

Class 5 Outline

Experiment Design and Output Analysis:

- 1. Theory and Construction of Confidence Intervals**
- 2. Monte-Carlo and Terminating Simulations**
- 3. Non-Terminating Simulations (Steady State)**

Experimental Design Issues

**Static Simulation
(Monte-Carlo)**

- *How many replications should be run ?*

**Dynamic Simulation
(Discrete-Event)**

Terminating

- *How many replications should be run ?*

Non-terminating

- *How many replications should be run?*
- For each replication:*
 - *When to start collecting data?*
 - *How much data should be collected?*

How Many Replications?

- **Simulation output: $Y_1, Y_2, Y_3, \dots, Y_n$**
We (typically) want to estimate $E[Y]$!

1. **What is the accuracy of the estimator:**

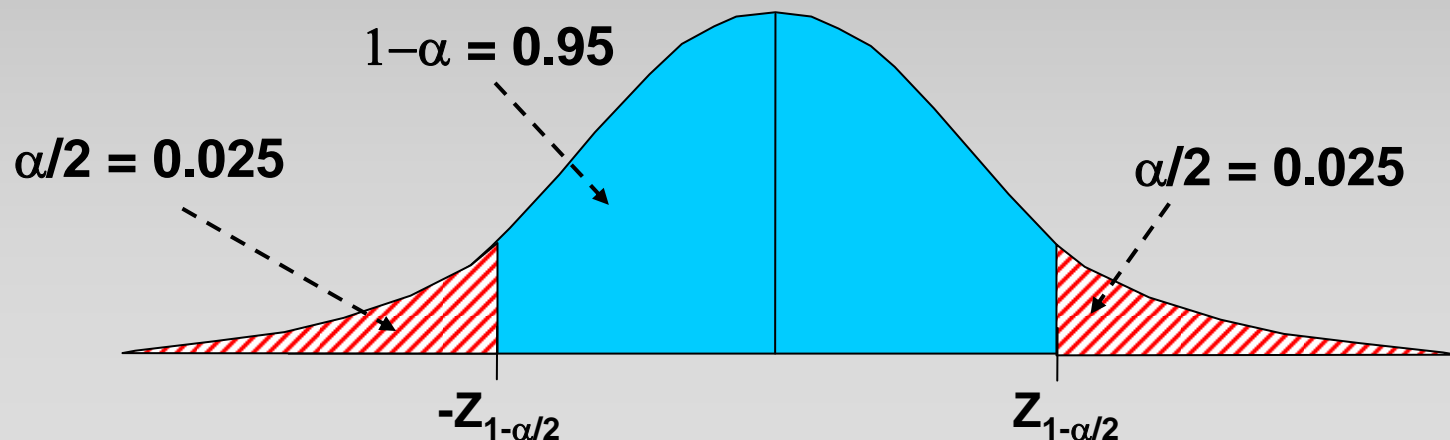
$$Y(n) = (Y_1 + Y_2 + Y_3 + \dots + Y_n) / n ?$$

2. **How much should n be (number of independent replications) in order to guarantee a given estimation accuracy?**

What is a "Fractile"?

- Let α be a number in $(0,1)$ e.g. 0.05
- $z_{1-\alpha/2}$ is the $(1-\alpha/2)$ -th fractile of a standard normal distribution, and is defined as:

$$P(N(0,1) \leq z_{1-\alpha/2}) = 1 - \alpha/2$$



Statistical Estimation Theory

- **Define:**
$$\bar{Y}_n = \frac{1}{n} \sum_{i=1}^n Y_i \quad S^2_n = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y}_n)^2$$

- **A version of the CLT says that when $n \rightarrow \infty$:**

$$\frac{\bar{Y}_n - E \bar{Y}}{\sqrt{\frac{S^2_n}{n}}} \xrightarrow{d} N(0, 1)$$

- **For smaller ($n < 30$) values of n , a good approx. is:**

$$\frac{\bar{Y}_n - E \bar{Y}}{\sqrt{\frac{S^2_n}{n}}} \xrightarrow{d} t_{n-1}$$

So What?

- From the CLT:

$$\frac{Y_n - E Y}{\sqrt{\frac{S^2_n}{n}}} \sim N(0, 1)$$

- So that when n is large, we can write:

$$P\left(-z_{1-\alpha/2} \leq \frac{Y_n - E Y}{\sqrt{\frac{S^2_n}{n}}} \leq z_{1-\alpha/2}\right) = 1 - \alpha$$

- Re-arranging gives:

$$P\left(Y_n - z_{1-\alpha/2} \sqrt{\frac{S^2_n}{n}} \leq E Y \leq Y_n + z_{1-\alpha/2} \sqrt{\frac{S^2_n}{n}}\right) = 1 - \alpha$$

- This is the definition of a $(1-\alpha)\%$ confidence interval!!!

Building Confidence Intervals

- For n large ($n > 30$), the $(1 - \alpha)\%$ confidence interval is:

$$\bar{Y} \pm z_{1-\alpha/2} \sqrt{\frac{S^2}{n}}$$

fractile of the
std. normal
distribution

- For n small ($n < 30$), use:

$$\bar{Y} \pm t_{n-1, 1-\alpha/2} \sqrt{\frac{S^2}{n}}$$

fractile of the
t (student)
distribution
with $n-1$ d.f.

So, How Many Replications?

- $W = UB - LB$ is the width of the confidence interval, centered around $Y(n)$
- A measure of the relative estimation error is thus $W / Y(n)$
- So a good termination criteria is to set an estimation error β and run a number of replications n such that:

$$W / Y(n) < \beta$$

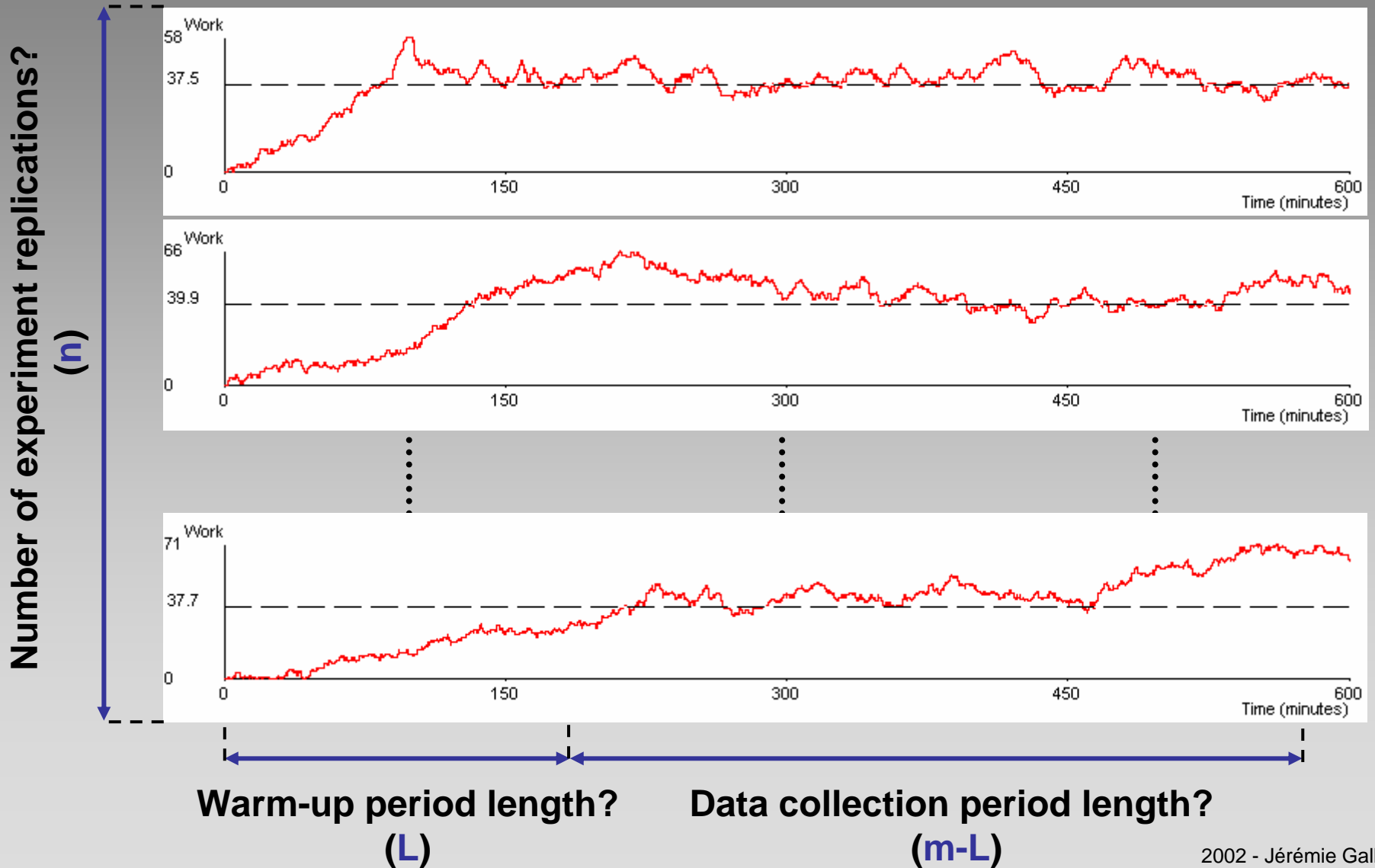
Example

Suppose we build a simulation model to assess the weekly cost of a proposed supply chain inventory policy

From the simulation data output (Spreadsheet “Confidence Interval” on SloanSpace), we want to estimate:

- 1. The average weekly cost C with CI**
- 2. $P(C > \$2M)$ with CI**

Steady-State Analysis

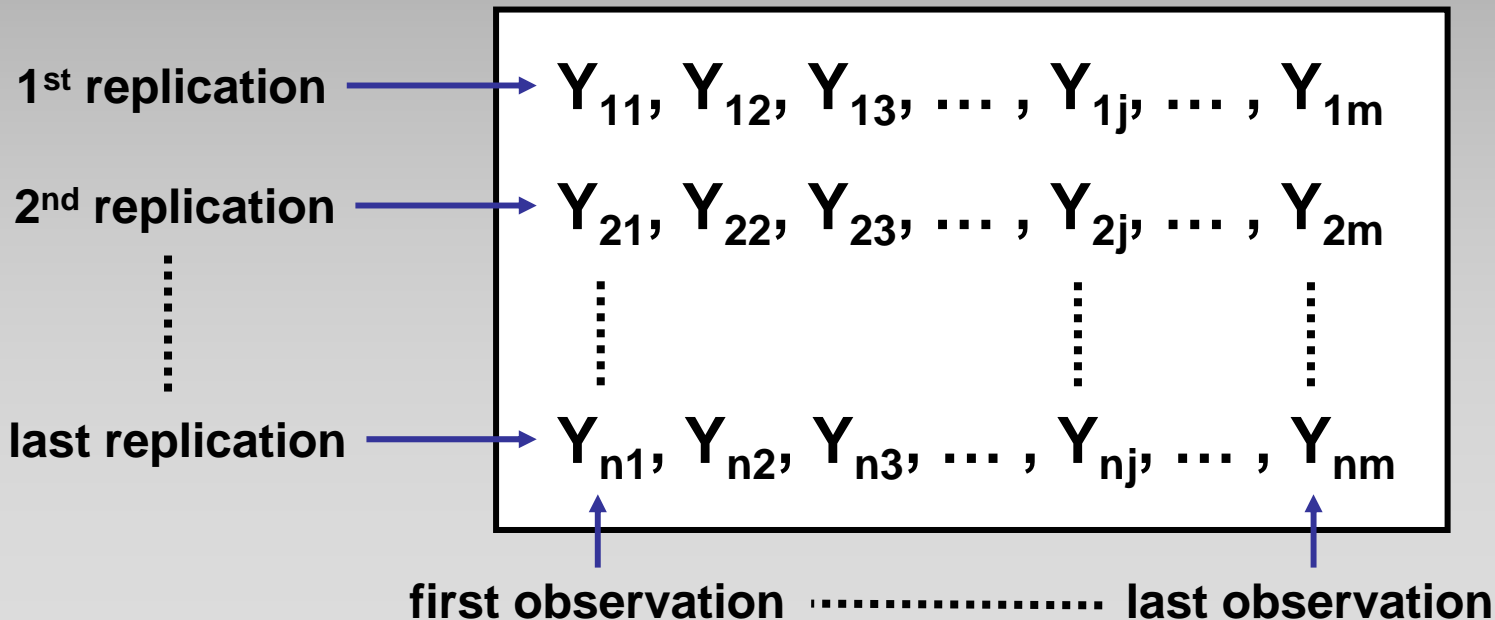


Steady-State Analysis

- Let $Y_1, Y_2, Y_3, \dots, Y_t, \dots$ be a stochastic process (e.g. queue length at time index t).

We want to estimate $\lim E[Y_t]$ when $t \rightarrow \infty$!

- Data Y_{ij} : j -th observation in the i -th replication



Replication/Deletion Approach

(Y_{ij} : j-th observation in the i-th replication)

- For each replication i, instead of the estimator:

$$Y_i(m) = (Y_{i1} + Y_{i2} + Y_{i3} + \dots + Y_{im}) / m,$$

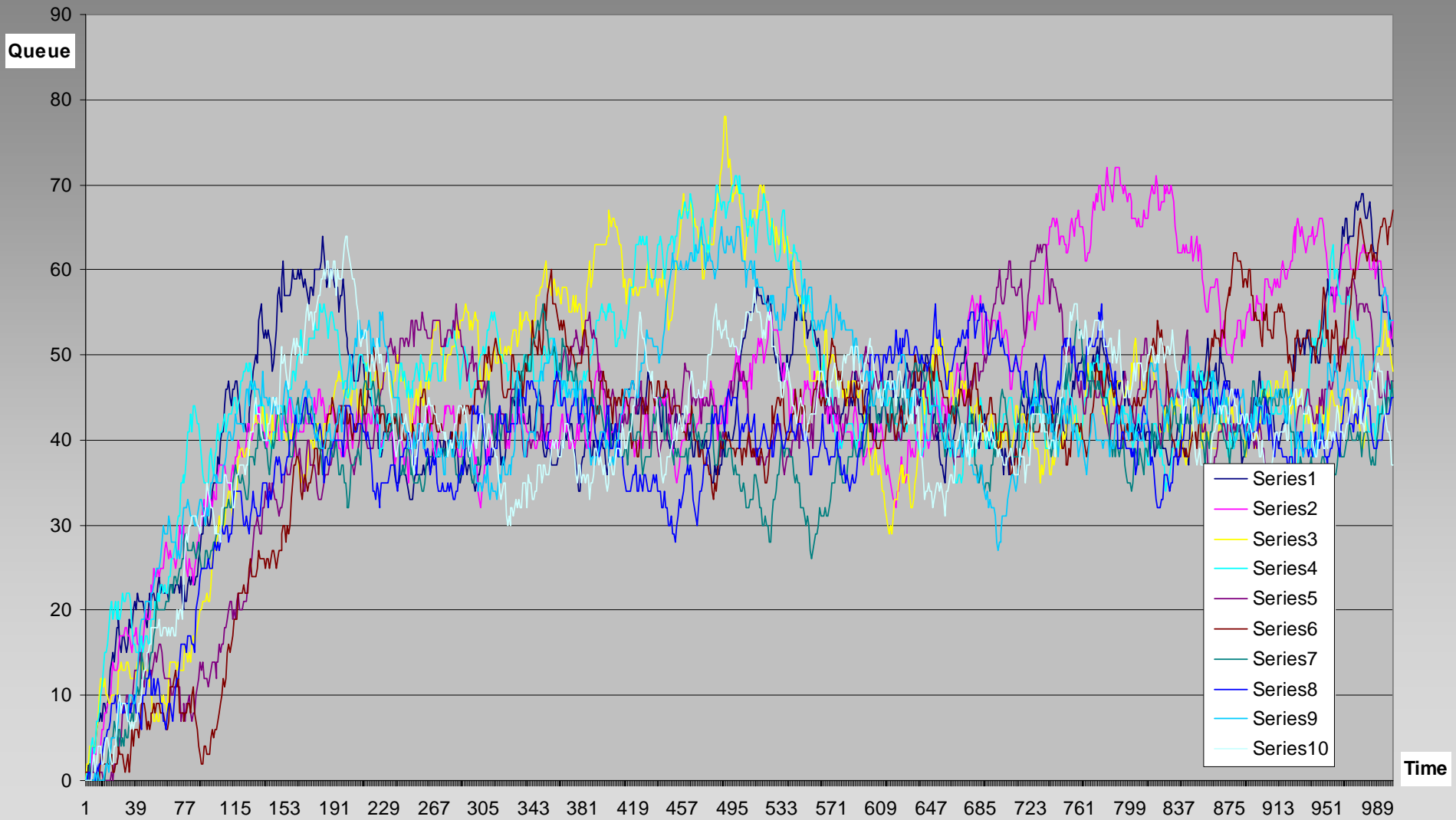
consider the modified estimator:

$$Y_i(m,L) = (Y_{iL} + Y_{i(L+1)} + Y_{i(L+2)} + \dots + Y_{im}) / (m-L+1)$$

- An estimator for $\lim E[Y_t]$ when $t \rightarrow \infty$ is then

$$Y(n) = (Y_1(m,L) + Y_2(m,L) \dots + Y_n(m,L)) / n$$

Experimental Data Plot



Welch's Method for Warm-up

(Y_{ij} : j-th observation in the i-th replication)

- Compute the average across replications for each time point:

$$Y_t[n] = (Y_{1t} + Y_{2t} + Y_{3t} + \dots + Y_{nt}) / n$$

- Welch's method is to plot the moving average process of $Y_t[n]$ based on various lags w :

$$Y_t[n, w] = (Y_{t-w}[n] + \dots + Y_t[n] + \dots + Y_{t+w}[n]) / (2w + 1)$$

Welch's Method for Warm-up

