

Toronto police annual statistical report arrested-and-charged-persons*

arrested-and-charged-person

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January 21, 2024

According to police statistics, as a branch of crime statistics, Toronto Police statistics comprehensively depict the gender/age groups/crime types of individuals arrested in Toronto from 2014 to 2022. Second sentence. Third sentence. Fourth sentence.

1 Introduction

Criminal statistics, particularly within the domain of policing, serve as a vital instrument in comprehending and addressing patterns of criminal behavior within society. Toronto Police statistics, as an exemplar in this context, offer a meticulous portrayal of the demographic dynamics and criminal typologies characterizing arrests within the city from the temporal span of 2014 to 2022. Such statistical analyses provide a nuanced understanding of the intricate interplay between law enforcement efforts and the evolving landscape of criminal activities.

The field of criminal statistics functions as a branch of criminology, offering empirical insights into the prevalence, distribution, and trends of criminal incidents. Policing agencies, including the Toronto Police, routinely engage in the systematic collection, analysis, and interpretation of data derived from their law enforcement activities. These statistics encapsulate a multifaceted depiction of criminal occurrences, spanning diverse facets such as the demographics of apprehended individuals, the temporal distribution of criminal incidents, and the categorization of offenses according to their nature and severity.

Toronto Police statistics, with their temporal range extending from 2014 to 2022, encapsulate an extensive period characterized by shifts in societal dynamics, legislative alterations, and advancements in law enforcement strategies. The juxtaposition of gender, age cohorts, and crime types in these statistics elucidates the differential impact of law enforcement efforts across

*Code and data are available at: [LINK](#).

various demographic groups and crime categories. Such granularity facilitates a more nuanced understanding of the socio-criminological landscape, enabling policymakers, researchers, and law enforcement agencies to tailor interventions effectively.

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

The remainder of this paper is structured as follows. Section [2](#)...

2 Data

Talk more about it.

And also planes (Figure [1](#)). (You can change the height and width, but don't worry about doing that until you have finished every other aspect of the paper - Quarto will try to make it look nice and the defaults usually work well once you have enough text.)

```
# A tibble: 5 x 2
  category                n
  <chr>                <int>
1 Controlled Drugs and Substances Act    150
2 Crimes Against Property              975
3 Crimes Against the Person            1253
4 Criminal Code Traffic                 108
5 Other Criminal Code Violations        811
```

Talk way more about it.

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](#).

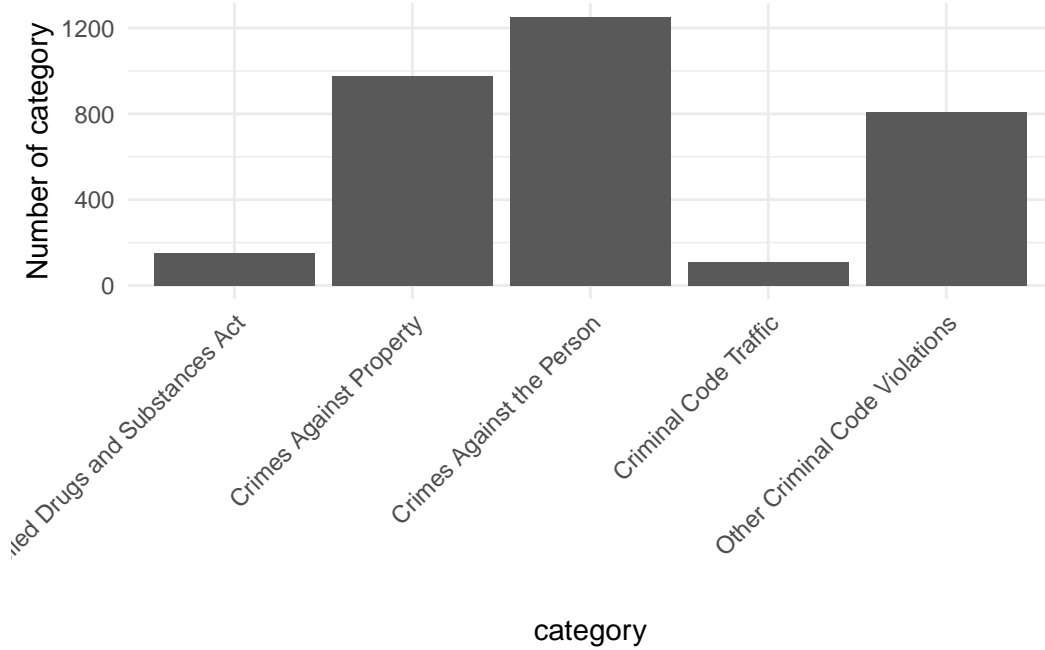


Figure 1: Relationship between crimes category and width

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.

$$y_i | \mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \quad (1)$$

$$\mu_i = \alpha + \beta_i + \gamma_i \quad (2)$$

$$\alpha \sim \text{Normal}(0, 2.5) \quad (3)$$

$$\beta \sim \text{Normal}(0, 2.5) \quad (4)$$

$$\gamma \sim \text{Normal}(0, 2.5) \quad (5)$$

$$\sigma \sim \text{Exponential}(1) \quad (6)$$

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`.

3.1.1 Model justification

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

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

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 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...

Examining how the model fits, and is affected
by, the data

Figure 2: `?(caption)`

B.2 Diagnostics

Figure 3a is a trace plot. It shows... This suggests...

Figure 3b is a Rhat plot. It shows... This suggests...

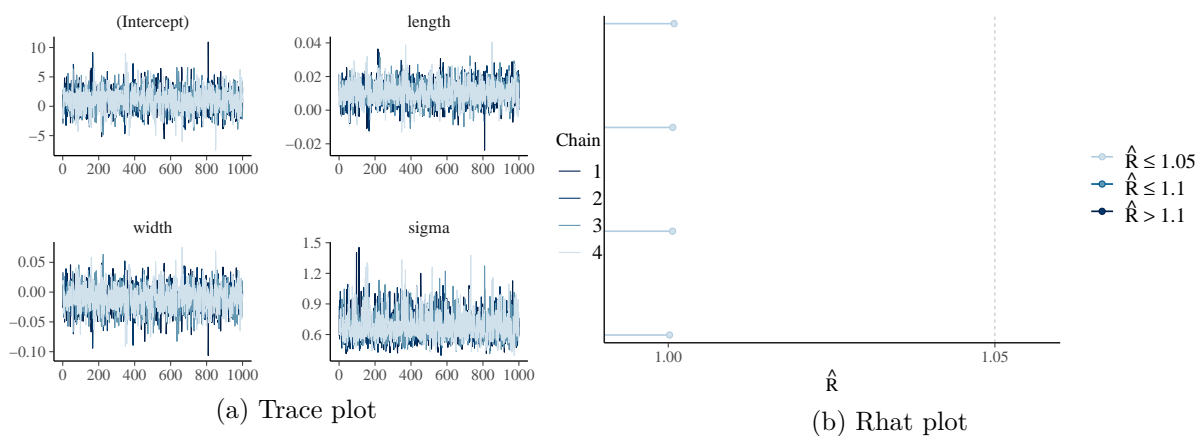


Figure 3: Checking the convergence of the MCMC algorithm

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/>.