

Inference of the interactions within the pathobiome of *Erysiphe alphitoides*

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Algorithmic issues for Inference in Graphical Models

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Microbial Interaction Networks

Plan-inhabiting microorganisms can interact with each other forming **complex interaction networks**.

- ▶ **Direct interactions**
 - ▶ Predation
 - ▶ Parasitism
 - ▶ Mutualism, etc
- ▶ **Indirect interactions**
 - ▶ Shared resources
 - ▶ Shared environments, etc



Photo by Zelimir Borzan, University of Zagreb,
Bugwood.org

- ▶ Pedunculate oak (*Quercus robur* L.)
- ▶ Infected by *Erysiphe alphitoides*
 - ▶ Species of fungus
 - ▶ Responsible for powdery mildew
- ▶ Pathogenicity resulting from **specific interactions with the microbial environment**
 - ▷ Pathobiome

Microbial Environment

- ▶ Operational taxonomic units (OTUs)
 - ▶ **Fungal** (among which *E. alphitoides*) 48 OTUs
 - ▶ **Bacterial** 66 OTUs
- 114 OTUs**
- ▶ Abundances measured on **120 leaves** taken from **3 trees**
 highly susceptible / intermediately resistant / strongly resistant

Covariates

- ▶ Distance to
 - ▶ the base of the branch
 - ▶ the tree trunk
 - ▶ the ground
- ▶ The orientation of the branch SW/NE

Problem

- ▶ Interactions can be concealed by **indirect relationships** resulting from **the environment**.

The inference of the interactions must take covariates into account.

Notations

p OTUs $V = \{1, \dots, p\}$
 n leaves

Y_i^k abundance of OTU i on leaf k $1 \leq i \leq p, 1 \leq k \leq n$

\mathbf{Y}^k abundances of all OTUs on leaf k $\mathbf{Y} = (\mathbf{Y}^1, \dots, \mathbf{Y}^n)$

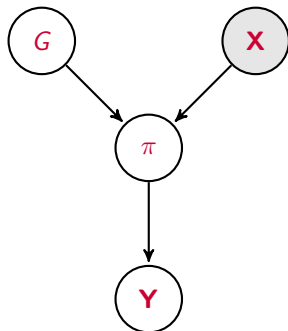
$\alpha^k \in \{1, 2, 3\}$ tree of leaf k

D^k orientation of the branch of leaf k

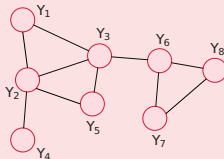
$\{X_d^k\}_{d=1}^3$ distance of leaf k to the
 {base of the branch, trunk, ground}

$\mathbf{X}^k = (\alpha^k, D^k, X_1^k, X_2^k, X_3^k)$ $\mathbf{X} = (\mathbf{X}^1, \dots, \mathbf{X}^n)$

Model



- ▶ $G = (V, E_G)$ decomposable graph

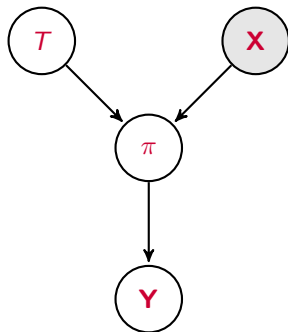


$$\mathcal{G} = \{ \text{decomposable graphs} \}$$

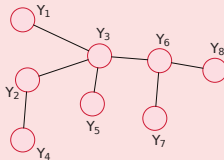
- ▶ π distribution for Y
Markov w.r.t. G
depending on X

$$\{i, j\} \notin E_G \Leftrightarrow Y_i \perp\!\!\!\perp Y_j \mid Y_{V \setminus \{i, j\}}$$

Model



- ▶ $T = (V, E_T)$ **spanning tree**

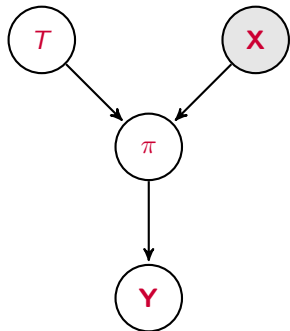


$$\mathcal{T} = \{ \text{spanning trees} \}$$

- ▶ π distribution for **Y**
Markov w.r.t. T
depending on **X**

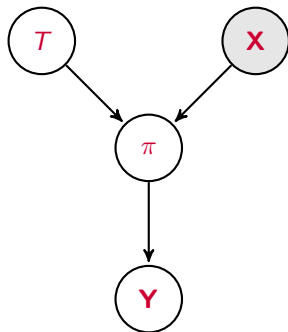
$$\{i, j\} \notin E_T \Leftrightarrow Y_i \perp\!\!\!\perp Y_j \mid Y_{V \setminus \{i, j\}}$$

Model



$$\begin{aligned} T &\sim \mathcal{U}(T) \\ \pi | T, \mathbf{X} &\sim \rho(T, \mathbf{X}) \\ \mathbf{Y} | \pi &\sim \pi \end{aligned}$$

Model



$$T \sim \mathcal{U}(\mathcal{T})$$

$$\pi | T, \mathbf{X} \sim \rho(T, \mathbf{X})$$

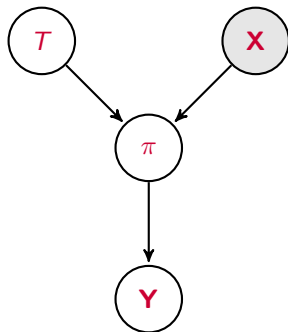
$$\mathbf{Y} | \pi \sim \pi$$

Posterior Edge Probabilities

$$p(\{i, j\} \in E_T | \mathbf{Y}, \mathbf{X})$$

$$= \sum_{\substack{T \in \mathcal{T} \\ T \ni \{i, j\}}} p(T | \mathbf{Y}, \mathbf{X})$$

Model



$$T \sim \mathcal{U}(\mathcal{T})$$

$$\pi | T, \mathbf{X} \sim \rho(T, \mathbf{X})$$

$$\mathbf{Y} | \pi \sim \pi$$

Posterior Edge Probabilities

$$\rho(\{i, j\} \in E_T | \mathbf{Y}, \mathbf{X})$$

$$= \sum_{\substack{T \in \mathcal{T} \\ T \ni \{i, j\}}} \rho(T | \mathbf{Y}, \mathbf{X})$$

- ▶ Summation over \mathcal{T}
- ▶ Choice of $\rho(T, \mathbf{X})$

Suppose that

$$p(T|\mathbf{Y}, \mathbf{X}) \propto \prod_{\{k,\ell\} \in E_T} \omega_{kl}(Y_k, Y_\ell, \mathbf{X})$$

Suppose that

$$p(T|\mathbf{Y}, \mathbf{X}) \propto \prod_{\{k,\ell\} \in E_T} \omega_{k\ell}(Y_k, Y_\ell, \mathbf{X})$$

then

$$p(\{i,j\} \in E_T | \mathbf{Y}, \mathbf{X}) = \frac{Z^{(ij)}}{Z}$$

with

$$Z = \sum_{T \in \mathcal{T}} \prod_{\{k,\ell\} \in E_T} \omega_{k\ell} \quad Z^{(ij)} = \sum_{\substack{T \in \mathcal{T} \\ T \ni \{i,j\}}} \prod_{\{k,\ell\} \in E_T} \omega_{k\ell}$$

Matrix-Tree Theorem

- ▶ ω weight matrix
- ▶ Δ Laplacian matrix

$$\Delta_{kl} = \begin{cases} -\omega_{kl} & \text{if } k \neq l \\ \sum_j \omega_{kj} & \text{if } k = l \end{cases}$$

Let $\bar{\Delta}_{uv}$ denote the $(u, v)^{th}$ minor of Δ .

Theorem (Matrix-Tree Theorem, Chaiken, 1982)

All $\bar{\Delta}_{uv}$ are equal and the following identity holds

$$\bar{\Delta}_{uv} = \sum_{T \in \mathcal{T}} \prod_{\{k,l\} \in E_T} \omega_{kl} = Z$$

Matrix-Tree Theorem

$$p(\{i,j\} \in E_T | \mathbf{Y}, \mathbf{X}) = \frac{Z^{(ij)}}{Z}$$

$$\underbrace{\begin{pmatrix} \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{pmatrix}}_{\omega} \xrightarrow{MT} Z$$

$$\underbrace{\begin{matrix} & i & & j \\ i & \begin{pmatrix} \cdot & \cdot & 0 & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{pmatrix} & & \\ j & \begin{pmatrix} 0 & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{pmatrix} & & \end{matrix}}_{\omega^{(ij)}} \xrightarrow{MT} Z - Z^{(ij)}$$

► **Posterior probabilities for the edges**

Naive implementation

Computing $Z^{(ij)}$	$O(p^3)$
Total complexity	$O(p^5)$

**Generalized MT theorem
and some algebra**

Total complexity	$O(p^3)$
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Hyperdistributions

$\{\rho(\mathcal{T}, \mathbf{X})\}_{\mathcal{T} \in \mathcal{T}}$ defined on **the set of distributions over \mathbf{N}^p**
▷ $\rho(\mathcal{T}, \mathbf{X})$ defined on $\{\pi \mid \text{Markov w.r.t. } \mathcal{T}\}$

Hyperdistributions

$\{\rho(T, \mathbf{X})\}_{T \in \mathcal{T}}$ defined on **the set of distributions over \mathbf{N}^p**

▷ $\rho(T, \mathbf{X})$ defined on $\{\pi \mid \text{Markov w.r.t. } T\}$

▶ required to satisfy some **Markov property** w.r.t. T

▷ **Factorisation property** for $\rho(T|\mathbf{Y}, \mathbf{X})$

$$\rho(T|\mathbf{Y}, \mathbf{X}) \propto \prod_{\{k, \ell\} \in E_T} \omega_{k\ell}(Y_k, Y_\ell, \mathbf{X}, T)$$

Hyperdistributions

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▶ **Compatible family** over \mathcal{T}

▷ **Local terms do not depend on T**

$$\omega_{k\ell}(Y_k, Y_\ell, \mathbf{X}, T) \longrightarrow \omega_{k\ell}(Y_k, Y_\ell, \mathbf{X})$$

Univariate GLMs & Copula

▶ $Y_i|X$ given by **Poisson GLMs**

▶ Dependence structure of $Y|X$ given by a **Gaussian copula**

Univariate GLMs & Copula

- ▶ $Y_i|\mathbf{X}$ given by **Poisson GLMs**

$$\begin{cases} Y_i^k & \sim \mathcal{P}(\Lambda_i^k) \\ \log(\Lambda_i^k) & = \mathbf{X}^k \beta_i \end{cases}$$

- ▶ Dependence structure of $\mathbf{Y}|\mathbf{X}$ given by a **Gaussian copula**

Univariate GLMs & Copula

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$\Phi_i^k(\cdot|\beta_i)$ cumulative distribution function of $Y_i^k|\mathbf{X}^k$

$C(\cdot|\Gamma)$ Gaussian copula with precision matrix Γ

$\Phi(\cdot|\Gamma, \beta) = C(\Phi_1^k(\cdot|\beta_1), \dots, \Phi_p^k(\cdot|\beta_p)|\Gamma)$
cumulative distribution function of $\mathbf{Y}^k|\mathbf{X}^k$

Univariate GLMs & Copula

- ▶ $Y_i|\mathbf{X}$ given by **Poisson GLMs**

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cumulative distribution function of $\mathbf{Y}^k|\mathbf{X}^k$

- ▶ $\rho(T, \mathbf{X})$ induced by a distribution on $\{\Gamma | \text{compatible with } T\}$
a distribution on β

Heuristic

- ▶ $Y_i|\mathbf{X}$ given by **Poisson GLMs**

$$\begin{cases} Y_i^k & \sim \mathcal{P}(\Lambda_i^k) \\ \log(\Lambda_i^k) & = \mathbf{X}^k \beta_i \end{cases} \longrightarrow \hat{\beta}$$

- ▶ Dependence structure of $\mathbf{Y}|\mathbf{X}$ given by a **Gaussian copula**

$\Phi_i^k(\cdot|\hat{\beta}_i)$ cumulative distribution function of $Y_i^k|\mathbf{X}^k$

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$\Phi(\cdot|\Gamma, \hat{\beta}) = C(\Phi_1^k(\cdot|\hat{\beta}_1), \dots, \Phi_p^k(\cdot|\hat{\beta}_p)|\Gamma)$
cumulative distribution function of $\mathbf{Y}^k|\mathbf{X}^k$

- ▶ $\rho(T)$ induced by a distribution on $\{\Gamma \mid \text{compatible with } T\}$

In Practice

- ▶ R_i^k Pearson residual of Y_i^k
- \tilde{F}_i Empirical cdf of $\{R_i^k\}_{k=1}^n$

$$\tilde{Y}_i^k = \tilde{F}_i(R_i^k)$$

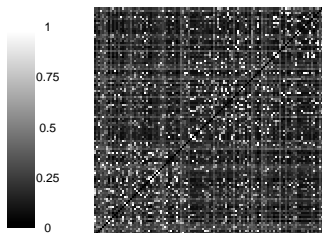


$$T \sim \mathcal{U}(T)$$

$$\Gamma_{ij} | T \sim \begin{cases} \mathcal{U}([-1; 1]) & \text{if } \{i, j\} \in E_T \\ \delta_0 & \text{otherwise} \end{cases}$$

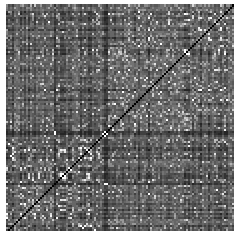
$$\tilde{Y} | \Gamma \sim C(\cdot | \Gamma)$$

Results

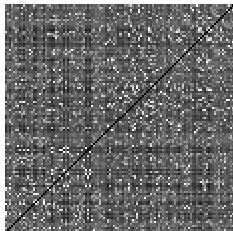


All Trees

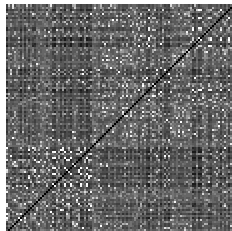
highly susceptible



intermediately resistant



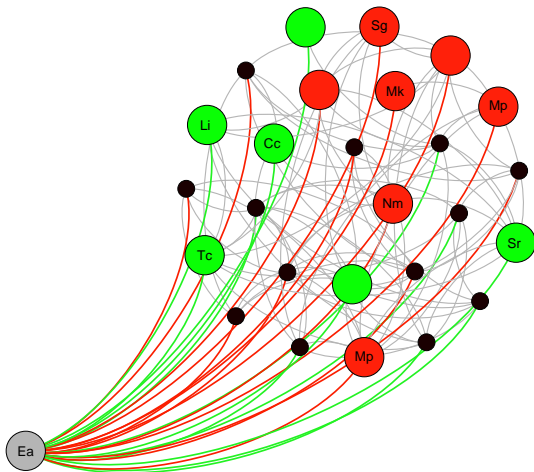
strongly resistant



Interactions of *Erysiphe alphitoides*

Susceptible tree

- Positive edges
- Negative edges
- Fungal species
- Bacterial species



- ▶ Exploration of graphs restricted to **tree structures**
 - ▶ Posterior edge appearance probabilities
 - ▶ Exact & efficient computation
thanks to the Matrix-Tree theorem

- ▶ Covariates
 - ▶ No full model
 - ▶ Inference performed after fitting univariate GLMs

- ▶ **Seth Chaiken.** “A Combinatorial Proof of the All Minors Matrix Tree Theorem”. In: *SIAM Journal on Algebraic Discrete Methods* 3.3 (1982), pp. 319–329.
- ▶ **A Philip Dawid and Steffen L. Lauritzen.** “Hyper Markov Laws in the Statistical Analysis of Decomposable Graphical Models”. In: *The Annals of Statistics* 21.3 (1993), pp. 1272–1317.
- ▶ **Marina Meilă and Tommi Jaakkola.** “Tractable Bayesian learning of tree belief networks”. In: *Statistics and Computing* 16.1 (2006), pp. 77–92.
- ▶ **L. Schwaller, S. Robin, and M. Stumpf.** “Bayesian Inference of Graphical Model Structures Using Trees”. In: *ArXiv e-prints* (Apr. 2015). arXiv: 1504.02723 [stat.ML]. URL: <http://arxiv.org/abs/1504.02723>.