Hierarchical Bayesian Time Series Model for Transportation Planning Use

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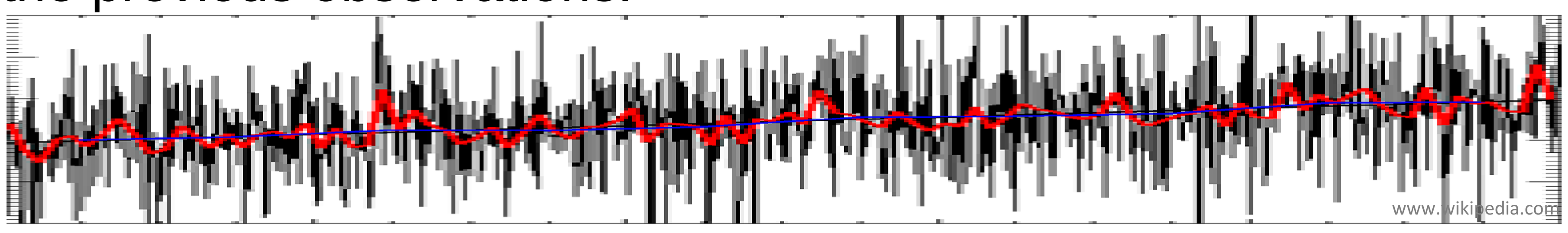
Introduction

Time series analysis as a technique that deals with data collected sequentially in time has been used extensively in transportation research in various areas such as traffic operations [1], transport planning [2], air transport [3], safety, environment [4], etc.

Time series analysis is used to identify the characteristics and nature of the phenomenon and to predict future values based on the previous observations.



Motivation

Modelling Approaches

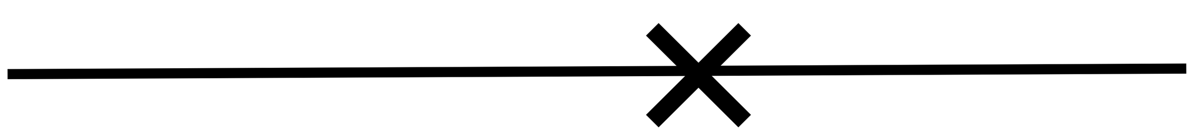
Frequentist	Bayesian
▪ Determines a fixed value for parameters	▪ Determines a posterior distribution for parameters
Dominant approach due to lower computation effort	Difficult to undertake with high computation effort
Does not impose modeler's knowledge Not precise non-gaussian process	Impose modeler's knowledge as the prior distribution Handle uncertainty better

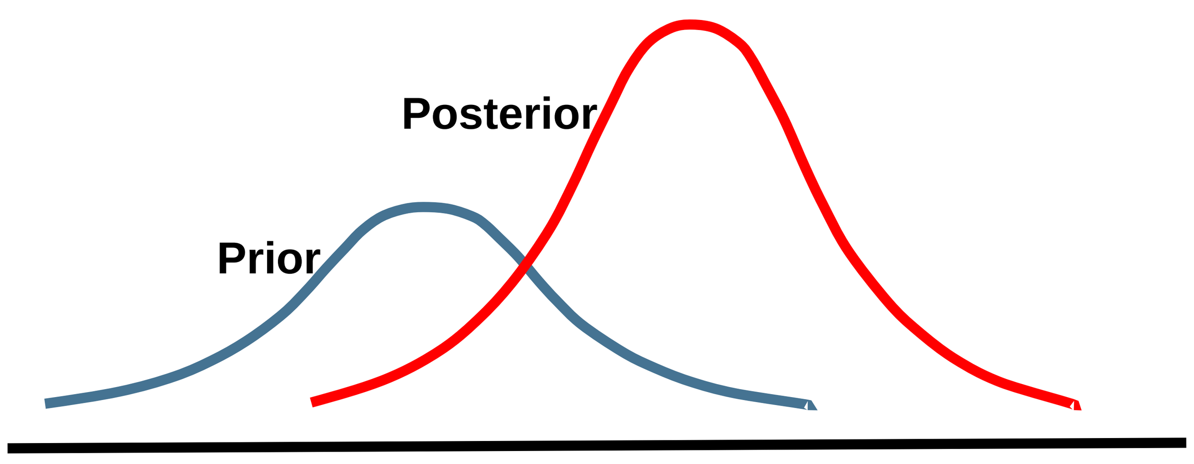
Box-Jenkins backshift operator **Observations** **Model intercept** **Error**

$$\left(\mathbf{1}-\boldsymbol{\phi}_{\mathbf{1}}\,\mathbf{B}-\cdots-\boldsymbol{\phi}_{\boldsymbol{p}}\boldsymbol{B}^{\boldsymbol{p}}\right)(\mathbf{1}-\boldsymbol{B})^{\boldsymbol{d}}\boldsymbol{Y}_{\boldsymbol{t}}=\boldsymbol{c}+\left(\mathbf{1}-\boldsymbol{\theta}_{\mathbf{1}}\,\mathbf{B}-\cdots-\boldsymbol{\theta}_{\boldsymbol{q}}\boldsymbol{B}^{\boldsymbol{q}}\right)\boldsymbol{a}_{\boldsymbol{t}}$$

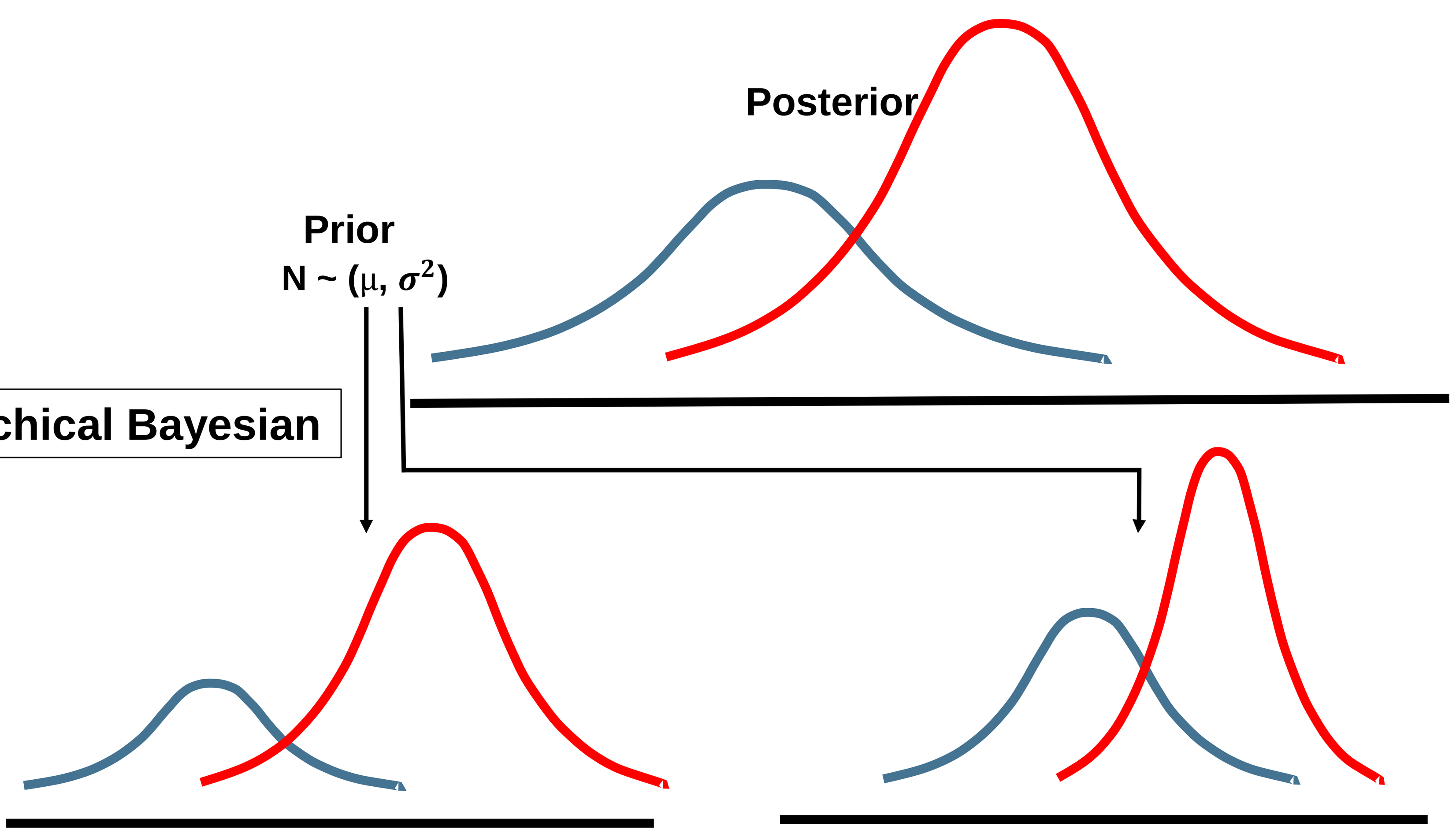
Autoregressive parameters **Moving average parameters**

Frequentist





Bayesian



Hierarchical Bayesian

Objective

Develop a hierarchical Bayesian model for time series prediction using Gibbs sampling and Metropolis-Hasting algorithm as a kind of MCMC method

- Better performance for small sample size
- Handle heteroscedasticity

Model Formulation

Metropolis-within-Gibbs- (MWG) model

$$f(\theta|y) \propto f(y|\theta)f(\theta)$$

$$\theta \sim f(\theta|\nu)$$

$$\nu \sim f(\nu|\nu^*) \qquad \mathrm{P(accept)} = \alpha = \min\left(\frac{f(\theta^*)q(\theta^*,\theta_{t-1})}{f(\theta_{t-1})q(\theta_{t-1},\theta^*)},1\right)$$

Result and Discussion

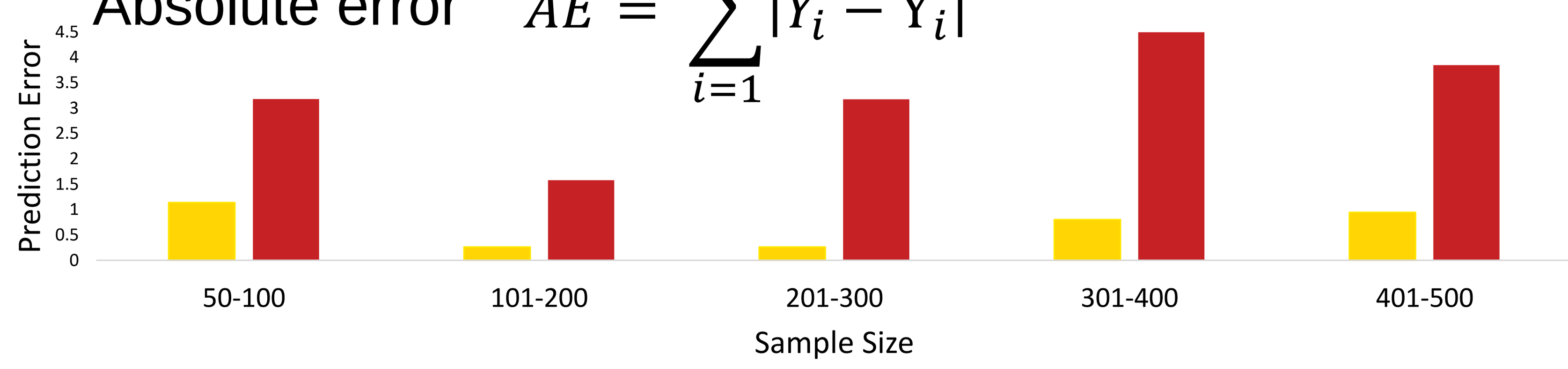
Controlled Experiment

- 450 time series datasets were generated
  length of 50 data points up to 500 data points

$$y_t = \phi_1\, y_{t-1} + \phi_2\, y_{t-2} + e_t$$

- Experiment was conducted 100 times to reduce randomness

Absolute error $AE = \sum_{i=1}^{n} |Y_i - \bar{Y}_i|$

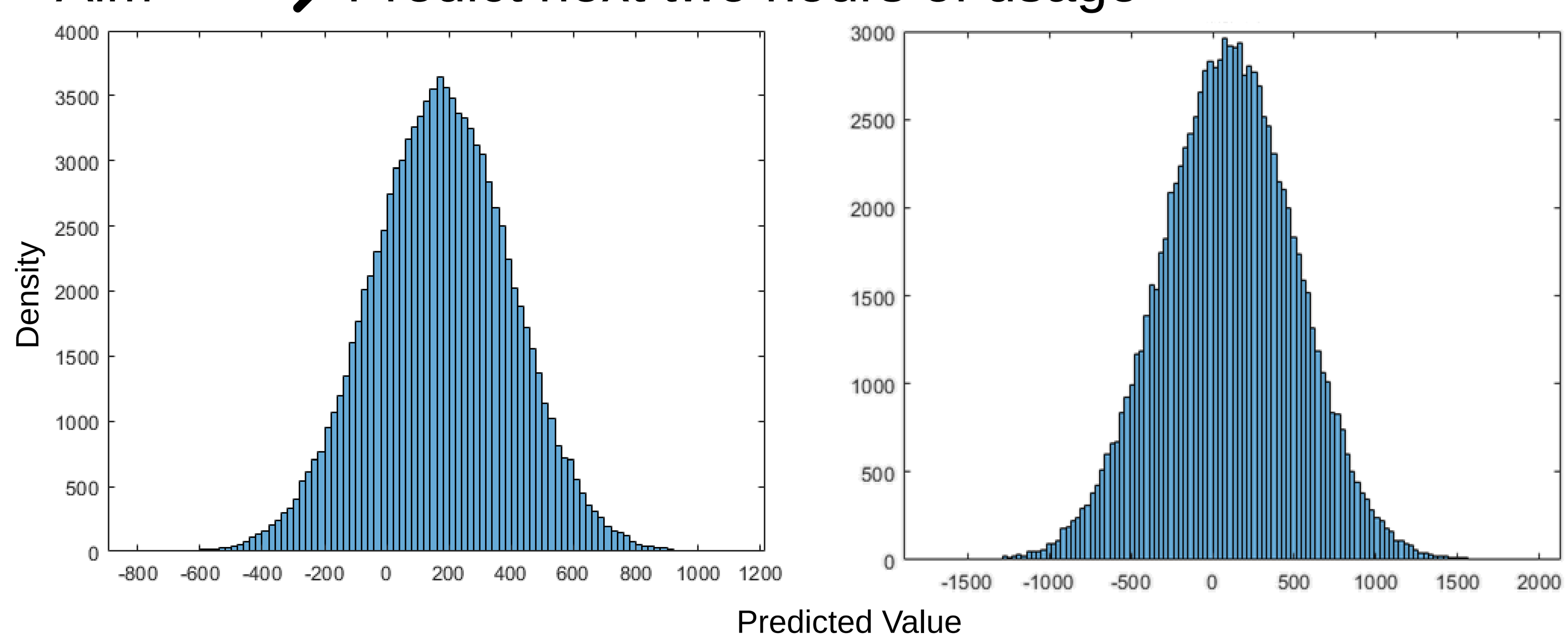


Case Study

Cycling Infrastructure usage

Data ⟶ Bike count data from Seattle

Aim ⟶ Predict next two hours of usage



Observed Value	168	Observed Value	110
Bayesian	175.57	Bayesian	98.30
Frequentist	133.88	Frequentist	89.27

Conclusion

- Improve prediction accuracy for small sample size
- Handle Heteroscedasticity
- More transparent as modeler can impose prior knowledge

Decision makers and planners on transport projects

■ Limited available data ■ Heteroscedastic data

References

[1] Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y. (2015). Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. *Transportation Research Part C: Emerging Technologies*, *54*, 187-197.

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[4] Gokhale, S., & Khare, M. (2004). A review of deterministic, stochastic and hybrid vehicular exhaust emission models. International Journal of Transport Management, 2(2), 59-74.