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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:

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

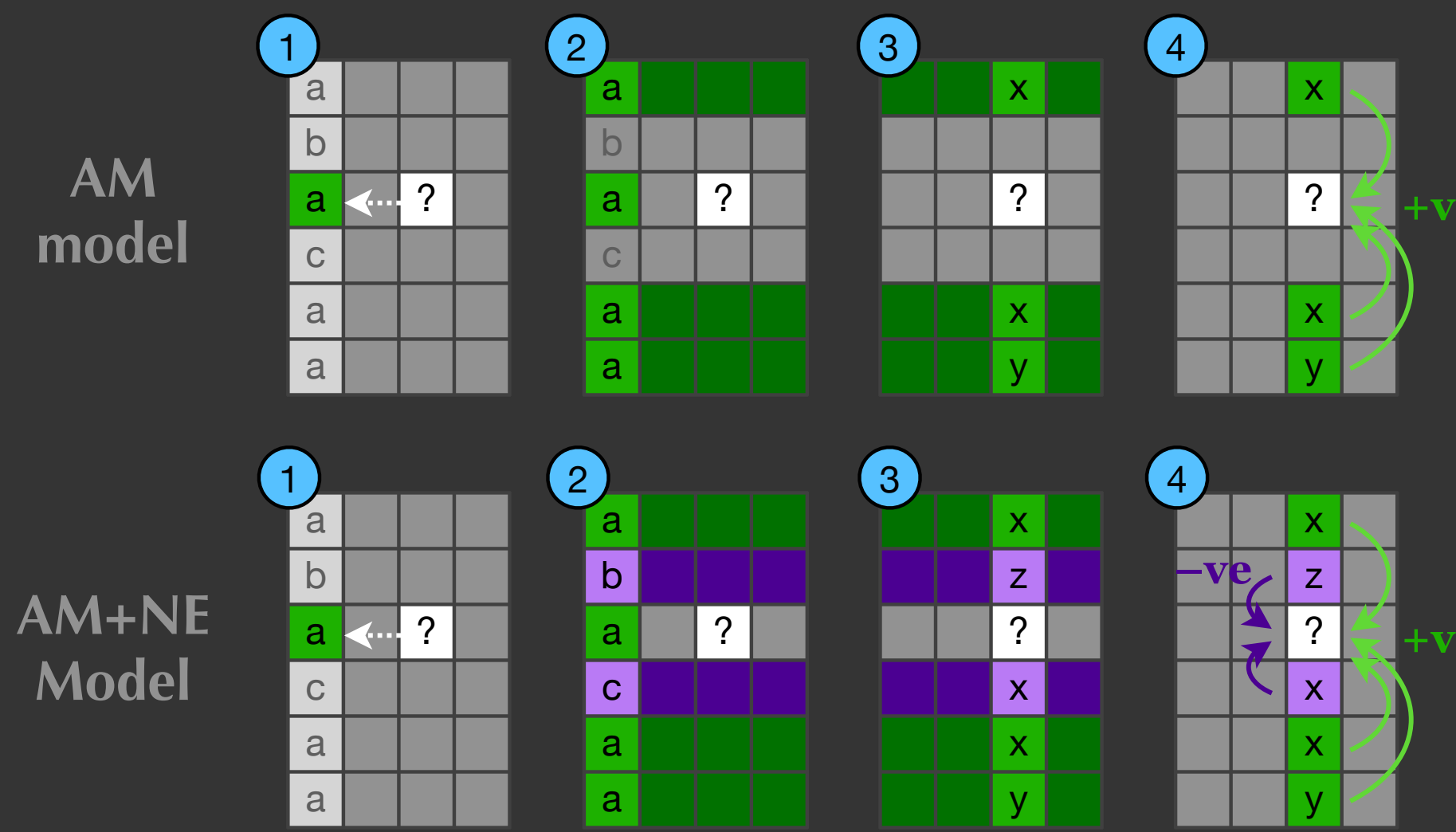
Suppose that for lexeme l my current estimate is that cell c has a 20% probability of containing exponent x , but then I observe that lexeme m , in a different inflectional class, has x in cell c , thus I learn that some of the x 's have been "used up" by m 's class. My rational response is to update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

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

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

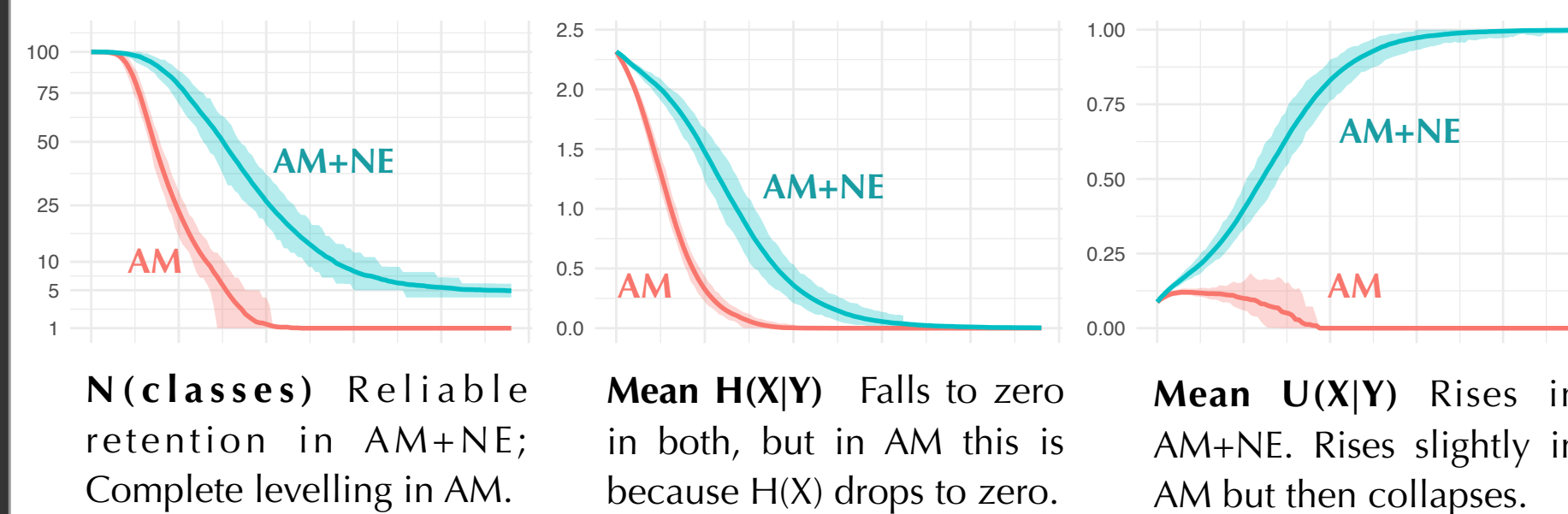
Here, our focus is on demonstrating the implications of negative evidence *in general*, so we implement k_{NE} as a simple, 'lumped' parameter. Future directions include clarifying individual contributions to k_{NE} under various inductive scenarios.



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.)



N(classes) Reliable retention in AM+NE; Complete levelling in AM.

Mean $H(X|Y)$ Falls to zero in both, but in AM this is because $H(X)$ drops to zero.

Mean $U(X|Y)$ Rises in AM+NE. Rises slightly in AM but then collapses.

Discussion

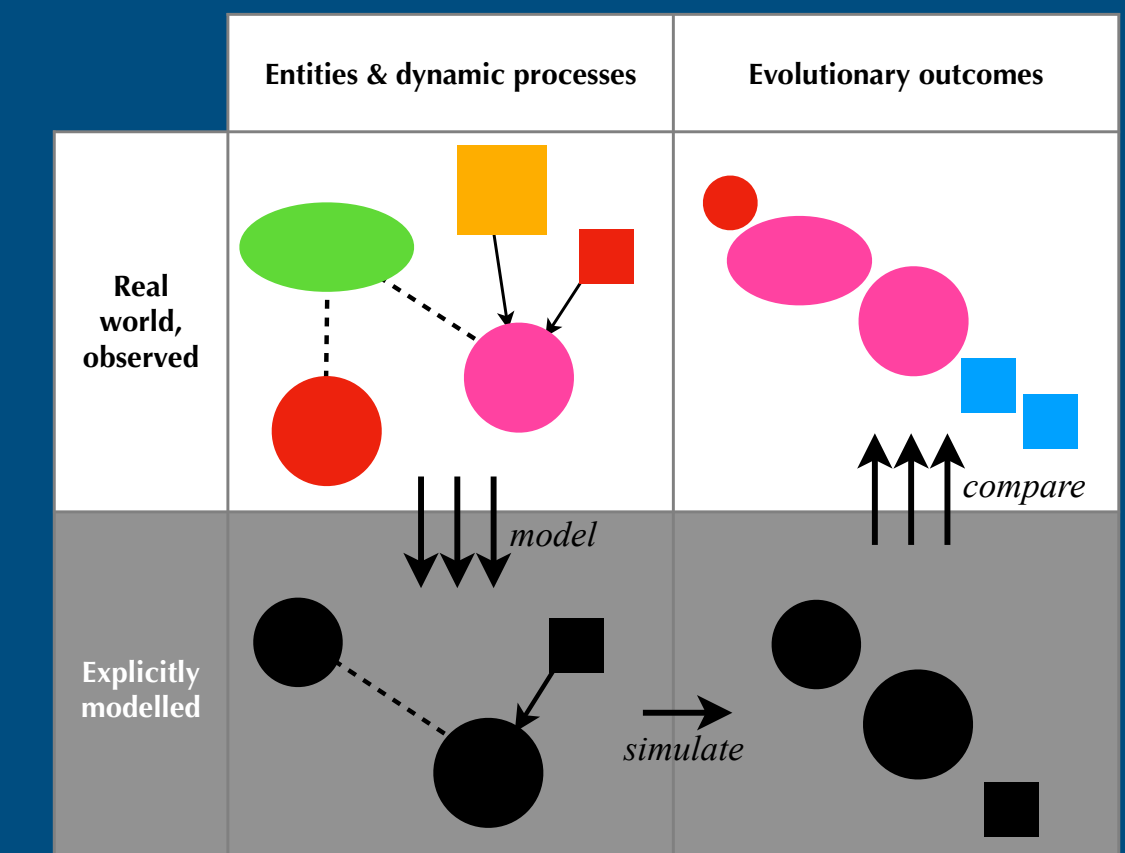
Different **processes** give rise to different evolutionary **dynamics**.

- AM**: positive-evidence inferential process \rightarrow attraction-only dynamic between inflection classes, so they inevitably collapse together.
- AM+NE**: positive and negative evidence \rightarrow 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).

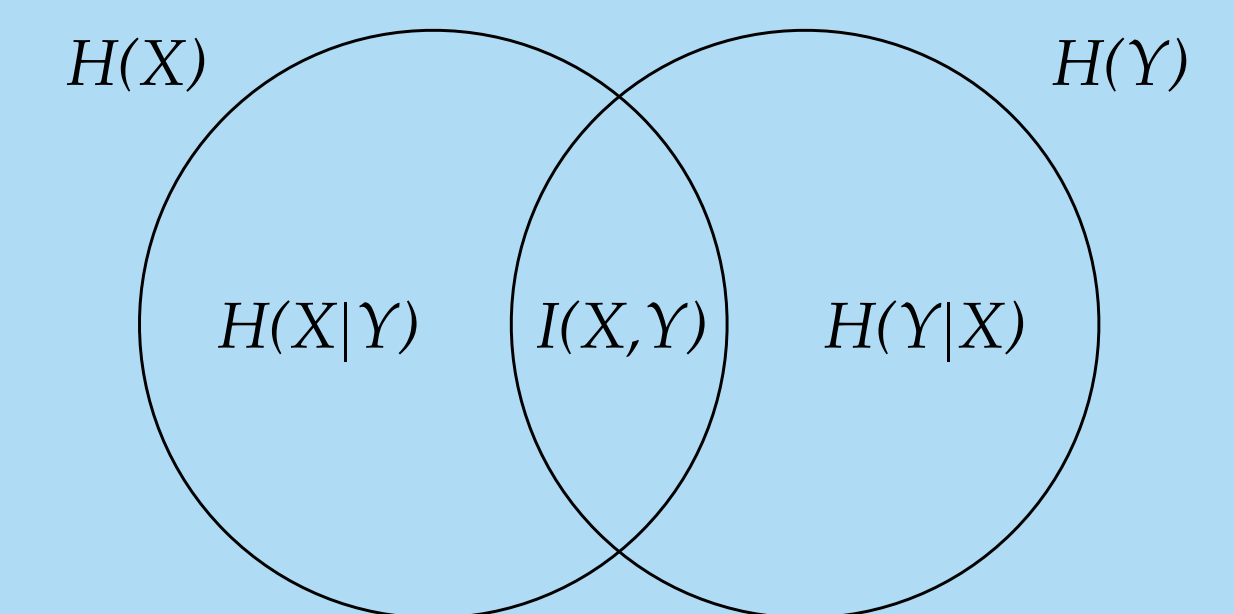
Box 1 Gaining understanding via modelling

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



- 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*.
- 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.

- We want to measure the uncertainty when guessing cell X given cell Y, and the change in uncertainty over time.
- 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).
- 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, $U(X|Y)$.
- $U(X|Y)$ always lies between 0 and 1, which aids more meaningful comparison among different systems, or across time in an evolving lineage (see Results).