

# Towards Automatic Forecasting: Evaluation of Time-Series Forecasting Models for Chickenpox Cases Estimation in Hungary

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**Abstract.** Time-Series Forecasting is a powerful data modeling discipline that analyzes historical observations to predict future values of a time-series. It has been utilized in numerous applications, including but not limited to economics, meteorology, and health. In this paper, we use time-series forecasting techniques to model and predict the future incidence of chickenpox. To achieve this, we implement and simulate multiple models and data preprocessing techniques on a Hungary-collected dataset. We demonstrate that the LSTM model outperforms all other models in the vast majority of the experiments in terms of county-level forecasting, whereas the SARIMAX model performs best at the national level. We also demonstrate that the performance of the traditional data preprocessing method is inferior to that of the data preprocessing method that we have proposed.

## 1 Introduction

Varicella Zoster Virus (VZV) is a member of the herpes virus family with double-stranded DNA [3]. This virus causes varicella (chickenpox), a highly contagious pediatric disease often contracted between the ages of 2 and 8 [3]. Chickenpox is generally a mild disease, although it can develop problems that necessitate hospitalization [4,12] and, in rare cases, be fatal [1]. Despite the fact that chickenpox is an extremely contagious disease in which over 90% of unvaccinated persons become infected [5], and despite the availability of vaccinations [1], Hungary has no explicit prescription for chickenpox vaccination in its national immunization policy [1]. Given this, and the fact that the reported cases throughout these years form a time-series of values, studies can be conducted to predict the number of future cases in the country, allowing the health system and necessary medications to be prepared. In this paper, we examine the various models of Time-Series Forecasting and perform model evaluation for the chickenpox cases forecasting use case in order to choose the model that achieves the best results at the county- and country-level. Our primary contributions are as follows: (1)

Conducting a comprehensive exploratory data analysis on this relatively new dataset in order to identify underlying patterns. (2) Examining the relationship between chickenpox cases and other variables such as the population. (3) Conducting comprehensive experiments on multiple time-series models and selecting the model that produces the best results for each county and at the national level.

The paper is structured as follows. First, we list and discuss related work, then we formalize and discuss the issue of time-series forecasting, after that, we do exploratory data analysis (EDA) in which we explore the dataset and list its key characteristics. Finally, we detail the experimental setup before reporting and summarizing our major findings.

## 2 Related Work

Time-Series Forecasting research dates back to 1985 [11], and since then, it has been a constantly expanding research area, especially in the past decade [2], due to the expansion of data volumes arising from users, industries, and markets, as well as the centrality of forecasting in various applications, such as economic, weather, stock price, business development, and health. As a result, numerous forecasting models have been developed, including ARIMA [20], SARIMA [20], ARIMAX [8], SARIMAX [8], N-BEATS [19], DeepAR [24], Long Short-Term Memory Neural Network (LSTM) [16], Gated Recurrent Unit Neural Networks (GRU) [29], and Temporal Fusion Transformer (TFT) [15]. These models and others have been utilized in a wide range of use cases, including but not limited to the following: energy and fuels [10, 18, 21] where accurate estimates are required to improve power system planning and operation, Finance [9, 26, 27], Environment [7, 17, 30], Industry [14, 22, 28], and Health [6, 13, 25]. In this paper, we contribute to the usage of time-series forecasting in the Health domain by predicting the number of cases of chickenpox in Hungary.

## 3 Time-Series Forecasting Problem Definition

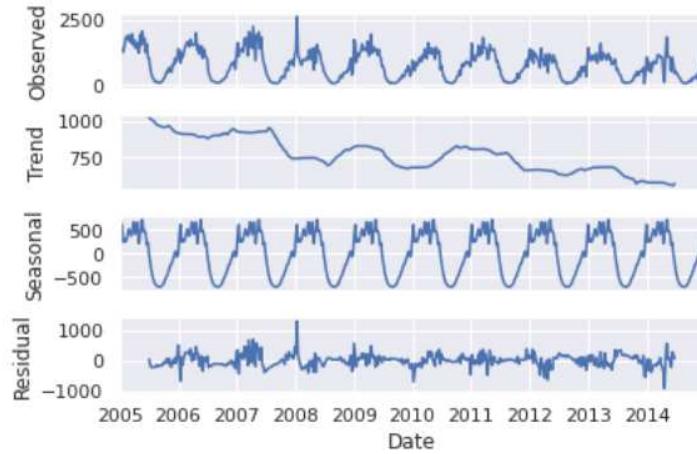
Time-series forecasting problem can be formalized as follows: given a univariate time-series, which represents a sequence of values  $X = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_t)$  forecasting is the process of predicting the value of future observations of a time-series  $(\mathbf{x}_{t+1}, \mathbf{x}_{t+2}, \dots, \mathbf{x}_{t+h})$  based on historical data, where  $\mathbf{x}_i \in \mathbb{R}$  ( $i \in [1, \dots, t + h]$ ) is the value of  $X$  at time  $i$ ,  $t$  is the length of  $X$ , and  $h$  is the forecasting horizon.

## 4 Exploratory Data Analysis (EDA)

The dataset used in this paper was made available by Rozemberczki, B. et al [23]. This dataset consists of county-level time series depicting the weekly number of chickenpox cases reported by general practitioners in Hungary from 2005 to 2015, subdivided into 20 vertices: Budapest, Pest, Borsod, Hajdu, Györ, Jász,

Veszprem, Bacs, Baranya, Fejer, Csongrad, Szabolcs, Heves, Bekes, Somogy, Komarom, Vas, Nograd, Torna, and Zala. The main characteristics of the data are as following:

1. As can be seen in Figure 2, the city of Budapest, Hungary's capital, has the highest average number of reported cases each week by a significant margin compared to other counties. This is primarily due to the difference in population, and consequently, if we calculate the average number of reported cases as a percentage of the population, we can deduce that Veszprem has the highest ratio.
2. In Figure 3, seasonality is evident, with the greatest number of cases occurring during the winter months and the smallest number occurring between the summer and fall seasons. This is also apparent by decomposing the country-level time series (Figure 1).
3. A downward trend can be noticed in the data (Figure 1).

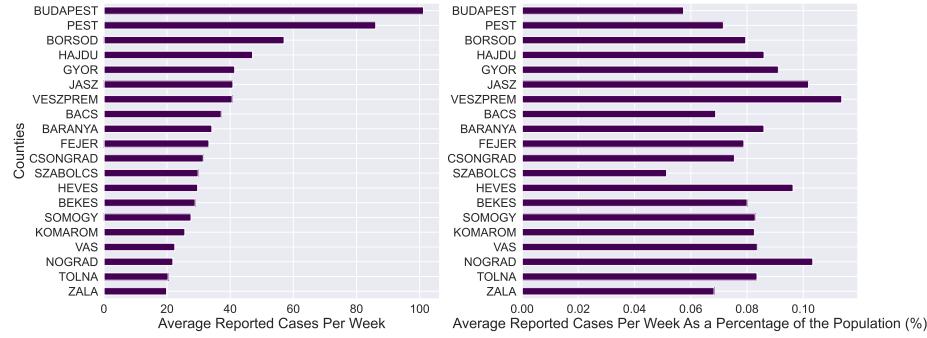


**Fig. 1.** Country-level Time-Series Data Decomposition

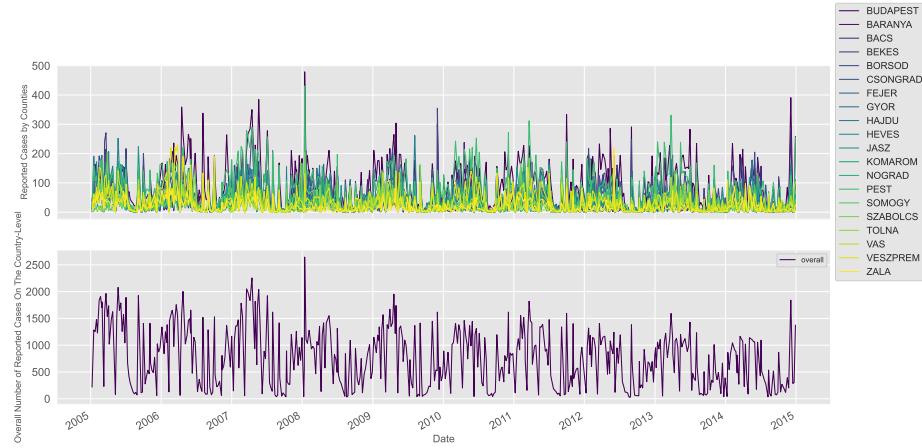
## 5 Experimental Setup

### 5.1 Data Splitting

In all of our experiments, we split the data so that 80 percent of the data is used for training and 20 percent is used for testing; accordingly, the last 20 percent of each series' values are used for testing.



**Fig. 2.** The average number of weekly reported cases per county



**Fig. 3.** Chickenpox weekly cases in Hungary reported between 2005 and 2015 broken by counties

## 5.2 Data Normalization

We experimented two methods of data normalization:

1. Method 1: We performed traditional data normalization so data would be within the range  $[-1, 1]$ .
2. Method 2: We performed normalization by converting each data sample to a percentage of the population at the time when cases were reported as shown in Equation 1

$$\mathbf{x}'_{c,d} = \frac{\mathbf{x}_{c,d}}{\mathbf{p}_{c,d}} \times 100 \quad (1)$$

Where  $\mathbf{s}_{c,d}$  denotes the reported cases in county  $c$  on date  $d$ , and  $\mathbf{p}_{c,d}$  denotes the population of county  $c$  on date  $d$ .

### 5.3 Models

We conducted experiments on the following models: ARIMA [20], SARIMA [20], SARIMAX [8], N-BEATS [19], DeepAR [24], Long Short-Term Memory Neural Network (LSTM) [16], Gated Recurrent Unit Neural Networks (GRU) [29], and Temporal Fusion Transformer (TFT) [15]. Throughout the experiments, each model was trained for 200 epochs using the Adam optimizer and a learning rate of  $\alpha = 0.01$ .

### 5.4 Evaluation Metrics

To evaluate the performance of the models, we calculated the Root Mean Square Error (RMSE) using the equation:

$$RMSE = \sqrt{\frac{1}{t} \sum_{i=1}^t [\hat{x}_i - x_i]^2} \quad (2)$$

Where  $\hat{x}_i$  denotes the  $i^{th}$  predicted value and  $x_i$  denotes the  $i^{th}$  original (observed) value.

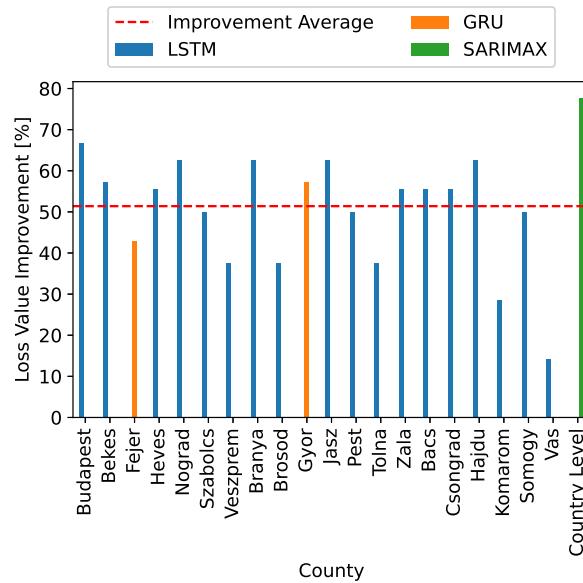
## 6 Benchmarking Results

The results of the experiments are summarized in table 1, which contains a collection of the results for each model, separated according to the county and the normalization methods. The column labeled "loss 1" refers to method 1, and the column labeled "loss 2" refers to method 2, both of which are described in section 5.2.

As can be seen in table 1, regarding forecasting of the individual county, the LSTM model performs better than any of the other models in a vast majority of the counties: Budapest, Bekes, Heves, Szabolcs, Veszprem, Baranya, Borsod, Jasz, Pest, Tolna, Zala, Bacs, Csongrad, Hajdu, Komarom, Somogy, and Vas with the RMSE loss values of 0.03, 0.03, 0.04, 0.04, 0.05, 0.03, 0.05, 0.03, 0.04, 0.05, 0.04, 0.04, 0.03, 0.05, 0.03, 0.06 respectively and the GRU Model performed better in Fejer, Nograd, and Gyor with RMSE loss values of 0.04, 0.02, and 0.03, respectively, whereas when it came to forecasting on the national level, SARIMAX achieved the best results when with an RMSE loss value of 0.02. The main reason the LSTM model outperformed other models in most cases was due to its ability to do long-term memorization more than the other models, and as can be seen in Figure 3, the vast majority of the series does not have a consistent pattern and would benefit from this long-term memorization; this also explains why SARIMAX performed better on the country-level series (Figures 3 and 1), where all the series were summed, resulting in a more consistent pattern that does not rely heavily on long-term memorization ability.

In addition, the normalization approach that we have proposed outperformed the traditional normalization approach (Method 1) in each and every (model,

county) pair experiment, achieving a significant improvement in terms of the RMSE loss value. By calculating the loss value improvement after applying Method 2 in comparison to Method 1 for the best performing model for each county (as highlighted in Table 1), we can see that the SARIMAX model for the country-level forecasting has the highest gain with a 77.78% improvement, while the LSTM model for Vas county has the lowest gain with a 14.29% improvement, and the average improvement across all models is 51.39%. (Figure 4).



**Fig. 4.** Improvements in RMSE Loss values after applying the Normalization Method 2 in comparison to Normalization Method 1

## 7 Conclusion

In this paper, we presented, discussed, and highlighted the results of a series of experiments that we conducted out on the chickenpox cases dataset. The purpose of these experiments was to evaluate time-series forecasting models for use in predicting the number of chickenpox cases in Hungary at the county and national levels. We demonstrated that the LSTM model performed better than other models for the majority of county-level forecasting except in the cases of Fejér, Nograd, and Győr counties, while the SARIMAX model produced the most accurate results at the country-level. In addition, we proposed a custom data preprocessing method for this dataset by dividing the proportion of cases by the population size, and demonstrated that this method outperformed conventional normalization in terms of achieving lower RMSE Loss values.

**Table 1.** Benchmarking Results

County	Model	Loss1	Loss2	County	Model	Loss1	Loss2	County	Model	Loss1	Loss2
Budapest	Sarimax	0.11	0.04	Baranya	Sarimax	0.12	0.04	Bacs	Sarimax	0.12	0.07
	Arima	0.35	0.21		Arima	0.33	0.18		Arima	0.35	0.21
	Sarima	0.24	0.14		Sarima	0.28	0.15		Sarima	0.22	0.12
	<b>LSTM</b>	<b>0.09</b>	<b>0.03</b>		<b>LSTM</b>	<b>0.08</b>	<b>0.03</b>		<b>LSTM</b>	<b>0.09</b>	<b>0.04</b>
	GRU	0.13	0.07		GRU	0.12	0.06		GRU	0.12	0.08
	N-BEATS	0.30	0.20		N-BEATS	0.22	0.05		N-BEATS	0.30	0.05
	DeepAR	0.17	0.09		DeepAR	0.15	0.05		DeepAR	0.14	0.08
	TFT	0.34	0.11		TFT	0.23	0.09		TFT	0.22	0.12
Bekes	Sarimax	0.13	0.05	Borsod	Sarimax	0.12	0.08	Csongrad	Sarimax	0.13	0.07
	Arima	0.35	0.20		Arima	0.27	0.13		Arima	0.34	0.21
	Sarima	0.19	0.11		Sarima	0.15	0.11		Sarima	0.19	0.11
	<b>LSTM</b>	<b>0.07</b>	<b>0.03</b>		<b>LSTM</b>	<b>0.08</b>	<b>0.05</b>		<b>LSTM</b>	<b>0.09</b>	<b>0.04</b>
	GRU	0.10	0.08		GRU	0.09	0.06		GRU	0.09	0.07
	N-BEATS	0.25	0.04		N-BEATS	0.20	0.07		N-BEATS	0.32	0.08
	DeepAR	0.16	0.09		DeepAR	0.18	0.08		DeepAR	0.14	0.07
	TFT	0.22	0.06		TFT	0.32	0.08		TFT	0.25	0.09
Fejer	Sarimax	0.11	0.06	Gyor	Sarimax	0.12	0.05	Hajdu	Sarimax	0.12	0.07
	Arima	0.35	0.21		Arima	0.33	0.18		Arima	0.34	0.21
	Sarima	0.24	0.14		Sarima	0.28	0.15		Sarima	0.19	0.11
	<b>LSTM</b>	<b>0.09</b>	<b>0.06</b>		<b>LSTM</b>	<b>0.07</b>	<b>0.04</b>		<b>LSTM</b>	<b>0.08</b>	<b>0.03</b>
	<b>GRU</b>	<b>0.07</b>	<b>0.04</b>		<b>GRU</b>	<b>0.07</b>	<b>0.03</b>		<b>GRU</b>	<b>0.12</b>	<b>0.08</b>
	N-BEATS	0.23	0.06		N-BEATS	0.30	0.04		N-BEATS	0.23	0.06
	DeepAR	0.15	0.08		DeepAR	0.18	0.07		DeepAR	0.15	0.07
	TFT	0.25	0.12		TFT	0.26	0.09		TFT	0.24	0.12
Heves	Sarimax	0.12	0.05	Jasz	Sarimax	0.10	0.04	Komarom	Sarimax	0.11	0.06
	Arima	0.36	0.18		Arima	0.35	0.22		Arima	0.33	0.13
	Sarima	0.26	0.12		Sarima	0.24	0.11		Sarima	0.21	0.12
	<b>LSTM</b>	<b>0.09</b>	<b>0.04</b>		<b>LSTM</b>	<b>0.08</b>	<b>0.03</b>		<b>LSTM</b>	<b>0.07</b>	<b>0.05</b>
	GRU	0.12	0.07		GRU	0.09	0.05		GRU	0.11	0.08
	N-BEATS	0.11	0.05		N-BEATS	0.22	0.06		N-BEATS	0.33	0.07
	DeepAR	0.13	0.06		DeepAR	0.14	0.07		DeepAR	0.16	0.07
	TFT	0.22	0.11		TFT	0.33	0.13		TFT	0.34	0.09
Nograd	Sarimax	0.12	0.06	Pest	Sarimax	0.13	0.05	Somogy	Sarimax	0.12	0.04
	Arima	0.33	0.18		Arima	0.33	0.13		Arima	0.36	0.18
	Sarima	0.28	0.15		Sarima	0.21	0.12		Sarima	0.26	0.12
	<b>LSTM</b>	<b>0.08</b>	<b>0.03</b>		<b>LSTM</b>	<b>0.08</b>	<b>0.04</b>		<b>LSTM</b>	<b>0.06</b>	<b>0.03</b>
	<b>GRU</b>	<b>0.09</b>	<b>0.02</b>		<b>GRU</b>	<b>0.11</b>	<b>0.06</b>		<b>GRU</b>	<b>0.12</b>	<b>0.07</b>
	N-BEATS	0.24	0.04		N-BEATS	0.33	0.05		N-BEATS	0.32	0.06
	DeepAR	0.14	0.07		DeepAR	0.14	0.07		DeepAR	0.13	0.06
	TFT	0.24	0.11		TFT	0.23	0.11		TFT	0.26	0.12
Szabolcs	Sarimax	0.14	0.08	Tolna	Sarimax	0.11	0.06	Vas	Sarimax	0.12	0.07
	Arima	0.38	0.22		Arima	0.34	0.21		Arima	0.33	0.13
	Sarima	0.26	0.13		Sarima	0.23	0.11		Sarima	0.21	0.12
	<b>LSTM</b>	<b>0.08</b>	<b>0.04</b>		<b>LSTM</b>	<b>0.08</b>	<b>0.05</b>		<b>LSTM</b>	<b>0.07</b>	<b>0.06</b>
	GRU	0.09	0.07		GRU	0.11	0.07		GRU	0.12	0.08
	N-BEATS	0.23	0.06		N-BEATS	0.33	0.06		N-BEATS	0.23	0.07
	DeepAR	0.15	0.09		DeepAR	0.19	0.08		DeepAR	0.18	0.08
	TFT	0.33	0.09		TFT	0.33	0.12		TFT	0.22	0.09
Veszprem	Sarimax	0.12	0.06	Zala	Sarimax	0.11	0.07	Country Level	<b>Sarimax</b>	0.09	<b>0.02</b>
	Arima	0.35	0.21		Arima	0.33	0.23		Arima	0.31	0.11
	Sarima	0.22	0.12		Sarima	0.35	0.21		Sarima	0.25	0.14
	<b>LSTM</b>	<b>0.08</b>	<b>0.05</b>		<b>LSTM</b>	<b>0.09</b>	<b>0.04</b>		<b>LSTM</b>	<b>0.09</b>	<b>0.07</b>
	GRU	0.12	0.07		GRU	0.13	0.08		GRU	0.08	0.06
	N-BEATS	0.22	0.06		N-BEATS	0.20	0.05		N-BEATS	0.23	0.03
	DeepAR	0.16	0.07		DeepAR	0.15	0.07		DeepAR	0.19	0.08
	TFT	0.34	0.12		TFT	0.30	0.11		TFT	0.33	0.12

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