plots

September 16, 2021

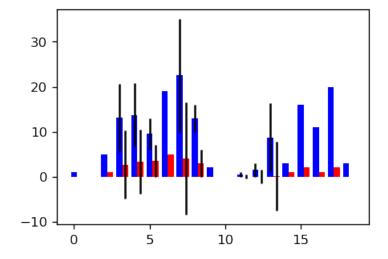
```
[334]: import pandas as pd
       import numpy as np
       import os.path
       import glob
       import distutils.dir_util
       import shutil
       import matplotlib.pyplot as plt
       import seaborn as sns
       import matplotlib
[225]: cm = 1/2.54
```

Cell type specific counts

```
[765]: df = pd.read_csv('D:/Manual Proximity Analysis_v4/Axon-Dendrite/Data_Comparison/

¬Users_All/All_Type_Counts_New2.csv',sep=';')
       df = df.dropna()
[766]: df['Pre-Post_Cell_Type'] = df['Cell_From'] +'->'+ df['Cell_To']
[767]: celltype_pairs = (np.unique(np.array(df['Pre-Post_Cell_Type'])))
       #df['Pre-Post_Cell_Type']
[768]: spine bouton counts = []
       spine_bouton_counts_means = []
       spine bouton counts stds = []
       #spine_bouton_counts_cellpair = []
       spine_counts = []
       spine_counts_means = []
       spine_counts_stds = []
       #spine_counts_cellpair = []
       all_counts = []
       all_counts_means = []
       all_counts_stds = []
       all_bouton_counts = []
       all_bouton_counts_means = []
```

```
all_bouton_counts_stds = []
Ns = []
i = 0
for cell_type_pair in celltype_pairs:
    spine_bouton_counts.
→append(df[(df['Pre-Post_Cell_Type']==cell_type_pair)]['Spine_Bouton'].values)
   spine_bouton_counts_means.append(spine_bouton_counts[i].mean())
   Ns.append(len(spine_bouton_counts[i]))
    #print(spine_bouton_counts[i], len(spine_bouton_counts[i]))
   if len(spine_bouton_counts[i])>1:
       spine_bouton_counts_stds.append(spine_bouton_counts[i].std())
   else:
       spine_bouton_counts_stds.append(0)
   spine_counts.
 →append(df[(df['Pre-Post_Cell_Type']==cell_type_pair)]['Spine_Bouton'].values_
                       df[(df['Pre-Post_Cell_Type']==cell_type_pair)]['Spine'].
⇒values)
   spine_counts_means.append(spine_counts[i].mean())
   if len(spine bouton counts[i])>1:
       spine_counts_stds.append(spine_counts[i].std())
   else:
       spine_counts_stds.append(0)
   all_counts.
 →append(df[(df['Pre-Post Cell Type']==cell type pair)]['Spine Bouton'].values,
 →+ \
→df[(df['Pre-Post_Cell_Type']==cell_type_pair)]['Soma_Bouton'].values + \
                     df[(df['Pre-Post_Cell_Type']==cell_type_pair)]['Spine'].
→values + \
                     df[(df['Pre-Post_Cell_Type'] == cell_type_pair)]['Shaft'].
 →values + \
                     df[(df['Pre-Post_Cell_Type'] == cell_type_pair)]['Soma'].
→values)
   all_counts_means.append(all_counts[i].mean())
   if len(all counts[i])>1:
       all_counts_stds.append(all_counts[i].std())
   else:
       all_counts_stds.append(0)
```



```
\#ax = fig.add\_subplot(111)
       b1 = axes[0].boxplot(all_counts)
       eb1 = axes[0].errorbar(x=np.
       →arange(1,len(all_counts)+1),y=all_counts_means,yerr=all_counts_stds,\
                    color='blue',marker='.',fmt='.')
       b2 = axes[1].boxplot(all_bouton_counts)
       eb2 = axes[1].errorbar(x=np.
       →arange(1,len(all_bouton_counts)+1),y=all_bouton_counts_means,yerr=all_bouton_counts_stds,\
                    color='blue',marker='.',fmt='.')
       plt.setp(b1['boxes'], color='black')
       plt.setp(b1['whiskers'], color='black')
       plt.setp(b1['medians'], color='black')
       plt.setp(b1['caps'], color='black')
       plt.setp(b2['boxes'], color='black')
       plt.setp(b2['whiskers'], color='black')
       plt.setp(b2['medians'], color='black')
       plt.setp(b2['caps'], color='black')
       plt.tight layout()
       fig.savefig('D:/Putatives/celltype_counts_all.eps')
[770]: fig,axes = plt.subplots(nrows=1,ncols=2,__
       →sharex=True,sharey=False,figsize=(20*cm,8*cm),dpi=120)
       \#ax = fiq.add\_subplot(111)
       b1 = axes[0].boxplot(spine_bouton_counts)
       eb1 = axes[0].errorbar(x=np.
       →arange(1,len(spine_bouton_counts)+1),y=spine_bouton_counts_means,yerr=spine_bouton_counts_s
                    color='blue',marker='.',fmt='.')
       b2 = axes[1].boxplot(spine_counts)
       eb2 = axes[1].errorbar(x=np.
       →arange(1,len(spine_counts)+1),y=spine_counts_means,yerr=spine_counts_stds,\
                    color='blue',marker='.',fmt='.')
       plt.setp(b1['boxes'], color='black')
       plt.setp(b1['whiskers'], color='black')
       plt.setp(b1['medians'], color='black')
       plt.setp(b1['caps'], color='black')
       plt.setp(b2['boxes'], color='black')
       plt.setp(b2['whiskers'], color='black')
```

[769]: fig,axes = plt.subplots(nrows=1,ncols=2,__

⇒sharex=True, sharey=False, figsize=(20*cm, 8*cm), dpi=120)

```
plt.setp(b2['medians'], color='black')
       plt.setp(b2['caps'], color='black')
       plt.yticks(np.arange(0,22,2))
       plt.tight_layout()
       fig.savefig('D:/Putatives/celltype_counts_spine_only.eps')
[763]: (celltype_pairs)
[763]: array(['L3_py->L4_ss', 'L3_py->L5_st', 'L4_sp->L4_sp', 'L4_sp->L5_st',
              'L4_sp->L5_tt', 'L4_ss->L3_py', 'L4_ss->L5_st', 'L4_ss->L5_tt',
              'L5_st->L3_py', 'L5_st->L4_sp', 'L5_st->L4_ss', 'L5_st->L5_st',
              'L5_st->L5_tt', 'L5_tt->L4_sp', 'VPM->L4_ss', 'VPM->L5_st',
              'VPM->L5_tt'], dtype=object)
[764]: (Ns)
[764]: [1, 1, 10, 8, 2, 1, 2, 1, 1, 8, 2, 2, 1, 2, 1, 1, 1]
[684]: spine_bouton_counts
[684]: [array([0.]),
        array([1.]),
        array([4., 6., 0., 0., 2., 3., 1., 3., 0., 1.]),
        array([2., 0., 1., 1., 0., 2., 2., 1.]),
        array([4., 2.]),
        array([4.]),
        array([5., 0.]),
        array([0.]),
        array([0.]),
        array([0., 0., 0., 0., 0., 0., 0., 0.]),
        array([0., 0.]),
        array([0., 0.]),
        array([1.]),
        array([0., 0.]),
        array([1.]),
        array([2.]),
        array([0.])]
[685]: spine_counts
[685]: [array([0.]),
        array([2.]),
        array([15., 12., 0., 5., 11., 15., 2., 19., 5., 8.]),
        array([3., 5., 4., 6., 10., 11., 6., 2.]),
        array([4., 9.]),
        array([16.]),
```

```
array([9., 4.]),
array([1.]),
array([0.]),
array([0., 0., 0., 0., 0., 1., 0.]),
array([2., 0.]),
array([1., 0.]),
array([2.]),
array([0., 0.]),
array([8.]),
array([16.]),
array([2.])]
```

2 Distribution of contacts

```
[772]: # Pre vs post synaptic contacts location: in terms of pathlengths, euclidean
        \rightarrow dist, branch number from soma
[773]: df = pd.read_csv('D:/Manual Proximity Analysis_v4/Axon-Dendrite/Data_Comparison/

¬Users_All/Proximities_with_manual_and_pathlengths_v1.csv',sep=',')
[774]: df = df[(df['From_Axon_of_Cell_#']!=df['To_dend_of_Cell_#'])]
[775]: df['Pre-Post_Cell_Type'] = df['Presynaptic_Cell_Type'] +'->'+_

→df['Postsynaptic Cell Type']
[777]: np.unique(df[df['Manual_Contact_Type_1']==1]['Pre-Post_Cell_Type'])
[777]: array(['L3_py->L5_st', 'L4_sp->L4_sp', 'L4_sp->L5_st', 'L4_sp->L5_tt',
              'L4_ss->L3_py', 'L4_ss->L5_st', 'L5_st->L5_tt', 'VPM->L4_ss',
              'VPM->L5_st'], dtype=object)
      df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']=='L5_st->L5_tt')]
                         ID Proximity_Location_X Proximity_Location_Y \
[784]:
            Unnamed: 0
       680
                   19 673
                                          474.486
                                                                292.103
            Proximity_Location_Z Distance From_Axon_of_Cell_# To_dend_of_Cell_# \
       680
                        -451.252 0.691941
            Lower_Section_# Upper_Section_# ... Manual_Contact_Y_1 \
                                                291.1361694335938
       680
            Manual Contact Z 1 Manual Contact Type 1 Manual Bouton X 1 \
       680
                -451.388671875
                                                  1.0
                                                              475.277405
```

```
Manual_Bouton_Y_1 Manual_Bouton_Z_1 Experiment_Name \
       680
                   291.463806
                                     -451.756958
                                                      DS 20140120
            Presynaptic_Cell_Type Postsynaptic_Cell_Type Pre-Post_Cell_Type
       680
                            L5 st
                                                    L5 tt
                                                                 L5_st->L5_tt
       [1 rows x 33 columns]
[752]: fig = plt.figure(figsize=(15*cm, 10*cm), dpi=120)
       ax = fig.add_subplot(111)
       #plt.cla()
       i=0
       for celltype in np.
       →unique(df[df['Manual_Contact_Type_1']==1]['Pre-Post_Cell_Type']):
           print(celltype)
           x = 1
        →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Presynaptic_Path
        →df [(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Postsynaptic_Pat
           print(x,y)
           ax.plot(x,y,marker='o', linestyle='', markersize=12, label=celltype )
                break
           i = i+1
       plt.legend()
       plt.tight_layout()
       fig.savefig('D:/Putatives/pathlen.eps')
      The PostScript backend does not support transparency; partially transparent
      artists will be rendered opaque.
      L3_py->L5_st
      1683
              447.001
      Name: Presynaptic_Pathlength_From_Soma, dtype: float64 1683
                                                                      108.792
      Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
      L4_sp->L4_sp
      1134
              181.7760
      1140
              138.9980
      1164
              150.7190
      1187
              209.5570
      1272
              395.2350
      1276
             416.6060
      1277
             422.9810
              231.2520
      1285
      1291
              277.5910
      1300
             218.3130
      2480
              94.5314
```

2505

325.8680

```
2550
        269.8760
2562
        162.8880
2593
        363.0750
2884
        521.3340
2971
        290.1090
2973
        288.4870
3047
        288.4870
3470
        338.0990
Name: Presynaptic_Pathlength_From_Soma, dtype: float64 1134
                                                                 132.3610
1140
         90.0437
         93.3790
1164
1187
        131.0400
1272
        151.8380
1276
         97.5195
1277
        106.1060
1285
        120.3230
1291
         92.9323
1300
        181.8250
2480
         45.3238
2505
        145.9030
2550
        122.7160
2562
         34.1896
2593
        223.1000
2884
         59.7255
2971
        162.9080
2973
        162.1960
3047
        162.1960
3470
         59.5418
Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
L4_sp->L5_st
1917
        339.477
1926
        305.126
2652
        933.045
2782
        576.829
3196
        209.210
3200
        146.280
3563
        329.425
3581
        312.934
3683
        253.991
Name: Presynaptic_Pathlength_From_Soma, dtype: float64 1917
                                                                 143.7360
1926
        119.8660
2652
        581.0570
2782
        182.6760
3196
         83.0035
3200
         52.1696
3563
        194.9710
3581
        180.1970
3683
        194.8120
```

```
Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
L4_sp->L5_tt
1014
        596.420
1016
        587.859
1019
        335.191
1021
        340.188
1194
       770.597
1201
        684.514
Name: Presynaptic_Pathlength_From_Soma, dtype: float64 1014
                                                                588.688
1016
        582.945
        270.557
1019
1021
       201.460
       727.226
1194
1201
        649.809
Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
L4_ss->L3_py
1493
        276.963
1516
        603.162
1544
        186.464
1587
        350.317
Name: Presynaptic_Pathlength_From_Soma, dtype: float64 1493
                                                                 95.1732
1516
        236.5480
1544
         57.6004
1587
        204.0390
Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
L4_ss->L5_st
124
       383.601
163
       360.856
434
       566.415
468
       283.077
472
       383.601
Name: Presynaptic_Pathlength_From_Soma, dtype: float64 124
                                                               240.413
163
       154.925
434
       138.371
468
        96.869
472
       240.413
Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
L5 st->L5 tt
680
       1331.76
Name: Presynaptic_Pathlength_From_Soma, dtype: float64 680
                                                               0.0
Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
VPM->L4_ss
829
       0.0
Name: Presynaptic_Pathlength_From_Soma, dtype: float64 829
                                                                168.641
Name: Postsynaptic_Pathlength_From_Soma, dtype: float64
VPM->L5_st
850
       0.0
860
       0.0
```

```
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     artists will be rendered opaque.
[753]: fig = plt.figure(figsize=(15*cm, 10*cm), dpi=120)
      ax = fig.add_subplot(111)
      #plt.cla()
      i=0
      for celltype in np.
       print(celltype)
          x =__
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Presynaptic_Eucl
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Postsynaptic_Euc
          print(x,y)
          ax.plot(x,y,marker='o', linestyle='', markersize=12, label=celltype )
          #if i > 2:
              break
          i = i+1
      plt.legend()
      plt.tight_layout()
      fig.savefig('D:/Putatives/pathlen_euclidean.eps')
     L3_py->L5_st
      1683
             158.395
     Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 1683
                                                                         66.2983
     Name: Postsynaptic_Euclidean_Distance_From_Soma, dtype: float64
     L4_sp->L4_sp
     1134
             106.4100
     1140
              89.7519
     1164
              99.8127
             98.8447
     1187
     1272
             156.2960
     1276
            127.7580
     1277
            131.9260
     1285
             58.7750
     1291
             78.4551
     1300
              86.5731
     2480
             74.2068
     2505
            154.4440
     2550
             14.3828
     2562
            116.1170
     2593
             82.3183
     2884
             161.8980
```

Name: Presynaptic_Pathlength_From_Soma, dtype: float64 850

Name: Postsynaptic_Pathlength_From_Soma, dtype: float64

860

82.6890

82.1752

```
2971
         95.2840
2973
         95.7870
3047
         95.7870
3470
         46.4624
Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 1134
                                                                          74.7550
1140
         48.9291
1164
         56.0298
1187
         83.3216
1272
        104.1860
1276
         70.3499
1277
         74.2294
1285
         67.9619
1291
         65.5385
1300
        124.3550
2480
         30.9120
2505
         86.3782
2550
        104.6280
2562
         30.2096
2593
        196.2470
2884
         55.4191
2971
         97.0871
2973
         97.2647
3047
         97.2647
3470
         45.5784
Name: Postsynaptic_Euclidean_Distance_From_Soma, dtype: float64
L4_sp->L5_st
1917
        172.1720
1926
        270.3730
2652
        326.6990
2782
        153.6250
3196
         51.8806
3200
         41.0206
3563
         99.1441
3581
         99.7672
3683
        106.8190
Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 1917
                                                                          121.9030
1926
         88.3931
2652
        503.2800
2782
         81.5510
3196
         28.6647
3200
         36.3753
3563
        120.6130
3581
        106.1230
3683
         93.4003
Name: Postsynaptic_Euclidean_Distance_From_Soma, dtype: float64
L4_sp->L5_tt
1014
        237.7060
1016
        232.1300
```

```
1019
         57.3383
1021
        106.2990
1194
        422.1680
1201
        348.7320
Name: Presynaptic Euclidean Distance From Soma, dtype: float64 1014
                                                                        504.873
1016
        499.266
1019
        221.044
1021
        166.038
1194
        631.642
1201
        558.455
Name: Postsynaptic Euclidean Distance From Soma, dtype: float64
L4_ss->L3_py
1493
         54.3904
1516
        173.6800
1544
         80.1189
1587
        197.3730
Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 1493
                                                                         75.9846
1516
        161.4010
1544
         51.5284
1587
        173.8830
Name: Postsynaptic_Euclidean_Distance_From_Soma, dtype: float64
L4 ss->L5 st
       216.923
163
       226.015
434
      255.678
       151.661
468
472
       216.923
Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 124
                                                                        145.9770
163
        69.5128
434
        90.3188
468
        57.8103
472
       145.9770
Name: Postsynaptic_Euclidean_Distance_From_Soma, dtype: float64
L5_st->L5_tt
680
       693.124
Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 680
                                                                       0.0
Name: Postsynaptic Euclidean Distance From Soma, dtype: float64
VPM->L4 ss
829
       0.0
Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 829
                                                                        113.628
Name: Postsynaptic_Euclidean_Distance_From_Soma, dtype: float64
VPM->L5_st
850
       0.0
       0.0
860
Name: Presynaptic_Euclidean_Distance_From_Soma, dtype: float64 850
                                                                       55.7351
Name: Postsynaptic_Euclidean_Distance_From_Soma, dtype: float64
```

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```
[754]: fig = plt.figure(figsize=(15*cm,10*cm),dpi=120)
       ax = fig.add_subplot(111)
       #plt.cla()
       i=0
       for celltype in np.
        →unique(df[df['Manual_Contact_Type_1']==1]['Pre-Post_Cell_Type']):
           print(celltype)
           x =__
        →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Presynaptic_Edge
        →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Postsynaptic_Edg
           print(x,y)
           ax.plot(x,y,marker='o', linestyle='', markersize=12, label=celltype )
           #if i > 2:
                break
           i = i+1
       #plt.legend()
       plt.tight_layout()
       fig.savefig('D:/Putatives/pathlen_branchnum.eps')
      L3_py->L5_st
      1683
              4
      Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 1683
                                                                    3
      Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
      L4_sp->L4_sp
      1134
               7
      1140
               4
               5
      1164
      1187
               8
      1272
               5
      1276
               7
      1277
               7
      1285
               6
      1291
               5
      1300
               4
               2
      2480
      2505
               8
      2550
               9
      2562
               4
      2593
              10
      2884
               8
      2971
               4
```

```
3047
         4
3470
         6
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 1134
                                                              4
1140
1164
        4
1187
        5
1272
        4
1276
        3
1277
        3
1285
        5
1291
        5
1300
        5
2480
        1
2505
        1
2550
        2
2562
        2
2593
        2
2884
        2
2971
        1
2973
        1
3047
        1
3470
        1
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
L4_sp->L5_st
1917
         7
1926
         7
2652
        11
2782
        10
3196
         4
3200
         5
3563
         6
3581
3683
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 1917
                                                              3
1926
        2
2652
        5
2782
        2
3196
        1
3200
        3
3563
        3
3581
        3
3683
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
L4_sp->L5_tt
1014
        12
1016
        12
1019
        12
1021
        14
```

```
1194
         6
1201
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 1014
                                                               5
1016
        5
1019
        5
1021
        5
1194
1201
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
L4_ss->L3_py
1493
         9
1516
        12
         9
1544
1587
        12
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 1493
1516
1544
        1
1587
        4
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
L4 ss->L5 st
124
        7
        7
163
434
        9
468
       11
472
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 124
                                                              3
163
       4
434
       2
468
472
       3
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
L5_st->L5_tt
680
       11
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 680
                                                              0
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
VPM->L4 ss
829
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 829
                                                              4
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
VPM->L5_st
850
       0
860
Name: Presynaptic_Edge_Level_From_Soma, dtype: int64 850
                                                              2
860
Name: Postsynaptic_Edge_Level_From_Soma, dtype: int64
```

```
[756]: fig,axes = plt.subplots(nrows=1,ncols=2,__
       \#ax = fig.add\_subplot(111)
      pre = []
      post = []
      pre_means = []
      post_means = []
      pre_stds = []
      post_stds = []
      cell_types = np.
       -unique(df[(df['Manual_Contact_Type_1']==1)]['Pre-Post_Cell_Type'])
      for celltype in np.
       →unique(df[df['Manual_Contact_Type_1']==1]['Pre-Post_Cell_Type']):
          print(celltype)
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Pre-synaptic_Path
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Postsynaptic_Pat
          pre.append(x)
          post.append(y)
          pre_means.append(np.array(x).mean())
          post_means.append(np.array(y).mean())
          if len(x)>1:
              pre_stds.append(np.array(x).std())
              post_stds.append(np.array(y).std())
          else:
              pre_stds.append(0)
              post_stds.append(0)
      b1 = axes[0].boxplot(pre)
      eb1 = axes[0].errorbar(x=np.
       →arange(1,len(pre_means)+1),y=pre_means,yerr=pre_stds,\
                   color='blue',marker='.',fmt='.')
      b2 = axes[1].boxplot(post)
      eb2 = axes[1].errorbar(x=np.
       →arange(1,len(post_means)+1),y=post_means,yerr=post_stds,\
                   color='blue',marker='.',fmt='.')
      plt.setp(b1['boxes'], color='black')
      plt.setp(b1['whiskers'], color='black')
      plt.setp(b1['medians'], color='black')
      plt.setp(b1['caps'], color='black')
      plt.setp(b2['boxes'], color='black')
      plt.setp(b2['whiskers'], color='black')
      plt.setp(b2['medians'], color='black')
      plt.setp(b2['caps'], color='black')
      plt.tight_layout()
```

```
fig.savefig('D:/Putatives/pathlen_boxplot.eps')
      L3 py->L5 st
      L4_sp->L4_sp
     L4_sp->L5_st
     L4_sp->L5_tt
      L4_ss->L3_py
     L4_ss->L5_st
      L5_st->L5_tt
      VPM->L4_ss
      VPM->L5_st
[771]: fig,axes = plt.subplots(nrows=1,ncols=2,__
      ⇒sharex=True, sharey=False, figsize=(20*cm, 8*cm), dpi=120)
      \#ax = fig.add\_subplot(111)
      pre = []
      post = []
      pre_means = []
      post_means = []
      pre_stds = []
      post_stds = []
      cell_types = np.
       -unique(df[(df['Manual_Contact_Type_1']==1))['Pre-Post_Cell_Type'])
      for celltype in np.
       x = 
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Presynaptic_Eucl
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Postsynaptic_Euc
          if x.any() and y.any():
              print(celltype)
              pre.append(x)
              post.append(y)
              pre_means.append(np.array(x).mean())
              post_means.append(np.array(y).mean())
              if len(x)>1:
                  pre_stds.append(np.array(x).std())
                  post_stds.append(np.array(y).std())
              else:
                  pre_stds.append(0)
                  post_stds.append(0)
      b1 = axes[0].boxplot(pre)
      eb1 = axes[0].errorbar(x=np.
       →arange(1,len(pre_means)+1),y=pre_means,yerr=pre_stds,\
                   color='blue',marker='.',fmt='.')
      b2 = axes[1].boxplot(post)
```

```
KevError
                                          Traceback (most recent call last)
~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in get_loc(self, key,
→method, tolerance)
   3079
-> 3080
                        return self. engine.get loc(casted key)
   3081
                    except KeyError as err:
pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()
pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()
pandas\_libs\hashtable_class_helper.pxi in pandas. libs.hashtable.
→PyObjectHashTable.get_item()
pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.
→PyObjectHashTable.get_item()
KeyError: 'Manual_Contact_Type_1'
The above exception was the direct cause of the following exception:
                                          Traceback (most recent call last)
KeyError
<ipython-input-771-c1d878c202d8> in <module>
      7 pre_stds = []
      8 post_stds = []
----> 9 cell_types = np.
Junique(df[(df['Manual_Contact_Type_1']==1)]['Pre-Post_Cell_Type'])
     10 for celltype in np.
 →unique(df[df['Manual_Contact_Type_1']==1]['Pre-Post_Cell_Type']):
     11
```

```
~\Anaconda3\lib\site-packages\pandas\core\frame.py in __getitem__(self, key)
                    if self.columns.nlevels > 1:
   3022
   3023
                        return self._getitem_multilevel(key)
-> 3024
                    indexer = self.columns.get_loc(key)
                    if is integer(indexer):
   3025
   3026
                        indexer = [indexer]
~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in get_loc(self, key,
 →method, tolerance)
   3080
                        return self._engine.get_loc(casted_key)
   3081
                    except KeyError as err:
-> 3082
                        raise KeyError(key) from err
   3083
   3084
                if tolerance is not None:
KeyError: 'Manual_Contact_Type_1'
```

```
[758]: fig,axes = plt.subplots(nrows=1,ncols=2,__
       ⇒sharex=True, sharey=False, figsize=(20*cm, 8*cm), dpi=120)
       \#ax = fig.add\_subplot(111)
       pre = []
       post = []
       pre means = []
       post_means = []
       pre_stds = []
       post_stds = []
       cell_types = np.
       -unique(df[(df['Manual_Contact_Type_1']==1)]['Pre-Post_Cell_Type'])
       for celltype in np.
       →unique(df[df['Manual_Contact_Type_1']==1]['Pre-Post_Cell_Type']):
           print(celltype)
           x =__
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Pre-synaptic_Edge
       →df[(df['Manual_Contact_Type_1']==1)&(df['Pre-Post_Cell_Type']==celltype)]['Postsynaptic_Edg
           pre.append(x)
           post.append(y)
           pre_means.append(np.array(x).mean())
           post_means.append(np.array(y).mean())
           if len(x)>1:
               pre_stds.append(np.array(x).std())
               post_stds.append(np.array(y).std())
           else:
               pre_stds.append(0)
               post_stds.append(0)
       b1 = axes[0].boxplot(pre)
```

```
eb1 = axes[0].errorbar(x=np.
 →arange(1,len(pre_means)+1),y=pre_means,yerr=pre_stds,\
              color='blue',marker='.',fmt='.')
b2 = axes[1].boxplot(post)
eb2 = axes[1].errorbar(x=np.
 ⇒arange(1,len(post means)+1),y=post means,yerr=post stds,\
              color='blue',marker='.',fmt='.')
plt.setp(b1['boxes'], color='black')
plt.setp(b1['whiskers'], color='black')
plt.setp(b1['medians'], color='black')
plt.setp(b1['caps'], color='black')
plt.setp(b2['boxes'], color='black')
plt.setp(b2['whiskers'], color='black')
plt.setp(b2['medians'], color='black')
plt.setp(b2['caps'], color='black')
plt.tight_layout()
fig.savefig('D:/Putatives/pathlen_branchnum_boxplot.eps')
L3_py->L5_st
L4_sp->L4_sp
L4_sp->L5_st
L4_sp->L5_tt
L4 ss->L3 py
L4_ss->L5_st
L5 st->L5 tt
VPM->L4 ss
VPM->L5_st
```

3 Interuser variability

```
[572]: touch_matches_david =
       touch_matches_mythreya =_

¬df[(df['User']=='Mythreya')&(df['Type']=='Contacts')]['Matches'].sum()

      synapse_matches_david =__
       →df[(df['User']=='David')&(df['Type']=='Putative_Synapses')]['Matches'].sum()
      synapse_matches_mythreya =_
       →df[(df['User']=='Mythreya')&(df['Type']=='Putative_Synapses')]['Matches'].
       ⇒sum()
[573]: touch david fp = df[(df['User']=='David')&(df['Type']=='Contacts')]['FP'].sum()
      touch_mysee_fp = df[(df['User']=='Mythreya')&(df['Type']=='Contacts')]['FP'].
       ⇒sum()
      touch_david_fn = df[(df['User']=='David')&(df['Type']=='Contacts')]['FN'].sum()
      touch mysee fn = df[(df['User']=='Mythreya')&(df['Type']=='Contacts')]['FN'].
       ⇒sum()
      synapse_david_fp =__
       →df[(df['User']=='David')&(df['Type']=='Putative Synapses')]['FP'].sum()
      synapse_mysee_fp = 

¬df[(df['User']=='Mythreya')&(df['Type']=='Putative Synapses')]['FP'].sum()
      synapse_david_fn =
       →df[(df['User']=='David')&(df['Type']=='Putative Synapses')]['FN'].sum()
      synapse_mysee_fn =
       →df[(df['User']=='Mythreya')&(df['Type']=='Putative_Synapses')]['FN'].sum()
[576]: N=3
      ind = np.arange(N)
      width = 0.4
      fig = plt.figure(figsize=(10*cm,7*cm),dpi=120)
      ax = fig.add_subplot(111)
      rects1 = ax.bar(ind,[(touch_matches_david/
       →total_touches)*100,(1-touch_matches_david/
       →total_touches)*100,touch_david_fp*100/total_touches],width, color='red',)
      rects2 = ax.bar(ind+width,[(touch_matches_mythreya/
       →total touches)*100,(1-touch matches mythreya/
       →total_touches)*100,touch_mysee_fp*100/total_touches],width, color='blue',)
      plt.yticks(np.arange(0,110,10))
      plt.tight_layout()
```

```
fig.savefig('D:/Putatives/interuservariability_touchpts.eps')
[577]: (touch_matches_david/total_touches)*100,(1-touch_matches_david/
       →total_touches)*100,touch_david_fp*100/total_touches
[577]: (95.23809523809523, 4.761904761904767, 12.807881773399014)
[578]: (touch_matches_mythreya/total_touches)*100,(1-touch_matches_mythreya/
       →total_touches)*100,touch_mysee_fp*100/total_touches
[578]: (91.62561576354679, 8.374384236453203, 0.8210180623973727)
Γ581]: N=3
      ind = np.arange(N)
      width = 0.4
      fig = plt.figure(figsize=(10*cm,7*cm),dpi=120)
      ax = fig.add subplot(111)
      rects1 = ax.bar(ind,[(synapse matches david/
       →total_synapses)*100,(1-synapse_matches_david/
       →total_synapses)*100,synapse_david_fp*100/total_synapses],width, color='red',)
      rects2 = ax.bar(ind+width,[(synapse matches mythreya/
       →total_synapses)*100,(1-synapse_matches_mythreya/
       →total_synapses)*100,synapse_mysee_fp*100/total_synapses],width,
       plt.yticks(np.arange(0,110,10))
      plt.tight_layout()
      fig.savefig('D:/Putatives/interuservariability_synapses.eps')
[582]: (synapse matches david/total synapses)*100,(1-synapse matches david/
       →total_synapses)*100,synapse_david_fp*100/total_synapses
[582]: (80.55555555555556, 19.444444444443, 41.666666666666666)
[583]: (synapse_matches_mythreya/total_synapses)*100,(1-synapse_matches_mythreya/
       →total_synapses)*100,synapse_mysee_fp*100/total_synapses
```

4 Spine lengths, radius stuff

```
[645]: df_spinelen = pd.read_csv('D:/Manual_Proximity_Analysis_v4/Axon-Dendrite/
        →Spine_Lengths/SpineLengths.csv')
       df_spinelen_full = pd.read_csv('D:/Manual_Proximity_Analysis_v4/Axon-Dendrite/
        →Spine_Lengths/MG20180527_WR51_cell7_SpineLengths.csv')
[646]: len(df_spinelen_full),len(df_spinelen),len(df_spinelen_full)+len(df_spinelen),
[646]: (4838, 1674, 6512)
[647]: spinelen total = []
       for leng in df_spinelen_full['Spine_Length_Euclidean']:
           spinelen total.append(leng)
       for leng in df_spinelen['Spine_Length_Euclidean']:
           spinelen_total.append(leng)
[648]: np.array(spinelen_total).mean(),np.array(spinelen_total).std(),np.
        →array(spinelen_total).max()
[648]: (1.851042467032772, 0.9256749448988925, 11.441111327042607)
[650]: (np.array(spinelen_total)>4).sum()/len(spinelen_total)
[650]: 0.028101965601965602
[659]: ((np.array(spinelen total)>0) & (np.array(spinelen total)<=1)).sum()
       ((np.array(spinelen_total)>1) & (np.array(spinelen_total)<=2)).sum()
       ((np.array(spinelen_total)>2) & (np.array(spinelen_total)<=3)).sum()</pre>
       ((np.array(spinelen_total)>3) & (np.array(spinelen_total)<=4)).sum()
       ((np.array(spinelen_total)>4) & (np.array(spinelen_total)<=5)).sum()
       ((np.array(spinelen_total)>5) & (np.array(spinelen_total)<=6)).sum()</pre>
       ((np.array(spinelen_total)>6) & (np.array(spinelen_total)<=7)).sum()</pre>
       ((np.array(spinelen_total)>7) & (np.array(spinelen_total)<=8)).sum()
       ((np.array(spinelen_total)>8) & (np.array(spinelen_total)<=9)).sum()
       ((np.array(spinelen total)>9) & (np.array(spinelen total)<=10)).sum()
       ((np.array(spinelen_total)>10) & (np.array(spinelen_total)<=11)).sum()
[659]: 0
[661]: fig = plt.figure(figsize=(10*cm, 7*cm), dpi=120)
       ax = fig.add_subplot(111)
       plt.hist(spinelen_total,bins=[0,1,2,3,4,5,6])
       plt.tight_layout()
       fig.savefig('D:/Putatives/spinelengths.eps')
```

```
[618]: df_radius = pd.read_csv('D:/Manual_Proximity_Analysis_v4/Axon-Dendrite/
        → Proximity_Radius_Determination/Proximity_Radius_Determination.csv')
[630]: proximities_count = []
       count_count = []
       syn_count = []
       for radius in [3,4,5,6]:
           proximities_count.
        →append(df_radius[(df_radius['Proximity_Radius']==radius)&(df_radius['Type']=='Proximities')
        \rightarrowsum())
        →append(df_radius[(df_radius['Proximity_Radius']==radius)&(df_radius['Type']=='Contacts')]['
        \rightarrowsum())
           syn count.
        →append(df_radius[(df_radius['Proximity_Radius']==radius)&(df_radius['Type']=='Putative_Syna
        \rightarrowsum())
[631]: proximities_count
[631]: [2301, 3973, 5803, 8379]
[632]: count_count
[632]: [533, 589, 589, 589]
[633]: syn_count
[633]: [90, 108, 108, 108]
Γ641]: N=1
       ind = np.arange(N)
       width = 0.5
       fig = plt.figure(figsize=(10*cm,7*cm),dpi=120)
       ax = fig.add_subplot(111)
       rects1 = ax.bar([3,4,5,6],proximities_count,width, color='red',)
       #rects2 = ax.bar(ind+width,[(synapse_matches_mythreya/
        →total_synapses)*100, (1-synapse_matches_mythreya/
        →total_synapses)*100,synapse_mysee_fp*100/total_synapses],width,
        \rightarrow color='blue',)
       #plt.yticks(np.arange(0,110,10))
       plt.tight_layout()
```

```
fig.savefig('D:/Putatives/radius_proximitiescount.eps')
[642]: N=1
       ind = np.arange(N)
       width = 0.4
       fig = plt.figure(figsize=(10*cm,7*cm),dpi=120)
       ax = fig.add_subplot(111)
       rects1 = ax.bar([3,4,5,6],count_count,width, color='green',)
       #rects2 = ax.bar(ind+width,syn_count,width, color='blue',)
       #plt.yticks(np.arange(0,110,10))
       plt.tight_layout()
       fig.savefig('D:/Putatives/radius_contactscount.eps')
Γ643]: N=1
       ind = np.arange(N)
       width = 0.4
       fig = plt.figure(figsize=(10*cm,7*cm),dpi=120)
       ax = fig.add_subplot(111)
       rects1 = ax.bar([3,4,5,6],syn_count,width, color='blue',)
       #rects2 = ax.bar(ind+width,syn_count,width, color='blue',)
       #plt.yticks(np.arange(0,110,10))
       plt.tight_layout()
       fig.savefig('D:/Putatives/radius_synapsescount.eps')
 []:
```