From language development to language evolution: A unified view of human lexical creativity

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A defining property of human language is the creative use of words to express multiple meanings through word meaning extension. Such lexical creativity is manifested at different timescales, ranging from language development in children to the evolution of word meanings over history. We explore whether different manifestations of lexical creativity build on a common foundation. Using computational models, we show that a parsimonious set of semantic knowledge types characterize developmental data as well as evolutionary products of meaning extension spanning over 1,400 languages. Crucially, models for evolutionary data account very well for developmental data, and vice versa. These findings suggest a unified foundation for human lexical creativity underlying both the fleeting products of individual ontogeny and the evolutionary products of phylogeny across languages.

Humans often need to talk about new entities and concepts but must rely on a limited vocabulary of known words to do so. A common solution to overcoming this bottleneck is the

creative use of single words to express multiple meanings through a process known as word meaning extension (*1–3*).

In linguistic development, Vygotsky among others documented word meaning extension in young children, noting that a word like 'quah' can be overextended to express "a duck", "water", "liquid", or "a coin with an eagle on it" (*4–6*). At the individual level, child overextension is transient: it occurs during the early stages of life and vanishes in later language development (*7*) (see Table 1 for a definition of overextension and other key terms). By contrast, at the population level in language evolution, more stable forms of lexical creativity become entrenched in language after longer periods of time because of cultural transmission. Colexification, the phenomenon by which related meanings (like "finger"–"toe") are expressed with the same word (e.g., 'dit' in Catalan), can be a product of this process and is attested across languages (*8–11*). Similarly, words can also acquire new meanings over time through semantic change (*1, 12–14*). For instance, the word 'mouse' was extended to refer to a computer device due to the visual similarity between the device and a rodent.

Despite these differences in the manifestations of lexical creativity across levels (individual vs. population) and timescales (short vs. long), we posit that children and language users in general tackle the same fundamental task: to extend known words to novel referents that lack a word, by relating those referents to the current meanings of words. If this is true, we expect the kinds of overextensions that appear in child development to be similar to the kinds of meaning extensions attested in language evolution, since both build on a common foundation grounded in human experience and cognition. We develop a computational framework to test this idea, and show that it receives support in a large-scale analysis.

Developmental and evolutionary phenomena pertaining to lexical creativity have been studied by different research communities. Research in developmental psychology suggests that child overextension relies on the ability to identify similarity relations among concepts. This

Table 1: Key terms and their definitions as operationalized in this study.

Term	Definition
affectiveness	Measure of how pleasant, intense, and dominant a term is perceived to be (e.g., 'sunshine' scores high on all three dimensions).
associativity	Measure of how relatable two terms are (e.g., 'key' and 'door' are more closely associated than either is to 'dog').
colexification	Meanings expressed by the same word are colexified (e.g., Catalan uses a single word, 'dit', to express both "finger" and "toe").
lexical / lexicon	Relating to words and their meanings, or the knowledge thereof.
ontogeny	An individual's developmental history (e.g., their language use from early acquisition to adulthood).
overextension	Extended use of a known term to referents outside its normal category (e.g., a child saying 'apple' for any round object or 'dog' for any animal).
phylogeny	Evolutionary history of a group (e.g., historical development of languages).
semantics	Meaning, or the study thereof.
semantic change	Historical change in word meaning (e.g., 'mouse' taking on the new meaning "computer device").
taxonomy	Hierarchical or tree-based classification (e.g., an apple is a fruit)
visual similarity	Measure of resemblance based on visual features (e.g., how similar apples and balls look across many images).

ability has been shown to draw on multiple types of semantic knowledge using perceptual, action-functional, affective, and contextual information (*6, 15*). Similarly, recent work has demonstrated that visual, taxonomic, and associative information can jointly explain a variety of child overextension patterns (*15*). Work in linguistics and cognitive psychology has similarly suggested that semantic relatedness plays a role in colexification (*10, 11, 16–18*) and historical semantic change (*1, 3, 13, 19, 20*). Here we integrate these separate lines of research by asking whether different forms of lexical creativity, from childhood to language evolution, rely on a common foundation.

Our study is relevant to the long-standing issue concerning the relation between linguistic development and the evolution of language. One locus of this issue is the possibility that ontogeny recapitulates phylogeny in language (*21, 22*). That is, whether there are recurring patterns in child development that inform or reflect patterns in language evolution, or vice versa. On the one hand, previous work has suggested that ontogeny is shaped by a particular language –emphasizing learning at the individual level– whereas phylogeny is a product of lasting innovations –emphasizing language use at the population level (*23*). On the other hand, recent studies have shown that crosslinguistic patterns can recur during individual language learning (*24–26*); that cultural evolution of linguistic structures can be recapitulated in the laboratory (*27*); and that some development data predict lexical evolution rates (*28*).

We investigate the relation between linguistic development at the level of individuals and language evolution at the population level by taking a different perspective, informed by word meaning extension. Fig. 1A shows that there is only a small subset of meaning extensions that directly overlap between child development and products of language evolution (see *Supplementary Material* for details). This might be taken as weak evidence for the idea that ontogeny at least partially recapitulates phylogeny, or vice versa. Our approach aims at understanding the non-overlapping, broader space of creative meaning extensions illustrated in Fig. 1A: not only

4

the intersection, but the union of these phenomena.

We present a unified view of lexical creativity by hypothesizing that there is a latent common foundation that children and language users in general both build on when using words creatively. This common foundation relies on two components. First, grounded knowledge about objects, events, properties, and relations such as objects having certain shapes, or belonging to certain categories. Second, the use of this knowledge to link new referents lacking a word with current meanings of known words, based on similarities between the two. We thus test the proposal that both the types of knowledge involved and the use of similarity in word meaning extension are shared in child overextension and products of lexical creativity from language users in general.

Fig. 1B summarizes the computational framework we develop to test our proposal, which involves 1) explicitly defining a set of semantic knowledge types as proxies for the hypothesized common foundation; 2) using them to make cross-predictions about products of lexical creativity in development and evolution. If the different forms of lexical creativity draw on different knowledge types or do so to very different degrees, we expect minimal carry-over between the phenomena. If instead our unified view is warranted, we expect good cross-predictability; that is, we expect that models built from child data will successfully account for data that are the product of language evolution, and vice versa.

Framework

We develop a framework that incorporates four semantic knowledge types discussed commonly in the literature in connection to child overextension, colexification, and semantic change (*6, 10, 11, 15, 18, 29, 30*): associativity, and similarities based on visual, taxonomic, and affective information (see Fig. 1B). These are largely complementary in the information they provide (see Tables S1-S3), but they are not exhaustive. We operationalize these knowledge types based

5

on English resources, a limitation to which we return below. Details on methods and materials employed are in *Supplementary Material*.

We operationalize visual similarity using computationally derived visual representations of meanings. We follow a two-step procedure, drawing on existing work (*15, 31*). First, we use a computer vision model (*32*) to produce representations for images of instances of meanings (e.g., for images of dogs for the meaning "dog"). Second, we average these instance representations, yielding average visual representations that we take as surrogate meaning representations. We use these average representations to calculate the visual similarity of different meanings.

We define associativity in terms of how closely meanings are relatable in semantic memory. We quantify this using large-scale experimental data (*29*) that records the responses produced by subjects when prompted with a cue word (e.g., 'dog' may elicit 'cat', 'bone', or 'cuddly'). To obtain a measure of associativity, we transform cue-response counts using the best method identified in the literature so far (*11, 29*).

We take taxonomic similarity as a proxy for the categorical relatedness of meanings (e.g., "dog" and "cat" are taxonomically closer than either is to "key" or "love"). Following previous work on child overextension (*15*), we use a measure based on a large lexical database (*33*). The measure yields a score for the similarity of two meanings based on their closest common ancestor in a taxonomy.

We operationalize affectiveness as the similarity of affective experiential features, such as emotional valence. More precisely, following (*30*), we quantify affective similarity between meanings as the cosine similarity of their vectors of ratings, built from two large-scale databases of affectiveness norms (*34, 35*). These norms encompass ratings for valence, arousal, and dominance.

We analyze three independent data sets that represent three phenomena of lexical creativity. The first includes 254 cases of overextension reported in English-speaking children (*15*), the

most comprehensive collection available. We focus on English because overextension data from other languages is sparse and not suitable for a scalable analysis. The second data set draws on CLICS (*36*), the largest resource for colexification. We work with 22,379 attested colexification cases from 1,486 languages. Accompanying CLICS on the longer, evolutionary, timescale, we also analyze a third data set, DatSemShift (*37*). This is the largest resource of historical semantic change, covering 1,792 attested cases of semantic change from 516 languages.

For modeling purposes, we balance the data to include an equal number of positive and negative cases. Positive cases exhaust the attested pairs in each data set after pre-processing. Negative cases are randomly sampled from pairings of attested meanings that result in unattested combinations. Following this procedure, the task of the models is to use one or multiple semantic knowledge types (visual similarity; associativity; taxonomic similarity; or affectiveness) to characterize each phenomenon by contrast to a backdrop of negative cases (*10, 11, 15*).

To test our proposal, we first identify the model that best characterizes each of the three phenomena in isolation, and then test each of these models on data from the other phenomena. For model selection, we fit several logistic regression models predicting whether a pair of meanings colexifies in a language; participates in semantic change in a language; or appears in overextension in English. For each phenomenon, the only parameters that vary across their models are the knowledge types that they have as predictors. We consider all possible combinations: from four univariate models per phenomenon (one for each knowledge type) to models with two, three, or all four knowledge types. Colexification and semantic change models have language and geographical region as population-level effects. For model comparison and validation, we use approximate leave-one-out cross-validation. Our measure for model selection is expected log predictive density (*38*).

Results

Types of semantic knowledge Fig. 2A-C shows the standardized estimates from the best model for each phenomenon. Details and model rankings are provided in *Supplementary Material*. These results generalize previous findings analyzing each phenomenon separately (*3, 10, 11, 15*) in several ways. First, they show that, across phenomena, a word is more likely to be creatively extended when its meaning shares properties with a novel target referent: All coefficients are positive, meaning that the higher the semantic relatedness between two meanings, the higher the likelihood that they be connected through lexical creativity. When meanings are similar along several dimensions, the likelihood that lexical creativity connects them grows. Second, the results suggest that the semantic properties that anchor lexical creativity are of diverse types. All the best models draw on multiple knowledge types: for developmental data (Fig. 2A), all four of them; for evolutionary data (Fig. 2B-C), all modalities but affectiveness. A third finding is the similarity in the ranking of the coefficients, with associativity being the highest.

There are also differences between the models, also apparent in Fig. 2A-C. The most salient one is that associativity is more predictive of colexification and semantic change than of overextension. Taxonomy and visual similarity are more predictive of overextension than of the other two phenomena; and overextension factors in affectiveness, unlike the other two. These differences are partly reflected in the literature on child overextension, where a prominently documented type of overextensional error is violation of taxonomic constraints, e.g., using words to describe referents from higher-order taxonomic categories (*6*). However, these differences might also be attributed to the resources we use as proxies for knowledge types. They are based on adult language use and may thus account less well for children's data (e.g., in word association, adult speakers are more likely to associate concepts based on situation as opposed to taxonomy (*39*)).

8

Cross-prediction We next show that lexical creativity builds on a common foundation more directly, by performing a cross-predictive analysis. Specifically, we evaluate models for one phenomenon (e.g., overextension) on how well they account for data from a different phenomenon (e.g., colexification). We term this "cross-prediction", and contrast it with "self-prediction", that is, prediction for unseen data from the same phenomenon (e.g., the overextension model being applied to unseen overextension data). To rule out any carry-over due to pairs that appear in multiple data sets (e.g., "moon"-"sun", a meaning pair that colexifies in some languages and children have linked via overextension; see the intersection in Fig. 1A), we excluded all pairs that appear in more than one data set. This makes the task harder but ensures that the models' performance reflects their capabilities to characterize truly out-of-sample data. For details, see *Supplementary Material*.

Fig. 2D reports self- and cross-predictive accuracies of the models. Cross-prediction is very successful, even when compared to self-prediction. Not only is there good carry-over among the longer timescale phenomena, but also, crucially, between developmental and evolutionary phenomena: In all cases, the difference between self- and cross-prediction is very small (between 0 and 0.03), and the difference to the baseline large (0.22-0.31).

Since the models differ in their coefficients (Fig. 2A-C), it could be that the self- and cross-predictions yield similar accuracies but make quite different predictions. Fig. 3 shows that this is not the case. Self- and cross-predictions are well aligned throughout.

Robustness checks Our study builds on English resources to derive proxies for semantic knowledge due to a lack of comparable large-scale resources in other languages. This may not fully capture variation that is culture- or language-specific (*17*). Moreover, it could introduce English-specific biases, for instance, because the overextension data are from English speaking children. To ensure that such biases do not drive our findings, we perform a series of robustness

checks (see *Supplementary Material* for details).

First, we re-evaluate the models' cross-predictive abilities on data that excludes Indo-European languages. That is, we evaluate them again but excluding data from languages in the family that English belongs to. This exclusion only concerns colexification and semantic change data since the overextension data are based on English speakers. If cross-prediction results were driven by an English bias, we would expect the models' predictive capabilities to decrease when tested on non-Indo European data only. As shown in Fig. 4A, our results are robust in this regard.

Next, we perform checks by manipulating the data on which the models are fit. We re-fit the best colexification and semantic change models, leaving out one-by-one each of the five major language families found within the data. The same leave-one-out re-fitting process was conducted for all large geographical regions. Fig. 4B-C show that, again, the results are stable.

Finally, we also re-do our analyses using alternative visual representations obtained from a model trained on a non-linguistic task. Our results are stable when using these representations as well (see Tables S15-S20 and Figure S1).

Discussion

Our findings suggest a shared human capacity to creatively extend words to novel meanings across timescales, and across the individual- and population-level. We argued that this capacity relies on a common foundation of knowledge, with different facets of semantic relatedness enabling novel meaning extensions.

While our results indicate that diverse manifestations of lexical creativity are related and share common ground, the current study cannot speak directly to the nature of this relationship. Our findings are compatible with at least two different explanations. The first explanation is a direct causal pathway, with child overextensions being adopted directly by linguistic communities, hence explaining their resemblance to products of language evolution. However,

we believe this account is implausible for several reasons. First, it is unlikely for children's spontaneous innovations to be regularly adopted by broader adult populations or in language change (*23, 40*); and more so to a degree that leaves a crosslinguistic signature. Second, this account would leave the attested non-intersecting cases of colexification and semantic change in Fig. 1A unexplained. Some of these meanings are encountered relatively late in language acquisition, making them less likely to appear in overextension. Third, functional pressures toward efficient communication shape word meanings across languages (*11, 41–44*). These pressures are independent of child overextension and suggest that phenomena such as colexification are partially shaped by a need to distinguish meanings that appear in similar contexts. This may explain why child overextensions such as 'baby' for "adult" or 'bus' for "train" are rarely expressed by a single word across languages: doing so may cause ambiguity that is hard to resolve even in context (*11, 44, 45*). A second explanation, which we suggest to be more likely, is an indirect relationship, wherein products of lexical creativity stem from a common latent source of multifaceted semantic knowledge (Fig. 1B). That is, children draw from this source for overextension; and adults do so as well when extending meaning in novel ways. Some instances of creative lexical uses by adults (e.g., the metaphorical extension of 'mouse' to computer device) are then adopted by their linguistic communities over time, making their way into the lexicon.

To summarize, we show that the products of lexical creativity of young learners and language users in general can both be explained by a single latent common ground. Our work identifies a shared knowledge foundation for this common ground, extending prior research suggesting that words tend to express related meanings (*10, 11*) due to cognitive advantages for learning, retrieving, and interpreting words (*3, 46–48*); and that, more generally, the use of the same word for multiple meanings allows for more compressible lexicons (*49*), and for the reuse of shorter words that are easier to produce (*45, 50*). Future work should further specify the origins of this common foundation and the cognitive mechanisms of human lexical creativity.
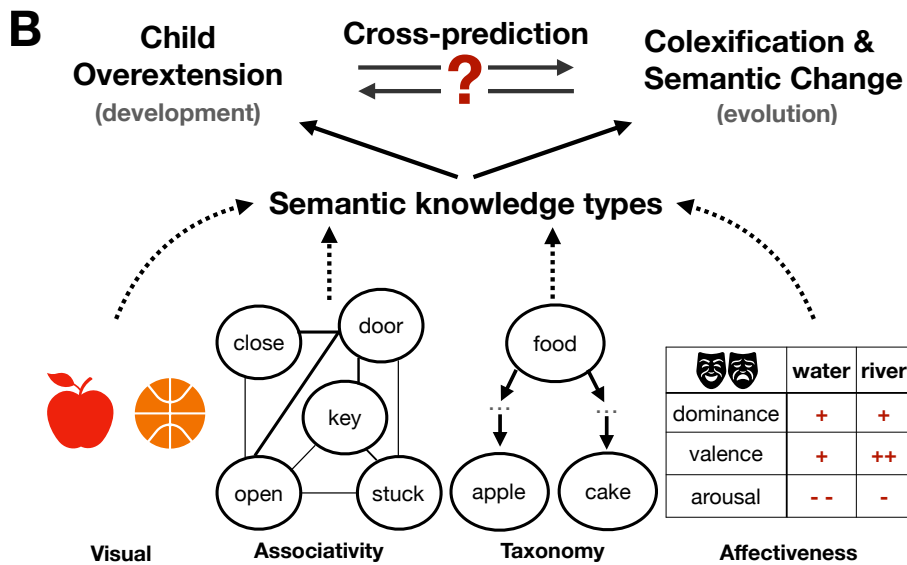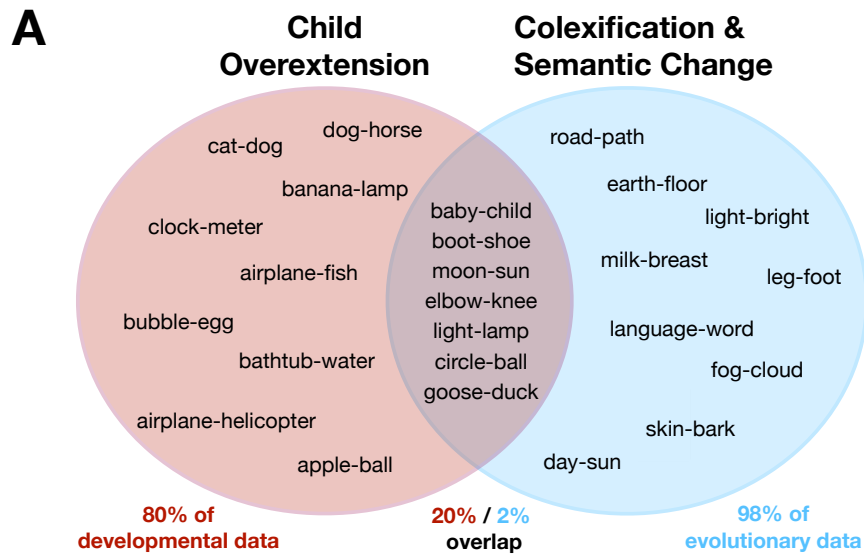
Figure 1: Illustrations of the phenomena of lexical creativity and the overall framework. A: Examples of word meaning extension as a common form of lexical creativity. Each is an attested pair of meanings that are co-expressed by a word form. The circle's intersection shows examples of child overextensions (in development) that are also attested in lexicons of the world's languages (through evolution). Cases outside this area are only attested at one timescale. B: Framework for investigating the possibility of a common foundation in lexical creativity. Four semantic knowledge types are considered: visual similarity, associativity, taxonomy, and affectiveness. The framework enables cross-prediction between developmental and evolutionary phenomena.
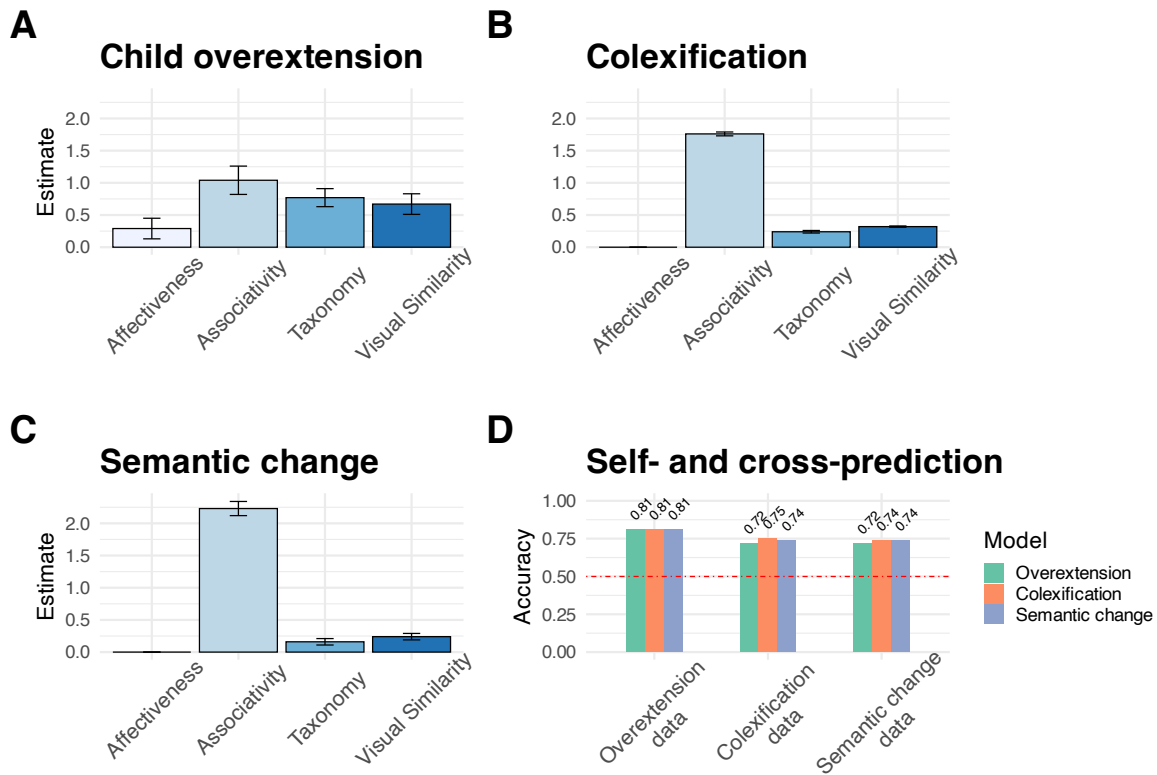
Figure 2: Summary of main results. A-C: Standardized estimates of the effect of knowledge types from best models of child overextension, colexification, and semantic change, respectively. The best models for evolutionary data (B-D) only use 3 predictors; we include a bar for affectiveness at 0 for illustration purposes. D: Accuracy of models when predicting new data. Self-predictions (e.g., colexification model's performance on colexification data) provide an upper-bound for cross-predictions. The random baseline of 0.5 (dashed line) provides a lower bound. Ceiling and bottom predictive accuracy are 1.0 and 0.
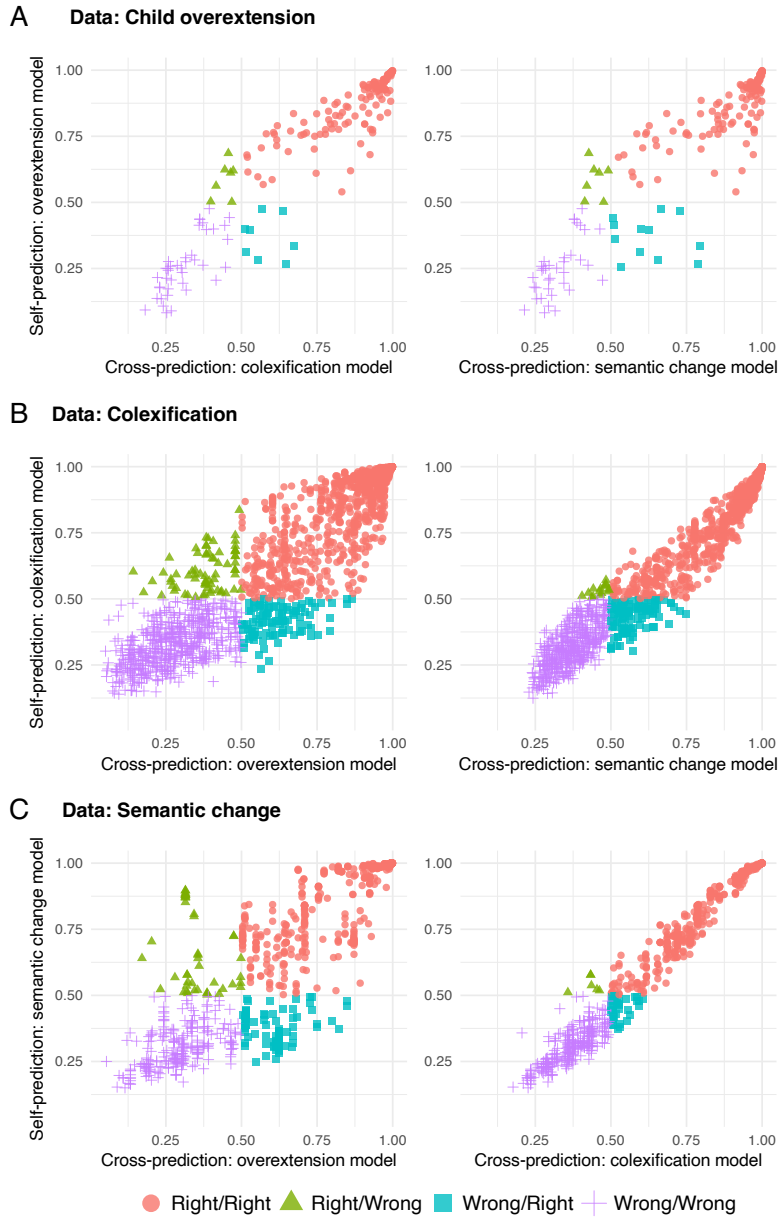
Figure 3: Comparisons of model self- and cross-predictions based on data from child overextension (A), colexification (B), and semantic change (C). Panels compare self-predictions made by the best model of a phenomenon (y-axis) against cross-predictions made by the best model for another phenomenon (x-axis). Data points are attested cases of each phenomenon (see Fig. S3 for a counterpart for unattested cases). Colors and shapes separate predictions into classes: 'Right/Right' are correct predictions by both the self- and cross-predicting models; 'Wrong/Wrong' are incorrect predictions by both; 'Right/Wrong' is a correct prediction from the self-predicting model but an incorrect one from the cross-predicting one, and conversely for 'Wrong/Right'. To make plots legible, colexification data were randomly subsampled to 8%.

14
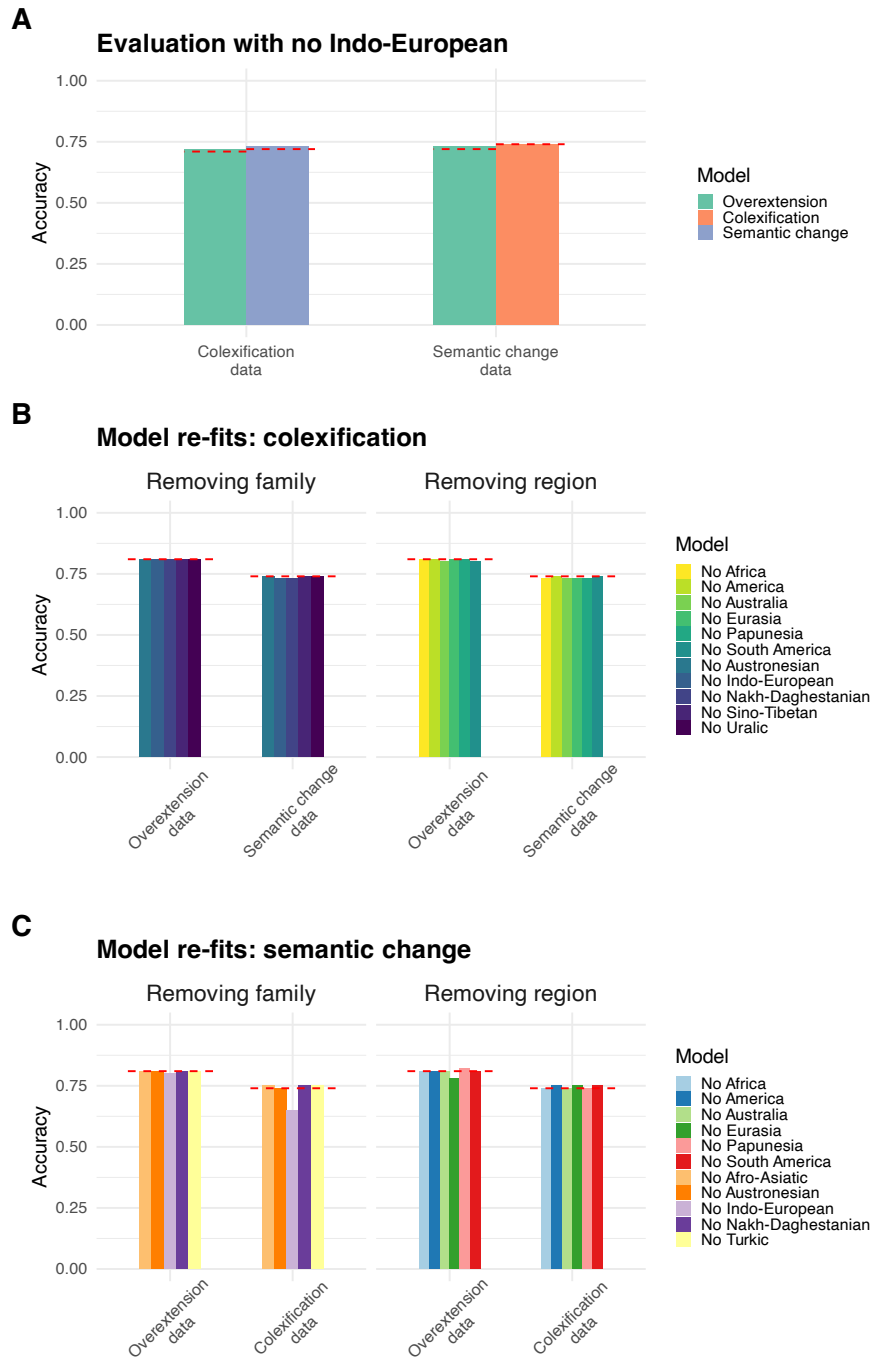
Figure 4: Robustness checks on cross-prediction against geographic or phylogenetic biases. Red dashed lines show accuracy of best models on original data (Fig 2D). A: Accuracy of best models when evaluated on data with no Indo-European data. B-C: Accuracy of colexification (B) and semantic change (C) models when re-fit either excluding data from one of their five largest language families (left) or without data from one of their six macro regions (right).

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Acknowledgments

20