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▶ To cite this version:

Erich Round, Sacha Beniamine, Louise Esher. Spontaneous emergence of inflectional class systems via attraction–repulsion dynamics. American International Morphology Meeting, 2021, Online, United States. hal-03466118

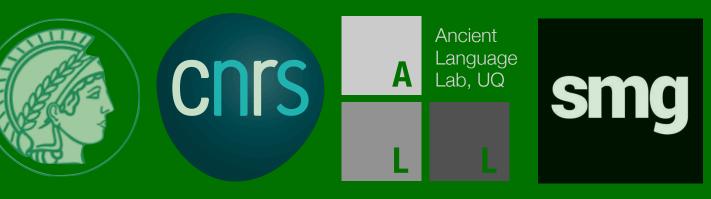
HAL Id: hal-03466118 https://hal.science/hal-03466118v1

Submitted on 4 Dec 2021

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Spontaneous emergence of inflectional class systems via attraction–repulsion dynamics



Erich Round, Sacha Beniamine, Louise Esher AIMM5, August 2021

Aim

Model paradigm dynamics (box 1), to explain why stable inflectional classes can exist.

Background

Inflectional systems exhibit:

- low conditional entropy between cells (box 2) [1–3]
- ② often: multiple, stable inflectional classes [4–6].

A seminal model ('AM') by Ackerman & Malouf [7] shows that a simple cell filling process [8–10] generates systems with low conditional entropy, satisfying ①.

However, inflectional classes are invariably eliminated because changes always increase classes' similarity, failing against **②**.

AM can be interpreted as a model of inductive reasoning with access solely to **positive evidence** due to lexemes' similarities (see **AM model**).

Novel contribution

Stable classes emerge, through attention to negative evidence (NE)

A rational agent will also have access to NE from dissimilarity [11]:

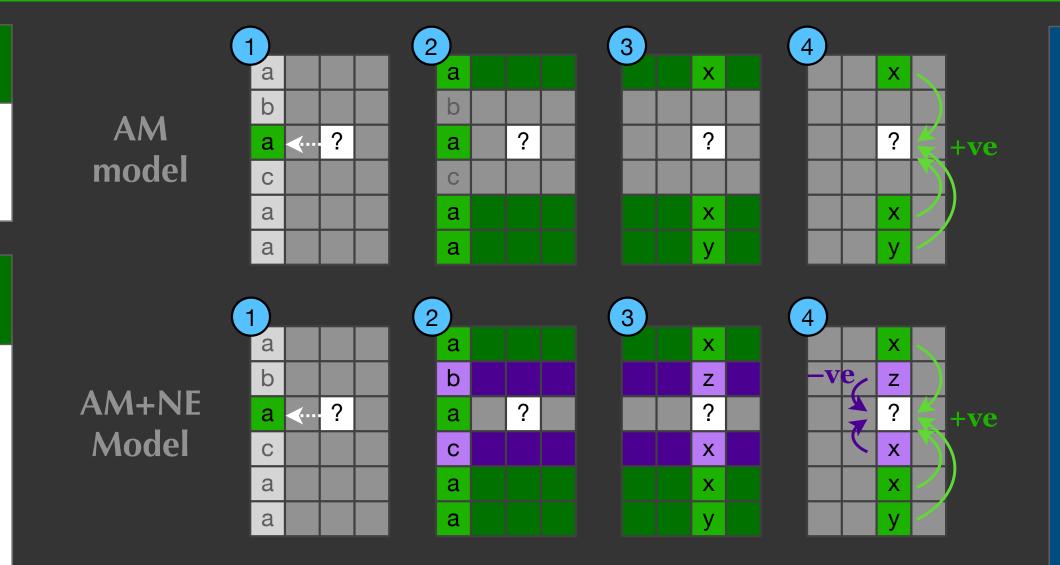
Suppose that for lexeme l my current estimate is that cell c has a 20% probability of containing exponent x, but then I observe that lexeme m, in a different inflectional class, has x in cell c, thus I learn that some of the x's have been "used up" by m's class. My rational response is to update the probability of x to <20%.

In Bayesian updating, if the nth piece of evidence about exponent x is NE, then the probability of x at step n+1 decreases:

$$P_{n+1}(\theta = x \mid NE) = k_{NE}P_n(\theta = x)$$
, where $k_{NE} < 1$.

The value of $k_{\rm NE}$ will depend on the inductive context [12], including number of exponent options and speakers' inferential assumptions.

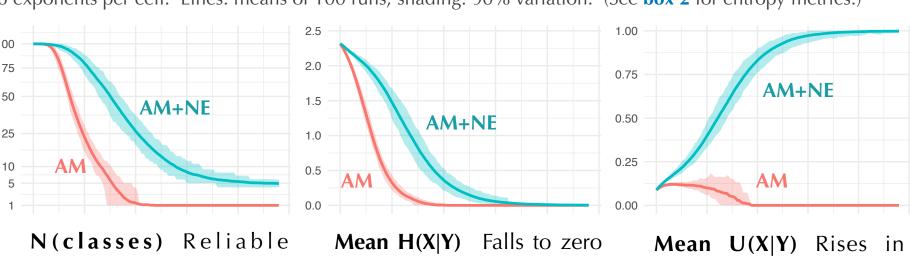
Here, our focus is on demonstrating the implications of negative evidence *in general*, so we implement $k_{\rm NE}$ as a simple, 'lumped' parameter. Future directions include clarifying individual contributions to $k_{\rm NE}$ under various inductive scenarios.



One cycle of the models. Lexemes are in rows. Paradigm cells are in columns. Task is to predict a focal (held-out) cell, ? . AM model: ① pick another cell, ② select/sample other lexemes with the *same* exponent, ③ in these lexemes, examine their focal cell, ④ count all evidence as positive: the more x's, the more likely that ? = x. AM+NE model: at ②, also select/sample dissimilar cells, which at ④ count as negative evidence.

Results

12,000 evolutionary cycles of AM and AM+NE, from the same initial random conditions: 100 lexemes, 8 cells, 6 exponents per cell. Lines: means of 100 runs, shading: 90% variation. (See **box 2** for entropy metrics.)



in both, but in AM this is

because H(X) drops to zero.

AM+NE. Rises slightly in

AM but then collapses.

Discussion

Different processes give rise to different evolutionary dynamics.

retention in AM+NE;

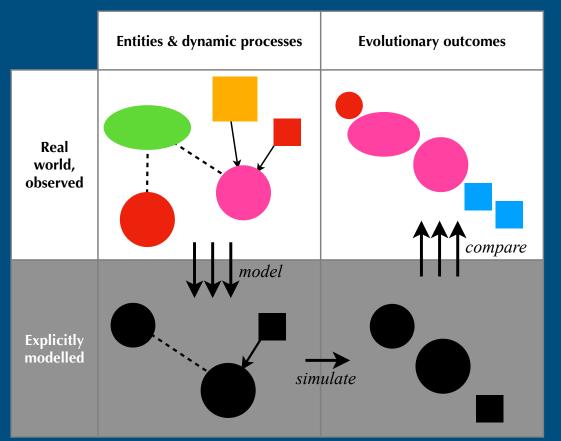
Complete levelling in AM.

- AM: positive-evidence inferential process → attraction-only dynamic between inflection classes, so they inevitably collapse together.
- AM+NE: positive and negative evidence → additional repulsion dynamic pushing classes apart, meaning complete collapse is avoided.

The **outcome** (stable classes) is explained by the **dynamic** (attraction–repulsion), which is explained by the **change process** (cell-filling inductive inference including attention to negative evidence).

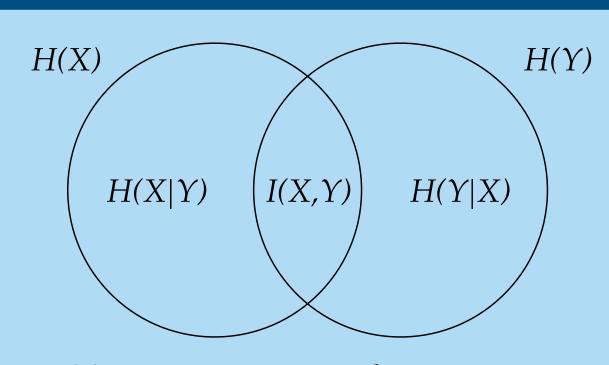
Box 1 Gaining understanding via modelling

- i. Real world dynamics of observable entities leads to observable outcomes.
- ii. Verbal explanations "x leads to y because z" can sound compelling but may hide flaws [13].
- iii. Models pair *aspects* of observations with explicit processes and generate explicit results, which we relate back to *aspects* of observed outcomes [14].



- iv. In our study, we show for the first time how a *cell filling process* can result in the emergent *outcome of stable, distinct inflection classes*.
- v. We explain not only why the seminal AM model lacks this outcome, but also why a more complete representation of inductive inference produces it.

Box 2 Entropy measures



H(X): ENTROPY \approx uncertainty when guessing cell X

H(X|Y): CONDITIONAL ENTROPY \approx uncertainty of guessing cell X, given cell Y

I(X,Y): MUTUAL INFORMATION \approx reduction in uncertainty of guessing either X or Y, upon being given the other.

- i. We want to measure the uncertainty when guessing cell X given cell Y, and the change in uncertainty over time.
- ii. AM use H(X|Y). However, $H(X|Y) \le H(X)$, thus H(X|Y) can decrease merely because H(X) decreases, irrespective of overlap with H(Y) [15] (see Results).
- iii. For our purposes: measure H(X|Y) as a proportion of H(X), or conversely I(X,Y) as a proportion of H(X). The latter is the UNCERTAINTY COEFFICIENT, U(X|Y).
- iv. U(X|Y) always lies between 0 and 1, which aids more meaningful comparison among different systems, or across time in an evolving lineage (see Results).

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