# Forecasting Robbery in Chicago

Team #5: Irsa, Ryoya, Taka, Sarah
Time Series Analysis and Forecasting





#### Our Team



**Ryoya Hashimoto** 



Irsa Ashraf



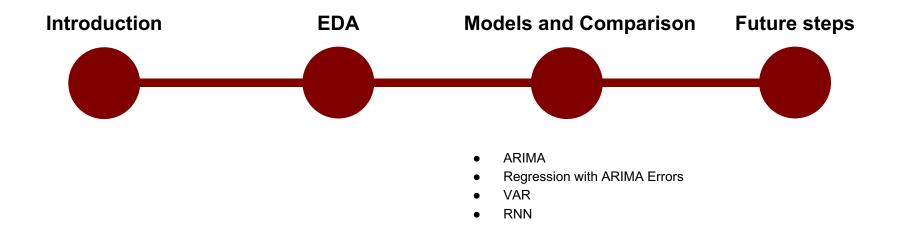
Taka Nitta



**Sarah Lueling** 

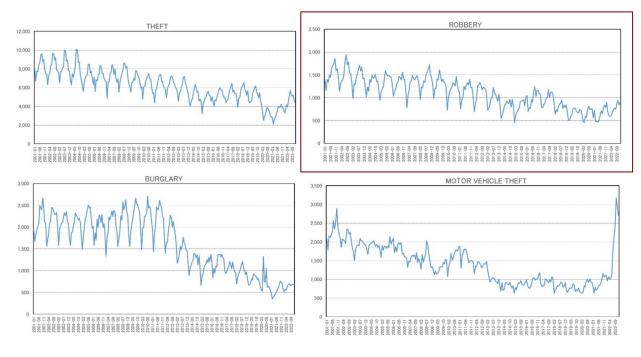


## Today's Agenda





## Why did we select robbery?



- Theft/Burglary:
   Dramatic change in seasonal pattern since the pandemic
- Motor vehicle theft: Huge spike in 2022
- Robbery: Relatively stable and unbiased

Source: Chicago Data Portal



#### Dataset

Data	Source	Note	
Robbery cases	Chicago Data Portal	-	
Unemployment rate	Bureau of Labor Statistics	Chicago-Naperville-Arlington Heights IL Metropolitan Division	
Average temperature	National Oceanic and Atmospheric	-	
Average precipitation	Administration	-	
Average snowfall		-	
Rainy days		Count days of > 0.1 inches	
Snowy days		Count days of > 0.1 inches	

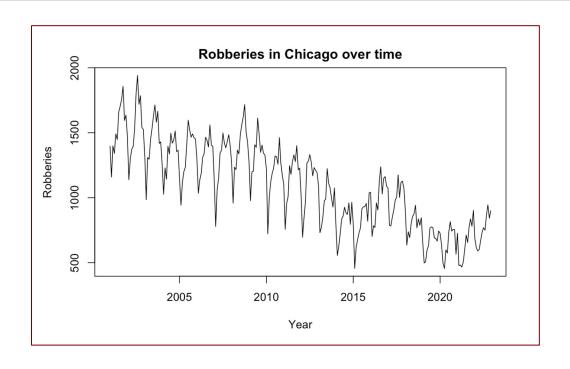
#### Period

Training Set: 2001 Jan - 2021 Dec Test Set: 2022 Jan - 2022 Dec

Frequency: Monthly



## **Analyzing Dataset**



- Downwards trend
- Annual seasonality (additive)
- Non-stationary data



#### **Data Transformation**

To transform to stationary data, we need to apply the following:

- 1. Box-cox transformation (lambda=0.3580306)
- 2. First order and seasonal differencing

#### 

## 

Time

2010

2015

2020

2005

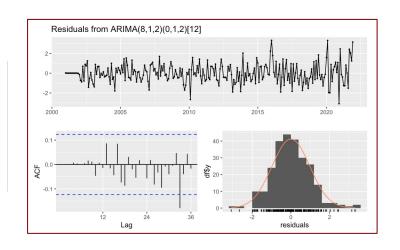
**Stationary Dataset** 



#### sArima Model

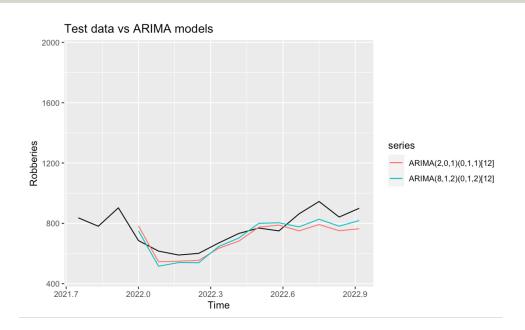
**Best manual model:** ARIMA(4,1,2)(2,1,3)[12]

Liung-Box p=0.20





#### sARIMA Forecast



**ARIMA (2,0,1)(0,1,1)** RMSE = 84.85595, MAE = 73.17060 **ARIMA (8,1,2)(0,1,2)** RMSE = 74.37062, MAE = 67.13100

#### **Takeaway**

- Best ARIMA (8,1,2)(0,1,2)
- Manual model performs better
- Auto.generated model not always best model



#### Regression with ARIMA Errors

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + n_t,$$

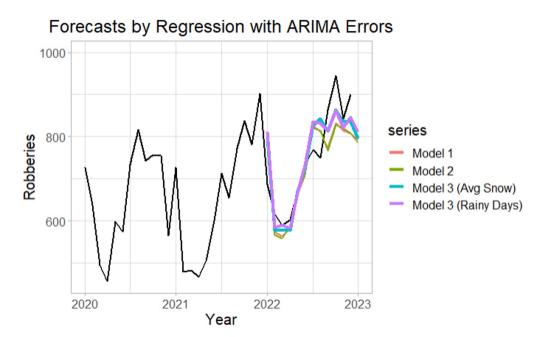
Where:  $n_t$  follows an ARIMA model (i.e.,  $\phi(B)n_t = \theta(B)e_t$ )

Source: Lecture 7 Slide 14

- Model : ARIMA(1,0,1)(0,1,1)[12] (Selected by auto.arima)
- Different Combinations of independent variable(s)
- Box-cox transformed all dependent and independent variables



## Regression with ARIMA Errors



Source: Chicago Data Portal, Bureau of Labor Statistics, NOAA

Model 1: Average Temperature, Rainy Days, Snowy days, Unemployment Rate

RMSE = 66.54 MAE = 55.96

Model 2: Average Temperature, Precipitation, Snowfall, Unemployment Rate

RMSE = 66.89 MAE = 55.59

Model 3: Pick up One Variable

Best RMSE = 57.76 (Avg Snowfall)

Best MAE = 44.66 (Rainy Days)



#### **VAR Model**

#### Variable selection by checking correlations

	ROBBERY	avg_temp	snowy_days	rainy_days	unemp
ROBBERY	1.00000000	0.22921873	-0.23893068	-0.0863701092	0.0755475288
avg_temp	0.22921873	1.00000000	-0.79305332	0.2542184083	0.0473275317
snowy_days	-0.23893068	-0.79305332	1.00000000	-0.1212782183	0.0128097485
rainy_days	-0.08637011	0.25421841	-0.12127822	1.0000000000	0.0007460362
unemp	0.07554753	0.04732753	0.01280975	0.0007460362	1.0000000000



#### **VAR: Models Implemented**

- **1. Model 1**: Robbery and Average Temperature
- 2. Model 2: Robbery and Snowy Days
- **3. Model 3**: Robbery and Unemployment
- 4. Model 4: Robbery, Average Temperature and Unemployment
- 5. Model 5: Robbery, Snowy Days and Unemployment



#### **Model Results**

Model 1: Robbery, Avg

temp

**Rmse:** 167.3 **Mae:** 121.9

Model 2: Robbery,

Snowy Days Rmse: 173.9 Mae: 125.0 Model 3: Robbery, Unemployment

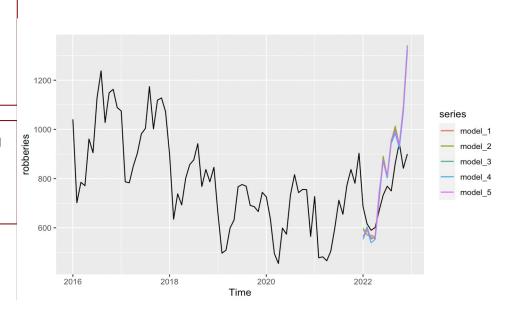
**Rmse:** 172.3 **Mae:** 123.8

**Model 4:** Robbery, Avg temp, Unemployment

Rmse: 164.8 Mae: 121.8

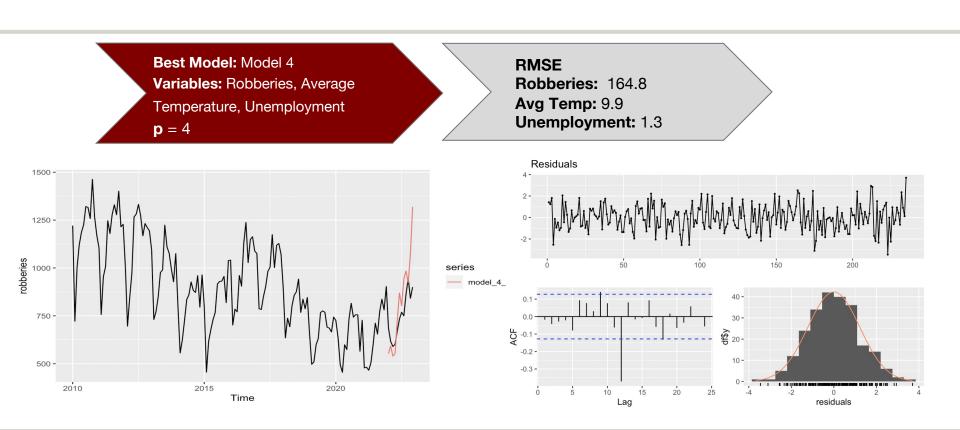
**Model 5:** Robbery, Snowy Days, Unemployment

Rmse: 171.8 Mae: 125.1





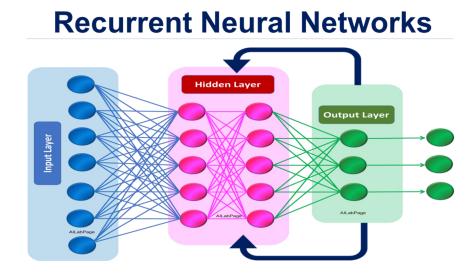
#### **VAR: Best Model**





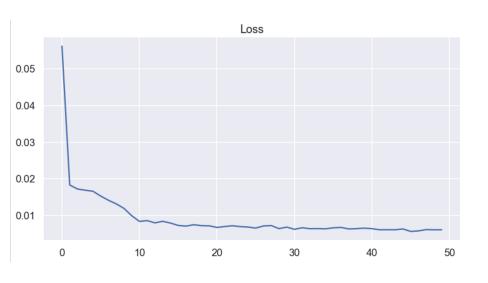
#### Recurrent Neural Network (LSTM)

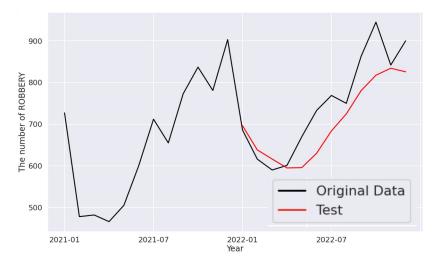
- RNN produce predictive results in sequential data.
- Compared to conventional RNN, LSTM is able to retain past information even longer.





## Recurrent Neural Network (LSTM)





Epoch Size: 50

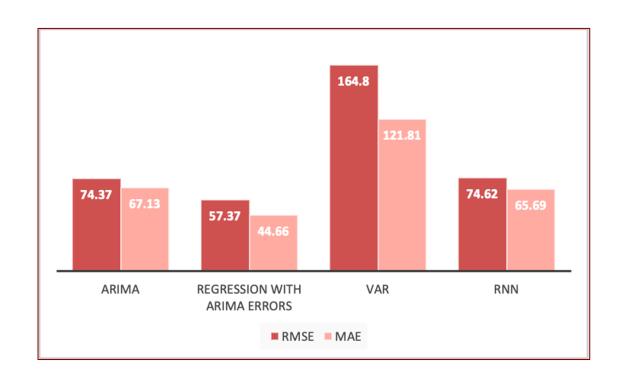
Look Back Period: 12

RMSE = 74.600, MAE = 65.692



#### Comparison of each model

- Lowest RMSE:
   Regression with ARIMA errors we include relevant independent variables
- Similar RMSE for exponential smoothing, sARIMA and RNN





#### Conclusion & Next Steps

#### Conclusion: Simpler is better

- Regression with ARIMA Errors have better score
- Complex models (VAR and RNN) have larger errors

#### Next Steps

- Intervention analysis with shocks such as Covid
- Include other criminal data such as Burglary
- Try Expanding Window or Sliding Window



## **Questions?**

