proteiNorm – A user-friendly tool for normalization and analysis of TMT and label-free protein/proteome quantification

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ABSTRACT (Word Style “BD\_Abstract”). All manuscripts must be accompanied by an abstract. The abstract should briefly state the problem or purpose of the research, indicate the theoretical or experimental plan used, summarize the principal findings, and point out major conclusions. Abstract length is one paragraph.

KEYWORDS: Proteomics, Normalization, Differential analysis

1. **Introduction**

With the latest technological advances in the development of mass spectrometer, the detection accuracy of the instruments has increased as well as the speed with which data is being produced. The amount of data generated by these high-throughput devices increases rapidly and the need for tools that allow to streamline analyses becomes more apparent.

The peptide level of thousands of proteins are being measured for up to several patients at once. However, data generated from mass spectrometry is often affected by systemic bias, variation caused by non-biological sources, which can lead to incorrect conclusions [1]. This can include, but is not limited to, sample preparation and handling, device calibration, changes in temperature and other unknown sources [2]. Unlike the effect of batching, these sources of variation are either not measured or simply cannot be measured, and therefore cannot be controlled for in statistical modelling. Normalization is a techniques that aims to account for these systematic biases and make samples more comparable, while preserving the signal. Many normalization methods have been proposed with most of them being adopted from DNA microarray technology [3]. Välikangas et al. systemically evaluated normalization methods used in quantitative label-free proteomics and while there are normalization methods like VSN, linear regression normalization and local regression normalization, that consistently rank amount the top performing methods, it is curial to select a suitable normalization method depending on the data set [2, 4]. The need for tools that identify proper normalization methods was recognized and addressed by Webb-Robertson et al. and Chawade et al. with their tools SPAN and Normalyzer. SPAN combines eight peptides selection methods, to select peptides subsequently used during the normalization, and five normalization methods [4]. Normalyzer includes popular normalization methods such as linear regression, local regression, total intensity, average intensity, median intensity, VSN, and quantile normalization. The performance of each normalization methods is individually evaluated by comparing their pooled coefficient of variance (PCV), pooled median absolute deviation (PMAD), and pooled estimate of variance (PEV) [1].

However, there remains an outstanding need for a publicly available tool that provides a systematically evaluation of normalization methods, but also facilities imputation of missing data and compares different differential abundance methods depending on a chosen normalization methods.

Here, we present proteiNorm, a user-friendly tool for a systematic evaluation of normalization methods, imputation of missing values and comparisons of different differential abundance methods. Our tool provides a point-and-click R-Shiny interface for researchers that are unfamiliar or less comfortable with the R environment. After loading the raw peptide data, the user can choose to remove peptide outliers and create and load a filtered protein file or to load a raw protein file. The meta data (i.e., custom sample names, group labels and batch labels) can be specified in the user-interface after loading peptide and protein data. Next, unwanted samples such as blanks, samples with poop quality or pooled samples can be remove from subsequent steps. The remaining data is then subjected to different normalization methods, which are compared among each other. Once a suitable normalization methods is identified, missing values can be imputed, the data can be saved and evaluation of different differential abundance methods can be performed for a selected normalization method. In addition, the statistical power of a given test of differential abundance can be assessed.

1. **Methods**
   1. **Implementation**

proteiNorm implemented in R statistical language (<http://r-project.org>, version 3.6) using the package “shiny” to provide a user-friendly user interface. proteiNorm can be downloaded from GitHub (<https://github.com/ByrumLab/proteiNorm>).

* 1. **Data Requirements**

As input, proteiNorm expects tab-separated raw peptide and/or protein data (not on logarithmic scale) as produced by software such as XXX (where is the data coming from), where the column names of the measured intensities start with “Reporter intensity corrected” followed by an integer and an optional label (e.g. “Reporter intensity corrected 5 TMT2”,), and each row represents a peptide or protein. Data from both quantitation method, Tandem Mass Tag (TMT) and label-free, are supported.

Due to the detection limit of mass spectrometry instruments many peptide/protein measurements have an intensity measurement of zero. These values will be considered as missing values (denoted as NA) and can be imputed with precaution.

* 1. **Normalization Methods**

The current implementation of proteiNorm includes several popular normalization methods, including log2 normalization, median normalization, mean normalization, variance stabilizing normalization (VSN), quantile normalization, cyclic loess normalization, global robust linear regression normalization, and global intensity normalization. The individual performance of each methods can be evaluated in comparisons of the following metrics: total intensity, Pooled intragroup Coefficient of Variation (PCV), Pooled intragroup Median Absolute Deviation (PMAD), Pooled intragroup estimate of variance (PEV), intragroup correlation, sample correlation heatmap (Pearson), and log2-ratio distributions.

* 1. **Differential Analysis**

DAtest is an available R packages that allows to compare different differential abundance and expression methods . As the DAtest package requires complete data (no missing values), the user can user can select appropriate methods for normalization and imputation for the differential analysis, based on the comparison of the normalization methods and a heatmap visualizing patterns of missing values (missing at random (MAR) or missing not at random (MNAR)). The current implementation of proteiNorm provides the following imputation methods: k-nearest neighbors (KNN), Quantile Regression Imputation of Left-Censored data (QRILC), deterministic minimal value imputation (MinDet), stochastic minimal value imputation (MinProb), minimal value imputation, and zero imputation.

In addition, proteiNorm provides the opportunity to adjust DAtest-specific parameters (i.e., number of times to run the tests, effect size for the spike-ins (on log2 scale), and number of cores to use for parallel computing) and to exclude certain statistical tests. This latter option can be useful, as the exclusion of test with high computation demand (such as the permutation-based test), will drastically reduce the run-time.

DAtest will automatically select appropriate statistical tests from the pool of tests provided by DAtest and evaluate their performance. Therefore, the data is shuffled and spiked-in for randomly chosen features. DAtest then assesses if the spiked-in features are correctly identified by each test and whether the false discovery rate is controlled. The results are summarized in a table and figures comparing and ranking the performance of each individual test. Additionally, proteiNorm provides the opportunity to investigate the performance of each individual test by estimating statistical power (probability of correctly detecting a true signals) over a range of effect sizes (around the previously specified effect size for the spike-ins), utilizing the “powerDA” function from the “DAtest” package.

1. **Results**
2. **Discussion**
3. **Conclusion**
4. **Author Information**

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Author Contributions

The manuscript was written through contributions of all authors. All authors have given approval to the final version of the manuscript. ‡These authors contributed equally. (match statement to author names with a symbol)

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1. **Abbreviations**
2. **References**

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