

# Large time behaviour of finite state mean-field interacting particle systems

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Joint work with Rajesh Sundaresan

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- ▶  $\{(X_n^N(t), 1 \leq n \leq N), t \geq 0\}$  is a Markov process on  $\mathcal{Z}^N$ .

# The empirical measure process $\mu_N$

- ▶  $\{\mu_N(t), t \geq 0\}$  is also a Markov process on  $M_1(\mathcal{Z})$  with infinitesimal generator

$$L^N f(\xi) = \sum_{(z, z') \in \mathcal{E}} N \xi(z) \lambda_{z, z'}(\xi) \left[ f \left( \xi + \frac{\delta_{z'}}{N} - \frac{\delta_z}{N} \right) - f(\xi) \right].$$

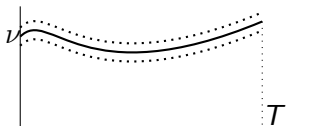
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- ▶ Typical behaviour of  $\mu_N$  (mean-field limit):  
Let  $\mu_N(0) \rightarrow \nu$  weakly as  $N \rightarrow \infty$ . Then  $\{\mu_N(t), t \geq 0\}$  is “close to” the solution to the McKean-Vlasov equation:

$$\dot{\mu}(t) = \Lambda^*(\mu(t))\mu(t), \quad \mu(0) = \nu.$$





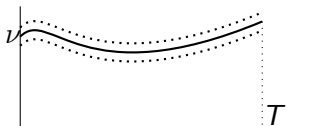
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- ▶ Our interest: study of the large time behaviour of  $\mu_N$  when the above ODE has multiple stable equilibria.

## An Example: Interaction in WiFi networks

- ▶  $N$  nodes accessing a common wireless medium.
- ▶ Interaction among nodes via the distributed MAC protocol.

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- ▶  $N$  nodes accessing a common wireless medium.
- ▶ Interaction among nodes via the distributed MAC protocol.
- ▶ State  $X_n^N(t)$  represents aggressiveness of packet transmission.

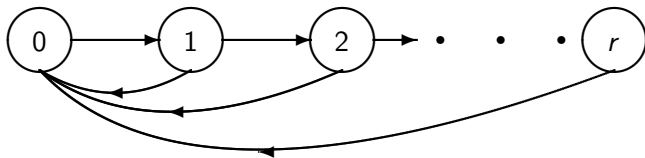


Figure: Set of allowed transitions in WiFi example

- ▶ State evolution:
  - ▶ Becomes less aggressive after a collision.
  - ▶ Moves to the most aggressive state after a successful packet transmission.

## A sample path of $\mu_N$ in WiFi example

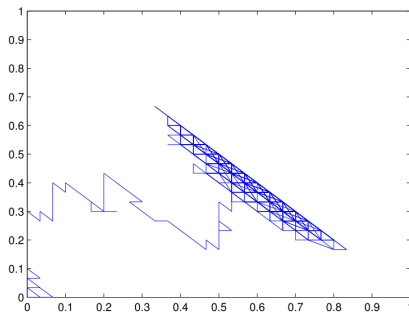


Figure: Evolution of states in a WiFi network under the MAC protocol

- Multiple stable regions in the system. Transition between two stable region occur over large time durations.

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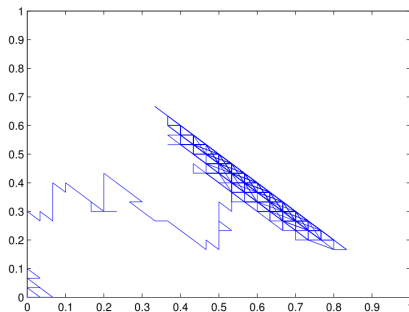


Figure: Evolution of states in a WiFi network under the MAC protocol

- ▶ Multiple stable regions in the system. Transition between two stable region occur over large time durations.
- ▶ Goals:
  - ▶ Study large time behaviour of  $\mu_N$
  - ▶ Mixing time of  $\mu_N$
  - ▶ Control  $\mu_N$  to a desired equilibrium

# Large deviations

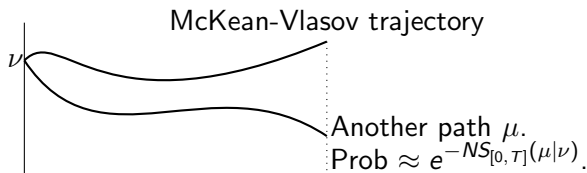
- ▶  $S$ : a metric space.  $\{X_N\}_{N \geq 1}$  is a sequence of  $S$ -valued random variables.
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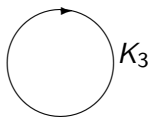
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- ▶ Consider  $\mu_N$  as a trajectory-valued random variable
- ▶ We want probability of deviations of  $\mu_N$  from its typical trajectory

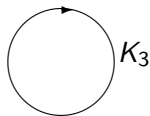




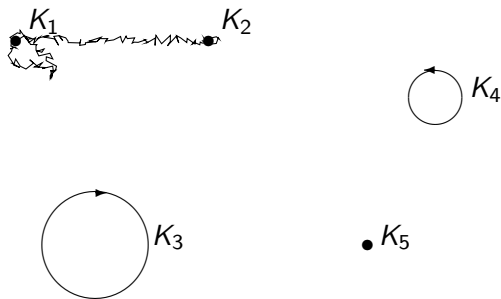
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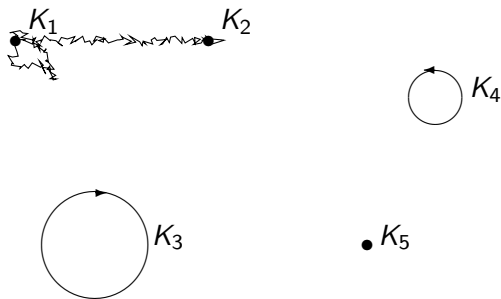


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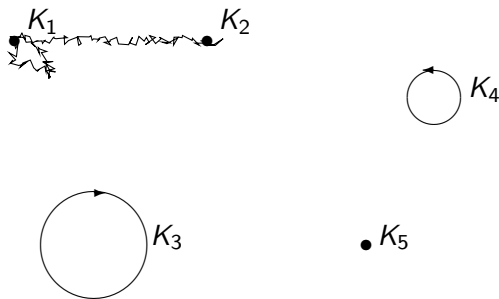
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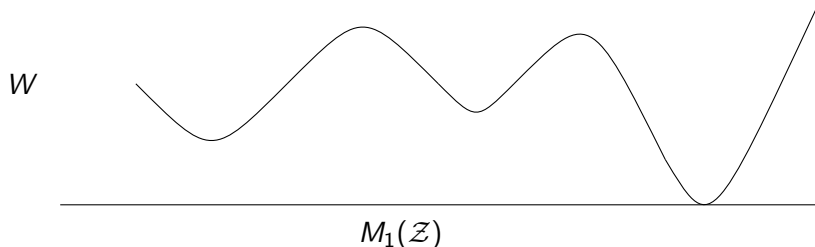
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- ▶ Freidlin-Wentzell quasipotential  $\tilde{V} : M_1(\mathcal{Z}) \times M_1(\mathcal{Z}) \rightarrow \mathbb{R}_+$ .
  - ▶  $\tilde{V}(K_i, K_j)$ : cost to go from  $K_i$  to  $K_j$ .

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- ▶ One-step transition probability of  $Z^N$ :  
 $P(K_i, K_j) \sim \exp\{-N\tilde{V}(K_i, K_j)\}$ .

## An entropy function

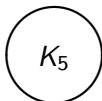
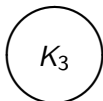
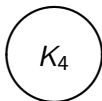
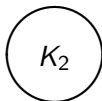
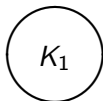


- ▶  $W(\xi) = \min_{1 \leq i \leq I} (W(K_i) + V(K_i, \xi)) - \min_{1 \leq i \leq I} W_i$ .
- ▶ Stationary distribution scales like  $\varphi_N(\xi) \sim \exp\{-NW(\xi)\}$ .
- ▶ Under stationarity, we find  $\mu_N$  to be in a neighbourhood of the set of minimisers of  $W$ , with very high probability.

## Decomposition into cycles - example

- Recall:  $P(K_i, K_j) \sim \exp\{-N\tilde{V}(K_i, K_j)\}$

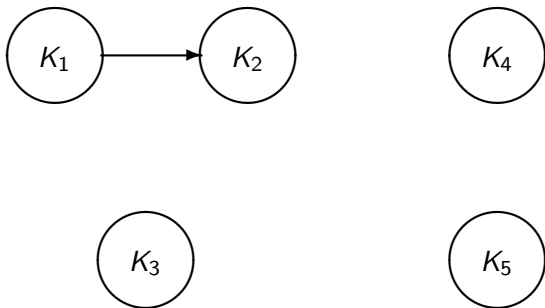
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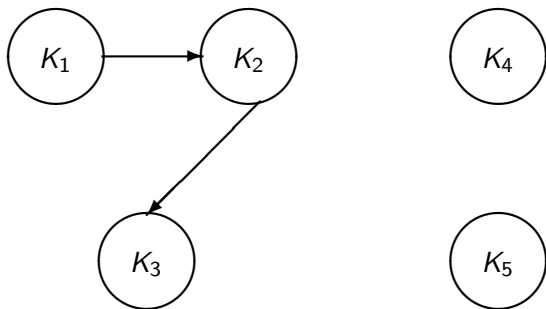




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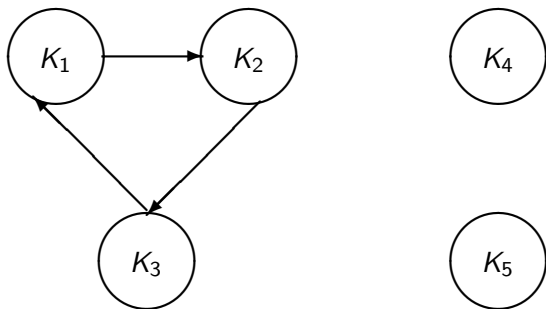
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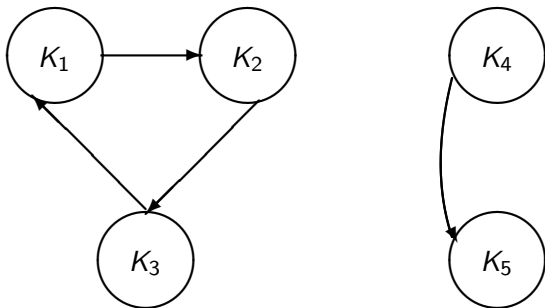
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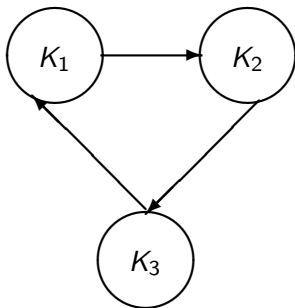
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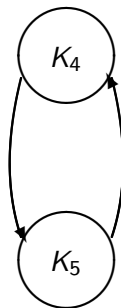
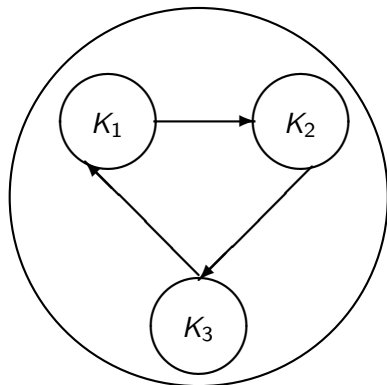
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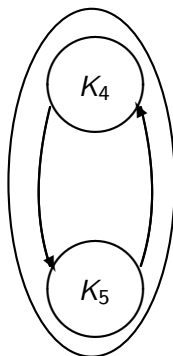
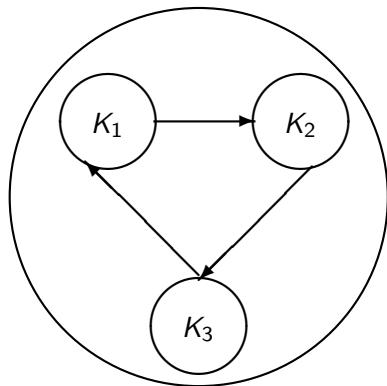
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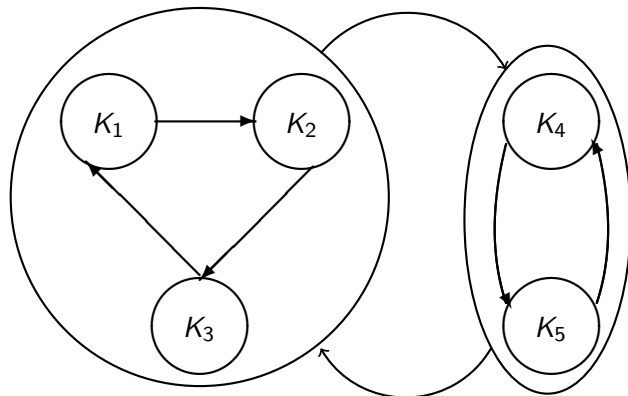
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# Large time behaviour

- Cycles are “very stable” subsets of  $M_1(\mathcal{Z})$ .

## Theorem

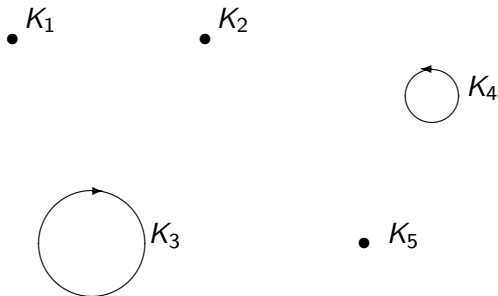
*Let  $\pi_1^k, \pi_2^k$  be  $k$ -cycles,  $\pi_1^k \neq \pi_2^k$ , and  $K_i \in \pi_1^k$ . Let  $W = L \setminus \pi_1^k$ . Given  $\varepsilon > 0$ , there exist  $\rho > 0$  and  $N_0 \geq 1$  such that for all  $\rho_1 \leq \rho$ ,  $\nu \in \gamma_i \cap M_1^N(\mathcal{Z})$  and  $N \geq N_0$ , we have*

$$\begin{aligned} \exp\{-N(\tilde{V}(\pi_1^k, \pi_2^k) - \tilde{V}(\pi_1^k) + \varepsilon)\} &\leq P_\nu(\mu_N(\hat{\tau}_W) \in \gamma_{\pi_2^k}) \\ &\leq \exp\{-N(\tilde{V}(\pi_1^k, \pi_2^k) - \tilde{V}(\pi_1^k) - \varepsilon)\} \end{aligned}$$

- Lower bound: construct a specific path.
- Upper bound: Use strong Markov property and the uniform LDP of  $\mu_N$ .

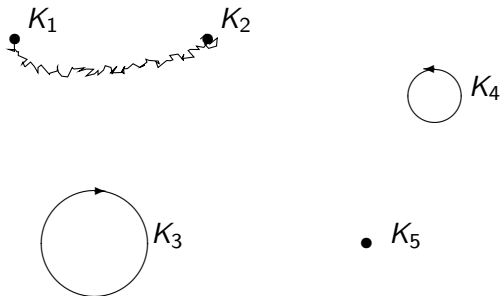


## Mixing of $\mu_N$



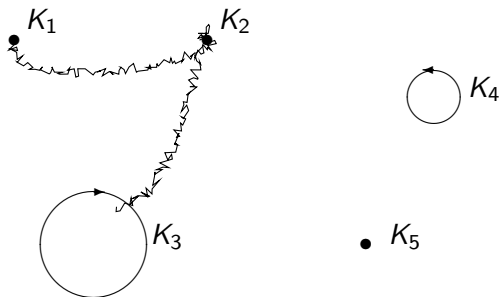
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- ▶ Suppose that  $W(K_3) = \min_{i \neq 3} W(K_i)$ .
- ▶  $\mu_N$  mixes well if it reaches a neighbourhood of  $K_3$ .

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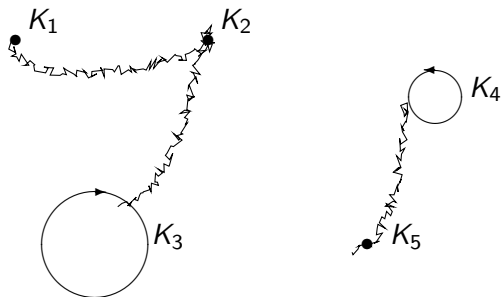
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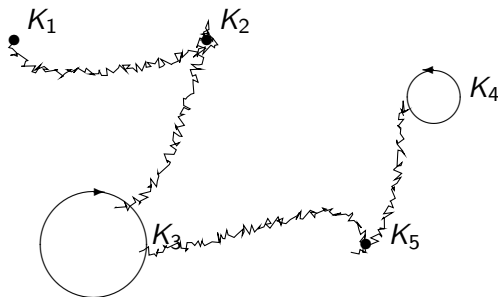
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# Mixing of $\mu_N$

- Define

$$\Lambda = \min\{\tilde{V}(g) : g \in G(i), i \in L\} \\ - \min\{\tilde{V}(g) : g \in G(i,j), i,j \in L, i \neq j\}.$$

## Theorem

*Given  $\delta > 0$ , there exist  $\varepsilon > 0$  and  $N_0 \geq 1$  such that for all  $\nu \in M_1^N(\mathcal{Z})$  and  $N \geq N_0$*

$$|E_\nu(f(\mu_N(T))) - \langle f, \varphi_N \rangle| \leq \|f\|_\infty \exp\{-\exp(N\varepsilon)\},$$

*where  $T = \exp\{N(\Lambda + \delta)\}$  and  $f \in B(M_1(\mathcal{Z}))$ .*

- Proof via the estimates of large time behaviour.

# Asymptotics of the second eigenvalue

- ▶ If  $\mu_N$  is reversible (i.e.  $L^N$  is self-adjoint in  $L^2(\wp_N)$ ), spectral decomposition of  $L^N$  tells us that

$$E_\nu f(\mu_N(t)) = \langle f, \wp_N \rangle + \sum_{k \geq 2} e^{-t\lambda_k^N} (f, u_k^N) u_k^N(\nu),$$

- ▶ Mixing time of  $\mu_N$  is governed by  $\lambda_2^N$ .

## Theorem

$$\lim_{N \rightarrow \infty} \frac{1}{N} \log \lambda_2^N = -\Lambda.$$

## Convergence to a global minimum

- ▶ Fix  $c > 0$ . Start with  $N_0 = \min\{n \in \mathbb{N} : \exp\{nc\} - 2 \geq 0\}$  particles.
- ▶ Let  $t_{N_0} = 0$ . Add a particle at times  $t_N = \exp\{Nc\} - 2$ ,  $N > N_0$ , with a certain state.
- ▶  $\bar{\mu}$ : the resulting process.



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- ▶  $\bar{\mu}$ : the resulting process.
- ▶ Small  $c$ : particles are added too frequently;  $\bar{\mu}$  could get trapped in a local minimum of the entropy function depending on  $\bar{\mu}(0)$ .

## Convergence to a global minimum

- ▶ Fix  $c > 0$ . Start with  $N_0 = \min\{n \in \mathbb{N} : \exp\{nc\} - 2 \geq 0\}$  particles.
- ▶ Let  $t_{N_0} = 0$ . Add a particle at times  $t_N = \exp\{Nc\} - 2$ ,  $N > N_0$ , with a certain state.
- ▶  $\bar{\mu}$ : the resulting process.
- ▶ Small  $c$ : particles are added too frequently;  $\bar{\mu}$  could get trapped in a local minimum of the entropy function depending on  $\bar{\mu}(0)$ .
- ▶ Large  $c$ : sufficient time for exploration,  $\bar{\mu}$  converges to a global minimum of the entropy function.

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## Theorem

For  $c > c^*$  and any  $\rho_1 > 0$ ,

$$P_{0,\nu}(\bar{\mu}(t) \in \gamma_{i_0}) \rightarrow 1$$

as  $t \rightarrow \infty$ , uniformly for all  $\nu \in M_1^{N_0}(\mathcal{Z})$ .

# Conclusion

- ▶ Study of large time behaviour of finite state mean-field interacting particle systems
  - ▶ Exit time estimates. Decomposition into cycles.
  - ▶ Convergence of  $\mu_N$  to its invariant measure.
- ▶ Scaling of  $\lambda_2^N \sim \exp\{-N\Lambda\}$  when  $\mu_N$  is reversible.
- ▶ Convergence of a controlled process to the global minimum of a certain entropy functional.

Reference: arXiv:1909.03805

Thank You