



# Spontaneous emergence of inflectional class systems via attraction–repulsion dynamics

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# Spontaneous emergence of inflectional class systems via attraction–repulsion dynamics

## Aim

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

## Background

Inflectional systems exhibit:

- ❶ low conditional entropy between cells (**box 2**) [1–3]
- ❷ 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 ❶.

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

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]:

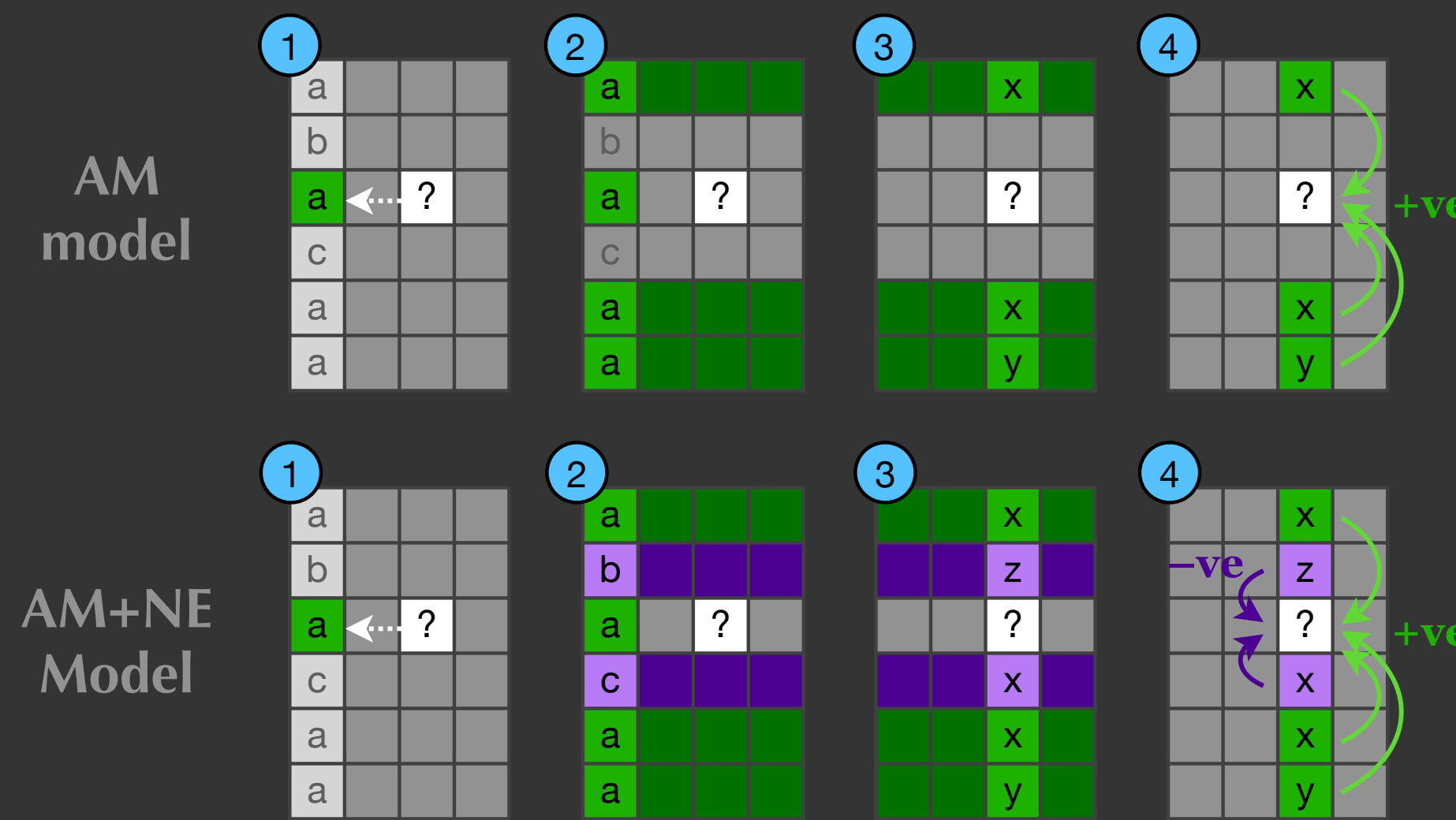
Suppose that for lexeme *l* my current estimate is that cell *c* has a 20% probability of containing exponent *x*, but then I observe that lexeme *m*, in a different inflectional class, has *x* in cell *c*, thus I learn that some of the *x*'s have been "used up" by *m*'s class. My rational response is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

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

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

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

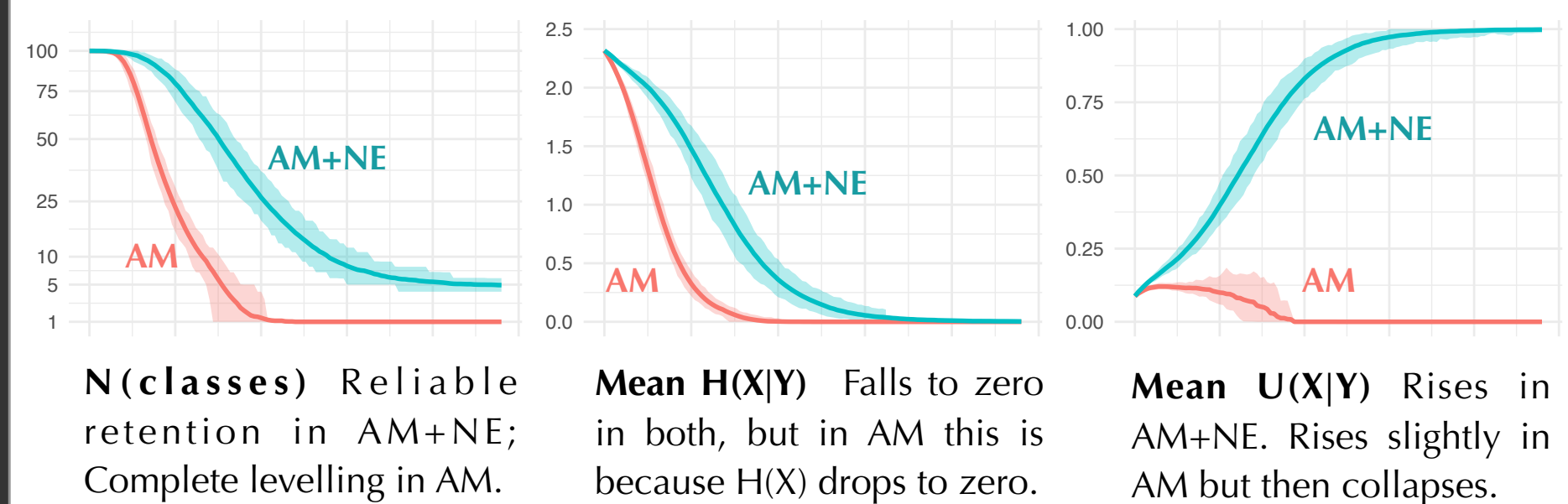
Here, our focus is on demonstrating the implications of negative evidence *in general*, so we implement  $k_{\text{NE}}$  as a simple, 'lumped' parameter. Future directions include clarifying individual contributions to  $k_{\text{NE}}$  under various inductive scenarios.



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**: ❶ pick another cell, ❷ select/sample other lexemes with the same exponent, ❸ in these lexemes, examine their focal cell, ❹ count all evidence as positive: the more *x*'s, the more likely that **?** = *x*. **AM+NE model**: at ❷, also select/sample dissimilar cells, which at ❹ 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.)



## Discussion

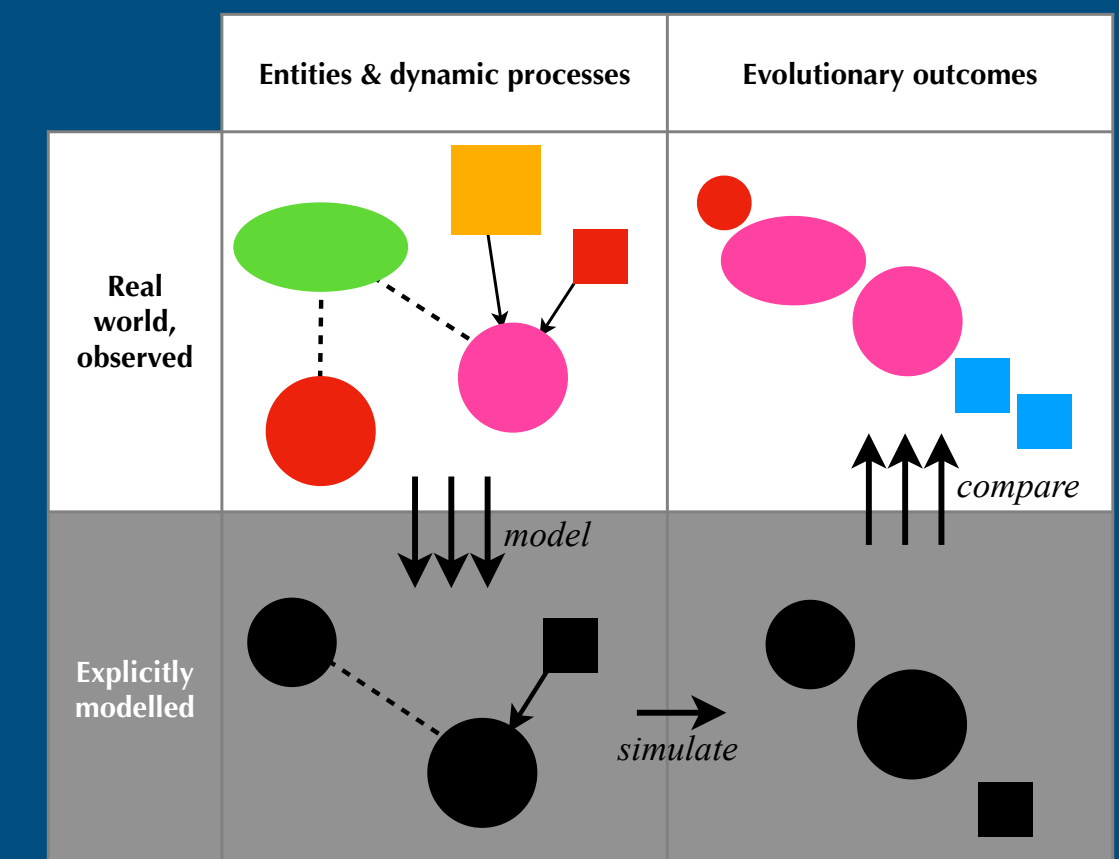
Different **processes** give rise to different evolutionary **dynamics**.

- **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.

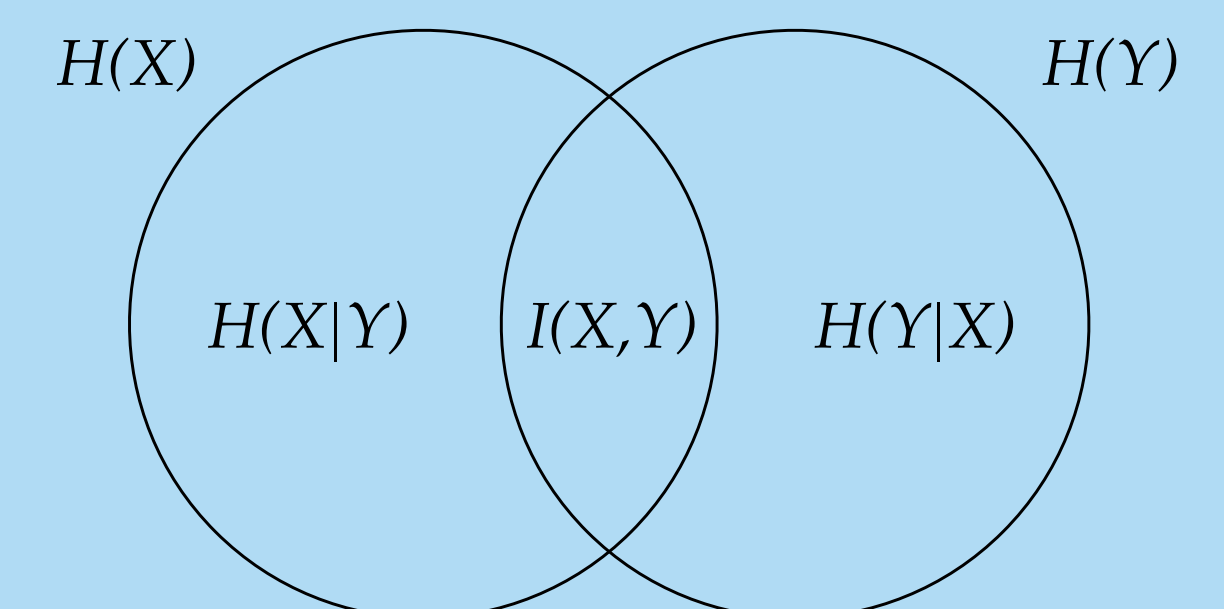
The **outcome** (stable classes) is explained by the **dynamic** (attraction–repulsion), which is explained by the **change process** (cell-filling inductive inference including attention to negative evidence).

## 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,  $H(X|Y) \leq H(X)$ , 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).