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Conference on Innovative Applications of Artificial Intelligence (IAAI-21)
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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

Many U.S. Hospitals Are Running Critically Short Of ICU Beds
ICU occupancy rates at or above 100% in U.S. hospital service areas with high populations*

COVID-19 Causes Unprecedented Job Crisis
Weekly initial jobless claims in the United States (seasonally adjusted)

* Based on seven-day averages for the week ending Thursday, Dec. 3
Source: Department of Health and Human Services via The New York Times

Source: U.S. Department of Labor
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

Oklahoma Incidence Mortality

Rodríguez, et al., 2020
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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
• ...

Rodríguez, et al., 2020
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

Rodríguez, et al., 2020
Our Participation in CDC Forecasting Initiatives

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

**Target 2:** Weekly reported Covid Mortality

**Target 3:** Daily Covid-induced Hospitalizations

Since April End 2020

Rodríguez, et al., 2020
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Our Operational Framework

- Alignment of delayed signals
- Normalize temporal granularities
- Spatial aggregation and de-aggregation
- Imputation

Rodríguez, et al., 2020
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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Rodríguez, et al., 2020
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
Data Sources

• Line-list based
• Testing
• Crowdsourced
• Mobility
• Exposure
• Social Media surveys
# Data Signals

<table>
<thead>
<tr>
<th>Type/Rationale</th>
<th>Signals</th>
</tr>
</thead>
<tbody>
<tr>
<td>(DS1) <em>Line list:</em> Traditional surveillance for tracking patients and symptoms</td>
<td>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;</td>
</tr>
<tr>
<td>(DS3) <em>Crowdsourced:</em> Symptomatic surveillance</td>
<td>13. Digital thermometer readings provide ILI%;</td>
</tr>
<tr>
<td>(DS5) <em>Exposure:</em> Measure social contacts</td>
<td>21-22. Device exposures (normal &amp; adjusted);</td>
</tr>
<tr>
<td>(DS6) <em>Social Surveys:</em> Measure symptomatic burden</td>
<td>23. CLI%; 24. ILI%</td>
</tr>
</tbody>
</table>
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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

Rodríguez, et al., 2020
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

Historical ILI model

High-level abstraction

Accepted in AAAI-21 main track
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

Input Data → Bootstrapping → Individual Neural Models → Probabilistic Predictions

Self-regressive forecasting

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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
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
Interface + Data Ablation

Retrospective 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

Rodriguez, et al., 2020
Obs. 2: Capture Finer Grained Reporting Patterns

Micro-patterns:
P1. Weekend drop
P2. Rise on Monday, stable in weekdays
Obs. 3: Excels in US National Short-term Forecasting

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

Rodríguez, et al., 2020
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

Rodríguez, et al., 2020
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

Rodriguez, et al., 2020
Thanks!

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

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

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