Strategies for Handling Missing Data

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Section 1

The Problem

Data, in theory

Suppose we want to mine sales records to see what kind of customer buys more from us.

sales	female	education	income
1209	0	high school	35000
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13265	1	grad degree	65000
2298	0	some college	49000

Data, in practice

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- Mass hysteria

Today's talk

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Section 2

Typical Method Versus a Better Method

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- We know where this leads

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- Both are wrong, but one is a better (more likely to be true) guess than the other.
- The better guess will be less likely to lead you to bad decisions, algorithms, hysteria, etc.

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- cf. Donald Rubin (1976)

Section 3

Naive Imputation

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How we guess (hopefully) depends on what we expect to be there.

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- Categorical (states; colors): mode
  StatMode <- function(x)
  names(table(x))[which.max(table(x))]

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mean	mode	median

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  - "Making up data" makes us more certain than we should be.

Section 4

Home-Rolled Imputation

Imputation with Regression

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4. Fill with predict(reg, names(X)[obs.cols]=X[i,obs.cols])

Imputation with Regression (continued)

y	x1	x2
7.44	1.21	1.95
3.25	-1.35	0.11
3.90	NA	0.63
5.19	0.16	2.27
5.57	0.17	1.53
...	...	...

Imputation with Regression (continued)

y	x1	x2
7.44	1.21	1.95
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- Missing value: -0.89

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- Missing value: -0.89
- Predicted value: -0.89

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Categorical	Multinomial logit with nnet::multinom

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Section 5

Existing Tools

Small Data Sets

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4. Check distribution of observed versus imputed values (plot, ks.test)

Amelia Example

```
library(Amelia)
data(africa)
```

```
a.out <- amelia(x = africa, cs = "country", ts = "year", lo
```

```
## -- Imputation 1 --
##
##  1  2
##
## -- Imputation 2 --
##
##  1  2  3
##
## -- Imputation 3 --
##
##  1  2
##
## -- Imputation 4 --
##
```

Amelia Example (continued)

```
summary(a.out)

##
## Amelia output with 5 imputed datasets.
## Return code:  1
## Message:  Normal EM convergence.
##
## Chain Lengths:
## --------------
## Imputation 1:  2
## Imputation 2:  3
## Imputation 3:  2
## Imputation 4:  2
## Imputation 5:  2
##
## Rows after Listwise Deletion:  115
## Rows after Imputation:  120
## Patterns of missingness in the data:  3
```

Amelia Example (continued)

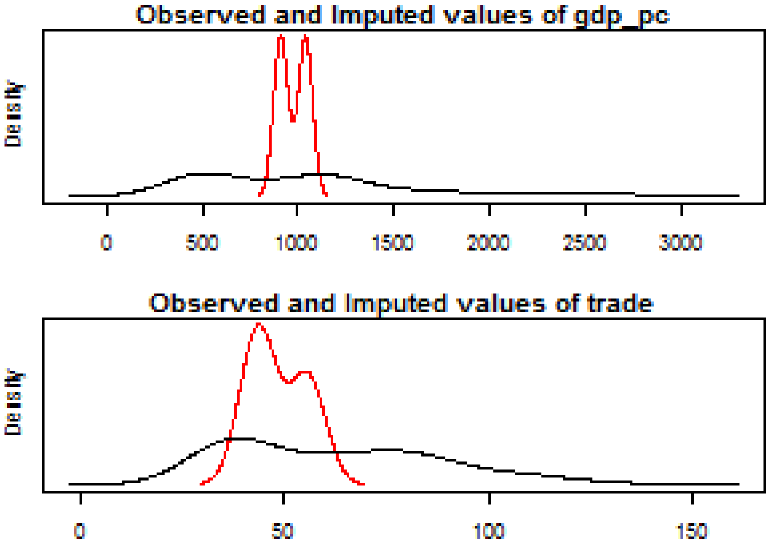

Figure : plot of chunk Amelia4

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- Not scalable

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- The algorithm will give draws from the posterior distribution of the missing values.
- It uses the model defined (whatever it is) to impute.

Large Data Sets: Bayes (continued)

Problems

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- Convergence can be tricky
- Expertise required for custom samplers, but libraries for implementing custom solutions: rcppbugs in R, others for C++, Python, etc.

Large Data Sets: Bayes (continued)

Example: Using Bayes for IRT on network links to generate DILS (data-informed link strength)

linkid	net1	net2	net3	...	netk
1	1	0	0	...	1
2	0	0	1	...	0
3	1	NA	1	...	1
4	1	0	NA	...	0
5	NA	0	0	...	1

becomes...

Large Data Sets: Bayes (continued)

Example: Using Bayes for IRT on network links to generate DILS (data-informed link strength)

linkid	dils
1	.12
2	.01
3	.34
4	.08
5	.03

Large Data Sets: Random Forest Classifier

Easy solution: use missForest

```
library(Amelia)  # to provide the data
data(africa)
library(missForest)

africa.rf <- missForest(africa)
```

```
##   missForest iteration 1 in progress...done!
##   missForest iteration 2 in progress...done!
##   missForest iteration 3 in progress...done!
##   missForest iteration 4 in progress...done!
##   missForest iteration 5 in progress...done!
```

- Keep **all** of the trees in the forest.

Large Data Sets: Random Forest Classifier

Easy solution: use missForest

```
library(Amelia)  # to provide the data
data(africa)
library(missForest)

africa.rf <- missForest(africa)
```

```
##   missForest iteration 1 in progress...done!
##   missForest iteration 2 in progress...done!
##   missForest iteration 3 in progress...done!
##   missForest iteration 4 in progress...done!
##   missForest iteration 5 in progress...done!
```

- Keep **all** of the trees in the forest.
- Aggregate as with other simulations

Large Data Sets: Random Forest Classifier (continued)

- Scales well.

Large Data Sets: Random Forest Classifier (continued)

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- Forest gives us reasonable measures of uncertainty.

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Large Data Sets: Random Forest Classifier (continued)

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- Forest gives us reasonable measures of uncertainty.
- Requires a **lot** of data (think non-parametric).
- Without care might give silly values.
- Still should check imputed distributions against observed distributions.

Real-Time: FastImputation

- Project: Improve fraud detection classifier

Real-Time: FastImputation

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- Same model as Amelia

Real-Time: FastImputation

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- Learns (slowly) using lots of data

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Real-Time: FastImputation

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- On CRAN
- Caveat emptor (as with all R packages)

Section 6

When Imputation Fails

To Imputate or Not?

- Assumptions of Imputation

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  - Data is MCAR or MAR+PD

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  - "Small" fraction of data missing

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  - Data is MCAR or MAR+PD
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    - $< 10\%$: usually no problem

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    - 10%-20%: Be careful

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    - *20%: There be dragons*

To Impute or Not?

- Assumptions of Imputation
  - Data is MCAR or MAR+PD
  - "Small" fraction of data missing
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    - 10%-20%: Be careful
    - *20%: There be dragons*
- Always* better than row deletion

What to Do When Imputation Fails

- Explicitly model the reason observations are missing

or

What to Do When Imputation Fails

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  - Tobit (incomes censored, displayed as zero)

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or

What to Do When Imputation Fails

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  - Tobit (incomes censored, displayed as zero)
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  - Abstentions in voting (more likely if you disagree with party)

  or
- Impute anyway and warn the consumer (worth considering)

Section 7

Fin

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- Great place to work: http://www.bericotechnologies.com
- Stephen Haptonstahl – srh@haptonstahl.org – @polimath