

Frequentists and Bayesian methods to incorporate recruitment rate stochasticity at the design stage of a clinical trial

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Why recruitment rates?

According to Carter (2004)

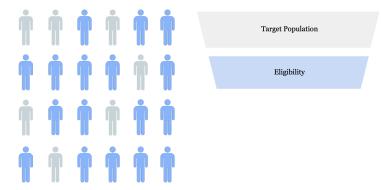
- Timely recruitment vital to the success of a clinical trial
- Inadequate number of subjects → lack of power
- Recruitment period too long → competing treatments
- Recruitment of patients varies at each stage

Target Population

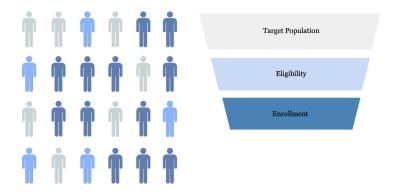


Target Population

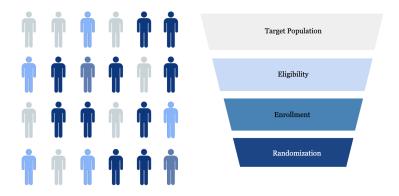
Eligibility



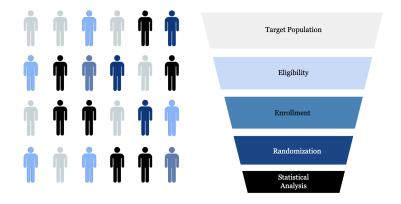
Enrollment



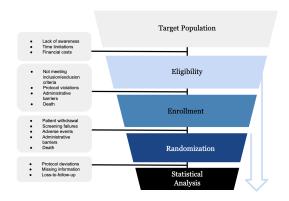
Randomization



Statistical Analysis



Patient Leakage





Definitions

- Recruitment rate = Per time-unit (Piantadosi, 2024)
- Accrual = Cumulative Recruitment
- Aleatory uncertainty: randomness inherent and unpredictable
- Epistemic uncertainty: arises from limited knowledge about parameters

Models for Counts

Methods	Counts	Expectation	Variance	Aleatory	Epistemic
Expectation	$C = \lambda$	λ	0	No	No
Poisson	$C \sim Po(\lambda)$	λ	λ	Yes	No
Negative Binomial	$C \sim Po(\Lambda); \Lambda \sim G(\alpha, \beta)$	$\frac{\alpha}{B}$	$\frac{\alpha(\beta+1)}{\beta^2}$	Yes	Yes

Table: Moments, aleatory and epistemic uncertainty in recruitment shown by different models for counts.

Methods	Counts	Expectation	Variance	Aleatory	Epistemic
Expectation	$C(t) = \lambda t$	λt	0	No	No
Poisson	$C(t) \sim Po(\lambda t)$	λt	λt	Yes	No
Negative Binomial	$C(t) \sim Po(\Lambda t); \Lambda \sim G(\alpha, \beta)$??	??	Yes	Yes

Table: Moments, aleatory and epistemic uncertainty in accrual shown by different models for counts.

Multicenter Trial on Palliation in Terminal Esophageal Cancer

Example from Carter (2004):

- Recruitment Rate $\lambda = \frac{Counts}{Time} = 0.591$ per day
- Time t = 550 days

Multicenter Trial on Palliation in Terminal Esophageal Cancer

Example from Carter (2004):

- Recruitment Rate $\lambda = \frac{Counts}{Time} = 0.591$ per day
- Time t = 550 days
- Models for Counts:
 - − **Expectation**: $EC(t) = \lambda t = 0.591 \cdot 550 = 325$
 - − **Poisson**: $C(t) \sim Po(\lambda t)$



Accrual at time point t

- Expectation:
$$EC(t) = \underbrace{EC + \ldots + C}_{t \text{ times}} = tEC = \lambda t$$

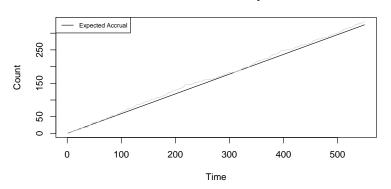
- **Poisson**:
$$\underbrace{\operatorname{Po}(\lambda) + \ldots + \operatorname{Po}(\lambda)}_{t \text{ times}} = \operatorname{Po}(\lambda t)$$



Accrual of 1 study

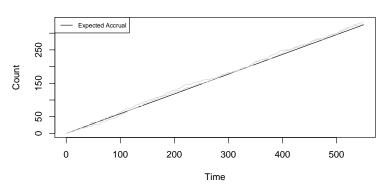
Master Thesis Biostatistics

Accrual of 1 study

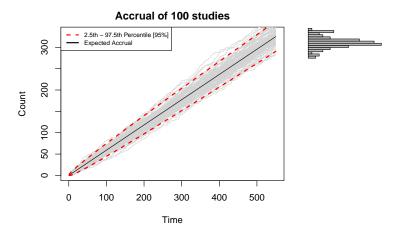


Accrual of 2 studies

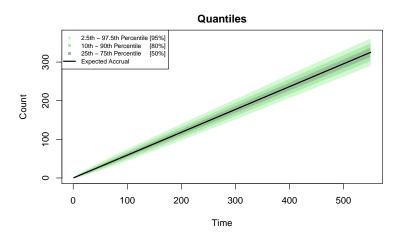
Accrual of 2 studies



Accrual of 100 studies

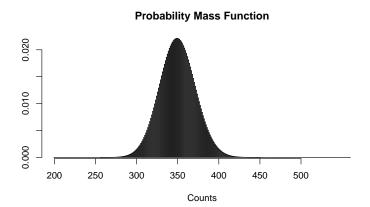


Poisson's uncertainty bands



Poisson's exact PMF at time point t = 550 with

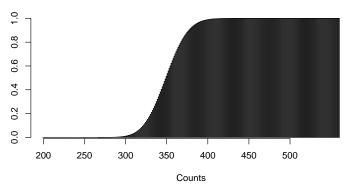
 $\lambda = 0.591$



Poisson's exact CDF at time point t = 550 with

 $\lambda = 0.591$

Cummulative Distribution Function





Multicenter Trial on Palliation in Terminal Esophageal Cancer

Example from Carter (2004):

- Recruitment Rate $\lambda = \frac{\textit{Counts}}{\textit{Time}} = 0.591$ per day
- Time t = 550 days
- Models for Counts:
 - Negative Binomial: $C \sim Po(\Lambda)$; $\Lambda \sim G(\alpha, \beta)$
 - $\alpha = 325$
 - $-\beta = 548$
 - $E\Lambda = \frac{\alpha}{\beta} = 0.591 = \lambda$

Negative binomial derived from Poisson-Gamma model (t=1)

Let
$$C|\Lambda \sim Po(\Lambda)$$
 and $\Lambda \sim G(\alpha, \beta)$

$$\begin{split} \rho(c) &= \int_0^\infty \rho(c|\lambda) \rho(\lambda) d\lambda \\ &= \int_0^\infty \frac{\lambda^c \exp(-\lambda)}{c!} \left[\lambda^{\alpha - 1} \exp(-\beta \lambda) \frac{\beta^\alpha}{\Gamma(\alpha)} \right] d\lambda \\ &= \frac{\beta^\alpha}{c! \Gamma(\alpha)} \int_0^\infty \lambda^{\alpha + c - 1} \exp(-\lambda) \exp(-\lambda \beta) d\lambda \\ &= \frac{\beta^\alpha \Gamma(\alpha + c)}{c! \Gamma(\alpha)(\beta + 1)^{\alpha + c}} \underbrace{\int_0^\infty \frac{(\beta + 1)^{\alpha + c}}{\Gamma(\alpha + c)} \lambda^{\alpha + c - 1} \exp(-(\beta + 1)\lambda) d\lambda}_{=1} \\ &= \beta^\alpha \binom{\alpha + c - 1}{\alpha - 1} \left(\frac{1}{\beta + 1} \right)^{\alpha + c} \\ &= \binom{\alpha + c - 1}{\alpha - 1} \left(\frac{1}{\beta + 1} \right)^c \left(\frac{\beta}{\beta + 1} \right)^\alpha, \ C|\Lambda \sim \text{NBin} \left(\alpha, \frac{\beta}{\beta + 1} \right) \end{split}$$

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Expectation and Variance

Using the expressions of iterated expectation and variance (Held and Bové, 2014)

$$EC = E_{\Lambda}[E_{C}(C|\Lambda)] = E_{\Lambda}[\Lambda] = \alpha/\beta$$

$$Var(\mathbf{C}) = Var_{\Lambda}[E_{\mathbf{C}}(\mathbf{C}|\Lambda)] + E_{\Lambda}[Var_{\mathbf{C}}(\mathbf{C}|\Lambda)]$$
$$= Var_{\Lambda}[\Lambda] + E_{\Lambda}[\Lambda]$$
$$= \alpha/\beta^{2} + \alpha/\beta = \frac{\alpha(\beta+1)}{\beta^{2}}$$

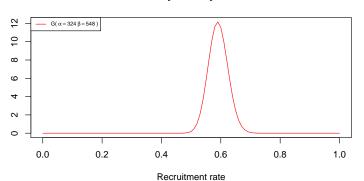
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Gamma Prior

$$\Lambda \sim G(\alpha, \beta)$$

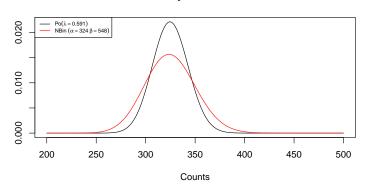
Probability Density Function



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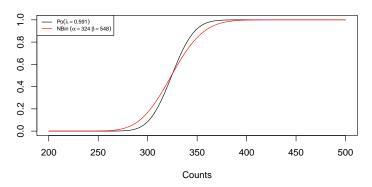
Comparison between Poisson and Negative Binomial

Probability Mass Function

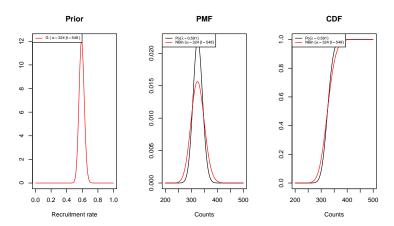


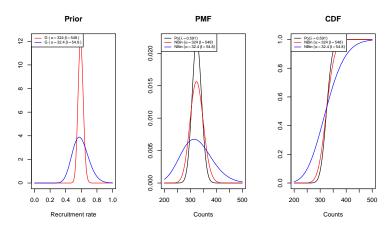
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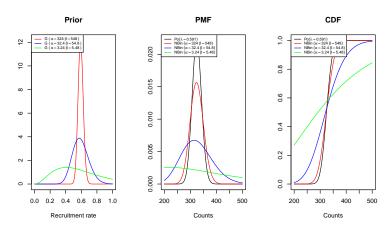
Cummulative Distribution Function











Summary

- Extension of Carter's approach based on MC simulations
- Exact models for counts
- Unified notation
- Visualization of study accrual and uncertainty bands
- Sensitivity analysis



Next steps

- Extend Negative Binomial proof for accrual
- Compare exact models for counts to those provided by Carter (2004)
- Models for time
 - Exact models
 - Compare them to those provided by Carter
- Shiny App
- Apply theoretical results to dataset



References

Master Thesis Biostatistics

- Carter, R. E. (2004). Application of stochastic processes to participant recruitment in clinical trials. Controlled clinical trials, 25(5):429-436.
- Held, L. and Bové, D. S. (2014). Applied statistical inference. Springer, Berlin Heidelberg, doi, 10(978-3):16.
- Piantadosi, S. (2024). Clinical trials: a methodologic perspective. John Wiley & Sons.



Thank you for your attention