

# FastPCA: An R package for fast singular value decomposition

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## Summary

The **FastPCA** package provides an interface to optimized matrix multiplication libraries (**libtorch**) for the purpose of singular value decomposition. Using **FastPCA** to perform randomized singular value decomposition (SVD, Halko, Martinsson, & Tropp (2011)) with the **torch** or **pytorch** backend drastically reduces the computational time compared to base R **prcomp** and other truncated singular value decomposition. Developed for biological data such as single-cell RNA-sequencing, spatial transcriptomics, or matrix-assisted laser desorption/ionization (MALDI imaging), **FastPCA** can efficiently and accurately identify the leading singular values in high-dimensional data.

## Statement of Need

Over the last decade, advances in single-cell and spatial profiling technologies have dramatically increased the scale and resolution of biological data (Lim, Wang, Buzdin, & Li (2025)). Multiple custom and commercially available technologies produce tens of thousands of samples (e.g., spots, cells, pixels) and thousands of measured features (i.e., genes, peaks, etc) per sample which can require tens to hundreds of gigabytes (Zaima, Hayasaka, Goto-Inoue, & Setou (2010)). Creating linear or non-linear combinations of the input space in lower-dimensional space enables more efficient downstream analysis. However, this is typically done with packages like **irlba** (Baglama, Reichel, & Lewis (2011)) where the process of identifying singular values is iterative and single-thread limited. Other packages can improve efficiency by using an API for R (such as **reticulate** for python) but is not multithreaded without modification to the source code (Li, Meisner, & Albrechtsen (2023)). The **qrPCA** R package (S. de Souza, Quanfeng, Shen, Peng, & Mu (2022)) uses **torch** (Falbel & Luraschi (2020); Paszke et al. (2019)) to perform QR-based principal component analysis (PCA), but doesn't produce truncated singular values resulting in incredibly large memory requirements for large matrices. For biological studies, parameter tuning and rapid iteration (e.g., normalization methods, subclustering for identifying specific cell types) are essential to identify biologically meaningful signals, which typically reside in early dimensions, enabling the avoidance of the full decomposition.

The **FastPCA** R package was developed to address this critical need. **FastPCA** has access to the **torch** backend through R, as well as **pytorch** with **reticulate** (Ushey, Allaire, & Tang (2017)). We've also included vignettes to demonstrate **FastPCA**'s utility and functionality (<https://acsoupir.github.io/FastPCA/>).

## Functionality

**FastPCA** uses **irlba** as the default backend for calculating singular values for compatibility, but offers access to **libtorch** via python **pytorch** or R **torch** packages. Using the **pytorch** or **torch** backends support setting the number of threads where the backend provides it. There are two functions within **FastPCA** that aid in the setup of the environments:

- **setup\_py\_env()**: creates a python environment (either with ‘conda’ or ‘virtualenv’) for using in the event that **pytorch** is wanted for the backend
- **start\_FastPCA\_env()**: starts the environment created with **setup\_py\_env()** to use for **pytorch** backend

Then, there are processing functions that work on input matrices or intermediate lists produced by **FastPCA**:

- **prep\_matrix()**: converts expected data types (rows/columns) into **FastPCA** format (rows as samples, columns as features). Also supports transformations such as log2 and scaling.
- **FastPCA()**: performs either exact SVD (though not recommended other than benchmarking) or truncated singular value decomposition with **irlba** or randomized SVD. Returns a list containing matrices of singular vectors  $U$  and  $V^T$ , and vector of singular values  $S$
- **get\_pc\_scores()**: calculates the principal component scores from the output of **FastPCA()** ( $U$  matrix which contains left singular vectors,  $S$  vector containing the singular values, and  $V^T$  matrix of the right singular vectors) which are typically expected for downstream analyses
- **umap()**: uses either **uwot** (R) or **umap-learn** (python) for visualization of the principal component scores

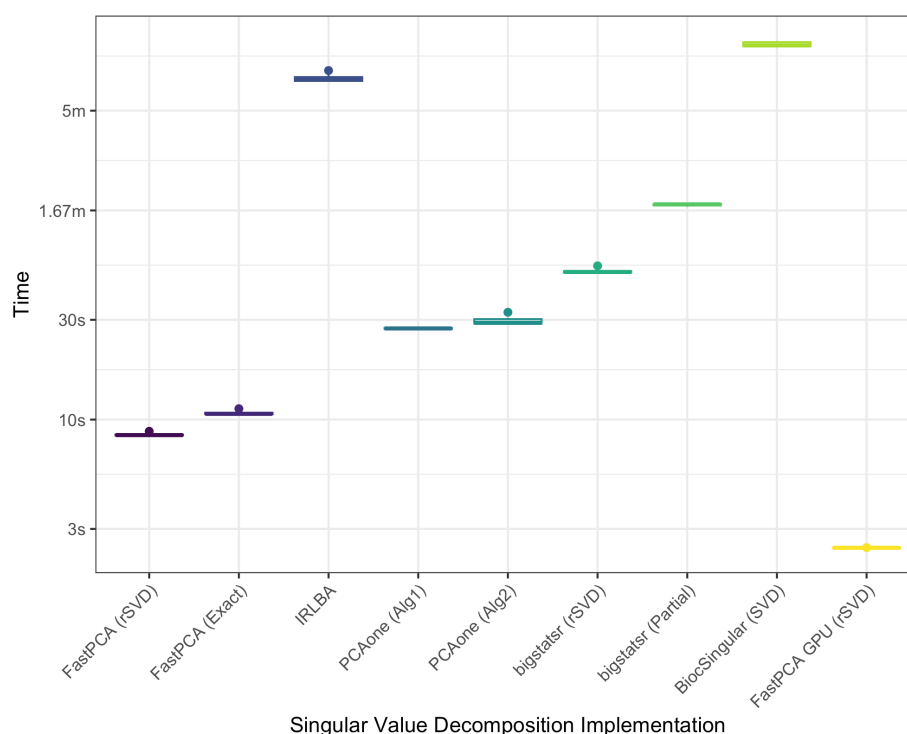
## Research Impact

To demonstrate the improvements of **FastPCA**, we use our previous data set of single-cell spatial transcriptomics of kidney cancer. The dataset is publicly available on [Zenodo](#) and can be downloaded locally to be used (Soupir et al. (2024)). Since the main benefits of **FastPCA** are in its application of singular value decomposition, that is what will be focused on. The counts for each cell were extracted from the Seurat object in the Nanostring assay, which contains the expression of 978 probes (959 genes, 19 negative control probes) in 199,112 cells. Normalization was performed using **prep\_matrix()**, applying a log transformation, scaling (mean centering and unit variance), and transposing for samples to be rows and columns to be the gene features. The full script can be found [https://github.com/ACSoupir/FastPCA/blob/main/docs\\_acs/paper/benchmarking\\_script.R](https://github.com/ACSoupir/FastPCA/blob/main/docs_acs/paper/benchmarking_script.R).

Experiments were performed using **FastPCA**, both randomized SVD and exact, **irlba**, **pcaone** (Li et al. (2023)), and **bigstatsr** (Privé, Aschard, Ziyatdinov, & Blum (2018)), both partial and randomized partial SVD. Performance measures were collected from a M3 Pro MacBook Pro with 36GB unified RAM. **FastPCA** (4 cores), **bigstatsr** partial (1 core) and random (4 cores), **irlba** (1 core), and **pcaone** (1 core) were assessed. Time was profiled with **bench::mark()** function over 10 repetitions for each implementation. The elapsed time of **FastPCA** calculating the singular value decomposition on the full data took 10.74 seconds on average (range 10.61 to 11.27 seconds) and the randomized SVD with **FastPCA** taking 8.46 (8.35 to 8.79) seconds on average **Table 1, Figure 1**). The next fastest were the implementations with PCAone which took 27.29 (27.1 to 27.54) and 29.58 (28.59 to 32.59) seconds on average for “Alg1” and “Alg2”, respectively.

**Table 1:** Time to calculate singular value decomposition using different R packages and implementations over 10 replicates.

Implementation	Min	Median	Mean	Max
FastPCA (rSVD)	8.35s	8.43s	8.46s	8.79s
FastPCA (Exact)	10.61s	10.65s	10.74s	11.27s
irlba	413.15s	423.73s	429.99s	466.80s
pcaone (Alg1)	27.1s	27.27s	27.29s	27.54s
pcaone (Alg2)	28.59s	29.01s	29.58s	32.59s
bigstatsr (rSVD)	50.0s	50.8s	51.15s	54.34s
bigstatsr (Partial)	104.08s	106.94s	106.43s	107.73s
BiocSingular (rSVD)	606.71s	615.53s	623.30s	646.58s
FastPCA GPU (rSVD)	2.44s	2.44s	2.44s	2.44s



**Figure 1:** Time of singular value decomposition implementations over 10 replicates.

The `pytorch` backend also has the ability to use a CUDA-enabled GPU (using `device = "GPU"`), leveraging the highly parallel processing commonly used in deep learning applications (Paszke et al. (2019)). Enabling GPU acceleration with **FastPCA** further improves compute time to 2.44 (2.44 to 2.44) seconds. While current GPU implementation significantly improves speed for same operation (CPU time between 8.35 and 8.27 seconds; GPU time between 2.44 and 2.44 seconds), it is limited to CUDA due to lack of access to other hardware. Future development of **FastPCA** aims to be hardware agnostic through added support or adding other hardware agnostic backends like `tinygrad` (<https://tinygrad.org/>).

Reconstruction error was calculated for all implementations. Because the three matrices (left eigenvectors, eigenvalues, and right eigenvectors) should contain all of the information decomposed from the original matrix when calculated in full, exact **FastPCA** was used

as reference. To determine how much information was captured in the truncated methods compared to the full decomposition, the output from exact **FastPCA** was directly truncated to the first 100 dimensions and sum of squares error ratio was calculated (reduced SSE / exact truncated SSE; **Table 2**; Eckart & Young (1936)). Values of 1 are interpreted as containing the same variance in the reconstructed data as the first 100 dimensions of the truncated exact SVD, and values greater than 1 indicate how much error over optimal reconstruction the method or implementation had. These demonstrate that **irlba** with its iterative approach captures the first 100 dimensions extremely well (1.000) compared to the exact SVD; similar with the **bigstatsr** implementations. **FastPCA** randomized SVD and **PCAone** approaches contain slightly greater error (~0.14% to ~0.33% greater than the optimal reconstruction with exact **FastPCA**) just like **BiocSingular** randomized SVD (~0.33%). These errors indicate that with **FastPCA** being more than 50x faster using the randomized SVD approach than IRLBA, it is within the error of other common implementations, and while being greater than 40x faster using the exact approach perfectly reconstructs the original data.

**Table 2:** Reconstruction error of the truncated singular value decomposition. **FastPCA** using the exact approach was used as reference as it produces the full singular value decomposition.

Implementation	SSE Ratio
<b>FastPCA</b> (rSVD)	1.003191
<b>FastPCA</b> (Exact)	—
<b>irlba</b>	1.000000
<b>pcaone</b> (Alg1)	1.003316
<b>pcaone</b> (Alg2)	1.001383
<b>bigstatsr</b> (rSVD)	1.000000
<b>bigstatsr</b> (Partial)	1.000000
<b>BiocSingular</b> (rSVD)	1.003275

Further, for the first 100 singular values, and first and second left singular vectors (samples), we used the concordance correlation coefficient (CCC) to demonstrate agreement of each with the exact **FastPCA**. Singular values produced by **irlba** and both implementations from **bigstatsr** were identical to those from the full SVD (**Table 3**). Again, **FastPCA** using randomized SVD, both algorithms from **pcaone**, and **BiocSingular** deviated slightly from the exact yet were considered “almost perfect” having CCC values greater than 0.99 (actually > 0.9999; Akoglu (2018)). For both principal component (PC) 1 and 2, the CCC was 1.0000 indicating perfect agreement (PCs calculated by multiplying the left singular vectors by the singular values).

**Table 3:** Concordance correlation coefficient estimates for how well each implementation agrees with the true full **FastPCA** singular value decomposition on the singular values and principal component 1 and 2 values.

Implementation	Singular Values	Principal Component 1	Principal Component 2
<b>FastPCA</b> (rSVD)	0.9999	1.0000	1.0000
<b>FastPCA</b> (Exact)	—	—	—
<b>irlba</b>	1.0000	1.0000	1.0000
<b>pcaone</b> (Alg1)	0.9999	1.0000	1.0000
<b>pcaone</b> (Alg2)	1.0000	1.0000	1.0000
<b>bigstatsr</b> (rSVD)	1.0000	1.0000	1.0000
<b>bigstatsr</b> (Partial)	1.0000	1.0000	1.0000
<b>BiocSingular</b> (rSVD)	0.9999	1.0000	1.0000

To demonstrate that the **FastPCA** exact is mathematically sound for the comparison above, we assessed its error compared to the original expression matrix. The absolute error (using the `r_norm` function with `type = "F"`) of the reconstructed data from the exact method is  $2.11\text{e-}09$ . Relative error, calculated by dividing absolute error by square root of variance within the original data, was calculated to be  $1.51\text{e-}13$ .

## Conclusion

**FastPCA** provides an accelerated route to principal component analysis on large matrices by coupling randomized SVD with **torch/pytorch** backends and a familiar R API. In our kidney cancer spatial-transcriptomics benchmark ( $199,112$  cells  $\times$   $978$  features), **FastPCA**'s randomized SVD achieved  $8.5$  s mean runtime on commodity hardware while matching the early singular values from exact decompositions and widely used methods (IRLBA in **irlba**). Memory use remained modest for **FastPCA**'s randomized SVD implementation ( $321.4$  MB), with predictable increase for exact decompositions when full matrices are returned. These results, together with setup helpers (optional Python via **reticulate**, otherwise R-only), make **FastPCA** a practical default for exploratory analyses and iterative pipelines (e.g., normalization alternatives, sub-clustering, visualization) where the top components contain the most biological information. Future work will extend functionality to sparse-matrix coverage and GPU pathways.

## Community Guidelines

Contributions by others is welcome for **FastPCA** as we believe it is a significant improvement to the field, allowing more people to analyze large datasets locally. To contribute, pull requests can be made to allow review before merging. Issues found should be submitted to <https://github.com/ACSoupir/FastPCA/issues> so we can fix them, improving user experience.

## Acknowledgements

This work was supported in part by effort on NIH R01CA279065. We would like to thank Dr. Oscar Ospina for his testing of the **FastPCA** in a single-cell workflow to validate its similarity to values derived from Seurat (**irlba**) in real data.

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