

# The missing link: discerning true from false negatives when sampling species interaction networks

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**Abstract:** Ecosystems are composed of networks of interacting species. These interactions allow communities of species to persist through time through both neutral and adaptive processes. Despite their importance, a robust understanding of (and ability to predict and forecast) interactions among species remains elusive. This knowledge-gap is largely driven by a shortfall of data—although species occurrence data has rapidly increased in the last decade, species interaction data has not kept pace, largely due to the effort required to sample interactions. This means there are many interactions between species that occur in nature, but we do not know these interactions occur because we have never observed them. These so-called “false-negatives” bias data and hinder inference about the structure and dynamics of interaction networks. Here, we show the realized number of false-negatives in data can be quite high, even in thoroughly sampled systems, due to variation in abundances in a community. We provide a null model of occurrence detection to estimate the false-negative rate in a given dataset. We also show how to directly incorporate uncertainty due to observation error into model-based predictions of interactions between species. One hypothesis is interactions between “rare” species are themselves rare because these species are less likely to encounter one-another than species of higher relative abundance, and this can (in part) explain the common pattern of nestedness in bipartite interaction networks. However, we demonstrate that across several datasets of spatial/temporally replicated networks, there are positive associations between species co-occurrence and interactions, which suggests these interactions among “rare” species actually exist but simply are not observed. Finally, we assess how false negatives influence various models of network prediction, and recommend directly accounting for observation error in predictive models. We conclude by discussing how the understanding of false-negatives can inform how we design monitoring schemes for species interaction surveys.

# 1 Introduction

2 Species interactions drive many processes in evolution and ecology. A better understanding of species  
3 interactions is an imperative to understand the evolution of life on Earth, to mitigate the impacts of  
4 anthropogenic change on biodiversity (Makiola *et al.* 2020), and for predicting zoonotic spillover of  
5 disease to prevent future pandemics (Becker *et al.* 2021). At the moment we lack sufficient data to meet  
6 these challenges (Poisot *et al.* 2021), largely because species interactions are hard to sample (Jordano  
7 2016). Over the past few decades biodiversity data has become increasingly available through remotely  
8 collected data and adoption of open data practices (Kenall *et al.* 2014; Stephenson 2020). Still, interaction  
9 data remains relatively scarce because sampling typically requires human observation. This induces a  
10 constraint on the amount, spatial scale, and temporal frequency of resulting data that it is feasible to  
11 collect by humans. Many crowdsourced methods for biodiversity data aggregation (e.g. GBIF, eBird) still  
12 rely on automated identification of species, which does not easily generalize to interaction sampling.  
13 There is interest in using remote methods for interaction sampling, which primarily detect co-occurrence  
14 and derive properties like species avoidance from this data (Niedballa *et al.* 2019). However, co-occurrence  
15 itself is not necessarily indicative of an interaction (Blanchet *et al.* 2020). This is an example of semantic  
16 confusion around the word “interaction”—for example one might consider competition a type of species  
17 interaction, even though it is marked by a lack of co-occurrence between species, unlike other types of  
18 interactions, like predation or parasitism, which require both species to be together at the same place and  
19 time. Here we consider interaction in the latter sense, where two species have fitness consequences on  
20 one-another if (and only if) they are in the sample place at the same time. In addition, here we only  
21 consider direct (not higher-order) interactions.

22 We cannot feasibly observe all (or even most) of the interactions that occur in an ecosystem. This means  
23 we can be confident two species actually interact if we have a record of it (assuming they are correctly  
24 identified), but not at all confident that a pair of species *do not* interact if we have *no record* of those  
25 species observed together. In other words, it is difficult to distinguish *true-negatives* (two species never  
26 interact) from *false-negatives* (two species interact sometimes, but we do not have a record of this  
27 interaction). For a concrete example of a false-negative in a food web, see fig. 1. Because even the most  
28 highly sampled systems will still contain false-negatives, there is increasing interest in combining  
29 species-level data (e.g. traits, abundance, range, phylogenetic relatedness, etc.) to build models to predict

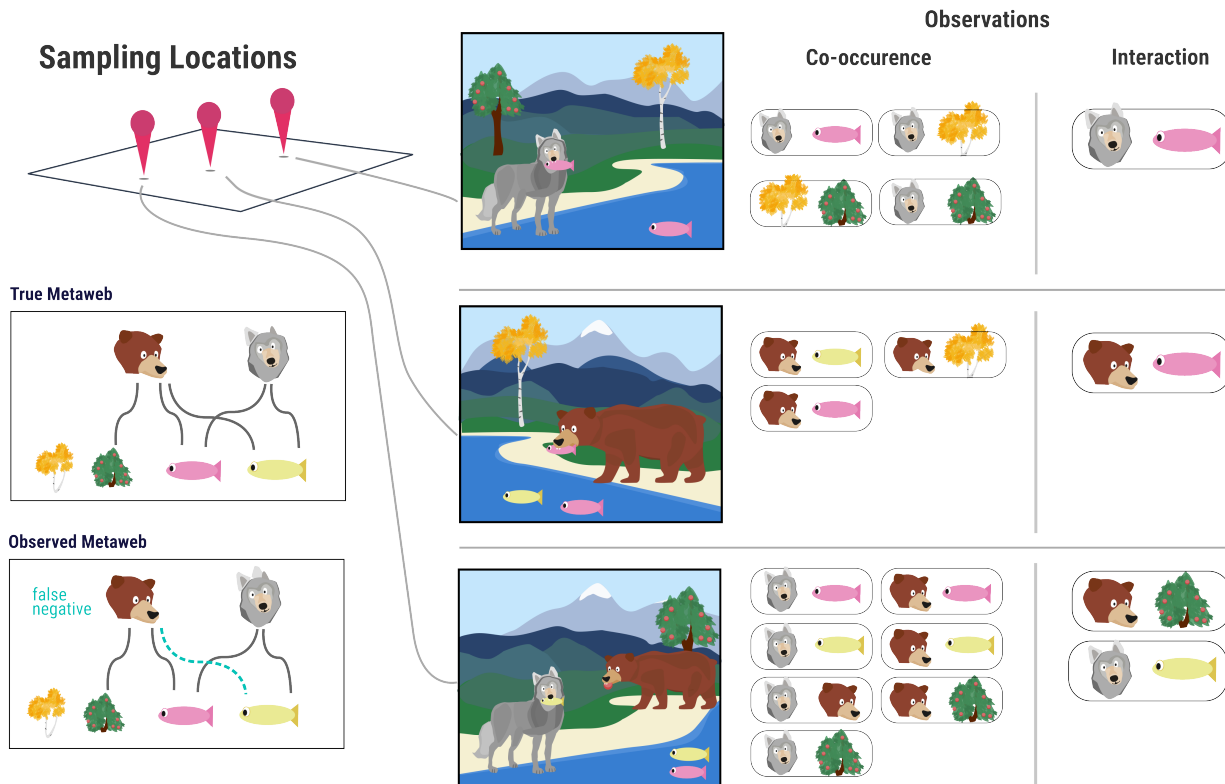


Figure 1: This conceptual example considers a sample of the trophic community of bears, wolves, salmon (pink fish), pike (yellow fish), berry trees, and aspen trees. The true metaweb (all realized interactions across the entire spatial extent) is shown on the left. In the center is what a hypothetical ecologist samples at each site. Notice that although bears are observed co-occurring with both salmon and pike, there was never a direct observation of bears eating pike, even though they actually do. Therefore, this interaction between bears and pike is a false-negative.

interactions between species we haven't observed together before (Strydom *et al.* 2021). However, the noise of false-negatives could impact the efficacy of our predictive models and have practical consequences for answering questions about interactions (de Aguiar *et al.* 2019). This data constraint is amplified as the interaction data we have is geographically biased toward the usual suspects (Poisot *et al.* 2021). We therefore need a statistical approach to assessing these biases in the observation process and their consequences for our understanding of interaction networks.

The importance of *sampling effort* and its impact on resulting ecological data has produced a rich body of literature. The recorded number of species in a dataset or sample depends on the total number of observations (Walther *et al.* 1995; Willott 2001), as do estimates of population abundance (Griffiths 1998). This relationship between sampling effort, spatial coverage, and species detectability has motivated more

quantitatively robust approaches to account for error in sampling data in many contexts: to determine if a given species is extinct (Boakes *et al.* 2015), to determine sampling design (Moore & McCarthy 2016), and to measure species richness across large scales (Carlson *et al.* 2020). In the context of interactions, an initial concern was the compounding effects of limited sampling effort combined with the amalgamation of data (across both study sites, time of year, and taxonomic scales) could lead any empirical set of observations to inadequately reflect the reality of how species interact (Paine 1988) or the structure of the network as a whole (Martinez *et al.* 1999; McLeod *et al.* 2021). Martinez *et al.* (1999) showed that in a plant-endophyte trophic network, network connectance is robust to sampling effort, but this was done in the context of a system for which observation of 62,000 total interactions derived from 164,000 plant-stems was feasible. In some systems (e.g. megafauna food-webs) this many observations is either impractical or infeasible due to the absolute abundance of the species in question.

The intrinsic properties of ecological communities create several challenges for sampling: first, species are not observed with equal probability—we are much more likely to observe a species of high abundance than one of very low abundance (Poisot *et al.* 2015). Canard *et al.* (2012) presents a null model of food-web structure where species encounter one-another in proportion to each species' relative-abundance. This assumes that there are no associations in species co-occurrence due to an interaction (perhaps because this interaction is “important” for both species; Cazelles *et al.* (2016)), but in this paper we later show increasing strength of these associations leads to increasing probability of false-negatives in interaction data, and that these positive associations are common in existing network data. Second, observed co-occurrence is often equated with meaningful interaction strength, but this is not necessarily the case (Blanchet *et al.* 2020)—a true “non-interaction” would require that neither of two species, regardless of whether they co-occur, ever exhibit any meaningful effect on the fitness of the other. So, although co-occurrence is not directly indicative of an interaction, it is a precondition for an interaction.

Here, we illustrate how our confidence that a pair of species never interacts highly depends on sampling effort. We demonstrate how the realized false-negative-rate of interactions is related to the relative abundance of the species pool, and introduce a method to produce a null estimate of the false-negative-rate given total sampling effort (the total count of all interactions seen among all species-pairs) and a method for including uncertainty into model predictions of interaction probabilities to account for observation error. We then confront these models with data, by showing that positive associations in co-occurrence data can increase the realized number of false-negatives and by showing these positive associations are

70 rampant in network datasets. We conclude by recommending that the simulation of sampling effort and  
71 species occurrence can and should be used to help design surveys of species interaction diversity (Moore &  
72 McCarthy 2016), and by advocating use of null models like those presented here as a tool for both guiding  
73 design of surveys of species interactions and for including detection error into predictive models.

## 74 **Accounting for false-negatives in species interactions**

75 In this section, we demonstrate how differences in species' relative-abundance can lead to many  
76 false-negatives in interaction data. We also introduce a method for producing a null estimate of the  
77 false-negative-rate in datasets via simulation. Because the true false-negative-rate is latent, we can never  
78 actually be sure how many false-negatives are in our data. However, here we outline an approach to deal  
79 with this fact—first by using simulation to estimate the false-negative-rate for a dataset of a fixed size  
80 using neutral models of observation. We then illustrate how to incorporate uncertainty directly into  
81 predictions of species interactions to account for observation error based on null estimates of both the  
82 false-positive rate (as an *a priori* estimate of species misidentification probability) and false-negative rate  
83 (as generated via the method we introduce).

### 84 **How many observations of a non-interaction do we need to be confident it's a true** 85 **negative?**

86 We start with a naive model of interaction detection: we assume that every interacting pair of species is  
87 incorrectly observed as not-interacting with an independent and fixed probability, which we denote  $p_{fn}$   
88 and subsequently refer to as the False-Negative-Rate (FNR). If we observe the same species not-interacting  
89  $N$  times, then the probability of a true-negative (denoted  $p_{tn}$ ) is given by  $p_{tn} = 1 - (p_{fn})^N$ . This relation  
90 (the cumulative-distribution-function of geometric distribution, a special case of the negative-binomial  
91 distribution) is shown in fig. 2(a) for varying values of  $p_{fn}$  and illustrates a fundamental link between our  
92 ability to reliably say an interaction doesn't exist— $p_{tn}$ —and the number of times  $N$  we have observed a  
93 given species. In addition, note that there is no non-zero  $p_{fn}$  for which we can ever *prove* that an  
94 interaction does not exist—no matter how many observations of non-interactions  $N$  we have,  $p_{tn} < 1$ .

95 From fig. 2(a) it is clear that the more often we see two species co-occurring, but *not interacting*, the more  
96 likely the interaction is a true-negative. This has several practical consequences: first it means negatives

97 taken outside the overlap of the range of each species aren't informative because co-occurrence was not  
 98 possible, and therefore neither was an interaction. In the next section we demonstrate that the  
 99 distribution of abundance in ecosystems can lead to very high realized values of FNR ( $p_{fn}$ ) simply as an  
 100 artifact of sampling effort. Second, we can use this relation to compute the expected number of total  
 101 observations needed to obtain a “goal” number of observations of a particular pair of species (fig. 2(b)). As  
 102 an example, if we hypothesize that  $A$  and  $B$  do not interact, and we want to see species  $A$  and  $B$  both  
 103 co-occurring and *not interacting* 10 times to be confident this is a true negative, then we need an expected  
 104 1000 observations of all species if the relative abundances of  $A$  and  $B$  are both 0.1.

### 105 **False-negatives as a product of relative abundance**

106 We now show that the realized FNR changes drastically with sampling effort due to the intrinsic variation  
 107 of the abundance of individuals of each species within a community. We do this by simulating the process  
 108 of observation of species interactions, applied both to 243 empirical food webs from the Mangal database  
 109 (Banville *et al.* 2021) and random food-webs generated using the niche model, a simple generative model  
 110 of food-web structure that accounts for allometric scaling (Williams & Martinez 2000). Our neutral model  
 111 of observation assumes each observed species is drawn in proportion to each species' abundance at that  
 112 place and time. The abundance distribution of a community can be reasonably-well described by a  
 113 log-normal distribution (Volkov *et al.* 2003). In addition to the log-normal distribution, we also tested the  
 114 case where the abundance distribution is derived from power-law scaling  $Z^{(\log(T_i)-1)}$  where  $T_i$  is the  
 115 trophic level of species  $i$  and  $Z$  is a scaling coefficient (Savage *et al.* 2004), which yields the same  
 116 qualitative behavior. The practical consequence of abundance distributions spanning many orders of  
 117 magnitude is that observing two “rare” species interacting requires two low probability events: observing  
 118 two rare species *at the same time*.

119 To simulate the process of observation, for an ecological network  $M$  with  $S$  species, we sample relative  
 120 abundances for each species from a standard-log-normal distribution. For each true interaction in the  
 121 adjacency matrix  $M$  (i.e.  $M_{ij} = 1$ ) we estimate the probability of observing both species  $i$  and  $j$  at a given  
 122 place and time by simulating  $n$  observations of all individuals of any species, where the species of the  
 123 individual observed at the  $\{1, 2, \dots, n\}$ -th observation is drawn from the generated categorical distribution  
 124 of abundances. For each pair of species  $(i, j)$ , if both  $i$  and  $j$  are observed within the  $n$ -observations, the  
 125 interaction is tallied as a true positive if  $M_{ij} = 1$ . If only one of  $i$  or  $j$  are observed—but not both—in these



Figure 2: **(a)** The probability that an observed interaction is a true negative (y-axis) given how many times it has been sampled as a non-interaction (x-axis). Each color reflects a different value of  $p_{fn}$ , the false-negative-rate (FNR)—this is effectively the cumulative distribution function (cdf) of the geometric distribution. **(b)** The expected number of total observations needed (colors) to observe 10 co-occurrences between a species with relative abundance  $P(A)$  (x-axis) and a second species with relative abundance  $P(Y)$ . **(c)**: false-negative-rate (y-axis) as a function of total sampling effort (x-axis) and network size, computed using the method described above. For 500 independent draws from the niche model (Williams & Martinez (2000)) at varying levels of species richness (colors) with connectance drawn according to the flexible-links model (MacDonald *et al.* (2020)) as described in the main text. For each draw from the niche model, 200 sets of 1500 observations are simulated, for which the mean false-negative-rate at each observation-step is computed. Means denoted with points, with 1 in the first shade and 2 in the second. **(d)**: Same as **(c)**, except using empirical food webs from Mangal database, where richness. The outlier on **(d)** is a 714 species food-web.



126  $n$  observations, but  $M_{ij} = 1$ , this is counted as a false-negative, and a true-negative otherwise. For each  
 127 pair of species  $(i, j)$ , if both  $i$  and  $j$  are observed within the  $n$ -observations, the interaction is tallied as a  
 128 true positive if  $M_{ij} = 1$ . If only one of  $i$  or  $j$  are observed—but not both—in these  $n$  observations, but  
 129  $M_{ij} = 1$ , this is counted as a false-negative, and a true-negative otherwise ( $M_{ij} = 0$ ). This process is  
 130 illustrated conceptually in fig. 3(a).

131 In fig. 2(c) we see this model of observation applied to niche model networks across varying levels of  
 132 species richness, and in fig. 2(d) the observation model applied to Mangal food webs. For all niche model  
 133 simulations in this manuscript, for a given number of species  $S$  the number of interactions is drawn from  
 134 the flexible-links model fit to Mangal data (MacDonald *et al.* 2020), effectively drawing the number of  
 135 interactions  $L$  for a random niche model food-web as

$$L \sim \text{BetaBinomial}(S^2 - S + 1, \mu\phi, 1 - \mu\phi)$$

136 where the maximum *a posteriori* (MAP) estimate of  $(\mu, \phi)$  applied to Mangal data from (MacDonald *et al.*  
 137 2020) is  $(\mu = 0.086, \phi = 24.3)$ . All simulations were done with 500 independent replicates of unique niche  
 138 model networks per unique number of total interactions observed  $n$ . All analyses presented here are done  
 139 in Julia v1.8 (Bezanson *et al.* 2015) using both EcologicalNetworks.jl v0.5 and Mangal.jl v0.4 (Banville *et*  
 140 *al.* 2021) and are hosted on [Github](#)). Note that the empirical data, for the reasons described above, very  
 141 likely already contains many false-negatives, we'll revisit this issue in the final section.

142 From fig. 2(c) it is evident that the number of species considered in a study is inseparable from the  
 143 false-negative-rate in that study, and this effect should be taken into account when designing samples of  
 144 ecological networks in the future. We see a similar qualitative pattern in empirical networks (fig. 2(d))  
 145 where the FNR drops off quickly as a function of observation effort, mediated by total richness. The  
 146 practical consequence of the bottom row of fig. 2 when conducting an analysis is whether there are  
 147 enough total number of observed interactions (the x-axis) for the threshold FNR we deem acceptable (the  
 148 y-axis) is feasible. This raises two points: first, empirical data on interactions are subject to the practical  
 149 limitations of funding and human-work hours, and therefore existing data tend to fall on the order of  
 150 hundreds or thousands observations of individuals per site. Clear aggregation of data on sampling effort  
 151 has proven difficult to find and a meta-analysis of network data and sampling effort seems both pertinent  
 152 and necessary, in addition to the effects of aggregation of interactions across taxonomic scales (Gauzens *et*

153 *al.* 2013; Giacomuzzo & Jordán 2021). This inherent limitation on in-situ sampling means we should  
 154 optimize where we sample across space so that for a given number of samples, we obtain the maximum  
 155 information possible. Second, what is meant by “acceptable” FNR? This raises the question: does a shifting  
 156 FNR lead to rapid transitions in our ability inference and predictions about the structure and dynamics of  
 157 networks, or does it produce a roughly linear decay in model efficacy? We explore this in the final section.  
 158 We conclude this section by advocating for the use of neutral models similar to above to generate  
 159 expectations about the number of false-negatives in a dataset of a given size. This could prove fruitful both  
 160 for designing surveys of interactions but also because we may want to incorporate models of imperfect  
 161 detection error into predictive interactions models, as Joseph (2020) does for species occurrence modeling.  
 162 Additionally, we emphasize that one must consider the context for sampling—is the goal to detect a  
 163 particular species (as in fig. 2(c)), or to get a representative sample of interactions across the species pool?  
 164 These arguments are well-considered when sampling individual species (Willott 2001), but have not yet  
 165 been adopted for designing samples of communities.

## 166 **Including observation error in interaction predictions**

167 Here we show how to incorporate uncertainty into model predictions of interaction probability to account  
 168 for imperfect observation (both false-negatives and false-positives). Models for interaction prediction  
 169 typically yield a probability of interaction between each pair of species,  $p_{ij}$ . When these are considered  
 170 with uncertainty, it is usually model-uncertainty, e.g. the variance in the interaction probability prediction  
 171 across several cross-validation folds, where the data is split into training and test sets several times. The  
 172 method we introduce adjusts the value of a model’s predictions to produce a distribution of interaction  
 173 probabilities corrected by a given false-negative-rate  $p_{fn}$  and false-positive-rate  $p_{fp}$  (outlined in figure  
 174 fig. 3). First we describe how to sample from this distribution of adjusted interaction probabilities via  
 175 simulation, and show that this distribution can be well-approximated analytically.

176 To get an estimate of each interaction probability that accounts for observation error, we resample the  
 177 output prediction from an arbitrary model for each interaction  $p_{ij}$  by simulating a set of several ‘particles.’  
 178 Each particle is a realization of an interaction *actually occurring* assuming  $p_{ij}$  is a correct estimate of the  
 179 probability of an interaction being *observed*. Each particle starts as being drawn as true or false according  
 180 to  $p_{ij}$ , and then adjusting this by the rate of observation error given by  $p_{fp}$  and  $p_{fn}$  to yield a single

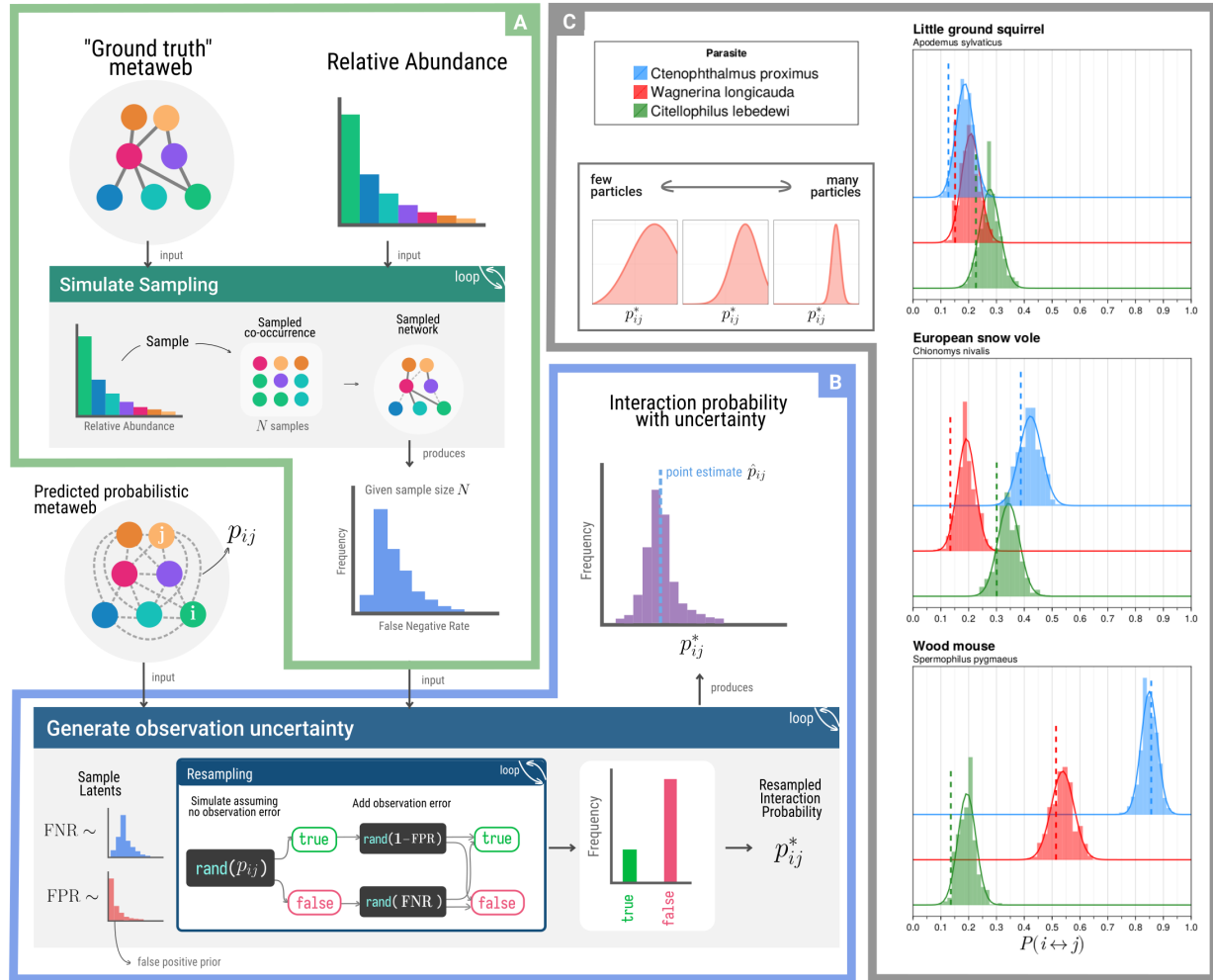


Figure 3: (a) The process for estimating the false-negative-rate (FNR) for an interaction dataset consisting of  $N$  total observed interactions. (b) The method for resampling interaction probability based on estimates of false-negative and false-positive rates. (c) The method for interaction probability resampling applied to three mammals and three parasites from the Hadfield *et al.* (2014) dataset. The original probability  $p_{ij}$  is indicated with a vertical dashed line. The histogram is simulated from the resampling process, and the line indicates the gaussian approximation to this distribution. Both resampling simulations and the gaussian approximation is applied with  $n_p = 150$

181 boolean outcome for each particle (“Resampling” within fig. 3(b)). Across of many particles, the resulting  
 182 frequency of ‘true’ outcomes is a single resample of the probability  $p_{ij}^*$  that the interaction actually  
 183 occurred, not just that it was *observed*. Across several samples each of several particles, this forms a  
 184 distribution of probabilities which are adjusted by the true and false-negative-rates.

185 There is also an analytic way to approximate this distribution using the normal approximation to binomial.  
 186 As a reminder, as the total number of samples  $N$  from a binomial distribution for  $n$  trials with success  
 187 probability  $p$  from approaches infinity, the sum of total successes across all samples approaches a normal  
 188 distribution with mean  $np$  and variance  $np(1 - p)$ . For notation, here we refer to a normal distribution  
 189 with mean  $\mu$  and standard-deviation  $\sigma$  as  $\mathcal{N}(\mu, \sigma)$ . We can use this to correct the estimate  $p_{ij}$  based on the  
 190 expected false-negative-rate  $p_{fn}$  and false-positive rate  $p_{fp}$  to obtain the limiting distribution as the  
 191 number of resamples approaches infinity for the resampled  $p_{ij}^*$  for a given number of particles  $n_p$ . We do  
 192 this by first adjusting for the rates of observation error to get the mean resampled probability,  $\mathbb{E}[p_{ij}^*]$ , as

$$\mathbb{E}[p_{ij}^*] = p_{ij}(1 - p_{fp}) + (1 - p_{ij})p_{fn}$$

193 This yields the normal approximation

$$\sum_{i=1}^{n_p} p_{ij}^* \sim \mathcal{N}\left(n_p \cdot \mathbb{E}[p_{ij}^*], \sqrt{n_p \mathbb{E}[p_{ij}^*](1 - \mathbb{E}[p_{ij}^*])}\right)$$

194 which then can be converted back to a distribution of frequency of successes to yield the final  
 195 approximation

$$p_{ij}^* \sim \mathcal{N}\left(\mathbb{E}[p_{ij}^*], \sqrt{\frac{\mathbb{E}[p_{ij}^*](1 - \mathbb{E}[p_{ij}^*])}{n_p}}\right) \quad (1)$$

196 We can then further truncate this distribution to remain on the interval  $(0, 1)$ , as the output is a  
 197 probability, although in practice often the probability mass outside  $(0, 1)$  is extremely low except for  $p_{ij}$   
 198 values very close to 0 or 1. As an example case study, we use a boosted-regression-tree to predict  
 199 interactions in a host-parasite network (Hadfield *et al.* 2014) (with features derived in the same manner as  
 200 Strydom *et al.* (2021) derives features on this data) to produce a set of interaction predictions. We then  
 201 applied this method to a set of a few resampled interaction probabilities between mammals and parasite

species shown in figure fig. 3(c).

Why is this useful? For one, this analytic method avoids the extra computation required by simulating samples from this distribution directly. Further, it enables the extension of the natural analogue between  $n_p$  (the number of particles) and the number of observations of co-occurrence for a given pair of species—the fewer the particles, the higher the variance of the resulting approximation. The normal approximation is undefined for 0 particles (i.e. 0 observations co-occurrence), although as  $n_p$  approaches 0 the approximated normal (once truncated) approaches the uniform distribution on the interval (0, 1), the maximum entropy distribution where we have no information about the possibility of an interaction.

This also has implications for what we mean by ‘uncertainty’ in interaction predictions. A model’s prediction can be ‘uncertain’ in two different ways: (1) the model’s predictions may have high variance, or (2) the model’s predictions may be centered around a probability of interaction of 0.5, where we are the most unsure about whether this interaction exists. Improving the incorporation of different forms of uncertainty in probabilistic interaction predictions seems a necessary next step toward understanding what pairs of species we know the least about, in order to prioritize sampling to provide the most new information possible.

## **Positive associations in co-occurrence increase the false-negative-rate**

The model above doesn’t consider the possibility that there are positive or negative associations which shift the probability of species cooccurrence away from what is expected based on their relative abundances due to their interaction (Cazelles *et al.* 2016). However, here we demonstrate that the probability of having a false-negative can be higher if there is some positive association in the occurrence of species  $A$  and  $B$ . If we denote the probability that we observe the co-occurrence of two species  $A$  and  $B$  as  $P(AB)$  and if there is no association between the marginal probabilities of observing  $A$  and observing  $B$ , denoted  $P(A)$  and  $P(B)$  respectively, then the probability of observing their co-occurrence is the product of the marginal probabilities for each species,  $P(AB) = P(A)P(B)$ . In the other case where there is some positive strength of association between observing both  $A$  and  $B$  because this interaction is “important” for each species, then the probability of observation both  $A$  and  $B$ ,  $P(AB)$ , is greater than  $P(A)P(B)$  as  $P(A)$  and  $P(B)$  are not independent and instead are positively correlated, i.e.  $P(AB) > P(A)P(B)$ . In this case, the probability of observing a single false-negative in our naive model from fig. 2(a) is  $p_{fn} = 1 - P(AB)$ , which due to the

above inequality implies  $p_{fn} > 1 - P(A)P(B)$ . This indicates an increasingly greater probability of a false negative as the strength of association gets stronger,  $P(AB) \rightarrow P(AB) \gg P(A)P(B)$ . However, this still does not consider variation in species abundance in space and time (Poisot *et al.* 2015). If positive or negative associations between species structure variation in the distribution of  $P(AB)$  across space/time, then the spatial/temporal biases induced by data collection would further impact the realized false-negative-rate, as the probability of false negative would not be constant for each pair of species across sites.

To test for these positive associations in data we scoured Mangal for datasets with many spatial or temporal replicates of the same system, which led to the resulting seven datasets set in figure fig. 4. For each dataset, we compute the marginal probability  $P(A)$  of occurrence of each species  $A$  across all networks in the dataset. For each pair of interacting species  $A$  and  $B$ , we then compute and compare the probability of co-occurrence if each species occurs independently,  $P(A)P(B)$ , to the empirical joint probability of co-occurrence,  $P(AB)$ . Following our analysis above, if  $P(AB)$  is greater than  $P(A)P(B)$ , then we expect our neutral estimates of the FNR above to underestimate the realized FNR. In fig. 4, we see the difference between  $P(AB)$  and  $P(A)P(B)$  for the seven suitable datasets with enough spatio-temporal replicates and a shared taxonomic backbone (meaning all individual networks use common species identifiers) found on Mangal to perform this analysis. Further details about each dataset are reported in tbl. 1.

In each of these datasets, the joint probability of co-occurrence  $P(AB)$  is decisively greater than our expectation if species co-occur in proportion to their relative abundance  $P(A)P(B)$ . This suggests that there may not be as many “neutrally forbidden links” (Canard *et al.* 2012) as we might think, and that the reason we do not have records of interactions between rare species is probably due to observation error. This has serious ramifications for the widely observed property of nestedness seen in bipartite networks (Bascompte & Jordano 2007)—perhaps the reason we have lots of observations between generalists is because they are more abundant, and this is particularly relevant as we have strong evidence that generalism drives abundance (Song *et al.* 2022a), not vice-versa.

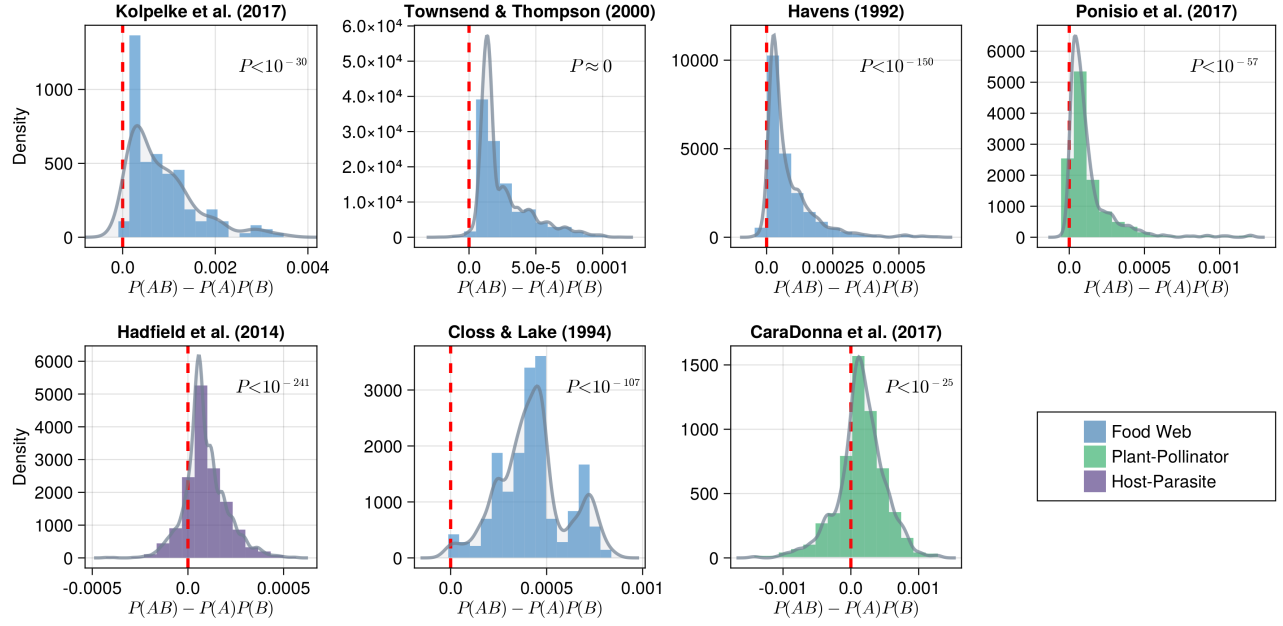


Figure 4: The difference between joint-probability of co-occurrence ( $P(AB)$ ) and expected probability of co-occurrence under independence ( $P(A)P(B)$ ) for interacting species for each dataset. The red-dashed line indicates 0 (no association). Each histogram represents a density, meaning the area of the entire curve sums to 1. The continuous density estimate (computed using local smoothing) is shown in grey. The p-value on each plot is the result of a one-sided t-test comparing the mean of each distribution to 0.

Table 1: The datasets used in the above analysis (Fig 2). The table reports the type of each dataset, the total number of networks in each dataset ( $N$ ), the total species richness in each dataset ( $S$ ), the connectance of each metaweb (all interactions across the entire spatial-temporal extent) ( $C$ ), the mean species richness across each local network  $\bar{S}$ , the mean connectance of each local network  $\bar{C}$ , the mean  $\beta$ -diversity among overlapping species across all pairs of network species ( $\bar{\beta}_{OS}$ ), and the mean  $\beta$ -diversity among all species in the metaweb ( $\bar{\beta}_{WN}$ ). Both metrics are computed using KGL  $\beta$ -diversity (Koleff *et al.* 2003)

Network	Type	$N$	$S$	$C$	$\bar{S}$	$\bar{C}$	$\bar{\beta}_{OS}$	$\bar{\beta}_{WN}$
Kopelke <i>et al.</i> (2017)	Food Web	100	98	0.037	7.87	0.142	1.383	1.972
Thompson & Townsend (2000)	Food Web	18	566	0.014	80.67	0.049	1.617	1.594
Havens (1992)	Food Web	50	188	0.065	33.58	0.099	1.468	1.881
Ponisio <i>et al.</i> (2017)	Pollinator	100	226	0.079	23.0	0.056	1.436	1.870
Hadfield <i>et al.</i> (2014)	Host-Parasite	51	327	0.085	32.71	0.337	1.477	1.952
Closs & Lake (1994)	Food Web	12	61	0.14	29.09	0.080	1.736	1.864
CaraDonna <i>et al.</i> (2017)	Pollinator	86	122	0.18	21.42	0.312	1.527	1.907

## The impact of false-negatives on network properties and prediction

Here, we assess the effect of false-negatives on our ability to make predictions about interactions, as well as their effect on network structure. The prevalence of false-negatives in data is the catalyst for interaction prediction in the first place, and as a result methods have been proposed to counteract this bias (Stock *et al.* 2017; Poisot *et al.* 2022). However, it is feasible that the FNR in a given dataset is so high that it could induce too much noise for an interaction prediction model to detect the signal of possible interaction between species.

To test this we use the dataset from Hadfield *et al.* (2014) that describes host-parasite interaction networks sampled across 51 sites, and the same method as Strydom *et al.* (2021) to extract latent features for each species in this dataset based on applying PCA to the co-occurrence matrix. We then predict a metaweb (equivalent to predicting true or false for an interaction between each species pair, effectively a binary classification problem) from these species-level features using four candidate models for binary classification—three often used machine-learning (ML) methods (Boosted Regression Tree (BRT), Random Forest (RF), Decision Tree (DT)), and one naive model from classic statistics (Logistic Regression (LR)). Each of the ML models are bootstrap aggregated (or bagged) with 100 replicates each. We partition the data into 80-20 training-test splits, and then seed the training data with false negatives at varying rates, but crucially do *nothing* to the test data. We fit all of these models using MLJ.jl, a high-level Julia framework for a wide-variety of ML models (Blaom *et al.* 2020). We evaluate the efficacy of these models using two common measures of binary classifier performance: the area under the receiver-operator curve (ROC-AUC) and the area under the precision-recall curve (PR-AUC), for more details see Poisot (2022). Here, PR-AUC is slightly more relevant as it is a better indicator of prediction of false-negatives. The results of these simulations are shown in fig. 5(a & b).

One interesting result seen in fig. 5(a & b) is that the ROC-AUC value does not approach random in the same way the PR-AUC curve does as we increase the added FNR. The reason for this is that ROC-AUC is fundamentally not as useful a metric in assessing predictive capacity as PR-AUC. As we keep adding more false-negatives, the network eventually becomes a zeros matrix, and these models can still learn to predict “no-interaction” for all possible species pairs, which does far better than random guessing (ROC-AUC = 0.5) in terms of the false positive rate (one of the components of ROC-AUC). This highlights a more broad issue of label class imbalance, meaning there are far more non-interactions than interactions in data. A





Figure 5: **(a)** The area-under the receiver-operator curve (ROC-AUC) and **(b)** The area-under the precision-recall curve (PR-AUC; right) for each different predictive model (colors/shapes) across a spectrum of the proportion of added false-negatives (x-axis). **(c)** The mean trophic-level of all species in a network generated with the niche model across different species richnesses (colors). For each value of the FNR, the mean trophic level was computed across 50 replicates. The shaded region for each line is one standard-deviation across those replicates.

283 full treatment of the importance of class-balance is outside the scope of this paper, but is explored in-depth  
284 in Poisot (2022). Further we see, if anything, gradual decline in the performance of the model until we  
285 reach very high FNR levels (i.e.  $p_{fn} > 0.7$ ). This is consistent with other recent work (Gupta *et al.* 2023),  
286 although it must be considered that the empirical data on which these models are trained already are  
287 almost certain to already contain false-negatives.

288 Although these ML models are surprisingly performant at link prediction given their simplicity, there  
289 have been several major developments in applying deep-learning methods to many tasks in network  
290 inference and prediction—namely graph-representation learning (GRL, Khoshraftar & An (2022)) and  
291 graph convolutional networks (Zhang *et al.* 2019). At this time, these advances can not yet be applied to  
292 ecological networks because they require far more data than we currently have. We already have lots of  
293 features that could be used as inputs into these models (i.e. species level data about occurrence, genomes,  
294 abundance, etc.), but our network datasets barely get into the hundreds of local networks sampled across  
295 space and time (tbl. 1). Once we start to get into the thousands, these models will become more useful, but  
296 this can only be done with systematic monitoring of interactions. This again highlights the need to  
297 optimize our sampling effort to maximize the amount of information contained in our data given the  
298 expense of sampling interactions.

299 We also consider how the FNR affects network properties. In fig. 5(c) we see the mean trophic level across  
300 networks simulated using the niche model (as above), across a spectrum of FNR values. In addition to the  
301 clear dependence on richness, we see that mean trophic level, despite varying widely between niche model  
302 simulations, tends to be relatively robust to false-negatives and does not deviate widely from the true value  
303 until very large FNRs. This is not entirely unsurprising. Removing links randomly from a food-web is  
304 effectively the inverse problem of the emergence of a giant component (more than half of the nodes are in  
305 a connected network) in random graphs (see Li *et al.* (2021) for a thorough review). The primary  
306 difference being that we are removing edges, not adding them, and thus we are witnessing the dissolution  
307 of a giant component, rather than the emergence of one. Further applications of percolation theory (Li *et*  
308 *al.* 2021) to the topology of sampled ecological networks could improve our understanding of how  
309 false-negatives impact the inferences about the structure and dynamics on these networks.

## 310 Discussion

311 Species interactions enable the persistence and functioning of ecosystems, but our understanding of  
312 interactions is limited due to the intrinsic difficulty of sampling them. Here we have provided a null  
313 model for the expected number of false-negatives in an interaction dataset. We demonstrated that we  
314 expect many false-negatives in species interaction datasets purely due to the intrinsic variation of  
315 abundances within a community. We also, for the first time to our knowledge, measured the strength of  
316 association between co-occurrence and interactions (Cazelles *et al.* 2016) across many empirical systems,  
317 and found that these positive associations are both very common, and showed algebraically that they  
318 increase the realized FNR. We have also shown that false-negatives could further impact our ability to  
319 both predict interactions and infer properties of the networks, which highlights the need for further  
320 research into methods for correcting this bias in existing data.

321 A better understanding of how false-negatives impact species interaction data is a practical  
322 necessity—both for inference of network structure and dynamics, but also for prediction of interactions by  
323 using species level information. False-negatives could pose a problem for many forms of inference in  
324 network ecology. For example, inferring the dynamic stability of a network could be prone to error if the  
325 observed network is not sampled “enough.” What exactly “enough” means is then specific to the  
326 application, and should be assessed via methods like those here when designing samples. Further,  
327 predictions about network rewiring (Thompson & Gonzalez 2017) due to range shifts in response to  
328 climate change could be error-prone without accounting for interactions that have not been observed but  
329 that still may become climatically infeasible. As is evident from fig. 2(a), we can never guarantee there are  
330 no false-negatives in data. In recent years, there has been interest toward explicitly accounting for  
331 false-negatives in models (Stock *et al.* 2017; Young *et al.* 2021), and a predictive approach to  
332 networks—rather than expecting our samples to fully capture all interactions (Strydom *et al.* 2021). As a  
333 result, better models for predicting interactions are needed for interaction networks. This includes  
334 explicitly accounting for observation error (Johnson & Larremore 2021)—certain classes of models have  
335 been used to reflect hidden states which account for detection error in occupancy modeling (Joseph 2020),  
336 and could be integrated in the predictive models of interactions in the future.

337 This work has several practical consequences for the design of surveys for species’ interactions.

338 Simulating the process of observation could be a powerful tool for estimating the sampling effort required

339 by a study that takes relative abundance into account, and provides a null baseline for expected FNR. It is  
340 necessary to take the size of the species pool into account when deciding how many total samples is  
341 sufficient for an “acceptable” FNR (fig. 2(c & d)). Further the spatial and temporal turnover of interactions  
342 means any approach to sampling prioritization must be spatiotemporal. We demonstrated earlier that  
343 observed negatives outside of the range of both species aren’t informative, and therefore using species  
344 distribution models could aid in this spatial prioritization of sampling sites.

345 We also should address the impact of false-negatives on the inference of process and causality in  
346 community ecology. We demonstrated that in model food webs, false-negatives do not impact the measure  
347 of total trophic levels until very high FNR (figure fig. 5(c)), although we cannot generalize this further to  
348 other properties. This has immediate practical concern for how we design what taxa to sample—does it  
349 matter if the sampled network is fully connected? It has been shown that the stability of subnetworks can  
350 be used to infer the stability of the metaweb paper beyond a threshold of samples (Song *et al.* 2022b). But  
351 does this extend to other network properties? And how can we be sure we are at the threshold at which we  
352 can be confident our sample characterizes the whole system? We suggest that modeling observation error  
353 as we have done here can address these questions and aid in the design of samples of species interactions.  
354 To try to survey to avoid all false-negatives is a fool’s errand. Species ranges overlap to form mosaics,  
355 which themselves are often changing in time. Communities and networks don’t end in space, and the  
356 interactions that connect species on the ‘periphery’ of a given network to species outside the spatial extent  
357 of a given sample will inevitably appear as false-negatives in practical samples. The goal should instead be  
358 to sample a system enough to have a statistically robust estimate of the current state and empirical change  
359 over time of an ecological community at a given spatial extent and temporal resolution, and to determine  
360 what the sampling effort required should be prior to sampling.

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