

# clustering\_comparison

May 18, 2024

## 1 Clustering Comparision

### 1.1 Preamble

```
[1]: import pandas as pd
import numpy as np
import scanpy as sc
from sklearn.metrics.cluster import normalized_mutual_info_score, u
    ↪adjusted_rand_score
from sklearn.metrics import homogeneity_score, completeness_score, u
    ↪fowlkes_mallows_score, silhouette_score, davies_bouldin_score
from src.utils import sankey_plot
import kaleido
from sklearn.preprocessing import StandardScaler
import plotly.io as pio
```

```
[2]: DIR = 'Data/'
DATASET_NAMES = ['PBMC1', 'PBMC2', 'PBMC3', 'PBMC4']
TOOLS = ['monocle', 'scanpy', 'scvi-tools', 'seurat', 'COTAN']
PARAMS_TUNING = ['default', 'celltypist', 'antibody']
```

```
[3]: def compute_scores(dir, dataset, labels_df, labels_matched, u
    ↪ground_truth_labels):
    scores = {}
    scores['NMI'] = {}
    scores['ARI'] = {}
    scores['homogeneity'] = {}
    scores['completeness'] = {}
    scores['fowlkes_mallows'] = {}
    for tool in TOOLS:
        scores['NMI'][tool] = u
        ↪normalized_mutual_info_score(labels_pred=labels_df['cluster_'+tool], u
            ↪labels_true=labels_df[f'cluster_{ground_truth_labels}'], u
            ↪average_method='arithmetic')
        scores['ARI'][tool] = u
        ↪adjusted_rand_score(labels_pred=labels_df['cluster_'+tool], u
            ↪labels_true=labels_df[f'cluster_{ground_truth_labels}'])
```

```

        scores['homogeneity'][tool] =_
        ↵homogeneity_score(labels_pred=labels_df['cluster_'+tool],_
        ↵labels_true=labels_df[f'cluster_{ground_truth_labels}'])
        scores['completeness'][tool] =_
        ↵completeness_score(labels_pred=labels_df['cluster_'+tool],_
        ↵labels_true=labels_df[f'cluster_{ground_truth_labels}'])
        scores['fowlkes_mallows'][tool] =_
        ↵fowlkes_mallows_score(labels_pred=labels_df['cluster_'+tool],_
        ↵labels_true=labels_df[f'cluster_{ground_truth_labels}'])
    scores_df = pd.DataFrame(scores)
    scores_df.to_csv(f'{dir}{dataset}/_
    ↵scores_{labels_matched}_{ground_truth_labels}.csv')
    scores_df.to_latex(f'{dir}{dataset}/_
    ↵scores_{labels_matched}_{ground_truth_labels}.tex')
    display(scores_df)

def print_scores(dataset,tuning):

    # concat tools labels
    labels_df = pd.read_csv(f'{DIR}{dataset}/COTAN/{tuning}/clustering_labels.-
    ↵csv', index_col=0)
    labels_df.rename(columns={"cluster": "cluster_COTAN"}, inplace=True)
    for tool in [t for t in TOOLS if t != 'COTAN']:
        tool_labels_df = pd.read_csv(f'{DIR}{dataset}/{tool}/{tuning}/_
        ↵clustering_labels.csv', index_col=0)
        labels_df = labels_df.merge(tool_labels_df, how='inner', on='cell')
        labels_df.rename(columns={"cluster": f"cluster_{tool}"}, inplace=True)

    # load and concat celltypist labels
    celltypist_df = pd.read_csv(f'{DIR}{dataset}/celltypist/celltypist_labels.-
    ↵csv', index_col=0)
    celltypist_df.index = celltypist_df.index.str[:-2]
    celltypist_df = labels_df.merge(celltypist_df, how='inner', on='cell')
    celltypist_df.rename(columns={"cluster.ids": f"cluster_celltypist"},_
    ↵inplace=True)
    celltypist_mapping_df = pd.read_csv(f'{DIR}{dataset}/celltypist/
    ↵celltypist_mapping.csv', index_col=0)

    # load and concat protein surface labels
    antibody_df = pd.read_csv(f'{DIR}{dataset}/antibody_annotation/
    ↵antibody_labels.csv', index_col=0)
    antibody_df = labels_df.merge(antibody_df, how='inner', on='cell')
    antibody_df.rename(columns={"cluster.ids": f"cluster_antibody"},_
    ↵inplace=True)

```

```

antibody_mapping_df = pd.read_csv(f'{DIR}{dataset}/antibody_annotation/
↪antibody_mapping.csv', index_col=1)

# read dataset
adata = sc.read_10x_mtx(
    f'{DIR}{dataset}/filtered/10X/',
    var_names='gene_symbols',
    cache=False
)
# keep only labelled cells
adata.var_names_make_unique()
subset_cells = adata.obs_names.isin(labels_df.index)
adata = adata[subset_cells, :]

mito_genes = adata.var_names.str.startswith('MT-')
# for each cell compute fraction of counts in mito genes vs. all genes
# the `^A1` is only necessary as X is sparse (to transform to a dense array
↪after summing)
adata.obs['percent_mito'] = np.sum(adata[:, mito_genes].X, axis=1).A1 / np.
↪sum(adata.X, axis=1).A1
# add the total counts per cell as observations-annotation to adata
adata.obs['n_counts'] = adata.X.sum(axis=1).A1

sc.pp.normalize_total(adata, target_sum=1e4)
sc.pp.log1p(adata)
sc.pp.highly_variable_genes(adata, min_mean=0.0125, max_mean=3, min_disp=0.
↪5)
adata.raw = adata
adata = adata[:, adata.var.highly_variable]
sc.pp.regress_out(adata, ['n_counts', 'percent_mito'])
sc.pp.scale(adata, max_value=10)
sc.tl.pca(adata, svd_solver='arpack', n_comps=20)
pca_matrix = adata.obsm['X_pca']
scaler = StandardScaler()
scaled_pca_matrix = scaler.fit_transform(pca_matrix)

#Custers number

df = {}
for tool in TOOLS:
    df[tool] = labels_df[f'cluster_{tool}'].unique().shape[0]
df_size = pd.DataFrame(df, index=[0])
display(f'{dataset} - number of clusters')
display(df_size)

# compute silhouette score
silhouette = {}

```

```

for tool in TOOLS:
    silhouette[tool] = silhouette_score(scaled_pca_matrix, □
    ↵labels_df[f'cluster_{tool}'])
    if tuning=='celltypist':
        silhouette['celltypist'] = silhouette_score(scaled_pca_matrix, □
    ↵celltypist_df[f'cluster_celltypist'])
    elif tuning=='antibody':
        silhouette['antibody'] = silhouette_score(scaled_pca_matrix, □
    ↵antibody_df[f'cluster_antibody'])
    silhouette_df = pd.DataFrame(silhouette, index=[0])
    silhouette_df.to_csv(f'{DIR}{dataset}/{tuning}_silhouette.csv')
    silhouette_df.to_latex(f'{DIR}{dataset}/{tuning}_silhouette.tex')
    display(f'{dataset} - Silhouette (higher is better)')
    display(silhouette_df)

#From https://evafast.github.io/blog/2019/06/28/example_content/
davies_bouldin = {}
for tool in TOOLS:
    davies_bouldin[tool] = davies_bouldin_score(adata.obsm['X_pca'], □
    ↵labels_df[f'cluster_{tool}'])
    if tuning=='celltypist':
        davies_bouldin['celltypist'] = davies_bouldin_score(adata.
    ↵obsm['X_pca'], celltypist_df[f'cluster_celltypist'])
    elif tuning=='antibody':
        davies_bouldin['antibody'] = davies_bouldin_score(adata.obsm['X_pca'], □
    ↵antibody_df[f'cluster_antibody'])
    davies_bouldin_df = pd.DataFrame(davies_bouldin, index=[0])
    davies_bouldin_df.to_csv(f'{DIR}{dataset}/{tuning}_davies_bouldin.csv')
    davies_bouldin_df.to_latex(f'{DIR}{dataset}/{tuning}_davies_bouldin.tex')
    display(f'{dataset} - davies_bouldin (lower is better)')
    display(davies_bouldin_df)

    display(f'{dataset} - matching {tuning} labels' if tuning != 'default' else
    ↵f'{dataset} - default labels')

# compute scores comparing each tool labels with celltypist labels
if tuning == 'celltypist' or tuning == 'default':
    compute_scores(DIR, dataset, celltypist_df, tuning, 'celltypist')
    labels = []
    labels_titles = []
    for tool in TOOLS:
        labels.append(celltypist_df[f'cluster_{tool}'].to_list())
        labels_titles.append(tool)
    labels.append(celltypist_df[f'cluster_celltypist'].
    ↵map(celltypist_mapping_df['go'].to_dict()).to_list())
    labels_titles.append('celltypist')

```

```

        title = f'{dataset} - matching {tuning} labels' if tuning != 'default' else f'{dataset} - default labels'
        sankey_plot(labels=labels, labels_titles=labels_titles, title=title, path=f'{DIR}{dataset}/{tuning}_celltypist.html')

# compute scores comparing each tool labels with protein labels
if tuning == 'antibody' or tuning == 'default':
    compute_scores(DIR, dataset, antibody_df, tuning, 'antibody')
    labels = []
    labels_titles = []
    for tool in TOOLS:
        labels.append(antibody_df[f'cluster_{tool}'].to_list())
        labels_titles.append(tool)
    labels.append(antibody_df[f'cluster_antibody'].
    ↪map(antibody_mapping_df['go'].to_dict()).to_list())
    labels_titles.append('antibody')
    title = f'{dataset} - matching {tuning} labels' if tuning != 'default' else f'{dataset} - default labels'
    sankey_plot(labels=labels, labels_titles=labels_titles, title=title, path=f'{DIR}{dataset}/{tuning}_antibody.html')

```

## 1.2 Default parameters

[169]: print\_scores(tuning = 'default', dataset="PBMC1")

/tmp/ipykernel\_70563/2944004898.py:58: ImplicitModificationWarning:

Trying to modify attribute `obs` of view, initializing view as actual.

```

'PBMC1 - number of clusters'

monocle  scanpy  scvi-tools  seurat  COTAN
0       3       18          13      11      14

'PBMC1 - Silhouette (higher is better)'

monocle  scanpy  scvi-tools  seurat  COTAN
0  0.100032  0.043761   0.065534  0.148254  0.13383

'PBMC1 - davies_bouldin (lower is better)'

monocle  scanpy  scvi-tools  seurat  COTAN
0  0.893661  2.47358   2.574291  1.392309  1.728304

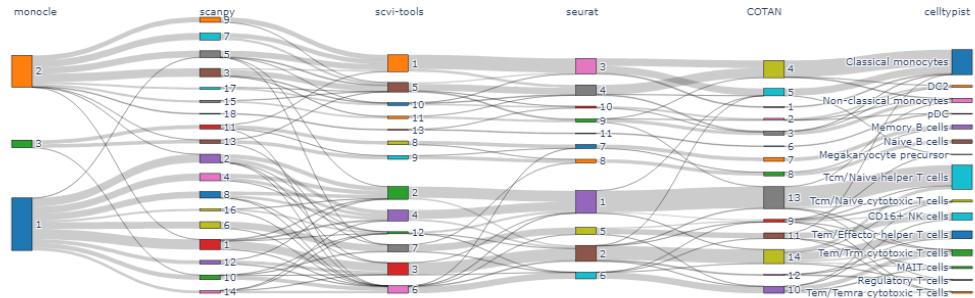
'PBMC1 - default labels'

          NMI      ARI  homogeneity  completeness  fowlkes_mallows
monocle  0.578257  0.384609   0.410140     0.979930      0.602512
scanpy   0.721042  0.404607   0.824980     0.640363      0.508176
scvi-tools 0.776232  0.599664   0.809790     0.745344      0.666244

```

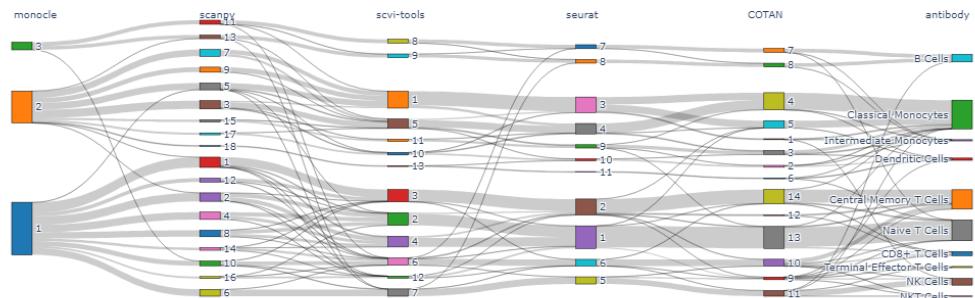
seurat	0.793630	0.649593	0.784165	0.803327	0.705921
COTAN	0.787289	0.670392	0.803876	0.771373	0.723485

PBMC1 - default labels



	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.611988	0.425929	0.446299	0.973344	0.635502
scanpy	0.659645	0.391203	0.795577	0.563386	0.507730
scvi-tools	0.708581	0.551051	0.776228	0.651780	0.632750
seurat	0.738344	0.643097	0.764146	0.714228	0.706018
COTAN	0.732140	0.651092	0.784252	0.686521	0.713737

PBMC1 - default labels



```
[12]: print_scores(tuning = 'default',dataset="PBMC2")
```

```
/tmp/ipykernel_8461/2944004898.py:58: ImplicitModificationWarning:
```

```
Trying to modify attribute `obs` of view, initializing view as actual.
```

```
'PBMC2 - number of clusters'

monocle    scanpy    scvi-tools    seurat    COTAN
0          2         18           20        14        19

'PBMC2 - Silhouette (higher is better)'

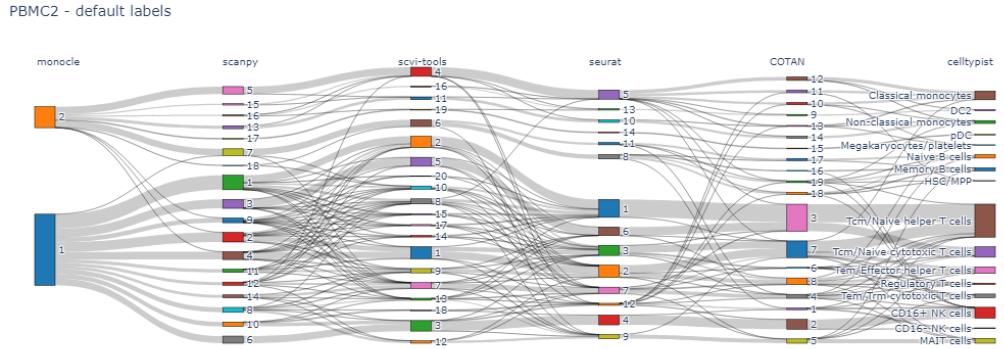
monocle    scanpy    scvi-tools    seurat    COTAN
0  0.224441  0.059225  0.000832  0.111509  0.101869

'PBMC2 - davies_bouldin (lower is better)'

monocle    scanpy    scvi-tools    seurat    COTAN
0  1.866736  2.073818  3.935702  1.630557  2.241596

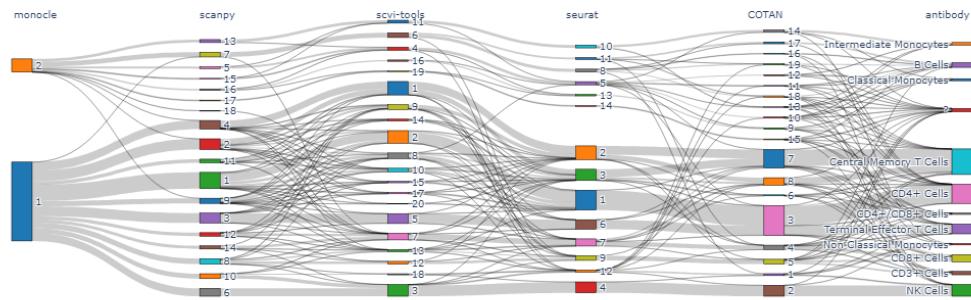
'PBMC2 - default labels'

      NMI      ARI  homogeneity  completeness  fowlkes_mallows
monocle  0.393166  0.207180   0.245998     0.978626       0.521364
scanpy   0.718820  0.457213   0.804000     0.649960       0.556684
scvi-tools  0.699788  0.424696   0.785920     0.630670       0.525031
seurat   0.775988  0.562430   0.819560     0.736815       0.640108
COTAN    0.689037  0.441866   0.724779     0.656654       0.533910
```



```
      NMI      ARI  homogeneity  completeness  fowlkes_mallows
monocle  0.277314  0.107135   0.165534     0.853977       0.450594
scanpy   0.682604  0.524109   0.759388     0.619922       0.602311
scvi-tools  0.652891  0.485961   0.734303     0.587729       0.567847
seurat   0.743681  0.679941   0.777650     0.712555       0.730603
COTAN    0.653065  0.544334   0.662016     0.644353       0.621068
```

PBMC2 - default labels



```
[10]: print_scores(tuning = 'default', dataset="PBMC3")
```

/tmp/ipykernel\_8461/2944004898.py:58: ImplicitModificationWarning:

Trying to modify attribute `obs` of view, initializing view as actual.

'PBMC3 - number of clusters'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	3	22	17	18	32

'PBMC3 - Silhouette (higher is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	0.171584	0.007616	0.055559	0.111834	0.092445

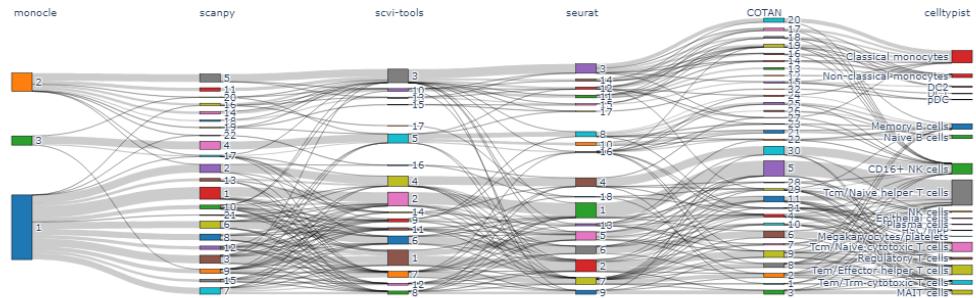
'PBMC3 - davies\_bouldin (lower is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	0.999779	2.376915	2.058343	1.698551	2.281481

'PBMC3 - default labels'

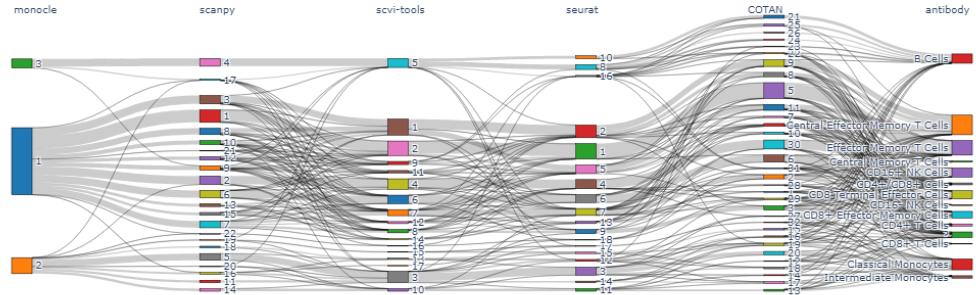
	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.500696	0.233560	0.338609	0.960446	0.500077
scanpy	0.685919	0.462762	0.763719	0.622505	0.541286
scvi-tools	0.738418	0.579677	0.757237	0.720511	0.635237
seurat	0.770512	0.585110	0.821173	0.725738	0.644073
COTAN	0.723833	0.527470	0.849029	0.630815	0.609217

PBMC3 - default labels



	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.429744	0.168276	0.280823	0.914939	0.437511
scanpy	0.664567	0.542630	0.702416	0.630588	0.596647
scvi-tools	0.691391	0.620339	0.677930	0.705398	0.662580
seurat	0.735217	0.664188	0.744324	0.726330	0.701375
COTAN	0.670484	0.541727	0.743155	0.610759	0.598370

PBMC3 - default labels



```
[4]: print_scores(tuning = 'default', dataset="PBMC4")
```

```
/tmp/ipykernel_8461/2944004898.py:58: ImplicitModificationWarning:
```

```
Trying to modify attribute `obs` of view, initializing view as actual.
```

```
'PBMC4 - number of clusters'
```

```
monocle    scanpy    scvi-tools    seurat    COTAN
```

```

0      3      22      16      19      24
'PBMC4 - Silhouette (higher is better)'

monocle    scanpy    scvi-tools    seurat      COTAN
0  0.081765  0.050853  0.061618  0.112255  0.103418

```

```

'PBMC4 - davies_bouldin (lower is better)'

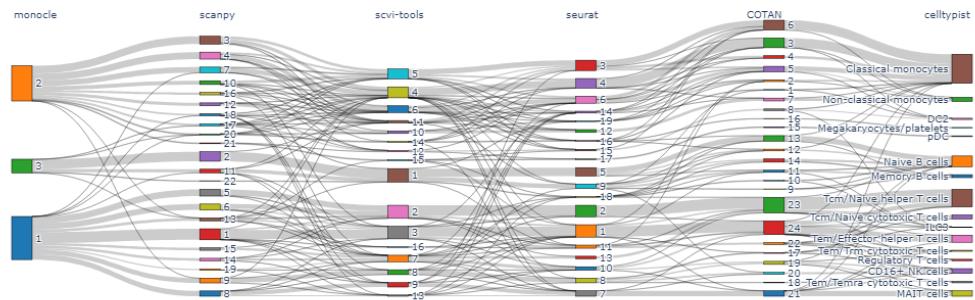
monocle    scanpy    scvi-tools    seurat      COTAN
0  0.954689  2.100956  2.087707  1.442075  1.823095

```

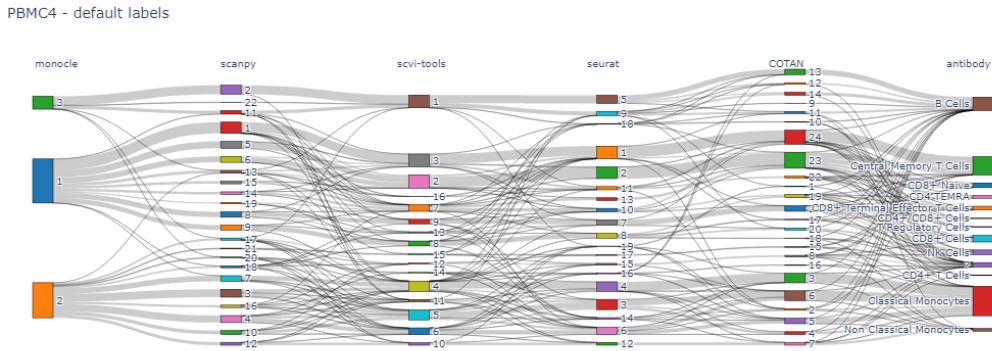
'PBMC4 - default labels'

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.617025	0.470070	0.453383	0.965513	0.647279
scanpy	0.701228	0.380357	0.819943	0.612541	0.487560
scvi-tools	0.739299	0.504966	0.788229	0.696088	0.584900
seurat	0.760207	0.494746	0.847372	0.689301	0.583823
COTAN	0.716555	0.435917	0.808134	0.643618	0.526063

PBMC4 - default labels



	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.536861	0.325029	0.372515	0.960701	0.532810
scanpy	0.622945	0.371655	0.659143	0.590516	0.439575
scvi-tools	0.651550	0.425369	0.634107	0.669980	0.487767
seurat	0.669274	0.436706	0.676741	0.661971	0.496402
COTAN	0.622356	0.367136	0.635352	0.609880	0.433784



### 1.3 Matching cellTypist clusters number

```
[173]: print_scores(tuning = 'celltypist',dataset="PBMC1")
```

/tmp/ipykernel\_70563/2944004898.py:58: ImplicitModificationWarning:

Trying to modify attribute `obs` of view, initializing view as actual.

'PBMC1 - number of clusters'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	18	17	20	21	14

'PBMC1 - Silhouette (higher is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	0.005501	0.050843	0.063871	0.088209	0.13383	0.090989

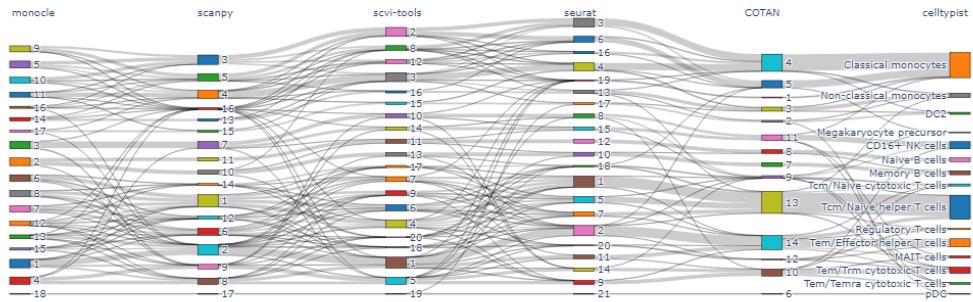
'PBMCl - davies bouldin (lower is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	2.83457	2.286672	2.797123	1.984746	1.728304	1.491801

'PBMC1 - matching celltypist labels'

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.658065	0.341945	0.757164	0.581903	0.448601
scanpy	0.735830	0.459735	0.822412	0.665742	0.553086
scvi-tools	0.699950	0.375082	0.808964	0.616828	0.479652
seurat	0.730468	0.423069	0.849278	0.640820	0.527386
COTAN	0.787289	0.670392	0.803876	0.771373	0.723485

PBMC1 - matching celltypist labels



```
[174]: print_scores(tuning = 'celltypist', dataset="PBMC2")
```

/tmp/ipykernel\_70563/2944004898.py:58: ImplicitModificationWarning:

Trying to modify attribute `obs` of view, initializing view as actual.

'PBMC2 - number of clusters'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	18	20	19	20	17

'PBMC2 - Silhouette (higher is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	-0.03374	0.025173	0.030773	0.060901	0.12581	0.131097

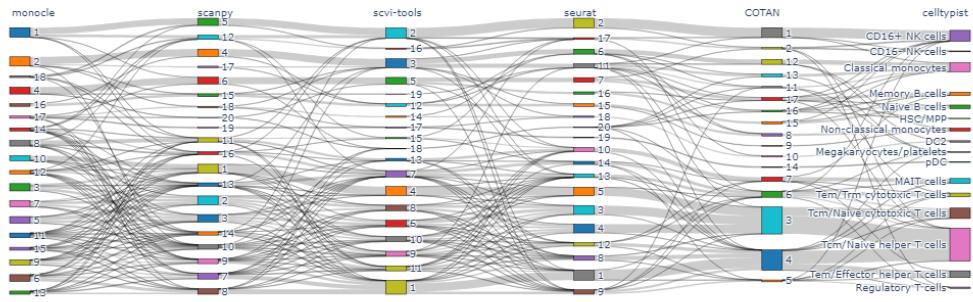
'PBMC2 - davies\_bouldin (lower is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	3.167255	2.376025	3.431314	2.147939	1.855098	1.231923

'PBMC2 - matching celltypist labels'

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.605942	0.312112	0.699644	0.534375	0.425421
scanpy	0.697287	0.377675	0.809335	0.612491	0.492889
scvi-tools	0.709450	0.398779	0.791930	0.642531	0.500807
seurat	0.738307	0.418942	0.850535	0.652244	0.529176
COTAN	0.729355	0.472800	0.745550	0.713848	0.562480

PBMC2 - matching celltypist labels



```
[11]: print_scores(tuning = 'celltypist', dataset="PBMC3")
```

```
/tmp/ipykernel_8461/2944004898.py:58: ImplicitModificationWarning:
```

```
Trying to modify attribute `obs` of view, initializing view as actual.
```

'PBMC3 - number of clusters'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	17	18	20	18	21

'PBMC3 - Silhouette (higher is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	-0.039293	0.040964	0.003634	0.112264	0.047585	0.130032

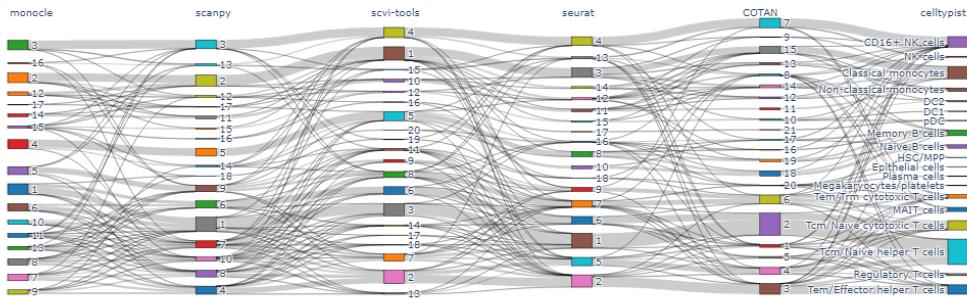
'PBMC3 - davies\_bouldin (lower is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	3.778924	1.889045	2.221019	1.698481	2.344713	1.140713

'PBMC3 - matching celltypist labels'

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.593459	0.350206	0.643738	0.550465	0.432058
scanpy	0.712344	0.545918	0.758076	0.671816	0.609354
scvi-tools	0.735127	0.565025	0.767444	0.705423	0.623277
seurat	0.771047	0.586941	0.821567	0.726381	0.645653
COTAN	0.677393	0.470051	0.717462	0.641563	0.538494

PBMC3 - matching celltypist labels



```
[5]: print_scores(tuning = 'celltypist', dataset="PBMC4")
```

```
/tmp/ipykernel_8461/2944004898.py:58: ImplicitModificationWarning:
```

```
Trying to modify attribute `~.obs` of view, initializing view as actual.
```

```
'PBMC4 - number of clusters'
```

	monocle	scanpy	scvi-tools	seurat	COTAN
0	16	18	18	19	19

```
'PBMC4 - Silhouette (higher is better)'
```

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	0.022385	0.048061	0.107921	0.111704	0.098387	0.081772

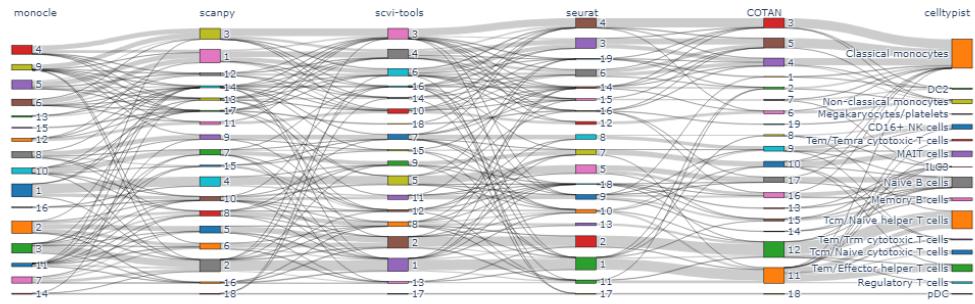
```
'PBMC4 - davies_bouldin (lower is better)'
```

	monocle	scanpy	scvi-tools	seurat	COTAN	celltypist
0	2.007518	1.898663	1.612564	1.442525	1.969481	1.194603

```
'PBMC4 - matching celltypist labels'
```

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.686019	0.421166	0.747399	0.633956	0.512728
scanpy	0.730100	0.473433	0.810168	0.664434	0.562407
scvi-tools	0.752718	0.500477	0.831022	0.687899	0.587099
seurat	0.759495	0.492528	0.846776	0.688525	0.581840
COTAN	0.724052	0.447103	0.782942	0.673402	0.532939

PBMC4 - matching celltypist labels



## 1.4 Matching antibody clusters number

```
[177]: print_scores(tuning = 'antibody', dataset="PBMC1")
```

```
/tmp/ipykernel_70563/2944004898.py:58: ImplicitModificationWarning:
```

```
Trying to modify attribute `obs` of view, initializing view as actual.
```

```
'PBMC1 - number of clusters'
```

	monocle	scanpy	scvi-tools	seurat	COTAN
0	9	11		10	11

```
'PBMC1 - Silhouette (higher is better)'
```

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	0.099643	0.073115	0.069687	0.150193	0.090531	0.042617

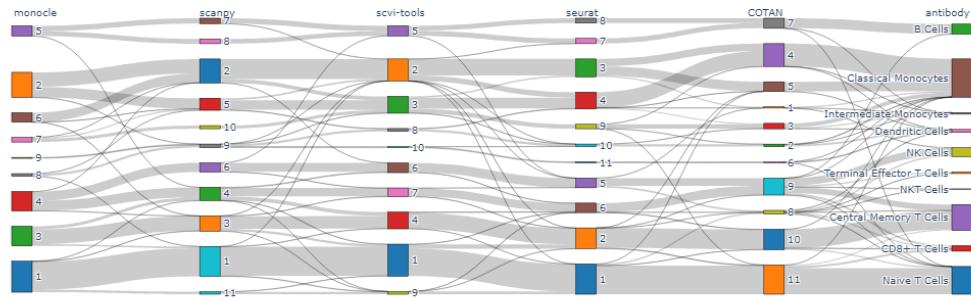
```
'PBMC1 - davies_bouldin (lower is better)'
```

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	1.498221	1.689467	1.560514	1.392406	2.067883	1.721174

```
'PBMC1 - matching antibody labels'
```

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.715777	0.633217	0.707203	0.724563	0.698798
scanpy	0.736466	0.645073	0.769273	0.706342	0.707927
scvi-tools	0.746355	0.650567	0.757864	0.735189	0.712214
seurat	0.739813	0.640616	0.767621	0.713949	0.704048
COTAN	0.721550	0.649977	0.737446	0.706326	0.711698

PBMC1 - matching antibody labels



```
[178]: print_scores(tuning = 'antibody', dataset="PBMC2")
```

```
/tmp/ipykernel_70563/2944004898.py:58: ImplicitModificationWarning:
```

```
Trying to modify attribute `obs` of view, initializing view as actual.
```

'PBMC2 - number of clusters'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	11	10	12	12	12

'PBMC2 - Silhouette (higher is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	-0.041184	0.037491	-0.021431	0.091472	0.074925	0.04853

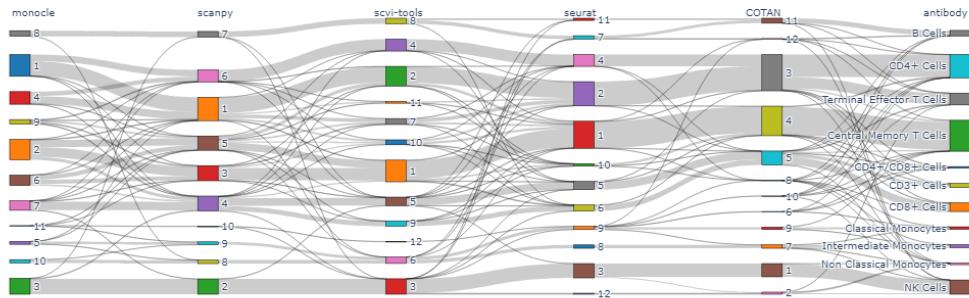
'PBMC2 - davies\_bouldin (lower is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	3.22287	1.702317	4.327977	1.463008	2.077179	2.208843

'PBMC2 - matching antibody labels'

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.585175	0.443933	0.599091	0.571891	0.531050
scanpy	0.739559	0.636764	0.742414	0.736726	0.695610
scvi-tools	0.666315	0.562966	0.694832	0.640047	0.632909
seurat	0.763984	0.764614	0.773986	0.754238	0.803575
COTAN	0.740643	0.676510	0.686522	0.804027	0.746725

PBMC2 - matching antibody labels



```
[185]: print_scores(tuning = 'antibody', dataset="PBMC3")
```

```
/tmp/ipykernel_70563/2944004898.py:58: ImplicitModificationWarning:
```

```
Trying to modify attribute `~.obs` of view, initializing view as actual.
```

```
'PBMC3 - number of clusters'
```

	monocle	scanpy	scvi-tools	seurat	COTAN
0	12	14	13	14	12

```
'PBMC3 - Silhouette (higher is better)'
```

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	-0.048747	0.024448	-0.007328	0.063501	0.05861	0.031805

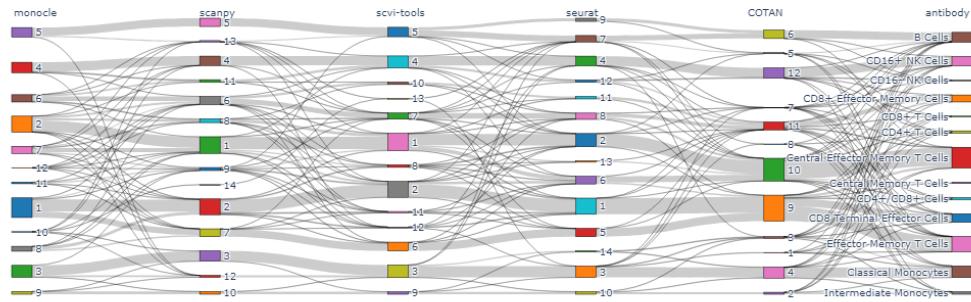
```
'PBMC3 - davies_bouldin (lower is better)'
```

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	3.082757	2.048357	2.967632	1.617082	1.813171	3.287867

```
'PBMC3 - matching antibody labels'
```

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.633333	0.503352	0.609373	0.659256	0.567586
scanpy	0.737439	0.695008	0.736412	0.738468	0.732379
scvi-tools	0.712286	0.638310	0.692394	0.733355	0.684119
seurat	0.760367	0.695131	0.769539	0.751412	0.732928
COTAN	0.701448	0.613050	0.634888	0.783598	0.683175

PBMC3 - matching antibody labels



```
[6]: print_scores(tuning = 'antibody', dataset="PBMC4")
```

```
/tmp/ipykernel_8461/2944004898.py:58: ImplicitModificationWarning:
```

Trying to modify attribute `obs` of view, initializing view as actual.

'PBMC4 - number of clusters'

	monocle	scanpy	scvi-tools	seurat	COTAN
0	13	11	11	13	12

'PBMC4 - Silhouette (higher is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	-0.009349	0.036425	0.038929	0.059369	0.03044	-0.038177

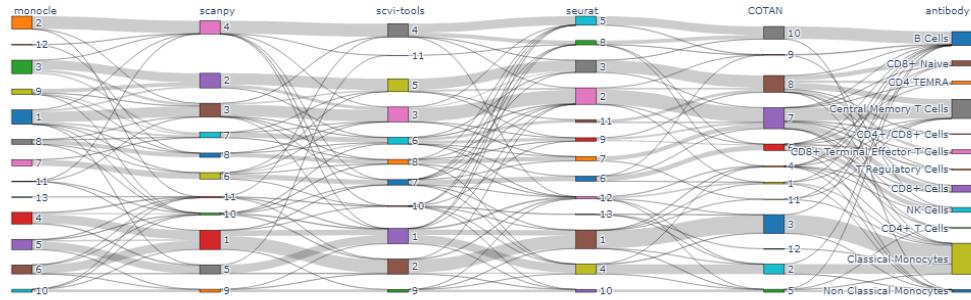
'PBMC4 - davies\_bouldin (lower is better)'

	monocle	scanpy	scvi-tools	seurat	COTAN	antibody
0	2.412446	1.784603	1.670777	1.621226	1.822676	9.337289

'PBMC4 - matching antibody labels'

	NMI	ARI	homogeneity	completeness	fowlkes_mallows
monocle	0.606252	0.394823	0.583563	0.630776	0.467547
scanpy	0.684939	0.495584	0.645785	0.729147	0.560952
scvi-tools	0.673692	0.484543	0.629449	0.724624	0.551156
seurat	0.687849	0.514398	0.665613	0.711622	0.574629
COTAN	0.648815	0.441054	0.584713	0.728703	0.525102

PBMC4 - matching antibody labels



## 1.5 Check cellTypist vs Antibody

```
[181]: def compute_clustering_scores(celltypist_df, antibody_df, output_dir, dataset):
    # Merge the dataframes on the common 'cell' column
    #cotan_df = pd.read_csv(f'{DIR}{dataset}/COTAN/antibody/clustering_labels.
    ↪csv', index_col=0)
    #display("Cotan clusters objetc dimension ", cotan_df.shape)
    #display("-----")

    celltypist_df = pd.read_csv(f'{DIR}{dataset}/celltypist/celltypist_labels.
    ↪csv', index_col=0)
    celltypist_df.index = celltypist_df.index.str[:-2]
    antibody_df = pd.read_csv(f'{DIR}{dataset}/antibody_annotation/
    ↪antibody_labels.csv', index_col=0)
    #antibody_df = labels_df.merge(antibody_df, how='inner', on='cell')
    #all_in_antibody = celltypist_df.index.isin(antibody_df.index).all()
    #all_in_celltypist = antibody_df.index.isin(celltypist_df.index).all()

    #display("All celltypist indices in antibody: ", all_in_antibody, □
    ↪celltypist_df.index.isin(antibody_df.index).sum(), celltypist_df.shape)
    #display("All antibody indices in cellTypist:", all_in_celltypist)

    #display("-----")

    merged_df = celltypist_df.merge(antibody_df, how='inner', left_index=True, □
    ↪right_index=True) # on='cell'

    merged_df.columns = ['cluster_celltypist', 'cluster_antibody']

    # Initialize scores dictionary
    scores = {
```

```

    'NMI': normalized_mutual_info_score(merged_df['cluster_celltypist'],  

    ↪merged_df['cluster_antibody'], average_method='arithmetic'),  

    'ARI': adjusted_rand_score(merged_df['cluster_celltypist'],  

    ↪merged_df['cluster_antibody']),  

    'Homogeneity': homogeneity_score(merged_df['cluster_celltypist'],  

    ↪merged_df['cluster_antibody']),  

    'Completeness': completeness_score(merged_df['cluster_celltypist'],  

    ↪merged_df['cluster_antibody']),  

    'Fowlkes_Mallows':  

    ↪fowlkes_mallows_score(merged_df['cluster_celltypist'],  

    ↪merged_df['cluster_antibody'])  

}

# Convert scores to DataFrame
scores_df = pd.DataFrame([scores])

# Save scores to CSV and LaTeX
#scores_df.to_csv(f'{output_dir}{dataset}/clustering_comparison_scores.csv')
#scores_df.to_latex(f'{output_dir}{dataset}/clustering_comparison_scores.
↪tex')

# Display scores DataFrame
display(scores_df)

```

```
[182]: for dataset in DATASET_NAMES:  

    #display('-----')  

    display(f'{dataset} - Clustering Comparison between CellTypist and  

    ↪Antibody')  

    # Assuming celltypist_df and antibody_df are defined elsewhere and  

    ↪available here  

    compute_clustering_scores(celltypist_df, antibody_df, DIR, dataset)
```

```
'PBMC1 - Clustering Comparison between CellTypist and Antibody'  

      NMI      ARI  Homogeneity  Completeness  Fowlkes_Mallows  

0  0.742338  0.713159      0.709696      0.778128      0.764437
```

```
'PBMC2 - Clustering Comparison between CellTypist and Antibody'
```

```
      NMI      ARI  Homogeneity  Completeness  Fowlkes_Mallows  

0  0.660455  0.48564      0.673828      0.647602      0.582832
```

```
'PBMC3 - Clustering Comparison between CellTypist and Antibody'
```

```
      NMI      ARI  Homogeneity  Completeness  Fowlkes_Mallows  

0  0.665993  0.513896      0.698774      0.636149      0.57817
```

```
'PBMC4 - Clustering Comparison between CellTypist and Antibody'
```

```
NMI          ARI   Homogeneity  Completeness  Fowlkes_Mallows  
0  0.690424  0.505103      0.758068      0.633863      0.582394
```

```
[1]: !export PATH=/Library/TeX/texbin:$PATH
```