DeepOutbreak: A Deep Learning Framework for Improved Situational Awareness of the Spread of Covid-19 and Influenza

Team

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Project website:

cc.gatech.edu/~badityap/covid.html

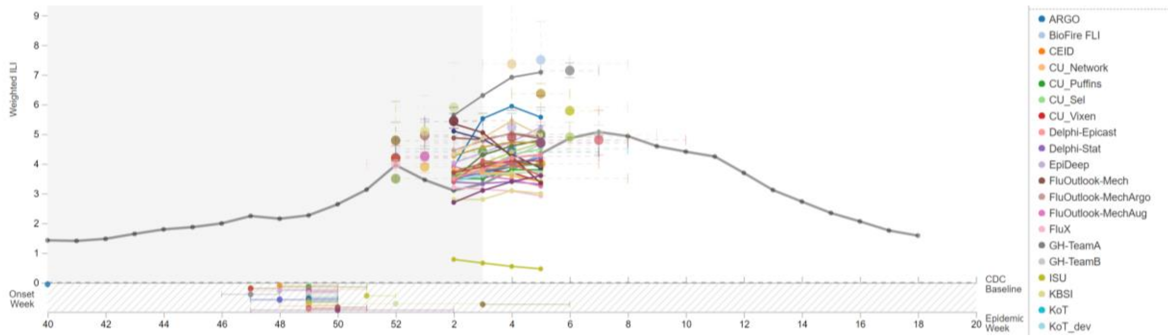
Georgia Tech

Team's Background

Georgia Tech Institute for Data Engineering and Science ML@GT	Prof. B. Aditya Prakash **Lab interests:** Data Science, ML and AI with applications to computational epidemiology/public health, urban computing, and web.	• Covid and flu forecasting • Epidemics over networks • Urban Analytics
Virginia Tech Discovery Analytics Center	Prof. Naren Ramakrishnan **Lab interests:** Data Science, ML applied to Comp. Epidemiology, Natural Language Processing, Urban Computing, Data-driven modeling of Cyber-Physical Systems.	• Ebola and flu forecasting • Forecasting disruptive events (EMBERS)
The University of Iowa comp|epi computational epidemiology research	Prof. Bijaya Adhikari **Lab interests:** Data Science and ML to model dynamical processes (e.g., spread of misinformation, disease) on large networks (e.g., web, human contact networks).	• Covid and flu forecasting • Hospital acquired infections (HAIs)

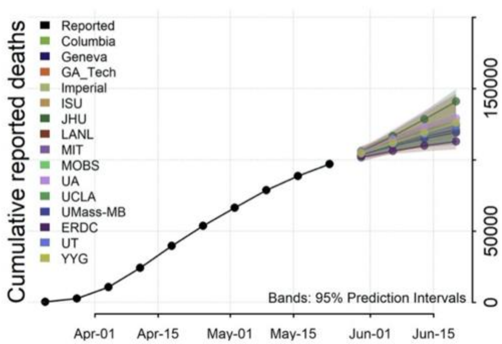
Our Participation in CDC Forecasting Initiatives

Target 1: Weighted influenza like illness count per week



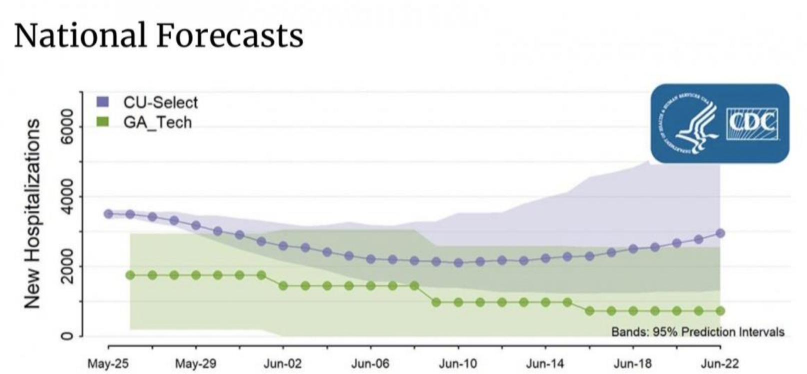
Last few years
Also in COVID-ILI (March 2020)

Target 2: Weekly reported Covid Mortality



Since April End 2020

Target 3: Daily Covid-induced Hospitalizations



Introduction

- Goal:
  - Improve situational awareness for Covid and flu
  - Characterize different faces of the utility of the symptom survey data for forecasting
- Motivation:
  - A second wave of Covid is likely to coincide with the flu season and forecasting flu burden becomes even more crucial[1].
  - Give policymakers valuable lead time to plan interventions and optimize supply chain decisions.
- Our approach is to jointly forecast Covid and flu

[1] **US CDC Director:** https://www.washingtonpost.com/health/2020/04/21/coronavirus-secondwave-cdcdirector/

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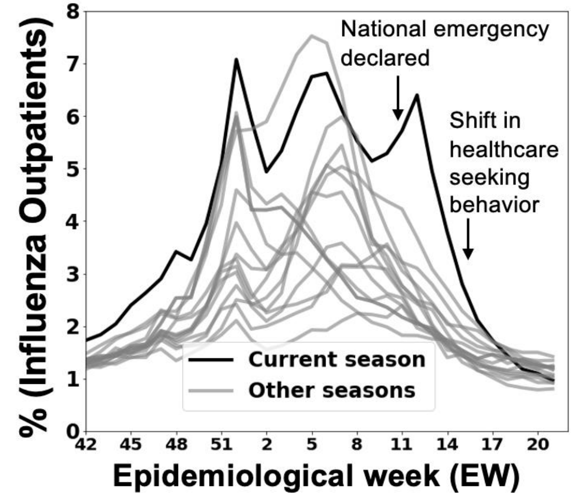
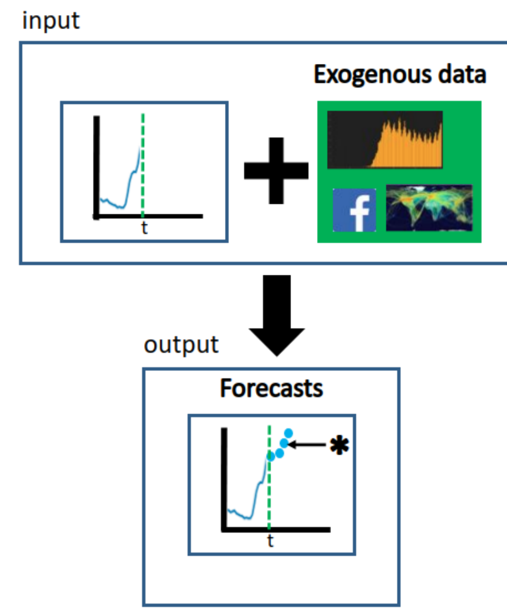
Tasks and Problem Formulation

- Surveillance systems are susceptible to symptomatic similarities.
- This makes it hard to recognize actual flu outbreaks.
- Task 1: Forecasting ILI in the Presence of Covid (Covid-ILI)
  - Use patterns from historical ILI
  - Leverage new data signals, e.g. symptom survey, mobility, Covid-related signals
- Task 2: Forecasting Covid Mortality and Hospitalizations





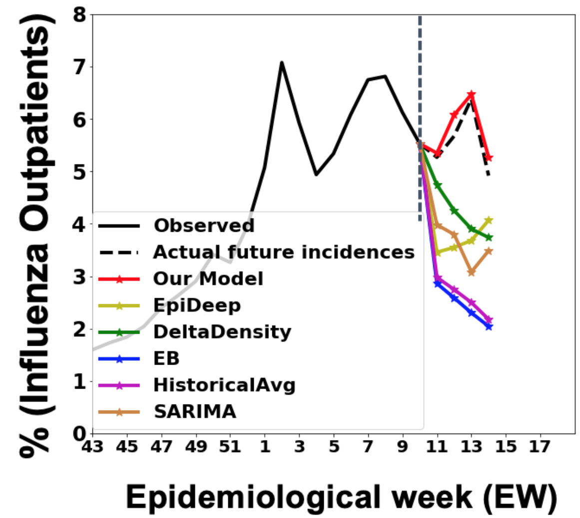
Our Approach: DeepOutbreak

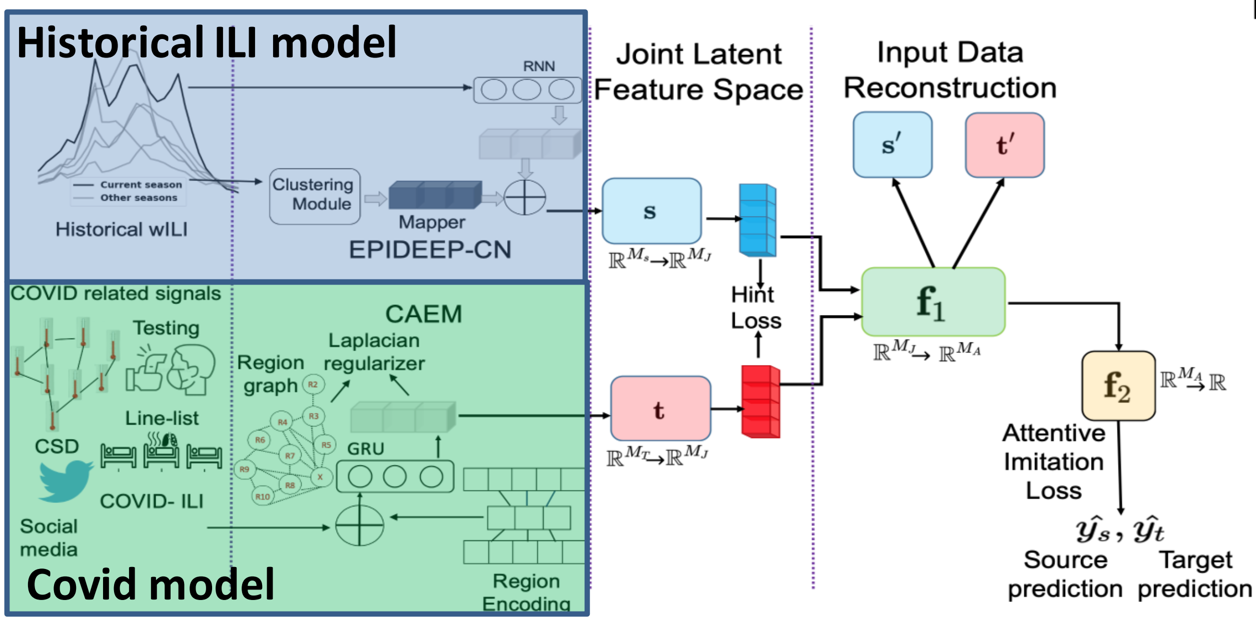
- Two forecasting modules:
  - **Covid-ILI:** Steer a historical ILI model with Covid-related signals
  - **Covid:** Covid-19 forecasting using Covid-related signals
- Data sources (selected with epidemiological rationale):
  - FB Symptom Survey Data
  - Line-list based data from CDC, JHU, and CovidTracking
  - Mobility from Apple and Google
  - Testing from CovidTracking

- Approach features:
  - Deep learning-based approach allow us to omit laborious feature engineering.
  - Can ingest many heterogeneous signals that are more sensitive to what is happening on the ground
  - Robustness to noise and principled uncertainty estimation
  - Explainability module enables:
    - Epidemiological explanation of forecasts
    - Assess contribution of signal(s)

Task 1: Forecasting Covid-ILI When Historical Data Exists

- Steer an existing historical ILI model (EpiDeep, KDD 2019) with new Covid-related signals
- Goal: enable structured knowledge transfer from our historical ILI model to a spatio-temporal Covid-ILI model
- We use heterogenous transfer learning and knowledge distillation



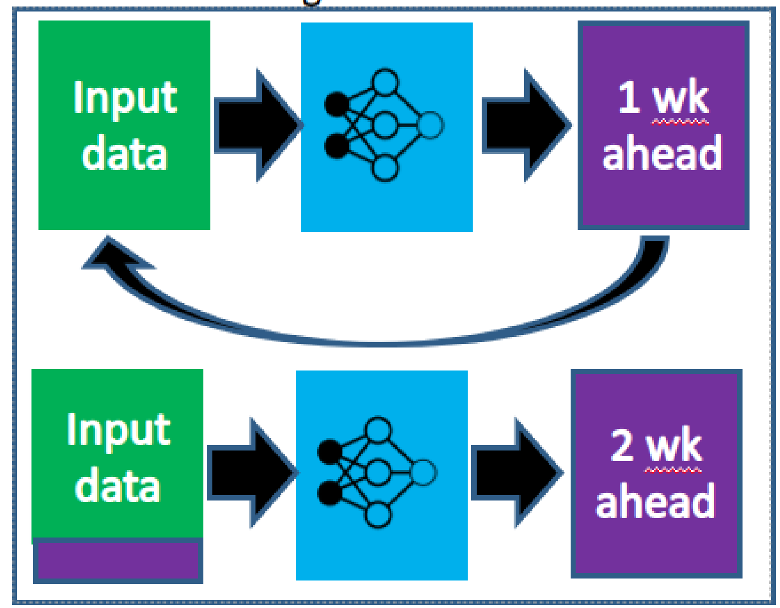


High-level abstraction

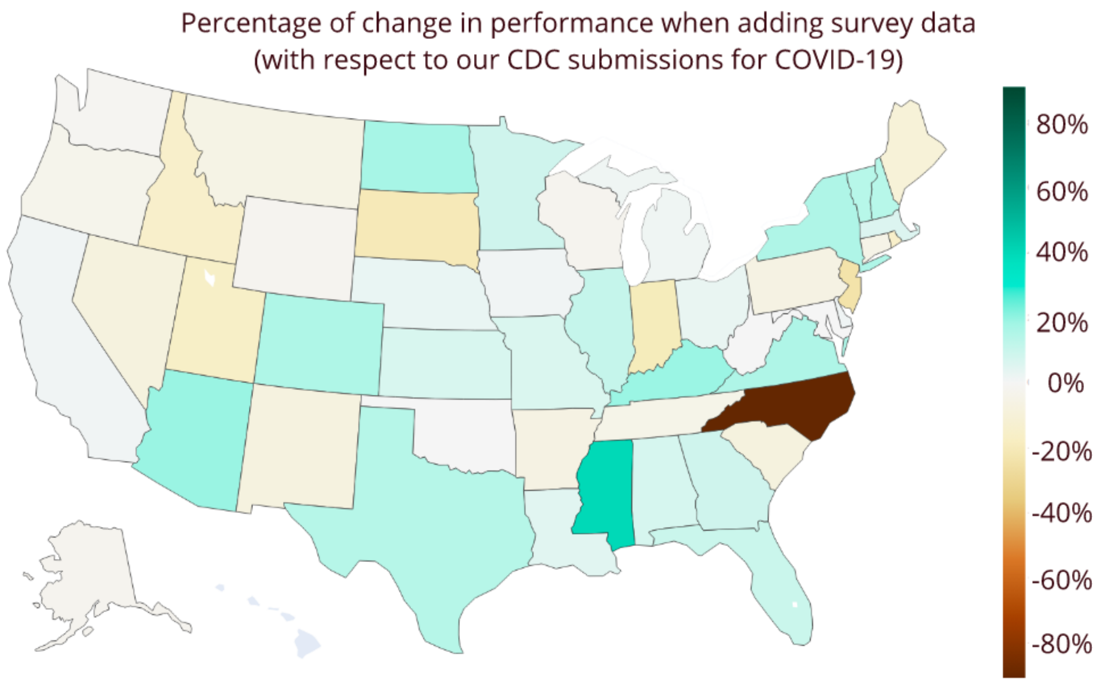
Task 2: Forecasting Covid-19 No historical data Available

- Unable to steer an existing model and unable to train temporal neural models (e.g. RNN)
- Use only Covid-related data sources.
- Principally propagate uncertainties in forecast from noise in data
- We use autoregressive training on bootstrap samples

High-level abstraction



Contribution of Symptom Survey Data in Overall Performance

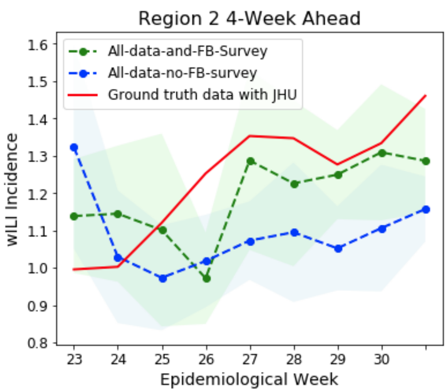


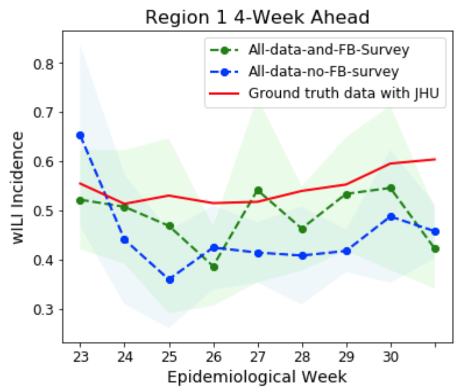
Green (positive) represents increase in performance; brown (negative) decrease. Survey data improves performance in 29 of the 51 regions.

Contribution of Symptom Survey Data

More results in our white paper

Task 1: Covid-ILI Forecasting





Medium pandemic impact

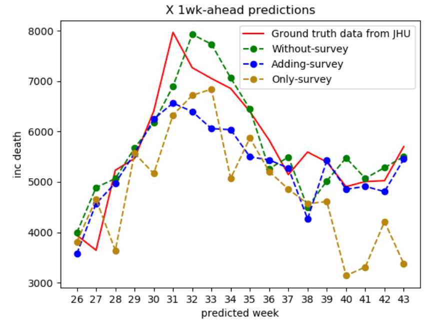
Low pandemic impact

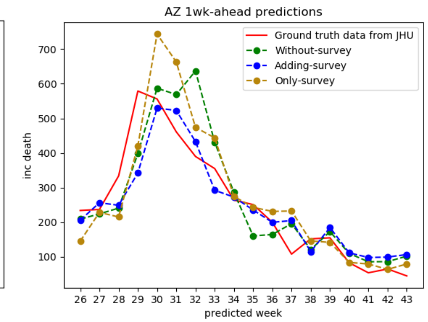
1. Forecasting models with survey data achieves better forecasting performance.

2. Models without survey data underestimate wILI dynamics in long-term forecasting performance.

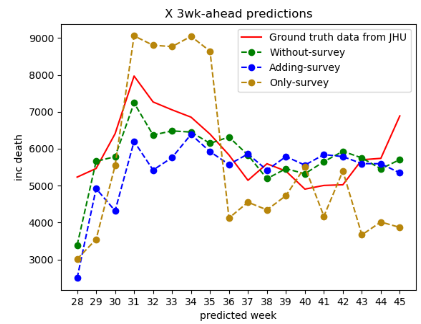
3. Plots showcase similar behavior with different regions (1,2) with varying degrees of pandemic impact.

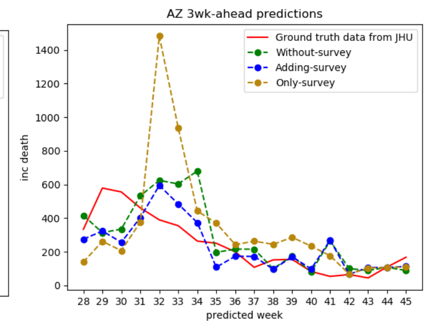
Task 2: Covid Forecasting





Short-term forecasts: Using survey data independently is comparatively as effective as using in conjunction with other signals for COVID-19 mortality forecasting.



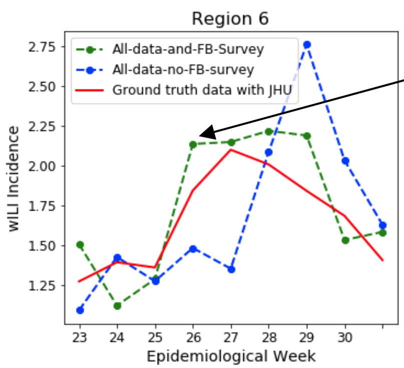


Long-term forecasts: Using survey data in conjunction with other signals is more effective for COVID-19 mortality forecasting.

Contribution of Symptom Survey Data

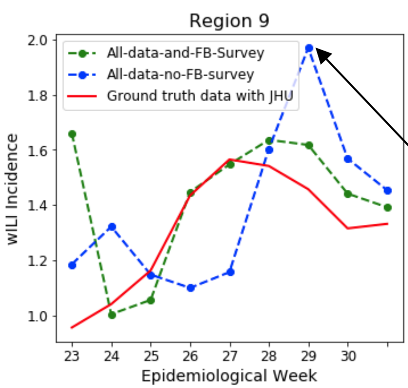
More results in our white paper

Task 1: Covid-ILI Forecasting



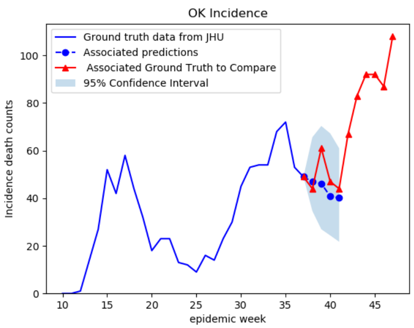
FB survey data helps anticipate peak one week ahead

Models with survey data achieve better performance

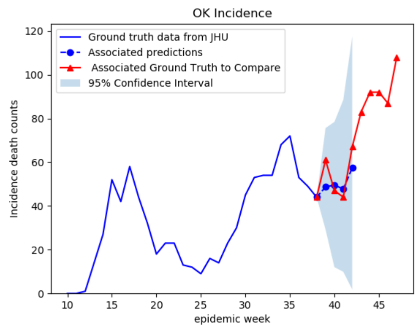


Models without survey data overestimate peaks

Task 2: Covid Forecasting



Additional Signals



Survey Data + Additional Signals

FB survey data in conjunction with other signals can forecast important changes in trend that were not possible only with the other signals

We also found interesting negative findings! (see white paper)

Results Summary

Facebook Survey Data Usage Notable Highlights:

- In general, **survey signals are orthogonal** to other available signals that we included in our models. We found them useful to improve our performance in the majority of geographical regions.
- We showed that survey signals help guide our forecasts to effectively **anticipate future trends**, which is the general case; however, there are some cases where it may lead to hinder some good trend predictions.
- In general, survey signals **should be used in conjunction** with others; however, we found a few interesting cases when they alone offer a different and more accurate forecasting perspective.
- Survey signals capture and help us in forecasting in regions with important **differences** such as **epidemic activity**. In particular, we found that in ILI forecasting, not using symptom survey data may lead to underestimating the epidemic curve.

Thanks!

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