Supplementary Data 2

In silico decision point qualitative method simulation

All scripts are available for download at https://www.researchgate.net/profile/Brigitte_Desharnais.

1 Standard model

```
1 # QUAL_Simulation_Standard.R
2 # In silico decision point qualitative method simulation
3 # By Brigitte Desharnais, last modification 2019-01-23
9 # Establishing the concentration at cut-off
10 CO_Conc <- 20
12 # Concentrations to be simulated
Conc \leftarrow c(0, 2, 4, 6, 8, 10, 11, 12, 14, 16, 17, 18, 20, 22, 23, 24, 26, 28, 29, 30,
     32, 34, 36, 38, 40)
15 # Establish the range of possible measurements at cut-off
16 # To be set, for example, based on preliminary experimental values collected.
17 Min_Meas <- 0.008
18 Max_Meas <- 1.050
20 # Number of total simulations to be performed
21 # Suggested: >50. Purely guides the number of simulations, can increase this number
    a lot.
```

```
22 Nb_Sim <- 100
24 # Number of measurements (i.e. virtual "spiked samples") at each concentration
25 # Value will depend on what you are trying to model: an experimental setup? (Use
     experimental value.)
26 # The underlying true value? (Use at least > 50.)
27 Nb_Meas <- 100
29 # %RSD at cut-off (will be used to calculate the homoscedastic error)
30 RSD <- 0.15
36 # Load necessary packages
37 library (dplyr)
 library (ggplot2)
  library (extrafont)
41 # Initializing an empty data frame to receive the results
 Data <- data.frame(Conc = double(), Rate = double(), Iter = integer())
43
44 # Perform the specified number of simulations
  for (i in 1:Nb_Sim) {
   # Setting a known, true measurement at cut-off
   TR_CO <- runif(1, min = Min_Meas, max = Max_Meas)
47
48
   # Calculating the B1 value in y = B1*x
49
   B1 <- TR_CO/CO_Conc
   # Calculating the standard deviation value (homoscedastic data is simulated here)
   SD <- RSD*TR_CO
54
   # Initializing a vector for the positivity rates to be calculated
   Rate \leftarrow rep (0, times = length(Conc))
```

```
# For each concentration, calculate the positivity rate
58
     for(j in 1:length(Conc)){
       # Generate a measurements vector under a normal model
       Meas <- rnorm(Nb_Meas, mean = B1*Conc[j], sd = SD)
       # Calculate the positivity rate and store in the Rate vector
       # Number of measurements which are above the known, true cut-off value
       Rate[j] \leftarrow sum(Meas > TR_CO)/Nb_Meas*100
     }
     # Create an iteration vector
68
     Iter <- rep(i, times = length(Conc))</pre>
     # Bind together Conc, Rate and Iter column and append to Data data.frame.
71
     Temp <- cbind (Conc, Rate, Iter)
     Data <- rbind (Data, Temp)
74 }
76 # Convert data.frame to tbl.
  Data <- tbl_df(Data)
78
79 # Generate a positivity graph (Figure 1(b))
  ggplot(Data, aes(x = Conc, y = Rate)) +
     geom\_smooth(size = 2, col = "#1824cc") +
81
     \operatorname{coord}_{\operatorname{\mathsf{cartesian}}}(\operatorname{xlim} = \operatorname{\mathsf{c}}(10, 30), \operatorname{ylim} = \operatorname{\mathsf{c}}(0, 100)) +
82
     scale_x_continuous(name = "Concentration (ng/mL)") +
83
     scale_y_continuous(name = "Positivity Rate (%)") +
84
     theme(axis.title = element_text(size = 26, family = "Century Gothic"),
85
             axis. title.y = element_text(margin = margin(t = 0, r = 20, b = 0, l = 0)),
             \frac{\text{axis.title.}}{\text{axis.title.}} = \text{element\_text} \left( \frac{\text{margin}}{\text{margin}} = \frac{\text{margin}}{\text{margin}} \left( \text{t} = 20, \text{ r} = 0, \text{ b} = 0, \text{ l} = 0 \right) \right),
87
             axis.text = element_text(size = 22, family = "Century Gothic")) +
     geom_vline(xintercept = 20, col = "black", linetype = "longdash", size = 1)
```

2 Model corrected for sampled cut-off and heteroscedasticity

```
1 # QUAL_Simulation_Corrected.R
2 # In silico decision point qualitative method simulation
3 # Modified simulation: sampled cut-off, heteroscedasticity
4 # By Brigitte Desharnais, last modification 2019-01-23
7 ######## Parameters to be set by the user ##########
9 # Establishing the concentration at cut-off
10 CO_Conc <- 20
12 # Concentrations to be simulated
13 Conc \leftarrow c(0, 2, 4, 6, 8, 10, 11, 12, 14, 16, 17, 18, 20, 22, 23, 24, 26, 28, 29, 30,
      32, 34, 36, 38, 40)
15 # Establish the range of possible measurements at cut-off
16 # To be set, for example, based on preliminary experimental values collected.
17 Min_Meas <- 0.008
18 Max_Meas <- 1.050
20 # Number of total simulations to be performed
21 # Suggested: >50. Purely guides the number of simulations, can increase this number
     a lot.
22 Nb_Sim <- 100
24 # Number of measurements (i.e. virtual "spiked samples") at each concentration
25 # Value will depend on what you are trying to model: an experimental setup? (Use
     experimental value.)
26 # The underlying true value? (Use at least > 50.)
27 Nb_Meas <- 30
29 # Number of cut-off measurements to be performed with each batch (sampled cut-off)
30 # Can set it up to reflect actual experimental work, or to explore the impact of
     changing its value.
31 Nb_CO <- 2
```

```
33 # %RSD at all levels (heteroscedastic data)
34 # Set based on experimental data or hypothesis (e.g. SWGTOX dictates %RSD below 20%)
35 RSD <- 0.15
36
 41 # Load necessary packages
42 library (dplyr)
43 library (ggplot2)
 library (extrafont)
46 # Initializing an empty data frame to receive the results
47 Data <- data.frame(Conc = double(), Rate = double(), Iter = integer())
49 # Perform the specified number of simulations
  for(i in 1:Nb_Sim){
   # Setting a known, true measurement at cut-off
   TR_TR_CO <- runif(1, min = Min_Meas, max = Max_Meas)
   TR_CO <- mean(rnorm(Nb_CO, mean = TR_TR_CO, sd = RSD*TR_TR_CO))
54
   # Calculating the B1 value in y = B1*x
   B1 <- TR_CO/CO_Conc
   # Initializing a vector for the positivity rates to be calculated
58
   Rate \leftarrow rep (0, times = length(Conc))
   # For each concentration, calculate the positivity rate
61
    for(j in 1:length(Conc)){
     # Generate a measurements vector under a normal model
     Meas <- rnorm(Nb_Meas, mean = B1*Conc[j], sd = RSD*B1*Conc[j])
64
     # Calculate the positivity rate and store in the Rate vector
```

```
# Number of measurements which are above the known, true cut-off value
       Rate[j] \leftarrow sum(Meas > TR_CO)/Nb_Meas*100
68
     }
    # Create an iteration vector
     Iter <- rep(i, times = length(Conc))</pre>
72
    # Bind together Conc, Rate and Iter column and append to Data data.frame.
74
    Temp <- cbind (Conc, Rate, Iter)
75
    Data <- rbind (Data, Temp)
77
  # Convert data.frame to tbl.
  Data <- tbl_df(Data)
  # Generate a positivity graph
  ggplot(Data, aes(x = Conc, y = Rate)) +
     geom\_smooth(size = 2, col = "#1824cc") +
84
     \operatorname{coord\_cartesian}(\operatorname{xlim} = c(10, 30), \operatorname{ylim} = c(0, 100)) +
85
     scale_x_continuous(name = "Concentration (ng/mL)") +
86
     scale_y_continuous(name = "Positivity Rate (%)") +
87
     theme(axis.title = element_text(size = 26, family = "Century Gothic"),
            axis.title.y = element_text(margin = margin(t = 0, r = 20, b = 0, l = 0)),
             \underline{\text{axis.title.x}} = \text{element\_text} \left( \underline{\text{margin}} = \underline{\text{margin}} \left( t = 20, \ r = 0, \ b = 0, \ l = 0 \right) \right), 
90
            axis.text = element_text(size = 22, family = "Century Gothic")) +
     geom_vline(xintercept = 20, col = "black", linetype = "longdash", size = 1)
92
  Summary <- Data %% group_by(Conc) %%
94
     summarise (\min = \min(Rate), \max = \max(Rate), \max = \max(Rate),
                Q5 = quantile (Rate, prob = 0.05), Q95 = quantile (Rate, prob = 0.95))
```

3 Corrected model and expected performance evaluation

Use this script to set validation criteria for your own validation (number of samples analyzed to evaluate FNR, FPR, RLR, SLR and SNR) and production (number of cut-off samples analyzed to estimate signal at threshold) conditions. Remember that for samples actually negative, only a TN or FP result is possible; for samples actually positive, only a TP or FN result is possible. The Summary Tables generated should be consulted to obtain validation criteria:

- FPR: $\leq 95\%$ quantile at LURL;
- FNR: $\leq 95\%$ quantile at UURL;
- RLR: $\geq 5\%$ quantile at UURL;
- SLR: $\geq 5\%$ quantile at LURL;
- SNR: $\geq 5\%$ quantile at UURL;

Note that the RLR is calculated both from LURL and UURL data (indeed, RLR = 100 - FPR - FNR). The 5% quantile at UURL is taken as the validation criteria because in an heteroscedastic system (like mass spectrometry systems), this value will always be lower than at the LURL.

Quantiles (5%, 95%) are used as validation criteria instead of the minimum or maximum value obtained, which would also be a valid, albeit less conservative, choice. What is the rationale behind this choice? It parallels hypothesis testing and confidence intervals, in that if, e.g., an FNR of a value $\leq 95\%$ quantile at UURL is obtained, the probability of obtaining this value or a more extreme one if the method indeed behaves as it should be is less than 5%, i.e., very unlikely. Other, stricter validation criteria (e.g., the mean rate obtained from the simulations) could be used, but then the risk of unecessarily rejecting perfectly adequate methods would be much higher.

```
_{1} # QUAL_Simulation_Performance.R
```

^{2 #} In silico decision point qualitative method simulation

^{3 #} Modified simulation & calculation of all performance statistics

```
4 # By Brigitte Desharnais, last modification 2019-01-23
9 # Establishing the concentration at cut-off
10 CO_Conc <- 20
12 # Concentrations to be simulated
13 # You can input a series of concentrations to simulate positivity curves.
14 # Or you can input only the LURL, CO and UURL if you want to set validation criteria
conc \leftarrow c(11, 20, 29)
17 # Establish the range of possible measurements at cut-off
18 Min_Meas <- 0.008
19 Max_Meas <- 1.050
21 # Number of total simulations to be performed
22 # Suggested: >50. Purely guides the number of simulations, can increase this number
     a lot.
23 Nb_Sim <- 100
24
25 # Number of measurements (i.e. virtual "spiked samples") at each concentration
26 # Value will depend on what you are trying to model: an experimental setup? (Use
     experimental value.)
27 # The underlying true value? (Use at least > 50.)
28 Nb_Meas <- 30
30 # Number of cut-off measurements to be performed with each batch (sampled cut-off)
31 # Can set it up to reflect actual experimental work, or to explore the impact of
     changing its value.
32 Nb_CO <- 2
34 # %RSD at all levels (heteroscedastic data)
35 # Set based on experimental data or hypothesis (e.g. SWGTOX dictates %RSD below 20%)
```

```
36 RSD <- 0.15
 42 # Load necessary packages
43 library (dplyr)
44 library (ggplot2)
  library (extrafont)
47 # Initializing an empty data frame to receive the results
48 Data <- data.frame(Conc = double(), Nb_Pos = double(), Iter = integer())
50 # Perform the specified number of simulations
  for (i in 1:Nb_Sim) {
   # Setting a known, true measurement at cut-off
   TR_TR_CO <- runif(1, min = Min_Meas, max = Max_Meas)
   TR_CO <- mean(rnorm(Nb_CO, mean = TR_TR_CO, sd = RSD*TR_TR_CO))
54
   # Calculating the B1 value in y = B1*x
56
   B1 <- TR_CO/CO_Conc
   # Initializing a vector for the positivity rates to be calculated
   Nb_Pos \leftarrow rep(0, times = length(Conc))
   # For each concentration, calculate the positivity rate
62
    for(j in 1:length(Conc)){
63
     # Generate a measurements vector under a normal model
     Meas <- rnorm(Nb_Meas, mean = B1*Conc[j], sd = RSD*B1*Conc[j])
     # Calculate the positivity rate and store in the Rate vector
     # Number of measurements which are above the known, true cut-off value
68
     Nb_Pos[j] \leftarrow sum(Meas > TR_CO)
   }
```

```
71
     # Create an iteration vector
72
     Iter <- rep(i, times = length(Conc))</pre>
74
     # Bind together Conc, Rate and Iter column and append to Data data.frame.
     Temp <- cbind (Conc, Nb_Pos, Iter)
76
     Data <- rbind (Data, Temp)
78
79
80 # Convert data.frame to tbl.
81 Data <- tbl_df(Data)
83 # Remove all observations at the cut-off concentration
84 #(which can't be classified into "true" or "false" positive/negative)
85 Data <- Data %% filter (Conc!= CO_Conc)
87 # Initialize empty columns for true/false positives/negatives
88 Data$TP <- 0
89 Data$FP <- 0
90 Data$TN <- 0
  Data$FN <- 0
93 # Calculate the number of TP, TN, FP, FN for each concentration
   for(k in 1:length(Data$Nb_Pos)){
     if (Data$Conc[k] < CO_Conc){</pre>
       # For samples actually negative, only a TN or FP result is possible.
       Data$FP[k] <- Data$Nb_Pos[k]
97
       Data$TN[k] <- Nb_Meas - Data$Nb_Pos[k]
     }else{
99
       # For samples actually positive, only a TP or FN result is possible.
100
       Data$TP[k] <- Data$Nb_Pos[k]
101
       Data$FN[k] <- Nb_Meas - Data$Nb_Pos[k]
104 }
106 # Calculation of the performance statistics
```

```
Data$FNR <- Data$FN/(Data$FN + Data$TP)*100
  Data$FPR <- Data$FP/(Data$FP + Data$TN)*100
  Data$REL <- (Data$TP + Data$TN) / (Data$TP + Data$TN + Data$FP + Data$FN)
  Data$SEL <- Data$TN / (Data$TN + Data$FP)*100
   Data$SEN <- Data$TP / (Data$TP +Data$FN)*100
# Summary table of the performance statistic per concentration level.
114 # Table lists the minimum and maximum value observed, the mean rate for all
      simulations
^{115} # performed, and the 5% and 95% percentile values observed.
116 # These summary tables were used to set the threshold values stated in the paper.
   Summary_FNR <- Data %% group_by(Conc) %% arrange(FNR) %%
     summarise(min = min(FNR), Q5 = nth(FNR, 5), mean = mean(FNR),
118
               Q95 = nth(FNR, 95), max = max(FNR)
   Summary_FPR <- Data %% group_by(Conc) %% arrange(FPR) %%
     summarise (\min = \min(FPR), Q5 = \text{nth}(FPR, 5), \max = \max(FPR),
               Q95 = nth(FPR, 95), max = max(FPR)
124
   Summary_REL <- Data %% group_by(Conc) %% arrange(REL) %%
125
     summarise (\min = \min(REL), Q5 = nth(REL, 5), \max = \max(REL),
               Q95 = nth(REL, 95), max = max(REL)
128
   Summary_SEL <- Data %% group_by(Conc) %% arrange(SEL) %%
     summarise (\min = \min(SEL), Q5 = \text{nth}(SEL, 5), \max = \max(SEL),
               Q95 = nth(SEL, 95), max = max(SEL)
  Summary_SEN <- Data %% group_by(Conc) %% arrange(SEN) %%
     summarise (\min = \min(SEN), Q5 = \text{nth}(SEN, 5), \max = \max(SEN),
134
               Q95 = nth(SEN, 95), max = max(SEN)
```