

- In-silico perturbation
  - Material
  - Methods
    - Training Process
    - process the dataset
  - Result
    - Training dataset Visualization
    - In-silico perturbation Visualization

# In-silico perturbation

## Material

NCBI dataset: <https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE90546>

Paper Adamson B, Norman TM, Jost M, Cho MY et al. A Multiplexed Single-Cell CRISPR Screening Platform Enables Systematic Dissection of the Unfolded Protein Response. Cell 2016 Dec 15;167(7):1867-1882.e21. PMID: 27984733

## Methods

### Training Process

All Catagory

```
{'3x_neg_ctrl_pMJ144-1',  
'3x_neg_ctrl_pMJ144-2',  
'ATF6_IRE1_pMJ152',  
'ATF6_PERK_IRE1_pMJ158',  
'ATF6_PERK_pMJ150',  
'ATF6_only_pMJ145',  
'IRE1_only_pMJ148',  
'PERK_IRE1_pMJ154',  
'PERK_only_pMJ146'}
```

Training Dataset

```
{'3x_neg_ctrl_pMJ144-1',
```

```
'ATF6_only_pMJ145',  
'IRE1_only_pMJ148',  
'PERK_only_pMJ146']
```

Test Dataset

```
{'ATF6_IRE1_pMJ152',  
  
'ATF6_PERK_pMJ150',  
'PERK_IRE1_pMJ154',}
```

## process the dataset

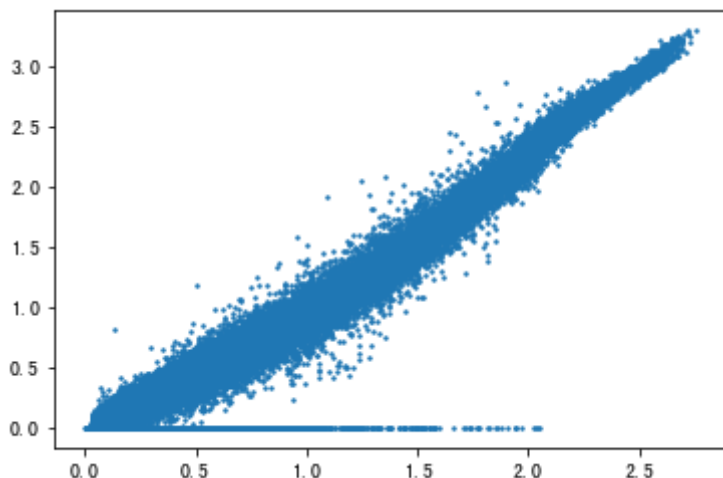
Use the mean value of each type of cell type

```
test_z_genes = np.array([np.mean(adata[adata.obs['cell_type'].str.startswith('3x_neg_ctrl_pMJ144-1')].X,axis=0),  
np.mean(adata[adata.obs['cell_type'].str.startswith('ATF6_only_pMJ145')].X,axis=0),  
np.mean(adata[adata.obs['cell_type'].str.startswith('IRE1_only_pMJ148')].X,axis=0),  
np.mean(adata[adata.obs['cell_type'].str.startswith('PERK_only_pMJ146')].X,axis=0)  
)  
test_z = np.array([np.mean(adata[adata.obs['cell_type'].str.startswith('3x_neg_ctrl_pMJ144-1')].X,axis=0),  
np.mean(adata[adata.obs['cell_type'].str.startswith('ATF6_only_pMJ145')].X,axis=0),  
np.mean(adata[adata.obs['cell_type'].str.startswith('IRE1_only_pMJ148')].X,axis=0),  
np.mean(adata[adata.obs['cell_type'].str.startswith('PERK_only_pMJ146')].X,axis=0)  
)
```

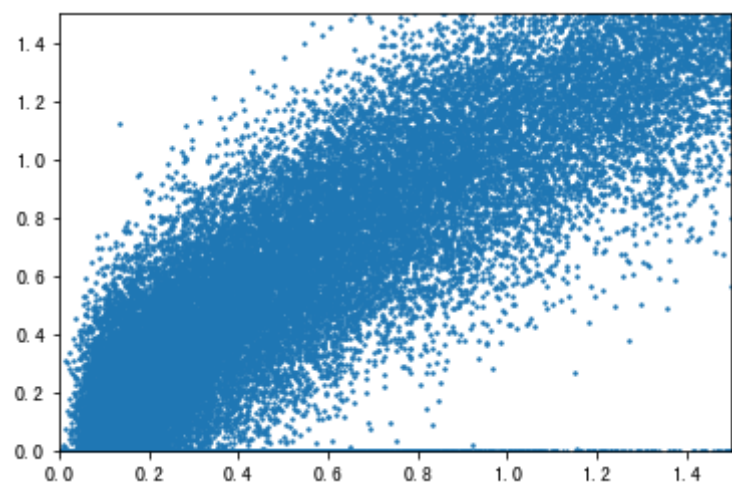
## Result

### Training dataset Visualization

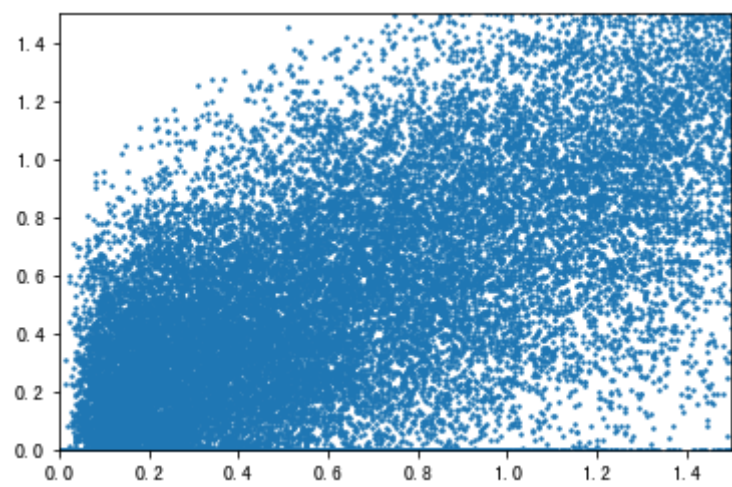
reconstruction plot



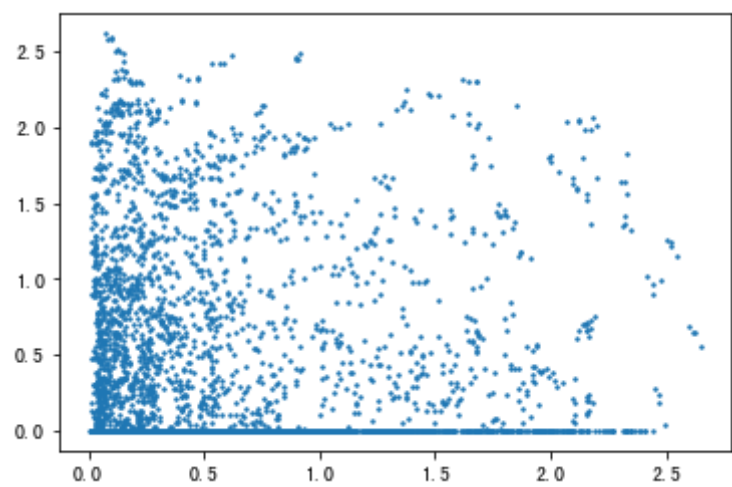
**level1 tf to genes plot**

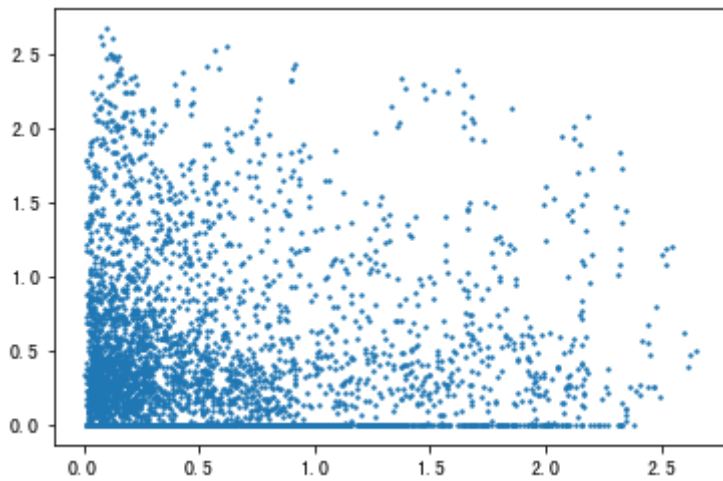
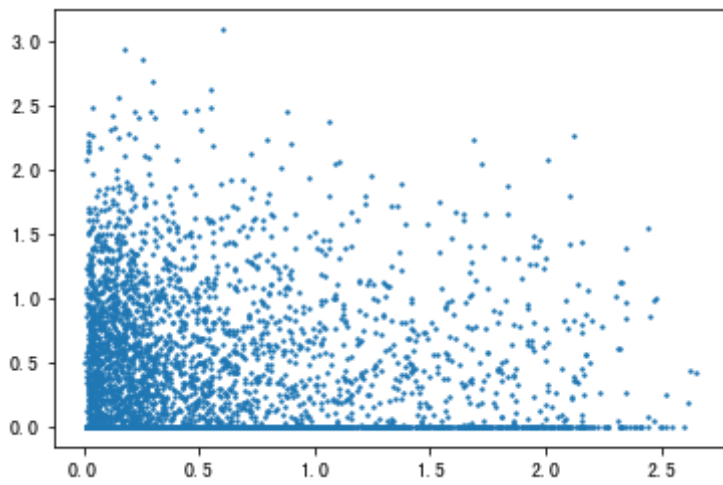


**level3 tf to genes plot**



**tf reconstruction plots (L1 L2 L3)**





## In-silico perturbation Visualization

First I get the mean tfs value of each cell type

```
test_z = np.array([np.mean(adata[adata.obs['cell_type'].str.startswith('PERK_IRE1_pMJ154')],tfs
np.mean(adata[adata.obs['cell_type'].str.startswith('ATF6_PERK_pMJ150')],tfs_pmbc].X,axis=0),
np.mean(adata[adata.obs['cell_type'].str.startswith('ATF6_IRE1_pMJ152')],tfs_pmbc].X,axis=0)
])
```

Utilizing L1 tf to predict the genes will be better.

