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

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   - 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

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Examining policies to reduce homelessness using a general equilibrium model of the housing market

Erin T. Mansur,[a,c] John M. Quigley,[a,b] Steven Raphael,[b,*] and Eugene Smolensky[b]

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”.

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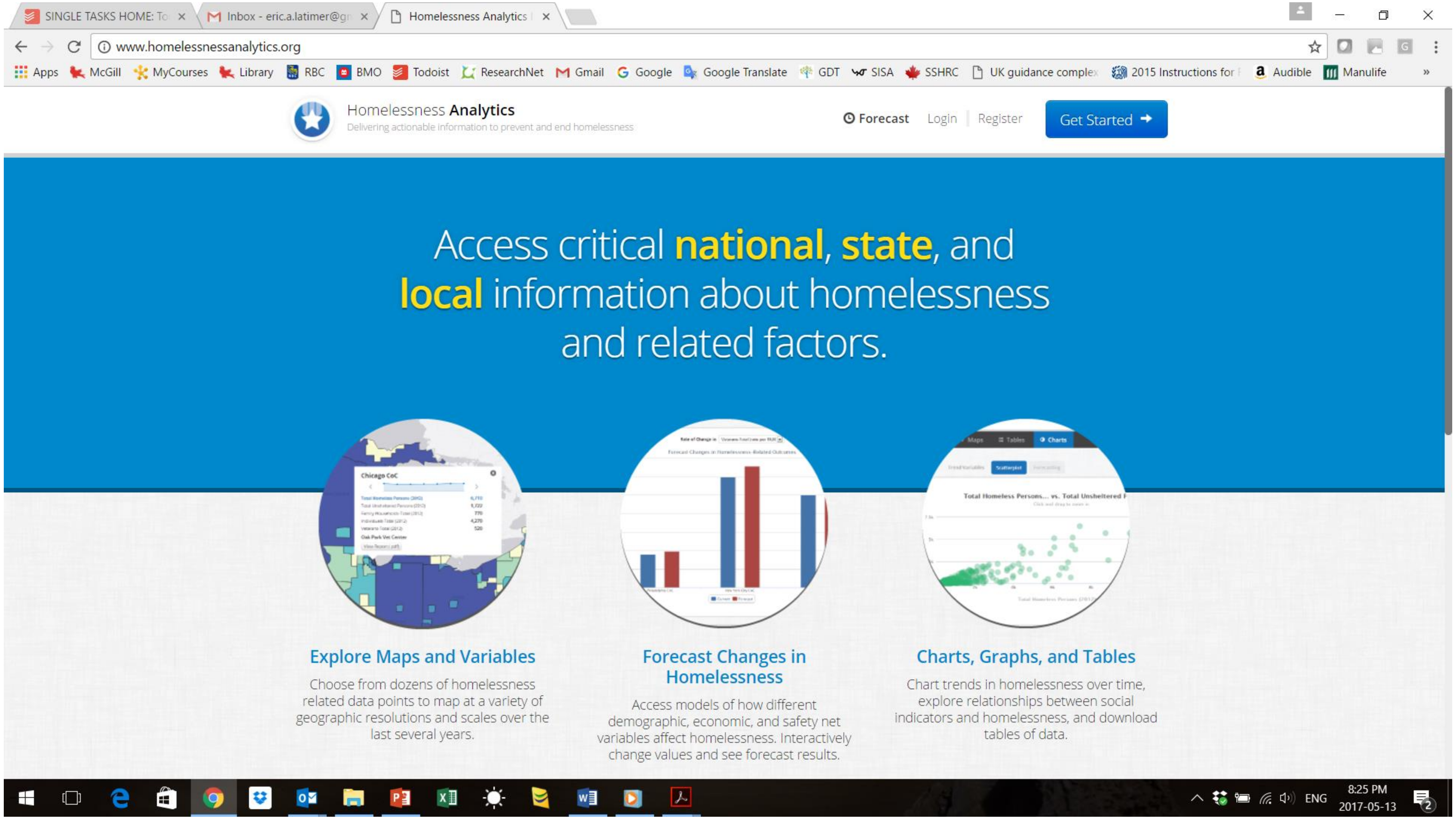


Project objectives

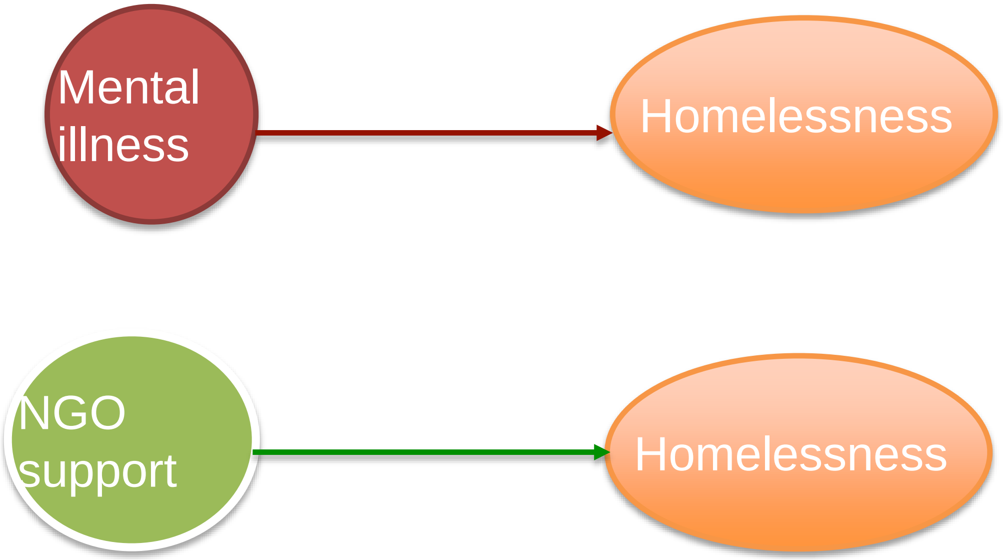
- To construct a computer simulation model designed to shed light on how contextual factors and policies interact to influence the number of homeless people and their composition over time.

- 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

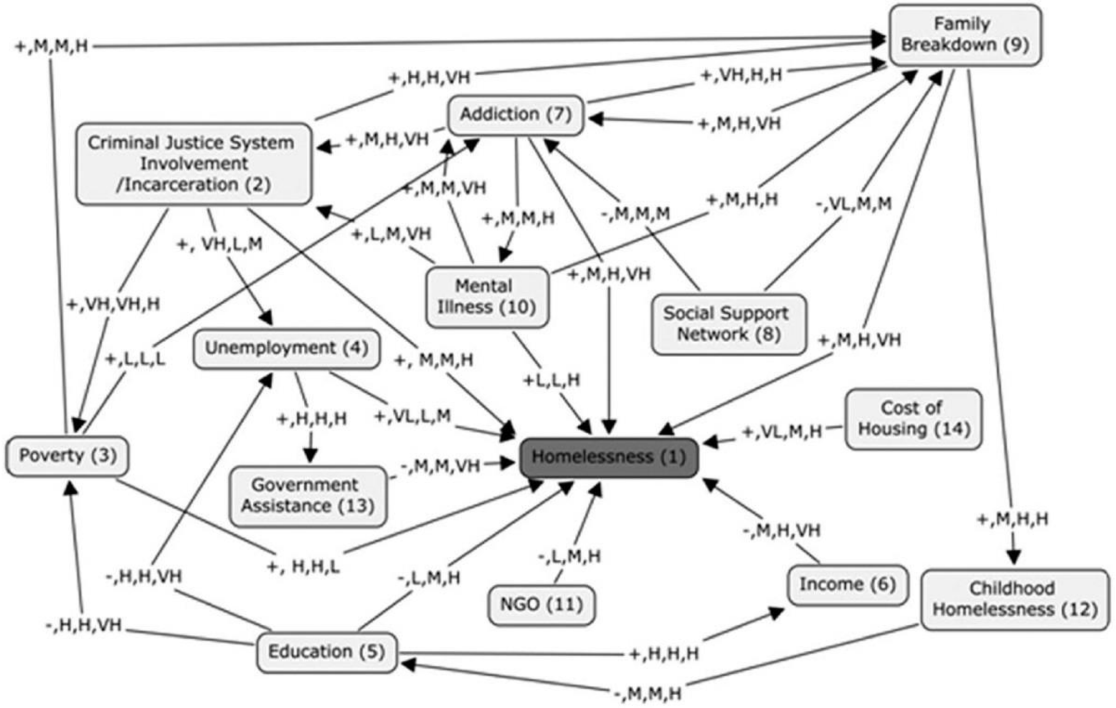
- Edge weights can be positive (excitatory) or negative (inhibitory)

Modelling Approaches - Fuzzy Cognitive Maps

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

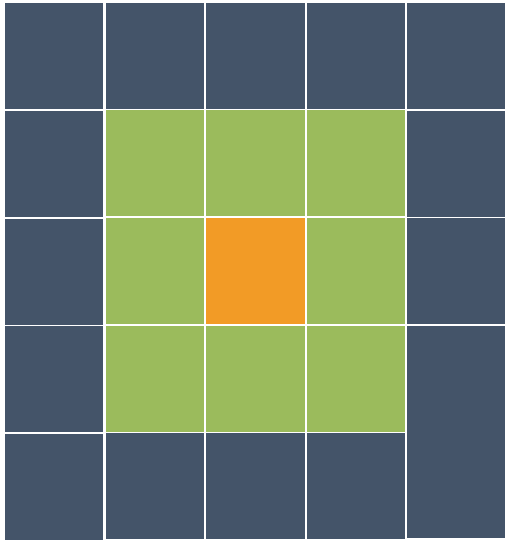
- Edge Weights
  + Learned from the data
  + Aggregate opinion (expressed in linguistic terms) of the experts

Modelling Approaches - Fuzzy Cognitive Maps



Mago, V. K., Morden, H. K., Fritz, C., Wu, T., Namazi, S., Geranmayeh, P., ... & Dabbaghian, V. (2013). Analyzing the impact of social factors on homelessness: a Fuzzy Cognitive Map approach. *BMC medical informatics and decision making*, *13*(1), 94.

Modelling Approaches - Cellular Automata



The Grid – Homeless population

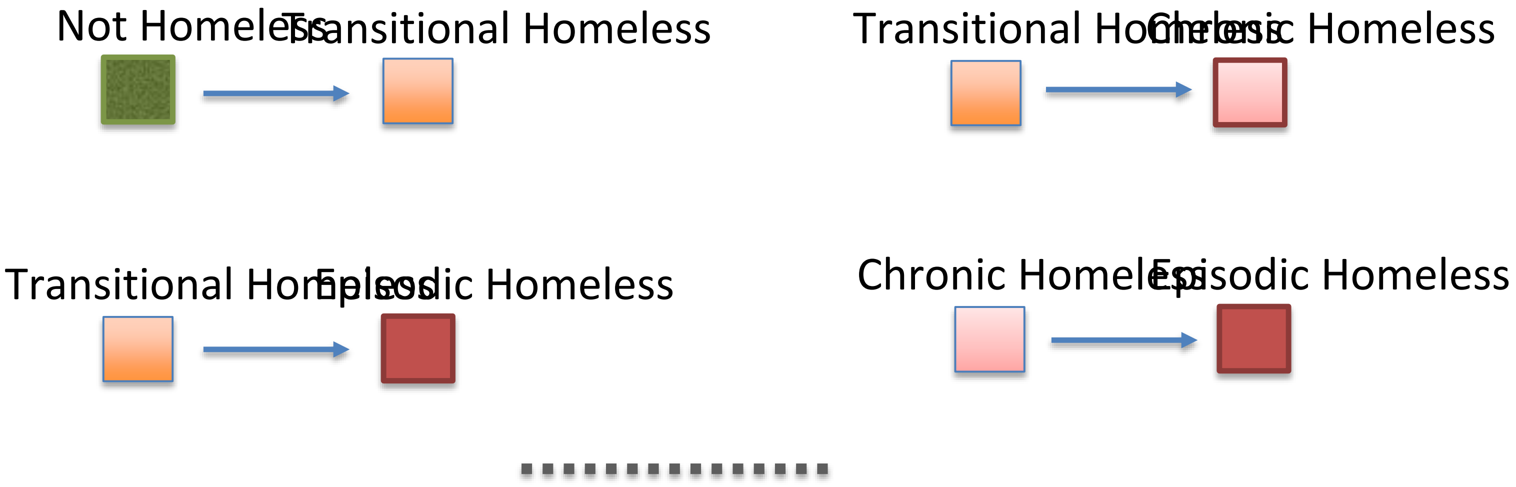
A Cell – Homeless individual

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***



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

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)

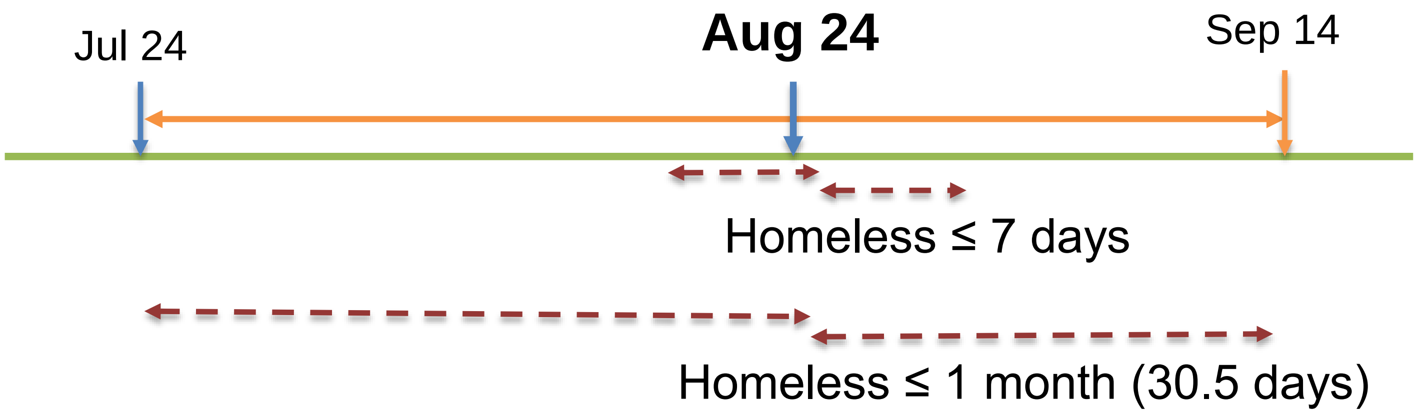
- What do the data tell us about these transitions?

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)

To From	Street	Emergency shelter	Transitional housing	Other*	Hidden homeless
Homeless ≤ 7 days	0	8	0	1	0
Homeless ≤ 30 days	13	39	4	2	7

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

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

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)

To / From	Mix	Street	Shel-ter	Tran-sitio-nal	Other	Hidden Hmlss	Not Hmlss	Death	ROW SUM
Mix[a]	7.40	1.32	2.14	0.5	1.85	1.85	1.16	0.03	16.25
Street	1.22	7.37	0.18	0.03	0.32	0.18	0.03	0	9.32
Shelter	2.30	0.18	8.48	0.24	0.21	0.98	0.16	0	12.55
Trans.	0.21	0	0.03	11.39	0.05	0.05	0.03	0	11.76
Other	1.35	0.18	0.18	0.16	11.55	0.55	0.13	0	14.11
Hidden	2.17	0.16	0.63	0.16	0.42	16.91	0.66	0	21.11
Not HL	0.66	0.03	0.05	0.03	0.05	0.40	13.03	0.03	14.27
Death								0.63	0.63
SUM	15.31	9.24	11.69	12.51	14.45	20.92	15.20	0.69	100

[a] 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

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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

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