In partnership with

Curating a COVID-19 data repository and forecasting county-level death counts in the US

Yu Group

UC Berkeley Statistics, EECS, CCB

Presenter: Tiffany Tang

github.com/Yu-Group/covid19-severity-prediction

Website: covidseverity.com

Our Team

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Y. Tan

T. Tang (Data Team)

Y. Wang (Data Team)

A.Agarwal

M. Shen

C. Zhang

P. Norvig

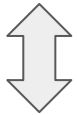
Many others at UC Berkeley, UCSF, Stanford, Northeastern, Univ. of Chicago, UW-Madison, ...

Goal: Help Aid Resource Allocation

RESPONSE 4LIFE

Want to predict...

~~hospital PPE/supply need~~



~~number of COVID-19 hospitalizations~~

number of COVID-19 deaths at the county-level

Overview: Current Data Repository & Prediction Pipeline

GitHub

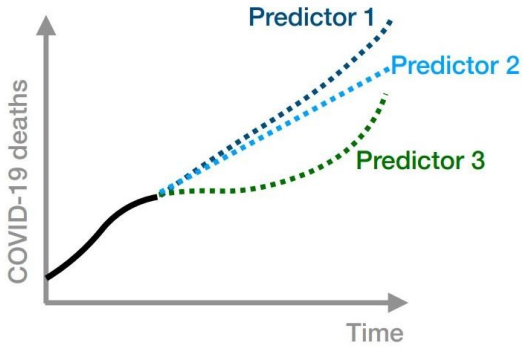
COVID-19 Data Repository

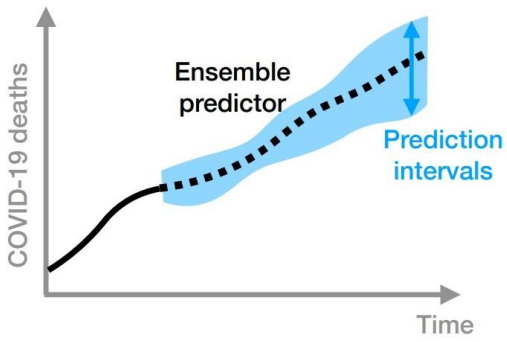
COVID-19 Cases/Deaths + County-level Data + Hospital-level Data

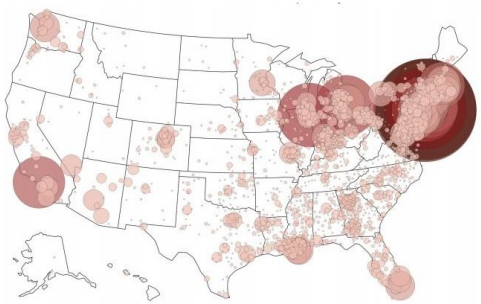
open source initiative

USAFACTS · KHN · Social Distancing Scoreboard · COVID-19 GIS Hub · STREETLIGHT · cuebiq · Maps Mobility Trends Reports · Google COVID-19 Community Mobility Reports · SAFEGRAPH · ArcGIS Hub · The New York Times · kinsa · JOHNS HOPKINS UNIVERSITY · USDSS · GHDx · HRSA · CDC Centers for Disease Control and Prevention · Division for Heart Disease and Stroke Prevention · THE CENTER FOR SPATIAL DATA SCIENCE THE UNIVERSITY OF CHICAGO · United States Census Bureau · County Health Rankings & Roadmaps · esri

Multiple county-level predictors → CLEP Ensemble + MEPI intervals + Visualizations







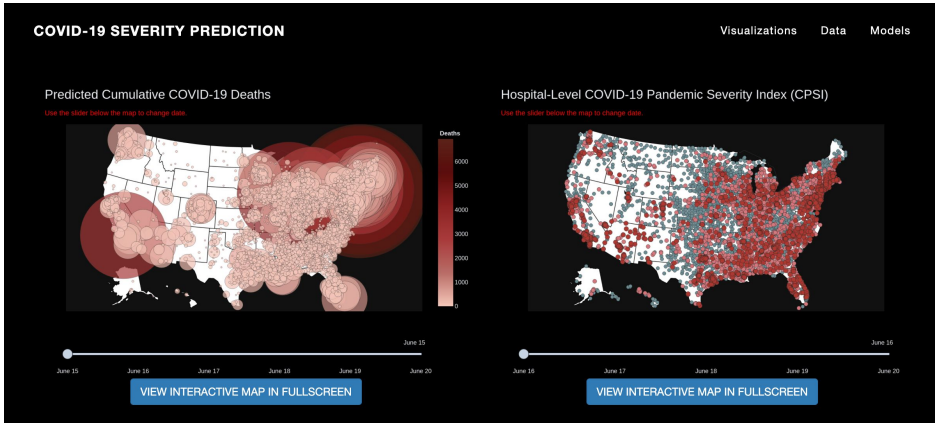
Altieri, Nick, et al. "Curating a COVID-19 data repository and forecasting county-level death counts in the United States." *arXiv preprint arXiv:2005.07882* (2020).

Impacts

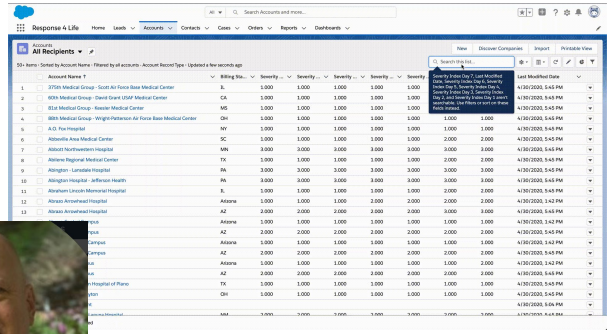
Sending PPE through R4L

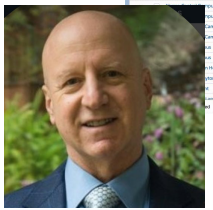
- >5000 face shields to Santa Clara + Temple University Med Center in Philadelphia in collaboration with GetUsPPE, AeroBridge, Maker Nexus, Synergy Mill maker space, R4L
- +65k to 25 recipients in 15

Visualizations (covidseverity.com)



Salesforce system





Don Landwirth, R4L

Curating data repository

Data variable	Description	Source data set
countyFIPS	state-county FIPS Code	county_fips
STATEFP	state FIPS Code	county_popcenters
COUNTYFP	county FIPS Code	county_popcenters
CountyName	county name	county_fips
StateName	state abbreviation	county_fips
State	state name	county_latlong

Curating a COVID-19 Data Repository

Outline

- Our data curation pipeline
- Overview of the data
- A closer look at the COVID-19 daily cases/deaths data
- Navigating the data repo on GitHub

Image Source: https://info.aldensys.com/joint-use/how-the-iot-will-move-companies-from-data-collection-to-data-driven

Data Processing Pipeline

Data Scraping → **Data Cleaning** → **Data Validity**

- **Collect 1M records from 20+ data sources**
- **Monitor data changes 24/7 powered by AWS**
- **Handling missing and erratic entries**
- **Automated python script**
- **Compare data across different sources**
- **Search for emerging data sources**

For almost a month, 2 full-time students, and on-going with 1 full-time student

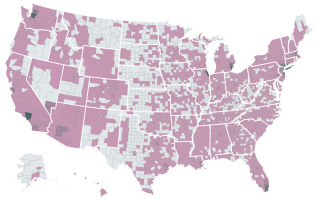
Data and code available: https://github.com/Yu-Group/covid19-severity-prediction

★ Being used by multiple research groups across the country

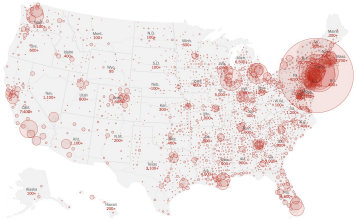
Our Data Repository: scraped from **20+ sources**

COVID-19 Cases/Deaths

USAFACTS



The New York Times



County-level Data

(Risk Factors, Demographics, Social Mobility)

CDC Centers for Disease Control and Prevention
CDC 24/7: Saving Lives, Protecting People™

Division for Heart Disease and Stroke Prevention

DEPARTMENT OF TRANSPORTATION · UNITED STATES OF AMERICA

esri COVID-19 GIS Hub

IHME GHDx

County Health Rankings & Roadmaps
Building a Culture of Health, County by County

USDSS UNITED STATES DIABETES SURVEILLANCE SYSTEM
Division of Diabetes Translation, CDC

CMS.gov
Centers for Medicare & Medicaid Services

United States® Census Bureau

SAFEGRAPH

kinsa®

STREETLIGHT

Introducing the Unacast
Social Distancing Scoreboard

KHN KAISER HEALTH NEWS

cuebiq

Maps Mobility Trends Reports

JOHNS HOPKINS UNIVERSITY

Google COVID-19 Community Mobility Reports

Hospital-level Data

(e.g., #ICU beds, staff)

HRSA
Health Resources & Services Administration

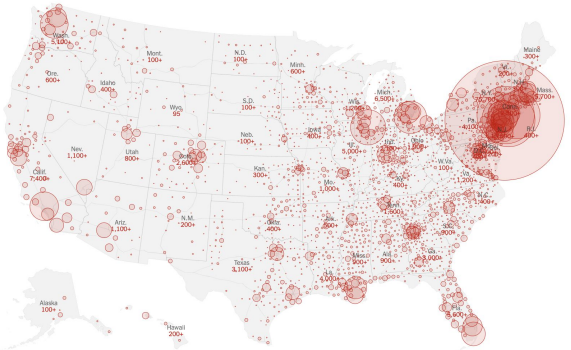
ArcGIS Hub

HOSPITAL INFRASTRUCTURE FOUNDATION-LEVEL DATA SUBCOMMITTEE

Samuel Scarpino

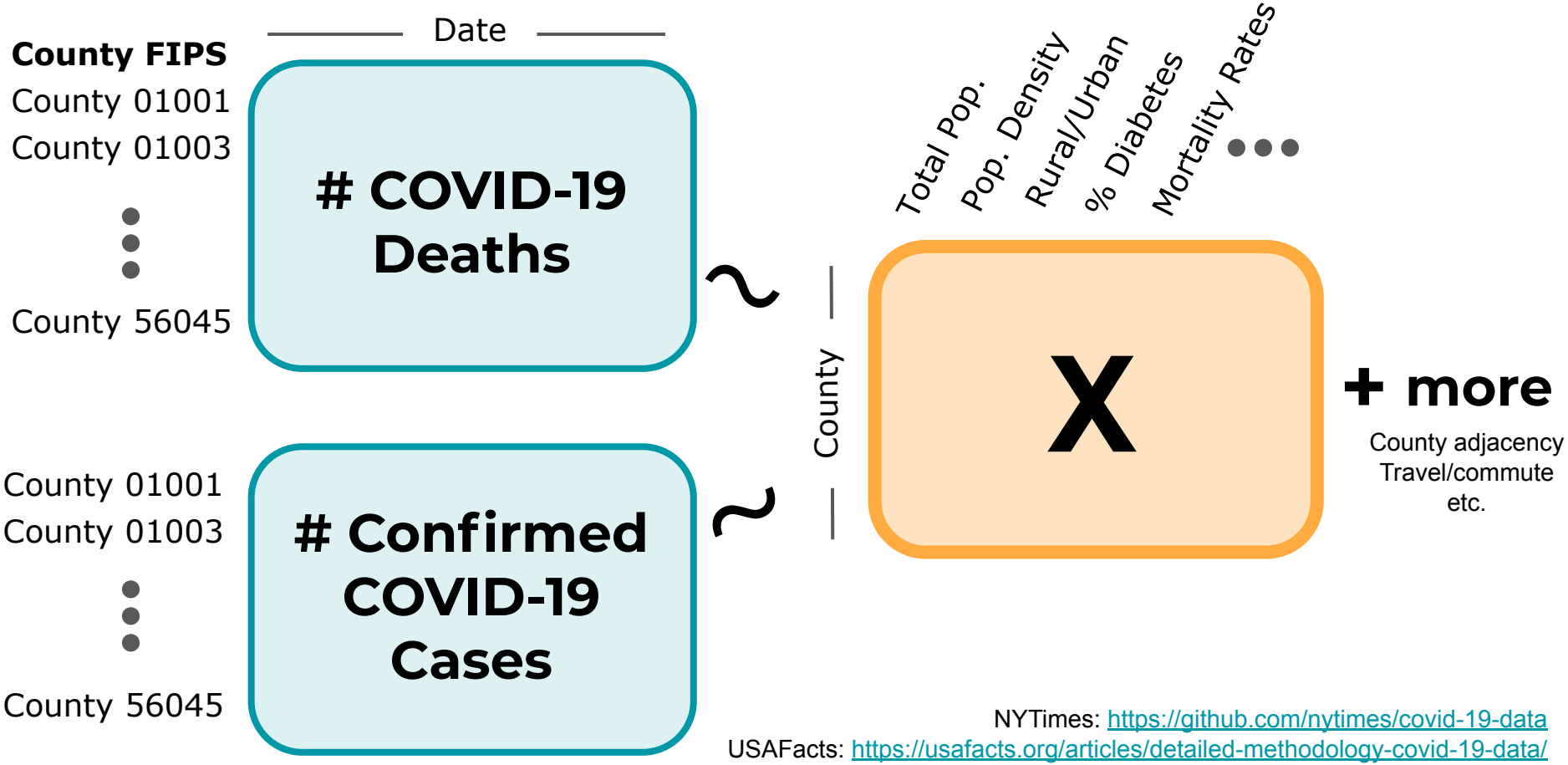
NORTHEASTERN UNIVERSITY

A bird’s-eye view of the **county-level data**



- COVID-19 cases and deaths (NYT and USAFacts)
- Demographics
  - Population, population density, age structure
- Health risk factors
  - Heart disease, stroke, respiratory disease, smoking, diabetes, overall mortality
- Socioeconomic risk factors
  - Social vulnerability index, unemployment, poverty, education, severe housing
- Social distancing and mobility
  - County-to-county work commute, change in distance traveled, government orders
- Other relevant data
  - Sample of flight itineraries in 2019, Kinsa temperature data, voting data

A bird's-eye view of the **county-level data**

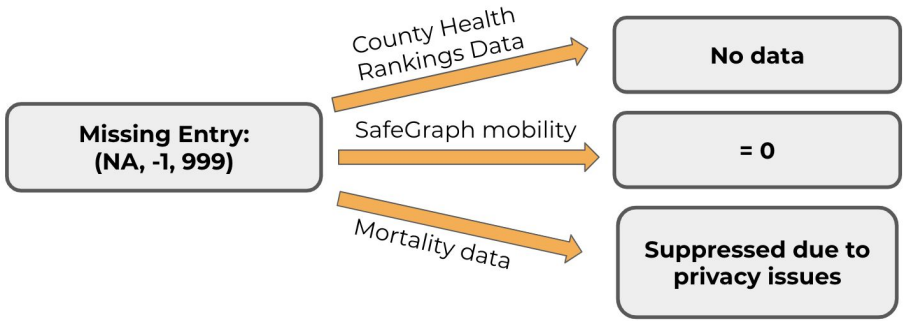


NYTimes: https://github.com/nytimes/covid-19-data
USAFacts: https://usafacts.org/articles/detailed-methodology-covid-19-data/

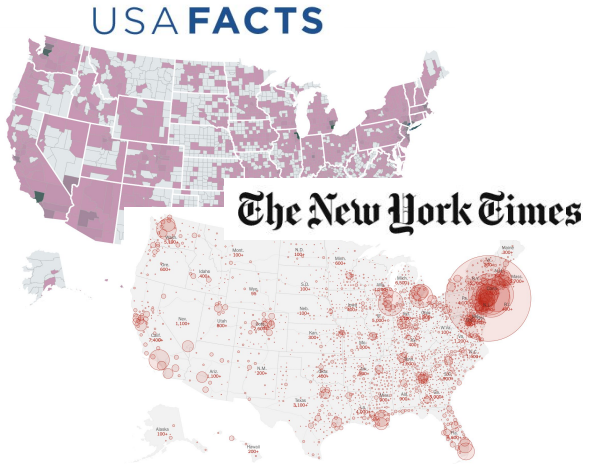
A closer look at the USAFacts and NYTimes COVID-19 cases/deaths data...

Data Cleaning!!

- Duplicated counties
- Some cases/deaths cannot be allocated to a county
- Cumulative deaths counts sometimes decrease
- Aside: data cleaning beyond USAFacts/NYTimes
  - Some counties changed their countyFIPS code
  - Missing data entries encoded as NAs, -1, 999, and more...
    - Meaning can depend on the data set



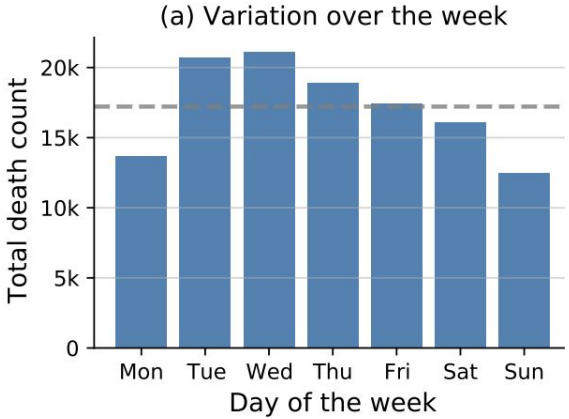
Which to choose: NYTimes vs USAFacts?

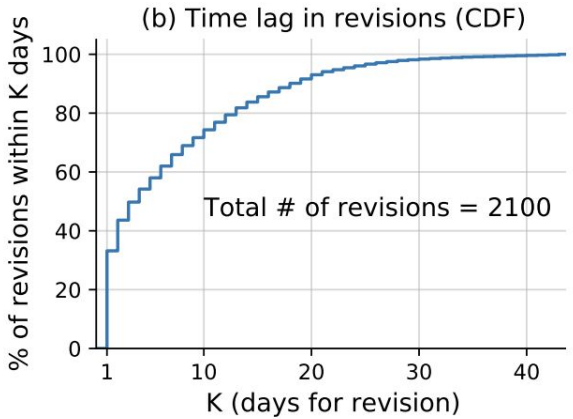


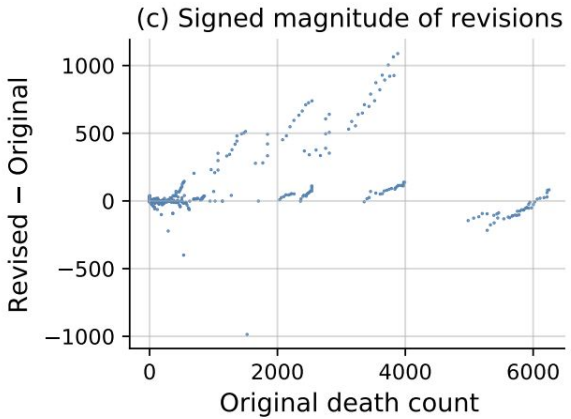
- Out of all possible (county, day) combinations, **98.4%** of the COVID-19 case and death counts in USAFacts and NYT datasets are identical
- Possible reasons for the slight discrepancies
  - Different time to update data
  - How to deal with probable deaths?
  - Different data processing pipelines
- NYTimes aggregates cases/deaths over the NYC counties while USAFacts does not
- Multiple data sources give us insights into the caveats of the data.

Some interesting data biases from the USAFacts data

(a) Weekly patterns: cumulative death counts per weekday
(b) Historical data revision: around 2100 revisions until June 21
(c) Magnitude of the revisions are mostly upward.







Navigating the COVID-19 Data Repository

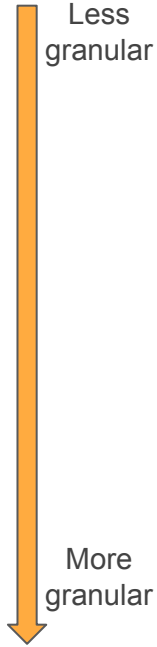
Our **data repository** can be found at the following link:

https://github.com/Yu-Group/covid19-severity-prediction

- Monitored and updated daily, powered by AWS
- Can easily download, clean, and merge (abridged or unabridged) data in one line of code
- Lots of documentation

A Hierarchy of Resources

- Overview of “main” features and datasets in Tables 1 and 3 in arXiv paper
  - Data Readme on GitHub with *all* data sets + brief descriptions
    - List of columns in county-level data set (contains descriptions for *most* county-level features)
      - Individual data folder readmes on GitHub at data/county_level/<raw or processed>/<source>/



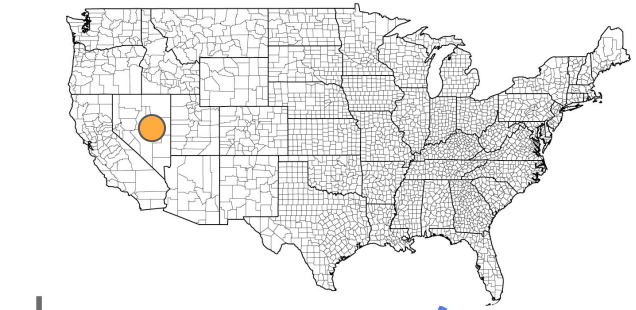
Thank you!

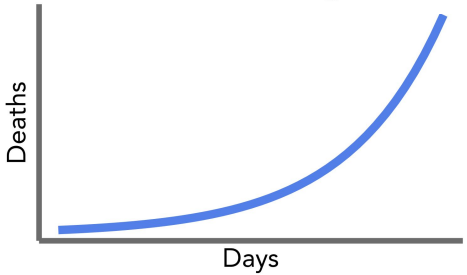
Ensemble different predictors

We combined many different prediction approaches

Ensemble predictors

1. Separate-county **exponential** model[1]





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Ensemble predictors

We combined many different model approaches

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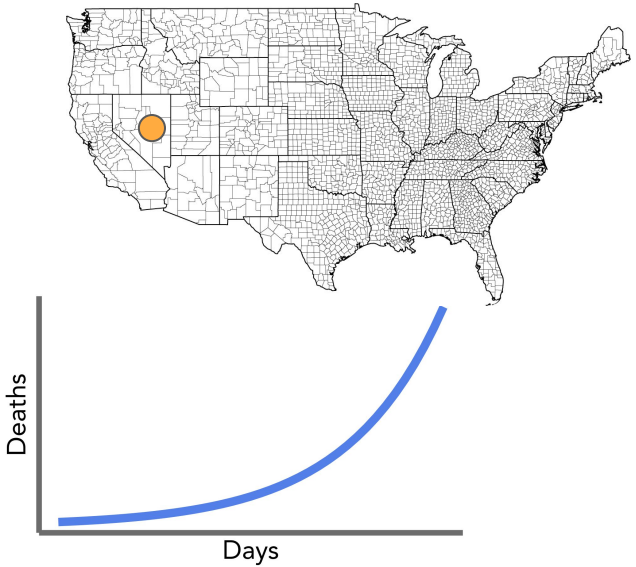

$$\mathrm{E}(\mathrm{deaths}_t \mid t) = e^{\beta_0 + \beta_1 t}$$

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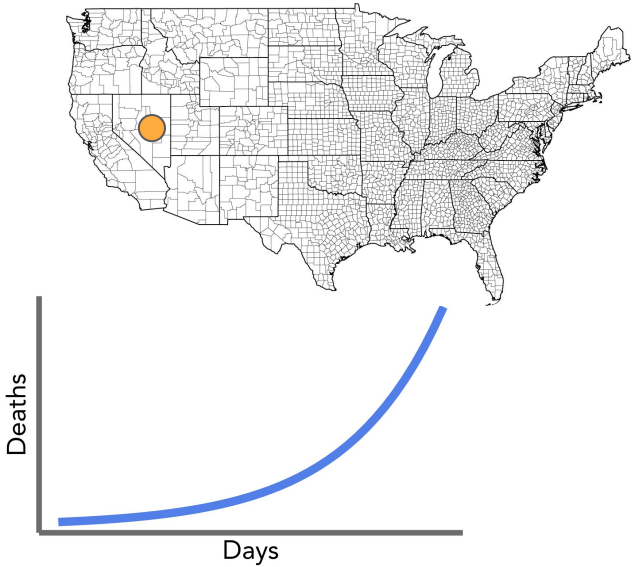
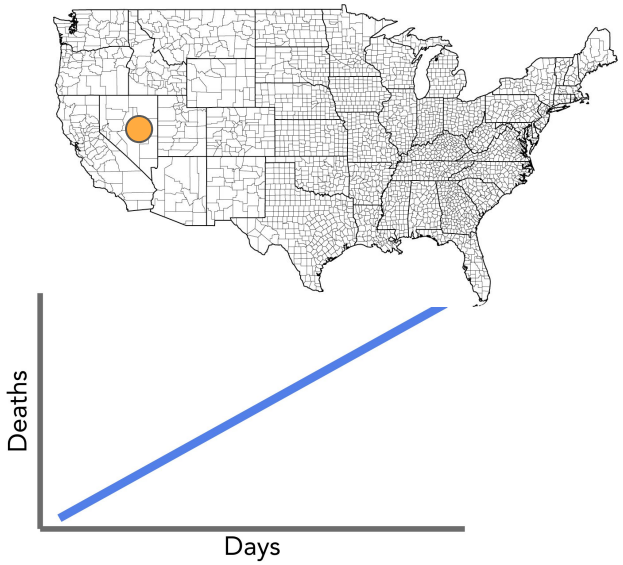


2. Separate-county **linear** model



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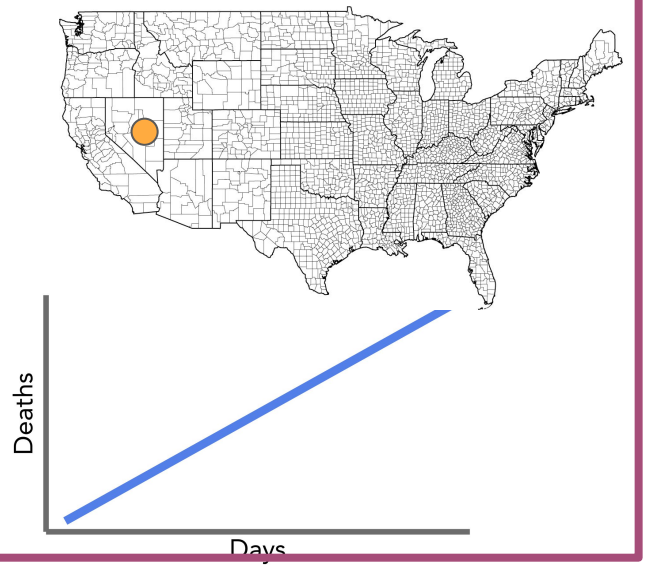

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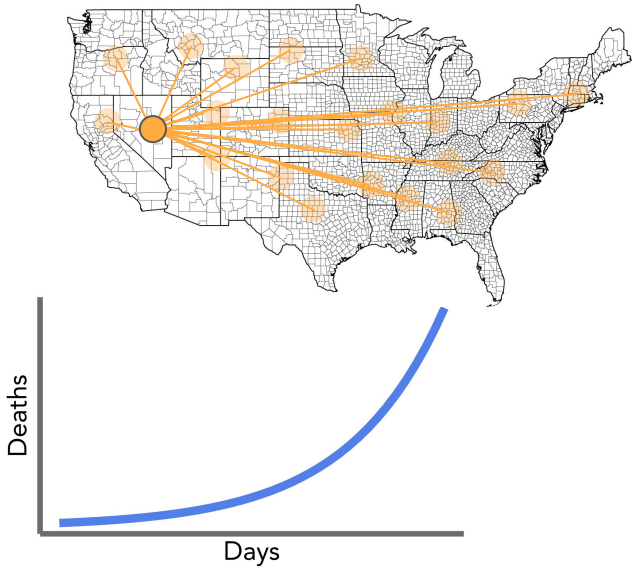
Ensemble predictors

We combined many different prediction approaches

3. **Shared**-county exponential model



Ensemble predictors

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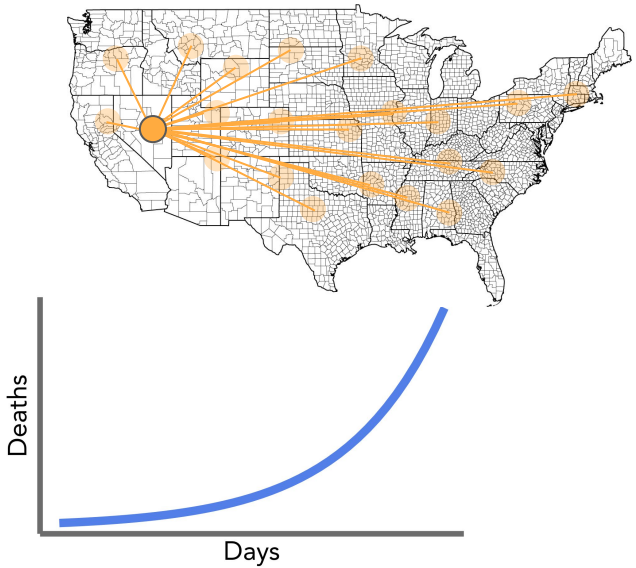
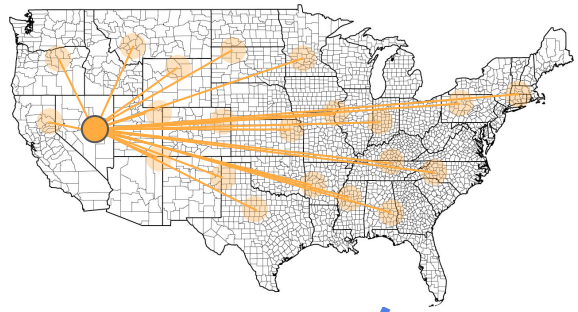


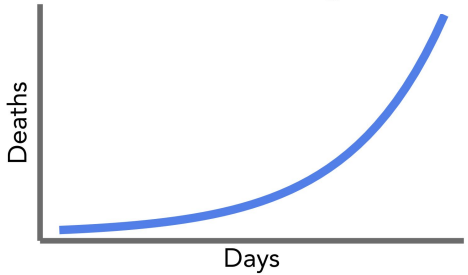
$$\mathrm{E}(\mathrm{deaths}_t \mid t) = e^{\beta_0 + \beta_1 \log(\mathrm{deaths}_{t-1} + 1)}$$

Ensemble predictors

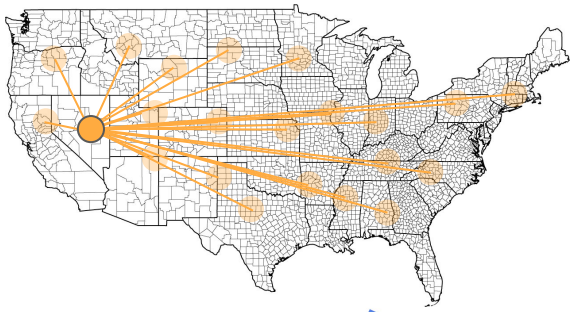
We combined many different prediction approaches

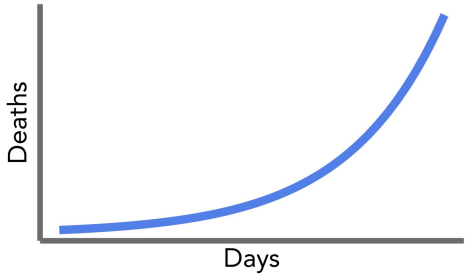
3. **Shared**-county exponential model





4. **Shared**-county exponential **+ demographics** model



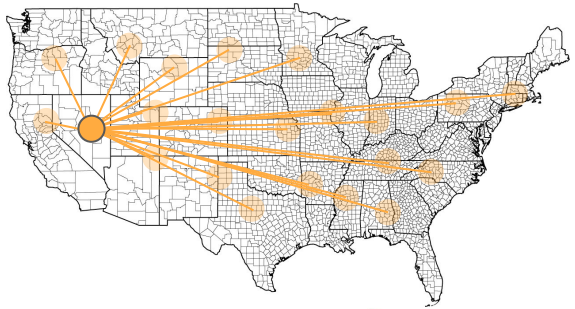


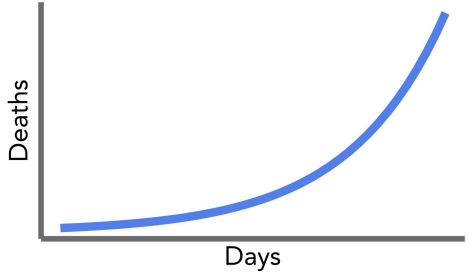
+ Age
+ ICU Beds
+ # Hospitals
+ ....

Ensemble predictors

We combined many different prediction approaches

4. **Shared**-county exponential **+ demographics** model





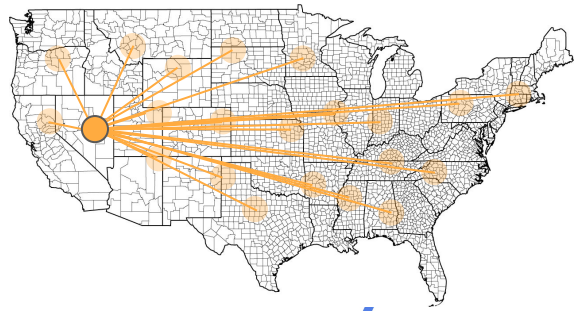
+ Age
+ ICU Beds
+ # Hospitals
+ ....

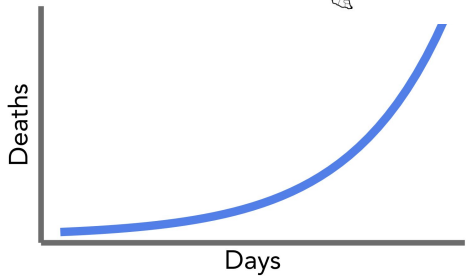
- County density and size
- County healthcare resources
- Demographic information

Ensemble predictors

We combined many different prediction approaches

5. **<u>Expanded Shared</u>**-county exponential model

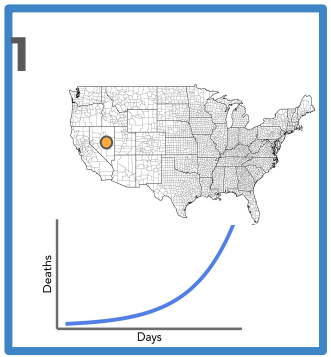




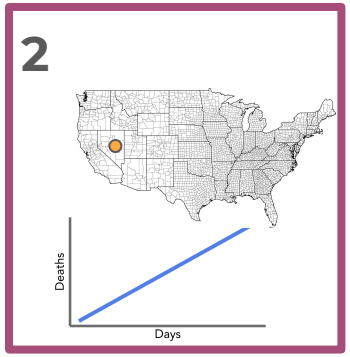
+ Cases
+ Neighboring cases
+ Neighboring deaths

- log(Cases)
- log(Cases in Neighboring counties)
- log(Deaths in neighboring counties)

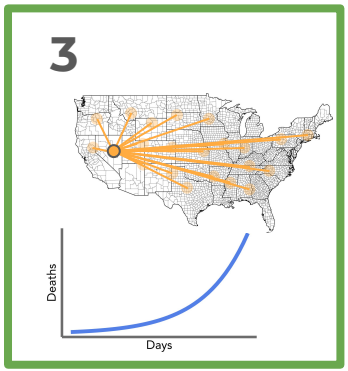
Combined Linear and Exponential Predictors (CLEP)



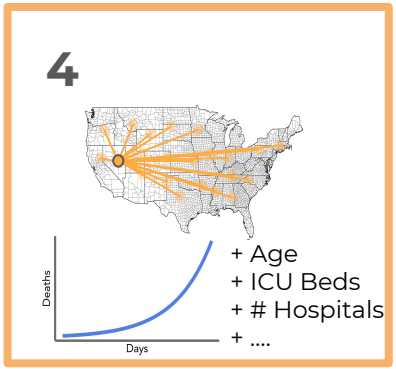
Separate-county exponential predictor



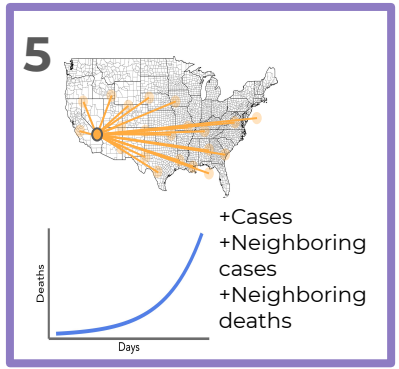
Separate-county linear predictor



Shared-county exponential predictor



Shared-county exponential predictor + demographics



Expanded Shared-county exponential predictor

Calculate a **weighted average of the predictions**: higher weight to the models with better historical performance[2]

[2]. Schuller, Gerald DT, et al. "Perceptual audio coding using adaptive pre-and post-filters and lossless compression." *IEEE Transactions on Speech and Audio Processing* 10.6 (2002): 379-390.

Combined Linear and Exponential Predictors (CLEP)

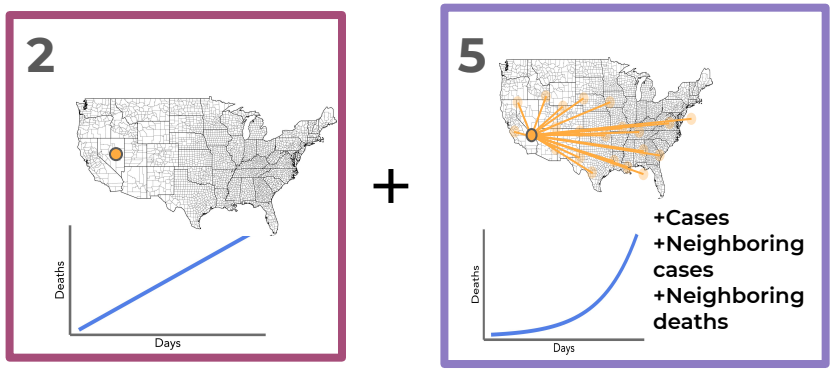
Calculate a **weighted average of the predictions**: higher weight to the models with better historical performance[2]

$$w_t^m \propto \exp\left(-c(1-\mu)\sum_{i=t_0}^{t-1}\mu^{t-i}\ell(\widehat{y}_i^m, y_i)\right)$$

[2]. Schuller, Gerald DT, et al. "Perceptual audio coding using adaptive pre-and post-filters and lossless compression." *IEEE Transactions on Speech and Audio Processing* 10.6 (2002): 379-390.

Combined Linear and Exponential Predictors (CLEP)

A smaller combination performed better in practice:



Separate-county linear predictor

Expanded Shared-county exponential predictor

Calculate a **weighted average of the predictions**: higher weight to the models with better historical performance[2]

[2]. Schuller, Gerald DT, et al. "Perceptual audio coding using adaptive pre-and post-filters and lossless compression." *IEEE Transactions on Speech and Audio Processing* 10.6 (2002): 379-390.