

# Fiducial prediction

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# Outline

- 1 Statistical models
- 2 The fiducial compromise
  - The Gosset process
- 3 Various extensions

# Statistical models

Components of a statistical model?

A parameter space  $\Theta$  (non-empty)

Space of r.vs.  $\mathcal{S} = \mathcal{R}^\infty$  (with  $\sigma$ -field)

$P: \theta \mapsto P_\theta$  (prob distn on  $\mathcal{S}$ )

Population, sample and observation (structure of  $\mathcal{S}$ )

Population (index set)  $\mathbb{N} = \{1, 2, \dots\}$

Random variable  $Y = (Y_1, Y_2, \dots)$   $Y: \mathbb{N} \rightarrow \mathcal{R}$

Sample units  $S = \{u_1, \dots, u_n\} \subset \mathbb{N}$  finite

Sample values  $Y[S] = \{(u_i, Y(u_i)) : 1 \leq i \leq n\}$

or  $\{(u_i, x(u_i), Y(u_i)) : 1 \leq i \leq n\}$  if covariates present

Generating mechanism:

For some  $\theta \in \Theta$ ,  $Y \sim P_\theta$ ,  $Y[S] \sim P_{n,\theta}$

# Inferential goals, parametric and non-parametric

Observation  $\mathbf{y} = Y[S]$  on sample  $S \subset \mathbb{N}$

Parametric inference:

Statement about  $\theta \in \Theta$

principles: likelihood, sufficiency, conditionality,...

Non-parametric (sample-space) inference:

Statements about  $Y$  such as

prequential:  $\text{pr}(Y(u') > 7.1 \mid Y[S] = \mathbf{y}) = ??$

test sample predictions (classification)

tail events  $\text{pr}(\bar{Y}_\infty < 6.8 \mid \mathbf{y}) = ??$

$p$ -value calculations?

# Techniques for inference

Inference concerned with events  $E$ , in principle observable

Root problem:  $P_\theta(E) \neq P_{\theta'}(E)$

Solution: replace  $\{P_\theta\}$  with a single compromise distn

Standard Bayes solution: (three steps)

(i) Extend space to  $\mathcal{S} \times \Theta$

(ii) Use joint distn  $P_\pi(d\theta dy) = P_\theta(dy)\pi(d\theta)$

... or use mixture  $P_\pi(dy) = \int P_\theta(dy) \pi(d\theta)$  on  $\mathcal{S}$

(iii) Compute conditional distribution  $P_\pi(E | \mathbf{y})$

Q: Are there any principled alternatives to Bayes?

(i) Fiducial?

(ii) Improper priors?

# The fiducial compromise: my interpretation

Ancillary events:  $P_\theta(A) = P_{\theta'}(A)$  for  $\theta, \theta' \in \Theta$

Full agreement on the value of  $P(A)$  for  $A \in \mathcal{A}$

Problems: ....

Suppose in addition that  $\mathcal{A}$  is a  $\sigma$ -field

Fiducial/pivotal compromise:

replace set  $\{(\mathcal{F}, P_\theta)\}$  with distn  $(\mathcal{A}, P)$  by restriction to  $A \subset \mathcal{F}$

Bayes compromise:

replace set  $\{(\mathcal{F}, P_\theta)\}$  with the average  $(\mathcal{F}, P_\pi)$

What useful inferences can we draw using the fiducial model?

We can compute  $P(E | Y = y)$  for  $E \in \mathcal{A}$  ( $E \subset \mathcal{S}$ )

Is this potentially useful or is it a dead end?

Where are the parameters?

## The standard location-scale example

$$\mathcal{S} = \mathcal{R}^\infty = \{(y_1, y_2, \dots) : y_i \in \mathcal{R}\}$$

Location-scale group elements  $g = [a, b]$

$$\text{Multiplication } [a, b][a', b'] = [a + ba', bb']$$

$\mathcal{G}$  acts on  $\mathcal{R}^\infty$  component-wise  $gy_i = a + by_i$

$\mathcal{G}$ -invariant events:  $gE = E$  for each  $g \in \mathcal{G}$

Examples:  $\{y \in \mathcal{R}^\infty : (y_n - y_1)/|y_2 - y_1| < 1\}$

$$\{y \in \mathcal{R}^\infty : (y_{n+1} - \bar{y}_n)/s_n < 1.4\}$$

$$\{y \in \mathcal{R}^\infty : (\bar{y}_{n+1:n+m} - \bar{y}_n)/s_n < 1.4\}$$

$$\{y \in \mathcal{R}^\infty : (\bar{y}_\infty - \bar{y}_n)/s_n < 1.4\}$$

$\mathcal{G}$ -invariant events are ancillary wrt *any* location-scale model

Set  $\mathcal{A} = \mathcal{B}/\mathcal{G}$  of  $\mathcal{G}$ -invariant Borel events is a  $\sigma$ -field

$\mathcal{G}$ -invariant events in  $\mathcal{R}^n$ :  $\mathcal{A}_n = \mathcal{A} \cap \mathcal{B}_n$

But there may be ancillary events that are not in  $\mathcal{A}$

## The location-scale model contd.

Fiducial compromise:

Replace  $\{(\mathcal{R}^\infty, \mathcal{B}, P_\theta)\}$  with restriction  $(\mathcal{R}^\infty, \mathcal{A}, P)$

... rather than average  $(\mathcal{R}^\infty, \mathcal{B}, P_\pi)$

Given an obs  $Y^{(n)}: (\mathcal{R}^\infty, \mathcal{A}) \rightarrow (\mathcal{R}^n, \mathcal{A}_n)$

Fiducial inference  $P(A | \mathcal{A}_n)$  for events  $A$

Fundamental problem I:

No parameters, nothing to estimate!

Fundamental problem II:

Discussion limited to invariant (ancillary) events

$P(Y_{n+1} > 4 | Y^{(n)} = \mathbf{y})$  meaningless

But we can talk about events in a relative sense

$P(Y_{n+1} > \bar{Y}_n + 4s_n | \mathbf{y})$



## Digression: Quotient-space distributions

New symbol:  $Y \sim N_n(\mathcal{K}, \mu, \Sigma)$ ;  $\mathcal{K} \subset \mathcal{R}^n$

Prob distn on  $(\mathcal{R}^n, \mathcal{B}_n/\mathcal{K})$

if  $\ker(L) = \mathcal{X}$ , then  $LY \sim N(L\mu, L\Sigma L')$   $\iff Y \sim N_n(\mathcal{K}, \mu, \Sigma)$

Many reasons for working directly with  $Y$  rather than  $LY$

directness of prediction (Kriging)

relative to what is observed (equivariant, not absolute)

Log likelihood based on  $Y \sim N_n(\mathcal{K}, \mu, \Sigma)$

$$l(\mu, \Sigma) = \frac{1}{2} \log \text{Det}(WQ) - \frac{1}{2} (y - \mu)' WQ (y - \mu)$$

$$W = \Sigma^{-1}, \quad Q = I - K(K'WK)^{-1}K'W$$

same as REML if  $\mu \in \mathcal{K}$

# Gaussian processes

Brownian motion:  $Y \sim GP(0, K)$  where

$$K(x, x') = -|x - x'|/2$$

What does this mean?

$$\Rightarrow Y(x) - Y(x') \sim N(0, K(x) + K(x') - 2K(x, x')) = N(0, |x - x'|)$$

$$Y(x_1), \dots, Y(x_n) \sim N_n(\mathbf{1}, 0, K): \mathcal{F} = \mathcal{B}_n/\mathbf{1}$$

Gaussian spline model:  $Y \sim GP(0, \delta_{x,x'} - |x - x'|^3)$

Kernel  $\mathcal{K} = \text{span}\{1, x\}$  dimension 2

meaning depends on  $\mathcal{K}$  and the implied  $\sigma$ -field

Conditional expectation is such that

$$E(Y(x^*) - \hat{\mu}(x^*) \mid Y(x_1), \dots, Y(x_n)) = \text{cubic spline in } x^*$$

Kriging = fiducial prediction = equivariant prediction

# Gaussian families and Gosset families

Parameter space  $\Theta = \mathcal{R} \times \mathcal{R}^+ = \{(\mu, \sigma) : \sigma > 0\}$

Gaussian family:  $N_\infty(\mu, \sigma^2)$  iid sequences

Gosset family:  $G_\infty(\mu, \sigma)$

$$Y_1 = \mu, \quad Y_2 = \mu \pm \sigma \quad Y_{n+1} = \bar{Y}_n + s_n \epsilon_n \sqrt{1 + 1/n}$$

- (i) Both families defined on Borel sets
- (ii) Mathematically, as dissimilar as two families can be
- (iii) Inguishable from observation on one sequence
- (iv) Identical on  $\mathcal{G}$ -invariant events
- (v) Likelihood ratio always selects Gosset
- (vi) Identical as point processes in  $\mathcal{R}^\infty (d\mu d\sigma/\sigma)$
- (vii) Gosset process gives predictions in a relative sense

## Gauss and Gosset contd

Why are these families essentially indistinguishable?

Transformation properties:

$$X = (X_1, X_2, \dots) \sim N_\infty(\mu, \sigma^2)$$

$$\text{Define } Y_i = (X_i - X_1) / |X_2 - X_1|$$

$$\text{Then } Y \sim G_\infty(0, 1)$$

$$Y = (Y_1, Y_2, \dots) \sim G_\infty(\mu', \sigma')$$

$$\text{Define } X_i = (Y_i - \bar{Y}_\infty) / s_\infty$$

$$\text{Then } X \sim N_\infty(0, 1)$$

For every invariant event  $N_\infty(\mu, \sigma^2)(A) = G_\infty(\mu, \sigma)(A)$

Gosset process is a Borel extension of the fiducial process giving the same predictions.

# Inversion: the fatal fiducial flaw?

The Fisherian argument:

location model:  $P_\mu$  such that  $Y_1, \dots \sim N(\mu, 1)$

$$P_\mu(\bar{Y}_n - \mu \in B) = N(0, 1/n)(B) \quad B \subset \mathcal{R}$$

$$\text{pr}(\bar{Y}_n - \mu < z/\sqrt{n} \mid \mu) = \Phi(z) \text{ same thing!}$$

$$\text{pr}(\mu > \bar{Y}_n - z/\sqrt{n} \mid \mathbf{y}^{(n)}) = \Phi(z) \text{ false?}$$

But ...

# The fiducial compromise

Let  $F$  be the restriction of  $P_\mu$  to  $\mathcal{A} = \mathcal{B}/\mathbf{1}$

$F$  is the inferential compromise distn/process

$B \subset \mathcal{R}$  Borel set

$A = \{y : \bar{y}_n - \bar{y}_\infty \in B\}$  is invariant event in  $\mathcal{A}$

$F(\{y : \bar{y}_n - \bar{y}_\infty \in B\}) = N(0, 1/n)(B)$  correct!

$F(\{y : \bar{y}_n - \bar{y}_\infty < z/\sqrt{n}\}) = \Phi(z)$  correct!

$F(\bar{Y}_\infty > \bar{Y}_n - z/\sqrt{n} | \mathcal{A}_n) = \Phi(z)$  also correct!

$F(\bar{Y}_\infty > \bar{Y}_n - z/\sqrt{n} | y^{(n)}) = \Phi(z)$  same thing!

Where does that leave Student, Fisher, Barnard, Fraser,...?

# Extensions

Behrens-Fisher type models

Non-Gaussian models  
Fisher (1934)

Linear regression:

Sequential prediction

Computational issues  
McC, V.V., I.N., D.D. and A.G. (2009)