

# Optimal Sequential Experimental Design for Stochastic Root-finding in Drug Development

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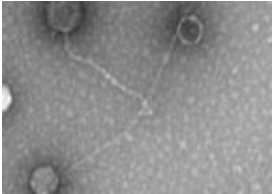
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Tuesday June 21, 2011  
INFORMS Healthcare Conference  
Montreal, Quebec

Research supported by the Atkinson Center for a Sustainable Future

# The Disease: Metritis



- Metritis is a bacterial infection of the uterus.
  - It is a leading cause of loss of milk production and fertility in dairy cows.
  - It also occurs in other animals and people.
- The treatments developed may also be useful for other problematic bacterial infections, in both animals and people (e.g. MRSA).

# Current Treatment: Broad-Spectrum Antibiotics

- Metritis is caused primarily by *E. coli* and *A. pyogenes* bacteria.
- Antibiotics are used to treat metritis in sick cows.
- Antibiotics are also given to well cows as a preventative measure.
- Causes to be concerned about the indiscriminate use of broad-spectrum antibiotics:
  - ① Bacteria develop **resistance to antibiotics** if they are used too widely.
  - ② Releasing large quantities of antibiotics into the environment via farm effluent may have negative **environmental effects**.

# An Alternative Treatment: Bacteriophages



- Bacteriophages (abbreviated phages) are **viruses that kill bacteria.**
- Can we treat bacterial infections with **phages instead of antibiotics?**

# Bacteriophage-based Treatments: Advantages

- Reduced risk of **bacterial resistance**
  - Phages are a new type of treatment.
  - Each phage would be used against a few bacteria, limiting its use.
  - Increasing the number of available treatments, and limiting their use, mitigates the problem of bacterial resistance.
- Reduced **environmental impact**:
  - Each phage kills a few very specific strains of bacteria, and nothing else. In contrast, each type of antibiotic kills a wide variety of bacteria.
  - Phages already exist naturally at dairy farms.

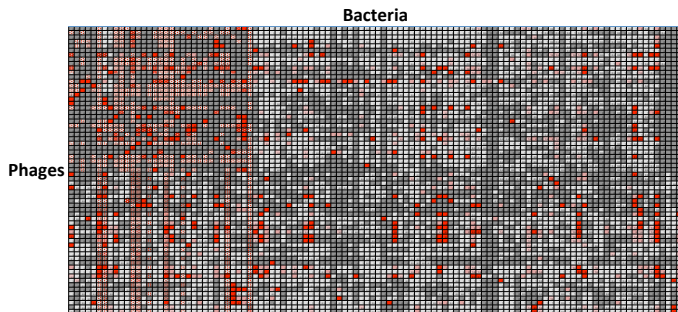
# Specificity and Cocktails

- Specificity:
  - Each phage kills only a few very specific strains of bacteria.
  - An infection could be caused by any one of a number of strains of bacteria.
  - An effective treatment must then be a cocktail of phages that will be effective against each common metritis-causing strains of bacteria.
- A **cocktail** is a collection of phages.
  - We also specify a concentration (# phages/mL) for each phage in the cocktail.

# Production Costs

- A cocktail is a collection of phages, with a concentration specified for each phage.
- Production costs
  - A cocktail is cheaper to produce if it contains few phages.
  - A cocktail is cheaper to produce if the concentrations are small.
- **What is the cheapest cocktail that kills all targeted bacteria?**

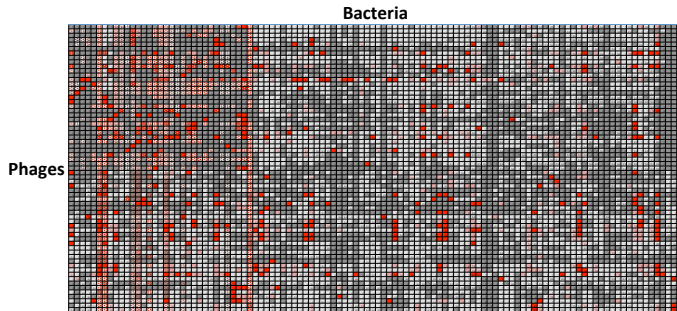
# The Matrix



- Given many lab experiments (**600 days of experiments**), we could create a matrix like the one above, but with accurate values.
- The color in each cell would give the minimum concentration of that phage needed to kill that bacteria.
  - Red cells: the phage kills the bacteria at very low concentrations.
  - White cells: the phage kills the bacteria at high concentrations.
  - Gray cells: the phage does not kill the bacteria at any concentration.



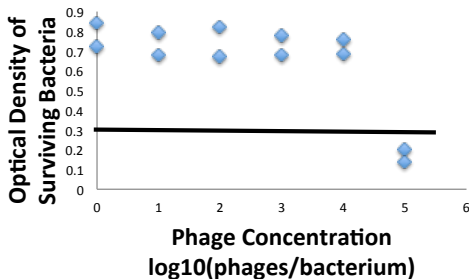
# The Matrix



- With this matrix, we could find the cheapest cocktail that kills every bacteria.
  - (Actually, a partially filled matrix would be sufficient — This is a subject of ongoing work)
  - The matrix is also of independent scientific interest.
- The goal of this talk is to develop an efficient method to create this matrix.

# Stochastic Root-finding

- Problem: Given a phage and a bacteria, find the **minimal** concentration of the phage that kills the bacteria.



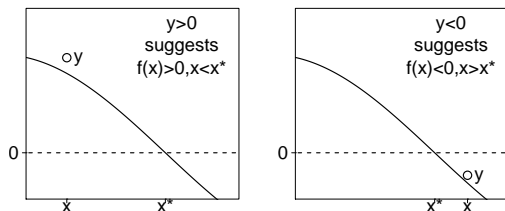
- Each experiment is time consuming (1 day), so we should **use as few experiments as possible** ( $< 10$  experiments).
- We act **sequentially**, basing each new experiment on previous results. (Experiments are done in batches of 96 per day. To allow sequential decision-making, we consider 96 phage-bacteria pairs simultaneously.)

# Stochastic Root-Finding

- The standard approach is stochastic approximation [Robbins and Monro, 1951].
- This approach requires many (20 or more) samples to be reliable.
- We can afford  $< 10$  samples per phage-bacteria pair.
- We use methods from sequential Bayesian experimental design.

# Stochastic Root-Finding: Motivation

Motivation for our approach:



- We think of  $z = \text{sgn}(y)$  as a noisy bit indicating whether  $x_*$  is left or right of  $x_n$ .
- When  $|y|$  is big, this bit is more likely to be correct.

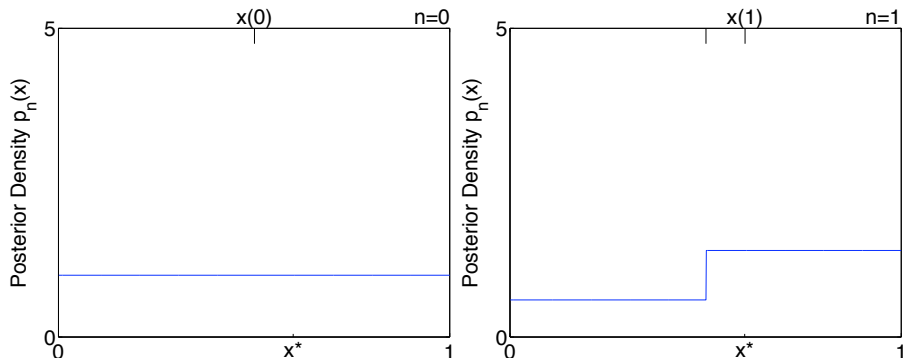
# Stochastic Root-Finding: Mathematical Model

- $f : \mathbb{R} \mapsto \mathbb{R}$  is a decreasing function, with root  $x_*$ , so  $f(x_*) = 0$ .
- When we measure  $x_n$  we see a direction  $z_n \in \{-1, +1\}$  and a probability  $r_n$ .
- The true direction,  $\text{sgn}(x_n - x_*)$ , is equal to  $z_n$  with probability  $r_n$ . (Nature gives the right direction with probability  $r_n$ ).
- We choose each  $x_n$  given the available information,  $(x_m, z_m, r_m), m < n$ .
- Central Question: Given a budget of  $N$  measurements,  $x_1, \dots, x_N$ , how should we place them to find  $x_*$  as accurately as possible?

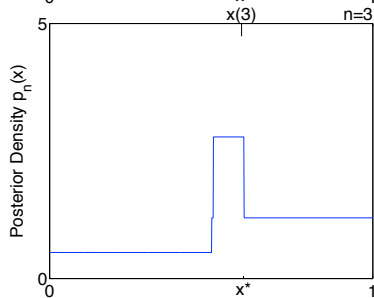
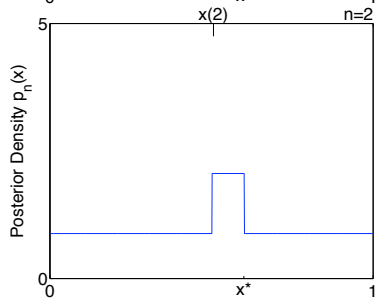
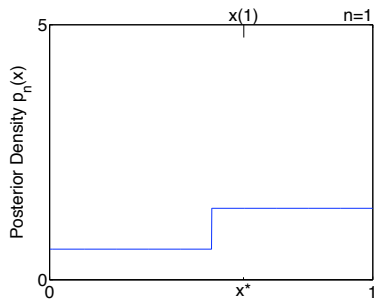
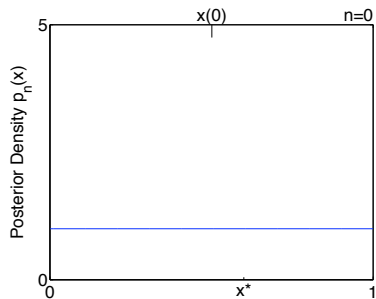
# Posterior Distributions

- Place a prior density  $p_0$  on the root  $x_*$ , e.g., uniform on  $[0, 1]$ .
- Each measurement  $x_n$  produces a new posterior density  $p_n$  on  $x_*$ :

$$p_n(x) = \mathbb{P}\{X_* \in dx \mid x_{1:n}, z_{1:n}, r_{1:n}\}$$



# Posterior Distributions



# Optimality and Dynamic Programming

- One measure of success is the entropy of the final posterior distribution,

$$H(p_N) = - \int p_N(x) \log p_N(x) dx.$$

- A policy  $\pi$  is a method for choosing the next experiment based on the results so far.
- The optimal policy  $\pi^*$  is the solution to the stochastic optimization problem

$$\inf_{\pi} \mathbb{E}^{\pi} [H(p_N)],$$

- Given a very large computer, we could compute  $\pi^*$  by **dynamic programming**.



## Theorem

*If  $r_n$  is chosen independently, and its distribution does not depend on  $x_n$ , then **the policy that chooses  $x_n$  at the median of  $p_n$  is the Bayes optimal fully sequential policy** for the entropy loss function.*

- The assumption on  $r_n$  is not met in our application, but the policy can still be used here.
- This policy was introduced by [Horstein, 1963], and is called probabilistic bisection.
- For  $r_n$  constant, the proof is due to [Waeber, Frazier, Henderson 2011]. For more general  $r_n$ , the proof follows [Jedynak, Frazier, Sznitman 2011].

## Estimating the Probability of Correctness, $r_n$

- In practice we observe  $y_n$ , not  $r_n$ .
- One can use training data to fit a parametric statistical model,

$$r_n \approx g(y_n, \beta),$$

where  $\beta$  is one or more parameters to be fit.

- In experimental results to be shown later, we use  $g(y, \beta) = \Phi(\beta|y|)$ ,

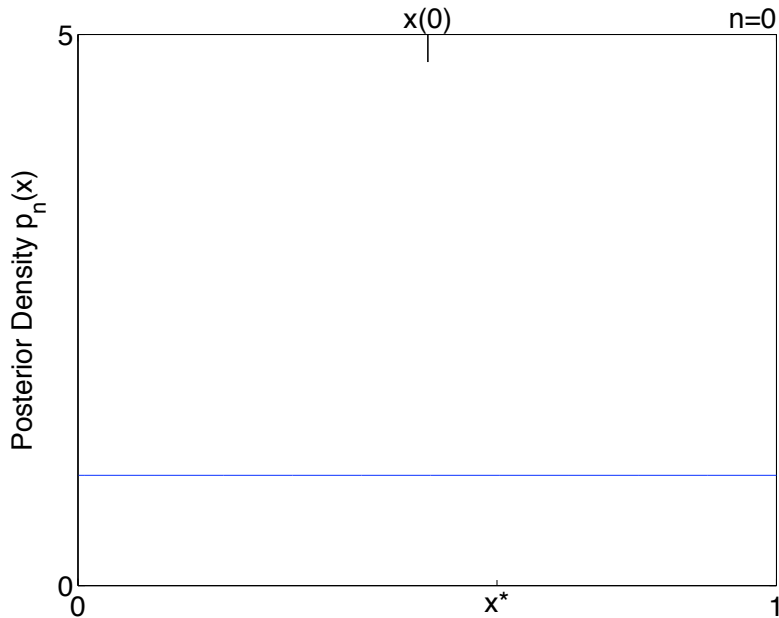
$$r_n \approx \Phi(\beta|y_n|).$$

- For applications allowing more measurements, we could include the whole history  $x_{1:n}, y_{1:n}$  into the fit to obtain asymptotically consistent estimates of  $r_n$ ,

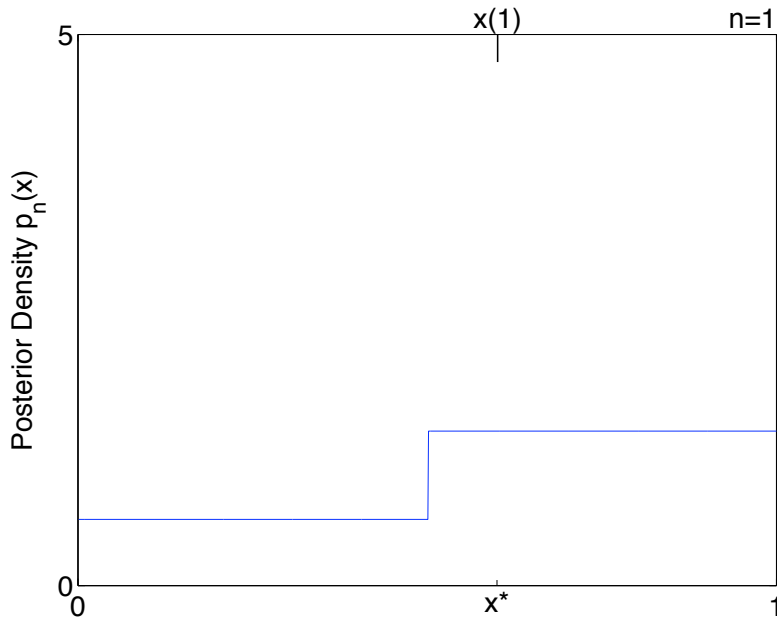
$$r_n \approx g(x_{1:n}, y_{1:n}, \beta),$$

Open question: Would the resulting procedure provide an asymptotically consistent estimator of  $x_*$ ?

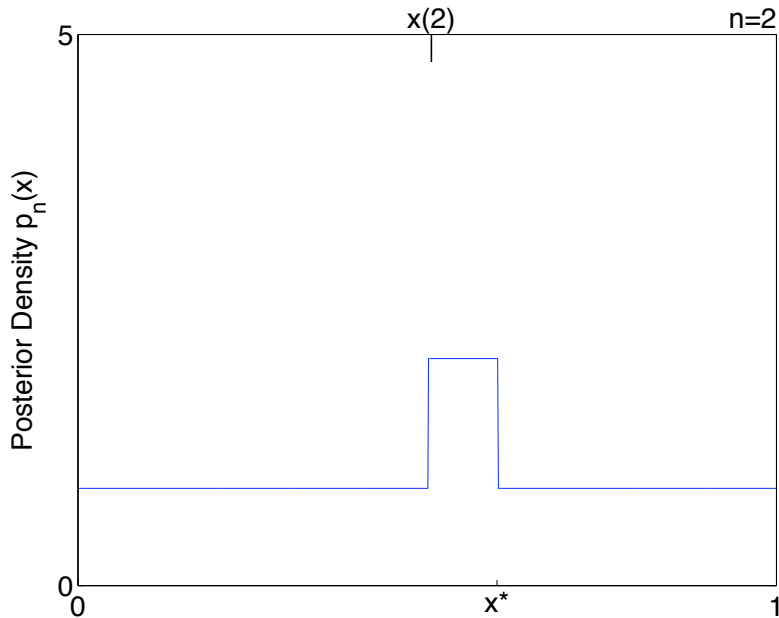
# Example



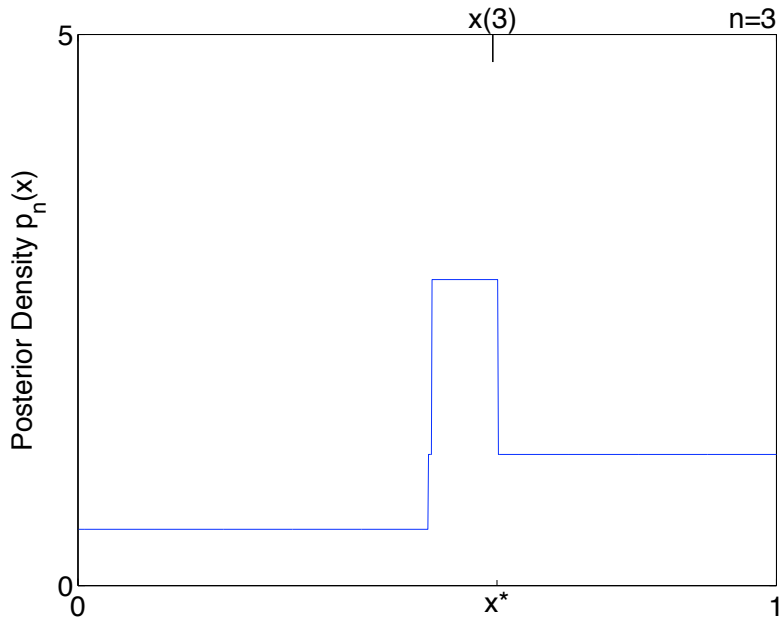
# Example



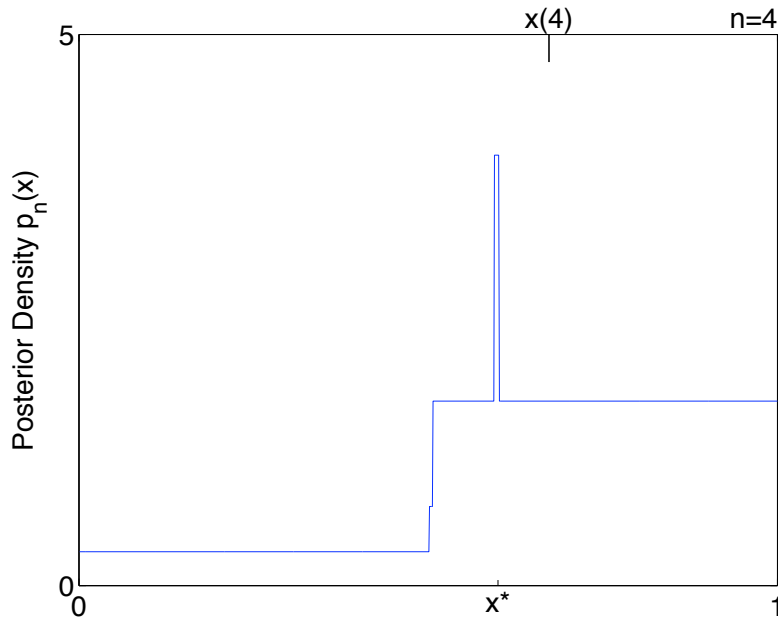
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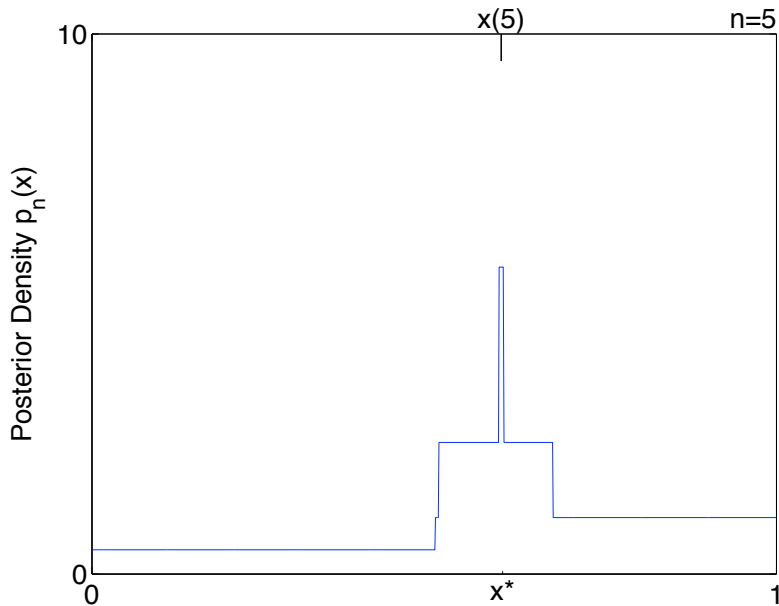
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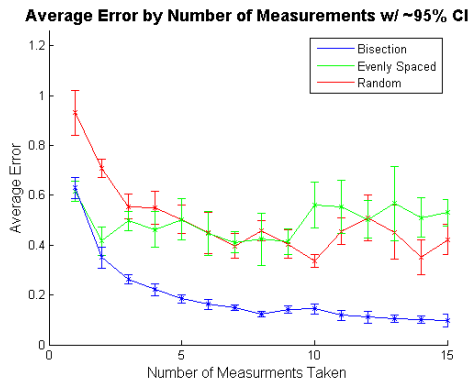


# Example





# Experimental Results



- Caveat: graph presents initial results based on a small amount of experimental data.
- These results suggest we can use 3 experiments per phage-bacteria pair instead of 6 (currently used), and get better accuracy.
- This would reduce the time required to **300 days** down from **600**.

## Ongoing work: Bayesian global optimization






- We can use structure in the phage-bacteria matrix for prediction.
  - We use low rank matrix approximation, as in collaborative filtering.
  - Results so far suggest that bacteria and phages are described by a small number of features.
- Finding a good cocktail with as few measurements as possible is a Bayesian global optimization problem.
  - We do not need to evaluate every cell in the matrix to find a good cocktail.
  - We are planning to use methods based on the value of information, e.g., knowledge-gradient methods, or expected improvement methods.

# Conclusion

- We are using fully sequential Bayesian learning methods to make drug development for bacteriophage-based therapies **faster, cheaper, and more likely to succeed**.
- **Dynamic programming** is an excellent tool for analyzing and developing these methods.
- **Ongoing work** in implementing this approach, analysis of the algorithm, and in Bayesian global optimization.

We gratefully acknowledge support from the Atkinson Center for a Sustainable Future.

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Thank you for coming!