main

March 17, 2023

1 Calculate RXE for public dataset, females only based on Apua's script

This has been edited from Apua's script.

```
[1]: import numpy as np
     import pandas as pd
     from os import environ
     from plotnine import *
     from pyhere import here
     import re, session_info
     import statsmodels.api as sm
     from functools import lru_cache
     from scipy.stats import variation
     from warnings import filterwarnings
     from scipy.stats import mannwhitneyu
     from statsmodels.formula.api import ols
     from matplotlib.cbook import mplDeprecation
[2]: filterwarnings('ignore', category=mplDeprecation)
     filterwarnings('ignore', category=UserWarning, module='plotnine.*')
     filterwarnings('ignore', category=DeprecationWarning, module='plotnine.*')
[3]: environ['NUMEXPR_MAX_THREADS'] = '4'
```

1.1 Functions

```
return pd.read_csv(fn, index_col=0)
     @lru_cache()
     def get_annotation():
         Get the annotation file for genes.
         fn = here('input/counts/text files counts/ m',
                   'caudate/gene_annotation.txt')
         return pd.read csv(fn, sep='\t')
[5]: def save_ggplot(p, fn):
         for ext in ['.pdf', '.png', '.svg']:
             p.save(fn+ext, width=10, height=7)
     def rge(df, chrom):
         return df[df['seqname'] == chrom][samples].mean() \
         - df[(df['chrom_type'] == 'autosome') & (df['seqname']! = chrom)][samples].
      →mean()
     def annotate_chrom(df):
         df.loc[:, 'chrom_types'] = 'Other'
         df.loc[df['seqnames'].isin(['chrX', 'chrY']), 'chrom_types'] = 'Allosome'
         df.loc[df['seqnames'].str.contains('chr\d+'), 'chrom_types'] = 'Autosome'
         df.loc[df['seqnames'] == 'chrM', 'chrom_types'] = 'Mitochondria'
         df.loc[df['seqnames'] == 'chrX', 'chrom_types'] = 'X'
```

1.2 Load and merge data

return df

```
[6]: log2tpm = pd.DataFrame()
    for tissue in ['caudate', 'dlpfc', 'hippocampus']:
        log2tpm = pd.concat([log2tpm, get_logTPM(tissue)], axis=1)
    print(log2tpm.shape)
    log2tpm.iloc[0:2, 0:5]
    (52569, 1217)
[6]:
                                 R12864
                                           R12865
                                                     R12866
                                                               R12867
                                                                         R12868
    TSPAN6|ENSG0000000003.15 2.441001 3.844446 3.045605 2.788269
                                                                       2.901279
    TNMD | ENSG00000000005.6
                               0.000000 0.000000 0.082527 0.000000 0.000000
```

1.3 Annotate TPM

```
[7]: get_annotation().head(2)
                                                                    width gene_name
 [7]:
                              name segnames
                                                  start
                                                               end
       TSPAN6 | ENSG00000000003.15
                                       chrX
                                             100627108
                                                         100639991
                                                                    12884
                                                                             TSPAN6
            TNMD | ENSG00000000005.6
                                       chrX
                                             100584936
                                                         100599885
                                                                    14950
                                                                               TNMD
 [8]: df0 = log2tpm.merge(get_annotation().loc[:, ['name', 'gene_name', 'seqnames']],
                          left_index=True, right_on='name')
      df0 = annotate_chrom(df0)
      print(df0.shape)
      df0.groupby('chrom_types').size()
     (52569, 1221)
 [8]: chrom_types
      Allosome
                        501
      Autosome
                      50034
     Mitochondria
                         14
                       2020
      dtype: int64
     1.4 Filtering genes
 [9]: samples = [x for x in log2tpm.columns if re.match('R\d+', x)]
      df = df0[(df0[samples].sum(axis=1) >= 0.2 * len(samples)) &
               (df0['chrom_types'].isin(['X', 'Autosome']))].copy()
      df.shape
 [9]: (24499, 1221)
          Generate RXE
     1.5
[10]: df1 = df.groupby('chrom_types').mean(numeric_only=True).transpose()
      df1.head(2)
[10]: chrom_types Autosome
                                    Х
      R12864
                   2.332196
                             2.461731
      R12865
                   2.740215 2.829693
[11]: df1['sample'] = df1.index
      df1['RXE'] = df1['X'] - df1['Autosome']
      df1.head(2)
```

```
[11]: chrom_types Autosome X sample RXE
R12864 2.332196 2.461731 R12864 0.129535
R12865 2.740215 2.829693 R12865 0.089478
```

1.6 Annotated sample IDs

[12]:			RXE						\
			count	mean	std	min	25%	50%	
	Region	Sex							
	Caudate	F	129.0	0.072434	0.066423	-0.116318	0.037158	0.087259	
		M	289.0	0.073250	0.055947	-0.144156	0.046930	0.085875	
	DLPFC	F	125.0	0.105212	0.042601	-0.026092	0.089677	0.119341	
		M	263.0	0.102371	0.068521	-0.919013	0.093479	0.109438	
	HIPPO	F	132.0	0.111335	0.032613	0.018946	0.094986	0.114084	
		M	276.0	0.106895	0.032326	-0.005364	0.090518	0.112290	

```
75%
                            max
Region Sex
             0.120710 0.180794
Caudate F
        Μ
             0.111217 0.162486
DLPFC
             0.132669 0.171622
        F
             0.124097 0.155076
HIPPO
        F
             0.133184 0.178053
             0.127329 0.208088
        Μ
```

1.7 Metrics summary

1.7.1 Variation of RXE

```
[13]: for tissue in ['Caudate', 'DLPFC', 'HIPPO']:
    for sex in ['F', 'M']:
        var = variation(df2[(df2['Region']==tissue) & (df2['Sex']==sex)].RXE)
        print(f'There is {var:.3} variation for {sex} in {tissue}.')

There is 0.913 variation for F in Caudate.
There is 0.762 variation for M in Caudate.
There is 0.403 variation for F in DLPFC.
There is 0.668 variation for M in DLPFC.
There is 0.292 variation for F in HIPPO.
There is 0.302 variation for M in HIPPO.
```

```
[14]: ## Separate out tissues

caudate = df2[(df2['Region']=='Caudate')].copy()
dlpfc = df2[(df2['Region']=='DLPFC')].copy()
hippo = df2[(df2['Region']=='HIPPO')].copy()
```

1.7.2 Mann-WhitneyU (Female to Male)

```
Mann-WhitneyU for female vs male (RXE) for caudate: 0.5742
Mann-WhitneyU for female vs male (RXE) for DLPFC: 0.04684
Mann-WhitneyU for female vs male (RXE) for hippocampus: 0.1329
```

1.7.3 Mann-WhitneyU (CTL vs SZ)

```
Mann-WhitneyU for ctl vs sz (RXE) for caudate: 0.6328
Mann-WhitneyU for ctl vs sz (RXE) for DLPFC: 0.0736
Mann-WhitneyU for ctl vs sz (RXE) for hippocampus: 0.004401
```

1.7.4 Subset by sex: diagnosis status

```
print(f'Mann-WhitneyU of female, ctl vs sz (RXE) for {tissue}: {pval_f:.4}')
print(f'Mann-WhitneyU of male, ctl vs sz (RXE) for {tissue}: {pval_m:.4}')
```

```
Mann-WhitneyU of female, ctl vs sz (RXE) for caudate: 0.2795
Mann-WhitneyU of male, ctl vs sz (RXE) for caudate: 0.1496
Mann-WhitneyU of female, ctl vs sz (RXE) for DLPFC: 0.6639
Mann-WhitneyU of male, ctl vs sz (RXE) for DLPFC: 0.06367
Mann-WhitneyU of female, ctl vs sz (RXE) for hippocampus: 0.2548
Mann-WhitneyU of male, ctl vs sz (RXE) for hippocampus: 0.004064
```

1.7.5 X chromosome expression differences

```
Mann-WhitneyU of female, ctl vs sz (RXE) for caudate: 0.132
Mann-WhitneyU of male, ctl vs sz (RXE) for caudate: 0.2937
Mann-WhitneyU of female, ctl vs sz (RXE) for DLPFC: 0.2231
Mann-WhitneyU of male, ctl vs sz (RXE) for DLPFC: 0.01622
Mann-WhitneyU of female, ctl vs sz (RXE) for hippocampus: 0.9944
Mann-WhitneyU of male, ctl vs sz (RXE) for hippocampus: 0.1167
```

1.7.6 Autosome expression

```
Mann-WhitneyU of female, ctl vs sz (RXE) for caudate: 0.2489
    Mann-WhitneyU of male, ctl vs sz (RXE) for caudate: 0.2242
    Mann-WhitneyU of female, ctl vs sz (RXE) for DLPFC: 0.251
    Mann-WhitneyU of male, ctl vs sz (RXE) for DLPFC: 0.006911
    Mann-WhitneyU of female, ctl vs sz (RXE) for hippocampus: 0.7817
    Mann-WhitneyU of male, ctl vs sz (RXE) for hippocampus: 0.6085
    1.7.7 Interaction model
[20]: df2.Sex = df2.Sex.astype('category').cat.rename_categories({'F': 'Female', 'M':
      df2.head(2)
                                                                  Sex Dx \
[20]:
                     Autosome
                                     X sample
                                                   RXE
                                                          RNum
     SAMPLE_ID
     R12864 H5FM2BBXX 2.332196 2.461731 R12864 0.129535 R12864 Female SZ
     R12865_H5FM2BBXX 2.740215 2.829693 R12865 0.089478 R12865
                                                                 Male SZ
                      Region
     SAMPLE_ID
     R12864_H5FM2BBXX Caudate
     R12865_H5FM2BBXX
                     Caudate
[21]: df3 = df2.reset_index()[['RNum', 'RXE', 'Sex', 'Dx', 'Region']].
      ⇔set_index('RNum')
     df3[df3.columns[1]] = df3.Sex.cat.codes
     df3[df3.columns[2]] = df3.Dx.cat.codes
     df3[df3.columns[3]] = df3.Region.astype('category').cat.codes
     df3.head(2)
[21]:
                 RXE Sex Dx Region
     RNum
     R12864 0.129535
                           1
                                  0
     R12865 0.089478
[22]: anova_df = df2.loc[:,['RXE','Sex','Dx','Region']]
     # ANOVA results with combinations of 2 groups:
     formula = 'RXE ~ C(Sex) + C(Dx) + C(Region) + C(Sex):C(Dx) + C(Sex):C(Region) +
```

GC(Dx):C(Region)'

print(table)

lm = ols(formula, anova_df).fit()
table = sm.stats.anova_lm(lm, typ=2)

```
df
                                                     PR(>F)
                   sum_sq
C(Sex)
                  0.001895
                               1.0
                                     0.690473 4.061684e-01
C(Dx)
                  0.030385
                               1.0 11.072889 9.024554e-04
C(Region)
                  0.296575
                               2.0 54.038442 3.354717e-23
C(Sex):C(Dx)
                               1.0
                                     3.916503 4.804177e-02
                  0.010747
C(Sex):C(Region) 0.001777
                               2.0
                                     0.323846 7.234250e-01
C(Dx):C(Region)
                  0.003186
                               2.0
                                     0.580494 5.597787e-01
Residual
                  3.303914 1204.0
                                          NaN
                                                        NaN
```

By tissue interaction

```
[23]: from statsmodels.stats.multicomp import pairwise_tukeyhsd
      # Assumes parametric
      for tissue in ['caudate', 'DLPFC', 'hippocampus']:
          df_config = {'caudate': caudate, 'DLPFC': dlpfc, 'hippocampus': hippo}
          anova_df = df_config[tissue].loc[:, ['RXE', 'Sex', 'Dx']]
          # ANOVA results with combinations of 2 groups:
          formula = 'RXE ~ C(Sex) + C(Dx) + C(Sex):C(Dx)'
          lm = ols(formula, anova_df).fit()
          table = sm.stats.anova_lm(lm, typ=2)
          print(tissue)
          print(table)
          print('\n')
          anova_df['combination'] = anova_df.Sex.astype('str') + ' / ' + anova_df.Dx.
          anova_df['combination'] = anova_df.Sex.astype('str') + ' / ' + anova df.Dx.
       ⇔astype('str')
          # perform multiple pairwise comparison (Tukey HSD)
          m_comp = pairwise_tukeyhsd(endog=anova_df['RXE'],__
       ⇒groups=anova_df['combination'], alpha=0.05)
          # coerce the tukeyhsd table to a DataFrame
          tukey_data = pd.DataFrame(data=m_comp._results_table.data[1:], columns =__
       →m_comp._results_table.data[0])
          if tukey data[(tukey data['p-adj'] < 0.05)].shape[0] == 0:</pre>
              print('There is no significant interactions!')
              print(tukey_data[(tukey_data['p-adj'] < 0.05)])</pre>
          print('\n')
```

caudate

```
sum_sq
                          df
                                     F
                                          PR(>F)
C(Sex)
             0.000021
                         1.0 0.006019 0.938196
C(Dx)
             0.003460
                         1.0 0.983331 0.321957
C(Sex):C(Dx) 0.006188
                         1.0 1.758856 0.185499
             1.456543 414.0
Residual
                                   NaN
                                             NaN
```

There is no significant interactions!

DLPFC

	sum_sq	df	F	PR(>F)
C(Sex)	0.000870	1.0	0.232827	0.629711
C(Dx)	0.015831	1.0	4.236993	0.040226
C(Sex):C(Dx)	0.004534	1.0	1.213578	0.271315
Residual	1.434789	384.0	NaN	NaN

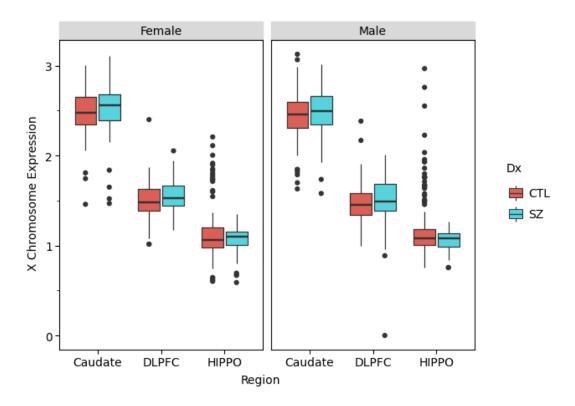
There is no significant interactions!

hippocampus

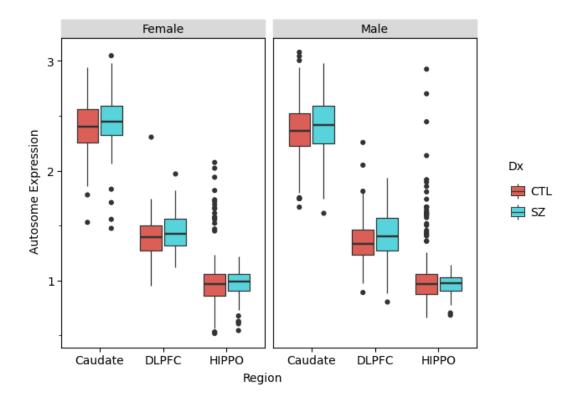
	sum_sq	df	F	PR(>F)
C(Sex)	0.002564	1.0	2.516841	0.113418
C(Dx)	0.014101	1.0	13.843822	0.000227
C(Sex):C(Dx)	0.001110	1.0	1.089551	0.297195
Residual	0.411496	404.0	NaN	NaN

```
group1 group2 meandiff p-adj lower upper reject
2 F / Control M / SCZD -0.0176 0.0022 -0.0303 -0.0049 True
5 M / Control M / SCZD -0.0149 0.0018 -0.0256 -0.0043 True
```

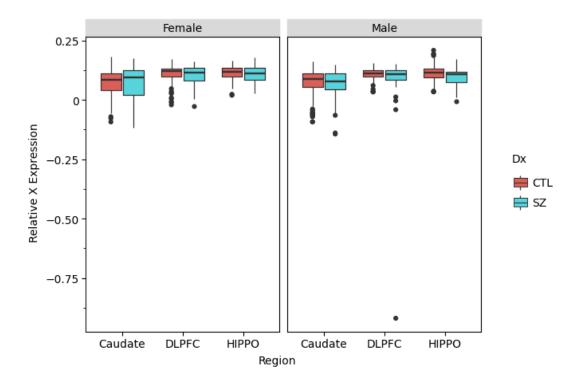
1.8 Plot RXE



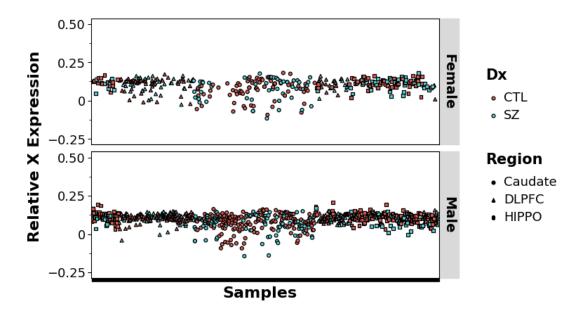
```
[24]: <ggplot: (8792500059356)>
```



```
[25]: <ggplot: (8792499901486)>
```



```
[26]: <ggplot: (8792499801338)>
```



```
[27]: <ggplot: (8792499708100)>
```

```
[28]: df2.to_csv('RXE_public.csv')
save_ggplot(p, 'RXE_public_bySex')
```

/users/jbenjami/.local/lib/python3.9/site-packages/plotnine/utils.py:371: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead. /users/jbenjami/.local/lib/python3.9/site-packages/plotnine/utils.py:371:

FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.

/users/jbenjami/.local/lib/python3.9/site-packages/plotnine/utils.py:371: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.

1.9 Session information

```
[29]: session_info.show()
```

[29]: <IPython.core.display.HTML object>