



PREDICTING THE SLIDE TO LONG-TERM HOMELESSNESS

Sandeep Puroo, Professor
Monica Garfield, Professor
Xin Gu, Graduate Student
Prakash Bhetwal, Graduate Student

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Agenda



- **The Challenge of Homelessness**
 - Causes and Contributors to Homelessness
 - Chronic and Long-term Homelessness
- **Predicting the Slide to Long-term Homelessness**
 - Context and Data Sources
 - Exploratory data analysis
 - Developing a predictive model
 - Model validation
- **Application of the Predictive Model**
- **Limitations and Future Work**

The Challenge of Homelessness



- Being homeless is not a condition, it is something people experience.
- **Defining Homeless:** “a person who lacks a fixed, regular, and an adequate nighttime residence”
- An ecosystem of care agencies (shelters, hospitals, correctional facilities) respond to the concerns of the homeless (CoC)



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Contributors to Homelessness



- **What causes homelessness?**
 - Lack of affordable housing
- What contributes to homelessness?
 - Unemployment, poverty, low wages, mental illness, substance abuse, and domestic violence (for women)
- What impacts the intensity of homelessness?
 - Gender, family support, veteran status, combat status and education level impact the intensity (e.g. frequency, duration)

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Homelessness: Chronic



- **Chronically homeless:** someone who is continuously homeless for a year or more or has 4 or more episodes of homelessness adding to a year or more in the previous three years (US HUD)
- Incidence: ~10% of the population
- Burden: ~50% of the bed space
- Problem: How to track individuals across the ecosystem (shelters, hospitals), as well as streets, prisons ...

Why is this important?

- It drives policy
- It drives funding

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Homelessness: Long-Term



- **Long-term homelessness:** being homeless (during a continuous period of 365 days) for a significant fraction of time
- Operationalization: Fraction = at least one out of every three days
- **Purpose:**
 - Not merely meeting the US HUD definition (chronically homeless) for the purpose of counting
 - Instead, identifying the propensity for long-term homeless quickly, so that this can lead to more effective action at different points within the ecosystem of care.

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Context of Our Work



- **Context:** City of Boston, and Pine Street Inn (PSI), the largest homeless shelter in New England
- Homeless population in Massachusetts: 20,068 (in 2018)
- Homeless population in Boston: 6,144 (in 2018)
- Data source: what PSI and the City of Boston collect, primarily for reporting (e.g. US HUD)
- Coverage: About 4.5 years (early 2014 to May 2018)

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Exploratory Analysis



- **Data:** Entrances and Exits of 22,693 individuals recorded by Pine Street Inn
- Key Attributes: Enrollment Entry Date (the earliest entry date of all enrollments for an individual) and Enrollment Exit Date (the latest exit date of all enrollments for an individual)
- Exploring correlation with long term homelessness with no initial filtering of any of the characteristics

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Exploratory Analysis



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■ $avg (length (homelessness_k)) = length (episode_{ik}) / \{time-periods\}$

TABLE II. DIFFERENCES LONG- VS. SHORT-TERM GROUPS - A

Group	Variables (see Table I)					
	AI	AS	AF	PI	WH	G
Short-term	0.011	0.016	0.397	0.013	0.536	0.207
Long-term	0.013	0.014	0.485	0.009	0.468	0.205

TABLE III. DIFFERENCES LONG- VS. SHORT-TERM GROUPS - B

Group	Variables (see Table I)				
	V	Age	Dom	Inc	Sub
Short-term	0.063629	42.32759	0.17763	0.472659	0.61715
Long-term	0.053934	47.96416	0.184598	0.628301	0.773144

TABLE IV. DIFFERENCES LONG- VS. SHORT-TERM GROUPS - C

Group	Variables (see Table I)						
	Dis	DisT5	DisT6	DisT7	DisT8	DisT9	DisT10
Short-term	0.62	0.306	0.142	0.344	0.029	0.512	1.064
Long-term	0.77	0.443	0.200	0.481	0.032	0.623	1.230

← Ethnicity

← Background

← Disability

TABLE I. POTENTIAL INDEPENDENT VARIABLES

Variables Description and Type
(AI) American Indian: Is the individual American Indian (native)? (B)
(AS) Asian: Is the individual Asian? (B)
(AF) African American: Is the individual Black /African American? (B)
(PI) Pacific Islander: Is the individual Native HI/ Pacific Islander? (B)
(WH) White: Is the individual White? (B)
(HI) Hispanic: Is the individual Hispanic? (B)
(G) Gender: What is the individual's gender? (Is it Male?) (B)
(V) Veteran: Is the individual a veteran? (B)
(Age) Date of Birth: What is your DOB? (to compute Age)
(Dom) Domestic Violence Victim: Is the individual a Victim? (B)
(Inc) Income: Does the individual have income? (B)
(Sub) Substance Abuse: Was there substance abuse? (converted to Ordinal)
(Dis) Disabled: Does the individual have a disability? (B)
(DisT) Disability Type: What is the disability type? (converted to B for each)

(B) Binary variable; Gender: Female, Male, Transfemale, Transmale, Does not identify as male, female or transgender; Substance abuse: No, Alcohol abuse, Drug abuse, Both alcohol and drug abuse; Disability type: Physical, Developmental, Chronic condition, HIV, Mental health)

Developing a Predictive Model



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Log-odds of the probability of the individual being in the Long-term Group

$$\ln (p/(1-p)) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n$$

p = probability (of an individual being a long term homeless, given the status of the individual as a homeless individual.

```

Coefficients:
              estimate  std. error  z value  Pr(>|z|)
(Intercept) -1.046350    0.245885  -24.259  < 2e-16 ***
AmIndanative  0.382145    0.193528   1.975  0.046016 *
Asian         0.366593    0.192214   1.907  0.056494 *
BlackAfrican  0.588332    0.124469   4.731  5.49e-07 ***
NativeOtherPacific  0.051600    0.225837   0.229  0.819113
White        0.196495    0.133522   1.473  0.082385 .
ethnicity    0.156061    0.051396   3.048  0.002302 **
gender       -0.063623    0.050347  -1.264  0.206347
veteranstatus -0.487058    0.086676  -5.606  1.07e-08 ***
age          0.028034    0.001685  16.642  < 2e-16 ***
disable      0.442732    0.054982   8.052  8.15e-16 ***
distype1     0.072665    0.047277   1.537  0.124185
distype2     0.156221    0.053764   2.906  0.003665 **
distype3     0.120881    0.045989   2.624  0.008887 **
distype4    -0.346134    0.113733  -3.043  0.002341 **
distype5     0.144977    0.042272   3.427  0.000763 ***
distype6     0.059271    0.037908   1.560  0.000934 ***
domesticviolencevictm -0.086562    0.057325  -1.515  0.129693
income1      0.282445    0.042293   6.674  6.84e-11 ***
                    
```

Initial Model
No variables removed

Final Version of the Predictive Model



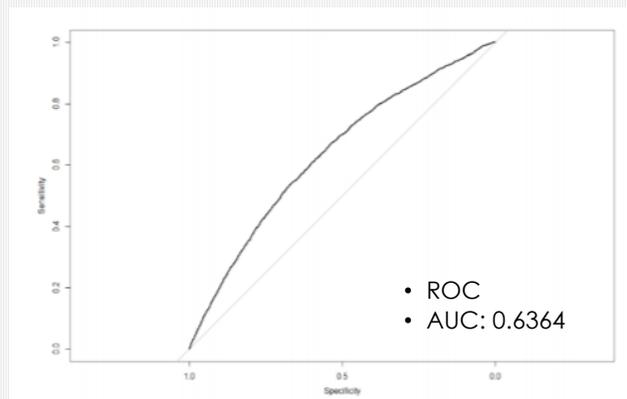
```

Coefficients:
      Estimate Std. Error z value Pr(>|z|)
(Intercept)  -3.298134  0.082580 -39.939 < 2e-16 ***
BlackAfAmerican  0.385994  0.039645  9.736 < 2e-16 ***
VeteranStatus  -0.512541  0.085794 -5.974 2.31e-09 ***
age             0.028818  0.001587 18.164 < 2e-16 ***
Disable        0.569002  0.049504 11.494 < 2e-16 ***
DisType10     0.055994  0.017491  3.201 0.00137 **
income1       0.333501  0.041762  7.986 1.40e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Removing variables not considered significant. Being African American (AF), being a Veteran (V), being above a certain age (Age), having a disability (Dis), and reporting an income (Inc) significant (at 0.001), substance abuse disability (DisT10) is significant (at 0.01).

Model validation



50% is Random Chance
Closer to 1 = Better

Jay presents himself at the shelter. What can we predict?

Emily presents herself at the shelter. What can we predict?

Application of the Model



Jay presents himself at the shelter. Jay happens to be Black/African American, 60 years old, has a disability, reports having an income, and reports no substance abuse.

Assessing the probability that a guest will slide into long-term homelessness				
Factors to consider	Enter Data		Choices	
Age	60	Numner		
Race - Black	1	Yes/No		
Veteran Status	0	Yes/No	Yes	1
Disability Status	1	Yes/No	No	0
Disability Type - Substance Abuse	0	Yes/No		
Income	1	Yes/No		
Log Odds	-0.280657			
Computed initial probability	43.03%			
Interpretation:				
The initial probability that this individual will slide to long-term homelessness	43.03%			

Anticipatory identification of at-risk individuals, those with a greater propensity to slide into **Long-Term** homelessness.

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Application of the Model



Emily presents herself at the shelter. Emily happens to be Asian, 40 years old, does not have a disability, is a veteran, reports no income.

Assessing the probability that a guest will slide into long-term homelessness				
Factors to consider	Enter Data		Choices	
Age	40	Numner		
Race - Black	0	Yes/No		
Veteran Status	1	Yes/No	Yes	1
Disability Status	0	Yes/No	No	0
Disability Type - Substance Abuse	0	Yes/No		
Income	0	Yes/No		
Log Odds	-2.657955			
Computed initial probability	6.55%			
Interpretation:				
The initial probability that this individual will slide to long-term homelessness	6.55%			

Anticipatory identification of at-risk individuals, those with a greater propensity to slide into **Long-Term** homelessness.

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Limitations, Ongoing Work



- **Limitations**

- A slice of time (four and a half years)
- Tied to a single city

- **Ongoing Work**

- Introducing the predictive model within the work practice
- Developing meaningful variations of the predictive model

For more information and to reach the research team
<http://homelessness.researchproject.us>