# Package 'dilutionrisk'

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AQL\_LQL\_heterogeneous AQL and LQL estimations for given dilution schemes when diluted samples are collected from a heterogeneous batch.

### Description

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 $\label{eq:local_AQL_LQL_heterogeneous} \ provides \ estimated \ AQL \ and \ LQL \ values \ for \ given \ dilution \ schemes \ when samples are collected from a heterogeneous batch.$ 

### Usage

 $AQL\_LQL\_heterogeneous(c,mu\_low,mu\_high,sd,a,b,f,u,USL,n,type,alpha,beta,OC,n\_sim)$ 

С	acceptance number
mu_low	the lower value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
mu_high	the upper value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n	number of samples which are used for inspection.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
alpha	producer's risk
beta	consumer's risk
OC	if we need AQL and LQL displayed with the OC curve, set OC = "TRUE"; otherwise, the output only provides the estimated values.
n_sim	number of simulations (large simulations provide more precise estimations).

#### **Details**

AQL\_LQL\_heterogeneous provides estimated AQL and LQL values for given dilution schemes when samples are collected from a heterogeneous batch. Acceptable Quality Level (AQL) is the acceptable or good quality level at which the probability of acceptance is kept at a high level, which is associated with the producer's risk. Conversely, the limiting Quality Level (LQL) refers to the rejectable or poor quality level at which the probability of acceptance is kept at a low level, which is associated with the consumer's risk.

#### Value

AQL and LQL when diluted samples are collected from a heterogeneous batch.

### Examples

```
c <- 2
mu_low <- 4
mu_high <- 9
sd <- 0.2
a <- 0
b <- 300
f <- 0.01
u <- 0.1
USL <- 1000
alpha <- 0.05
beta <- 0.10
n <- 5
AQL_LQL_heterogeneous(c, mu_low, mu_high, sd, a, b, f, u, USL, n, type = "theory",</pre>
```

AQL\_LQL\_homogeneous AQL and LQL

AQL and LQL estimations for given dilution schemes when diluted samples are collected from a homogeneous batch.

#### **Description**

AQL\_LQL\_homogeneous provides estimated AQL and LQL values for given dilution schemes when samples are collected from a homogeneous batch.

#### Usage

```
AQL\_LQL\_homogeneous(c,lambda\_low,lambda\_high,a,b,f,u,USL,n,type,alpha,beta,OC,n\_sim)
```

#### **Arguments**

С	acceptance number
lambda_low	the lower value of the expected microbial count( $\lambda$ ) for use in the graphical display's x-axis.
lambda_high	the upper value of the expected microbial $\operatorname{count}(\lambda)$ for use in the graphical display's x-axis.
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n	number of samples which are used for inspection.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
alpha	producer's risk
beta	consumer's risk
OC	if we need AQL and LQL displayed with the OC curve, set OC = "TRUE"; otherwise, the output only provides the estimated values.
n_sim	number of simulations (large simulations provide more precise estimations).

### **Details**

AQL\_LQL\_homogeneous provides estimated AQL and LQL values for given dilution schemes when samples are collected from a homogeneous batch. Acceptable Quality Level (AQL) is the acceptable or good quality level at which the probability of acceptance is kept at a high level, which is associated with the producer's risk. Conversely, the limiting Quality Level (LQL) refers to the rejectable or poor quality level at which the probability of acceptance is kept at a low level, which is associated with the consumer's risk.

#### Value

AQL and LQL when diluted samples are collected from a homogeneous batch.

#### **Examples**

```
compare_plans_dilution_1_pd_betabinom_pln
```

Comparison based on beta binomial distribution-based probability of detection curves for different dilution schemes in the first dilution stage.

### **Description**

compare\_plans\_dilution\_1\_pd\_betabinom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

#### Usage

```
compare\_plans\_dilution\_1\_pd\_betabinom\_pln(S, sd, V0, V1, mu\_lower, mu\_upper, alpha, beta)
```

S	amount of sample (in grams) used for diluted solution preparation
sd	the standard deviation of the normal distribution (on the log scale).
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
mu_lower	the lower value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
mu_upper	the upper value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
alpha	non-negative parameters of the beta distribution.
beta	non-negative parameters of the beta distribution.

compare\_plans\_dilution\_1\_pd\_betabinom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the first dilution stage.

#### **Examples**

```
S <- c(1,10,20)
V0 <- 100
V1 <- 1
mu_lower <- -4
mu_upper <- -1
alpha <- 1
beta <- 5
compare_plans_dilution_1_pd_betabinom_pln(S, sd, V0, V1, mu_lower, mu_upper, alpha, beta)</pre>
```

```
compare_plans_dilution_1_pd_betabinom_pois
```

Comparison based on beta binomial distribution-based probability of detection curves for different dilution schemes in the first dilution stage.

#### **Description**

compare\_plans\_dilution\_1\_pd\_betabinom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

### Usage

```
compare_plans_dilution_1_pd_betabinom_pois(S, V0, V1, lambda_lower, lambda_upper, alpha, beta)
```

S	amount of sample (in grams) used for diluted solution preparation
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
lambda_lower	an lower value of the expected number of microorganisms count per gram.
lambda_upper	an upper value of the expected number of microorganisms count per gram.
alpha	non-negative parameters of the beta distribution.
beta	non-negative parameters of the beta distribution.

compare\_plans\_dilution\_1\_pd\_betabinom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the first dilution stage.

#### **Examples**

```
S <- c(1,10,20)
V0 <- 100
V1 <- 1
lambda_lower <- 0
lambda_upper <- 50
alpha <- 1
beta <- 5
compare_plans_dilution_1_pd_betabinom_pois(S, V0, V1, lambda_lower, lambda_upper, alpha, beta)</pre>
```

```
compare_plans_dilution_1_pd_binom_pln
```

Comparison based on binomial distribution-based probability of detection curves for different dilution schemes in the first dilution stage.

#### **Description**

compare\_plans\_dilution\_1\_pd\_binom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

#### Usage

```
compare_plans_dilution_1_pd_binom_pln(S, sd, V0, V1, mu_lower, mu_upper)
```

S	amount of sample (in grams) used for diluted solution preparation
sd	the standard deviation of the normal distribution (on the log scale).
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
mu_lower	the lower value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
mu_upper	the upper value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.

compare\_plans\_dilution\_1\_pd\_binom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the first dilution stage.

#### **Examples**

```
S \leftarrow c(1,10,20)
sd <- 0.8
V0 <- 100
V1 <- 1
mu_lower <- -3
mu_upper <- -1
compare_plans_dilution_1_pd_binom_pln(S, sd, V0, V1, mu_lower, mu_upper)
```

```
compare_plans_dilution_1_pd_binom_pois
```

Comparison based on binomial distribution-based probability of detection curves for different dilution schemes in the first dilution stage.

#### **Description**

compare\_plans\_dilution\_1\_pd\_binom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

#### Usage

```
compare_plans_dilution_1_pd_binom_pois (S, V0, V1, lambda_lower, lambda_upper)
```

#### **Arguments**

S amount of sample (in grams) used for diluted solution preparation ۷0 dilution volume in the first dilution stage testing.

۷1

the volume of the diluted solution used for testing (which is equal to the plated

amount in this study)

lambda\_lower an lower value of the expected number of microorganisms count per gram. lambda\_upper an upper value of the expected number of microorganisms count per gram.

#### **Details**

compare\_plans\_dilution\_1\_pd\_binom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the first dilution stage.

#### **Examples**

```
S \leftarrow c(1,10,20) \\ V0 \leftarrow 100 \\ V1 \leftarrow 1 \\ lambda\_lower \leftarrow 0 \\ lambda\_upper \leftarrow 75 \\ compare\_plans\_dilution\_1\_pd\_binom\_pois (S, V0, V1, lambda\_lower, lambda\_upper)
```

```
compare_plans_dilution_2_pd_betabinom_pln
```

Comparison based on beta binomial distribution-based probability of detection curves for different dilution schemes in the second dilution stage.

#### **Description**

compare\_plans\_dilution\_2\_pd\_betabinom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

#### Usage

```
compare_plans_dilution_2_pd_betabinom_pln (S,sd, V0, V1, V2, V3, n_sim, mu_lower, mu_upper, alpha,
```

S	amount of sample (in grams) used for diluted solution preparation
sd	the standard deviation of the normal distribution (on the log scale).
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study) $\frac{1}{2}$
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
n_sim	number of simulations (large simulations provide a more precise estimation).
mu_lower	the lower value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
mu_upper	the upper value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
alpha	non-negative parameters of the beta distribution.
beta	non-negative parameters of the beta distribution.

compare\_plans\_dilution\_2\_pd\_betabinom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the second dilution stage.

### **Examples**

```
S <- c(1,10,20)
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 20000
mu_lower <- -4
mu_upper <- -1
alpha <- 1
beta <- 5
compare_plans_dilution_2_pd_betabinom_pln (S,sd, V0, V1, V2, V3, n_sim, mu_lower, mu_upper, alpha, beta)</pre>
```

```
compare_plans_dilution_2_pd_betabinom_pois
```

Comparison based on beta binomial distribution-based probability of detection curves for different dilution schemes in the second dilution stage.

### Description

compare\_plans\_dilution\_2\_pd\_betabinom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

#### Usage

```
compare_plans_dilution_2_pd_betabinom_pois(S, V0, V1, V2, V3, n_sim, lambda_lower, lambda_upper, a
```

S	amount of sample (in grams) used for diluted solution preparation
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)

n\_sim number of simulations (large simulations provide a more precise estimation).

lambda\_lower an lower value of the expected number of microorganisms count per gram.

lambda\_upper an upper value of the expected number of microorganisms count per gram alpha non-negative parameters of the beta distribution.

beta non-negative parameters of the beta distribution.

#### **Details**

compare\_plans\_dilution\_2\_pd\_betabinom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the second dilution stage.

#### **Examples**

```
S <- c(1,10,20)
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 20000
lambda_lower <- 0
lambda_upper <- 1000
alpha <- 1
beta <- 5
compare_plans_dilution_2_pd_betabinom_pois(S, V0, V1, V2, V3, n_sim, lambda_lower, lambda_upper, alpha, beta)</pre>
```

```
compare_plans_dilution_2_pd_binom_pln
```

Comparison based on binomial distribution-based probability of detection curves for different dilution schemes in the second dilution stage.

#### **Description**

compare\_plans\_dilution\_2\_pd\_binom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

```
compare_plans_dilution_2_pd_binom_pln(S, sd,V0, V1, V2, V3, n_sim, mu_lower, mu_upper)
```

S	amount of sample (in grams) used for diluted solution preparation
sd	the standard deviation of the normal distribution (on the log scale).
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
n_sim	number of simulations (large simulations provide a more precise estimation).
mu_lower	the lower value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
mu_upper	the upper value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.

#### **Details**

compare\_plans\_dilution\_2\_pd\_binom\_pln provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the second dilution stage.

### Examples

```
S <- c(1,10,20)
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 20000
mu_lower <- -3
mu_upper <- 1
compare_plans_dilution_2_pd_binom_pln(S, sd,V0, V1, V2, V3, n_sim, mu_lower, mu_upper)</pre>
```

```
compare_plans_dilution_2_pd_binom_pois
```

Comparison based on binomial distribution-based probability of detection curves for different dilution schemes in the second dilution stage.

### **Description**

compare\_plans\_dilution\_2\_pd\_binom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

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#### Usage

```
compare_plans_dilution_2_pd_binom_pois(S, V0, V1, V2, V3, n_sim, lambda_lower, lambda_upper)
```

#### **Arguments**

S	amount of sample (in grams) used for diluted solution preparation
VØ	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
n_sim	number of simulations (large simulations provide a more precise estimation).
lambda_lower	an lower value of the expected number of microorganisms count per gram.
lambda_upper	an upper value of the expected number of microorganisms count per gram.

#### **Details**

compare\_plans\_dilution\_2\_pd\_binom\_pois provides graphical displays of the probability of the detection curves for dilution schemes in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution. (This section will be updated later on.)

#### Value

Comparison based on probability of detection curves for different dilution schemes in the second dilution stage.

### **Examples**

```
S <- c(1,10,20)
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 20000
lambda_lower <- 1
lambda_upper <- 100
compare_plans_dilution_2_pd_binom_pois(S, V0, V1, V2, V3, n_sim, lambda_lower, lambda_upper)</pre>
```

cv\_heterogeneous coefficient of variation estimation when diluted sample collected from a heterogeneous batch.

#### **Description**

These functions provides coefficient of variation in the original sample when diluted samples collected from a heterogeneous batch.

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#### Usage

```
cv_heterogeneous(mu, sd, a, b, f, u, USL, n_sim)
cv_heterogeneous_multiple(mu, sd, a, b, f, u, USL, n_sim)
cv_curves_heterogeneous(mu_low, mu_high, sd, a, b, f, u, USL, n_sim)
```

#### **Arguments**

mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n_sim	number of simulations (large simulations provide a more precise estimation).
mu_low	the lower value of the mean microbial count $(\mu)$ for use in the graphical display's x-axis (on the log scale).
mu_high	the upper value of the mean microbial count $(\mu)$ for use in the graphical display's x-axis (on the log scale).

### **Details**

These functions provides coefficient of variation in the original sample when diluted samples collected from a heterogeneous batch.

### Value

coefficient of variation when sample collected from a heterogeneous batch.

### **Examples**

```
mu_low <- -5
mu_high <- 10
sd <- 0.2
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
n_sim <- 500
cv_curves_heterogeneous(mu_low, mu_high, sd, a, b, f, u, USL, n_sim)</pre>
```

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cv_homogeneous	coefficient of variation estimation when diluted sample collected from a homogeneous batch.

#### **Description**

These functions provides coefficient of variation in the original sample when diluted samples collected from a homogeneous batch.

### Usage

```
cv_homogeneous(lambda, a, b, f, u, USL, n_sim)
cv_homogeneous_multiple(lambda, a, b, f, u, USL, n_sim)
cv_curves_homogeneous(lambda_low, lambda_high, a, b, f, u, USL, n_sim)
```

#### **Arguments**

lambda	the expected microbial count $(\lambda)$ .
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n_sim	number of simulations (large simulations provide a more precise estimation).
lambda_low	the lower value of the expected microbial count ( $\lambda$ ) for use in the graphical display's x-axis.
lambda_high	the upper value of the expected microbial count ( $\lambda$ ) for use in the graphical display's x-axis.

#### **Details**

These functions provides coefficient of variation in the original sample when diluted samples collected from a homogeneous batch.

### Value

coefficient of variation when the diluted sample collected from a homogeneous batch.

### **Examples**

```
lambda_low <- 1000
lambda_high <- 8000
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
n_sim <- 500
cv_curves_homogeneous(lambda_low, lambda_high, a, b, f, u, USL, n_sim)</pre>
```

dilutionrisk	Probability estimations and graphical displays in modelling and assessment of risk based on aerobic plate count (APC) on diluted testing

### Description

This package aims to develop for getting probability estimations and graphical displays in the study associated with Modelling and assessment of risk based on aerobic plate count (APC) on diluted testing.

#### **Details**

This package aims to develop probability estimations and graphical displays in the modelling and assessing risk based on aerobic plate count (APC) on diluted testing. Mainly focuses on the risk assessment based on bounded distributions such as truncated Poisson and truncated Poisson lognormal distributions to model homogeneous and heterogeneous scenarios, respectively. Also, this package attempts to develop truncated Poisson lognormal distributions theory with validation by simulation-based results (this part will be updated later on).

OC\_curves\_heterogeneous

Comparison based on OC curves for different dilution schemes when the diluted samples collected from a heterogeneous batch.

### Description

OC\_curves\_heterogeneous provides the operating characteristic(OC) curves when samples collected from a heterogeneous batch.

### Usage

```
OC_curves_heterogeneous(c, mu_low, mu_high, sd, a, b, f, u, USL, n, type, n_sim)
```

С	acceptance number
mu_low	the lower value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
mu_high	the upper value of the mean microbial $\operatorname{count}(\mu)$ for use in the graphical display's x-axis.
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.

n number of samples which are used for inspection.

type what type of the results you would like to consider such as "theory" or "simula-

tion" (default "theory").

n\_sim number of simulations (large simulations provide more precise estimations).

#### **Details**

OC\_curves\_heterogeneous provides OC curves for different dilution schemes when the diluted samples collected from a heterogeneous batch (this section will be updated later on).

#### Value

OC curves when samples collected from a heterogeneous batch.

#### **Examples**

```
c <- 2
mu_low <- 4
mu_high <- 9
sd <- 0.2
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
n <- 5
OC_curves_heterogeneous(c, mu_low, mu_high, sd, a, b, f, u, USL, n)</pre>
```

OC\_curves\_homogeneous Comparison based on OC curves for different dilution schemes when diluted samples collected from a homogeneous batch.

### Description

 ${\tt OC\_curves\_homogeneous}$  provides the operating characteristic (OC) curves when diluted sample has homogeneous contaminants.

### Usage

```
OC_curves_homogeneous(c, lambda_low, lambda_high, a, b, f, u, USL, n, type, n_sim)
```

С	acceptance number
lambda_low	the lower value of the expected microbial count( $\lambda$ ) for use in the graphical display's x-axis.
lambda_high	the upper value of the expected microbial count( $\lambda$ ) for use in the graphical display's x-axis.
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.

u amount put on the plate.USL upper specification limit.

n number of samples which are used for inspection.

type what type of the results you would like to consider such as "theory" or "simula-

tion" (default "theory").

n\_sim number of simulations (large simulations provide more precise estimations).

#### **Details**

OC\_curves\_homogeneous provides OC curves for different dilution schemes when samples collected from a homogeneous batch (this section will be updated later on).

#### Value

OC curves when diluted samples collected from a homogeneous batch.

#### **Examples**

```
c <- 2
lambda_low <- 1
lambda_high <- 5000
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
n <- 5
OC_curves_homogeneous(c, lambda_low, lambda_high, a, b, f, u, USL, n)</pre>
```

#### pd\_curves\_heterogeneous

Comparison based on probability of detection curves for different dilution schemes when the diluted samples collected from a heterogeneous batch.

#### **Description**

pd\_curves\_heterogeneous provides the probability of detection curves when samples collected from a heterogeneous batch.

#### Usage

```
pd_curves_heterogeneous(mu_low, mu_high, sd, a, b, f, u, USL, type, n_sim)
```

mu_low	the lower value of the mean microbial count ( $\mu$ ) for use in the graphical display's x-axis (on the log scale).
mu_high	the upper value of the mean microbial count $(\mu)$ for use in the graphical display's x-axis (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).

a	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide more precise estimations).

pd\_curves\_heterogeneous provides probability of detection curves for different dilution schemes when the diluted samples collected from a heterogeneous batch (this section will be updated later on).

#### Value

Probability of detection curves when samples collected from a heterogeneous batch.

#### **Examples**

```
mu_low <- 0
mu_high <- 10
sd <- 0.2
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
pd_curves_heterogeneous(mu_low, mu_high, sd, a, b, f, u, USL)</pre>
```

pd\_curves\_homogeneous Comparison based on probability of detection curves for different dilution schemes when diluted samples collected from a homogeneous batch.

#### **Description**

pd\_curves\_homogeneous provides the probability of detection curves when samples collected from a homogeneous batch.

```
pd_curves_homogeneous(lambda_low, lambda_high, a, b, f, u, USL, type, n_sim)
```

lambda_low	the lower value of the expected microbial count $(\lambda)$ for use in the graphical display's x-axis.
lambda_high	the upper value of the expected microbial count $(\lambda)$ for use in the graphical display's x-axis.
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide more precise estimations).

#### **Details**

pd\_curves\_homogeneous provides probability of detection curves for different dilution schemes when samples collected from a homogeneous batch (this section will be updated later on).

#### Value

Probability of detection curves when diluted samples collected from a homogeneous batch.

#### **Examples**

```
lambda_low <- 0
lambda_high <- 5000
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
pd_curves_homogeneous(lambda_low, lambda_high, a, b, f, u, USL)</pre>
```

pd\_validation\_heterogeneous

Comparison based on probability of detection curves for different dilution schemes when diluted samples collected from a heterogeneous batch.

#### **Description**

pd\_validation\_heterogeneous provides the probability of detection curves for validate the results when samples collected from a heterogeneous batch.

```
pd_validation_heterogeneous(mu_low, mu_high, sd, a, b, f, u, USL, n_sim)
```

mu_low	the lower value of the mean microbial count $(\mu)$ for use in the graphical display's x-axis (on the log scale).
mu_high	the upper value of the mean microbial count $(\mu)$ for use in the graphical display's x-axis (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n_sim	number of simulations (large simulations provide more precise estimations).

#### **Details**

pd\_curves\_heterogeneous provides probability of detection curves for different dilution schemes when samples collected from a heterogeneous batch (this section will be updated later on).

#### Value

Probability of detection curves when diluted samples collected from a heterogeneous batch.

### **Examples**

```
mu_low <- 1
mu_high <- 12
sd <- 0.2
a <- 0
b <- 300
f <- 0.01
u <- 0.1
USL <- 1000
n_sim <- 50000
pd_validation_heterogeneous(mu_low, mu_high, sd, a, b, f, u, USL, n_sim)</pre>
```

pd\_validation\_homogeneous

Comparison based on probability of detection curves for different dilution schemes when diluted samples collected from a homogeneous batch.

### Description

pd\_validation\_homogeneous provides the probability of detection curves for validate the results when samples collected from a homogeneous batch.

```
pd_validation_homogeneous(lambda_low, lambda_high, a, b, f, u, USL, n_sim)
```

lambda_low	the lower value of the expected microbial count $(\lambda)$ for use in the graphical display's x-axis.
lambda_high	the upper value of the expected microbial count $(\lambda)$ for use in the graphical display's x-axis.
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n_sim	number of simulations (large simulations provide more precise estimations).

#### **Details**

pd\_curves\_homogeneous provides probability of detection curves for different dilution schemes when samples collected from a homogeneous batch (this section will be updated later on).

#### Value

Probability of detection curves when diluted samples collected from a homogeneous batch.

#### **Examples**

```
lambda_low <- 0
lambda_high <- 5000
a <- 0
b <- 300
f <- 0.01
u <- 0.1
USL <- 1000
n_sim <- 50000
pd_validation_homogeneous(lambda_low, lambda_high, a, b, f, u, USL, n_sim = 500)
pd_validation_homogeneous(lambda_low, lambda_high, a, b, f, u, USL, n_sim = 50000)</pre>
```

prob\_acceptance\_heterogeneous

Probability of acceptance estimation when diluted sample collected from a heterogeneous batch.

### **Description**

prob\_acceptance\_heterogeneous provides a probability of acceptance in the original sample when samples collected from a heterogeneous batch.

```
prob_acceptance_heterogeneous(c, mu, sd, a, b, f, u, USL, n, type, n_sim)
```

С	acceptance number
mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n	number of samples which are used for inspection.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide a more precise estimation).

#### **Details**

prob\_detection\_heterogeneous provides a probability of acceptance when diluted sample collected from a heterogeneous batch (this section will be updated later on).

#### Value

Probability of acceptance when sample collected from a heterogeneous batch.

### **Examples**

```
 \begin{array}{l} c <- 2 \\ mu <- 7 \\ sd <- 0.2 \\ a <- 0 \\ b <- 300 \\ f <- 0.01 \\ u <- 0.1 \\ USL <- 1000 \\ n <- 5 \\ prob_acceptance_heterogeneous(c, mu, sd, a, b, f, u, USL, n) \\ \end{array}
```

```
prob_acceptance_heterogeneous_multiple
```

Probability of acceptance estimation when diluted samples are collected from a heterogeneous batch.

### Description

prob\_acceptance\_heterogeneous\_multiple provides a probability of acceptance in the original sample when samples collected from a heterogeneous batch.

```
prob_acceptance_heterogeneous_multiple (c, mu, sd, a, b, f, u, USL, n, type, n_sim)
```

С	acceptance number
mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n	number of samples which are used for inspection.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide more precise estimations).

#### **Details**

prob\_acceptance\_heterogeneous\_multiple provides a probability of acceptance when diluted samples are collected from a heterogeneous batch (this section will be updated later on).

### Value

Probability of acceptance when samples collected from a heterogeneous batch.

### **Examples**

```
 c <- 2 \\ mu <- 7 \\ sd <- 0.2 \\ a <- 0 \\ b <- 300 \\ f <- c(0.01,0.1) \\ u <- c(0.1,0.1) \\ USL <- 1000 \\ n <- 5 \\ prob_acceptance_heterogeneous_multiple (c, mu, sd, a, b, f, u, USL, n)
```

prob\_acceptance\_homogeneous

Probability of acceptance estimation when diluted sample collected from a homogeneous batch.

### Description

prob\_acceptance\_homogeneous provides a probability of acceptance in the original sample when samples collected from a homogeneous batch.

```
prob_acceptance_homogeneous(c, lambda, a, b, f, u, USL, n, type, n_sim)
```

С	acceptance number
lambda	the expected cell count $(\lambda)$ .
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n	number of samples which are used for inspection.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide a more precise estimation).

#### **Details**

prob\_detection\_homogeneous provides a probability of acceptance when samples collected from a homogeneous batch (this section will be updated later on).

#### Value

Probability of acceptance when the diluted sample collected from a homogeneous batch.

### **Examples**

```
c <- 2
lambda <- 2000
a <- 0
b <- 300
f <- 0.01
u <- 0.1
USL <- 1000
n <- 5
prob_acceptance_homogeneous(c, lambda, a, b, f, u, USL, n)</pre>
```

```
prob_acceptance_homogeneous_multiple
```

Probability of acceptance estimation for multiple dilution schemes when diluted samples are collected from a homogeneous batch.

### **Description**

prob\_acceptance\_homogeneous\_multiple provides a probability of acceptance for multiple dilution schemes in the original sample when samples collected from a homogeneous batch

```
prob_acceptance_homogeneous_multiple(c, lambda, a, b, f, u, USL, n, type, n_sim)
```

С	acceptance number
lambda	the expected microbial count $(\lambda)$ .
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n	number of samples which are used for inspection.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide more precise estimations).

#### **Details**

prob\_detection\_homogeneous\_multiple provides a probability of acceptance for multiple dilution schemes in the original sample when samples collected from a homogeneous batch (this section will be updated later on).

#### Value

Probability of acceptance when diluted samples are collected from a homogeneous batch.

### **Examples**

```
 \begin{array}{l} c <- 2 \\ lambda <- \ 1000 \\ a <- \ 0 \\ b <- \ 300 \\ f <- \ c(0.01,0.1) \\ u <- \ c(0.1,0.1) \\ USL <- \ 1000 \\ n <- \ 5 \\ prob_acceptance_homogeneous_multiple(c, \ lambda, \ a, \ b, \ f, \ u, \ USL, \ n) \\ \end{array}
```

prob\_detection\_heterogeneous

Probability of detection estimation when diluted sample collected from a heterogeneous batch.

### Description

prob\_detection\_heterogeneous provides a probability of detection in the original sample when samples collected from a heterogeneous batch.

```
prob_detection_heterogeneous(mu, sd, a, b, f, u, USL, type, n_sim)
```

mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide a more precise estimation).

#### **Details**

prob\_detection\_heterogeneous provides a probability of detection when the diluted sample has heterogeneous contaminants. We define the random variable  $X_i$  is the number of colonies on the  $i^{th}$  plate. In practice, the acceptance for countable numbers of colonies on a plate must be between 30 and 300. Therefore, we can utilise bounded distributions to model the number of colonies on a plate. In the heterogeneous case, we employed truncated Poisson lognormal distribution to model (this section will be updated later on).

#### Value

Probability of detection when sample collected from a heterogeneous batch.

### **Examples**

```
mu <- 2
sd <- 0.2
a <- 0
b <- 300
f <- 0.01
u <- 0.1
USL <- 1000
prob_detection_heterogeneous(mu, sd, a, b, f, u, USL)</pre>
```

```
prob_detection_heterogeneous_multiple
```

Probability of detection estimation for multiple dilution schemes when diluted samples are collected from a heterogeneous batch.

### Description

prob\_detection\_heterogeneous\_multiple provides a probability of detection for multiple dilution schemes in the original sample when samples collected from a heterogeneous batch.

```
prob_detection_heterogeneous_multiple(mu, sd, a, b, f, u, USL, type , n_sim)
```

mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	vector of final dilution factor.
u	vector of amount put on the plate.
USL	upper specification limit.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide a more precise estimation).

#### **Details**

prob\_detection\_heterogeneous\_multiple provides a probability of detection when diluted samples are collected from a heterogeneous batch. We define the random variable  $X_i$  is the number of colonies on the  $i^{th}$  plate. In practice, the acceptance for countable numbers of colonies on a plate must be between 30 and 300. Therefore, we can utilise bounded distributions to model the number of colonies on a plate. In the heterogeneous case, we employed truncated Poisson lognormal distribution to the model. (this section will be updated later on).

#### Value

Probability of detection when samples collected from a heterogeneous batch.

### Examples

```
\begin{array}{l} mu <- \ 7 \\ sd <- \ 0.2 \\ a <- \ 0 \\ b <- \ 300 \\ f <- \ c(0.01,0.1) \\ u <- \ c(0.1,0.1) \\ USL <- \ 1000 \\ prob_detection_heterogeneous_multiple(mu, sd, a, b, f, u, USL) \end{array}
```

prob\_detection\_homogeneous

Probability of detection estimation when diluted sample collected from a homogeneous batch.

### Description

prob\_detection\_homogeneous provides a probability of detection in the original sample when samples collected from a homogeneous batch.

```
prob_detection_homogeneous(lambda, a, b, f, u, USL, type, n_sim)
```

lambda	the expected microbial count $(\lambda)$ .
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide a more precise estimation).

#### **Details**

prob\_detection\_homogeneous provides a probability of detection when the diluted sample has homogeneous contaminants. We define the random variable  $X_i$  is the number of colonies on the  $i^{th}$  plate. In practice, the acceptance for countable numbers of colonies on a plate must be between 30 and 300. Therefore, we can utilise bounded distributions to model the number of colonies on a plate. In the homogeneous case, we employed truncated Poisson distribution to model (this section will be updated later on).

#### Value

Probability of detection when the diluted sample collected from a homogeneous batch.

#### **Examples**

```
lambda <- 2000
a <- 0
b <- 300
f <- 0.01
u <- 0.1
USL <- 1000
n_sim <- 50000
prob_detection_homogeneous(lambda, a, b, f, u, USL)
prob_detection_homogeneous(lambda, a, b, f, u, USL, type = "simulation", n_sim)</pre>
```

prob\_detection\_homogeneous\_multiple

Probability of detection estimation for multiple dilution schemes when diluted samples are collected from a homogeneous batch.

### Description

prob\_detection\_homogeneous\_multiple provides a probability of detection for multiple dilution schemes in the original sample when samples collected from a homogeneous batch.

```
prob_detection_homogeneous_multiple(lambda, a, b, f, u, USL, type, n_sim)
```

lambda	the expected microbial count $(\lambda)$ .
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
type	what type of the results you would like to consider such as "theory" or "simulation" (default "theory").
n_sim	number of simulations (large simulations provide more precise estimations).

#### **Details**

prob\_detection\_homogeneous\_multiple provides a probability of detection when the diluted sample has homogeneous contaminants. We define the random variable  $X_i$  is the number of colonies on the  $i^{th}$  plate. In practice, the acceptance for countable numbers of colonies on a plate must be between 30 and 300. Therefore, we can utilise bounded distributions to model the number of colonies on a plate. In the homogeneous case, we employed truncated Poisson distribution to model (this section will be updated later on).

#### Value

Probability of detection when diluted samples are collected from a homogeneous batch.

#### **Examples**

```
lambda <- 1000
a <- 0
b <- 300
f <- c(0.01,0.1,1)
u <- c(0.1,0.1,0.1)
USL <- 1000
n_sim <- 50000
prob_detection_homogeneous_multiple(lambda, a, b, f, u, USL)</pre>
```

```
prob_detect_dilution_1_betabinom_pln
```

Beta binomial distribution-based probability of detection for a dilution scheme in the first dilution stage testing.

#### **Description**

prob\_detect\_dilution\_1\_betabinom\_pln provides a probability of detection for a dilution scheme in the first dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

```
prob_detect_dilution_1_betabinom_pln(S, mu, sd, V0, V1, alpha, beta)
```

S	amount of sample (in grams) used for diluted solution preparation
mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
alpha	non-negative parameters of the beta distribution.
beta	non-negative parameters of the beta distribution.

#### **Details**

prob\_detect\_dilution\_1\_betabinom\_pln provides a probability of detection for a dilution scheme in the first dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

#### Value

Probability of detection for a dilution scheme in the first dilution stage testing.

### **Examples**

```
S <- 25
mu <- -1
sd <- 0.8
V0 <- 100
V1 <- 1
alpha <- 1
beta <- 5
prob_detect_dilution_1_betabinom_pln(S, mu, sd, V0, V1, alpha, beta)</pre>
```

```
prob_detect_dilution_1_betabinom_pois
```

Beta binomial distribution-based probability of detection for a dilution scheme in the first dilution stage testing.

### Description

prob\_detect\_dilution\_1\_betabinom\_pois provides a probability of detection for a dilution scheme in the first dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

```
prob_detect_dilution_1_betabinom_pois(S, lambda, V0, V1, alpha, beta)
```

S	amount of sample (in grams) used for diluted solution preparation
lambda	the expected number of microorganisms count per gram
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
alpha	non-negative parameters of the beta distribution.
beta	non-negative parameters of the beta distribution.

#### **Details**

prob\_detect\_dilution\_1\_betabinom\_pois provides a probability of detection for a dilution scheme in the first dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution.(This section will be updated later on.)

### Value

Probability of detection for a dilution scheme in the first dilution stage testing.

#### **Examples**

```
S <- 25
lambda <- 10
V0 <- 100
V1 <- 1
alpha <- 1
beta <- 5
prob_detect_dilution_1_betabinom_pois(S, lambda, V0, V1, alpha, beta)</pre>
```

```
prob_detect_dilution_1_binom_pln
```

Binomial distribution-based probability of detection for a dilution scheme in the first dilution stage testing.

#### **Description**

prob\_detect\_dilution\_1\_binom\_pln provides a probability of detection for a dilution scheme in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

### Usage

```
prob_detect_dilution_1_binom_pln(S,mu,sd, V0, V1)
```

S	amount of sample (in grams) used for diluted solution preparation
mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)

prob\_detect\_dilution\_1\_binom\_pln provides a probability of detection for a dilution scheme in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

#### Value

Probability of detection for a dilution scheme in the first dilution stage testing.

### **Examples**

```
S \leftarrow c(1,10,20)
mu <- 25
sd <- 0.8
V0 <- 100
V1 <- 1
prob_detect_dilution_1_binom_pln(S,mu,sd, V0, V1)
```

```
prob_detect_dilution_1_binom_pois
```

Binomial distribution-based probability of detection for a dilution scheme in the first dilution stage testing.

#### **Description**

prob\_detect\_dilution\_1\_binom\_pois provides a probability of detection for a dilution scheme in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

#### **Usage**

```
prob_detect_dilution_1_binom_pois(S,lambda, V0, V1)
```

#### **Arguments**

S amount of sample (in grams) used for diluted solution preparation lambda

the expected number of microorganisms count per gram

۷0 dilution volume in the first dilution stage testing.

the volume of the diluted solution used for testing (which is equal to the plated ۷1

amount in this study)

#### **Details**

prob\_detect\_dilution\_1\_binom\_pois provides a probability of detection for a dilution scheme in the first dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution.(This section will be updated later on.)

#### Value

Probability of detection for a dilution scheme in the first dilution stage testing.

#### **Examples**

```
S <- c(1,10,20)
lambda <- 10
V0 <- 100
V1 <- 1
prob_detect_dilution_1_binom_pois(S,lambda, V0, V1)</pre>
```

```
prob_detect_dilution_2_betabinom_pln
```

Beta binomial distribution-based probability of detection for a dilution scheme in the second dilution stage testing.

### **Description**

prob\_detect\_dilution\_2\_betabinom\_pln provides a probability of detection for a dilution scheme in the second dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

### Usage

```
prob_detect_dilution_2_betabinom_pln(S,mu,sd, V0, V1, V2, V3, n_sim, alpha, beta)
```

#### **Arguments**

S	amount of sample (in grams) used for diluted solution preparation
mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
VØ	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
n_sim	number of simulations (large simulations provide a more precise estimation).
alpha	non-negative parameters of the beta distribution.
beta	non-negative parameters of the beta distribution.

#### **Details**

prob\_detect\_dilution\_2\_betabinom\_pln provides a probability of detection for a dilution scheme
in the second dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

### Value

Probability of detection for a dilution scheme in the second dilution stage testing.

#### **Examples**

```
S <- 20
mu <- -1
sd <- 0.8
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 25000
alpha <- 1
beta <- 5
prob_detect_dilution_2_betabinom_pln(S,mu,sd, V0, V1, V2, V3, n_sim, alpha, beta)</pre>
```

```
prob_detect_dilution_2_betabinom_pois
```

Beta binomial distribution-based probability of detection for a dilution scheme in the second dilution stage testing.

#### **Description**

prob\_detect\_dilution\_2\_betabinom\_pois provides a probability of detection for a dilution scheme in the second dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

### Usage

```
prob_detect_dilution_2_betabinom_pois(S, lambda, V0, V1, V2, V3, n_sim, alpha, beta)
```

#### **Arguments**

S	amount of sample (in grams) used for diluted solution preparation
lambda	the expected number of microorganisms count per gram
VØ	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
n_sim	number of simulations (large simulations provide a more precise estimation).
alpha	non-negative parameters of the beta distribution.
beta	non-negative parameters of the beta distribution.

### **Details**

prob\_detect\_dilution\_2\_betabinom\_pois provides a probability of detection for a dilution scheme in the second dilution stage based on the beta binomial distribution, while the count of microorganisms is modelled by Poisson distribution.(This section will be updated later on.)

#### Value

Probability of detection for a dilution scheme in the second dilution stage testing.

#### **Examples**

```
S <- 20
lambda <- 10
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 25000
alpha <- 1
beta <- 5
prob_detect_dilution_2_betabinom_pois(S, lambda, V0, V1, V2, V3, n_sim, alpha, beta)</pre>
```

```
prob_detect_dilution_2_binom_pln
```

Binomial distribution-based probability of detection for a dilution scheme in the second dilution stage testing.

#### **Description**

prob\_detect\_dilution\_2\_binom\_pln provides a probability of detection for a dilution scheme in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution.

#### Usage

```
prob_detect_dilution_2_binom_pln (S,mu,sd, V0, V1, V2, V3, n_sim)
```

#### **Arguments**

S	amount of sample (in grams) used for diluted solution preparation
mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
n_sim	number of simulations (large simulations provide a more precise estimation).

### **Details**

prob\_detect\_dilution\_2\_binom\_pln provides a probability of detection for a dilution scheme in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson lognormal distribution. (This section will be updated later on.)

#### Value

Probability of detection for a dilution scheme in the second dilution stage testing.

#### **Examples**

```
S <- 20
mu <- 25
sd <- 0.8
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 25000
prob_detect_dilution_2_binom_pln (S,mu,sd, V0, V1, V2, V3, n_sim)</pre>
```

```
prob_detect_dilution_2_binom_pois
```

Binomial distribution-based probability of detection for a dilution scheme in the second dilution stage testing.

#### **Description**

prob\_detect\_dilution\_2\_binom\_pois provides a probability of detection for a dilution scheme in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution.

### Usage

```
prob_detect_dilution_2_binom_pois(S,lambda, V0, V1, V2, V3, n_sim)
```

#### **Arguments**

S	amount of sample (in grams) used for diluted solution preparation
lambda	the expected number of microorganisms count per gram
V0	dilution volume in the first dilution stage testing.
V1	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
V2	dilution volume in the first dilution stage testing.
V3	the volume of the diluted solution used for testing (which is equal to the plated amount in this study)
n_sim	number of simulations (large simulations provide a more precise estimation).

#### **Details**

prob\_detect\_dilution\_2\_binom\_pois provides a probability of detection for a dilution scheme in the second dilution stage based on the binomial distribution, while the count of microorganisms is modelled by Poisson distribution.(This section will be updated later on.)

### Value

Probability of detection for a dilution scheme in the second dilution stage testing.

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#### **Examples**

```
S <- 20
lambda <- 10
V0 <- 100
V1 <- 1
V2 <- 10
V3 <- 1
n_sim <- 25000
prob_detect_dilution_2_binom_pois(S,lambda, V0, V1, V2, V3, n_sim)</pre>
```

rtrunpoilog

Generates random deviates from truncated Poisson lognormal distribution.

### Description

rtrunpoilog provides generated random numbers from truncated Poisson lognormal distribution with given parameters.

### Usage

```
rtrunpoilog(n, mu, sd, a, b)
```

### Arguments

n	number of observations. If $length(n) > 1$ then the length is taken to be the number required.
mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower truncation points (lower domain of the number of microbial count).
b	upper truncation points (upper domain of the number of microbial count).

#### **Details**

rtrunpoilog provides generated random numbers from truncated Poisson lognormal distribution with given parameters. (this section will be updated later on).

#### Value

rtrunpoilog generates random numbers from truncated Poisson lognormal distribution.

### **Examples**

```
n <- 100
mu <- 0
sd <- 1
a <- 0
b <- 300
rtrunpoilog(n, mu, sd, a, b)</pre>
```

```
true_concentration_heterogeneous
```

True concentration level estimation when diluted sample collected from a heterogeneous batch.

### **Description**

These functions provides true concentration level in the original sample when diluted samples collected from a heterogeneous batch.

### Usage

```
true_concentration_heterogeneous(mu, sd, a, b, f, u, USL, n_sim)

true_concentration_heterogeneous_multiple(mu, sd, a, b, f, u, USL, n_sim)

true_concentration_curves_heterogeneous(
    mu_low,
    mu_high,
    sd,
    a,
    b,
    f,
    u,
    USL,
    n_sim
)
```

### Arguments

mu	the mean microbial count (on the log scale).
sd	the standard deviation of the normal distribution (on the log scale).
а	lower domain of the number of cell counts.
b	upper domain of the number of cell counts.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n_sim	number of simulations (large simulations provide a more precise estimation).
mu_low	the lower value of the mean microbial count $(\mu)$ for use in the graphical display's x-axis (on the log scale).
mu_high	the upper value of the mean microbial count ( $\mu$ ) for use in the graphical display's x-axis (on the log scale).

### **Details**

Let Y be the count of microorganisms and C be the true concentration level (in counts per ml). When diluted sample collected from heterogeneous (non-homogeneous) batch, Y can be modelled by Poisson lognormal distribution with parameter  $\mu, \sigma$ . Let X be the count of microorganisms

on a plate, and it can be modelled by truncated Poisson lognormal distribution with parameters  $\mu_d$ ,  $\sigma$ , a, b. Also,  $\lambda_d$  can be written in terms of  $\mu$ , f and g. It is given by

$$\mu_d = \mu + \log(f) + \log(u)$$

And the true concentration level is given by

$$C = \frac{X}{f * u}$$

where f is final dilution factor and u is amount of diluted sample on plate. Based on the literatures, we used  $\sigma = 0.2$  in these dilution process; see Gonzales-Barron et al. (2013, p. 370) and Schothorst et al. (2009).

#### Value

true concentration level when sample collected from a heterogeneous batch.

#### References

- Gonzales-Barron, U.A., Pilão Cadavez, V.A., Butler, F., 2013. Statistical approaches for the design of sampling plans for microbiological monitoring of foods, in: Mathematical and Statistical Methods in Food Science and Technology. Wiley, Chichester, UK, pp.363–384.
- Schothorst, M. van, Zwietering, M.H., Ross, T., Buchanan, R.L., Cole, M.B., 2009. Relating microbiological criteria to food safety objectives and performance objectives. Food Control 20, 967–979.

### **Examples**

```
mu_low <- 0
mu_high <- 10
sd <- 0.2
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
n_sim <- 5000
true_concentration_curves_heterogeneous(mu_low, mu_high, sd, a, b, f, u, USL, n_sim)</pre>
```

true\_concentration\_homogeneous

True concentration level estimation when diluted sample collected from a homogeneous batch.

#### **Description**

These functions provides true concentration level in the original sample when diluted samples collected from a homogeneous batch.

#### Usage

```
true_concentration_homogeneous(lambda, a, b, f, u, USL, n_sim)

true_concentration_homogeneous_multiple(lambda, a, b, f, u, USL, n_sim)

true_concentration_curves_homogeneous(
   lambda_low,
   lambda_high,
   a,
   b,
   f,
   u,
   USL,
   n_sim
)
```

#### **Arguments**

lambda	the expected microbial count ( $\lambda$ ).
а	lower domain of the number of microbial count.
b	upper domain of the number of microbial count.
f	final dilution factor.
u	amount put on the plate.
USL	upper specification limit.
n_sim	number of simulations (large simulations provide a more precise estimation).
lambda_low	the lower value of the expected microbial count $(\lambda)$ for use in the graphical display's x-axis.
lambda_high	the upper value of the expected microbial count $(\lambda)$ for use in the graphical display's x-axis.

### **Details**

Let Y be the count of microorganisms and C be the true concentration level (in counts per ml). When diluted sample collected from homogeneous batch, Y can be modelled by Poisson distribution with parameter  $\lambda$ . Let X be the count of microorganisms on a plate, and it can be modelled by truncated Poisson distribution with parameters  $\lambda_d$ , a, b. Also,  $\lambda_d$  can be written in terms of  $\lambda$ , f and u. It is given by

$$\lambda_d = \lambda * f * u$$

And the true concentration level is given by

$$C = \frac{X}{f * u}$$

#### Value

true concentration level when the diluted sample collected from a homogeneous batch.

### Examples

```
lambda_low <- 1
lambda_high <- 5000
a <- 0
b <- 300
f <- c(0.01,0.1)
u <- c(0.1,0.1)
USL <- 1000
n_sim <- 50000
true_concentration_curves_homogeneous(lambda_low, lambda_high, a, b, f, u, USL, n_sim)</pre>
```

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