Segmentation strategies for inflection class inference

Sacha Beniamine (LLF), Benoît Sagot (Alpage)
Université Paris Diderot

Décembrettes 9, Toulouse, 2015

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  - The definition of IC is crucial for many linguistic and psycholinguistic studies, yet they are often taken for granted.
- **No consensus** on how to obtain the classification
- **We explore the concept through computational means**: Brown and Evans, 2012; Lee and Goldsmith, 2013; Bonami, 2014
  - Formal definitions of the concept
  - Large datasets
  - Reproducible classifications
  - Commensurable across languages
  - Basis for theoretical and typological comparisons

Groups of lexemes that inflect alike.

	INF	PRES.3.SG	PRES.3.PL	PP
TENIR ‘hold’	təniʁ	tjɛ̃	tjɛn	təny
FINIR ‘finish’	finiʁ	fini	finis	fini
HAÏR ‘hate’	aiʁ	ɛ	ais	ai
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What is needed to infer IC from paradigmatic data*.

1. What form should an IC system take?
2. What Inflectional Realisations should we infer from the data?
3. How do we measure which lexemes inflect alike?
4. How do we find the best classes among all possible ones?

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- **Micro-classes**
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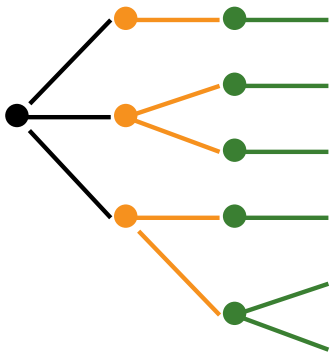
- Combined in a hierarchy. (Corbett and Fraser, 1993; Dressler and Thornton, 1996; Brown and Evans, 2012)



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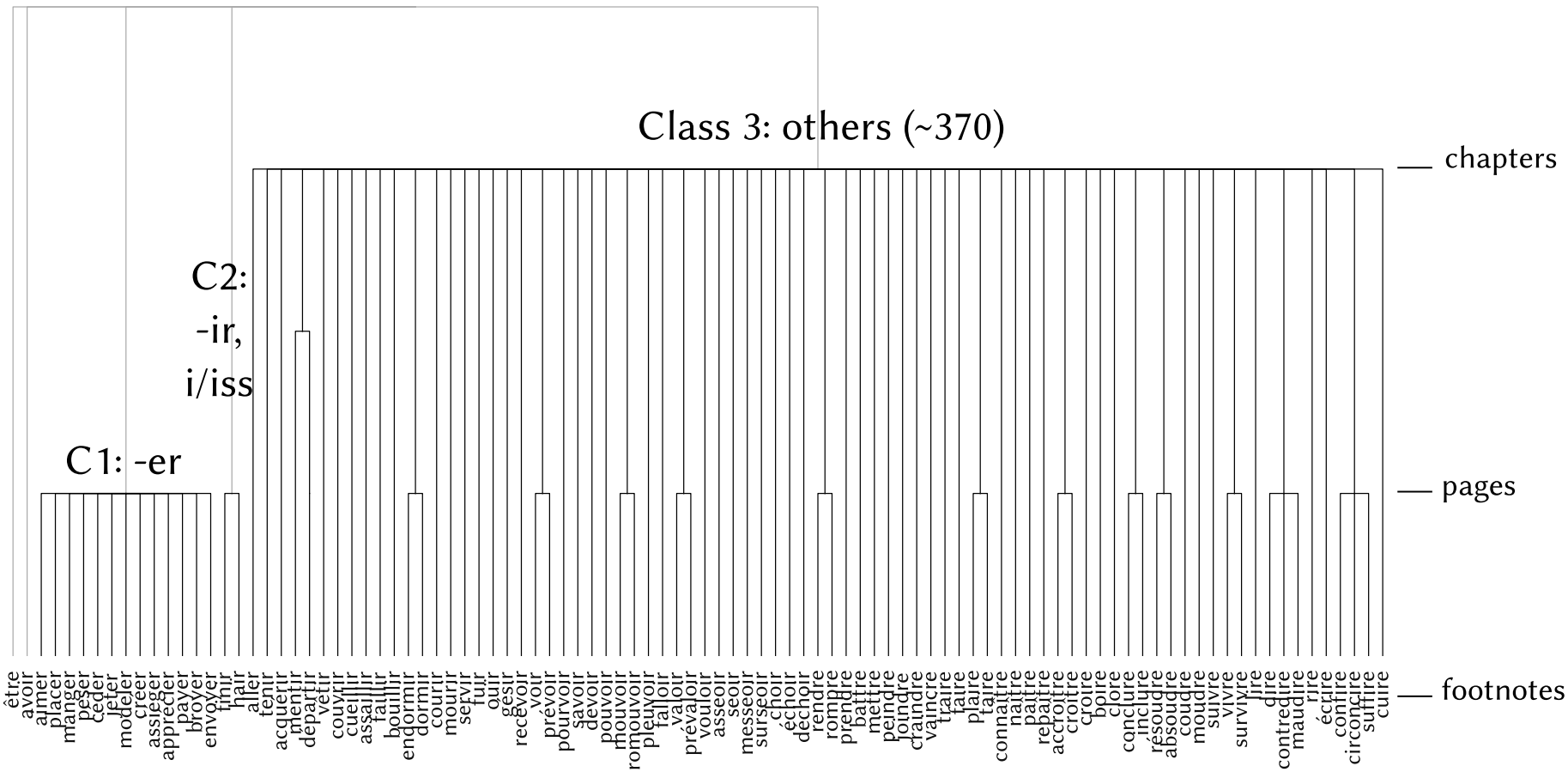
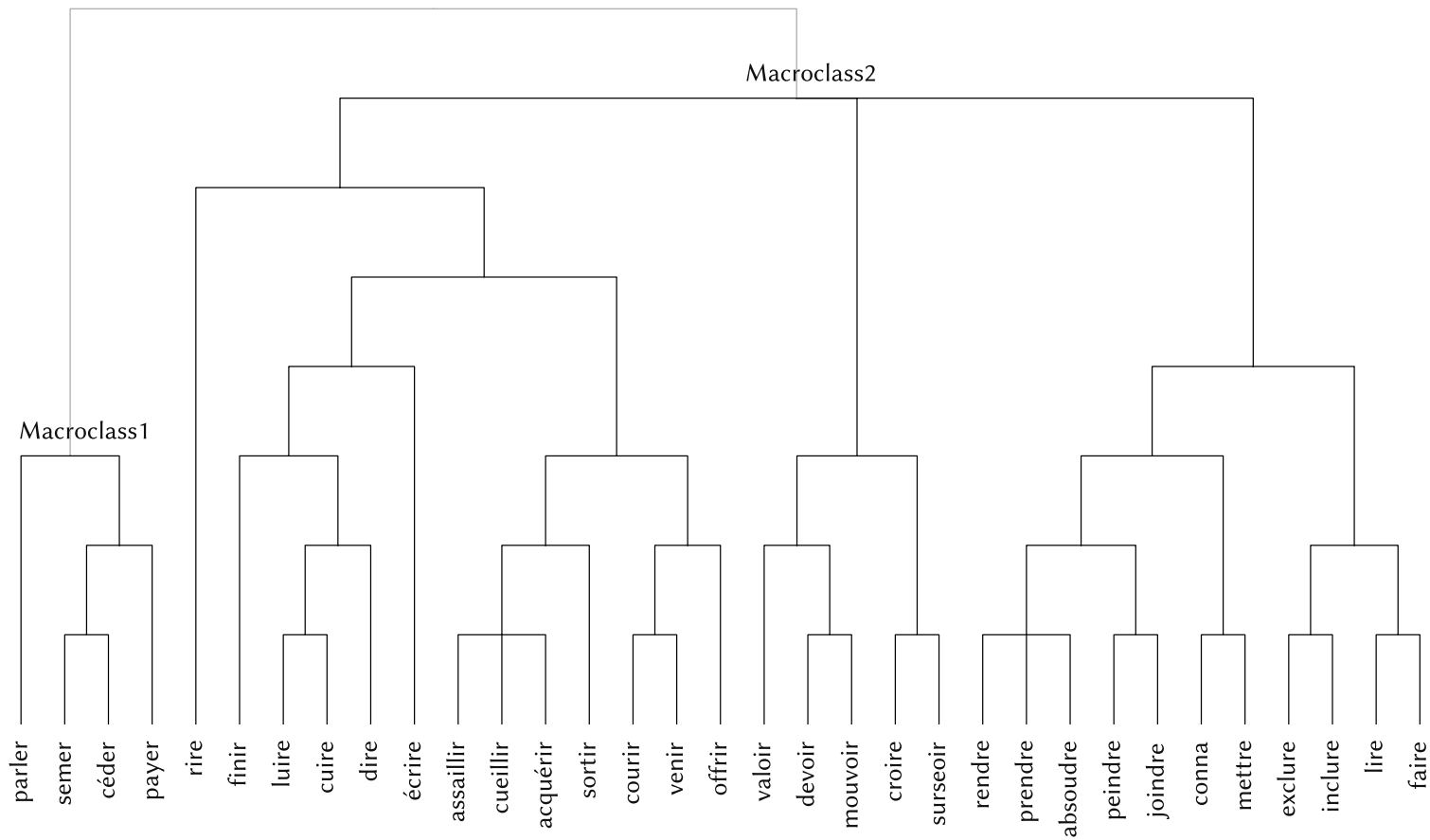
The example of french verbal inflection

- School grammar (Bescherelle) :



The example of french verbal inflection

- School grammar (Bescherelle)
- Kilani-Schoch and Dressler, 2005: different microclasses, some dropped, two macroclasses (dual route).



Inflection classes: Macro and microclasses?

- **Micro-classes**
  - Homogenous: *Numerous small, similar classes.*
  - Inventories vary across accounts.
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Are macroclasses a descriptive artefact?

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- **Binary alternation patterns**
  - *Captures the* ***implicative relation*** *between each pair of cells.*
  - *cf. (Blevins, 2006)'s notion of abstractive approach.*
- Both rely on a **segmentation** of forms.
  - global segmentation over the whole paradigm.
  - local segmentation over pairs of forms.

- **Global**: On the basis of a whole paradigm.
- **Local**: On each pair of cells.

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LAVER ‘wash’	Xe	X	X	Xe
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FINIR ‘finish’	Xʁ ⇌ X	Yʁ ⇌ Ys	Zʁ ⇌ Z	
HAÏR ‘hate’	aiʁ ⇌ ɛ	Yʁ ⇌ Ys	Zʁ ⇌ Z	…
PELER ‘peel’	X_1əX_2e ⇌ X_1ɛX_2	Y_1əY_2e ⇌ Y_1ɛY_2	Z ⇌ Z	
LAVER ‘wash’	Xe ⇌ X	Ye ⇌ Y	Z ⇌ Z	
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- In general, grouping elements into classes is a clustering problem.
- There are many well-known solutions in computer science to address such problems.
- All of them require two things:
  - A criterion to evaluate the quality of clusters (classes).
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    $\rightarrow$ *Minimum description length*
  - An algorithm to explore the search space of all possible groupings.
    $\rightarrow$ *Greedy bottom-up algorithm*

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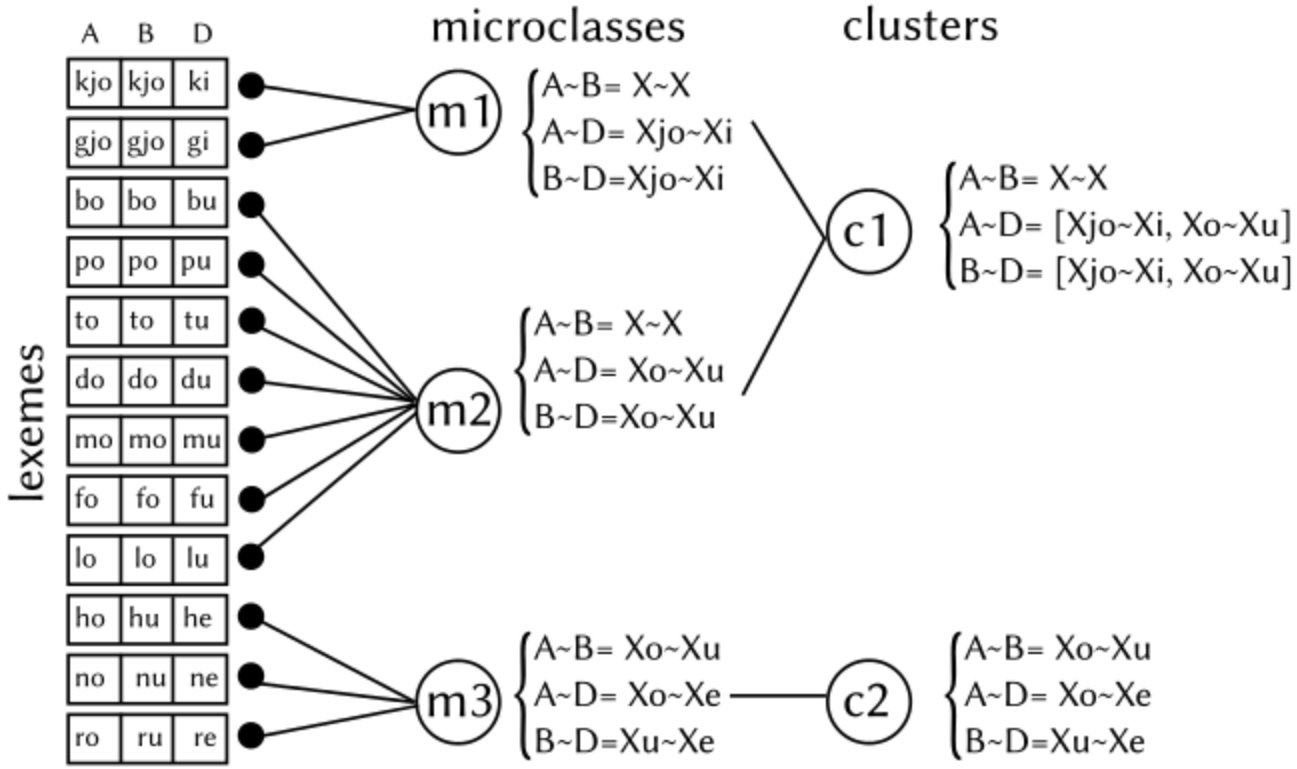
- **Minimum description length** (Rissanen, 1984): Choose the model allowing for the shortest description of the data.
- A partition of the set of lexemes is better than another one if it leads to a more economical description of the system. (Sagot and Walther, 2011; Walther, 2013)

$$DL(system) =$$

$$number\ of\ symbols \times \underbrace{- \sum_{x \in symbols} P(x) \times log_2\left(P(x)\right)}_{\text{entropy}}$$

Description length of a partition of the set of lexemes

- We break down the description length into four components:



Toy imaginary dataset with three cells A, B and D.

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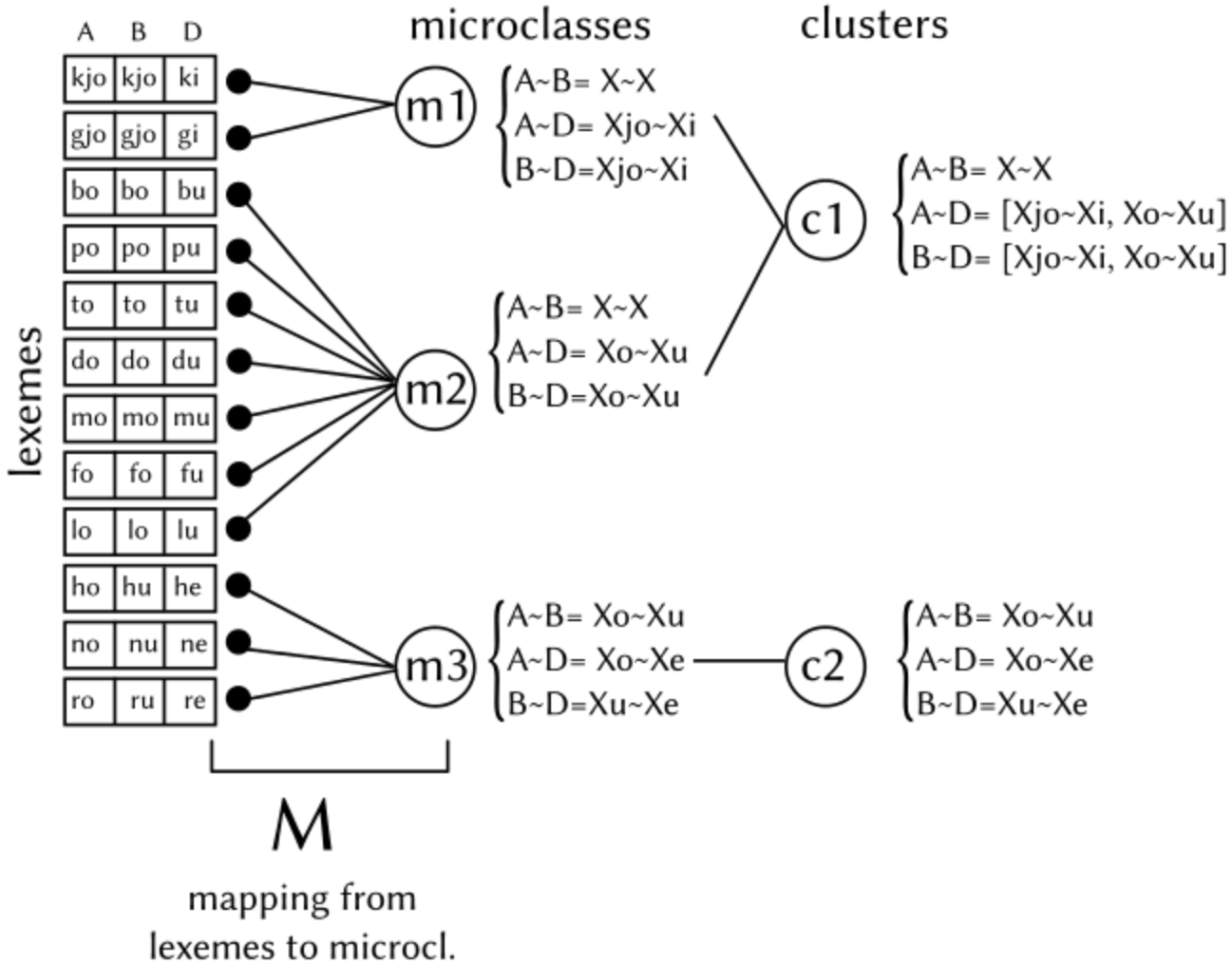

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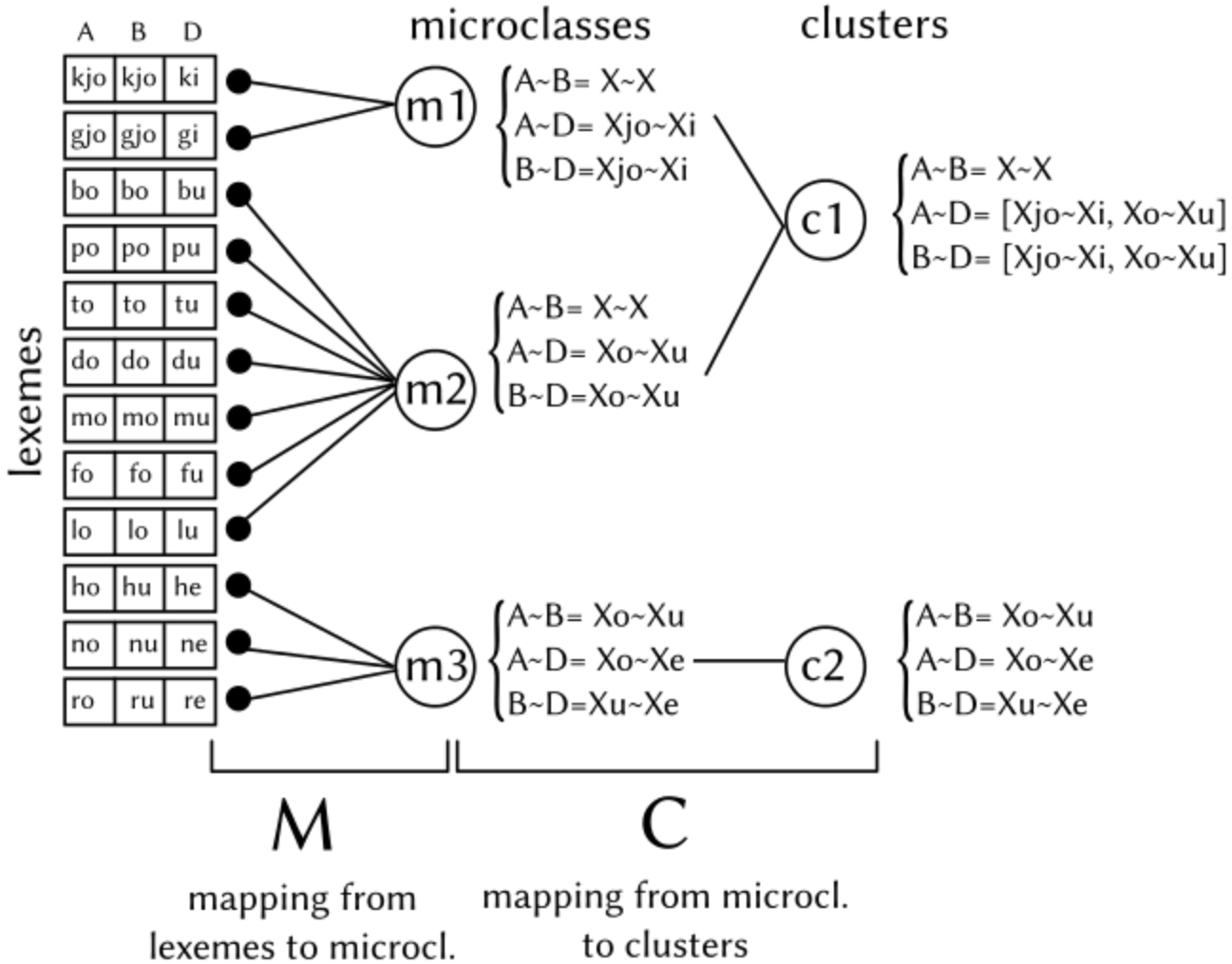

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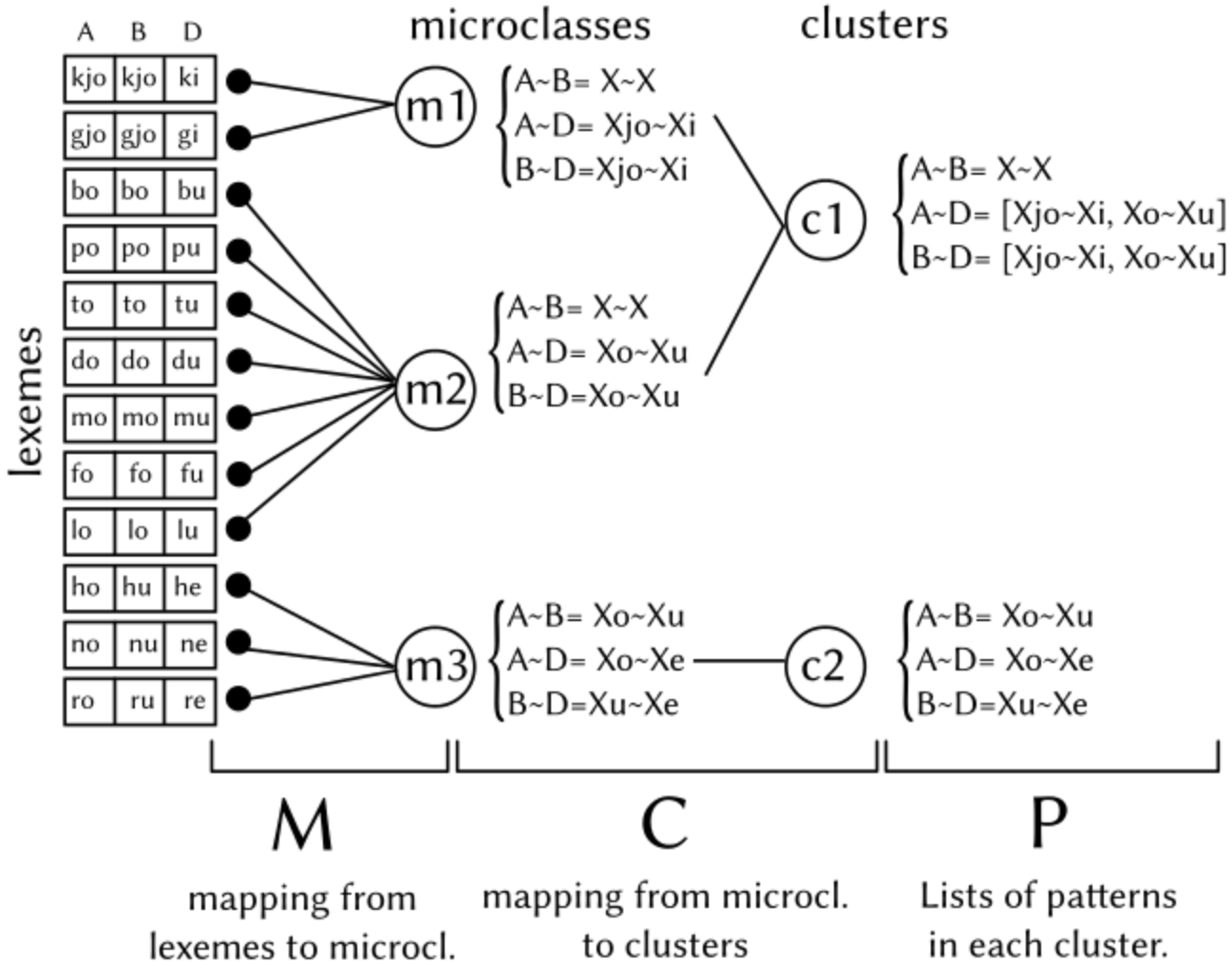

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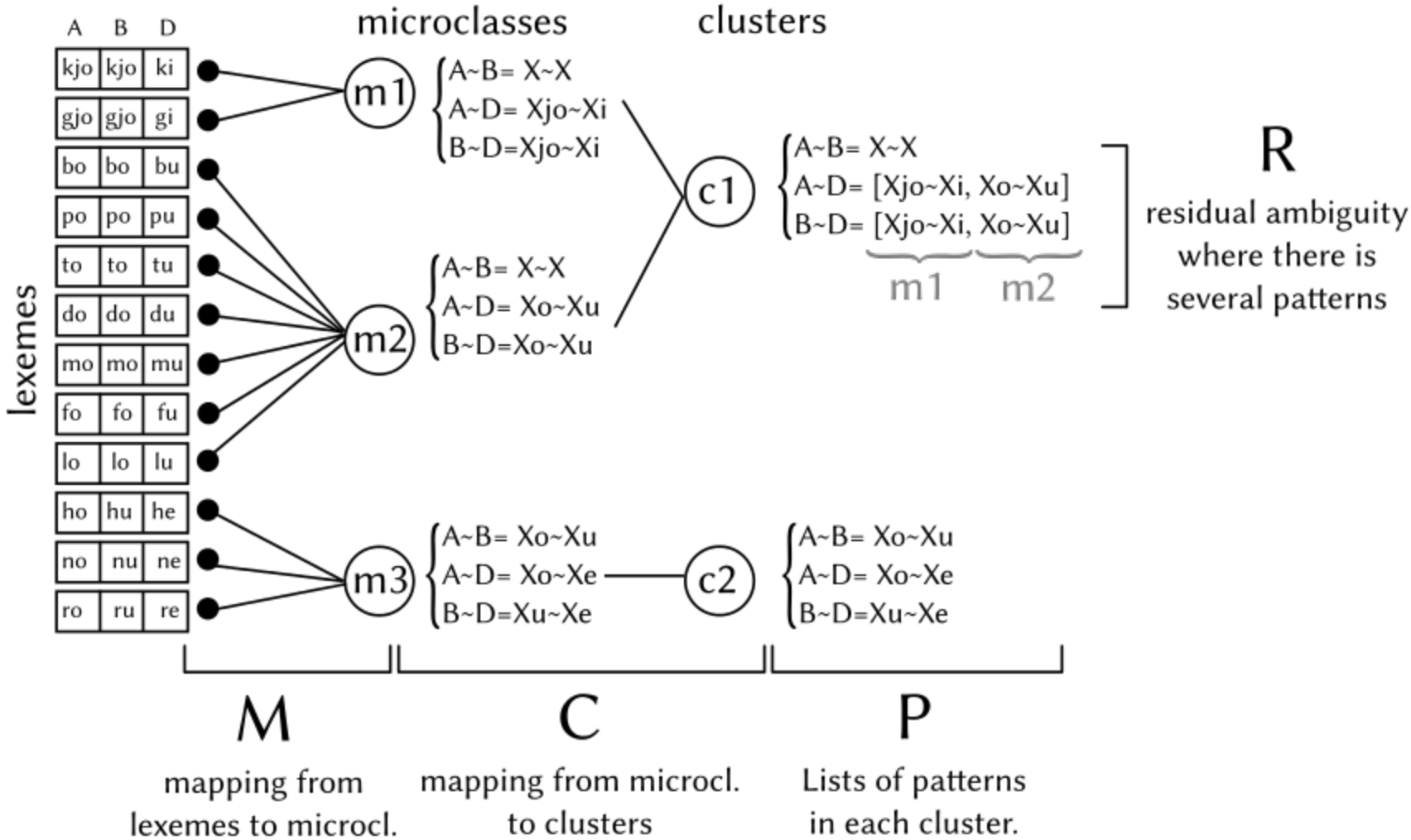

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Description length of a partition of the set of lexemes

- We break down the description length into four components:

$$DL = M + C + P + R$$

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Clustering algorithm, ex. on European Portuguese conjugation.

(a) Begin with a partition into microclasses.

passar	pagar	chegar	achar	abandonar	voar	desempenhar	nomear	levar	jogar	ficar	ganhar
(155)	(1)	(20)	(3)	(12)	(17)	(4)	(53)	(162)	(177)	(911)	(1)

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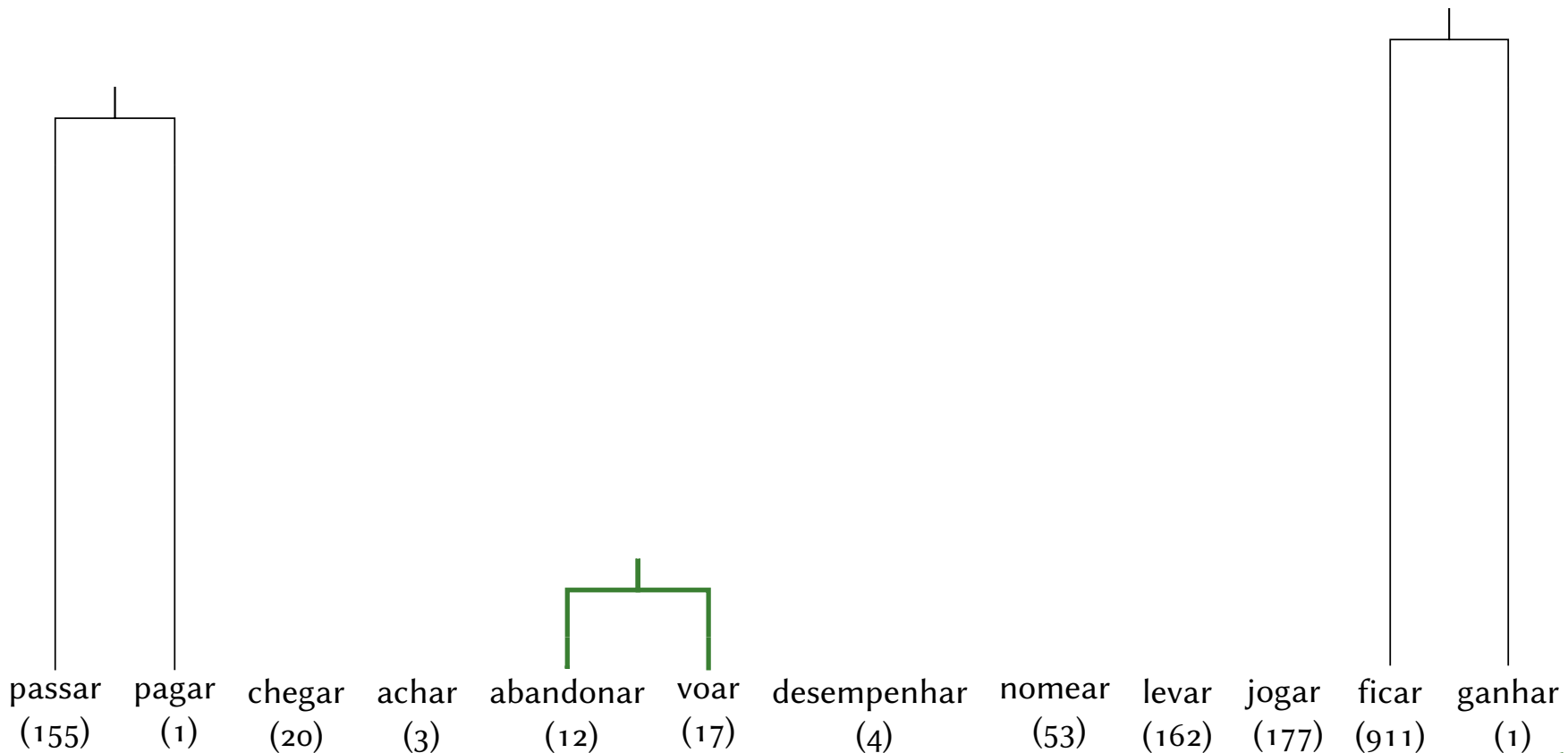

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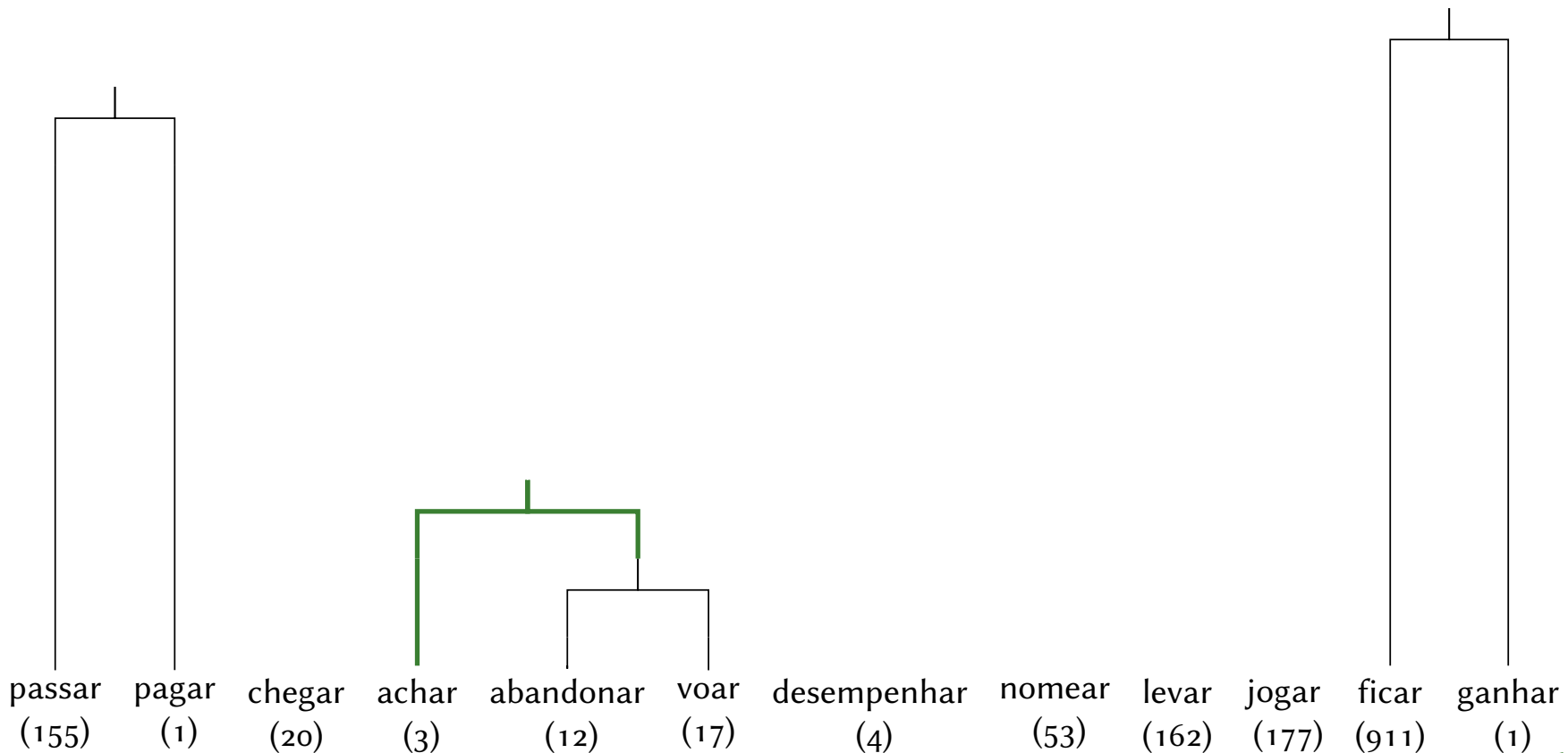

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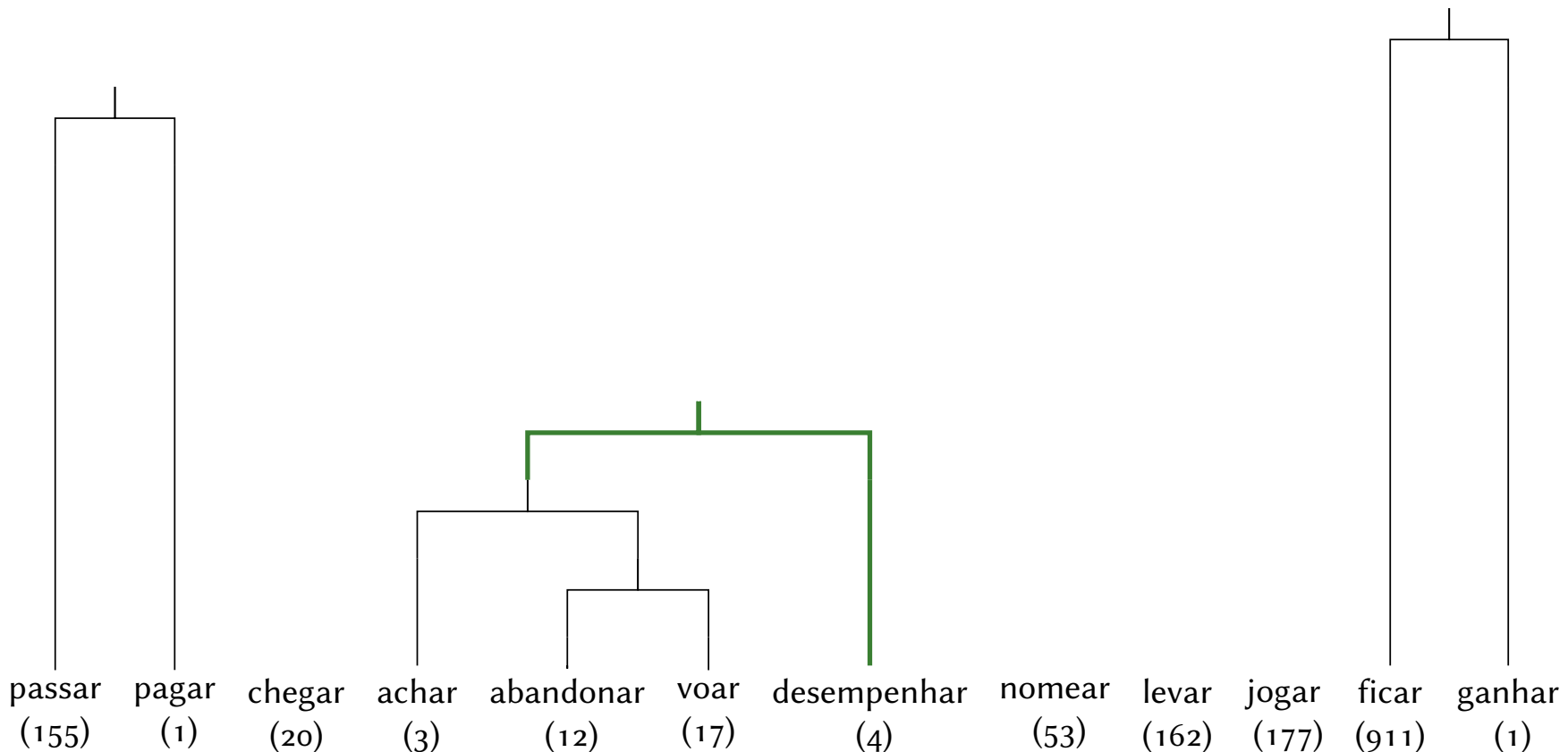

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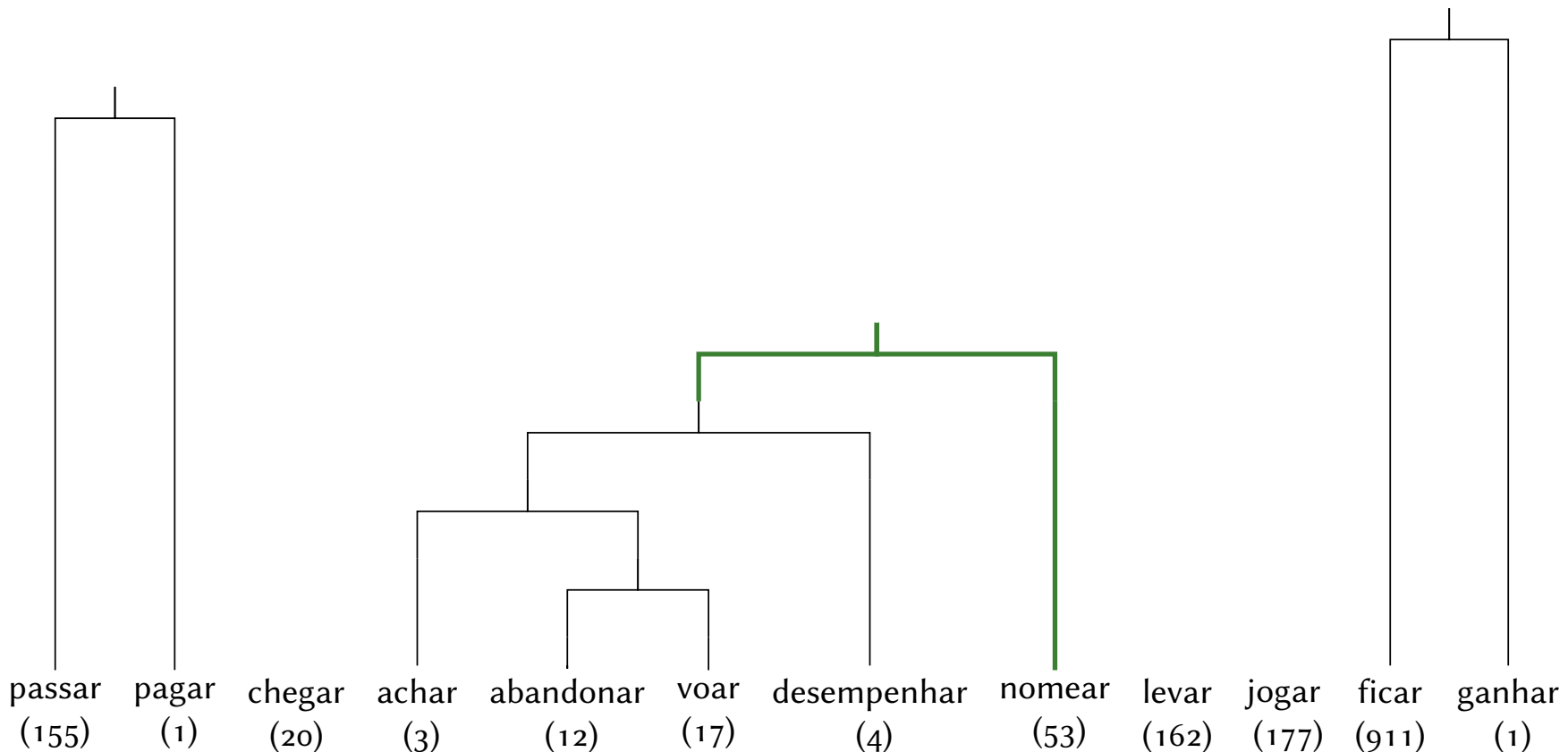

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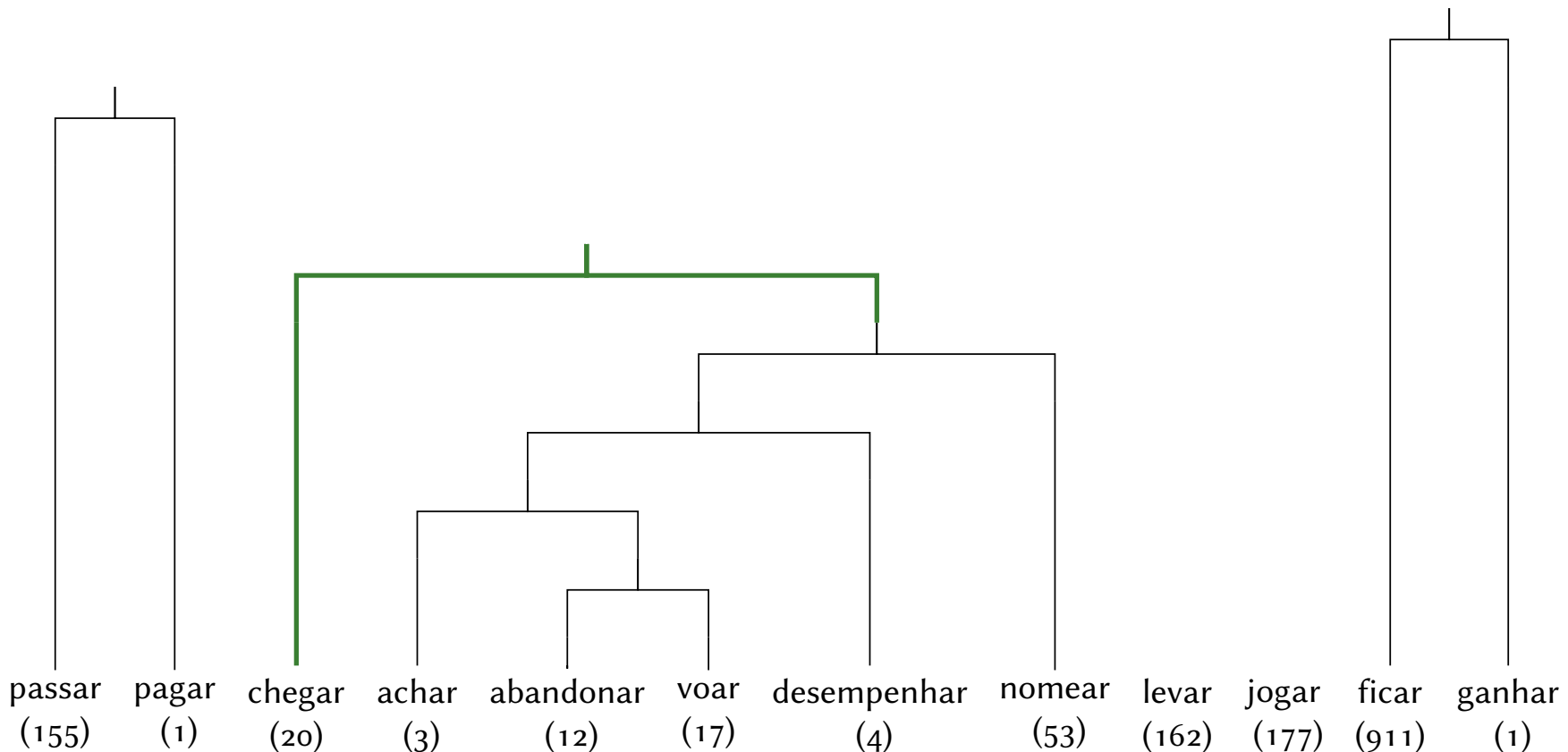

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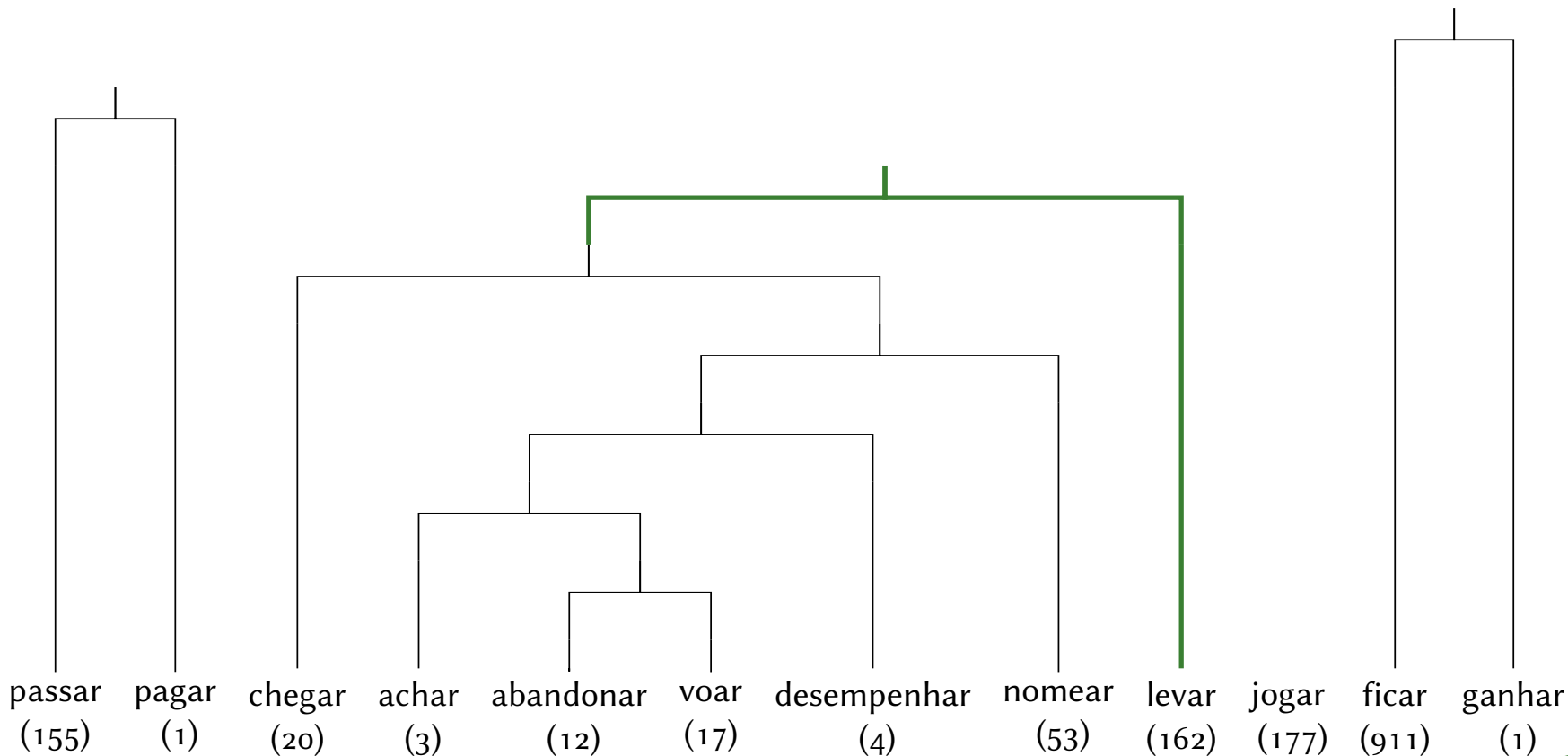

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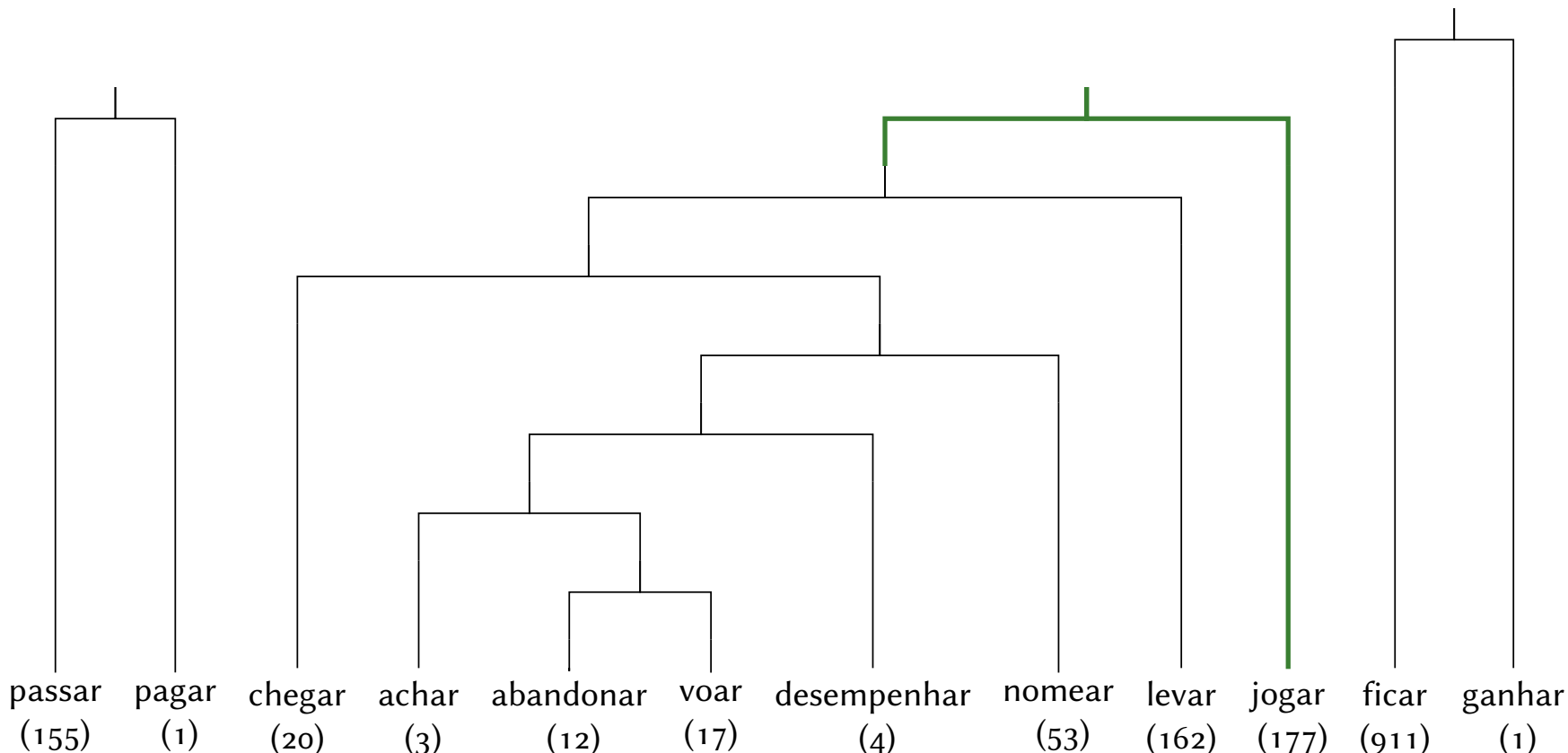

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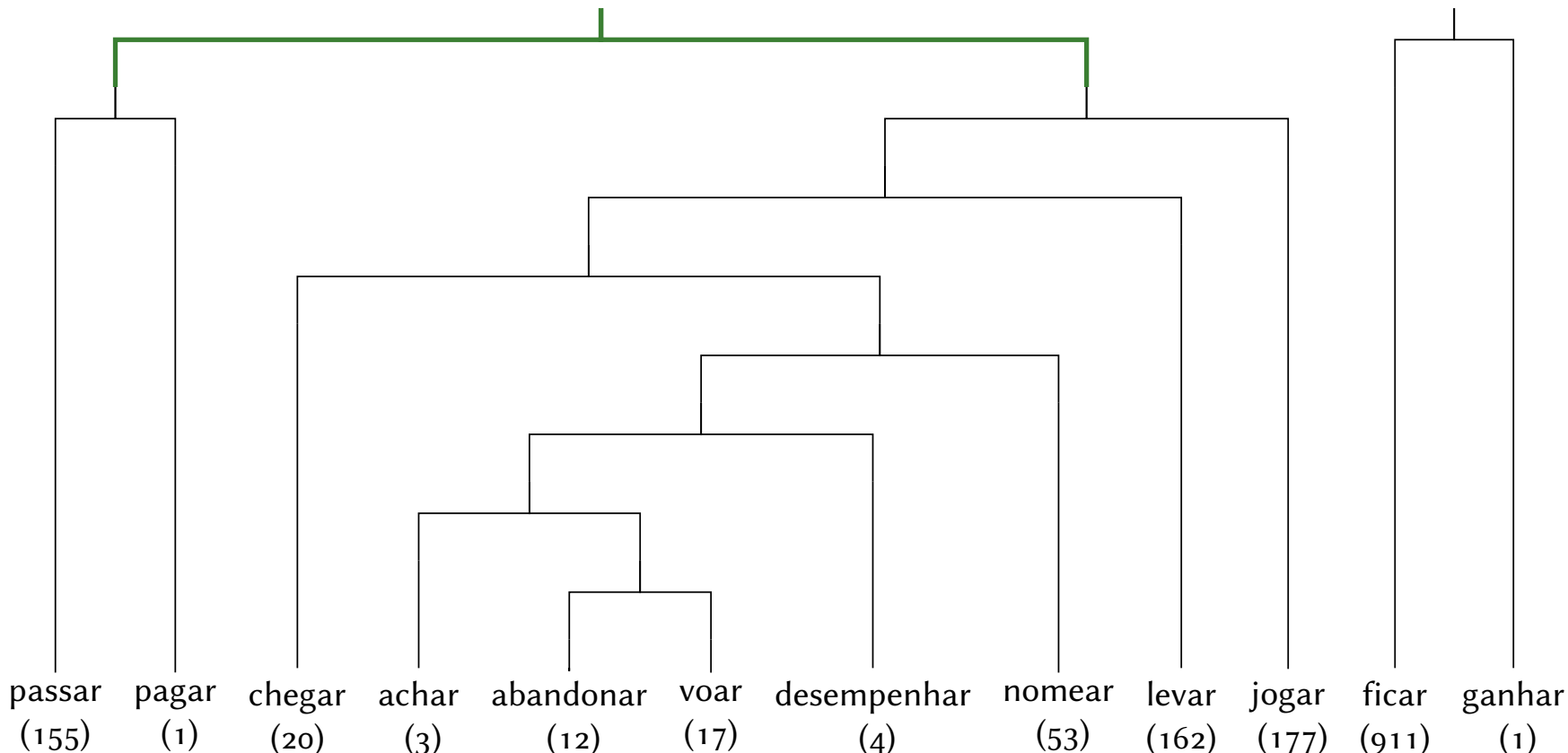

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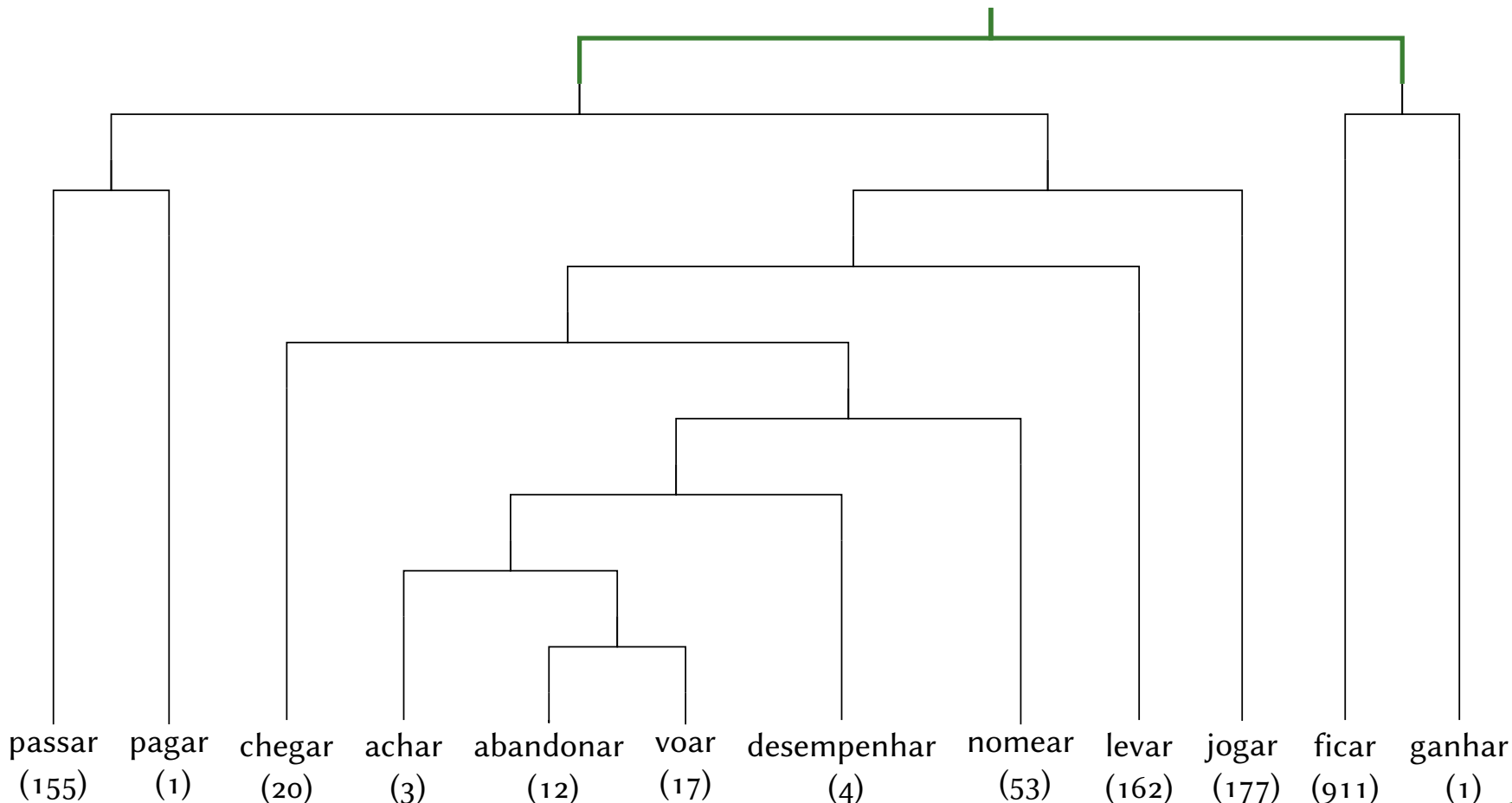

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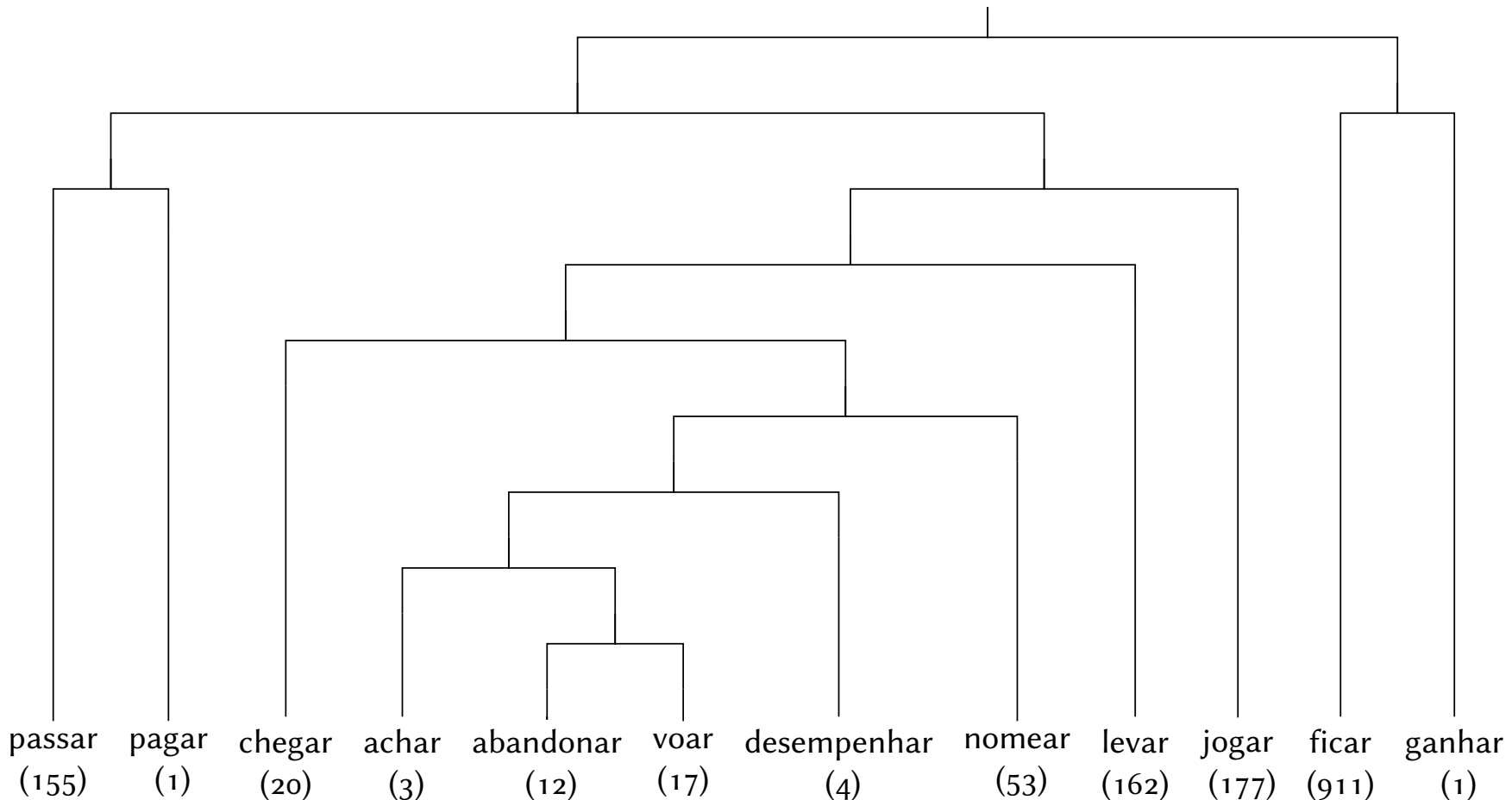

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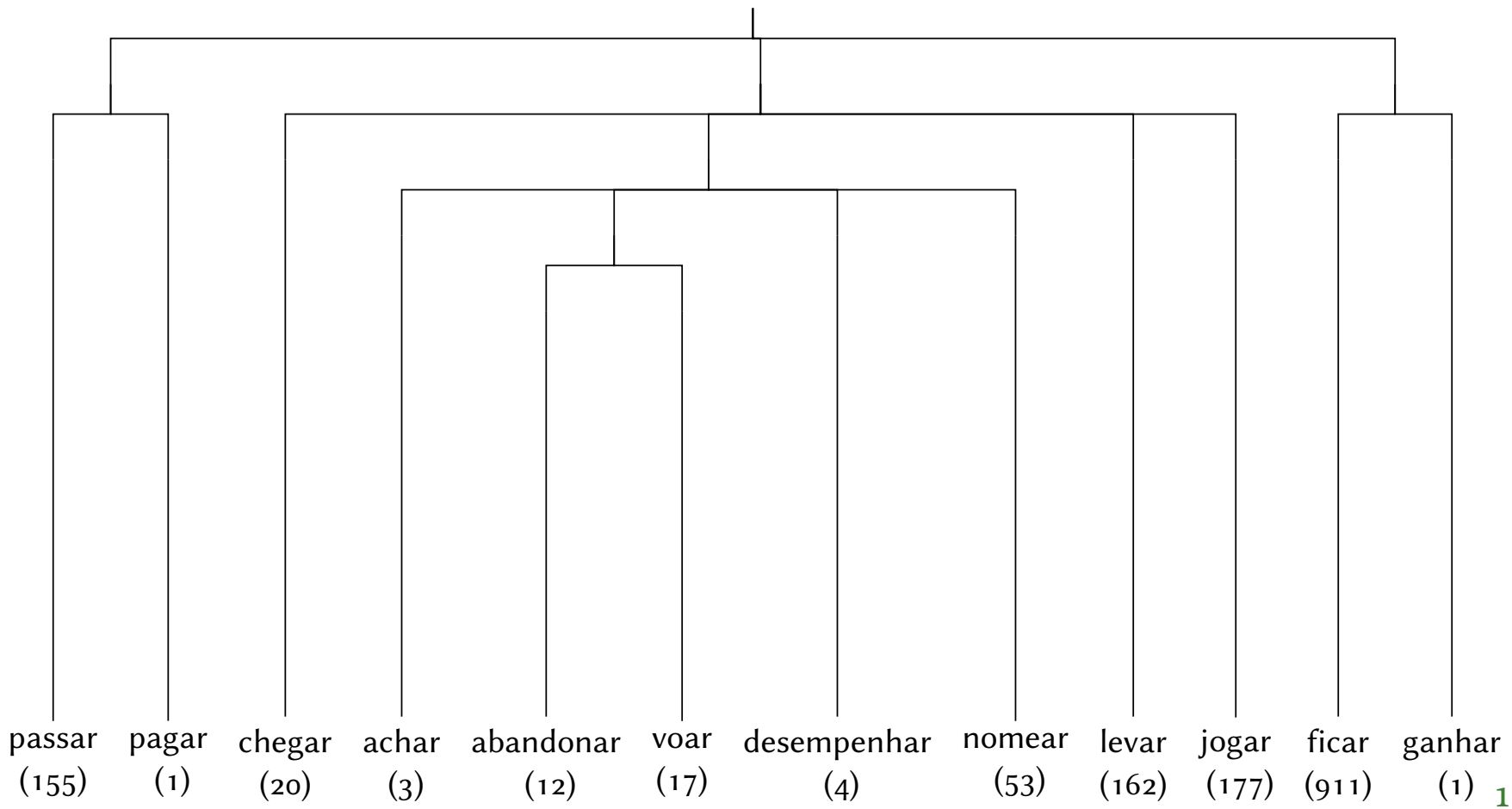
(d) Run several times, merge variations.



- This allows for an intuitive formal definition of macroclasses
- Macroclasses: The partition that best optimises the description length.
  - As we merge clusters, we first expect the DL to decrease.
  - Macroclasses are reached when DL stops decreasing.
- It is an empirical issue whether a system has macroclasses or not.

  We demonstrate their existence in French and European Portuguese conjugation systems.

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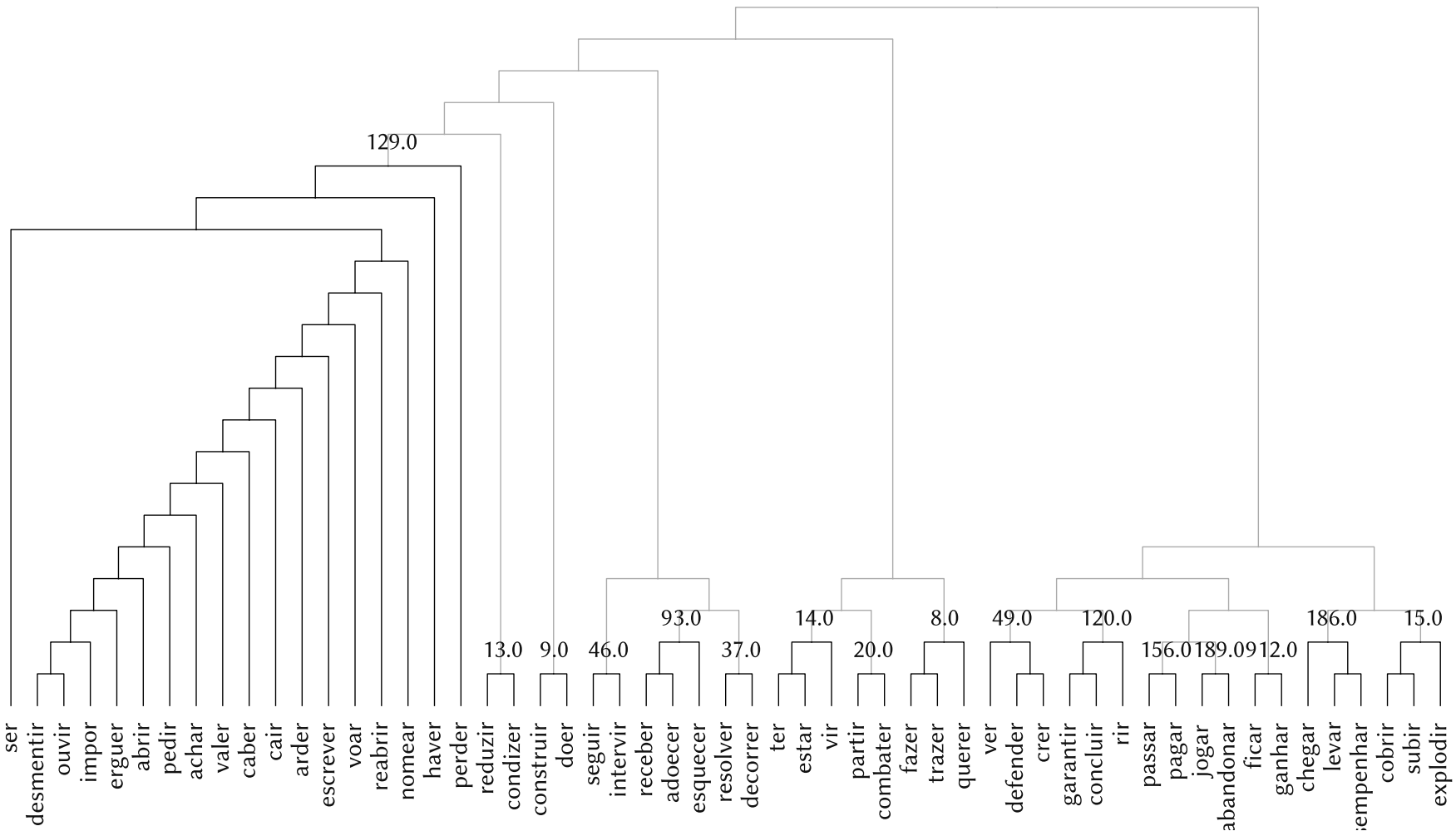
Datasets

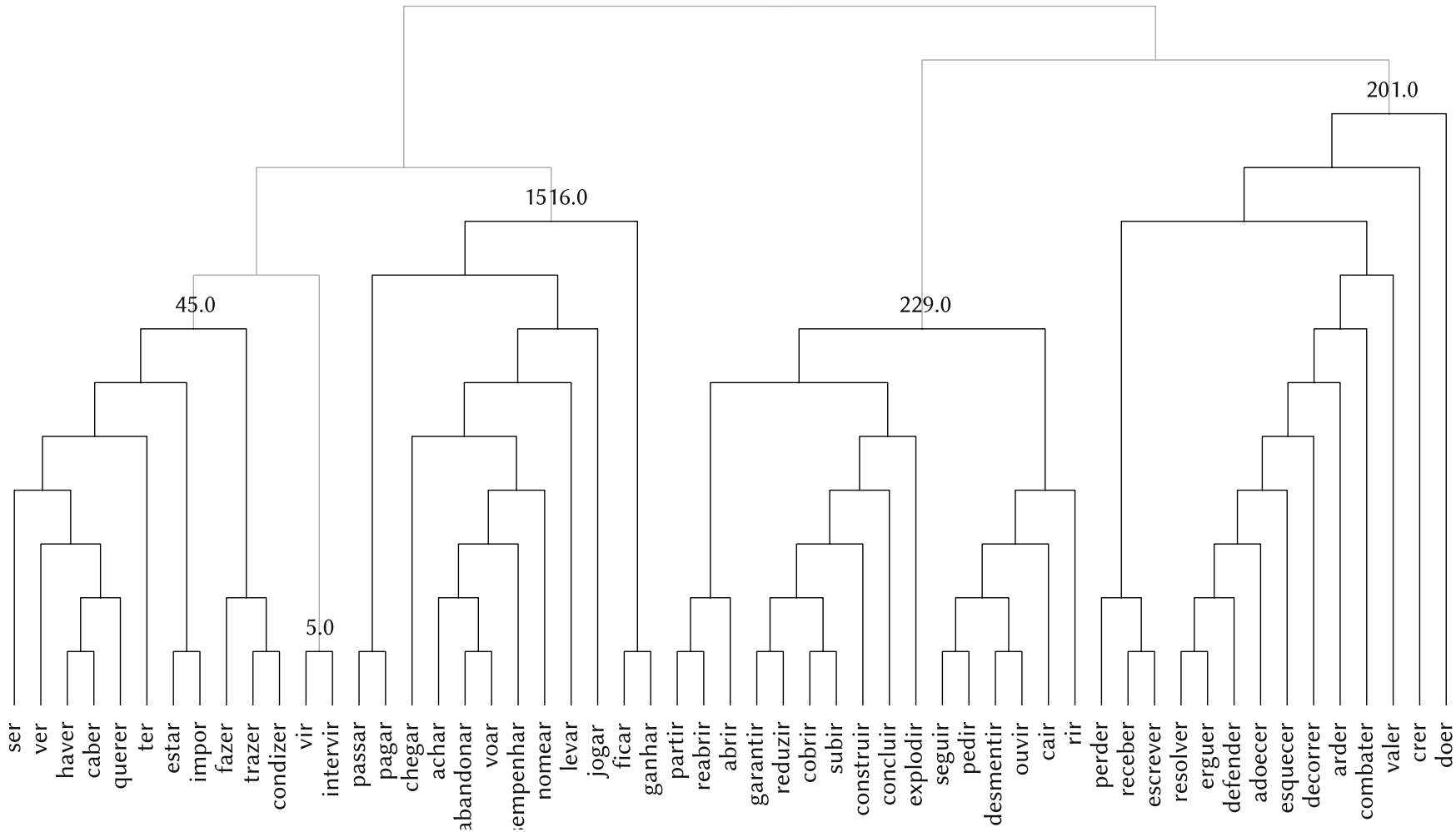
- Paradigm tables contain phonemically transcribed forms.
- **European Portuguese**: Coimbra pronunciation dictionary (Veiga, Candeias, and Perdigão, 2013) (1995 verbal entries).
- **French**: Flexique (Bonami, Caron, and Plancq, 2014) (5406 verbal entries).
- Comparing **local and global** segmentation strategies

- **Global strategy** (stem & exponents): Produces scattered classes with no relationship to conventional knowledge of Portuguese verbal IC.



Portuguese classification, local patterns

- **Local strategy** (alternation patterns): finds generalisations that display interesting relationship with traditional accounts.



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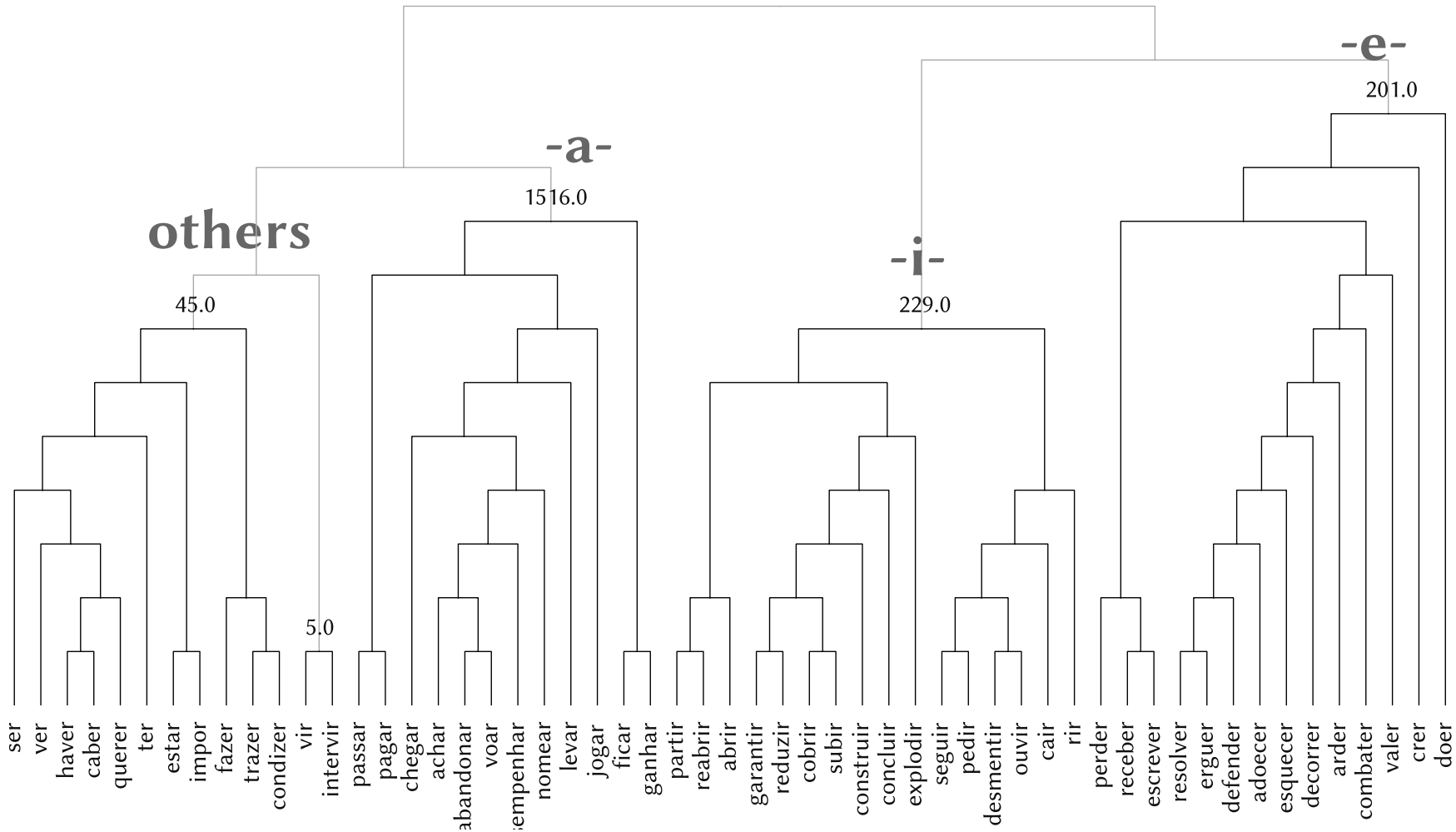
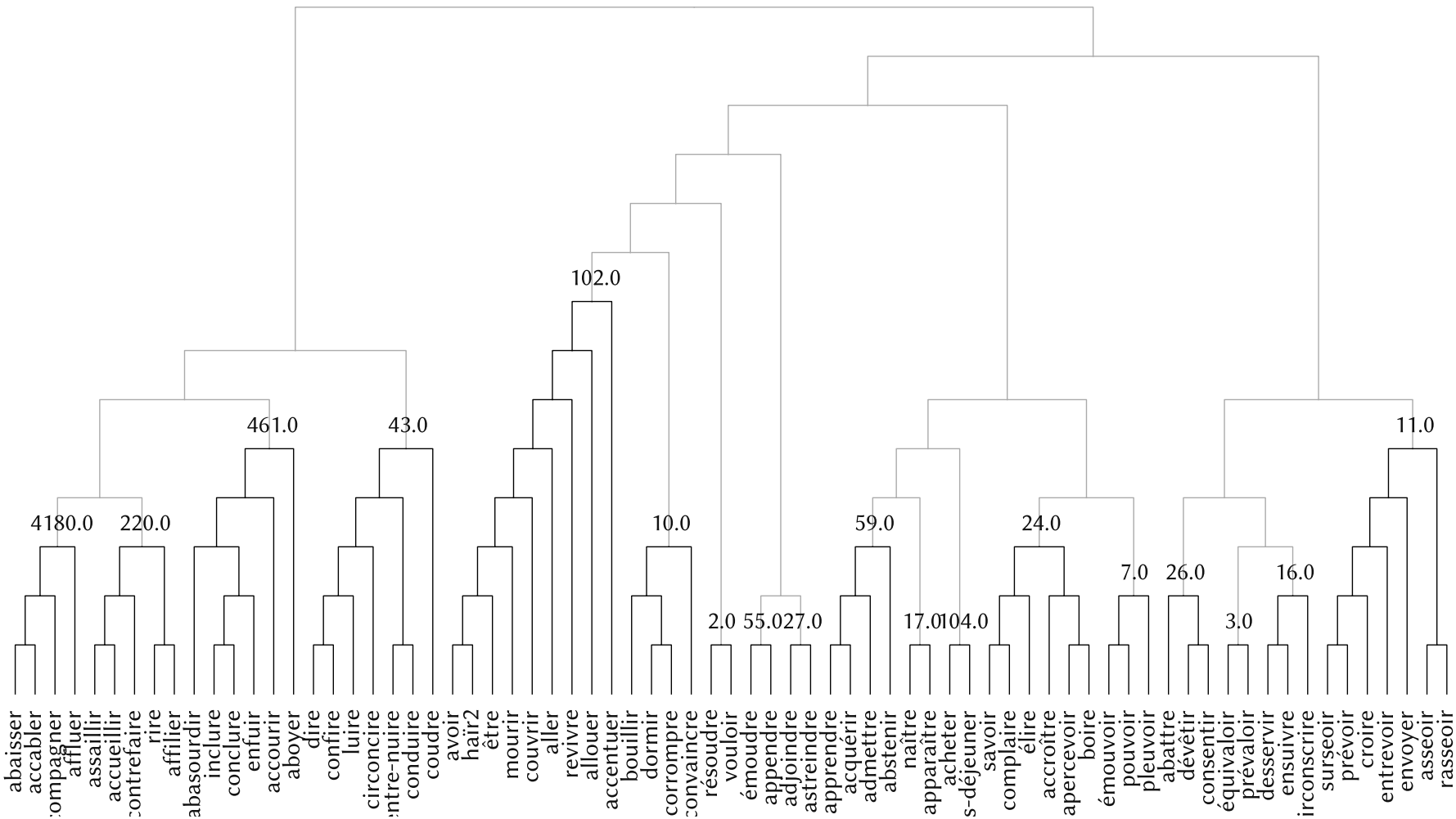


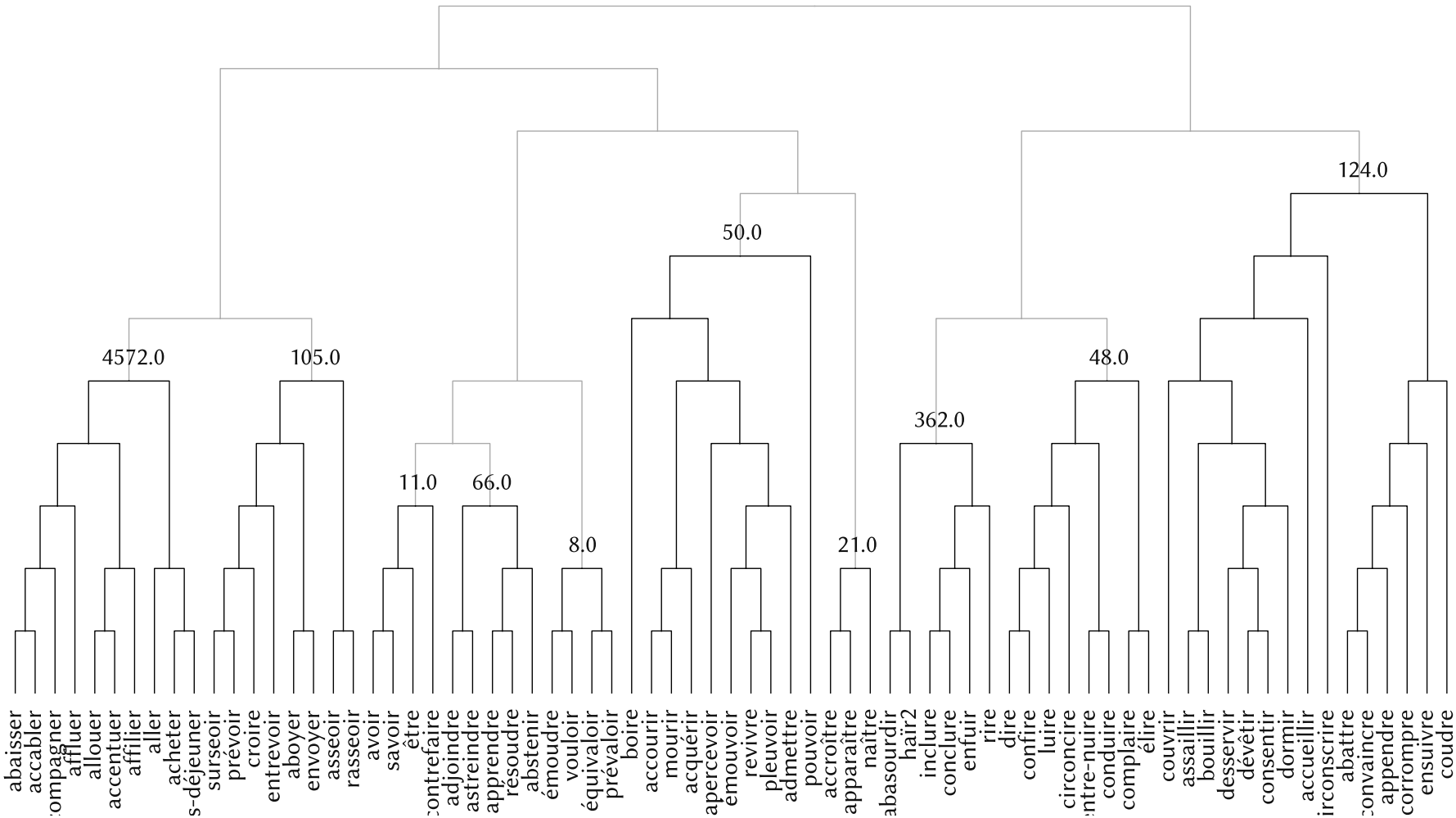
French classification, global patterns

- **Global strategy** (stem & exponents): Produces scattered classes with no relationship to conventional knowledge of French verbal IC.



French classification, local patterns

- **Local strategy** (alternation patterns): finds generalisations that display interesting relationship with traditional accounts.



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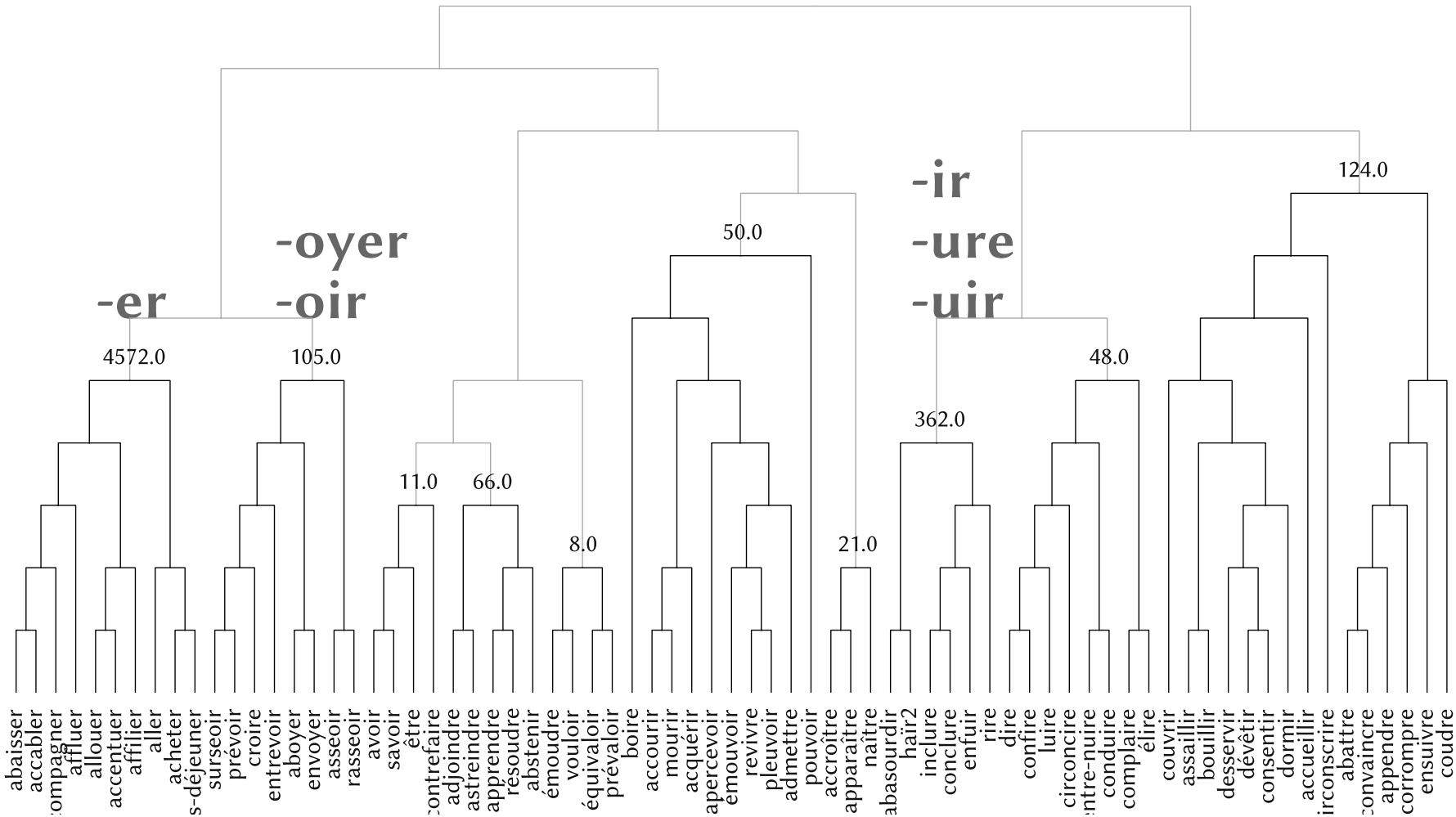

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  - Portuguese: two “irregular” groups.

Comparison to other works

	Generalisations	Criterion	Algorithm
Brown and Evans, 2012	raw paradigms	Compression distance	CompLearn
Bonami, 2014	Affixes	Edit distance	UPGMA
Bonami, 2014	Patterns	Hamming distance	UPGMA
Lee and Goldsmith, 2013	Sets of characters	DL variant	greedy bottom-up
This work	Local patterns	DL	greedy bottom-up
This work	Global patterns	DL	greedy bottom-up

Features of our approach:

- Principled notion of Inflectional Realization.
- Using a measure that evaluates the quality of the system allows us to infer macroscopic generalisations.
- No parameters to adjust: **Occam's razor** is the only criterion.

Table of Contents

- **Main properties**:
  - Based on information-theoretic measures.
  - Relies on automatically inferred generalisations.
  - Aims at cross-linguistic applications.
  - Formal definition of macroclasses and microclasses.
- An analysis into macroclasses can be empirically motivated.
- **Local segmentation** better captures the structure in inflection systems than global segmentation.
  - Supports the relevance of local patterns of alternation in abstractive approaches (Blevins, 2006).
  - Complementary to work on information-theoretic modelling of implicative structure (Ackerman, Blevins, and Malouf, 2009; Ackerman and Malouf, 2013; Bonami and Beniamine, 2015)

Code available on my webpage:
`http://www.llf.cnrs.fr/fr/Gens/Beniamine`

Qumín

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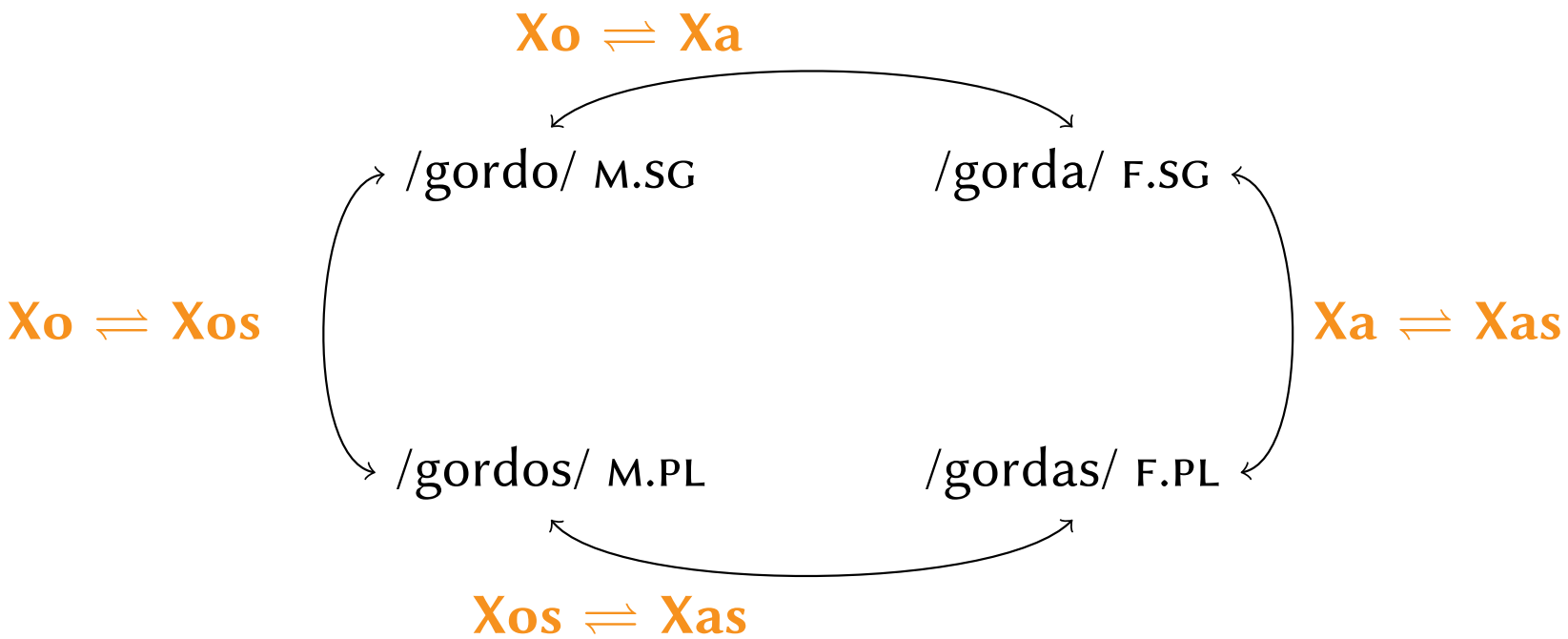
Both can be used in an abstractive approach:



global segmentation

Spanish adjective GORDO ‘fat’.

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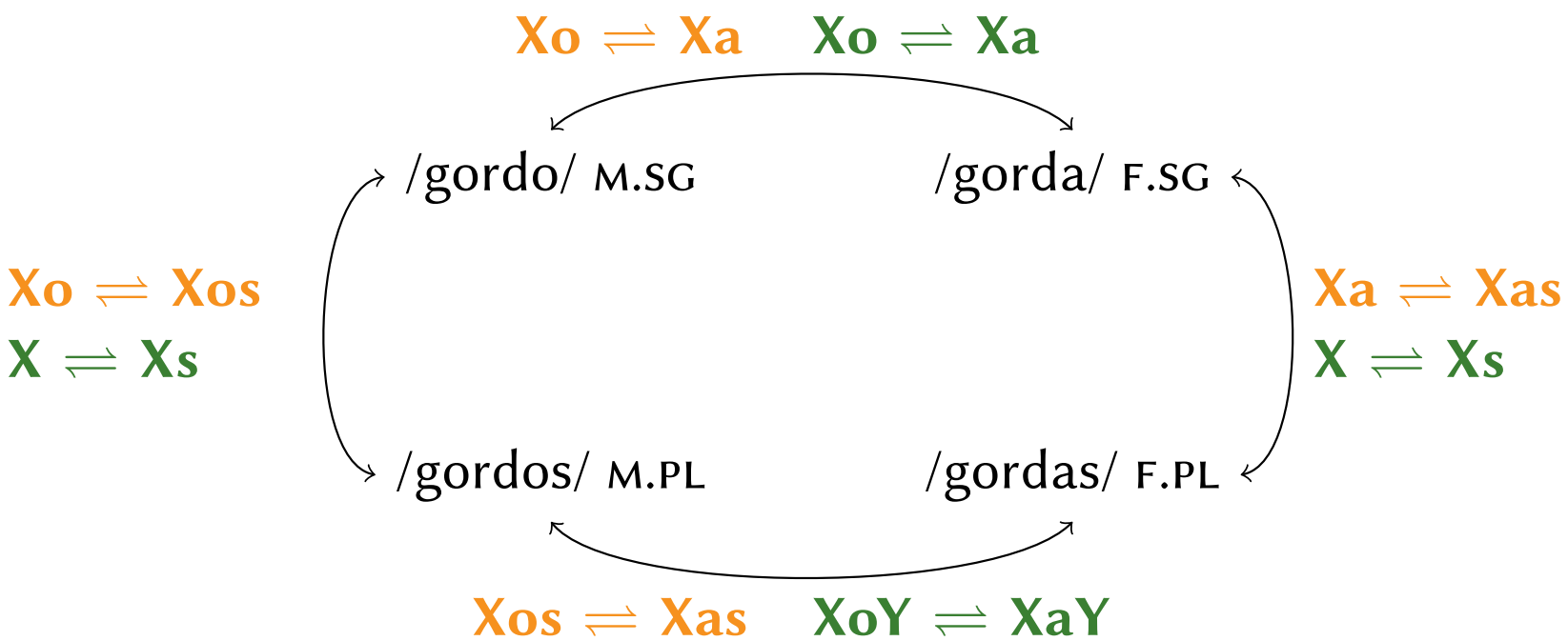

global segmentation vs **local segmentation**

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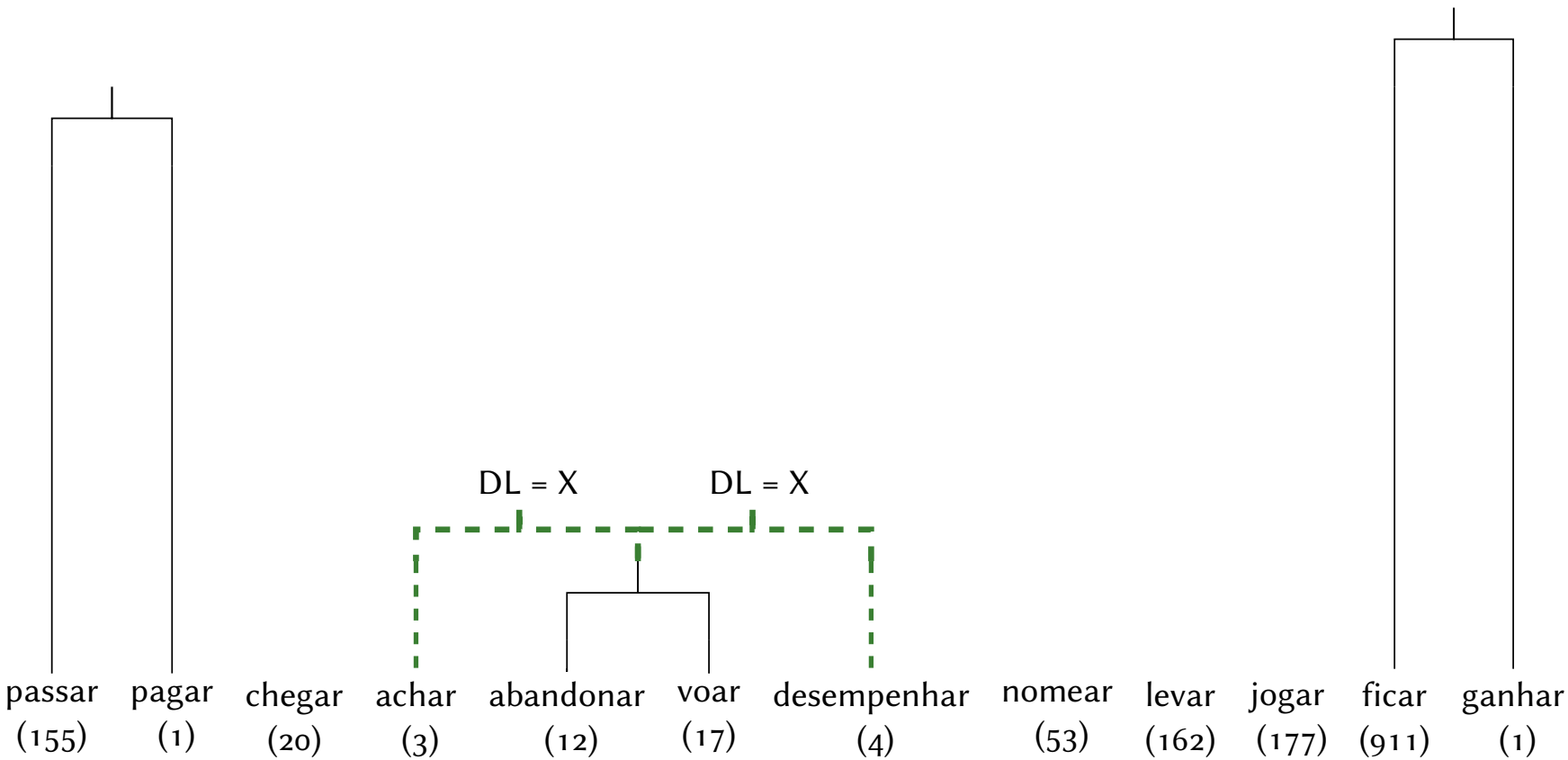
Non Determinism



French classification, local patterns, merged results

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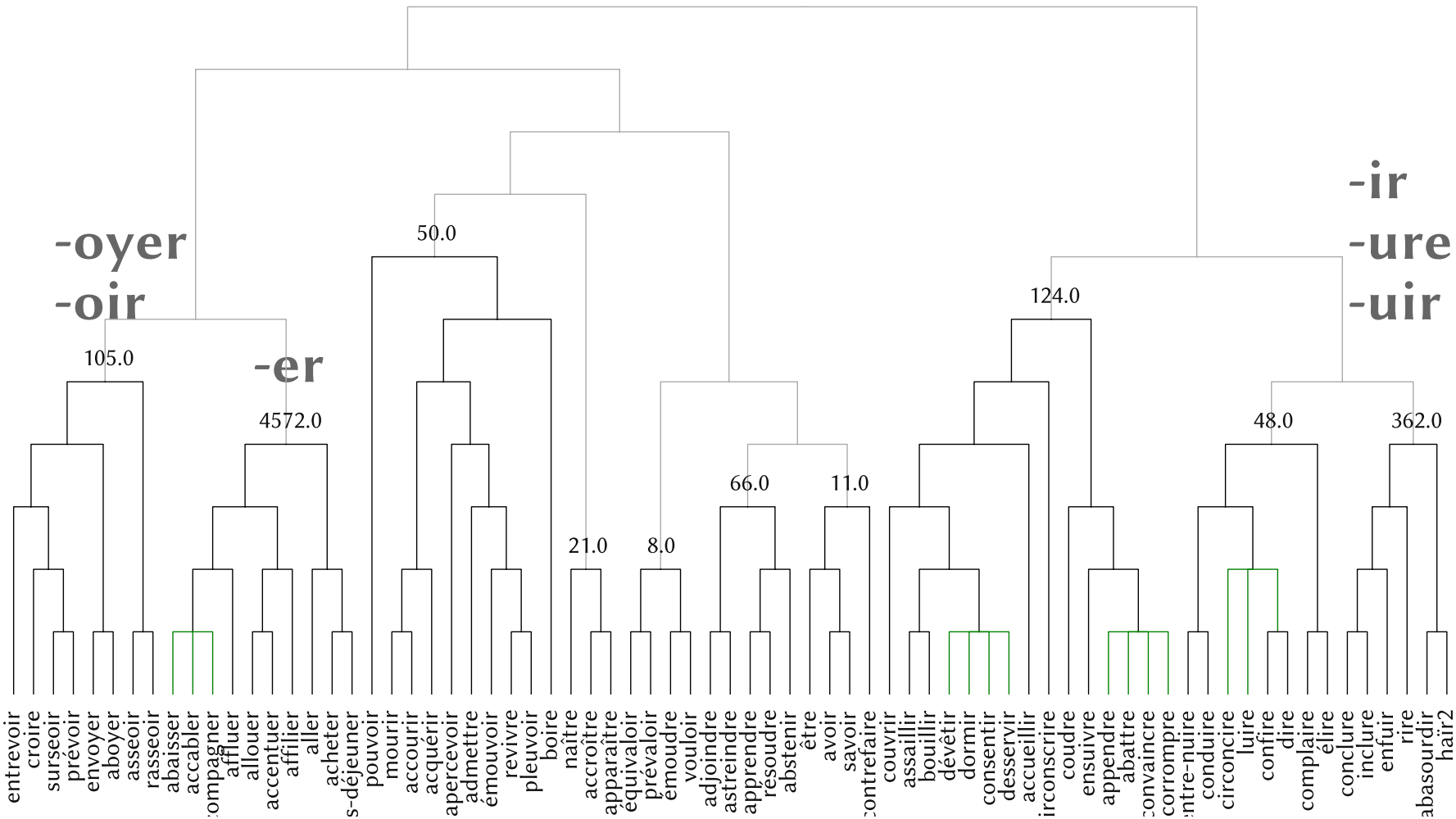

Portuguese classification, local patterns, merged results

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