CAMARINES SUR POLYTECHNIC COLLEGES
COLLEGE of COMPUTER STUDIES

CSAC 224 - Machine Learning

Forecasting Purchasing Power Parity (PPP) Changes in the Philippine Peso using Linear Regression Algorithm

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Abstract

The study of purchasing power parity alongside other economic factors is a great interest that should be focused on. This project proposed to investigate the feasibility of using a linear regression algorithm to forecast purchasing power parity (PPP). This paper uses the said algorithm to predict the PPP based on historical input data. The project's dataset will include two important features which are the Date and the PPP in Philippine Peso value obtained from the "Purchasing Power Parity in Philippine Peso" dataset. The linear regression model will be trained and tested. The model's performance will be evaluated using mean squared error (MSE) and R-squared for determination. This study can potentially contribute to the existing tools in analyzing and predicting factors affecting the economy, particularly the PPP.

1 Introduction

According to Tim Callen, purchasing power parity is the rate at which every country's currency would have to be swapped into the other country's currency to buy the same amount of goods and services in each country. For instance, a hamburger costs 1 dollar in the USA but this hamburger would probably cost 2 European pounds in London. Succinctly, the purchasing power exchange rate is 2 euros for 1 US dollar. Moreover, the stock market exchange (PSEi) and global exchange rates are the only news trends in the Philippines. This is the problem because purchasing power parity (PPP) is not being paid attention to, that is another important fundamental analysis of the growing economy. The relevance of studying a country's purchasing power helps to analyze the current market situation. It shows the overall economic performance of a certain country. This study uses the linear regression algorithm to analyze and predict the purchasing power parity (PPP) changes in the Philippine peso. A regression model that can forecast PPP changes can help investors manage their money to buy assets and liabilities in the future.

CS230: Deep Learning, Winter 2018, Stanford University, CA. (LateX template borrowed from NIPS 2017.)

This study uses the "Purchasing Power of Peso" dataset which contains monthly records from January 1957 to December 2021. The input features for the linear regression algorithm are the months for each year from 1957 to 2021 and their purchasing power values. The output features are the predicted PPP values and visualization models, which are crucial for further analyses.

2 Related work

Purchasing power parity has always been an indicator of the standard of living of constituents in various countries. Different research articles and studies about PPP changes among specified countries have emerged. These related studies that analyze and predict the PPP changes of their chosen type of currencies were to be discussed.

Özkan, F. (2013) compared the performance of forecasting purchasing power parity between the US dollar and euro using artificial neural networks (ANN). The data sets consist of US dollar rates for every month between 1986 and 2010 and European rates between 1999 and 2010. The result shows that the ANN is an effective tool in forecasting exchange rates based on empirical results.

Similarly, Ilie et al. (2021) studied the macro-management indices and their influences on purchasing power parities using an artificial neural networks (ANN) model. They used the Feed Forward Neural Network with Adam algorithm optimization. They obtained a small amount of absolute and mean square errors that demonstrate the efficiency of their model.

Kasem, J. et al. (2022) analyzed the relationship between the time-series records of Middle-east countries' currencies. They tested the validity of purchasing power parity among these currencies using Unit root tests and the Johansen cointegration test from Q1 of 2000 to Q4 of 2020. The results showed a cointegrating relationship between these countries and the PPP model is a dynamic indicator that can hold in the long run of economic sustenance particularly in the Jordanian economy.

Zhang Y. et al. (2020) conducted a study on predicting exchange rates using machine learning methods and fundamental models. The study used random forest, support vector machine (SVM), and neural network models for fundamental theories including purchasing power parity. The root squared mean error (RSME) result showed that their methods outperformed the random walk model.

Wang, C. et al. (2022) in their study measured the purchasing power parity in some cities in China. They used the stochastic method to analyze the PPP among cities that identify the real income disparities. The results showed economic conditions vary depending on geographical locations. Furthermore, the difference between their highest and lowest real incomes decreased from 2.62 to 2.02. This study showed that minor cities in China are realizing economic prosperity.

Tanvir, M. (2016) analyzed the volatility of the exchange rate and its impacts on the global economy. He carefully examined the empirical evidence of foreign exchange rate volatility and how it affects the world transition economy. According to him, some standard business modeling such as ARCH and GARCH models still cannot purely forecast volatility rates. In conclusion, such empirical findings implied that amplified exchange rate volatility hinders economic growth.

Rabe, C. et al. (2020) studied the evolution of purchasing power parity (PPP) using the dynamic common correlated effects (DCCE) framework and applied it to several countries' exchange rates between 1960 and 2015. The results showed that the PPP half-life over the years has fallen indicating a threat to the economy. In place of this, the consumer price index (CPI) across the USA tends to increase drastically due to the increased globalization rate.

Bueno D. (2021) in his study on Philippine macroeconomics, analyzed the primary factors that have affected the country's economic development for the past five years. The statistical data from the World Bank, Philippine Statistics Authority, and UN were examined using meta-data analysis. The results showed that the country is expected to have a gross domestic product (GDP) of $590.86 by the year 2026. Even with the other factors considerably showing positive results, the country is expected to resolve the economy's growth prospect.

Bahramian, P. et al. (2021) studied the purchasing power parity from pioneering members of the ASEAN namely the Philippines, Singapore, Thailand, Indonesia, and Malaysia. This study examined the data obtained from these countries using the Fourier quantile unit root test and in turn, developed a structural model. The results from the root test indicate that the real effective exchange rate time-series were only stationary for the first four countries aforementioned above.

Moreover, Raihanum, K. J. et al. (2023, August) analyzed the purchasing power of cities in Indonesia between 2018 and 2021. They used the K-means algorithm with the CRISP-DM method to analyze the spending factor that affects the PPP among these cities. Results showed that those from urban areas in West Java have a high PPP making these a good spot for business establishments.

These studies are all related to the forecasting of purchasing power parity changes in the Philippine peso using a linear regression algorithm. Some studies have used artificial neural networks (ANN), random forests, K-means algorithms, and support vector machines (SVM). Other studies examined the historical data using the stochastic method, meta-data analysis, and statistical tools such as the Fourier quantile unit root test and the ARCH-GARCH model. Overall, the results show that purchasing power parity changes can be predicted very well using machine learning algorithms and statistical methods. However, these studies have limitations, such as limited periods, data availability, geographical scope, data analysis techniques, and other external events. The findings of these studies may have implications on the business management, and investment strategies of investors. Future research could focus on exploring another machine-learning algorithm, particularly the linear regression algorithm to imply a simpler yet accurate forecasting method.

3 Methods

Linear Regression algorithm will be used in this study. Linear regression is an algorithm that provides a relationship between the independent and dependent variable to predict the outcome of future events. This type of machine learning algorithm is easy to implement, relatively straightforward approach, and can utilize big data through scaling.

Our algorithm will use the dataset obtained from the Philippine Statistics Authority's (PSA) official website. This will be fed into our model and the quantitative and qualitative results will be explained. The mean squared error (MSE) as a loss function will be used.

The Dataset

The dataset that will be used is the "Purchasing Power of Peso", derived from the PSA's official website. It contains monthly records of purchasing power parity values from January 1957 to December 2021. Month-year and Purchasing Power of Peso value composed the dataset. To forecast the PPP, we will be using the Purchasing Power of Peso as our output feature. As for the input feature, we will use the Month-year column. Any null values will be removed from the dataset. The data set will be partitioned into 67-33 ratio for training and testing sets but this will depend on how the process goes out.

Structure of the Dataset

Date	Purchasing Power of Philippine Peso
1957 Jan	101.64
1957 Feb	101.64
1957 Mar	101.64
1957 Apr	101.64
1957 May	101.64
1957 Jun	100.85
1957 Jul	99.31
1957 Aug	98.56
1957 Sep	97.82
1957 Oct	96.37

4 Results and Discussion

The researcher used linear regression as a model and the training and testing sets of data were visualized using matplotlib library. Thirty-three percent of the total data were assigned to be testing

set while sixty-seven percent were to be training set. A random state value of 42 was applied for the reproducibility of the results. The primary metrics used were Mean Square Error (MSE) and R^2.

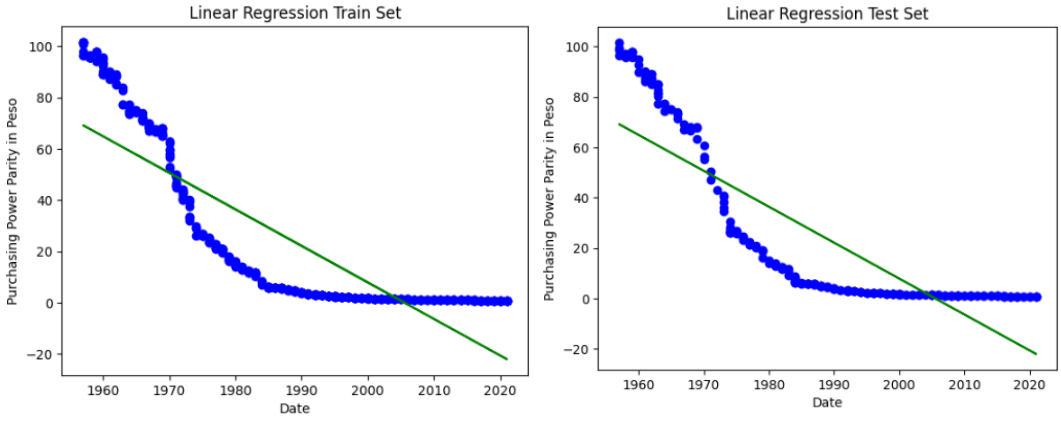

Figure 1: Visualization using Scatterplot

The figure above shows the scattered points follow a curvature trend both in training and testing groups. This means that there is no existing direct linear relationship between the date as a feature and the PPP as another feature. Moreover, we computed the values for our MSE and R-squared. Our MSE value result is approximately 299.528 while the R-squared value is approximately 0.722. An MSE score of 299.53 tells that the dataset considering its values with a maxima of 101 is a bit high for itself. This means that the model may not fit well with the data. Future predictions might be far off from the actual values. Moreover, an R-squared score of 0.72 tells that 72 percent of the variance or the variability in the target variable of the dataset which is the PPP value is explained in the model. Considering that the value of 1 is a perfect number of R-squared, our score is quite near this range. This means that our model might not that too bad to fit our dataset as I have stated before in MSE evaluation.

5 Conclusion

This study on the PPP of the Philippine Peso is a great field to ponder since our economy is quite broad to explore and find the most optimal way to save in terms of crises. However, due to the limited resources available that we can obtain from the Philippine Statistics Authority's official website, we can only manage to explore our dataset in a quite inclusive manner. For clearance, the timeframe and peso value are not yet enough to test considering the result of our experiment. This study needs to further add more variables to consider in creating a program that will forecast the PPP of the Philippine Peso. Also, future researchers might consider continuing this study and using a polynomial regression algorithm instead of linear regression for more productive and broader results.

6 References

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