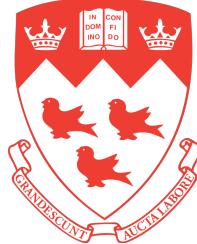


Computational Intractability Generates the Topology of Biological Networks

Ali Atiia

atiia@cs.mcgill.ca

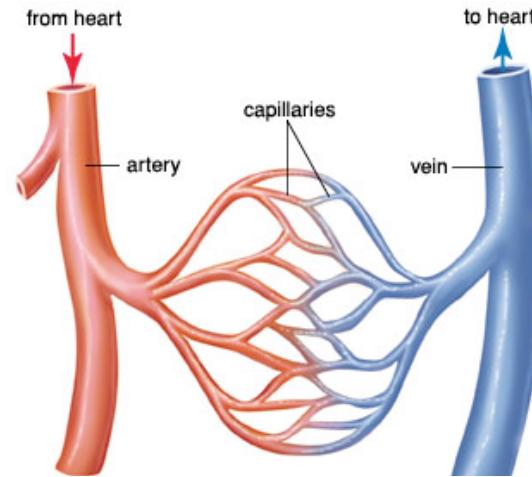


McGill University
Montreal, Canada

The signs of **hardware** natural selection are everywhere:



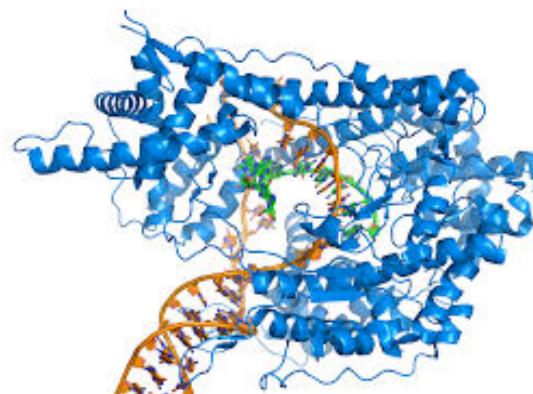
Allometry



Sturdy material

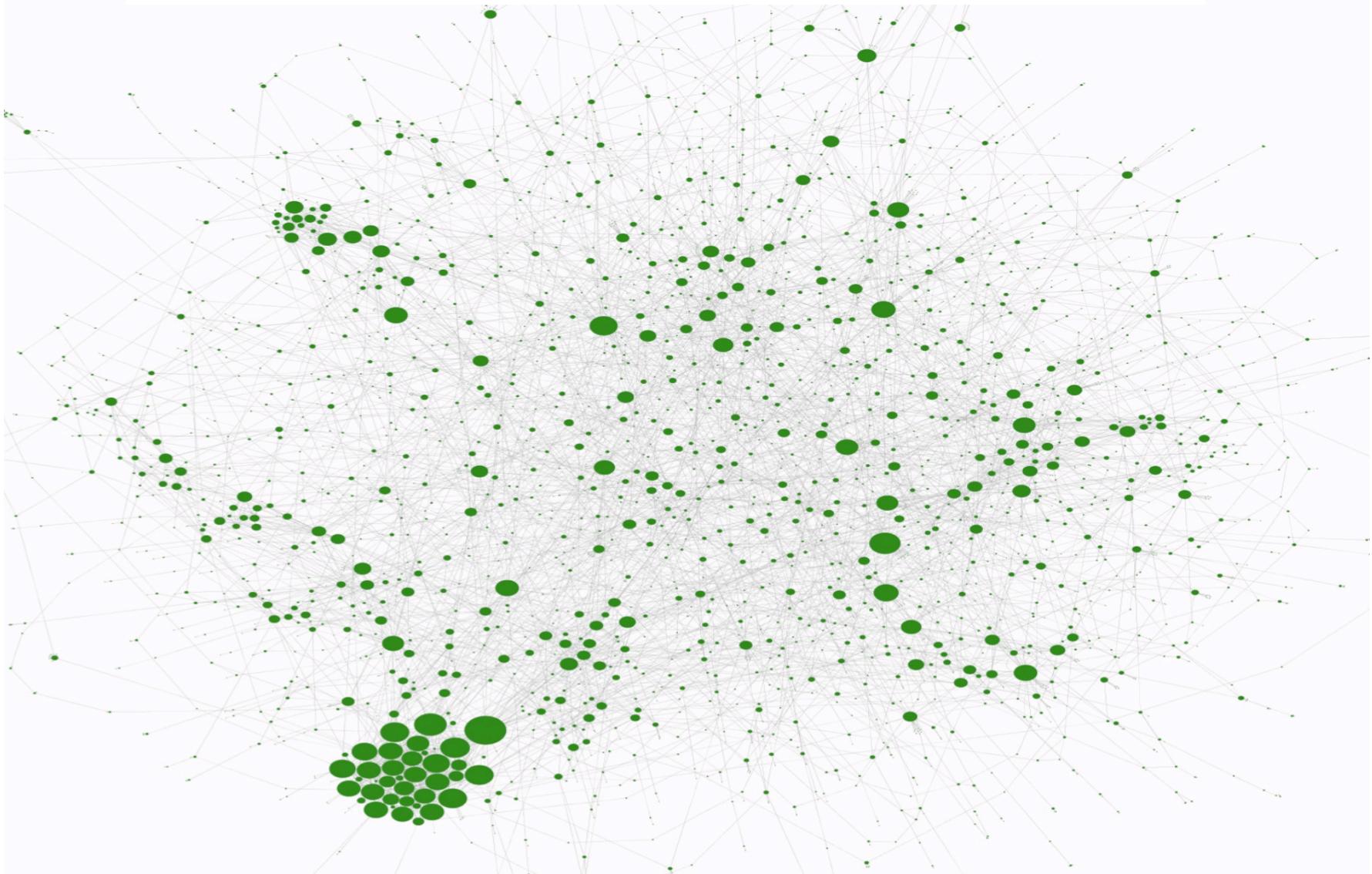


Cell diameter



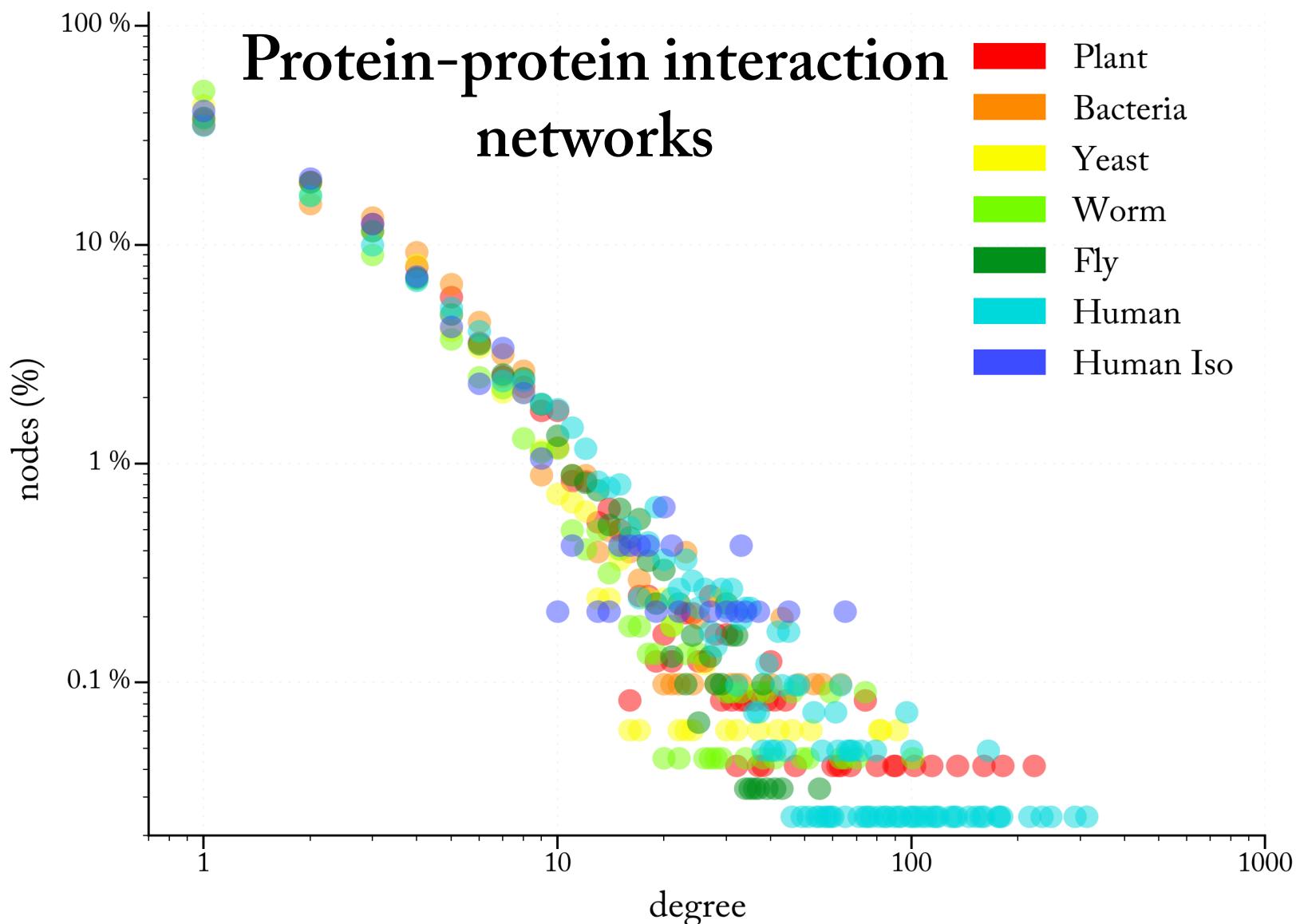
Stable folding at extreme temperature

Does natural selection act on software?

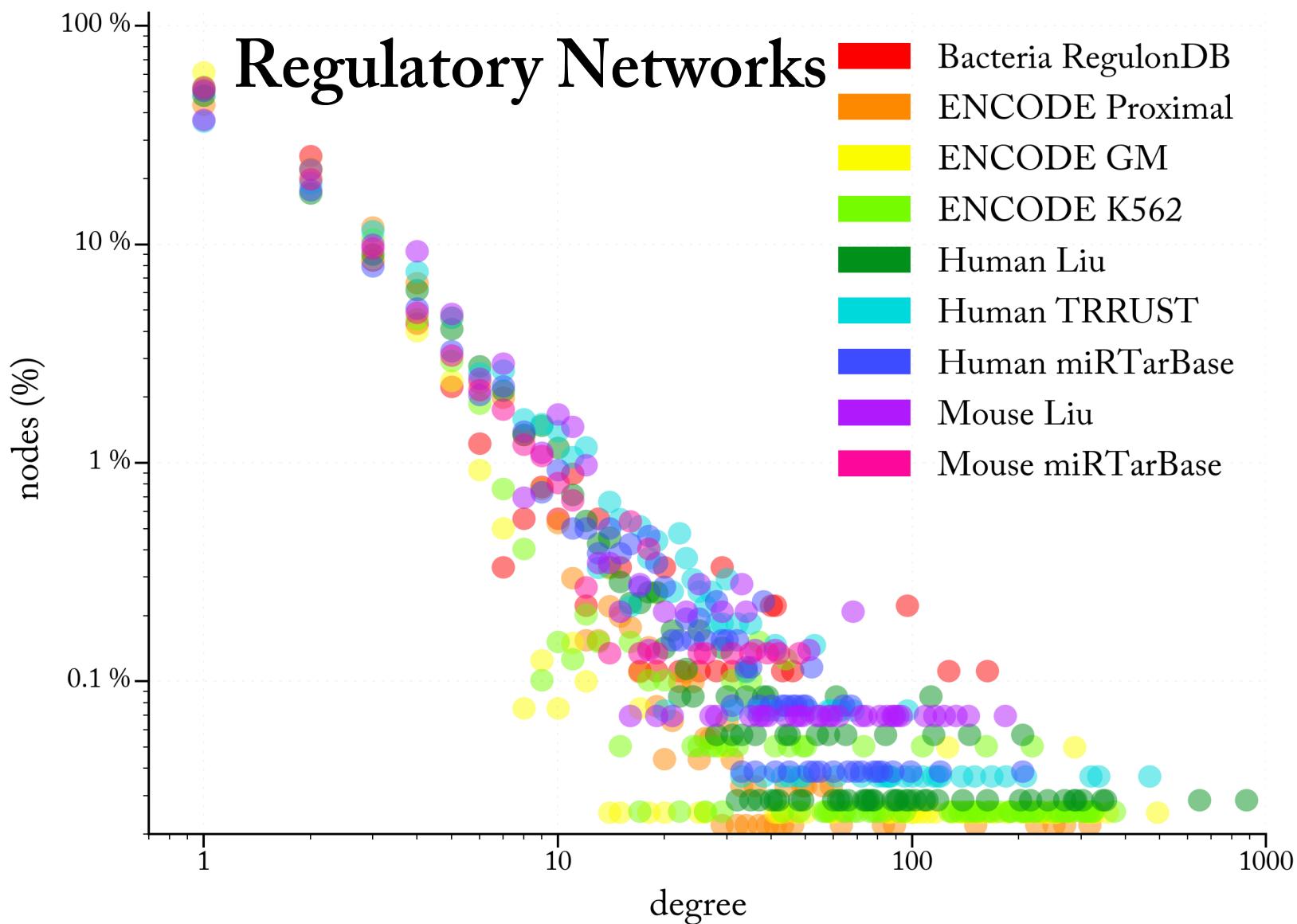


“software” = “connectivity” between bio-molecules

Majority-leaves Minority-hubs (mLmH) topology



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Is natural selection behind the mLmH property?

Majority-leaves Minority-hubs (mLmH) topology

Is natural selection behind the mLmH property?

Our approach:

1. Model the evolution of biological networks as a computational problem.
2. This problem is fundamentally hard (NP-hard).
3. Show empirical evidence that mLmH produces easy instances of this problem

Majority-leaves Minority-hubs (mLmH) topology

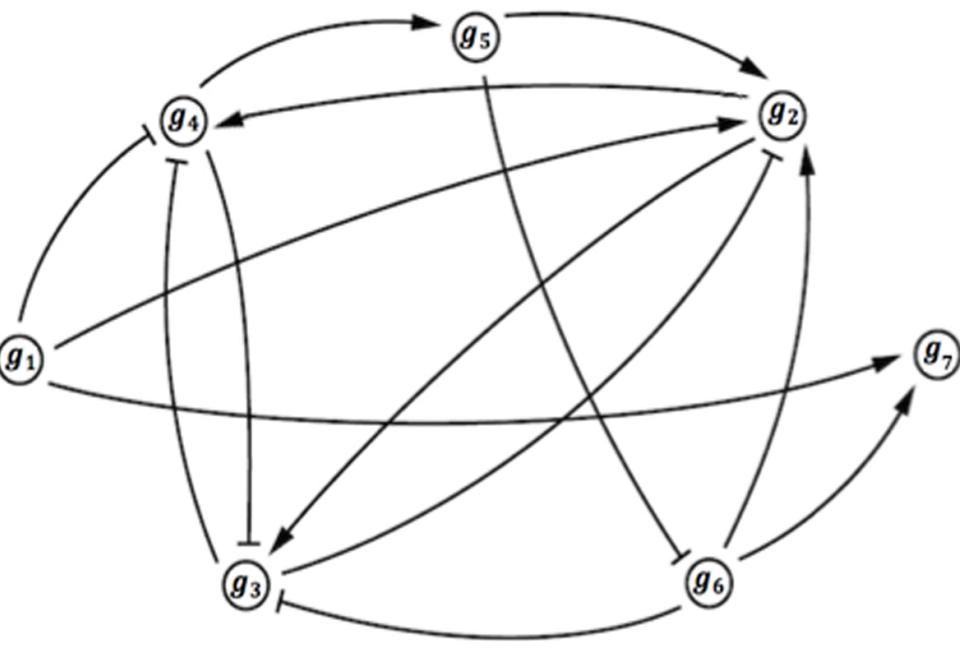
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The Network Evolution Problem (NEP)

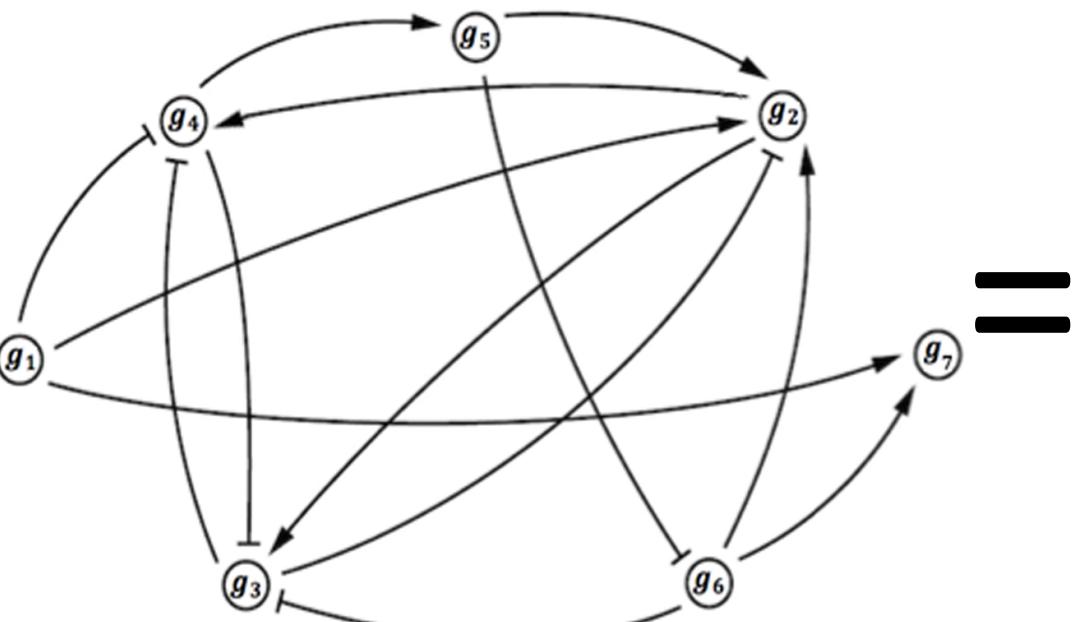
Consider this hypothetical biological network:



- = promotional interaction
- ⊣ = inhibitory interaction

Nodes = biomolecules
Edges = interactions

The Network Evolution Problem (NEP)



→ = promotional interaction
— = inhibitory interaction

Adjacency matrix

	g_1	g_2	g_3	g_4	g_5	g_6	g_7
g_1	0	+1	0	-1	0	0	+1
g_2	0	0	+1	+1	0	0	0
g_3	0	-1	0	-1	0	0	0
g_4	0	+1	-1	0	+1	0	0
g_5	0	+1	0	0	0	-1	0
g_6	0	+1	-1	0	0	0	+1
g_7	0	0	0	0	0	0	0

+1 = promotional interaction
-1 = inhibitory interaction
0 = no interaction

The Network Evolution Problem (NEP)

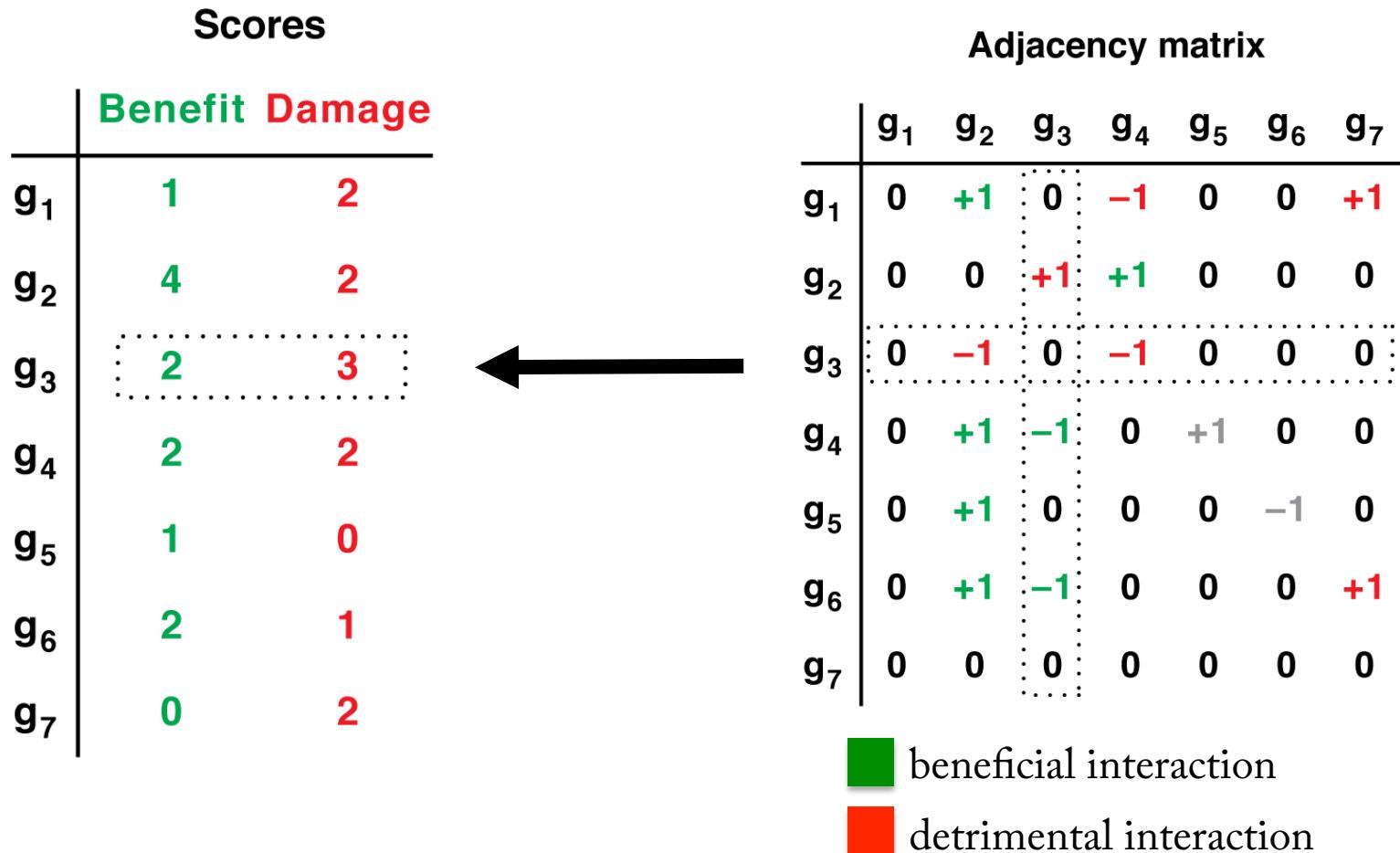
Adjacency matrix

	g_1	g_2	g_3	g_4	g_5	g_6	g_7
g_1	0	+1	0	-1	0	0	+1
g_2	0	0	+1	+1	0	0	0
g_3	0	-1	0	-1	0	0	0
g_4	0	+1	-1	0	+1	0	0
g_5	0	+1	0	0	0	-1	0
g_6	0	+1	-1	0	0	0	+1
g_7	0	0	0	0	0	0	0

 beneficial interaction

 detrimental interaction

The Network Evolution Problem (NEP)



The Network Evolution Problem (NEP)

	Scores	
	Benefit	Damage
g_1	1	2
g_2	4	2
g_3	2	3
g_4	2	2
g_5	1	0
g_6	2	1
g_7	0	2

NEP
=

Which genes should ideally be conserved/
deleted so as to maximize the total benefits
while the total damages \leq some threshold?

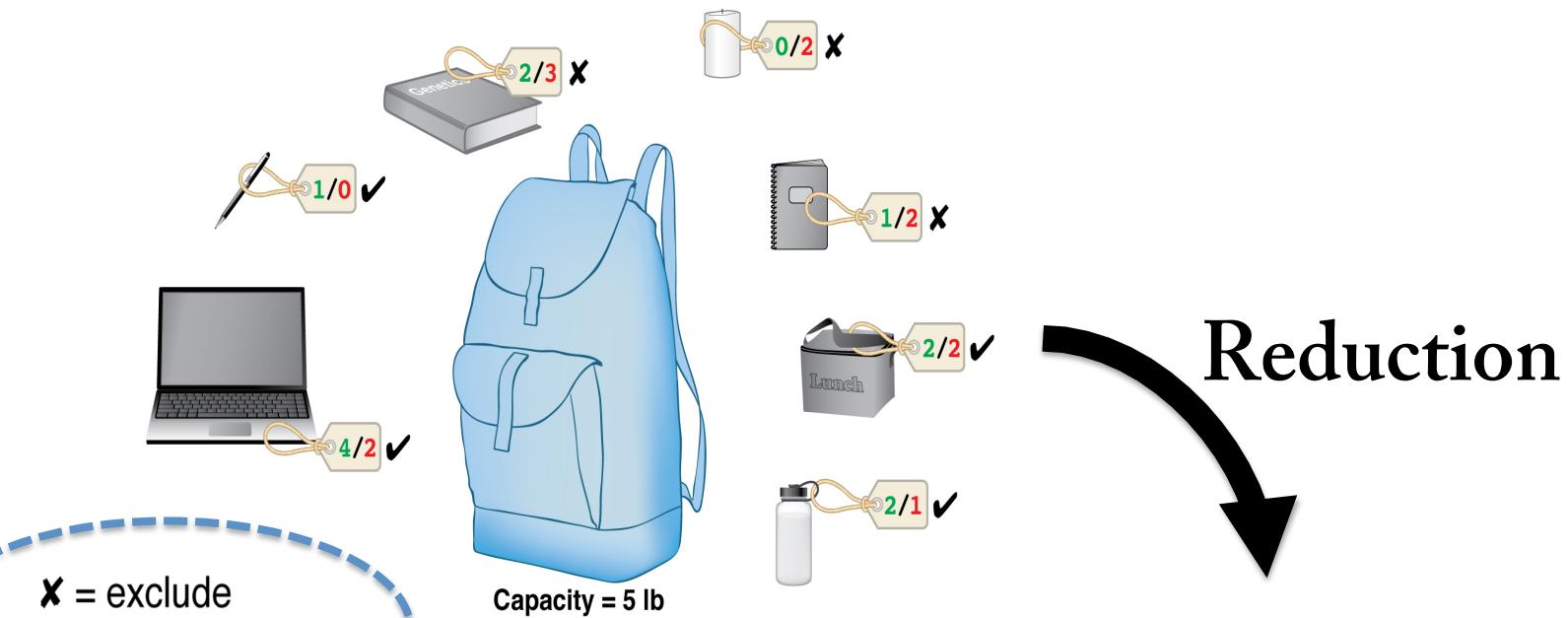
Majority-leaves Minority-hubs (mLmH) topology

Is natural selection behind the mLmH property?

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1. Model the evolution of biological networks as a computational problem.
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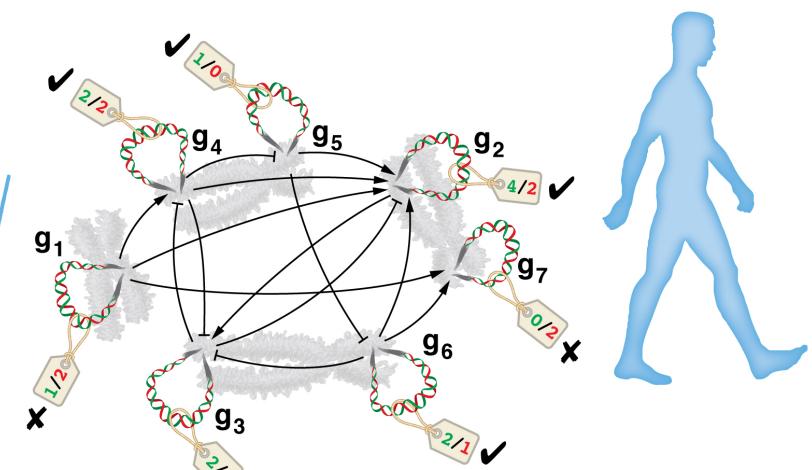
NEP is NP-hard



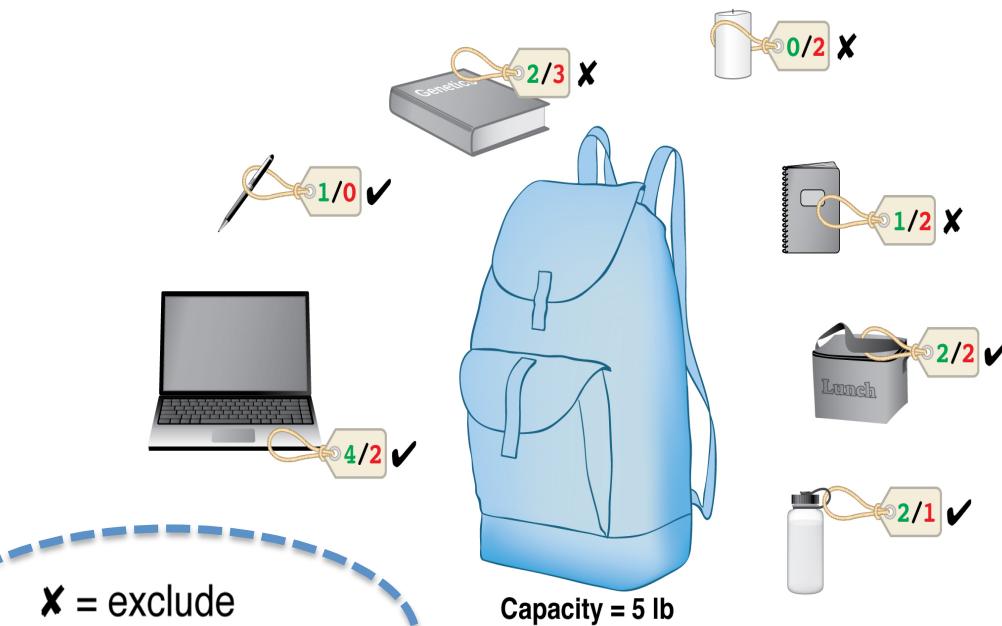
X = exclude
✓ = include

semantics

X = delete
✓ = conserve



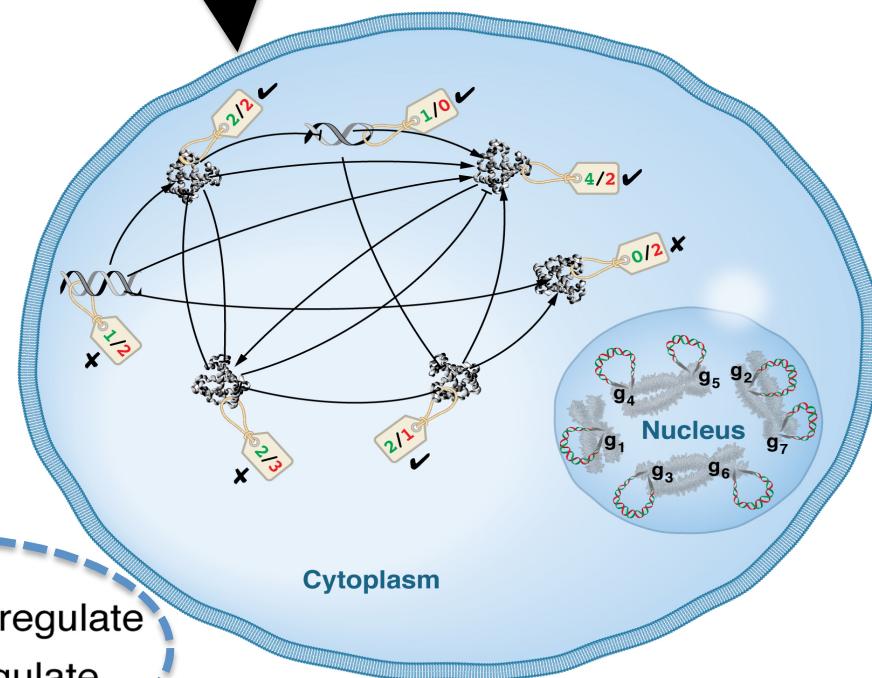
NEP is NP-hard



X = exclude
✓ = include

semantics

Reduction



X = down-regulate
✓ = up-regulate

Majority-leaves Minority-hubs (mLmH) topology

Is natural selection behind the mLmH property?

Our approach

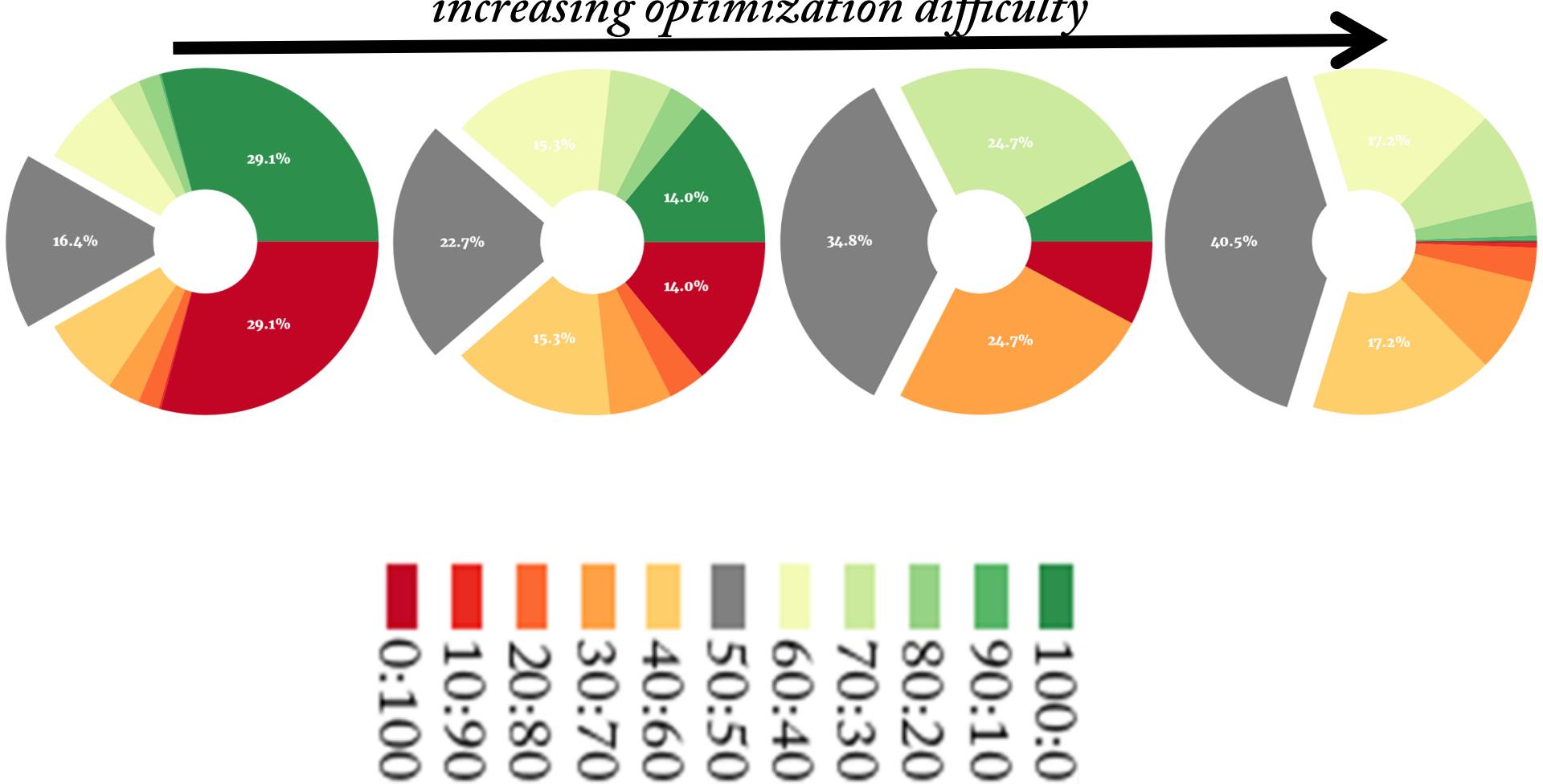
1. Model the evolution of biological networks as a computational problem.
2. This problem is fundamentally hard (NP-hard).
3. Show empirical evidence that mLmH produces easy instances of this problem → less iterations of random-variation non-random selection are needed to conserve(invent)/delete(mutate) the right set of genes

Basic idea

- i. evolve a population of synthetic networks
 -  ii. select-and-breed from those that “circumvent” computational intractability more successfully
 - ii.
 - iii. How does the topology look after N generations?
3. Show empirical evidence that mLmH produces easy instances of this problem → less iterations of random-variation non-random selection are needed to conserve(invent)/delete(mutate) the right set of genes

fitness criteria (1)

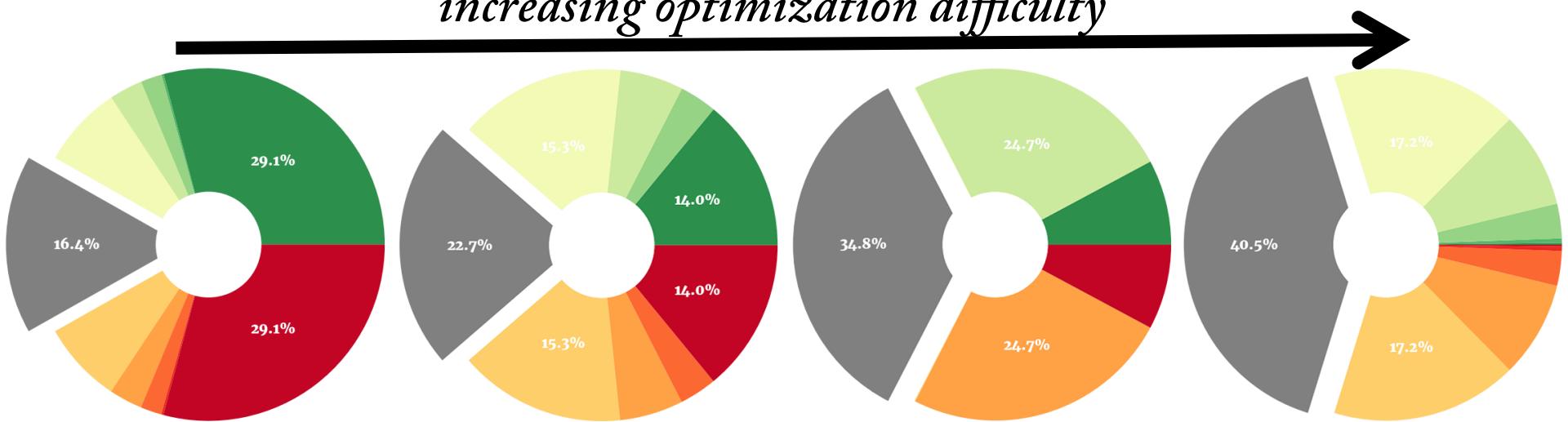
increasing optimization difficulty



benefit:damage ratio (%)

fitness criteria (1)

increasing optimization difficulty



The smaller the number of “ambiguous” nodes, the less optimization needed

fitness criteria (2)

Effective Total Benefits :

Accumulating (cleansing) **as many** beneficial (detrimental) interactions with **as few** genes to conserve (delete) as possible



Algorithmic workflow: adaptation

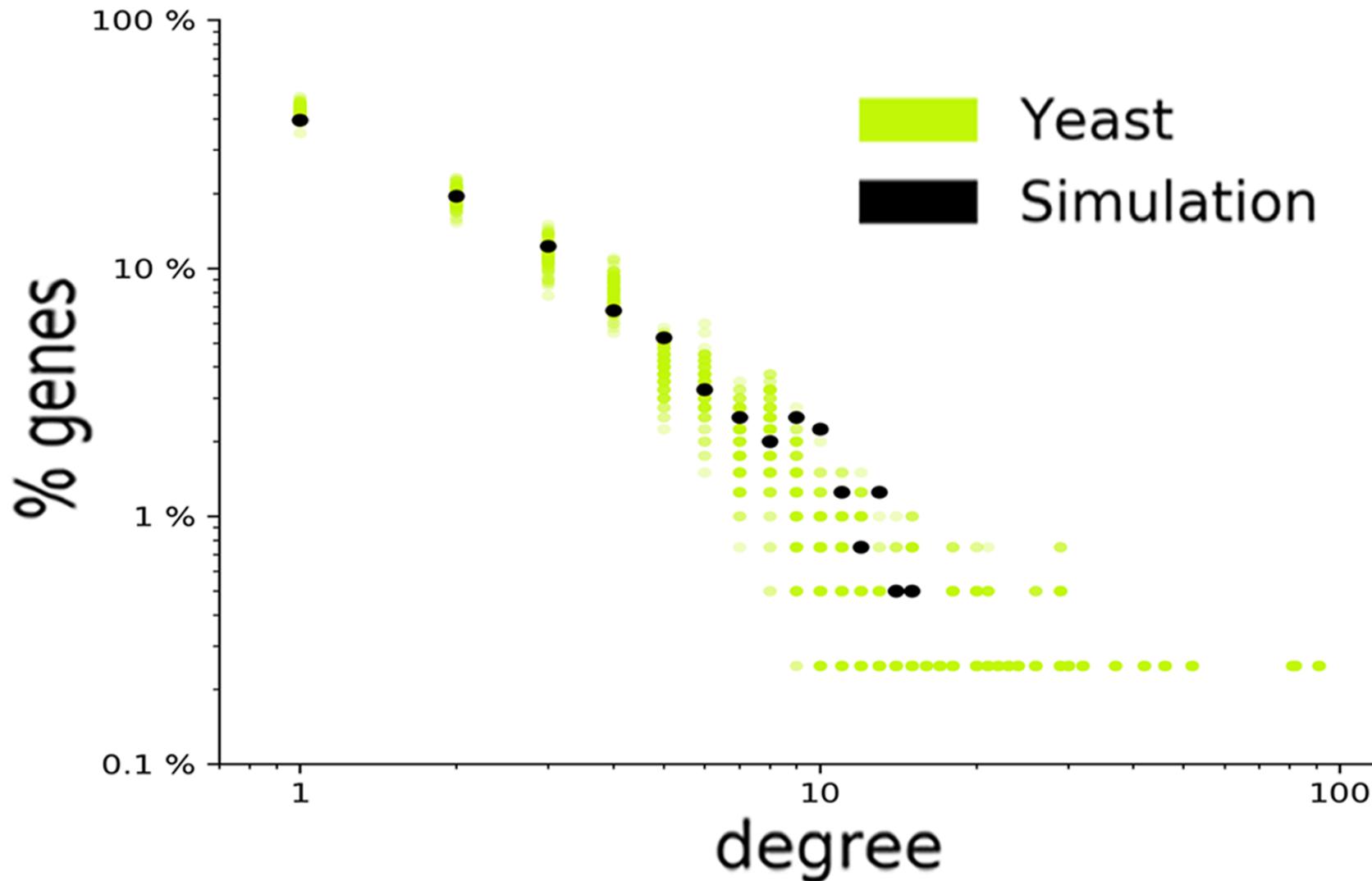
1. Start with a population of N random networks whose edge:node ratio = that of a real biological network

Algorithmic workflow: adaptation

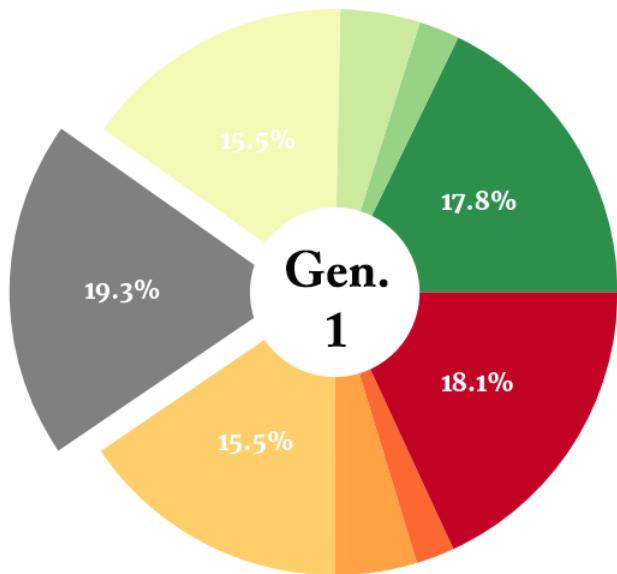
Loop: 2000 generations.

1. Start with a population of N random networks whose edge:node ratio = that of a real biological network
2. Mutate each one of those
3. Generate random NEP instances
4. Top 10% fittest networks per fitness criteria (1)x(2)
5. New population = 10 replicas of each mutated network

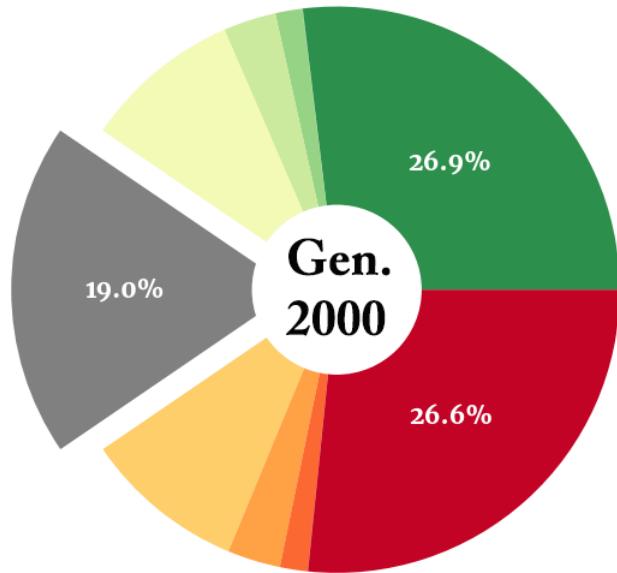
Results: adaptation



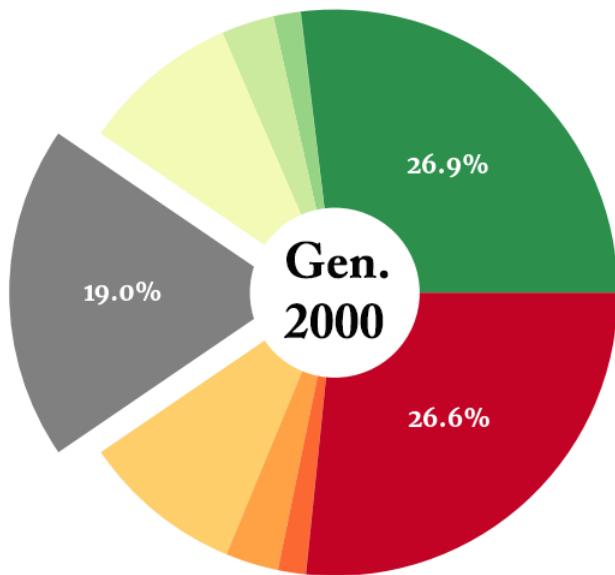
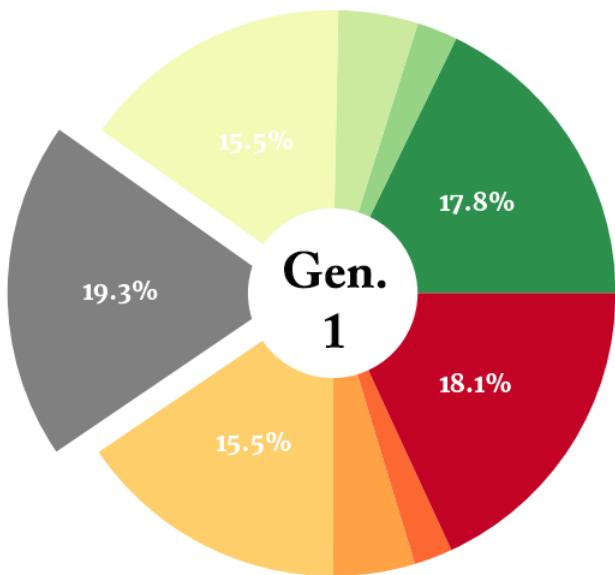
Results: adaptation



**benefit:damage
ratio (%):**

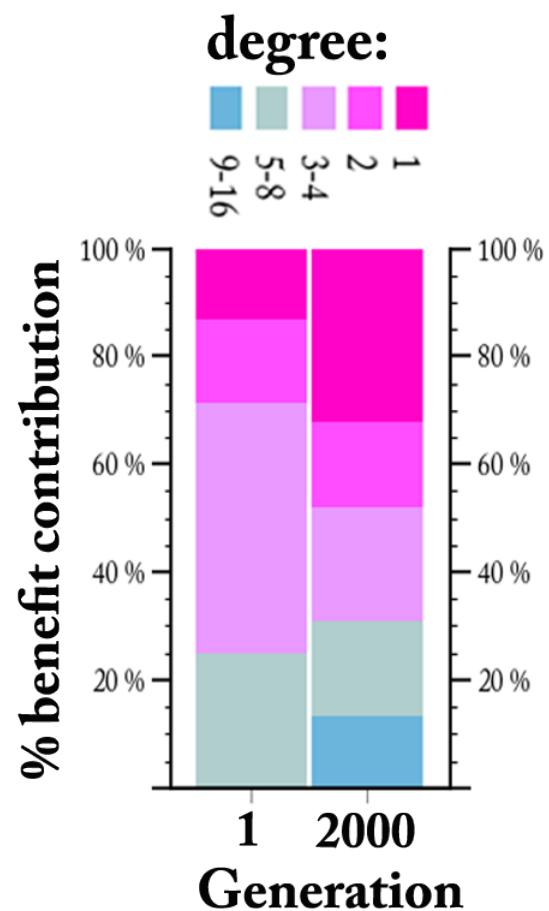


Results: adaptation

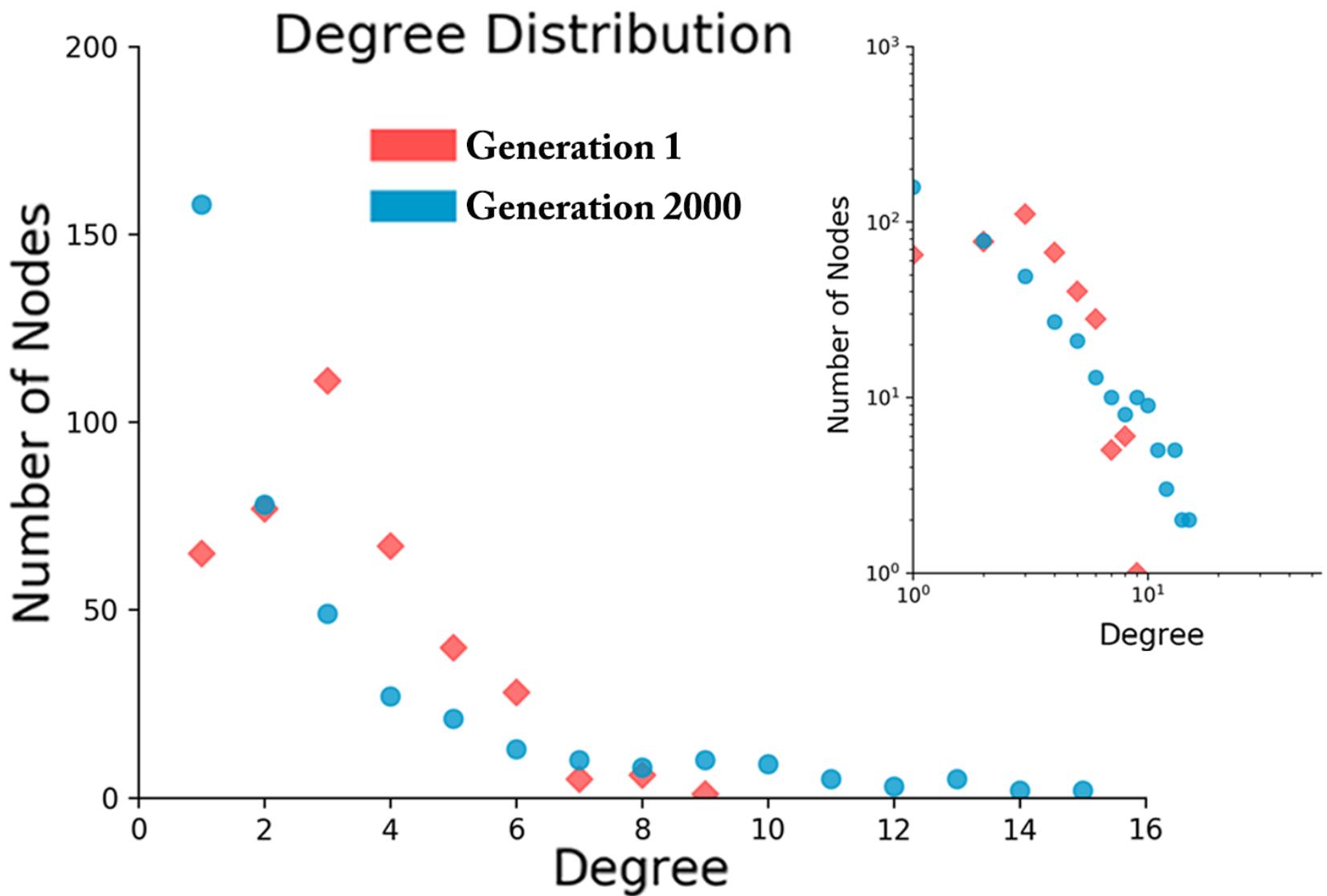


**benefit:damage
ratio (%):**

- 100:0
- 90:10
- 80:20
- 70:30
- 60:40
- 50:50
- 40:60
- 30:70
- 20:80
- 10:90
- 0:100



Results: adaptation



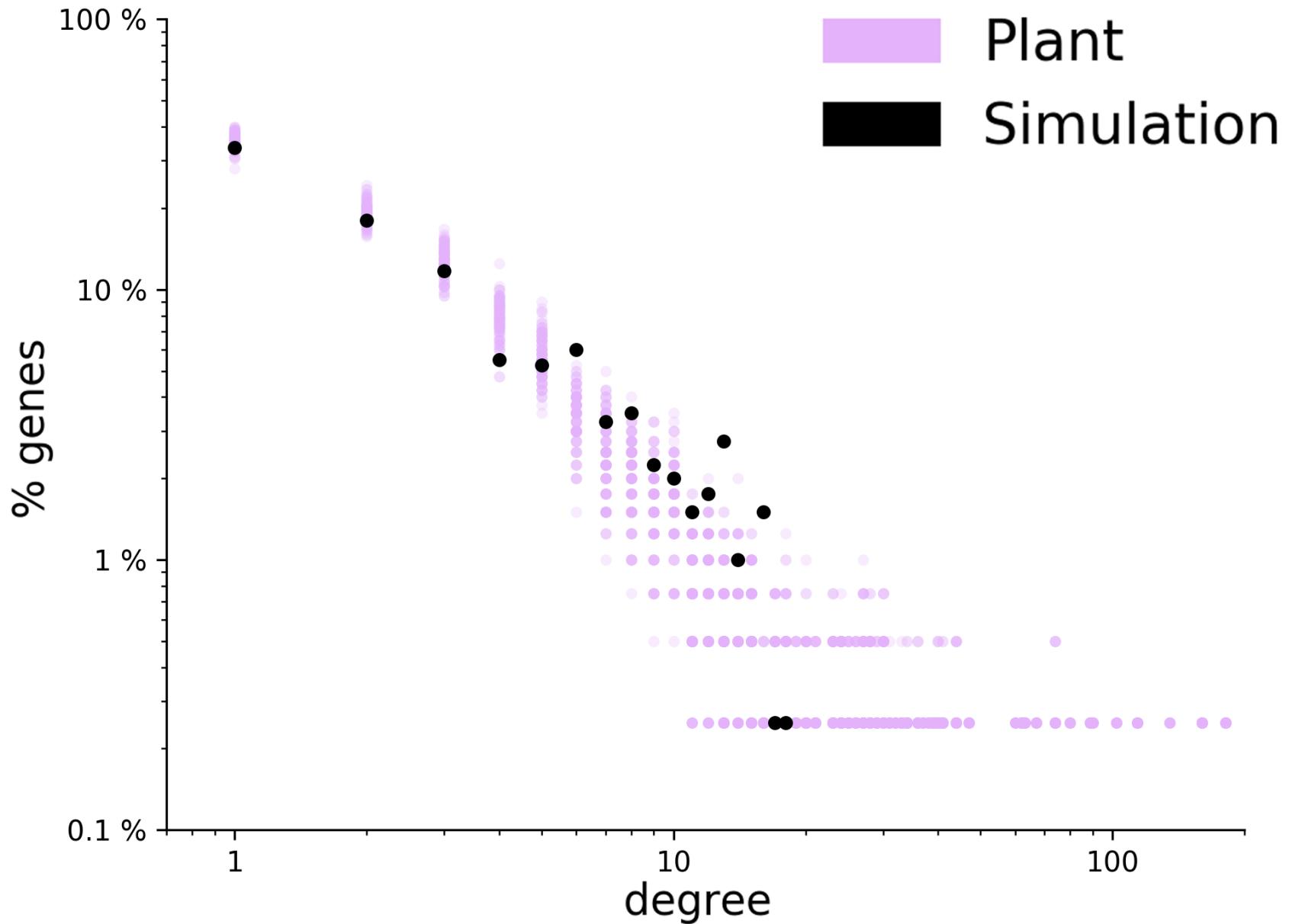
Results: adaptation with growth

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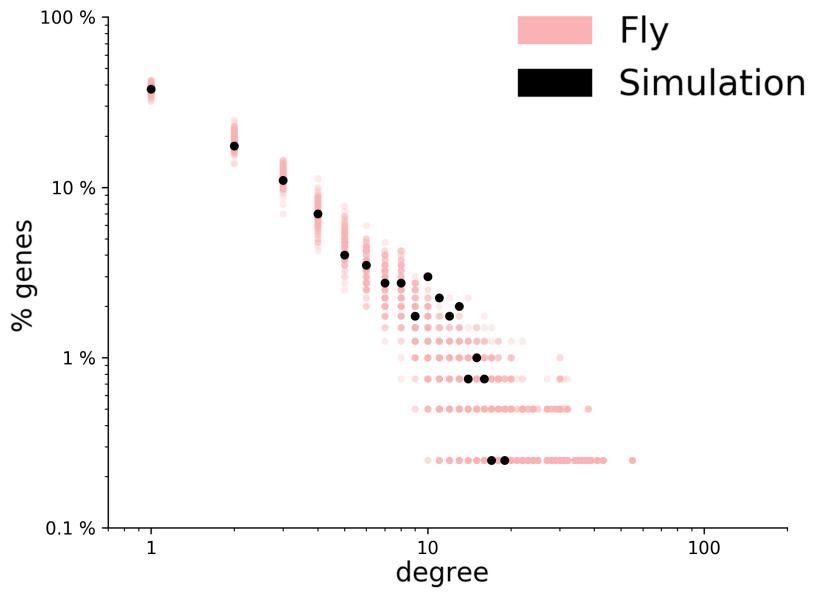
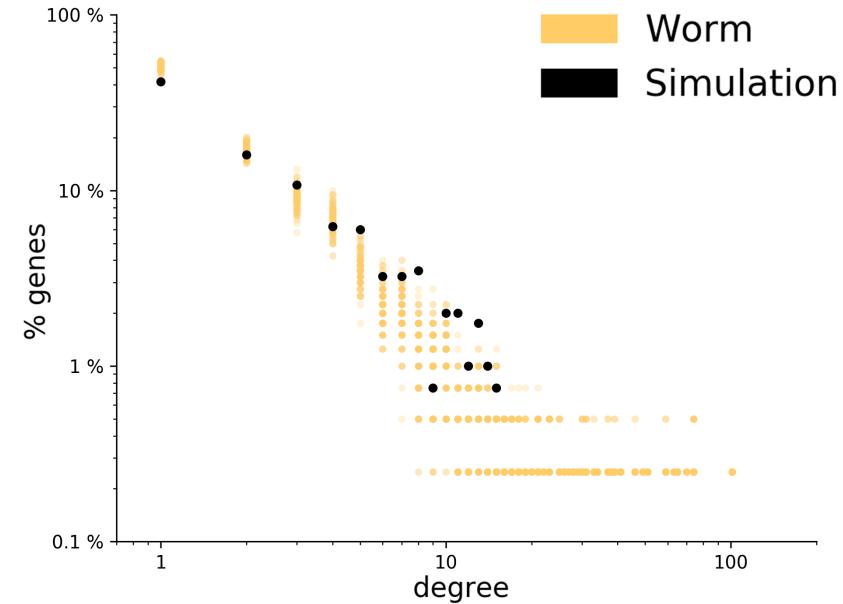
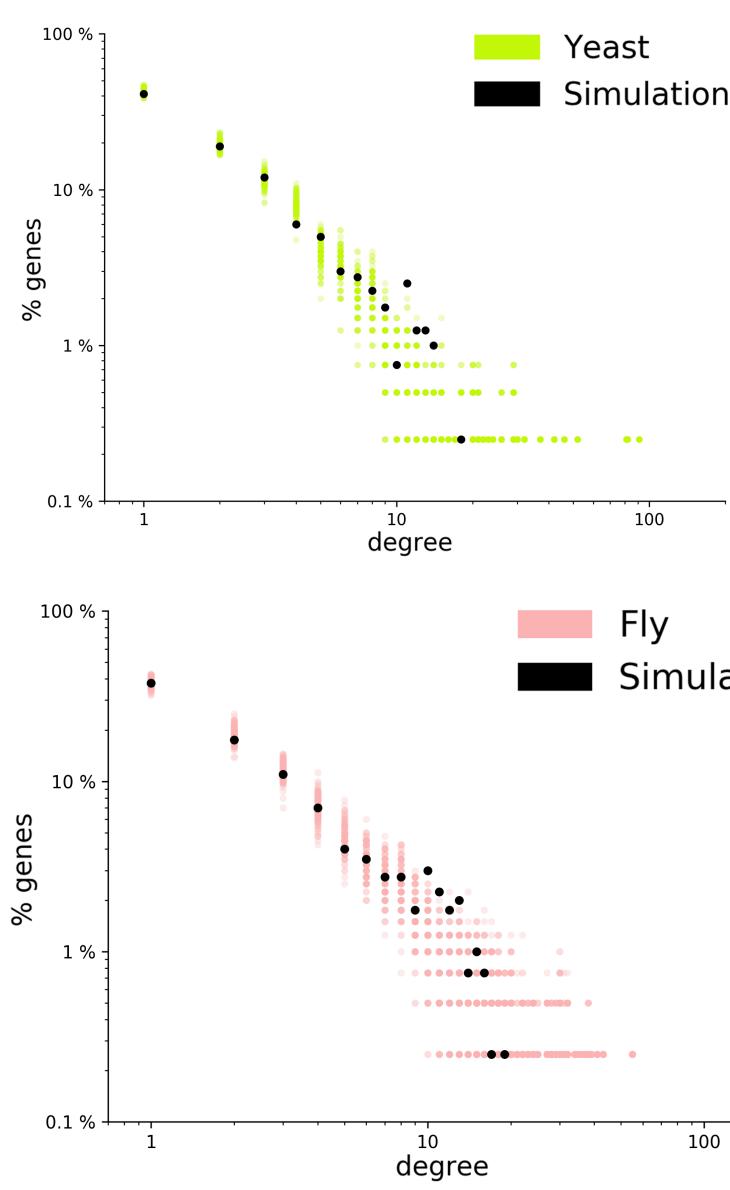
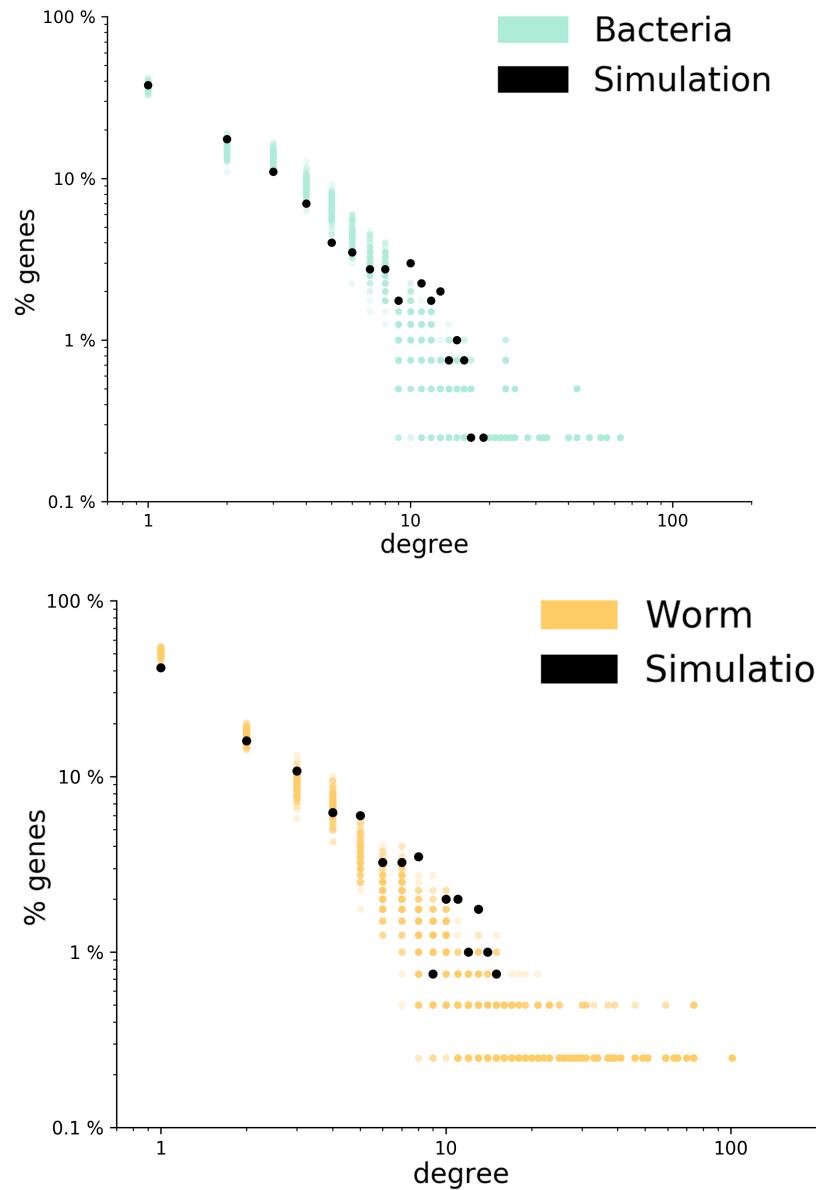
In these simulations:

- start with empty networks that slowly grow in size over the generations.
- all else is the same as before

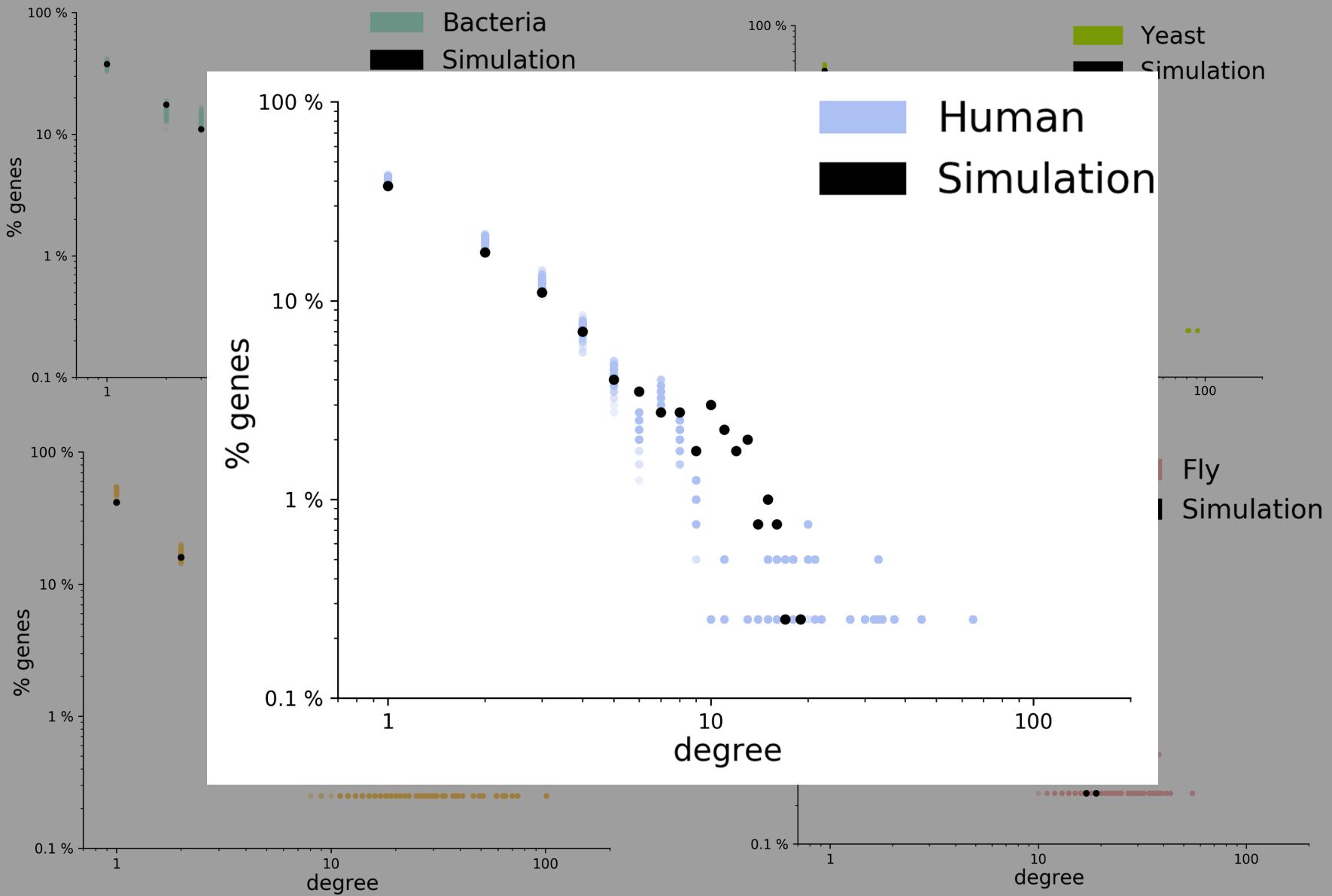
Results: adaptation with growth



Results: adaptation with growth



Results: adaptation with growth



Results: adaptation with growth

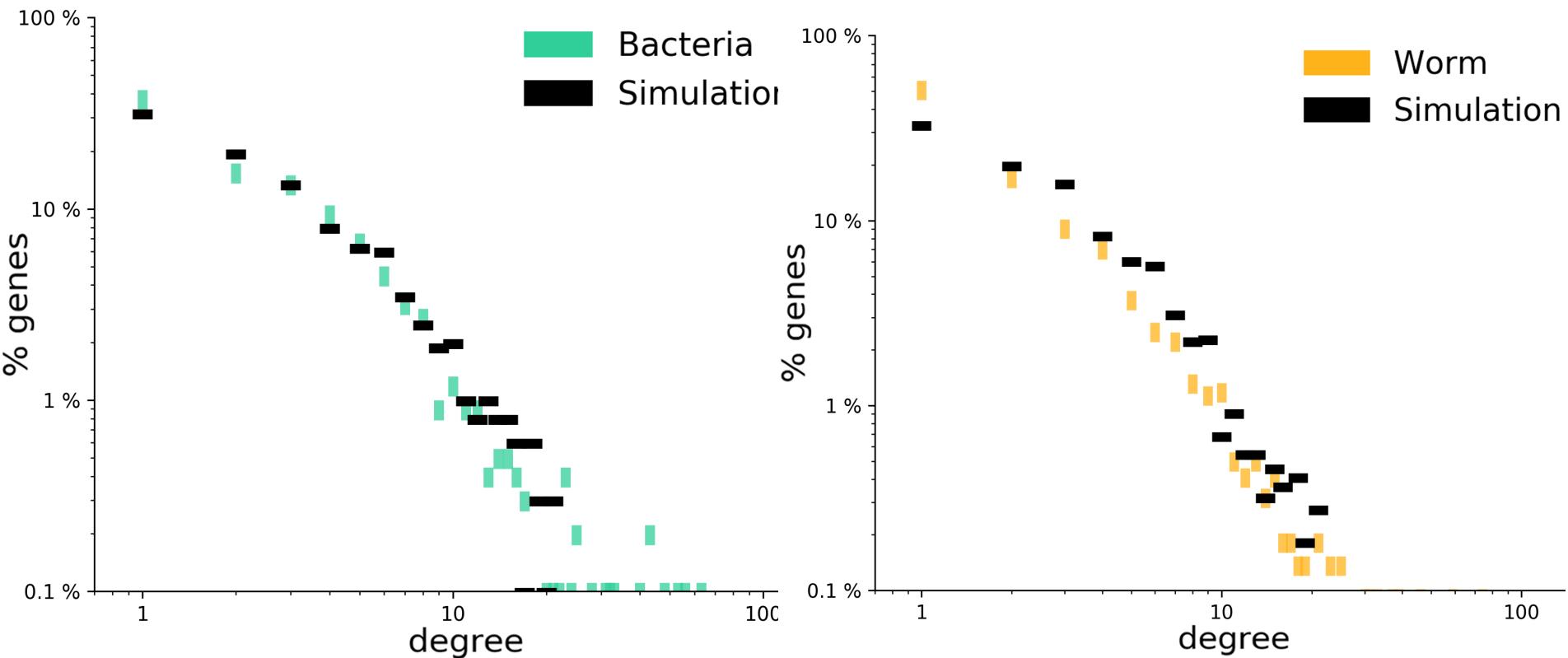
Results: adaptation with growth

Next ...

- Evolve larger networks equal in size to real networks from diverse physiological contexts

Results: adaptation with growth

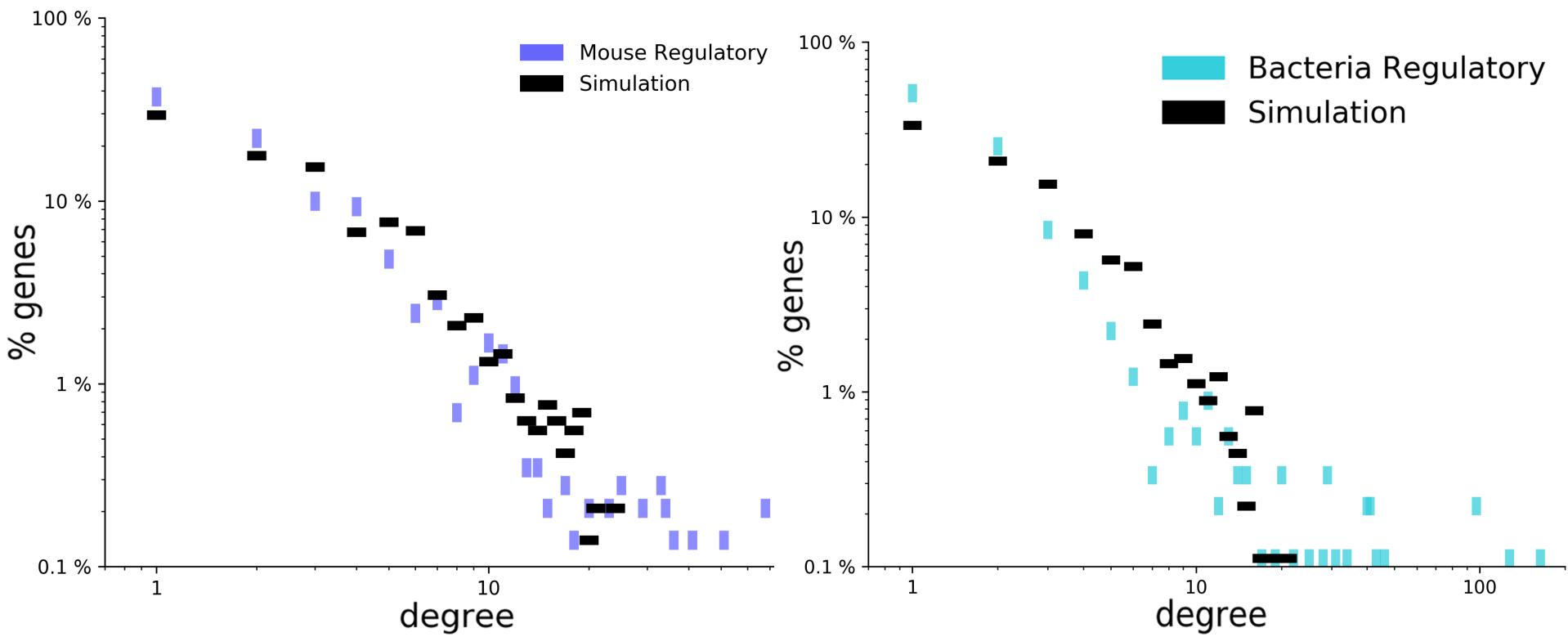
(larger and more diverse networks)



Protein-protein interaction networks

Results: adaptation with growth

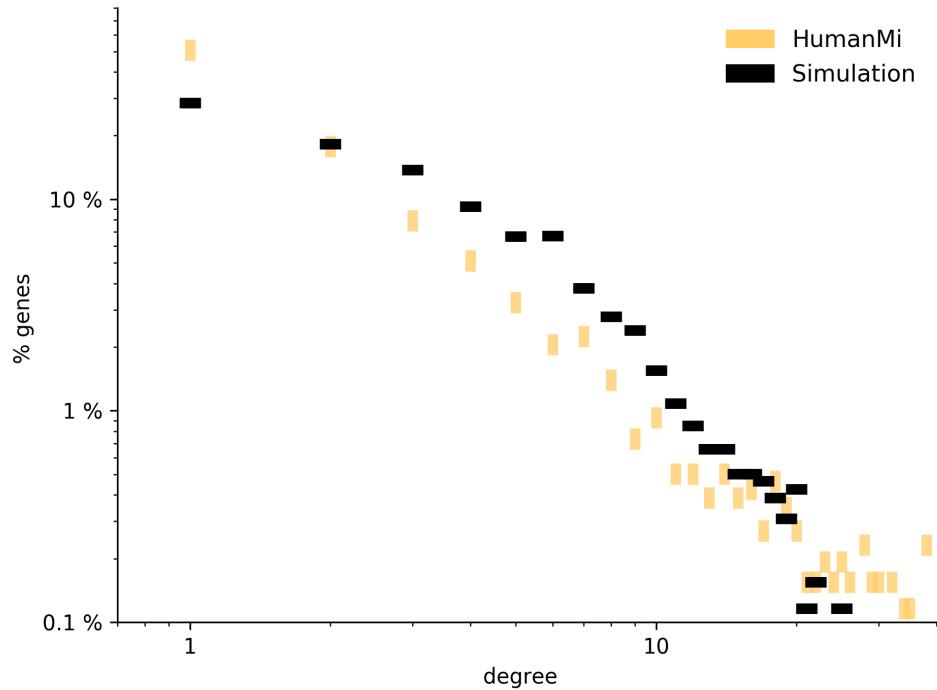
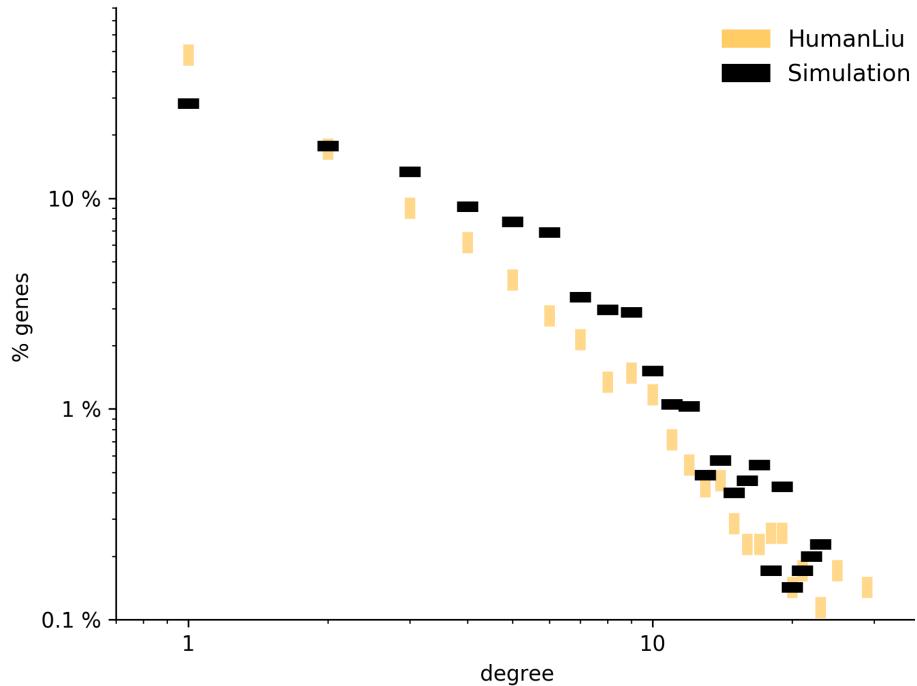
(larger and more diverse networks)



Regulatory networks

Results: adaptation with growth

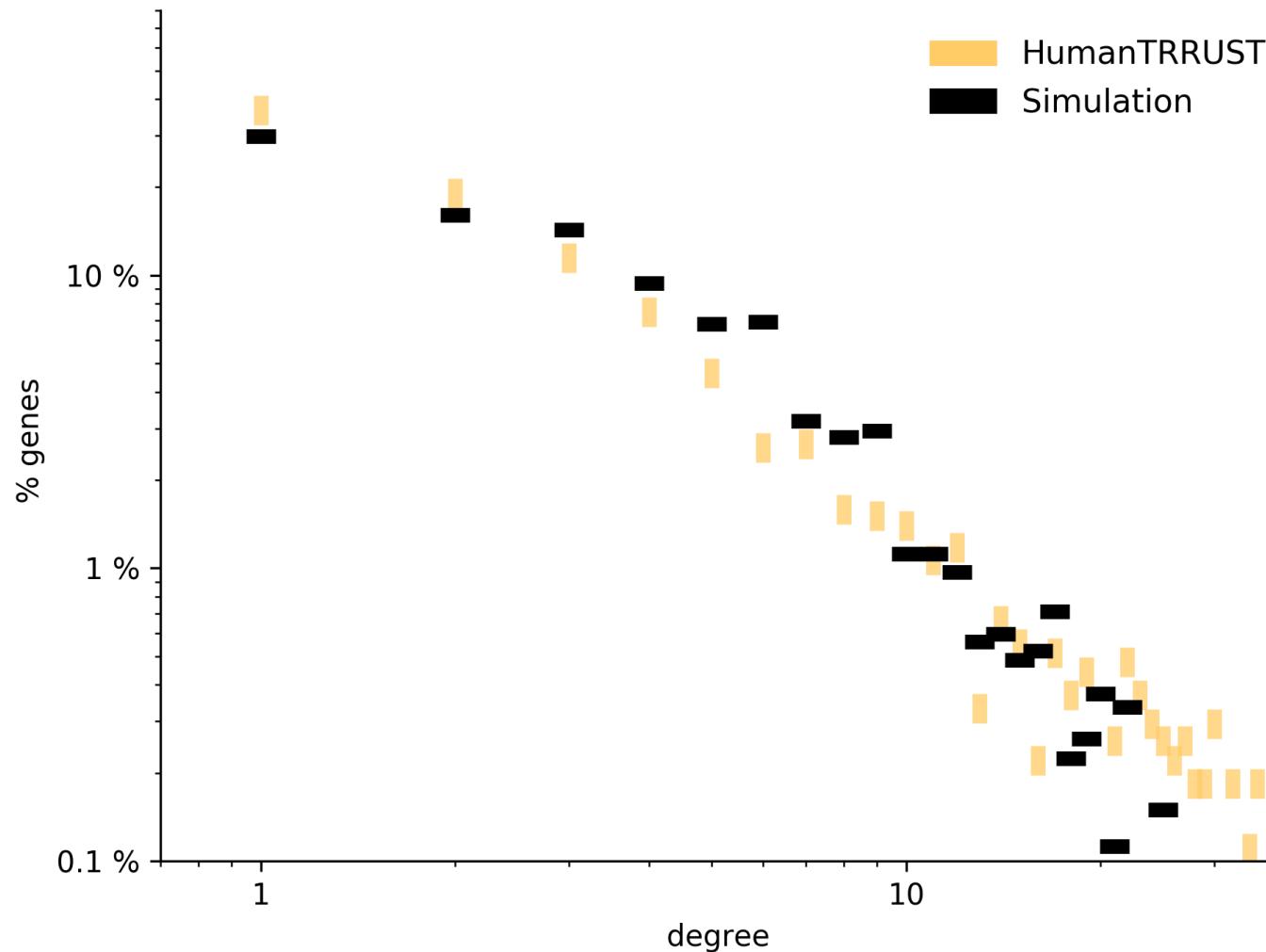
(larger and more diverse networks)



Regulatory networks

Results: adaptation with growth

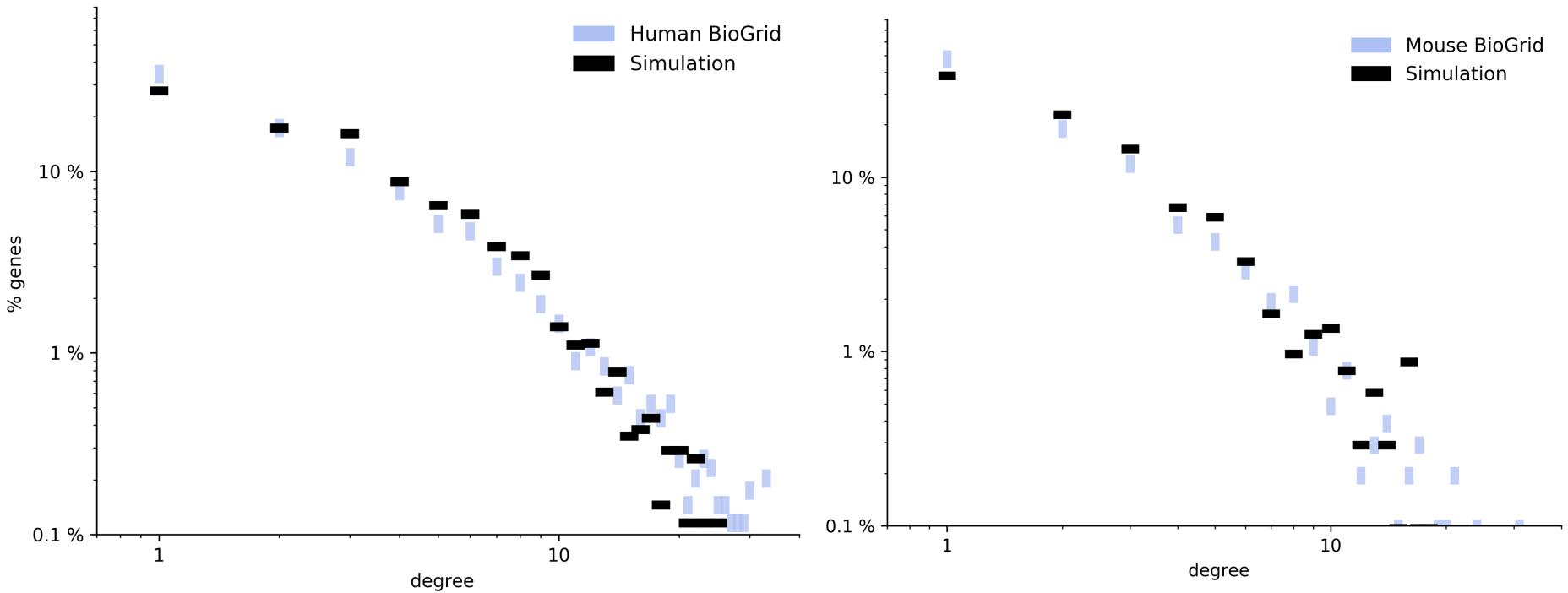
(larger and more diverse networks)



Regulatory networks

Results: adaptation with growth

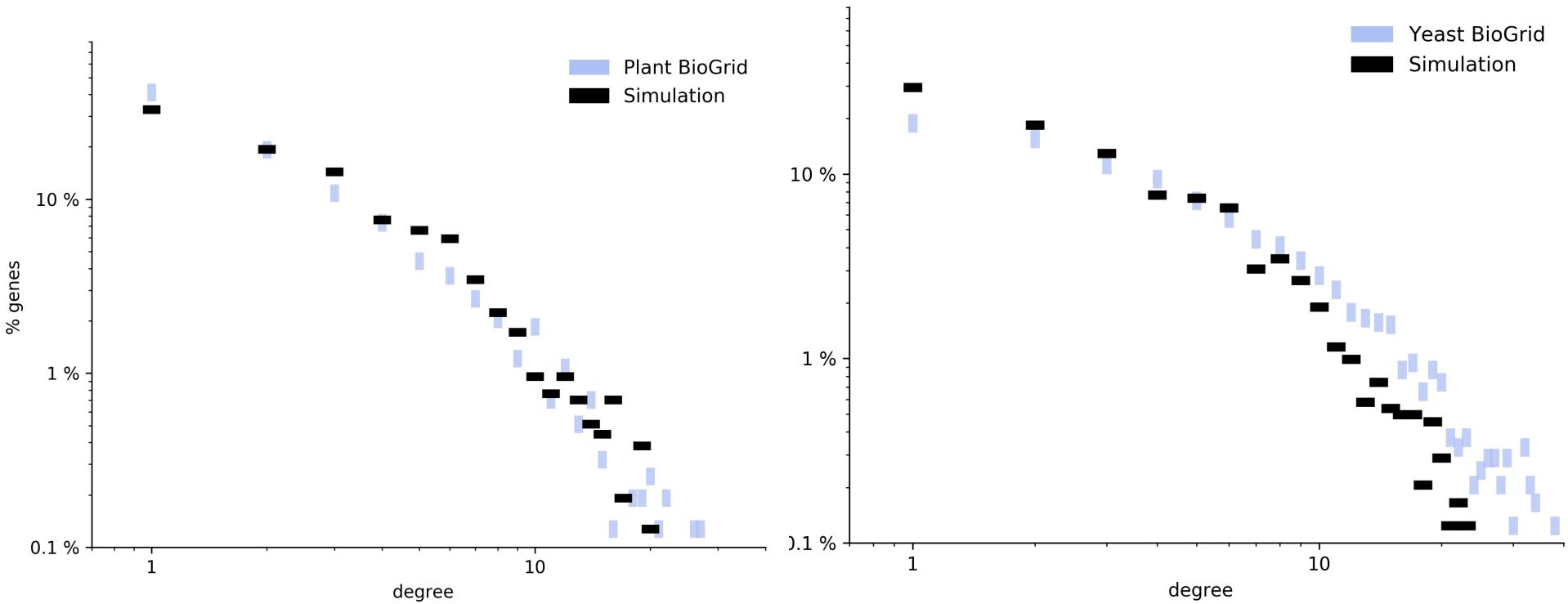
(larger and more diverse networks)



Database-sourced networks

Results: adaptation with growth

(larger and more diverse networks)



Database-sourced networks

Summary

- The topology of BNs is (at least in part) an adaptation to circumvent computational intractability.

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- Sufficiency vs Necessity

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- The topology of BNs is (at least in part) an adaptation to circumvent computational intractability.
- Sufficiency vs Necessity
- mLmH: concentrate **essential** functions in **hub** genes, and respond to evolutionary pressure by experimenting, on the **cheap**, with **leaf** nodes at the periphery of the network

Ongoing Work

- Use the model to explain the modularity of biological networks
- Intractability-based deterministic algorithm for generating mLmH-possessing synthetic networks

Near Future Work

- Is computational intractability behind cancer intractability?

Collaborators:

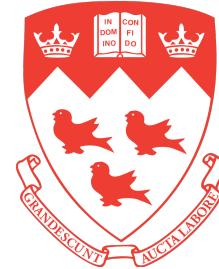
Dr. Jérôme Waldspühl
Corbin Hopper

School of Computer Science
McGill University, Montreal, Canada

<http://csb.cs.mcgill.ca/>



NSERC
CRSNG



Thanks

Results: adaptation

