# Machine Learning in Population and Public Health: Challenges and Opportunities

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ACM CHIL 2020 Tutorial





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### **Tutorial Goals**

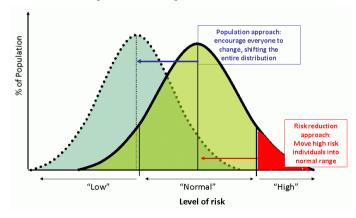


Familiarize with research in public and population health Identify open areas related to health equity Activate the machine learning community

- Introduce Public and Population Health
- Theory and framework of social determinants of health (SoDH)
- Measurement of SoDH
- SoDH interventions
- Integration of SoDH in machine learning models
- Taxonomy of health tasks
- Causal inference in public health
- Challenges with using proxies
- Algorithmic fairness and health disparities

## **Population Health**

Focus is on what makes and keeps people healthy (holistically). Aim is to improve the health of the entire population and to reduce health inequities among population groups [Rose, 1985].



# What is Health Equity?

# Health equity

"Minimizing avoidable disparities in health and its determinants-including but not limited to health care-between groups of people who have different levels of underlying social advantage or privilege, i.e., different levels of power. wealth, or prestige due to their positions in society relative to other groups." [Braveman, 2006]

#### Inequality in life expectancy widens for women

Wealthier women can expect to live longer than their parents did, while life expectancy for poor women may have declined. 91.9 Richest 90 85 85 79.7 Lower middle 78.3 Poorest 1980 2010

Life expectancy for 50-year-olds in a given year, by quintile of income over the previous 10 years  $% \left( 1-\frac{1}{2}\right) =0$ 

Source: National Academies of Science, Engineering and Medicine

Figure 1: Growing inequalities for women in the United States [National Academies, 2015].

## Public Health



Figure 2: Socio-ecological model of health [Bronfenbrenner, 1977].

Impact



United States Social factors account for 25–60 percent of deaths in any given year according to results from various meta-analyses. [Heiman and Artiga, 2015]

Worldwide: Eighty per cent of noncommunicable diseases could be prevented through primary prevention – through modifying behaviours such as reducing tobacco consumption and fat, alcohol and salt intake, preventing obesity, and promoting physical activity, and improving environmental conditions such as air quality and urban planning [WHO, 2009].

# Figure 3: [CDC, 2014]

# Importance of considering all determinants of health - COVID-19 case study



Figure 4: "Highway to health".

# Determinant (COVID relevance [Rollston and Galea, 2020])

- Housing conditions (crowding, poor sanitation)
- Healthy food access (increased comorbidities)
- Education access and quality (health literacy, future socioeconomic status)
- Socio-economic status (occupation/essential worker, ability to self-isolate)
- Healthcare trust (access treatment)
- Racism/discrimination (socioeconomic status, segregation, housing quality, health care access, quality, etc..)

# ML in Population and Public Health



For a complete list of related articles, more information and to give feedback: https://ChunaraLab.github.io/MLPH/ Ahsan, G. T., Addo, I. D., Ahamed, S. I., Petereit, D., Kanekar, S., Burhansstipanov, L., and Krebs, L. U. (2013). Toward an mhealth intervention for smoking cessation. In *2013 IEEE 37th Annual Computer Software and Applications Conference Workshops*, pages 345–350. IEEE.

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