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Macroeconomic Indicators In International Mass Media Perspective

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Abstract— *This paper is quantitative research to analyze the correlation of the international news sentiment on macroeconomic indicators in ASEAN countries. The analyzed news sentiment data was obtained from the Global Database on Events, Location, and Tone (GDELT) site and the economic index data was obtained from the World Development Indicator (WDI) dataset provided by the World Bank. Machine-learning was used to determine the positive or negative correlation and effects of the two variables. A regression analysis was performed to find out the form of the forecasting equation of the two variables. The data types of the two variables were taken in the form of numerical data (numbers) by following the steps of the Cheat Sheet Algorithm from Scikit-Learn. All data analysis methods were performed using Python software. The long-term goal to be achieved is to contribute in improving macroeconomic forecasting models and developing predictive models with new approaches based on the results of macroeconomic index analysis, and international sentiment by combining data from GDELT and WDI. Thus, The particular target of the results of this research is to determine whether positive or negative correlation and effects of the international mass media sentiment variable on macroeconomic indicators variable in Indonesia, Malaysia, Thailand, Singapore, and Brunei Darussalam. Then to find out the form of the regression equation of the two variables that will be useful for the media in the countries above in conducting international reporting. This research used a quantitative research method by utilizing machine-learning to determine the direction of the research, defining background and goals, formulating research questions, and looking for relevant basic arguments for developing hypotheses, initial data support, research design, and alternative methodologies. The research plan will start from data collection, data preparation and preprocession, data filtering, data deduplication, dataset preparation, data normalization, then statistical description, regression analysis, t-test, to reporting research results.*

Keywords : *ASEAN, big data, GDELT, international mass media, news sentiment, macroeconomic, world development indicators.*

I. INTRODUCTION

The economic sector is formed based on the behavior of actors from various levels, national, companies, investors, and consumers, The majority of them are influenced by past and current economic conditions, and their prospects for the future (Haren, 2017). In the past 20 years, the large expansion of international trade has been a major driver of economic growth. The increase of integration and interconnection of the world economy, global crisis, and new trade flow patterns are the key factors that have changed the dynamics of international trade (WTO, 2013). Until now, various forecasting models for economic development have been developed. One of them is a proposed model for predicting future trade flows by combining various factors such as the geographical location and economic size of a country (Tinbergen 1962; McCallum 1995; Anderson & Wincoop 2003; Rose 2004) against international relations concerning conflict and cooperation (Pollins 1989; Polachek et al 2007). The use of international media sentiment can provide benefits for explaining and predicting macroeconomic variable, such as several studies that are able to prove a significant relationship between sentiment and economic activity (Blanchard 1993; Angeletos & La'O 2013; Feasel & Kanazawa 2013) and the ability to predict future economic developments (Hwang 2011; Barsky & Sins 2012; Juriova 2015).

Recent literature has found a way to measure sentiment based on text using computational techniques. The application of computational text analysis in digital formats enables sentiment analysis with a wider scope.

In addition, the results of the analysis were found to be less bias compared to survey-based measures because the active participation of respondents were no longer needed. Online news articles were found to be very suitable for the application of this automated method considering their important role in sentiment formation (Doms & Morin, 2004). On one hand, news articles provide the public with information about economic conditions in the form of statistics and expert opinions. On the other hand, the tone of the article, as well as the number of articles on a particular news topic, were found to affect the formation of sentiments. A recent study from Shapiro, Sudhof, and Wilson (2017) conducted sentiment analysis using computational text analysis and found that sentiment can predict future economic results. In addition, their results outperformed traditional sentiment measures on the predictions of various economic variables (Shapiro et al, 2017).

In this study, correlation analysis is used to see the relationship between variables and Regression Analysis is used to find out how the form of the equation. The two variables that the relationship will be sought are the sentiment of online media reporting whose data is obtained from the Global Database on Events, Location, and Tone (GDELT) site and economic index data which obtained from the World Development Indicator (WDI) dataset provided by the World Bank. The research period is 16 years, from 2003 to 2019 (GDELT 2019; World Bank 2018). The economic indexes that become variables in this research are Tax Revenue, Export Value, Import Value, GDP Growth, GDP Per Capita, Inflation, Unemployment Figures, Foreign Direct Investment Confidence (FDI), and Current Account Balance (CAB). Meanwhile, The News Sentiment variable that has gone through the normalization process using the Mean Substraction method is named AvgTone_Norm (World Bank, 2018). Image media reports that can be known from the news content sentiments towards a country from the GDELT site is processed to find out the average sentiment per year, then the correlation is analyzed with macroeconomic indicators. The countries that became the sample of the project are countries in the ASEAN region, namely Indonesia, Malaysia, Thailand, Singapore, and Brunei Darussalam. The research data analysis was conducted for a period of 16 years, namely from 2003 to 2019.

II. LITERATUR REVIEW

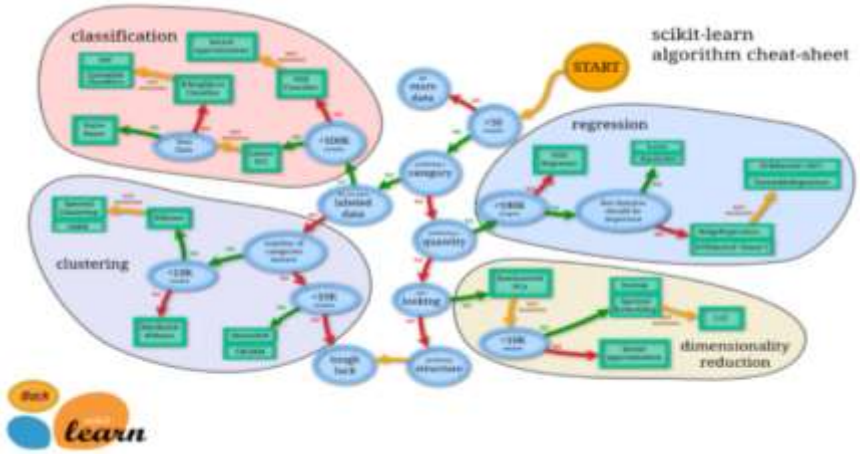
1.1 Research State of Art and Roadmap

The research on the effect of mass media sentiment on the economic sector using the same method has been conducted by several experts, such as Haren's research conducted to predict the strength of dyadic sentiments and international trade flow, from GDELT data coupled with UN Comtrade. But the focus of the research lies in the role of the sentiment of countries in the international trade flow. The countries in question amounted to 40 countries from Asia, America and Europe from 1995 to 2015 using the same machine-learning (Haren, 2017). Meanwhile, Lammers' research focuses on forecasting population migration by analyzing the relationship between tone and migration flow whose data are taken from GDELT and OECD, so that it can produce a migration model that can help the government predict the impact of certain migration policies (Lammers, 2017).

Another research conducted by Wang focused on three issues related to events from news articles, namely analysis of performance and challenges in the current large-scale event coding system, detection of event and extraction of critical information from news articles, and efforts concentrated on event coding that has the purpose to filter broad events and arguments from news article texts, but are not focused on their effects on macroeconomics (Wang, 2017). The research conducted by Dario Buono et al, presents several types of big data including GDELT which can be used for nowcasting macroeconomics by reviewing sources from big data, availability, special characteristics, and literature used, so as to identify the types of big data that can be adopted in real applications, but does not significantly mention the countries that are the objects and the time range of data collection (Buono et al, 2019).

Embun Purwanta et al, investigated the relationship between macroeconomic variables and the stock price indexes of five ASEAN countries (Indonesia, Malaysia, Singapore, Thailand, and the Philippines) from 2006 to 2015. But data retrieval does not use machine-learning and sources of big data (Prowanta et al, 2017). Whereas in this research, the focus of the research lies in the analysis of the effects of international mass media sentiment on the macroeconomic index of ASEAN countries (Indonesia, Malaysia, Thailand, Singapore, and Brunei Darussalam). International news sentiment variable data is taken through the normalization process using the mean substraction method, namely AvgTone_Norm from GDELT using machine-learning from 2003-2019. Then the macroeconomic variable indicators taken from WDI published by the World Bank, namely Tax Revenue, Export Value, Import Value, GDP Growth, GDP Per Capita, Inflation, Unemployment, Foreign Direct Investment Confidence (FDI), and Current Account Balance (CAB), so the forecasting results obtained are far more comprehensive to predict the effect of these two variables.

Machine-learning in Figure 1 in this research is used to find the right estimator for the types of data and problems related to macroeconomic sentiment and index, as described in full in the flowchart of Scikit-learn below as a rough guide and research roadmap (scikit-learn.org).



Source: https://scikit-learn.org
FIGURE 1. Research Roadmap

1.2 Theoretical Basis

The outline of the remainder of this research is providing background information related to international news sentiment and macroeconomic indicators. Describing the experimental setup and elaborates on the data preprocessing, the construction of the dataset and gives an overview of the algorithms that will be used. Presenting the results of the conducted experiments. Providing a general discussion and Discusing the limitations of this work and the recommendations for future research. Finally, the last step gives the conclusion of this work by reflecting on the research questions. This research requires supporting theories both basic and applied theories as well as clear concepts to formulate definitively the relationship between the two variables to be examined using machine-learning.

1.2.1 The Concept of Sentimen

Sentiment can be described as a public evaluation of current conditions and future prospects. There is a growing interest in the use of sentiment in analyzing, explaining, and predicting economic phenomena. To direct the level of accuracy in predicting macroeconomic variables, predictive models increasingly depend on objective and subjective variables. Literally, there is an agreement about the relationship between sentiment and future economic activity, albeit with a different explanation. Blanchard (1993), and Angeletos and La'O (2013) use the theory of "animal spirits" to explain that economic activity is driven by sentiment (Blanchard 1993; Angeletos & La'O 2013). On the other hand, Barsky and Sims (2012) shows that the correlation between sentiment and related economic activity in the future is due to the information aspect of the sentiment itself (Barsky & Sims, 2012)

1.2.2 The Measurement of Sentiment

Traditionally, the measurement of sentiment is usually based on survey-based index. This sentiment index is built from answers given by respondents to questions about current economic conditions and future prospects. Although its acceptance and application are broad, there has been some discussion about its usefulness in economic forecasting, and the reliability and validity of measurements (Garner 1991; Kellstedt et al 2015). The latest method is done by computational techniques to extract sentiment from digital sources such as online newspaper articles. The advantages of text-based economic actions are low costs and has a broad coverage (Fraiberger, 2016).

1.2.3 The Relationship of Sentiment with Mass Media News

News articles are able to create certain opinion sentiments through evaluation of news topics by reported actors, implicit or explicit judgments (Noelle-Neuman & Mathes, 1987). Online news articles were found to be very suitable for the application of this automated method considering its important role in sentiment formation (Doms & Morin, 2004). On the one hand, news articles give the public information about economic conditions in the form of statistics and expert opinions. On the other hand, the tone of the article as well as the number of articles on a particular news topic were found to influence the formation of sentiments. One finding is that the role of the media largely influences the formation of sentiment because people renew their beliefs according to the content and volume in news articles. In addition, text-based sentiment measures were found to be faster in responding to news events compared to measurements based on survey responses (O'Conner, 2014).

1.2.4 The Relationship of Sentiment with Economic Variables

Several studies have shown the relationship of sentiment on the macroeconomic variables and their predictive power. Barsky and Sims (2012) stated that sentiment can convey information that cannot be observed in objective economic variables (Barsky & Sims, 2012). According to Juriová (2015), sentiments towards foreign trading partners can be used to explain the real fluctuations in Gross Domestic Product (GDP), consumer prices and exchange rates. Meanwhile, Li and Makino (2015) found that positive sentiment towards foreign countries facilitated foreign direct investment (FDI), while negative sentiment led to lower investment. They also stated that the effects of negative sentiment had a stronger impact compared to positive sentiment (Juriova 2015; Li & Makino 2015)

1.2.5 The Strength of Forecasting Sentiment in Economic Activity

In his research, Fraiberger (2016) found that sentiment extracted from economic news articles tracks fluctuations in GDP growth, and is a key indicator for GDP growth at the country level. According to Shapiro, Sudhof, and Wilson (2017) show that news sentiment has the strength to predict future economic activity (Shapiro et al 2017 & Fraiberger 2016). Gerrish and Blei (2011), assumed that the strength of sentiment prediction for macroeconomic variables of two countries is reflected in the news articles mentioned together (Gerish & Blei, 2011).

III. METHODOLOGY

This research will be conducted through the following stages:

a. Literature study with relevant research themes and methods
b. Designing algorithms needed in Python for the data collection process
c. The trial process of the algorithm that has been made
d. The process of analyzing numerical text data by exploring statistics and describing statistics
e. The process of regression analysis of the data that has been fixed to determine the correlation and influence of one another
f. The process of testing data by t-test

The subject in this research is machine-learning that is used by the author based on a series of cheat sheet algorithms with the help of Python software as an analysis tool. While the object of this research is international media mass sentiment and macroeconomic indicators in Indonesia, Malaysia, Thailand, Singapore, and Brunei Darussalam. Sentiment data of international online media reports was obtained from the GDELT site by conducting a preparation and preprocessing process before being processed statistically with data on the economic indexes of the five ASEAN countries obtained from World Development Indicators (WDI) of the World Bank. The data used in this research were taken over a span of 16 years, from 2003 to 2019.

Data analysis is a process in a series of studies conducted to solve the problem under study. The accuracy in the use of research analysis tools largely determines the accuracy in taking hypotheses. The analysis of this research belongs to the type of inferential-correlational quantitative analysis, which is a statistical analysis that seeks to find relationships or influences between two or more variables consisting of independent variables and dependent variables. Table 1 explains the types of correlational analysis seen from the scale of the research data used (Neter & Kutner, 1983).

TABLE 1. Types of correlational analysis with data scale

Variable & Data Scale		**Dependent Variable**		
		Nominal	**Ordinal**	**Interval**
Independent Variable	**Nominal**	Contingency Coefficient		• Eta • Serial Correlation • Regression with dummy variables
	Ordinal		Rank Spearman Tau Kendall	
	Interval	Discriminant Analysis		• Product Moment Correlation • Partial Correlation • Semi-Partial Correlation • Regression Analysis

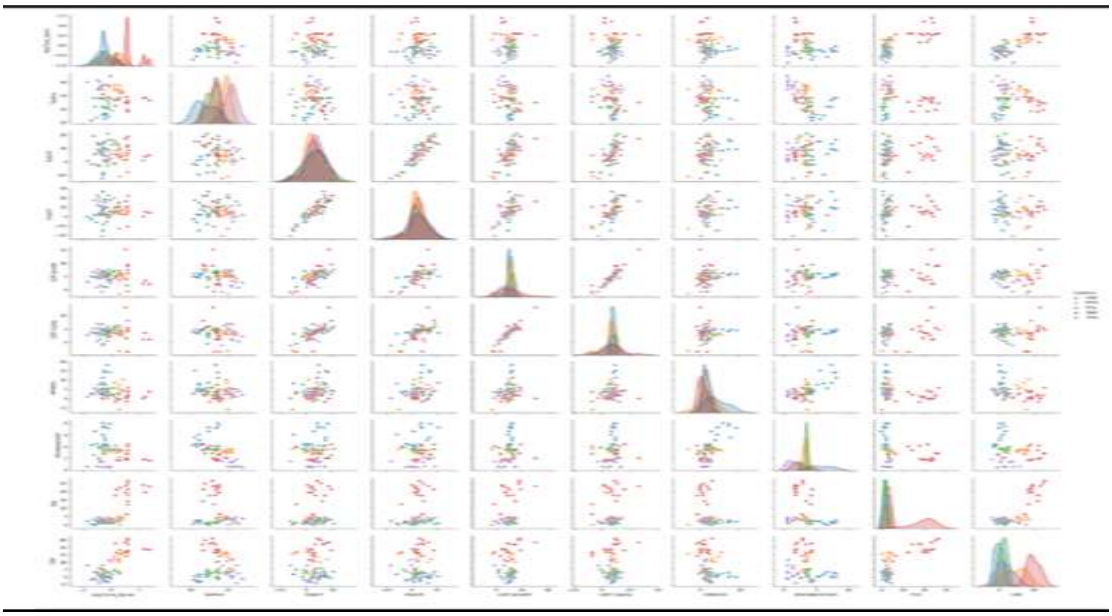
Source: Python processed data

Descriptive analysis is used to understand data reflection of GDELT to real-world event, then conducted descriptive anslysis by visualizing the simple count of news. The datasets provide near-realtime insights into what is happening in different places in five ASEAN countries. There are several important things, especially in GDELT data that the author has confirmed as well as several other research that revealed the same problem. After all raw GDELT data stored in MySQL is cleansed and filtered, then proceed by querying SQL to recapitulate data annually and subsequently stored in a dataset to facilitate further analysis. The dataset is then combined with indicator data on the WDI into a Subset and stored in file.csv to simplify the analysis of the data. As explained earlier, there is an issue regarding the difference in the AvgTone calculation range in GDELT data for the news of 2013 and below and for the news of 2013 and above where the average AvgTone values for 2013 and above are calculated lower than in 2013 and below. As the last step, this research combined the information from GDELT (discussed about international news sentiment) and WDI (World Development Indicators) from World Bank data sets on macroeconomic indicators of five ASEAN Countries in the period of 2002-2019.

IV. RESULTS AND DISCUSSION

4.1 Correlation Analysis

The linear regression model analysis the relationship between a response variable and one / more predictor variables. The model parameters are estimated from the data and used to model the relationship as a linear function. This is done by fitting the model coefficients to the data using the least squares approach to minimize the residual sum of squared errors (Haren, 2017). Correlation analysis is used to see the togetherness between the news sentiment variable and economic indicator variable. In countries where togetherness is not found (or the correlation value approaches and equal to 0), it will not be analyzed further because it means there is no relationship or correlation between these variables. The range of values in this analysis is -1 to 1. Correlation analysis used is Pearson Correlation. The sns.pairplot function (data.hue = 'Country') in the Pandas library is used to display the scatterplot shape results and the calculation of correlation values, with the output shown in the figure.



Source: Python processed data

FIGURE 2. The plot shows the relationship between variables

The numbers in the table show the correlation values between variables. From the above values, it can be concluded that each economic index variable has a correlation to the news sentiment variable. Negative correlations are shown by Tax Rev, GDP Capita, Inflation, and Unemployment Rate. While the positive correlation as shown in the figure, in sequence from the most correlated to the news sentiment variable are CAB, FDI, GDP Growth, Import Value, and Export Value. Of the nine economic index variables above, the most correlated with the news sentiment variable are CAB (0.777628), FDI (0.727840), and inflation (-0.223941). The following is a machine-learning model of the three economic index variables compared with news sentiment (AvgTone_Norm). Statistical regression calculations for variables that have a significant correlation: AvgTone-CAB, AvgTone-FDI and AvgTone–Inflation in the following table:

TABLE 6. Statistical regression

Coeffisients	AvgTone-CAB	AvgTone-FDI	AvgTone–Inflation
a	10.62296577	8.89958287	3.20713538
b	12.33578554	10.89407501	-2.56330405

Source: Python processed data

Based on the table above, the regression formula can be written as follows:

AvgTone - CAB : y = 10.63 + 12.33x
AvgTone - Inflation : y = 3.27 - 2.56x
AvgTone - FDI : y = 8.89 + 10.89x

This research analysed the effect of international news sentiment on macroeconomic indicators in five ASEAN countries. News articles are able to create certain opinion sentiments through evaluation of news topics by reported actors, implicit or explicit judgments (Noelle-Neuman & Mathes, 1987). News articles can give the public information about economic conditions in the form of statistics and expert opinions. Several studies have shown the relationship of sentiment on the macroeconomic variables and their predictive power but not specific to one particular indicator of macroeconomic. Barsky and Sims (2012) stated that sentiment can convey information that cannot be observed in objective economic variables (Barsky & Sims, 2012). According to Juriová (2015), sentiments towards foreign trading partners can be used to explain the real fluctuations in Gross Domestic Product (GDP), consumer prices and exchange rates. Li and Makino (2015) found that positive sentiment towards foreign countries facilitated foreign direct investment (FDI), while negative sentiment led to lower investment. They also stated that the effects of negative sentiment had a stronger impact compared to positive sentiment (Juriova 2015; Li & Makino 2015). Fraiberger (2016) found that sentiment extracted from economic news articles tracks fluctuations in GDP growth, and is a key indicator for GDP growth at the country level. According to Shapiro, Sudhof, and Wilson (2017) show that international news sentiment has the strength to predict future economic activity (Shapiro et al 2017 & Fraiberger 2016). Gerrish and Blei (2011), assumed that the strength of sentiment prediction for macroeconomic variables of two countries is reflected in the news articles mentioned together (Gerish & Blei, 2011).

Meanwhile, in line with the concept above, this research concluded that each economic index variable has a correlation to the news sentiment variable. Negative correlations are shown by Tax Rev, GDP Capita, Inflation, and Unemployment Rate. While, the positive correlation as shown in the figure, in sequence from the most correlated to the news sentiment variable are CAB, FDI, GDP Growth, Import Value, and Export Value. This research found that the most correlated with the news sentiment variable are CAB (0.777628), FDI (0.727840), and inflation (-0.223941). The following is a machine-learning model of the three economic index variables compared with news sentiment (AvgTone_Norm). Statistical regression calculation is performed for variables that have a significant correlation to the news sentiment: CAB (AvgTone-CAB), FDI (AvgTone-FDI) and Inflation (AvgTone–Inflation).

4.2 T-Test (Model Feasibility Test)

a. One-Sample T-Test

Testing using the T-Test is used to evaluate the null hypothesis where the average sample dataset is equal to the population from which the sample dataset is. The results of the AvgTone_Norm T-Test can be seen in the appendix.

```
import scipy
true_mu = 0
onesample_results = scipy.stats.ttest_1samp(a,true_mu)
print(str(onesample_results))

   Ttest_1sampResult(statistic=2.2448584442337268e-15, pvalue=0.9999999999999982)
```

Source: Python processed data

FIGURE 3. The result of One-Sample T-test of AvgTone_Norm variable

The results of the AvgTone_Norm T-Test can be concluded that the p-value is greater than the t-statistic, so it does not reject the null hypothesis (H-0) at the significant level of 0.05.

b. Two Sample T-Test

The test involves 2 separate datasets on the same variant to investigate whether the average of the two are identical, if taken from the same population.

```
import scipy

a = data['AvgTone_Norm'].values
b = data['FDI'].values
twosample_results = scipy.stats.ttest_ind(a, b)
print(str(twosample_results))
```

```
Ttest_indResult(statistic=-6.7856890655659345, pvalue=2.594559996004258e-10)
```

Source: Python processed data

FIGURE 4. The result of Two Sample T-test of AvgTone_Norm and FDI variables

Wherefore the p-value is much smaller than statistics test, it is proven to reject the null hypothesis (H-0) about identical assumptions. Economic policymakers (governments of each country) and market participants rely on a broad array of models that incorporate soft information. As opposed to hard information which includes objective and directly quantifiable variables such as production and employment, soft information includes subjective measures concerning attitudes about current and future economic conditions (Shapiro et al, 2017). In this section, we aggregate the news article sentiment scores into macroeconomic indexes and assess its correlation with these survey measures. A strong correlation would help validate that our news sentiment measure is not pure noise and is capturing similar information to that of the surveys.

V. CONCLUSION

Analysis and testing of the correlation as well as the influence (significance) of international media news sentiment from GDELT site on macroeconomic indicators of countries in ASEAN obtained various results both negative and positive, by using a machine-learning model, namely Multiple Linear Regression Analysis accompanied by the selection of methods based on the alleged existence of a link between the independent variable and the dependent variable which is linear. So that, the results obtained are international mass media sentiment that have been normalized using the Mean Substraction method named AvgTone_Norm known to be able to give positive and negative signals to the macroeconomic conditions of countries in ASEAN which is obtained from the measurement of various indicators, namely: Tax Revenue, Current Account Balance (CAB), GDP Capita, GDP Growth, Inflation, Unemployment, Foreign Direct Investment (FDI), Export and Import. As well as the international news sentiment variable is related (correlated) to the macroeconomic index of countries in ASEAN which is indicated by the existence of a positive correlation and negative correlation. Positive correlation is shown by the variables of CAB, FDI, GDP Growth, Import Value, and Export Value to the international news sentiment. Meanwhile, the negative correlation is shown by the variables of Tax Revenue, GDP Capita, Inflation, and Unemployment Value to the international news sentiment. From the table above, it is known that not all of these indicators can reflect the macroeconomic conditions of the ASEAN countries. Of the 9 economic index variables, there are 3 that have the most correlation with news sentiment variable, namely CAB (0.777628), FDI (0.727840), and Inflation (- 0.223941).

Then after the two variables (dependent and independent) are analyzed the correlation and its influence, then testing the regression coefficient or t-test which is intended to test the parameters (regression coefficients and constants) which are thought to estimate the multiple linear regression model is an appropriate parameter or not. Then the two steps of t-test are conducted, namely One-Sample t-test and two sample t-test. The result of One-Sample t-test from the results of AvgTone_Norm, it can be concluded that the p-value is greater than the t-statistic that is 0.9999, then it does not reject the null hypothesis (H-0) at the 0.05 significance level. Meanwhile, the result of the two sample t-test shows that the p-value is much smaller than the t-statistic value of 2.5945599 - 10, so that it is proven to be able to reject the null hypothesis (H-0) about identical assumptions.

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