## Supplementary Information

## Supplementary Figure 1



Supplementary Figure 1. Average run time in seconds of 100 repetitions of $k_{\max }-1$ greedy algorithm runs that solve the shortest Hamiltonian path problem for distance matrices with $k \in\left\{2, \ldots, k_{\max }\right\}$ clusters, where $k_{\max }$ is the maximum number of clusters. The greedy algorithm is implemented in Rcpp in the scShaper $R$ package.

## Supplementary Figure 2



Supplementary Figure 2. Absolute values of Pearson correlation coefficients from 1000 scShaper runs to study robustness of scShaper. The runs were initialized with different random number generation seeds so that the random shuffling of cells before analysis and the results of the $k$-means clustering varied between the runs. The data set was a 3D spiral trajectory (see Supplementary Table 1), which is the same trajectory that is available on Github as an example (https://github.com/elolab/scshaper). The noise added to the coordinates was randomly sampled from a Gaussian distribution with standard deviation of 0.05 .

## Supplementary Figure 3



Supplementary Figure 3. Comparison of two approaches for pseudotime aggregation. Approach 1 denotes the aggregation approach of scShaper that selects the features that have a higher contribution to the 1st principal component than the 2nd principal component (see Section 2.1). Approach 2 uses the 1st principal component directly as the ensemble. In addition, the aggregated pseudotimes of both approaches were smoothed using LOESS to obtain the final continuous pseudotime. Each data point signifies the absolute value of the Pearson's correlation coefficient for one of the 50 trigonometric trajectories (see Section 2.4 and Supplementary Table 1). The correlation was calculated between the estimated and ground truth pseudotime of each trajectory. The rest of the parameters were set to their default values (see Section 3.1).

## Supplementary Figure 4



F1＿branches



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Supplementary Figure 4．The first part of the 17 benchmarking metrics computed using the dynbenchmark framework．See Supplementary Figs．5－6 for the visualizations of the rest of the metrics．Descriptions of the metrics are in Supplementary Table 2.

## Supplementary Figure 5



Supplementary Figure 5. The second part of the 17 benchmarking metrics computed using the dynbenchmark framework. See Supplementary Figs. 4 and 6 for the visualizations of the rest of the metrics. Descriptions of the metrics are in Supplementary Table 2.

## Supplementary Figure 6


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Supplementary Figure 6．The third part the 17 benchmarking metrics computed using the dynbenchmark framework．See Supplementary Figs．4－5 for the visualizations of the rest of the metrics．Descriptions of the metrics are in Supplementary Table 2.

## Supplementary Figure 7



Supplementary Figure 7. Comparison of scShaper and the principal curve method from the princurve R package with data simulated using four trigonometric functions (Section 2.4 of manuscript). The correlation value above each plot denotes the Pearson correlation coefficient between the inferred and ground truth pseudotimes.

## Supplementary Table 1

Supplementary Table 1. Details of the trigonometric trajectories.

| Name | Function | Range of $\boldsymbol{t}$ |
| :--- | :--- | :--- |
| 2D spiral | $x=t \cos (t), y=t \sin (t)$ | $[1,4 \pi]$ |
| Quadratically growing 2D spiral | $x=t^{2} \cos (t), y=t^{2} \sin (t)$ | $[1,4 \pi]$ |
| 3D spiral | $x=t \cos (t), y=t \sin (t)$, <br> $z=t$ | $[1,6 \pi]$ |
| Quadratically growing 3D spiral | $x=t^{2} \cos (t), y=t^{2} \sin (t)$, <br> $z=t$ | $[1,6 \pi]$ |
| Sine wave | $x=t, y=\sin (t)$ | $[0,4 \pi]$ |

## Supplementary Table 2

Supplementary Table 2. Details of the dynbenchmark metrics. Descriptions taken from the documentation of the dyneval R package and https://github.com/dynverse/dynbenchmark results. The metrics with "time_" prefix were excluded, because they measure the run time for calculating the metrics.

| Metric ID | Long name | Category | Perfect score | Worst score | Comment |
| :---: | :---: | :---: | :---: | :---: | :---: |
| correlation | Geodesic distance correlation | cell positions | 1 | 0 | Correlation between geodesic distances |
| rf_mse | Random Forest MSE | neighbourhood | 0 | 0.3 | Using use the positions of one trajectory to predict the positions within the other trajectory |
| rf_nmse | Random Forest Normalised MSE | neighbourhood | 1 | 0 |  |
| rf_rsq | Random Forest $\mathrm{R}^{2}$ | neighbourhood | 1 | 0 |  |
| $1 \mathrm{~m}_{\text {n }} \mathrm{nmse}$ | Linear regression Normalised MSE | neighbourhood | 1 | 0 |  |
| 1 m _mse | Linear regression MSE | neighbourhood | 0 | 0.3 |  |
| lm_rsq | Linear regression $\mathrm{R}^{2}$ | neighbourhood | 1 | 0 |  |
| edge_flip | Edge flip | topology | 1 | 0 | the minimal number of edges which should be added or removed to convert one network into the other, divided by the total number of edges in both networks |
| him | Hamming-Ipse n-Mikhailov similarity | topology | 1 | 0 | Hamming-Ipsen-Mikhailov distance |

$\left.\begin{array}{|l|l|l|l|l|l|}\hline \text { isomorphic } & \text { isomorphic } & \text { topology } & 1 & 0 & \begin{array}{l}\text { Running the BLISS } \\ \text { algorithm to see if two } \\ \text { graphs are isomorphic }\end{array} \\ \hline \text { featureimp_cor } & \begin{array}{l}\text { Feature } \\ \text { importance } \\ \text { correlation }\end{array} & \text { features } & 1 & 0 & \begin{array}{l}\text { 1) Random forest regression } \\ \text { to rank all the features } \\ \text { according to their importance } \\ \text { in predicting the positions of } \\ \text { cells in the trajectory 2) } \\ \text { Pearson correlation between } \\ \text { the rankings of the reference } \\ \text { and the prediction. }\end{array} \\ \hline \text { featureimp_wc } \\ \text { or } & \begin{array}{l}\text { Feature } \\ \text { importance } \\ \text { weighted } \\ \text { correlation }\end{array} & \text { features } & 1 & 0 & \begin{array}{l}\text { Same as featureimp_cor, but } \\ \text { the feature importance scores } \\ \text { in the reference are weighted } \\ \text { so that the top features have } \\ \text { relatively more impact on the } \\ \text { score }\end{array} \\ \hline \text { featureimp_ks } & \begin{array}{l}\text { Feature } \\ \text { importance } \\ \text { enrichment ks }\end{array} & \text { features } & 1 & 0 & \begin{array}{l}\text { Kolmogorov-Smirnov for } \\ \text { gene set enrichment analysis. }\end{array} \\ \text { Not mentioned in the original } \\ \text { comparison by Saelens et al. }\end{array}\right\}$

