

Information Geometry of Polytopes

general theory and applications to stochastic matrices

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Notation

Simplex of probability measures

$$\begin{aligned}\mathbb{R}^{\mathcal{X}} &:= \text{real valued functions on a finite set } \mathcal{X} \\ \delta_x &\in \left(\mathbb{R}^{\mathcal{X}}\right)^*, \quad x \in \mathcal{X}, \quad (\text{dual of the canonical basis}) \\ \mathcal{P} &:= \left\{ \sum_x p_x \delta_x \in \left(\mathbb{R}^{\mathcal{X}}\right)^* : p_x > 0, \quad \sum_x p_x = 1 \right\}\end{aligned}$$

Quotient vector space

$\mathcal{C} :=$ subspace of constant functions

$$\mathbb{R}^{\mathcal{X}} / \mathcal{C} = \left\{ f + \mathcal{C} : f \in \mathbb{R}^{\mathcal{X}} \right\}$$

\mathcal{P} as a Manifold

Tangent and cotangent space of \mathcal{P}

- Tangent space of \mathcal{P} :

$$\mathcal{T} := \left\{ \varphi \in (\mathbb{R}^{\mathcal{X}})^* : \varphi(f) = 0 \text{ for all } f \in \mathcal{C} \right\}$$

- Cotangent space of \mathcal{P} :

$$\mathbb{R}^{\mathcal{X}} / \mathcal{C} \cong \mathcal{T}^*$$

$$\mathbb{R}^{\mathcal{X}} / \mathcal{C} \rightarrow \mathcal{T}^*, \quad f + \mathcal{C} \mapsto (\varphi \mapsto \varphi(f))$$

Remark

$$\mathcal{U} \subseteq \mathcal{V}, \quad \mathcal{U}^0 := \{ \varphi \in \mathcal{V}^* : \varphi(f) = 0 \text{ for all } f \in \mathcal{U} \}$$

$$\Rightarrow \mathcal{V}^* / \mathcal{U}^0 \rightarrow \mathcal{U}^*, \quad \varphi + \mathcal{U}^0 \mapsto \varphi|_{\mathcal{U}}, \quad \text{natural isomorphism}$$

\mathcal{P} as a Riemannian Manifold

- Scalar product on $\mathbb{R}^{\mathcal{X}}/\mathcal{C}$:

$$\langle f + \mathcal{C}, g + \mathcal{C} \rangle_p := \text{cov}(f, g) = \langle f \cdot g \rangle_p - \langle f \rangle_p \cdot \langle g \rangle_p$$

- Identification of $\mathbb{R}^{\mathcal{X}}/\mathcal{C}$ and \mathcal{T} with respect to $\langle \cdot, \cdot \rangle_p$:

$$\phi_p : \mathbb{R}^{\mathcal{X}}/\mathcal{C} \rightarrow \mathcal{T}, \quad f + \mathcal{C} \mapsto \sum_x p_x \left(f_x - \langle f \rangle_p \right) \delta_x$$

- Natural bundle isomorphism:

$$T^*\mathcal{P} = \mathcal{P} \times (\mathbb{R}^{\mathcal{X}}/\mathcal{C}) \xrightarrow{\phi} \mathcal{P} \times \mathcal{T} = T\mathcal{P}$$

- Fisher metric, Shahshahani inner product:

$$\langle \cdot, \cdot \rangle_p : \mathcal{T} \times \mathcal{T} \rightarrow \mathbb{R}, \quad \langle A, B \rangle_p := \sum_x \frac{1}{p_x} A_x B_x$$

Vector Fields and Differential Equations

Replicator equations

Consider a map $f : \mathcal{P} \rightarrow \mathbb{R}^{\mathcal{X}}$ and the induced section

$$\mathcal{P} \rightarrow \mathbb{R}^{\mathcal{X}} / \mathcal{C}, \quad p \mapsto f(p) + \mathcal{C}.$$

in $T^*\mathcal{P}$. This can be identified with the vector field

$$\mathcal{P} \rightarrow \mathcal{T}, \quad p \mapsto \sum_x p_x \left(f_x(p) - \langle f(p) \rangle_p \right) \delta_x$$

and the corresponding differential equations

$$\dot{p}_x = p_x \left(f_x(p) - \langle f(p) \rangle_p \right), \quad x \in \mathcal{X}.$$

These equations are known as *replicator equations*.

Observation

Replicator equations are nothing but ordinary differential equations expressed in terms of a section in the cotangent bundle $T^*\mathcal{P}$ instead of a section in the tangent bundle $T\mathcal{P}$.

Gradient fields

Consider a function $F : \mathcal{P} \rightarrow \mathbb{R}$. Then the gradient of F with respect to the Fisher metric is given by

$$(\text{grad}_p F)_x = p_x \left(\partial_x F(p) - \sum_{x'} p_{x'} \partial_{x'} F(p) \right)$$

- J. Hofbauer & K. Sigmund. *Evolutionary Games and Population Dynamics*. Cambridge University Press 2002.
- N. Ay & I. Erb. *On a Notion of Linear Replicator Equations*. Journal of Dynamics and Differential Equations 2005.

Example: Darwinian selection, "survival of the fittest"

Consider a function $f : \mathcal{X} \rightarrow \mathbb{R}$ (f_x is called *fitness of species x*) and

$$\dot{p}_x = p_x \left(f_x - \langle f \rangle_p \right) = \text{grad}_p \langle f \rangle, \quad p(0) = p.$$

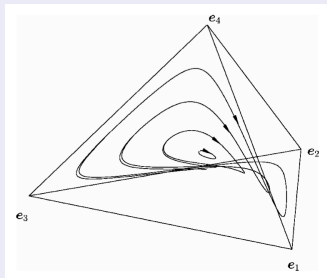
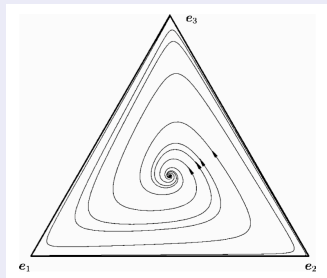
Solution curves satisfy the Price-equation and Fisher's fundamental theorem of natural selection:

$$\frac{d}{dt} \langle g \rangle_{p(t)} = \text{cov}(f, g) \qquad \frac{d}{dt} \langle f \rangle_{p(t)} = \text{var}(f)$$

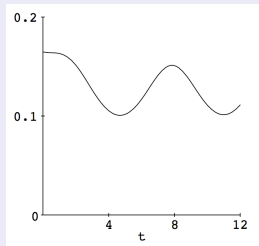
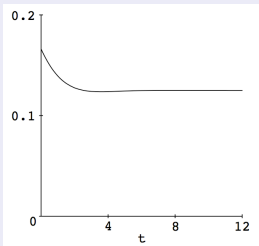
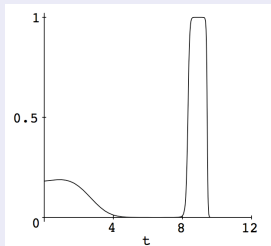
Solution curves: $t \mapsto p(t) = \frac{p e^{tf}}{\langle e^{tf} \rangle_p}$

$$\lim_{t \rightarrow -\infty} p(t) = \begin{cases} \frac{p_x}{\sum_{x \in \text{argmin}(f)} p_x}, & \text{falls } x \in \text{argmin}(f) \\ 0, & \text{sonst} \end{cases}$$
$$\lim_{t \rightarrow \infty} p(t) = \begin{cases} \frac{p_x}{\sum_{x \in \text{argmax}(f)} p_x}, & \text{falls } x \in \text{argmax}(f) \\ 0, & \text{sonst} \end{cases}$$

Hypercycle dynamics (Eigen und Schuster) with three and four species



Hypercycle dynamics with eight species for different initial conditions



Natural Connections

Mixture Connection

$$\overset{m}{\Pi}_{p,q}: T_p\mathcal{P} \longrightarrow T_q\mathcal{P}, \quad (p, A) \longmapsto (q, A)$$

Exponential Connection

$$\overset{e}{\Pi}_{p,q}: T_p^*\mathcal{P} \longrightarrow T_q^*\mathcal{P}, \quad (p, f + \mathcal{C}) \longmapsto (q, f + \mathcal{C})$$

$$\overset{e}{\Pi}_{p,q}: T_p\mathcal{P} \longrightarrow T_q\mathcal{P}, \quad (p, A) \longmapsto (q, (\phi_q \circ \phi_p^{-1})(A))$$

Duality

$$\left\langle \overset{e}{\Pi}_{p,q} A, \overset{m}{\Pi}_{p,q} B \right\rangle_q = \langle A, B \rangle_p$$

Differential version

$$\nabla_{AB}^{m,e} \Big|_p := \lim_{t \rightarrow 0} \frac{1}{t} \left(\prod_{\gamma(t),p}^{m,e} (B_{\gamma(t)}) - B_p \right) \in T_p \mathcal{P}.$$

Geodesics satisfying $\gamma^{m,e}(0) = p$ and $\gamma^{m,e}(1) = q$

① m -geodesics:

$$\gamma_{p,q}^m: [0, 1] \rightarrow \mathcal{P}, \quad t \mapsto (1-t)p + tq$$

② e -geodesics:

$$\gamma_{p,q}^e: [0, 1] \rightarrow \mathcal{P}, \quad t \mapsto \frac{p^{1-t} q^t}{\sum_x p_x^{1-t} q_x^t}$$

Corresponding exponential maps

① m -exponential map:

$$\exp^m: \{(p, q - p) \in T\mathcal{P} : p, q \in \mathcal{P}\} \rightarrow \mathcal{P}, \quad (p, A) \mapsto p + A,$$

② e -exponential map:

$$\exp^e: T\mathcal{P} \rightarrow \mathcal{P}, \quad (p, A) \mapsto \frac{p e^{\frac{A}{p}}}{\sum_x p_x e^{\frac{A_x}{p_x}}}$$

Relative entropy

$$D(p \| q) = \begin{cases} \sum_x p_x \ln \frac{p_x}{q_x}, & \text{if } \text{supp}(p) \subseteq \text{supp}(q) \\ +\infty, & \text{otherwise} \end{cases}$$

$$\exp_q^m{}^{-1}(p) = -\text{grad}_q D(p \| \cdot) \quad \exp_q^e{}^{-1}(p) = -\text{grad}_q D(\cdot \| p)$$

Motivation of the previous relations

- Squared distance from q :

$$D_q : \mathbb{R}^n \rightarrow \mathbb{R}, \quad p \mapsto \frac{1}{2} \|q - p\|^2 = \frac{1}{2} \sum_{i=1}^n (q_i - p_i)^2$$

- The differential $d_p D_q \in (\mathbb{R}^n)^*$:

$$d_p D_q : \mathbb{R}^n \rightarrow \mathbb{R}, \quad v \mapsto \frac{\partial D_q}{\partial v}(p)$$

- Identification of the differential with a vector in \mathbb{R}^n :

$$-\text{grad}_p D_q = -\text{grad}(d_p D_q) = q - p = \overrightarrow{p q}$$

\mathcal{P} as an Affine Space

Note that \exp^e is not an affine action:

$$\exp^e(\exp^e(p, A), B) \neq \exp^e(p, A + B)$$

Consider instead the composition

$$\begin{aligned} \mathfrak{t} : \mathcal{P} \times (\mathbb{R}^{\mathcal{X}} / \mathcal{C}) = T^*\mathcal{P} &\xrightarrow{\phi} T\mathcal{P} \xrightarrow{\exp^e} \mathcal{P}, \\ (p, f + \mathcal{C}) &\mapsto \frac{p e^f}{\langle e^f \rangle_p} \end{aligned}$$

This is an affine action with difference vector

$$\text{vec} : \mathcal{P} \times \mathcal{P} \rightarrow \mathbb{R}^{\mathcal{X}} / \mathcal{C}, \quad (p, q) \mapsto \text{vec}(p, q) = \ln \left(\frac{q}{p} \right) + \mathcal{C}$$

and \mathcal{P} is an affine space over $\mathbb{R}^{\mathcal{X}} / \mathcal{C}$.

Definition: Exponential families

An affine subspace \mathcal{E} of \mathcal{P} with respect to t is called *exponential family*. Given a probability measure q and a linear subspace \mathcal{L} of $\mathbb{R}^{\mathcal{X}}$, the following submanifold of \mathcal{P} is an exponential family:

$$\mathcal{E}(q, \mathcal{L}) := \left\{ \frac{q e^f}{\langle e^f \rangle_q} : f \in \mathcal{L} \right\}$$

Clearly, all exponential families are of this structure. We always assume $\mathcal{C} \subseteq \mathcal{L}$ and thereby ensure uniqueness of \mathcal{L} . Furthermore, with this assumption we have $\dim(\mathcal{E}) = \dim(\mathcal{L}) - 1$.

Remark

An exponential family can be identified with a polytope via the expectation value map.

Extension to Polytopes

work in progress with Johannes Rauh

Consider a polytope $\bar{C} \subset \mathbb{R}^d$, and its set $\text{ext}(\bar{C})$ of extreme points.

$$\bar{C} = \left\{ \sum_{x \in \text{ext}(\bar{C})} p(x) x \in \mathbb{R}^d : p \in \bar{\mathcal{P}}(\text{ext}(\bar{C})) \right\}$$

$$\varphi : \bar{\mathcal{P}}(\text{ext}(\bar{C})) \rightarrow \bar{C}, \quad p \mapsto \varphi(p) := \sum_{x \in \text{ext}(\bar{C})} p(x) x$$

The set $\varphi^{-1}(\{\kappa\})$ is a convex set. Choose that member p_κ that has maximal entropy. This corresponds to the canonical representation.

Information geometry of polytopes, the main idea

The image of the map $\kappa \mapsto p_\kappa$ is the closure of an exponential family $\mathcal{E} = \mathcal{E}(\mathcal{C})$. Take the push-forward of the induced geometry

$(\mathcal{E}, g|_{\mathcal{E}}, \overset{m}{\nabla}|_{\mathcal{E}}, \overset{e}{\nabla}|_{\mathcal{E}})$. In particular,

$$D(\kappa \parallel \sigma) := D(p_\kappa \parallel p_\sigma).$$

Application of this idea to the setting of Markov kernels

Polytope of Markov kernels

$$\bar{\mathcal{C}} := \bar{\mathcal{C}}(\mathcal{X}; \mathcal{Y}) = \left\{ \kappa \in \mathbb{R}^{\mathcal{X} \times \mathcal{Y}} : \kappa(x; y) \geq 0, \quad \sum_y \kappa(x; y) = 1 \right\}$$

$$f \in \mathcal{Y}^{\mathcal{X}}, \quad \kappa_f(x; y) := \delta_{f(x)}(y), \quad \text{ext}(\bar{\mathcal{C}}) = \left\{ \kappa_f : f \in \mathcal{Y}^{\mathcal{X}} \right\}$$

$$\varphi : \bar{\mathcal{P}}(\mathcal{Y}^{\mathcal{X}}) \rightarrow \bar{\mathcal{C}}, \quad p \mapsto \varphi(p) := \sum_f p(f) \kappa_f$$

Corresponding exponential family

$$\mathcal{E} = \mathcal{E}(\mathcal{C}) = \frac{e^{\sum_{x,y} \theta_{x,y} \kappa_{\cdot}(x;y)}}{\sum_{f \in \mathcal{Y}^{\mathcal{X}}} e^{\sum_{x,y} \theta_{x,y} \kappa_f(x;y)}}$$

Proposition

The restriction $\varphi|_{\bar{\mathcal{E}}}$ has the inverse

$$\varphi^{-1} : \bar{\mathcal{C}} \rightarrow \bar{\mathcal{E}}, \quad \kappa \mapsto p_{\kappa} := \bigotimes_{x \in \mathcal{X}} \kappa(x; \cdot).$$

Example: Structural equation model and Markov kernels

Structural equation model

Consider \mathcal{Z} and $F : \mathcal{X} \times \mathcal{Z} \rightarrow \mathcal{Y}$

$$y = F(x, z), \quad z \text{ disturbance with distribution } p$$

$$\leadsto \quad \kappa(x; y) := \sum_{z \in \mathcal{Z}} p(z) \delta_{F(x, z)}(y) = \sum_{z \in \mathcal{Z}} p(z) \delta_{F_z(x)}(y)$$

$$\Rightarrow \quad \kappa(x; \cdot) \in \bar{\mathcal{P}}(\mathcal{Y}) \quad \text{for all } x$$

Canonical representation

Given κ , choose $\mathcal{Z} := \mathcal{Y}^{\mathcal{X}}$,

$$F : \mathcal{X} \times \mathcal{Y}^{\mathcal{X}} \rightarrow \mathcal{Y}, \quad (x, f) \mapsto f(x), \quad \text{and}$$

$$p_{\kappa}(f) := \prod_{x \in \mathcal{X}} \kappa(x; f(x))$$

Fisher metric

$$g_{\kappa}(A, B) := \sum_{x,y} \frac{1}{\kappa(x; y)} A(x; y) B(x; y)$$

m -Geodesics

$$\gamma^{(m)}(t) := (1 - t) \kappa(x; y) + t \sigma(x; y)$$

e -Geodesics

$$\gamma^{(e)}(t) := \frac{\kappa(x; y)^{1-t} \sigma(x; y)^t}{\sum_{y'} \kappa(x; y')^{1-t} \sigma(x; y')^t}$$

Relative entropy

$$D(\kappa \parallel \sigma) := D(p_{\kappa} \parallel p_{\sigma}) = \sum_{x,y} \kappa(x; y) \ln \frac{\kappa(x; y)}{\sigma(x; y)}$$

Affine action

$f, g \in \mathbb{R}^{\mathcal{X} \times \mathcal{Y}}$:

$$f \sim g \quad :\Leftrightarrow \quad f - g \in \mathbb{R}^{\mathcal{X}}$$

$$\mathcal{V} := \mathbb{R}^{\mathcal{X} \times \mathcal{Y}} / \mathbb{R}^{\mathcal{X}}$$

$$\mathcal{C} \times \mathcal{V} \rightarrow \mathcal{C}, \quad (\kappa, f + \mathbb{R}^{\mathcal{X}}) \mapsto \frac{\kappa e^f}{\sum_y \kappa(\cdot; y) e^{f(\cdot; y)}}$$

Proposition

The affine subspaces of $\mathcal{C}(\mathcal{X}; \mathcal{Y})$ are the exponential families in $\mathcal{C}(\mathcal{X}; \mathcal{Y})$. Given a subspace \mathcal{L} of dimension $|\mathcal{X}| + d$ with $\mathbb{R}^{\mathcal{X}} \subseteq \mathcal{L} \subseteq \mathbb{R}^{\mathcal{X} \times \mathcal{Y}}$, and given a reference element κ , the following subfamily is a d -dimensional exponential family:

$$\mathcal{E}(\kappa, \mathcal{L}) := \left\{ \frac{\kappa e^f}{\sum_y \kappa(\cdot; y) e^{f(\cdot; y)}} : f \in \mathcal{L} \right\}$$

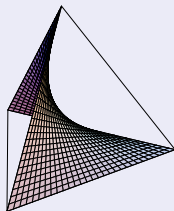
Maximization of Entropy Distance from Exponential Families

based on Ay 2002, Matúš & Ay 2003

Multi-Information as an Example

Family of product distributions

$$\begin{aligned}\otimes : \bar{\mathcal{P}}(\mathcal{X}_1) \times \cdots \times \bar{\mathcal{P}}(\mathcal{X}_N) &\rightarrow \bar{\mathcal{P}}(\mathcal{X}_1 \times \cdots \times \mathcal{X}_N) \\ (p_1, \dots, p_N) &\mapsto p_1 \otimes \cdots \otimes p_N\end{aligned}$$



Definition of multi-information

$$I : \bar{\mathcal{P}}(\mathcal{X}_1 \times \cdots \times \mathcal{X}_N) \rightarrow \mathbb{R}, \quad p \mapsto I(p) := \inf_{q \in \text{im}(\otimes)} D(p \parallel q)$$

General problem

Given an exponential family \mathcal{E} , maximize the function

$$D_{\mathcal{E}} : \bar{\mathcal{P}} \rightarrow \mathbb{R}, \quad p \mapsto \inf_{q \in \mathcal{E}} D(p \parallel q).$$

Results

- 1 Support bound: Let p be a local maximizer of $D_{\mathcal{E}}$. Then

$$|\text{supp}(p)| \leq \dim(\mathcal{E}) + 1$$

In particular, $H(p) \leq \ln(\dim(\mathcal{E}) + 1)$.

- 2 Extended exponential families: There exists an exponential family $\tilde{\mathcal{E}}$ of dimension

$$\dim(\tilde{\mathcal{E}}) \leq 3 \dim(\mathcal{E}) + 2$$

that contains \mathcal{E} and all local maximizers of $D_{\mathcal{E}}$ in its closure.

Applied to multi-information

- ① Let p be a local maximizer of the multi-information. Then

$$|\text{supp}(p)| \leq \sum_{i=1}^N (|\mathcal{X}_i| - 1) + 1 \quad (= N + 1 \ll 2^N \text{ for binary nodes})$$

In particular

$$H(p) \leq \ln \left(\sum_{i=1}^N (|\mathcal{X}_i| - 1) + 1 \right).$$

- ② There exists an exponential family of dimension at most

$$3 \sum_{i=1}^N (|\mathcal{X}_i| - 1) + 2 \quad (3N + 2 \ll 2^N - 1 \text{ for binary nodes})$$

that contains all local maximizers of the multi-information in its closure.

Multi-Information for Kernels

Factorized kernels

Consider a set $[N]$ of nodes with input symbols \mathcal{X}_i and output symbols \mathcal{Y}_i and denote with \mathcal{X} and \mathcal{Y} the products.

$$\otimes : \prod_{i \in [N]} \bar{\mathcal{C}}(\mathcal{X}_i; \mathcal{Y}_i) \hookrightarrow \bar{\mathcal{C}}(\mathcal{X}; \mathcal{Y})$$

$$(\kappa_i)_i \mapsto (\otimes_i \kappa_i)(x; y) := \kappa_1(x_1; y_1) \cdots \kappa_N(x_N; y_N)$$

This is the closure of an exponential family in $\mathcal{C}(\mathcal{X}; \mathcal{Y})$ of dimension

$$\sum_{i=1}^N |\mathcal{X}_i| (|\mathcal{Y}_i| - 1)$$

Multi-information

$$I(\kappa) := \inf_{\sigma \in \text{im}(\otimes)} D(\kappa \| \sigma)$$

Local maximizers

Let κ be a local maximizer of I . Then the dimension of the face $F(\kappa)$ of $\bar{\mathcal{C}}(\mathcal{X}; \mathcal{Y})$ in which κ is contained is upper bounded by

$$d := \sum_{i=1}^N |\mathcal{X}_i| (|\mathcal{Y}_i| - 1) \quad (d = 2N \text{ for binary nodes})$$

The theorem of Carathéodory implies there are at most $d + 1$ functions so that κ can be written as their convex combination:

$$\kappa = \sum_f p(f) \kappa_f$$

This implies

$$|\text{supp } \kappa(x; \cdot)| \leq d + 1$$

and therefore $H(Y | X) \leq \ln(d + 1)$ for any distribution of X .

Low-dimensional exponential families

There exists an exponential family \mathcal{E} of dimension at most $3d + 2$ such that all maximizers of the multi-information are contained in the set

$$\left\{ \sum_{f \in \mathcal{Y}^{\mathcal{X}}} p(f) \kappa_f : p \in \bar{\mathcal{E}} \right\} \subseteq \bar{\mathcal{C}}(\mathcal{X}; \mathcal{Y})$$

A second approach based on Stephan Weis' dissertation, University of Erlangen Nuremberg 2009

A different way to see the previous approach

The previous geometry can also be obtained by the affine embedding

$$\bar{\mathcal{C}}(\mathcal{X}; \mathcal{Y}) \hookrightarrow \bar{\mathcal{P}}(\mathcal{X} \times \mathcal{Y}), \quad \kappa \mapsto \frac{1}{|\mathcal{X}|} \kappa$$

The more general affine embedding:

$$\kappa \mapsto \rho \otimes \kappa, \quad (\rho \otimes \kappa)(x; y) := \rho(x) \kappa(x; y).$$

It does change the geometry but does not change the results on maximizers of multi-information.

Stationarity and the Kirchoff polytope

Consider

$$\begin{aligned}\otimes : \bar{\mathcal{P}}(\mathcal{X}) \times \bar{\mathcal{C}}(\mathcal{X}; \mathcal{X}) &\rightarrow \bar{\mathcal{P}}(\mathcal{X} \times \mathcal{X}), \\ (\rho, \kappa) &\mapsto (\rho \otimes \kappa)(x; x') := \rho(x) \kappa(x; x')\end{aligned}$$

Remark: This map is surjective but at the boundary not injective.

Assume stationarity:

$$\bar{\mathcal{S}}(\mathcal{X}) := \left\{ \rho \in \bar{\mathcal{P}}(\mathcal{X} \times \mathcal{X}) : \sum_{x'} \rho(x, x') = \sum_{x'} \rho(x', x) \right\}$$

We have the following correspondence:

$$\mathcal{S}(\mathcal{X}) \longleftrightarrow \mathcal{C}(\mathcal{X}; \mathcal{X})$$

Multi-information

Consider N nodes with state sets \mathcal{X}_i and the following map:

$$\otimes : \bar{\mathcal{S}}(\mathcal{X}_1) \times \cdots \times \bar{\mathcal{S}}(\mathcal{X}_N) \rightarrow \bar{\mathcal{S}}(\mathcal{X}_1 \times \cdots \times \mathcal{X}_N)$$

Note that $\text{im}(\otimes)$ is not an exponential family. It is the intersection of an exponential family with a convex set.

$$I(p) := \inf_{q \in \text{im}(\otimes)} D(p \parallel q)$$

Extreme points of $\bar{\mathcal{S}}(\mathcal{X})$

Consider a set $\emptyset \neq \mathcal{U} \subseteq \mathcal{X}$ and a cyclic permutation $\pi : \mathcal{U} \rightarrow \mathcal{U}$.

$$c(\mathcal{U}, \pi)(x, x') := \frac{1}{|\mathcal{U}|} \cdot \begin{cases} 1, & \text{if } \pi(x) = x' \\ 0, & \text{otherwise} \end{cases}$$

The number of extreme points

$$|\text{ext}(\bar{\mathcal{S}}(\mathcal{X}))| = \sum_{k=1}^{|\mathcal{X}|} \binom{|\mathcal{X}|}{k} (k-1)! \leq |\mathcal{X}|^{|\mathcal{X}|} = |\text{ext}(\bar{\mathcal{C}}(\mathcal{X}; \mathcal{X}))|$$

$ \mathcal{X} $	dim	$ \text{ext}(\bar{\mathcal{S}}(\mathcal{X})) $	$ \text{ext}(\bar{\mathcal{C}}(\mathcal{X}; \mathcal{X})) $
2	2	3	4
3	6	8	27
4	12	24	256
5	20	89	3125

Local maximizers

Each local maximizer p of I satisfies

$$\dim(F(p)) \leq \sum_{i=1}^N (|\mathcal{X}_i|^2 - |\mathcal{X}_i|) \quad (= 2N \text{ for binary nodes})$$

With the Carathéodory theorem there are at most $\sum_{i=1}^N (|\mathcal{X}_i|^2 - |\mathcal{X}_i|) + 1$ cycles so that p can be represented as convex combination of them. This implies that for all x with $\sum_{x'} p(x, x') > 0$:

$$|\text{supp} p(\cdot | x)| \leq \sum_{i=1}^N (|\mathcal{X}_i|^2 - |\mathcal{X}_i|) + 1,$$

which implies

$$H(X' | X) \leq \ln \left(\sum_{i=1}^N (|\mathcal{X}_i|^2 - |\mathcal{X}_i|) + 1 \right)$$

Information Geometry and its Applications III

August 2 - 6, 2010 MPI for Mathematics in the Sciences, Leipzig, Germany

<http://www.mis.mpg.de/calendar/conferences/2010/infgeo.html>