



Cognition and Inference in an abstract setting

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Two examples

Shannon Theory, MaxEnt:

states: Distributions $x = (x_i)_{i=0,1,\dots}$;

Kerridge inaccuracy: $\Phi(x, y) = \sum x_i \log \frac{1}{y_i}$;

Entropy: $H(x) = \sum x_i \log \frac{1}{x_i}$;

Divergence: $D(x, y) = \sum x_i \log \frac{x_i}{y_i}$;

preparation: A set \mathcal{P} of distributions, say those with given mean "energy": $\mathcal{P} = \{x \mid \sum_0^\infty x_i E_i = \bar{E}\}$.

Problem: Search for the MaxEnt distribution in \mathcal{P} .

Euclidean space, projection:

states: Elements in $X = \mathbb{R}^2$, say;

prior: $y_0 \in X$;

preparation: some (convex) subset \mathcal{P} of X ;

Problem: Find the projection of y_0 on \mathcal{P} .



Information triples, I

Goal of talk: Indicate to you that information theoretical thinking is useful in a much broader context than that known from Shannon theory; we may even free ourselves from the tie to probability based modelling.

Our start for an abstract theory: **information triples**:

Either **effort-based**: (Φ, H, D) if \dots (see next slide)
 or **utility-based**: (U, M, D) , i.e. $(-U, -M, D)$ is effort-based.

Examples:

$$\mathbf{1:} \quad \Phi(x, y) = \sum x_i \log \frac{1}{y_i}, \quad H(x) = \sum x_i \log \frac{1}{x_i}, \\ D(x, y) = \sum x_i \log \frac{x_i}{y_i}.$$

$$\mathbf{2:} \quad U(x, y) = \|x - y_0\|^2 - \|x - y\|^2, \\ M(x) = \|x - y_0\|^2, \quad D(x, y) = \|x - y\|^2.$$

State space X ; elements are **states** or **truth instances**, (x) .

Will study **preparations**, i.e. non-empty subsets $\mathcal{P} \subseteq X$.

Belief reservoir Y ; elements are **belief instances**, (y) .

For this talk: $X = Y$.



Information Triples, II, (Φ, H, D) and (U, M, D)

Φ and D (U and D) are defined on $X \times Y$, H (M) on X .

AXIOM 1 (the basics) $\Phi > -\infty$ ($U < +\infty$)

$\Phi(x, y) = H(x) + D(x, y)$, the **linking identity** ($U = M - D$)

$D(x, y) \geq 0$ with equality iff $y = x$, the **fundamental inequality**.

Φ is the **description** or the **effort function**,

H is **min-effort** or **entropy**, D is **divergence**.

(U the **utility** M the **max-utility**)

Add convexity! Use $\bar{x} = \sum \alpha_j x_j$ for a convex combination.

AXIOM 2 (affinity) X is a convex space and, for each y , the marginal function Φ^y (U^y) is affine.



First consequences, convexity properties

Lemma

$$(i) \quad H(\bar{x}) = \sum \alpha_i H(x_i) + \sum \alpha_i D(x_i, \bar{x}).$$

(ii) If $H(\bar{x}) < \infty$, $y \in Y$, then **compensation identity** holds:

$$\sum \alpha_i D(x_i, y) = \sum \alpha_i D(x_i, \bar{x}) + D(\bar{x}, y).$$

Proof (i): rhs = $\sum \alpha_i \Phi(x_i, \bar{x}) = \Phi(\bar{x}, \bar{x}) = H(\bar{x})$.

(ii): lhs of (i)+lhs of (ii)

$$= \sum \alpha_i H(x_i) + \sum \alpha_i D(x_i, y) + \sum \alpha_i D(x_i, \bar{x})$$

$$= \sum \alpha_i \Phi(x_i, y) + \sum \alpha_i D(x_i, \bar{x})$$

$$= \Phi(\bar{x}, y) + \sum \alpha_i D(x_i, \bar{x})$$

$$= H(\bar{x}) + D(\bar{x}, y) + \sum \alpha_i D(x_i, \bar{x}).$$

Now subtract $H(\bar{x})$. \square



Updating

Problem: Given **prior** y_0 , to define utility function $U_{|y_0}$ such that $U_{|y_0}(x, y)$ is a measure of the **updating gain** when truth is x and your **posterior belief** is y . Typically, the posterior is sought among y 's in a given preparation \mathcal{P} .

1. **Defined as saved effort:** Based on triple (Φ, H, D) :

$$U_{|y_0}(x, y) = \Phi(x, y_0) - \Phi(x, y) \quad (1)$$

$$= D(x, y_0) - D(x, y). \quad (2)$$

2. **Directly via D:** Given only D , use (2) as definition. This gives utility-based triple $(U_{|y_0}, D^{y_0}, D)$. Technically, assume that $D^{y_0} < \infty$ on preparations \mathcal{P} you want to consider.

This defines genuine triples satisfying axioms 1 and 2 iff D satisfies the fundamental inequality and the compensation identity.

Conclude: Problems of updating can be treated as special cases of inference for information triples.



Games of information: Observer versus Nature

Game $\gamma = \gamma(\mathcal{P}) = \gamma(\mathcal{P}|\Phi)$ has Φ as **objective function**, Nature as **maximizer** with **strategies** $x \in \mathcal{P}$, Observer as **minimizer** with **strategies** $y \in Y$.

Values of γ are, for Nature MaxEnt and, for Observer, MinRisk:

$$H_{\max}(\mathcal{P}) = \sup_{x \in \mathcal{P}} H(x) = \sup_{x \in \mathcal{P}} \inf_y \Phi(x, y).$$

$$Ri_{\min}(\mathcal{P}) = \inf_y Ri(y) = \inf_y \sup_{x \in \mathcal{P}} \Phi(x, y).$$

$x^* \in \mathcal{P}$ **optimal strategy for Nature** $\therefore H(x^*) = H_{\max}(\mathcal{P})$.

$y^* \in Y$ **optimal strategy for Observer** $\therefore Ri(y^*) = Ri_{\min}(\mathcal{P})$.

Minimax inequality: $H_{\max} \leq Ri_{\min}$.

If $H_{\max} = Ri_{\min} < \infty$, γ is in **equilibrium**.

If γ is in equilibrium and both players have optimal strategies, these are unique and coincide. The strategy in question $y^* = x^*$ is the **bi-optimal strategy**.



Nash and Pythagoras

Theorem [Axiom 1] Given $y^* = x^* \in \mathcal{P}$ with $H(x^*) < \infty$. Then the following conditions are equivalent:

- $\gamma(\mathcal{P})$ is in equilibrium with x^* as bi-optimal strategy;
- The Nash-saddle-value inequalities hold;
- For all $x \in \mathcal{P}$, the abstract Pythagorean inequality holds:

$$H(x) + D(x, y^*) \leq H(x^*) \quad (3)$$

$$\left(M(x) \geq D(x, y^*) + M(x^*) \text{ for utility-based model} \right) \quad (4)$$

$$\left(D(x, y_0) \geq D(x, y^*) + D(x^*, y_0) \text{ for updating} \right). \quad (5)$$

With $D(x, y) = \|x - y\|^2$, (5) is the classical inequality.

Theorem [Axioms 1+2] The condition that x^* is an optimal strategy for Nature is sufficient to ensure that (3)[(4)/(5)] holds. For the updating model the condition is that x^* is the D-projection of y_0 on \mathcal{P} .



Adding a geometric flavour

We only do this for the models of updating. Two type of sets will be involved: **open divergence balls** and **open half spaces**:

$$B(y_0, r) = \{D(x, y_0) < r\}$$

$$\begin{aligned} \sigma^+(y|y_0) &= \{U_{|y_0} < D(y, y_0)\} \\ &= \{D(x, y_0) < D(x, y) + D(y, y_0)\}. \end{aligned}$$

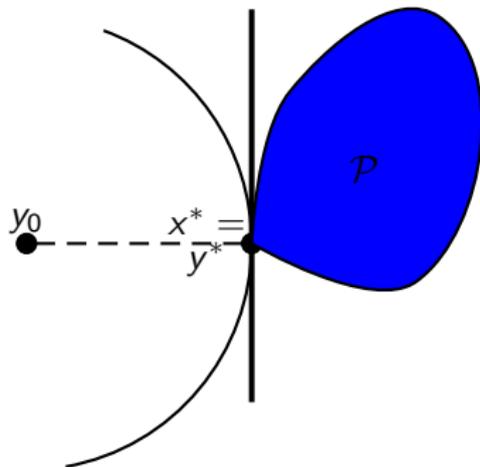
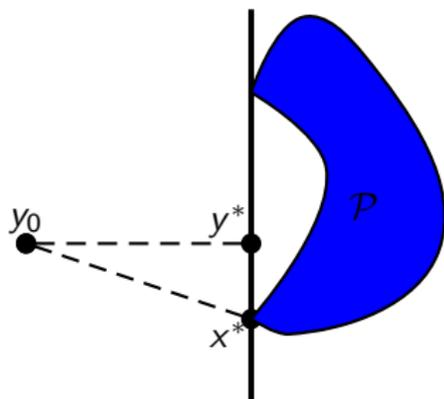
The **sizes** of these sets are, respectively, r and $D(y, y_0)$.

For the updating game $\gamma(\mathcal{P} | U_{|y_0})$, the MinDiv-value $D_{\min}^{y_0}(\mathcal{P})$ is the size of the largest ball $B(y_0, r)$ which is **external to \mathcal{P}** (i.e. contained in the complement of \mathcal{P}), and the other value of the game, the **maximal guaranteed updating gain** is, loosely expressed, the size of the largest half space external to \mathcal{P} .

In particular, $\gamma(\mathcal{P} | U_{|y_0})$ is in equilibrium and has a bi-optimal strategy if and only if, for some $y \in \mathcal{P}$, the half-space $\sigma^+(y|y_0)$ is external to \mathcal{P} . When this condition holds, y is the bi-optimal strategy, in particular, y is the D -projection of y_0 on \mathcal{P} .



optimal strategies under no equilibrium/
and under equilibrium



Topics left out

- Tsallis entropy
- Bregman divergencies
- Feasible preparations
- Control and description
- Core, an abstract notion generalizing exponential families



Instead of conclusions

- Should Shannon Theory be taught and learned this way?
- Is the philosophical approach important – and helpful?
- Is the focus on game theory justified?
- Is the abstract approach also the right entrance point to areas of pure mathematics (optimization, duality theory ...)?
- – and to areas of (statistical) physics?
- Is the theory a good “selling argument” which could pave the way for more widespread adoption and recognition of ideas of Information Theory as initiated by Shannon?

My preliminary answers: I believe in a great potential of the theory indicated, but to which extent it is justified as a “stand alone theory” and to which extent it is a supplement to existing theories is of course not clear right now.

