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Dmytro Krukovets

EXPLORING AN LSTM-SARIMA ROUTINE FOR CORE INFLATION FORECASTING

The object of the research is the Core Inflation Forecasting. The paper investigates the performance of the novel model routine in the exercise of the Core Inflation Forecasting. It aggregates 300+ components into 6 by the similarity of their dynamics using an updated DTW algorithm fine-tuned for monthly time series and the K-Means algorithm for grouping. Then the SARIMA model extracts linear and seasonal components, which is followed by an LSTM model that captures non-linearities and interdependencies. It solves the problem of high-quality inflation forecasting using a disaggregated dataset. While standard and traditional econometric techniques are focused on the limited sets of data that consists just a couple of variables, proposed methodology is able to capture richer part of the volatility comprising more information. The model is compared with a huge pool of other models, simple ones like Random Walk and SARIMA, to ML models like XGBoost, Random Forest and simple LSTM. While all Data Science model shows decent performance, the DTW+K-Means+SARIMA+LSTM routine gives the best RMSE over 1-month ahead and 2-month ahead forecasts, which proves the high quality of the proposed forecasting model and solves the key problem of the paper. It is explained by the model's capability to capture both linear/seasonal patterns from the data using SARIMA part as long as it non-linear and interdependent using LSTM approach. Models are fitted for the case of Ukraine as long as they've been estimated on the corresponding data and may be actively used for further inflation forecasting.

Keywords: *dynamic time warping, clustering, K-Means, recurrent neural network, machine learning, core inflation.*

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1. Introduction

Forecasting the Consumer Price Index (CPI) has long been a focal point in econometric research, with continuous expansion fueled by the emergence of novel models and methodologies. Some of these innovations stem from evolving economic theories, while others reflect the global trend toward maximizing information utilization. As advancements in data collection, storage, and processing capabilities surge, the demand for models capable of handling vast datasets and extracting maximum insights intensifies. Notably, certain models, though originally designed for «Big Data» applications, have found relevance beyond their intended scope, bridging the gap between economics and computer science. Such a trend allows to explore cutting-edge mathematical and computer science techniques in the economics domain. This paper delves into one such interdisciplinary application, approaching the subject matter from a technical standpoint rather than an economic one.

The study is a direct successor of [1], with a deeper investigation of model performance and proposals on how to increase model quality using chained techniques. It aims to develop a suite of forecasting techniques tailored to the Consumer Prices dataset, which encompasses various components. While some techniques are traditional for the domain, others derive from the realm of «Data Science» and have been adapted to accommodate large datasets that appear in economics mostly from disaggregated forms of the entity such as inflation of various components, bread or shoes or gas price for consumers or hundreds of others. Notably, let's explore the application of Dynamic Time Warping (DTW) and K-Means algorithms to identify similarities and aggregate diverse CPI components. Previous research has explored these methods across different datasets, including artificial signals, deposit rates from Ukrainian banks, and nominal wages from regions. The adaptation of DTW is a key focus, particularly its modification to address challenges posed by a high volume of corresponding points and lag in series alignment – a crucial aspect for analyzing series similarity with less than a year's lag and avoiding issues arising from prolonged periods of stable inflation.

The combined components are then integrated into either an ARIMA/SARIMA routine or an RNN/LSTM model to forecast aggregated core inflation. Also, the combined approach between LSTM and SARIMA is developed to catch both linear dependencies and non-linear in a two-stage approach. As other benchmarks, Random Forest and XGBoost are used as common models from the Data Science world. In the scenario with traditional econometric models, namely SARIMA-type, forecasts are weighted and combined to yield a total forecast, a method previously employed and referred to as a «studied approach». On the other hand, RNN/LSTM models inherently aggregate components within the algorithm, leveraging their architecture's capacity for nonlinear pattern recognition – a valuable asset in economic analysis. Despite being relatively novel in economic research, RNNs exhibit promise in capturing nonlinearities, an attribute of particular significance in economic dynamics. Additionally, the seasonal aspect is addressed through the X-12 technique for ARIMA, naturally extended to SARIMA and RNN models. This comprehensive approach underscores the critical importance of inflation forecasting in real-world applications, particularly in shaping monetary policy decisions by central banks striving for price stability within the framework of inflation targeting.

The topic of inflation forecasting is deeply investigated by many international researchers, which goes from traditional econometric methods like ARIMA or VAR to more advanced ones that investigate the performance of neural network algorithms or machine learning models for above-mentioned task. In the first group, I may pay attention to paper [2], where authors are forecasting inflation using a similarly disaggregated dataset of inflation components like is taken in the current paper, but for Ukraine. However, the authors are using a simple ARIMA technique instead of more modern and curious approaches. Authors in [3] are exploiting the ARIMA model for financial forecasting of stock prices on the Indian market by sectors of interest thus using quite disaggregated datasets. This article also contributes as an example of a high-quality data preparation stage that is necessary for projects with disaggregated datasets. Paper [4] shows an investigation of rice prices in Indonesia using ARIMAX and VAR approaches instead of their simpler alternatives namely ARIMA. Authors are investigating how much better the model will perform when counting for supportive data such as volumes of rice production, area, prices in main economic partners etc. This shows that the dynamics of a series may be explained not only by its own dynamics but by the dynamics of interconnected variables. Paper [5] majorly contributes to the investigation of neural network possibilities for inflation forecasting, particularly in the US. The authors show an unusual approach to working with the quite rich FRED-MD dataset and a lot of machine learning algorithms that help to produce high-quality forecasts.

Thus, *the aim of this research* is to development of novel model that will help to produce high-quality forecasts. From the scientific point of view, the algorithm is thoroughly investigated and may be used in the different datasets that have properties of disaggregation which may help to further investigate, find curious insights from the own datasets. From the practical point of view, this model may be already used for core inflation forecasting in Ukraine. With some adaptation it may be used not only for the case of Ukraine, but for other cases too if the problem with data presence will be solved.

2. Materials and Methods

2.1. Data. This research utilizes time series data from the economics domain, continuing the tradition of my previous papers which investigate a similar yet not that advanced set of techniques and models from different perspectives. Specifically, in this paper the Core Consumer Price Index (Core CPI) in Ukraine and developing corresponding forecasting models is of primary attention. Those models are trying to make the best possible forecast counting for many subcomponents of the total index and their non-linear relationship between each other and with other, supportive, variables. Thus, the deep investigation of properties for those subcomponents and supportive variables is an integral part of the successful research and some attention, even in the more technical paper, should be given to the data.

The Consumer Price Index (CPI) measures the overall cost of a basket of goods and services representing average consumer spending. The State Statistics Service of Ukraine (Ukrstat) collects CPI data across over 350 categories covering food, clothing, housing, transportation, and more, as detailed in [6]. The CPI data allows for checking price and cost of living changes. It is one among two penultimate variables, along with an exchange rate, for people to track down many perceptional and expected measures. For example, perception of well-being, preference of consumption versus saving, expectations about future economy etc. and many other indicators. By the way, it's forecasting also crucial for managing to understand the future stance of things like minimal wage, the cost to live and others that are frequently used in many tax-based initiatives, which is crucial for budget planning. Thus, the forecasting of such variables is of key importance for the majority of spheres in the economy. Thus, there are a lot of papers focused on Core CPI forecasting with different methods starting from traditional to advanced ones. [7] and [8] are great examples of papers that are focused on Ukrainian Core CPI. The first among them is dedicated to the Combined ARMA approach that uses disaggregated datasets to forecast inflation, while the second one produces a large set of models including AR, VAR, BVAR, and BiVAR models to forecast the core inflation in Ukraine. [9–11] are examples of international papers that investigate the same issue but for other countries and shows methods from traditional like ARIMA as a comparative model to advanced ones like Neural networks and their adaptations such as RNN. Each of the abovementioned papers shows slightly different architecture, for example [9] shows only RNN for inflation forecasting, while [11] gives a glimpse of the LSTM model for the same task. [10] among them is dedicated to GDP forecasting instead of the inflation yet the exercise is done using again RNN. It shows that these models are quite frequently used in the economic domain.

The Core CPI focuses on the more stable CPI components less prone to administrative decisions, weather impacts, or global price shocks. It covers processed foods, clothing, services, and other categories, which month-to-month dynamics can be seen in Fig. 1. It is possible to utilize monthly Core CPI data from either January 2012 or January 2007 through August 2023, depending on data availability per component. Some of the components appear in the data later (in 2012 or even 2017–2022) because every five years the set of series is remade. The threshold for a series to appear is that the good should take more than 0.1 % of the annual basket of goods for an average Ukrainian. Thus, a car, even bought rarely, due to the extremely high cost appears in the dataset. So as bread or sausages which are bought in an everyday manner.

To enable effective forecasting, the data requires processing to achieve stationarity and account for seasonality. Stationarity is partially addressed by using the Core Inflation metric (percent change in Core CPI) instead of absolute levels. Seasonality is another story. For some models, it's handled automatically, for example for a SARIMA model which comes as the one we'll compare with. However, previous research [1] shows that a pure LSTM model is unable to catch seasonality as perfectly as it should. Moreover, some series exhibit a change in seasonality, which appears at some point in time because of methodology changes. The overall seasonally adjusted Core CPI is in Fig. 1.

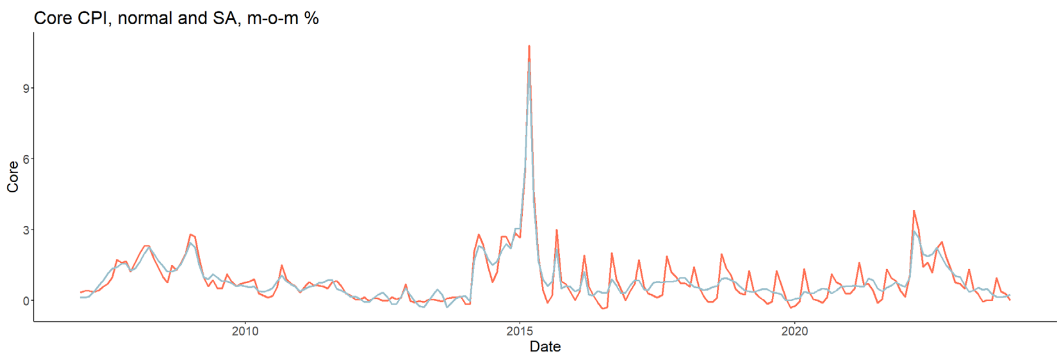

Fig. 1. Core CPI, normal and SA, m-o-m %

Core CPI components also pose a methodological aggregation challenge for the overall Core CPI forecast. The solution is to supplement the disaggregated forecasting models with an additional model to determine category weights. It will be explained in more detail in the upcoming section.

The final issue to address concerns a segment of the dataset comprising over 300 components. As previously noted, certain components were incorporated by Ukrstat well after 2007, resulting in a proliferation of missing values (NA). While various approaches exist to mitigate this issue, the selected and simplest method involves deleting all columns with NA values and subsequently adjusting the weights, reducing the total number of components from 335 to 270. Detailed documentation of this dataset can be found in reference [7].

2.2. Model. Let's continue with an explanation of the model set used in the research. It comprises classical models commonly employed in Time Series analysis, augmented with an LSTM model and a curious combination of LSTM with SARIMA, Random Forest, XGBoost. These models are applied to the Core Inflation components set derived from 270 components at a finer level of disaggregation, coupled with an innovative DTW+K-Means methodology explored across paper [1] and other author previous works. The conventional set featuring processed food, clothing, services, and others was studied in the previous research [1] yet showing unsatisfying results in comparison, thus it'll be avoided. When utilized with ARIMA-type models, it becomes imperative to aggregate components back to Core Inflation. This aggregation can be accomplished using an additional OLS model, which computes the requisite weights based on historical data and can be leveraged in the forecasting process.

2.2.1. Random Walk. Random Walk is an absolute classic in terms of time series forecasting models. While Random Walk may seem rudimentary, it serves as a crucial baseline against which the performance of more sophisticated models can be compared. However, it's important to acknowledge that the quality of Random Walk forecasts can be significantly influenced by the nature of data preparation, particularly concerning seasonality.

The Random Walk model posits that future values of a time series variable, such as Core CPI, will be equal to the most recent observed value. Mathematically, it can be represented as:

$$\hat{Y}_{t+1} = Y_t \Leftrightarrow \Delta Y_{t+1} = 0. \qquad (1)$$

The Random Walk model assumes that changes in the variable being forecasted are unpredictable and occur randomly. While simplistic, it's a useful starting point for forecasting, particularly when dealing with highly volatile or unpredictable data series, quite frequently appearing in the finances. However, when applied to Core CPI, its accuracy can be influenced by the presence or absence of seasonality in the data.

If seasonality is not properly addressed in the data preparation phase, the Random Walk model may fail to capture periodic patterns and produce inaccurate forecasts. Then the exercise requires to empirical investigation of the performance of both models.

2.2.2. SARIMA. Starting with a standard Autoregressive Integrated Moving Average (ARIMA), a widely adopted method for time series forecasting across various fields involved in time series analysis. ARIMA stands as a cornerstone model in econometrics and time series research and is also a reference model in Data Science and Big Data contexts. The general formula is represented as:

$$\left(1-\phi_1 L-\phi_2 L\mathrm{I}- \ldots -\phi_p L^p\right)\left(1-L\right)^d X_t = \\ =\left(1+\theta_1 L+\theta_2 L\mathrm{I}+ \ldots +\theta_m L^{\varphi}\right) Z_t, \qquad (2)$$

where X_t is a series in a period t; Z_t is an error in a period t; L is a backward shift operator; ϕ_p and θ_m are estimated coefficients.

As delineated in the data section, the time series may present seasonality issues, for which two potential solutions are proposed, both of which will be employed in this study. The first solution involves applying a seasonal adjustment to the series utilizing the X-12 approach, a conventional method for addressing seasonality concerns. More detailed information on this approach can be found in [1].

Another approach to address seasonality issues is the utilization of the Seasonal ARIMA (SARIMA) model. Functioning similarly to a standard ARIMA model, SARIMA incorporates seasonal parameters denoted as p, d, and q, which are based on the frequency of the series (monthly in this context, resulting in a seasonal lag of 12). Additionally, SARIMA augments the standard ARIMA formula with a seasonal component (the 12th lag for monthly data). This model proves advantageous in accounting for seasonality within data-driven models. The general formula is represented as:

$$\left(1-\phi^1 L-\phi^2 L^2-\ldots-\phi_p L^p\right)\cdot\left(1-L\right)\times \\ \times\left(1-\Phi^1 L^s-\Phi^2 L^{2s}-\ldots-\Phi_p L^{ps}\right)\cdot\left(1-L^s\right)^D X_t = \\ =\left(1+\theta^1 L+\theta^2 L^2+ \ldots +\theta_m L^{\varphi}\right)\times \\ \times\left(1+\Theta^1 L^s+\Theta^2 L^{2s}+ \ldots +\Theta_m L^{qs}\right)\cdot Z_t, \qquad (3)$$

where X_t – series in a period t; Z_t – an error in a period t; L – a backward shift operator; ϕ_p and θ_m – estimated coefficients; s – a seasonal frequency which defines the lag that should be taken (12 for monthly series).

In both scenarios, the specifications – namely, p, d, q, P, D, Q are determined using the auto.arima() procedure. This procedure, based on the Akaike Information Criteria (AIC), systematically evaluates models with various combinations of p, d, q, P, D, Q in a grid-search manner. It estimates the AIC for each model and selects the model with the smallest AIC. Unlike the Sum of Squared Errors (SSE), the AIC penalizes excessive lag inclusion in the model, thus favoring models with fewer coefficients that yield comparable likelihood improvements. The AIC is calculated as follows:

$$AIC = 2k - 2\ln(L), \quad (4)$$

where k – the number of coefficients; L – the maximum likelihood of the model with the corresponding set of coefficients.

The approach to estimate coefficients is better described in the paper [12].

2.2.3. LSTM. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are recurrent neural network architectures primarily used for processing time series data. In the latest econometric research, it is possible to observe rising interest in Data Science methods, including RNN and other neural networks like in [6, 7]. The model of choice is an LSTM instead of a simple RNN and the corresponding discussion may be accessed in [1].

After thorough research and investigation of the model quality, the authors came up with the necessity to use 100 epochs of training instead of recommended in the literature 1000+ because of the overfitting problem. The model performed worse with 500+ epochs than in the case of 50–200 epochs of training due to overcapturing non-linearity and random noise.

The architecture was chosen to be more difficult than in [1] and it comprises of a single LSTM layer with 24 units and 2 sequential dense layers with decreasing amount of nodes. Such an approach allows enough complexity and was chosen through the method of trials and error so as to use insights from the literature.

The model is trained on the dataset where X values are taken with the corresponding lag (depending on the exercise, whether we're talking about forecasting 1-month ahead or 6-months ahead). Y values are taken without the lag in order to make the model able to, actually, forecast with the available data. Then, in the test exercise, the last row of available data is taken to produce a forecast on 1 or 6 months ahead depending on the model.

2.2.4. DTW+K-Means. A critical aspect of this research, one of its focal points of interest, involves a novel algorithm that employs an adapted Dynamic Time Warping (DTW) algorithm alongside a K-Means approach. This algorithm aims to explore the similarity among CPI components and categorize them into groups based on this similarity, as described above. This data-driven grouping approach enables the identification of patterns that may not be discernible through traditional economic logic alone. The algorithm is thoroughly explained in [1].

In short, the classic Dynamic Time Warping (DTW) algorithm constructs a matrix illustrating the distances between each data point in one sequence with every data point in another sequence. Then, the path through this Cost Matrix with a minimal sum can be found and it'll make a direct correspondence between each i-th and j-th points. The FastDTW adaptation decreases Cost Matrix using a mask over the squared table. However, it is not enough for the particular research. Here, the monthly time series with 12 periods throughout each year are expected to have not more than 12 periods away correspondence. To tackle this issue, let's introduce a restriction in the Cost Matrix, necessary for building correspondence between series, disallowing either «i» or «j» to remain the same for more than 12 consecutive instances. This is achieved through dynamic masking at each step, similar to the approach employed in the FastDTW algorithm. The formula for the Cost Matrix is as follows:

$$C(i,j) = d(x_i, y_j) + \\ + \min\{C(i-1,j), C(i,j-1), C(i-1,j-1)\}. \quad (5)$$

Having obtained a two-dimensional plane with a set of points in the preceding stage, it is possible to apply a clustering technique to group similar series together, which is a K-Means in this research, according the results and discussion in [1].

2.2.5. SARIMA+LSTM. In this paper, as one of the key models of interest, we'll build a combined approach that recognizes the complex dynamics of inflation and aims to capture both the linear and non-linear parts of the CPI components dynamics separately using the models for this task.

The first step of this model involves utilizing SARIMA to decompose the Core CPI time series into linearly-explained, seasonal and residual components. It may not fully account for all the stochastic fluctuations in the data and nonlinearities, thus they're expected to be in the residuals term. Hence, let's focus on them, which represent the unexplained variation in the Core CPI components after removing seasonality and linear autoregressive effects and need to concentrate on non-linear effects and interdependencies.

Then, let's employ an LSTM neural network by feeding the residuals from SARIMA into the LSTM model as input matrices. Let's allow the neural network to catch the intricate relationships and nonlinear patterns present in unexplained part of the data. LSTM's inherent memory capabilities enable it to effectively capture the dynamic nature of inflation, incorporating information from past observations to make accurate forecasts of future Core CPI values.

Through this hybrid approach, let's aim to harness the complementary strengths of SARIMA and LSTM to enhance the accuracy of Core CPI forecasts. By combining the robust statistical framework of SARIMA with the deep learning capabilities of LSTM, our model offers a comprehensive solution for predicting Core CPI movements, enabling policymakers and analysts to make more informed decisions in response to changing economic conditions.

2.2.6. Random Forest and XGBoost. As models from the world of Machine Learning, the paper will provide results from simple Random Forest and XGBoost. The variation of the models is simple thus there is not much necessity to dive deeper into the technical aspects as long as they're standard. Both models are based on the tree algorithms. The train and test set are similar to those that are fed to LSTM model. Both models are also able to capture non-linearities and cross-dependencies yet they're way simpler to build than the SARIMA+LSTM routine. The details of usage of Random Forest may be accessed, for example, from paper [13] that develops the model specifically for the case of short-term time series which is the case for this paper too. Another paper that also add to the overall

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discussion about such models is [14], because it shows the principle of combination between couple of models that is used in the current paper. Yet it shows it on the example of AR-type of models and Random Forest, but it also shows a combination of AR with Neural Network.

2.2.7. OLS for Weights. The final aspect of this section pertains to the aggregation challenge encountered in ARIMA forecasting. Following this process, it is possible to obtain a set of forecasts for components. However, aggregating these forecasts into total forecasts can be burdensome.

To address this challenge in a straightforward yet effective manner, it is possible to employ simple OLS (linear regression) on historical data to determine the correct weights for aggregating components. Naturally, as the economy evolves, these weights may also change, reflecting shifts in consumer preferences and spending patterns. For instance, as countries become wealthier, individuals typically allocate a smaller percentage of their income to food and basic necessities and more to services. However, these changes occur gradually, allowing to assume relative stability in the weights and utilize OLS-based estimates. The formula is as follows:

$$\pi_t^{core} = \beta_1 \cdot \pi_t^{component^1} + \beta \cdot \pi_t^{component^2} + \ldots + \beta_p \cdot \pi_t^{component^p}, \qquad (6)$$

where π_t – a Core or Component inflation; β_p – an estimated coefficient for component p.

Subsequently, the coefficients obtained are utilized to aggregate the forecasted components' inflation back into the forecast of Core Inflation.

3. Results and Discussions

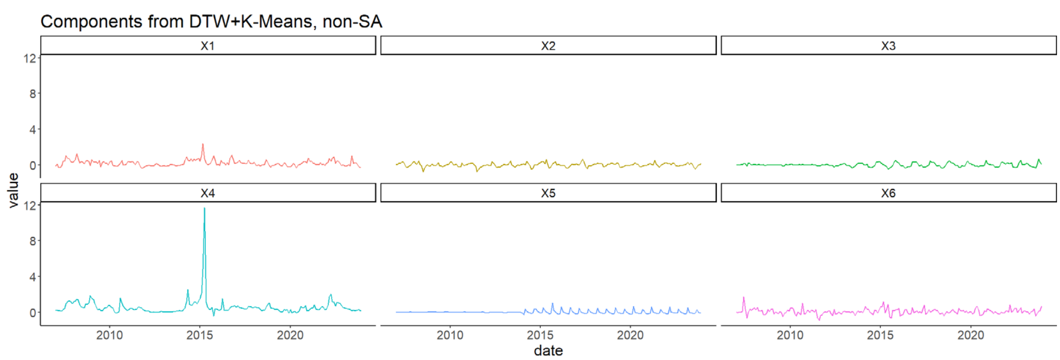
3.1. Model results. As we endeavour to generate robust forecasts of Core Inflation, the quality of our models remains paramount. To ensure their efficacy, let's employ a rigorous evaluation methodology that involves estimating models across multiple databases in a shifting window framework. This approach entails utilizing historical data up to a certain point as a training dataset, followed by the generation of pseudo-out-of-sample forecasts for periods ranging from 1 to 6 months ahead. Subsequently, the dataset is expanded by a single time period, and the process is iteratively repeated. This iterative procedure spans from January 2021 to December 2023 (full 3 years) for 1-month or 2-months ahead forecasts. The pseudo-forecasts thus obtained are aggregated into a vector and assessed against actual values using the Root Mean Squared Error (RMSE), a widely accepted metric for evaluating forecast accuracy, calculated as follows:

$$RMSE = \sqrt{\frac{\sum\left(x_t - \hat{x}_t\right)^2}{n}}, \qquad (7)$$

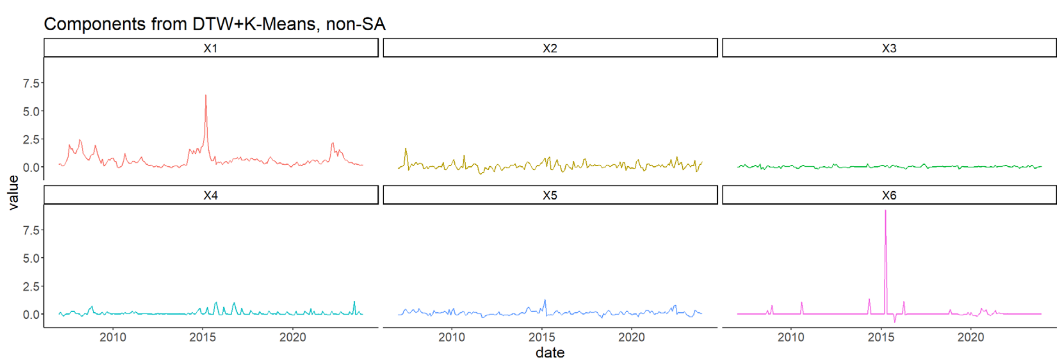
where x_t – an actual value and $\hat{x}_t$ – the predicted value, and n – the number of points.

This systematic approach affords the ability to account for both substantial deviations and minor discrepancies, aligning with our objective of developing a forecasting model that exhibits resilience against significant errors while remaining sensitive to moderate deviations over time.

Prior to proceeding, let's examine the outcomes of the DTW+K-Means routine applied to the Core CPI components, a procedure integrated into half of the models showcased. By visualizing the temporal dynamics of these series on a two-dimensional plot, it is possible to gain insights into their proximity and can subsequently categorize them into clusters. But the most interesting is the actual resulting sub-component after the transformation, which can be observed in Fig. 2.



a



b

Fig. 2. Aggregated components from the DTW+K-Means procedure over: *a* – seasonally unadjusted set of series; *b* – seasonally adjusted set of series

In the graph it is possible to see that DTW+K-Means routine over not seasonally adjusted components produce categories that have a clear presence of seasonality in most series. It may be crucial for the performance according to the results from [1] thus the seasonally adjusted components were also fed to the algorithm which produces the next set of categories. Here it is possible to see only occasional seasonality that comes from the problem with change in methodology, known and common problem for data collection. It should be treated distinctly; however, it is more of a scope for paper with a focus on the economic analysis.

Then we'd fit actual models over those components. In all models we'll use them over DTW+K-Means routine and show 1 month ahead and 2 months ahead forecasts results. Such a choice dictated by the short-run nature of those forecasting models that are not able to capture structural. The result can be seen in the Table 1.

Table 1

Rolling RMSE for 1 and 2 months ahead forecasts in 2021m1–2023m12

RMSE of models	1 m ahead	2 m ahead
RW	1.073	1.167
RW (SA)	0.992	1.092
SARIMA	0.914	0.961
SARIMA (categories)	0.831	0.887
ARIMA (SA comps)	0.796	0.825
LSTM	0.830	0.939
LSTM (SA comps)	0.651	0.777
LSTM+SARIMA routine	0.575	0.783
Random Forest	0.665	0.808
Random Forest (SA comps)	0.604	0.713
XGBoost	0.674	1.038
XGBoost (SA comps)	0.638	0.744
Standard deviation of Core CPI	0.895	

3.2. Discussion. Results in the table clearly suggests outperformance of novel models over Random Walk, traditional models like ARIMA and SARIMA in different interpretations and another benchmark which is a standard deviation of the series on forecasted period. The statement is true for both 1-month ahead and 2-month ahead forecasts.

Moreover, throughout the table, it is possible to see minor outperformance of the model where some kind of seasonal adjustment is present.

Among all non-traditional models, the best performance goes to the LSTM+SARIMA routine. This powerful approach managed to capture linear, non-linear and interdependent patterns better than any other model. Yet this model is difficult to build which allows to simple Machine Learning methods like XGBoost and Random Forest to shine brightly.

As long as this model outperforms all other benchmarks, it may be quite beneficial to use it as a work-horse model for Core inflation forecasting which, in its turn, may improve the decision-making process for government facilities and for businesses who are building their pricing strategy and short-to-medium term plans.

Despite the good results, such approaches to assessing the model quality are not resilient to unexpected shocks such as the war. There is a minority of pre-signals that could give the information about such a shock, yet this problem goes for all and every statistical forecasting model. This is the reason to evaluate comparative model performance and check whether the built key model outperforms others.

Further development of such models is based on the continuous fitting and deeper investigation of economic fundamentals and results, specifically from the first stage where series are grouped by the similarity of their dynamics. Also, the major improvement may come from the addition of series from different nature yet those that have some effect on the investigated series. For example, exchange rate or risk premia. This may improve model forecasting ability and overall results quality yet it's an economic question, not computer science question. Thus, it will be investigated in the corresponding paper.

4. Conclusions

A set of models is built and compared throughout the research. Most of those models are default, for example SARIMA or XGBoost/Random Forest, however the key and the most interesting ones are pretty unique in the literature. The word is about LSTM routine based on components from adapted DTW+K-Means algorithm. This pipeline is further reinforced with a SARIMA to capture linear and seasonal parts distinctly and leave the non-linearity and cross-correspondence to the LSTM.

LSTM+SARIMA routine shown the best performance both in 1-month ahead and 2-months ahead exercises. Yet XGBoost and Random Forest provides a favourable performance too and may also be used in the forecasting toolboxes in Central Banks as a simple-to-build variation in line with traditional models.

Further research will comprise an investigation of those algorithm performance from the macroeconomic side, which will involve an investigation of models' ability to capture particular shocks interpreting preliminary signals.

Conflict of interest

The author declares that he has no conflict of interest concerning this research, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

The paper has no associated data.

Use of artificial intelligence

The author confirms that he did not use artificial intelligence technologies when creating this work.

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Dmytro Krukovets, *Postgraduate Student, Department of Computer Science and Cybernetics, Taras Shevchenko National University of Kyiv, Kyiv, Ukraine, e-mail: dkrukovets@kse.org.ua, ORCID: https://orcid.org/0009-0002-8803-0580*