2021 Müller et al scRNA seq analysis OTR vs transduction

Code for the scRNA seq analysis shown in the Paper "Targeted T cell receptor gene editing provides predictable T cell product function for immunotherapy" by Müller et al.

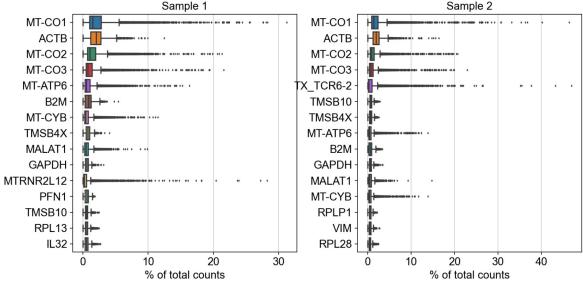
Initialisation and reading data

```
In [1]: import numpy as np
                                                                                                                       # scientific computing toolkit
                import pandas as pd
                                                                                                                      # data analysis toolkit
                 import scanpy as sc
                                                                                                                      # scanpy is referred to with sc. ***
                                                                                                                      # Matplotlib is referred to with plt.***
                 import matplotlib.pyplot as plt
                 from scipy import stats
                                                                                                                      # for linear regressions
                 import seaborn as sns
                                                                                                                      # for easy heatmaps
                 from scipy.sparse import *
                 import anndata
                 sc.settings.verbosity = 0
                                                                                                                       # verbosity: errors (0), warnings (1), info (2), hints
                                                                                                                   # check if all needed versions are installed and up to d
                 sc.logging.print_header()
                 ate
                 results_file = './write/results.h5ad'
                                                                                                                       # the file that will store the analysis results
                 scanpy==1.4.3 anndata==0.7.5 umap==0.4.6 numpy==1.19.4 scipy==1.5.1 pandas==1.1.5 scikit-learn==0.21.3
                 \verb|statsmodels==0.11.1| python-igraph==0.7.1+4.bed07760| louvain==0.6.1| leidenalg==0.7.0| leidenalg=
In [2]: | sc.settings.set_figure_params(dpi=80, dpi_save=200, color_map='viridis')
In [3]: adata_1 = sc.read_10x_mtx("./GEX_1_all_TCR/filtered_feature_bc_matrix/",var_names='gene_symbols',cache=T
                 rue)
                 adata_1.var_names_make_unique()
                adata 1
Out[3]: AnnData object with n_obs \times n_vars = 9211 \times 33547
                       var: 'gene_ids', 'feature_types'
In [4]: adata_2 = sc.read_10x_mtx("./GEX_2_all_TCR/filtered_feature_bc_matrix/",var_names='gene_symbols',cache=T
                rue)
                 adata 2.var names make unique()
                adata 2
Out[4]: AnnData object with n_obs × n_vars = 10101 × 33547
                       var: 'gene ids', 'feature types'
In [5]: # combine the two files into an array
                 adatas = [adata_1,adata_2]
                names = ["Sample 1", "Sample 2"]
In [6]: # generate TRBC_total artificial gene as the sum of TRBC1 and TRBC2 per cell
                 adatas new=[0,0]
                 for i, adata in enumerate(adatas):
                        adata.var.loc['TRBC total']=['TRBC_total', 'Gene Expression']
                         TRBC\_total\_values = [sum(x) \  \, \textbf{for} \  \, x \  \, \textbf{in} \  \, zip([x[0] \  \, \textbf{for} \  \, x \  \, \textbf{in} \  \, adata[:,adata.var_names == 'TRBC1'].X.todense(). 
                 tolist()],
                                                                                                        [x[0] for x in adata[:,adata.var_names=='TRBC2'].X.todense().
                 tolist()])]
                        adatas_new[i]=anndata.AnnData(X=hstack([adata.X,coo_matrix([[x] for x in TRBC_total_values])]).tocsr
                 (), obs=adata.obs, var=adata.var)
In [7]: adatas=adatas new.copy()
```

Preprocessing

```
Tx OTR mueller 2021
```

```
In [8]: fig, ax = plt.subplots(ncols=len(adatas), figsize=(10,5))
    fig.tight_layout(w_pad=3)
    for i, adata in enumerate(adatas):
        sc.pl.highest_expr_genes(adata, n_top=15, ax=ax[i], show=False)
        ax[i].set_title(names[i])
    fig.savefig('./figures/highest_expr_genes.pdf')
```



```
In [9]: for adata in adatas:
                                sc.pp.filter_cells(adata, min_genes=200)
                                sc.pp.filter_genes(adata, min_cells=3)
In [10]: | # generate adata with only fluorescent proteins for demultiplexing, filter out triple positive cells and
                      normalize
                      adatas FL 1=adata 1[:, adata 1.var names.isin(['GFP','BFP','CFP-1'])]
                      adatas FL 2=adata 2[:, adata 2.var names.isin(['GFP','BFP','CFP-1'])]
                      adatas_FL = [adatas_FL_1,adatas_FL_2]
                      for i, adata_FL in enumerate(adatas_FL):
                               sc.pp.filter_cells(adata_FL, max_genes=1)
                                sc.pp.normalize per cell(adata FL, counts per cell after=1e4, min counts=0)
                               sc.pp.log1p(adata FL)
                               sc.pp.scale(adata_FL, max_value=10)
                      Trying to set attribute `.obs` of view, copying. Trying to set attribute `.obs` of view, copying.
In [11]: for adata_FL in adatas_FL: sc.tl.pca(adata_FL)
In [12]: for adata_FL in adatas_FL:
                                sc.pp.neighbors(adata FL, n neighbors=20, n pcs=2)
                                sc.tl.umap(adata_FL, spread=65, min_dist=1.9)
                                sc.tl.leiden(adata_FL)
                      C:\Users\Administrator\AppData\Roaming\Python\Python36\site-packages\umap\umap_.py:1158: RuntimeWarnin
                      g: divide by zero encountered in power
                          return 1.0 / (1.0 + a * x ** (2 * b))
                      C:\Users\Administrator\AppData\Roaming\Python\Python36\site-packages\umap\umap .py:1158: RuntimeWarnin
                      g: divide by zero encountered in power
                          return 1.0 / (1.0 + a * x ** (2 * b))
In [13]: | for adata_FL in adatas FL:
                               adata FL.obs.leiden= adata FL.obs.leiden.astype(str)
adata FL.obs.leiden[~adata FL.obs.leiden.isin(['0','1','2','3'])]='doublets'
adata FL.uns['leiden_colors']=['#078dde','#000000','#ffa55c','#606060','#adadad']
                      \verb|C:\Pr| ogramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:3: SettingWithCopyWarning: | ogramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:3: SettingWithCopyW
                      A value is trying to be set on a copy of a slice from a DataFrame
                      See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
```

This is separate from the ipykernel package so we can avoid doing imports until

g.html#returning-a-view-versus-a-copy

```
In [14]: for adata_FL in adatas_FL:
                           sc.pl.pca(adata_FL, color=['GFP','BFP','CFP-1','leiden'], s=1000)
                   ... storing 'leiden' as categorical
                   ... storing 'feature_types' as categorical
                                                                                                                                               CFP-1
                                                                                                                                                                                                   leiden
                                                                                                                     1.0
                                                                                                                                                                        - 2.5
                                                                 2.0
                                                                                                                                                                         20
                                                                                                                     0.5
                                                                 1.5
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                    PC2
                                                                       PC2
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                                                                                                                                                                               PC2
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                                                                                            PC1
                                                                                                                                                PC1
                                                                                                                                                                                                    PC1
                   ... storing 'leiden' as categorical
                   ... storing 'feature types' as categorical
                                        GFP
                                                                                                                                               CFP-1
                                                                                                                                                                                                   leiden
                                                                                                                     1.0
                                                                 2.0
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                                                                 1.5
                                                                                                                                                                         1.5
                    PC2
                                                                       2C2
                                                                 1.0
                                                                                                                     0.0
                                                                                                                                                                                                                            23
                                                                                                                                                                         1.0
                                                                 0.5
                                                                                                                                                                         0.5
                                                                                                                      -0.5
                                                                 0.0
                                        PC1
                                                                                                                                                PC1
                                                                                            PC1
                                                                                                                                                                                                    PC1
In [15]: for adata FL in adatas FL:
                          new_cluster_names = ['KI (BFP)', 'negative', 'low MOI (GFP)', 'high MOI (CFP)'] # name according to PC
                           adata_FL.rename_categories('leiden', new_cluster_names)
                           adata_FL.uns['leiden_colors']=['#078dde','#000000','#ffa55c','#606060','#adadad']
In [16]: fig, ax = plt.subplots(ncols=2, figsize=(10,4))
                   fig.tight_layout(w_pad=10)
                   for i, adata FL in enumerate (adatas FL):
                           downsampled_adatas=np.zeros(3).tolist()
                           for j, fluorophore in enumerate(['KI (BFP)', 'low MOI (GFP)', 'high MOI (CFP)']):
                                   \verb|downsampled_adatas[j]| = \verb|sc.pp.subsample(adata_FL[adata_FL.obs.leiden==fluorophore]|, n_obs=482, copside | n
                   y=True)
                           \verb|downsampled_adata=downsampled_adatas[0].concatenate(|downsampled_adatas[1:])|
                           sc.pp.neighbors(downsampled adata, n neighbors=20, n pcs=2)
                           sc.tl.umap(downsampled adata, spread=50, min dist=1.9)
                           sc.tl.leiden(downsampled_adata)
                           new_cluster_names = ['KI (BFP)', 'low MOI (GFP)', 'high MOI (CFP)']
                           downsampled_adata.rename_categories('leiden', new_cluster_names)
                           downsampled adata.uns['leiden colors']=['#078dde','#606060','#ffa55c']
                           sc.pl.umap(downsampled_adata, color=['leiden'], s=30, ax=ax[i], show=False, title=['TCR 1-4', 'TCR 6
                   -2'][i])
                   fig.savefig('./figures/final_UMAPs_fluorophores_downsampled.svg', dpi=500)
                   C:\Users\Administrator\AppData\Roaming\Python\Python36\site-packages\umap\umap_.py:1158: RuntimeWarnin
                   g: divide by zero encountered in power
                       return 1.0 / (1.0 + a * x ** (2 * b))
                   C:\Users\Administrator\AppData\Roaming\Python\Python36\site-packages\umap\umap_.py:1158: RuntimeWarnin
                   g: divide by zero encountered in power
                       return 1.0 / (1.0 + a * x ** (2 * b))
                                                 TCR 1-4
                                                                                                                                                            TCR 6-2
                                                                                         KI (BFP)

    KI (BFP)

                                                                                         low MOI (GFP)
                                                                                                                                                                                                    low MOI (GFP)
                                                                                         high MOI (CFP)
                                                                                                                                                                                                    high MOI (CFP)
                                                 UMAP1
                                                                                                                                                            UMAP1
```

```
In [17]: for i, adata_FL in enumerate(adatas_FL):
             print(str(adata_FL.obs.leiden.value_counts()[['KI (BFP)','low MOI (GFP)','high MOI (CFP)']].sum
          ())+'/'+str(adata_FL.shape[0])+' cells identified in '+names[i])
             print('\t - '-str(adata_FL.obs.leiden.value_counts()['low MOI (GFP)'])+' for TX low MOI')
             print('\t - '+str(adata_FL.obs.leiden.value_counts()['high MOI (CFP)'])+' for TX high MOI')
              print('\t - '+str(adata_FL.obs.leiden.value_counts()['KI (BFP)'])+' KI')
              print('')
          3433/4671 cells identified in Sample 1
                   - 654 for TX low MOI
                   - 575 for TX high MOI
                   - 2204 KI
          3477/4739 cells identified in Sample 2
                   - 692 for TX low MOI
                   - 482 for TX high MOI
                   - 2303 KI
In [18]: fig, ax = plt.subplots(ncols=2, figsize=(15,7))
          for i, adata_FL in enumerate(adatas_FL):
              adata_FL.obs.leiden.value_counts().plot(kind='pie', ax=ax[i], colors=['#078dde','#000000','#606060
          ','#ffa55c'])
             ax[i].set_ylabel('')
ax[i].set_title(names[i])
                             Sample 1
                                                                                   Sample 2
                                  KI (BFP)
                                                                                       KI (BFP)
                                                                                                         high MOI (CFP)
                                                   high MOI (CFP)
           negative
                                                                 negative
                                                                                               low MOI (GFP)
                                       low MOI (GFP)
In [19]: # remove fluorescent genes from adata object
          adatas noFL=[0,0]
          \verb| adatas_noFL[0] = \verb| adatas[0][:, \verb| adatas[0].var_names.isin(['GFP', 'BFP', 'CFP-1'])].copy()|
          adatas_noFL[1] = adatas[1][:,~adatas[1].var_names.isin(['GFP','BFP','CFP-1'])].copy()
          adatas=[adatas_noFL[0],adatas_noFL[1]]
In [20]: for adata in adatas:
              mito_genes = adata.var_names.str.startswith('MT-')
              adata.obs['percent_mito'] = np.sum(
              adata[:, mito genes].X, axis=1).A1 / np.sum(adata.X, axis=1).A1
              adata.obs['n_counts'] = adata.X.sum(axis=1).A1
In [21]: for adata in adatas:
             ribo_genes = ((adata.var_names.str.startswith("RPL")) | (adata.var_names.str.startswith("RPS"))| (ad
          ata.var names.str.startswith("MPL")))
              adata.obs['percent_ribo'] = np.sum(
```

adata[:, ribo_genes].X, axis=1) / np.sum(adata.X, axis=1)

adata.var['ribo'] = ribo_genes

```
In [22]: for adata in adatas:
                 sc.pl.violin(adata, ['n_genes', 'n_counts', 'percent_mito', 'percent_ribo'],
                            jitter=0.5, multi_panel=True)
            \dots storing 'feature_types' as categorical
                                                                                                                          percent_ribo
                          n_genes
                                                          n_counts
                                                                                         percent_mito
                                                                                                                0.4
                                                                               0.6
                                            20000
                                                                                                                0.3
             4000
                                                                                0.4
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                                            10000
             2000
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                                                                                0.0 -
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                0
            ... storing 'feature_types' as categorical
                          n_genes
                                                          n_counts
                                                                                         percent_mito
                                                                                                                          percent_ribo
                                                                                0.6
                                                                                                                0.3
                                            20000
             4000
                                            10000
             2000
                                                                                0.0
                                                                                                                0.0
In [23]: for adata in adatas:
                 counts = adata.obs['n_counts']
                 mito = adata.obs['percent_mito']
                 genes = adata.obs['n genes']
                 ribo = adata.obs['percent_ribo']
                 fig = plt.figure(figsize=(15, 4))
                 grid = plt.GridSpec(1, 3, hspace=0, wspace=0.5)
                percent_mito = fig.add_subplot(grid[0, 0], xlabel='n_counts', ylabel='percent_mito')
percent_ribo = fig.add_subplot(grid[0, 1], xlabel='n_counts', ylabel='percent_ribo')
                n_genes = fig.add_subplot(grid[0, 2], xlabel='n_counts', ylabel='n_genes')
percent_mito.scatter(counts, mito, s=2, c='gray')
                 percent_ribo.scatter(counts, ribo, s=2, c='gray')
                 n_genes.scatter(counts, genes, s=2, c='gray')
                                                                                                        5000
               0.6
                                                            0.3
                                                                                                        4000
            bercent_mito
                                                         percent_ribo
                                                                                                        3000
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                                                                                                       2000
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                                                                          10000
                                                                                     20000
                                                                                                                                  20000
                   0
                              n_counts
                                                                           n_counts
                                                                                                                        n_counts
```

```
In [24]: counts_before=[adatas[0].n_obs, adatas[1].n_obs]
           adatas[0] = adatas[0][adatas[0].obs['n_genes'] < 4000, :]
           adatas[0] = adatas[0][adatas[0].obs['n_counts'] < 15000, :]
           adatas[0] = adatas[0][adatas[0].obs['percent mito'] < 0.2, :]</pre>
           adatas[1] = adatas[1][adatas[1].obs['n_genes'] < 4000, :]
adatas[1] = adatas[1][adatas[1].obs['n_counts'] < 15000, :]
adatas[1] = adatas[1][adatas[1].obs['percent_mito'] < 0.2, :]</pre>
In [25]: for adata in adatas:
                counts2 = adata.obs['n_counts']
                mito2 = adata.obs['percent_mito']
                genes2 = adata.obs['n_genes']
                ribo2 = adata.obs['percent_ribo']
                fig = plt.figure(figsize=(15, 4))
                grid = plt.GridSpec(1, 3, hspace=0, wspace=0.5)
                percent_mito = fig.add_subplot(grid[0, 0], xlabel='n_counts', ylabel='percent_mito')
                percent ribo = fig.add subplot(grid[0, 1], xlabel='n counts', ylabel='percent ribo')
                n_genes = fig.add_subplot(grid[0, 2], xlabel='n_counts', ylabel='n_genes')
                percent_mito.scatter(counts, mito, s=3, c='gray')
                percent_ribo.scatter(counts, ribo, s=3, c='gray')
                n_genes.scatter(counts, genes, s=3, c='gray')
                percent_mito.scatter(counts2, mito2, s=2, c='black')
percent_ribo.scatter(counts2, ribo2, s=2, c='black')
                n_genes.scatter(counts2, genes2, s=2, c='black')
           fig.savefig('./figures/filtering.pdf', dpi=2000)
              0.6
                                                                                                   5000
              0.5
                                                         0.3
                                                                                                   4000
                                                       percent_ribo
              0.4
                                                                                                   3000
            0.3
0.2
                                                          0.2
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0.10
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                                                                                                   1000
              0.0
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                                                                                                                  10000
                  0
                           10000
                                      20000
                                                                       10000
                                                                                 20000
                                                                                                                             20000
                            n_counts
                                                                                                                   n_counts
                                                                        n_counts
In [26]: for i, adata in enumerate(adatas):
                print(names[i]+': '+str(counts_before[i])+' --> '+str(adata.n_obs))
           Sample 1: 9178 --> 8203
           Sample 2: 10040 --> 9560
```

```
Annotation of Subsamples
```

```
In [27]: adatas[0].obs["subsample"]='not specified'
    adatas[1].obs["subsample"]='not specified'

Trying to set attribute `.obs` of view, copying.
    Trying to set attribute `.obs` of view, copying.
```

```
In [28]: adatas[0].obs.subsample[adatas[0].obs_names.isin(adatas_FL[0][adatas_FL[0].obs.leiden=='KI (BFP)'].obs_n
                                    ames)]='KI (BFP)'
                                    adatas[0].obs.subsample[adatas[0].obs_names.isin(adatas_FL[0][adatas_FL[0].obs.leiden=='low MOI (GFP)'].
                                    obs names)]='low MOI (GFP)
                                    adatas[0].obs.subsample[adatas[0].obs_names.isin(adatas_FL[0][adatas_FL[0].obs.leiden=='high MOI (CF
                                   P)'].obs_names)]='high MOI (CFP)'
                                    adatas[1].obs.subsample[adatas[1].obs names.isin(adatas FL[1][adatas FL[1].obs.leiden=='KI (BFP)'].obs n
                                    adatas[1].obs.subsample[adatas[1].obs names.isin(adatas FL[1][adatas FL[1].obs.leiden=='low MOI (GFP)'].
                                    obs names)]='low MOI (GFP)'
                                    adatas[1].obs.subsample[adatas[1].obs_names.isin(adatas_FL[1][adatas_FL[1].obs.leiden=='high MOI (CF
                                    P)'].obs names)]='high MOI (CFP)'
                                   \verb|C:\Pr| ogramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:1: SettingWithCopyWarning: | ogramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:1: SettingWithCopyW
                                   A value is trying to be set on a copy of a slice from a {\tt DataFrame}
                                   See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
                                   g.html#returning-a-view-versus-a-copy
                                              ""Entry point for launching an IPython kernel.
                                   A value is trying to be set on a copy of a slice from a DataFrame
                                    See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexin
                                   g.html#returning-a-view-versus-a-copy
                                   \verb|C:\Pr| orange = ackages in ykernel_launcher.py:3: Setting \verb|WithCopyWarning:| orange = ackages in ykernel_launcher.py:3: Setting orange = ackages in ykernel_launcher.py:3: Setting orange = ackages in ykernel_launcher.py:3: Setting orange = ackages = a
                                   A value is trying to be set on a copy of a slice from a DataFrame
                                    See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
                                   g.html#returning-a-view-versus-a-copy
                                         This is separate from the ipykernel package so we can avoid doing imports until
                                   \verb|C:\Pr| ogramData\Anaconda3| ib\site-packages\ipykernel\_launcher.py:5: SettingWithCopyWarning: | ogramData\Anaconda3| ib\site-packages\ipykernel=| ogramData\Anaconda3| ib\site-packages\ipykernel=| ogramData\Anaconda3| ib\site-packages\ipykernel=| ogramData\Anaconda
                                   A value is trying to be set on a copy of a slice from a DataFrame
                                   See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
                                   g.html#returning-a-view-versus-a-copy
                                   C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: SettingWithCopyWarning:
                                   A value is trying to be set on a copy of a slice from a DataFrame
                                   See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexin
                                   g.html#returning-a-view-versus-a-copy
                                   \verb|C:\Pr| ogramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:7: SettingWithCopyWarning: | ogramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:7: SettingWithCopyWarning: | ogramData\Anaconda3\lib\site-packages\lipykernel\_launcher.py:7: SettingWithCopyWarning: | ogramData\Anaconda3 \lib\site-packages\lipykernel\_launcher.
                                  A value is trying to be set on a copy of a slice from a DataFrame
                                   See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
                                    g.html#returning-a-view-versus-a-copy
                                          import sys
In [29]: | adatas_sub=[0,0]
                                    adatas_sub[0]=adatas[0][adatas[0].obs.subsample!='not specified'].copy()
                                    adatas sub[1]=adatas[1][adatas[1].obs.subsample!='not specified'].copy()
                                    adatas=[adatas_sub[0],adatas_sub[1]]
In [30]: | # Remove background in the specific groups (TX: - HDR construct=0, KI: TX- construct=0)
                                    for adata in adatas:
                                                  adata[adata.obs.subsample=='low MOI (GFP)',adata.var_names.isin(['HDR_KI_TCR1-4', 'HDR_KI_TCR6-2
                                    '])].X=0
                                                 adata[adata.obs.subsample=='high MOI (CFP)',adata.var names.isin(['HDR KI TCR1-4', 'HDR KI TCR6-2
                                    '])].X=0
                                                  adata[adata.obs.subsample=='KI (BFP)',adata.var_names.isin(['TX_TCR1-4', 'TX_TCR6-2'])].X=0
                                   \verb|C:\ProgramData\Anaconda3\lib\site-packages\scipy\sparse\_index.py:124: SparseEfficiencyWarning: Changi | Cha
                                   ng the sparsity structure of a csr_matrix is expensive. Iil_matrix is more efficient.
                                           self._set_arrayXarray(i, j, x)
```

Total-count normalize (library-size correct) the data matrix to 10,000 reads per cell, so that counts become comparable among cells.

```
In [31]: for adata in adatas:
    sc.pp.normalize_per_cell(adata, counts_per_cell_after=1e4)
    sc.pp.log1p(adata)
```

Cell cycle scoring

```
In [32]: cc_genes=pd.read_csv("./analysis_info/regev_lab_cell_cycle_genes.txt")
           s_genes=cc_genes[:46]
           g2m_genes=cc_genes[47:]
           s genes.columns=['genes']
           g2m_genes.columns=['genes']
           \quad \textbf{for} \ \text{adata} \ \underline{\textbf{in}} \ \text{adatas:}
               sc.tl.score_genes_cell_cycle(adata, s_genes.genes, g2m_genes.genes)
In [33]: fig, ax = plt.subplots(ncols=len(adatas), figsize=(7,3))
           fig.tight_layout(w_pad=5)
           for i, adata in enumerate(adatas):
               {\tt sc.pl.scatter(adata, x='S\_score', y='G2M\_score', color='phase', ax=ax[i], show={\tt False})}
           \dots storing 'subsample' as categorical
           ... storing 'phase' as categorical
           ... storing 'subsample' as categorical
           ... storing 'phase' as categorical
                            phase
                                                                      phase
              1.0
                                                         1.0
                                             • G1 60
• G2M 60
           G2M score
                                                                                        G1
              0.5
                                                        0.5
                                                                                       G2M
                                                     G2M

    S

    S

                                                         0.0
              0.0
                                                        -0.5
                         0.0
                                  0.5
                                                                     0.0
                                                                               0.5
                           S_score
                                                                     S_score
```

Set the .raw attribute of AnnData object to the logarithmized raw gene expression for later use in differential testing and visualizations of gene expression. This simply freezes the state of the AnnData object. While many people consider the normalized data matrix as the "relevant data" for visualization and differential testing, some would prefer to store the unnormalized data.

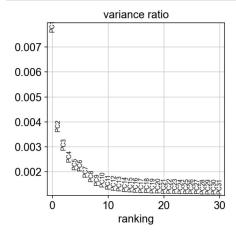
```
In [34]: adata=adatas[0].concatenate(adatas[1])
    adata.raw=adata
In [35]: adata.uns['subsample_colors']=['#078dde','#606060','#ffa55c']
```

Identify highly-variable genes.

Principal component analysis

Reduce the dimensionality of the data by running principal component analysis (PCA), which reveals the main axes of variation and denoises the data.





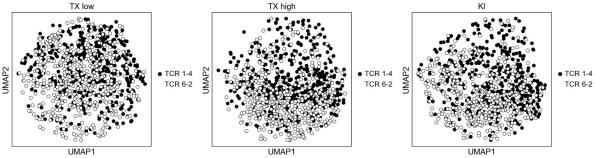
Computing the neighborhood graph

Let us compute the neighborhood graph of cells using the PCA representation of the data matrix. You might simply use default values here. For the sake of reproducing Seurat's results, let's take the following values.

```
In [41]: sc.pp.neighbors(adata_for_pca, n_neighbors=10, n_pcs=7)
```

Embedding the neighborhood graph

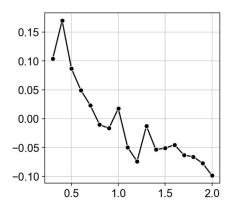
```
In [42]: sc.tl.umap(adata for pca)
In [43]: # Move back to all genes including the constructs
          adata.uns=adata_for_pca.uns
          adata.obsm=adata_for_pca.obsm
          adata.obsp=adata_for_pca.obsp
In [44]: titles=['TCR 1-4', 'TCR 6-2']
          fig, ax = plt.subplots(ncols=2, figsize=(10,4))
          fig.tight layout(w pad=10)
          for i, batch in enumerate(adata.obs.batch.unique()):
              downsampled_adatas=np.zeros(3).tolist()
              for j, subsample in enumerate(adata.obs.subsample.unique()):
                   downsampled_adatas[j]=sc.pp.subsample(adata[np.logical_and(adata.obs.batch==batch,adata.obs.subs
          ample==subsample)], n_obs=450, copy=True)
              downsampled_adata=downsampled_adatas[0].concatenate(downsampled_adatas[1:])downsampled_adata.uns['subsample_colors']=['#078dde','#ffa55c','#606060']
              sc.pl.umap(downsampled_adata, color='subsample', title=titles[i], ax=ax[i], show=False)
          fig.savefig('./figures/final_UMAPs_editing_method_per_TCR.svg', dpi=500)
          ... storing 'subsample' as categorical
          ... storing 'subsample' as categorical
                                                                                    TCR 6-2
                                                KI (BFP)
                                                                                                          • KI (BFP)
                                                high MOI (CFP)
                                                                                                          high MOI (CFP)
                                                low MOI (GFP)
                                                                                                          low MOI (GFP)
                           UMAP1
                                                                                     UMAP1
```



Clustering the neighborhood graph

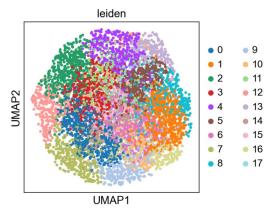
```
In [47]: titrate_leiden_resolution(adata)
```

 $[\text{nan, nan, 0.10384194, 0.16971079, 0.08649233, 0.04930613, 0.02317551, -0.010473365, -0.016712414, 0.017659063, -0.0498321, -0.07392946, -0.012762512, -0.053683866, -0.051172193, -0.045233022, -0.06321185, -0.065943345, -0.07732258, -0.09851311]$



```
In [48]: sc.tl.leiden(adata, resolution=1)
    print(silhouette_score(adata.obsm['X_umap'],adata.obs[f'leiden'],metric='euclidean'))
    0.017659063
```

```
In [49]: sc.pl.umap(adata, color=['leiden'], save='_leiden.pdf', s=50)
         WARNING: saving figure to file figures\umap leiden.pdf
```



```
In [53]: result = adata.uns['rank_genes_groups']
         groups = result['names'].dtype.names
         pd.DataFrame(
             {group + '_' + key: result[key][group]
             for group in groups for key in ['names', 'pvals']}).to csv('marker genes.csv')
```

Analyze TX and KI reads

```
In [54]: #filter BG according to the fluorescent protein subsamples
          adata.X[adata.obs.subsample=='GFP',-4:-2]=0
          adata.X[adata.obs.subsample=='CFP',-4:-2]=0
          adata.X[adata.obs.subsample=='BFP',-2:]=0
In [55]: #sc.pl.umap(adata, color=['leiden','CFP-1', 'GFP', 'BFP'], s=100)
          sc.pl.umap(adata, color=['HDR_KI_TCR1-4', 'HDR_KI_TCR6-2', 'TX_TCR1-4', 'TX_TCR6-2'], s=100, use_raw=Tru
                  HDR_KI_TCR1-4
                                              HDR_KI_TCR6-2
                                                                             TX_TCR1-4
                                                                                                         TX_TCR6-2
                                                                              UMAP1
                     UMAP1
                                                 UMAP1
                                                                                                          UMAP1
In [56]: selected_genes=['MALAT1','ACTB','B2M', 'GAPDH', 'VIM', 'HDR_KI TCR1-4', 'HDR KI TCR6-2', 'TX TCR1-4', 'T
          X_TCR6-2','TRAC','TRBC1','TRBC2','TRBC_total']
          selecte_genes_raw_index=[adata.raw.var_names.tolist().index(x) for x in selected_genes]
          for batch in adata.obs.batch.unique():
               for subsample in adata.obs.subsample.unique():
                   selected cells = adata[np.logical and(adata.obs.batch==batch,adata.obs.subsample==subsample)].ob
          s names
                   \texttt{selected\_cells\_index} = [\texttt{adata.obs\_names.tolist().index(x)} \ \ \textbf{for} \ \ x \ \ \textbf{in} \ \ \texttt{selected\_cells}]
          pd.DataFrame(adata.raw.X.todense()[:,selecte_genes_raw_index], columns=selected_genes).iloc[sele
cted_cells_index].to_csv(batch+'_'+subsample+'.csv')
In [57]: selected_genes=['HDR_KI_TCR1-4', 'HDR_KI_TCR6-2', 'TX_TCR1-4', 'TX_TCR6-2']+adata.var_names[adata.var_names]
          mes.str.contains('TRAV')].tolist()
          selecte_genes_raw_index=[adata.raw.var_names.tolist().index(x) for x in selected_genes]
          for batch in adata.obs.batch.unique():
              \quad \textbf{for} \  \, \text{subsample in adata.obs.subsample.unique():} \\
                   selected_cells = adata[np.logical_and(adata.obs.batch==batch,adata.obs.subsample==subsample)].ob
          s_names
                   selected_cells_index = [adata.obs_names.tolist().index(x) for x in selected_cells]
                   pd.DataFrame(adata.raw.X.todense()[:,selecte_genes_raw_index], columns=selected_genes).iloc[sele
          cted_cells_index].to_csv(batch+'_'+subsample+'_TRAV.csv')
```

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