

¹ scpviz: A Python bioinformatics toolkit for Single-cell Proteomics and multi-omics analysis

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DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

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Submitted: 01 January 1970

Published: unpublished

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⁸ Summary

⁹ Proteomics seeks to characterize protein dynamics by measuring both protein abundance and ¹⁰ post-translational modifications (PTMs), such as phosphorylation, acetylation, and ubiquitination, which regulate protein activity, localization, and interactions. In bottom-up proteomics ¹¹ workflows, proteins are enzymatically digested into peptides that are measured as spectra, ¹² from which these peptide-spectrum matches (PSMs) are aggregated to infer protein-level ¹³ identifications and quantitative abundance estimates. Analyzing the two levels of data at ¹⁴ both the peptide level (short fragments observed directly) and the protein level (assembled ¹⁵ from peptide evidence) in tandem is crucial for translating raw measurements into biologically ¹⁶ interpretable results.

¹⁸ Single-cell proteomics extends these approaches to resolve protein expression at the level of individual cells or microdissected tissue regions. Such data are typically sparse, with many ¹⁹ missing values, and are generated within complex experimental designs involving multiple ²⁰ classes of samples (e.g., cell type, treatment, condition). These properties distinguish single-cell ²¹ proteomics from bulk experiments and create unique challenges in data processing, normalization, ²² and interpretation. The single-cell transcriptomics community has established a mature ²³ ecosystem for managing similar challenges, exemplified by the scanpy package ([Wolf et al., 2018](#)) and the broader scverse ecosystem ([Virshup et al., 2023](#)). Building on these foundations, ²⁴ scpviz extends the AnnData data structure to the domain of proteomics, supporting a complete ²⁵ analysis pipeline from raw peptide-level data to protein-level summaries and downstream ²⁶ interpretation through differential expression, enrichment analysis, and network analysis. The ²⁷ core of scpviz is the pAnnData class, an AnnData-affiliated data structure specialized for ²⁸ proteomics. Together, these components make scpviz a comprehensive and extensible framework ²⁹ for single-cell proteomics. By combining flexible data structures, reproducible workflows, and ³⁰ seamless integration with the AnnData, scanpy and extended scverse ecosystem, the package ³¹ enables researchers to efficiently connect peptide-level evidence to protein-level interpretation, ³² thereby accelerating methodological development and biological discovery in proteomics.

³⁵ Statement of need

³⁶ Although general-purpose data analysis frameworks such as scanpy ([Wolf et al., 2018](#)) and ³⁷ the broader scverse ecosystem have become indispensable for single-cell transcriptomics, ³⁸ comparable tools for proteomics remain limited. Existing proteomics software often focus on ³⁹ specialized tasks (e.g., peptide identification or spectrum assignment) and do not provide a ⁴⁰ unified framework for downstream analysis of peptide- and protein-level data within single-cell ⁴¹ and spatial contexts.

42 scpviz addresses these gaps by offering an integrated system for the complete proteomics work-
43 flow, from raw peptide-level evidence to protein-level summaries and biological interpretation.
44 It is designed for computational biologists and proteomics researchers working with low-input
45 or single-cell datasets from data sources such as Proteome Discoverer or DIA-NN([Demichev et](#)
46 al., 2020).
47 At the core of scpviz is the pAnnData class, an AnnData-affiliated data structure specialized
48 for proteomics. It organizes peptide (.pep) and protein (.prot) AnnData objects alongside
49 supporting attributes such as .summary, .metadata, .rs matrices (protein-peptide relation-
50 ships), and .stats. This design allows users to move flexibly between peptides and
51 proteins while maintaining compatibility with established Python libraries for data science and
52 visualization.
53 Beyond data organization, scpviz implements proteomics-specific operations, including filter-
54 ing (e.g., requiring proteins supported by at least two unique peptides), normalization and
55 imputation methods tailored for sparse datasets, and visualization tools such as PCA (Principal
56 Component Analysis), UMAP (Uniform Manifold Approximation and Projection for Dimension
57 Reduction), clustermaps, and abundance plots. For downstream interpretation, it integrates
58 with UniProt for annotation and string-db for enrichment and network analysis ([McInnes et al.](#),
59 2018; [Snel et al.](#), 2000; [Szklarczyk et al.](#), 2023). The framework also incorporates single-cell
60 proteomics-specific normalization strategies such as directLFQ ([Ammar et al.](#), 2023), ensuring
61 robust quantification across heterogeneous samples. Finally, pAnnData objects interface seam-
62 lessly with scanpy ([Wolf et al.](#), 2018) and other ecosystem tools such as harmony ([Korsunsky](#)
63 et al., 2019), enabling direct incorporation into established single-cell workflows.
64 The design philosophy of scpviz emphasizes both usability and extensibility. General users can
65 rely on its streamlined API to import, process, and visualize single-cell proteomics data without
66 deep programming expertise, while advanced users can extend the framework to accommodate
67 custom analysis pipelines. The package has already been applied in published papers and
68 preprints ([Dutta, Pang, Coughlin, et al.](#), 2025; [Dutta, Pang, Donahue, et al.](#), 2025; [Pang et al.](#),
69 2025; [Uslan et al.](#), 2025) as well as manuscripts in preparation, and it has been incorporated
70 into graduate-level training to illustrate how proteomics workflows parallel to those in single-cell
71 transcriptomics.
72 The applications of scpviz span diverse areas of life sciences research, from studying protein
73 dynamics and signaling pathways to integrating proteomics with transcriptomics for multi-
74 omics analysis. By bridging the gap between raw mass spectrometry data and systems-level
75 interpretation, scpviz provides a versatile and reproducible platform for advancing single-cell
76 and spatial proteomics.

77 Acknowledgements

78 We thank Pierre Walker for his many insightful discussions and guidance. We also acknowledge
79 support from the A*STAR BS-PhD Scholarship. The Proteome Exploration Laboratory is
80 partially supported by the Caltech Beckman Institute Endowment Funds.

81 References

- 82 Ammar, C., Schessner, J. P., Willems, S., Michaelis, A. C., & Mann, M. (2023). Accurate
83 Label-Free Quantification by directLFQ to Compare Unlimited Numbers of Proteomes.
84 *Molecular & Cellular Proteomics*, 22(7). <https://doi.org/10.1016/j.mcpro.2023.100581>
- 85 Demichev, V., Messner, C. B., Vernardis, S. I., Lilley, K. S., & Ralser, M. (2020). DIA-
86 NN: Neural networks and interference correction enable deep proteome coverage in high
87 throughput. *Nature Methods*, 17(1), 41–44. <https://doi.org/10.1038/s41592-019-0638-x>

- 88 Dutta, S., Pang, M., Coughlin, G. M., Gudavalli, S., Roukes, M. L., Chou, T.-F., & Gradinaru,
89 V. (2025, February 11). *Molecularly-guided spatial proteomics captures single-cell identity*
90 *and heterogeneity of the nervous system.* <https://doi.org/10.1101/2025.02.10.637505>
- 91 Dutta, S., Pang, M., Donahue, R. R., Chou, T.-F., Seifert, A. W., & Gradinaru, V. (2025).
92 *Parkinson's disease modeling in regenerative spiny mice (Acomys dimidiatus) captures key*
93 *disease-relevant behavioral, histological, and molecular signatures* (p. 2025.11.06.687049).
94 bioRxiv. <https://doi.org/10.1101/2025.11.06.687049>
- 95 Korsunsky, I., Millard, N., Fan, J., Slowikowski, K., Zhang, F., Wei, K., Baglaenko, Y., Brenner,
96 M., Loh, P., & Raychaudhuri, S. (2019). Fast, sensitive and accurate integration of
97 single-cell data with Harmony. *Nature Methods*, 16(12), 1289–1296. <https://doi.org/10.1038/s41592-019-0619-0>
- 99 McInnes, L., Healy, J., Saul, N., & Großberger, L. (2018). UMAP: Uniform Manifold
100 Approximation and Projection. *Journal of Open Source Software*, 3(29), 861. <https://doi.org/10.21105/joss.00861>
- 102 Pang, M., Jones, J. J., Wang, T.-Y., Quan, B., Kubat, N. J., Qiu, Y., Roukes, M. L., & Chou,
103 T.-F. (2025). Increasing Proteome Coverage Through a Reduction in Analyte Complexity
104 in Single-Cell Equivalent Samples. *Journal of Proteome Research*, 24(4), 1528–1538.
105 <https://doi.org/10.1021/acs.jproteome.4c00062>
- 106 Snel, B., Lehmann, G., Bork, P., & Huynen, M. A. (2000). STRING: A web-server to retrieve
107 and display the repeatedly occurring neighbourhood of a gene. *Nucleic Acids Research*,
108 28(18), 3442–3444. <https://doi.org/10.1093/nar/28.18.3442>
- 109 Szklarczyk, D., Kirsch, R., Koutrouli, M., Nastou, K., Mehryary, F., Hachilif, R., Gable, A.
110 L., Fang, T., Doncheva, N. T., Pyysalo, S., Bork, P., Jensen, L. J., & von Mering, C.
111 (2023). The STRING database in 2023: Protein-protein association networks and functional
112 enrichment analyses for any sequenced genome of interest. *Nucleic Acids Research*, 51(D1),
113 D638–D646. <https://doi.org/10.1093/nar/gkac1000>
- 114 Uslan, T., Quan, B., Wang, T.-Y., Pang, M., Qiu, Y., & Chou, T.-F. (2025). In-Depth
115 Comparison of Reagent-Based Digestion Methods and Two Commercially Available Kits
116 for Bottom-Up Proteomics. *ACS Omega*, 10(10), 10642–10652. <https://doi.org/10.1021/acsomega.4c11585>
- 118 Virshup, I., Bredikhin, D., Heumos, L., Palla, G., Sturm, G., Gayoso, A., Kats, I., Koutrouli,
119 M., Berger, B., Pe'er, D., Regev, A., Teichmann, S. A., Finotello, F., Wolf, F. A., Yosef,
120 N., Stegle, O., & Theis, F. J. (2023). The scverse project provides a computational
121 ecosystem for single-cell omics data analysis. *Nature Biotechnology*, 41(5), 604–606.
122 <https://doi.org/10.1038/s41587-023-01733-8>
- 123 Wolf, F. A., Angerer, P., & Theis, F. J. (2018). SCANPY: Large-scale single-cell gene expression
124 data analysis. *Genome Biology*, 19(1), 15. <https://doi.org/10.1186/s13059-017-1382-0>