China Data Institute

Center for Geographic Analysis
Harvard University

社会地理计算联合研究中心
Geocomputation Center for Social Science

Quantifying human mobility behavior changes using Social Distancing Index Developed by University of Maryland

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June 04, 2021

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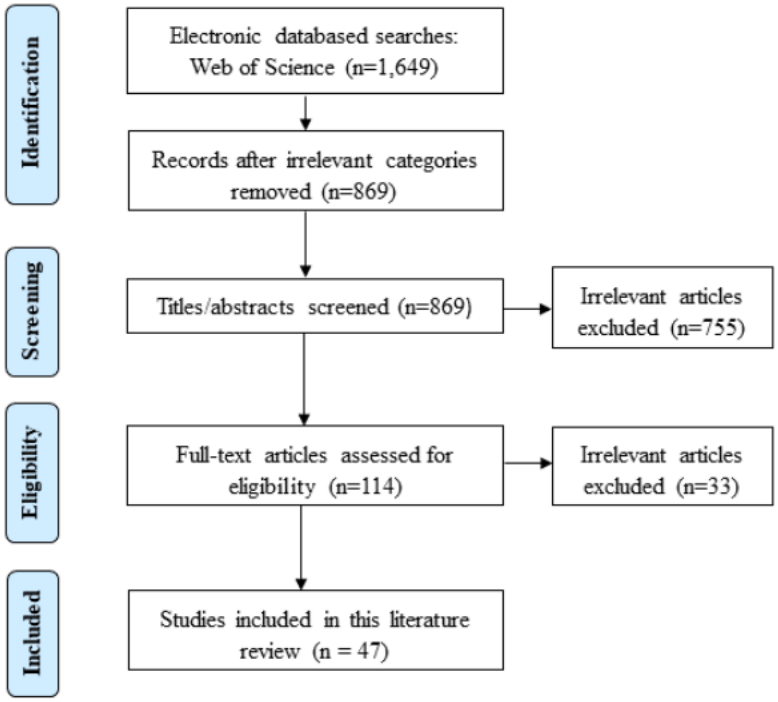
Human Mobility Open Data

Zhang, Mengxi, et al. "Human mobility and COVID-19 transmission: a systematic review and future directions." *medRxiv* (2021). https://doi.org/10.1101/2021.02.02.21250889



Human mobility and COVID-19 transmission: a systematic review and future directions

Mengxi Zhang [1*], Siqin Wang [2*], Tao Hu [3*], Xiaokang Fu [4*], Xiaoyue Wang [4], Yaxin Hu [4], Briana Halloran [1], Yunhe Cui [5], Haokun Liu [6], Zhimin Liu [7], Shuming Bao [8]

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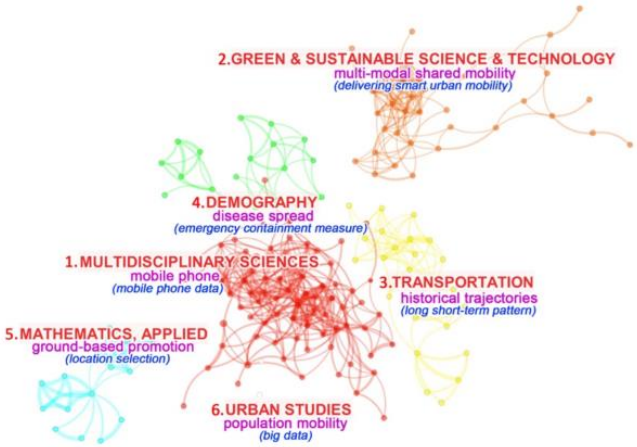
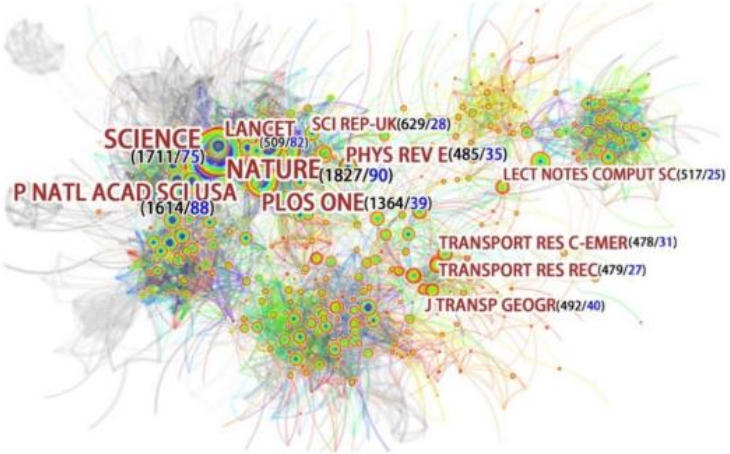
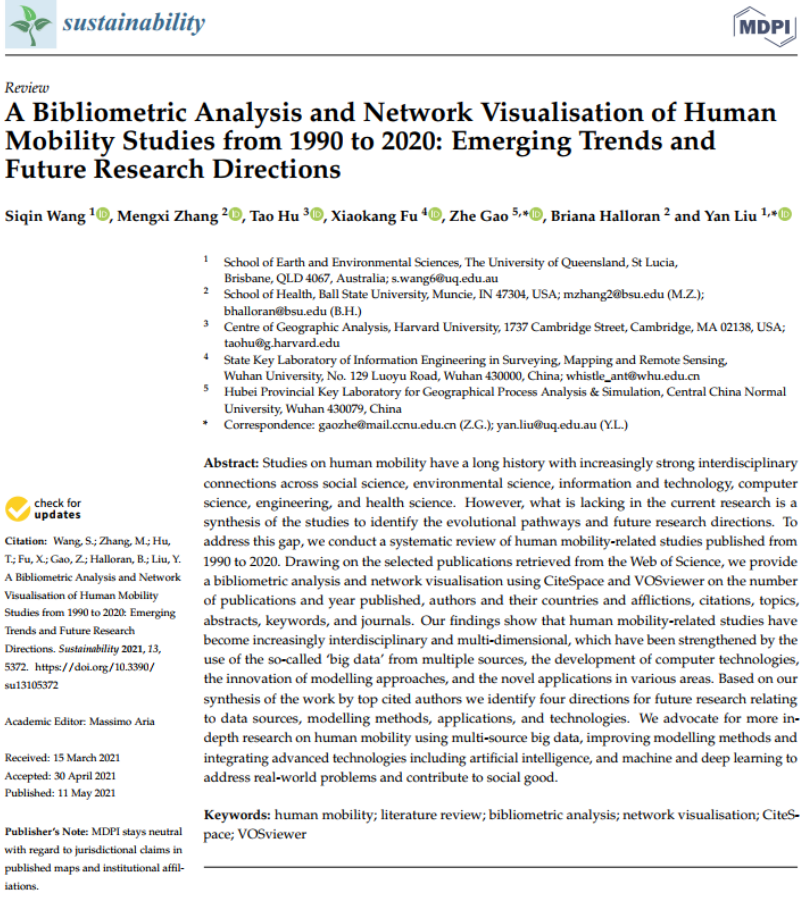
Human Mobility Open Data

Wang, S., Zhang, M., Hu, T., Fu, X., Gao, Z., Halloran, B., & Liu, Y. (2021). A Bibliometric Analysis and Network Visualisation of Human Mobility Studies from 1990 to 2020: Emerging Trends and Future Research Directions. *Sustainability*, *13*(10), 5372.







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Review

A Bibliometric Analysis and Network Visualisation of Human Mobility Studies from 1990 to 2020: Emerging Trends and Future Research Directions

Siqin Wang [1], Mengxi Zhang [2], Tao Hu [3], Xiaokang Fu [4], Zhe Gao [5,*], Briana Halloran [2] and Yan Liu [1,*]

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Abstract: Studies on human mobility have a long history with increasingly strong interdisciplinary connections across social science, environmental science, information and technology, computer science, engineering, and health science. However, what is lacking in the current research is a synthesis of the studies to identify the evolutional pathways and future research directions. To address this gap, we conduct a systematic review of human mobility-related studies published from 1990 to 2020. Drawing on the selected publications retrieved from the Web of Science, we provide a bibliometric analysis and network visualisation using CiteSpace and VOSviewer on the number of publications and year published, authors and their countries and afflictions, citations, topics, abstracts, keywords, and journals. Our findings show that human mobility-related studies have become increasingly interdisciplinary and multi-dimensional, which have been strengthened by the use of the so-called 'big data' from multiple sources, the development of computer technologies, the innovation of modelling approaches, and the novel applications in various areas. Based on our synthesis of the work by top cited authors we identify four directions for future research relating to data sources, modelling methods, applications, and technologies. We advocate for more in-depth research on human mobility using multi-source big data, improving modelling methods and integrating advanced technologies including artificial intelligence, and machine and deep learning to address real-world problems and contribute to social good.

Keywords: human mobility; literature review; bibliometric analysis; network visualisation; CiteSpace; VOSviewer

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Human Mobility Data in the COVID-19 Pandemic: Characteristics, Applications, and Challenges

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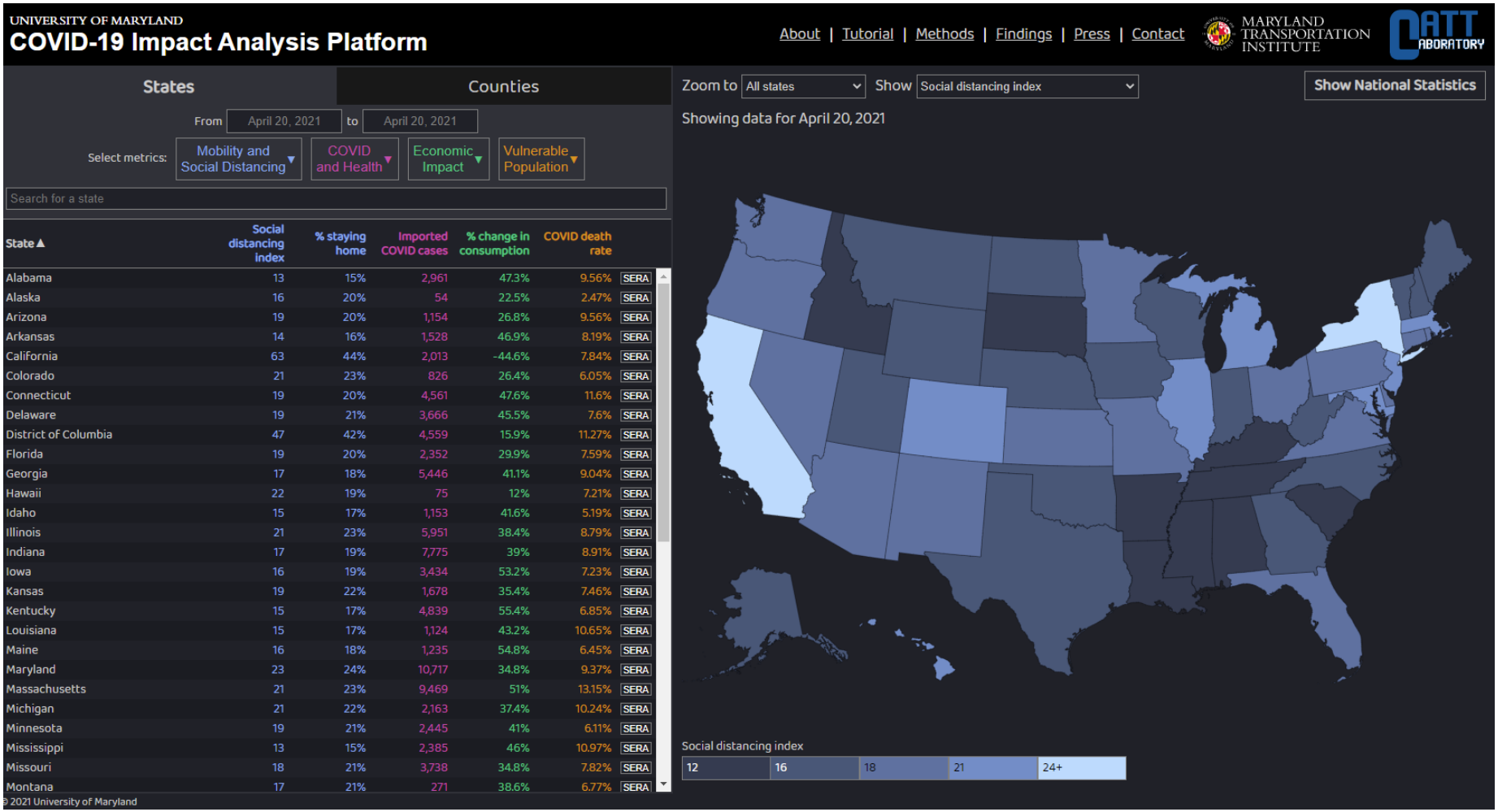
Human Mobility Open Data

Data Category		Name and Provider	Region and scale	Available Time	OD Flow	Availability	Strengths	Weaknesses	Selected References
Public Transit System	Air flight	International Air Transport Association (IATA)	Worldwide	Since 2010	Yes	Private	Rich information for business intelligence. Aggregated statistics for various applications	Mostly private data	Menkir et al., 2021 Bogoch et al., 2020
		OpenSky-Network	Worldwide, mostly for Europe and North America	Since 2012	Yes	Public	Detailed tracking information	API limitations	Zhuang et al., 2020 Iacus et al., 2020
	Train	Transit system / dataset in different countries (e.g., China, U.S., Italy)	China, USA, Italy (by state, city, district)	Different for different regions	Yes	Public	Available in countries where there is a booking website	Real-time data but without history data o sometimes web crawling needed	Zhang et al.,2020; Carteni et al., 2020 Hu et al., 2020
	Metro	Transport authority (e.g., MATSim-NYC)	U.S.	Different for different regions	No	Public	Detailed ridership data, at the station level	Non-trackable; no route record	Zheng et al.,2020; Ahangari et al., 2020
Social Activity		Apple Mobility Trends Report	Worldwide/city, county, state	04/14/2020 ~ present	No	Public	global wide; one single file; data divided by country/region, sub-region, city	data source method (requests for direction in Apple Maps)	Huang et al., 2020b Kurita et al., 2021; Hadjidemetriou et al., 2020
		Google Mobility Reports	Worldwide/city, county, state	2/15/2020 ~ present	No	Public	global wide; one single file	not comparable among countries	Pepe et al.,2020; Delen et al., 2020; Rutz et al., 2020
		Foursquare Mobility Reports	U.S./county, state	02/19/202 ~present.	No	Submit Application	Available in 25 types of POI and by age group	Only available in U.S	Gao et al., 2020 Fathi-Kazerooni et al.,2020 Ding et al.,2020
		SafeGraph Mobility Reports	U.S./census tract, county, and state	01/01/2019 ~present	Yes	Submit Application	Varieties of data categories	Data are only availabl on Amazon S3	Li et al., 2020 Kang et al. 2020
Index-based Mobility Data		Cuebiq Mobility Index	U.S. at multiple geographic levels	01/01/2020	No	Submit Application	Available in DMA level; index allows counties to be compared to one another	Only available in U.S.	Fraiberger et al., 2020 Pepe et al., 2020
		Baidu Mobility Index	China/city and province	1/1/2020 ~ 5/7/2020 & 9/3/2020 ~ presen	Yes	Public	inter/intro-city mobility index	Not publicly accessible after May 7 2020, only available for Mainland China	Ze-Liang et al., 2020 Liu et al., 2020 Xu et al., 2020

Human Mobility Open Data

	Descartes Lab Mobility Index	U.S./county and state	03/01/2020 – 06/06/2020	No	Submit Application	accurate positioning data (m50 score based on normalization methods)	Inter-city index not covered; only freely available in a certain period of time and scale	Warren et al., 2020 Gao et al., 2020; Chen et al., 2020
	Unacast Social Distancing Index	U.S.	02/24/2020 ~ present	No	Submit Application	Granular data, available down to specific data points; bias correction based on classifications of businesses	Since data is coming from third party sources, people may have to agree to consent on those sources	Brodeur et al., 2021
	University of Maryland Mobility Metrics and Social Distancing Index	U.S./county and state	01/01/2020 ~ present	No	Submit Application	Integrated and cleaned location data from multiple sources; be highly representative	Only available in the U.S.	Zhang et al., 2020 Lee et al., 2020 Ghader, et al., 2020
	Camber Systems Social Distancing Reporter	U.S./county	08/01/2020 ~ present	No	Submit Application	Integrating multiple data sources; less biased and more representative; easy to interpret	subject to calibration, only available in U.S. county level; no data before August 2020	Jeffrey et al., 2020
Social Media-Derived Mobility Data	Geotagged Tweets	Worldwide/any spatiotemporal scale	01/01/2018 ~ present	Yes	Public	Worldwide coverage, real-time, aggregation-flexible	Bias in population, low penetration	Huang et al., 2020a Li et al., 2021 Su et al., 2020
	Facebook Movement Range Maps	Worldwide	01/03/2020 ~ 31/08/2020	No	Submit Application	Machine-readable format that is global and free of charge	Only provided by mobile phone users who have enabled location history	Lau et al.,2020; Kuchler et al., 2020 Beria et al., 2021

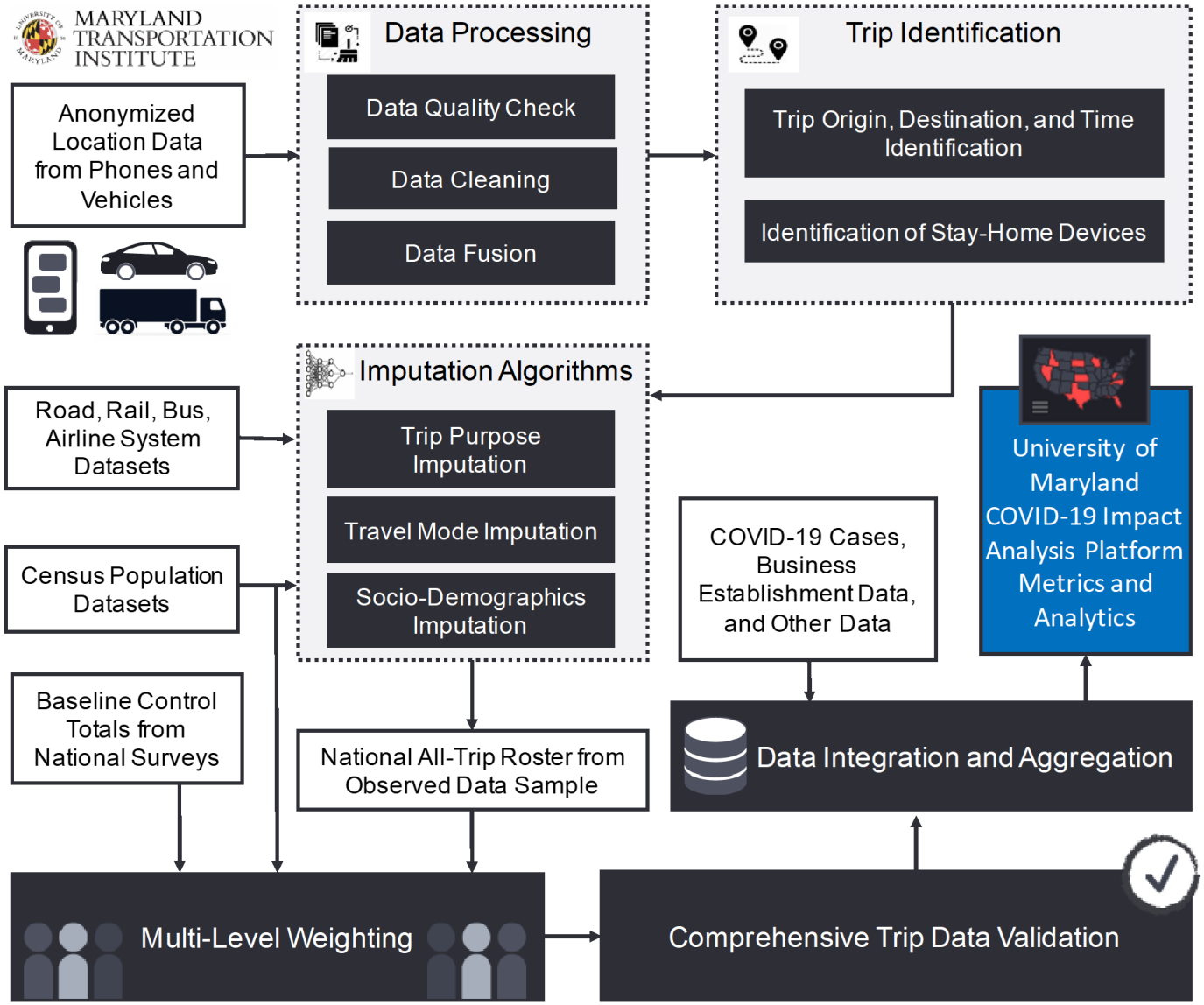
Social Distancing Index by UMD



State	Social distancing index	% staying home	Imported COVID cases	% change in consumption	COVID death rate	
Alabama	13	15%	2,961	47.3%	9.56%	SERA
Alaska	16	20%	54	22.5%	2.47%	SERA
Arizona	19	20%	1,154	26.8%	9.56%	SERA
Arkansas	14	16%	1,528	46.9%	8.19%	SERA
California	63	44%	2,013	-44.6%	7.84%	SERA
Colorado	21	23%	826	26.4%	6.05%	SERA
Connecticut	19	20%	4,561	47.6%	11.6%	SERA
Delaware	19	21%	3,666	45.5%	7.6%	SERA
District of Columbia	47	42%	4,559	15.9%	11.27%	SERA
Florida	19	20%	2,352	29.9%	7.59%	SERA
Georgia	17	18%	5,446	41.1%	9.04%	SERA
Hawaii	22	19%	75	12%	7.21%	SERA
Idaho	15	17%	1,153	41.6%	5.19%	SERA
Illinois	21	23%	5,951	38.4%	8.79%	SERA
Indiana	17	19%	7,775	39%	8.91%	SERA
Iowa	16	19%	3,434	53.2%	7.23%	SERA
Kansas	19	22%	1,678	35.4%	7.46%	SERA
Kentucky	15	17%	4,839	55.4%	6.85%	SERA
Louisiana	15	17%	1,124	43.2%	10.65%	SERA
Maine	16	18%	1,235	54.8%	6.45%	SERA
Maryland	23	24%	10,717	34.8%	9.37%	SERA
Massachusetts	21	23%	9,469	51%	13.15%	SERA
Michigan	21	22%	2,163	37.4%	10.24%	SERA
Minnesota	19	21%	2,445	41%	6.11%	SERA
Mississippi	13	15%	2,385	46%	10.97%	SERA
Missouri	18	21%	3,738	34.8%	7.82%	SERA
Montana	17	21%	271	38.6%	6.77%	SERA

https://data.covid.umd.edu/

Social Distancing Index by UMD



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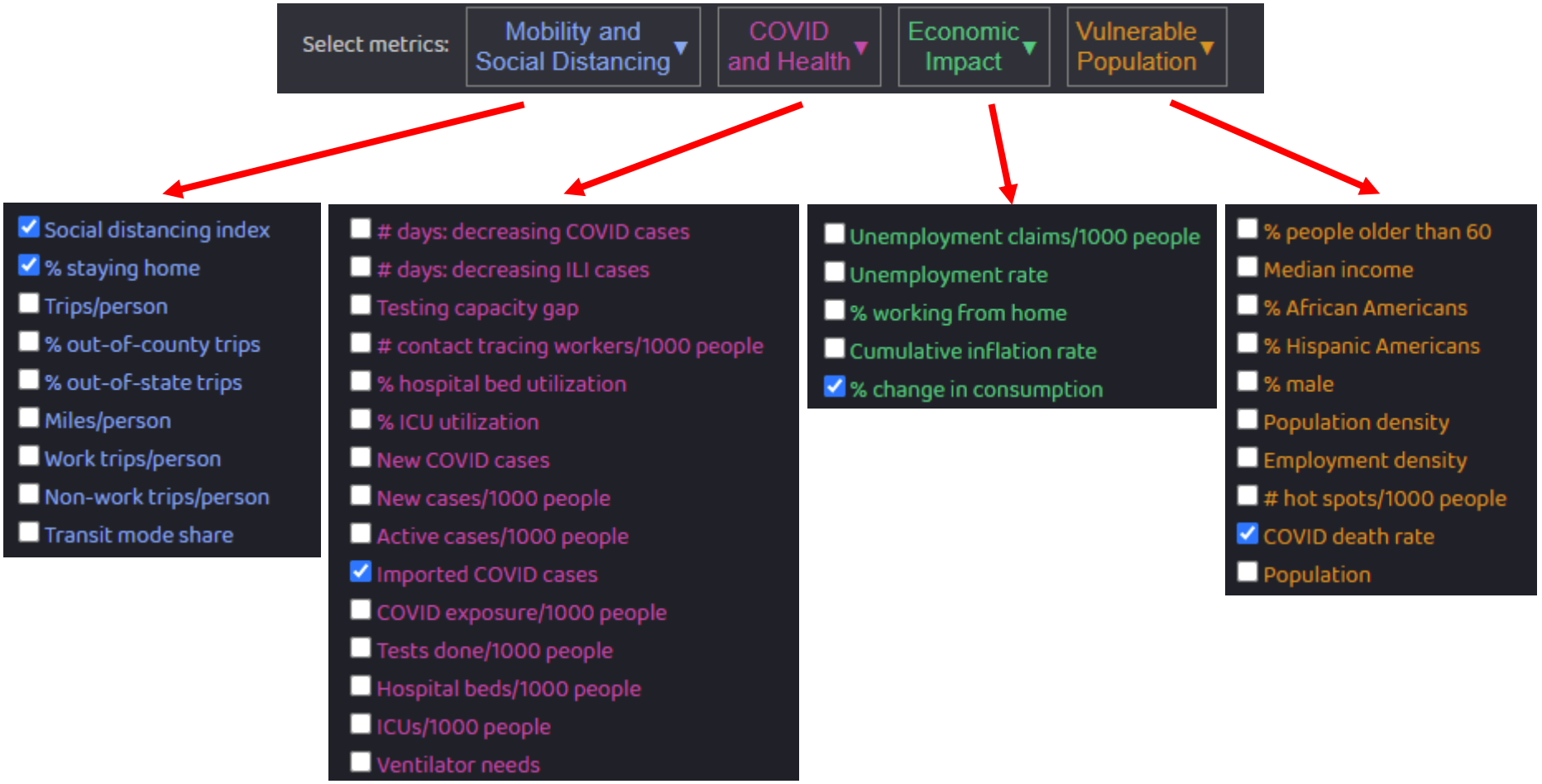


https://data.covid.umd.edu/

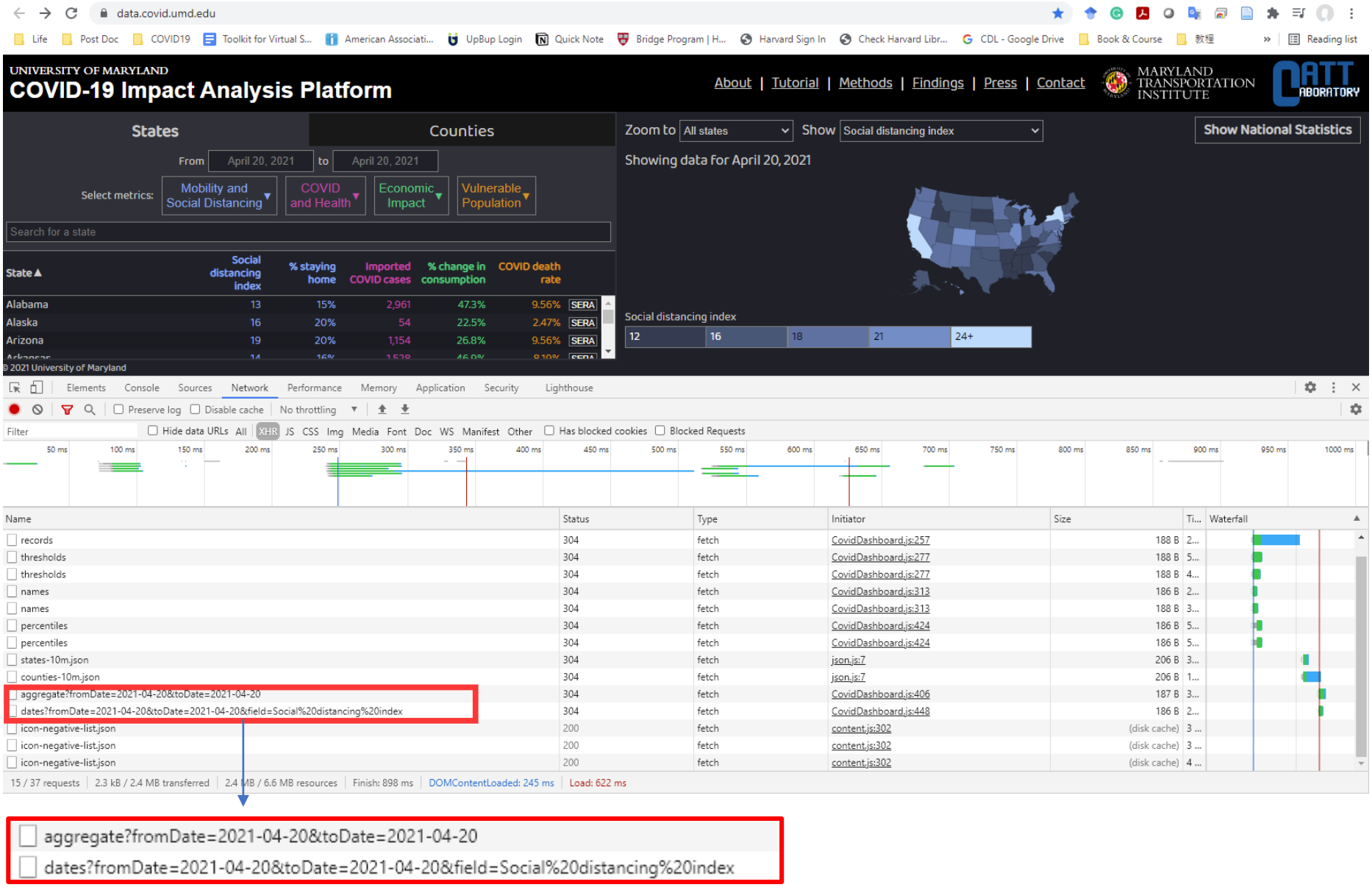
Data Source

Variable Name	Source
X1: Percentage of residents staying home	Percentage of residents that make no trips more than 1.61 km away from home
X2: Daily work trips per person	Average number of work trips made per person. A work trip is a trip going to or from one's imputed work location
X3: Daily non-work trips per person	Average number of non-work trips made per person
X4: Distances travelled per person	Distances in kilometres travelled per person on all travel modes
X5: Out-of-county trips (in thousands)	Number of all trips that travels from and to the outside of the county

$$SDI = [X_1 + 0.01 \times (100 - X_1) \times (0.25X_2 + 0.45X_3 + 0.3X_4)] \times 0.8 + 0.2X_5$$

Pan, Y., Darzi, A., Kabiri, A., Zhao, G., Luo, W., Xiong, C., & Zhang, L. (2020). Quantifying human mobility behaviour changes during the COVID-19 outbreak in the United States. *Scientific Reports*, *10*(1), 1-9.

Data Collection



Data Collection

https://data.covid.umd.edu/state/field/dates?fromDate=2021-04-20&toDate=2021-04-20&field=Social%20distancing%20index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https://data.covid.umd.edu/state/records/aggregate?fromDate=2021-04-20&toDate=2021-04-20


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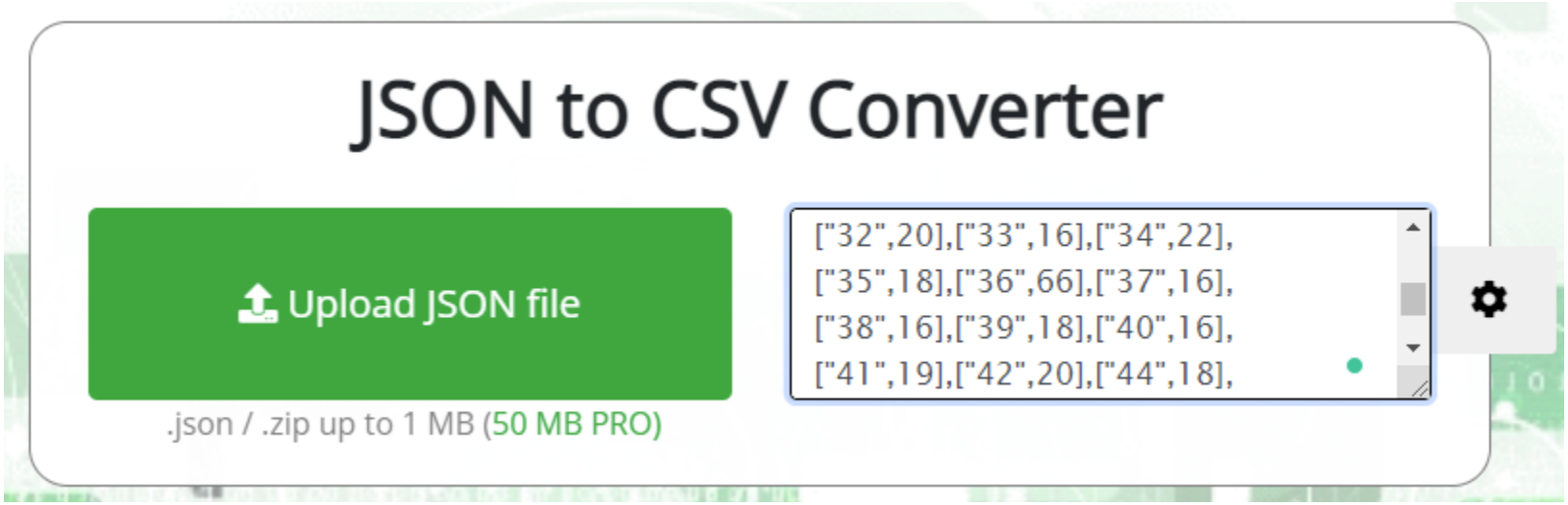
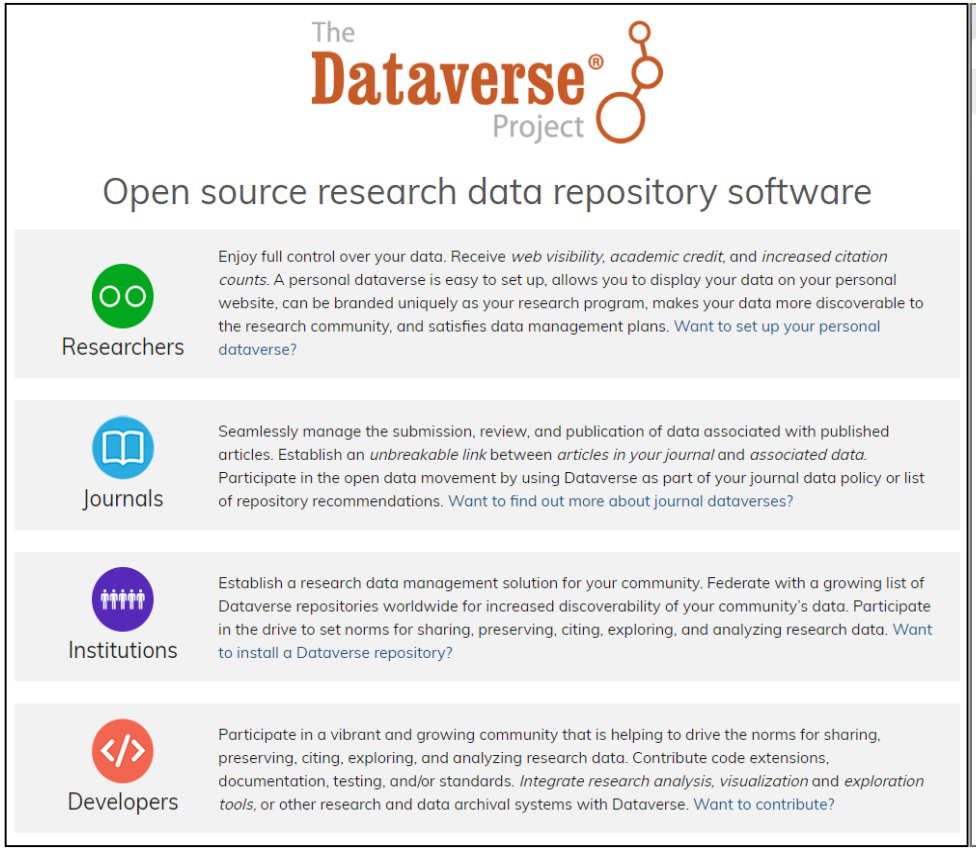
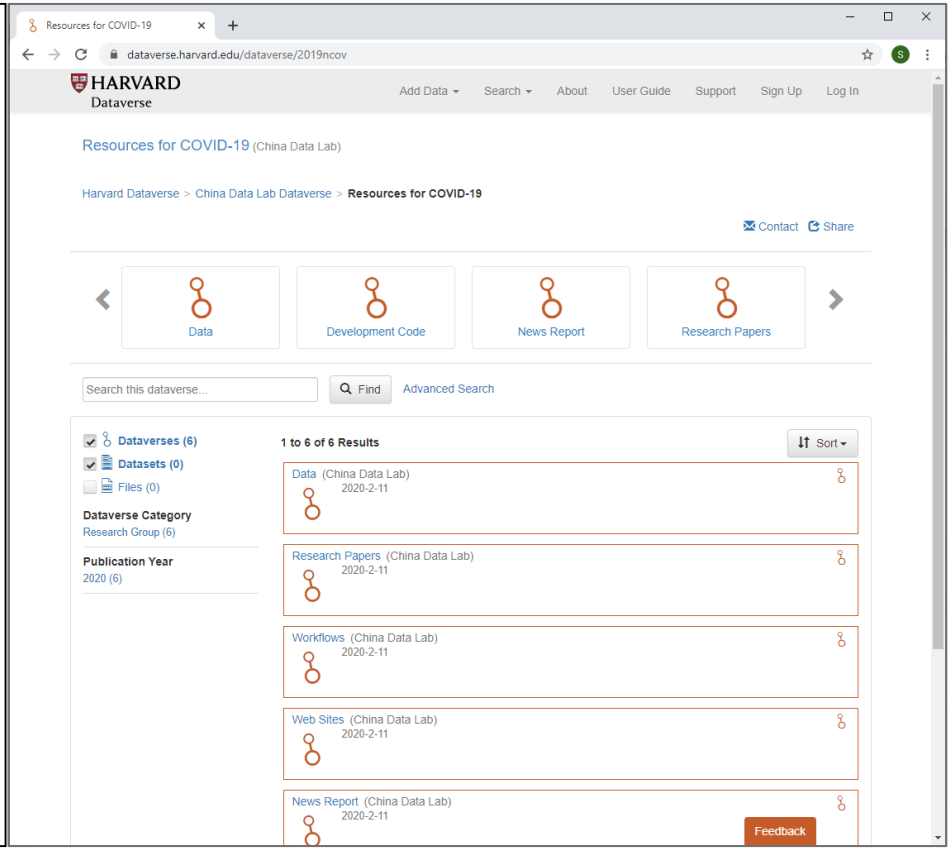
Data Collection



https://json-csv.com/

Data Sharing



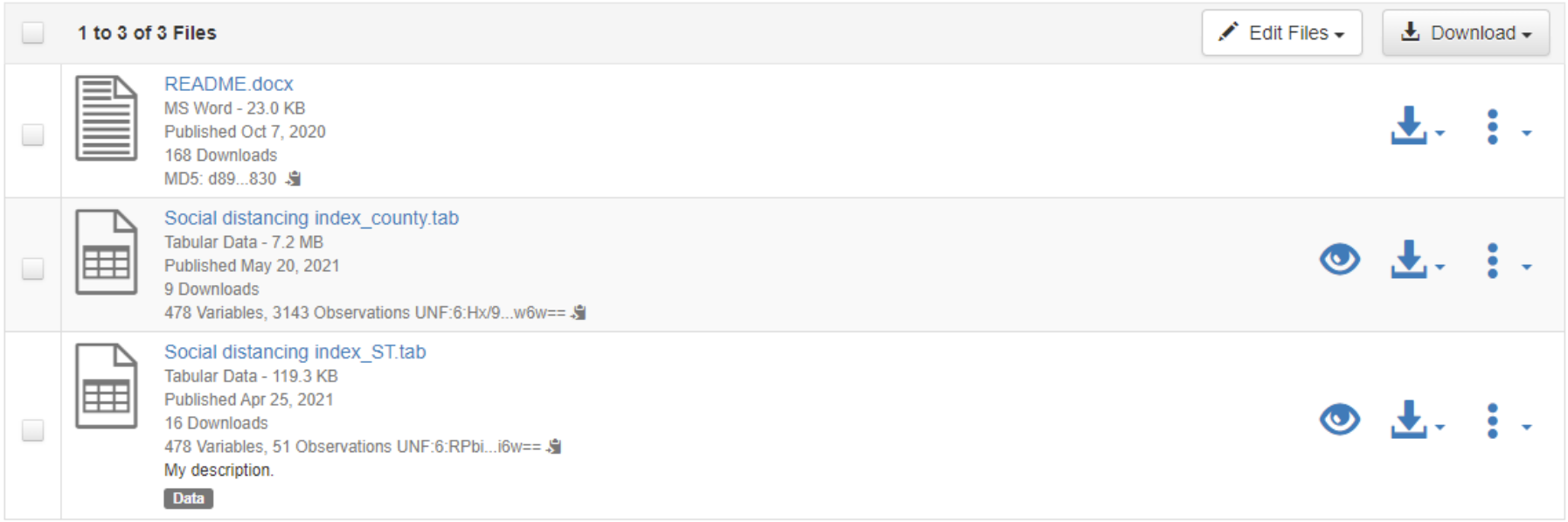


https://dataverse.org/

https://dataverse.harvard.edu/dataverse/data_ncov

Data Sharing

China Data Lab, 2020, "Social Distancing Index from University of Maryland (US)", https://doi.org/10.7910/DVN/ZAKKCE, Harvard Dataverse, V31



Data Sharing

China Data Lab, 2020, "Social Distancing Index from University of Maryland (US)", https://doi.org/10.7910/DVN/ZAKKCE, Harvard Dataverse,

Explore on View Data

	STATE	NAME	01/01/2020	01/02/2020	01/03/2020	01/04/2020	01/05/2020	01/06/2020	01/07/2020	01/08/2020
1	01	Alabama	52.0	27.0	17.0	28.0	41.0	14.0	13.0	12.0
2	02	Alaska	54.0	23.0	20.0	37.0	47.0	23.0	21.0	23.0
3	04	Arizona	46.0	19.0	16.0	27.0	39.0	19.0	18.0	17.0
4	05	Arkansas	49.0	23.0	14.0	28.0	40.0	17.0	14.0	12.0
5	06	California	50.0	22.0	18.0	31.0	43.0	20.0	19.0	18.0
6	08	Colorado	49.0	16.0	15.0	25.0	40.0	15.0	14.0	14.0
7	09	Connecticut	56.0	17.0	15.0	33.0	47.0	19.0	17.0	17.0
8	10	Delaware	54.0	17.0	17.0	33.0	49.0	17.0	20.0	17.0
9	11	District of Columbia	48.0	25.0	22.0	37.0	49.0	23.0	28.0	24.0
10	12	Florida	47.0	19.0	16.0	33.0	41.0	18.0	16.0	15.0
11	13	Georgia	52.0	27.0	20.0	32.0	43.0	17.0	16.0	14.0
12	15	Hawaii	43.0	21.0	17.0	30.0	35.0	19.0	18.0	19.0
13	16	Idaho	52.0	19.0	16.0	31.0	49.0	19.0	16.0	17.0
14	17	Illinois	56.0	21.0	17.0	33.0	46.0	19.0	17.0	17.0
15	18	Indiana	53.0	20.0	16.0	33.0	45.0	18.0	16.0	16.0
16	19	Iowa	55.0	17.0	15.0	31.0	47.0	18.0	16.0	16.0
17	20	Kansas	50.0	18.0	15.0	29.0	43.0	17.0	15.0	15.0
18	21	Kentucky	49.0	22.0	16.0	34.0	43.0	17.0	16.0	15.0
19	22	Louisiana	53.0	28.0	18.0	29.0	44.0	17.0	16.0	15.0
20	23	Maine	47.0	14.0	13.0	31.0	46.0	17.0	16.0	16.0
21	24	Maryland	54.0	18.0	16.0	35.0	48.0	17.0	24.0	19.0
22	25	Massachusetts	54.0	17.0	16.0	34.0	46.0	19.0	17.0	18.0
23	26	Michigan	56.0	20.0	16.0	33.0	49.0	18.0	17.0	18.0
24	27	Minnesota	53.0	17.0	15.0	30.0	49.0	17.0	17.0	18.0
25	28	Mississippi	50.0	28.0	16.0	27.0	41.0	14.0	13.0	12.0
26	29	Missouri	49.0	17.0	15.0	29.0	42.0	16.0	14.0	14.0
27	30	Montana	51.0	20.0	17.0	32.0	44.0	23.0	19.0	17.0

Related Research

Objective: to evaluate the proposed CAS and other mobility factors on confirmed COVID-19 cases with various temporal delays at a county-level and study the impacts of travel-related factors and social distancing measures on COVID-19 ca

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Exploring the impacts of travel-implied policy factors on COVID-19 spread within communities based on multi-source data interpretations

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ABSTRACT

The global Coronavirus Disease 2019 (COVID-19) pandemic has led to the implementation of social distancing measures such as work-from-home orders that have drastically changed people's travel-related behavior. As countries are easing up these measures and people are resuming their pre-pandemic activities, the second wave of COVID-19 is observed in many countries. This study proposes a Community Activity Score (CAS) based on inter-community traffic characteristics (in and out of community traffic volume and travel distance) to capture the current travel-related activity level compared to the pre-pandemic baseline and study its relationship with confirmed COVID-19 cases. Fourteen other travel-related factors belonging to five categories (Social Distancing Index, residents staying at home, travel frequency and distance, mobility trend, and out-of-county visitors) and three social distancing measures (stay-at-home order, face-covering order, and self-quarantine for out-of-county travels) are also considered to reflect the likelihood of exposure to the COVID-19. Considering that it usually takes days from exposure to confirming the infection, the exposure-to-confirm temporal delay between the time-varying travel-related factors and their impacts on the number of confirmed COVID-19 cases is considered in this study. Honolulu County in the State of Hawaii is used as a case study to evaluate the proposed CAS and other factors on confirmed COVID-19 cases with various temporal delays at a county-level. Negative Binomial models were chosen to study the impacts of travel-related factors and social distancing measures on COVID-19 cases. The case study results show that CAS and other factors are correlated with COVID-19 spread, and models that factor in the exposure-to-confirm temporal delay perform better in forecasting COVID-19 cases later. Policymakers can use the study's various findings and insights to evaluate the impacts of social distancing policies on travel and effectively allocate resources for the possible increase in confirmed COVID-19 cases.

Variables	Data description	Data source
COVID	Daily confirmed cases of COVID-19	The New York Times (2020)
CAS	Proposed Community Activity Score (CAS)	HDOT (2020)
SDI	Social Distance Index: ranging from 0 (no social distancing is observed) to 100 (everyone staying at home and no visitors are entering the county)	Maryland Transportation Institute (2020)
Travel frequency and distance		
Home	Percentage of people traveling less than 1 mile away from their residence place compared to the pandemic baseline.	USDOT (2020)
Trip	The number of trips made per day	USDOT (2020)
Drive	Daily Volume of driving directions requests compared to the pandemic baseline.	Apple (2020)
Transit	Daily Volume of transit directions requests compared to the pandemic baseline.	Apple (2020)
Walk	Daily Volume of walking directions requests compared to the pandemic baseline.	Apple (2020)
Distance	The maximum travel distance to a point from the initial point of the day (i.e., the max-distance mobility) compared to the pandemic baseline.	Descartes Labs (2020)
Mobility trend		
Retail	The number of visits to restaurants,	Google (2020)
Grocery	The number of visits to grocery markets, food warehouses, farmers' markets, specialty food shops, drug stores, and pharmacies compared to the pandemic baseline.	Google (2020)
Park	The number of visits to national parks, public beaches, marinas, dog parks, plazas, and public gardens compared to the pandemic baseline.	Google (2020)
Stations	The number of visits to national parks, public beaches, marinas, dog parks, plazas, and public gardens compared to the pandemic baseline.	Google (2020)
Work	The number of visits to places of work compared to the pandemic baseline.	Google (2020)
Residences	The number of visits to places of residence compared to the pandemic baseline.	Google (2020)
Out-of-county visitors		
Airport	The number of people through Hawaii airport (hundreds).	Hawaii Tourism Authority (2020)

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Methodology

Community Activity Score (CAS)

$$A_{mn} = \left(a\frac{I_{mn}D_{mn}}{I_{m0}D_{m0}} + b\frac{O_{mn}D_{mn}}{O_{m0}D_{m0}} \right) * 100 \quad (1)$$

where A_{mn} is the activity score of community m on day n during the pandemic.

a and b are predetermined coefficients, and a + b = 1,
I_{mn} is the incoming traffic volume of the community m on day n,
I_{m0} is the average incoming traffic volume of the community during the pre-pandemic baseline,
O_{mn} is the outgoing traffic volume of the community m on day n,
O_{m0} is the average outgoing traffic volume of the community during the pre-pandemic baseline,
D_{mn} is the average travel distance of the community m on day n,
D_{m0} is the average travel distance of the community during the pre-pandemic baseline.
As CAS is a relative activity level compared to the pre-pandemic baseline, the baseline value for CAS is 100. In this study, a = b = 0.5.

$$A_n = \sum_{m=1}^{M} w_m A_{mn}$$

Zero-inflated Negative Binomial (ZINB) models

$$P(c_n) = \frac{EXP(-\lambda_n)\lambda_n^{c_n}}{c_n!}$$

$$\lambda_n = EXP(\beta x_n + \varepsilon_n)$$

Results

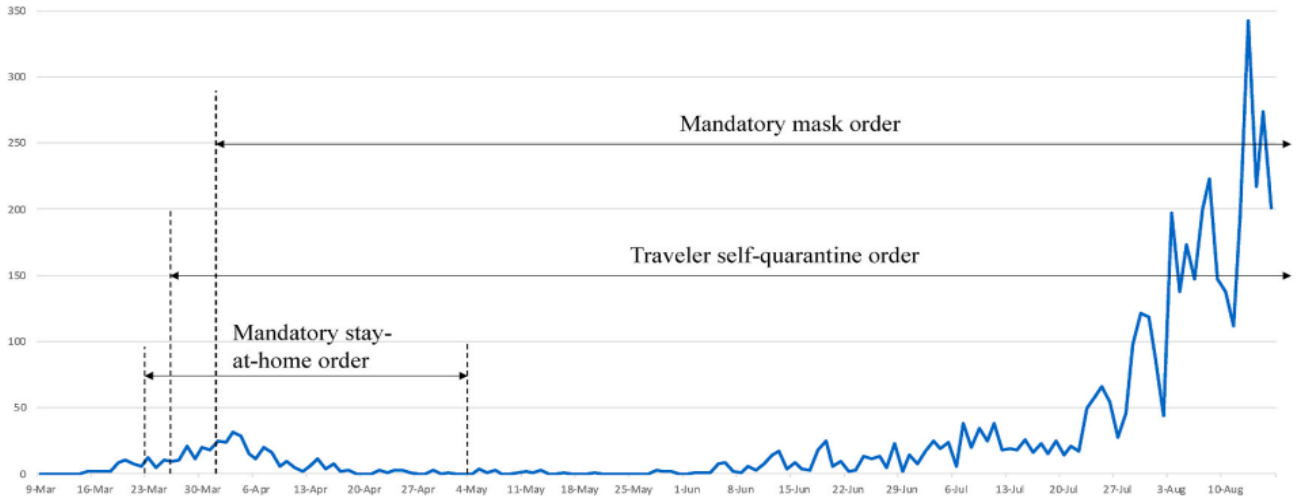


Fig. 2. Daily COVID-19 cases and important policies.

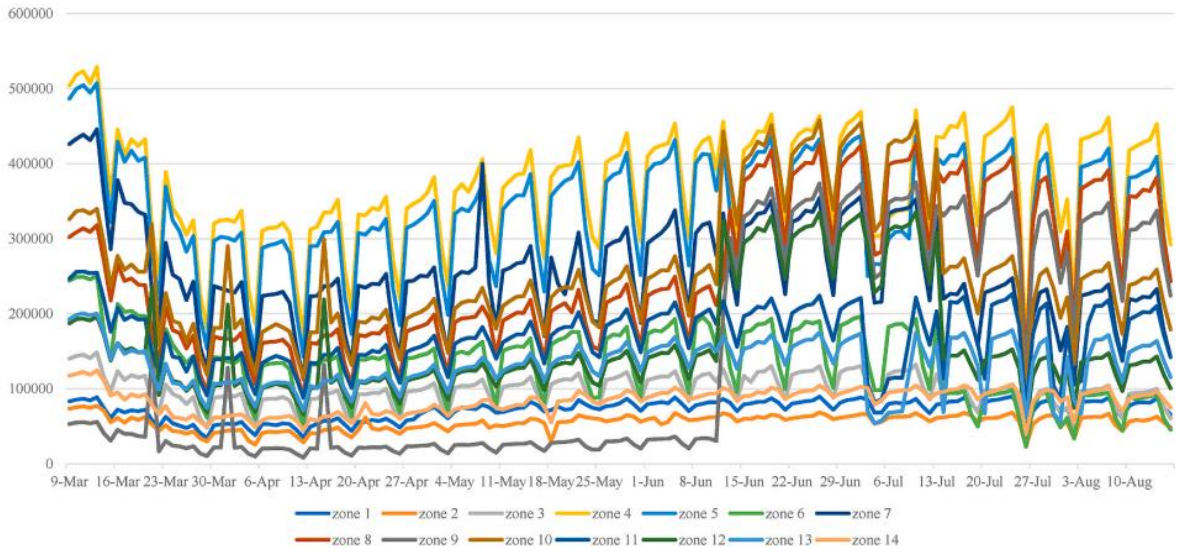


Fig. 3. Daily traffic volume (in-and-out of the zone) for each zone during the study period.

Results

Weekly average of COVID-19 cases and travel-related factors.

	COVID	CAS	SDI	Home	Trip	Drive	Transit	Walk	Distance	Retail	Grocery	Park	Station	Work	Residence	Airport
1	0.3	95.1	*21.6*	*104.5*	**82.5**	**92.9**	**79.6**	**94.4**	**95.8**	**96.0**	**105.1**	**94.3**	**89.7**	**98.7**	*101.6*	**165.6**
2	5.3	64.1	42.3	142.7	66.8	61.0	**39.8**	**54.1**	54.4	**74.9**	**98.0**	64.4	**67.6**	**74.1**	112.7	**82.7**
3	11.1	32.7	66.4	148.5	*54.9*	34.5	15.1	21.6	18.8	52.9	*72.9*	*39.1*	41.3	55.4	121.7	17.9
4	23.1	*28.6*	69.4	148.1	*56.0*	*33.0*	12.0	*19.9*	16.8	52.6	74.7	40.1	34.4	52.4	122.1	5.3
5	9.9	*26.8*	**71.9**	**151.8**	58.6	*31.9*	*11.1*	*19.0*	*13.4*	*49.3*	*73.7*	*37.4*	*32.1*	*49.0*	**123.3**	*4.8*
6	4.7	*28.6*	**70.1**	142.8	65.2	34.9	*11.2*	20.0	17.6	*50.1*	74.9	41.1	*33.3*	*52.3*	**122.3**	*4.8*
7	1.6	31.8	67.7	146.4	63.7	36.4	11.4	20.3	17.8	51.9	75.4	44.6	33.9	53.4	121.7	*4.3*
8	*0.6*	37.6	63.0	145.1	64.0	40.5	12.6	22.3	24.6	54.9	79.3	53.0	36.1	55.6	119.0	5.8
9	1.3	42.4	58.7	143.0	64.7	46.0	14.1	25.1	*11.0*	58.1	85.7	61.0	38.4	58.4	118.4	7.2
10	1.0	43.4	57.4	136.5	67.5	50.1	14.2	27.7	25.0	57.7	82.1	65.1	38.1	59.7	117.9	8.6
11	*0.1*	46.4	54.3	*118.6*	**72.3**	57.2	17.8	32.0	42.0	62.1	87.3	70.0	39.6	61.6	116.7	9.7
12	1.0	58.8	51.9	134.6	65.3	59.4	19.5	33.9	42.2	63.7	86.9	77.3	41.0	60.6	116.6	10.2
13	2.9	70.5	45.4	130.9	68.0	63.6	21.9	38.4	49.8	66.9	88.6	76.0	43.1	68.4	114.0	14.2
14	7.4	76.4	45.7	135.7	65.9	65.0	21.9	39.2	53.9	68.3	85.0	76.4	42.3	67.0	113.7	14.7
15	10.4	80.0	43.3	140.3	65.2	68.7	22.7	40.9	54.9	69.7	85.9	75.4	45.0	69.1	112.6	14.4
16	10	91.6	39.6	139.0	64.5	70.0	23.4	42.2	57.1	69.7	83.3	**77.9**	45.3	69.3	112.3	14.4
17	15.4	79.3	43.1	149.1	61.1	70.2	22.1	45.0	54.6	70.9	88.9	77.1	44.4	63.1	113.0	19.0
18	25.6	72.8	44.3	143.3	58.5	69.6	22.6	43.8	**59.0**	70.0	86.0	74.7	46.6	68.9	112.1	21.3
19	20.3	**102.9**	43.9	145.4	60.1	70.6	21.9	44.2	46.1	71.3	84.1	76.3	44.7	68.7	*112.0*	20.0
20	40	94.1	44.6	151.2	58.1	65.9	20.8	41.4	37.9	68.0	86.9	66.4	41.9	65.9	113.6	17.6
21	77.3	95.9	40.3	148.3	58.2	**70.6**	20.9	43.6	34.6	69.3	80.0	71.1	43.3	67.0	113.0	23.8
22	**175**	95.6	45.4	**148.7**	59.7	68.7	20.3	43.9	35.2	67.7	83.6	61.7	43.3	67.4	113.1	23.9
23	**211.4**	**97.8**	*38.1*	137.3	68.2	67.1	19.7	44.3	31.0	65.7	80.3	44.1	41.9	66.0	114.4	19.2

Note: The highest and the second-highest value of each variable are bold, and the lowest and the second-lowest value of each variable are italic during the study period.

Table 6

Model Estimation Results ($N = 161$). D represents exposure-to-confirm temporal delays.

	Constant	CAS	Park	Trip	Walk	Mask	No Stay-home
D0	11.636	0.034**	−0.059**	0.022**	−0.144*	–	0.978**
D1	11.656	0.040**	−0.063**	0.029**	−0.149**	–	0.707*
D2	8.979	0.042**	−0.051**	–	−0.104**	–	0.859*
D3	9.801	0.042**	−0.051**	–	−0.117**	–	0.929**
D4	8.424	0.040**	−0.045**	–	−0.100**	–	0.953**
D5	6.840	0.039**	−0.036**	–	−0.078**	–	0.915**
D6	7.154	0.038**	−0.033**	–	−0.083**	−0.743*	1.565**
D7	8.618	0.046**	−0.035**	–	−0.111**	−0.854**	1.421**
D8	7.968	0.043**	−0.043**	–	−0.094**	−0.887**	1.806**
D9	7.895	0.046**	−0.039**	–	−0.097**	−0.872**	1.593**
D10	8.132	0.046**	−0.035**	–	−0.104**	−0.893**	1.552**
D11	5.209	0.046**	−0.029**	–	−0.063**	–	0.755**
D12	5.098	0.040**	−0.023**	–	−0.064**	–	1.111**
D13	7.273	0.033**	−0.028**	0.025**	−0.104**	–	1.326**
D14	6.251	0.037**	−0.030**	0.028**	−0.091**	–	1.186**

Summary

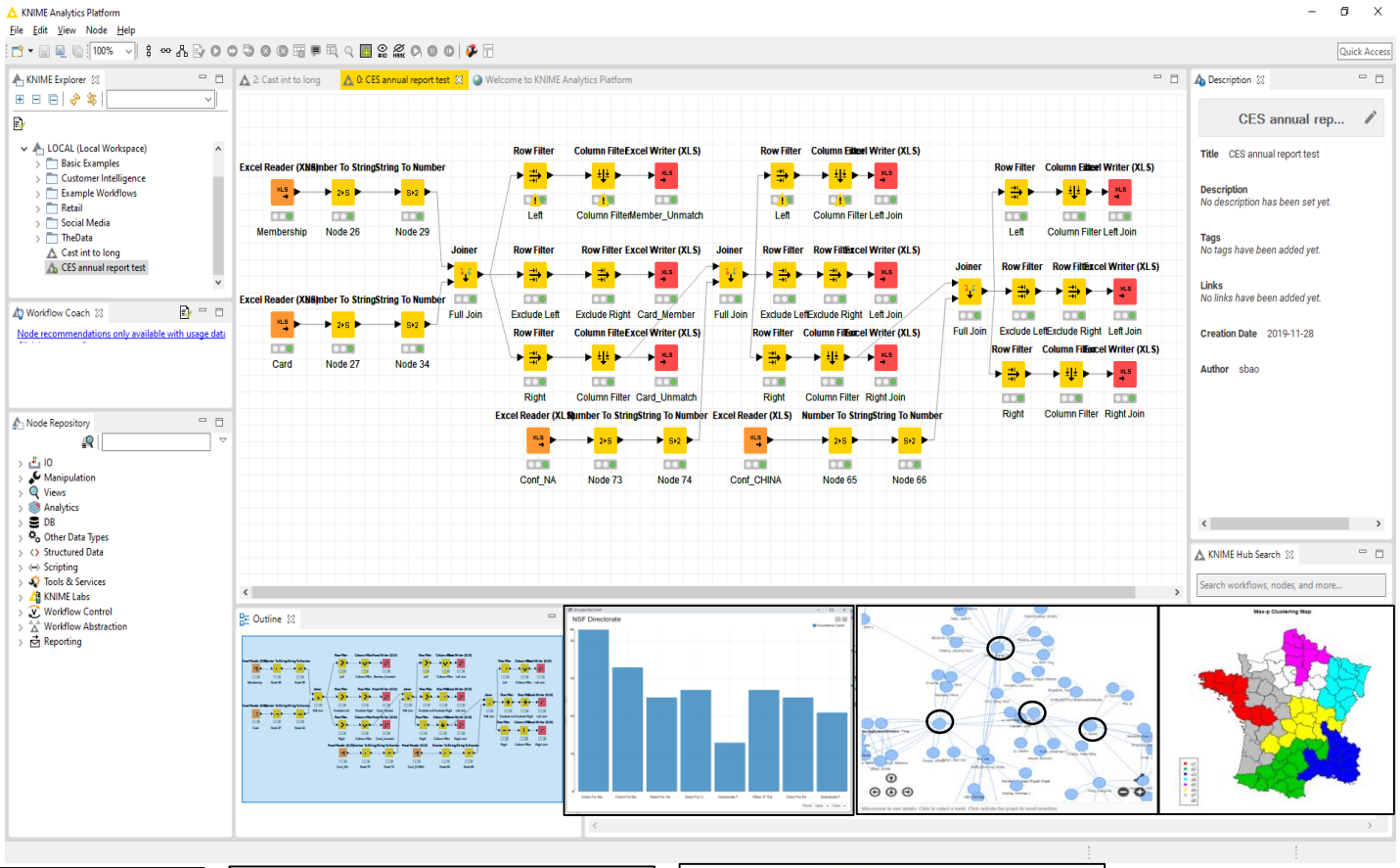
Findings

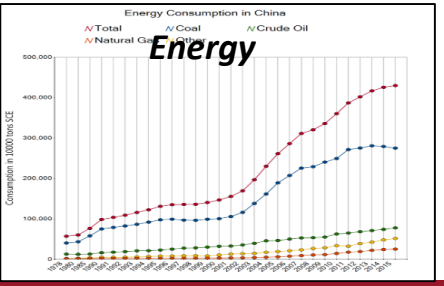
- Daily confirmed COVID-19 cases increase as the number of trips increases, while the daily confirmed COVID-19 cases decrease when the walking frequency increases.
- Increasing visits to locations such as parks and beaches contribute negatively to the daily confirmed COVID-19 cases.
- The modeling results show that both mandatory face-covering policy and mandatory work-from-home policy contribute positively toward reducing COVID-19 infection in Honolulu County.

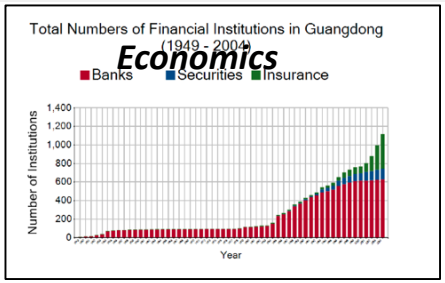
Limitations

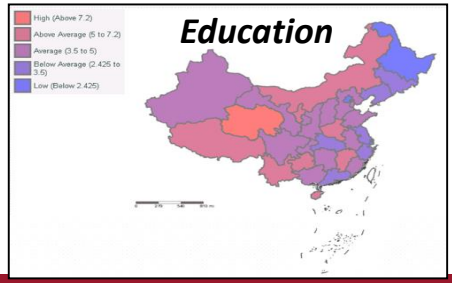
- Honolulu County is relatively unique compared to most of the counties in the U.S. as most of its out-of-county travels are through the airport.
- Some of the other factors found by some studies related to neighborhood built environment were not included in this study

Replicable, Reproducible and Expandable Data Analysis





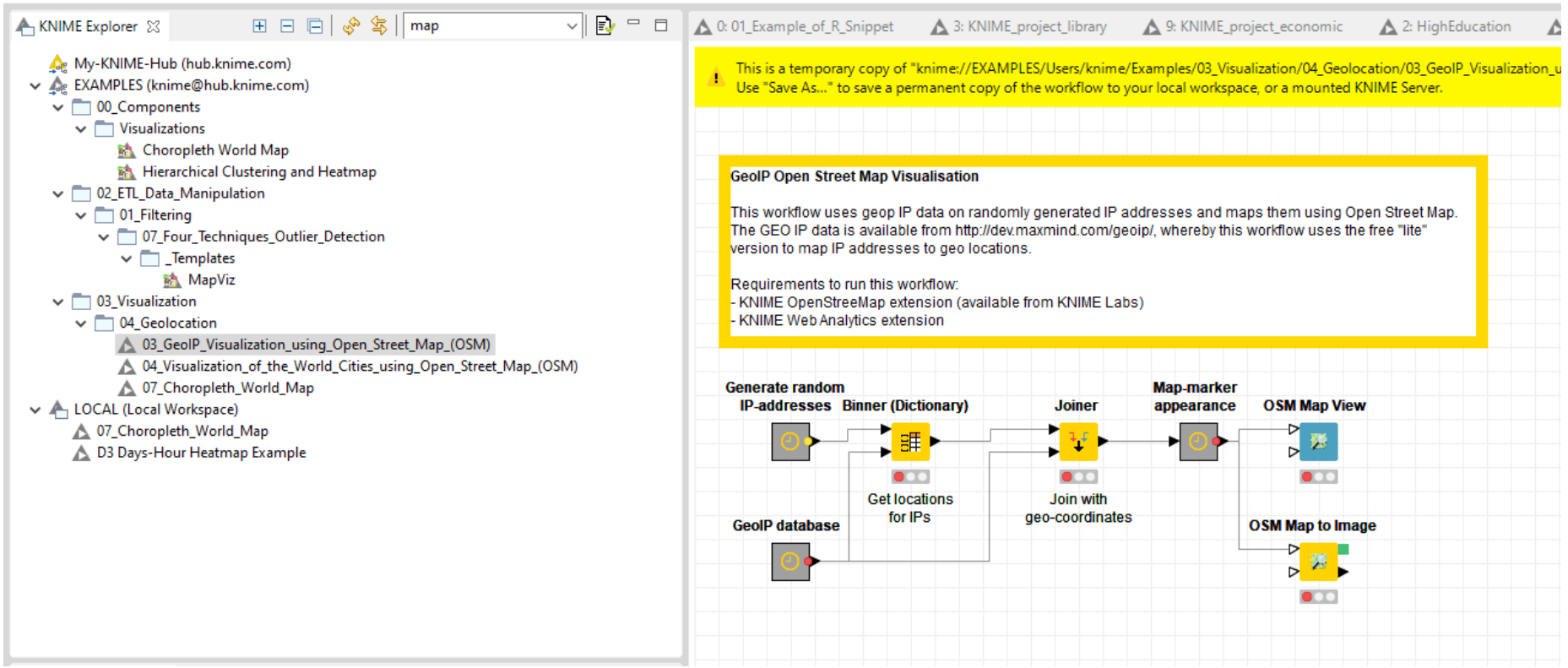




Introduction to Workflow Tool KNIME

Open for Innovation
KNIME

https://www.knime.com/



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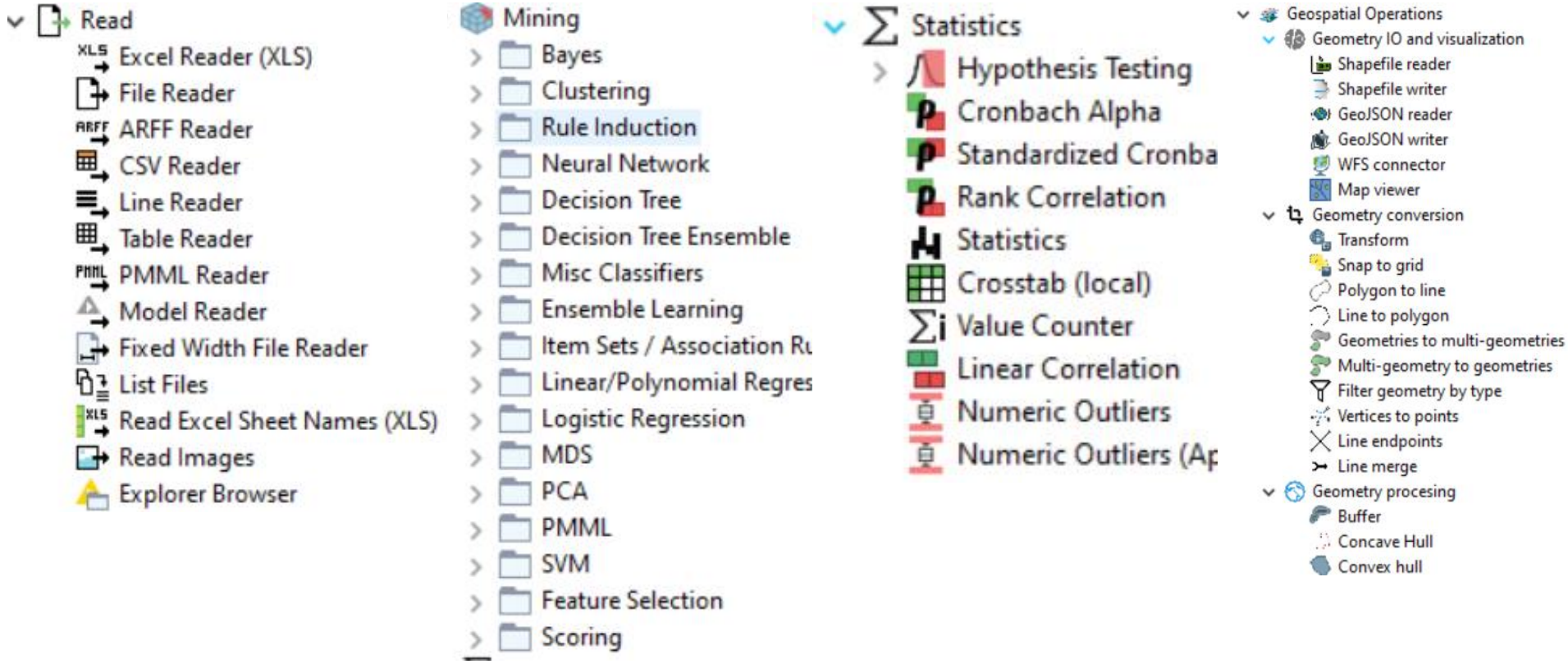
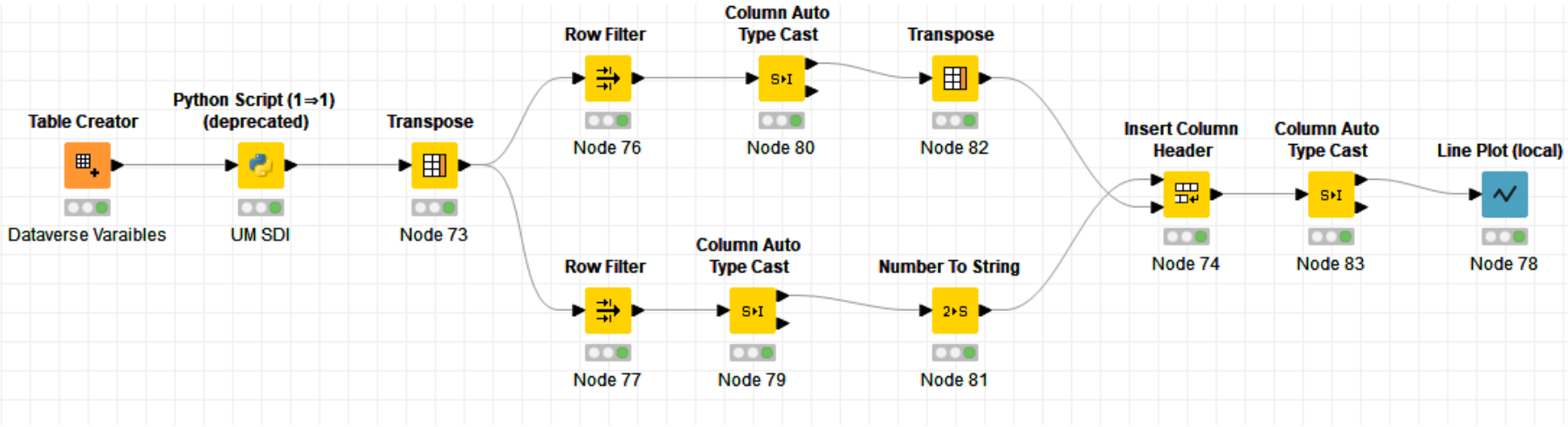


Introduction to Workflow Tool KNIME

https://www.knime.com/

- Workflow is displayed as connected nodes which makes it easy to troubleshoot and visualize
- Easy to use without much knowledge of coding
- Great extensions for data preprocessing, analysis, and visualization
- Connection to other languages, such as JS, R, Python, etc.
- Open-source
- Cross platform interoperability
- Has a decent size community that supports Q&A.

SDI Data Access by Workflow



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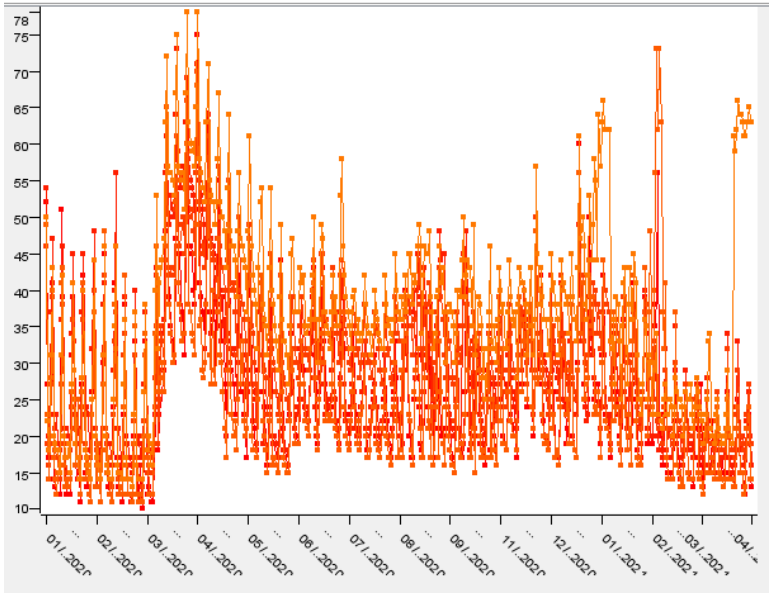

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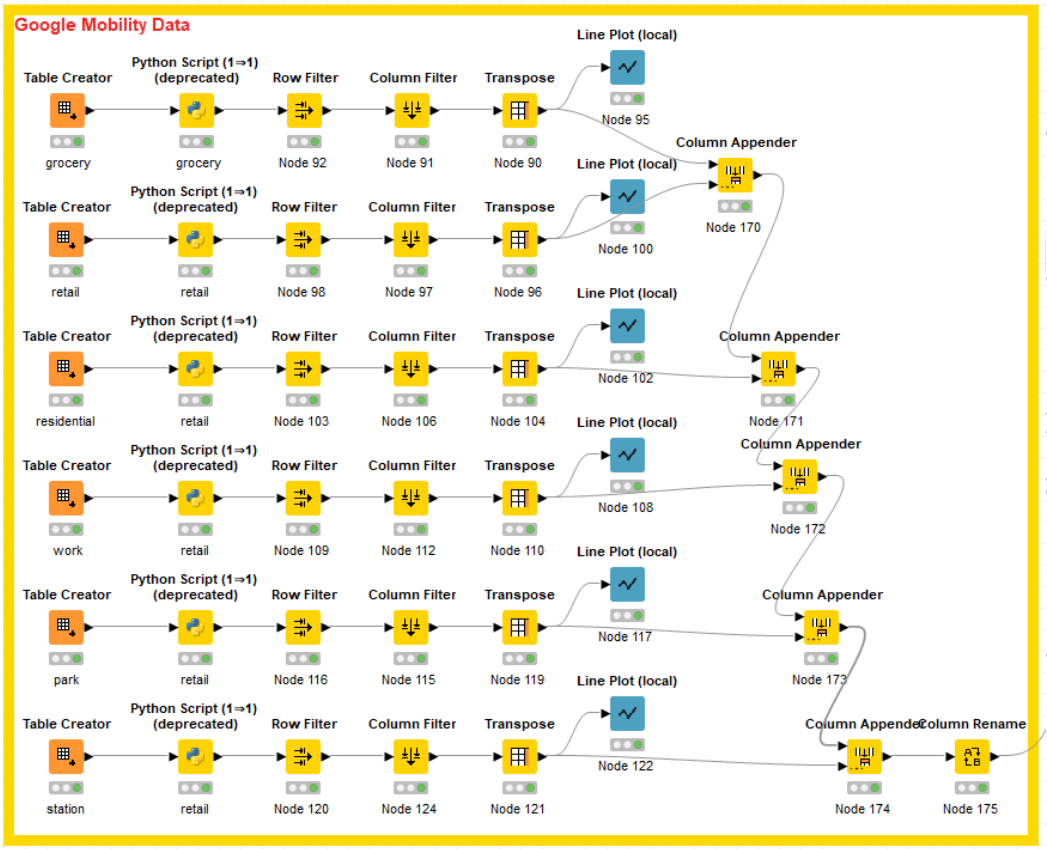
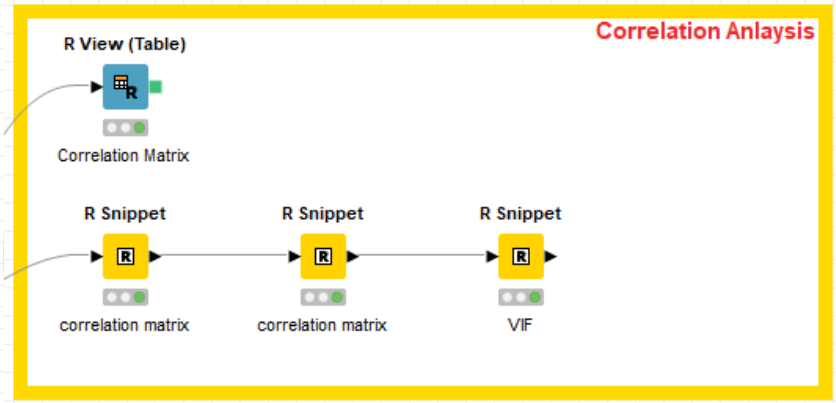
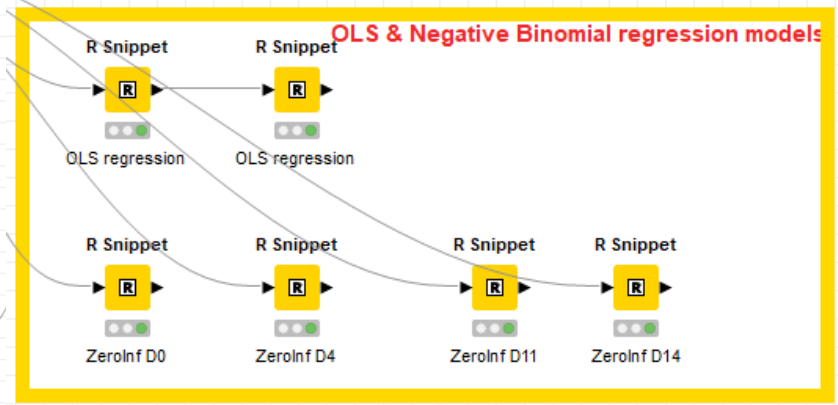
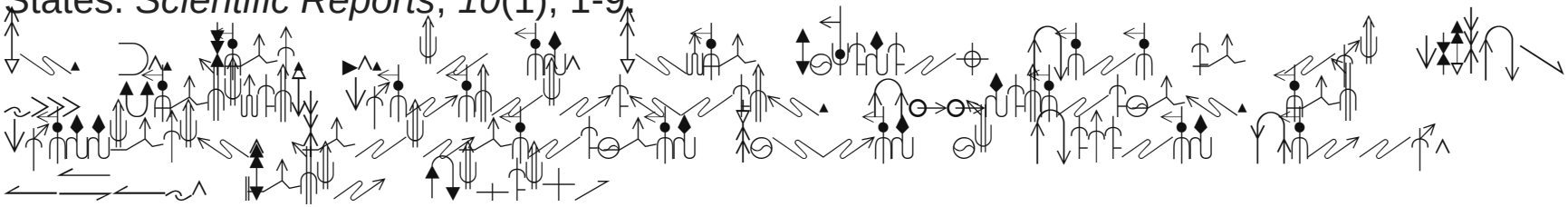






Demonstration

References

- Guo, Y., Yu, H., Zhang, G., & Ma, D. T. (2021). Exploring the impacts of travel-implied policy factors on COVID-19 spread within communities based on multi-source data interpretations. ***Health & Place***, *69*, 102538.
- Pan, Y., Darzi, A., Kabiri, A., Zhao, G., Luo, W., Xiong, C., & Zhang, L. (2020). Quantifying human mobility behaviour changes during the COVID-19 outbreak in the United States. *Scientific Reports*, *10*(1), 1-9.
- 

  https://www.researchgate.net/publication/349537730_Human_Mobility_Data_in_the_COVID-19_Pandemic_Characteristics_Applications_and_Challenges
- Li, Zhenlong, al. "ODT FLOW: A Scalable Platform for Extracting, Analyzing, and Sharing Multi-source Multi-scale Human Mobility." *arXiv preprint arXiv:2104.05040* (2021).
- Zhang, M., Wang, S., Hu, T., Fu, X., Wang, X., Hu, Y., ... & Bao, S. (2021). Human mobility and COVID-19 transmission: a systematic review and future directions. *medRxiv*.

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Thank you!

Q & A

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