Model

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#### Characterizing the Distribution of Lysis Time and Burst Size in Lytic Phage

Paul Joyce<sup>1</sup>, Craig Miller<sup>1</sup>, Dan Weinreich<sup>2</sup>

University of Idaho 1, Brown University 2

June 14, 2012

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#### Outline

- Briefly explain cycle of a Virus (phage)
- Briefly explain the experiment that monitor a small number of phage through their life cycle
- Use a three step statistical procedure to understand lysis time and burst size that
  - estimates the number of phage in the well
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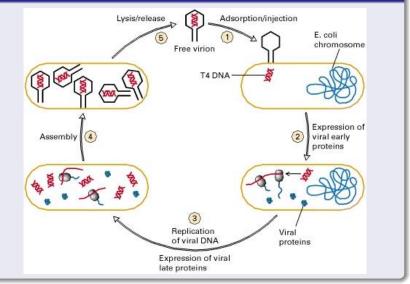
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#### Lytic Phage Life Cycle

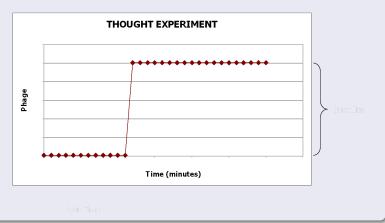


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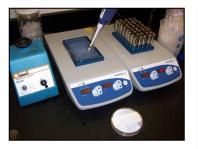
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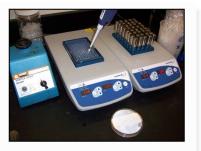


 Phage: φX174
 In 60 wells add 100 μl host cells.

- Target of <sup>1</sup>/<sub>2</sub> phage particle.
- Titrate 20 wells at 5 minutes prior to burst to
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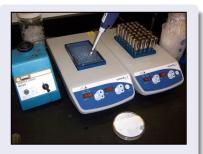
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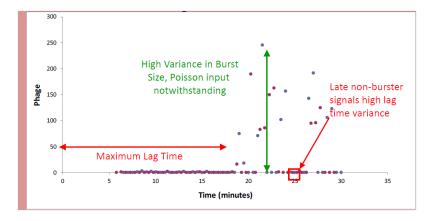
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#### Example Sample Data



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- t = time when well is sampled
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- $C_t$  = observed count in well sampled at time t.
- B = the number of phage in the well.
- *N<sub>t</sub>* = the number of phage in a well that have burst by time *t*, when well is sampled.
- $X_t =$ sum of burst times,  $T_i$ , for all phage that have burst
- $\alpha$  = slope of the linear function relating burst size to time.
- $\mu$  = intercept at time when burst is first possible  $t > t_0$ .
- σ=standard deviation or average error of predicted versus observed burst size.

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Introductio	on

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# Three Step Algorithm for Estimating Lysis Time and Burst Size

### Step 1: Model and Estimate the mean number of phage per well

- Assume a Poisson number of phage in a well with mean  $\beta_d$  for day d.
- Use the early time point data as direct observations.
- Use late time points as indirect observation.
  - If a burst occurs by time t then there was at least one phage in that well. Assign that event probability  $1 e^{-\beta_d}$
  - If no burst occurs by time t assign that event probability e<sup>-β<sub>d</sub></sup>
  - Treat the late burst times as binary data.
- Combine early and late data using maximum likelihood to estimate β<sub>d</sub>-the mean number of phage in a well on day d.

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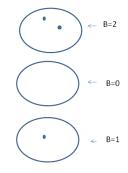
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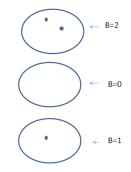
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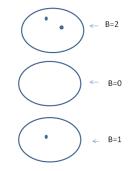
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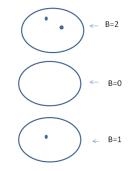


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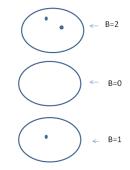


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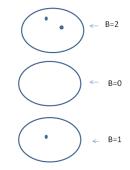


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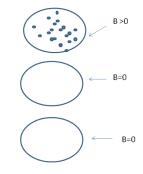


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- If a burst occurs by time then there was at least one phage in that well. Assign that event probability 1—e<sup>-24</sup>
- If no burst occurs by time t assign that event probability c<sup>-0</sup>
- Treat the late burst times as binary data.

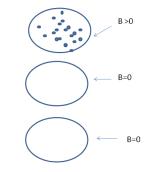


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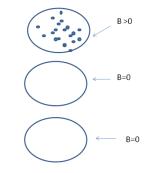
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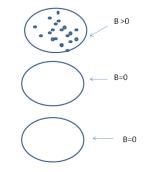
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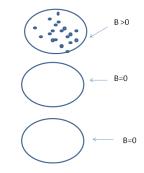
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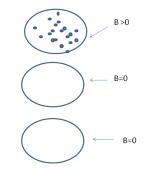
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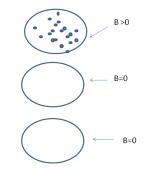
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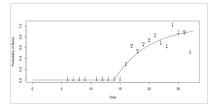
# Step 1: Model and Estimate the mean number of phage per well

- If a burst occurs by time t then there was at least one phage in that well. Assign that event probability  $1 - e^{-\beta_d}$
- If no burst occurs by time t assign that event probability  $e^{-\beta_d}$
- Treat the late burst times as binary data.



Model

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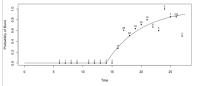


#### Step 2: Model and Estimate Lysis Time

$$P(T < t) = w_t = 1 - e^{-(t-t_0)/\lambda}$$

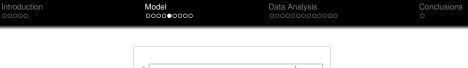
- $N_t$  = the number of phage in a well that have burst by time t, when well is sampled.  $N_t$  is Poisson with mean  $\beta w_t$ .
- Let  $Y_t$  be 1 if  $N_t > 0$  and 0 otherwise
- Use binary  $Y_t$  to estimate  $\lambda$  and  $t_0$

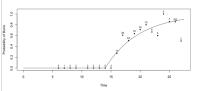




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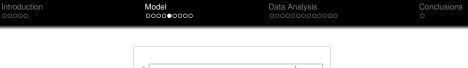
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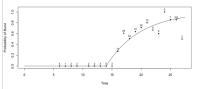




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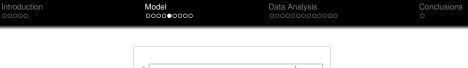
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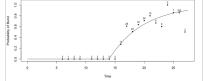




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Three Step Algo Burst Size	orithm for Estir	mating Lysis Tim	ie and

#### Step 3: Model and Estimate Burst Size

$$C_T = \alpha T + \mu + \epsilon$$

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where  $\epsilon$  is normally distributed with mean 0 and variance  $\sigma^2$ . Note that none of the terms in the equation are directly observable

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### Step 3: Model and Estimate Burst Size

#### **Observable Counts Equation**

$$C_{t} = \alpha \sum_{i=1}^{B} T_{i}I\{T_{i} < t\} + \mu \sum_{i=1}^{B} I\{T_{i} < t\} + \sum_{i=1}^{B} \epsilon_{i}I\{T_{i} < t\}$$
$$C_{t} = \alpha X_{t} + \mu N_{t} + \delta$$

where  $\delta$  is normally distributed with mean zero and variance  $N_t\sigma^2$ 

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#### Step 3: Model and Estimate Burst Size using EM Algorithm

- **D** Begin with initial guesses for  $N_t$  and  $X_t$  for each well.
- 2 Given these values, estimate lpha and  $\mu$  using least-squares

$$\min_{\alpha,\mu} \sum_{t,r} \frac{(C_{t,r} - \alpha X_{t,r} - \mu N_{t,r})^2}{N_{t,r}} = \sum_{t,r} \frac{(C_{t,r} - \hat{\alpha} X_{t,r} - \hat{\mu} N_{t,r})^2}{N_{t,r}}$$

where r indexes the well.

Given estimates  $\hat{lpha}$  and  $\hat{\mu}$  estimate  $\sigma^2$  using

$$\hat{\sigma}^{2} = \frac{1}{n} \sum_{t,r} \frac{(C_{t,r} - \hat{\alpha}X_{t,r} - \hat{\mu}N_{t,r})^{2}}{N_{t,r}}$$

Impute the values  $X_t$  and  $N_t$  using their posterior expected values

$$E(X_t|C_{t,r}\hat{\alpha},\hat{\mu},\hat{\sigma}^2)$$

$$E(N_t|C_{t,r}\hat{\alpha},\hat{\mu},\hat{\sigma}^2)$$

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Interpretation of the step 2 until convergence occurs.

$$E(N_t|C_t) = \sum_{x_t} \sum_{n_t} \frac{n_t f_{N_t, X_t}(n_t, x_t|\beta, t_0, \lambda) f_{C_t}(c_t|n_t, x_t, \alpha, \mu, \sigma^2)}{f_{C_t}(c_t)}$$

$$E(X_t|C_t) = \sum_{x_t} \sum_{n_t} \frac{x_t f_{N_t, X_t}(n_t, x_t|\beta, t_0, \lambda) f_{C_t}(c_t|n_t, x_t, \alpha, \mu, \sigma^2)}{f_{C_t}(c_t)}$$

$$f_{C_t}(C_t) = \sum_{n_t, x_t} f_{N_t, X_t}(n_t, x_t | \beta, t_0, \lambda) f_{C_t}(c_t | n_t, x_t, \alpha, \mu, \sigma^2)$$

- $\beta$  is estimated in step 1
- $\lambda, t_0$  is estimated in step 2
- $\mu, \sigma^2$  are updated from the "M" part of the EM algorithm in step 3

$$E(N_t|C_t) = \sum_{x_t} \sum_{n_t} \frac{n_t f_{N_t, X_t}(n_t, x_t|\beta, t_0, \lambda) f_{C_t}(c_t|n_t, x_t, \alpha, \mu, \sigma^2)}{f_{C_t}(c_t)}$$

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$$\begin{array}{ccc} & {\rm Model} & {\rm Data \ Analysis} & {\rm Conclusions} \\ {\rm occoccc} & {\rm occoccccc} & {\rm occocccccc} \\ \end{array} \\ \hline {\rm Imputing \ } X_t \ {\rm and \ } N_t \end{array}$$

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### Initial Data on Burst Size

- Burst size was only recorded after 26 minutes. Thus there was no way to detect a time trend for this data.
- This would appear to make data analysis easier. Since we would need to assume  $\alpha = 0$ , so the observed burst counts depend only on  $N_t$  the initial number of phage in the well.

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### Special case of no time trend $\alpha = 0$

#### **Observable Counts Equation**

$$C_t = \mu \sum_{i=1}^B I\{T_i < t\} + \sum_{i=1}^B \epsilon_i I\{T_i < t\}$$
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## Estimating Mean Burst Size $\mu$ with Low Variance

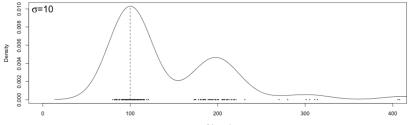


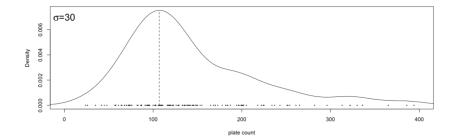
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## Estimating Mean Burst Size $\mu$ with high Variance



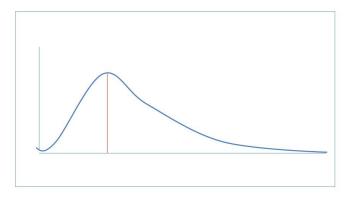
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## Estimating Mean Burst Size $\mu$ with high Variance



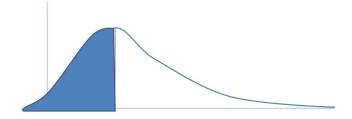
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## Estimating Mean Burst Size $\mu$ with high Variance



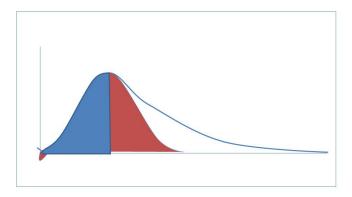
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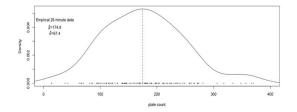
## Estimating Mean Burst Size $\mu$ with high Variance



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## Estimating Mean Burst Size $\mu$ from 26 Minute Data



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## More Data Came in

- Process was monitored more extensively so bursts events and multiple time points were recorded.
- This revealed a time trend in burst size, which helped explain the data.
- This produced lower variance, and better imputation.
- The EM algorithm now worked.

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## Estimating Slope $\alpha$ and Intercept $\mu$

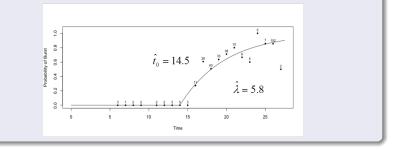
#### **Observable Counts Equation**

$$C_{t} = \alpha \sum_{i=1}^{B} T_{i}I\{T_{i} < t\} + \mu \sum_{i=1}^{B} I\{T_{i} < t\} + \sum_{i=1}^{B} \epsilon_{i}I\{T_{i} < t\}$$
$$C_{t} = \alpha X_{t} + \mu N_{t} + \delta$$

where  $\delta$  is normally distributed with mean zero and variance  $N_t\sigma^2$ 



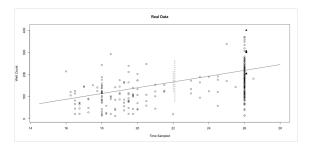
The estimated lysis time until burst probability > 0,  $t_0$ = 14.5 minutes. Estimated mean lysis time is  $\lambda + t_0 = 5.8 + 14.5 = 20.3$  minutes.



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# Full Data



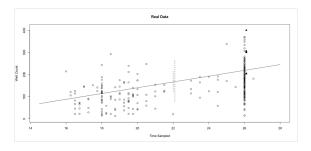
#### Slope intercept

- The estimated burst size at  $t_0$  is  $\mu = 67.0$ . The estimated increase in burst size per minute is  $\alpha = 13.1$ .
- The estimated mean burst size is 143 phage: 67 + 13.1(5.8).

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# Full Data



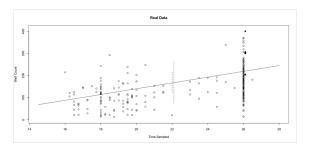
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Parameter estimates			
Parameter $lpha \ \mu \ \sigma$	Estimate 13.1 67.0 47.7	Confidence Interval (6.0, 22.5) (56.8, 87.0) (36.3, 57.8)	

- Either 'Missing data' or 'censored data' challenge any statistical modeling effort. This data set has both.
- We address the challenges in 3 steps: (1) estimating the number of phage in each well, (2) estimating the lysis time, and (3) estimate the burst size.
- A rigorously validation process using simulations offers credibility to the lysis time and size estimates for φ X 174 and indicates the methods may be extended to other lytic phage.

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- Either 'Missing data' or 'censored data' challenge any statistical modeling effort. This data set has both.
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