## Matrix equilibrium states

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# Equilibrium/Gibbs states

Let  $\Sigma = \{0, \dots, M-1\}$  and  $\sigma : \Sigma^{\mathbb{Z}} \to \Sigma^{\mathbb{Z}}$  be the shift map.

- "Scalar" equilibrium/Gibbs states. Let  $\varphi: \Sigma^{\mathbb{Z}} \to \mathbb{R}$ .
  - Equilibrium: Maximize

$$h_{\mu}(\sigma) + \int \varphi d\mu$$

over  $\sigma$  invariant measures.

• Gibbs: There exist constants C > 0 and P such that

$$C^{-1}e^{-nP+S_n\varphi(x)} \le \mu_{\varphi}[x_0x_1\cdots x_{n-1}] \le Ce^{-nP+S_n\varphi(x)}$$

for all  $x \in \Sigma^{\mathbb{Z}}$ .

- "Matrix" equilibrium/Gibbs states.
  - $\varphi: \Sigma^{\mathbb{Z}} \to \mathbb{R}$  is replaced by  $\mathcal{A}: \Sigma^{\mathbb{Z}} \to M_d(\mathbb{R})$ .
  - $S_n \varphi(x)$  is replaced by  $\log \|\mathcal{A}(\sigma^{n-1}x) \cdots \mathcal{A}(\sigma x)\mathcal{A}(x)\|$ .



## Equilibrium/Gibbs states

Let  $\mathcal{A}: \Sigma^{\mathbb{Z}} \to M_d(\mathbb{R})$  depend only on 1-coordinate,  $\mathcal{A} = (A_0, A_1, \dots, A_{M-1})$  and  $\beta \in \mathbb{R}$ .

Equilibrium: Maximize

$$h_{\mu}(\sigma) + \beta \underbrace{\lim_{n \to \infty} \frac{1}{n} \int \log \|A_{x_{n-1}} \cdots A_{x_1} A_{x_0}\| d\mu}_{\Lambda(\mathcal{A}, \mu)}$$

over  $\sigma$  invariant measures.

• Gibbs: There exist constants C > 0 and P such that

$$C^{-1}e^{-nP} \|A_{x_{n-1}} \cdots A_{x_0}\|^{\beta} \le \mu_{\mathcal{A},\beta} [x_0 \cdots x_{n-1}] \le Ce^{-nP} \|A_{x_{n-1}} \cdots A_{x_0}\|^{\beta}$$

for all  $x \in \Sigma^{\mathbb{Z}}$ .

**Comment:** P is the maximum of  $h_{\mu}(\sigma) + \beta \Lambda(\mathcal{A}, \mu)$ ,  $\beta \mapsto P(\beta)$  is called the (matrix) pressure function.

#### Some reasons to care about MES

- They appear "in the wild"
  - Hidden Markov measures.
  - The Kusuoka measure.
- You care about their "cousin": equilibrium states for the singular value potential.
  - Applications to self-affine fractals.
- You care about the function  $P(\beta)$ .

•

$$\left. \frac{dP}{d\beta} \right|_{\beta=0} = \lambda$$

where  $\lambda$  is maximal Lyapunov exponent with respect to the uniform Bernoulli measure.

• Provided you take some assumptions on  ${\cal A}$  and  $\lambda$  = 0

$$\frac{\log \|A_{x_{n-1}}\cdots A_{x_1}A_{x_0}\|}{\sqrt{n}} \xrightarrow{\text{dist}} \mathcal{N}(0,\sigma^2) \text{ and } \frac{d^2P}{d\beta^2}\Big|_{\beta=0} = \sigma^2.$$

# Some questions about MES

- Existence and uniqueness:
  - Provided the collection  $\mathcal A$  does not preserve a proper and non-trivial subspace and  $\beta>0$  matrix equilibrium states are unique and satisfy the Gibbs inequality. (Feng and Käenmäki '11)
- Ergodic and statistical properties:
  - Mixing? If yes can we find a mixing rate?
  - Isomorphic to a Bernoulli shift?
- Equilibrium states for (regular enough) scalar potentials are known to have very nice properties to what extent is the same true for matrix equilibrium states?

## Constructing matrix Gibbs states

• **Sketch:** Assume A is irreducible and  $\beta > 0$ . Define

$$\nu_{n}[x_{0}\cdots x_{n-1}] = \frac{\|A_{x_{n-1}}\cdots A_{x_{1}}A_{x_{0}}\|^{\beta}}{\sum_{y_{0}\cdots y_{n-1}}\|A_{y_{n-1}}\cdots A_{x_{1}}A_{x_{0}}\|^{\beta}}$$

take a weak\* limit point  $\nu$ . Satisfies Gibbs inequality but might not be shift invariant so average it

$$\frac{1}{N} \sum_{k=0}^{N-1} \sigma_*^k \nu$$

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- If you use this construction you have to rely exclusively on the Gibbs inequality to prove ergodic properties.
- We need a new construction.



Set 
$$\mathcal{A} = (A_0, A_1)$$
 where  $A_0 = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, A_1 = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$ .



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$$A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \text{ notice } A \begin{bmatrix} 1 \\ 1 \end{bmatrix} = 3 \begin{bmatrix} 1 \\ 1 \end{bmatrix}, A^T \begin{bmatrix} 1 \\ 1 \end{bmatrix} = 3 \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$



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The formula

$$\mu_{\mathcal{A},1}[x_0x_1\cdots x_{n-1}] = 3^{-n}\begin{bmatrix} 1 & 1 \end{bmatrix} A_{x_{n-1}}\cdots A_{x_1}A_{x_0}\begin{bmatrix} 1/2\\ 1/2 \end{bmatrix}$$

extends to a measure on  $\{0,1\}^{\mathbb{Z}}$  by Kolmogorov consistency.



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extends to a measure on  $\{0,1\}^{\mathbb{Z}}$  by Kolmogorov consistency. This is the 1-Gibbs state for  $\mathcal{A}$  as

$$\begin{bmatrix} 1 & 1 \end{bmatrix} A_{x_{n-1}} \cdots A_{x_1} A_{x_0} \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} \approx \|A_{x_{n-1}} \cdots A_{x_1} A_{x_0}\|_1$$

moreover we can see that  $P = \log 3$ .

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We can deduce mixing properties from spectral properties of  $A = A_0 + A_1$ .

$$\mu_{\mathcal{A},1}([i_{0}\cdots i_{m-1}]\cap\sigma^{-n}[j_{0}\cdots j_{m'-1}])$$

$$=3^{-(m+m'+n-m)}\sum_{k_{0}\cdots k_{n-m-1}}\left(\underbrace{A_{j_{m'}}\cdots A_{j_{0}}}_{A_{J}}\underbrace{A_{k_{n-m-1}}\cdots A_{k_{0}}}_{A_{K}}\underbrace{A_{i_{m}}\cdots A_{i_{0}}}_{A_{I}}[1/2],[1]\right)$$

$$=3^{-(m+m')}\left(A_{J}3^{-(n-m)}A^{n-m}A_{I}[1/2],[1]\right) \text{ because } \sum_{|K|=n-m}A_{K}=A^{n-m}$$

$$\xrightarrow{n\to\infty}3^{-m}\left\langle A_{I}[1/2],[1]\right\rangle 3^{-m'}\left\langle A_{J}[1/2],[1]\right\rangle \text{ because } A \text{ is positive }$$

$$=\mu_{A,1}([i_{0}\cdots i_{m-1}])\mu_{A,1}([i_{0}\cdots j_{m'-1}])$$

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**Question:** How do we deal with  $\beta \neq 1$ ? Matrices which are not non-negative?

Start with  $\mathcal{A} = (A_0, A_1 \cdots, A_{M-1})$  and  $\beta$ .



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**Trick:** Consider the action of the matrices on norm one vectors weighted by  $||A_iu||^{\beta}$ . Define

$$L_i: C(\mathbb{RP}^{d-1}) \to C(\mathbb{RP}^{d-1}) \text{ by } L_i f(\overline{u}) = \left\| A_i \frac{u}{\|u\|} \right\|^{\beta} f(\overline{A_i u}).$$

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Transfer operator:

$$L_{\mathcal{A},\beta} = \sum_{i} L_{i} \text{ that is } L_{\mathcal{A},\beta} f(\overline{u}) = \sum_{i} \left\| A_{i} \frac{u}{\|u\|} \right\|^{\beta} f(\overline{A_{i}u}).$$

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Take (if they exist) h > 0  $\nu$  with  $L_{\mathcal{A},\beta}h = \rho(L_{\mathcal{A},\beta})h$  and  $L_{\mathcal{A},\beta}^*\nu = \rho(L_{\mathcal{A},\beta})\nu$ .

$$\mu_{\mathcal{A},\beta}[x_0x_1\cdots x_{n-1}] = \rho(L_{\mathcal{A},\beta})^{-n} \int_{\mathbb{RP}^{d-1}} L_{x_0}L_{x_1}\cdots L_{x_{n-1}}hd\nu.$$

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Provided the collection  $\mathcal A$  is proximal (read contracting) and strongly irreducible (read topologically mixing) then  $L_{\mathcal A,\beta}$  has a spectral gap (Guivarc'h and Le Page '04). This implies h and  $\nu$  exist and

$$\rho(L_{\mathcal{A},\beta})^{-n}L_{\mathcal{A},\beta}^n f \xrightarrow{n\to\infty} \langle f,\nu\rangle h.$$



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This makes the analog of the computation

$$\begin{split} \mu_{\mathcal{A},1}([I] \cap \sigma^{-n}[J]) &= 3^{-|I|-|J|} \left\langle A_J 3^{-n+|J|} A^{n-|J|} A_I[1/2], [1] \right\rangle \\ &\xrightarrow{n \to \infty} 3^{-|I|} \left\langle A_I[1/2], [1] \right\rangle 3^{-|J|} \left\langle A_J[1/2], [1] \right\rangle \\ &= \mu_{\mathcal{A},1}([I]) \mu_{\mathcal{A},1}([J]). \end{split}$$

work which yields the following result...



#### Result

#### Theorem (P.)

Suppose that  $A = (A_0, ... A_{M-1})$  is a collection of real invertible  $d \times d$  matrices which is proximal and strongly irreducible. Then for any  $\beta \geq 0$  there exists a unique Gibbs state for  $(A, \beta)$ ,  $\mu_{A,\beta}$ . Moreover

- **1**  $\mu_{A,\beta}$  is weak Bernoulli.
- **2**  $\mu_{\mathcal{A},\beta}$  has exponential decay of correlations for Hölder continuous functions. That is, for a fixed  $\theta \in (0,1)$  there are constants D and  $\gamma \in (0,1)$  such that

$$\left| \int f \cdot g \circ \sigma^n d\mu_{\mathcal{A},\beta} - \int f d\mu_{\mathcal{A},\beta} \int g d\mu_{\mathcal{A},\beta} \right| \le D \|f\|_{\theta} \|g\|_{\theta} \gamma^n$$

for all  $f, g \in \mathcal{H}_{\theta}$ ,  $n \ge 0$ .



## Where do we go from here?

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- Irreducible collections:
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  - Isomorphic to a Bernoulli shift cross a finite rotation?
- What is the connection between  $L_{\mathcal{A},\beta}:C(\mathbb{RP}^{d-1})\to C(\mathbb{RP}^{d-1})$  and the transfer operator  $\mathcal{L}:L^1(\mu_{\mathcal{A},\beta})\to L^1(\mu_{\mathcal{A},\beta})$ ?

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- Lots other questions:
  - β < 0?</li>
  - Singular value potential?
  - $\mathcal{A}: \Sigma^{\mathbb{Z}} \to M_d(\mathbb{R})$  Hölder?
  - etc...

