

A network diagram with several nodes (circles) connected by lines. One node is highlighted with a blue circular logo. The background is dark gray with a fine grid pattern.

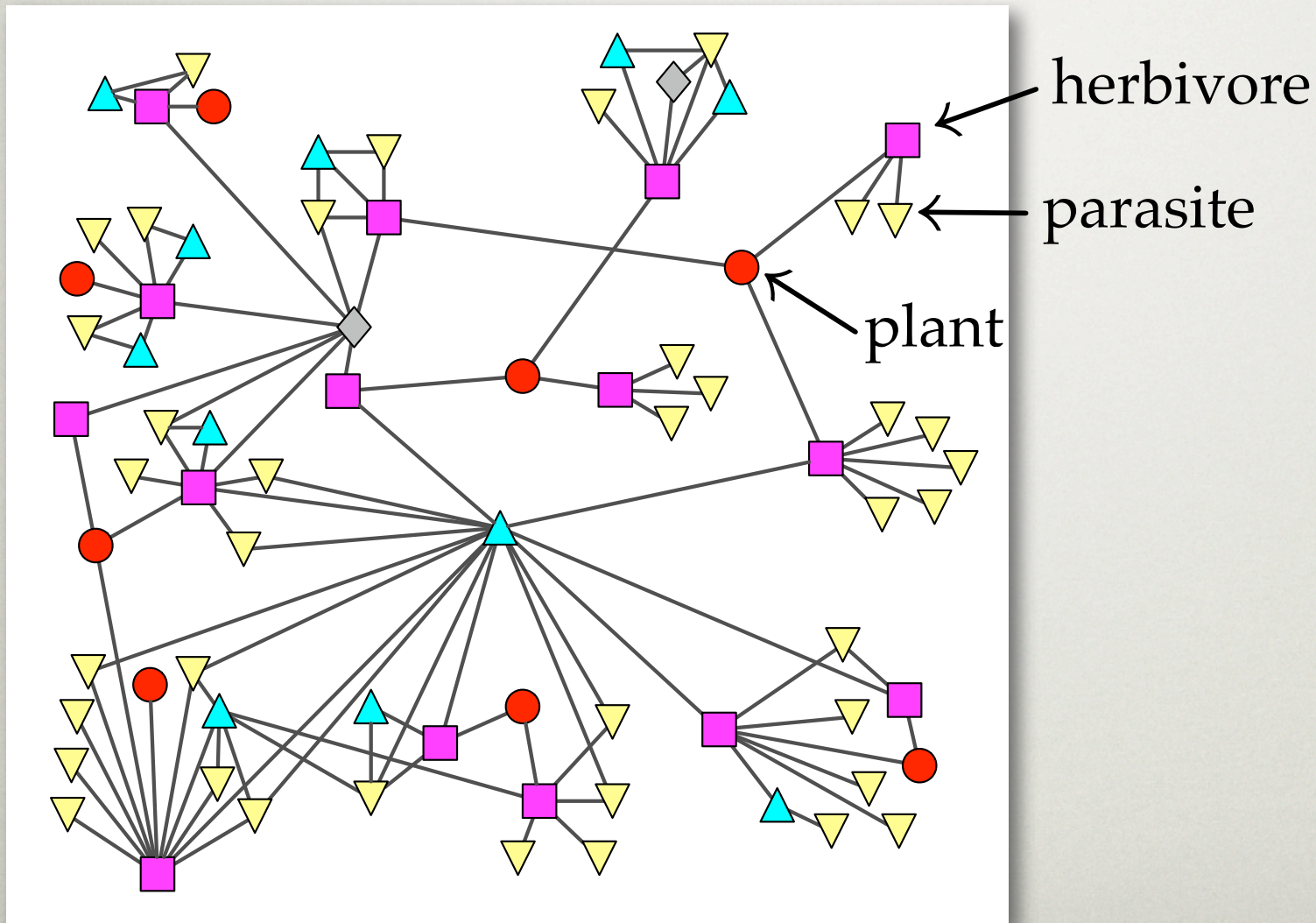
HIERARCHICALLY MODULAR STRUCTURE IN COMPLEX NETWORKS

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Santa Fe Institute

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DIMACS / DyDAn

“Network Models of Biological and Social Contagion”

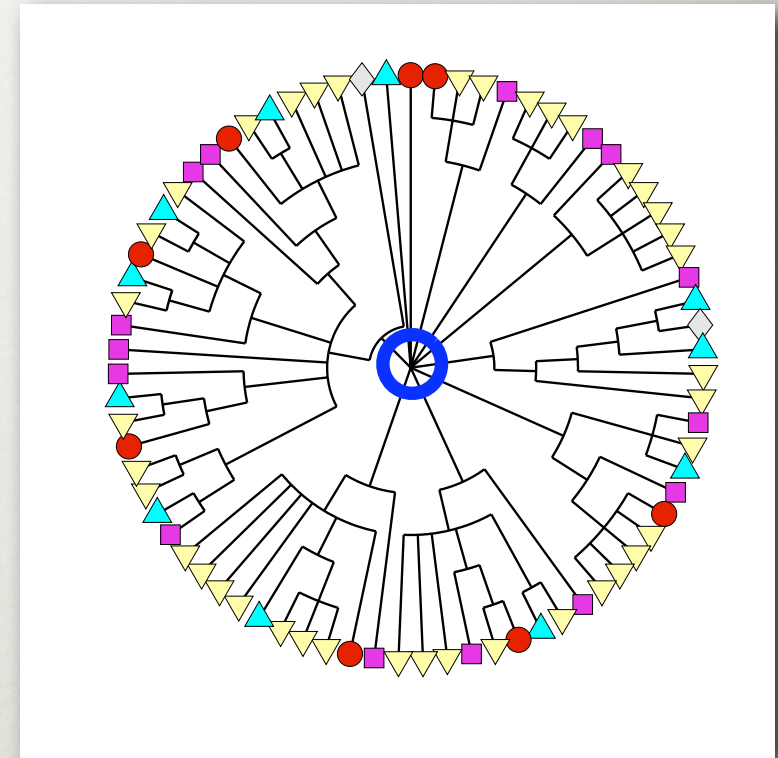
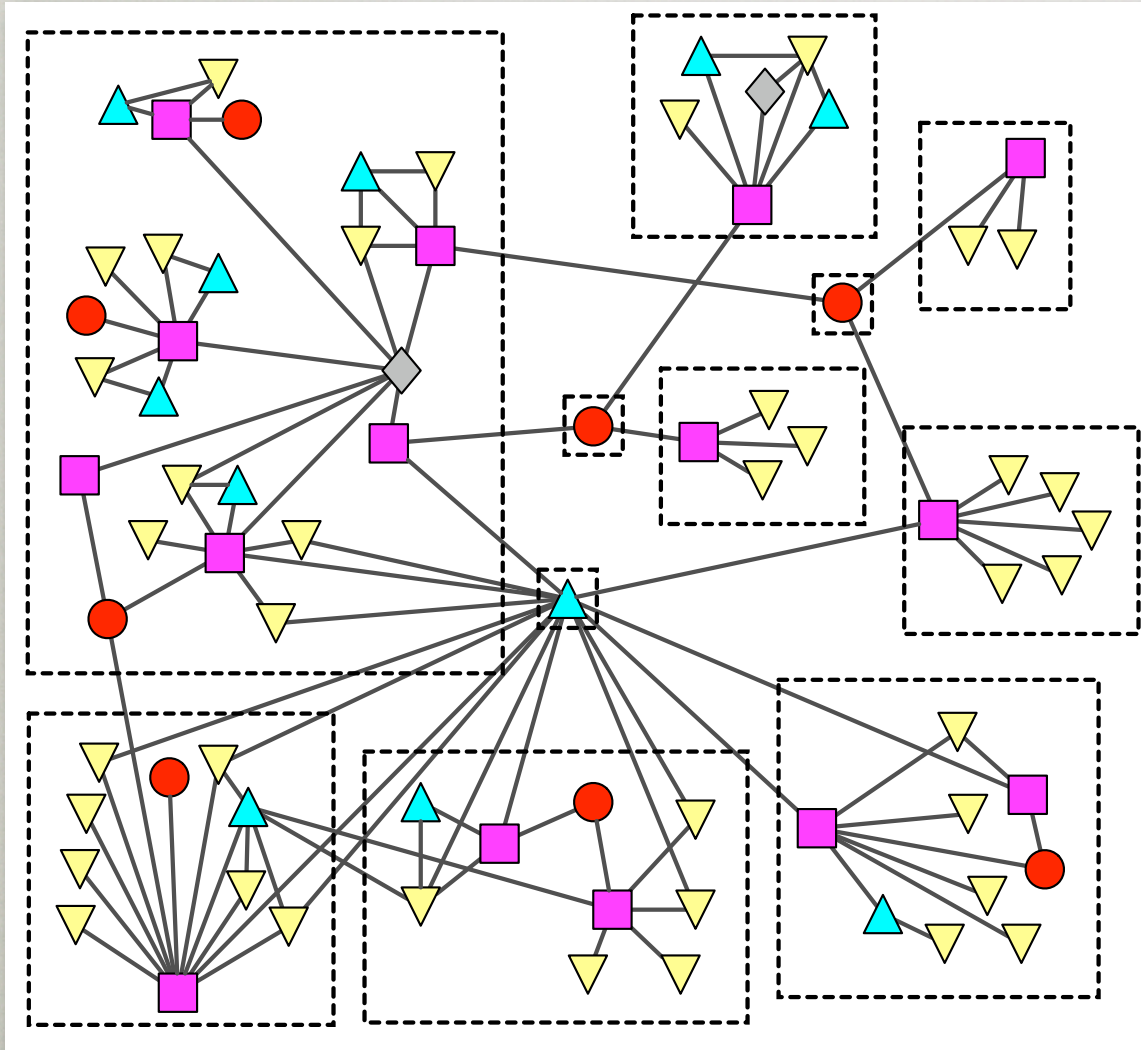
MODULAR HIERARCHIES



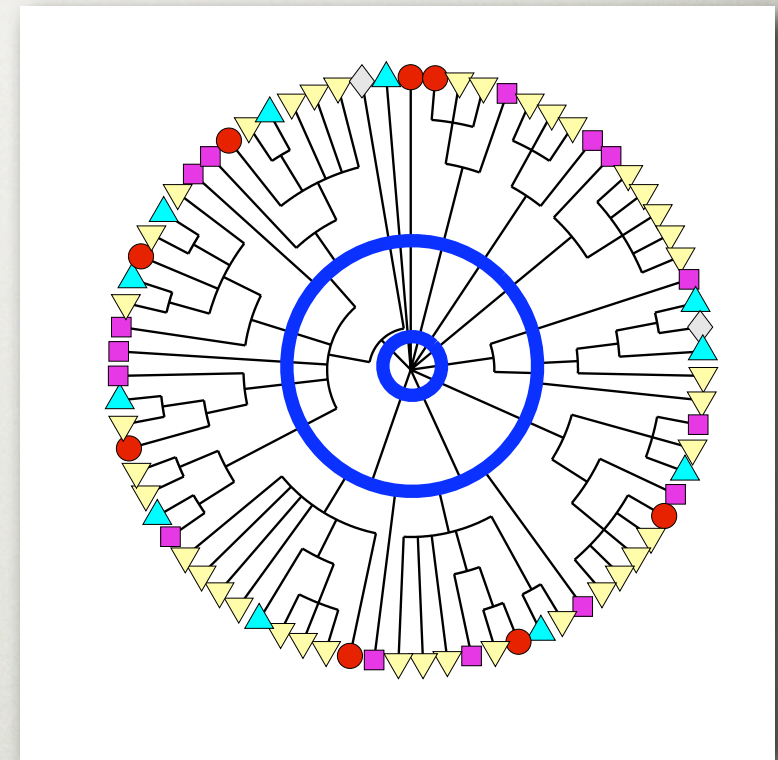
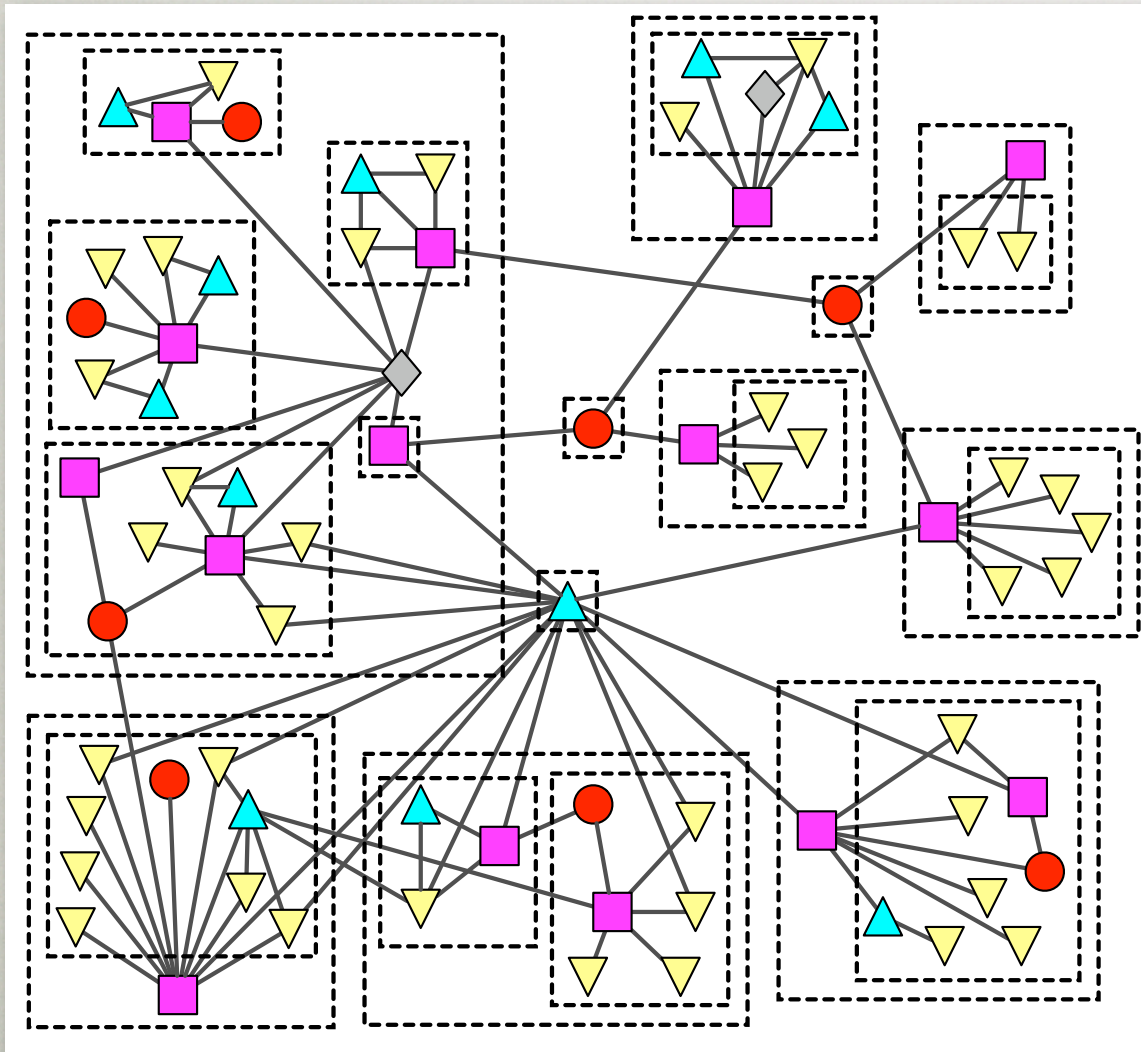
Grassland species*

*thank you: Jennifer Dunne

MODULAR HIERARCHIES



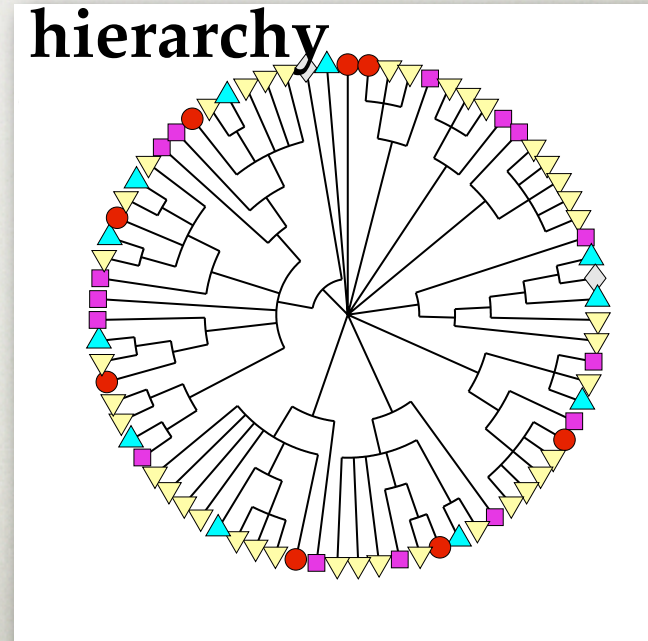
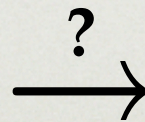
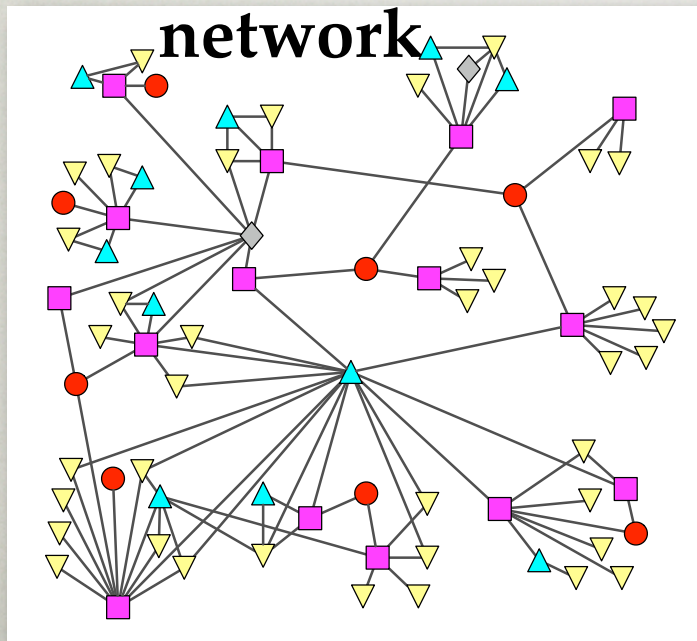
MODULAR HIERARCHIES



THE TASK

How can we extract

- **this hierarchical (multi-scale) structure** from complex networks?



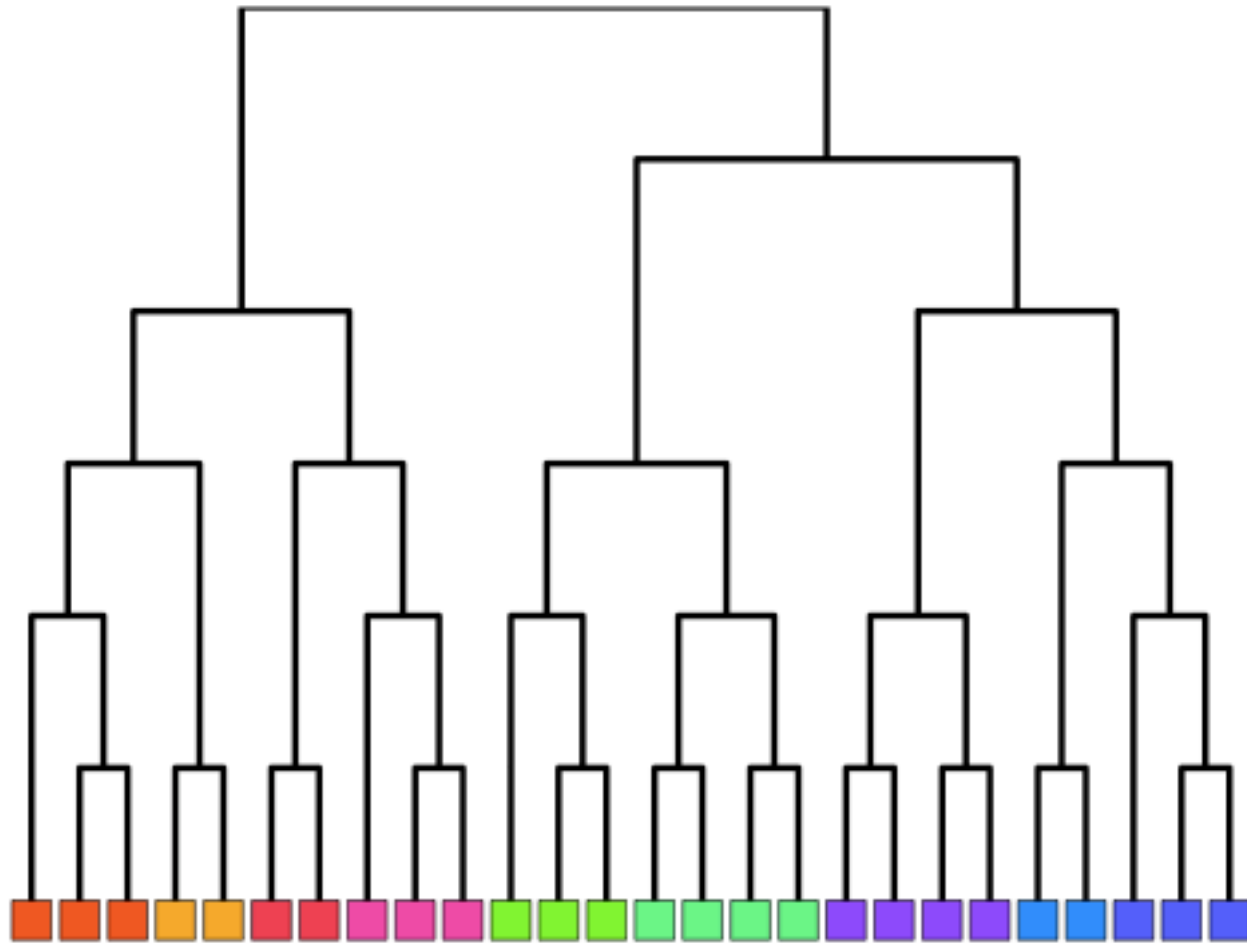
ONE APPROACH

Model-based inference

1. describe how to generate hierarchies (a model)
2. “fit” model to empirical data
3. test “fitted” model
4. extract predictions + insight
5. profit!

A MODEL OF HIERARCHY

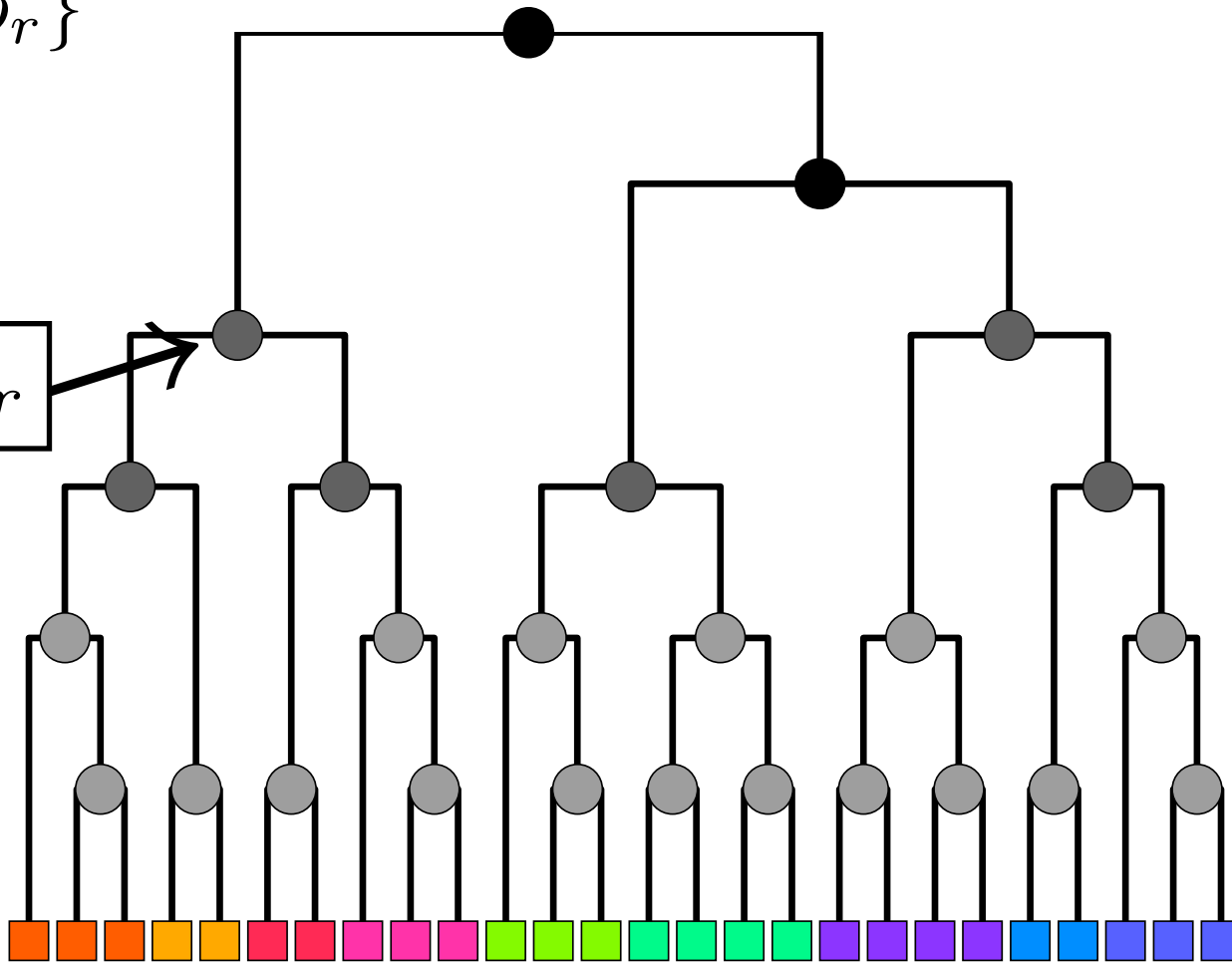
D



A MODEL OF HIERARCHY

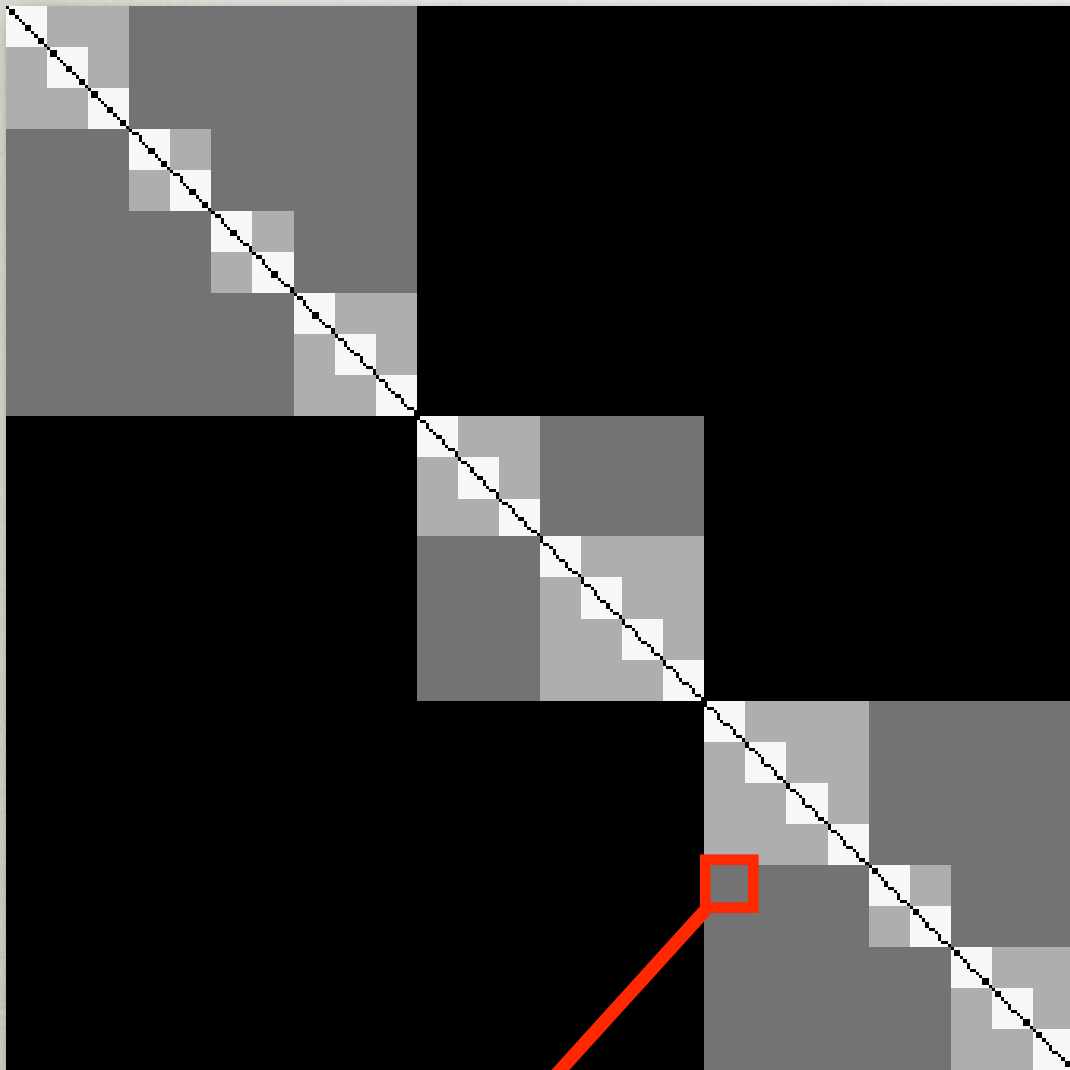
$\mathcal{D}, \{p_r\}$

probability p_r



assortative modules

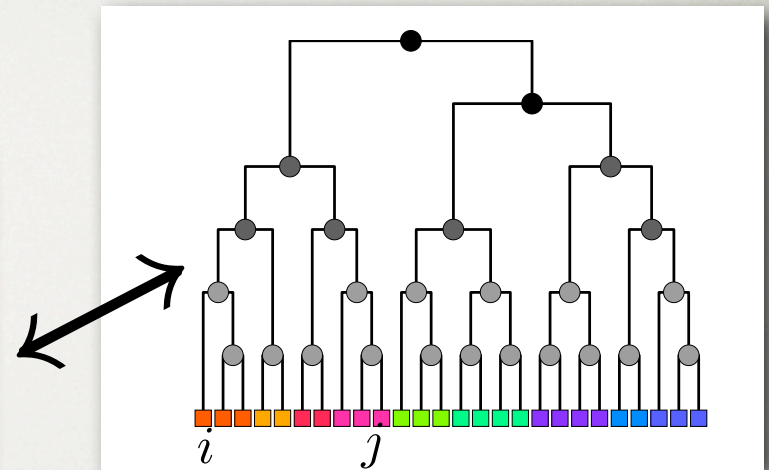
“inhomogeneous” random graph



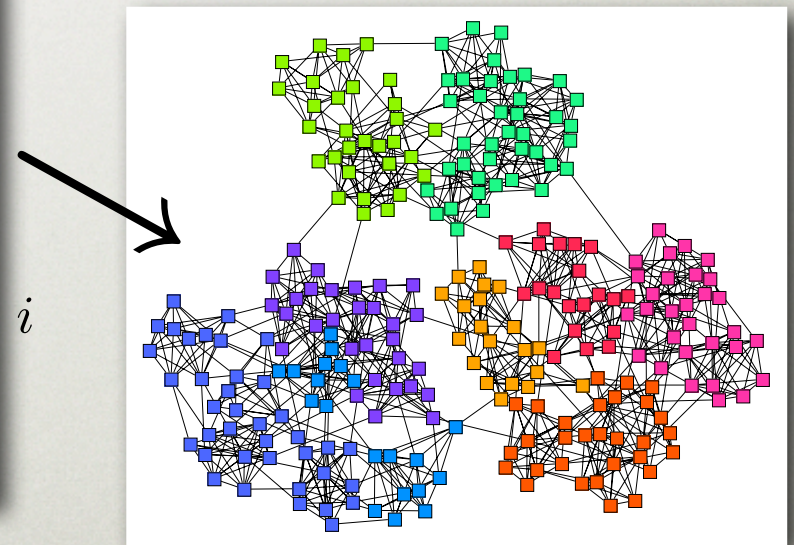
$$\Pr(i, j \text{ connected}) = p_r$$

$$= p(\text{lowest common ancestor of } i, j)$$

model



instance



MODEL FEATURES

- explicit model = explicit assumptions
- very flexible (many parameters)
- captures structure at all scales
- arbitrary mixtures of assortativity, disassortativity
- learnable directly from data

LEARNING FROM DATA

a direct approach

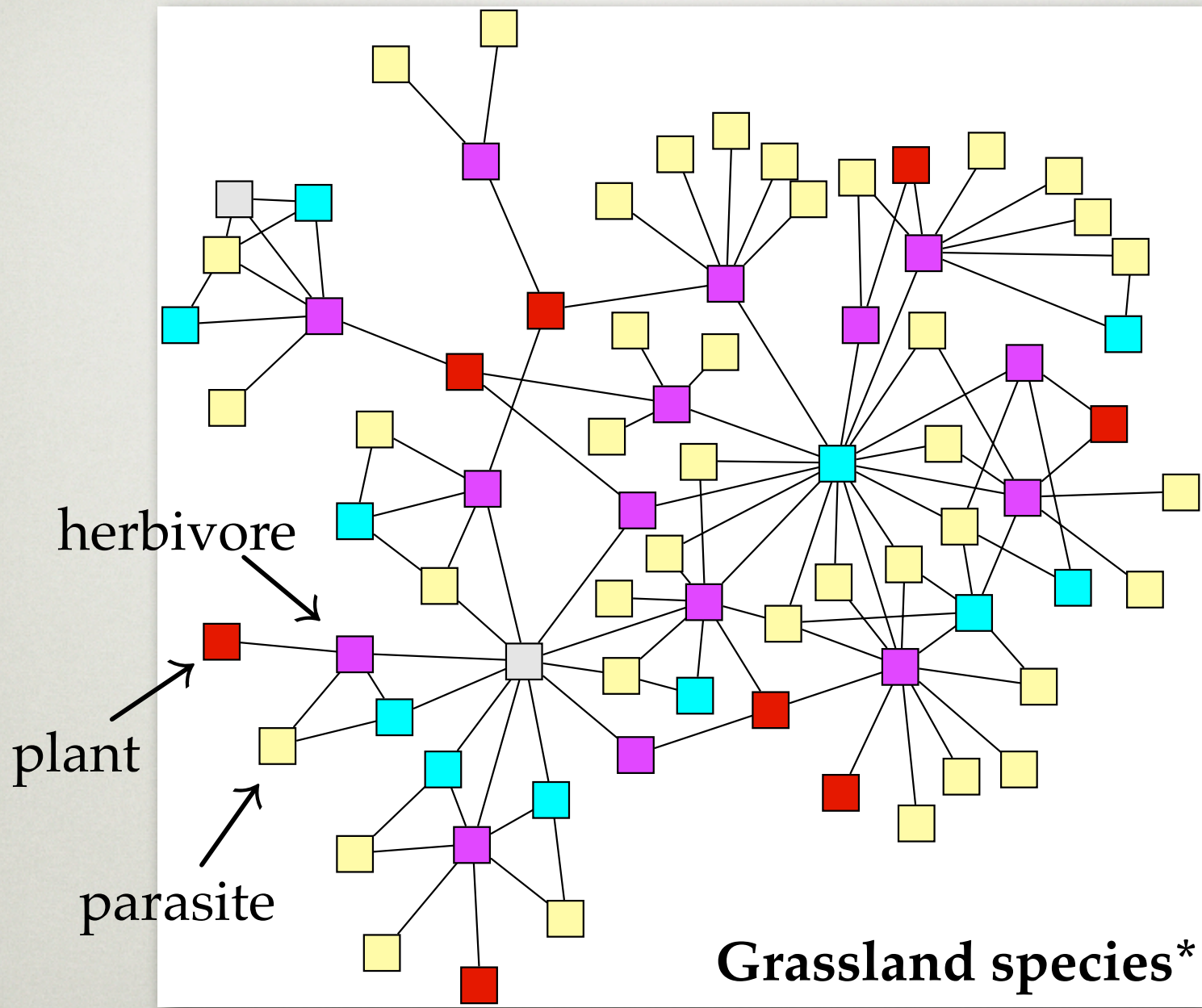
- **likelihood function** $\mathcal{L} = \text{Pr}(\text{ data } | \text{ model })$
(\mathcal{L} scores **quality** of model)
- **sample** the **good** models
via Markov chain Monte Carlo
- technical details in arXiv : *physics/0610051*

FROM GRAPH TO ENSEMBLE

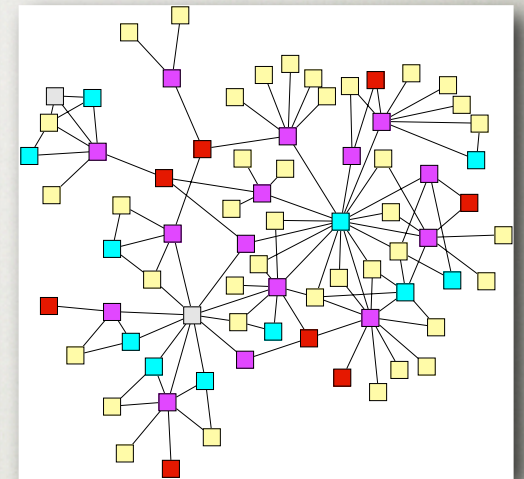
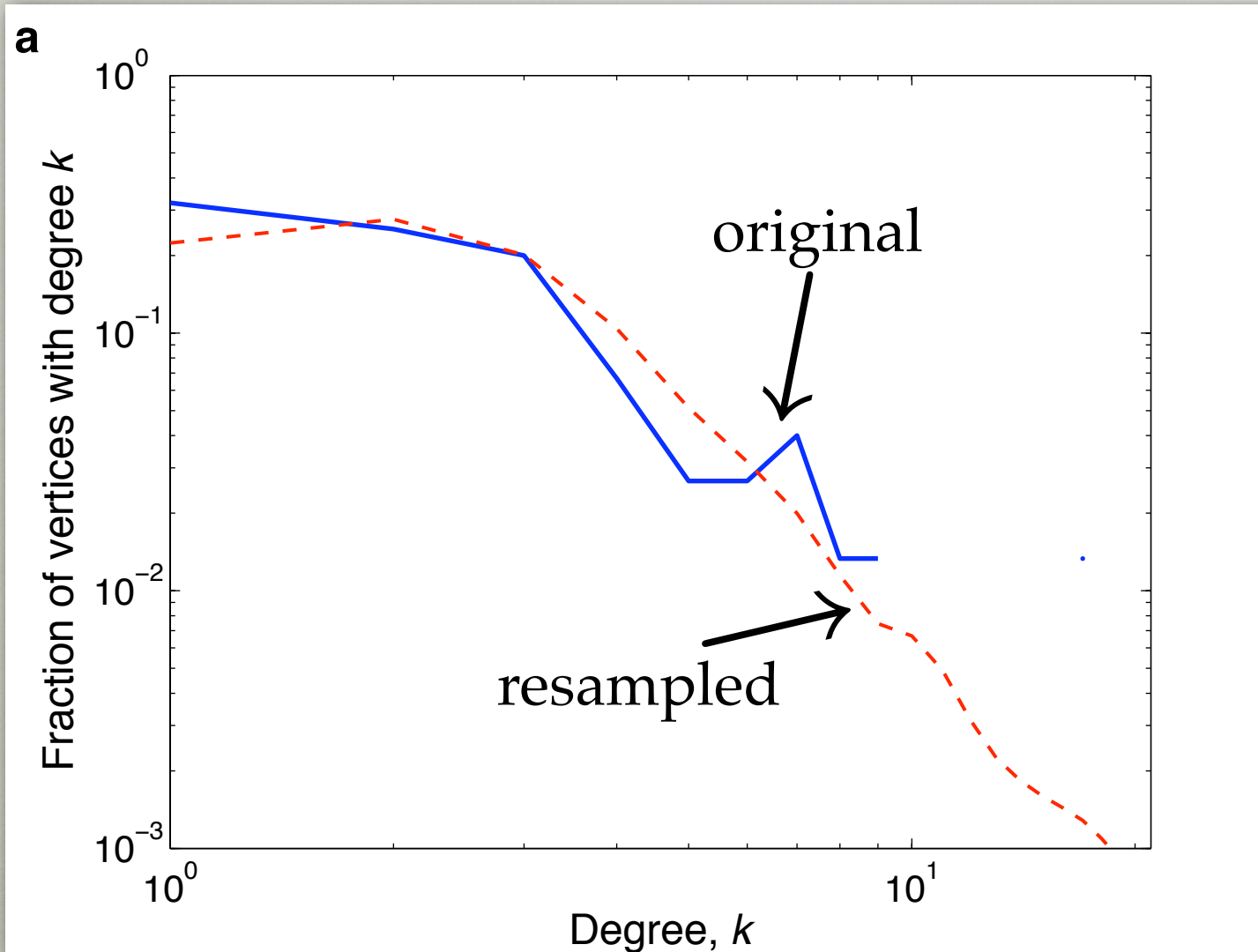
FROM GRAPH TO ENSEMBLE

- Given graph G
- run MCMC to equilibrium
- then, for each sampled \mathcal{D} , draw a **resampled** graph G' from ensemble

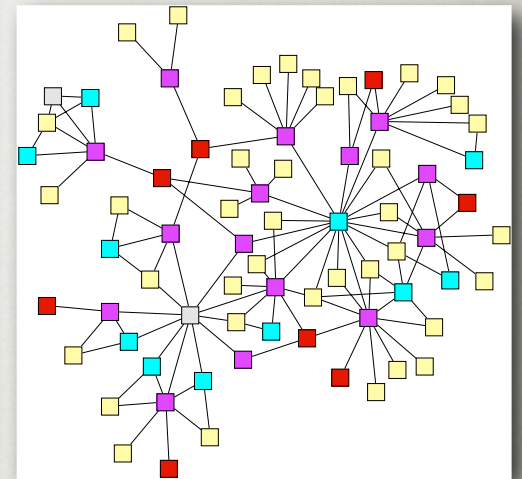
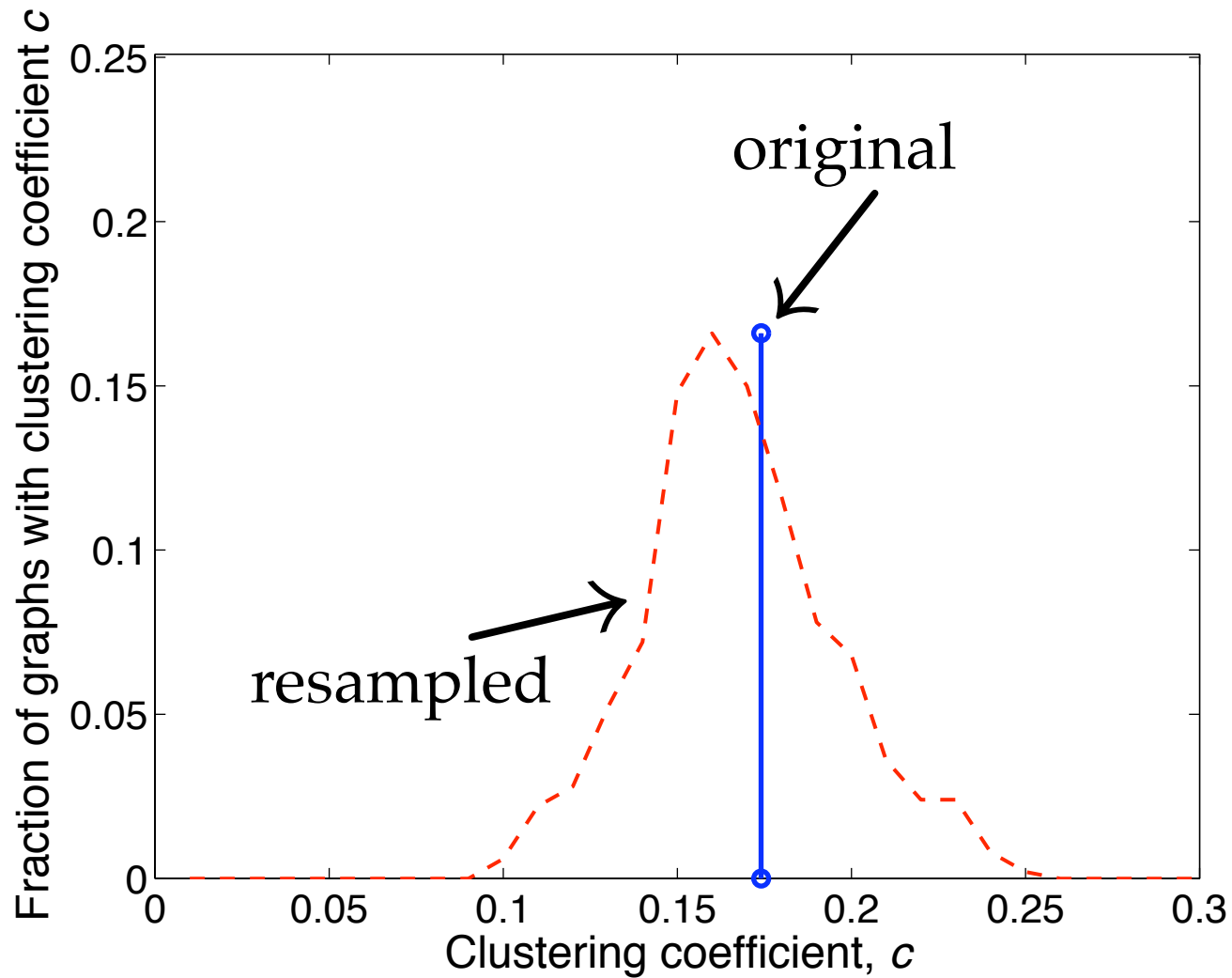
A test: do resampled graphs look like original?



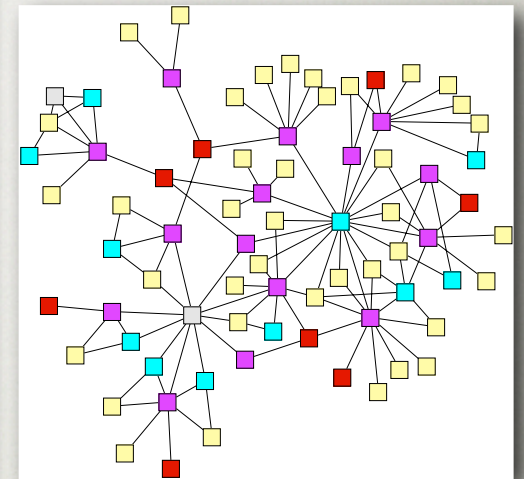
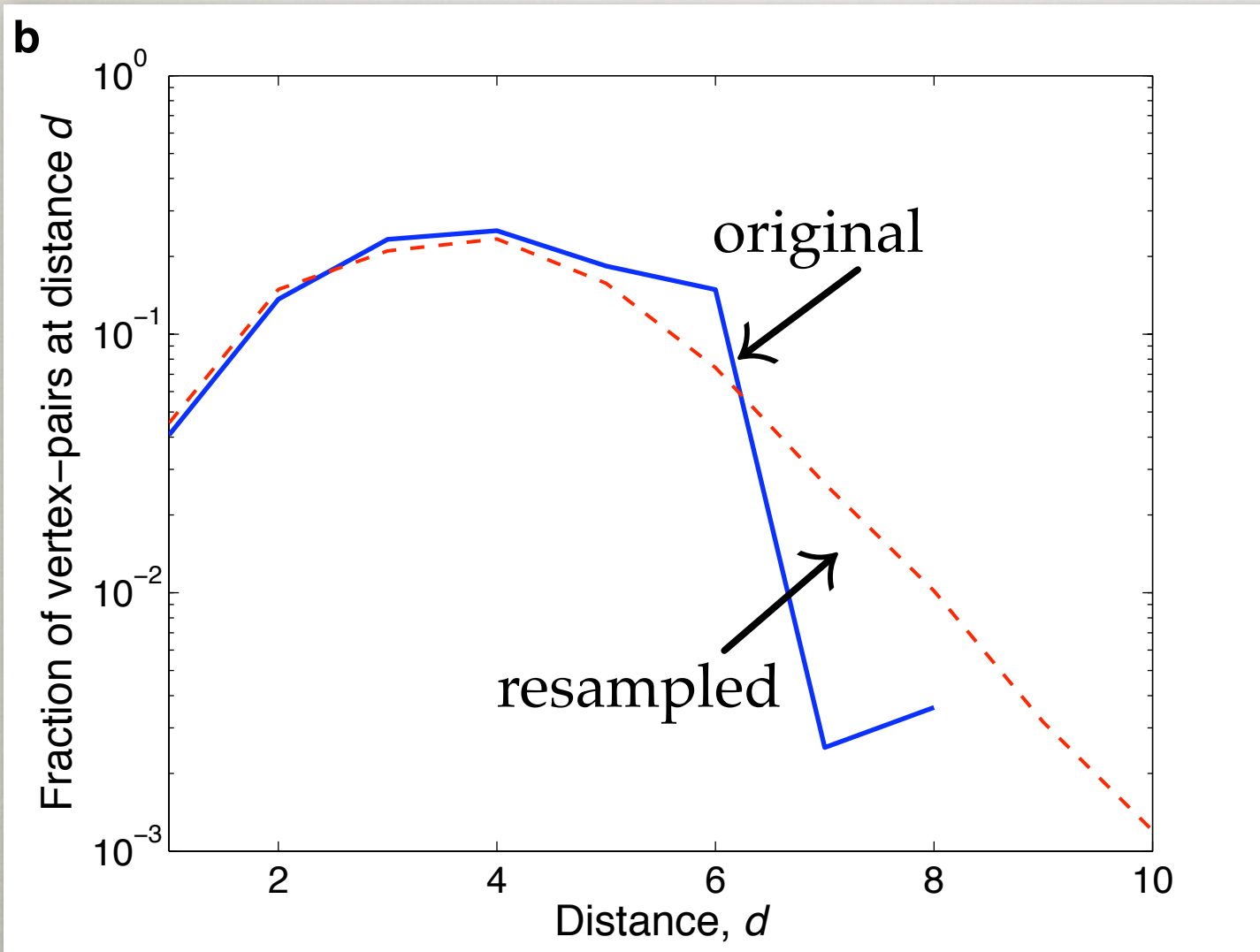
DEGREE DISTRIBUTION



CLUSTERING COEFFICIENT



DISTANCE DISTRIBUTION



MISSING LINKS

A test: can model predict missing links?

PREDICTING IS HARD

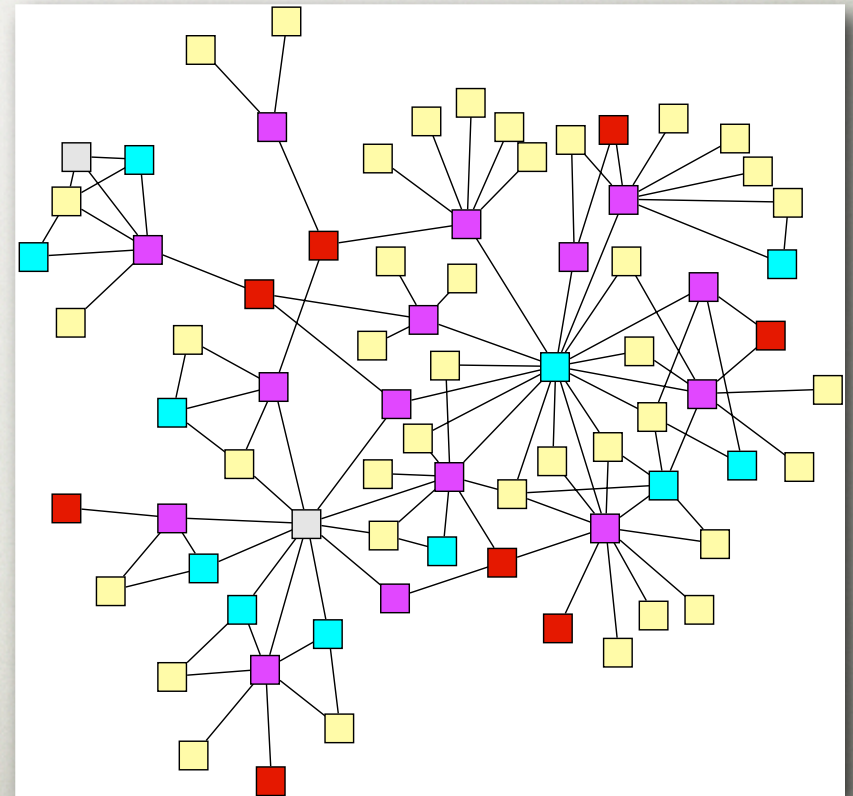
- remove k edges from G
- how easy to guess a missing link?

$$p_{\text{guess}} \approx \frac{k}{n^2 - m + k}$$
$$= O(n^{-2})$$

$$n = 75$$

$$m = 113$$

$$p_{\text{guess}} = k / (2662 + k)$$



PREDICTING MISSING LINKS

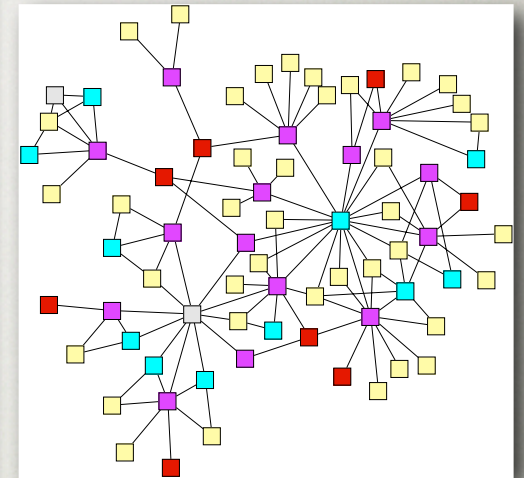
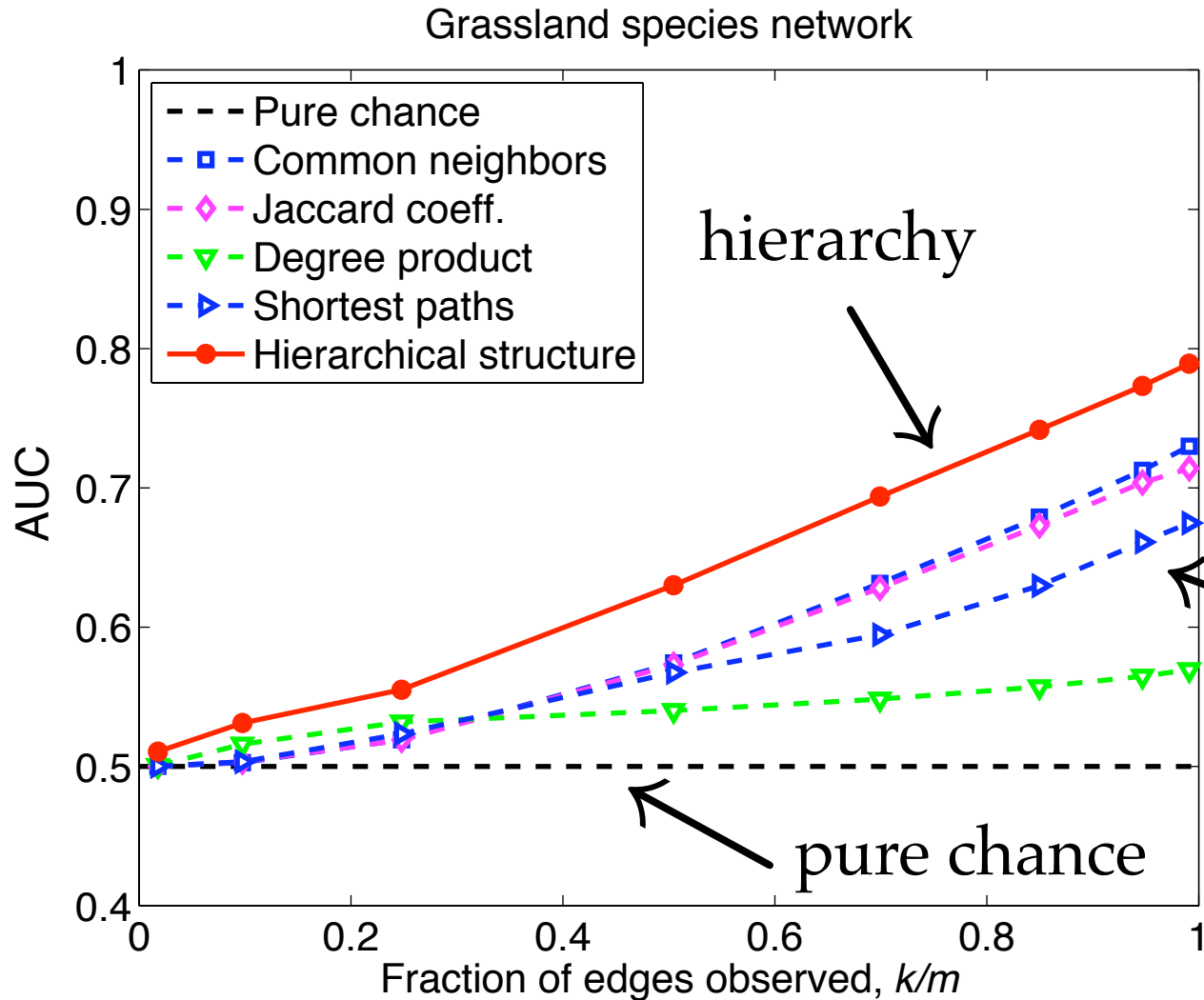
- Given incomplete graph G
- run MCMC to equilibrium
- then, over sampled \mathcal{D} , compute average $\langle p_r \rangle$ for links $(i, j) \notin G$
- predict links with high $\langle p_r \rangle$ values are missing

Test idea via leave- k -out cross-validation

perfect accuracy: $\text{AUC} = 1$

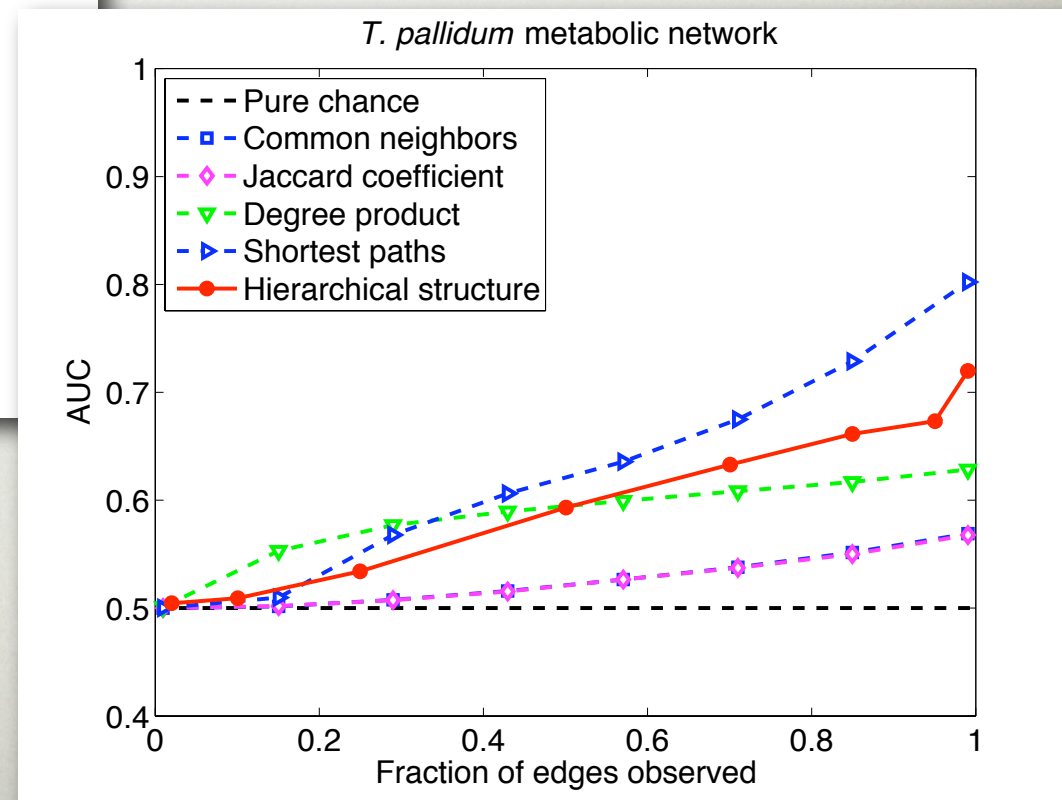
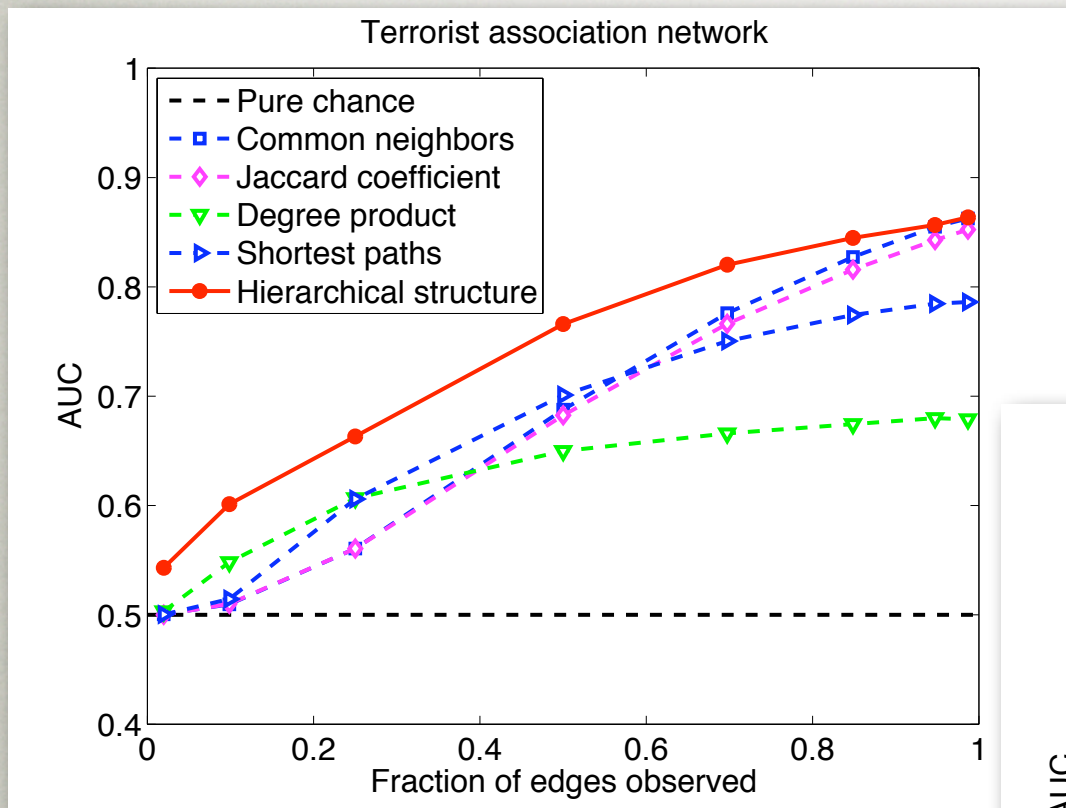
no better than chance: $\text{AUC} = 1/2$

MISSING STRUCTURE



simple predictors

OTHER NETWORKS



SUMMARY

- Many real networks are hierarchically modular
- Hierarchies can
 - model multi-scale structure
 - generalize a single network
 - predict missing links
- Model-based inference is very powerful

Acknowledgments:

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FIN
