# CPSC 503 - Final project presentation: Inferring history of Austronesian languages using language models 

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## Abstract:

- In this project, we use language models, including edit distances and N -gram methods, to measure the dissimilarity of languages, in order to reconstruct a phylogenetic tree for the history of languages.
- We propose a new dissimilarity measure for the sound of words describing the same content in different languages based on N -grams.
- We show that this dissimilarity measure performs best in identifying the correct history of languages in our data analysis compared with other dissimilarity measures derived from edit distances.
- This work can be applied to larger number of languages to assist human annotators to classify word cognates and languages.


## Method: Edit Distances for two words $A$ and $B$

- Minimum Edit Distance: insertion (1), deletion (1), and replacement (2).

$$
d_{M E D}<I_{A}+I_{B}
$$

- Normalized Minimum Edit Distance:

$$
d_{N M E D}=\frac{d_{M E D}}{I_{A}+I_{B}}, \quad 0 \leq d_{N M E D} \leq 1
$$

- Levenshtein Edit Distance: insertion (1), deletion (1), and replacement (1).

$$
d_{L E D} \leq \max \left\{I_{A}, I_{B}\right\}
$$

- Normalized Levenshtein Edit Distance:

$$
d_{N L E D}=\frac{d_{L E D}}{\max \left\{I_{A}, I_{B}\right\}}, \quad 0 \leq d_{N M E D} \leq 1
$$

## Method: $N$-grams model for two words $A$ and $B$

- grams(A): all $N$-grams of characters in $A$.

For example, $A=a d d$.

$$
\operatorname{grams}(A)=\{\{a\},\{d\},\{a, d\},\{d, d\},\{a, d, d\}\}
$$

- $\operatorname{grams}(\mathrm{A}, \mathrm{B}):$ common $\operatorname{grams}$ of $\operatorname{grams}(A)$ and $\operatorname{grams}(B)$.

$$
\operatorname{grams}(A, B)=\{x \mid x \in \operatorname{grams}(A) \text { and } x \in \operatorname{grams}(B)\}
$$

- $d_{\text {grams }}$ : dissimilarity of $A$ and $B$.

$$
d_{g r a m s}=1-\frac{2 \times \operatorname{grams}(A, B)}{\operatorname{grams}(A)+\operatorname{grams}(B)}
$$

Therefore,

$$
0 \leq d_{\text {grams }} \leq 1
$$

## Dissimilarity Matrix for Languages

- The dissimilarity of two languages $L_{1}$ and $L_{2}$ is defined as the average of dissimilarities of $N$ words, i.e.,

$$
d_{L}\left(L_{1}, L_{2}\right)=\frac{\sum_{i=1}^{N} d\left(W_{i, 1}, W_{i, 2}\right)}{N}
$$

- The dissimilarity of $M$ languages $L_{1}, L_{2}, \ldots, L_{M}$ forms a dissimilarity matrix $\mathbf{D}$, which is $M \times M$, and the $(i, j)$ element of $\mathbf{D}$ is

$$
d_{i j}=d_{L}\left(L_{i}, L_{j}\right)
$$

The diagonal elements of $\mathbf{D}$ are set to 0 .

## Constructing a Tree Using D

- Neighbour-Joining algorithm.
- Input: dissimilarity matrix D.
- Output: an unrooted bifurcating tree $T$.
- Guaranteed to return the "correct tree" under some conditions.


## Data: Summary

- 14 languages are chosen.
- 87 items are annotated for all 14 languages.
- Some items are annotated with more than one sounds.
- Choose the last one if more than one annotations exist.

Table: Three different annotations for the item "to walk" in Fagani language.

| ID | Item | annotation | notes | cognacy |
| :---: | :---: | :---: | :---: | :---: |
| 137031 | to walk | pwapwahe | walk | 81 |
| 137032 | to walk | sio | go down | 38 |
| 137034 | to walk | akau | go up | 1 |

## Data: Relations of the 14 Languages.

Table: Classification of 14 languages chosen.

| Language | Classification |
| :--- | :--- |
| Rukai Tona | A:F:Rukai |
| Rukai Budai | A:F:Rukai |
| Ivasay | A:M:P:B:Ivatan |
| Isamorong | A:M:P:B:Ivatan |
| Babuyan | $\mathrm{A}: \mathrm{M}: \mathrm{P}: \mathrm{B}: I v a t a n$ |
| Muna | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{S}: \mathrm{M}: \mathrm{N}: \mathrm{M}: \mathrm{M}:$ Western |
| Wuna | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{S}: \mathrm{M}: \mathrm{N}: \mathrm{M}: \mathrm{M}: W$ Western |
| Bonerate | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{S}: \mathrm{M}:$ Tukangbesi-Bonerate |
| Popalia | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{S}: \mathrm{M}: T u k a n g b e s i-B o n e r a t e$ |
| Mouk | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{O}: \mathrm{W}: \mathrm{N}: \mathrm{N}: \mathrm{V}: \mathrm{S}:$ Bibling |
| Aria | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{O}: \mathrm{W}: \mathrm{N}: \mathrm{N}: \mathrm{V}: \mathrm{S}:$ Bibling |
| Megiar | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{O}: \mathrm{W}: \mathrm{N}: \mathrm{N}: \mathrm{V}: \mathrm{B}: \mathrm{N}:$ Northern |
| Matukar | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{O}: \mathrm{W}: \mathrm{N}: \mathrm{N}: \mathrm{V}: \mathrm{B}: \mathrm{N}:$ Northern |
| Fagani | $\mathrm{A}: \mathrm{M}: \mathrm{C}: \mathrm{E}: \mathrm{O}: \mathrm{C}: \mathrm{S}: \mathrm{M}:$ San Cristobal |

## Results:


4.Estimated tree using LED

2.Estimated tree using MED

5.Estimated tree using NLED

3.Estimated tree using NMED

6.Estimated tree using grams


Figure: The annotated tree and estimated trees using different language models.

## Conclusions and Limitations

Conclusions:

- Edit distances can be used to infer history of languages, although not very accurate at some details.
- Our proposed $N$-grams model performs best in this analysis (but it may be too early to claim this is true in general).
Limitations and Future Work:
- Create a larger experiment to check the accuracy of the results automatically.
- Repeat the analysis on other languages
- Repeat the analysis with more languages.


## Thank you!

