Geospatial-Temporal Modeling of Alcohol Acute Events

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Background

- The use of alcohol in a societal framework often leads to acute outcomes such as assault, domestic violence, child abuse and fatalities while DWI.
- This societal framework involves interactions of people and the institutions within the society...this is the alcohol ecological system.
- The alcohol ecological system is essentially a complex system.
- Interventions to reduce acute outcomes need to be assessed because they may result in unanticipated outcomes.
- It is difficult to assess the interventions and to carry out experiments in the real world because of time and cost constraints, so that an agent-based simulation is appropriate.

Background

- Alcohol misuse is associated with about 100,000 deaths every year and creates social, legal problem (Enoch).
- 15 % of adult U.S. population have a serious drinking problem, e.g. alcohol use disorder (Grant).
- 15,121 traffic deaths in 2006 involved alcohol impaired drivers (NHTSA).

Purpose of the Research

- To model the alcohol ecological system with geospatial and temporal dependence including demographic and socioeconomic variables.

- The ABM is designed to explore interventions in order to seek interventions or combinations of interventions that simultaneously suppress acute outcomes, e.g. assault, murder, sexual assault, domestic violence, child abuse, suicide, and alcohol-related automobile crashes with fatalities and serious injuries.

Dr. Yasmin Said's Architecture

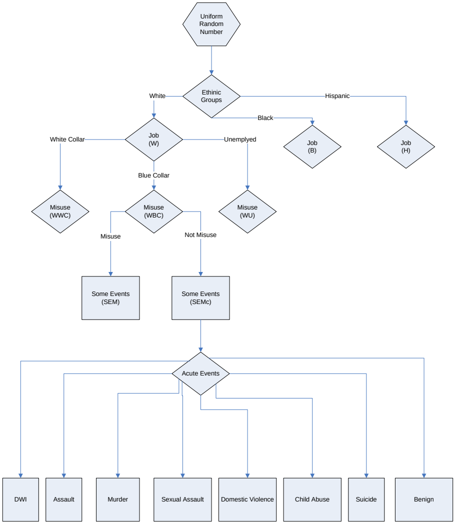


Figure: Flow Chart of Architecture

Dr. Yasmin Said's Simulations

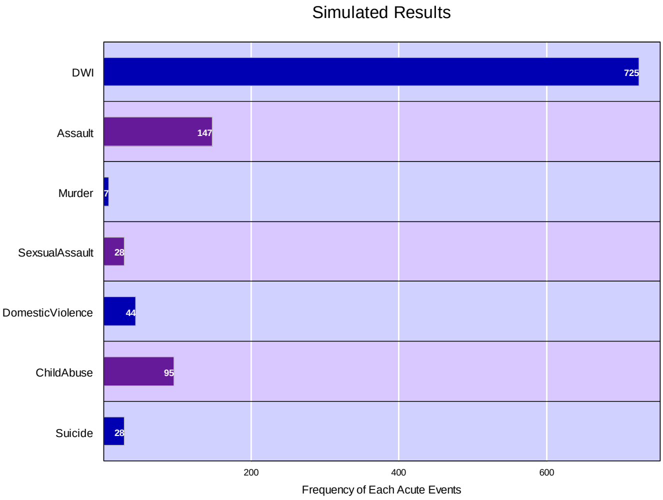
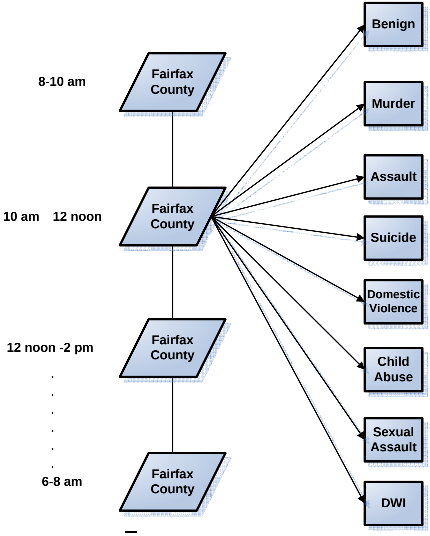


Figure: Simulated Result

Expanded Agent-Based Model

- Expanded Agent-Based Model with Time-of-Day
- Suggested by Wegman and Said (2008)



Expanded Agent-Based Model

- The expanded agent-based model includes additional factors including job class, ethnicity/race, alcohol availability, zip code, alcohol abuse status, age, gender, socioeconomic status, temporal variables (hourly, weekly, seasonal), and geospatial variables (commuting and travel, and neighborhood factors).
- Based on Said (2005, 2009).

Social Networks and Agent-Based Simulation

Multi-Mode Social Network Analysis as discussed yesterday by Dr. Wegman.

- Social networks are graph models of agents and their ties.
- Agents may be people or institutions, interactions can be of many types, including, for example, family, friendship, authority, and business.
- Individuals in the network interacting with each other or with social institutions can be mirrored on the social network graph.
- There is a fundamental duality between graph representation of social network and its adjacency matrix.

Social Networks and Agent-Based Simulation

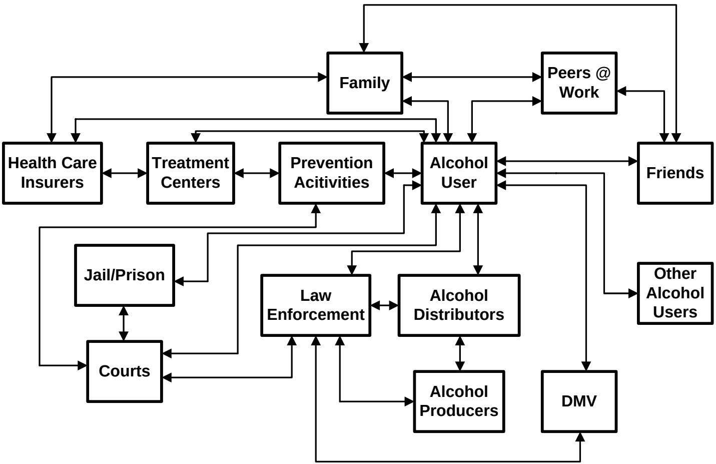
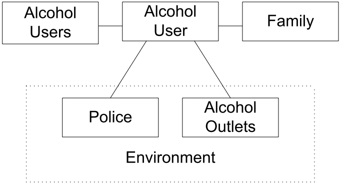


Figure: Social Network for Alcohol Users by Wegman and Said (2008)

Example of Building an Agent-Based Model

- Family (Supportive/Non-supportive, 50% of family are supportive)
  1. Supportive family: probability of DWI lowers 10%.
  2. Non-supportive family: probability of DWI increases 17%.
- Other alcohol user (50% of time intoxicated with A.U.)
  1. If intoxicated, raises probability of DWI by 20%.
  2. If not, no effect.



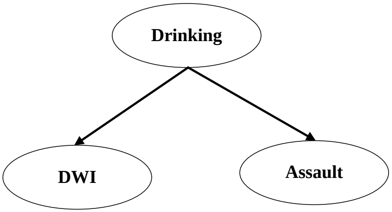
Bayesian Networks

- A Bayesian Network can allow us to infer causal relationships (Pearl, 2000).
- Bayesian Networks provide a formalism for reasoning about partial beliefs under conditions of uncertainty.
- They are based on **directed acyclic graphs** (DAG) and **joint probabilities**.

Bayesian Networks

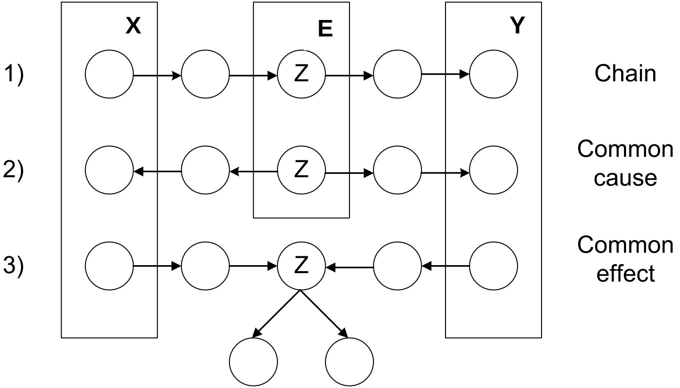
- **DAG**: a set of conditional independence relationships among variables.

$$
\begin{aligned}
I(A, B|C) \\
P(B|A, C) = P(B|C) \\
P(A|B, C) = P(A|C)
\end{aligned}
\tag{1}
$$

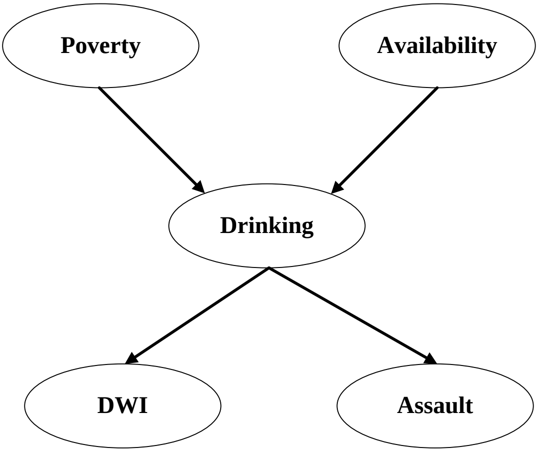


D-Separation

X is d-separated from Y, given Z, if all paths from a node in X to a node in Y are blocked, given Z (Korb).



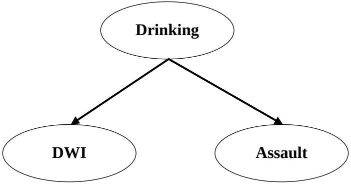
Example of D-Separation



Bayesian Networks

Joint Probability

$$P(D, D_w, A) = P(D)P(D_w|D)P(A|D, D_w)$$
$$= P(D)P(D_w|D)P(A|D) \quad (2)$$



Chain Rule

$$P(X_1, X_2, ..., X_n) =$$
$$P(X_1)P(X_2|X_1)P(X_3|X_1, X_2), ..., P(X_n|X_1, X_2, ...X_{n-1}) \quad (3)$$

$$\prod_{i=1}^{n} P(X_i|pa(X_i)) \quad (4)$$

Example of Decomposition

- $$P(A, B, C, D) \tag{5}$$

- By Chain Rule

$$P(A|BCD)P(B|CD)P(C|D)P(D) \tag{6}$$

- By Fundamental Rule

$$P(A|BCD)P(B|CD)P(CD) \tag{7}$$

Example of Decomposition

$$P(A|BCD)P(B|CD)P(CD) \tag{8}$$

- Suppose, $I(A, B)$ given CD, $I(A, B|CD)$

$$P(A|CD)P(B|CD)P(CD) \tag{9}$$

- By Bayes' Theorem

$$\frac{P(CD|A)P(A)}{P(CD)} \frac{P(CD|B)P(B)}{P(CD)} P(CD) \tag{10}$$

Example of Decomposition

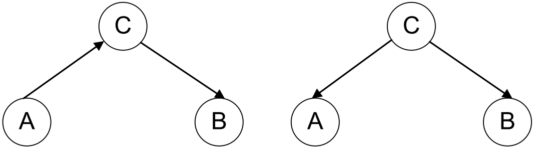
- By Fundamental Rule

$$\frac{P(ACD)P(A)}{P(A)P(CD)}\frac{P(BCD)P(B)}{P(B)P(CD)}P(CD) \tag{11}$$

- Decompose $P(ABCD)$ into $P(ACD)$ and $P(BCD)$

$$\frac{P(ACD)P(BCD)}{P(CD)} \tag{12}$$

Markov Equivalence



$$P(A,B,C) = P(A)P(C|A)P(B|C) \tag{13}$$

$$\begin{aligned} P(A,B,C) &= P(C)P(A|C)P(B|C) \\ &= P(C)\frac{P(C|A)P(A)}{P(C)}P(B|C) \\ &= P(A)P(C|A)P(B|C) \end{aligned} \tag{14}$$

Bayesian Networks

Causal Bayesian Networks

- Causal interpretations for Bayesian Networks have been proposed by Pearl and Verma (1991, 2000).
- Bayesian Networks are defined as **causal** networks with the strength of the causal links represented as conditional probabilities (Jensen).

Bayesian Networks

Example of Bayesian Network vs. Causal Bayesian Network

$$X \longrightarrow Y \qquad\qquad X \longleftarrow Y$$

$$\begin{aligned} P(Y|do(X=x)) &= P(Y|X=x) \\ P(X|do(Y=y)) &= P(X) \end{aligned} \tag{15}$$

$$\begin{aligned} P(Y|do(X=x)) &= P(Y) \\ P(X|do(Y=y)) &= P(X|Y=y) \end{aligned} \tag{16}$$

Causal Bayesian Network Model

- Causal Bayesian Network produce a model with CPTs for each node and a representation of the edges.

Applications of Causal Bayesian Network

- The main application of causal Bayesian networks can be the understanding of what kind of variables are conditionally dependent so that we can make inferences about the causality.
- Eventually, we can investigate what causes alcohol dependence.

Contribution of Causal Bayesian Network Model

- Capture how characteristics of individuals and socioeconomic status are related to crimes and enhance our understanding of alcohol and alcohol related problems based on the limited and disparate sources of information.
- A Causal Bayesian Network enables us to update a model and modeling structure, reflecting the emergence of new knowledge and understanding (additional data).

Expanded Agent-Based Simulation

Contribution

- Results could have important theoretical and policy implications for future research and practice.
- Help to understand alcohol related social structures and processes that shape the development of social problems such as crimes over time.

Q & A

Thank You!