Project Document: Economics Specialist Group (ESG)

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Abstract

The first milestone we propose two ideas that we would like to dive into for the next several months. The second milestone we narrowed it down to only one idea and found a data set to use. That idea is, using economic factors to predict real GDP and conduct performance analysis on it. We then identified two different approaches for solving this problem. The first approach is to use statistical hypothesis testing and the second approach is to linear algebra technique to predict real GDP.

Chapter 1

Milestone 1: Project Ideas

1.1 Introduction

As a group, we first began to look for common but long standing issues in the field of economics. We went through many different ideas, like the problem of modelling inflation, predicting GDP of an economy, and analyzing consumer behavior. We noticed that a lot of the modelling of economic ideas are always based on strict assumptions that are unrealistic or too abstract and logical to be applicable to real world situations. This led us to reach our main motivation for our proposals; we wanted to model an economic problem such that is more grounded in reality and has falsifiable ideas.

For the first proposal, we were very interested in rigorously modelling what affects real GDP and how can we predict it in the future. We wanted to create a Deep Learning model that does not just predict real GDP, but also gives information on narrowing down which assumptions lead to rise or drop in real GDP by experimenting with the parameters using more of the scientific method. Most models are either using statistics which lacks accuracy when there is too much data, or it is too mathematical that the prediction lacks any basis in reality. We wanted to model the problem such that the prediction is both correct and has practical application.

The second proposal inspiration is from curiosity in learning how people make decisions. We make buying decisions everyday, from simple items like food for breakfasts to large payments that require savings like a car or house. Sometimes, it is challenging to explain our reasoning behind our decisions. Hence, we want to propose a project that not only allows us to predict whether a consumer will buy a product and how much they will pay but also enables us to make inference on those decisions. Why is a product popular in one region but not in others? Does means of payment affect people's tendencies to spend? Does income affect the type of products consumers will buy? Those are questions

that we hope to answer in this proposal.

1.2 Project Idea 1: Predicting real GDP using Macroeconomic indicators and a combination of other short-term economic factors

1.2.1 Definition and explanation of GDP

In modern economic theory, Gross Domestic Product (GDP) is used as one of the main indicators to measure the performance of a country or region. GDP is the monetary value of total goods and services that is produced by a country or region over a certain period of time. As defined by the OECD [4], GDP is 'an aggregate measure of production equal to the sum of the gross values added of all resident and institutional units engaged in production (plus any taxes, and minus any subsidies, on products not included in the value of their outputs)'. Put simply, it represents the aggregate statistic of all economic activity.

There are 2 types of GDP, Nominal GDP and Real GDP and both are usually measured in quarterly or yearly time periods. The reason GDP is commonly used to measure the performance of a country or region is because it is easy to compare one country or region with another for a certain span of time. This allows for quick analysis and provides a quick glimpse of the overall economic situation of the country.

There are three ways of measuring GDP:
1) The production approach
2) The expenditure approach
3) The income approach

The production approach looks at the total gross value added by various industries or sectors plus taxes and less subsidies. The expenditure approach would look at the total consumption of goods and services by all groups participating in the economy plus exports and minus imports of goods and services. The final approach, would look at the total income that is generated in the economy. Each approach has it's own pros and cons in terms of trying to measure GDP, but we will mainly focus on the expenditure approach as it most common around thw world and it is also used in the United States.

1.2.2 Why look at real GDP?

The problem we would like to tackle in this proposal is how to accurately predict Real GDP of a country by looking at both macroeconomic factors and other short term factors economic in a country or region. Real GDP is Nominal GDP adjusted for inflation. The equation for Real GDP is:

$$\text{Real GDP} = \frac{\text{Nominal GDP}}{R}$$

Where R = 'GDP deflator', and it measures the price change of goods and services produced in an economy.

The reason we will be looking at Real GDP compared to Nominal GDP is because nominal GDP figures can easily be influenced by the price increase of goods and services in a given year. If GDP increases because of price increase, this is not the same as an increase in the total goods and services produced in a country or region. Hence, using nominal GDP can easily lead to incorrect analysis of both the performance of a country and the performance of our model due to surrounding noise.

1.2.3 Other existing approaches to the solution and related studies

The first concept of GDP was to attack landlords against unfair taxation in the mid 1600s [2] and the modern concept of GDP was first developed by Simon Kuznets for a US Congress report in 1934 [3]. The earliest models to predict GDP date back to the late 80s and early 90s. These early studies mostly used linear and uni-variate regression models using current growth rates of macroeconomic factors for predictions [18, 11]. It was not until the 90s that Neural Networks started being used to build prediction models [8] and not soon after until Neural Networks were used to predict GDP. The first models started appearing around the late 90's and early 2000's [20, 18, 21].

In 1997 Swanson and White found that artificial neural network models marginal improvements in the forecasts over linear and uni-variate regression models by using nine macroeconomic variables [20]. In 2001 Tkacz built a Neural network to forecast Canadian GDP growth and compared it to linear and uni-variate models. Their model was based off one and four-quarter cumulative growth rates of real GDP in Canada, US and Canadian interest rate yield spreads, the real 90-day Corporate Paper rate, the growth rates of real narrow and broad monetary aggregates and the growth rate of real stock prices. Their study showed that an artificial neural network had lower forecast errors for year to year growth rate of real GDP relative to linear and uni-variate models, but had no notable improvements when forecasting quarterly real GDP [21].

Soon after that neural networks started consistently outperforming the more traditional methods. In 2004 Junoh conducted a study for predicting Malaysia's GDP using knowledge based economy indicators such as: Computer Infrastructure, Infostructure, Education and Training, Research and Development, and Technology. Their study showed that it was possible to build a prediction model

using knowledge based economy factors [15]. The best network model that they obtained had a Root Mean Square Error of 0.587, Mean Absolute error of 0.334 and Percentage of Correctness of 83.33. The network consisted of four input units; Internet subscribers per 1,000 population, mobile telephone subscribers per 1,000 population, number of computers per 1,000 population, and personal computer installation per 1,000 population. Their model had one hidden layer with one hidden unit, one output layer, a learning rate set to 0.1, and a normalized cumulative delta rule with 15 epochs.

In 2016 Vrbka applied neural networks to predict the GDP growth of Eurozone countries until the year 2025 [22]. They generated a 1000 artificial neural structures and selected the 5 most appropriate models. They used Neural Network of the Radial Basic Functions (RBF) and Multiple Perceptron of Neural Network architectures with a maximum of 11 neurons used in the hidden layer of the RBF to build their networks. Variables used in their model consisted of lagged real per-capita GDP growth and lagged real per-capita GPD and several variables relating to the compositing of domestic output and expenditures. They claim that each of their models all reached a performance above 99% accuracy.

1.2.4 Team's general approach

To measure GDP most countries would use the expenditure approach which measures the amount of spending that is done in the economy. But the factors that affect the amount of consumer spending in the economy could easily be affected by short term economic shocks like a weak job market, natural disasters, and other macroeconomic shocks like the rise in the price of oil, outbreaks of crime, or full fledged wars. These shocks could lead to unemployment, loss in capital, price increase in goods and services, and instability in general, which could all lead to the reduction of spending and production in an economy. This issue is further worsened by the unique situations of each country or region. An example is that some countries are more likely affected by job unemployment due to unstable government institutions and regulations, while others might be affected more by loss of capital due to regular natural disasters which reduces production in the economy. Thus, the main problem at hand is how to create a model that is general enough to take into account these factors, and predict real GDP in the future with reliable accuracy. This is our project proposal and the general plan for the project would be:

1. Implement and verify previous models in a published paper.

2. Begin from macroeconomic indicators, like using the Economic Freedom Index, Demographic and worker characteristics, government spending for a country, etc. and check their accuracy in terms of predicting real GDP for up to 3 years. Macroeconomic indicators are theoretically good estimators of long-term growth of real GDP because as the population becomes more advanced and capable of innovative ideas, the amount of value they will

be able to add to the economy should rise. But if the macro indicators show otherwise, there should be a drop in GDP in the near future.

3. After finishing with the macro indicators, we will begin with factoring in short-term economic shocks like natural disasters, a sluggish economy due to layoffs (tracked by business investments in a country), and other unexpected factors like a global pandemic which is an event that rarely happens. Theoretically, by combining short-term economic shock factors with long term macro indicators, the model should be able to generalize and at the same take into account the short term drops in the real GDP of an economy with reasonable precision.

4. The last step for our project, is to compare the accuracy of different models and try and explain by conducting statistical analyses of those factors and check whether they have any relationship with real GDP growth. This will be used to either explain why our hypothesis is true or disprove wrong assumptions about those factors and their relationship with real GDP.

1.2.5 Benefits of this proposal

Some benefits of the project is that it allows for a greater understanding of what factors might affect Real GDP figures in the future. The main issue with the above 3 approaches at measuring GDP, is that there have many limitations. For example, tracking consumer consumption or government spending in the expenditure approach is not reliable as each population would change year to year and the stability of the government is dependent up the region that it is located in. For example, in the United States, after COVID-19 started spreading there was a massive rush to buy toilet paper and other necessities [9]. This led to shortages and price increase for toilet paper and other necessities [12, 6]. This kind of panic buying are not predictable, and hence we may need to include indicators that track both regional and overall consumer behavior. Put simply, consumer consumption is not always rational, and we plan to implement a model that can take into account irrational behaviors in the economy. In terms of Government spending, it changes year to year because either the government is a republic like the US, where changes in government due to an election can lead to the reallocation of government resources, or it is an unstable governmental institutions due to military coups that can prevent the government from functioning effectively. In short, reality is often ugly, unpredictable and pure madness, and modern economic models have a tough time of taking into account the "human" aspects and behavior in an economy. By running many experiments with different long and short term factors, we can start narrowing down which factors are actually important when predicting real GDP. We can then begin practically implementing the models and analyze the economy effectively, instead of it being just another thought exercise written with mathematical jargon and statistical buzzwords.

While this project is very complex, we have high hopes of positive results as we believe it is a feasible idea. Many ideas in economics can be understood using common sense and Statistical, Mathematical, and Deep Learning methods are only used to verify our ideas. For example, an increase in education spending by the government should not instantaneously produce better employees which produce higher quality products. The effect of the spending can only be seen $5 - 10$ years in the future when the students graduate from High School or University. This also holds true for business investments, trade and other forms government spending. Short term indicators on the other hand, like the size of the shadow economy, the crime statistics of a country, stability of the region, etc. should track the behavior of consumers as it is an aggregate of short term consumer needs and actions. So our model theoretically should be able to predict 1, 2 and 3 years ahead based on the short term and long term indicators. If prediction goes well, this will shed new lights into different events in the economy and what factors caused a specific rise or dip in real GDP of a country. The main goal of the project is shown below:

1. To read and understand previous papers in this field and the models that are implemented.
2. To create a model that can predict real GDP of most countries with reliable accuracy.

   And if everything goes well
3. To create a model that allows for analysis of previous economic events and understand the underlying assumptions that hold or don't hold during those events

1.3 Project Idea 2: Predicting and analyzing customers' behaviors based on buying trends

1.3.1 What is customer behavior?

"Consumer behavior is the actions and the decision processes of people who purchase goods and services for personal consumption" – according to Engel, Blackwell, and Mansard [7].

Understanding consumer behavior is to understand how people make purchases, why they do so, and when they do it. It is a complicated area to study because there are many factors that contribute to the ultimate answer whether consumers will buy the products or not.

1.3.2 Problem summary

Customer shopping behavior has been an interested problem for decades. Big corporations like Google create algorithm that displays personalized ads based

on customers' recent web browsing history. We have seen companies experiencing up and down based on consumer's fluctuating behavior. One prime example was phone's touchscreen. In 2007, Nokia dominated the mobile phone industry with 50% market share. However, only within 6 years, the market value of Nokia plummeted by 90% [16]. At the same time, Samsung understood the new market trend and quickly adopt the new mobile phone designs, leading to it being one of the two global mobile phone powerhouses today. Hence, understanding customers is the first step to creating a successful product.

In this project, we would like to not only predict whether a customer will buy products and for how much but also take a deeper look into why customers make certain decisions. In other words, we would like to discover which factors have a bigger impact on customers' final decisions. Those factors can be generic factors such as gender, races, income level, occupations, marriage status, types of payments, product types, and tax rate. While those factors might be sufficient in comprehending the local market trends, those trends may not carry to another city or even country. Hence, we would like to understand how other regions' customers value the same factor. One such question could be if modes of payment is an important factor in Europe and Asia.

1.3.3 Project application

1. By knowing which factors are important to customers, companies can adapt their marketing strategy to highlight features on their existing products to local customers. At the same time, companies can make better investments on products that are more likely to generate higher marginal profits since it fits the need of the public.

2. In this project, we also focus on analyzing which factors are likely to change between different regions. This knowledge is important because many companies are expanding their businesses beyond the border of their home country, In a different culture, many decision rules may no longer hold true. Hence, by knowing how customers' behavior may shift, companies can better prepare their products to suit the needs of local market. Some global branches like Starbucks and McDonald's are experiencing this problem firsthand as they expand their business to Asian countries. Their success indicated by sales vary significantly from one region to another. In China, Starbucks dominates the coffee industry [5] while in Vietnam, Starbucks fails to compete with top local branches [10]. Hence, if successful, we hope to lay a good foundation for smaller companies to have a smoother transition to global market without suffering significant loss.

1.3.4 Other existing approaches to the solution

1. **Logistics Regression model to predict consumer behavior regarding purchasing re-manufactured products**. Re-manufactured prod-

ucts are products made from materials from other returned products. This project is similar to our project in that it also predicts customer behavior in the market. However, we differ in the market sector in that we focus on general and new products while the paper focuses on products from a specific origin. Nevertheless, we can use the paper as a stepping stone in understanding the thinking process. [23]

2. **Neural network Verifier.** Paper *Property Inference for Deep Neural Network* explores ways to analyze neurons and layers in relations to the output. It shows how to use input and layer invariants to infer about the outputs classification class. Hence, those invariants can be confirmed as network property. For instance, if a neural network has a property that if $x1 > x2$, then $y1 > y2$, then the algorithm will attempt to find such property given the neural network. The paper also details two ways to analyze those properties [13]. Using the paper described strategy, we can translate the property to answer which property is significant. However, the application is rather limited since they were not initially created to answer such questions. Other existing verifiers such as Marabou, Neurify, and ERAN are also available. Nevertheless, they come with limitation on property and inference that they can verify.

1.3.5 Team's general approach

1. We start off with gathering datasets from different regions and sources. The goal is to have datasets from retailers or supermarket stores from a variety of regions. We will also clean the data to avoid using sensitive information.

2. Then, we create a machine learning model that that can predict whether a consumer will buy a product and for how much given different factors. We will stay away from linear or logistic regression as many other papers have covered such techniques. We will take some risks and try other methods, which, hopefully, yield better accuracy and consistencies.

3. After that, we will create an artificial intelligence that can analyze the model from step 2 and decide which factors are significant for the prediction. For each price range, we plan to create a decision tree model to analyze how significant a factor is to a customer who is willing to pay a certain amount. We will also take a closer look into how those factors change over time or change from one region to another.

1.4 Conclusions

The project proposals that we have are within the realm of reality. The foundations for the project are already in place. Both ideas are relevant to the field of economics, which is looking at identifying and analyzing economic factors.

We believe the first proposal has a high probability of success and there are a lot of possibilities that we could explore. The prediction of real GDP is a very popular research idea and with the advancement in Neural Network models and Statistical techniques, our project proposal will explore the border of what is possible. In the second proposal, consumers' behavior prediction and analysis are also long-standing questions. There have been many researches that we can rely on to verify our results, but not many researchers directly discuss the problem. Focusing on analyzing consumers' behavior may be beneficial because it may reveal insight into how consumers act and how factors that affect the decision process changes between different regions and different time frames. This is particularly significant in today's world when companies are globalizing their products and services to other countries and they are more exposed to different cultures and traditions.

Chapter 2

Milestone 2: Project Selection

2.1 Introduction

We decided to go with project idea 1, Predicting real GDP using Macroeconomic indicators and a combination of other short-term economic factors. Before the class started this semester our team met and agreed that we all wanted to work on this problem. The main reasons why we chose this problem was that our group was interested in economic data in some way and thought that this project would benefit everyone in our group. The second reason was that there only a few papers that used Neural Networks to try to predict real GDP and we could use those papers as a starting point.

2.2 Problem Specification

In short, our project ultimate goal is to predict how real GDP is affected by a combination of economic factors. Those factors vary from macroeconomic indicators to short-term economic factors such as national unemployment rate, national interest, market cash flow and its velocity, etc.

In long, we will try to create a model that has good predictive capabilities and at the same time allows for analysis of the effectiveness of certain types of parameters. For our project, we will be looking at 2 types of parameters, long term and short term parameters. Long term parameters would hypothetically affect results of up to 3 time stamps ahead while short term factors only affect the result of the current time stamp. For our project, we will be looking at specifically studying long term parameters and their influence on the predictive capabilities of the Neural Network model. We will keep the inputs of short term parameters constant throughout each model.

There are 2 approaches to studying long term parameters, we can either test a specific long term parameter or a combination of long term parameters and verify how influential the long term parameter/s is by running statistical tests on the error of the model when tested on test data, or we can look at the assignment of weights to these parameters and analyze the changes in vector length and direction to understand the parameter's relationship with certain types of events at different time stamps. In conclusion, we aim to build a reasonably accurate model and explain why the model and specific long term parameters improve prediction capabilities.

2.3 Motivation

The importance of our project that there are possibilities of new insight into the field of economics. Currently, many economics papers have only scratched the surface, implementing basic architectures to predict real GDP in the future. Current papers in the application of neural networks in economics also lack the rigorous explanation of how and why the model works. Our group intend to apply new methodologies for studying factors that affect economic events to produce results that are more accurate and useful. These new methods of studying economic factors can then be used by both government and private organizations to either increase the prosperity of a country's population by identifying general population behavior, or increase the profit of a company by identifying current market trends.

2.4 Related work and limits of current practice

In 2004 Junoh conducted a study for predicting Malaysia's GDP using knowledge based economy indicators such as: Computer Infrastructure, Infostructure, Education and Training, Research and Development, and Technology. Their study showed that it was possible to build a prediction model using knowledge based economy factors [15]. The best network model that they obtained had a Root Mean Square Error of 0.587, Mean Absolute error of 0.334 and Percentage of Correctness of 83.33. The network consisted of four input units: Internet subscribers per 1,000 population, mobile telephone subscribers per 1,000 population, number of computers per 1,000 population, and personal computer installation per 1,000 population. Their model had one hidden layer with one hidden unit, one output layer, a learning rate set to 0.1, and a normalized cumulative delta rule with 15 epochs.The paper also talked about how the model can be improved by including other factors such as firm and industry market structure, demography and worker characteristics, and price behaviours as suggested by Haltiwanger and Jarmin (1999) [14]. Therefore, one of the many limitations is the accuracy or cleanliness of the data inputs. Since the methodology for

the collection of the data such that it estimates population data is in the field of statistical sampling, we will assume the data set we have is accurate and sufficient for our model.

In Susnjak et al.'s paper, "Nowcasting: Towards Real-time GDP Prediction paper", they mentioned the cleanliness of the data in a subtopic called "input data acquisition" [19]. It is one of the main challenges in predicting real GDP in real time because the sampling methods to get the information relies on statistical methods and thus imperfect by nature. Besides that, the Nowcasting paper also mentioned the problem of "Uncertainty of Value of Dependent variable". Because obtaining values of real GDP is a difficult and complex process, previous values might be revised as new and more effective methods of obtaining such information is used. This implies that the model could be learning the wrong the information at any given time and thus, producing bad predictions. Another main issue brought up by the paper is which machine learning algorithm is appropriate to model the problem. The danger of believing one machine learning algorithm is better than another is that if the data distribution begins to change due to changes in the underlying nature of economic events, the chosen model would under-perform on the new information and face difficulties in taking into account new random changes. In conclusion, problems of data inputs, uncertainty in dependent variables, and randomness or changes in data distributions are problems that would be faced by current Neural Network architectures and would limit the effectiveness of these Neural Network models.

2.5 Data

The data that we are going to use is pulled from The Global Economy website [1]. This website has every data set that we will need to complete this problem. It will cost us around $8.00 to have unlimited access to the data for one month. The data that we will pull will be for different countries. The first country will be Malaysia so that we can compare our results to Junoh's [15] as a starting point. We will also pull data from the USA, Canada, UK, Spain, Greece, Japan, and Venezuela. These countries where selected because they are either in the top GDP countries in the world or would give us extreme cases to test our models on. Most papers have built and tested their models for specific countries but do not test on multiple different countries.

We have selected the following list of factors for each country that we will use to train out model on. These factors have been selected because either they have been used in previous study or because we believe that they will help build a better predictive model. Some of these factors were suggested by a University of Nebraska-Lincoln professor, Dr. Christopher Mann. Each of the factors is formatted to be a percentage over 100 to keep consistency across all factors.

- Long term parameters
  - Education expenditure as percent of public spending
  - Investment in the economy (Yearly change)
  - Labor force participation
  - Research and development expenditure
  - Student teacher ratio, primary school
  - Internet subscribers
  - Heritage Freedom Index
  - Population above 65 years old
- Short term parameters or constant variables
  - Growth of companies: Tracked by tracking number of passenger and commercial car spending per capita
  - Real Interest rates
  - Unemployment
  - Stock market access for smaller firms
  - Cost of starting a business,
  - Rural population as a percent of total population
  - Human flight and brain drain index.
  - Percent urban population

2.6 Pre-processing

Data will be compiled into a csv file. Everything will be normalized based on the characteristics of its factor. For example, if the parameter is government spending in a country, then we will normalize it by dividing it by total government spending to get a ratio based on the country. Missing data will be handled in a case by case situation based on what sounds more appropriate for each factor (mean, median or omitted). Some data is also timed stamped by month and other data is time stamped by year. We will ensure all data is time stamped by year. This will be done by either; taking the mean value over the year, or the raw value at the end of the year depending on how the data is formatted.

2.7 Proposed Method 1: Statistical Hypothesis Testing

For the first approach we plan to use statistical hypothesis testing, combined with Randomized Complete Block Design (RCBD), to measure the performance and effectiveness of the models with different long-term parameters. The main idea is that LSTM Cells that take the high quality information about combinations of constant short term parameters; as well as raw inputs of both short term and long-run parameters, will be able to discern short and long run trends

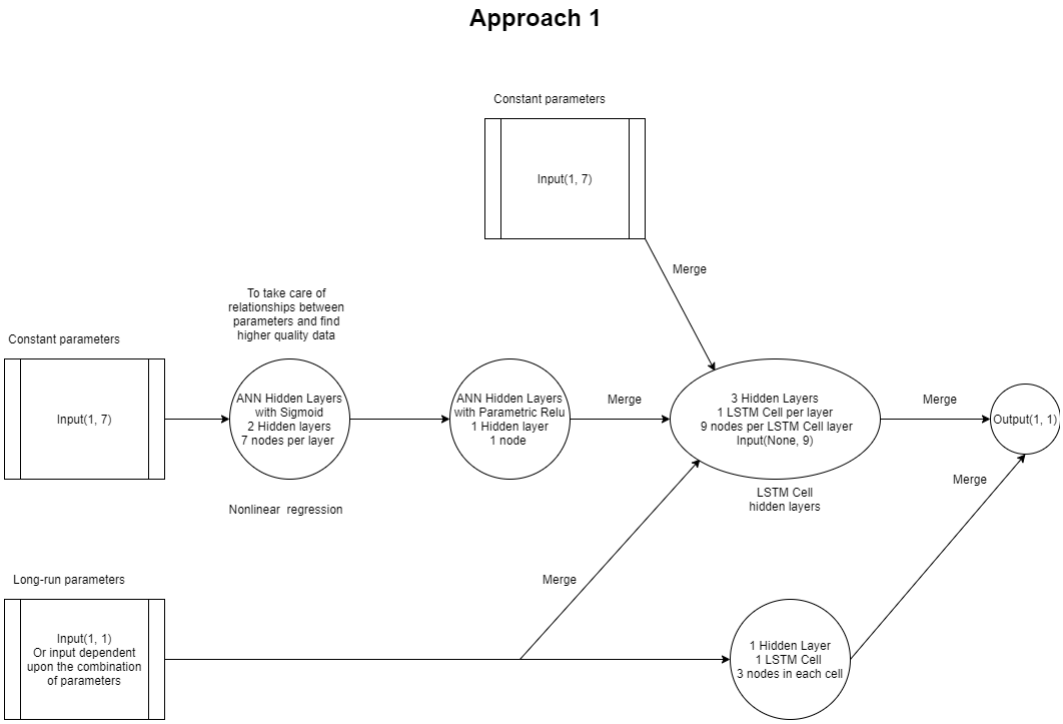

Figure 2.1: Model 1's General structure

in the data. We will test the performance of each long-run parameter or a combination of parameters on test data to study the effectiveness of the long-run parameters. The general plan for the model is depicted in Figure 2.1.

- **Model Assumptions**: The analysis of which parameters are short term or long term are not rigorously identified as they are not part of the project. This means that for the project, our assumption is that all parameters are separated and filtered in appropriate groups in terms of short/long term characteristics.
- **Type of model inputs**: A vector of the parameters at each time step.
- **Type of Neural Network model**: Implement a custom made model made up of LSTM CELL nodes plus functional APIs.
- **Loss Function**: Mean Absolute Errror (MAE) and Root Mean Square Error (RMSE)
- **Outputs**: Prediction of Economic growth for each time stamp.

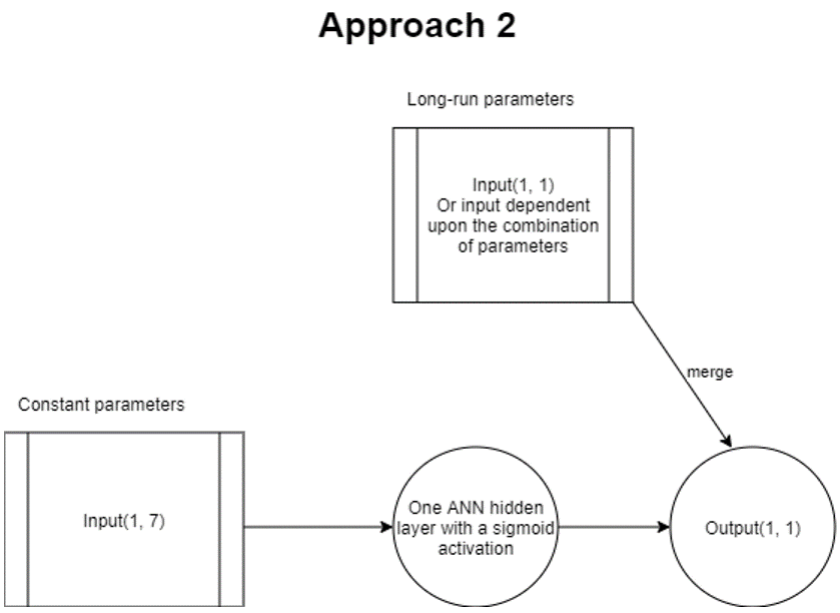

Figure 2.2: Model 2's General Structure

- **Evaluation of performance**: Using hypothesis testing combined with Randomized Complete Block Design (RCBD) to study the difference in performance due to change in a long term parameter or change in a combination of long term parameters. If the error of the model on test data is low and it is statistically different compared to other long term parameters, we can conclude about the characteristics of the long term parameter in predicting change in real GDP.

2.8 Proposed Method 2: Linear Algebra techniques

For the second approach we plan to use Linear Algebra techniques to study the behavior of the Neural Network models with different parameters. Main idea for this model: Use concatenation to study the related weights assigned to the long term variables and how those weights change over time. If the weights change correctly in line with the volatility in the economic growth across different time stamps, it shows that the parameter is important or is associated with specific economic events. This means that we will be studying the weight vectors that are assigned at each time stamp, and analyzing the weights assigned to long term variables. We can then compile the weights assigned to long term variables across all time stamps and evaluate for any drastic changes to the long term variable weights. The general plan for the model is depicted in Figure 2.2

- **Model Assumptions**: The analysis of which parameters are short term or long term are not rigorously identified as they are not part of theproject. This means that for the project, our assumption is that all parameters are separated and filtered in appropriate groups in terms of short/long term characteristics
- **Type of model inputs**: A vector of the parameters at each time step.
- **Type of Neural Network model**: Implement a custom ANN model.
- **Loss Function**: Mean Absolute Errror (MAE) and Root Mean Square Error (RMSE)
- **Outputs**: Prediction of Economic growth for each time stamp.
- **Evaluation of performance**: Conduct an analysis on the weights assigned to long term variables and see whether the Neural Network Architecture assigns the right weights before a prediction of an event at different time stamps. If the architecture manages to assign the right weights, and the model performs well on test data, it is implied that the model is doing well.

2.9 Timeline

Below is a tentative timeline for our project goals.

- Week 1 (3/7): Collect and pre-processes data
- Week 2 (3/14): Start building models
- Week 3 (3/21): Analysis preliminary results and write Milestone 3
- Week 4 (4/4): Revise and rebuild models
- Week 5 (4/11): Analysis new revisions and write Milestone 4 (Presentation)
- Week 6 (4/18): Finalize revisions
- Week 7 (4/25): Analysis final revisions and write Milestone 5

2.10 Midterm and Final Exams

The midterm exam for success would be mainly the performance of the model for one specific country. If the model is acting correctly, we should get low errors for the one country that we have randomly chosen. If the errors are very significant we will either have to explain by breaking down the underlying characteristics of the data or make tweaks and corrections to the model in terms of choosing better activation functions, employing drop outs and regularization, or even choose to simplify the model by removing hidden layers, to improve overall model performance.

The final exam is how well the model performs on all of the countries that we have chosen and running the analysis on the performance of the model.The evaluation of performance across countries can be controlled by running Hypothesis testing with Randomized Complete Block Design. This will allow apple to apple comparisons when evaluating the performance of the model across countries for predicting real GDP change on the testing data for each country.

2.11 Conclusions

In conclusion, both approaches have good potential of succeeding and could have an impact on the field of economics. The first approach is a blending of ideas from Statistics, Economics, and Deep Learning. This blend allows for more rigorous analysis of Neural Network architectures in the field of economics. The second approach is more about using mathematical techniques to study the vectors associated with the parameters of a Neural Network model. This approach allows for easy mathematical analysis of the characteristics of a parameter.

We are hopeful that our models for both approaches will be successful thanks to the nature of the architecture we are using. The first approach allows for a wide variety of experimentation while the second approach is just an extension of the model in Junoh's study. Based on the Warren et al.'s study and Junoh's study [15, 17], those papers discovered that statistical models were equivalent to Neural Network models and how it could be successfully applied in coding. This indicated that we could experiment combinations of Neural Network models that would be equivalent to running multiple statistical modelling on a set of parameters. In conclusion, both approaches should work and bring in results as expected.

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