

# Overlapping Batches for Variance Reduction in Optimality Gap Estimation in Stochastic Programming

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# The Basics

- Stochastic Process  $\{X_t, t \geq 0\}$ , discrete- or continuous-time or state space.
- (Long Term) Mean  $\mu$ , Variance  $R_0$ .
- Want an estimate of  $\mu$  given a realization  $\{X^n\}$ .

# The Basics

- Stochastic Process  $\{X_t, t \geq 0\}$ , discrete- or continuous-time or state space.
- (Long Term) Mean  $\mu$ , Variance  $R_0$ .
- Want an estimate of  $\mu$  given a realization  $\{X^n\}$ .
- A family of point estimators, considered as  $\bar{X} = \sum_{i=1}^n \alpha_i X_i$ , where  $\sum_{i=1}^n \alpha_i = 1$ .
- Non-stationary: earlier observations given less weight. Stationary:  $\alpha_i \equiv 1/n$ .
- Evaluate performance of  $\bar{X}$  by looking at its variance:  $s_n^2/n$ .

(Overlapping batches improves this measure of performance)

# Nonoverlapping Batch Means

$n = 12$  Total sample size

$m = 4$  Batch size

$k = \frac{n}{m} = 3$  Number of batches

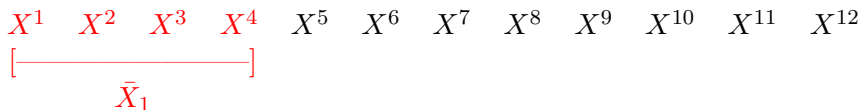
$X^1$   $X^2$   $X^3$   $X^4$   $X^5$   $X^6$   $X^7$   $X^8$   $X^9$   $X^{10}$   $X^{11}$   $X^{12}$

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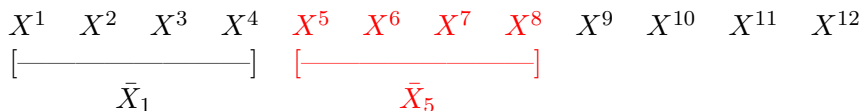


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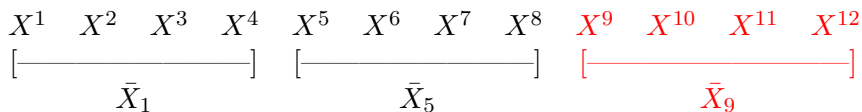


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# Batch Means

Why not overlap the batches? (Meketon & Schmeiser, 1984)

# Overlapping Batch Means

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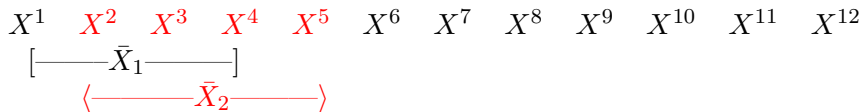
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 [———— $\bar{X}_1$ ————]

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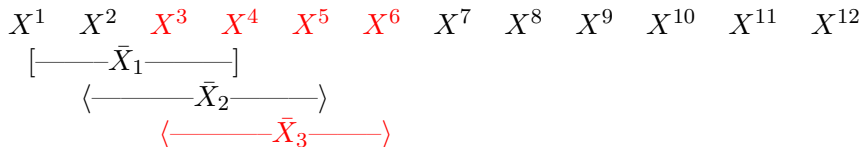


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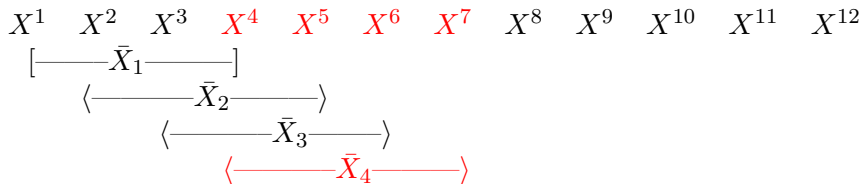


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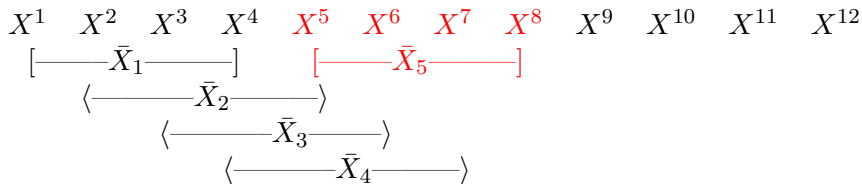


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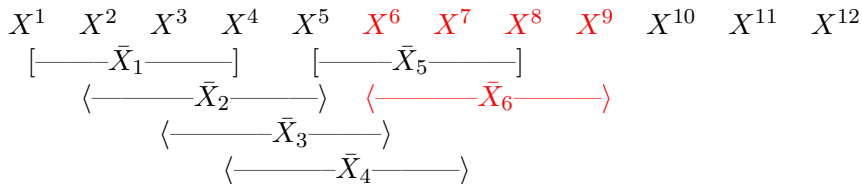


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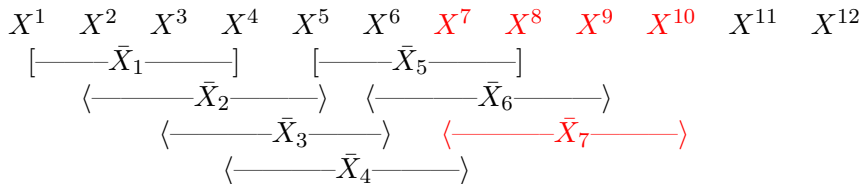


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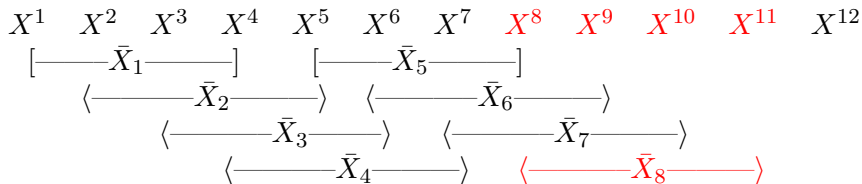


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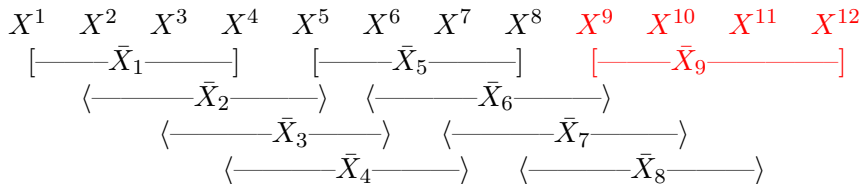


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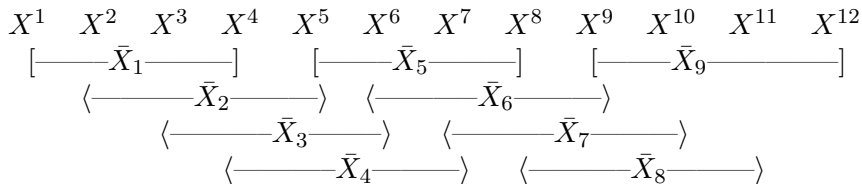


# Overlapping Batch Means

$n = 12$  Total sample size

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$$\widetilde{\text{Var}}_m(\bar{X}) = \frac{m}{n} \sum_{j=1}^{n-m+1} \frac{(\bar{X}_j(m) - \bar{X})^2}{n - 2m + 1}$$

# Different Variance Estimators

Batch Mean  $\bar{X}_j(m) = \frac{1}{m} \sum_{i=0}^{m-1} X_{j+i}$

Overall Mean  $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$

Nonoverlapping Variance  $\widehat{\text{Var}}_{k,m}(\bar{X}) = \frac{m}{n} \sum_{j=1}^k \frac{(\bar{X}_{m(j-1)(m)} - \bar{X})^2}{k-1}$

Overlapping Variance  $\widetilde{\text{Var}}_m(\bar{X}) = \frac{m}{n} \sum_{j=1}^{n-m+1} \frac{(\bar{X}_j(m) - \bar{X})^2}{n-2m+1}$

# Important Results

- The variance estimator obtained by use of overlapping batches has essentially the same bias as the nonoverlapping estimator.
- Both estimators are unbiased in the limit as  $n, m, k \rightarrow \infty$ .
- Overlapping the batches reduces the variability of the variance estimator to  $2/3$  of the original.

$$\lim_{n,m,k \rightarrow \infty} \frac{\text{Var} \left( \widetilde{\text{Var}}_m (\bar{X}) \right)}{\text{Var} \left( \widehat{\text{Var}}_{k,m}^i (\bar{X}) \right)} = \frac{2}{3}$$

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# Stochastic Optimization

$$z^* = \min_{\mathbf{x} \in X} \mathbb{E}f(\mathbf{x}, \tilde{\xi}) \quad (\text{SP})$$

$$\mathbf{x}^* \in \operatorname{argmin}_{\mathbf{x} \in X} \mathbb{E}f(\mathbf{x}, \tilde{\xi})$$

where

$f,$	a real-valued function
$\mathbf{x},$	a vector of decision variables
$\tilde{\xi},$	a vector of random variables

## Approximating Problem

We set up the approximating problem

$$z_n^* = \min_{\mathbf{x} \in X} \frac{1}{n} \sum_{i=1}^n f(\mathbf{x}, \tilde{\xi}^i) \quad (\text{SP}_n)$$

$$\mathbf{x}_n^* \in \operatorname{argmin}_{\mathbf{x} \in X} \frac{1}{n} \sum_{i=1}^n f(\mathbf{x}, \tilde{\xi}^i)$$

where

$\tilde{\xi}^i$ ,      i.i.d. samples from the distribution of  $\tilde{\xi}$ ,  $i = 1, \dots, n$   
 $z_n^*$ ,      optimal objective value of the approximating problem  
 $\mathbf{x}_n^*$ ,      optimal solution of the approximating problem

## Defining a “Good” Candidate Solution

Suppose we have a candidate solution  $\hat{\mathbf{x}} \in X$  (maybe we solved  $(SP_n)$ ).  
How good is it?

- We can look at its “optimality gap”,

$$\mathbb{E}f(\hat{\mathbf{x}}, \tilde{\xi}) - z^*.$$

- Clearly is positive.
- Want a statistical estimate on size.

## Bounds on $z^*$

**Upper Bound** Since  $\hat{\mathbf{x}}$  is probably not optimal, we can use  $\mathbb{E}f(\hat{\mathbf{x}}, \tilde{\xi})$  as an upper bound on  $z^*$ .

**Lower Bound**  $\mathbb{E}z_n^* = \mathbb{E} \left[ \min_{\mathbf{x} \in X} \frac{1}{n} \sum_{i=1}^n f(\mathbf{x}, \tilde{\xi}^i) \right]$  is a lower bound on  $z^*$ .

$$\mathbb{E} \left[ \min_{\mathbf{x} \in X} \frac{1}{n} \sum_{i=1}^n f(\mathbf{x}, \tilde{\xi}^i) \right] \leq z^* \leq \mathbb{E}f(\hat{\mathbf{x}}, \tilde{\xi})$$

(Mak & Morton (1999), Norikin, Pflug, Ruszczyński (1998))

# Optimality Gap Estimation

The optimality gap  $\mathbb{E} \left[ f(\hat{\mathbf{x}}, \tilde{\xi}) \right] - z^*$  is approximated by

$$\bar{G}_m = \frac{1}{m} \sum_{i=1}^m f(\hat{\mathbf{x}}, \tilde{\xi}^i) - \min_{\mathbf{x} \in X} \frac{1}{m} \sum_{i=1}^m f(\mathbf{x}, \tilde{\xi}^i)$$

- Since the approximated optimal solution is biased, the gap estimator is positively biased.
- Split our random sample into batches...

# Multiple Replications Procedure

$m$ , batch size;  $k$ , # of batches;  $n = km$ , total sample size

① For  $j = 1, \dots, k$ :

① Generate batch of samples  $\tilde{\xi}^{(j-1)m+1}, \dots, \tilde{\xi}^{jm}$ .

② Find gap estimate

$$\bar{G}_m^j = \frac{1}{m} \sum_{i=(j-1)m+1}^{jm} f(\hat{\mathbf{x}}, \tilde{\xi}^i) - \min_{\mathbf{x} \in X} \frac{1}{m} \sum_{i=(j-1)m+1}^{jm} f(\mathbf{x}, \tilde{\xi}^i)$$

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② Calculate average gap estimate  $\bar{G} = \frac{1}{k} \sum_{j=1}^k \bar{G}_m^j$ .

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② Calculate average gap estimate  $\bar{\bar{G}} = \frac{1}{k} \sum_{j=1}^k \bar{G}_m^j$ .

③ Calculate sample variance  $VG = \frac{1}{k(k-1)} \sum_{i=j}^k (\bar{G}_m^j - \bar{\bar{G}})^2$ .

# Multiple Replications Procedure

$m$ , batch size;  $k$ , # of batches;  $n = km$ , total sample size

1 For  $j = 1, \dots, k$ :

1 Generate batch of samples  $\tilde{\xi}^{(j-1)m+1}, \dots, \tilde{\xi}^{jm}$ .

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$$\bar{G}_m^j = \frac{1}{m} \sum_{i=(j-1)m+1}^{jm} f(\hat{\mathbf{x}}, \tilde{\xi}^i) - \min_{\mathbf{x} \in X} \frac{1}{m} \sum_{i=(j-1)m+1}^{jm} f(\mathbf{x}, \tilde{\xi}^i)$$

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4 Find one-sided confidence interval  $[0, \bar{\bar{G}} + t_{\alpha, k-1} \sqrt{VG}]$ .

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# Overlapping Batches in MRP

- Now, we want to overlap the batches in the MRP.
- All of Meketon and Schmeiser's results occurred as  $n, m, n/m \rightarrow \infty$ . (Need  $r \in (0, 1)$ , with  $m \approx n^r$ .)
- Choose sequences  $n_j, m_j$  to fit these properties as  $j \rightarrow \infty$ .

# Assumptions

**A1** Samples of the random variable  $\tilde{\xi}$  are i.i.d.

**A2**  $z_n^* \rightarrow z^*$  a.s.

**A3**  $\exists \epsilon > 0$  such that  $\mathbb{E} \left[ \left( \sup_{x \in X} f(x, \tilde{\xi}) \right)^{4+\epsilon} \right] < \infty$ .

# Partial Overlap

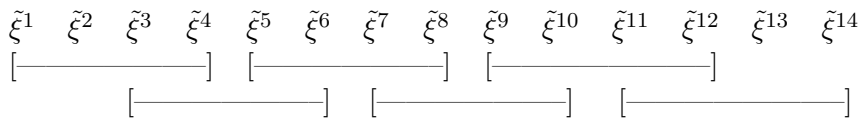


Figure: Graphical representation of  $\gamma = 2$ .

Let  $\gamma$  be the batch nonoverlap parameter.

- Number of new samples added to each new batch.
- $\gamma = 1$ , maximally overlapping case discussed above.
- $\gamma = m$ , classical nonoverlapping case.
- Could change along with  $n_j, m_j$ , use  $\gamma_j$ .

# Definitions

## A series of estimators

$$\bar{G}_{m_j}^i = \frac{1}{m_j} \sum_{I=i}^{i+m_j-1} f(\hat{\mathbf{x}}, \tilde{\xi}^I) - \min_{\mathbf{x} \in X} \frac{1}{m_j} \sum_{I=i}^{i+m_j-1} f(\mathbf{x}, \tilde{\xi}^I)$$

$$\bar{\bar{G}}_j = \frac{1}{|K(j)|} \sum_{i \in K(j)} \bar{G}_{m_j}^i$$

$$VG_j = \frac{m}{n} \frac{1}{df(j)} \sum_{i \in K(j)} (\bar{G}_{m_j}^i - \bar{\bar{G}}_j)^2$$

where

- $K(j)$ , set of batches in the estimator (related to  $\gamma_j$ ).
- $df(j)$ , degrees of freedom of variance estimator.

## Further Definitions

$$|K(j)| = \left\lfloor \frac{n_j - m_j}{\gamma_j} + 1 \right\rfloor$$

$$df(j) = \frac{n_j - k_j m_j}{\gamma_j} + (k_j - 2) \left\lceil \frac{m_j}{\gamma_j} \right\rceil + 1$$

Special cases:

<p>Nonoverlapping</p> $\gamma_j = m_j$ $ K(j)  = k_j,$ $df(j) = k_j - 1$	<p>Maximally Overlapping</p> $\gamma_j \equiv 1$ $ K(j)  = n_j - m_j + 1$ $df(j) = n_j - 2m_j + 1$
--	--

# A Small Problem

**Problem** The internal minimization of

$$\bar{G}_{m_j}^i = \frac{1}{m_j} \sum_{I=i}^{i+m_j-1} f(\hat{\mathbf{x}}, \tilde{\xi}^I) - \min_{\mathbf{x} \in X} \frac{1}{m_j} \sum_{I=i}^{i+m_j-1} f(\mathbf{x}, \tilde{\xi}^I)$$

means we do not have the nice properties we want.

**Solution** Introduce a sequence of “non-minimized” gap estimators,  $\bar{D}_{m_j}^i$ . Show convergence between these two series.

# Beginnings of Proof

## Unbiased Gap Estimator

$$\bar{D}_{m_j}^i = \frac{1}{m_j} \sum_{I=i}^{i+m_j-1} f(\hat{\mathbf{x}}, \tilde{\xi}^I) - \frac{1}{m_j} \sum_{I=i}^{i+m_j-1} f(\mathbf{x}^*, \tilde{\xi}^I)$$

$$\bar{\bar{D}}_j = \frac{1}{|K(j)|} \sum_{i \in K(j)} \bar{D}_{m_j}^i$$

$$VD_j = \frac{m}{n} \frac{1}{df(j)} \sum_{i \in K(j)} (\bar{D}_{m_j}^i - \bar{\bar{D}}_j)^2$$

- By (A2),  $\bar{G}_m^i \rightarrow \bar{D}_m^i$  as  $m \rightarrow \infty$ .
- By Meketon,  $VD_j$  has decreased variance for overlapping batches.
- Show that  $\text{Var}(VG_j) \rightarrow \text{Var}(VD_j)$ . Equivalently,  $VG_j \xrightarrow{L^2} VD_j$ .

# Sketch of Proof

- 1 Show that  $VG_j \xrightarrow{P} VD_j$ .
- 2 Show that  $VG_j^2$  is uniformly integrable.
- 3 Then  $VG_j \xrightarrow{L^2} VD_j$ .

# Convergence in Probability

Easier to show convergence in expectation

$$\begin{aligned} \mathbb{E} [|VG_j - VD_j|] &= \frac{1}{df(j)} \sum_{i \in K(j)} \mathbb{E} \left[ |(\bar{G}_{m_j}^i - \bar{\bar{G}}_j)^2 - (\bar{D}_{m_j}^i - \bar{\bar{D}}_j)^2| \right] \\ &\leq 2\mathbb{E} \left[ |(\bar{G}_{m_j}^i)^2 - (\bar{D}_{m_j}^i)^2| \right. \\ &\quad \left. + 2(\bar{G}_{m_j}^i \bar{\bar{G}}_j - \bar{D}_{m_j}^i \bar{\bar{D}}_j) + |\bar{G}_j^2 - \bar{\bar{D}}_j^2| \right]. \end{aligned}$$

All terms converge to zero pointwise (A2). Dominating function exists by (A3).

# Uniform Integrability

Let

$$h(\tilde{\xi}^i) = \sup_{\hat{\mathbf{x}} \in X} f(\hat{\mathbf{x}}, \tilde{\xi}^i) - \min_{x \in X} f(x, \tilde{\xi}^i)$$

Then

$$\text{Var}(VG_j^2) \leq 4\mathbb{E}[(\bar{G}_{m_j}^1)^4] \leq 4\mathbb{E}[h^4(\tilde{\xi})]$$

and for uniform integrability

$$\begin{aligned} \mathbb{E}[(\bar{G}_1^m)^4 I_{(\bar{G}_1^m)^4 > t}] &\leq \mathbb{E}[h^4(\tilde{\xi}^i) I_{(\bar{G}_1^m)^4 > t}] \\ &\leq {}^{1+\epsilon/4}\sqrt{\mathbb{E}[h^{4+\epsilon}(\tilde{\xi}^i)]} {}^{(4+\epsilon)/\epsilon}\sqrt{\mathbb{P}\{(\bar{G}_1^m)^4 > t\}} \end{aligned}$$

And the  $\mathbb{P}\{(\bar{G}_1^m)^4 > t\} \rightarrow 0$  as  $t \rightarrow \infty$ .

## Result

Then  $\text{Var}(VG_j) \rightarrow \text{Var}(VD_j)$ , so we get the same variance reduction as we did in simulation!

### Variance reduction

- $\gamma_j \equiv 1$ , variance is reduced to  $\frac{2}{3}$  of original.
- $\gamma_j = \frac{1}{3}m$ , variance is reduced to  $\frac{19}{27}$  of original.
- $\gamma_j = \frac{1}{2}m$ , variance is reduced to  $\frac{3}{4}$  of original.
- $\gamma_j = \frac{1}{N}m$ , variance is reduced to  $\frac{2N^2 + 1}{3N^2}$  of original.

# Confidence Intervals

- Finally, given the above, we want to generate some one-sided confidence intervals on the true optimality gap,  $\mu_{\hat{\mathbf{x}}}$ .
- The interval estimators take the form

$$I_{G_j} = \bar{\bar{G}}_j + t_{\alpha, k-1} \sqrt{V G_j}$$

$$I_{D_j} = \bar{\bar{D}}_j + t_{\alpha, k-1} \sqrt{V D_j},$$

for some  $\alpha \in (0, 1)$ .

- We want to show that  $\mathbb{P} \{ \mu_{\hat{\mathbf{x}}} \leq I_{G_j} \}$  is a  $100(1 - \alpha)\%$  confidence interval.
- That is,  $\mathbb{P} \{ \mu_{\hat{\mathbf{x}}} \leq I_{G_j} \} \rightarrow 1 - \alpha$ .

# Convergence of CI

We know that  $I_{G_j} \xrightarrow{P} I_{D_j}$ . The function  $f(X) = 1_{X \in I}$  for some interval  $I$  is continuous a.s. for continuous random variables  $X$ . Then

$$\mathbb{P} \left\{ |1_{\mu_{\hat{\mathbf{x}}} \leq I_{G_j}} - 1_{\mu_{\hat{\mathbf{x}}} \leq I_{D_j}}| > \epsilon \right\} \rightarrow 0$$

and so we must have

$$\mathbb{P} \left\{ \mu_{\hat{\mathbf{x}}} \leq I_{G_j} \right\} \rightarrow \mathbb{P} \left\{ \mu_{\hat{\mathbf{x}}} \leq I_{D_j} \right\}$$

# Result

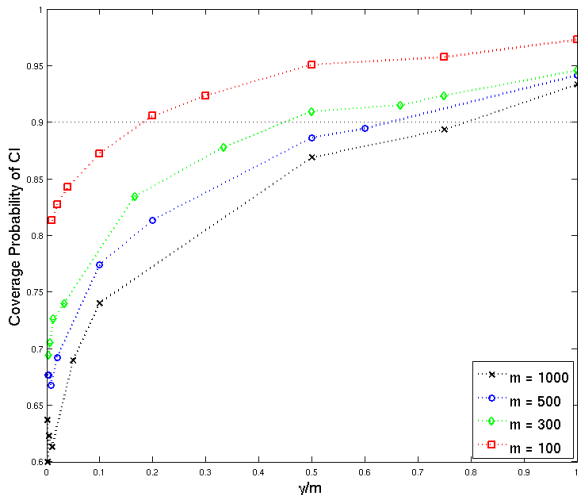
- We know from simulation theory the conditions that  $\mathbb{P} \{ \mu_{\hat{\mathbf{x}}} \leq I_{D_j} \} \rightarrow 1 - \alpha$ .
- Now, we have an asymptotically valid confidence interval for stochastic optimization!

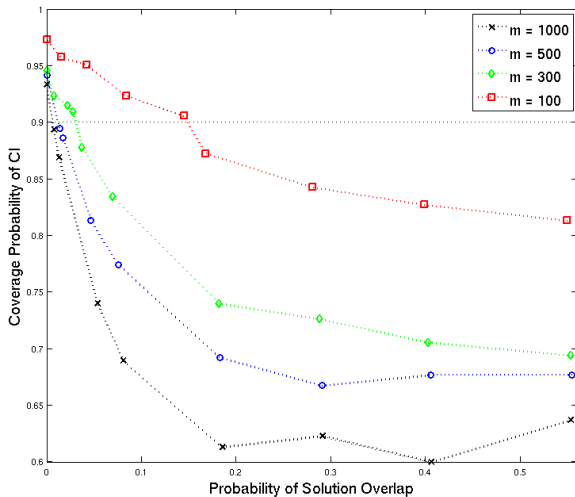
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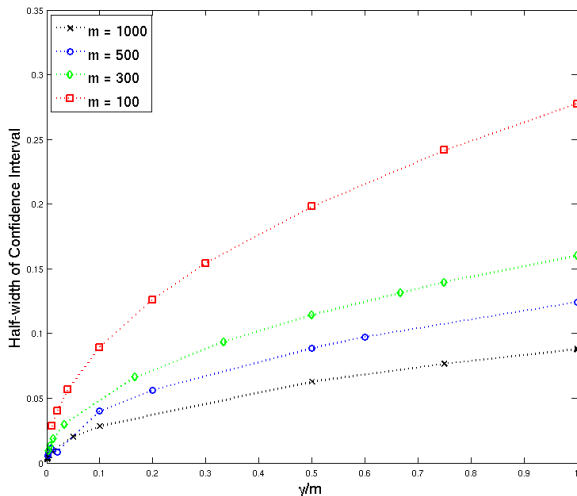
# News vendor Problem

We tested the computational properties of our method on the news vendor problem, with

- Selling price  $r = 15$ .
- Cost of paper  $c = 5$ .
- Distribution of  $\tilde{d}$  is  $U(0, 10)$ .
- Optimal quantile  $\frac{r-c}{r} = \frac{2}{3}$ .

Coverage Probability with  $k = 30$ 

Coverage Probability with  $k = 30$ 

Width of CI with  $k = 30$ 

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# Bibliography

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