

Empowering Disaster Response with Social Media and GeoAl: Opportunities and Challenges

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Increasingly Frequent Disasters







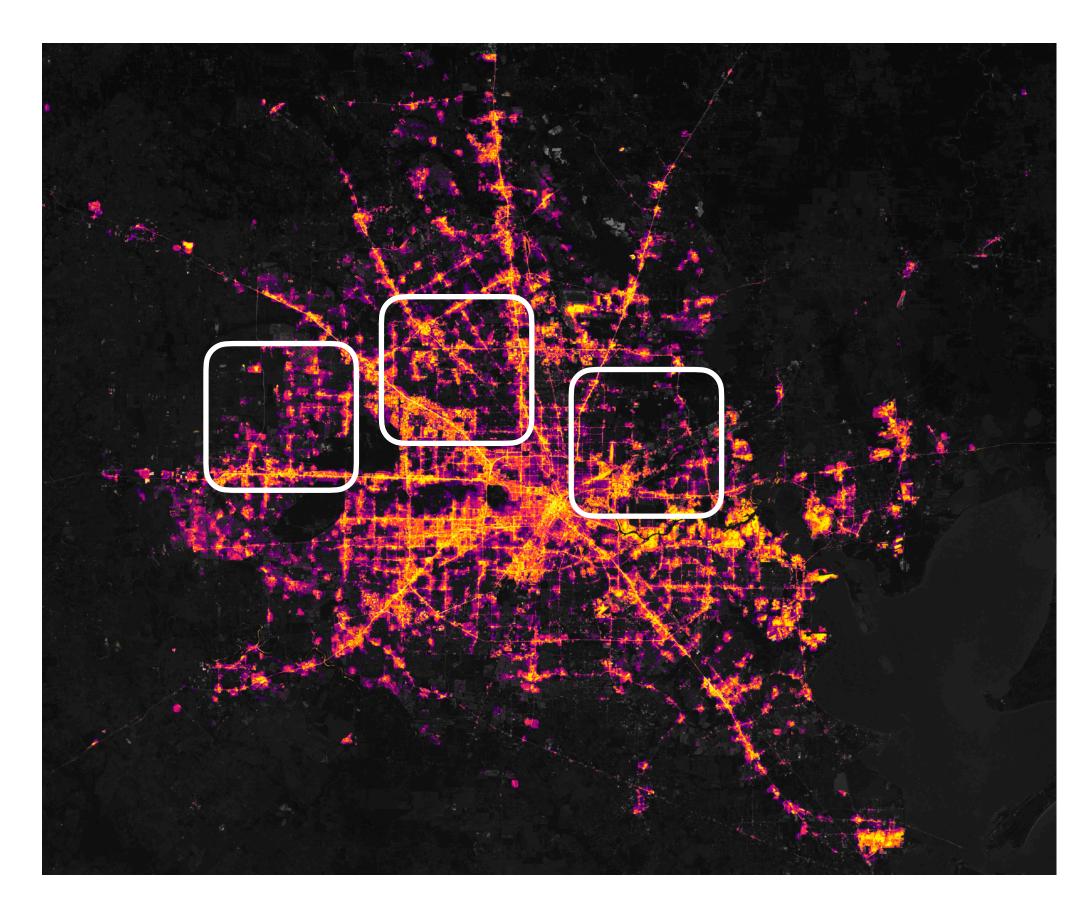
Wildfire, California 2020 (Source: New York Times)

Winter storm Uri, Texas 2021 (Source: Wikipedia)

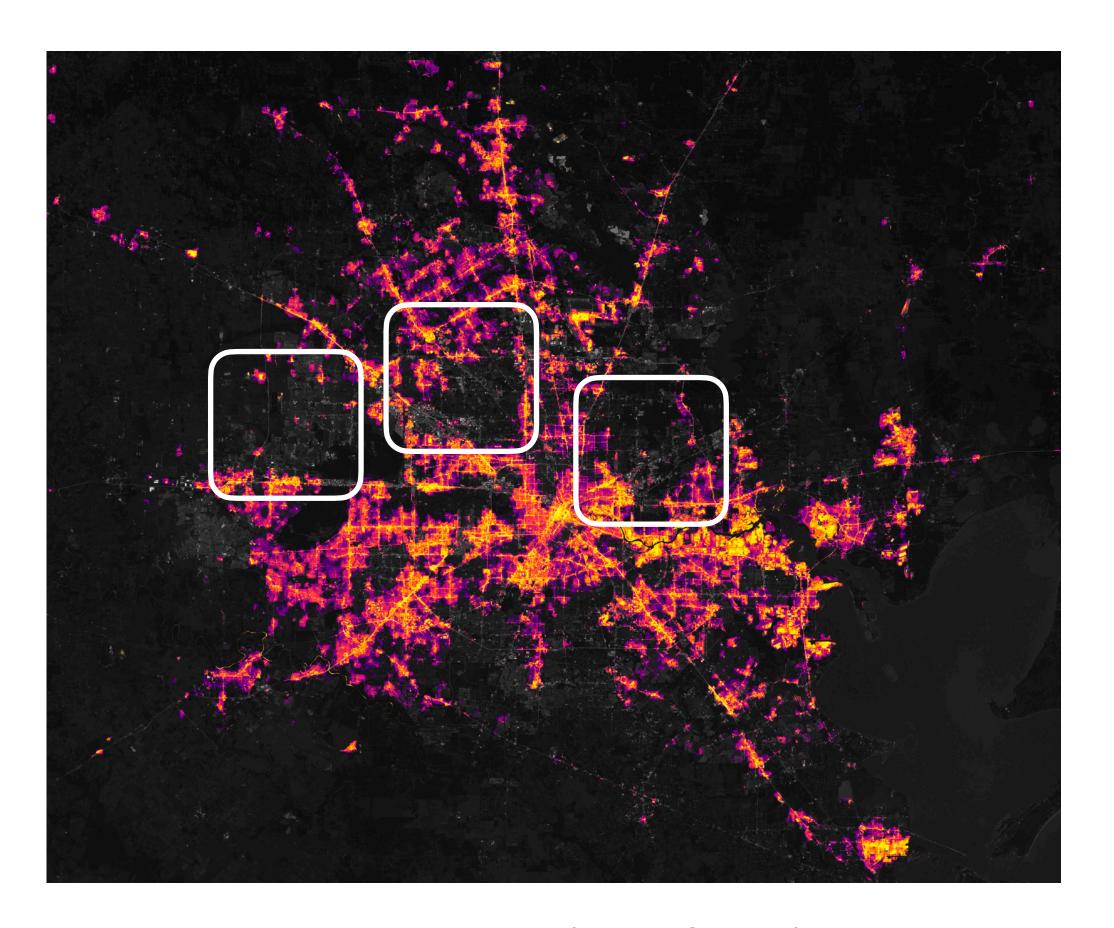
Beichuan Flash Flood, Sichuan 2022 (Source: NetEase)

Uneven Disaster Impacts

VIIRS Nighttime Light Image in Houston, United States



Feb 7, 2021 (Pre-Storm)



Feb 16, 2021 (Post-Storm)

Image Source: NASA

Social Media Data

Social media users in US

2008: 24%

2021: 82%



Accessible via any online devices at any place



Twitter: 500 million/day Facebook: 1 billion/day Instagram: 40 million/day









Geographic information: Geo-tags, coordinates, addresses, etc.



Real-time streaming data



Connections between human and events



Social Media Data - Challenges



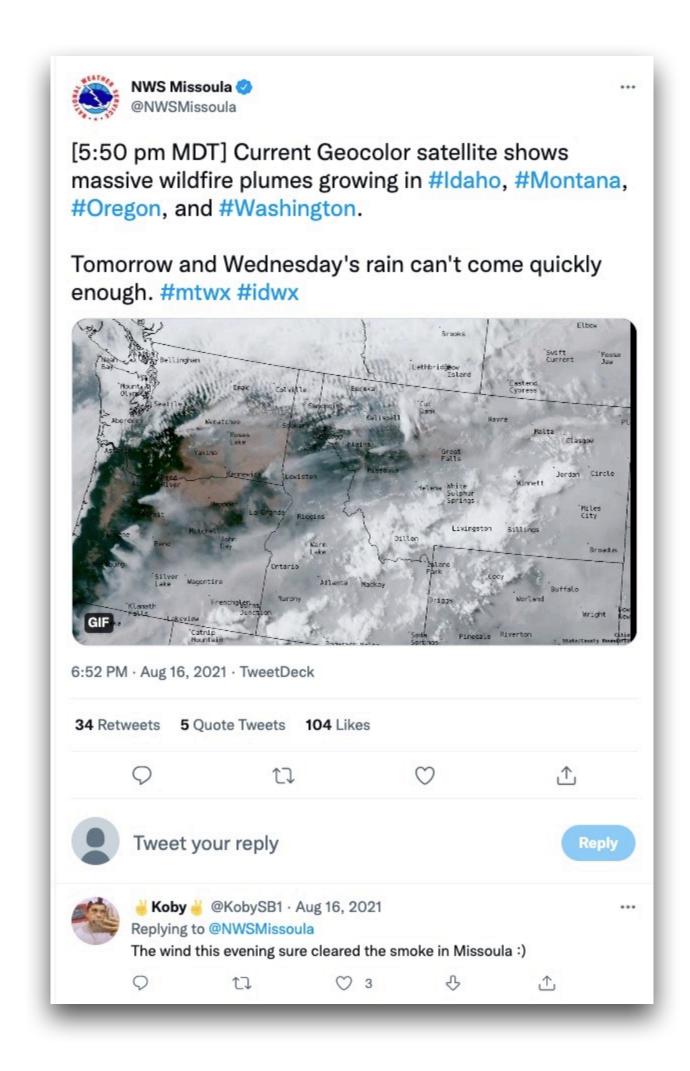
Research Questions

- How can we extract disaster information from noisy social media?
- Can social media data be used to improve disaster response?
- How can we remove the bias in social media data?

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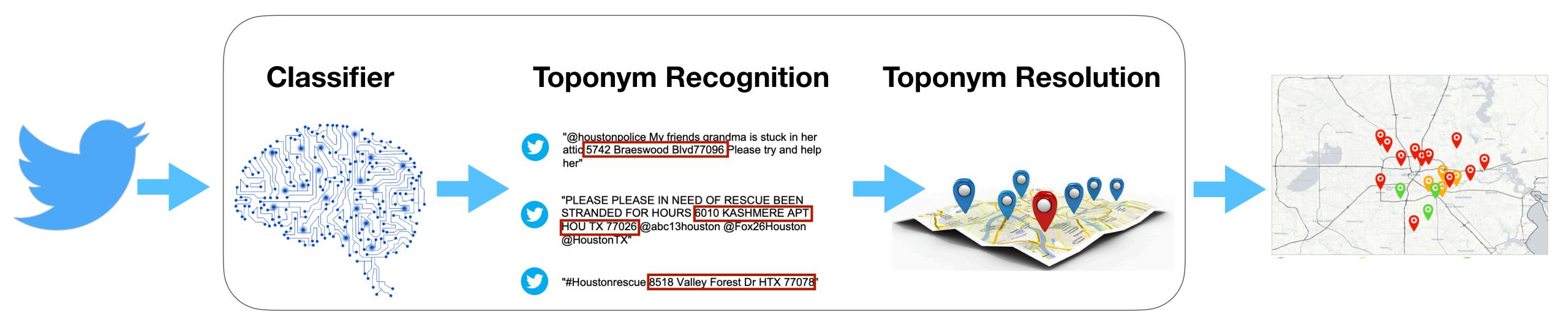
Disaster Information on Social Media



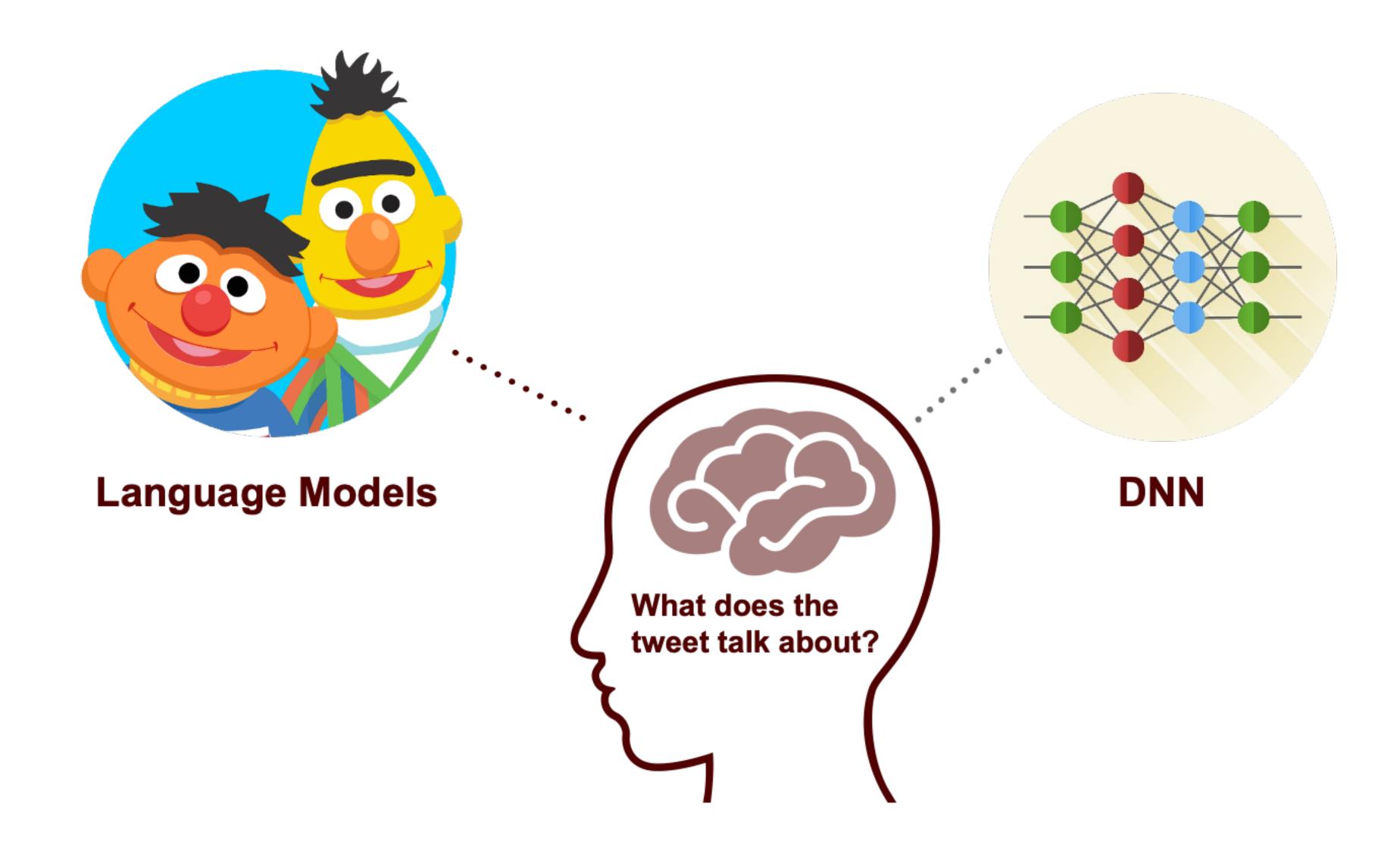




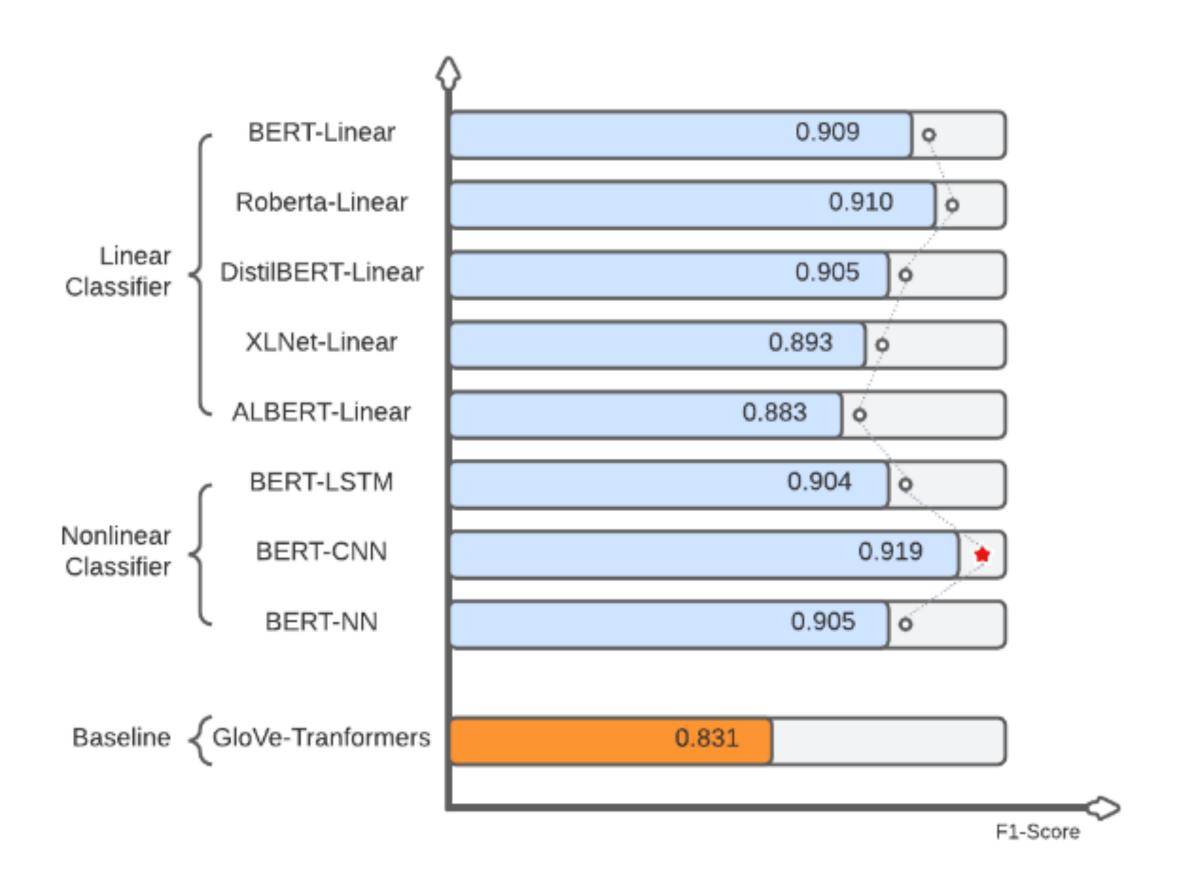
Mining Location-Based Disaster Information from Social Media

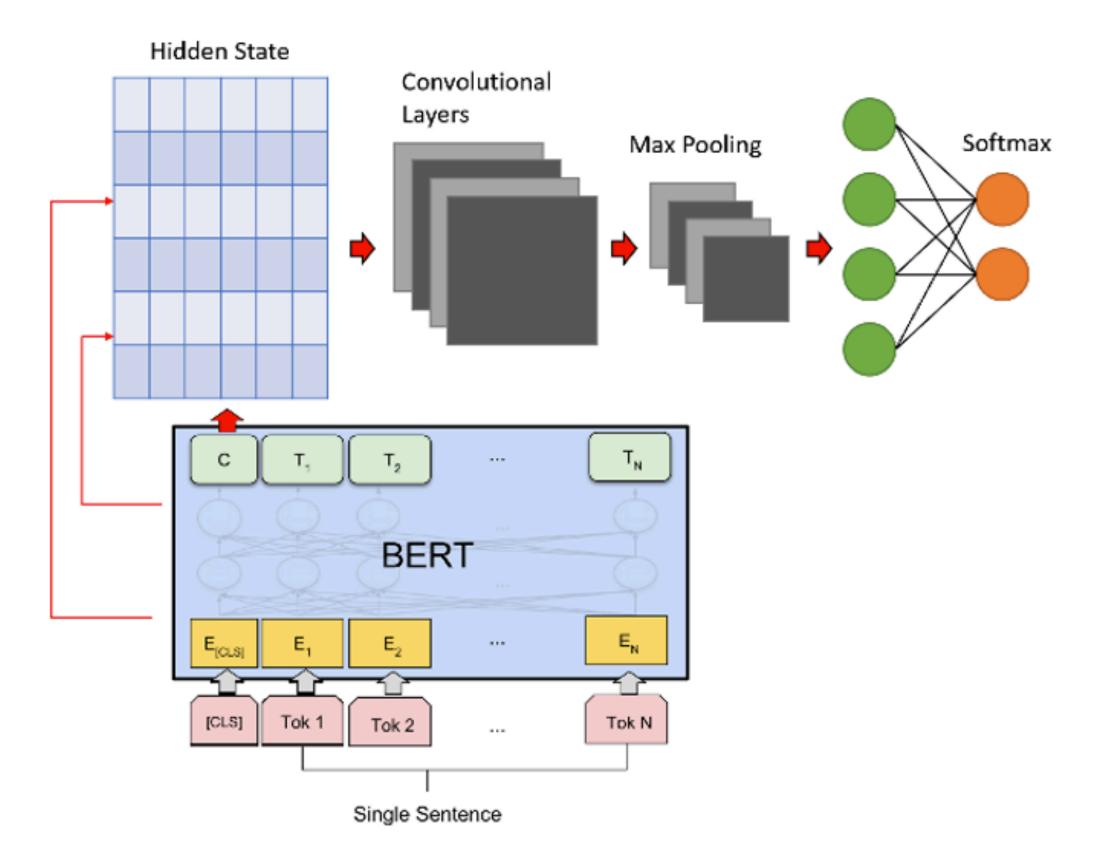


Mining Location-Based Disaster Information from Social Media



Intelligent Classifier





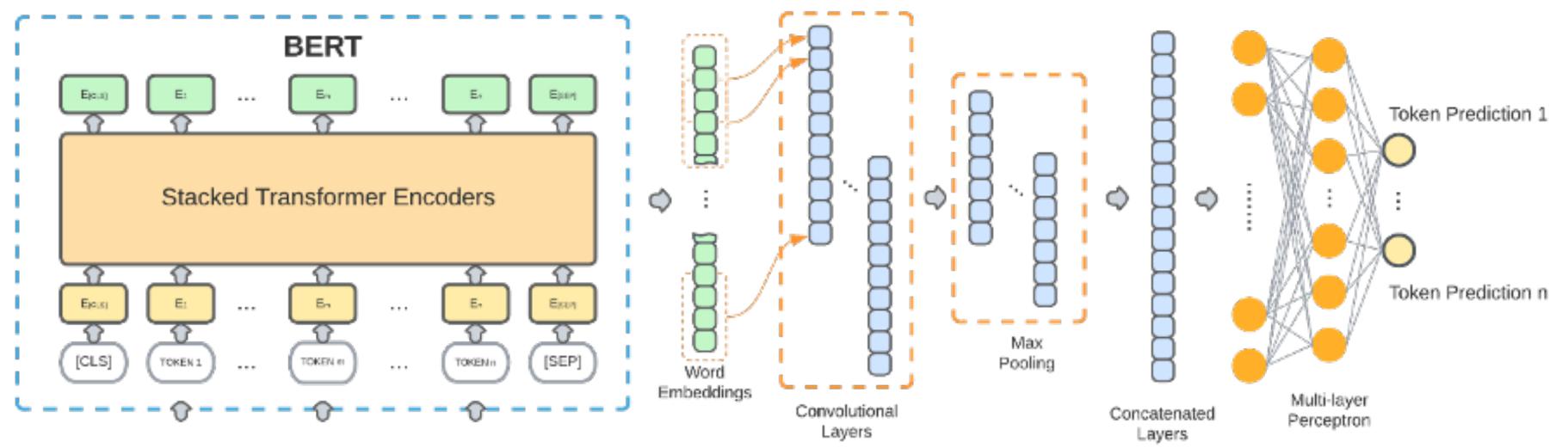
Model Performance

Optimal Model: BERT-CNN

Zhou, B., Zou, L., Mostafavi, A., Lin, B., Yang, M., Gharaibeh, N., Cai, H., Abedin, J. and Mandal, D., 2022. VictimFinder: Harvesting rescue requests in disaster response from social media with BERT. Computers, Environment and Urban Systems, 95, p.101824.

Intelligent Toponym Recognition

Model	Precision	Recall	F1-score
Stanford NER (broad location)	0.729	0.440	0.548
SpaCy NER (broad location)	0.461	0.304	0.366
BiLSTM-CRF	0.703	0.600	0.649
DM_NLP	0.729	0.680	0.703
NeuroTPR	0.787	0.678	0.728
TopoBERT	0.898	0.835	0.865

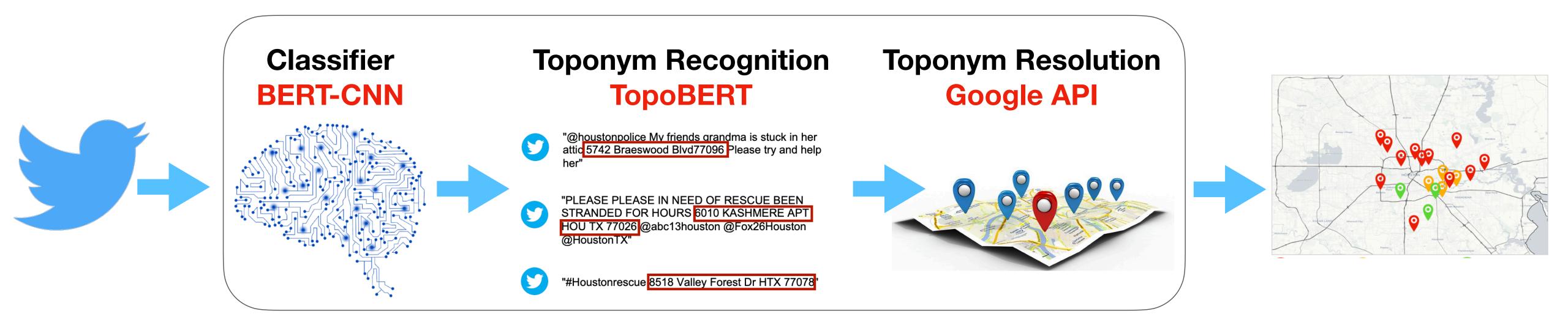


*The European Comission said on Tuesday ... to human beings.

Optimal Model: BERT-CNN1D

Zhou, B., Zou, L., Hu, Y., Qiang, Y., Goldberg, D. 2022. TopoBERT: A Plug and Play Toponym Recognition Module Harnessing Fine-tuned BERT. (Under Review)

Mining Disaster/Location Information from Social Media with Al

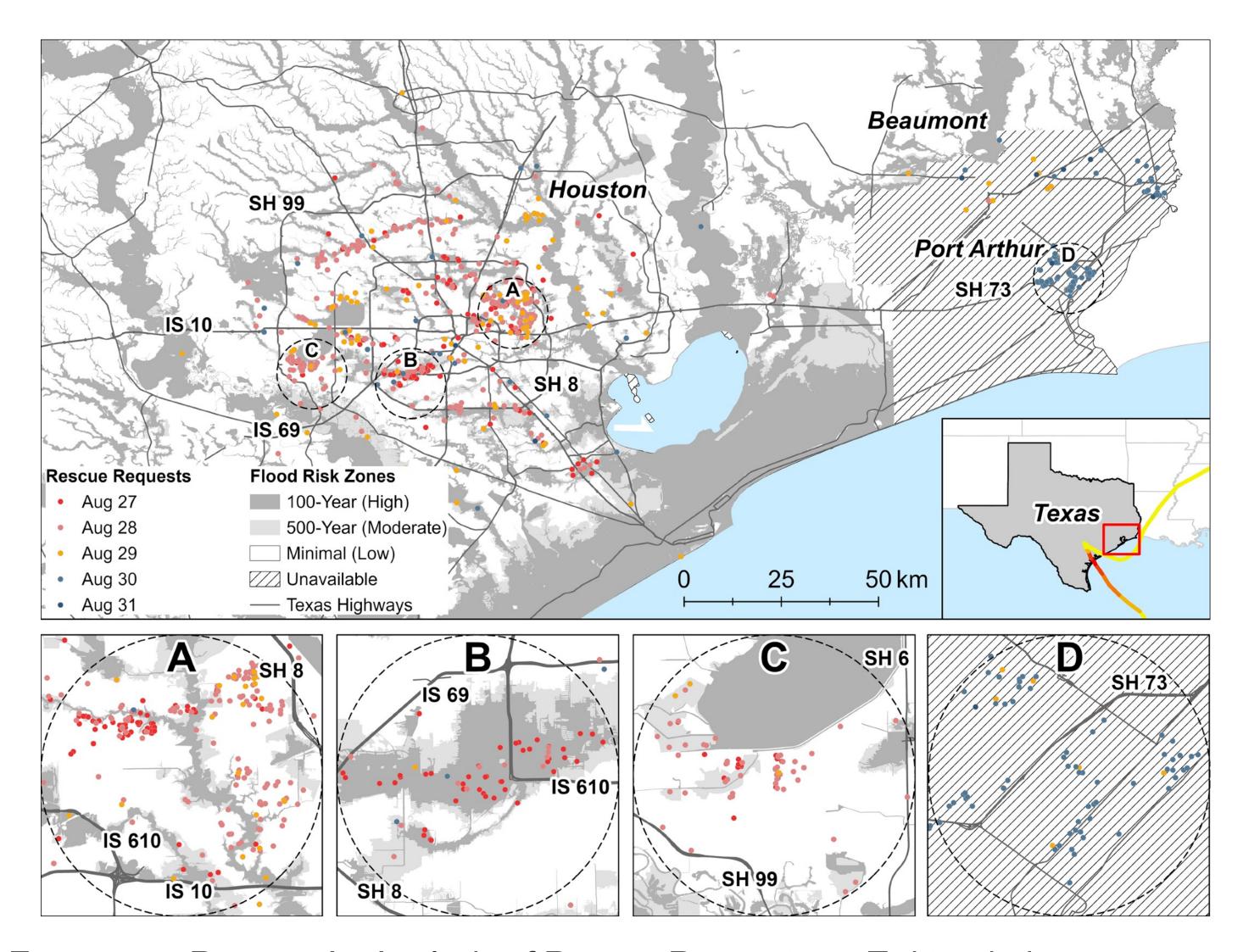


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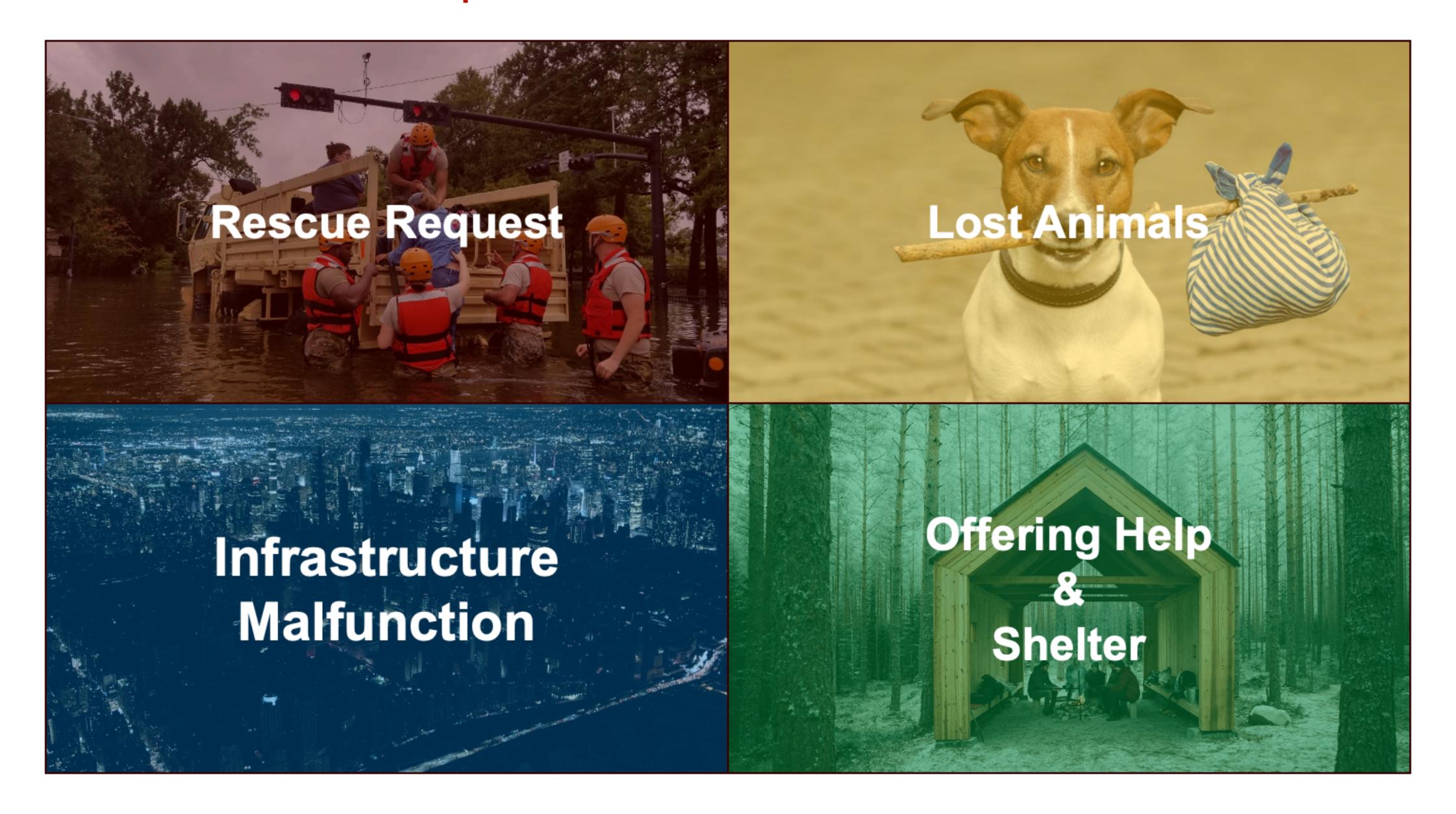
Social Media in Disaster Response: Emergency Rescue

- 41.38% of rescue requests on Twitter were sent from minimal flood risk zones defined by FEMA
- Communities with high rescue request rates were belowaverage elevations, received more rainfall, and had more socially vulnerable populations

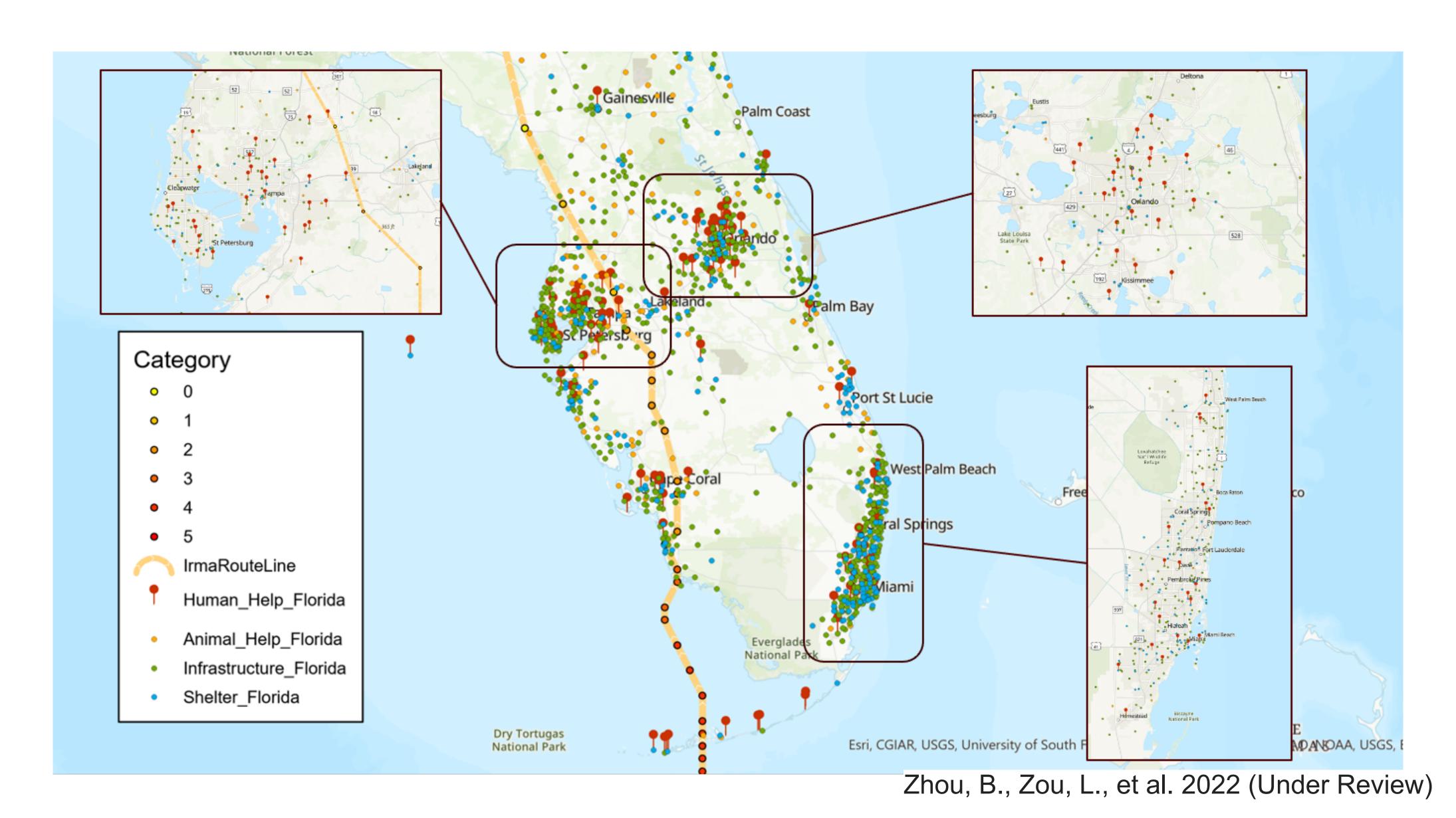


Zou et al. 2021. Social Media for Emergency Rescue: An Analysis of Rescue Requests on Twitter during Hurricane Harvey. arXiv preprint arXiv:2111.07187.

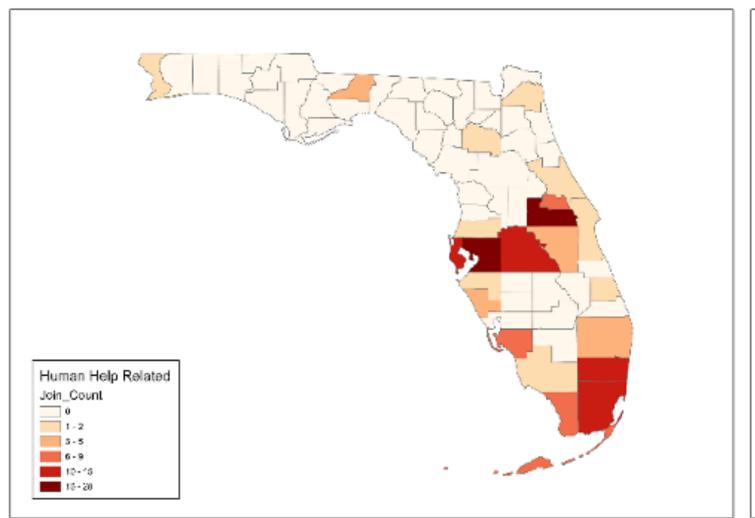
Social Media in Disaster Response

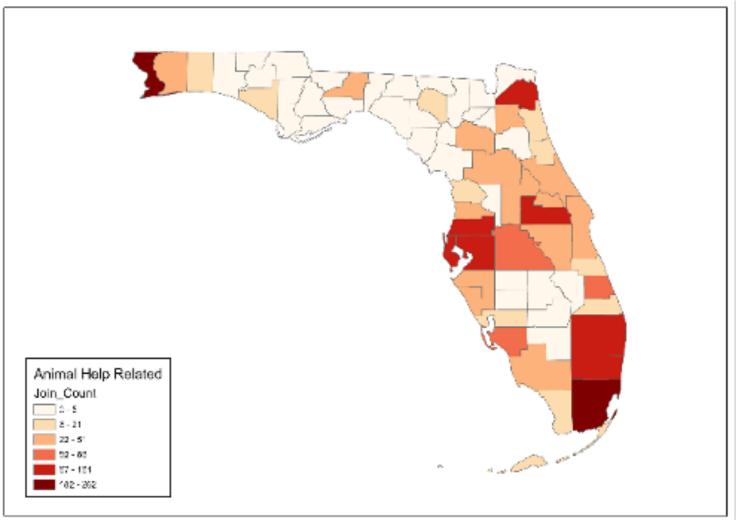


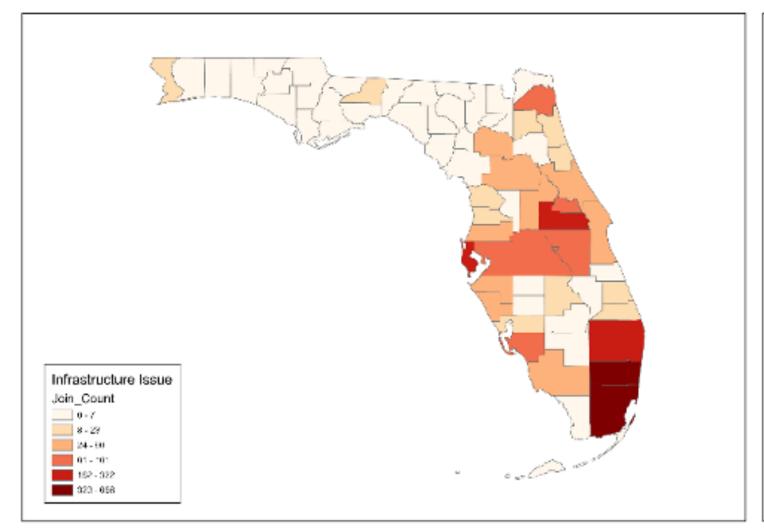
Social Media in Disaster Response: 2017 Hurricane Irma

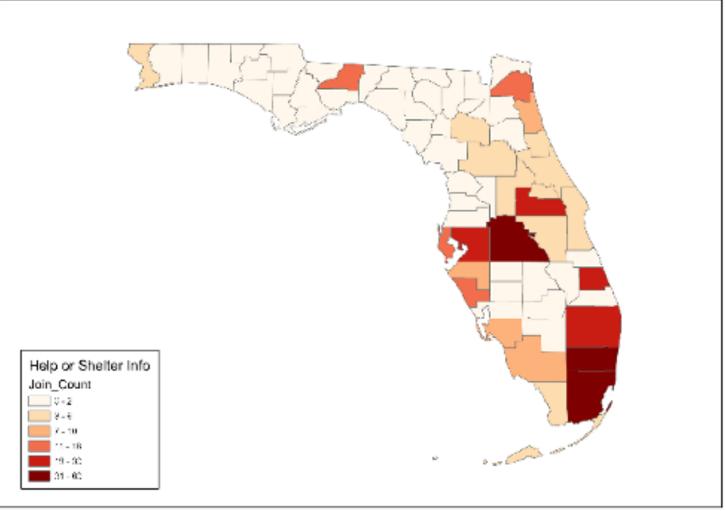


Social Media in Disaster Response: Damage Estimation





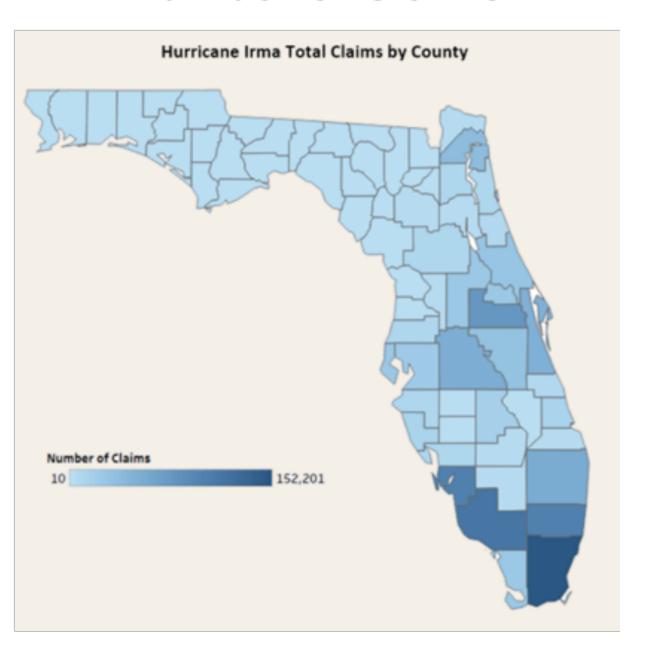




Damage Assessment based on Infrastructure Malfunction Reports on Social Media:

R-square = **0.64**

Number of Claims



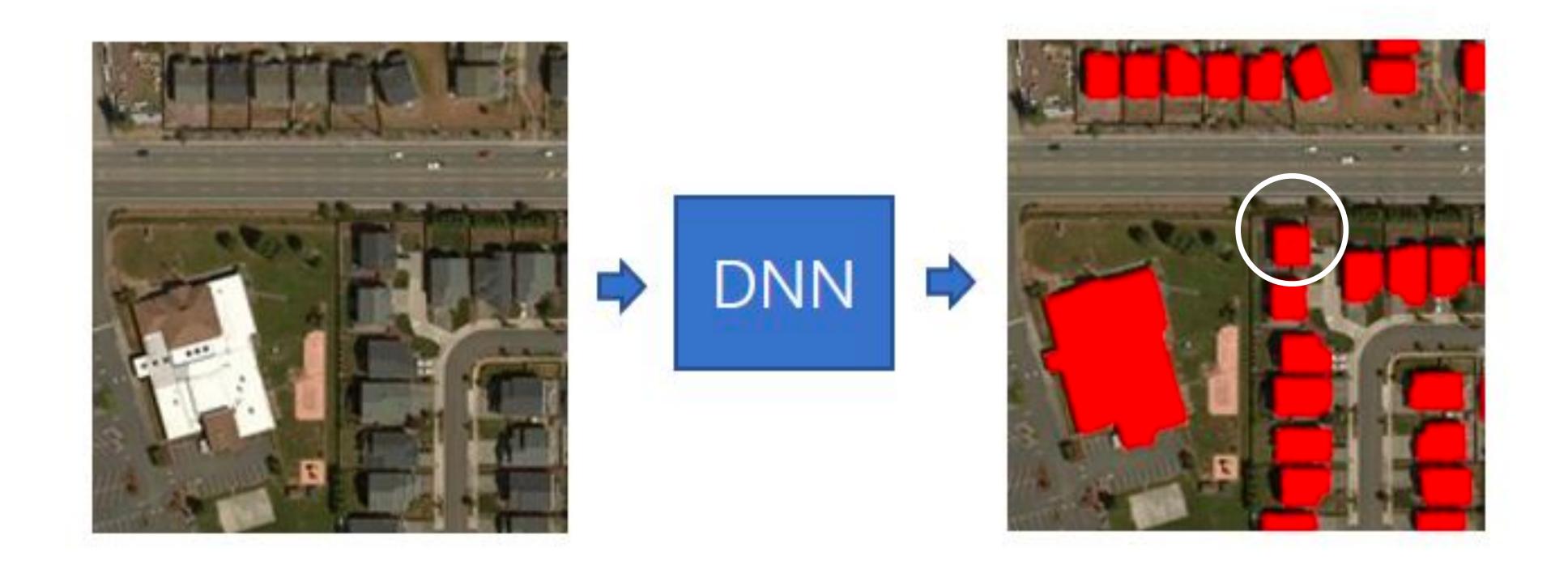
Zhou, B., Zou, L., et al. 2022 (Under Review)

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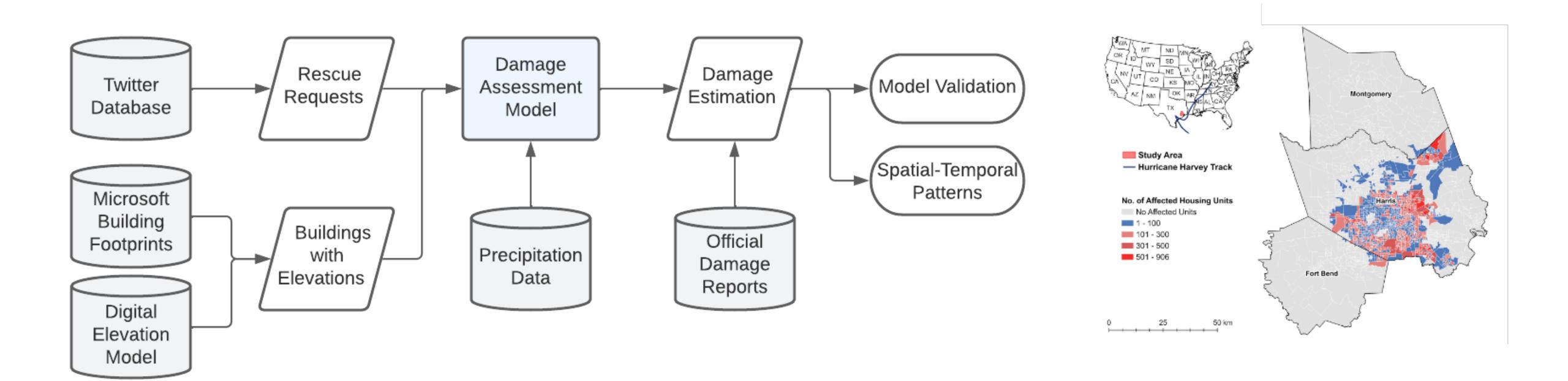
Use Bias in Social Media

$$flooded_i = \begin{cases} 1, & elevation_i + rainfall_i \ge elevation_0 + rainfall_0 \\ 0, & else \end{cases}$$



Microsoft Building Footprints Data: https://github.com/microsoft/USBuildingFootprints

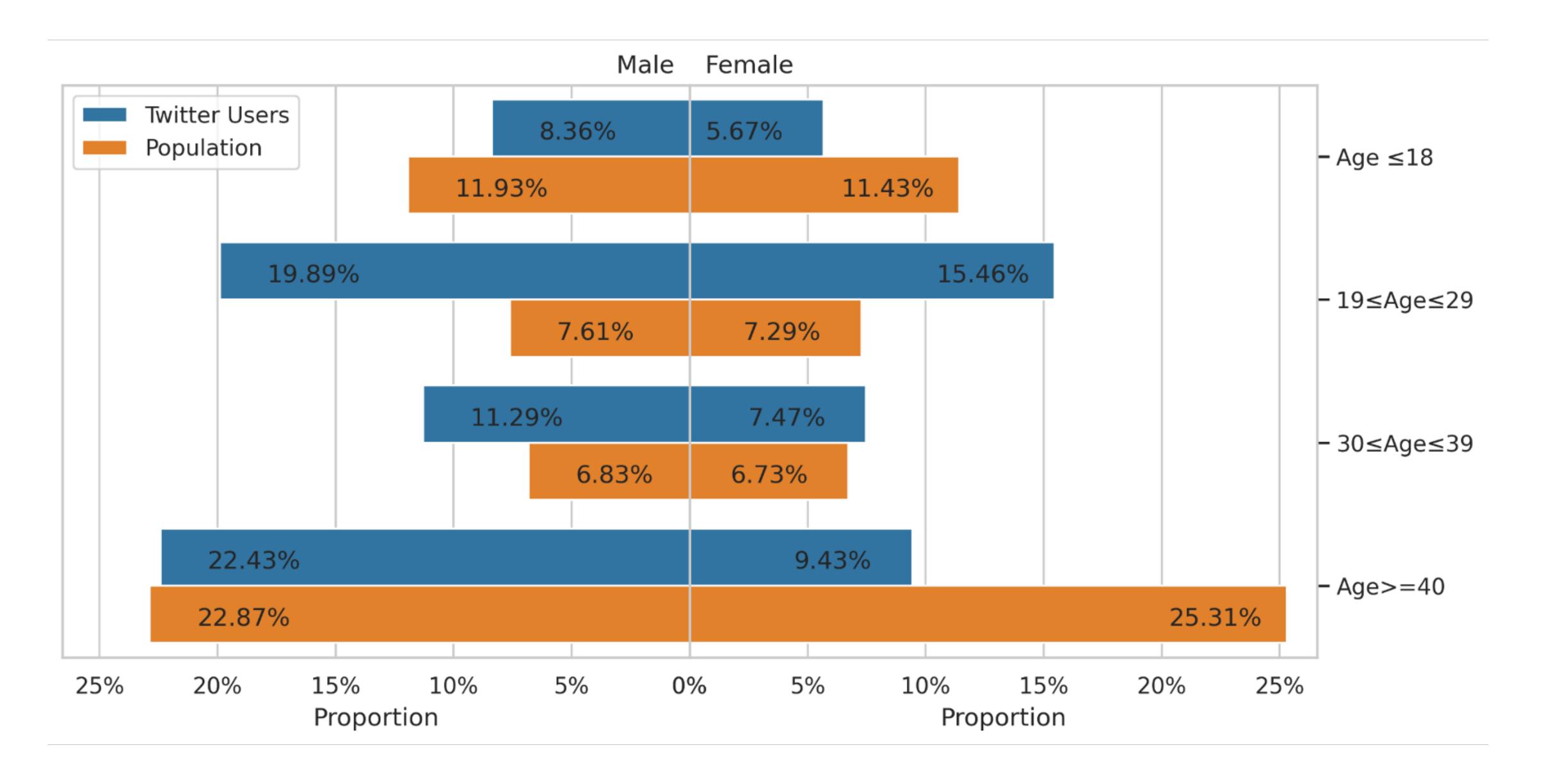
Use Bias in Social Media



- (1) The estimated affected households highly agree with the official damage report.
- (2) The model performs better in communities closer to the locations of people requesting rescue or reporting damage on social media
- (3) The developed model reveals overlooked communities in official damage reports.

Zou et al. 2022

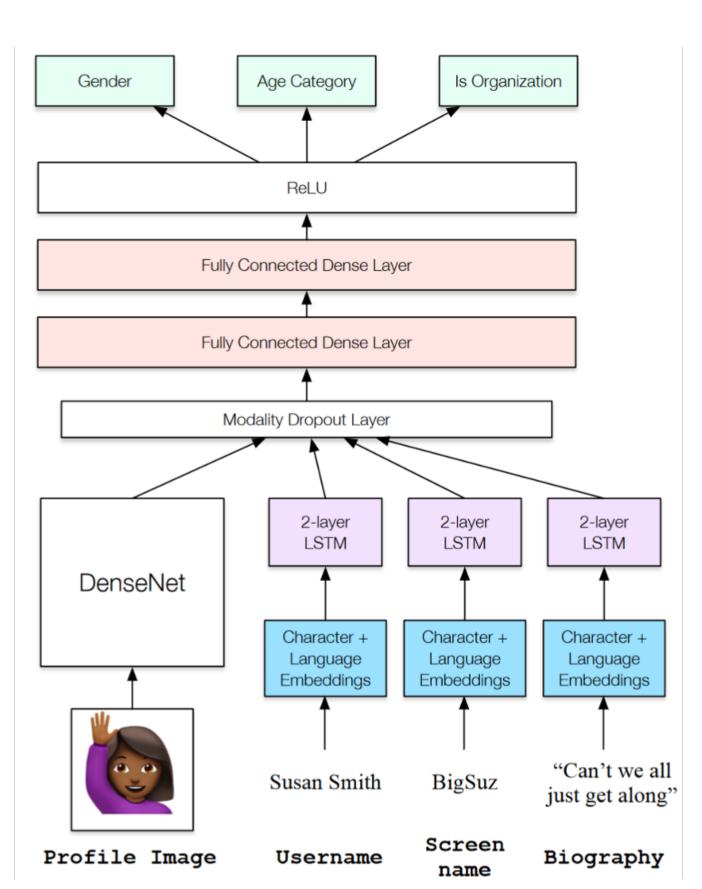
User Demographic Bias in Social Media

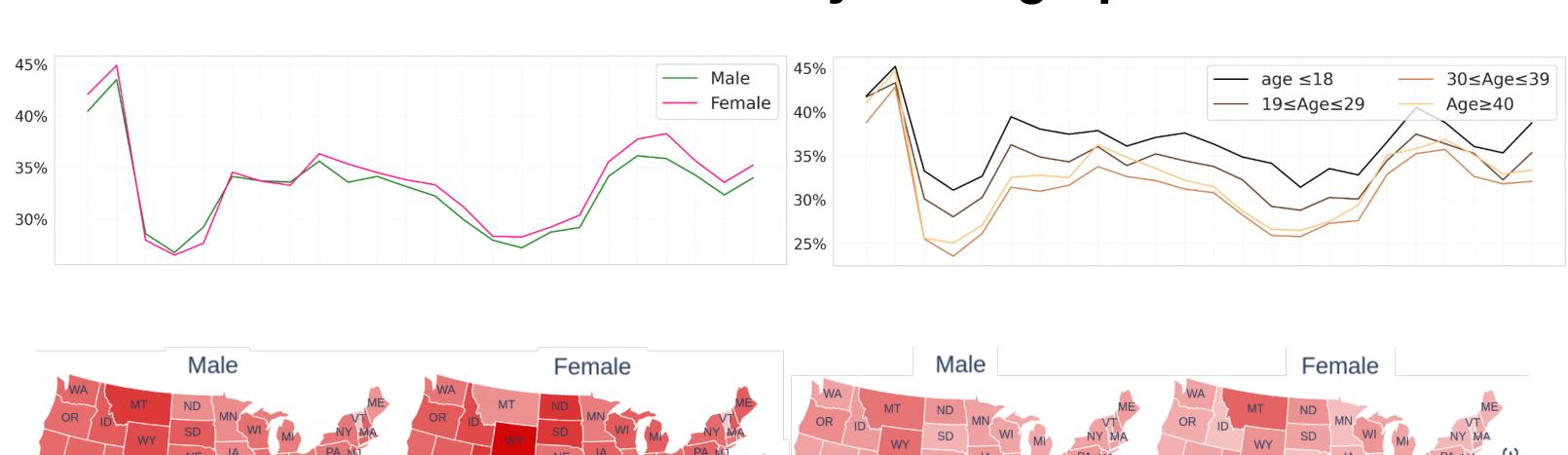


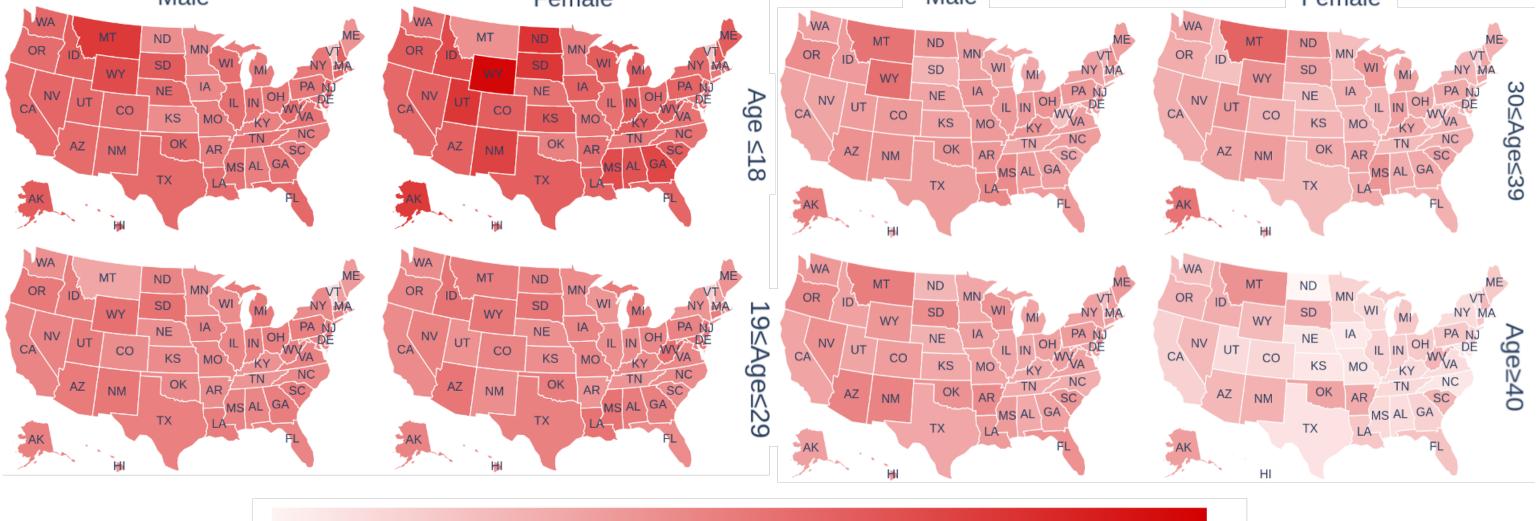
User Demographic Bias in Social Media

M3 Model

COVID-19 Sentiment Scores by Demographics in the U.S.







Percentage of Negative Users toward Covid-19 in 2020 and 2021

14%

Wang, Zijian, et al. "Demographic inference and representative population estimates from multilingual social media data." The world wide web conference. 2019.

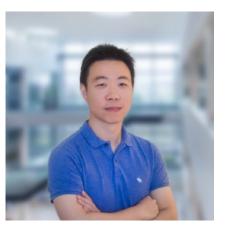
Lin, Zou, et al. AutoCarto 2022





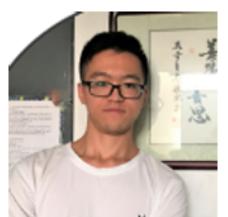
Responsible Spatial Thinking for a Resilient Future!

Lei Zou (Izou@tamu.edu) Assistant Professor, Texas A&M University GEAR Lab Website: https://www.geoearlab.com/

























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NSF-HDBE (Award #: 1931301): Reducing the Human Impacts of Flash Floods - Development of Microdata and Causal Model to Inform Mitigation and Preparedness TAMU PRISE Program: Leveraging Geospatial Big Data and Artificial Intelligence (AI) to Enhance Disaster Resilience in Vulnerable Communities TAMIDS Data Source Development Program: Revealing Social and Governmental Responses to COVID-19 through Geospatial Big Data