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Predicting the Results of the 2019 Indonesian Presidential Election with Google Trends

Analysis of Accuracy, Precision, and Its Opportunity

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ABSTRACT

In electoral competitions, voter behavior research is conducted to develop effective campaign strategies, but survey methods tend to be expensive. By contrast, in the internet era where political campaigns evolve by using digital data and channels, Google Trends offers free services that display search interest indexes for certain keywords and topics measured through search volumes on Google search engines over a period of time and certain areas. Thus, Google Trends could be a tool that increases the efficiency of voter behavior research. By using the election real count data released by the General Election Commission on May 21, 2019, this study conducted an accuracy and precision analysis of the Google Trends topic query index that represented presidential candidate number 01 and number 02 in predicting the real count of the two candidates' votes. The analysis indicated that using Google Trends as a tool to predict the results of the 2019 Indonesian Presidential Election produced imprecise results. However, Google Trends could better predict election outcomes by adding features for sentiment analysis and a more representative understanding of users' search activity.

Keywords: *Google Trends, Political Choice, Accuracy, precision, 2019 Presidential Election*

1. INTRODUCTION

On April 17, 2019, the General Election Commission (KPU) held a legislative and presidential election simultaneously. The election participants were candidates for president, vice president, and the legislature, and parties competed for voter support from Indonesian citizens through political campaigns. Political campaigning closely intersects with marketing, that is, candidates are in the electoral market and use marketing strategies to maximize the "purchase" of voters in the form of votes. The electorate is a *market*, and parties and candidates participating in the election are *brands*, especially the candidate's personality (Aaker, 1997). In business marketing and elections, market research is critical, and campaigns conduct research to determine the areas of potential voters before formulating further campaign strategies.

In the current context of voter behavior research in Indonesia, to examine political choices in the 2019 election at the national level, research must be conducted using the survey method because of its validity and reliability. This assumes that the methodology uses sample data in the of hundreds to thousands and systematically samples the population across Indonesia. This process involves a large surveyor team, a long time to collect all the survey and/or interview data, and a large amount of funding to access the samples nationally (Donsbach and Traugott, 2008) and has become a challenge for voter behavior researchers, increasing the need for alternative methodologies that can collect data regarding the Indonesian population more efficiently.

Notably, the development of today's political campaigns is entering the fourth era, a period of evolutionary development in which political campaigns began to use big data (Stephen-Davidowitz, 2017), social media, and online news as distribution channels for campaign strategies. This resulted in a data-driven digital campaign strategy that used digital information channels to distribute political campaign content to voters (Fisher and E., 2018). Along with the development of digital campaign trends, the number of internet users in Indonesia is increasing rapidly (APJII, 2018). Hence, internet users' activities generate vast amounts of data on voter behavior on internet media as digital agents (Stephen-Davidowitz, 2017). This phenomenon allows voter behavior researchers to collect voter data through data on internet users' activities.

Most of the data of internet users are publicly accessible. Some internet-based service companies provide social trend analytics services that display public issues that appear based on data on their services (Han *et al.*, 2012). One such service is from Google, which in 2009 released search queries for its users through a publicly accessible interface called Google Trends. Google is the search service with the most users; thus, researchers can examine topics relevant to the community in real-time by using Google Trends as an alternative to or replacement for survey methods (Reilly *et al.*, 2012). This novel method is possible because data searching on the internet offers considerable benefits compared with surveys for the speed and cost of data collection (Yasseri and Bright, 2014).

Several studies have used this method and found that the data collected from the internet was useful (Wicaksono, 2017). However, what remains unknown is whether internet data searches represent the behavior of voters. A study showed that the basic nowcasting model for examining unemployment rates in the United States could be substantially increased by examining search results data on related search terms (Choi and Varian, 2012). In another area, a private consumption index in the United States calculated using search results on the internet could be a better predictor than the Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index, which are commonly used (Huang and Penna, 2009). Other studies have conducted analyses using a similar principle component approach and found that indexes compiled using internet search data were more accurate than indexes based on the surveys that had been used (Vosen and Schmidt, 2011).

Some research findings have supported that Google Trends is an effective tool for predicting, nowcasting, and forecasting. This assertion is supported because Google is the dominant internet search engine, used by 64.2% of the population (Reilly *et al.*, 2012). Google Trends generates scaled and normalized output by showing the search volume for keywords based on area and in a time series. Another advantage is that Google Trends data is open source.

Overall, the literature has demonstrated that Google's search data is a useful predictor of data despite its imperfections (Butler, 2013; Lazer *et al.*, 2014; Yang *et al.*, 2015). However, a paradigm that directly compares Google Trends data with conventional methods found that the data has a relative utility function (Ma-Kellams *et al.*, 2016). Although Google data might become a better predictor than survey data in certain domains, clarification is necessary on how the data compares with other forms of big data and small data in other domains (Ma-Kellams *et al.*, 2018).

In the context of Indonesia, according to the 2017 APJII survey, the number of internet users in Indonesia was 143.26 million, or 54.68% of the population. Of the total usage, 74.84% were activities to access search engine services (APJII, 2018). Because Google is the dominant internet search engine, search queries data on Google Trends in Indonesia can represent up to 107.26 million persons', or approximately 40% of the population. In addition, the figure also represents the distribution of users spread across Indonesia. Thus, when used as a sample, Google Trends data have a high representation value and wide area coverage. This is an argument for assessing the use of Google Trends as a methodological tool for researching voter behavior efficiently, especially in predicting voters' choices in general elections.

The results of the general elections (real count) announced by the KPU on May 21, 2019, are an opportunity to test the validity and accuracy of Google Trends as a tool to examine voter behavior in Indonesia, namely, voter choices. This study aims to test the accuracy and precision of Google Trends in representing the political choices of the Indonesian electorate in its 2019 presidential election. Real count data of the election results are used because the data is original and describes the political choices of the Indonesian electorate (i.e., the presidential candidate), not speculative opinions or opinions. Presidential election data rather than legislative election data is used to conduct a focused comparative analysis because the former had only two candidates and the latter had, 16 choices of political parties. The research question is as follows: How accurate and precise is Google Trends data in predicting the result of Indonesia's 2019 presidential election?

2. CONCEPTUAL FRAMEWORK

2.1. Google Trends

Google Trends is a service of Google that provides a time series index of the search request volume or queries input in Google search in specific geographic areas. The query index is based on query share: the total query volume for keyword searches in a geographic area divided by the total number of queries in the region over a period of time. The maximum share query in the specified time period is displayed in a normalized index to 100, and the query share at the initial date checked is normalized to zero (Choi and Varian, 2012).

The two types of query indexes are the topic query index and search term index. The topic query index is *broad matched*, that is, queries such as "used car" and related ones are calculated in the search query index for the topic "car." Although the search term query index is *exact match*, that is, the query index "used car" represents only the term "used car." In addition, because of privacy considerations, only queries with significant search volumes can be tracked. Online help is available through a link on the Google Trends site that explains the details of how the data are collected. Query index data are available at the country, state, and district/city level (Choi and Varian, 2012).

2.2. Voter Behavior: 2019 Indonesian Presidential Election

Voter behavior is closely related to, or even assumes, the existence of a democratic political system adopted by a country where the voter is located. Four main concepts define the political system of democracy (Fisher and E., 2018): (1) accountability that guarantees citizens to hold elections regularly to maintain a government in charge of power; (2) governments are elected by a popular legislator who is popular (popularly elected legislature), can be held accountable, and can be dismissed if necessary; (3) political parties as agents of mass mobilization and mechanisms for the operation of responsible governments and (4) a ruling party/government to guarantee the system fulfills the aspirations of citizens.

Thus, in a democracy, citizens have the right to, for example, participate in the political system by electing legislators to head the government. Voter behavior assumes that voters have political abilities: (1) level of knowledge, (2) understanding, and (3) attention to politics (Zakina, 2008). A public provided with an adequate level of information and political understanding is a prerequisite for the success of a democratic system.

Indonesia is the world's third-largest democracy. In the 2019 elections, voters determined the legislators and the president for the next 5 years. In this context, voter behavior can be observed, for example, their choice of political parties, legislators, vice president, and president.

In the book *The American Voter* (in Evans, 2004) Campbell et al. said, "(in the contemporary world) voting activities are juxtaposed only with markets as a way to reach collective decisions from individual choices."

3. METHOD

This study used a quantitative research design (Neuman, 2011; Gorard, 2003), to analyze the predictive power of search query index data on Google Trends with actual data on Indonesians' political choices (election *real count*) on the same issue. The data analyzed was the Google Trends index data on the topic query "Joko Widodo" (presidential candidate number 01 [PCN1]) and the topic query "Prabowo Subianto" (presidential candidate number 02 [PCN2]). The data were collected using accuracy and precision analysis by comparing the *real count* data of the 2019 presidential election votes for both candidates.

Of the two types of queries available on the Google Trends interface, namely, *search terms* and *search topic* queries, the data used was a search topic query because it is *broad match* and captures keywords of the same topic. This was chosen because the search keywords for the presidential candidates could be diverse, for example, to find PCN1, several keywords could be used such as "Joko Widodo" or "Jokowi." With topic queries, different keywords that refer to the same topic can be combined into one search topic query. This process applies to the topic queries of PCN1 and PCN2.

Retrieval of query index data on the topics "Joko Widodo" and "Prabowo Subianto" was performed on Google Trends (http://trends.google.com) on May 19, 2019. Some of the interface settings during the data retrieval process were as follows: location was set to Indonesia; the query data period was between September 23, 2018, and May 16, 2019; query categories were set to all categories; and search type was set to Web Search. Indonesia was set as a query area is to adjust the presidential election *real count* data on a national scale by dividing the data area at the provincial level. The time range was started on September 23, 2018, according to the starting date of the campaign period (KPU, 2018), until May 16, 2019, according to the last query data that could be accessed during the data retrieval process. The category was set to *all categories*, and the search type in Web Search was set to capture all related queries that enter the search engine more broadly across all search categories and types.

The *real count* data of the 2019 presidential election votes were obtained from the KPU's official website on May 22, 2019 (KPU, 2019), one day after the announcement date. The data obtained is the number of votes for PCN1 and PCN2 nationally divided into provincial levels.

This study analyzed the accuracy and precision of Google Trends index data on the topic queries of PCN1 and PCN2 in predicting *real count* results of the 2019 presidential election. The analysis technique was adapted from the *predictive accuracy (A)* technique proposed by Martin, Traugott, and Kennedy (Martin *et al.*, 2005; Traugott, 2005). This method used a measure based on a winning odds ratio instead of using a percentage point difference.

In Google Trends data, if the candidate topic query index PCN1 symbolized by (j) and the topic query index of PCN2 is symbolized by (p), the odds of winning for both candidates was calculated using the formula j/p. If the value of the calculation was more than one, PCN1, according to Google Trends, has a greater chance of winning. Conversely, if the value of the calculation was less than one, PCN2 was predicted to have a greater chance of victory. If the calculation was exactly one, the candidates had the same chance of victory.

In the *real count* data, if the votes for PCN1 and PCN2 are symbolized by (J) and (P), the measure of a candidate winning is calculated with formula J/P. If the value of the calculation is exactly one, the figure illustrates that both candidates are very competitive and achieve the same support. Values greater than one illustrate that PCN1 is getting more votes than PCN2, and vice versa. Values smaller than one illustrate that PCN2 is getting more votes in the election.

A measure of predictive accuracy A *is* defined by the following formula:

$$A = \log[(j/p)/(J/P)] \quad (1)$$

A statistical value A can be zero, or positive or negative, and has properties as follows:

- A is zero, indicating perfect uniformity between Google Trends and the election results (*real count*).
- A significant negative value A indicates that Google Trends tends to win the PCN2. A significant positive value A indicates the contrary: Google Trends tend to win the PCN1.
- Negative values are comparable with positive values.
- A is a logarithm on the basis of e, and its value represents an exponential value.

4. RESULTS

The following are the findings from the query index data on the topics “Joko Widodo” and “Prabowo Subianto” obtained from Google Trends. The query index data has a scale of 1 to 100, and the KPU *real count* data is real voting numbers with a range of values up to millions. To bridge the differences in the range of data, normalization was conducted in the second to convert the *real count* data into the percentage of vote count calculated at the provincial level.

Table 1. Google Trends Index and Real Count Election of the two Presidential Candidates. [12].

	Google Trends Index		Real Count (%)		A
	01	02	01	02	
Aceh	46,00	54,00	14,41	85,59	**0,704**
North Sumatera	49,00	51,00	52,32	47,68	− 0,058
West Sumatera	44,00	56,00	14,08	85,92	**0,681**
Riau	48,00	52,00	38,73	61,27	**0,164**
Riau Islands	50,00	50,00	54,19	45,81	− 0,073
Jambi	47,00	53,00	41,68	58,32	**0,094**
South Sumatera	47,00	53,00	40,30	59,70	**0,118**
Bengkulu	43,00	57,00	49,89	50,11	− 0,121
Lampung	49,00	51,00	59,34	40,66	− 0,181
Bangka Islands	47,00	53,00	63,23	36,77	− 0,288
DKI Jakarta	50,00	50,00	51,68	48,32	− 0,029
West Java	48,00	52,00	40,07	59,93	**0,140**
Banten	49,00	51,00	38,46	61,54	**0,187**
Central Java	52,00	48,00	77,29	22,71	− 0,497
DI Yogyakarta	50,00	50,00	69,03	30,97	− 0,348
East Java	50,00	50,00	65,79	34,21	− 0,284
Bali	55,00	45,00	91,68	8,32	− 0,955
West Nusa Tenggara	47,00	53,00	32,11	67,89	**0,273**
East Nusa Tenggara	56,00	44,00	88,57	11,43	− 0,785
West Kalimantan	49,00	51,00	57,50	42,50	− 0,149
Central Kalimantan	52,00	48,00	60,74	39,26	− 0,155
South Kalimantan	49,00	51,00	35,92	64,08	**0,234**
East Kalimantan	50,00	50,00	55,71	44,29	− 0,100
North Kalimantan	52,00	48,00	70,04	29,96	− 0,334

North Sulawesi	53,00	47,00	77,24	22,76	− 0,478
Gorontalo	49,00	51,00	51,73	48,27	− 0,047
Central Sulawesi	47,00	53,00	56,41	43,59	− 0,164
South Sulawesi	49,00	51,00	42,98	57,02	**0,105**
Southeast Sulawesi	49,00	51,00	39,75	60,25	**0,163**
West Sulawesi	48,00	52,00	64,32	35,68	− 0,291
Maluku	48,00	52,00	60,40	39,60	− 0,218
North Maluku	50,00	50,00	47,39	52,61	**0,045**
Papua	52,00	48,00	90,66	9,34	− 0,952
West Papua	55,00	45,00	79,81	20,19	− 0,510
Average	**49,38**	**50,62**	**55,10**	**44,90**	− 0,121

5. DISCUSSION

5.1. Google Trends' Accuracy and Precision in Predicting the 2019 Presidential Election

The national results of the 2019 presidential election (*real count*) demonstrated that PCN1 won with 55.50% of the vote, and PCN2 had 44.50% of the vote. With these results, the correct predictive value (*A)* of Google Trends is positive, which is the calculation that predicted victory for PCN1. Overall, 12 of 34 (*A)* values are positive, and the remaining 22 are negative. This finding shows that Google Trends only accurately predicted PCN1's victory in 12 provinces (North Maluku, Jambi, South Sulawesi, South Sumatra, West Java, Southeast Sulawesi, Riau, Banten, South Kalimantan, West Nusa Tenggara, West Sumatra, Aceh) and was inaccurate for the remaining 22 provinces.

However, the real count of the 2019 presidential election demonstrated that PCN1 did not win in all 34 provinces. In the real count, PCN1 won in 21 provinces, and PCN2 won in 13 provinces. When comparing the (*A*) value in each province with the real count of the presidential election in each province, Google Trends accurately predicts election results in 13 provinces and makes inaccurate predictions in the 21 remaining provinces. Of the 13 provinces, 12 provinces are the same provinces accurately predicted when referring to the real count aggregate nationally, and the one remaining province is Bengkulu province.

Whether compared with the real count nationally or provincially, Google Trends accurately predicted less than half of the total provinces. Thus, the predictive accuracy of Google Trends for the 2019 presidential election is low.

Next, a precision analysis of Google Trends was conducted by interpreting the value *(A)* further. The closer the value (*A)* to 0, positive or negative values, the higher the level of precision of the Google Trends index. Conversely, the farther the value (*A*) from 0, positive and negative, the lower the precision level of the Google Trends index in predicting the real count of the 2019 presidential election.

The variation in the precision level of Google Trends is illustrated in Figure 1, which was processed from the value (*A*).

FIGURE I. Google Trends Precision Chart in Predicting the Real Count of the 2019 Presidential Election by Province

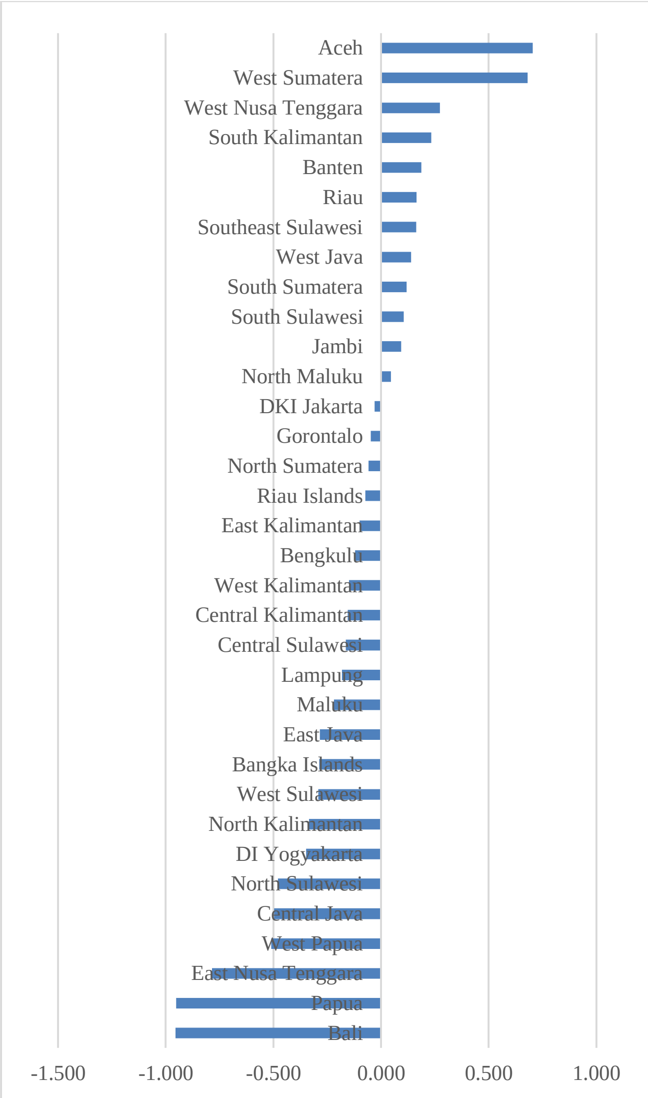

Figure 1 The more A values close to 0, the higher the precision of Google Trends in predicting the real count of the province.

The Google Trends index in the least precise range of positive (accurate) values is in the provinces of Aceh and West Sumatra, respectively, at 0.704 and 0.681. Whereas in the range of negative (inaccurate) values, the least precise Google Trends index is in the provinces of Bali and Papua, respectively, at −0.9955 and −0,952. Additionally, the province with the most accurate and precise Google Trends index is North Maluku (0.045) and Jambi (0.094), and although in DKI Jakarta Google Trends is inaccurate in predicting the real count, in this province, the Google Trends index has the highest level of precision, with A value −0.029.

The variation range of the precision value of the Google Trends index as illustrated in Figure 1 shows that Google Trends has low consistency in predicting real counts of the 2019 presidential elections. Variations in the precision value of Google Trends range from 0.029 to 0.955; thus, this tool is unreliable for predictive analysis.

5.2. Weaknesses and Potentials of Google Trends as an Election Prediction Tool

To explain the low level of accuracy and precision of Google Trends in predicting election results, notably, the Google Trends query index value is not the real number of query queries but numbers after normalization based on area and number of searches from time to time. The index represents the query search volume of aggregated keywords of a topic in an area and time period. Thus, the index value of Google Trends represents the search volume of voters but does not represent direct voter preferences manifested in real count election results.

If the electorate of Indonesia had had an alternative political choice (i.e., a third choice), based on that choice, the population would be divided into groups according to the alternative choice of candidates or parties available. In the context of the 2019 presidential election, the population of Indonesia in general was divided into 3 groups: supporters of PCN1, supporters of PCN2, and the undecided. In the process of the political campaigns conducted to obtain votes from each group, a communication process occurs. Voters search for information on the candidate before they decide which candidate to vote for (Kotler, 1975).

Because voters have access to the internet and Google search services, the process of searching for this information is performed through the Google search engine interface, for example, browsers and Google search applications. Thus, population groups with certain political choices will be reflected in the number of political choice topic search queries in the Google search engine, and members of these groups act as internet users who use Google search services. If the number of voters for PCN1 is significantly greater than the number of voters for PCN2, the search query volume in the Google search engine will reflect this.

The aggregate number of winnings of the Google Trends index and real count at the provincial level is insufficiently close to conclude that Google Trends is representative or an accurate predictor. Based on the index in Google Trends, PCN2 got more votes in 20 provinces, and in real count, PCN1 got more votes in 21 provinces. This finding contradicts the argument that a group of people with a particular political choice will be represented in the search volume query of the candidate on the Google search engine. The map shows that although PCN2 tends to be superior in search volume on Google search engines in 20 provinces, the political choice of the Indonesian's is PCN1 in 21 provinces.

A contradiction was observed in national aggregate according to the provincial-level data: the Google Trends topic query index predicted PCN2 would win, whereas in real count, PCN2's numbers were greater in 21 provinces. This map illustrates the low accuracy of Google Trends in predicting election real counts. This occurs because of the data not captured by Google Trends in the process of searching for information on presidential candidates by voters.

The higher intensity of voters in searching for information for a candidate does not necessarily mean that the voter prefers a specific candidate. Sentiment factors are also a factor (Metaxas *et al.*, 2011; Wang and Lei, 2016), namely, the voters' positive and negative views on candidates whose information is being searched for using Google search. A possibility is that a population that prefers candidate A can search for information by using the Google search engine for candidate B, but with negative motivation and sentiment. This weakness is a limitation of Google Trends as a useful tool for predicting political choices.

However, Google Trends could be developed as a tool to predict voters' political choices in a general election. Google Trends has advantages in terms of efficiency in measuring the dominance of certain issues (salience) (Mellon, 2014) in the population by observing the volume of searches for keywords and/or topics on Google search engines. To be an accurate tool for predicting the winner of general elections, Google Trends should develop features that analyze sentiments from search activities performed by users. Additionally, to increase the precision level of Google Trends as a predictor, features that capture search volumes that are more representative of one individual must be developed to ensure no double calculation if one user is more intensive in searching for certain data than other users.

6. CONCLUSION

This study tests the accuracy and precision of the Google Trends index in predicting the 2019 Indonesian presidential election. By using the general election *real count* data released by the General Election Commission on May 21, 2019, this research analyzed the predictive accuracy (*A*) and the precision of the topic queries index of Google Trends that represented PCN1 and PCN2 in predicting votes for candidates in the 2019 presidential election. The conclusion based on the analysis is as follows: based on the observed features of Google Trends, this tool has low accuracy and precision in predicting the political choices of Indonesian voters on the basis of *real count* data of the 2019 presidential election.

Thus, Google Trends is not a valid and reliable voter behavior research tool because of the low accuracy and low precision of data. Research on voter behavior should thus continue to use survey and interview methods—and will not be replaced by Google Trends anytime soon. However, this study found that Google Trends could be a tool to predict general elections if the following are added: a more representative sentiment analysis and a search index feature for each user's search activity. Further research could assess the application of Google Trends data compared with legislative election data, political surveys, or censuses data. Through extensive assessments, Google Trends application models could be developed as an alternative tool that supports voter behavior research and is methodologically efficient, valid, and reliable.

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