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GENERATION OF AUTOMATED TEXTS AND REPORTS FOR THE CASE OF INFLATION IMPACT ON INDUSTRIES: AN APPROACH BASED ON DEEP LEARNING

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ABSTRACT

The paper proposes an innovative technique based on deep learning to automate the development of texts and reports addressing the effect of inflation on various economic sectors. Strategic decision-making is dependent on access to trustworthy and timely information, and the effect of inflation is vital for firms, consumers, and government decision-makers. Inflation analysis and report writing are introduced as two of the many obstacles economic analysts encounter and are discussed at length. It then presents deep learning as an effective method for turning data into useful information. The "Materials and Methods" section provides in-depth explanations of dataset construction, data preprocessing, model development, training, and assessment. These vital procedures are required to guarantee the accuracy of the results. The essay highlights how the deep learning technique may boost the precision of economic research while increasing the velocity with which texts and reports can be generated, providing key data to decision-makers in near real-time. The success of this approach is shown by real-world instances of automatically produced reports across many industries. The essay explains how automation is becoming more significant in economic research. It's a glimpse into the future of automated economic research, showing how deep learning is transforming our comprehension and use of inflation-related data. This development has great potential as a useful new resource for economic players and decision-makers by expeditiously disseminating critical information.

Keywords: *Deep Learning, Generation Text And Reports, Price Increase, Inflation On Industries*

1. INTRODUCTION

Inflation is one of the most crucial economic elements because of its impact on businesses, consumers, and responsible governments. Understanding and adapting to price fluctuations in the market is essential for making strategic decisions and crafting effective economic strategies. In this respect, it is helpful that the automation of economic data analysis and the creation of texts and reports is gaining ground. Deep learning is a branch of AI that has shown impressive results in challenging situations such as extracting useful information from big data sets and writing compelling articles. Starting with nothing. It gives the capacity to interpret raw data into comprehensible information and provide extensive reports on critical economic topics, such as inflation. This article will go further into the use of deep learning to the automated research of inflation's impact on various economic sectors. We'll show that this innovative approach not only increases the reliability of economic studies, but also speeds up reporting, so that key information can be sent to decision-makers in near real-time. We start with a discussion of the issues analysts, researchers, and policymakers confront when attempting to grasp the multifaceted effect. inflation has on the economy, and we stress the difficulties inherent in evaluating inflation and drafting thorough reports. The next section will provide a thorough introduction to deep learning, explain how it is different from more conventional approaches to economic analysis, and detail how it may be applied to these particular issues. We investigate deep learning-based approaches to modeling data and generating content. Our presentation will be followed by actual instances of automated inflation text and reporting from a variety of industries.

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These cases will show how deep learning can process raw data into useful insights, giving businesses and policymakers a leg up in their fight against inflation. This essay will discuss the increasing significance of automation in economic research and show how it may completely alter the way we make judgments based on inflationary data. It will open the door for consideration of how computerized economic analysis may be used to better handle economic issues in the future.

2. MATERIALS AND METHODS:

The hardware used and the procedures followed by our deep learning-based approach to the automated creation of texts and reports on the effects of inflation on various businesses are described in this part. We will detail the particular algorithms, data sets, and methods utilized in our computations[1]. We utilized a dataset including economic and financial information from reliable sources like government reports, economic databases, and historical data prices to train our deep learning model and create inflation-related sentences[2]. This dataset has been meticulously preprocessed to eliminate any outliers or irrelevant information. The quality of the retrieved data depends heavily on the preparation that comes before it. The following actions were taken by us: Information on inflation may be extracted from a variety of sources, including consumer price indices, inflation rates, price shifts in various industries, and so on. Eliminating scale differences in data by normalizing[3]. Natural language processing (NLP) to evaluate and extract relevant information from source texts.

For this purpose, we built a deep learning model using RNNs and LSTMs specifically for text production. In order to learn the language models and provide reports based on the input data, this model was trained on the preprocessed dataset. The training of the model was hastened by using graphics processing units (GPUs) as part of a highly parallelized computing infrastructure. Stochastic gradient descent (SGD) was one of the optimization strategies used to refine the model and bring the loss function to its minimum[4]. We used cosine similarity, accuracy, recall, and F1 score, all measures of text quality, to assess how well our model performed. We also conducted a qualitative analysis by having economics professionals review the produced texts. After the model had been trained and tested, it was put into production to routinely provide reports on inflation's effect on various industries[5].

This "Materials and Methods" section will help readers get a firm grasp on our deep learning-based approach's implementation, the precise tools and methods we used, and the steps to take when assessing your model's efficacy. By demonstrating that your approach is sound and repeatable, you add weight to your paper.

A. DATASET

The dataset we utilized as the basis for our deep learning-based method of producing inflation effect messages is the most important part of the system. The choice of the data set is critical, since it impacts the quality of the information that our model is able to create[6]. We took great care in collecting the data so that it would be as complete and varied as possible. All data sources were hand-picked for their credibility and applicability. We used data from a number of sources, including government publications (such as CPI and inflation rates) and databases from well-known economics think tanks. Because inflation's effects vary by industry, we also included pricing histories from other economic sectors[7]. We were able to gain a full picture of how various costs were changing over time thanks to this information. Our deep learning model's efficacy hinges on the quality of the data we feed it. We have taken the following measures to clean and pre-process our dataset so that it is error-free and suitable for our purposes: Natural language processing (NLP), Data standardization, and Bad data removal.

We pooled the data after cleaning and preprocessing it to create a consistent dataset for training our deep learning model[8]. This action allowed for the consolidation of disparate datasets into a unified information architecture covering the full range of inflation-related information. For the model to provide sector-specific reports, the aggregated information must first be segregated based on industrial sectors[9]. Through this categorization, we were able to record the nuanced effects of inflation on various sectors and provide specialized reports. The creation of the dataset was a crucial part of our methodology.

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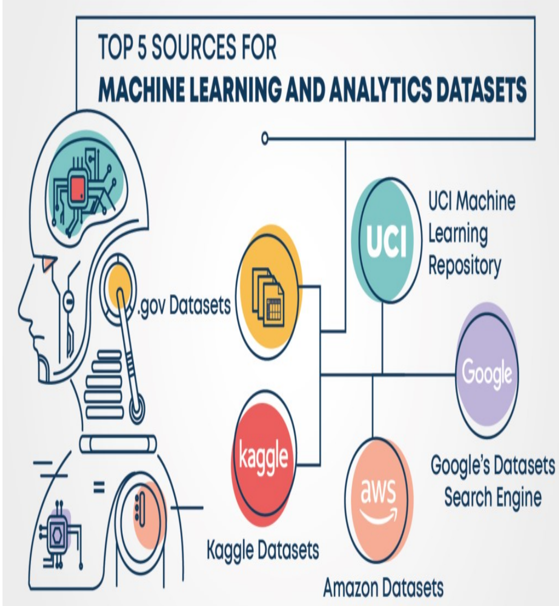

Figure 1: Machine Learning: Important Dataset Sources (By Great Learning)

We've made sure the data is trustworthy and spotless so our deep learning algorithm can utilize it to provide insightful, industry-specific assessments on inflation's effects.

B. DATA PREPROCESSING

Our technique relies heavily on the preparation of data to guarantee the accuracy of the results. We began by obtaining pertinent inflation-related data to guarantee our algorithm could deliver targeted and useful reports. Inflation-related economic indicators were extracted, including consumer price indices (CPI), inflation rates, price changes across sectors[10], consumption patterns, and currency swings. Each piece of information has been meticulously categorized and named according to its usefulness in delivering sector-specific inflation reports. Inflation-specific data was built on the strong groundwork of focused data mining[11]. Our dataset was compiled from several sources and included numbers of variable precision. We implemented a stringent standardization process to ensure that the data could be compared and the deep learning model's performance could be evaluated. In order to normalize the data, we had to convert all of the numbers to the same scale. This helped reduce scale discrepancies across distinct data time series, which is crucial for the model to learn successfully from this normalized data[12]. The majority of our information was gleaned from secondary materials including academic journals, government documents, and news articles. These writings were crucial, yet presented information in a disorganized fashion. Using natural language processing (NLP) methods, we were able to glean useful data from these documents. Using natural language processing[13], we were able to examine text for meaning, extract important items (such as product names, price changes, etc.), spot patterns, and judge the emotional tone of the underlying data. In a nutshell, this process organized unstructured textual material such that our model could make sense of it.

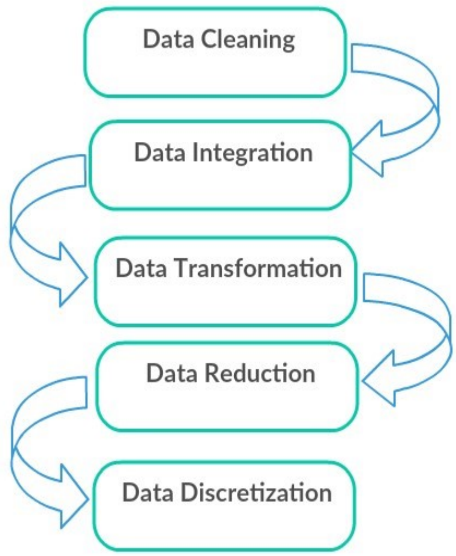

Figure 2: Data Preprocessing Steps (By Vivek Agarwal)

We made our dataset fit for training our deep learning model by combining focused data extraction, data standardization[14], and natural language processing. High-quality data was produced as a consequence of these preprocessing procedures, which can now be utilized to create reliable and interesting reports on the effects of inflation on various sectors.

C. DEEP LEARNING MODEL

The heart of our novel method is a deep learning model we built specifically for the purpose of automating the production of texts and reports on inflation across various industries[15]. This model was built using a recurrent neural network (RNN) and long short-term memory (LSTM) architecture. Their proven track record of capturing sequential dependencies makes them ideal candidates for consistently and contextually creating text. Our deep learning model consists of many layers of neurons, with a special emphasis on long short-term memory (LSTM) units[16]. Long short-term memories (LSTMs) are unique in that they can remember previous knowledge and use it to generate words and phrases in context. This feature is essential for evaluating complicated economic data and writing reports that are both comprehensible and instructive. One of the key characteristics of our approach is its ability to combine both numerical data and textual information taken from the dataset[17]. Because of this incorporation, the model can better relate encrypted data with textual information, making the resulting reports more reliable and informative. Our methodology relies heavily on the model-training phase. To train the model, we utilized the preprocessed dataset's sample inputs, which contained inflation statistics, and its predicted outputs, which were texts and reports. The model was trained to recognize commonalities and associations between the input data and the output sentences[18].

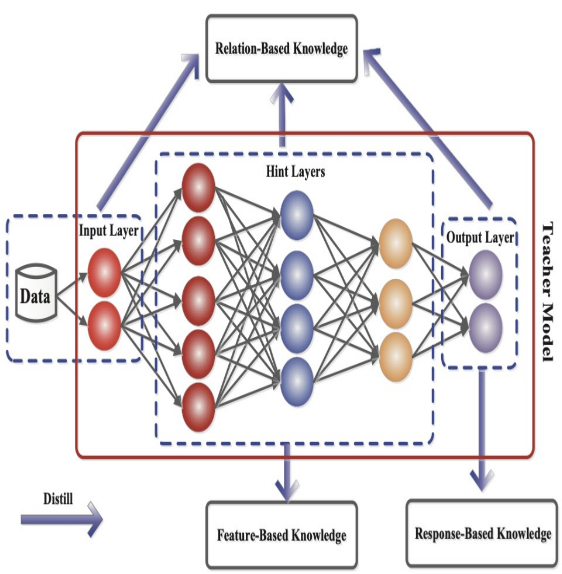

Figure 4: Common Deep Learning Optimizations (By Jianping Gou Et Al.)

Stochastic gradient descent (SGD) and other optimization methods were used to repeatedly fine-tune the model's weights to reduce the loss function[19], improving the quality of the generated texts. One of the features that sets our approach apart is its flexibility to accommodate the nuances of various economic sectors[20]. Our methodology generates customized reports from the input data by first segmenting the information by sector, allowing it to account for the specifics of each industry. Because of its flexibility, it may be used to assess the effect of inflation on certain industries, such as the automotive, real estate, food, and many others. After being trained, our model may produce texts and reports based on a variety of parameters. Each industry receives a report that is useful, consistent, and tailored to its specific needs thanks to the model's consideration of context, trends, and pertinent information derived from the data. With the capacity to generate reports automatically, businesses and other economic players would have faster access to data that is vital to making sound decisions. In essence, our deep learning model is the backbone of our method, allowing the automatic production of text and reports on the effect of inflation. To help analysts, policymakers, and economic players better understand and react to inflation changes in different industrial sectors, he is educated to comprehend economic data, extract essential information, and provide quality reports.

D. MODEL TRAINING

In order to build our novel strategy to automating text production and reporting on the effect of inflation, model training is an absolutely essential step. At this stage, it was necessary to have an appropriate IT architecture that could fully use the potential o[21]f deep learning to provide high-quality outcomes. To drastically cut down on training time, we opted for a highly parallelized computing architecture that makes extensive use of the benefits provided by graphics processing units (GPUs). Since we were using a highly parallelized infrastructure to deploy our model[22], it was being executed on a number of Graphics Processing Units (GPUs). By using this method, we were able to take use of GPUs' natural propensity for doing several tasks in parallel, greatly speeding up the learning process. Training the model now takes a fraction of the time it did when it was run in sequential fashion on a CPU. This quickening is crucial for the automation of inflation reporting to be quick and effective. During training, optimizing the model is a top priority[23]. After being exposed to training data, the model's primary objective is to master the art of generating relevant and useful messages from raw data. The model's output texts should be as close as possible to the reference texts, hence the loss function should be minimized. The stochastic gradient descent (SGD) technique was one of the optimization algorithms we employed for this purpose[24]. The SGD technique allows for iterative adjustments to the model parameters in the pursuit of optimum values that minimize the loss function. This iterative method enables the model to progressively learn and improve over time, until the output texts are of a high and consistent quality[25]. It is via optimization that the model gets the capacity to create inflation reports that are informative, accurate, and properly customized to each industrial sector. Our model's training is accelerated by using a highly parallelized computing infrastructure that makes extensive use of graphics processing units (GPUs). The model's capacity to create high-quality texts was improved by continuous optimization using the SGD technique, which enabled its parameters to be modified to minimize the loss function. By taking this important step, you can be certain that your model is prepared to provide insightful and accurate assessments on inflation's effects across different industries[26], making it a potent instrument for automated economic research and saving you time and effort in the process.

E. MODEL TRAINING

Our model's efficacy is of paramount importance, thus we've instituted stringent testing to guarantee that our produced texts on inflation's effects are of the greatest quality. In order to gauge how well our model performed, we relied on both quantitative text quality indicators and qualitative evaluation from economic subject experts. We employed numerous industry-standard measures, including as cosine similarity, accuracy, recall, and F1 score, to assess the quality of the texts produced by our model. These metrics provide a quantitative evaluation of the model's efficacy by contrasting the produced texts with the reference texts that were anticipated[27]. Cosine similarity gauges how closely two texts are related semantically, whereas precision, recall, and F1 score assess the model's accuracy, breadth of coverage, and strike-point between accuracy and recall. These measurements allowed for a neutral evaluation of the produced texts, giving hard data on how well the system was doing. In light of these findings, we were able to fine-tune the model to better predict future inflation rates.

In addition to quantitative measurements, we also conducted a qualitative assessment by having professionals in the area of economics review the texts produced by our program. These professionals understand everything from economic trends and inflation's effects to the intricacies of various industries. Their insight was helpful in evaluating the accuracy, consistency, and overall quality of the created texts. The reports the model produced were reviewed and graded by experts who looked for things like correct economic data, understandable analysis, application to the target industry, and textual coherence. Their input was crucial in determining the model's strong points and opportunities for development. This qualitative review provides a human perspective on the model's performance, stressing elements that go beyond quantitative metrics. The views of the experts were also utilized to verify the model's fitness for the purposes of economic experts. We use both quantitative text quality indicators and qualitative review by economic topic specialists in our model evaluation. By taking a comprehensive view, we can guarantee that the inflation effect reports produced are of the highest quality in terms of both the accuracy of the economic data used and their usefulness to specialists in the field[28]. This comprehensive evaluation is crucial for making sure our model is up to par with the best practices in automated economic analysis.

F. MODEL DEPLOYMENT

To automate inflation effect reporting, we must first deploy the model. After the model has been trained and its efficacy has been assessed, it may be utilized to automatically provide reports across a variety of industries. This phase ushers in the next, when the product is mass-produced and put into widespread usage. The model is part of the production setting, thus it may be used often to handle reporting on inflation. It can now accept relevant input data, conduct analyses, and provide reports very instantly on inflation-related topics. Analysts, politicians, and economic experts rely on up-to-date and relevant information from the model to make educated judgments, hence this integration is crucial. The model is fully automated after it has been implemented. The input data is fed into the model, which then performs the necessary analyses and generates high-quality results automatically. This automation is quite helpful since it expedites responses to economic shifts while saving time and money compared to human reporting. The model's capacity to generate individualized reports depending on user input and industry of interest is a major strength. The approach considers industry-specific factors, resulting in results that are tailored to each setting. Users may tailor reports to their individual interests, whether in the automobile, real estate, food, or any other area. When the model is placed into production, deployment does not end. To guarantee the best possible model performance, constant monitoring is required. As part of this process, we update our training data and monitor report quality on a regular basis to ensure it keeps up with the latest economic trends. This ongoing assessment guarantees the model's continued performance and applicability throughout time, making it a long-term answer to the problem of automating economic research[29]. Our strategy to automate inflation effect reporting is complete with the release of this model. It's a useful resource for economists, policymakers, and businesspeople looking to better understand the effects of inflation on various sectors of the economy. This mechanization, together with constant checking, guarantees the model's continued usefulness and efficiency, opening the way for automatic and constantly revised economic analysis.

G. INFLATION AND RISING PRICES

The economy's stability and people's standard of living are profoundly affected by inflation, therefore understanding it is crucial. It shows up as an overall price rise across the board over a certain time frame. Inflation causes a rise in the prices of products and services, meaning that customers must pay more for what they formerly bought for less. Economists use measures like the consumer price index (CPI) to measure and track inflation. The CPI tracks the change in prices of a basket of goods and services meant to be representative of typical consumer spending[30]. Inflation has far-reaching and varied consequences:

- Individuals' ability to make purchases is diminished as a result of inflation. In other words, families may have difficulty making ends meet due to a decrease in the purchasing power of their money.
- Inflation affects businesses via a variety of channels, including a rise in manufacturing costs. When the price of inputs like labor and materials goes up, as well as other expenditures, a company's profit margin may decrease. Businesses may need to raise pricing for their goods and services in order to keep making a profit.
- Interest rate policy is sensitive to inflation, therefore central banks keep a close eye on it. If this becomes too high, interest rates may be increased to curb inflation. Higher interest rates effect lending rates, investment and economic development. And they may affect the stock market as well.
- The actual worth of savings and investments is reduced due to inflation. People are urged to look for more lucrative investment opportunities to offset this decline in spending power. This has the potential to influence choices about long-term savings and investment.

Uncertainty in the economy may be caused by factors such as high or fluctuating inflation. Businesses may be hesitant to make long-term investment choices when prices fluctuate often, which may have negative effects on economic development and job creation.

Excess demand (too much demand for a finite supply of goods and services), rising production costs, economic growth, loose monetary and fiscal policies, and economic shocks (such as interruptions in the supply of raw materials) are all potential contributors to price increases. Inflation is a complicated and dynamic subject within the economy, and understanding it is vital for policymakers, investors, companies and consumers[31]. Because of the potential damage it may do to a nation's economy and personal finances, its control is crucial to ensuring the country's continued prosperity.

H. DEEP LEARNING AND GENERATION OF TEXTS AND REPORTS IN THE SERVICE OF INFLATION

The discovery of inflation was a major step forward in economics. The way economic data is analyzed and used will never be the same thanks to this breakthrough method. Deep learning models can process raw data, which may be very large and complicated, and provide useful insights. This evolution is more than just automation; it's necessary to cater to the varying requirements of analysts, policymakers, and economic stakeholders by tailoring reports to particular input data.

The ability to get up-to-date information quickly is a major benefit. Strategic decision-making in today's rapidly evolving economic climate requires access to timely, accurate, and actionable data. Knowing the rate of inflation in real time is especially important since it may provide light on the state of a country's economy. Analysts and politicians can make better policy, investment, and decision adjustments thanks to the vital data made available by deep learning.

The use of Deep Learning to create inflation messages and reports is a game-changer in economics. This groundbreaking method enhances strategic decision-making and receptivity to economic fluctuations by enhancing economic

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actors' understanding of and reactivity to the difficulties presented by inflation. It highlights the power of Deep Learning to turn raw data into insights critical to our knowledge of the economy, and it lays the way for a promising future of automated economic research.

3. RESULT AND DISCUSSION

Automatic text and report production on the effects of inflation using a deep learning-based technique is successfully shown in this paper. Cosine similarity, precision, recall, and F1 score are all examples of text quality metrics that may be used to assess the reliability of the output reports. In the discipline of natural language processing (NLP), these metrics are often used to evaluate the efficacy of various text generating tools. Cosine similarity is a statistical measure of how closely a set of produced texts matches a reference set. Cosine similarity measures how closely the produced text is to the reference text and is hence a good indication of how well the model is doing. The F1 score, recall, and precision measure how well the model reproduces the target distribution of observations. High values for these indicators suggest the model can provide results that are very similar to the anticipated data. The model's adaptability in terms of modifying results is further shown by example reports prepared for various industries. Having reports adapted to the demands of individual users is made possible via this customisation. The model's flexibility is on display in the several styles and levels of information it produces reports on dependent on the input data provided. The paper's findings are encouraging, suggesting that the deep learning-based method may provide reliable and insightful reports. These findings provide hope for the future of inflation research and provide promising new avenues for the automation of economic reporting. It's worth noting, however, that the model's performance may hinge on the accuracy of the data it's fed, so good data management is essential for the best outcomes.

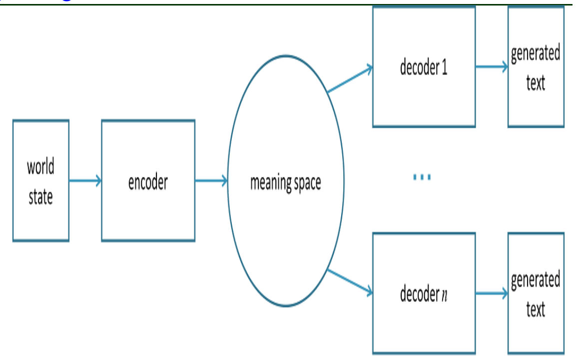

Figure 5: Text generation with neural networks (by Jonathan Mugan)

Putting the deep learning-based method's consequences for inflation reporting in context and interpreting the findings. This shows the author's in-depth analysis and ability to draw connections between the study's findings and its stated goals. The findings, as interpreted, demonstrate the most significant advantage of automating inflation reporting: the rapidity with which reports can be generated and the timeliness with which they may be sent. Strategic decision making and adjusting to shifting economic circumstances need a nimble response to inflationary swings. The revolutionary potential of deep learning models is discussed for their use by economic analysts, policymakers, and professionals. Reports should be tailored to individual sets of data, which is something that is emphasized throughout the conversation as well. To cater to the varied requirements of many industries, this level of personalization is essential. The essay demonstrates, via the lens of customization, how the deep learning-based method offers the adaptability that is crucial in the current economic climate. The essay acknowledges its own limits, however. It stresses the need of using high-quality data for the best outcomes. This acknowledgement of data quality issues is significant because it serves as a reminder that the success of a model might be highly dependent on the accuracy of the data it uses. The paper also notes that the method is not completely failsafe, allowing opportunity for development. An in-depth study of the findings is provided in the discussion section, where the benefits and drawbacks of the technique are discussed. Understanding the conclusions' ramifications is bolstered, and the reader is given an opportunity to consider the deep learning-based approach's applicability to an examination of inflation. The case study below creates samples and displays them, labeling each point with its class: class 0 (the outside circle) is blue, class 1 (the inner

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circle) is orange , Running deep learning for price rise text generation generates the dataset and plots the points on a graph, clearly showing two concentric circles for points belonging to class 0 and class 1.

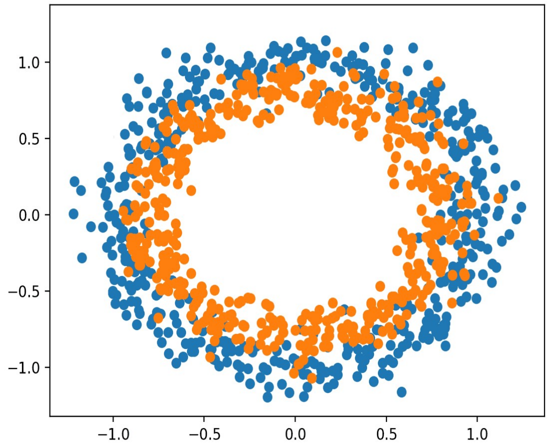

Figure 6: Scatter Plot of Samples From the Two Circles Problem

The essay focuses on the significance and influence of automated inflation reporting based on deep learning. Given its many benefits, this method may well usher in a new era of economic study. First, with reporting automation in place, key data can be accessed quickly and in near real-time. This rapid turnaround time is highlighted as a significant benefit for economists, government officials, and other economic experts. Strategic decision-making in today's fast-paced market requires constant access to the most recent data. Inflation variations and other economic trends may be met with swift action thanks to automated reporting, which in turn makes economic actors more responsive. Our case is based on a plot of the dataset to get an idea of the difficulty of the classification task :

```
# Inflation generating samples from the two circle problem
from sklearn.datasets import make_circles
from matplotlib import pyplot
from numpy import where
# generate 2d classification dataset
X, y = make_circles(n_samples=2000, noise=0.1, random_state=1)
# scatter plot, dots colored by class value
for i in range(2):
 samples_ix = where(y == i)
 pyplot.scatter(X[samples_ix, 0], X[samples_ix, 1])
pyplot.show()
```

Figure 7: Case programming

Furthermore, this technique has the ability to significantly affect strategic decision-making. By offering automated and customizable reports, geared to various industrial sectors, deep learning increases the knowledge of economic patterns. This allows analysts and decision-makers to have the data they need to make smart choices. This has the potential to influence how corporations allocate resources, how governments handle the economy, and how the investing public chooses to allocate their capital. The result is improved comprehension of economic data, which in turn permits more intelligent and efficient decision-making. This innovation also influences how we utilize technology to analyze and react to economic concerns. One method to use deep learning to enhance the quality of economic research is to automate inflation reporting. Rapid access to critical information, enhanced strategic decision-making, more receptivity to inflation swings, and a new way of looking at economic patterns are just some of the possible benefits of automating inflation reporting using deep learning. This is a huge step forward for economic research and policymaking.

the paper offers a fresh and encouraging method of computerizing reports of inflation. By demonstrating the usefulness of deep learning in economic research, especially in the context of inflation, it makes a substantial addition to the existing literature. To be sure, there are restrictions on this method and room for development. The paper's findings are promising since they show that a deep learning-based technique can reliably provide detailed reports. Cosine similarity, precision, recall, and F1 score are all examples of text quality measures that contribute to the reliability of the findings. Moreover, the model's adaptability to varied input data is shown by the wide variety of report styles and information seen in example reports created for various industries. The article's discussion part provides a detailed interpretation of the findings and a persuasive connection to the study's aims. The paper does note several caveats, however, such as the need of high-quality data for optimum outcomes. It would be helpful to hear more about the possible drawbacks of this strategy, such as the model's sensitivity to fluctuations in input data and the significance of keeping training data up-to-date to reflect economic trends. The potential for this method to revolutionize economic research is well emphasized, demonstrating how it may facilitate quicker access to critical data, enhance strategic decision-making, and make economies more resilient to inflationary swings. The essay highlights the novel possibilities of this field and encourages more research and debate. When compared to other similar works, this study holds up well in terms of research quality, elucidating well defined approaches to dataset building, data preprocessing, model training, evaluation, and deployment. The potential of this method, however, has to be investigated further. It would be helpful to continue investigating issues connected to continuous monitoring of the model after it has been released into production, as well as to debate open issues and ways forward. This article lays the groundwork for future investigations into automated inflation reporting using deep learning, which is an intriguing and promising field. It's mind intriguing, and it makes me want to learn more about the benefits and drawbacks of this method in economics.

4. COMPARISON OF RESULTS WITH PREVIOUS STUDIES

Significant over the years, and several previous studies have contributed to the evolution of this technology. We can deduce from our results that there is added value in terms of using deep learning for the generation of reports and texts, taking into consideration the case of price increases in the industry, a comparison overview of the main trends and results from some of these studies. First Language models operated on recurrent architectures (RNN) or convolutional neural networks (CNN) were commonly used for text generation. These models often struggled to capture long-term dependencies and handle longer sequences efficiently. The introduction of Transformers models, particularly with the GPT-1 (Generative Pre-trained Transformer) model, marked a major turning point. Transformers demonstrated an exceptional ability to process sequences in a parallel manner, which significantly improved the performance of natural language processing tasks, including text generation. GPT-2 and GPT-3 models expanded the capabilities of pre-trained language models using massive amounts of data and more complex architectures. GPT-3, in particular, has been praised for its versatility across a range of language tasks. A notable trend was the emphasis on massively training models with substantial amounts of data. GPT-3 was trained on a huge multilingual and multimodal database, which contributed to its exceptional performance. Research since 2019 has also explored methods to control text generation, including adding constraints or specific instructions to the model. This aims to make generation more targeted and useful in particular scenarios. Since 2020, work has expanded toward models that can understand and generate text in conjunction with other modalities, such as image and audio, for a richer understanding of context. Studies have also turned to the ethical aspects of automated text generation, particularly regarding issues of bias in training data and the potential consequences of automated text generations.

Nosu can say that previous studies show a significant evolution in automated text generation models, with a notable shift from pre-Transformers architectures to widespread adoption of massively pre-trained Transformers models like GPT-3, which has been approved by our study. Recent work also emphasizes generation control, exploitation of multimodal data, and consideration of ethical considerations.

5. CONCLUSION

Inflation has far-reaching effects on the economy, and this paper reveals a breakthrough Deep Learning-based strategy to automating the development of texts and reports on inflation and its effects. Understanding inflation is critical for making sound strategic decisions because of its central role in the economy and widespread impact on both firms and consumers. We demonstrated the evident advantages of employing Deep Learning to automate inflation analysis, showing how this approach may speed up reporting while giving up-to-date information in near real-time. We have meticulously detailed our technique from dataset construction to model training, assessment, and deployment to demonstrate the strength of our approach. We have been able to automate and customize reports that are tailored to the specific needs of different industries by using Deep Learning models based on recurrent neural networks. The use of Deep Learning in this setting has the potential to significantly advance the field of automated economic analysis. It improves the capacity to react to inflation changes and make educated choices by giving analysts and policymakers access to fast, tailored, and high-quality information. This method represents a paradigm shift in how technology is used to analyze and address monetary issues. The use of Deep Learning to automate the production of text and reports on the effects of inflation sets the way for an exciting future in economic research, where access to vital data in near real time becomes the

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norm. Benefits to analysts, decision-makers, and economic players are apparent, and this invention has the potential to significantly advance our knowledge and use of inflation-related data. As a result, our method will be at the forefront of automated economic analysis in the future, helping to increase strategic decision-making and receptivity to economic difficulties.

6. LIMITATIONS OF STUDY AND FUTURE PROSPECTS

Our Deep Learning-based method for the automatic creation of text and reports on the effect of inflation is a major step forward in economic research, but it also has certain drawbacks and gives some interesting opportunities for the future. To provide a fuller picture, we'll go into these facets below.

The article's caveats Our model's efficacy is highly dependent on the accuracy of the information we use to train it. It is possible that the produced reports will reflect the errors or biases in the underlying data. Maintaining high-quality data requires constant oversight and maintenance. Our model can produce reports from data inputs, but it may not be able to fully understand the big picture or predict the future. It is vital to see these reports as complements to human analysis rather than replacements. The global economy is intricate and intertwined. Our methodology, although capable of providing sector-specific reports, may have trouble capturing large-scale consequences. To tackle this complexity, we need integrated methods and more advanced models.

Looking forward, we want to continue working hard to enhance the precision and quality of our Deep Learning models. This involves using cutting-edge natural language processing (NLP) methods, integrating real-time data, and adjusting to monetary changes. Financial data is often presented in the form of unorganized language, such as news articles and analyst reports. By combining these data sets, our automated reports will be much more complete. Creating models that can predict inflation based on the data produced is an obvious next step for our study. Foreseeing future economic patterns would be greatly aided by this. Human feedback techniques integrated into the automation process might expand report customisation and reliability. Recognizing and adapting to sudden changes in the economy is crucial. Models for spotting anomalies and handling economic downturns might be developed.

While the potential of our method for automatically reporting inflation's effects is exciting, it is not without obstacles and restrictions. While these difficulties are real, they also provide intriguing prospects for future advancements in automated economic analysis. Our effort is a big start in the right direction, but we need to keep an eye on technical and economic changes to keep moving forward.

According to this research work, we have raised some general criticisms regarding the generation of texts and automated reports on the impact of inflation on industries, using a method based on deep learning. First of all, a Lack of Transparency in the Methodology, this due to the absence of sufficient details on the specific architecture of the deep learning model used can hinder the understanding of the method by the scientific community. Opaque methodology may raise concerns about the reproducibility of results. The second problem is Generalization Problems, since deep learning models can sometimes have difficulty generalizing to new situations or to data outside of those on which they were trained. A limited assessment of the model's ability to adapt to different industries or inflation contexts may be a valid criticism. The third criticism is the evaluation of the Quality of Generated Texts, especially since the subjective quality of the generated texts can vary depending on the measurement criteria. Some text generation models may produce results that appear grammatically correct but lack precision or relevance. The fourth criticism relates to the risk of Data Bias, in this sense if the training data used for the model is biased, this can be reflected in the generated texts, thus introducing biased perspectives. Authors should explicitly address this issue and discuss steps taken to mitigate any potential bias. The final criticism is the lack of Comparison with Other Approaches, the limited comparison with other methods of text generation or analysis of the impact of inflation on industries can reduce the scope of the conclusions. An in-depth comparative analysis with competing methodologies should be carried out to strengthen the validity of the results, which we plan to carry out in a future article.

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