

Fairness & bias in algorithmic decision-making: Examples from 311 data

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The Urban Intelligence Lab uses high-resolution, large-scale data and multidisciplinary computational methods to advance the understanding of complex urban dynamics and applied data-driven decision-making for sustainability & resilience, energy & climate, and social justice.

Data and computation in the urban domain



Kontokosta, C.E. 2021. "Urban Informatics in the Science and Practice of Planning." *Journal of Planning Education and Research*, 41: 382-395.

From $n \rightarrow N$



Research areas



Bias and fairness in data-driven decision-making

Uncovering data and algorithmic bias in urban predictive analytics and developing fair and transparent methods for public resource allocation.



Data for climate action

Advancing energy and carbon modeling to enable data-driven climate policy and energy efficiency investment decisions for more sustainable, resilient, and just cities.



Neighborhood dynamics and inequality

Using large-scale mobility and social media data to understand neighborhood change and community connectedness, and to develop privacy-preserving approaches to geolocational analytics.



Al for city management

Building computational methods to support efficient, equitable, and sustainable city operations.



Data for Climate Action

What is the effect of building morphology on energy use?







Bonczak, B., & **Kontokosta, C. E.** (2019). Large-scale parameterization of 3D building morphology in complex urban landscapes using aerial LiDAR and city administrative data. *Computers, Environment and Urban Systems*, 73, 126-142.



Data for Climate Action



Can we fairly and effectively grade buildings on energy use? Does EnergyStar work?

Papadopoulos, Sokratis and Constantine E. Kontokosta. 2019. "Grading Buildings on Energy Performance: Leveraging City Benchmarking Data and Statistical Learning to Overcome Uncertainty," *Applied Energy*, 233: 244-253.

Do energy cost burdens disproportinately impact low-income and minority communities? How could equity-based retrofitting help?

Kontokosta, C. E., Reina, V. J., & Bonczak, B. 2020. "Energy cost burdens for low-income and minority households: Evidence from energy benchmarking and audit data in five US cities." *Journal of the American Planning Association*, 86: 89-105.



Neighborhood Dynamics

Measuring Neighborhood Inequality in Response to Natural Disasters



Exposure Density, Mobility Behavior, and COVID-19 Risk

Exposure density change (%)

COVID-19 Positivity Rate (Zip codes)



Hong, B., Bonczak, B.J., Gupta, A., & Kontokosta, C.E. (2021). Measuring inequality incommunity resilience to natural disasters using large-scale mobility data. *Nature Communications*, 12, 1870. doi.org/10.1038/s41467-021-22160-w

Hong, B., Bonczak, B. J., Gupta, A., Thorpe, L. E., & Kontokosta, C. E. (2021). Exposure density and neighborhood disparities in COVID-19 infection risk. *Proceedings of the National Academy of Sciences*, 118(13). doi.org/10.1073/pnas.2021258118



AI for City Management

Is it possible to predict return to shelters and length-of-stay for homeless families?



Do street trees – and tree species – impact respiratory illness?



Can we model household waste generation to improve the efficiency and fairness of waste collection?

Hong, B., A. Malik, J. Lundquist, I. Bellach, & **C. E. Kontokosta**. 2018. "Applications of Machine Learning Methods to Predict Re-admission and Length-of-Stay for Homeless Families: The Case of WIN Shelters in New York City," *Journal of Technology in Human Services*, 36: 89-104. Lai, Y., & **Kontokosta, C. E.** (2019). The impact of urban street tree species on air quality and respiratory illness: A spatial analysis of large-scale, high-resolution urban data. *Health & Place*, 56, 80-87.

Kontokosta, C. E., B. Hong, N. Johnson, & D. Starobin. 2018. "Using Machine Learning and Small Area Estimation to Predict Building-Level Municipal Solid Waste Generation in Cities," *Computers. Environment, and Urban Systems*, 70: 151-162.

Bias and Fairness in Algorithmic Decision-Making: 311 Data

^{'311'} Systems

Co-production:

Practice in the delivery of public services in which residents are involved in the creation and allocation of public policies and services

E-government

Use of information and communication technologies, such as mobile devices and the Internet, to provide public services to residents

311 systems across North America

More than 100 Cities

Marker size: population

- NOT open to public [53]
- Esri [4] •
- Files (excel or csv) [8] 0
- Opengov [3] ۰
- Socrata [30]



311 Open Data

More than 50% cities using 311 system publish **data open to the public** through different data sharing methods (Socrata, Esri, OpenGov, etc.)



Research Case

Street Condition Complaints and Pothole Maintenance Kansas City, MO

Source: Kontokosta, C. E., & Hong, B. (2021). Bias in smart city governance: How socio-spatial disparities in 311 complaint behavior impact the fairness of data-driven decisions. *Sustainable Cities and Society*, *64*, 102503.

Disparities in resident-government interactions

depending on the nature of problems





Unequal level of pothole repair services

for under- and over-reporting neighborhoods



35

Undr Over

Research Case

Measuring Social Distancing Sensitivity in New York City

Source: Kontokosta, C. E., Hong, B., & Bonczak, B. J. (2022). Measuring sensitivity to social distancing behavior during the COVID-19 pandemic. *Scientific reports*, *12*(1), 1-15.

Social Distancing Complaints

- Total 72K complaints (03/29/2020 ~ 07/04/2020)
- ~500 on daily average



Measuring Social Distancing Sensitivity

using 311 Complaints and POI visits



"An illustration of the Weber–Fechner law. On each side, the lower square contains 10 more dots than the upper one. However the perception is different: On the left side, the difference between upper and lower square is clearly visible. On the right side, the two squares look almost the same."



Lowest sensitivity Medium low sensitivity (< 25 percentile) (25-50 percentile) **Measuring Social Distancing** SDS score = 67.01 SDS score = 61.38 **Sensitivity** using 311 Complaints and POI visits POI level analysis example Brookl Haru Sush Staten (Isla GupShup Ainsworth Park/ Kimball Office Irving Cleaners MinuteClinic Friend of A Farmer Zen Palate AJavelina Medium high sensitivity Highest sensitivity CVS rving Farm New York WholeLife HealthCare E 18st Stree (50-75 percentile) Weymouth Sheilagh DC (> 75 percentile) Tommy Lasagna Candid Green Cafe APaul & Jimmy's The Recovery Spot Bedford Cheese Shop Kage On Irving Irvington SDS score = 69.79SDS score = 72.84 W Hotels Pete's Tavern ▲Taco Électrico sweetareen E 18St Street Traces Sal/Anthony's Live Raw Organic Kitchen Franks Liquor Shop E 17St Street Integrated Aesthetics Dentistry GlamDerm Trevi Coffee Shop The House Adalya Dear Irving Crane Daniel MD Khan Zafar Nails Pierre Loti Union Sau ure Food And Wine Cibar POI Category food and drink Casa Mono beuty_personal_care Bar Jamon Staten aroceries Staten One Lucky Duck A health facilities hotels stores Rus Mechanical Unit of Analysis (BBL)

Closing thoughts

- 1. Bias emerges in both the *data* and the *algorithm*
- Reporting propensity the likelihood of different subgroups to report a problem – leads to *implicit bias* in service allocation using resident-reported information
- 3. Analysis can help to unpack the problem of fairness, but is *insufficient*
- 4. Connecting *bias-aware* algorithmic decision-making with *practical knowledge* can improve the fairness and equity of outcomes





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