

How to keep an expert honest or how to prevent misinformation

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CONTENT

PART I: how to **prevent misinformation** , abstractly and in concrete probabilistic models. **Entropy** and **divergence**

PART II: Philosophy connecting **truth**, **belief** and **knowledge** with applications to probabilistic models related to **Tsallis entropy**.

PART III: Outlook

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MORE INFORMATION: See
<http://www.math.ku.dk/topsoe/manuscripts/>
(The ms. **"Paradigms of Cognition"** will be available primo October, I think)

Adviser \leftrightarrow Investor

x : Advisers best advice.

y : Advice actually given.

For dubious reasons, **misinformation** ($y \neq x$) may take place.

task: **prevent misinformation!**

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Same problem in another setting: **Expert** \leftrightarrow **You**, say a meteorologist giving advice to you.

task: **keep expert honest, encourage professionalism!**

Solution strategy

Select a function $\Phi = \Phi(x, y)$ such that

$$\Phi(x, y) \geq \Phi(x, x)$$

with equality only if there is a **perfect match**, i.e. $y = x$.

Strategy: Pay Adviser an up-front fee and supply with an **insurance scheme**, according to which Adviser has to pay you a **penalty** $\Phi(x, y)$ as soon as you have seen what really happened.

This prevents misinformation, encourages honesty!

The principle (penalty minimized only if there is a perfect match) we call the **Perfect Match Principle** (PMP) and a function Φ with the required properties we call a **PMP-function**.

entropy and divergence (assuming Φ is PMP-function)

Define:

entropy = minimal penalty and divergence = excess penalty:

$$H(x) = \Phi(x, x),$$
$$D(x, y) = \Phi(x, y) - \Phi(x, x).$$

Then $\Phi(x, y) = H(x) + D(x, y)$, the **linking identity**.

The PMP-property may be turned into the inequality

$$D(x, y) \geq 0 \text{ with equality iff } y = x.$$

This is the **fundamental inequality** (FI).

... but how to find a PMP-function? Let us turn to an example!

Example: A probabilistic model

\mathbb{A}	x	y	local penalty
\cdot	\cdot	\cdot	\cdot
i	x_i	y_i	$\phi(x_i, y_i)$
\cdot	\cdot	\cdot	\cdot

x 's and y 's are *probability distributions* over an **alphabet** \mathbb{A} . Assume that $\Phi(x, y) = \sum_{i \in \mathbb{A}} \phi(x_i, y_i)$ where $\phi(s, t) = s\kappa(t)$ for a suitable **penalty generator** κ (a smooth function on $[0, 1]$ with $\kappa(1) = 0$, normalized so that $\kappa'(1) = -1$).

Φ is **average penalty**: $\Phi(x, y) = \sum_{i \in \mathbb{A}} x_i \kappa(y_i)$.

Theorem: Only *one* penalty generator turns Φ into a PMP-function: $\kappa(t) = \ln \frac{1}{t}$. With this choice, entropy becomes **Shannon entropy** and divergence becomes **Kulback-Leibler divergence**: $H(x) = \sum x_i \ln \frac{1}{x_i}$, $D(x, y) = \sum x_i \ln \frac{x_i}{y_i}$.

the pointwise fundamental inequality

Proof of PMP-property when $\kappa(t) = \ln \frac{1}{t}$:

First adjust ϕ : $\tilde{\phi}(s, t) = \phi(s, t) + t$,

then, instead of proving

$$\sum \phi(x_i, y_i) \geq \sum \phi(x_i, x_i),$$

we prove that

$$\sum \tilde{\phi}(x_i, y_i) \geq \sum \tilde{\phi}(x_i, x_i).$$

Even the **pointwise fundamental inequality** (PFI) holds:

$$\tilde{\phi}(s, t) \geq \tilde{\phi}(s, s).$$

Indeed,

$$s \ln \frac{1}{t} + t \geq s \ln \frac{1}{s} + s$$

as

$$s \ln \frac{s}{t} \geq s(1 - \frac{t}{s}) = s - t.$$

□

PART II: philosophy ...

truth, belief and knowledge

Before, x was a kind of truth. Now change the underlying interpretations so that x is **truth**, conceived as “genuine truth” or even “absolute truth”— a truth which is held by **Nature** .

Introduce also **Observer**, (could be a physicist, a statistician or a probabilist).

Nature does not give advice. So instead of advice, we now take y to represent Observers **belief**.

Knowledge is conceived as the *synthesis of extensive experience*, in probabilistic models corresponding to the regime where the laws of large numbers have taken over.

Worlds and interactors

The interaction Nature \leftrightarrow Observer takes place in a **world**, \mathcal{W} .
Observer studies **situations** from the world, characterized by **instances** of the central concepts.

Another aspect of knowledge: *it is the way the world presents truth to Observer in any situation.*

C r u c i a l assumption: This depends on the **truth instance** x and on the **belief instance** y .

The **knowledge instance**, z , is thus a function of x and y :

$$z = \Pi(x, y) \text{ with } \Pi \text{ the } \mathbf{interactor}.$$

examples of worlds

The **classical world**, \mathcal{W}_1 , is characterized by the interactor

$$\Pi_1(x, y) = x.$$

It is a *world of observable truth*. *What you see is what is true* (WYSIWIT).

Another extreme: a **black hole**, \mathcal{W}_0 , characterized by the interactor

$$\Pi_0(x, y) = y.$$

In this world, *what you see is what you believe* (WYSIWYB).

Mixtures: $\Pi_q(x, y) = qx + (1 - q)y$ define **Tsallis worlds**, \mathcal{W}_q .

All worlds we shall consider will be **sound**, that is $\Pi(x, y) = x$ provided *belief matches truth* ($y = x$).

probabilistic modeling

\mathbb{A}	x	y	z	effort
\cdot	\cdot	\cdot	\cdot	\cdot
i	x_i	y_i	z_i	$\phi(x_i, y_i) = z_i \kappa(y_i)$
\cdot	\cdot	\cdot	\cdot	\cdot

Modeling as before except now

$$\Pi(x, y) = (\pi(x_i, y_i))_{i \in \mathbb{A}}$$

with π the **local interactor** and

$$\phi(s, t) = \pi(s, t) \kappa(t)$$

Interpretations: Now ϕ determines the **description effort** or the **description cost** and κ is the **generator**. The PMP is now the natural principle for Observer to strive for a generator which ensures that effort is minimized when there is a perfect match.

Theorem: Given π , only one generator could possibly lead to a ϕ which satisfies the PMP.

proof

Proof: Assume PMP holds with κ as generator. For $0 < t < 1$ put

$$f(t) = \chi(t)\kappa(t) + t\kappa'(t)$$

where

$$\chi(t) = \frac{\partial \pi}{\partial t}(t, t).$$

Consider a probability vector $x = (x_1, x_2, x_3)$ with positive point probabilities. By PMP F given by

$$F(y) = F(y_1, y_2, y_3) = \sum_1^3 \pi(x_i, y_i)\kappa(y_i)$$

on $]0, 1[\times]0, 1[\times]0, 1[$ assumes its minimal value for the interior point $y = x$ when restricted to probability distributions. Thus, there exists a Lagrange multiplier λ such that

... continued ...

$$\frac{\partial}{\partial y_i} (F(y_1, y_2, y_3) - \lambda \sum_1^3 y_i) = 0 \text{ for } i = 1, 2, 3$$

when $y = x$. This shows that $f(x_1) = f(x_2) = f(x_3)$. Using this with $(x_1, x_2, x_3) = (\frac{1}{2}, x, \frac{1}{2} - x)$ for $x \in]0, \frac{1}{2}[$, we find that f is constant on $]0, \frac{1}{2}[$. probability vector $(x, \frac{1}{2}(1 - x), \frac{1}{2}(1 - x))$ and conclude from the first part of the proof that $f(x) = f(\frac{1}{2}(1 - x))$. As $0 < \frac{1}{2}(1 - x) < \frac{1}{2}$, we conclude that $f(x) = f(\frac{1}{2})$. Thus f is constant on $]0, 1[$. By letting $t \rightarrow 1$ and assuming suitable smooth behaviour, we conclude that the constant is -1 . We have seen that κ must be the unique solution in $]0, 1[$ to

$$x(t)\kappa(t) + t\kappa'(t) = -1$$

for which $\kappa(1) = 0$. \square

Tsallis entropy

Below, \ln_q is the q -logarithm:

$$\ln_q t = \begin{cases} \ln t & \text{if } q = 1 \\ \frac{1}{1-q} (t^{1-q} - 1) & \text{otherwise.} \end{cases}$$

Theorem: If π is **consistent**, (i.e. $\sum z_i = 1$ is ensured), then the world must be one of the Tsallis worlds \mathcal{W}_q . If $q < 0$, PMP cannot be realized. If $q \geq 0$ there is a unique generator s.t. PMP holds, viz. the generator $\kappa_q(t) = \ln_q \frac{1}{t}$. The case $q = 0$ is a singular case for which divergence vanishes. When $q > 0$, PMP holds in its full form. The entropy obtained for $q \geq 0$ coincides with **Tsallis entropy**.

Proof (sketch): Consistency \Rightarrow Tsallis world: easy! Differential equation from previous theorem: $(1 - q)\kappa(t) + t\kappa'(t) = -1$ gives $\kappa(t) = \ln_q \frac{1}{t}$. Counterexamples rules out $q < 0$ if PMP is to hold. That PMP does hold when $q \geq 0$ follows as PFI holds (apply geometric/arithmetical mean inequality). \square

PART III: Outlook

- ▶ information without probability, paradigms of cognition
- ▶ belief as a tendency to act
- ▶ **control** derived from belief
- ▶ **description effort**, or **description cost**
- ▶ multiple worlds with the same generator (κ -function)
- ▶ the choice of **unit** (as cost pr. observation)
- ▶ “what *can* you know?”, **feasible preparations**
- ▶ notions of **equilibrium** (**robustness**, **Nash equilibrium**)
- ▶ **exponential families**, the **maximum entropy principle**
- ▶ **information projections**, **pythagorean theorems**