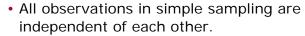


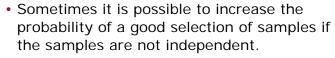


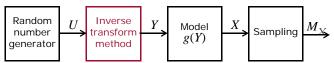
Theme 4

COMPLEMENTARY RANDOM NUMBERS & DAGGER SAMPLING

INTRODUCTION







MEAN OF TWO ESTIMATES

• Consider two estimates M_{X1} and M_{X2} of the same expectation value $\mu_{X^{\prime}}$ i.e.,

$$E[M_{X1}] = E[M_{X2}] = \mu_X.$$

• Study the mean of these estimates, i.e.,

$$M_X = \frac{M_{X1} + M_{X2}}{2}.$$



MEAN OF TWO ESTIMATES

• Expectation value:

$$E[M_X] = E\left[\frac{M_{X1} + M_{X2}}{2}\right] =$$

$$= \frac{1}{2}(E[M_{X1}] + E[M_{X2}]) = \frac{1}{2}(\mu_X + \mu_X)$$

$$= \mu_{X'}$$
(5)

i.e., the combined estimate M_X is also an estimate of $\mu_{\!\scriptscriptstyle X}$.



MEAN OF TWO ESTIMATES

Variance:



$$\begin{aligned} Var[M_X] &= Var\Big[\frac{M_{X1} + M_{X2}}{2}\Big] = \\ &= \frac{1}{4}Var[M_{X1}] + \frac{1}{4}Var[M_{X2}] + \\ &+ \frac{1}{4} \cdot 2Cov(M_{X1}, M_{X2}). \end{aligned} \tag{6}$$

MEAN OF TWO ESTIMATES



• If M_{X1} and M_{X2} both are independent estimates obtained with simple sampling and the number of samples is the same in both simulations, then we get $Var[M_{X1}] = Var[M_{X2}]$ and $Cov[M_{X1}, M_{X2}] = 0$. Hence, (6) yields

$$Var[M_X] = Var\left[\frac{M_{X1} + M_{X2}}{2}\right] =$$

$$= \frac{1}{4}(Var[M_{X1}] + Var[M_{X1}]) = \frac{Var[M_{X1}]}{2}. (7)$$

MEAN OF TWO ESTIMATES



- The variance obtained in (7) is equivalent to one run of simple sampling using 2n samples; according to theorem 11 we should get half the variance when the number of samples is doubled.
- However, if the M_{X1} and M_{X2} are not independent but negatively correlated then the covariance term in (6) will make $Var[M_X]$ smaller than the corresponding variance for simple sampling using the same number of samples.

COMPLEMENTARY RANDOM NUMBERS



- A negative correlation between estimates can be created using complementary random numbers.
- The complementary random number of a U(0, 1)-distributed random variable is $U^* = 1 U$.
 - Correlation coefficient: $\rho_{II\ II^{\star}}$ = -1.

COMPLEMENTARY RANDOM NUMBERS



- If a random value is calculated using the inverse transform method, i.e., $Y = F_Y^{-1}(U)$, then the complementary random number is given by $Y^* = F_Y^{-1}(1-U)$.
 - The complementary random number is calculated in the same way also for normally distributed random numbers generated according to the approximative inverse transform method.
 - For symmetrical distributions we get that if $Y = \mu_Y + \delta$ then $Y^* = \mu_Y \delta$.
 - Correlation coefficient: $\rho_{Y, Y^{\star}} \geq \rho_{U, U^{\star}}$

COMPLEMENTARY RANDOM NUMBERS



- If a random value is calculated by analysing a scenario, i.e., X = g(Y), then the complementary random number is given by $X^* = g(Y^*)$.
 - Correlation coefficient: $\rho_{X, X^*} \ge \rho_{Y, Y^*}$.

10

ESTIMATES USING COMPLE-MENTARY RANDOM NUMBERS



- Let M_{X1} be an estimate based on $x_1, ..., x_n$.
- Let M_{X2} be an estimate based on the corresponding complementary random numbers, $x_1^*, ..., x_n^*$.
- Obviously ${\cal M}_{X1}$ and ${\cal M}_{X2}$ are negatively correlated.



ESTIMATES USING COMPLE-MENTARY RANDOM NUMBERS

 In practice, there is no need to differentiate between the origin of the samples; the final estimate is simply

$$m_X = \frac{1}{2n} \sum_{i=1}^{n} (x_i + x_i^*).$$

MULTIPLE INPUTS



- Generally, the input vector Y has more than one element.
- The complementary random numbers of a vector can be created by combining the original and complementary random numbers of each element in the vector.
 - It can be noted that each scenario y_i will have more than one complementary scenario.
- It is possible to apply complementary random numbers only to a selection of the elements in Y.

EXAMPLE 16 - Complementary random vector



The input vector Y has the three elements A, B, C. The outcomes a_i , b_i , c_i have been randomised for each element, and the corresponding complementary random numbers, a_i^* , b_i^* , c_i^* , have been calculated.

Enumerate the original and complementary scenarios if complementary random numbers are applied to the following elements:

- a) A, B, C.
- b) A, B.

13

14

EXAMPLE 16 - Complementary random vector



Solution: a) Randomise three values, *a*, *b*, *c* and calculate their complementary random numbers. The results are combined as follows:

$$[a,b,c]$$
, $[a,b,c^*]$, $[a,b^*,c]$, $[a,b^*,c^*]$, $[a^*,b,c]$, $[a^*,b,c^*]$, $[a^*,b^*,c]$, $[a^*,b^*,c^*]$, $[a^*,b^*,c]$, $[a^*,b^*,c^*]$,

b) Randomise six values, a, b, c_1 , c_2 , c_3 , c_4 and calculate the random numbers a^* and b^* . The results are combined as follows:

$$[a,b,c_1]$$
, $[a,b^*,c_2]$, $[a^*,b,c_3]$, $[a^*,b^*,c_4]$.

EFFECTIVENESS



- The variance reduction effect is depending on the correlation between $x_i = g(y_i)$ and $x_i^* = g(y_i^*)$. This correlation depends on the correlation between Y and X.
- All inputs may not have a significant correlation to the outputs

 no use in applying complementary random numbers to these inputs.
- Sometimes a stronger correlation can be obtained by modifying the input probability distribution.

MODIFIED INPUTS



- It might be possible to find a subset of the inputs, $Y_{i'}$ i=1,...,J such that there is a strong correlation between $Y_E=h(Y_1,...,Y_J)$ (where h is an arbitrary function) and X.
- When it can be worthwhile to introduce Y_E as an extra input variable to the system, and apply complementary random numbers to Y_E instead of $Y_{i'}$, $i=1,\ldots,J$.





- In example 15, the net income is correlated to the demand.
- The correlation between the demand for an individual flavour and the net income is not as strong as the correlation between the total demand and the net income.
- Hence, we can introduce the input variable

$$D_{tot} = \sum_{f \in \mathcal{F}} D_f.$$

EXAMPLE 17 - Modifying discrete random variables



- We now have to find a joint probability distribution for D_{tot} and D_{f} , f = 1, ..., 6.
- The demand for each flavour has three possible states. The total number of combinations is then $3^6 = 729$.
- Enumerate all possible states, calculate the probability for each state and sort the states according to increasing values of D_{tot} .



EXAMPLE 17 - Modifying discrete random variables

- The demand for each flavour can now be randomised with one value from the pseudorandom number generator, $\it U.$
- The complementary demand for each flavour is calculated using $U^* = 1 U$.
- The total demand based on U will be negatively correlated to the total demand based on U^{\star} .

EXAMPLE 18 - Modifying normal distributions



- Gismo Inc. is selling their products to K retailers, and the demand of each retailer, $D_{k'}$ is $N(\mu_k,\,\sigma_k)$ -distributed.
- The costs of Gismo Inc. has a stronger correlation to the total demand compared to the demand of an individual retailer.
- Introduce the input variable $D_{tot} = D_I + ... + D_K$.





- ullet The probability distribution of D_{tot} is calculated using the addition theorems for normally distributed random variables.
- To generate the original scenario, randomise D_{tot} as well as temporary values of $D_1, ..., D_K$. Then scale the individual retailer demands to match D_{tot} , i.e., let

$$D_k = \frac{D_{tot}}{\sum_{j}^{K} D_j'} D_k', \quad \text{where } D_k' \text{ is the temporary value.}$$

2

22

EXAMPLE 18 - Modifying normal distributions

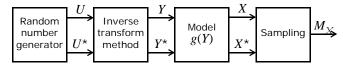


• To generate the complementary scenario, calculate the complementary random value of D_{tot} and randomise new temporary values of D_1, \ldots, D_K . Then scale the individual retailer demands to match D_{tot}^* .



- Complementary random numbers





- Step 1. Generate a random number $u_{k, i}$ and calculate $y_i = F_{Yk}^{-1}(u_{i, k})$. If applicable to this scenario parameter, also calculate $y_i^* = F_{Yk}^{-1}(1 u_{i, k})$.
- Step 2. Repeat step 1 for all scenario parameters. Create all complementary scenarios and calculate $x_i = g(y_i)$.

SIMULATION PROCEDURE

- Complementary random numbers
- Step 3. Repeat step 1 and 2 until enough scenarios have been analysed for this batch.
- Step 4. Update the sums

$$\sum_{i=1}^{n} x_i \text{ and } \sum_{i=1}^{n} x_i^2$$

or store all samples x_i (depending on the objective of the simulation).



SIMULATION PROCEDURE

- Complementary random numbers
- Step 5. Test stopping rule. If not fulfilled, repeat step 1–4 for the next batch.
- Step 6. Calculate estimates and present results.

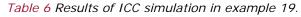
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EXAMPLE 19 - Effectiveness of ICC simulation



Consider the same system as in example 15. Compare the true expectation values to the probability distribution of estimates from a complementary random number simulation using 200 samples.

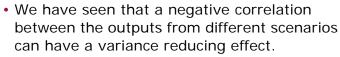


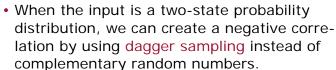




Simulation method		ected ne [€/ Av.			for mi very Av.		Average simulation time [h:min:s]
Enumeration		874			0.32		0:34:54
Simple sam- pling	829	872	909	0.00	0.27	1.00	0:02:25
Complemen- tary ran- dom numbers	842	875	914	0.00	0.27	1.00	0:02:25

DAGGER SAMPLING







DAGGER SAMPLING

 Consider a two-state input variable Y with the frequency function

$$f_{Y}(x) = \begin{cases} 1-p & x = A, \\ p & x = B, \\ 0 & \text{all other } x, \end{cases}$$
 (8)

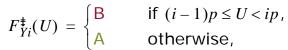
where p < 0.5.

 In dagger sampling, the inverse transform method is replaced by a dagger transform function.

30

DAGGER TRANSFORM

Definition 13: Assume that Y is distributed according to (8) and let S be the largest integer such that $S \leq 1/p$.* Then, Y_i , i = 1, ..., S, is randomised according to



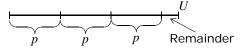
where U is a random value from a U(0, 1)-distribution.

* The value of S is referred to as the dagger cycle length.



DAGGER TRANSFORM

- The dagger transform can be illustrated by dividing an interval between 0 and 1 in S sections, where each section has the width p.
- There will also be a remainder interval if S·p < 1.



- Each value of *U* generates *S* values of *Y*.
- $y_k = B$ if U is found in the k: th section, and all other $y_i = A$, i = 1, ..., S, $i \neq k$.

ii |



EXAMPLE 20 - Dagger transform

The random variable Y is either equal to 2 (70% probability) or 5 (30% probability).



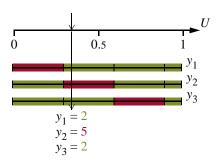
- a) Randomise three values of Y using dagger sampling and the random value U=0.34 from a U(0,1)-distribution.
- b) Randomise three values of Y using dagger sampling and the random value U=0.94 from a U(0, 1)-distribution.

EXAMPLE 20 - Dagger transform

Solution: Here $p = 0.3 \Rightarrow S = 3$. Moreover, we have A = 2 and B = 5.



a)



33

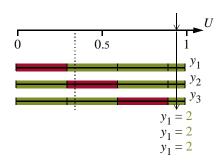
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EXAMPLE 20 - Dagger transform

Solution (cont.)

b)





CORRELATION OF DAGGER SAMPLES



- The outputs $X_1, ..., X_S$ from the scenarios generated in a dagger cycle will be negatively correlated if the inputs $Y_1, ..., Y_S$ are negatively correlated (but the correlation might be weaker).
- Are the input values $Y_i=F_{Yi}^{\sharp}(U)$, i=1,...,S negatively correlated, i.e., what is the value of

$$Cov[Y_i, Y_j] = E[Y_iY_j] - E[Y_i]E[Y_j]$$
?

CORRELATION OF DAGGER SAMPLES



• There are two possible values for the product Y_iY_j : AB or AA. There are two sections there either Y_i or Y_j will be transformed to B; hence, the probability for this event is 2p. Thus, we get

$$E[Y_iY_j] = 2pAB + (1 - 2p)AA.$$



CORRELATION OF DAGGER SAMPLES



Moreover, we have

$$E[Y_i] = E[Y_i] = (1 - p)A + pB.$$

• The covariance can now be calculated as $Cov[Y_i, Y_j] = E[Y_iY_j] - E[Y_i]E[Y_j] = \\ = 2p\mathsf{AB} + (1-2p)\mathsf{AA} - ((1-p)\mathsf{A} + p\mathsf{B})^2 = \\ = \dots = -p^2(\mathsf{A} + \mathsf{B})^2 < 0.$

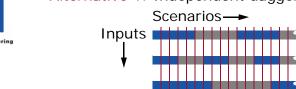
 The input values are negatively correlated and we can therefore expect a negative correlation in the outputs too.

3

MULTIPLE INPUTS

Assume that a computer simulation has several two-state input variables. Which dagger cycle length should be chosen?

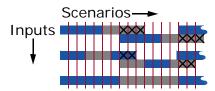
• Alternative 1: Independent dagger cycles.



MULTIPLE INPUTS

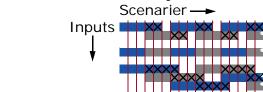
• Alternative 2: Reset all dagger cycles at the end of the longest cycle.





MULTIPLE INPUTS

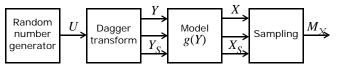
• Alternative 3: Reset all dagger cycles at the end of the shortest cycle.





SIMULATION PROCEDURE

- Dagger sampling



- Step 1. Generate a random number $u_{k, i}$ and calculate $y_i = F_{Yi}^{\sharp}(u_{i, k})$ for one dagger cycle.
- Step 2. Repeat step 1 for all scenario parameters. Combine the dagger cycles and calculate $x_i = g(y_i)$.

4

42

SIMULATION PROCEDURE

- Dagger sampling
- Step 3. Repeat step 1 and 2 until enough scenarios have been analysed for this batch.
- Step 4. Update the sums

$$\sum_{i=1}^{n} x_i \text{ and } \sum_{i=1}^{n} x_i^2$$

or store all samples x_i (depending on the objective of the simulation).



SIMULATION PROCEDURE

- Dagger sampling
- Step 5. Test stopping rule. If not fulfilled, repeat step 1–4 for the next batch.
- Step 6. Calculate estimates and present results.

EXAMPLE 21 - Effectiveness of ICC simulation



Consider the same system as in example 15. Compare the true expectation values to the probability distribution of estimates from a dagger sampling simulation using 200 samples.

EXAMPLE 21 - Effectiveness of ICC simulation

Table 7 Results of ICC simulation in example 21.



Simulation method		ected ne [€/ Av.			for mi very Av.		Average simulation time [h:min:s]
Enumeration		874			0.32		0:34:54
Simple samp.	829	872	909	0.00	0.27	1.00	0:02:25
Compl. r.n.	842	875	914	0.00	0.27	1.00	0:02:25
Dagger sam- pling	856	877	900	0.00	0.27	1.00	0:02:27

45

VARIANCE REDUCTION

- To achieve a variance reduction, we need to have some information of the simulated system.
- For complementary random numbers, we need to identify the inputs where a negative correlation between scenarios will result in negative correlations for one or more outputs.
- For dagger sampling, we need to identify twostate inputs where a negative correlation between the scenarios will result in negative correlations for one or more outputs.

