Person's multiple intelligence classification based on tweet post using SentiStrength and processed on the Apache Spark framework

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Abstract. A person’s self-development is influenced by his ability in solving problems and adapting to his environment. This ability is commonly known as intelligence. Every person has a different dominant intelligence. Honed intelligence can result in managed self-development and self-mastery. A person can discover his talent and expertise to be more advanced in his field. However, discovering one’s dominant intelligence requires several variables to assess his behaviours. This research makes use of a person's activities on the social media Twitter. Twitter is a platform on which its users share thoughts. Posted tweets are used as objects to determine the corresponding user’s dominant intelligence. The user’s tweet will go through a sentiment analysis and intelligence type classification by applying the SentiStrength method to the Apache Spark framework. This research was conducted on 20 Twitter user accounts with the types of intelligence consisting of musical-rhythmic, visual-spatial, verbal-linguistic, logical-mathematical, bodily-kinesthetics, interpersonal, intrapersonal, naturalistic, and spiritual intelligence. The 72% average accuracy is obtained by calculating the correlation between manual testing and the system using the Spearman's rank correlation coefficient ($\alpha = 0.05$ and the Spearman's value of 0.700).

1. Introduction
Intelligence is often defined as the ability to understand something and the ability to have an opinion [1]. However, intelligence no longer only relies on the intellectual quotient (IQ) aspect. A person who has a high IQ does not guarantee that he will achieve success in life. Recent findings show that the IQ is at its highest, only contributing about 20 percent of the factors that determine success in life, while 80 percent is determined by other forces, such as social class to good fortune, and prayer [2]. In 1983, a psychologist named Howard Gardner developed a theory about multiple intelligence. Gardner defines intelligence as the ability to solve problems and produce products in a variety of settings and in real situations. Gardner also defines intelligence as the ability to solve problems and produce products in a variety of settings and in real situations. The intelligences according to Gardner consist of nine intelligences, namely linguistic intelligence, logical-mathematical intelligence, spatial intelligence,
bodily-kinesthetic intelligence, musical intelligence, interpersonal intelligence, intrapersonal intelligence, naturalist intelligence, and existential intelligence. According to Gardner, a person has all nine types of intelligence, it's just that the levels are not always the same. There is a type of intelligence that is more prominent than other types of intelligence. Intelligence which is more prominent is very good if it can be used for one's personal development. The development of intelligence in a person will be more optimal when a person knows what kind of intelligence is dominant in him. Intelligence itself can be analyzed from individual behavior. There was a positive relationship between adaptive behavior and intelligence. The higher the development of a person's intellectual function, the higher the ability for adaptive behavior. The characteristics of a logically-mathematically intelligent person include the ability to analyze, sort, reason logically, think in a cause-and-effect pattern, look for conceptual regularities or numerical patterns, create hypotheses, and a general view of life is rational [3].

Twitter social media user activity data in the form of tweets can support the multiple intelligence classification of its users. To be able to determine the classification of multiple intelligence requires data in the form of multiple user tweets. The use of Apache Spark can support tweet data processing where Apache Spark is a cluster-computing framework for large-scale data processing [4]. In 2019, research was applied to a system for the classification of multiple intelligence in children based on posting activity on social media. Social media in this research was built by researchers who applied SentiStrength and Spearman's rank correlation coefficient as research algorithms. The system is capable of producing output in the form of several types of multiple intelligence with a system correlation of 80% with a standard deviation of 0.09 [5]. In 2017, Fafalios et al. [6] also leveraged SentiStrength for sentiment analysis on multi-aspect analysis on entity-centric Twitter. This research uses Hadoop and Apache Spark for processing the CSV format dataset. The processed tweets resulted in a temporal analysis of entities in terms of: popularity, attitude (dominant sentiment), sentimentality (the amount of sentiment), controversy, and relationship with other entities. Sentiment analysis is the process of detecting the contextual polarity of the text which determines whether the given text is positive, negative or neutral. Sentiment analysis is also referred to as opinion mining, because it comes from the opinion or attitude of the speaker [7]. Some of the challenges faced in sentiment analysis are that positive opinion words in one situation can become negative in other situations and the opinions expressed can be different by each person. Most of the reviews have positive and negative comments and are analyzed sentence by sentence. However, in more informal media such as on Twitter or blogs, people are more likely to combine different opinions in the same sentence which may not be easy to understand, but algorithms will be difficult to analyze [8]. Etaiwi et al. in 2017 [9] implemented Apache Spark in his research. The data processed in this study consists of information and personal behavior of customers from Santander Bank, which is an international financial institution that offers financial products to their customers. Through this data set it predicts which products customers will use next month based on their past behavior and their personal information. The dataset contains more than 13 million records for model training and about 1 million records for model testing. This study is more focused on the comparison between two classification algorithms, namely Naive Bayes and Support Vector Machine, where the results obtained are that Naive Bayes is more efficient in predicting and superior in terms of precision, recall, and F-measure.

Based on the background, this research carried out is to build a person's multiple intelligence classification system based on data obtained from Twitter social media by utilizing Apache Spark as a framework for data processing and Spearman's correlation coefficient as an algorithm to obtain data correlation results.
2. Method

The complexity of knowing a person's personality affects the difficulty of finding the dominant intelligence type. This also leads to less-than-optimal self-development. The intelligence that a person has is related to his behavior. A person's adaptive behavior needs to be observed through his involvement in the use of social media. Therefore, an approach is made using social media to determine the type of intelligence of a person. Measuring a person's intelligence is basically done by comparing tested individuals with certain norms. The norm used is peer group intelligence. According to Binet, as quoted by Sunaryo [10], the way to find out a person's intelligence quotient (IQ) is to compare the intelligence age (mental age / MA) and calendar age (CA). So far, the determination of the type of intelligence is done by utilizing a balanced list of questions for each type. The yield value of each intelligence is obtained by calculating the average value of each type of intelligence divided by its quantity. The calculation formula can be seen in Equation 1.

\[
MI_x = \frac{\sum_{i=1}^{n} T_i \times S_i}{n}
\]

where

\(MI_x = \text{the mean score for each type of multiple intelligence}\)

\(n = \text{the amount of input data processed}\)

\(T_i = \text{intelligence type value weights for the \(i^{th}\) tweet}\)

\(S_i = \text{the sentiment value weight for the \(i^{th}\) tweet}\)

The method used in this research to produce multiple intelligence classifications is divided into several processes. These processes can be seen in the general architecture shown in Figure 1.

![Figure 1. General architecture.](image-url)
2.1. **Spearman’s rank correlation coefficient**

The Spearman's rank correlation coefficient is a nonparametric technique for evaluating the level of a linear relationship or correlation between two variables. The advantage is in nonparametric technology which is not influenced by population distribution. Spearman's rank correlation coefficient is also related to rank data, so it is relatively insensitive to external objects and does not require data to be collected over a certain distance interval. In addition, its application is also easy to use for very small data sample sizes. The algorithm for calculating the Spearman's rank correlation coefficient can be seen in Equation 2.

\[
\rho = \frac{6\sum d_i^2}{n(n^2-1)}
\]

where

\(\rho = \text{Spearman's rank correlation coefficient}\)

\(d_i = X_i - Y_i\)

\(X_i = \text{The position of certain values on list } X \text{ is seen in ascending order of values}\)

\(Y_i = \text{The position of certain values on list } Y \text{ is seen in ascending order of values}\)

\(n = \text{The sum of the values in list } X \text{ and list } Y\)

After obtaining the correlation value \(\rho\), then this value will be compared with the critical value in Table 1.

| \(n(\alpha = 0.05)\) | \(\rho\) |
|----------------------|--------|
| 5                    | 1.000  |
| 6                    | 0.886  |
| 7                    | 0.786  |
| 8                    | 0.738  |
| 9                    | 0.700  |

For \(n\) values in the range 5 to 9 and \(\alpha = 0.05\), if \(\rho\) is greater than the critical value, the two lists have a fairly large correlation. Spearman rank-order correlation is a statistical procedure designed to measure the relationship between two variables on an ordinal measurement scale. The correlation value generated from calculations through the Spearman's rank correlation coefficient equation will be associated with a predetermined critical value. The correlation is formulated in the type of hypothesis as a statistical hypothesis test, \(H_0\) and \(H_1\). Where, the null hypothesis \((H_0)\) is a hypothesis which states that there is no relationship between the two variables. In contrast, the working hypothesis \((H_1)\) is a hypothesis which states that there is a relationship between two variables. Based on the application of Spearman correlation in this research, if the \(\rho_s \leq \rho_c\) value is not correlated and \(H_0\) is accepted. Conversely, if \(\rho_s > \rho_c\) then the sample correlates and \(H_0\) is rejected. With the \(\rho_s\) value as the correlation value generated by the manual system value correlation calculation, and \(\rho_c\) as the critical value in Table 1.
2.2. SentiStrength
SentiStrength is an opinion mining program developed by CyberEmotion [11]. SentiStrength is an example of a positive or negative classifier. By utilizing a lexical dual scale system, SentiStrength wants to show that humans can feel positive emotion and negative emotion simultaneously to a certain extent independently [12].

2.3. Dataset
The input data used is in the form of a collection of tweets owned by an account which is obtained from the Request data feature on Twitter. Data is downloaded in the form of a ZIP file which is used as input to the system. A collection of tweets is available in CSV format contained in the ZIP file. The number of accounts collected consisted of 20 Twitter users. Each account represents the entire tweet it has, counting until the last tweet in data collection in March 2019. Tweets that are posted will be processed by the system to be identified so that their sentiment score can be taken.

2.4. Pre-processing stage
The pre-processing stage is the process of processing tweet data before entering the classification stage. The pre-processing stage consists of four stages, namely data selection, data cleaning, normalization, and tokenizing.

2.5. Classification stage
The classification stage is the stage that plays a role in the data classification process in order to determine the level of intelligence of the user by giving weight to words that use the SentiStrength method. This stage consists of the sentiment stage and intelligence stage. In the sentiment classification stage, words are classified into likes, dislikes and neutral. Each word will be weighted according to the dictionary compiled by Wahid and Azhari [13]. The dictionary has several types of classification, including a dictionary of sentiments, idioms, booster words, negations, and question words. Each dictionary contains words for which a numeric value is included as the weight of the word. At the intelligence classification stage, the focus of the discussion is words related to the type of activity that users tell in their tweets. Words are weighted according to the values found in research conducted by Siregar et al. in 2019 [5].

All words contained in the word array generated at the tokenizing stage will be weighted based on the values listed in the dictionary. An example of giving weight to words at the classification sentiment and intelligence stage can be seen in Table 1. Each word is weighted based on the word classification whether it is a sentiment or types of intelligence.

For example, on the Twitter User X account ten tweets were taken to be processed and weighted as shown in Table 2. These weights are used to find the average value of user intelligence. Using Equation 1, each weighted value of each type of intelligence shown in Table 2 is multiplied by the weighted value of the sentiment. The values of the multiplication results for each type of intelligence can be seen in Table 3.
Table 2. Examples of word weighting.

| Word          | Type             | Weight |
|---------------|------------------|--------|
| tv            | -                | 0      |
| keren         | sentiment        | 4      |
| lagu          | interpersonal    | 0.6    |
|               | intrapersonal    | 0.24   |
|               | visual-spatial   | 0.24   |
|               | spiritual        | 0.24   |
|               | musical-rhythmic | 3.69   |
| dimainin      | -                | 0      |
| alat          | -                | 0      |
| musik         | interpersonal    | 0.6    |
|               | intrapersonal    | 0.24   |
|               | visual-spatial   | 0.24   |
|               | spiritual        | 0.24   |
|               | musical-rhythmic | 3.69   |
| tradisional   | -                | 0      |
| indonesia      | verbal-linguistic| 0.42   |
| angklung      | verbal-linguistic| 0.14   |

Table 3. Word weighted value on user X's tweets.

| Tweet | Weight of the Sentiment | The Product of the Weight of Type of Intelligence and the Weight of the Sentiment |
|-------|-------------------------|---------------------------------------------------------------------------------|
|       |                         | MR  | VS  | VL  | LM  | BK  | ITE | IIA | NA  | SP  |
| 1     | +4                      | 14.76 | 3.52 | 1.68 | 1.12 | 0   | 11.68 | 6.68 | 0.56 | 0.96 |
| 2     | +4                      | 0    | 4.44 | 2.0  | 20.0 | 0   | 7.32  | 6.68 | 1.12 | 2.68 |
| 3     | -4                      | -0.36 | -3.72 | -1.48 | -1.48 | -0.36 | -7.04 | -2.6  | -1.48 | -1.48 |
| 4     | +4                      | 0    | 4.44 | 1.12 | 8.88 | 0   | 0     | 4.44  | 1.12 | 0    |
| 5     | +4                      | 0    | 0    | 0    | 0    | 0   | 1.32  | 16.0  | 1.32 | 1.32 |
| 6     | +5                      | 0    | 0    | 2.5  | 1.65 | 0   | 9.15  | 8.35  | 0    | 3.35 |
| 7     | 0                       | 0    | 0    | 0    | 0    | 0   | 0     | 0     | 0    | 0    |
| 8     | +4                      | 0    | 0    | 2.0  | 1.32 | 0   | 7.32  | 6.68  | 0    | 2.68 |
| 9     | +4                      | 0    | 1.44 | 0    | 17.25 | 0.72 | 0.36  | 0.36  | 0    | 2.52 |
| 10    | 0                       | 0    | 0    | 0    | 0    | 0   | 0     | 0     | 0    | 0    |
| Average|                        | 1.44 | 1.0  | 0.78 | 4.9  | 0.03 | 3.0   | 4.65  | 0.26 | 1.20 |

The classification of user tweets at this stage is assessed based on the sum of the weight values obtained from each word. To get the average value, the value of the product is divided by the total number of user tweets. The output of this system is the level of user intelligence for each type of intelligence which is presented in the form of a bar chart. The value of each type of intelligence is taken from the average
score previously obtained from the classification stage. The average value of each type of intelligence of the user is then sorted according to the highest value so that the order of intelligence types is obtained: logical-mathematical (4.9), intrapersonal (4.65), interpersonal (3.0), musical-rhythmic (1.44), spiritual (1.20), visual-spatial (1.0), verbal-linguistic (0.78), naturalistic (0.26), and bodily-kinesthetics (0.03).

2.6. Back-end system development

In designing the back-end system, input data processing is carried out in the form of a collection of Twitter user tweets. The input data processing consists of two stages, namely the pre-processing stage and the classification stage which consists of the process of weighting the values of sentiment and intelligence. The entire pre-processing and classification stages utilize the Apache Spark framework as big data processing to improve system performance in large tweet data processing. Apache Spark is a powerful processing engine built for data analysis that is available open-source. Apache Spark is optimized for iterative algorithms and interactive data analysis that perform cyclic operations on the same data set [14]. Twitter social media user activity data in the form of tweets can support the multiple intelligence classification of its users. To be able to determine the classification of multiple intelligence requires data in the form of a lot of user tweets. The use of Apache Spark can support tweet data processing where Apache Spark is a cluster-computing framework for large-scale data processing [15].

![Cluster manager in Apache Spark.](image)

Tweets from an account can amount to thousands of tweets that are processed to produce multiple intelligence classifications against users. To support the increase in system performance, this research
uses 6 servers that are tasked with retrieving and processing input data. The first server acts as a program driver to run the main function of the application, and creates SparkContext. Meanwhile, the other 5 servers act as worker nodes that execute input. Through Figure 2 it can be seen that the Apache Spark architecture works where data is distributed to each cluster managed by the cluster manager, as an external service for acquiring resources. Resources in the form of tweets from Twitter users are then executed by each executor in each cluster. The executor is responsible for running tasks and storing data. There are 3 tasks in each cluster that work in parallel so that data processing is faster.

2.7. Calculation of correlation value between manual and system results acquisition

At this stage, the value of each type of intelligence that has been generated by the system is then compared with the value of the calculation manually. Twitter users were asked to answer a questionnaire containing questions. The user's answer is in the range of 1 (expressing very dislike) to 5 (expressing very much like it). Furthermore, the scores from the questionnaire are added and sorted from the type of intelligence with the highest to the lowest scores. The calculation of the correlation value is carried out to compare the acquisition value generated through the system by utilizing user tweets and the acquisition value of questionnaire answers. In Table 3.7, there are details of the classification results of User X's intelligence manually and the acquisition through the system. The correlation value is calculated using the Spearman's rank correlation coefficient using Equation 2.

Table 4. Examples of classification results of Twitter user intelligence type manually and the system built.

| Type of Intelligence | Ranking Results from the Classification of Intelligence Types | The difference value from the position between the classification results manually and the system built. |
|----------------------|-------------------------------------------------------------|--------------------------------------------------------------------------------------------------|
|                      | Manual | System Built |                                                                                                 |
| Naturalistic         | 1      | 1            | 0                                                                                                 |
| Interpersonal        | 2      | 7            | 5                                                                                                 |
| Verbal-Linguistic    | 3      | 2            | 1                                                                                                 |
| Spiritual            | 4      | 3            | 1                                                                                                 |
| Musical-Rhythmic     | 5      | 5            | 0                                                                                                 |
| Visual-Spatial       | 6      | 4            | 2                                                                                                 |
| Intrapersonal        | 7      | 6            | 1                                                                                                 |
| Bodily-Kinesthetics  | 8      | 8            | 0                                                                                                 |
| Logical-Mathematical | 9      | 9            | 0                                                                                                 |

The value of the difference in position between the results of manual and system classification is used as the $d$ value and the number of types of intelligence is used as the $n$ value. From the results of these calculations as shown in Equation 3, the Spearman's rank correlation coefficient or $\rho$ value is 0.73 with an $\alpha$ value of 0.05. When compared, the acquisition value of $\rho$ is greater than the critical value in Table 1, where for $\alpha$ 0.05, the value of $\rho$ is 0.700. This proves that both lists are quite correlated and $H_1$ is accepted.

$$\rho = 1 - \frac{6(0^2+5^2+1^2+1^2+0^2+2^2+1^2+0^2+0^2)}{9(9^2-1)}$$

(3)
3. Result and Discussion
This research was built involving the Apache Spark framework. Spark provides a web interface for monitoring various information related to running applications. Some of the information displayed includes number of workers, number of cores, memory usage, drivers, task and application status, as well as other detailed information. Apart from that, Spark also provides another interface that contains various information on jobs, stages, storages, environment, and executors.

As shown in Figure 3, it can be seen that the application runs 15 tasks which are divided into 5 executors, where each executor carries out 3 tasks. Each task has a different acquisition duration and delay in processing data. Utilization of Apache Spark in processing user tweet data is very influential on the time generated. The greater the number of tweets, the longer it will take. In addition, the number of cores used also affects the duration of data processing. Based on the graph in Figure 4, it can be concluded that the utilization of more cores affects the processing duration of a number of tweets. Processing a number of tweets using 15 cores takes a lot faster than using 3 cores. In addition, the greater the number of tweets that are executed, the longer the duration is required.

System testing is carried out to produce output in the form of intelligence types from each uploaded Twitter user tweet data. Meanwhile, the types of intelligence are musical-rhythmic (MR), visual-spatial (VS), verbal-linguistic (VL), logical-mathematical (LM), bodily-kinesthetics (BK), interpersonal (ITE), intrapersonal (ITA), naturalistic (NA), and spiritual (SP). The algorithm used to obtain the correlation of the resulting data is the Spearman's correlation coefficient.

![Figure 3. Comparison of tweet processing speed based on number of CPU cores.](image_url)
3.1. Example of Test Results on User X

The multiple intelligence graph in Figure 5 shows the level of intelligence of User X of each type of intelligence. The percentage on each bar shows the percentage of intelligence in the user. The greater the percentage, the more talented the user is in the type of intelligence involved.

![Figure 4. Graph of intelligence classification results for user X.](image)

Based on the graph in Figure 4, the intelligence level of User X starts from the most dominant to the lowest in order are Interpersonal, Intrapersonal, Naturalistic, Mathematical, Musical, Kinesthetics, Visual, Spiritual, and Linguistic.

3.2. Correlation between Manual and System Retrieval of Results

The average accuracy of the Spearman's rank correlation coefficient or \( \rho \) is 0.72 or 72% with a deviation value of 0.09. This value is obtained from the average \( \rho \) calculation of manual and system acquisition values related to the type of intelligence of each user. The correlation of \( \rho \) values is slightly greater than the critical value in Table 1, where for \( \alpha \) is 0.05 and \( n \) is 9, the value of \( \rho \) is 0.700. Overall, the average correlation value from manual and system acquisition to the critical value is 0.72 > 0.70, which means that the sample is quite correlated and \( H_1 \) is accepted.

4. Conclusion

Based on testing and research conducted on a person's multiple intelligence classification system based on posts on Twitter using the Spearman's rank correlation coefficient, the following conclusions can be drawn: The type of user intelligence is determined based on the user's tweet on Twitter which is obtained by analyzing the parameters related to sentiment analysis, namely words related to activity and also those that indicate a sentiment of excitement; In this research, the use of Apache Spark framework in data processing can make the process run faster. This is because Apache Spark is a powerful processing engine and is often used in large-scale data processing; Manual and system correlation with manual results to get the level of accuracy of this research using the Spearman's Rank Correlation Coefficient method. The correlation result is 72% with a standard deviation of 0.09.
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