Learning about social and political polarization using "How many X's do you know" surveys

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Overview

- Social and political polarization
- "How many X's do you know" surveys
- 3 models and Bayesian inference
- Our research plan

- collaborators:
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  - Matt Salganik, Dept of Sociology, Columbia University
  - Tom DiPrete, Dept of Sociology, Columbia University
  - Julien Teitler, School of Social Work, Columbia University
  - others in our research group
  - Peter Killworth and Chris McCarty shared their survey data

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Increasing social/economic heterogeneity in U.S. since 1950s?

- Social polarization:
  - More variety in domestic arrangements
  - Greater income inequality
  - We tend to know people of similar social class to ourselves
  - Counter-trend: more interracial marriages
- Decline in social capital:

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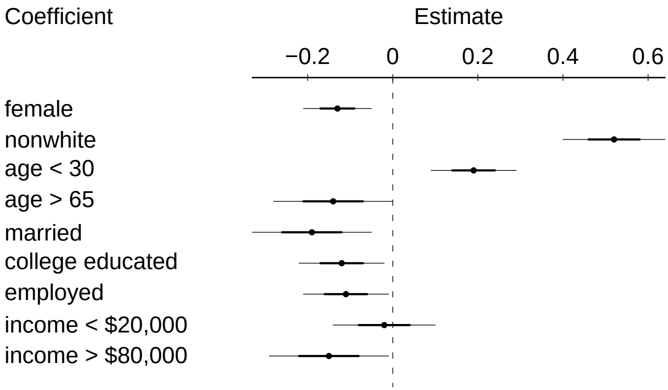
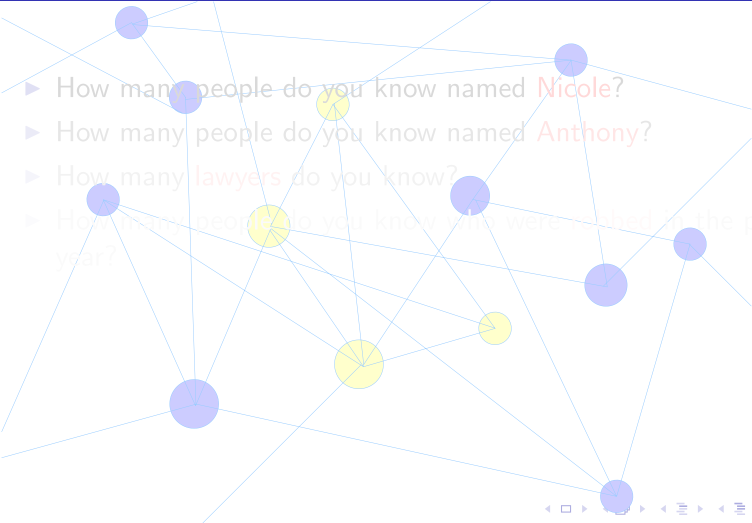
Example analysis: regression of residuals for "How many prisoners do you know?"



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?



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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 $0.8/0.0031 = 260$ people

- Why do these differ?

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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
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- 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
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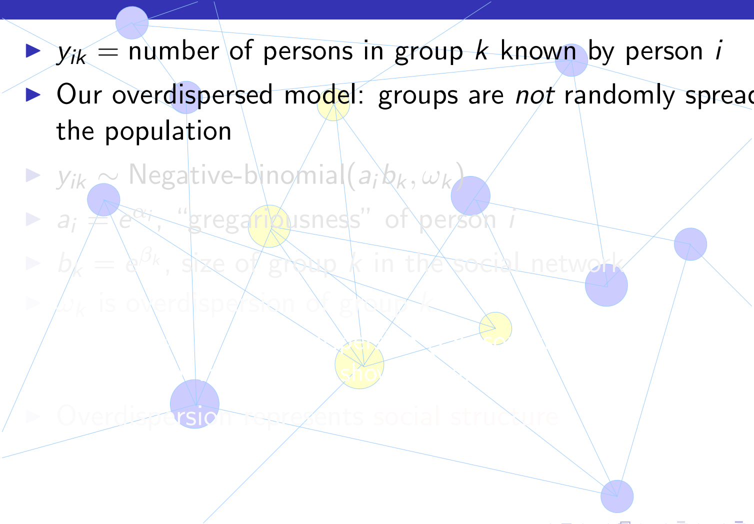
Our overdispersed model



- 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
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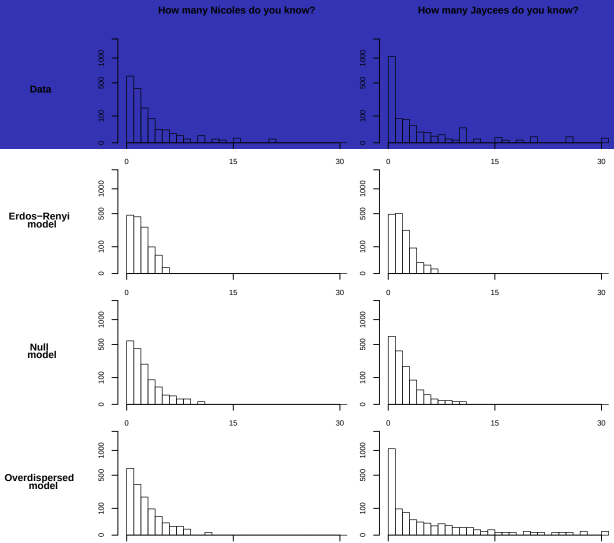

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- data model: $y_{ik} \sim \text{Negative-binomial}(e^{\alpha_i+\beta_k}, \omega_k)$, for $i = 1, \ldots, 1370$, $k = 1, \ldots, 32$
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Gibbs-Metropolis algorithm: updating α, β, ω

- For each i, update α_i using Metropolis with jumping dist. $\alpha_i^* \sim \mathrm{N}(\alpha_i^{(t-1)}, (\text{jumping scale of } \alpha_i)^2)$.
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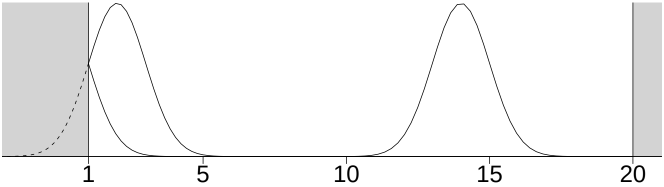

Gibbs-Metropolis algorithm: updating hyperparameters

- Update $\mu_\alpha \sim \mathrm{N}\left(\frac{1}{n}\sum_{i=1}^{n}\alpha_i, \frac{1}{n}\sigma^2\right)$
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Renormalizing the α_i's and β_k's

- 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)
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Adaptive Metropolis jumping

- Parallel scalar updating of the components of α, β, ω
- Adapt each of $1370 + 32 + 32$ jumping scales to have $E(p_{\rm jump}) \approx 0.44$
- Save $p_{\rm jump}$ from each Metropolis step, then average them and rescale every 50 iterations:
  - Where avg $p_{\rm jump} > 0.44$, increase the jump scale
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- If we had vector jumps, we would adapt the scale so that $E(p_{\rm jump}) \approx 0.23$
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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)
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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))
```

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```

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() {
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```

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
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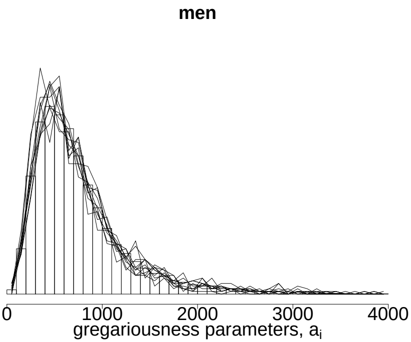
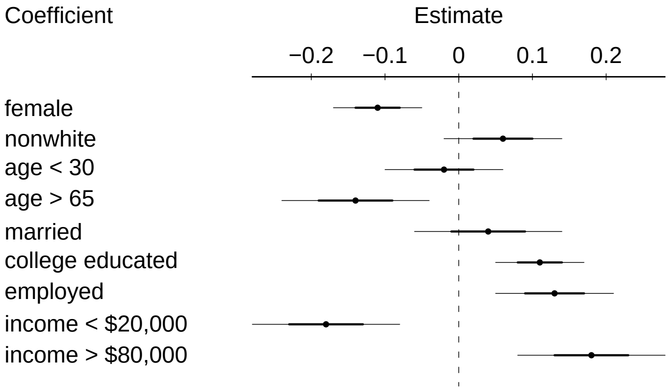
Estimated distributions of network sizes for men and women



Regression of log(gregariousness)



Parameter estimates for the 32 subpopulations

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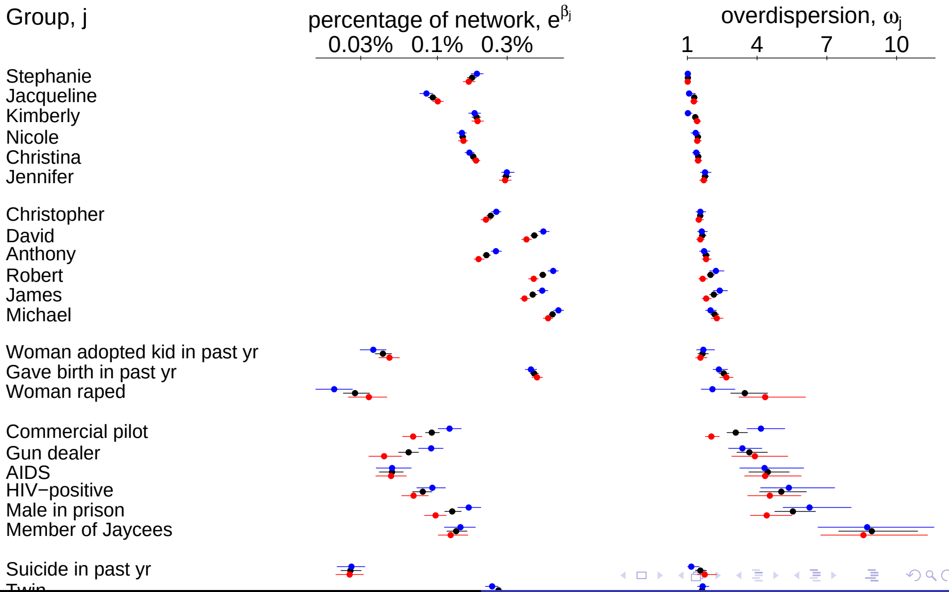
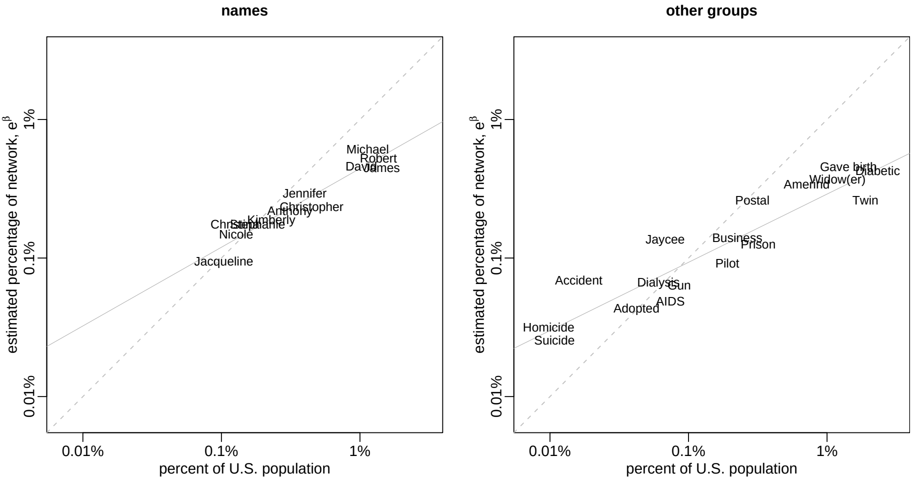

Group, j
percentage of network, e^{β_j}
0.03%
0.1%
0.3%
overdispersion, ω_j
1
4
7
10
Stephanie
Jacqueline
Kimberly
Nicole
Christina
Jennifer
Christopher
David
Anthony
Robert
James
Michael
Woman adopted kid in past yr
Gave birth in past yr
Woman raped
Commercial pilot
Gun dealer
AIDS
HIV−positive
Male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

Comparing estimated and actual group sizes



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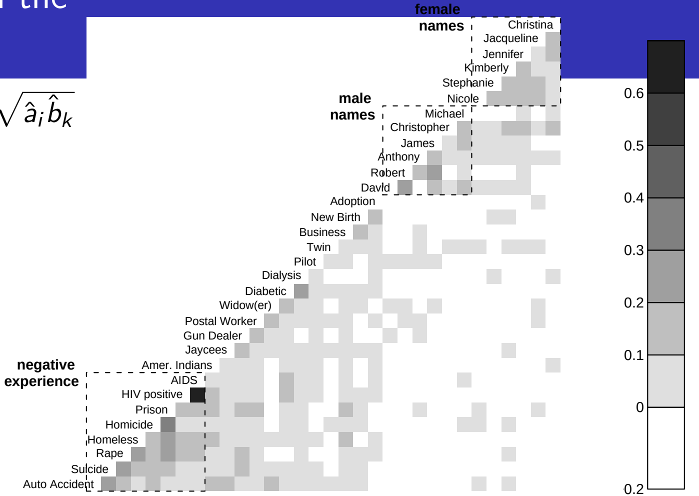
Correlations in the residuals

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



Confidence building

- Posterior predictive checking: compare data to simulated replications from the model
  - Model fit is good, not perfect
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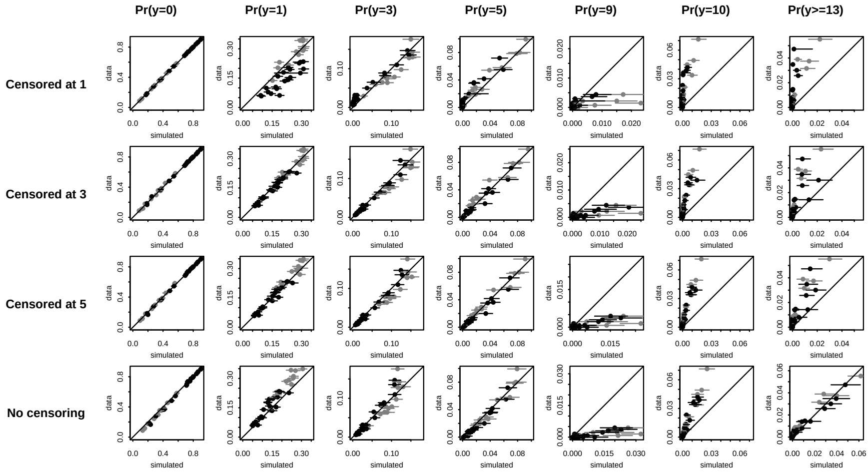
Actual vs. simulated proportions of $y = 0, 1, \ldots$



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: $\Pr(y=0)$, $\Pr(y=1)$, $\Pr(y=2)$, $1 - \Pr(y=0) - \Pr(y=1) - \Pr(y=2)$
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- Check with our data: parameter estimates are similar but problems with model fit for high values of y

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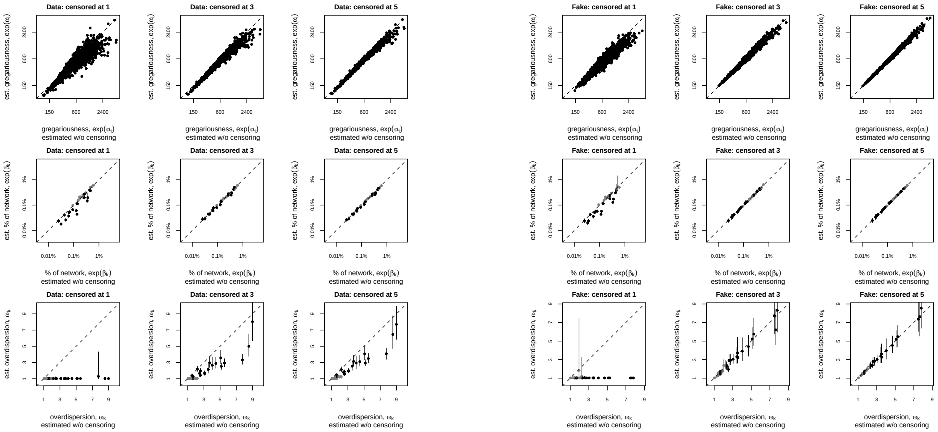
- Censored-data model
- $y_{ik} = 0,\ 1,\ 2,\ \text{or} \geq 3$
- Use negative-binomial likelihood function:
  $\Pr(y=0)$, $\Pr(y=1)$, $\Pr(y=2)$,
  $1 - \Pr(y=0) - \Pr(y=1) - \Pr(y=2)$
- Gibbs-Metropolis algorithm is otherwise unchanged
- Check with our data: parameter estimates are similar but problems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

Evaluation of inferences using fake data



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
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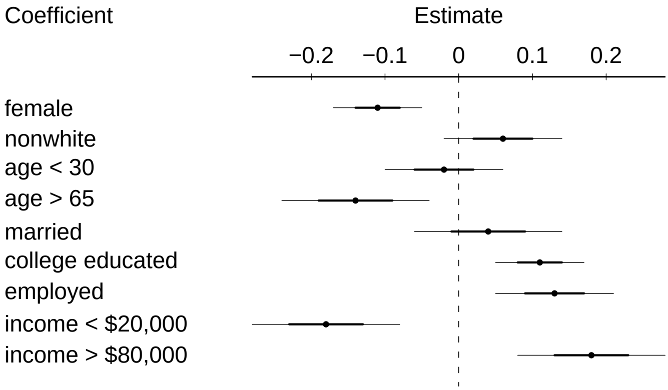
Regression of log(gregariousness): as a table

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)

Regression of log(gregariousness): as a graph



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- Network info from a non-network sample
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- Implicit survey of $1500 \times 750 = 1$ *million* people!
- Characterising people by how they are perceived
- Potentially useful for small or hard-to-reach groups (prisoners, ...)
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