spatial_analysis

June 16, 2019

In [5]: import numpy as np

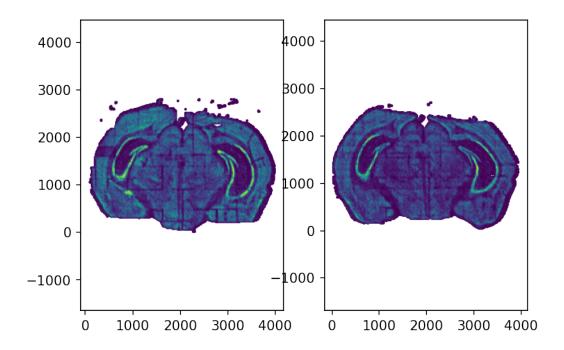
```
import pandas as pd
        from matplotlib import pyplot as plt
        from matplotlib import gridspec
        import NaiveDE
        import SpatialDE
        from sklearn.preprocessing import scale
        from sklearn.mixture import BayesianGaussianMixture
        import scipy.cluster.hierarchy as sch
        import seaborn as sns
        import pickle
        import umap
        import nimfa
        from tqdm import tqdm
0.1 Import datasets
In [7]: def T_quality(x):
            return np.clip(1-np.\log(1+x)/2.5,0,1)
        Q_{th} = 2
        min_count = 500
        barcodes_df = []
        tagList_df = pd.read_csv("/home/gapartel/TissueMaps/161230_161220_3_1/tagList_84-gene.
        datasets = ['170315_161220_hippo_4_1','161230_161220_3_1']
        for sample in datasets:
            df = pd.read_csv("/home/gapartel/TissueMaps/"+sample+"/barcodes.csv", sep = ",")
            df.seq_quality_min=df.seq_quality_min*df.general_stain_min.apply(T_quality)
            # Add gene names to dataframe
            d = pd.Series(tagList_df.Gene.values,index=tagList_df.Seq).to_dict()
            df["Gene"] = df['letters'].map(d)
            # Downsample barcode coordinate space by factor 8 for easier visualization
            df["global_X_pos"] = df.global_X_pos/8
            df["global_Y_pos"]=df.global_Y_pos/8
            # Remove reads not in the codebook
            df = df.dropna()
```

```
# Filter reads by quality
df = df[df.seq_quality_min>Q_th]
# Filter reads by min count per gene
df["count"] = 0
for i,row in tagList_df.iterrows():
    df.loc[df["Gene"] == tagList_df.Gene[i],["count"]] = len(df[df["Gene"] == tagL
df = df[df["count"]>min_count]
barcodes_df.append(df)
```

0.2 Generate expression tables

```
In [4]: # Import and downsample by factor 8 image shape
        img_shape = np.round(np.array([[22508, 33566],[22563, 31782]])/8).astype(np.uint)
        # Create gene expression table
        expression_df = []
        sample_df = []
        for s_idx, df in enumerate(barcodes_df):
            x_min = 0; x_max= img_shape[s_idx,1];
            y_min = 0; y_max= img_shape[s_idx,0];
            batch_size_px=16
            overlap = 16
            express_table = pd.DataFrame(data={}, columns=df.Gene.unique(), index=list((str(x)-
            for i in tqdm(range(x_min,x_max,batch_size_px)):
                for j in range(y_min,y_max,batch_size_px):
                    batch_df=df[(df.global_X_pos>=i-(batch_size_px/2)-overlap) & (df.global_X_s
                    if len(batch_df):
                        batch_counts = batch_df['Gene'].value_counts()
                        express_table.loc[str(i)+'x'+str(j),batch_counts.index]=batch_counts
            express_table = express_table.fillna(0)
            # Create sample_info
            sample_info = pd.DataFrame(data={'x':list(x for x in range(x_min,x_max,batch_size_)
            sample_info['total_counts'] = express_table.sum(axis=1)
            # Dropping empty batches
            express_table = express_table[sample_info.total_counts>10]
            sample_info = sample_info[sample_info.total_counts>10]
            expression_df.append(express_table)
            sample_df.append(sample_info)
100%|| 263/263 [59:45<00:00, 3.76s/it]
100%|| 249/249 [54:04<00:00, 5.85s/it]
```

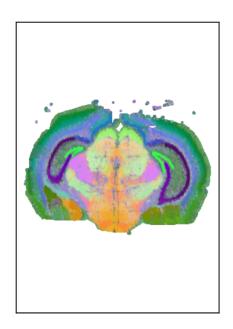
```
for i,dataset in enumerate(datasets):
            expression_df[i].to_pickle('/home/gapartel/TissueMaps/'+dataset+'/express_table.hd
            sample_df[i].to_pickle('/home/gapartel/TissueMaps/'+dataset+'/sample_info.hdf5')
In [8]: # load dataframes
        img_shape = np.round(np.array([[22508, 33566],[22563, 31782]])/8).astype(np.uint)
        expression_df = []
        sample_df = []
        for i,dataset in enumerate(datasets):
            plt.rcParams["figure.dpi"] = 150
            plt.subplot(1,2,i+1)
            x_min = 0; x_max= img_shape[i,1];
            y_min = 0; y_max= img_shape[i,0];
            batch_size_px=16
            overlap = 16
            express_table = pd.read_pickle('/home/gapartel/TissueMaps/'+dataset+'/express_table
            # Create sample_info
            sample_info = pd.DataFrame(data={'x':list(x for x in range(x_min,x_max,batch_size_)
            sample_info['total_counts'] = express_table.sum(axis=1)
            # Dropping empty batches
            express_table = express_table[sample_info.total_counts>10]
            sample_info = sample_info[sample_info.total_counts>10]
            expression_df.append(express_table)
            expression_df[i] = expression_df[i].rename(('{}_'+str(i)).format)
            sample_df.append(sample_info)
            sample_df[i] = sample_df[i].rename(('{}_'+str(i)).format)
            sample_df[i]['s'] = i
            plt.scatter(sample_df[i]['x'], sample_df[i]['y'], c=sample_df[i]['total_counts'],sample_df[i]['x']
            plt.axis('equal');
```

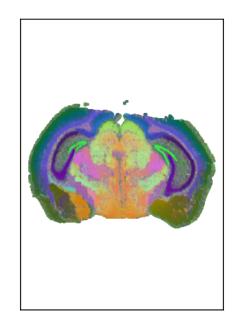


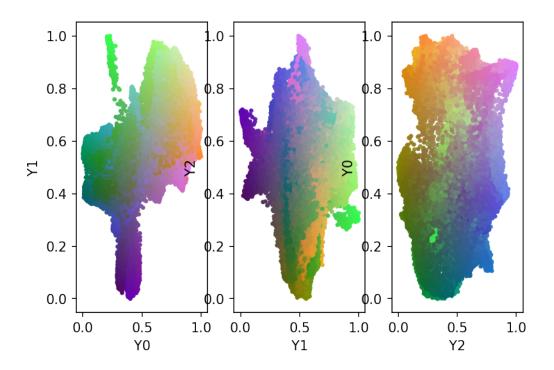
0.3 Normalize Gene Expression Table

0.4 Gene Expression Continuum

```
In [12]: plt.rcParams["figure.dpi"] = 150
        plt.figure()
        plt.subplot(1,2,1)
        plt.scatter(sample_df.loc[sample_df.s==0,:].x, sample_df.loc[sample_df.s==0,:].y, c=Y
        plt.xticks([])
        plt.yticks([]);
        plt.axis('equal');
        plt.subplot(1,2,2)
        plt.scatter(sample_df.loc[sample_df.s==1,:].x, sample_df.loc[sample_df.s==1,:].y, c=Y
        plt.xticks([])
        plt.yticks([]);
        plt.axis('equal');
        plt.figure()
         cycled = [0,1,2,0]
        for i in range(3):
             plt.subplot(1,3,i+1)
            plt.scatter(Y_umap[:,cycled[i]], Y_umap[:,cycled[i+1]], c=Y_umap,s=5)
            plt.xlabel("Y"+str(cycled[i]))
            plt.ylabel("Y"+str(cycled[i+1]))
```







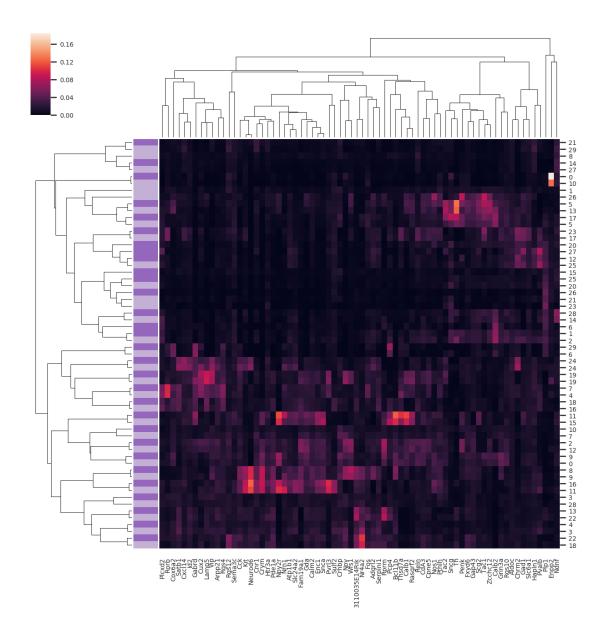
0.5 Gene Expression Clusters

In [52]: # Clusters Gene Expression Table

```
In [51]: for i,df in enumerate(datasets):
             # UMAP projection
             idx = resid_expr.loc[sample_df.s==i,:].var().sort_values(ascending=False).index
             reducer = umap.UMAP(
                     n_neighbors=100,
                     min_dist=0.25,
                     n_components=10,
                     metric='correlation',
                     random_state=42,
                     init='random'
                 )
             Y_umap = reducer.fit_transform(scale(resid_expr.loc[sample_df.s==i,idx], 1))
             Y=Y_umap
             # Gaussina Mixture Model Clustering
             gmm = BayesianGaussianMixture(n_components=30, max_iter=100000,random_state=33)
             gmm.fit(Y)
             phi_hat = gmm.predict(Y)
             sample_df.loc[sample_df.s==i,'U1'] = Y[:, 0]
             sample_df.loc[sample_df.s==i,'U2'] = Y[:, 1]
             sample_df.loc[sample_df.s==i,'cluster'] = phi_hat
```

```
cluster_df = []
for i,df in enumerate(datasets):
                    clusters=[]
                    for c in np.unique(sample_df.loc[sample_df.s==i,'cluster']):
                                         clusters.append(expression_df.loc[sample_df[(sample_df.s==i) & (sample_df.clusters.append(expression_df.loc[sample_df[(sample_df.s==i) & (sample_df.clusters.append(expression_df.loc[sample_df[(sample_df.s==i) & (sample_df.clusters.append(expression_df.loc[sample_df[(sample_df.s==i) & (sample_df.s==i) & (sample_df.clusters.append(expression_df.loc[sample_df[(sample_df.s==i) & (sample_df.s==i) & (sample_df.s==i
                    cluster_exp_tab = np.zeros((len(np.unique(sample_df.loc[sample_df.s==i,'cluster']
                    for c, cluster in enumerate(np.unique(sample_df.loc[sample_df.s==i,'cluster'])):
                                        for g, gene in enumerate(expression_df.columns.values):
                                                             # Normalizationtion by cluster area
                                                             cluster_exp_tab[c,g] = clusters[c].loc[:,gene].sum()/len(clusters[c])
                     # Normalize by gene (column)
                    cluster_exp_tab=cluster_exp_tab/cluster_exp_tab.sum(axis=0) [None,:]
                     # Normalize by cluster (row)
                     #cluster_exp_tab=cluster_exp_tab/cluster_exp_tab.sum(axis=1)[:,None]
                    cluster_df.append(pd.DataFrame(cluster_exp_tab,columns=expression_df.columns))
c=np.array(["#9467bd"]*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"]*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"]*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"]*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"]*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0])).tolist()+np.array(["#c5b0d5"])*len(cluster_df[0]))*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])*len(cluster_df[0])
cluster_exp_tab=pd.concat(cluster_df,sort=True)
cluster_exp_tab=cluster_exp_tab.fillna(0)
```

Clustering regions from the two brains are then combined togheter with hierarchical clustering based on the gene expression profile of each cluster regions



Extract top 12 cluster subgroups from the dendogram

```
def nodes_connected(u, v, G):
                                return u in G.neighbors(v)
                      import networkx as nx
                      from scipy.cluster.hierarchy import dendrogram, to_tree
                      from matplotlib.colors import to_rgb
                      sample_df.loc[sample_df.s==1,'cluster'] = sample_df.loc[sample_df.s==1,'cluster'] + loc[sample_df.s==1,'cluster'] + loc[s
                      G= nx.DiGraph()
                      Z= g.dendrogram_row.linkage
                      T = to_tree( Z , rd=False )
                      inorder(T,G)
                      dend = dendrogram(Z,
                                                  truncate_mode='lastp', # show only the last p merged clusters
                                                  p=12, # show only the last p merged clusters
                                                  no_plot=True
                      leafs = [x for x in G.nodes() if G.out_degree(x)==0]
                      truncated_dend_leafs = dend["leaves"]
                      color_clusters = []
                      i=0
                      for n in truncated_dend_leafs:
                                n list =[]
                                for l in leafs:
                                           if nx.has_path(G,n,1):
                                                    n_list.append(1)
                                 color_clusters.append(n_list)
                                 i=i+1
                      cluster_exp_tab_idx = cluster_exp_tab.index.tolist()
       Plot top 12 clusters on samples
In [55]: from cycler import cycler
                      import matplotlib as mpl
                      from matplotlib.colors import to_rgb
                      mpl.rcParams['axes.prop_cycle'] = cycler(color=["#1f77b4","#aec7e8","#ff7f0e","#ffbb76
                      c_list=["#1f77b4","#aec7e8","#ff7f0e","#ffbb78","#2ca02c","#98df8a","#d62728","#ff989
                      plt.subplot(1,2,1)
                      c_{label} = [chr(x) for x in range(65,91)]
                      i=0
                      for c in color_clusters:
                                g = sample_df.loc[(sample_df.s==0) & (sample_df.cluster.isin(c)),:]
                                plt.scatter(g.x, g.y, label=c_label[i], c=np.array([np.array(to_rgb(c_list[i])),]
```

```
i = i+1

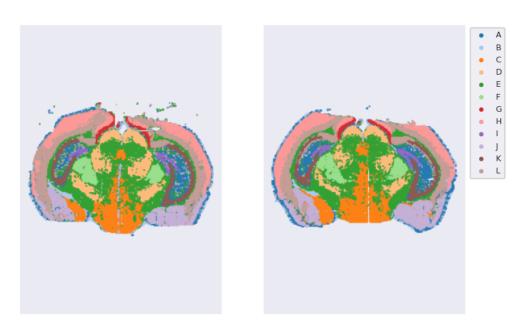
plt.xticks([])
plt.yticks([]);
plt.axis('equal');

plt.subplot(1,2,2)
i=0

for c in color_clusters:
    g = sample_df.loc[(sample_df.s==1) & (sample_df.cluster.isin(c)),:]
    plt.scatter(g.x, g.y, label=c_label[i], c=np.array([np.array(to_rgb(c_list[i])),]
    i = i+1

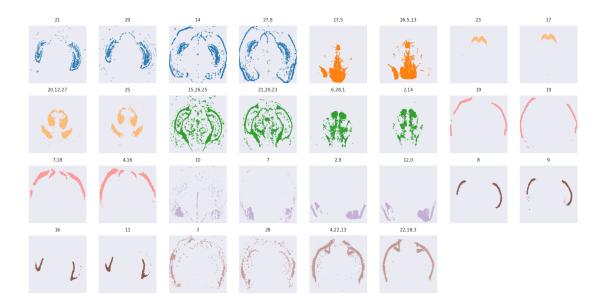
plt.xticks([])
plt.yticks([]);
plt.axis('equal');
plt.legend(bbox_to_anchor=(1, 1),loc=2, markerscale=10. ,prop={'size': 6})
```

Out[55]: <matplotlib.legend.Legend at 0x7f8a8a12ea20>



Plot subclusters of 12 top cluster regions

```
In [41]: c1 = cluster_df[0]; s1 = sample_df[sample_df.s==0]
         c2 = cluster_df[1]; s2 = sample_df[sample_df.s==1]
         # Find sub-clusters
         color_clusters = []
         for n in truncated_dend_leafs:
             leafs = [x for x in G.nodes() if G.out_degree(x)==0 and nx.has_path(G,n,x)]
             succ = list(G.successors(n))
             color_subclusters = []
             for s in succ:
                 if not s in leafs:# cluster composed by multiple sub-clusters
                     color_subclusters.append([x for x in G.nodes() if G.out_degree(x)==0 and :
             color_clusters.append(color_subclusters)
         plt.figure(figsize=(16,8))
         j=1
         i=0
         for c1 in color_clusters:
             if c1:
                 for c2 in c1:
                      plt.figure()
                     plt.subplot(4,8,j)
                     j = j+1
                     g = s1[s1.cluster.isin(c2)]
                     plt.scatter(g.x, g.y, label=f'Cluster {i}', c=np.array([np.array(to_rgb(c])])
                     plt.ylim((s1.y.min(),s1.y.max()))
                     plt.xlim((s1.x.min(),s1.x.max()))
                     plt.title(','.join([str(int(x)) for x in g.cluster.unique().tolist()]))
                     plt.xticks([])
                     plt.yticks([]);
                     #plt.axis('equal');
                   plt.axis('equal');
                     plt.subplot(4,8,j)
                     j = j+1
                     g = s2[s2.cluster.isin(c2)]
                     plt.scatter(g.x, g.y, label=f'Cluster {i}', c=np.array([np.array(to_rgb(c
                     plt.ylim((s2.y.min(),s2.y.max()))
                     plt.xlim((s2.x.min(),s2.x.max()))
                     plt.title(','.join([str(int(x)-30) for x in g.cluster.unique().tolist()])
                     plt.xticks([])
                     plt.yticks([]);
                     #plt.axis('equal');
             i=i+1
```



Annotate 12 top cluster regions based on known markers

0.6 Find differentially expressed features (cluster biomarkers)

```
In [20]: def get_label(x):
             c_{label} = [chr(x) for x in range(65,91)]
             return c_label[x]
         markers = pd.read_csv('/home/gapartel/Desktop/folder1/markers.csv')
         markers.cluster = markers.cluster.astype(np.uint).apply(get_label)
         print(markers.drop(['pct.1','pct.2'],axis=1))
                    avg_logFC
                                   p_val_adj cluster
            p_val
                                                                 gene
0
     0.000000e+00
                     2.847550
                                0.000000e+00
                                                    В
                                                                Enpp2
    1.782190e-136
1
                     0.288780
                               1.283177e-134
                                                    В
                                                                Rgs12
2
     1.731085e-99
                     0.430315
                                1.246381e-97
                                                    В
                                                                  Id2
3
                                6.515676e-42
                                                    В
                                                                  Nov
     9.049550e-44
                     0.525782
4
                     0.846134
                                6.697708e-28
                                                    В
     9.302372e-30
                                                                Pde1a
5
     0.000000e+00
                     0.452995
                                0.000000e+00
                                                    Α
                                                                 Reln
6
     0.000000e+00
                     0.424967
                                0.000000e+00
                                                    Α
                                                                  Id2
7
     0.000000e+00
                     0.412049
                                0.000000e+00
                                                                 Cnr1
                                                    Α
8
     0.000000e+00
                     0.361897
                                0.000000e+00
                                                               Cxcl14
                                                    Α
9
    3.025244e-294
                     0.487115
                               2.178176e-292
                                                    Α
                                                                 Ndnf
     0.000000e+00
                                0.000000e+00
                                                    Ε
10
                     1.382197
                                                                 Plp1
     0.000000e+00
                     0.599548
                                0.000000e+00
                                                    Ε
                                                                Calb2
11
12
     0.000000e+00
                     0.388421
                                0.000000e+00
                                                    Ε
                                                                Enpp2
                                                    L
                                                       3110035E14Rik
13
     0.000000e+00
                     1.321783
                                0.000000e+00
14
     0.000000e+00
                     0.706664
                                0.00000e+00
                                                    L
                                                              Neurod6
15
     0.000000e+00
                     0.686218
                                0.000000e+00
                                                    L
                                                                Satb1
```

```
0.766928
                                                     L
                                                                 Nr4a2
16
    1.108826e-128
                                7.983550e-127
                                                     L
17
     2.264197e-30
                     0.601713
                                 1.630222e-28
                                                                  Rprm
18
     0.000000e+00
                                 0.000000e+00
                                                     J
                                                                  Crym
                     1.095241
19
                                                     J
                                                               Fam19a1
     0.000000e+00
                     1.025245
                                 0.00000e+00
20
     0.000000e+00
                     0.991395
                                 0.000000e+00
                                                     J
                                                                  Wfs1
21
                                                     J
     0.000000e+00
                     0.832475
                                 0.00000e+00
                                                                  Enc1
22
     0.000000e+00
                     0.803720
                                 0.00000e+00
                                                     J
                                                                   Gda
23
     0.000000e+00
                     1.688802
                                 0.00000e+00
                                                     Η
                                                                 Lamp5
24
                                                     Η
     0.000000e+00
                     1.241667
                                 0.00000e+00
                                                                  Rorb
25
     0.000000e+00
                     1.096478
                                 0.00000e+00
                                                     Η
                                                                  Rgs4
26
                                                     Η
                                                                 Satb1
     0.000000e+00
                     0.881687
                                 0.000000e+00
27
                                                     Η
     8.775818e-79
                     1.051703
                                 6.318589e-77
                                                                  Cux2
28
     0.000000e+00
                                                     K
                                                               Neurod6
                     2.338086
                                 0.000000e+00
                                                     K
29
     0.000000e+00
                     1.851732
                                 0.000000e+00
                                                                  Crym
30
     0.000000e+00
                     1.474187
                                 0.000000e+00
                                                     K
                                                                   Kit
31
     0.000000e+00
                                                     K
                                                               Fam19a1
                     0.856438
                                 0.000000e+00
32
     4.540700e-64
                     0.897629
                                 3.269304e-62
                                                     K
                                                                 Pvr13
33
                                                     F
     0.000000e+00
                     1.640292
                                 0.000000e+00
                                                                  Pcp4
34
                                                     F
     0.000000e+00
                     1.002921
                                 0.00000e+00
                                                                  Rgs4
                                                     F
35
     0.000000e+00
                     0.603634
                                 0.000000e+00
                                                                  Plp1
                                                     F
36
    2.353946e-288
                     1.011019
                                1.694841e-286
                                                                 Gabrd
                                                     F
37
    4.012217e-174
                     0.798069
                                2.888796e-172
                                                                Cox6a2
38
     0.000000e+00
                     1.550668
                                 0.000000e+00
                                                     C
                                                                  Tac1
39
                                                     С
                                                               Zcchc12
     0.000000e+00
                     1.346391
                                 0.00000e+00
40
     0.000000e+00
                                 0.00000e+00
                                                     С
                                                                 Calb2
                     1.339277
41
                                                     С
     0.000000e+00
                                 0.00000e+00
                     1.287157
                                                                  Scg2
                                                     С
42
     0.000000e+00
                     1.283049
                                 0.000000e+00
                                                                  Penk
                                                     Ι
43
     0.000000e+00
                     1.833286
                                 0.000000e+00
                                                                 Calb1
                                                     Ι
44
     0.000000e+00
                     1.784510
                                 0.000000e+00
                                                                Bcl11b
45
     0.000000e+00
                     1.235225
                                 0.000000e+00
                                                     Ι
                                                                  Enc1
46
                                                     Ι
    5.643295e-161
                     1.363001
                                4.063172e-159
                                                                 Npy2r
47
    8.042638e-108
                     1.310914
                                5.790699e-106
                                                     Ι
                                                                  Nrn1
                                                     D
48
     0.000000e+00
                     1.613648
                                 0.000000e+00
                                                                 Pvalb
49
     0.000000e+00
                                                     D
                                                                  Gad1
                     1.234926
                                 0.00000e+00
                                                     D
50
     0.000000e+00
                                 0.00000e+00
                                                                 Chrm2
                     1.010967
51
     0.000000e+00
                     0.691007
                                 0.00000e+00
                                                     D
                                                                  Plp1
                                                     D
52
     0.000000e+00
                     0.461820
                                 0.00000e+00
                                                                Slc6a1
53
     0.000000e+00
                                 0.00000e+00
                                                     G
                                                               Neurod6
                     1.615530
54
                                                     G
     0.000000e+00
                     1.227552
                                 0.00000e+00
                                                                 Satb1
55
     0.000000e+00
                     1.040380
                                 0.000000e+00
                                                     G
                                                                   Id2
                                                     G
                                                                Cxcl14
56
    4.549199e-275
                     1.265473
                                3.275424e-273
                                                     G
                                                                 Chrm2
57
    5.025915e-155
                     1.101947
                                3.618659e-153
```

```
plt.figure(figsize=(8,64))
for i,gene in enumerate(idx):
    gene_exp = pd.DataFrame({'Normalized_Expression':pos_res_exp.loc[:,gene], 's':samplt.subplot(len(idx),2,i+1)
    ax = sns.violinplot(x="top_cluster", y="Normalized_Expression", hue="s", data=general.legend_.remove()
    plt.title(gene)
    plt.subplots_adjust(hspace=0.4)
```

