Very Simple Models of Transport in Fungal Networks

With Luke Heaton, Eduardo Lopez, Philip Maini and Mark Fricker.

Imperial College London

Our work with Nets breaks in 3

1) Cellular energy variability

- Mitochondrial networks
- Networks of cells (via gap junctions)

2) Principles of Natural networks

- Transport in vascular systems
- Parameterized complexity and community structure
- Public health networks
- Ensembles of noisy coupled elements inferring and tracking
- Evolutionary morphings along nets for inference (see Evolution of Complexity meeting in Sept)

3) Highly comparative data analysis

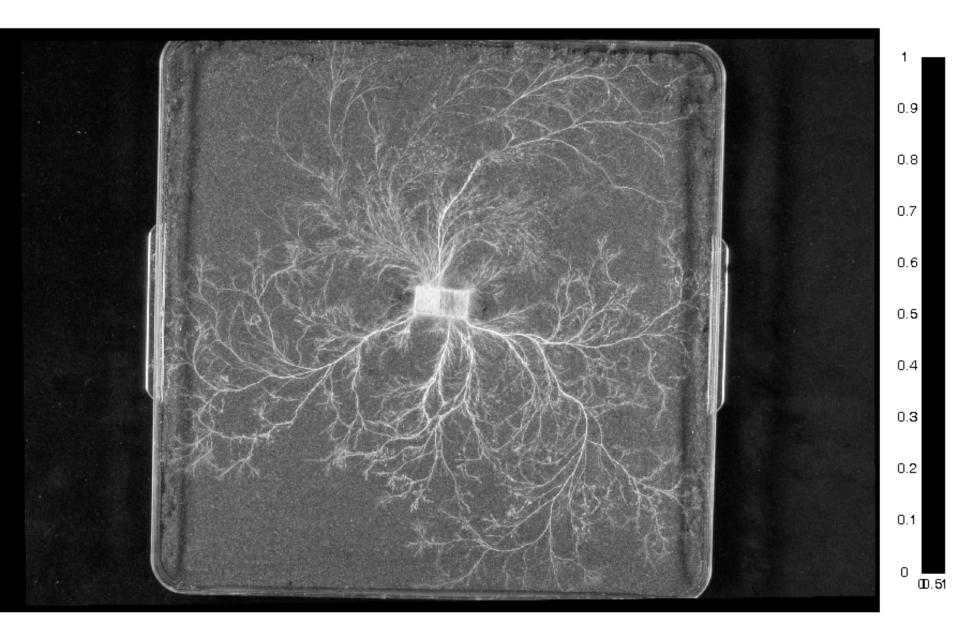
- Finding common structure in sets of net-methods & nets

Very Simple Models of Transport in Fungal Networks

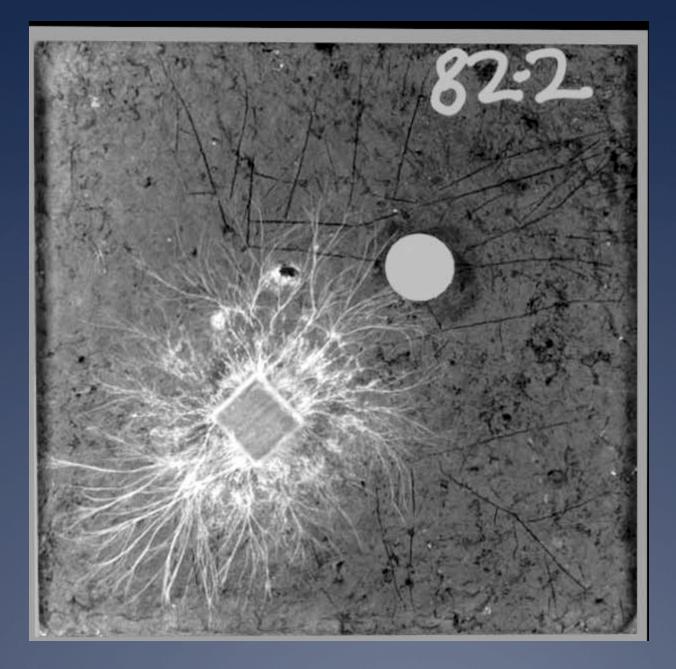
With Luke Heaton, Eduardo Lopez, Philip Maini and Mark Fricker.

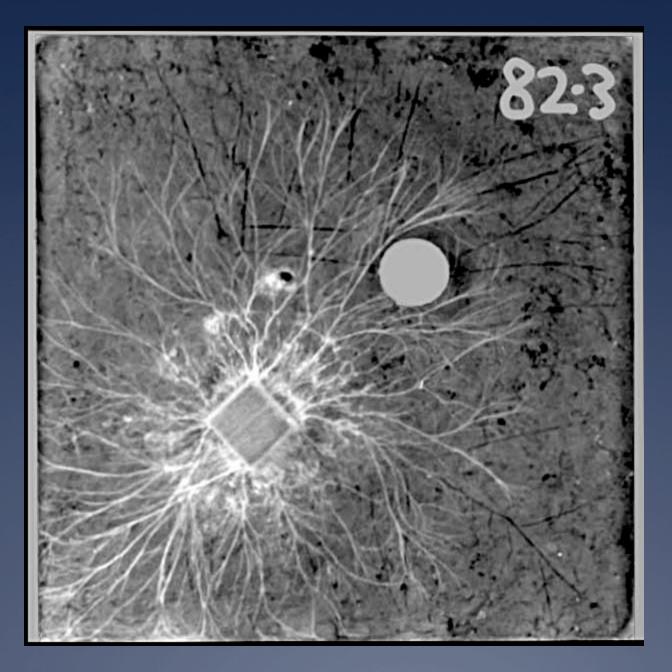


Luke Heaton











Transport - What we will discuss:

1) Introduce a simple view

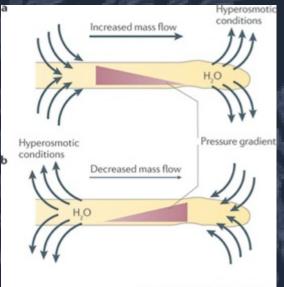
2) Discuss its implications

3) Refine the view slightly

4) Discuss further implications

How to transport? Three possible views

 Active transport of nutrients
Contractile elements
Concentration gradients inside the organism drive flows

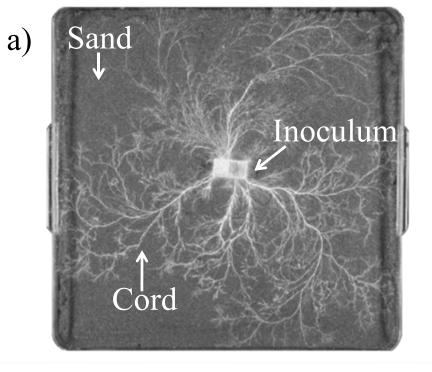


Nature Reviews | Microbiology

Roger Lew Nat. Rev. Microb. 2011

How to transport? Three possible views

... or "There's nothing too special about fungi".



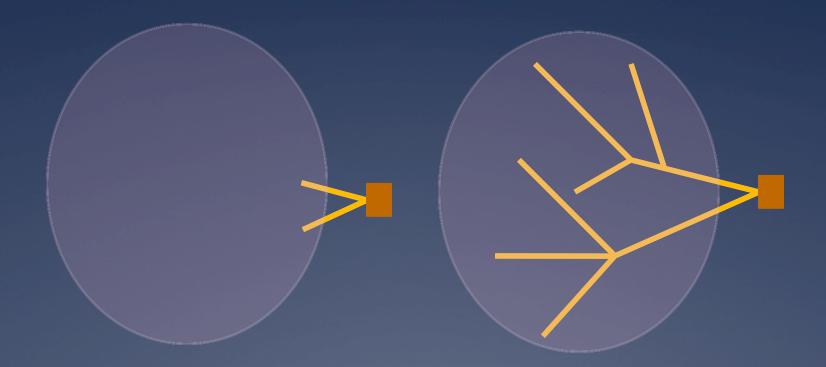
b)

1) System is under pressure

2) Sites of water uptake are distal from sites of growth

3) If you grow you flow.

Growth-induced mass flows



Resistor Model

Growing edges are sinks, while shrinking edges are sources.

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Inflow at the inoculum equals the total rate of growth.

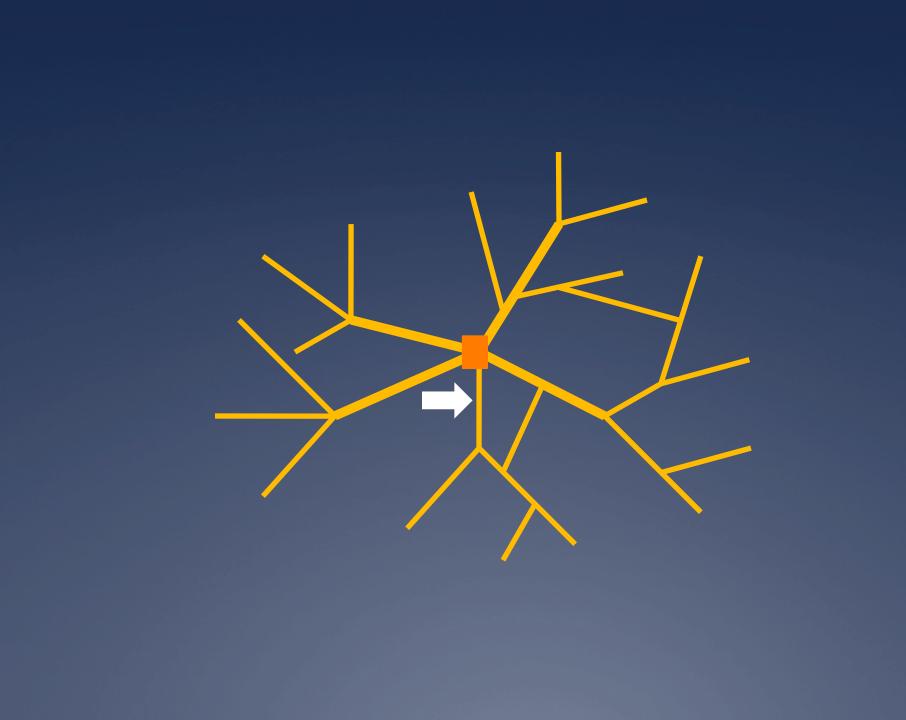
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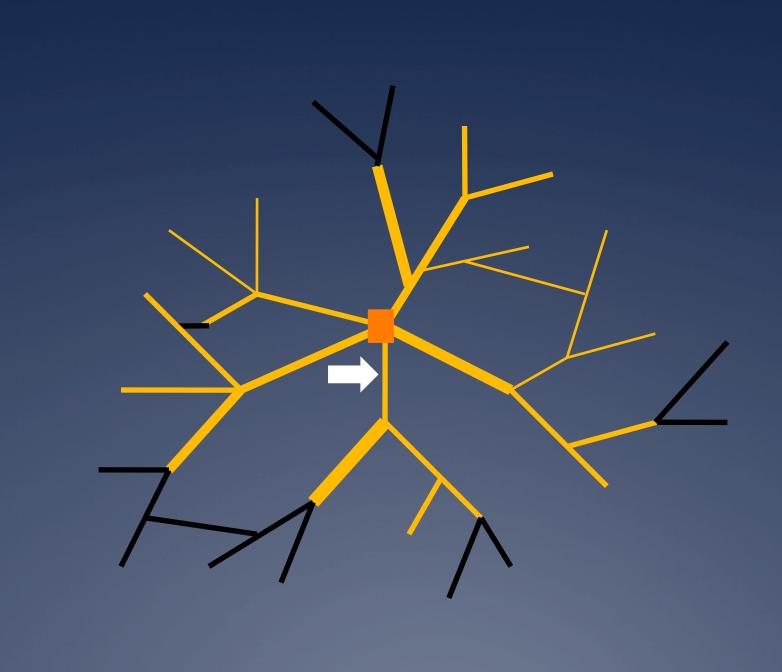
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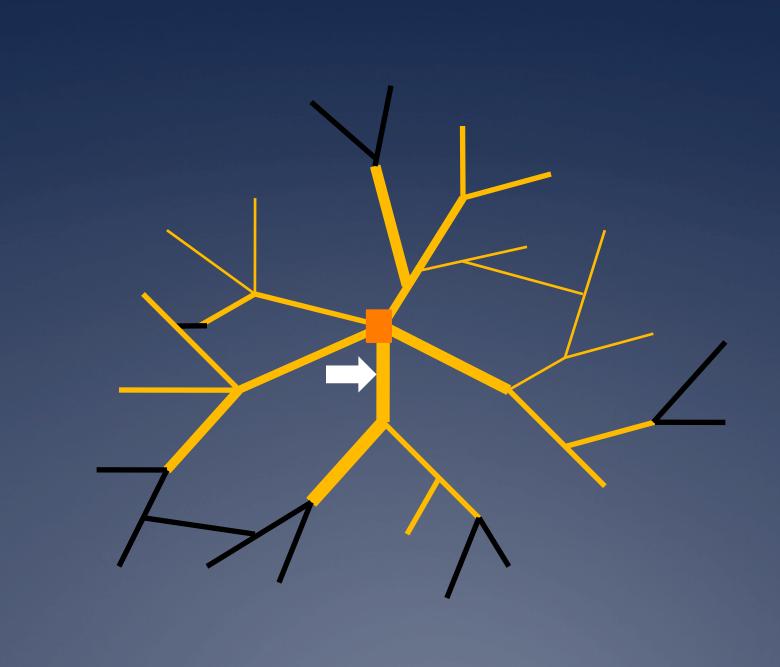
For every other node, the total in-current must equal the total out current (Kirchhoff's law).

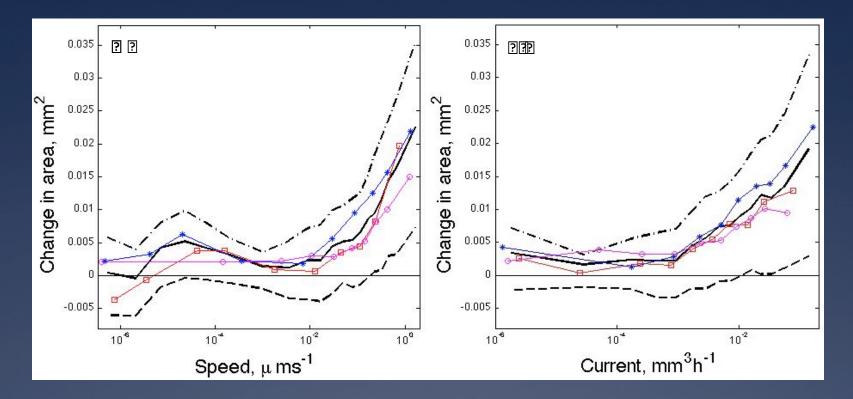
Can this crude model predict anything?

1) It allows us to calculate currents when a network grows. 2) We make an assumption: "cords with high current will get thicker" 3) If our model is relevant and the assumption is true the links with high predicted current will thicken.









Spearman's rank correlation coefficient between speed and change in area was 0.33.

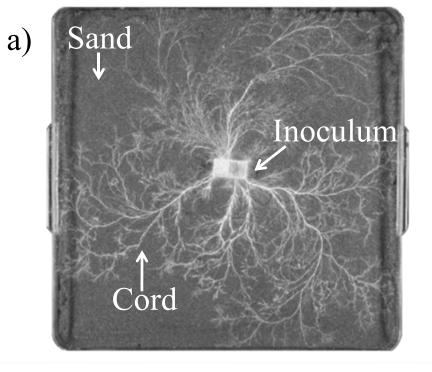
Some indirect evidence to suggest that growth and flows are coupled.

But clearly nutrients and flows are not the same thing.

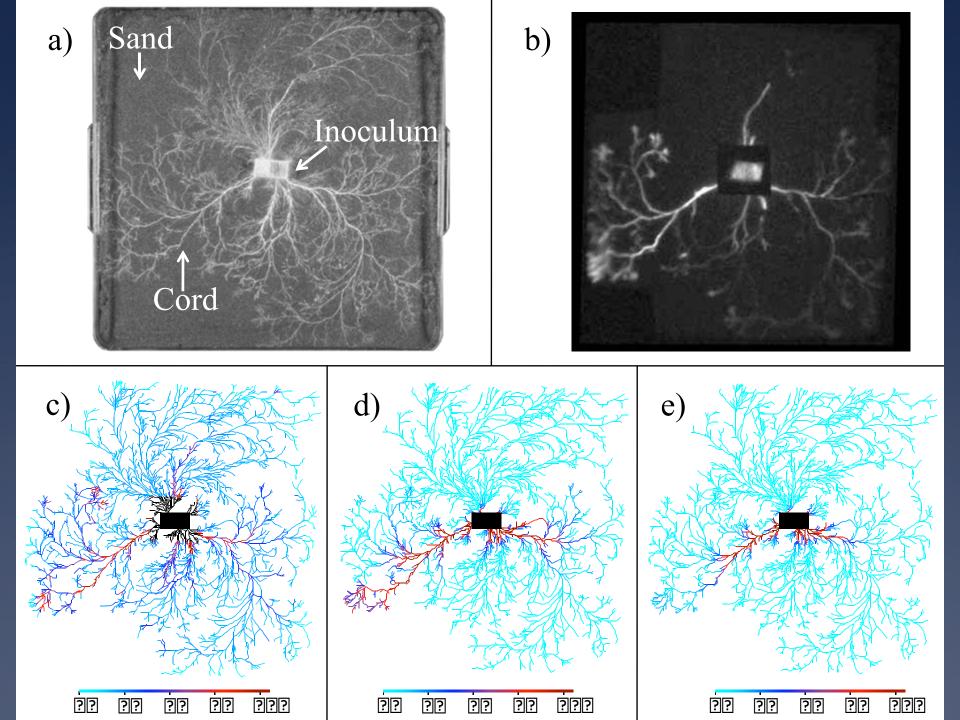
Advection, Diffusion and Delivery

 $\frac{\partial q_{ij}}{\partial t} + R_{ij}q_{ij} + u_{ij}\frac{\partial q_{ij}}{\partial x} - D_{ij}\frac{\partial^2 q_{ij}}{\partial x^2} = 0,$

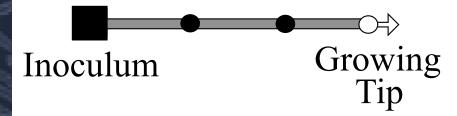
Nutrient amount per length: q
Rate of Delivery: R
Link velocity: u
Dispersion coefficient: D

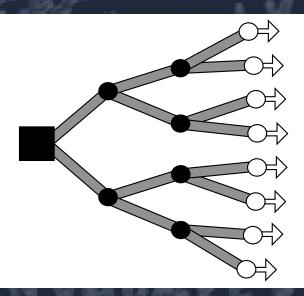


b)



 Effective incompressibility = high speed comms?
No growth = death?
Growth control = flow control Effective incompressibility = high speed comms?
No growth = death?
Growth control = flow control





Thanks to these chaps:

Luke Heaton, Eduardo Lopez, Philip Maini and Mark Fricker.



Luke Heaton

Thanks to you!

(1) L. L. M Heaton, E Lopez, P. K Maini, M. D Fricker, N. S Jones, 2010, Growthinduced mass flows in fungal networks, Proc. Roy. Soc. B. 277: 3265-3274.

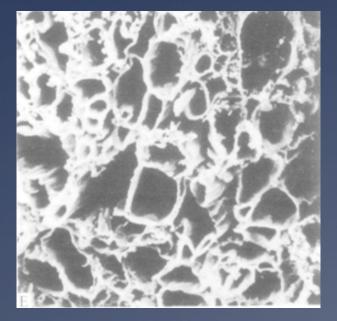
(2) L. L. M Heaton, E Lopez, P. K Maini, M. D Fricker, N. S Jones, 2011, Advection, diffusion and delivery over a network. at http://arxiv.org/abs/1105.1647

(3) L. L. M Heaton et al, 2012, Analysis of Fungal Networks, Fungal Biology Reviews

Comments:

If models as simple as those I've just presented constitute advances, this suggests we've a long way to go. We can also estimate the hydraulic conductance of each edge, and assume it is proportional to cross-sectional area.

Conductance x Pressure drop = Current



Modeling uptake and consumption

Pearson's linear correlation coefficient between photon count and predicted intensity

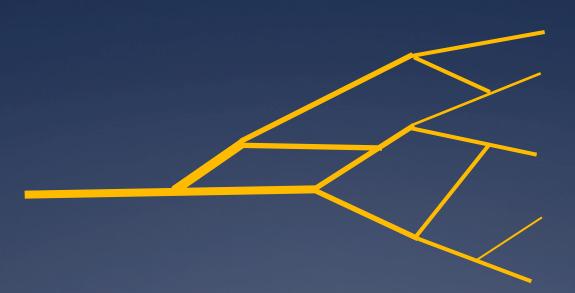
lambda	Experiment 1	Experiment 2
0.05	0.45	0.38
0.10	0.56	0.31
0.15	0.56	0.31
0.20	0.56	0.30

C.F. Pearson's coefficient between photon count and distance to the inoculum is -0.28



Network structure is critical



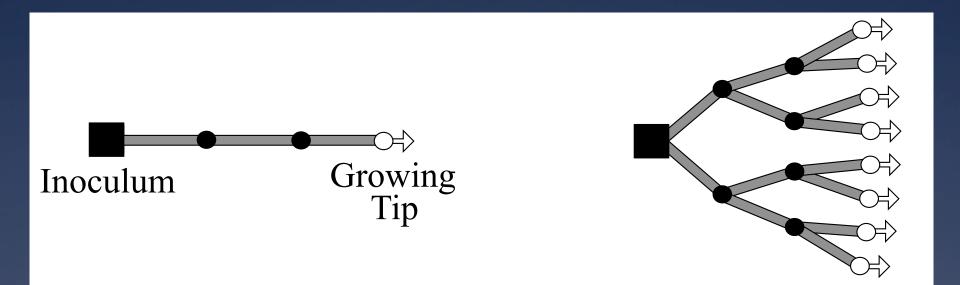


The current is determined by the volumetric rate of growth at the tips

Reducing the cross-sectional area of the supporting mycelium increases the velocity of flow







Diffusion and active transport (vesicles and motor proteins) are needed near the tips, but regulation of the sites of growth and water uptake may be sufficient for long range transport in fungi. Because aqueous fluids are incompressible, changes in one part of the network can have a rapid effect elsewhere in the network. Because aqueous fluids are incompressible, changes in one part of the network can have a rapid effect elsewhere in the network.

The local velocity of fluid flow provides quasiglobal information about the role of the cord in the network. Because aqueous fluids are incompressible, changes in one part of the network can have a rapid effect elsewhere in the network.

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If this really is the mechanism of long range transport, no growth = death.

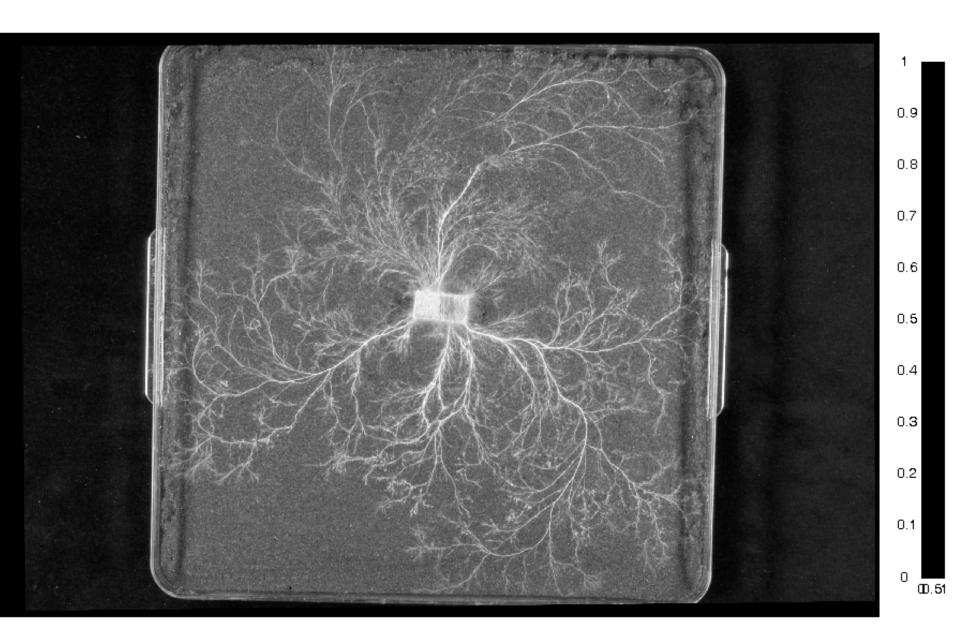
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Fungi may not need to coordinate solute concentration across the network as fluid flows towards the growing regions.

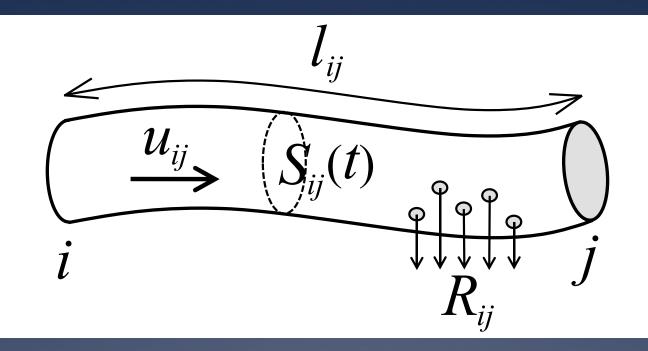






Advection, diffusion, delivery



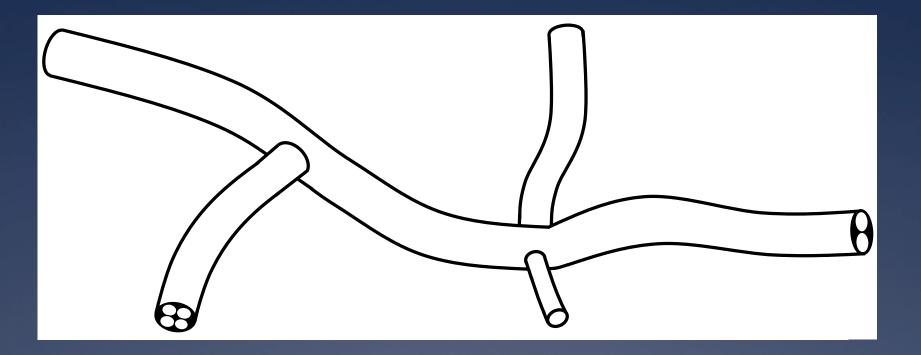


Each edge in the network has a length, cross sectional area, mean velocity, decay rate/local delivery rate and dispersion coefficient.



Advection, diffusion, delivery





Consistent concentration at the nodes, with perfect mixing.

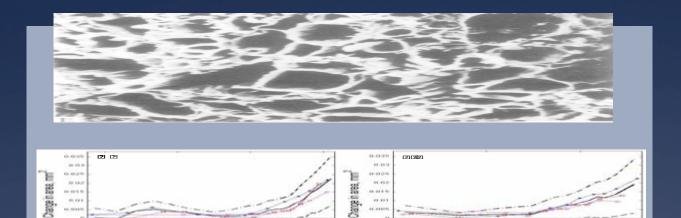
Velocities may vary over several orders of magnitude.

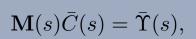


Advection, diffusion, delivery

Current, mm^ah⁻¹







where

Speed, µ me'

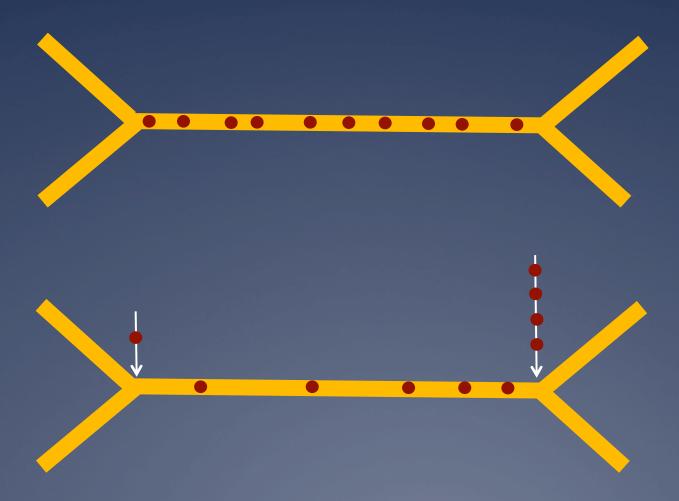
$$\mathbf{M}_{ij}(s) = \begin{cases} \sum_{k} S_{ik} \left[\frac{u_{ik}}{2} + \frac{\alpha_{ik}}{2 \tanh\left(\frac{\alpha_{ik}l_{ik}}{2D_{ik}}\right)} \right] & \text{if } i = j, \\ \frac{-S_{ij}\alpha_{ij}e^{\frac{-u_{ij}l_{ij}}{2D_{ij}}}}{2 \sinh\left(\frac{\alpha_{ij}l_{ij}}{2D_{ij}}\right)} & \text{otherwise.} \end{cases}$$

J. Koplik, S. Redner, and D. Wilkinson, Phys. Rev. A, **37** (1988).





M(s) C(s) = I(s)





Mass flows occur in transport vessels of radius $6\square m$, which occupy some fraction \square of each edge.



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The diffusion coefficient D = $3.5 \times 10 \text{ cm}^2\text{s}^-$, and we use Taylor's dispersion formula to calculate the dispersion coefficient for each edge.

Modelling uptake and consumption



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Modelling uptake and consumption



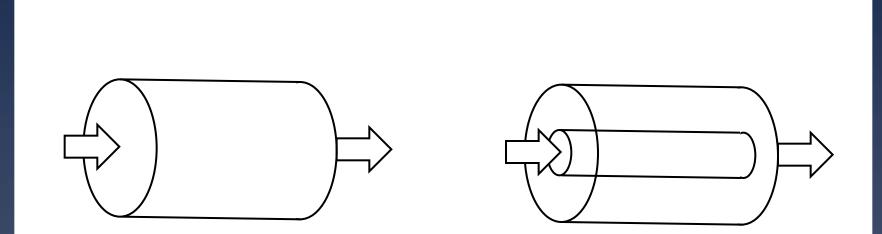
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AIB enters the network at the inoculum at a constant rate, the local delivery rate R is small. The number of photons leaving node *i* over time *t* is proportional to $\int_{0}^{t} c_{i}(\tau) d\tau$



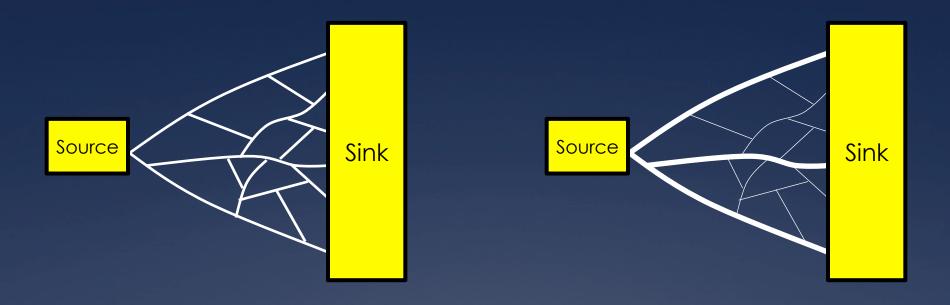


Current = Cross sectional area x Velocity Velocity $\propto \frac{1}{\lambda}$ Fluid flows from the site of water uptake to the extending tips regardless of the concentration gradient.

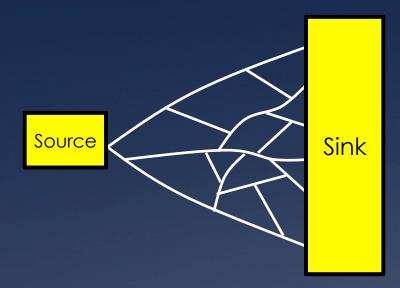


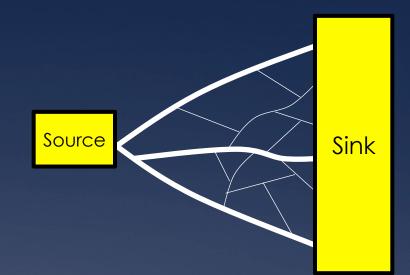
Cords are unlike phloem vessels because they are waxy and insulated from the environment.





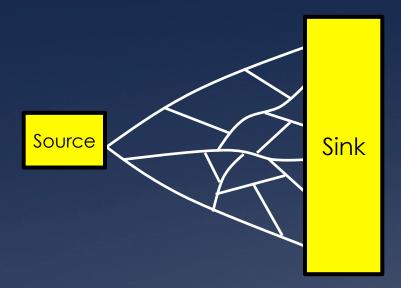
Thickening high current edges is more energy efficient than thickening low current edges.

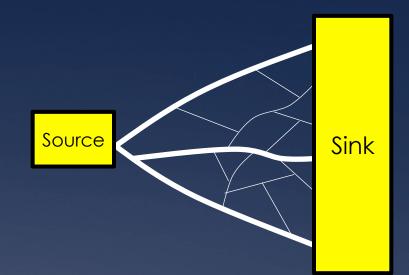




Thickening high current edges is more energy efficient than thickening low current edges.

Shorter paths have lower resistance, and hence more current.





Thickening high current edges is more energy efficient than thickening low current edges.

Shorter paths have lower resistance, and hence more current.

If carrying a large current results in thickening, the rich get richer. Systems and Signals Group

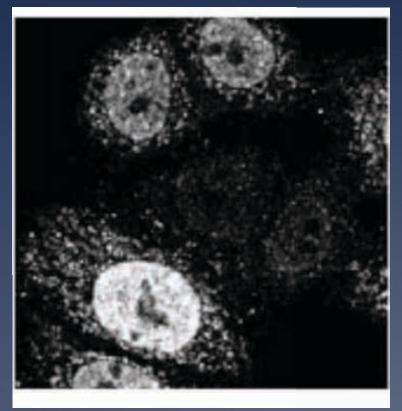
* Current research topics

- * Cellular variability
- * Principles of natural networks
- * Highly comparative data analysis

* Specific project for fungal networks

Cellular variability

Mitochondrial Variability

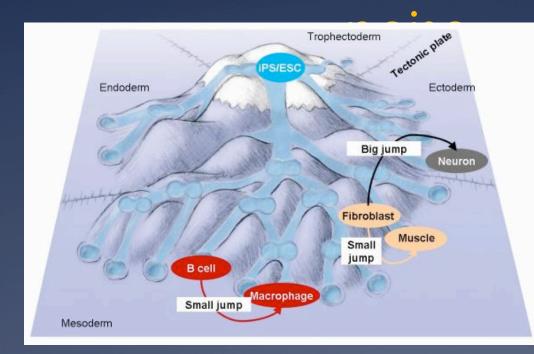


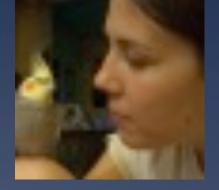


lain Johnston

Why are genetically identical cells phenotypically different? Is the modulated by (time varying) networks of mitochondria?

Stem cell differentiation landscapes and mitochondrial

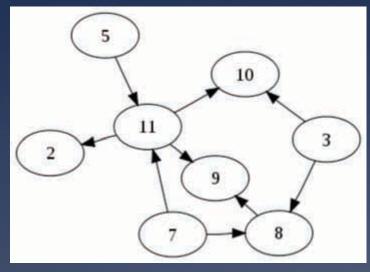




Bernadett Gaal

* What is the source of noise that leads to cell fate decisions?

Processing by noisy cells

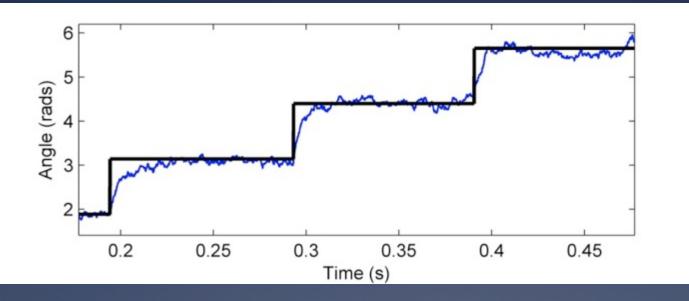




Sam Johnson

- * How do noisy cells process both as individuals and as coupled ensembles?
- * How do they perform inference, decisions and control their relationships?

Steppy Signal Processing



Ga

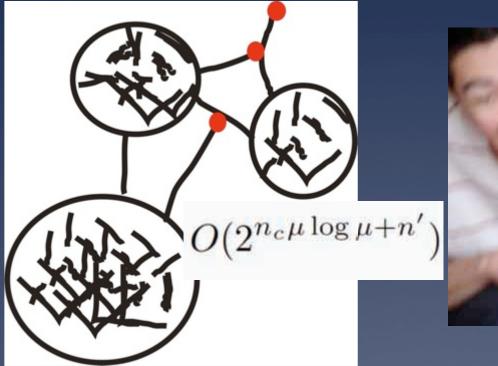
Max Little (now MIT and Oxford)

Generalized Methods and Solvers for Noise Removal from Piecewise Constant Signals Parts I and II: Proceedings of the Royal Society A (2011)

Steps and bumps: precision extraction of discrete states of molecular machines using physically-based, high-throughput time series analysis. Biophysical Journal (2011) to appear.

Principles of Natural Networks

Parameterized Complexity

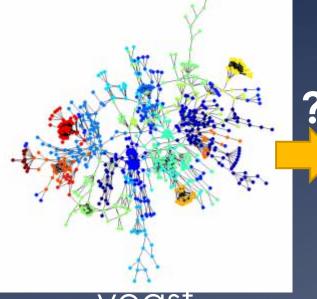




Binh-Minh Bui-Xuan

* How do dense regions in networks affect the time it take to solve problems on them?

Inter-species network inference







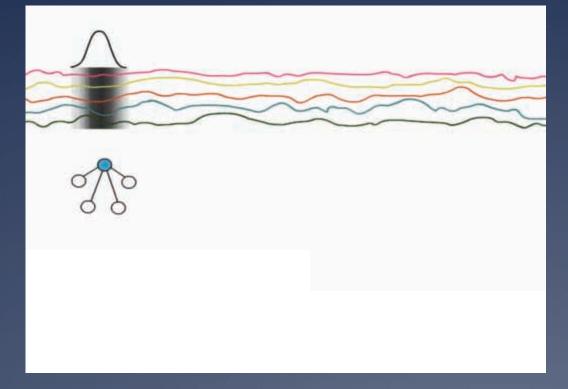
Anna Lewis

yeast

human

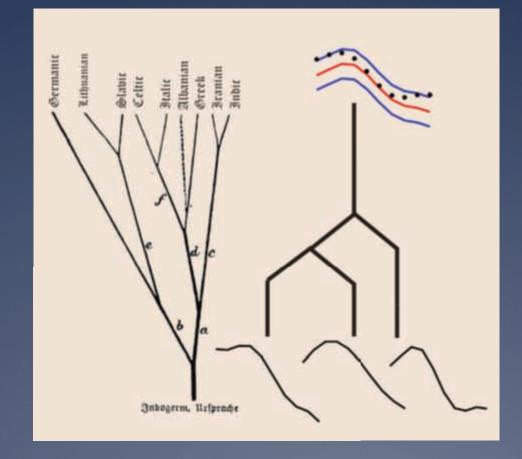
 Using one protein interaction network to guess the protein interaction network of another species. With Mason Porter and Charlotte Deane.

Dynamic network inference from multivariate signals

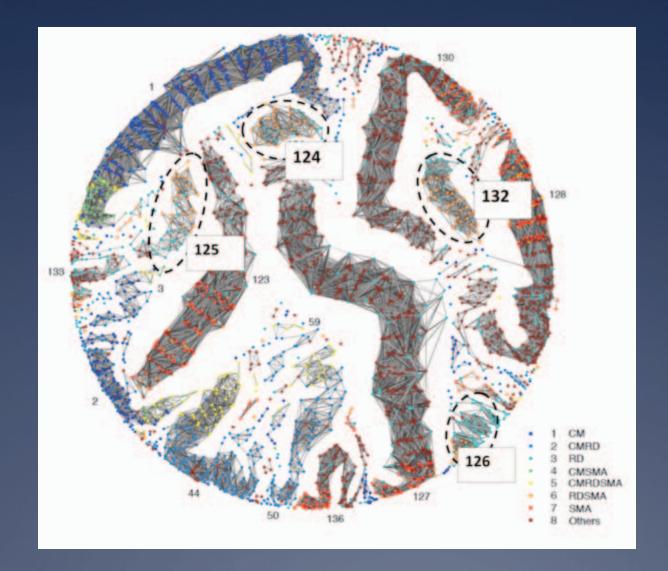


How to go from a set of signals to a sequence of time evolving networks?

Ancestral inference with shapes and functions

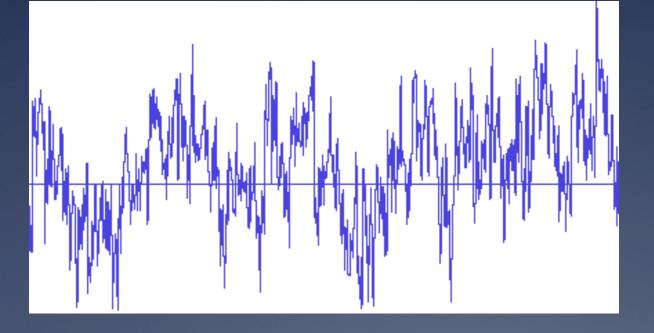


Community detection and disease subtypes



Highly Comparative Data Analysis

Highly Comparative Analysis of Signals



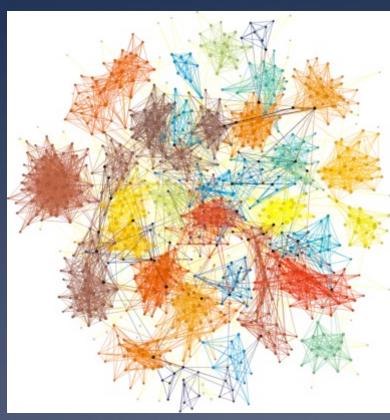


Ben Fulcher



* What is the empirical structure of our signals and our methods?

Highly Comparative Analysis of Networks





Sumeet Agarwal



What is the empirical structure of our networks and our methods?

Highly Comparative Analysis of Fitness landscapes [Functions on (Discrete) Configuration

EE 1EF9 DO C9 08 AD DO C8**C8** EE FF DO 19 DO 29 6E 20 8D 19 DO 2C38 CE 16 DO DO AD C9 DO 2F EE F9 C9 20 AB D8 DO 1 A 88 **C8** C9 20 FE OC AD 82 A9 FF 90 03 EE C1 A9 8D F9 C8 20 3D 31 75 DO EO 06 DO 9D 7 B 75 FD EO 8D **C8** 8B 06 F5 DO 80 AD 65 8D 15 DO 60 EA 8D A9 87 CO A 2 03 58 07 20



Jamie King

What is the empirical structure of our landscapes and our methods?

