

Statistical Analysis on icl knockout experiments

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Data and Statistical Analysis regarding ICL mutants

Statistical analysis conducted on the results obtained from both ICL mutants. **icl knockout** measure differences in growth and respiration rates under different levels of iron limitation **icl bioreporter** measure gene expression under different levels of iron limitation

```
exp=read.table('icl_expression.txt', na.strings="NA", sep='\t', header=T, dec=',')
exp1=subset(exp, iron=="replete")
exp1 # inspect data
```

```
##      iron dfob luminescence
## 30 replete    0  2.842889088
## 31 replete    0  4.041059807
## 32 replete    0  4.331404024
## 33 replete   10 13.48810378
## 34 replete   10 14.13670492
## 35 replete   10 15.22671627
## 36 replete   50 16.87912485
## 37 replete   50 19.47637717
## 38 replete   50 18.95493243
## 39 replete  100 30.96405413
## 40 replete  100 30.29318557
## 41 replete  100 23.62707085
## 42 replete  500 23.55657247
## 43 replete  500 19.89361131
## 44 replete  500 21.34877925
## 45 replete    0  3.020356847
## 46 replete    0  3.594393491
## 47 replete    0  3.528756866
## 48 replete   10 13.12134066
## 49 replete   10 17.48387984
## 50 replete   10 14.19237542
## 51 replete   50 20.77272413
## 52 replete   50 21.52469875
## 53 replete   50 16.66442481
## 54 replete  100 28.75253252
## 55 replete  100 26.34827204
## 56 replete  100 22.95847964
## 57 replete  500 25.39999756
## 58 replete  500 26.33389248
## 59 replete  500 19.42245774
```

ICL bioreporter

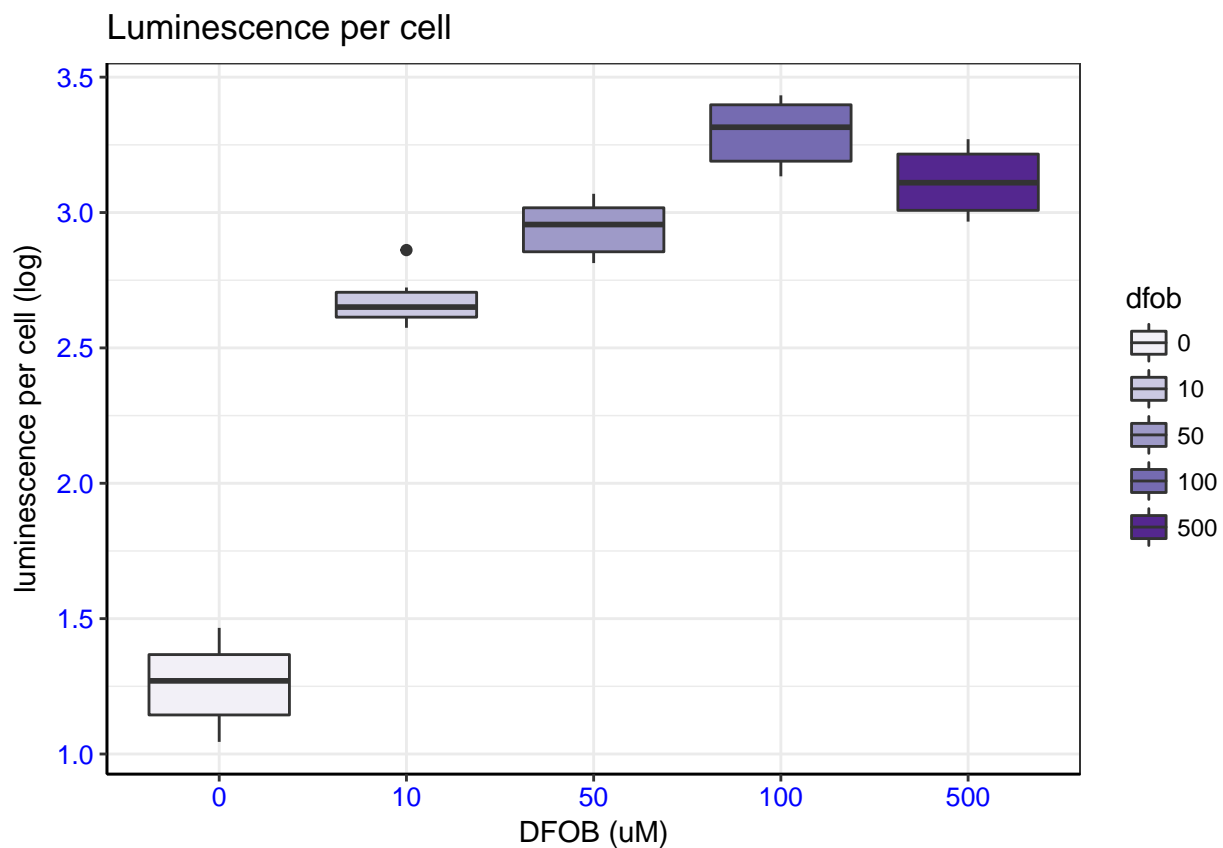
Luminescence Plot the luminescence per 1000 cells of bioreporter bacteria grown under different levels of iron limitation. Data is log transformed due to an improved homoskedasticity. This is because of an increased variance as calculations are done with much lower cell counts as opposed to in the absence of iron limitation.

```

library(ggplot2)
library(car)
library(knitr)
exp1$dfob=as.factor(exp1$dfob)
exp1$luminescence=as.numeric(as.character(exp1$luminescence))
exp1$loglumi=log(exp1$luminescence)
exp1$loglumi=as.numeric(as.character(exp1$loglumi))

lum=ggplot(exp1, aes(x=factor(dfob), y=as.numeric(as.character(loglumi)), fill=dfob))+geom_boxplot()
lum=lum+theme_bw()
lum=lum+scale_x_discrete("DFOB (uM)") + scale_y_continuous("luminescence per cell (log)")
lum=lum+ggtitle("Luminescence per cell")
lum=lum+scale_fill_brewer(palette = 12)
lum=lum+theme(axis.line = element_line(colour = "black",
                                         size = 0.5, linetype = "solid"))
lum=lum+theme(axis.text = element_text(color="blue",size=10))
lum

```



```

# ANOVA one way
lumi=lm(loglumi ~ dfob,
        data = exp1)

l1 <- Anova(lumi, type = 3)
kable(l1, digits = 10 ,results = 'asis')

```

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	9.5077553	1	590.7227	0

	Sum Sq	Df	F value	Pr(>F)
dfob	15.9142706	4	247.1909	0
Residuals	0.4023781	25	NA	NA

```
shapiro.test(residuals(lumi))  #ok
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(lumi)
## W = 0.96025, p-value = 0.3143
```

```
leveneTest(lumi) #ok
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group 4  0.5933 0.6707
##      25
```

```
# Summary of the analysis
```

```
l11 <- aov(loglumi ~ dfob, data = exp1)
TukeyHSD(l11)
```

```
##  Tukey multiple comparisons of means
##    95% family-wise confidence level
##
## Fit: aov(formula = loglumi ~ dfob, data = exp1)
##
## $dfob
##           diff           lwr           upr           p adj
## 10-0         1.4181572    1.20304179    1.63327252    0.0000000
## 50-0         1.6834245    1.46830908    1.89853982    0.0000000
## 100-0        2.0361739    1.82105852    2.25128926    0.0000000
## 500-0        1.8549864    1.63987105    2.07010179    0.0000000
## 50-10        0.2652673    0.05015193    0.48038267    0.0103848
## 100-10       0.6180167    0.40290137    0.83313211    0.0000001
## 500-10       0.4368293    0.22171389    0.65194463    0.0000291
## 100-50       0.3527494    0.13763407    0.56786481    0.0005298
## 500-50       0.1715620   -0.04355340    0.38667733    0.1650511
## 500-100     -0.1811875   -0.39630284    0.03392789    0.1290819
```

Data is highly significant between the luminescence and different levels of iron limitation ($p > 0.000001$). Data was shown to be normally distributed using a shapiro wilk test ($p = 0.3143$). Homoskedasticity was also met ($p = 0.6707$) using a Levene Test. The Tukey test reveals that these differences mainly lie between replete iron conditions and strong iron limitation and that at strong iron limitation luminescence does not differ significantly amongst each other. At 500 umol DFOB the luminescence seems to decrease, but this is likely due the fact that growth rate is so severely impacted by iron limitation that the results of luminescence data are unreliable.

ICL knockout

Differences in both growth and respiration rate between the wildtype and gene knockout of ICL subjected to different levels of iron limitation

```
data1=read.table('icl_alldates.txt', na.strings="NA", sep='\t', header=T, dec=',')
data1 # inspect data
```

##	date	iron	strain	conditions	substrate	respiration	growth
## 1	20141015	Fe	WT	wt_fe	glucose	3.71	10.28
## 2	20141013	Fe	WT	wt_fe	glucose	3.26	9.85
## 3	20141013	Fe	WT	wt_fe	glucose	2.92	10.45
## 4	20141013	Fe	WT	wt_fe	glucose	3.17	10.97
## 5	20141013	Fe	WT	wt_fe	glucose	2.89	10.45
## 6	20141020	Fe	KO	ko_fe	glucose	4.79	10.37
## 7	20141022	Fe	KO	ko_fe	glucose	4.62	10.11
## 8	20141022	Fe	KO	ko_fe	glucose	4.51	9.94
## 9	20141022	Fe	KO	ko_fe	glucose	4.84	10.54
## 10	20141105	Fe	KO	ko_fe	glucose	3.67	7.69
## 11	20141105	Fe	KO	ko_fe	glucose	4.12	8.47
## 12	20141105	Fe	KO	ko_fe	glucose	4.05	8.99
## 13	20151011	10DFOB	WT	wt_10dfob	glucose	3.08	6.19
## 14	20151011	10DFOB	WT	wt_10dfob	glucose	1.94	5.99
## 15	20151011	10DFOB	WT	wt_10dfob	glucose	1.86	6.4
## 16	20151011	10DFOB	KO	ko_10dfob	glucose	1.4	4.04
## 17	20151011	10DFOB	KO	ko_10dfob	glucose	2.17	6.73
## 18	20151011	10DFOB	KO	ko_10dfob	glucose	2.31	7.68
## 19	20141020	100DFOB	KO	ko_100dfob	glucose	0.78	1.21
## 20	20141020	100DFOB	KO	ko_100dfob	glucose	0.97	1.93
## 21	20141020	100DFOB	KO	ko_100dfob	glucose	0.9	1.17
## 22	20141025	100DFOB	WT	wt_100dfob	glucose	1.41	3.02
## 23	20141025	100DFOB	WT	wt_100dfob	glucose	1.63	3.44
## 24	20141025	100DFOB	WT	wt_100dfob	glucose	1.66	3.08
## 25	20141025	100DFOB	WT	wt_100dfob	glucose	1.02	3.33
## 26	20141119	Fe	WT	wt_fe	glucose	3.88	9.85
## 27	20141119	Fe	WT	wt_fe	glucose	6.62	6.46
## 28	20141119	Fe	WT	wt_fe	glucose	5.25	8.9

Luminescence for Different Carbon Concentrations

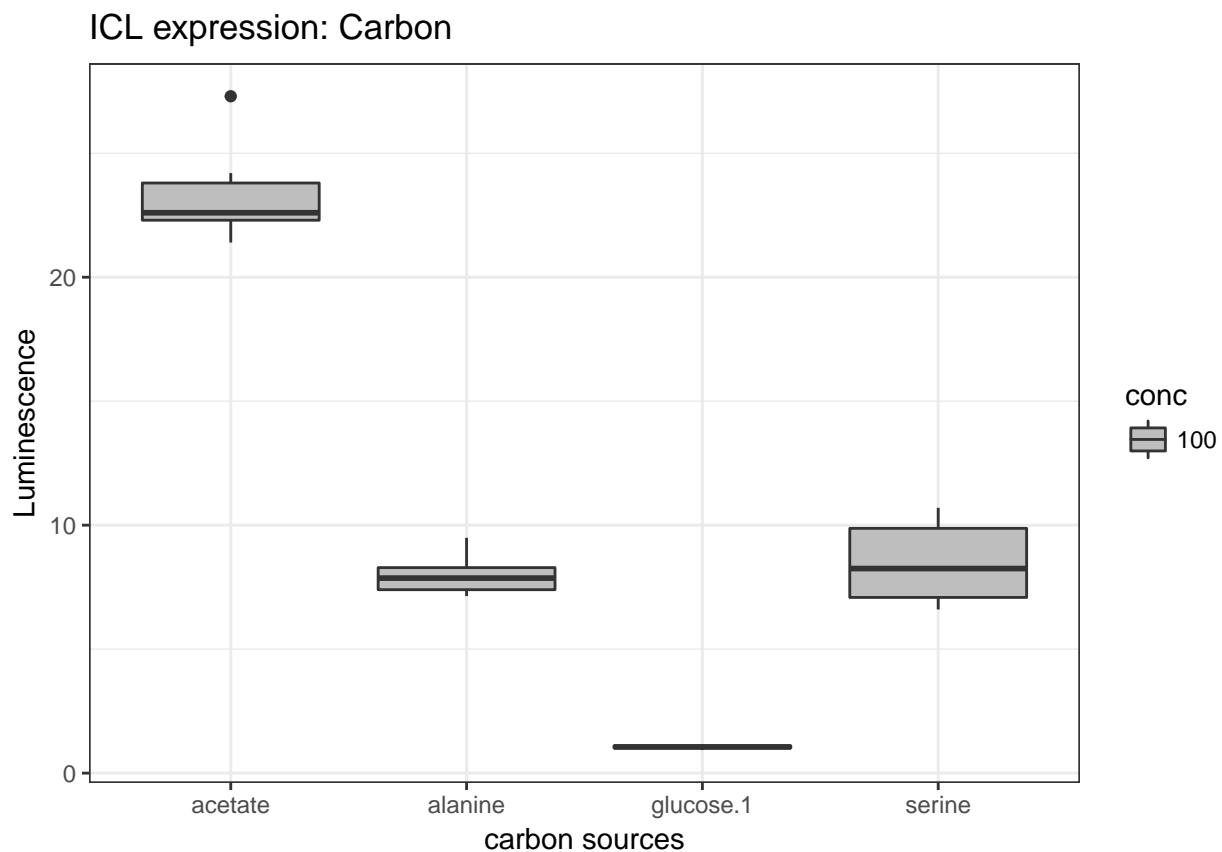
```
carb=read.table('PUBLICATION_carbonconc.txt', na.strings="NA", sep='\t', header=T, dec=',')
carb1=subset(carb, carbon!="glucose.6")
carb1 # inspect data
```

##	iron	conc	carbon	counts	lumi
## 1	replete	100	glucose.1	2174.42	1.11
## 2	replete	100	glucose.1	2190.52	1.01
## 3	replete	100	glucose.1	1802.27	1.15
## 4	replete	100	glucose.1	2331.95	0.93
## 5	replete	100	glucose.1	2110.26	1.08
## 6	replete	100	glucose.1	2180.65	1.03
## 13	replete	100	acetate	2567.66	24.2
## 14	replete	100	acetate	2634.09	22.6
## 15	replete	100	acetate	2154.61	27.3
## 16	replete	100	acetate	2574.61	22.2
## 17	replete	100	acetate	2615.06	21.4
## 18	replete	100	acetate	2521.43	22.6
## 19	replete	100	alanine	1827.21	9.49

```
## 20 replete 100 alanine 1742.34 8.34
## 21 replete 100 alanine 1586.88 8.13
## 22 replete 100 alanine 1755.45 7.14
## 23 replete 100 alanine 1625.58 7.33
## 24 replete 100 alanine 1621.62 7.6
## 25 replete 100 serine 2638.18 10.7
## 26 replete 100 serine 2293.12 10.2
## 27 replete 100 serine 1833.44 7.61
## 28 replete 100 serine 1966.49 6.6
## 29 replete 100 serine 2037.86 6.91
## 30 replete 100 serine 1828.77 8.89
```

```
carb1$conc=as.character(carb1$conc)
carb1$lumi=as.numeric(as.character(carb1$lumi))
```

```
c=ggplot(carb1, aes(x=carbon, y=lumi, fill=conc))+geom_boxplot()
c=c+theme_bw()
c=c+scale_x_discrete("carbon sources")+scale_y_continuous("Luminescence")
c=c+ggtitle("ICL expression: Carbon")
c=c+scale_fill_manual(values=c("grey"))
c
```



```
##anova - untransformed data
cc=lm(lumi ~ carbon,
      data = carb1)
ccc <- Anova(cc, type = 3)
kable(ccc, digits = 10, results = 'asis')
```

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	3280.68167	1	1596.0071	0
carbon	1591.48575	3	258.0787	0
Residuals	41.11112	20	NA	NA

```
shapiro.test(residuals(cc)) #ok
```

```
##
## Shapiro-Wilk normality test
##
## data: residuals(cc)
## W = 0.92028, p-value = 0.05926
```

```
leveneTest(cc) #ok
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group 3  2.4944 0.08934 .
##      20
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
cccc <- aov(lumi ~ carbon, data = carb1)
TukeyHSD(cccc)
```

```
## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = lumi ~ carbon, data = carb1)
##
## $carbon
##              diff          lwr          upr      p adj
## alanine-acetate -15.378333 -17.695178 -13.061488 0.0000000
## glucose.1-acetate -22.331667 -24.648512 -20.014822 0.0000000
## serine-acetate    -14.898333 -17.215178 -12.581488 0.0000000
## glucose.1-alanine  -6.953333  -9.270178  -4.636488 0.0000003
## serine-alanine     0.480000  -1.836845   2.796845 0.9369716
## serine-glucose.1   7.433333   5.116488   9.750178 0.0000001
```

Normality was met ($p = 0.05926$) and homoskedasticity ($p = 0.08934$) Significant differences ($p < 0.0005$) in the luminescence between different carbon sources. A tukey test further revealed that there was no significant difference between alanine and serine ($p = 0.9369716$).

Different Glucose Concentrations

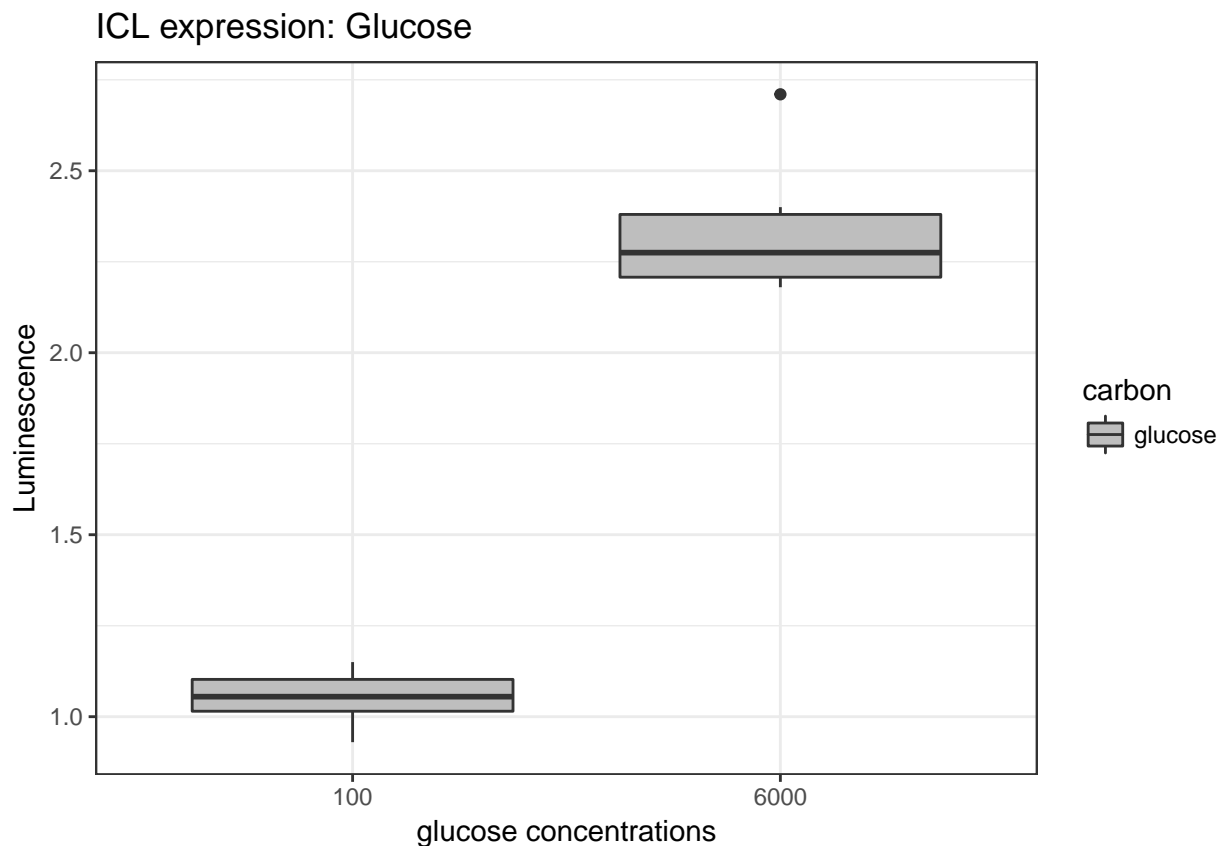
```
glu=read.table('glucose.txt', na.strings="NA", sep='\t', header=T, dec=',')
glu=subset(glu, carbon=="glucose")
glu # inspect data
```

```
##      iron conc  carbon  counts lumi
## 1 replete  100 glucose 2174.42 1.11
## 2 replete  100 glucose 2190.52 1.01
## 3 replete  100 glucose 1802.27 1.15
## 4 replete  100 glucose 2331.95 0.93
```

```
## 5 replete 100 glucose 2110.26 1.08
## 6 replete 100 glucose 2180.65 1.03
## 7 replete 6000 glucose 2605.52 2.23
## 8 replete 6000 glucose 2760.13 2.2
## 9 replete 6000 glucose 2445.97 2.4
## 10 replete 6000 glucose 2694.87 2.18
## 11 replete 6000 glucose 2616.04 2.32
## 12 replete 6000 glucose 2088.18 2.71
```

```
glu$conc=as.character(glu$conc)
glu$lumi=as.numeric(as.character(glu$lumi))

gluc=ggplot(glu, aes(x=conc, y=lumi, fill=carbon))+geom_boxplot()
gluc=gluc+theme_bw()
gluc=gluc+scale_x_discrete("glucose concentrations")+scale_y_continuous("Luminescence")
gluc=gluc+ggtitle("ICL expression: Glucose")
gluc=gluc+scale_fill_manual(values=c("grey"))
gluc
```



```
##anova - untransformed data
gluco=lm(lumi ~ conc,
         data = glu)
glucose <- Anova(gluc, type = 3)
kable(glucose, digits = 10, results = 'asis')
```

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	6.6360167	1	289.6770	1.03e-08

	Sum Sq	Df	F value	Pr(>F)
conc	4.9794083	1	217.3623	4.13e-08
Residuals	0.2290833	10	NA	NA

```
shapiro.test(residuals(gluco)) #ok
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals(gluco)
## W = 0.86549, p-value = 0.0573
```

```
leveneTest(gluco) #ok
```

```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

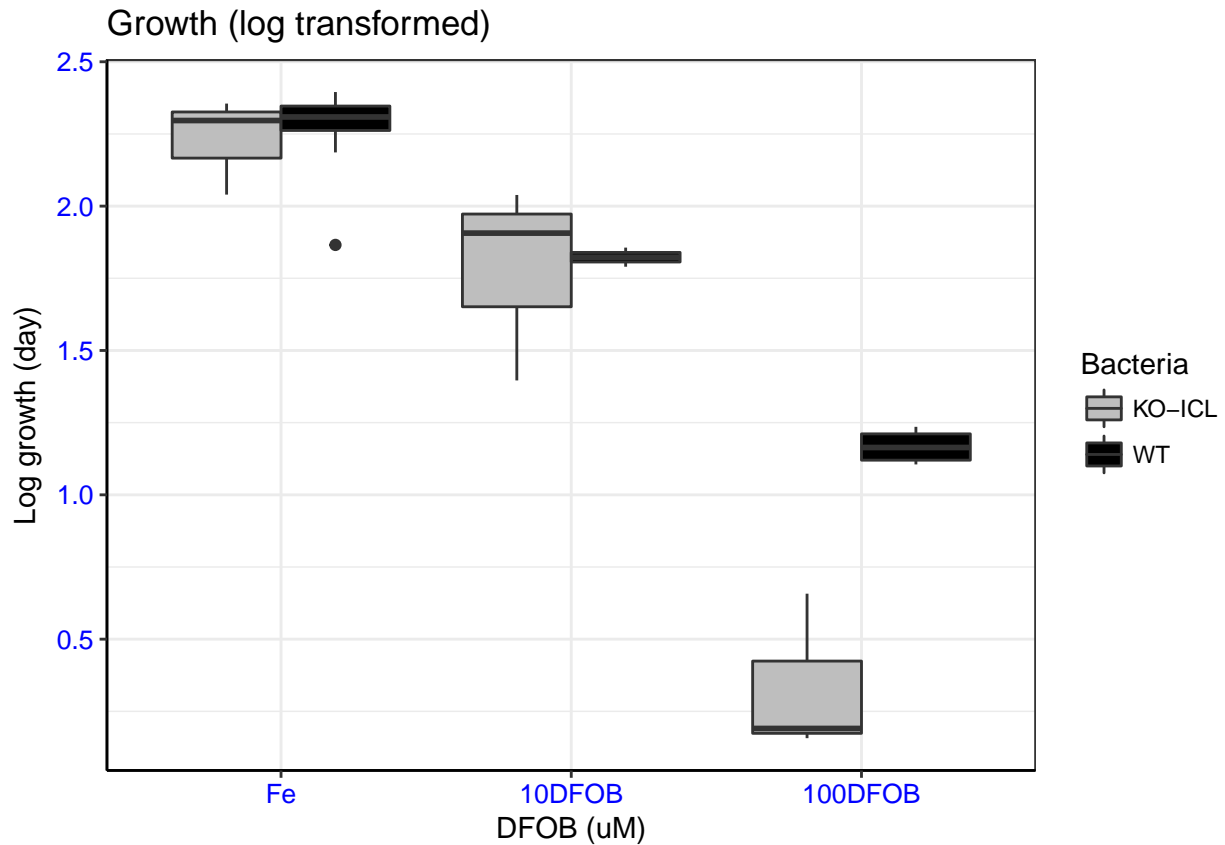
```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group 1  1.4108 0.2624
##      10
```

Growth Rate

```
data1$strain=as.factor(data1$strain)
data1$iron=as.factor(data1$iron)
data1$growth=as.numeric(as.character(data1$growth))
data1$respiration=as.numeric(as.character(data1$respiration))

### graph ###
data1$loggrowth=log(data1$growth)

graph=ggplot(data1, aes(x=iron, y=loggrowth, fill=strain))+geom_boxplot()
graph=graph+theme_bw()
graph=graph+scale_x_discrete("DFOB (uM)", limits=c("Fe", "10DFOB", "100DFOB"))+scale_y_continuous("Log growth rate")
graph=graph+ggtitle("Growth (log transformed)")
graph=graph+scale_fill_manual(values=c("grey","black"), name="Bacteria", labels=c("KO-ICL", "WT"))
graph=graph+theme(axis.line = element_line(colour = "black",
                                             size = 0.5, linetype = "solid"))
graph=graph+theme(axis.text = element_text(color="blue",size=10))
graph
```

```
##anova - untransformed data
orig=lm(growth ~ iron * strain,
        data = data1,
        contrasts = list(iron = "contr.sum", strain = "contr.poly"))
gg <- Anova(orig, type = 3)

##anova - log transformed data
model=lm(loggrowth ~ iron * strain,
          data = data1,
          contrasts = list(iron = "contr.sum", strain = "contr.poly"))

gg <- Anova(model, type = 3)
kable(gg, digits = 10, results = 'asis')
```

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	60.7295529	1	1949.45240	0.0000000000
iron	10.5269653	2	168.96072	0.0000000000
strain	0.5228526	1	16.78386	0.0004762854
iron:strain	0.8446201	2	13.55639	0.0001457171
Residuals	0.6853464	22	NA	NA

```
#check normality
shapiro.test(residuals(model)) #ok
```

```
##
## Shapiro-Wilk normality test
```

```
##
## data: residuals(model)
## W = 0.93603, p-value = 0.08762
leveneTest(model) #ok

## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group 5  0.7502 0.5947
##      22

rrr <- aov(loggrowth ~ iron*strain, data = data1)
TukeyHSD(rrr)

## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = loggrowth ~ iron * strain, data = data1)
##
## $iron
##              diff          lwr          upr      p adj
## 10DFOB-100DFOB 0.9912548 0.7445820 1.2379276 0.00e+00
## Fe-100DFOB    1.4375903 1.2346394 1.6405412 0.00e+00
## Fe-10DFOB     0.4463355 0.2321635 0.6605075 8.56e-05
##
## $strain
##              diff          lwr          upr      p adj
## WT-KO 0.2226462 0.08394267 0.3613498 0.0030452
##
## $`iron:strain`
##              diff          lwr          upr      p adj
## 10DFOB:KO-100DFOB:KO 1.44543176 0.99650524 1.89435827 0.0000000
## Fe:KO-100DFOB:KO    1.90448779 1.52507563 2.28389994 0.0000000
## 100DFOB:WT-100DFOB:KO 0.83210951 0.41217721 1.25204182 0.0000433
## 10DFOB:WT-100DFOB:KO 1.48806013 1.03913361 1.93698664 0.0000000
## Fe:WT-100DFOB:KO    1.92060096 1.54837076 2.29283116 0.0000000
## Fe:KO-10DFOB:KO     0.45905603 0.07964388 0.83846818 0.0118421
## 100DFOB:WT-10DFOB:KO -0.61332224 -1.03325454 -0.19338994 0.0019212
## 10DFOB:WT-10DFOB:KO 0.04262837 -0.40629814 0.49155488 0.9996490
## Fe:WT-10DFOB:KO     0.47516921 0.10293900 0.84739941 0.0073495
## 100DFOB:WT-Fe:KO    -1.07237827 -1.41699647 -0.72776007 0.0000000
## 10DFOB:WT-Fe:KO     -0.41642766 -0.79583981 -0.03701551 0.0259753
## Fe:WT-Fe:KO         0.01611318 -0.26844594 0.30067229 0.9999725
## 10DFOB:WT-100DFOB:WT 0.65595061 0.23601831 1.07588291 0.0009104
## Fe:WT-100DFOB:WT    1.08849145 0.75179656 1.42518633 0.0000000
## Fe:WT-10DFOB:WT     0.43254084 0.06031064 0.80477104 0.0166068
```

Summary Growth Rate Data Analysis

Data reveals a skewed data set where differences between the KO and WT are shown particularly in 100 DFOB conditions, while differences do not seem to be present for 10 DFOB and Fe conditions. In this particular case, it is appropriate to conduct a log transformation in order to discern a pattern. This is highlighted by the fact that a log transformation gives a normal distribution of the data ($p = 0.08762$) using a shapiro wilk test. Homoskedasticity was also met ($p = 0.5947$).

The first ANOVA table shows the data untransformed. While the second ANOVA table shows data after transformation. This is followed by tests to check whether data meet the assumptions of the ANOVA (**note that assumptions of normality were not met for untransformed data)

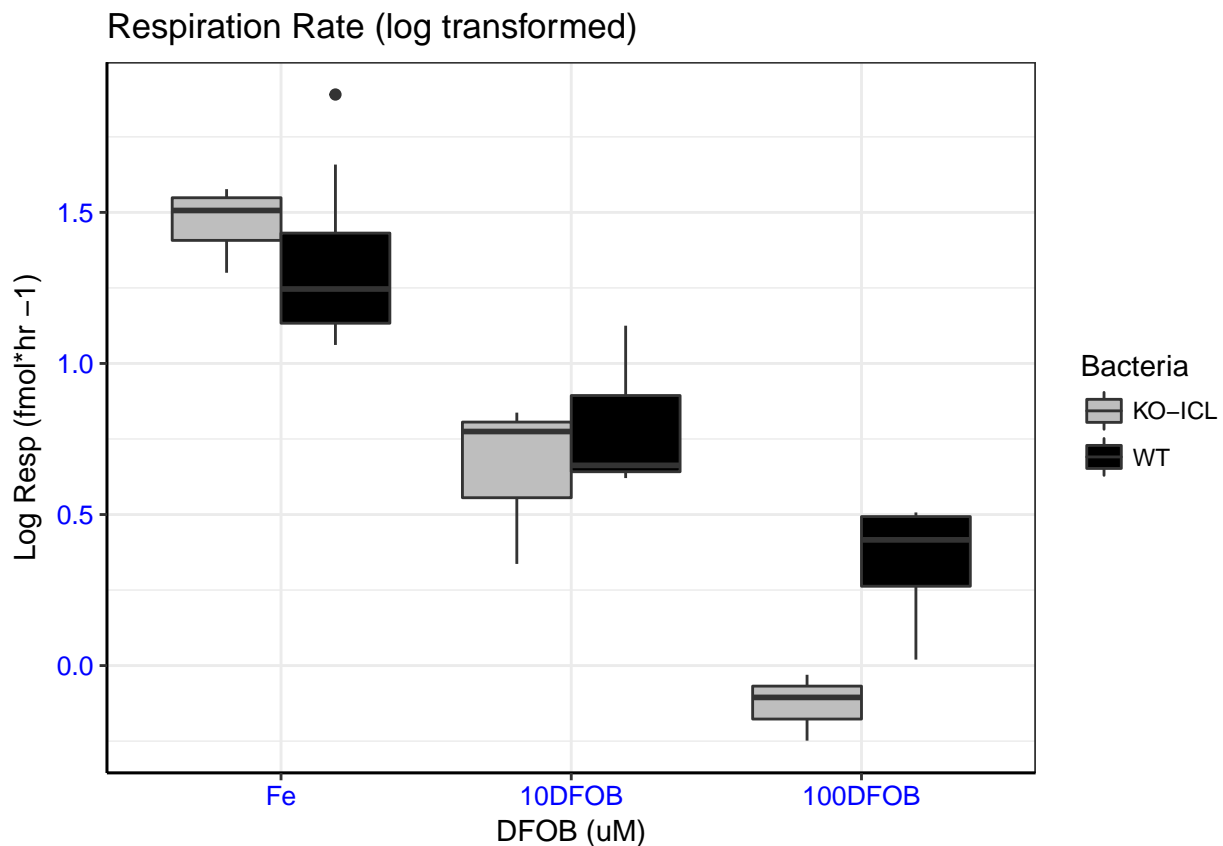
A tukey test reveals a significant differences between WT and KO grown in strong iron limitation of 100uM DFOB (p = 0.0000433).

Respiration Rate

```
data2=read.table('icl_alldates.txt', na.strings="NA", sep='\t', header=T, dec=',')

data1$strain=as.factor(data1$strain)
data1$iron=as.factor(data1$iron)
data1$respiration=as.numeric(as.character(data1$respiration))

data1$logresp=log(data1$respiration)
graph2=ggplot(data1, aes(x=iron, y=logresp, fill=strain))+geom_boxplot()
graph2=graph2+scale_fill_manual(values=c("grey","black"), name="Bacteria", labels=c("KO-ICL", "WT"))
graph2=graph2+theme_bw()
graph2=graph2+scale_x_discrete("DFOB (uM)", limits=c("Fe", "10DFOB", "100DFOB"))+scale_y_continuous("Log Resp (fmol*hr -1)")
graph2=graph2+ggtitle("Respiration Rate (log transformed)")
graph2=graph2+theme(axis.line = element_line(colour = "black",
                                                size = 0.5, linetype = "solid"))
graph2=graph2+theme(axis.text = element_text(color="blue",size=10))
graph2
```



```
data1$logresp=as.numeric(as.character(data1$logresp))
r=lm(logresp ~ iron * strain,
      data = data1,
      contrasts = list(iron = "contr.sum", strain = "contr.poly"))

rr <- Anova(r, type = 3)
kable(rr, digits = 10, results = 'asis')
```

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	13.1636128	1	249.794791	0.0000000000
iron	8.2481974	2	78.259546	0.0000000001
strain	0.1554684	1	2.950194	0.0999130426
iron:strain	0.4387217	2	4.162626	0.0292954996
Residuals	1.1593496	22	NA	NA

```
#check normality
shapiro.test(residuals(r)) #ok
```

```
##
## Shapiro-Wilk normality test
##
## data: residuals(r)
## W = 0.96411, p-value = 0.4343
```

```
leveneTest(r) #ok
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group 5  0.6193 0.6865
##      22
```

```
rrr <- aov(logresp ~ iron*strain, data = data1)
TukeyHSD(rrr)
```

```
## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = logresp ~ iron * strain, data = data1)
##
## $iron
##              diff          lwr          upr          p adj
## 10DFOB-100DFOB 0.5868913 0.2660624 0.9077202 0.0003991
## Fe-100DFOB     1.2593437 0.9953806 1.5233067 0.0000000
## Fe-10DFOB      0.6724524 0.3938949 0.9510098 0.0000121
##
## $strain
##              diff          lwr          upr          p adj
## WT-KO 0.07564552 -0.1047558 0.2560468 0.3939015
##
## $`iron:strain`
##              diff          lwr          upr          p adj
## 10DFOB:KO-100DFOB:KO 0.7775760 0.19369090 1.3614611 0.0049290
## Fe:KO-100DFOB:KO    1.5987935 1.10532053 2.0922665 0.0000000
## 100DFOB:WT-100DFOB:KO 0.4677912 -0.07838332 1.0139657 0.1225341
```

## 10DFOB:WT-10DFOB:KO	0.9308250	0.34693995	1.5147101	0.0007186
## Fe:WT-10DFOB:KO	1.4635299	0.97939792	1.9476618	0.0000000
## Fe:KO-10DFOB:KO	0.8212175	0.32774453	1.3146905	0.0004298
## 10DFOB:WT-10DFOB:KO	-0.3097848	-0.85595932	0.2363897	0.5055363
## 10DFOB:WT-10DFOB:KO	0.1532490	-0.43063606	0.7371341	0.9611117
## Fe:WT-10DFOB:KO	0.6859539	0.20182191	1.1700858	0.0026468
## 10DFOB:WT-Fe:KO	-1.1310023	-1.57922142	-0.6827832	0.0000011
## 10DFOB:WT-Fe:KO	-0.6679685	-1.16144144	-0.1744955	0.0042034
## Fe:WT-Fe:KO	-0.1352636	-0.50536837	0.2348411	0.8600070
## 10DFOB:WT-10DFOB:WT	0.4630339	-0.08314063	1.0092084	0.1289673
## Fe:WT-10DFOB:WT	0.9957387	0.55782486	1.4336525	0.0000057
## Fe:WT-10DFOB:WT	0.5327048	0.04857287	1.0168368	0.0254862

Summary Respiration Rate Data Analysis

Data again was log transformed due to skewedness of data. Assumptions of the ANOVA were met through a shapiro test ($p = 0.4343$) on the log transformed residuals to test for normality while a levene test ($p = 0.6865$) was conducted to confirm homoskedasticity.

Data is significant for interaction effects between strain and iron conditions but a tukey test reveals that these differences are not statistically significant between WT and KO grown in 100DFOB conditions ($p = 0.1225341$). It is therefore tricky to discern how ICL affects the respiration rate under iron limitation.