Can formal features be predicted from form? Using Machine Learning to predict transitivity class from the form of pantomime and ASL classifier constructions
(For poster presentation)

This project investigates the iconicity[1] of transitivity distinctions in ASL classifier constructions (CCs) and pantomimes produced by non-signers, and addresses whether there are universally available mapping biases between form and argument structure. The present work uses machine learning to discover what features of classifier construction and pantomime production are relevant to transitivity classification, and informs work elsewhere exploring how non-signers classify these manual actions. Patterned responses lend weight to a gesture-first origin of Language, bootstrapped by 'visual' transitivity.

While most research on iconicity concerns form-meaning mappings (e.g., Strickland et al., 2015) this project addresses motivated links between form and *structure*. This project piggybacks off Abner & King (2018) who did not find transitivity marking distinctions in pantomime based off event boundedness *i.a.*, and Brentari et al. (2012), who noted a distinction in production of intransitive and transitive pantomimes w.r.t. handshape complexity. The latter note that transitivity distinctions are coded *differently* in pantomimes than in CCs. We incorporate these findings into the present work and hypothesize that (a) non-signers code transitivity distinctions in their pantomimes, (b) both non-signers and signer recruit the same strategies for coding these distinctions (e.g., handshape, telicity, *i.a.*) but (c) the specific features used to code this distinction will differ between groups.

Five hearing non-signers pantomimed 70 videotaped actions. [2] One native Deaf signer signed these actions. 35 of the actions were intransitive and 35 transitive.[3] Video presentation was randomized for each subject; subjects were filmed individually. All videos were hand-coded by one undergraduate researcher and the authors for features representing the following strategies: handshape (Eccarius & Brentari, 2008), articulators involved (elbow, fingers, etc.), eye-gaze (towards hands, camera or other), end-marking (Wilbur, 2008), the behavior of the second hand (static, active, copy, etc.), *i.a.*

To determine if there is a consistent transitivity coding strategy within and across non-signing subjects, we used a binary Multinomial Naive Bayes classifier.[4] For the within-subject analysis, we divided each subject's feature set into 7 subsets, for a 7-fold leave-one-out cross-validation paradigm. Cross-subject classifiers were instead trained on feature sets from 5 non-signers and tested on the 6th's. All classifiers identified their targets with significantly above chance accuracy ($\geq$51/ 70 trials correct; p=0.000), where chance is 50% (transitive or intransitive), except for Subject 2 classifiers (41/70; p=0.06). Results are shown in Fig. 1. The 10 most informative features for classification were extracted for each fold per subject. Of these, the following were the 5 most frequent features common to all non-signers: [wiggle], [crossed], eye-gaze: other, 2nd-hand: ground, [stacked]. For the signer, the following features were most frequently informative: [stacked], [loop], [wiggle], [crossed],

[1] Here, I intend *iconicity* to refer to a motivated correspondence between visual features of a pantomime or CC and its meaning, here whether it's transitive or not.

[2] Participants were asked to represent only the actions, not the objects/ agents involved.

[3] All transitive videos were of a male agent manipulating an object by hand. All intransitive videos depicted the movement of an agent or object.

[4] *Classifier* here means an algorithm that sorts raw input into different categories, or *class*. It should not be confused with 'classifier construction.'

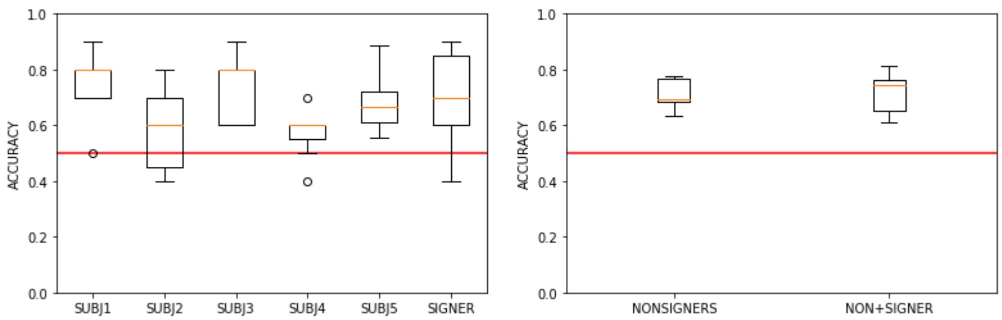

Figure 1: **Left**: Boxplots showing accuracy of within-subject classifiers. **Right**: Boxplot of cross-subject classifiers. "NONSIGNERS" shows accuracy of classifiers excluding signer's data; "NON+SIGNER" with. Red line = chance performance (50%).

[contact]. Despite Abner & King's results, elements of boundedness were informative for transitivity distinctions. Consistent with Brentari et al. (2012) handshape features were also significant predictors (including joint complexity, but to a lesser degree). Further, many of the same features were shared between the non-signers and signer, implying that the same visual resources are employed by both populations for this function.

To determine if there is a consistent transitivity coding strategy between populations, the data from the 5 non-signers formed the training set and the data from the native signer the test set. This classifier achieved 74% accuracy (52/ 70 trials; p=0.00), with the most informative features being [wiggle], [crossed], aperture change, [wide], and joint complexity. The features [wiggle] and [crossed] appear in every analysis.[5]

We conclude that transitivity distinctions are coded using the same general strategies in both non-signers and our signer (e.g., using handshape), suggesting a deep-rooted connection between praxis, vision, and communication. This is consistent with gesture-first theories of Language evolution which take iconicity as a means to achieve parity (Arbib, 2012). The present work sheds light on how parity can be achieved in a syntactic rather than lexical/ semantic domain. We also found that specific features vary in significance between populations, suggesting that conventionalization/ grammaticalization builds atop general communicative strategies.

References

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[5]The features reported here are not common to all productions, but are the most consistent predictors of transitivity. We elsewhere manipulate these features in a pantomime/ transitivity perception task.