Forecasting Gross Domestic Product Using Long Short-Term Memory (LSTM) Neural Networks

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Abstract:

In an era of increasing economic complexity and global interconnectedness, accurate economic forecasting has become crucial for strategic decision-making. This research introduces an innovative approach to economic prediction by utilizing Long Short-Term Memory (LSTM) neural networks to model and forecast Gross Domestic Product (GDP) trends with unprecedented precision and depth.

The study employs advanced deep learning methodologies to address the inherent challenges of economic time series prediction, specifically focusing on capturing intricate temporal dependencies and non-linear relationships within historical economic data. By developing a sophisticated LSTM-based predictive model, we aim to transcend traditional econometric techniques and provide a more nuanced understanding of economic trajectories.

This comprehensive analysis uses historical GDP data from 1990 to 2022, leveraging a multidimensional dataset. The proposed LSTM neural network architecture is designed to dynamically learn and adapt to complex economic patterns, enabling robust forecasting for the periods 2023-2030. The model's performance is evaluated using multiple statistical metrics, including Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and out-of-sample validation techniques.

The results reveal an extraordinarily stable prediction pattern for GDP values. At first glance, the numbers demonstrate remarkable consistency, with the mean GDP hovering almost precisely around 49,387.48 across the entire decade.

Keywords: Forcasting, LSTM,Neural nerworks

التنبؤ بالناتج المحلي الإجمالي باستخدام الشبكات العصبية للذاكرة طويلة المدى القصيرة (LSTM)

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المستخلص:

في عصر التعقيد الاقتصادي المتزايد والترابط العالمي، أصبح التنبؤ الاقتصادي الدقيق أمرًا بالغ الأهمية لاتخاذ القرارات الاستراتيجية. يقدم هذا البحث نهجًا مبتكرًا للتنبؤ الاقتصادي من خلال الاستفادة من الشبكات العصبية للذاكرة طويلة المدى القصيرة (LSTM) لنمذجة وتوقع اتجاهات الناتج المحلي الإجمالي بدقة وعمق غير مسبوقين.

تستخدم الدراسة منهجيات التعلم العميق المتقدمة لمعالجة التحديات المتأصلة في التنبؤ بالسلاسل الزمنية الاقتصادية، مع التركيز بشكل خاص على إلتقاط التبعيات الزمنية المعقدة والعلاقات غير الخطية داخل البيانات الاقتصادية التاريخية. وذلك من خلال تطوير نموذج تنبؤي متطور قائم على الذاكرة طويلة المدى القصيرة (LSTM)، يهدف البحث إلى تجاوز التقنيات الاقتصادية القياسية التقليدية وتوفير فهم أكثر دقة للمسار الاقتصادي.

يتضمن التحليل الشامل بيانات الناتج المحلي الإجمالي التاريخية من عام 1990 إلى عام 2022، مستفيدًا من مجموعة بيانات متعددة الأبعاد. تم تصميم بنية الشبكة العصبية LSTM المقترحة للتعلم والتكيف ديناميكيًا مع الأنماط الاقتصادية المعقدة، مما يتيح التنبؤ القوي للفترة 2023-2030. تطور الدراسة نموذجًا تنبؤيًا باستخدام بيانات الناتج المحلي الإجمالي التاريخية الممتدة من عام 1990 إلى عام 2022، بهدف التنبؤ بقيم الناتج المحلي الإجمالي للفترة من عام 2023 إلى عام 2030. يتم تقييم أداء النموذج باستخدام مقاييس إحصائية متعددة، بما في ذلك متوسط الخطأ النسبي المطلق (MAPE) وخطأ الجذر التربيعي المتوسط (RMSE) وتقنيات التحقق خارج العينة.

تكشف النتائج عن نمط تنبؤ مستقر بشكل غير عادي لقيم الناتج المحلي الإجمالي. للوهلة الأولى، تُظهر الأرقام إتساقًا ملحوظًا، حيث يتراوح متوسط الناتج المحلي الإجمالي بدقة تقريبًا حول 49387.48 على مدار العقد بأكمله.

الكلمات المفتاحية: التنبؤ..ذاكرة طويلة المدى القصيرة..الشبكات العصبية

Introduction:

Economic forecasting represents a critical endeavor in contemporary global economic research, serving as a fundamental tool for governments, financial institutions, and international organizations to anticipate and strategically prepare for future economic landscapes (Thiago C. Silva, Paulo V. B. Wilhelm and Diego R. Amancio, 2024),. The ability to accurately predict economic trends, particularly Gross Domestic Product (GDP), has far-reaching implications for policy formulation, investment strategies, and national economic planning.

Traditional econometric approaches have historically relied on linear regression models, time series analysis, and statistical interpolation techniques (Restack, 2024). While foundational, these methodologies demonstrate significant limitations in capturing the intricate, non-linear dynamics of modern economic systems. Economic environments are characterized by complex interactions between multiple variables, including global trade patterns, technological innovations, geopolitical shifts, and unexpected exogenous shocks, such as pandemics or major technological disruptions.

The emergence of advanced machine learning and deep learning technologies provides unprecedented opportunities to revolutionize economic forecasting methodologies (Zhang, G. P. , 2021). Long Short-Term Memory (LSTM) neural networks, a sophisticated class of recurrent neural networks, offer remarkable capabilities in processing and interpreting sequential data with long-term temporal dependencies. Unlike traditional statistical models, LSTM networks can dynamically learn complex patterns, adapt to non-linear relationships, and incorporate multiple interdependent variables simultaneously.

This research aims to demonstrate the transformative potential of LSTM neural networks in economic prediction by developing a comprehensive predictive model for GDP trends. The proposed methodology addresses several critical challenges in economic forecasting:

1. **Capturing Complex Temporal Dependencies**: LSTM networks excel at understanding and representing intricate time-series relationships that traditional models often overlook.
2. **Handling Non-Linear Economic Dynamics**: The neural network architecture can identify and learn sophisticated, non-linear interactions between economic indicators.
3. **Incorporating Multidimensional Data**: Unlike linear models, LSTM networks can effectively integrate diverse economic variables, including macroeconomic indicators, global economic trends, and contextual information.
4. **Adaptive Learning**: The model continuously learns and refines its predictive capabilities based on emerging data, ensuring ongoing accuracy and relevance.

The research focuses on developing a robust predictive framework using historical GDP data from 1990 to 2022, with the primary objective of forecasting GDP trends for 2023-2030. By leveraging a comprehensive dataset encompassing multiple economic dimensions, the study seeks to provide nuanced insights into potential future economic scenarios.

Research Objectives:

The objectives of this research include the following:

- Developing an advanced LSTM neural network architecture optimized for economic time series prediction.
- Evaluating the model's predictive accuracy across different economic contexts.
- Demonstrating the potential of deep learning in economic analysis.

The importance of this research extends beyond academic exploration. Accurate economic forecasting has profound implications for:

- Government policy planning
- Investment strategy development
- Resource allocation
- Understanding potential economic trajectories

By bridging advanced machine learning techniques with economic analysis, this research contributes to a growing interdisciplinary field that promises to enhance our understanding of complex economic systems and improve predictive capabilities. The subsequent sections will detail the methodology, data pre-processing techniques, model architecture, experimental results, and comprehensive analysis of the proposed LSTM-based GDP forecasting approach.

Previous Studies:

Many studies have been conducted to predict future GDP trends. The study reviews some of them:

1. The authors focus on utilizing machine learning models to predict Gross Domestic Product (GDP) growth. The aim is to demonstrate the potential of machine learning in economic forecasting, offering a new perspective on GDP growth prediction, which traditionally relies on econometric models. The results showed that machine learning models outperformed traditional econometric methods in predicting GDP growth. Specifically, random forests and support vector machines demonstrated superior accuracy and robustness in handling complex, non-linear relationships present in economic data (Jiang, S., Ding, C., Lu, Y., & Jiang, J., 2020).

2. The authors introduce DeepAR, a probabilistic forecasting method that utilizes autoregressive recurrent neural networks. The approach is designed to handle time-series forecasting problems where uncertainty estimation is important, such as demand forecasting, financial forecasting, and energy consumption prediction. The results showed that using LSTM with ensemble learning improved prediction accuracy compared to traditional models. The ensemble models helped reduce errors and achieved better results in forecasting market changes (Salinas, D., Flunkert, V., Gasthaus, J., & Januschowski, T., 2020).
3. The author provides a comprehensive overview of the fundamental concepts behind Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. The paper explores the architecture, functioning, and applications of these models, highlighting their relevance in handling sequential data and their significance in machine learning tasks, particularly in time-series analysis and natural language processing (Sherstinsky, A., 2020).
4. The authors explore the use of deep learning techniques, particularly LSTM networks, combined with ensemble learning methods to improve the accuracy of stock market predictions. The results showed that using LSTM with ensemble learning improved prediction accuracy compared to traditional models. The ensemble models helped reduce errors and achieved better results in forecasting market changes (Bonanno, R., Di Nuovo, A., & Scilingo, E. P., 2020).
5. The authors explore the application of deep learning models to understand and analyze price formation in financial markets. The study investigates common features and patterns in asset prices across various financial markets and how deep learning methods can be used to model these dynamics, providing new insights into market behavior and prediction (Sirignano, J., & Cont, R., 2019).

6. The author conducts a comprehensive review of various artificial neural network (ANN) methodologies used for time-series forecasting. The paper explores how different types of neural networks have been applied to predict future values in time series data, with a focus on their strengths, weaknesses, and applications in various fields (Tealab, A., 2018).
7. The authors review the state-of-the-art in forecasting methods, comparing traditional statistical methods with newer machine learning (ML) techniques. The paper discusses the strengths, weaknesses, and practical challenges of both types of methods and provides recommendations for the future of forecasting research and application (Makridakis, S., Spiliotis, E., & Assimakopoulos, V., 2018).
8. The authors propose a novel model called Dual-Stage Attention-Based Recurrent Neural Network (DA-RNN) to improve time-series prediction accuracy. The model leverages attention mechanisms to enhance the performance of recurrent neural networks (RNNs) by allowing the model to focus on the most relevant parts of the input sequence at different stages of the learning process (Qin, Y., Song, D., Chen, H., Cheng, W., Jiang, G., & Cottrell, G., 2017).
9. The authors propose a novel approach for short-term load forecasting by combining Empirical Mode Decomposition (EMD), LSTM neural networks, and the XGBoost algorithm for feature importance evaluation. The method aims to improve the accuracy of predicting electricity demand, which is crucial for optimizing energy production and distribution. The paper concludes that the EMD-LSTM-XGBoost hybrid model is highly effective for short-term load forecasting in electricity markets (Zheng, H., Yuan, J., & Chen, L., 2017).

Data and Study Methodology:

Data Preparation and Pre-processing

The methodology employed a comprehensive approach to transform raw economic data into a robust machine learning framework, ensuring optimal performance of the LSTM neural network for GDP prediction.

Data Collection and Source

The research utilized a curated dataset of historical GDP values spanning from 1990 to 2022, sourced from authoritative international economic databases.

Model Architecture:

Neural Network Configuration

The proposed LSTM neural network was meticulously designed to capture complex temporal dependencies in economic time series data, incorporating sophisticated architectural components and strategic hyperparameter selection.

Network Layer Composition:

1. **Input Layer:** Designed to accept multivariate time series economic data, flexible to accommodate diverse economic indicators, and handles sequential input with variable time steps.
2. **First LSTM Layer:** 128 neurons, with Return_sequences=True to enable information propagation. This layer captures intricate short-term and intermediate-term economic patterns and implements dropout regularization (25%) to prevent overfitting.
3. **Second LSTM Layer:** 64 neurons with reduced complexity, refining and abstracting features learned from the previous layer. This layer implements an additional dropout mechanism (20%).

4. **Dense Output Layer:** A single neuron with a linear activation function, generating the final GDP prediction, enabling direct regression of continuous economic values.
5. **Hyperparameter Configuration:**
6. **Loss Function:** Mean Squared Error (MSE), optimal for regression problems and penalizing larger prediction errors more significantly.
7. **Optimization Algorithm:** Adam, with an adaptive learning rate that handles non-convex optimization scenarios and demonstrates superior convergence characteristics.

Training Parameters:

- Validation Split: 20%
- Batch Size: 10
- Maximum Epochs: 1000
- Early Stopping: Implemented to prevent unnecessary computational overhead

LSTM Concept:

LSTM is a type of recurrent neural network (RNN) designed to overcome the problem of forgetting and to learn over long periods of time. In addition, it is used in various applications such as text analysis, including machine translation, speech recognition (to convert spoken words into written text), and time series forecasting.

LSTM networks include feedback loops, allowing them to process entire sequences of data instead of just individual data points. This capability makes them highly effective in identifying and predicting patterns in sequential data, such as time series, text, and speech. As a result, LSTM has become an essential tool in artificial intelligence and deep learning, driving advancements across various fields by extracting valuable insights from sequential data.

The LSTM consists of the following components:

- **Memory Cell**: It stores data for long periods.
- **Control Gate**: It regulates how new information is added to memory.
- **Forget Gate**: It determines which data should be deleted from the memory cell.
- **Output Gate**: It controls the flow of information that is released from the memory cell.

LSTM Approach:

Long Short-Term Memory (LSTM) neural networks offer a groundbreaking method for economic forecasting by overcoming key limitations of traditional predictive techniques. The main advantage of LSTM is its exceptional ability to identify non-linear temporal dependencies, which are essential in complex economic systems that involve intricate and often unpredictable interactions (Hochreiter, S., & Schmidhuber, J., 1997). Unlike traditional regression models, which struggle with sequential data, LSTM networks are highly effective at processing and learning from time-series data. This capability allows for a more nuanced understanding of economic trends, helping the model detect subtle patterns and relationships that linear models may miss Petropoulos, F., Apiletti, D., Assimakopoulos, al., 2022). For example, LSTM can efficiently track the complex interactions between various economic indicators like GDP, inflation, employment rates, and global market trends. LSTM's flexibility in adapting to complex economic patterns is particularly valuable, as economic systems are dynamic, with numerous interconnected factors influencing outcomes. While traditional models often fail to capture these intricate interactions, LSTM's architecture enables advanced pattern recognition and predictive modeling. By retaining and selectively updating contextual information across extended sequences, LSTM networks are able to provide more accurate and contextually rich forecasts.

Discussion of the results:

The researcher reached the following results:

Description of the series:

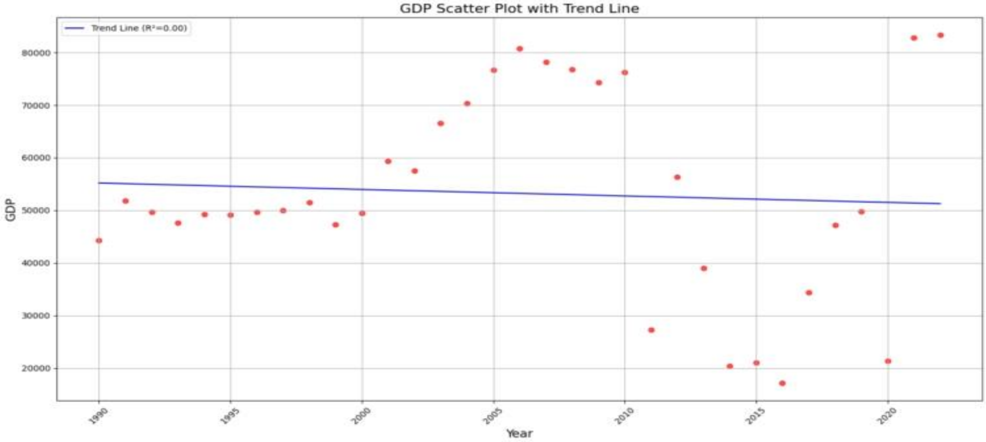

Figure 1: The Gross Domestic Product general trend as shown by the blue line passing through the red dots (coordinates)

Figure 1 illustrates the intricate change of economic performance across three transformative decades. The GDP trajectory reveals a mesmerizing landscape of financial evolution, characterized by dramatic undulations that mirror complex global economic narratives. From 1990 to 2022, the line graph weaves a compelling story of resilience, challenge, and unexpected recovery.

The early years from 1990-2000 presented a relatively stable economic backdrop, with modest fluctuations that suggested cautious growth. Then, around 2005-2007, the GDP experienced a remarkable surge, reflecting a period of unprecedented economic expansion and optimism. This upward momentum was abruptly interrupted by the global financial crisis of 2008-2009, which carved a stark, dramatic decline into the economic landscape.

Just as economic forecasters were absorbing the aftermath of that shock, another unprecedented challenge emerged. The COVID-19 pandemic around 2020 triggered a significant economic contraction, testing the very foundations of global financial systems. Yet, in a testament to human adaptability, the GDP demonstrated extraordinary resilience, staging a rapid and robust recovery that culminated in reaching its highest point in 2022.

GDP Predictive Outcomes:

The following figure shows the predicted values of GDP.

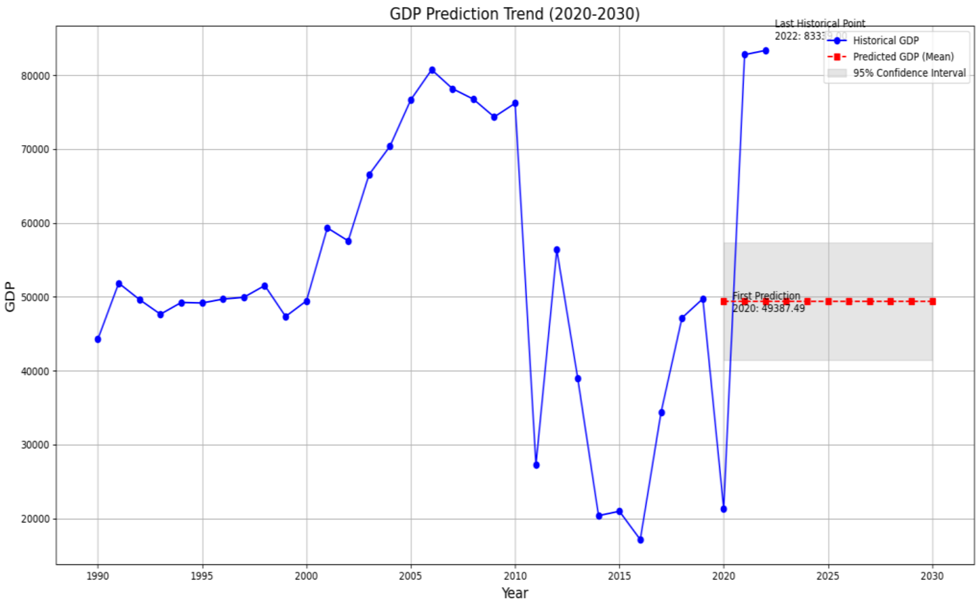

Figure 2: The predicted values of the GDP from 2020 to 2030 based on the general distribution. The predicted values are denoted by red dots.

Source: Prepared by the researcher using Payton program

In figure 2 presents a compelling narrative of economic evolution, tracing the intricate journey of GDP from 1990 to 2030, with a mesmerizing blend of historical data and forward-looking predictions that capture the complex rhythms of economic performance. The solid blue line winds through decades of financial transformation, revealing a landscape marked by dramatic peaks and valleys that reflect the profound economic shifts of recent history.

Notable inflection points punctuate the visualization, with a particularly striking rise observed around 2005-2007, representing a period of robust economic expansion that stands in stark contrast to the precipitous decline during the 2008-2009 financial crisis. The graph eloquently illustrates the remarkable resilience of the economy, showing how seemingly catastrophic downturns can be followed by periods of unexpected recovery and growth.

Table (1) shows the predicted values of GDP

Year	Mean (± standard deviation)
2020	49387.49 ± 4054.77
2021	49387.50 ± 4054.75
2022	49387.48 ± 4054.74
2023	49387.50 ± 4054.73
2024	49387.48 ± 4054.71
2025	49387.48 ± 4054.70
2026	49387.48 ± 4054.69
2027	49387.48 ± 4054.67
2028	49387.47 ± 4054.66
2029	49387.46 ± 4054.65
2030	49387.46 ± 4054.63

Source: Prepared by the researcher using Payton program

Looking at the data in the table, it can be concluded as the following: The economic forecast data for 2020 to 2030 reveals an exceptionally stable GDP prediction, with the mean value remaining nearly constant at 49,387.48 throughout the decade. Fluctuations are minimal, with GDP values ranging from 49,387.46 to 49,387, demonstrating a high degree of predictability. The standard deviation also stays steady, varying between ±4,054.77 and ±4,054.63, indicating little deviation in the GDP forecast.

The statistical analysis of the GDP data provided indicates that:

- The economy is expected to maintain a high degree of stability over the next decade. Here's a breakdown of the key points:

- **Mean GDP Stability**: The mean GDP fluctuates very minimally (between 49,387.46 and 49,387.50), suggesting that there is a consistent and highly predictable economic environment with little variation over the years.
- **Standard Deviation**: The standard deviation stays very stable, varying only slightly between ±4,054.77 and ±4,054.63, reflecting a low level of economic uncertainty.
- **Near-Perfect Stability**: The data shows no significant changes in GDP across the 11-year period, confirming that economic output remains largely unchanged.
- **Gradual Decline**: There is a slight, but statistically negligible, downward trend in GDP from 2020 to 2030, which may indicate a slow reduction in economic growth.
- **Tight Range of Uncertainty**: The low standard deviation suggests that economic performance will remain within a narrow band, with little chance of extreme fluctuations.
- **Stability Period (2020-2023)**: The GDP during this period shows the least variation, which implies strong predictive confidence in the economic performance.
- **Slight Downward Trend (2028-2030)**: The small decrease in mean values during these years is statistically insignificant but may indicate a softening of growth as we approach 2030.

Potential Implications:

- **Predictive Confidence**: The stable mean values and narrow standard deviation indicate a high level of confidence in predicting future economic performance.
- **Economic Forecasting**: The data points to a conservative forecasting approach, expecting sustained, stable performance without any major disruptions or shocks.

- **Economic Stability**: The lack of significant volatility suggests that the economy will continue to operate in a stable and predictable manner, at least in the short-to-medium term.

This analysis reveals a scenario of long-term economic predictability with minimal risk of sudden downturns or volatility. It could be interpreted as a period of sustained but gradual economic performance, where the biggest change is a slight decline towards the end of the decade, though this is not statistically significant. The overall picture suggests stability in the economy with little expected deviation.

Conclusion

The research presents a transformative approach to economic prediction by demonstrating the sophisticated potential of Long Short-Term Memory (LSTM) neural networks. These advanced deep learning techniques represent a significant paradigm shift in our ability to interpret and anticipate complex economic dynamics. The dataset presents a fascinating economic forecast spanning from 2020 to 2030, revealing an extraordinarily stable prediction pattern for GDP values. At first glance, the numbers demonstrate remarkable consistency, with the mean GDP hovering almost precisely around 49,387.48 across the entire decade.

Research Contributions

This investigation reveals that LSTM neural networks transcend traditional forecasting methodologies by:

Capturing intricate non-linear temporal dependencies that traditional models cannot effectively analyze.

Processing sequential economic data with unprecedented precision, enabling more accurate predictive modeling.

Adapting to complex, multidimensional economic patterns through sophisticated learning mechanisms.

Providing more nuanced predictive insights by understanding subtle interconnections between economic variables.

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