Examples of Uncertainty Propagation

Table of Contents

Introduction
Example 1 Uncertainty of corellated variables
Example 2 Uncertainty based on GUM
Example 3 Combination of custom and normal distribution

Copyright (C) 2022 Bolic

This program is free software: you can redistribute it and/or modify it under the terms of the GNU General Public License as published by the Free Software Foundation, either version 3 of the License, or (at your option) any later version. This program is distributed in the hope that it will be useful, but WITHOUT ANY WARRANTY; without even the implied warranty of MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE. See the GNU General Public License for more details https://www.gnu.org/licenses/.

This code was developed by Miodrag Bolic for the book PERVASIVE CARDIAC AND RESPIRATORY MONITORING DEVICES. The author thanks Joe Klebba for developing the toolbox for uncertainty propagation in Matlab.

Introduction

This notebook provides introduction to uncertainty propagation through several simple models. Uncertainty Quantification (UQ) aims at developing rigorous methods to characterize the impact of "limited knowledge" on quantities of interest.

Example 1 Uncertainty of corellated variables

Let us define a ratio R of AC currents obtained from a photodetector after emitting red and infrared light as:

$$R = I_R/I_{IR}$$

Assume the AC currents at the photodiode obtained after emitting red (I_0) and infrared (I_0) light are measured with the standard deviation of 0.5 μ 4. The values of I_0 and I_0 are I_0 = 10 μ 4 and I_0 = 20 μ 4. Let us assume that the

measurements are correlated, and that the correlation coefficient is P = 0.7. What is the uncertainty of the ratio R? Let us assume that the current follow normal distribution. Also, the distribution of R obtain after dividing the random variable that follow normal distribution will be also normal.

Solution:

Method 1 Perturbation

```
I_R=10; I_IR=20;
u_R=0.5; u_IR=0.5;
corrMatrix=[1 0.7; 0.7 1];
R = @(I_R,I_IR)I_R./I_IR;

[uncertCD,valCD]=propUncertCD(R,[I_R I_IR],[u_R u_IR],corrMatrix)

uncertCD = 0.0185
valCD = 0.5000

%Computation based on the formula from the text book
un_R=sqrt((u_R*1/I_IR)^2+(-u_IR*I_R/I_IR^2)^2-2*corrMatrix(1,2)*u_R*u_IR*I_R/I_IR^3)
un_R = 0.0185
```

Method 2 Monte Carlo

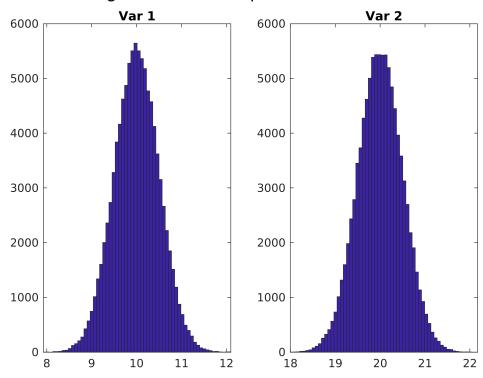
The same result ==0.0185 can be obtained using Monte Carlo sampling. First, we need to sample from two-

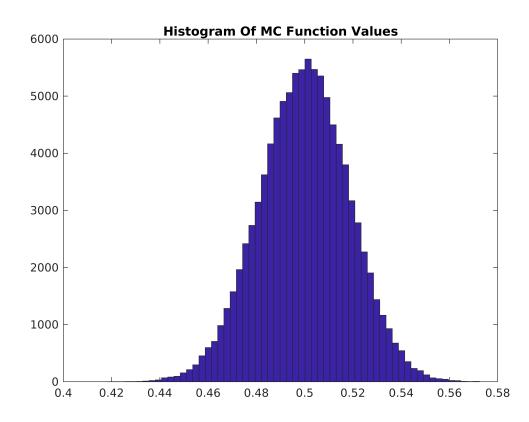
dimensional multivariate Gaussian distribution and obtain correlated samples # and # for = 1.... where where is the number of Monte Carlo samples. We are using M=100,000 samples. Then, these samples are passed

through the function $\mathbb{R}^m = \mathbb{R}^m / \mathbb{R}^m$. Values \mathbb{R}^m are fitted to a normal distribution and confidence intervals are computed. The solution in Matlab is shown in the book web page.

```
% Monte Carlo computation based on the method proposed by Joe Klebba [CI, funcVal, MCfuncVals, MCsamples]=propUncertMC(R,{{'Corr',{{I_R u_R};{I_IR u_IR}}},co
```

Histogram Of MC Samples For Each Variable





uncertMC = (CI(2)-CI(1))/2

uncertMC = 0.0184

valCD valCD = 0.5000 % Monte Carlo computation based on the method from the text book Cov=[u_R^2 corrMatrix(1,2)*u_R*u_IR; corrMatrix(1,2)*u_R*u_IR u_IR^2] Cov = 2x2 0.2500 0.1750 0.1750 0.2500

```
rng('default') % For reproducibility
MvRnd = mvnrnd([I_R I_IR],Cov,100000);

MCfuncVals1=R(MvRnd(:,1),MvRnd(:,2));
pd = fitdist(MCfuncVals1,'Normal');
ci = paramci(pd,'Alpha',.33);
ci(2,2)
```

ans = 0.0186

Example 2 Uncertainty based on GUM

- a. For a transducer with the following calibration curve, y = bx, estimate the expanded uncertainty for x = 5.00, if b = 1 with Ub =0.01 and $\frac{u}{x} = 0.05$ at 95% confidence. Assume that all variables follow normal distribution. Please note that we did not introduce units here and that we assume that all the values are relative.
- b. Compute the expanded uncertainty at 99% confidence.

Solution:

```
clear all
x=5; u_x=0.05/2;
b=1; u_b=0.01/2;
y=@(x,b)x.*b;
[uncertCD,valCD]=propUncertCD(y,[x b],[u_x u_b])

uncertCD = 0.0354
valCD = 5

U_95=uncertCD*2

U_95 = 0.0707

U_99=uncertCD*3

U_99 = 0.1061

% Calculation from the textbook
u_y=sqrt((x*u_b)^2+(b*u_x)^2)

u_y = 0.0354
```

```
[CI,valMC]=propUncertMC(y,{{x u_x};{b u_b}},100000);
 uncertMC = (CI(2)-CI(1))/2
 uncertMC = 0.0352
 valMC
 valMC = 4.9997
 % Uncertainty can be directly computed to the desired level
 [CI, valMC]=propUncertMC(y, \{\{x u_x\}; \{b u_b\}\}, 100000, 'CI', 0.99\};
 uncertMC = (CI(2)-CI(1))/2
 uncertMC = 0.0913
 valMC
 valMC = 4.9990
Example 3 Combination of custom and normal distribution
Here, we will consider and example in which the data that is coming from a normal distribution and is quantized
```

using ADC converter with the resulution of 8 bits and the range of 5 V.

```
n=100000;
x_{data} = unifrnd(3,4,1,15);
x = normrnd(1, 0.01, n, 1);
ADC_res=5/2^8;
u_ADC=ADC_res/sqrt(12); % standard uncertainty for the "rounding" ADC
% Uncertainty in the measurements of x is Type A uncertainty while ADC
% converter uncertainty is type B. The total uncertainty based on GUM is:
u_total=sqrt(u_ADC^2+0.01^2)
```

```
u_total = 0.0115
f = @(x,u)x+u;
[CI,valMC]=propUncertMC(f,{{'Custom',x};{'uniform',0,ADC_res}},n);
uncertMC = (CI(2)-CI(1))/2
```

```
uncertMC = 0.0115
valMC
```

valMC = 1.0102