# Assessing quality control for repeated bioassay data by parametric and non-parametric prediction intervals 

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## Outline

- Evaluating quality control of repeated bioassay data
- Multiple historical observations to characterize bioassay variability
- Test sample to judge about process control
- Using prediction intervals to define a tolerable region
- Retrieving the test sample in the tolerable region
- R package predIntervals
- GUI available [Rohmeyer, Gerhard 2008]


## Tolerance- vs. Prediction-Intervals

Tolerance Intervals

- With probability $\alpha$, the probability that a future observation $y_{i}$ falls in the interval [ $\left.\delta_{\text {lower }} ; \delta_{\text {upper }}\right]$ is at least $\beta$

Prediction Intervals

- With probability $\alpha$, a proportion $\beta$ (or equally $k$ out of $n$ ) future observations $y_{1}, \ldots, y_{n}$ will fall in the interval [ $\delta_{\text {lower }} ; \delta_{\text {upper }}$ ]
- With probability $\alpha$, the mean/median of $n$ future observations $y_{1}, \ldots, y_{n}$ will fall in the interval $\left[\delta_{\text {lower }} ; \delta_{\text {upper }}\right]$


## Data Example



## Data Example

log-transformation


## Prediction interval

to include at least $k$ out of $n$ future observations (Odeh 1990)
historical sample $x_{i}$, with $i=1, \ldots, m$

$$
\left[\hat{\delta}_{\text {lower }} ; \hat{\delta}_{\text {upper }}\right]=\bar{x} \pm q_{1-\alpha, m, n, k} s \sqrt{1+\frac{1}{m}}
$$

$\bar{x}, s$ is the arithmetic mean and the estimated standard error of the historical observations
$q_{1-\alpha, m, n, k}$ is a two-sided $1-\alpha$ quantile of a multivariate $t$-distribution considering the restricted number of future observations contained in the interval

If $k=n, q_{1-\alpha, m, n}$ is a two-sided $1-\alpha$ quantile of a multivariate $t$-distribution with $d f=m-1$ and correlation $\boldsymbol{R}$, which is a $n \times n$ matrix with off-diagonal elements $\rho=\frac{1}{1+m}$ (Chew 1968)

## Prediction interval

to include at least $k$ out of $n$ future observations (Odeh 1990)


## Data Example

original scale


## Nonparametric prediction interval

to include at least $k$ out of $n$ future observations (Danziger, Davis 1964)
ordered historical sample $x_{1} \leq \cdots \leq x_{m}$
ordered test sample $y_{1} \leq \cdots \leq y_{n}$
Probability that $p$ of $n$ future observations are larger than the historical observation $x_{r}$ :

$$
P\left(x_{r}<y_{p}, \ldots, y_{n}\right)=\binom{p+m-r}{p}\binom{n-p+r-1}{n-p} /\binom{n+m}{n}
$$

Searching the $r$ that satisfies

$$
\sum_{k=p}^{n} P\left(x_{r}<y_{p}, \ldots, y_{n}\right) \leq 1-\alpha
$$

Prediction interval limits are found as $\left[x_{r / 2} ; x_{m-r / 2+1}\right]$.
At $r=0$ the limits are set to $-\infty$ and $\infty$.
If $r / 2$ is not an integral number, the mean of the observations with the neighboring ranks are chosen.

## Nonparametric prediction interval

to include at least $k$ out of $n$ future observations (Danziger, Davis 1964)
$\square \mathrm{k}=7 \square \mathrm{k}=6 \square \mathrm{k}=5 \square \mathrm{k}=4 \square \mathrm{k}=3 \square \mathrm{k}=2 \square \mathrm{k}=1$


## Prediction interval

to include the mean of $n$ future observations (Hahn, Meeker 1991)

$$
\left[\hat{\delta}_{\text {lower }} ; \hat{\delta}_{\text {upper }}\right]=\bar{x} \pm t s \sqrt{\frac{1}{m}+\frac{1}{n}}
$$

$\bar{x}, s$ is the arithmetic mean and the estimated standard error of the historical observations
$t$ is a two-sided $1-\alpha$ quantile of a univariate $t$-distribution with $d f=m-1$

## Prediction interval

to include the mean of $n$ future observations (Hahn, Meeker 1991)


## Nonparametric prediction interval

to include the median of $n$ future observations (Chakraborti et al. 2004)
ordered historical sample $x_{1} \leq \cdots \leq x_{m}$ ordered test sample $y_{1} \leq \cdots \leq y_{n}$
Probability that $p$ of $n$ future observations are larger than the historical observation $x_{r}$ :

$$
P\left(x_{1} \leq \cdots \leq x_{r} \leq y_{p}\right)=\binom{p+r-1}{r}\binom{m+n-p-r}{m-r} /\binom{n+m}{m}
$$

Prediction interval limits $\left[x_{l} ; x_{u}\right]$ are found by

$$
\sum_{r=l}^{u+1} P\left(x_{r}<y_{p}, \ldots, y_{n}\right) \geq 1-\alpha
$$

## Nonparametric prediction interval

to include the median of $n$ future observations (Chakraborti et al. 2004)


## Package predlntervals

## on R-Forge:

http://predintervals.r-forge.r-project.org

R Functions
> predint (x, k, m, level=0.95,
alternative="two.sided", quantile=NULL)
> nparpredint(x, $k, m, ~ l e v e l=0.95$, alternative="two.sided")
> precint (x, m, level=0.95, alternative="two.sided")
> nparprecint(x, m, level=0.95,
alternative="two.sided")

## Coverage Simulations

$x_{i} \sim$ Normal

- Parametric PI
- Non-Parametric PI
$x_{i} \sim$ logNormal
- Parametric PI
- Non-Parametric PI


## Discussion

- At least $m \approx 20$ observations needed to obtain accurate intervals
- Better performance at small $k$

Parametric intervals

- Calculation inaccuracy at small $n$
- Dependent on parametric assumptions

Nonparametric intervals

- Dependent on the actual sample ( $m>20$ needed)
- Distribution-free


## References

Q Hahn, GJ and Meeker, WQ (1991): Statistical Intervals. Wiley, New York.

- Chakraborti, S, Van der LaAn, P, Van de Wiel, MA (2004): A class of distribution-free control charts. Applied Statistics 53(3):443-462.
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國 ODEH, RE (1990): 2-Sided prediction intervals to contain at least $k$ out of $m$ future observations from a normal distribution. Technometrics 32(2): 203-216.
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## Simulated coverage: $x_{i} \sim \operatorname{Normal}(0,1)$

## Parametric prediction interval



## Simulated coverage: $x_{i} \sim \operatorname{Normal}(0,1)$

Non-Parametric prediction interval


## Simulated coverage: $x_{i} \sim \log \operatorname{Normal}(0,1)$

Parametric prediction interval


## Simulated coverage: $x_{i} \sim \log \operatorname{Normal}(0,1)$

Non-Parametric prediction interval


## Quantile calculation for a prediction interval

to include $k$ out of $n$ future observations (Odeh 1990)

$$
\begin{aligned}
& r=\sqrt{\frac{m+1}{m} u^{\star}} \quad \text { satisfying } \quad \sum_{j=k}^{m} P\left(f_{j}\left(u^{\star}\right)\right)=1-\alpha \\
& P\left(f_{j}\left(u^{\star}\right)\right)=\int_{0}^{\infty}\left\{\int_{-\infty}^{\infty}\binom{n}{j}[\Phi(b)-\Phi(a)]^{j} \times[\Phi(b)-\Phi(a)]^{n-j} \phi(y) d y\right\} f_{\nu}(s) d s \\
& a=-u s+\frac{\sqrt{\rho} y}{\sqrt{1-\rho}} \quad b=u s+\frac{\sqrt{\rho} y}{\sqrt{1-\rho}} \quad \rho=\frac{1}{m+1}
\end{aligned}
$$

$\Phi(\cdot), \phi(\cdot)$ are the standard normal density and distribution functions
$f_{\nu}(s)$ is the density function of $S$, where $\nu S^{2}$ is $\chi^{2}$ distributed with $d f=m-1$ and $\nu=m-1$

