

# Simple Missing Data Treatments

## Utrecht University Winter School: Missing Data in R



**Utrecht  
University**

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# Outline

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## Bad Methods

- Deletion-Based Methods

- Deterministic Imputation Methods

## OK Methods

## Comparisons



# Bad Methods (These almost never work)

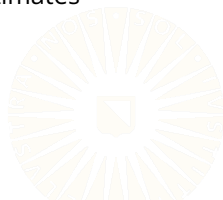
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## Listwise Deletion (Complete Case Analysis)

- Use only complete observations for the analysis
  - Very wasteful (can throw out lots of useful data)
  - Loss of statistical power

## Pairwise Deletion (Available Case Analysis)

- Use only complete pairs of observations for analysis
  - Different samples sizes for different parameter estimates
  - Can cause computational issues



# Example

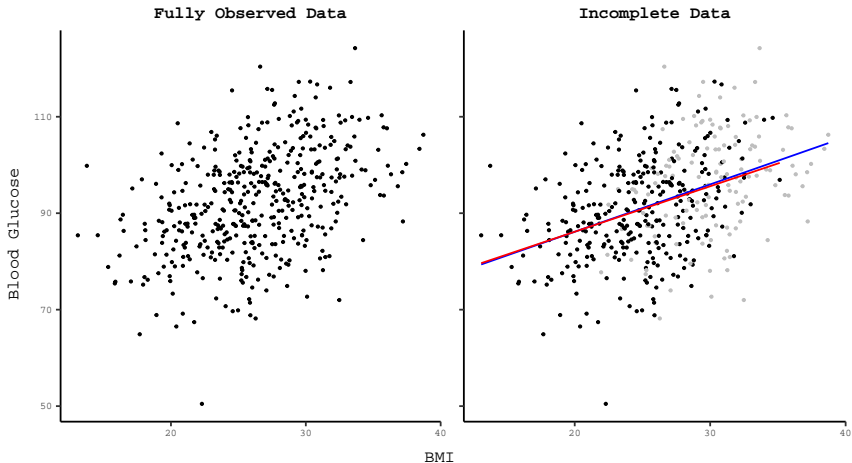
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```
## Read in some example data:
dat0 <- dat1 <- readRDS(paste0(dataDir, "diabetes_norm.rds"))

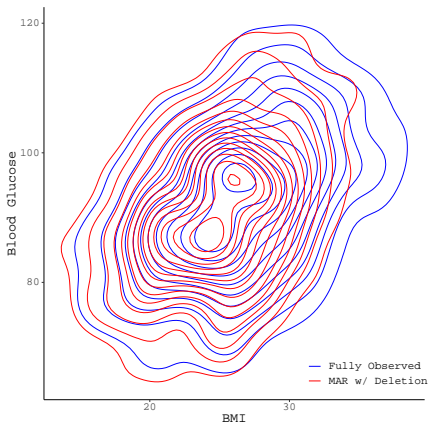
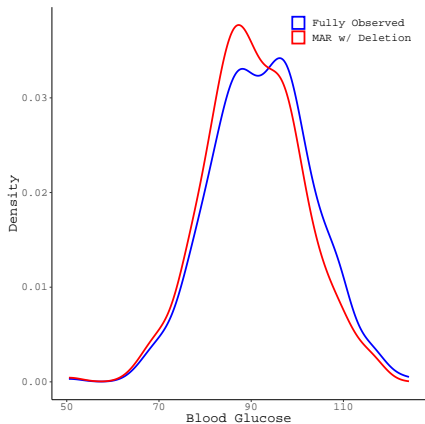
## Simulated missingness based on 'bmi':
m <- simLinearMissingness(data = dat1,
                           pm    = 0.30,
                           preds = "bmi",
                           auc   = 0.85)$r

## Impose missing on 'glu' according to the missingness above:
dat1[m, "glu"] <- NA
```

# Example



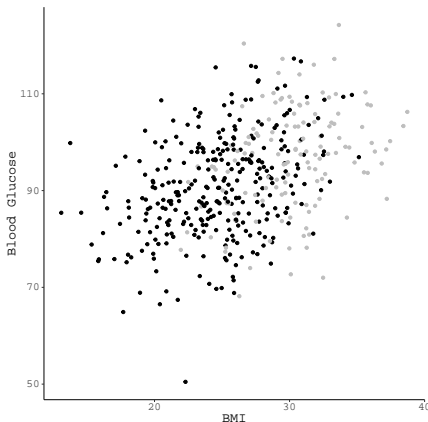
# Example



# Bad Methods (These almost never work)

## (Unconditional) Mean Substitution

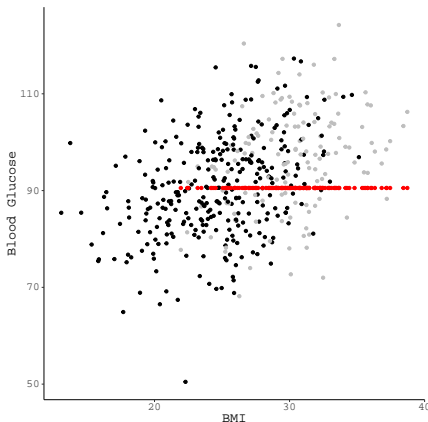
- Replace  $Y_{mis}$  with  $\bar{Y}_{obs}$ 
  - Negatively biases regression slopes and correlations
  - Attenuates measures of linear association



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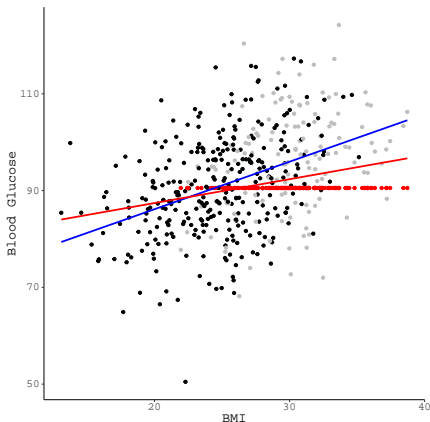




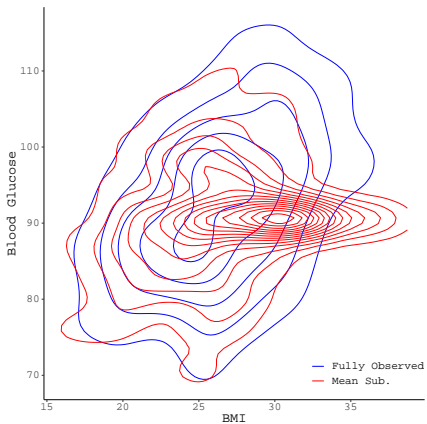
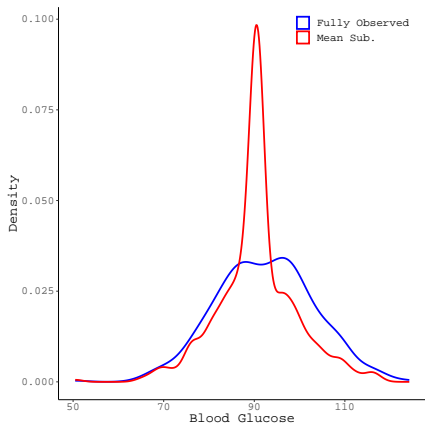
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# Example



# Implementation

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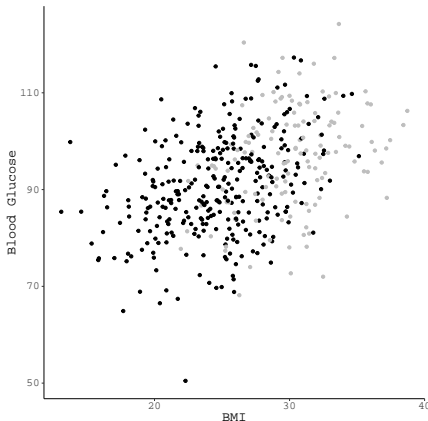
```
dat1[m, "glu"] <- mean(dat1$glu, na.rm = TRUE)

miceOut <- mice(data = dat1, m = 1, maxit = 1, method = "mean")
impData <- complete(miceOut, 1)
```

# Bad Methods ('These almost never work')

## Deterministic Regression Imputation (Conditional Mean Substitution)

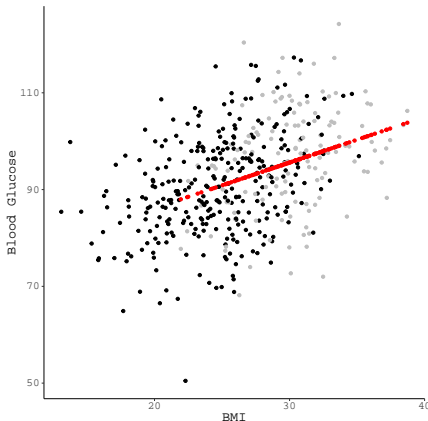
- Replace  $Y_{mis}$  with  $\hat{Y}_{mis}$  from some regression equation
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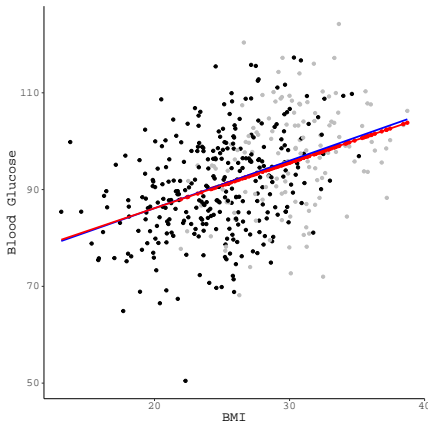
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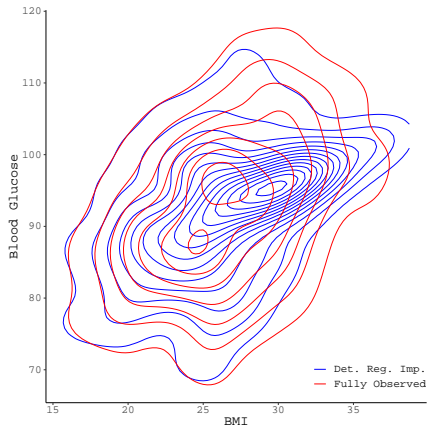
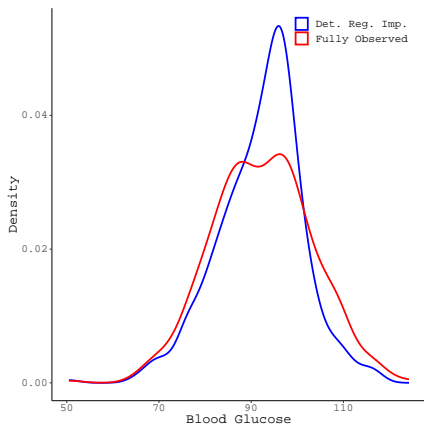
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# Example



# Implementation

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```
miceOut <- mice(data = dat1, m = 1, method = "norm.predict")  
impData <- complete(miceOut, 1)
```





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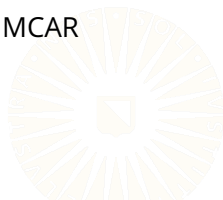
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## General Issues with Deletion-Based Methods

- Biased parameter estimates unless data are MCAR
- Generalizability issues

## General Issues with Simple Single Imputation Methods

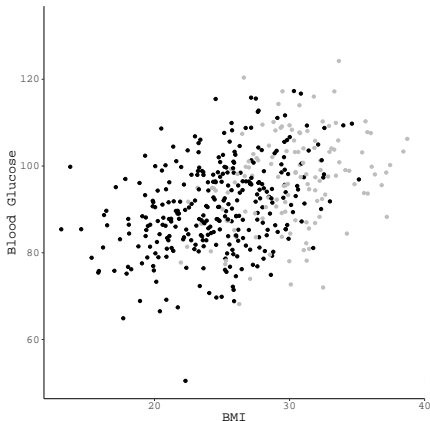
- Biased parameter estimates even when data are MCAR
- Attenuates variability in any treated variables



# OK Methods (These sometimes work)

## Stochastic Regression Imputation

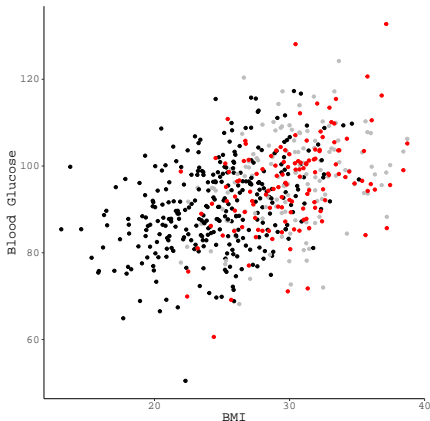
- Fill  $Y_{mis}$  with  $\hat{Y}_{mis}$  plus some random noise.
  - Produces unbiased parameter estimates and predictions
  - Computationally efficient
  - Attenuates standard errors
  - Makes CIs and prediction intervals too narrow



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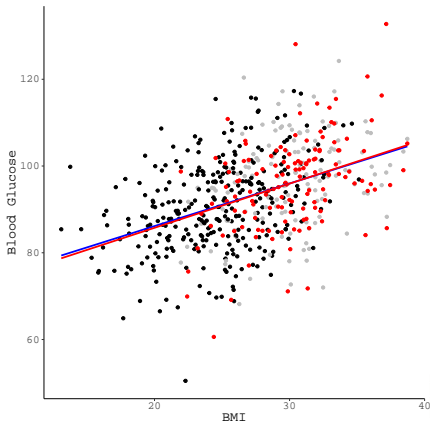
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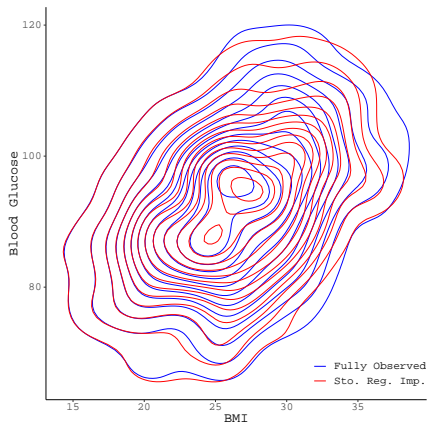
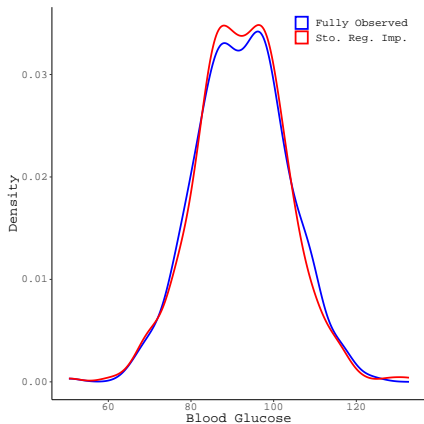
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# Example



# Implementation

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```
miceOut <- mice(data = dat1, m = 1, seed = 42, method = "norm.nob")  
impData <- complete(1)
```



# OK Methods (These sometimes work)

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## Nonresponse Weighting

- Weight the observed cases to correct for nonresponse bias
  - Popular in survey research and official statistics
  - Only worth considering with *Unit Nonresponse*
  - Doesn't make any sense with *Item Nonresponse*



# Comparison

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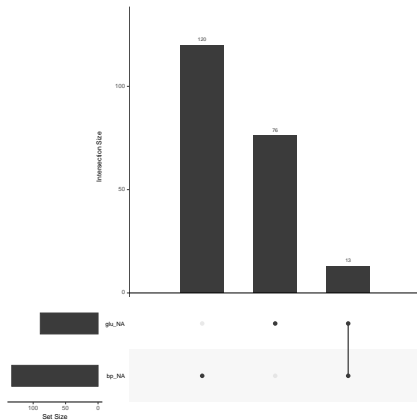
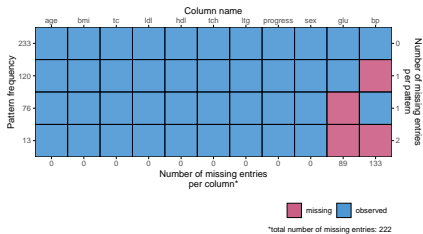
Run a Monte Carlo simulation to compare the treatments.

- Use the synthetic diabetes data as the population.
- Simulate MAR missingness.
  - Blood Glucose
    - $PM = 20\%$ ,  $P(M) \sim \{bmi, age\}$
  - Blood Pressure
    - $PM = 30\%$ ,  $P(M) \sim \{bmi, tc\}$
- Treat the missing data as above.
- Use the treated data to estimate several statistics.
- Repeat the process 250 times and pool the results.





# Comparison



# Comparison

	MS	DRI	SRI	CC	FO
glu	91.30	92.43	92.41	91.30	92.35
bp	97.29	95.50	95.55	97.29	95.50

Variable Means

	MS	DRI	SRI	CC	FO
glu	92.98	105.69	120.70	112.26	117.29
bp	117.22	139.89	175.35	158.40	177.85

Variable Variances

# Comparison

$$Y_{BP} = \beta_0 + \beta_1 X_{BMI} + \beta_2 X_{Glucose} + \beta_3 X_{Age} + \varepsilon$$

	MS	DRI	SRI	CC	FO
$\beta_0$	65.06	31.85	39.41	40.65	39.74
$\beta_{bmi}$	0.39	0.51	0.62	0.61	0.66
$\beta_{glu}$	0.16	0.44	0.32	0.32	0.30
$\beta_{age}$	0.16	0.19	0.22	0.19	0.22
$R^2$	0.12	0.37	0.26	0.21	0.25

Linear Regression Estimates

# Comparison

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	age	bmi	bp	tc	ltg
MS	29.46	15.42	25.29	92.26	1.74
DRI	44.53	21.78	66.47	118.07	2.32
SRI	43.99	21.66	61.16	118.12	2.32
CC	29.76	14.28	50.35	67.44	1.85
FO	40.52	21.19	58.19	107.83	2.28

Covariances with Blood Glucose



# Comparison

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	age	bmi	tc	ltg	glu
MS	33.11	12.29	34.57	1.51	25.29
DRI	54.20	22.46	92.89	2.54	66.47
SRI	54.19	22.27	90.86	2.54	61.16
CC	36.42	14.87	50.73	2.05	50.35
FO	52.50	22.65	86.00	2.60	58.19

Covariances with Blood Pressure

