

Food web reconstruction through phylogenetic transfer of low-rank network representation

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Despite their importance in many ecological processes, collecting data and information on ecological interactions, and therefore species interaction networks, is an exceedingly challenging task. For this reason, large parts of the world have a data deficit when it comes to species interactions, and how the resulting networks are structured. As data collection alone is unlikely to be sufficient at filling these global gaps, community ecologists must adopt predictive methods. In this contribution, we develop such a method, relying on graph embedding (the extraction of explanatory latent variables from known graph structures) and transfer learning (the application of previous solutions to novel problems with limited predictors overlap) in order to assemble a predicted list of trophic interactions between mammals of Canada. This interaction list is derived from extensive knowledge of the mammalian food web of Europe, despite the fact that there are fewer than 5% of common species between the two locations. The results of the predictive model are compared against databases of recorded pairwise interactions, showing that we correctly recover over 95% of known interactions. We provide guidance on how this method can be adapted by substituting some approaches or predictors in order to make it more generally applicable.

¹ Introduction

² There are two core challenges we are faced with in furthering our understanding of ecological networks
³ across space, particularly at macro-ecologically relevant scales (e.g. Trøjelsgaard & Olesen 2016). First,
⁴ networks within a location are difficult to sample properly (Jordano 2016a, b), resulting in a widespread
⁵ “Eltonian shortfall” (Hortal *et al.* 2015), *i.e.* a lack of knowledge about inter and intra specific
⁶ relationships. This first challenge has been, in large part, addressed by the recent emergence of a suite of
⁷ methods aiming to predict interactions within *existing* networks, many of which are reviewed in Strydom
⁸ *et al.* (2021a). Second, recent analyses based on collected data (Poisot *et al.* 2021a) or metadata (Cameron
⁹ *et al.* 2019) highlight that ecological networks are currently studied in a biased subset of space and
¹⁰ bioclimates, which impedes our ability to generalize any local understanding of network structure.
¹¹ Meaning that, although the framework to address incompleteness *within* networks exists, there would still
¹² be regions for which, due to a *lack* of local interaction data, we are unable to infer potential species
¹³ interactions. Having a general solution for inferring a *plausible* metaweb (despite the unavailability of
¹⁴ interaction data) could be the catalyst for significant breakthroughs in our ability to start thinking about
¹⁵ species interactions networks over large spatial scales.
¹⁶ Here, we present a general method for the transfer learning of network representations, relying on the
¹⁷ similarities of species in a biologically/ecologically relevant proxy space (e.g. shared morphology or
¹⁸ ancestry). Transfer learning is a machine learning methodology that uses the knowledge gained from
¹⁹ solving one problem and applying it to a related (destination) problem (Pan & Yang 2010; Torrey & Shavlik
²⁰ 2010). In this instance, we solve the problem of predicting trophic interactions between species, based on
²¹ knowledge extracted from another species pool for which interactions are known by using phylogenetic
²² structure as a medium for transfer. This allows us to construct a *probabilistic* metaweb for a community
²³ for which we have *no* prior trophic interaction data for the desired species pool. Our methodology is
²⁴ outlined in fig. 1, where we provide an illustration based on learning the embedding of a metaweb of
²⁵ trophic interactions for European mammals (known interactions; Maiorano *et al.* 2020b, a) and, based on
²⁶ phylogenetic relationships between mammals globally (*i.e.*, phylogenetic tree Upham *et al.* 2019), infer a
²⁷ metaweb for the Canadian mammalian species pool (interactions are treated as unknown in this instance).

²⁸

[Figure 1 about here.]

29 There is a plurality of measures of species similarities that can be used for metaweb reconstruction (see e.g.
30 Morales-Castilla *et al.* 2015); however, phylogenetic proximity has several desirable properties when
31 working at large scales. Gerhold *et al.* (2015) made the point that phylogenetic signal captures
32 diversification of characters (large macro-evolutionary process), but not necessarily community assembly
33 (fine ecological process); Dormann *et al.* (2010) previously found very similar conclusions. Interactions
34 tend reflect a phylogenetic signal because they have a conserved pattern of evolutionary convergence that
35 encompasses a wide range of ecological and evolutionary mechanisms (Cavender-Bares *et al.* 2009;
36 Mouquet *et al.* 2012), and - most importantly - retain this signal even when it is not detectable at the
37 community scale (Hutchinson *et al.* 2017; Poisot & Stouffer 2018). Finally, species interactions at
38 macro-ecological scales seem to respond mostly to macro-evolutionary processes (Price 2003); which is
39 evidenced by the presence of conserved backbones in food webs (Dalla Riva & Stouffer 2016), strong
40 evolutionary signature on prey choice (Stouffer *et al.* 2012), and strong phylogenetic signature in food web
41 intervality (Eklöf & Stouffer 2016). Phylogenetic reconstruction has also previously been used within the
42 context of ecological networks, namely understanding ancestral plant-insect interactions (Braga *et al.*
43 2021). Taken together, these considerations suggest that phylogenies can reliably be used to transfer
44 knowledge on species interactions.

45 Our case study shows that phylogenetic transfer learning is indeed an effective approach to predict the
46 Canadian mammalian metaweb. This showcases that although the components (species) that make up
47 the Canadian and European communities may be *minimally* shared, if the medium (proxy space) selected
48 in the transfer step is biologically plausible, we can still effectively learn from the known network and
49 make biologically relevant predictions of interactions. It should be reiterated that the framework
50 presented in fig. 1 is amenable to changes; notably, the measure of similarity may not be phylogeny, and
51 can be replaced by information on foraging (Beckerman *et al.* 2006), cell-level mechanisms (Boeckaerts *et*
52 *al.* 2021), or a combination of traits and phylogenetic structure (Stock 2021).

53 Data used for the case study

54 We use data from the European metaweb assembled by Maiorano *et al.* (2020b), following the definition of
55 the metaweb first introduced by Dunne (2006), *i.e.* an inventory of all possible interactions within species
56 from a spatially delimited pool. Notably the metaweb is not a prediction of the food web at any specific

57 locale within the frontiers of the species pool – in fact, these local food webs are expected to have a subset
58 of both the species and the interactions of their metaweb (Poisot *et al.* 2012). This being said, as the
59 metaweb represents the total of functional, phylogenetic, and macroecological processes (Morales-Castilla
60 *et al.* 2015), it is thus still worthy of ecological attention. We deduced the subgraph corresponding to all
61 mammals by matching species names in the original network to the GBIF taxonomic backbone (GBIF
62 Secretariat 2021) and retaining all those who matched to mammals. This serves a dual purpose 1) to
63 extract only mammals from the European network and 2) to match and standardize species names when
64 aggregating the different data sources further downstream (which is an important consideration when
65 combining datasets Grenié *et al.* (2021)). All nodes had valid matches to GBIF at this step, and so this
66 backbone is used for all name reconciliation steps as outlined below.

67 The European metaweb represents the knowledge we want to learn and transfer; the phylogenetic
68 similarity of mammals here represents the information for transfer. We used the mammalian consensus
69 supertree by Upham *et al.* (2019), for which all approximatively 6000 names have been similarly matched
70 to their GBIF valid names. This step allows us to place each node of the mammalian European metaweb
71 in the phylogeny.

72 The destination problem to which we want to transfer knowledge is the trophic interactions between
73 mammals in Canada. We obtained the list of extant species from the IUCN checklist, and selected the
74 terrestrial and semi-aquatic species (this corresponds to the same selection that was applied by Maiorano
75 *et al.* (2020b) in the European metaweb). The IUCN names were, as previously, reconciled against GBIF to
76 have an exact match to the taxonomy.

77 After taxonomic cleaning and reconciliation as outlined in the following sections, the mammalian
78 European metaweb has 260 species, and the Canadian species pool has 163; of these, 17 (about 4% of the
79 total) are shared, and 89 species from Canada (54%) had at least one congeneric species in Europe. The
80 similarity for both species pools predictably increases with higher taxonomic order, with 19% of shared
81 genera, 47% of shared families, and 75% of shared orders; for the last point, Canada and Europe each had a
82 single unique order (*Didelphimorphia* for Canada, *Erinaceomorpha* for Europe).

83 In the following sections, we describe the representational learning step applied to European data, the
84 transfer step through phylogenetic similarity, and the generation of a probabilistic metaweb for the
85 destination species pool.

86 **Method description**

87 The crux of the method is the transfer of knowledge of a known network, in order to predict interactions
88 between species from another location. In fig. 1, we give a high-level overview of the approach; in the
89 example around which this manuscript is built (leveraging detailed knowledge about binary trophic
90 interactions between Mammalia in Europe to predict the less known trophic interactions between closely
91 phylogenetically related Mammalia in Canada), we use a series of specific steps for network embedding,
92 trait inference, network prediction and thresholding.

93 Specifically, our approach can be summarized as follows: from the known network in Europe, we use a
94 truncated Singular Value Decomposition (t-SVD; Halko *et al.* 2011) to generate latent traits representing a
95 low-dimensional embedding of the network; these traits give an unbiased estimate of the node's position
96 in the latent feature spaces. Then, we map these latent traits onto a reference phylogeny (other
97 distance-based measures of species proximity that allow for the inference of features in the latent space
98 can be used, for example the dissimilarity in functional traits). Based on the reconstructed latent traits for
99 species in the destination species pool, a Random Dot Product Graph model (hereafter RDPG; Young &
100 Scheinerman 2007) predicts the interaction between species through a function of the nodes' features
101 through matrix multiplication. Thus, from latent traits and node position, we can infer interactions.

102 **Implementation and code availability**

103 The entire pipeline is implemented in *Julia* 1.6 (Bezanson *et al.* 2017) and is available under the
104 permissive MIT License at <https://osf.io/2zwqm/>. The taxonomic cleanup steps are done using GBIF.jl
105 (Dansereau & Poisot 2021). The network embedding and analysis is done using EcologicalNetworks.jl
106 (Poisot *et al.* 2019; Banville *et al.* 2021). The phylogenetic simulations are done using PhyloNetworks.jl
107 (Solís-Lemus *et al.* 2017) and Phylo.jl (Reeve *et al.* 2016). A complete Project.toml file specifying the
108 full tree of dependencies is available alongside the code. This material also includes a fully annotated copy
109 of the entire code required to run this project (describing both the intent of the code and discussing some
110 technical implementation details), a vignette for every step of the process, and a series of Jupyter
111 notebooks with the text and code. The pipeline can be executed on a laptop in a matter of minutes, and
112 therefore does not require extensive computational power.

113 **Step 1: Learning the origin network representation**

114 The first step in transfer learning is to learn the structure of the original dataset. In order to do so, we rely
115 on an approach inspired from representational learning, where we learn a *representation* of the metaweb
116 (in the form of the latent subspaces), rather than a list of interactions (species *a* eats *b*). This approach is
117 conceptually different from other metaweb-scale predictions (e.g. Albouy *et al.* 2019), in that the metaweb
118 representation is easily transferable. Specifically, we use RDPG to create a number of latent variables that
119 can be combined into an approximation of the network adjacency matrix. RDPG results are known to
120 have strong phylogenetic signal, and to capture the evolutionary backbone of food webs (Dalla Riva &
121 Stouffer 2016). In addition, recent advances show that the latent variables produced this way can be used
122 to predict *de novo* network edges (*i.e.* interactions; Runghen *et al.* 2021).

123 The latent variables are created by performing a truncated Singular Value Decomposition (t-SVD) on the
124 adjacency matrix. SVD is an appropriate embedding of ecological networks, which has recently been
125 shown to both capture their complex, emerging properties (Strydom *et al.* 2021b) and to allow highly
126 accurate prediction of the interactions within a single network (Poisot *et al.* 2021b). Under SVD, an
127 adjacency matrix \mathbf{A} (where $\mathbf{A}_{m,n} \in \mathbb{B}$ where 1 indicates predation and 0 an absence thereof) is
128 decomposed into three components resulting in $\mathbf{A} = \mathbf{L}\Sigma\mathbf{R}'$. Here, Σ is a $m \times n$ diagonal matrix and
129 contains only singular (σ) values along its diagonal, \mathbf{L} is a $m \times m$ unitary matrix, and \mathbf{R}' a $n \times n$ unitary
130 matrix. Truncating the SVD removes additional noise in the dataset by omitting non-zero and/or smaller
131 σ values from Σ using the rank of the matrix. Under a t-SVD $\mathbf{A}_{m,n}$ is decomposed so that Σ is a square $r \times r$
132 diagonal matrix (whith $1 \leq r \leq r_{full}$ where r_{full} is the full rank of \mathbf{A} and r the rank at which we truncate
133 the matrix) containing only non-zero σ values. Additionally, \mathbf{L} is now a $m \times r$ semi unitary matrix and \mathbf{R}' a
134 $n \times r$ semi-unitary matrix.

135 The specific rank at which the SVD ought to be truncated is a difficult question. The purpose of SVD is to
136 remove the noise (expressed at high dimensions) and to focus on the signal, (expressed at low dimensions).
137 In datasets with a clear signal/noise demarcation, a scree plot of Σ can show a sharp drop at the rank where
138 noise starts (Zhu & Ghodsi 2006). Because the European metaweb is almost entirely known, the amount
139 of noise (uncertainty) is low; this is reflected in fig. 2 (left), where the scree plot shows no important drop,
140 and in fig. 2 (right) where the proportion of variance explained increases smoothly at higher dimensions.
141 For this reason, we default back to a threshold that explains 60% of the variance in the underlying data,

142 corresponding to 12 dimensions - *i.e.* a tradeoff between accuracy and a reduced number of features.

143 A RDPG estimates the probability of observing interactions between nodes (species) as a function of the
144 nodes' latent variables. The latent variables used for the RDPG, called the left and right subspaces, are
145 defined as $\mathcal{L} = \mathbf{L}\sqrt{\Sigma}$, and $\mathcal{R} = \sqrt{\Sigma}\mathbf{R}$ – using the full rank of \mathbf{A} , $\mathcal{L}\mathcal{R}' = \mathbf{A}$, and using any smaller rank
146 results in $\mathcal{L}\mathcal{R}' \approx \mathbf{A}$. Using a rank of 1 for the t-SVD provides a first-order approximation of the network.

147 [Figure 2 about here.]

148 Because RDPG relies on matrix multiplication, the higher dimensions essentially serve to make specific
149 interactions converge towards 0 or 1; therefore, for reasonably low ranks, there is no guarantee that the
150 values in the reconstructed network will be within the unit range. In order to determine what constitutes
151 an appropriate threshold for probability, we performed the RDPG approach on the European metaweb,
152 and evaluated the probability threshold by treating this as a binary classification problem, specifically
153 assuming that both 0 and 1 in the European metaweb are all true. Given the methodological details given
154 in Maiorano *et al.* (2020b) and O'Connor *et al.* (2020), this seems like a reasonable assumption, although
155 one that does not hold for all metawebs. We used the thresholding approach presented in Poisot *et al.*
156 (2021b), and picked a cutoff that maximized Youden's *J* statistic (a measure of the informedness (trust) of
157 predictions; Youden (1950)); the resulting cutoff was 0.22, and gave an accuracy above 0.99.

158 The left and right subspaces for the European metaweb, accompanied by the threshold for prediction,
159 represent the knowledge we seek to transfer. In the next section, we explain how we rely on phylogenetic
160 similarity to do so.

161 **Steps 2 and 3: Transfer learning through phylogenetic relatedness**

162 In order to transfer the knowledge from the European metaweb to the Canadian species pool, we
163 performed ancestral character estimation using a Brownian motion model, which is a conservative
164 approach in the absence of strong hypotheses about the nature of phylogenetic signal in the network
165 decomposition (Litsios & Salamin 2012). This uses the estimated feature vectors for the European
166 mammals to create a state reconstruction for all species (conceptually something akin to a trait-based
167 mammalian phylogeny using generality and vulnerability traits) and allows us to impute the missing
168 (latent) trait data for the Canadian species that are not already in the European network; as we are focused

169 on predicting contemporary interactions, we only retained the values for the tips of the tree. We assumed
170 that all traits (*i.e.* the feature vectors for the left and right subspaces) were independent, which is a
171 reasonable assumption as every trait/dimension added to the t-SVD has an *additive* effect to the one before
172 it. Note that the Upham *et al.* (2019) tree itself has some uncertainty associated to inner nodes of the
173 phylogeny. In this case study, we have decided to not propagate this uncertainty, as it would complexify
174 the process. The Brownian motion algorithm returns the *average* value of the trait, and its upper and
175 lower bounds. Because we do not estimate other parameters of the traits' distributions, we considered that
176 every species trait is represented as a uniform distribution between these bounds; in a situation where the
177 algorithm would return point values for all simulations, one could in theory either estimate the
178 parameters of a distribution for each tip, or draw randomly from the outputs. In all cases, the inferred left
179 and right sub-spaces for the Canadian species pool ($\hat{\mathcal{L}}$ and $\hat{\mathcal{R}}$) have entries that are distributions,
180 representing the range of values for a given species at a given dimension.

181 These objects represent the transferred knowledge, which we can use for prediction of the Canadian
182 metaweb.

183 Step 4: Probabilistic prediction of the destination network

184 The phylogenetic reconstruction of $\hat{\mathcal{L}}$ and $\hat{\mathcal{R}}$ has an associated uncertainty, represented by the breadth of
185 the uniform distribution associated to each of their entries. Therefore, we can use this information to
186 assemble a *probabilistic* metaweb in the sense of Poisot *et al.* (2016), *i.e.* in which every interaction is
187 represented as a single, independent, Bernoulli event of probability p .

188 [Figure 3 about here.]

189 Specifically, we have adopted the following approach. For every entry in $\hat{\mathcal{L}}$ and $\hat{\mathcal{R}}$, we draw a value from
190 its distribution. This results in one instance of the possible left ($\hat{\ell}$) and right (\hat{r}) subspaces for the
191 Canadian metaweb. These can be multiplied, to produce one matrix of real values. Because the entries in
192 $\hat{\ell}$ and \hat{r} are in the same space where \mathcal{L} and \mathcal{R} were originally predicted, it follows that the threshold ρ
193 estimated for the European metaweb also applies. We use this information to produce one random
194 Canadian metaweb, $N = \hat{\mathcal{L}}\hat{\mathcal{R}}' \geq \rho$. As we can see in (fig. 3) the European and Canadian metawebs are
195 structurally similar (as would be expected given the biogeographic similarities) and the two (left and right)
196 subspaces are distinct *i.e.* capturing predation (generality) and prey (vulnerability) traits.

197 Because the intervals around some trait values can be broad (in fact, probably broader than what they
198 would actually be, see e.g. Garland *et al.* 1999), we repeat the above process 2×10^5 times, which results in
199 a probabilistic metaweb P , where the probability of an interaction (here conveying our degree of trust that
200 it exists given the inferred trait distributions) is given by the number of times where it appears across all
201 random draws N , divided by the number of samples. An interaction with $P_{i,j} = 1$ means that these two
202 species were predicted to interact in all 2×10^5 random draws.

203 **Data cleanup, discovery, validation, and thresholding**

204 Once the probabilistic metaweb for Canada has been produced, we followed a number of data inflation
205 steps to finalize it. This step is external to the actual transfer learning framework but rather serves as a
206 way to augment and validate the predicted metaweb.

207 [Figure 4 about here.]

208 First, we extracted the subgraph corresponding to the 17 species shared between the European and
209 Canadian pools and replaced these interactions with a probability of 0 (non-interaction) or 1 (interaction),
210 according to their value in the European metaweb. This represents a minute modification of the inferred
211 network (about 0.8% of all species pairs from the Canadian web), but ensures that we are directly re-using
212 knowledge from Europe.

213 Second, we looked for all species in the Canadian pool known to the Global Biotic Interactions (GLOBI)
214 database (Poelen *et al.* 2014), and extracted their known interactions. Because GLOBI aggregates observed
215 interactions, it is not a *networks* data source, and therefore the only information we can reliably extract
216 from it is that a species pair *was reported to interact at least once*. This last statement should yet be taken
217 with caution, as some sources in GLOBI (e.g. Thessen & Parr 2014) are produced through text analysis,
218 and therefore may not document direct evidence of the interaction. Nevertheless, should the predictive
219 model work, we would expect that a majority of interactions known to GLOBI would also be predicted.
220 After performing this check, we set the probability of all interactions known to GLOBI (366 in total, 33 of
221 which were not predicted by the model, for a success rate of 91%) to 1.

222 Finally, we downloaded the data from Strong & Leroux (2014), who mined various literature sources to
223 identify trophic interactions in Newfoundland. This dataset documented 25 interactions between

224 mammals, only two of which were not part of our (Canada-level) predictions, resulting in a success rate of
225 92%. These two interactions were added to our predicted metaweb with a probability of 1.

226 [Figure 5 about here.]

227 Because the confidence intervals on the inferred trait space are probably over-estimates, we decided to
228 apply a thresholding step to the interactions after the data inflation (fig. 5). Cirtwill & Hambäck (2021)
229 proposed a number of strategies to threshold probabilistic networks. Their methods assume the
230 underlying data to be tag-based sequencing, which represents interactions as co-occurrences of predator
231 and prey within the same tags; this is conceptually identical to our Bernoulli-trial based reconstruction of
232 a probabilistic network. We performed a full analysis of the effect of various cutoffs, and as they either
233 resulted in removing too few interactions, or removing enough interactions that species started to be
234 disconnected from the network, we set this threshold for a probability equivalent to 0 to the largest
235 possible value that still allowed all species to have at least one interaction with a non-zero probability. The
236 need for this slight deviation from the Cirtwill & Hambäck (2021) method highlights the need for
237 additional development on network thresholding.

238 **Results and discussion of the case study**

239 In fig. 5, we examine the effect of varying the cutoff on $P(i \rightarrow j)$ on the number of links, species, and
240 connectance. Determining a cutoff using the maximum curvature, or central difference approximation of
241 the second order partial derivative, as suggested by e.g. Cirtwill & Hambäck (2021), results in species being
242 lost, or almost all links being kept. We therefore settled on the value that allowed all species to remain
243 with at least one interaction. This result, in and of itself, suggests that additional methodological
244 developments for the thresholding of probabilistic networks are required.

245 [Figure 6 about here.]

246 The t-SVD embedding is able to learn relevant ecological features for the network. fig. 6 shows that the
247 first rank correlates linearly with generality and vulnerability (Schoener 1989), i.e. the number of preys
248 and predators. Importantly, this implies that a rank 1 approximation represents the configuration model

249 for the metaweb, *i.e.* a set of random networks generated from a given degree sequence (Park & Newman
250 2004). Accounting for the probabilistic nature of the degrees, the rank 1 approximation also represents the
251 soft configuration model (van der Hoorn *et al.* 2018). Both models are maximum entropy graph models
252 (Garlaschelli *et al.* 2018), with sharp (all network realizations satisfy the specified degree sequence) and
253 soft (network realizations satisfy the degree sequence on average) local constraints, respectively. The (soft)
254 configuration model is an unbiased random graph model widely used by ecologists in the context of null
255 hypothesis significance testing of network structure (*e.g.* Bascompte *et al.* 2003) and can provide
256 informative priors for Bayesian inference of network structure (*e.g.* Young *et al.* 2021). It is noteworthy
257 that for this metaweb, the relevant information was extracted at the first rank. Because the first rank
258 corresponds to the leading singular value of the system, the results of fig. 6 have a straightforward
259 interpretation: degree-based processes are the most important in structuring the mammalian food web.

260 Discussion

261 One important aspect in which Europe and Canada differ (despite their comparable bioclimatic
262 conditions) is the degree of the legacy of human impacts, which have been much longer in Europe.
263 Nenzén *et al.* (2014) showed that even at small scales (the Iberian peninsula), mammal food webs retain
264 the signal of both climate change and human activity, even when this human activity was orders of
265 magnitude less important than it is now. Similarly, Yeakel *et al.* (2014) showed that changes in human
266 occupation over several centuries can lead to food web collapse. Megafauna in particular seems to be very
267 sensitive to human arrival (Pires *et al.* 2015). In short, there is well-substantiated support for the idea that
268 human footprint affects more than the risk of species extinction (Marco *et al.* 2018), and can lead to
269 changes in interaction structure. Yet, owing to the inherent plasticity of interactions, there have been
270 documented instances of food webs undergoing rapid collapse/recovery cycles over short periods of time
271 (Pedersen *et al.* 2017). The embedding of a network, in a sense, embeds its macro-evolutionary history,
272 especially as RDPG captures ecological signal (Dalla Riva & Stouffer 2016); at this point, it is important to
273 recall that a metaweb is intended as a catalogue of all possible interactions, which should then be filtered
274 (Morales-Castilla *et al.* 2015). In practice (and in this instance) the reconstructed metaweb will predict
275 interactions that are plausible based on the species' evolutionary history, however some interactions
276 would not be realized due to human impact.

277 Cirtwill *et al.* (2019) previously made the point that network inference techniques based on Bayesian
278 approaches would perform far better in the presence of an interaction-level informative prior; the
279 desirable properties of such a prior would be that it is expressed as a probability, preferably representing a
280 Bernoulli event, the value of which would be representative of relevant biological processes (probability of
281 predation in this case). We argue that the probability returned at the very last step of our framework may
282 serve as this informative prior; indeed, the output of our analysis can be used in subsequent steps, also
283 possibly involving expert elicitation to validate some of the most strongly recommended interactions. One
284 important *caveat* to keep in mind when working with interaction inference is that interactions can never
285 really be true negatives (in the current state of our methodological framework and data collection
286 limitations); this renders the task of validating a model through the usual application of binary
287 classification statistics very difficult (although see Strydom *et al.* 2021a for a discussion of alternative
288 suggestions). The other way through which our framework can be improved is by substituting the
289 predictors that are used for transfer. For example, in the presence of information on species traits that are
290 known to be predictive of species interactions, one might want to rely on functional rather than
291 phylogenetic distances – in food webs, body size (and allometrically related variables) has been established
292 as such a variable (Brose *et al.* 2006); the identification of relevant functional traits is facilitated by recent
293 methodological developments (Rosado *et al.* 2013). It should be noted that Xing & Fayle (2021) highlight
294 phylogenetic relatedness as one of the core components of network comparison at the global scale. In this
295 case study, we have embedded the original metaweb using t-SVD, because it lends itself to a RDPC
296 reconstruction, which is known to capture the consequences of evolutionary processes (Dalla Riva &
297 Stouffer 2016); this being said, there are others ways to embed graphs (Cai *et al.* 2017; Arsov & Mirceva
298 2019; Cao *et al.* 2019), which can be used as alternatives.

299 As Herbert (1965) rightfully pointed out, “[y]ou can’t draw neat lines around planet-wide problems”; in
300 this regard, our approach must contend with two interesting problems. The first is the limit of the
301 metaweb to embed and transfer. If the initial metaweb is too narrow in scope, notably from a taxonomic
302 point of view, the chances of finding another area with enough related species to make a reliable inference
303 decrease. This is notably true if the metaweb is assembled in an area with mostly endemic species.
304 Conversely, the metaweb should be reliably filled, which assumes that the S^2 interactions in a pool of S
305 species have been examined, either through literature surveys or expert elicitation. The second problem is
306 to determine which area should be used to infer the new metaweb in, as this determines the species pool

307 that must be used. In our application, we focused on the mammals of Canada. The upside of this
308 approach is that information at the country level is likely to be required by policy makers and stakeholders
309 for their biodiversity assessment, as each country tends to set goals at the national level (Buxton *et al.*
310 2021) for which quantitative instruments are designed (Turak *et al.* 2017), with specific strategies often
311 enacted at smaller scales (Ray *et al.* 2021). Yet these national divisions, in large parts of the world, reflect
312 nothing except for the legacy of settler colonialism, and operating under them must be done under the
313 clear realization that they contributed to the ongoing biodiversity crisis (Adam 2014), can reinforce
314 environmental injustice (Choudry 2013; Domínguez & Luoma 2020), and on Turtle Island especially, will
315 probably end up being replaced by Indigenous principles of land management (Eichhorn *et al.* 2019;
316 No'kmaq *et al.* 2021).

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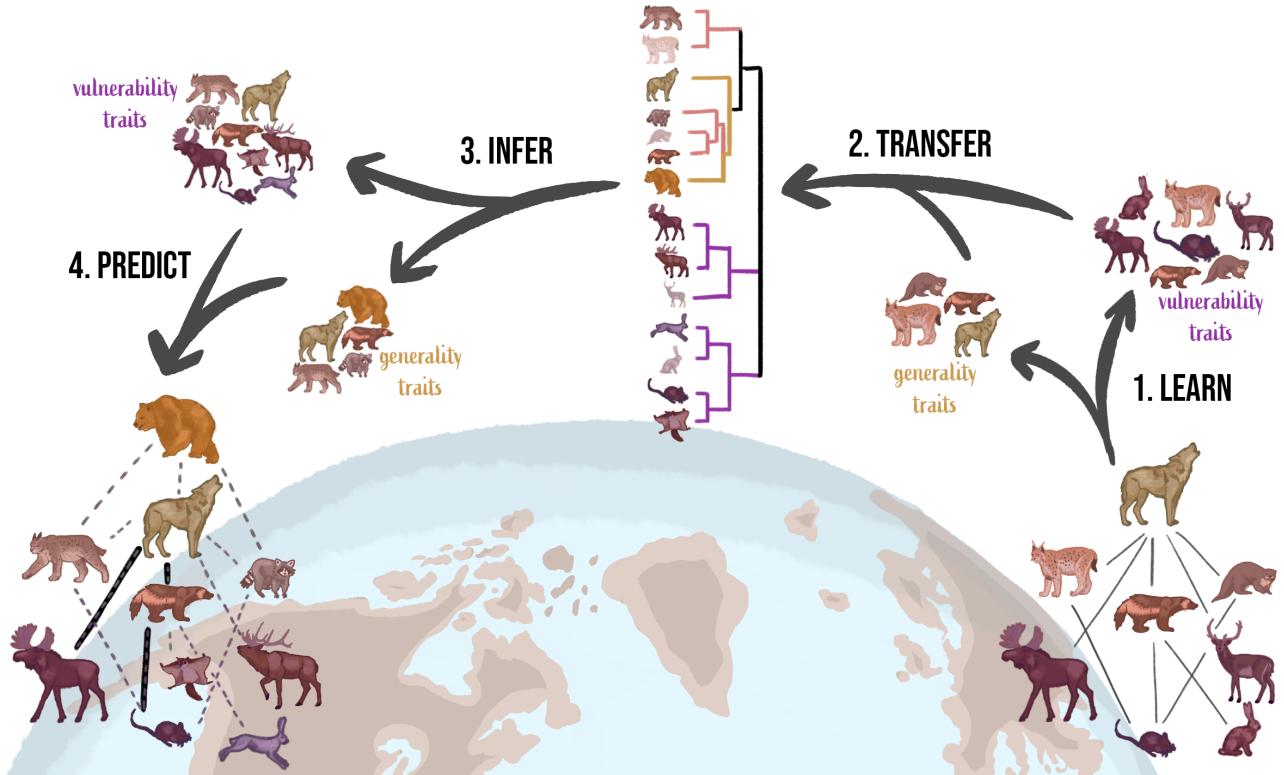


Figure 1: Overview of the phylogenetic transfer learning (and prediction) of species interaction networks. Starting from an initial, known, network, we learn its representation through a graph embedding step (here, a truncated Singular Value Decomposition; Step 1), yielding a series of latent traits (vulnerability traits representing species at the lower trophic-level and generality traits representing species at higher trophic-levels; *sensu* Schoener (1989)); second, for the destination species pool, we perform ancestral character estimation using a phylogeny (here, using a Brownian model for the latent traits; Step 2); we then sample from the reconstructed distribution of latent traits (Step 3) to generate a probabilistic metaweb at the destination (here, assuming a uniform distribution of traits), and threshold it to yield the final list of interactions (Step 4).

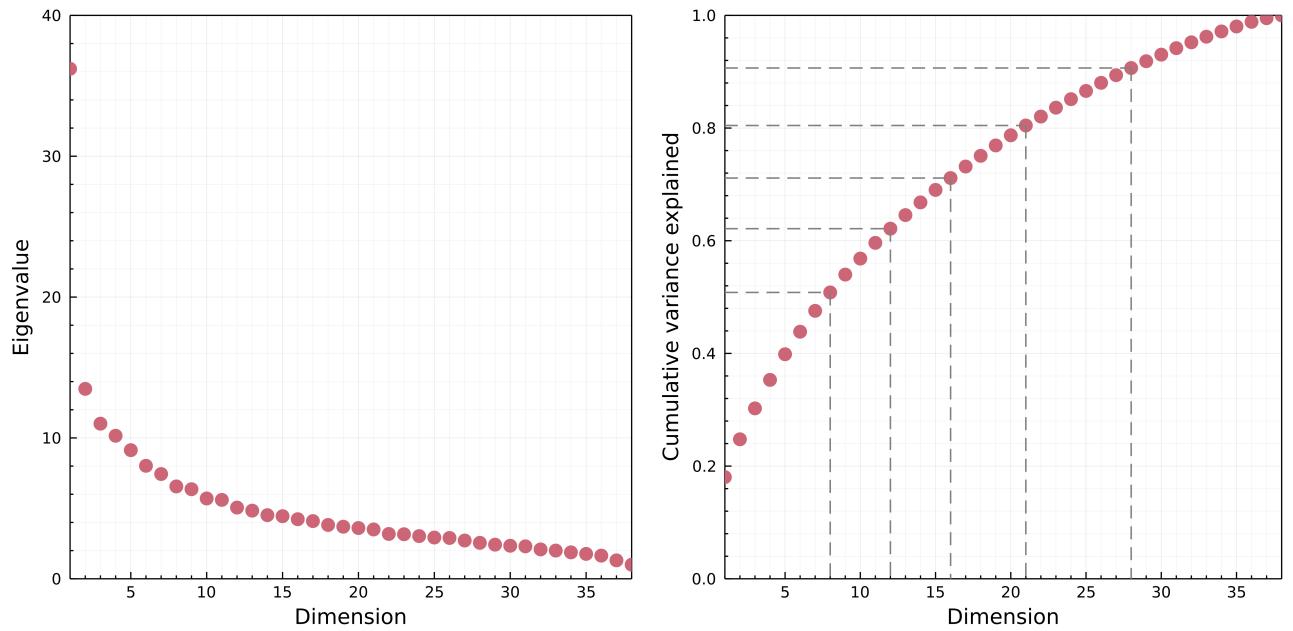


Figure 2: Left: representation of the screeplot of the singular values from the t-SVD on the European metaweb. The screeplot shows no obvious drop in the singular values that may be leveraged to automatically detect a minimal dimension for embedding, after e.g. Zhu & Ghodsi (2006). Right: cumulative fraction of variance explained by each dimension up to the rank of the European metaweb. The grey lines represent cutoffs at 50, 60... 90% of variance explained. For the rest of the analysis, we reverted to an arbitrary threshold of 60% of variance explained, which represented a good tradeoff between accuracy and reduced number of features.

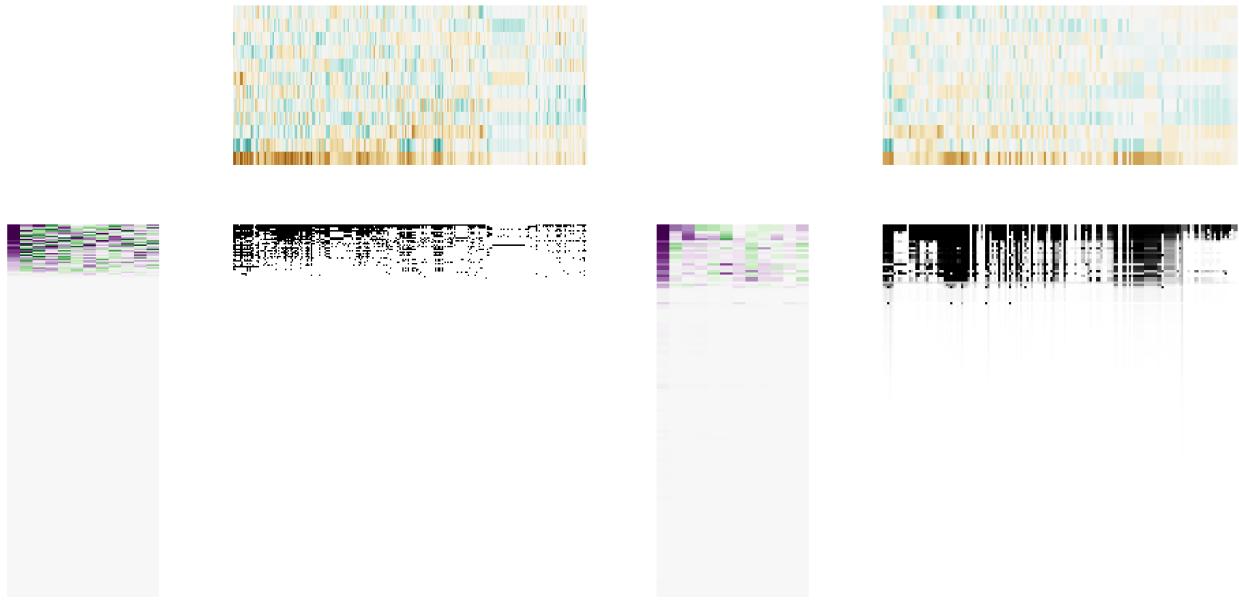


Figure 3: Visual representation of the left (green/purple) and right (green/brown) subspaces, alongside the adjacency matrix of the food web they encode (greyscale). The European metaweb is on the left, and the imputed Canadian metaweb (before data inflation) on the right. This figure illustrates how much structure the left sub-space captures. As we show in fig. 6, the species with a value of 0 in the left subspace are species without any prey.

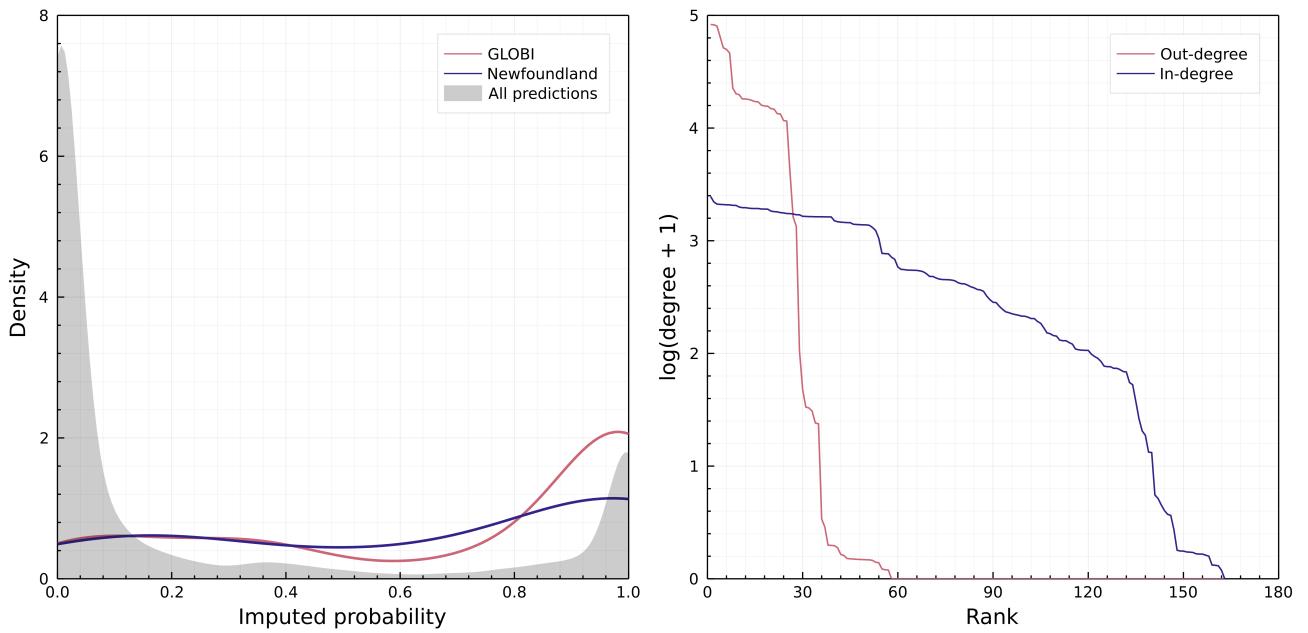


Figure 4: Left, comparison of the probabilities of interactions assigned by the model to all interactions (grey curve), the subset of interactions found in GLOBI (red), and in the Strong & Leroux (2014) Newfoundland dataset (blue). The model recovers more interaction with a low probability compared to data mining, which can suggest that collected datasets are biased towards more common or easy to identify interactions. Right, distribution of the in-degree and out-degree of the mammals from Canada in the reconstructed metaweb. This figure describes a flat, relatively short food web, in which there are few predators but a large number of preys.

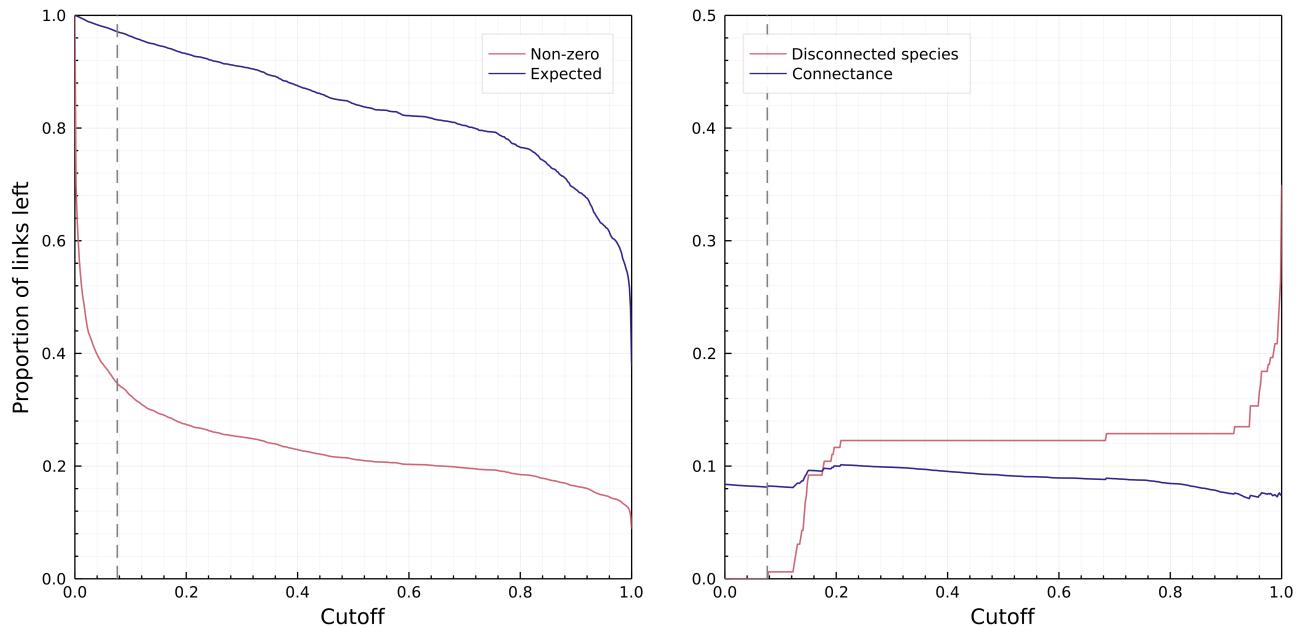


Figure 5: Left: effect of varying the cutoff for probabilities to be considered non-zero on the number of unique links and on \hat{L} , the probabilistic estimate of the number of links assuming that all interactions are independent. Right: effect of varying the cutoff on the number of disconnected species, and on network connectance. In both panels, the grey line indicates the cutoff $P(i \rightarrow j) \approx 0.08$ that resulted in the first species losing all of its interactions.

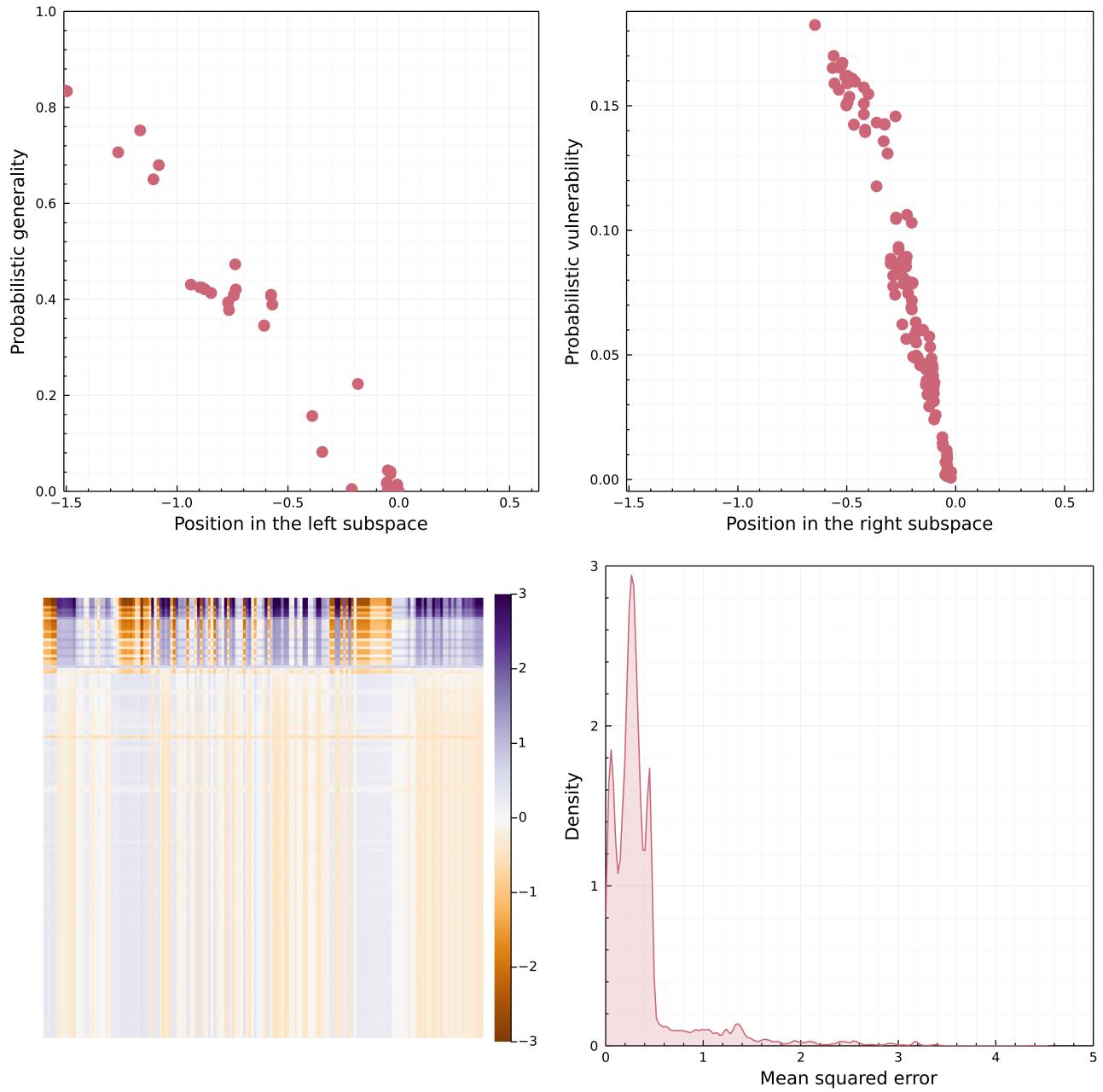


Figure 6: Top: biological significance of the first dimension. Left: there is a linear relationship between the values on the first dimension of the left subspace and the generality, *i.e.* the relative number of preys, *sensu* Schoener (1989). Species with a value of 0 in this subspace are at the bottom-most trophic level. Right: there is, similarly, a linear relationship between the position of a species on the first dimension of the right subspace and its vulnerability, *i.e.* the relative number of predators. Taken together, these two figures show that the first-order representation of this network would capture its degree distribution. Bottom: topological consequences of the first dimension. Left: differences in the z-score of the actual configuration model for the reconstructed network, and the prediction based only on the first dimension. Right: distribution of the differences in the left panel.