

# Random Optimisation Problems

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partly based on joint work with  
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*thanks to Philipp for helping with the pictures!*

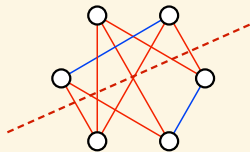
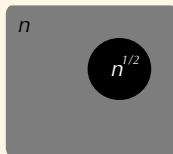
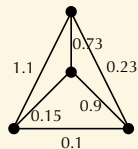
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# Part 1

## Motivation

- ▶ what are random optimisation problems?
- ▶ and what are they good for?

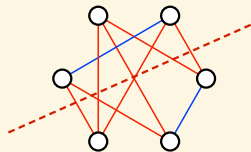
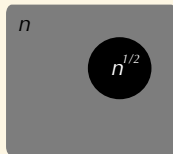
# What are random optimisation problems?



## Examples

- ▶ minimum spanning trees with random weights [F85,...]
- ▶ planted clique [AKS98,...]
- ▶ MAX CUT on random graphs [CGHS04,...]

# The average case myth

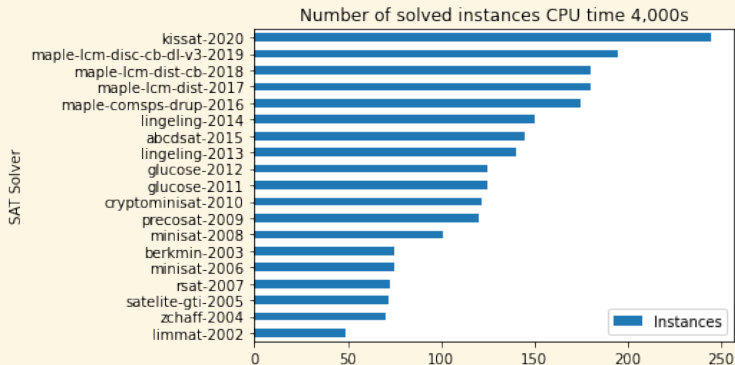


Hypothesis: hard instances are rare...

- ▶ ... but real-world instances are easy!
- ▶ random models of real-world problems?
- ▶ semi-random, smoothed, power law...
- ▶ where are the really hard problems?

[FK01,ST01,FR19]

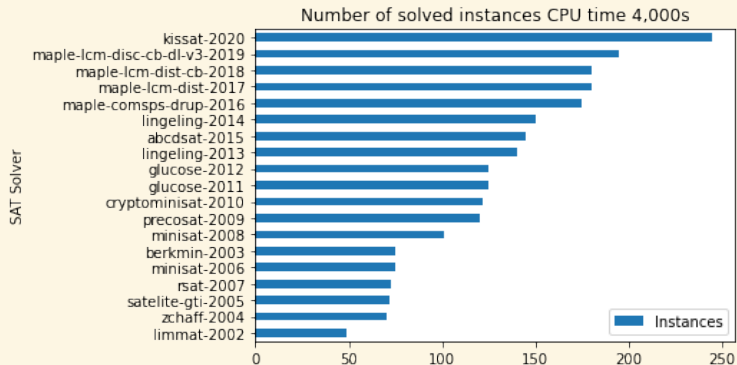
# The average case myth



## Example: SAT solving

- ▶ 10m variables, 32m clauses
- ▶ 2020 winner KISSAT based on clause learning [BFFH2020]
- ▶ real-world SAT instances solved on an industrial scale

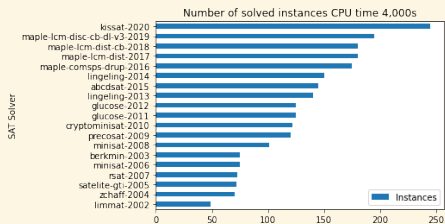
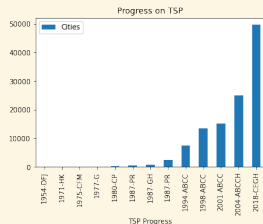
# The average case myth



## Example: random $k$ -SAT

- ▶ satisfiability threshold  $m/n \sim 2^k \log 2$  [DSS15]
- ▶ algorithmic barrier  $m/n \sim 2^k \log(k)/k$  [ACO08,CO09]

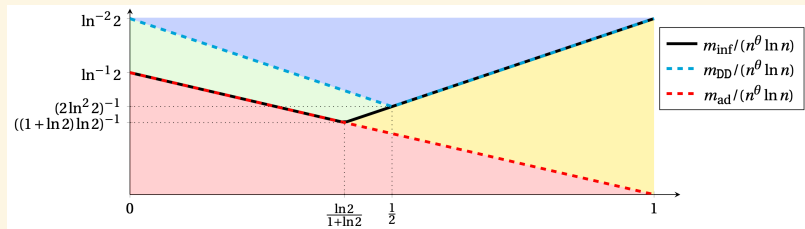
# The average case myth



Hypothesis: hard instances are rare...

- ▶ ... but real-world instances are easy! *[they are structured]*
- ▶ can random instances model real-world problems? *[not really]*
- ▶ semi-random, smoothed, power law... *[excess entropy]*
- ▶ where are the really hard problems? *[try random ones!]*

# The probabilistic method



## Success stories

- ▶ low-density parity check codes
- ▶ compressed sensing
- ▶ group testing

[personal selection]

[G63,KRU11]

[KMSSZ12,DJM13]

[COGHKL20]



# A glimpse of complexity?

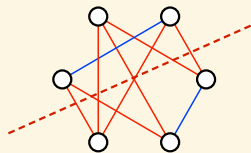
- ▶ proof complexity [BSW00,...]
- ▶ planted clique vs SOS [DM15,BHKKMP19,...]
- ▶  $k$ -SAT refutation [F02,FO07,COGL04,KMODW17,...]
- ▶ overlap gap property [GS14,GZ19,BAWZ20,...]
- ▶ statistical algorithms [FPV13,SW20]

## Part 2

### Techniques

- ▶ what can we prove about random optimisation problems?
- ▶ what techniques do we have at our disposal?

## Running example

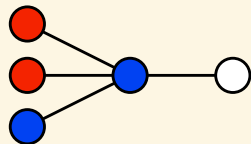


### MAXCUT on random regular graphs

$\mathbb{G} = \mathbb{G}(n, d)$  random  $d$ -regular graph of order  $n$

$$\text{MAXCUT}(\mathbb{G}) = \max_{\sigma \in \{\pm 1\}^n} \sum_{vw \in E(\mathbb{G})} \frac{1 - \sigma_v \sigma_w}{2}.$$

# Combinatorial bounds

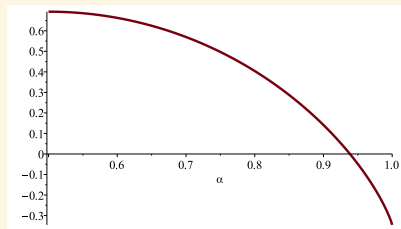


## Greedy algorithms

[DDSW03]

- ▶ assign each vertex the minority spin amongst its neighbours
- ▶ method of differential equations

# Combinatorial bounds

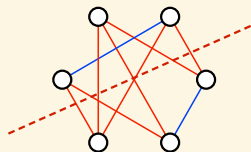


## The first moment bound

The expected number of cuts of size  $\alpha dn/2$  equals

$$\exp\left(n\left[\left(1 - \frac{d}{2}\right)\log 2 + \frac{d}{2}H(\alpha) + o(1)\right]\right)$$

# The physics perspective



## The Ising antiferromagnet

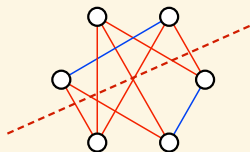
For an inverse temperature  $\beta \geq 0$  introduce

$$\mathcal{H}_{\mathbb{G}}(\sigma) = \sum_{vw \in E(\mathbb{G})} \frac{1 + \sigma_v \sigma_w}{2}$$

$$Z_{\mathbb{G}, \beta} = \sum_{\sigma \in \{\pm 1\}^n} \exp(-\beta \mathcal{H}_{\mathbb{G}}(\sigma))$$

$$\mu_{\mathbb{G}, \beta}(\sigma) = \exp(-\beta \mathcal{H}_{\mathbb{G}}(\sigma)) / Z_{\mathbb{G}, \beta}$$

# The physics perspective



## The Ising antiferromagnet

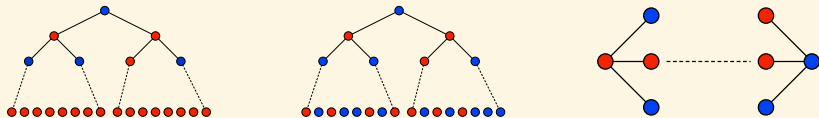
- ▶ The average number of edges cut equals

$$\frac{dn}{2} - \langle \mathcal{H}_{\mathbb{G}}(\boldsymbol{\sigma}), \mu_{\mathbb{G}, \beta} \rangle = \frac{dn}{2} + \frac{\partial}{\partial \beta} \log Z_{\mathbb{G}, \beta}$$

- ▶ Taking  $\beta \rightarrow \infty$  yields

$$\text{MAXCUT}(\mathbb{G}) = \lim_{\beta \rightarrow \infty} \frac{dn}{2} + \frac{\partial}{\partial \beta} \log Z_{\mathbb{G}, \beta}$$

## Replica symmetry breaking



Absence of long-range correlations

[KMRTSZ07]

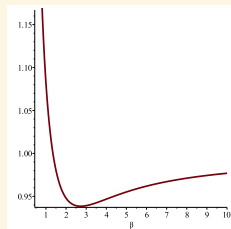
Gibbs uniqueness: the root decouples from the boundary

Non-reconstruction: decoupling from a typical boundary

Static replica symmetry:  $\mathbb{E} \left| \mu_{\mathbb{G}, \beta} (\{\sigma_{v_1} = \sigma_{v_2}\}) - \frac{1}{2} \right| = o(1)$



# Replica symmetry breaking



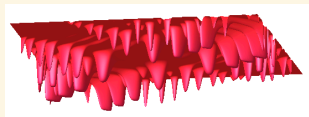
## First moment redux

- ▶ assume static replica symmetry, assemble  $\mathbb{G}$  one edge at a time
- ▶ every time we insert a new edge  $e = vw$ ,

$$\frac{Z_{\mathbb{G},\beta}(\mathbb{G} + e)}{Z_{\mathbb{G},\beta}} \sim 1 - (1 - e^{-\beta})\mu_{\mathbb{G},\beta}(\{\sigma_v = \sigma_w\}) \sim \frac{1 + e^{-\beta}}{2}$$

$$\frac{1}{n} \log Z_{\mathbb{G},\beta} \sim \log 2 + \frac{d}{2} \log \frac{1 + e^{-\beta}}{2} = \frac{1}{n} \log \mathbb{E}[Z_{\mathbb{G},\beta}]$$

## Replica symmetry breaking



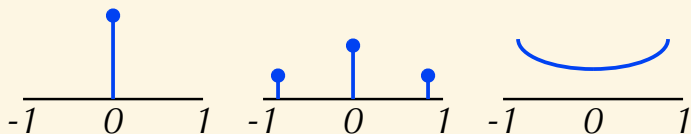
Pure states

[KMRTSZ07]

low  $\beta$  the cross-section is contiguous

high  $\beta$  decomposition into separate pure states

## Replica symmetry breaking



The overlap

[KMRTSZ07]

replica symmetry the overlap  $\sigma \cdot \sigma' / n$  concentrates about 0

1-step replica symmetry breaking concentration on two points

full replica symmetry breaking no overlap concentration

# The replica symmetry breaking transition

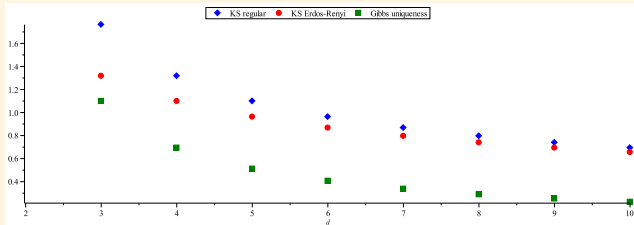
The free energy

The singularities of

$$\phi_d(\beta) = \lim_{n \rightarrow \infty} \frac{1}{n} \mathbb{E}[\log Z_{\mathbb{G}, \beta}]$$

are called *phase transitions*.

# The replica symmetry breaking transition



## Theorem

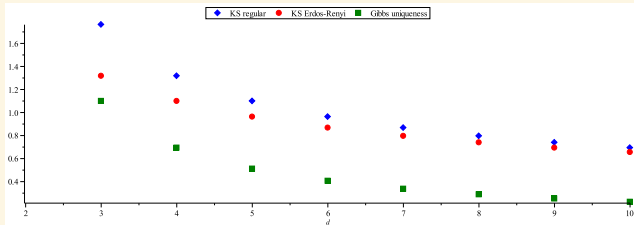
[COLMS20]

For any  $d \geq 3$  we have

$$\phi_d(\beta) = \log 2 + \frac{d}{2} \log \frac{1 + e^{-\beta}}{2} \quad \text{if } \beta \leq \beta^*(d) = \log \frac{\sqrt{d-1} + 1}{\sqrt{d-1} - 1}$$

$$\phi_d(\beta) < \log 2 + \frac{d}{2} \log \frac{1 + e^{-\beta}}{2} \quad \text{if } \beta > \beta^*(d)$$

# The replica symmetry breaking transition



## Non-reconstruction/Kesten-Stigum

- ▶ broadcasting on the  $(d - 1)$ -ary tree
- ▶ reconstruction threshold at  $\beta^*(d) = \log \frac{\sqrt{d-1}+1}{\sqrt{d-1}-1}$
- ▶ Gibbs uniqueness threshold at  $\beta^\dagger(d) = \log \frac{d}{d-2}$

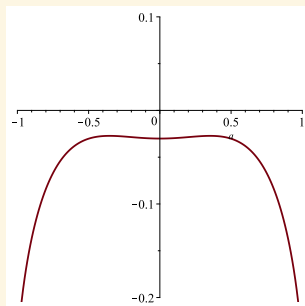
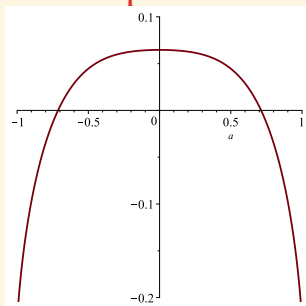
## First attempt

### The second moment method

$$\begin{aligned}\mathbb{E}[Z_{\mathbb{G},\beta}^2] &= \sum_{\sigma,\sigma' \in \{\pm 1\}^n} \mathbb{E}[\exp(-\beta \mathcal{H}_{\mathbb{G}}(\sigma) - \beta \mathcal{H}_{\mathbb{G}}(\sigma'))] \\ &= \sum_{a=-n}^n \sum_{\sigma,\sigma'=a} \mathbb{E}[\exp(-\beta \mathcal{H}_{\mathbb{G}}(\sigma) - \beta \mathcal{H}_{\mathbb{G}}(\sigma'))] \\ &= \exp\left(n \max_{\alpha \in [-1,1]} f_{d,\beta}(\alpha) + o(n)\right)\end{aligned}$$

$$f_{d,\beta}(\alpha) = (1-d) \log 2 + H\left(\frac{1+\alpha}{2}\right) + \frac{d}{2} \log\left((1+e^{-\beta})^2 + \alpha^2(1-e^{-\beta})^2\right).$$

## First attempt

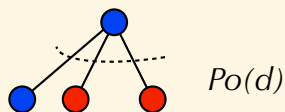
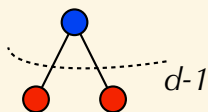


## The second moment method

- ▶  $\mathbb{E}[Z_{\mathbb{G},\beta}^2] = O(\mathbb{E}[Z_{\mathbb{G},\beta}]^2)$  iff  $f_{d,\beta}(\alpha)$  attains its max at  $\alpha = 0$
- ▶ this is the case iff  $\beta < \beta^*(d+1) < \beta^*(d)$



## First attempt

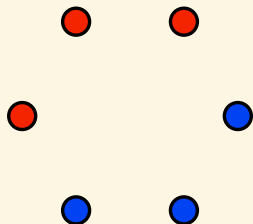


## The Erdős-Rényi model

- ▶ identical first/second moments
- ▶  $Po(d)$  offspring in the Erdős-Rényi model
- ▶ phase transition at  $\beta^*(d+1)$

[MNS15]

# The planted model



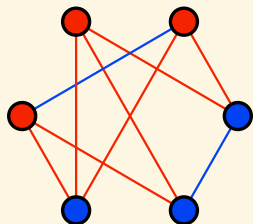
... aka stochastic block model

- ▶ draw a configuration  $\sigma^* \in \{\pm 1\}^n$
- ▶ draw a  $d$ -regular graph  $\mathbb{G}^*$  from

$$\mathbb{P}[\mathbb{G}^* = G \mid \sigma^*] \propto \exp(-\beta \mathcal{H}_G(\sigma^*))$$

- ▶  $\mathbb{P}[\mathbb{G}^* \in \mathcal{E}] = \Theta(\mathbb{E}[Z_{\mathbb{G}, \beta} \cdot \mathbb{1}\{\mathbb{G} \in \mathcal{E}\}])$

# The planted model



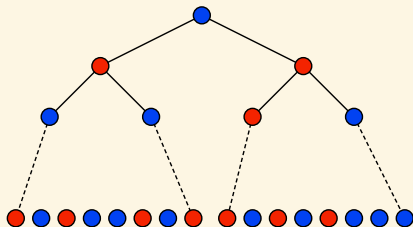
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- ▶ draw a configuration  $\sigma^* \in \{\pm 1\}^n$
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- ▶  $\mathbb{P}[G^* \in \mathcal{E}] = \Theta(\mathbb{E}[Z_{G,\beta} \cdot \mathbf{1}\{G \in \mathcal{E}\}])$

# The planted model



## The broadcasting process

- ▶ locally  $(\mathbb{G}^*, \sigma^*)$  resembles the broadcasting process
- ▶  $\Rightarrow \mu_{\mathbb{G}^*, \beta}$  has static replica symmetry for  $\beta < \beta^*(d)$
- ▶  $\Rightarrow$  overlap concentrates about zero for  $\beta < \beta^*(d)$  [cf. MNS15]

$$\mu_{\mathbb{G}^*, \beta}(\{\sigma \cdot \sigma' / n < \varepsilon\}) \sim 1$$

# The planted model

## The truncated second moment

- ▶  $\mathcal{E} = \{\mu_{\mathbb{G},\beta}(\{\boldsymbol{\sigma} \cdot \boldsymbol{\sigma}' / n < \varepsilon\}) \sim 1\}$
- ▶  $\mathbb{E}[Z_{\mathbb{G},\beta} \cdot \mathbb{1}\{\mathbb{G} \in \mathcal{E}\}] \sim \mathbb{E}[Z_{\mathbb{G},\beta}]$
- ▶  $\mathbb{E}[Z_{\mathbb{G},\beta}^2 \cdot \mathbb{1}\{\mathbb{G} \in \mathcal{E}\}] = \mathbb{E}[Z_{\mathbb{G},\beta}]^2 \cdot \exp(\varepsilon^2 n)$
- ▶ Paley-Zygmund inequality

$$\Rightarrow Z_{\mathbb{G},\beta} \geq Z_{\mathbb{G},\beta} \cdot \mathbb{1}\{\mathbb{G} \in \mathcal{E}\} \geq \mathbb{E}[Z_{\mathbb{G},\beta}] \cdot \exp(o(n)) \text{ w.h.p.}$$

*The first part of the theorem follows.*

# The planted model diverges

## Quiet vs noisy planting

- ▶  $\log Z_{\mathbb{G},\beta}$  is tightly concentrated about  $\mathbb{E}[\log Z_{\mathbb{G},\beta}]$
- ▶  $\Rightarrow$  if  $\mathbb{E}[\log Z_{\mathbb{G},\beta}] \sim \log \mathbb{E}[Z_{\mathbb{G},\beta}]$ , then  $\mathbb{G} \approx \mathbb{G}^*$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \mathbb{E}[\log Z_{\mathbb{G}^*,\beta}] > \log 2 + \frac{d}{2} \log \frac{1 + e^{-\beta}}{2} \geq \phi_d(\beta)$$

$$\Rightarrow \phi_d(\beta) < \log 2 + \frac{d}{2} \log \frac{1 + e^{-\beta}}{2}$$

# The planted model diverges

The planted free energy

[COHKLMPP20]

$$\lim_{n \rightarrow \infty} \frac{1}{n} \mathbb{E}[\log Z_{\mathbb{G}^*, \beta}] = \sup_{\pi} \mathcal{B}_{d, \beta}^*(\pi)$$

$$\mathcal{B}_{d, \beta}^*(\pi) = \mathbb{E} \left[ \frac{\Lambda \left( \sum_{\sigma = \pm 1} \prod_{i=1}^d 1 - (1 - e^{-\beta})(1 + \sigma \rho_i) / 2 \right)}{2^{1-d} (1 + e^{-\beta})^d} - \frac{d \Lambda \left( 1 - (1 - e^{-\beta})(1 + \rho_1 \rho_2) / 2 \right)}{1 + e^{-\beta}} \right]$$

$$\Lambda(x) = x \log x$$

# The planted model diverges

## Lemma

For  $\beta > \beta^*(d)$  there is  $\varepsilon > 0$  such that  $\pi_\varepsilon = \frac{1}{2}(\delta_{-\varepsilon} + \delta_\varepsilon)$  satisfies

$$\mathcal{B}_{d,\beta}^*(\pi_\varepsilon) > \log 2 + \frac{d}{2} \log \frac{1 + e^{-\beta}}{2}$$

## Proof

- ▶ Compute the first four derivatives of  $\varepsilon \mapsto \mathcal{B}_{d,\beta}^*(\pi_\varepsilon)$
- ▶ (seriously...)

*We thus obtain the second part of the theorem.*



# The interpolation method

## Theorem

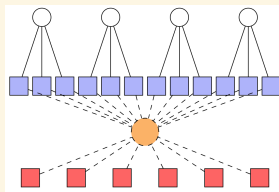
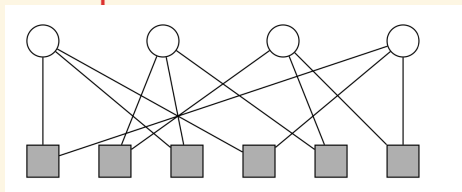
[SSZ16]

For any  $d \geq 3$ ,  $\beta > 0$ , any probability measure  $r$  on  $(-1, 1)$  and any  $0 < y < 1$  we have

$$\begin{aligned}\phi_d(\beta) &\leq \frac{1}{y} \log \mathbb{E}[\mathbf{X}^y] - \frac{d}{2y} \log \mathbb{E}[\mathbf{Y}^y] \\ \mathbf{X} &= \sum_{\tau=\pm 1} \prod_{i=1}^d 1 - (1 - e^{-\beta}) \frac{1 + \tau \rho_i}{2} \\ \mathbf{Y} &= 1 - (1 - e^{-\beta}) \sum_{\tau=\pm 1} \frac{(1 + \tau \rho_1)(1 + \tau \rho_2)}{4}\end{aligned}$$

*Regular variant of [G03, FL03, PT04].*

# The interpolation method



## Pure states and Poisson–Dirichlet weights

- ▶ auxiliary model that represents the 1-step rsb scenario
- ▶ interpolation along time  $t \in [0, 1]$
- ▶ *Hypothesis*: the weights of the pure states are Poisson–Dirichlet
- ▶ to bound MAX CUT we use  $\text{MAXCUT}(\mathbb{G}) \leq \frac{dn}{2} + \frac{1}{\beta} \log Z_{\mathbb{G}, \beta}$

# The interpolation method

## Theorem

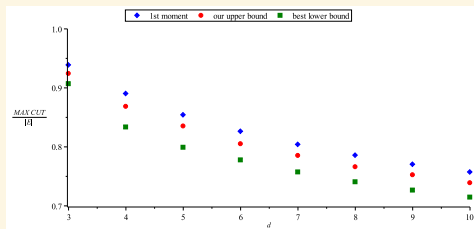
For any  $d \geq 3$  we have

$$\text{MAXCUT}(\mathbb{G}) \leq \frac{dn}{2} \left( 1 + \inf_{\alpha, z} \frac{\log \zeta \mathcal{A}^d \xi}{\log z} + \frac{d \log(1 - 2\alpha^2 + 2\alpha^2 z)}{2 \log z} \right)$$

$$\zeta = (1, 0, 0, \dots) \quad \xi = (1, z^{-1/2}, z^{-1}, \dots)^T$$

$$\mathcal{A} = (1 - 2\alpha)\text{id} + 2\alpha\sqrt{z} \begin{bmatrix} 0 & 1 & 0 & \cdots & \cdots & \cdots \\ \frac{1}{2} & 0 & \frac{1}{2} & \ddots & & \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} & \ddots & \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots \\ \vdots & & \ddots & \ddots & \ddots & \ddots \\ \vdots & & & 0 & 1 & 0 \end{bmatrix}$$

# The interpolation method



## Some numbers

$d$	3	4	5	6	7	8	9	10
1st mmt	0.9385	0.8900	0.8539	0.8260	0.8038	0.7855	0.7701	0.7570
new bound	0.9241	0.8683	0.8350	0.8049	0.7851	0.7659	0.7523	0.7388
greedy	0.9067	0.8333	0.7989	0.7775	0.7571	0.7404	0.7263	0.7144

*Match the numbers of [ZB10].*

# Outlook

- ▶ Bethe states and precise variational formulas [COP19]
- ▶ convergence to Sherrington–Kirkpatrick as  $d \rightarrow \infty$  [DMS19]
- ▶ proof of the 1RSB formula in  $k$ -NAESAT [SSZ16]
- ▶ breaking of 1RSB [BSZ19]
- ▶ *open*: the Zdeborová–Boettcher conjecture [ZB10]
- ▶ *open*: better MAX CUT algorithms [see Eliran's talk]
- ▶ *open*: planted MAX CUT [CO05]
- ▶ *open*: ultrametricity and the Gibbs measure [P13]

# Summary

## Random optimisation problems

- ▶ hard but rewarding
- ▶ algorithmic challenges and new algorithms
- ▶ probabilistic constructions
- ▶ techniques:
  - ▶ physics-enhanced moment methods
  - ▶ the planted model
  - ▶ spatial mixing and asymptotic Gibbs measures
  - ▶ the interpolation method
  - ▶ coupling arguments