Computation for Bayesian Data Analysis

Andrew Gelman

10 August 2004

An example of Bayesian data analysis

- A problem in the study of social networks
- 3 models and Bayesian inference
- BUGS was too slow, so we used a program in R for Gibbs/Metropolis
- collaborators:
  - Tian Zheng, Dept of Statistics, Columbia University
  - Matt Salganik, Dept of Sociology, Columbia University
  - Jouni Kerman, Dept of Statistics, Columbia University
  - Peter Killworth and Chris McCarty shared their survey data

An example of Bayesian data analysis

- A problem in the study of social networks
- 3 models and Bayesian inference
- BUGS was too slow, so we used a program in R for Gibbs/Metropolis
- collaborators:
  - Tian Zheng, Dept of Statistics, Columbia University
  - Matt Salganik, Dept of Sociology, Columbia University
  - Jouni Kerman, Dept of Statistics, Columbia University
  - Peter Killworth and Chris McCarty shared their survey data

An example of Bayesian data analysis

- A problem in the study of social networks
- 3 models and Bayesian inference
- BUGS was too slow, so we used a program in R for Gibbs/Metropolis

- collaborators:
  - Tian Zheng, Dept of Statistics, Columbia University
  - Matt Salganik, Dept of Sociology, Columbia University
  - Jouni Kerman, Dept of Statistics, Columbia University
  - Peter Killworth and Chris McCarty shared their survey data

An example of Bayesian data analysis

- A problem in the study of social networks
- 3 models and Bayesian inference
- BUGS was too slow, so we used a program in R for Gibbs/Metropolis

- collaborators:
  - Tian Zheng, Dept of Statistics, Columbia University
  - Matt Salganik, Dept of Sociology, Columbia University
  - Jouni Kerman, Dept of Statistics, Columbia University
  - Peter Killworth and Chris McCarty shared their survey data

How many people do you know? Demonstration

- How many people do you know named Nicole?
- How many people do you know named Anthony?
- How many lawyers do you know?
- How many people do you know who were robbed in the past year?

How many people do you know? Demonstration

- How many people do you know named Nicole?
- How many people do you know named Anthony?
- How many lawyers do you know?
- How many people do you know who were robbed in the past year?

How many people do you know? Demonstration

- How many people do you know named Nicole?
- How many people do you know named Anthony?
- How many lawyers do you know?
- How many people do you know who were robbed in the past year?

How many people do you know? Demonstration

- How many people do you know named Nicole?
- How many people do you know named Anthony?
- How many lawyers do you know?
- How many people do you know who were robbed in the past year?

How many people do you know? Demonstration

- How many people do you know named Nicole?
- How many people do you know named Anthony?
- How many lawyers do you know?
- How many people do you know who were robbed in the past year?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Scale-up method: demonstration

- On average, you knew 0.6 Nicoles
- 0.13% of Americans are named Nicole
- Assume 0.13% of your acquaintances are Nicoles
- Estimate: on average, you know $0.6/0.0013 = 450$ people

- On average, you know 0.8 Anthonys
- 0.31% of Americans are named Anthony
- Estimate: on average, you know $1.6/0.0031 = 260$ people

- Why do these differ?

Estimating group sizes: demonstration

- On average, you know 2.6 lawyers
- Assume average network size is 450 people
- Estimate: lawyers represent $2.6/450 = 0.58\%$ of the network
- Estimate: $0.0058 \cdot 290\,\text{million} = 1.7$ million lawyers in the U.S.

- On average, you know 0.25 people who were robbed last year
- Estimate: $\frac{0.25}{450} \cdot 290\,\text{million} = 160{,}000$ people robbed

Estimating group sizes: demonstration

- On average, you know 2.6 lawyers
- Assume average network size is 450 people
- Estimate: lawyers represent $2.6/450 = 0.58\%$ of the network
- Estimate: $0.0058 \cdot 290\,\text{million} = 1.7$ million lawyers in the U.S.

- On average, you know 0.25 people who were robbed last year
- Estimate: $\frac{0.25}{450} \cdot 290\,\text{million} = 160{,}000$ people robbed

Estimating group sizes: demonstration

- On average, you know 2.6 lawyers
- Assume average network size is 450 people
- Estimate: lawyers represent $2.6/450 = 0.58\%$ of the network
- Estimate: $0.0058 \cdot 290\,\text{million} = 1.7$ million lawyers in the U.S.

- On average, you know 0.25 people who were robbed last year
- Estimate: $\frac{0.25}{450} \cdot 290\,\text{million} = 160{,}000$ people robbed

Estimating group sizes: demonstration

- On average, you know 2.6 lawyers
- Assume average network size is 450 people
- Estimate: lawyers represent $2.6/450 = 0.58\%$ of the network
- Estimate: $0.0058 \cdot 290\,\text{million} = 1.7$ million lawyers in the U.S.

- On average, you know 0.25 people who were robbed last year
- Estimate: $\frac{0.25}{450} \cdot 290\,\text{million} = 160{,}000$ people robbed

Estimating group sizes: demonstration

- On average, you know 2.6 lawyers
- Assume average network size is 450 people
- Estimate: lawyers represent $2.6/450 = 0.58\%$ of the network
- Estimate: $0.0058 \cdot 290\,\text{million} = 1.7$ million lawyers in the U.S.

- On average, you know 0.25 people who were robbed last year
- Estimate: $\frac{0.25}{450} \cdot 290\,\text{million} = 160{,}000$ people robbed

Estimating group sizes: demonstration

- On average, you know 2.6 lawyers
- Assume average network size is 450 people
- Estimate: lawyers represent $2.6/450 = 0.58\%$ of the network
- Estimate: $0.0058 \cdot 290\,\text{million} = 1.7$ million lawyers in the U.S.

- On average, you know 0.25 people who were robbed last year
- Estimate: $\frac{0.25}{450} \cdot 290\,\text{million} = 160{,}000$ people robbed

How many people do you know?

- Killworth, McCarty et al. surveys
- Scale-up method: how large is the average personal network?
- Estimating group sizes (e.g., American Indians)
- Can something be done with the 2-way data structure?

How many people do you know?

- Killworth, McCarty et al. surveys
- Scale-up method: how large is the average personal network?
- Estimating group sizes (e.g., American Indians)
- Can something be done with the 2-way data structure?

How many people do you know?

- Killworth, McCarty et al. surveys
- Scale-up method: how large is the average personal network?
- Estimating group sizes (e.g., American Indians)
- Can something be done with the 2-way data structure?

How many people do you know?

- Killworth, McCarty et al. surveys
- Scale-up method: how large is the average personal network?
- Estimating group sizes (e.g., American Indians)
- Can something be done with the 2-way data structure?

Killworth, McCarty et al. surveys

- How many X's do you know?
- Stephanie, Jacqueline, Kimberly, Nicole, Christina, Jennifer
- Christopher, David, Anthony, Robert, James, Michael
- Twin, woman adopted kid in past year, gave birth in past year, widow(er) under 65
- Commercial pilot, gun dealer, postal worker, member of Jaycees, opened business in past year, American Indian
- Suicide in past year, died in auto accident, diabetic, kidney dialysis, AIDS, HIV-positive, rape victim, homicide victim, male in prison, homeless

Killworth, McCarty et al. surveys

- How many X's do you know?
- Stephanie, Jacqueline, Kimberly, Nicole, Christina, Jennifer
- Christopher, David, Anthony, Robert, James, Michael
- Twin, woman adopted kid in past year, gave birth in past year, widow(er) under 65
- Commercial pilot, gun dealer, postal worker, member of Jaycees, opened business in past year, American Indian
- Suicide in past year, died in auto accident, diabetic, kidney dialysis, AIDS, HIV-positive, rape victim, homicide victim, male in prison, homeless

Killworth, McCarty et al. surveys

- How many X's do you know?
- Stephanie, Jacqueline, Kimberly, Nicole, Christina, Jennifer
- Christopher, David, Anthony, Robert, James, Michael
- Twin, woman adopted kid in past year, gave birth in past year, widow(er) under 65
- Commercial pilot, gun dealer, postal worker, member of Jaycees, opened business in past year, American Indian
- Suicide in past year, died in auto accident, diabetic, kidney dialysis, AIDS, HIV-positive, rape victim, homicide victim, male in prison, homeless

Killworth, McCarty et al. surveys

- How many X's do you know?
- Stephanie, Jacqueline, Kimberly, Nicole, Christina, Jennifer
- Christopher, David, Anthony, Robert, James, Michael
- Twin, woman adopted kid in past year, gave birth in past year, widow(er) under 65
- Commercial pilot, gun dealer, postal worker, member of Jaycees, opened business in past year, American Indian
- Suicide in past year, died in auto accident, diabetic, kidney dialysis, AIDS, HIV-positive, rape victim, homicide victim, male in prison, homeless

Killworth, McCarty et al. surveys

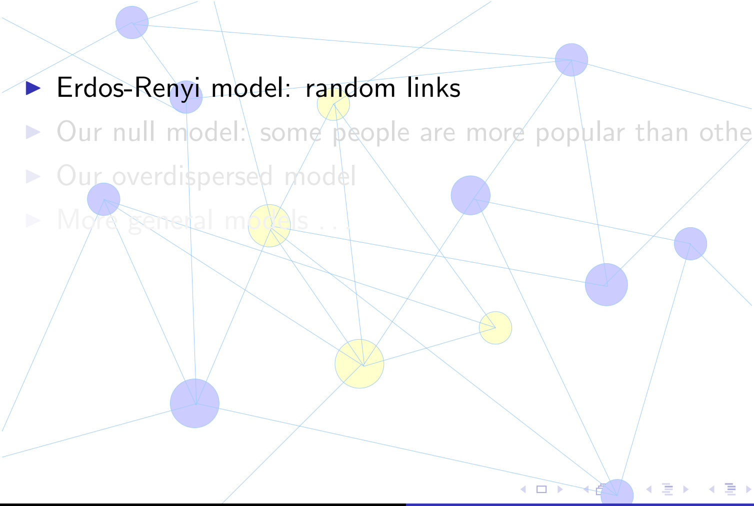
- How many X's do you know?
- Stephanie, Jacqueline, Kimberly, Nicole, Christina, Jennifer
- Christopher, David, Anthony, Robert, James, Michael
- Twin, woman adopted kid in past year, gave birth in past year, widow(er) under 65
- Commercial pilot, gun dealer, postal worker, member of Jaycees, opened business in past year, American Indian
- Suicide in past year, died in auto accident, diabetic, kidney dialysis, AIDS, HIV-positive, rape victim, homicide victim, male in prison, homeless

Killworth, McCarty et al. surveys

- How many X's do you know?
- Stephanie, Jacqueline, Kimberly, Nicole, Christina, Jennifer
- Christopher, David, Anthony, Robert, James, Michael
- Twin, woman adopted kid in past year, gave birth in past year, widow(er) under 65
- Commercial pilot, gun dealer, postal worker, member of Jaycees, opened business in past year, American Indian
- Suicide in past year, died in auto accident, diabetic, kidney dialysis, AIDS, HIV-positive, rape victim, homicide victim, male in prison, homeless

Models of social network data

- Erdos-Renyi model: random links
- Our null model: some people are more popular than others
- Our overdispersed model
- More general models . . .



Models of social network data

- Erdos-Renyi model: random links
- Our null model: some people are more popular than others
- Our overdispersed model
- More general models . . .

Models of social network data

- Erdos-Renyi model: random links
- Our null model: some people are more popular than others
- Our overdispersed model
- More general models . . .

Models of social network data

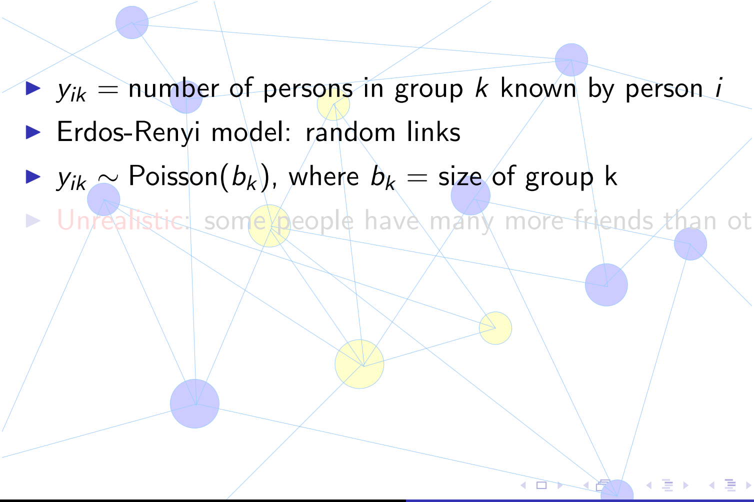
- Erdos-Renyi model: random links
- Our null model: some people are more popular than others
- Our overdispersed model
- More general models . . .

Erdos-Renyi model

- y_{ik} = number of persons in group k known by person i
- Erdos-Renyi model: random links
- $y_{ik} \sim$ Poisson(b_k), where b_k = size of group k
- Unrealistic: some people have many more friends than others

Erdos-Renyi model

- y_{ik} = number of persons in group k known by person i
- Erdos-Renyi model: random links
- $y_{ik} \sim \text{Poisson}(b_k)$, where b_k = size of group k
- Unrealistic: some people have many more friends than others



Erdos-Renyi model

- y_{ik} = number of persons in group k known by person i
- Erdos-Renyi model: random links
- $y_{ik} \sim \text{Poisson}(b_k)$, where b_k = size of group k
- Unrealistic: some people have many more friends than others

Our null model

- y_{ik} = number of persons in group k known by person i
- Our null model: some people are more popular than others
- $y_{ik} \sim \text{Poisson}(a_i b_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- Unrealistic: data are actually *overdispersed* (for example, do χ^2 test)

Our null model

- y_{ik} = number of persons in group k known by person i
- Our null model: some people are more popular than others
- $y_{ik} \sim \text{Poisson}(a_i b_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- Unrealistic: data are actually *overdispersed* (for example, do χ^2 test)

Our null model

- y_{ik} = number of persons in group k known by person i
- Our null model: some people are more popular than others
- $y_{ik} \sim \text{Poisson}(a_i b_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- Unrealistic: data are actually *overdispersed* (for example, do χ^2 test)

Our null model

- y_{ik} = number of persons in group k known by person i
- Our null model: some people are more popular than others
- $y_{ik} \sim \text{Poisson}(a_i b_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- Unrealistic: data are actually *overdispersed* (for example, do χ^2 test)

Our null model

- y_{ik} = number of persons in group k known by person i
- Our null model: some people are more popular than others
- $y_{ik} \sim \text{Poisson}(a_i b_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- Unrealistic: data are actually *overdispersed* (for example, do χ^2 test)

Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim$ Negative-binomial$(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
- Overdispersion represents social structure

Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim$ Negative-binomial$(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
- Overdispersion represents social structure

Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim \text{Negative-binomial}(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
  - $\omega_k = 1$ is no overdispersion (Poisson model). Higher values of ω_k show overdispersion
- Overdispersion represents social structure

Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim$ Negative-binomial$(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
  - $\omega_k = 1$ is no overdispersion (Poisson model)
  - Higher values of ω_k show overdispersion
- Overdispersion represents social structure

Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim$ Negative-binomial$(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
  - $\omega_k = 1$ is no overdispersion (Poisson model)
  - Higher values of ω_k show overdispersion
- Overdispersion represents social structure

Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim$ Negative-binomial$(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
  - $\omega_k = 1$ is no overdispersion (Poisson model)
  - Higher values of ω_k show overdispersion
- Overdispersion represents social structure

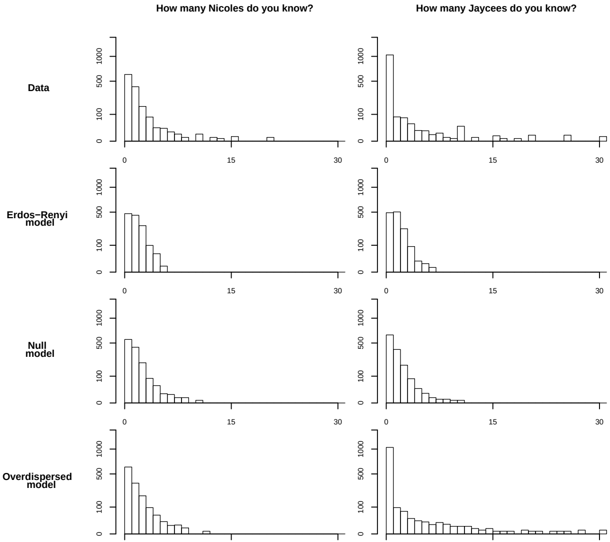
Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim \text{Negative-binomial}(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
  - $\omega_k = 1$ is no overdispersion (Poisson model)
  - Higher values of ω_k show overdispersion
- Overdispersion represents social structure

Our overdispersed model

- y_{ik} = number of persons in group k known by person i
- Our overdispersed model: groups are *not* randomly spread in the population
- $y_{ik} \sim$ Negative-binomial$(a_i b_k, \omega_k)$
- $a_i = e^{\alpha_i}$, "gregariousness" of person i
- $b_k = e^{\beta_k}$, size of group k in the social network
- ω_k is overdispersion of group k
  - $\omega_k = 1$ is no overdispersion (Poisson model)
  - Higher values of ω_k show overdispersion
- Overdispersion represents social structure

Data, compared to simulations from 3 models



The overdispersed model

- data model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$, for $i = 1, \ldots, 1370$, $k = 1, \ldots, 32$
- prior dists
  - $\alpha_i \sim \text{N}(\mu_\alpha, \sigma_\alpha^2)$, for $i = 1, \ldots, 1370$
  - $\beta_k \sim \text{N}(\mu_\beta, \sigma_\beta^2)$, for $k = 1, \ldots, 32$
  - $\omega_k \sim \text{U}(1, 20)$, for $k = 1, \ldots, 32$
- hyperprior dist: $p(\mu_\alpha, \mu_\beta, \sigma_\alpha, \sigma_\beta) \propto 1$
- $1370 + 32 + 32 + 4$ parameters to estimate
- Nonidentifiability in $\alpha + \beta$ (to be discussed soon)

The overdispersed model

- data model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$, for $i = 1, \ldots, 1370$, $k = 1, \ldots, 32$
- prior dists
  - $\alpha_i \sim \text{N}(\mu_\alpha, \sigma^2_\alpha)$, for $i = 1, \ldots, 1370$
  - $\beta_k \sim \text{N}(\mu_\beta, \sigma^2_\beta)$, for $k = 1, \ldots, 32$
  - $\omega_k \sim \text{U}(1, 20)$, for $k = 1, \ldots, 32$
- hyperprior dist: $p(\mu_\alpha, \mu_\beta, \sigma_\alpha, \sigma_\beta) \propto 1$
- $1370 + 32 + 32 + 4$ parameters to estimate
- Nonidentifiability in $\alpha + \beta$ (to be discussed soon)

The overdispersed model

- data model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$, for $i = 1, \ldots, 1370$, $k = 1, \ldots, 32$
- prior dists
  - $\alpha_i \sim \text{N}(\mu_\alpha, \sigma_\alpha^2)$, for $i = 1, \ldots, 1370$
  - $\beta_k \sim \text{N}(\mu_\beta, \sigma_\beta^2)$, for $k = 1, \ldots, 32$
  - $\omega_k \sim \text{U}(1, 20)$, for $k = 1, \ldots, 32$
- hyperprior dist: $p(\mu_\alpha, \mu_\beta, \sigma_\alpha, \sigma_\beta) \propto 1$
- $1370 + 32 + 32 + 4$ parameters to estimate
- Nonidentifiability in $\alpha + \beta$ (to be discussed soon)

The overdispersed model

- data model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$, for $i = 1, \ldots, 1370$, $k = 1, \ldots, 32$
- prior dists
  - $\alpha_i \sim \text{N}(\mu_\alpha, \sigma^2_\alpha)$, for $i = 1, \ldots, 1370$
  - $\beta_k \sim \text{N}(\mu_\beta, \sigma^2_\beta)$, for $k = 1, \ldots, 32$
  - $\omega_k \sim \text{U}(1, 20)$, for $k = 1, \ldots, 32$
- hyperprior dist: $p(\mu_\alpha, \mu_\beta, \sigma_\alpha, \sigma_\beta) \propto 1$
- $1370 + 32 + 32 + 4$ parameters to estimate
- Nonidentifiability in $\alpha + \beta$ (to be discussed soon)

The overdispersed model

- data model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$, for $i = 1, \ldots, 1370$, $k = 1, \ldots, 32$
- prior dists
  - $\alpha_i \sim \text{N}(\mu_\alpha, \sigma_\alpha^2)$, for $i = 1, \ldots, 1370$
  - $\beta_k \sim \text{N}(\mu_\beta, \sigma_\beta^2)$, for $k = 1, \ldots, 32$
  - $\omega_k \sim \text{U}(1, 20)$, for $k = 1, \ldots, 32$
- hyperprior dist: $p(\mu_\alpha, \mu_\beta, \sigma_\alpha, \sigma_\beta) \propto 1$
- $1370 + 32 + 32 + 4$ parameters to estimate
- Nonidentifiability in $\alpha + \beta$ (to be discussed soon)

Latent-data parameterization

- our model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- alternative using latent data γ_{ik}:
  - $y_{ik} \sim \text{Poisson}(e^{\alpha_i+\beta_k+\gamma_{ik}})$
  - $\gamma_{ik} \sim \text{log-gamma}(\text{shape parameter of } 1/(\omega_k - 1))$
- Not so helpful here, but this "data augmentation" idea is useful in other settings

Latent-data parameterization

- our model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- alternative using latent data γ_{ik}:
  - $y_{ik} \sim \text{Poisson}(e^{\alpha_i+\beta_k+\gamma_{ik}})$
  - $\gamma_{ik} \sim \text{log-gamma}(\text{shape parameter of } 1/(\omega_k - 1))$
- Not so helpful here, but this "data augmentation" idea is useful in other settings

Latent-data parameterization

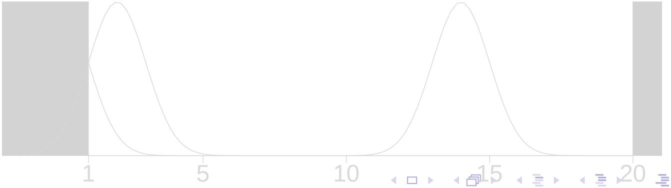
- our model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- alternative using latent data γ_{ik}:
  - $y_{ik} \sim \text{Poisson}(e^{\alpha_i+\beta_k+\gamma_{ik}})$
  - $\gamma_{ik} \sim \text{log-gamma(shape parameter of } 1/(\omega_k - 1))$
- Not so helpful here, but this "data augmentation" idea is useful in other settings

Gibbs-Metropolis algorithm: updating α, β, ω

- For each i, update α_i using Metropolis with jumping dist. $\alpha_i^* \sim \mathrm{N}(\alpha_i^{(t-1)}, (\text{jumping scale of } \alpha_i)^2)$.
- For each k, update β_k using Metropolis with jumping dist. $\beta_k^* \sim \mathrm{N}(\beta_k^{(t-1)}, (\text{jumping scale of } \beta_k)^2)$.
- For each k, update ω_k using Metropolis with jumping dist. $\omega_k^* \sim \mathrm{N}(\omega_k^{(t-1)}, (\text{jumping scale of } \omega_k)^2)$.
  Reflect jumps off the edges:

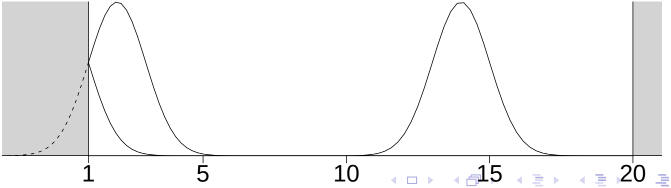
Gibbs-Metropolis algorithm: updating α, β, ω

- For each i, update α_i using Metropolis with jumping dist. $\alpha_i^* \sim \mathrm{N}(\alpha_i^{(t-1)}, (\text{jumping scale of } \alpha_i)^2)$.
- For each k, update β_k using Metropolis with jumping dist. $\beta_k^* \sim \mathrm{N}(\beta_k^{(t-1)}, (\text{jumping scale of } \beta_k)^2)$.
- For each k, update ω_k using Metropolis with jumping dist. $\omega_k^* \sim \mathrm{N}(\omega_k^{(t-1)}, (\text{jumping scale of } \omega_k)^2)$. Reflect jumps off the edges:



Gibbs-Metropolis algorithm: updating α, β, ω

- For each i, update α_i using Metropolis with jumping dist. $\alpha_i^* \sim \mathrm{N}(\alpha_i^{(t-1)}, (\text{jumping scale of } \alpha_i)^2)$.
- For each k, update β_k using Metropolis with jumping dist. $\beta_k^* \sim \mathrm{N}(\beta_k^{(t-1)}, (\text{jumping scale of } \beta_k)^2)$.
- For each k, update ω_k using Metropolis with jumping dist. $\omega_k^* \sim \mathrm{N}(\omega_k^{(t-1)}, (\text{jumping scale of } \omega_k)^2)$.
  Reflect jumps off the edges:



Gibbs-Metropolis algorithm: updating hyperparameters

- Update $\mu_\alpha \sim \mathrm{N}\left(\frac{1}{n}\sum_{i=1}^{n}\alpha_i, \frac{1}{n}\sigma^2\right)$
- Update $\sigma_\alpha^2 \sim \text{Inv-}\chi^2\left(n-1, \frac{1}{n}\sum_{i=1}^{n}(\alpha_i - \mu_\alpha)^2\right)$
- Similarly with μ_β, σ_β

- Renormalize to identify the α's and β's ...

Gibbs-Metropolis algorithm: updating hyperparameters

- Update $\mu_\alpha \sim \mathrm{N}\left(\frac{1}{n}\sum_{i=1}^{n}\alpha_i, \frac{1}{n}\sigma^2\right)$
- Update $\sigma_\alpha^2 \sim \text{Inv-}\chi^2\left(n-1, \frac{1}{n}\sum_{i=1}^{n}(\alpha_i - \mu_\alpha)^2\right)$
- Similarly with μ_β, σ_β
- Renormalize to identify the α's and β's ...

Gibbs-Metropolis algorithm: updating hyperparameters

- Update $\mu_\alpha \sim \mathrm{N}\left(\frac{1}{n}\sum_{i=1}^n \alpha_i, \frac{1}{n}\sigma^2\right)$
- Update $\sigma_\alpha^2 \sim \text{Inv-}\chi^2\left(n-1, \frac{1}{n}\sum_{i=1}^n (\alpha_i - \mu_\alpha)^2\right)$
- Similarly with μ_β, σ_β

- Renormalize to identify the α's and β's ...

Gibbs-Metropolis algorithm: updating hyperparameters

- Update $\mu_\alpha \sim \mathrm{N}\left(\frac{1}{n}\sum_{i=1}^{n}\alpha_i, \frac{1}{n}\sigma^2\right)$
- Update $\sigma_\alpha^2 \sim \text{Inv-}\chi^2\left(n-1, \frac{1}{n}\sum_{i=1}^{n}(\alpha_i - \mu_\alpha)^2\right)$
- Similarly with μ_β, σ_β

- Renormalize to identify the α's and β's ...

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population.

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:
  - Compute $C = \log\left(\sum_{k=1}^{12} e^{\beta_k}/0.069\right)$
  - Add C to all the α_i's and μ_α
  - Subtract C from all the β_k's and μ_β

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:
  - Compute $C = \log\left(\sum_{k=1}^{12} e^{\beta_k} / 0.069\right)$
  - Add C to all the α_i's and μ_α
  - Subtract C from all the β_k's and μ_β

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:
  - Compute $C = \log\left(\sum_{k=1}^{12} e^{\beta_k}/0.069\right)$
  - Add C to all the α_i's and μ_α
  - Subtract C from all the β_k's and μ_β

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:
  - Compute $C = \log\left(\sum_{k=1}^{12} e^{\beta_k}/0.069\right)$
  - Add C to all the α_i's and μ_α
  - Subtract C from all the β_k's and μ_β

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:
  - Compute $C = \log\left(\sum_{k=1}^{12} e^{\beta_k}/0.069\right)$
  - Add C to all the α_i's and μ_α
  - Subtract C from all the β_k's and μ_β

Renormalizing

- Problem: α_i's and β_k's are not separately identified in the model, $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$
- Possible solutions:
  - Choose a "baseline" value: set $\alpha_1 = 0$ (for example)
  - Renormalize a group of parameters: set $\sum_{i=1}^{n} \alpha_i = 0$
  - Anchor the prior distribution: set $\mu_\alpha = 0$
- Our solution: rescale so that the b_k's for the names (Nicole, Anthony, etc.) equal their proportion in the population:
  - Compute $C = \log\left(\sum_{k=1}^{12} e^{\beta_k}/0.069\right)$
  - Add C to all the α_i's and μ_α
  - Subtract C from all the β_k's and μ_β

Adaptive Metropolis jumping

- Parallel scalar updating of the components of α, β, ω
- Adapt each of $1370 + 32 + 32$ jumping scales to have $E(p_{\text{jump}}) \approx 0.44$
- Save p_{jump} from each Metropolis step, then average them and rescale every 50 iterations:
  - Where avg $p_{\text{jump}} > 0.44$, increase the jump scale
  - Where avg $p_{\text{jump}} < 0.44$, decrease the jump scale
- After burn-in, stop adapting
- If we had vector jumps, we would adapt the scale so that $E(p_{\text{jump}}) \approx 0.23$
- More effective adaptation uses avg. squared jumped distance

Adaptive Metropolis jumping

- Parallel scalar updating of the components of α, β, ω
- Adapt each of $1370 + 32 + 32$ jumping scales to have $E(p_{\text{jump}}) \approx 0.44$
- Save p_{jump} from each Metropolis step, then average them and rescale every 50 iterations:
  - Where avg $p_{\text{jump}} > 0.44$, increase the jump scale
  - Where avg $p_{\text{jump}} < 0.44$, decrease the jump scale
- After burn-in, stop adapting
- If we had vector jumps, we would adapt the scale so that $E(p_{\text{jump}}) \approx 0.23$
- More effective adaptation uses avg. squared jumped distance

Adaptive Metropolis jumping

- Parallel scalar updating of the components of α, β, ω
- Adapt each of $1370 + 32 + 32$ jumping scales to have $E(p_{\text{jump}}) \approx 0.44$
- Save p_{jump} from each Metropolis step, then average them and rescale every 50 iterations:
  - Where avg $p_{\text{jump}} > 0.44$, increase the jump scale
  - Where avg $p_{\text{jump}} < 0.44$, decrease the jump scale
- After burn-in, stop adapting
- If we had vector jumps, we would adapt the scale so that $E(p_{\text{jump}}) \approx 0.23$
- More effective adaptation uses avg. squared jumped distance

Adaptive Metropolis jumping

- Parallel scalar updating of the components of α, β, ω
- Adapt each of $1370 + 32 + 32$ jumping scales to have $E(p_{\text{jump}}) \approx 0.44$
- Save p_{jump} from each Metropolis step, then average them and rescale every 50 iterations:
  - Where avg $p_{\text{jump}} > 0.44$, increase the jump scale
  - Where avg $p_{\text{jump}} < 0.44$, decrease the jump scale
- After burn-in, stop adapting
- If we had vector jumps, we would adapt the scale so that $E(p_{\text{jump}}) \approx 0.23$
- More effective adaptation uses avg. squared jumped distance

Adaptive Metropolis jumping

- Parallel scalar updating of the components of α, β, ω
- Adapt each of $1370 + 32 + 32$ jumping scales to have $E(p_{\text{jump}}) \approx 0.44$
- Save p_{jump} from each Metropolis step, then average them and rescale every 50 iterations:
  - Where avg $p_{\text{jump}} > 0.44$, increase the jump scale
  - Where avg $p_{\text{jump}} < 0.44$, decrease the jump scale
- After burn-in, stop adapting
- If we had vector jumps, we would adapt the scale so that $E(p_{\text{jump}}) \approx 0.23$
- More effective adaptation uses avg. squared jumped distance

Adaptive Metropolis jumping

- Parallel scalar updating of the components of α, β, ω
- Adapt each of $1370 + 32 + 32$ jumping scales to have $E(p_{\text{jump}}) \approx 0.44$
- Save p_{jump} from each Metropolis step, then average them and rescale every 50 iterations:
  - Where avg $p_{\text{jump}} > 0.44$, increase the jump scale
  - Where avg $p_{\text{jump}} < 0.44$, decrease the jump scale
- After burn-in, stop adapting
- If we had vector jumps, we would adapt the scale so that $E(p_{\text{jump}}) \approx 0.23$
- More effective adaptation uses avg. squared jumped distance

Mixing (convergence) of simulations

- Simulate 3 parallel sequences, starting with draws from the prior distribution
- Run 200 iterations, discard first half: not yet mixed ($\hat{R} \approx 2$ for some parameters) ...
- Run 2000 iterations, discard first half: mixed ($\hat{R} \leq 1.1$ for all parameters)
- Earlier versions took longer to converge, motivating adaptive updating

Mixing (convergence) of simulations

- Simulate 3 parallel sequences, starting with draws from the prior distribution
- Run 200 iterations, discard first half: not yet mixed ($\hat{R} \approx 2$ for some parameters) . . .
- Run 2000 iterations, discard first half: mixed ($\hat{R} \leq 1.1$ for all parameters)
- Earlier versions took longer to converge, motivating adaptive updating

Mixing (convergence) of simulations

- Simulate 3 parallel sequences, starting with draws from the prior distribution
- Run 200 iterations, discard first half: not yet mixed ($\hat{R} \approx 2$ for some parameters) . . .
- Run 2000 iterations, discard first half: mixed ($\hat{R} \leq 1.1$ for all parameters)
- Earlier versions took longer to converge, motivating adaptive updating

Mixing (convergence) of simulations

- Simulate 3 parallel sequences, starting with draws from the prior distribution
- Run 200 iterations, discard first half: not yet mixed ($\hat{R} \approx 2$ for some parameters) ...
- Run 2000 iterations, discard first half: mixed ($\hat{R} \leq 1.1$ for all parameters)
- Earlier versions took longer to converge, motivating adaptive updating

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Computation in R

- BUGS was too slow (over 1400 parameters)
- Programming from scratch in R is awkward, buggy
- Instead, we use our general Gibbs/Metropolis programming environment
- Set up MCMC object
- Specify Gibbs updates
- Log-posterior density for Metropolis steps
- Bounds on overdispersion parameters $\omega \in [1, 20]$
- Renormalization step
- Result is a set of posterior simulations

Setting up the MCMC object

```
network.1 <- mcmcEngine (network.data, network.init,
  update=network.update, n.iter=1000, n.chains=3)
network.update <- list(
  alpha = Metropolis (f.logpost.alpha),
  beta = Metropolis (f.logpost.beta),
  omega = Metropolis (f.logpost.omega,
    jump=Jump("omega.jump", lower=1.01, upper=20)),
  mu.alpha = Gibbs (mu.alpha.update),
  mu.beta = Gibbs (mu.beta.update),
  sigma.alpha = Gibbs (sigma.alpha.update),
  sigma.beta = Gibbs (sigma.beta.update),
  renorm.network)
```

Setting up the MCMC object

```
network.1 <- mcmcEngine (network.data, network.init,
  update=network.update, n.iter=1000, n.chains=3)
network.update <- list(
  alpha = Metropolis (f.logpost.alpha),
  beta = Metropolis (f.logpost.beta),
  omega = Metropolis (f.logpost.omega,
    jump=Jump("omega.jump", lower=1.01, upper=20)),
  mu.alpha = Gibbs (mu.alpha.update),
  mu.beta = Gibbs (mu.beta.update),
  sigma.alpha = Gibbs (sigma.alpha.update),
  sigma.beta = Gibbs (sigma.beta.update),
  renorm.network)
```

Setting up the MCMC object

```
network.1 <- mcmcEngine (network.data, network.init,
  update=network.update, n.iter=1000, n.chains=3)
network.update <- list(
  alpha = Metropolis (f.logpost.alpha),
  beta = Metropolis (f.logpost.beta),
  omega = Metropolis (f.logpost.omega,
    jump=Jump("omega.jump", lower=1.01, upper=20)),
  mu.alpha = Gibbs (mu.alpha.update),
  mu.beta = Gibbs (mu.beta.update),
  sigma.alpha = Gibbs (sigma.alpha.update),
  sigma.beta = Gibbs (sigma.beta.update),
  renorm.network)
```

Setting up the MCMC object

```
network.1 <- mcmcEngine (network.data, network.init,
  update=network.update, n.iter=1000, n.chains=3)
network.update <- list(
  alpha = Metropolis (f.logpost.alpha),
  beta = Metropolis (f.logpost.beta),
  omega = Metropolis (f.logpost.omega,
    jump=Jump("omega.jump", lower=1.01, upper=20)),
  mu.alpha = Gibbs (mu.alpha.update),
  mu.beta = Gibbs (mu.beta.update),
  sigma.alpha = Gibbs (sigma.alpha.update),
  sigma.beta = Gibbs (sigma.beta.update),
  renorm.network)
```

Setting up the MCMC object

```
network.1 <- mcmcEngine (network.data, network.init,
  update=network.update, n.iter=1000, n.chains=3)
network.update <- list(
  alpha = Metropolis (f.logpost.alpha),
  beta = Metropolis (f.logpost.beta),
  omega = Metropolis (f.logpost.omega,
    jump=Jump("omega.jump", lower=1.01, upper=20)),
  mu.alpha = Gibbs (mu.alpha.update),
  mu.beta = Gibbs (mu.beta.update),
  sigma.alpha = Gibbs (sigma.alpha.update),
  sigma.beta = Gibbs (sigma.beta.update),
  renorm.network)
```

Setting up the MCMC object

```
network.1 <- mcmcEngine (network.data, network.init,
  update=network.update, n.iter=1000, n.chains=3)
network.update <- list(
  alpha = Metropolis (f.logpost.alpha),
  beta = Metropolis (f.logpost.beta),
  omega = Metropolis (f.logpost.omega,
    jump=Jump("omega.jump", lower=1.01, upper=20)),
  mu.alpha = Gibbs (mu.alpha.update),
  mu.beta = Gibbs (mu.beta.update),
  sigma.alpha = Gibbs (sigma.alpha.update),
  sigma.beta = Gibbs (sigma.beta.update),
  renorm.network)
```

Setting up the MCMC object

```
network.1 <- mcmcEngine (network.data, network.init,
  update=network.update, n.iter=1000, n.chains=3)
network.update <- list(
  alpha = Metropolis (f.logpost.alpha),
  beta = Metropolis (f.logpost.beta),
  omega = Metropolis (f.logpost.omega,
    jump=Jump("omega.jump", lower=1.01, upper=20)),
  mu.alpha = Gibbs (mu.alpha.update),
  mu.beta = Gibbs (mu.beta.update),
  sigma.alpha = Gibbs (sigma.alpha.update),
  sigma.beta = Gibbs (sigma.beta.update),
  renorm.network)
```

Data and initial values

```
y <- as.matrix (read.dta ("social.dta"))
y <- y[1:50,]
network.data <- list (y=y, data.n=nrow(y),
  data.j=ncol(y))
network.init <- function(){
  alpha <- rnorm(data.n)
  beta <- rnorm(data.j)
  omega <- runif(data.j,1.01,20)
  mu.alpha <- rnorm(1)
  mu.beta <- rnorm(1)
  sigma.alpha <- runif(1)
  sigma.beta <- runif(1)}
```

Data and initial values

```
y <- as.matrix (read.dta ("social.dta"))
y <- y[1:50,]
network.data <- list (y=y, data.n=nrow(y),
  data.j=ncol(y))
network.init <- function(){
  alpha <- rnorm(data.n)
  beta <- rnorm(data.j)
  omega <- runif(data.j,1.01,20)
  mu.alpha <- rnorm(1)
  mu.beta <- rnorm(1)
  sigma.alpha <- runif(1)
  sigma.beta <- runif(1)}
```

Data and initial values

```
y <- as.matrix (read.dta ("social.dta"))
y <- y[1:50,]
network.data <- list (y=y, data.n=nrow(y),
  data.j=ncol(y))
network.init <- function(){
  alpha <- rnorm(data.n)
  beta <- rnorm(data.j)
  omega <- runif(data.j,1.01,20)
  mu.alpha <- rnorm(1)
  mu.beta <- rnorm(1)
  sigma.alpha <- runif(1)
  sigma.beta <- runif(1)}
```

Data and initial values

```
y <- as.matrix (read.dta ("social.dta"))
y <- y[1:50,]
network.data <- list (y=y, data.n=nrow(y),
  data.j=ncol(y))
network.init <- function(){
  alpha <- rnorm(data.n)
  beta <- rnorm(data.j)
  omega <- runif(data.j,1.01,20)
  mu.alpha <- rnorm(1)
  mu.beta <- rnorm(1)
  sigma.alpha <- runif(1)
  sigma.beta <- runif(1)}
```

Gibbs samplers for the hyperparameters

```
mu.alpha.update <- function()
  rnorm (1, mean(alpha), sigma.alpha/sqrt(data.n))
mu.beta.update <- function()
  rnorm (1, mean(beta), sigma.beta/sqrt(data.j))
sigma.alpha.update <- function()
  sqrt (sum((alpha-mu.alpha)^2)/rchisq(1, data.n-1))
sigma.beta.update <- function()
  sqrt (sum((beta-mu.beta)^2)/rchisq(1, data.j-1))
```

Gibbs samplers for the hyperparameters

```
mu.alpha.update <- function()
  rnorm (1, mean(alpha), sigma.alpha/sqrt(data.n))
mu.beta.update <- function()
  rnorm (1, mean(beta), sigma.beta/sqrt(data.j))
sigma.alpha.update <- function()
  sqrt (sum((alpha-mu.alpha)^2)/rchisq(1, data.n-1))
sigma.beta.update <- function()
  sqrt (sum((beta-mu.beta)^2)/rchisq(1, data.j-1))
```

Gibbs samplers for the hyperparameters

```
mu.alpha.update <- function()
  rnorm (1, mean(alpha), sigma.alpha/sqrt(data.n))
mu.beta.update <- function()
  rnorm (1, mean(beta), sigma.beta/sqrt(data.j))
sigma.alpha.update <- function()
  sqrt (sum((alpha-mu.alpha)^2)/rchisq(1, data.n-1))
sigma.beta.update <- function()
  sqrt (sum((beta-mu.beta)^2)/rchisq(1, data.j-1))
```

Gibbs samplers for the hyperparameters

```
mu.alpha.update <- function()
  rnorm (1, mean(alpha), sigma.alpha/sqrt(data.n))
mu.beta.update <- function()
  rnorm (1, mean(beta), sigma.beta/sqrt(data.j))
sigma.alpha.update <- function()
  sqrt (sum((alpha-mu.alpha)^2)/rchisq(1, data.n-1))
sigma.beta.update <- function()
  sqrt (sum((beta-mu.beta)^2)/rchisq(1, data.j-1))
```

Log-likelihood for each data point

```
f.loglik <- function (y, alpha, beta, omega, data.n){
  theta.mat <- exp(outer(alpha, beta, "+"))
  omega.mat <- outer(rep(0, data.n), omega, "+")
  dnbinom (y, theta.mat/(omega.mat-1), 1/omega.mat,
    log=T)}
```

Log-posterior density for each vector parameter

```
f.logpost.alpha <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  rowSums (loglik, na.rm=TRUE) +
    dnorm (alpha, mu.alpha, sigma.alpha, log=TRUE)}
f.logpost.beta <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  colSums (loglik, na.rm=TRUE) +
    dnorm (beta, mu.beta, sigma.beta, log=TRUE)}
f.logpost.omega <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  colSums (loglik, na.rm=T)}
```

Log-posterior density for each vector parameter

```
f.logpost.alpha <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  rowSums (loglik, na.rm=TRUE) +
    dnorm (alpha, mu.alpha, sigma.alpha, log=TRUE)}
f.logpost.beta <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  colSums (loglik, na.rm=TRUE) +
    dnorm (beta, mu.beta, sigma.beta, log=TRUE)}
f.logpost.omega <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  colSums (loglik, na.rm=T)}
```

Log-posterior density for each vector parameter

```
f.logpost.alpha <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  rowSums (loglik, na.rm=TRUE) +
    dnorm (alpha, mu.alpha, sigma.alpha, log=TRUE)}
f.logpost.beta <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  colSums (loglik, na.rm=TRUE) +
    dnorm (beta, mu.beta, sigma.beta, log=TRUE)}
f.logpost.omega <- function() {
  loglik <- f.loglik (y, alpha, beta, omega, data.n)
  colSums (loglik, na.rm=T)}
```

Bounded jumping for the ω_k's

Customized Metropolis jumping rule for the components of ω:

```
omega.jump <- function (omega, sigma) {
  reflect (rnorm (length(omega), omega, sigma),
    .lower, .upper)}
```

Renormalization of the α_i's and β_k's

```
renorm.network <- function() {
  const <- log (sum(exp(beta[1:12]))/0.069)
  alpha <- alpha + const
  mu.alpha <- mu.alpha + const
  beta <- beta - const
  mu.beta <- mu.beta - const}
```

Running MCMC and looking at the output

```
net <- run(network.1)
attach (as.rv (net))

Some output:
name       mean    sd    25%  50%  75%   Rhat
beta[1]   -5.1   0.1   (-5.4 -5.2 -5.1)  1.0
beta[2]   -6.4   0.1   (-6.9 -6.7 -6.5)  1.2
beta[3]   -6.1   0.1   (-6.5 -6.3 -6.2)  1.1
beta[4]   -7.0   0.2   (-7.6 -7.4 -7.1)  1.0
beta[5]   -5.1   0.1   (-5.4 -5.3 -5.2)  1.2
beta[6]   -5.6   0.2   (-6.1 -5.9 -5.8)  1.0
```

Running MCMC and looking at the output

```
net <- run(network.1)
attach (as.rv (net))
```

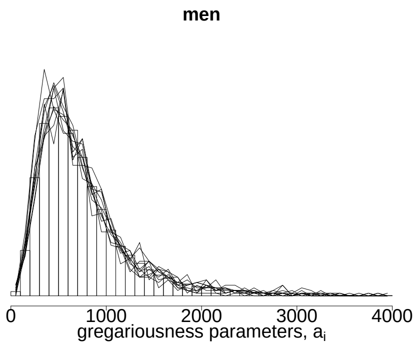
```
Some output:
name      mean    sd    25%   50%   75%   Rhat
beta[1]   -5.1   0.1   (-5.4  -5.2  -5.1)   1.0
beta[2]   -6.4   0.1   (-6.9  -6.7  -6.5)   1.2
beta[3]   -6.1   0.1   (-6.5  -6.3  -6.2)   1.1
beta[4]   -7.0   0.2   (-7.6  -7.4  -7.1)   1.0
beta[5]   -5.1   0.1   (-5.4  -5.3  -5.2)   1.2
beta[6]   -5.6   0.2   (-6.1  -5.9  -5.8)   1.0
```

Running MCMC and looking at the output

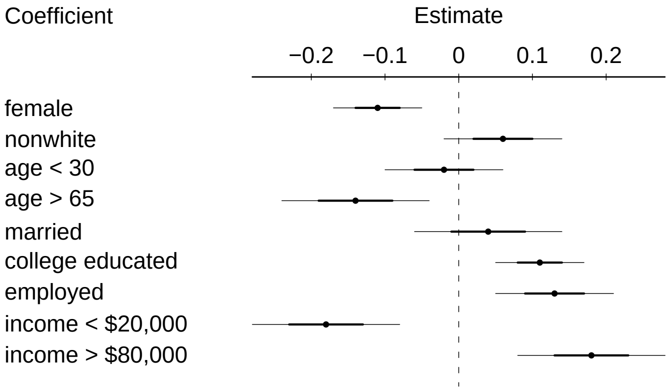
```
net <- run(network.1)
attach (as.rv (net))
```

```
Some output:
name      mean    sd   25%  50%  75%   Rhat
beta[1]   -5.1   0.1  (-5.4 -5.2 -5.1)  1.0
beta[2]   -6.4   0.1  (-6.9 -6.7 -6.5)  1.2
beta[3]   -6.1   0.1  (-6.5 -6.3 -6.2)  1.1
beta[4]   -7.0   0.2  (-7.6 -7.4 -7.1)  1.0
beta[5]   -5.1   0.1  (-5.4 -5.3 -5.2)  1.2
beta[6]   -5.6   0.2  (-6.1 -5.9 -5.8)  1.0
```

Estimated distributions of network sizes for men and women



Regression of log(gregariousness)



Parameter estimates for the 32 subpopulations

- Subpopulations
  - Names (Stephanie, Michael, etc.)
  - Other groups (pilots, diabetics, etc.)
- Parameters

Parameter estimates for the 32 subpopulations

- Subpopulations
  - Names (Stephanie, Michael, etc.)
  - Other groups (pilots, diabetics, etc.)
- Parameters
  - Proportion of the social network, e^{β_k}
  - Overdispersion, ω_k

Parameter estimates for the 32 subpopulations

- Subpopulations
  - Names (Stephanie, Michael, etc.)
  - Other groups (pilots, diabetics, etc.)
- Parameters
  - Proportion of the social network, e^{β_k}
  - Overdispersion, ω_k

Parameter estimates for the 32 subpopulations

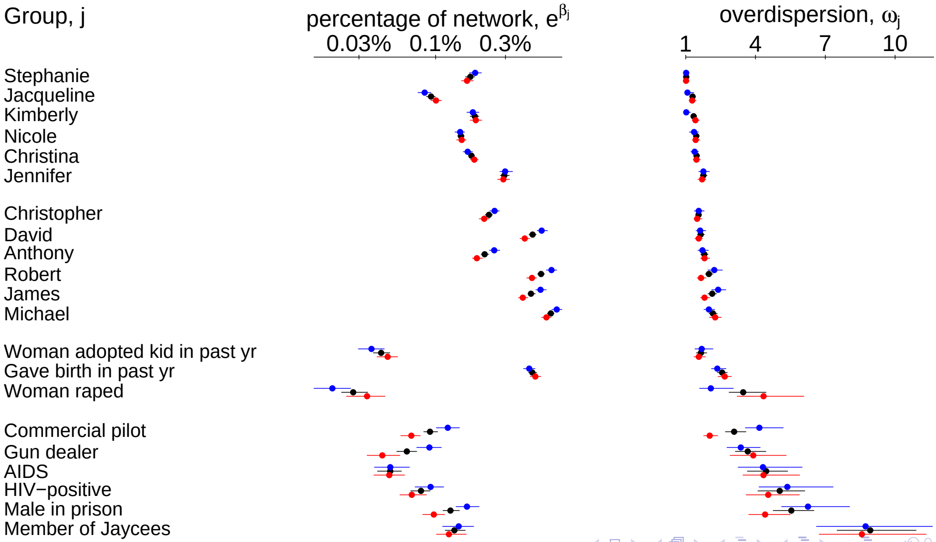
- Subpopulations
  - Names (Stephanie, Michael, etc.)
  - Other groups (pilots, diabetics, etc.)
- Parameters
  - Proportion of the social network, e^{β_k}
  - Overdispersion, ω_k

Parameter estimates for the 32 subpopulations

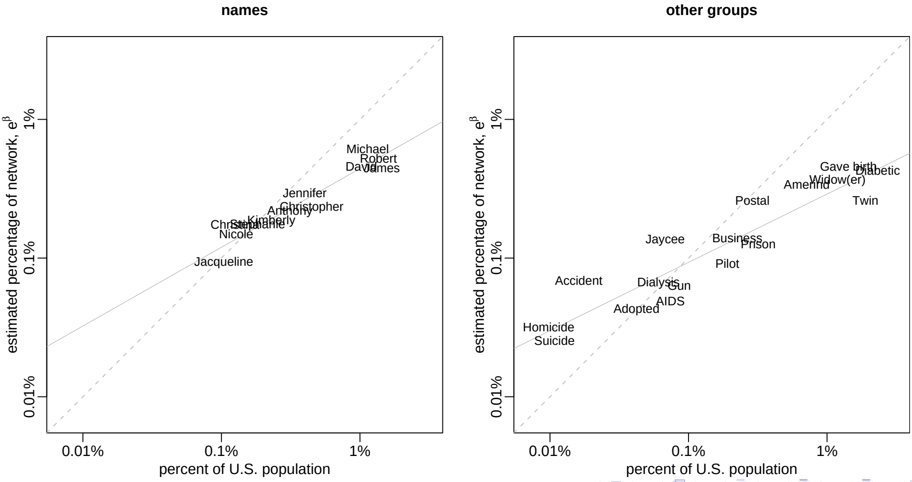
- Subpopulations
  - Names (Stephanie, Michael, etc.)
  - Other groups (pilots, diabetics, etc.)
- Parameters
  - Proportion of the social network, e^{β_k}
  - Overdispersion, ω_k

Parameter estimates for the 32 subpopulations

- Subpopulations
  - Names (Stephanie, Michael, etc.)
  - Other groups (pilots, diabetics, etc.)
- Parameters
  - Proportion of the social network, e^{β_k}
  - Overdispersion, ω_k


Group, j
percentage of network, e^{β_j}
0.03%
0.1%
0.3%
overdispersion, ω_j
1
4
7
10
Stephanie
Jacqueline
Kimberly
Nicole
Christina
Jennifer
Christopher
David
Anthony
Robert
James
Michael
Woman adopted kid in past yr
Gave birth in past yr
Woman raped
Commercial pilot
Gun dealer
AIDS
HIV−positive
Male in prison
Member of Jaycees

Comparing estimated and actual group sizes



Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
- Explanations
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
- Explanations
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
  - Difficulty recalling all the Michaels you know
  - Salience of rare events in memory
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
  - Difficulty recalling all the Michaels you know
  - Salience of rare events in memory
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
  - Difficulty recalling all the Michaels you know
  - Salience of rare events in memory
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
  - Difficulty recalling all the Michaels you know
  - Salience of rare events in memory
- Recall Nicole and Anthony from the demo!

Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
  - Difficulty recalling all the Michaels you know
  - Salience of rare events in memory
- Recall Nicole and Anthony from the demo!

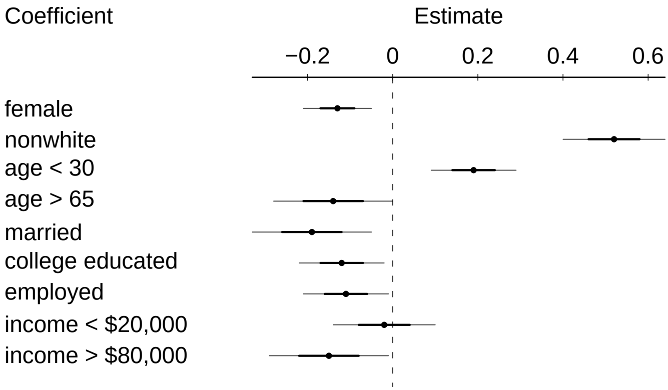
Comparing estimated and actual group sizes

- Names
  - Rare names (Stephanie, Nicole, etc.) fit their population frequencies
  - Common names (Michael, Robert, etc.) are underrepresented in the friendship network
- Other groups
  - Rare groups (homicide, accident, etc.) are over-recalled
  - Common groups (new mothers, diabetics, etc.) are under-recalled
- Explanations
  - Difficulty recalling all the Michaels you know
  - Salience of rare events in memory
- Recall Nicole and Anthony from the demo!

Correlations in the residuals

$$r_{ik} = \sqrt{y_{ik}} - \sqrt{\hat{a}_i \hat{b}_k}$$

Regression of residuals for "How many prisoners do you know?"



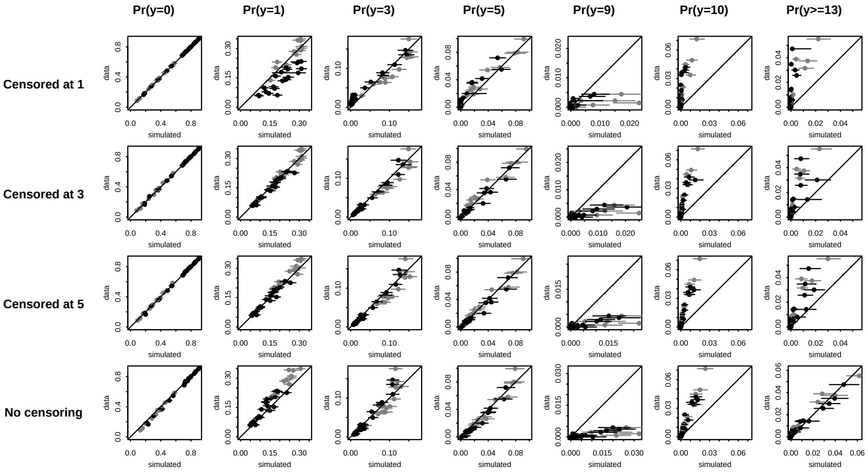
Building confidence in the model

- Comparing data to simulated replications from the model
- Checking parameter estimates under fake-data simulation

Building confidence in the model

- Comparing data to simulated replications from the model
- Checking parameter estimates under fake-data simulation

Actual vs. simulated proportions of $y = 0, 1, \ldots$



Comparison of actual to simulated data

- Posterior predictive checking
- Model fit is good, not perfect
- Consistent patterns with names compared to other groups
- Many fewer 9's and more 10's in data than predicted by the model

Comparison of actual to simulated data

- Posterior predictive checking
- Model fit is good, not perfect
- Consistent patterns with names compared to other groups
- Many fewer 9's and more 10's in data than predicted by the model

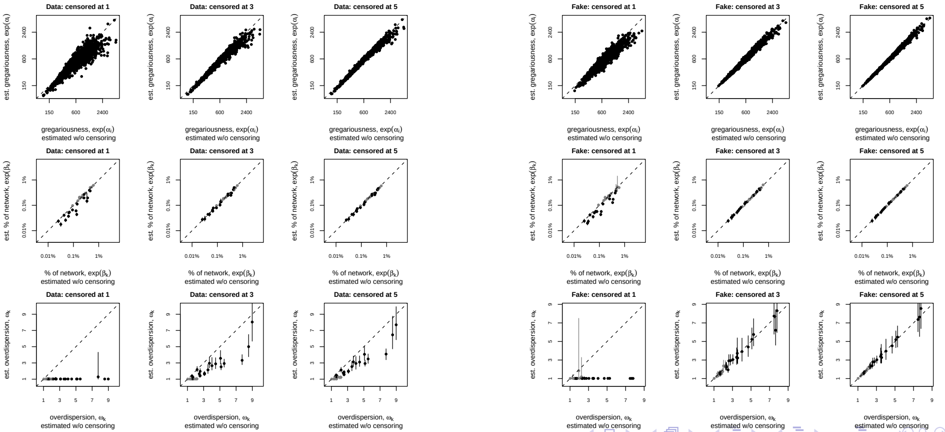
Comparison of actual to simulated data

- Posterior predictive checking
- Model fit is good, not perfect
- Consistent patterns with names compared to other groups
- Many fewer 9's and more 10's in data than predicted by the model

Comparison of actual to simulated data

- Posterior predictive checking
- Model fit is good, not perfect
- Consistent patterns with names compared to other groups
- Many fewer 9's and more 10's in data than predicted by the model

Evaluation of inferences using fake data



Summary

- What have we learned about social networks?
- What computational methods have we used?
- Results of the demo
- Conclusion

Summary

- What have we learned about social networks?
- What computational methods have we used?
- Results of the demo
- Conclusion

Summary

- What have we learned about social networks?
- What computational methods have we used?
- Results of the demo
- Conclusion

Summary

- What have we learned about social networks?
- What computational methods have we used?
- Results of the demo
- Conclusion

Social networks

- Network size
  - On average, people know about 750 people
  - Distribution is similar for men and women
- Overdispersion

Social networks

- Network size
  - On average, people know about 750 people
  - Distribution is similar for men and women
- Overdispersion
  - Names are roughly uniformly distributed
  - Some other groups show more structure
  - Potential for regression models (with geographic and social predictors)

Social networks

- Network size
  - On average, people know about 750 people
  - Distribution is similar for men and women
- Overdispersion
  - Names are roughly uniformly distributed
  - Some other groups show more structure
  - Potential for regression models (with geographic and social predictors)

Social networks

- Network size
  - On average, people know about 750 people
  - Distribution is similar for men and women
- Overdispersion
  - Names are roughly uniformly distributed
  - Some other groups show more structure
  - Potential for regression models (with geographic and social predictors)

Social networks

- Network size
  - On average, people know about 750 people
  - Distribution is similar for men and women
- Overdispersion
  - Names are roughly uniformly distributed
  - Some other groups show more structure
  - Potential for regression models (with geographic and social predictors)

Social networks

- Network size
  - On average, people know about 750 people
  - Distribution is similar for men and women
- Overdispersion
  - Names are roughly uniformly distributed
  - Some other groups show more structure
  - Potential for regression models (with geographic and social predictors)

Social networks

- Network size
  - On average, people know about 750 people
  - Distribution is similar for men and women
- Overdispersion
  - Names are roughly uniformly distributed
  - Some other groups show more structure
  - Potential for regression models (with geographic and social predictors)

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:
  - Do you know any Nicoles?
    Do you know 0, 1, 2, or 3 or more Nicoles?

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:
  - Do you know any Nicoles?
  - Do you know 0, 1, 2, or 3 or more Nicoles?

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:
  - Do you know any Nicoles?
  - Do you know 0, 1, 2, or 3 or more Nicoles?

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:
  - Do you know any Nicoles?
  - Do you know 0, 1, 2, or 3 or more Nicoles?

Data collection

- We can learn network info from a non-network sample
- We can even learn about small groups, less than 0.3% of population
- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Potentially useful for small or hard-to-reach groups
- Difficulty with recall
- Potential design using partial information:
  - Do you know any Nicoles?
  - Do you know 0, 1, 2, or 3 or more Nicoles?

Do you know 0, 1, 2, or 3 or more Nicoles?

- Censored-data model
- $y_{ik} = 0,\ 1,\ 2,\ \text{or} \geq 3$
- Use negative-binomial likelihood function:
  $\Pr(y=0)$, $\Pr(y=1)$, $\Pr(y=2)$,
  $1 - \Pr(y=0) - \Pr(y=1) - \Pr(y=2)$
- Gibbs-Metropolis algorithm is otherwise unchanged
- Check with our data: parameter estimates are similar but problems with model fit for high values of y

Do you know 0, 1, 2, or 3 or more Nicoles?

- Censored-data model
- $y_{ik} = 0, 1, 2, \text{ or } \geq 3$
- Use negative-binomial likelihood function:
  $\Pr(y=0)$, $\Pr(y=1)$, $\Pr(y=2)$,
  $1 - \Pr(y=0) - \Pr(y=1) - \Pr(y=2)$
- Gibbs-Metropolis algorithm is otherwise unchanged
- Check with our data: parameter estimates are similar but problems with model fit for high values of y

Do you know 0, 1, 2, or 3 or more Nicoles?

- Censored-data model
- $y_{ik} = 0, 1, 2, \text{ or } \geq 3$
- Use negative-binomial likelihood function:
  $\Pr(y=0)$, $\Pr(y=1)$, $\Pr(y=2)$,
  $1 - \Pr(y=0) - \Pr(y=1) - \Pr(y=2)$
- Gibbs-Metropolis algorithm is otherwise unchanged
- Check with our data: parameter estimates are similar but problems with model fit for high values of y

Do you know 0, 1, 2, or 3 or more Nicoles?

- Censored-data model
- $y_{ik} = 0, 1, 2, \text{ or } \geq 3$
- Use negative-binomial likelihood function:
  $\Pr(y=0)$, $\Pr(y=1)$, $\Pr(y=2)$,
  $1 - \Pr(y=0) - \Pr(y=1) - \Pr(y=2)$
- Gibbs-Metropolis algorithm is otherwise unchanged
- Check with our data: parameter estimates are similar but problems with model fit for high values of y

Do you know 0, 1, 2, or 3 or more Nicoles?

- Censored-data model
- $y_{ik} = 0,\ 1,\ 2,$ or ≥ 3
- Use negative-binomial likelihood function:
  $\Pr(y\!=\!0)$, $\Pr(y\!=\!1)$, $\Pr(y\!=\!2)$,
  $1 - \Pr(y\!=\!0) - \Pr(y\!=\!1) - \Pr(y\!=\!2)$
- Gibbs-Metropolis algorithm is otherwise unchanged
- Check with our data: parameter estimates are similar but problems with model fit for high values of y

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas
  - Genetics
  - Political science

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas
  - Genetics
  - Political science

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas
  - Genetics
  - Political science

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas
  - Genetics
  - Political science

Other applications?

- Models for overdispersion in two-way tables
- Social surveys
  - Learning about children by interviewing adults
  - Targeted surveys for hard-to-reach groups
  - Combining with network sampling
- Other application areas
  - Genetics
  - Political science

Gibbs-Metropolis algorithm

- Parallel Metropolis updating for each vector α, β, ω
- Automated adaptive updating
- Automated convergence monitoring
- Modular, expandable framework
- Goal of inference is parameters, not posterior means; for example:

Gibbs-Metropolis algorithm

- Parallel Metropolis updating for each vector α, β, ω
- Automated adaptive updating
- Automated convergence monitoring
- Modular, expandable framework
- Goal of inference is parameters, not posterior means; for example:

Gibbs-Metropolis algorithm

- Parallel Metropolis updating for each vector α, β, ω
- Automated adaptive updating
- Automated convergence monitoring
- Modular, expandable framework
- Goal of inference is parameters, not posterior means; for example:

Gibbs-Metropolis algorithm

- Parallel Metropolis updating for each vector α, β, ω
- Automated adaptive updating
- Automated convergence monitoring
- Modular, expandable framework
- Goal of inference is parameters, not posterior means; for example:
  - Good: "θ is estimated at 3.5 ± 0.4, or $[3.1, 3.9]$"
  - Bad: "$\mathrm{E}(\theta)$ is estimated at 3.514 ± 0.003"

Gibbs-Metropolis algorithm

- Parallel Metropolis updating for each vector α, β, ω
- Automated adaptive updating
- Automated convergence monitoring
- Modular, expandable framework
- Goal of inference is parameters, not posterior means; for example:
  - Good: "θ is estimated at 3.5 ± 0.4, or $[3.1, 3.9]$"
  - Bad: "$\mathrm{E}(\theta)$ is estimated at 3.514 ± 0.003"

Gibbs-Metropolis algorithm

- Parallel Metropolis updating for each vector α, β, ω
- Automated adaptive updating
- Automated convergence monitoring
- Modular, expandable framework
- Goal of inference is parameters, not posterior means; for example:
  - Good: "θ is estimated at 3.5 ± 0.4, or $[3.1, 3.9]$"
  - Bad: "$\mathrm{E}(\theta)$ is estimated at 3.514 ± 0.003"

Gibbs-Metropolis algorithm

- Parallel Metropolis updating for each vector α, β, ω
- Automated adaptive updating
- Automated convergence monitoring
- Modular, expandable framework
- Goal of inference is parameters, not posterior means; for example:
  - Good: "θ is estimated at 3.5 ± 0.4, or $[3.1, 3.9]$"
  - Bad: "$\mathrm{E}(\theta)$ is estimated at 3.514 ± 0.003"

Bayesian data analysis

- Model-building motivated by failures of simpler models
- The model can be further improved!
- Checking model by comparing data to predictive replications
- Checking computer program by checking inferences from fake data
- Inferences summarized graphically . . .

Bayesian data analysis

- Model-building motivated by failures of simpler models
- The model can be further improved!
- Checking model by comparing data to predictive replications
- Checking computer program by checking inferences from fake data
- Inferences summarized graphically ...

Bayesian data analysis

- Model-building motivated by failures of simpler models
- The model can be further improved!
- Checking model by comparing data to predictive replications
- Checking computer program by checking inferences from fake data
- Inferences summarized graphically . . .

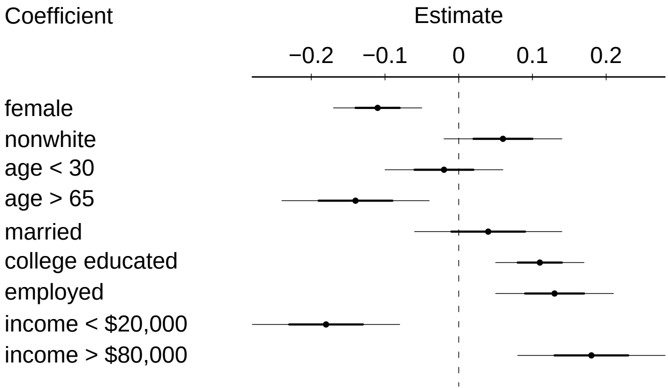
Bayesian data analysis

- Model-building motivated by failures of simpler models
- The model can be further improved!
- Checking model by comparing data to predictive replications
- Checking computer program by checking inferences from fake data
- Inferences summarized graphically . . .

Bayesian data analysis

- Model-building motivated by failures of simpler models
- The model can be further improved!
- Checking model by comparing data to predictive replications
- Checking computer program by checking inferences from fake data
- Inferences summarized graphically ...

Regression of log(gregariousness): as a graph



Regression of log(gregariousness): as a table

Coefficient	Estimate (s.e.)
female	−0.11 (0.03)
nonwhite	0.06 (0.04)
age < 30	−0.02 (0.04)
age > 65	−0.14 (0.05)
married	0.04 (0.05)
college educated	0.11 (0.03)
employed	0.13 (0.04)
income $< \$20,000$	−0.18 (0.05)
income $> \$80,000$	0.18 (0.05)

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Running the demo

- How many Nicoles, Anthonys, lawyers, people robbed?
- Real-time data analysis
  - Entering in the data: 20 minutes
  - Running the program: 500 iterations (40 seconds), 1000 iterations (80 seconds)
  - Real-time debugging: 15 minutes!
  - Altering the presentation: 15 minutes!
- Results for social network sizes, α
- Results for group sizes, β
- Results for overdispersions, ω

Results of the demo

- Social network sizes, α
  - Mean network size estimated at 370 ± 20
  - We don't really believe this precision!
  - Implicit hierarchical model
- Sorry, no graph

Results of the demo

- Social network sizes, α
  - Mean network size estimated at 370 ± 20
  - We don't really believe this precision!
  - Implicit hierarchical model
- Sorry, no graph

Results of the demo

- Social network sizes, α
  - Mean network size estimated at 370 ± 20
  - We don't really believe this precision!
  - Implicit hierarchical model
- Sorry, no graph

Results of the demo

- Social network sizes, α
  - Mean network size estimated at 370 ± 20
  - We don't really believe this precision!
  - Implicit hierarchical model
- Sorry, no graph

Results of the demo

- Social network sizes, α
  - Mean network size estimated at 370 ± 20
  - We don't really believe this precision!
  - Implicit hierarchical model
- Sorry, no graph

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up
  - Nicole: 500,000
  - Anthony: 800,000
  - Lawyers: 2.6 million
  - Robbed last year: 600,000

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up
  - Nicole: 500,000
  - Anthony: 800,000
  - Lawyers: 2.6 million
  - Robbed last year: 200,000

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up
  - Nicole: 500,000
  - Anthony: 800,000
  - Lawyers: 2.6 million
  - Robbed last year: 200,000

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up
  - Nicole: 500,000
  - Anthony: 800,000
  - Lawyers: 2.6 million
  - Robbed last year: 200,000

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up
  - Nicole: 500,000
  - Anthony: 800,000
  - Lawyers: 2.6 million
  - Robbed last year: 200,000

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up
  - Nicole: 500,000
  - Anthony: 800,000
  - Lawyers: 2.6 million
  - Robbed last year: 200,000

Results of the demo

- Group sizes, β
  - Nicole: 0.17% of the social network
  - Anthony: 0.27% of the social network
  - Lawyers: 0.90% of the social network
  - Robbed last yeare: 0.20% of the social network
- Scale-up
  - Nicole: 500,000
  - Anthony: 800,000
  - Lawyers: 2.6 million
  - Robbed last year: 200,000

Results of the demo

- Overdispersions, ω
  - Nicole: 1.1 ± 0.1
  - Anthony: 1.2 ± 0.1
  - Lawyers: 4.2 ± 0.9
  - Robbed last yeare: 1.3 ± 0.3
- Sorry, no graph

Results of the demo

- Overdispersions, ω
  - Nicole: 1.1 ± 0.1
  - Anthony: 1.2 ± 0.1
  - Lawyers: 4.2 ± 0.9
  - Robbed last yeare: 1.3 ± 0.3
- Sorry, no graph

Results of the demo

- Overdispersions, ω
  - Nicole: 1.1 ± 0.1
  - Anthony: 1.2 ± 0.1
  - Lawyers: 4.2 ± 0.9
  - Robbed last yeare: 1.3 ± 0.3
- Sorry, no graph

Results of the demo

- Overdispersions, ω
  - Nicole: 1.1 ± 0.1
  - Anthony: 1.2 ± 0.1
  - Lawyers: 4.2 ± 0.9
  - Robbed last yeare: 1.3 ± 0.3
- Sorry, no graph

Results of the demo

- Overdispersions, ω
  - Nicole: 1.1 ± 0.1
  - Anthony: 1.2 ± 0.1
  - Lawyers: 4.2 ± 0.9
  - Robbed last yeare: 1.3 ± 0.3
- Sorry, no graph

Results of the demo

- Overdispersions, ω
  - Nicole: 1.1 ± 0.1
  - Anthony: 1.2 ± 0.1
  - Lawyers: 4.2 ± 0.9
  - Robbed last yeare: 1.3 ± 0.3
- Sorry, no graph

Conclusion

- Bayesian data analysis is a convenient way to understand complex sources of variation
- Gibbs sampler and Metropolis algorithm can be programmed in R
- Graphical methods are also useful in summarizing inferences and checking the model

Conclusion

- Bayesian data analysis is a convenient way to understand complex sources of variation
- Gibbs sampler and Metropolis algorithm can be programmed in R
- Graphical methods are also useful in summarizing inferences and checking the model

Conclusion

- Bayesian data analysis is a convenient way to understand complex sources of variation
- Gibbs sampler and Metropolis algorithm can be programmed in R
- Graphical methods are also useful in summarizing inferences and checking the model