

Bayesian Prediction for Cancer Rates

February 28, 2019

Bayesian Methods for Kidney Cancer Mortality Rates

- This example is example 2.7 in *Bayesian Data Analysis*, by Andrew Gelman et al.
- **Goal:** Estimate yearly kidney cancer death rates per county.

A Age-standardized mortality rate from kidney cancer, both sexes, 2014

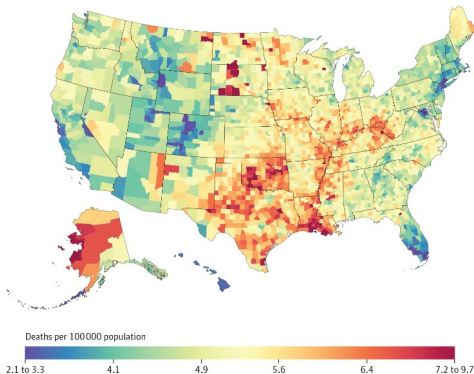


Figure 1: Age-adjusted mortality rates for kidney cancer in 2014. Highest counties are in Kentucky and the south.

Setting up the models

- Let x_j be the number of deaths in county j due to kidney cancer.
- Let n_j be the population of county j
- Let θ_j be the underlying "true" kidney cancer mortality rate for the county.
- Since the units of x_j are counts, use a Poisson distribution as our model,
 $p(x_j|\theta_j) \sim \text{Poisson}(10n_j\theta_j)$.
- For mathematical convenience choose a **Conjugate Prior**
 $p(\theta_j) \sim \text{Gamma}(\alpha, \beta)$, where, α and β are parameters TBD.

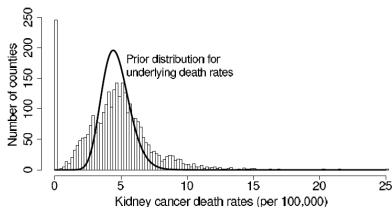


Figure 2: We will estimate the prior from the empirical data in a later slide

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$$\propto p(x_j | \theta_j) p(\theta_j) = \frac{(10n_j \theta_j)^{x_j} e^{-10n_j \theta_j}}{x_j!} \frac{\beta^\alpha}{\Gamma(\alpha)} \theta_j^{\alpha-1} e^{-\beta \theta_j}$$

$$\propto \theta_j^{x_j} e^{-10n_j \theta_j} \theta_j^{\alpha-1} e^{-\beta \theta_j}$$

$$\propto \theta_j^{x_j + \alpha - 1} e^{-(10n_j + \beta) \theta_j}$$

$$\propto \text{Gamma}(\alpha + x_j, \beta + 10n_j)$$

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 \end{aligned}$$

- From this, we can see that α is an "average" mortality count and β is an "average" (scaled) county population in the prior.

Finding the right prior parameters

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- We know all these distributions!

$$\begin{aligned}
 p(x_j) &= \frac{\text{Poisson}(10n_j\theta_j)\text{Gamma}(\alpha, \beta)}{\text{Gamma}(\alpha + x_j, \beta + 10n_j)} \\
 &= \frac{\Gamma(\alpha + x_j)\beta^\alpha}{\Gamma(\alpha)x_j!(10n_j + \beta)^{\alpha+x_j}} \\
 &= \binom{\alpha + x_j - 1}{x_j} \left(\frac{\beta}{\beta + 10n_j}\right)^\alpha \left(\frac{1}{\beta + 10n_j}\right)^{x_j} \\
 &\sim \text{Neg - Binomial}\left(\alpha, \frac{\beta}{10n_j}\right)
 \end{aligned}$$

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- Setting these equal to the sample mean and variance yields $\alpha \approx 20$, $\beta \approx 430,000$.
- Then the estimated of mortality rates for each county are given by

$$\mathbb{E}(\theta_j | x_j) = \frac{20 + x_j}{430000 + 10n_j}$$

$$\text{var}(\theta_j | x_j) = \frac{20 + x_j}{(430000 + 10n_j)^2}$$

- As the county population increases, the mortality rate goes down. As the number of recorded deaths increases, the mortality rate increases.

Comments

- We used a "poor man's hierarchical model" to estimate the prior distribution. A better way to find the parameters is to assign them their own prior and apply bayesian inference again.
- All the data are used to estimate the prior parameters, but each county's mortality rate is estimated individually.
- Figure 1 Clearly shows some spatial correlation. A more involved model could make use of something called a [variogram](#).
- To do this idea model mortality rates as a function of location,
 $x_j = x(\text{county } j \text{ location})$.
- The variogram is given by

$$v(x_i, x_j) = \frac{1}{2} \mathbb{E}[(x(\text{county } i \text{ location}) - x(\text{county } j \text{ location}))^2]$$
- Then describe the likelihood as non-independent poisson random variables with covariances given by the variogram, pick a prior, and repeat the process.
- Other models might include information about other risk factors determined by doctors.