UNITED NATIONS

Politecnico di Torino

1859

UNITED NATIONS SYSTEM STAFF COLLEGE

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Predictive Models for Humanitarian Aid

Predicting conflicts in the Sahel region

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ADSP Final Presentation
A.Y. 2023/24

PROJECT PROPOSITION

Help people in the Sahel region with a faster and effective response to conflicts and social tensions

OUTPUT

AI System

- Research report on standard framework and alternatives
- Process log to help future learners
- Dashboard for communication and helping users understand the results

RESEARCH QUESTIONS

What we try to answer?

RESEARCH QUESTIONS

PREDICTORS

What are the best predictors for the task?

- Action-driven predictors
- Interpretable predictors
- Informative predictors

RESEARCH QUESTIONS

PREDICTORS - EVENTS

Our goal is to predict the fatalities for a certain number of months.

Political Violence

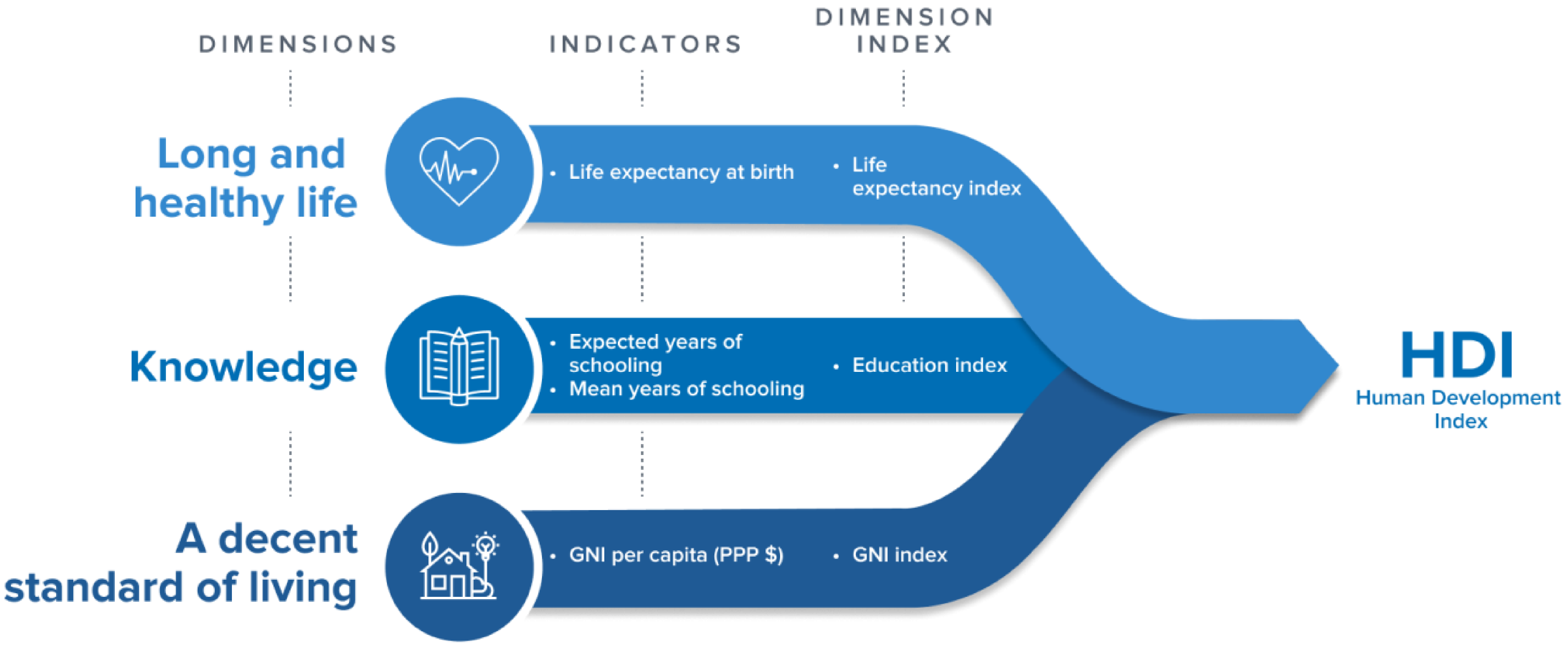
Demonstrations

Strategic developments

RESEARCH QUESTIONS

PREDICTORS - HDI

Human Development Index



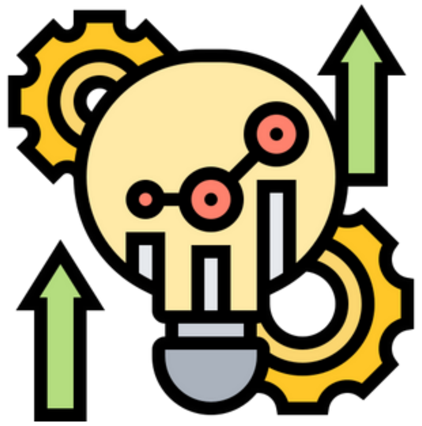
Reference to the image: https://hdr.undp.org/data-center/human-development-index#/indicies/HDI

RESEARCH QUESTIONS

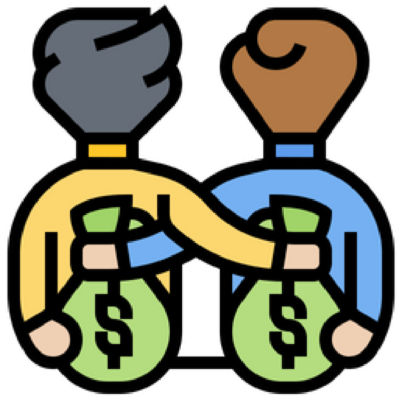
PREDICTORS - GDI

THE WORLD BANK

Voice and Accountability



Regulatory Quality



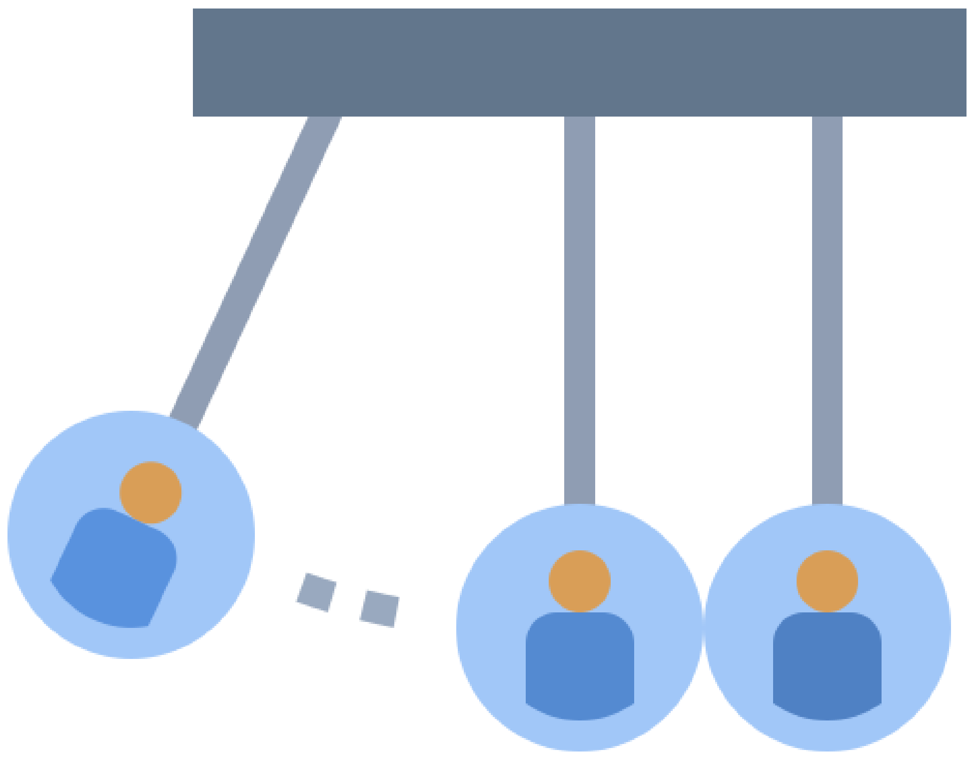
Control of Corruption

Political Stability & Absence of Violence/Terrorism

Rule of Law

RESEARCH QUESTIONS
CAUSAL DISCOVERY

Can we explore the task with causal discovery?

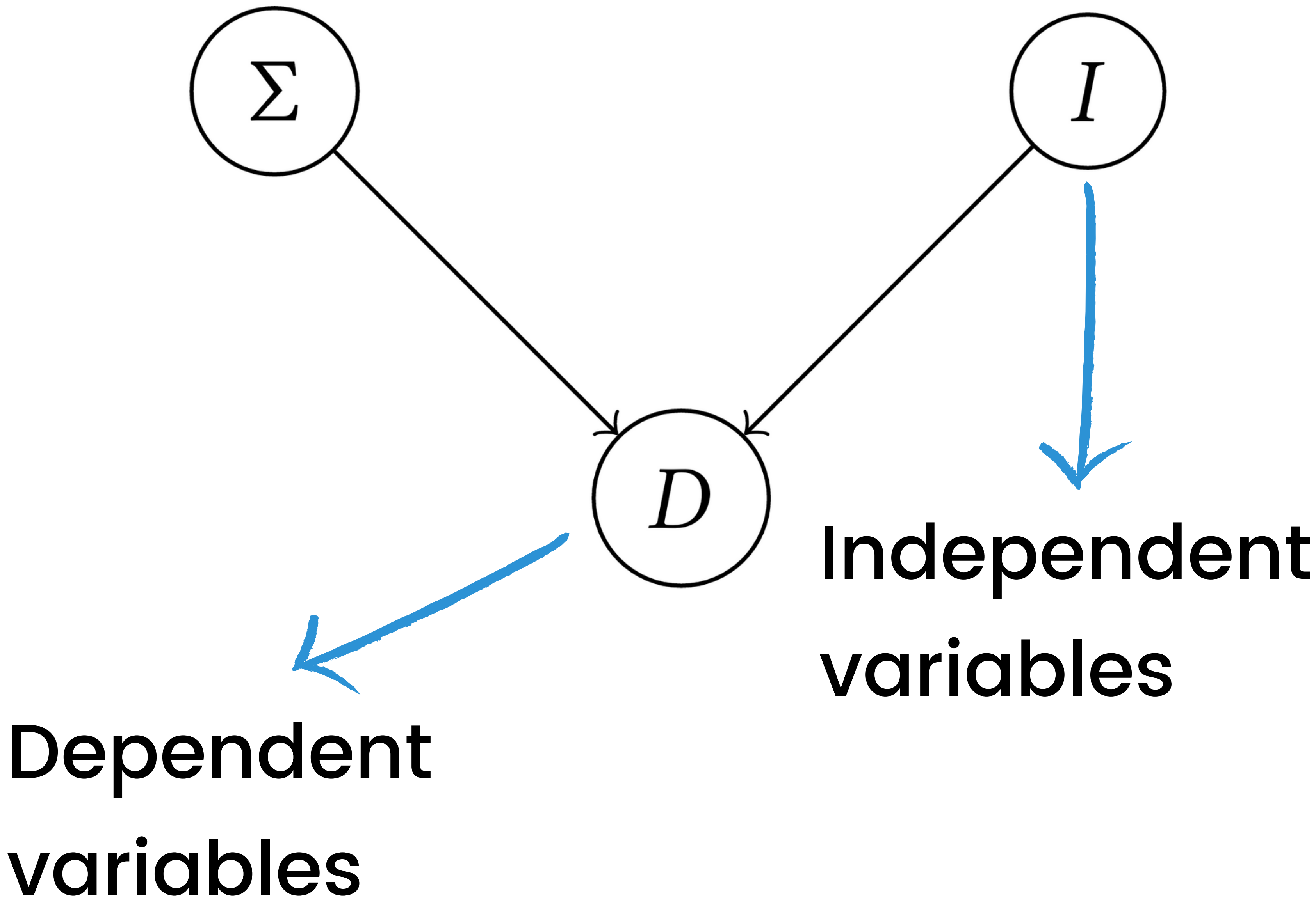


- Highlight few independent factors
- Beyond statistics: can we highlight causation directly from data?

RESEARCH QUESTIONS

CAUSAL DISCOVERY-CAUSAL GRAPHS

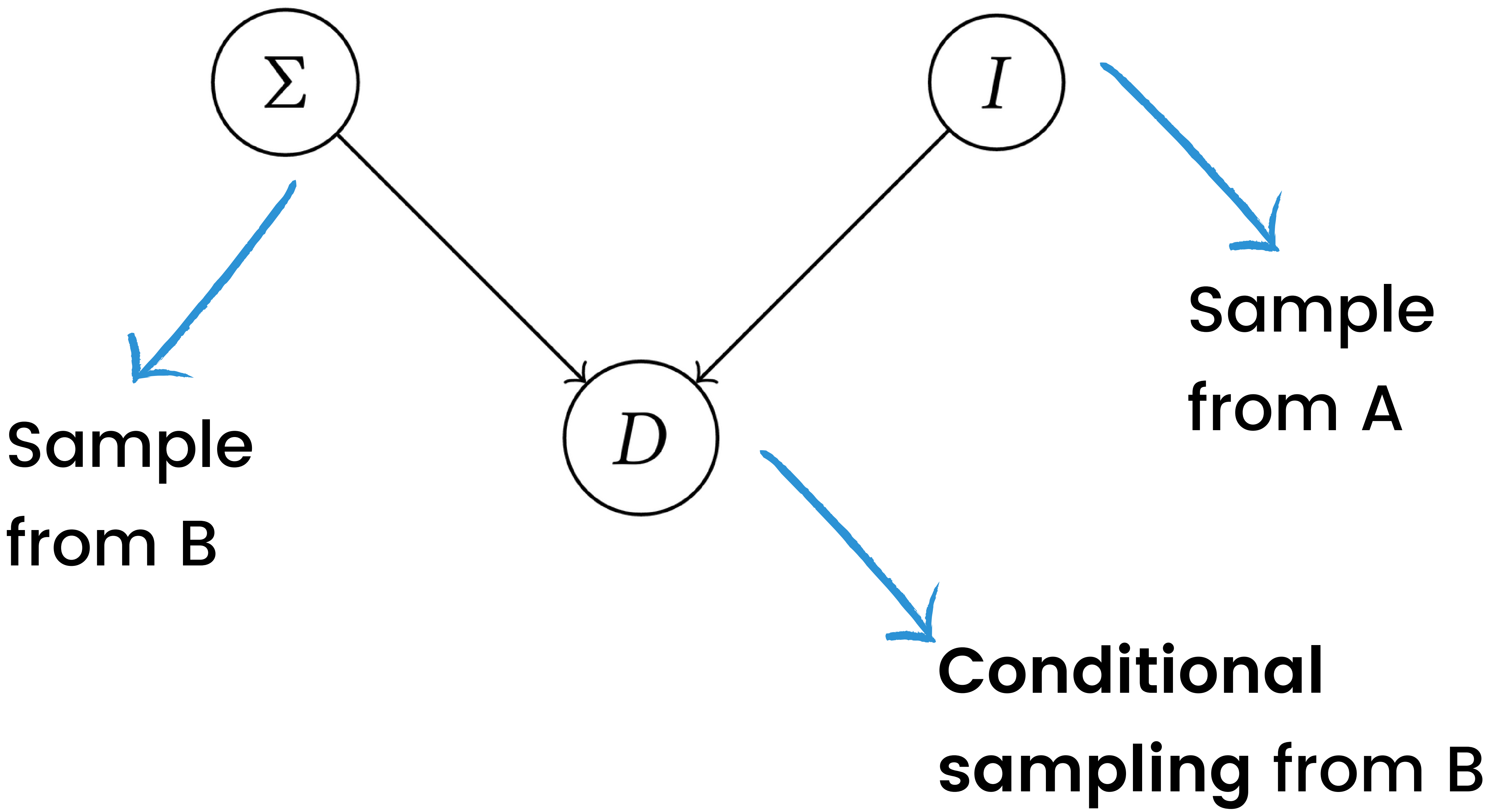
We sample new data with causal awareness



- We set a **shift variable:** Σ
- We start sampling from parent nodes: **causal parents**
- We sample new features by **conditioning** on causal parents

RESEARCH QUESTIONS
CAUSAL DISCOVERY-CAUSAL DATA AUGMENTATION

Our sampling uses a dataset split



Two datasets:

- **A**: the dataset we want to augment
- **B**: the dataset sampled from the target distribution

RESEARCH QUESTIONS

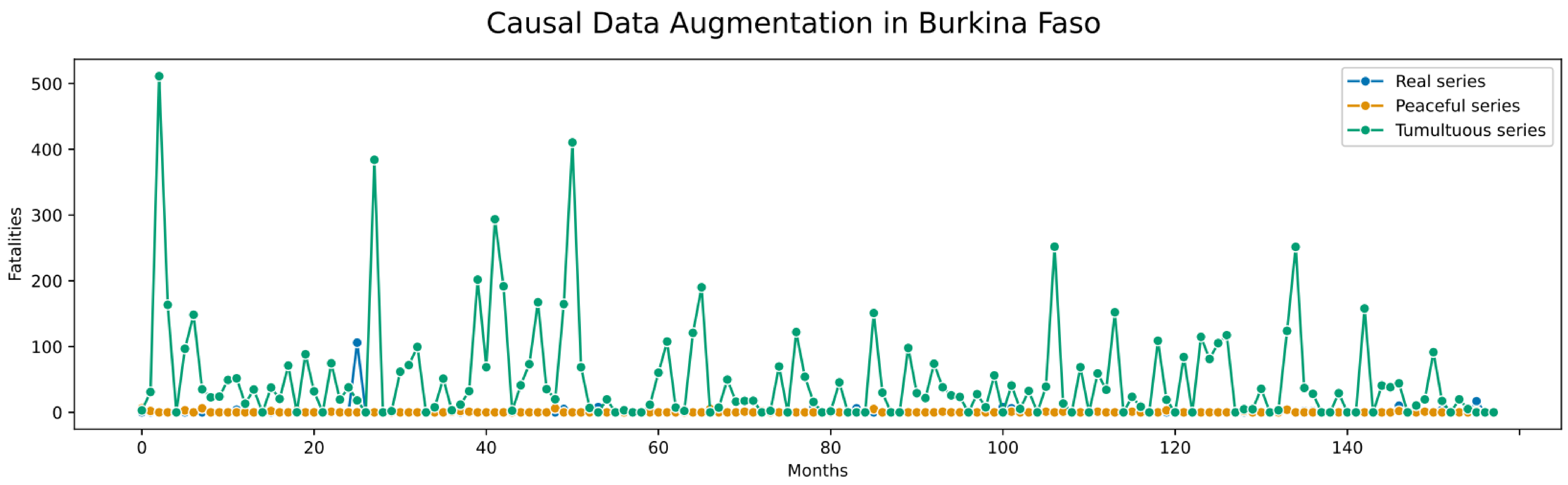
CAUSAL DISCOVERY-CAUSAL DATA AUGMENTATION

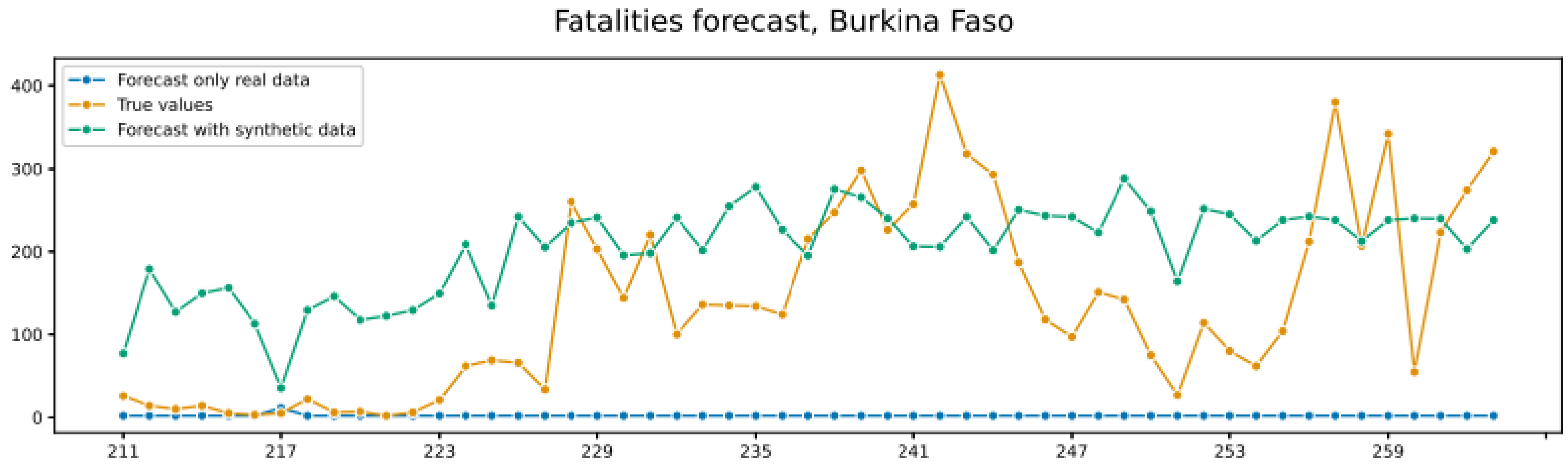
Our method:

- For every country we simulate a change of scenario using causal graphs and we create synthetic **distributions**
- We **sample** data from the new distributions
- We use synthetic and real data to train **robust** ML models

RESEARCH QUESTIONS

CAUSAL DISCOVERY-CAUSAL DATA AUGMENTATION





RESEARCH QUESTIONS

CAUSAL DISCOVERY-CAUSAL DATA AUGMENTATION

Advantages

- Model agnostic
- Regularization
- Robust

Drawbacks

- Risk of catastrophic forgetting
- Slow

RESEARCH QUESTIONS

METRICS

Can we find better metrics?

Time Series Forecast Error Metrics

Scale-Dependent Metrics

- Mean Absolute Error
- Mean Squared Error
- Root Mean Square Error

Percentage-Error Metrics

- Mean Absolute Percentage Error
- Symmetric Mean Absolute Percentage Error

Relative-Error Metrics

- Median Relative Absolute Error
- Geometric Mean Relative Absolute Error

Scale-Free Error Metrics

- Mean Absolute Scaled Error

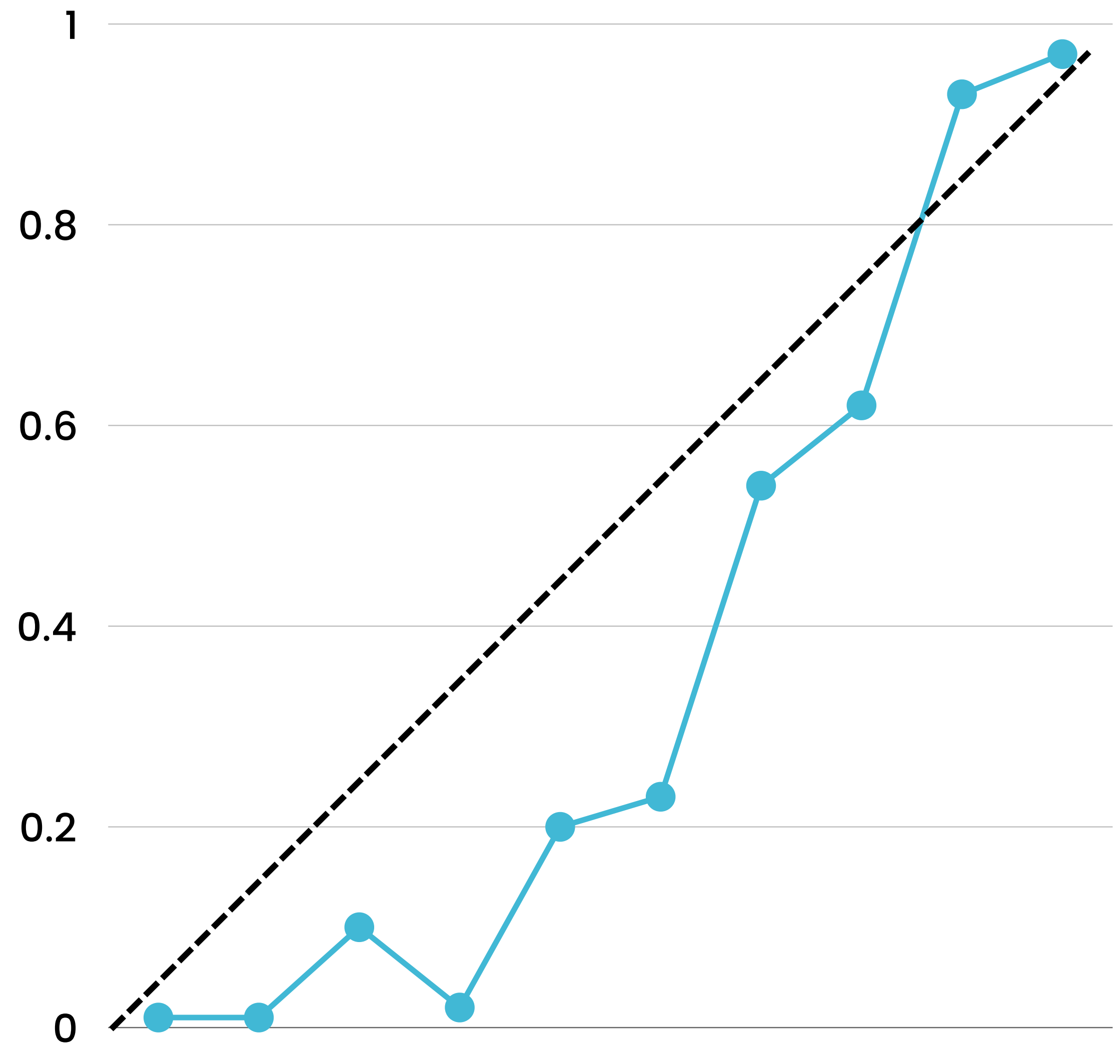
RESEARCH QUESTIONS
METRICS

- **Spike precision**: the fraction of spikes the model is able to predict
- **Spike recall**: the fraction of spikes, among the predicted, that are actually spikes

RESEARCH QUESTIONS

CALIBRATION

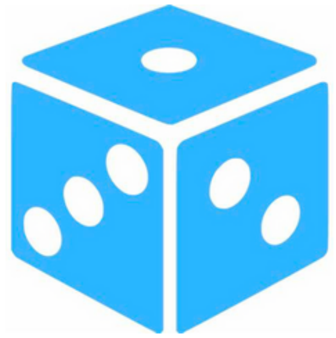
Can we find a general calibration strategy?



- Machine learning models do not provide real probabilities: we need calibration
- Drawback: calibration strategies rely on assumptions, we cannot assume much in the time series domain

RESEARCH QUESTIONS

CALIBRATION



Our tool:

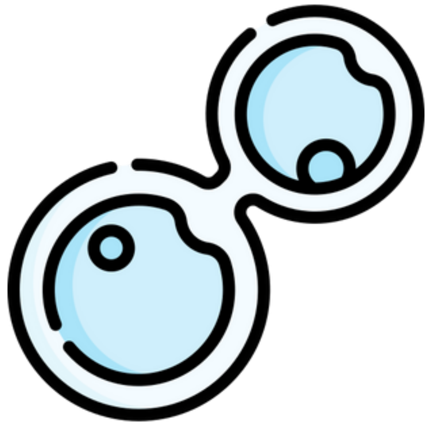
Conformal Prediction

Model agnostic framework with guarantees on real probabilities

Problem:

It relies on IID assumption

Not robust to distribution shifts

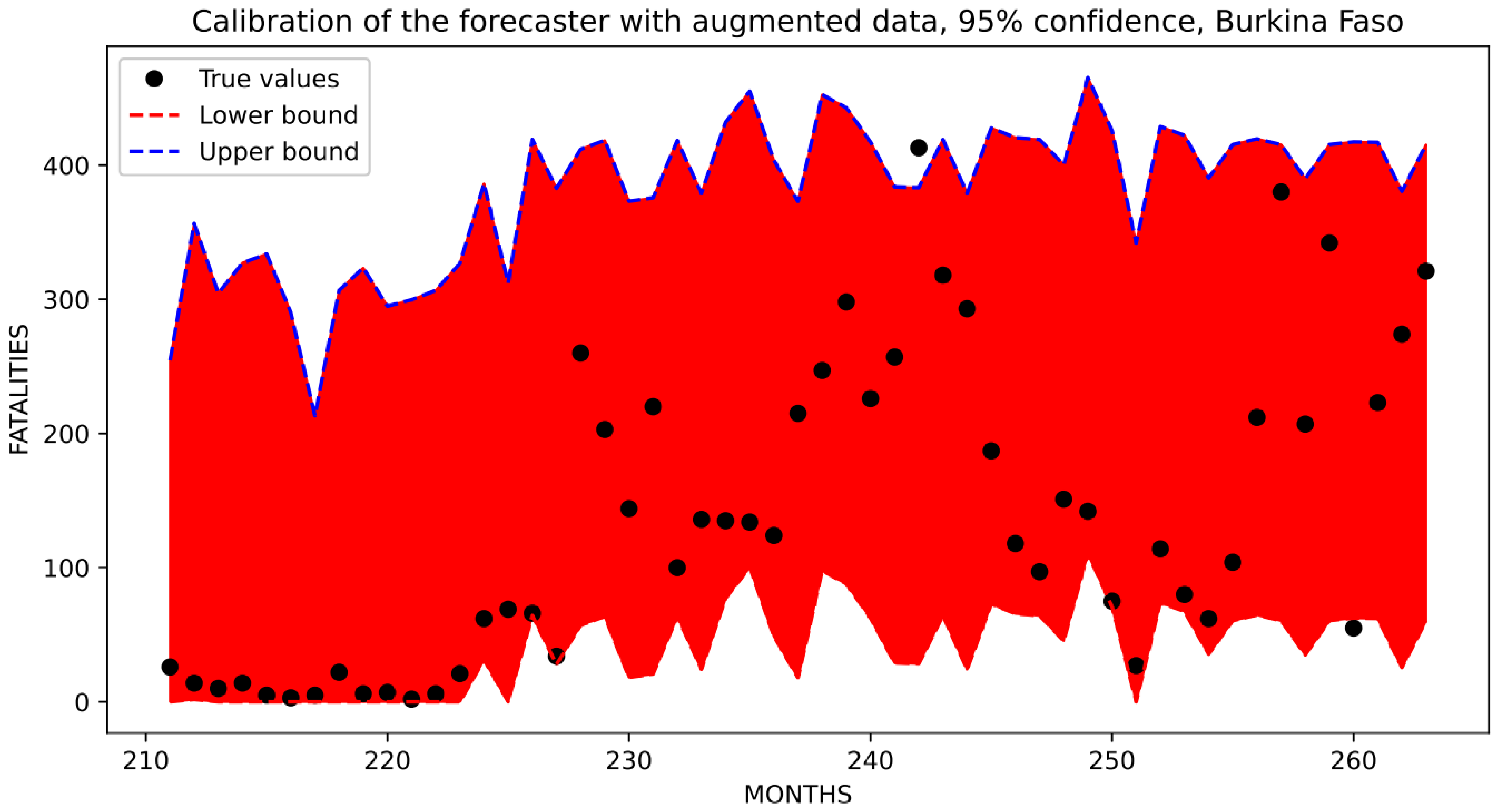


Solution:

Causal data augmentation

Augment also the calibration set

RESEARCH QUESTIONS
CALIBRATION



ACHIEVEMENTS

What did we achieve?

PERFORMANCE

	MEAN ABSOLUTE ERROR	SPIKE PRECISION	SPIKE RECALL
RANDOM FOREST - REAL DATA	116.47	0.33	0.40
RANDOM FOREST - REAL + SYNTETHIC DATA	104.48	0.37	0.43
LIGHTGBM - REAL DATA	92.82	0.33	0.55
LIGHTGBM - REAL + SYNTHETIC DATA	79.75	0.37	0.44
XGBOOST - REAL DATA	103.83	0.34	0.40
XGBOOST - REAL + SYNTHETIC DATA	76.51	0.35	0.42

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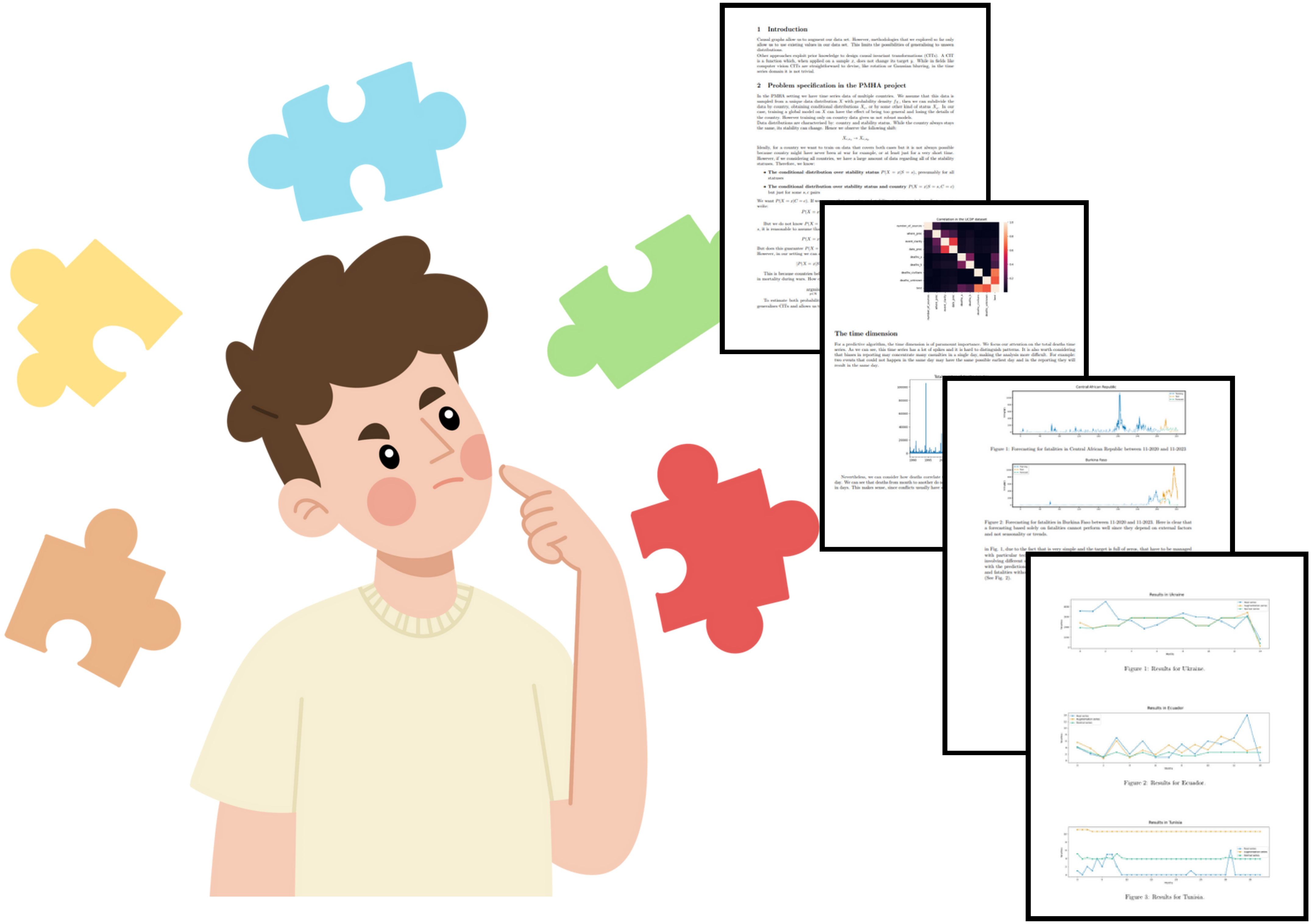
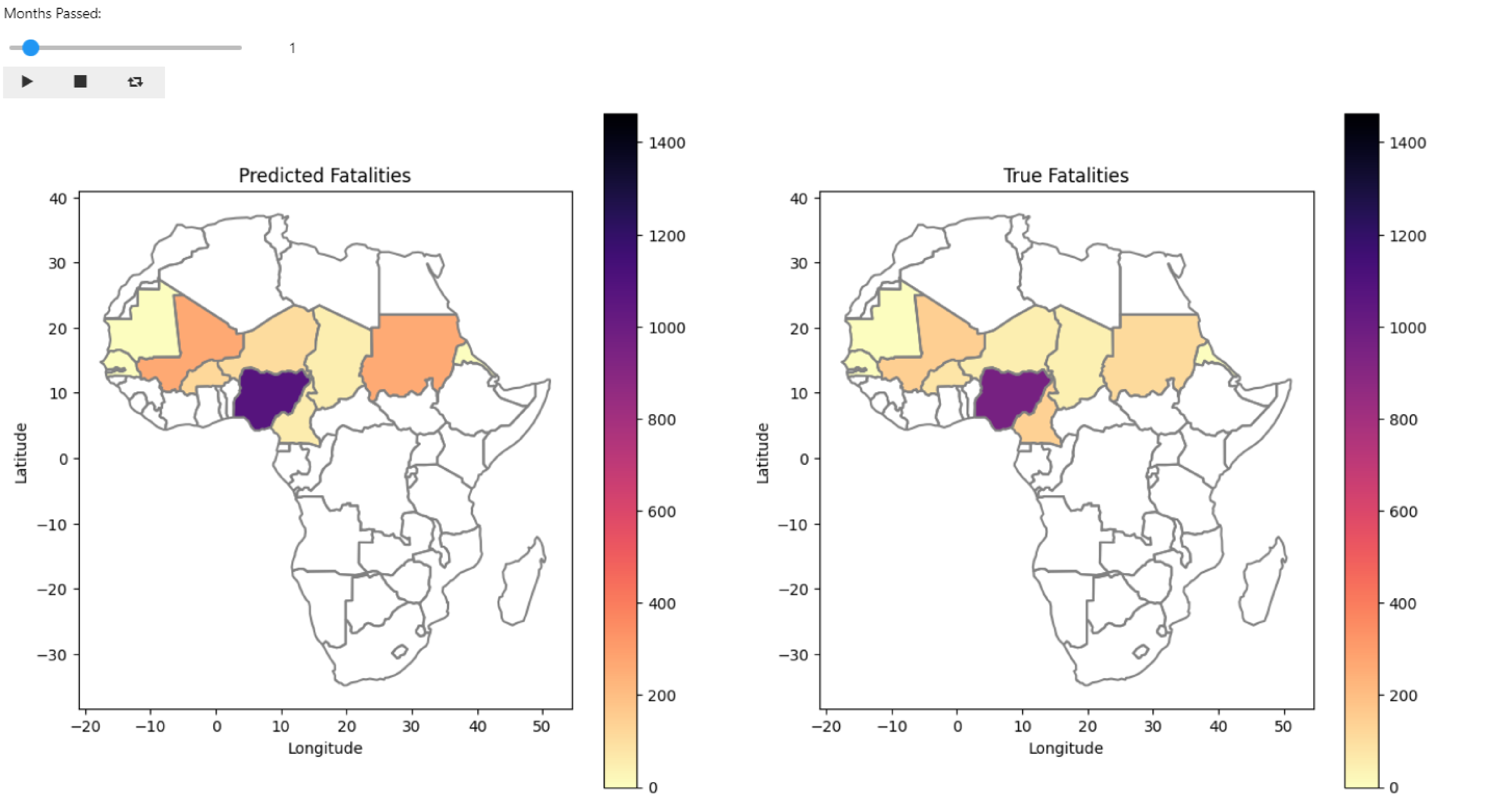
LOGS

Continuous production of short process logs for enhancing the understanding of our researches



DASHBOARD



Months Passed:
1
Predicted Fatalities
True Fatalities
Latitude
Longitude
40
30
20
10
0
−10
−20
−30
−20
−10
0
10
20
30
40
50
1400
1200
1000
800
600
400
200
0

CONCLUSIONS

What we have seen so far?

- Proposition
- Objective
- Research Questions
- Achievements

CONCLUSIONS
ACHIEVEMENTS

Dataset Construction for Sahel Region Fatality Prediction

Causal Data Augmentation for Distribution Shifts

Causal Data Augmentation for Calibration

CONCLUSIONS
FUTURE WORKS

- Integration of described methods on current early-warning systems
- Stability Enhancement for Causal Data Augmentation
- Efficiency Improvement in CDA Data Generation
- Automated Domain Split Selection

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Thank you for your attention!

Scan me!

Questions?

Link to our repository: GitHub

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