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# Determining Characteristics of Popular Local Songs in Indonesia's Music Market

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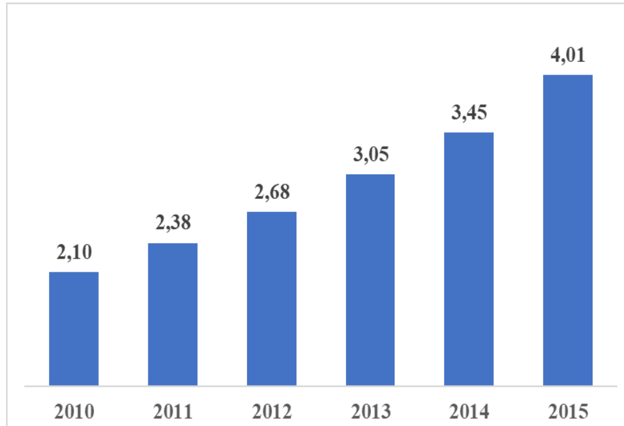
***Abstract*— The music industry in Indonesia has the potential to improve its competitiveness. However, there are challenges in how to improve the competitiveness. Nowadays, the internet, especially the developing online streaming service, provides the music industry to be able to promote and publish music or songs. The online streaming service provides accessible data, e.g. TOP Charts data and audio features, with opportunities to analyze the data in order to help create a new marketing strategy. These data may help the music industry know hidden information in local songs or music markets. However, research based on data in popular local songs, particularly using more understandable audio features provided by Spotify to know the characteristics distinguishing popular songs to non-popular songs has not been conducted. In this study, CART decision tree was conducted aiming to determine the characteristics of popular local songs in Indonesia's music market. The local songs from the Daily TOP 200 Spotify were collected and divided into 163 training data songs and 70 test data songs. From the results, there were several attributes representing the characteristics of popular local songs. The evaluation of the model resulted in an accuracy of 72.8%.**

***Keywords- music industry; machine learning; popular songs; CART; decision tree; data mining***

## I. INTRODUCTION

The music industry in Indonesia has the potential to improve its competitiveness as it is prioritized to be developed. However, it has only contributed 0.47% each year from total GDP of creative economy in average [1]. The competitiveness of Indonesia's music industry is also considered as low compared with others. Based on TOP 200 Spotify in Indonesia, Indonesia's users listened for only 271 million times streaming for local songs in total of 1,3 billion times streaming have been listened.

Based on Statistics Indonesia, the GDP of music industry is increasing from year to year as shown in Fig 1. The average GDP growth rate of music industry from 2011-2015 is 7.06%. It is considered higher than the average GDP growth rate of creative economy itself which is 5.47% [1]. This fact leads to hidden potential in Indonesia's music industry. To improve and develop its competitiveness, Indonesia's music industry still has main challenges such as insufficient creative resources and unoptimized market utilization [2]. In fact, music industry is helped by the internet to promote and publish the music or songs, especially from online streaming services, e.g. Spotify,




*in trillion Rupiah

Figure 1. GDP of Music Industry in Indonesia

JOOX, Youtube or even from social media. Additionally, online streaming services are predicted to keep growing as becoming the future of music industry [3].

The developing of online streaming music service not only gives artists and producers opportunity to promote and publish the music or songs but also gives the data of music e.g. metadata data for tracks, artists, top charts, streams count, etc. The data may be able to obtain useful information if they are used properly. Spotify, one of the most developing online streaming service, provides access to their data such as top charts, tracks, artists, streams, and even the audio features of songs. These audio features consisting of tempo, loudness, energy, key, mode, time signature, liveness, valence, speechiness, acousticness, danceability, and instrumentalness are considered as a breakthrough in music information retrieval as they give more understandable features especially for music industry such as artists and producers [4].

These data are potential to obtain useful information for marketing strategy. The researches in popular music data become an important thing to do in music market intelligence. The research based on popular music data is able to know real conditions that has not been known yet in music market. There are researches focusing on data-based analysis especially in popular music data using classification method and machine learning to predict popular songs [5][6][7]. The decision tree, SVM, regression, and other classification methods have been conducted on the researches and give proper method to predict popular songs.

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The decision tree is also able to give the characteristics based on the tree.

The research using classification method and machine learning in music industry especially to help marketing strategy is rarely done in Indonesia. Besides, determining the characteristics of popular songs using more understandable features also hasn't been conducted. Thus, in this paper, local songs from the Daily TOP 200 Spotify are analyzed particularly using decision tree to determine the characteristics of popular local songs.

## II. Research Method

The brief method conducted in this study is shown in Fig. 2. which mainly elaborates the steps done such as the pre-processing local songs data, extracting audio features, and modeling the training data using CART decision tree, and evaluating the model.

### A. Data Collection and Pre-Processing

Indonesian local songs in the Daily TOP 200 Spotify from January 2017 – March 2018 were collected in this paper. There were 233 songs used to be analyzed. For the first step of pre-processing data, determining the label for popular and non-popular songs from the cumulative number of streams was done. The songs with streams more than 2 million labeled as popular and the songs with streams less than 2 million labeled as non-popular.

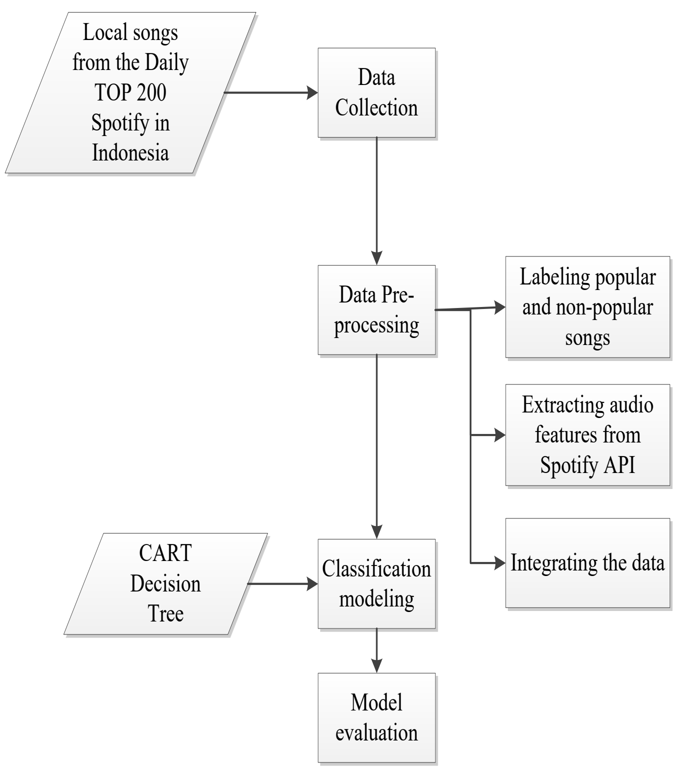


Figure 2. Methodology Steps

Audio features were extracted from Spotify API consisted of several features explained below [8]:

- Acousticness, an acoustic level of a song that is played with acoustic instruments. The measurement uses confident measure from 0 to 1. 0 represents that a song is not played with acoustic instruments such as guitar, piano, etc, while 1 represents an acoustic song.
- Danceability, a feature describing a level of a song which is suitably enjoyed with dancing based on tempo, rhythm stability, beat intensity, etc. Its is ranging from 0 to 1, which 1 represents that a song is very suitable enjoyed with dancing.
- Energy, a level represents intensity and activity from a song based on how fast, loud, and noisy is the song. It also considers the dynamic range and perceived timbre. Energy uses confident measure from 0 to 1.
- Instrumentalness, a feature that predicts a song consists of non-vocal elements. An instrumentalness value higher than 0.5 is considered as an instrumental song.
- Key, a base key that is used in a song and denoted by number which 0 is for C, 1 is for C#, 2 is for D and so on.
- Liveness, a feature representing the audience existence in the recording of the song. A value higher than 0.8 states that the song is a live song.
- Mode, a feature describing that a song is played in major or minor mode. 1 for major and 0 for minor mode.
- Speechiness, a feature that predicts a song consists of vocal elements. A value higher than 0.66 represents a song is made fully with vocals, value 0.33-0.66 represents a song has balanced vocal, music elements, and speechiness value less than 0.33 represents a song has few vocal elements.
- Tempo, a feature that represents how fast or how slow is a song is made stated with beats per minute (BPM).
- Time signature, a conventional notation specifies on how much beats in a bar.
- Valence, a positivity level of a song. The songs with high positivity indicate songs are made with happiness and euphoria elements. The songs with low positivity indicate songs are made with sad and anger elements.

The pre-processed data is shown in Fig. 3. Each of the song were integrated with the extracted features as variables and label. The pre-processed data become the input for classification model.

| Docs | danceabili | energy | key | loudness | mode | speechine | acousticne | instrume | livenes | valence | tempo | time_ | Label |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intuisi - Yura Y | 0,453 | 0,0531 | 1 | -19,956 | 1 | 0,0355 | 0,946 | 0,0002 | 0,08 | 0,354 | 79,863 | 4 | Non Popular |
| Akad - Payung | 0,502 | 0,708 | 9 | -7,522 | 1 | 0,0771 | 0,316 | 0,0391 | 0,112 | 0,774 | 91,533 | 4 | Popular |
| Selalu Muda - | 0,57 | 0,487 | 0 | -6,432 | 1 | 0,026 | 0,47 | 0,0002 | 0,124 | 0,487 | 87,997 | 4 | Non Popular |
| Aku Tenang - F | 0,458 | 0,149 | 11 | -8,64 | 1 | 0,0391 | 0,919 | 0 | 0,1 | 0,165 | 113,632 | 3 | Popular |
| Mata Ke Hati ( | 0,871 | 0,522 | 0 | -5,601 | 1 | 0,0419 | 0,225 | 0 | 0,206 | 0,887 | 123,991 | 4 | Popular |
| Sempurna - An | 0,313 | 0,32 | 4 | -9,952 | 1 | 0,0292 | 0,725 | 0 | 0,105 | 0,395 | 98,046 | 4 | Popular |
| Puan Bermain | 0,703 | 0,487 | 9 | -8,646 | 1 | 0,034 | 0,745 | 2E-05 | 0,248 | 0,531 | 94,032 | 4 | Non Popular |
| Setengah Hati - | 0,444 | 0,567 | 0 | -7,794 | 1 | 0,0288 | 0,13 | 9E-05 | 0,109 | 0,258 | 136,589 | 4 | Non Popular |
| Indonesia Ray | 0,591 | 0,324 | 4 | -6,929 | 1 | 0,0281 | 0,796 | 0 | 0,382 | 0,456 | 97,891 | 4 | Non Popular |
| Tak Pernah Set | 0,394 | 0,288 | 7 | -8,26 | 1 | 0,0309 | 0,678 | 0 | 0,132 | 0,199 | 128,173 | 4 | Non Popular |
| Kesempurnaan | 0,499 | 0,601 | 7 | -6,454 | 1 | 0,0304 | 0,113 | 0 | 0,136 | 0,483 | 143,984 | 4 | Non Popular |
| I Love You - Jud | 0,63 | 0,416 | 5 | -7,205 | 1 | 0,0416 | 0,66 | 2E-06 | 0,096 | 0,423 | 127,097 | 3 | Non Popular |
| Pulang - Float | 0,734 | 0,431 | 0 | -9,436 | 1 | 0,0266 | 0,679 | 0,056 | 0,071 | 0,76 | 94,03 | 4 | Popular |
| Anganku Angar | 0,492 | 0,689 | 0 | -4,638 | 0 | 0,0346 | 0,424 | 1E-06 | 0,086 | 0,294 | 155,952 | 4 | Non Popular |
| Slow - Young Le | 0,701 | 0,664 | 6 | -6,259 | 0 | 0,0738 | 0,109 | 0 | 0,063 | 0,575 | 100 | 4 | Non Popular |
| Seniman - Adhi | 0,685 | 0,322 | 2 | -11,725 | 1 | 0,0278 | 0,838 | 0,0031 | 0,11 | 0,403 | 108,177 | 4 | Non Popular |
| Biarkanlah - R | 0,545 | 0,319 | 5 | -9,76 | 0 | 0,0308 | 0,786 | 6E-06 | 0,109 | 0,256 | 120,154 | 4 | Non Popular |
| Silver Rain - Re | 0,672 | 0,73 | 1 | -4,74 | 1 | 0,029 | 0,0107 | 0 | 0,139 | 0,609 | 119,984 | 4 | Non Popular |
| Kamu Cukup - | 0,743 | 0,389 | 10 | -9,616 | 1 | 0,0317 | 0,428 | 3E-06 | 0,113 | 0,56 | 86,036 | 4 | Non Popular |
| I Still Love You | 0,446 | 0,159 | 1 | -12,129 | 1 | 0,0376 | 0,906 | 5E-06 | 0,11 | 0,172 | 119,93 | 4 | Non Popular |
| Cinta Dalam Hi | 0,602 | 0,464 | 6 | -6,365 | 0 | 0,027 | 0,691 | 4E-05 | 0,28 | 0,286 | 104,061 | 4 | Non Popular |

Figure 3. Pre-Processed Data for Decision Tree Model

## B. *Decision Tree*

Classification is able to predict and categorize objects into the classes [9]. Decision tree is a method in classification that is easy to understand from its systematic structure and is able to be used both for categoric and continuous variables. Basic concept of decision tree is using visual approach to identify the attributes from data in form of a tree. Those attributes are depicted in hierarchical structure consisted of three parts; root node as a beginning node of a tree, internal node as a result of branching that also produces branch, and leaf as a last node [10].

In this paper, classification and regression tree (CART) was used to determine characteristics of popular local songs. CART is a machine learning algorithm that is constructed by splitting two nodes. CART is able to characterize outcomes from many variables, use the same variables more than once in different parts of a tree to uncover interdependencies between variables, form simpler and optimal size of tree as it split based on two nodes, and handle with outliers easier [11], which are suitable for this study.

CART has basic concept of possible splitting, as if $X$ is a categorical variable of $K$ categories, there will be $2^{K-1}$-1 possible splits. In the other side, if $X$ is a continuous variable with different $V$ value, there will be $V$-1 different splits on $X$. There are measures used to select the best split [12]. The most commonly used measures are entropy, gini, and classification error as represent in (1),(2), and (3). Dataset used is denoted as $T$ that consists of $n$ samples marked based on different class attributes $k_i$. [10].

$$Entropy\,(T) = -\sum_{i=1}^{K} p_i \log_2 p_i \tag{1}$$

$$Gini\,(T) = 1 - \sum_{i=1}^{K} (p_i)^2 \tag{2}$$

$$Classification\ error\,(T) = 1 - \max(p_i) \tag{3}$$

TABLE I. CONFUSION MATRIX

| | | Predicted as | |
|---|---|---|---|
| | | A | B |
| Class Data | A | *True positive* | *False Negative* |
| | B | *False positive* | *True Negative* |

$$Accuracy = \frac{True\ positive + True\ Negative}{All\ data} \tag{4}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ positive} \tag{5}$$

$$Recall = \frac{True\ positive}{True\ positive + False\ Negative} \tag{6}$$

Training data are used to conduct the CART decision tree model. To evaluate that model, test data are used to predict the label of songs and match the prediction result to the actual label of songs in test data. This evaluation is able to give the accuracy of the model which is represented in a table called confusion matrix shown in Table I. The confusion matrix is able to represent the model performance by calculating the accuracy, precision, and recall which are shown in (4),(5),(6).

In this paper, the dataset was divided into training data and test data. There were 163 songs used for training data and 70 songs were used for test data. Training data were used to conduct the decision tree model and test data were used to evaluate the accuracy of the model based on model obtained. The variables used were audio features extracted from Spotify API.

# III. RESULT AND ANALYSIS

In this section, the result of decision tree model and evaluation in determining characteristics of popular local songs in Indonesia is explained.

The CART decision tree was obtained using Rstudio as shown in Fig. 4. Based the decision tree CART model result, variables used most were acousticness, liveness, energy, valence, and key. The root node for the decision tree was acousticness followed by other internal nodes such as liveness, energy, valence, and key. From the result, it is shown that characteristics determining the popularity of local songs in Indonesia are dominated by those five attributes.

The CART decision tree model depicts on what characteristics of each attribute determining the popularity of songs. For attribute acousticness, value of >= 0.82 with liveness <0.12 are considered as popular songs, while acousticness of >= 0.82 with liveness >= 0.12 are considered as non-popular songs. In other words, songs played with acoustic instrument such as guitar and piano rather than other instruments e.g. electronic instruments are considered as popular songs. Thus, acoustic local songs are demanded in Indonesia.

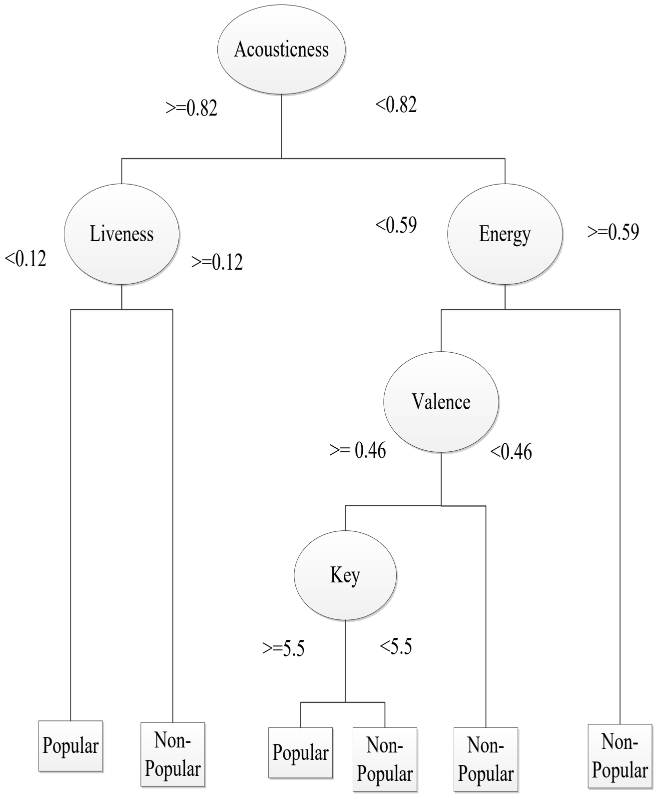


Figure 4. Decision Tree using CART Result

Attribute acousticness with value <0.82 also gives another characteristic on determining the popularity of songs. This characteristic is followed by three other attributes. Energy with value <0.59 followed by valence >= 0.46 and key >= 5.5 are considered as popular songs. Meanwhile, energy with value >= 0.59 followed by valence <0.46 and key <5.5 are considered as non-popular songs. From this finding, songs which have medium energy, happiness and euphoria theme, and are played in relatively high key are likely considered as popular songs in Indonesia. This finding is supported by the fact that most popular local songs in Indonesia are dominated by slow pop songs and are not dominated by high energy songs like rock or metal songs. Songs with moderate level of happiness theme and low aspect of sorrow and sadness also are considered as popular songs.

The CART decision tree has been successfully represented the attribute characteristics of popular songs and non-popular songs resulted of five dominated attributes. Those attributes are able to determine the characteristics of popular song. However, there are attributes considered as insignificant attributes determining the characteristics of popular songs.

Evaluating the CART decision tree model was conducted in this study. The model has successfully obtained the accuracy of 72.8%. This accuracy is supported by weighted average precision of 73.4% and weighted average recall of 72.8%. From the evaluation, the model has relatively good result as represented by the accuracy.

## IV. Conclusions

As the music industry in Indonesia has potential to be developed, the new marketing strategy should be conducted. One of the strategy is knowing the hidden potential condition in the market by conducting research on what characteristics of popular local songs that distinguish them from others. Machine learning especially decision tree is able to represent the characteristics with more understandable attributes provided by Spotify. However, study in determining characteristics of popular songs using these more understandable audio features has not been conducted. The purpose of this study is to determine the characteristics of popular local songs in Indonesia for recommendation to music industry in producing songs. The CART decision tree has been conducted to 233 local songs in the Daily TOP 200 Spotify from January 2017- March 2018. There were 163 songs used as training data and 70 songs were used as test data. The attributes used in this study were audio features obtained from Spotify API. There were 11 attributes used in this study. From the CART decision tree result, five dominated attributes represented the characteristics such as acousticness, livenees, energy, valence, and key. Songs played with acoustic instruments are likely to be the characteristic of popular songs. Songs with medium energy, moderate valence, and high base key played on them are also considered as popular songs. The evaluation of the model resulted in an accuracy of 72.8%. It can be concluded that the model has obtained relatively good result.

The accuracy may be increased by adding more training data and other attributes influencing the popularity of songs for further research. Using another algorithm that is able to represent the characteristics of popular songs is also suggested.

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