Supporting Manual for:

NAguideR: performing and prioritizing missing value imputations

for consistent bottom-up proteomic analyses

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Table 1. Description of 20 missing value imputation methods.

Class	Abbrevia	Manipulation	Remark	Function	Package/Refer
	tion zero	Method zero	Replaces the missing values by 0.	0	base (1)
	minimu m	minimum	Replaces the missing values by the smallest non-missing value in the data.	min	base (2)
	colmedia n	Column median	Replaces the missing values by the median of non-missing value in each column.	impute	e1071 (3)
	rowmedi an	Row median	Replaces the missing values by the median of non-missing value in each row.	impute	e1071 (3)
	SVD	Singular value decompositio n imputation	Initializes all missing elements with zero then estimate them as a linear combination of the k most significant eigen-variables iteratively until reaches certain convergence threshold.	svdPca	pcaMethods (4)
Fast	KNN	K Nearest Neighbors imputation	K-nearest neighbors in the space of peptides/proteins to impute missing expression values.	impute.knn	impute (4)
	Seq-KN N	Sequential K-nearest neighbor	Imputes the missing values sequentially from the peptide/protein having least missing values based on KNN method, and uses the imputed values for the later imputation.	SeqKNN	SeqKnn (5)
	LLS	Local least squares imputation	K variables (peptides/ proteins) are selected by Pearson, spearman or Kendall correlation coefficients. Then missing values are imputed by a linear combination of the k selected variables. The optimal combination is found by LLS regression.	llsImpute	pcaMethods (6)
	QR	Quantile regression imputation of left-censored data	A missing data imputation method that performs the imputation of left-censored missing data using random draws from a truncated	impute.QRILC	imputeLCMD (7)

		distribution with parameters		
		estimated using quantile		
	Imputation	regression.		
MLE	based on maximum likelihood estimation	Maximum likelihood-based imputation method using the EM algorithm.	prelim.norm, em.norm, imp.norm	norm (8)
Mindet	Deterministic minimum imputation	Perform the imputation of left-censored missing data using a deterministic minimal value approach. Considering an expression data with n samples and p features, for each sample, the missing entries are replaced with a minimal value observed in that sample. The minimal value observed is estimated as being the q-th quantile of the observed values in that sample.	impute.MinDet	imputeLCMD (9)
Minprob	Probabilistic minimum imputation	Performs the imputation of left-censored missing data by random draws from a Gaussian distribution centred to a minimal value. Considering an expression data matrix with n samples and p features, for each sample, the mean value of the Gaussian distribution is set to a minimal observed value in that sample. The minimal value observed is estimated as being the q-th quantile of the observed values in that sample. The standard deviation is estimated as the median of the feature standard deviations.	impute.MinPro b	imputeLCMD (9)
Impseq	Sequential imputation of missing values	Estimates sequentially the missing values in an incomplete observation by minimizing the determinant of the covariance of the augmented data matrix. Then the observation is added to the complete data matrix and	impSeq	rrcovNA (10)

		Dolorest	the algorithm continues with the next observation with missing values.		
	Impseqr ob	Robust sequential imputation of missing values	Similar to Impseq, but improved by plugging in robust estimators of location and scatter.	impSeqRob	rrcovNA (11)
	Mice-nor m	Multivariate Imputation by Chained Equations- Bayesian linear regression	Generates multiple imputations for incomplete multivariate data by Gibbs sampling. Missing data can occur anywhere in the data. The algorithm imputes an incomplete column (the target column) by generating 'plausible' synthetic values given other columns in the data. Each incomplete column must act as a target column, and has its own specific set of predictors. The default set of predictors for a given target consists of all other columns in the data. For predictors that are incomplete themselves, the most recently generated imputations are used to complete the predictors prior to imputation of the target column. The imputation method depends on Bayesian linear regression.	mice (method='nor m')	mice (12)
	BPCA	Bayesian PCA missing value estimation	An iterative method using a Bayesian model to handle missing values.	bpca	pcaMethods (13)
Slow	trKNN	Truncation k-nearest neighbors imputation	Applies a Newton-Raphson (NR) optimization to estimate the truncated mean and standard deviation. Then, Pearson correlation was calculated based on standardized data followed by correlation-based kNN imputation.	sim_trKNN_wr apper	Imput_funcs.R (14)
	IRM	Iterative	In each step of the iteration, one	irmi	VIM (15)

	robust model-based imputation	variable is used as a response variable and the remaining variables serve as the regressors.		
Mice-car t	Multivariate Imputation by Chained Equations- classification and regression trees	Generates multiple imputations for incomplete multivariate data by Gibbs sampling. Missing data can occur anywhere in the data. The algorithm imputes an incomplete column (the target column) by generating 'plausible' synthetic values given other columns in the data. Each incomplete column must act as a target column, and has its own specific set of predictors. The default set of predictors for a given target consists of all other columns in the data. For predictors that are incomplete themselves, the most recently generated imputations are used to complete the predictors prior to imputation of the target column. The imputation method depends on classification and regression trees.	mice (method='cart')	mice (12)
RF	Random forest	Imputes missing values particularly in the case of mixed-type data based on a random forest. It can be used to impute continuous and/or categorical data including complex interactions and nonlinear relations. It yields an out-of-bag (OOB) imputation error estimate.	missForest	missForest (16)

Supplementary notes

NAguideR integrates up to 20 common missing value imputation methods (described in Table S1) and provides two categories of evaluation criteria (four classic computational criteria and four common knowledge-based proteomics criteria) to assess the imputation performance of various methods. Here we present the detailed introduction and operation of NAguideR, users can follow this manuscript to analyze their own data freely and conveniently.

Users can visit this site: http://www.omicsolution.org/wukong/NAguideR. Then the website homepage can be shown like this:



~~ Dear Users, Welcome to NAguideR ~~

NAguideR is a web-based tool, which integrates 20 common missing value imputation methods and provides two categories of evaluation criteria (4 classic criteria and 4 proteomic criteria) to assess the imputation performance of various methods. We hope this tool could help scientists impute the missing values systematically and present valuable guidance to select one proper method for their own data. In addition, this tool supports both online access and local installation.



Basically, there are four main steps in NAquideR:

- 1. Uploading proteomics expression data and sample information data;
- 2. Data quality control;
- 3. Missing value imputation;
- 4. Performance evaluation;

After this, NAguideR can provide valuable guidance for users to select one proper method for their own data based on the evaluation results. Detailed introduction can be found in the *Help* part.

Finally, NAguideR is developed by R shiny (Version 1.3.2), and is free and open to all users with no login requirement. It can be readily accessed by all popular web browsers including Google Chrome, Mozilla Firefox, Safari and Internet Explorer 10 (or later), and so on. We would highly appreciate that if you could send your feedback about any bug or feature request to Shisheng Wang at wssdandan2009@outlook.com.

^_^ Enjoy yourself in NAguideR ^_^

1. Data Preparation

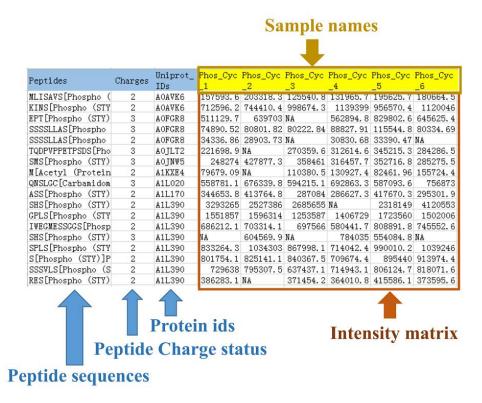
NAguideR supports four basic file formats (.csv, .txt, .xlsx, .xls). Before analysis, users should prepare two required data: (1) Proteomics expression data and (2) Sample information data. The data required here could be readily generated based on results of several popular tools such as MaxQuant, PEAKS, Spectronaut, and so on. Then can upload the two data into NAguideR with right formats respectively and start subsequent analysis.

1.1 Expression data

There are four types of proteomics expression data supported in NAguideR, among which the main differences are the first few columns.

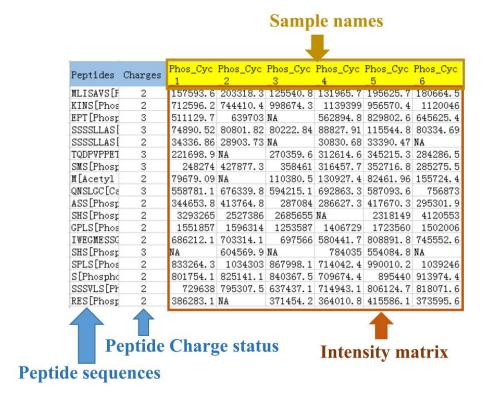
1.1.1 Expression data with peptide sequences, peptide charge status, and protein ids

In this situation, peptide sequences, peptide charge status, and protein ids are sequentially provided in the first three columns of input file. Peptide sequences in the first column can be peptides with post-translational modification (PTM) or stripped peptides (without PTM). The second column is peptide charge status. The protein ids in the third column should be UniProt ids. From the fourth column on, they are peptides/proteins expression intensity in every sample. The data structure is shown as below:



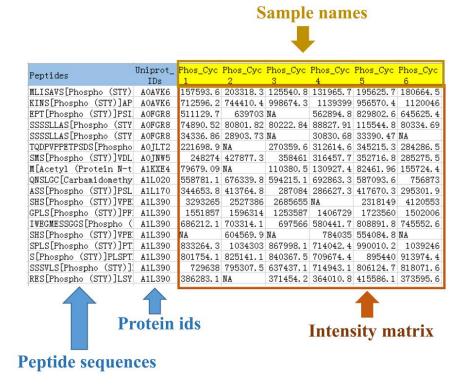
1.1.2 Expression data with peptide sequences and peptide charge status

Similar to the above situation, peptide sequences and peptide charge status are sequentially provided in the first two columns of input file. Peptide sequences in the first column can be peptides with post-translational modification (PTM) or stripped peptides (without PTM). The second column is peptide charge status. From the third column on, they are peptides/proteins expression intensity in every sample. The data structure is shown as below:



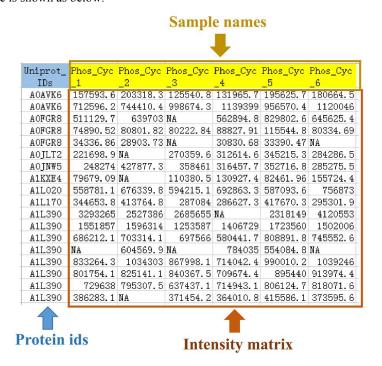
1.1.3 Expression data with peptide sequences, and protein ids

Under this circumstance, peptide sequences, and protein ids are sequentially provided in the first two columns of input file. Peptide sequences in the first column can be peptides with post-translational modification (PTM) or stripped peptides (without PTM). The protein ids in the second column should be UniProt ids. From the third column on, they are peptides/proteins expression intensity in every sample. The data structure is shown as below:



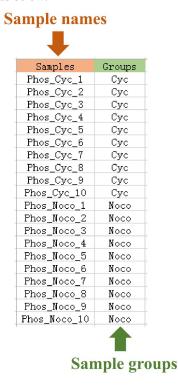
1.1.4 Expression data with protein ids

In this situation, protein ids are provided in the first two columns of input file. The protein ids here should be UniProt ids. From the second column on, they are peptides/proteins expression intensity in every sample. The data structure is shown as below:



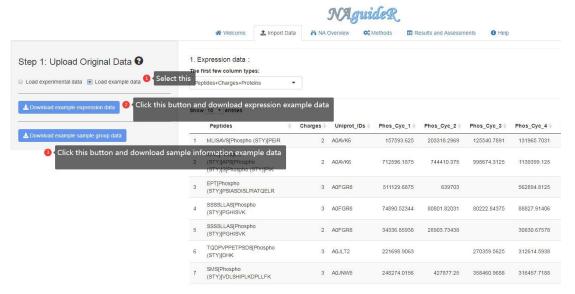
1.2 Samples information data

Sample information here means users should identify sample group information. The sample names are in the first column and their orders are same as those in the expression data. Group information is in the second column. The data structure is shown as below:



1.3 Download example datasets

If users want to download the example datasets to their own computer and check the data format locally, they can download them from here:



First, select "Load example data" and the example data will be shown on the right panel interactively. Users can visually observe what the data looks like.

Second, users can download the example data (expression data and sample information data) by clicking the corresponding button. The data are save as .csv format and users can open them in other software, such as Excel.

2. Import data.

This is the first step, users should upload data here or load the example data to learn the data formats. By default, we use the example data to show each result of every step.

2.1 Uploading data. When users prepare their data (expression and sample information data set), they can upload these data from here:



There are two main panels: first, *parameters panel*, users can adjust some parameters here; second, *results panel*, many results after users set the parameters will be shown here and users can also download these results.

In the parameters panel of "Import Data", there are two choices for users:

a. Load experimental data. When users choose this option, they can upload their own data from here. Users should select the right format based on their own data and then click "Browse" button to import the data;

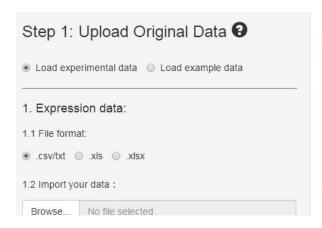
First row as column names: this means whether the first row is column names. If true, you should choose this parameter.

First column as row names: this means whether the first column is row names. If true, you should choose this parameter.

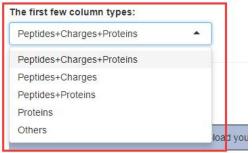
b. Load example data. As described in part 1.3, users can choose this option and download the example data to check them locally.

In the *results panel* of "Import Data", if users don't upload their data, here will show "NAguideR detects that you do not upload your data. Please upload the expression data (or sample information data), or load the example data to check first" to warn users.

Before uploading expression data, users should also recognize which type their data belongs to and choose the right parameter by adjusting the "*The first few column types*". The instruction of the column types can be found above (part 1).



1. Expression data:



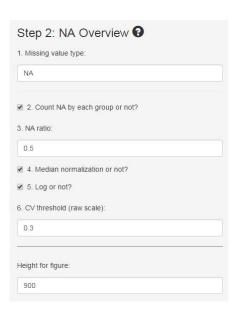
Showing 1 to 1 of 1 entries

3. NA Overview

Users can check the missing value situation of their own data and filter those data with high proportion of missing value in this step. NA is short for Not Available, which means missing value here.



3.1 Parameters



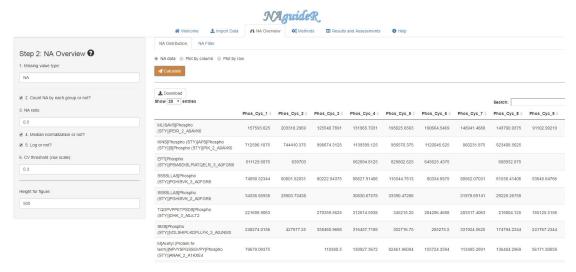
- 1. Missing value type: what the missing values look like in the expression data, for example, Spectronaut (17,18) software usually export "Filtered" as missing values, so users should change this parameter to "Filtered" if their data contain "Filtered". NAguideR will recognize these characters and replace them with NAs.
- 2. Count NA by each group or not: if true, NAguideR will count the number of missing value by each group and calculate the NA ratio, otherwise, calculate the NA ratio across all groups, for example, as below:



There are 2 groups (10 biological replicates in each group) here, if users select this parameter, NAguideR will calculate 2 NA ratios for this peptide (first group: 1/10=0.1, second group: 5/10=0.5), otherwise, only one NA ratio: 6/20=0.3.

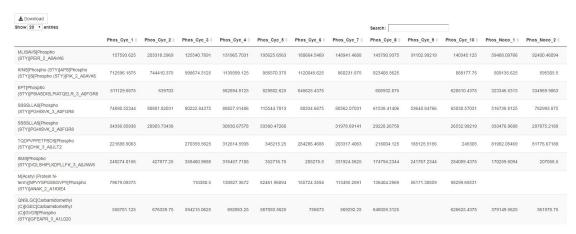
- 3. NA ratio: the threshold of NA ratio. Those peptides/proteins with NA ratio above this threshold will be removed.
- 4. Median normalization or not: if true, NAguideR will process median normalization for original data.
- 5. Log or not: if true, the data will be logarithmic with base 2.
- 6. CV threshold (raw scale): the threshold of coefficient of variation. Those peptides/proteins with NA ratio above this threshold will be removed. "raw scale" here means the CV of each peptide/protein is calculate using the data before logarithm transformation.
- 7. Height for figure: users can adjust the height of figures by changing this parameter.

If users set these parameters well, then click "calculate" button, the results will appear on the right panel.

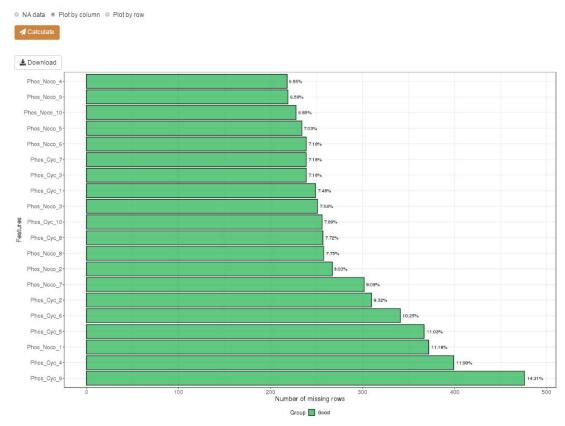


3.2 results

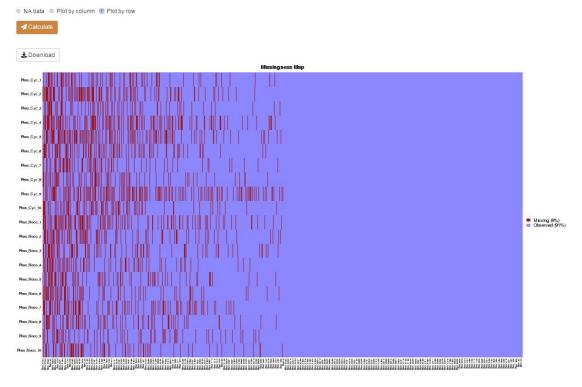
- a. NA Distribution. This part contains three sub-parts:
- a.1 NA data. Here shows the result where the "Missing value type" will be replaced with NA and users can click "Download" button to download this result to their own computer:



a.2 Plot by column. Here shows the result of the NA distribution of every sample.



a.2 Plot by row. Here shows the result of the NA distribution of every peptide/protein.



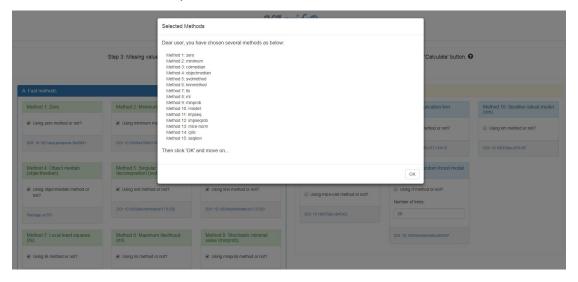
b. NA filter. This part will show the filtered result.

4. Methods

In this step, users can choose or cancel any missing value imputation method. With regard to the running time, we set these fast methods (left part, 15 methods) chosen by default. If users choose those slow methods (right part, 5 methods), that means the running time will be longer. By default, the fast methods are selected. If users want to try these slow methods, they just select the corresponding methods. The detailed information about each method can be found in Table S2. In addition, we also provide the reference for every method just blow each option on the web:

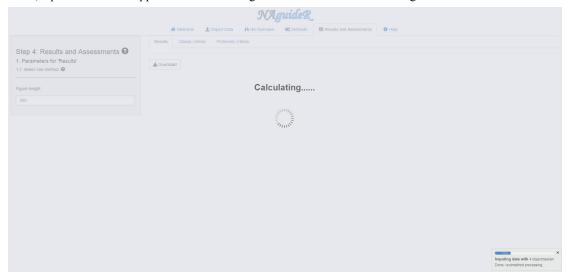


After selecting suitable methods, users need to click 'Calculate' button, and a popup window will be jumped out to show the selected methods, then click 'OK' button and continue:

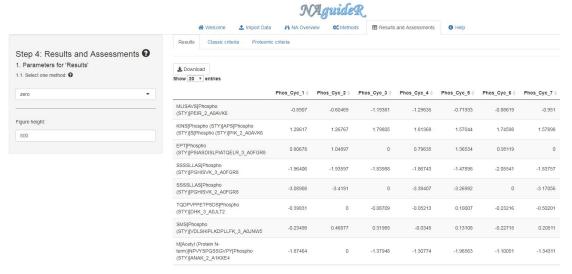


5. Results and Assessments

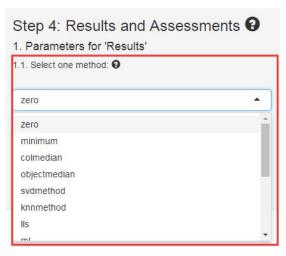
This step will process missing value imputation and performance evaluation of every method that users select in "Methods" step. Click "Results and Assessments", NAguideR will start to impute these missing value, a process bar will appear in the bottom right corner to tell users where it goes:



The result from every imputation method will be shown on the "Results" panel:



Users can change the parameter "Select one method" on the left panel to check relative result, for example, if users select "zero", it will show the result derived from zero method:



Next, click "Classic criteria" and "Calculate" button. NAguideR will assess every method under the four classic criteria:



The tables and figures are provided here under the four classic criteria.

- 1. This table shows the comprehensive ranks of every imputation method;
- 2-5, the tables show the scores of every imputation method based on 'Normalized root mean squared Error (NRMSE)', 'NRMSE-based sum of ranks (SOR)', 'Procrustes sum of squared errors (PSS)', and 'Average correlation coefficient between original value and imputated value (ACC_OI)', respectively;
- 6. Figures here show the normalized scores of every imputation method under the four classic criteria. 'Normalized Values' here means every score divides by corresponding max value.

1. Comprehensive ranks under classic criteria:

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how 20 * entries						Search:	
	Methods	φ	NRMSE_Rank (SOR_Rank	ACC_OI_Rank (PSS_Rank (Rank_Mean
Method 2	impseq		1	1	1	.1	
Method 3	impseqrob		2	2	2	2	
Method 13	seqknn		4	3	3	6	
Method 10	ml		3	6	5	3	4.2
Method 4	knnmethod		5	4	4	5	4.
Method 5	lis		6	5	6	4	5.2
Method 6	mice-norm		7	7	7	7	
Method 11	objectmedian		8	8	8	8	
Method 12	qrilc		9	10	9	11	9.7
Method 14	sydmethod		10	9	10	12	10.2
Method 1	colmedian		11	12	11	10	1
Method 15	zero		12	11	12	9	1
Method 7	mindet		13	13	13	13	11
Method 9	minprob		14	14	14	14	1-
Method 8	minimum		15	15	15	15	1

Normalized root mean squared Error (NRMSE):	
	Normalized root mean squared Error (NRMSE)

♣ Download Show 20 ▼ entries Method 11 0.07796 Method 12 0.07814 Method 8 Method 15 ml 0.10625 0.11049 Method 6 0.11513 Method 7 0.1237 Method 13 mice-norm 0.16857 Method 4 Method 14 0.8632 Method 5 Method 3 0.93162 colmedian 1.00393 zero mindet minprob minimum Method 1 Method 10 Method 9

Method 2 Showing 1 to 3.28021 Next

ing 1 to 15 of 15 entries	Previous	1	N
ocrustes sum of squared errors (PSS):			

≛ Download			
Show 20 v entries		Search:	
	Methods		PSS
Method 11	impseq		0.00048
Method 12	impseqrob		0.00051
Method 8	ml		0.00064
Method 7	lls		0.00094
Method 6	knnmethod		0.00109
Method 15	seqknn		0.00129
Method 13	mice-norm		0.00556
Method 4	objectmedian		0.02591
Method 1	zero		0.05313
Method 3	colmedian		0.05389
Method 14	qrilc		0.05468
Method 5	svdmethod		0.06779
Method 10	mindet		0.10707
Method 9	minprob		0.10904
Method 2	minimum		0.13141

3. NRMSE-based sum of ranks (SOR):

▲ Download

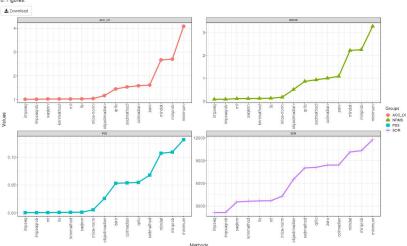
Show 20 * entries		Search:		
	Methods	\$	SOR	
Method 11	impseq		2122	
Method 12	Impseqrob		2142	
Method 15	seqknn		3536	
Method 6	knnmethod		3625	
Method 7	IIs		3676	
Method 8	mi		3696	
Method 13	mice-norm		4296	
Method 4	objectmedian		6526	
Method 5	sydmethod		8030	
Method 14	qrilc		8110	
Method 1	zero		8406	
Method 3	colmedian		8418	
Method 10	mindet		10135	
Method 9	minprob		10313	
Method 2	minimum		11769	

5. Average correlation coefficient between original value and imputated value (ACC_0I):

± Download

1.08355 2.2209 2.25375

	Show 20 ▼ entries		Search:	
PSS (Methods		Cor_mean
0.00048	Method 11	impseq		0.98755
0.00051	Method 12	impsegrob		0.98748
0.00064				
0.00094	Method 15	seqknn		0.9757
0.00109	Method 6	knnmethod		0.975
0.00129	Method 8	ml		0.97447
0.00123	Method 7	lls		0.97116
	Method 13	mice-norm		0.95947
0.02591	Method 4	objectmedian		0.8567
0.05313	Method 14	qrilc		0.69105
0.05389	Method 5	sydmethod		0.653
0.05468	Method 3	colmedian		0.63258
0.06779	Method 1	zero		0.62062
0.10707	Method 10	mindet		0.37464
0.10904				
0.13141	Method 9	minprob		0.37038
Previous 1 Next	Method 2	minimum		0.24487



Then click "Proteomic criteria" and "Calculate" button. NAguideR will assess every method under the four proteomic criteria:



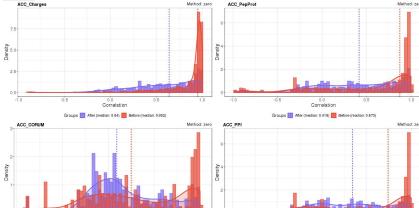
The tables and figures are provided here under the four proteomic criteria.

- 1. This table shows the comprehensive ranks of every imputation method;
- 2-5, the tables show the scores of every imputation method based on 'Average correlation coefficient between peptides with different charges (ACC_Charge)', 'Average correlation coefficient between peptides in a same protein (ACC_PepProt)', 'Average correlation coefficient between protein complexes (ACC_CORUM)', 'Average correlation coefficient between protein complexes (ACC_PPI)', respectively;
- 6. Figures here show the correlation coefficient distribution of the original values and the imputed values from every imputation method under the four proteomic criteria.

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Show 20 * entr	ries					Search:	
	Methods	¢	Charge_Rank	PepProt_Rank	CORUM_Rank	PPI_Rank	Rank_Mean (
Method 4	knnmethod		2	1	1	2	1.5
Method 13	seqknn		1	2	4	1	2
Method 2	impseq		3	3	2	3	2.75
Method 3	impsegrob		4	4	3	4	3.75
Method 5	lls		5	5	6	5	5.25
Method 10	ml		6	6	5	6	5.75
Method 6	mice-norm		7	7	7	7	7
Method 11	objectmedian		8	8	8	8	8
Method 12	qrilc		9	9	9	11	9.5
Method 14	sydmethod		10	10	10	9	9.75
Method 1	colmedian		11	11	12	10	11
Method 15	zero		12	12	11	12	11.75
Method 7	mindet		13	13	13	13	13
Method 9	minprob		14	14	14	14	14
Method 8	minimum		15	15	15	15	15

2. Average correlation coefficient between peptides with different charges (ACC_Charge): 3. Average correlation coefficient between peptides in a same protein (ACC_PepProt): ♣ Download
Show 20 ▼ entries ♣ Download
Show 20 ▼ entries Search: ACC_Charge ACC_peppro Method 15 seqknn 0.84803 knnmethod 0.54888 Method 6 Method 6 0.54877 0.84666 Method 15 seqknn Method 11 impseq 0.84525 Method 11 impseq 0.54602 Method 12 0.84508 0.54588 Method 12 impsegrot Method 7 0.84018 Method 7 0.54151 Method 8 0.83723 0.54064 Method 8 Method 13 0.82996 Method 13 mice-norm 0.53333 0.47951 Method 4 0.73897 Method 4 Method 14 qrilc 0.62586 Method 14 qriic 0.40258 0.38689 Method 5 0.60933 Method 5 0.37715 Method 3 0.59157 Method 3 Method 1 0.58832 0.37693 Method 10 0.43458 0.27806 Method 10 Method 9 0.42645 0.27274 Method 9 Method 2 Method 2 0.22728 Showing 1 to 15 of 15 entries Previous 1 Next Previous 1 Next Showing 1 to 15 of 15 entries Average correlation coefficient between protein complexes (ACC_CORUM): 5. Average correlation coefficient between protein complexes (ACC_PPI): **≛** Download **≛** Download Show 20 v entries Show 20 * entries ACC_CORUM ACC_PPI Method 6 0.30498 seqknn 0.48217 Method 11 0.30475 0.48201 Method 12 0.30471 0.48111 Method 15 0.48108 Method 8 0.29933 IIs 0.4779 Method 7 0.29666 0.47428 Method 13 0.29583 mice-norm 0.46884 Method 4 0.2485 0.41256 Method 14 qriic 0.21802 Method 5 sydmethod 0.35871 Method 5 0.19725 Method 3 0.34504 Method 1 zero Method 14 0.19269 0.33687 Method 3 0.18941 Method 1 0.33539 Method 10 Method 10 mindet 0.15264 0.22936 Method 9 0.15054 Method 9 0.22714 Method 2 0.127 Method 2 0.18582 Previous 1 Next Previous 1 Next 6. Figures: **≛** Dov ACC_Charges ACC_PepProt



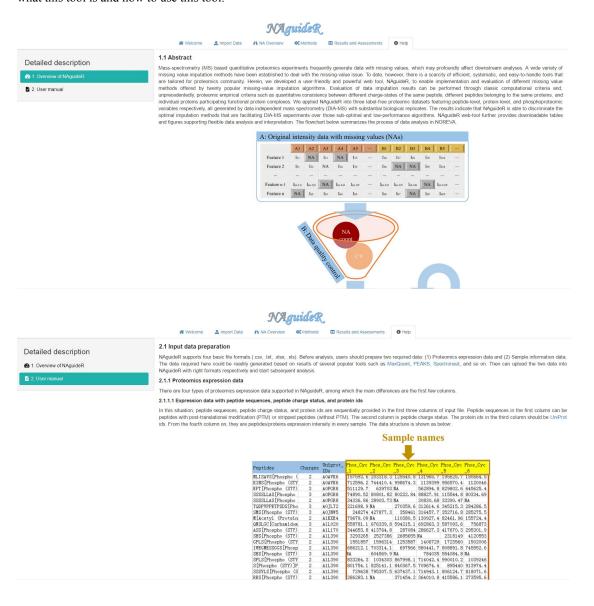
-0.5 0.0 0.5 Correlation
Groups After (median: 0.09) Before (median: 0.249)

0.0 Correlation

Groups 🔝 After (median: 0.34) 🧾 Before (median: 0.739)

6. Help

This part provides some introduction and operation manual about NAguideR, so that users can quickly learn what this tool is and how to use this tool.



7. How to run this tool locally?

NAguideR is an open source software for non-commercial use and all codes can be obtained on our GitHub: https://github.com/wangshisheng/NAguideR. If users want to run *NAguideR* on their own computer, they should operate as below:

- 7.1 As this tool was developed with R, you may:
- a) Install R. You can download R from here: https://www.r-project.org/.
- b) Install RStudio. (Recommendatory but not necessary). You can download RStudio from here: https://www.rstudio.com/.
- c) Check packages. After installing R and RStudio, you should check whether you have installed these packages (shiny, shinyBS, shinyjs, shinyWidgets, DT, gdata, ggplot2, ggsci, openxlsx, data.table, DT, raster, Metrics, vegan, tidyverse, ggExtra, cowplot, Amelia, e1071, impute, SeqKnn, pcaMethods, norm, imputeLCMD, VIM, rrcovNA, mice, missForest). You may run the codes below to check them:

```
if(!require(pacman)) install.packages("pacman")
pacman::p_load(shiny, shinyBS, shinyjs, shinyWidgets, DT, gdata, ggplot2, ggsci,
openxlsx, data.table, DT, raster, Metrics, vegan, tidyverse, ggExtra, cowplot,
Amelia, e1071, impute, SeqKnn, pcaMethods, norm, imputeLCMD, VIM, rrcovNA, mice,
missForest)
```

Please note, you may find the SeqKnn package (https://github.com/cran/SeqKnn) can not be installed rightly as it has not been updated for a long time. If so, please download this package from here: https://github.com/wangshisheng/NAguideR/blob/master/SeqKnn_1.0.1.tar.gz. Then you can install this package locally:

```
setwd('path') #path is where the two packages are.
install.packages("SeqKnn_1.0.1.tar.gz", repos = NULL, type="source")
```

d) Run this tool locally

```
if(!require(NAguideR)) devtools::install_github("wangshisheng/NAguideR")
library(NAguideR)
NAguideR_app()
```

Then NAguideR will be started as below, and the detailed operation about NAguideR can be found in the Supplementary Notes part 1-6:



1 Import Data

NA Overview

Methods

Results and Assessments

1 Help

~~ Dear Users, Welcome to NAguideR ~~

NAguideR is a web-based tool, which integrates 20 common missing value imputation methods and provides two categories of evaluation criteria (4 classic criteria and 4 proteomic criteria) to assess the imputation performance of various methods. We hope this tool could help scientists impute the missing values systematically and present valuable guidance to select one proper method for their own data. In addition, this tool supports both online access and local installation.



Basically, there are four main steps in NAguideR:

- Uploading proteomics expression data and sample information data;
- 2. Data quality control;
- 3. Missing value imputation;
- 4. Performance evaluation;

After this, NAguideR can provide valuable guidance for users to select one proper method for their own data based on the evaluation results. Detailed introduction can be found in the *Help* part.

Finally, NAguideR is developed by R shiny (Version 1.3.2), and is free and open to all users with no login requirement. It can be readily accessed by all popular web browsers including Google Chrome, Mozilla Firefox, Safari and Internet Explorer 10 (or later), and so on. We would highly appreciate that if you could send your feedback about any bug or feature request to Shisheng Wang at wssdandan2009@outlook.com.

^ ^ Enjoy yourself in NAguideR ^ ^

III. Reference

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