

Optimal Experiment Design

for Dose-Response Screening of Enzyme Inhibitors

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PROBLEM

- Most assays in a typical screening program are *not informative*

SOLUTION

- Abandon "batch design" of dose-response experiments
- Use "sequential design" based on *D-Optimal Design Theory*

- Save 50% of screening time, labor, and material resources

 Optimal Design for Screening

Two basic types of experiments

BATCH VS. SEQUENTIAL DESIGN OF ANY RESEARCH PROJECT

BATCH DESIGN OF EXPERIMENTS

design = choice of screening concentrations

- decide beforehand on the design of a *complete series of experiments*
- perform all experiments in the series *without analyzing interim results*
- analyze entire batch* of accumulated data
- issue final report

SEQUENTIAL DESIGN OF EXPERIMENTS

- decide on the design of only *one* (or a small number of) *experiment(s)*
- perform one experiment
- analyze interim results; did we accumulate enough experiments?
- if not, *go back to step 1*, otherwise ...
- issue final report

 Optimal Design for Screening 2

Analogy with clinical trials

ADAPTIVE CLINICAL TRIALS (ACT): ADJUST THE EXPERIMENT DESIGN AS TIME GOES ON
Borfitz, D.: "Adaptive Designs in the Real World" *BioIT World*, June 2008

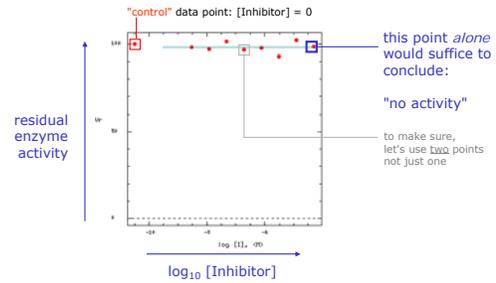
- assortment of statistical approaches including "early stopping" and "dose-finding"
- interim data analysis
- reducing development timelines and costs by utilizing *actionable information sooner*
- experts*: Donald Berry, chairman of the Department of Biostatistics University of Texas MD Anderson Cancer Center
- software vendors*: Cytel, Tessela
- industry pioneers*: Wyeth 1997 "Learn and Confirm" model of drug development

"slow but sure restyling of the research enterprise"

 Optimal Design for Screening 3

What is wrong with this dose-response curve?

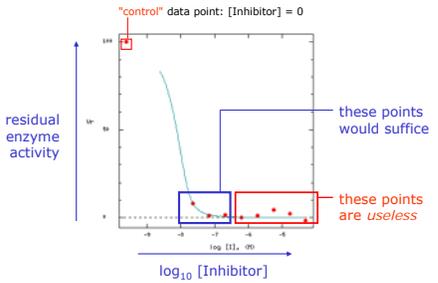
THE "RESPONSE" IS INDEPENDENT OF "DOSE": NOTHING LEARNED FROM MOST DATA POINTS



 Optimal Design for Screening 4

What is wrong with *this* dose-response curve?

THE SAME STORY: MOST DATA POINTS ARE USELESS



 Optimal Design for Screening 5

Why worry about doing useless experiments?

IN CASE THE REASONS ARE NOT OBVIOUS:

Academia:

- time: Publish your paper on time for grant renewal.
- money: Spend less on chemicals, hire a post-doc.
- fame: Invent a drug, get the Nobel Prize. 

Industry:

- time: Beat "the competition" to market.
- money: Spend less on chemicals, hire a post-doc.
- security: Invent a drug, avoid closure of Corporate R&D. 

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On a more serious note...

THERE ARE VERY GOOD REASONS TO GET SCREENING PROJECTS DONE AS QUICKLY AS POSSIBLE

guardian.co.uk

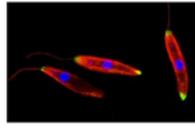
News | Sport | Comment | Culture | Business | Money | Life & style
 News | Society | International aid and development

University hunts cure for parasitic infections

Tim Radford
 The Guardian, Wednesday October 26 2005
 Article history

Six Scottish scientists have been given £13m to find a drug to treat three of the world's most unpleasant diseases. Sleeping sickness, leishmaniasis and Chagas' disease are all caused by parasites

The next step is to build a library of 100,000 compounds, and begin testing to see which might afflict the parasites without harming the host. In effect, university scientists will begin the sifting process normally funded by pharmaceutical companies. The aim is to have within five years something that the World Health Organisation, or a drug manufacturer, or one of the big charities, could develop.

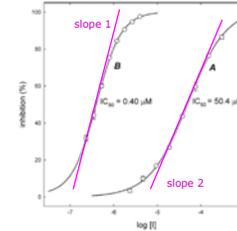


Leishmania major
 Photo: E. Dráberová
 Academy of Sciences of the Czech Republic

Theoretical foundations: The inhibition constant

DO NOT USE IC₅₀. THE INHIBITION CONSTANT IS MORE INFORMATIVE

Kuzmíč et al. (2003) Anal. Biochem. 319, 272-279



"Morrison equation" ✓

$$r = r_0 \frac{[E]_0 - [I]_0 - K_T + \sqrt{([E]_0 - [I]_0 - K_T)^2 + 4[E]_0 K_T}}{2[E]_0}$$

~~Four-parameter logistic equation~~

$$p = p_{min} + \frac{p_{max} - p_{min}}{1 + ([I]_0 / I_{50})^n}$$

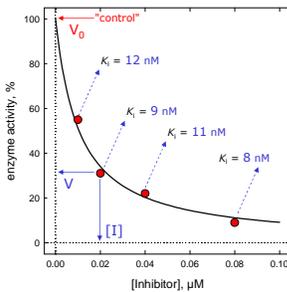
"Hill slope"

no clear physical meaning!

Theoretical foundations: The "single-point" method

AN APPROXIMATE VALUE OF THE INHIBITION CONSTANT FROM A SINGLE DATA POINT

Kuzmíč et al. (2000) Anal. Biochem. 281, 62-67



Relative rate

$$V_r = V/V_0$$

Single-point formula:

$$K_i = \frac{[I] - [E](V_r - 1)}{1/V_r - 1}$$

Theoretical foundations: Optimal Design Theory

NOT ALL POSSIBLE EXPERIMENTS ARE EQUALLY INFORMATIVE

BOOKS:

- Fedorov (1972) "Theory of Optimal Experiments"
- Atkinson & Donev (1992) "Optimum Experimental Designs"

EDITED BOOKS:

- Endrényi (Ed.) (1981) "Kinetic Data Analysis: Design and Analysis of Enzyme and Pharmacokinetic Experiments"
- Atkinson et al. (Eds.) (2000) "Optimum Design 2000"

JOURNAL ARTICLES:

- Thousands of articles in many journals.
- Several articles deal with experiments in **enzymology / pharmacology**.

Optimal design of ligand-binding experiments

SIMPLE LIGAND BINDING AND HYPERBOLIC SATURATION CURVES

Endrényi & Chang (1981) J. Theor. Biol. 90, 241-263

SUMMARY:

- Protein (P) binding with ligand (L)
- Vary total ligand concentration [L]
Observe bound ligand concentration [L_B]
- Fit data to nonlinear model:

$$[L_B] = \frac{1}{2} \left([L] + K_d + [P] + \sqrt{([L] + K_d + [P])^2 - 4[P][L]} \right)$$



dissociation constant

TWO OPTIMAL LIGAND CONCENTRATIONS (we need at least two data points):

$$[L]_1 = [L]_{max} \dots \dots \dots \text{maximum feasible [Ligand]}$$

$$[L]_2 = (K_d + [P]) \frac{+ (K_d - [P])[L]_1 - \sqrt{([L]_1 + K_d + [P])^2 - 4[P][L]_1} - K_d - [P]}{- (K_d + [P])[L]_1 + \sqrt{([L]_1 + K_d + [P])^2 - 4[P][L]_1} - K_d - [P]} (K_d - [P])$$

Optimal design of enzyme inhibition experiments

THIS TREATMENT APPLIES BOTH TO "TIGHT BINDING" AND "CLASSICAL" INHIBITORS

Kuzmíč (2008) manuscript in preparation

SUMMARY:

- Enzyme (E) binding with inhibitor (I)
- Vary total inhibitor concentration [I]
Observe residual enzyme activity, proportional to [E]_{free}
- Fit data to nonlinear model:

$$V = V_0 \frac{1}{2[E]} \left([E] - [I] - K_i + \sqrt{([E] - [I] - K_i)^2 + 4K_i[E]} \right) \quad \text{"Morrison Equation"}$$

TWO OPTIMAL INHIBITOR CONCENTRATIONS (we need at least two data points):

$$[I]_1 = 0 \dots \dots \dots \text{control experiment (zero inhibitor)}$$

$$[I]_2 = K_i + [E]$$

A problem with optimal design for *nonlinear* models

A CLASSIC CHICKEN & EGG PROBLEM

Endrényi & Chang (1981) *J. Theor. Biol.* **90**, 241-263

PROTEIN/LIGAND BINDING

$$[L]_1 = [L]_{\max}$$

$$[L]_2 = \frac{(K_d + [P]) - \sqrt{(K_d + [P])^2 - 4[P][L]_1 - K_d - [P]}}{2}$$

$$[L]_2 = \frac{(K_d + [P]) + \sqrt{(K_d + [P])^2 - 4[P][L]_1 - K_d - [P]}}{2}$$

Kuzmič (2008) *manuscript in preparation*

ENZYME INHIBITION

$$[I]_1 = 0$$

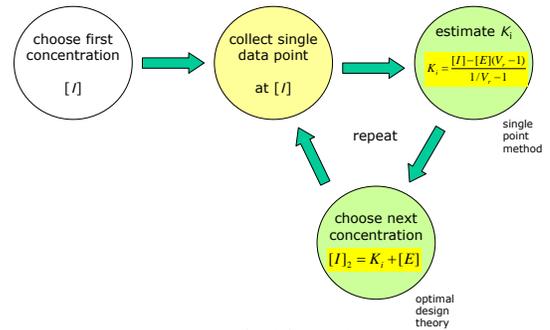
$$[I]_2 = K_i + [E]$$

a model parameter ("final answer") we are trying to determine by the experiment ... being planned!

We must guess the answer before we begin designing the experiment.

A solution for designed enzyme inhibition studies

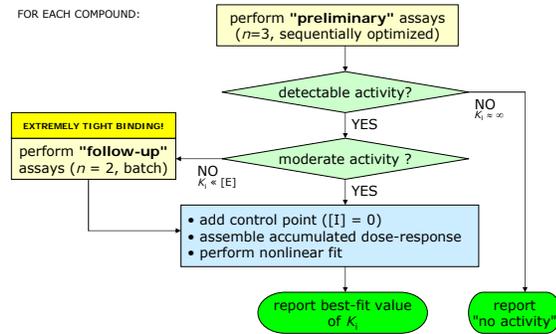
PUT TOGETHER OPTIMAL DESIGN AND THE SINGLE-POINT METHOD



Sequential optimal design: Overall outline

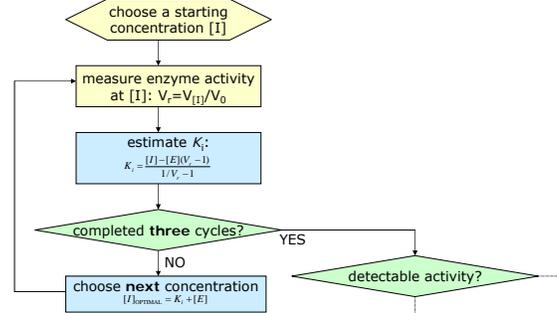
PUTTING IT ALL TOGETHER: "SINGLE-POINT METHOD" + OPTIMAL DESIGN THEORY

FOR EACH COMPOUND:



Sequential optimal design: Preliminary phase

ASSAY EVERY COMPOUND AT THREE DIFFERENT CONCENTRATIONS



Sequential optimal design: Follow-up phase

WE DO THIS ONLY FOR EXTREMELY TIGHT BINDING COMPOUNDS ($K_i \ll [E]_{\max}$)

choose $[I] = [E]$ — optimal $[I]$ at K_i approaching zero:
 $[I]_{\text{opt}} = [E] + K_i$

EXTRA POINT #1
 measure enzyme activity at $[I]: V_r = V_{r1}/V_0$

choose $[I] = [E]/2$ — "rule of thumb"

EXTRA POINT #2
 measure enzyme activity at $[I]: V_r = V_{r1}/V_0$

- combine with three "preliminary" data points
- add control point ($[I] = 0$)
- assemble accumulated dose-response curve
- perform nonlinear fit ("Morrison equation")

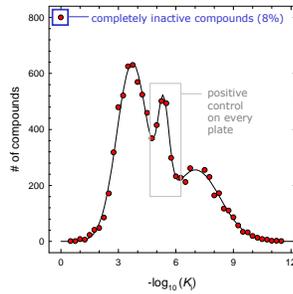
Sequential optimal design: The gory details

The actual "designer" algorithm is more complex:

- We need safeguards against concluding too much from *marginal* data:
 - greater than 95% inhibition, or
 - less than 5% inhibition.
- We need safeguards against falling outside the *feasible concentration range*.
- We use other safeguards and rules of thumb.
- The overall algorithm is a hybrid creation:
 - rigorous theory, and
 - practical rules, learned over many years of consulting work.

Anatomy of a screening campaign: K_i Distribution

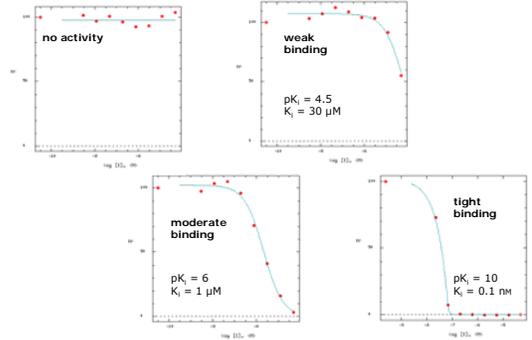
A REAL-WORLD SCREENING PROGRAM AT AXYS PHARMA (LATER CELERA GENOMICS)
 DATA COURTESY CRAIG HILL & JAMES JANC, CELERA GENOMICS
 PRESENTED IN PART (BY P.K.) AT 10TH ANNUAL SOCIETY FOR BIOMOLECULAR SCREENING, ORLANDO, 2004



- 10,008 dose response curves
- Maximum concentration 0.5–50 μM
- Serial dilution ratio 1:4
- Eight data points per curve
- 3% Random error of initial rates
- Enzyme concentration 0.6–10 nM

Anatomy of a screening campaign: Examples

A REAL-WORLD SCREENING PROGRAM AT AXYS PHARMA (LATER CELERA GENOMICS)



Monte-Carlo simulation: Virtual sequential screen

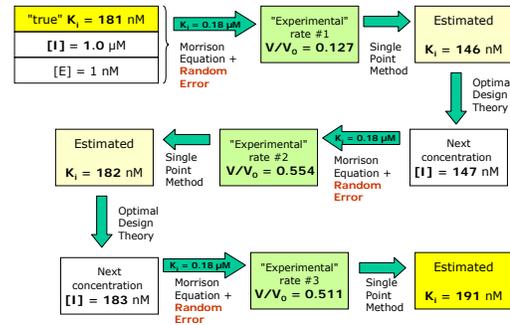
SIMULATE A POPULATION OF INHIBITORS THAT MATCHES THE AXYS/CELERA CAMPAIGN

PLAN OF A HEURISTIC MONTE-CARLO SIMULATION STUDY:

1. Simulate 10,000 pK_i values that match Celera's "two-Gaussian" distribution
2. Simulate enzyme activities assuming 3% random experimental error
3. Virtually "screen" the 10,000 compounds using the **sequential optimal** method
4. Compare resulting 10,000 pK_i values with the "true" (assumed) values
5. Repeat the virtual "screen" using the classic **serial dilution** method
6. Compare accuracy and efficiency of sequential and serial-dilution methods

Monte-Carlo study: Example 1 - Preliminary phase

A TYPICAL MODERATELY POTENT (SIMULATED) ENZYME INHIBITOR



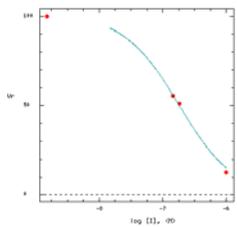
Monte-Carlo study: Example 1 - Regression phase

A TYPICAL MODERATELY POTENT (SIMULATED) ENZYME INHIBITOR - CONTINUED

"true" $K_i = 181$ nM
 $[E] = 1$ nM
 $V_0 = 100$

ASSEMBLE AND FIT DOSE-RESPONSE CURVE

#	[I], μM	Rate	note
1	0.0	100	negative control
2	1.0	12.7	arbitrary initial [I]
3	0.147	55.4	optimally designed [I]
4	0.183	51.1	optimally designed [I]



$K_i = (178 \pm 9)$ nM

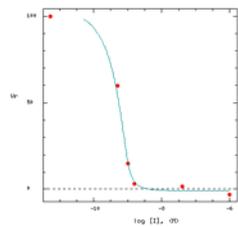
Monte-Carlo study: Example 2 - Regression phase

A TYPICAL TIGHT-BINDING (SIMULATED) ENZYME INHIBITOR

"true" $K_i = 0.021$ nM
 $[E] = 1$ nM
 $V_0 = 100$

ASSEMBLE AND FIT DOSE-RESPONSE CURVE

#	[I], μM	Rate	note
1	0.0	100	negative control
2	1.0	-3.3	arbitrary initial [I]
3	0.04	1.6	maximum jump 25x
4	0.0016	3.1	maximum jump 25x
5	0.001	13.1	optimally designed
6	0.0005	49.5	rule of thumb



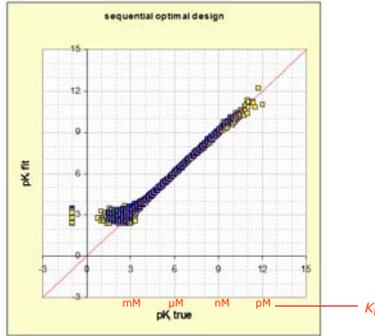
$K_i = (0.033 \pm 0.011)$ nM

Monte-Carlo study: "True" vs. estimated pK_i values

DISTRIBUTION OF "TRUE" pK_i VALUES IS SIMILAR TO THE AXYS/CELERA CAMPAIGN

SEQUENTIAL OPTIMAL DESIGN

$n = 3$ (or 5) + control



Optimal Design for Screening

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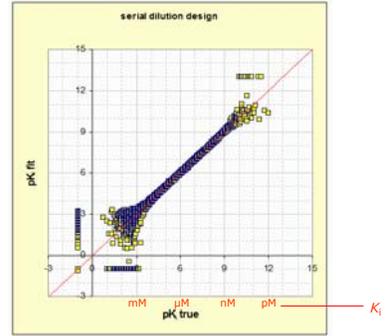
Monte-Carlo study: Dilution series results

DISTRIBUTION OF "TRUE" pK_i VALUES IS SIMILAR TO THE AXYS/CELERA CAMPAIGN

SERIAL DILUTION DESIGN

$n = 8$ + control

- $[I]_{max} = 50 \mu M$
- Dilution 4x
- Eight wells



Optimal Design for Screening

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Efficiency of serial dilution vs. sequential design

HOW MANY WELLS / PLATES DO WE END UP USING?

SCREEN 10,000 COMPOUNDS (DOSE-RESPONSE) TO DETERMINE K_i 's

	SERIAL DILUTION	SEQUENTIAL DESIGN	SAVINGS
total 96-well plates	909	343	62.3 %
compounds per plate	11	88	
control wells per plate	8	8	
wells with inhibitors	79992	30042	62.4 %
control wells ($[I] = 0$)	7272	2744	62.3 %
total wells	87264	32786	62.4 %
wells per compound	8.73	3.28	62.4 %

Optimal Design for Screening

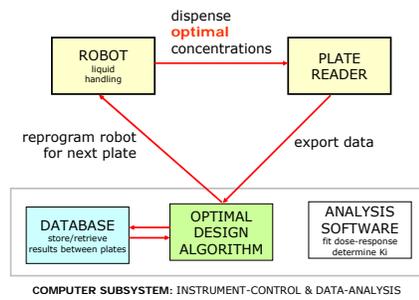
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Toward optimized screening: Preliminary phase

PROPOSAL FOR FULLY AUTOMATED OPTIMIZED SCREENING

1. Accumulate minimal (optimized) dose-response curves



COMPUTER SUBSYSTEM: INSTRUMENT-CONTROL & DATA-ANALYSIS

Optimal Design for Screening

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Efficiency comparison: ~100 compounds to screen

HOW MANY WELLS / PLATES DO WE END UP USING WITH FEWER COMPOUNDS TO SCREEN?

SCREEN 88 COMPOUNDS (DOSE-RESPONSE) TO DETERMINE K_i 's

	SERIAL DILUTION	SEQUENTIAL DESIGN	SAVINGS
total 96-well plates	8	3	62.5 %
compounds per plate	11	88	
control wells per plate	8	8	
wells with inhibitors	704	264	62.5 %
control wells ($[I] = 0$)	64	24	62.5 %
total wells	768	288	62.5 %
wells per compound	8.73	3.27	62.5 %

Optimal Design for Screening

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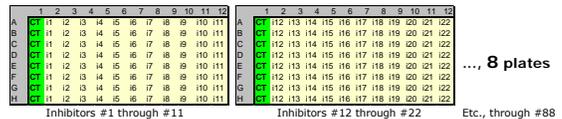


Example: Plate layout for 88 inhibitors

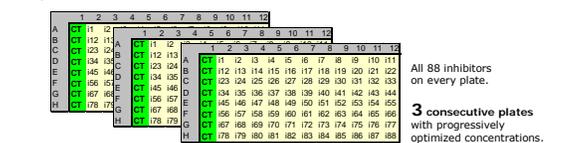
HOW MANY WELLS / PLATES DO WE END UP USING WITH FEWER COMPOUNDS TO SCREEN?

SERIAL DILUTION

CT = control



SEQUENTIAL DESIGN



...., 8 plates

All 88 inhibitors on every plate.
3 consecutive plates with progressively optimized concentrations.

Optimal Design for Screening

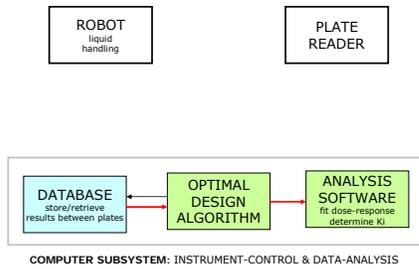
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Toward optimized screening: Data-analysis phase

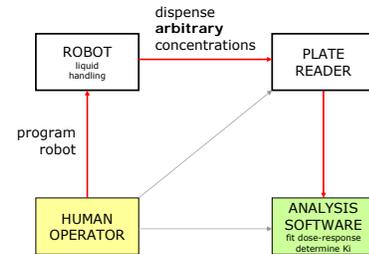
PROPOSAL FOR A FULLY AUTOMATED OPTIMIZED SCREENING

2. Analyze accumulated data



Toward optimized screening: Current status

THE WAY WE SCREEN TODAY:



Optimal design in biochemistry: Earlier reports

SEARCH KEYWORDS: "OPTIMAL DESIGN", "OPTIMUM DESIGN", "OPTIM* EXPERIMENT DESIGN"

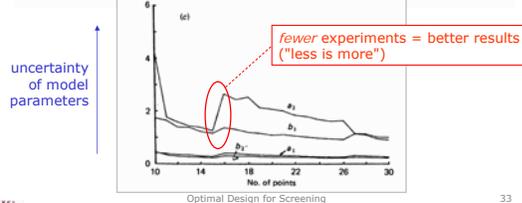
Franco et al. (1986) *Biochem. J.* **238**, 855-862

Biochem. J. (1986) **238**, 855-862 (Printed in Great Britain)

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A computer program for enzyme kinetics that combines model discrimination, parameter refinement and sequential experimental design

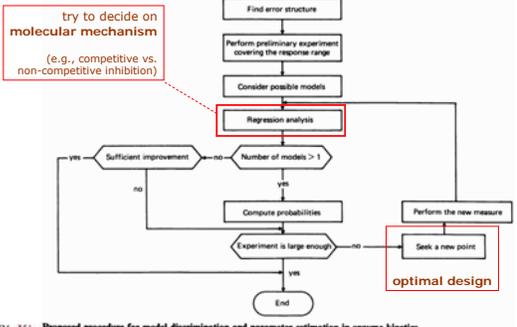
Rafael FRANCO, Maria Teresa GAYALDÀ and Enrique I. CANELA
Departament de Bioquímica, Facultat de Química, Universitat de Barcelona, Martí i Franqués 1, 08028 Barcelona, Catalunya, Spain



Optimal experiments for model discrimination

OPTIMAL DESIGN IS IMPORTANT FOR MECHANISTIC ANALYSIS

Franco et al. (1986) *Biochem. J.* **238**, 855-862



Integration with the BatchKi software

THE BATCHKI SOFTWARE IS WELL SUITED FOR PROCESSING "SMALL", OPTIMAL DATA SETS

- Automatic initial estimates of model parameters
Kuzmič et al. (2000) Anal. Biochem. **281**, 62-67
- Automatic active-site titration (for ultra-tight binding compounds)
Kuzmič et al. (2000) Anal. Biochem. **286**, 45-50
- Automatic detection of chemical impurities in samples
Kuzmič et al. (2003) Anal. Biochem. **319**, 272-279
- Automatic handling of outlier data points ("Robust Regression")
Kuzmič et al. (2004) Meth. Enzymol. **281**, 62-67

ALGORITHMS
theoretical foundation

- Handles enzyme inhibition and cell-based assays
- Fifteen years of experience
- Approximately 100,000 compounds analyzed by this consultant alone

Conclusions

SEQUENTIAL OPTIMAL DESIGN FOR INHIBITOR SCREENING HAS BEEN TESTED "IN SILICO"

Advantages of sequential optimal design:

- reduce material expenditures by more than 50%
- reduce screening time by more than 50%
- increase accuracy & precision of the final answer (K_i)



Disadvantages, limitations, and caveats:

- works best for large number of compounds ($n > 100$)
- has not been tested in practice
- to avoid programming liquid handler manually, needs "closing the loop": robot → reader → computer

Collaboration, anyone?

Acknowledgments

Craig Hill & James Janc

Theravance Inc.
South San Francisco, CA

formerly Celera Genomics - South San Francisco
formerly Aysis Pharmaceuticals
formerly Arris Pharmaceuticals



Optimal Design for Screening

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Thank you for your attention

• Questions 

• More info: www.biokin.com

• Contact: +1 617 209 4242
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