Nonpara clustering

2023-10-19

Table of contents

Simulation	1
Data Generating mechanism	6
PPMx fits	6
Two ancestries	6

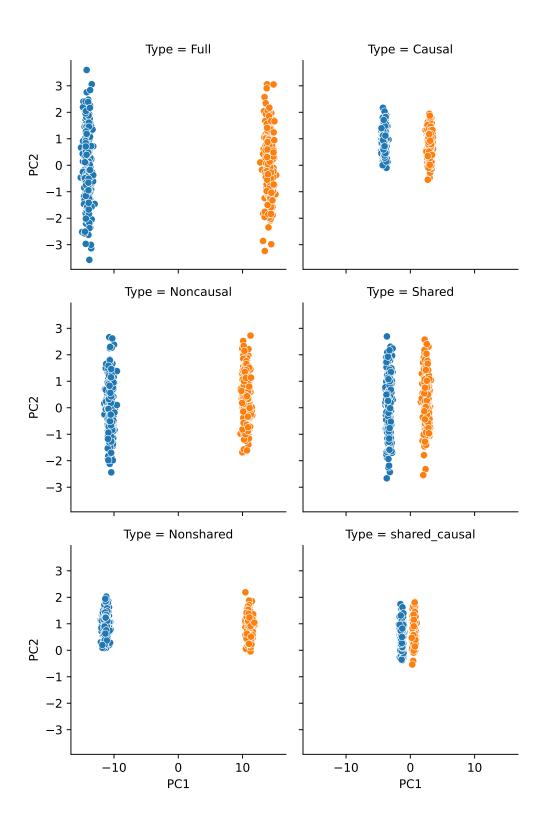
Simulation

- #SNPs = \$ python print(nSNPs) < 2000 is typical
- \$#Subjects = \$ python print(nsubjects)

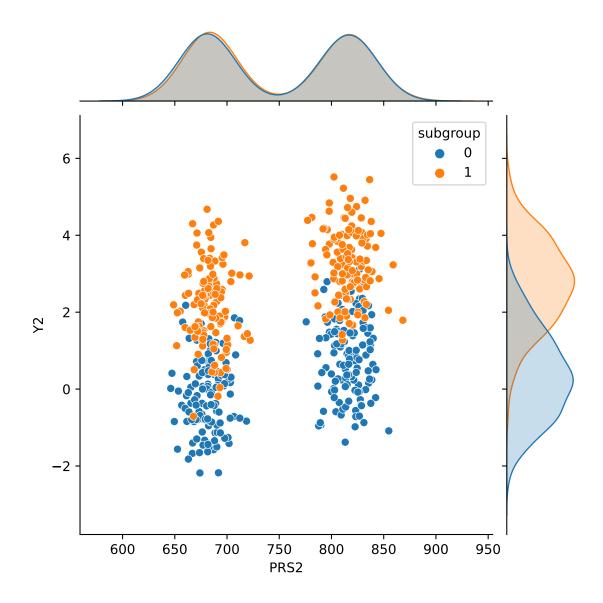
```
nSNPs = 1000
nsubjects = 500
nclusts = 1
nphenos = 2
shared = 0.5
prop_causal = [0.25, 0.25]
theta_alleles = [0.75, 0.25]
h2Hom = 0.5
# Add this for transfer learning
h2Het = [0, 0]
rng = np.random.default_rng()
nclusts = 2
sim = pheno_simulator(nsubjects = nsubjects, nSNPs = nSNPs)
```

```
sim.sim_sites()
sim.sim_pops(nclusts = nclusts, theta_alleles = theta_alleles, shared = shared)
sim.sim_genos()
sim.sim_pheno(h2Hom =h2Hom, h2Het = h2Het, nphenos = nphenos, prop_causal = prop_causal, alp
# Subtract the mean from every column starting with Y and store them in the dataframe
/home/christian/Research/Stat_gen/tools/MASH/Simulate/simulation_helpers/pheno.py:79: Runtim
    prop = (cluster_freq * (1- cluster_freq)) ** alpha
/home/christian/Research/Stat_gen/tools/MASH/Simulate/simulation_helpers/pheno.py:79: Runtimediates
    prop = (cluster_freq * (1- cluster_freq)) ** alpha
sim.df.iloc[:,30:(30+nphenos)] = sim.df.filter(regex='^Y') - sim.df.filter(regex= "^Y").mean
# Add a mean for subgroups
sim.df["subgroup"] = np.repeat([0, 1], 250)
sim.df.Y1 = sim.df.Y1 + sim.df.subgroup * 2
# Create confounding variable that is related to risk subgorup
sim.df["confounder"] = np.array([rng.choice([1.0, 0.0], p = [0.75, 0.25])) if (group == 1) expressions and the state of 
# And affects the outcome
sim.df["Y2"] = sim.df.Y1 + sim.df.confounder
sim.df["Y3"] = sim.df.Y1 + sim.df.confounder * 3 + sim.df.subgroup * 4
# for each columns starting with letter Y, run a simple linear regression with the
GWASBetas = np.zeros(shape = (sim.genotypes.shape[1], sim.df.filter(regex="^Y").shape[1]))
for j in range(sim.df.filter(regex="^Y").shape[1]):
        for i in range(sim.genotypes.shape[1]):
                 mod = OLS(sim.df["Y" + str(j)], sim.genotypes[:,i]).fit()
                 if mod.pvalues[0] < 1e-2:
                      GWASBetas[i,j] = OLS(sim.df["Y" + str(j)] , sim.genotypes[:,i]).fit().params[0]
                 else :
                      GWASBetas[i,j] = 0
        sim.df[f"PRS{j}"] = np.matmul(sim.genotypes, GWASBetas[:,j])
np.save("genos2Anc.npy", sim.genotypes)
# Save GWAS results
np.save("gwas2Anc.npy", GWASBetas)
# Save dataframe
sim.df.to_csv("data2Anc.csv", index = False)
```

plotClusters(sim)



```
# make two subplots
# one for phenotype y0 and another for phenotype y1
p1 = sns.jointplot(x= "PRSO" , y ="Y0", data = sim.df, hue = "subgroup")
p2 = sns.jointplot(x= "PRS1" , y ="Y1", data = sim.df, hue = "subgroup")
p3 = sns.jointplot(x= "PRS2" , y ="Y2", data = sim.df, hue = "subgroup")
plt.show()
```



Data Generating mechanism

Trying to detect risk subgroups while simultatenously compute a PRS.

$$Y = X_c \beta_c + X_G \beta_G + X_R \beta_R + \epsilon$$

Implies

$$Y = X_c \beta_c + PRS\beta_{PRS} + PC\beta_{PC} + \epsilon$$

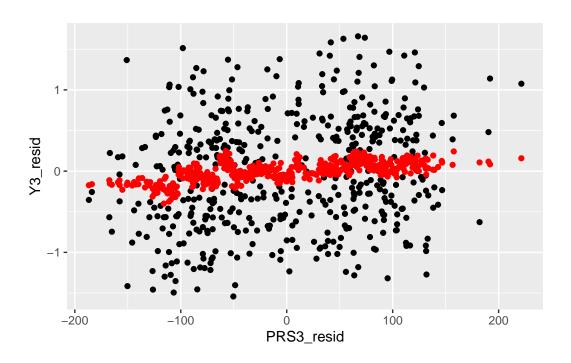
Where X is the confounding variable, X_G is the genetic variable, β is the effect of the confounding variable, β_G is the effect of the genetic variable, β_{PRS} is the effect of the PRS, β_{PC} is the effect of the principal components, X_R is the risk group, β_R is the risk group effect, and ϵ is the error term. Additionally, X_c depends on X_R

$$p(X_c|X_R) = \begin{cases} 0.75 & \text{if } X_R = 1 \\ 0.25 & \text{if } X_R = 0 \end{cases}$$

PPMx fits

Two ancestries

```
df["pc1_resid"] <- lm(pc_1 ~ confounder, data= df) $resid
df["PRS3_resid"] <- lm(PRS3 ~ confounder, data= df) $resid
df["Y3_resid"] <- lm(Y3 ~ confounder, data= df) $resid
df["Y3_superresid"] <- lm(Y3 ~ confounder + subj_ancestries, data= df) $resid
df["PRS3_superresid"] <- lm(PRS3 ~ confounder + subj_ancestries, data= df) $resid
resid = gaussian_ppmx(y = df$Y3_resid, X = df[c("PRS3_resid", "pc1_resid")], meanModel = mean
ppmxsummary(resid, df, x = "PRS3_resid", y= "Y3_resid")</pre>
```



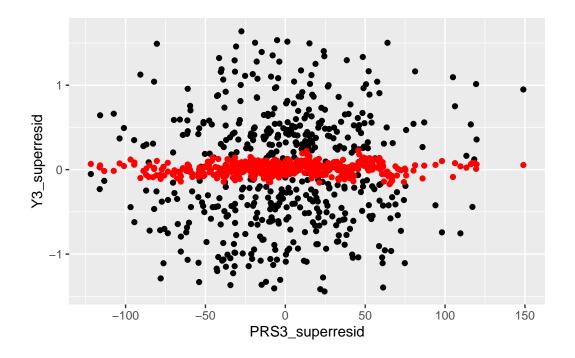
, , subj_ancestries = 0

```
7 20 24
8 0 2
9 24 18
10 5 6
11 0 0
12 10 7
13 1 1
14 12 9
15 0 4
16 4 4
17 6 7
18 0 0
19 3 5
20 3 0
```

, , $subj_ancestries = 1$

```
subgroup
label 0 1
     4 4
  1
  2
     4 1
  3
    0 0
    0 0
  5 22 27
  6 27 23
  7
    0 0
  8
    4 5
  9
     0 0
  10 0 1
  11 26 24
  12 0 0
  13 15 16
  14 1 1
  15 14 12
  16 1 2
  17 0 2
  18 1 5
  19 5 1
  20 1 1
```

superresid = gaussian_ppmx(y = df\$Y3_superresid, X = df["PRS3_superresid"], meanModel = meanI
ppmxsummary(superresid, df, x = "PRS3_superresid", y= "Y3_superresid")



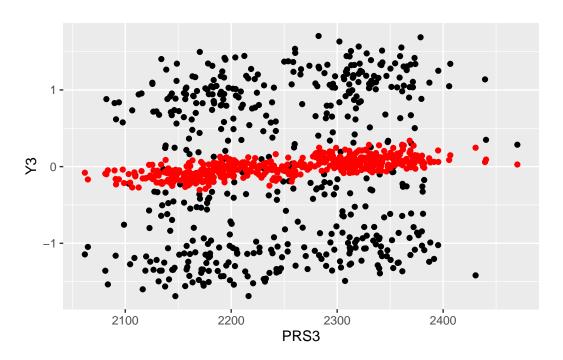
, , subj_ancestries = 0

```
subgroup
label 0 1
  1 12 13
  2
      5 12
  3
    10 9
     5 5
  5
     8 9
  6
     8 10
  8
      8 5
  9
      4 1
  10 8 10
  11 14 9
  12
     3 5
  13 6 10
  14 8 11
  15 8 5
  16 11 4
```

, , $subj_ancestries = 1$

```
\verb"subgroup"
label 0 1
   1
      8 8
   2
      6 11
   3
      9 8
   4
   5
     10 14
   6
      8
         6
   7
      9
         4
   8
     10 9
   9
      1
   10 11 10
   11 6
   12 1
         3
   13 12 7
   14 10 6
   15 9 9
   16 7 15
```

ppmx = gaussian_ppmx(y = df\$Y3, X = df[c("PRS3", "pc_1", "confounder")], meanModel = meanModel
ppmxsummary(ppmx, df, x = "PRS3", y= "Y3")



, , subj_ancestries = 0

subgroup label 0 1 1 44 53 2 1 5 3 80 67

, , subj_ancestries = 1

subgroup label 0 1 1 19 18 2 106 107 3 0 0