

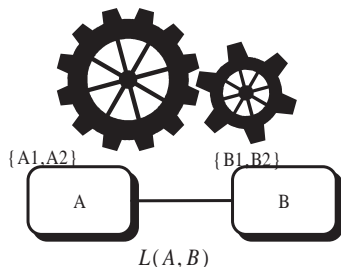
# RFID & Item-Level Information Visibility

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# 1. Manufacturing an Engine



- $B_1 = 10\text{cm}$  &  $B_2 = 10.2\text{cm}$
- $T_1 = 10.2\text{cm}$  &  $T_2 = 10.4\text{cm}$
- $L(B_1, T_1) = L(B_2, T_2) = 10$  years
- $L(B_1, T_2) = L(B_2, T_1) = 9$  years

Link: Shandong Province Adopts RFID For Quality Control

### Building one engine:

- Without RFID visibility
  - $E[L] = E[E(B|T)] = 9.5$  years.
- With RFID visibility
  - $L = \max\{L(B_1, T_1), L(B_2, T_2), L(B_1, T_2), L(B_2, T_1)\} = 10$  years

### Building two engine:

- Without RFID visibility
  - 19 years.
- With RFID visibility
  - 20 years

## 2. Replenish Retail Shelf



- There's only one client in the store
- The client has 50 % possibility to buy a bottle of shampoo
- Original stock: 20 bottles
- Remaining number of shampoo can be any number in  $\{0, 1, 2, \dots, 20\}$
- If the shelf is empty, the client leaves without buying the shampoo.



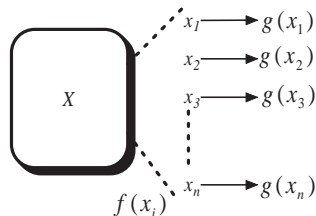
- Without RFID visibility
  - Expected sale =  $50\% \cdot \frac{20}{21} = 0.476$
- With RFID visibility
  - store clerk replenish the shelf once it's empty
  - Expected sale = 0.5 bottle

# Notations

- $\{X_1, X_2, \dots, X_m\}$ :  $m$  components
- $\{X_i | x_{i1}, x_{i2}, \dots, x_{in_i}\}$ : tagged information of cases in a component
- $X \sim f_x(X)$ : statistical property of the tagged information
- $y_i = g(x_i)$ : production function of  $x_i$
- $O$ : the outcome without RFID visibility
- $\tilde{O}$ : the outcome with RFID visibility

# Model Setup

- $X \sim f_x(X)$
- $\{X|x_1, x_2, x_3, \dots, x_n\}$
- $y = g(x_i)$
- $O : O = E[g(X)]$
- $\tilde{O} : \tilde{O} = \max\{g(X)\}$



The p.d.f. of the sample without information visibility is:

$$f_y(y) = f_x(g^{-1}(y))g'(y)$$

The p.d.f. of the sample with information visibility is:

$$f_n^y(y) = n \cdot f_x(g^{-1}(y))g'(y) \cdot \left( \int_{-\infty}^y f_x(g^{-1}(y))g'(y)dy \right)^{n-1}$$



The difference (benefit) of having information visibility is:

$$\begin{aligned}\delta &= \tilde{O} - O \\ &= \int_y yu'(nu^{n-1} - 1)dy\end{aligned}$$

where

$$u = \int_{-\infty}^y f_x(g^{-1}(y)g'(y))dy$$

## Best k outcomes

The p.d.f. of the kth best production is:

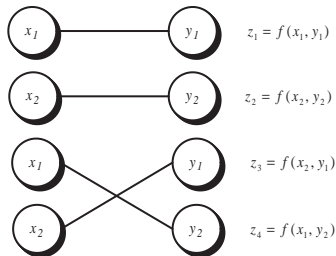
$$f_{k:n}^y(y) = \frac{n!}{(k-1)!(n-k)!} u^{k-1} (1-u)^{n-k} f_y(y)$$

Hence the benefit of having information visibility is:

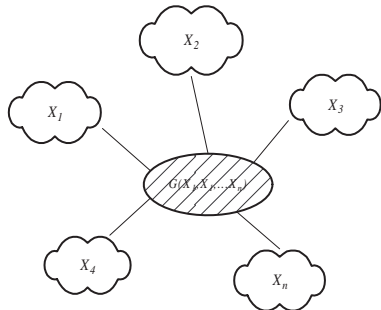
$$\begin{aligned} \delta &= \sum_{i=1}^k (E[y_{i:n}] - E[y]) \\ &= \int_y (nF_{\text{binomial}(n-1,u)}(k) - k) \cdot y f_y(y) dy \end{aligned}$$

# Setup

Two components:



n components:



Assume that we have  $m$  components:  $\{X|X_1, X_2 \cdots X_m\}$

$$\begin{aligned} &\{X_1|x_{11}, x_{12}, x_{13} \cdots x_{1n_1}\} \\ &\{X_2|x_{21}, x_{22}, x_{23} \cdots x_{2n_2}\} \\ &\quad \vdots \\ &\{X_m|x_{m1}, x_{m2}, x_{m3} \cdots x_{mn_m}\} \end{aligned}$$

$X_1, X_2 \cdots X_m$  follow joint distribution

$$f_{X_1, X_2 \cdots X_m}(X_1, X_2 \cdots X_m)$$

- $Y = g(X_1, X_2 \cdots X_m)$
- The c.d.f. of the sample with information visibility is:

$$\begin{aligned}
 F_y^N(y) &= Pr[g(X_1, X_2 \cdots X_m) \leq y] \\
 &= \\
 &\int \cdots \int_{g(X_1, X_2 \cdots X_m) \leq y} f_{X_1, X_2 \cdots X_m}(X_1, X_2 \cdots X_m) dX_1 dX_2 \cdots dX_m
 \end{aligned}$$

- The difference (benefit) with information visibility is:

$$\delta = \int_y u^{n_1 n_2 \cdots n_m} (u^{n_1 n_2 \cdots n_m - 1} - 1) y dy$$

where

$$u = \int \cdots \int_{g(X_1, X_2 \cdots X_m) \leq y} f_{X_1, X_2 \cdots X_m}(X_1, X_2 \cdots X_m) dX_1 dX_2 \cdots dX_m$$

## The k best outcomes

$$f_{k:N}^y(y) = \frac{N!}{(k-1)!(N-k)!} u^{k-1} (1-u)^{N-k} f_y(y)$$

$$\begin{aligned} \sum_{i=1}^k E[y_{i:N}] &= \sum_{i=1}^k \int_y y \cdot \frac{N!}{(i-1)!(N-i)!} u^{i-1} (1-u)^{N-i} f_y(y) dy \\ &= \int_y n F_{\text{binomial}(N-1,u)}(k) \cdot y f_y(y) dy \end{aligned}$$

Hence the benefit of having information visibility,  $\delta$  is:

$$\delta = \int_y (n F_{\text{binomial}(N-1,u)}(k) - k) \cdot y f_y(y) dy$$

## Theorem (1)

*The lower bound for  $\delta$  is:*

$$\delta \geq 0$$

## Theorem (2)

When  $k \leq n$ ,  $\delta$  is upper bounded as:

$$\delta \leq \int_y (ne^{-2\frac{(n-k)^2}{n}} - k) \cdot yf_y(y)dy \leq \int_y (n - k) \cdot yf_y(y)dy$$

Proof.

Hoeffding's inequality & Chernoff's inequality:

$$F_{binomial}(k; n, u) \leq e^{-2\frac{(n-k)^2}{n}} \leq 1$$





### Theorem (3)

*If  $k = n$ ,  $\delta = 0$*

### Theorem (4)

*Larger the sample space variance, larger the benefit  $\delta$ .*

### Theorem (5)

*if  $Y$  is positive,  $\delta$  is a monotonic increasing function of  $n$ .*

### Theorem (6)

*If all the resources are used, the benefit of having information visibility is zero if there's only one component; the benefit is greater than zero if there are multiple components.*

# Control Function



$$\psi(X) = \begin{cases} 19 & \text{if } X = 0 \\ X & \text{otherwise} \end{cases}$$

$$\begin{aligned} X &\sim \psi(X) \\ &\Downarrow \\ Y &= g(\psi(X)) \\ &\Downarrow \\ \delta &= \Omega(k, X, \psi(X), g(X)) \end{aligned}$$

# Finite Horizon

Using Bellman's Method, the recursive function is:

$$V(X_{T-k}, k) = \max_{v_{T-k}} \{ \delta_{T-k}(X_{T-k}, v_{T-k}) + V(X_{T-k+1}, k-1) \}$$

$$\equiv \delta_{T-k}(X_{T-k}, \psi_{T-k}(X_{T-k})) + V(\xi_{T-k}(X_{T-k}, \psi_{T-k}(X_{T-k})), k-1)$$

subject to:

1.  $X_{T-k+1} = \xi_{T-k}(X_{T-k}, v_{T-k}, G(v_{T-k}))$
2.  $X_0 = \tilde{X}_0$
3.  $v_{T-k} = \psi_{T-k}(X_{T-k})$
4.  $v_t \in \Theta$  for all  $t = 0, 1, \dots, T-1$

# Infinite Horizon

$$V_t(X_t) = \max_{v_t} \{ \beta \delta(X_t, v_t) + V_{t+1}(X_{t+1}) \} \quad (1)$$

subject to:

1.  $X_{t+1} = \xi_0(X_t, v_t)$
2.  $X_0 = \tilde{X}_0$
3.  $v_t = \psi(X_t)$

where  $\beta$  is the discount factor and  $0 \leq \beta \leq 1$ .

Sargent (1987) and Stokey (1989): starting from any bounded continuous  $W_0$  will cause  $W$  to converge as  $t \rightarrow \infty$ .

# Simulation of Fabrication Quality Control

$$X_1 \sim \text{Uniform}(-0.5, 0.5)$$

$$X_2 \sim \text{Uniform}(-0.5, 0.5)$$

$$G(x_1, x_2) = e^{x_1 - x_2}$$

$$\psi(X) = X$$

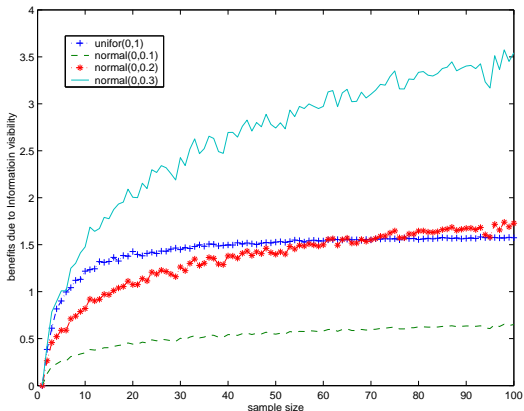


Figure: Benefit of having information visibility for fabrication quality control.

# Analysis

The results show:

- The benefit of information visibility increases if the scale of the manufacturing increases
- The benefit function is concave and bounded.
- If the samples are more volatile, more is the benefit of having RFID information visibility.

Merci!