

Manifold-valued Dirichlet Processes

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<http://pages.cs.wisc.edu/~hwkim/projects/dp-mglm/>



Motivation

Regression

$$f : \mathbf{R}^d \rightarrow \mathcal{M}$$

$$\mathcal{M} = \text{SPD}(n)$$

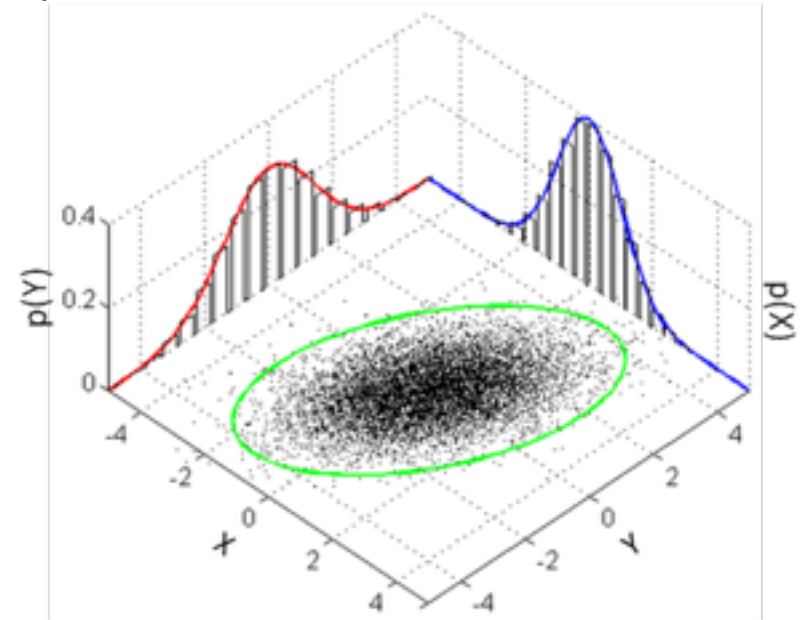
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$$f : \mathbf{R}^d \rightarrow \mathcal{M}$$

$$\mathcal{M} = \text{SPD}(n)$$

- Covariance matrix



Motivation

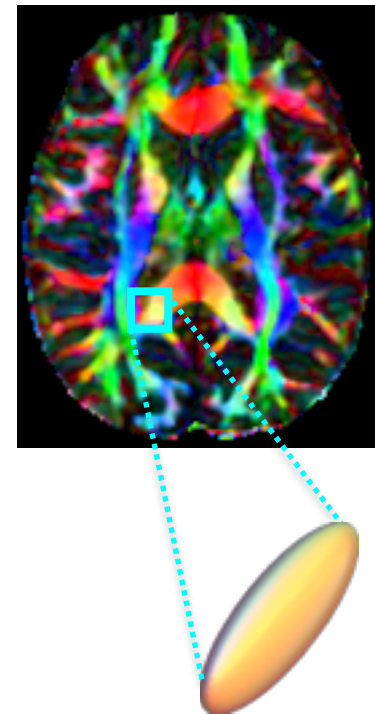
Regression

$$f : \mathbf{R}^d \rightarrow \mathcal{M}$$

$$\mathcal{M} = \text{SPD}(n)$$

- Covariance matrix
- Diffusion tensor imaging

DTI



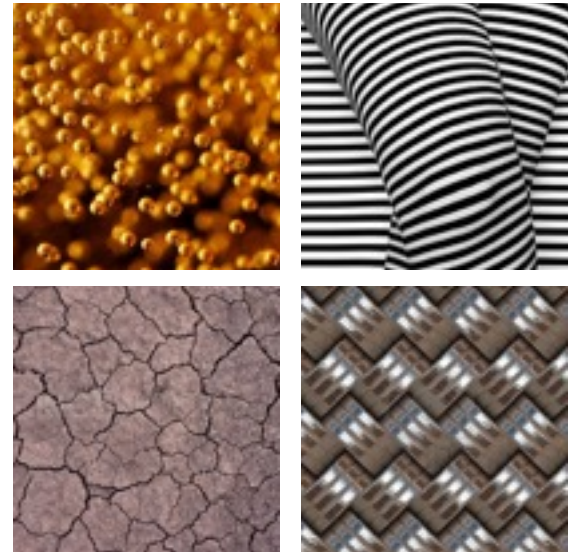
Motivation

Regression

$$f : \mathbf{R}^d \rightarrow \mathcal{M}$$

$$\mathcal{M} = \text{SPD}(n)$$

- Covariance matrix
- Diffusion tensor imaging
- Region covariance
- ...



M.Cimpoi et al., CVPR 2014

Linear regression on manifolds

$$f : R \rightarrow \mathcal{M} \quad y_i = \text{EXP}(\text{EXP}(B, vx_i), \epsilon)$$

GR

Fletcher, IJCV 2013.



$$f : R^n \rightarrow \mathcal{M}$$

$$y_i = \text{EXP}(\text{EXP}(B, \sum_{j=1}^d V^j x_i^j), \epsilon)$$

MGLM

Kim et al., CVPR 2014.

IR

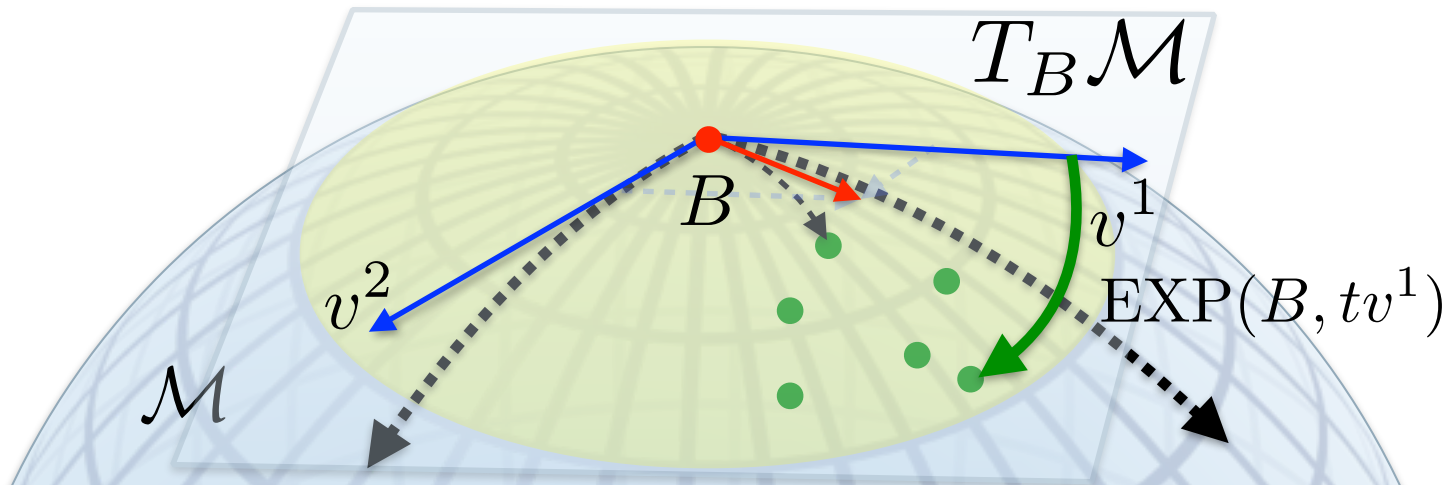
Zhu et al., JASA, 2009.

Motivations

Build models on manifolds

Locally defined parametric models

PGA (Fletcher et al., 2004), GR (Fletcher, IJCV 2013),
MGLM (Kim et al., CVPR 2014), RCCA (Kim et al., ECCV 2014)



Euclidean models

- General Linear Model

$$y_i = \beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d + \epsilon$$

What if data have nonlinear correlation?

Euclidean models

- General Linear Model

$$\mathbf{y}_i = \beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d + \epsilon$$

- Generalized Linear Model (**fixed link function**)

$$\mathbf{y}_i = g^{-1}(\beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d) + \epsilon$$

- Single Index Model (**searching link function**)

$$\mathbf{y}_i = g^{-1}(\beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d) + \epsilon$$

Euclidean models

- General Linear Model

$$\mathbf{y}_i = \beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d + \epsilon$$

- Generalized Linear Model (fixed link function)

$$\mathbf{y}_i = g^{-1}(\beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d) + \epsilon$$

- Single Index Model (searching link function)

$$\mathbf{y}_i = g^{-1}(\beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d) + \epsilon$$

Link functions for manifold-valued response?

Euclidean models

- GLM

$$y_i = \beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d + \epsilon$$

- ?-GLM

$$y_i = \underline{\beta}_i^0 + \underline{\beta}_i^1 x_i^1 + \dots + \underline{\beta}_i^d x_i^d + \epsilon$$

Euclidean models

- GLM

$$\mathbf{y}_i = \beta^0 + \beta^1 x_i^1 + \dots + \beta^d x_i^d + \epsilon$$

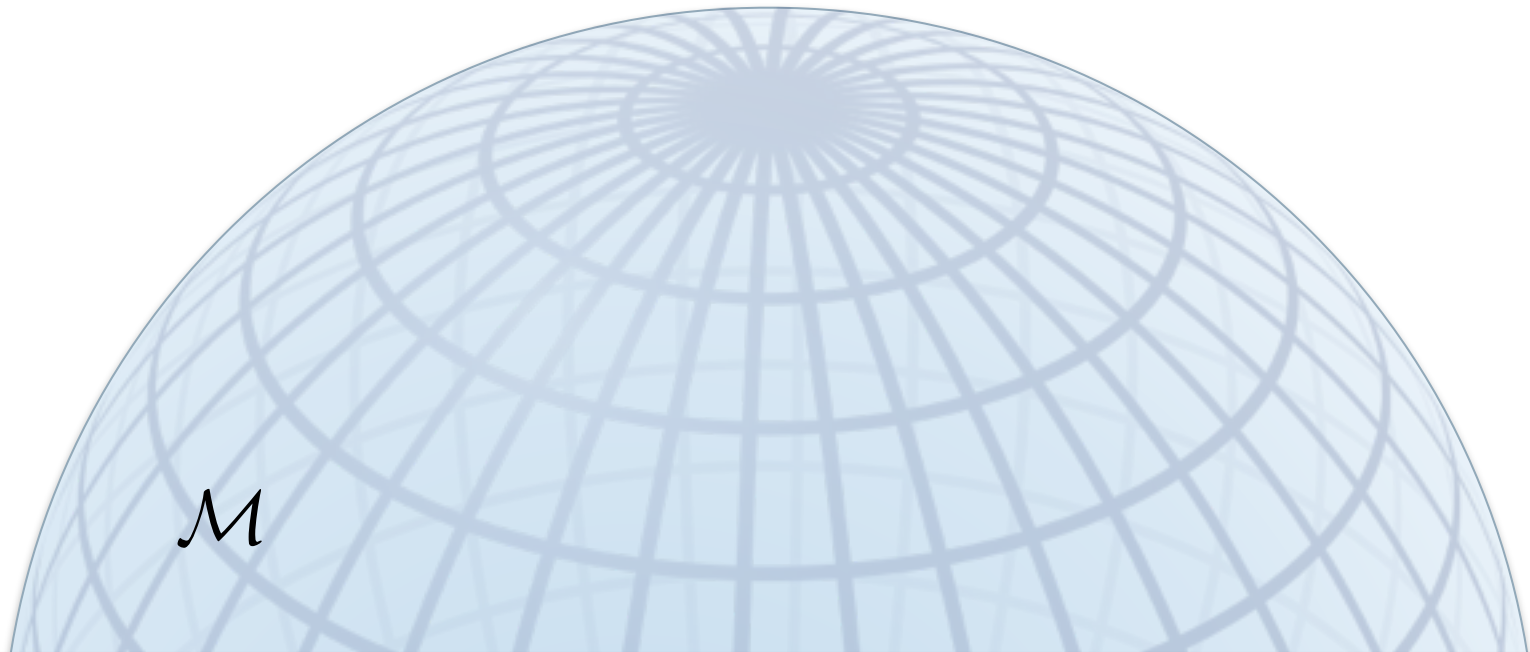
- DP-GLM

$$\mathbf{y}_i = \underline{\beta}_i^0 + \underline{\beta}_i^1 x_i^1 + \dots + \underline{\beta}_i^d x_i^d + \epsilon$$

$$(x_i, y_i) | \theta_i \sim F(\theta_i), \theta_i | G \sim G, G \sim DP(G_0, \nu)$$

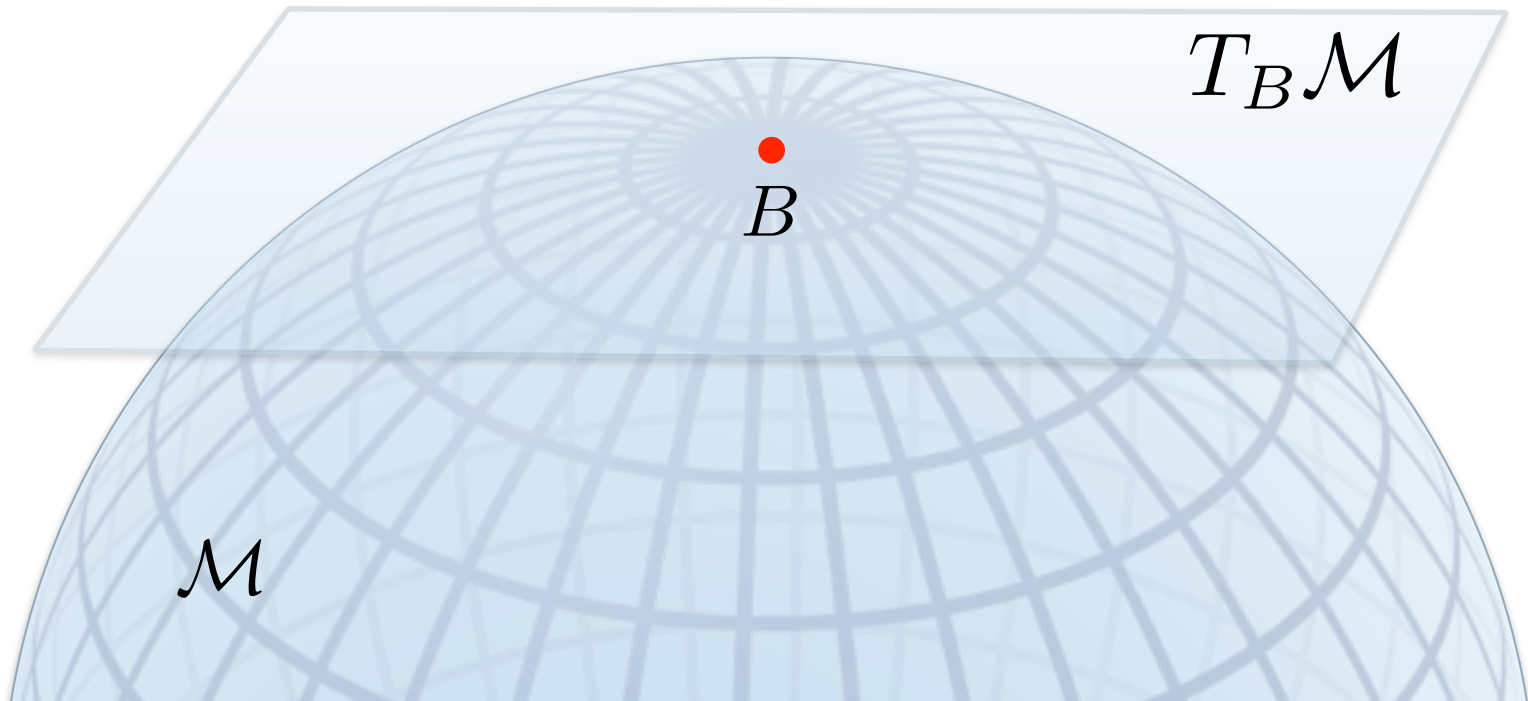
MGLM on manifolds

$$y_i = \text{EXP}(\text{EXP}(B, \sum_{j=1}^d V^j x_i^j), \epsilon)$$



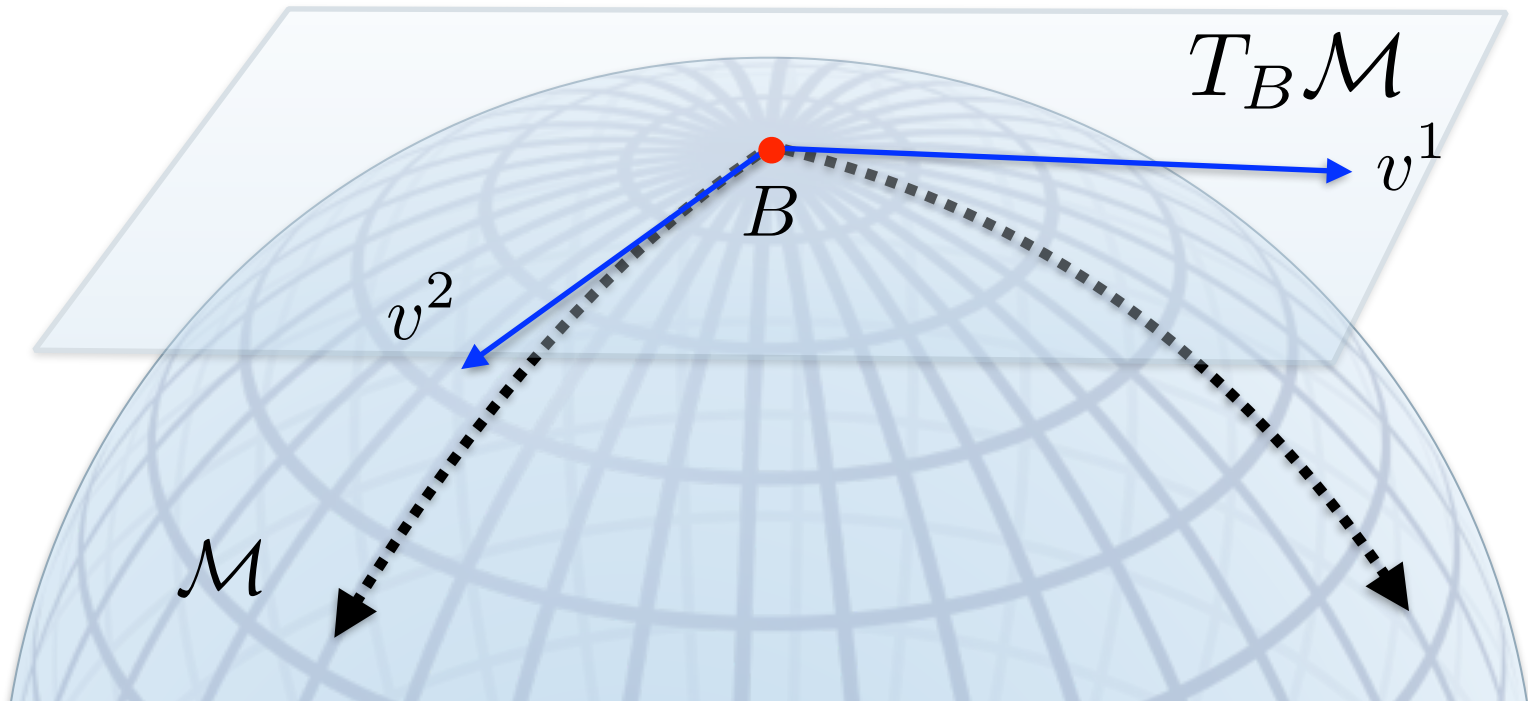
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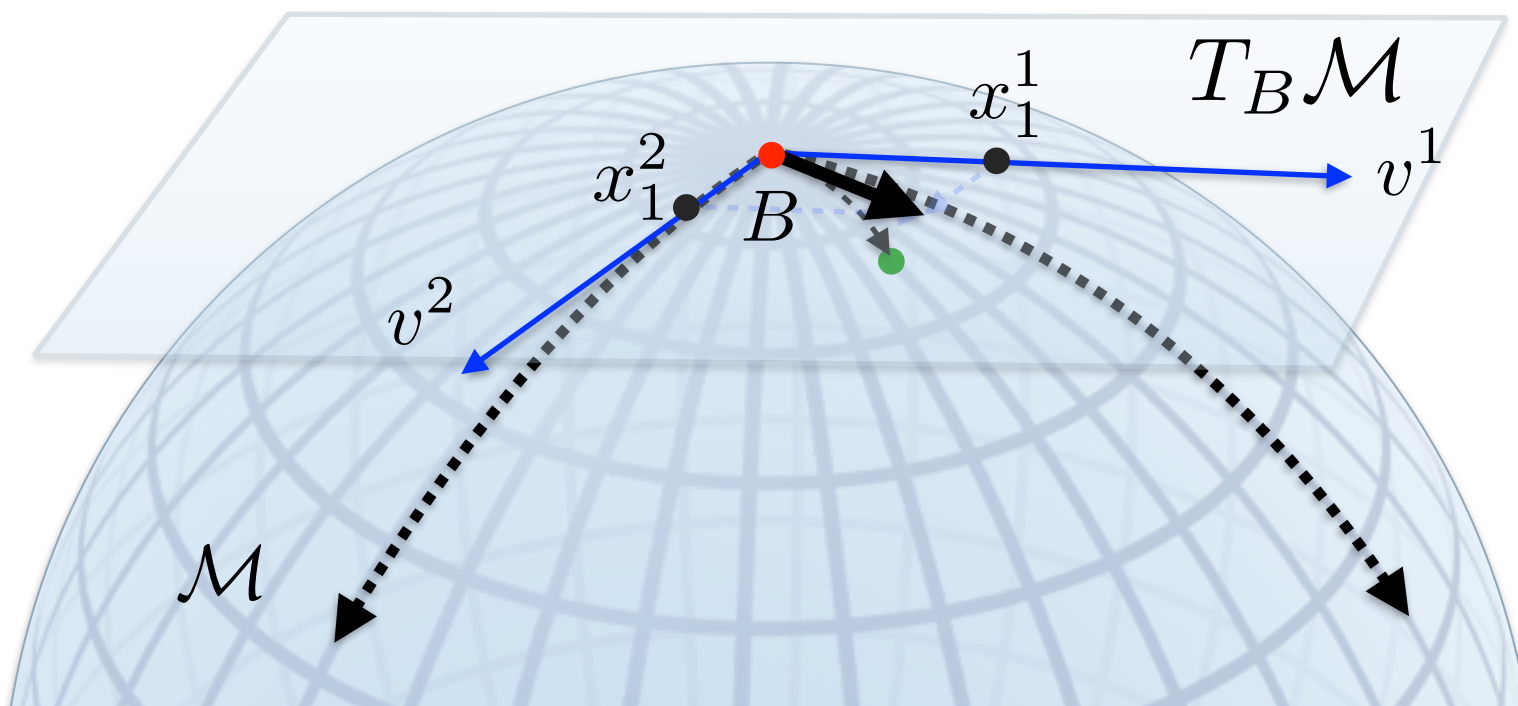
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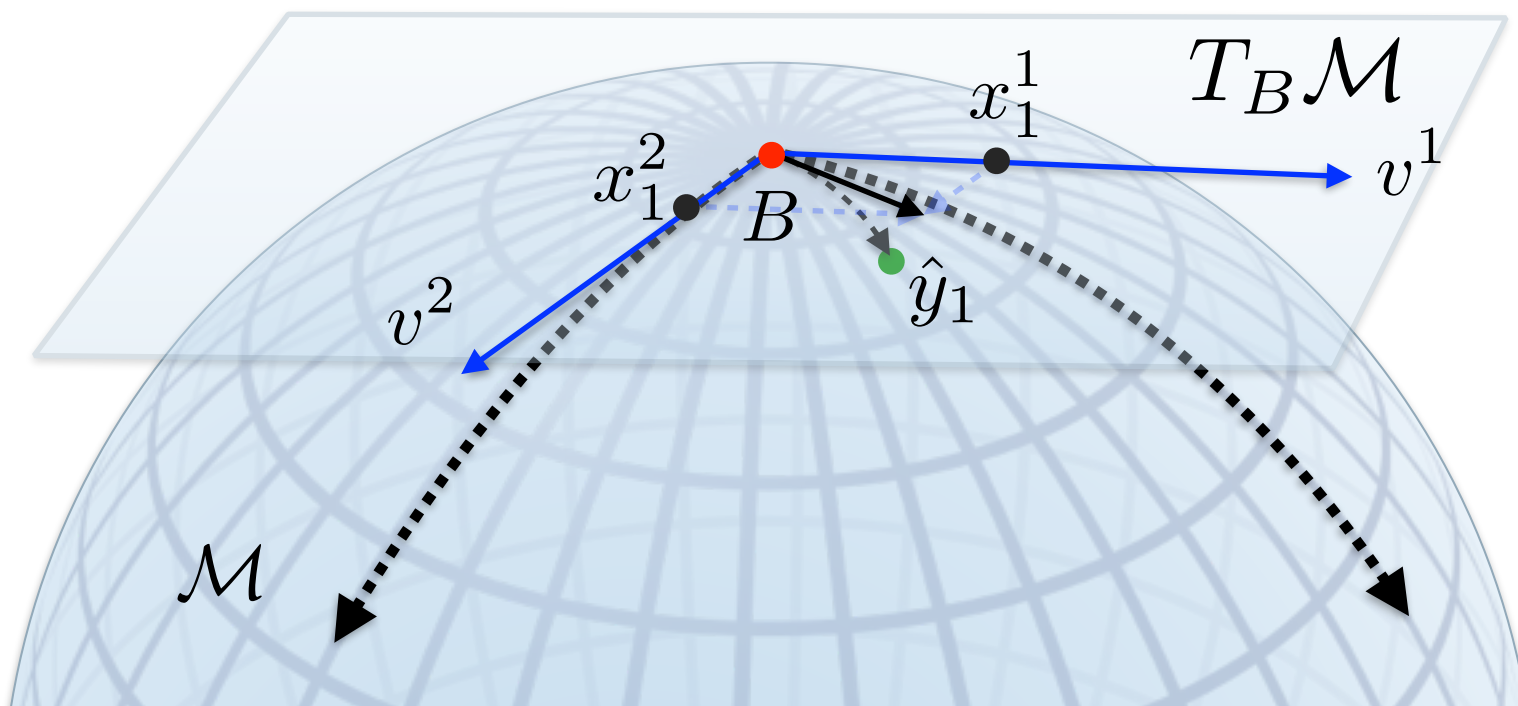
MGLM on manifolds

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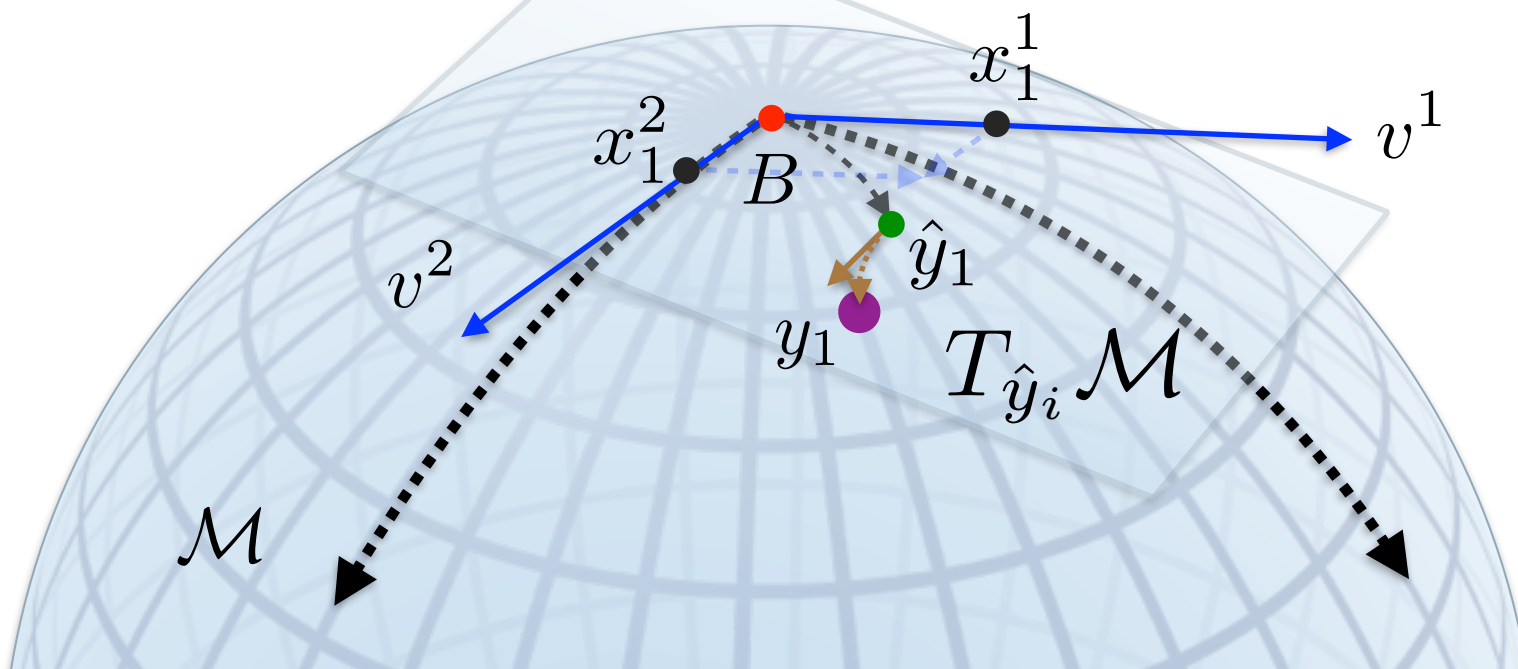
MGLM on manifolds

$$y_i = \text{EXP}\left(\text{EXP}\left(\underline{B}, \sum_{j=1}^d V^j x_i^j\right), \epsilon\right)$$



MGLM on manifolds

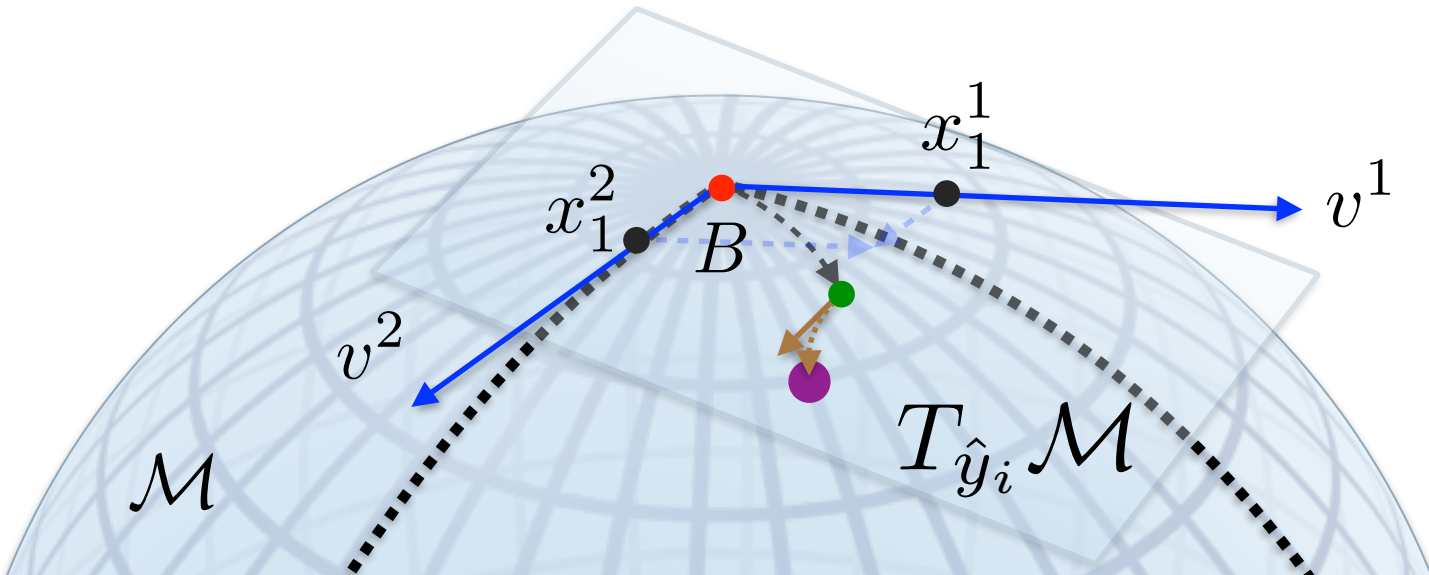
$$y_i = \text{EXP}(\text{EXP}(B, \sum_{j=1}^d V^j x_i^j), \epsilon)$$



MGLM on manifolds

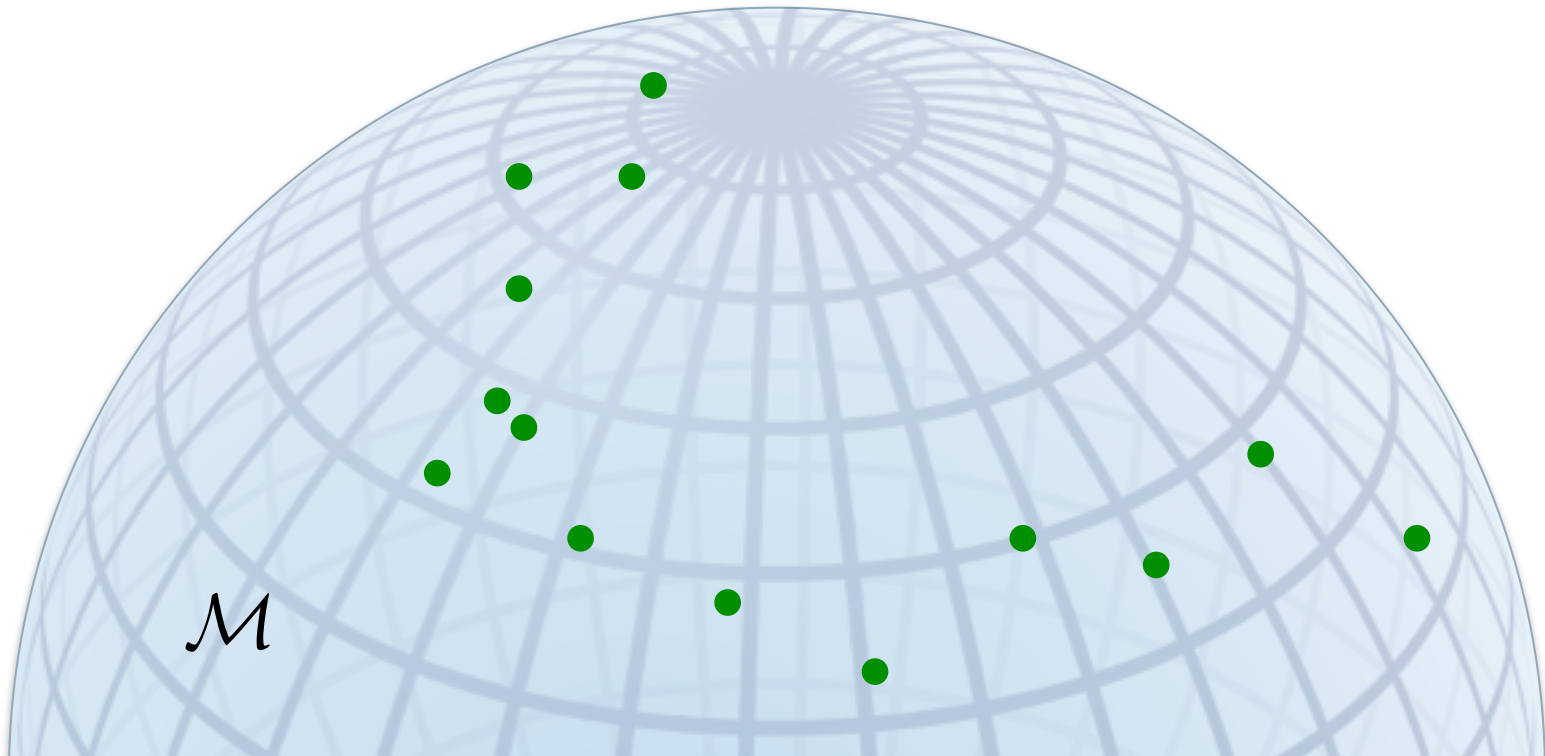
$$\underline{y}_i = \text{EXP}(\text{EXP}(\underline{B}, \sum_{j=1}^d \underline{V}^j x_i^j), \underline{\epsilon})$$

$$\underline{y}_i = \underline{\beta}^0 + \underline{\beta}^1 x_i^1 + \underline{\beta}^2 x_i^2 + \dots + \underline{\beta}^d x_i^d + \underline{\epsilon}$$



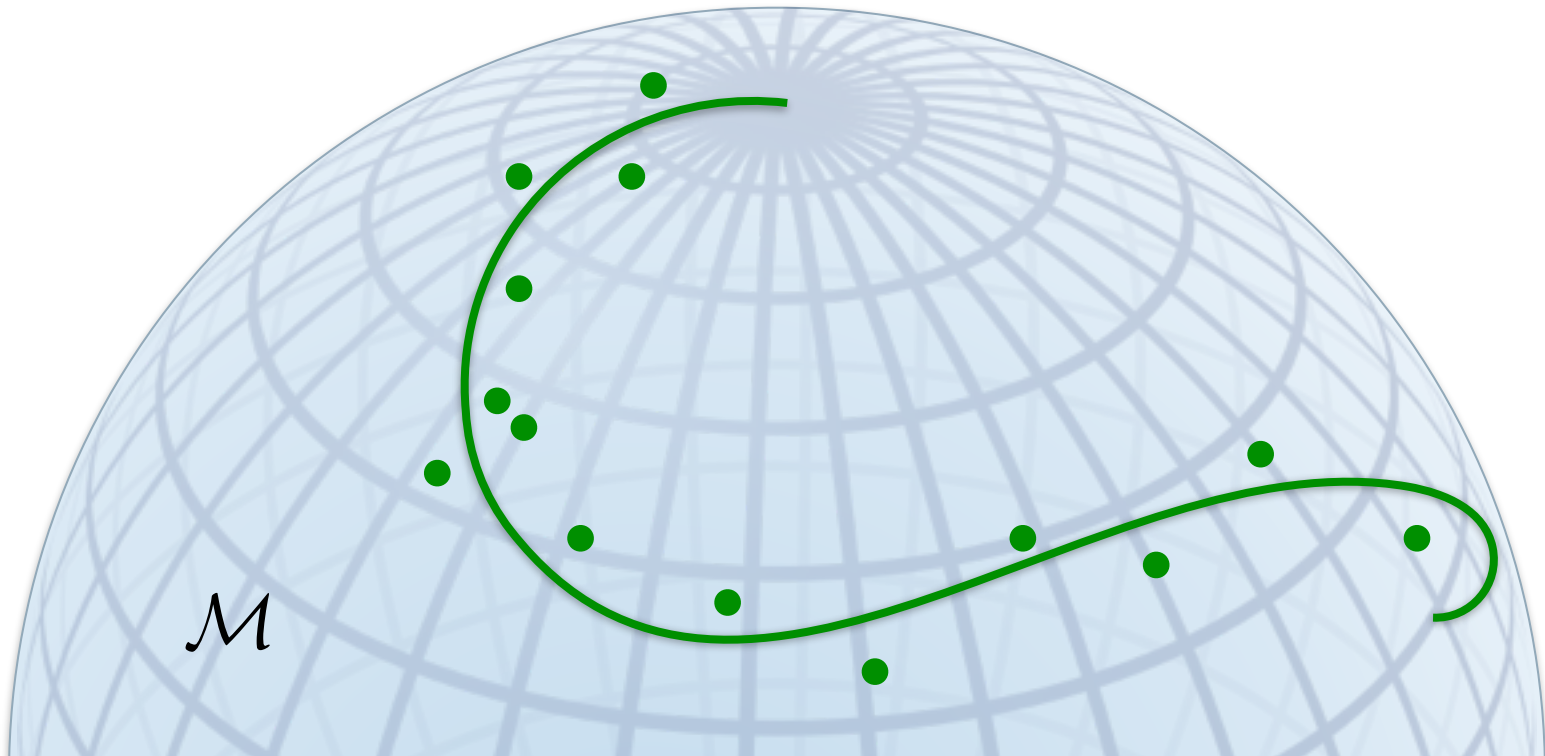
DP-MGLM

$$y_i = \text{EXP}(\text{EXP}(B_i, \sum_{j=1}^d V_i^j x_i^j), \epsilon)$$



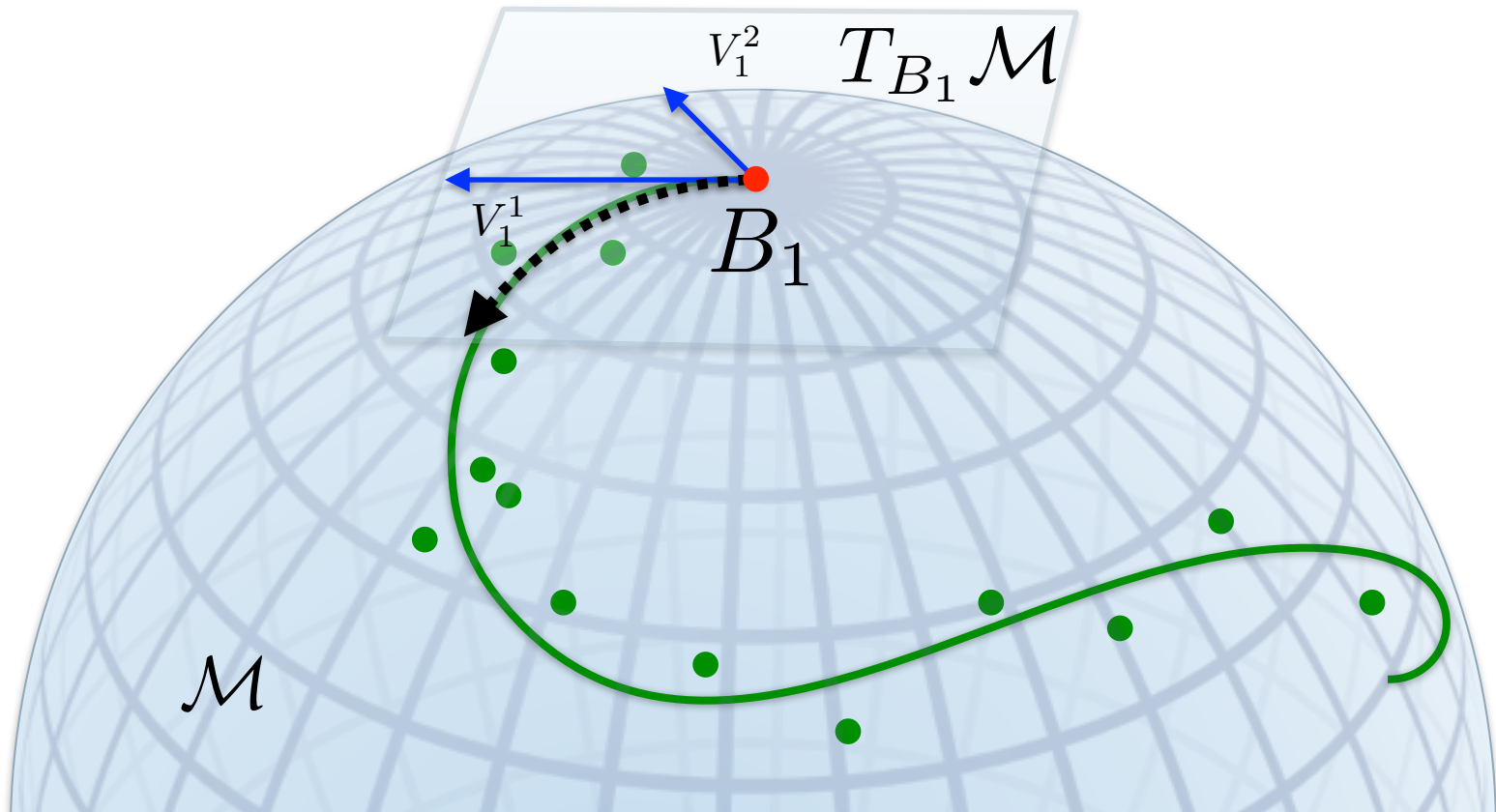
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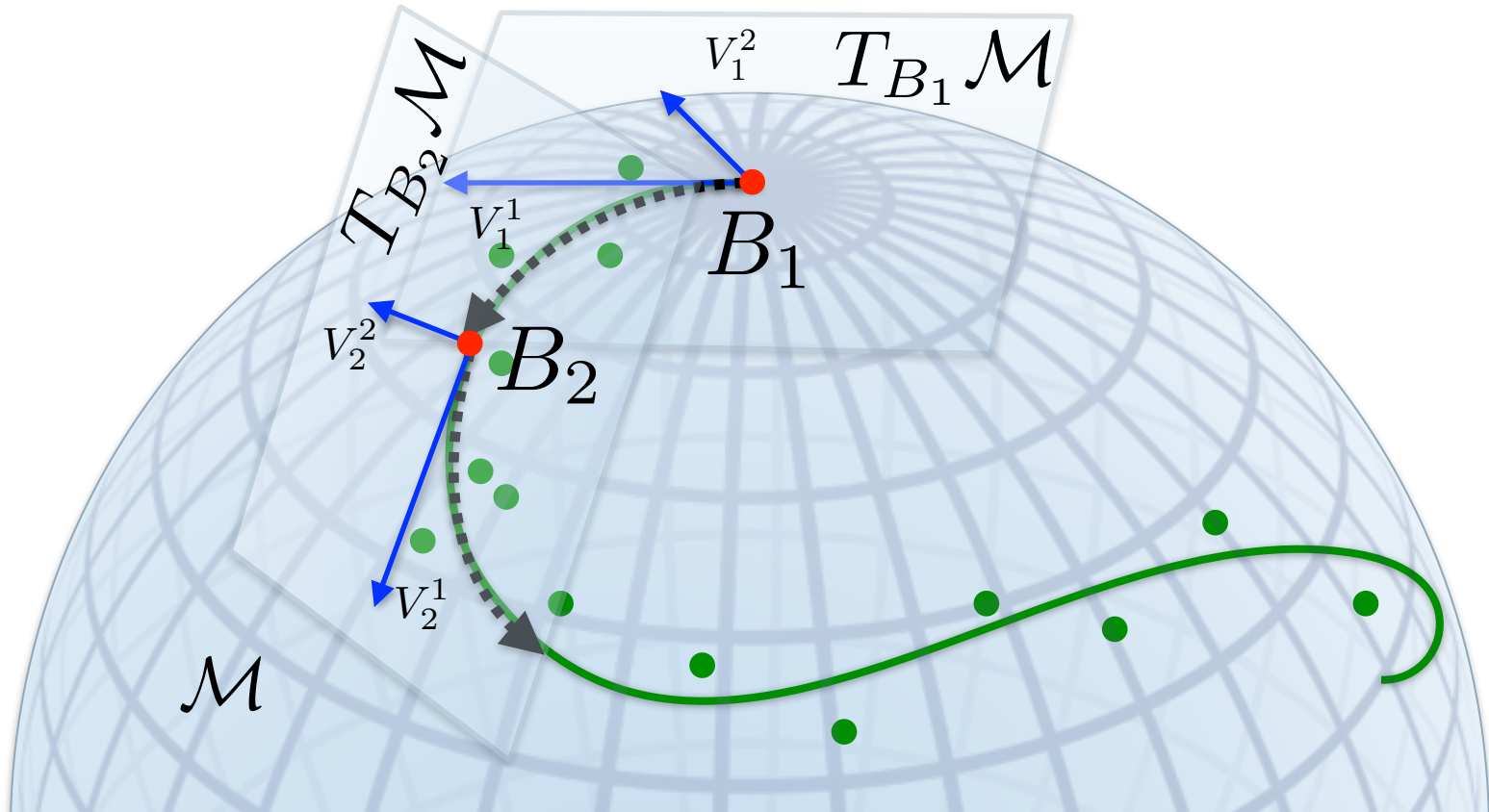
DP-MGLM

$$y_i = \text{EXP}(\underbrace{\text{EXP}(B_i)}_{\text{red}}, \underbrace{\sum_{j=1}^d V_i^j x_i^j}_{\text{blue}}), \epsilon)$$



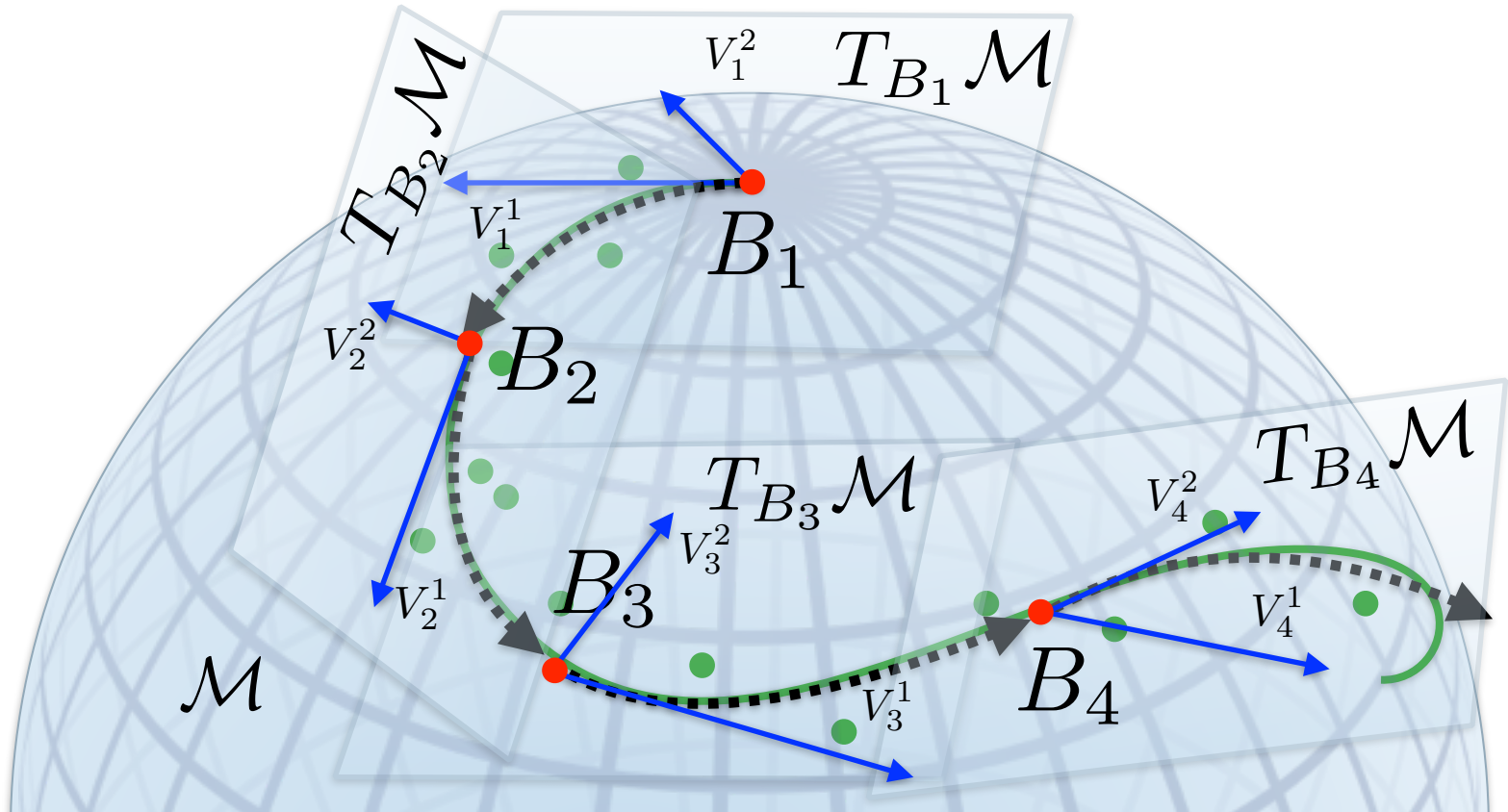
DP-MGLM

$$y_i = \text{EXP}(\underbrace{\text{EXP}(B_i)}_{\text{red}}, \underbrace{\sum_{j=1}^d V_i^j x_i^j}_{\text{blue}}), \epsilon)$$



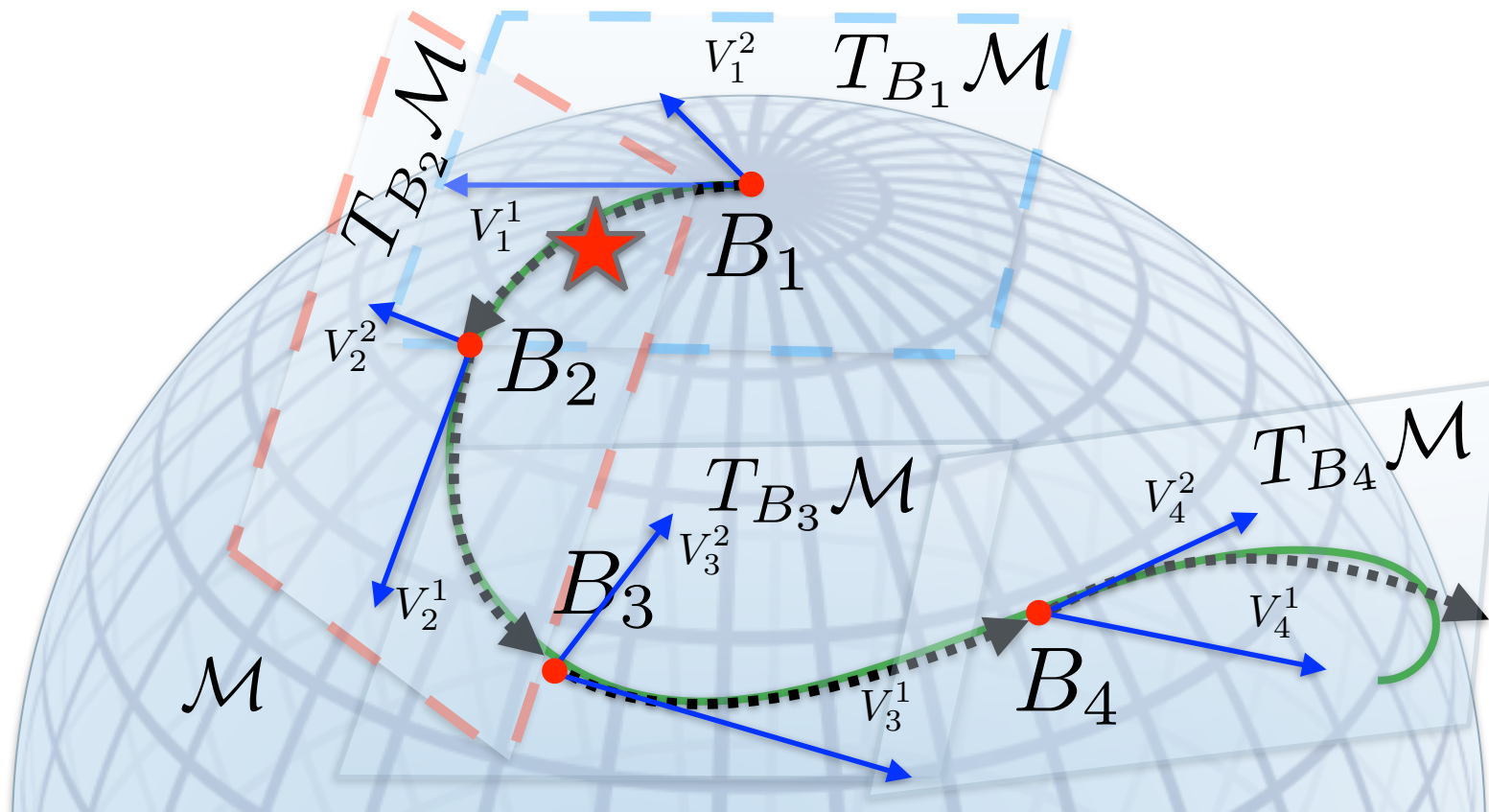
DP-MGLM

$$y_i = \text{EXP}(\underbrace{\text{EXP}(B_i)}_{\text{red}}, \underbrace{\sum_{j=1}^d V_i^j x_i^j}_{\text{blue}}), \epsilon)$$



DP-MGLM

$$y_i = \text{EXP}(\underbrace{\text{EXP}(B_i, \sum_{j=1}^d \underbrace{V_i^j x_i^j}_{\text{blue}}))}_{\text{red}}, \epsilon)$$



DP-GLM

$$G \sim DP(G_0, \nu)$$

$$\theta_i = (\theta_{x_i}, \theta_{y_i}) | G \sim G,$$

$$x_i | \theta_{x_i} \sim f_x(\theta_{x_i}),$$

$$y_i | x_i, \theta_{y_i} \sim GLM(x_i, \theta_{y_i}),$$

DP-GLM

Manifold-valued?

$$y_i \in \mathcal{M}$$

$$G \sim DP(G_0, \nu)$$

$$\theta_i = (\theta_{x_i}, \theta_{y_i}) | G \sim G,$$

$$x_i | \theta_{x_i} \sim f_x(\theta_{x_i}),$$

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DP-MGLM

$$G \sim DP(G_0, \nu)$$

$$\theta_i = (\theta_{x_i}, \theta_{y_i}) | G \sim G,$$

MGLM on
manifolds

$$x_i | \theta_{x_i} \sim f_x(\theta_{x_i}),$$

$$y_i | x_i, \theta_{y_i} \sim \text{MGLM}(x_i, \theta_{y_i}),$$

DP-MGLM

$$G \sim DP(G_0, \nu)$$

$$\theta_i = (\theta_{x_i}, \theta_{y_i}) | G \sim G,$$

$$x_i | \theta_{x_i} \sim f_x(\theta_{x_i}),$$

$$y_i | x_i, \theta_{y_i} \sim MGLM(x_i, \theta_{y_i}),$$

manifold-valued
parameters?

$$\theta_{y_i} \in SPD(n) \times \text{Sym}(n)^d$$

DP-MGLM

- Distribution on manifolds
- Intrinsic metric

$$G \sim DP(G_0, \nu)$$

$$\theta_i = (\theta_{x_i}, \theta_{y_i}) | G \sim G,$$

$$x_i | \theta_{x_i} \sim f_x(\theta_{x_i}),$$

$$y_i | x_i, \theta_{y_i} \sim MGLM(x_i, \theta_{y_i}),$$

$$\theta_{y_i} \in SPD(n) \times \text{Sym}(n)^d$$

DP-MGLM

Hamiltonian Monte Carlo (HMC) sampling

$$G \sim DP(G_0, \nu)$$

$$\theta_i = (\theta_{x_i}, \theta_{y_i}) | G \sim G,$$

$$x_i | \theta_{x_i} \sim f_x(\theta_{x_i}),$$

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$$\theta_{y_i} \in \text{SPD}(n) \times \text{Sym}(n)^d$$

HMC

Hamiltonian/Hybrid Monte Carlo

$$H(q, p) = U(q) + K(p)$$

Duane, S., et al, “Hybrid Monte Carlo”, 1987.

Neal, R. “MCMC using Hamiltonian dynamics”, 2011

HMC

Hamiltonian/Hybrid Monte Carlo

$$H(q, p) = U(q) + K(p)$$

$$q = \theta \in \mathbf{R}^d$$

$$p = \dot{\theta} \in \mathbf{R}^d$$

Duane, S., et al, “Hybrid Monte Carlo”, 1987.

Neal, R. “MCMC using Hamiltonian dynamics”, 2011

HMC

Hamiltonian/Hybrid Monte Carlo

$$H(q, p) = U(q) + K(p)$$

$$U(q) := -\log f(q)$$

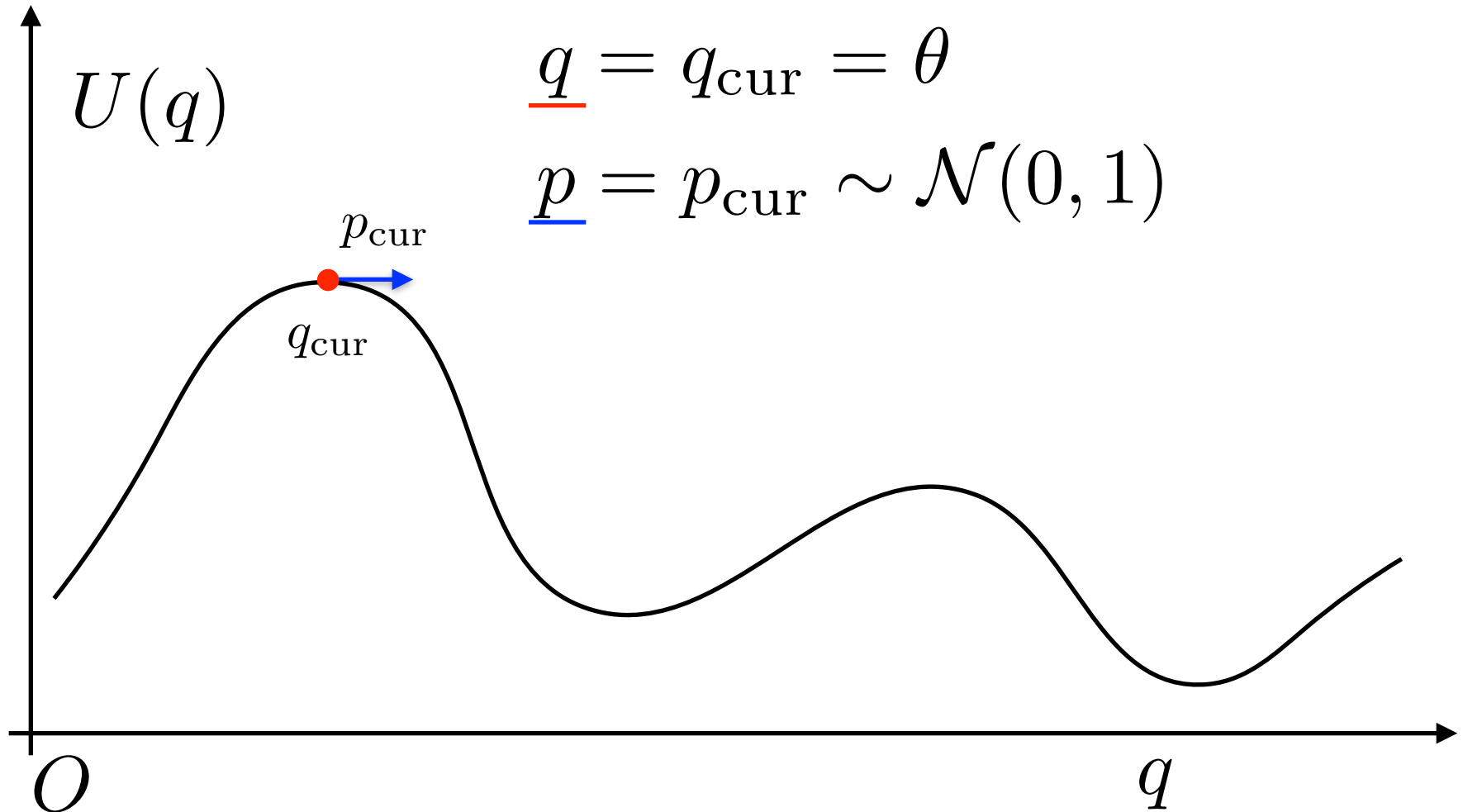
$$K(p) := \frac{1}{2} p^T M^{-1} p$$

Duane, S., et al, “Hybrid Monte Carlo”, 1987.

Neal, R. “MCMC using Hamiltonian dynamics”, 2011

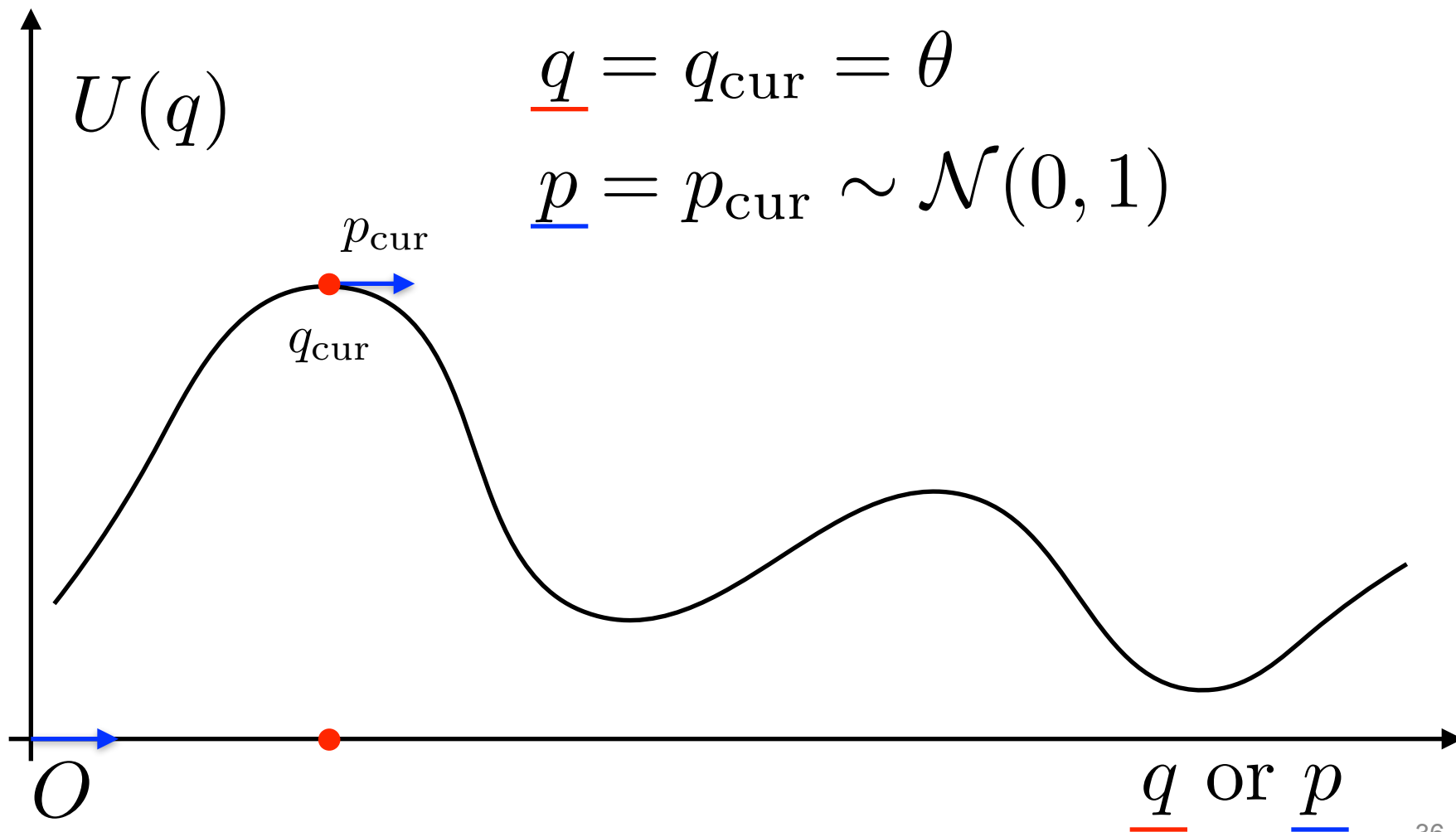
HMC

Hamiltonian/Hybrid Monte Carlo



HMC

Hamiltonian/Hybrid Monte Carlo

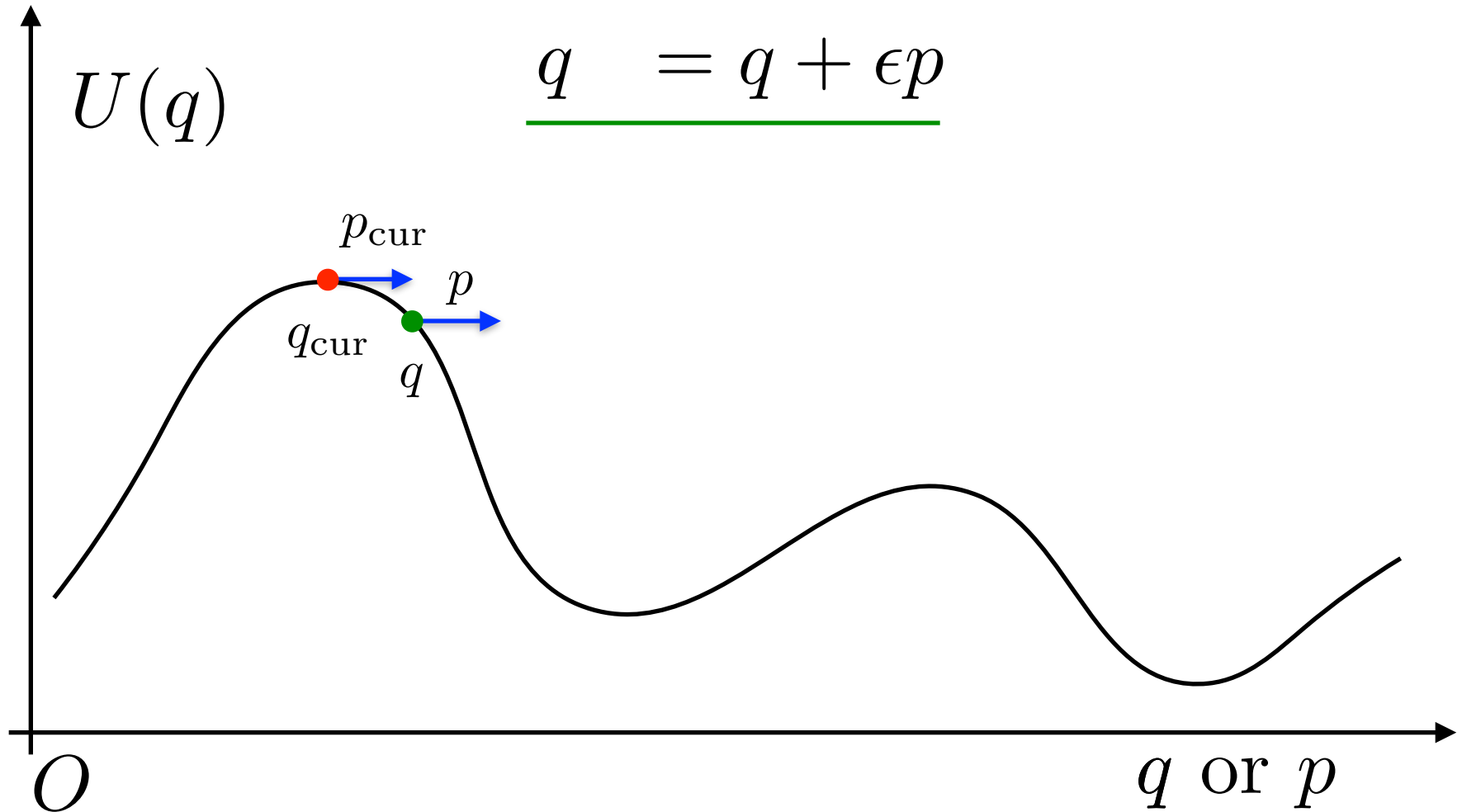


$$\underline{q} = q_{\text{cur}} = \theta$$

$$\underline{p} = p_{\text{cur}} \sim \mathcal{N}(0, 1)$$

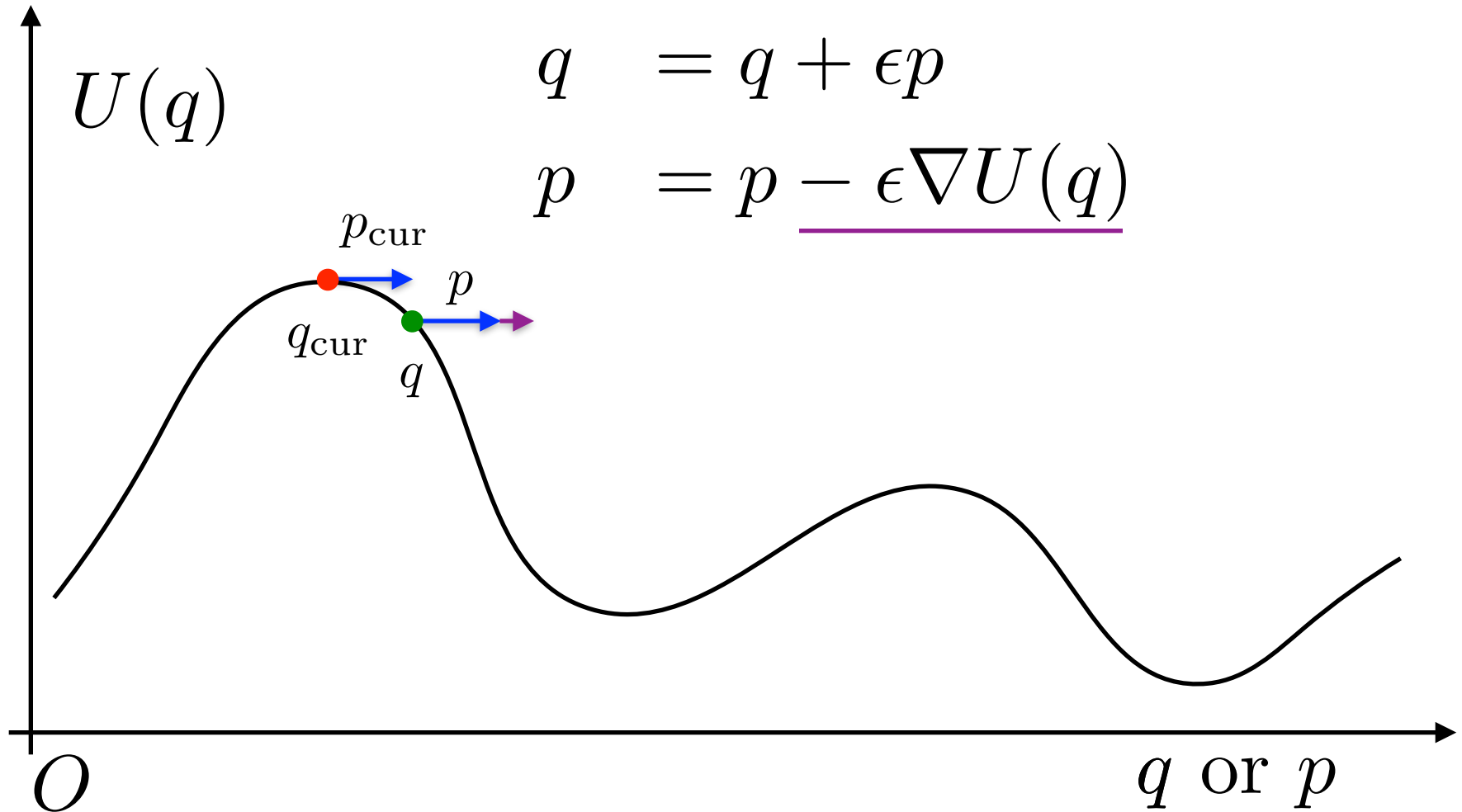
HMC

Hamiltonian/Hybrid Monte Carlo



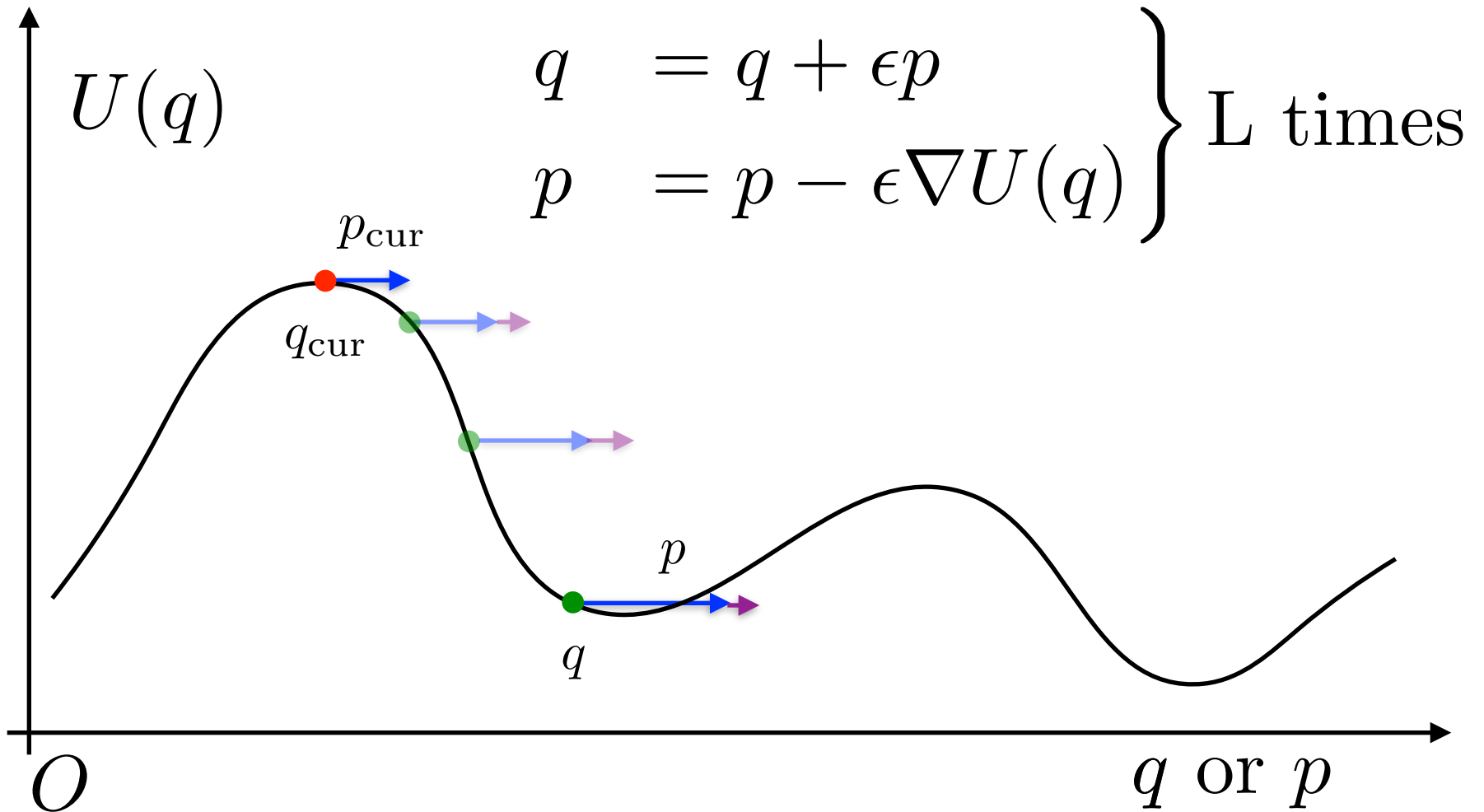
HMC

Hamiltonian/Hybrid Monte Carlo



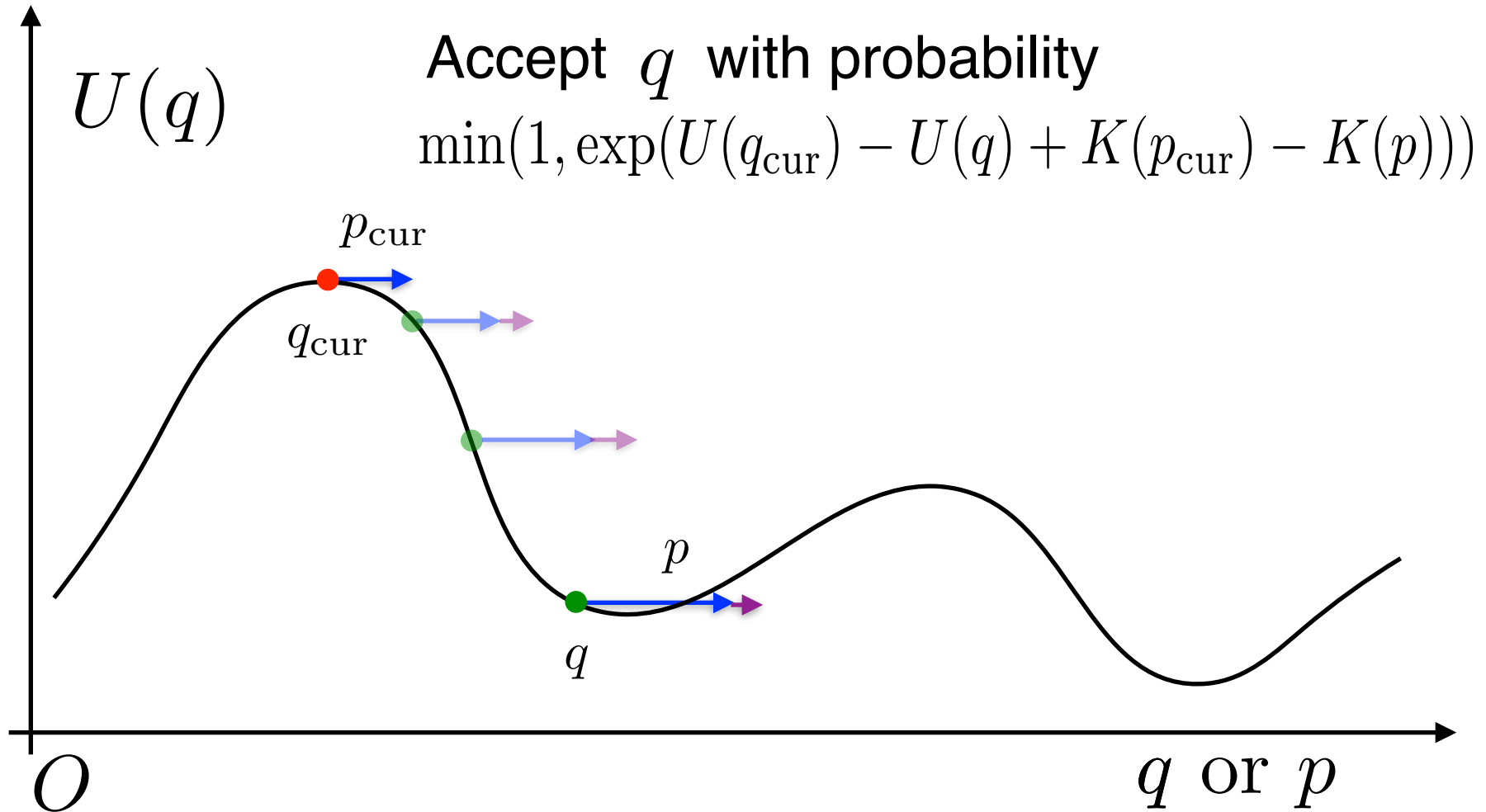
HMC

Hamiltonian/Hybrid Monte Carlo

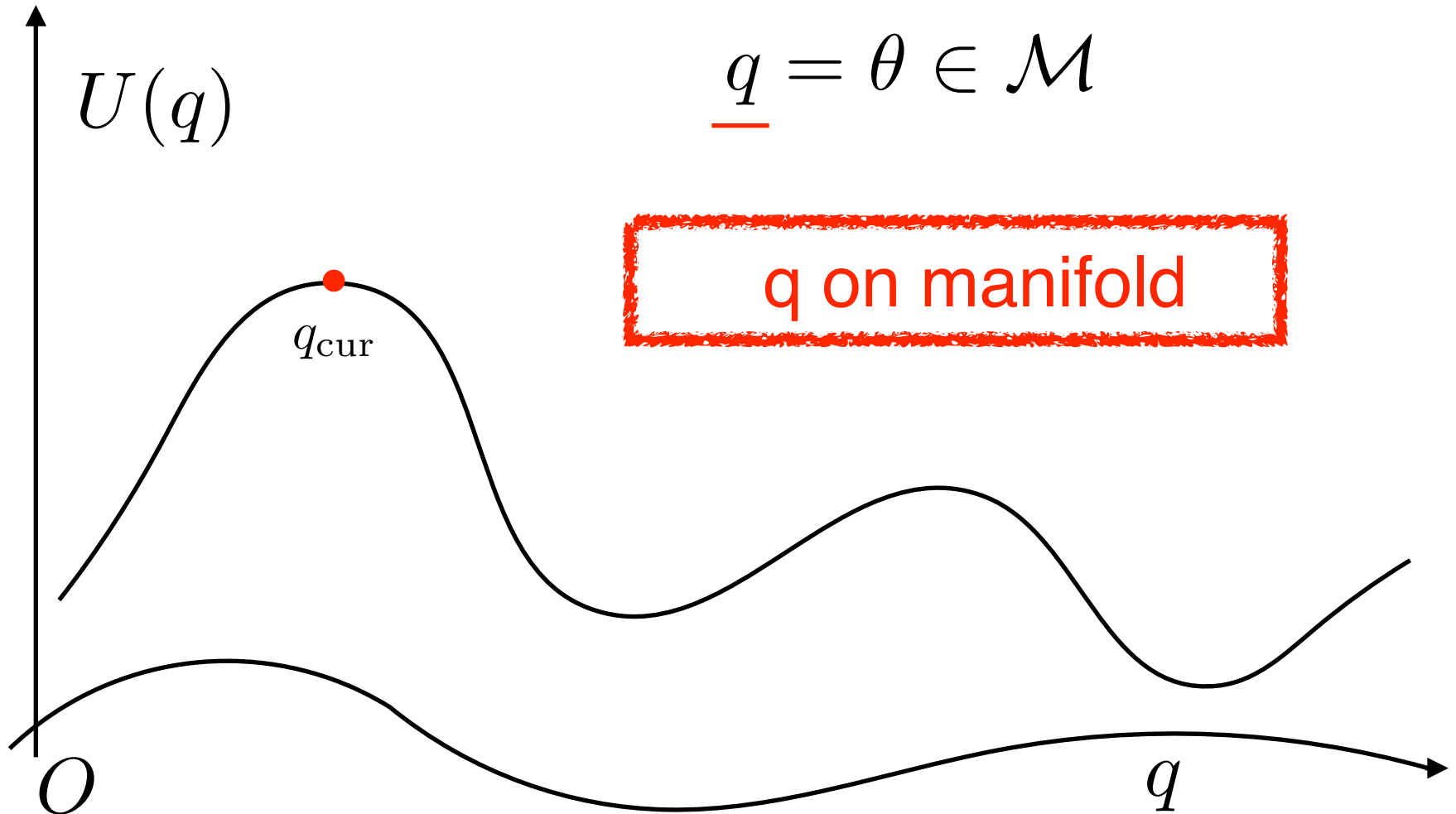


HMC

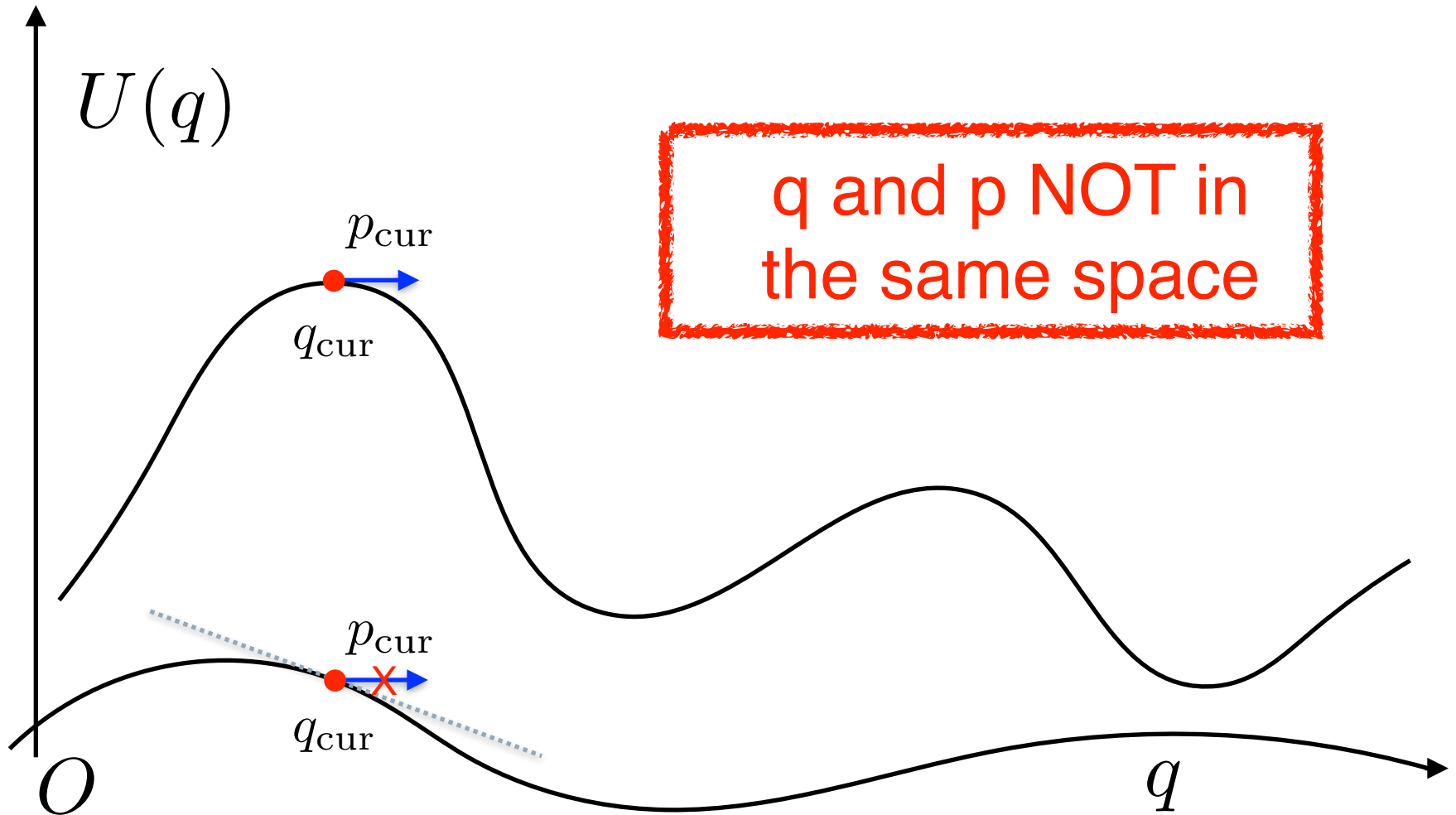
Hamiltonian/Hybrid Monte Carlo



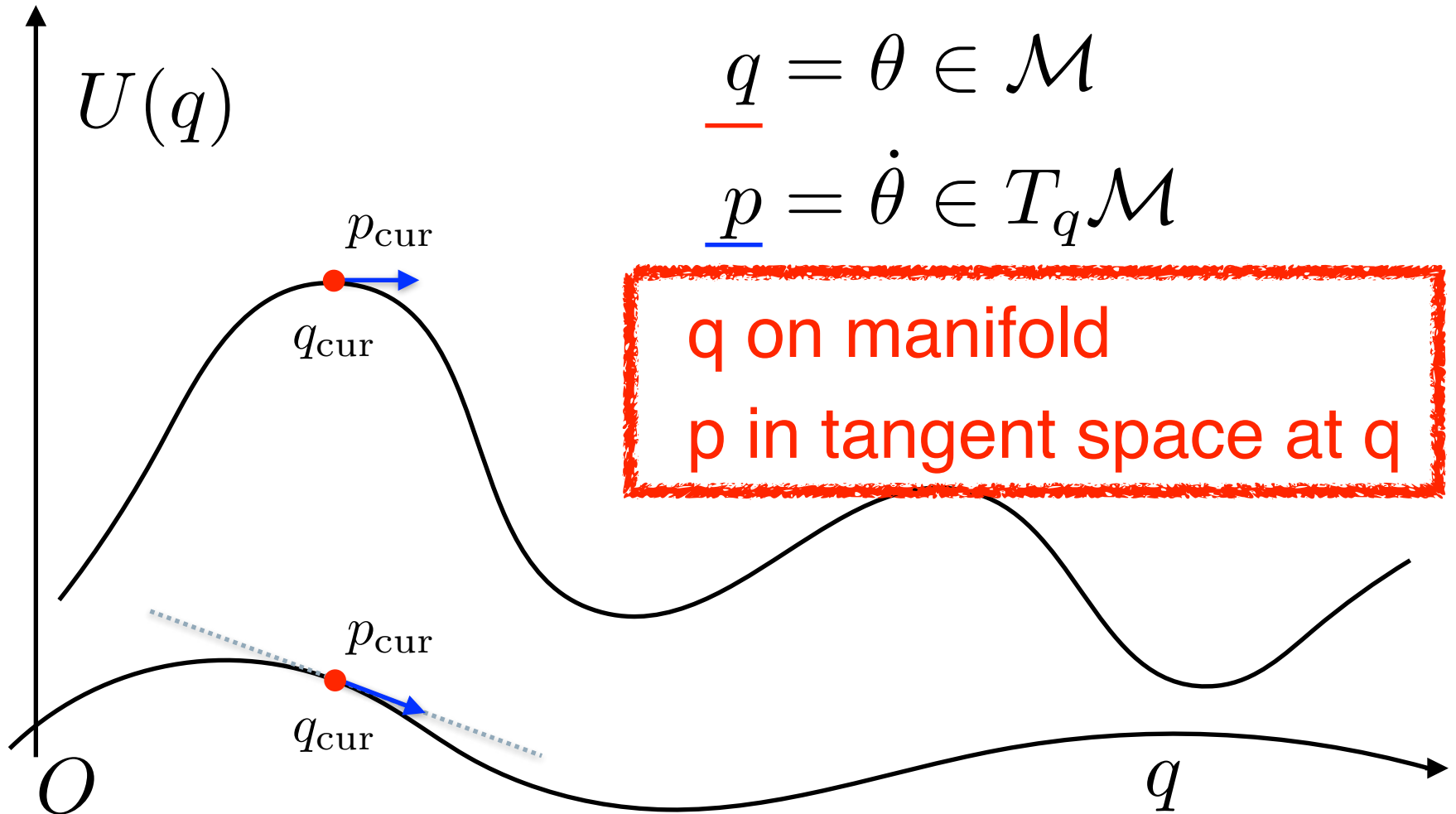
HMC for DP-MGLM



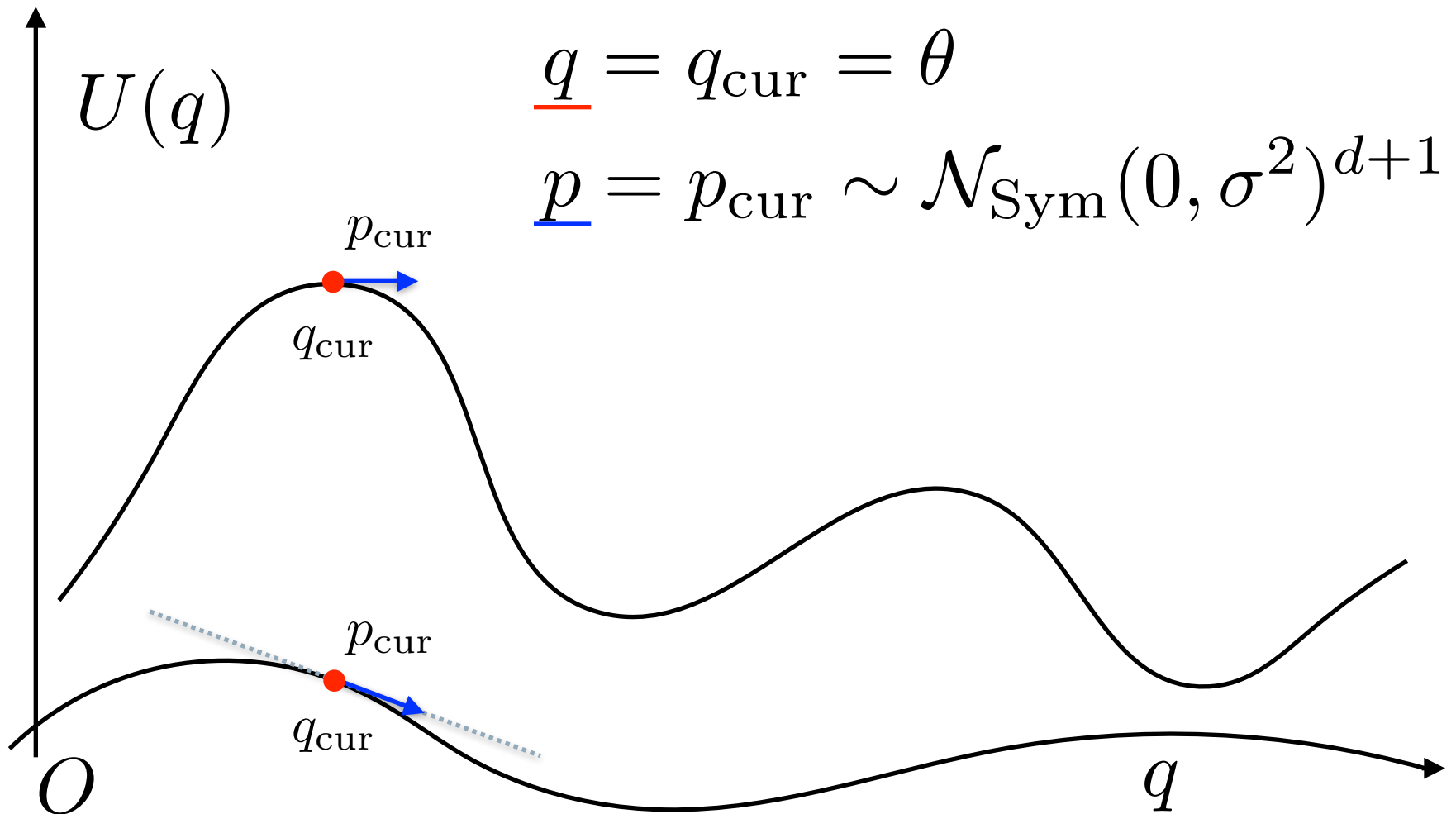
HMC for DP-MGLM



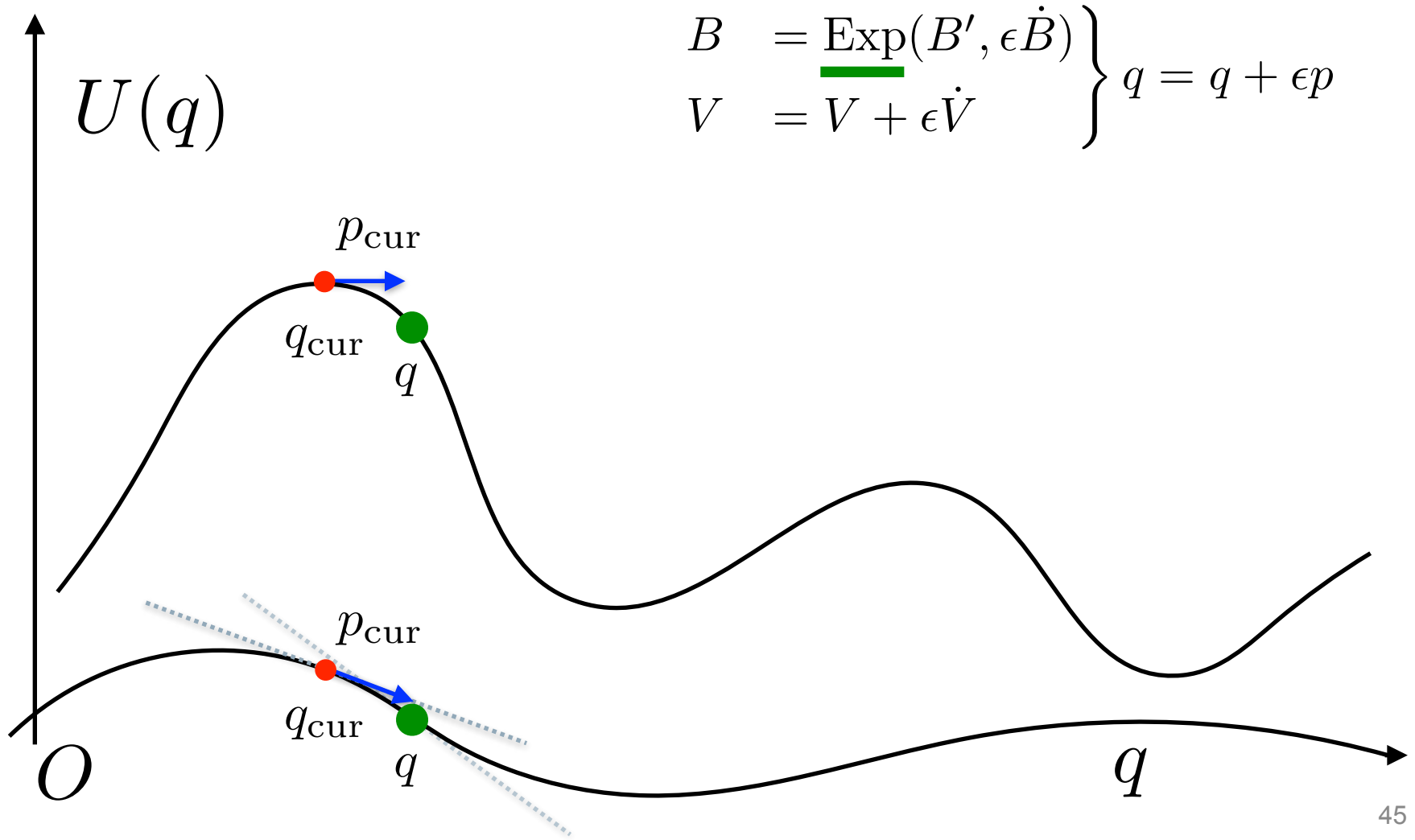
HMC for DP-MGLM



HMC for DP-MGLM

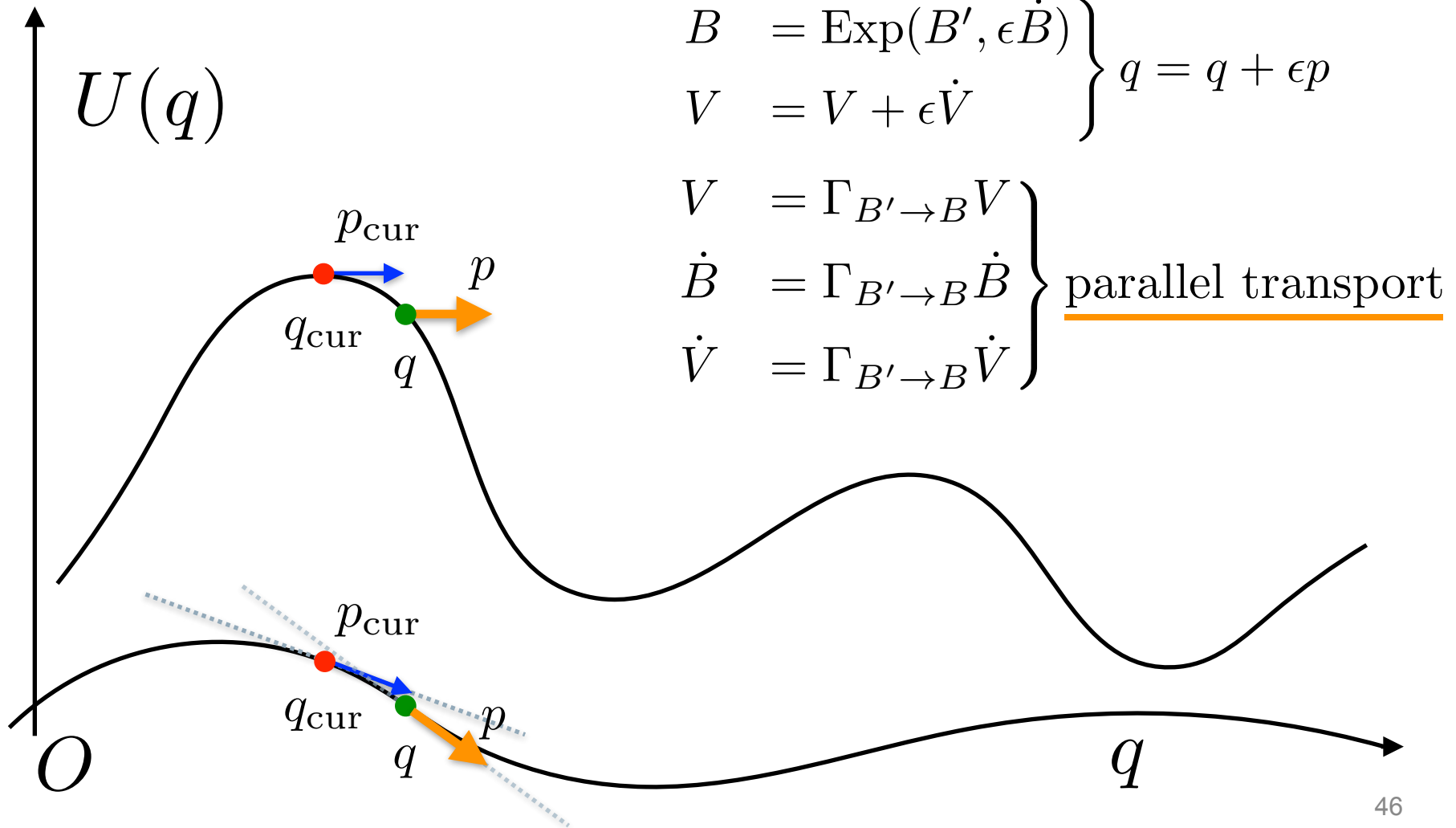


HMC for DP-MGLM

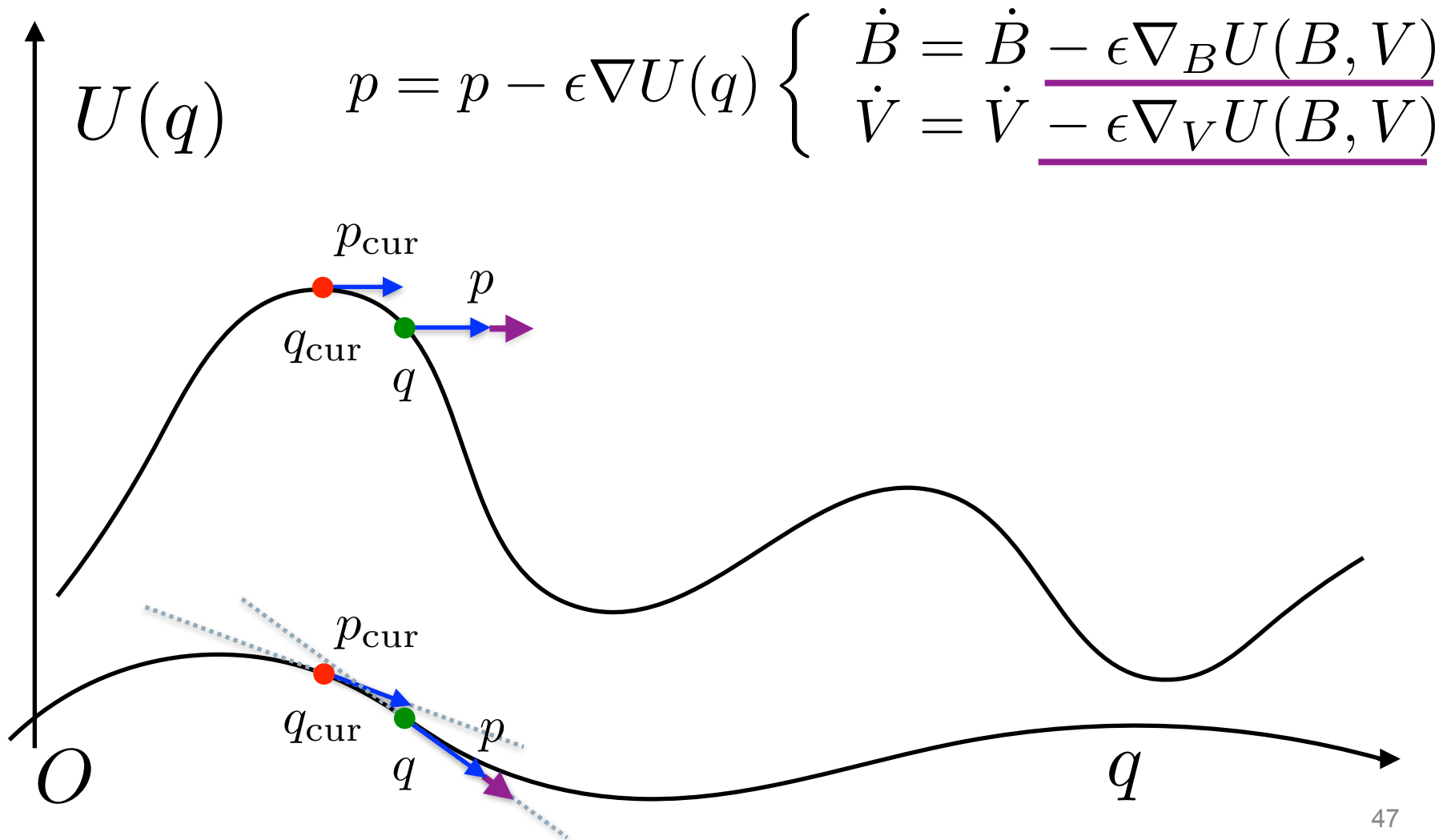


$$\left. \begin{aligned} B &= \underline{\text{Exp}}(B', \epsilon \dot{B}) \\ V &= V + \epsilon \dot{V} \end{aligned} \right\} q = q + \epsilon p$$

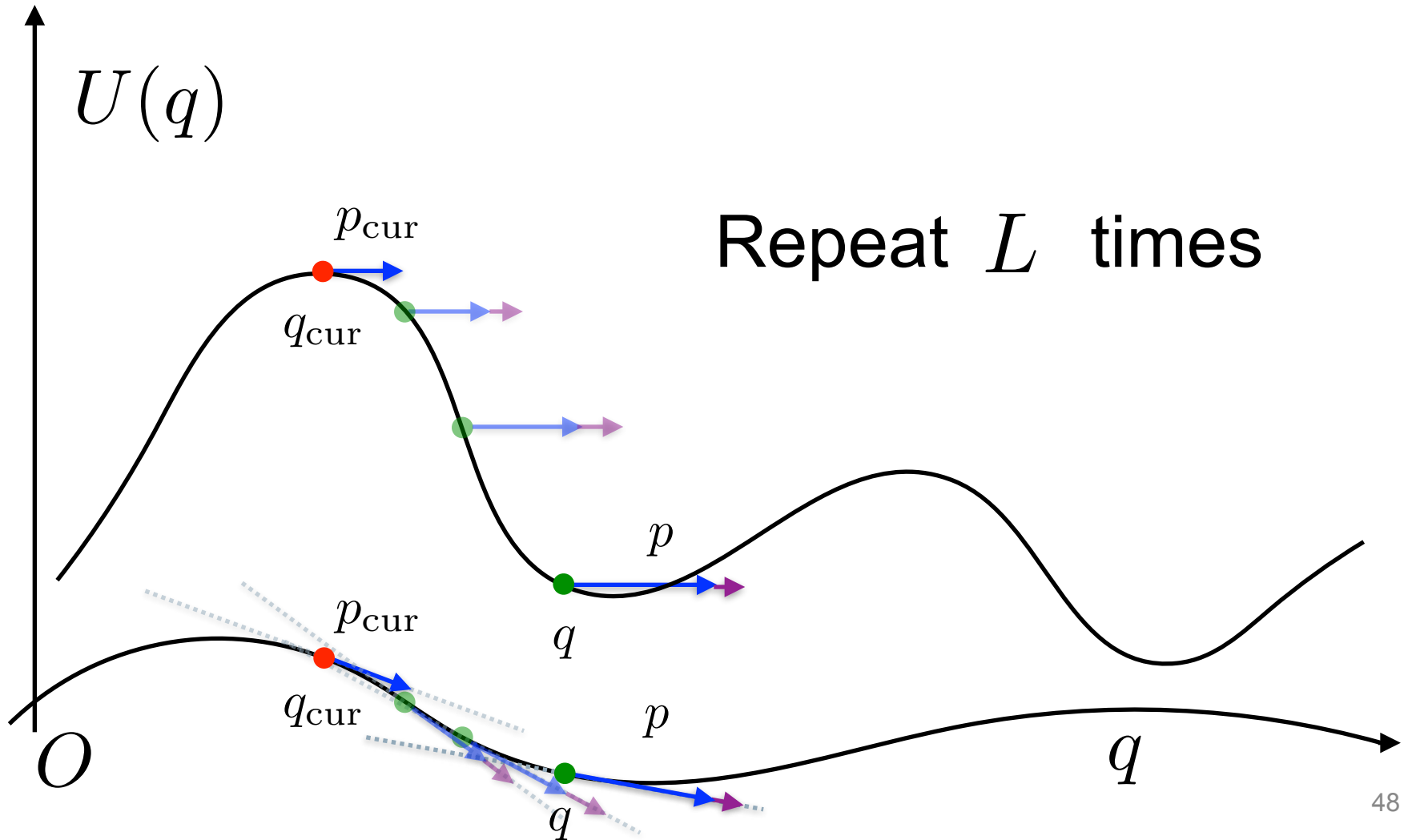
HMC for DP-MGLM



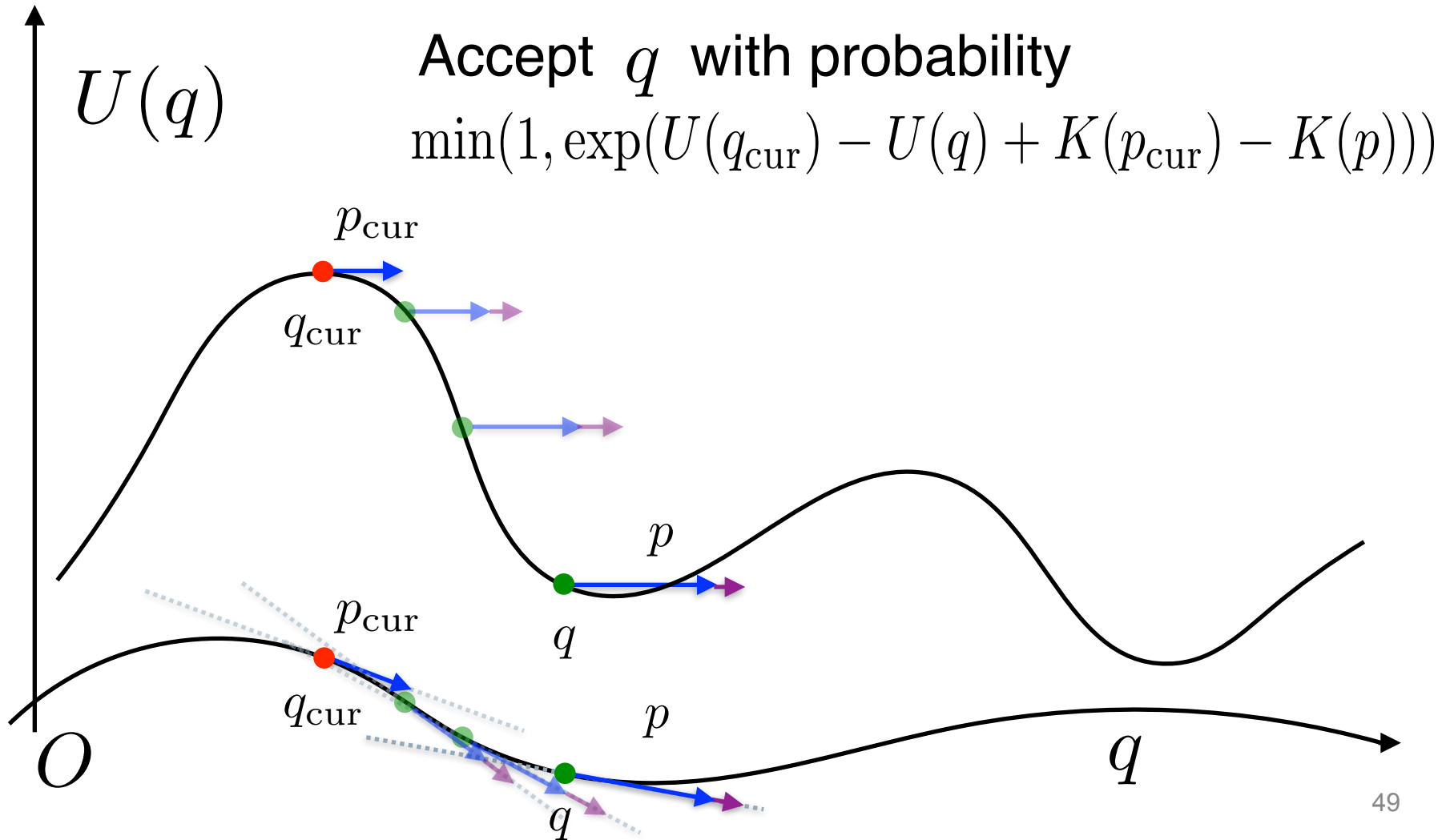
HMC for DP-MGLM



HMC for DP-MGLM



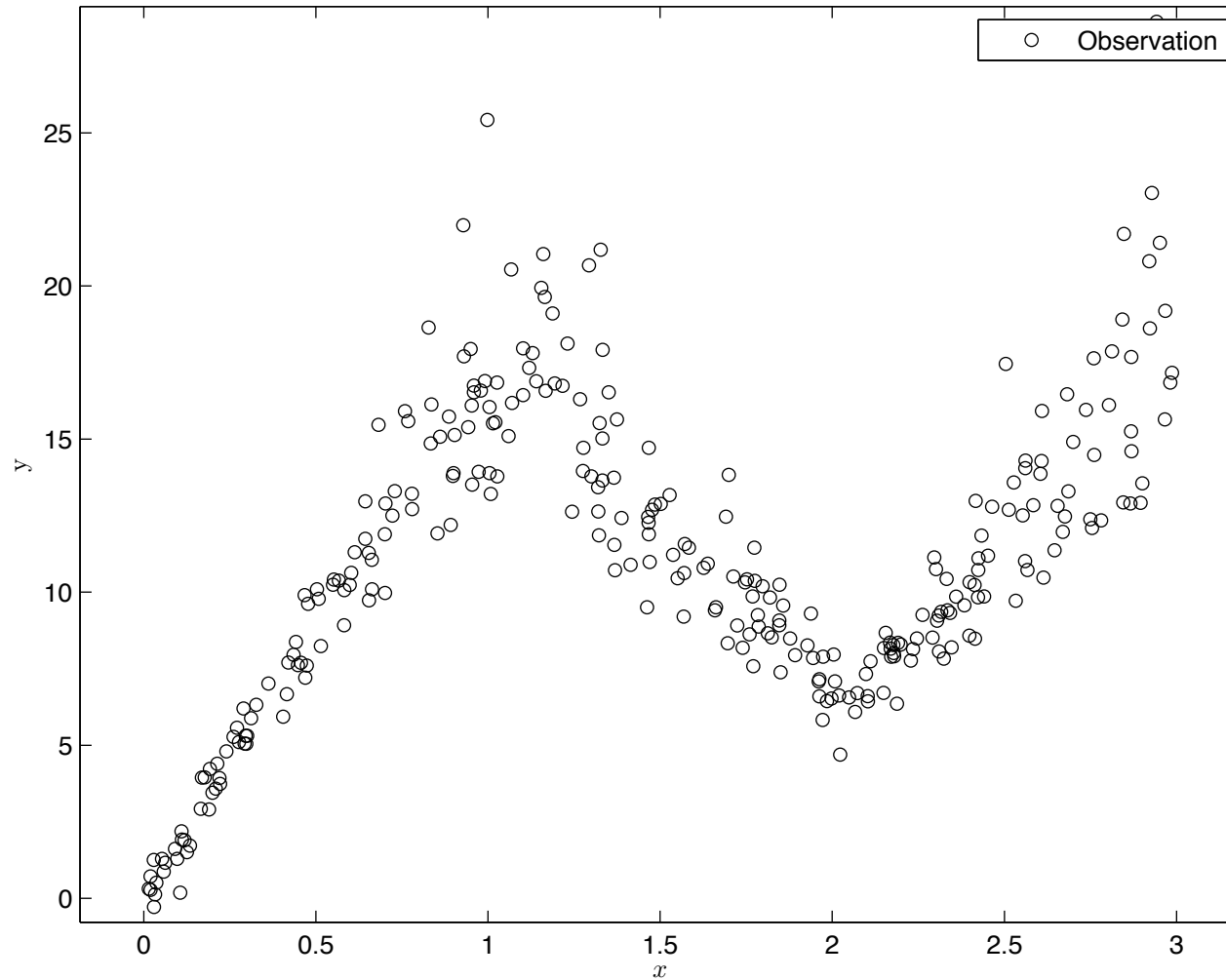
HMC for DP-MGLM



Experiments

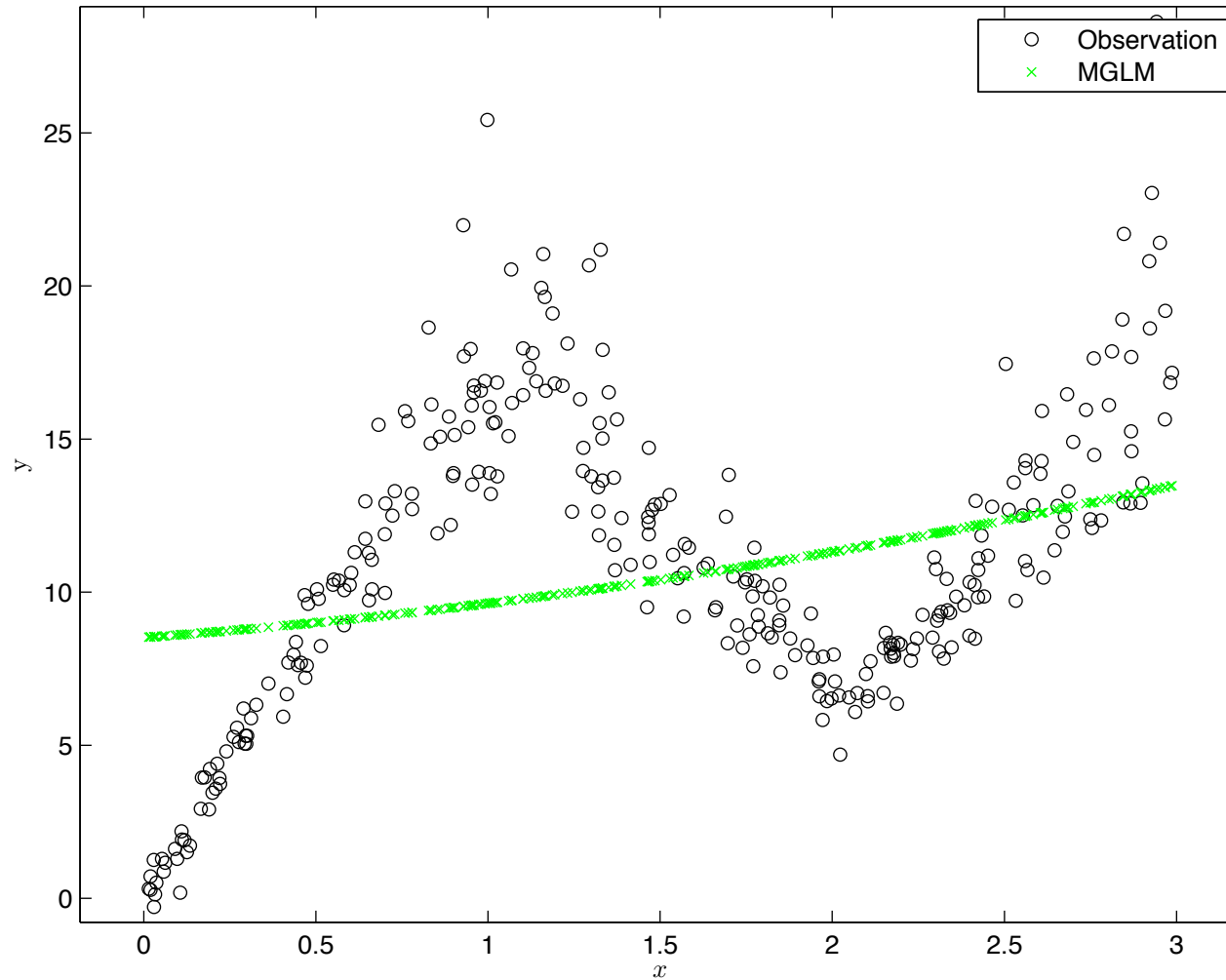
Experiment 1

MGLM vs DP-MGLM



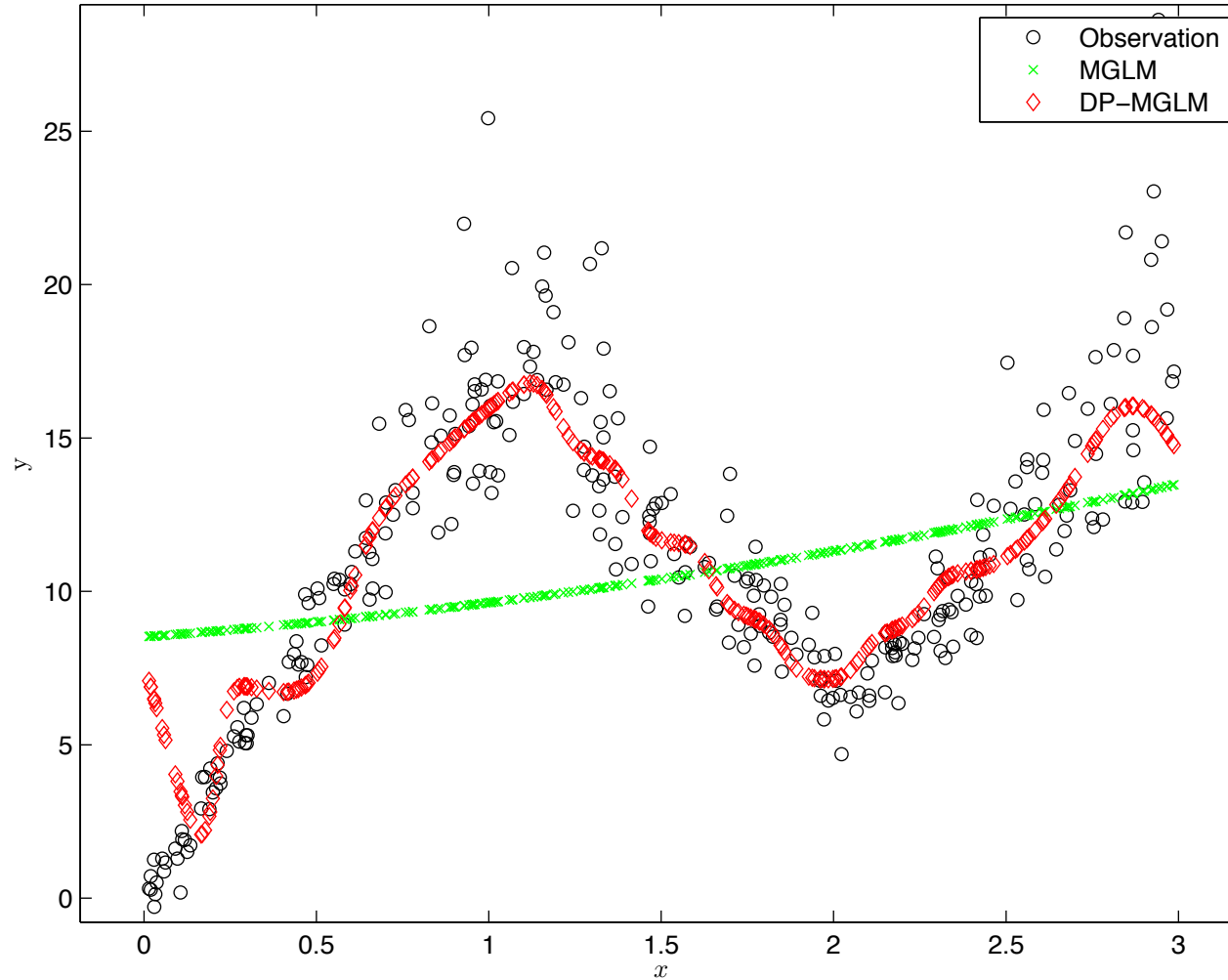
Experiment 1

MGLM vs DP-MGLM



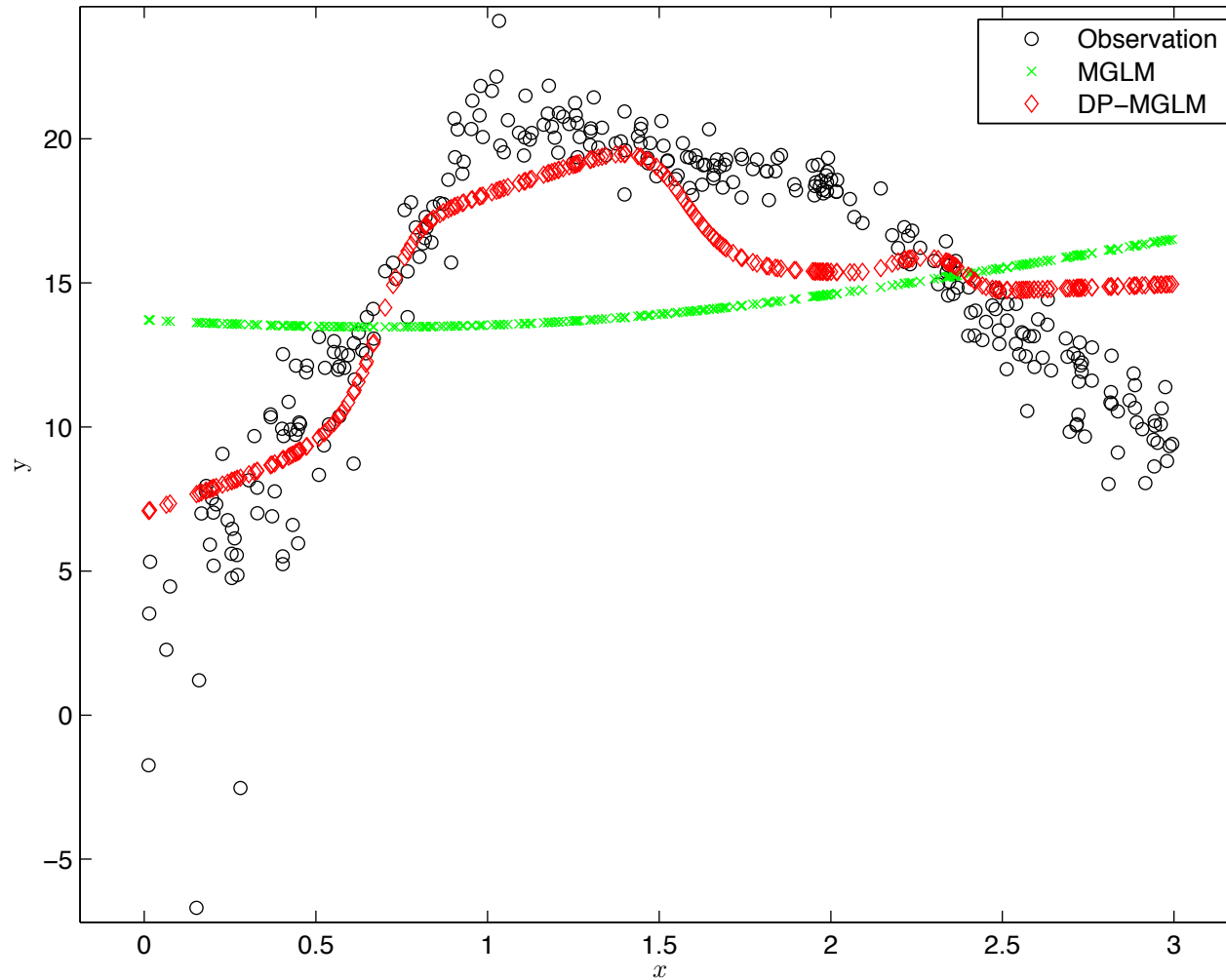
Experiment 1

MGLM vs DP-MGLM



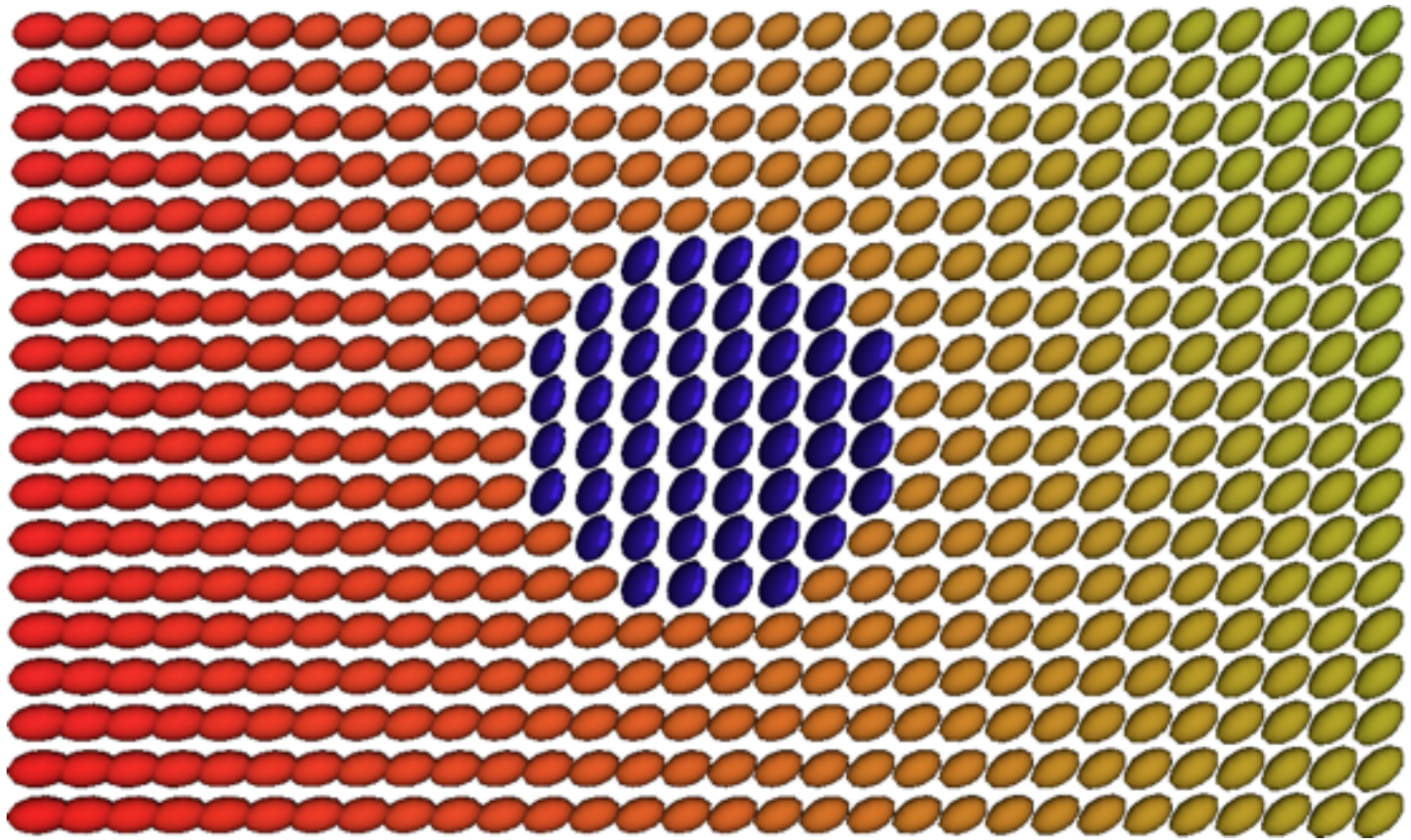
Experiment 1

MGLM vs DP-MGLM

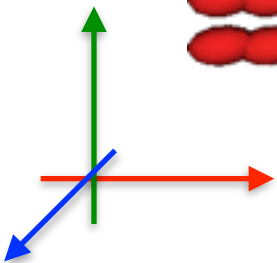


Experiment 2

Clustering on SPD(3)

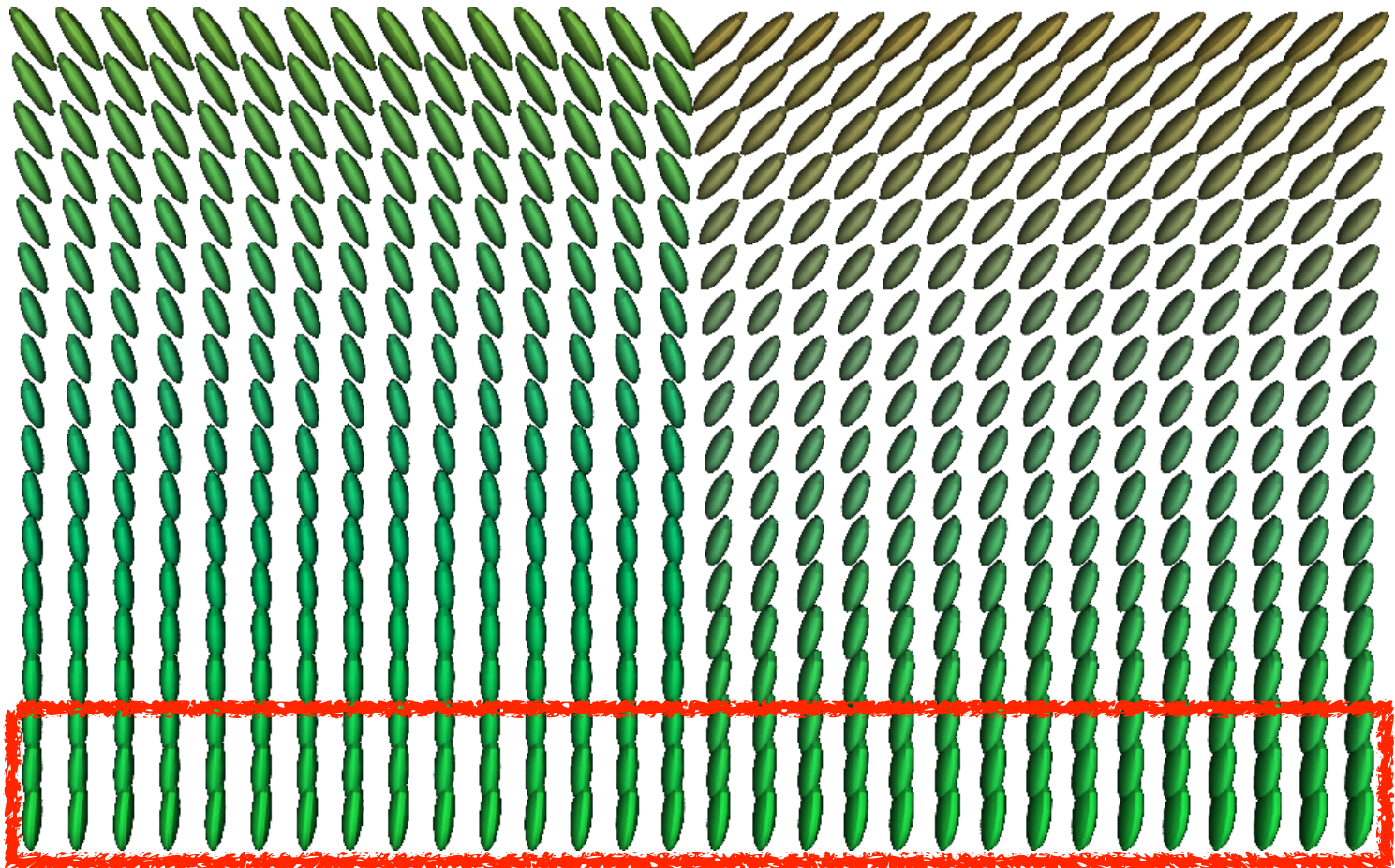


3D ellipsoid patch 1



Experiment 2

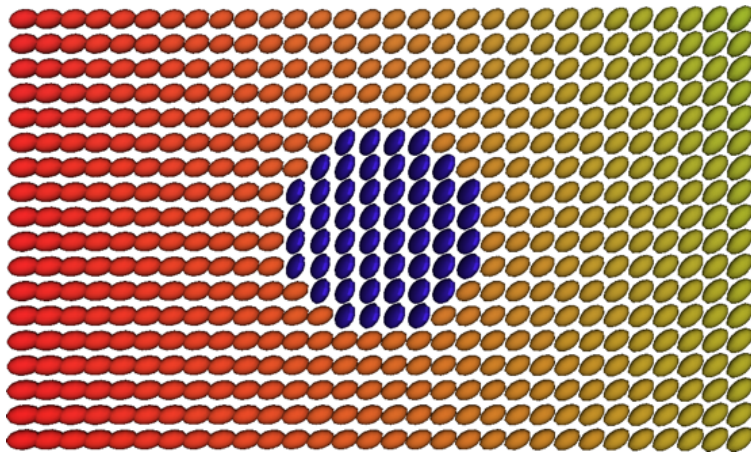
Clustering on SPD(3)



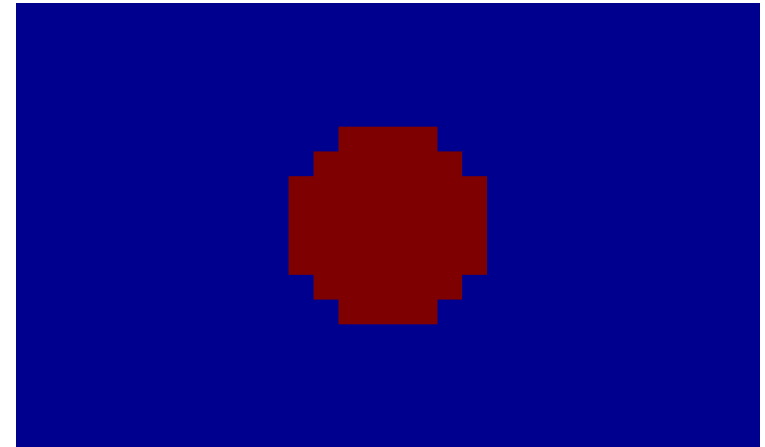
3D ellipsoid patch 2

Experiment 2

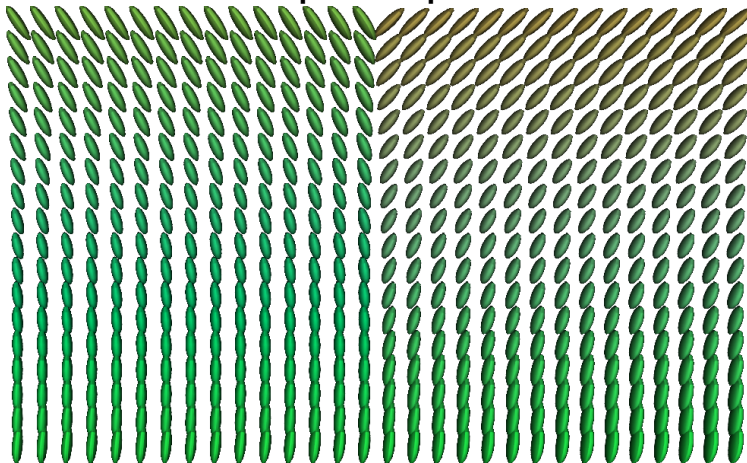
Clustering on SPD(3)



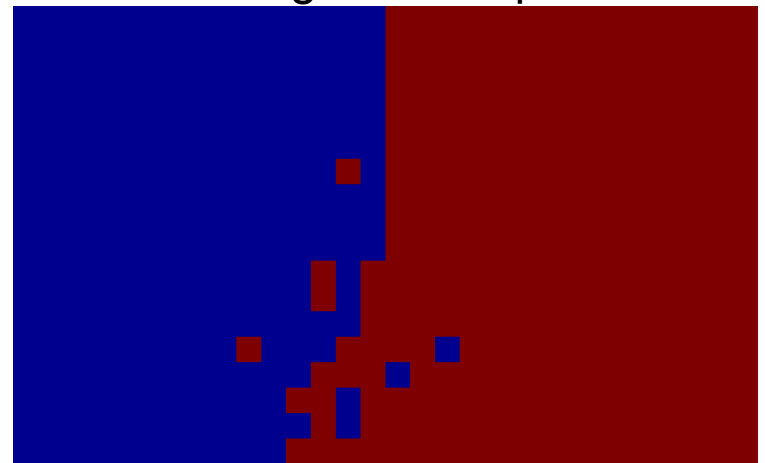
3D ellipsoid patch 1



Clustering result of patch 1



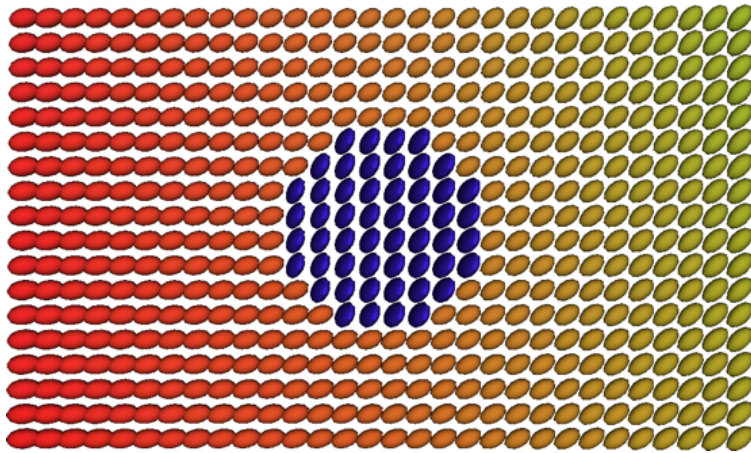
3D ellipsoid patch 2



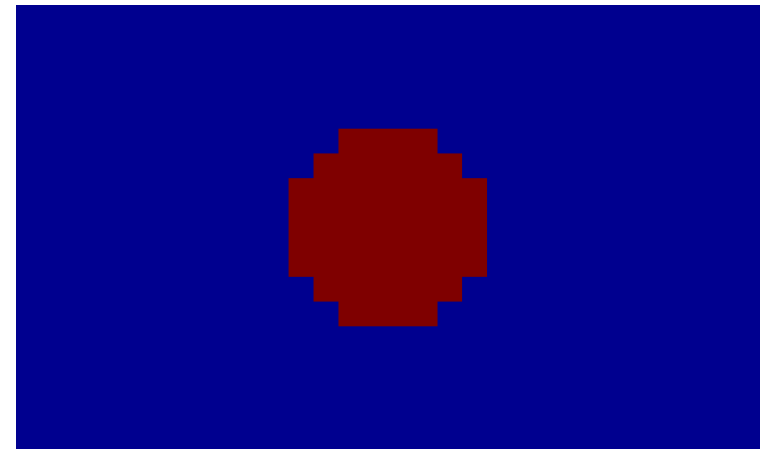
Clustering result of patch 2

Experiment 2

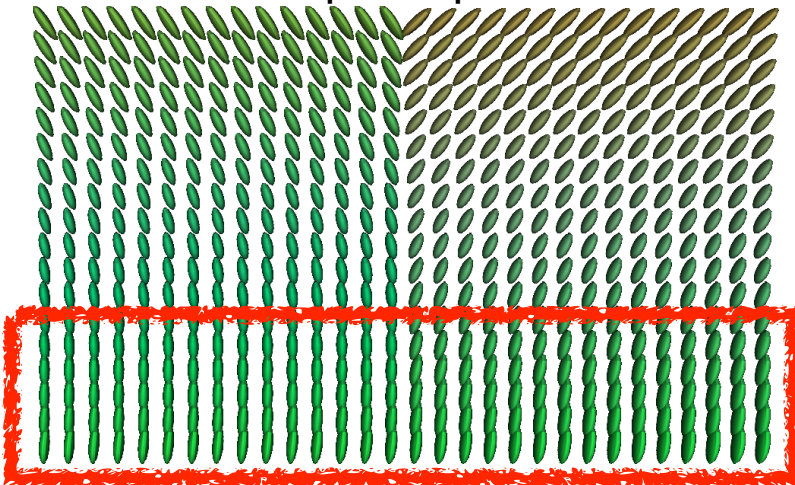
Clustering on SPD(3)



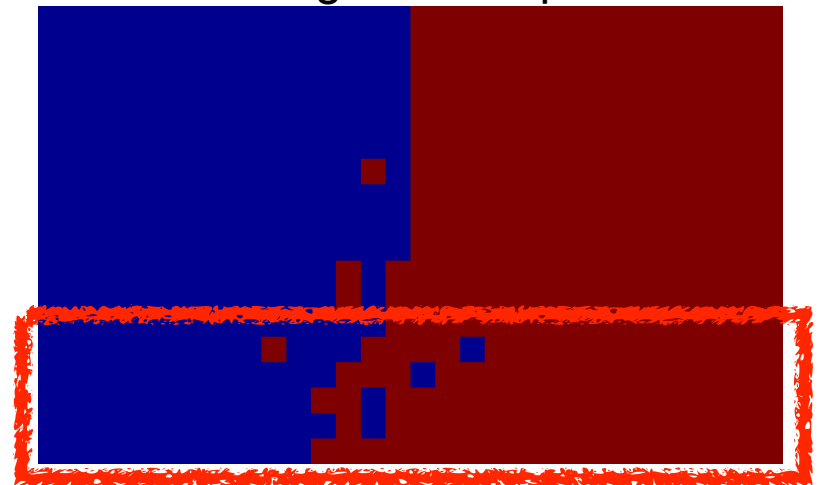
3D ellipsoid patch 1



Clustering result of patch 1



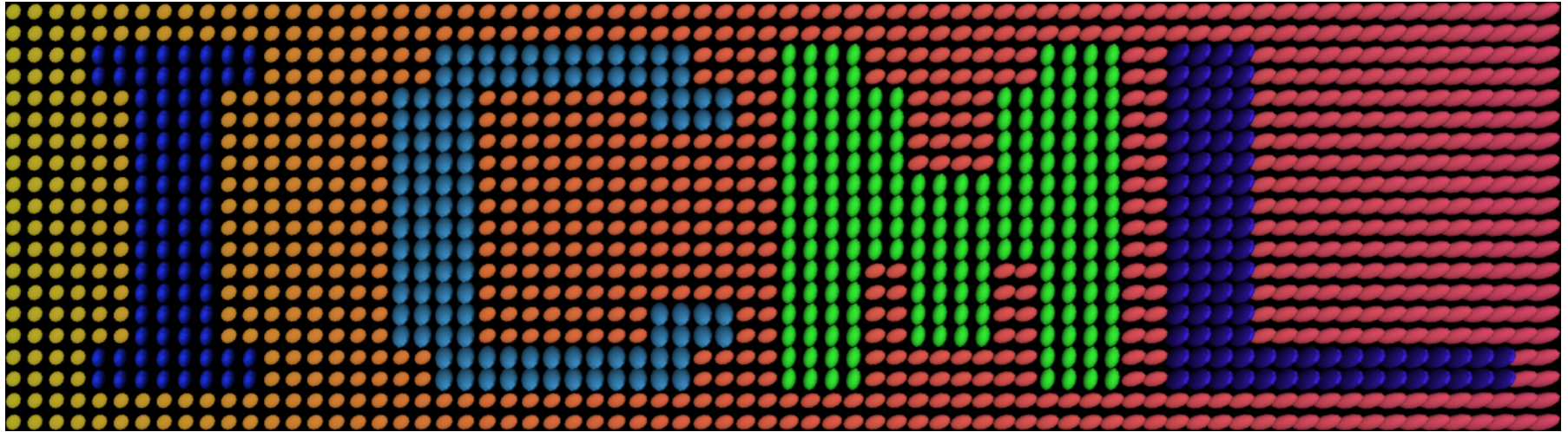
3D ellipsoid patch 2



Clustering result of patch 2

Experiment 2

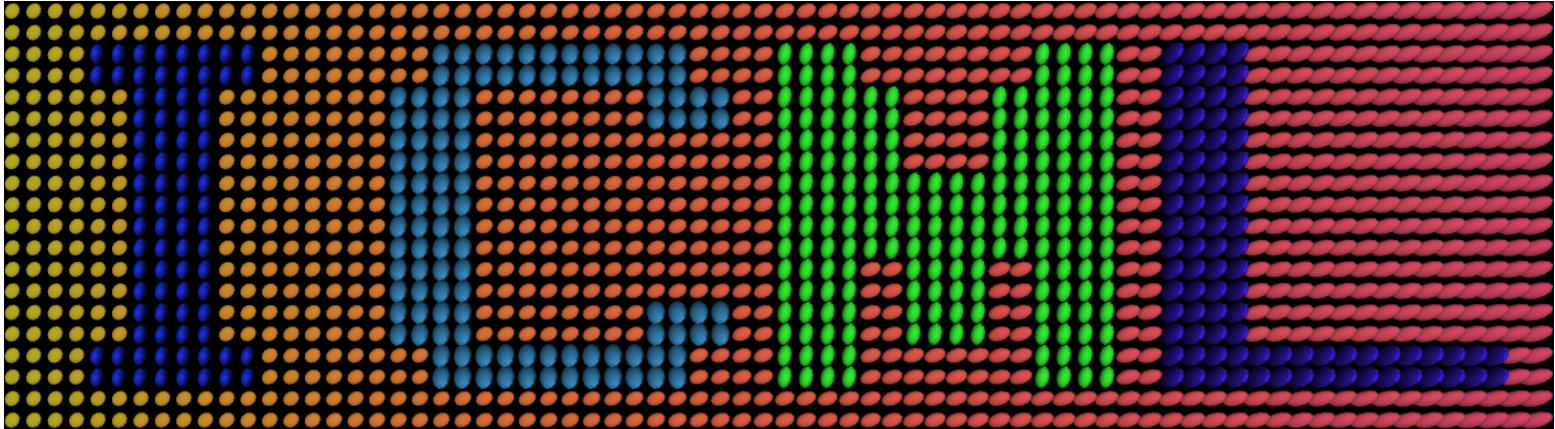
Clustering on SPD(3)



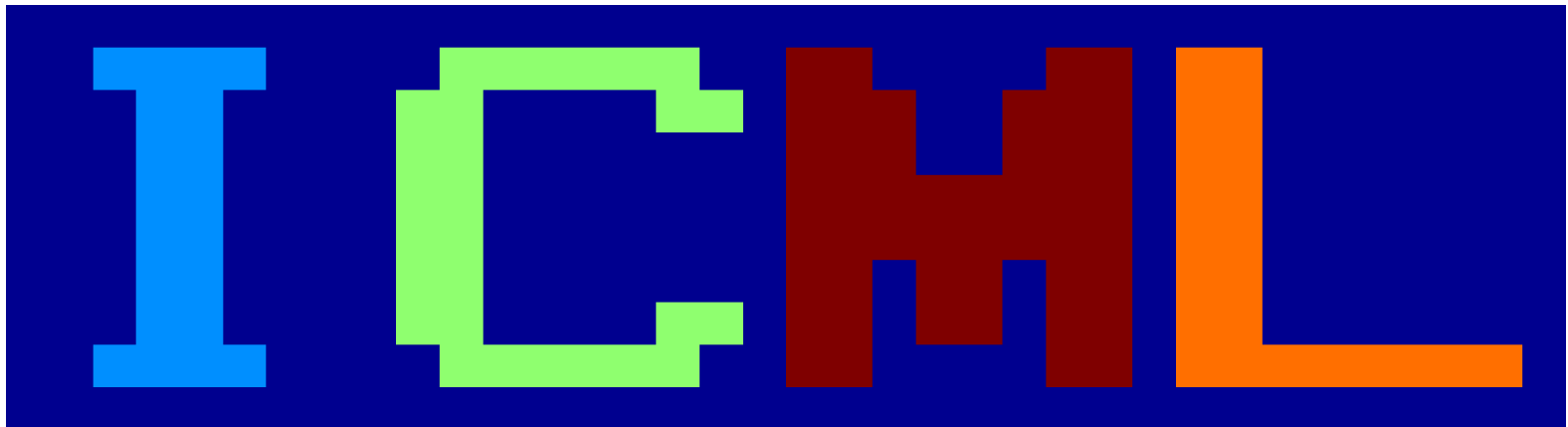
3D ellipsoid patch of ICML

Experiment 2

Clustering on SPD(3)



3D ellipsoid patch of ICML



Clustering results

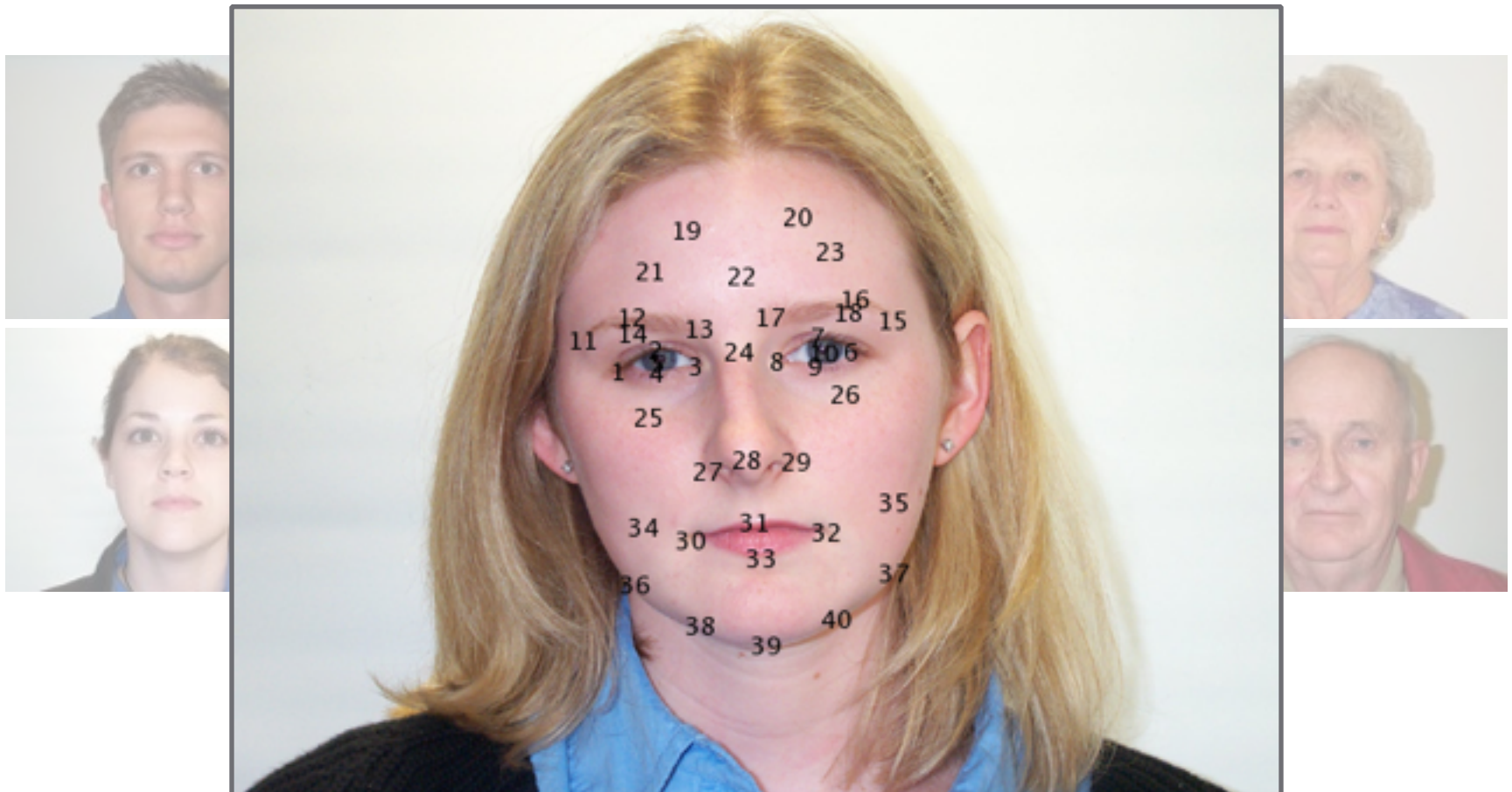
Experiment 3

Age versus landmark appearance



Experiment 3

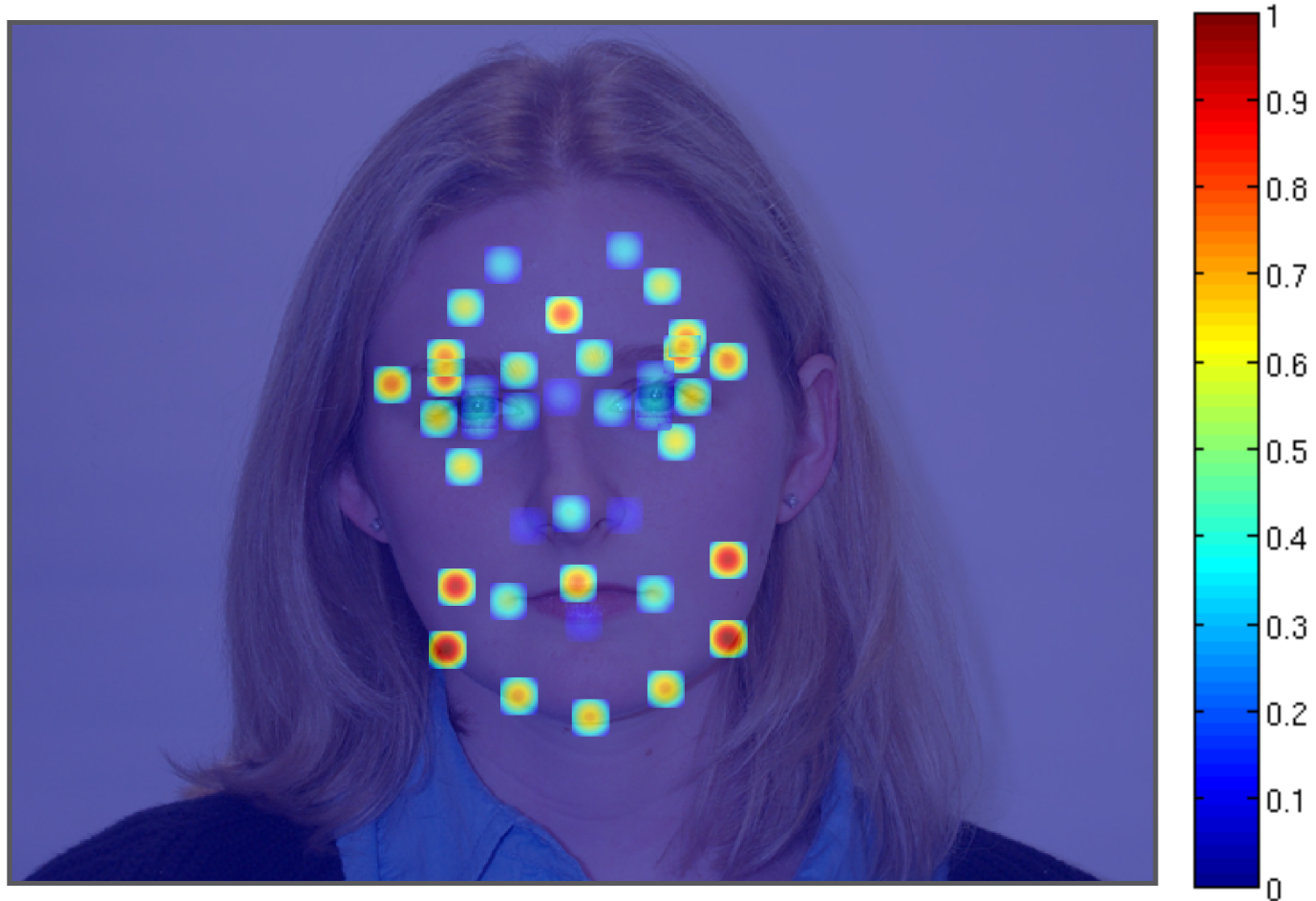
Age versus landmark appearance



Landmarks

Experiment 3

Age versus landmark appearance



Correlation Magnitude

Conclusion

- **DP-MGLM** (Dirichlet process multivariate general linear model) for Riemannian manifolds ($\text{SPD}(n)$) learns more complicated models than MGLM
- **Clustering** based on **nonlinear correlation** between Euclidian covariates and manifold-valued response
- **New distribution** (over base point and tangent vectors) and **HMC** algorithm for DP-MGLM on $\text{SPD}(n)$.

Thank you!