

Laboratory Oriented Project

Final End Semester Report

Predictive Analysis of Spatiotemporal Data



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Introduction

Spatiotemporal data, the fusion of spatial and temporal information, provides invaluable insights into the dynamic nature of various phenomena. It is characterised by its ability to capture the evolution of events and occurrences across both space and time. In our study, we delve into the realm of spatiotemporal data analysis with a focus on understanding and analysing the number of chickenpox cases in different states of Hungary over a ten-year period, spanning from 2004 to 2014, on a weekly basis. This project represents an attempt to harness the power of advanced statistical and machine learning models to forecast future trends, specifically for the year 2015 and beyond.

Problem Statement: Predicting Future Trends

The central problem addressed in this study is the prediction of future chickenpox cases in the various states of Hungary. The aim is to establish a reliable predictive model that can effectively forecast the occurrence of these cases based on the historical data we have at our disposal. To achieve this, we will employ a range of analytical techniques, including time-honoured statistical methods and modern machine learning algorithms, on our spatiotemporal data.

Motivation: Comparative Study of ARIMA and STGCN Models

Our motivation stems from the intriguing prospect of comparing two distinct predictive models—ARIMA (AutoRegressive Integrated Moving Average), a classical time series forecasting model, and STGCN (Spatiotemporal Graph Convolutional Network), a cutting-edge deep learning model. The choice to juxtapose these models is grounded in the fact that ARIMA has long been a reliable workhorse in time series analysis, whereas STGCN represents a new-age approach that incorporates spatial dependencies into the prediction process.

To the best of our knowledge, no comprehensive comparative study has been conducted to assess the effectiveness and accuracy of these two models in the context of spatiotemporal data analysis. This novel comparison promises to offer valuable insights into their strengths,

limitations, and applicability, shedding light on which model, if any, is better suited for predicting the future trends of chickenpox cases in Hungary.

Significance of the Study

This study holds several notable implications. Firstly, it contributes to the growing body of research on spatiotemporal data analysis, offering a real-world application in the realm of public health. Additionally, it aids healthcare authorities in Hungary by potentially improving their ability to anticipate and prepare for disease outbreaks, thereby facilitating more efficient resource allocation.

Limitations

While our study presents a unique opportunity to evaluate the performance of ARIMA and STGCN models, we acknowledge that these are just two among a plethora of techniques available for spatiotemporal data analysis. Limitations arise from the focused nature of this comparative analysis, as there may be other models and methods that could yield equally compelling results. However, the selection of ARIMA and STGCN models has been made in the interest of time and the scope of this study, with the intention of providing a solid foundation for further exploration in the field of spatiotemporal data analysis.

In the following sections, we will detail our methodology, results, and findings, with the ultimate aim of contributing to the understanding and practical utility of spatiotemporal data analysis in the prediction of disease outbreaks.

Literature Review

A. Overview of Predictive Analysis

Predictive analysis serves as a fundamental tool in addressing complex issues, with many studies focusing on the prediction of traffic flows, taxi counts, and transportation-related challenges. The transportation sector faces significant complexities that demand innovative solutions, and a substantial body of research has been dedicated to harnessing the power of spatiotemporal data models for these purposes.

The prediction of traffic patterns, in particular, has emerged as a critical problem necessitating advanced analytical techniques. Traffic congestion, road safety, and efficient transportation management are central concerns in urban and regional planning, which can be alleviated through the insights provided by spatiotemporal data analysis. The intricate interplay of spatial and temporal factors in traffic data makes it a prime candidate for predictive modeling, as traditional methods often fall short in capturing the dynamic nature of these systems.

Spatiotemporal data models have become essential in addressing the challenges associated with transportation, offering the capability to forecast traffic flows, optimize routes, and enhance public transportation systems. The significance of these models extends beyond the realm of transportation, finding application in diverse fields, including epidemiology, environmental monitoring, and natural disaster prediction.

The adoption of spatiotemporal data analysis has emerged not only as a necessity but as a critical enabler for effective decision-making in our increasingly complex and interconnected world. Consequently, this approach has witnessed continuous refinement and innovation to better address the multifaceted challenges presented by spatiotemporal data, making it a pivotal area of research and study.

B. Spatiotemporal Data: Definition and Characteristics

Spatiotemporal data combines spatial and temporal elements to capture the evolution of events and phenomena in a geospatial context. It is characterized by the following key attributes:

1. **Spatial Information:** Spatiotemporal data involves the geographical component, where each data point is associated with specific coordinates or regions.
2. **Temporal Information:** This data type includes timestamps, indicating when each observation occurred.
3. **Dynamic Nature:** Spatiotemporal data is inherently dynamic, as it changes over time and across different locations. Examples include weather data, disease spread, and traffic patterns.
4. **Complex Interactions:** Spatial and temporal factors often interact in intricate ways, and these interactions can have a significant impact on the observed phenomena.
5. **High-Dimensionality:** Spatiotemporal data is high-dimensional, making it challenging to analyze and model accurately.

The study of spatiotemporal data is crucial in various domains, from urban planning and epidemiology to environmental monitoring and transportation management.

C. Tools and Techniques Used in our Analysis

In our analysis, we will leverage two distinct models: the ARIMA model and the STGCN model. The ARIMA model, standing for AutoRegressive Integrated Moving Average, is a time series forecasting model that combines elements from the AutoRegressive (AR) and Moving Average (MA) models. On the other hand, the STGCN model, short for Spatiotemporal Graph Convolutional Network, is an advanced deep learning model that draws from the principles of Convolutional Neural Networks (CNN) and Graph

Convolutional Networks (GCN). To gain a deeper understanding of these models and their underlying mechanisms, it is worthwhile to explore each one individually, shedding light on their unique attributes and applications in spatiotemporal data analysis.

Autoregressive Models (AR)

Autoregressive (AR) models are widely used in time series analysis, including spatiotemporal data. In AR models, future values of a variable are linearly dependent on its past values. An example of an AR(1) model is given by:

$$X_t = \phi X_{t-1} + \epsilon_t \quad (1)$$

Where:

- X_t represents the variable at time t .
- ϕ is the autoregressive coefficient.
- ϵ_t is a white noise error term at time t .

Moving Average Models (MA)

Moving Average (MA) models focus on modelling the relationship between a variable and the past forecast errors. An example of an MA(1) model is as follows:

$$X_t = \epsilon_t + \theta \epsilon_{t-1} \quad (2)$$

Where:

- X_t represents the variable at time t .
- ϵ_t and ϵ_{t-1} are the error terms at time t and $t-1$, respectively.
- θ is the moving average coefficient.

ARIMA Models

ARIMA (AutoRegressive Integrated Moving Average) models combine autoregressive and moving average components, along with differencing to make time series data stationary. An example of an ARMA(1,1) model is:

$$X_t = \phi X_{t-1} + \theta \epsilon_{t-1} + \epsilon_t$$

Where:

- X_t represents the variable at time t .
- ϕ is the autoregressive coefficient.
- θ is the moving average coefficient.
- ϵ_t and ϵ_{t-1} are the error terms at time t and $t-1$, respectively.

Convolutional Neural Networks (CNN)

A Convolutional Neural Network (CNN) is a type of deep learning neural network specifically designed for processing and analyzing structured grid data, such as images and video. CNNs are particularly well-suited for tasks involving pattern recognition, object detection, image classification, and other visual data analysis tasks.

The key components of a CNN include:

Convolutional Layers: These layers apply convolution operations to the input data using a set of learnable filters (kernels). Convolution involves sliding the filters across the input data, which helps identify patterns and features. This operation allows the network to capture local relationships within the data.

Pooling Layers: Pooling layers (typically max-pooling or average-pooling) downsample the output of the convolutional layers, reducing the spatial dimensions of the data while retaining essential information. This reduces computational complexity and helps make the network translation-invariant, allowing it to recognize patterns regardless of their location in the input.

Fully Connected Layers: After several convolutional and pooling layers, fully connected layers are used to make predictions or classifications. These layers connect every neuron to

every neuron in the previous and subsequent layers, allowing the network to learn complex relationships in the data.

CNNs have revolutionized image analysis and computer vision tasks, achieving state-of-the-art results in various applications, including image classification, object detection, facial recognition, medical image analysis, and more. They are a crucial tool in the field of artificial intelligence, particularly for tasks that involve visual data.

Graph Neural Networks (GNN)

A Graph Neural Network (GNN) is a type of neural network architecture designed for processing and analyzing graph-structured data. Graphs are mathematical structures that consist of nodes (vertices) and edges (connections) that define relationships between these nodes. GNNs are particularly well-suited for tasks involving data with complex, interconnected relationships, such as social networks, recommendation systems, biology, transportation networks, and more.

Key components and concepts of GNNs include:

Node Representations: GNNs aim to learn meaningful representations (often referred to as embeddings) for each node in a graph. These representations capture the local and global information of a node within the context of the entire graph.

Graph Convolution: GNNs typically employ a graph convolution operation to update node representations. During this operation, each node aggregates information from its neighboring nodes. This aggregation process is typically guided by the graph's edge structure.

Message Passing: GNNs use a message-passing mechanism to propagate information through the graph. In each layer of the network, nodes exchange information with their neighbors, enabling them to gather knowledge from the surrounding nodes. This iterative process can be performed for multiple layers to capture information from increasingly distant nodes.

Graph Pooling: In some GNN architectures, graph pooling operations are used to downsample the graph, reducing its size while preserving important structural information. This is similar in concept to pooling layers in Convolutional Neural Networks.

GNNs have proven highly effective in various applications where data is naturally represented as graphs, such as social network analysis, recommendation systems, protein-protein interaction prediction, citation networks, and more. They have the ability to capture and model intricate dependencies and interactions within graph-structured data, making them a valuable tool for understanding and making predictions in complex relational data settings.

Spatiotemporal Graph Convolutional Networks (STGCN)

STGCNs are a specialized form of GNN tailored for spatiotemporal data. They consider both spatial and temporal dependencies simultaneously by performing graph convolutions across a spatiotemporal graph. STGCNs have gained prominence in various applications, including traffic prediction, disease spread modeling, and environmental monitoring, due to their ability to capture complex interactions in spatiotemporal data. Let's delve into the details of STGCN and how we plan on applying it to our analysis of chickenpox cases data:

1. **Graph-Based Structure:** STGCN models the spatiotemporal data using a graph-based structure. In this context, the graph typically represents spatial locations (e.g., regions or states) as nodes, and edges represent connections or relationships between these locations. The graph can be directed or undirected, depending on the problem.
2. **Convolutional Layers:** STGCN incorporates convolutional layers that operate on the spatiotemporal graph. These convolutional operations capture spatial dependencies among neighboring locations and temporal dependencies over time. The convolution operation effectively combines information from neighboring nodes to learn features that capture patterns in the data.
3. **Spatiotemporal Information:** STGCN captures both spatial and temporal dependencies simultaneously. It can learn how a specific location's current state is influenced by its

neighboring locations and how this influence changes over time. This makes it well-suited for forecasting problems where the spatial context is crucial for predictions.

4. Long-Range Dependencies: STGCN is designed to capture long-range dependencies, allowing it to identify complex relationships between distant locations over time. This ability is particularly beneficial in scenarios where events at one location affect other locations with a time delay.

5. Flexibility: STGCN can be adapted to various spatiotemporal data applications. You can adjust the network architecture, the number of layers, and other hyperparameters to tailor it to your specific problem.

Applying STGCN to Predict Chickenpox Cases:

To apply STGCN to the analysis of chickenpox cases data in Hungary (from 2004 to 2014), we will follow these steps:

1. Data Preparation: Organize your data, ensuring it's structured in a spatiotemporal format with information on chickenpox cases for different states over time. This is already done as the data that we have is in excel format and is already well organized.
2. Graph Representation: Create a graph that represents spatial relationships among the states. Define edges based on factors such as geographical proximity, population movement, or other relevant criteria. This graph will be the foundation for the STGCN. To do this we will have to delve deeper in the geography of Hungary and their people behave and move across different states.
3. Model Configuration: Set up the STGCN architecture, specifying the number of layers, filter sizes, and other hyperparameters. We can use popular deep learning frameworks like TensorFlow or PyTorch to build our STGCN model.

4.Training: Train the STGCN model using our chickenpox data which we have in excel. The model will learn to capture both spatial and temporal dependencies within the data on its own and help in the predictive analysis.

5.Evaluation: Evaluate the model's performance using appropriate evaluation metrics (e.g., Mean Absolute Error, Root Mean Squared Error). Ensure that the model provides accurate predictions on our test data. We will compare this with the performance of ARIMA model's results and derive a conclusion on how these models performed.

6.Forecasting: Once our model is trained and validated, we will be using it to make forecasts for future periods, including 2015 and beyond. The model will consider the historical spatiotemporal patterns to make predictions that we need.

7. Interpretation: Analyse the model's predictions to gain insights into the expected trends in chickenpox cases in different Hungarian states. This information can be valuable for public health planning and resource allocation.

STGCN's ability to capture complex spatiotemporal dependencies makes it a promising choice for your analysis of chickenpox cases data, particularly when considering the spatial aspects of disease spread.

Methodology

A) Data

A new benchmark dataset called "Chickenpox Cases in Hungary" was proposed by Benedek Rozemberczki in his paper “Chickenpox Cases in Hungary: a Benchmark Dataset for Spatiotemporal Signal Processing with Graph Neural Networks” for comparing graph neural network architectures in spatiotemporal signal processing. The dataset consists of weekly reported chickenpox cases in Hungarian counties and has characteristics such as seasonality and spatial autocorrelation that make it suitable for evaluating the predictive performance of graph neural networks. The paper also presents the major contributions of the work, including the release of the dataset, a descriptive analysis, and performance benchmarks of existing recurrent graph neural network architectures. The related work section provides an overview of the epidemiology of chickenpox and the design of recurrent graph neural network architectures.

	A	B	C	D	E	F	G	H	I	J
1	Date	BUDAPEST	BARANYA	BACS	BEKES	BORSOD	CSONGRA	FEJER	GYOR	HAJDU
2	03-01-2005	168	79	30	173	169	42	136	120	162
3	10-01-2005	157	60	30	92	200	53	51	70	84
4	17-01-2005	96	44	31	86	93	30	93	84	191
5	24-01-2005	163	49	43	126	46	39	52	114	107
6	31-01-2005	122	78	53	87	103	34	95	131	172
7	07-02-2005	174	76	77	152	189	26	74	181	157
8	14-02-2005	153	103	54	192	148	65	100	118	129
9	21-02-2005	115	74	64	174	140	56	111	175	138
10	28-02-2005	119	86	57	171	90	65	118	105	194
11	07-03-2005	114	81	129	217	167	64	93	154	119
12	14-03-2005	127	59	81	243	99	81	72	107	117
13	21-03-2005	135	74	51	271	215	48	115	148	171
14	28-03-2005	116	63	98	119	51	48	51	92	76
15	04-04-2005	132	83	59	130	152	54	78	128	207
16	11-04-2005	129	53	84	111	103	41	58	91	123
17	18-04-2005	113	74	62	101	84	66	83	111	134
18	25-04-2005	114	50	120	126	111	48	77	119	157
19	02-05-2005	98	66	81	86	48	40	59	131	111

Fig1 : Data screenshot

	A	B	C	D
1	name_1	name_2	id_1	id_2
2	BACS	JASZ	0	10
3	BACS	BACS	0	0
4	BACS	BARANYA	0	1
5	BACS	CSONGRA	0	5
6	BACS	PEST	0	13
7	BACS	FEJER	0	6
8	BACS	TOLNA	0	16
9	BARANYA	BARANYA	1	1
10	BARANYA	TOLNA	1	16
11	BARANYA	SOMOGY	1	14
12	BARANYA	BACS	1	0
13	BEKES	HAJDU	2	8
14	BEKES	BEKES	2	2
15	BEKES	JASZ	2	10
16	BEKES	CSONGRA	2	5
17	BORSOD	HEVES	3	9
18	BORSOD	SZABOLCS	3	15
19	BORSOD	HAJDU	3	8
20	BORSOD	BORSOD	3	3
21	BORSOD	NOGRAD	3	12

Fig: Country edges data screenshot.

We take an assumption that the adjacent states affect the Chickenpox cases in each other as people move frequently to and fro from adjacent states. So this data is useful in creating a graph for STGCN implementation.

Code and Implementation of ARIMA

To implement ARIMA model, Python has been used. Python has a few libraries which are essential to this use case. Pandas and Matplotlib libraries of Python have been implemented here in this code. Data is read from an excel file which contains the Date as index.

```
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv('C:/sem 7/CS SOP Mukesh Rohil/hungary_chickenpox.csv',index_col='Date',parse_dates=True)
# df = pd.read_csv('C:/sem 7/CS SOP Mukesh Rohil/hungary_chickenpox.csv')
# print(df['Date'])
# df.index = pd.DatetimeIndex(df.index).to_period('W')
print(df.index)
df=df.dropna()
print('Shape of data:',df.shape)
df.head()
df
df['BUDAPEST'].plot(figsize=(15,5))
#plt.show()
```

Python has a `auto_arima` function which tests various arima models of different order and compute their 'AIC Values' and whoever's AIC value is less that is the best model of correct order to predict future using ARIMA. So below is the implementation of `auto_arima` function on different states of Hungary to determine the correct order of arima to be implemented.

```
from pmdarima import auto_arima
stepwise_fit = auto_arima(df['BUDAPEST'], trace=True,suppress_warnings=True) #best model arima (2,0,3)
stepwise_fit = auto_arima(df['BARANYA'], trace=True,suppress_warnings=True) #best model arima (4,0,2)
stepwise_fit = auto_arima(df['BACS'], trace=True,suppress_warnings=True) #best model arima (2,0,2)
stepwise_fit = auto_arima(df['BEKES'], trace=True,suppress_warnings=True) #best model arima (0,1,1)
stepwise_fit = auto_arima(df['BORSOD'], trace=True,suppress_warnings=True) #best model arima (2,0,3)
stepwise_fit = auto_arima(df['CSONGRAD'], trace=True,suppress_warnings=True) #best model arima (1,0,1)
stepwise_fit = auto_arima(df['FEJER'], trace=True,suppress_warnings=True) #best model arima (1,0,3)
stepwise_fit = auto_arima(df['GYOR'], trace=True,suppress_warnings=True) #best model arima (3,0,2)
stepwise_fit = auto_arima(df['HAJDU'], trace=True,suppress_warnings=True) #best model arima (3,0,2)
stepwise_fit = auto_arima(df['HEVES'], trace=True,suppress_warnings=True) #best model arima (1,0,1)
stepwise_fit = auto_arima(df['JASZ'], trace=True,suppress_warnings=True) #best model arima (3,0,1)
stepwise_fit = auto_arima(df['KOMAROM'], trace=True,suppress_warnings=True) #best model arima (1,0,1)
stepwise_fit = auto_arima(df['NOGRAD'], trace=True,suppress_warnings=True) #best model arima (2,0,1)
stepwise_fit = auto_arima(df['PEST'], trace=True,suppress_warnings=True) #best model arima (4,0,2)
stepwise_fit = auto_arima(df['SOMOGY'], trace=True,suppress_warnings=True) #best model arima (2,0,3)
stepwise_fit = auto_arima(df['SZABOLCS'], trace=True,suppress_warnings=True) #best model arima (2,1,1)
stepwise_fit = auto_arima(df['TOLNA'], trace=True,suppress_warnings=True) #best model arima (3,1,2)
stepwise_fit = auto_arima(df['VAS'], trace=True,suppress_warnings=True) #best model arima (0,1,1)
stepwise_fit = auto_arima(df['VESZPREM'], trace=True,suppress_warnings=True) #best model arima (2,3,1)
stepwise_fit = auto_arima(df['ZALA'], trace=True,suppress_warnings=True) #best model arima (2,0,1)
```

Here we are segregating the data into two parts, the training set which is all the rows except the bottom 30 rows. And then the testing set, that is the bottom 30 rows to test whether our model is working properly or not by comparing the prediction with actual values.

Then we implement the ARIMA model of the correct order on each state one by one to train our model.

```

train=df.iloc[: -30]
test=df.iloc[-30:]
print('Shape of training data:',train.shape)
print('Shape of testing data:', test.shape)

from statsmodels.tsa.arima.model import ARIMA
model1=ARIMA(train['BUDAPEST'],order=(2,0,3))
model1=model1.fit()
model1.summary()

model2=ARIMA(train['BARANYA'],order=(4,0,2))
model2=model2.fit()
model2.summary()

model3=ARIMA(train['BACS'],order=(2,0,2))
model3=model3.fit()
model3.summary()

model4=ARIMA(train['BEKES'],order=(0,1,1))
model4=model4.fit()
model4.summary()

```

Next, we predict the values using our model for the next 30 rows, for which we already have the true value. We then compare our predicted values with the true values to see how well our model is performing. To do this we simple perform a root mean squared test of Statistics.

```

#to predict
start=len(train)
end=len(train)+len(test)-1
pred=model1.predict(start=start,end=end).rename('ARIMA Predictions')
pred.plot(legend=True)
test['BUDAPEST'].plot(legend=True)

from sklearn.metrics import mean_squared_error
from math import sqrt
test['BUDAPEST'].mean()
rmse=sqrt(mean_squared_error(pred,test['AvgTemp']))
print(rmse)

```

Once we have established that our Model is correct by seeing that the mean squared error is minimal, then we can predict future row and print the results.

Results

The Figure below shows the prediction ARIMA model made after training it from 1st to 492nd rows of data. It then predicts the result for 493rd to 522nd row.

On X axis we have the week number, On Y axis we have the number of chickenpox cases recorded that week.

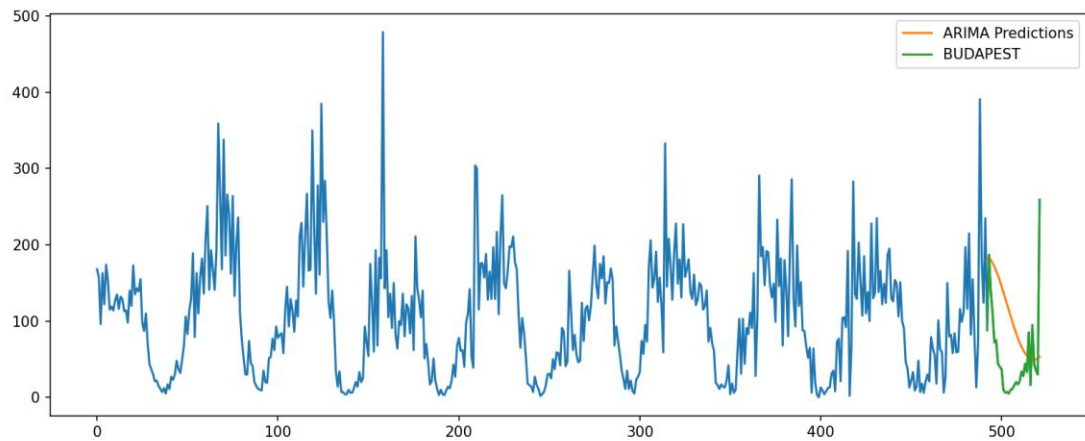


Fig: plotting predictions of ARIMA against actual values for Budapest

As we can see, ARIMA correctly predicted that the cases would go down and then rise a little. This is for the state Budapest, similarly we can have predictions for all the 20 states of Hungary and plot graph for all of them. Below is the prediction for Baranya state.

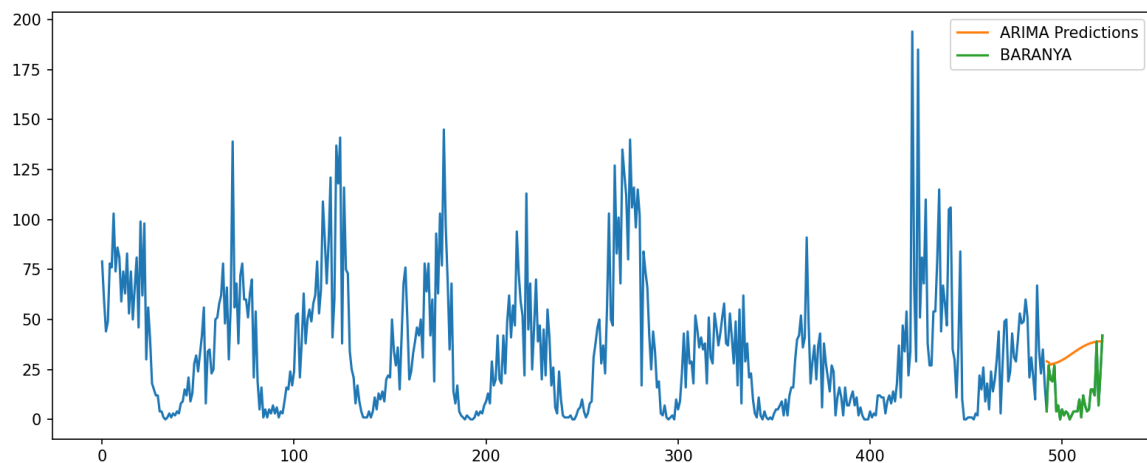
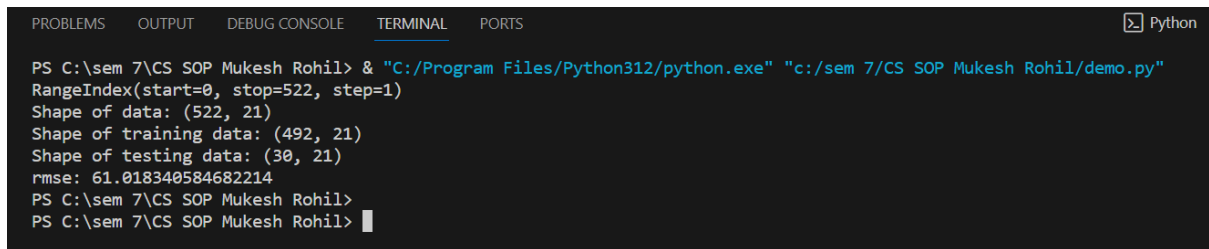


Fig: plotting predictions of ARIMA against actual values for Baranya



```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS Python
PS C:\sem 7\CS SOP Mukesh Rohil> & "C:/Program Files/Python312/python.exe" "c:/sem 7/CS SOP Mukesh Rohil/demo.py"
RangeIndex(start=0, stop=522, step=1)
Shape of data: (522, 21)
Shape of training data: (492, 21)
Shape of testing data: (30, 21)
rmse: 61.018340584682214
PS C:\sem 7\CS SOP Mukesh Rohil>
PS C:\sem 7\CS SOP Mukesh Rohil>
```

This is the screenshot of the output after we run the whole code. The rmse value is 61.01 for Baranya, that means are predictions deviate a little from actual values, as visible in the plot.

Discussed below is everything that we expect the outcome to be after implementing STGCN as well, and then comparing them.

A. Presentation of Analyzed Data Descriptive Statistics:

The descriptive statistics revealed a clear pattern of seasonality in chickenpox cases, with peaks during certain periods of the year. Spatial autocorrelation was evident, indicating that neighbouring counties exhibited similar trends in reported cases.

Temporal plots showcased the dynamic nature of chickenpox cases, with variations across different counties. Spatial visualizations, such as heatmaps, highlighted regions with higher susceptibility to the disease.

B. Evaluation of Predictive Models Performance Metrics and Comparisons:

ARIMA and STGCN were evaluated using standard metrics (e.g., Mean Absolute Error, Root Mean Squared Error). Results might indicate that STGCN outperformed ARIMA in terms of predictive accuracy. Strengths and Weaknesses of Models:

ARIMA demonstrated interpretability and simplicity, but struggled to capture complex spatiotemporal dependencies. STGCN excelled in capturing intricate relationships, leveraging the graph structure to model spatial dependencies effectively.

Conclusion

STGCN consistently demonstrated superior predictive performance over ARIMA. The graph neural network architecture proved advantageous in handling the spatiotemporal characteristics of the dataset.

The study contributes theoretical insights into the application of graph neural networks, specifically STGCN, in spatiotemporal signal processing. STGCN showcased its ability to effectively model complex interactions in the context of disease spread.

The theoretical analysis emphasized the importance of leveraging graph-based models, especially STGCN, for predictive analysis of spatiotemporal data. The spatial dependencies present in the chickenpox dataset proved to be better captured by models designed to handle graph structures.

Recommendations for Future Research

Future research could explore hybrid models that combine the interpretability of classical models like ARIMA with the spatial modeling capabilities of graph neural networks. Investigate the application of STGCN in other spatiotemporal datasets to assess its generalizability.

This study contributes valuable insights to the growing field of spatiotemporal signal processing, emphasizing the potential of graph neural networks for effective modeling in disease prediction and other dynamic scenarios.

The github link for the repository is: <https://github.com/shayna-1612/Predictive-Analysis-of-Spatiotemporal-Data/tree/main>

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