On the universal structure of human lexical semantics

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How universal is human conceptual structure? The way concepts are organized in the human brain may reflect distinct features of cultural, historical, and environmental background in addition to properties universal to human cognition. Semantics, or meaning expressed through language, provides indirect access to the underlying conceptual structure, but meaning is notoriously difficult to measure, let alone parameterize. Here, we provide an empirical measure of semantic proximity between concepts using cross-linguistic dictionaries to translate words to and from languages carefully selected to be representative of worldwide diversity. These translations reveal cases where a particular language uses a single "polysemous" word to express multiple concepts that another language represents using distinct words. We use the frequency of such polysemies linking two concepts as a measure of their semantic proximity and represent the pattern of these linkages by a weighted network. This network is highly structured: Certain concepts are far more prone to polysemy than others, and naturally interpretable clusters of closely related concepts emerge. Statistical analysis of the polysemies observed in a subset of the basic vocabulary shows that these structural properties are consistent across different language groups, and largely independent of geography, environment, and the presence or absence of a literary tradition. The methods developed here can be applied to any semantic domain to reveal the extent to which its conceptual structure is, similarly, a universal attribute of human cognition and language use.

polysemy | human cognition | semantic universals | conceptual structure | network comparison

The space of concepts expressible in any language is vast. There has been much debate about whether semantic similarity of concepts (i.e., the layout of this space) is shared across languages (1–9). On the one hand, all human beings belong to a single species characterized by, among other things, a shared set of cognitive abilities. On the other hand, the 6,000 or so extant human languages spoken by different societies in different environments across the globe are extremely diverse (10–12). This diversity reflects accidents of history as well as adaptations to local environments. Notwithstanding the vast and multifarious forms of culture and language, most psychological experiments about semantic universality have been conducted on members of Western, educated, industrial, rich, democratic (WEIRD) societies, and it has been questioned whether the results of such research are valid across all types of societies (13). The fundamental problem of quantifying the degree to which conceptual structures expressed in language are due to universal properties of human cognition, as opposed to the particulars of cultural history or the environment inhabited by a society, remains unresolved.

A resolution of this problem has been hampered by a major methodological difficulty. Linguistic meaning is an abstract construct that needs to be inferred indirectly from observations, and hence is extremely difficult to measure. This difficulty is even more apparent in the field of lexical semantics, which deals with how concepts are expressed by individual words. In this regard, meaning contrasts both with phonetics, in which instrumental measurement of physical properties of articulation and acoustics is relatively straightforward, and with grammatical structure, for which there is general agreement on a number of basic units of analysis (14). Much lexical semantic analysis relies on linguists' introspection, and the multifaceted dimensions of meaning currently lack a formal characterization. To address our primary question, it is necessary to develop an empirical method to characterize the space of concepts.

We arrive at such a measure by noting that translations uncover the alternate ways that languages partition meanings into words. Many words are polysemous (i.e., they have more than one meaning); thus, they refer to multiple concepts to the extent that these meanings or senses can be individuated (15). Translations uncover instances of polysemy where two or more concepts are fundamentally different enough to receive distinct words in some languages, yet similar enough to share a common word in other languages. The frequency with which two concepts share a single polysemous word in a sample of unrelated languages provides a measure of semantic similarity between them.

We chose an unbiased sample of 81 languages in a phylogenetically and geographically stratified way, according to the methods of typology and universals research (12, 16–18) (*SI Appendix*, section I). Our large and diverse sample of languages allows us to avoid the pitfalls of research based solely on WEIRD societies. Using it, we can distinguish the empirical patterns we detect in the linguistic data as contributions arising from universal conceptual structure from those contributions arising from artifacts of the speakers' history or way of life.

Significance

Semantics, or meaning expressed through language, provides indirect access to an underlying level of conceptual structure. To what degree this conceptual structure is universal or is due to properties of cultural histories, or to the environment inhabited by a speech community, is still controversial. Meaning is notoriously difficult to measure, let alone parameterize, for quantitative comparative studies. Using cross-linguistic dictionaries across languages carefully selected as an unbiased sample reflecting the diversity of human languages, we provide an empirical measure of semantic relatedness between concepts. Our analysis uncovers a universal structure underlying the sampled vocabulary across language groups independent of their phylogenetic relations, their speakers' culture, and geographic environment.

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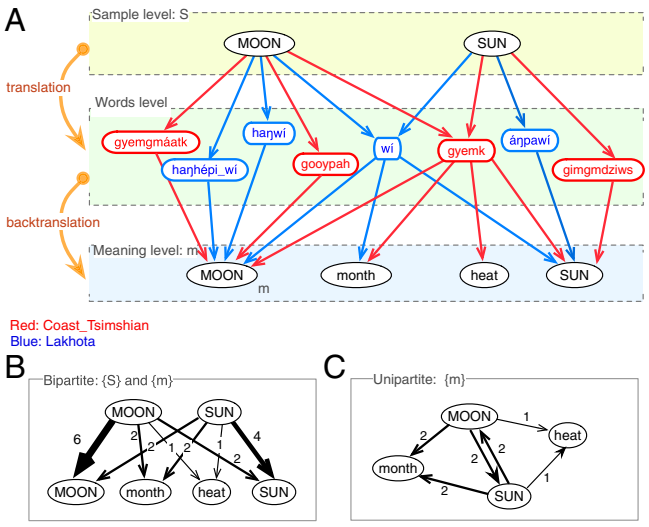


Fig. 1. Schematic figure of the construction of semantic networks. (*A*) Bipartite semantic network constructed through translation (links from the first layer to the second layer) and back-translation (links from the second layer to the third layer) for the cases of MOON and SUN in two American languages: Coast Tsimshian (red links) and Lakhota (blue links). We write the starting concepts from the Swadesh list (SUN, MOON) in capital letters, whereas other concepts that arise through translation (month, heat) are in written in lowercase letters. (*B*) We link each pair of concepts with a weight equal to the number of translation–back-translation paths. (*C*) Resulting weighted graph. More methodological information can be found in *SI Appendix*, section II.

There have been several cross-linguistic surveys of lexical polysemy, and its potential for understanding historical changes in meaning (19) in domains such as body parts (20), cardinal directions (21), perception verbs (22), concepts associated with fire (23), and color metaphors (24). We add a new dimension to this existing body of research by using polysemy data from a systematically stratified global sample of languages to measure degrees of semantic similarity between concepts.

Our cross-linguistic study starts with a subset of concepts from the Swadesh list (25–28). Most languages express these concepts using single words. From the list, we chose 22 concepts that refer to material entities (e.g., STONE, EARTH, SAND, ASHES), celestial objects (e.g., SUN, MOON, STAR), natural settings (e.g., DAY, NIGHT), and geographic features (e.g., LAKE. MOUNTAIN) rather than body parts, social relations, or abstract concepts. The chosen concepts are not defined a priori with respect to culture, perception, or the self; yet, familiarity and experience with them are influenced by the physical environment that speakers inhabit. Therefore, any claim of universality of lexical semantics needs to be demonstrated in these domains first. The detailed criteria of data selection are elaborated in *Materials and Methods* and *SI Appendix*, section I.

Constructing Semantic Network from Translations

We represent semantic relations obtained from dictionary translations of the chosen concepts as a network. Two meanings are linked if they can be reached from one another by a translation into some language and then back. The link is weighted by the number of such paths (of length 2), that is, the number of polysemous words that represent both meanings (details are provided in *Materials and Methods*). Fig. 1 illustrates the construction with examples from two languages. Translating the word SUN into Lakhota results in *wí* and *áŋpawí*. Although the latter picks up no other meaning, *wí* is polysemous: it possesses additional meanings of MOON and month, so they are linked to SUN in the network. A similar polysemy is observed in Coast Tsimshian, where *gyemk*, the translation of SUN, also means heat, thus providing a link between SUN and heat. We write the initial Swadesh concepts (SUN and MOON in this example) in capital letters, whereas other concepts that arise through translations (month and heat here) are written in lowercase letters. We restrict our study to the neighborhood of the initial Swadesh concepts, so further translations of these latter concepts are not followed.

With this approach, we can construct a semantic network for each individual language. It is conceivable, however, that a group of languages bears structural resemblances as a result of the speakers' sharing common historical or environmental features. A link between SUN and MOON, for example, recurs in both languages illustrated in Fig. 1, yet does not appear in many other languages, where other links are seen instead. Thus, for example, SUN is linked to divinity and time in Japanese and to thirst and DAY/DAYTIME in the Khoisan language !Xóõ. The question is then the degree to which these semantic networks are similar across language groups, reflecting universal conceptual structure, and the extent to which they are sensitive to cultural or environmental variables, such as phylogenetic history, climate, geography, or the presence of a literary tradition. We test such questions by constructing aggregate networks from groups of languages that share a common cultural and environmental property and comparing these networks between different language groups.

Semantic Clusterings

As a point of comparison for the networks obtained from such groups of languages, we show the network obtained from the entire set of languages in Fig. 2 and *SI Appendix*, Fig. S6, displaying only the links that appear more than once. This network exhibits the broad topological structure of polysemies observed in our data. It reveals three almost disconnected clusters of concepts that are far more prone to polysemy within each cluster than between them. These clusters admit a natural semantic interpretation. Thus, for example, the semantically most uniform cluster, colored in blue, includes concepts related to water. A second, smaller cluster, colored in yellow, groups concepts related to solid natural materials (e.g., STONE/ROCK, MOUNTAIN) and associated landscape features (e.g., forest, clearing, highlands). The third cluster, colored in red, is more diverse, containing terrestrial terms (e.g., field, floor, ground, EARTH/SOIL), celestial objects [e.g., CLOUD(S), SKY, SUN, MOON], and units of time (e.g., DAY, NIGHT, YEAR). Although the clustering is strong, there do exist rare polysemies that occur only once in our dataset (and are thus not displayed in Fig. 2) connecting the three clusters. Thus, for example, CLOUD(S) is polysemous with lightning in Albanian, whereas the latter is polysemous with STONE/ROCK in !Xóõ, and whereas holy place is a polysemy for MOUNTAIN in Kisi, it is instead polysemous with LAKE in Wintu. The individual networks including such weak links can be accessed in our web-based platform (29).

The links defining each of the three clusters can be understood in terms of well-known kinds of polysemies: metonymies (polysemy between part and whole) and commonly found semantic extension to hypernyms (more general concepts), hyponyms (more specific concepts), and cohyponyms (specific concepts belonging to the same category). The first cluster contains both liquid substances and topographic features metonymically related to water. The substance polysemies in this cluster are various liquids, cohyponyms of WATER. The topographic polysemies (e.g., LAKE, RIVER) are also linked as cohyponyms under "body of water" and "flowing water." Similarly, in the third cluster, the bridge between the terrestrial and celestial components is provided by the hyponyms of "granular aggregates," which span both the terrestrial EARTH/SOIL, DUST, and SAND and the airborne SMOKE and CLOUD(S).

Evidence for Universal Semantic Structure

The semantic network across languages reveals a universal set of relationships among these concepts that possibly reflects human

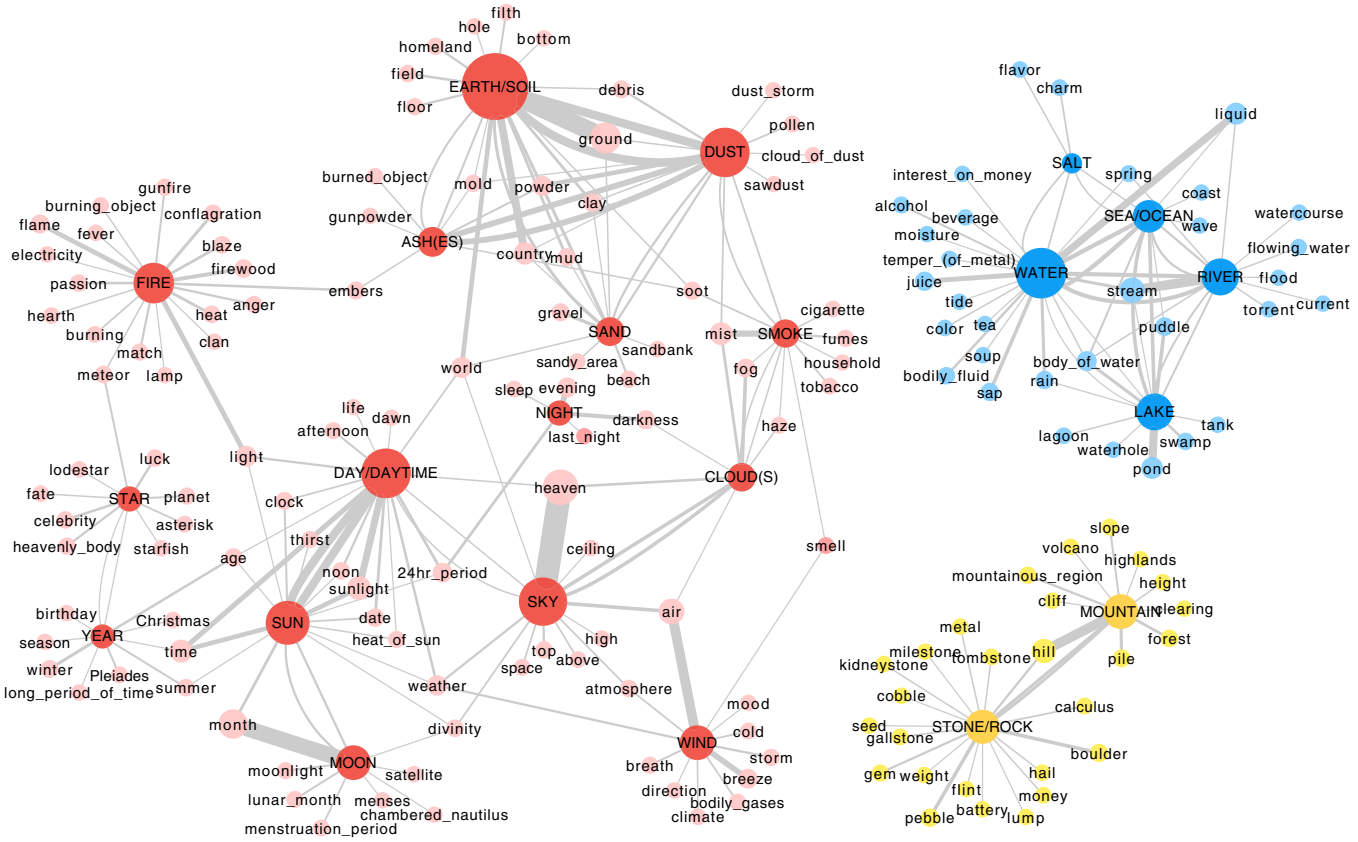


Fig. 2. Semantic network inferred from polysemy data. Concepts are linked when polysemous words cover both concepts. Swadesh words (the starting concepts) are capitalized. The size of a node and the width of a link to another node are proportional to the number of polysemies associated with the concept and with the two connected concepts, respectively. Links whose weights are at least 2 are shown, and their directions are omitted for simplicity. The thick link from SKY to heaven, for example, shows that a large number of words in various languages have both SKY and heaven as meanings. Three distinct clusters, colored in red, blue, and yellow, are identified. These clusters may indicate a set of relationships among concepts that reflects a universal human conceptual structure in these domains.

conceptualization of these semantic domains (8, 12, 30). Alternatively, it has been postulated that such semantic relations are strongly influenced by the physical environment that human societies inhabit (31).

To address this question, we group the languages by various factors (*SI Appendix*, Table SIII) comprising the geography, climate, or topography of the region where they are spoken, and the presence or absence of a literary tradition in them, and we test the effect of these factors on the semantic network. We measured the similarity between these groups' semantic networks in several ways. First, we measured the correlation between the commute distances (32) between nearby concepts (*Materials and Methods* and *SI Appendix*, section III A 1). Then, to compare these networks' large-scale structure, we clustered the concepts in each network hierarchically as a dendrogram (*SI Appendix*, Fig. S8) and compared them using two standard tree metrics (33–35): the triplet distance (D_{triplet}) and the Robinson–Foulds distance (D_{RF}) (*Materials and Methods* and *SI Appendix*, section III A). To test whether these networks are more similar than what we would expect by chance, we performed bootstrap experiments, where we compared each network with the one where the concepts were randomly permuted (*SI Appendix*, section III). As shown by the p_1 values in Fig. 3, in every case, the networks of real language groups are far more similar to each other than to these randomly permuted networks, allowing us to reject decisively the null hypothesis that these semantic networks are completely uncorrelated (statistical details are provided in *SI Appendix*, section III B).

All these tests thus establish that different language groups do indeed have semantic structure in common. To explore this universal semantic structure further, we tested a null hypothesis at the other extreme, that cultural and environmental variables have no effect on the semantic network. For this purpose, we performed a different kind of bootstrap experiment, where we replaced each language group with a random sample of the same size from the set of languages. As denoted by p_2 in Fig. 3, we find that, with rare exceptions, there is no statistical support (*SI Appendix*, section III B) for the hypothesis that the differences between the language groups studied are any larger than between random groups of the same size. This fact means that the impacts of cultural and environmental factors are weaker than what can be established with our dataset; thus, our results are consistent with the hypothesis that semantic clustering structure is independent of culture and environment in these semantic domains.

Heterogeneity of the Semantic Network

The universal semantic network shown in Fig. 2 is heterogeneous in both node degrees and link weights. The numbers of polysemies involving individual meanings are uneven, possibly trending toward a heavy-tailed distribution (Fig. 4). This distribution indicates that concepts have different tendencies of being polysemous. For example, EARTH/SOIL has more than 100 polysemies, whereas SALT has only a few.

Interestingly, we find that this heterogeneity is also universal: The numbers of polysemies of the various concepts that we studied in any two languages are strongly correlated with each other. This

correlation holds despite the observation that the languages differ in the overall magnitude of polysemy, so that the same concepts are far more polysemous in some languages than in others (*SI Appendix*, Fig. S2). In fact, a simple formula predicts the number of polysemies, n_{SL}, involving sense S in language L rather well (*SI Appendix*, Fig. S9):

$$n_{SL}^{\text{model}} \equiv n_S \times \frac{n_L}{N}, \quad [1]$$

where n_S is the number of polysemies involving sense S in the aggregate network from all languages, N is the total number of polysemies in this aggregate network, and n_L is the number of polysemies in the language L. This formula is exactly what we would expect (*Materials and Methods* and *SI Appendix*, section II B) if each language randomly and independently draws a subset of polysemies for each concept S from the universal aggregate network, which we can identify as an underlying "universal semantic space" (*SI Appendix*, Fig. S5). The data for only three concepts, MOON, SUN, and ASHES, deviate from this linear pattern by more than the expected sampling errors ($p \approx 0.01$) in that they display an initial rapid increase in n_{SL} with n_L, followed by a saturation or slower increase at larger values of n_L (*SI Appendix*, Fig. S10). These deviations can be accommodated using a slightly more complicated model described in *SI Appendix*, section IV.

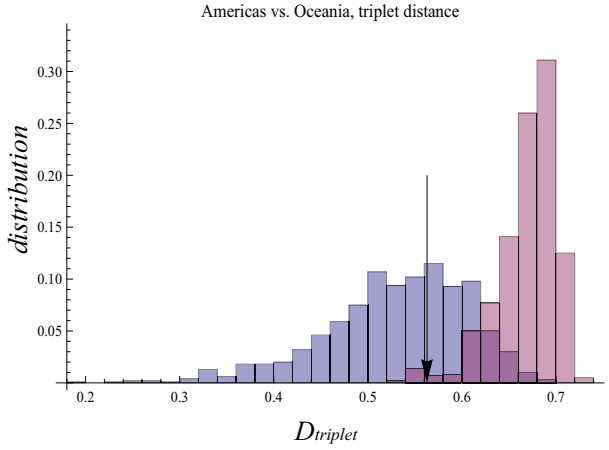
Discussion

We propose a principled method to construct semantic networks linking concepts via polysemous words identified by cross-linguistic dictionaries. Based on the method, we found overwhelming evidence that the semantic networks for different groups share a large amount of structure in common across geographic and cultural differences. Indeed, our results are consistent with the hypothesis that cultural and environmental factors have little statistically significant effect on the semantic network of the subset of basic concepts studied here. To a large extent, the semantic network appears to be a human universal: For instance, SEA/OCEAN and SALT are more closely related to each other than either is to SUN, and this pattern is true for both coastal and inland languages.

These findings have broad implications. Universal structures in lexical semantics such as we observe can greatly aid reconstruction of human history using linguistic data (37, 38). Much progress has been made in reconstructing the phylogenies of word forms from known cognates in various languages, thanks to the ability to measure phonetic similarity and our knowledge of the processes of sound change. The relationship between semantic similarity and semantic shift, however, is still poorly understood. The standard view in historical linguistics is that any meaning can change to any other meaning (39, 40), and no constraint is imposed on what meanings can be compared with detect cognates (41). In contrast to this view, we find that at least some similarities occur in a heterogeneous and clustered fashion.

Previous studies (9, 19–21, 23, 24, 42–45) have investigated the presence or absence of universality in how languages structure the lexicon in a few semantic domains dealing with personal items like body parts, perceptual elements like color metaphors, and cultural items like kinship relations. In this work, we study instead the domain of celestial and landscape objects that one may a priori expect to be strongly affected by the environment. We find, however, that the semantic networks on which these natural objects lie are universal. It is generally accepted among historical linguists that language change is gradual: Over historical time, words gain meanings when their use is extended to similar meanings and lose meanings when another word is extended to the first word's meaning. If such transitional situations are common among polysemies, then the meaning shifts in this domain are likely to be equally universal, and the observed weights on different links of the semantic network reflect the

A



B

Language groups	r	p_1	p_2	D_{triplet}	p_1	p_2	D_{RF}	p_1	p_2
Region									
Americas vs. Eurasia	0.13	0.007	0.003†	0.59	0.06	0.20	30	0*	0.42
Americas vs. Africa	0.73	0*	0.98	0.59	0.02	0.20	30	0*	0.46
Americas vs. Oceania	0.25	0*	0.06	0.56	0.02	0.38	26	0*	0.87
Eurasia vs. Africa	0.41	0*	0.25	0.52	0*	0.62	32	0.01	0.31
Eurasia vs. Oceania	0.27	0*	0.08	0.60	0.06	0.16	28	0*	0.78
Africa vs. Oceania	0.59	0*	0.78	0.46	0*	0.82	34	0.01	0.18
Climate									
Humid vs. Cold	0.59	0*	0.84	0.58	0.04	0.17	28	0*	0.49
Humid vs. Arid	0.07	0.20	0.005†	0.61	0.12	0.10	34	0.01	0.13
Cold vs. Arid	0.33	0*	0.13	0.50	0.01	0.71	30	0*	0.53
Topography									
Inland vs. Coastal	0.74	0*	0.97	0.59	0.04	0.14	28	0*	0.39
Literacy									
Literacy vs. No literacy	0.34	0*	0.08	0.49	0.01	0.62	28	0*	0.45

Fig. 3. (*A*) Illustration of our bootstrap experiments. The D_{triplet} between the dendrograms of the Americas and Oceania is 0.56 (indicated by the downward arrow) (33, 34). This value sits at the very low end of the distribution of distances generated by randomly permuted networks (the red-shaded profile on the right), but it is well within the distribution that we obtain by resampling random groups from the set of languages (the blue-shaded profile on the left). This fact gives strong evidence that each pair of groups shares an underlying semantic network, and that the differences between them are no larger than would result from random sampling (details are provided in *Materials and Methods*). Therefore, these two language groups are much more closely related than if concepts were permuted randomly, showing they share a common semantic structure, but they are roughly as related as any pair of language groups of these sizes, suggesting that the geographic and cultural difference between them have little effect on their structure. (*B*) Comparing distance metrics, the Pearson correlation (r) between commute distances (32) on the semantic networks of groups and the D_{triplet} and D_{RF} among the corresponding dendrograms (33–35), on two bootstrap experiments to obtain p_1 (Mantel test or randomly permuted dendrograms) and p_2 (surrogate groups). The p_1 values for the former bootstrap (p_2 values for the latter) are the fraction of 1,000 bootstrap samples whose distances are smaller (larger) than the observed distance. In either case, 0* denotes a value below 0.001 (i.e., no bootstrap sample satisfied the condition). The Mantel test used 999 replicates for Pearson correlations to calculate p_1 values, and 99 bootstrap samples (or 999 when marked with †) were used for p_2. Given that we make 11 independent comparisons for any quantity, a Bonferroni-corrected (36) significance threshold of $p_{1,2} = 0.005$ is appropriate for a nominal test size of $p = 0.05$ (more extensively discussed in *SI Appendix*, section III B).

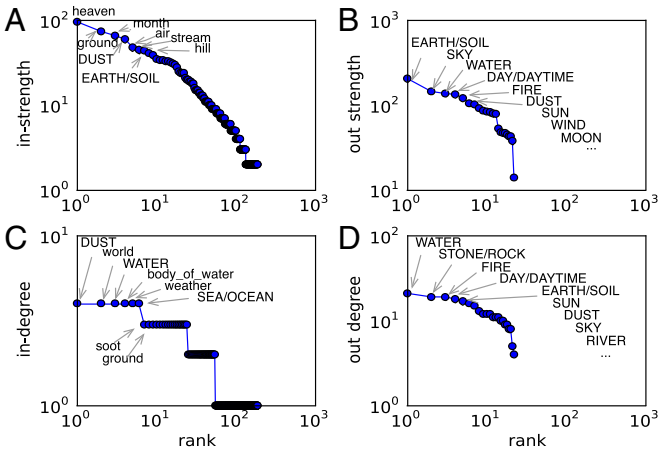


Fig. 4. Rank plot of concepts in descending order of their strengths (total weight of links) and degrees (number of links) shown in Fig. 2. Entries from the initial Swadesh list are distinguished with capital letters. (*A*) In-strengths of concepts: sum of weighted links to a node. (*B*) Out-strengths of Swadesh entries: sum of weighted links from a Swadesh entry. (*C*) In-degree of the concepts: number of unweighted links to a node. (*D*) Out-degree of Swadesh entries: number of unweighted links from a node. A node strength in this context indicates the total number of polysemies associated with the concept in 81 languages, whereas a node degree means the number of distinct concepts associated with the node regardless of the number of synonymous polysemies associated with it. The word "heaven," for example, has the largest number of polysemies, but most of them are with SUN, so that its degree is only three.

probabilities of words to be in transition. As such, semantic shifts can be modeled as diffusion in the conceptual space, or along a universal semantic network, and thus our constructed networks can serve as important input to methods of inferring cognates.

Our results are obtained from detailed typological studies from a sample of the world's languages. We chose to collect data manually from printed dictionaries. This approach ensures that our sample is unbiased and representative of the variation known among languages but foregoes the large sample size that online digital resources offer, because these data are dominated by a few languages from developed countries with long-established writing systems and large speaker populations. We find, however, that the patterns of polysemy in our data have little correlation with environmental, social, and other linguistic attributes of the language. This consistency across language groups suggests that languages for which digital resources are available are likely to produce networks similar to those networks created from the full sample. Therefore, the semantic network constructed here can be extended with more extensive data from online dictionaries and digital corpora by automated means (46). In such analysis with digitally available resources, one can examine if patterns of polysemy could be shared among more closely related language groups than the genus level, and if universality holds for other semantic domains.

Materials and Methods

Polysemy Data. High-quality bilingual dictionaries between a sample of languages and well-known European languages were used to identify polysemies. The samples of 81 languages were selected to be phylogenetically and geographically diverse, covering many low-level language families or genera (16–18, 31) (*SI Appendix*, section I B). The concepts studied were taken from the Swadesh list (25), because these concepts are likely to have historically stable single-word representation in many languages. The domain of study was chosen to extend the existing body of cross-linguistic surveys of lexical polysemy (19–24), and its potential for understanding historical changes in meaning (19) (*SI Appendix*, section I).

We use multiple modern European languages (English, Spanish, French, German, or Russian) interchangeably as semantic metalanguages because sufficiently high-quality bilingual dictionaries were not available in any one of these languages (*SI Appendix*, sections I C and I D). Polysemies were then identified by looking up the translations (and back-translations) of each of the 22 concepts to be studied (*SI Appendix*, section I A) in each language in our sample. All translations (i.e., all synonyms) were retained. The semantic metalanguages themselves sometimes display polysemies: English "day," for example, expresses both DAYTIME and 24HR PERIOD. In our chosen domain, however, the metalanguage polysemy did not create a problem because the lexicographer usually annotates the translation sufficiently. *SI Appendix*, section I elaborate the bases for the procedure and methodology.

Mantel Test. The commute distance between two nodes in a network is the expected number of steps it takes a random walker to travel from one node to another and back, when the probability of a step along a link is proportional to its link weight (32). We connect all word senses with a small weight to provide a finite, although large, distance between disconnected components. To avoid the effect of this modification, the final calculation excludes distances larger than the number of nodes. We then compare the Pearson correlation, r^*, of the commute distances between networks of empirical language groups with the distribution of r that is derived from the bootstrap experiments. The first bootstrap performs the Mantel test (47) by randomly permuting nodes (word senses) of the observed network (p_1), and the second bootstrap compares random groups of languages of the same size (p_2). These tests are carried out for classification by each of the following four variables: geography (Americas, Eurasia, Africa, or Oceania), climate (humid, cold, or arid), topography (inland or coastal), and literary tradition (presence or absence). The language groups and their sizes are listed in *SI Appendix*, Table SIII, and the details of bootstrap methods are provided in *SI Appendix*, section III A 1. All these calculations were done using the statistical package R (48–51).

Hierarchical Clustering Test. A hierarchical spectral algorithm clusters the Swadesh word senses. Each sense i is assigned to a position in $\mathbb{R}^n$ based on the ith components of the n eigenvectors of the weighted adjacency matrix. Each eigenvector is weighted by the square of its eigenvalue and clustered by a greedy agglomerative algorithm to merge the pair of clusters having the smallest Euclidean distance between their centers of mass, through which a binary tree or dendrogram is constructed (*SI Appendix*, Fig. S8).

The distance between the dendrograms obtained from each pair of language groups is measured by two standard tree metrics. The D_{triplet} (33, 34) is the fraction of the $\binom{n}{3}$ distinct triplets of senses that are assigned a different topology in the two trees (i.e., those triplets for which the trees disagree as to which pair of senses are more closely related to each other than they are to the third). The D_{RF} (35), is the number of "cuts" on which the two trees disagree, where a cut is a separation of the leaves into two sets resulting from removing an edge of the tree.

For each pair of groups, we perform two types of bootstrap experiments. First, we compare the distance between their dendrograms with the distribution of distances we would see under a hypothesis that the two groups have no shared lexical structure. Were this null hypothesis true, the distribution of distances would be unchanged under the random permutation of the concepts at the leaves of each tree, despite holding fixed the topologies of the dendrograms. Comparing the observed distance against the resulting distribution gives a P value, called p_1 in Fig. 3. These P values are small enough to reject decisively the null hypothesis. Indeed, for most pairs of groups the D_{RF} is smaller than the distance observed in any of the 1,000 bootstrap trials ($P \lesssim 0.001$), marked as 0* in the table. These small P values give overwhelming evidence that the hierarchical clusters in the semantic networks have universal aspects that apply across language groups.

In the second bootstrap experiment, the null hypothesis is that the nonlinguistic variables, such as culture, climate, and geography, have no effect on the semantic network, and that the differences between language groups simply result from random sampling: For instance, the similarity between the Americas and Eurasia is what one would expect from any disjoint groups of the 81 languages of given sizes 29 and 20, respectively. To test this null hypothesis, we generate random pairs of disjoint language groups with the same sizes as the groups in question and measure the distribution of their distances. The P values, called p_2 in Fig. 3, are not small enough to reject this null hypothesis. Thus, at least given the current dataset, there is no statistical distinction between random sampling and empirical data, further supporting our claims of universality of conceptual structure (*SI Appendix*, section III A).

Null Model of Degree Distributions. The simplest model of degree distributions assumes no interaction between concept and languages. The number of polysemies of concept S in language L, that is, n_{SL}^{model}, is linearly proportional to both the tendency of the concept to be polysemous and the tendency of the

language to distinguish word senses. These tendencies are estimated from the marginal distribution of the observed data as the fraction of polysemy associated with the concept, $p_S^{\text{data}} = n_S^{\text{data}}/N$, and the fraction of polysemy in the language, $p_L^{\text{data}} = n_L^{\text{data}}/N$, respectively. The model, then, can be expressed as $p_{SL}^{\text{model}} = p_S^{\text{data}} p_L^{\text{data}}$, a product of the two.

The Kullback–Leibler (KL) divergence is a standard measure of the difference between an empirical distribution, such as $p_{SL}^{\text{data}} \equiv n_{SL}^{\text{data}}/N$, and a theoretical prediction, p_{SL}^{model} (52, 53). This distance is expressed as:

$$D\left(p_{SL}^{\text{data}} \| p_{SL}^{\text{model}}\right) \equiv \sum_{S,L} p_{SL}^{\text{data}} \log\left(p_{SL}^{\text{data}} \Big/ p_{SL}^{\text{model}}\right).$$

We evaluated the statistical significance of the differences between our model predictions and the experimental degree distribution by comparing the observed KL divergence with the one expected under multinomial sampling with probability p_{SL}^{model}. The P value was calculated as the area under the expected distribution to the right of the observed value (details are provided in *SI Appendix*, section IV).

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Supporting Information: On the Universal Structure of Human Lexical Semantics

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CONTENTS

I. METHODOLOGY FOR DATA COLLECTION AND ANALYSIS

The following selection criteria for languages and words, and recording criteria from dictionaries, were used to provide a uniform treatment across language groups, and to compensate where possible for systematic variations in documenting conventions. These choices are based on the expert judgment of authors WC, LS, and IM in typology and comparative historical linguistics.

A. Criteria for selection of meanings

Our translations use only lexical concepts as opposed to grammatical inflections or function words. For the purpose of universality and stability of meanings across cultures, we chose entries from the Swadesh 200-word list of basic vocabulary. Among these, we have selected categories that are likely to have single-word representation for meanings, and for which the referents are material entities or natural settings rather than social or conceptual abstractions. We have selected 22 words in domains concerning natural and geographic features, so that the web of polysemy will produce a connected graph whose structure we can analyze, rather than having an excess of disconnected singletons. We have omitted body parts—which by the same criteria would provide a similarly appropriate connected domain—because these have been considered previously [1–4]. The final set of 22 words are as follows:

- Celestial Phenomena and Related Time Units:
  STAR, SUN, MOON, YEAR, DAY/DAYTIME, NIGHT

- Landscape Features:
  SKY, CLOUD(S), SEA/OCEAN, LAKE, RIVER, MOUNTAIN

- Natural Substances:
  STONE/ROCK, EARTH/SOIL, SAND, ASH(ES), SALT, SMOKE, DUST, FIRE, WATER, WIND

B. Criteria for selection of languages

The statistical analysis of typological features of languages inevitably requires assumptions about which observations are independent samples from an underlying generative process. Since languages of the world have varying degrees of relatedness, language features are subject to Galton's problem of non-independence of samples, which can only be overcome with a full historical reconstruction of relations. However, long-range historical relations are not known or not accepted for most language families of the world [5]. It has become accepted practice to restrict to single representatives of each genus in statistical typological analyses [6, 7].[1]

In order to minimize redundant samples within our data, we selected only one language from each genus-level family [8]. The sample consists of 81 languages chosen from 535 genera in order to maximize geographical diversity, taking into consideration population size, presence or absence of a written language, environment and climate, and availability of a good quality bilingual dictionary. The list of languages in our sample, sorted by geographical region and phylogenetic affiliation is given in Table I, and the geographical distribution is shown in Fig. 1. The contributions of languages to our dataset, including numbers of words and of polysemies, are shown as a function of language ranked by each language's number of speakers in Fig. 2.

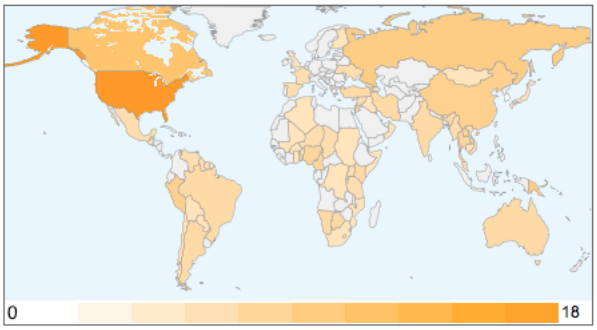

FIG. 1. Geographical distribution of selected languages. The color map represents the number of languages included in our study for each country. White indicates that no language is selected and the dark orange implies that 18 languages are selected. For example, the United States has 18 languages included in our study because of the diversity of Native American languages.

[1] As long as the proliferation of members within a language family is not correlated with their typological characteristics, this restriction provides no protection against systematic bias, and in general it must be weighed against the contribution of more languages to resolution or statistical power.

Region	Family	Genus	Language
Africa	Khoisan	Northern	Ju|'hoan
		Central	Khoekhoegowab
		Southern	!Xóõ
	Niger-Kordofanian	NW Mande	Bambara
		Southern W. Atlantic	Kisi
		Defoid	Yorùbá
		Igboid	Igbo
		Cross River	Efik
		Bantoid	Swahili
	Nilo-Saharan	Saharan	Kanuri
		Kuliak	Ik
		Nilotic	Nandi
		Bango-Bagirmi-Kresh	Kaba Démé
	Afro-Asiatic	Berber	Tumazabt
		West Chadic	Hausa
		E Cushitic	Rendille
		Semitic	Iraqi Arabic
Eurasia	Basque	Basque	Basque
	Indo-European	Armenian	Armenian
		Indic	Hindi
		Albanian	Albanian
		Italic	Spanish
		Slavic	Russian
	Uralic	Finnic	Finnish
	Altaic	Turkic	Turkish
		Mongolian	Khalkha Mongolian
	Japanese	Japanese	Japanese
	Chukotkan	Kamchatkan	Itelmen (Kamchadal)
	Caucasian	NW Caucasian	Kabardian
		Nax	Chechen
	Katvelian	Kartvelian	Georgian
	Dravidian	Dravidian Proper	Badaga
	Sino-Tibetan	Chinese	Mandarin
		Karen	Karen (Bwe)
		Kuki-Chin-Naga	Mikir
		Burmese-Lolo	Hani
		Naxi	Naxi
Oceania	Hmong-Mien	Hmong-Mien	Hmong Njua
	Austroasiatic	Munda	Sora
		Palaung-Khmuic	Minor Mlabri
		Aslian	Semai (Sengoi)
	Daic	Kam-Tai	Thai
	Austronesian	Oceanic	Trukese
	Papuan	Middle Sepik	Kwoma
		E NG Highlands	Yagaria
		Angan	Baruya
		C and SE New Guinea	Kolari
		West Bougainville	Rotokas
		East Bougainville	Buin
	Australian	Gunwinyguan	Nunggubuyu
		Maran	Mara
		Pama-Nyungan	E and C Arrernte
Americas	Eskimo-Aleut	Aleut	Aleut
	Na-Dene	Haida	Haida
		Athapaskan	Koyukon
	Algic	Algonquian	Western Abenaki
	Salishan	Interior Salish	Thompson Salish
	Wakashan	Wakashan	Nootka (Nuuchahnulth)
	Siouan	Siouan	Lakhota
	Caddoan	Caddoan	Pawnee
	Iroqoian	Iroquoian	Onondaga
	Coastal Penutian	Tsimshianic	Coast Tsimshian
		Klamath	Klamath
		Wintuan	Wintu
		Miwok	Northern Sierra Miwok
	Gulf	Muskogean	Creek
	Mayan	Mayan	Itzá Maya
	Hokan	Yanan	Yana
		Yuman	Cocopa
	Uto-Aztecan	Numic	Tümpisa Shoshone
		Hopi	Hopi
	Otomanguean	Zapotecan	Quiavini Zapotec
	Paezan	Warao	Warao
		Chimúan	Mochica/Chimu
	Quechuan	Quechua	Huallaga Quechua
	Araucanian	Araucanian	Mapudungun (Mapuche)
	Tupí-Guaraní	Tupí-Guaraní	Guaraní
	Macro-Arawakan	Harákmbut	Amarakaeri
		Maipuran	Piro
	Macro-Carib	Carib	Carib
		Peba-Yaguan	Yagua

TABLE I. The languages included in our study. Notes: Oceania includes Southeast Asia; the Papuan languages do not form a single phylogenetic group in the view of most historical linguists; other families in the table vary in their degree of acceptance by historical linguists. The classification at the genus level, which is of greater importance to our analysis, is more generally agreed upon.

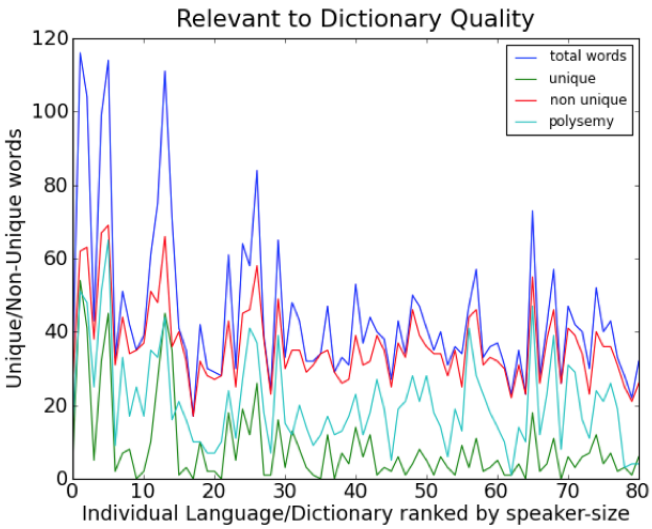

FIG. 2. Vocabulary measures of languages in the dataset ranked in descending order of the size of the speaker populations. Population sizes are taken from Ethnologue. Each language is characterized by the number of meanings in our polysemy dataset, of unique meanings, of non-unique meanings defined by exclusion of all single occurrences, and of polysemous words (those having multiple meanings), plotted in blue, green, red, and cyan, respectively. We find a nontrivial correlation between population of speakers and data size of languages.

C. Semantic analysis of word senses

All of the bilingual dictionaries translated object language words into English, or in some cases, Spanish, French, German or Russian (bilingual dictionaries in the other major languages were used in order to gain maximal phylogenetic and geographic distribution). That is, we use English and the other major languages as the semantic metalanguage for the word senses of the object language words used in the analysis. English (or any natural language) is an imperfect semantic metalanguage, because English itself has many polysemous words and divides the space of concepts in a partly idiosyncratic way. This is already apparent in Swadesh's own list: he treated STONE/ROCK and EARTH/SOIL as synonyms, and had to specify that DAY referred to DAYTIME as opposed to NIGHT, rather than a 24-hour period. However, the selection of a concrete semantic domain including many discrete objects such as SUN and MOON allowed us to avoid the much greater problems of semantic comparison in individuating properties and actions or social and psychological concepts.

We followed lexicographic practice in individuating word senses across the languages. Lexicographers are aware of polysemies such as DAYTIME vs. 24 HOUR PERIOD and usually indicate these semantic distinctions in their dictionary entries. There were a number of cases in which

different lexicographers appeared to use near-synonyms when the dictionaries were compared in our cross-linguistic analysis. We believe that these choices of near-synonyms in English translations may not reflect genuine subtle semantic differences but may simply represent different choices among near-synonyms made by different lexicographers. These near-synonyms were treated as a single sense in the polysemy analysis; they are listed in Table II.

anger	fury, rage
ASH(ES)	cinders
bodily gases	fart, flatulence, etc.
celebrity	famous person, luminary
country	countryside, region, area, territory, etc. [bounded area]
darkness	dark (n.)
darkness	dark
dawn	daybreak, sunrise
debris	rubbish, trash, garbage
EARTH/SOIL	dirt, loam, humus [= substance]
evening	twilight, dusk, nightfall
feces	dung, excrement, excreta
fireplace	hearth
flood	deluge
flow	flowing water
ground	land [= non-water surface]
haze	smog
heat	warmth
heaven	heavens, Heaven, firmament, space [= place, surface up above]
liquid	fluid
lodestar	Pole star
mark	dot, spot, print, design, letter, etc.
mist	steam, vapor, spray
mold	mildew, downy mildew
MOUNTAIN	mount, peak
mountainous region	mountain range
NIGHT	nighttime
noon	midday
passion	ardor, fervor, enthusiasm, strong desire, intensity
pile	heap, mound
pond	pool [= small body of still water]
slope	hillside
spring	water source
steam	vapor
storm	gale, tempest
stream	brook, creek [small flowing water in channel]
sunlight	daylight, sunshine
swamp	marsh
time	time of day (e.g. 'what time is it?')
world	earth/place

TABLE II. Senses treated as synonyms in our study.

D. Bidirectional translation, and linguists' judgments on aggregation of meanings

For each of the initial 22 Swadesh entries, we have recorded all translations from the metalanguage into the target languages, and then the back-translations of each of these into the metalanguage. Back-translation results in the additional meanings beyond the original 22 Swadesh meanings.

A word in a target language is considered polysemous if its back-translation includes multiple words representing multiple senses as described in subsection I C. In cases where the back-translation produces the same sense through more than one word in the target language, we call it *synonymous polysemy*, and we take into account the degeneracy of each such polysemy in our analysis as weighted links. The set of translations/back-translations of all 22 Swadesh meanings for each target language constitutes our characterization of that language. The pool of translations over the 81 target languages is the complete data set.

The dictionaries used in our study are listed below.

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E. Trimming, collapsing, projecting

Our choice of starting categories is meant to minimize culturally or geographically specific associations, but inevitably these enter through polysemy that results from metaphor or metonymy. To attempt to identify polysemies that express some degree of cognitive universality rather than pure cultural "accident", we include in this report only polysemies that occurred in two or more languages in the sample. The original data comprises 2263 words, translated from a starting list of 22 Swadesh meanings, and 826 meanings as distinguished by English translations. After removal of the polysemies occurring in only a single language, the dataset was reduced to 2257 words and

236 meanings. Figure 3 shows that this results in little difference in the statistics of weighted and unweighted degrees.

Finally, as detailed below, the most fine-grained representation of the data preserves all English translations to all words in each target language. To produce aggregate summary statistics, we have projected this fine-grained, heterogeneous, directed graph onto the shared English-language nodes, with appropriately redefined links, to produce coarser-level directed and undirected graphs. Specifically, we define a weighted graph whose nodes are English words, where each link has an integer-valued weight equal to the number of translation-back-translation paths between them. We show this procedure in more detail in the next section.

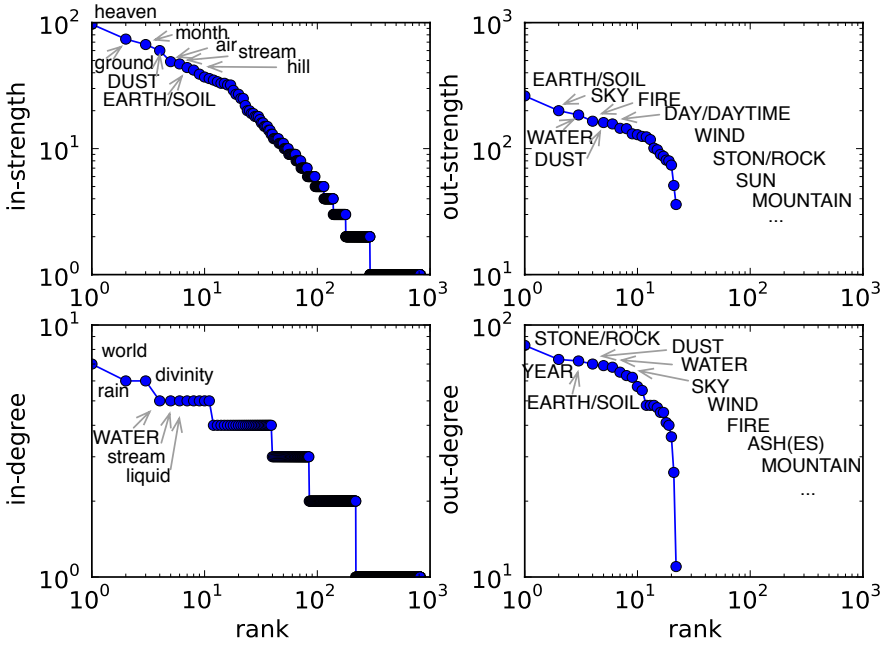


FIG. 3. Rank plot of meanings in descending order of their degree and strengths. This figure is an expanded version of Fig. 4 from the main text, in which singly-attested polysemies are retained.

II. NOTATION AND METHODS OF NETWORK REPRESENTATION

A. Network representations

Networks provide a general and flexible class of topological representations for relations in data [9]. Here we define the network representations that we construct from translations and

back-translation to identify polysemies.

1. *Multi-layer network representation*

We represent translation and back-translation with three levels of graphs, as shown in Fig. 4. Panel (a) shows the treatment of two target languages: Coast Tsimshian and Lakhota, by a multi-layer graph. To specify the procedure, the nodes are separated into three types shown in the three layers, corresponding to the input and output English words, and their target-language translations. Two types of links represent translation from English to target languages, and back-translations to English, indicated as arrows bridging the layers.[2]

Two initial Swadesh entries, labeled $S \in \{\texttt{MOON}, \texttt{SUN}\}$, are shown in the first row. Words w_S^L in language $L \in \{\text{Coast\_Tsimshian}, \text{Lakhota}\}$ obtained by translation of entry S are shown in the second row, *i.e.,* $w_{\texttt{MOON}}^{\text{Coast\_Tsimshian}} = \{\texttt{gooypah}, \texttt{gyemk}, \ldots\}$ and $w_{\texttt{MOON}}^{\text{Lakhota}} = \{\texttt{ha}\eta\texttt{hépi wí}, \texttt{ha}\eta\texttt{wí}, \texttt{wí}, \ldots\}$. Directed links t_{Sw} take values

$$t_{Sw} = \begin{cases} 1 & \text{if } S \text{ is translated into } w \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

The bottom row shows targets m_S obtained by back-translation of all words $\left\{w_S^L\right\}$ (fixing S or L as appropriate) into English. Here $m_{\texttt{MOON}} = \{\texttt{MOON}, \texttt{month}, \texttt{heat}, \texttt{SUN}\}$. By construction, S is always present in the set of values taken by m_S. Back-translation links t_{wm} take values

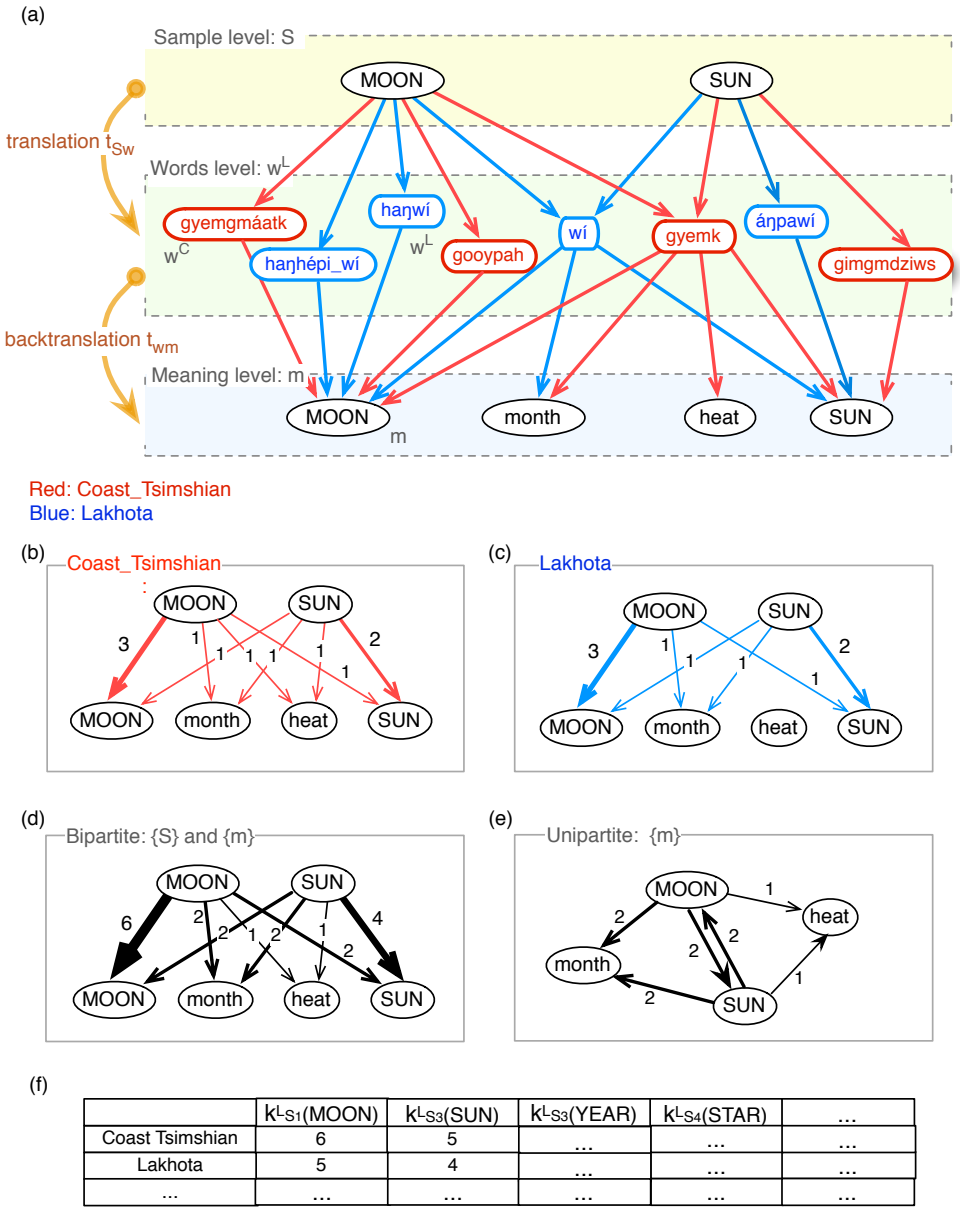
$$t_{wm} = \begin{cases} 1 & \text{if } w \text{ is translated into } m \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The sets $[t_{Sw}]$ and $[t_{wm}]$ can therefore be considered adjacency matrices that link the Swadesh list to each target-language dictionary and the target-language dictionary to the full English lexicon.[3]

We denote the multi-layer network representing a single target language L by $\mathcal{G}^L$ composed of nodes $\{S\}$, $\{w\}$ and $\{m\}$ and matrices of links $[t_{Sw}]$ and $[t_{wm}]$ connecting them. Continuing with the example of $\mathcal{G}^{\text{Coast\_Tsimshian}}$, we see that $t_{\texttt{gooypah},\texttt{month}} = 0$, while $t_{\texttt{gooypah},\texttt{MOON}} = 1$. One such network is constructed for each language, leading to 81 polysemy networks $\left\{\mathcal{G}^L\right\}$ for this study.

[2] In this graph, we regard English inputs and outputs as having different type to emphasize the asymmetric roles of the Swadesh entries from secondary English words introduced by back-translation. The graph could equivalently be regarded as a bipartite graph with only English and non-English nodes, and directed links representing translation. Link direction would then implicitly distinguish Swadesh from non-Swadesh English entries.

[3] More formally, indices S, w, and m are *random variables* taking values, respectively, in the sets of 22 Swadesh entries, target-language entries in all 81 languages, and the full English lexicon. Subscripts and superscripts are then used to restrict the values of these random variables, so that w_S^L takes values only among the words in language L that translate Swadesh entry S, and m_S takes values only among the English words that are polysemes of S in some target language. We indicate random variables in math italic, and the values they take in Roman.



(f)

	k^L_{S1}(MOON)	k^L_{S3}(SUN)	k^L_{S3}(YEAR)	k^L_{S4}(STAR)	...
Coast Tsimshian	6	5	...	...	...
Lakhota	5	4	...	...	...
...	...	...	...	...	...

FIG. 4. Schematic figure of the construction of network representations. Panel (a) illustrates the multi-layer polysemy network from inputs MOON and SUN for two American languages: Coast Tsimshian and Lakhota. Panels (b) and (c) show the directed bipartite graphs for the two languages individually, which lose information about the multiple-polysemes "gyemk" and "wí' found respectively in Coast Tsimshian and Lakhota. Panel (d) shows the bipartite directed graph formed from the union of links in graphs (b) and (c). Link weights indicate the total number of translation/back-translation paths that connect each pair of English-language words. Panel (e) shows the unipartite directed graph formed by identifying and merging Swadesh entries in two different layers. Link weights here are the number of polysemies across languages in which at least one polysemous word connects the two concepts. Directed links go from the Swadesh-list seed words (MOON and SUN here) to English words found in the back-translation step. Panel (f) is a table of link numbers $n_S^L = \sum_{w,m} t_{Sw} t_{wm}$ where t_{Sw} and t_{wm} are binary (0 or 1) to express, respectively, a link from S to w, and from w to m in this paper. $\sum_w t_{Sw} t_{wm}$ gives the number of paths between S and m in network representations.

The forward translation matrix $\mathbf{T}^L_> \equiv [t_{Sw}]$ has size $22 \times Y^L$, where Y^L is the number of distinct translation in language L of all Swadesh entries, and the reverse translation matrix $\mathbf{T}^L_< \equiv [t_{wm}]$ has size $Y^L \times Z^L$, where Z^L is the number of distinct back-translation to English through all targets in language L. For example, $Y^{\text{Coast\_Tsimshian}} = 27$ and $Z^{\text{Coast\_Tsimshian}} = 33$.

2. Directed-hyper-graph representation

It is common that multipartite simple graphs have an equivalent expression in terms of *directed hyper-graphs* [10]. A hyper-graph, like a simple graph, is defined from a set of nodes and a collection of *hyper-edges*. Unlike edges in a simple graph, each of which has exactly two nodes as boundary (dyadic), a hyper-edge can have an arbitrary set of nodes as its boundary. Directed hyper-edges have boundaries defined by pairs of sets of nodes, called inputs and outputs, to the hyper-edge.

In a hyper-graph representation, we may regard all English entries as nodes, and words w^L_S as hyper-edges. The input to each hyper-edge is a single Swadesh entry S, and the outputs are the set of all back-translation m_w. It is perhaps more convenient to regard the simple graph in its bipartite, directed form, as the starting point for conversion to the equivalent hyper-graph. A separate hyper-graph may be formed for each language, or the words from multiple languages may be pooled as hyper-edges in an aggregate hyper-graph.

3. Projection to directed simple graphs and aggregation over target languages

The hyper-graph representation is a complete reflection of the input data. However, hyper-graphs are more cumbersome to analyze than simple networks, and the heterogeneous character of hyper-edges can be an obstacle to simple forms of aggregation. Therefore, most of our analysis is performed on a projection of the tri-partite graph onto a simple network with only one kind of node (English words). The node set may continue to be regarded as segregated between inputs and outputs to (now bidirectional) translation, leaving a bipartite network with two node types, or alternatively we may pass directly to a simple directed graph in which all English entries are of identical type, and the directionality of bidirectional translations carries all information about the asymmetry between Swadesh and non-Swadesh entries with respect to our translation procedure. Directed bipartite graph representations for Coast Tsimshian and Lakhota separately are shown in Fig. 4 (b) and (c), respectively, and the aggregate bipartite network for the two target languages is shown in Fig. 4 (d).

Projection of a tripartite graph to a simpler form implicitly entails a statistical model of aggregation. The projection we will use creates links with integer weights that are the sums of link variables in the tripartite graph. The associated aggregation model is complicated to define: link summation treats any single polysemy as a sample from an underlying process assumed to be uniform across words and languages; however, correlations arise due to multi-way polysemy, when a Swadesh word translates to multiple words in a target language, and more than one of these words translates back to the same English word. This creates multiple output-nodes on the boundaries of hyper-edges, rendering these link weights non-independent, so that graph statistics are not automatically recovered by Poisson sampling defined only from the aggregate weights given to links. We count the link polysemy between any Swadesh node S and any English output of bidirectional translation m as a sum (*e.g.*, within a single language L)[4]

$$\begin{aligned} t^L_{Sm} &= \sum_{w^L_S} t_{Sw^L_S} t_{w^L_S m} \\ &= \left(\mathbf{T}^L_> \mathbf{T}^L_<\right)_{Sm}. \end{aligned} \tag{3}$$

B. Model for semantic space represented as a topology

As a mnemonic for the asymmetry between English entries as "meanings" and target-language entries as "words", we may think of these graphs as overlying a topological space of meanings, and of words as "catching meanings in a set", analogous to catching fish in the ocean using a variety of nets. Any original Swadesh meaning is a "fish" at a fixed position in the ocean, and each target-language word w^L_S is one net that catches this fish. The back-translations $\left\{m \mid t_{w^L_S m} = 1\right\}$ are all other fish caught in the same net. If all distinct words $\left\{w^L_S\right\}$ are interpreted as random samples of nets (a proposition which we must yet justify by showing the absence of other significant sources of correlation), then the relative distance of fish (intrinsic separation of concepts in semantic space) determines their joint-capture statistics within nets (the participation of different concept pairs in polysemies).

The "ocean" in our underlying geometry is not 2- or 3-dimensional, but has a dimension corresponding to the number of significant principal components in the summary statistics from our data. If we use a spectral embedding to define the underlying topology from a geometry based on diffusion in Euclidean space, the dimension D of this embedding will equal to the number of

[4] Note that for unidirectional links t_{Sw} or t_{wm}, we need not identify the language explicitly in the notation because that identification is carried implicitly by the word w. For links in projected graphs it is convenient to label with superscript L, because both arguments in all such links are English-language entries.

English-language entries recovered in the total sample, and a projection such as multi-dimensional scaling may be used to select a smaller number of dimensions [11, 12]. In this embedding, diffusion is isotropic and all "nets" are spherical. More generally, we could envision a lower-dimensional "ocean" of meanings, and consider nets as ellipsoids characterized by eccentricity and principal directions as well as central locations. This picture of the origin of polysemy from an inherent semantic topology is illustrated in Fig. 5, and explained in further detail in the next section.

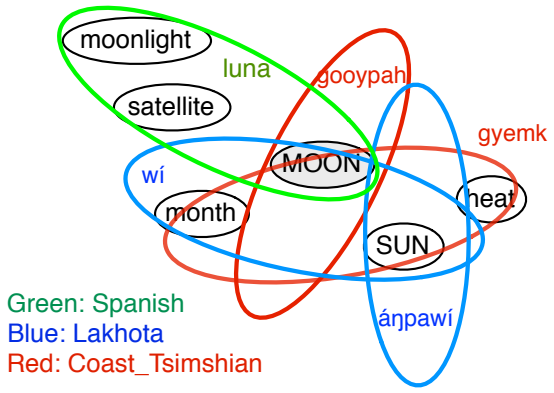


FIG. 5. Hypothetical word-meaning and meaning-meaning relationships using a subset of the data from Fig. 4. In this relation, translation and back-translation across different languages reveal polysemies through which we measure a distance between one concept and another concept.

1. *Interpretation of the model into network representation*

For an example, consider the projection of the small set of data shown in Fig. 4 (b) and (c). Words in L = Coast_Tsimshian are colored red. For these, we find S = `MOON` is connected to m = `MOON` via the three w_S^L values `gyemgmáatk`, `gooypah`, and `gyemk`. $t^{\text{Coast\_Tshimshian}}_{\texttt{MOON MOON}}$ is, hence, 3, whereas $t^{\text{Coast\_Tshimshian}}_{\texttt{SUN heat}} = 1$ (*via* gyemk). From the words in L = Lakhota, colored blue in Fig. 4(c), we see that again $t^{\text{Lakhota}}_{\texttt{MOON MOON}} = 3$, while $t^{\text{Lakhota}}_{\texttt{SUN heat}} = 0$ because there is no polysemy between these entries in Lakhota.

Diffusion models of projection, which might be of interest of diachronic meaning shift in historical linguistics, is mediated by polysemous intermediates, suggest alternative choices of projection as well. Instead of counting numbers of polysemes $\left|\{w_S^L\}\right|$ between some S and a given m, a link might be labeled with the share of polysemy of S that goes to that m. This weighting gives $t^{\text{Coast\_Tshimshian}}_{\texttt{MOON MOON}} = 3/6$, because only gyemgmáatk, gooypah, and gyemk are in common out of 6 and $t^{\text{Coast\_Tshimshian}}_{\texttt{MOON heat}} = 1/6$, because only `gyemk` is associated out of six polysemes

between `MOON` and `heat`. In the interpretation of networks as Markov chains of diffusion processes, this weight gives the (normalized) probability of transition to m when starting from S, as $\hat{t}^L_{Sm} = \left(\sum_{w^L_S} t_{Sw^L_S} t_{w^L_S m}\right) / \left(\sum_{m'} \sum_{w'^L_S} t_{Sw'^L_S} t_{w'^L_S m'}\right)$.

We may return to the analogy of catching fish in a high-dimensional sea, which is the underlying (geometric or topological) semantic space, referring to Fig. 5. Due to the high dimensionality of this sea, whether any particular fish m is caught depends on both the position and the angle with which the net are cast. When the distance between S and m is very small, the angle may matter little. A cast at a slightly different angle, if it caught S, would again catch m as well. If, instead, m is far from the center of a net cast to catch S, only for a narrow range of angles will both S and m be caught. An integer-weighted network measures the number of successes in catching the fish m as a proxy for relative distance from S. The fractionally-weighted network allows us to consider the probability of success of catching any fish other than S. If we cast a net many times but only one succeeds in producing a polysemy, we should think that other meanings m are all remote from S. Under a fractional weighting, the target language and the English Swadesh categorization may have different rates of sampling, which appear in the translation dictionary. Our analysis uses primarily the integer-weighted network.

2. Beyond the available sample data

In the representation of the fine-grained graph as a directed, bipartite graph, English words S and m, and target-language words w, are formally equivalent. The asymmetry in their roles comes only from the asymmetry in our sampling protocol over instances of translation. An ideal, fully symmetric dataset might contain translations between all pairs of languages (L, L'). In such a dataset, polysemy with respect to any language L could be obtained by an equivalent projection of all languages other than L. A test for the symmetry of the initial words in such a dataset can come from projecting out all intermediate languages other than L and L', and comparing the projected links from L to L' through other intermediate languages, against the direct translation dictionary. A possible area for future work from our current dataset (since curated all-to-all translation will not be available in the foreseeable future), is to attempt to infer the best approximate translation maps, *e.g.* between Coast Tsimshian and Lakhota, through an intermediate sum $\mathbf{T}^{\text{Coast\_Tsimshian}}_{<} \mathbf{T}^{\text{Lakhota}}_{>}$ analogous to Eq. (3), as a measure of the overlap of graphs $\mathcal{G}^{\text{Coast\_Tsimshian}}$ and $\mathcal{G}^{\text{Lakhota}}$.

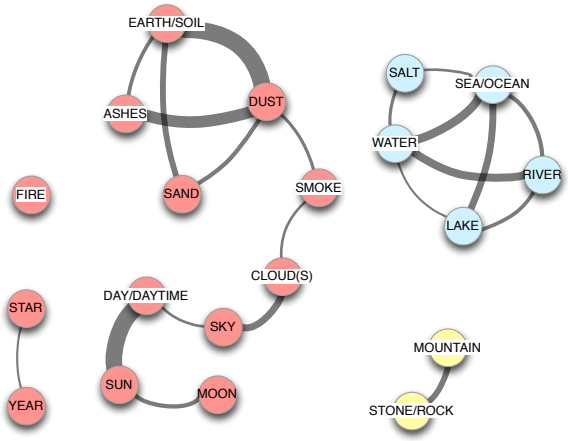


FIG. 6. Connectance graph of Swadesh meanings excluding non-Swadesh English words.

C. The aggregated network of meanings

The polysemy networks of 81 languages, constructed in the previous subsection, are aggregated into one network structure as shown in Fig. 2 in the main text. Two types of nodes are distinguished by the case of the label on each node. All-capital labels indicate Swadesh words while all-lowercase indicate non-Swadesh words. The width of each link is the number of polysemes joining the two meanings at its endpoints, including in this count the sum of all synonyms within each target language that reproduce the same polysemy. For example, the thick link between SKY and heaven implies the existence of the largest number of distinct polysemes between these two compared to those between any two other entries in the graph.

D. Synonymous polysemy: correlations within and among languages

Synonymous polysemy provides the first, in a series of tests that we will perform, to determine whether the aggregate graph generated by addition of polysemy-links is a good summary statistic for the process of word-meaning pairing in actual languages that leads to polysemy. The null model for sampling from the aggregate graph is that each word from a some Swadesh entry S has a fixed probability to be polysemous with a given meaning entry m, independent of the presence or absence of any other polysemes of S with m in the same language. Violations of the null model include excess synonymous polysemy (suggesting, in our picture of an underlying semantic space, that the "proximity" of meanings is in part dynamically created by formation of polysemies, increasing their likelihood of duplication), or deficit synonymous polysemy (suggesting that languages economize

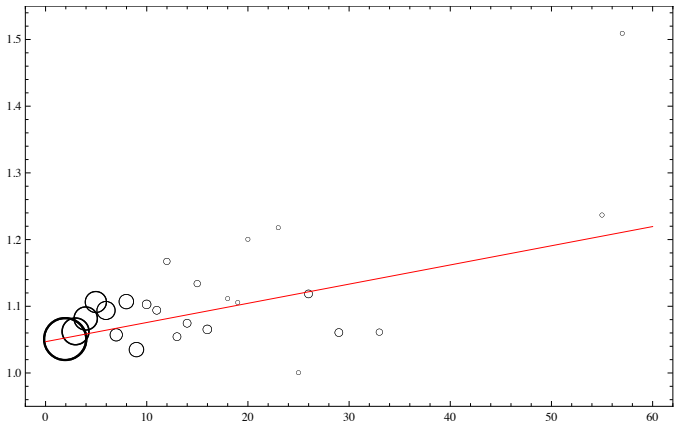


FIG. 7. The number of synonymous polysemies within a language is correlated with the number of languages containing a given polysemy. The horizontal axis indicates the number of languages (out of 81) in which a Swadesh entry S is polysemous with a given meaning m for meanings found to be polysemous in at least two languages. The vertical axis indicates the average number of synonymous polysemies per language in which the polysemous meaning is represented. Circle areas are proportional to the number of meanings m over which the average was taken. The red line represents the least-squares regression over all (non-averaged) data and has slope and intercept of 0.0029 and 1.05, respectively.

on the semantic scope of words by avoiding duplications).

The data presented in Fig. 7 shows that if a given polysemy is represented in more languages, it is also more likely to be captured by more than one word within a given language. This is consistent with a model in which proximity relationships among meanings are preexisting. Models in which the probability of a synonymous polysemy was either independent of the number of polysemous languages (corresponding to a slope of zero in Fig. 7) or quadratic in the number of languages were rejected by both AIC and BIC tests.

We partitioned the synonymous polysemy data and performed a series of Mann-Whitney U tests. We partitioned all polysemies according to the following scheme: a polysemy was a member of the set $c_{s,p}$ if the language contained the number of polysemies, p, for the given Swadesh word, s of which shared this polysemous meaning. For each category, we constructed a list $D_{s,p}$ of the numbers of languages in which each polysemous meaning in the set $c_{s,p}$ is found. We then tested all pairs of $D_{s_1,p}$ and $D_{s_2,p}$ for whether they could have been drawn from the same distribution.

$D_{0,1}$	$D_{1,1}$	0.167	2.53×10^{-433}
$D_{0,2}$	$D_{1,2}$	0.333	1.08×10^{-170}
$D_{0,2}$	$D_{2,2}$	0.0526	1.39×10^{-56}
$D_{1,2}$	$D_{2,2}$	0.158	2.10×10^{-14}
$D_{0,3}$	$D_{1,3}$	0.500	7.18×10^{-44}
$D_{0,3}$	$D_{2,3}$	0.167	1.11×10^{-28}
$D_{0,3}$	$D_{3,3}$	0.0222	4.81×10^{-9}
$D_{1,3}$	$D_{2,3}$	0.333	6.50×10^{-5}
$D_{1,3}$	$D_{2,3}$	0.0444	4.53×10^{-5}
$D_{2,3}$	$D_{3,3}$	0.133	9.28×10^{-4}
$D_{0,4}$	$D_{1,4}$	1.00	3.15×10^{-17}
$D_{0,4}$	$D_{2,4}$	0.0714	1.86×10^{-13}
$D_{0,4}$	$D_{3,4}$	0.0667	5.63×10^{-5}
$D_{1,4}$	$D_{2,4}$	0.0714	7.66×10^{-4}
$D_{1,4}$	$D_{3,4}$	0.0667	0.084
$D_{2,4}$	$D_{3,4}$	0.993	1.0
$D_{0,5}$	$D_{1,5}$	0.143	1.03×10^{-27}
$D_{0,5}$	$D_{2,5}$	0.182	6.20×10^{-7}
$D_{0,5}$	$D_{3,5}$	0.0323	5.09×10^{-6}
$D_{1,5}$	$D_{2,5}$	1.27	0.35
$D_{1,5}$	$D_{3,5}$	0.226	0.15
$D_{2,5}$	$D_{3,5}$	0.177	0.06
$D_{0,6}$	$D_{1,6}$	1.00	0.15
$D_{0,6}$	$D_{2,6}$	0.0247	1.44×10^{-5}
$D_{1,6}$	$D_{2,6}$	0.0247	0.06
$D_{0,7}$	$D_{1,7}$	1.00	0.20

In most comparisons, the null hypothesis that the two lists were drawn from the same distribution was strongly rejected, always in the direction where the list with the larger number of synonymous polysemies (larger values of s) contained larger numbers, meaning that those polysemies were found in more different languages. For a few of the comparisons, the null hypothesis was not rejected, corresponding to those cases where one or both lists included a small number of entries (< 10).

The table II D shows all comparisons for lists of greater than length one. The first two columns indicate which two lists are being compared. The third column gives the ratio of the median values of the two lists, with values less than one indicating that the median of the list in the column one is lower than the median of the list in the column two.

We return to demonstrate a slight excess of probability to include individual entries in polysemies, in Sec. IV.

E. Node degree and link presence/absence data

The goodness of this graph as a summary statistic, and the extent to which the heterogeneity of its node degree and the link topology reflect universals in the sense advocated by Greenberg [13], may be defined as the extent to which individual language differences are explained as fluctuations in random samples. We begin systematic tests of the goodness of the aggregate graph with the degrees of its nodes, a coarse-grained statistic that is most likely to admit the null model of random sampling, but which also has the best statistical resolution among the observables in our data. These tests may later be systematically refined by considering the presence/absence statistics of the set of polysemy links, their covariances, or higher-order moments of the network topology. At each level of refinement we introduce a more restrictive test, but at the same time we lose statistical power because the number of possible states grows faster than the data in our sample.

We let n_m^L denote the degree of meaning m—defined as the sum of weights of links to m—in language L. Here m may stand for either Swadesh or non-Swadesh entries ($\{S\} \subset \{m\}$). $n_m \equiv \sum_L n_m^L$ is then the degree of meaning m in the aggregated graph of Fig. 2 (main text), shown in a rank-size plot in Fig. 3. $N \equiv \sum_m n_m = \sum_{m,L} n_m^L$ denotes the sum of all link weights in the aggregated graph.

F. Node degree and Swadesh meanings

The Swadesh list was introduced to provide a priority for the use of lexical items, which favored universality, stability, and some notion of "core" or "basic" vocabulary. Experience within historical linguistics suggests qualitatively that it satisfies these criteria well, but the role of the Swadesh list within semantics has not been studied with quantitative metrics. We may check the degree to which the items in our basic list are consistent with a notion of core vocabulary by studying their position in the rank-size distribution of Fig. 4 in the main text.

Our sampling methodology naturally places the starting search words (capitalized black characters) high in the distribution, such as EARTH/SOIL, WATER and DAY/DAYTIME with more than 100 polysemous words, because they are all connected to other polysemes produced by polysemy sampling. Words that are not in the original Swadesh list, but which are uncovered as polysemes (red), are less fully sampled. They show high degree only if they are connected to multiple Swadesh entries.[5] These derived polysemes fall mostly in the power-law tail of the rank-size distribution in Fig. 3. The few entries of high degree serve as candidates for inclusion in an expanded Swadesh list, on the grounds that they are frequently recovered in basic vocabulary. Any severe violation of the segregation of Swadesh from non-Swadesh entries (hence, the appearance of many derived polysemes high in the rank-size distribution) would have indicated that the Swadesh entries were embedded in a larger graph with high clustering coefficient, and would have suggested that the low-ranking Swadesh words were not statistically favored as starting points to sample a semantic network.[6]

III. UNIVERSAL STRUCTURE: CONDITIONAL DEPENDENCE

We performed an extensive range of tests to determine whether language differences in the distribution of 1) the number of polysemies, 2) the number of meanings (unweighted node degree), and 3) the average proximity of meanings (weighted node degree, or "strength") are correlated with language relatedness, or with geographic or cultural characteristics of the speaker populations, including the presence or absence of a writing system. The interpretation is analogous to that of population-level gene frequencies in biology. Language differences that covary with relatedness disfavor the Greenbergian view of typological universals of human language, and support a Whorfian view that most language differences are historically contingent and recur due to vertical transmission within language families. Differences that covary with cultural or geographical parameters suggest that language structure responds to extra-linguistic conditions instead of following universal endogenous constraints. We find no significant regression of the patterns in our degree distribution on any cladistic, cultural, or geographical parameters. At the same time, we found single-language degree distributions consistent with a model of random sampling (defined below), suggesting that the degree distribution of polysemies is an instance of a Greenbergian universal.

Ruling out dummy variables of clade and culture has a second important implication for studies

[5] Note that two non-Swadesh entries cannot be linked to each other, even if they appear in a multi-way polysemy, because our protocol for projecting hypergraphs to simple graphs only generates links between the (Swadesh) inputs and the outputs of bidirectional translation.

[6] With greater resources, a bootstrapping method to extend the Swadesh list by following second- and higher-order polysemes could provide a quantitative measure of the network position of the Swadesh entries among all related words.

of this kind. We chose to collect data by hand from printed dictionaries, foregoing the sample size and speed of the many online language resources now available, to ensure that our sample represents the fullest variation known among languages. Online dictionaries and digital corpora are dominated by a few languages from developed countries, with long-established writing systems and large speaker populations, but most of these fall within a small number of European or Asian language families. Our demonstration that relatedness does not produce a strong signal in the parameters we have measured opens the possibility of more extensive sampling from digital sources. We note two caveats regarding such a program, however. First, languages for this study were selected to maximize phylogenetic distance, with no two languages being drawn from the same genus. It is possible that patterns of polysemy could be shared among more closely related groups of languages. Second, the strength of any phylogenetic signal might be expected to vary across semantic domains, so any future analysis will need to be accompanied by explicit universality tests like those performed here.

A. Comparing semantic networks between language groups

We performed several tests to see if the structure of the polysemy network depends, in a statistically significant way, on typological features, including the presence or absence of a literary tradition, geography, topography, and climate. The geographical information is obtained from the LAPSyD database [14]. We choose the climate categories as the major types A (Humid), B (Arid), and C–E (Cold) from the Köppen-Geiger climate classification [15], where C–E have been merged since each of those had few or no languages in our sample. We list the typological features that are tested, and the numbers of languages for each feature shown in parentheses in the table III

1. Mantel test

Given a set S of languages, we define a weighted graph between English words as shown in Fig. 2 in the main text. Each matrix entry A_{ij} is the total number of foreign words, summed over all languages in S, that can be translated or back-translated to or from both i^{th} and j. From this network, we find the commute distance between the vertices. The commute distance is the expected number of steps a random walker needs to take to go from one vertex to another [16]. It is proportional to the more commonly used resistance distance by a proportionality factor of the sum of all resistances (inverse link weights) in the network.

Variable	Subset	Size
Geography	Americas	29
	Eurasia	20
	Africa	17
	Oceania	15
Climate	Humid	38
	Cold	30
	Arid	13
Topography	Inland	45
	Coastal	36
Literary tradition	Some or long literary tradition	28
	No literary tradition	53

TABLE III. Various groups of languages based on nonlinguistic variables. For each variable we measured the difference between the subsets' semantic networks, defined as the tree distance between the dendrograms of Swadesh words generated by spectral clustering.

For the subgroups of languages, the networks are often disconnected. So, we regularize them by adding links between all vertices with a small weight of $0.1/[n*(n-1)]$, where n is the number of vertices in the graph, when calculating the resistance distance. We do not include this regularization in calculating the proportionality constant between the resistance and commute distances. Finally, we ignore all resulting distances that are larger than n when making comparisons.

The actual comparison of the distance matrices from two graphs is done by calculating the Pearson correlation coefficient, r, between the two. This is then compared to the null expectation of no correlation by generating the distribution of correlation coefficients on randomizing the concepts in one distance matrix, holding the other fixed. The Mantel test p-value, p_1, is the proportion of this distribution that is higher than the observed correlation coefficient.

To test whether the observed correlation is typical of random language groups, we randomly sample without replacement from available languages to form groups of the same size, and calculate the correlation coefficient between the corresponding distances. The proportion of this distribution that lies lower than the observed correlation coefficient provided p_2.

2. Hierarchical clustering test

The commute measures used in the Mantel test, however, only examine the sets that are connected in the networks from the language groups. To understand the longer distance structure, we instead look at the hierarchical classification obtained from the networks. We cluster the vertices of the graphs, i.e., the English words, using a hierarchical spectral clustering algorithm. Specifically,

we assign each word i a point in $\mathbb{R}^n$ based on the ith components of the eigenvectors of the $n \times n$ weighted adjacency matrix, where each eigenvector is weighted by the square of its eigenvalue. We then cluster these points with a greedy agglomerative algorithm, which at each step merges the pair of clusters with the smallest squared Euclidean distance between their centers of mass. This produces a binary tree or *dendrogram*, where the leaves are English words, and internal nodes correspond to groups and subgroups of words. We obtained these for all 826 English words, but for simplicity we we show results here for the 22 Swadesh words.

Doing this where S is the set of all 81 languages produces the dendrogram shown in Fig. 8. We applied the same approach where S is a subgroup of the 81 languages, based on nonlinguistic variables such as geography, topography, climate, and the presence or absence of a literary tradition. These groups are shown, along with the number of languages in each, in Table III.

For each nonlinguistic variable, we measured the difference between the semantic network for each pair of language groups, defined as the distance between their dendrograms. We used two standard tree metrics taken from the phylogenetic literature. The triplet distance D_{triplet} [17, 18] is the fraction of the $\binom{n}{3}$ distinct triplets of words that are assigned a different topology in the two trees: that is, such that the trees disagree as to which pair of these three words is more closely related to each other than to the third. The Robinson-Foulds distance D_{RF} [19] is the number of "cuts" on which the two trees disagree, where a cut is a separation of the leaves into two sets resulting from removing an edge of the tree.

We then performed two types of bootstrap experiments, comparing these distances to those one would expect under the null hypotheses. First we considered the hypothesis that there is no underlying notion of relatedness between senses—for instance, that every pair of words is equally likely to be siblings in the dendrogram. If this were true, then the dendrograms of each pair of groups would be no closer than if we permuted the senses on their leaves randomly (while keeping the structure of the dendrograms the same). Comparing the actual distance between each pair of groups to the resulting distribution gives the p-values, labeled p_1, shown in Figure 3 in the main text. These p-values are small enough to decisively reject the null hypothesis; indeed, for most pairs of groups the Robinson-Foulds distance is smaller than that observed in any of the 1000 bootstrap trials, making the p-value effectively zero. This gives overwhelming evidence that the semantic network has universal aspects, applying across language groups: for instance, in every group we tried, SEA/OCEAN and SALT are more related than either is to SUN.

In the second type of bootstrap experiment, the null hypothesis is that the nonlinguistic variables have no effect on the semantic network, and that the differences between language groups simply

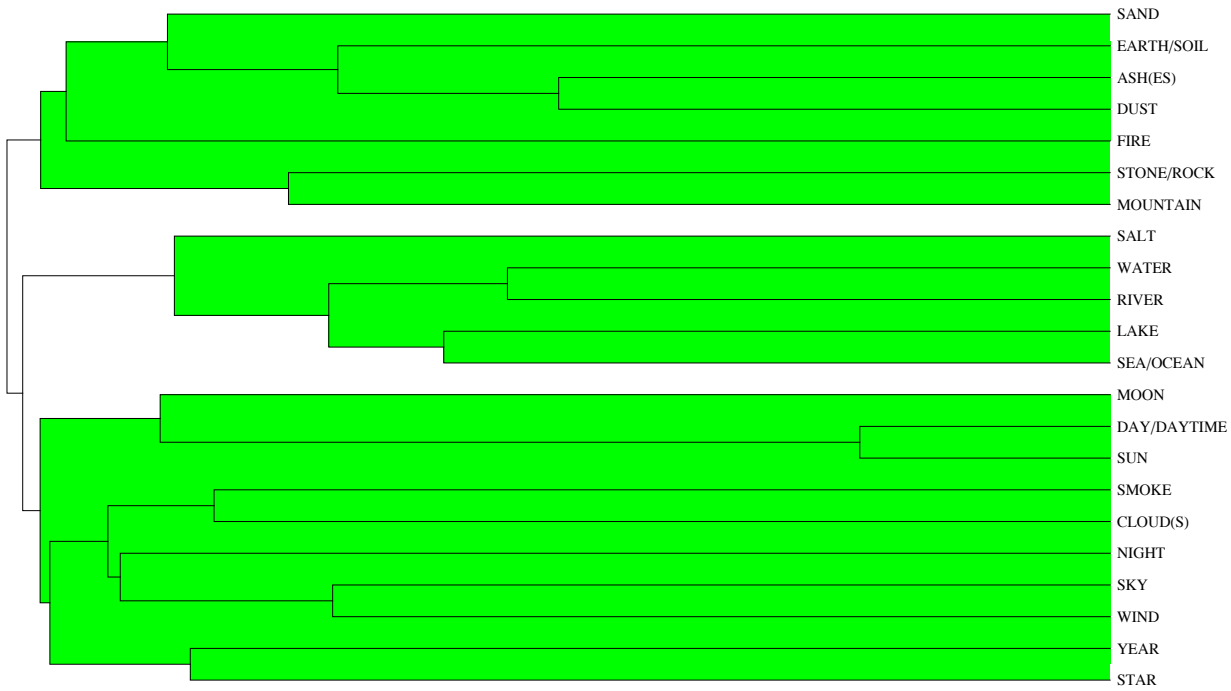


FIG. 8. The dendrogram of Swadesh words generated from spectral clustering on the polysemy network taken over all 81 languages. The three largest groups are highlighted; roughly speaking, they comprise earth-related, water-related, and sky-related concepts.

result from random sampling: for instance, that the distance between the dendrograms for the Americas and Eurasia is what one would expect from any disjoint subsets S_1, S_2 of the 81 languages of sizes $|S_1| = 29$ and $|S_2| = 20$ respectively. To test this, we generate random pairs of disjoint subsets with the same sizes as the groups in question, and measure the resulting distribution of distances. The resulting p-values are labeled p_2 in Table 1. These p-values are not small enough to reject the null hypothesis. Thus, at least given the current data set, it does not appear that these nonlinguistic variables have a statistically significant effect on the semantic network—further supporting our thesis that it is, at least in part, universal.

For illustration, in Fig. 3 (main text) we compare the triplet distance between the dendrograms for Americas and Oceania with the distributions from the two bootstrap experiments. These two groups are closer than less than 2% of the trees where senses have been permuted randomly, but 38% of the random pairs of subsets of size 29 and 15 are farther away. Using a p-value of 0.05 as the usual threshold, we can reject the hypothesis that these two groups have no semantic structure in common; moreover, we cannot reject the hypothesis that the differences between them are due to random sampling rather than geographic differences.

B. Statistical significance

The p-values reported in Fig. 3 have to be corrected for multiple tests. Eleven independent comparisons are performed for each of the metrics, so a low p-value is occasionally expected simply by chance. In fact, under the null hypothesis, a column will contain a single $p = 0.01$ by chance about 10% of the time. To correct for this, one can employ a Bonferroni correction [20] leading to a significance threshold of 0.005 for each of the 11 tests, corresponding to a test size of $p = 0.05$. Most of the comparisons in the p_1 columns for r and D_{RF} are comfortably are below this threshold, implying that the networks obtained from different language groups are indeed significantly more similar than comparable random networks.

A Bonferroni correction, however, is known to be aggressive: it controls the false positive error rate but leads to many false negatives [21], and is not appropriate for establishing the *lack of significance* for the p_2 columns. The composite hypothesis that none of the comparisons are statistically significant leads to the predictions that the corresponding p-values are uniformly distributed between 0 and 1. One can, therefore, test the obtained p-values against this expected uniform distribution. We performed a Kolmogorov-Smirnov test for uniformity for each column of the table. This composite p-value is about 0.11 and 0.27 for the p_2 columns corresponding to D_{triplet} and D_{RF}, showing that these columns are consistent with chance fluctuations. The p-value corresponding to the p_2 column for r is about 0.03, evidence that at least one pair of networks are more dissimilar than expected for a random grouping of languages. This is consistent with the indication from the Bonferroni threshold as well—the comparison of Americas and Eurasia has a significant p-value, as possibly also the comparison between Humid and Arid. Removing either of these comparisons raises the composite p-value to 0.10, showing that such a distribution containing one low p-value (but not two) would be expected to occur by chance about 10% of the time.

C. Single-language graph size is a significant summary statistic

The only important language-dependent variable not attached to words in the aggregate graph of Fig. 2 (main text), which is a strongly significant summary statistic for samples, is the total link weight in the language, $n^L \equiv \sum_S n_S^L$. In the next section we will quantify the role of this variable in producing single-language graphs as samples from the aggregate graph, conditioned on the total weight of the language.

Whereas we *do* associate node degree and link weight in the aggregate graph with inherent and

universal aspects of human language, we cannot justify a similar interpretation for the total weight of links within each language. The reason is that total weight — which *may* reflect a systematic variation among languages in the propensity to create polysemous words — may also be affected by reporting biases that differ among dictionaries. Different dictionary writers may be more or less inclusive in the meaning range they report for words. Additional factors, such as the influence of poetic traditions in languages with long written histories, may preserve archaic usages alongside current vernacular, leading to systematic differences in the data available to the field linguist.

D. Conclusion

By ruling out correlation and dependence on the exogenous variables we have tested, our data are broadly consistent with a Greenbergian picture in which whatever conceptual relations underlie polysemy are a class of typological universals. They are quantitatively captured in the node degrees and link weights of a graph produced by simple aggregation over languages. The polysemes in individual languages appear to be conditionally independent given the graph and a collection of language-specific propensities toward meaning aggregation, which may reflect true differences in language types but may also reflect systematic reporting differences.

IV. MODEL FOR DEGREE OF POLYSEMY

A. Aggregation of language samples

We now consider more formally the reasons sample aggregates may not simply be presumed as summary statistics, because they entail implicit generating processes that must be tested. By demonstrating an explicit algorithm that assigns probabilities to samples of Swadesh node degrees, presenting significance measures consistent with the aggregate graph and the sampling algorithm, and showing that the languages in our dataset are typical by these measures, we justify the use and interpretation of the aggregate graph (Fig. 2 in the main text).

We begin by introducing an error measure appropriate to independent sampling from a general mean degree distribution. We then introduce calibrated forms for this distribution that reproduce the correct sample means as functions of both Swadesh-entry and language-weight properties.

The notion of consistency with random sampling is generally scale-dependent. In particular, the existence of synonymous polysemy may cause individual languages to violate criteria of randomness, but if the particular duplicated polysemes are not correlated across languages, even small groups

of languages may rapidly converge toward consistency with a random sample. Indeed the section II D shows the independence of synonymous polysemy. Therefore, we do not present only a single acceptance/rejection criterion for our dataset, but rather show the smallest groupings for which sampling is consistent with randomness, and then demonstrate a model that reproduces the excess but uncorrelated synonymous polysemy within individual languages.

B. Independent sampling from the aggregate graph

Figure 2 (main text) treats all words in all languages as independent members of an unbiased sample. To test the appropriateness of the aggregate as a summary statistic, we ask: do random samples, with link numbers equal to those in observed languages, and with link probabilities proportional to the weights in the aggregate graph, yield ensembles of graphs within which the actual languages in our data are typical?

1. Statistical tests

The appropriate summary statistic to test for typicality, in ensembles produced by random sampling (of links or link-ends) is the Kullback-Leibler (KL) divergence of the sample counts from the probabilities with which the samples were drawn [22, 23]. This is because the KL divergence is the leading exponential approximation (by Stirling's formula) to the log of the multinomial distribution produced by Poisson sampling.

The appropriateness of a random-sampling model may be tested independently of how the aggregate link numbers are used to generate an underlying probability model. In this section, we will first evaluate a variety of underlying probability models under Poisson sampling, and then we will return to tests for deviations from independent Poisson samples. We first introduce notation: For a single language, the relative degree (link frequency), which is used as the normalization of a probability, is denoted as $p^{\rm data}_{S|L} \equiv n^L_S/n^L$, and for the joint configuration of all words in all languages, the link frequency of a single entry relative to the total N will be denoted $p^{\rm data}_{SL} \equiv n^L_S/N = \left(n^L_S/n^L\right)\left(n^L/N\right) \equiv p^{\rm data}_{S|L}p^{\rm data}_L$.

Corresponding to any of these, we may generate samples of links to define the null model for a random process, which we denote $\hat{n}^L_S$, $\hat{n}^L$, etc. We will generally use samples with exactly the same number of total links N as the data. The corresponding sample frequencies will be denoted by $p^{\rm sample}_{S|L} \equiv \hat{n}^L_S/\hat{n}^L$ and $p^{\rm sample}_{SL} \equiv \hat{n}^L_S/N = \left(\hat{n}^L_S/\hat{n}^L\right)\left(\hat{n}^L/N\right) \equiv p^{\rm sample}_{S|L}p^{\rm sample}_L$, respectively.

Finally, the calibrated model, which we define from properties of aggregated graphs, will be the prior probability from which samples are drawn to produce p-values for the data. We denote the model probabilities (which are used in sampling as "true" probabilities rather than sample frequencies) by $p^{\rm model}_{S|L}$, $p^{\rm model}_{SL}$, and $p^{\rm model}_{L}$.

For n^L links sampled independently from the distribution $p^{\rm sample}_{S|L}$ for language L, the multinomial probability of a particular set $\{n^L_S\}$ may be written, using Stirling's formula to leading exponential order, as

$$p\big(\{n^L_S\} \mid n^L\big) \sim e^{-n^L D\left(p^{\rm sample}_{S|L} \middle\| p^{\rm model}_{S|L}\right)} \tag{4}$$

where the Kullback-Leibler (KL) divergence [22, 23]

$$D\left(p^{\rm sample}_{S|L} \middle\| p^{\rm model}_{S|L}\right) \equiv \sum_S p^{\rm sample}_{S|L} \log\left(\frac{p^{\rm sample}_{S|L}}{p^{\rm model}_{S|L}}\right). \tag{5}$$

For later reference, note that the leading quadratic approximation to Eq. (5) is

$$n^L D\left(p^{\rm sample}_{S|L} \middle\| p^{\rm model}_{S|L}\right) \approx \frac{1}{2}\sum_S \frac{\left(\hat{n}^L_S - n^L p^{\rm model}_{S|L}\right)^2}{n^L p^{\rm model}_{S|L}}, \tag{6}$$

so that the variance of fluctuations in each word is proportional to its expected frequency.

As a null model for the joint configuration over all languages in our set, if N links are drawn independently from the distribution $p^{\rm sample}_{SL}$, the multinomial probability of a particular set $\{n^L_S\}$ is given by

$$p\big(\{n^L_S\} \mid N\big) \sim e^{-N D\left(p^{\rm sample}_{SL} \middle\| p^{\rm model}_{SL}\right)} \tag{7}$$

where[7]

$$\begin{aligned} D\left(p^{\rm sample}_{SL} \middle\| p^{\rm model}_{SL}\right) &\equiv \sum_{S,L} p^{\rm sample}_{SL} \log\left(\frac{p^{\rm sample}_{SL}}{p^{\rm model}_{SL}}\right) \\ &= D\left(p^{\rm sample}_{L} \middle\| p^{\rm model}_{L}\right) + \sum_L p^{\rm sample}_L D\left(p^{\rm sample}_{S|L} \middle\| p^{\rm model}_{S|L}\right). \end{aligned} \tag{8}$$

[7] As long as we calibrate $p^{\rm model}_L$ to agree with the per-language link frequencies n^L/N in the data, the data will always be counted as more typical than almost-all random samples, and its probability will come entirely from the KL divergences in the individual languages.

Multinomial samples of assignments $\hat{n}_S^L$ to each of the 22×81 (Swadesh, Language) pairs, with N links total drawn from distribution $p_S^{L\,\mathrm{null}}$, will produce KL divergences uniformly distributed in the coordinate $d\Phi \equiv e^{-D_{KL}} dD_{KL}$, corresponding to the uniform increment of cumulative probability in the model distribution. We may therefore use the cumulative probability to the right of $D\left(p_{SL}^{\mathrm{data}} \middle\| p_{SL}^{\mathrm{model}}\right)$ (one-sided p-value), in the distribution of samples $\hat{n}_S^L$, as a test of consistency of our data with the model of random sampling.

In the next two subsections we will generate and test candidates for p^{model} which are different functions of the mean link numbers on Swadesh concepts and the total links numbers in languages.

2. Product model with intrinsic property of concepts

In general we wish to consider the consistency of joint configurations with random sampling, as a function of an aggregation scale. To do this, we will rank-order languages by increasing n^L, form non-overlapping bins of 1, 3, or 9 languages, and test the resulting binned degree distributions against different mean-degree and sampling models. We denote by $\langle n^L \rangle$ the average total link number in a bin, and by $\langle n_S^L \rangle$ the average link number per Swadesh entry in the bin. The simplest model, which assumes no interaction between concept and language properties, makes the model probability p_{SL}^{model} a product of its marginals. It is estimated from data without regard to binning, as

$$p_{SL}^{\mathrm{product}} \equiv \frac{n_S}{N} \times \frac{n^L}{N}. \tag{9}$$

The 22×81 independent mean values are thereby specified in terms of $22 + 81$ sample estimators.

The KL divergence of the joint configuration of links in the actual data from this model, under whichever binning is used, becomes

$$D\left(p_{SL}^{\mathrm{data}} \middle\| p_{SL}^{\mathrm{model}}\right) = D\left(\frac{\langle n_S^L \rangle}{N} \middle\| \frac{n_S}{N} \frac{\langle n^L \rangle}{N}\right) \tag{10}$$

As we show in Fig. 11 below, even for 9-language bins which we expect to average over a large amount of language-specific fluctuation, the product model is ruled out at the 1% level.

We now show that a richer model, describing interaction between word and language properties, accepts not only the 9-language aggregate, but also the 3-language aggregate with a small adjustment of the language size to which words respond (to produce consistency with word-size and language-size marginals). Only fluctuation statistics at the level of the joint configuration of

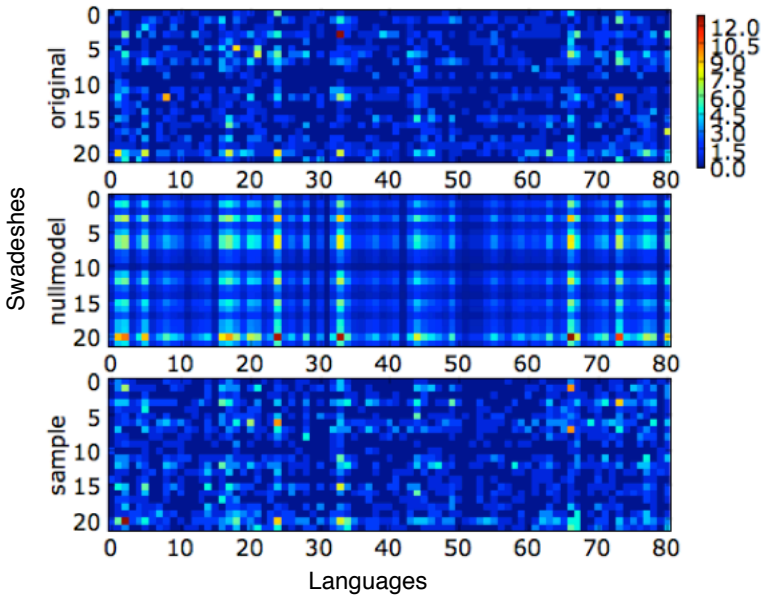


FIG. 9. Plots for the data n_S^L, $Np_{SL}^{product}$, n_{SL}^{sample} in accordance with Fig. 4S (f). The colors denote corresponding numbers of the scale. The original data in the first panel with the sample in the last panel seems to agree reasonably well.

81 individual languages remains strongly excluded by the null model of random sampling.

3. Product model with saturation

An inspection of the deviations of our data from the product model shows that the initial propensity of a word to participate in polysemies, as inferred in languages where that word has few links, in general overestimates the number of links (degree). Put it differently, languages seem to place limits on the weight of single polysemies, favoring distribution over distinct polysemies, but the number of potential distinct polysemies is an independent parameter from the likelihood that the available polysemies will be formed. Interpreted in terms of our supposed semantic space, the proximity of target words to a Swadesh entry may determine the likelihood that they will be polysemous with it, but the total number of proximal targets may vary independently of their absolute proximity. These limits on the number of neighbors of each concept are captured by additional 22 parameters.

To accommodate such characteristic, we revise the model Eq. (9) to the following function:

$$\frac{A_S \langle n^L \rangle}{B_S + \langle n^L \rangle}.$$

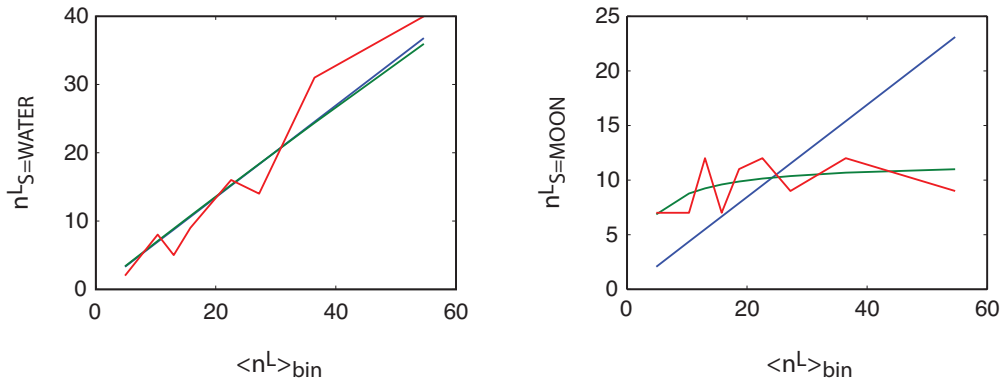


FIG. 10. Plots of the saturating function (11) with the parameters given in Table IV, compared to $\langle n_S^L \rangle$ (ordinate) in 9-language bins (to increase sample size), versus bin-averages $\langle n^L \rangle$ (abscissa). Red line is drawn through data values, blue is the product model, and green is the saturation model. WATER requires no significant deviation from the product model ($B_{\rm WATER}/N \gg 20$), while MOON shows the lowest saturation value among the Swadesh entries, at $B_{\rm MOON} \approx 3.4$.

where degree numbers $\langle n_S^L \rangle$ for each Swadesh S is proportional to A_S and language size, but is bounded by B_S, the number of proximal concepts. The corresponding model probability for each language then becomes

$$p_{SL}^{\rm sat} = \frac{(A_S/B_S)(n^L/N)}{1 + n^L/B_S} \equiv \frac{\tilde{p}_S p_L^{\rm data}}{1 + p_L^{\rm data} N/B_S}. \tag{11}$$

As all $B_S/N \to \infty$ we recover the product model, with $p_L^{\rm data} \equiv n^L/N$ and $\tilde{p}_S \to n_S/N$.

A first-level approximation to fit parameters A_S and B_S is given by minimizing the weighted mean-square error

$$E \equiv \sum_L \frac{1}{\langle n^L \rangle} \sum_S \left(\langle n_S^L \rangle - \frac{A_S \langle n^L \rangle}{B_S + \langle n^L \rangle} \right)^2. \tag{12}$$

The function (12) assigns equal penalty to squared error within each language bin $\sim \langle n^L \rangle$, proportional to the variance expected from Poisson sampling. The fit values obtained for A_S and B_S do not depend sensitively on the size of bins except for the Swadesh entry MOON in the case where all 81 single-language bins are used. MOON has so few polysemies, but the MOON/month polysemy is so likely to be found, that the language Itelman, with only one link, has this polysemy. This point leads to instabilities in fitting $B_{\rm MOON}$ in single-language bins. For bins of size 3–9 the instability is removed. Representative fit parameters across this range are shown in Table IV. Examples of the saturation model for two words, plotted against the 9-language binned degree data in Fig. 10,

Meaning category	Saturation: B_S	Propensity $\tilde{p}_S$
STAR	1234.2	0.025
SUN	25.0	0.126
YEAR	1234.2	0.021
SKY	1234.2	0.080
SEA/OCEAN	1234.2	0.026
STONE/ROCK	1234.2	0.041
MOUNTAIN	1085.9	0.049
DAY/DAYTIME	195.7	0.087
SAND	1234.2	0.026
ASH(ES)	13.8	0.068
SALT	1234.2	0.007
FIRE	1234.2	0.065
SMOKE	1234.2	0.031
NIGHT	89.3	0.034
DUST	246.8	0.065
RIVER	336.8	0.048
WATER	1234.2	0.073
LAKE	1234.2	0.047
MOON	1.2	0.997
EARTH/SOIL	1234.2	0.116
CLOUD(S)	53.4	0.033
WIND	1234.2	0.051

TABLE IV. A table of fitted values of parameters B_S and $\tilde{p}_S$ for the saturation model of Eq. (11) . The saturation value B_S is an asymptotic number of meanings associated with the entry S, and the propensity $\tilde{p}_S$ is a rate at which the number of polysemies increases with n^L at low n_S^L.

show the range of behaviors spanned by Swadesh entries.

The least-squares fits to A_S and B_S do not directly yield a probability model consistent with the marginals for language size that, in our data, are fixed parameters rather than sample variables to be explained. They closely approximate the marginal N $\sum_L p_{SL}^{\rm sat} \approx n_S$ (deviations < 1 link for every S) but lead to mild violations $N \sum_S p_{SL}^{\rm sat} \neq n^L$. We corrected for this by altering the saturation model to suppose that, rather than word properties' interacting with the exact value n^L, they interact with a (word-independent but language-dependent) multiplier $\left(1+\varphi^L\right) n_L$, so that the model for n_S^L in each language becomes becomes

$$\frac{A_S \left(1+\varphi^L\right) n^L}{B_S + \left(1+\varphi^L\right) n^L},$$

in terms of the least-squares coefficients A_S and B_S of Table IV. The values of φ^L are solved with

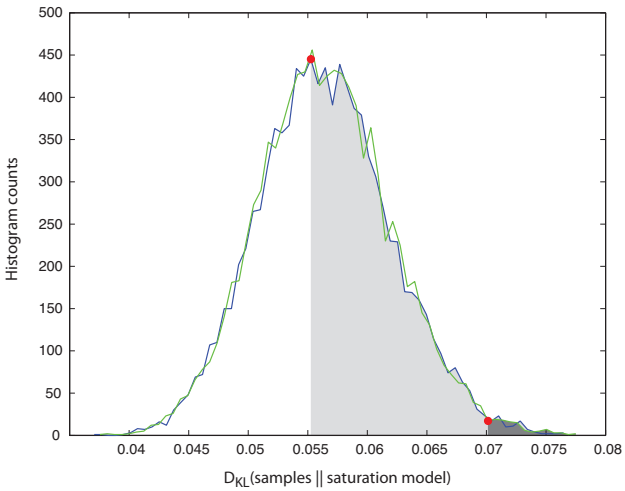


FIG. 11. Kullback-Leibler divergence of link frequencies in our data, grouped into non-overlapping 9-language bins ordered by rank, from the product distribution (9) and the saturation model (11). Parameters A_S and B_S have been adjusted (as explained in the text) to match the word- and language-marginals. From 10,000 random samples $\hat{n}_S^L$, (green) histogram for the product model; (blue) histogram for the saturation model; (red dots) data. The product model rejects the 9-language joint binned configuration at the at 1% level (dark shading), while the saturation model is typical of the same configuration at $\sim 59\%$ (light shading).

Newton's method to produce $N \sum_S p_{SL}^{\rm sat} \to n^L$, and we checked that they preserve $N \sum_L p_{SL}^{\rm sat} \approx n_S$ within small fractions of a link. The resulting adjustment parameters are plotted versus n^L for individual languages in Fig. 12. Although they were computed individually for each L, they form a smooth function of n^L, possibly suggesting a refinement of the product model, but also perhaps reflecting systematic interaction of small-language degree distributions with the error function (12).

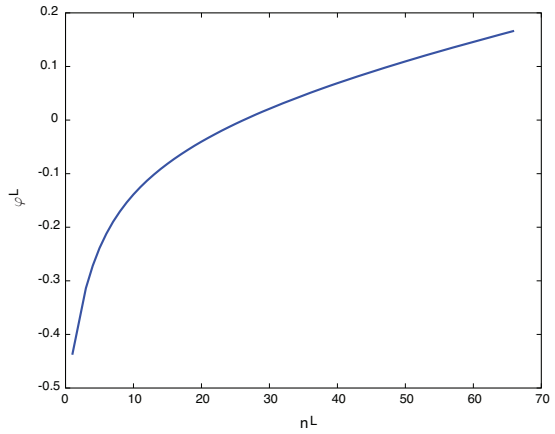


FIG. 12. Plot of the correction factor φ^L versus n^L for individual languages in the probability model used in text, with parameters B_S and $\tilde{p}_S$ shown in Table IV. Although φ^L values were individually solved with Newton's method to ensure that the probability model matched the whole-language link values, the resulting correction factors are a smooth function of n^L.

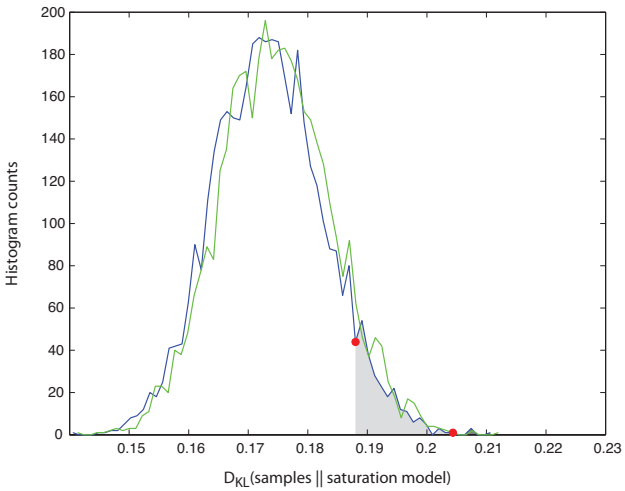


FIG. 13. The same model parameters as in Fig. 11 is now marginally plausible for the joint configuration of 27 three-language bins in the data, at the 7% level (light shading). For reference, this fine-grained joint configuration rejects the null model of independent sampling from the product model at p-value $\approx 10^{-3}$ (dark shading in the extreme tail). 4000 samples were used to generate this test distribution. The blue histogram is for the saturation model, the green histogram for the product model, and the red dots are generated data.

With the resulting joint distribution $p_{SL}^{\rm sat}$, tests of the joint degree counts in our dataset for consistency with multinomial sampling in 9 nine-language bins are shown in Fig. 11, and results of tests using 27 three-language bins are shown in Fig. 13. Binning nine languages clearly averages over enough language-specific variation to make the data strongly typical of a random sample ($P \sim 59\%$), while the product model (which also preserves marginals) is excluded at the 1% level. The marginal acceptance of the data even for the joint configuration of three-language bins ($P \sim 7\%$) suggests that language size n^L is an excellent explanatory variable and that residual language variations cancel to good approximation even in small aggregations.

C. Single instances as to aggregate representation

The preceding subsection showed intermediate scales of aggregation of our language data are sufficiently random that they can be used to refine probability models for mean degree as a function of parameters in the globally-aggregated graph. The saturation model, with data-consistent marginals and multinomial sampling, is weakly plausible by bins of as few as three languages. Down to this scale, we have therefore not been able to show a requirement for deviations from the independent sampling of links entailed by the use of the aggregate graph as a summary statistic. However, we were unable to find a further refinement of the mean distribution that would

reproduce the properties of single language samples. In this section we characterize the nature of their deviation from independent samples of the saturation model, show that it may be reproduced by models of non-independent (clumpy) link sampling, and suggest that these reflect excess synonymous polysemy.

1. Power tests and uneven distribution of single-language p-values

To evaluate the contribution of individual languages versus language aggregates to the acceptance or rejection of random-sampling models, we computed p-values for individual languages or language bins, using the KL-divergence (5). A plot of the single-language p-values for both the null (product) model and the saturation model is shown in Fig. 14. Histograms for both single languages (from the values in Fig. 14) and aggregate samples formed by binning consecutive groups of three languages are shown in Fig. 15.

For samples from a random model, p-values would be uniformly distributed in the unit interval, and histogram counts would have a multinomial distribution with single-bin fluctuations depending on the total sample size and bin width. Therefore, Fig. 15 provides a power test of our summary statistics. The variance of the multinomial may be estimated from the large-p-value body where the distribution is roughly uniform, and the excess of counts in the small-p-value tail, more than one standard deviation above the mean, provides an estimate of the number of languages that can be confidently said to violate the random-sampling model.

From the upper panel of Fig. 15, with a total sample of 81 languages, we can estimate a number of $\sim 0.05 \times 81 \approx 4$–5 excess languages at the lowest p-values of 0.05 and 0.1, with an additional 2–3 languages rejected by the product model in the range p-value ~ 0.2. Comparable plots in Fig. 15 (lower panel) for the 27 three-language aggregate distributions are marginally consistent with random sampling for the saturation model, as expected from Fig. 13 above. We will show in the next section that a more systematic trend in language fluctuations with size provides evidence that the cause for these rejections is excess variance due to repeated attachment of links to a subset of nodes.

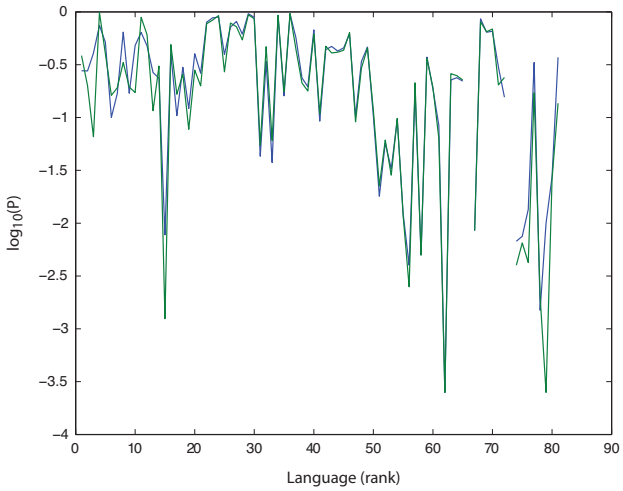


FIG. 14. $\log_{10}(p-\text{value})$ by KL divergence, relative to 4000 random samples per language, plotted versus language rank in order of increasing n^L. Product model (green) shows equal or lower p-values for almost all languages than the saturation model (blue). Three languages – Basque, Haida, and Yorùbá – had value $p = 0$ consistently across samples in both models, and are removed from subsequent regression estimates. A trend toward decreasing p is seen with increase in n^L.

2. *Excess fluctuations in degree of polysemy*

If we define the size-weighted relative variance of a language analogously to the error term in Eq. (12), as

$$\left(\sigma^2\right)^L \equiv \frac{1}{n^L} \sum_S \left(n_S^L - n^L p_{S|L}^{\text{model}}\right)^2, \tag{13}$$

Fig. 16 shows that $-\log_{10}(p-\text{value})$ has high rank correlation with $\left(\sigma^2\right)^L$ and a roughly linear regression over most of the range.[8] Two languages (Itelmen and Hindi), which appear as large outliers relative to the product model, are within the main dispersion in the saturation model, showing that their discrepancy is corrected in the mean link number. We may therefore understand a large fraction of the improbability of languages as resulting from excess fluctuations of their degree numbers relative to the expectation from Poisson sampling.

Fig. 17 then shows the relative variance from the saturation model, plotted versus total average link number for both individual languages and three-language bins. The binned languages show no significant regression of relative variance away from the value unity for Poisson sampling, whereas single languages show a systematic trend toward larger variance in larger languages, a pattern that

[8] Recall from Eq. (6) that the leading quadratic term in the KL-divergence differs from $\left(\sigma^2\right)^L$ in that it presumes Poisson fluctuation with variance $n^L p_{S|L}^{\text{model}}$ at the level of each *word*, rather than uniform variance $\propto n^L$ across all words in a language. The relative variance is thus a less specific error measure.

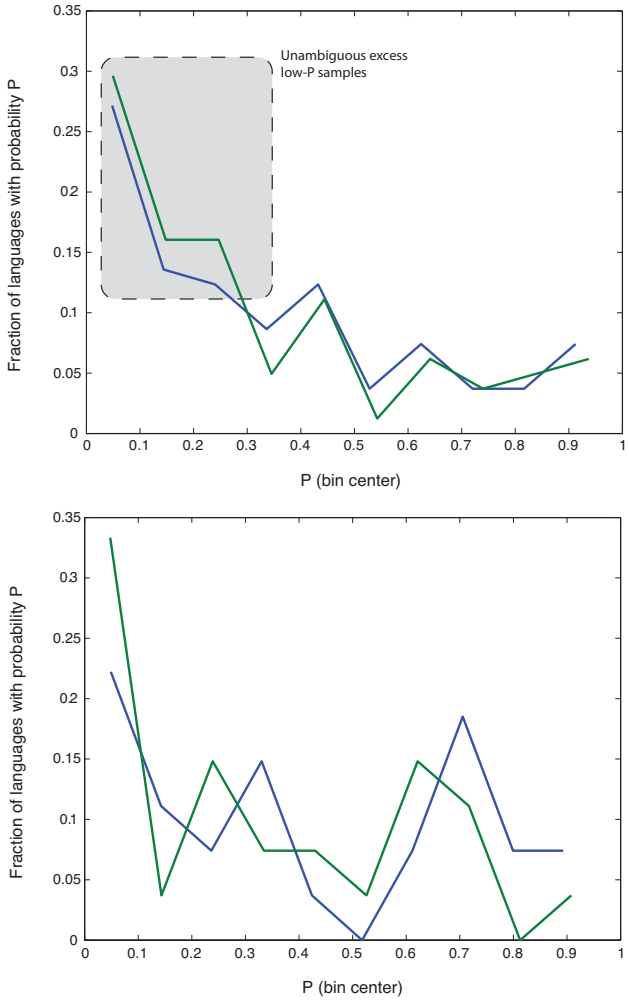


FIG. 15. (Upper panel) Normalized histogram of p-values from the 81 languages plotted in Fig. 14. The saturation model (blue) produces a fraction $\sim 0.05 \times 81 \approx 4$–5 languages in the lowest p-values $\{0.05, 0.1\}$ above the roughly-uniform background for the rest of the interval (shaded area with dashed boundary). A further excess of 2–3 languages with p-values in the range $[0, 0.2]$ for the product model (green) reflects the part of the mismatch corrected through mean values in the saturation model. (Lower panel) Corresponding histogram of p-values for 27 three-language aggregate degree distributions. Saturation model (blue) is now marginally consistent with a uniform distribution, while the product model (green) still shows slight excess of low-p bins. Coarse histogram bins have been used in both panels to compensate for small sample numbers in the lower panel, while producing comparable histograms.

we will show is consistent with "clumpy" sampling of a subset of nodes. The disappearance of this clumping in binned distributions shows that the clumps are uncorrelated among languages at similar n^L.

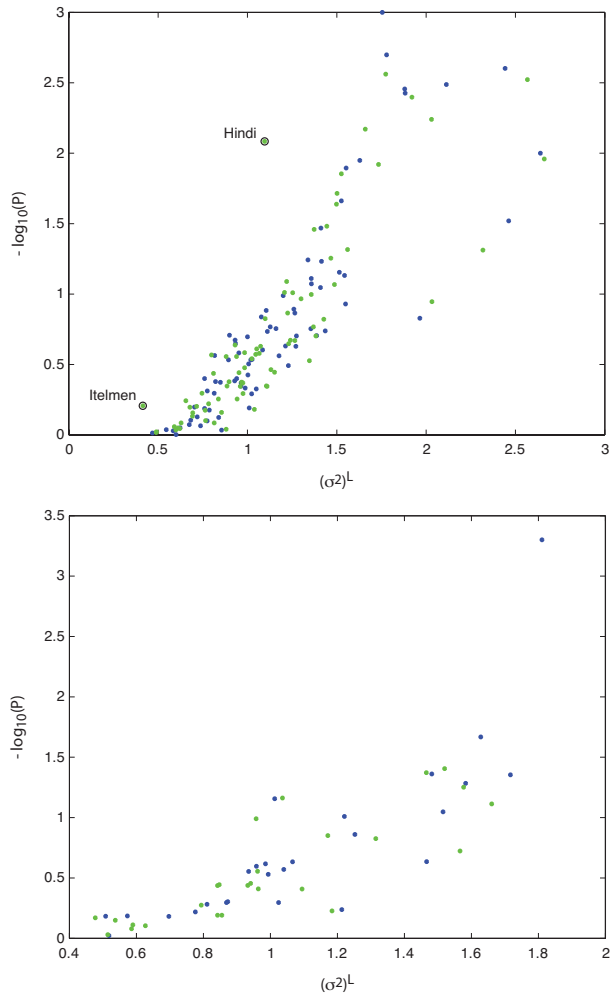


FIG. 16. (Upper panel:) $-\log_{10}(P)$ plotted versus relative variance $\left(\sigma^2\right)^L$ from Eq. (13) for the 78 languages with non-zero p-values from Fig. 14. (blue) saturation model; (green) product model. Two languages (circled) which appear as outliers with anomalously small relative variance in the product model—Itelman and Hindi—disappear into the central tendency with the saturation model. (Lower panel:) an equivalent plot for 26 three-language bins. Notably, the apparent separation of individual large-n^L languages into two groups has vanished under binning, and a unimodal and smooth dependence of $-\log_{10}(P)$ on $\left(\sigma^2\right)^L$ is seen.

3. Correlated link assignments

We may retain the mean degree distributions, while introducing a systematic trend of relative variance with n^L, by modifying our sampling model away from strict Poisson sampling to introduce "clumps" of links. To remain within the use of minimal models, we modify the sampling procedure by a single parameter which is independent of word S, language-size n^L, or particular language L.

We introduce the sampling model as a function of two parameters, and show that one function of these is constrained by the regression of excess variance. (The other may take any interior value,

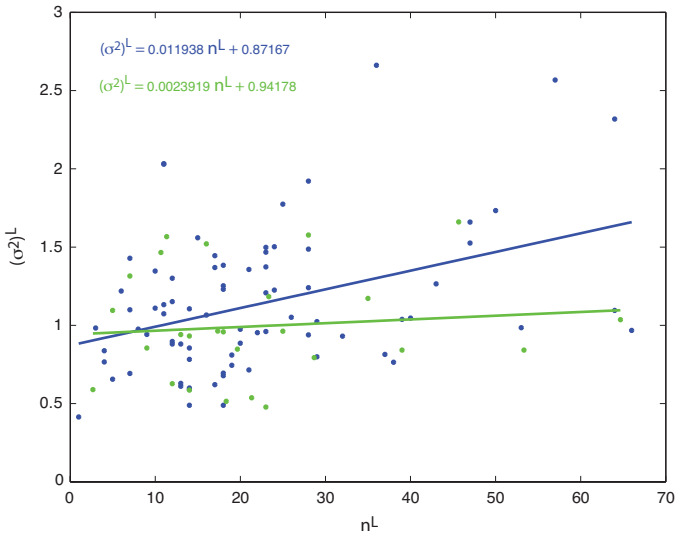


FIG. 17. Relative variance from the saturation model versus total link number n^L for 78 languages excluding Basque, Haida, and Yorùbá. Least-squares regression are shown for three-language bins (green) and individual languages (blue), with regression coefficients inset. Three-language bins are consistent with Poisson sampling at all n^L, whereas single languages show systematic increase of relative variance with increasing n^L.

so we have an equivalence class of models.) In each language, select a number $\mathcal{B}$ of Swadesh entries randomly. Let the Swadesh indices be denoted $\{S_\beta\}_{\beta\in 1,\ldots\mathcal{B}}$. We will take some fraction of the total links in that language, and assign them only to the Swadeshes whose indices are in this privileged set. Introduce a parameter q that will determine that fraction.

We require correlated link assignments be consistent with the mean determined by our model fit, since binning of data has shown no systematic effect on mean parameters. Therefore, for the random choice $\{S_\beta\}_{\beta\in 1,\ldots\mathcal{B}}$, introduce the normalized density on the privileged links

$$\pi_{S|L} \equiv \frac{p^{\rm model}_{S|L}}{\sum_{\beta=1}^{\mathcal{B}} p^{\rm model}_{S_\beta|L}} \tag{14}$$

if $S \in \{S_\beta\}_{\beta\in 1,\ldots\mathcal{B}}$ and $\pi_{S|L} = 0$ otherwise. Denote the aggregated weight of the links in the privileged set by

$$W \equiv \sum_{\beta=1}^{\mathcal{B}} p_{S_\beta|L}. \tag{15}$$

Then introduce a modified probability distribution based on the randomly selected links, in the

form

$$\tilde{p}_{S|L} \equiv (1 - qW)\, p_{S|L} + qW \pi_{S|L}. \tag{16}$$

Multinomial sampling of n^L links from the distribution $\tilde{p}_{S|L}$ will produce a size-dependent variance of the kind we see in the data. The expected degrees given any particular set $\{S_\beta\}$ will not agree with the means in the aggregate graph, but the ensemble mean over random samples of languages will equal $p_{S|L}$, and binned groups of languages will converge toward it according to the central-limit theorem.

The proof that the relative variance increases linearly in n^L comes from the expansion of the expectation of Eq. (13) for random samples, denoted

$$\begin{aligned}
\left\langle \left(\hat{\sigma}^2\right)^L \right\rangle &\equiv \left\langle \frac{1}{n^L} \sum_S \left(\hat{n}_S^L - n^L p_{S|L}^{\text{model}} \right)^2 \right\rangle \\
&= \left\langle \frac{1}{n^L} \sum_S \left[\left(\hat{n}_S^L - n^L \tilde{p}_{S|L} \right) + n^L \left(\tilde{p}_{S|L} - p_{S|L}^{\text{model}} \right) \right]^2 \right\rangle \\
&= \left\langle \frac{1}{n^L} \sum_S \left(\hat{n}_S^L - n^L \tilde{p}_{S|L} \right)^2 \right\rangle + \\
&\qquad n^L \left\langle \sum_S \left(\tilde{p}_{S|L} - p_{S|L}^{\text{model}} \right)^2 \right\rangle .
\end{aligned} \tag{17}$$

The first expectation over $\hat{n}_S^L$ is constant (of order unity) for Poisson samples, and the second expectation (over the sets $\{S_\beta\}$ that generate $\tilde{p}_{S|L}$) does not depend on n^L except in the prefactor. Cross-terms vanish because link samples are not correlated with samples of $\{S_\beta\}$. Both terms in the third line of Eq. (17) scale under binning as (bin-size)^0. The first term is invariant due to Poisson sampling, while in the second term, the central-limit theorem reduction of the variance in samples over $\tilde{p}_{S|L}$ cancels growth in the prefactor n^L due to aggregation.

Because the linear term in Eq. (17) does not systematically change under binning, we interpret the vanishing of the regression for three-language bins in Fig. 17 as a consequence of fitting of the mean value to binned data as sample estimators.[9] Therefore, we require to choose parameters $\mathcal{B}$ and q so that regression coefficients in the data are typical in the model of clumpy sampling, while regressions including zero have non-vanishing weight in models of three-bin aggregations.

Fig. 18 compares the range of regression coefficients obtained for random samples of languages

[9] We have verified this by generating random samples from the model (17), fitting a saturation model to binned sample configurations using the same algorithms as we applied to our data, and then performing regressions equivalent to those in Fig. 17. In about 1/3 of cases the fitted model showed regression coefficients consistent with zero for three-language bins. The typical behavior when such models were fit to random sample data was that the three-bin regression coefficient decreased from the single-language regression by $\sim 1/3$.

with the values $\{n^L\}$ in our data, from either the original saturation model $p^{\rm sat}_{S|L}$, or the clumpy model $\tilde{p}_{S|L}$ randomly re-sampled for each language in the joint configuration. Parameters used were ($\mathcal{B} = 7$, $q = 0.975$).[10] With these parameters, $\sim 1/3$ of links were assigned in excess to $\sim 1/3$ of words, with the remaining 2/3 of links assigned according to the mean distribution.

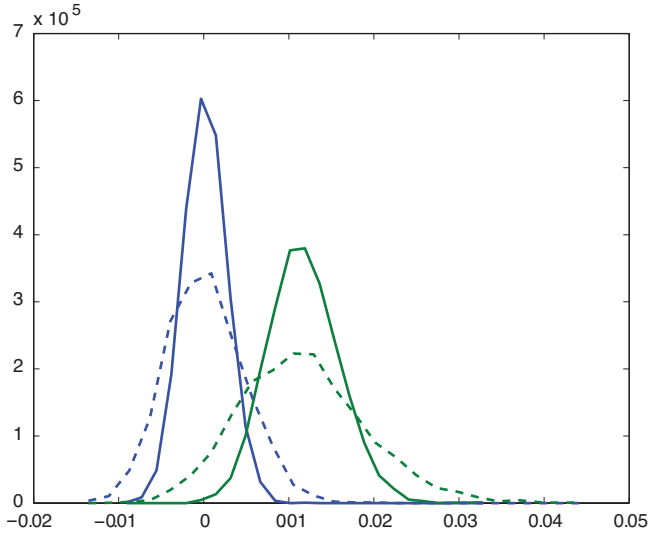


FIG. 18. Histograms of regression coefficients for language link samples $\{\hat{n}^L_S\}$ either generated by Poisson sampling from the saturation model $p^{\rm model}_{S|L}$ fitted to the data (blue), or drawn from clumped probabilities $\tilde{p}_{S|L}$ defined in Eq. (16), with the set of privileged words $\{S_\beta\}$ independently drawn for each language (green). Solid lines refer to joint configurations of 78 individual languages with the n^L values in Fig. 17. Dashed lines are 26 non-overlapping three-language bins.

The important features of the graph are: 1) Binning does not change the mean regression coefficient, verifying that Eq. (17) scales homogeneously as (bin-size)^0. However, the variance for binned data increases due to reduced number of sample points; 2) the observed regression slope 0.012 seen in the data is far out of the support of multinomial sampling from $p^{\rm sat}_{S|L}$, whereas with these parameters, it becomes typical under $\{\tilde{p}_{S|L}\}$ while still leaving significant probability for the three-language binned regression around zero (even without ex-post fitting).

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