## Cross-species cell-type assignment of single-cell RNA-seq by a heterogeneous graph neural network

Xingyan Liu<sup>1,2†</sup>, Qunlun Shen<sup>1,2†</sup> and Shihua Zhang<sup>1,2,3,4\*</sup>

<sup>1</sup>NCMIS, CEMS, RCSDS, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China;

<sup>2</sup>School of Mathematical Sciences, University of Chinese Academy of Sciences, Beijing 100049, China;

<sup>3</sup>Center for Excellence in Animal Evolution and Genetics, Chinese Academy of Sciences, Kunming 650223, China;

<sup>4</sup>Key Laboratory of Systems Health Science of Zhejiang Province, School of Life Science, Hangzhou Institute for Advanced Study, University of Chinese Academy of Sciences, Chinese Academy of Sciences, Hangzhou 310024, China.

<sup>†</sup>These authors contributed equally to this work.

\*To whom correspondence should be addressed. Tel/Fax: +86 01 82541360; Email: zsh@amss.ac.cn.

## **Supplemental Figures**



**Figure S1. Performance evaluation during the training process and ablation experiments about six key factors of CAME.** (A) (Left) Classification accuracy of training and test during the training process of CAME. (Right) The changes of test classification accuracy and the adjusted mutual information (AMI) between the predicted labels and pre-clustered ones of query cells during the training process of CAME. (B) Ablation experiments showing the importance of each part or key hyperparameters adopted by CAME, where the values in parentheses represent the average accuracy across all the reference-query pairs.



**Figure S2. Multi-label cell-type prediction analysis.** (**A**, **C**) Distribution of predicted probabilities of mouse brain cells (A) and turtle brain cells (C) with the human reference respectively, where each column shows a query cell type. The probabilities are calculated in a multi-label manner. (**B**, **D**) Reference type-removal experiments. Upper, both inhibitory and excitatory neurons were removed from the reference for two cases, and the neurons in the query data were predicted with much more uncertainty. Lower, predictions with the removal of oligodendrocytes from the reference for two cases, where most of the oligodendrocytes were assigned higher probability to its precursor type.



**Figure S3. Performance of CAME for cross-species cell-type assignment. (A)** Overview of datasets. (**B**) Proportion (lower triangular) and number (upper triangular) of homologous genes between each pair of species. (**C**) Density plot of the proportions of the non-one-to-one homologous genes in HIGs (**Methods**) for two groups of dataset pairs. (**D**) Box plots showing the cell-type assignment performance of CAME and CAME\* (using only one-to-one homologous genes) based on zebrafish-excluded and zebrafish-associated dataset pairs.



**Figure S4. Statistics of gene homologies and comparison between CAME and CAME\*.** (A) Performance comparison between CAME and CAME\* in terms of cross-species cell-type assignment for zebrafish-excluded dataset pairs. (B) Performance comparison between CAME and CAME\* in terms of cross-species cell-type assignment for zebrafish-associated dataset pairs, where "X-Y" indicates the label transfer from species X to Y. C: chick, H: human, M: mouse, Z: zebrafish.

| A | Method     | Index  | Brain  | Kidney | Pancreas | Retina | Testis |
|---|------------|--------|--------|--------|----------|--------|--------|
|   | 0.4.14     | mean   | 0.0595 | 0.2212 | 0.1377   | 0.0644 | 0.0944 |
|   | БАмар      | median | 0.0299 | 0.1455 | 0.1485   | 0.0182 | 0.0561 |
|   | Scmap      | mean   | 0.6884 | 0.4705 | 0.7278   | 0.6101 | 0.7457 |
|   |            | median | 0.7139 | 0.489  | 0.7739   | 0.7003 | 0.758  |
|   | ltClust    | mean   | 0.5742 | 0.3036 | 0.397    | 0.6437 | 0.6181 |
|   |            | median | 0.6338 | 0.2243 | 0.0693   | 0.7158 | 0.6852 |
|   | SCN        | mean   | 0.6466 | 0.44   | 0.5611   | 0.6138 | 0.7028 |
|   |            | median | 0.6714 | 0.5262 | 0.5962   | 0.5974 | 0.7029 |
|   | Cell BLAST | mean   | 0.6638 | 0.307  | 0.8059   | 0.6423 | 0.6434 |
|   |            | median | 0.6808 | 0.288  | 0.848    | 0.6381 | 0.6894 |
|   | SciBet     | mean   | 0.8275 | 0.5173 | 0.618    | 0.7258 | 0.749  |
|   |            | median | 0.8486 | 0.48   | 0.6139   | 0.7251 | 0.7345 |
|   | Courset    | mean   | 0.72   | 0.4891 | 0.7321   | 0.8211 | 0.7505 |
|   | Seural     | median | 0.7391 | 0.471  | 0.7396   | 0.8454 | 0.7457 |
|   | CAME*      | mean   | 0.8352 | 0.5767 | 0.8544   | 0.8719 | 0.7984 |
|   | CAME       | median | 0.8176 | 0.5972 | 0.8636   | 0.9099 | 0.7978 |
|   | CAME       | mean   | 0.8413 | 0.593  | 0.8846   | 0.8936 | 0.8022 |
|   | CAME       | median | 0.8401 | 0.6549 | 0.8749   | 0.915  | 0.7821 |

| В | Mathad  | Reference | Chick  | Human     | Mouse  |        | Zebrafish |        |
|---|---------|-----------|--------|-----------|--------|--------|-----------|--------|
|   | method  | Query     |        | Zebrafish |        | Chick  | Human     | Mouse  |
|   | C A Man | mean      | 0.2373 | 0.0874    | 0.0898 | 0.0513 | 0.0608    | 0.075  |
|   | ЗАмар   | median    | 0.1588 | 0.0679    | 0.0762 | 0.0185 | 0.0015    | 0.0069 |
|   | 0       | mean      | 0.2105 | 0.1631    | 0.3542 | 0.1496 | 0.2971    | 0.1924 |
|   | Scmap   | median    | 0.2086 | 0.1605    | 0.3512 | 0.0977 | 0.2739    | 0.1387 |
|   | 401     | mean      | 0.4754 | 0.4595    | 0.4395 | 0.2487 | 0.1352    | 0.2505 |
|   | itclust | median    | 0.4755 | 0.4482    | 0.4743 | 0.1439 | 0.0693    | 0.1587 |
|   | CON     | mean      | 0.2687 | 0.1862    | 0.2791 | 0.3217 | 0.3357    | 0.3374 |
|   | SCN     | median    | 0.2653 | 0.1808    | 0.2827 | 0.34   | 0.3877    | 0.3477 |
|   | Cell    | mean      | 0.5496 | 0.3457    | 0.3691 | 0.5731 | 0.3622    | 0.465  |
|   | BLAST   | median    | 0.5438 | 0.3495    | 0.3807 | 0.5479 | 0.3524    | 0.4663 |
|   | CaiDat  | mean      | 0.428  | 0.4137    | 0.4799 | 0.5234 | 0.3847    | 0.4329 |
|   | SCIBEL  | median    | 0.4163 | 0.425     | 0.4807 | 0.5262 | 0.3882    | 0.4286 |
|   | Courat  | mean      | 0.3234 | 0.3736    | 0.5533 | 0.492  | 0.5167    | 0.5511 |
|   | Seural  | median    | 0.2848 | 0.3688    | 0.5657 | 0.5024 | 0.5376    | 0.548  |
|   |         | mean      | 0.5525 | 0.4726    | 0.5937 | 0.6201 | 0.5605    | 0.5935 |
|   |         | median    | 0.5326 | 0.48      | 0.6049 | 0.6621 | 0.6293    | 0.6268 |
|   | CAME    | mean      | 0.5679 | 0.5044    | 0.6385 | 0.6685 | 0.6466    | 0.6808 |
|   | CAME    | median    | 0.5918 | 0.5153    | 0.6405 | 0.6767 | 0.6872    | 0.7307 |

Figure S5. Performance comparison of classification accuracy between CAME and other benchmarking methods. (A) Mean and median classification accuracies of CAME and other benchmarking methods on 139 pairs of cross-species scRNA-seq datasets (zebrafish excluded). Each column corresponds to a specific tissue. (B) Mean and median classification accuracies of CAME and baseline methods on the crossspecies scRNA-seq data associated with zebrafish. Each column corresponds to different species pairing with each other respectively.



**Figure S6. Performance comparison of cell-type classification of CAME and six benchmarking methods.** (**A**) Pairwise comparison of the cell-typing performance of CAME and other six benchmarking methods on 139 pairs of cross-species scRNA-seq datasets in terms of macro-F1 and weighted-F1 (zebrafish-excluded). (**B**) Pairwise comparison of the cell-typing performance of CAME and other six benchmarking methods on 510 pairs of cross-species scRNA-seq datasets in terms of macro-F1 and weighted-F1 (zebrafish-associated). The notation "X-Y" indicates that X is the reference and Y is the query. H: Human, M: Mouse, C: Chick, Z: Zebrafish.



**Figure S7. Robustness to inconsistent and insufficient sequencing depths (zebrafish-excluded).** (**A**) Violin plots of classification accuracies of CAME and six benchmarking methods with different down-sampling rates (0.75, 0.5, 0.25, 0.1) for read counts on the reference data. (**B**) Violin plots of classification accuracies of CAME and six benchmarking methods with different down-sampling rates (0.75, 0.5, 0.25, 0.1) on both reference and query data.



**Figure S8. Robustness to inconsistent and insufficient sequencing depths (zebrafish-associated).** Violin plots of classification accuracies of CAME and six benchmarking methods with different down-sampling rates (0.75, 0.5, 0.25, 0.1) for read counts on reference, query, and both datasets respectively.

| Α |                          |        | Brain  | Kidney | Pancreas | Retina | Testis |
|---|--------------------------|--------|--------|--------|----------|--------|--------|
|   | byg1000+dog50            | mean   | 0.8386 | 0.5939 | 0.8159   | 0.9038 | 0.8002 |
|   | nvg rooo+degoo           | median | 0.8118 | 0.6278 | 0.8563   | 0.9127 | 0.7898 |
|   | hvg1000+deg100           | mean   | 0.8414 | 0.6506 | 0.7896   | 0.8981 | 0.7492 |
|   |                          | median | 0.8280 | 0.6647 | 0.8331   | 0.9127 | 0.7620 |
|   | byg2000±dog100           | mean   | 0.8361 | 0.5883 | 0.7866   | 0.8906 | 0.7787 |
|   | nvg2000+deg100           | median | 0.8243 | 0.6279 | 0.8092   | 0.9058 | 0.7723 |
|   | hvg3000+deg50            | mean   | 0.8323 | 0.5474 | 0.8169   | 0.9028 | 0.7904 |
|   |                          | median | 0.8306 | 0.6210 | 0.8570   | 0.9108 | 0.7933 |
|   | hvg3000+deg100           | mean   | 0.8345 | 0.5721 | 0.8187   | 0.8901 | 0.7628 |
|   |                          | median | 0.8310 | 0.5637 | 0.8414   | 0.9090 | 0.7629 |
|   | Seurat hvg2000<br>+deg50 | mean   | 0.8331 | 0.5429 | 0.8297   | 0.9031 | 0.7644 |
|   |                          | median | 0.8047 | 0.5772 | 0.8640   | 0.9169 | 0.7847 |
|   |                          | mean   | 0.8529 | 0.5572 | 0.8345   | 0.9097 | 0.7805 |
|   | 256 hidden units         | median | 0.8457 | 0.5931 | 0.8496   | 0.9221 | 0.8053 |
|   | 512 hiddon unito         | mean   | 0.8479 | 0.6078 | 0.8624   | 0.9151 | 0.8139 |
|   | 512 hidden units         | median | 0.8616 | 0.6806 | 0.8802   | 0.9207 | 0.8080 |
|   | 1021 hiddon unito        | mean   | 0.8398 | 0.5255 | 0.8498   | 0.9004 | 0.7766 |
|   | 1024 hidden units        | median | 0.8445 | 0.5576 | 0.8705   | 0.9146 | 0.8041 |
|   | three hidden lavers      | mean   | 0.8377 | 0.5678 | 0.8295   | 0.9003 | 0.7803 |
|   | three hidden layers      | median | 0.8565 | 0.6326 | 0.8553   | 0.9167 | 0.7808 |
|   | defeult                  | mean   | 0.8413 | 0.5930 | 0.8315   | 0.8936 | 0.8022 |
|   | deiðult                  | median | 0.8401 | 0.6549 | 0.8590   | 0.9150 | 0.7821 |

| в |                      | Reference | Chick  | Human     | Mouse  | Zebrafish |        |        |
|---|----------------------|-----------|--------|-----------|--------|-----------|--------|--------|
| _ |                      | Query     |        | Zebrafish |        | Chick     | Human  | Mouse  |
|   | byg1000±dog50        | mean      | 0.5917 | 0.5288    | 0.6295 | 0.5665    | 0.6719 | 0.6734 |
|   | nvg looo+degoo       | median    | 0.5879 | 0.5562    | 0.6354 | 0.6335    | 0.7124 | 0.7408 |
|   | hvg1000+deg100       | mean      | 0.5742 | 0.5383    | 0.6399 | 0.5889    | 0.6634 | 0.6567 |
|   |                      | median    | 0.5879 | 0.5377    | 0.6539 | 0.6508    | 0.7143 | 0.7297 |
|   | hvg2000+deg100       | mean      | 0.5816 | 0.5506    | 0.6399 | 0.6049    | 0.6543 | 0.6554 |
|   |                      | median    | 0.5687 | 0.5405    | 0.6444 | 0.6432    | 0.6872 | 0.7094 |
|   | hvg3000+deg50        | mean      | 0.5671 | 0.4934    | 0.6453 | 0.6324    | 0.6662 | 0.6630 |
|   |                      | median    | 0.5781 | 0.4921    | 0.6502 | 0.6603    | 0.7063 | 0.7157 |
|   | hvg3000+deg100       | mean      | 0.5860 | 0.4910    | 0.6300 | 0.5795    | 0.6326 | 0.6501 |
|   |                      | median    | 0.5868 | 0.5202    | 0.6368 | 0.6583    | 0.6925 | 0.7044 |
|   | Seurat hvg2000+deg50 | mean      | 0.5554 | 0.5250    | 0.6255 | 0.6729    | 0.6989 | 0.6856 |
|   |                      | median    | 0.5718 | 0.5225    | 0.6332 | 0.6678    | 0.7389 | 0.7228 |
|   | 256                  | mean      | 0.6039 | 0.5477    | 0.6476 | 0.6401    | 0.7003 | 0.7084 |
|   | 250 units            | median    | 0.5978 | 0.5770    | 0.6528 | 0.6715    | 0.7446 | 0.7606 |
|   | E42 unito            | mean      | 0.5928 | 0.5947    | 0.6558 | 0.6402    | 0.6241 | 0.7168 |
|   | 512 units            | median    | 0.5777 | 0.6114    | 0.6553 | 0.7132    | 0.7238 | 0.7971 |
|   | 1024 unite           | mean      | 0.5912 | 0.5515    | 0.6424 | 0.7000    | 0.5940 | 0.6945 |
|   | 1024 units           | median    | 0.5816 | 0.5427    | 0.6411 | 0.7457    | 0.6349 | 0.7717 |
|   | three hidden lovers  | mean      | 0.5895 | 0.5273    | 0.6449 | 0.6044    | 0.6362 | 0.6464 |
|   | unee muden layers    | median    | 0.5883 | 0.5432    | 0.6504 | 0.6576    | 0.6387 | 0.7105 |
|   | dofoult              | mean      | 0.5679 | 0.5044    | 0.6385 | 0.6685    | 0.6466 | 0.6808 |
|   | default              | median    | 0.5918 | 0.5153    | 0.6405 | 0.6767    | 0.6873 | 0.7307 |

**Figure S9**. Performance comparison of classification accuracy of CAME under different gene selection strategies and hyperparameters. (A) Mean and median classification accuracies of CAME of CAME under different gene selection strategies and hyperparameters on 139 pairs of cross-species scRNA-seq datasets (zebrafish excluded). Each column corresponds to a specific tissue. (B) Mean and median classification accuracies of CAME under different gene selection strategies and hyperparameters on the cross-species scRNA-seq data associated with zebrafish. Each column corresponds to different species pairing with each other respectively.



Figure S10. Cross-species alignment of homologous cell types by CAME and other five methods. UMAP plots of cell embeddings based on CAME and five typical data integration methods including FastMNN, Harmony, LIGER, Cell BLAST, and Seurat on four pairs of datasets, including human and mouse pancreas data, ("panc8" and "FACS"), human and lizard brains ("Lake\_2018" and "Tosches\_lizard"), human and mouse brains ("Lake\_2018" and "Tasic18"), human and mouse retinal cells ("Menon\_microfluidics" and "Macosko"). Cells are colored by their dataset identities (the first row) or cell types (the second row) respectively.



**Figure S11. Robustness to multi-reference batch effects with given batch labels.** UMAP plots of cell embeddings based on the output of CAME and five typical data integration methods including FastMNN, Harmony, LIGER, Cell BLAST, and Seurat. The reference datasets are the human pancreatic scRNA-seq data from eight batches by five different platforms and the query is from mouse pancreas cells. Cells are colored by their cell types (the first column) and dataset identities (the second column) respectively. The UMAP plots on the third column show the reference datasets, colored by batch identities.



**Figure S12. Genes of top attentions and gene embeddings of human and mouse brains.** (A) Dot plots showing the expressions of genes with top attentions in the corresponding cell types. (B) UMAP plots of genes showing the average expression patterns (z-scored across cell-types for each gene) of the major types for human and mouse brain, where each point represents a gene and the color of each scatter is scaled by the expression level of that cell type in each gene. SMC is short for "smooth muscle cell", and VLMC is short for "vascular and leptomeningeal cell".



**Figure S13. Comparisons of the four interneuron subtypes between human and mouse brains.** (**A**) The predicted cell-type probabilities for each cell (each column) in the scRNA-seq data of the mouse brain, taking the gene expressions of the human brain as the reference (each row shows a cell type in human data). (**B**) The UMAP plots of cell embeddings by CAME, colored by datasets (left) or cell type (right). (**C**) The gene expression profiles of each inhibitory neural subtype in humans (upper, blue dots) or mice (lower, red dots), where the genes were detected as the top DEGs of each human interneuron subtype. (**D**) Similar to (C), the top DEGs of each mouse interneuron subtype are shown.



**Figure S14. Explorations of the Meis2 inhibitory cell which is mouse-specific in cell-type transferring.** (**A**) The predicted cell-type probabilities for each cell (each column) in the scRNA-seq data of the human cortex, taking the gene expressions of the human brain as the reference (each row shows a cell type in human data). (**B**) The UMAP plots of cell embeddings by CAME, colored by datasets (left) or cell type (right). (**C**) Abstracted graph of the heterogeneous cell-gene graph. Each node represents a cell type (pink) or a gene module (light blue). The size of a node is scaled by the number of single cells in that type or the number of genes in that gene module. The width of an edge is scaled by either the normalized mean expression levels of a cell type in the connected gene module or the conservancy of inter-species gene modules based on the gene embeddings learned by CAME. (**D**) Enrichment analysis of gene module 8 which is related to mouse-specific Meis2 cells.



Figure S15. Separate module extraction based on gene embeddings by CAME on human and macaque testicular data respectively. (A) The abstracted heterogeneous cell-gene graph. (B) Gene modules detected by separate module extraction of genes from humans (above) and macaques (below). Non-one-to-one homologous gene pairs and species-specific genes were included.

|      |                      |   | cell  |  | cell  | cell   | neuron  | cone cell   | ganglion<br>cell                                      | cell  | cell   |
|------|----------------------|---|---|--|---|--|---|---|---|---|--|
| uman | common1v1            | 1   | 17  | 6  | 57  | 4  | 1   | 0   | 4   | 3   |  |
|      | common1              | 4   | 34  | 16   | 75  | 9  | 3   | 11  | 15  | 17  |  |
|      | common2              | 3   | 29  | 16   | 75  | 9  | 3   | 9   | 13  | 11  |  |
|      | private1             | 117   | 188   | 152  | 249   | 132  | 66  | 129   | 121   | 47  |  |
|      | private2             | 27  | 102   | 124  | 162   | 91   | 52  | 82  | 67  | 87  |  |
| ouse | common1v1            | 12  | 12  | 9  | 25  | 3  | 1   | 4   | 10  | 5   | 6  |
|      | common1              | 19  | 24  | 28   | 44  | 10   | 5   | 16  | 28  | 20  | 10   |
|      | common2              | 18  | 22  | 26   | 43  | 9  | 5   | 12  | 24  | 14  | 10   |
|      | private1             | 117   | 188   | 152  | 249   | 132  | 66  | 129   | 121   | 47  | 150  |
|      | private2             | 66  | 163   | 139  | 190   | 126  | 68  | 23  | 126   | 82  | 150  |
| nick | common1v1            | 10  |   | 7  |   |  | 2   | 11  | 5   | 10  |  |
|      | common1              | 21  |   | 18   |   |  | 3   | 31  | 27  | 20  |  |
|      | common2              | 19  |   | 17   |   |  | 3   | 27  | 21  | 16  |  |
|      | private1             | 117   |   | 152  |   |  | 66  | 129   | 121   | 47  |  |
|      | private2             | 65  |   | 133  |   |  | 90  | 127   | 117   | 86  |  |
| ouse | common1v1            | 10  | 28  | 32   | 46  | 18   | 14  | 4   | 12  | 35  |  |
|      | common1              | 10  | 32  | 34   | - 53  | 18   | 14  | 5   | 13  | 35  |  |
|      | common2              | 10  | 32  | 34   | 51  | 18   | 14  | 5   | 13  | 35  |  |
|      | private1             | 27  | 102   | 124  | 162   | 91   | 52  | 82  | 67  | 87  |  |
|      | private2             | 66  | 163   | 139  | 190   | 126  | 68  | 23  | 126   | 82  |  |
|      | buse<br>hick<br>buse | common1<br>common2<br>private1<br>private2<br>puse common1v1<br>common1<br>common2<br>private1<br>private2<br>private1<br>private2<br>private1<br>private2<br>private1<br>private2<br>private1<br>private2<br>private1<br>private2<br>private1<br>private2<br>private1<br>private2<br>private1<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>private2<br>p | common1     4       common2     3       private1     117       private2     27       puse     common1v1     12       common1     19     common1     19       common1     19     common1     19       private1     117     private2     66       nick     common1     21     common2     19       private1     117     private1     117       private1     117     private1     117       private1     117     10     common2     19       private1     117     private1     117       private1     117     private1     117       private2     65     5     5       puse     common1v1     10     0       common2     10     10     10       private1     27     66     6 | common1     4     34       common2     3     29       private1     117     188       private2     27     102       puse     common1v1     12     12       common1     19     24       private1     117     18     22       private1     117     188     22       private1     117     188     22       private1     117     188     22       private1     117     188     22       private2     66     163     163       nick     common1v1     10     28     20       common1     10     32     265     103       private1     27     102     32     10     32       private1     27     102     10     32     32       private2     66     163     163     163 | common1     4     34     166       common2     3     29     166       private1     117     188     152       private2     27     102     124       puse     common1v1     19     24     28       common1     18     22     26       private1     117     188     152       common1     21     18     18     152       common2     19     17     17     152       private1     117     16     28     32       common2     10     32     34       common2     10     32     34       private1     27     102 <td>common1     4     34     16     75       private1     117     188     152     249       private1     117     188     152     249       private2     27     102     124     162       puse     common1v1     12   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&amp; 26 &amp; 43 &amp; 9\\ private1 &amp; 117 &amp; 188 &amp; 152 &amp; 249 &amp; 132\\ private2 &amp; 66 &amp; 163 &amp; 139 &amp; 190 &amp; 126\\ tick &amp; common1v1 &amp; 10 &amp; 7 &amp; \\ common2 &amp; 19 &amp; 17 &amp; \\ private1 &amp; 117 &amp; 152 &amp; \\ ouse &amp; common1v1 &amp; 10 &amp; 28 &amp; 32 &amp; 46 &amp; 18\\ common2 &amp; 19 &amp; 17 &amp; \\ private2 &amp; 65 &amp; 133 &amp; \\ ouse &amp; common1v1 &amp; 10 &amp; 28 &amp; 32 &amp; 46 &amp; 18\\ common2 &amp; 10 &amp; 32 &amp; 34 &amp; 53 &amp; 18\\ common2 &amp; 10 &amp; 32 &amp; 34 &amp; 51 &amp; 18\\ private1 &amp; 27 &amp; 102 &amp; 124 &amp; 162 &amp; 91\\ private2 &amp; 66 &amp; 163 &amp; 139 &amp; 190 &amp; 126\\ \end{array}</math></td> <td><math display="block">\begin{array}{c ccccccccccccccccccccccccccccccccccc</math></td> <td><math display="block">\begin{array}{c ccccccccccccccccccccccccccccccccccc</math></td> <td><math display="block">\begin{array}{c ccccccccccccccccccccccccccccccccccc</math></td> 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    122     24     14       private1     117     188     152     249     132     66     129     121     47 < |

Mean expression

in group

0.5

1.0



0

C1QA CSF1R CSF1R

C1QC

CD74

CD74

Amacrine cell

Microalial cell

Chick

0

SCG2

0

SYT1

SLC6A1

PAX6 -RTN1 -PAX6 -RASL10A -





**Figure S17. Performance comparison of CAME with homologous gene relationships inferred by Ensembl\_Compara and Domainoid. (A)** Venn plot showing the intersection and difference set of the homologous genes inferred by Ensembl\_Compara and Domainoid. **(B)** Mean and median classification accuracies of CAME with homologous gene relationships inferred by Ensembl\_Compara and Domainoid on cross-species scRNA-seq datasets. The notation "X-Y" indicates that X is the reference and Y is the query. H: Human, M: Mouse, C: Chick, T: Turtle, L: Lizard, E: Macaque. **(C)** Performance comparison of CAME in terms of cell-typing accuracy where each point represents a pair of cross-species datasets and is colored by different tissues. **(D)** Performance comparison of CAME in terms of cell-typing accuracy with a boxplot.



Figure S18. Performance comparison for model training on the whole graph (WG) and sub-graphs (SG) (i.e., mini-batches). The reference data and query data are upsampled from the human and mouse pancreas dataset (the number of cells in reference and query is equal and the number of total cells is ranging from 20000 to 600000). To make a fair comparison, the genes were calculated from raw datasets. (A) Cell-typing performance comparison between the WG and SG training strategies based on 649 pairs of cross-species datasets in terms of Accuracy, Macro-F1, and Weighted-F1 scores. (B) The training time and peak graphical memory usage are showed for a different number of total cells.

## Supplemental Tables

| Table S1. scRNA-sec | datasets used for | benchmarking studies. |
|---------------------|-------------------|-----------------------|
|                     |                   |                       |

| Dataset                  | Organism            | Organ      | Platform      | Number   |
|--------------------------|---------------------|------------|---------------|----------|
|                          |                     |            |               | of cells |
| Baron_human [1]          | Homo sapiens        | Pancreas   | inDrop        | 8,569    |
| Baron_mouse [1]          | Mus musculus        | Pancreas   | inDrop        | 1,886    |
| panc8 (SeuratData)       | Homo sapiens        | Pancreas   | mixed         | 14,890   |
| FACS [2]                 | Mus musculus        | Pancreas   | Smart-seq2    | 1,328    |
| testis_human [3]         | Homo sapiens        | Testis     | Drop-seq      | 13,837   |
| testis_monkey [3]        | Macaca fascicularis | Testis     | Drop-seq      | 21,574   |
| testis_mouse [3]         | Mus musculus        | Testis     | Drop-seq      | 34,633   |
| Lake_2018 [4]            | Homo sapiens        | Brain      | snDrop-seq    | 35,289   |
| Tasic18 [5]              | Mus musculus        | Brain      | Smart-seq2    | 22,614   |
| Campbell [6]             | Mus musculus        | Brain      | Drop-seq      | 20,921   |
| Chen [7]                 | Mus musculus        | Brain      | Drop-seq      | 12,089   |
| Quake_Smart-seq2_Brain   | Mus musculus        | Brain Non- | Smart-seq2    | 3,401    |
| _Non-Myeloid [2]         |                     | Myeloid    |               |          |
| Tosches_lizard [8]       | Pohona vitticeps    | Brain      | Drop-seq      | 4,187    |
| Tosches_turtle [8]       | Trachemys scripta   | Brain      | Drop-seq      | 18,664   |
|                          | elegans             |            |               |          |
| Adam [9]                 | Mus musculus        | Kidney     | Drop-seq      | 3,660    |
| Karaiskos_mouse [10]     | Mus musculus        | Kidney     | Drop-seq      | 12,954   |
| Park [11]                | Mus musculus        | Kidney     | 10x           | 43,745   |
| Quake_10x_Kidney [2]     | Mus musculus        | Kidney     | 10x           | 2,781    |
| Wu_human [12]            | Homo sapiens        | Kidney     | 10x_snRNA-    | 4,298    |
|                          |                     |            | seq           |          |
| Young [13]               | Homo sapiens        | Kidney     | 10x           | 5,685    |
| Hochane [14]             | Homo sapiens        | Kidney     | 10x           | 14,606   |
| Alemany_Kidney [15]      | Danio rerio         | Kidney     | ScarTrace     | 4,415    |
| Menon_microfluidics [16] | Homo sapiens        | Retina     | microfluidics | 20,091   |
| Menon_seqwell [16]       | Homo sapiens        | Retina     | Seq-Well      | 3,014    |
| Macosko [17]             | Mus musculus        | Retina     | Drop-seq      | 44,808   |
| mouse_NMDA_3hr [18]      | Mus musculus        | Retina     | 10x           | 7,442    |
| mouse_NMDA_6hr [18]      | Mus musculus        | Retina     | 10x           | 6,202    |
| mouse_NMDA_12hr [18]     | Mus musculus        | Retina     | 10x           | 4,225    |
| mouse_NMDA_24hr [18]     | Mus musculus        | Retina     | 10x           | 4,194    |
| mouse_NMDA_36hr [18]     | Mus musculus        | Retina     | 10x           | 1,573    |
| mouse_NMDA_48hr [18]     | Mus musculus        | Retina     | 10x           | 5,189    |
| mouse_NMDA_72hr [18]     | Mus musculus        | Retina     | 10x           | 2,591    |
| mouse_NMDA_P60 [18]      | Mus musculus        | Retina     | 10x           | 6,889    |
| mouse_LD_0hr [18]        | Mus musculus        | Retina     | 10x           | 11,383   |

| mouse_LD_4hr [18]         | Mus musculus                | Retina | 10x | 3,094  |
|---------------------------|-----------------------------|--------|-----|--------|
| mouse_LD_10hr [18]        | Mus musculus                | Retina | 10x | 6,371  |
| mouse_LD_24hr [18]        | Mus musculus                | Retina | 10x | 4,756  |
| mouse_LD_P60 [18]         | Mus musculus                | Retina | 10x | 15,256 |
| zebrafish_LD_4hr [18]     | Danio rerio                 | Retina | 10x | 3,475  |
| zebrafish_LD_10hr [18]    | Danio rerio                 | Retina | 10x | 5,226  |
| zebrafish_LD_20hr [18]    | Danio rerio                 | Retina | 10x | 6,784  |
| zebrafish_LD_36hr [18]    | Danio rerio                 | Retina | 10x | 10,183 |
| zebrafish_LD_Adult [18]   | Danio rerio                 | Retina | 10x | 19,485 |
| zebrafish_NMDA_4hr [18]   | Danio rerio                 | Retina | 10x | 7,387  |
| zebrafish_NMDA_10hr [18]  | Danio rerio                 | Retina | 10x | 4,727  |
| zebrafish_NMDA_20hr [18]  | Danio rerio                 | Retina | 10x | 4,603  |
| zebrafish_NMDA_36hr [18]  | Danio rerio                 | Retina | 10x | 4,034  |
| zebrafish_NMDA_Adult [18] | Danio rerio                 | Retina | 10x | 19,485 |
| zebrafish_TNFa_10hr [18]  | Danio rerio                 | Retina | 10x | 9,769  |
| zebrafish_TNFa_20hr [18]  | Danio rerio                 | Retina | 10x | 5,086  |
| zebrafish_TNFa_36hr [18]  | Danio rerio                 | Retina | 10x | 6,269  |
| zebrafish_TNFa_72hr [18]  | Danio rerio                 | Retina | 10x | 7,931  |
| zebrafish_TNFa_Adult [18] | Danio rerio                 | Retina | 10x | 19,485 |
| chick_P10 [18]            | Gallus gallus<br>domesticus | Retina | 10x | 13,819 |

Table S2. Top 10 enriched GO terms for each of the gene modules extracted fromscRNA-seq data of human and mouse brains. All the GO terms are filtered by theBenjamini-Hochberg adjusted *p*-value < 0.1 (see the Excel table).</td>

**Table S3. Top 10 enriched GO terms for each of the gene modules extracted from scRNA-seq data of human and macaque testis.** All the GO terms are filtered by the Benjamini-Hochberg adjusted *p*-value < 0.1 (see the Excel table).

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