

# Graph ensemble design for channel coding

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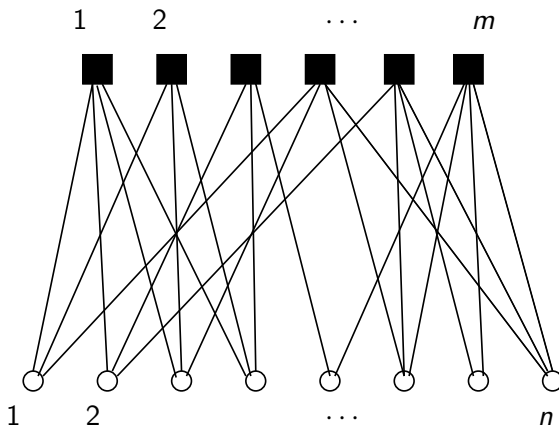
October 18, 2006

## Outline

- 1 The optimization problem
- 2 A probabilistic strategy
- 2 The approximate formula
- 3 Future directions

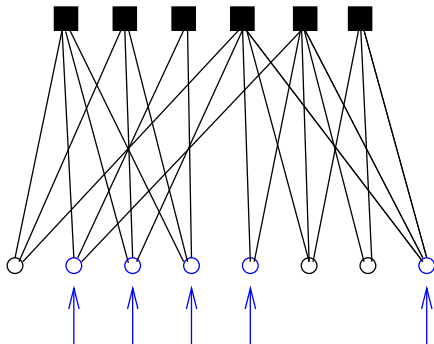
## The optimization problem

# The object to be optimized: A code, i.e. a graph



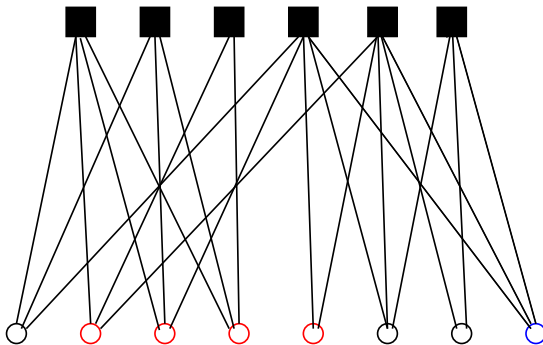
# The objective function

Let  $\mathcal{S} \subseteq [n]$  be random with density  $\epsilon \in [0, 1]$ ...



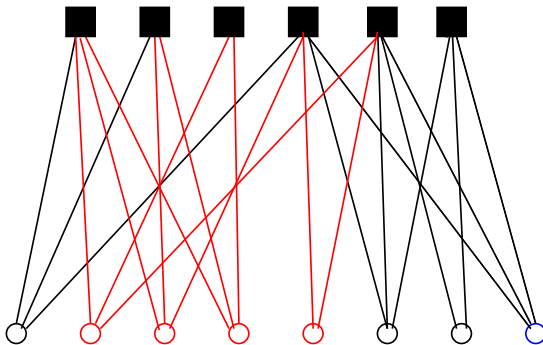
$$P_B(G) = \mathbb{P}_\epsilon \{ \mathcal{S} \text{ contains a 'stopping set'} \}$$

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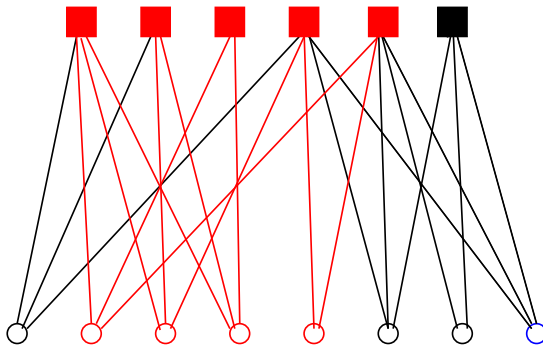
up-degree  $\geq 2$

# The objective function



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Bipartite graph  $G \leftrightarrow$  hypergraph  $H$

$$P_B = \mathbb{P}_\epsilon \{ \text{a random subgraph of } H \text{ contains a } 2\text{-core} \}$$

## A probabilistic strategy

# General strategy

- 1 Define a graph ensemble with parameters  $n$ ,  $m$ ,  
 $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_k)$ ,  $\rho = (\rho_1, \rho_2, \dots, \rho_k)$ .
- 2 Prove an approximate formula  $\mathbb{E}_{\lambda, \rho} P_B \simeq Q(\lambda, \rho)$ . [\*]
- 3 Find  $(\lambda_*, \rho_*) = \arg \min Q(\lambda, \rho)$ .
- 4 Sample  $G$  from the  $(\lambda_*, \rho_*)$ -ensemble and check it.  
*[Concentration]*

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# A 'standard' ensemble

$G$  random (configuration model) with

→ Up-degree distribution:  $\rho = (\rho_1, \dots, \rho_k)$

→ Down-degree distribution:  $\lambda = (\lambda_1, \dots, \lambda_k)$

*Good for  $n = \infty!$  [Luby et al.]*



# Approximate formula for $\mathbb{E}_{\lambda,\rho} P_B$

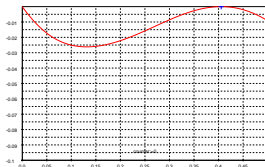
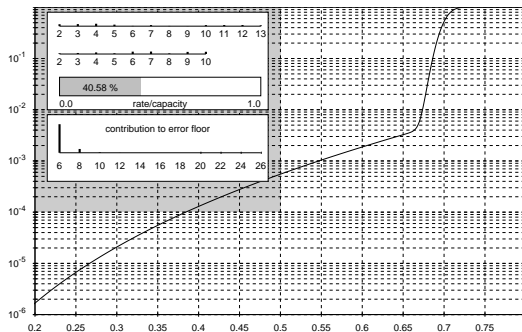
LATER!!!

Sample Run:

Minimize  $m/n$ , given  $P_B = 10^{-4}$

- $\epsilon = 0.5$
- $n = 5000$
- Largest degree 13
- Expurgation 6 [*I did not explain this*]

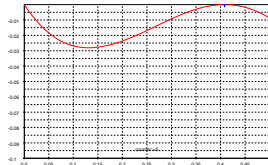
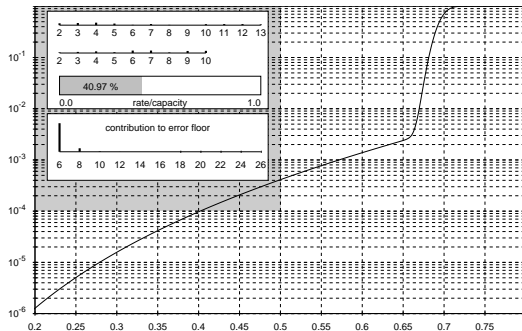
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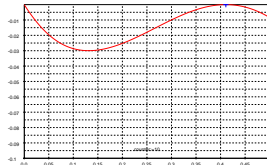
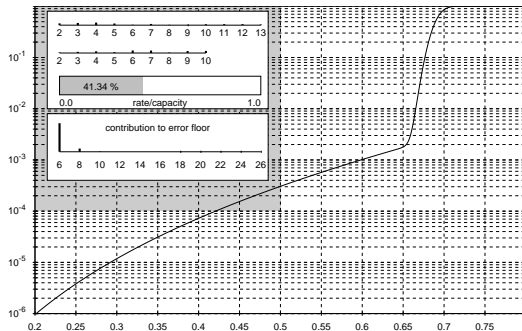
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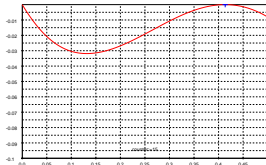
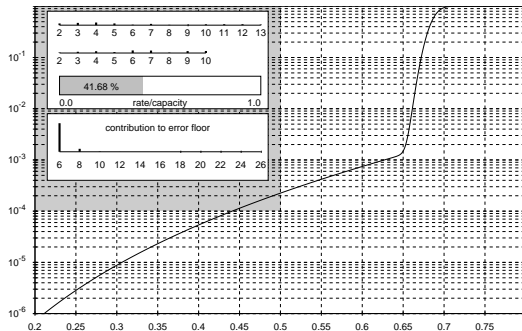
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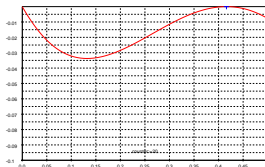
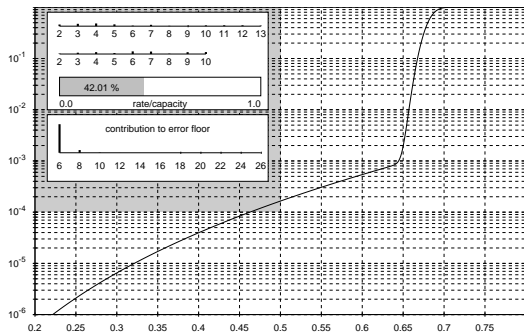
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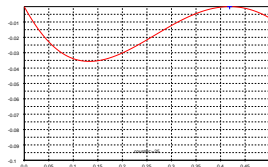
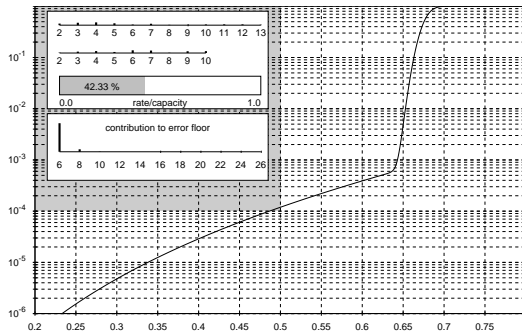
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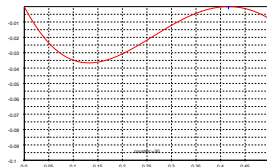
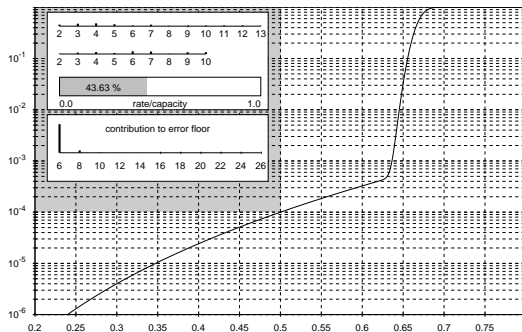


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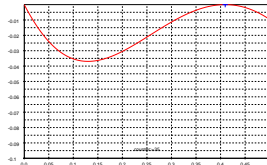
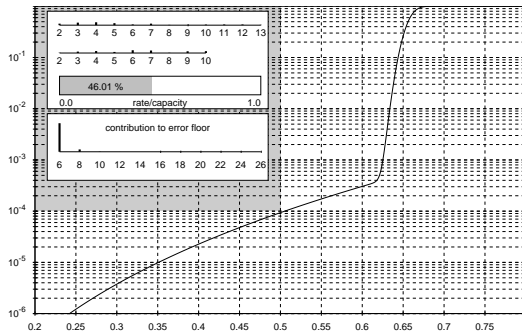
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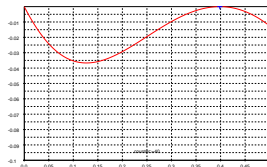
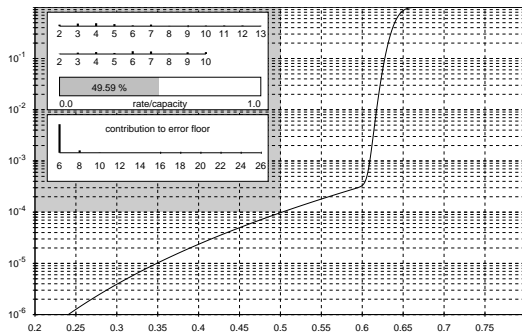
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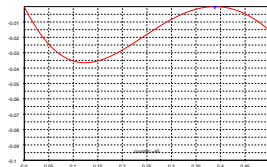
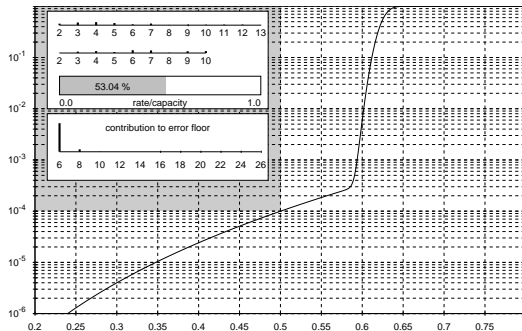
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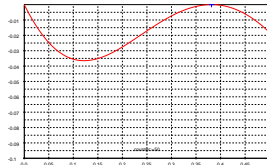
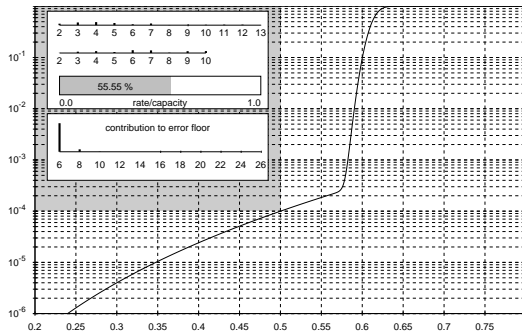
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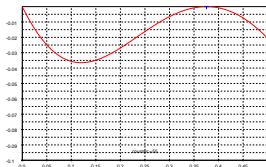
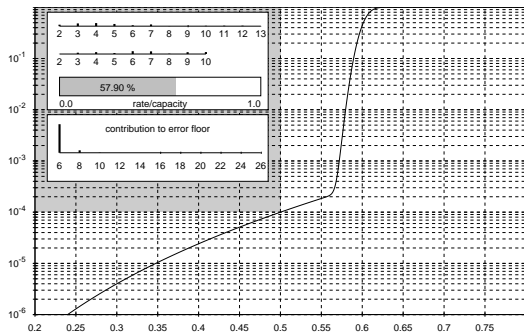
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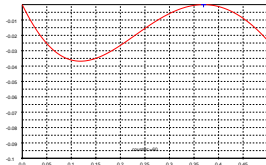
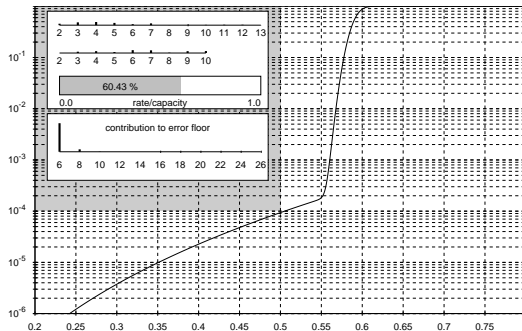
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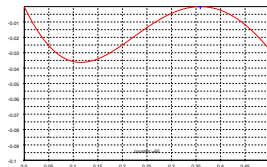
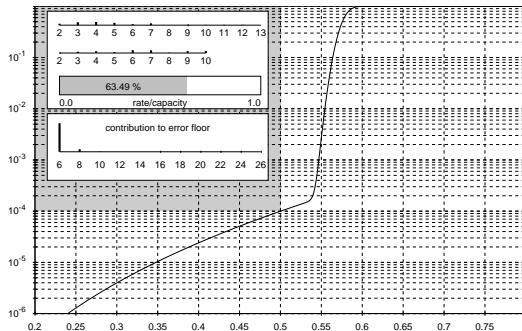
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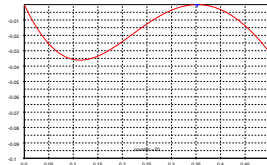
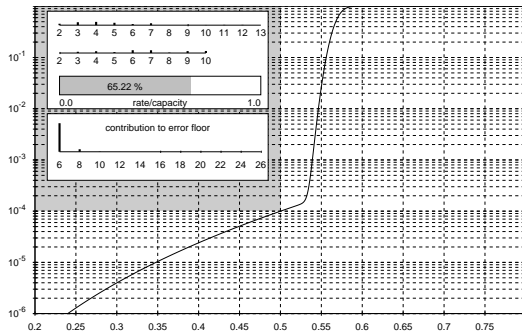


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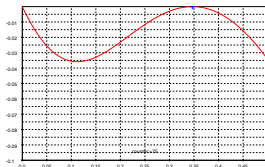
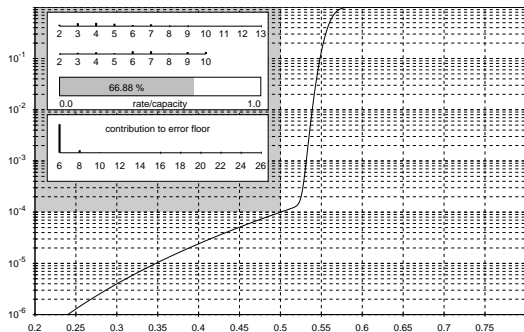
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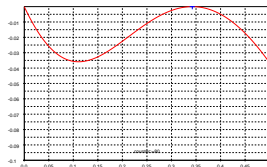
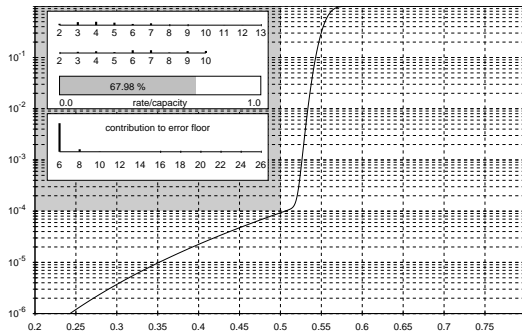
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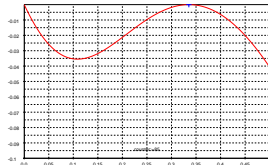
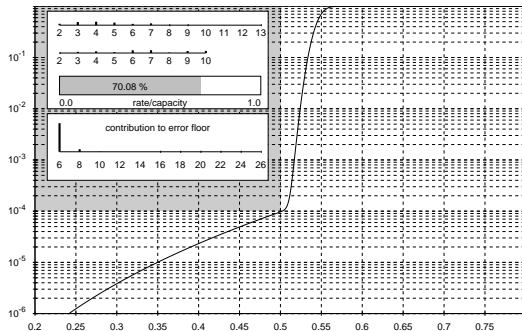
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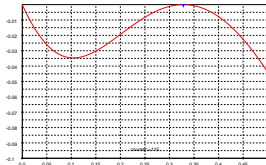
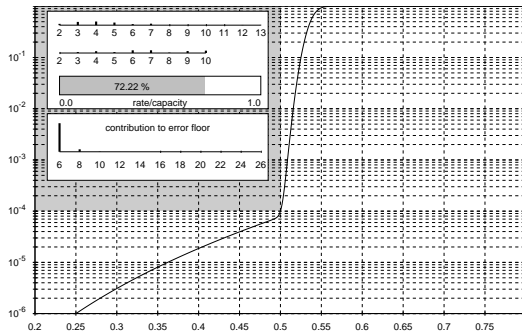
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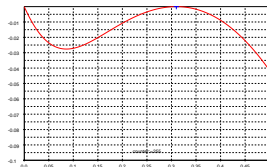
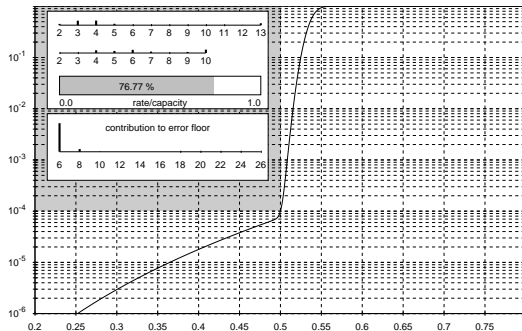
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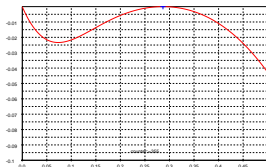
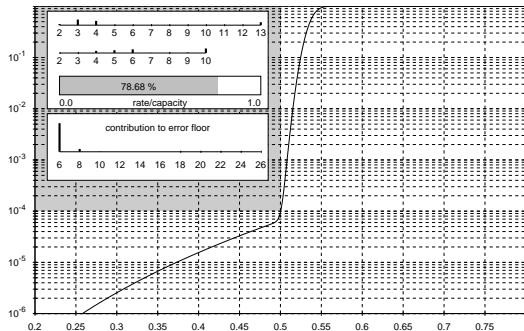
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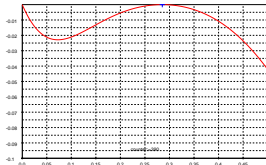
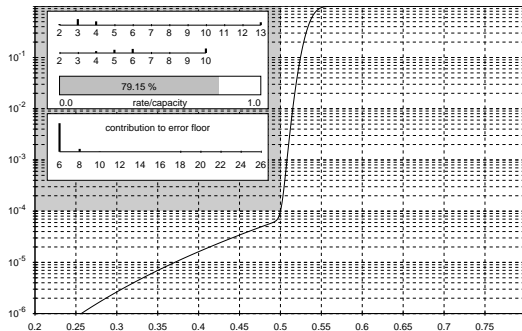
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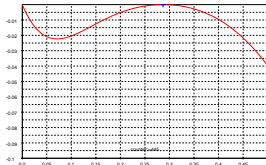
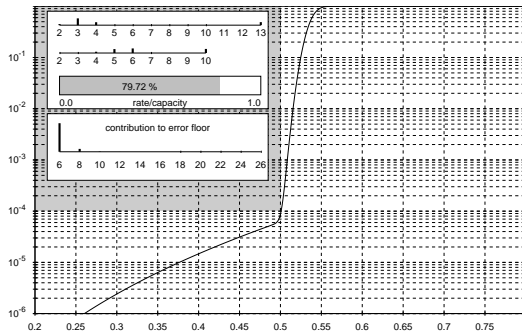


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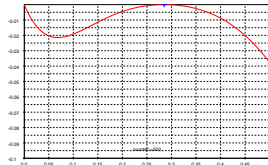
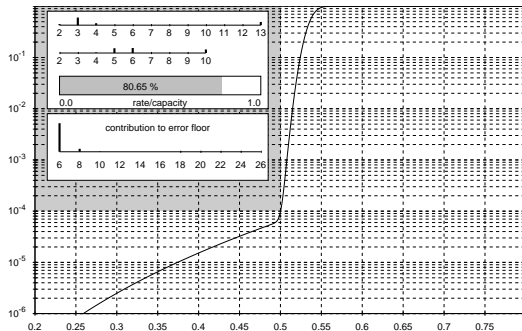
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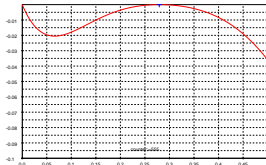
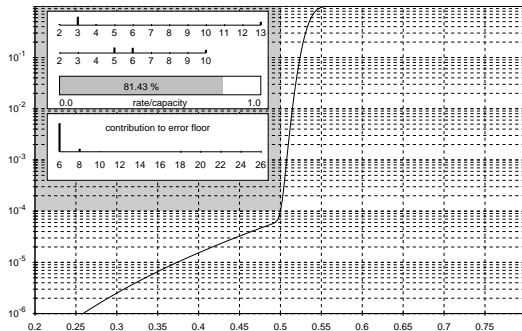
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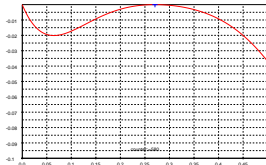
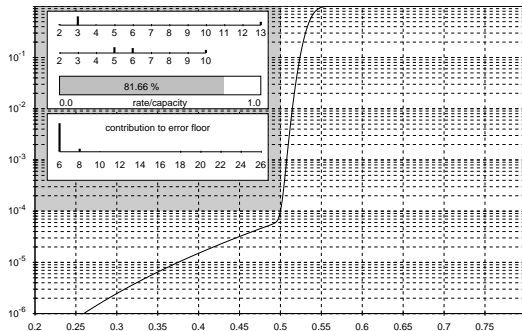


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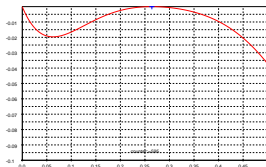
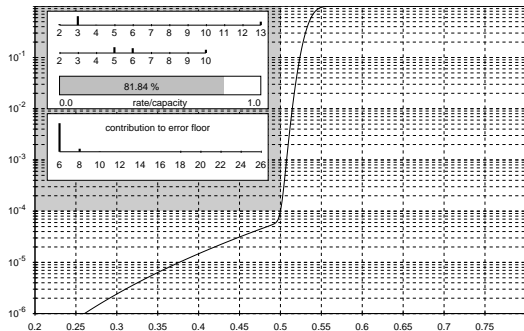
# Example Run



$$\lambda = 0.0739196x + 0.65789x^2 + 0.2681x^{12},$$
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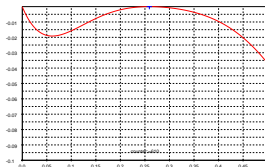
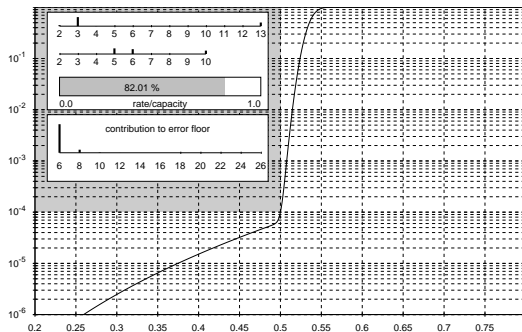
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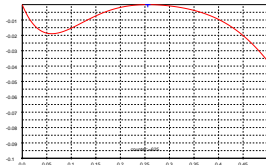
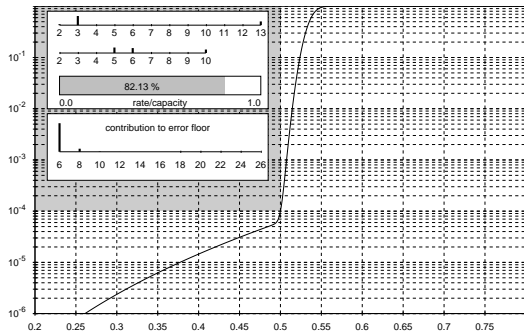
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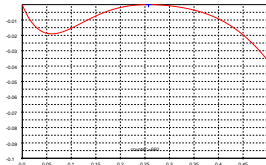
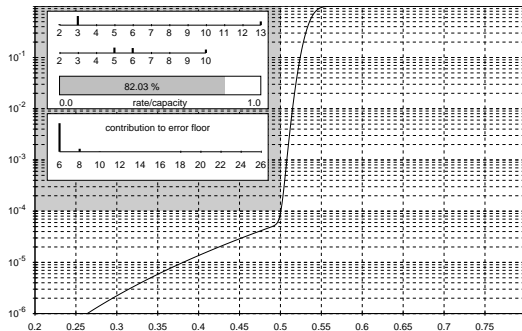


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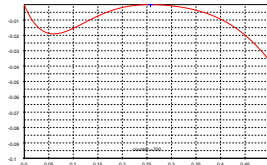
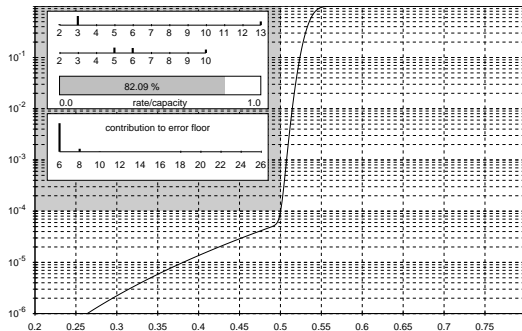


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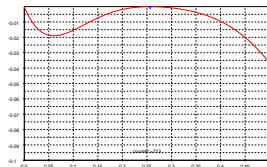
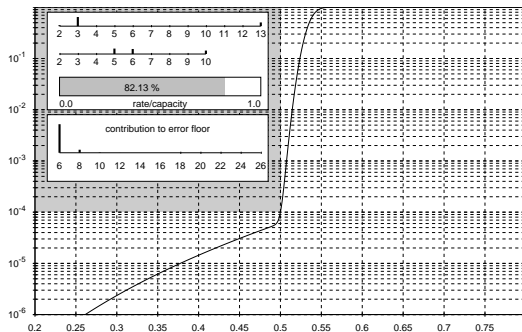
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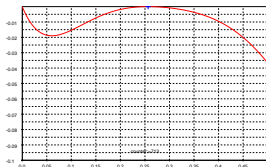
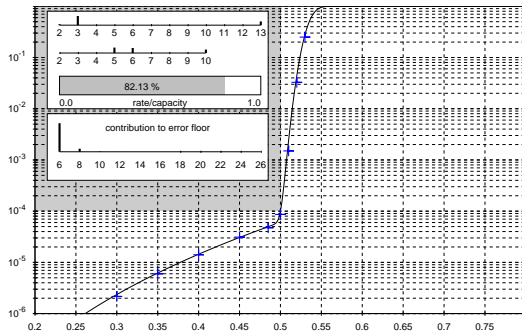
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## The approximate formula

I'll just consider the interesting part of the formula.

Up-degree Poisson, down regular

Want to approximate the probability that a random  $l$ -hypergraph contains a 2-core

# For the sake of simplicity

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Want to approximate the probability that a random  $l$ -hypergraph contains a 2-core

## Theorem (Luby et al., 1997, Darling/Norris, 2003)

Consider a random  $l$ -hypergraph over  $n$  edges and  $m = n/\gamma$  vertices.

There exists  $\gamma_d > 0$ , such that  $P_B(\gamma, n) \rightarrow 0$  if  $\gamma < \gamma_d$  and  $P(\gamma, n) \rightarrow 1$  if  $\gamma > \gamma_d$ . Furthermore

$$\gamma_d = \sup\{\gamma \mid x > 1 - e^{-l\gamma x^{l-1}} \quad \forall x \in (0, 1]\}.$$

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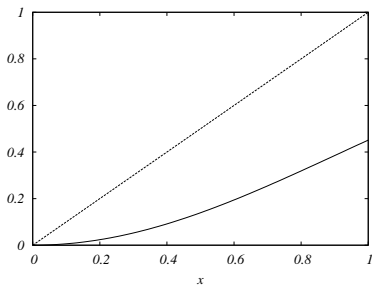


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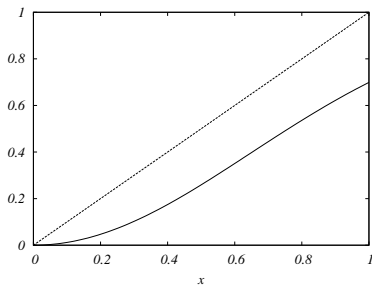


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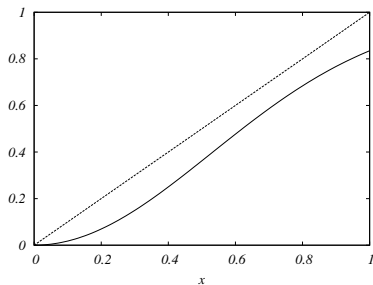


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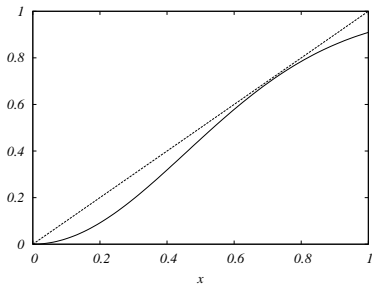


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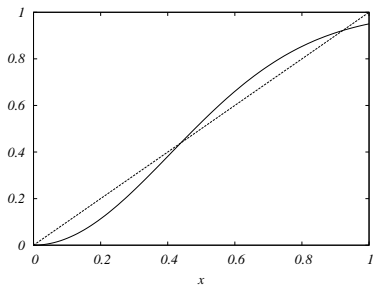


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Pittel, Spencer, Wormald, 1996:  
Analogous [classic!] theorem for  $k$ -cores of random graphs.

## Theorem (Dembo/Montanari 2006)

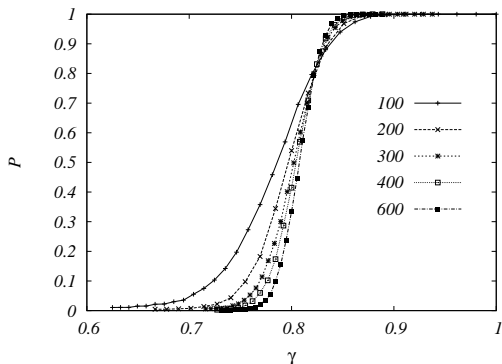
Let  $\gamma_n = \gamma_d + r n^{-1/2}$ . Then

$$P(\gamma_n, n) = \Phi(r/\alpha) + \beta\Omega \Phi'(r/\alpha) n^{-1/6} + o(n^{-1/6}),$$

where  $\Phi(x)$  is the error function,  $\Omega \equiv \int_0^\infty [1 - \mathcal{K}(z)^2] dz$ , and

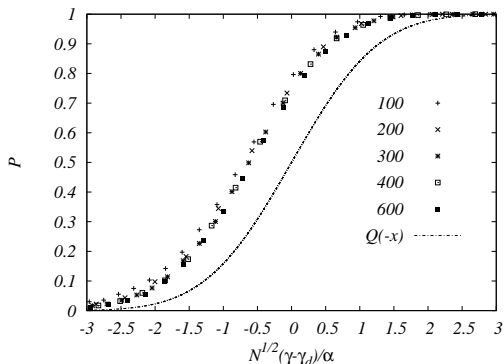
$$\mathcal{K}(z) \equiv \frac{1}{2} \int \frac{\text{Ai}(iy)\text{Bi}(2^{1/3}z + iy) - \text{Ai}(2^{1/3}z + iy)\text{Bi}(iy)}{\text{Ai}(iy)} dy.$$

Finally  $\alpha$  and  $\beta$ ... [solution ODE's]

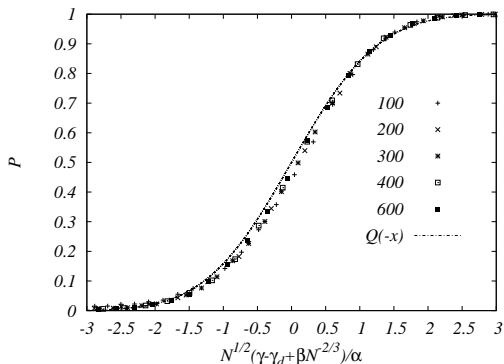




# Scaling: Without correction



# Scaling: With correction



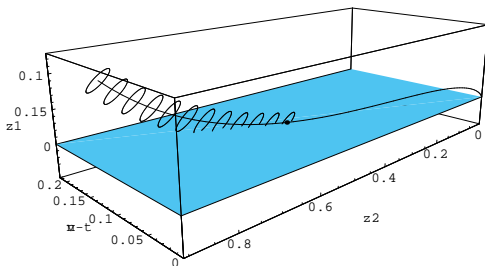
# Analytical (!) expression for the scaling parameters

$$\alpha = \left( \frac{\rho(\bar{x})^2 - \rho(\bar{x}^2) + \rho'(\bar{x})(1 - 2x\rho(\bar{x})) - \bar{x}^2\rho'(\bar{x}^2)}{L'(1)\lambda(y)^2\rho'(\bar{x})^2} + \frac{\epsilon^2\lambda(y)^2 - \epsilon^2\lambda(y^2) - y^2\epsilon^2\lambda'(y^2)}{L'(1)\lambda(y)^2} \right)^{1/2},$$

$$\beta = \dots$$

## Basic ideas in the proof

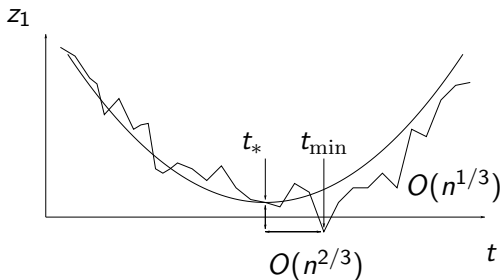
- Graph-pruning procedure as a Markov process in  $\mathbb{R}^{2k}$ .
- Prove a local CLT for the state.
- Approximate by parabola + Brownian near critical point (KMT).



$(z_1(t), z_2(t))$  discrete time Markov process

$$P_B = \mathbb{P}_{\text{gauss}} \left\{ \min_t z_1(t) \leq 0 \right\} .$$

# Correction term



Model:  $z_1(t) = t^2/2n + \text{BM}(t)$

$\Rightarrow O(n^{-1/2}) \cdot O(n^{1/3}) = O(n^{-1/6})$  corrections.

## Future directions

# Future directions

- Other ensembles (Turbo, RA, multi-edge, etc.)
- Code dependency within the ensemble.
- *General memoryless channels.*