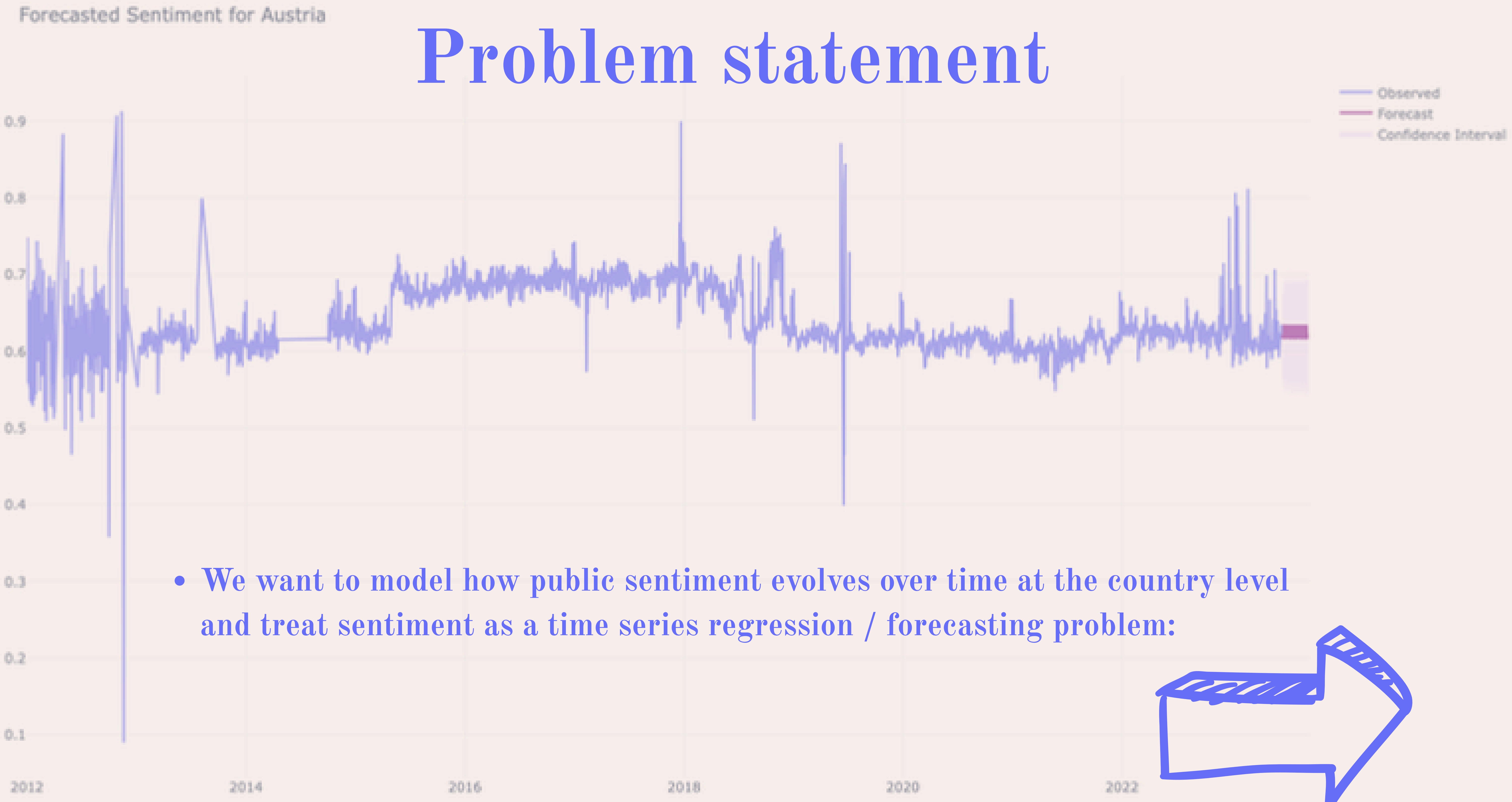
Motivation: Why do we care about mood?

reat in
!

- UN Sustaina
subjective w
- Traditional i
unemployme
- Social media
frequency, g
- Question: Ca
systematic "u
forecaster?

There is a gap between economic metrics and emotional reality

Problem statement



- We want to model how public sentiment evolves over time at the country level and treat sentiment as a time series regression / forecasting problem:

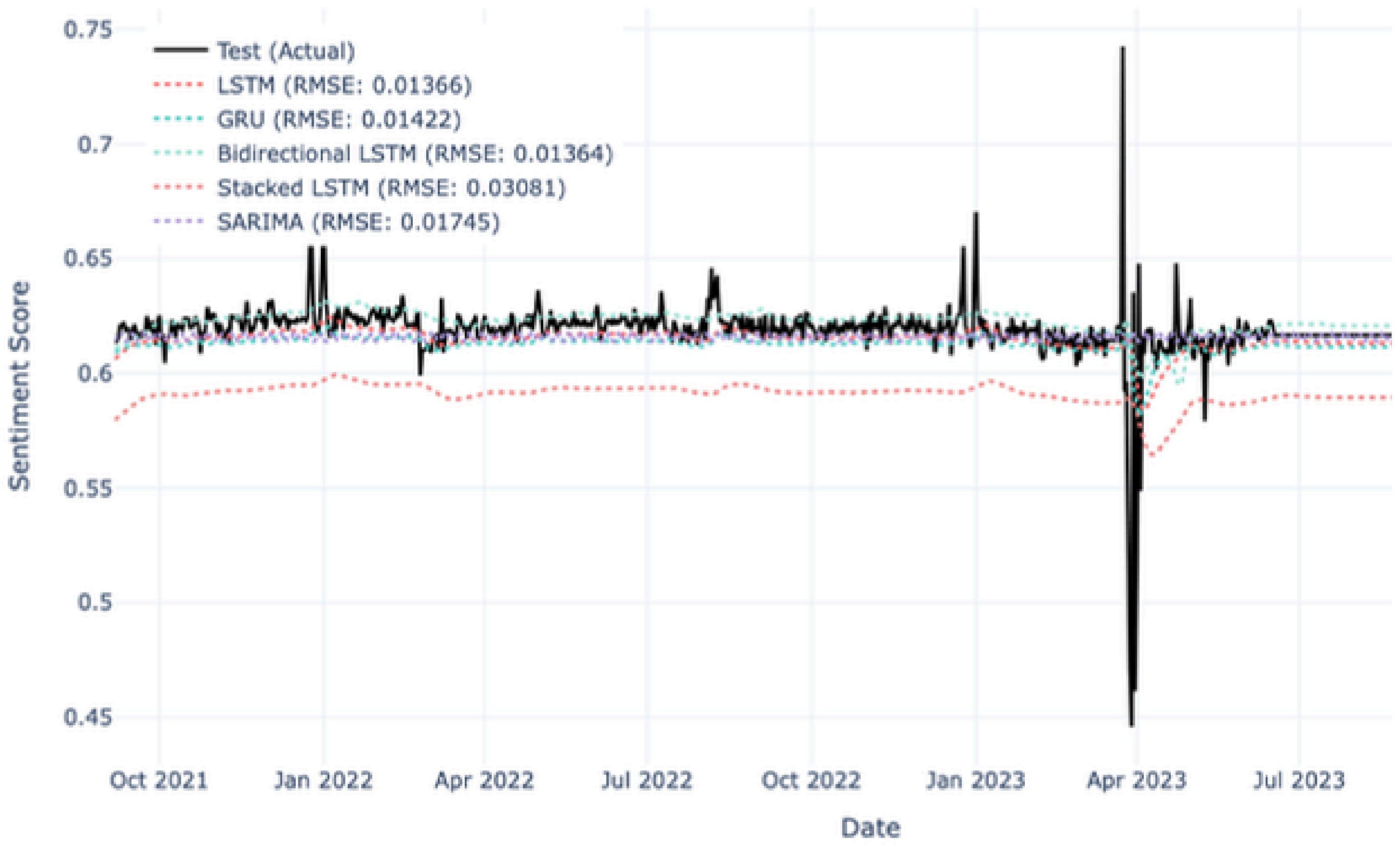
past daily sentiment scores...

DATE	country	N	SCORE	year	
196	03/01/...	Afghanista	2	0.388336	2012
302	04/01/...	Afghanista	1	0.719559	2012
1266	13/01/...	Afghanista	1	0.613117	2012
1371	14/01/...	Afghanista	2	0.53986	2012
1588	16/01/...	Afghanista	2	0.481106	2012
...	...	...	...	...	...
412047	02/06/...	Zimbabwe	3338	0.618421	2023
412196	03/06/...	Zimbabwe	503	0.662444	2023
412346	04/06/...	Zimbabwe	252	0.629384	2023
412494	06/06/...	Zimbabwe	293	0.602974	2023
412642	07/06/...	Zimbabwe	195	0.61463	2023

past daily sentiment scores...

DATE	country	N	SCORE	year	
196	03/01/...	Afghanista	2	0.388336	2012
302	04/01/...	Afghanista	1	0.719559	2012
1266	13/01/...	Afghanista	1	0.613117	2012
1371	14/01/...	Afghanista	2	0.53986	2012
1588	16/01/...	Afghanista	2	0.481106	2012
...	...	...	...	...	...
412047	02/06/...	Zimbabwe	3338	0.618421	2023
412196	03/06/...	Zimbabwe	503	0.662444	2023
412346	04/06/...	Zimbabwe	252	0.629384	2023
412494	06/06/...	Zimbabwe	293	0.602974	2023
412642	07/06/...	Zimbabwe	195	0.61463	2023

... future sentiment values



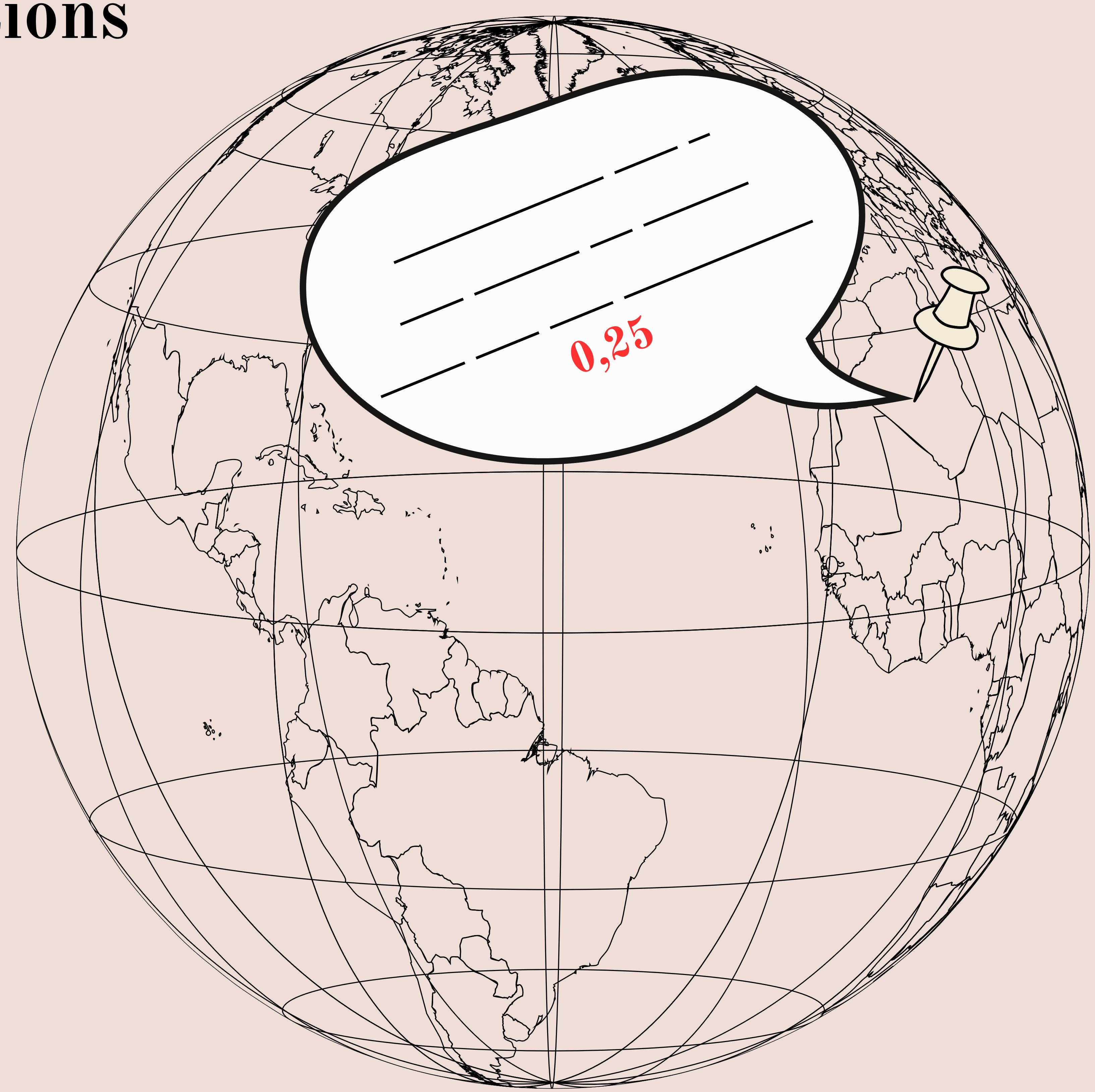
Research methods and important questions

RQ1: How well can classical time series models (AR, MA, ARIMA, SARIMA, Holt–Winters) forecast sentiment?

RQ2: Do deep RNN models (LSTM, GRU, Bidirectional LSTM, Stacked LSTM) improve forecasting accuracy?

RQ3: Which seasons are “happiest” for each country?

RQ4: Which countries are happiest in a given season, and can we use this for travel recommendations?



Dataset details: TSGI overview

- Dataset -> Twitter Sentiment Geographical Index (TSGI).
- Source: Sustainable Urbanization Lab (MIT) + Center for Geographic Analysis (Harvard).
- Domain: Social media–based subjective well-being.
- Temporal coverage: 2012–2023
- Granularity: global, country, state/province, county/city.
- We use: country-level daily indices.

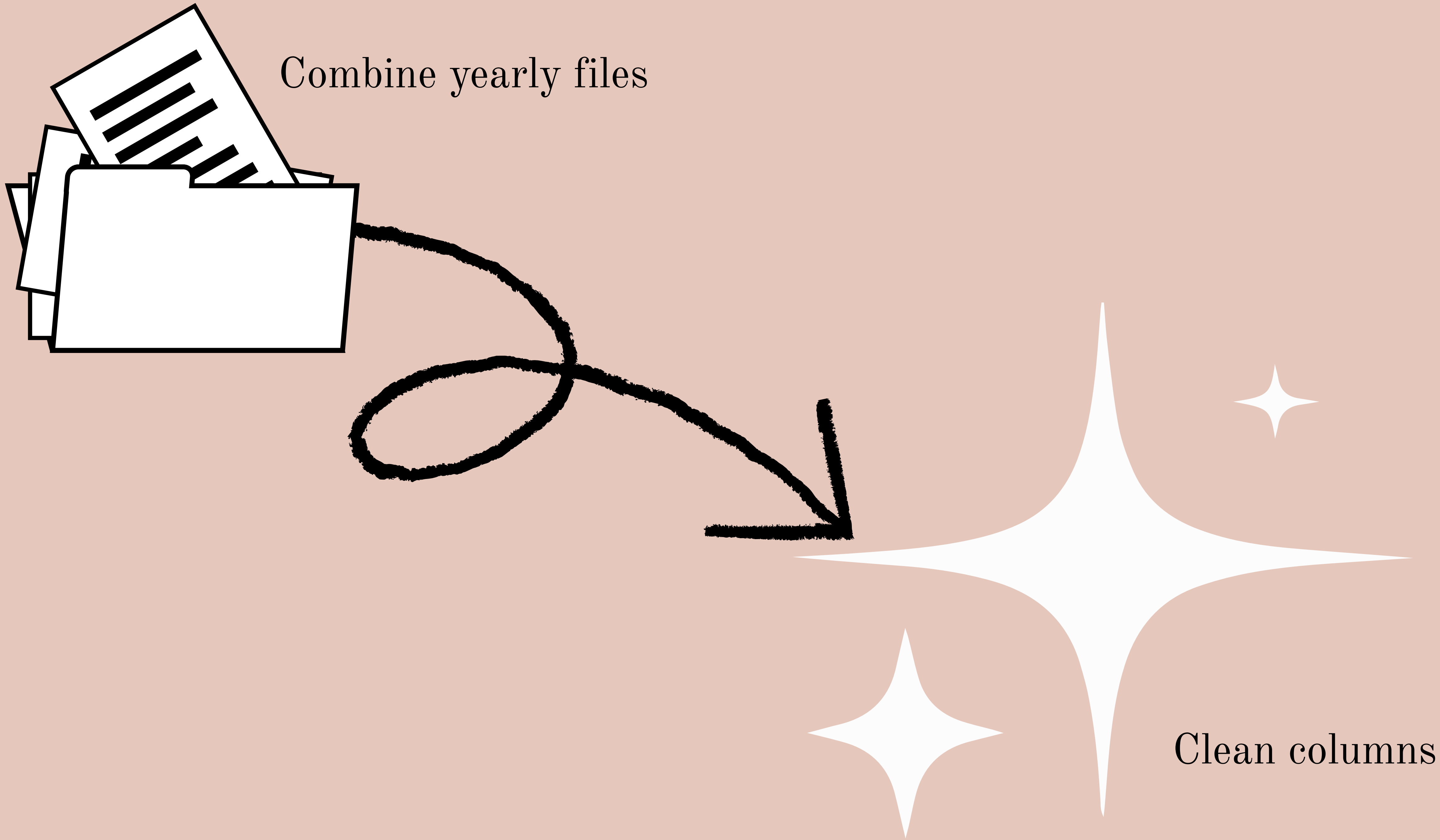
Data organization:
One CSV per year: TSGI_country_2012.csv, ...
In total: X years (say 2012–2023 → 12 files),
thousands of country–day records.

index	date	country	N of posts that day	score	year
196	03/01/2012	Afghanistan	2	0.388336	2012
302	04/01/2012	Afghanistan	1	0.719559	2012
1266	13/01/2012	Afghanistan	1	0.613117	2012
1371	14/01/2012	Afghanistan	2	0.53986	2012
1588	16/01/2012	Afghanistan	2	0.481106	2012
...	...	...	...	...	...
412047	02/06/2023	Zimbabwe	3338	0.618421	2023
412196	03/06/2023	Zimbabwe	503	0.662444	2023
412346	04/06/2023	Zimbabwe	252	0.629384	2023
412494	06/06/2023	Zimbabwe	293	0.602974	2023
412642	07/06/2023	Zimbabwe	195	0.61463	2023

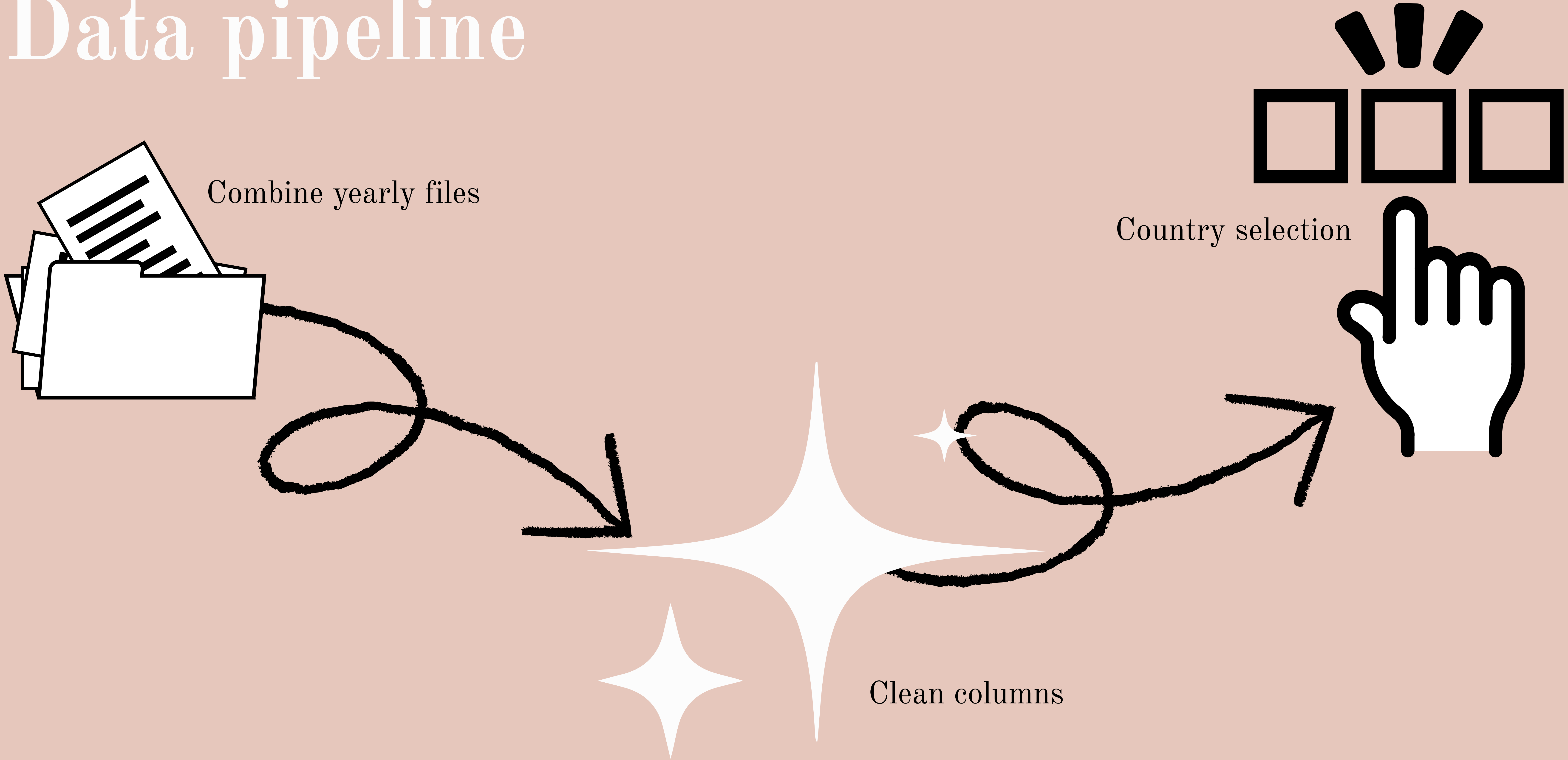
Data pipeline

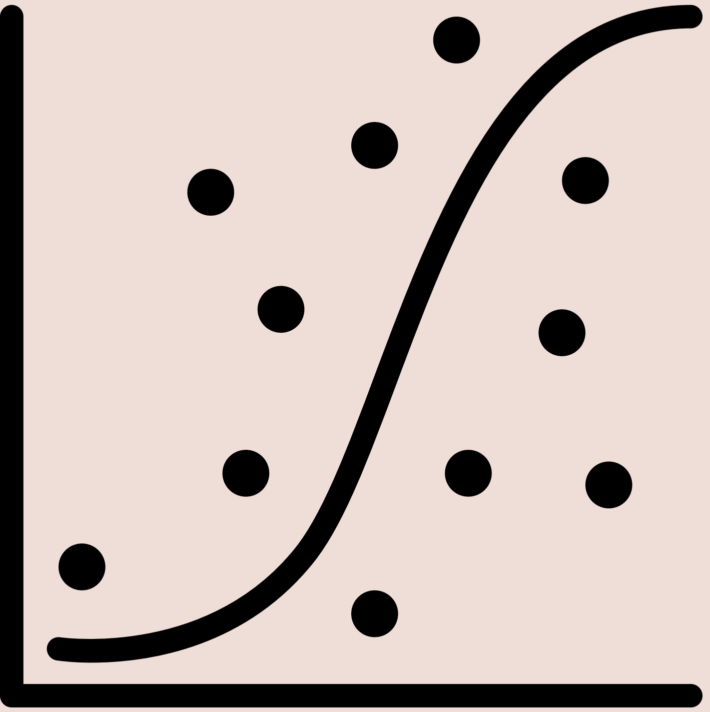
Combine yearly files

Data pipeline



Data pipeline





Time series construction and missing values

Enforce daily frequency:

(.asfreq('D') to make the index every calendar day.)

Handle missing days/scores:

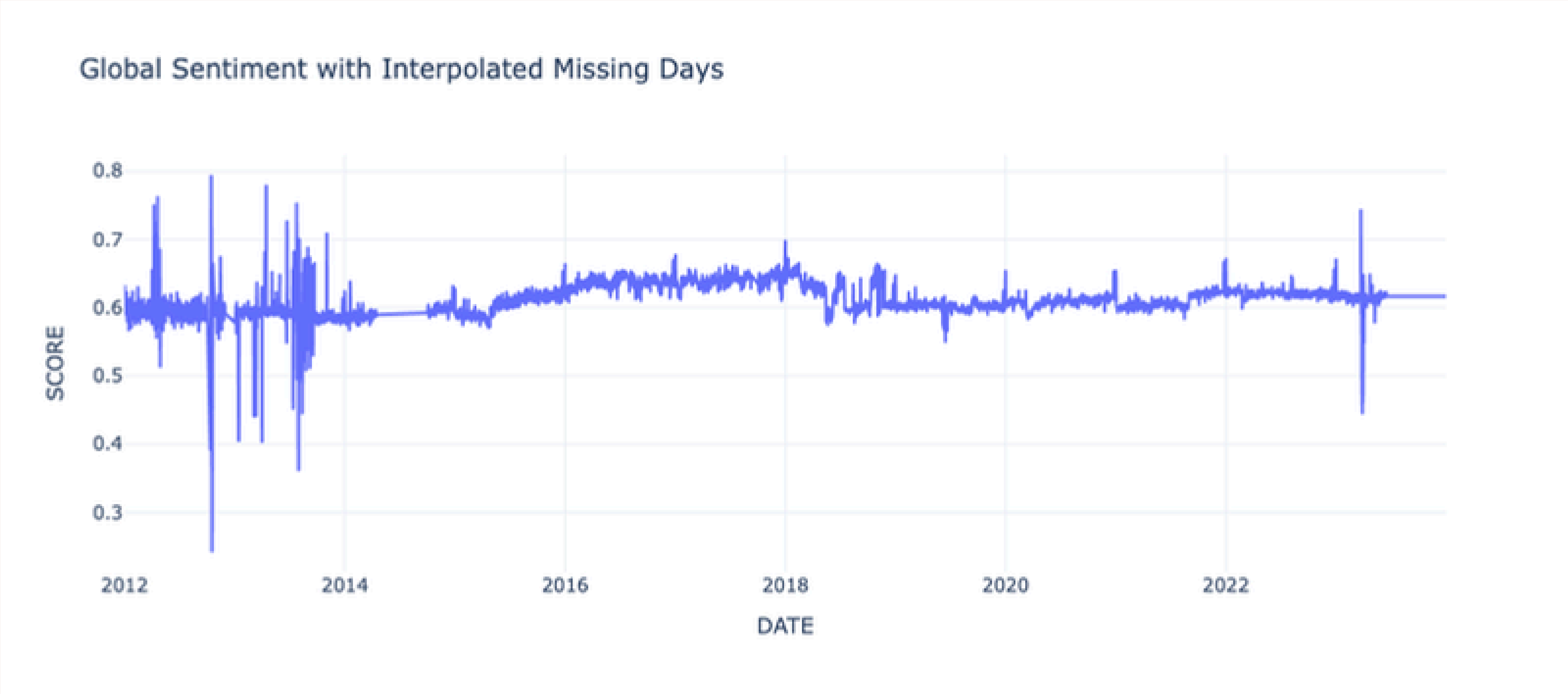
(Linear interpolation of SCORE between known dates.)

Train–test split:

(**First 80% of days → train; last 20% → test** (chronological split).)

For global experiments:

Average SCORE over all countries per day → global sentiment series.


Global Sentiment with Interpolated Missing Days
0.8
0.7
0.6
0.5
0.4
0.3
SCORE
2012
2014
2016
2018
2020
2022
DATE

Global Sentiment with Interpolated Missing Days

=== Stationarity Tests on Global Sentiment (Daily) ===

ADF Test:

Test Statistic : -4.4823

p-value : 0.0002

Critical Values: {'1%': -3.4318510679201006, '5%': -2.8622032882383506, '10%': -2.5671230728180445}

=>Reject H_0 → Series is likely stationary.

2012 2014 2016 2018 2020 2022

DATE

Methodology overview: model families and metrics

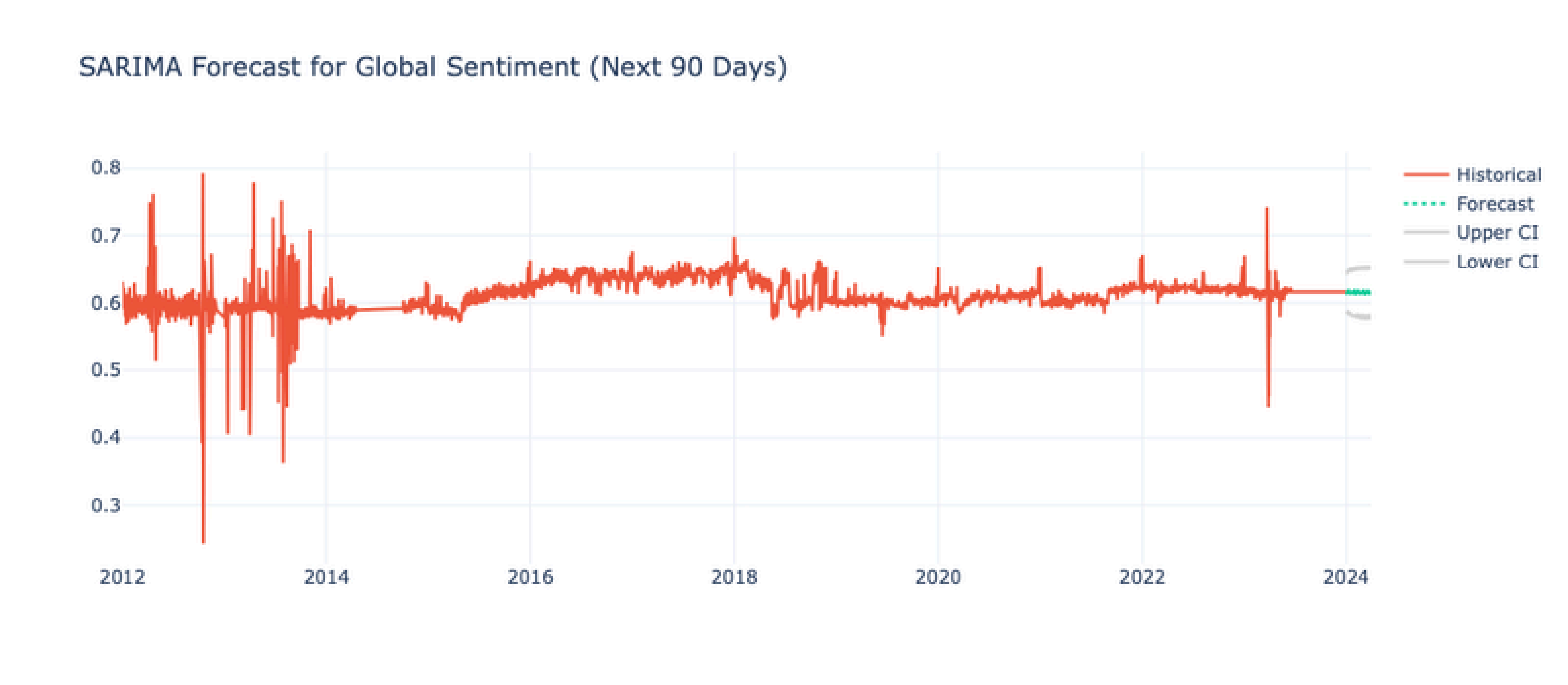
Classical Statistical Models:
AR, MA, ARIMA, and SARIMA

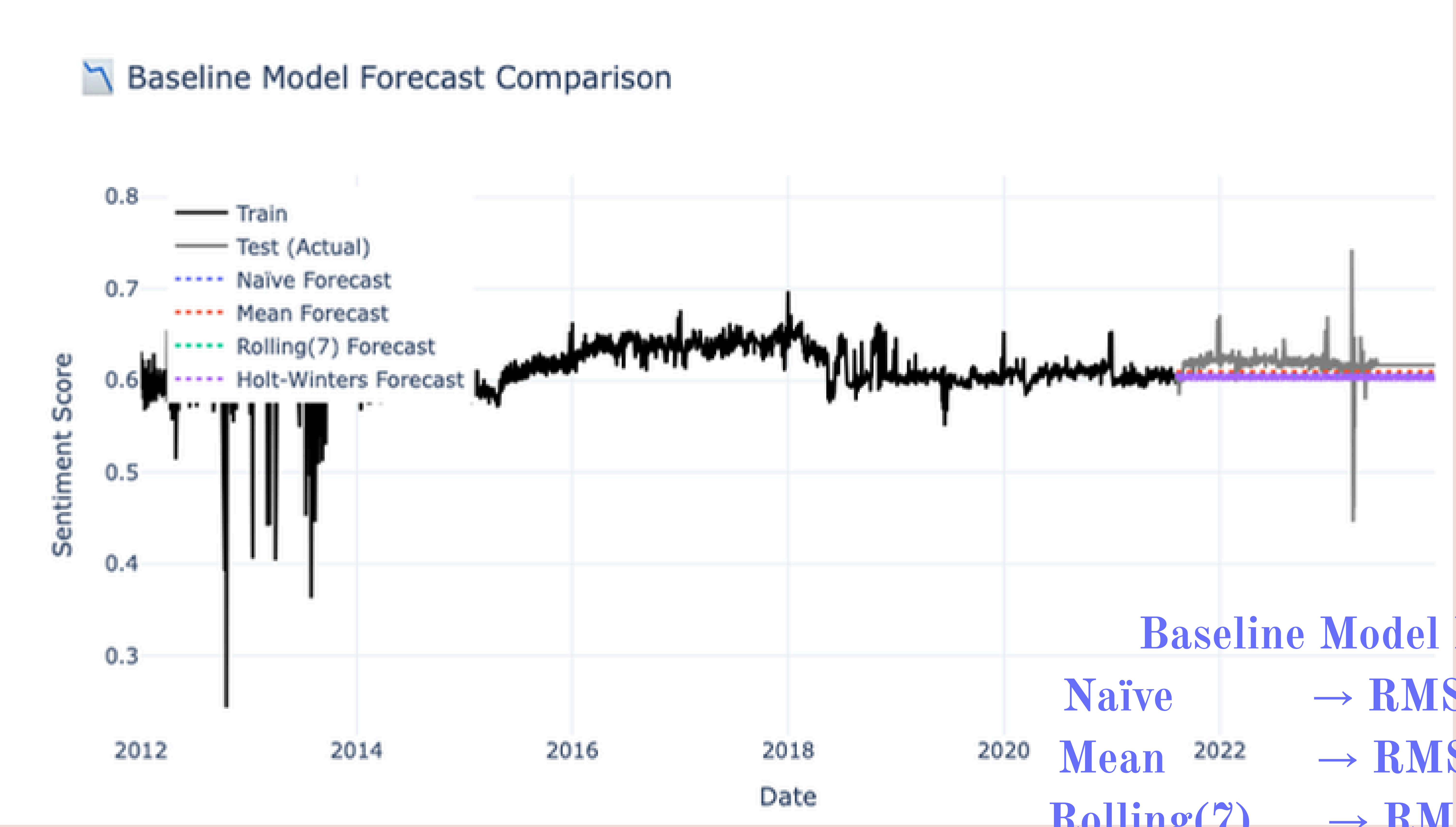
Baseline Models :
Naive forecasting & rolling mean

Deep learning approaches:
LSTM, GRU, Bidirectional, and Stacked LSTM.

*Evaluation metrics:
Main: RMSE on held-out test set.
Also: MAE, AIC/BIC for ARIMA/SARIMA during selection.

Best SARIMA order: (1, 0, 1) seasonal: (0, 1, 1, 7)





Baseline Model RMSEs:

Naïve → RMSE: 0.01815

Mean → RMSE: 0.01603

Rolling(7) → RMSE: 0.01988

Holt-Winters → RMSE: 0.01977

Deep Learning models:

LSTM
(Long Short-Term Memory)

- What it does

Designed to learn long-term dependencies in sequential data.
Uses three gates (input, forget, output) and a cell state for controlled memory.

- Strengths

Excellent at capturing temporal patterns, even when relationships span many timesteps.
Reduces vanishing gradient problems common in vanilla RNNs.

- Weaknesses

More parameters → slower to train than GRU.
More memory-heavy.

Deep Learning models:

LSTM
(Long Short-Term Memory)

- What it does

Designed to learn long-term dependencies in sequential data.
Uses three gates (input, forget, output) and a cell state for controlled memory.

- Strengths

Excellent at capturing temporal patterns, even when relationships span many timesteps.
Reduces vanishing gradient problems common in vanilla RNNs.

- Weaknesses

More parameters → slower to train than GRU.
More memory-heavy.

GRU
(Gated Recurrent Unit)

- What it does

A simplified version of LSTM with two gates (update, reset).
No separate cell state → only uses the hidden state.

- Strengths

Faster training, fewer parameters.
Often performs similarly to LSTM on many tasks.
Works well with smaller datasets.

- Weaknesses

Slightly less expressive than LSTM because of fewer gates.

Deep Learning models:

LSTM (Long Short-Term Memory)

- What it does

Designed to learn long-term dependencies in sequential data.
Uses three gates (input, forget, output) and a cell state for controlled memory.

- Strengths

Excellent at capturing temporal patterns, even when relationships span many timesteps.
Reduces vanishing gradient problems common in vanilla RNNs.

- Weaknesses

More parameters → slower to train than GRU.
More memory-heavy.

GRU (Gated Recurrent Unit)

- What it does

A simplified version of LSTM with two gates (update, reset).
No separate cell state → only uses the hidden state.

- Strengths

Faster training, fewer parameters.
Often performs similarly to LSTM on many tasks.
Works well with smaller datasets.

- Weaknesses

Slightly less expressive than LSTM because of fewer gates.

Bidirectional LSTM

- What it does

Processes the sequence forward and backward.
Concatenates both directional outputs.

- Why useful

Captures patterns where the future context within a window also matters.
More powerful than a standard one-direction LSTM for fixed-window forecasting.

- Strengths

Learns richer patterns (past + “future” inside the window).
Often provides the best accuracy in time series with local symmetric patterns.

- Weaknesses

More computationally expensive (two LSTMs running in parallel).
Cannot be used where true future values must be unknown during training (but works for our sliding-window setup).

Deep Learning models:

Stacked LSTM \ (Multi-layer LSTM)

- What it does

Multiple LSTM layers stacked on top of each other.
Each layer learns increasingly abstract representations of the sequence.

- Strengths

Higher learning capacity for complex, nonlinear patterns.
In theory, more expressive than a single LSTM layer.

- Weaknesses

Very heavy: more parameters → more likely to overfit (which happened in your results).
Needs more data and more tuning.
Slowest to train.

GRU (Gated Recurrent Unit)

- What it does

A simplified version of LSTM with two gates (update, reset).
No separate cell state → only uses the hidden state.

- Strengths

Faster training, fewer parameters.
Often performs similarly to LSTM on many tasks.
Works well with smaller datasets.

- Weaknesses

Slightly less expressive than LSTM because of fewer gates.

Bidirectional LSTM

- What it does

Processes the sequence forward and backward.
Concatenates both directional outputs.

- Why useful

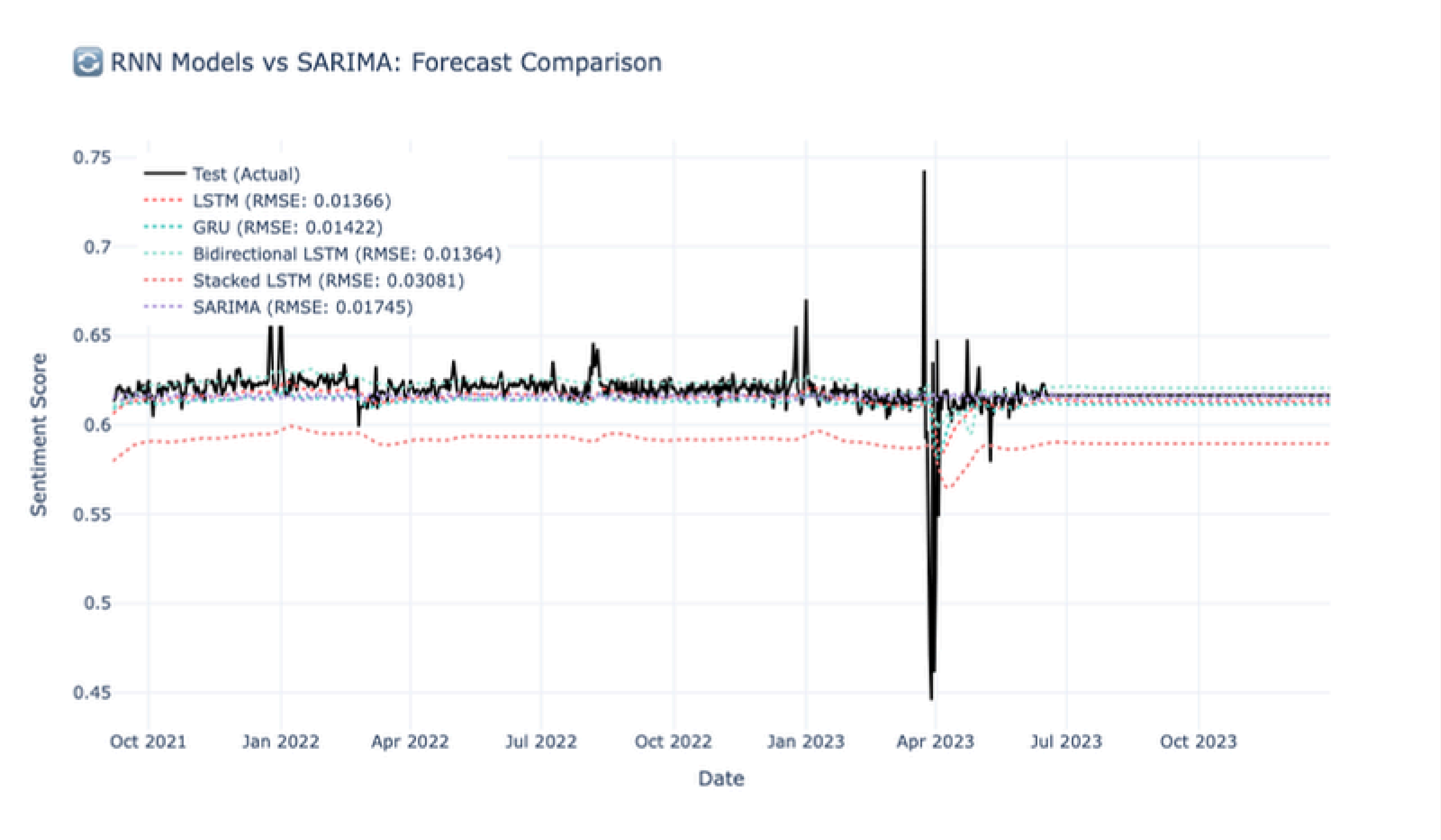
Captures patterns where the future context within a window also matters.
More powerful than a standard one-direction LSTM for fixed-window forecasting.

- Strengths

Learns richer patterns (past + "future" inside the window).
Often provides the best accuracy in time series with local symmetric patterns.

- Weaknesses

More computationally expensive (two LSTMs running in parallel).
Cannot be used where true future values must be unknown during training (but works for our sliding-window setup).


RNN Models vs SARIMA: Forecast Comparison
Test (Actual)
LSTM (RMSE: 0.01366)
GRU (RMSE: 0.01422)
Bidirectional LSTM (RMSE: 0.01364)
Stacked LSTM (RMSE: 0.03081)
SARIMA (RMSE: 0.01745)
Sentiment Score
0.75
0.7
0.65
0.6
0.55
0.5
0.45
Oct 2021
Jan 2022
Apr 2022
Jul 2022
Oct 2022
Jan 2023
Apr 2023
Jul 2023
Oct 2023
Date

RNN Models vs SARIMA: Forecast Comparison

Project Structure – What We Did & Expected Outcomes

- time_series_urban_mood_analysis
  - app.py
  - backend.py
  - user_input.py
  - Urban_Mood_Analysis.ipynb
  - dataverse_files

Project Structure – What We Did & Expected Outcomes

time_series_urban_mood_analysis

- **app.py** → Urban Mood Forecaster Streamlit app
- **backend.py** → Classical and deep learning forecasting models
- **user_input.py** → Terminal-based application for forecasting
- **Urban_Mood_Analysis.ipynb** → EDA & modeling experiments
- **dataverse_files** → sentiment scores by country/state/country

Expected Outcomes:

- Accurate daily sentiment forecasts for any country
- A clear comparison between classical models vs. RNNs
- Discovery of seasonal mood patterns across countries
- An interactive forecasting & travel advisory app
- A reusable forecasting backend with saved models
- Insights into how global sentiment behaves over time

Demonstration: