Efficient communication drives the semantic structure of kinship terminology

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Abstract

Semantic distinctions are encoded variably in kinship terminology, the set of words that denotes family members. Nonetheless, it has been suggested that kinship terminology, like other linguistic domains, is constrained by opposing pressures to be simple yet expressive. Here, we use this insight to explore how the meaning space for kinship is structured cross-linguistically. Under the assumption that kinship systems map forms to meanings in a compressible, structure-preserving manner, we designed a metric for identifying which semantic features are most important for distinguishing individuals in a kinship system. For 1229 kinship systems, we calculated the correlation between semantic similarity (the weighted sum of shared semantic features between individuals) and wordform similarity (the edit similarity between terms). We then identified the optimal weight for each semantic feature in each language, confirming that kinship systems vary in which semantic features they encode, and that the features themselves vary in the extent to which they are encoded. Additionally, we identified that semantic features are encoded hierarchically; more simple and more informative features are weighted highest in general. By identifying this constraint on the distribution of forms and meanings in kinship terminology, our results provide new insights on how kin terms are structured for efficient communication.

Keywords: kinship terminology; semantic structure; efficient communication

Introduction

Kin terms, the words we use to denote our family members, differ cross-linguistically in the semantic distinctions they encode (Murdock, 1949; Greenberg, 1990; Nerlove & Romney, 1967; Kemp & Regier, 2012). To illustrate: an English speaker uses the kin terms *brother* and *sister* to denote their siblings, making a distinction on the basis of gender. An Indonesian speaker, on the other hand, distinguishes siblings by their relative age: *kakak* 'older sibling' and *adik* 'younger sibling'. And a Hindi speaker encodes both gender and relative age among their siblings, distinguishing *dīdī* 'older sister' from *behna* 'younger sister' and *bhaiya* 'older brother' from *choṭā bhāī* 'younger brother'. Meanwhile, Hawaiian speakers extend their sibling terminology to collateral kin, using *kaikuahine* to group female siblings with female cousins and *kaikua'ana* to group male siblings with male cousins.

The potential variation in kin terms is vast, but it has been argued that – as in other linguistic domains – there are constraints on this variation. A recent influential approach has characterised constraints on kinship terminology in terms of efficient communication (Kemp & Regier, 2012; Kemp, Xu, & Regier, 2018). Systems of kinship terminology optimally balance opposing pressures for simplicity and informativity. For a given level of communicative precision, the meanings of kin terms are as compressible as possible, and for a given level of compression they are as precise as possible. Kinship systems that fail to trade-off these pressures efficiently are unattested. Here, we expand on this idea that kinship systems are structured for efficient communication, exploring how semantic features are encoded in kinship terminology.

One way that language achieves compressibility is by mapping similar meanings to similar forms; the mapping between form and meaning is structure-preserving, or *topographic* (Brighton & Kirby, 2006). In the general lexicon, we see that more similar meanings are more likely to be co-lexified (i.e., referred to by the same wordform: Xu, Liu, & Regier, 2020), and there is also a subtle tendency for words with similar meanings to have similar forms (Monaghan et al., 2014; Dautriche et al., 2017). Experimental work suggests that people prefer to co-lexify similar meanings unless this is detrimental to communication (for instance, if two similar meanings need to be distinguished frequently: Karjus et al., 2021). We can see this in practice if we compare kinship systems. In English, we co-lexify the highly similar concepts 'older brother' and 'younger brother', while in Indonesian this distinction is preserved. Languages are also topographic at the morphosyntactic level, where we see compositional structure – a pervasive tendency of languages where the meaning of complex expressions is composed of the meanings of parts of the expression. Compositionality ensures that similar meanings map to similar forms, since shared elements of meaning will map to shared elements of form (Kirby, Cornish, & Smith, 2008; Kirby, Tamariz, Cornish, & Smith, 2015). Kin terms are often compositional; in English, the term *grandson* is composed of the morphemes *grand*, shared with *grandparent* and indicating a similar genealogical distance from the speaker, and *son*, indicating a male descendent.

Here, we use this insight about the expected relationship between meaning and form to explore how the meaning space for kinship is structured cross-linguistically. We explore whether kinship operates similarly to other linguistic domains, such that there universal tendencies in the encoding of particular semantics, or whether languages are free to elaborate any semantic feature at the expense of any other (as seems to be the case for encoding of sensory perception: Ma-

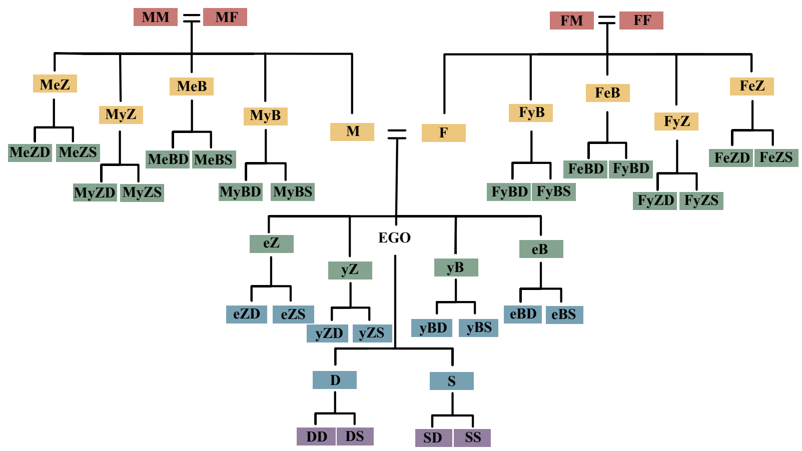

Figure 1: A schematic of the kin types we included in our analysis, organised in a family tree structure. 'Ego', at the centre, represents the reference individual. Shorter branch length indicates elder individuals, longer branch length indicates younger. Relative age is variably encoded, so only some kin types are marked for the elder/younger distinction. Kin types are given in shorthand: e.g. 'M' = mother, 'FyB' = father's younger brother, 'eZ' = elder sister, 'DS' = daughter's son, etc. Colours indicate kin types in the same generation for clarity.

jid et al., 2018). We report a metric for extracting the extent to which kinship terms encode particular semantic features, based on the assumption that kinship terminology will reflect semantics in a topographic manner, and we apply the metric to a large cross-linguistic database of kinship terminology. We find that languages indeed differ in the extent to which they encode semantic features, and that the semantic features themselves differ in the extent to which they are encoded. We identify a common structuring hierarchy for kin term semantics, and we suggest that this hierarchy emerges in response to pressures for kin terms to be simple and informative.

Measuring topographicity in the mapping from form to meaning in kin terms

Our metric assumes that kinship terminology is topographic, i.e. similar meanings will map to similar forms. We measure topographicity as the correlation between semantic similarity and form similarity. In order to determine which semantic features are encoded by a particular language, we ask: in this language, which features contribute to producing the maximal correlation between forms and meanings? In the following section, we describe our measures of semantic similarity and form similarity, and how we manipulated semantic similarity to produce the maximal correlation between these two measures.

Methodology

Data We used data from Kinbank, a database of kinship terminology spanning 1229 languages across 21 language families (Passmore et al., 2023). The database uses an etic framework for the definitions of kin terms – i.e., each kin term is associated with an objective, language-independent meaning. These meanings code a number of defining features for each type of relative, such as their gender, their connecting relative, or their age relative to another individual. For example, in English, the kin term *uncle* is associated with four etic definitions: 'mother's elder brother', 'mother's younger brother', 'father's elder brother', and 'father's younger brother'. We do not make these distinctions terminologically in English, but they are nonetheless distinctions that are encoded in kinship terminology in other languages (for instance in Myene, which uses the terms *ngw'onèró, ngw'erumbe, rer'onèró* and *rer'erumbe* respectively). Henceforth, we refer to these etic definitions as *kin types*.

For our analysis, we looked at kin types spanning five generations, from grandparents to grandchildren. To keep the meaning space within a reasonable scope, we only looked at consanguineal (blood-related) kin, not affinal kin (related by marriage). Figure 1 gives a schematic of the kin types we included in our analysis.

Measuring semantic similarity We built a feature matrix for every individual in the tree in Figure 1, looking at six features compiled from the anthropological literature on kinship (Goodenough, 1956; Murdock, 1949; Greenberg, 2005): Generation, Gender, Lineality, Gender of Connecting Relative (GCR), Relative Age, and Speaker Gender. The coding scheme for each feature is given in Table 1.

To measure the semantic similarity between two individuals, we compared their feature matrices. For each feature f_i in the set of features F we assigned a similarity score for individuals x and y based on their similarity for that feature. The pair could differ on the feature ($f_i(x,y) = -1$) or share the feature ($f_i(x,y) = 1$). If one or both individuals in the pair had an NA value for feature f_i, $f_i(x,y) = 0$.

The semantic similarity between two individuals is then a weighted sum of the by-feature similarities:

Table 1: Coding scheme for semantic similarity.

Feature	Description	Possible values
Generation	Which generation relative belongs to. (e.g. G0 = Ego's generation, G+1 = Ego's parents' generation).	G+2, G+1, G0, G-1, G-2
Gender	Gender of relative.	woman, man
Lineality	Whether relative is in Ego's direct lineage. (e.g. grandparents, parents, children or grandchildren).	lineal, collateral
Gender of connecting relative (GCR)	Gender of the individual who links Ego with relative (e.g. maternal aunt is linked by mother). NA values are assigned to Ego's direct descendents, as they are not linked by another relative.	woman, man, NA
Relative age	Whether relative is elder or younger relative to their counterpart. (e.g. elder brother vs younger brother) NA values are assigned when there is no counterpart with whom to compare relative age, e.g. grandparents.	elder, younger, NA
Speaker gender	Gender of Ego, the person using the term.	woman, man

$$Sem(x,y) \equiv \sum_{i \in F} f_i(x,y) w_i \tag{1}$$

where w_i is a weight between 0 and 1, such that $\sum_{i \in F} w_i = 1$. These weights determine the relative importance of similarity on a given semantic feature in determining similarity between individuals in the kinship system as a whole. If all semantic features were treated equally, $w_n = 1/|F|$. But if, for example, Gender had a higher weight, that would mean that individuals of the same gender were considered more similar than individuals differing in gender. Or, if Gender had weight of 0, that would indicate that similarity or difference in gender did not contribute to similarity between individuals. We searched for values of these weights that maximise the topographicity of kinship systems; i.e. they maximise the correlation between semantic similarity and form similarity.

Measuring form similarity We used normalised Levenshtein edit distance (Levenshtein, 1965) to measure the similarity between pairs of kin terms (the number of single-letter insertions, deletions, or replacements needed to turn one string into another, proportional to the length of the longer string). To make this a similarity measure, we took form similarity to be $1-$ the edit distance value for each pair, i.e. the proportion of the two strings that is the same.

Measuring topographicity Following e.g. Kirby et al. (2008) and Monaghan et al. (2014), we measure the topographicity of a kinship system by calculating the correlation between semantic similarity and form similarity. For all pairs of kin types in Figure 1, we compute the pairwise semantic similarities and the pairwise form similarities, and calculate the correlation between the resulting distribution of semantic similarities and form similarities. This tells us the extent to which similar meanings map to similar forms – we search for the weights on each semantic feature that maximise this correlation.

Finding optimal feature weights by language Different semantic features presumably contribute different amounts to the mapping between form and meaning in different languages. For each language in our dataset, we searched for the semantic feature weights which resulted in maximally topographic form-meaning mappings. For a given language, what measure of semantic similarity would produce the most structure-preserving relationship between meaning and form?

We used a Gradient Descent algorithm to optimise our semantic similarity measure to a particular language[1]. In our case, the function we want to optimise is our topographicity metric: we are searching for the maximum correlation between all pairwise semantic similarities and all pairwise form similarities. Our parameters are the relative weight each feature contributes to semantic similarity. By updating the weights on each semantic feature, our algorithm searches for the semantic similarities that correlate best with the form similarities distribution for each language[2].

The algorithm starts with a random set of parameter values, and finishes when no single change to the parameter settings will improve the correlation between form and meaning, leaving us with a set of optimal parameter values on each feature for each language – optimal in the sense that they are the most informative about which features matter to determine which individuals share all or part of their form. Higher weights indicate that sharing that feature is highly correlated with sharing parts of form, and lower weights indicate that sharing that feature has little or no impact on sharing form.

Results

Our results are dependent on the assumption that kin terms are topographic, so first we confirm that there is indeed a robust correlation between meanings and forms. Figure 2 (top) displays the distribution of correlations semantic similarity and edit similarity across all kinship systems, before and after we optimised their semantic similarity metric. A Kolmogorov-Smirnov test confirmed that correlations are reliably greater after optimisation ($D = 0.68, p < 0.01$). Additionally, a Monte Carlo analysis established that the correlations we observe between form and meaning are more robust than we would expect under the null assumption that the mapping between forms and meanings is random and un-

[1] Gradient descent was implemented using the `optimize.minimize` function from the Python `scipy` package, with parameters `method = L-BFGS-B` and `bounds = (0,1)`.

[2] Since gradient descent searches for the lowest possible function output, but we want the highest possible correlation, we minimised the negative of the correlation.

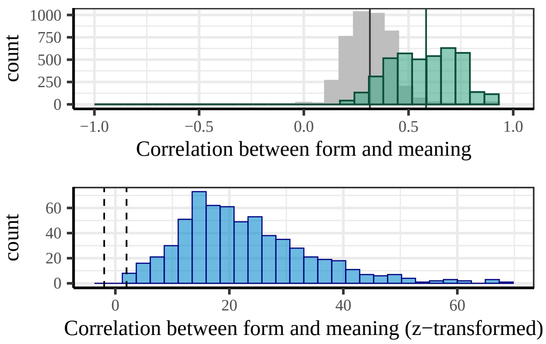

Figure 2: Top: Correlations between meaning and form when all semantic features are treated equally (grey) and after optimising the semantic similarity measure (green). Lines indicate mean correlation values. After optimisation, correlations range [0.2, 1] with a mean of 0.58. Bottom: Z-transformed correlations after optimisation. Dotted lines indicate significance thresholds (1.96 standard deviations; $p < 0.05$).

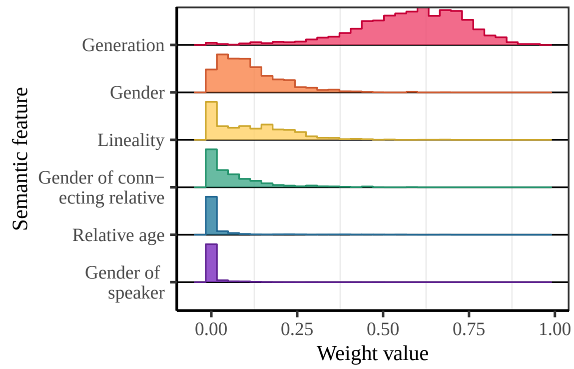

Figure 3: Distribution of weights for each semantic feature, in order of descending median value. Generation is weighted much higher than all other features, and never receives a weight of 0. Other than Generation, features are variably encoded, with Relative Age and Speaker Gender the most often weighted 0.

structured (following e.g. Kirby et al., 2008). For each language in our dataset, we compared the veridical correlation to a Monte Carlo sample created by permuting which kin terms are associated with which meanings. Figure 2 (bottom) shows z-scores generated by comparing the veridical correlation with 1000 such permutations: 99% of correlations are significantly larger than we would expect if there were no relationship between form and meaning.

Having shown that the correlation between form and meaning is robust, we turn to our main predictions. We expected that kinship systems would vary in which semantic features they encode, but that there may be common tendencies that hold across languages.

Our results corroborate that kinship systems vary in the distinctions they encode terminologically. Figure 4 shows the optimal weights on each feature for a sample of languages in our dataset. The weights for English are as expected. Generation has the highest weight, reflecting the fact that individuals are likely to share a term if they are in the same generation (but not otherwise). Lineality is second, capturing the re-use of the morphemes *grand-*, *son*, *daughter*, *mother* and *father* for individuals in Ego's direct lineage. Last is Gender, as because individuals who share a term often share a gender (e.g. mother's sister and father's sister are both *aunt*), but the weight is small since overall, sharing a gender is not a reliable indicator of form similarity in English (e.g. *mother* and *daughter* both denote women but share no part of their form). The remaining features receive a weight of 0, as they do not contribute to kin term distinctions in English. Looking across the other languages in Figure 4, features show variability in their weighting. Generation is often weighted much higher than the other features, though not exclusively – e.g. for Seki, GCR is the highest weighted feature. After Generation, the order of weights varies more; in English the second ranked feature is Lineality, but in Hawaiian it is Gender.

We also confirm that there is by-feature variation in encoding. Figure 3 shows the distribution of weights by feature across the languages in our sample, reflecting substantial variation between features, but clear universal trends in the distribution of weights. Generation is the only feature that always receives a non-zero weighting, while all other features are commonly weighted 0 (though Gender less commonly than the others). In other words, Generation is invariably encoded in kinship terminology, while the remaining features may or may not be encoded. To support this observation there is variation in feature weights, we fit a mixed effects beta regression predicting the effect of semantic feature (sum-coded) on weight with random intercepts for language and language family. Model comparison to a null model without the fixed effect for feature indicated that semantic features differ systematically in the their weights, i.e. the degree to which they are encoded terminologically across the languages in our sample ($\chi^2 = 6287.3, df = 5, p < 0.001$).

Features vary in the extent to which they are encoded, but is there a reliable hierarchy between the weightings across languages? We fit a second beta regression model, again predicting weight by semantic feature with random intercepts for language and language family, but this time using successive differences contrast coding to compare each level of the semantic feature factor with the next. This allowed us to investigate incremental changes in weights across the features. Factor levels were arranged in descending order by their median value, such that e.g. Generation (median = 0.59) was compared against Gender (median = 0.10) and Gender against Lineality (median = 0.09) – full model output and contrasts are given in Table . The model revealed a significant decrease

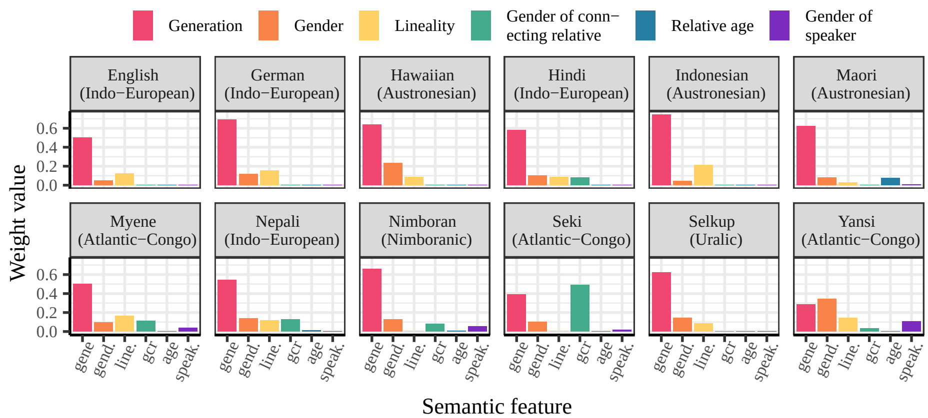

Figure 4: Final parameter values for a sample of languages in our dataset. Generation is weighted very highly in many languages, there is variation in the extent to which other features are encoded.

in weight between each pair of successive contrasts, suggesting that there is a reliable cross-linguistic hierarchy in the encoding of semantic features. However, effect sizes vary considerably: the difference between Generation and Gender is the largest ($b =$ -2.13). The differences between Gender and Lineality ($b =$ -0.47, and Lineality and GCR ($b =$ -0.45) are comparatively smaller. Then there is a larger difference between GCR and Relative Age ($b =$ -0.68) and a smaller difference between Relative Age and Speaker Gender ($b =$ -0.20). Variation in effect size suggests that the hierarchy is more robust for some features than others. Generation is reliably the top ranked, but the relative order of Gender, Lineality, and GCR is more likely to vary between languages. Relative Age and Speaker Gender are reliably weighted lower than all other features, but may vary in order between themselves. Based on this analysis, we propose the following cross-linguistic hierarchy: Generation, {Gender, Lineality, GCR} – {Relative Age, Speaker Gender}, where curly brackets indicate multiple features are similarly likely to be encoded.

Discussion

We have presented a new method for measuring how different semantic features are reflected in the mapping between form and meaning. Cross-linguistically, we have identified that features are encoded hierarchically, with a strong tendency for Generation to be encoded, followed by Gender, Lineality or GCR, and Relative Age and Speaker Gender the least likely. We now discuss how these results align with an account of kinship variation as constrained by efficient communication, and propose efficient communication as the mechanism underlying the hierarchy we have identified.

Efficient communication about kin

Our results contribute to a growing body of work on how communicative efficiency constrains variation in kinship terminology. Kemp and Regier (2012) identified that systems of kinship terminology are designed for efficient communication: they achieve an optimal trade-off between simplicity and informativeness, balancing precise expression of meanings with compression. Their approach focused on balancing the length of the grammar that generates kin term meanings against the degree of expression of those meanings given the frequency with which particular kin need to be distinguished in communication.

Here, we have approached their claim about efficiency from another angle. Firstly, by looking at topographic mappings between kin term forms and meanings (rather than taking the word as the primary unit of distinction), we have been able to look at lexical *and* sub-lexical regularities in the way that the kin term meaning space is structured — to our knowledge sub-lexical regularities have not previously been considered as a source of compression in kinship terminology.

Additionally, our measure of kin term semantics focuses on feature distinctions between individuals rather than the minimum description length measure employed by Kemp and Regier (2012). While their measure permits an understanding of how recursion is employed in kin term semantics, our measure offers a language-specific way to measure the communicative importance of particular distinctions — by assuming that kinship systems are topographic, we are able to extract inferences about their semantics from the terminology itself. Both approaches are needed for a complete perspective on how kin term semantics are structured.

Finally, by measuring semantic similarity between individuals as a matrix of shared semantic features, we have been able to draw cross-linguistic generalisations about the way that the meaning space is structured. The semantic hierarchy we have identified here is one way in which kinship systems are constrained in their variation; below we offer insight on how this variation is a joint adaptation to pressures for simplicity and expressivity imposed during the transmission of language.

Table 2: Beta regression model estimates predicting weight by semantic feature using successive differences coding.

Predictor	*b* (log-odds)	*se*	*z*	*p*	95% CIs (log-odds)
Gender - Generation	-2.12535	0.03942	-53.92	<0.001	(-2.17643, -2.07427)
Lineality - Gender	-0.47488	0.04154	-11.43	<0.001	(-0.55630, -0.39326)
Gender of Connecting Relative - Lineality	-0.44978	-0.04277	-10.52	<0.001	(-0.53361, -0.36596)
Relative Age - Gender of Connecting Relative	-0.68180	0.04322	-15.78	<0.001	(-0.76651, -0.59709)
Speaker Gender - Relative Age	-0.19795	0.04312	-4.59	<0.001	(-0.28247,-0.11343)

Category structure vs category informativeness

We assume that constraints on language variation are not random, but rather reflect evolutionary adaptations to the transmission of language. Structures that are easily learned and useful for communicating proliferate (Kirby et al., 2008, 2015; Smith, 2022). We therefore suggest that the relative ordering of features represents a trade-off between how easy a feature is to learn and the amount of information that the feature provides about the referent.

Some features require knowledge of a single individual, like Generation, Gender, or Speaker Gender. These features are *intrinsic* to the individual – they encode information about a single individual, either the referent or the speaker. On the other hand, features like Lineality, GCR, or relative are *relational*: they require knowledge about another individual. For example, to identify the GCR value of an individual requires that you also know the Gender value of the relative who connects you. In short, intrinsic features are simple, but relational features are comparatively more complex: learning relational features requires an extra level of abstraction, and requires that you have more knowledge about other individuals in the kinship system.

Evidence from children's kin term acquisition emphasises that intrinsic features are easier to learn. Children commonly misinterpret kin terms by associating them with intrinsic features rather than relational ones; they preferentially choose that a *grandfather* is any kindly old man, rather than specifically the father of their parent (Keil & Batterman, 1984). Additionally, children are prone to overextending intrinsic features, and will make errors like overextending the term *brother* to boys in general (Blythe et al., 2020). These errors suggest that children are tuned in to intrinsic features of the individual, which means distinctions of Generation and Gender are easier for them to learn. And once they establish intrinsic features to be distinctive, they are likely to extend them to other kin. Overgeneralisation could lead to a feature distinction being used more prolifically within the kinship paradigm - thereby ending up not just more frequent cross-linguistically, but also weighted more strongly.

However, the pressure for categories to be simple is modulated by a pressure for them to be informative, favouring encoding distinctions that are communicatively relevant, and underspecifying on communicatively less-important dimensions (Kirby et al., 2015; Silvey, Kirby, & Smith, 2015; Winters, Kirby, & Smith, 2018). This can operate at two levels: the amount of information encoded by the feature, and how important that information is to communicative success. Generation is a highly informative feature; by encoding Generation terminologically, you narrow down the possible referent of a kin term to a single generation of kin out of five. By comparison, encoding Gender, Lineality or GCR only narrows the space by half: the referent is either a man or a woman. Relative Age narrows the space of possible meanings even less, as only some relatives have a relative age value. Speaker Gender does not narrow the possibilities at all, because it only encodes information about the speaker, not the referent.

However, different languages still encode features to a varying extent, likely because the communicative necessity of features varies cross-culturally. It is commonly proposed that our kin terms can provide an important marker of who is involved in kin-based social practices (Jones, 2010; Murdock, 1949). For example, the Diné (Navajo) are a matrilineal society, and as a consequence inheritance is passed down through women (Witherspoon, 1975); accordingly, Navajo makes fine-grained distinctions by GCR, and further distinguishes by Gender and Relative Age in female-connected relatives only. As a result, Navajo kinship system distinguishes with high precision the individuals from whom you will inherit, and the individuals who will inherit from you.

We therefore propose that there are competing pressures imposed on the categorisation of kin between (a) the ease of learning feature distinctions that are intrinsic to a single individual and therefore require no abstraction and (b) the expressive power of distinctions that are culturally important, even if they are more complex.

Conclusion

We have presented a new measure for extracting the extent to which semantic features are encoded in kinship terminology cross-linguistically by employing assumptions about topographicity in form-meaning mappings. We found that languages vary in the features they encode, and the features themselves vary in the extent to which they tend to be encoded. Nonetheless, there is a clear hierarchy in which features are likely to be encoded cross-linguistically. We suggest that the hierarchy reflects a trade-off between a preference for kin terms to encode simpler features, but also to encode as much information as possible. Our findings contribute to the growing canon on how kinship terminology is structured for efficient communication.

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