SCelVis: Powerful explorative single cell data analysis on the desktop and in the cloud

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16 Abstract

- 17 **Background:** Single cell omics technologies present unique opportunities for biomedical and
- 18 life sciences from lab to clinic, but the high dimensional nature of such data poses challenges for
- 19 computational analysis and interpretation. Furthermore, FAIR data management as well as data
- 20 privacy and security become crucial when working with clinical data, especially in cross-
- 21 institutional and translational settings. Existing solutions are either bound to the desktop of one

22 researcher or come with dependencies on vendor-specific technology for cloud storage or user

- authentication.
- 24 **Results:** To facilitate analysis and interpretation of single-cell data by users without
- 25 bioinformatics expertise, we present SCelVis, a flexible, interactive and user-friendly app for
- 26 web-based visualization of pre-processed single-cell data. Users can survey multiple interactive
- 27 visualizations of their single cell expression data and cell annotation, and download raw or
- 28 processed data for further offline analysis. SCelVis can be run both on the desktop and cloud
- 29 systems, accepts input from local and various remote sources using standard and open protocols,
- 30 and allows for hosting data in the cloud and locally.
- 31 Methods: SCelVis is implemented in Python using Dash by Plotly. It is available as a standalone
- 32 application as a Python package, via Conda/Bioconda and as a Docker image. All components
- are available as open source under the permissive MIT license and are based on open standards
- 34 and interfaces, enabling further development and integration with third party pipelines and
- analysis components. The GitHub repository is https://github.com/bihealth/scelvis.

36 Introduction

37 Single-cell omics technologies, in particular single-cell RNA sequencing (scRNA-seq), allow for

- the high-throughput profiling of gene expression in thousands to millions of cells with
- 39 unprecedented resolution. Recent large-scale efforts to catalogue and describe all human cell
- 40 types (Regev et al., 2017) dovetail with ongoing investigations to study cells and tissues in health
- 41 and disease, e.g., as proposed by the LifeTime consortium (https://lifetime-fetflagship.eu).
- 42 Single-cell sequencing could therefore become a routine tool in the clinic for comprehensive
- 43 assessments of molecular and physiological alterations in diseased organs as well as systemic
- 44 responses, e.g., of the immune system. The enormous scale and high-dimensional nature of the
- 45 resulting data presents an ongoing challenge for computational analysis (Stegle, Teichmann, &
- Marioni, 2015). Ever more sophisticated methods combining more conventional genomics
 approaches with deep learning frameworks (Eraslan, Avsec, Gagneur, & Theis, 2019) allow to
- 47 approaches with deep learning frameworks (Eraslan, Avsec, Gagneur, & Theis, 2019) allow to
 48 overcome technical limitations and biases and extract multiple layers of information, e.g. from
- 48 overcome technical initiations and olases and extract multiple layers of information, e.g. non 49 cell types to lineages and differentiation programs. Many of these methods, their mathematical
- 50 background, and the underlying assumptions will remain opaque to users without specific
- 50 bioinformatics expertise. At the same time, an in-depth understanding of cell types, their
- bioinformatics expertise. At the same time, an in-depth understanding of cen types, then 52
- 52 functional specialization and modification by diseases, and underlying molecular correlates is
- 53 often beyond the biological know-how of typical bioinformatics researchers. More than ever,
- 54 single-cell omics requires close communication and close collaboration from wet and dry lab 55 experts. Due to the large amount of data, communication need to be based on interactive
- 56 channels (e.g., web-based apps) rather than static tables. Further, as single-cell omics moves
- 57 towards the clinic, FAIR (Wilkinson et al., 2016) data management, data privacy, and data
- 58 security issues need to be handled appropriately. All employed methods should be able to scale
- 59 towards handling a large number of users and even larger numbers of samples.
- 60 **State of the Art.** Web apps have been used extensively in the single-cell literature and are most
- 61 commonly built on Shiny (RStudio Inc., 2014). However, standalone and general-purpose tools
- 62 are to our knowledge quite rare. Pagoda (Fan et al., 2016) comes with a simple intuitive web app,
- 63 which is limited to Pagoda output and requires manual preprocessing. Cerebro (Hillie, Pelicci, &
- 64 Luzi, 2019) is a Shiny web app combined with a Docker container and an Electron
- 65 (https://github.com/electron/electron) standalone app and provides relatively rich functionality
- 66 such as gene set enrichments and quality control statistics, but relies on extensive manual
- 67 preprocessing and is not (yet) ready for larger frameworks. On the other hand, the Broad Single
- 68 Cell Portal (https://portals.broadinstitute.org/single_cell) provides a large-scale web service for a
- 69 large number of users and studies. It includes a 10X Genomics data processing pipeline and user
- 70 authentication/account management. However, the underlying Docker image strongly depend on
- vendor-specific cloud systems such as Google cloud and Broad Firecloud services. Its
- 72 implementation thus poses practical hurdles, in particular if it is to be integrated into existing
- 73 clinical infrastructure.

74 Materials & Methods

- SCelVis is based on Dash by Plotly (Plotly Technologies Inc., 2015) and accepts data in HDF5
- 76 format as AnnData objects, which can be created using Scanpy (Wolf, Angerer, & Theis, 2018).
- 77 It also provides conversion functionality from raw text or 10X Genomics CellRanger output. The
- built-in converter is accessible from the command line and a web-based user interface (Figure 1).
- 79 It allows for converting pipeline output with an optional description file into a single AnnData
- 80 HDF5 file. One HDF5 file or a folder containing multiple such files can then be provided to
- 81 SCelVis for visualization, and data sets can be selected for exploration on the graphic web
- 82 interface. To enable both local and cloud access, data can be read from the file system or remote
- data sources via the standard internet protocols FTP, SFTP, and HTTP(S). SCelVis also provides
- data access through the open source iRODS protocol (Rajasekar et al., 2010) or the widely-used
- Amazon S3 object storage protocol. The data sources can be given on the command line and as
- 86 environment variables as is best practice for cloud deployments (Adam Wiggins, 2011). The
- 87 latter allows for easy "serverless" and cloud deployments.
- 88 SCelVis is built around two perspectives on single-cell data (Figure 1). On the one hand, it
- 89 provides a cell-based view, where users can browse and investigate cell annotations (such as cell
- 90 type) and cell-specific statistics (such as sequencing depth or cell type proportions) in multiple
- 91 visualizations, e.g., on a t-SNE or UMAP embedding, as violin plots or bar charts. On the other
- hand, it provides a gene-based view that lets users explore gene expression in multiple
- 93 visualizations on embeddings or as violin or dot plots. Relevant genes can be specified by hand
- 94 or selected directly from lists of marker genes.
- 95 The source code is available under the permissive MIT license on the GitHub repository at
- 96 <u>https://github.com/bihealth/scelvis</u>. The software can be run both in the cloud and on workstation
- 97 desktops via Docker.

98 Usage Example

- 99 We provide two example datasets within our Github repository (see above, it also contains a link
- to a public demonstration instance). First, a small synthetic simulated dataset created for
- 101 illustration purposes, and secondly a publicly available processed scRNA-seq dataset from 10X
- 102 Genomics containing ~1000 cells of a mix of human HEK293T and murine NIH3T3 cells
- 103 (Figure 2).

104 **Discussion**

- 105 In this manuscript, we have presented SCelVis, a method for the interactive visualization of
- 106 single-cell RNA-seq data. It provides easy-to-use yet flexible means of scRNA-seq data
- 107 exploration for researchers without computational background. SCelVis takes processed data,
- 108 e.g., provided by CellRanger or a bioinformatics collaboration partner, as input, and focuses
- solely on visualization and explorative analysis. Great care has been taken to make the method
- 110 flexible in usage and deployment. It can be used both on a researcher's desktop with minimal
- training yet its usage scales up to a cloud deployment. Data can be read from local file systems
- but also from a variety of remote data sources, e.g., via the widely deployed (S)FTP, S3, and

- 113 HTTP(S) protocols. This allows for deploying it in a Docker container on "serverless" cloud
- systems. As both the application and data can be hosted on the network or cloud systems, the
- application facilitates cross-institutional research. For example, a sequencing or bioinformatics
- 116 core unit can use it for giving access to non-computational collaboration partners over the
- 117 internet. This is particularly interesting as it comes with no dependency on any vendor-specific
- technology such as the Google or Facebook authentication that appears to become pervasive in
- 119 today's life science.

120 **Conclusions**

- 121 SCelVis is a flexible and powerful method for the visualization of single-cell RNA-seq
- 122 experiments and the explorative data analysis thereof. It comes with a number of unique features,
- in particular complete independence of vendor-specific software or services. At the same time, it
- remains simple enough to be integrated as a component in more complex framework.

125 Acknowledgements

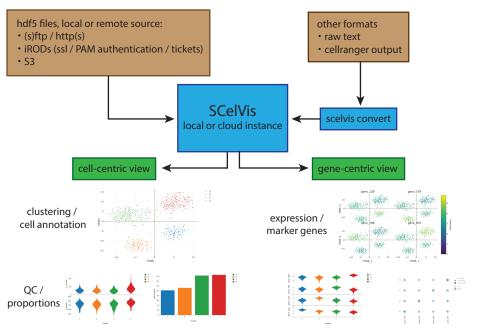
- 126 The example dataset for the 1:1 mixture of human and mouse cells processed with CellRanger
- 127 (v3) was taken from the 10X genomics website https://support.10xgenomics.com/single-cell-
- 128 gene-expression/datasets/3.0.0/hgmm_1k_v3.

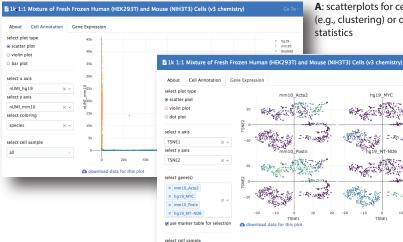
129 **References**

- Adam Wiggins. (2011). The Twelve-Factor App. Retrieved March 22, 2019, from
 https://12factor.net/
- Eraslan, G., Avsec, Ž., Gagneur, J., & Theis, F. J. (2019). Deep learning: new computational
 modelling techniques for genomics. *Nature Reviews Genetics*, 20(7), 389–403.
 https://doi.org/10.1038/s41576-019-0122-6
- 135 Fan, J., Salathia, N., Liu, R., Kaeser, G. E., Yung, Y. C., Herman, J. L., ... Kharchenko, P. V.
- (2016). Characterizing transcriptional heterogeneity through pathway and gene set
 overdispersion analysis. *Nature Methods*, *13*(3), 241–244.
 https://doi.org/10.1038/nmeth.3734
- Hillje, R., Pelicci, P. G., & Luzi, L. (2019). Cerebro: Interactive visualization of scRNA-seq
 data. *BioRxiv*, 631705. https://doi.org/10.1101/631705
- 141 Plotly Technologies Inc. (2015). *Collaborative data science*. Retrieved from https://plot.ly
- 142 Rajasekar, A., Moore, R., Hou, C.-Y., Lee, C. A., Marciano, R., de Torcy, A., ... Zhu, B. (2010).
- iRODS Primer: Integrated Rule-Oriented Data System. Synthesis Lectures on Information
 Concepts, Retrieval, and Services, 2(1), 1–143.
- 145 https://doi.org/10.2200/S00233ED1V01Y200912ICR012
- Regev, A., Teichmann, S. A., Lander, E. S., Amit, I., Benoist, C., Birney, E., ... Human Cell
 Atlas Meeting Participants. (2017). The Human Cell Atlas. *ELife*, 6.
 https://doi.org/10.7554/eLife.27041
- 149 RStudio Inc. (2014). *shiny: Easy web applications in R*. Retrieved from http://shiny.rstudio.com
- Stegle, O., Teichmann, S. A., & Marioni, J. C. (2015). Computational and analytical challenges
 in single-cell transcriptomics. *Nature Reviews Genetics*, 16(3), 133–145.
 https://doi.org/10.1038/nrg3833
- 153 Wilkinson, M. D., Dumontier, M., Aalbersberg, Ij. J., Appleton, G., Axton, M., Baak, A., ...

- 154 Mons, B. (2016). The FAIR Guiding Principles for scientific data management and 155 stewardship. *Scientific Data 2016 3*.
- Wolf, F. A., Angerer, P., & Theis, F. J. (2018). SCANPY: large-scale single-cell gene expression
- 157 data analysis. *Genome Biology*, 19(1), 15. https://doi.org/10.1186/s13059-017-1382-0

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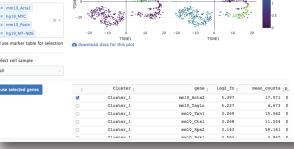




all

A: scatterplots for cell annotation (e.g., clustering) or quality control statistics

hg19 MYC



B: plot gene expression as scatter, violin or dot plots (select genes from table)