The role of generalisation in an Adaptive Resonance Theory model of learning inflection classes

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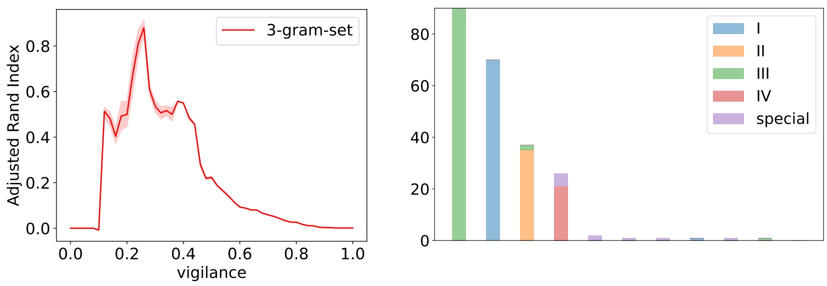
Humans are capable of generalising linguistic rules, e.g. by applying already acquired morphological patterns to unseen words (i.e. Prasada & Pinker, 1993; Krott, Baayen, & Schreuder, 2001). Inflection classes, groups of words that are inflected in the same way, help language users to deduce unseen word forms based on the patterns characteristic to the class (Milin, Filipović Durdević, & Moscoso Del Prado Martín, 2009; Veríssimo & Clahsen, 2014). Through this function in language processing, inflection classes can play a role in language change: inflection classes can attract new words to them (Round et al., 2022) and have been shown to become more distinct from one another over time (Enger, 2014). Any diachronic simulation of emergence or evolution of inflection classes needs a component for their acquisition on the individual level. In this study we investigate the role of generalisation in the individual learning task, with the ultimate goal of extending this to a diachronic model. We perform *unsupervised inflection class clustering* (cf. Guzmán Naranjo, 2020; LeFevre, Elsner, & Sims, 2021; Beniamine, Bonami, & Sagot, 2018 for related approaches) to investigate under which levels of generalisation a computer model is able to cluster verb paradigms together into inflection classes and which representations it learns. As a model, we use Adaptive Resonance Theory 1 (ART1) (Carpenter, 1987), a cognitively inspired neural network of category learning with one parameter, *vigilance*, controlling the degree of generalisation. The model learns in an online fashion, simulating the fact that a learner incrementally encounters data (Ackerman, Blevins, & Malouf, 2009; Blevins, Milin, & Ramscar, 2017). If the vigilance parameter is low, a new input sample is more likely to be added to an existing category, while if it is high, it is more likely that a new category will be created. The top-down weights in this two-layer network directly represent the features a certain category attends to, which provides interpretability of the learned representations (Grossberg, 2020)

We used the Latin present tense portion[1] of the Romance Verbal Inflection

[1]In Latin, inflection classes determine the inflection in the present tense and other tenses based on the present stem, but not in some other tenses like perfect (Pellegrini, 2019).

dataset (Beniamine, Maiden, & Round, 2020), which consists of phonetic forms of different paradigm cells for different verbs, as well as to which inflection classes these belong. We represent the data as trigrams, omitting temporal ordering of segments. As inputs to ART1 are binary vectors, we only register presence or absence of features. To combine the trigrams of all forms (1SG, 2SG, ... 3PL) for a verb (e.g. *stare* 'to stand') into one representation, we take the set of trigrams over the whole paradigm (i.e. presence of a trigram occurring in multiple forms is only registered once). 229 verbs (consisting of 971 trigram features) are run through the model two times. Figure 1a shows the classification accuracy for different vigilance values, evaluated using Adjusted Rand Index, a similarity measure between the inferred classification and the attested inflection classes. The model learns the inflection classes almost perfectly for a vigilance value of 0.25: this shows that a relatively high degree of generalisation (lower vigilance) is needed to obtain a good clustering. Analysis of the clustering of the best-performing model (Figure 1b) shows that the clusters roughly follow the real inflection classes in Latin, with the two first clusters perfectly matching with inflection classes III and I.

We conclude that ART1 is able to incrementally learn feature sets for groups of verb paradigms, that match well with known inflection classes for Latin. We find a narrow region of low vigilance parameter values (high generalisation) where the match is the best. An interesting next step would be to study evolution of inflection classes in an agent-based setting, where ART1 serves as an acquisition model for each agent. This setup would need an additional production model for transmitting word forms to other agents (cf. Hare & Elman, 1995; Cotterell, Kirov, Hulden, & Eisner, 2018; Parker, Reynolds, & Sims, 2018; Round et al., 2022 for agent-based models of inflection generation). If the agents would be initialised with word forms without a developed inflection class system, such experiments could also be used to study emergence of inflection classes.



(a) Clustering similarity to real inflection classes (Adjusted Rand Index), for different vigilance values, after 2 runs of data.

(b) Cluster analysis for vigilance 0.25 after 2 runs of data. Bar: discovered cluster, colour: real inflection class of assigned datapoints.

Figure 1.: Results ART1 on Latin present tense (trigram, set representation).

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