Gradient structures and discrete Markov chain models for reaction-diffusion systems

Alexander Mielke

Weierstraß-Institut für Angewandte Analysis und Stochastik, Berlin



Institut für Mathematik, Humboldt-Universität zu Berlin www.wias-berlin.de/people/mielke/



From Particle Systems to Differential Equations WIAS Workshop. Berlin, 21. – 23. Februar 2012



Partial support via "Analysis of multiscale dystems driven by functionals"

Overview

- 1. Introduction
- 2. Markov chains as gradient systems
- 3. Reaction-diffusion systems as gradient systems
- 4. Discrete-to-continuum passage
- 5. Limit of chemical master equations
- 6. Coupling reaction and diffusion



A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21-23.2.2012





Semiconductor model: van Roosbroeck system

$$\begin{split} &-\operatorname{div}(\varepsilon\nabla\phi) = d - n + p \\ &\dot{n} = \operatorname{div}\left(\mu_n(\nabla n - n\nabla\phi)\right) + g - rnp \\ &\dot{p} = \operatorname{div}\left(\mu_p\left(\nabla p + p\nabla\phi\right)\right) + g - rnp \end{split}$$

electrostatics electron balance hole balance

Motivation:

- understand the van Roosbroeck system as the limit of a many-particle system
- learn how to model diffusion in random media (organic semiconductors)





particle system	~>	differential equation
random walk	\sim	diffusion equation
$\dot{u}_m = \mu M^2 \big(u_{m-1} - 2u_m + u_{m+1} \big)$		$\dot{U} = \mu \Delta U$
chemical master equations	~>	reaction kinetic
$\dot{u}_n = \gamma u_{n-1} + \alpha \frac{n^p}{N^p} u_{n+1} - (\dots) u_n$		$\dot{U}=\gamma-\alpha U^p$
Markov chain		ODEs / PDEs



particle system	\rightsquigarrow	differential equation
random walk	\sim	diffusion equation
$\dot{u}_m = \mu M^2 \big(u_{m-1} - 2u_m + u_{m+1} \big)$		$\dot{U} = \mu \Delta U$
chemical master equations	~>	reaction kinetic
$\dot{u}_n = \gamma u_{n-1} + \alpha \frac{n^p}{N^p} u_{n+1} - (\dots) u_n$		$\dot{U}=\gamma-\alpha U^p$
Markov chain		ODEs / PDEs

Main philosophy:

Use gradient structure
$$\dot{oldsymbol{u}} = -\mathcal{K}(oldsymbol{u})\mathsf{D}\mathcal{E}(oldsymbol{u})$$

 $(\mathcal{X}, \mathcal{E}, \mathcal{K})$ gradient system

 \mathcal{X} state space containing the states $u \in \mathcal{X}$.

 $\mathcal{E}: \mathcal{X} \to \mathbb{R}$ energy functional with differential $\mathsf{D}\mathcal{E}(u) \in \mathsf{T}^*_u \mathcal{X}$

 $\mathcal{G}(\boldsymbol{u})^{-1} = \mathcal{K}(\boldsymbol{u}): \mathsf{T}_{\boldsymbol{u}}^* \mathcal{X} \to \mathsf{T}_{\boldsymbol{u}} \mathcal{X} \text{ inverse of metric: Onsager oper. } \quad \mathcal{K} = \mathcal{K}^* \geq 0$



 $(\mathcal{X}, \mathcal{E}, \mathcal{K})$ gradient system

$$\dot{\boldsymbol{u}} = -\mathcal{K}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u})$$

 ${\mathcal X}$ state space containing the states ${oldsymbol u}\in {\mathcal X}.$

 $\mathcal{E}:\mathcal{X} o \mathbb{R}$ energy functional with differential $\mathsf{D}\mathcal{E}(u) \in \mathsf{T}^*_u\mathcal{X}$

 $\mathcal{G}(\boldsymbol{u})^{-1} = \mathcal{K}(\boldsymbol{u}) : \mathsf{T}_{\boldsymbol{u}}^* \mathcal{X} \to \mathsf{T}_{\boldsymbol{u}}^* \mathcal{X}$ inverse of metric (Onsager operator)

Study discrete-to-continuum limit for gradient structures u^{ε} solves $(\mathcal{X}, \mathcal{E}_{\varepsilon}, \mathcal{K}_{\varepsilon})$ discrete model $\varepsilon = \frac{1}{N}$, N = # particles $\downarrow \downarrow$ u solves $(\mathcal{X}, \mathcal{E}, \mathcal{K})$ continuum model

We want to conclude $u^{\varepsilon}(t) \rightarrow u(t)$ from $(\mathcal{E}_{\varepsilon}, \mathcal{K}_{\varepsilon}) \rightsquigarrow (\mathcal{E}, \mathcal{K})$!!



Overview

- 1. Introduction
- 2. Markov chains as gradient systems
- 3. Reaction-diffusion systems as gradient systems
- 4. Discrete-to-continuum passage
- 5. Limit of chemical master equations
- 6. Coupling reaction and diffusion



A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21-23.2.2012





■ Otto 1999: Fokker-Planck equation $\dot{U} = \operatorname{div} (\nabla U + U\nabla V)$ is a gradient system $(\mathcal{X}, \mathcal{E}, \mathcal{K})$: $\mathcal{E}(U) = \int_{\Omega} U \log(U/W)$ with $W(x) = c e^{-V(x)}$ $\rightsquigarrow D\mathcal{E}(U) = \log U + V$ $\mathcal{K}(U)\xi = -\operatorname{div}(U\nabla\xi)$ $\rightsquigarrow \dot{U} = -\mathcal{K}(U)D\mathcal{E}(U)$

M'10: Reaction-diffusion systems satisfying the detailed-balance condition (and possibly including temperature or drift due to electric charges) have a gradient structure for the relative entropy.

Maas'11, M'11: Discrete Markov chains with detailed-balance condition have a gradient structure for the relative entropy.





Discrete Markov chain on states $j \in J$ (e.g. \mathbb{Z}_M^d or \mathbb{N}_0^m) $\mathcal{X} = \operatorname{Prob}(J) = \{ u = (u_j)_{j \in J} \in \ell^1(J) \mid u_j \ge 0, \sum_J u_j = 1 \}$ $\dot{u} = Qu$ linear evolution with unique steady state $w = (w_j)_J$





Discrete Markov chain on states $j \in J$ (e.g. \mathbb{Z}_M^d or \mathbb{N}_0^m) $\mathcal{X} = \operatorname{Prob}(J) = \{ u = (u_j)_{j \in J} \in \ell^1(J) \mid u_j \ge 0, \sum_J u_j = 1 \}$ $\dot{u} = Qu$ linear evolution with unique steady state $w = (w_j)_J$





$$\begin{split} \mathcal{E}(\boldsymbol{u}) &= \sum_{J} u_j \log(u_j/w_j) \text{ and } \mathcal{K}_{\mathsf{Mv}}(\boldsymbol{u}) = \sum_{j,k \in J} \frac{1}{2} Q_{jk} w_k \Lambda\left(\frac{u_j}{w_j}, \frac{u_k}{w_k}\right) \mathbb{E}_{jk} \\ \mathbb{E}_{jk} &= \mathbb{E}_{jk}^* = (e_j - e_k) \otimes (e_j - e_k) \ge 0 \text{ and } \Lambda(a, b) = \frac{a - b}{\log(a/b)} \ge 0. \end{split}$$

To be proved: $\dot{\boldsymbol{u}} = Q \boldsymbol{u} = -\mathcal{K}_{\mathsf{Mv}}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u})$

•
$$\mathsf{D}\mathcal{E}(\boldsymbol{u}) = (\log(u_j/w_j) + 1)_J \implies$$

 $\mathbb{E}_{jk}\mathsf{D}\mathcal{E}(\boldsymbol{u}) = (\log(u_j/w_j) - \log(u_k/w_k)) (e_j - e_k)$



$$\begin{aligned} \mathcal{E}(\boldsymbol{u}) &= \sum_{J} u_j \log(u_j/w_j) \text{ and } \mathcal{K}_{\mathsf{Mv}}(\boldsymbol{u}) = \sum_{j,k \in J} \frac{1}{2} Q_{jk} w_k \Lambda\left(\frac{u_j}{w_j}, \frac{u_k}{w_k}\right) \mathbb{E}_{jk} \\ \mathbb{E}_{jk} &= \mathbb{E}_{jk}^* = (e_j - e_k) \otimes (e_j - e_k) \ge 0 \text{ and } \Lambda(a, b) = \frac{a - b}{\log(a/b)} \ge 0. \end{aligned}$$

To be proved: $\dot{\boldsymbol{u}} = Q \boldsymbol{u} = -\mathcal{K}_{\mathsf{Mv}}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u})$

•
$$\mathsf{D}\mathcal{E}(\boldsymbol{u}) = (\log(u_j/w_j) + 1)_J \implies$$

 $\mathbb{E}_{jk}\mathsf{D}\mathcal{E}(\boldsymbol{u}) = (\log(u_j/w_j) - \log(u_k/w_k)) (e_j - e_k)$

- Using the cancellation $\Lambda(a, b) (\log a \log b) = (a-b)$ gives $\mathcal{K}_{\mathsf{Mv}}(u)\mathsf{D}\mathcal{E}(u) = \sum_{j,k\in J} \frac{Q_{jk}w_k}{2} (\frac{u_j}{w_j} - \frac{u_k}{w_k}) (e_j - e_k)$ (already linear)
- Using detailed balance gives $\mathcal{K}_{\mathsf{Mv}}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u}) = -Q\boldsymbol{u}.$

QED



Overview

- 1. Introduction
- 2. Markov chains as gradient systems
- 3. Reaction-diffusion systems as gradient systems
- 4. Discrete-to-continuum passage
- 5. Limit of chemical master equations
- 6. Coupling reaction and diffusion



A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21-23.2.2012



$$\boldsymbol{u} = (u_1(t,x),...,u_I(t,x))$$
 densities of chemical species

Reaction-diffusion systems $\dot{\boldsymbol{u}} = \operatorname{div} \left(M(\boldsymbol{u}) \nabla \boldsymbol{u} \right) + \boldsymbol{R}(\boldsymbol{u})$

Example: Ammonia synthesis

$$\begin{split} \mathsf{N}_{2} + 3H_{2} & \rightleftharpoons \mathsf{2NH}_{3} \qquad \mathbf{u} = (u_{\mathsf{N}_{2}}, u_{\mathsf{H}_{2}}, u_{\mathsf{NH}_{3}}) = (u_{1}, u_{2}, u_{3}) \\ \begin{pmatrix} \dot{u}_{1} \\ \dot{u}_{2} \\ \dot{u}_{3} \end{pmatrix} & = \begin{pmatrix} m_{1} \Delta u_{1} \\ m_{2} \Delta u_{2} \\ m_{3} \Delta u_{3} \end{pmatrix} + \underbrace{\begin{pmatrix} -(k_{\mathsf{f}} u_{1} u_{2}^{3} - k_{\mathsf{b}} u_{3}^{2}) \\ -3(k_{\mathsf{f}} u_{1} u_{2}^{3} - k_{\mathsf{b}} u_{3}^{2}) \\ +2(k_{\mathsf{f}} u_{1} u_{2}^{3} - k_{\mathsf{b}} u_{3}^{2}) \\ = \mathbf{R}(\mathbf{u}) \end{split}$$

The usual guess of Allen-Cahn or Cahn-Hillard type

$$\begin{split} \mathcal{E}(\pmb{u}) &= \int_\Omega m_1 |\nabla u_1|^2 + m_2 |\nabla u_2|^2 + m_3 |\nabla u_3|^2 + F(\pmb{u}) \, \mathrm{d}x \text{ does NOT work,} \\ & \text{ since curl } \pmb{R} \not\equiv 0 \; ! \end{split}$$



Reaction-diffusion systems (RDS) $\dot{\boldsymbol{u}} = \operatorname{div} \left(M(\boldsymbol{u}) \nabla \boldsymbol{u} \right) + \boldsymbol{R}(\boldsymbol{u})$

Reaction kinetic of mass-action type with detailed balance cond. (DBC)

$$\dot{\boldsymbol{u}} = \boldsymbol{R}(\boldsymbol{u}) = -\sum_{r=1}^{R} k_r \left(\underbrace{\boldsymbol{u}^{\boldsymbol{\alpha}^r}}_{\text{educts}} - \underbrace{\boldsymbol{u}^{\boldsymbol{\beta}^r}}_{\text{products}} \right) \left(\underbrace{\boldsymbol{\alpha}^r}_{\text{stoich. vect.}} - \boldsymbol{\beta}^r \right) \qquad \boldsymbol{u}^{\boldsymbol{\gamma}} = \prod_{i=1}^{I} u_i^{\boldsymbol{\gamma}_i}$$

(DBC = for u = w each reaction r = 1, ..., R is balanced)





Reaction-diffusion systems (RDS) $\dot{\boldsymbol{u}} = \mathsf{div} \left(M(\boldsymbol{u})
abla \boldsymbol{u}
ight) + \boldsymbol{R}(\boldsymbol{u})$

Reaction kinetic of mass-action type with detailed balance cond. (DBC)

$$\dot{\boldsymbol{u}} = \boldsymbol{R}(\boldsymbol{u}) = -\sum_{r=1}^{R} k_r \left(\underbrace{\boldsymbol{u}^{\boldsymbol{\alpha}^r}}_{\text{educts}} - \underbrace{\boldsymbol{u}^{\boldsymbol{\beta}^r}}_{\text{products}} \right) \left(\underbrace{\boldsymbol{\alpha}^r}_{\text{stoich. vect.}} - \boldsymbol{\beta}^r_{i} \right) \qquad \boldsymbol{u}^{\boldsymbol{\gamma}} = \prod_{i=1}^{I} u_i^{\gamma_i}$$

(DBC = for u = w each reaction r = 1, ..., R is balanced)

 $\begin{array}{ll} \text{Gradient structure for reaction kinetics:} \quad \dot{\boldsymbol{u}} = \boldsymbol{R}(\boldsymbol{u}) = -\mathbb{K}(\boldsymbol{u})\mathsf{D}\boldsymbol{E}(\boldsymbol{u}) \\ E(\boldsymbol{u}) = \sum_{i}^{I} u_{i}\log(u_{i}/w_{i}) \text{ and} \\ \mathbb{K}(\boldsymbol{u}) = \sum_{r=1}^{R} k_{r} \Lambda\Big(\frac{\boldsymbol{u}^{\boldsymbol{\alpha}^{r}}}{\boldsymbol{w}^{\boldsymbol{\alpha}^{r}}}, \frac{\boldsymbol{u}^{\boldsymbol{\beta}^{r}}}{\boldsymbol{w}^{\boldsymbol{\beta}^{r}}}\Big) \left(\boldsymbol{\alpha}^{r} - \boldsymbol{\beta}^{r}\right) \otimes \left(\boldsymbol{\alpha}^{r} - \boldsymbol{\beta}^{r}\right) \in \mathbb{R}_{\geq 0}^{I \times I} \\ \text{with } \Lambda(a, b) = \frac{a-b}{\log a - \log b} > 0 \qquad [\text{ use again } \boldsymbol{\gamma} \cdot (\log v_{i}) = \log(\boldsymbol{v}^{\boldsymbol{\gamma}})] \end{array}$



, i

Reaction-diffusion systems (RDS) $\dot{\boldsymbol{u}} = {\sf div} \left(M(\boldsymbol{u}) \nabla \boldsymbol{u} \right) + \boldsymbol{R}(\boldsymbol{u})$

Reaction kinetic of mass-action type with detailed balance cond. (DBC)

$$\dot{\boldsymbol{u}} = \boldsymbol{R}(\boldsymbol{u}) = -\sum_{r=1}^{R} k_r \left(\frac{\boldsymbol{u}^{\boldsymbol{\alpha}^r}}{\boldsymbol{w}^{\boldsymbol{\alpha}^r}} - \frac{\boldsymbol{u}^{\boldsymbol{\beta}^r}}{\boldsymbol{w}^{\boldsymbol{\beta}^r}} \right) \left(\underbrace{\boldsymbol{\alpha}^r - \boldsymbol{\beta}^r}_{\text{stoich. vect.}} \right) \qquad \boldsymbol{u}^{\gamma} = \prod_{i=1}^{I} u_i^{\gamma_i}$$

$$(\text{DBC} = \text{for } \boldsymbol{u} = \boldsymbol{w} \text{ each reaction } r = 1, ..., R \text{ is balanced})$$

$$\text{Gradient structure for RDS with DBC:} \quad \dot{\boldsymbol{u}} = -\mathcal{K}_{\text{RDS}}(\boldsymbol{u})\text{D}\mathcal{E}(\boldsymbol{u})$$

$$\mathcal{E}(\boldsymbol{u}) = \int_{\Omega} E(\boldsymbol{u}(x)) \, \mathrm{d}x = \int_{\Omega} u_i(x) \log(u_i(x)/w_i(x)) \, \mathrm{d}x$$

$$\mathcal{K}_{\text{RDS}}(\boldsymbol{u})\boldsymbol{\xi} = -\operatorname{div}\left(\mathbb{M}(\boldsymbol{u})\nabla\boldsymbol{\xi}\right) + \underbrace{\mathbb{K}(\boldsymbol{u})\boldsymbol{\xi}}_{\text{react}}$$

$$\text{Onsager'31:} \quad \mathbb{K} = \mathbb{K}^* \ge 0 \text{ and } \mathbb{M} = \mathbb{M}^* \ge 0 \text{ mobilities}$$

$$M(\boldsymbol{u}) = \mathbb{M}(\boldsymbol{u})\text{D}^2 E(\boldsymbol{u}) = \mathbb{M}(\boldsymbol{u})\text{diag}(\frac{1}{u_1}, ..., \frac{1}{u_I}) \text{ not necess. symm.}$$



Example: Ammonia synthesis N₂ + 3H₂ \Leftarrow 2NH₂ $\begin{pmatrix} \dot{u}_1 \\ \dot{u}_2 \\ \dot{u}_3 \end{pmatrix} = \begin{pmatrix} m_1 \Delta u_1 \\ m_2 \Delta u_2 \\ m_3 \Delta u_3 \end{pmatrix} + \begin{pmatrix} -(k_{\rm f} u_1 u_2^3 - k_{\rm b} u_3^2) \\ -3(k_{\rm f} u_1 u_2^3 - k_{\rm b} u_3^2) \\ +2(k_{\rm f} u_1 u_2^3 - k_{\rm b} u_3^2) \end{pmatrix}$

 \blacksquare reference density ${m w}=(k_{\sf b},k_{\sf f},k_{\sf f}^2)$

■ relative entropy $\mathcal{E}(\boldsymbol{u}) = \int_{\Omega} u_1 \log(u_1/w_1) + u_2 \log(u_2/w_2) + u_3 \log(u_3/w_3) \, \mathrm{d}x$

erc A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21-23.2.2012



Semiconductor model: van Roosbroeck system

$$\begin{split} &-\operatorname{div}(\varepsilon\nabla\phi) = d - n + p & \text{electrostatics} \\ &\dot{n} = \operatorname{div}\left(\mu_n(\nabla n - n\nabla\phi)\right) + g - rnp & \text{electron balance} \\ &\dot{p} = \operatorname{div}\left(\mu_p\left(\nabla p + p\nabla\phi\right)\right) + g - rnp & \text{hole balance} \end{split}$$

Gradient structure¹ $(\dot{n}, \dot{p}) = -\mathcal{K}_{\mathsf{vR}}(n, p)\mathsf{D}\mathcal{E}(n, p)$

¹M.: Grad. structures for RDS and energy-drift-diffusion systems, Nonlin. 2011



Semiconductor model: van Roosbroeck system

$$\begin{aligned} -\operatorname{div}(\varepsilon\nabla\phi) &= d - n + p & \text{electrostatics} \\ \dot{n} &= \operatorname{div}\left(\mu_n(\nabla n - n\nabla\phi)\right) + g - rnp & \text{electron balance} \\ \dot{p} &= \operatorname{div}\left(\mu_p\left(\nabla p + p\nabla\phi\right)\right) + g - rnp & \text{hole balance} \end{aligned}$$

Gradient structure¹ $(\dot{n}, \dot{p}) = -\mathcal{K}_{\mathsf{vR}}(n, p)\mathsf{D}\mathcal{E}(n, p)$

 \blacksquare Reference density ${\pmb w} = (w,w)$ with $w = (g/r)^{1/2}$

 \blacksquare Free energy $\mathcal{E}_{\mathsf{VR}}(n,p) = \int_\Omega n \log(n/w) + p \log(p/w) + \frac{\varepsilon}{2} |\nabla \phi_{n,p}|^2 \, \mathrm{d} x$

• Onsager oper. $\mathcal{K}_{\mathsf{VR}}(n,p)\binom{\xi_n}{\xi_p} = -\binom{\mathsf{div}(n\mu_n\nabla\xi_n)}{\mathsf{div}(p\mu_p\nabla\xi_p)} + g\Lambda(1,\frac{np}{w^2})\binom{1}{1}\binom{1}{1}\binom{\xi_n}{\xi_p}$

Crucial observation (AlbGajHün'01) $D\mathcal{E}_{vR} = {\binom{\log(n/w)+1}{\log(p/w)+1}} + \phi_{n,p} {\binom{-1}{+1}}$

¹M.: Grad. structures for RDS and energy-drift-diffusion systems, Nonlin. 2011



Overview

- 1. Introduction
- 2. Markov chains as gradient systems
- 3. Reaction-diffusion systems as gradient systems
- 4. Discrete-to-continuum passage
- 5. Limit of chemical master equations
- 6. Coupling reaction and diffusion



A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21-23.2.2012



From random walk to diffusion

- already very well understood with many approaches
- here: add another approach that will be compatible with reactions



From random walk to diffusion

- already very well understood with many approaches
- here: add another approach that will be compatible with reactions

State space
$$J = \mathbb{Z}_M = \mathbb{Z}/_{M\mathbb{Z}}$$

 $\dot{u}_m = \mu M^2 (u_{m-1} - 2u_m + u_{m+1})$ $\dot{\boldsymbol{u}} = Q \boldsymbol{u} = -\mathcal{K}^M(\boldsymbol{u}) \mathsf{D} \mathcal{E}^M(\boldsymbol{u})$
• $\mathcal{E}^M(\boldsymbol{u}) = \sum_1^M u_i \log(M u_i)$ where $\boldsymbol{w} = \frac{1}{M}(1, ..., 1)$ and
• $\mathcal{K}^M(\boldsymbol{u}) = \sum_1^M \mu M^2 \Lambda(u_m, u_{m+1}) \mathbb{E}_{m,m+1} \ge 0$ (tridiagonal)



From random walk to diffusion

- already very well understood with many approaches
- here: add another approach that will be compatible with reactions

State space
$$J = \mathbb{Z}_M = \mathbb{Z}_{/M\mathbb{Z}}$$

 $\dot{u}_m = \mu M^2 (u_{m-1} - 2u_m + u_{m+1})$ $\dot{u} = Qu = -\mathcal{K}^M(u) D\mathcal{E}^M(u)$
• $\mathcal{E}^M(u) = \sum_1^M u_i \log(Mu_i)$ where $w = \frac{1}{M}(1, ..., 1)$ and
• $\mathcal{K}^M(u) = \sum_1^M \mu M^2 \Lambda(u_m, u_{m+1}) \mathbb{E}_{m,m+1} \ge 0$ (tridiagonal)
Riemannian transport distance on $\mathcal{X}^M = \operatorname{Prob}(\mathbb{Z}_M)$
 $d_{\mathcal{K}^M} : \mathcal{X}^M \times \mathcal{X}^M \to [0, \infty[$ defined via
 $d_{\mathcal{K}^M}(u_0, u_1)^2 = \inf \left\{ \int_0^1 u'(s) \cdot \underbrace{\mathcal{K}^M(u(s))^{-1}}_{\text{Riemannian tensor}} u'(s) \, ds \mid u_0 \stackrel{u}{\leadsto} u_1 \right\}.$

Markov chain is metric gradient flow $(\mathcal{X}^M, \mathcal{E}^M, d_{\mathcal{K}^M})$ in De Giorgi's sense!



$$\dot{u}_m = \mu M^2 (u_{m-1} - 2u_m + u_{m+1}), \ m \in \mathbb{Z}_M \qquad \qquad \dot{\boldsymbol{u}} = -\mathcal{K}^M (\boldsymbol{u}) \mathsf{D} \mathcal{E}^M (\boldsymbol{u})$$

Limit passage: embed
$$\mathcal{X}^M = \operatorname{Prob}(\mathbb{Z}_M)$$
 into $\mathcal{X} = \operatorname{Prob}(\mathbb{S}^1)$
 $U = I_M u$ with $U(x) = \sum_{m=1}^M M u_m \chi_{](m-1)/M,m/M]}(x)$
 $\dot{u}_m = \mu M^2(u_{m-1} - 2u_m + u_{m+1}) \xrightarrow{\text{to be shown}} \dot{U} = \mu U_{xx}$



$$\dot{u}_m = \mu M^2 (u_{m-1} - 2u_m + u_{m+1}), \ m \in \mathbb{Z}_M \qquad \qquad \dot{\boldsymbol{u}} = -\mathcal{K}^M(\boldsymbol{u}) \mathsf{D}\mathcal{E}^M(\boldsymbol{u})$$

Limit passage: embed
$$\mathcal{X}^M = \operatorname{Prob}(\mathbb{Z}_M)$$
 into $\mathcal{X} = \operatorname{Prob}(\mathbb{S}^1)$
 $U = I_M \boldsymbol{u}$ with $U(x) = \sum_{m=1}^M M u_m \chi_{](m-1)/M,m/M]}(x)$
 $\dot{u}_m = \mu M^2 (u_{m-1} - 2u_m + u_{m+1}) \xrightarrow{\text{to be shown}} \dot{U} = \mu U_{xx}$
 $\mathcal{E}^M(\boldsymbol{u}) = \sum_1^M u_i \log(M u_i) \xrightarrow{\text{trivial via } I_M} \mathcal{E}(U) = \int_0^1 U \log U \, \mathrm{d}x$
 $\boldsymbol{\xi} \cdot \mathcal{K}^M(\boldsymbol{u}) \boldsymbol{\xi} = \langle \boldsymbol{\Xi}, \mathcal{K}(U) \boldsymbol{\Xi} \rangle =$
 $\sum_1^M \mu \Lambda(u_m, u_{m+1}) M^2 (\boldsymbol{\xi}_m - \boldsymbol{\xi}_{m+1})^2 \xrightarrow{\text{in what sense?}} \int_0^1 \mu U |\boldsymbol{\Xi}'|^2 \, \mathrm{d}x$

• formally $\mathcal{K}^M(\boldsymbol{u}) \rightsquigarrow \mathcal{K}(U)$ as quadratic forms

• but in what sense do we need convergence to guarantee convergence of solutions?



Limit passage:
$$\dot{u}_m = \mu M^2 (u_{m-1} - 2u_m + u_{m+1}) \xrightarrow{\text{to be shown}} \dot{U} = \mu U_{xx}$$

Use metric approach instead:

Evolutionary variational inequality (EVI) (cf. Ambrosio,Gigli,Savaré'05) If \mathcal{E} is geodesically convex with respect to $d_{\mathcal{K}}$, then $\dot{\boldsymbol{u}} = -\mathcal{K}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u}) \iff (\mathsf{EVI}) \quad \frac{\mathsf{d}^+}{\mathsf{d}t}d(\boldsymbol{u}(t),\boldsymbol{v})^2 + \mathcal{E}(\boldsymbol{u}(t)) \leq \mathcal{E}(\boldsymbol{v})$ for all t > 0 and $\boldsymbol{v} \in \mathcal{X}$



Limit passage:
$$\dot{u}_m = \mu M^2 (u_{m-1} - 2u_m + u_{m+1}) \xrightarrow{\text{to be shown}} \dot{U} = \mu U_{xx}$$

Use metric approach instead:

Evolutionary variational inequality (EVI) (cf. Ambrosio,Gigli,Savaré'05) If \mathcal{E} is geodesically convex with respect to $d_{\mathcal{K}}$, then $\dot{\boldsymbol{u}} = -\mathcal{K}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u}) \iff (\mathsf{EVI}) \quad \frac{\mathsf{d}^+}{\mathsf{d}t}d(\boldsymbol{u}(t),\boldsymbol{v})^2 + \mathcal{E}(\boldsymbol{u}(t)) \leq \mathcal{E}(\boldsymbol{v})$ for all $t \geq 0$ and $\boldsymbol{v} \in \mathcal{X}$

Theorem M'12.

If $(\mathcal{X}^M, \mathcal{E}^M, d_{\mathcal{K}^M})$ and $(\mathcal{X}, \mathcal{E}, d_W)$ are given as above, then $I_M \boldsymbol{u}^M(0) \stackrel{d_W}{\to} U(0) \implies I_M \boldsymbol{u}^M(t) \stackrel{d_W}{\to} U(t)$ for all $t \ge 0$.

 $\blacksquare \mathsf{M.11:} \ (\mathcal{X}^M, \mathcal{E}^M, d_{\mathcal{K}^M}) \text{ is geodesically } 0\text{-convex (indep. of } M)$

• Gigli-Maas'11/12:
$$d_{\mathsf{W}} = \Gamma \operatorname{-lim}_{M \to \infty} d_{\mathcal{K}^M}$$

$$\blacksquare$$
 Use EVI and $\mathcal{E} = \Gamma - \lim_{M \to \infty} \mathcal{E}^M$.



Overview

- 1. Introduction
- 2. Markov chains as gradient systems
- 3. Reaction-diffusion systems as gradient systems
- 4. Discrete-to-continuum passage
- 5. Limit of chemical master equations
- 6. Coupling reaction and diffusion



A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21-23.2.2012



Simple reaction equation $\dot{a} = 1 - a^p$ (1=generation, $-a^p$ annihilation) Gradient system ($[0, \infty[, a \log a - a, \mathbb{K})$ with $\mathbb{K}(a) = \Lambda(1, a^p)p$

Chemical master equation: keep track of number of particles!

 $a = \frac{1}{N} \#$ number of particles, where N = typical number of particles $u_n =$ probability of having exactly n particles

Markov chain:
$$\dot{u}_n = \underbrace{1 u_{n-1}}_{\text{generation}} - \underbrace{\left(1 + \left(\frac{n}{N}\right)^p\right)u_n}_{\text{losses}} + \underbrace{\left(\frac{n+1}{N}\right)^p u_{n+1}}_{\text{annihilation}}$$





Simple reaction equation $\dot{a} = 1 - a^p$ (1=generation, $-a^p$ annihilation) Gradient system ([0, ∞ [, $a \log a - a$, K) with K(a) = $\Lambda(1, a^p)p$

Chemical master equation: keep track of number of particles!

 $a=\frac{1}{N}\,\#$ number of particles, where N= typical number of particles $u_n=$ probability of having exactly n particles

Markov chain:
$$\dot{u}_n = \underbrace{1}_{\text{generation}} - \underbrace{\left(1 + \left(\frac{n}{N}\right)^p\right)u_n}_{\text{losses}} + \underbrace{\left(\frac{n+1}{N}\right)^p u_{n+1}}_{\text{annihilation}}$$

■ DBC holds for $\boldsymbol{w}^N = (w_n^N)$ with $w_n^N = \left(\frac{N^n}{n!}\right)^p w_0^N$ ■ We have the gradient structure $(\mathcal{X}_{\mathsf{CME}}, \mathcal{E}^N, \mathcal{K}^N)$ with

•
$$\mathcal{X}_{\mathsf{CME}} = \{ \boldsymbol{u} \in \ell_1(\mathbb{N}_0) \mid u_n \ge 1, \|\boldsymbol{u}\|_1 = 1 \}$$

• $\mathcal{E}^N(\boldsymbol{u}) = \sum_{n=0}^{\infty} u_n \log(u_n/w_n^N)$
• $\mathcal{K}^N(\boldsymbol{u}) = \sum_{n=1}^{\infty} w_{n-1}^N \Lambda(\frac{u_{n-1}}{w_{n-1}^N}, \frac{u_n}{w_n^N}) \mathbb{E}_{n-1,n} \ge 0$



Limit passage
$$N \to \infty$$

We embed $\mathcal{X}_{\mathsf{CME}}$ into $\mathsf{Prob}([0,\infty[) \text{ via}$
 $U = I_N \boldsymbol{u}$ with $U(a) = \sum_{n=1}^M N \, u_n \, \chi_{](n-1)/N,n/N]}(a)$ " $a \approx n/N$ "
We use the expansion (large deviation argument)
 $-\frac{1}{N} \log w_n^N \approx E(n/N)$ where $E(a) = p(a \log a - a + 1)$ (rate fcn.)
 $\rightsquigarrow \mathcal{E}^N(\boldsymbol{u}) \approx \sum_0^\infty (u_n \log u_n + N u_n E(n/N))$

We find Γ -convergence $\frac{1}{N}\mathcal{E}^N \xrightarrow{\Gamma} E$ where $E(U) = \int_0^\infty U(a)E(a) \, \mathrm{d}a$



Limit passage
$$N \to \infty$$

We embed $\mathcal{X}_{\mathsf{CME}}$ into $\mathsf{Prob}([0,\infty[) \text{ via}$
 $U = I_N \boldsymbol{u}$ with $U(a) = \sum_{n=1}^M N \, u_n \, \chi_{](n-1)/N,n/N]}(a)$ " $a \approx n/N$ "
We use the expansion (large deviation argument)
 $-\frac{1}{N} \log w_n^N \approx E(n/N)$ where $E(a) = p(a \log a - a + 1)$ (rate fcn.)
 $\rightsquigarrow \mathcal{E}^N(\boldsymbol{u}) \approx \sum_0^\infty (u_n \log u_n + N u_n E(n/N))$

We find Γ -convergence $\frac{1}{N}\mathcal{E}^N \xrightarrow{\Gamma} \mathbf{E}$ where $\mathbf{E}(U) = \int_0^\infty U(a)E(a) \, \mathrm{d}a$ Moreover,

$$\begin{split} \boldsymbol{\xi} \cdot N \mathcal{K}^{N}(\boldsymbol{u}^{N}) \boldsymbol{\xi} &= \sum_{1}^{\infty} \underbrace{w_{n-1}^{N} \Lambda\left(\frac{u_{n-1}}{w_{n-1}^{N}}, \frac{u_{n}}{w_{n}^{N}}\right)}_{\approx U(n/N) \Lambda\left(1, (n/N)^{p}\right)} N^{2} (\xi_{n} - \xi_{n-1})^{2} \frac{1}{N} \\ \underbrace{\underbrace{sU(n/N) \Lambda\left(1, (n/N)^{p}\right)}_{\text{formally}} \int_{0}^{\infty} U(a) \Lambda(1, a^{p}) (\Xi'(a))^{2} \, \mathrm{d}a} \end{split}$$



Markov chain:
$$\dot{u}_n = u_{n-1} - \left(1 + \left(\frac{n}{N}\right)^p\right)u_n + \left(\frac{n+1}{N}\right)^p u_{n+1}$$

Gradient structure $(\mathcal{X}, \mathcal{E}^N, \mathcal{K}^N)$ with
 $\mathcal{X} = \left\{ \boldsymbol{u} \in \ell_1(\mathbb{N}_0) \mid u_n \ge 1, \|\boldsymbol{u}\|_1 = 1 \right\}$
 $\mathcal{E}^N(\boldsymbol{u}) = \sum_{n=0}^{\infty} u_n \log(u_n/w_n^N),$
 $\mathcal{K}^N(\boldsymbol{u}) = \sum_{n=1}^{\infty} w_{n-1}^N \Lambda\left(\frac{u_{n-1}}{w_{n-1}^N}, \frac{u_n}{w_n^N}\right) \mathbb{E}_{n-1,n}$

The embedding $(\operatorname{Prob}([0,\infty[), \mathcal{E}^N \circ I_N, \mathcal{K}^N \circ I_N))$ converges formally to the limiting gradient system $(\operatorname{Prob}([0,\infty[), \boldsymbol{E}, \boldsymbol{K})))$ with $\boldsymbol{E}(U) = \int_0^\infty U(a)E(a) \, \mathrm{d} a$ where $E(a) = p(a\log a - a + 1)$ $\boldsymbol{K}(U)\Xi = -(U(a)K(a)\Xi'(a))'$ where $K(a) = \Lambda(1, a^p) = \frac{a^p - 1}{\log(a^p)}$



Ŵ

Markov chain:
$$\dot{u}_n = u_{n-1} - \left(1 + \left(\frac{n}{N}\right)^p\right)u_n + \left(\frac{n+1}{N}\right)^p u_{n+1}$$

Gradient structure $(\mathcal{X}, \mathcal{E}^N, \mathcal{K}^N)$ with
 $\mathcal{X} = \left\{ \boldsymbol{u} \in \ell_1(\mathbb{N}_0) \mid u_n \ge 1, \|\boldsymbol{u}\|_1 = 1 \right\}$
 $\mathcal{E}^N(\boldsymbol{u}) = \sum_{n=0}^{\infty} u_n \log(u_n/w_n^N),$
 $\mathcal{K}^N(\boldsymbol{u}) = \sum_{n=1}^{\infty} w_{n-1}^N \left(\frac{u_{n-1}}{w_{n-1}^N}, \frac{u_n}{w_n^N}\right) \mathbb{E}_{n-1,n}$

The embedding $(\operatorname{Prob}([0,\infty[), \mathcal{E}^N \circ I_N, \mathcal{K}^N \circ I_N))$ converges formally to the limiting gradient system $(\operatorname{Prob}([0,\infty[), \boldsymbol{E}, \boldsymbol{K})))$ with $\boldsymbol{E}(U) = \int_0^\infty U(a)E(a) \, \mathrm{d}a$ where $E(a) = p(a\log a - a + 1)$ $\boldsymbol{K}(U)\Xi = -(U(a)K(a)\Xi'(a))'$ where $K(a) = \Lambda(1, a^p) = \frac{a^p - 1}{\log(a^p)}$

Result: Liouville equation = transport equation (cf. T.R.Kurtz'67-70) $\dot{U}(t,a) = -((1-a^p)U(t,a))'$ since DE = E and $K(a)E'(a) = a^p - 1$

Inspired by Eindhoven group (Mark Peletier, Michiel Renger,) A similar result holds for N-particle Markov chains

 $\dot{oldsymbol{u}}=Qoldsymbol{u}$ single-particle process

 $\boldsymbol{u} = (u_j)_{j \in J} \in \operatorname{Prob}(J), \quad \mathcal{E}_{\mathsf{Mv}}(\boldsymbol{u}) = \sum_{j \in J} u_j \log(u_j/w_j)$

$$\begin{split} N \text{ independent particles: } \dot{\mathbb{U}} &= \frac{1}{N} \mathbb{Q}^N \mathbb{U} \qquad \text{(time rescaling)} \\ \mathbb{U} &= (\mathbb{U}_n)_{n \in \mathbb{J}_N} \in \mathsf{Prob}(\mathbb{J}_N) \text{ where } \mathbb{J}_N = \{ n \in \mathbb{N}_0^J \mid \sum_{j \in J} n_j = N \} \end{split}$$



Inspired by Eindhoven group (Mark Peletier, Michiel Renger,) A similar result holds for N-particle Markov chains

$$\dot{oldsymbol{u}}=Qoldsymbol{u}$$
 single-particle process

 $\boldsymbol{u} = (u_j)_{j \in J} \in \operatorname{Prob}(J), \quad \mathcal{E}_{\mathsf{Mv}}(\boldsymbol{u}) = \sum_{j \in J} u_j \log(u_j/w_j)$

 $N \text{ independent particles: } \dot{\mathbb{U}} = \frac{1}{N} \mathbb{Q}^N \mathbb{U} \qquad \text{(time rescaling)}$ $\mathbb{U} = (\mathbb{U}_n)_{n \in \mathbb{J}_N} \in \mathsf{Prob}(\mathbb{J}_N) \text{ where } \mathbb{J}_N = \{ n \in \mathbb{N}_0^J \mid \sum_{j \in J} n_j = N \}$

Lemma If $\dot{\boldsymbol{u}} = Q\boldsymbol{u}$ satisfies DBC for \boldsymbol{w} , then $\dot{\mathbb{U}} = \frac{1}{N}\mathbb{Q}^{N}\mathbb{U}$ satisfies DBC for \mathbb{W} with $\mathbb{W} = (\mathbb{W}_{\boldsymbol{n}})_{\boldsymbol{n}\in\mathbb{J}_{N}}$ with $\mathbb{W}_{\boldsymbol{n}} = N!\prod_{j\in J} w_{j}^{n_{j}}/(n_{j}!)$

Gradient structure $(\operatorname{Prob}(\mathbb{J}_N), \mathbb{E}_N, \mathbb{K}_N)$ with $\mathbb{E}_N(\mathbb{U}) = \sum_{\boldsymbol{n} \in \mathbb{J}_N} \mathbb{U}_{\boldsymbol{n}} \log(\mathbb{U}_{\boldsymbol{n}}/\mathbb{W}_{\boldsymbol{n}})$



Independence of particles gives a large-deviation result $\frac{1}{N} \log \mathbb{W}_{n} \approx -\mathcal{E}_{\mathsf{Mv}}(\frac{1}{N}\boldsymbol{n}) \qquad \leftarrow \text{single-part. energy!}$ We again embed $\operatorname{Prob}(\mathbb{J}_{N})$ into $\operatorname{Prob}(\underbrace{\operatorname{Prob}(J)}_{\operatorname{Gibbs simplex}})$ via $U = I_{N}\mathbb{U} \text{ where } U(\boldsymbol{u}) = \sum_{\boldsymbol{n} \in \mathbb{J}_{N}} \mathbb{U}_{\boldsymbol{n}}c^{N}\chi_{0}(\boldsymbol{u} - \frac{1}{N}\boldsymbol{n})$ As above $\frac{1}{N}\mathbb{E}_{N} \circ I_{N} \xrightarrow{\Gamma} \boldsymbol{E} \text{ with } \boldsymbol{E}(U) = \int_{\operatorname{Prob}(J)} U(\boldsymbol{u})\mathcal{E}_{\mathsf{Mv}}(\boldsymbol{u}) \, \mathrm{d}\boldsymbol{u}$ $\mathbb{K}_{N} \xrightarrow{\text{formally}} \boldsymbol{K} \text{ with } \boldsymbol{K}(U) = -\operatorname{div}_{\boldsymbol{u}}\left(U\mathcal{K}_{\mathsf{Mv}}(\boldsymbol{u})\nabla_{\boldsymbol{u}}\boldsymbol{\xi}\right)$



Independence of particles gives a large-deviation result $\frac{1}{N}\log \mathbb{W}_n \approx -\mathcal{E}_{\mathsf{Mv}}(\frac{1}{N}n)$ \leftarrow single-part. energy! We again embed $\operatorname{Prob}(\mathbb{J}_N)$ into $\operatorname{Prob}(\operatorname{Prob}(J))$ via Gibbs simplex $U = I_N \mathbb{U}$ where $U(\boldsymbol{u}) = \sum \mathbb{U}_{\boldsymbol{n}} c^N \chi_0(\boldsymbol{u} - \frac{1}{N} \boldsymbol{n})$ $n \in \mathbb{I}_N$ $\tfrac{1}{N} \mathbb{E}_N \circ I_N \xrightarrow{\Gamma} \boldsymbol{E} \text{ with } \boldsymbol{E}(U) = \int_{\mathsf{Prob}(J)} U(\boldsymbol{u}) \mathcal{E}_{\mathsf{Mv}}(\boldsymbol{u}) \, \mathrm{d}\boldsymbol{u}$ As above $\mathbb{K}_N \xrightarrow{\text{formally}} K$ with $K(U) = -\operatorname{div}_{u} \left(U \mathcal{K}_{\mathsf{M}_V}(u) \nabla_{u} \xi \right)$ **Limiting system:** Liouville equation = transport equation

$$\dot{U}(t,\boldsymbol{u}) = -\operatorname{div}_{\boldsymbol{u}}\left(U(t,\boldsymbol{u})Q\boldsymbol{u}\right)$$

since
$$\mathsf{D}_U \boldsymbol{E} = \mathcal{E}_{\mathsf{Mv}}$$
 and $-\boldsymbol{K}(U)\mathsf{D}\boldsymbol{E} = \mathsf{div}_{\boldsymbol{u}}(U\underbrace{\mathcal{K}_{\mathsf{Mv}}\mathsf{D}_{\boldsymbol{u}}\mathcal{E}_{\mathsf{Mv}}}_{=-Q\boldsymbol{u}}) = -\operatorname{div}_{\boldsymbol{u}}(UQ\boldsymbol{u})$

^c A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21–23.2.2012

Overview

- 1. Introduction
- 2. Markov chains as gradient systems
- 3. Reaction-diffusion systems as gradient systems
- 4. Discrete-to-continuum passage
- 5. Limit of chemical master equations
- 6. Coupling reaction and diffusion



A. Mielke, Discr.Markov & RDS, Particle Systems to Diff. Eqns, 21-23.2.2012



6. Coupling reaction and diffusion

Open problem: Can we find similar PDE limits for a **Markov chain** coupling reaction and diffusion?

Attempt: Model $\dot{U} = \mu U_{xx} + 1 - U^2$



using $\mathbb{J}_{K,N} = \{ \boldsymbol{n} = (n_1, ..., n_M) \in \mathbb{N}_0^M \mid \sum_1^M n_m = KN \}$ and $u_{\boldsymbol{n}} = u_{(n_1, ..., n_M)}$ = prob. that site m has n_m part. (m = 1, ..., M)



6. Coupling reaction and diffusion

Open problem: Can we find similar PDE limits for a **Markov chain** coupling reaction and diffusion?

Attempt: Model $\dot{U} = \mu U_{xx} + 1 - U^2$

erc





Conclusion

- Markov chains and RDS with DBC have gradient structures
- \blacksquare The Onsager form $\dot{\boldsymbol{u}} = -\mathcal{K}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u})$ allows for easy modeling



Conclusion

- Markov chains and RDS with DBC have gradient structures
- The Onsager form $\dot{\boldsymbol{u}} = -\mathcal{K}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u})$ allows for easy modeling
- For discrete systems the concave logarithmic mean $\Lambda(u_j, u_k) = \frac{u_j u_k}{\log(u_j/u_k)}$ replaces the density "u" in Wasserstein metric.
- Limit passages in many-particle systems often lead to Liouville-type equations which need further reduction.
- Metric gradient structures allow for easy limit passages with uniform geodesic λ-convexity holds ↔ (EVI)_λ evolutionary variational inequality



Conclusion

- Markov chains and RDS with DBC have gradient structures
- The Onsager form $\dot{\boldsymbol{u}} = -\mathcal{K}(\boldsymbol{u})\mathsf{D}\mathcal{E}(\boldsymbol{u})$ allows for easy modeling
- For discrete systems the concave logarithmic mean $\Lambda(u_j, u_k) = \frac{u_j u_k}{\log(u_j/u_k)}$ replaces the density "u" in Wasserstein metric.
- Limit passages in many-particle systems often lead to Liouville-type equations which need further reduction.
- Metric gradient structures allow for easy limit passages with uniform geodesic λ-convexity holds ↔ (EVI)_λ evolutionary variational inequality

Thank you for your attention

WIAS preprints at http://www.wias-berlin.de/people/mielke/

M.: Geodesic convexity of the relative entropy in reversible Markov chains. WIAS prep.1650 Arnrich, Mielke, Peletier, Savaré, Veneroni: Passing to the limit in a Wasserstein gradient flow: From diffusion to reaction. Calc. Var. PDE to appear, WIAS prep. 1593.

M.: A gradient structure for RDS and for energy-drift-diffusion systems. Nonlinearity 2011.

