Doubly autoparallelism on the space of probability distributions

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Introduction

- Information geometry is a branch of differential geometry with Riemannian metric and a pair of affine connections.
- It originates from the study of geometric structure for the family of probability densities in 80's, and is now developing in many ways.
- Widely related to information science, mathematics and statistical physics.

Information geometry on \mathcal{M} <u>Def.</u> Statistical manifold: $(\mathcal{M}, g, \nabla, \nabla^*)$

 $Xg(Y,Z) = g(\nabla_X Y, Z) + g(Y, \nabla_X^* Z)$ X, Y and Z : arbitrary vector fields on \mathcal{M}

★ g : Riemannian metric
 ★ (∇, ∇*) : torsion-free affine connections
 $R^{\nabla} = 0, \ R^{\nabla^*} = 0 \implies$ dually flat

$$\bigstar \nabla^{(\alpha)} = \frac{1+\alpha}{2} \nabla + \frac{1-\alpha}{2} \nabla^* : \alpha \text{-connections}$$

Definition

- <u>Def.</u> Let (S, g, ∇, ∇*) be a statitical manifold and M be its submanifold. We call M a doubly autoparallel submanifold in S when the followings hold:
 - $\forall X, Y \in \mathcal{X}(M), \ \nabla_X Y \in \mathcal{X}(M)$ • $\forall X, Y \in \mathcal{X}(M), \ \nabla_X^* Y \in \mathcal{X}(M)$

DA on symmetric cones Ω

<u>Thm.</u> [UOo4] The α-connection is represented by the mutation of Jordan algebra:

$$\left(\nabla^*_{\frac{\partial}{\partial x^i}}\frac{\partial}{\partial x^j}\right)_x = -2u_i \bot_{x^{-1}} u_j.$$

• <u>Thm.</u> [OI] Submanifolds $M = (W + p) \cap \Omega$ in a symmetric cone Ω iff the subspace *W* is a Jordan subalgebra.

Related facts or applications

- MLE for structured covariance matrices is tractable (cast to convex program: inversely linear structure) [Anderson70, Malley94]
- Explicitly solvable SDP problems [O99]
- Structure of α-power means on symmetric cones [Oo4]

• The self-similar (*Barenblatt–Pattle*) solution for the porous medium equation [OW10]

Important Properties

<u>Proposition</u> The following statements are equivalent:

- A submanifold *M* is doubly autoparallel (DA)
- *M* is autoparallel w.r.t. the α -connections $\nabla^{(\alpha)} = \{(1 + \alpha)\nabla + (1 - \alpha)\nabla^*\}/2$ for two different α 's.
- *M* is autoparallel w.r.t. all the α -connections.
- all the α -geodesics connecting two points on M lay in M (if it is simply connected).
- *M* is affinely constrained in both ∇- and ∇*-affine coordinates.

Furthermore,

 If *M* is DA, then *α* -projections (*q*-MaxEnt) from *p* to *M* are unique for all *α* if they exist.



The purpose of this talk

Study of DA submanifolds in the space of probability distributions

• Probability simplex = the space of distributions on finite samples

 \Rightarrow Linear algebraic approach

Outline

- Preliminaries & examples
- Characterization of DA on the probability simplex
- Classification of DA
- Concluding remarks

Preliminaries

Positive orthant

$$\mathbf{R}_{++}^{n+1} := \{ p \in \mathbf{R}^{n+1} | p_i > 0, \ i = 1, \cdots, n+1 \},\$$

Probability simplex

$$S^{n} := \left\{ p \in \mathbf{R}_{++}^{n+1} \left| \sum_{i=1}^{n+1} p_{i} = 1 \right. \right\}$$

• The set of finite events $\Omega = \{1, 2, ..., n+1\}$

• Discrete probability distributions:

$$p(X = i) = p_i > 0, \ i = 1, \cdots, n+1$$
$$p(X) = \sum_{i=1}^{n+1} p_i \delta_i(X), \ p = (p_i) \in \mathcal{S}^n \quad \delta_i(j) = \delta_{ij}$$

• **statistical model** (p_i is parameterized by ξ)

$$p(X;\xi) = \sum_{i=1}^{n+1} p_i(\xi)\delta_i(X)$$

• Ex: full model \mathcal{P}_n : $p_i = \xi^i, i = 1, \cdots, n$

$$p(X;\xi) = \sum_{i=1}^{n} \xi^{i} \delta_{i}(X) + \left(1 - \sum_{i=1}^{n} \xi^{i}\right) \delta_{n+1}(X)$$

IG on the simplex (full model)

• Riemannian metric g_{i} (=Fisher information matrix) $\partial_{i} = \frac{\partial}{\partial p_{i}}$

$$g_{ij}(p) = \sum_{X \in \Omega} p(X)(\partial_i \log p(X))(\partial_j \log p(X)) \quad i, j = 1, \cdots, n$$

- mutually dual affine connections $\nabla^{(e)}$ and $\nabla^{(m)}$
 - $\nabla^{(e)}$: exponential connection (α =1)

 $\Gamma_{ij,k}^{(e)}(p) = \Gamma_{ijk}^{(1)}(p) = \sum_{X \in \Omega} p(X)(\partial_i \partial_j \log p(X))(\partial_k \log p(X)) \quad i, j, k = 1, \cdots, n$

• $\nabla^{(m)}$: mixture connection (α =-1) $\Gamma^{(m)}_{ij,k}(p) = \Gamma^{(-1)}_{ijk}(p) = \sum_{X \in \Omega} p(X)(\partial_i \partial_j p(X))(\partial_k \log p(X))$ $i, j, k = 1, \cdots, n$

affine coordinates

• $\nabla^{(m)}$ -affine coordinates: (η_i)

$$\eta_i = \sum_{X \in \Omega} p(X) \delta_i(X) = p_i$$

Each p_i is affine w.r.t. $\xi \Leftrightarrow$ the model is $\nabla^{(m)}$ -autoparallel

• $\nabla^{(e)}$ -affine coordinates: (θ^i)

$$\begin{aligned} \theta^{i} &= \log\left(\frac{p_{i}}{1-\sum_{i=1}^{n}p_{i}}\right) \\ p(X) &= \exp\left\{\sum_{i=1}^{n}\theta^{i}\delta_{i}(X) - \psi(\theta)\right\} \quad \psi(\theta) := \log\left(1+\sum_{i=1}^{n}\exp\theta^{i}\right) \\ \text{Each } \theta^{i} \text{ is affine w.r.t. } \xi \Leftrightarrow \text{ the model is } \nabla^{(e)} \text{ -autoparallel}_{I4} \end{aligned}$$

Example 1 (1)

- S^n : the probability simlex in \mathbb{R}^{n+1}
- $(S^n, g, \nabla^{(e)}, \nabla^{(m)})$, g: the Fisher metric.
- *W*: a subspace spanned by
 - d (<n) vertices $v^{(k)} = (\delta_i^k) \in \mathbf{R}^{n+1}$ in $\overline{S^n}$, and
 - non-vertex point $v^{(0)}$ in $\overline{S^n}$ linearly independent of $\{v^{(k)}\}_{k=1}^d$

$$W = \operatorname{span}\{v^{(0)}, v^{(1)}, \cdots, v^{(d)}\}\$$

• $M = W \cap S^n$ is doubly autoparallel.

Example 1 (2)

<u>Proof for d=2</u> (Similar arguments hold for arbitrary d.) • The m-affine coordinates $\eta = (\eta_i)$ of $v^{(i)}$, i = 0, 1, 2:

$$v^{(1)} = (1 \ 0 \ \cdots \ 0)^T, \quad v^{(2)} = (0 \ 1 \ 0 \ \cdots \ 0)^T, v^{(0)} = (0 \ 0 \ p_3 \cdots p_{n+1}), \sum_{i=3}^{\cdot} p_i = 1, \quad p_i > 0$$

• The m-affine coordinates of p in M: $p = \xi_1 v^{(1)} + \xi_2 v^{(2)} + (1 - \xi_1 - \xi_2) v^{(0)} \in M = W \cap S^n$ $\eta_1 = \xi_1, \ \eta_2 = \xi_2, \ \eta_i = (1 - \xi_1 - \xi_2) p_i, \ i = 3, \cdots, n+1,$ $(\xi_1 > 0, \ \xi_2 > 0, \ \xi_1 + \xi_2 < 1).$

affine in ξ_i , *i*=1,2

Example 1 (3)

• The e-affine coordinates of *p* in *M*:

$$\theta^{i} = \log\left(\frac{p_{i}}{1 - \sum_{i=1}^{n} p_{i}}\right)$$

$$\theta^{1} = \zeta_{1}, \ \theta^{2} = \zeta_{2}, \ \theta^{i} = \log p_{i} + c, \ i = 3, \cdots, n+1,$$

$$(\zeta_{i} = \log\{\xi_{i}/(1-\xi_{1}-\xi_{2})\}, \ i = 1, 2, \ c = -\log p_{n+1}).$$

affine in ζ_i , i=1,2

IG on the positive orthant \mathbf{R}_{++}^{n+1}

• Riemannian metric \widetilde{g}

$$\tilde{g}_{ij}(p) = \sum_{X \in \Omega} p(X)(\partial_i \log p(X))(\partial_j \log p(X)) = \frac{\partial_{ij}}{p_i}$$

• $\tilde{\nabla}^{(m)}$: m-connection (α =-1)
 $\tilde{\Gamma}^{(m)}_{ij,k}(p) = \sum_{X \in \Omega} p(X)(\partial_i \partial_j p(X))(\partial_k \log p(X)) = 0$

 $\partial_i = \frac{\partial}{\partial p_i}$

ch

• $\tilde{\nabla}^{(e)}$: e-connection ($\alpha = 1$) (p_i): $\tilde{\nabla}^{(m)}$ -affine coordinates

$$\tilde{\Gamma}_{ij,k}^{(e)}(p) = \sum_{X \in \Omega} p(X)(\partial_i \partial_j \log p(X))(\partial_k \log p(X)) = -\frac{\delta_{ij}^n}{p_i}$$

 $\log p(X) = \sum_{X \in \Omega} (\log p_i) \delta_i(X) \qquad (\log p_i) : \tilde{\nabla}^{(e)} \text{-affine coordinates}_{18}$

Denormalization

• <u>Def.</u> denormalization of a submanifold M in S^n

$$\tilde{M} = \{ \tau p \in \mathbf{R}_{++}^{n+1} | p \in M, \ \tau > 0 \}$$

Lem [Amari & Nagaoka 2000]

The following statements are equivalent:

- A submanifold M is $abla^{(\pm 1)}$ autoparallel in \mathcal{S}^n ,
- A denormalization \tilde{M} is $\tilde{\nabla}^{(\pm 1)}$ -autoparallel in \mathbf{R}^{n+1}_{++} .

observations

W: a subspace in Rⁿ⁺¹ M = W ∩ Sⁿ ⇔ M̃ = W ∩ Rⁿ⁺¹₊₊ is ∇̃^(m)-autoparallel ⇔ M is ∇^(m) -autoparallel
log M̃ = b+W', W' is another subspace of the same dim. b is a constant vector in Rⁿ⁺¹.
⇔ M̃ is ∇̃^(e) -autoparallel ⇔ M is ∇^(e) -autoparallel

where $\log W = \{\log p | p \in W\}, \quad \log p = (\log p_i) \in \mathbb{R}^{n+1}$

Main results

• Thm Assume
$$a \in \tilde{M} = W \cap \mathbf{R}_{++}^{n+1} (= W_{++})$$
.
 $\exists W', \log(a+W)_{++} = \log a + W'$
 $\Leftrightarrow 1)W' = a^{-1} \circ W, \quad 2) \forall u, v \in W, \ u \circ a^{-1} \circ w \in W$

• Here, $(\mathbf{R}^{n+1}, \circ)$ is defined by Hadamard product \circ , i.e.,

$$x \circ y = (x^i) \circ (y^i) = (x^i y^i), \quad e = \mathbf{1}, \quad x^{-1} = \left(\frac{1}{x^i}\right)$$

• <u>Rem</u> 2) implies *W* should be a subalgebra in $(\mathbb{R}^{n+1}, \circ_{a^{-1}})$. where $\circ_{a^{-1}} := \circ a^{-1} \circ$ is a mutation of \circ by *a*.

Main results

Characterization of DA

Cor A $\nabla^{(m)}$ -autoparallel submanifold $M = W \cap S^n$ is DA iff the subspace W is a subalgebra of $(\mathbf{R}^{n+1}, \circ_{a^{-1}})$ with the identity element $a \in \tilde{M}$.

Main results Classification for W

• <u>Thm</u> (Classification for W)

W is a subalgebra in $(\mathbf{R}^{n+1}, \circ_{a^{-1}})$ with $a \in \tilde{M}$ iff W is of the form:

$$W = \mathbf{R}^q \times \mathbf{R}a_1 \times \cdots \times \mathbf{R}a_r$$

i.e.,

 $W = \{x = (y^T \ t_1 a_1^T \ \cdots \ t_r a_r^T)^T \mid y \in \mathbf{R}^q, \ a_i \in \mathbf{R}_{++}^{n_i}, \ t_i \in \mathbf{R}, i = 1, \cdots, r\}$, where $q + \sum_{i=1}^r n_i = n+1$, $q \ge 0$, r > 0, $2 \le n_1 \le \cdots \le n_r$ up to permutations of elements. <u>Rem</u> dim W = q + r.

Example (continued)

• For $a \in \tilde{M} = W \cap \mathbf{R}^{n+1}$, we set

$$a = (1 \ 2 \ p_3 \ \cdots \ p_{n+1})^T, \ a_0 = (1 \ 2)^T, \ a_1 = (p_3 \ \cdots \ p_{n+1})^T.$$

$$\left(\sum_{i=3}^{n+1} p_i = 1, \ p_i > 0, \ i = 3, \cdots, n+1\right)$$

$$(2 \ r=1, \ p_1 - n - 1)$$

•
$$q=2, r=1, n_1 = n-1$$

 $V = a^{-1} \circ W = \{ (z^T \ t\mathbf{1}^T)^T \in \mathbf{R}^{n+1} | \ \forall z \in \mathbf{R}^2, \ t\mathbf{1} \in \mathbf{R}^{n-1}, \ \forall t \in \mathbf{R} \}$

• $W=\{w=(\xi_1 \ \xi_2 \ tp_3 \ \cdots \ tp_{n+1})^T\}$

• Every elements in $M = W \cap S^n$ is represented by $w = (\xi_1 \ \xi_2 \ tp_3 \ \cdots \ tp_{n+1})^T, \quad t := 1 - \xi_1 - \xi_2,$

Conclusions

- Characterization of DA submanifolds for the space of discrete probability distributions
- Its classification
 - Algebraic structure is closely related.
- Applications (future work)
 - Statistical modeling
 - Stochastic reasoning (Belief Propagation [Ikeda et al 04])?
 - Explicitly solvable LP problems
- Relation with Markov embeddings [Nagaoka 2017] Ref. A. Ohara and H. Ishi, arXiv:1711.11456v1 (2017)