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Population optimal experimental design for discrete type data

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Background

- Discrete type data are increasingly popular describing e.g. pharmacodynamic outcomes.
- Optimal design (OD) is a useful tool for optimizing studies.

=> Need for OD on models for discrete type data



Some previous work in the area

- This concept is not new, e.g. Generalized Linear Models.*
- However, currently numerous issues arise with OD computation:
 - Exponential family (binomial, Poisson,...)
 - One must know link function, mean function for each model family
- In this work we attempt to provide a general method for categorical data models based on simulation of data.

* Longford, Breslow, Duffull, Ogungbenro etc.



Introduction Optimal design

Cramér-Rao inequality*:

$$FIM \left(\vec{\Theta}, \vec{x} \right)^{-1} \leq COV \left(\vec{\Theta}, \vec{x} \right)$$

for an unbiased estimator

* holds regardless of whether the data is discrete or not



Derivation of FIM for discrete type data

$$FIM(\vec{\Theta}, \vec{x}) = E_x \left[FIM(\vec{\Theta}, \vec{x}_{obs}) \right]$$

$$FIM(\vec{\Theta}, \vec{x}_{obs}) = - \frac{\partial^2 \log L(\vec{\Theta}, \vec{x}_{obs})}{\partial \vec{\Theta} \partial \vec{\Theta}^T} *$$

No analytic solution to likelihood for ME – models.

We need higher order approximation than FO=>
Pop likelihood calculate with Laplace or Monte Carlo

* FIM_{obs} is what you get from \$COV MATRIX=R



Design setup

- D-optimal design – maximizing the determinant of FIM
- Expectation over data evaluated by Monte Carlo Integration
 1. Generate a data set from some distribution
 2. Calculate FIM_{obs} given the data by calculating pop likelihood with:
 - Laplace Approximation
 - Monte Carlo Integration (“exact” if $n \rightarrow \infty$)



Dichotomous Model

1 random effect, 50 individuals with 30 doses/individual each split into 3 dose levels (one fixed to 0).

$$\theta_1 = -0.5 \quad \omega_1^2 = 0.1$$

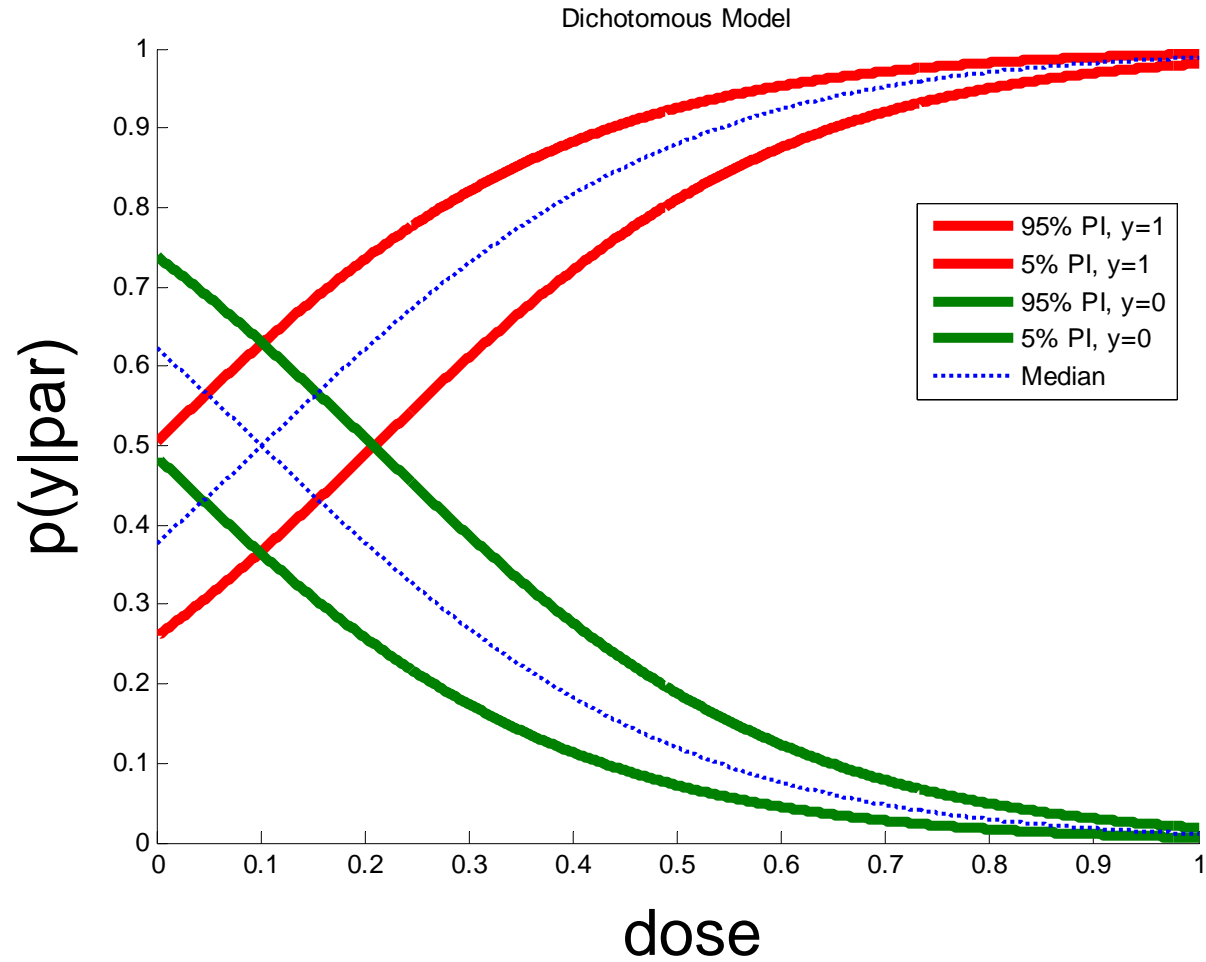
$$\theta_2 = 5 \quad D = [0, 1]$$

$$p = \frac{e^{\theta_1 + \eta_1 + \theta_2 \cdot D}}{1 + e^{\theta_1 + \eta_1 + \theta_2 \cdot D}}$$

$$like = \begin{cases} p & \text{if } DV = 1 \\ 1 - p & \text{if } DV = 0 \end{cases}$$



Dichotomous Model – PI





Dichotomous Model - Results

	NONMEM Laplace	PopED Laplace	PopED MC
-2LL observed	1631.912	1631.912	1631.877
Avg RSE(FIM_{obs})	26.8%	26.8%	26.0%
Avg RSE(E[FIM_{obs}])	27.9%*	26.8%	26.8%

* 1000 sim/est empirical SE calculated from estimates

Observed: For each individual: 10 obs at placebo, 0.25 & 0.45 units.

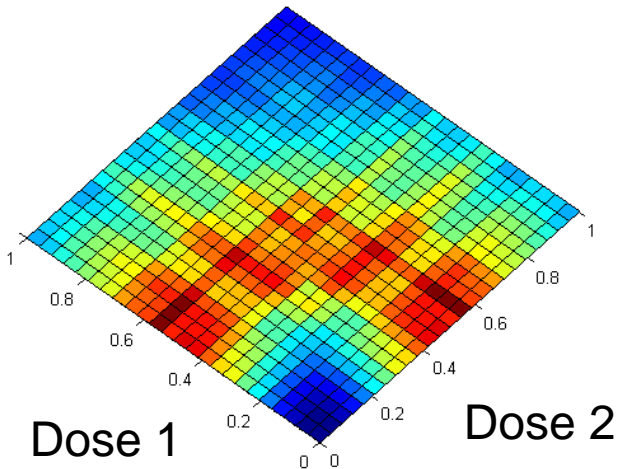


1 Observed |FIM| versus Dose

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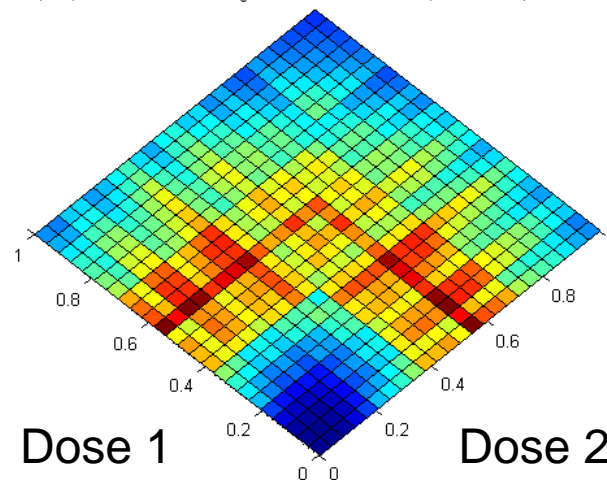
Laplace

1 Obs|FIM| Surface from Laplace integrated Dichotomous data, seed=5489



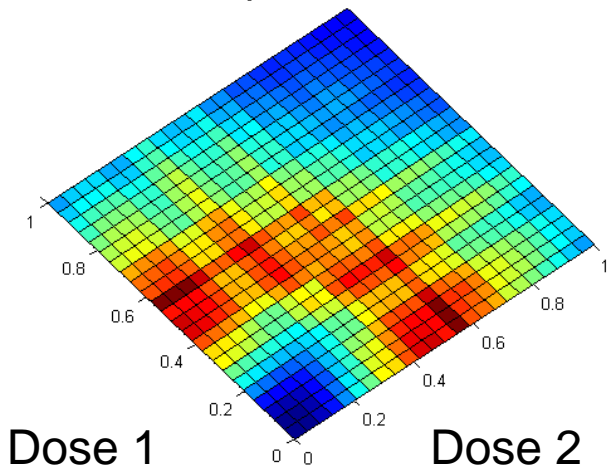
MC, LHS = 10

|FIM| Surface from MC integrated Dichotomous data, seed=5489, LHS=10



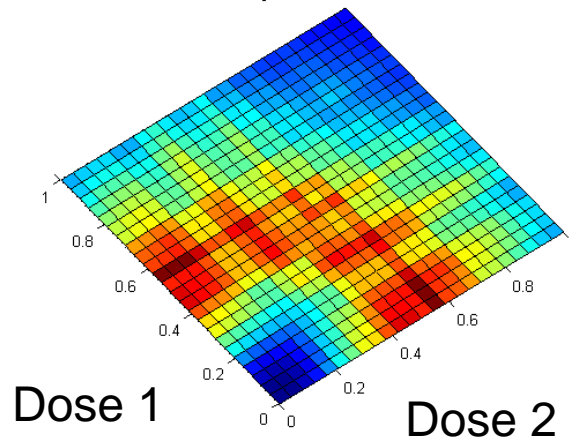
MC, LHS = 20

|FIM| Surface from MC integrated Dichotomous data, seed=5489, LHS=20



MC, LHS = 40

1 Obs|FIM| Surface from MC integrated Dichotomous data, seed =5489, LHS=40





Results - Optimal Designs – 100 obs FIM

Dose1 = 0, Dose2 dependent on the method

Dose2 (units)	Laplace, det(FIM)	MC, det(FIM)
0.44	5.89e+5	6.00e+5
0.50	5.91e+5	5.98e+5

Red = optimal

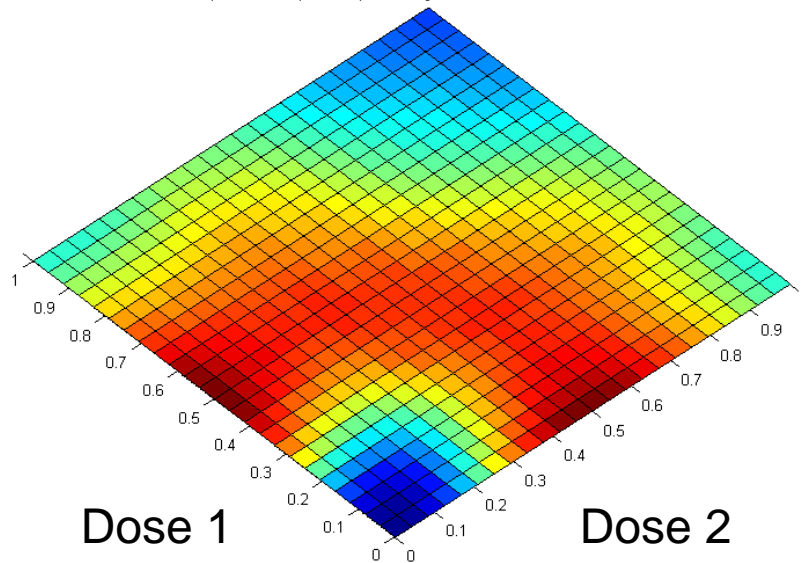
Different results with different calculation methods!



Expected $|FIM|$ – Laplace vs. MC

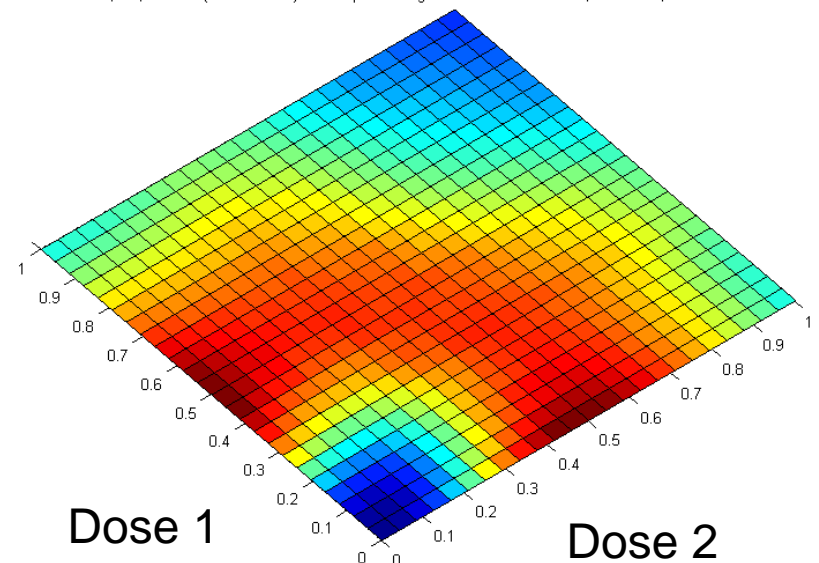
Laplace $|FIM|$

$|FIM|$ Surface (100 Obs FIM) from Laplace integrated Dichotomous data, state seed=563



MC $|FIM|$

$|FIM|$ Surface (100 Obs FIM) from Laplace integrated Dichotomous data, seed=563, LHS=50

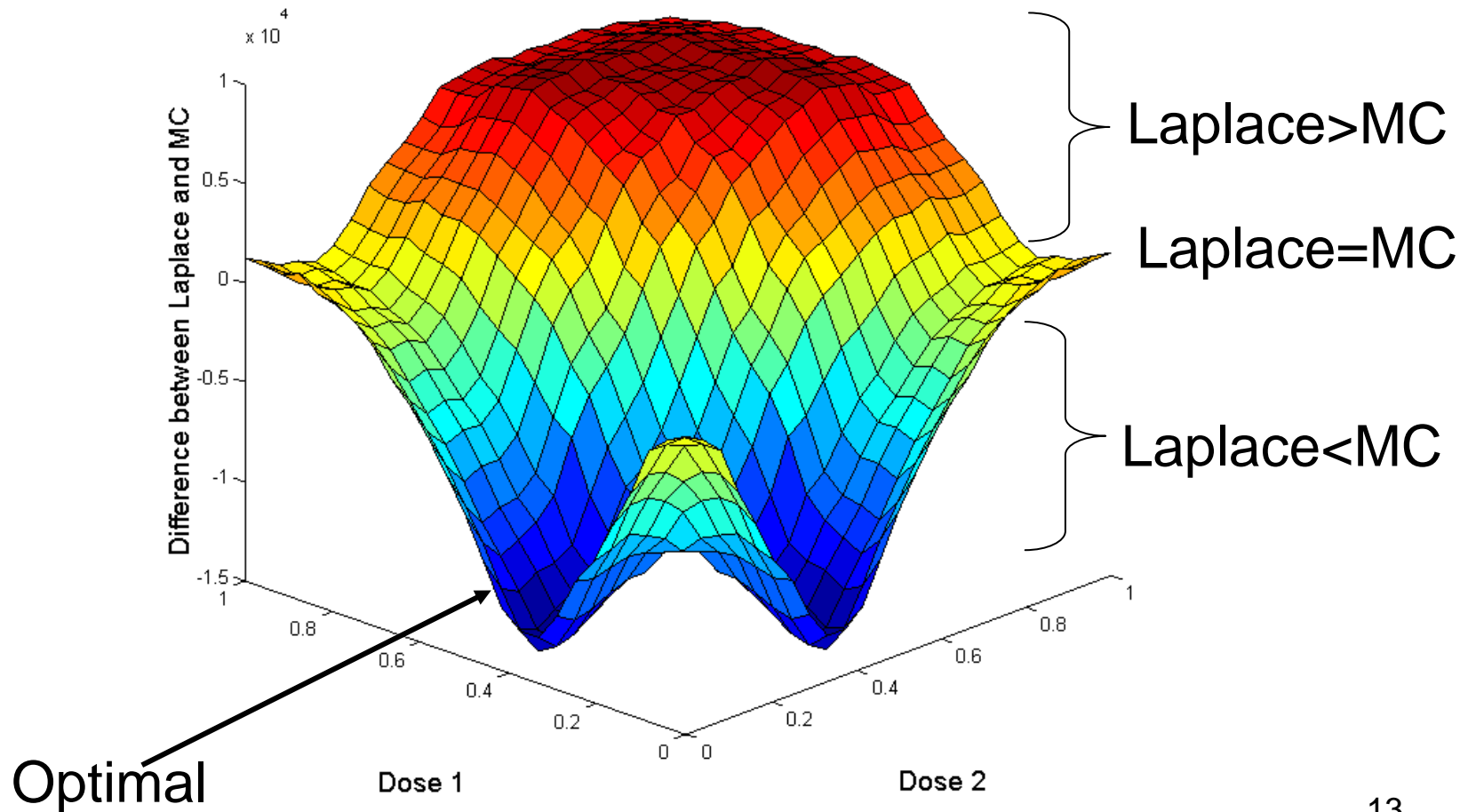


Expected FIM, calculated as 100 Obs FIM



Expected |FIM| – Differences (Lap, MC)

Surface of det FIM Laplace - MC





Poisson Model – 1 Random effect

1 random effect, 20 individuals with 90 obs./ind. split into 3 dose levels.

$$\theta_1 = 1 \quad \omega_1^2 = 0.1$$

$$\theta_2 = 0.5 \quad D = [0, 1]$$

$$B = \theta_1 \cdot e^{\eta}$$

$$D_{50} = \theta_2$$

$$\lambda = B \cdot \left(1 - \frac{D}{D + D_{50}} \right)$$

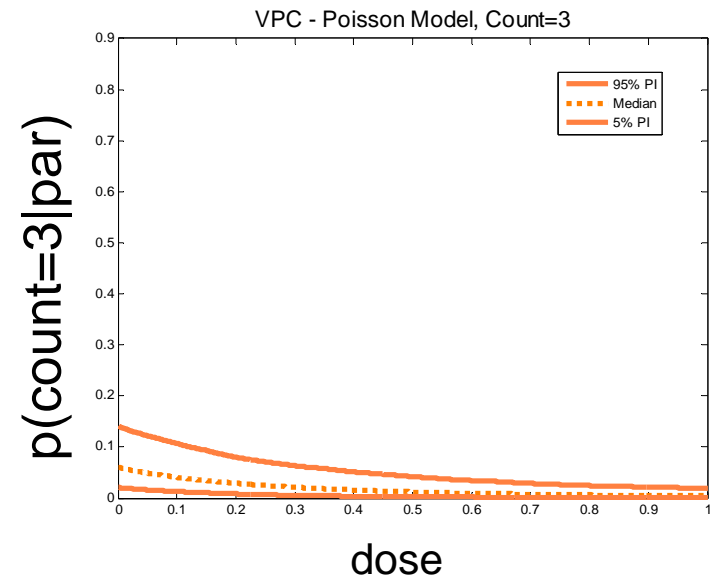
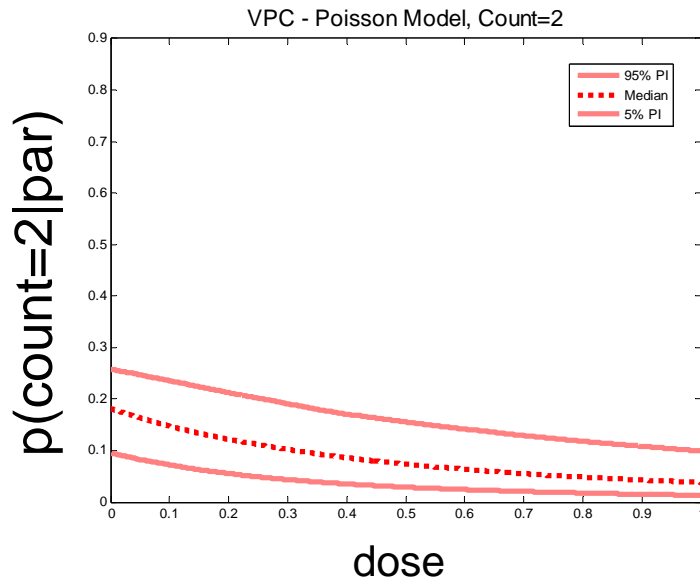
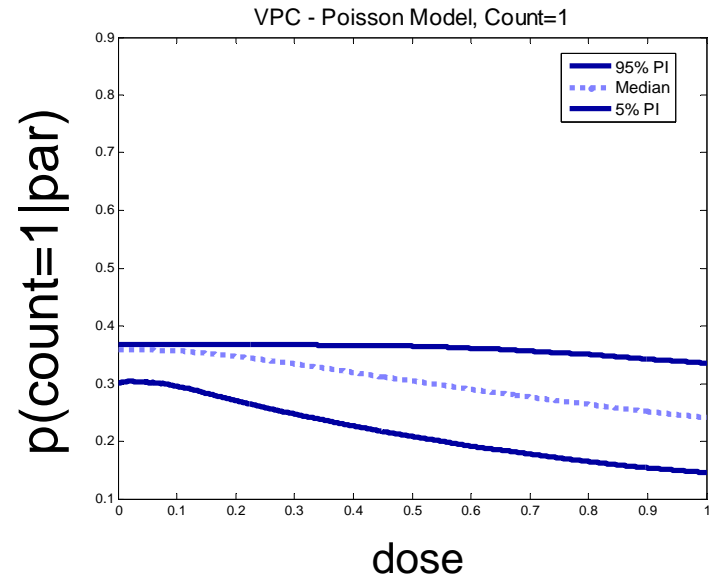
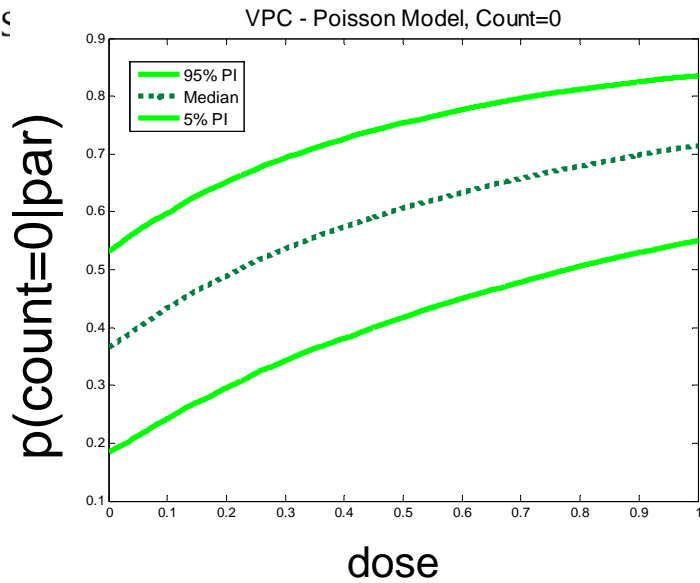
$$-2ll = -2 \cdot \left(-\lambda + n \cdot \ln(\lambda) - \ln(n!) \right)$$

$$\ln(n!) = \begin{cases} n \cdot \ln(n) - n + \frac{\ln(n \cdot (1 + 4n \cdot (1 + 2n)))}{6} + \frac{\ln(\pi)}{2} & \text{if } n > 0 \\ 0 & \text{if } n = 0 \end{cases}$$



PI - Poisson Model

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Poisson Model - Results

	NONMEM Laplace	PopED Laplace	PopED MC (1 000 000 samples)
-2LL observed	3809.66	3809.66	3809.63
Avg RSE(FIM_{obs})	22.0%	21.9%	22.2%
Avg RSE(E[FIM_{obs}])	19.1%*	18.6%	18.4%

* 1000 sim/est empirical SE calculated from estimates
30 obs/ind at dose 0, 0.4 0.7

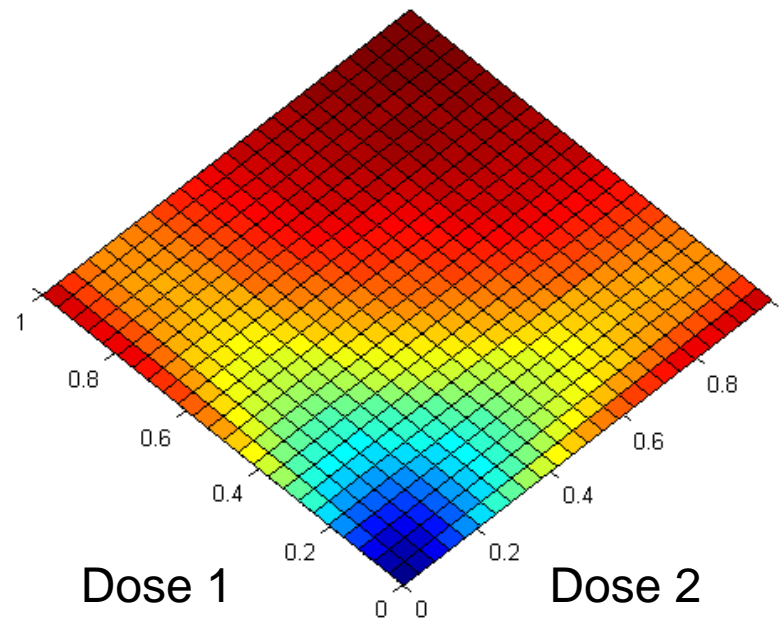
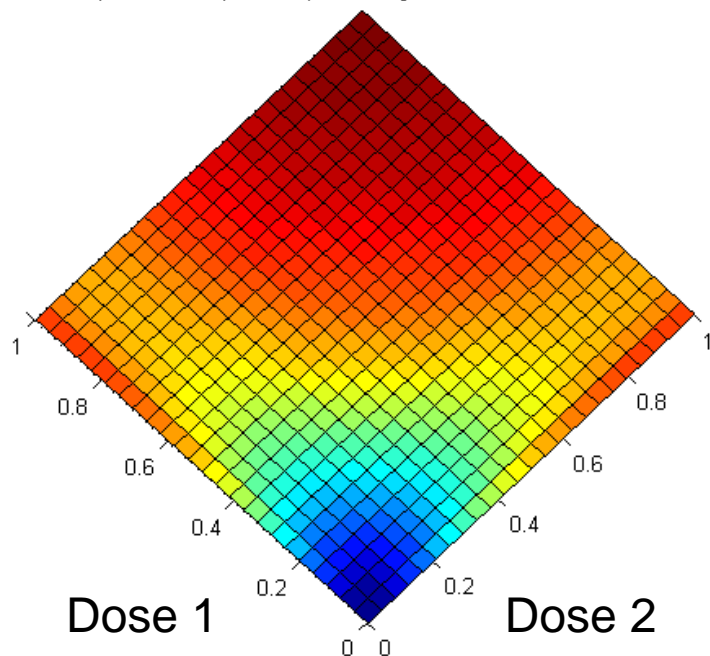


Expected $|FIM|$ Laplace versus MC

Laplace $|FIM|$

MC $|FIM|$

$|FIM|$ Surface (100 Obs FIM) from Laplace integrated Dichotomous data, seed=12312 $|FIM|$ Surface (100 Obs FIM) from MC integrated Dichotomous data, seed=12312, LHS=50





Conclusions

- Optimal design on Mixed Effects models for discrete type data was successfully implemented in PopED 2.09 with:
 - Laplace approximation
 - Monte Carlo Integration
- Optimal design differs between calculation methods
- Time consuming => faster/more efficient algorithms are needed, e.g. parallelization, SAEM.
- This technique is general (if likelihood can be calculated method should work). Applicable for OD on models for other types of data/models, e.g. BQL-data, TTE/RTTE, Order/Non-order categorical, Markov model, discrete distributions etc.



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Thank you

Thank you for your attention!