

Spatial coupling: a tool for rigorous analysis in Bayesian inference

Nicolas Macris

School of Computer and Communication Science
Ecole Polytechnique Fédérale de Lausanne

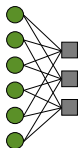
Plan

- ▶ Brief flavour of "spatial coupling" through:
 - ▶ Its origin in theory of error correcting codes for channel communication.
 - ▶ An application to lower bounds on thresholds of constraint satisfaction problems.

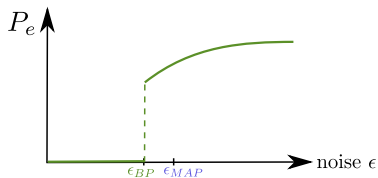
- ▶ **Main focus of the talk:** proof technique for replica formulas
 - ▶ Example of rank-one matrix factorisation.
[joint work with J. Barbier, M. Dia, F. Krzakala, T. Lesieur, and L. Zdeborova]

Spatial Coupling in coding theory: cartoon view

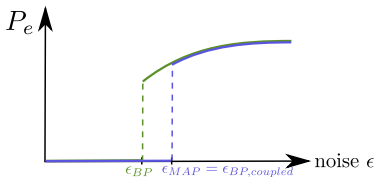
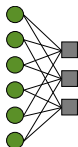
- ▶ standard LDPC code



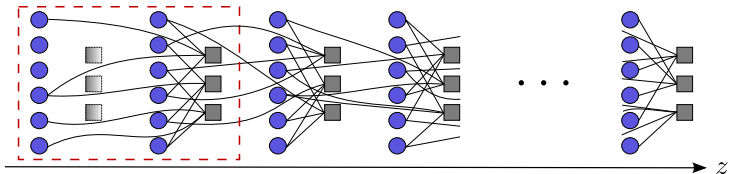
Belief Propagation decoding of transmitted bits \rightarrow Prob error



▶ standard LDPC code



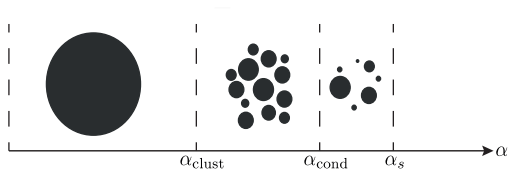
- ▶ Spatially Coupled LDPC code - bits at boundary are known and act as a seed



An engineering construction of Felstroem, Zigangirov (1999); Proofs that these codes are capacity achieving on general classes of channels [S.Kudekar, T.Richardson, R.Urbanke (2013) and H.Pfister, S.Kumar, A.Young, N.M (2013)]

Application to lower bounds for thresholds of constraint satisfaction problems

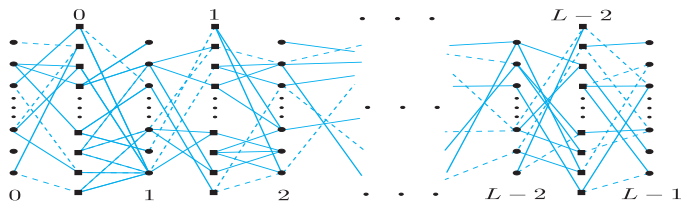
[by the cavity method: Parisi-Mézard-Zecchina 2002, Montanari-Ricci Tersenghi-Semerjian, Krzakala-Zdeborova 2007]



- ▶ Clustered phase is a problem for proving algorithmic lower bounds on α_s .
- ▶ Idea: remove clustered phase by spatial coupling - at the same time maintain α_s .
- ▶ Analyze simple algorithms to get lower bounds.

Coupled K -SAT model:

Chain of K -SAT models with constraints at boundaries removed.



Lower bounds by running Unit Clause:

K	3	4	...	large K
$\alpha_{\text{spa-coup}}$	3.67	7.81	...	$\sim 2^K \times \frac{1}{2}$
usual algo bound	3.52	5.54	...	$\sim 2^K \times \frac{\ln K}{K}$

Rank one matrix factorisation: proof of the replica predictions

We are given noisy observations w_{ij} of pairwise products $s_i s_j$ for $\mathbf{s} = (s_1, \dots, s_n)$ with i.i.d $s_i \sim P_0$ known,

$$w_{ij} = \frac{s_i s_j}{\sqrt{n}} + z_{ij} \sqrt{\Delta},$$

where $Z_{ij} \sim \mathcal{N}(0, 1)$, $1 \leq i \leq j \leq n$ (symmetric i.i.d).

Bayesian formulation:

$$p(\mathbf{X}|\mathbf{W}) = \frac{1}{P(\mathbf{W})} P_0(x_i) \exp \left(- \frac{1}{2\Delta} \sum_{i \leq j} (w_{ij} - x_i x_j / \sqrt{n})^2 \right)$$

Key quantities

- ▶ Optimal "MMSE estimators" are averages with respect to this Gibbs distribution:

$$\mathbb{E}[\mathbf{X}|\mathbf{W}] = \langle \mathbf{X} \rangle, \quad \mathbb{E}[\mathbf{X}\mathbf{X}^T|\mathbf{W}] = \langle \mathbf{X}\mathbf{X}^T \rangle$$

- ▶ Matrix-MMSE and Mutual Information (I-MMSE formula):

$$\frac{d}{d\Delta^{-1}} \frac{1}{n} I(\mathbf{S}; \mathbf{W}) = \frac{1}{4n^2} \mathbb{E}_{\mathbf{s}, \mathbf{w}} \|\mathbf{S}\mathbf{S}^T - \langle \mathbf{X}\mathbf{X}^T \rangle\|_F^2$$

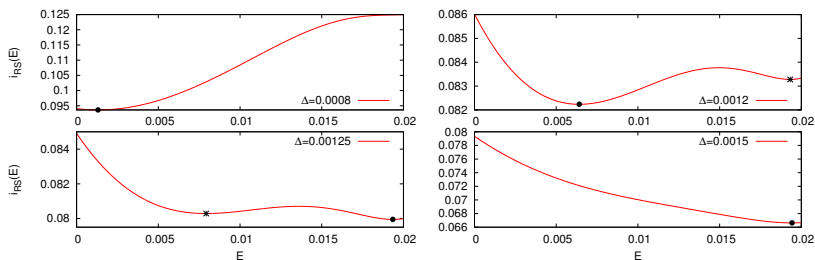
where

$$I(\mathbf{S}; \mathbf{W}) = \underbrace{H(\mathbf{W})}_{-\mathbb{E}_{\mathbf{W}} \log P(\mathbf{W})} - \underbrace{H(\mathbf{W}|\mathbf{S})}_{\text{trivial term}}$$

Replica symmetric potential

$$\begin{aligned}
 i_{\text{RS}}(E; \Delta) &= \frac{E^2}{4\Delta} + \mathbb{I}(S; S + \Sigma Z) \\
 &= \frac{(v - E)^2 + v^2}{4\Delta} - \mathbb{E}_{S, Z} \left[\ln \left(\int dx P_0(x) e^{-\frac{x^2}{2\Sigma^2} + x \left(\frac{S}{\Sigma^2} + \frac{Z}{\Sigma} \right)} \right) \right]
 \end{aligned}$$

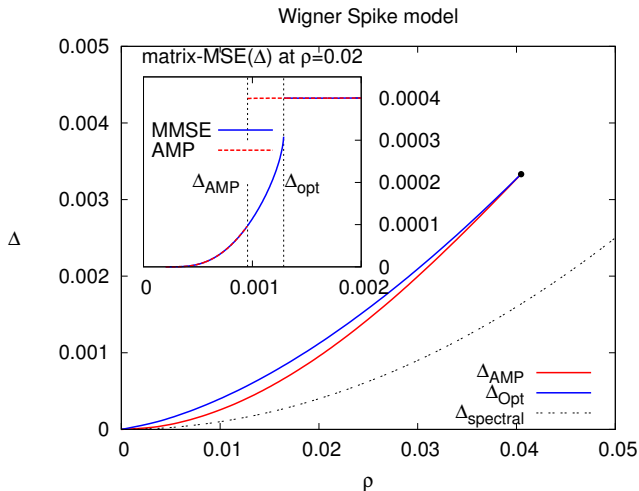
with $Z \sim \mathcal{N}(0, 1)$, $S \sim P_0$, $\mathbb{E}[S^2] = v$ and $\Sigma^2 := \Delta / (v - E)$.



$\text{argmin}_E i_{\text{RS}}$ is analytic in Δ except at Δ_{RS} where it has a jump discontinuity.

Phase diagram: example of the spiked Wigner model

$$P_0(s) = (1 - \rho)\delta(s) + \rho\delta(s - 1).$$



Theorem (One letter formula for the mutual information)

Assume $P_0(s) = \sum_{\alpha=1}^{\nu} p_{\alpha} \delta(s - a_{\alpha})$ and $i_{\text{RS}}(E; \Delta)$ has at most three stationary points.

$$\lim_{n \rightarrow +\infty} \frac{1}{n} I(\mathbf{S}; \mathbf{W}) = \min_{E \in [0, \nu]} i_{\text{RS}}(E; \Delta)$$

Corollary (Exact formula for the MMSE)

Consider $\text{Mmmse}_n := \frac{1}{n^2} \mathbb{E}_{\mathbf{s}, \mathbf{w}} \|\mathbf{S}\mathbf{S}^T - \langle \mathbf{X}\mathbf{X}^T \rangle\|_F^2$. For $\Delta \neq \Delta_{\text{RS}}$

$$\lim_{n \rightarrow +\infty} \text{Mmmse}_n = \nu^2 - (\nu - \tilde{E}(\Delta))^2$$

where $\tilde{E}(\Delta) = \operatorname{argmin}_{E \in [0, \nu]} i_{\text{RS}}(E; \Delta)$.

Remark: General bound \leq [Krzakala, Zdeborova, Xu] and $=$ when there is no phase transition [Deshpande, Montanari].

Performance of Approximate Message Passing

Estimate $\langle \mathbf{X} \rangle$ by the AMP iterative algorithm $\rightarrow \hat{\mathbf{S}}^t$.

MSE of AMP $E^t := \frac{1}{n} \lim_{n \rightarrow +\infty} \mathbb{E}_{\mathbf{s}, \mathbf{z}} [\|\mathbf{S} - \hat{\mathbf{S}}^t\|_2^2]$ is
tracked by State Evolution equation [M. Bayati, A. Montanari]

$$E^{t+1} = \text{mmse}(\Sigma(E^t; \Delta)^{-2}), \quad E^0 = \nu,$$

where $\text{mmse}(\Sigma^{-2})$ is associated to the scalar AWGN channel

$$Y = S + \Sigma Z, \quad Z \sim \mathcal{N}(0, 1) \text{ and } \Sigma^2 = \Delta / (\nu - E).$$

Connection with RS solution:

$$E = \text{mmse}(\Sigma(E; \Delta)^{-2}) \leftrightarrow \frac{d}{dE} i_{\text{RS}}(E; \Delta) = 0$$

So performance of AMP is governed by the RS potential.

Definition (AMP algorithmic threshold)

Δ_{AMP} is the first noise threshold s.t fixed point equation has a non-unique solution.

This is also a spinodal point or solution of

$$\frac{d}{dE} i_{\text{RS}}(E; \Delta) = \frac{d^2}{dE^2} i_{\text{RS}}(E; \Delta) = 0.$$

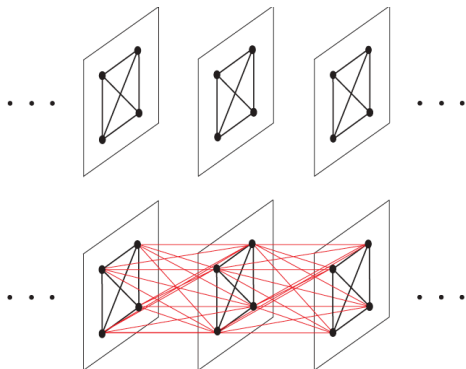
Corollary (Performance of AMP)

AMP yields upon convergence the matrix-MMSE as well as the vector-MMSE iff $\Delta < \Delta_{\text{AMP}}$ or $\Delta > \Delta_{\text{RS}}$:

$$E^\infty = \operatorname{argmin}_{E \in [0, \nu]} i_{\text{RS}}(E; \Delta).$$

Spatially coupled model I: periodic construction

Ring of length $L+1$ with *blocks* positioned at $\mu \in \{0, \dots, L\}$ and coupled to neighboring blocks $\{\mu - w, \dots, \mu + w\}$.



$$w_{i_{\mu}j_{\nu}} = s_{i_{\mu}} s_{j_{\nu}} \sqrt{\frac{\Lambda_{\mu\nu}}{n}} + z_{i_{\mu}j_{\nu}} \sqrt{\Delta},$$

Spatially coupled model II: seeded construction

The construction is completed by introducing a **seed** in the ring:

Assume perfect knowledge of the signal components

$$s_{i_\mu} \text{ for } \mu \in \{-w-1, \dots, +w-1\} \text{ mod } L+1$$

This seed allows to close the gap between the algorithmic and information theoretical limits for the chain.

Two fundamental claims

Lemma (Equality of mutual informations)

For any fixed w the following limits exist and are equal:

$$\lim_{n \rightarrow +\infty} I_{w,L}^{\text{periodic}}(\mathbf{S}; \mathbf{W})/nL = \lim_{n \rightarrow +\infty} I(\mathbf{S}; \mathbf{W})/n$$

$$\lim_{L \rightarrow +\infty} \lim_{n \rightarrow +\infty} I_{w,L}^{\text{seeded}}(\mathbf{S}; \mathbf{W})/nL = \lim_{n \rightarrow +\infty} I(\mathbf{S}; \mathbf{W})/n$$

Lemma (Threshold saturation)

Let $\Delta_{\text{AMP,coup}} := \liminf_{w \rightarrow +\infty} \liminf_{L \rightarrow +\infty} \Delta_{\text{AMP},w,L}$. We have

$$\Delta_{\text{AMP,coup}} \geq \Delta_{\text{RS}}$$

First lemma: A Guerra style interpolation method.

MI is the free energy associated to

$$\begin{aligned} \mathcal{H}(\mathbf{x}, \mathbf{z}, \Lambda) &= \frac{1}{\Delta} \sum_{\mu=0}^L \Lambda_{\mu\mu} \sum_{i_{\mu} \leq j_{\mu}} \left(\frac{x_{i_{\mu}}^2 x_{j_{\mu}}^2}{2n} - \frac{s_{i_{\mu}} s_{j_{\mu}} x_{i_{\mu}} x_{j_{\mu}}}{n} - \frac{x_{i_{\mu}} x_{j_{\mu}} z_{i_{\mu} j_{\mu}} \sqrt{\Delta}}{\sqrt{n \Lambda_{\mu\mu}}} \right) \\ &+ \frac{1}{\Delta} \sum_{\mu=0}^L \sum_{\nu=\mu+1}^{\mu+L} \Lambda_{\mu\nu} \sum_{i_{\mu}, j_{\nu}} \left(\frac{x_{i_{\mu}}^2 x_{j_{\nu}}^2}{2n} - \frac{s_{i_{\mu}} s_{j_{\nu}} x_{i_{\mu}} x_{j_{\nu}}}{n} - \frac{x_{i_{\mu}} x_{j_{\nu}} z_{i_{\mu} j_{\nu}} \sqrt{\Delta}}{\sqrt{n \Lambda_{\mu\nu}}} \right). \end{aligned}$$

Take a pair of systems Λ and Λ' and an *interpolated Hamiltonian*, $t \in [0, 1]$, $\mathcal{H}(\mathbf{x}, \mathbf{z}, t\Lambda) + \mathcal{H}(\mathbf{x}, \mathbf{z}', (1-t)\Lambda')$.

After differentiation, Gaussian integration by parts, and Nishimori identities:

$$-\frac{1}{nL} \frac{d}{dt} \mathbb{E}_{\mathbf{s}, \mathbf{z}, \mathbf{z}'} [\ln \mathcal{Z}_t] = \frac{1}{4\Delta L} \mathbb{E}_{\mathbf{s}, \mathbf{z}, \mathbf{z}'} [\langle \mathbf{q}^T \Lambda \mathbf{q} - \mathbf{q}^T \Lambda' \mathbf{q} \rangle_t] + \mathcal{O}\left(\frac{1}{nL}\right)$$

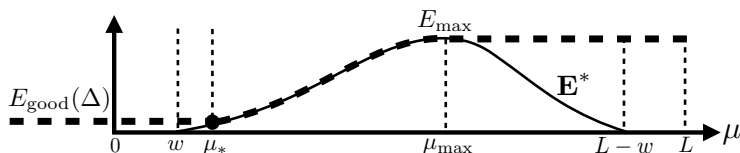
where $q_{\mu} = \frac{1}{n} \sum_{i_{\mu}=1}^n s_{i_{\mu}} x_{i_{\mu}}$. Choose suitable Λ and Λ' to compare quadratic forms and get

$$\lim_n \frac{1}{nL} I_{w=0, L} \leq \lim_n \frac{1}{nL} I_{w, L} \leq \lim_n \frac{1}{nL} I_{w=L/2, L}$$

Threshold saturation: rough sketch

Coupled AMP is controlled by the coupled version of RS potential: $i_{w,L}(\{E_\mu\}_0^L; \Delta)$.

Main intuition: initial MSE profile is driven to flat E_{good} for all $\mu \in \{0, \dots, L\}$, because it is energetically favourable for the seed grows and a reconstruction wave develops.



Proof idea: suppose there is an increasing fixed point of state evolution and show that a small shift lowers the free energy.

$$i_{w,L}(\mathcal{S}(\mathbf{E}^S); \Delta) - i_{w,L}(\mathbf{E}^S; \Delta) \leq -|i_{\text{RS}}(E_{\text{bad}}; \Delta) - i_{\text{RS}}(E_{\text{good}}; \Delta)|$$

Back to uncoupled system: proof of RS formula

Consequence of the two lemmas:

$$\Delta_{\text{RS}} \underbrace{\leq}_{\text{threshold saturation}} \Delta_{\text{AMP,coup}} \underbrace{\leq}_{\text{sub-optimal alg}} \Delta_{\text{Opt,coup}} \underbrace{=}_{\text{equality MI}} \Delta_{\text{Opt}}$$

We can also argue that:

$$\Delta_{\text{Opt}} \leq \Delta_{\text{RS}}$$

- ▶ This argument combines sub optimality of AMP and a "Guerra-Toninelli interpolation bound" for original (uncoupled) system.
- ▶ **In summary we get $\Delta_{\text{Opt}} = \Delta_{\text{RS}}$.** In the process we get the whole replica formula as a bonus.

Proof of $\Delta_{\text{Opt}} \leq \Delta_{\text{RS}}$

- ▶ We use Matrix $\text{MSE}_{\text{AMP}} \geq \text{Matrix MMSE}$:

$$\frac{\partial i_{\text{RS}}(E^\infty; \Delta)}{\partial \Delta} \geq \limsup_{n \rightarrow +\infty} \frac{1}{n} \frac{dI(\mathbf{S}; \mathbf{W})}{d\Delta^{-1}}$$

- ▶ $\Delta \leq \Delta_{\text{AMP}} \rightarrow E^\infty = \text{argmin } i_{\text{RS}}(E, \Delta)$ thus

$$\frac{d}{d\Delta^{-1}} \min_E i_{\text{RS}}(E; \Delta) \geq \limsup_{n \rightarrow +\infty} \frac{1}{n} \frac{dI(\mathbf{S}; \mathbf{W})}{d\Delta^{-1}}.$$

- ▶ Integrate on $[0, \Delta] \subset [0, \Delta_{\text{AMP}}]$ to obtain

$$\min_{E \in [0, v]} i_{\text{RS}}(E; \Delta) \leq \liminf_{n \rightarrow +\infty} I(\mathbf{S}; \mathbf{W})/n$$

- ▶ But we know " \geq " by Guerra-Toninelli interpolation.

Thus we already get equality for $\Delta \leq \Delta_{\text{AMP}}$.

Proof of $\Delta_{\text{Opt}} \leq \Delta_{\text{RS}}$ continued

- ▶ By definition of thresholds we know already $\Delta_{\text{AMP}} \leq \Delta_{\text{RS}}$.
- ▶ Suppose $\Delta_{\text{AMP}} \leq \Delta_{\text{RS}} < \Delta_{\text{Opt}}$. Then, by analyticity, both $\lim_{n \rightarrow \infty} I(\mathbf{S}; \mathbf{W})/n$ and $\min_E i_{\text{RS}}(E; \Delta)$ are equal up to Δ_{RS} .
- ▶ Repeat the integration argument on $[\Delta_{\text{RS}}, \Delta]$:

$$\int_{\Delta_{\text{RS}}}^{\Delta} d\Delta \frac{d}{d\Delta} \min_E i_{\text{RS}}(E; \Delta) \leq \liminf_{n \rightarrow +\infty} \frac{1}{n} \int_{\Delta_{\text{RS}}}^{\Delta} d\Delta \frac{dI(\mathbf{S}; \mathbf{W})}{d\Delta}.$$

which leads again to

$$\min_{E \in [0, v]} i_{\text{RS}}(E; \Delta) \leq \liminf_{n \rightarrow +\infty} I(\mathbf{S}; \mathbf{W})/n$$

- ▶ and to equality with the help of Guerra-Toninelli: \geq
- ▶ But equality for all $\Delta \in [0, \Delta_{\text{Opt}}[$ with $\Delta_{\text{RS}} < \Delta_{\text{Opt}}$ means $\min_E i_{\text{RS}}(E; \Delta)$ is analytic at Δ_{RS} which is a contradiction.

To summarize:

- ▶ The integration argument gave RS formula for $\Delta < \Delta_{\text{AMP}}$.
- ▶ We managed to show $\Delta_{\text{RS}} = \Delta_{\text{Opt}}$.
- ▶ By analyticity the RS formula extends up to Δ_{Opt} .
- ▶ A final integration argument on $[\Delta_{\text{Opt}}, \Delta]$ finishes the proof.

Remark:

- ▶ the integration argument does not work for $\Delta \in [\Delta_{\text{AMP}}, \Delta_{\text{RS}}]$.

$$\underbrace{\frac{\partial i_{\text{RS}}(E^\infty; \Delta)}{\partial \Delta^{-1}}}_{\neq \frac{d}{d\Delta^{-1}} \min_E i_{\text{RS}}(E; \Delta)} \geq \limsup_{n \rightarrow +\infty} \frac{1}{n} \frac{dI(\mathbf{S}; \mathbf{W})}{d\Delta^{-1}}$$

Conclusion

- ▶ The ideas are more or less generic.
- ▶ Proof of RS formulas in coding LDPC, LDGM (spin systems on sparse graph on their Nishimori line). [A. Giurgiu, R. Urbanke, H. Pfister, S. Kumar, A. Young, N.M]
- ▶ In linear estimation/ compressive sensing [J. Barbier, M. Dia, F. Krzakala, N.M]. [case without phase transition: Montanari-Tse 2006; other recent proof G. Reeves, H. Pfister]
- ▶ New provable lower bounds on K -SAT, Q -COL thresholds [D. Achlioptas, H. Hassani, R. Urbanke, N.M].
- ▶ Work in progress: non-linear estimation, low rank matrix factorisation etc.