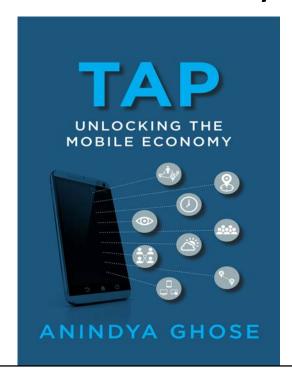
# Unlocking Technology and Data Science to Combat Health Pandemics

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## **Agenda**

- How tech and data were used in the early days of Covid 19?
- Insights from mobile location data
- Relevant lessons from epidemiology
- How should we open the economy?
- Privacy and data cultures

#### **Technology For Predictive Analytics in Pandemics**

- Canadian Al startup BlueDot spotted COVID-19 nine days before the WHO alerted people.
- Predicted the extent of the outbreak internationally using airline ticketing data.
- Google's DeepMind used deep learning to analyze the structure of proteins associated with COVID 19.
- Baidu used infrared and AI-powered facial recognition to screen people for fever.

#### **Technology For Consumer Empowerment**

- Alibaba and Tencent devised color coding via mobile QR codes to stratify users.
- Apps let people check if they have taken the same flight or train as Covid 19 patients.
- FaceMask App in Taiwan shows inventory of masks
- TraceTogether App in Singapore informs users about infected carriers.
- Robots performed contactless delivery of food and medicine in hospitals in lieu of nurses.

#### **Data Science Modeling in Health Pandemics**

- Significant transformation in the ability to collect massive datasets and harness them using AI and machine learning.
- Aggregate level tools include 'shelter-in-place' + 'social distancing analyses'.
  - Italy?
- Individual user level tools are 'active contact tracing' and 'individual quarantine analyses'.
- Geo-location data from smartphones, CCTV surveillance footage, GPS data from cars, offline credit card transactions, ATM banking records, etc.
- Successful use cases in Taiwan, China, Singapore, Israel, South Korea

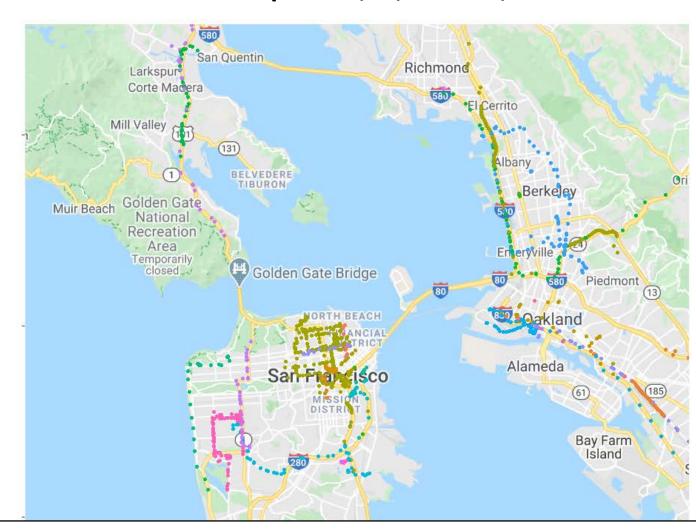
#### **Contact Tracing For Pandemic Surveillance**

- Location data accuracy + tech sophistication in Covid (2020) vs. SARS/H1N1/ MERS (2003-2012)
- Covid 19 transmission occurs between people who are within 1m of each other for 15 minutes or more.
- My work with telecom providers, digital platforms, wearable tech firms, mobile app developers and mobile advertisers. (TAP, MIT Press 2017)
- Using machine learning techniques on atomic and granular consumers' location and trajectory data. (Ghose et al. 2019 Management Science)

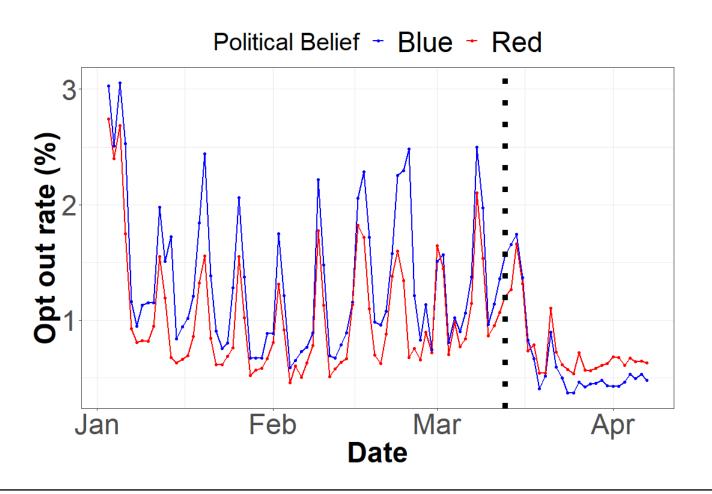
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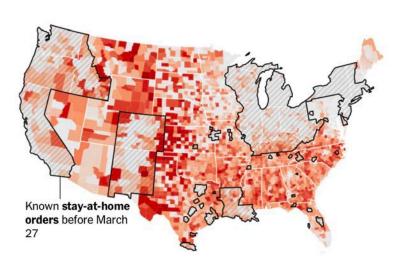
#### Mobile location data (Ghose, Li, Macha, Sun & Foutz 2020)







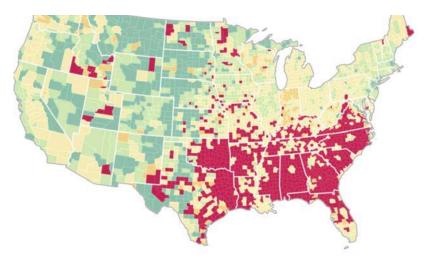
## How mobile phones help measure compliance with social distancing



#### Where people were still traveling last week

Percent change in average travel for the week of March 23, compared with travel before the coronavirus outbreak.

Closer to normal travel →
No travel Half of normal Normal travel



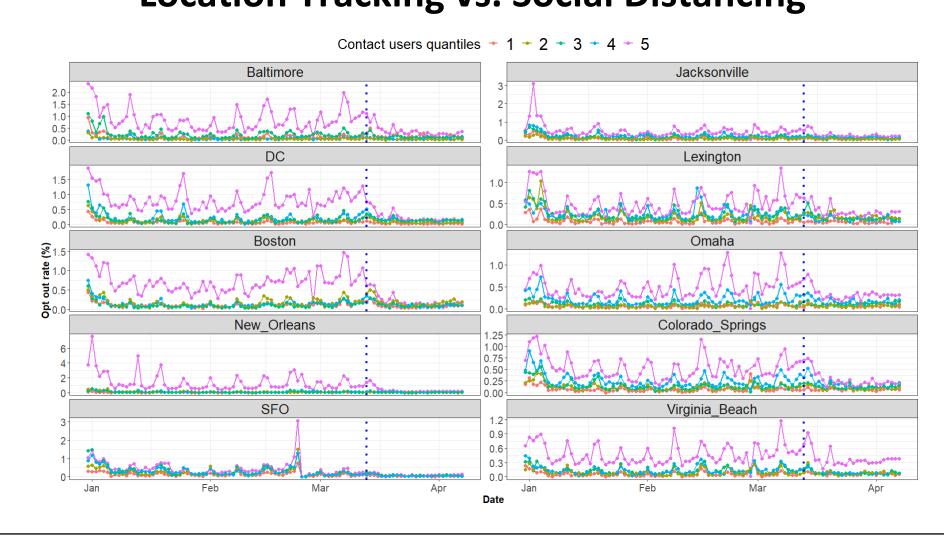
## When average distance traveled first fell below 2 miles

By Mar. 16 Mar. 19 Mar. 24 Mar. 26 Not by Mar. 26

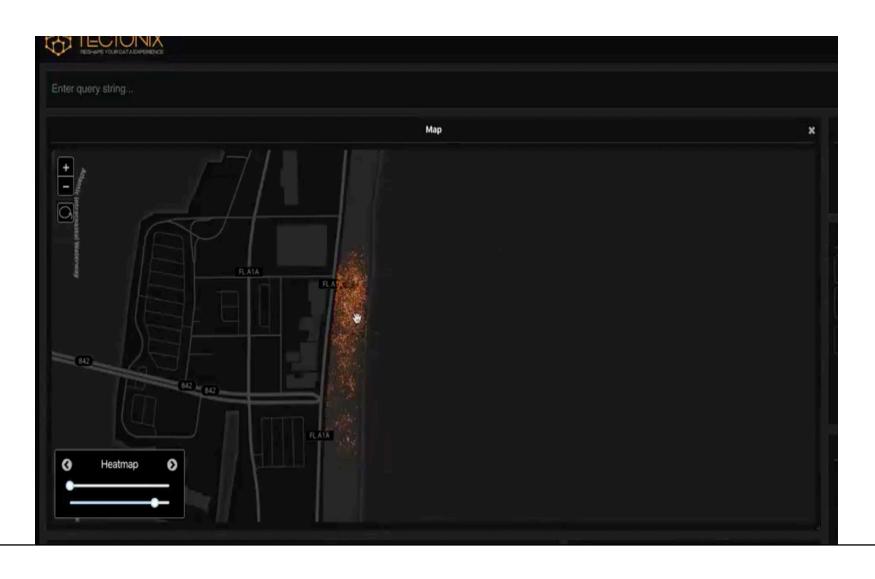
Data is through March 26. Only

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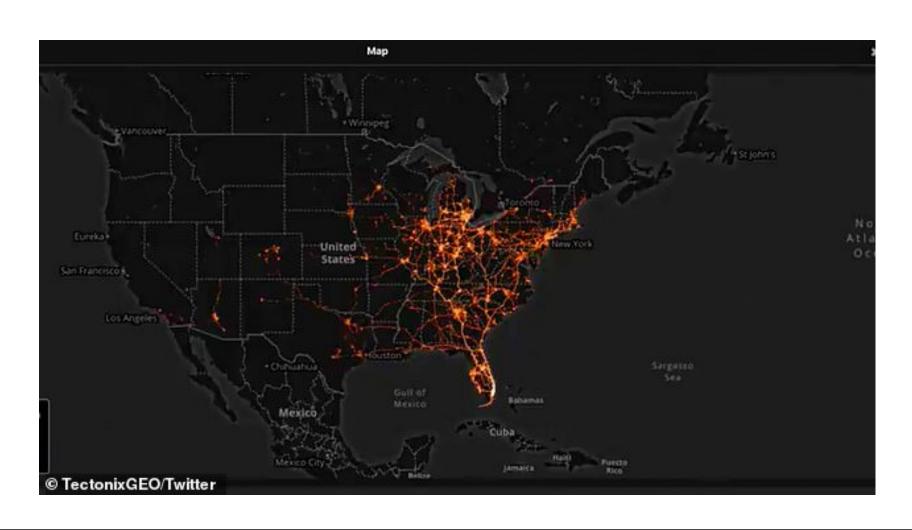
## **Location Tracking vs. Social Distancing**

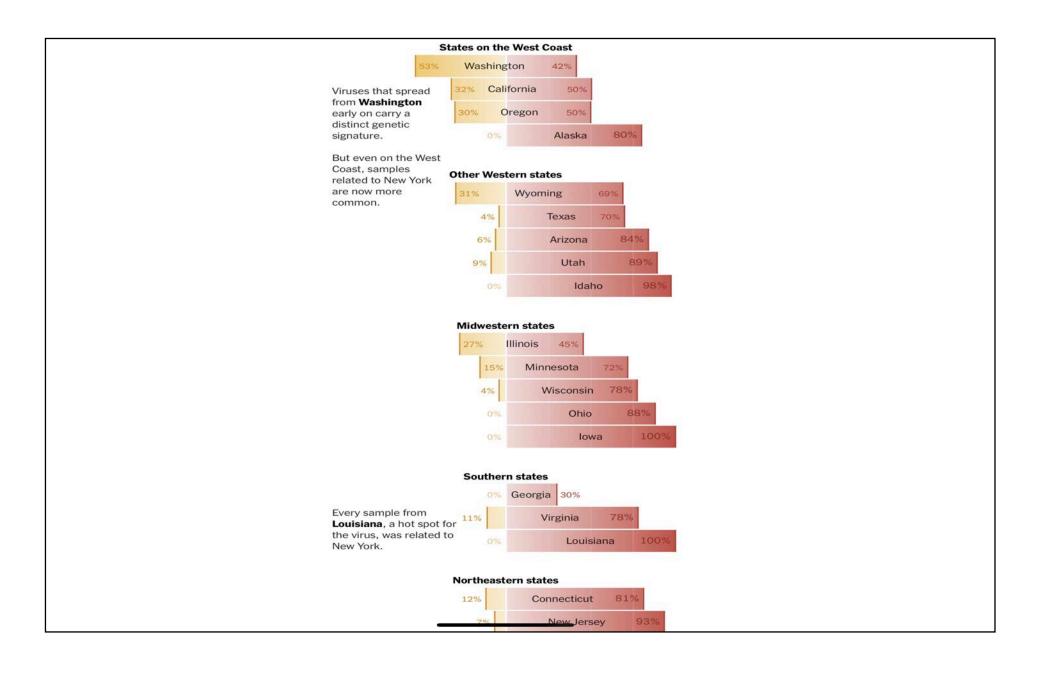


#### Florida 2020 Spring Break Beachgoers



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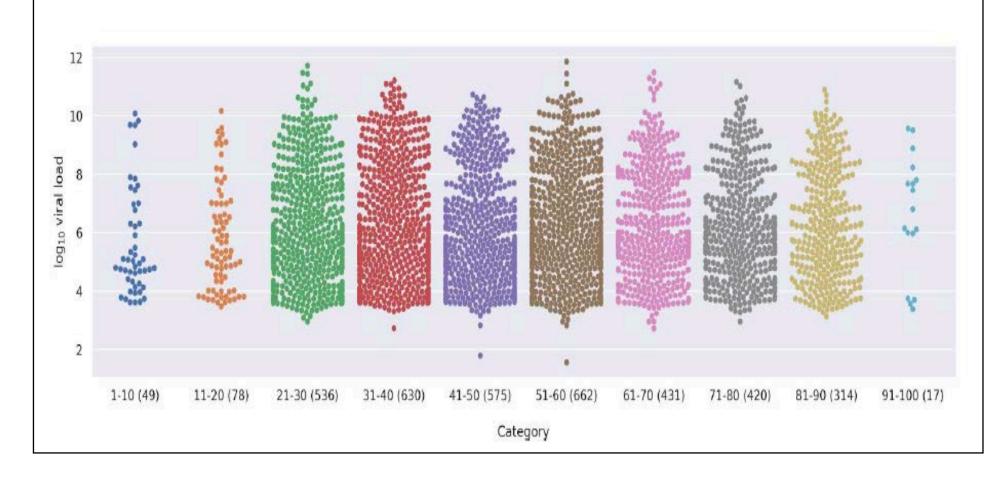
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#### What about undetected cases?

- Three reasons for lack of detection:
  - 1. Asymptomatic cases
  - 2. Limited testing
  - 3. Restricted testing criteria.
- Asymptomatic users constitute between 52% and 86% of cases.
- Examples:
  - Diamond Princess cruise
  - Vo Euganeo (Italy)
  - Hubei (China).

# Infectious people come in all ages, and they all shed different amounts of virus!



#### "Those who are dying would have died anyway?" Wrong!

Multimorbidity	Men				Women			
	50-59	60-69	70-79	80+	50-59	60-69	70-79	80+
0	35.81	26.78	18.43	11.02	35.28	25.50	17.70	10.42
1	35.03	26.09	17.58	10.05	34.83	25.59	17.13	8.92
2	29.67	22.07	14.72	8.15	29.06	21.35	14.20	7.19
3	25.01	19.05	12.50	6.59	26.27	18.08	11.98	5.85
4	23.55	16.28	10.64	4.95	20.44	15.58	9.97	4.52
5	19.39	13.43	8.61	3.51	16.88	11.61	8.23	3.54
6	-	6.24	7.04	2.42	17.67	10.09	6.44	2.70
7		7.99	6.32	2.03	12	7.96	4.83	2.32
8		6.60	4.79	1.65	140	6.23	3.94	1.85
9		5.97	3.95	1.40			3.04	1.58
10		-	2.62	1.17		2.81	2.55	1.22
11	-		-	1.40	-	-	2.05	1.20

- Years of life lost?
- 13 years for Men
- 11 years for Women
- Hanlon P, Chadwick F,
   Shah A et al. April 2020.

## **Agenda**

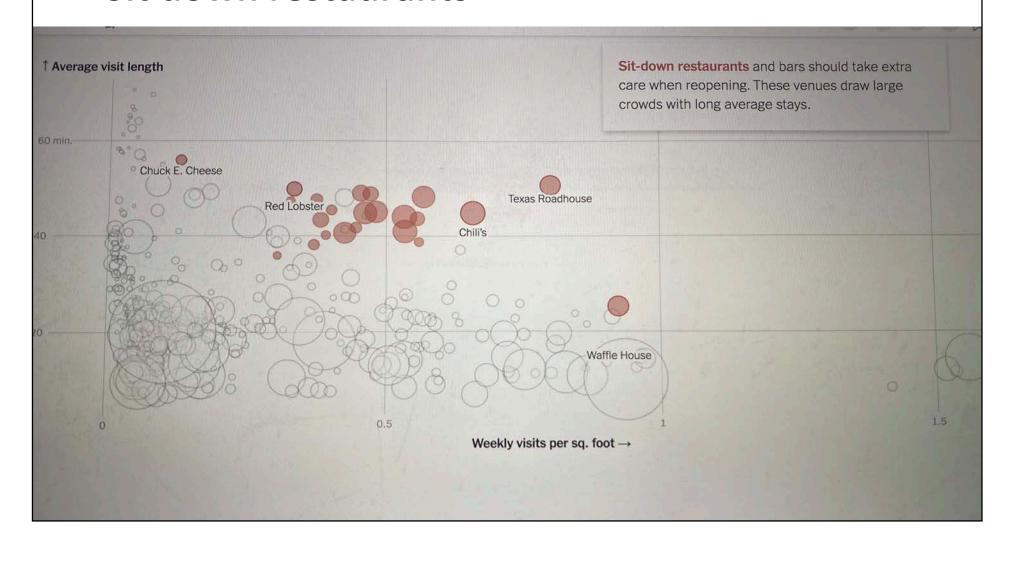
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## How should we open the economy?

Which businesses to open first and how should we assess the risk?

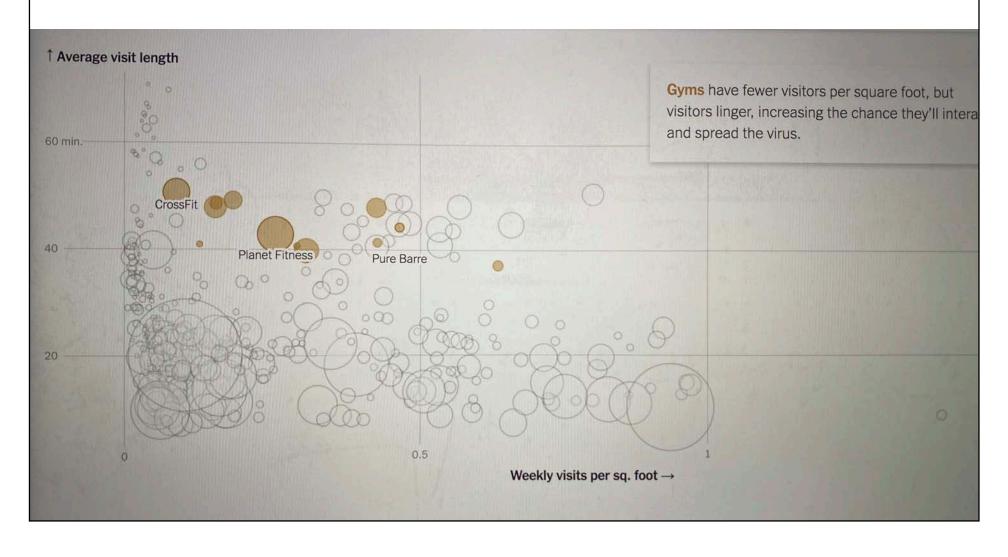
Successful Infection = Exposure to Virus x Time

#### **Sit down restaurants**



## Super spreaders (Lu et al. 2020) Glass screen wall Glass screen wall C1 Jan 31 B1 Feb 1 B2 Feb 5 Jan 24 Jan 29 **A4** B A3 Jan 29 A5 Feb 2 **A2** Exhaust fan D

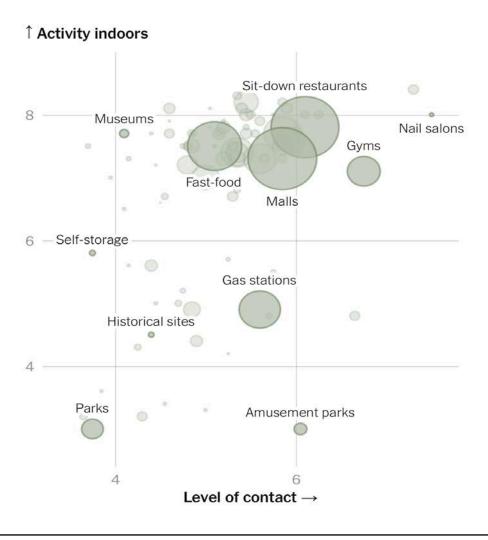
## **Gyms**



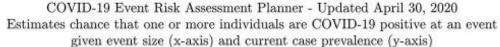
## **Fast food restaurants**

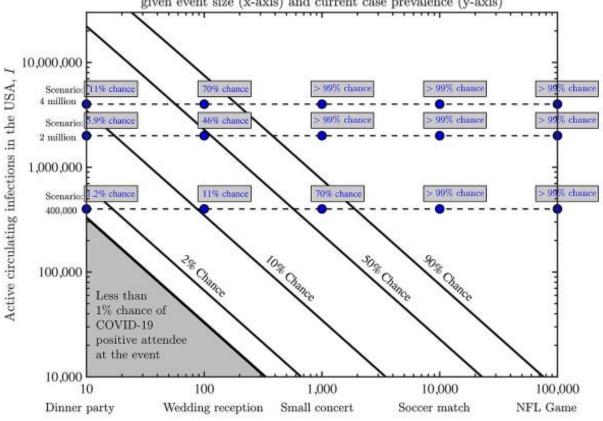


### Which businesses to patronize?



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Calculation note - J.S.Weitz - jsweitz@gatech.edu - 4/30/20 - Risk is  $\epsilon \approx 1 - (1 - p_I)^n$  where  $p_I = I/(330 \times 10^6)$  and n is event size Updated: April 30, 2020, License: Creative Commons BY-SA 4.0, i.e., Share, Adapt, Attribute Assumes incidence homogeneity, uses last 2 weeks cumulative as baseline with 5x and 10x undercounts for alternative scenarios Code https://github.com/jsweitz/covid-19-event-risk-planner

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#### **Regulations, Exemptions and Privacy**

- To enable coordination between public and private sectors:
  - Assurances that data sharing will be exempt from any adverse regulatory action or private lawsuits.
  - Creating narrow exceptions to data sharing, just like competition laws.
  - Tech platforms are going out of their way to help us.
  - Our health privacy system was created at a time in which bioethicists worked within a 1970s framework.
  - Caveats needed such that there is zero tolerance for the misuse of data.

#### **Four Data Cultures**

- America's data model maybe too elitist
- Mainland China's data model maybe too stringent
- Germany's data protection angst maybe too technophobic
- South Korea's model maybe too collectivist for the West.
- Best role model? Taiwan's hybrid information-collecting model (participatory self-surveillance)

#### Thank you & Stay Safe!

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