DeepCOVID: An Operational Deep Learning-driven Framework for Explainable Real-time COVID-19 Forecasting

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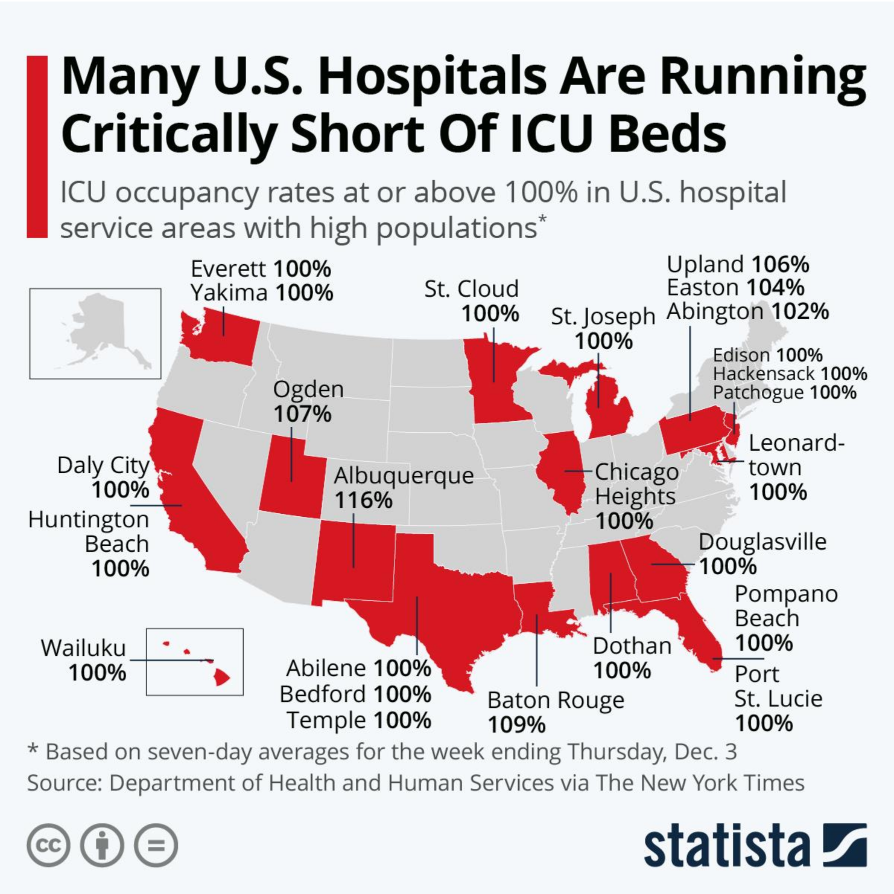
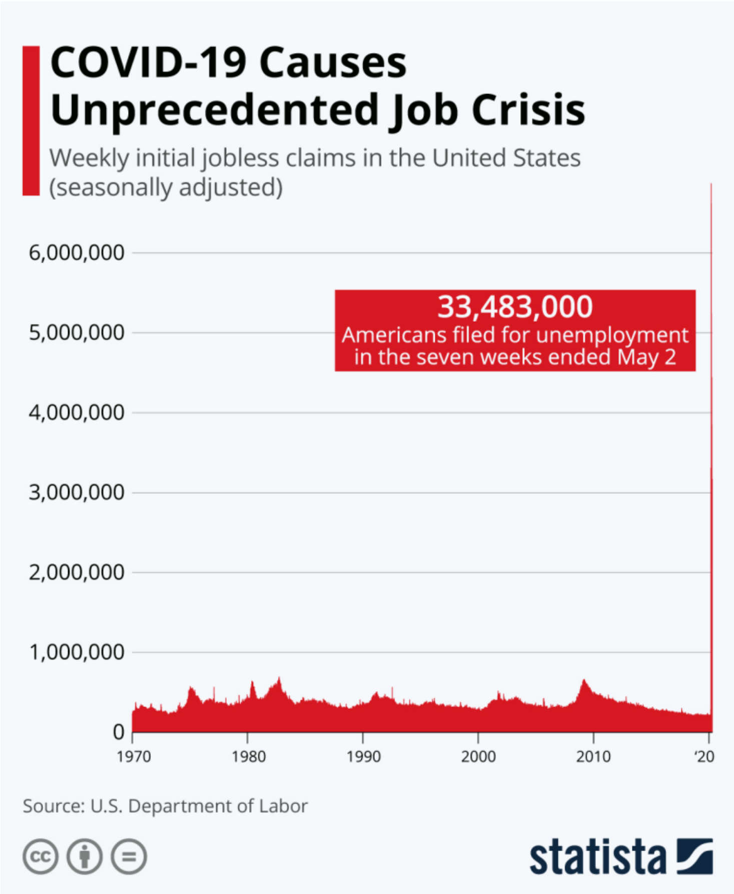
Outline

- Motivation
- Approach
  - Data module
  - Prediction module
  - Explainability module
- Results and discussion
- Conclusion and future work

Impact of a Pandemic in Modern Society





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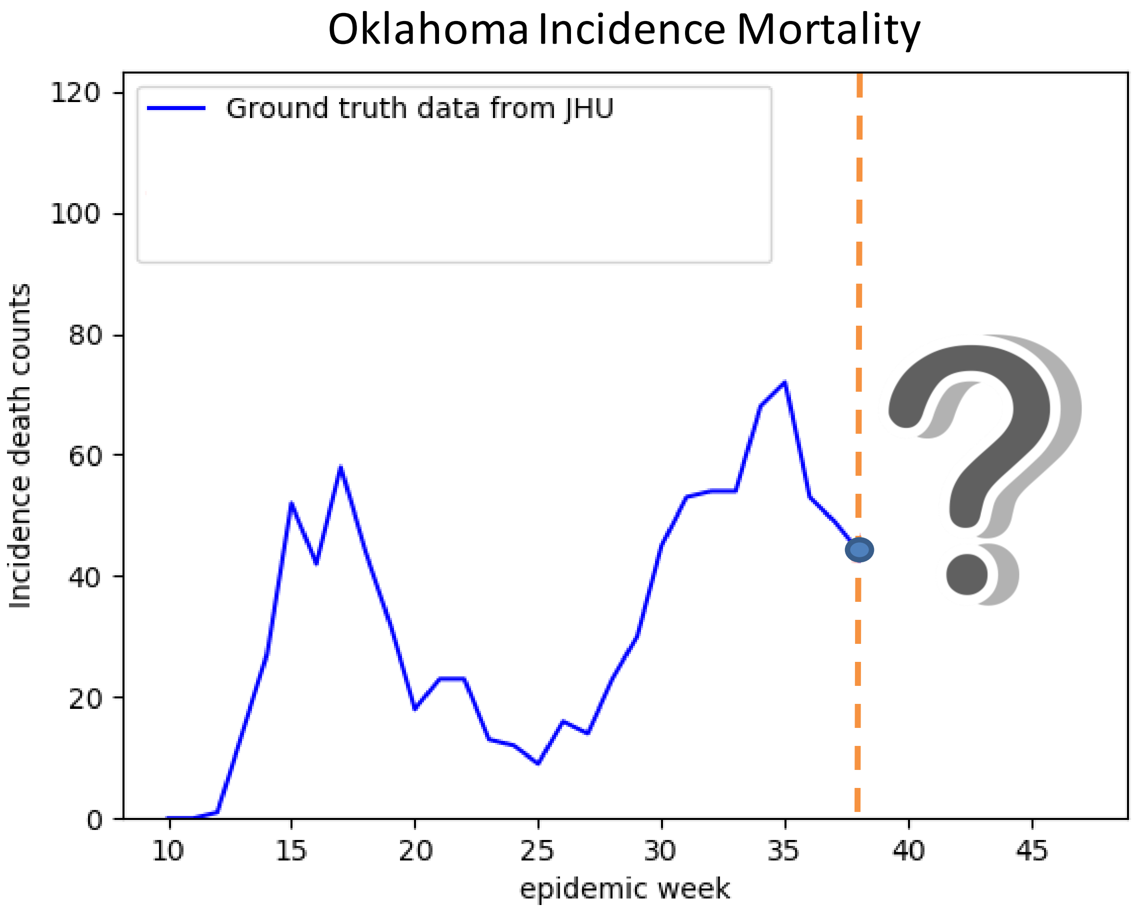
Real-time COVID-19 Forecasting



Possible near future:

- Goes down
- Stays still
- Goes up

Depends on:

- Interventions in place
- Current number of infections
- Contact patterns
- Exposure to disease
- Etc

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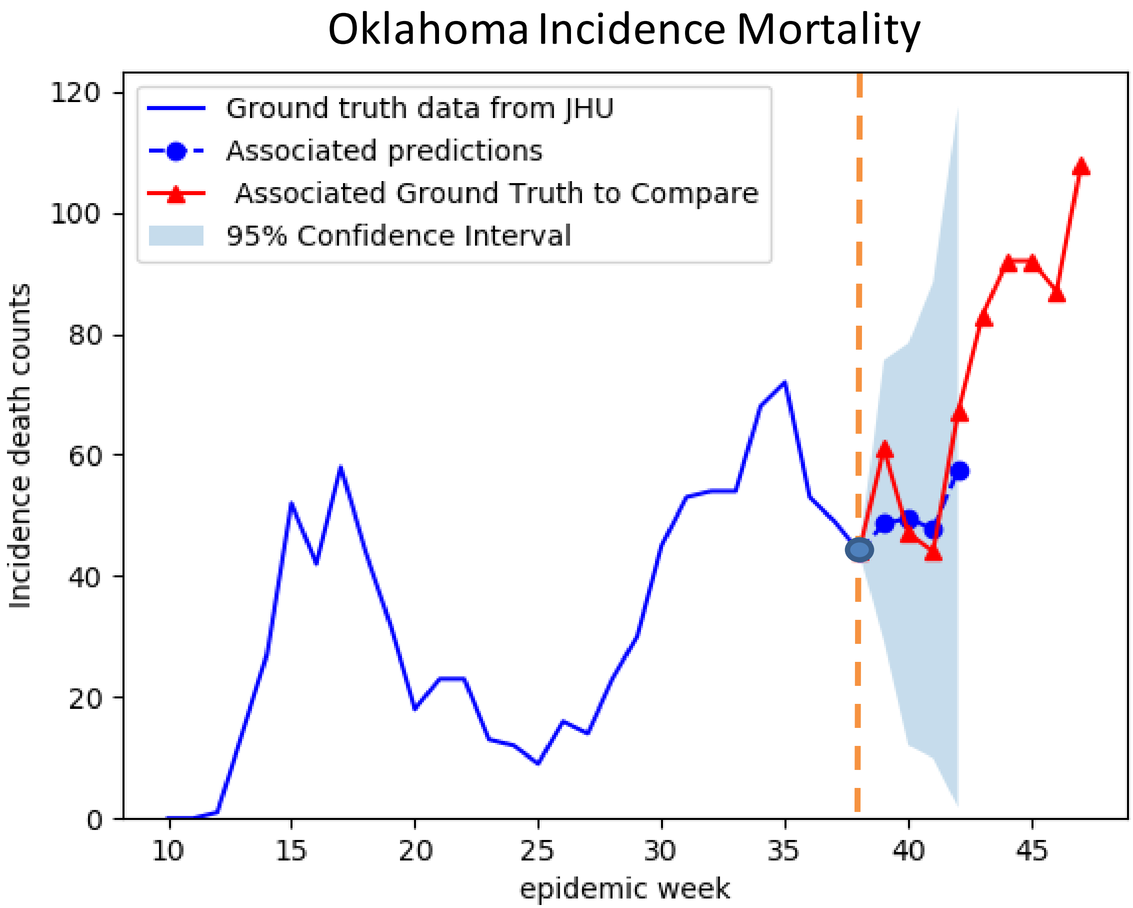
Real-time COVID-19 Forecasting



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Why Forecasting?

An outlook to the future allow communities to

- Allocate resources/budget
  - Ventilators, enable more ICU beds
- Inform public policy
  - E.g., mandate shelter in place?
- Improve preparedness
- …

Data-driven Models for COVID-19 Forecasting

- Most methods in COVID Forecast Hub were mechanistic or agent-based models.
- Our approach's goal: explore performance and utility of **purely data-driven models** in short-term forecasting
  - Give a different perspective
- Pros:
  - See what the data says with minimal assumptions
  - Update very quickly
  - Ingest multiple signals
  - Techniques for robustness
- Challenges: interpretability; principled uncertainty estimation; data quality issues; nontrivial for what-if forecasting
- Past success in forecasting other infectious diseases

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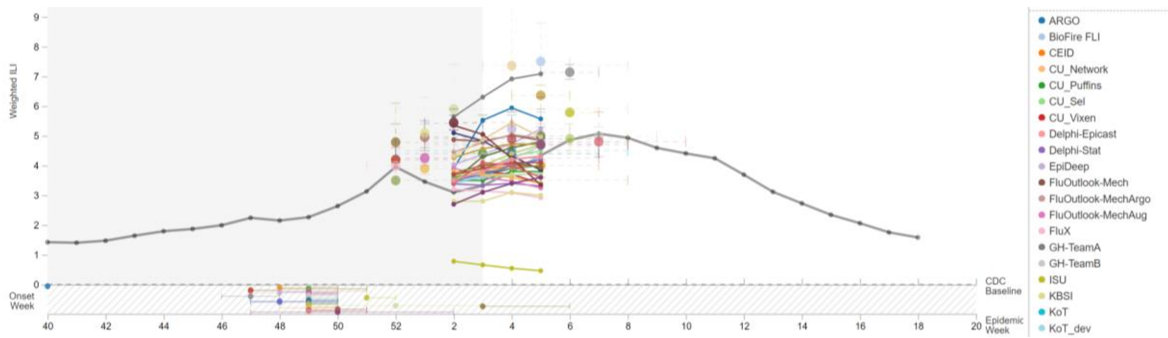
Our Participation in CDC Forecasting Initiatives

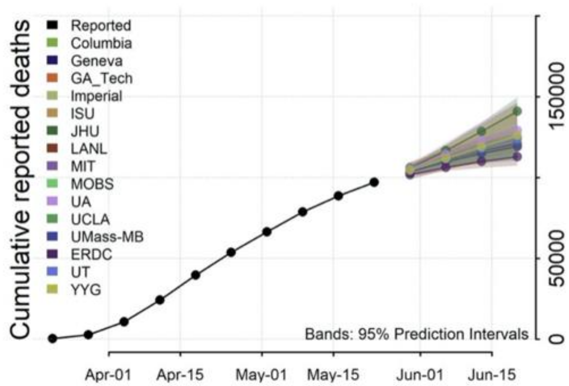
Target 1: Weighted influenza like illness (wILI) count per week

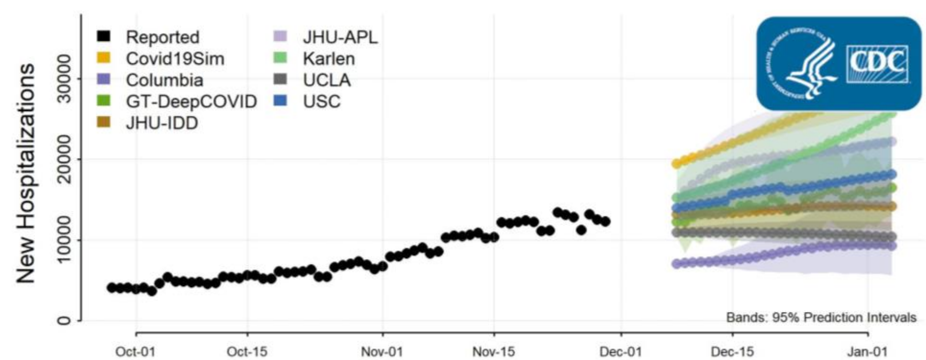


Multiple years

Target 2: Weekly reported Covid Mortality

Target 3: Daily Covid-induced Hospitalizations





Since April End 2020

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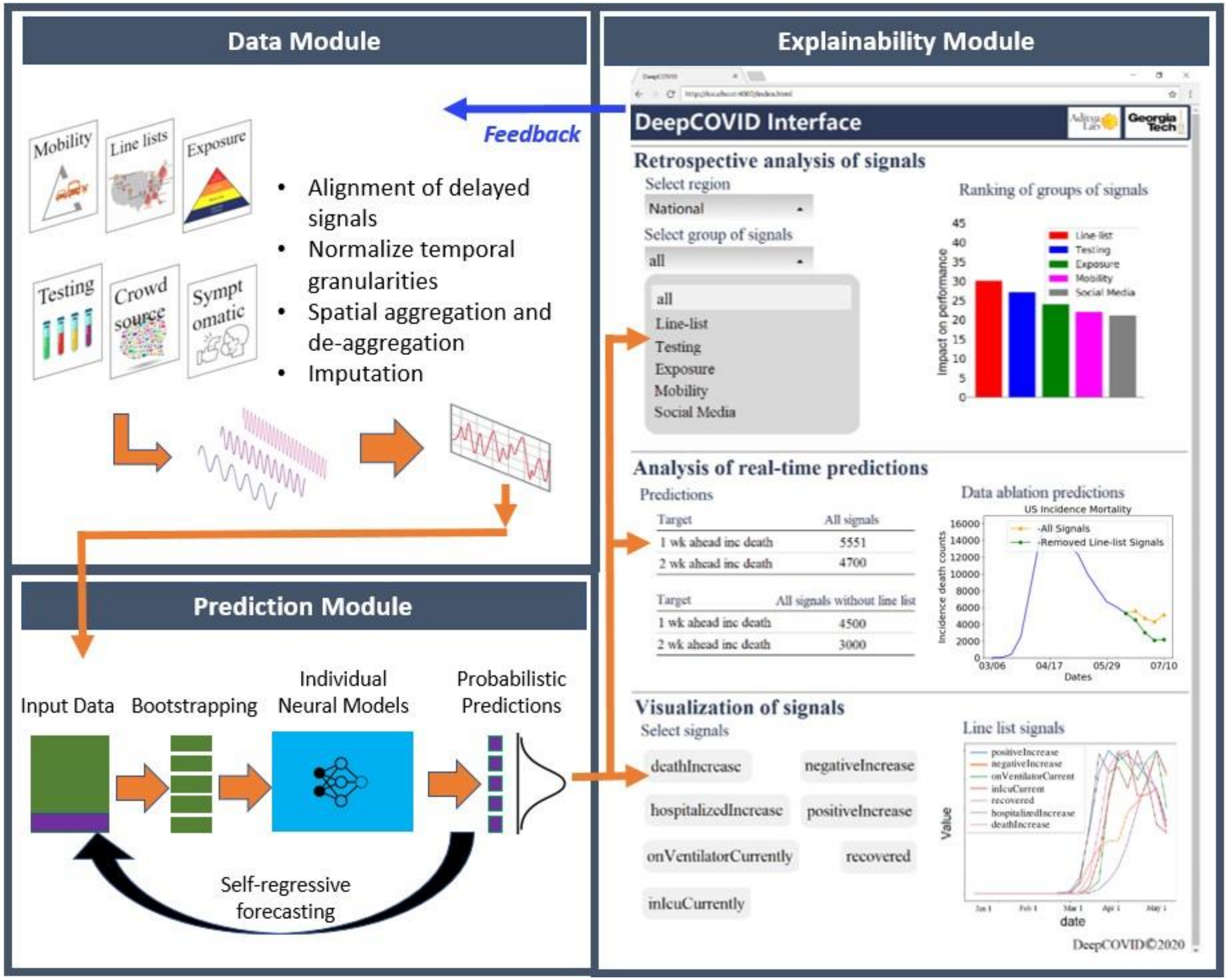
Our Operational Framework



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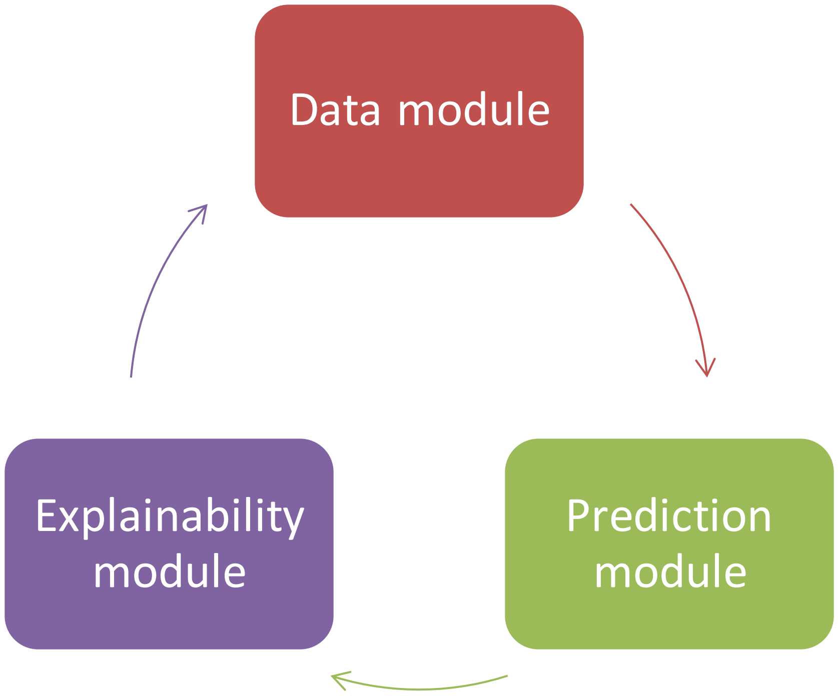
Rationale of the Framework

- Separate noisy data from the learning process
- Explainability is a challenge in data-driven models
- Understand and connect forecasts with epidemiological reasons
- Feedback to improve performance



Why Deep Learning?

- Flexible, scalable, efficient technology
- Excellent choice to model non-linearities
- Able to incorporate different knowledge representations
- Very active research area

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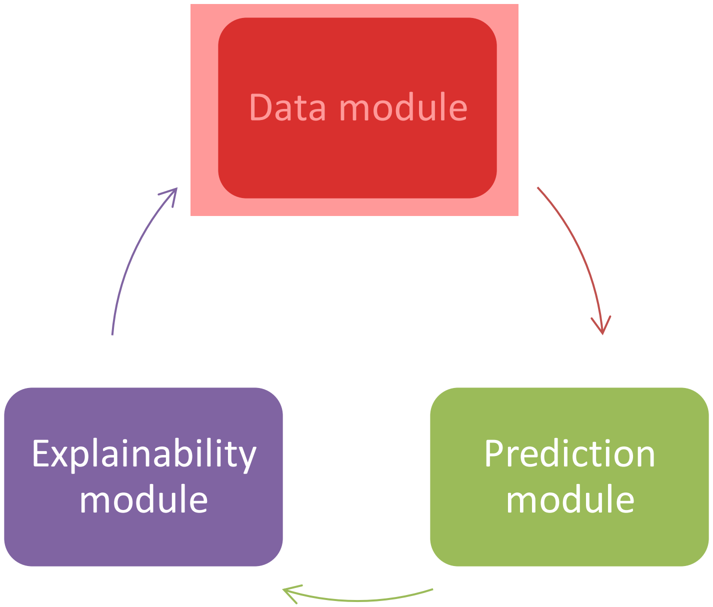
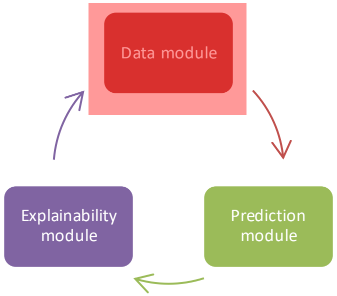


Data Challenges: Don't Underestimate!



(C1) Multiple data sources and formats

- Format varies over time

(C2) Select signals with epidemiological significance

(C3) Temporal misalignment

- Delays, pause in reporting, differ in granularity

(C4) Spatial misalignment

- Differ in granularity: county vs state vs national

(C5) Data quality and missing data

- Noisy and unreliable for some states
- New hospitalizations (target) is not reported by all states

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Data Sources

- Line-list based
- Testing
- Crowdsourced
- Mobility
- Exposure
- Social Media surveys

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Details in Paper & Appendix

Data Signals

Type/Rationale	**Signals**
(DS1) *Line list*: Traditional surveillance for tracking patients and symptoms	1. Confirmed cases; 2. UCI beds currently occupied; 3. People on ventilation; 4. Recovered; 5. Hospitalization rate (COVID-Net); 6. ILI% ER visits; 7. CLI% ER visits; 8. Excess Deaths;
(DS2) *Testing*: Capture changing screening artifacts	9. People tested; 10. Negative cases; 11. Emergency facilities reporting; 12. Number of providers;
(DS3) *Crowdsourced*: Symptomatic surveillance	13. Digital thermometer readings provide ILI%;
(DS4) *Mobility*: Evidence of changing contact patterns	14. Retail and recreation; 15. Grocery and pharmacy; 16. Parks; 17. Transit stations; 18. Residential; 19. Workplaces; 20. Overall-region-based
(DS5) *Exposure*: Measure social contacts	21-22. Device exposures (normal & adjusted);
(DS6) *Social Surveys*: Measure symptomatic burden	23. CLI%; 24. ILI%

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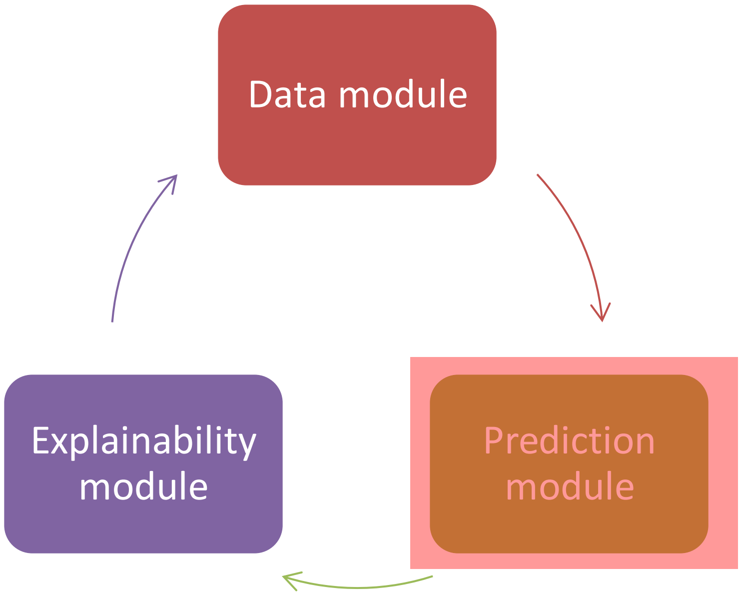
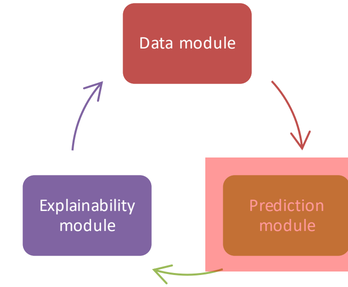
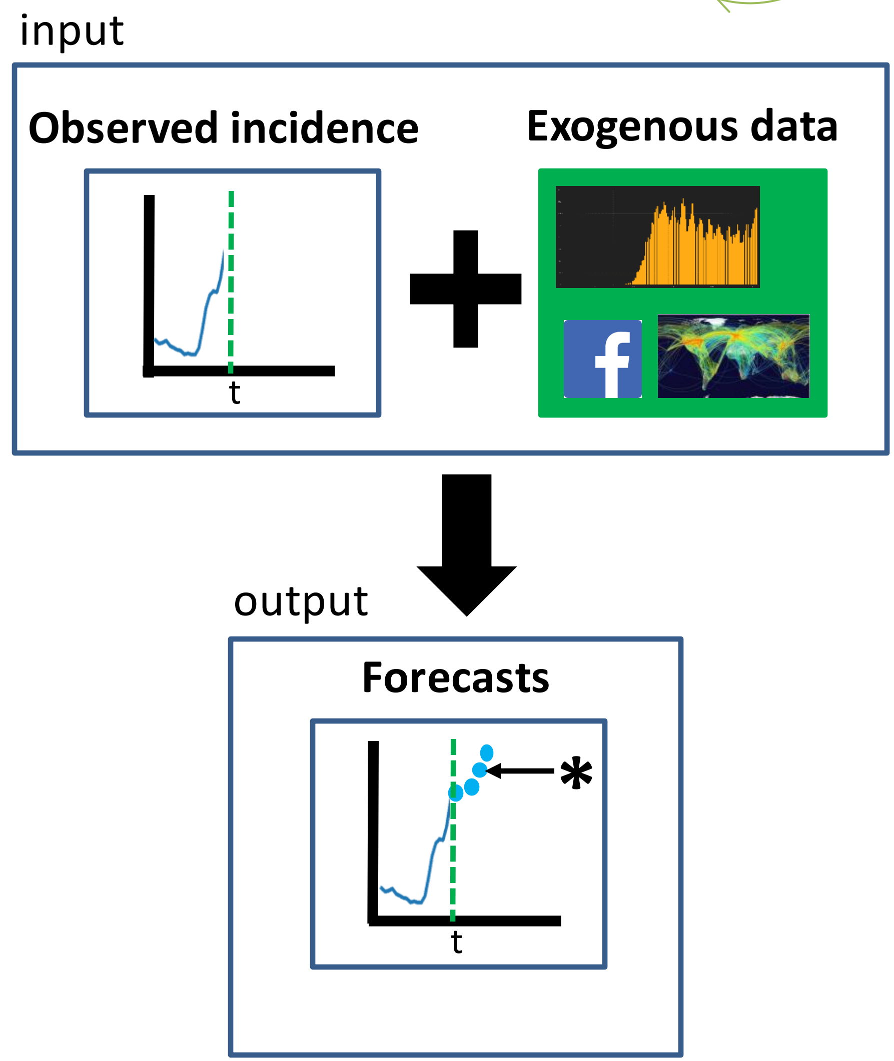


No historical data!

Problem Formulation



- **Given**
  - Partially observed mortality and hospitalization incidence curve till day t.
  - Exogenous data sources
- **Predict**
  - Future **weekly mortality** incidence and cumulative for next four weeks
  - Future **daily hospitalization** incidence for next four weeks



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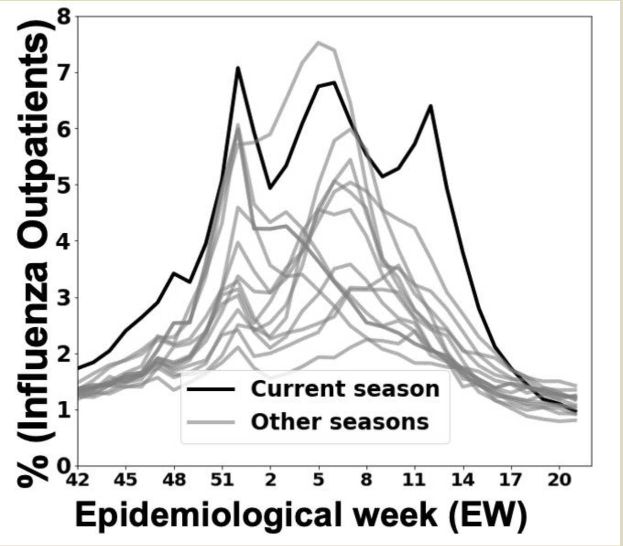
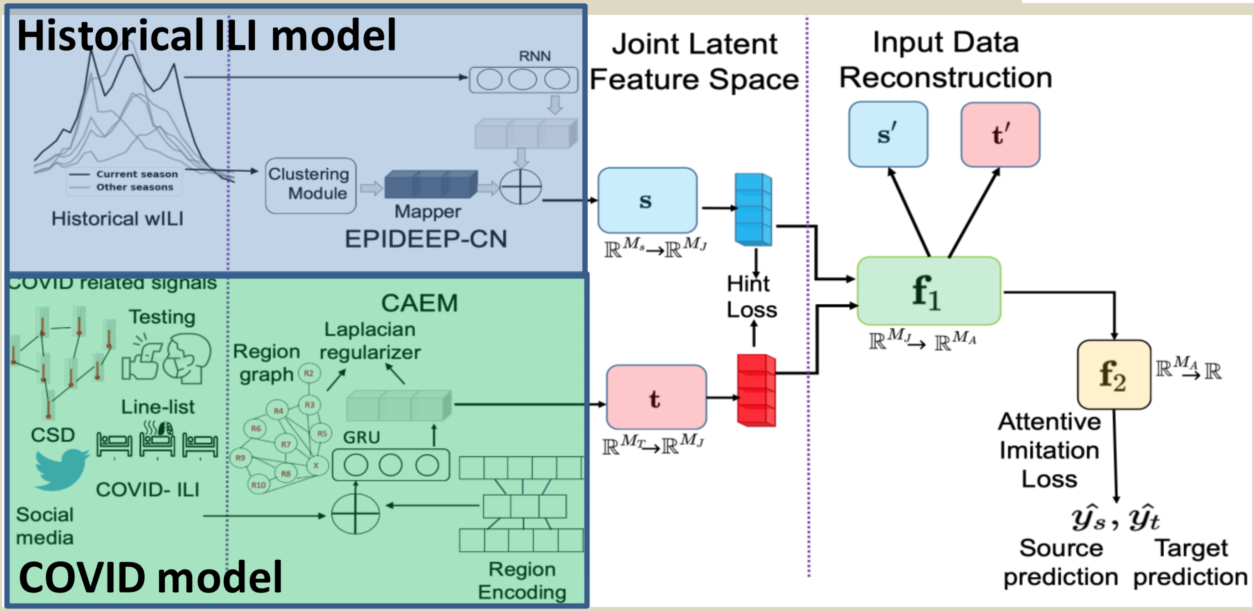
Separate project w/ VIRGINIA TECH

Detour

If Historical Data Exists…

- This is the scenario for Covid-ILI
- Steer an existing historical ILI model with new Covid-related signals
- Able to train large deep learning models





High-level abstraction

Accepted in AAAI-21 main track

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Current Situation: No historical data

- Unable to steer an existing model
- Use only Covid-related data sources.
- Covid data signals observed only since March.
- Observed data sparse, noisy and heterogeneous.

Prediction Module Challenges

(C6) Data sparsity due to the novel and dynamic nature of the disease

- NN with small number of params to avoid overfitting

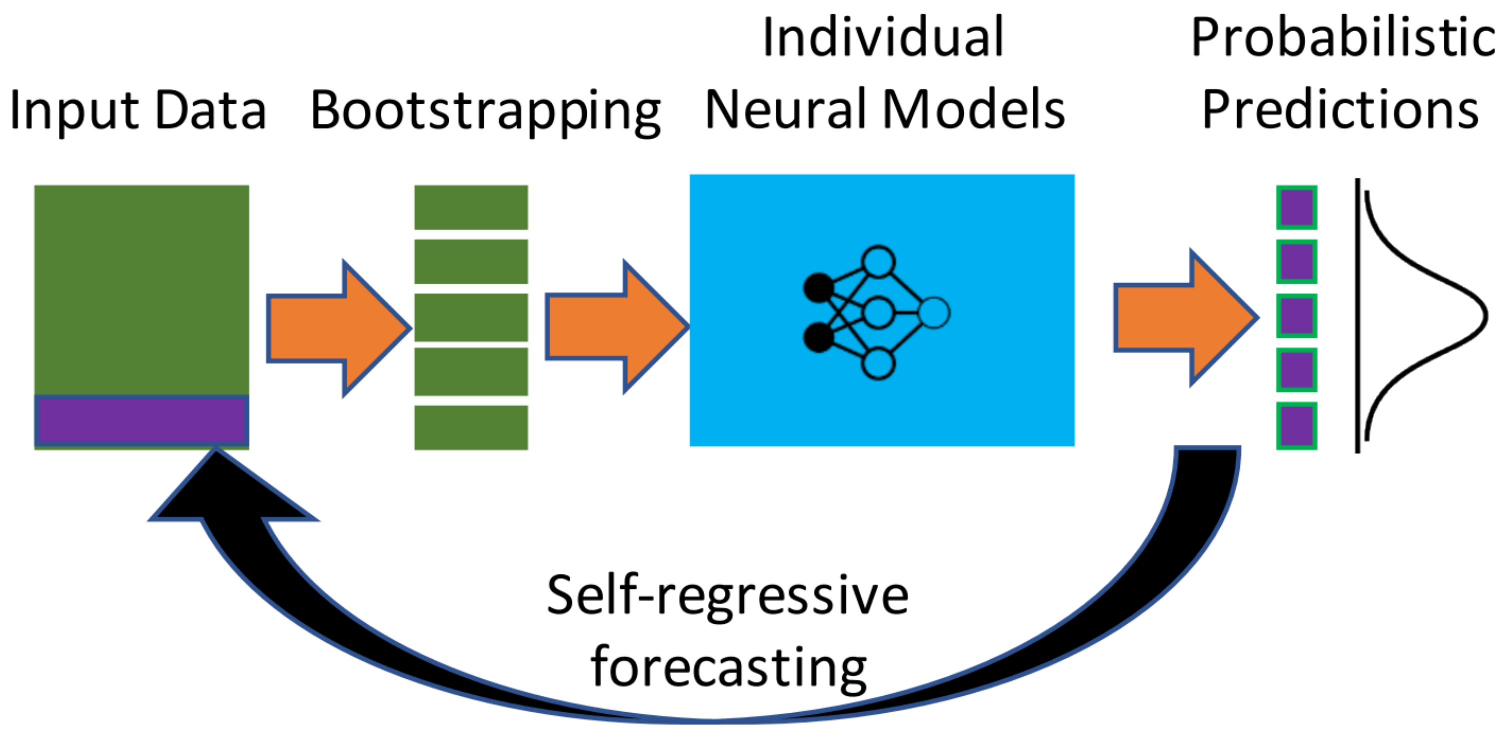
(C7) Robust point and probabilistic forecasting

- Robustness to noise via batch normalization
- Multiple initializations of optimization
- Principled uncertainty estimation via bootstrapping

(C8) Temporal consistency between consecutive forecasts

- Due to sparsity, we cannot train recurrent net
- We use self-regressive forecasting

Schematic of Prediction Module



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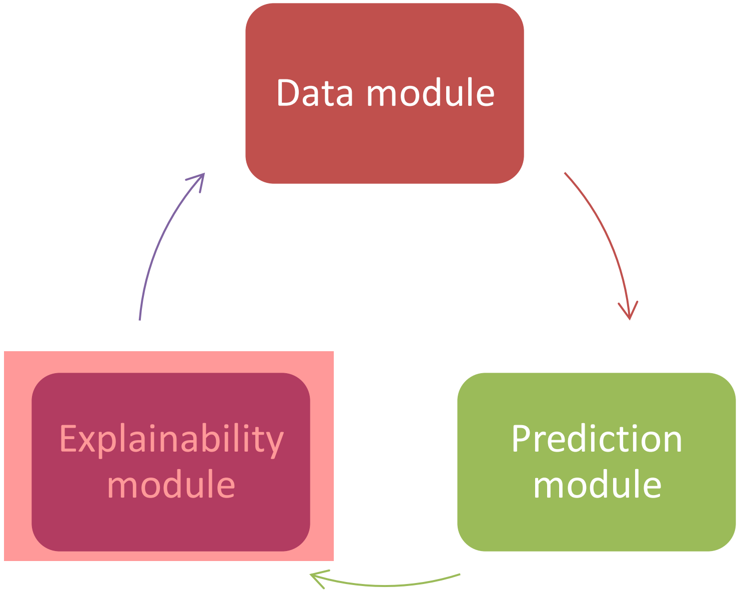

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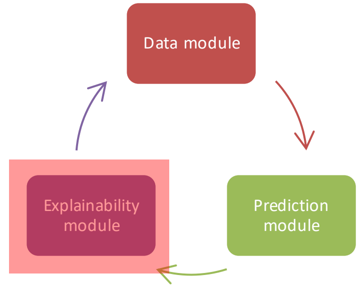
Explainability Module



- Why needed?
  - Understand the impact of various signals
  - Drive epidemiological observations
  - To improve our own predictions
- Data ablation: systematic removal of signals
- Evaluate signals that impact the most to our predictions and make sense of them
- Insights in real-time and in retrospective

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Explainability Module Challenges

(C9) Real-time insights of forecasts for decision-making and communication

- Data ablation for current week predictions
- Use an interface to visualize signals and their predictive contribution

(C10) Retrospectively understand signal strengths

- This allows continual improvement of forecasts
- We use data ablation for past predictions

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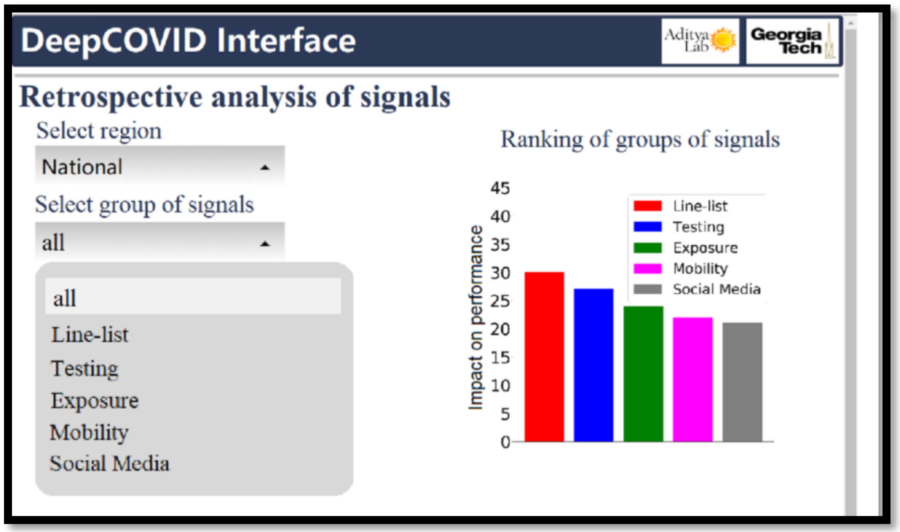
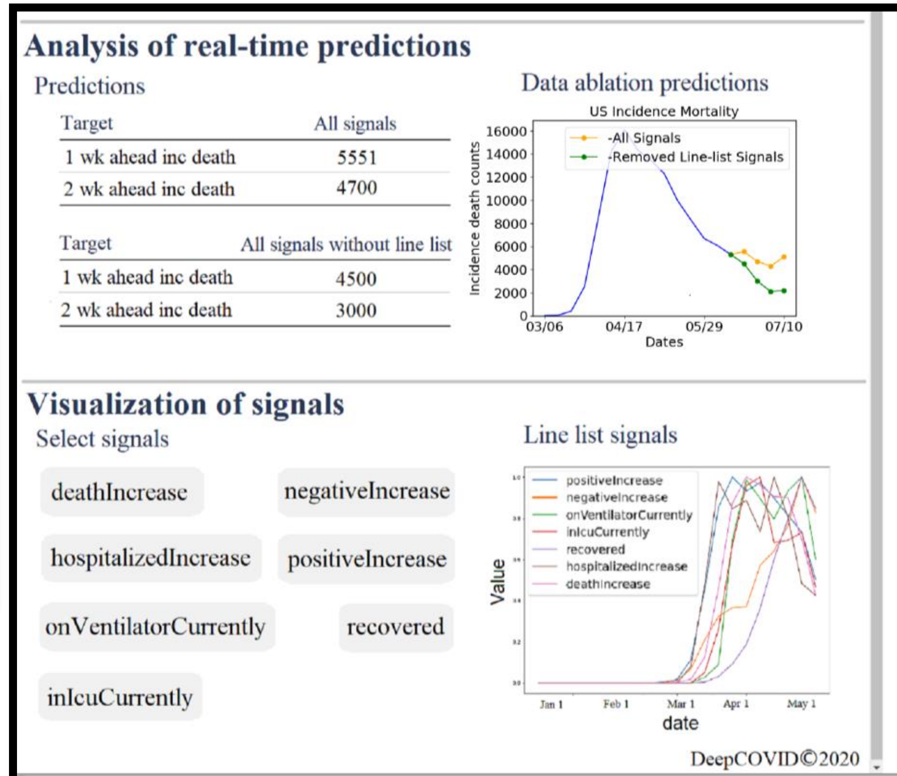
Interface + Data Ablation

Retrospectice Analysis

Real-time Analysis



Understand contribution to
past performance



Understand signals driving
current predictions

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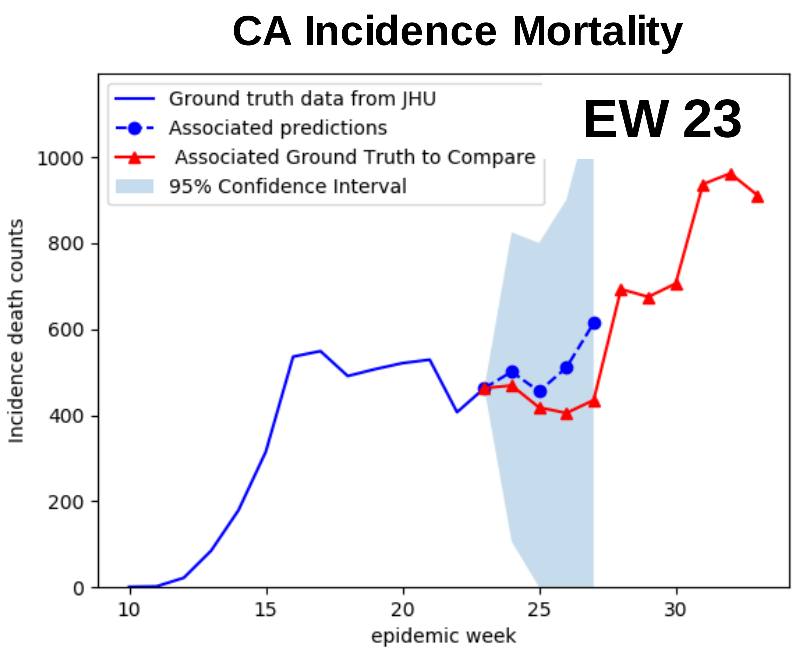
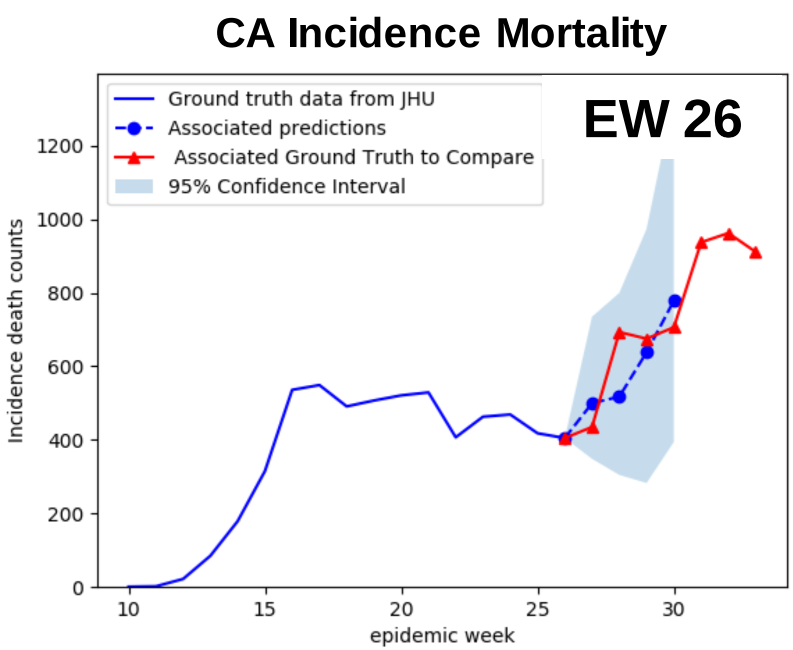
Setup

- All results are based on the real-time forecasts submitted during three months (June 8 to September 7 2020)
- Metrics: MAPE for point estimate performance; interval score (Bracher et al. 2020) for probabilistic interval performance

Obs. 1: Anticipate Trend Changes





We anticipated trend change **3 weeks early**

Accurately predict ramp up
+
Adapt uncertainty

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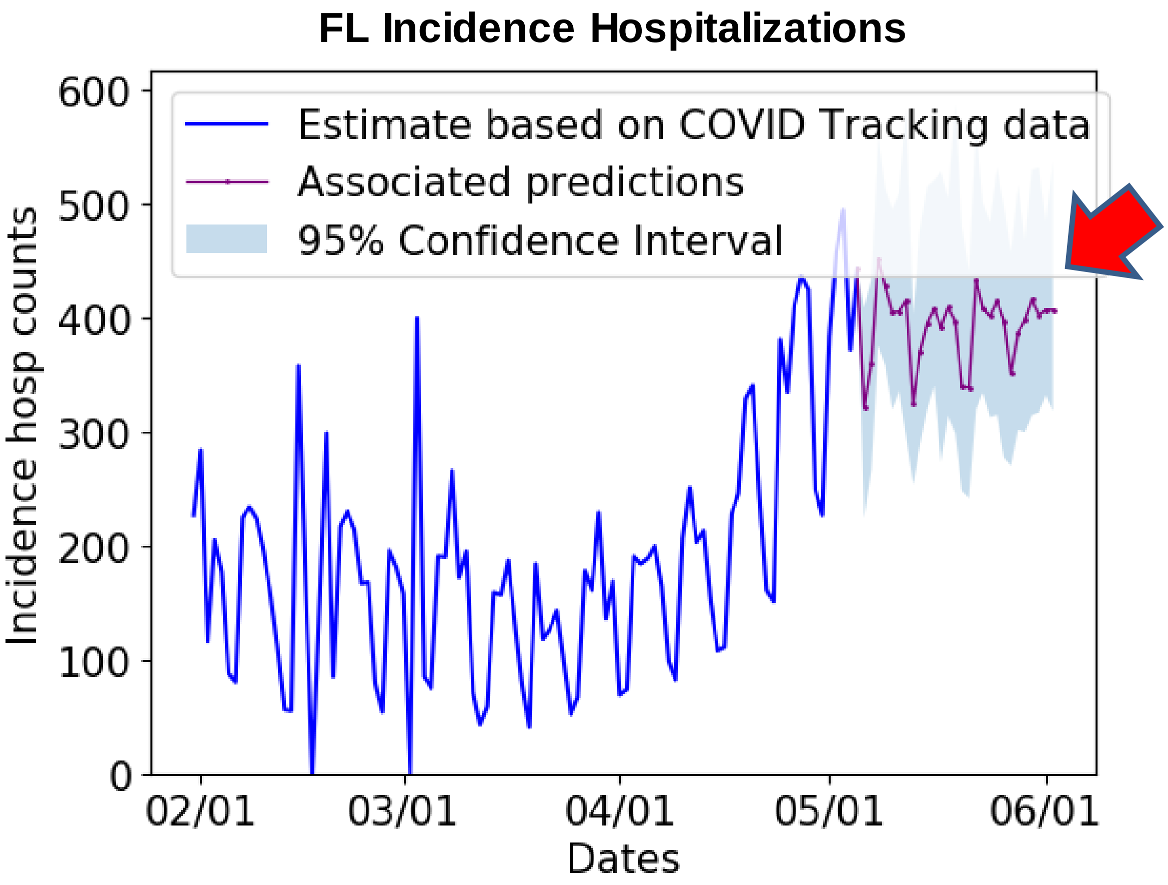
Obs. 2: Capture Finer Grained Reporting Patterns



Micro-patterns:
P1. Weekend drop
P2. Rise on Monday, stable in weekdays

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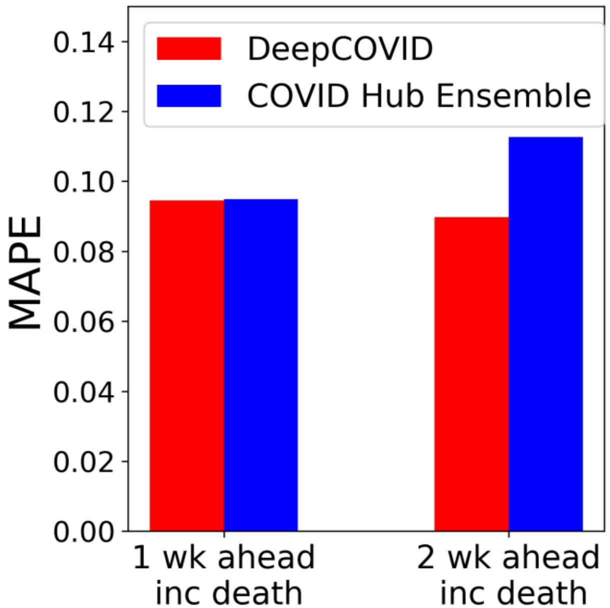
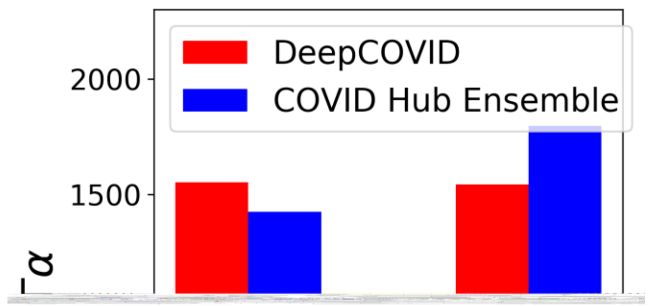
Obs. 3: Excels in US National Short-term Forecasting

Lower is better

Point estimate performance



Probabilistic interval performance



US National point estimate performance is better that the COVIDHub ensemble and close in probabilistic interval performance

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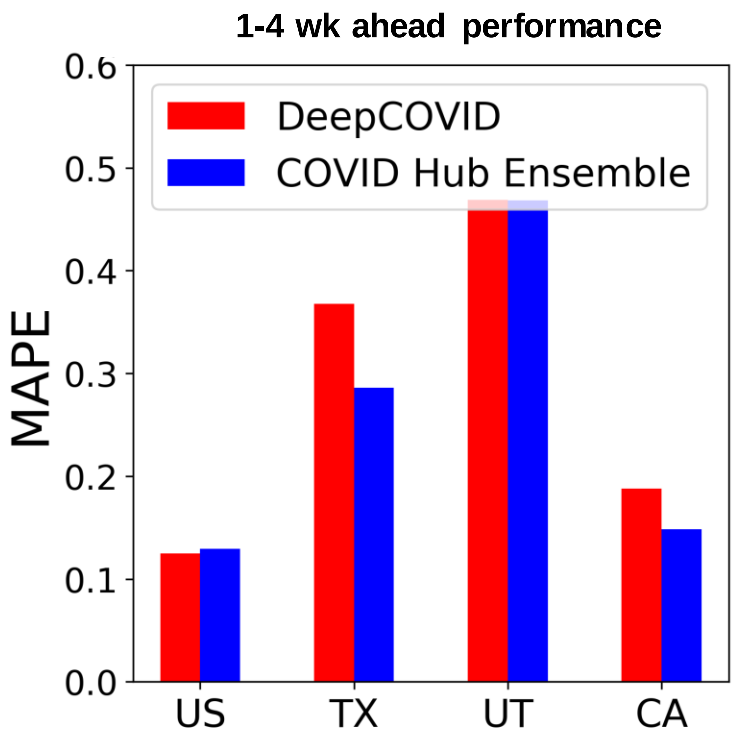
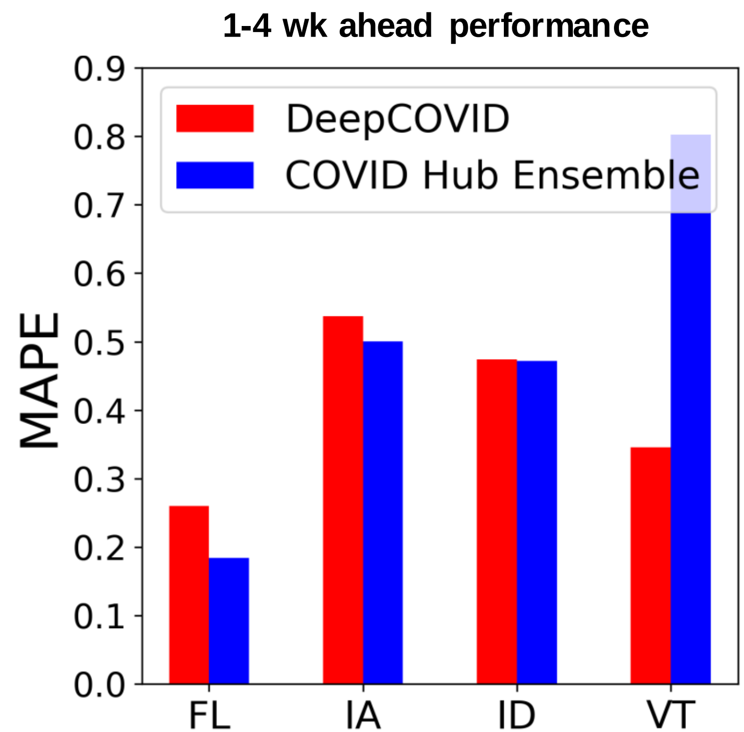
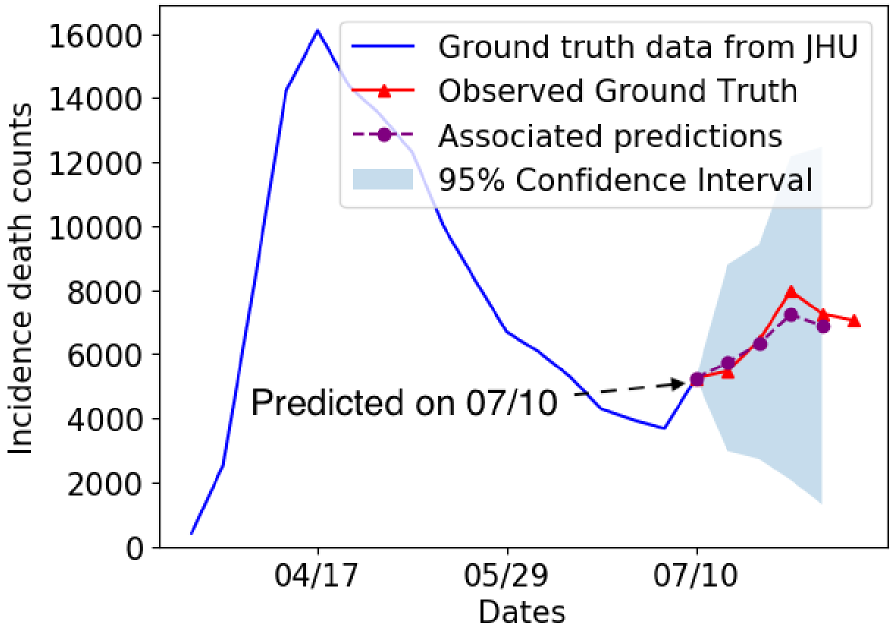
Obs. 4: Longer-term Performance is not Compromised





States suffer more of data quality issues and that affects our performance, but overall we are competitive

Obs. 5: Explainability of Predictions



- Signals contributing to US second peak prediction:
  - Mobility
  - Testing
- Sanity check to have confidence in predictions

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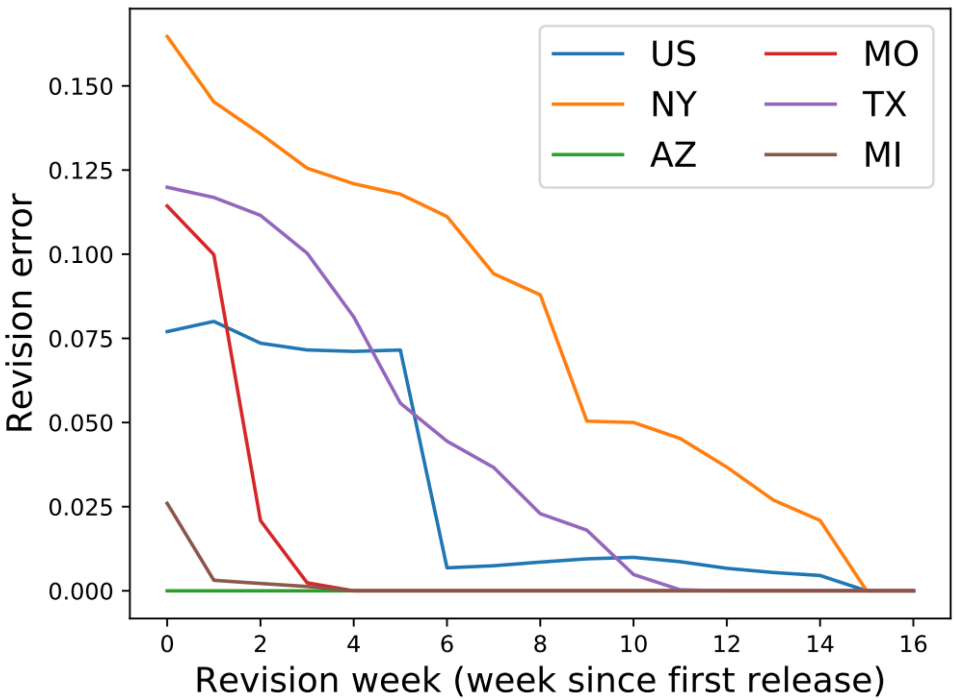
Future Steps

- Model non-pharmaceutical interventions explicitly
- Look at smaller geographical granularities
- Differentiate outbreaks of COVID and symptomatically similar diseases (e.g., flu)
- Handle backfill revisions

Lessons Being Learnt: Data Revisions



- Data revisions error has potential to mislead predictions.
- Evaluations in short term are not always reliable
  - Validation based on recent data may not always work

Takeaways

- DeepCOVID, a purely data-driven approach
  - Complementary perspective to the ensemble
  - Competitive performance, excels in short-term forecasting
- Allows some epidemiological insights
- Capable of ingesting a large amount of signals
- Easy to adapt to target and time resolution
- Active research area with open questions

Thanks!

Pre-print:
https://www.medrxiv.org/content/10.1101/2020.09.28.20203109v2

Resources:
https://deepcovid.github.io/

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