

Tensor Balancing on Statistical Manifold

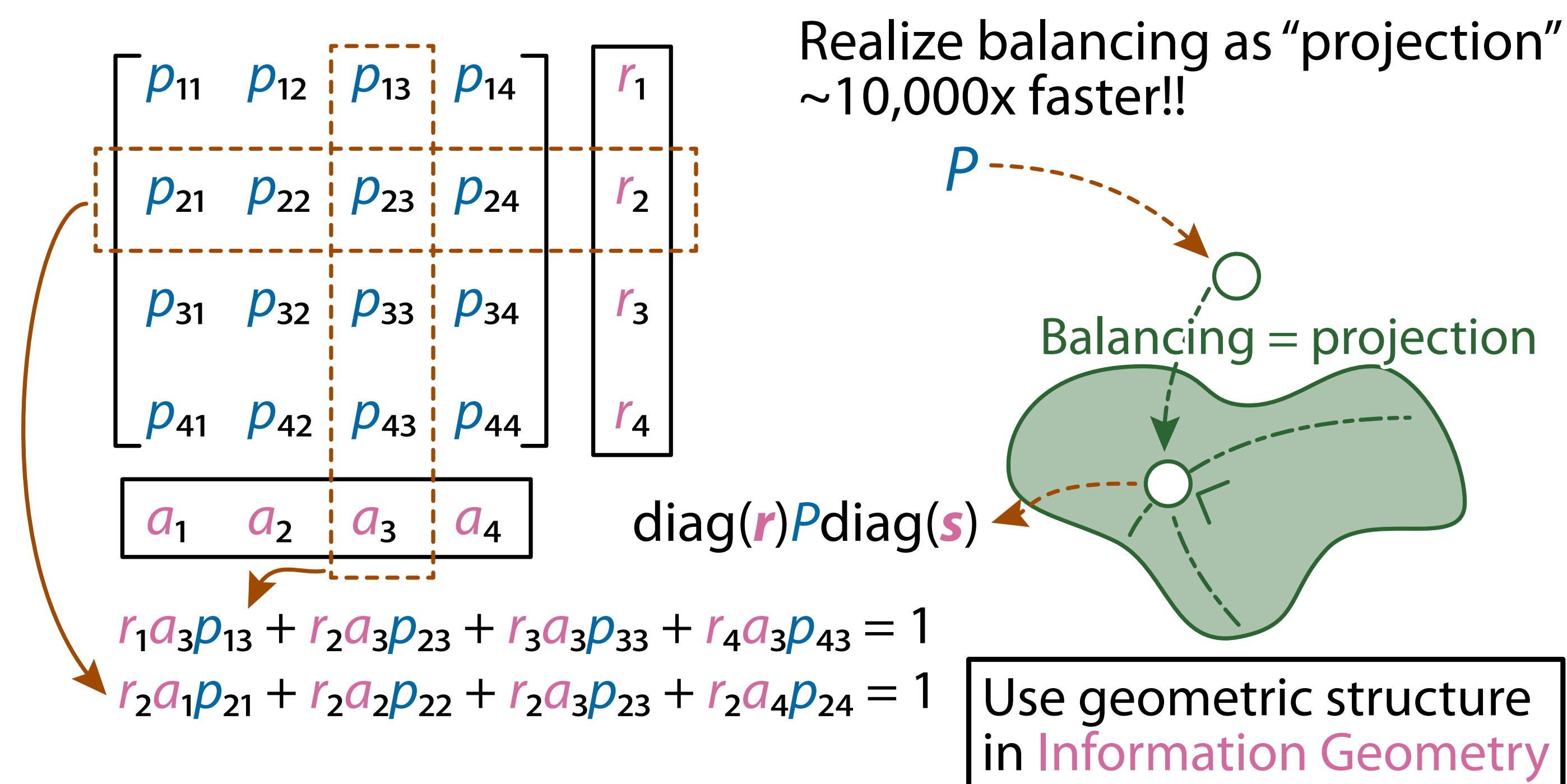
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Results

- **Balancing** of higher order (more than two) tensors is firstly (theoretically) achieved
- A fast balancing algorithm with **quadratic convergence** using **Newton's method** (an existing algorithm is linear convergence)
- **[Theory]** We provide **dually flat Riemannian manifold** of probability distributions with the **structured outcome space**

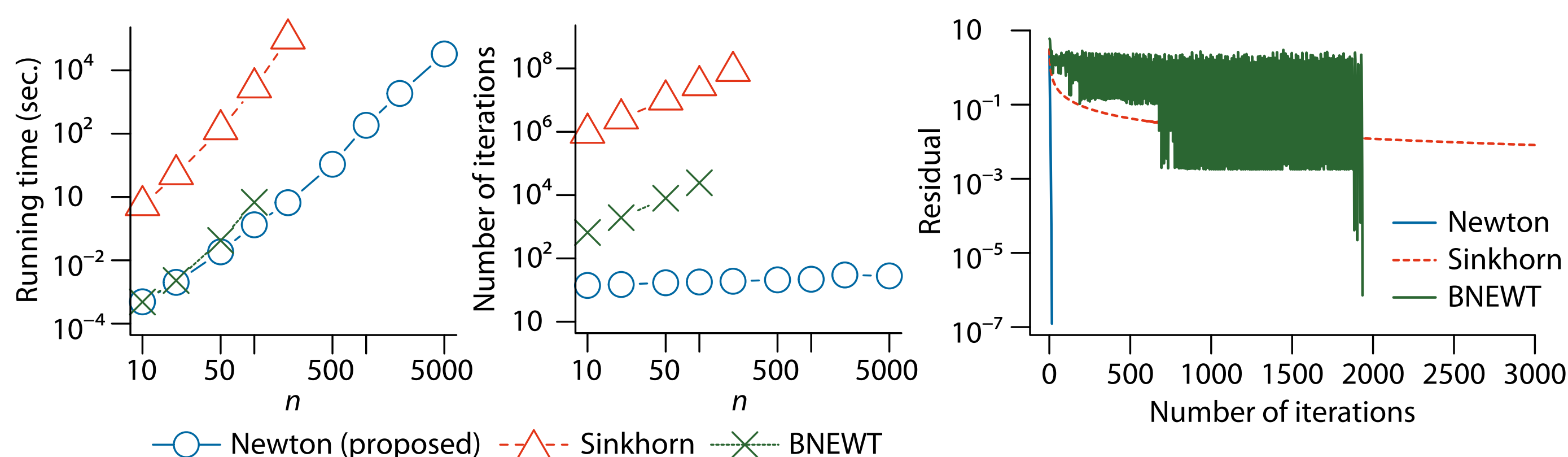
Matrix (Tensor) Balancing



- **Matrix balancing:** Given a nonnegative matrix $P = (p_{ij}) \in \mathbb{R}_+^{n \times n}$, find $r, s \in \mathbb{R}^n$ s.t.

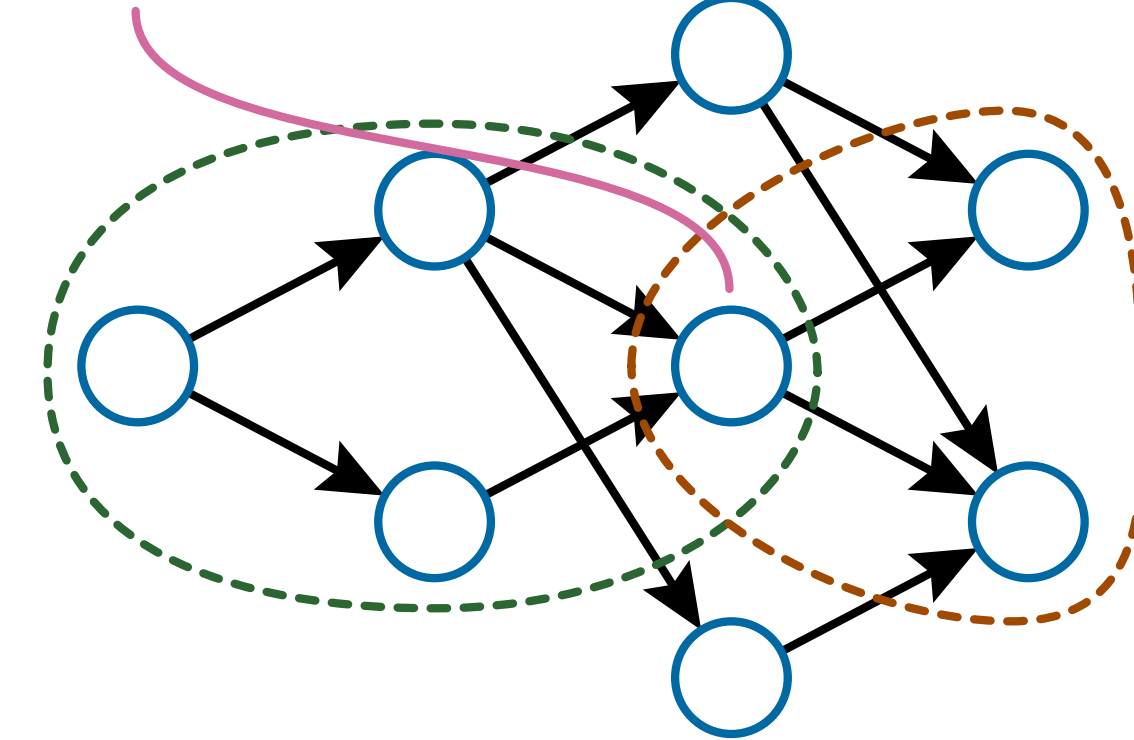
$$(RPS)\mathbf{1} = \mathbf{1} \quad \text{and} \quad (RPS)^T\mathbf{1} = \mathbf{1}$$

- $R = \text{diag}(r), S = \text{diag}(s)$, each entry is given as $p'_{ij} = p_{ij}r_i s_j$
- Applications: input-output analysis, Hi-C data analysis, the Sudoku puzzle, and Wasserstein metric approximation
- Standard balancing algorithm: **Sinkhorn-Knopp algorithm**

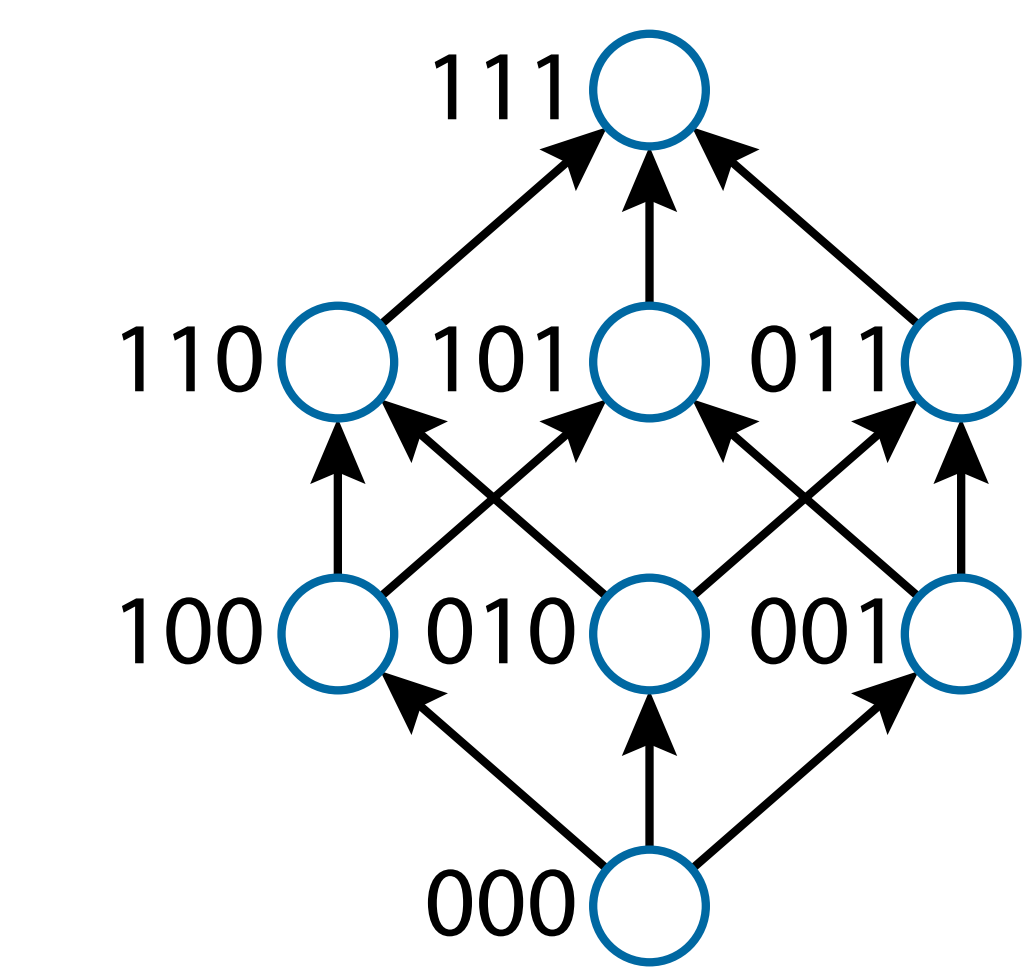


Log-Linear Model on Poset

Each $x \in S$ has a triple: $(p(x), \theta(x), \eta(x))$



- Let (S, \leq) be a poset (= DAG)
- A probability vector $p: S \rightarrow (0, 1)$ s.t. $\sum_{x \in S} p(x) = 1$
 - (Normalized) weight for each node
- We introduce $\theta: S \rightarrow \mathbb{R}$ and $\eta: S \rightarrow \mathbb{R}$ as $\log p(x) = \sum_{s \leq x} \theta(s), \eta(x) = \sum_{s \geq x} p(s)$



- Our model is generalization of the log-linear model on binary vectors with $\mathbf{x} \in \{0, 1\}^n = S$: $\log p(\mathbf{x}) = \sum_i \theta^i x^i + \sum_{i < j} \theta^{ij} x^i x^j + \dots + \theta^{1 \dots n} x^1 x^2 \dots x^n - \psi$
- $\eta^i = \mathbf{E}[x^i] = \Pr(x^i = 1)$
- $\eta^{ij} = \mathbf{E}[x^i x^j] = \Pr(x^i = x^j = 1), \dots$

Dually Flat Structure

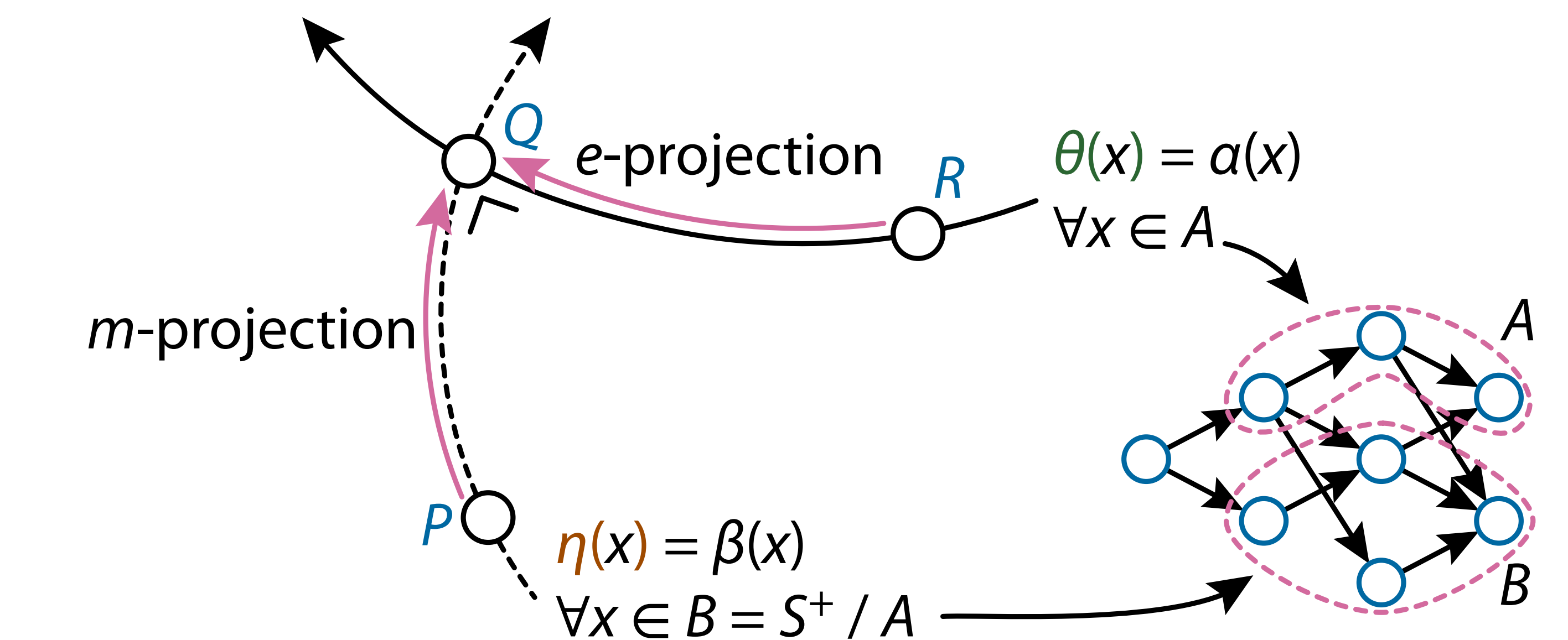
- θ and η form a **dual coordinate system**: $\nabla \psi(\theta) = \eta, \nabla \varphi(\eta) = \theta$
 - $\psi(\theta) = -\theta(\perp) = -\log p(\perp), \varphi(\eta) = \sum_{x \in S} p(x) \log p(x)$
 - $\psi(\theta)$ and $\varphi(\eta)$ are connected via the **Legendre transformation**: $\varphi(\eta) = \max_{\theta'} (\theta' \eta - \psi(\theta')), \theta' \eta = \sum_{x \in S \setminus \{\perp\}} \theta'(x) \eta(x)$

- The gradients: $g(\theta) = \nabla \nabla \psi(\theta) = \nabla \eta, g(\eta) = \nabla \nabla \varphi(\eta) = \nabla \theta$

$$\begin{cases} g_{xy}(\theta) = \frac{\partial \eta(x)}{\partial \theta(y)} = \sum_{s \in S} \zeta(x, s) \zeta(y, s) p(s) - \eta(x) \eta(y) \\ g_{xy}(\eta) = \frac{\partial \theta(x)}{\partial \eta(y)} = \sum_{s \in S} \mu(s, x) \mu(s, y) p(s)^{-1} \end{cases}$$

- **Zeta function**: $\zeta(x, s) = 1$ if $s \leq x, \zeta(s, x) = 0$ otherwise
- **Möbius function**: $\mu: S \times S \rightarrow \mathbb{Z}$ satisfying $\zeta \mu = I$
- The manifold $(\mathcal{S}, g(\xi))$ is a **Riemannian manifold** with the set \mathcal{S} of probability vectors and the **Riemannian metric** $g(\xi)$

e-Projection and m-Projection



- e-projection and m-projection can be computed by **Newton's Method**

- Each step of Newton's method in e-projection:

$$\begin{bmatrix} \eta_{p_\beta}^{(t)}(x) - \beta(x) \\ \vdots \\ \eta_{p_\beta}^{(t)}(x) - \beta(x) \end{bmatrix} + J \begin{bmatrix} \theta_{p_\beta}^{(t+1)}(y) - \theta_{p_\beta}^{(t)}(y) \\ \vdots \\ \theta_{p_\beta}^{(t+1)}(y) - \theta_{p_\beta}^{(t)}(y) \end{bmatrix} = \mathbf{0},$$

- J is the $|B| \times |B|$ Jacobian matrix given as

$$J_{xy} = \frac{\partial \eta_{p_\beta}^{(t)}(x)}{\partial \theta_{p_\beta}^{(t)}(y)} = \sum_{s \in S} \zeta(x, s) \zeta(y, s) p_\beta^{(t)}(s) - \eta_{p_\beta}^{(t)}(x) \eta_{p_\beta}^{(t)}(y)$$

for each $x, y \in B$

Balancing = e-Projection

