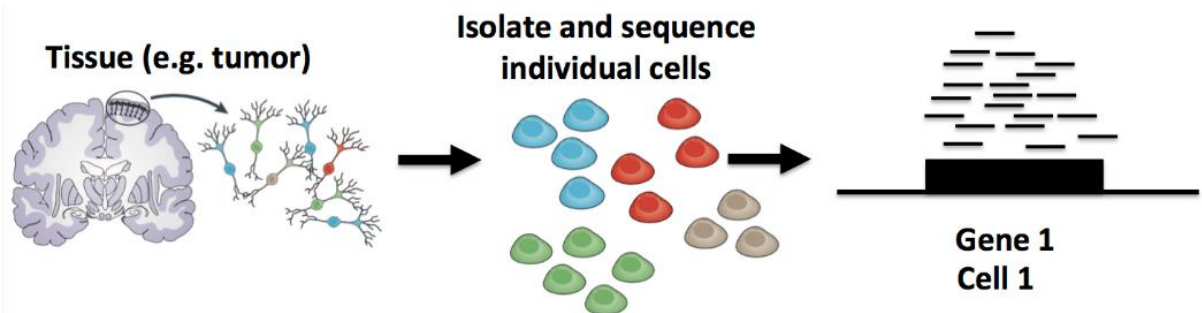


Background

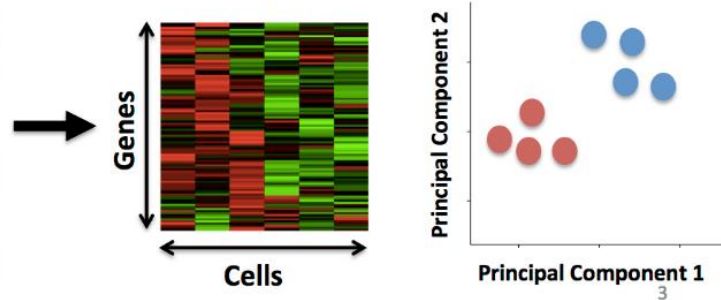
Single-cell RNA-seq



Read Counts

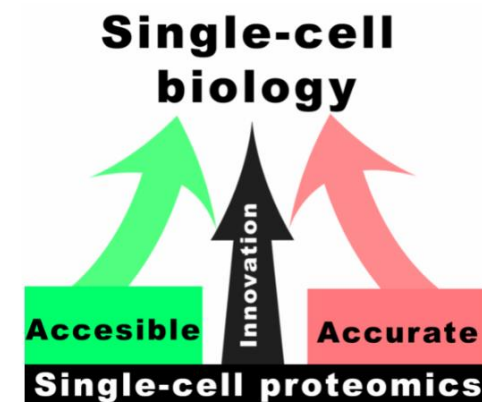
	Cell 1	Cell 2	...
Gene 1	18	0	
Gene 2	1010	506	
Gene 3	0	49	
Gene 4	22	0	
...			

Compare gene expression profiles of single cells



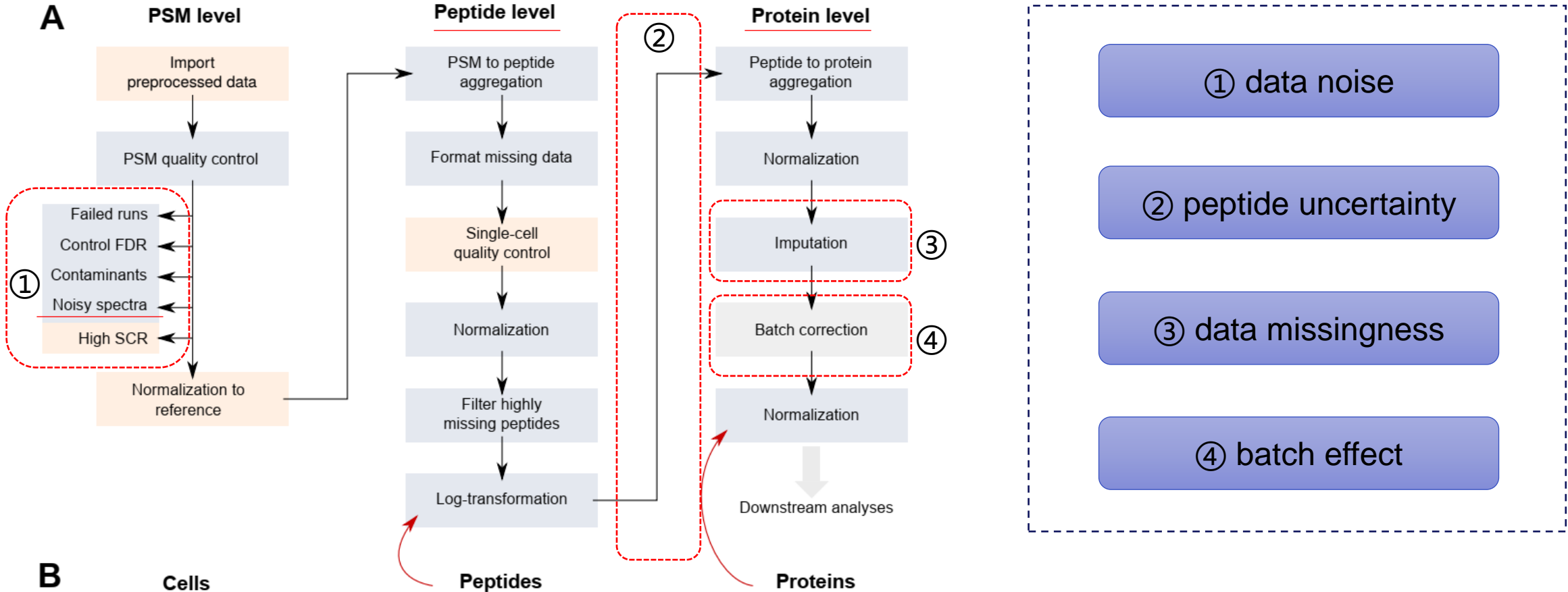
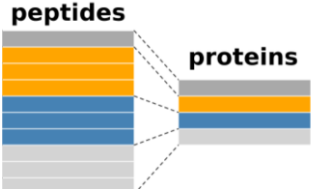
translation

Single-cell proteomics



	Cell1	Cell2	Cell3	...
Protein1				
Protein2				
Protein3				
Protein4				
...				

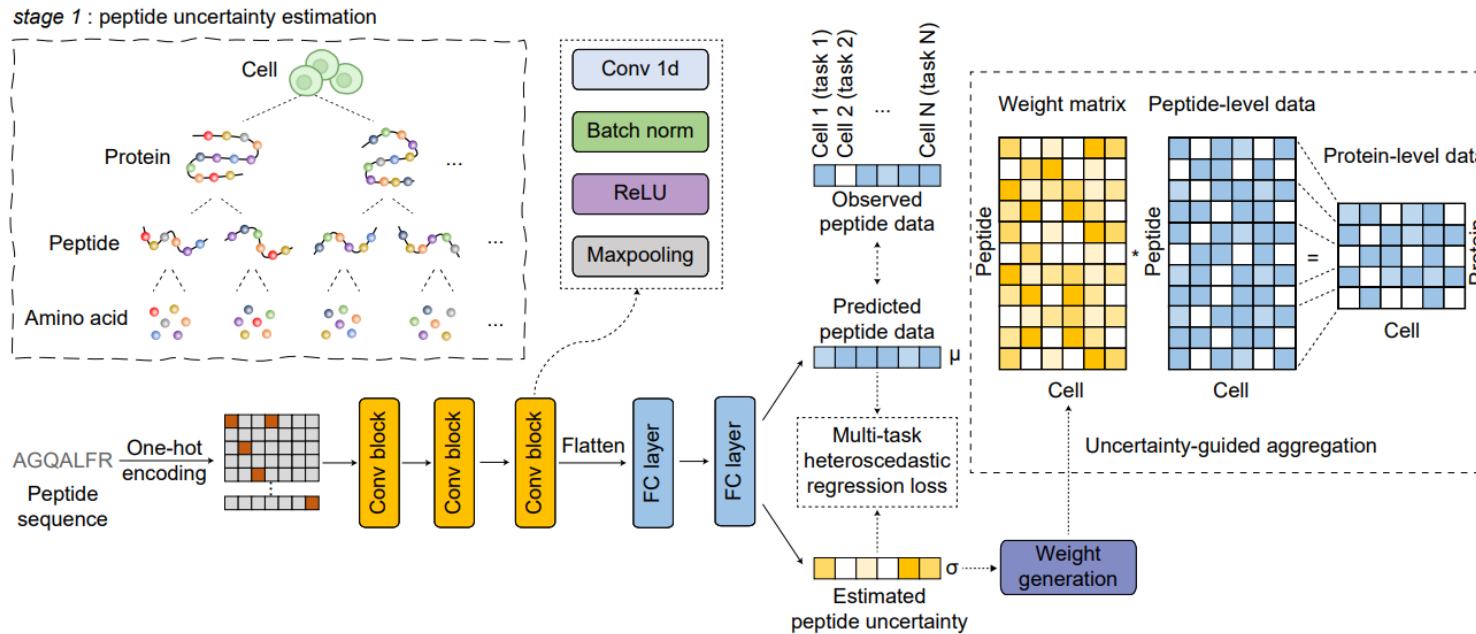
Existing single-cell proteomic processing pipeline



[1] Specht H, Emmott E, et al. Single-cell proteomic and transcriptomic analysis of macrophage heterogeneity using SCoPE2. Genome biology, 2021
 [2] <https://uclouvain-cbio.github.io/scp/articles/scp.html>

Method

- A versatile Deep Graph Contrastive Learning Framework (**scPROTEIN**) was developed for Single-cell Proteomics to tackle with this set of problems together
- stage 1: peptide uncertainty estimation

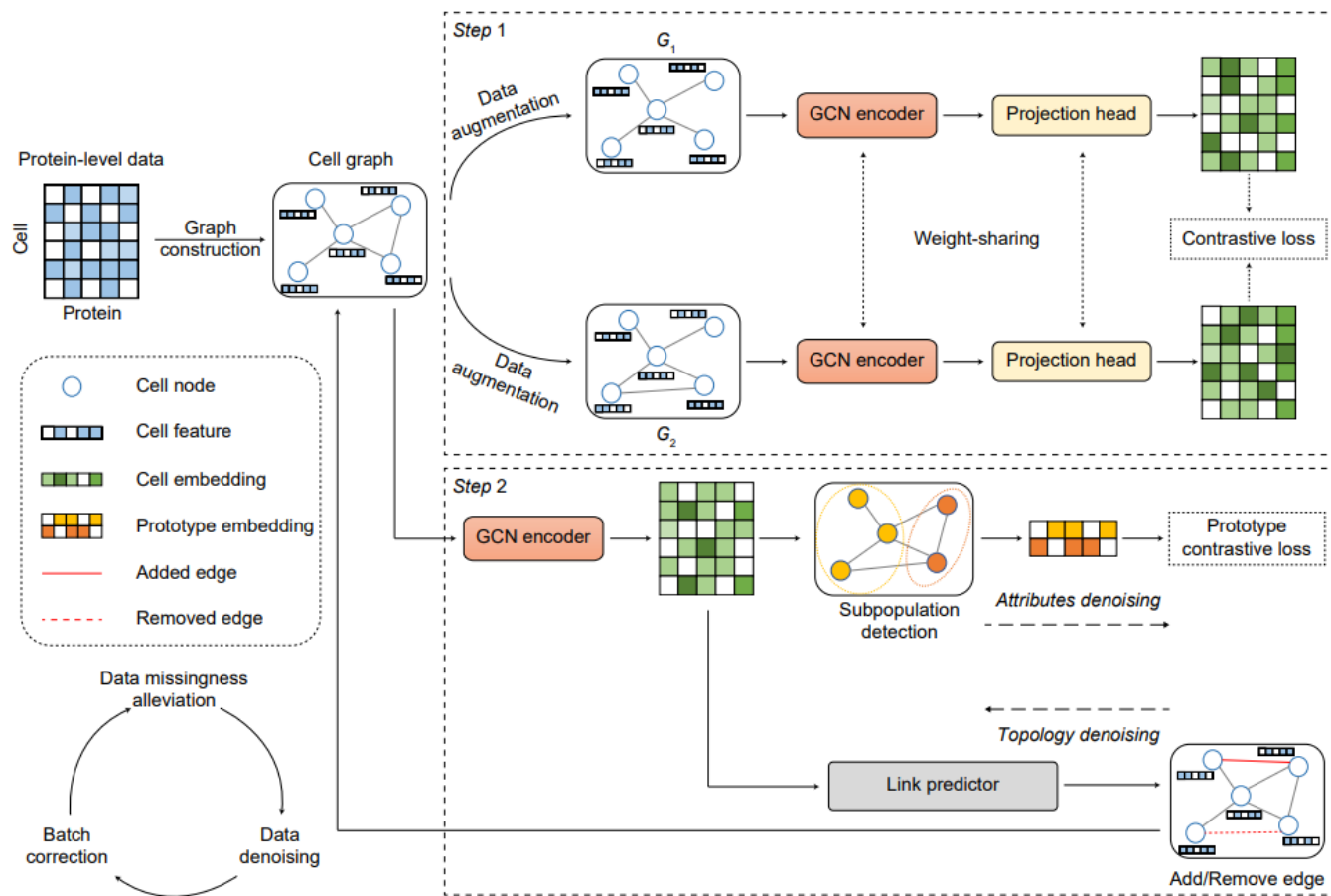


- ◆ Multi-task heteroscedastic regression model
- multi-task: estimate different uncertainties of all cells
- heteroscedastic: estimate different uncertainties across different peptides
- ◆ Uncertainty-guided peptide aggregation

Method

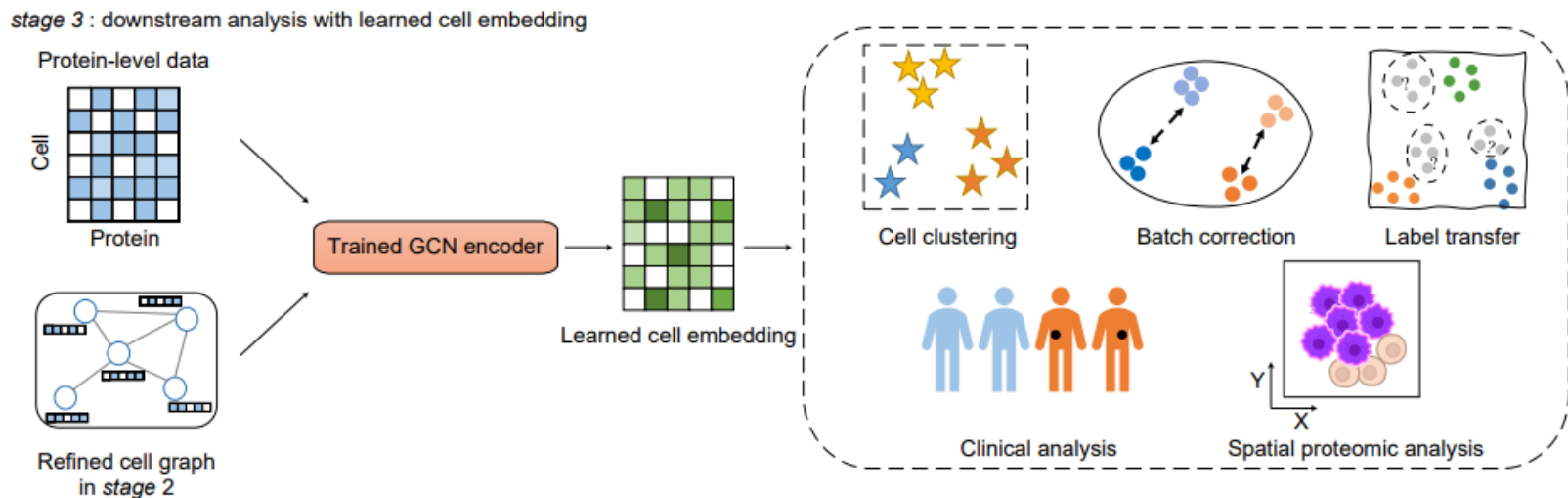
- stage 2: unsupervised cell embedding learning

stage 2 : unsupervised cell embedding learning



- ◆ Graph contrastive learning
 - Message passing process among neighborhood can help alleviate the data missingness
 - Batch effect can be implicitly alleviated by aligning the semantic information of the same cell type through contrastive loss
- ◆ Attribute-topology alternative denoising module
 - Two denoising modules are alternated to mitigate the noise problem in the proteomic profile.

Method



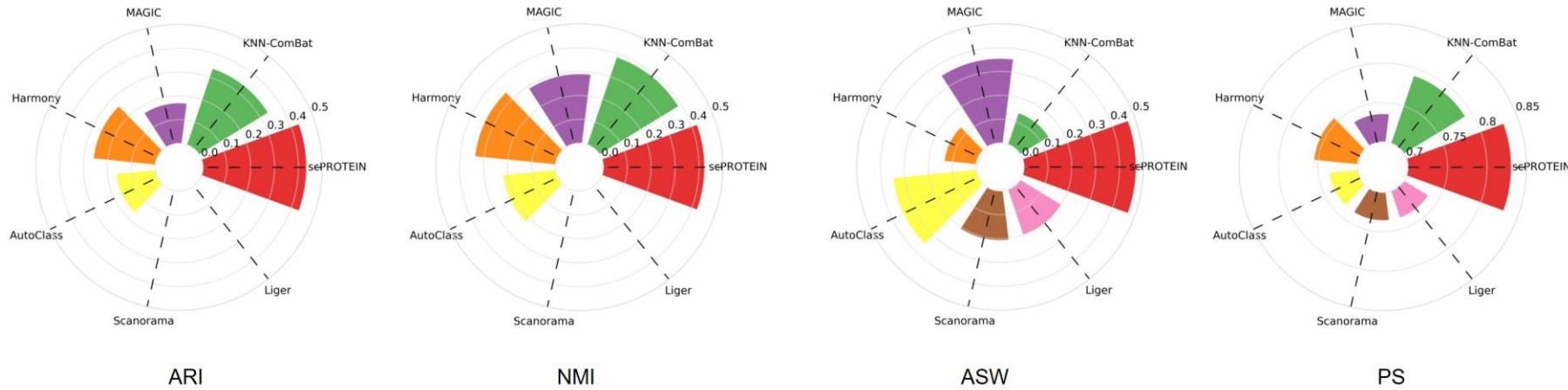
- stage 3: downstream analysis with learned embedding

The learned versatile embedding can be applied in a variety of downstream tasks:

- ✓ cell clustering
- ✓ batch correction
- ✓ label transfer
- ✓ clinical analysis
- ✓ spatial proteome analysis

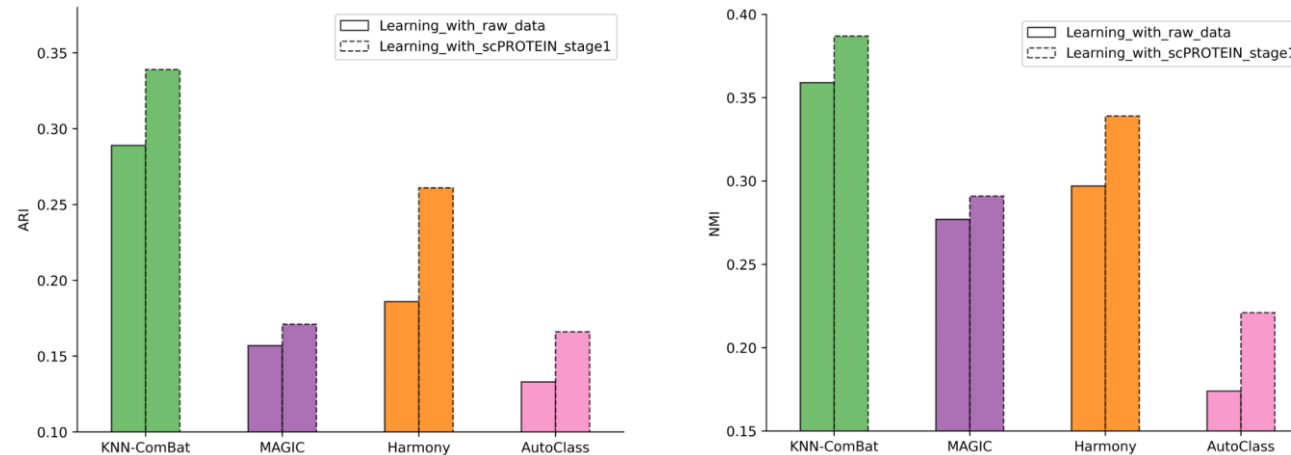
Results

➤ Cell clustering performance comparison on SCoPE2_Specht (1490 cells, 3042 proteins, two cell types)



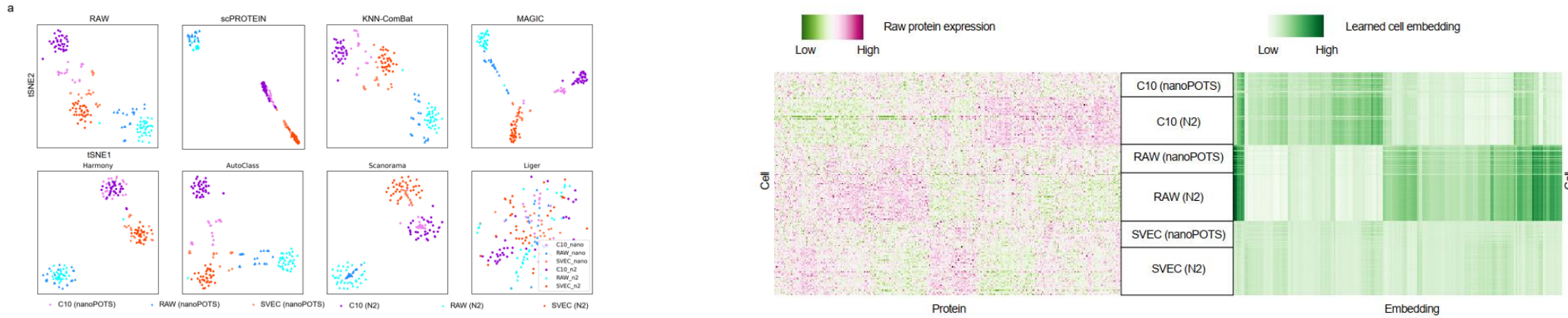
➤ Other methods with/wo scPROTEIN stage1

utilize the protein-level data from scPROTEIN stage1 as input for other methods



Results

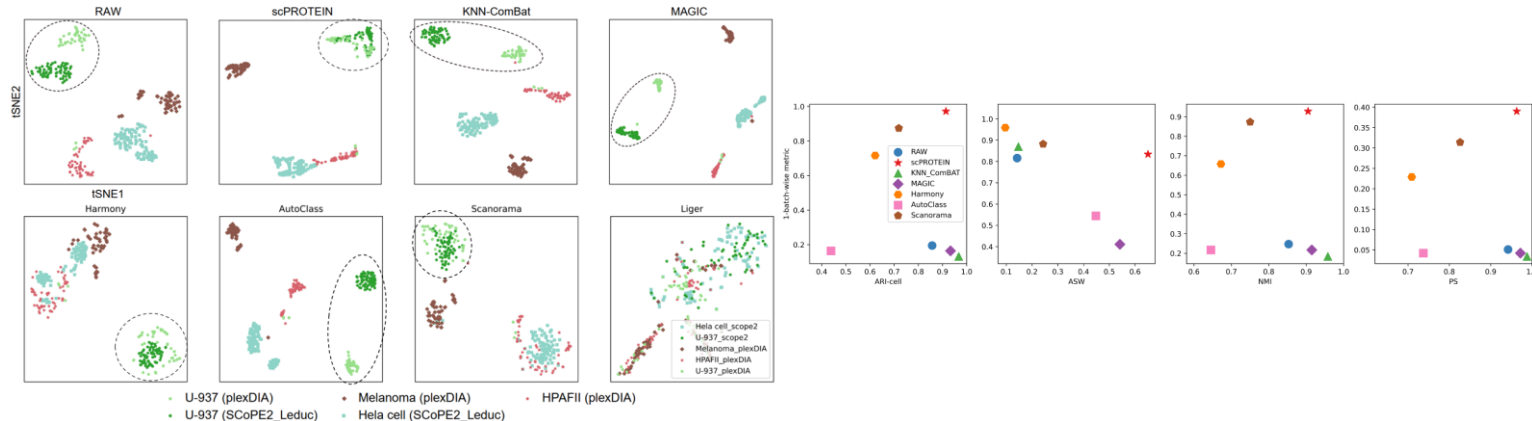
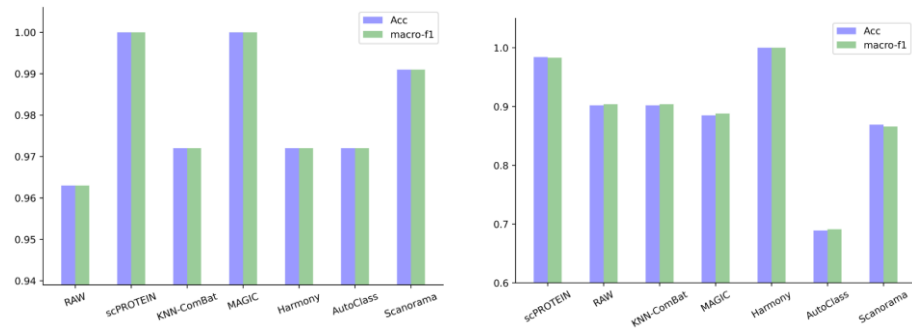
- Integrate N2 dataset (108 cells and 1068 proteins) with nanoPOTS dataset (61 cells and 1225 proteins)



- Integrate SCoPE2_Leduc (163 cells and 1647 proteins) and plexDIA (164 cells and 1242 proteins) dataset

These two datasets have different cell types, task is more challenging.

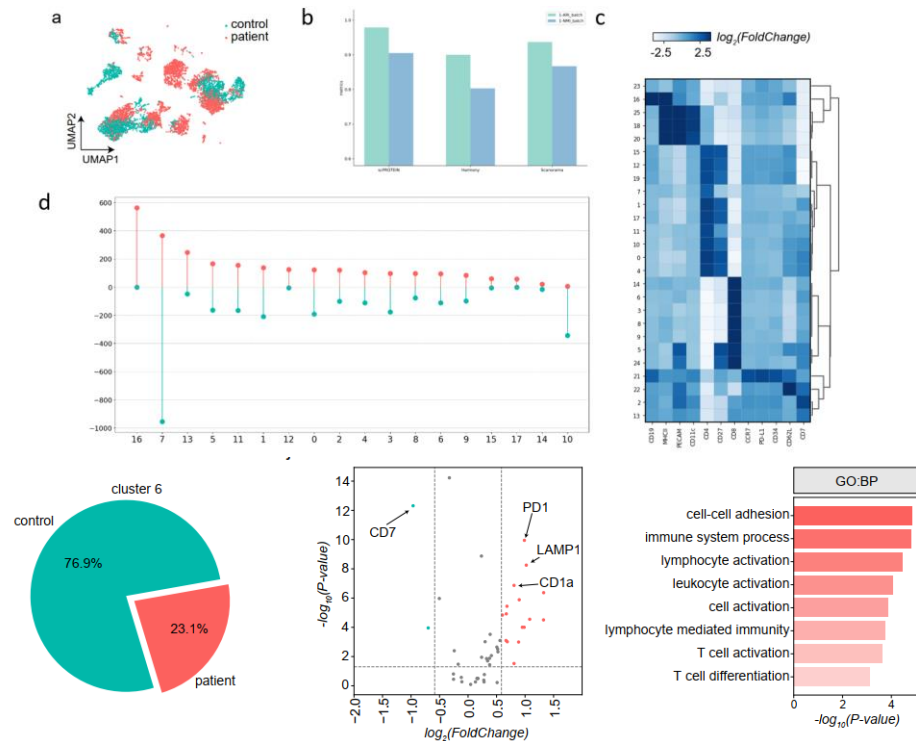
- Label transfer on N2 and nanoPOTS



Results

➤ Clinic proteomics data analysis

- ECCITE-seq dataset (6500 cells from a healthy donor and 6500 cells from a patient with CTCL)
- Correct batch effect between two donors
- Find PD1, which is vital marker of CTCL



➤ Spatial proteomics data analysis

- BaseITMA dataset includes 281 patients with breast cancer, with 38 marker proteins.
- Use spatial location for graph construction
- The cell embedding can be used to analysis tumor/non-tumor slices

