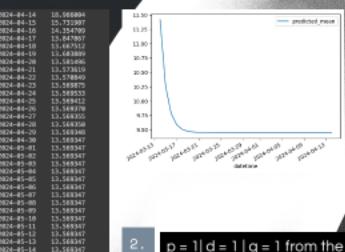


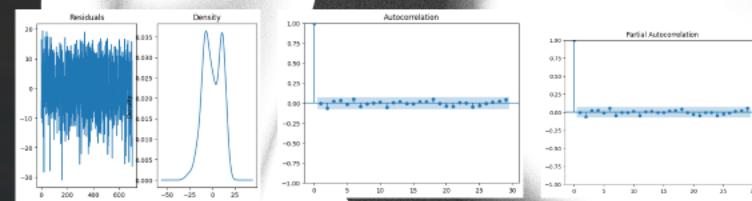
# ARIMA

```
ARIMA(1,1,1) Fit on log-transformed data
Date: 2024-04-10 10:00:00
Model: ARIMA(1,1,1)
Log Likelihood: -2054.400
AIC: 4108.800
BIC: 4120.818
HQIC: 4108.818
Covariance Type: opg
p-value: 0.0000000000000002
wllf: 0.0000000000000002
qstat: 0.0000000000000002
aic: 4108.800
bic: 4120.818
hqic: 4108.818
Ljung-Box (Q): 0.00 (Jarque-Bera LjB): 200.00
Pr(Q): 0.00
Pr(LjB): 0.00
Hannan-Quinn (HQ): 40.00
Pr(HQ): 0.00
Ksprob: 0.74
```

This class of ARIMA models has a general term  $\text{ARIM}(p, d, q)$  that includes three components (or terms): autoregressive (AR), integrated (or differencing), and moving average (MA) terms with the corresponding order of  $p$ ,  $d$ , and  $q$ . The magnitude of temporal correlation exhibited in the time series will determine the AR and MA terms while the differencing term can transform a nonstationary series to be stationary.



1.  $p = 1 | d = 1 | q = 1$  from the ACF and PACF plots as well as the AIC and BIC values based on Python model fit.



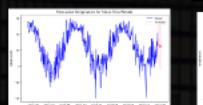
2. **Residuals** should be white noise and make sure not to display seasonality.

## MATH 546-01: INTRODUCTION TO TIME SERIES:



### SARIMAX

SARIMAX (Seasonal Autoregressive Integrated Moving Average) is a generalization of the ARIMA model to include seasonal data. It adds seasonal data to independent variables of any possible periodicity.



### FUTURE WORK



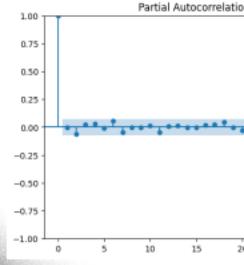
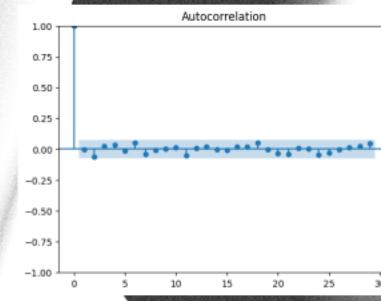
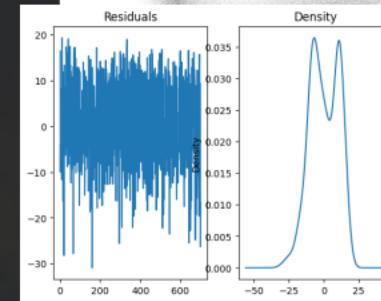
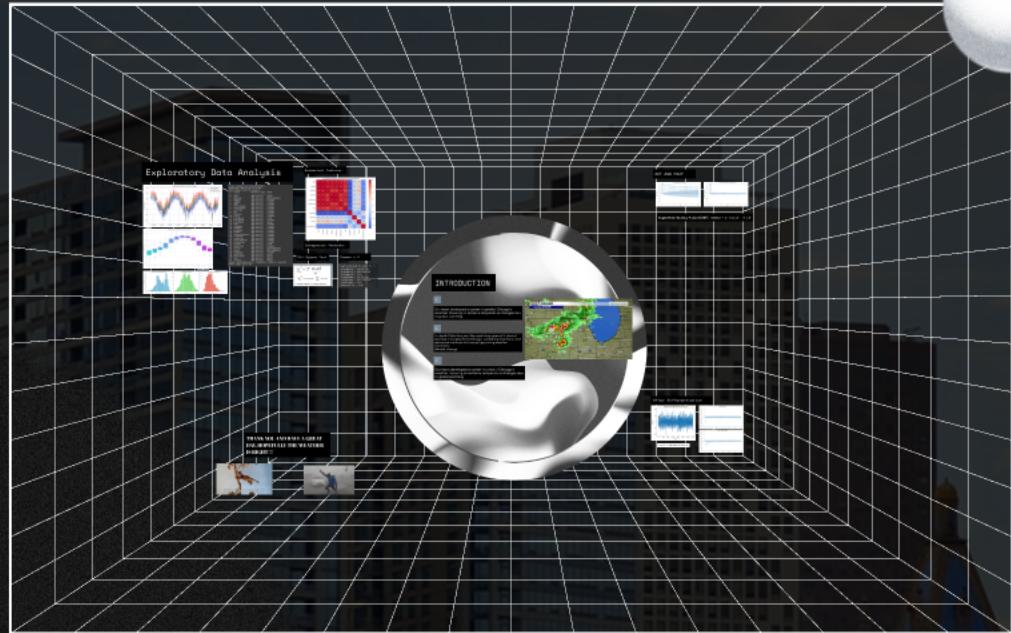
- A wider array of data is to be included for more accurate predictions.
- Add categorical features in the model.
- Integrate machine learning model.

## Chicago Climate Forecasting

Priyadarshini Rajendran | A20476470 | Kyung Jin Kwak | A20497336 |  
Shwetha Srinivasan | A20514543 |



## MATH 546-01: INTRODUCTION TO TIME SERIES:



# Chicago Climate Forecasting

Priyadarshini Rajendran | A20476470 | Kyung Jin Kwak | A20497336 |  
Shwedha Srinivasan | A20514543 |

# INTRODUCTION

1.

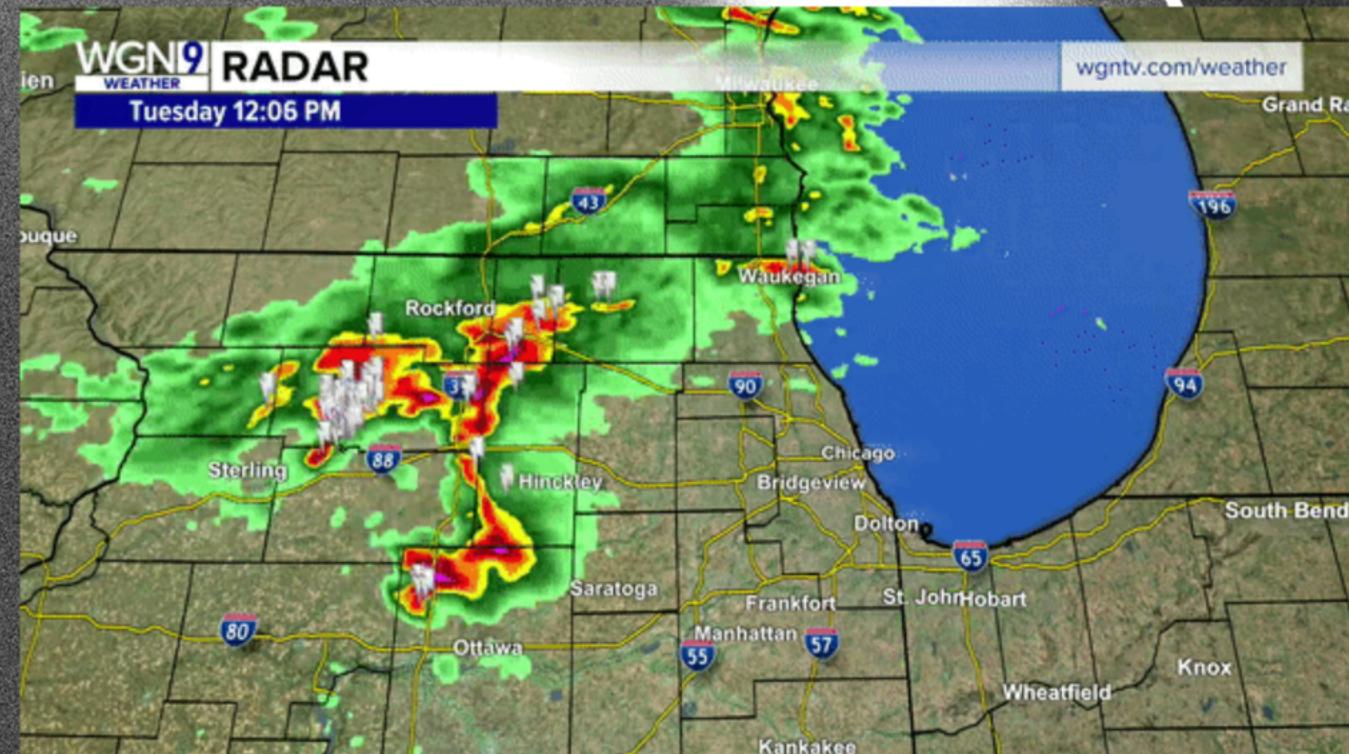
Our team developed a system to predict Chicago's weather, focusing on extreme temperature changes due to global warming.

2.

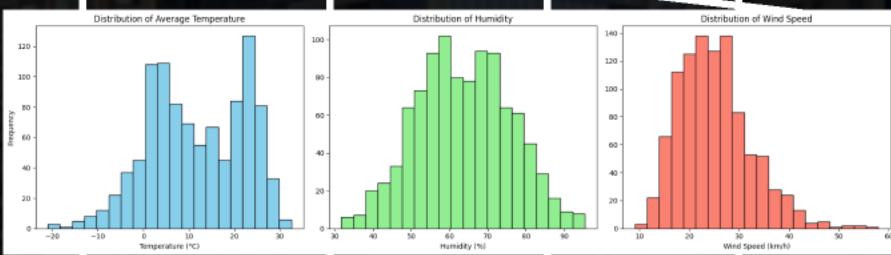
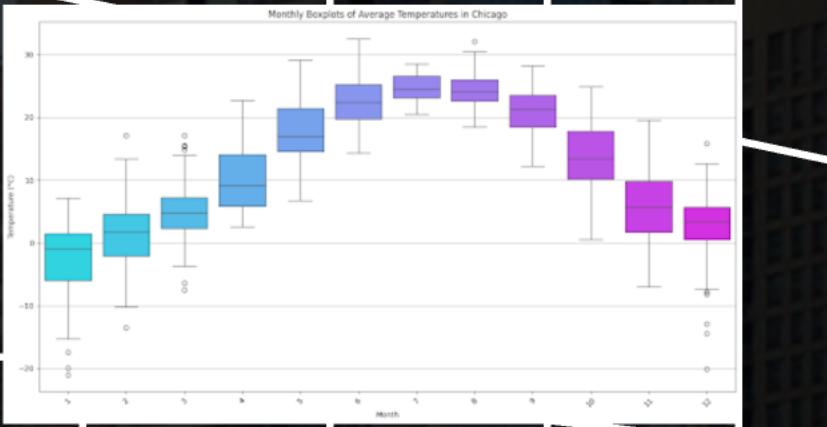
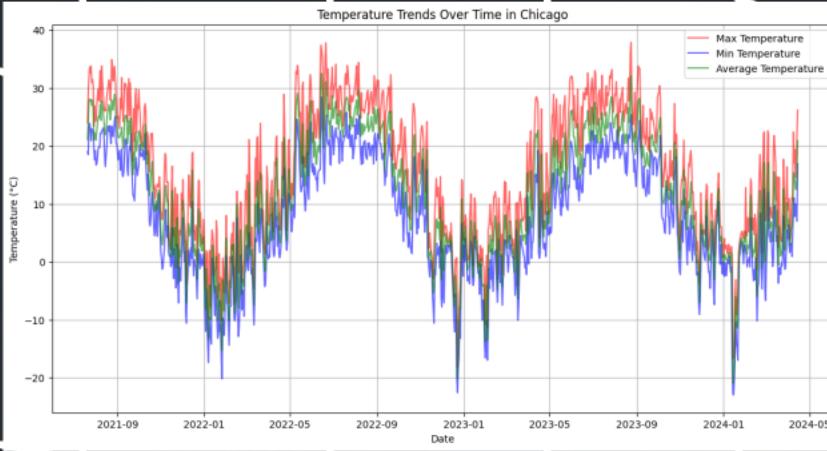
In-depth Data Analysis: We used three years of historical and real-time data from Chicago, combining traditional and advanced methods to forecast upcoming weather conditions.  
climate change.

3.

Our team developed a system to predict Chicago's weather, focusing on extreme temperature changes due to global warming.

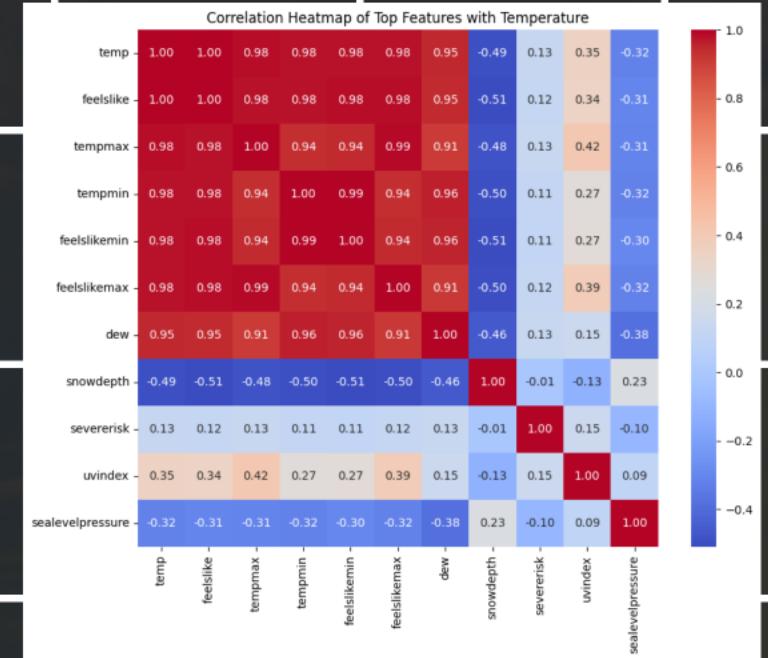


# Exploratory Data Analysis



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 0 to 998
Data columns (total 33 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   name             999 non-null    object  
 1   datetime         999 non-null    datetime64[ns]
 2   tempmax          999 non-null    float64 
 3   tempmin          999 non-null    float64 
 4   temp              999 non-null    float64 
 5   feelslikemax     999 non-null    float64 
 6   feelslikemin     999 non-null    float64 
 7   feelslike         999 non-null    float64 
 8   dew               999 non-null    float64 
 9   humidity          999 non-null    float64 
 10  precip            999 non-null    float64 
 11  precipprob       999 non-null    int64   
 12  precipcover      999 non-null    float64 
 13  preciptype        558 non-null   object  
 14  snow              999 non-null    float64 
 15  snowdepth         999 non-null    float64 
 16  windgust          999 non-null    float64 
 17  windspeed         999 non-null    float64 
 18  winddir            999 non-null    float64 
 19  sealevelpressure  999 non-null    float64 
 20  cloudcover        999 non-null    float64 
 21  visibility         999 non-null    float64 
 22  solarradiation    999 non-null    float64 
 23  solarenergy        999 non-null    float64 
 24  uvindex            999 non-null    int64  
 25  severerisk         826 non-null   float64 
 26  sunrise            999 non-null    datetime64[ns]
 27  sunset             999 non-null    datetime64[ns]
 28  moonphase          999 non-null    float64 
 29  conditions          999 non-null   object  
 30  description         999 non-null   object  
 31  icon               999 non-null   object  
 32  stations            999 non-null   object  
dtypes: datetime64[ns](3), float64(22), int64(2), object(6)
memory usage: 257.7+ KB
```

## Numberical Features:



## Categorical Features:

### Chi-Square Test

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

$\chi^2$  = the test statistic     $\sum$  = the sum of

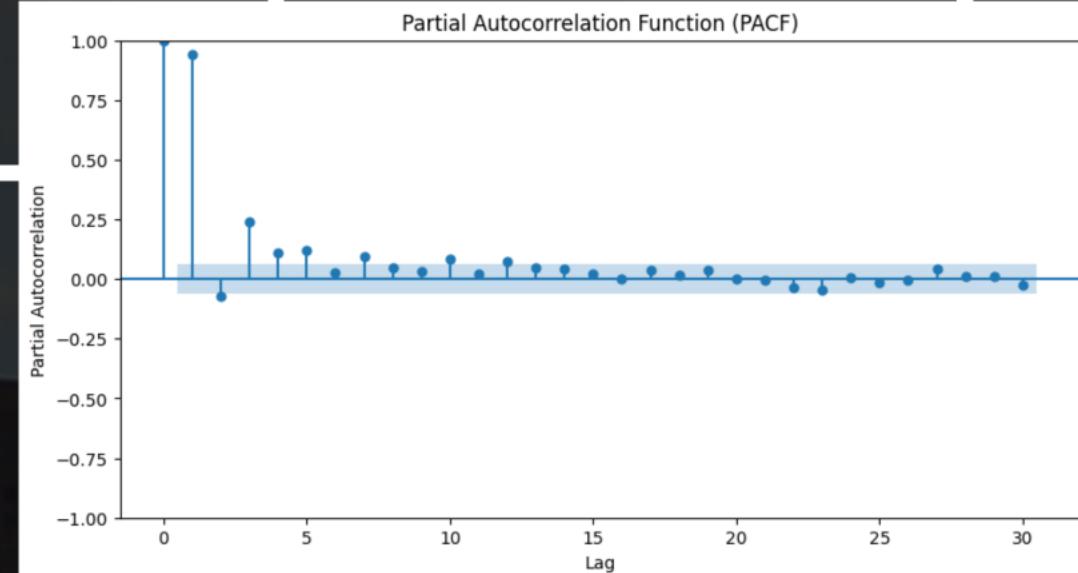
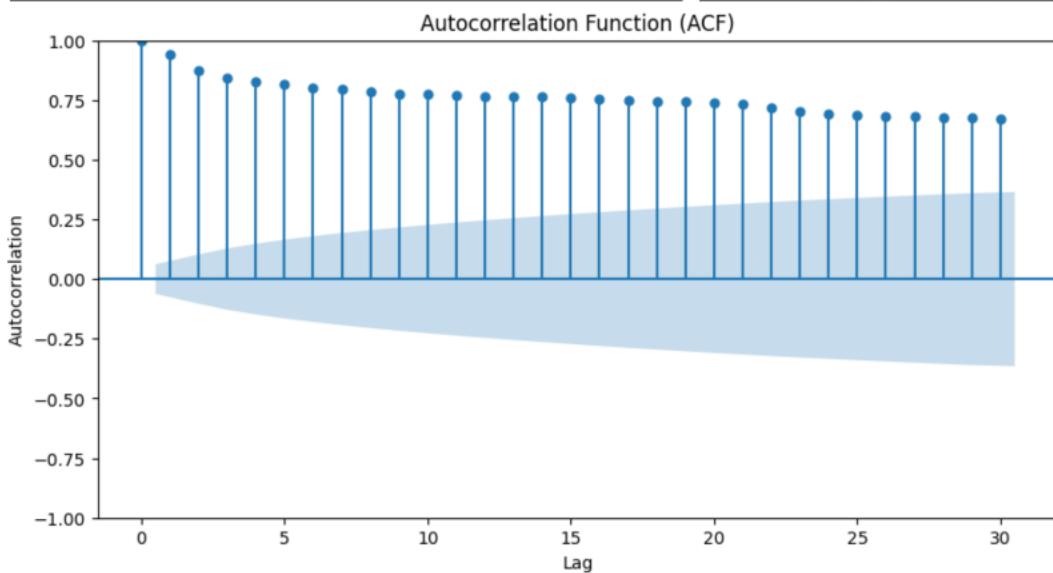
O = Observed frequencies    E = Expected frequencies

### Cramer's V

Highly Related Variable Pairs:

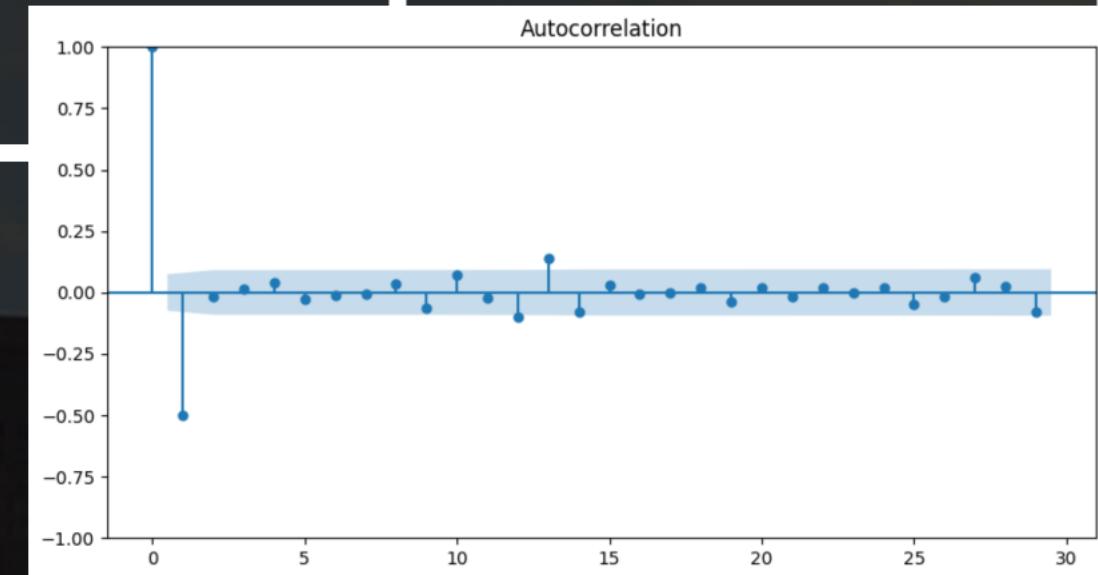
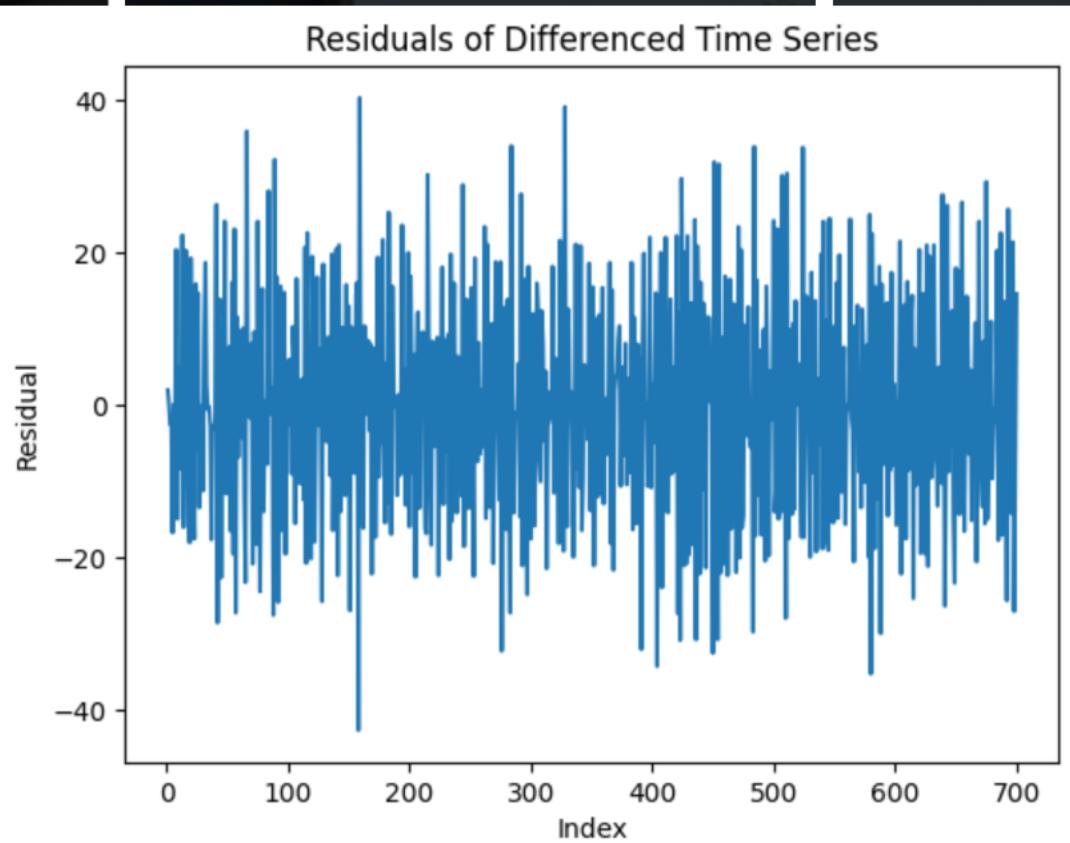
- 'precipprob - conditions'
- 'precipprob - description'
- 'precipprob - icon'
- 'preciptype - conditions'
- 'conditions - description'
- 'conditions - icon'
- 'description - icon'

# ACF AND PACF



Augmented Dickey-Fuller (ADF) method → p-value: 0.19

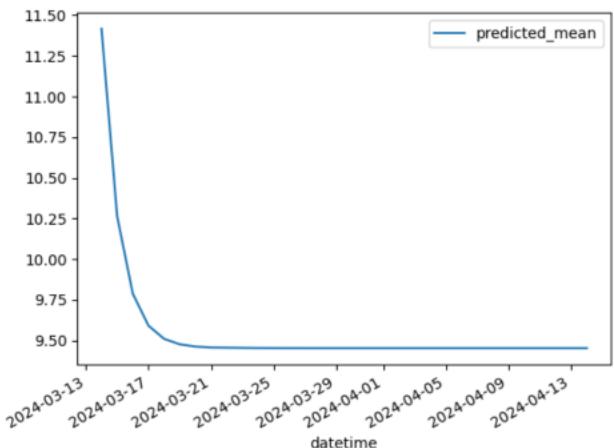
# After Differentiation



p-value: 2.480128867451355e-21

# ARIMA

2024-04-14	18.966004
2024-04-15	15.731907
2024-04-16	14.354709
2024-04-17	13.847867
2024-04-18	13.667512
2024-04-19	13.603889
2024-04-20	13.581496
2024-04-21	13.573619
2024-04-22	13.570849
2024-04-23	13.569875
2024-04-24	13.569533
2024-04-25	13.569412
2024-04-26	13.569370
2024-04-27	13.569355
2024-04-28	13.569350
2024-04-29	13.569348
2024-04-30	13.569347
2024-05-01	13.569347
2024-05-02	13.569347
2024-05-03	13.569347
2024-05-04	13.569347
2024-05-05	13.569347
2024-05-06	13.569347
2024-05-07	13.569347
2024-05-08	13.569347
2024-05-09	13.569347
2024-05-10	13.569347
2024-05-11	13.569347
2024-05-12	13.569347
2024-05-13	13.569347
2024-05-14	13.569347



1.

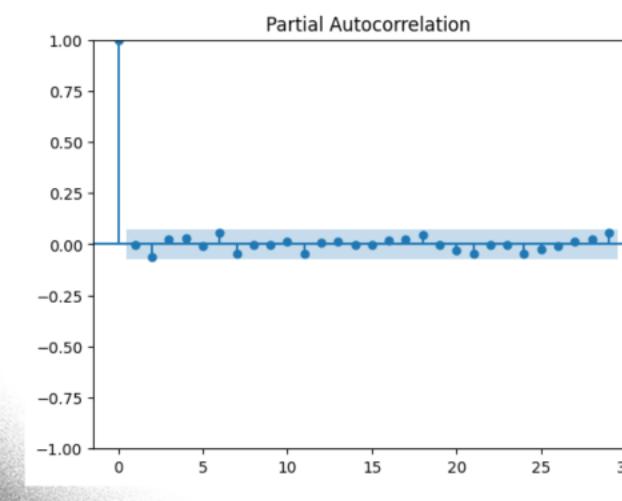
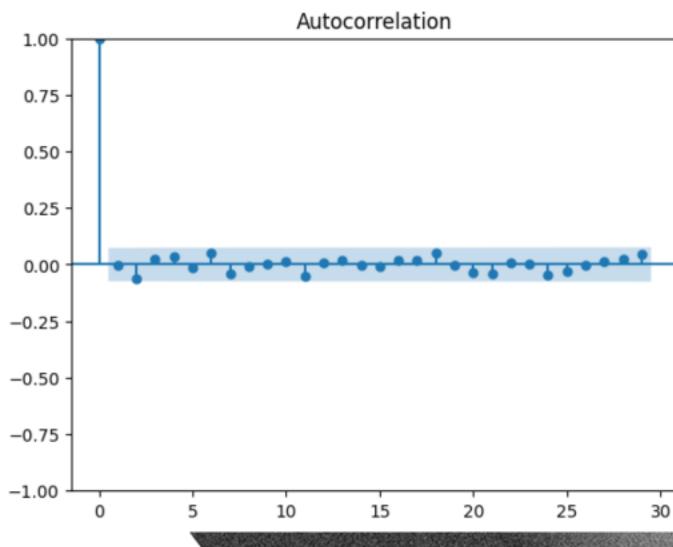
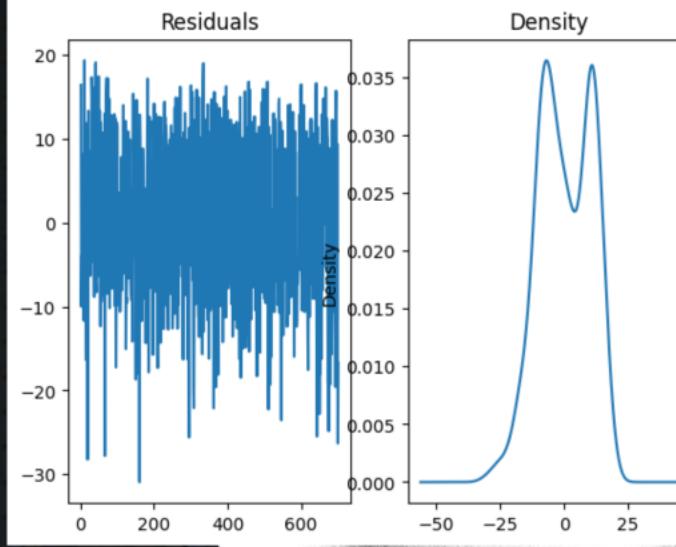
This class of ARIMA models has a general term  $\text{ARIMA}(p, d, q)$  that includes three components (or terms): autoregressive (AR), integrated (or differencing), and moving average (MA) terms with the corresponding order of p, d, and q. The magnitude of temporal correlation exhibited in the time series will determine the AR and MA terms while the differencing term can transform a nonstationary series to be stationary

```
from statsmodels.tsa.arima.model import ARIMA
model = ARIMA(train['temp'],order=(1,1,2))
model = model.fit()
model.summary()
```

Dep. Variable:	temp	No. Observations:	846	
Model:	ARIMA(1, 1, 2)	Log Likelihood:	-2258.480	
Date:	Fri, 26 Apr 2024	AIC:	4524.960	
Time:	00:01:31	BIC:	4543.918	
Sample:	0	HQIC:	4532.224	
	- 846			
Covariance Type:	copg			
coef	std err	z	P> z	[0.025 0.975]
ar.L1	0.4129	0.061	6.723	0.000 0.293
ma.L1	-0.4801	0.061	-7.880	0.000 -0.600
ma.L2	-0.3403	0.041	-8.373	0.000 -0.420
sigma2	12.2675	0.397	30.938	0.000 11.490
Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	306.58	
Prob(Q):	0.96	Prob(JB):	0.00	
Heteroskedasticity (H):	0.79	Skew:	-0.55	
Prob(H) (two-sided):	0.05	Kurtosis:	5.74	

2.

$p = 1 | d = 1 | q = 1$  from the ACF and PACF plots as well as the AIC and BIC values based on Python model fit.



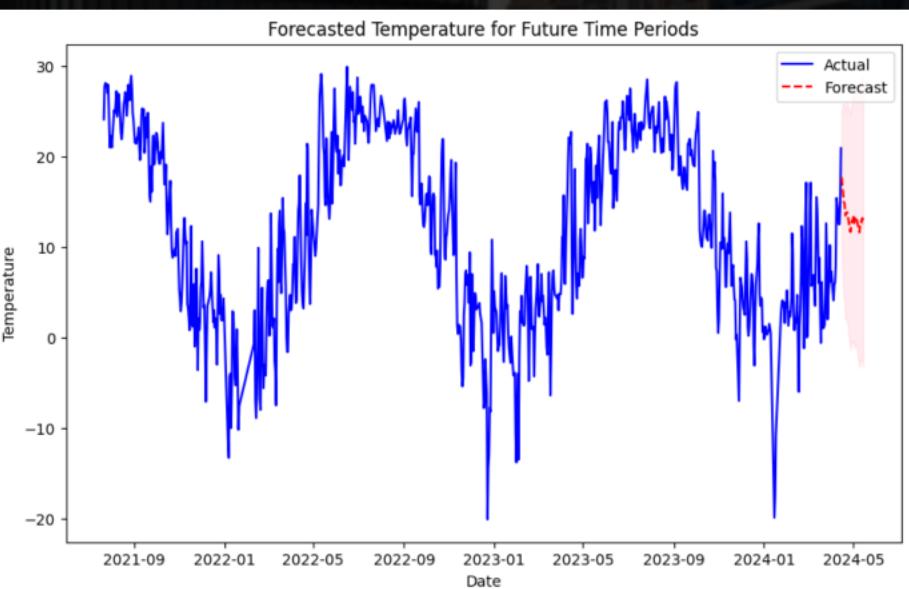
3.

Residuals should be white noise and make sure not to display seasonality.

# SARIMAX

1.

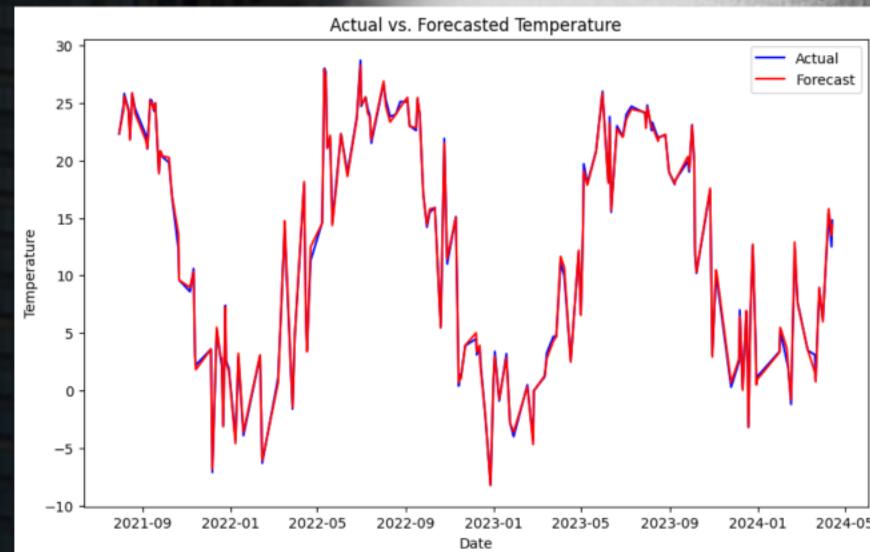
SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Variables) is an extension of the ARIMA model that incorporates additional variables, known as exogenous variables or regressors, into the model.



2.

The (P,D,Q,M) Order refers to the seasonal component of the model for the Auto Regressive parameters, differences, Moving Average parameters, and periodicity:

- D indicates the integration order of the seasonal process (the number of transformation needed to make stationary the time series)
- P indicates the Auto Regressive order for the seasonal component
- Q indicated the Moving Average order for the seasonal component
- M indicates the periodicity, i.e. the number of periods in season, such as 12 for monthly data.



	Date	Temperature
876	2024-04-15	17.679708
877	2024-04-16	16.735517
878	2024-04-17	15.844386
879	2024-04-18	14.930744
880	2024-04-19	14.791846
881	2024-04-20	13.477907
882	2024-04-21	13.800308
883	2024-04-22	13.720334
884	2024-04-23	13.772164
885	2024-04-24	13.069728
886	2024-04-25	12.550053
887	2024-04-26	12.055914
888	2024-04-27	11.650195
889	2024-04-28	12.501227
890	2024-04-29	12.911662
891	2024-04-30	12.850900
892	2024-05-01	13.318255
893	2024-05-02	12.631241
894	2024-05-03	13.168284
895	2024-05-04	13.225209
896	2024-05-05	13.341076
897	2024-05-06	12.731912
898	2024-05-07	12.345577
899	2024-05-08	12.082945
900	2024-05-09	11.613497
901	2024-05-10	12.424509
902	2024-05-11	12.805104
903	2024-05-12	12.724904
904	2024-05-13	13.178164
905	2024-05-14	12.475019

# FUTURE WORK

1. A wider array of data is to be included for more accurate predictions.
2. Add categorical features in the model.
3. Integrate machine learning model.



**THANK YOU AND HAVE A GREAT  
DAY, HOPEFULLY THE WEATHER  
IS RIGHT!!!**

