Gary King

April 20, 2013
Readings

- Amelia II: A Program for Missing Data
- http://gking.harvard.edu/amelia
Some common but biased or inefficient missing data practices:
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**Multiple imputation**:
- fill in five data sets with different imputations for missing values
- analyze each one as you would without missingness
- use a special method to combine the results
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Missingness Notation

\[ D = \begin{bmatrix} 1 & 2.5 & 4.3 & 0 \\ 5.2 & 3 & 2.5 & 4.3 \\ 7.4 & 21.9 & 1.6 & 9.2 \\ 23.4 & 1.3 & 2.1 & 0.7 \\ 9.5 & 1 \\ \end{bmatrix}, \quad M = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 \\ \end{bmatrix} \]

\[ D_{\text{mis}} = \text{missing elements in } D \text{ (in Red)} \]

\[ D_{\text{obs}} = \text{observed elements in } D \]

\[ \Rightarrow \text{ Missing elements must exist} \]

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Missing Data
Missingness Notation

\[
D = \begin{pmatrix}
1 & 2.5 & 432 & 0 \\
5 & 3.2 & 543 & 1 \\
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6 & 1.9 & 234 & 1 \\
3 & 1.2 & 108 & 0 \\
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\end{pmatrix}, \quad
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### Possible Assumptions

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- Reasons for the odd terminology are historical.
Missingness Assumptions, again

1. **MCAR**: Coin flips determine whether to answer survey questions (naïve)
   \[ P(M | D) = P(M) \]

2. **MAR**: missingness is a function of measured variables (empirical)
   \[ P(M | D) \equiv P(M | D_{\text{obs}}, D_{\text{mis}}) = P(M | D_{\text{obs}}) \]
   e.g., Independents are less likely to answer vote choice question (with PID measured)
   e.g., Some occupations are less likely to answer the income question (with occupation measured)

3. **NI**: missingness depends on unobservables (fatalistic)
   \[ P(M | D) \text{ doesn't simplify} \]
   e.g., censoring income if income is $100K and you can't predict high income with other measured variables
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Goal: estimate $\beta_1$, where $X_2$ has $\lambda$ missing values ($y$, $X_1$ are fully observed).
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The choice in real research:
How Bad Is Listwise Deletion?

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$$E(y) = X_1\beta_1 + X_2\beta_2$$

**The choice in real research:**

**Infeasible Estimator** Regress $y$ on $X_1$ and a fully observed $X_2$, and use $b_1^I$, the coefficient on $X_1$. 

**Omitted Variable Estimator** Omit $X_2$ and estimate $\beta_1$ by $b_{O1}$, the slope from regressing $y$ on $X_1$.

**Listwise Deletion Estimator** Perform listwise deletion on \{y, $X_1$, $X_2$\}, and then estimate $\beta_1$ as $b_{L1}$, the coefficient on $X_1$ when regressing $y$ on $X_1$ and $X_2$. 

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Listwise Deletion Estimator  Perform listwise deletion on $\{y, X_1, X_2\}$, and then estimate $\beta_1$ as $b_1^L$, the coefficient on $X_1$ when regressing $y$ on $X_1$ and $X_2$. 

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In the *best* case scenario for listwise deletion (MCAR), should we delete listwise or omit the variable?

Mean Square Error as a measure of the badness of an estimator \( \hat{a} \) of \( a \).
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$$\text{MSE}(b_1^L) - \text{MSE}(b_1^O) =$$
In the best case scenario for listwise deletion (MCAR), should we delete listwise or omit the variable?

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\[
\text{MSE}(b_1^L) - \text{MSE}(b_1^O) = \begin{cases} > 0 & \text{when omitting the variable is better} \\ < 0 & \text{when listwise deletion is better} \end{cases}
\]
Derivation and Implications

\[ \text{MSE}(b_L) - \text{MSE}(b_O) = (\lambda_1 - \lambda V(b_I)) + F[V(b_I_2) - \beta_2 \beta'] \]

1. Missingness part (> 0) is an extra tilt away from listwise deletion
2. Observed part is the standard bias-efficiency tradeoff of omitting variables, even without missingness
3. How big is \( \lambda \) usually?
   \( \lambda \approx 1/3 \) on average in real political science articles
   \( > 1/2 \) at a recent SPM Conference
   Larger for authors who work harder to avoid omitted variable bias

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Derivation and Implications

\[ \text{MSE} (b_1^L) - \text{MSE} (b_1^O) \]

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Derivation and Implications

\[ \text{MSE}(b^L_1) - \text{MSE}(b^O_1) = \left( \frac{\lambda}{1 - \lambda} V(b^l_1) \right) + F[V(b^l_2) - \beta_2 \beta'_2] F' \]

1. Missingness part \((> 0)\) is an extra tilt away from listwise deletion
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   - \(\lambda \approx 1/3\) on average in real political science articles
   - \(> 1/2\) at a recent SPM Conference
   - Larger for authors who work harder to avoid omitted variable bias
4. If $\lambda \approx 0.5$, the contribution of the missingness (tilting away from choosing listwise deletion over omitting variables) is
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Derivation and Implications

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5. **Result:** The point estimate in the average political science article is about an additional standard error farther away from the truth because of listwise deletion (as compared to omitting $X_2$ entirely).
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5. **Result:** The point estimate in the average political science article is about an additional standard error farther away from the truth because of listwise deletion (as compared to omitting $X_2$ entirely).

6. **Conclusion:** Listwise deletion is often as bad a problem as the much better known omitted variable bias — in the best case scenario (MCAR)
Existing General Purpose Missing Data Methods

1. Listwise deletion (RMSE is 1 SE off if MCAR holds; biased under MAR)
2. Best guess imputation (depends on guesser!)
3. Imputing a zero and then adding an additional dummy variable to control for the imputed value (biased)
4. Pairwise deletion (assumes MCAR)
5. Hot deck imputation, (inefficient, standard errors wrong)
6. Mean substitution (attenuates estimated relationships)
Fill in or delete the missing data, and then act as if there were no missing data. None work in general under MAR.
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Base inferences on the likelihood function or posterior distribution, by conditioning on observed data only, $P(\theta | Y_{obs})$.

- E.g., models of censoring, truncation, etc.
- Optimal theoretically, if specification is correct
- Not robust (i.e., sensitive to distributional assumptions) if model is incorrect
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How to create application-specific methods?

1. We observe $M$ always. Suppose we also see all the contents of $D$.

2. Then the likelihood is $P(D, M | \theta, \gamma) = P(D | \theta) P(M | D, \gamma)$, the likelihood if $D$ were observed, and the model for missingness.

If $D$ and $M$ are observed, when can we drop $P(M | D, \gamma)$?

3. Suppose now $D$ is observed (as usual) only when $M$ is 1.
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and if assume MAR (\(D\) and \(M\) are stochastically and parametrically independent), then

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because \(P(M | D_{\text{obs}}, \gamma)\) is constant w.r.t. \(\theta\).

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Multiple Imputation

Point estimates are consistent, efficient, and the standard errors are right.

To compute:

1. **Impute** $m$ values for each missing element
   - Imputation method assumes MAR
   - Uses a model with stochastic and systematic components
   - Produces independent imputations
   - (We'll give you a model to impute later)

2. **Create** $m$ completed data sets
   - Observed data are the same across the data sets
   - Imputations of missing data differ
     - Cells we can predict well don't differ much
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3. Run whatever statistical method you would have with no missing data for each completed data set
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Standard error:

\[ SE(q) = \sqrt{\text{mean}(SE_j^2) + \text{variance}(q_j)}(1 + 1/m) \]

Last piece vanishes as $m$ increases.

5. Easier by simulation:

- Draw $1/m$ sims from each data set of the QOI,
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A General Model for Imputations

1. If data were complete, we could use:
   \[ L(\mu, \Sigma | D) \propto n \prod_{i=1}^N (D_i | \mu, \Sigma) \]
   (a SURM model without \( X \))

2. With missing data, this becomes:
   \[ L(\mu, \Sigma | D_{obs}) \propto n \prod_{i=1}^N \int N(D_i | \mu, \Sigma) dD_{mis} = n \prod_{i=1}^N N(D_i, obs | \mu_{obs}, \Sigma_{obs}) \]
   since marginals of MVN's are normal.

3. Simple theoretically: merely a likelihood model for data (\( D_{obs}, M \)) and same parameters as when fully observed (\( \mu, \Sigma \)).

4. Difficult computationally: \( D_i, obs \) has different elements observed for each \( i \) and so each observation is informative about different pieces of (\( \mu, \Sigma \)).
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(a SURM model without \(X\))

2. With missing data, this becomes:

\[ L(\mu, \Sigma | D_{obs}) \propto \prod_{i=1}^{n} \int N(D_i | \mu, \Sigma) dD_{mis} \]

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3. Simple theoretically: merely a likelihood model for data \((D_{obs}, M)\) and same parameters as when fully observed \((\mu, \Sigma)\).

4. Difficult computationally: \(D_{i, obs}\) has different elements observed for each \(i\) and so each observation is informative about different pieces of \((\mu, \Sigma)\).
5. **Difficult Statistically**: number of parameters increases quickly in the number of variables ($p$, columns of $D$):

\[
\text{parameters} = \text{parameters(\(\mu\))} + \text{parameters(\(\Sigma\))} = p + p\left(\frac{p+1}{2}\right) = \frac{p(p+3)}{2}.
\]

E.g., for $p = 5$, parameters = 20; for $p = 40$ parameters = 860 (Compare to $n$).

6. More appropriate models, such as for categorical or mixed variables, are harder to apply and do not usually perform better than this model (If you're going to use a difficult imputation method, you might as well use an application-specific method. Our goal is an easy-to-apply, generally applicable, method even if 2nd best.)

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How to create imputations from this model

1. E.g., suppose $D$ has only 2 variables, $D = \{X, Y\}$

2. $X$ is fully observed, $Y$ has some missingness.

3. Then $D = \{Y, X\}$ is bivariate normal: $D \sim N(D|\mu, \Sigma) = N\left(\begin{pmatrix} Y \\ X \end{pmatrix} \bigg| \begin{pmatrix} \mu_y \\ \mu_x \end{pmatrix}, \begin{pmatrix} \sigma_y^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_x^2 \end{pmatrix}\right)$

4. Conditionals of bivariate normals are normal: $Y \mid X \sim N\left(\begin{pmatrix} y \\ \mathbb{E}(Y \mid X) \end{pmatrix} \bigg| \begin{pmatrix} \mu_y \\ \mathbb{E}(Y \mid X) \end{pmatrix}, \begin{pmatrix} \sigma_y^2 & 0 \\ 0 & \sigma_x^2 \end{pmatrix}\right)$

   $\mathbb{E}(Y \mid X) = \mu_y + \beta (X - \mu_x)$ (a linear regression!)

   $\beta = \frac{\sigma_{xy}}{\sigma_x^2}$

   $\mathbb{V}(Y \mid X) = \sigma_y^2 - \frac{\sigma_{xy}^2}{\sigma_x^2}$
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Gary King (Harvard, IQSS)
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(ii) We will improve on this shortly

(b) Draw $\mu$ and $\Sigma$ from their posterior density

(c) Compute simulations of $E(Y|X)$ and $V(Y|X)$ deterministically

(d) Draw a simulation of the missing $Y$ from the conditional normal

6. In this simple example ($X$ fully observed), this is equivalent to simulating from a linear regression of $Y$ on $X$, 

\[ \tilde{y}_i = x_i \tilde{\beta} + \tilde{\epsilon}_i, \]

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1. Optim with hundreds of parameters would work but slowly.

2. EM (expectation maximization): another algorithm for finding the maximum. (a) Much faster than optim (b) Intuition: i. Without missingness, estimating $\beta$ would be easy: run LS. ii. If $\beta$ were known, imputation would be easy: draw $\tilde{\epsilon}$ from normal, and use $\tilde{y} = x \hat{\beta} + \tilde{\epsilon}$. (c) EM works by iterating between i. Impute $\hat{Y}$ with $x \hat{\beta}$, given current estimates, $\hat{\beta}$ ii. Estimate parameters $\hat{\beta}$ (by LS) on data filled in with current imputations for $Y$ (d) Can easily do imputation via $x \hat{\beta} + \tilde{\epsilon}$, but SEs too small due to no estimation uncertainty ($\hat{\beta} \neq \beta$); i.e., we need to draw $\beta$ from its posterior first
Computational Algorithms

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- EMs adds estimation uncertainty to EM imputations by drawing $\tilde{\beta}$ from its asymptotic normal distribution, $N(\hat{\beta}, \hat{V}(\hat{\beta}))$.
- The central limit theorem guarantees that this works as $n \to \infty$, but for real sample sizes it may be inadequate.

4. **EMis**: EM with simulation via importance resampling (probabilistic rejection sampling to draw from the posterior).

Keep $\tilde{\theta}_1$ with probability $\propto a / b$ (the importance ratio). Keep $\tilde{\theta}_2$ with probability 1.
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![Diagram](image-url)
3. **EMs**: EM for maximization and then simulation (as usual) from asymptotic normal posterior

   (a) EMs adds estimation uncertainty to EM imputations by drawing $\tilde{\beta}$ from its asymptotic normal distribution, $N(\hat{\beta}, \hat{V}(\hat{\beta}))$

   (b) The central limit theorem guarantees that this works as $n \to \infty$, but for real sample sizes it may be inadequate.

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Keep $\tilde{\theta}_1$ with probability $\propto a/b$ (the importance ratio). Keep $\tilde{\theta}_2$ with probability 1.
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(b) The algorithm. For $\theta = \{\mu, \Sigma\}$,

\[\text{i. I-Step: draw } D_{\text{mis}} \text{ from } P(D_{\text{mis}} | D_{\text{obs}}, \tilde{\theta}) \text{ (i.e., } \tilde{y} = \tilde{x} \tilde{\beta} + \tilde{\epsilon}) \text{ given current draw of } \tilde{\theta}\]

\[\text{ii. P-Step: draw } \theta \text{ from } P(\theta | D_{\text{obs}}, \tilde{D}_{\text{mis}}), \text{ given current imputation } \tilde{D}_{\text{mis}}\]

(c) Example of MCMC (Markov-Chain Monte Carlo) methods, one of the most important developments in statistics in the 1990s

(d) MCMC enabled statisticians to do things they never previously dreamed possible, but it requires considerable expertise to use and so didn't help others do these things. (Few MCMC routines have appeared in canned packages.)

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Randomly draw \( n \) obs (with replacement) from the data
Use EM to estimate \( \beta \) and \( \Sigma \) in each (for estimation uncertainty)
Impute \( D_{mis} \) from each from the model (for fundamental uncertainty)

Lightning fast; works with very large data sets
Basis for Amelia II

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Multiple Imputation: Amelia Style

Missing Data

Gary King (Harvard, IQSS)
Multiple Imputation: Amelia Style

incomplete data
Multiple Imputation: Amelia Style

incomplete data

bootstrap

bootstrapped data
Multiple Imputation: Amelia Style

- **incomplete data**
- **bootstrap**
- **bootstrapped data**
- **EM**
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Multiple Imputation: Amelia Style

incomplete data

bootstrap

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analysis
Multiple Imputation: Amelia Style

- incomplete data
- bootstrap
- bootstrapped data
- EM
- imputed datasets
- analysis
- combination
- final results

Gary King (Harvard, IQSS)

Missing Data
Comparisons of Posterior Density Approximations

\( \beta_0 \)

\( \beta_1 \)

\( \beta_2 \)

\( \hat{E} \text{MB} \)  
\( \text{IP} - \text{EMis} \)  
\( \text{Complete Data} \)  
\( \text{List-wise Del.} \)
What Can Go Wrong and What to Do

Inference is learning about facts we don’t have with facts we have; we assume the two are related!

Imputation and analysis are estimated separately → robustness because imputation affects only missing observations. High missingness reduces the property.

Include at least as much information in the imputation model as in the analysis model: all vars in analysis model; others that would help predict (e.g., all measures of a variable, post-treatment variables)

Fit imputation model distributional assumptions by transformation to unbounded scales: \( \sqrt{\text{counts}} \), \( \ln(p/(1-p)) \), \( \ln(\text{money}) \), etc.

Code ordinal variables as close to interval as possible.
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Code ordinal variables as close to interval as possible.
Represent severe nonlinear relationships in the imputation model with transformations or added quadratic terms.

If the imputation model has as much information as the analysis model, but the specification (such as the functional form) differs, CIs are conservative (e.g., $\geq 95\%$ CIs).

When the imputation model includes more information than the analysis model, it can be more efficient than the "optimal" application-specific model (known as "super-efficiency").

Bad intuitions:
- If $X$ is randomly imputed, why no attenuation (the usual consequence of random measurement error in an explanatory variable)?
- If $X$ is imputed with information from $Y$, why no endogeneity?

Answer to both: the draws are from the joint posterior and put back into the data. Nothing is being changed.
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The Best Case for Listwise Deletion

Listwise deletion is better than MI when all 4 hold:

1. The analysis model is conditional on $X$ (like regression) and functional form is correct (so listwise deletion is consistent and the characteristic robustness of regression is not lost when applied to data with slight measurement error, endogeneity, nonlinearity, etc.).

2. NI missingness in $X$ and no external variables are available that could be used in an imputation stage to fix the problem.

3. Missingness in $X$ is not a function of $Y$

4. The $n$ left after listwise deletion is so large that the efficiency loss does not counterbalance the biases induced by the other conditions. I.e., you don't trust data to impute $D_{mis}$ but still trust it to analyze $D_{obs}$.
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Root Mean Square Error Comparisons

Each point is RMSE averaged over two regression coefficients in each of 100 simulated data sets. (IP and EMis have the same RMSE, which is lower than listwise deletion and higher than the complete data; its the same for EMB.)
Detailed Example: Support for Perot

1. Research question: were voters who did not share in the economic recovery more likely to support Perot in the 1996 presidential election?

2. Analysis model: linear regression

3. Data: 1996 National Election Survey (n=1714)

4. Dependent variable: Perot Feeling Thermometer

5. Key explanatory variables: retrospective and prospective evaluations of national economic performance and personal financial circumstances

6. Control variables: age, education, family income, race, gender, union membership, ideology

7. Extra variables included in the imputation model to help prediction: attention to the campaign; feeling thermometers for Clinton, Dole, Democrats, Republicans; PID; Partisan moderation; vote intention; martial status; Hispanic; party contact, number of organizations R is a paying member of, and active member of.

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   - Listwise deletion: 0.43 (0.90)
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(a) MI estimator is more efficient, with a smaller SE

(b) The MI estimator is 4 times larger

(c) Based on listwise deletion, there is no evidence that perception of poor economic performance is related to support for Perot

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MI in Time Series Cross-Section Data

Include: (1) fixed effects, (2) time trends, and (3) priors for cells


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Read: James Honaker and Gary King, "What to do About Missing Values in Time Series Cross-Section Data,”
http://gking.harvard.edu/files/abs/pr-abs.shtml
Imputation one Observation at a time

Circles = true GDP; green = no time trends; blue = polynomials; red = LOESS
Recall:

$$p(\theta | y) = p(\theta) \prod_{i=1}^{n} L_i(\theta | y)$$

take logs: $\ln p(\theta | y) = \ln [p(\theta)] + \sum_{i=1}^{n} \ln L_i(\theta | y)$

$\Rightarrow$ Suppose prior is of the same form, $p(\theta | y) = L_i(\theta | y)$; then its just another observation: $\ln p(\theta | y) = \sum_{i=1}^{n+1} \ln L_i(\theta | y)$

Honaker and King show how to modify these "data augmentation priors" to put priors on missing values rather than on $\mu$ and $\sigma$ (or $\beta$).
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Honaker and King show how to modify these "data augmentation priors" to put priors on missing values rather than on \( \mu \) and \( \sigma \) (or \( \beta \)).
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take logs: \( \ln p(\theta|y) = \ln[p(\theta)] + \sum_{i=1}^{n} \ln L_i(\theta|y) \)
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\( \iff \) Suppose prior is of the same form, \( p(\theta|y) = L_i(\theta|y) \); then its just another observation: \( \ln p(\theta|y) = \sum_{i=1}^{n+1} \ln L_i(\theta|y) \)
Priors on Cell Values

- Recall: \( p(\theta | y) = p(\theta) \prod_{i=1}^{n} L_i(\theta | y) \)
- Take logs: \( \ln p(\theta | y) = \ln[p(\theta)] + \sum_{i=1}^{n} \ln L_i(\theta | y) \)
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- Honaker and King show how to modify these “data augmentation priors” to put priors on missing values rather than on \( \mu \) and \( \sigma \) (or \( \beta \)).
Posterior imputation: mean=0, prior mean=5

**Left column**: holds prior $N(5, \lambda)$ constant ($\lambda = 1$) and changes predictive strength (the covariance, $\sigma_{12}$).
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Right column: holds predictive strength of data constant (at $\sigma_{12} = 0.5$) and changes the strength of the prior ($\lambda$).
Prior: $p(x_{12}) = N(5, \lambda)$. The parameter approaches the theoretical limits (dashed lines), upper bound is what is generated when the missing value is filled in with the expectation; lower bound is the parameter when the model is estimated without priors. The overall movement is small.
Replication of Baum and Lake; Imputation Model Fit

Black = observed. Blue circles = five imputations; Bars = 95% CIs
<table>
<thead>
<tr>
<th></th>
<th>Listwise Deletion</th>
<th>Multiple Imputation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Life Expectancy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>.233</td>
</tr>
<tr>
<td></td>
<td>(.179)</td>
<td>(.037)</td>
</tr>
<tr>
<td>Poor Democracies</td>
<td>−.082</td>
<td>.120</td>
</tr>
<tr>
<td></td>
<td>(.040)</td>
<td>(.099)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>1789</td>
<td>5627</td>
</tr>
<tr>
<td><strong>Secondary Education</strong></td>
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<tr>
<td>Rich Democracies</td>
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<td></td>
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<tr>
<td>Poor Democracies</td>
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<td>.393</td>
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<tr>
<td></td>
<td>(.094)</td>
<td>(.081)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>1966</td>
<td>5627</td>
</tr>
</tbody>
</table>

Replication of Baum and Lake; the effect of being a democracy on life expectancy and on the percentage enrolled in secondary education (with p-values in parentheses).
Making Multiple Imputation Useful

1. MI was invented 20 years ago. Despite having won many theoretical wars over its appropriateness, it was not often used.
2. Frequentists don't like it because it had a Bayesian justification.
3. Bayesians don't like it because once you do the hard work you might as well just use an application-specific method.
4. The idea was that data providers would use inside information to make imputations, but this is rare.
5. Applied people love the idea, since it doesn't disrupt analysis methods. But it wasn't used because creating proper imputations is hard without easy algorithms & software.
6. The new algorithms allow users to create the imputations themselves.
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