Spatial and Temporal Analysis of Trends in Opioid Abuse within the US

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Introduction

- Prescription opioid abuse as a growing epidemic
- Need analytical tools to address problems specific to any given region
- **Our goal:** develop a tool to use data to determine which factors local public health departments need to address in order to reduce harm from opioid abuse

How is it done today? What are current limits?

- Use of machine learning to predict the risk of opioid use disorder on a population level (Hasan et al. ML with App 2021), find variation in prescription trends (Hu et al., 2015) or prescription hot-spot within a state (Basak et al. 2019)
- Highlighted clear predictive value in urban/rural (Cerda et al., 2017, Sun et al. 2022, Duan & Hand, 2021) and demographics (Unick et al., PLoS One 2013)
- Limits: often restricted to small regional approaches or limited in the scope of potential factors

Expected Innovations

- Recognize opioid abuse trends over time to determine geographic or demographic hot-spots at a more specific scale than current research.
- Identify potential factors that may have led to the increasing trend specific to the hot-spot.
- Allows public health, government and physicians to efficiently allocate the appropriate resources at a particular opioid crisis area.
- If successful, would provide an additional tool to fight this ongoing crisis in the U.S. to ultimately lower opioid abuse rates.

Risks and Payoffs

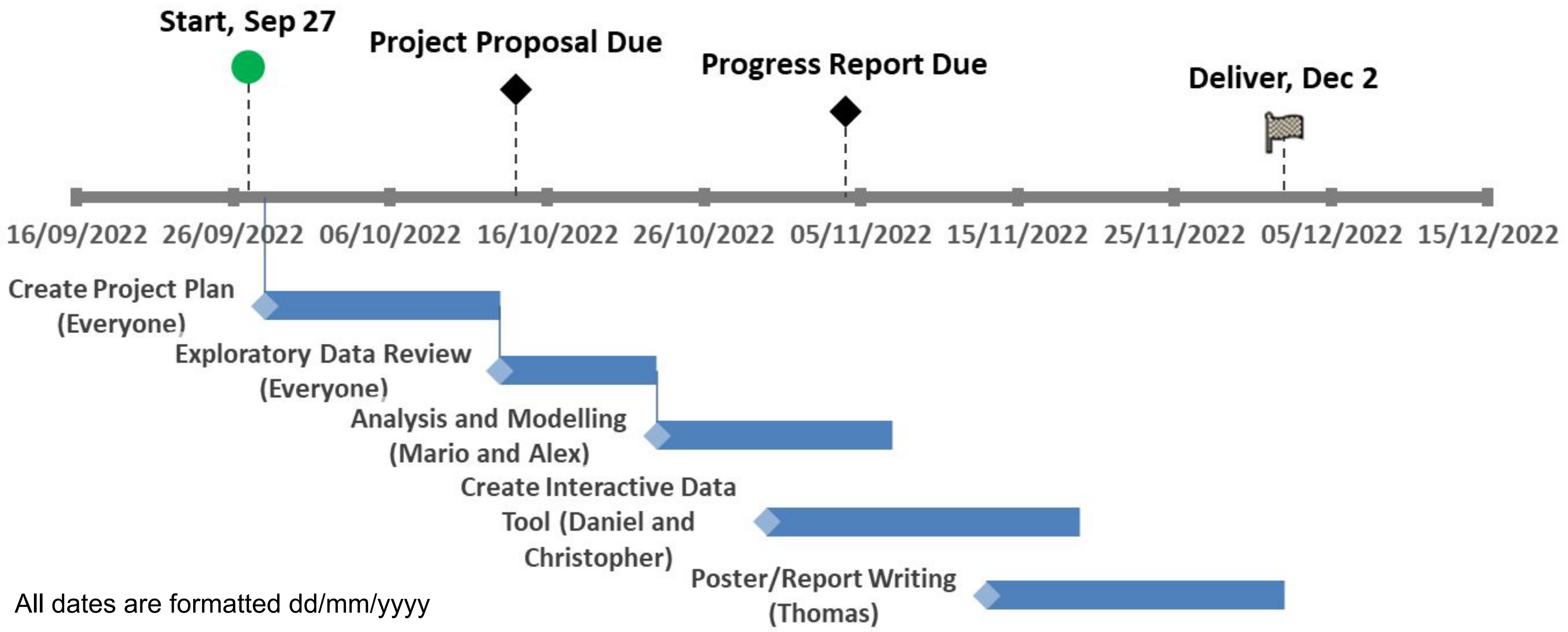
Risk:

- Misallocate resources to a potential factor identified in our study that does not truly contribute to the opioid crisis.
    - Lots of research in the area to compare and coincide with our results so this does not happen.

Payoff:

- Provide public health with an additional resource at a more granular level to combat the opioid crisis in the U.S.

Project Delivery Schedule



All dates are formatted dd/mm/yyyy

References

1. Basak, A., Cadena, J., Marathe, A., & Vullikanti, A. (2019). Detection of Spatiotemporal Prescription Opioid Hot Spots With Network Scan Statistics: Multistate Analysis. *JMIR Public Health Surveill*, *5*(2). 10.2196/12110
2. Cerda, M., Gaidus, A., Keys, K. M., Ponicki, W., Martins, S., Galea, S., & Gruenewald, P. (2017). Prescription opioid poisoning across urban and rural areas: identifying vulnerable groups and geographic areas. *Addiction*, *112*(1), 103-112. https://doi.org/10.1111/add.13543
3. Duan, W. R., & Hand, D. J. (2021). Association between opioid overdose death rates and educational attainment – United States, 2010-2019. *Preventive Medicine*, *153*. https://doi.org/10.1016/j.ypmed.2021.106785.
4. Hasan, M. M., Young, G. J., Patel, M. R., Modestino, A., Sanchez, L. D., & Noor-E-Alam, M. (2021). A machine learning framework to predict the risk of opioid use disorder. *Machine Learning with Applications*, *6*. 100144
5. Hu, X., Gallagher, M., Loveday, W., Connor, J.P., & Wiles, J. (2015). Detecting anomalies in controlled drug prescription data using probabilistic models. *Australasian Conference on Artificial Life and Computational Intelligence*, 337-349. https://doi.org/10.1007/978-3-319-14803-8_26
6. Sun, F. (2022). Rurality and opioid prescribing rates in U.S. counties from 2006 to 2018: A spatiotemporal investigation. *Social Science & Medicine*, *296*(1), 114788–114788. https://doi.org/10.1016/j.socscimed.2022.114788
7. Unick, G. J., Rosenblum, D., Mars, S., & Ciccarone, D. (2013). Intertwined epidemics: national demographic trends in hospitalizations for heroin- and opioid-related overdoses, 1993-2009. *PloS one*, *8*(2). https://doi.org/10.1371/journal.pone.0054496