# IDENTIFICATION OF FEATURES IN PREDICTING PROMINENT MALAY WORDS USING DECISION TREE

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***ABSTRACT***

*Predicting word prominence is a major topic in the field of speech synthesis where predicting prominent words is necessary to produce a natural-sounding speech synthesis. In our previous work, marking prominent words in a speech corpus is required to select the most suitable unit for speech synthesis; however, given that marking is performed manually, building a large speech corpus will be expensive in terms of labor and time-consuming. Thus, predicting prominent words automatically for which features represent an important aspect is required. This study presents an experimental work on identifying features (including part-of-speech (POS) sequence, phrasal break, and word position) in predicting prominent Malay words using decision tree and WEKA feature selection correlation method. Results show that using the decision tree for predicting prominent words (Precision = 85.0%, Recall = 84.2%, and F-measure = 83.5%) is optimal when the phrasal break is omitted as a feature. In addition, the results (Precision = 66.40%, Recall = 67.2%, and F-measure = 66.60%) are poorest when the POS sequence is excluded from the features. Therefore, this study concludes that phrasal break is a weak (noisy) feature, whereas POS sequence is an important feature in predicting prominent Malay words.*

**Keywords:** ***Malay prosody, Prominent words, Prominent Features, Decision Tree***

## 1.0 INTRODUCTION

Prosody is a term for speech properties, such as pitch, loudness, and syllable length [9][6][13]; it is sometimes attributed to properties, such as tempo (speech rate) and rhythm [7][9]. Prosody is considered synonymous to suprasegmental [7] because prosodic events appear to be syllable-timed [7]. At the acoustic level, pitch, loudness, and length correlate with fundamental frequency (F0), intensity (amplitude and energy), and duration, respectively [9]. In language processing, prosody is used to cue a speaker's mood, disambiguate meaning, and mark semantic focus. In the present study, prosody functions are regarded as similar to Dutoit's [9] definition of using prosody, i.e., (1) to utter a sentence in short phrases and (2) to cue the message of an utterance by contrasting word stresses or emphasizing relevant words. The utterance of a sentence into short segments (i.e., phrases) involves pausing or lengthening the final syllables [9] or phrasal break insertion. A property similar to prominence will be considered for cueing utterance. Prominence property in speech utterance can be observed either in a syllable or in words [18]. The specific definition of prominence is still debated [18]; however, considering that this study focuses on prominent words in speech utterance, prominence indicates that a word when perceived can be obviously distinguished from the other words in a sentence. A speaker can create prominent words in a sentence by stressing the words with high pitch and loudness and extended duration [19], i.e., with a combination of all or either one or two of those prosodic features.

Previous studies on prominent words are largely motivated by the demand in the speech synthesis research field [20][21]. In this field, predicting prominent words automatically is necessary to produce a natural-sounding speech synthesis, and an important aspect of predicting prominent words is the features. Numerous features have been suggested for predicting word prominence. However, most studies have focused on the English language. In [22], the textual features considered include the syllables, part-of-speech (POS) tag of word, function and content word class, consonant/vowel (CV) types, and position at the beginning, middle, and end phrases, plus the consideration of being a negation word or not. Several works have only highlighted certain features; in [20], the authors only used the features of open and close categories of words, the position of words in a clause, and the preceding/following words; in [18], content words were confirmed to have differences in prominence scores (content words have high prominence scores). In their work of speech synthesis, the authors in [21] considered the features of word prominence at a syllable unit. The selected features include the CV types and POS of syllables. As discussed previously, the works on speech synthesis, especially those concerning the resources (e.g., corpus, dictionary, or rules), are language-dependent; thus, despite numerous works on predicting prominence for non-Malay languages, these works can only be used as a rough guide for conducting research on prominent Malay words. Works on predicting prominent Malay words driven by the demand in speech synthesis are few to none, and most related research probably resemble the work of [3], which focuses on predicting prominent syllables in Malay using features such as the POS, CV types, position of syllables in a sentence, and the word position containing the target syllables. The work in [3] obtained favorable results, but the emphasis was solely on the syllable unit.

Our previous work on Malay speech synthesis [16][15][14] required a speech corpus labeled with the prosodic features of prominent words. In this previous work, the prominent feature was labeled manually, thus consuming considerable time and resources. Thus, as part of continuing these works, we automated the labeling of the prominent feature. The prominent mark is useful not only for our speech synthesis approach but also for other speech synthesis systems or any linguists who are working with the Malay language. This paper is organized into four sections. The Introduction section discusses prosody and the state-of-the-art Malay prosody. Then, in Material and Method section, our speech data and the construction of the decision tree are described to predict the prominent Malay words. Afterward, the results and findings are presented in Result and Discussion section. The conclusions drawn from this study are subsequently provided in the Conclusion section.

## 2.0 MALAY PROSODY

In this section, we discuss Malay prosody and the significance of our work in the field of linguistics and in speech processing for the Malay language.

References on Malay prosody have indicated that certain issues, such as whether Malay is syllable-timed or whether Malay words are stressed, are still very much debated. An interesting study on the rhythmic classification of language in [10] shows that the classification of whether Malay is a syllable- or stressed-timed language is unclear. Don et al. [8] confirmed that Malay is not a syllable-timed language because the timing length of the studied syllables was found to be unequal. These authors also claimed that no word stress exists in the Malay language. Their claims are based on the observation of the duration and F0 patterns of 111 sets of Malay content words. Kassin [11] studied the Malay word stress assignment and found that the Malay language has two types of stresses, i.e., primary and secondary. According to Kassin [11], the primary or main stress is typically at the penultimate syllable, and the initial secondary stress is at the first syllable. For example, in the word */bi.da.da.ri/* "angel," the syllable */da/* receives the primary stress, and the first syllable */bi/* receives the secondary stress [11]. However, this word stress pattern will change if the word is not a root word or the word contains schwa.

Payne [12] described Malay intonation tunes on the basis of the types of sentences and phrase locations (either at the initial, middle, or end of a sentence). The division of a sentence into phrases are marked by pauses called "suspense breaks" [12]. According to Payne [12], the "suspense break" or phrasal break can be in terms of silence or vowel or consonant lengthening. Payne [12] further emphasized that the intonation tune in Malay marks syntactic constituents, i.e., the rising and declining intonations in Malay signify the boundary of subject and predicate. The same argument was presented by Abdul-Wahab [1], who stated that intonation correlates with syntactic structure and thus, by listening to one's intonation, the knowledge of a person on Malay syntax can be evaluated. In particular, syntactic structure is strongly related to prosody in Malay. In Malay, a sentence can be uttered with more than one type of intonation tune. The combination of intonation tunes in a sentence depends on the type of sentence. For example, Payne [12] highlighted that a declarative sentence commonly has three types of combined intonation tunes, and all of them end with falling toward a final pause. The interrogative tune has a rising pitch at the end, in which the pitch is higher at the end than at the beginning. Exclamations or imperative tunes have a high pitch at the beginning and a low pitch at the end.

Abdul-Wahab [1] categorized Malay tunes into four levels; "1" is the lowest range, and "4" is the highest. Abdul-Wahab [1] stated that, for a declarative sentence, the intonation commonly follows a 2-4-2-3 pattern; an interrogative sentence can demonstrate either 2-4-3-4, 2-4-2-4, or 2-4-1 pattern; and the intonation pattern for an exclamation sentence is either 2-3 or 2-3-1. These intonation patterns were further investigated by Zahid and Shah Omar [17] using an experimental approach (with visual aid). By replacing the lower pitch with label "L" and the higher pitch with "H", Zahid and Shah Omar [17] determined that all the intonation patterns suggested by Abdul-Wahab [17], except for the declarative intonation of 2-4-2-3, which was perceived as awkward and did not map onto the Malay syntactic structure, are acceptable.

Our limited literature review on Malay stresses and patterns of intonation supported the statement by Don et al. [8] that "Malay is viewed as a simple language yet should not be assumed as an easy language to be studied with."

According to all the debate, Malay prosody is clearly not fully explored, and this situation motivates us to contribute to this field. Moreover, we emphasize the necessity for additional investigations into verifying the existing theories or discovering new theories in Malay prosody. In terms of prominent words, which in this study specifically focused on the Malay language, the perception of the influences of prominent words in Malay is based on the description provided by Terken and Hermes [19], i.e., the distinguished words in an utterance with an additional value to pitch, loudness, and duration.

## 3.0 MATERIAL AND METHOD

Our experiment on predicting Malay prosody using the decision tree classifier, i.e., the J48 algorithm consisted of two phases, namely, *Phase I*-Build Training Data and *Phase II*-Constructing the Decision Tree and performing an evaluation. These phases are described in detail in the following sections.

### 3.1 Material: Dataset and training data

*Audio recording*. The recording script of speech data is a collection of text sentences selected randomly from Malay religious articles. A total of 422 Malay sentences were recorded in a sound-treated room (UTMK Usability and Acoustic Lab) using the following equipment specifications: *Pre-amp microphone Samson C01U-based, Toshiba laptop (model protege),* and *Headset AK model K.66* with recording software *Adobe Audition 2.0*. Two Malay native speakers, i.e., a male and a female, recorded their voices. The selected speakers have clear articulation and previous experiences in recording their voices for other speech corpora. The recording was conducted in four sessions for approximately 100 sentences per session. All the recorded voices were saved in a 44 kHz, mono, and.wav format.

The speech data were manually annotated with prosodic features of prominence and phrasal breaks. An annotator, who is a Malay native speaker, would listen to the recorded sentences and use the symbol "*" to mark words that are perceived as prominent. For break types, only the following two types were considered: phrasal and full boundary breaks. The same annotator would listen for obvious pauses and label the pause manually with a phrasal break and mark it with the symbol "/". The text recording was annotated. Given that two voice sources were present, only the overlapped marks of prominent words "*" and phrasal breaks "/" were considered. The full corpus can be accessed through this http://www.ftsm.ukm.my/sabrina/resources/. Furthermore, a sample of the corpus annotated with prominence and phrasal breaks is presented as follows:

1. `Jadi/ *sistem bagi apa-apa *pun bentuk yang diamalkan oleh dunia *barat/ tidak *akan/, dengan sendirinya sahaja,/ menjamin yang pihak berkuasa tidak akan zalim.`
2. `Oleh itu/ *hendaklah dikaji sesuatu sistem itu dari dua *segi/ iaitu segi kandungan/ dan segi bentuk/ bagi memastikan/ *apakah ia sebenarnya/ boleh membawa kepada tercapainya tujuan ataupun tidak.`
3. `Maka,/ mana-mana pun jua perlembangan *sekalipun/ rakyat *boleh mengubahnya.`
4. `*Perubahan itu/ *tidaklah semestnya hanya melalui pemberontakan dan rampasan kuasa/ *tetap tidak juga secara demokrasi.`

*Phase I-Training data*. To prepare the training data for Phase II, the text file mentioned above is converted into a plain text file and inputted into a Malay POS tagger. The tagging process will tag every word in the text file as (i) open words, which contain nouns, verbs, adjectives, and adverbs (see

Table 1**), and (ii) closed words that contain determiners, pronouns, adverbs, conjunctions, and prepositions (see**

**Table 2**).

Table 1: List of POS in Open Class Word

| POS | POS symbol | Example |
|---|---|---|
| Noun | N | Pokok (*tree*), kotak (*box*), meja (*table*) |
| Verb | V | Menjamin (*gurantee*), mempastikan (*making sure*), membawa (*carry*) |
| Adjective | A | Tinggi (*tall*), indah (*beautiful*), besar (*big*) |

| | | |
|---|---|---|
| Adverb | ADV | Pun (*even though)*, sebenarnya (*actually*), sahaja (*only*) |

Table 2: List of POS in Closed Class Word

| **POS** | **POS symbol** | **Example** |
|---|---|---|
| Preposition | PREP | Pada (*on*), oleh (*by*), dengan (*with*) |
| Determiner | DET | Pihak (*on behalf*), itu (*that*), kepada (*to*) |
| Pronoun | PRON | Ia (*it*), apakah (*what*), sesuatu (*it*) |
| Numeral | NUM | Dua (*two*), ketiga (*third*), lapan (*eight*) |
| Auxiliaries | AU_V | Boleh (*be*), hendaklah (*have*) |
| Conjunction | CC | Tetapi (*but*), dan (*and*), atau (*or*) |

Considering that we used the J48 algorithm on the basis of a WEKA environment, we should prepare a WEKA-readable file. The speech data were in a specified format, i.e., *Attribute-Relation File Format* (ARFF). The descriptions of our ARFF header files are summarized in **Table 3**, which indicates that the *types of POS*, *position of POS*, and existence of *phrasal break* were used as the attributes of our decision tree.

Table 3: ARFF Header File Features

| **Title** | **Name** | **Value** | **Remark** |
|---|---|---|---|
| **Relation** | Dataset | ---- | File name |
| | Position | 0.00 to 1 | The position of a word in a sentence divided by the total number of words |
| | BPOS | NA,V,N,PREP,DET,ADV,OTHERS, AU_V,PRON,NUM,CC,A | POS before the target word |
| | Wtype | Open, Close | Class type of the target word |
| **Attributes** | POS | V,N,PREP,DET,ADV,OTHERS,AU _V,PRON,NUM,CC,A | POS of the target word |
| | APOS | N,PREP,DET,ADV,OTHERS,V,AU _V,NA,PRON,NUM,CC,A | POS after the target word |
| | Prominent | No, Yes | Is the word prominent or not |
| | PBreak | False, True | Is a phrasal break present or not |

Fig. 1 Illustrates an example of the data for the ARFF file attributes, and such data were used in the training process. In each of the lines in the file, all the data for the attributes are separated with a comma.

```
@relation DataSet

@attribute Position numeric
@attribute BPOS {NA,V,N,PREP,DET,ADV,OTHERS,AU_V,PRON,NUM,CC,A}
@attribute Wtype {Open,Close}
@attribute POS {V,N,PREP,DET,ADV,OTHERS,AU_V,PRON,NUM,CC,A}
@attribute APOS {N,PREP,DET,ADV,OTHERS,V,AU_V,NA,PRON,NUM,CC,A}
@attribute Prominence {No,Yes}
@attribute Pbreak {TRUE,FALSE}

@data
0.04,NA,Open,V,N,No,TRUE
0.09,V,Open,N,PREP,Yes,TRUE
0.13,N,Close,PREP,DET,No,FALSE
0.17,PREP,Close,DET,ADV,Yes,TRUE
0.22,DET,Open,ADV,N,Yes,TRUE
0.26,ADV,Open,N,OTHERS,No,FALSE
0.3,N,Close,OTHERS,OTHERS,No,FALSE
0.35,OTHERS,Close,OTHERS,PREP,No,FALSE
0.39,OTHERS,Close,PREP,N,No,FALSE
0.43,PREP,Open,N,ADV,Yes,TRUE
0.48,N,Open,ADV,OTHERS,Yes,TRUE
0.52,ADV,Close,OTHERS,OTHERS,No,TRUE
0.57,OTHERS,Close,OTHERS,PREP,No,TRUE
0.61,OTHERS,Close,PREP,OTHERS,No,TRUE
0.65,PREP,Close,OTHERS,N,No,TRUE
0.7,OTHERS,Open,N,V,Yes,TRUE
0.74,N,Open,V,OTHERS,No,FALSE
0.78,V,Close,OTHERS,DET,No,FALSE
0.83,OTHERS,Close,DET,N,Yes,FALSE
```

Fig. 1: Sample of an ARFF File for the Prominent Word Decision Tree

These datasets, as depicted in Fig. 1, were inputted into a WEKA program as the training data. We selected a WEKA–decision tree classifier, namely, J48, in our experiment.

### 3.2 Decision tree: Prominent Malay word

*Phase II-Tree Construction*. In the present study, a decision tree was used to observe the classification of words into prominent and non-prominent. A decision tree was selected because it is simple and easy to use over other machine learning methods because it requires a relatively minimal effort from users to prepare data, plus missing or outlier data will not prevent the building of a decision tree [5][22]. In addition, by using a decision tree, we could visually observe the prediction in accordance with the tree that is built on the selected features. A decision tree is a classification tree which has leaf nodes that show the value of target features or example target classes or has nodes as results. These leaf nodes will indicate a few tests on the feature value, with a branch or sub-tree for each of the probability results from the test. In summary, decision tree is a tree that contains a root node, leaf nodes that represent any class or case, and internal nodes that represent test conditions [4]. In the present study, we used a WEKA–J48 algorithm, which is a C4.5 algorithm type of decision tree. We utilized a univariate decision tree, which has only one attribute at its internal nodes. The attributes used to construct the decision tree include the POS types, phrasal break-YES/NO, and word position information. These attributes are the features we examined in relation to their effect on predicting prominent Malay words.

In this phase, the decision tree J48 in WEKA was constructed to predict prominent words in the training data discussed in Section 3.1. In accordance with the training data demonstrated in **Fig. 1**, a decision tree for predicting prominent words was constructed. At the evaluation stage, we ran a testing process through a 10-fold cross-validation test mode. The findings are discussed in the succeeding section.

## 4.0 RESULTS AND DISCUSSION

We evaluated the effectiveness of the WEKA–J48 algorithm in predicting prominent Malay words from a given Malay text in accordance with the following measures: Precision, Recall, and F-Measure. For the evaluation, we selected a 10-fold cross-validation test mode. In WEKA, the calculations of Precision (Eq. 1), Recall (Eq. 2), and F-Measure (Eq. 3) were based on true positive (TF), true negative (TN), false positive (FP), and false negative (FN). These calculations are performed as follows:

$$\text{Precision} = TP / (TP+FP) \quad (1)$$

$$\text{Recall} = TP / (TP + FN) \quad (2)$$

$$\text{F-measure} = 2 \times ((\text{precision} \times \text{recall}) / (\text{Precision} + \text{Recall})) \quad (3)$$

Given the constructed decision tree (**Fig. 2**), POS seems to be the most influential attribute (most predictive attribute) because it is located at the highest node, followed by the APOS, BPOS, then the other types of attributes, such as “position” to predict whether the target word is prominent or not.

```
POS = V
|   APOS = N: No (8.0)
|   APOS = PREP
|   |   Position <= 0.5: No (2.0)
|   |   Position > 0.5: Yes (2.0)
|   APOS = DET: No (0.0)
|   APOS = ADV: Yes (2.0)
|   APOS = OTHERS: No (6.0)
|   APOS = V: No (0.0)
|   APOS = AU_V: No (0.0)
|   APOS = NA: No (0.0)
|   APOS = PRON: Yes (2.0)
|   APOS = NUM: No (0.0)
|   APOS = CC: No (0.0)
|   APOS = A: No (0.0)
POS = N
|   APOS = N
|   |   Position <= 0.39: Yes (2.0)
|   |   Position > 0.39: No (7.0)
|   APOS = PREP: Yes (8.0)
|   APOS = DET
|   |   BPOS = NA: Yes (2.0)
|   |   BPOS = V: Yes (0.0)
|   |   BPOS = N: Yes (0.0)
|   |   BPOS = PREP: Yes (0.0)
|   |   BPOS = DET: Yes (0.0)
|   |   BPOS = ADV: Yes (0.0)
|   |   BPOS = OTHERS: Yes (0.0)
|   |   BPOS = AU_V: Yes (0.0)
|   |   BPOS = PRON: No (2.0)
|   |   BPOS = NUM: Yes (0.0)
|   |   BPOS = CC: Yes (2.0)
|   |   BPOS = A: Yes (0.0)
|   APOS = ADV: Yes (6.0)
|   APOS = OTHERS
|   |   Pbreak = TRUE
|   |   |   Position <= 0.52: Yes (2.0)
|   |   |   Position > 0.52: No (4.0)
|   |   Pbreak = FALSE: No (6.0/2.0)
|   APOS = V: Yes (2.0)
```

Fig. 2: Partial Tree of the Constructed Decision Tree for Prominent Words

In addition, we used the WEKA feature selection method of “select attribute” and “rank method” on the basis of the correlation approach to rank the most to the least predictive attributes in predicting the prominent word. **Table 4** lists the ranking from the most to the least predictive attribute.

Table 4: Descending Rank of the Most Predictive Attributes through Correlation

| **Value** | ***Attribute*** |
|---|---|
| 0.2962 | Wtype |
| 0.1412 | PBreak |
| 0.1397 | APOS |
| 0.1102 | POS |
| 0.0985 | Position |
| 0.0725 | BPOS |

**Table 4** lists that the least predictive (lowest rank) attribute is “BPOS,” followed by the “Position” attribute. Thus, we conducted further analysis by omitting the weak influential attributes and observing the performance of the DT classifier. In the literature review on Malay prosody, most linguists agreed that syntax influences Malay prosody; therefore, we also ran a test by omitting the POS types (BPOS, POS, and APOS) to observe the impact and the absence of POS sequence in predicting prominent words. The obtained results are summarized in Table 5.

Table 5: Prominent Word Prediction Attribute Test

| **Attributes omitted** | **Precision (%)** | **Recall (%)** | **F-measure (%)** |
|---|---|---|---|
| None | 0.843 | 0.838 | 0.832 |
| Position | 0.835 | 0.826 | 0.818 |
| BPOS | 0.788 | 0.788 | 0.781 |
| PBreak | 0.850 | 0.842 | 0.835 |
| POS (APOS, POS, BPOS) | 0.664 | 0.672 | 0.666 |

In assessing the performance of the classifier model, omitting the “PBreak” attribute seems to obtain the optimal results with an F-measure of 83.5%, which shows an increase of 0.03% (the benchmark F-measure is set at 83.2%, for which all attributes were included). An obvious decline of the F-measure occurred when BPOS was excluded in the prediction, where the F-measure obtained was only 78.1%. A drastic decline of performance occurred when the POS types of attributes were omitted, with an F-measure of only 66.6%.

In terms of the overall results, with the optimal values of 85% for Precision, 84.2 % for Recall, and 83.5% for F-measure, our classification model has the potential to be improved as a tool for predicting the prominent words because our expectation was approximately 90% or higher. Many angles could be pursued for improving the current model. These angles include (1) exploring additional potential influential attributes, e.g., syllable position or phrase chunk position or (2) increasing the size of the training data because a large size would allow for supervised classification, and an improved result can be obtained. However, the findings demonstrated in **Fig. 2** and **Table 5** show that “PBreak” is a noisy attribute in predicting prominent Malay words and requires further investigation if one insists to include it. Moreover, we could safely claim that the POS sequence is the most influential attribute, and this finding conforms to the agreement among linguists that syntax (POS sequence) influences Malay prosody.

## 5.0 CONCLUSION

In this study, we present an experimental work on investigating features, which include POS sequence, phrasal break, and word position for predicting prominent Malay words using decision tree and WEKA feature selection correlation method. As stated previously, the motivation of this study stems from our previous work, in which prominent words were manually marked. Manual labeling is very time- and resource-consuming (human resources). Thus, we require an automatic predicting tool for prominent words. To build such a tool, we must identify the features that influence prominent words the most. The optimal result obtained by the decision tree for predicting prominent words (Precision = 85.0%, Recall = 84.2%, and F-measure = 83.5%) is when the phrasal break has been omitted from the features. The worst result (Precision = 66.40%, Recall = 67.2%, and F-measure = 66.60%) is when the POS sequence is excluded from the features. Therefore, the phrasal break is a weak (noisy) feature, whereas the POS sequence is the required feature in predicting prominent Malay words. However, with only approximately 83.5% of F-measure, our prominent prediction model needs to be further improved. As a future work, we will investigate other influential attributes, select an improved feature selection approach, and adding data to the dataset on the premise that these features can help boost the prediction performance to 90% or higher.

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