Analyzing Geographic and Demographic Patterns of Homelessness*

Exploring Spatial Variations in Shelter Demand and Gender/Age-Based Disparities

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This study examines the challenges faced by the homeless despite the presence of shelters, triggered by a recent incident of a homeless person succumbing to severe cold. It investigates geographic and demographic trends in homelessness, analyzing variations in shelter demand based on location and gender/age disparities. Utilizing data from the Shelter Support and Housing Administration division's Shelter Management Information System database, the research forecasts demand and provides critical insights: (1) geographic analysis identifies areas with the highest demand for shelter services, (2) demographic analysis uncovers gender and age-based disparities. These insights empower policymakers, shelter providers, and advocacy groups to allocate resources efficiently and proactively address homelessness challenges, ultimately preventing future hardships and tragedies.

1 Introduction

You can and should cross-reference sections and sub-sections.

The remainder of this paper is structured as follows. Section 2….

*Code and data are available at: https://github.com/jwonc4602/Analyzing-Geographic-and-Demographic-Patterns-of-Homelessness.

2 Data

2.1 Data Source

The dataset at the core of this research is drawn from the Shelter Support and Housing Administration (SSHA) division's Shelter Management Information System (SMIS) database. This database serves as a comprehensive repository of daily records of active overnight shelter and allied services. It represents the most recent and extensive source of data available for analysis in the context of homelessness support services.

2.2 Data Collection

The data collection process is designed to provide a comprehensive and up-to-date view of shelter and overnight service programs. Key aspects of data collection include:

2.2.1 Daily Updates

The dataset encompasses daily updated information regarding shelter and overnight service programs. Data is collected and reported on a daily basis, ensuring that the information reflects the most current state of affairs in the shelter system.

2.2.2 Inclusion of Overnight Service Types

One notable enhancement in the data collection process is the inclusion of various overnight service types. Previously, the dataset primarily focused on traditional shelter programs. However, the revised approach now encompasses all overnight service types for which occupancy data is tracked in the SMIS. This expansion allows for a more comprehensive analysis of the services available to homeless individuals.

2.2.3 Capacity Categorization

Programs within the dataset are categorized based on their capacity type. This categorization classifies programs as either bed-based or room-based. Bed-based capacity is typically applicable to programs with communal sleeping areas, while room-based capacity is typically associated with family programs and hotel-based programs where individual sleeping rooms are provided. This classification ensures that capacity reporting accurately reflects the nature of the program, preventing over-reporting in room-based programs.

2.2.4 Dual Capacity Measures

To better evaluate program occupancy rates, the dataset provides two measures of capacity. The first measure, known as funding capacity, reports the intended number of beds or rooms that a program is designed to provide. The second measure, referred to as actual capacity, reflects the number of beds or rooms in service and available for occupancy at the time of reporting. This dual measurement approach enhances the accuracy of assessing program occupancy rates.

Overall, the data collection process is underpinned by a commitment to maintaining accurate and timely records of shelter and overnight service programs. By leveraging this dataset, we gain valuable insights into the dynamic landscape of homelessness, facilitating a more informed and data-driven approach to addressing the needs of homeless individuals.

2.3 Data Analysis

3 Model

The goal of our modelling strategy is twofold. Firstly,...

Here we briefly describe the Bayesian analysis model used to investigate... Background details and diagnostics are included in Appendix B.

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \alpha + \beta_i + \gamma_i && (2)\\
\alpha &\sim \text{Normal}(0, 2.5) && (3)\\
\beta &\sim \text{Normal}(0, 2.5) && (4)\\
\gamma &\sim \text{Normal}(0, 2.5) && (5)\\
\sigma &\sim \text{Exponential}(1) && (6)
\end{aligned}
$$

We run the model in R (R Core Team 2022) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

Table 1: Explanatory models of flight time based on wing width and wing length

	First model
(Intercept)	1.12
	(1.70)
length	0.01
	(0.01)
width	−0.01
	(0.02)
Num.Obs.	19
R2	0.320
R2 Adj.	0.019
Log.Lik.	−18.128
ELPD	−21.6
ELPD s.e.	2.1
LOOIC	43.2
LOOIC s.e.	4.3
WAIC	42.7
RMSE	0.60

3.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular…

We can use maths by including latex between dollar signs, for instance θ.

4 Results

Our results are summarized in Table 1.

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

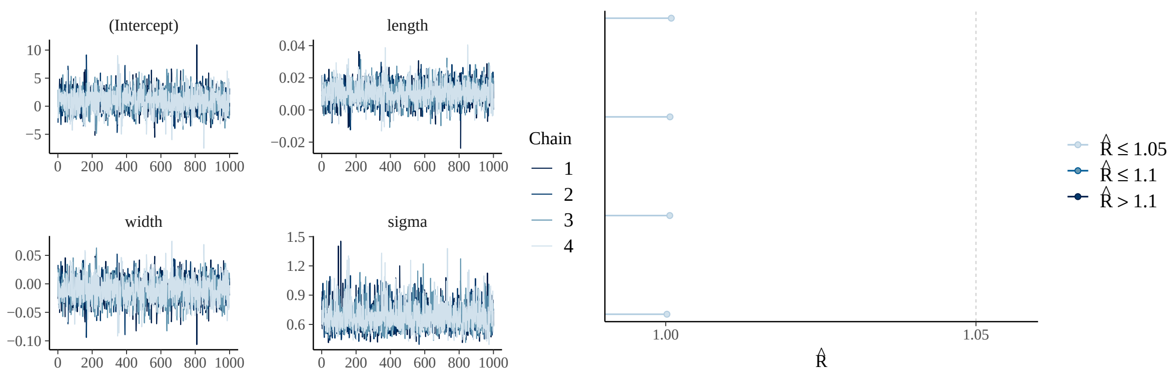
In **?@fig-ppcheckandposteriorvsprior-1** we implement a posterior predictive check. This shows...

In **?@fig-ppcheckandposteriorvsprior-2** we compare the posterior with the prior. This shows...

B.2 Diagnostics

Figure 1a is a trace plot. It shows... This suggests...

Figure 1b is a Rhat plot. It shows... This suggests...



(a) Trace plot

(b) Rhat plot

Figure 1: Checking the convergence of the MCMC algorithm

References

Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. "Rstanarm: Bayesian Applied Regression Modeling via Stan." https://mc-stan.org/rstanarm/.

R Core Team. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.