Using computer simulation modeling to address homelessness: A project based on fuzzy cognitive maps and cellular automata

Eric Latimer\textsuperscript{a} and Vijay Mago\textsuperscript{b}

\textsuperscript{a}Department of Psychiatry, McGill University; Douglas Hospital Research Centre, Montreal, Quebec

\textsuperscript{b}Department of Computer Science, Lakehead University, Thunder Bay, Ontario
This research is supported by the Social Sciences and Humanities Research Council of Canada.

**Grant title:** Computer modeling to address homelessness: An exploratory study

**Period:** March 15 2016 – March 31 2019

PI: Eric Latimer   Co-PI: Vijay Mago  
Co-Investigators: Tim Aubry, Stephen Gaetz, Laurence Roy  
Collaborator: Philippe Giabbanelli  
Knowledge users: Mike Bulthuis, James McGregor  
Analysts: Erik Tillberg, Zhirong Cao

We also wish to acknowledge periodic informal exchanges with Mark Fox, Michael Gruninger and Bart Gajderowicz of the Center for Social Services Engineering at the University of Toronto
1. Introduction
2. Modelling approaches
   - Fuzzy cognitive Maps
   - Cellular Automata
   - Rule-Based Models
3. Current modeling approach with preliminary transition probability estimates
4. Projected future work
5. Concerns and limitations
Introduction

Simulation modeling: an approach for estimating the effects of policy scenarios
- Mansur et al. (2002)
- Culhane et al. (ongoing) – Homelessness analytics initiative
- Mago et al. 2013
Calibrated to 4 California cities, this model-based analysis concludes that “a very large fraction of homelessness can be eliminated through increased reliance upon well-known housing subsidy policies”.
Access critical **national**, **state**, and **local** information about homelessness and related factors.

**Explore Maps and Variables**
Choose from dozens of homelessness related data points to map at a variety of geographic resolutions and scales over the last several years.

**Forecast Changes in Homelessness**
Access models of how different demographic, economic, and safety net variables affect homelessness. Interactively change values and see forecast results.

**Charts, Graphs, and Tables**
Chart trends in homelessness over time, explore relationships between social indicators and homelessness, and download tables of data.
Project objectives

- To construct a computer simulation model designed to shed light on how contextual factors and policies interact to influence the number of homeless people and their composition over time.

- Estimate the costs of the policies themselves, and their net costs to service systems in Montreal and Ottawa.
Strategy

- Construct and calibrate model based on:
  - Literature review
  - Expert panels where lit review insufficient
  - Available data sets
Modelling Approaches - Fuzzy Cognitive Maps

- Edges are weighted between 0-1, i.e., strength of the relationship
- Edge weights can be positive (excitatory) or negative (inhibitory)

Mental illness ➔ Homelessness

NGO support ➔ Homelessness
Modelling Approaches - Fuzzy Cognitive Maps

- Levels
  + Individual (mental maps)
  + Contextualized (policies)

- Edge Weights
  + Learned from the data
  + Aggregate opinion (expressed in linguistic terms) of the experts
Modelling Approaches - Fuzzy Cognitive Maps

Modelling Approaches - **Cellular Automata**

- **The Grid** – Homeless population
- **A Cell** – Homeless individual
- **The Neighbourhood** – Surrounding homeless individuals
- **States** – Unstable, Street, Sheltered, Not Homeless, others.
Modelling Approaches - **Cellular Automata**

- Rules of updating the states - *Influenced by the neighbourhood*

Not Homeless → Transitional Homeless

Transitional Homeless → Episodic Homeless

Transitional Homeless → Chronic Homeless

Chronic Homeless → Episodic Homeless

---

Using computer simulation modeling to address homelessness: A project based on fuzzy cognitive maps and cellular automata

Eric Latimer & Vijay Mago
Modelling Approaches - *Rule Based Model*

Set of assertions (rules) - “if-then”
Transition from one state to another can be deterministic or probabilistic
Fairly simplistic and easy to encode knowledge of experts

Demo: [http://mcgill.thicketlabs.com](http://mcgill.thicketlabs.com)
Current modeling approach (1)

- Assimilate couch surfing and SROs with not homeless as we have no way of counting people in those types of homelessness.

- When people first become homeless, they can enter one of the following states:
  - Street
  - Emergency shelter
  - Transitional housing
  - Other (hospital, detox, substance use Tx, prison)
Current modeling approach (2)

- Assimilate couch surfing and SROs with not homeless as we have no way of counting people in those types of homelessness.

- When people first become homeless, they can enter one of the following states:
  - Street
  - Emergency shelter
  - Transitional housing
  - Other (hospital, detox, substance use Tx, prison) (after a possibly very brief period of days)

- What do the data tell us about these transitions?
Montreal complementary summer homelessness survey Aug – Sep 2015

- Where were you on the night of August 24?
- How long since you had a permanent place to stay? (Interviews Aug 25 – Sep 14)
Survey results: Where people said they were on the night of Aug 24, according to whether at time of interview they had been homeless 7 days or less, or one month or less (Total N: 1083)

<table>
<thead>
<tr>
<th></th>
<th>To from</th>
<th>Street</th>
<th>Emergency shelter</th>
<th>Transitional housing</th>
<th>Other*</th>
<th>Hidden homeless</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homeless ≤ 7 days</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Homeless ≤ 30 days</td>
<td>13</td>
<td>39</td>
<td>4</td>
<td>2</td>
<td>7</td>
<td></td>
</tr>
</tbody>
</table>

*Other: hospital, detox, substance use Tx, prison

When people begin a homelessness episode, they appear in general to first go to a homeless shelter, then possibly transition to other types of settings.
Transition probabilities from the Treatment-as-usual group of At Home/Chez Soi in Montreal – up to 24-month follow-up, data grouped in months (based on 3,785 non-missing transitions)

<table>
<thead>
<tr>
<th>From To</th>
<th>Mix</th>
<th>Street</th>
<th>Shelter</th>
<th>Transitional</th>
<th>Other</th>
<th>Hidden Hmlss</th>
<th>Not Hmlss</th>
<th>Death</th>
<th>ROW SUM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mix</td>
<td>7.40</td>
<td>1.32</td>
<td>2.14</td>
<td>0.5</td>
<td>1.85</td>
<td>1.85</td>
<td>1.16</td>
<td>0.03</td>
<td>16.25</td>
</tr>
<tr>
<td>Street</td>
<td>1.22</td>
<td>7.37</td>
<td>0.18</td>
<td>0.03</td>
<td>0.32</td>
<td>0.18</td>
<td>0.03</td>
<td>0</td>
<td>9.32</td>
</tr>
<tr>
<td>Shelter</td>
<td>2.30</td>
<td>0.18</td>
<td>8.48</td>
<td>0.24</td>
<td>0.21</td>
<td>0.98</td>
<td>0.16</td>
<td>0</td>
<td>12.55</td>
</tr>
<tr>
<td>Trans.</td>
<td>0.21</td>
<td>0</td>
<td>0.03</td>
<td>11.39</td>
<td>0.05</td>
<td>0.05</td>
<td>0.03</td>
<td>0</td>
<td>11.76</td>
</tr>
<tr>
<td>Other</td>
<td>1.35</td>
<td>0.18</td>
<td>0.18</td>
<td>0.16</td>
<td>11.55</td>
<td>0.55</td>
<td>0.13</td>
<td>0</td>
<td>14.11</td>
</tr>
<tr>
<td>Hidden</td>
<td>2.17</td>
<td>0.16</td>
<td>0.63</td>
<td>0.16</td>
<td>0.42</td>
<td>16.91</td>
<td>0.66</td>
<td>0</td>
<td>21.11</td>
</tr>
<tr>
<td>Not HL</td>
<td>0.66</td>
<td>0.03</td>
<td>0.05</td>
<td>0.03</td>
<td>0.05</td>
<td>0.40</td>
<td>13.03</td>
<td>0.03</td>
<td>14.27</td>
</tr>
<tr>
<td>Death</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.63</td>
<td>0.63</td>
</tr>
<tr>
<td>SUM</td>
<td>15.31</td>
<td>9.24</td>
<td>11.69</td>
<td>12.51</td>
<td>14.45</td>
<td>20.92</td>
<td>15.20</td>
<td>0.69</td>
<td>100</td>
</tr>
</tbody>
</table>

*Note: Mix = mixed. Less than 75% of the time in one type of place over one month. To be reduced by re-analyzing using one-week cycles; b includes some permanent supportive housing.
In Montreal, people tend to stay in transitional housing, rarely exiting homelessness; somewhat true of people in street as well.

<table>
<thead>
<tr>
<th>To</th>
<th>Mix</th>
<th>Street</th>
<th>Shelter</th>
<th>Transitional</th>
<th>Other</th>
<th>Hidden Hmlss</th>
<th>Not Hmlss</th>
<th>Death</th>
<th>ROW SUM</th>
</tr>
</thead>
<tbody>
<tr>
<td>From</td>
<td>Mix</td>
<td>Street</td>
<td>Shelter</td>
<td>Transitional</td>
<td>Other</td>
<td>Hidden Hmlss</td>
<td>Not Hmlss</td>
<td>Death</td>
<td>ROW SUM</td>
</tr>
<tr>
<td>Mix*</td>
<td>7.40</td>
<td>1.32</td>
<td>2.14</td>
<td>0.5</td>
<td>1.85</td>
<td>1.85</td>
<td>1.16</td>
<td>0.03</td>
<td>16.25</td>
</tr>
<tr>
<td>Street</td>
<td>1.22</td>
<td>7.37</td>
<td>0.18</td>
<td>0.03</td>
<td>0.32</td>
<td>0.18</td>
<td>0.03</td>
<td>0</td>
<td>9.32</td>
</tr>
<tr>
<td>Shelter</td>
<td>2.30</td>
<td>0.18</td>
<td>8.48</td>
<td>0.24</td>
<td>0.21</td>
<td>0.98</td>
<td>0.16</td>
<td>0</td>
<td>12.55</td>
</tr>
<tr>
<td>Trans.</td>
<td>0.21</td>
<td>0</td>
<td>0.03</td>
<td>11.39</td>
<td>0.05</td>
<td>0.05</td>
<td>0.03</td>
<td>0</td>
<td>11.76</td>
</tr>
<tr>
<td>Other</td>
<td>1.35</td>
<td>0.18</td>
<td>0.18</td>
<td>0.16</td>
<td>11.55</td>
<td>0.55</td>
<td>0.13</td>
<td>0</td>
<td>14.11</td>
</tr>
<tr>
<td>Hidden</td>
<td>2.17</td>
<td>0.16</td>
<td>0.63</td>
<td>0.16</td>
<td>0.42</td>
<td>16.91</td>
<td>0.66</td>
<td>0</td>
<td>21.11</td>
</tr>
<tr>
<td>Not HL</td>
<td>0.66</td>
<td>0.03</td>
<td>0.05</td>
<td>0.03</td>
<td>0.05</td>
<td>0.40</td>
<td>13.03</td>
<td>0.03</td>
<td>14.27</td>
</tr>
<tr>
<td>Death</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.63</td>
<td>0.63</td>
</tr>
<tr>
<td>SUM</td>
<td>15.31</td>
<td>9.24</td>
<td>11.69</td>
<td>12.51</td>
<td>14.45</td>
<td>20.92</td>
<td>15.20</td>
<td>0.69</td>
<td>100</td>
</tr>
</tbody>
</table>

*Mix = mixed. Less than 75% of the time in one type of place over one month. To be reduced by re-analyzing using one-week cycles.
Modeling probability of becoming homeless

- Everyone has a certain vulnerability to become homeless – denoted by v – if v = 0 person has 0 probability of becoming homeless from one cycle to the next; if v=1, 100% chance of becoming homeless

- “Context-level” fuzzy cognitive map to be used to determine distribution of v in the population (combination of personal or predisposing factors, and environmental factors)

- Important to do modeling separately for men and women, Indigenous and non-Indigenous, probably older vs younger
Modeling transition probabilities: effects of programs

- Programs have two possible effects:
  - Reduce individual’s “vulnerability”
  - Directly house individual (eg HF) or not (day centre)

- Programs also characterized by duration

- These 3 parameters to be based on combination of literature and expert opinion

- Cost also to be included – can vary according to how program implemented, which also influences effects
Projected future work

- Develop context-level FCM
- Model transition probabilities (rule-based rather than cellular automata?)
- Extend to Ottawa data
Concerns / limitations

- Challenging to move quickly – much developmental work required of core investigators

- Too many parameters make model intractable, but too few mean oversimplification

- Exploratory study: May not be possible to develop a credible model; at least will help synthesize knowledge and derive implications for effects and costs of different program combinations in different contexts
Thank you for your attention

eric.latimer@mcgill.ca

vijay.mago@lakeheadu.ca