

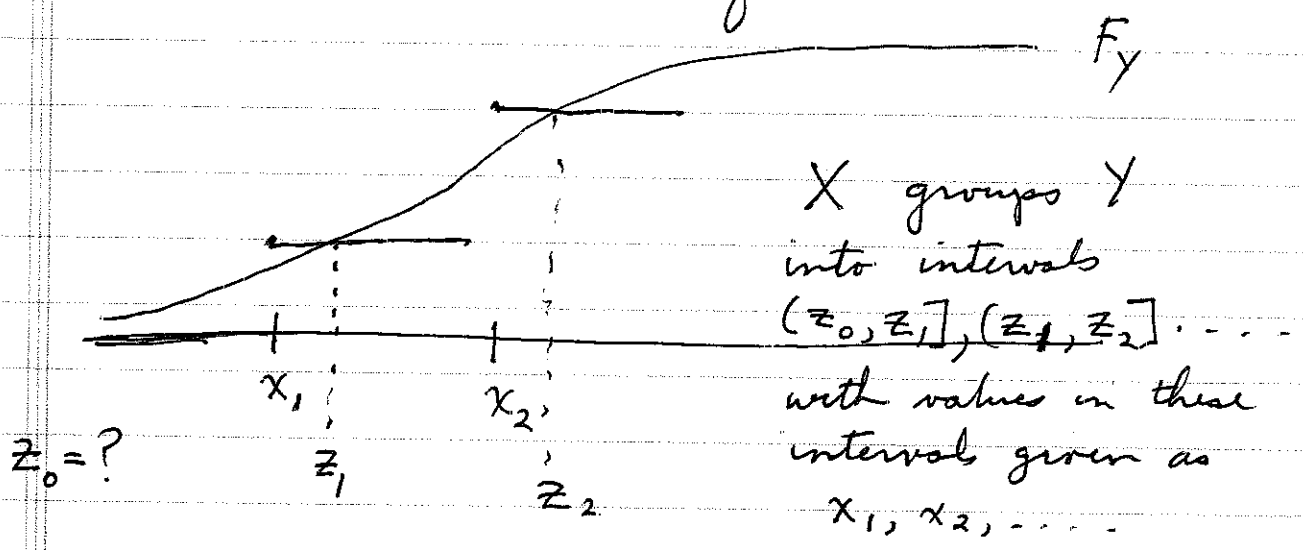
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Some Observations from Last Week

Framework:

- Univariate Pop Y
- Approximate Y by X where
 - X has k support point
 - $E(X^j) = E(Y^j) \quad j=1, \dots, 2k-1$

$X \overset{k}{\approx} Y \iff E(f(X)) \leq E(f(Y))$
 where f is k -convex.



A Digression: $X \overset{k}{\approx} Y$ is a marginal concept. For technical reasons I want to ~~have~~ ^{construct} a joint (X', Y') + $X' \stackrel{d}{=} X, Y' \stackrel{d}{=} Y$ where the joint distribution has a "meaningful" structure between $X' + Y'$ that accounts for using X to approximate Y . I will call this "constructive probability" since the construction of the joint is done to account for some special structure.

Examples: (1) de Finetti's Theorem

Special Structure - infinite exchangeable sequence.

$\{0, 1\}$ exchangeable r.v.'s $\Leftrightarrow X_1, X_2, \dots \mid \mathcal{E}$
are iid Bernoulli

$\mathcal{E} \equiv$ exchangeable σ -field.

Proved by moment sequence arguments
(Feller Vol II) or reverse martingale

(2) Row Column Exchangeable Arrays (Aldous)

$X_{ij} \equiv f(R_i, C_j, \varepsilon_{ij})$ - Reverse Martingale

(3) Load Sharing Rules (LS)

Fubini

- independent Weibull components X_1, \dots, X_k
- dynamic system where as components fail load is transferred to unfailed components. Based on L.S

$R(t) = P(\frac{S}{\Lambda} > t)$ where $S \parallel \Lambda$

Based on X_1, \dots, X_k

(4) Extreme values of Order Stats

~~Exponential~~

Exponential

$X_{k,n} = S_k / \Lambda_{k,n}$

$S_k \parallel \Lambda_{k,n}$ \leftarrow complicated but closed form.
 \uparrow gamma shape k

In our problem $X \stackrel{k}{\rightarrow} Y \Leftrightarrow$

k -mart ~~structure~~ construction given in (*).

(*) X_1, X_2, \dots, X_k iid $\sim X$ with

$$E(Y^j | X_1, \dots, X_k) = \frac{1}{k} \sum_{i=1}^k X_i^j \quad \left(\begin{array}{l} \text{comparator} \\ \text{of experiment} \end{array} \right)$$

$j = 1, \dots, 2k-1.$

($k=1$, a one-mart, Blackwell, Stein, Sherman, Strassen)

Q How can I predict Y from X ?

A Let $j = 1, \dots, 2k-1$. Then,

$$E(Y^j | X_1) = E(E(Y^j | X_1, \dots, X_k) | X_1)$$

$$= E\left(\frac{1}{k} \sum_{i=1}^k X_i^j \mid X_1\right) = \frac{X_1^j}{k} + \frac{1}{k} \sum_{i=2}^k E(X_i^j | X_1)$$

$X_2, \dots, X_k \perp\!\!\!\perp X_1$

$$\stackrel{\perp}{=} \frac{X_1^j}{k} + \frac{k-1}{k} (E(X_1^j)) \leftrightarrow \text{smoothing formula.}$$

$$= E(X_1^j) + \frac{X_1^j - E(X_1^j)}{k} \leftrightarrow \text{adjustment/control formula.}$$

Above, we have specified $2k-1$ conditional moments for $Y_1 | X_1$. Now you can construct a "narrow" distribution Y_n +

$$(*) \quad E(Y_n^j | X_1) = E(Y^j | X_1) \quad j = 1, \dots, 2k-1$$

with

$$(**) \quad E(Y_n^{2k} | X_1) \leq E(Y^{2k} | X_1)$$

If you know the "endpoints of X_1 "

you can construct a "broad" dist Y_b

where (*) holds with Y_n replaced by Y_b and

$$(***) \quad E(Y_b^{2k} | X_1) \leq E(Y^{2k} | X_1).$$

Remark (**) + (***) seem to be analogous to putting bounds on cells in tabular data.