

# Missing Value Imputation using Low-Rank and Low-Norm Models

Knowledge Lab Team Presentation

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# Introduction

- ▶ Missing data arise in almost all empirical analysis.
- ▶ Distracts from main goal of study.
- ▶ **Ad-hoc methods**
  - ▶ Complete case analysis.
  - ▶ Available case analysis.
  - ▶ Mean Imputation.
- ▶ Concerns about validity of inferences.
- ▶ **Types of Missing Data**
  - ▶ Missing Completely at Random.
  - ▶ Missing at Random.
  - ▶ Missingness depends on unobservables.

# Multiple Imputation

- ▶ Rubin (1976), Schafer (1998), Van Buuren et al (1999), King et al (2000, 2015)
- ▶ **Idea:** Analysis should reflect uncertainty inherent in imputation.
- ▶ **Assumption:** MAR
- ▶ 3 stage scheme
  - ▶ **Imputation**
  - ▶ **Analysis**
  - ▶ **Combining Results**
- ▶ Imputation Step:
  - ▶ Parametric Assumptions (like multivariate normality).
  - ▶ Iterative procedures used.

# Multiple Imputation

- ▶ **Two Standard Imputation Approaches:**

- ▶ MCMC mechanism:  $(Y_{miss}^{(1)}, \theta^{(1)}), (Y_{miss}^{(2)}, \theta^{(2)}), \dots$
- ▶ Chained Equations: iteratively fit univariate regression models.

- ▶ **Analysis:** perform as if full data is observed.

- ▶ **Combining Results:**

- ▶ **Point Estimate:**  $\bar{Q} = \frac{1}{m} \sum_{i=1}^m \widehat{Q}_i$  ;  $\widehat{Q}_i$  = point estimate from imputation  $i$ .

- ▶ **Variance:**  $T = \bar{U} + (1 + \frac{1}{m}) B$  ;  $U$  = within imputation variance ;  $B$  = between imputation variance.

- ▶ 'R' Packages: Amelia, MICE, MI.

# Low Norm and Low Rank Models

- ▶ Matrix Factorization approaches.
- ▶ Srebro (2004), Udell et al (2014).
- ▶ Approximate matrix  $A$  ( dimension  $m \times n$ ) by  $X'Y$ .
- ▶ minimize  $\sum_{i,j} L_{i,j}(x_i y_j, a_{ij}) + \sum_{i=1}^m r_i(x_i) + \sum_{j=1}^n r_j(y_j)$ .
  - ▶  $L$ : Loss function (over columns).
  - ▶  $r(\cdot)$  : regularization functions.
  - ▶  $X, Y$  initialization: SVD good starting point.
  - ▶ **Low Norm Models:**  $r(x) = \gamma \|X^2\|$ .
  - ▶ **Low Rank Models:**  $\text{Rank}(X'Y) \leq k$ .
  - ▶ **Low Rank, Low Norm Models:** Both
  - ▶  $k, \gamma$  chosen via crossvalidation.
- ▶ Julia Implementation: LowRankModels

Dataset with missing values

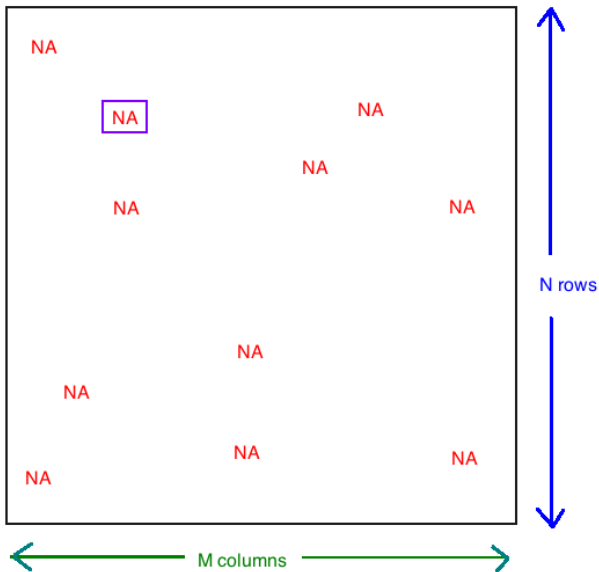
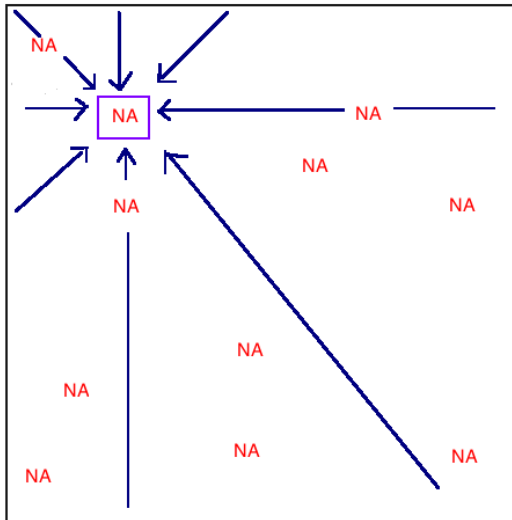


Diagram illustrating a vertical queue structure. A vertical container (queue) is shown with a red box at the top. Arrows point to the red box from the left and right. The text "NA" is written in red in the top-left, top-right, and inside the red box. The text "NA" is written in black in the bottom-left, bottom-right, and in the center. The text "NA" is written in red in the middle-left and middle-right.

M columns    N rows

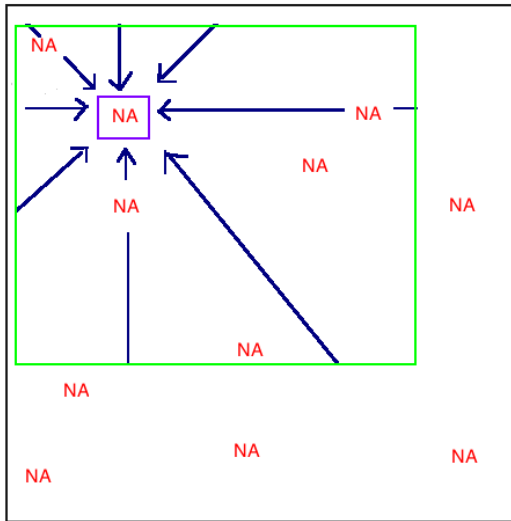
## Low Norm Models



M columns N rows



## Low Rank Models



M columns N rows

# Application 1: General Social Survey Data (GSS)

- ▶ Sociological survey: adults in randomly selected US households.
- ▶ Data on attitudes and demographic characteristics of adults.
- ▶ **Subset of GSS 2014 data used for analysis**
  - ▶ columns corresponding to identifying variables
  - ▶ columns with non-varying entries
  - ▶  $\geq 33\%$  missing entries
  - ▶ highly correlated columns ( $\rho > 0.70$ ).
- ▶ **Evaluation Strategy**
  - ▶ 10% of observed data are randomly assumed missing ( $N_{miss,ind}$ )
  - ▶ Imputations using
    - ▶ **Low Rank (Scaled), Low Rank (Unscaled), Trace Norm (Full Rank), Trace Norm (Low Rank), MICE.**
  - ▶ Loss calculated over  $N_{miss,ind}$  observations:
    - ▶ **scale columns, quadratic loss over non-categorical columns, zero-one loss over categorical columns.**

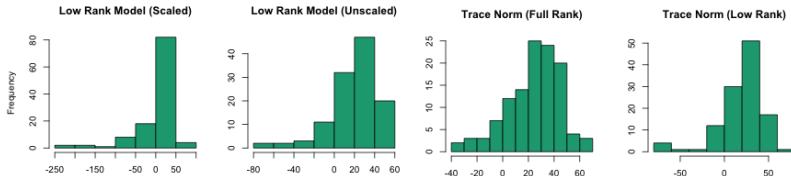
# Results

- ▶ Overall Trace (Full Rank) had lowest loss, all Low Rank and Low Norm models outperformed MICE
- ▶ Column-wise:  $\approx 80\%$  columns had lower loss compared to MICE

## ▶ Summary Table

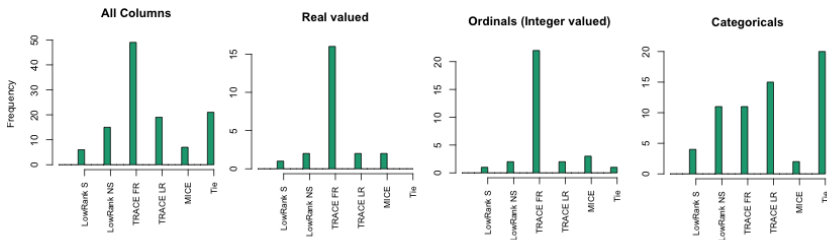
	LowRank (S)	LowRank (NS)	Trace (FR)	Trace (LR)	MICE
Scaled Loss/( $10^3$ )	18.50	15.80	14.40	15.80	20.60
%age reduction over MICE	10.10 %	23.40 %	30.10 %	23.00 %	—
%age cols w/ lower loss	73.50 %	84.60 %	87.20 %	84.60 %	—

## ▶ Columnwise percentage reduction in Loss over MICE

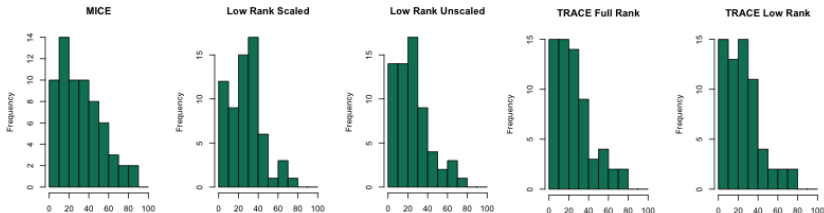


# Results

## ► Method with lowest loss across columns



## ► Categorical columns misclassification by method



## Next Steps

- ▶ Replicating missingness patterns before applying imputation techniques.
- ▶ Extending and applying to longitudinal survey data (e.g. National Longitudinal Survey of Youth).
- ▶ Applying to larger subsets of GSS data.
- ▶ Working with more advanced options of MICE and LowRankModels.
- ▶ Extending to Max and Frobenius norms.
- ▶ Extending Low Rank and Low Norm methods to Multiple Imputation setting.

Thank you!  
(Comments and Suggestions Welcome)