

# Predicting metawebs: transfer of graph embeddings can help alleviate spatial data deficiencies

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1. Metawebs, i.e. networks of potential interactions within a species pool, are a powerful abstraction to understand how large-scales species interaction networks are structured.
2. Because metawebs are typically expressed at large spatial and taxonomic scales, assembling them is a tedious and costly process; predictive methods can help circumvent the limitations in data deficiencies, by providing 'draft' metawebs.
3. One way to improve the predictive ability is to maximize the information used for prediction, by using graph embeddings rather than the list of species interactions. Graph embedding is an emerging field in machine learning that holds great potential for ecological problems.
4. In this perspective, we outline how the challenges associated with inferring metawebs line-up with the advantages of graph embeddings; furthermore, because metawebs are inherently spatial objects, we discuss how the choice of the species pool has consequences on the reconstructed network, but also embeds hypotheses about which human-made boundaries are ecologically meaningful.

1 Being able to infer *potential* interactions could be the catalyst for significant breakthroughs in our ability  
2 to start thinking about species interaction networks over large spatial scales (Hortal et al., 2015). In a  
3 recent overview of the field of ecological network prediction, Strydom, Catchen, et al. (2021) identified  
4 two challenges of interest to the prediction of interactions at large scales. First, there is a relative scarcity  
5 of relevant data in most places globally – paradoxically, this restricts our ability to infer interactions to  
6 locations where inference is perhaps the least required; second, accurate predictions often demand  
7 accurate predictors, and the lack of methods that can leverage small amount of data is a serious  
8 impediment to our global predictive ability. In most places, our most reliable biodiversity knowledge is  
9 that of a species pool: through the analysis of databases like GBIF or IUCN, it is possible to establish a list  
10 of species in a region of interest; but establishing the interactions between these species is difficult.

11 Following the definition of Dunne (2006), a metaweb is the ecological network analogue to the species  
12 pool; specifically, it inventories *potential* interactions between species for a spatially delimited area (and so  
13 captures the  $\gamma$  diversity of interactions). The metaweb is not a prediction of the network at a specific point  
14 within the spatial area it covers: it will have a different structure, notably by having a larger connectance  
15 (see *e.g.* Wood et al., 2015) and complexity (see *e.g.* Galiana et al., 2022), from any of these local networks.  
16 These local networks (capturing the  $\alpha$  diversity of interactions) are a subset of the metaweb’s species and  
17 interactions, and have been called “metaweb realizations” (Poisot et al., 2015). Differences between local  
18 networks and their metawebs are due to chance, species abundance and co-occurrence, local  
19 environmental conditions, and local distribution of functional traits, among others. Yet, recent results by  
20 Saravia et al. (2021) strongly suggest that the local realizations only respond weakly to local conditions:  
21 instead, they reflect constraints inherited by the structure of their metaweb. This establishes the metaweb  
22 structure as the core goal of predictive network ecology, as it is a required information to accurately  
23 produce downscaled, local predictions.

24 Because the metaweb represents the joint effect of functional, phylogenetic, and macroecological  
25 processes (Morales-Castilla et al., 2015), it holds valuable ecological information. Specifically, it is the  
26 “upper bounds” on what the composition of the local networks can be (see *e.g.* McLeod et al., 2021); this  
27 information can help evaluate the ability of ecological assemblages to withstand the effects of, for  
28 example, climate change (Fricke et al., 2022). These local networks may be reconstructed given  
29 appropriate knowledge of local species composition, providing information on structure of food webs at  
30 finer spatial scales. This has been done for example for tree-galler-parasitoid systems (Gravel et al., 2018),

31 fish trophic interactions (Albouy et al., 2019), tetrapod trophic interactions (O'Connor et al., 2020), and  
32 crop-pest networks (Grünig et al., 2020). In this contribution, we highlight the *probabilistic* nature of  
33 metawebs, discuss how a family of machine learning tools (graph embeddings and transfer learning) can  
34 be used to overcome data limitations to metaweb inference, and highlight how the use of metawebs  
35 introduces important questions for the field of network ecology.

## 36 **The metaweb is an inherently probabilistic object**

37 Dallas et al. (2017) suggested that most links in ecological networks are cryptic, *i.e.* uncommon or hard to  
38 observe. This argument echoes Jordano (2016): sampling ecological interactions is difficult because it  
39 requires first the joint observation of two species, and then the observation of their interaction. In addition,  
40 it is generally expected that weak or rare links would be more common in networks (Csermely, 2004),  
41 compared to strong, persistent links; this is notably the case in food chains, wherein many weaker links  
42 are key to the stability of a system (Neutel et al., 2002). In the light of these observations, we expect to see  
43 an over-representation of low-probability interactions under a model that accurately predicts interaction  
44 probabilities. Yet the original metaweb definition, and indeed most past uses of metawebs, was based on  
45 the presence/absence of interactions. Moving towards *probabilistic* metawebs, by represent interactions as  
46 Bernoulli events (see *e.g.* Poisot et al., 2016), offers the opportunity to weigh these rare interactions  
47 appropriately. The inherent plasticity of interactions is important to capture: there have been documented  
48 instances of food webs undergoing rapid collapse/recovery cycles over short periods of time (*e.g.* Pedersen  
49 et al., 2017). These considerations emphasize why metaweb predictions should focus on quantitative  
50 (preferentially probabilistic) predictions; this should constrain the suite of appropriate models.

51 Yet it is important to recall that a metaweb is intended as a catalogue of all potential interactions, which is  
52 then filtered (Morales-Castilla et al., 2015). In a sense, that most ecological interactions are elusive can call  
53 for a slightly different approach to sampling: once the common interactions are documented, the effort  
54 required in documenting each rare interaction will increase exponentially, and will do so for each  
55 undocumented interaction. Recent proposals suggest that machine learning algorithms, in these  
56 situations, can act as data generators (Hoffmann et al., 2019): high quality observational data can generate  
57 the core rules underpinning the network structure, and be supplemented with synthetic data coming from  
58 predictive models, increasing the volume of information available for inference. Indeed, Strydom,

59 Catchen, et al. (2021) suggested that knowing the metaweb may render the prediction of local networks  
60 easier, because it fixes an “upper bound” on which interactions can exist. A probabilistic metaweb  
61 represents an aggregation of informative priors on the interactions, an elusive information with the  
62 potential to boost our predictive ability (Bartomeus et al., 2016).

63 [Figure 1 about here.]

## 64 **Graph embedding offers promises for the inference of potential** 65 **interactions**

66 Graph embedding fig. 1 is a varied family of machine learning techniques aiming to transform nodes and  
67 edges into a vector space (Arsov & Mirceva, 2019), usually of a lower dimension, whilst maximally  
68 retaining key properties of the graph (Yan et al., 2005). Ecological networks are an interesting candidate  
69 for the widespread application of embeddings, as they tend to possess a shared structural backbone (Mora  
70 et al., 2018), which hints at structural invariants that can be revealed a lower dimensions. Indeed,  
71 previous work by Eklöf et al. (2013) suggests that food webs are inherently low-dimensional objects, and  
72 can be adequately represented with less than ten dimensions. Simulation results by Botella et al. (2022)  
73 suggest that there is no best method to identify architectural similarities between networks, and that  
74 multiple approaches need to be tested and compared to the network descriptor of interest. This matches  
75 with previous, more general results on graph embedding, which suggest that embedding algorithm choice  
76 matters for the results (Goyal & Ferrara, 2018). In tbl. 1, we present a selection of common graph  
77 embeddings methods, alongside examples of their use to predict species interactions (when they have  
78 been used this way).

Table 1: Overview of some common graph embedding approaches, by time of publication, alongside examples of their use in the prediction of species interactions. Surprisingly, these methods have not yet been used routinely to predict species interactions; most of the examples we identified were either statistical associations, or analogues to joint species distribution models. <sup>a</sup>: statistical interactions; <sup>b</sup>: joint-SDM-like approach.

Method	Embedding approach	Reference	Application
tSNE	nodes through statistical divergence	Hinton & Roweis (2002)	Cieslak et al. (2020) <sup>a</sup>
RDPG	graph through SVD	Young & Scheinerman (2007)	Poisot et al. (2021)
DeepWalk	graph walk	Perozzi et al. (2014)	Wardeh et al. (2021)
FastEmbed	graph through PCA/SVD analogue	Ramasamy & Madhow (2015)	
LINE	nodes through statistical divergence	Tang et al. (2015)	
SDNE	nodes through auto-encoding	D. Wang et al. (2016)	
node2vec	nodes embedding	Grover & Leskovec (2016)	
graph2vec	sub-graph embedding	Narayanan et al. (2017)	
DMSE	joint nodes embedding	D. Chen et al. (2017)	D. Chen et al. (2017) <sup>b</sup>
HARP	nodes through a meta-strategy	H. Chen et al. (2017)	
GraphKKE	graph embedding	Melnyk et al. (2020)	Melnyk et al. (2020) <sup>a</sup>
Joint methods	multiple graphs	S. Wang et al. (2021)	

79 The popularity of graph embedding techniques in machine learning is more prosaic than the search for  
80 structural invariants: graphs are discrete objects, and machine learning techniques tend to handle  
81 continuous data better. Bringing a sparse graph into a continuous, dense vector space (Xu, 2020) opens up

82 a broader variety of predictive algorithms, notably of the sort that are able to predict events as probabilities  
83 (Murphy, 2022). Furthermore, the projection of the graph itself is a representation that can be learned;  
84 Runghen et al. (2021), for example, used a neural network to learn the embedding of a network in which  
85 not all interactions were known, based on nodes metadata. This example has many parallels in ecology  
86 see 2, in which node metadata can be given by phylogeny or functional traits. Rather than directly  
87 predicting biological rules (see *e.g.* Pichler et al., 2020 for an overview), which may be confounded by the  
88 sparse nature of graph data, learning embeddings works in the low-dimensional space that maximizes  
89 information about the network structure. This approach is further justified by the observation, for  
90 example, that the macro-evolutionary history of a network is adequately represented by some graph  
91 embeddings (RDPG; see Dalla Riva & Stouffer, 2016).

92 [Figure 2 about here.]

## 93 **The metaweb embeds ecological hypotheses and practices**

94 The goal of metaweb inference is to provide information about the interactions between species at a large  
95 spatial scale. But as Herbert (1965) rightfully pointed out, “[y]ou can’t draw neat lines around planet-wide  
96 problems”; any inference of a metaweb at large scales must contend with several novel, and interwoven,  
97 families of problems.

98 The first is the spatial and taxonomic limit of the metaweb to embed and transfer. If the initial metaweb is  
99 too narrow in scope, notably from a taxonomic point of view, the chances of finding another area with  
100 enough related species (through phylogenetic relatedness or similarity of functional traits) to make a  
101 reliable inference decreases; this would likely be indicated by large confidence intervals during estimation  
102 of the values in the low-rank space, or by non-overlapping trait distributions in the known and unknown  
103 species. The lack of well documented metawebs is currently preventing the development of more concrete  
104 guidelines. The question of phylogenetic relatedness and dispersal is notably true if the metaweb is  
105 assembled in an area with mostly endemic species, and as with every predictive algorithm, there is room  
106 for the application of our best ecological judgement.

107 The second series of problems are related to determining which area should be used to infer the new  
108 metaweb in, as this determines the species pool that must be used. Metawebs can be constructed by

109 assigning interactions in a list of species within geographic boundaries. The upside of this approach is that  
110 information at the country level is likely to be required for biodiversity assessments, as countries set goals  
111 at the national level (Buxton et al., 2021), and as quantitative instruments are designed to work at these  
112 scales (Turak et al., 2017); specific strategies are often enacted at smaller scales, nested within a specific  
113 country (Ray et al., 2021). But there is no guarantee that these boundaries are meaningful. In fact, we do  
114 not have a satisfying answer to the question of “where does a food web stop?”; the most promising  
115 solutions involve examining the spatial consistency of network area relationships (Fortin et al., 2021; see  
116 e.g. Galiana et al., 2018, 2019, 2021), which is impossible in the absence of enough information about the  
117 network itself. This suggests that inferred metaweb should be further downscaled to allow *a posteriori*  
118 analyses.

119 The final family of problems relates less to ecological concepts and more to the praxis of ecological  
120 research. Operating under the context of national divisions, in large parts of the world, reflects nothing  
121 more than the legacy of settler colonialism. Indeed, the use of ecological data is not an apolitical act (Nost  
122 & Goldstein, 2021), as data infrastructures tend to be designed to answer questions within national  
123 boundaries, and their use both draws upon and reinforces territorial statecraft; as per Machen & Nost  
124 (2021), this is particularly true when the output of “algorithmic thinking” (e.g. relying on machine  
125 learning to generate knowledge) can be re-used for governance (e.g. enacting conservation decisions at the  
126 national scale). We therefore recognize that predictive approaches deployed at the continental scale, no  
127 matter their intent, originate in the framework that contributed to the ongoing biodiversity crisis (Adam,  
128 2014), reinforced environmental injustice (Choudry, 2013; Domínguez & Luoma, 2020), and on Turtle  
129 Island especially, should be replaced by Indigenous principles of land management (Eichhorn et al., 2019;  
130 No’kmaq et al., 2021). As we see AI/ML being increasingly mobilized to generate knowledge that is  
131 lacking for conservation decisions (e.g. Lamba et al., 2019; Mosebo Fernandes et al., 2020), our discussion  
132 of these tools need to go beyond the technical, and into the governance consequences they can have.

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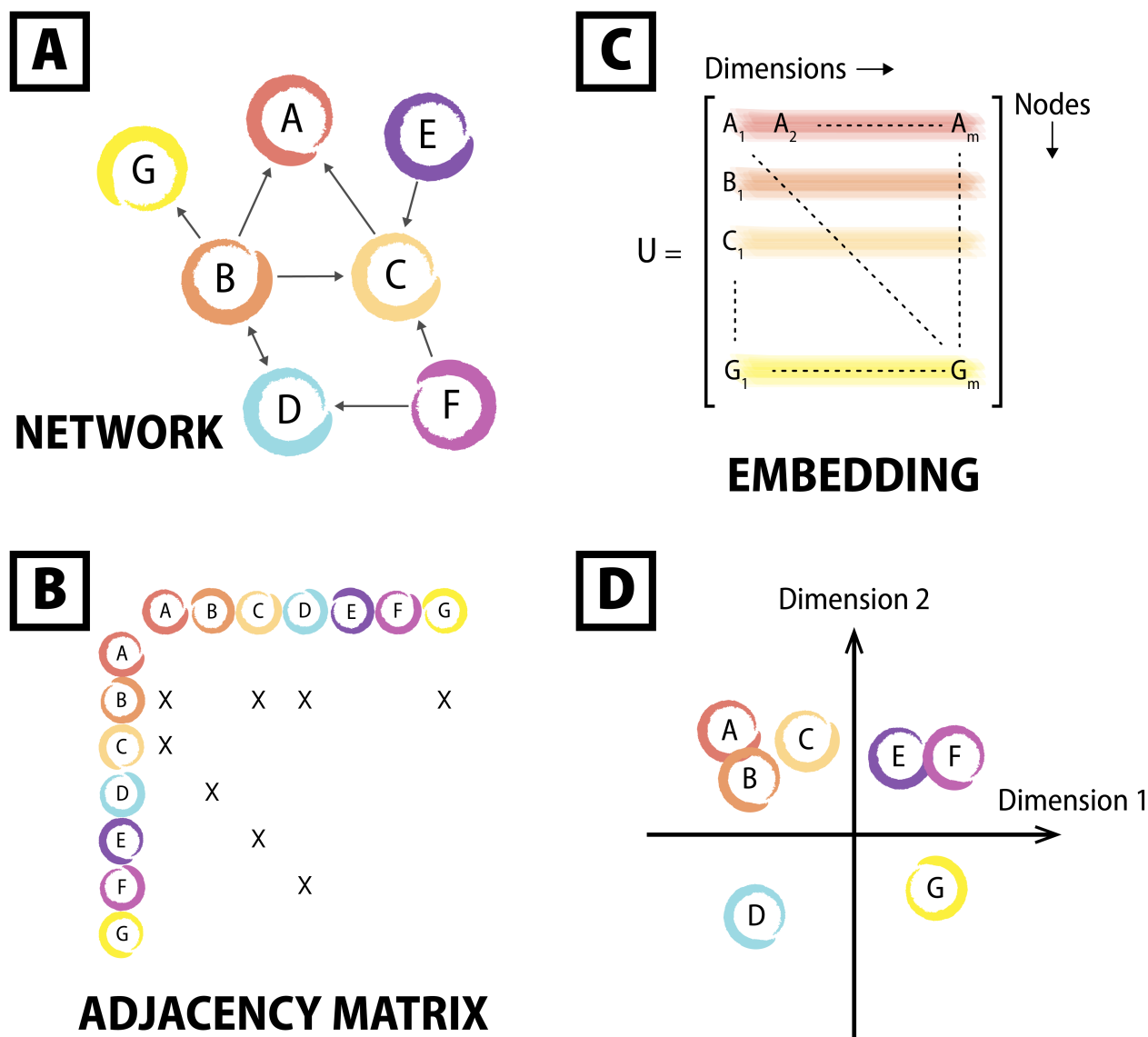


Figure 1: Overview of the embedding process. A network (A), possibly represented as its adjacency matrix (B), is converted into a lower-dimensional object (C) where nodes, subgraphs, or edges have specific values (see tbl. 1). For the purposes of prediction, this low-dimensional object encodes feature vectors for e.g. the nodes. Embedding also allows to visualize the structure in the data differently (D), much like with a principal component analysis.

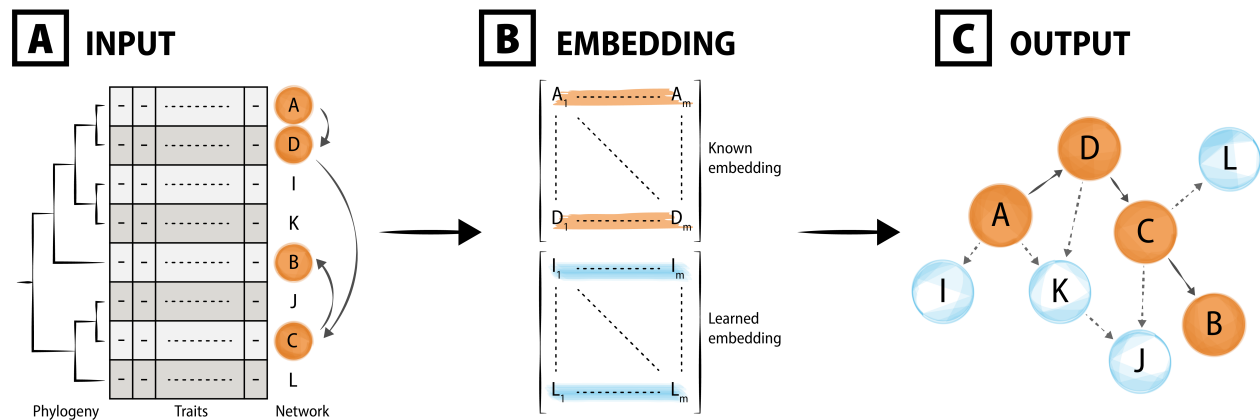


Figure 2: From a low-dimensional feature vector (see fig. 1), it is possible to develop predictive approaches. Nodes in an ecological network are species, for which we can leverage phylogenetic relatedness (*e.g.* Strydom, Bouskila, et al., 2021) or functional traits to fill the values of additional species we would like to project in this space (here, I, J, K, and L) from the embedding of known species (here, A, B, C, and D). Because embeddings can be projected back to a graph, this allows to reconstruct a network with these new species. This approach constitutes an instance of transfer learning.