Participatory risk assessment II
- Risk modelling I -

‘Learning Event’ on risk analysis and participatory methods
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Outline

• Stochastic processes

• Exposure assessment
  – Fault tree
  – Value chain
  – Mixture, separation, growth and inactivation

• Hazard characterization
  – Dose-response
Bayesian inference

Prior belief

Prior distribution

Posterior distribution

Learning from observations

Likelihood function

Current knowledge

\[ \pi(\theta) \rightarrow l(X | \theta) \rightarrow f(\theta | X) \]

Prior distribution: Beta (23,59)

Likelihood function: Beta (2,29)

Posterior distribution: Beta (25,88)
Bayesian inference

Bayes’ Theorem

\[
P(A_i \mid B) = \frac{P(B \mid A_i)P(A_i)} {\sum_{j=1}^{n} P(B \mid A_j)P(A_j)}
\]

Bayes’ Theorem expressed in a different way

\[
f(\theta \mid X) = \frac{\pi(\theta)l(X \mid \theta)} {\int \pi(\theta)l(X \mid \theta) d\theta}
\]

The denominator normalizes the Posterior distribution to have a total area equal to one.
Bayesian inference

Bayes’ Theorem

\[
P(A_i \mid B) = \frac{P(B \mid A_i)P(A_i)}{\sum_{j=1}^{n} P(B \mid A_j)P(A_j)}
\]

Bayes’ Theorem expressed in a different way

\[
f(\theta \mid X) = \frac{\pi(\theta)l(X \mid \theta)}{\int \pi(\theta)l(X \mid \theta)d\theta}
\]

So,

\[
f(\theta \mid X) \propto \pi(\theta)l(X \mid \theta)
\]

Posterior distribution Prior distribution Likelihood function
Stochastic processes

• Systems of countable events
• There are three fundamental stochastic processes
  – Binomial process
  – Poisson process
  – Hypergeometric process
Binomial process

• A random counting system where there are;
  – $n$ independent identical trials
  – each one of which has the same probability of success $p$
  – which produces $s$ successes from $n$ trials
Distributions for the binomial process

- $s = \text{Binomial}(n, p)$
- $n = s + \text{Negbin}(s, p)$ if we know trials stopped in the $s^{th}$ success
- $n = s + \text{Negbin}(s+1, p)$ if don’t know trials stopped in the $s^{th}$ success
- $p = \text{Beta}(s+1, n-s+1)$ for a Uniform(0,1) prior
- $p = \text{Beta}(s+a, n-s+b)$ for a Beta($a$, $b$) prior

- and $\text{Negbin}(1, p) = \text{Geomet}(p)$
- $\text{Binomial}(1, p) = \text{Bernoulli}(p)$
Exercise for Binomial process

Now start your @Risk

1. 3% of salad in a local restaurant in area A is known to be contaminated with *Cryptosporidium parvum*. When you sample 50 salads, how many of them are contaminated with *C. parvum*?

2. In the area B, a survey on prevalence of *C. parvum* in salad was conducted. Out of 156 samples, 5 were contaminated. What is the prevalence?

3. The probability of attending hospital if infected with *C. parvum* is 80%. We observed 53 patients who visited hospital and diagnosed with *C. parvum* infection in the outbreak last month. How many people were infected?
Binomial Process

- Number of trials $n$ (NegBin)
- Number of successes $s$ (Binomial)
- Probability of success $p$ (Beta)

Hypergeometric Process

- Number of trials $n$ (InvHypergeo)
- Number of successes $s$ (Hypergeo)
- Population $M$, Sub-population $D$ (...)

Poisson Process

- Exposure "time" $t$ (Beta)
- Number of observations $\alpha$ (Poisson)
- Mean number of events per unit time $\lambda$ (Gamma)

Back to the map...
Poisson process

There is a continuous and constant opportunity for an event to occur- this is explained by:

- the number of events that may occur in a period \( t \)
- the amount of “time” one will have to wait to observe \( \alpha \) events
- the average number of events that could occur, \( \lambda \)

\[
\begin{align*}
\text{Exposure 'time'} \quad t \text{ (Gamma)} \\
\text{Number of observations} \quad \alpha \text{ (Poisson)} \\
\text{Mean number of events per unit time} \quad \lambda \text{ (Gamma)}
\end{align*}
\]
Distributions for the Poisson process

- $\alpha = \text{Poisson}(\lambda t)$  \hspace{1cm} $P(\alpha=0) = \text{Exp}(-\lambda t)$

- $t = \text{Gamma}(\alpha, \beta)$  
  $\beta = 1/\lambda$ (Average time between events) 
  i.e. how much time until the next AI outbreak

- $\lambda = \text{Gamma}(\alpha, 1/t)$
  with a $\pi(\lambda) \propto 1/\lambda$ prior 
  and $\text{Gamma}(1, \beta) = \text{Expon}(\beta)$
Exercise

• Food poisoning was reported in a village A for 40 times last 5 years. If food poisoning occurs regardless the season (a constant risk),
  – how many outbreaks would be observed in the next three months?
  – how many months does it take to have the next outbreak since last one (suppose we had an outbreak yesterday)?

• If a bulk of raw milk contains 4 cfu/l of *E. coli* O157:H7,
  – how much milk can you drink before you ingest one *E. coli*
  – what is the probability that you ingest at least one *E. coli* if you drink 300ml of the milk?
Hypergeometric process

• When the population is not very large compared to the sample (population < 10 x sample size)

• Out of a group of $M$ individual items, $D$ have a certain characteristic. Randomly picking $n$ items from this group \textit{without replacement}, where each of the $M$ items has the same probability of being selected, is a hypergeometric process.
The hypergeometric format

\[ \begin{align*} 
& \text{M} \quad \text{(total population)} \\
& \text{D} \quad \text{(infected)} \\
& \text{n} \quad \text{(selected)} \\
& s = \text{number infected from selection} \\
\end{align*} \]

Examples:

- Sampling sheep from an infected flock
- Sampling food from a consignment
- Defective items in a consignment
- Capture-release-recapture surveys
Distributions for the hypergeometric process

• \( s = \text{Hypergeo}(n, D, M) \)

• \( n = s + \text{InvHypgeo}(s, D, M) \)

• D, M have no standard distributions
  – Have to be worked out manually (see problems)
Exercise

• In an informal market, Mrs A is selling 100 eggs of which 10 are contaminated with *Salmonella*. You purchased 5 eggs from Mrs A. How many contaminated eggs are included?
Outline

• Stochastic processes
• Exposure assessment
  – Fault tree
  – Value chain
  – Mixture, separation, growth and inactivation
• Hazard characterization
  – Dose-response
Fault tree

- Fault tree is a systematic method for acquiring information about a system

Figure 1-1. A Simplified Fault Tree

Points of fault tree analysis in food safety

- How the illness can occur

Onset of illness → Infection
Preceded by

Infection → Ingestion
Preceded by

Ingestion → Purchase
Preceded by

Or

Production
Risk assessment for staphylococcal poisoning through consumption of informally-marketed milk in Debre Zeit, Ethiopia
Makita K, Dessisa F et al. (2011) International Journal of Food Microbiology

Initiating event

Illness due to Staphylococcal poisoning due to milk consumption

A consumer is susceptible to SAET

SA multiply to reach enough cfu producing ET

Milk contains SA

Milk contains SA at production

Milk shed by SA Mastitis cow

Infected cow

Milk contaminated by a farmer

Human source

Milk contaminated with SA By traders/handlers

Human source

AND

OR
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Value chain

A producer ↔ A consumer
Value chain

Producers  ↔  Middle men  ↔  Consumers
Designing a study based on fault tree

- Design a study to collect information on the ‘Nodes’ identified in fault tree analysis
- ‘Nodes’ are similar to Critical Control Points (CCPs) in HACCP
- It usually include below segments

Consumer | Retail shop | Middle men | Producer

- In informal markets, marketing systems are sometimes not ‘linear’, which means unpredictable
- So combination of below techniques are useful
  - Rapid rural appraisal
  - Probabilistic survey using questionnaires
  - Tracing back, tracing forward
Categorizing actors

• Retail shops or middle men can be categorized even further

• In terms of risk modeling, it is important to have separate ‘branches’ to predict behavior more precisely

• Examples are shown in the next slide
Actors in informal milk sales in Kampala, Uganda

- Plus milk retail shop without refrigerator and dairy farmers selling at farms
Probabilistic survey

- Random selection of either small administrative units or shops or farmers in a probabilistic manner
- Collect quantitative information (e.g. number of shops, farmers, quantity of sales)
- Divide the quantity with sampling fraction in order to estimate the total amounts of sales in the study area
Fig. 1. Map of Kampala showing the locations of 48 urban LC1s studied. Areas highlighted are peri-urban parishes.

The University of Edinburgh
Field survey – Importance of diagnostic tests

Nyama-choma in Tanzania

My bitter experience in *Campylobacter* risk assessment...

<1st survey for prevalence>
High prevalence using culture without rigorous identification

<2nd survey for MPN>
Low prevalence using PCR after culturing
Tracing forward and/or backward

• Wholesale shops, abattoirs and markets identified in RRAs and interviews need to be trucked in order to complete the value chains

• Interviews at such ‘hubs’ will give you the information on the chains after the ‘hubs’

• Tracking will fill the ‘gaps’ of quantitative information of sales
Tracing forward and/or backward

Fig. 2. Spatial distributions of wholesale milk shop centres and milk boiling centres in Kampala

Tracing forward and/or backward

Fig. 3. Spatial distributions of milk shops with a bulk cooler.

The University of Edinburgh
Tracing forward and/or backward

Fig. 4. Spatial distributions of fresh milk shops with a small refrigerator

The University of Edinburgh
Quantitative dairy value chain in Kampala, Uganda

Dairy value chain - RRA and interviews

Makita K, Dessisa F et al. (2011) International Journal of Food Microbiology
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Modular Process Risk Model

Microbial processes
• Growth
• Inactivation

Food handling processes
• Mixing
• Partitioning
• Cutting
• Cross-contamination
Separation

- Separation in a value chain refers to sales to more than two customers

![Diagram]

- Bulk tank in a milk collection centre
- Traders with a bicycle
- Sales to customers
Mixing

• Mixing in a value chain refers to receiving from more than two sources

Urban smallholder dairy farmers  Peri-urban commercial dairy farmers

Bulk tank in a milk collection centre
Inactivation

- Inactivation in a value chain usually refers to heat treatment to kill pathogens (note: heat cannot inactivate heat-resistant toxins)

![Diagram showing milk sales and inactivation process](image-url)
Bacterial growth

Log, or exponential growth, phase

Stationary phase

Death, or logarithmic decline, phase

Time (hr.)

Log of numbers of bacteria

Lag phase

0 5 10

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Mathematical modeling of growth

• Several models exist
  – Logistic model
  – Michaelis-Menten model
  – Modified Gompertz model (Gibson et al., 1987)
  – Baranyi model (Baranyi and Roberts, 1994)
  – Modified logistic model (Fujikawa et al., 2003)

• Several factors affect on bacteria growth- careful choice from literature is required
  – Temperature
  – pH
  – Water activity (aW)
  – Salinity
Contamination- a survey

<table>
<thead>
<tr>
<th></th>
<th>Isolation of <em>S. aureus</em></th>
<th>Boiling before sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Milk collection centre (n=25)</td>
<td>18 (70.4%)</td>
<td>0</td>
</tr>
<tr>
<td>Dairy farm (n=170)</td>
<td>74 (43.6%)</td>
<td>0</td>
</tr>
</tbody>
</table>

Risk mitigation by consumers - participatory and interviews

<table>
<thead>
<tr>
<th></th>
<th>Boil milk before consumption</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dairy farming households (n=170)</td>
<td>116</td>
<td>68.2</td>
</tr>
<tr>
<td>Consumers (n=25)</td>
<td>16</td>
<td>64.0</td>
</tr>
</tbody>
</table>
Example: Fujikawa and Morozumi (2006) modified logistic model

Log of cfu/ml of *Staphylococcus aureus* in milk

- **Lag phase**
- **Exponential growth phase**
- **Stationary phase**
Example
Growth of *Staphylococcus aureus* in milk

- Mathematical model of *S. aureus* growth in milk
  - Modified logistic model reported by Fujikawa and Morozumi (2006)
  - Experts say it also applies to meats

\[
\frac{dN}{dt} = rN(1 - \frac{N}{N_{\text{max}}})\{1 - \left(\frac{N_{\text{min}}}{N}\right)^c\}
\]

Where $N$ is population of a microorganism at time $t$

- $r$ is rate constant or maximum specific rate of growth
- $N_{\text{min}}$ is minimum cell concentration and set as slightly lower value than initial concentration $N_0$
- $N_{\text{max}}$ is maximum concentration at stationary phase: $10^{8.5}$ cfu/ml
- $c$ is an adjustment factor – **variability of growth speed**: $4.7 \pm 1.1$

\[
0.5^r = 0.0442T - 0.239
\]

Where $T$ is temperature in Celsius
Modeling growth in @Risk

<table>
<thead>
<tr>
<th>Time(h)</th>
<th>Log N (D15)</th>
<th>r (E15)</th>
<th>dN/dt (F15)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>=N₀</td>
<td>=(0.0442*T-0.239)^2</td>
<td>=E₁₆<em>10^(D₁₆)</em>(1-10^(D₁₆)/10^(Nmax))*(1-(Nmin/10^(D₁₆))^c)</td>
</tr>
<tr>
<td>1</td>
<td>=LOG₁₀(10^(D₁₆)+F₁₆)</td>
<td>=(0.0442*T-0.239)^2</td>
<td>=E₁₇<em>10^(D₁₇)</em>(1-10^(D₁₇)/10^(Nmax))*(1-(Nmin/10^(D₁₇))^c)</td>
</tr>
<tr>
<td>2</td>
<td>=LOG₁₀(10^(D₁₇)+F₁₇)</td>
<td>=(0.0442*T-0.239)^2</td>
<td>=E₁₈<em>10^(D₁₈)</em>(1-10^(D₁₈)/10^(Nmax))*(1-(Nmin/10^(D₁₈))^c)</td>
</tr>
<tr>
<td>3</td>
<td>=LOG₁₀(10^(D₁₈)+F₁₈)</td>
<td>=(0.0442*T-0.239)^2</td>
<td>=E₁₉<em>10^(D₁₉)</em>(1-10^(D₁₉)/10^(Nmax))*(1-(Nmin/10^(D₁₉))^c)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time(h)</th>
<th>Log N</th>
<th>r</th>
<th>dN/dt</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.35916</td>
<td>0.234521</td>
<td>2.684E-06</td>
</tr>
<tr>
<td>1</td>
<td>0.35916</td>
<td>0.234521</td>
<td>5.837E-06</td>
</tr>
<tr>
<td>2</td>
<td>0.359162</td>
<td>0.234521</td>
<td>1.269E-05</td>
</tr>
<tr>
<td>3</td>
<td>0.359164</td>
<td>0.234521</td>
<td>2.759E-05</td>
</tr>
<tr>
<td>4</td>
<td>0.359169</td>
<td>0.409327</td>
<td>0.000104</td>
</tr>
<tr>
<td>5</td>
<td>0.359189</td>
<td>0.409327</td>
<td>0.000319</td>
</tr>
<tr>
<td>6</td>
<td>0.35925</td>
<td>0.409327</td>
<td>0.000973</td>
</tr>
<tr>
<td>7</td>
<td>0.359434</td>
<td>0.409327</td>
<td>0.002964</td>
</tr>
<tr>
<td>8</td>
<td>0.359997</td>
<td>0.409327</td>
<td>0.009008</td>
</tr>
<tr>
<td>9</td>
<td>0.361701</td>
<td>0.409327</td>
<td>0.027184</td>
</tr>
<tr>
<td>10</td>
<td>0.366805</td>
<td>0.409327</td>
<td>0.080358</td>
</tr>
</tbody>
</table>
Risk mitigation by traditional milk fermentation - Modeling using reported data (Gonfa et al., 1999)

Bacteria growth stops at pH 4.9

\[
\frac{1}{pH} = 0.002 \, t \, (h) + 1.187 \quad (df=3, \, r^2=0.90, \, p=0.009)
\]

Source: Makita et al., 2012 Int. J. Food Microbiol.
Stop of growth of *S. aureus* in milk by low pH

Log of cfu/ml of *S. aureus* at room temperature

Stop of bacterial growth due to milk fermentation
Outline

• Stochastic processes
• Exposure assessment
  – Fault tree
  – Value chain
  – Mixture, separation, growth and inactivation
• Hazard characterization
  – Dose-response
Overview

• Here we learn how to model the probability of infection/illness based on how much a person ingests pathogens
• We learn different types of model
• Later we work on an example of campylobacteriosis
The four most common no-threshold DR models

<table>
<thead>
<tr>
<th>D-R model</th>
<th>Dose measure</th>
<th>P(effect)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential</td>
<td>Mean dose $\lambda$</td>
<td>$= 1 - \exp(-\lambda p)$</td>
</tr>
<tr>
<td>Beta-Poisson</td>
<td>Mean dose $\lambda$</td>
<td>$\approx 1 - \left(1 + \frac{\lambda}{\beta}\right)^{-\alpha}$</td>
</tr>
<tr>
<td>Beta-binomial</td>
<td>Actual dose $D$</td>
<td>$= 1 - \frac{\Gamma(D + \beta)\Gamma(\alpha + \beta)}{\Gamma(\alpha + \beta + D)\Gamma(\beta)}$</td>
</tr>
<tr>
<td>Weibull-gamma</td>
<td>Actual dose $D$</td>
<td>$= 1 - \left(1 + \frac{D^b}{\beta}\right)^{-\alpha}$</td>
</tr>
</tbody>
</table>
Example Applications: *C. jejuni*

Data set for infection


<table>
<thead>
<tr>
<th>Mean dose</th>
<th>Tested</th>
<th>Infected</th>
</tr>
</thead>
<tbody>
<tr>
<td>8x10^2</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>8x10^3</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>9x10^4</td>
<td>13</td>
<td>11</td>
</tr>
<tr>
<td>8x10^5</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>1x10^6</td>
<td>19</td>
<td>15</td>
</tr>
<tr>
<td>1x10^8</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

![Graph showing observed fraction infected vs mean dose](image-url)
Example Applications: *C. jejuni*

Beta-Poisson model. MLE fit has $\alpha = 0.145$, $\beta = 7.589$

<table>
<thead>
<tr>
<th>Mean dose</th>
<th>Infected / Tested</th>
<th>B-P MLE probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>$8 \times 10^2$</td>
<td>5/10</td>
<td>49%</td>
</tr>
<tr>
<td>$8 \times 10^3$</td>
<td>6/10</td>
<td>64%</td>
</tr>
<tr>
<td>$9 \times 10^4$</td>
<td>11/13</td>
<td>74%</td>
</tr>
<tr>
<td>$8 \times 10^5$</td>
<td>8/11</td>
<td>81%</td>
</tr>
<tr>
<td>$1 \times 10^6$</td>
<td>15/19</td>
<td>82%</td>
</tr>
<tr>
<td>$1 \times 10^8$</td>
<td>5/5</td>
<td>91%</td>
</tr>
</tbody>
</table>
Questions?

Thank you for your efforts to catch up...