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# *The Blind Watchmaker Network: Scale-freeness and evolution*

Sebastian Bernhardsson

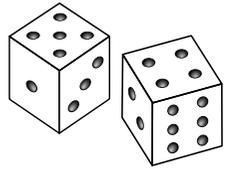
Umeå university, Sweden

*sebbeb@tp.umu.se*

*www.tp.umu.se/~sebbeb*

# Outline

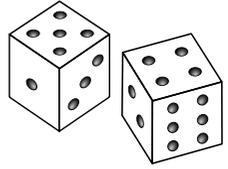
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- Statistical mechanics
- Balls in boxes model
- Variational calculus
- Variational calculus using a random process
- Constrained Balls in Boxes model
- Network constraints
- Comparison with real networks
- Other network properties (C-r space)
- Conclusions

# Statistical mechanics

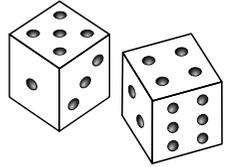
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## Maximum entropy principle

# Statistical mechanics

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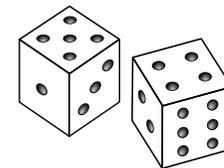


## Maximum entropy principle

*In the limit of large numbers, the outcome of a random process will be the distribution that has the largest entropy.*

# Statistical mechanics

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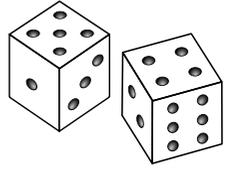


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**Example:** Flip a coin with sides **A** and **B**. How many **A**:s and **B**:s will you most likely have after four flips?

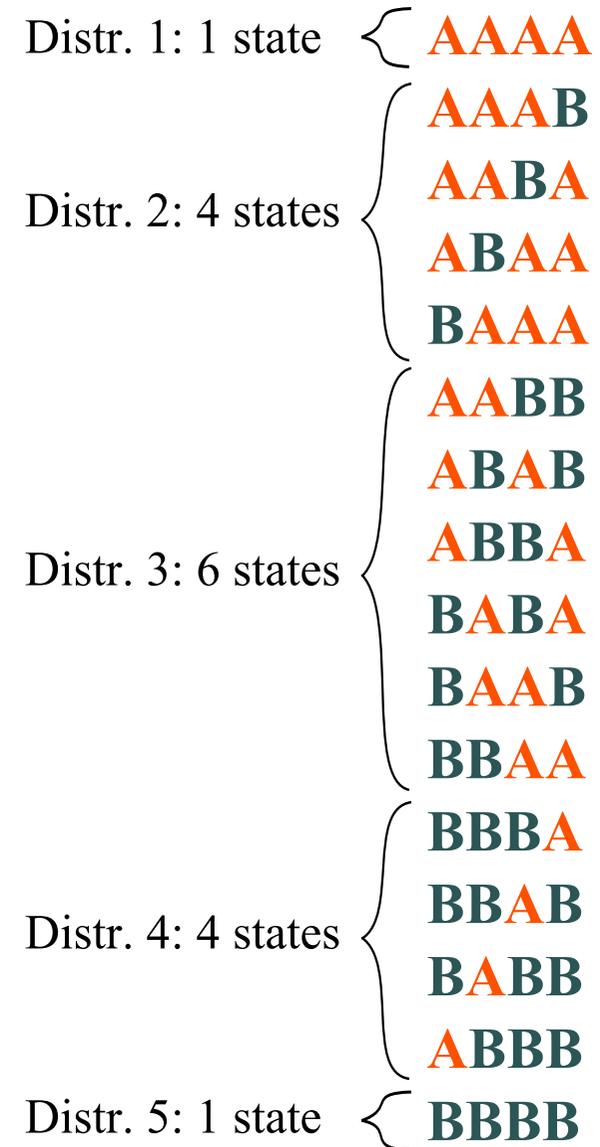
# Statistical mechanics



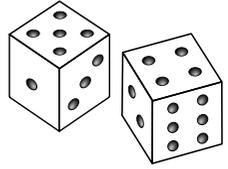
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# Statistical mechanics



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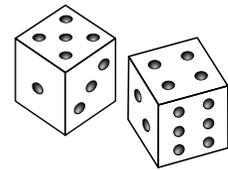
**Example:** Flip a coin with sides **A** and **B**. How many **A**:s and **B**:s will you most likely have after four flips?

**Answer:** The distribution (number of **A**:s and **B**:s) that has the most number of states (highest entropy) will win (in the long run)!

In this case distribution 3 is most likely to show up (prob =  $6/(1+4+6+4+1) = 3/8$ ).

Distr. 1: 1 state	{	<b>AAAA</b>
Distr. 2: 4 states	{	<b>AAAB</b>
		<b>AABA</b>
		<b>ABAA</b>
		<b>BAAA</b>
Distr. 3: 6 states	{	<b>AABB</b>
		<b>ABAB</b>
		<b>ABBA</b>
		<b>BABA</b>
		<b>BAAB</b>
		<b>BBAA</b>
Distr. 4: 4 states	{	<b>BBBA</b>
		<b>BBAB</b>
		<b>BABB</b>
		<b>ABBB</b>
Distr. 5: 1 state	{	<b>BBBB</b>

# Network $\rightarrow$ Balls in boxes model

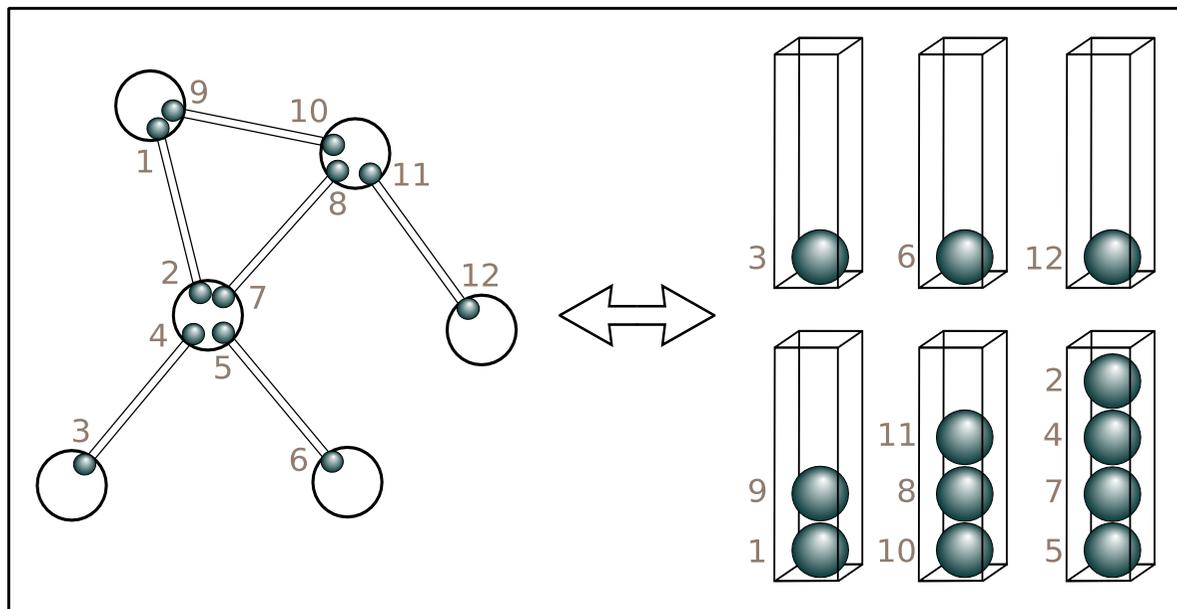


Map a network onto a set of balls and boxes.

Boxes  $\iff$  Nodes

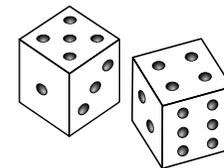
Balls  $\iff$  Link ends

A link is defined by two link ends, e.g. (7,8)



# Variational Calculus

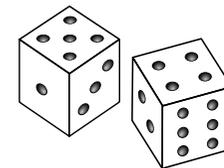
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In how many ways can you distribute  $M$  balls into  $N$  boxes?

# Variational Calculus

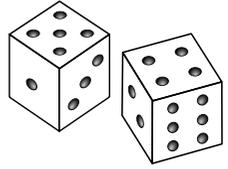
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$$\Omega = \frac{M!}{\prod_k N(k)! \cdot (k!)^{N(k)}} \text{ (Indistinguishable balls in a box)}$$

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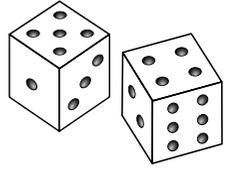


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$$\Rightarrow \ln \Omega \approx M \ln M - M - \sum_k N(k) [\ln N(k) - 1] - \sum_k N(k) \ln k!$$

# Variational Calculus



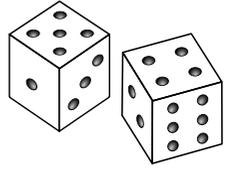
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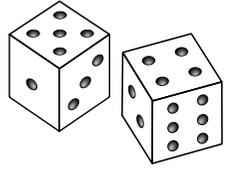
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(where  $a$  and  $b$  are Lagrange multipliers corresponding to the constraints)

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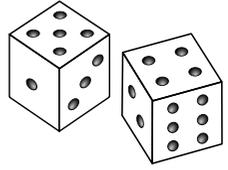
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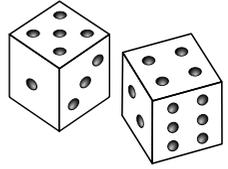
$$\Rightarrow N(k) = Ae^{-bk}/k! = A\langle k \rangle^k/k! \Rightarrow \text{Poisson distribution (Erdős-Renyi)}$$

# VC using a random process

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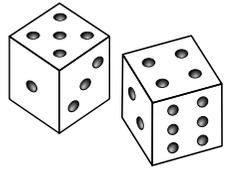


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Mapping changes in the states to changes in the degree distribution.

# VC using a random process

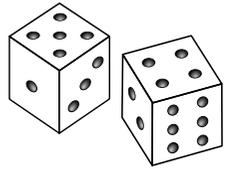
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If you, by moving one ball from box  $A$  to box  $B$ , can reach  $P$  different states, then this move should get a weight  $\propto P$ .

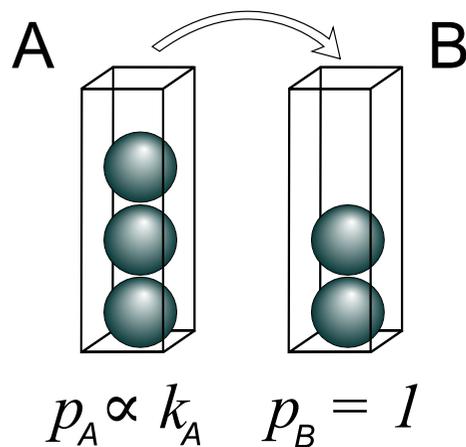
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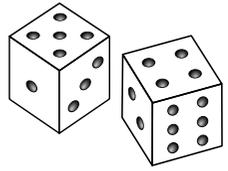
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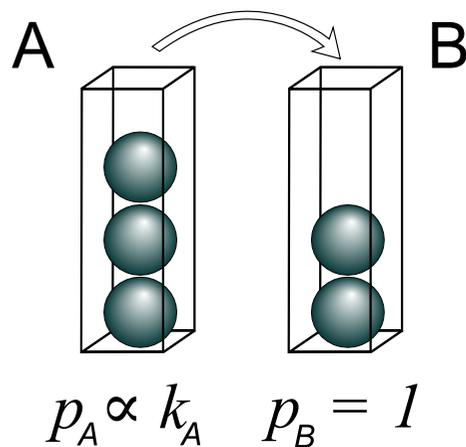
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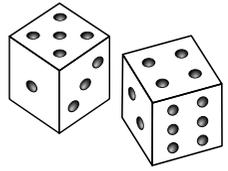
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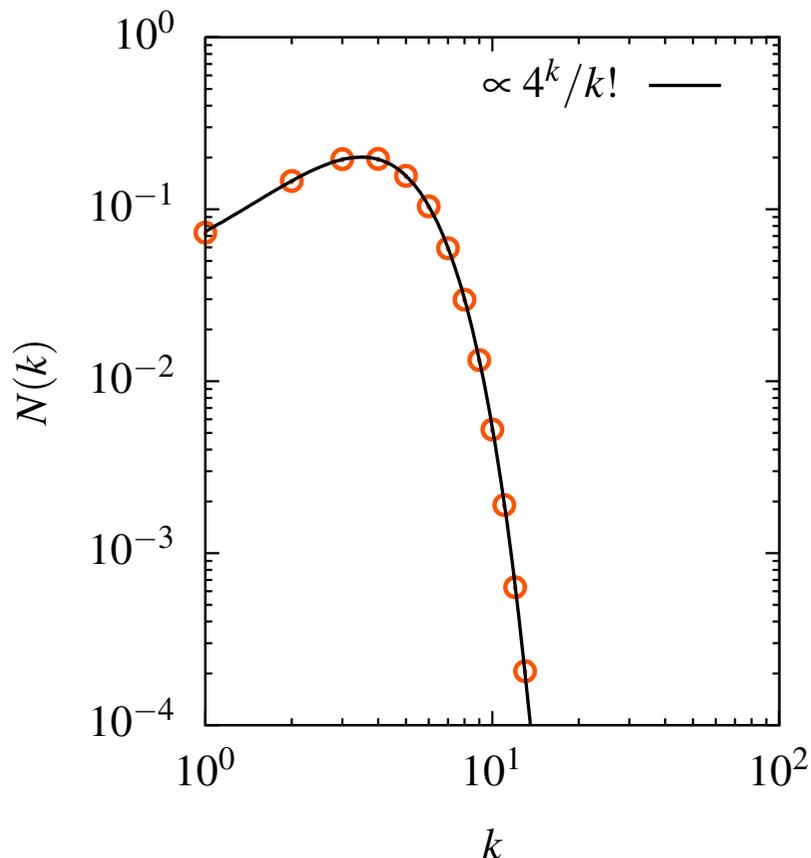
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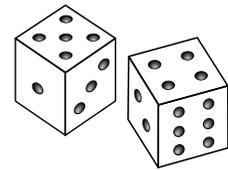
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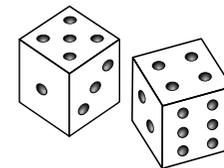
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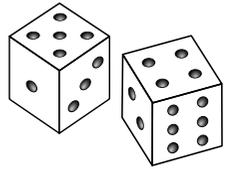
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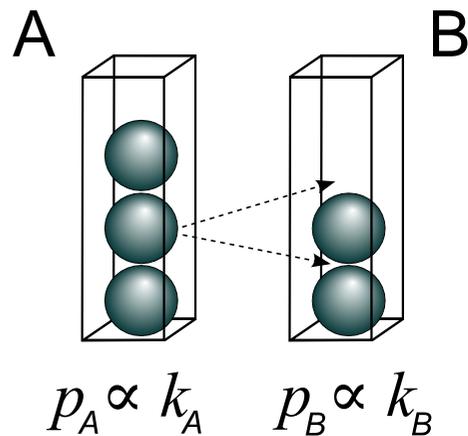
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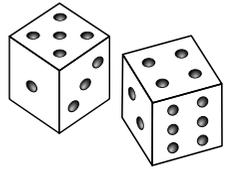


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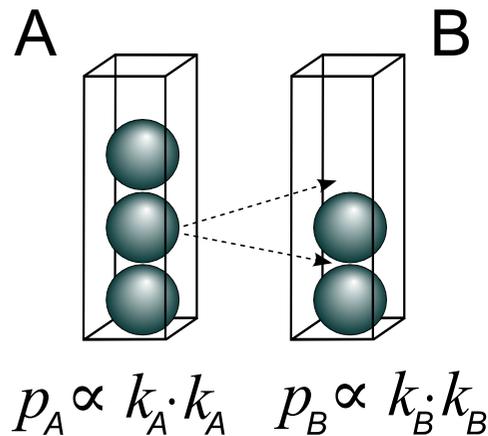
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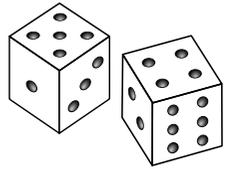
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If we also take into consideration that you can only choose a box by choosing a ball, we get an extra  $k$  for each box.



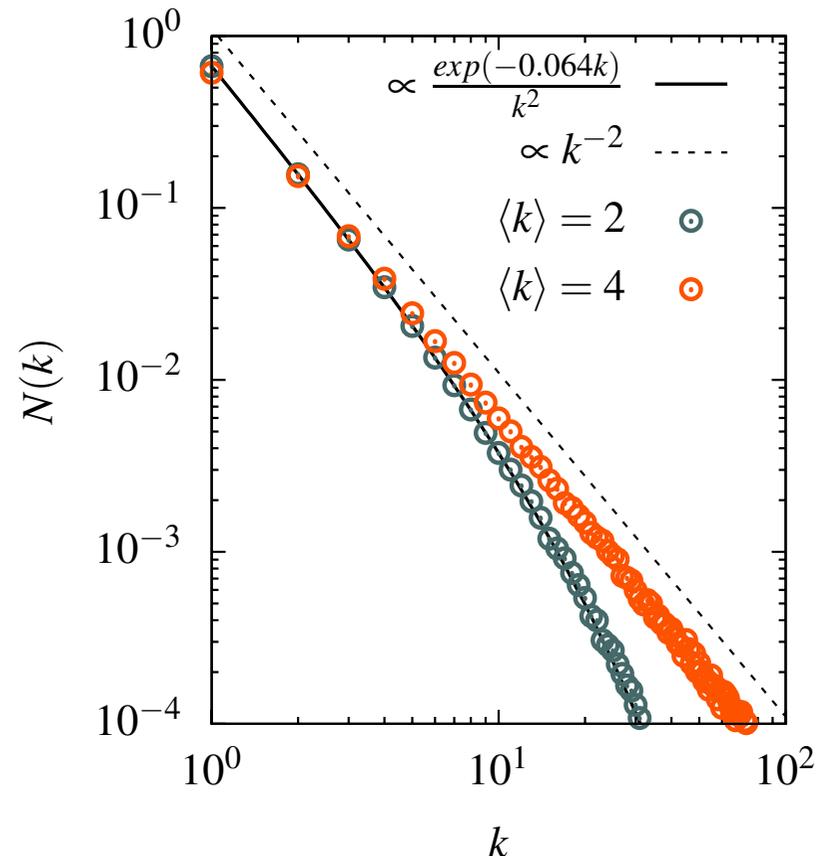
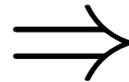
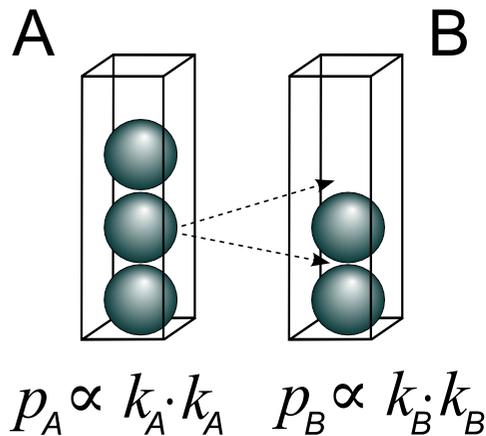
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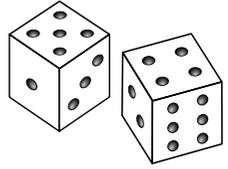


$$\Rightarrow N(k) = A e^{-bk} / k^2$$

You are not allowed to empty a box!

# The Blind Watchmaker Network

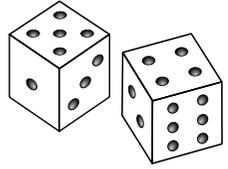
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Network constraints

# The Blind Watchmaker Network

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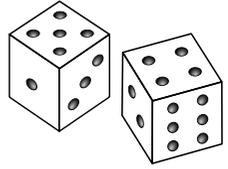


## Network constraints

- Only one link between two nodes

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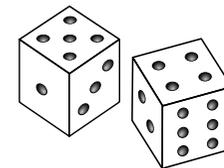
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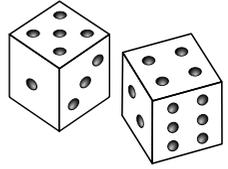
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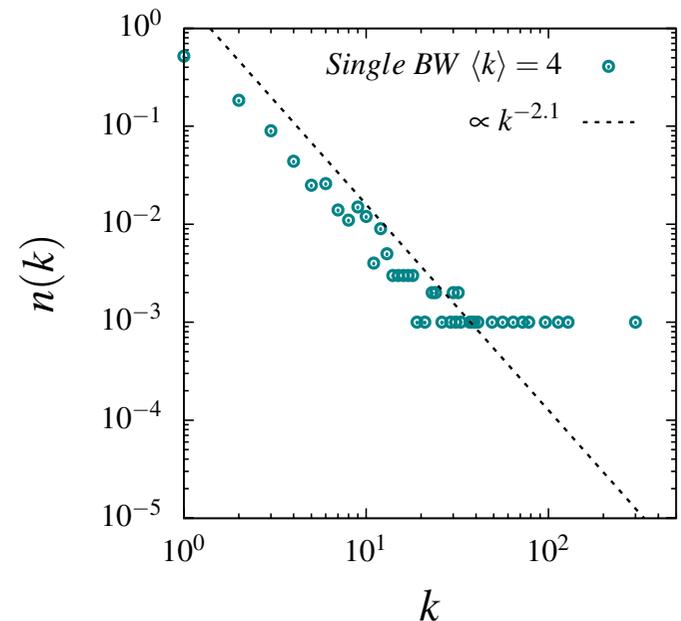
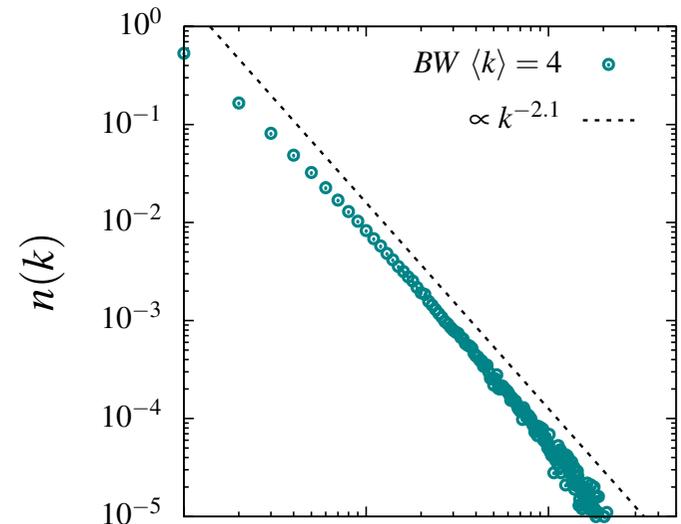


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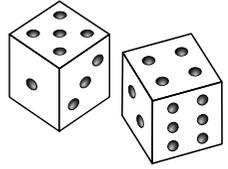
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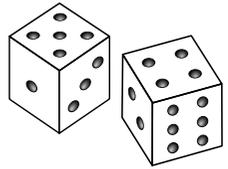


# Comparison with real data

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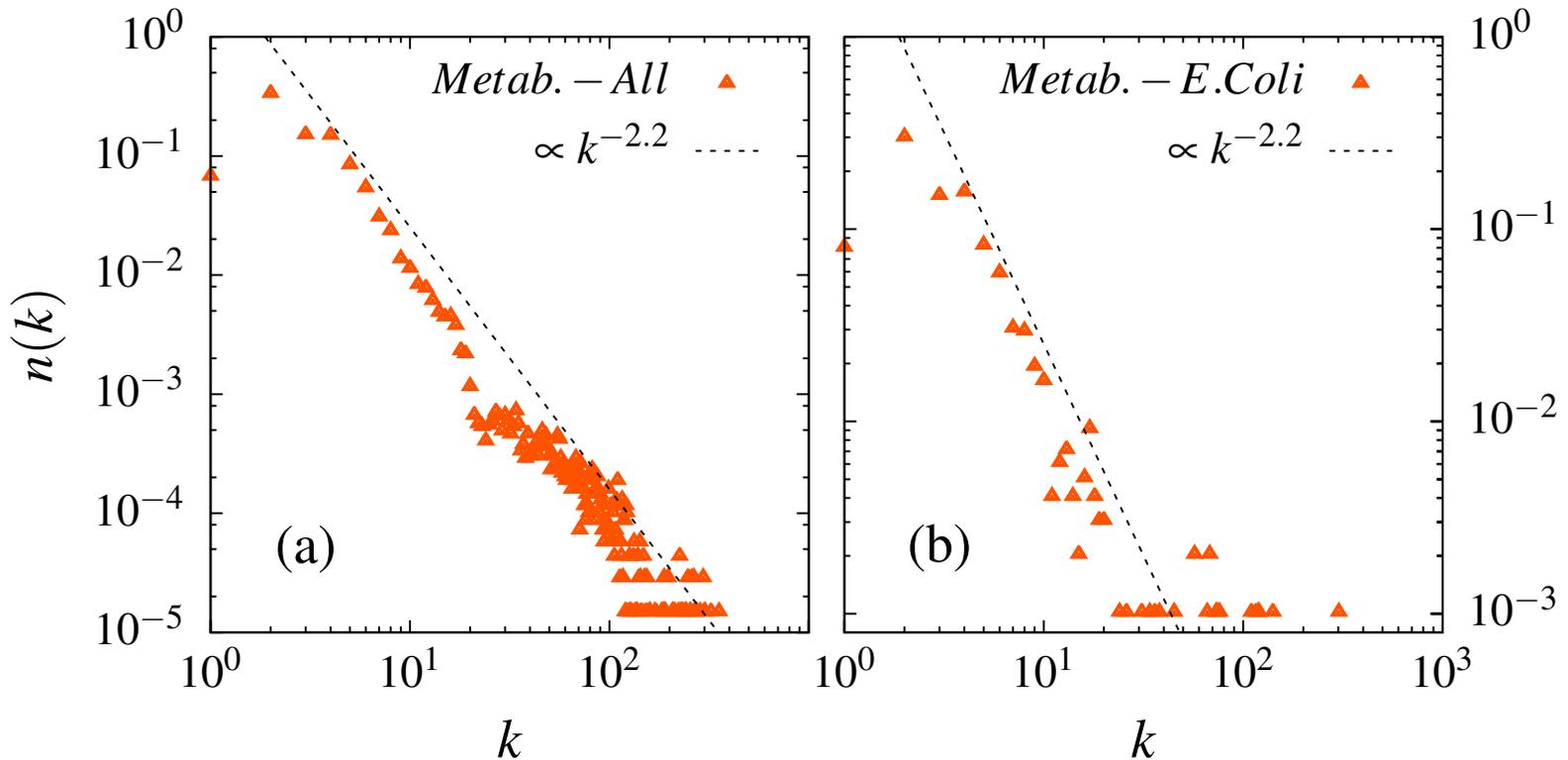
# Comparison with real data



Metabolic networks:

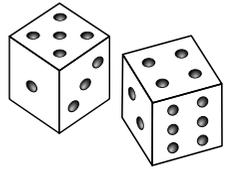
(a) Average over 107 organisms

(b) E. Coli



Ma H and Zeng A-P, Bioinformatics 19: 270-277 (2003).

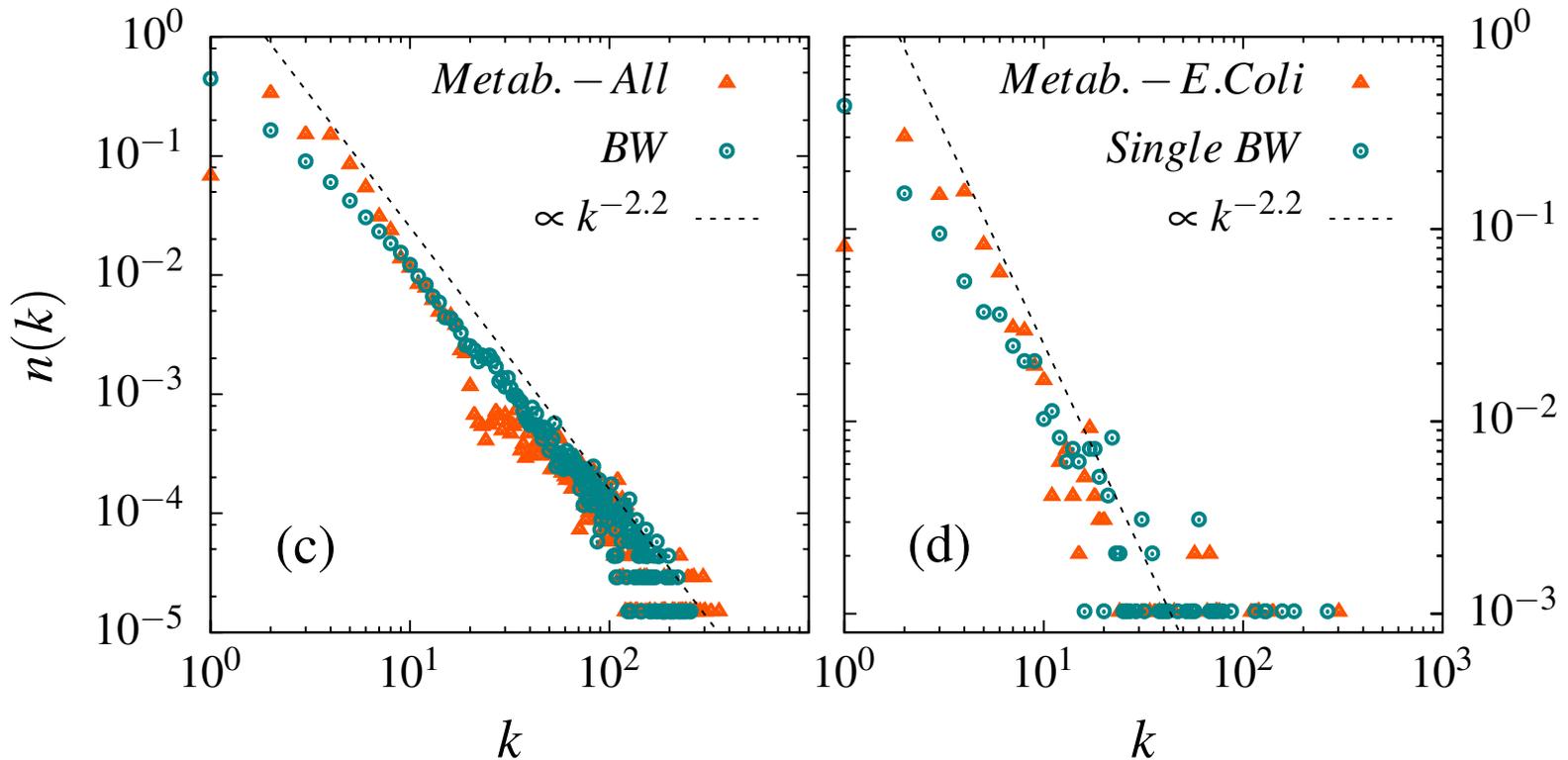
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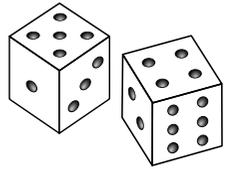
Comparison:

(c) BW vs Metabolic: same N and M

(d) BW vs E.Coli: same N and M



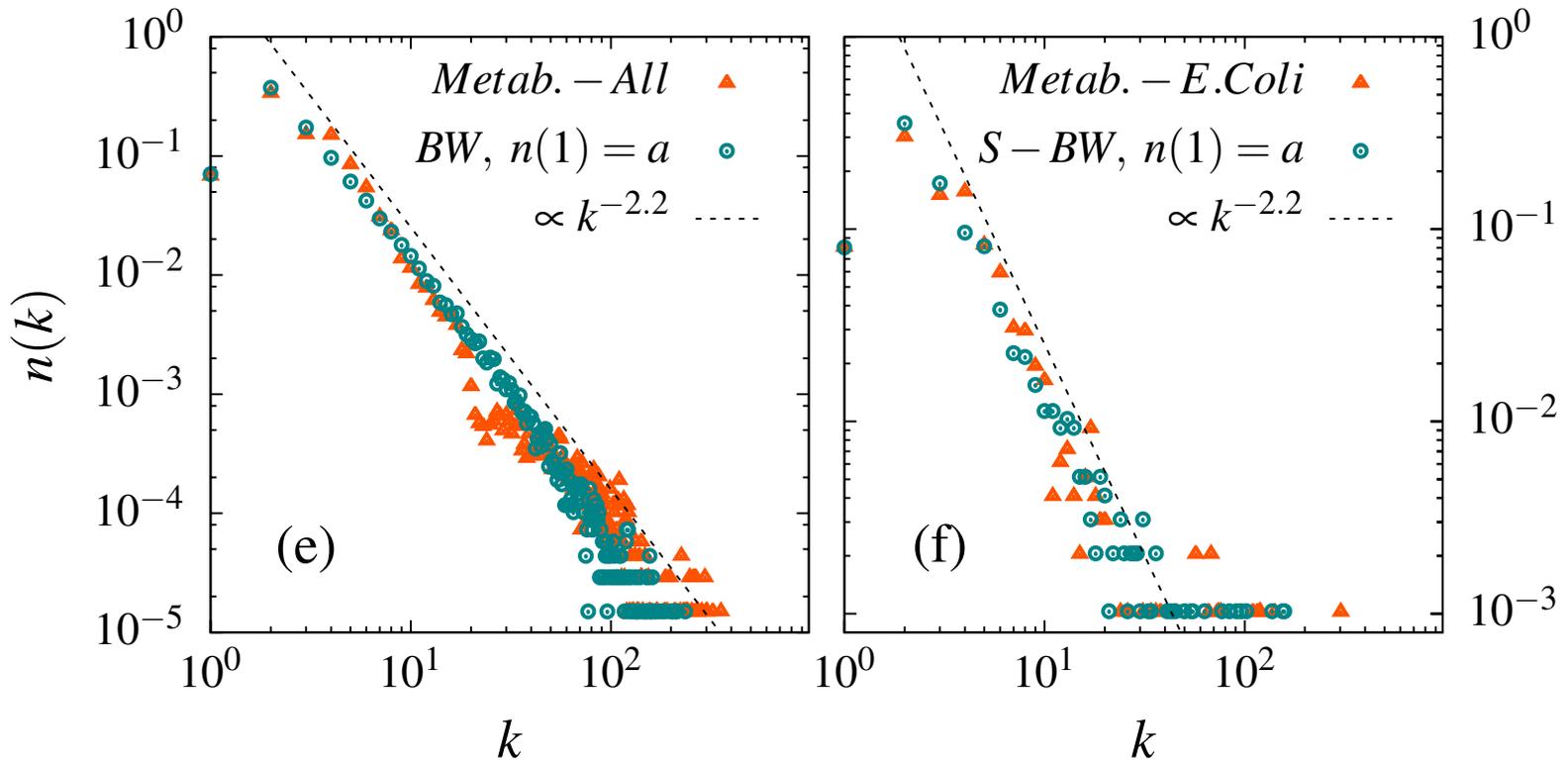
# Comparison with real data



Comparison, with extra constraint:

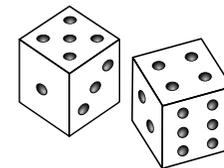
(e) Same as in c) but with fixed  $n(1)$

(f) Same as in d) but with fixed  $n(1)$



# Conclusions - Part I

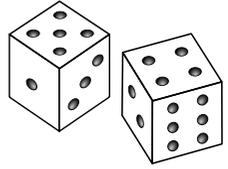
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PLoS ONE 3(2): e1690,(2008).

# Conclusions - Part I

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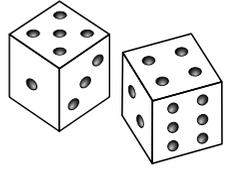


- Agreement between the BW network and metabolic networks looks very good  $\Rightarrow$   
Natural selection has had small effect on the Metabolic networks degree distribution.

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# Conclusions - Part I

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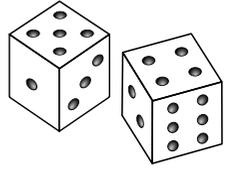


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Natural selection has had small effect on the Metabolic networks degree distribution.
- BW is a random network just as ER is a random network.

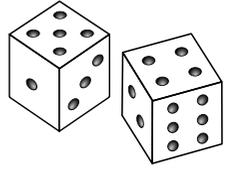
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# Network properties

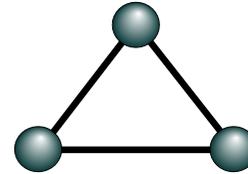
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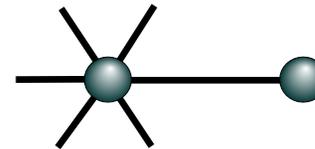


## Clustering Coefficient



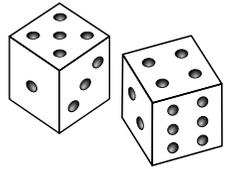
$$0 \leq C \leq 1$$

## Assortativity



$$-1 \leq r \leq 1$$

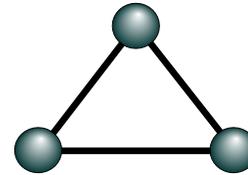
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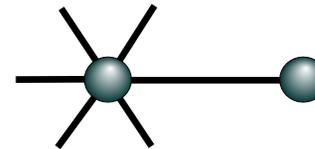
$$\langle C \rangle_{metab} = 0.139 \text{ (0.143)}$$

$$\langle C \rangle_{BW} = 0.103 \text{ (0.096)}$$



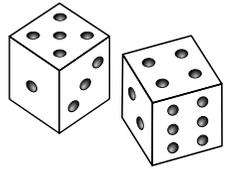
$$0 \leq C \leq 1$$

## Assortativity



$$-1 \leq r \leq 1$$

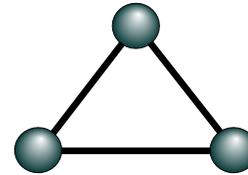
# Network properties



## Clustering Coefficient

$$\langle C \rangle_{metab} = 0.139 \text{ (0.143)}$$

$$\langle C \rangle_{BW} = 0.103 \text{ (0.096)}$$

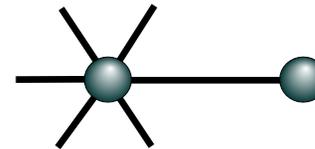


$$0 \leq C \leq 1$$

## Assortativity

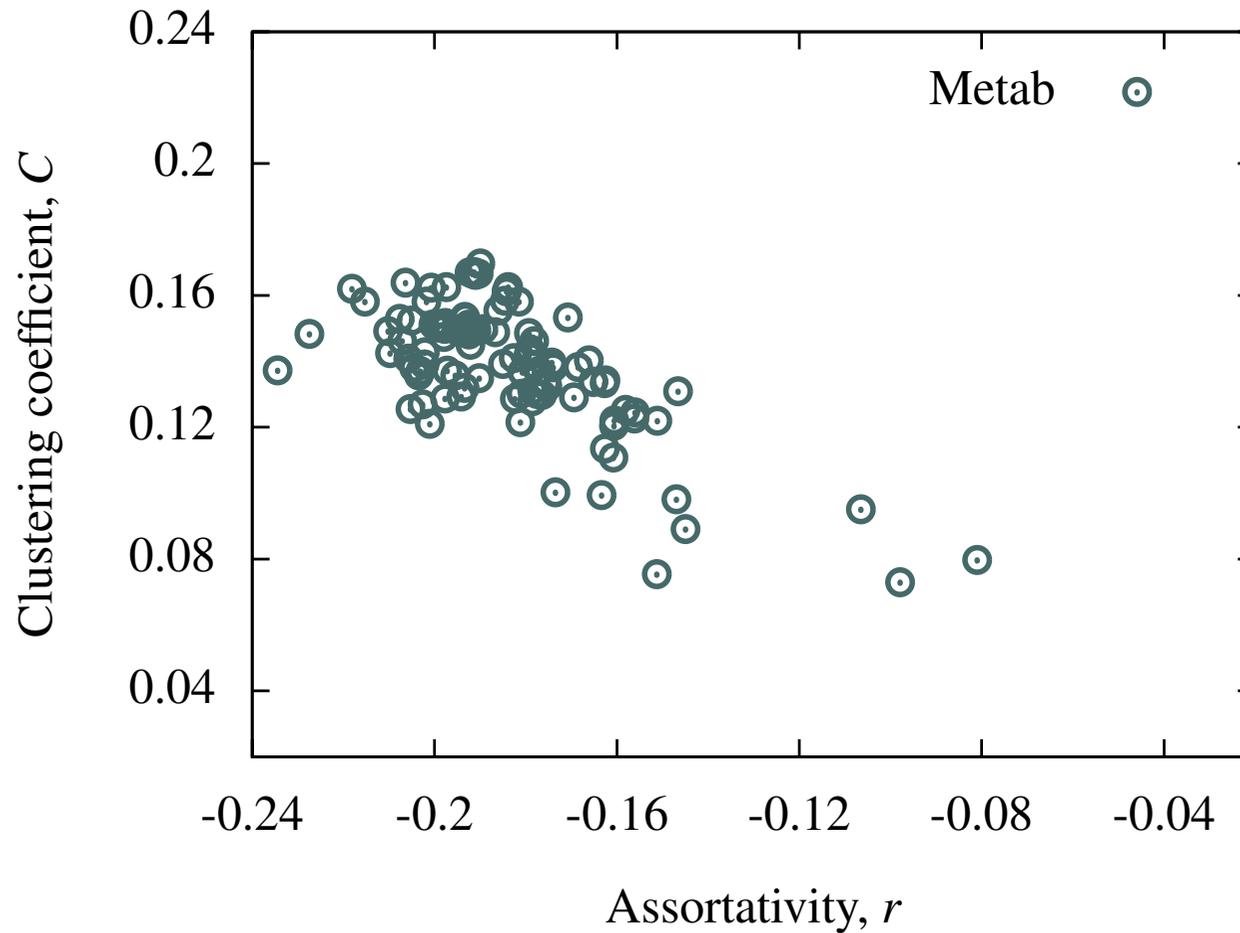
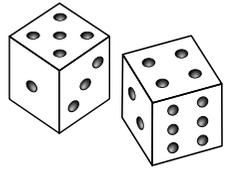
$$\langle r \rangle_{metab} = -0.18 \text{ (-0.178)}$$

$$\langle r \rangle_{BW} = -0.123 \text{ (-0.125)}$$

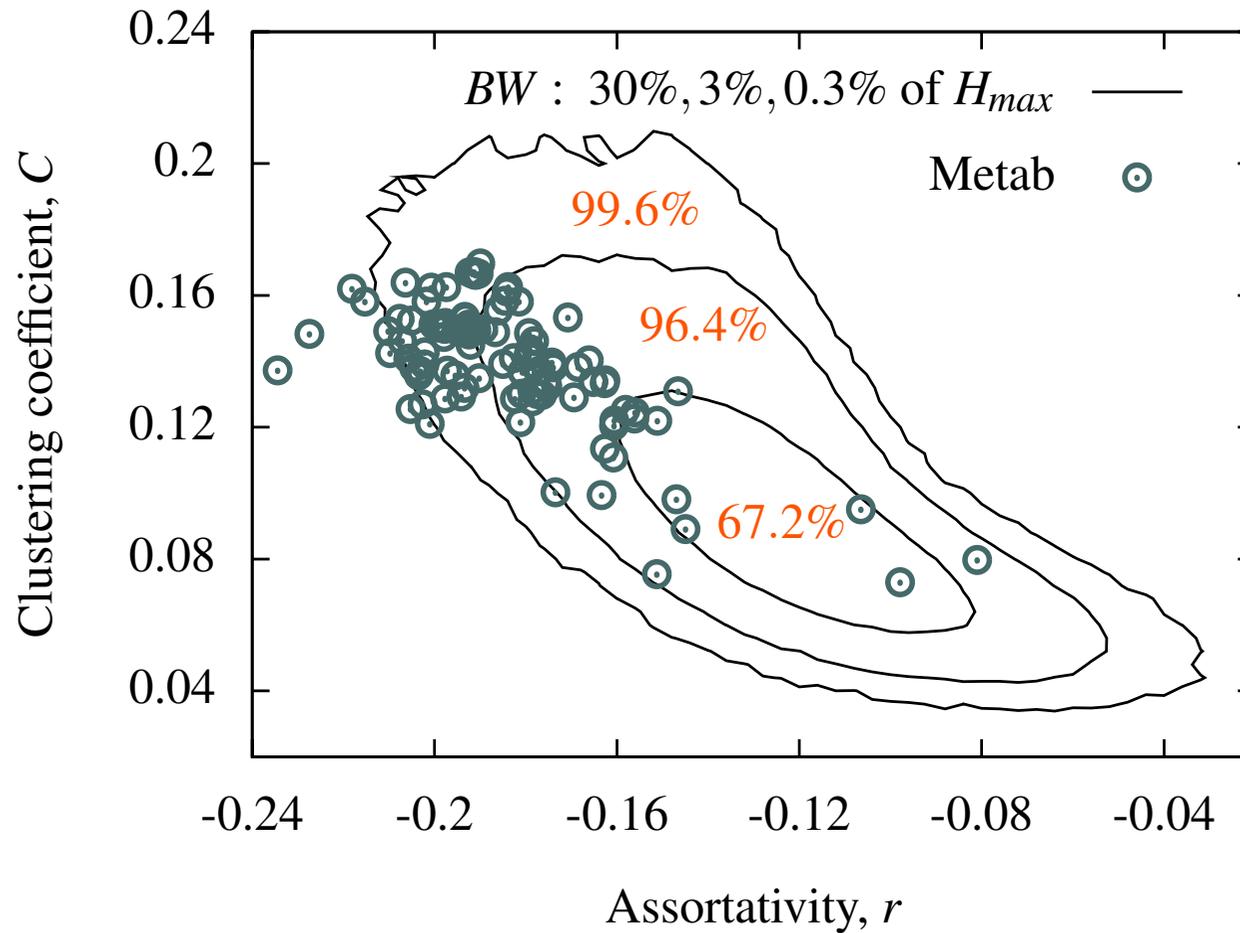
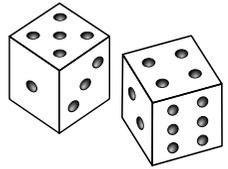


$$-1 \leq r \leq 1$$

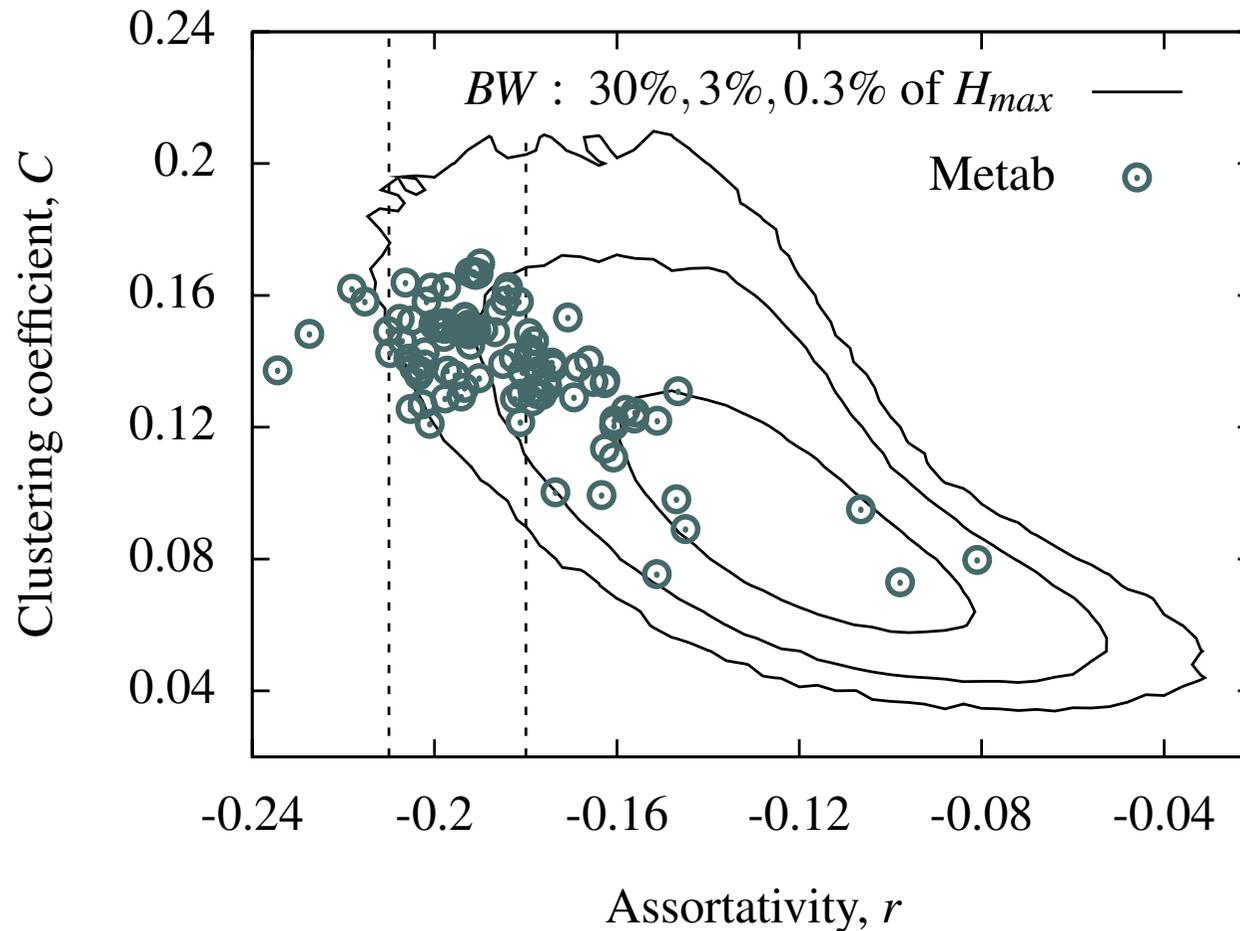
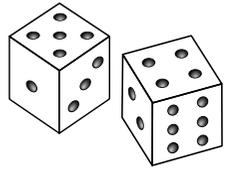
# Clustering-Assortativity space



# Clustering-Assortativity space

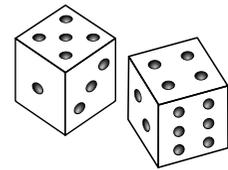


# Region of Low Assortativity



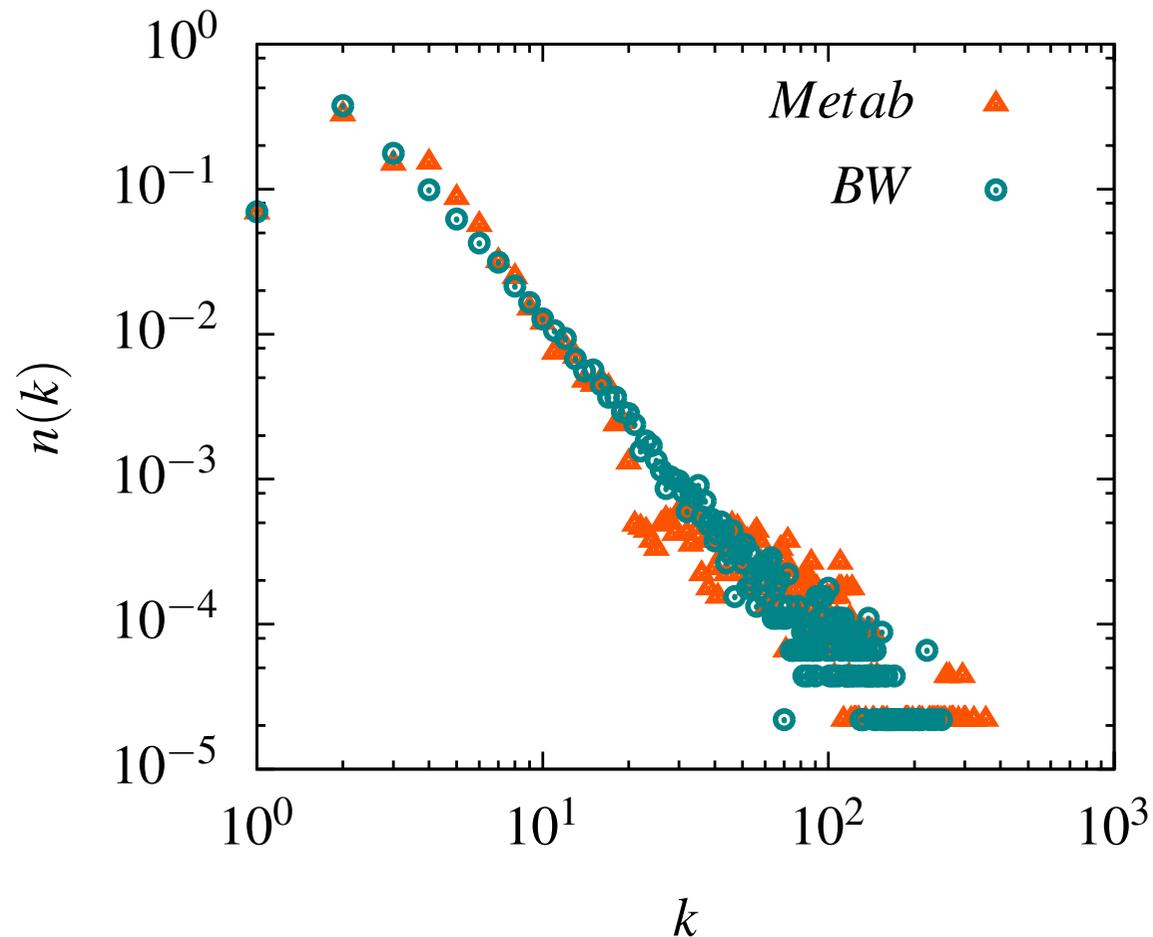
$$-0.21 < r < -0.18 \Rightarrow N_{metab} = 62$$

# Region of Low Assortativity



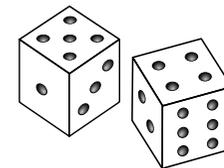
$$\langle C \rangle_{metab} = 0.148$$

$$\langle C \rangle_{BW} = 0.149$$



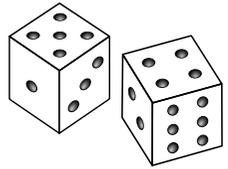
# Conclusions - Part II

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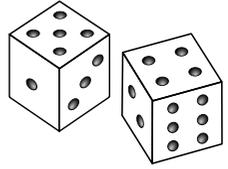
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- Metabolic networks are close to the null model (BW).

# Conclusions - Part II

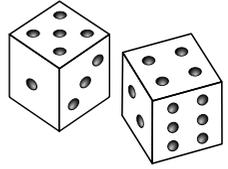
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- Metabolic networks are close to the null model (BW).
- Deviations indicates evolutionary pressure towards lower assortativity.

# Conclusions - Part II

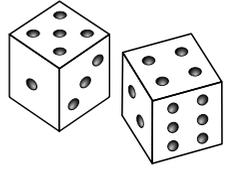
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- Metabolic networks are close to the null model (BW).
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- This pressure, to large extent, is reflected in a small change in the degree distribution.

# Conclusions - Part II

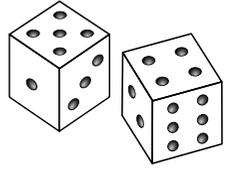
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- Metabolic networks are close to the null model (BW).
- Deviations indicates evolutionary pressure towards lower assortativity.
- This pressure, to large extent, is reflected in a small change in the degree distribution.
- No evolutionary pressure on clustering.

# Acknowledgment

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