*Zach Warren*

*Homework 3*

*Code:*

**import** numpy **as** np  
**import** math **as** math  
**import** matplotlib.pyplot **as** plt  
**from** scipy **import** spatial  
  
f, plts = plt.subplots(3,1,figsize=(15,15))  
  
*#constant bins for easy adjustment*BINSnotlog = np.linspace(-1,1.3,16)  
BINS = np.power(10,BINSnotlog)  
  
*#create X,Y,Z coordinates***def** toXYZ(RA,DEC,z):  
 x = []  
 y = []  
 zout = []  
 **for** i **in** range(0,len(RA)):  
 r = 3000\*z[i]  
 x.append(r\*math.cos(math.radians(DEC[i]))\*math.cos(math.radians(RA[i])))  
 y.append(r\*math.cos(math.radians(DEC[i]))\*math.sin(math.radians(RA[i])))  
 zout.append(r\*math.sin(math.radians(DEC[i])))  
 **return** list(zip(x,y,zout))  
  
*#get the bias***def** getBias(corr,corrDM):  
 bias =[np.sqrt(float(corr)/corrDM) **for** corr,corrDM **in** zip(corr,corrDM)]  
 **return** bias  
  
*#calculate the correlation, change to x,y,z coordinates only if using non-DM data  
#uses kdTrees to count neighbors***def** correlation(data, rand, DM, bins):  
 **if** (DM==**False**):  
 RA,DEC,z = np.loadtxt(data, unpack=**True**)  
 RAR,DECR,zr = np.loadtxt(rand, unpack=**True**)  
  
 xyz = toXYZ(RA,DEC,z)  
 xyzr = toXYZ(RAR,DECR,zr)  
  
 *#length of list* numD = len(RA)  
 numR = len(RAR)  
  
 **else**:  
 x,y,z = np.loadtxt(data,unpack=**True**)  
 xr,yr,zr = np.loadtxt(rand,unpack=**True**)  
  
 xyz=list(zip(x,y,z))  
 xyzr=list(zip(xr,yr,zr))  
  
 *#length of list* numD = len(x)  
 numR = len(xr)  
  
 kdD = spatial.cKDTree(xyz)  
 kdR = spatial.cKDTree(xyzr)  
  
 countD=[]  
 countR=[]  
  
 *#normalizing the correlation function* norm = ((numR/numD)\*\*2)  
  
 *#append counts for each bin from r=0 to r=x* **for** x **in** bins:  
 countD.append(kdD.count\_neighbors(kdD,x))  
 countR.append(kdR.count\_neighbors(kdR,x))  
  
 *# subtracting out length of list to eliminate the x1,x1  
 #comparison that says all points are neighbors with themselves* countD[:] = [x-numD **for** x **in** countD]  
 countR[:] = [x-numR **for** x **in** countR]  
  
 *#subtracts all counts from bins less than current bin* **for** i **in** range(1,16):  
 countD[i] = countD[i] - sum(countD[0:i])  
 countR[i] = countR[i] - sum(countR[0:i])  
  
 *#calculates correlation function* corr = [(norm\*(float(countD)/(countR+1))-1) **for** countD,countR **in** zip(countD,countR)]  
  
 **return** (corr)  
  
*#get correlations and bias*corr20 = correlation(**'SDSS\_Mr20\_rspace.dat'**, **'SDSS\_random.dat'**,DM=**False**, bins=BINS)  
corr21 = correlation(**'SDSS\_Mr21\_rspace.dat'**, **'SDSS\_random.dat'**,DM=**False**, bins=BINS)  
corr20z = correlation(**'SDSS\_Mr20\_zspace.dat'**, **'SDSS\_random.dat'**,DM=**False**, bins=BINS)  
corrDM = correlation(**'DM.dat'**,**'DM\_random.dat'**, DM=**True**, bins=BINS)  
bias20 = getBias(corr20, corrDM)  
bias21 = getBias(corr21, corrDM)  
  
*#set up plots*plts[0].plot(np.log10(BINS), np.log10(corr20))  
plts[0].plot(np.log10(BINS), np.log10(corr21), **'r'**)  
plts[1].plot(np.log10(BINS), np.log10(corr20))  
plts[1].plot(np.log10(BINS), np.log10(corr20z),**'r'**)  
plts[2].plot(np.log10(BINS),bias20)  
plts[2].plot(np.log10(BINS),bias21,**'r'**)  
  
plts[0].set\_title(**'Correlation vs Distance'**)  
plts[0].set\_xlabel(**'log(r)'**)  
plts[0].set\_ylabel(**'log(E(r))'**)  
plts[0].legend([**'Mr20'**,**'Mr21'**])  
  
plts[1].set\_title(**'Correlation vs Distance'**)  
plts[1].set\_xlabel(**'log(r)'**)  
plts[1].set\_ylabel(**'log(E(r))'**)  
plts[1].legend([**'Mr20 Real'**,**'Mr20 Z'**])  
  
plts[2].set\_xlabel(**'log(r)'**)  
plts[2].set\_ylabel(**'b(r)'**)  
plts[2].set\_title(**'Bias vs. Distance'**)  
plts[2].legend([**'Mr20'**,**'Mr21'**])  
  
plt.show()

*Questions:*

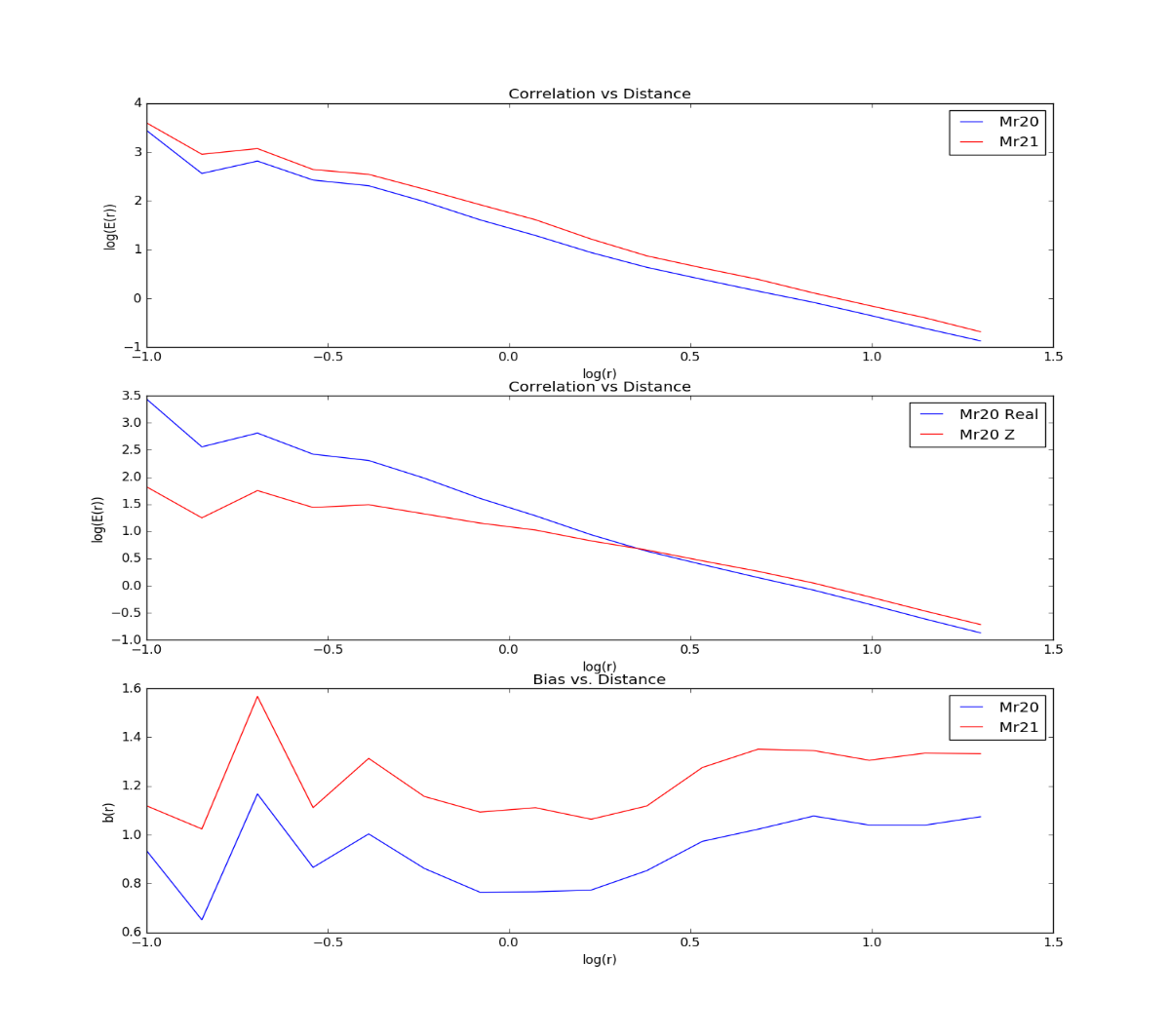
*Part 1:*

The real space graph shows a much stronger correlation than the redshift space distortions. This Is not surprising. In redshift space, we see the ‘fingers of god’ effect on clusters, essentially smearing them over larger distances. This makes galaxies that might actually be very close to each other be much further away. Because of this, galaxies that are close in real space are not counted in z-space. This leads to a much lower correlation at small distances. This effect is minimized as the distance for two points to be considered a pair is increased. Two points might be correlated at .1 Mpc in real space but are stretched further away from each other in z-space. These same two points, however, would still be a pair at 20 Mpc as the distortion is not significant enough to move the points that far away from each other.

*Part 2:*

The bias function varies at short correlation distances but as they get larger, the bias levels out to a single value. It becomes approximately scale independent at log(r) = .75 or r of 5.62 Mpc. This is the same for both the Mr20 and Mr21 graphs. For the Mr20, the bias when it becomes scale independent is ~1 and for Mr21 it is ~1.4.

*Chart:*

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