Adaptive Resonance Theory as a computational model of learning inflection classes

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How do humans use **generalisation** in production of verb morphology?
Which role do **inflection classes** play in this process?

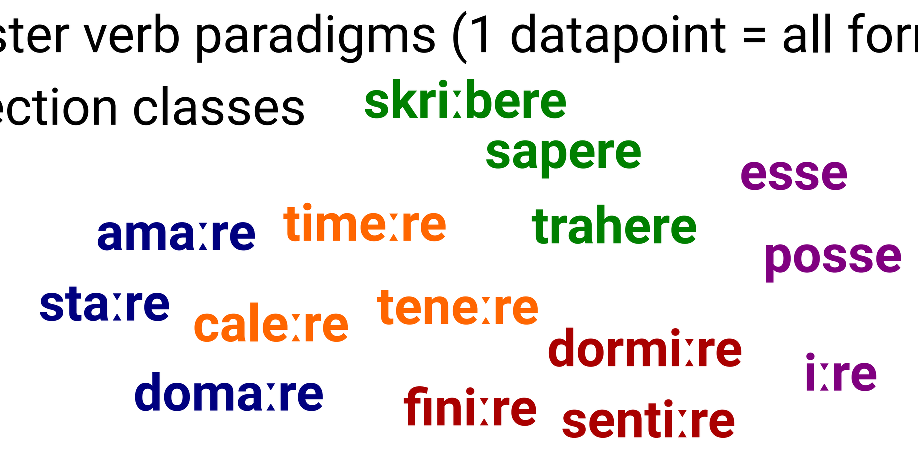
Recent computer models of morphological processing

Mostly generation of inflected forms (Elsner et al., 2019; Kodner et al., 2022)
Some work on clustering inflection classes: supervised (Guzman Naranjo 2019, 2020) and unsupervised approaches (Beniamine et al., 2018; Lefevre et al., 2021)

This study: Can Adaptive Resonance Theory learn a system of inflection classes?
Which features does the model attend to?

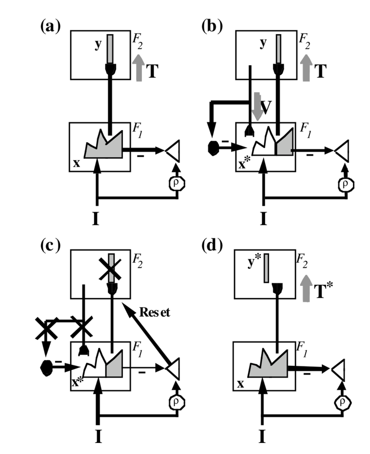
Task: Unsupervised inflection class clustering

Cluster verb paradigms (1 datapoint = all forms for one verb) into inflection classes



Adaptive Resonance Theory
(Carpenter & Grossberg 1987)

Cognitively inspired neural network of category learning
Input layer (new stimuli) and perception layer (learned categories)
Vigilance parameter: more or less **generalisation**
Explainability via **critical feature patterns** (Grossberg, 2020)
This study: **ART1 clustering model**



Carpenter & Grossberg (2002)

Data

Romance Verbal Inflection Dataset (Beniamine et al., 2020)
Phonetic word forms with **inflection classes** for evaluation.
Our study: **Latin present tense**
Representation of **n-grams** (n=2/3): **form concat** and **paradigm set**

	I	II	III	IV	special
	sta:re	**tene:re**	**sapere**	**dormi:re**	**esse**
1SG	sto:	teneo:	sapio:	dormio:	sum
2SG	sta:s	tene:s	sapis	dormi:s	es
3SG	stat	tenet	sapit	dormit	est
1PL	sta:mus	tene:mus	sapimus	dormi:mus	sumus
2PL	sta:tis	tene:tis	sapitis	dormi:tis	estis
3PL	sta:s	tenent	sapiunt	dormiunt	sunt

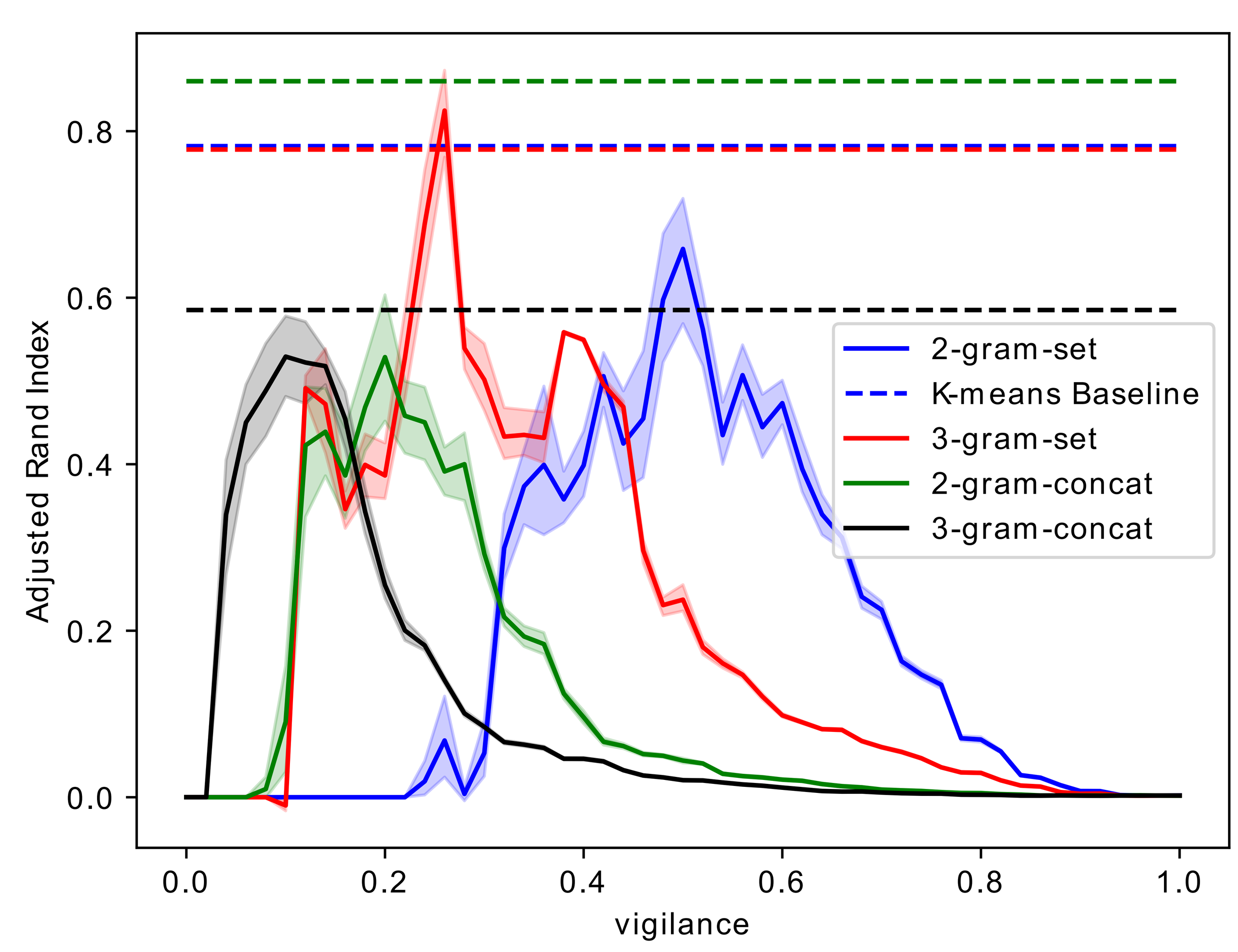
su	um	es	...	st	mu	us	...	ti	is	un	nt
1	1	1	0	1	1	1	0	1	1	1	1

Paradigm set: presence of n-gram in all forms together

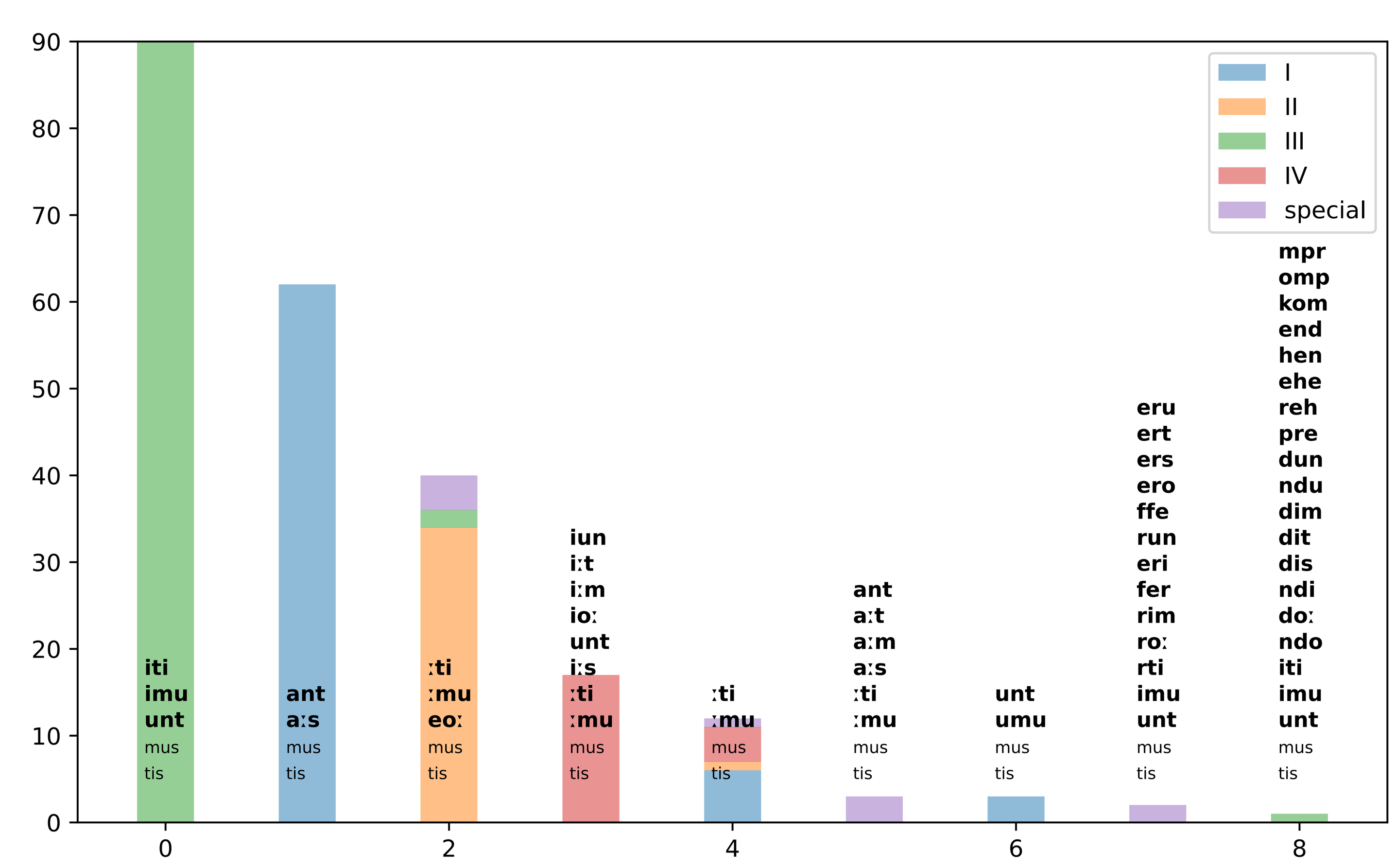
do ... o:	do ... :s	do ... it	do ... us	do ... is	do ... nt
1 000 1	1 000 1	1 000 1	1 000 1	1 000 1	1 000 1

Form concat: n-grams represented separately for each form and concatenated

Results



Clustering similarity to real inflection classes (Adjusted Rand Index).
Different representations (2/3-gram, set and concat) for different vigilance values



Analysis of clusters (model: 3-gram and paradigm set representation)
Bar: Cluster
Colour: **real inflection class** of assigned datapoints per cluster
Text in bar: **learned n-gram features** (distinctive features in bold)

Conclusion

ART learns system of inflection classes and **learned n-grams can be interpreted** using critical feature patterns
Trigrams and **set representation** for **moderate vigilance** give best results

Future work

Experiment with ordering of data
Study **language change** using **agent-based model** equipped with ART network (cf. Round et al. 2022; Parker et al., 2018; Hare & Elman, 1995; Cotterell et al., 2018).

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