

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

Tanya Strydom^{1,2,‡} Salomé Bouskila^{1,‡} Francis Banville^{1,3,2} Ceres Barros⁴ Dominique Caron^{5,2}
Maxwell J Farrell⁶ Marie-Josée Fortin⁶ Victoria Hemming⁷ Benjamin Mercier^{3,2} Laura
J. Pollock^{5,2} Rogini Runghen⁸ Giulio V. Dalla Riva⁹ Timothée Poisot^{1,2,‡}

¹ Département de Sciences Biologiques, Université de Montréal, Montréal, Canada ² Quebec Centre for Biodiversity Science, Montréal, Canada ³ Département de Biologie, Université de Sherbrooke, Sherbrooke, Canada ⁴ Department of Forest Resources Management, University of British Columbia, Vancouver, B.C., Canada ⁵ Department of Biology, McGill University, Montréal, Canada ⁶ Department of Ecology & Evolutionary Biology, University of Toronto, Toronto, Canada ⁷ Department of Forest and Conservation Sciences, University of British Columbia, Vancouver, Canada ⁸ Centre for Integrative Ecology, School of Biological Sciences, University of Canterbury, Canterbury, New Zealand ⁹ School of Mathematics and Statistics, University of Canterbury, Canterbury, New Zealand

‡ These authors contributed equally to the work

Correspondance to:

Timothée Poisot — timothee.poisot@umontreal.ca

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).
3 Understanding species interactions holds enormous potential to not only understand and more rapidly
4 learn about species interactions and metawebs, but also how changes in management of a single species
5 may impact non-target species. In a recent overview of the field of ecological network prediction, Strydom,
6 Catchen, et al. (2021) identified two challenges of interest to the prediction of interactions at large scales.
7 First, there is a relative scarcity of relevant data in most places globally – paradoxically, this restricts our
8 ability to infer interactions for locations where inference is perhaps the least required (and leaves us
9 unable to make inference in regions without interaction data); second, accurate predictions often demand
10 accurate predictors, and the lack of methods that can leverage small amount of *accurate* data is a serious
11 impediment to our global predictive ability. In most places, our most reliable biodiversity knowledge is
12 that of a species pool (*i.e.* a set of potentially interacting species in a given area): through the analysis of
13 databases like GBIF or IUCN, it is possible to construct a list of species in a region of interest; but inferring
14 the potential interactions between these species is difficult.

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

28 Because the metaweb represents the joint effect of functional, phylogenetic, and macroecological
29 processes (Morales-Castilla et al., 2015), it holds valuable ecological information. Specifically, it is the
30 “upper bounds” on what the composition of the local networks, given the local species pool, can be (see

31 *e.g.* McLeod et al., 2021); this information can help evaluate the ability of ecological assemblages to
32 withstand the effects of, for example, climate change (Fricke et al., 2022). These local networks may be
33 reconstructed given an appropriate knowledge of local species composition and provide information on
34 the structure of food webs at finer spatial scales. This has been done for example for tree-galler-parasitoid
35 systems (Gravel et al., 2018), fish trophic interactions (Albouy et al., 2019), tetrapod trophic interactions
36 (Braga et al., 2019; O'Connor et al., 2020), and crop-pest networks (Grünig et al., 2020). In this
37 contribution, we highlight the power in viewing (and constructing) metawebs as *probabilistic* objects in
38 the context of rare interactions, discuss how a family of machine learning tools (graph embeddings and
39 transfer learning) can be used to overcome data limitations to metaweb inference, and highlight how the
40 use of metawebs introduces important questions for the field of network ecology.

41 **The metaweb is an inherently probabilistic object**

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

58 Yet it is important to recall that a metaweb is intended as a catalogue of all potential interactions, which is

59 then filtered (Morales-Castilla et al., 2015). In a sense, that most ecological interactions are elusive can call
60 for a slightly different approach to sampling: once the common interactions are documented, the effort
61 required in documenting each rare interaction will increase exponentially. Recent proposals suggest that
62 machine learning algorithms, in these situations, can act as data generators (Hoffmann et al., 2019): high
63 quality observational data can generate the core rules underpinning the network structure, and be
64 supplemented with synthetic data coming from predictive models, increasing the volume of information
65 available for inference. Indeed, Strydom, Catchen, et al. (2021) suggested that knowing the metaweb may
66 render the prediction of local networks easier, because it fixes an “upper bound” on which interactions
67 can exist. In this context a probabilistic metaweb represents an aggregation of informative priors on the
68 interactions, elusive information with the potential to boost our predictive ability (Bartomeus et al., 2016).

69 [Figure 1 about here.]

70 **Graph embedding offers promises for the inference of potential** 71 **interactions**

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

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

Method	Embedding approach	Reference	Application in species interactions
tSNE	nodes through statistical divergence	Hinton & Roweis (2002)	Cieslak et al. (2020) ^a
RDPG	graph through SVD	Young & Scheinerman (2007)	Poisot et al. (2021); Dalla Riva & Stouffer (2016)
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) ^b
HARP	nodes through a meta-strategy	H. Chen et al. (2017)	
GraphKKE	graph embedding	Melnyk et al. (2020)	Melnyk et al. (2020) ^a
Joint methods	multiple graphs	S. Wang et al. (2021)	

84 The popularity of graph embedding techniques in machine learning is more than the search for structural
85 invariants: graphs are discrete objects, and machine learning techniques tend to handle continuous data
86 better. Bringing a sparse graph into a continuous, dense vector space (Xu, 2020) opens up a broader variety
87 of predictive algorithms, notably of the sort that are able to predict events as probabilities (Murphy, 2022).
88 Furthermore, the projection of the graph itself is a representation that can be learned; Runghen et al.
89 (2021), for example, used a neural network to learn the embedding of a network in which not all
90 interactions were known, based on nodes metadata. This example has many parallels in ecology (see
91 fig. 2), in which node metadata can be given by phylogeny or functional traits. Rather than directly
92 predicting biological rules (see *e.g.* Pichler et al., 2020 for an overview), which may be confounded by the
93 sparse nature of graph data, learning embeddings works in the low-dimensional space that maximizes
94 information about the network structure. This approach is further justified by the observation, for
95 example, that the macro-evolutionary history of a network is adequately represented by some graph
96 embeddings (RDPG; see Dalla Riva & Stouffer, 2016).

97 [Figure 2 about here.]

98 **The metaweb embeds ecological hypotheses and practices**

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

103 The first is the taxonomic and spatial limit of the metaweb to embed and transfer. If the initial metaweb is
104 too narrow in scope, notably from a taxonomic point of view, the chances of finding another area with
105 enough related species (through phylogenetic relatedness or similarity of functional traits) to make a
106 reliable inference decreases; this would likely be indicated by large confidence intervals during estimation
107 of the values in the low-rank space, or by non-overlapping trait distributions in the known and unknown
108 species. Alternatively a metaweb is too large (taxonomically), then the resulting embeddings would have
109 interactions relative to taxonomic groups that not present in the new location, resulting in the potential
110 under or over estimation of the strength of new predicted interactions. The lack of well documented

111 metawebs is currently preventing the development of more concrete guidelines. The question of
112 phylogenetic relatedness and dispersal is notably true if the metaweb is assembled in an area with mostly
113 endemic species (*e.g.* a system that has undergone recent radiation and might not have an analogous
114 system with which to draw knowledge from), and as with every predictive algorithm, there is room for the
115 application of our best ecological judgement.

116 The second series of problems relate to determining which area should be used to infer the new metaweb
117 in, as this determines the species pool that must be used. Metawebs can be constructed by assigning
118 interactions in a list of species within geographic boundaries. The upside of this approach is that
119 information at the country level is likely to be required for biodiversity assessments, as countries set goals
120 at the national level (Buxton et al., 2021), and as quantitative instruments are designed to work at these
121 scales (Turak et al., 2017); specific strategies are often enacted at smaller scales, nested within a specific
122 country (Ray et al., 2021). But there is no guarantee that these boundaries are meaningful. In fact, we do
123 not have a satisfying answer to the question of “where does a food web stop?”; the most promising
124 solutions involve examining the spatial consistency of network area relationships (Fortin et al., 2021; see
125 *e.g.* Galiana et al., 2018, 2019, 2021), which is impossible in the absence of enough information about the
126 network itself. This suggests that inferred metawebs should be further downscaled to allow for *a posteriori*
127 analyses.

128 The final family of problems relates less to ecological concepts and more to the praxis of ecological
129 research. Operating under the context of national divisions, in large parts of the world, reflects nothing
130 more than the legacy of settler colonialism, which not only drive a disparity in available ecological data,
131 but can entrench said biases with the machine learning models that make predictions with them. Indeed,
132 the use of ecological data is not an apolitical act (Nost & Goldstein, 2021), as data infrastructures tend to
133 be designed to answer questions within national boundaries, and their use often draws upon and
134 reinforces territorial statecraft. As per Machen & Nost (2021), this is particularly true when the output of
135 “algorithmic thinking” (*e.g.* relying on machine learning to generate knowledge) can be re-used for
136 governance (*e.g.* enacting conservation decisions at the national scale). We therefore recognize that
137 predictive approaches deployed at the continental scale, no matter their intent, originate in the framework
138 that contributed to the ongoing biodiversity crisis (Adam, 2014), reinforced environmental injustice
139 (Choudry, 2013; Domínguez & Luoma, 2020), and *e.g.* as on Turtle Island, should be replaced by
140 Indigenous principles of land management (Eichhorn et al., 2019; No’kmaq et al., 2021). As we see

artificial intelligence/machine learning being increasingly mobilized to generate knowledge that is lacking for conservation decisions (e.g. Lamba et al., 2019; Mosebo Fernandes et al., 2020) and drive policy decisions (Weiskopf et al., 2022), our discussion of these tools need to go beyond the technical, and into the governance consequences they can have.

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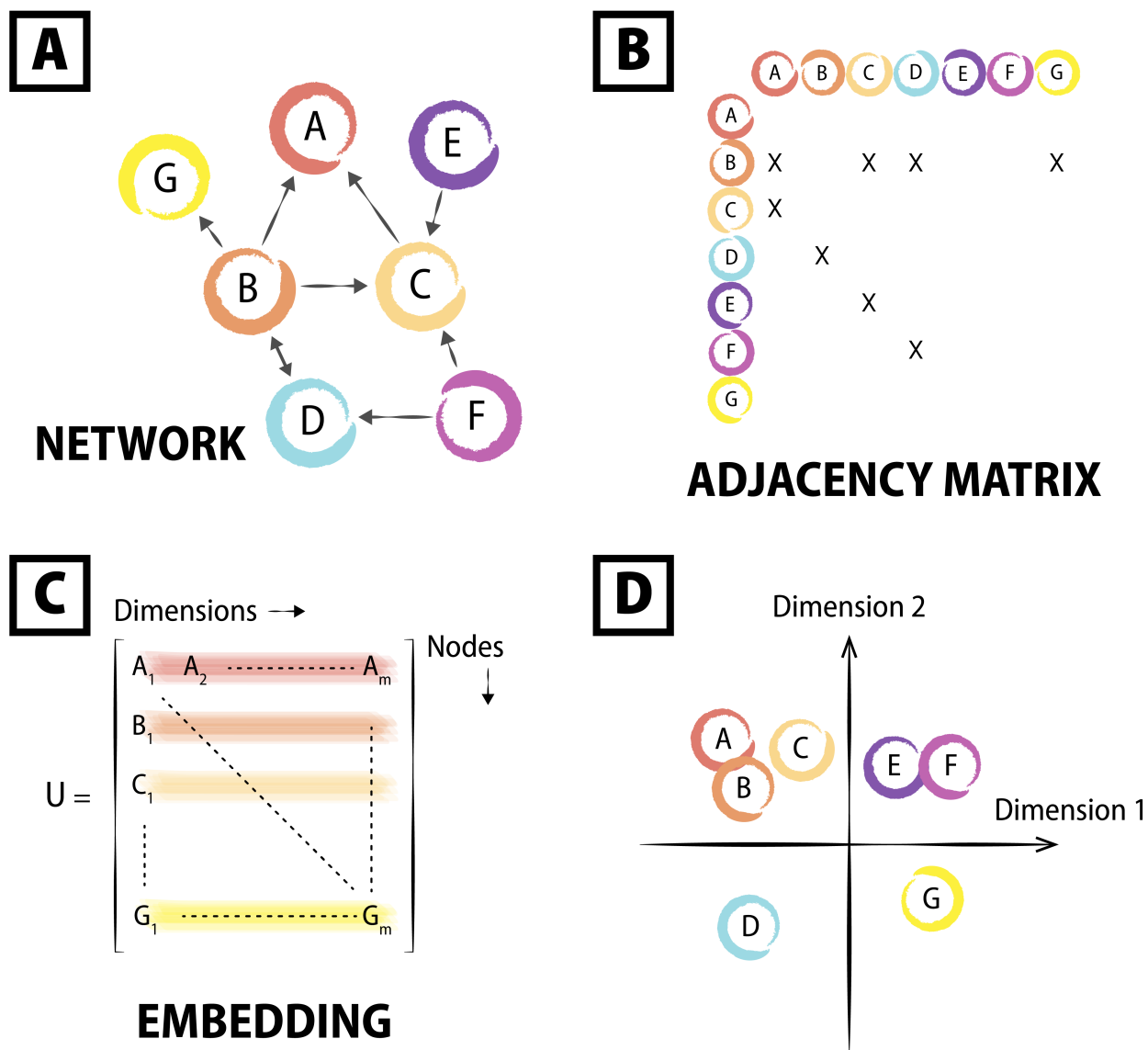


Figure 1: Overview of the embedding process. A network (A), represented as its adjacency matrix (B), is converted into a lower-dimensional object (C) where nodes, subgraphs, or edges have specific values (see tbl. 1). For the purposes of prediction, this low-dimensional object encodes feature vectors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

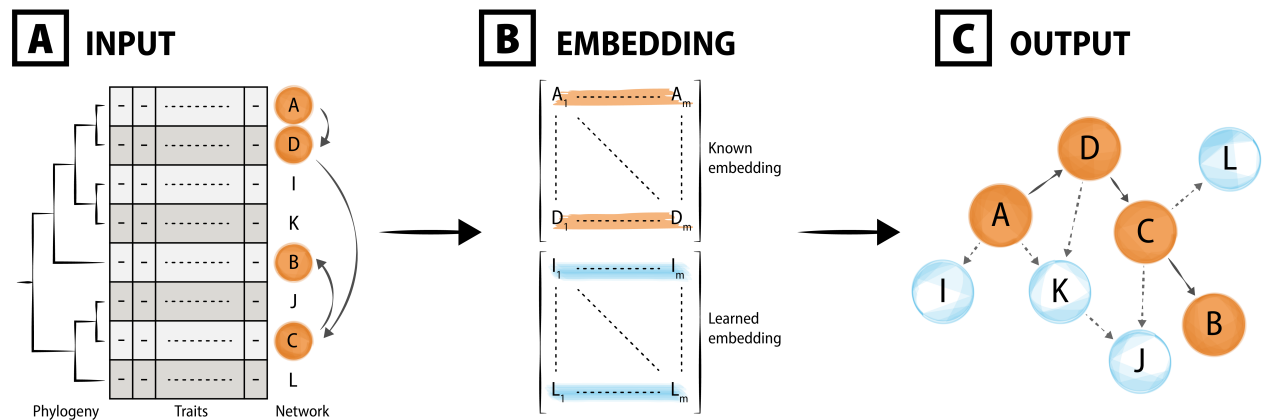


Figure 2: From a low-dimensional feature vector (see fig. 1), it is possible to develop predictive approaches. Nodes in an ecological network are species, for which we can leverage phylogenetic relatedness (*e.g.* Strydom, Bouskila, et al., 2021) or functional traits to fill the values of additional 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 us to reconstruct a network with these new species. This approach constitutes an instance of transfer learning.