



# Signal reconstruction in rough landscapes: *The BBP transition and beyond*

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*Ros, Ben Arous, Biroli, Cammarota PRX 2019*

*Sarao, Biroli, Cammarota, Krzakala, Urbani, Zdeborova PRX 2020*

*Sarao, Biroli, Cammarota, Krzakala, Zdeborova Spotlight at NIPS 2019*

*Biroli, Cammarota, Ricci-Tersenghi J. Phys. A: Math. and Theor. 2020*

*Sarao, Biroli, Cammarota, Krzakala, Urbani, Zdeborova NIPS 2020*

*Biroli, Cammarota, Ricci-Tersenghi in preparation*

Random Matrices and Random Landscapes 28.07.2022

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in honour of Yan Fyodorov

# Two examples of signal reconstruction

## MATRIX PCA, TENSOR PCA, MIXED MODELS

Estimation of rank-one k-tensor from a noisy channel(s)

Observation      Corrupting noise      Signal

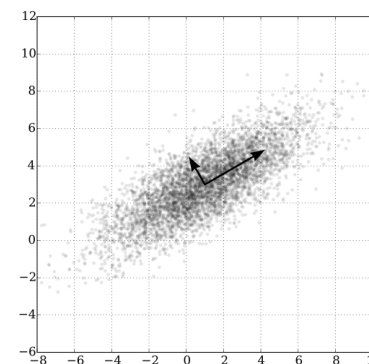
$$T_{i_1, \dots, i_k} = W_{i_1, \dots, i_k} + v_{i_1} \dots v_{i_k}$$

Maximum likelihood estimator: minimum squared distance

$$H_k = - \sum_{(i_1, \dots, i_k)} (T_{i_1, \dots, i_k} - x_{i_1} \dots x_{i_k})^2 \propto - \sum_{(i_1, \dots, i_k)} J_{i_1, \dots, i_k} x_{i_1} \dots x_{i_k} - rN \left( \sum_i \frac{x_i v_i}{N} \right)^k + \text{const}$$

with  $J_{i_1, \dots, i_k} \propto W_{i_1, \dots, i_k}$  and  $r$  signal to noise ratio

..also MIXED matrix / tensor models



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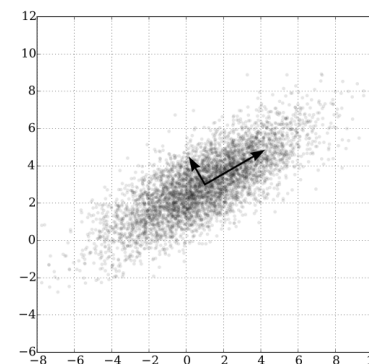
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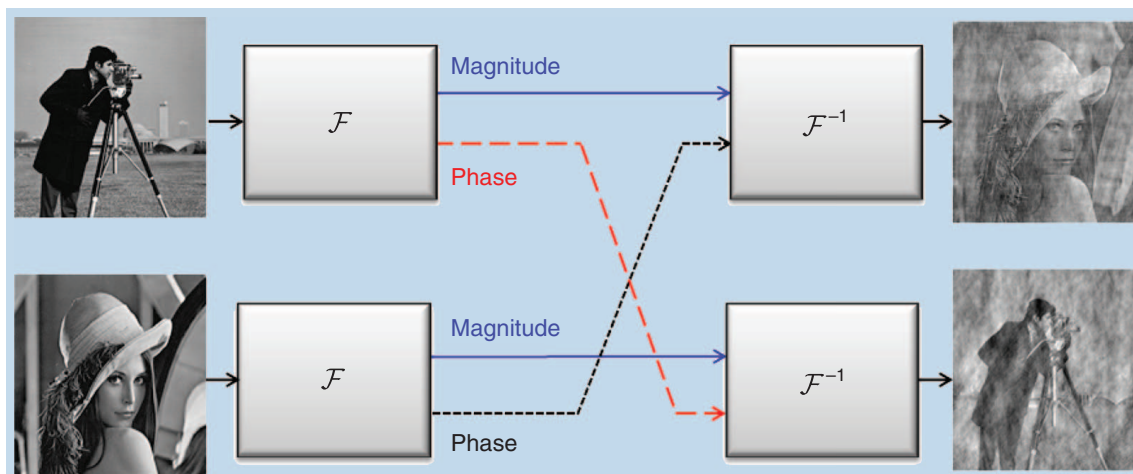
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## PHASE RETRIEVAL



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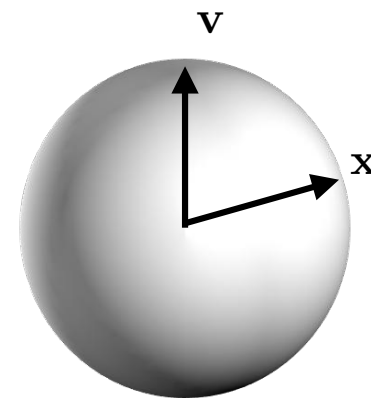
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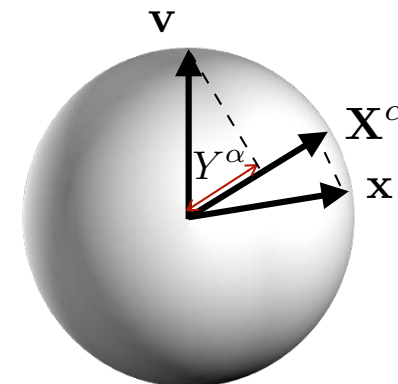
## PHASE RETRIEVAL

Retrieval of an  $N$ -dimensional vector  $\mathbf{v}$  from the knowledge of its projections  $Y^m$  on  $\alpha N$  random vectors  $\mathbf{X}^m$

Cost function

$$\mathcal{L}(\mathbf{x}) = \frac{1}{2} \sum_m^{\alpha N} \frac{(Y^{m2} - \langle \mathbf{x}, \mathbf{X}^m \rangle^2)^2}{g(Y)}$$

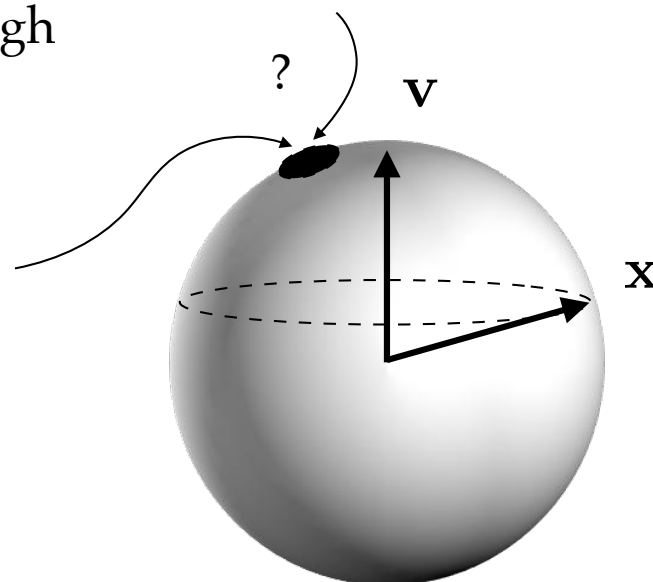
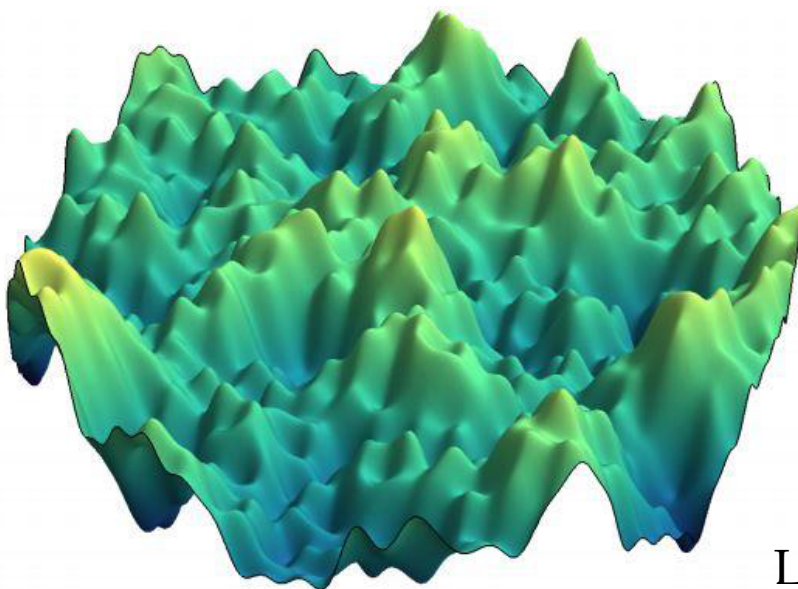
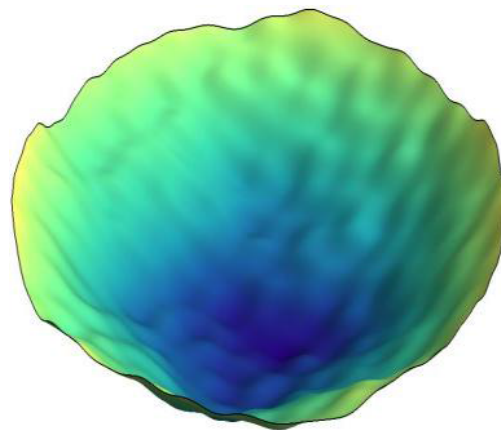
with  $\alpha$  signal to noise ratio



# Signal reconstruction in rough landscapes

$$\dot{\mathbf{x}} = -\nabla_{\mathbf{x}}\mathcal{L}(\mathbf{x}(t)) + \mu(t)\mathbf{x}(t)$$

Minimisation via gradient flow on the sphere from random initial condition, where likelihood / cost landscape is rough



Landscape matter: gradient, Hessian

# The Baik-Ben Arous-Péché (BBP) transition

*Baik, Ben Arous, Péché Annals of Prob 2005*

Change of statistics of the largest eigenvalue for non-null  $N \times N$  (complex) sample covariance matrices  $S = \frac{1}{M} \sum_m^M v_m v_m^T$  from multivariate Gaussian vectors  $v_m$  with covariance matrix  $\Sigma$

If population covariance is Identity or its largest eigenvalue is smaller than  $1 + \sqrt{N/M}$

$$\lambda_{MAX}(M) - \lambda_{MAX} \sim M^{-2/3}$$

If largest eigenvalue of population covariance is larger than  $1 + \sqrt{N/M}$

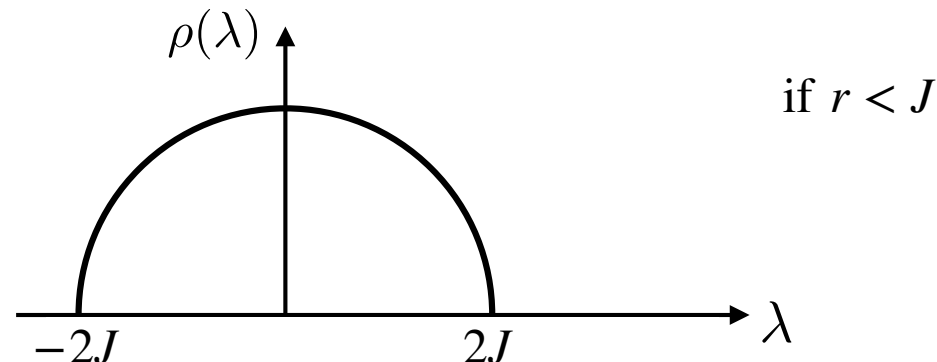
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*Wigner 1955, Bronk 1974*

*Edwards, Jones J. Phys A 1976*

Re-derivation of Semicircular Law with replicas for (modified) GOE  $N \times N$  matrix  $H(r)$

$$\text{with } H_{ij}(r) \sim \mathcal{N}\left(\frac{r}{N}, \frac{J^2}{N}\right)$$



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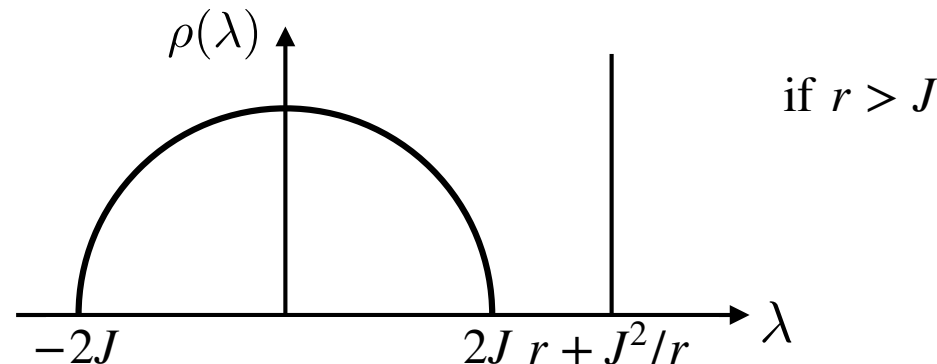
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# The ubiquity of BBP transition (some examples)

*Bouchaud, Potters The Oxford Handbook of RMT 2015*

Covariance matrices cleaning (e.g. finance..)

*Zebari et al. JASTT 2020*

Dimensional reduction and feature extraction in data science

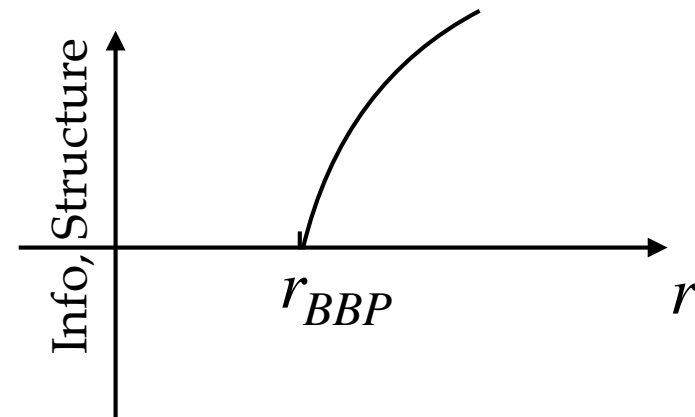
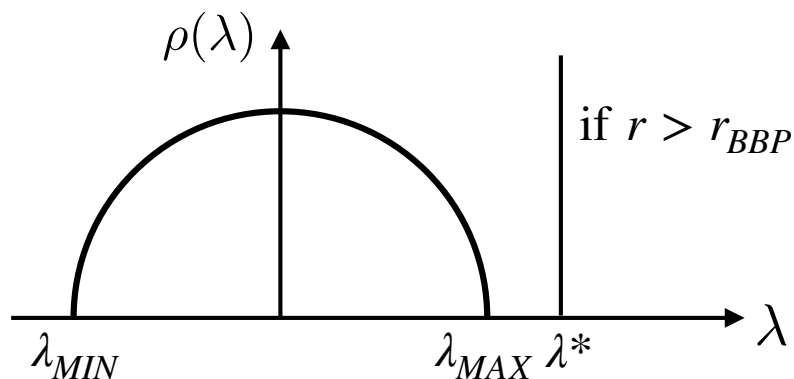
*Montanari, Reichman, Zeitouni IEEE Trans. Inf. Theo. 2014*

Inference (e.g. clique reconstruction task)

*Fraboul, Biroli, De Monte arXiv:2112.06845 2021*

Evolution of ecosystems under selection pressure

General mechanism for emergence of information (or specific underlying structure)



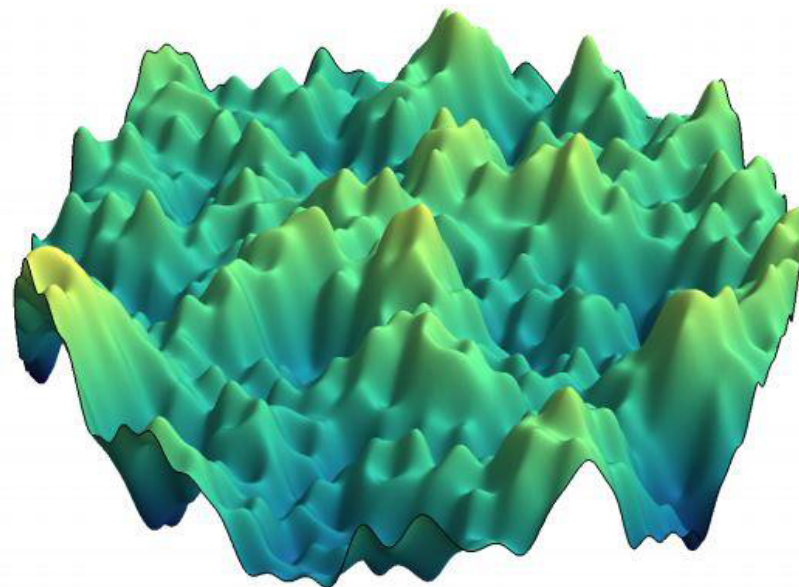
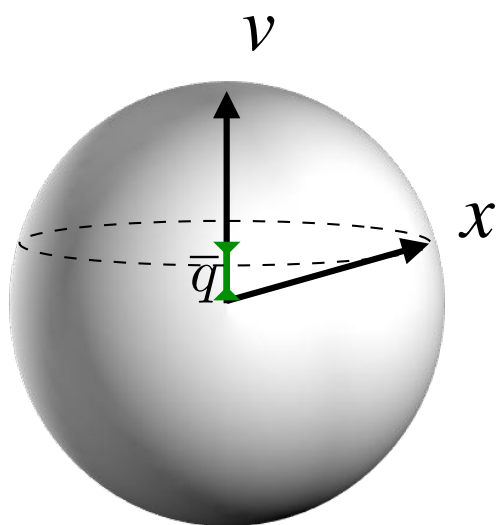


# Signal reconstruction as a BBP transition

Long time limit of **gradient flow**, are stationary points stable?

Information after a **warm start**: Hessian in specific regions of the landscape

Eigenvector of the smallest eigenvalue of the initial Hessian: **spectral initialisation**



TENSOR PCA

$$\mathcal{H}(H_k)_{ij} = - \sum_{(i_3, \dots, i_k)} J_{i,j,i_3, \dots, i_k} x_{i_3} \dots x_{i_k} - r \frac{k(k-1)}{N} v_i v_j \left( \sum_l \frac{x_l v_l}{N} \right)^{k-2}$$

PHASE RETRIEVAL

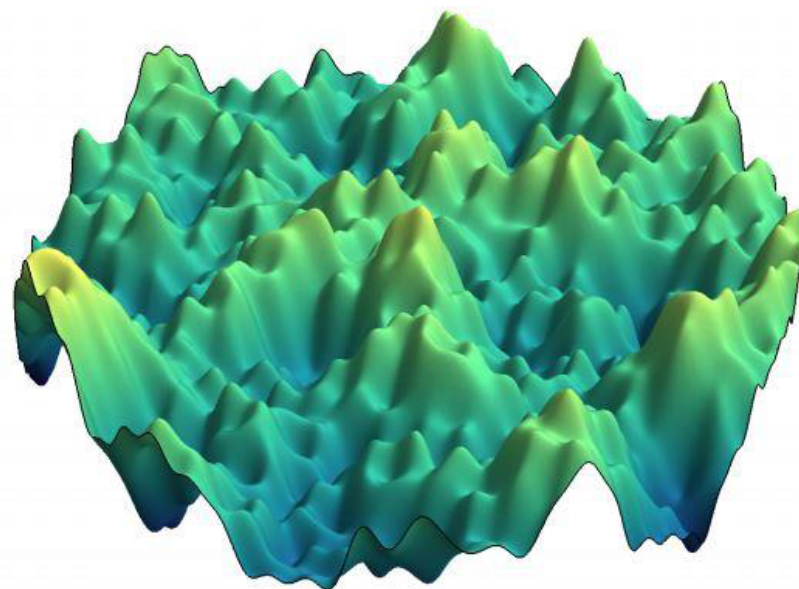
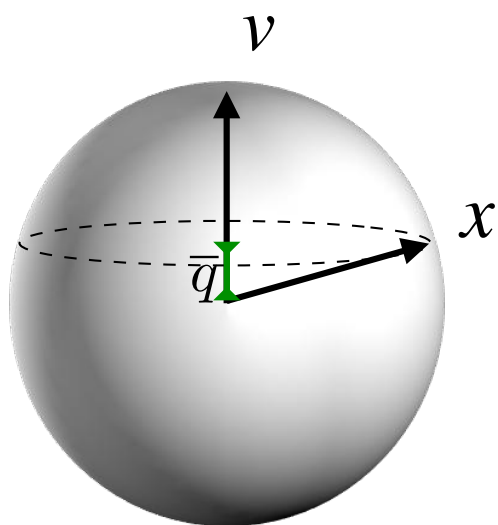
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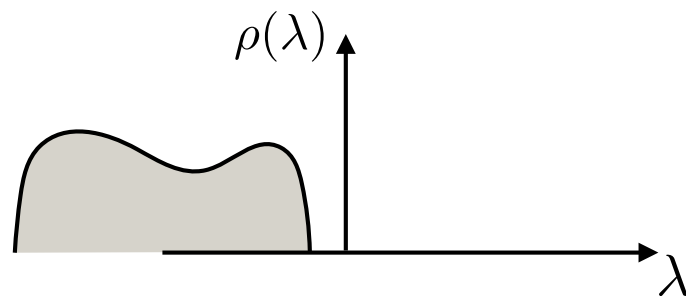
The simplest case, Matrix PCA:  $\mathcal{H}(H_2)_{ij} = -J_{ij} - r \frac{2}{N} v_i v_j$

PHASE RETRIEVAL

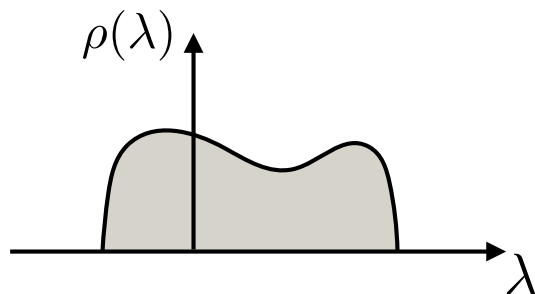
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# A large variety of stationary points

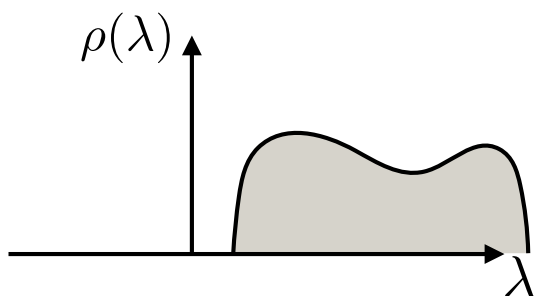
Density of eigenvalues of Hessian



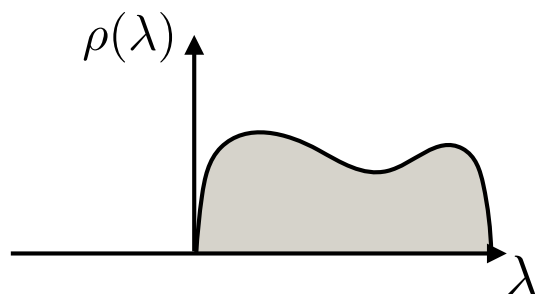
Maxima



Saddles

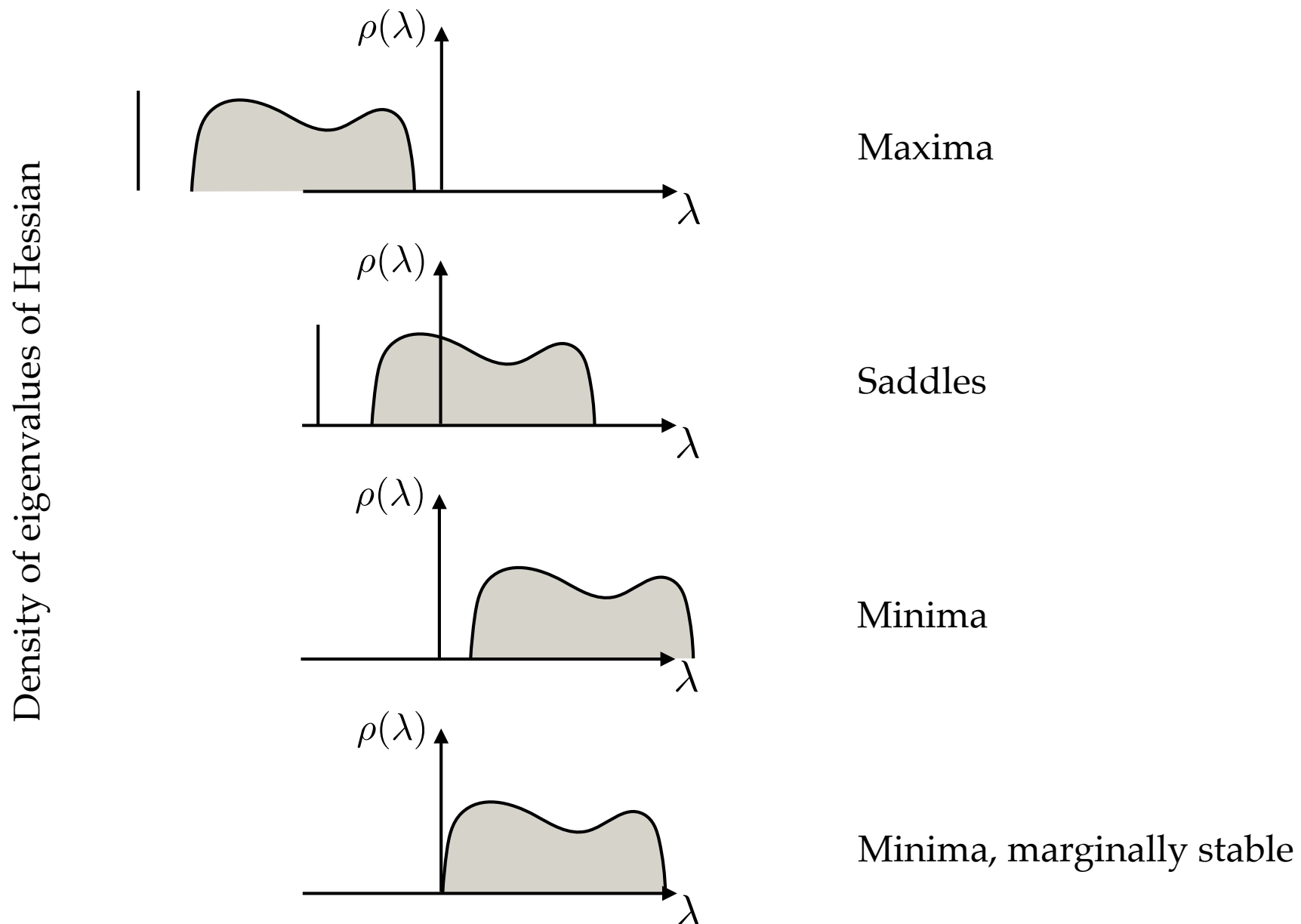


Minima

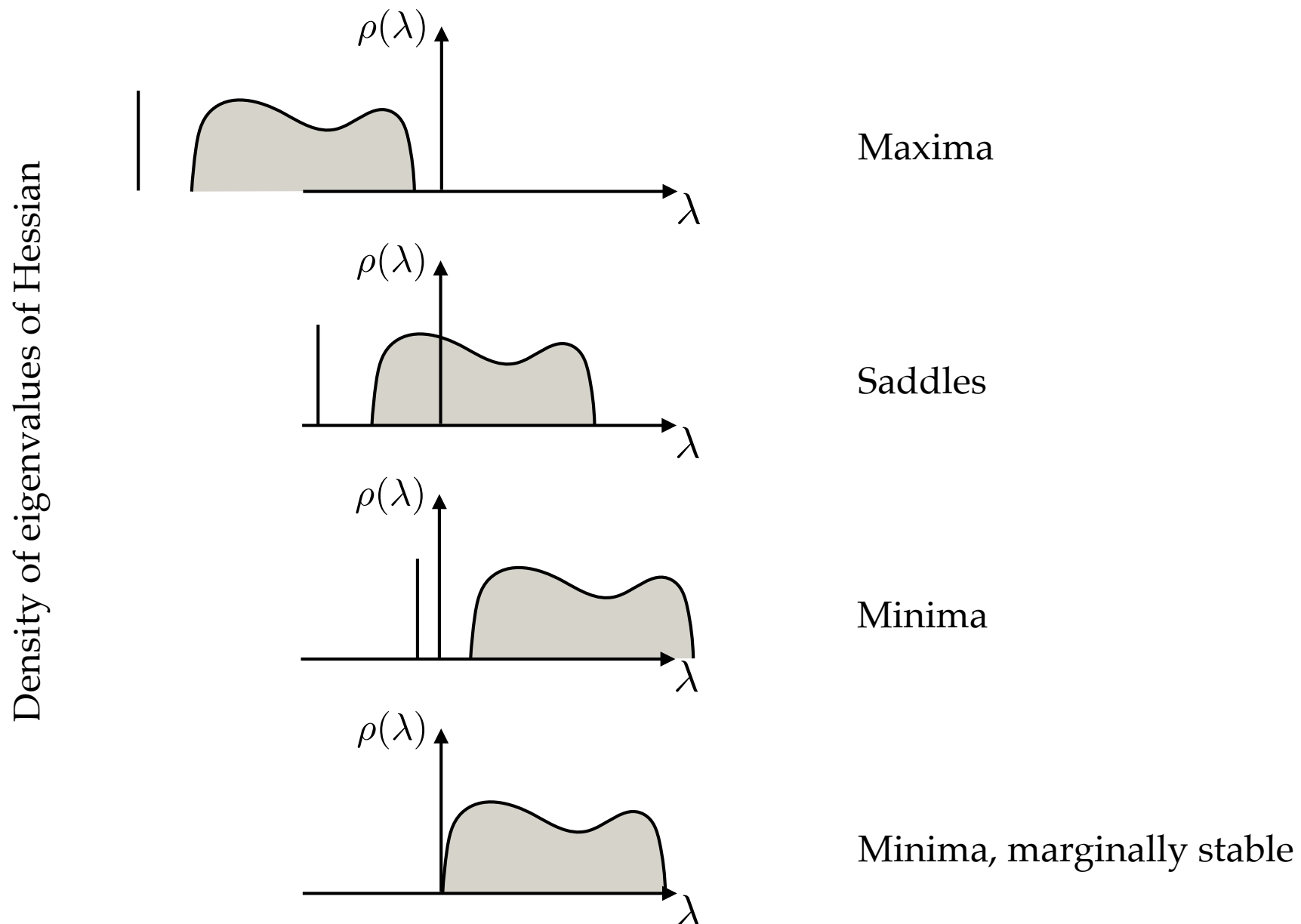


Minima, marginally stable

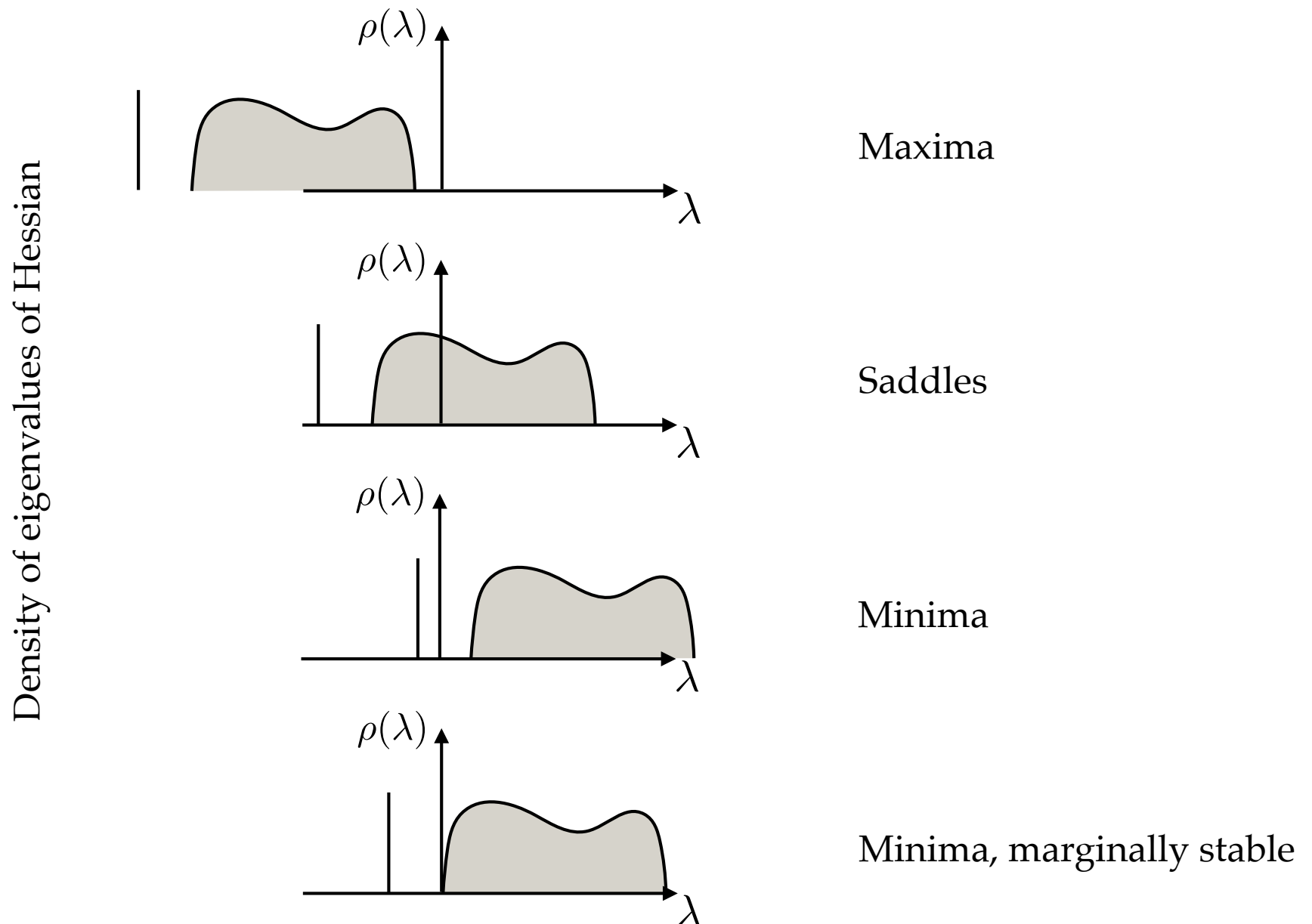
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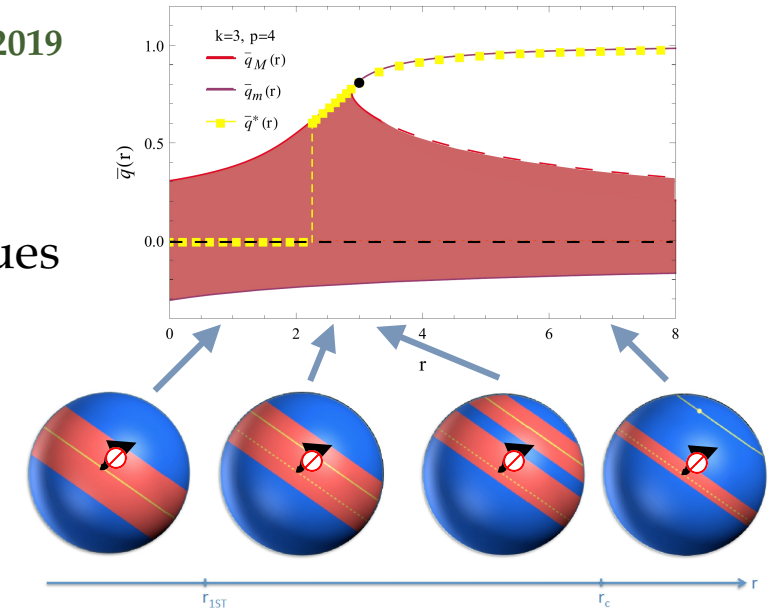
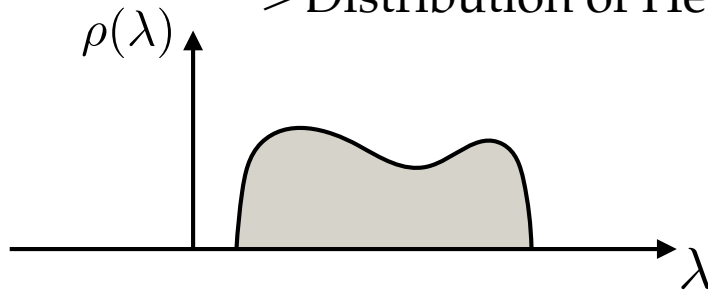


# Tensor PCA and mixed Matrix-Tensor PCA

(Fyodorov PRL 2004, ...) Ros, Ben Arous, Biroli, Cammarota PRX 2019

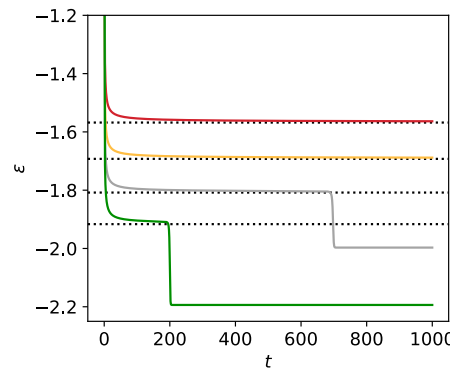
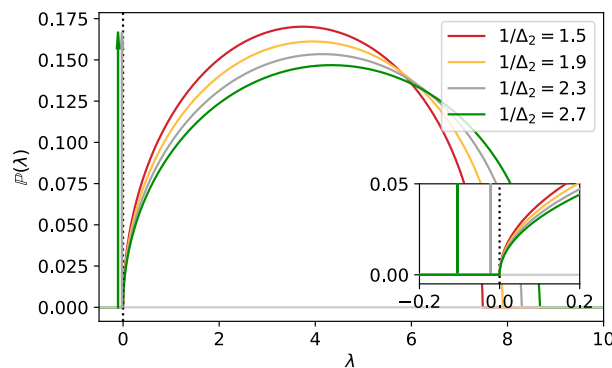
Hessian at special stationary points in the landscape:  
counting of **minima** > Structure of stationary points

> Distribution of Hessians eigenvalues



How gradient flow escapes minima? Sarao, Biroli, Cammarota, Krzakala, Zdeborova Spotlight at NIPS 2019

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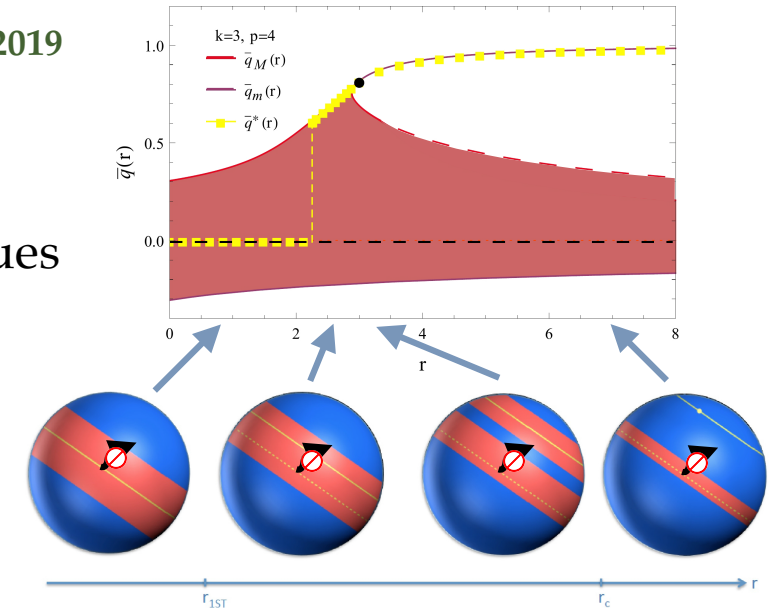
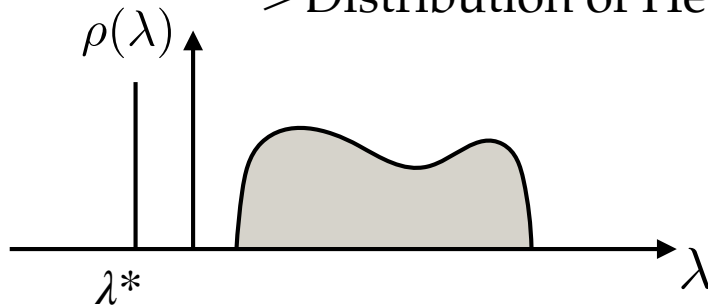


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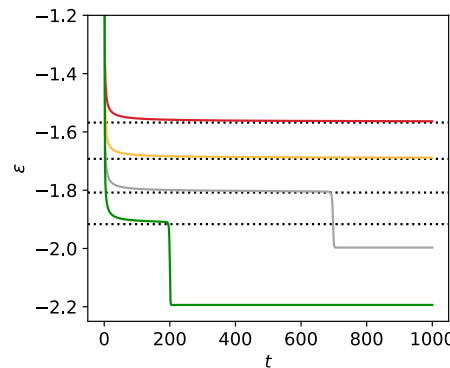
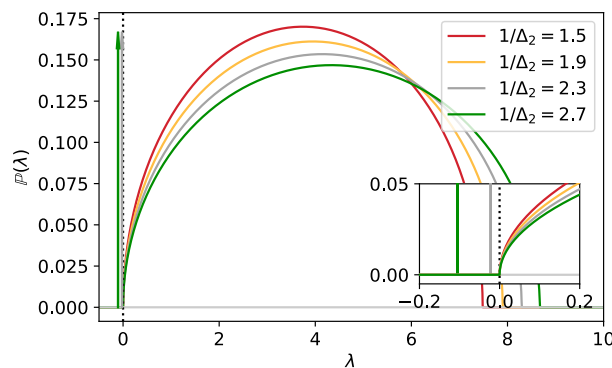
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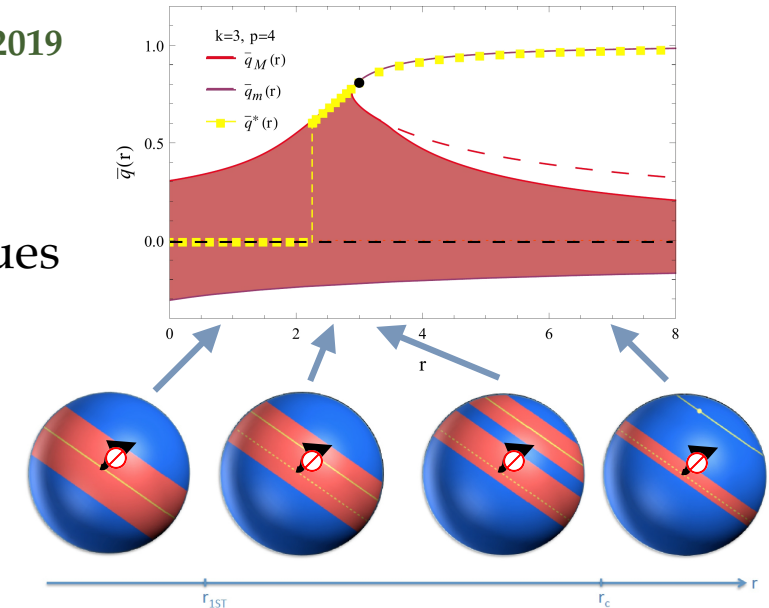
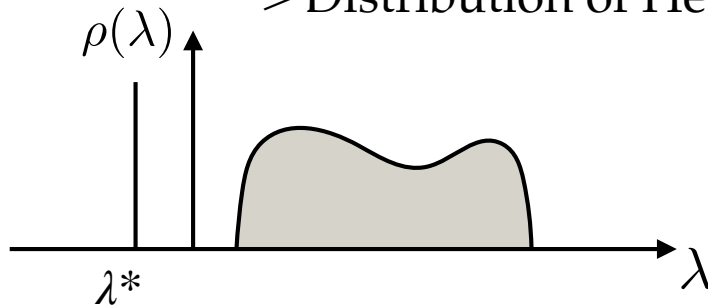


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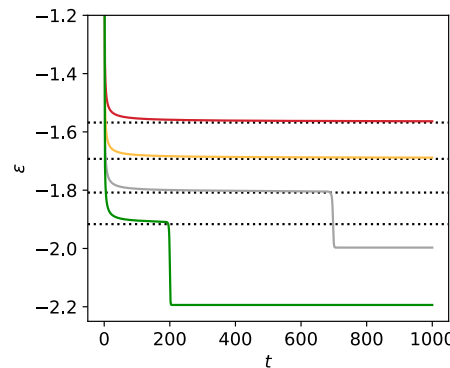
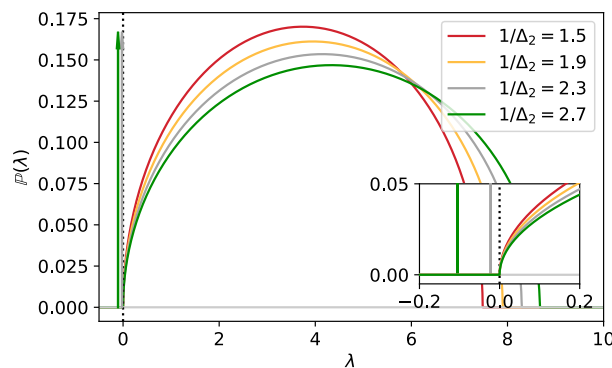
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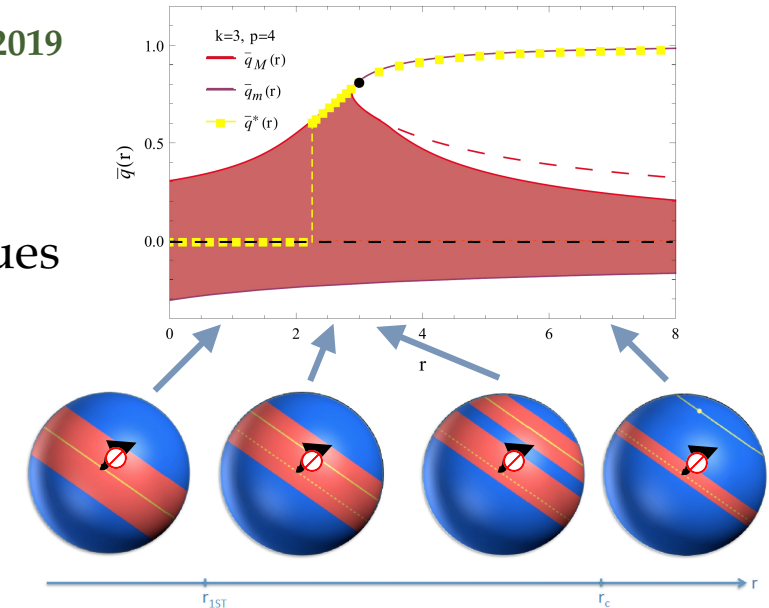
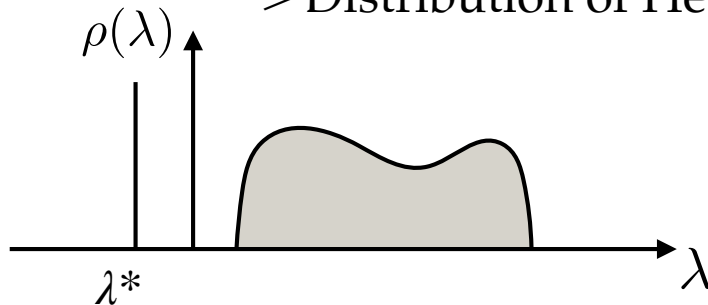


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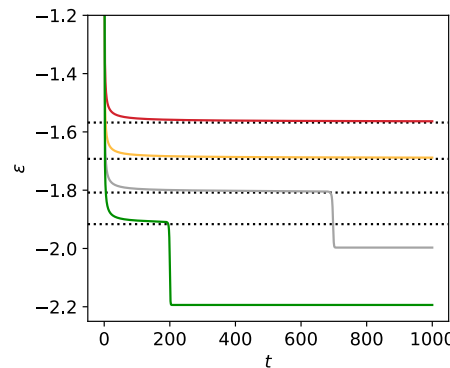
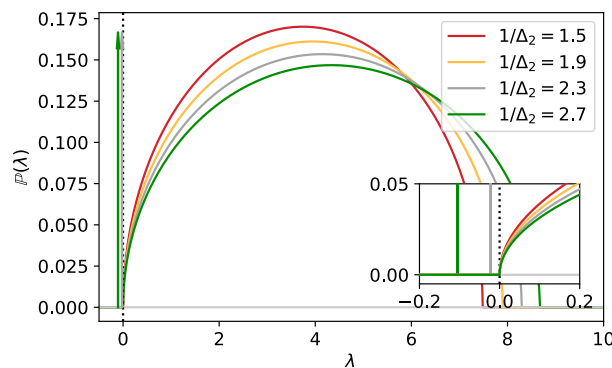
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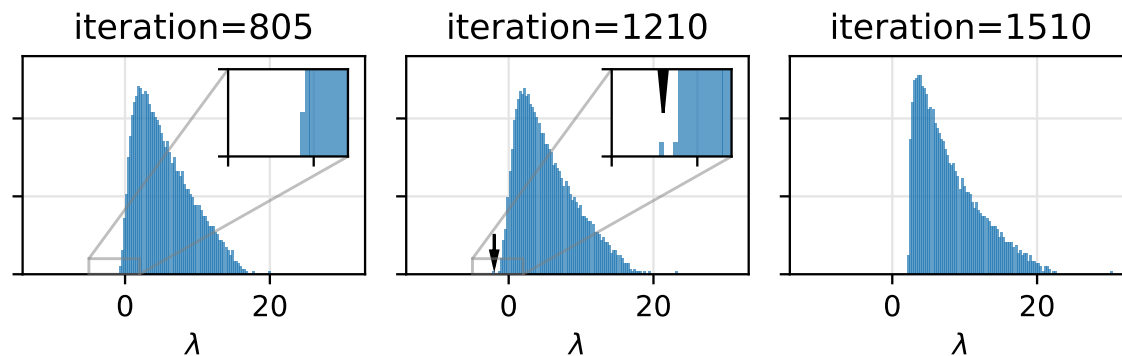
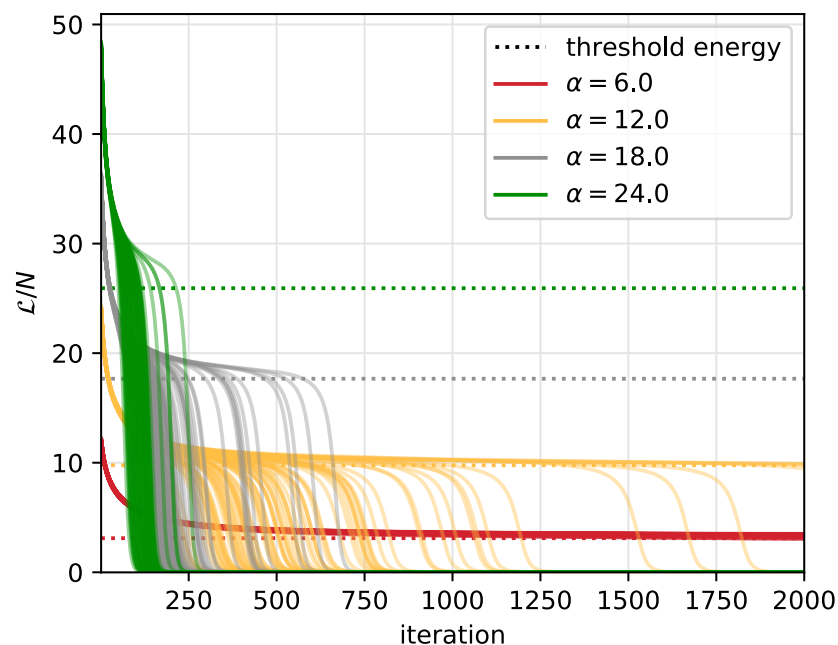
# Phase Retrieval: a very similar story but...

Structure of stationary points

*Maillard, Ben Arous, Biroli MSML 2020*

Similar mechanism to escape minima

*Sarao, Biroli, Cammarota, Krzakala, Urbani, Zdeborova NIPS 2020*



Evidence of BBP transition but disagreement with numerical results

Different mechanism at work?

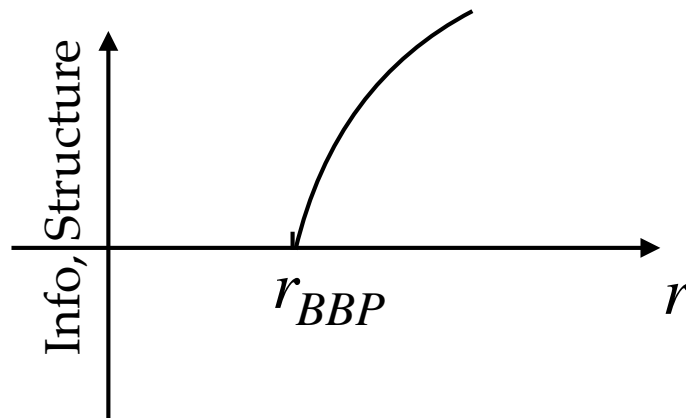
Only very strong and (favourable?) finite size effects?

# Phase Retrieval: spectra initialisation and a new BBP?

*Mondelli, Montanari PMLR 2017; Luo, Alghamdi, Lu 2018; Lu, Li 2019*

Spectra initialisation as alternative algorithmic approach:

$$\mathcal{H}(\mathcal{L})_{ij} = \sum_m^{\alpha N} X_i^m X_j^m \ell(Y^m) \quad \text{with} \quad \ell(Y) = \frac{Y^2 - A}{B + CY^2}$$



$$\ell(Y) = 1 \quad \text{if } Y^2 > t; \quad = 0 \quad \text{otherwise}$$

$$\ell(Y) = \frac{Y^2 - 1}{Y^2 + \sqrt{\delta} - 1}$$

$$\ell(Y) = \max \left( \frac{Y^2 - 1}{Y^2 + \sqrt{\delta} - 1}, 0 \right)$$

Hessian has identical structure, with special pre-processing function

$$\mathcal{H}(\mathcal{L})_{ij} = -2 \sum_m^{\alpha N} X_i^m X_j^m \frac{(Y^{m2} - 3\langle x X^m \rangle^2)}{g(Y^m)}$$

For some choices a **new type** of BBP transition is leading to signal reconstruction!

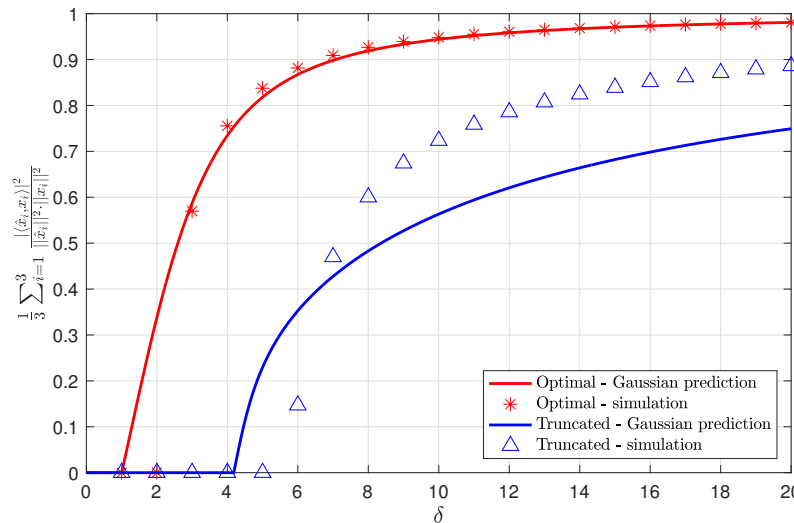
*Bouchaud Potters A First Course in Random Matrix Theory 2021*

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# Continuous vs discontinuous BBP transition

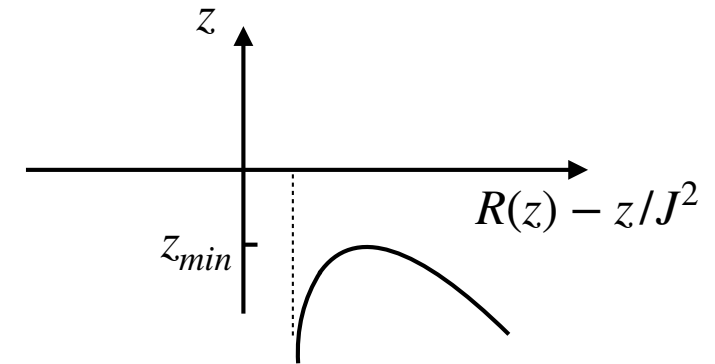
*Biroli, Cammarota, Ricci Tersenghi, in preparation*

Deformed GOE matrices and rank one perturbation

$$M_{ij} = \delta_{ij}a_i + H_{ij} \quad \text{with} \quad H_{ij}(r) \sim \mathcal{N}\left(\frac{r}{N}, \frac{J^2}{N}\right) \quad a_i \sim p(a) \simeq (a - a_{\min})^{\phi-1}$$

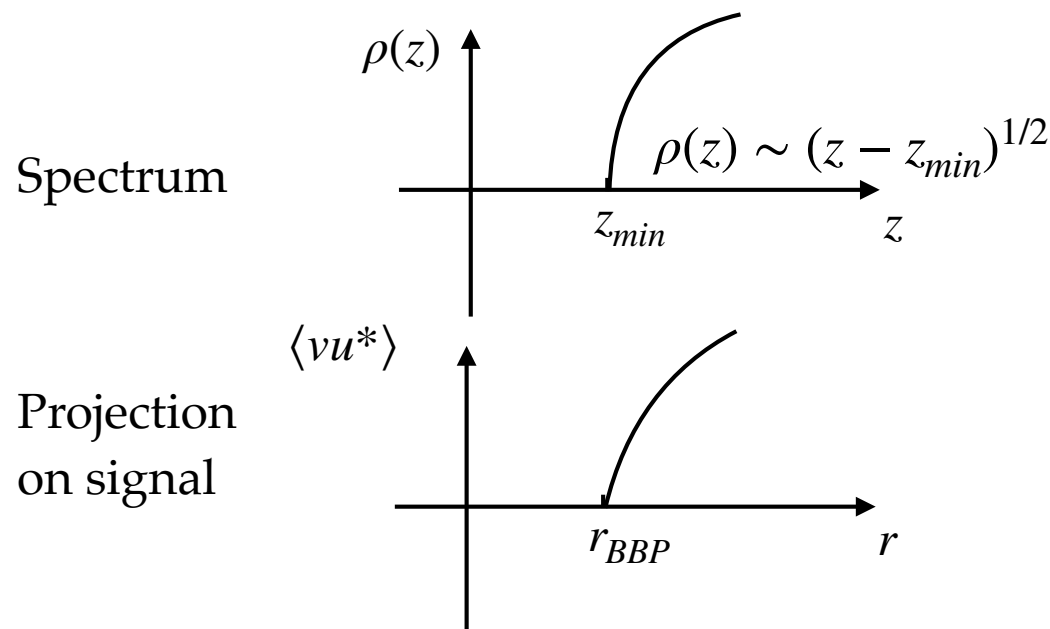
Equation for density of eigenvalues from the Resolvent

$$R(z) \left( = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_i \frac{1}{z - \lambda_i} \right) = \int_{a_{\min}}^{a_{\max}} da \, p(a) \frac{1}{z - a - J^2 R(z)}$$



Equation for isolated eigenvalue for  $z^* < z_{\min}$ :  $R(z^*) = 1/r$

Continuous BBP ( $\phi < 2$ )



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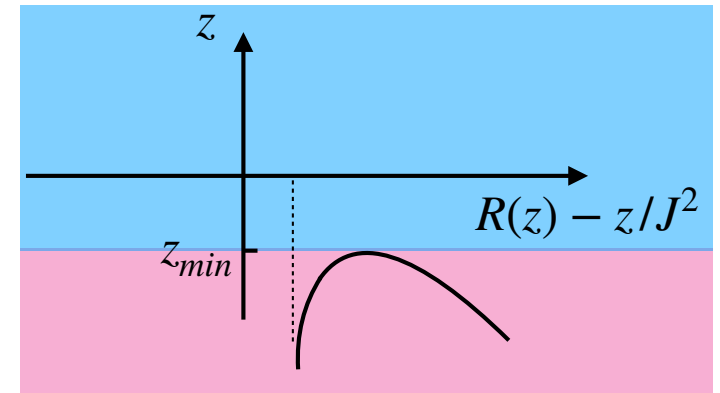
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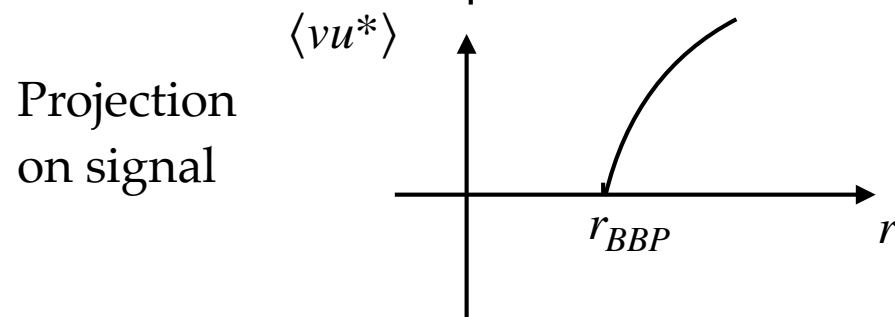
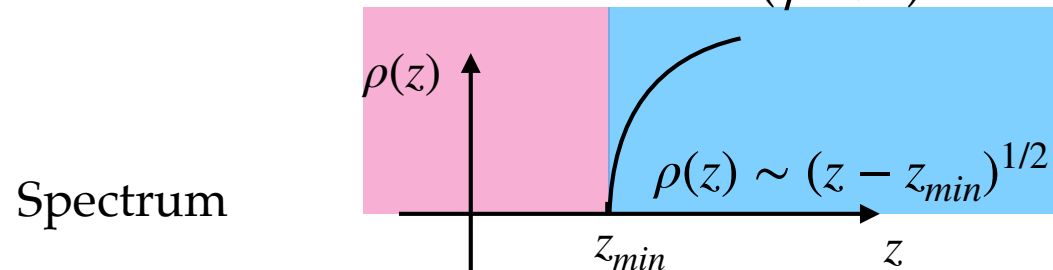
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Continuous BBP ( $\phi < 2$ )



# Continuous vs discontinuous BBP transition

*Biroli, Cammarota, Ricci Tersenghi, in preparation*

Deformed GOE matrices and rank one perturbation

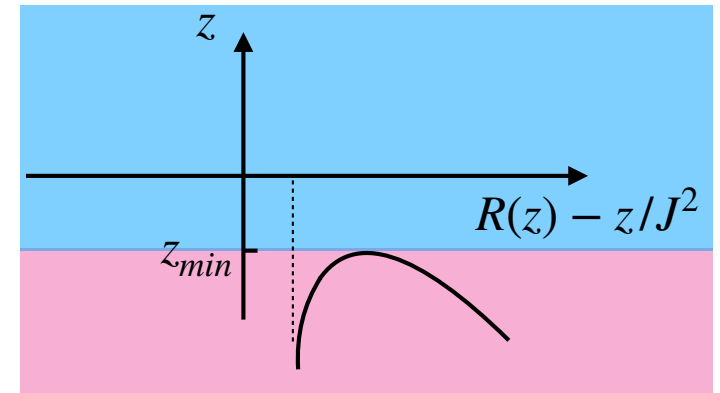
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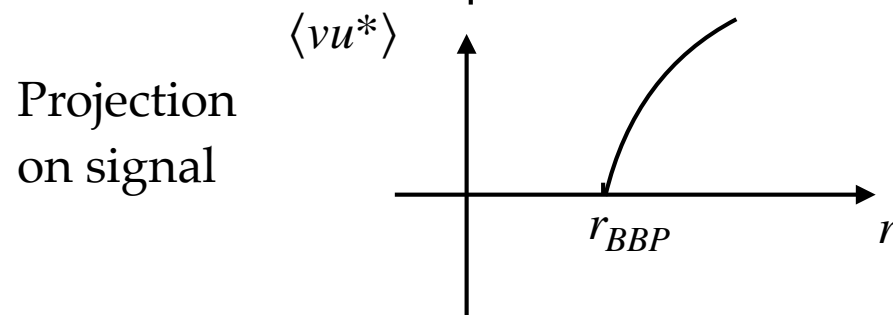
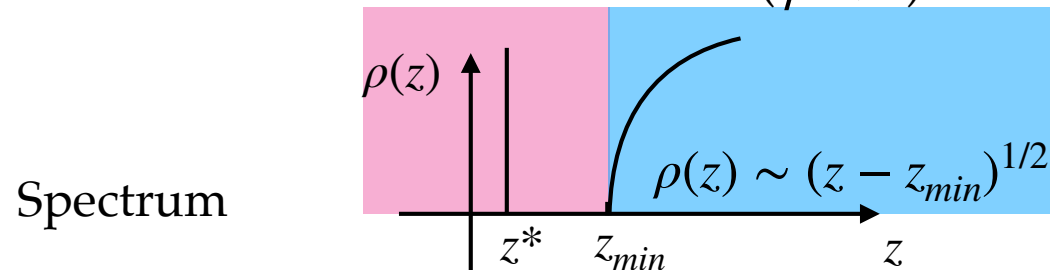
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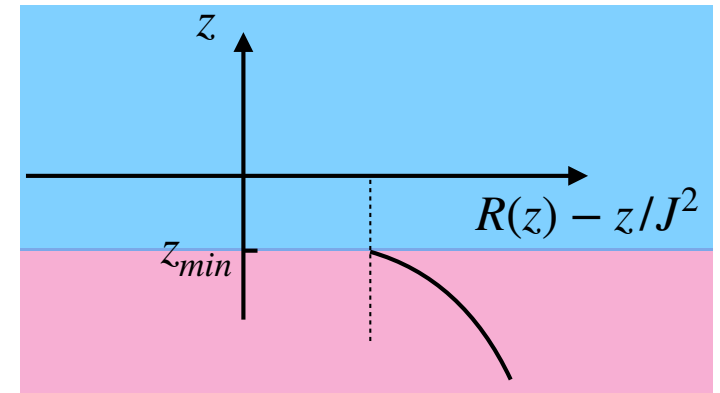
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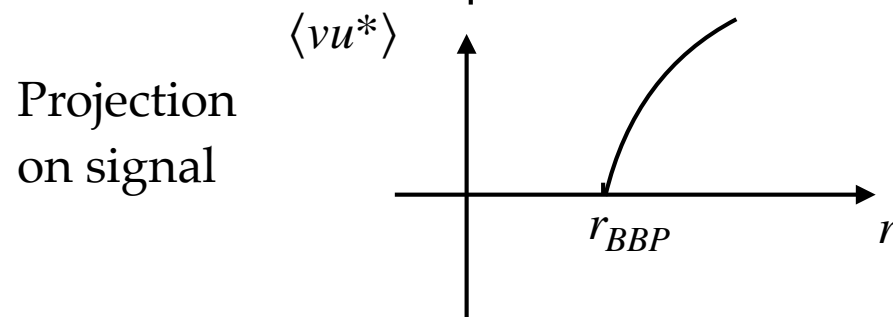
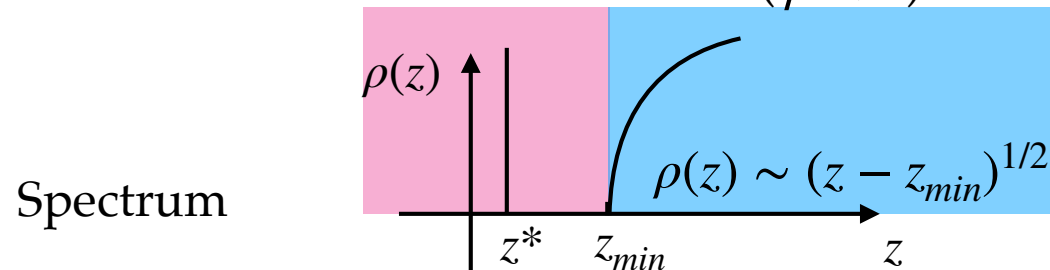
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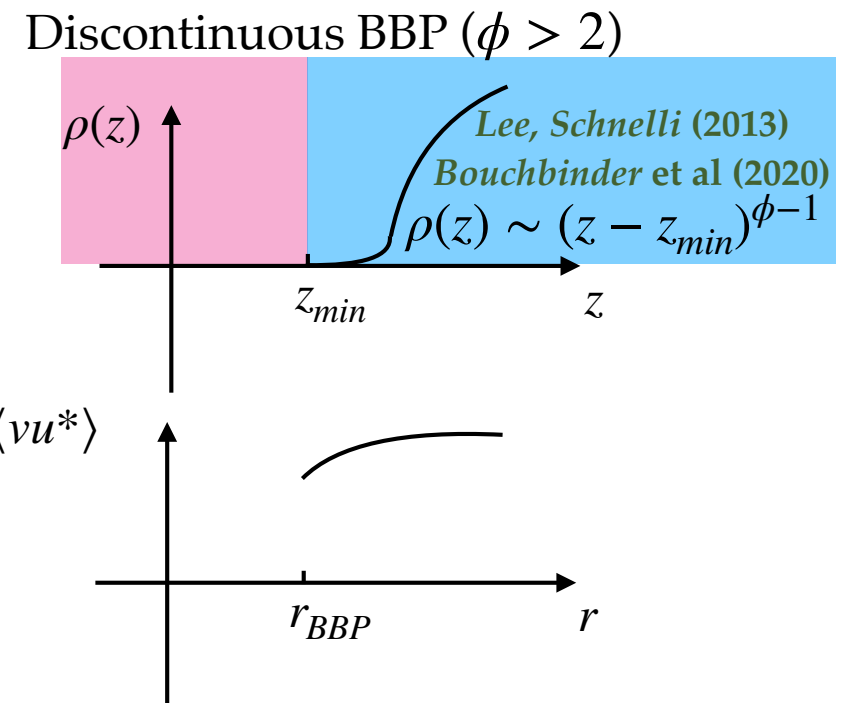
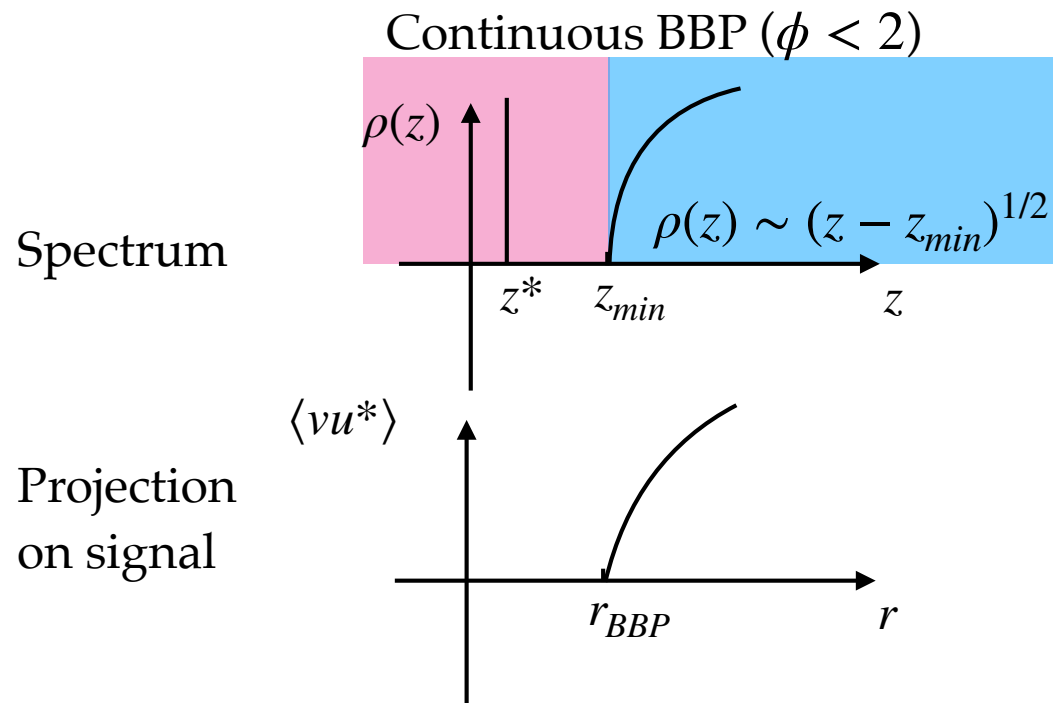
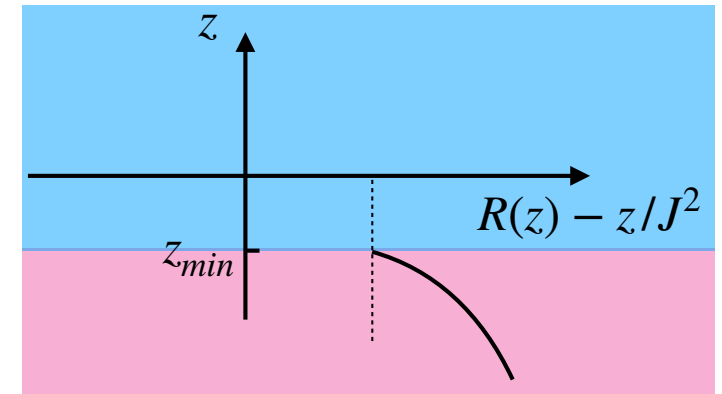
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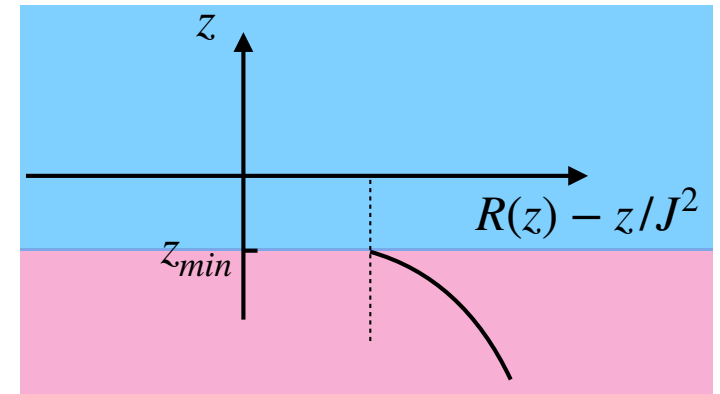
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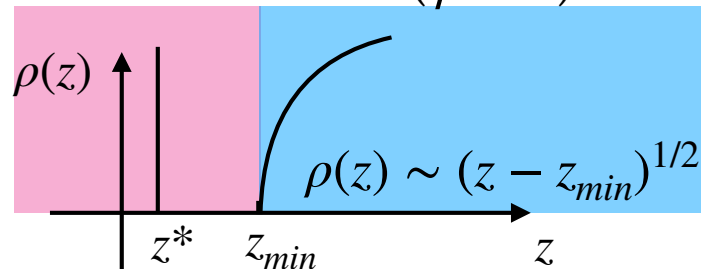
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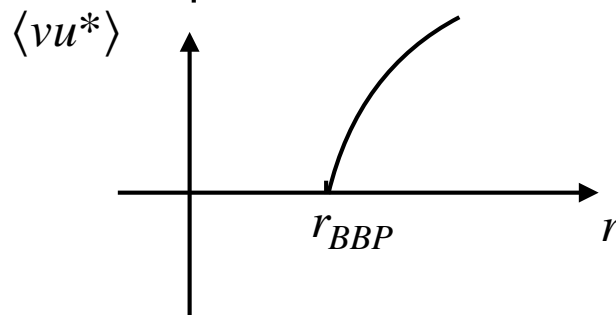
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Continuous BBP ( $\phi < 2$ )

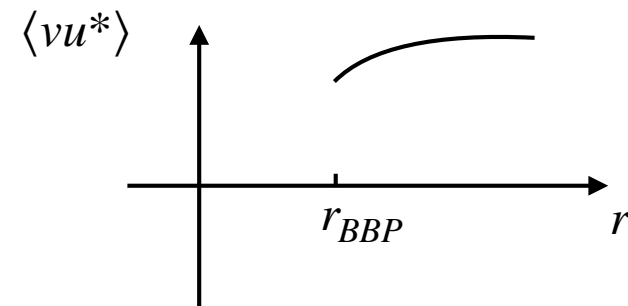
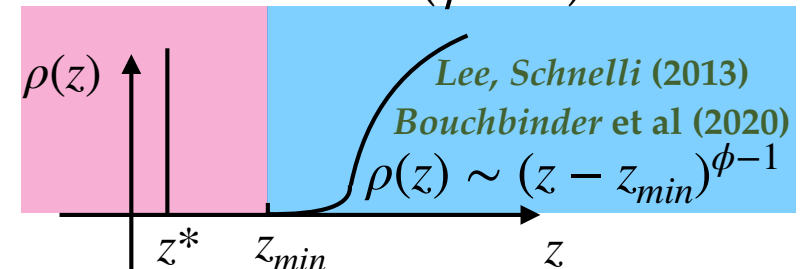


Spectrum



Projection  
on signal

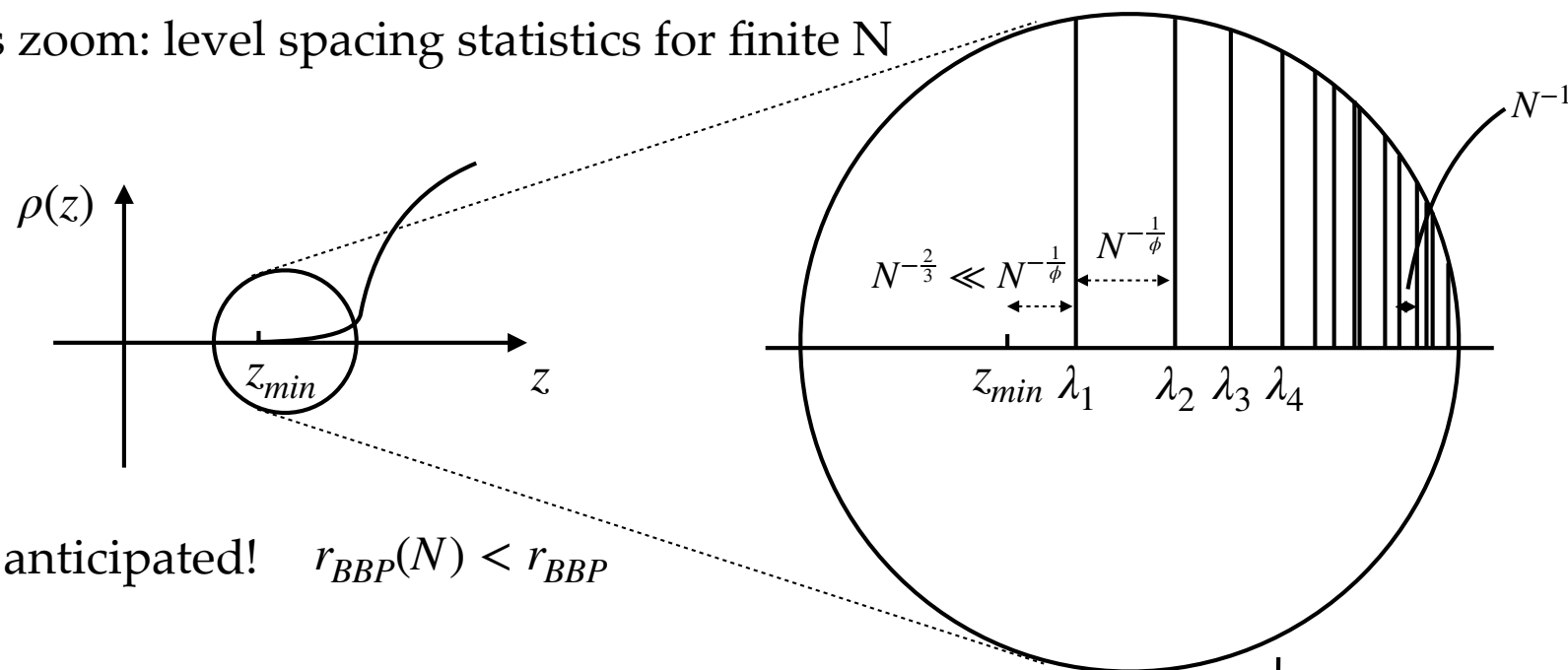
Discontinuous BBP ( $\phi > 2$ )



# Strong finite size effects

*Biroli, Cammarota, Ricci Tersenghi, in preparation*

Spectrum and its zoom: level spacing statistics for finite  $N$



The transition is anticipated!  $r_{BBP}(N) < r_{BBP}$

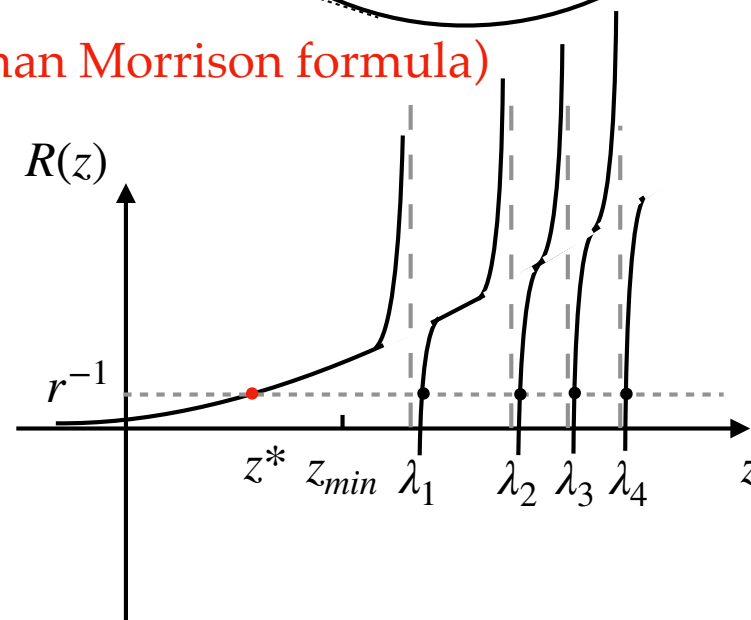
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Solutions:  $z^*, \tilde{\lambda}_j$

Different statistics  $\delta z^* \sim 1/\sqrt{N}$   $\delta \tilde{\lambda}_j \sim N^{-1/\phi}$

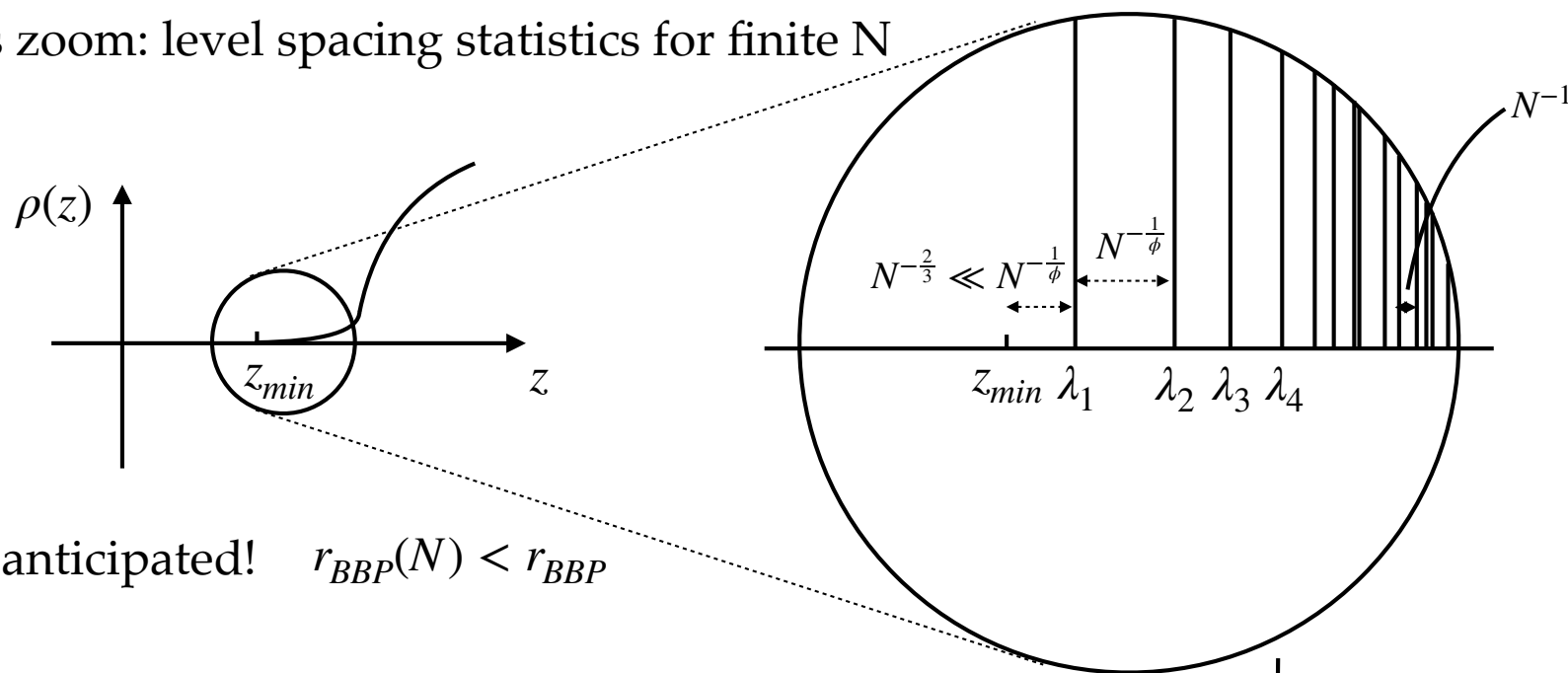
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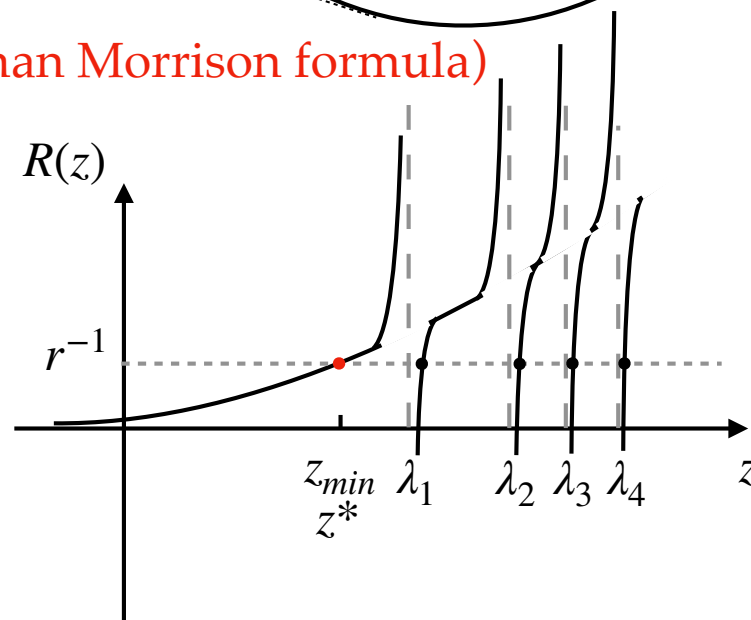
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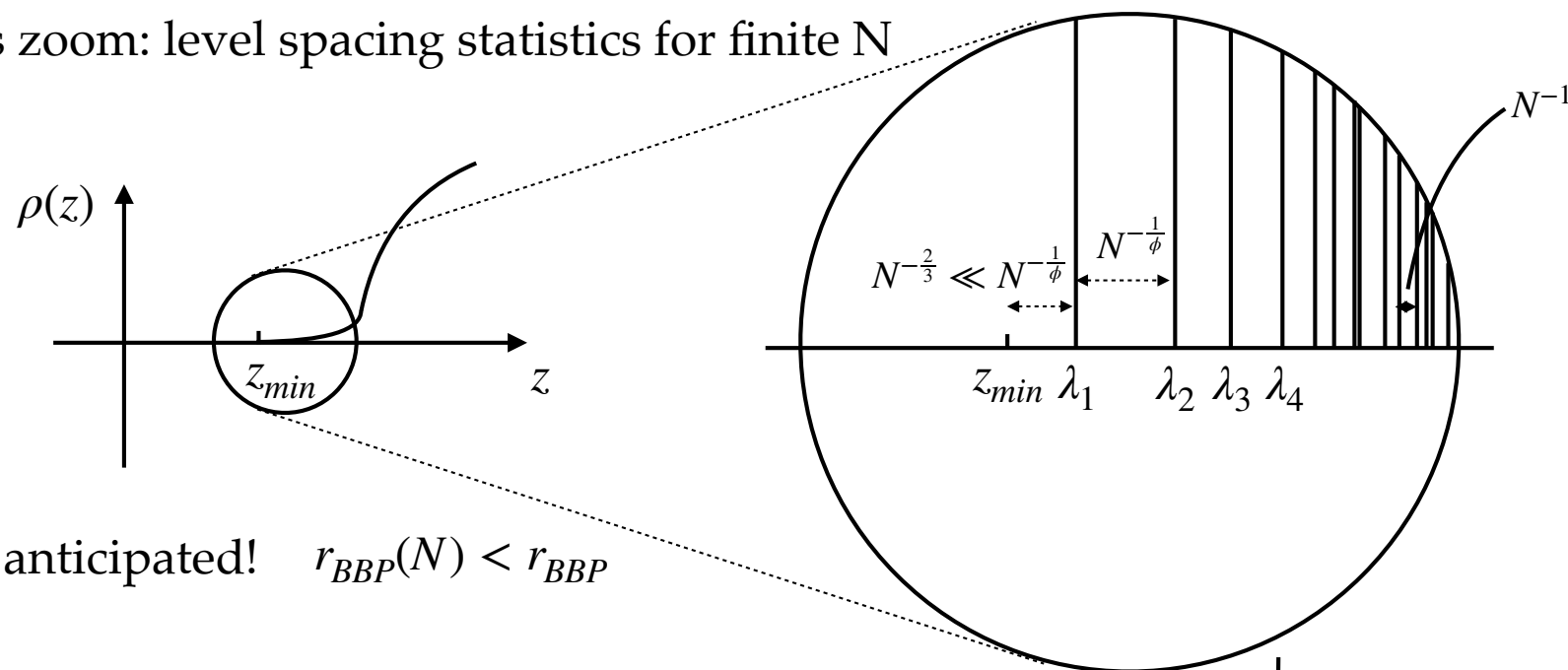
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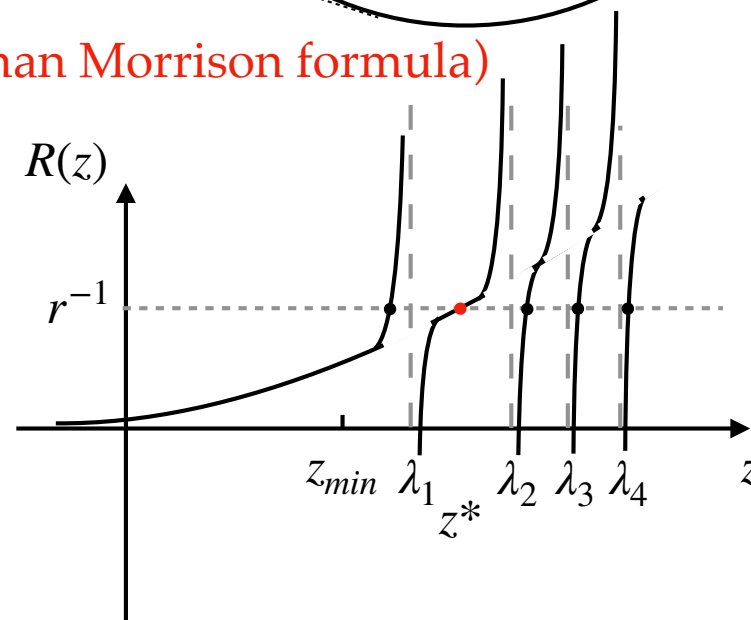
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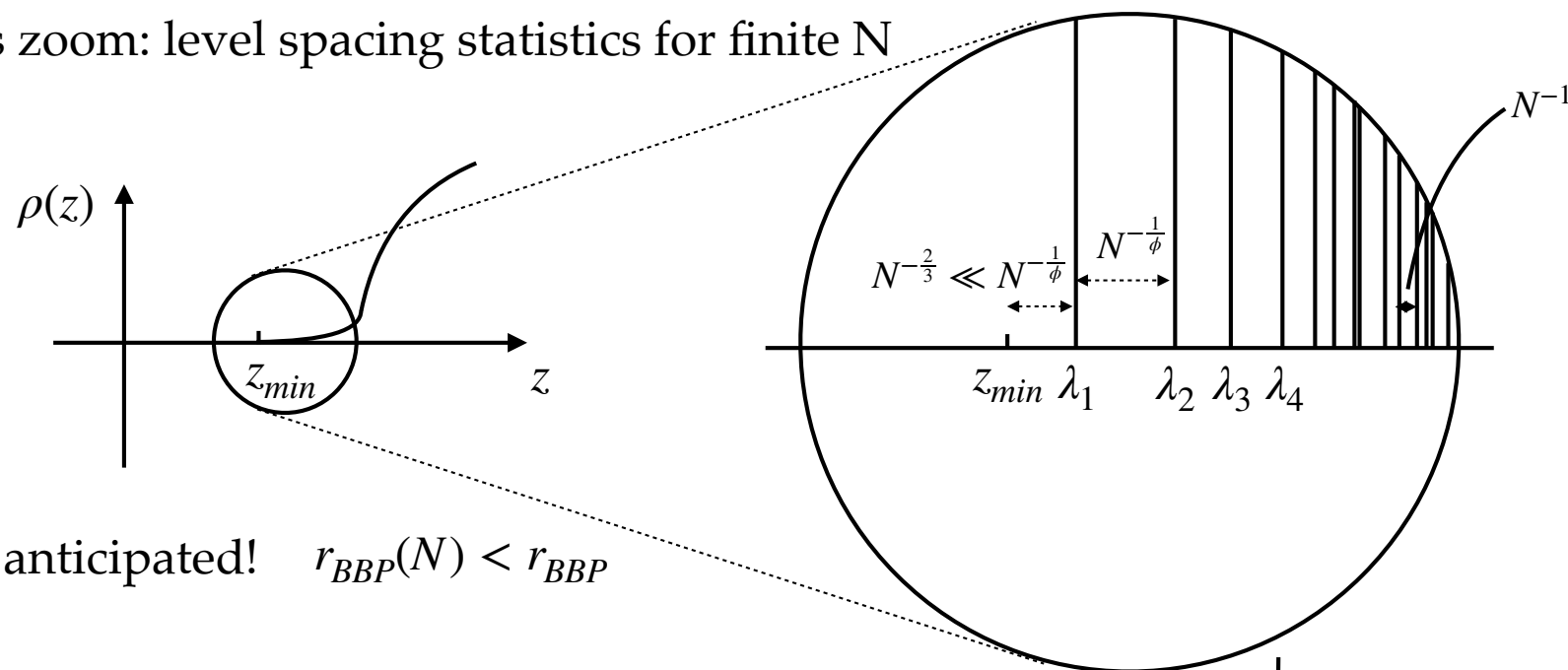
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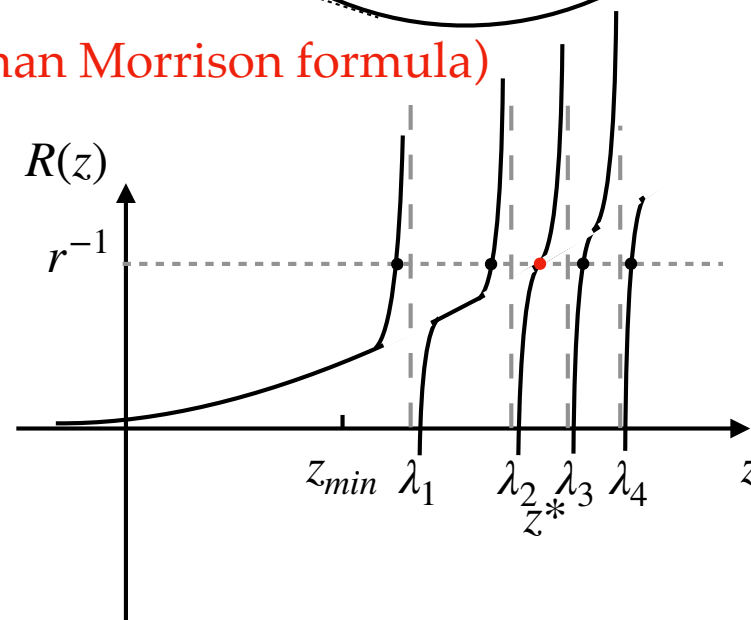
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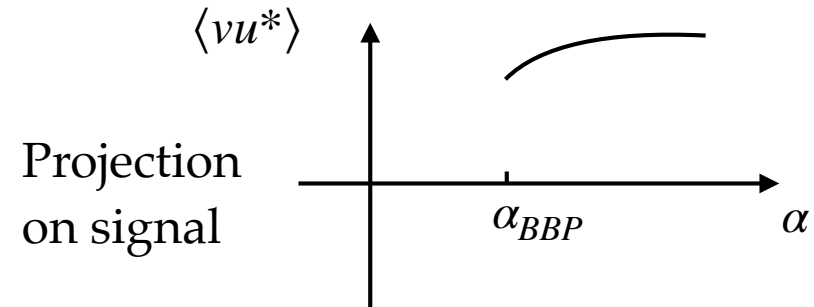
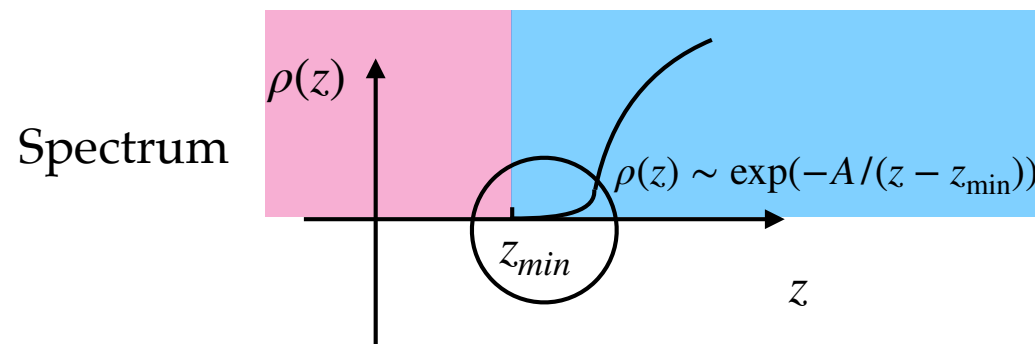
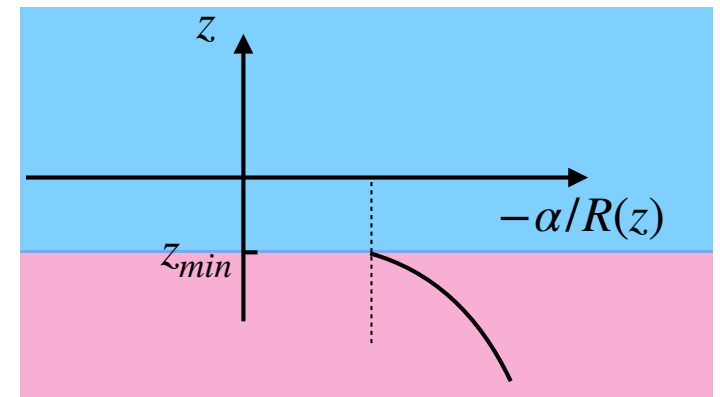
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Weighted Wishart matrices  $\mathcal{H}(\mathcal{L})_{ij} = \sum_m^{\alpha N} X_i^m X_j^m \ell(Y^m)$  with  $\ell(Y) = \frac{Y^2 - A}{B + CY^2}$  and  $Y \sim \mathcal{N}(0,1)$

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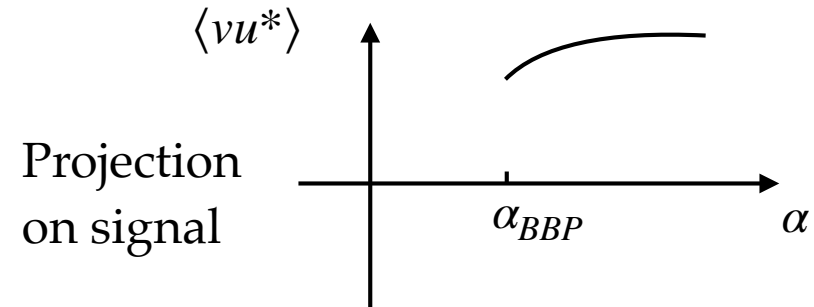
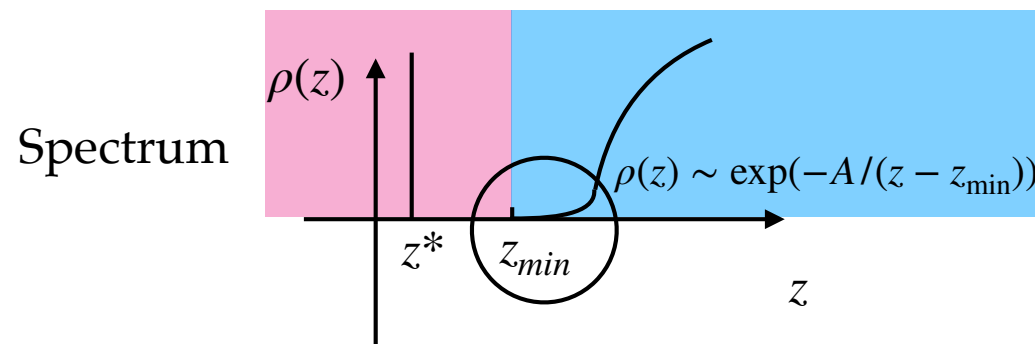
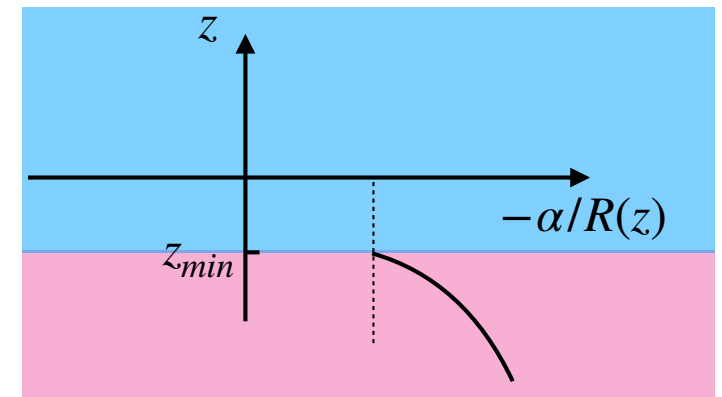
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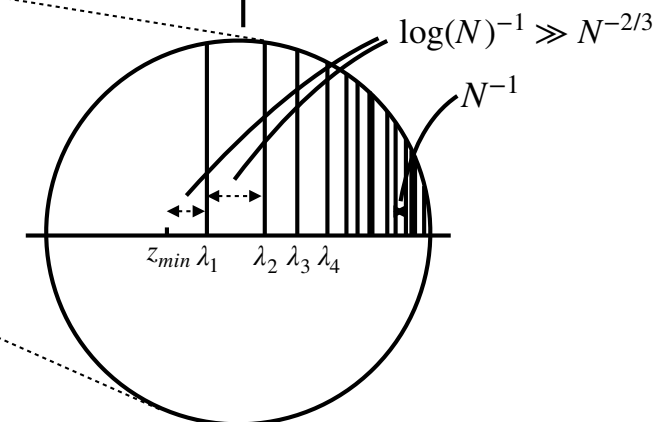
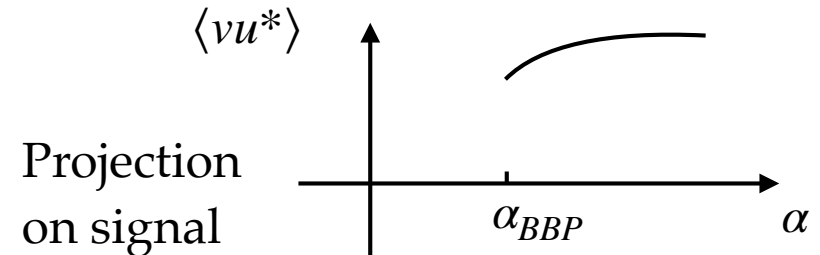
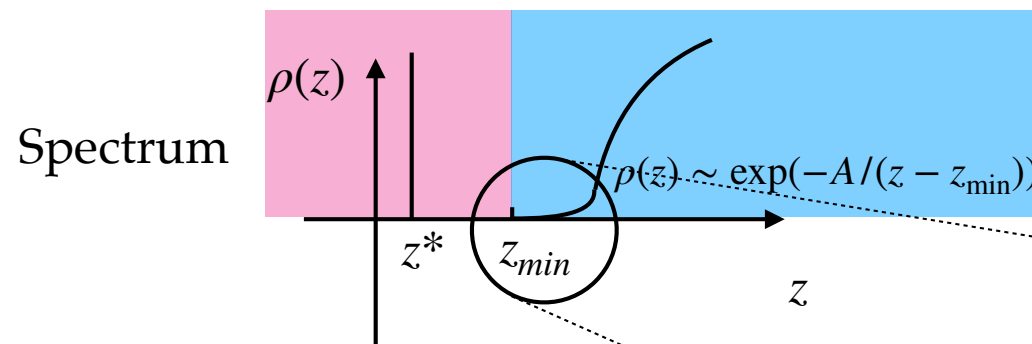
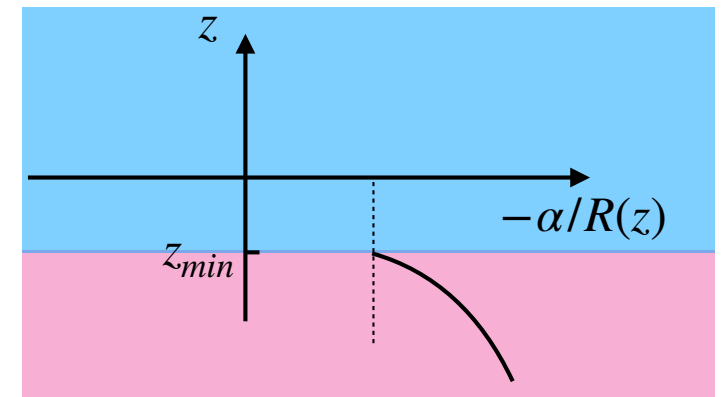
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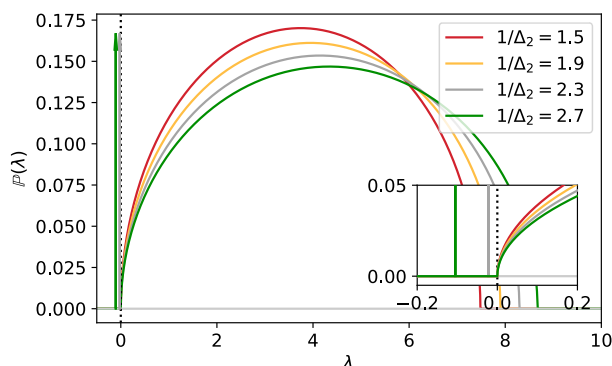
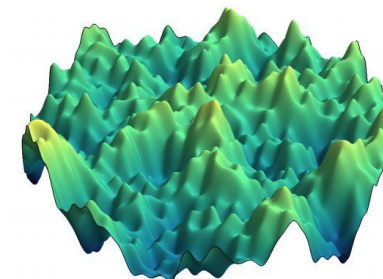
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# One transition, multiple results

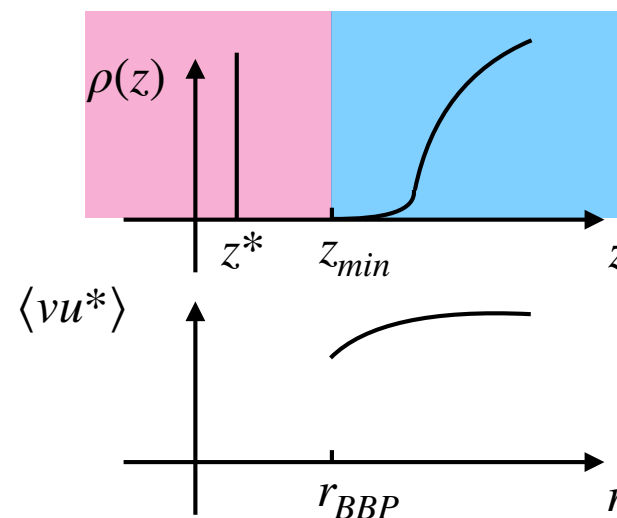
Signal in a noisy background from Hessian of risk / cost landscapes

BBP transition: isolated eigenvalue contains information



Tensor PCA: detailed information on landscape structure  
early retrieval in rough landscape

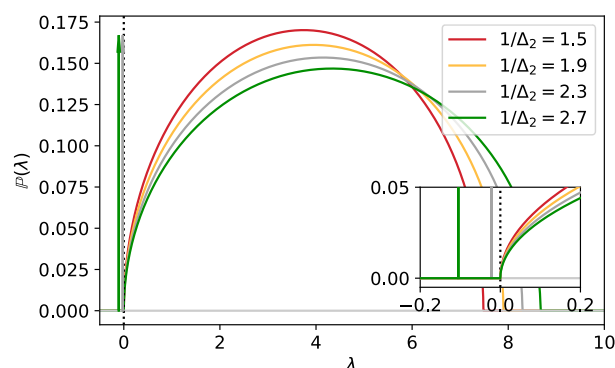
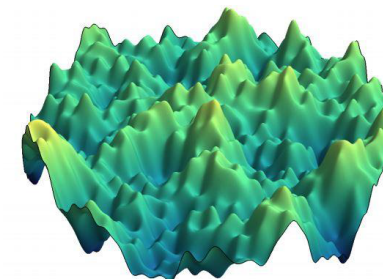
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early retrieval in rough landscapes (?)  
a large variety of spectral initialisation  
**BBP transition can be discontinuous**  
**the importance of finite size effects**



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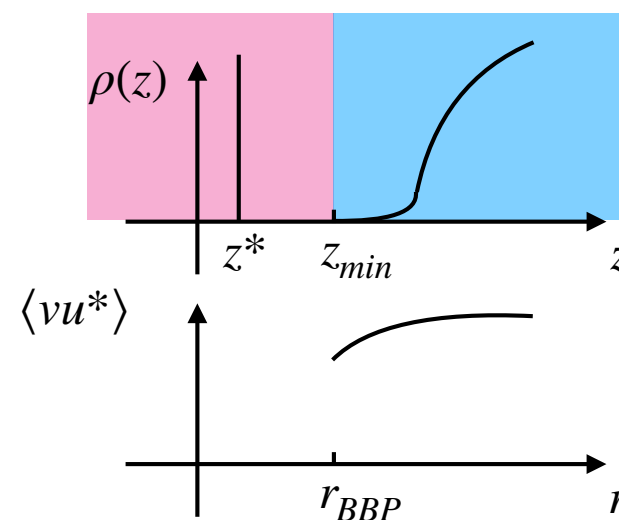
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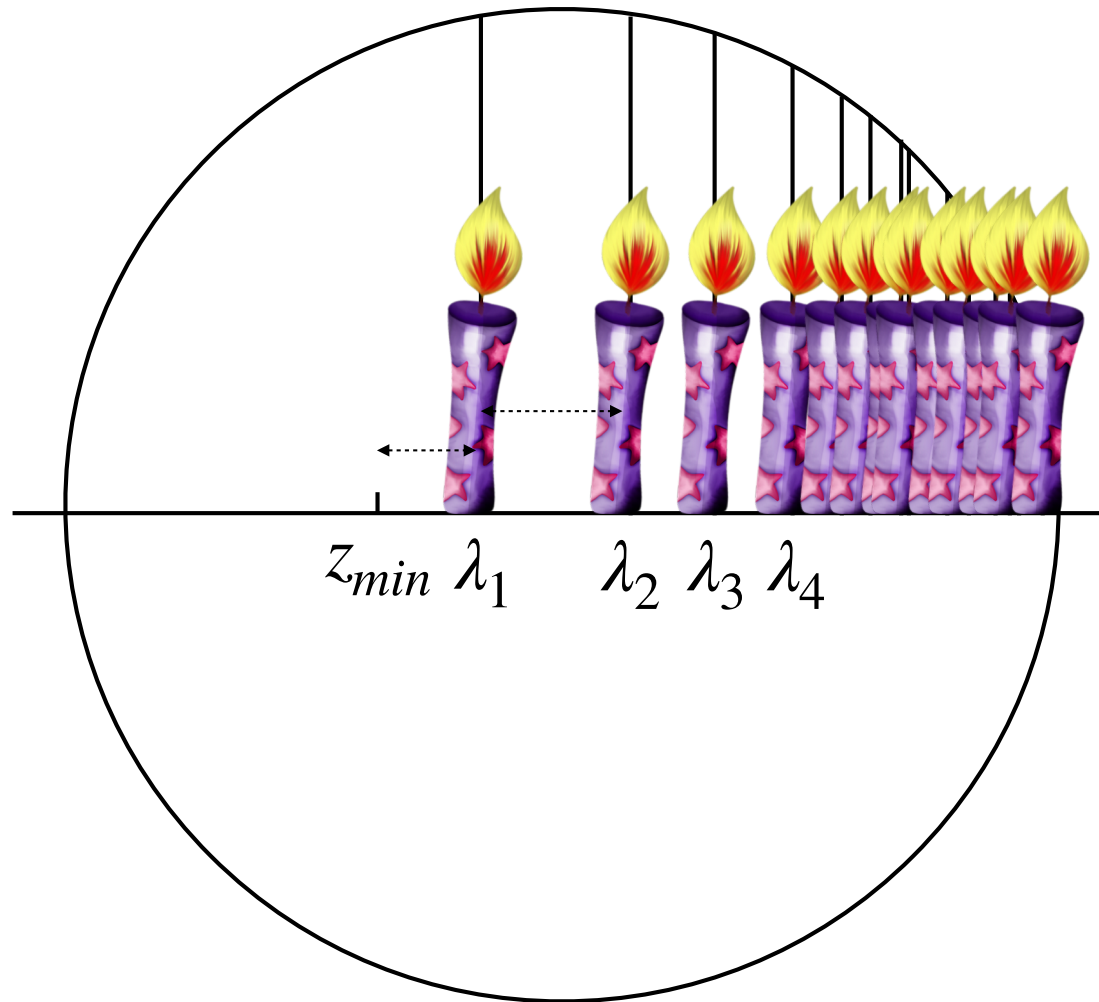
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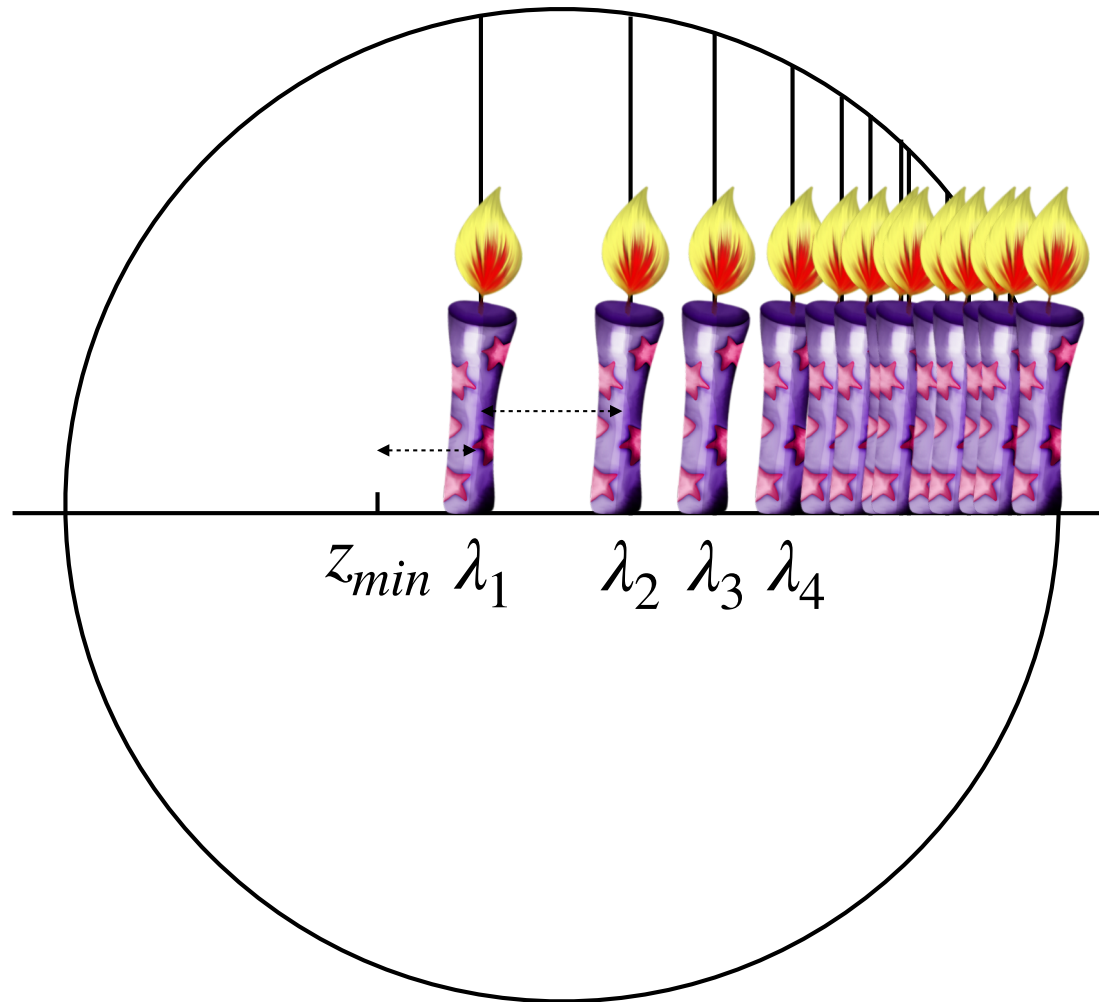
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# The birthday spectrum...



# The birthday spectrum...



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**Happy Birthday Yan!**

