

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

Tanya Strydom<sup>1,2,‡</sup> Salomé Bouskila<sup>1,‡</sup> Francis Banville<sup>1,3,2</sup> Ceres Barros<sup>4</sup> Dominique Caron<sup>5,2</sup>  
Maxwell J Farrell<sup>6</sup> Marie-Josée Fortin<sup>6</sup> Victoria Hemming<sup>7</sup> Benjamin Mercier<sup>3,2</sup> Laura  
J. Pollock<sup>5,2</sup> Rogini Runghen<sup>8</sup> Giulio V. Dalla Riva<sup>9</sup> Timothée Poisot<sup>1,2,‡</sup>

<sup>1</sup> Département de Sciences Biologiques, Université de Montréal, Montréal, Canada <sup>2</sup> Quebec Centre for Biodiversity Science, Montréal, Canada <sup>3</sup> Département de Biologie, Université de Sherbrooke, Sherbrooke, Canada <sup>4</sup> Department of Forest Resources Management, University of British Columbia, Vancouver, B.C., Canada <sup>5</sup> Department of Biology, McGill University, Montréal, Canada <sup>6</sup> Department of Ecology & Evolutionary Biology, University of Toronto, Toronto, Canada <sup>7</sup> Department of Forest and Conservation Sciences, University of British Columbia, Vancouver, Canada <sup>8</sup> Centre for Integrative Ecology, School of Biological Sciences, University of Canterbury, Canterbury, New Zealand <sup>9</sup> 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](mailto: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  $\gamma$  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  $\alpha$  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. <sup>a</sup>: statistical interactions; <sup>b</sup>: joint-SDM-like approach.

Method	Embedding approach	Reference	Application in species interactions
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); 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) <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)	

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.

**Acknowledgements:** We acknowledge that this study was conducted on land within the traditional unceded territory of the Saint Lawrence Iroquoian, Anishinabewaki, Mohawk, Huron-Wendat, and Omàmiwininiwak nations. TP, TS, DC, and LP received funding from the Canadian Institute for Ecology & Evolution. FB is funded by the Institute for Data Valorization (IVADO). TS, SB, and TP are funded by a donation from the Courtois Foundation. CB was awarded a Mitacs Elevate Fellowship no. IT12391, in partnership with fRI Research, and also acknowledges funding from Alberta Innovates and the Forest Resources Improvement Association of Alberta. M-JF acknowledges funding from NSERC Discovery Grant and NSERC CRC. RR is funded by New Zealand's Biological Heritage Ngā Koiora Tuku Iho National Science Challenge, administered by New Zealand Ministry of Business, Innovation, and Employment. BM is funded by the NSERC Alexander Graham Bell Canada Graduate Scholarship and the FRQNT master's scholarship. LP acknowledges funding from NSERC Discovery Grant (NSERC RGPIN-2019-05771). TP acknowledges financial support from NSERC through the Discovery Grants and Discovery Accelerator Supplement programs. MJF is supported by an NSERC PDF and an RBC Post-Doctoral Fellowship

**Conflict of interest:** The authors have no conflict interests to disclose

**Authors' contributions:** TS, and TP conceived the ideas discussed in the manuscript. All authors contributed to writing and editing the manuscript.

**Data availability:** There is no data associated with this manuscript.

## References

- Adam, R. (2014). *Elephant treaties: The Colonial legacy of the biodiversity crisis*. UPNE.
- Albouy, C., Archambault, P., Appeltans, W., Araújo, M. B., Beauchesne, D., Cazelles, K., Cirtwill, A. R., Fortin, M.-J., Galiana, N., Leroux, S. J., Pellissier, L., Poisot, T., Stouffer, D. B., Wood, S. A., & Gravel, D. (2019). The marine fish food web is globally connected. *Nature Ecology & Evolution*, 3(8, 8), 1153–1161. <https://doi.org/10.1038/s41559-019-0950-y>

168 Arsov, N., & Mirceva, G. (2019, November 26). *Network Embedding: An Overview*.  
169 <http://arxiv.org/abs/1911.11726>

170 Bartomeus, I., Gravel, D., Tylianakis, J. M., Aizen, M. A., Dickie, I. A., & Bernard-Verdier, M. (2016). A  
171 common framework for identifying linkage rules across different types of interactions. *Functional*  
172 *Ecology*, 30(12), 1894–1903.

173 Botella, C., Dray, S., Matias, C., Miele, V., & Thuiller, W. (2022). An appraisal of graph embeddings for  
174 comparing trophic network architectures. *Methods in Ecology and Evolution*, 13(1), 203–216.  
175 <https://doi.org/10.1111/2041-210X.13738>

176 Braga, J., Pollock, L. J., Barros, C., Galiana, N., Montoya, J. M., Gravel, D., Maiorano, L., Montemaggiore,  
177 A., Ficetola, G. F., Dray, S., & Thuiller, W. (2019). Spatial analyses of multi-trophic terrestrial vertebrate  
178 assemblages in Europe. *Global Ecology and Biogeography*, 28(11), 1636–1648.  
179 <https://doi.org/10.1111/geb.12981>

180 Bramon Mora, B., Gravel, D., Gilarranz, L. J., Poisot, T., & Stouffer, D. B. (2018). Identifying a common  
181 backbone of interactions underlying food webs from different ecosystems. *Nature Communications*,  
182 9(1), 2603. <https://doi.org/10.1038/s41467-018-05056-0>

183 Buxton, R. T., Bennett, J. R., Reid, A. J., Shulman, C., Cooke, S. J., Francis, C. M., Nyboer, E. A., Pritchard,  
184 G., Binley, A. D., Avery-Gomm, S., Ban, N. C., Beazley, K. F., Bennett, E., Blight, L. K., Bortolotti, L. E.,  
185 Camfield, A. F., Gadallah, F., Jacob, A. L., Naujokaitis-Lewis, I., ... Smith, P. A. (2021). Key  
186 information needs to move from knowledge to action for biodiversity conservation in Canada.  
187 *Biological Conservation*, 256, 108983. <https://doi.org/10.1016/j.biocon.2021.108983>

188 Chen, D., Xue, Y., Fink, D., Chen, S., & Gomes, C. P. (2017). *Deep Multi-species Embedding*. 3639–3646.

189 Chen, H., Perozzi, B., Hu, Y., & Skiena, S. (2017, November 16). *HARP: Hierarchical Representation*  
190 *Learning for Networks*. <http://arxiv.org/abs/1706.07845>

191 Choudry, A. (2013). Saving biodiversity, for whom and for what? Conservation NGOs, complicity,  
192 colonialism and conquest in an era of capitalist globalization. In *NGOization: Complicity,*  
193 *contradictions and prospects* (pp. 24–44). Bloomsbury Publishing.

194 Cieslak, M. C., Castelfranco, A. M., Roncalli, V., Lenz, P. H., & Hartline, D. K. (2020). T-Distributed  
195 Stochastic Neighbor Embedding (t-SNE): A tool for eco-physiological transcriptomic analysis. *Marine*

196 *Genomics*, 51, 100723. <https://doi.org/10.1016/j.margen.2019.100723>

197 Csermely, P. (2004). Strong links are important, but weak links stabilize them. *Trends in Biochemical*  
 198 *Sciences*, 29(7), 331–334. <https://doi.org/10.1016/j.tibs.2004.05.004>

199 Dalla Riva, G. V., & Stouffer, D. B. (2016). Exploring the evolutionary signature of food webs' backbones  
 200 using functional traits. *Oikos*, 125(4), 446–456. <https://doi.org/10.1111/oik.02305>

201 Dallas, T., Park, A. W., & Drake, J. M. (2017). Predicting cryptic links in host-parasite networks. *PLOS*  
 202 *Computational Biology*, 13(5), e1005557. <https://doi.org/10.1371/journal.pcbi.1005557>

203 Domínguez, L., & Luoma, C. (2020). Decolonising Conservation Policy: How Colonial Land and  
 204 Conservation Ideologies Persist and Perpetuate Indigenous Injustices at the Expense of the  
 205 Environment. *Land*, 9(3, 3), 65. <https://doi.org/10.3390/land9030065>

206 Dunne, J. A. (2006). The Network Structure of Food Webs. In J. A. Dunne & M. Pascual (Eds.), *Ecological*  
 207 *networks: Linking structure and dynamics* (pp. 27–86). Oxford University Press.

208 Eichhorn, M. P., Baker, K., & Griffiths, M. (2019). Steps towards decolonising biogeography. *Frontiers of*  
 209 *Biogeography*, 12(1), 1–7. <https://doi.org/10.21425/F5FBG44795>

210 Eklöf, A., Jacob, U., Kopp, J., Bosch, J., Castro-Urgal, R., Chacoff, N. P., Dalsgaard, B., de Sassi, C., Galetti,  
 211 M., Guimarães, P. R., Lomáscolo, S. B., Martín González, A. M., Pizo, M. A., Rader, R., Rodrigo, A.,  
 212 Tylíanakis, J. M., Vázquez, D. P., & Allesina, S. (2013). The dimensionality of ecological networks.  
 213 *Ecology Letters*, 16(5), 577–583. <https://doi.org/10.1111/ele.12081>

214 Fortin, M.-J., Dale, M. R. T., & Brimacombe, C. (2021). Network ecology in dynamic landscapes.  
 215 *Proceedings of the Royal Society B: Biological Sciences*, 288(1949), rspb.2020.1889, 20201889.  
 216 <https://doi.org/10.1098/rspb.2020.1889>

217 Fricke, E. C., Ordonez, A., Rogers, H. S., & Svenning, J.-C. (2022). The effects of defaunation on plants'  
 218 capacity to track climate change. *Science*.

219 Galiana, N., Barros, C., Braga, J., Ficetola, G. F., Maiorano, L., Thuiller, W., Montoya, J. M., & Lurgi, M.  
 220 (2021). The spatial scaling of food web structure across European biogeographical regions. *Ecography*,  
 221 *n/a(n/a)*. <https://doi.org/10.1111/ecog.05229>

222 Galiana, N., Hawkins, B. A., & Montoya, J. M. (2019). The geographical variation of network structure is  
 223 scale dependent: Understanding the biotic specialization of hostparasitoid networks. *Ecography*, 42(6),

1175–1187. <https://doi.org/10.1111/ecog.03684>

Galiana, N., Lurgi, M., Bastazini, V. A. G., Bosch, J., Cagnolo, L., Cazelles, K., Claramunt-López, B., Emer, C., Fortin, M.-J., Grass, I., Hernández-Castellano, C., Jauker, F., Leroux, S. J., McCann, K., McLeod, A. M., Montoya, D., Mulder, C., Osorio-Canadas, S., Reverté, S., ... Montoya, J. M. (2022). Ecological network complexity scales with area. *Nature Ecology & Evolution*, 1–8. <https://doi.org/10.1038/s41559-021-01644-4>

Galiana, N., Lurgi, M., Claramunt-López, B., Fortin, M.-J., Leroux, S., Cazelles, K., Gravel, D., & Montoya, J. M. (2018). The spatial scaling of species interaction networks. *Nature Ecology & Evolution*, 2(5), 782–790. <https://doi.org/10.1038/s41559-018-0517-3>

Goyal, P., & Ferrara, E. (2018). Graph embedding techniques, applications, and performance: A survey. *Knowledge-Based Systems*, 151, 78–94. <https://doi.org/10.1016/j.knosys.2018.03.022>

Gravel, D., Baiser, B., Dunne, J. A., Kopelke, J.-P., Martinez, N. D., Nyman, T., Poisot, T., Stouffer, D. B., Tylianakis, J. M., Wood, S. A., & Roslin, T. (2018). Bringing Elton and Grinnell together: A quantitative framework to represent the biogeography of ecological interaction networks. *Ecography*, 0(0). <https://doi.org/10.1111/ecog.04006>

Grover, A., & Leskovec, J. (2016). Node2vec: Scalable Feature Learning for Networks. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 855–864. <https://doi.org/10.1145/2939672.2939754>

Grünig, M., Mazzi, D., Calanca, P., Karger, D. N., & Pellissier, L. (2020). Crop and forest pest metawebs shift towards increased linkage and suitability overlap under climate change. *Communications Biology*, 3(1, 1), 1–10. <https://doi.org/10.1038/s42003-020-0962-9>

Herbert, F. (1965). *Dune* (1st ed.). Chilton Book Company.

Hinton, G., & Roweis, S. T. (2002). Stochastic neighbor embedding. *NIPS*, 15, 833–840.

Hoffmann, J., Bar-Sinai, Y., Lee, L. M., Andrejevic, J., Mishra, S., Rubinstein, S. M., & Rycroft, C. H. (2019). Machine learning in a data-limited regime: Augmenting experiments with synthetic data uncovers order in crumpled sheets. *Science Advances*, 5(4), eaau6792. <https://doi.org/10.1126/sciadv.aau6792>

Hortal, J., de Bello, F., Diniz-Filho, J. A. F., Lewinsohn, T. M., Lobo, J. M., & Ladle, R. J. (2015). Seven

Shortfalls that Beset Large-Scale Knowledge of Biodiversity. *Annual Review of Ecology, Evolution, and Systematics*, 46(1), 523–549. <https://doi.org/10.1146/annurev-ecolsys-112414-054400>

Jordano, P. (2016). Sampling networks of ecological interactions. *Functional Ecology*, 30(12), 1883–1893. <https://doi.org/10.1111/1365-2435.12763>

Lamba, A., Cassey, P., Segaran, R. R., & Koh, L. P. (2019). Deep learning for environmental conservation. *Current Biology*, 29(19), R977–R982. <https://doi.org/10.1016/j.cub.2019.08.016>

Machen, R., & Nost, E. (2021). Thinking algorithmically: The making of hegemonic knowledge in climate governance. *Transactions of the Institute of British Geographers*, 46(3), 555–569. <https://doi.org/10.1111/tran.12441>

McLeod, A., Leroux, S. J., Gravel, D., Chu, C., Cirtwill, A. R., Fortin, M.-J., Galiana, N., Poisot, T., & Wood, S. A. (2021). Sampling and asymptotic network properties of spatial multi-trophic networks. *Oikos*, n/a(n/a). <https://doi.org/10.1111/oik.08650>

Melnyk, K., Klus, S., Montavon, G., & Conrad, T. O. F. (2020). GraphKKE: Graph Kernel Koopman embedding for human microbiome analysis. *Applied Network Science*, 5(1), 96. <https://doi.org/10.1007/s41109-020-00339-2>

Morales-Castilla, I., Matias, M. G., Gravel, D., & Araújo, M. B. (2015). Inferring biotic interactions from proxies. *Trends in Ecology & Evolution*, 30(6), 347–356. <https://doi.org/10.1016/j.tree.2015.03.014>

Mosebo Fernandes, A. C., Quintero Gonzalez, R., Lenihan-Clarke, M. A., Leslie Trotter, E. F., & Jokar Arsanjani, J. (2020). Machine Learning for Conservation Planning in a Changing Climate. *Sustainability*, 12(18, 18), 7657. <https://doi.org/10.3390/su12187657>

Murphy, K. P. (2022). *Probabilistic machine learning: An introduction*. MIT Press.

Narayanan, A., Chandramohan, M., Venkatesan, R., Chen, L., Liu, Y., & Jaiswal, S. (2017, July 17). *Graph2vec: Learning Distributed Representations of Graphs*. <http://arxiv.org/abs/1707.05005>

Neutel, A.-M., Heesterbeek, J. A. P., & de Ruiter, P. C. (2002). Stability in Real Food Webs: Weak Links in Long Loops. *Science*, 296(5570), 1120–1123. <https://doi.org/10.1126/science.1068326>

No'kmaq, M., Marshall, A., Beazley, K. F., Hum, J., Joudry, shalan, Papadopoulos, A., Pictou, S., Rabesca, J., Young, L., & Zurba, M. (2021). “Awakening the sleeping giant”: Re-Indigenization principles for

transforming biodiversity conservation in Canada and beyond. *FACETS*, 6(1), 839–869.

Nost, E., & Goldstein, J. E. (2021). A political ecology of data. *Environment and Planning E: Nature and Space*, 25148486211043503. <https://doi.org/10.1177/25148486211043503>

O'Connor, L. M. J., Pollock, L. J., Braga, J., Ficetola, G. F., Maiorano, L., Martinez-Almoyna, C., Montemaggiore, A., Ohlmann, M., & Thuiller, W. (2020). Unveiling the food webs of tetrapods across Europe through the prism of the Eltonian niche. *Journal of Biogeography*, 47(1), 181–192. <https://doi.org/10.1111/jbi.13773>

Pedersen, E. J., Thompson, P. L., Ball, R. A., Fortin, M.-J., Gouhier, T. C., Link, H., Moritz, C., Nenzen, H., Stanley, R. R. E., Taranu, Z. E., Gonzalez, A., Guichard, F., & Pepin, P. (2017). Signatures of the collapse and incipient recovery of an overexploited marine ecosystem. *Royal Society Open Science*, 4(7), 170215. <https://doi.org/10.1098/rsos.170215>

Perozzi, B., Al-Rfou, R., & Skiena, S. (2014). DeepWalk: Online learning of social representations. *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 701–710. <https://doi.org/10.1145/2623330.2623732>

Pichler, M., Boreux, V., Klein, A.-M., Schleuning, M., & Hartig, F. (2020). Machine learning algorithms to infer trait-matching and predict species interactions in ecological networks. *Methods in Ecology and Evolution*, 11(2), 281–293. <https://doi.org/10.1111/2041-210X.13329>

Poisot, T., Cirtwill, A. R., Cazelles, K., Gravel, D., Fortin, M.-J., & Stouffer, D. B. (2016). The structure of probabilistic networks. *Methods in Ecology and Evolution*, 7(3), 303–312. <https://doi.org/10.1111/2041-210X.12468>

Poisot, T., Ouellet, M.-A., Mollentze, N., Farrell, M. J., Becker, D. J., Albery, G. F., Gibb, R. J., Seifert, S. N., & Carlson, C. J. (2021, May 31). *Imputing the mammalian virome with linear filtering and singular value decomposition*. <http://arxiv.org/abs/2105.14973>

Poisot, T., Stouffer, D. B., & Gravel, D. (2015). Beyond species: Why ecological interaction networks vary through space and time. *Oikos*, 124(3), 243–251. <https://doi.org/10.1111/oik.01719>

Ramasamy, D., & Madhow, U. (2015). Compressive spectral embedding: Sidestepping the SVD. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, & R. Garnett (Eds.), *Advances in neural information processing systems* (Vol. 28). Curran Associates, Inc.

Ray, J. C., Grimm, J., & Olive, A. (2021). The biodiversity crisis in Canada: Failures and challenges of federal and sub-national strategic and legal frameworks. *FACETS*, 6, 1044–1068.  
<https://doi.org/10.1139/facets-2020-0075>

Runghen, R., Stouffer, D. B., & Dalla Riva, G. V. (2021). *Exploiting node metadata to predict interactions in large networks using graph embedding and neural networks*.  
<https://doi.org/10.1101/2021.06.10.447991>

Saravia, L. A., Marina, T. I., Kristensen, N. P., De Troch, M., & Momo, F. R. (2021). Ecological network assembly: How the regional metaweb influences local food webs. *Journal of Animal Ecology*, n/a(n/a).  
<https://doi.org/10.1111/1365-2656.13652>

Strydom, T., Bouskila, S., Banville, F., Barros, C., Caron, D., Farrell, M. J., Fortin, M.-J., Hemming, V., Mercier, B., Pollock, L., Runghen, R., Riva, G. V. D., & Poisot, T. (2021). *Food web reconstruction through phylogenetic transfer of low-rank network representation*. <https://doi.org/10.32942/osf.io/y7sdz>

Strydom, T., Catchen, M. D., Banville, F., Caron, D., Dansereau, G., Desjardins-Proulx, P., Forero-Muñoz, N. R., Higino, G., Mercier, B., Gonzalez, A., Gravel, D., Pollock, L., & Poisot, T. (2021). A roadmap towards predicting species interaction networks (across space and time). *Philosophical Transactions of the Royal Society B: Biological Sciences*, 376(1837), 20210063.  
<https://doi.org/10.1098/rstb.2021.0063>

Tang, J., Qu, M., Wang, M., Zhang, M., Yan, J., & Mei, Q. (2015). LINE: Large-scale Information Network Embedding. *Proceedings of the 24th International Conference on World Wide Web*, 1067–1077.  
<https://doi.org/10.1145/2736277.2741093>

Turak, E., Brazill-Boast, J., Cooney, T., Drielsma, M., DelaCruz, J., Dunkerley, G., Fernandez, M., Ferrier, S., Gill, M., Jones, H., Koen, T., Leys, J., McGeoch, M., Mihoub, J.-B., Scanes, P., Schmeller, D., & Williams, K. (2017). Using the essential biodiversity variables framework to measure biodiversity change at national scale. *Biological Conservation*, 213, 264–271.  
<https://doi.org/10.1016/j.biocon.2016.08.019>

Wang, D., Cui, P., & Zhu, W. (2016). Structural Deep Network Embedding. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1225–1234.  
<https://doi.org/10.1145/2939672.2939753>

Wang, S., Arroyo, J., Vogelstein, J. T., & Priebe, C. E. (2021). Joint Embedding of Graphs. *IEEE*



337 *Transactions on Pattern Analysis and Machine Intelligence*, 43(4), 1324–1336.

338 <https://doi.org/10.1109/TPAMI.2019.2948619>

339 Wardeh, M., Baylis, M., & Blagrove, M. S. C. (2021). Predicting mammalian hosts in which novel  
 340 coronaviruses can be generated. *Nature Communications*, 12(1, 1), 780.

341 <https://doi.org/10.1038/s41467-021-21034-5>

342 Weiskopf, S. R., Harmáčková, Z. V., Johnson, C. G., Londoño-Murcia, M. C., Miller, B. W., Myers, B. J. E.,  
 343 Pereira, L., Arce-Plata, M. I., Blanchard, J. L., Ferrier, S., Fulton, E. A., Harfoot, M., Isbell, F., Johnson,  
 344 J. A., Mori, A. S., Weng, E., & Rosa, I. M. D. (2022). Increasing the uptake of ecological model results in  
 345 policy decisions to improve biodiversity outcomes. *Environmental Modelling & Software*, 149, 105318.

346 <https://doi.org/10.1016/j.envsoft.2022.105318>

347 Wood, S. A., Russell, R., Hanson, D., Williams, R. J., & Dunne, J. A. (2015). Effects of spatial scale of  
 348 sampling on food web structure. *Ecology and Evolution*, 5(17), 3769–3782.

349 <https://doi.org/10.1002/ece3.1640>

350 Xu, M. (2020, December 14). *Understanding graph embedding methods and their applications*.

351 <http://arxiv.org/abs/2012.08019>

352 Yan, S., Xu, D., Zhang, B., & Zhang, H.-J. (2005). Graph embedding: A general framework for  
 353 dimensionality reduction. *2005 IEEE Computer Society Conference on Computer Vision and Pattern*  
 354 *Recognition (CVPR'05)*, 2, 830–837 vol. 2. <https://doi.org/10.1109/CVPR.2005.170>

355 Young, S. J., & Scheinerman, E. R. (2007). Random Dot Product Graph Models for Social Networks. In A.  
 356 Bonato & F. R. K. Chung (Eds.), *Algorithms and Models for the Web-Graph* (pp. 138–149). Springer.

357 [https://doi.org/10.1007/978-3-540-77004-6\\_11](https://doi.org/10.1007/978-3-540-77004-6_11)



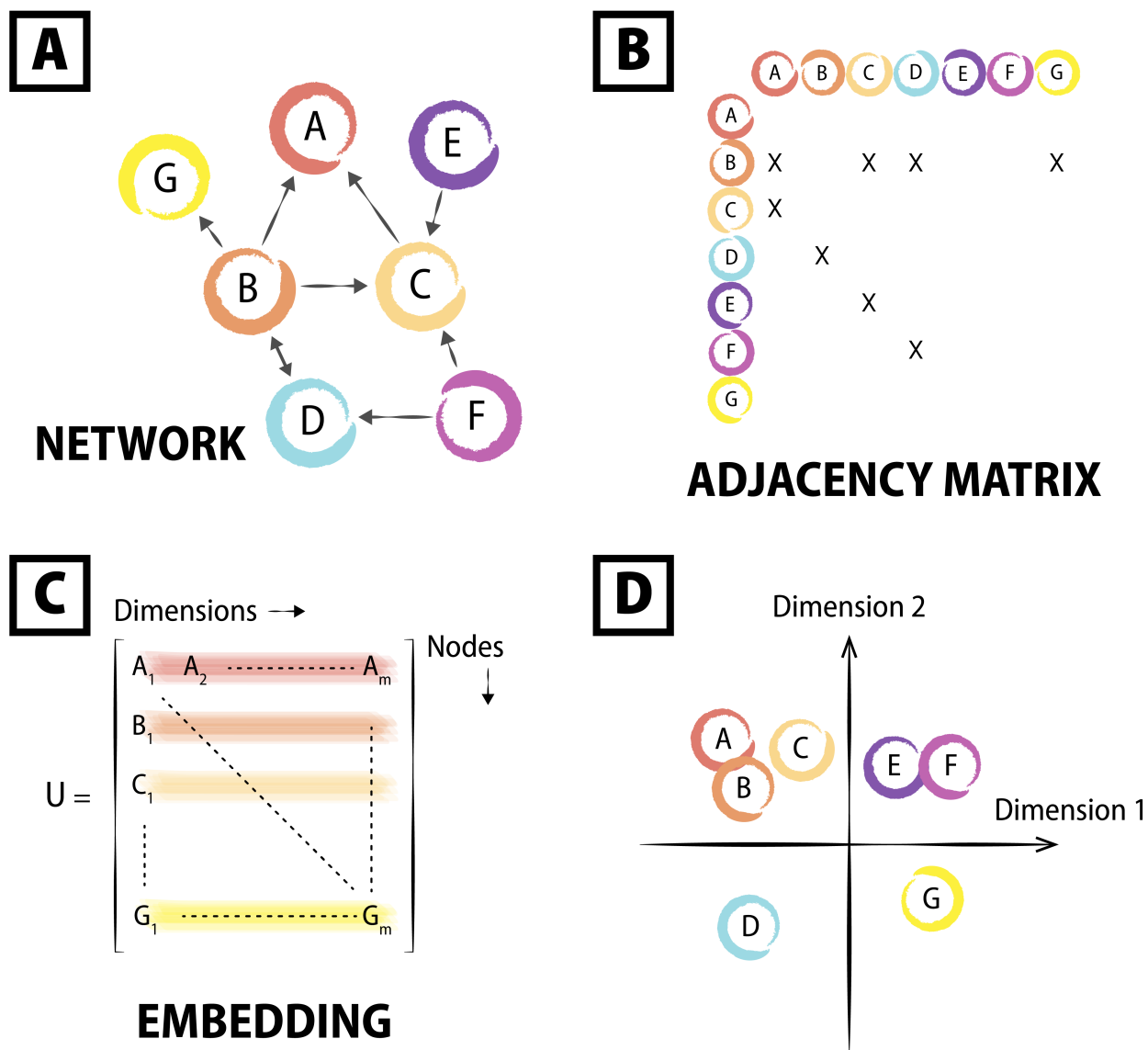


Figure 1: Overview of the embedding process. A network (A), represented as its adjacency matrix (B), is converted into a lower-dimensional object (C) where nodes, subgraphs, or edges have specific values (see tbl. 1). For the purposes of prediction, this low-dimensional object encodes feature vectors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

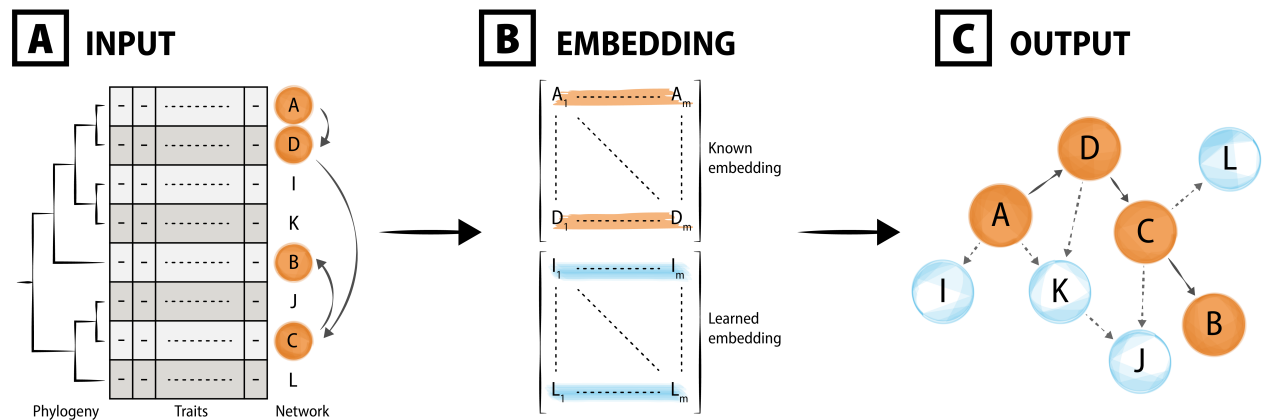


Figure 2: From a low-dimensional feature vector (see fig. 1), it is possible to develop predictive approaches. Nodes in an ecological network are species, for which we can leverage phylogenetic relatedness (*e.g.* Strydom, Bouskila, et al., 2021) or functional traits to fill the values of additional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