Machine Learning in Population and Public Health: Challenges and Opportunities

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ACM CHIL 2020 Tutorial

NYU SCHOOL OF GLOBAL PUBLIC HEALTH

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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

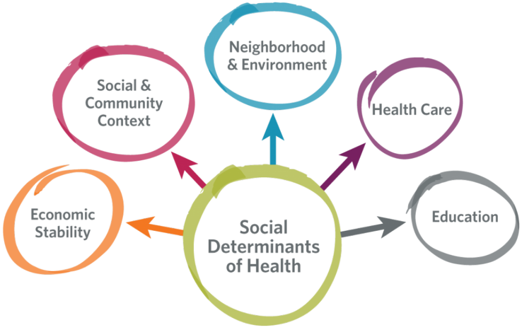


Figure 5: Five key areas of SoDH

"Conditions in which people are born, grow, live, work and age. These circumstances are shaped by the distribution of money, power and resources at global, national and local levels." [WHO, 2008]

Purposes of conceptual frameworks [WHO, 2010]:

- Guide empirical work to enhance understanding of determinants and mechanisms
- Guide policy-making to illuminate entry points for interventions and policies

Two Theories:

- Life course approach to inter-generational effects
- Intersectionality

Life Course Approach to Inter-generational Effects

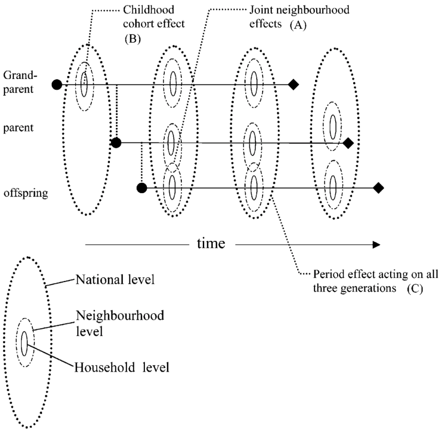
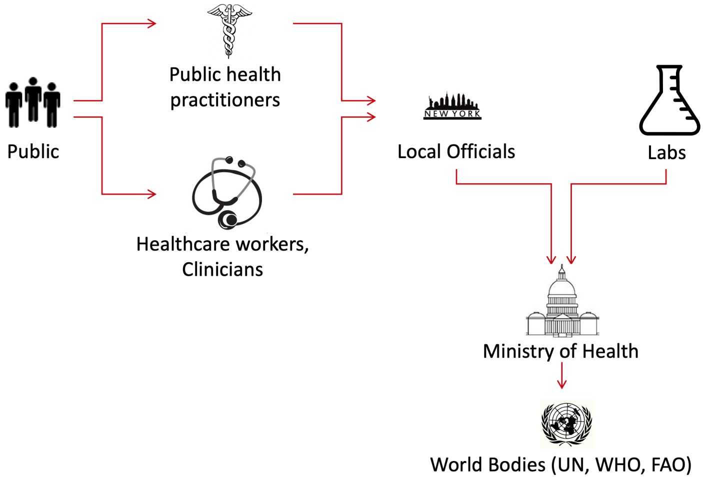


Figure 6: Hierarchical and life course exposures on disease risk across generations

- Longitudinal effects of socioeconomic adversities to which people are exposed to at various developmental stages on health. [Cable, 2014]
- Individual life-course perspective to inter-generational association between social determinants and diseases (e.g. parent adverse childhood experience was associated with higher odds of poor child overall health status [Lê-Scherban et al., 2018])

Traditional Data Collection in Public Health



Measurement of Social Determinants of Health

- Data sources at individual and population level: Electronic Medical Record (SoDH screening), American Community Survey (ACS), U.S. Census Bureau, Nationally representative surveys (e.g. NHANES, BRFSS)
- Each construct is measured by multiple indicators (e.g. Housing: has housing, rental housing, sanitation status, crowding, indoor air quality) [Kusnoor et al., 2018]

Internet and Mobile Data - examples

Figure 7: Person-generated data sources used today in public health

Health outcome (measured) examples

- Parkinsons (symptoms) [Zhan et al., 2018]
- Diabetes (mood, behaviors, diet) [Akbari and Chunara, 2019]
- Mental health (activity) [Quisel et al., 2016]

...while the fair ML literature has largely focused on "de-biasing" methods and viewed the training data as fixed, most of our interviews report that their teams consider data collection, rather than model development, as the most important place to intervene [Holstein et al., 2019].

- Data sharing; calls for centralized repository and open source assessment tools [National Academies of Sciences et al., 2019]
- Denominator challenges need to be addressed in order to understand and reach populations at risk [Chunara et al., 2017]
- **Internal validity**: the degree of confidence that the causal relationship being tested is trustworthy and not influenced by other factors or variables. **External validity**: the extent to which results from a study can be applied (generalized) to other situations, groups or events. [Mitchell and Jolley, 2004]

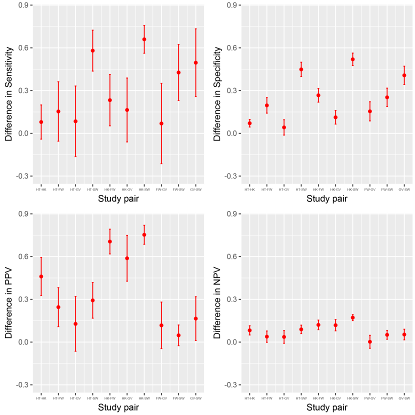


Figure 8: Varying specificity, sensitivity, NPV and PPV in multiple influenza syndromic surveillance systems.

Characteristics of the surveillance approach (data collection method, survey questions, the places/groups and time periods data are collected from) for which predictive performance of the same case definition can vary [Chunara et al., 2020].

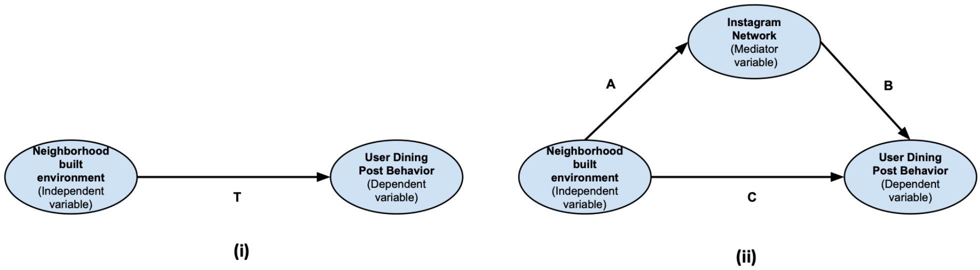


Figure 9: Role of the built and online social environments on expression of dining on Instagram [Mhasawade et al., 2020a]

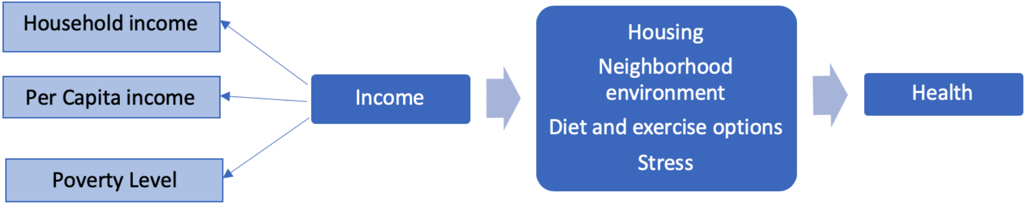


Figure 10: The Influence of Income on Health [Marmot, 2002]

- Mapping from construct space to observed space through imperfect proxy features and associated metrics [Friedler et al., 2016]

Construct space	Observed space
Intelligence	IQ
Success in High School	GPA
Propensity to commit crime	Family history of crime
Risk-averseness	Age
Knowledge of job	Number of Years of Experience

Definition (Observed space (OS)). The observed space (with respect to T) is a metric space OS $= (\hat{P}, \hat{d})$. We assume an observation process g : P $\rightarrow \hat{P}$ that generates an entity $\hat{p} = g(p)$ from a person $p \in CS$.

"There is a need for better understanding—both among data analysts and among consumers of data—of the weighty implications of analytic choices in measurement of health disparities, health inequities, and social determinants of health"

"Bias can stem not only from the value preferences or habits that inform choice of measurement practice(s) but also from the effect that different data presentation approaches have on audience perceptions or judgments of the resulting meaning of the data or analysis"

[Penman-Aguilar et al., 2016]

- Violating Stable Unit Treatment Value (SUTVA) assumption in causal inference
- Downstream manipulable mediators of social constructs as the exposures of interest (e.g. encouraging reading to children to improve cognitive development)
- Consider structural change for upstream social determinants (e.g. improving childhood SES)

Figure 11: From upstream to individual interventions [Lehman, 2019]

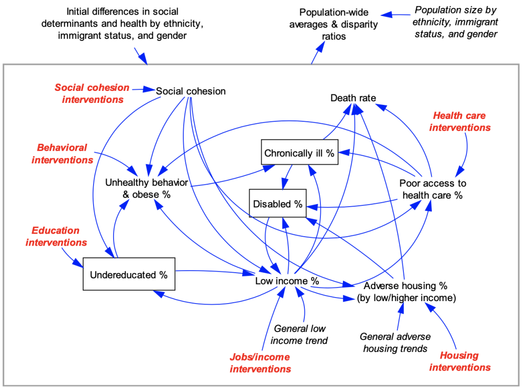


Figure 12: Hypothesized causal pathways of social and biological determinants of health [Mahamoud et al., 2013].

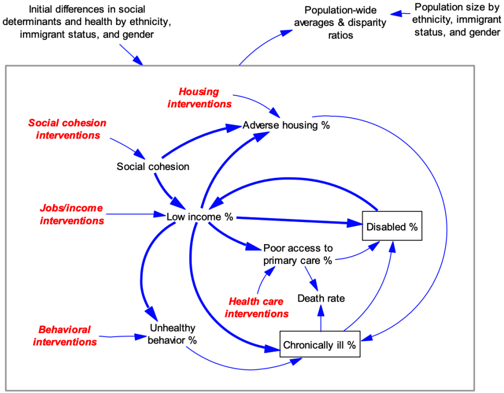


Figure 13: Modified causal graph based on relations in data [Mahamoud et al., 2013].

Social Determinants in Cardiovascular Disease Prediction Machine Learning Models

How are researchers incorporating social determinants in cardiovascular disease prediction models? [Zhao et al., 2020]

- 2728 publications were identified, and 120 publications were included
- Commonly measured social determinants: age, gender, ethnicity/race, education and income
- Most popular machine learning algorithms: random forest, SVM, decision tree, neural nets
- Data sources: cohort/observational studies, clinical trials, hospital electronic medical records

- Lack of comprehensive social determinants data (e.g. social environment, contextual information) from cohort studies or clinical datasets
- Most measurement at individual instead of community/population level
- Outcomes vary, including risk scores, prognosis of CVD and readmission to hospitals
- How to apply models and results to actionable interventions to address health disparity and improve health equity

ML in Population and Public Health

For a complete list of related articles, more information and to give feedback:
https://ChunaraLab.github.io/MLPH/

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