Statistics for data from Fig 2h Caillaud *et al* PLoS Biology

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## Pre-processing

Marie-Cecille Caillaud (MCC) sent me an Excel file of all the haemocytometry measurements she made - file raw/MCC-Dan corrected.xslx. The file annotates figures from the same biological replicates as colours which I can't parse programmatically. I therefore added columns to the sheet stating the replicate number. I also removed spaces in column headers and saved the file as raw/MCC-Dan corrected Reps added.xlsx and exported the sheet with the data to a csv file fig\_2h\_data\_manual.csv which I can operate on programmatically and will use as my input.

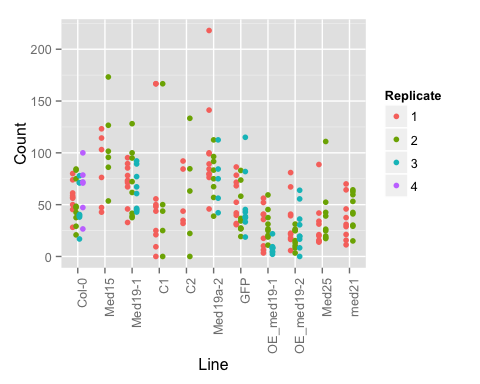
### Use some Python to get the data file into better shape

header = []  
results = []  
with open('raw/fig\_2h\_data\_manual.csv', 'r') as file:  
 for l in file:  
 l = l.rstrip('\r\n')  
 a = l.split(',')  
 if l.startswith("Rep"):  
 header = a  
 else:  
 for i in range(0,len(header),2):  
 rep,line,count = a[i],header[i+1],a[i+1]  
 if rep and line and count: ## if we have no empty values  
 results.append([rep,line,count])  
  
with open('data/reshaped\_data.csv','w') as outfile:  
 outfile.write("Replicate,Line,Count\n")  
 for r in results:  
 outfile.write(",".join(r) + "\n")

### Load data, reorder as per Figure 2H and do a straightforward plot

library(ggplot2)  
data <- read.csv('data/reshaped\_data.csv', header=TRUE)  
data$Replicate <- as.factor(data$Replicate)  
data$Line <- factor(data$Line, c("Col-0","Med15", "Med19-1","C1","C2","Med19a-2","GFP", "OE\_med19-1","OE\_med19-2","Med25","med21"))  
basic <- ggplot(data, aes(Line,Count))  
scatter <- basic + geom\_jitter(aes(colour=Replicate),position = position\_dodge(width=0.5)) + theme(axis.text.x = element\_text(angle = 90, hjust = 1))  
scatter

## ymax not defined: adjusting position using y instead

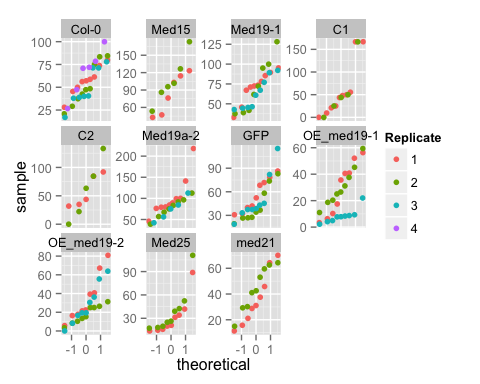


data

## Replicate Line Count  
## 1 1 Col-0 61.25  
## 2 1 Med19-1 78.13  
## 3 1 Med15 76.25  
## 4 1 Med19a-2 100.00  
## 5 1 GFP 30.68  
## 6 1 OE\_med19-1 6.25  
## 7 1 OE\_med19-2 16.43  
## 8 1 med21 64.29  
## 9 1 Med25 14.58  
## 10 1 C2 43.75  
## 11 1 C1 48.08  
## 12 1 Col-0 45.31  
## 13 1 Med19-1 32.81  
## 14 1 Med15 42.76  
## 15 1 Med19a-2 79.86  
## 16 1 GFP 31.82  
## 17 1 OE\_med19-1 52.04  
## 18 1 OE\_med19-2 40.82  
## 19 1 med21 11.25  
## 20 1 Med25 19.87  
## 21 1 C2 84.38  
## 22 1 C1 55.56  
## 23 1 Col-0 56.25  
## 24 1 Med19-1 95.31  
## 25 1 Med15 103.13  
## 26 1 Med19a-2 99.11  
## 27 1 GFP 78.41  
## 28 1 OE\_med19-1 40.48  
## 29 1 OE\_med19-2 39.29  
## 30 1 med21 21.20  
## 31 1 Med25 15.74  
## 32 1 C2 31.91  
## 33 1 C1 166.67  
## 34 1 Col-0 57.03  
## 35 1 Med19-1 71.14  
## 36 1 Med15 47.22  
## 37 1 Med19a-2 218.06  
## 38 1 GFP 39.77  
## 39 1 OE\_med19-1 56.25  
## 40 1 OE\_med19-2 22.45  
## 41 1 med21 45.83  
## 42 1 Med25 34.03  
## 43 1 C2 34.82  
## 44 1 C1 9.38  
## 45 1 Col-0 28.13  
## 46 1 Med19-1 72.50  
## 47 1 Med15 123.21  
## 48 1 Med19a-2 84.38  
## 49 1 GFP 86.36  
## 50 1 OE\_med19-1 35.71  
## 51 1 OE\_med19-2 67.14  
## 52 1 med21 28.85  
## 53 1 Med25 13.84  
## 54 1 C2 92.11  
## 55 1 C1 21.01  
## 56 1 Col-0 58.75  
## 57 1 Med19-1 85.42  
## 58 1 Med15 114.29  
## 59 1 Med19a-2 79.17  
## 60 1 GFP 42.05  
## 61 1 OE\_med19-1 10.20  
## 62 1 OE\_med19-2 5.71  
## 63 1 med21 15.63  
## 64 1 Med25 31.25  
## 65 2 C2 133.33  
## 66 1 C1 0.00  
## 67 1 Col-0 50.00  
## 68 1 Med19-1 73.44  
## 69 2 Med15 173.21  
## 70 1 Med19a-2 89.29  
## 71 1 GFP 71.59  
## 72 1 OE\_med19-1 40.82  
## 73 1 OE\_med19-2 80.95  
## 74 1 med21 37.50  
## 75 1 Med25 41.88  
## 76 2 C2 63.16  
## 77 1 C1 25.00  
## 78 1 Col-0 80.00  
## 79 1 Med19-1 67.19  
## 80 2 Med15 53.57  
## 81 1 Med19a-2 76.25  
## 82 1 GFP 68.18  
## 83 1 OE\_med19-1 17.53  
## 84 1 OE\_med19-2 21.43  
## 85 1 med21 30.98  
## 86 1 Med25 21.05  
## 87 2 C2 84.62  
## 88 1 C1 43.75  
## 89 1 Col-0 73.96  
## 90 1 Med19-1 89.58  
## 91 2 Med15 95.70  
## 92 1 Med19a-2 141.25  
## 93 1 GFP 52.27  
## 94 1 OE\_med19-1 3.37  
## 95 1 OE\_med19-2 17.86  
## 96 1 med21 70.00  
## 97 1 Med25 88.75  
## 98 2 C2 22.22  
## 99 1 C1 166.67  
## 100 2 Col-0 37.50  
## 101 1 Med19-1 45.83  
## 102 2 Med15 126.60  
## 103 1 Med19a-2 45.83  
## 104 2 GFP 58.13  
## 105 2 OE\_med19-1 26.56  
## 106 2 OE\_med19-2 10.42  
## 107 2 med21 53.13  
## 108 2 Med25 18.23  
## 109 2 C2 0.00  
## 110 1 C1 50.00  
## 111 2 Col-0 48.44  
## 112 2 Med19-1 61.76  
## 113 2 Med15 101.56  
## 114 2 Med19a-2 38.89  
## 115 2 GFP 27.50  
## 116 2 OE\_med19-1 37.50  
## 117 2 OE\_med19-2 3.33  
## 118 2 med21 30.26  
## 119 2 Med25 24.84  
## 120 2 C1 0.00  
## 121 2 Col-0 83.33  
## 122 2 Med19-1 41.67  
## 123 2 Med15 86.11  
## 124 2 Med19a-2 96.43  
## 125 2 GFP 36.75  
## 126 2 OE\_med19-1 45.31  
## 127 2 OE\_med19-2 8.33  
## 128 2 med21 42.50  
## 129 2 Med25 19.68  
## 130 2 C1 25.00  
## 131 2 Col-0 84.38  
## 132 2 Med19-1 37.50  
## 133 2 Med19a-2 112.50  
## 134 2 GFP 73.75  
## 135 2 OE\_med19-1 20.31  
## 136 2 OE\_med19-2 25.00  
## 137 2 med21 64.29  
## 138 2 Med25 42.53  
## 139 2 C1 43.75  
## 140 2 Col-0 42.50  
## 141 2 Med19-1 72.22  
## 142 2 Med19a-2 67.35  
## 143 2 GFP 83.00  
## 144 2 OE\_med19-1 59.38  
## 145 2 OE\_med19-2 13.33  
## 146 2 med21 62.50  
## 147 2 Med25 17.30  
## 148 2 C1 166.67  
## 149 2 Col-0 20.83  
## 150 2 Med19-1 95.00  
## 151 2 Med19a-2 75.00  
## 152 2 GFP 26.88  
## 153 2 OE\_med19-1 18.75  
## 154 2 OE\_med19-2 25.00  
## 155 2 med21 15.00  
## 156 2 Med25 39.06  
## 157 2 C1 50.00  
## 158 2 Col-0 75.00  
## 159 2 Med19-1 128.13  
## 160 2 Med19a-2 83.33  
## 161 2 GFP 26.67  
## 162 2 OE\_med19-1 31.25  
## 163 2 OE\_med19-2 31.25  
## 164 2 med21 29.17  
## 165 2 Med25 52.34  
## 166 2 Col-0 29.17  
## 167 2 Med19-1 100.00  
## 168 2 Med19a-2 56.94  
## 169 2 GFP 19.25  
## 170 2 OE\_med19-1 10.94  
## 171 2 OE\_med19-2 26.39  
## 172 2 med21 59.62  
## 173 2 Med25 26.32  
## 174 2 Col-0 47.22  
## 175 2 Med19-1 38.89  
## 176 2 Med19a-2 91.67  
## 177 2 GFP 34.25  
## 178 2 OE\_med19-1 25.00  
## 179 2 OE\_med19-2 15.28  
## 180 2 med21 41.07  
## 181 2 Med25 110.94  
## 182 3 Col-0 16.88  
## 183 3 Med19-1 44.32  
## 184 3 Med19a-2 75.00  
## 185 3 GFP 42.86  
## 186 3 OE\_med19-1 7.81  
## 187 3 OE\_med19-2 0.00  
## 188 3 Col-0 71.15  
## 189 3 Med19-1 89.29  
## 190 3 Med19a-2 56.25  
## 191 3 GFP 18.75  
## 192 3 OE\_med19-1 21.88  
## 193 3 OE\_med19-2 36.11  
## 194 3 Col-0 71.15  
## 195 3 Med19-1 60.71  
## 196 3 Med19a-2 112.50  
## 197 3 GFP 33.33  
## 198 3 OE\_med19-1 7.81  
## 199 3 OE\_med19-2 30.56  
## 200 3 Col-0 38.89  
## 201 3 Med19-1 45.31  
## 202 3 Med19a-2 84.38  
## 203 3 GFP 45.31  
## 204 3 OE\_med19-1 8.75  
## 205 3 OE\_med19-2 19.44  
## 206 3 Col-0 40.00  
## 207 3 Med19-1 67.19  
## 208 3 Med19a-2 42.19  
## 209 3 GFP 81.94  
## 210 3 OE\_med19-1 4.17  
## 211 3 OE\_med19-2 63.89  
## 212 3 Col-0 38.00  
## 213 3 Med19-1 42.86  
## 214 3 GFP 38.64  
## 215 3 OE\_med19-1 8.33  
## 216 3 OE\_med19-2 16.67  
## 217 3 Col-0 77.94  
## 218 3 Med19-1 92.19  
## 219 3 GFP 37.50  
## 220 3 OE\_med19-1 4.86  
## 221 3 OE\_med19-2 55.56  
## 222 3 Col-0 40.48  
## 223 3 Med19-1 77.08  
## 224 3 GFP 115.00  
## 225 3 OE\_med19-1 9.38  
## 226 3 OE\_med19-2 19.44  
## 227 4 Col-0 100.00  
## 228 3 Med19-1 46.43  
## 229 3 GFP 37.50  
## 230 3 OE\_med19-1 2.08  
## 231 3 OE\_med19-2 8.33  
## 232 4 Col-0 26.56  
## 233 4 Col-0 47.22  
## 234 4 Col-0 78.57  
## 235 4 Col-0 70.83  
## 236 4 Col-0 71.88

The data look ok, a few outliers in Med19a-2 and C1 that could affect summary statistics. Let's do some qqplots and see how  
they lie.

#qnorm is default distribution - we are testing for a normal distribution  
ggplot(data, aes(sample=Count)) + geom\_jitter(stat="qq", aes(colour=Replicate) ) + facet\_wrap( ~ Line, scales = "free\_y")



Those outliers could mess up summary statistics, they're off the curve, we have no good reason to ditch them though. I suppose they mean that occasionally the method used (spore counting) throws up some very extreme numbers. Overall these plots are ok, the variation seems normally distributed on the whole.

Let's have a look at summary statistics:

library(plyr)  
summary <- ddply(data,"Line",summarise, mean=mean(Count),median=median(Count),diff=abs(mean(Count) - median(Count)), std\_dev=sd(Count), std\_err=sd(Count)/sqrt(length(Count)))  
summary

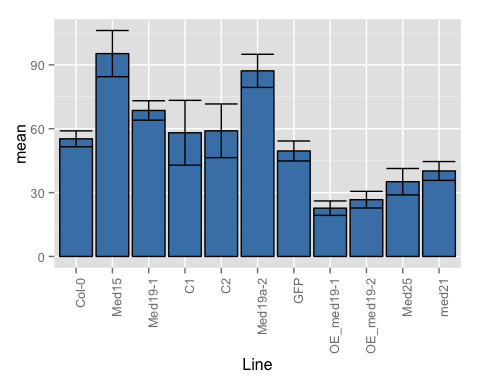
## Line mean median diff std\_dev std\_err  
## 1 Col-0 55.26875 53.125 2.1437500 21.11359 3.732392  
## 2 Med15 95.30083 98.630 3.3291667 37.59931 10.853987  
## 3 Med19-1 68.58889 71.140 2.5511111 23.73107 4.567046  
## 4 C1 58.10267 43.750 14.3526667 58.98184 15.229045  
## 5 C2 59.03000 53.455 5.5750000 39.89419 12.615651  
## 6 Med19a-2 87.20130 83.330 3.8713043 37.32340 7.782467  
## 7 GFP 49.56074 39.770 9.7907407 24.40441 4.696630  
## 8 OE\_med19-1 22.69333 18.750 3.9433333 17.61271 3.389568  
## 9 OE\_med19-2 26.68185 21.430 5.2518519 20.25470 3.898019  
## 10 Med25 35.12389 25.580 9.5438889 26.30013 6.199001  
## 11 med21 40.17056 39.285 0.8855556 18.79839 4.430822

The summary stats seem fine overall, similar SD and SE and not much drift of the median from the mean, the concern again is Med19a-2 and C1 with the high standard deviation and mean dragged up by that couple of points.

## Does a bar chart imply a higher effect than we see generally?

Let's make a bar graph with error bars on that first scatter to see how using a standard bar chart might be misleading our thinking.

ggplot(summary, aes(x=Line, y=mean)) + geom\_bar(position=position\_dodge(), stat="identity", fill="steelblue",colour="black") + geom\_errorbar(aes(ymin=mean-std\_err, ymax=mean+std\_err)) + theme(axis.text.x = element\_text(angle = 90, hjust = 1))



The barchart is definitely suggesting a higher overall effect than we see from the individual replicates in the scatter plot for Med19a-2 and C1 My conclusion here is that although the mean is calculated correctly, it's just that the mean is a slightly misleading number to boil our data down to in this case. Also that very slight increase in standard error isn't giving us a clue as to that messy single outlier. Taken together the mean and SE plotted like this convince of us a bigger effect in general so the plot style isn't helpful.

## Significance Tests

I need to boil down the data to the biological replicates.

library(reshape)

##   
## Attaching package: 'reshape'  
##   
## The following objects are masked from 'package:plyr':  
##   
## rename, round\_any

bioreps <- cast(data, Line~Replicate, mean)

## Using Count as value column. Use the value argument to cast to override this choice

bioreps <- melt(bioreps)  
bioreps

## Line value Replicate  
## X1 Col-0 56.742222 1  
## X1.1 Med15 84.476667 1  
## X1.2 Med19-1 71.135000 1  
## X1.3 C1 58.612000 1  
## X1.4 C2 57.394000 1  
## X1.5 Med19a-2 101.320000 1  
## X1.6 GFP 55.681111 1  
## X1.7 OE\_med19-1 29.183333 1  
## X1.8 OE\_med19-2 34.675556 1  
## X1.9 Med25 31.221111 1  
## X1.10 med21 36.170000 1  
## X2 Col-0 52.041111 2  
## X2.1 Med15 106.125000 2  
## X2.2 Med19-1 71.896250 2  
## X2.3 C1 57.084000 2  
## X2.4 C2 60.666000 2  
## X2.5 Med19a-2 77.763750 2  
## X2.6 GFP 42.908889 2  
## X2.7 OE\_med19-1 30.555556 2  
## X2.8 OE\_med19-2 17.592222 2  
## X2.9 Med25 39.026667 2  
## X2.10 med21 44.171111 2  
## X3 Col-0 49.311250 3  
## X3.1 Med15 NaN 3  
## X3.2 Med19-1 62.820000 3  
## X3.3 C1 NaN 3  
## X3.4 C2 NaN 3  
## X3.5 Med19a-2 74.064000 3  
## X3.6 GFP 50.092222 3  
## X3.7 OE\_med19-1 8.341111 3  
## X3.8 OE\_med19-2 27.777778 3  
## X3.9 Med25 NaN 3  
## X3.10 med21 NaN 3  
## X4 Col-0 65.843333 4  
## X4.1 Med15 NaN 4  
## X4.2 Med19-1 NaN 4  
## X4.3 C1 NaN 4  
## X4.4 C2 NaN 4  
## X4.5 Med19a-2 NaN 4  
## X4.6 GFP NaN 4  
## X4.7 OE\_med19-1 NaN 4  
## X4.8 OE\_med19-2 NaN 4  
## X4.9 Med25 NaN 4  
## X4.10 med21 NaN 4

I'll do an ANOVA and Tukey's HSD for multiple comparisons.

### ANOVA and Tukey's HSD on all pairwise - though really only interested in VS Col-0 the control  
fit <- aov(lm(value ~ Line,data=bioreps))  
TukeyHSD(fit)

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = lm(value ~ Line, data = bioreps))  
##   
## $Line  
## diff lwr upr p adj  
## Med15-Col-0 39.316354 10.505345 68.1273629 0.0033725  
## Med19-1-Col-0 12.632604 -12.776317 38.0415256 0.7560958  
## C1-Col-0 1.863521 -26.947488 30.6745296 1.0000000  
## C2-Col-0 3.045521 -25.765488 31.8565296 0.9999983  
## Med19a-2-Col-0 28.398104 2.989183 53.8070256 0.0213201  
## GFP-Col-0 -6.423738 -31.832660 18.9851830 0.9961024  
## OE\_med19-1-Col-0 -33.291146 -58.700067 -7.8822244 0.0050706  
## OE\_med19-2-Col-0 -29.302627 -54.711549 -3.8937059 0.0163874  
## Med25-Col-0 -20.860590 -49.671599 7.9504185 0.2940977  
## med21-Col-0 -15.813924 -44.624932 12.9970851 0.6466693  
## Med19-1-Med15 -26.683750 -57.053220 3.6857198 0.1149884  
## C1-Med15 -37.452833 -70.720921 -4.1847460 0.0200774  
## C2-Med15 -36.270833 -69.538921 -3.0027460 0.0260686  
## Med19a-2-Med15 -10.918250 -41.287720 19.4512198 0.9539136  
## GFP-Med15 -45.740093 -76.109562 -15.3706228 0.0011758  
## OE\_med19-1-Med15 -72.607500 -102.976970 -42.2380302 0.0000029  
## OE\_med19-2-Med15 -68.618981 -98.988451 -38.2495117 0.0000066  
## Med25-Med15 -60.176944 -93.445032 -26.9088571 0.0001323  
## med21-Med15 -55.130278 -88.398365 -21.8621905 0.0003896  
## C1-Med19-1 -10.769083 -41.138553 19.6003864 0.9576648  
## C2-Med19-1 -9.587083 -39.956553 20.7823864 0.9801671  
## Med19a-2-Med19-1 15.765500 -11.397780 42.9287795 0.5771317  
## GFP-Med19-1 -19.056343 -46.219622 8.1069370 0.3317637  
## OE\_med19-1-Med19-1 -45.923750 -73.087030 -18.7604705 0.0003061  
## OE\_med19-2-Med19-1 -41.935231 -69.098511 -14.7719519 0.0008904  
## Med25-Med19-1 -33.493194 -63.862664 -3.1237247 0.0237690  
## med21-Med19-1 -28.446528 -58.815998 1.9229420 0.0778077  
## C2-C1 1.182000 -32.086087 34.4500873 1.0000000  
## Med19a-2-C1 26.534583 -3.834886 56.9040531 0.1187604  
## GFP-C1 -8.287259 -38.656729 22.0822105 0.9930153  
## OE\_med19-1-C1 -35.154667 -65.524136 -4.7851969 0.0158700  
## OE\_med19-2-C1 -31.166148 -61.535618 -0.7966784 0.0414666  
## Med25-C1 -22.724111 -55.992198 10.5439762 0.3649176  
## med21-C1 -17.677444 -50.945532 15.5906429 0.6847841  
## Med19a-2-C2 25.352583 -5.016886 55.7220531 0.1526233  
## GFP-C2 -9.469259 -39.838729 20.9002105 0.9817785  
## OE\_med19-1-C2 -36.336667 -66.706136 -5.9671969 0.0118798  
## OE\_med19-2-C2 -32.348148 -62.717618 -1.9786784 0.0313070  
## Med25-C2 -23.906111 -57.174198 9.3619762 0.3029590  
## med21-C2 -18.859444 -52.127532 14.4086429 0.6069765  
## GFP-Med19a-2 -34.821843 -61.985122 -7.6585630 0.0062678  
## OE\_med19-1-Med19a-2 -61.689250 -88.852530 -34.5259705 0.0000061  
## OE\_med19-2-Med19a-2 -57.700731 -84.864011 -30.5374519 0.0000157  
## Med25-Med19a-2 -49.258694 -79.628164 -18.8892247 0.0005027  
## med21-Med19a-2 -44.212028 -74.581498 -13.8425580 0.0017075  
## OE\_med19-1-GFP -26.867407 -54.030687 0.2958721 0.0540066  
## OE\_med19-2-GFP -22.878889 -50.042168 4.2843907 0.1455538  
## Med25-GFP -14.436852 -44.806322 15.9326179 0.7982744  
## med21-GFP -9.390185 -39.759655 20.9792846 0.9828033  
## OE\_med19-2-OE\_med19-1 3.988519 -23.174761 31.1517981 0.9999631  
## Med25-OE\_med19-1 12.430556 -17.938914 42.8000253 0.9027929  
## med21-OE\_med19-1 17.477222 -12.892248 47.8466920 0.5879787  
## Med25-OE\_med19-2 8.442037 -21.927433 38.8115068 0.9919835  
## med21-OE\_med19-2 13.488704 -16.880766 43.8581735 0.8525396  
## med21-Med25 5.046667 -28.221421 38.3147540 0.9999503

A long table, but it's showing the overexpressers OE\_med19-1 and OE\_med19-2 are different from the Col-0 control, as is the one with the noted high outliers Med19a-2 and also Med15.

## P-Hacking

Let's see how removing those high (>=150) outliers affects the *p*-values, see if any signficance we have is coming from one or two atypical data.

under\_150 <- data[data$value < 150, ]  
bioreps\_under150 <- cast(data, Line~Replicate, mean)

## Using Count as value column. Use the value argument to cast to override this choice

bioreps\_under150 <- melt(bioreps\_under150)  
fit <- aov(lm(value ~ Line,data=bioreps\_under150))  
TukeyHSD(fit)

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = lm(value ~ Line, data = bioreps\_under150))  
##   
## $Line  
## diff lwr upr p adj  
## Med15-Col-0 39.316354 10.505345 68.1273629 0.0033725  
## Med19-1-Col-0 12.632604 -12.776317 38.0415256 0.7560958  
## C1-Col-0 1.863521 -26.947488 30.6745296 1.0000000  
## C2-Col-0 3.045521 -25.765488 31.8565296 0.9999983  
## Med19a-2-Col-0 28.398104 2.989183 53.8070256 0.0213201  
## GFP-Col-0 -6.423738 -31.832660 18.9851830 0.9961024  
## OE\_med19-1-Col-0 -33.291146 -58.700067 -7.8822244 0.0050706  
## OE\_med19-2-Col-0 -29.302627 -54.711549 -3.8937059 0.0163874  
## Med25-Col-0 -20.860590 -49.671599 7.9504185 0.2940977  
## med21-Col-0 -15.813924 -44.624932 12.9970851 0.6466693  
## Med19-1-Med15 -26.683750 -57.053220 3.6857198 0.1149884  
## C1-Med15 -37.452833 -70.720921 -4.1847460 0.0200774  
## C2-Med15 -36.270833 -69.538921 -3.0027460 0.0260686  
## Med19a-2-Med15 -10.918250 -41.287720 19.4512198 0.9539136  
## GFP-Med15 -45.740093 -76.109562 -15.3706228 0.0011758  
## OE\_med19-1-Med15 -72.607500 -102.976970 -42.2380302 0.0000029  
## OE\_med19-2-Med15 -68.618981 -98.988451 -38.2495117 0.0000066  
## Med25-Med15 -60.176944 -93.445032 -26.9088571 0.0001323  
## med21-Med15 -55.130278 -88.398365 -21.8621905 0.0003896  
## C1-Med19-1 -10.769083 -41.138553 19.6003864 0.9576648  
## C2-Med19-1 -9.587083 -39.956553 20.7823864 0.9801671  
## Med19a-2-Med19-1 15.765500 -11.397780 42.9287795 0.5771317  
## GFP-Med19-1 -19.056343 -46.219622 8.1069370 0.3317637  
## OE\_med19-1-Med19-1 -45.923750 -73.087030 -18.7604705 0.0003061  
## OE\_med19-2-Med19-1 -41.935231 -69.098511 -14.7719519 0.0008904  
## Med25-Med19-1 -33.493194 -63.862664 -3.1237247 0.0237690  
## med21-Med19-1 -28.446528 -58.815998 1.9229420 0.0778077  
## C2-C1 1.182000 -32.086087 34.4500873 1.0000000  
## Med19a-2-C1 26.534583 -3.834886 56.9040531 0.1187604  
## GFP-C1 -8.287259 -38.656729 22.0822105 0.9930153  
## OE\_med19-1-C1 -35.154667 -65.524136 -4.7851969 0.0158700  
## OE\_med19-2-C1 -31.166148 -61.535618 -0.7966784 0.0414666  
## Med25-C1 -22.724111 -55.992198 10.5439762 0.3649176  
## med21-C1 -17.677444 -50.945532 15.5906429 0.6847841  
## Med19a-2-C2 25.352583 -5.016886 55.7220531 0.1526233  
## GFP-C2 -9.469259 -39.838729 20.9002105 0.9817785  
## OE\_med19-1-C2 -36.336667 -66.706136 -5.9671969 0.0118798  
## OE\_med19-2-C2 -32.348148 -62.717618 -1.9786784 0.0313070  
## Med25-C2 -23.906111 -57.174198 9.3619762 0.3029590  
## med21-C2 -18.859444 -52.127532 14.4086429 0.6069765  
## GFP-Med19a-2 -34.821843 -61.985122 -7.6585630 0.0062678  
## OE\_med19-1-Med19a-2 -61.689250 -88.852530 -34.5259705 0.0000061  
## OE\_med19-2-Med19a-2 -57.700731 -84.864011 -30.5374519 0.0000157  
## Med25-Med19a-2 -49.258694 -79.628164 -18.8892247 0.0005027  
## med21-Med19a-2 -44.212028 -74.581498 -13.8425580 0.0017075  
## OE\_med19-1-GFP -26.867407 -54.030687 0.2958721 0.0540066  
## OE\_med19-2-GFP -22.878889 -50.042168 4.2843907 0.1455538  
## Med25-GFP -14.436852 -44.806322 15.9326179 0.7982744  
## med21-GFP -9.390185 -39.759655 20.9792846 0.9828033  
## OE\_med19-2-OE\_med19-1 3.988519 -23.174761 31.1517981 0.9999631  
## Med25-OE\_med19-1 12.430556 -17.938914 42.8000253 0.9027929  
## med21-OE\_med19-1 17.477222 -12.892248 47.8466920 0.5879787  
## Med25-OE\_med19-2 8.442037 -21.927433 38.8115068 0.9919835  
## med21-OE\_med19-2 13.488704 -16.880766 43.8581735 0.8525396  
## med21-Med25 5.046667 -28.221421 38.3147540 0.9999503

Looks good! The same Lines come up as significant - the outliers aren't messing with the overall significance result.

### More P-Hacking - ditching data originally in Figure 2H!

According to MCC and JJ then the lines of interest are really the med19-1, Med19a-2, OE\_med19-1 and OE\_med19-2. Let's do the same tests for the restricted set and see if it substantially affects the result.

of\_interest <- bioreps\_under150[bioreps\_under150$Line %in% c("Col-0", "Med19-1", "Med19a-2", "OE\_med19-1", "OE\_med19-2"), ]  
fit <- aov(lm(value ~ Line,data=of\_interest))  
TukeyHSD(fit)

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = lm(value ~ Line, data = of\_interest))  
##   
## $Line  
## diff lwr upr p adj  
## Med19-1-Col-0 12.632604 -12.105257 37.370466 0.4979780  
## Med19a-2-Col-0 28.398104 3.660243 53.135966 0.0228532  
## OE\_med19-1-Col-0 -33.291146 -58.029007 -8.553284 0.0081105  
## OE\_med19-2-Col-0 -29.302627 -54.040489 -4.564766 0.0188384  
## Med19a-2-Med19-1 15.765500 -10.680386 42.211386 0.3584632  
## OE\_med19-1-Med19-1 -45.923750 -72.369636 -19.477864 0.0011733  
## OE\_med19-2-Med19-1 -41.935231 -68.381118 -15.489345 0.0024215  
## OE\_med19-1-Med19a-2 -61.689250 -88.135136 -35.243364 0.0000889  
## OE\_med19-2-Med19a-2 -57.700731 -84.146618 -31.254845 0.0001638  
## OE\_med19-2-OE\_med19-1 3.988519 -22.457368 30.434405 0.9869299

The result is not substantially different from before, the same lines show up as significantly different, that is Med19a-2, OE\_med19-1, OE\_med19-2 and Med15 are signifcantly different from the Col-0 control. Med19-1 is not.

## Conclusion

The Med19-2 and Med15 lines get significantly more spores than the Col-0 wild-type and the two over-expressors of Med19 show significantly fewer spores than Col-0. There is no evidence for difference from the wild-type and other lines.

## Saving 5 x 4 in image  
## ymax not defined: adjusting position using y instead