

A review of geometric statistics

Peter Jupp

University of St. Andrews

<http://www.mcs.st-andrews.ac.uk/~pej/>

Plan of talk

1. Generalities
2. Geometric objects (Technicalities)
3. Statistical applications
4. The future?

1. GENERALITIES

Geometric Statistics

(a) Geometry of sample space:

Data analysis in \mathbb{R}^d (data inspection, PCA, . . . ,
persistent homology, . . .)

Spatial statistics (predictors in \mathbb{R}^d)

Image analysis

Directional statistics (directions, axes, rotations, . . .)

Shape statistics

(b) Geometry of parameter space:

'Information geometry'

'Information geometry'

~ 50,000 hits on Google

Differential geometry in parametric statistics
(higher-order asymptotics)

Computational geometry

Machine learning; Neural manifolds

Thermodynamics

Encouraging quotations

Differential geometry [in statistics] is dead

This reminds me of the time when we believed that differential geometry was the answer to everything

Why differential geometry?

(a) 'Causes':

Invariance under re-parameterisation

Parameter spaces not vector spaces but **manifolds**

Appropriate language for Taylor expansion

(typically, estimator 'close' to true parameter value)

(b) Purposes:

conceptual

computational

Differential geometry seems hard!

3 approaches:

(a) intuitive 'tangible' geometry

(b) coordinate-based dialect $g_{ij}d\theta^i d\theta^j$

(c) coordinate-free dialect g

2. GEOMETRIC OBJECTS

Geometric objects

manifolds

tensors

Riemannian metrics

(affine) connections

curvature

yokes

volumes

symplectic forms

manifolds

Manifold Θ locally like \mathbb{R}^d

Local coordinates $\theta^1, \dots, \theta^d$

Tangent space $T_\theta\Theta$ to Θ at θ spanned by 'arrows'

$$\frac{\partial}{\partial\theta^1}, \dots, \frac{\partial}{\partial\theta^d}$$

Cotangent space $T_\theta^*\Theta = (T_\theta\Theta)^*$ spanned by $d\theta^1, \dots, d\theta^d$

tensors

Tensor = **multi-linear** form on tangent and cotangent spaces

$$T_{\theta}\Theta \times \dots \times T_{\theta}\Theta \times T_{\theta}^*\Theta \times \dots \times T_{\theta}^*\Theta \rightarrow \mathbb{R}$$

E.g.

tangent $a^i \frac{\partial}{\partial \theta^i}$

cotangent $a_i d\theta^i$

score statistic $\frac{\partial l}{\partial \theta^i} d\theta^i$

Riemannian metric

Riemannian metrics

inner product on $T_\theta\Theta$

$$g_{ij}d\theta^i d\theta^j$$

measures length of infinitesimal vectors

E.g. Fisher information

$$E_\theta \left[\frac{\partial l}{\partial \theta^i} \frac{\partial l}{\partial \theta^j} \right] d\theta^i d\theta^j$$

(affine) connections

connection (\leftrightarrow covariant differentiation
 \leftrightarrow parallel translation)

[3 definitions!]

generalisation of directional derivative:

X, Y vector fields on Θ

$\nabla_X Y$ is derivative of Y in direction of X

$$\nabla_{\frac{\partial}{\partial \theta^i}} \frac{\partial}{\partial \theta^j} = \Gamma_{ij}^k \frac{\partial}{\partial \theta^k}$$

Curvature

- (a) **Riemann curvature** of connection ∇
measures asymmetry of 2nd derivative ∇^2

- (b) **Embedding curvature** (= second fundamental form
= Euler–Schouten curvature)
of inclusion $\Omega \subset \Theta$ using connection ∇ on Θ
measures how Ω curves inside Θ

Yokes

Yoke (\simeq contrast function \simeq divergence)

$$g : \Theta \times \Theta \rightarrow \mathbb{R}$$

Coordinates $(\theta^1, \dots, \theta^d; \theta'^1, \dots, \theta'^d)$ on $\Theta \times \Theta$.

g is **yoke** on Θ if

$$(i) \quad \not{g}_i(\theta) = \left. \frac{\partial g(\theta, \theta')}{\partial \theta^i} \right|_{\theta'=\theta} = 0,$$

$$(ii) \quad \text{the matrix } [\not{g}_{i;j}(\theta)] = \left[\left. \frac{\partial^2 g(\theta, \theta')}{\partial \theta^i \partial \theta'^j} \right|_{\theta'=\theta} \right] \text{ is non-singular}$$

Expected likelihood yoke

Parametric statistical model with parameter space Θ .

Expected likelihood yoke on Θ

$$g(\theta, \theta') = E_{\theta'}[l(\theta; x) - l(\theta'; x)] = -K(\theta', \theta)$$

Yokes yield natural coordinates

g yoke on Θ , $\theta \in \Theta$, $\alpha \in \mathbb{R}$

$$\overset{\alpha}{\Gamma}_{\theta}: \Theta \longrightarrow T_{\theta}\theta$$

$$\overset{\alpha}{\Gamma}_{\theta}(\theta') = \mathcal{g}^{r;u}(\theta) \left\{ \frac{1 + \alpha}{2} \frac{\partial g(\theta'; \theta)}{\partial \theta^u} + \frac{1 - \alpha}{2} \frac{\partial g(\theta; \theta')}{\partial \theta^u} \right\} \frac{\partial}{\partial \theta^r}$$

$$g \circ \left(\overset{\alpha}{\Gamma}_{\theta} \times \overset{\alpha}{\Gamma}_{\theta} \right)^{-1} : T_{\theta}\theta \times T_{\theta}\theta \longrightarrow \Theta \times \Theta \longrightarrow \mathbb{R}$$

Yokes yield tensors

$$g \circ \left(\overset{\alpha}{\Gamma}_\theta \times \overset{\alpha}{\Gamma}_\theta \right)^{-1} : \underbrace{T_\theta \Theta \times T_\theta \Theta}_{\text{vector space}} \longrightarrow \Theta \times \Theta \longrightarrow \mathbb{R}$$

Derivatives at $(0, 0)$ are **tensors**

$$\mathcal{T}_{r;s} = \mathcal{g}_{r;s}$$

Riemannian metric

$$\mathcal{T}_{r;st} = \mathcal{g}_{r;st} - \mathcal{g}_{st;r}$$

skewness tensor

$$\overset{\alpha}{\Gamma}_{st}^r = \mathcal{g}^{r;u} \left(\frac{1+\alpha}{2} \mathcal{g}_{ru;t} + \frac{1-\alpha}{2} \mathcal{g}_{t;ru} \right)$$

connection

Volumes

Volume on Θ

= measure on Θ with smooth, everywhere-positive density

$$a(\theta)d\theta^1 \wedge \dots \wedge d\theta^d = a(\theta)d\theta^1 \dots d\theta^d$$

Riemannian metrics yield volumes

Riemannian metric g on Θ gives **Riemannian volume**

$$|g_{i;j}(\theta)|^{1/2}d\theta^1 \wedge \dots \wedge d\theta^d$$

infinitesimal unit cuboids have unit infinitesimal volume

Fisher information \mapsto Jeffreys' prior

Symplectic forms

Riemannian metric:

non-singular symmetric $(0, 2)$ -tensor g

$$g_{ij}d\theta^i d\theta^j$$

Symplectic form:

non-singular *skew-symmetric* $(0, 2)$ -tensor

η

$$\eta_{ij}d\theta^i \wedge d\theta^j$$

Symplectic form η gives **symplectic volume**

$$\eta \wedge \dots \wedge \eta$$

$$|\eta_{ij}| d\theta^1 \wedge \dots \wedge d\theta^d$$

Yokes yield symplectic forms

Coordinates $(\theta^1, \dots, \theta^d)$ on Θ give
coordinates $(\theta^1, \dots, \theta^d, \theta'^1, \dots, \theta'^d)$ on $\Theta \times \Theta$

Yoke g on Θ gives symplectic form

$$\eta(\theta, \theta') = g_{i;j}(\theta, \theta') d\theta^i \wedge d\theta'^j$$

on neighbourhood of the diagonal $\{(\theta, \theta) : \theta \in \Theta\}$ of
 $\Theta \times \Theta$

Yokes yield volumes

Yoke g on Θ gives

(a) **Riemannian metric** $g_{i;j}(\theta)d\theta^i d\theta^j$ on Θ

(b) **symplectic form** $g_{i;j}(\theta, \theta')d\theta^i \wedge d\theta'^j$ on (part of) $\Theta \times \Theta$

and so

(a) **Riemannian volume**

$$\left|g_{r;s}(\theta)\right|^{1/2} \left|g_{i;j}(\theta')\right|^{1/2} d\theta^1 \wedge \dots \wedge d\theta^d \wedge d\theta'^1 \wedge \dots \wedge d\theta'^d$$

(b) **symplectic volume**

$$\left|g_{i;j}(\theta, \theta')\right| d\theta^1 \wedge \dots \wedge d\theta^d \wedge d\theta'^1 \wedge \dots \wedge d\theta'^d$$

on (part of) $\Theta \times \Theta$

Ratios of volumes

Yoke g on Θ gives ratio

$$\frac{|g_{i;j}(\theta, \theta')|}{\left| \not{g}_{i;j}(\theta) \right|^{1/2} \left| \not{g}_{i;j}(\theta') \right|^{1/2}}$$

of symplectic to Riemannian volumes

3. STATISTICAL APPLICATIONS

Applications

Concise formulae for

(a) information loss $t : \mathcal{X} \longrightarrow \mathcal{Y}$

$$i^X(\theta) - i^{t(X)}(\theta) = \text{functions of curvature}$$

(b) p^* formula for m.l.e.

$$\frac{p^*(\hat{\theta}; \theta | a)}{|\mathcal{J}_{i;j}(\hat{\theta})|^{1/2}} = c(\theta, a) \exp\{g(\theta, \hat{\theta})\}$$

g observed likelihood yoke

$$g(\theta, \theta') = l(\theta; \theta', a) - l(\theta'; \theta', a)$$

Applications

(c) Bartlett correction of likelihood ratio test

$$w^* = \left(1 + \frac{B}{n}\right) w$$

B quadratic in \mathcal{T}_{rstu} , $\mathcal{T}_{rs;tu}$ and $\mathcal{T}_{r;st}$

(d) prediction limits

(e) modified profile likelihood, adjusted profile likelihood
(ratios of volumes)

Applications

Sequential estimation

Geometric Wald tests

(natural coordinates $\overset{\alpha}{\Gamma}_{\theta}$)

Further developments

Parameters of interest ($\Theta \rightarrow \Omega$)

Infinite-dimensional/non-parametric (Pistone *et al.*)

Estimating functions (covectors)

Preferred point geometry

($\Theta \rightarrow$ Riemannian metrics on Θ)

Decision theory (Dawid, Lauritzen, Parry)

Sensitivity analysis (Anaya, Critchley, Marriott, Vos)

Intrinsic van Trees theorem (information on the prior)

Quantum geometries

Quantum geometries

state

complex $d \times d$ matrix ρ with $\rho = \rho^*$, $\rho \geq 0$, $\text{tr } \rho = 1$

$$\mathcal{S}(\mathbb{C}^d) = \{\rho : \rho = \rho^*, \rho \geq 0, \text{tr } \rho = 1\}$$

quantum model

$$\Theta \longrightarrow \mathcal{S}(\mathbb{C}^d)$$

measurement : quantum model \mapsto statistical model

Quantum score, quantum information,
quantum Cramér–Rao Theorem

4. THE FUTURE

What next?

That is up to us!