IGAIA'IV **Information Geometry** and its Applications IV

CONSTANT CURVATURE CONNECTIONS ON STATISTICAL MODELS

Alexander Rylov

IGAIA' IV, June 12 - 17, 2016, LIBLICE, Czech Republic Financial University, Russia, alexander_rylov@mail.ru

ABSTRACT



We discuss statistical manifolds [1] with connections of constant α - curvature. If the statistical manifold has some α - connection of constant curvature then it is a conjugate symmetric manifold [2]. But the converse is not true [3]. Statistical models on families of probability distributions provide important examples of above-mentioned connections. Normal statistical models have the constant α - curvature $k^{(\alpha)} = \frac{\alpha^2 - 1}{2}$ for any parameter α . We obtain that the Pareto two-dimensional statistical models [4] has such a structure: each of its α - connection has the constant curvature ($-2\alpha - 2$). The logistic two-dimensional statistical model [5] has the constant 2-curvature $k^{(2)} = -\frac{162}{(\pi^2+3)^2}$, so it is a conjugate symmetric manifold [6]. We consider a Weibull two-dimensional statistical model: its 1-connection has the constant curvature $k^{(1)} = \frac{12\pi^2 \gamma - 144\gamma + 72}{-4},$

where $\gamma = \lim_{n \to \infty} \left(\sum_{k=1}^{\infty} \frac{1}{k} - \log n \right)$ is Euler-Mascheroni constant. Thus, the Weibull model is a conjugate symmetric. We compare the values of α - curvatures for the different statistical models.

STATISTICAL MANIFOLD

Let **M** be a smooth manifold, dimM = n, $\langle \cdot, \cdot \rangle = g$ be a Riemannian metrics, K be a (2,1) - tensor such that (1) K(X, Y) = K(Y, X); (2) $\langle K(X, Y), Z \rangle = \langle Y, K(X, Z) \rangle$, where X, Y, Z are vector fields on M. Then a triple (*M*, *g*, *K*) is a statistical manifold. If **D** is the metric connection, i.e. Dg = 0, α is a real-valued parameter, then the linear connections of 1 - parameter family $\nabla^{\alpha} = \mathbf{D} + \alpha \cdot \mathbf{K}$ are called α - connections.

STATISTICAL MODEL

Let $S = \{P_{\theta^i} \mid i = 1, ..., n\}$ be a family of probability distributions on a measurable space with a probability measure **P**, $\partial_i = \frac{\partial}{\partial \theta^i}$

log $p(x \mid \theta^i)$ denotes the natural logarithm of the likelihood function.

Then **S** is called a **n** - dimensional statistical model.

The Fisher information matrix $I_{ii}(\theta) = \int \partial_i \log p \cdot \partial_i \log p \cdot p dP$

and the components $K_{ijk}(\theta) = -\frac{1}{2} \int \partial_i \log p \cdot \partial_j \log p \cdot \partial_k \log p \cdot p dP$ (j, k = 1, ..., n)

give the structure of the statistical manifold (P, I_{ij}, K_{ij}) on **S**.

The covariant components of α - connections named Amari-Chentsov connections are

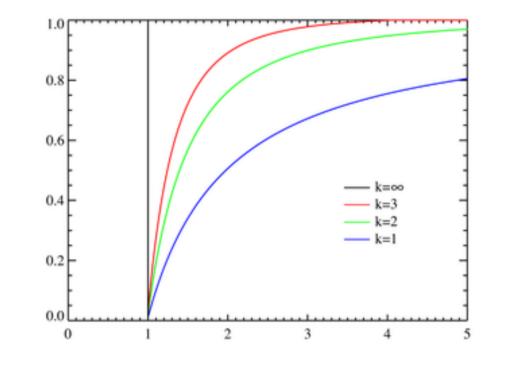
 $\Gamma_{iik}^{(\alpha)}(\theta) = \int (\partial_i \partial_j \log p \cdot \partial_k \log p + \frac{1-\alpha}{2} \partial_i \log p \cdot \partial_j \log p \cdot \partial_k \log p) \cdot pdP$

CONJUGATE STATISTICAL MANIFOLD

Denote $\mathbf{R}_{\mathbf{x}\mathbf{y}}^{\alpha}$ a curvature operator of ∇^{α} , Ric^{α} a Ricci tensor of ∇^{α} ω_{q} a volume element associated to the metrics. We call (M, g, K) a conjugate symmetric manifold, when $R_{XY}^{\alpha}g = 0$ for any parameter α . This is equivalent to the equality $\mathbf{R}^{\alpha} = \mathbf{R}^{-\alpha}$ for any dual α - connections. **Theorem 1.** If some α - connection has a constant α - curvature $k^{(\alpha)}$, i.e. $R^{\alpha}(X, Y)Z = k^{\alpha}(\langle Y, Z \rangle X - \langle X, Z \rangle Y)$, then (M, g, K) is a conjugate symmetric manifold. Theorem 2. If (M, g, K) is a conjugate symmetric manifold with α - connections which are (1) equiprojective, i.e. $R^{\alpha}(X, Y)Z = \frac{1}{n-1}(\operatorname{Ric}^{\alpha}(X, Z)Y - \operatorname{Ric}^{\alpha}(Y, Z)X)$, (2) strongly compatible with the metrics g, i.e. $(\bigtriangledown_X^{\alpha}g)(Y,Z)=(\bigtriangledown_Y^{\alpha}g)(X,Z); \bigtriangledown_Y^{\alpha}\omega_g=0$, then (M, g, K) is a statistical manifold of a constant α - curvature.

PARETO 2-DIM MODEL

 $p(x \mid a, \rho) = \rho a^{\rho} x^{-\rho-1}; a = \theta^1 > 0, \rho = \theta^2 > 0; x > a.$

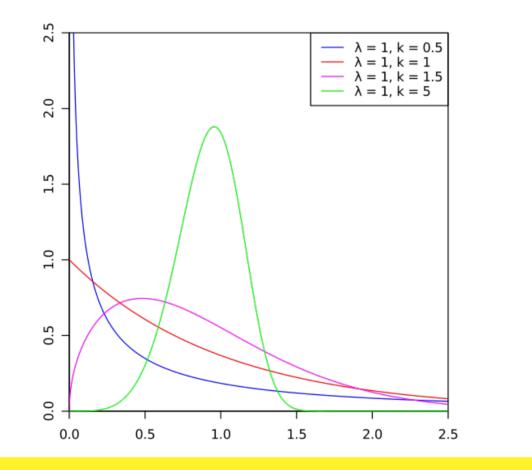


NORMAL 2-DIM MODEL

$$p(\boldsymbol{x} \mid \boldsymbol{\mu}, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\{-\frac{(\boldsymbol{x}-\boldsymbol{\mu})^2}{2\sigma^2}\}; \boldsymbol{\mu} = \theta^1, \sigma = \theta^2 > \mathbf{0};$$
$$I_{ij} = \begin{pmatrix} \frac{1}{\sigma^2} & \mathbf{0} \\ \mathbf{0} & \frac{1}{\sigma^2} \end{pmatrix}$$
$$\boldsymbol{k}^{(\alpha)} = \frac{\alpha^2 - \mathbf{1}}{2}$$

WEIBULL 2-DIM MODEL

$$p(x \mid \lambda, k) = (\frac{k}{\lambda}) \cdot (\frac{x}{\lambda})^{k-1} \cdot \exp\{-(\frac{x}{\lambda})^k\}; \lambda = \theta^1 > 0, k = \theta^2 > 0; x > 0.$$



The distribution function is $F(x \mid \lambda, k) = 1 - \exp\{-(\frac{x}{\lambda})^k\}$, logarithm of the likelihood function and its partial derivatives are

 $\ln p(x \mid \lambda, k) = \ln(\frac{k}{\lambda}) + (k - 1) \cdot \ln(\frac{x}{\lambda}) - (\frac{x}{\lambda})^{k}; \partial_{1} \ln p(x \mid \lambda, k) = -\frac{k}{\lambda} + \frac{k}{\lambda^{k+1}} x^{k};$ $\partial_{2} \ln p(x \mid \lambda, k) = \frac{1}{k} + (1 - (\frac{x}{\lambda})^{k}) \cdot \ln(\frac{x}{\lambda}).$ We obtain the non-zero components of the structure as $(k_{\lambda})^{2}$

$$I = \begin{pmatrix} \left(\frac{1}{\lambda}\right)^{-1} & \frac{1}{\lambda} \\ \frac{\gamma - 1}{\lambda} & \frac{\pi^{2} + 6\gamma^{2} - 12\gamma + 6}{6k^{2}} \end{pmatrix}$$

det $I_{ij} = \frac{\pi^{2}}{6\lambda^{2}}$;
 $K_{111} = -\left(\frac{k}{\lambda}\right)^{3}, \quad K_{112} = K_{211} = K_{211} = \frac{(2 - \gamma)k}{\lambda^{2}}, \quad K_{122} = K_{212} = K_{221} = -\frac{\pi^{2} + 6\gamma^{2} - 24\gamma + 12}{6\lambda k},$

The distribution function is $F(x \mid a, \rho) = 1 - (\frac{a}{x})^{\rho}$, the non-zero components of the structure are

$$\mathbf{I}_{ij} = \begin{pmatrix} \left(\frac{\rho}{a}\right)^2 & \mathbf{0} \\ \mathbf{0} & \frac{1}{\rho^2} \end{pmatrix}$$

 $K_{111} = -(\frac{1}{2}) \cdot (\frac{\rho}{a})^3$, $K_{112} = K_{212} = K_{221} = -\frac{1}{2a\rho}$, $K_{222} = \frac{1}{\rho^3}$. Then we have the non-zero components ${}^{(\alpha)}\Gamma^i_{jk}$ of Amari-Chentsov connections on the Pareto model as, ${}^{(\alpha)}\Gamma^{1}_{11} = -\frac{2+\alpha\rho}{2a}, \, {}^{(\alpha)}\Gamma^{2}_{11} = -\frac{\rho^{3}}{a^{2}}, \, {}^{(\alpha)}\Gamma^{1}_{12} = {}^{(\alpha)}\Gamma^{1}_{21} = \frac{1}{\rho}, \, {}^{(\alpha)}\Gamma^{2}_{12} = {}^{(\alpha)}\Gamma^{2}_{21} = -\frac{\alpha\rho}{2a}, \, {}^{(\alpha)}\Gamma^{1}_{22} = -\frac{\alpha a}{2\rho^{3}}, \, {}^{(\alpha)}\Gamma^{1}_{22$

 $(\alpha)\Gamma_{22}^2 = -\frac{1-\alpha}{\alpha}.$ Theorem 3. Pareto two-dimensional statistical model is a statistical manifold of a constant α -curvature

 $\mathbf{k}^{(\alpha)} = -\mathbf{2}\alpha - \mathbf{2}$

In particular, $k^{(0)} = -2$, i.e. Riemannian metrics on such manifold has the constant negative curvature.

LOGISTIC 2-DIM MODEL

The distribution function is $F(x \mid a, b) = \frac{1}{(1+exp(-ax-b))}$, the non-zero components of the structure are

$$I_{ij} = \frac{1}{3a^2} \begin{pmatrix} b^2 + \frac{\pi^2}{3} + 1 & -ab \\ -ab & a^2 \end{pmatrix}$$

 $K_{111}=\frac{1}{6a^3}$, $K_{122}=K_{212}=K_{211}=\frac{1}{6a}$, $K_{211}=K_{112}=K_{121}=-\frac{b}{3a^2}$ Consider the case $\alpha = 2$. Then we have the non-zero components ${}^{(2)}\Gamma^i_{jk}$ of Amari-Chentsov connections on the logistic model as

$${}^{(2)}\Gamma^{1}_{11} = \frac{2\pi^{2}-3}{(\pi^{2}+3)a}, {}^{(2)}\Gamma^{2}_{11} = -\frac{9b}{(\pi^{2}+3)a^{2}}, {}^{(2)}\Gamma^{2}_{12} = {}^{(2)}\Gamma^{2}_{21} = \frac{1}{a}.$$

Hence the logistic model has the constant 2-curvature

$$k^{(2)} = -rac{162}{(\pi^2 + 3)}$$

so it is a conjugate symmetric manifold [6].

 $K_{222} = \frac{\pi^2 (2 - \gamma) - 4\zeta(3) - 2\gamma^3 + 12\gamma^2 - 12\gamma + 2}{2k^3}$ Consider the case $\alpha = 1$. Then we have the non-zero components ${}^{(1)}\Gamma^{i}_{ik}$ of Amari-Chentsov connections on the Weibull model as

1-connection has the constant curvature

$$k^{(1)} = rac{12\pi^2\gamma - 144\gamma + 72}{\pi^4},$$

where $\gamma = \lim_{n \to \infty} \left(\sum_{k=1}^{\infty} \frac{1}{k} - \log n \right)$ is Euler-Mascheroni constant.

REFERENCES

[1] Amari S.-I., Nagaoka H. (2000) Metods of information geometry, Transl. Math. Monogr., 191, AMS, Oxford Univ. Press, Providence, Rhode Island.

[2] Lautitzen S. (1987) Conjugate connections in statistical theory, Geometrization of statistical theory, C.T.J., Dodson, ed. Lancaster, 33-51.

[3] Noguchi M. (1992) Geometry of statistical manifolds, Diff. Geom. Appl., 2, 197-222.

[4] Peng L., Sun H., Jiu L. (2007) The geometric structure of the Pareto distribution, Bol. Asoc. Math. *enez.*, **XIV,1-2**, 5-13.

[5] Ivanova R. (2010) A geometric observation on four statistical parameter spaces, Tensor, N. S., 72, 188-195.

[6] Rylov A. (2011) Amari-Chentsov connections on the logistic model, Izv. PGPU Belinskogo, 26, 195-206 (in Russian).

USEFUL IMPROPER INTEGRALS

$$\int_{a}^{+\infty} x^{-\rho-1} dx = \frac{1}{\rho a^{\rho}}; \ \int_{a}^{+\infty} \log x \cdot x^{-\rho-1} dx = \frac{1+\rho \log a}{\rho^{2} a^{\rho}}; \ \int_{a}^{+\infty} \log^{2} x \cdot x^{-\rho-1} dx = \frac{(1+\rho \log a)^{2}+1}{\rho^{3} a^{\rho}};$$

$$\int_{a}^{+\infty} \log^{3} x \cdot x^{-\rho-1} dx = \frac{(1+\rho \log a)^{3}+3(1+\rho \log a)+2}{\rho^{4} a^{\rho}};$$

$$\int_{0}^{+\infty} x^{nk-1} \cdot e^{-x^{k}} dx = \frac{(n-1)!}{k}, \ (n \in N, k > 0); \ \int_{0}^{+\infty} \log x \cdot x^{k-1} \cdot e^{-x^{k}} dx = -\frac{\gamma}{k^{2}};$$

$$\int_{0}^{+\infty} \log^{2} x \cdot x^{k-1} \cdot e^{-x^{k}} dx = \frac{\pi^{2}+6\gamma^{2}}{6k^{3}};$$

$$\int_{0}^{+\infty} \log^{3} x \cdot x^{k-1} \cdot e^{-x^{k}} dx = -\frac{4\zeta(3)+\gamma\pi^{2}+2\gamma^{3}}{2k^{4}},$$
where $n \in N, k > 0; \ \gamma = \lim_{n \to \infty} (\sum_{k=1}^{\infty} \frac{1}{k} - \log n) \approx 0, 577...$ is Euler-Mascheroni constant,

$$\zeta(3) = \sum_{k=1}^{\infty} \frac{1}{k^{3}} \approx 1, 202...$$
 is Apery's constant.

COMPARISON OF CURVATURES

$\nabla^{\alpha}\mathbf{n}$	Normal¤	Logistic ⁿ	Pareto¤	Weibull¤
<i>a</i> •=∙0¤	-0,5¤	≈ -1,4¤	-2¤	$\approx -1,22$ ¤
a = ·1 ª	0¤	¤	-4¤	≈ 0,59¤
<i>a</i> •=•2¤	1,5¤	≈ -0,98¤	-6¤	¤