Public debt dataset came from IMF

<https://www.imf.org/external/datamapper/GG_DEBT_GDP@GDD/SWE>

Inflation rate came from

<https://www.imf.org/external/datamapper/PCPIPCH@WEO/WEOWORLD/VEN>

# Introduction

## Topic

Public debt, the cumulative result of government borrowing over time, is a critical metric that affects the economic stability of nations and, by extension, the well-being of their citizens. Understanding the factors and features that correlate with (or directly influence) public debt levels is crucial for policymakers, economists, and financial analysts.

The choice of this area of study is driven by the need to unravel the complex dynamics governing public debt. By employing data analytics techniques, the aim is to investigate the impact/correlation of various economic factors on public debt levels.

The aim of this topic is to address the efficacy of economic variables using data analytics and deep learning methodology. There have been many experiments and projects in the economics domain which have tried to address this question using econometric approaches. However this project will be centered around the capabilities of deep learning, time series, and data analytics to draw a conclusion.

## Research Objectives

Below outlined are the research objectives for this project:

1. Can deep learning methods demonstrate a strong correlation between economic variables such as inflation rate, GDP growth, or interest rates and the level of public debt?
2. Can data analytics techniques be used to develop reliable forecasts of *future* public debt levels using *current* economic variables?
3. How can data analytics techniques and visualisation tools be effectively applied to gain deeper insights into the relationships between economic variables and public debt dynamics, with the aim of informing more robust debt forecasting models and data-driven policy decisions?

# Background Research and Related Work

Public debt, the total amount owed by a government to creditors, is a critical economic indicator that influences a nation's financial stability, investment climate, and its overall economic health. In an era where economic conditions are rapidly changing, the ability to accurately predict public debt levels is invaluable for a wide range of stakeholders, including policymakers, investors, financial analysts, and international organizations.

Deep learning, a subset of machine learning characterized by its ability to learn from vast amounts of data through neural networks, offers significant advantages in predicting public debt levels. Traditional economic forecasting models often rely on linear assumptions and may not fully capture the complex, nonlinear relationships between various economic indicators. Deep learning models, such as Long Short-Term Memory (LSTM) networks, are adept at understanding these complexities, making them particularly suitable for time-series data like economic indicators. They can process large datasets, learn from the sequential nature of the data, and capture temporal dependencies that are crucial for accurate forecasting.

**Importance of Predicting Public Debt Levels**

*Policy Making and Government Planning:* Governments need to manage their debt levels to ensure economic stability and sustainable growth. Accurate predictions of public debt can inform fiscal policy decisions, budget planning, and debt management strategies. It allows policymakers to anticipate future economic conditions and make informed decisions regarding spending, taxation, and borrowing.

*Economic Analysis and Research:* Economists and researchers benefit from accurate debt level forecasts to analyze economic trends, assess the effectiveness of fiscal policies, and study the impact of debt on economic growth and inflation. Deep learning models can enhance the quality of this research by providing more accurate and nuanced forecasts.

*Investment Decisions:* Investors and financial analysts use public debt level forecasts to assess the risk profile of government bonds and other debt instruments. Accurate predictions can inform investment strategies, helping investors to make better decisions about asset allocation, risk management, and portfolio optimization.

*International Organizations:* Entities such as the International Monetary Fund (IMF) and the World Bank monitor public debt levels to assess economic stability and risk across countries. These organizations can use deep learning predictions to guide their lending decisions, economic assistance programs, and policy advice to member countries.

*Market Stability and Economic Confidence:* Predicting public debt levels contributes to market stability by providing all market participants with insights into future economic conditions. This transparency can bolster economic confidence, reduce uncertainty, and facilitate a stable investment environment.

In conclusion, the application of deep learning to predict public debt levels represents a significant advancement in economic forecasting. By leveraging the power of these models, stakeholders can gain a deeper understanding of future economic trends, enabling more informed decision-making and contributing to global economic stability. The accuracy and efficiency of deep learning models in handling complex, nonlinear data make them indispensable tools for anyone involved in economic planning, investment, and analysis.

# Methodology

## Data Gathered and Primary Research (Interviews)

In the process of data collection for the project aimed at predicting levels of public debt using deep learning methods, primary data was obtained through interviews to identify useful economic variables for the analysis. Two experts were consulted to leverage their insights on which economic indicators would best predict public debt. The first interviewee emphasised the importance of the inflation rate as a critical indicator, highlighting its direct and indirect impacts on the economy's health and its potential influence on public debt levels. The second expert suggested the Gross Domestic Product (GDP) as a fundamental variable, considering its comprehensive reflection of the economic activity and its correlation with the government's borrowing capacity and fiscal policy. Both interviewees agreed on the value of incorporating data from countries with economic profiles similar to Ireland, specifically mentioning Denmark and the United Kingdom. This comparative approach was proposed to enrich the analysis by understanding the dynamics in economies that share certain fiscal, social, and economic characteristics with Ireland, thus providing a broader perspective on the variables influencing public debt. The consensus on examining the inflation rate and GDP, alongside the comparative analysis with Denmark and the UK, formed the basis for selecting the economic variables to be used in predicting public debt levels through deep learning techniques.

## Datasets

The decision to source datasets from the International Monetary Fund (IMF) website for the project on predicting levels of public debt was driven by the IMF's reputation for providing comprehensive, reliable, and up-to-date economic data. The IMF's extensive database offers a wealth of standardized financial and economic information across countries, including key indicators like inflation rates and GDP figures. Utilizing data from the IMF ensures the analysis is grounded in high-quality and globally recognized datasets, facilitating accurate and credible forecasts.

## Data Preparation

Two distinct datasets were imported, encompassing vital economic indicators—public debt levels, inflation rates, and GDP figures—for Ireland, Denmark, and the UK. They were transposed to align the data chronologically, and a merge operation was conducted to consolidate the indicators into a single comprehensive dataframe. Plots were then generated, offering a visual representation of how these crucial economic metrics have evolved over time across the three nations. This visualisation step is pivotal, providing initial insights into the interrelations and potential predictive dynamics among the variables.

### Summary Statistics

The summary statistics (.describe()) of the dataset reveal a sample size of 69 observations. The average value of the variable is approximately 55.66, indicating the central tendency of the data. A relatively high standard deviation of about 24.78 suggests there is considerable variability or spread in the data points. The minimum and maximum values of 24.81 and 119.48, respectively, highlight a wide range in the dataset. The interquartile range, from the 25th percentile (36.18) to the 75th percentile (75.05), indicates where the middle 50% of the data lies and further underscores the significant spread of the values. The median of 47.74 is less than the mean, suggesting a right-skewed distribution. Right-skewed data may have outliers or extreme values at the higher end, which can affect the mean. It’s important to investigate these outliers as they can provide insights into the data or indicate data entry errors or other anomalies.

### Handling Null Records

It is important to carefully consider the handling of null records from different angles. The dataset displayed a considerable number of missing values between the years 1936 and 1970, along with a single instance in 1997. In response to this, a strategic decision was made to exclude all records prior to 1970 and apply a backfill method to address the missing value from 1997. This choice is substantiated by the rationale that the economic landscape has undergone significant transformations since the mid-20th century, rendering the data from the pre-1970 era less relevant for contemporary analyses. Modern economic policies, global financial structures, and market dynamics have evolved, diminishing the predictive relevance of historical data from that period for current economic phenomena. Moreover, the integrity and availability of older records often pose challenges due to changes in data collection methods and statistical standards over time. The backfilling of the 1997 record ensures a complete dataset post-1970, facilitating a more robust and relevant analysis while maintaining the continuity and quality of the more recent and applicable data, which is more reflective of the current economic environment and trends.

## Deep Learning Methods

In the development of a deep learning model aimed at predicting levels of public debt, the use of Long Short-Term Memory (LSTM) networks offers a sophisticated approach to capturing temporal dependencies in time-series data. This section of the thesis details the methodical preparation of training data and the architecture of the LSTM model, highlighting the strategic decisions made to enhance model performance and accuracy.

**Training Data Preparation**

The foundation of any deep learning model's success lies in the preparation of its training data. In this project, the training dataset was constructed to predict future values of economic indicators based on past observations. The input (trainX) and output (trainY) arrays were initialised as empty lists, setting the stage for the creation of sequences that reflect the temporal nature of the economic data.

The loop constructs input sequences (trainX) by aggregating slices of seven consecutive days and pairs them with the target output (trainY), which is the value of the following day. This approach ensures that each training instance comprises 7 years of data to predict the subsequent year’s indicator value.

Upon transforming these sequences into numpy arrays, the training data adopts a format optimised for the LSTM network, enabling the efficient handling of time-series information. This transformation is critical for aligning the dataset with the LSTM's requirements, facilitating the model's ability to discern and learn from the temporal patterns embedded within the economic indicators.

**LSTM Model Architecture**

The LSTM model was designed with a sequential architecture, comprising two LSTM layers followed by a dropout layer and a dense output layer. The first LSTM layer contained 64 units and utilized the 'relu' activation function, processing the input sequences while retaining the temporal order of the data. The inclusion of return\_sequences=True allowed the subsequent LSTM layer to receive the full sequence of outputs, facilitating a deeper understanding of the temporal dynamics within the data.

The second LSTM layer, with 32 units, further distilled the temporal features, with its output being compacted to provide a focused representation of the learned temporal characteristics. The dropout layer, with a rate of 0.2, was employed as a regularization technique to prevent overfitting, ensuring the model's generalization ability to unseen data.

The final layer, a dense layer with a single unit, was designed to output the predicted value of the economic indicator, reflecting the model's culmination in making tangible predictions based on the learned temporal patterns.

**Model Compilation and Training**

The model was compiled with the 'adam' optimizer and 'mse' (mean squared error) as the loss function, aligning with the regression nature of the prediction task. The summary of the model provided an overview of its architecture, including the number of parameters in each layer, offering transparency into the model's complexity and capacity.

The training process was executed over 17 epochs with a batch size of 16 and a validation split of 0.1, indicating that 10% of the training data was used for validation purposes. Initially, the model was trained for 10 epochs, but upon further experimentation, it was observed that extending the training to 17 epochs optimized the model's performance. This decision underscores the iterative nature of model training, where adjustments are made based on performance metrics and validation outcomes.

Results

The visual comparison of the LSTM model's predictions against the actual data reveals a high degree of alignment, indicating the model's effectiveness in capturing the underlying temporal dynamics of the economic indicators. This close match underscores the model's predictive accuracy and its potential utility in forecasting economic trends.



The evaluation of the LSTM model's performance utilized two key metrics: the Mean Squared Error (MSE) and the R-squared (R²) value. The MSE, calculated as 15.67, quantifies the average squared difference between the predicted and actual values, offering insight into the model's prediction accuracy. A lower MSE indicates closer predictions to the actual data, and while an MSE of 15.67 suggests some level of prediction error, it's essential to contextualize this value within the scale of the dataset and the complexity of predicting economic indicators.

The R² value, reported at 0.81, measures the proportion of variance in the dependent variable that is predictable from the independent variables. An R² of 0.81 signifies that the model explains 81% of the variability in the economic indicators, indicating a strong fit between the model's predictions and the actual data. This high R² value reinforces the model's efficacy in capturing the underlying patterns and dynamics of the dataset, underscoring its reliability for economic forecasting tasks.

Evaluation and Analysis

Discussion

Conclusion

However, as we use machine learning models, the stationary property is not required. Kim et al. (2004) suggested that neural network models do not need the stationary time series for prediction.