

# Predicting One Kind of Link From Another

Cristopher Moore, Santa Fe Institute

*joint work with*

Caterina De Bacco, SFI/Columbia/Max Planck

Daniel Larremore, SFI/Boulder

Eleanor Power, SFI/London School of Economics



# Multilayer networks

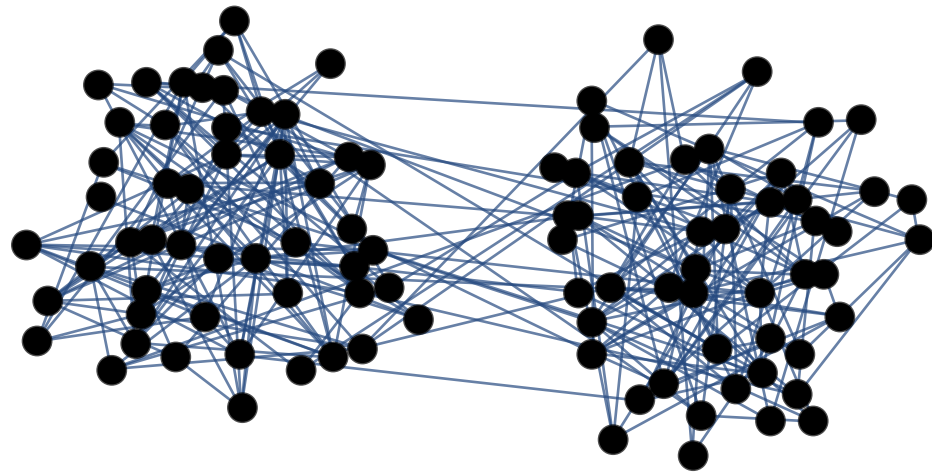
Different types of links: social relationships, modes of transportation, loci of similarity...

Hypothesis: explained by common community structure...

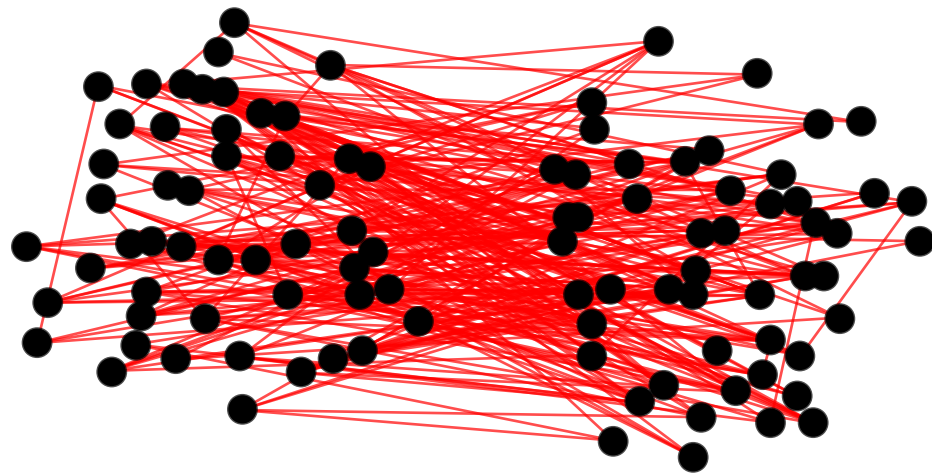
...even if the layers seem very different

Don't ask whether two layers are correlated:  
ask whether knowing one helps predict the other

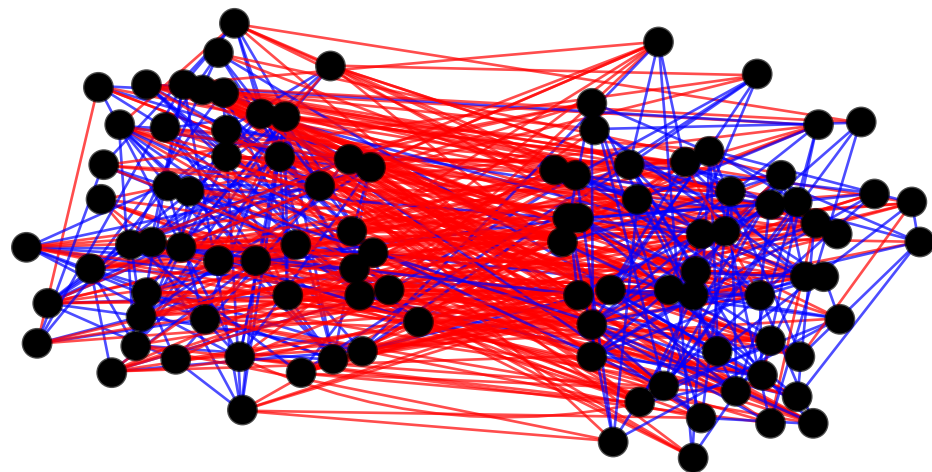
# Multilayer networks



assortative  
homophilic



disassortative  
heterophilic



aggregated

# Modeling the adjacency tensor

$A_{ij}^{(\alpha)} = \# \text{ of links from } i \text{ to } j \text{ in layer } \alpha$

$A_{ij}^{(\alpha)} \sim \text{Poisson with mean } M_{ij}^{(\alpha)}$

# of groups

$$M_{ij}^{(\alpha)} = \sum_{k,\ell=1}^K u_{ik} v_{j\ell} w_{k\ell}^{(\alpha)}$$

membership of vertex  $i$  in group  $k$

membership of vertex  $j$  in group  $\ell$

density of edges of type  $\alpha$   
from group  $k$  to group  $\ell$

Mixed-membership

Allows inhomogeneous degrees

Different roles for incoming and outgoing links

Arbitrary structure in each layer: assortative, core-periphery, etc.

# Aside: tensor factorization

rank-one matrix:  $A_{ij} = u_i v_j$

rank- $K$  matrix:  $A_{ij} = \sum_{\ell=1}^K u_i^{(\ell)} v_j^{(\ell)}$

to compute matrix rank, just use linear algebra  
can approximate (minimize  $L_2$ ) using singular values

rank-one tensor:  $A_{ijk} = u_i v_j w_k$

rank- $K$  tensor:  $A_{ijk} = \sum_{\ell=1}^K u_i^{(\ell)} v_j^{(\ell)} w_k^{(\ell)}$

tensor rank is NP-complete!

rank of matrix multiplication tensor is unknown  
even minimizing  $L_2$  requires an iterative algorithm



# Expectation Maximization (EM)

$\rho_{ijkl}^{(\alpha)}$  is our estimate of the probability that an edge  $i \rightarrow j$  in layer  $\alpha$  is due to their being in groups  $k$  and  $l$   
maximizing the likelihood gives update equations:

$$u_{ik} = \frac{\sum_{j,\alpha} A_{ij}^{(\alpha)} \sum_{\ell} \rho_{ijkl}^{(\alpha)}}{\sum_{\ell} \left( \sum_j v_{j\ell} \right) \left( \sum_{\alpha} w_{k\ell}^{(\alpha)} \right)}$$

$$v_{j\ell} = \frac{\sum_{i,\alpha} A_{ij}^{(\alpha)} \sum_k \rho_{ijkl}^{(\alpha)}}{\sum_k \left( \sum_i u_{ik} \right) \left( \sum_{\alpha} w_{k\ell}^{(\alpha)} \right)}$$

$$w_{k\ell}^{(\alpha)} = \frac{\sum_{ij} A_{ij}^{(\alpha)} \rho_{ijkl}^{(\alpha)}}{\left( \sum_i u_{ik} \right) \left( \sum_j v_{j\ell} \right)}$$

$$\rho_{ijkl}^{(\alpha)} = \frac{u_{ik} v_{j\ell} w_{k\ell}^{(\alpha)}}{\sum_{k'\ell'} u_{ik'} v_{j\ell'} w_{k'\ell'}^{(\alpha)}}$$

iterate until fixed point = local maximum of the likelihood  
(gives a point estimate: there are also Bayesian versions)

# Cross-validation and link prediction

Can the model fill in missing data?

Hide 20% of the links, use 80% as training data

Generative models assign probabilities to missing links: use AUC to measure accuracy

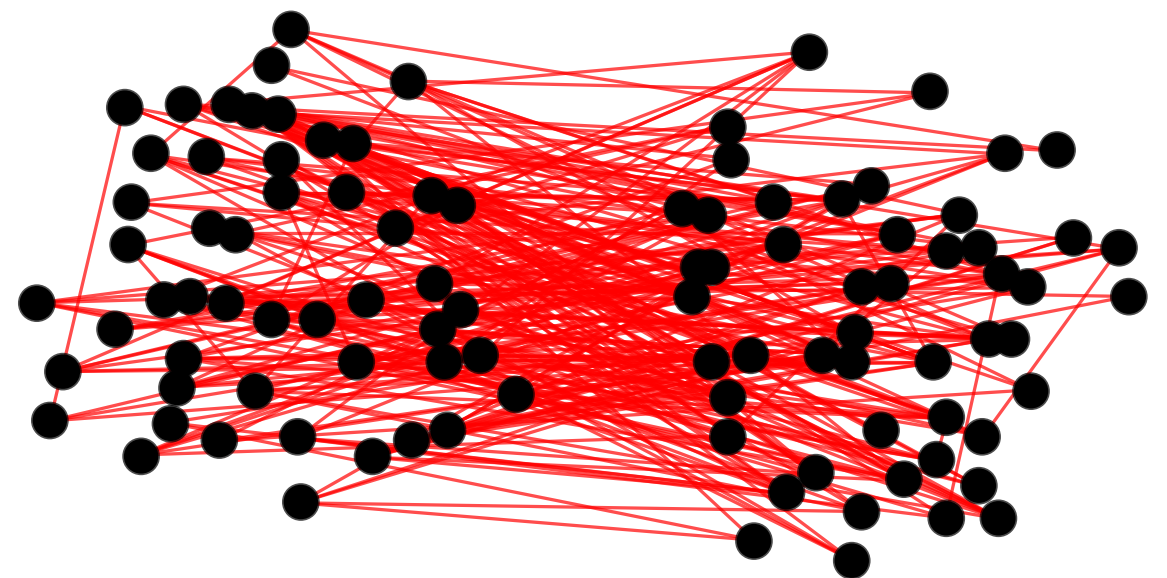
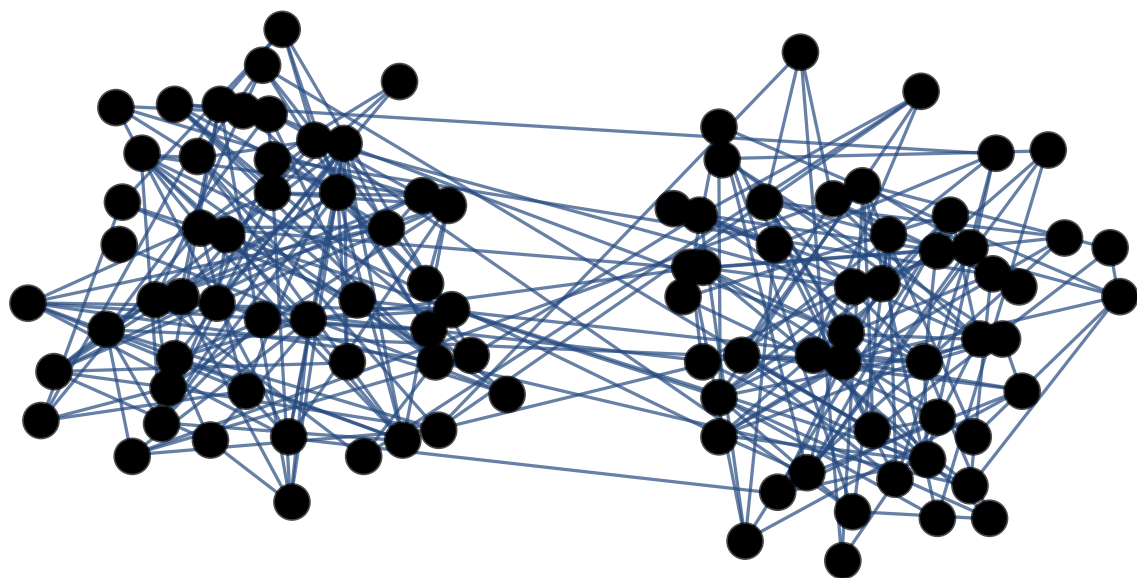
Avoid overfitting, and select # of communities

But! “Best” model depends on what kind of data is hidden, and what we are trying to predict:  
application-dependent (as it should be)

# Using link prediction to measure interdependence between layers

Does knowing one layer help predict links in another one?

“Similar” (not correlated!) layers have common community structure, and help predict each other





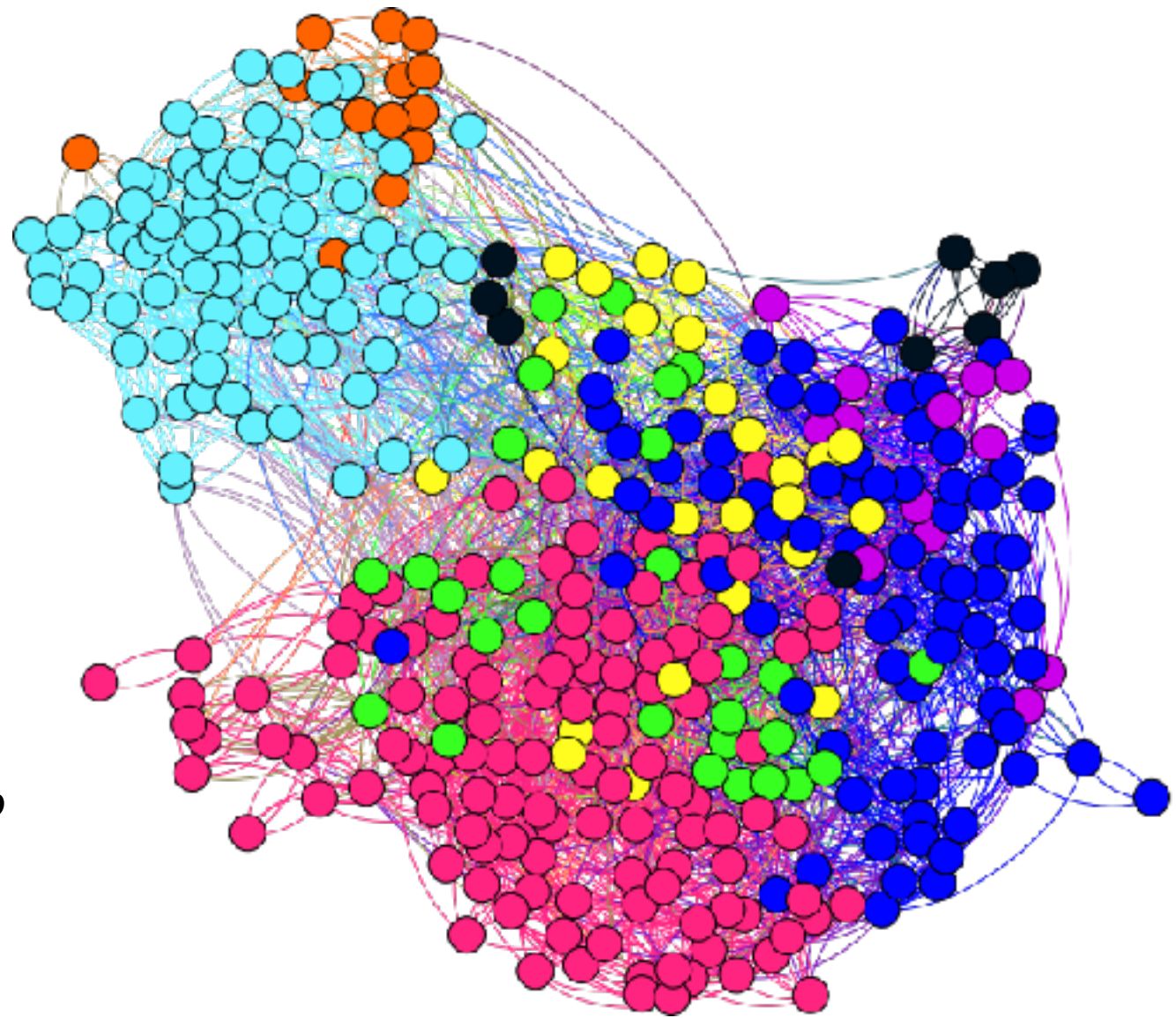
# Experiments on social networks

Two Indian villages

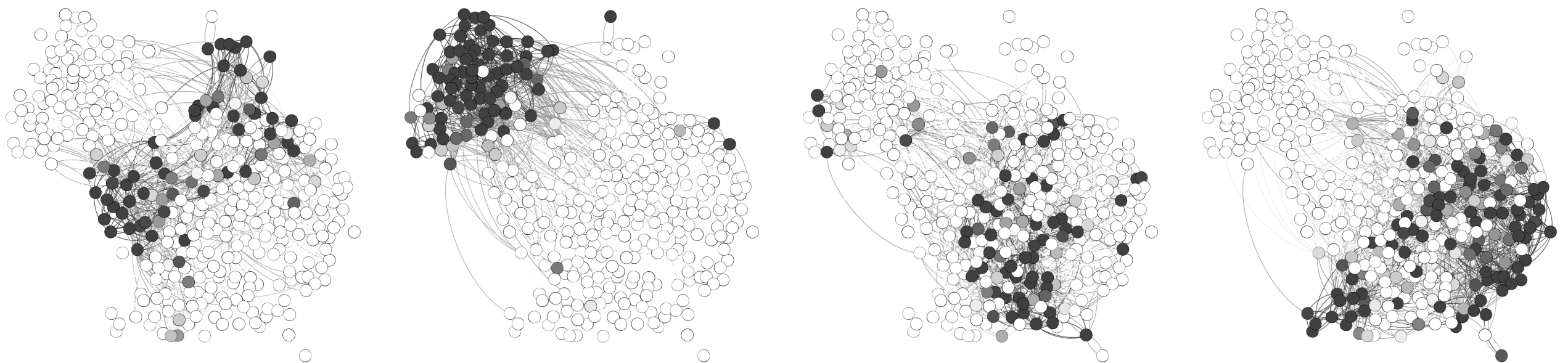
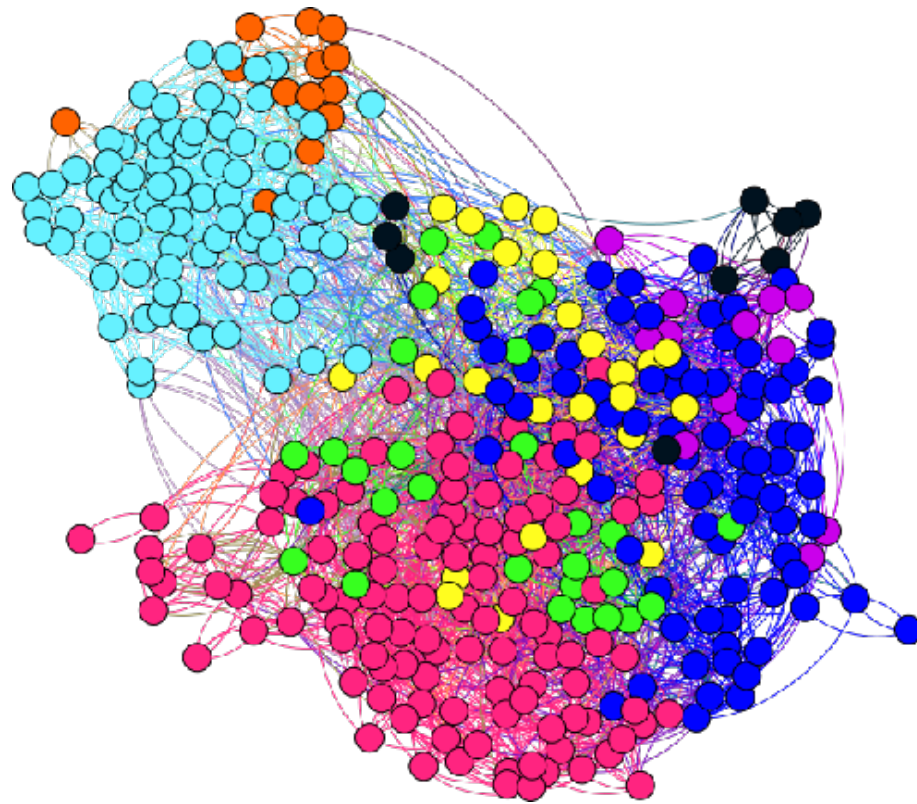
~400 nodes, ~7000 edges

One village consists of  
two separate hamlets

12 layers: looking for work,  
babysitting, borrowing,  
discussing important issues

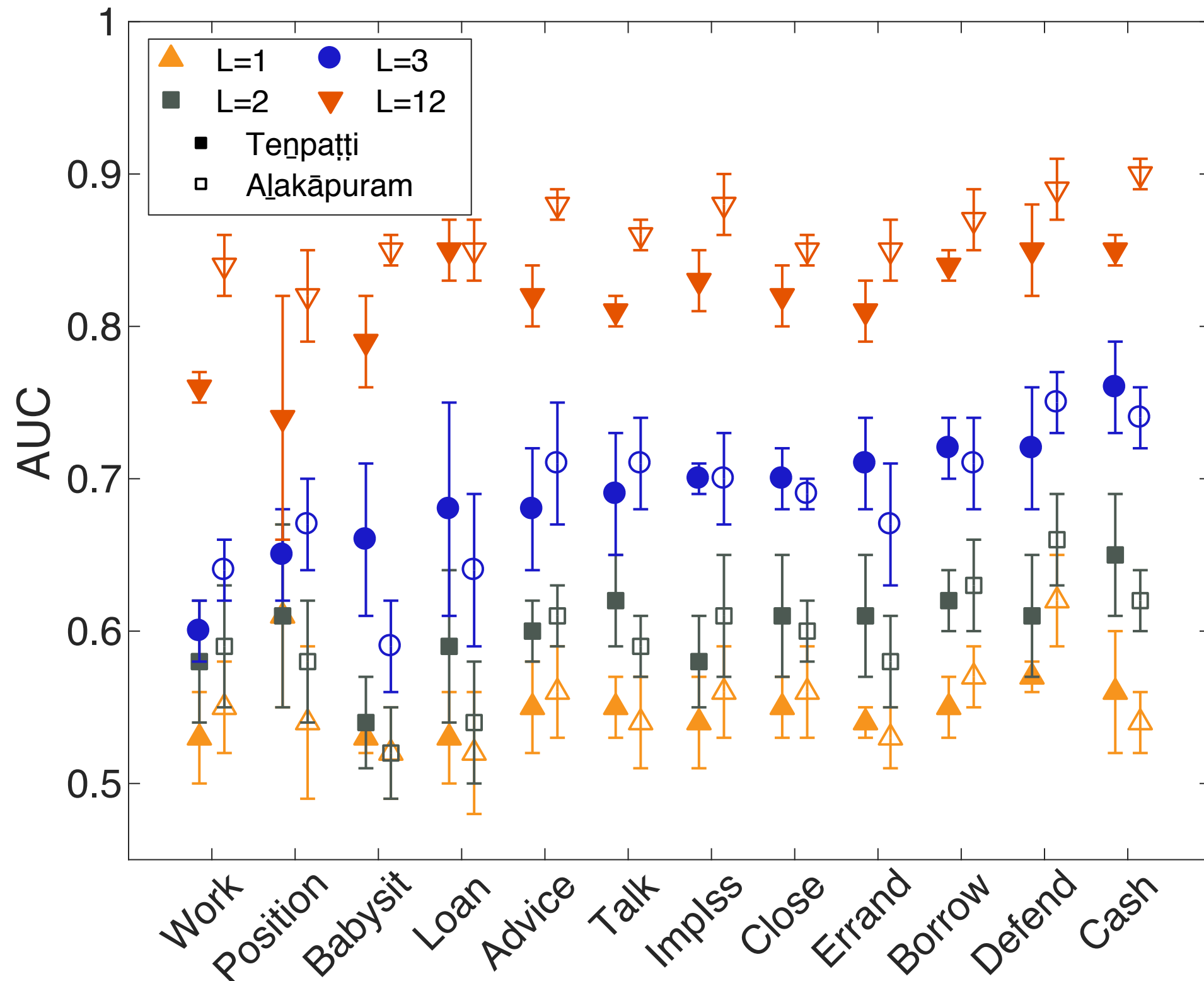


# A common community structure



Correlated with caste, gender, and geography

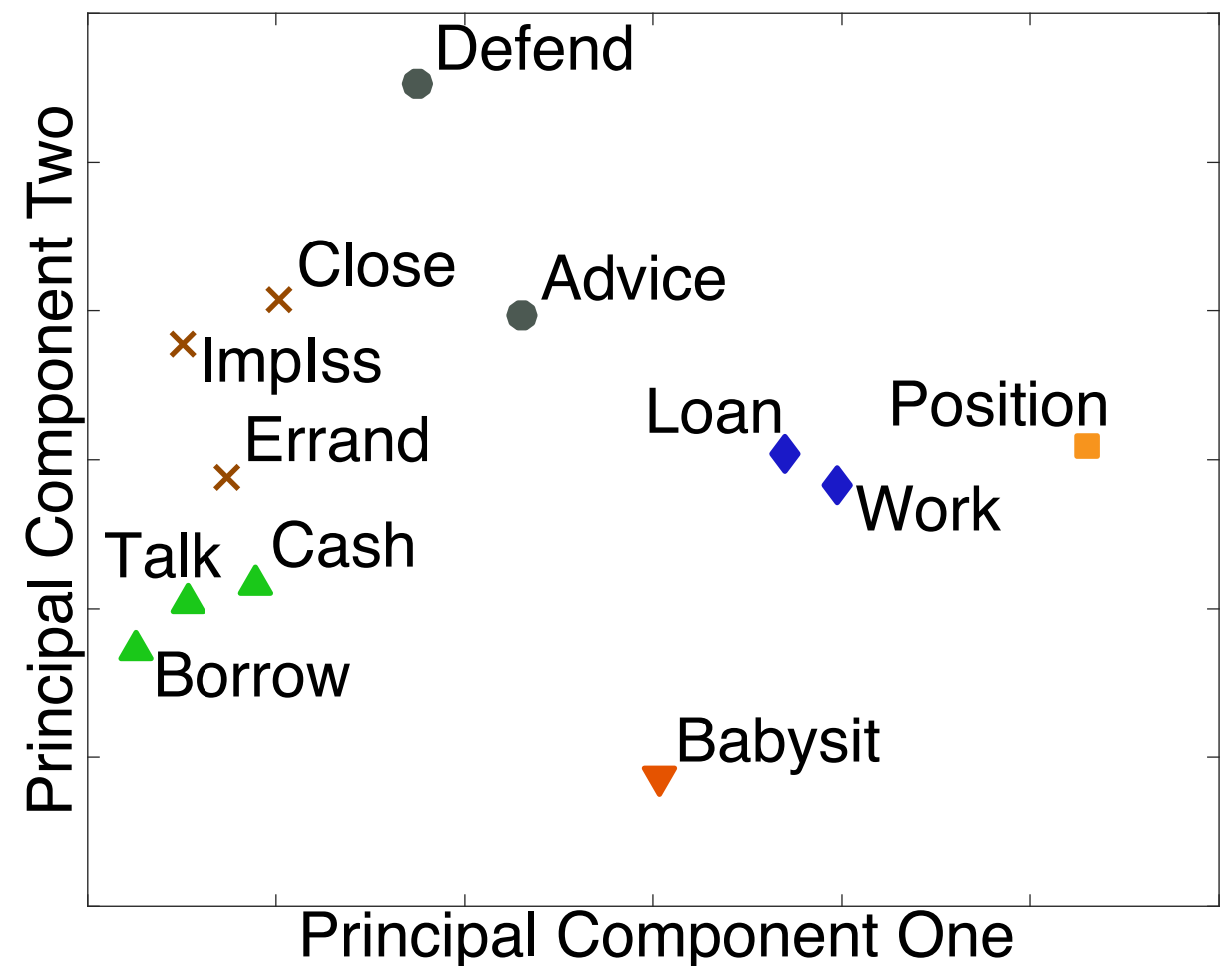
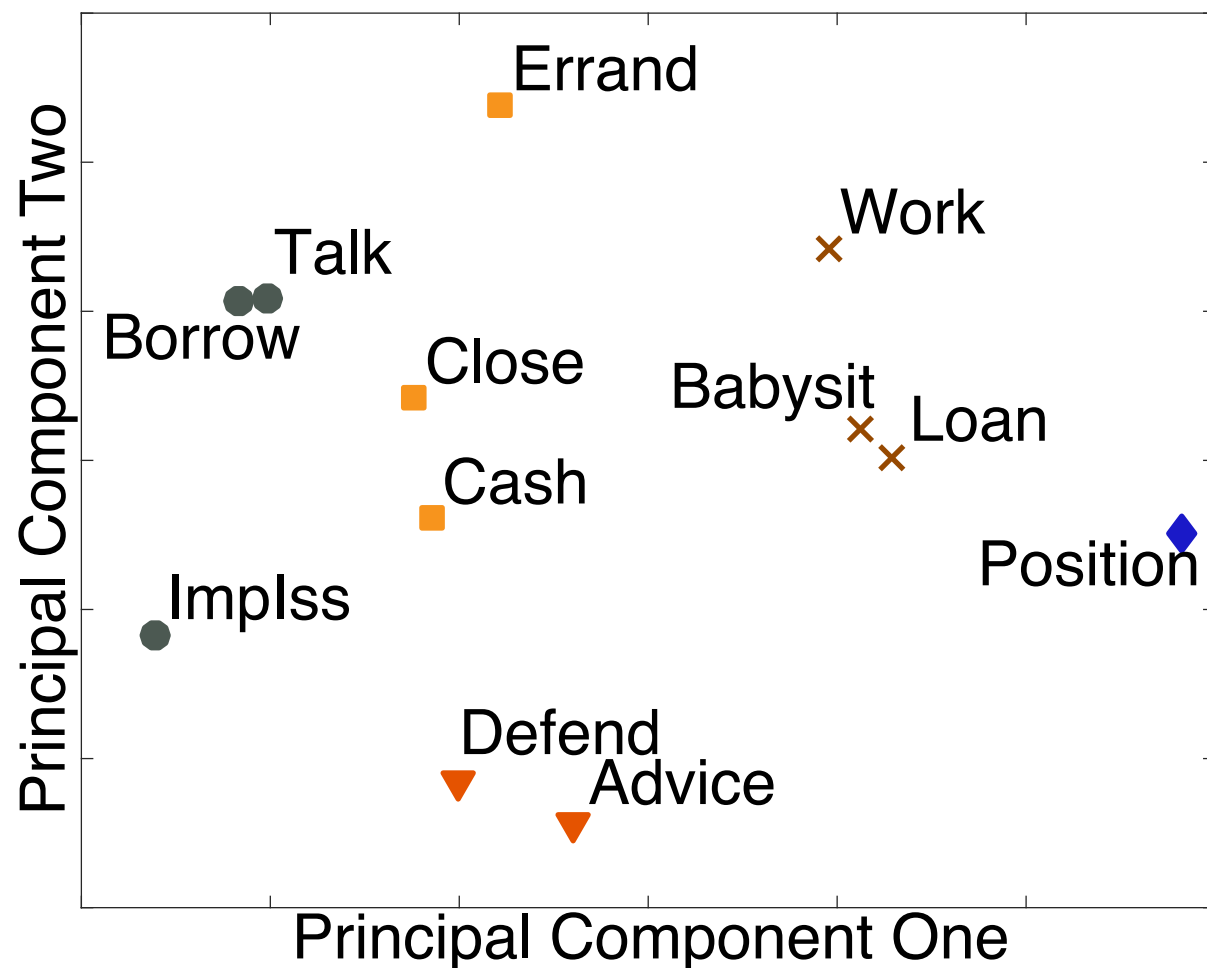
# Knowing more layers helps



# Interdependence and similarity

“Who do you discuss important issues with?” helps predict many layers; looking for work, babysitting less so

Can also cluster layers by affinity matrices  $w^{(\alpha)}$ :



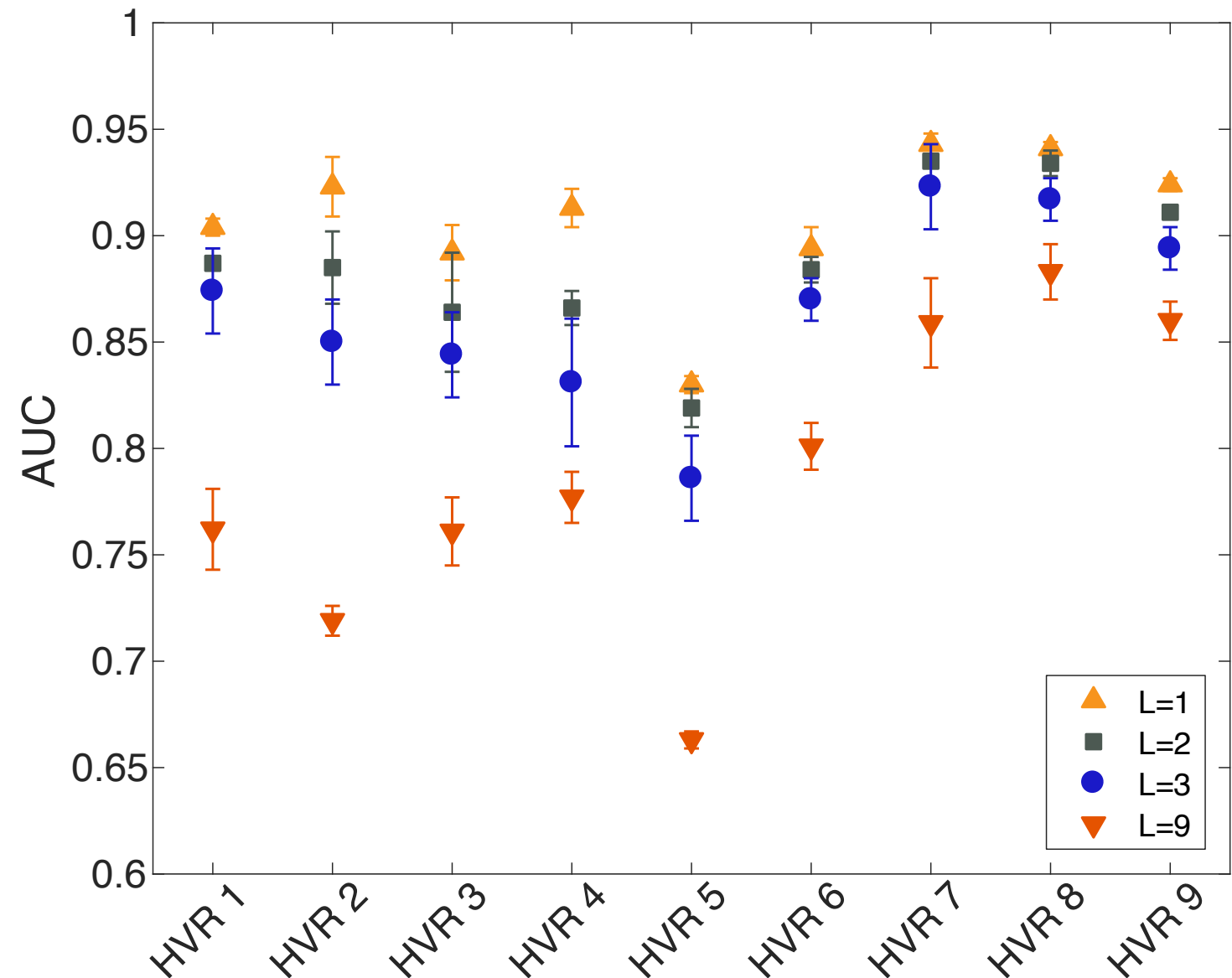


# In contrast: malaria genetics

~300 variants of a gene  
in the malaria parasite

9 layers, similarity at  
different loci

highly variable to avoid  
immune response



more layers, less accurate: no consistent communities  
the joy of negative results...



# Conclusions and questions

Can use tensor factorization to express models of multilayer networks

Instead of correlation, ask whether one layer helps predict another: do they reveal similar latent structures?

This is model-dependent... what are we missing?

Local rules, e.g. if  $(a,b)$  and  $(b,c)$  have relation #1, then  $(a,c)$  have relation #2

# Conclusions and questions

C. De Bacco, E.A. Power, D. B. Larremore, and C. Moore,  
“Community detection, link prediction, and layer interdependence  
in multilayer networks.” Physical Review E 95, 042317 (2017)

[caterina.debacco@tuebingen.mpg.de](mailto:caterina.debacco@tuebingen.mpg.de)

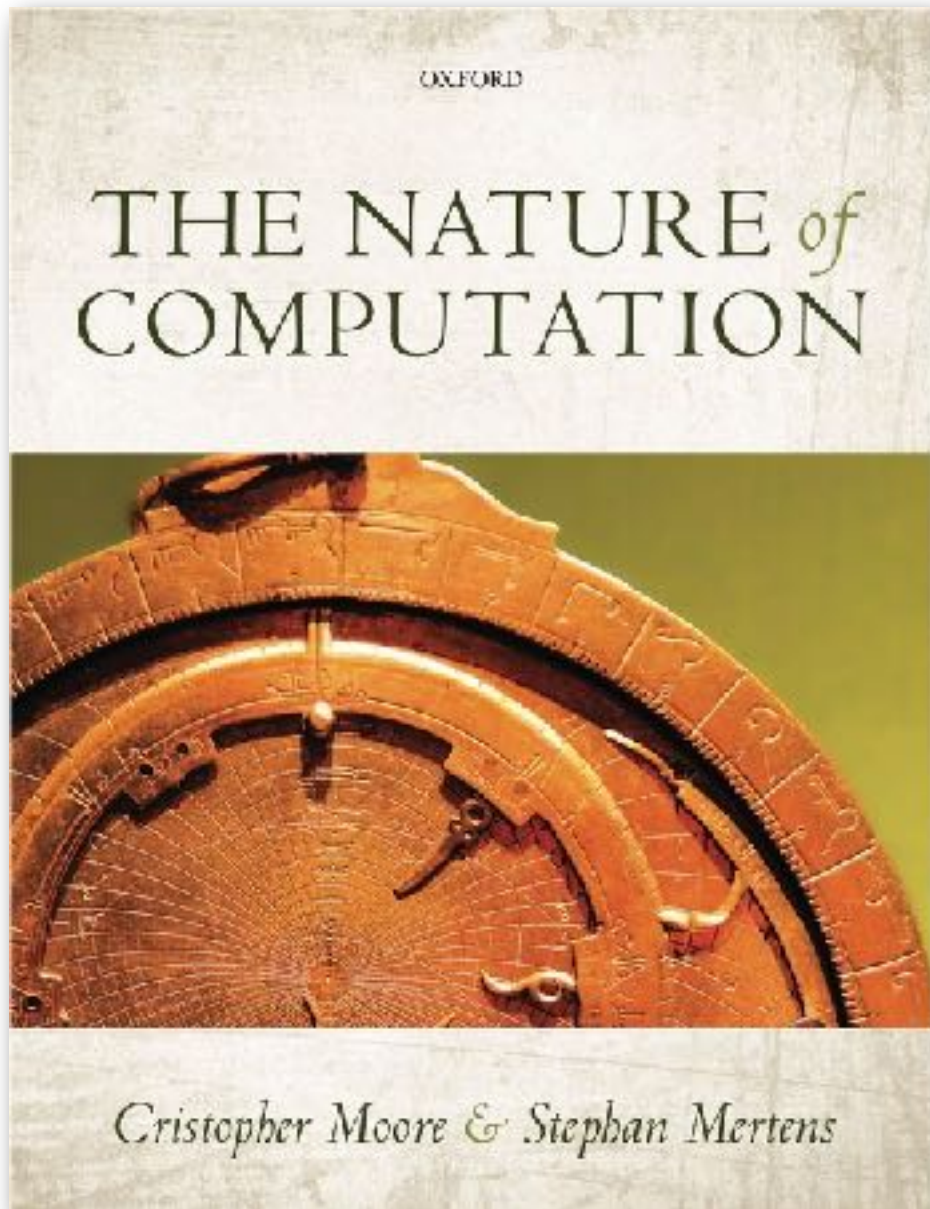
[E.A.Power@lse.ac.uk](mailto:E.A.Power@lse.ac.uk)

[daniel.larremore@colorado.edu](mailto:daniel.larremore@colorado.edu)

[moore@santafe.edu](mailto:moore@santafe.edu)

# Shameless plug

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