# Information Geometry - Hessian Geometry 

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## General

Probability distribution on a set $X$ is a non-negative real function function

$$
p: X \rightarrow \mathbb{R}
$$

1) if $X$ discrete and countable $\Sigma_{x \in X} p(x)=1$;
2) if $X=\mathbb{R}^{n} \int_{X} p(x) d x=1$.
$p$ is a probability density function.
Let $\wedge$ be a domain in $R^{m}$. We consider families of probability distributions on a set $\mathcal{X}$ parametrized by $\lambda \in \Lambda$.

$$
\mathcal{P}=\{p(x ; \lambda) \mid \lambda \in \Lambda\}
$$

(1) $\Lambda$ is a domain in $R^{m}$,
(2) $p(x ; \lambda)$ for a fixed $x$ is a smooth function in $\lambda$,
(3) the operation of integration with respect to $x$ and differentiation with respect to $\lambda$ are commutative.
$\Lambda$ is called an $m$-dimensional statistical model (parametric model).
Notation $\Lambda=\{p(x ; \lambda)\}=\left\{p_{\lambda}(x)\right\}, p(x ; \lambda)=p_{\lambda}(x)$

## Examples

## Example (Normal distribution)

$X=\mathbb{R}, \mathrm{m}=2$

$$
\begin{gathered}
\Lambda=\{(\mu, \sigma):-\infty<\mu<\infty, 0<\sigma<\infty\} \\
p(x ; \lambda)=\frac{1}{\sqrt{2 \pi \sigma}} \exp \left\{-\frac{(x-\mu)^{2}}{2 \sigma^{2}}\right\}
\end{gathered}
$$

Example (Multivariate normal distribution)

$$
X=\mathbb{R}^{k}, m=k+\frac{k(k+1)}{2}, \lambda=(\mu, \Sigma)
$$

$$
\Lambda=\left\{(\mu, \Sigma): \mu \in \mathbb{R}^{k}, \quad \Sigma \in \mathbb{R}^{k^{2}}: \text { positive definite }\right\}
$$

$$
p(x ; \lambda)=(2 \pi)^{-k / 2}(\operatorname{det} \Sigma)^{-1 / 2} \exp \left\{-\frac{1}{2}(x-\mu)^{t} \Sigma^{-1}(x-\mu)\right\}
$$

## Examples cont.

## Example (Poisson distribution)

$X=\mathbb{N}, m=1, \Lambda=(0, \infty)$

$$
p(x ; \lambda)=e^{-\lambda} \frac{\lambda^{x}}{x!}
$$

Example ( $P(X)$ for finite $X$ )

$$
X=\left\{x_{0}, x_{1}, \ldots, x_{n}\right\}, \Lambda=\left\{\left(\lambda^{1}, \ldots, \lambda^{n}\right): \lambda^{i}>0, \sum_{i=1}^{n} \lambda^{i}<1\right\}
$$

$$
p(x ; \lambda)= \begin{cases}\lambda^{i} & 1 \leq i \leq n \\ 1-\sum_{i=1}^{n} \lambda^{i} & i=0\end{cases}
$$

## Fisher metric

## Definition

Let $\mathcal{P}=\{p(x ; \lambda) \mid \lambda \in \Lambda\}$ be a family of probability distributions on a set $\mathcal{X}$ parametrized by $\lambda \in \Lambda$.

We set $I_{\lambda}=I(x ; \lambda)=\operatorname{logp}(x ; \lambda)$ and denote by $E_{\lambda}$ the expectation with respect to $p_{\lambda}(x)=p(x ; \lambda)$.
Then the matrix $g_{F}(\lambda)=\left[g_{i j}(\lambda)\right]$ defined by

$$
g_{i j}(\lambda)=E_{\lambda}\left[\frac{\partial I_{\lambda}}{\partial \lambda^{j}} \frac{\partial I_{\lambda}}{\partial \lambda^{j}}\right]=\int_{\mathcal{X}} \frac{\partial I(x ; \lambda)}{\partial \lambda^{i}} \frac{\partial I(x ; \lambda)}{\partial \lambda^{j}} p(x ; \lambda) d x
$$

is called the Fisher information matrix tensor.

## Fisher metric cont.

Simple calculations show that

$$
g_{i j}(\lambda)=-E_{\lambda}\left[\frac{\partial^{2} I_{\lambda}}{\partial \lambda^{i} \partial \lambda^{j}}\right] .
$$

The Fisher information matrix tensor $g_{F}(\lambda)=\left[g_{i j}(\lambda)\right]$ is positive semi-definite on $\Lambda$ :

$$
\Sigma_{i . j} g_{i j}(\lambda) c^{i} c^{j}=\int_{\mathcal{X}}\left\{\Sigma_{i} c^{i} \frac{\partial I(x ; \lambda)}{\partial \lambda^{i}}\right\}^{2} p(x ; \lambda) d x \geq 0 .
$$

In information geometry the standard assumption has been:
(4) For a family of probability distributions $\mathcal{P}=\{p(x ; \lambda) \mid \lambda \in \Lambda\}$ the Fisher information matrix tensor $g_{F}(\lambda)=\left[g_{i j}(\lambda)\right]$ is positive definite on $\Lambda$.

Remark The general case seems to be difficult to study if not hopeless. Therefore to develop a meaningful more general theory in our paper [BW] we assume that the Fisher information matrix tensor is parallel with respect to some torsion-free connection on $\wedge$. The condition permits us to construct a foliation, and under some reasonable assumptions it has a transverse Hessian structure.

## Connections

$$
\left(\Gamma_{i j, k}^{(\alpha)}\right)_{\lambda}=E_{\lambda}\left[\left(\partial_{i} \partial_{j} l_{\lambda}+\frac{1-\alpha}{2} \partial_{i} I_{\lambda} \partial_{j} l_{\lambda}\right)\left(\partial_{k} I_{\lambda}\right)\right]
$$

where $\alpha$ is an arbitrary real number.
We define an affine connection $\nabla^{(\alpha)}$ on $\wedge$ by

$$
g\left(\nabla_{\partial_{i}}^{(\alpha)} \partial_{j}, \partial_{k}\right)=\Gamma_{i j, k}^{(\alpha)} .
$$

$\nabla^{(\alpha)}$ is called the $\alpha$-connection. $\nabla^{(\alpha)}$ is a symmetric connection.

$$
\Gamma^{(\beta)}{ }_{i j, k}=\Gamma^{(\alpha)}{ }_{i j, k}+\frac{\alpha-\beta}{2} T_{i j k},
$$

where $T_{i j k}$ is a covariant symmetric tensor of degree 3 defined by

$$
\left(T_{i j k}\right)_{\lambda}=E_{\lambda}\left[\partial_{i} I_{\lambda} \partial_{j} I_{\lambda} \partial_{k} I_{\lambda}\right] .
$$

Moreover,

$$
\nabla^{(\alpha)}=(1-\alpha) \nabla^{(0)}+\alpha \nabla^{(1)}=\frac{1+\alpha}{2} \nabla^{(1)}+\frac{1-\alpha}{2} \nabla^{(-1)}
$$

## Connections cont.

## Theorem

The 0-connection is the Riemannian connection with respect to the Fisher metric.

## Exponential family

If an $m$-dimensional model

$$
S=\left\{p_{\theta}: \theta \in \Theta\right\}
$$

can be expressed in terms of functions $\left\{C, F_{1}, \ldots, F_{m}\right\}$ on $X$ and a function $\psi$ on $\Theta$ :

$$
p(x ; \theta)=\exp \left[C(x)+\sum_{i=1}^{n} \theta^{i} F_{i}(x)-\psi(\theta)\right],
$$

then $S$ is called an exponential family and $\left\{\theta^{i}\right\}$ are called natural or canonical parameters.
From the normality condition

$$
\psi(\theta)=\log \int \exp \left[C(x)+\sum_{i=1}^{n} \theta^{i} F_{i}(x)\right] d x .
$$

The parametrization $\theta \mapsto p_{\theta}$ is one-to-one iff the $\mathrm{m}+1$ functions $\left\{F_{1}, \ldots, F_{m}, 1\right\}$ are linearly independent.
Always assumed!

## Examples

## Example (Normal distribution)

$$
\begin{gathered}
C(x)=0, \quad F_{1}(x)=x, \quad F_{2}(x)=x^{2}, \quad \theta^{1}=\frac{\mu}{\sigma^{2}} \quad \theta^{2}=-\frac{1}{2 \sigma^{2}} \\
\psi(\theta)=\frac{\mu^{2}}{2 \sigma^{2}}+\log (\sqrt{2 \pi \sigma})=-\frac{\left(\theta^{1}\right)^{2}}{4 \theta^{2}}+\frac{1}{2} \log \left(-\frac{\pi}{\theta^{2}}\right) .
\end{gathered}
$$

## $S$ forms an affine subspace of $P(X)$ <br> $S$ is called a mixture family with mixt ure parameters

## Examples

## Example (Normal distribution)

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\end{gathered}
$$

## Example

Consider an m-dimensional model $S=\left\{p_{\theta}\right\}$ which can be expressed in terms of function $\left\{C, F_{1}, \ldots, F_{m}\right\}$ on $X$ as

$$
p(x ; \theta)=C(x)+\sum_{i} \theta^{i} F_{i}(x) .
$$

$S$ forms an affine subspace of $P(X)$.
$S$ is called a mixture family with mixture parameters $\theta^{i}$.

## Example (Multivariate normal distribution)

$$
\begin{gathered}
C(x)=0, \quad F_{i}(x)=x_{i}, \quad F_{i j}(x)=x_{i} x_{j} \quad(i \leq j) \\
\theta^{i}=\Sigma_{j}\left(\Sigma^{-1}\right)^{i j} \mu_{j}, \quad \theta^{i i}=(-1 / 2)\left(\Sigma^{-1}\right)^{i i}, \quad \theta^{i j}=-\left(\Sigma^{-1}\right)^{i j} \quad(i<j)
\end{gathered}
$$

and

$$
F_{A}(x)=x, \quad F_{B}(x)=x x^{t}, \quad \theta^{A}=\Sigma^{-1} \mu, \quad \theta^{B}=(-1 / 2) \Sigma^{-1}
$$

We have

$$
\begin{aligned}
p(x ; \theta) & =\exp \left[\Sigma_{1 \leq i \leq k} \theta^{i} F_{i}(x)+\Sigma_{1 \leq i \leq j \leq k} \theta^{i j} F_{i j}(x)-\psi(\theta)\right] \\
& =\exp \left[\left(\theta^{A}\right)^{t} F_{A}(x)+\operatorname{tr}\left(\theta^{B} F_{B}(x)\right)-\psi(\theta)\right]
\end{aligned}
$$

where $\psi(\theta)=\ldots$.

## Theorem

An exponential family (a mixture family, respectively) is $\nabla^{(1)}$-flat $\left(\nabla^{(-1)}\right.$-flat, respectively) and its natural parameters (mixture parameters, respectively) form a $\nabla^{(1)}$-affine $\left(\nabla^{(-1)}\right.$-affine, respectively) coordinate system.

## Theorem

An exponential family (a mixture family, respectively) is $\nabla^{(1)}$-flat $\left(\nabla^{(-1)}\right.$-flat, respectively) and its natural parameters (mixture parameters, respectively) form a $\nabla^{(1)}$-affine ( $\nabla^{(-1)}$-affine, respectively) coordinate system.

## Theorem

Let $S$ be an exponential family (a mixture family, respectively) and $M$ a submanifold of $S$. Them $M$ is an exponential family (a mixture family, respectively) iff $M$ is $\nabla^{(1)}$-autoparallel $\left(\nabla^{(-1)}\right.$-autoparallel) in $S$.

## Contents

## (1) Statistical models

(2) Dual Connections

## Dual connections

When investigating the properties of the Fisher metric $g$ and the $\alpha$-connection $\nabla^{(\alpha)}$ it is important to consider them not individually, but rather as the triple $\left(g, \nabla^{(\alpha)}, \nabla^{(-\alpha)}\right)$. The reason for this is that, through g , there exists a kind of duality between $\nabla^{(\alpha)}$ and $\nabla^{(-\alpha)}$ which is of fundamental significance. This notion of duality emerges not only when considering statistical models but also in many different problems related to information geometry.
$(S, g)$ a Riemannian manifold, $\nabla$ and $\nabla^{*}$ two connections.

## Definition

If for any $X, Y, Z \in \mathcal{X}(S)$

$$
Z g(X, Y)=g\left(\nabla_{Z} X, Y\right)+g\left(X, \nabla_{Z}^{*} Y\right)
$$

holds then the connections $\nabla$ and $\nabla^{*}$ are said to be dual (or conjugate).
The triple $\left(g, \nabla, \nabla^{*}\right)$ is called a dualistic structure on $S$.

In local coordinates we have

$$
\partial_{k} g_{i j}=\Gamma_{k i, j}+\Gamma_{k j, i}^{*}
$$

For given $g$ and $\nabla$ there exists a unique dual connection $\nabla^{*}$
Moreover,
(1) $\left(\nabla^{*}\right)^{*}=\nabla$,
(2) $\left(\nabla+\nabla^{*}\right) / 2$ is a metric connection,
(3) if a connection $\nabla^{\prime}$ has the same torsion as $\nabla^{*}$ and if $\left(\nabla+\nabla^{\prime}\right) / 2$ is metric, then $\nabla^{\prime}=\nabla^{*}$.

## Theorem

For any statistical model, the $(\alpha)$-connection and the $(-\alpha)$-connection are dual with respect to the Fisher metric.

## Theorem

Let $h_{\gamma}: T_{p} S \rightarrow T_{q} S$ (resp. $h_{\gamma}^{*}$ be the parallel transport along curve $\gamma$ from $p$ to $q$ with respect to $\nabla$ (resp. $\nabla^{*}$ ), then

$$
g\left(h_{\gamma}(X), h_{\gamma}^{*}(Y)\right)=g(X, Y)
$$

for any vectors $X, Y \in T_{p} S$.

For any vector fields $X, Y, Z, W \in \mathcal{X}(X)$

$$
g(R(X, Y) Z, W)=-g\left(R^{*}(X, Y) W, Z\right)
$$

thus

$$
R=0 \quad \text { iff } \quad R^{*}=0
$$

However, a similar property does not hold for the torsion tensors.

Let $\left(g, \nabla, \nabla^{*}\right)$ be a dualistic structure on a manifold $S$. If the connections $\nabla$ amd and $\nabla^{*}$ are both symmetric ( $T=T^{*}=0$ ), then the $\nabla$-flatness and $\nabla^{*}$-flatness are equivalent.

Since the $\alpha$-connections are always symmetric, for any statistical model $S$ and for any real number $\alpha \mathrm{S}$ is $\alpha$-flat iff S is $(-\alpha)$-flat.

We call $\left(S, g, \nabla, \nabla^{*}\right)$ a dually flat space if both dual connections are flat.

## Theorem

Let $\left(S, g, \nabla, \nabla^{*}\right)$ be a dually flat space. If a submanifold $M$ of $S$ is autoparallel with respect to either $\nabla$ or $\nabla^{*}$, then $M$ is a dually flat space with respect to the dualistic structure $\left(g_{M}, \nabla_{M}, \nabla_{M}^{*}\right)$ induced on $M$ by $\left(g, \nabla, \nabla^{*}\right)$.
$\hat{\xi}: X \rightarrow \mathbb{R}^{m}$ is called an estimator. $\hat{\xi}$ is called an unbiased estimator if $E_{\xi}[\hat{\xi}(X)]=\xi$ for any $\xi$.
The mean squared error of an inbiased estimator $\hat{\xi}$ may be expressed as the variance-covariance matrix $V_{\xi}[\hat{\xi}]=\left[v_{\xi}^{i j}\right]$ where

$$
v_{\xi}^{i j}=E_{\xi}\left[\left(\hat{\xi}^{i}(X)=\xi^{i}\right)\left(\hat{\xi}^{j}(X)=\xi^{j}\right)\right]
$$

An unbiased estimator $\hat{\xi}$ achieving the equality $V_{\xi}[\hat{\xi}]=G(\xi)^{-1}$ for all $\xi$ is called an efficient estimator.

## Theorem

A necessary and sufficient condition for a coordinate system $\xi$ of a model $S=\left\{p_{\xi}\right\}$ to have an efficient estimator is that $S$ is an exponential family and $\xi$ is $(-1)$-affine.

## Contents

(3) Hessian structures

## Hessian structures

## Definition

A Riemannian metric $g$ on a flat manifold $(M, D)$ is called a Hessian metric if for any point $x$ of $M$ there exists a local function $\phi$ defined on an open nbhd of $x$ such that

$$
g=D d \phi
$$

If $\left(x^{1}, \ldots, x^{m}\right)$ is an affine coordinate system for $D$ then

$$
g_{i j}=\frac{\partial^{2} \phi}{\partial x^{i} \partial x^{j}},
$$

The pair $(D, g)$ is called a Hessian structure on $M$; $M$ is called a Hessian manifold - notation ( $M, D, g$ ). A function $\phi$ is called a (local) potential of $(D, g)$.

## Definition

A Hessian structure $(\mathrm{D}, \mathrm{g})$ is said to be of Koszul type if there exists a closed 1 -form $\omega$ such that $g=D \omega$.

## Hessian structures cont.

Let $\nabla$ be the Levi-Civita connection of the Riemannian metric $g$. Let $\gamma$ be the difference tensor

$$
\gamma_{X} Y=\nabla_{X} Y-D_{X} Y
$$

As $\nabla$ and $D$ are torsion-free $\gamma_{X} Y=\gamma_{Y} X$.

## Proposition

Let ( $M, D$ ) be a flat manifold and $g$ a Riemannian metric on $M$. Then the following conditions are equivalent:
(1) g is a Hessian metric,
(2) $\left(D_{X} g\right)(Y, Z)=\left(D_{Y} g\right)(X, Z)$,
(3) $\frac{\partial g_{i j}}{\partial x^{k}}=\frac{\partial g_{k j}}{\partial x^{i}}$,
(a) $g\left(\gamma_{X} Y, Z\right)=g\left(Y, \gamma_{X} Z\right)$,
(6) $\gamma_{i j k}=\gamma_{j i k}$.

## cont.

Let $(M, D)$ be a flat manifold and $\pi: T M \rightarrow M$ its tangent bundle. To an affine chart $\left(x^{1}, \ldots, x^{m}\right)$ we associate a complex chart on TM

$$
z^{j}=\xi^{j}+i \xi^{m+j}
$$

where $\xi^{i}=x^{i} \pi$ and $\xi^{m+i}=d x^{i}$ for $i=1, \ldots, m$. $J_{D}$ the associated complex structure on $T M$.

On $T M$ we define the following Riemannian metric $g^{T}$

$$
g^{T}=\Sigma g_{i j} \pi d z^{i} d \bar{z}^{j}
$$

## Proposition

Let $(M, D)$ be a flat manifold and $g$ a Riemannian metric on $M$. Then the following conditions are equivalent:
(1) $g$ is a Hessian metric on $(M, D)$,
(2) $g^{T}$ is a Kählerian metric on $\left(T M, J_{D}\right)$.

## cont.

## Theorem

Let $(M, D, g)$ be a Hessian manifold and let $\nabla$ be the Levi-Civita connection of $g$. Define a connection $D^{\prime}$ by

$$
D^{\prime}=2 \nabla-D .
$$

Then
(1) $D^{\prime}$ is a flat connection,
(2) $X g(Y, Z)=g\left(D_{X} Y, Z\right)+g\left(Y, D_{X}^{\prime} Z\right)$,
(3) $\left(D^{\prime}, g\right)$ is a Hessian structure.

## Codazzi structures

## Proposition

Let $D$ be a torsion-free connection and let $g$ be a Riemannian metric. Let $D^{\prime}$ be a new connection defined by

$$
X g(Y, Z)=g\left(D_{X} Y, Z\right)+g\left(Y, D_{X}^{\prime} Z\right)
$$

Then the following conditions are equivalent:
(1) the connection $D^{\prime}$ is torsion-free,
(2) The pair $(D, g)$ satisfies the Codazzi equation

$$
\left(D_{X} g\right)(Y, Z)=\left(D_{Y} g\right)(X, Z)
$$

(3) Let $\nabla$ be the Levi-Civita connection for $g$, let $\gamma_{X} Y=\nabla_{X} Y-D_{X} Y$. Then

$$
\left.g_{\gamma X} Y, Z\right)=g\left(Y, \gamma_{X} Z\right)
$$

If the pair $(D, g)$ satisfies the Codazzi equation, so does the pair $\left(D^{\prime}, g\right)$ and

$$
D^{\prime}=2 \nabla-D \quad \text { and } \quad\left(D_{X} g\right)(Y, Z)=2 g\left(\gamma_{X} Y, Z\right)
$$

## Codazzi structures cont.

## Definition

A pair $(D, g)$ where $D$ is a torsion-free connection and $g$ a Riemannian metric on a manifold $M$ is called a Codazzi structure if it satisfies the Codazzi

$$
\left(D_{X} g\right)(Y, Z)=\left(D_{Y} g\right)(X, Z)
$$

For a Codazzi structure $(D, g)$ the connection $D^{\prime}$ defined by

$$
X g(Y, Z)=g\left(D_{X} Y, Z\right)+g\left(Y, D_{X}^{\prime} Z\right)
$$

is called the dual connection of $D$ with respect to $g$, and the pair $\left(D^{\prime}, g\right)$ the dual Codazzi structure of $(D, g)$.


## Codazzi structures cont.

## Definition

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is called the dual connection of $D$ with respect to $g$, and the pair $\left(D^{\prime}, g\right)$ the dual Codazzi structure of $(D, g)$.

## Definition

A Codazzi structure $(D, g)$ is of constant curvature $c$ if the curvature tensor $R_{D}$ of $D$ satisfies

$$
R_{D}(X, Y) Z=c\{g(Y, Z) X-g(X, Z) Y\}
$$

## Proposition

Let $(D, g)$ be a Codazzi structure nad $\left(D^{\prime}, g\right)$ its dual Codazzi structure. Then (1)

$$
g\left(R_{D}(X, Y) Z, W\right)+g\left(Z, R_{D^{\prime}}(X, Y) W\right)=0
$$

(2) if $(D, g)$ is a Codazzi struccture of constant curvature $c$, then $\left(D^{\prime}, g\right)$ is also of constant curvature $c$.


## Proposition

Let $(D, g)$ be a Codazzi structure nad $\left(D^{\prime}, g\right)$ its dual Codazzi structure. Then (1)

$$
g\left(R_{D}(X, Y) Z, W\right)+g\left(Z, R_{D^{\prime}}(X, Y) W\right)=0
$$

(2) if $(D, g)$ is a Codazzi struccture of constant curvature $c$, then $\left(D^{\prime}, g\right)$ is also of constant curvature $c$.

## Proposition

A Codazzi structure $(D, g)$ is of constant curvature 0 iff $(D, g)$ is a Hessian structure.


## Proposition

Let $(D, g)$ be a Codazzi structure nad $\left(D^{\prime}, g\right)$ its dual Codazzi structure. Then (1)

$$
g\left(R_{D}(X, Y) Z, W\right)+g\left(Z, R_{D^{\prime}}(X, Y) W\right)=0
$$

(2) if $(D, g)$ is a Codazzi struccture of constant curvature $c$, then $\left(D^{\prime}, g\right)$ is also of constant curvature $c$.

## Proposition

A Codazzi structure $(D, g)$ is of constant curvature 0 iff $(D, g)$ is a Hessian structure.

## Proposition

Let $(D, g)$ be a Codazzi structure of constant curvature. Then locally $g$ is of the form

$$
D d \phi+\frac{\phi}{m-1} R_{i c_{D}}
$$

where $R i c_{D}$ is the Ricci tensor of $D$ and $\phi$ is a local function.

## Example

Let $S(m)$ be the set of real symmetric matrices of degree $m$, and let $S(m)^{+}$be the subset of $S(m)$ consisting of of positive-definite symmetric matrices. Put

$$
p(x ; \mu, \sigma)=(2 \pi)^{-m / 2}(\operatorname{det} \sigma)^{-1 / 2} \exp \left(\left\{-\frac{{ }^{t}(x-\mu) \sigma^{-1}(x-\mu)}{2}\right\}\right),
$$

where $\mu \in \mathbb{R}^{m}$ and $\sigma \in S(m)^{+}$. Then $\left\{p(x ; \mu, \sigma):(\mu, \sigma) \in \mathbb{R}^{m} \times S(m)^{+}\right\}$is a family of probability distributions on $\mathbb{R}^{m}$ parametrized by $(\mu, \sigma)$ and called a family of $\mathbf{m}$-dimensional normal distributions.
Let $\Omega$ be a domain in a finite dimensional real vector space $V$, and let $\rho$ be an injective linear mapping from $\Omega$ into $S(m)^{+}$.

## Proposition

Let $\left\{p(x ; \mu, \omega):(\mu, \omega) \in \mathbb{R}^{m} \times \Omega\right\}$ be a family of probability distributions induced by $\rho$. Then the family is an exponential family parametrized by $\theta=\rho(\omega) \mu \in \mathbb{R}^{m}$ and $\omega \in \Omega$. The Fisher information metric is a Hessian metric on $\mathbb{R}^{m} \times \Omega$ with potential function

$$
\phi(\theta, \omega)=(1 / 2)\left\{^{t} \theta \rho(\omega)^{-1} \theta-\log \operatorname{det} \rho(\omega)\right\} .
$$

## References

1) Amari S-I and Nagaoka H.: Methods of Information Geometry, Translations of Mathematical monographs, AMS-OXFORD, vol 191
2) Shima, H.: The Geometry of Hessian Structures. World Scientific (2007)
3)[BW] Nguiffo Boyom M and W R.: Transversely Hessian foliations and information geometry, Int. J. Math. 27,11 (2016)

Conferences

1) Geometric Science of Information - GSI (Mines ParisTech, Paris 2014 and 2017)
2) Topological and Geometrical Structure of Information (CIRM 2017)

## Foliations

Let $\mathcal{F}$ be a foliation on an $m$-manifold $M$. Then $\mathcal{F}$ is defined by a cocycle $\mathcal{U}=\left\{U_{i}, f_{i}, k_{i j}\right\}_{i \in I}$ modeled on a $q$-manifold $N_{0}(0<q<m)$ such that
(1) $\left\{U_{i}\right\}_{i \in I}$ is an open covering of $M$,
(2) $f_{i}: U_{i} \rightarrow N_{0}$ are submersions with connected fibres,
(3) $k_{i j}: N_{0} \rightarrow N_{0}$ are local diffeomorphisms of $N_{0}$ with $f_{i}=k_{i j} f_{j}$ on $U_{i} \cap U_{j}$.

The connected components of the trace of any leaf of $\mathcal{F}$ on $U_{i}$ are fibres of $f_{i}$, and the trace itself consists of at most a denombrable number of these fibres.

The open subsets $N_{i}=f_{i}\left(U_{i}\right) \subset N_{0}$ form a $q$-dimensional manifold $N_{\mathcal{U}}=\bigsqcup N_{i}$, which can be considered to be a complete transverse manifold of the foliation $\mathcal{F}$. The pseudogroup $\mathcal{H}_{\mathcal{U}}$ of local diffeomorphisms of $N$ generated by $k_{i j}$ is called the holonomy pseudogroup of the foliated manifold $(M, \mathcal{F})$ defined by the cocycle $\mathcal{U}$.

A foliation on a smooth manifold $M$ understood as an involutive subbundle of $T M$, or equivalently, according to the Frobenius theorem as a partition of the manifold by submanifolds of the same dimension with some regularity condition, can be defined by many different cocycles.

There is a notion of equivalent cocycles, similar to the notion of equivalent atlases of a smooth manifold, and a foliation can be understood as an equivalence class of such cocycles. The equivalence class $\mathcal{H}$ of $\mathcal{H}_{\mathcal{U}}$, is called the holonomy group of $\mathcal{F}$, or of the foliated manifold $(M, \mathcal{F})$.

The vector bundle $N(M, \mathcal{F})=T M / T \mathcal{F}$ is called the normal bundle of the foliation $\mathcal{F}$. Then the tangent bundle TM is isomorphic to the direct sum $T \mathcal{F} \oplus N(M, \mathcal{F})$. These isomorphisms are determined by the choice of a supplementary subbundle $Q$ in $T M$ to the tangent bundle to the foliation $T \mathcal{F}$.

The cocycle $\mathcal{U}=\left\{U_{i}, f_{i}, k_{i j}\right\}_{i \in l}$ modeled on a $q$-manifold $N_{0}$ induces on the normal bundle a cocycle $\mathcal{V}=\left\{V_{i}, \bar{f}_{i}, \bar{k}_{i j}\right\}_{i \in I}$ modeled on the $2 q$-manifold $T N_{0}$, where $V_{i}=T U_{i}, \bar{f}_{i}$ is the mapping induced by $d f_{i}$, and $\bar{k}_{i j}=d k_{i j}$.
The foliation $\mathcal{F}_{N}$ of the normal bundle is of codimension $2 q$, its leaves project on leaves of $\mathcal{F}$. They are, in fact, coverings of these leaves.

In a similar way one can foliate any bundle obtained via a point-wise process from the normal bundle, e.g., the frame bundle of the normal bundle, the dual normal bundle, any tensor product of these bundles.

## Geometric structures on foliated manifolds

In the case of a foliated manifold we can consider three types of geometrical structures related to the foliation:
transverse - defined on the transverse manifold, the associated holonomy pseudogroup consists of automorphisms of this geometrical structure;
foliated - only defined on the normal bundle, and when expressed in a local adapted chart, depending only on the transverse coordinates; a foliated structure projects to a transverse structure along submersions of the cocycle defining the foliation.;
associated - defined globally, on the tangent bundle but adapted to the spliting, and defining a foliated structure on the normal bundle.

Foliated and transverse structures are in one-to-one correspondence, an associated structure defines a foliated structure, but different associated structures can define the same foliated structure.

