

# Operational Subjective Statistical Methods: a primer on subjective probability and statistics in the mode of Bruno de Finetti

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## Topics for this primer:

- Quantities
- Coherent prevision
- Coherent conditional prevision
- The Fundamental Theorem of Prevision
- Exchangeable assertions
- Sequential forecasting
- Proper Scoring Rules

## Basic Concepts and Definitions:

Observable quantities ...  $X$

Realm of  $X$  ...  $\mathfrak{R}(X) = \{x_1, x_2, \dots, x_K\}$

Your prevision for  $X$  ... by asserting  $P(X)$   
you avow your indifference to  $\$X$  or  $\$P(X)$   
scaling down the monetary units

Events ... When  $\mathfrak{R}(E) = \{0, 1\}$  ...

$P(E)$  is also called your probability for  $E$

Partition vector ...

$$\mathbf{Q}_K \equiv [(X = x_1), (X = x_2), \dots, (X = x_K)]^T$$

Your  $P(X)$  is coherent ... as long as

No  $s$  pos or neg for which

$s(x - P(X)) < 0$  for every  $x \in \mathfrak{R}(X)$ .

Otherwise you are a “sure loser” !

## Definitions for a Vector of Quantities:

A vector of quantities ...  $\mathbf{X}_N \in \mathfrak{R}(\mathbf{X}_N) = \{\mathbf{x}_{N1}, \mathbf{x}_{N2}, \dots, \mathbf{x}_{NK}\}$

Constituents of the partition it generates ...

specify the logical relations among its components:

$$\mathbf{Q}_K = [(\mathbf{X}_N = \mathbf{x}_{N1}), (\mathbf{X}_N = \mathbf{x}_{N2}), \dots, (\mathbf{X}_N = \mathbf{x}_{NK})]^T$$

$$\text{Note: } \mathbf{X}_N = \mathbf{R}(\mathbf{X}_N) \mathbf{Q}_K$$

where  $\mathbf{R}(\mathbf{X}_N)$  is an  $(N \times K)$  “realm matrix”

## Coherence of $P(\mathbf{X}_N)$

Your prevision for  $\mathbf{X}_N$  ... a vector of such prices

The assertion  $P(\mathbf{X}_N)$  is coherent ...

there is no vector  $\mathbf{s}_N$  for which

$$\mathbf{s}_N^T [\mathbf{x}_N - P(\mathbf{X}_N)] < 0$$

for every  $\mathbf{x}_N \in \mathfrak{R}(\mathbf{X}_N)$ .

Coherent  $P(\mathbf{X}_N)$  must lie within the convex hull of  $\mathfrak{R}(\mathbf{X}_N)$

since there is no hyperplane that can separate  $P(\mathbf{X}_N)$  from  $\mathfrak{R}(\mathbf{X}_N)$

Coherent  $P(\cdot)$  a linear operator:

your  $P(\mathbf{s}_N^T \mathbf{X}_N) = \mathbf{s}_N^T P(\mathbf{X}_N)$  for any coefficient vector  $\mathbf{s}_N$ .

# Fundamental Theorem of Prevision

Whatever you assert about any  $N$  quantities whatsoever,  
there are computable NASC bounds on your prevision for any further  
quantity  $X_{N+1}$   
if it is to cohere with your asserted  $P(\mathbf{X}_N)$ .

Think why.

This theorem includes all Prob inequalities as special cases, including  
Chebyshev and Kolmogorov

# Coherent Conditional Prevision and Conditional Quantities

Your asserting  $P(X|E)$  attests your indifference between  
 $\$P(X|E)$  and  $\$(XE + (1 - E)P(X|E))$

Having asserted  $P(X|E)$ , define  $(X|E) \equiv XE + (1 - E)P(X|E)$

Coherency requires  $P(XE) = P(X|E)P(E)$ .

Conditional probability has nothing at all to do with “before and after observing E”.



# Exchangeability and Inference

You regard  $E_1, E_2, \dots, E_N$  exchangeably if ...  
equivalently ... if you regard the sum and  $N$  as sufficient statistics!  
and exchangeably extendible to  $N + K$  if ...  
General extensions via numbers of sufficient stats.

If you regard the sequence as infinitely exchangeably extendible then your  $P(S_N = a)$  can be represented as

$\int_0^1 \theta^a (1 - \theta)^{(N-a)} dF(\theta)$  for some distribution function  $F(\cdot)$

and more

... and  $P(E_{N+1}) = \int_0^1 \theta dF(\theta|S_N = a)$

This is a representation of ...

# Proper Scoring Rules

$S(\mathbf{p}_N, X = x^o)$  is a scoring rule for  $\mathbf{p}_N$  on observing that  $X = x^o$

The rule is *proper* if

$$P\{S(\mathbf{p}_N, X = x^o)\} \geq P\{S(\mathbf{q}_N, X = x^o)\}$$

for any other  $\mathbf{q}_N$  in  $\mathbf{S}^{N-1}$ , when  $P\{\cdot\}$  is assessed with respect to  $\mathbf{p}_N$ .

## Uniqueness of the Logarithmic Scoring rule:

$$S_{\log}(\mathbf{p}_N, X = x^o) \equiv \sum_{i=1}^N E_i \log(p_i) = \log(p^o)$$

relative to other proper rules, such as :

$$\begin{aligned} S_{\text{Quadratic}}(\mathbf{p}_N, X = x^o) &\equiv -[ \sum_{i=1}^N E_i (1 - p_i)^2 + \sum_{i=1}^N \tilde{E}_i (0 - p_i)^2 ] \\ &= -[ \sum_{i=1}^N p_i^2 - 2p^o + 1 ] \end{aligned}$$

or

$$S_{\text{Spherical}}(\mathbf{p}_N, X = x^o) \equiv \sum_{i=1}^N E_i p_i / [ \sum_{i=1}^N p_i^2 ]^{1/2}$$

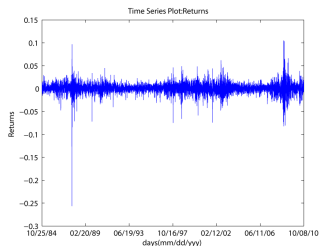
... “the only proper score that is a function only of the actual observation, not values of  $X$  that were not observed.”

... “like the likelihood principle” ... Bernardo (1979) ... WOOPS!

# Scoring forecasts of the of daily stock returns

Daily Dow-Jones returns

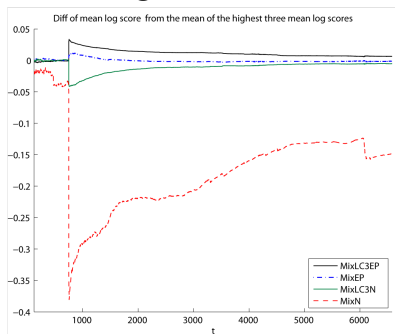
25/10/84 through 20/08/10



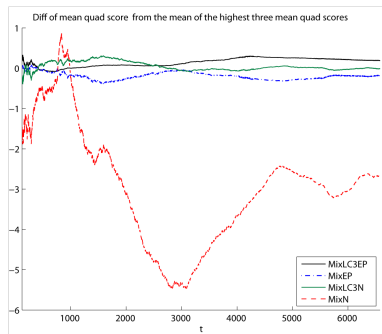
Notice the day 19/10/87 ...

# Comparative Mean Accumulating Scores

## Comparative Mean Log Scores



## Comparative Mean Quadratic Scores



Notice that larger parametric mixture structures  
do NOT ensure better scores !

MixN and MixLC3N have long periods of good Quad scoring