

Statistical Methods for High Dimensional Biology

STAT/BIOF/GSAT 540

Lecture 6 – Two Group Comparisons

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January 20 2016

****based on slides from Dr. Jenny Bryan, with edits by Sara Mostafavi****

Before we start

- Recap of last week
- Project groups

Outline

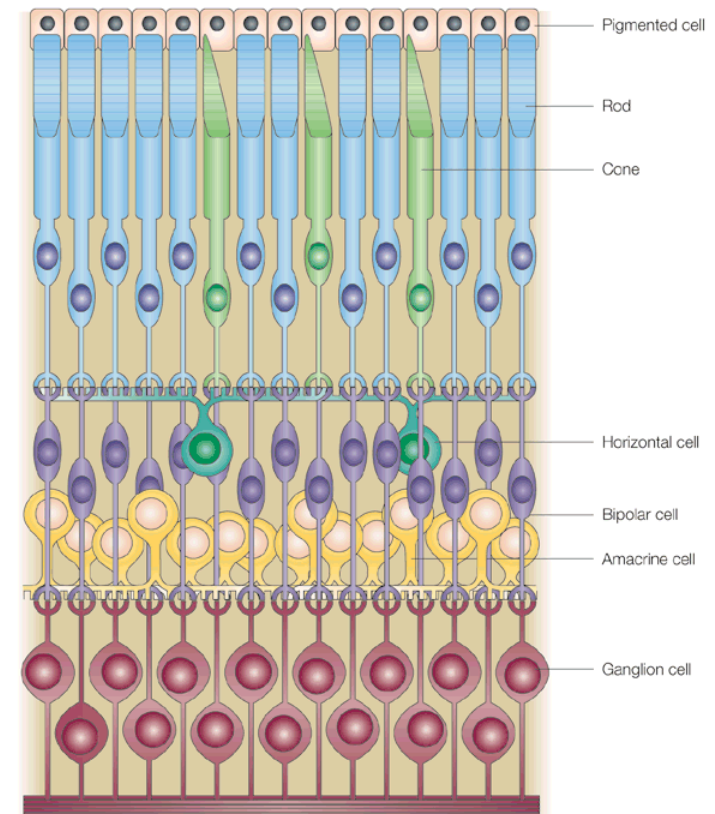
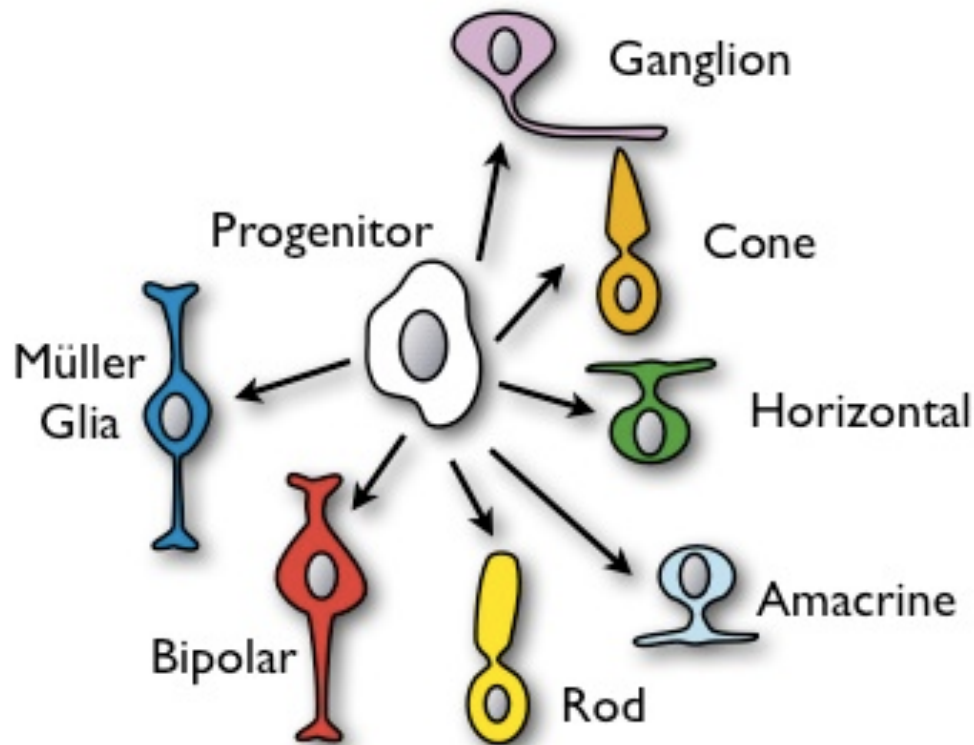
- Comparing Two Groups:
 - Deriving t-statistics/t-test
 - Reconstructing the null distribution based on simulation experiments
 - Brief intro: non parametric tests...
 - Statistical power

Comparing Two Groups

We will analyze data from this study...

Targeting of GFP to newborn rods by Nrl promoter and temporal expression profiling of flow-sorted photoreceptors

Masayuki Akimoto^{*†}, Hong Cheng[‡], Dongxiao Zhu^{§¶}, Joseph A. Brzezinski^{||}, Ritu Khanna^{*}, Elena Filippova^{*}, Edwin C. T. Oh[‡], Yuezhou Jing[¶], Jose-Luis Linares^{*}, Matthew Brooks^{*}, Sepideh Zareparsa^{*}, Alan J. Mears^{*,**}, Alfred Hero^{§¶††††}, Tom Glaser^{||§§}, and Anand Swaroop^{*,¶||¶}



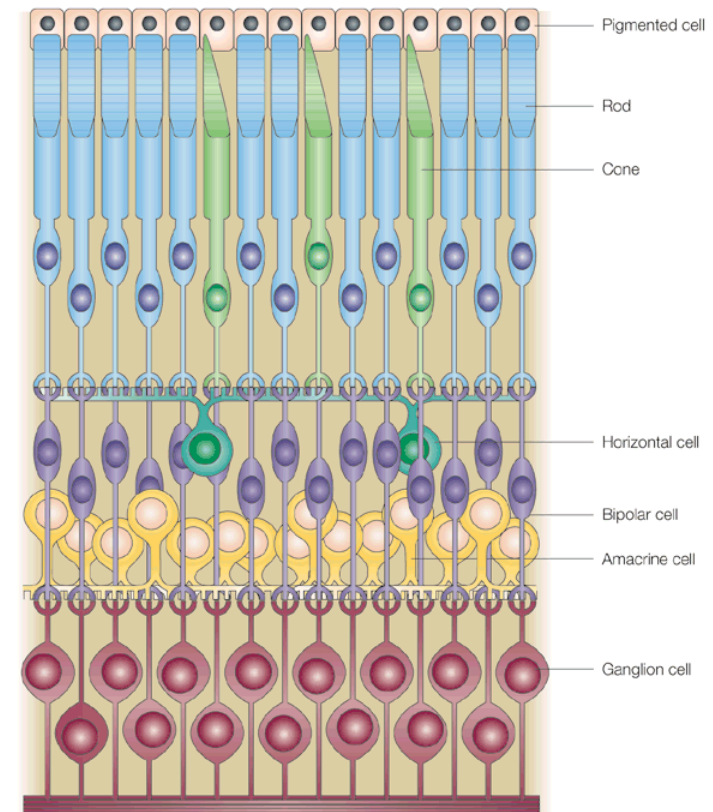
We will analyze data from this study...



Targeting of GFP to newborn rods by Nrl promoter and temporal expression profiling of flow-sorted photoreceptors

Masayuki Akimoto^{*†}, Hong Cheng[‡], Dongxiao Zhu^{§¶}, Joseph A. Brzezinski^{||}, Ritu Khanna^{*}, Elena Filippova^{*}, Edwin C. T. Oh[‡], Yuezhou Jing[¶], Jose-Luis Linares^{*}, Matthew Brooks^{*}, Sepideh Zareparsa^{*}, Alan J. Mears^{*,**}, Alfred Hero^{§¶††††}, Tom Glaser^{||§§}, and Anand Swaroop^{*,¶||¶¶}

- Retina presents a model system for investigating **regulatory networks** underlying neuronal differentiation.
- **Nrl** transcription factor (TF) known to be important for Rod development.
- What happens if you delete Nrl?
- **Hypothesis:** Gene expression levels pre/post deletion will inform us of regulatory network involved in rod/cone development.



Developing mouse retina – time course for the experiment

5 distinct developmental stages:

Embryonic day 16 (E16)

Postnatal days 2, 6 and 10 (P2, P6, P10)

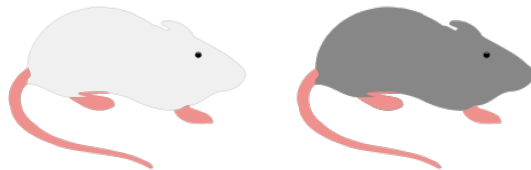
4 week spostnatal (4_weeks)

2 genotypes

wild-type (wt) vs. Nrl knockout (KO)

NrlKO

wt



Experimental design

devStage	wt	NrlKO
E16	4	3
P2	4	4
P6	4	4
P10	4	4
4_weeks	4	4

```
> str(prDes)
'data.frame': 39 obs. of 3 variables:
 $ sample : num 20 21 22 23 16 17 6 24 25 26 ...
 $ devStage: Factor w/ 5 levels "E16","P2","P6",...: 1 1 1 1 1 1 1 2 2 2 ...
 $ gType : Factor w/ 2 levels "wt","NrlKO": 1 1 1 1 2 2 2 1 1 1 ...
```

```
> str(prDat, max.level = 0)
'data.frame': 29949 obs. of 39 variables:
```

```
> peek(subset(prDat, select = 1:5))
```

	Sample_20	Sample_21	Sample_22	Sample_23	Sample_16
1416535_at	8.133	8.143	7.899	8.054	7.867
1437399_at	8.567	8.554	7.931	8.182	6.257
1441587_at	6.134	5.745	6.137	5.953	6.575
1445975_at	6.022	5.960	5.994	6.069	6.418
1446741_at	6.024	6.009	6.073	5.961	7.046
1450103_a_at	8.376	8.902	8.570	8.755	7.991
1452844_at	8.490	8.700	8.288	8.544	7.256

```
> with(prDes, table(devStage, gType))
```

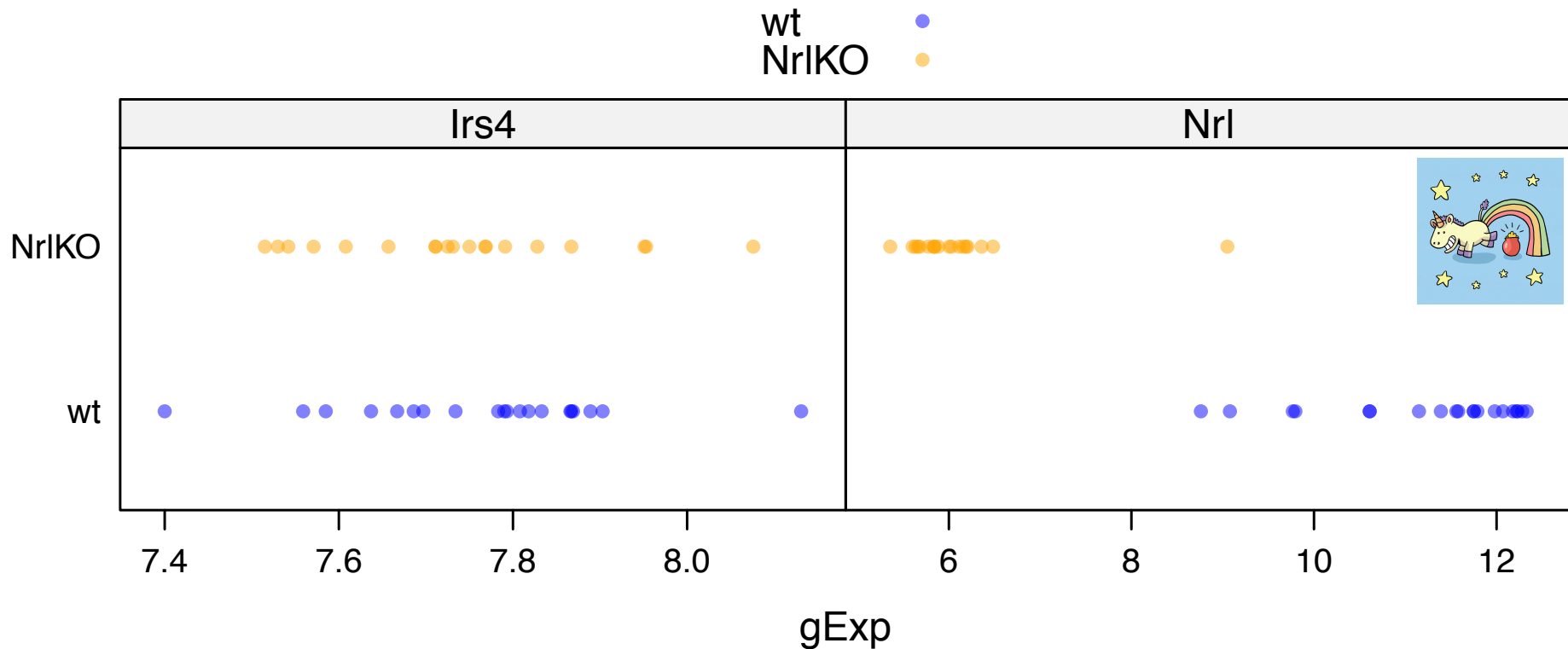
devStage	gType	
	wt	NrlKO
E16	4	3
P2	4	4
P6	4	4
P10	4	4
4_weeks	4	4

photoRec dataset
mouse photoreceptors
Affy

Which genes are *differentially expressed* between WT and NrlKO?

Let's do it for 2 genes ... we can then apply the same procedure to all genes, one at a time

Do we think the orange's and blue's are generated by different underlying distributions?



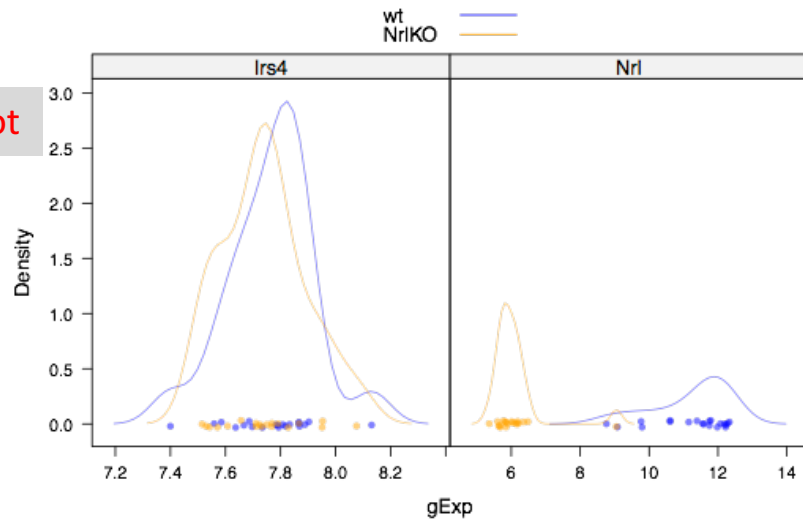
Irs4 (insulin receptor substrate 4) was selected at random as a boring non differentially expressed gene; Nr1KO \approx wt

Nrl (neural retina leucine zipper gene) is the gene that was knocked out in half the mice; obviously should be differentially expressed; Nr1KO \ll wt

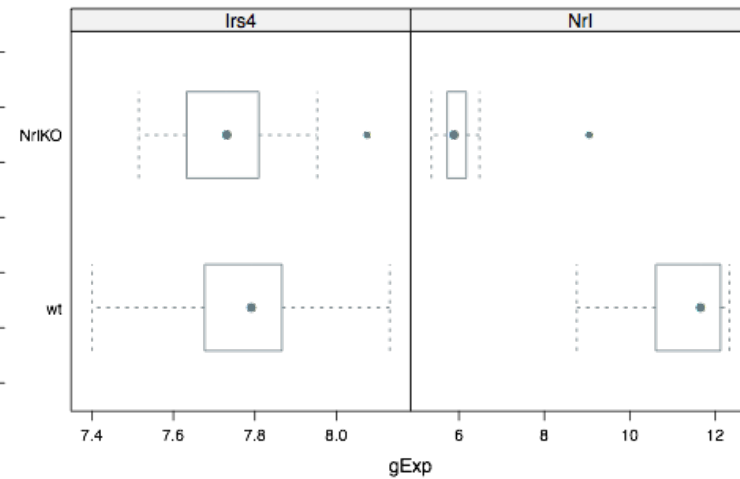
Do we think expression of gene [Irs4 | Nrl] in wild type vs. knockout mice comes from different underlying distributions?

First line of attack: let's look at the data in several ways!

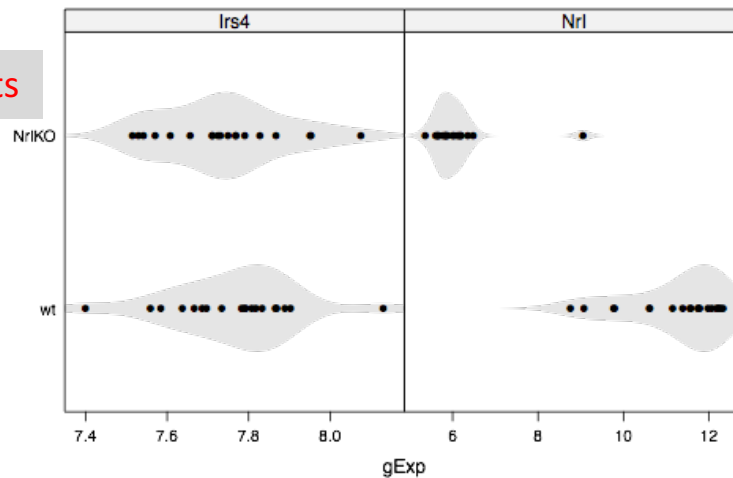
Density plot



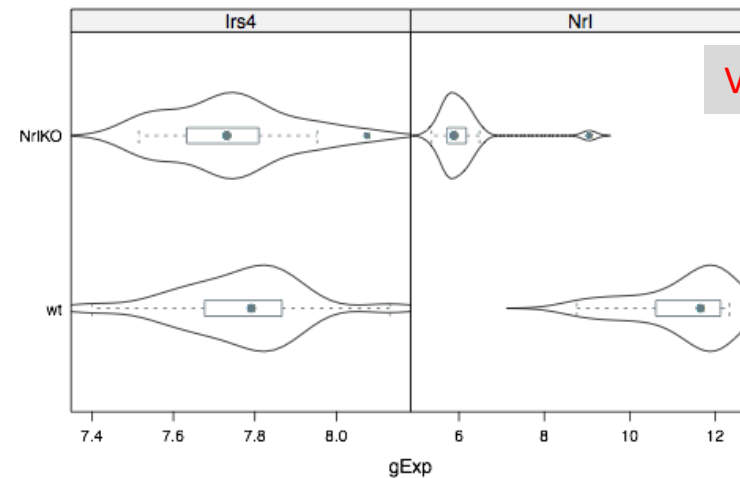
Boxplots



Violin dotplots

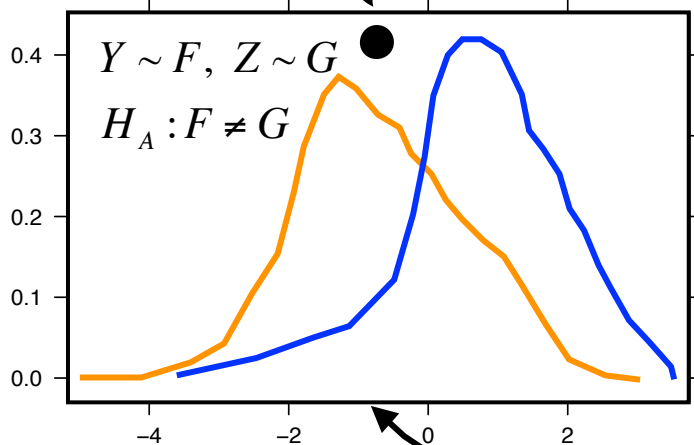
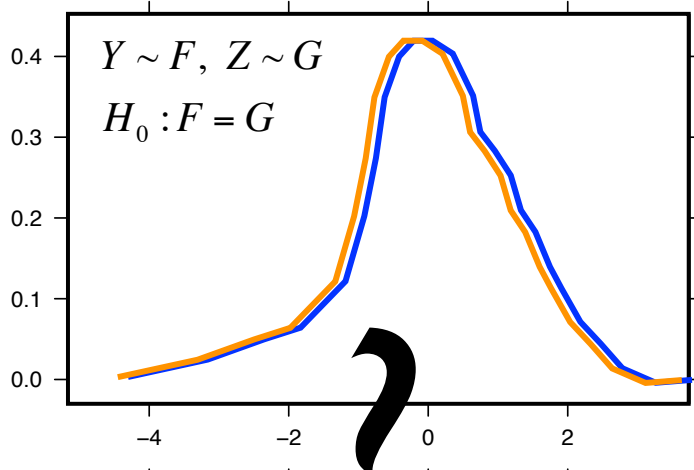


Violin boxplots

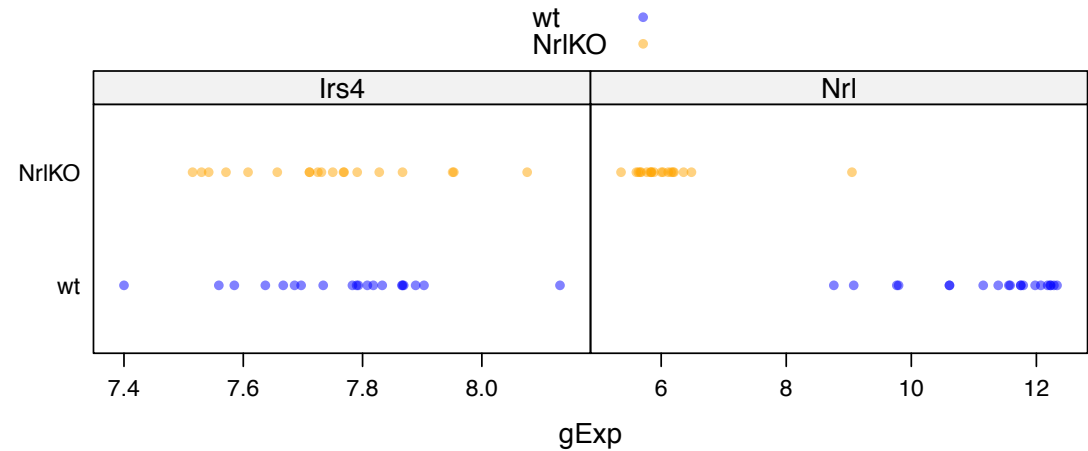


probability

data generating model



observed data

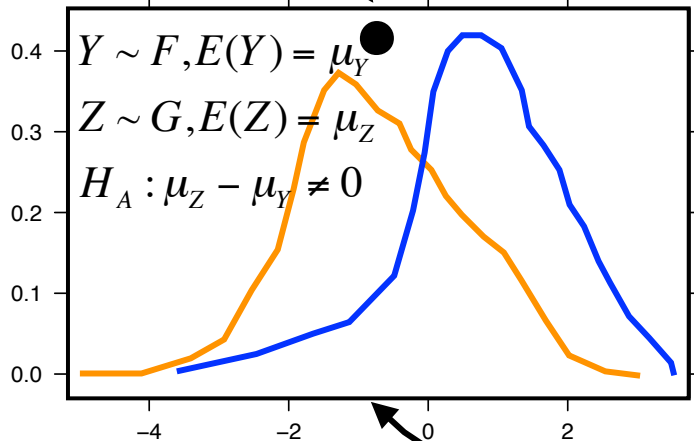
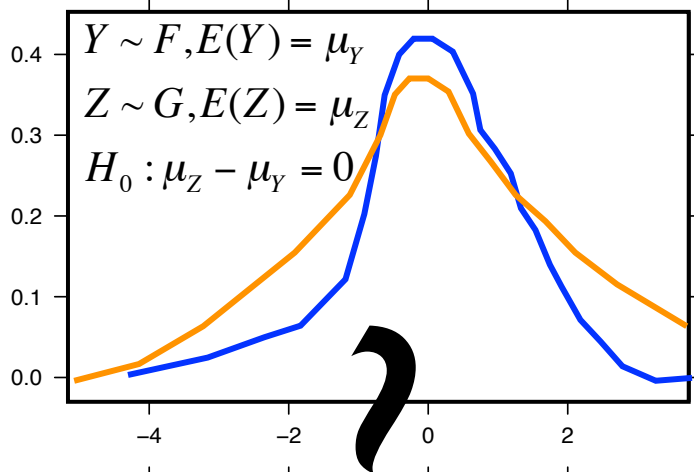


Pick your favorite explanation
for the observed data

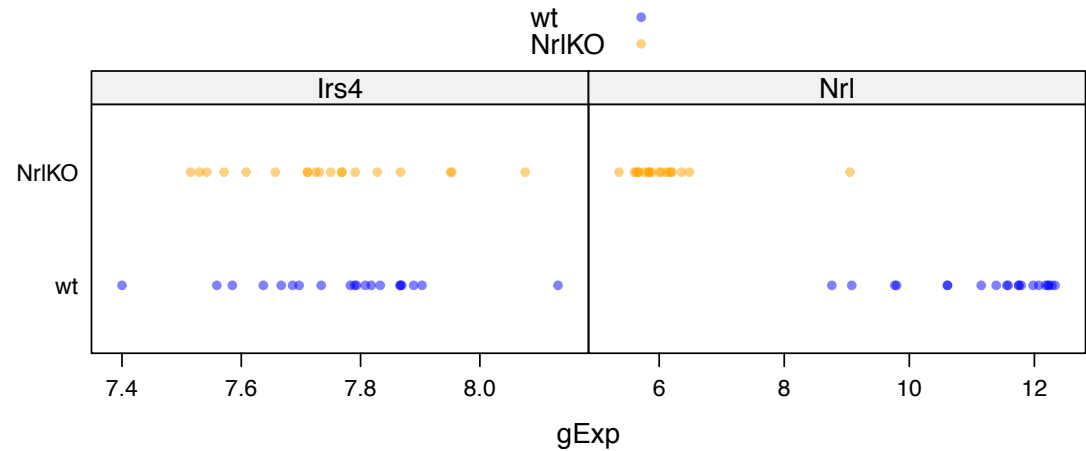
statistical
inference

probability

data generating model

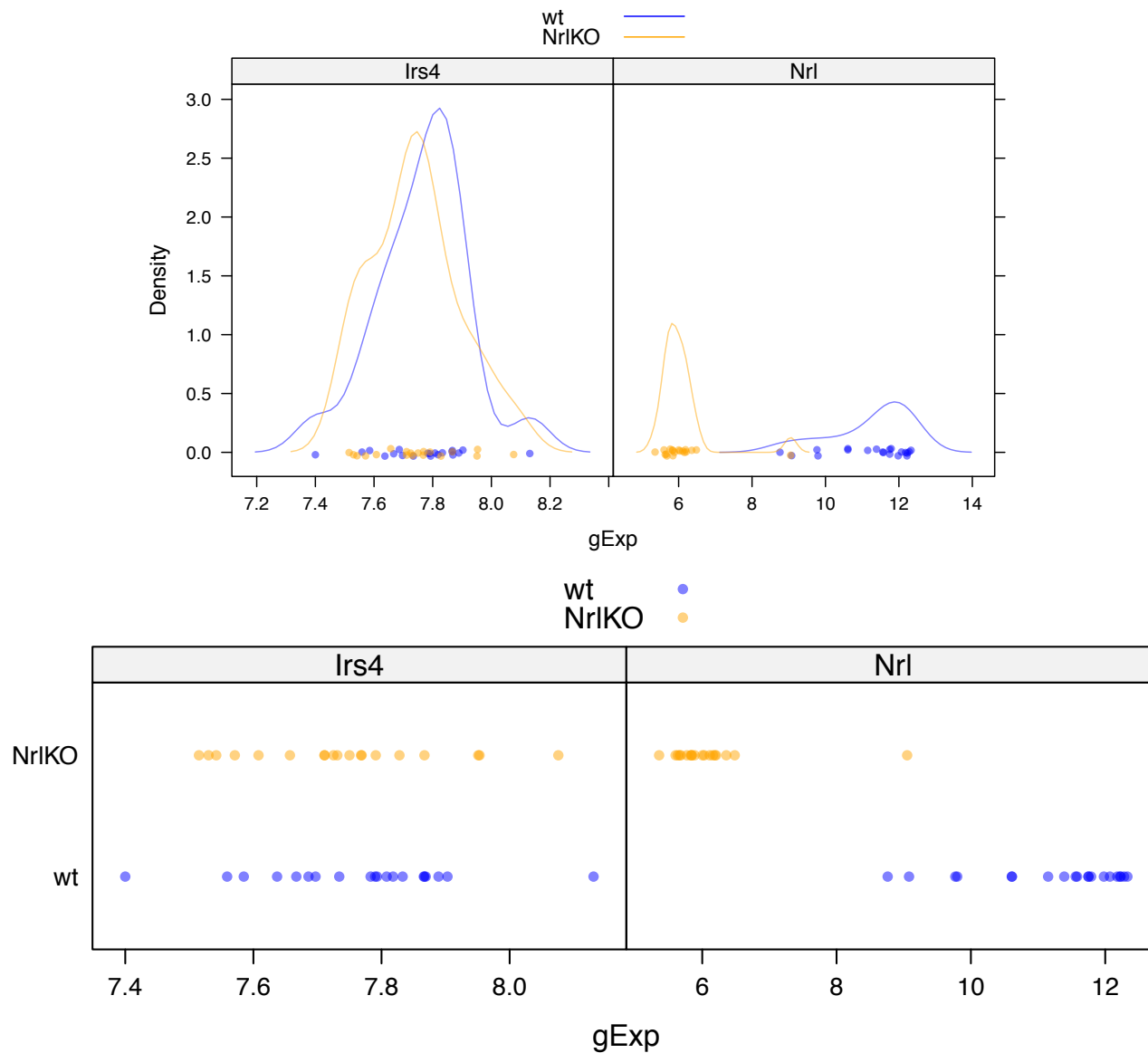


observed data



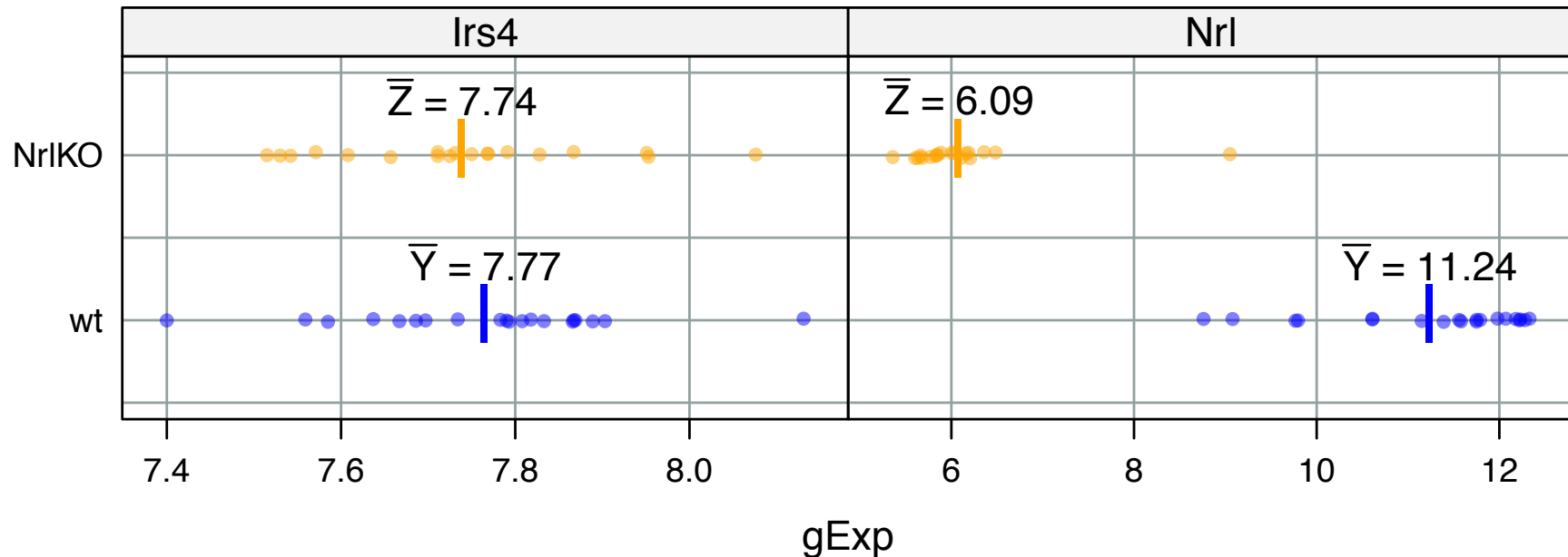
Common simplification: test only for equality of means

statistical inference



What's your quick-and-dirty best guess at $\mu_Z - \mu_Y$?

... the difference between the sample averages!



```
> (theAvg <- with(miniDat,
+               tapply(gExp, list(gType, gene), mean)))
      Irs4      Nrl
wt      7.765750 11.244200
NrlKO 7.739684  6.089632

> (theDiff <- theAvg["NrlKO", ] - theAvg["wt", ])
      Irs4      Nrl
-0.02606579 -5.15456842
```

Are these observed differences **convincing** evidence that $\mu_Z - \mu_Y \neq 0$?

Are these differences *convincing*?

- How can we judge the size of the differences?
- The between groups difference for Irs4 looks small and for Nrl looks big...
- We judge size of differences ***between*** the group means relative to the differences ***within*** the groups (i.e., differences seen sample to sample)

Are these differences *convincing*?

We need to know the background variability in the difference of sample averages under the null hypothesis that $\mu_Z - \mu_Y = 0$.

Then we can divide by the relevant standard deviation -- also called a standard error, in this setting -- and have a better idea.

$$V(\bar{Z}_n - \bar{Y}_n) = V(\bar{Z}_n) + (-1)^2 V(\bar{Y}_n) + 2(-1)\text{cov}(\bar{Y}_n, \bar{Z}_n) \quad [1]$$

$$= V(\bar{Z}_n) + V(\bar{Y}_n) - 2\text{cov}(\bar{Y}_n, \bar{Z}_n)$$

$$= V(\bar{Z}_n) + V(\bar{Y}_n) \quad [2]$$

$$= \frac{\sigma_Z^2}{n_Z} + \frac{\sigma_Y^2}{n_Y} \quad [3]$$

Note: variance of sample mean

[1] basic probability result about variance of sums of scaled rvs

[2] by assuming the Y's and Z's are independent from each other, we get that covariance is zero

[3] basic result about variance of a mean of an iid sample

* See how independence assumptions are sprinkled everywhere?

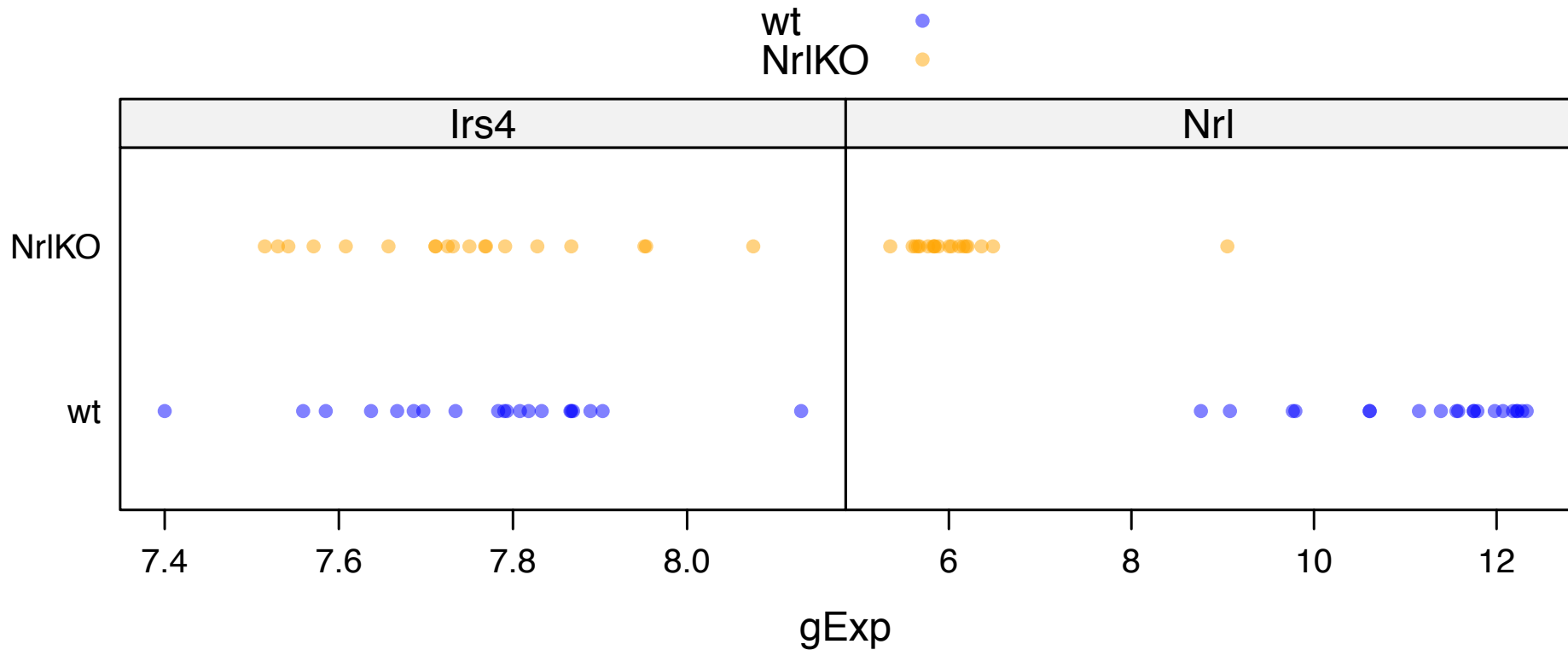
$$V(\bar{Z}_n - \bar{Y}_n) = \frac{\sigma_Z^2}{n_Z} + \frac{\sigma_Y^2}{n_Y}$$

if we assume that $\sigma_Z^2 = \sigma_Y^2 = \sigma^2$

$$\begin{aligned} V(\bar{Z}_n - \bar{Y}_n) &= \frac{\sigma^2}{n_Z} + \frac{\sigma^2}{n_Y} \\ &= \sigma^2 \left[\frac{1}{n_Z} + \frac{1}{n_Y} \right] \end{aligned}$$

What's your quick-and-dirty best guess at σ^2 ?

... the sample variances (combined, somehow)!



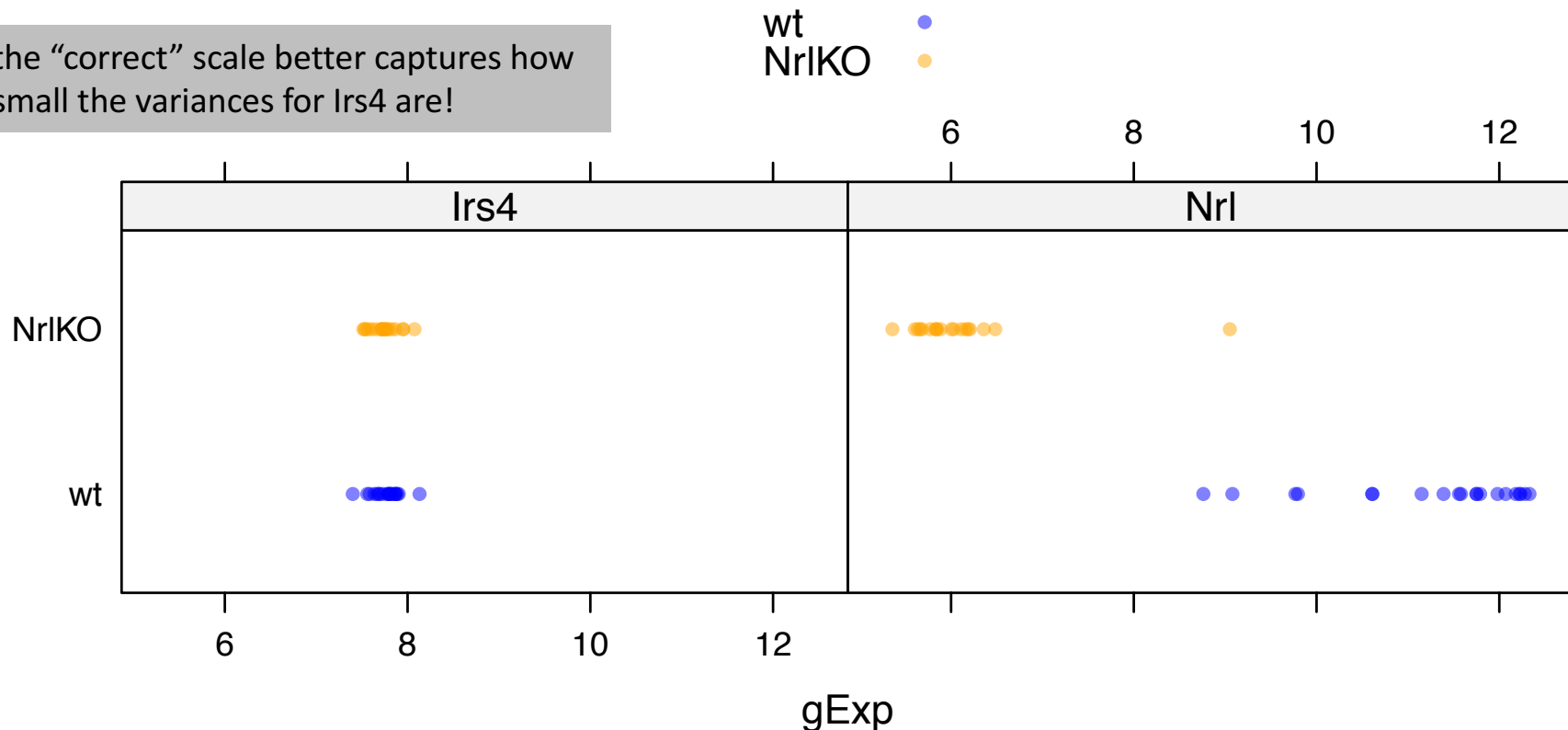
```
> (theVars <- with(miniDat,
+                   tapply(gExp, list(gType, gene), var)))
```

	Irs4	Nr1
wt	0.02403557	1.2243331
Nr1KO	0.02332078	0.5942802

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y}_n)^2$$

... the sample variances (combined, somehow)!

the “correct” scale better captures how small the variances for Irs4 are!



```
> (theVars <- with(miniDat,
+                   tapply(gExp, list(gType, gene), var)))
               Irs4      Nr1
wt           0.02403557 1.2243331
Nr1KO        0.02332078 0.5942802
```

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y}_n)^2$$

Plug these sample variances into your chosen formula for the variance of the difference of sample means.

assuming equal variance of Y's and Z's

$$\text{"pooled"} \hat{\sigma}^2 = s_Y^2 \frac{n_Y - 1}{n_Y + n_Z - 2} + s_Z^2 \frac{n_Z - 1}{n_Y + n_Z - 2}$$

$$\hat{V}(\bar{Z}_n - \bar{Y}_n) = \text{"pooled"} \hat{\sigma}^2 \left[\frac{1}{n_Y} + \frac{1}{n_Z} \right]$$

assuming unequal variance of Y's and Z's

$$\hat{V}(\bar{Z}_n - \bar{Y}_n) = \hat{\sigma}_{\bar{Z}_n - \bar{Y}_n}^2 = \frac{s_Y^2}{n_Y} + \frac{s_Z^2}{n_Z}$$

```
> (nY <- with(miniDat, sum(gType == "wt" & gene == "Nr1")))  
[1] 20  
> (nZ <- with(miniDat, sum(gType == "Nr1KO" & gene == "Nr1")))  
[1] 19
```

$$\text{"pooled"} \hat{\sigma}^2 = s_Y^2 \frac{n_Y - 1}{n_Y + n_Z - 2} + s_Z^2 \frac{n_Z - 1}{n_Y + n_Z - 2}$$

$$\hat{V}(\bar{Z}_n - \bar{Y}_n) = \text{"pooled"} \hat{\sigma}^2 \left[\frac{1}{n_Y} + \frac{1}{n_Z} \right]$$

```
> (s2Pooled <- colSums(theVars * c((nY - 1) / (nY + nZ - 2),  
+ (nZ - 1) / (nY + nZ - 2))))
```

```
      Irs4      Nr1  
0.02368783 0.91782091
```

```
> (s2Diff <- s2Pooled * (1/nY + 1/nZ))
```

```
      Irs4      Nr1  
0.00243112 0.09419741
```

$$\hat{V}(\bar{Z}_n - \bar{Y}_n) = \hat{\sigma}_{\bar{Z}_n - \bar{Y}_n}^2 = \frac{s_Y^2}{n_Y} + \frac{s_Z^2}{n_Z}$$

```
> (s2DiffWelch <- colSums(theVars / c(nY, nZ)))
```

```
      Irs4      Nr1  
0.002429188 0.092494563
```

Let's calculate the relative difference by dividing the difference between the group means by our best guess at the standard deviation under the null hypothesis H_0 : no difference between group means.

$$T = \frac{\bar{Z}_n - \bar{Y}_n}{\hat{\sigma}_{\bar{Z}_n - \bar{Y}_n}}$$

This permits us to describe the difference between the group means in terms of standard deviations (SD). This is a unitless quantity – and one we have encountered before and whose properties are well studied.

We have just re-invented the t-test statistic!

$$T = \frac{\bar{Z}_n - \bar{Y}_n}{\hat{\sigma}_{\bar{Z}_n - \bar{Y}_n}}$$

```
> (welchStat <- theDiff / sqrt(s2DiffWelch))
      Irs4      Nrl
-0.5288595 -16.9486146
```

R's default is to NOT assume equal variance, i.e. to perform “Welch’s Two sample t-test”

```
> by(miniDat, miniDat$gene, function(theDat) {
+   t.test(gExp ~ gType, theDat)
+ })
```

```
miniDat$gene: Irs4
```

```
Welch Two Sample t-test
```

```
data: gExp by gType
t = -0.5289, df = 36.948, p-value = 0.6001
```

```
<snip, snip>
```

```
-----
miniDat$gene: Nrl
```

```
Welch Two Sample t-test
```

```
data: gExp by gType
t = -16.9486, df = 34.005, p-value < 2.2e-16
```

```
<snip, snip>
```

$$T = \frac{\bar{Z}_n - \bar{Y}_n}{\hat{\sigma}_{\bar{Z}_n - \bar{Y}_n}}$$

```
> (tstStat <- theDiff / sqrt(s2Diff))
      Irs4      Nrl
-0.5286494 -16.7947224

> (welchStat <- theDiff / sqrt(s2DiffWelch))
      Irs4      Nrl
-0.5288595 -16.9486146
```

Now can we say the observed differences are “big”?

The difference is about half a standard deviation for Irs4 and 16 or 17 standard deviations for Nrl.

I predict we will conclude that true means are same for Irs4 and different for Nrl.

Theory now tells us specific null distributions for this test statistic, depending on your assumptions.

Willing to assume that F and G are normal distributions?

eq var

$$T \sim t_{n_Y + n_Z - 2}$$

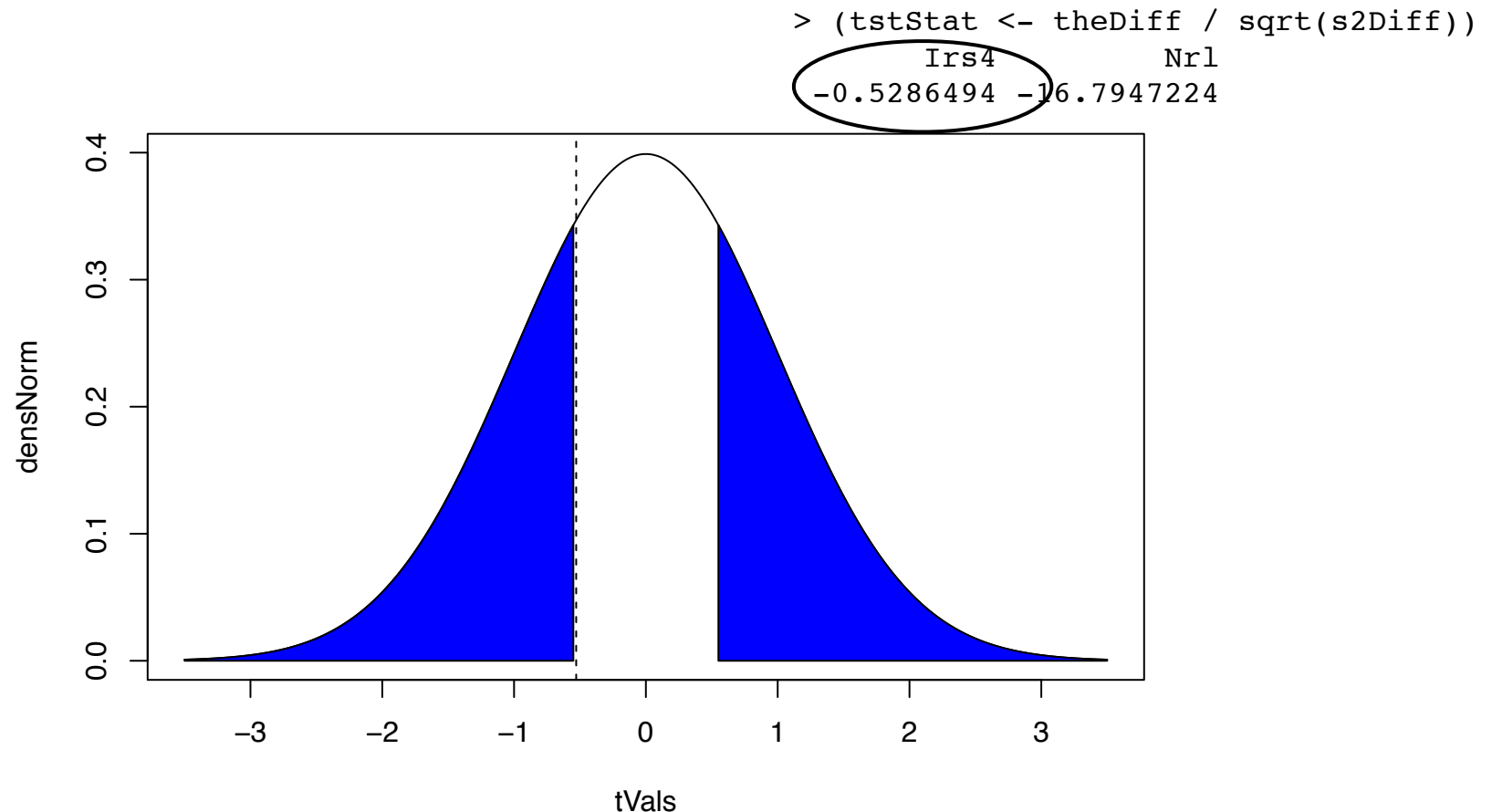
uneq var

$$T \sim t_{\text{<sthg ugly>}}$$

“Welch’s t test”

Unwilling to assume that F and G are normal distributions? But you feel n_Y and n_Z are “large enough”? Then go right ahead use the t dist’n above or even a normal distribution as a decent approximation.

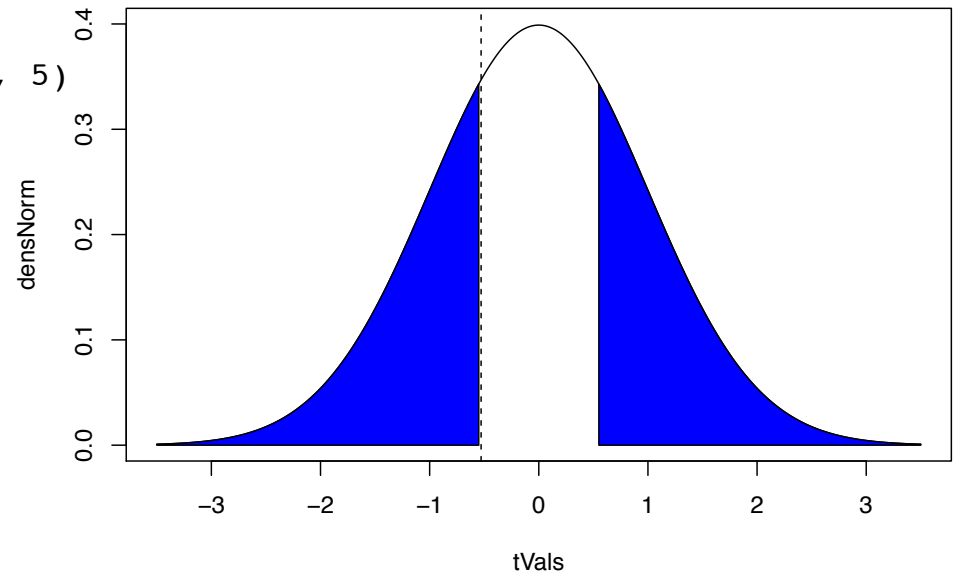
Depicted here is the standard normal distribution (which is visually indistinguishable from t w/ 58 df).



We see that prob. of seeing a test stat as or more extreme than observed ($T = -0.53$) is pretty high.

```
> round(pt(-1 * abs(tstStat), df = nY + nZ - 2) * 2, 5)
      Irs4      Nrl
0.60021 0.00000
```

```
> round(pnorm(-1 * abs(tstStat)) * 2, 5)
      Irs4      Nrl
0.59705 0.00000
```



```
miniDat$gene: Irs4
```

Two Sample t-test

```
data: gExp by gType
```

```
t = -0.5286, df = 37, p-value = 0.6002
```

```
alternative hypothesis: true difference in means is not equal to 0
```

```
95 percent confidence interval:
```

```
-0.07383844 0.12597002
```

```
sample estimates:
```

```
mean in group wt mean in group NrlKO
      7.765750      7.739684
```

```
miniDat$gene: Irs4
```

Welch Two Sample t-test

```
data: gExp by gType
```

```
t = -0.5289, df = 36.948, p-value = 0.6001
```

```
alternative hypothesis: true difference in means is
```

```
95 percent confidence interval:
```

```
-0.0738035 0.1259351
```

```
sample estimates:
```

```
mean in group wt mean in group NrlKO
      7.765750      7.739684
```

we knew we'd see extreme statistical significance for Nrl ... and we do

```
miniDat$gene: Nrl
```

```
Two Sample t-test
```

```
data: gExp by gType
```

```
t = -16.7947, df = 37, p-value < 2.2e-16
```

```
alternative hypothesis: true difference in means is not equal to 0
```

```
95 percent confidence interval:
```

```
4.532698 5.776439
```

```
sample estimates:
```

```
mean in group wt mean in group NrlKO
```

```
11.244200          6.089632
```

```
miniDat$gene: Nrl
```

```
Welch Two Sample t-test
```

```
data: gExp by gType
```

```
t = -16.9486, df = 34.005, p-value < 2.2e-16
```

```
alternative hypothesis: true difference in means is not equal to 0
```

```
95 percent confidence interval:
```

```
4.536507 5.772630
```

```
sample estimates:
```

```
mean in group wt mean in group NrlKO
```

```
11.244200          6.089632
```

In real life, working with just one (or two) genes, it's hard to believe in your gut that a difference of sample means or a two sample t statistic has a null *distribution*. It feels like it's just a particular number -- e.g. t stat = 0.53 for Irs4 in our current example.

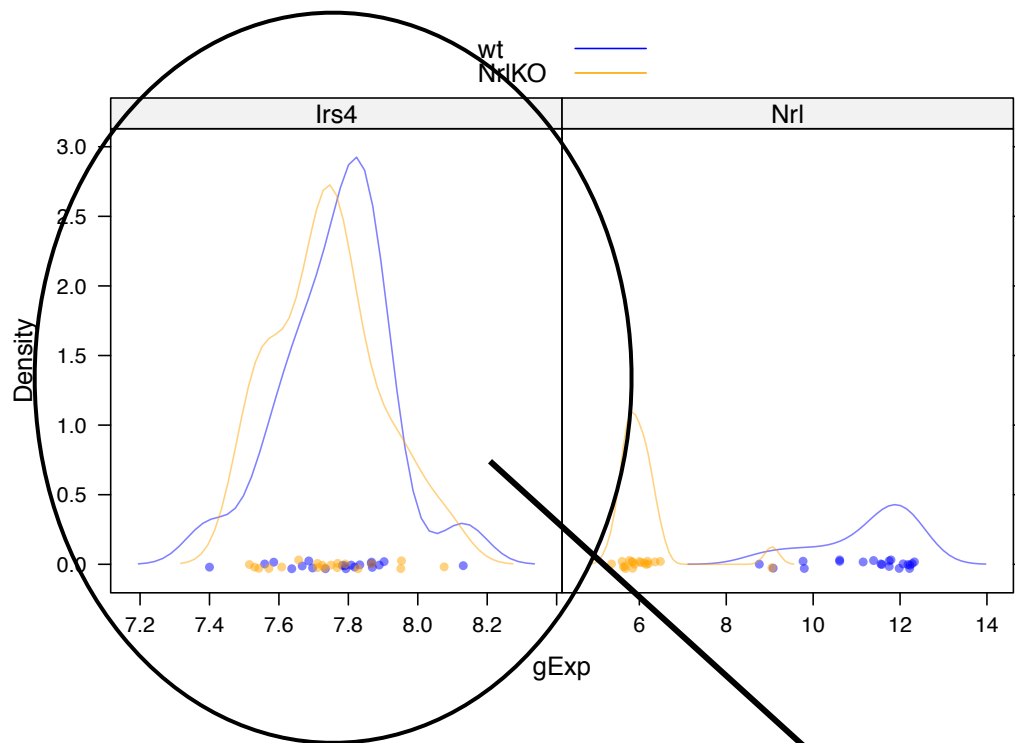
But you must think of it as a fleeting realization of a specific random variable.

You've simply observed one of an infinity of possible values and it's the underlying null distribution that speaks to that and puts your specific observation into context.

I will simulate data -- more blue Y's and more orange Z's -- and compute the observed difference of sample means and the t statistic.

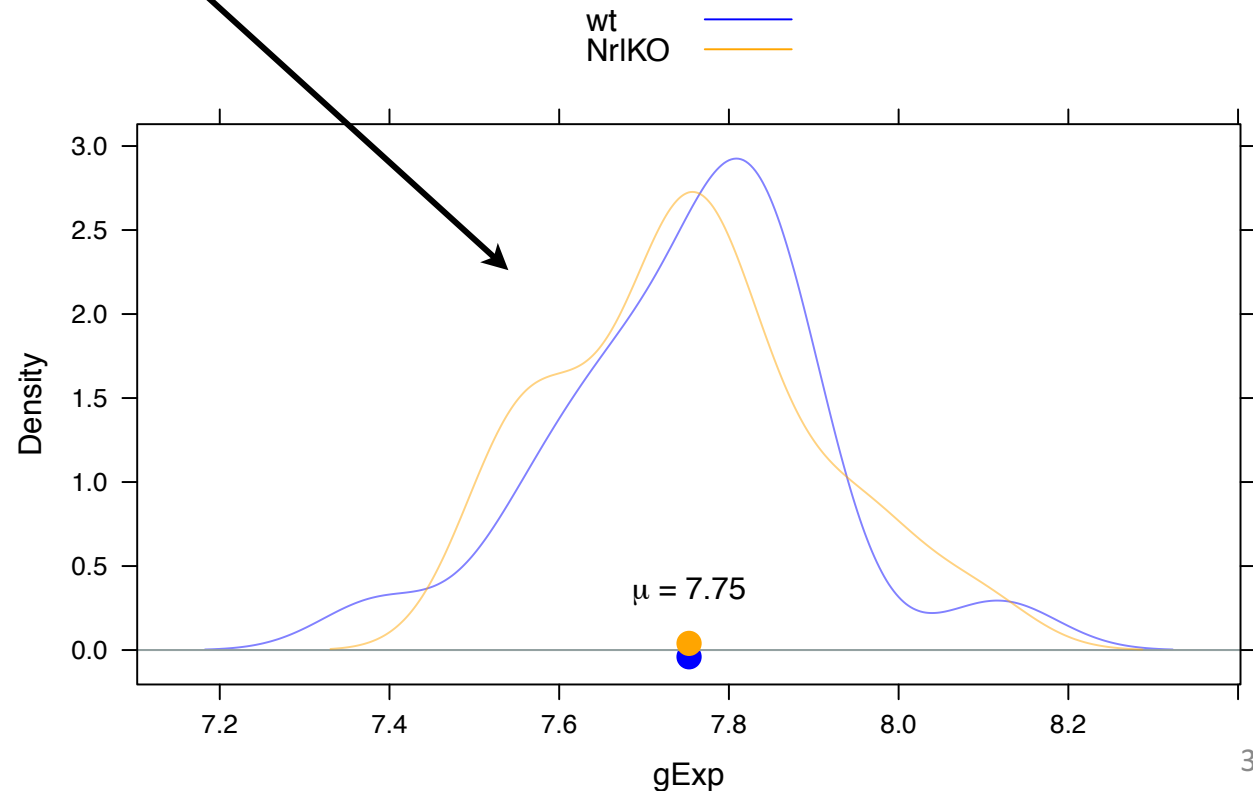
We'll compare the empirical distribution of this larger set of observations to the theoretical distributions just mentioned and used.

We'll feel really good about how this all works, at least when the *assumptions truly hold*.

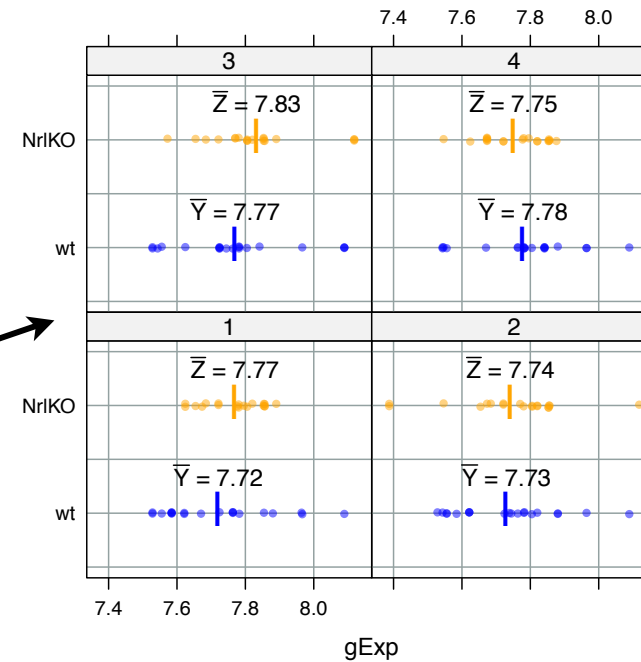
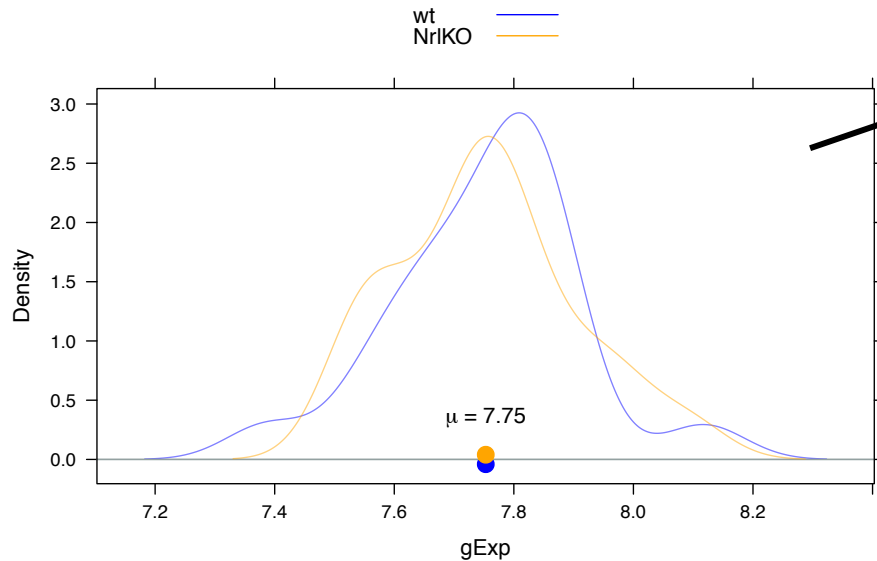


Our data-generating distributions are inspired by the observed data from Irs4.

Exact match except wt and NrlKO groups have common mean.



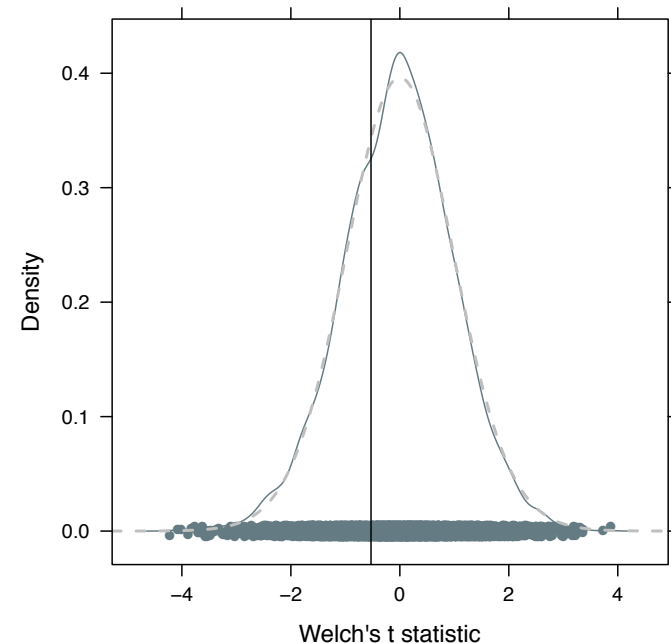
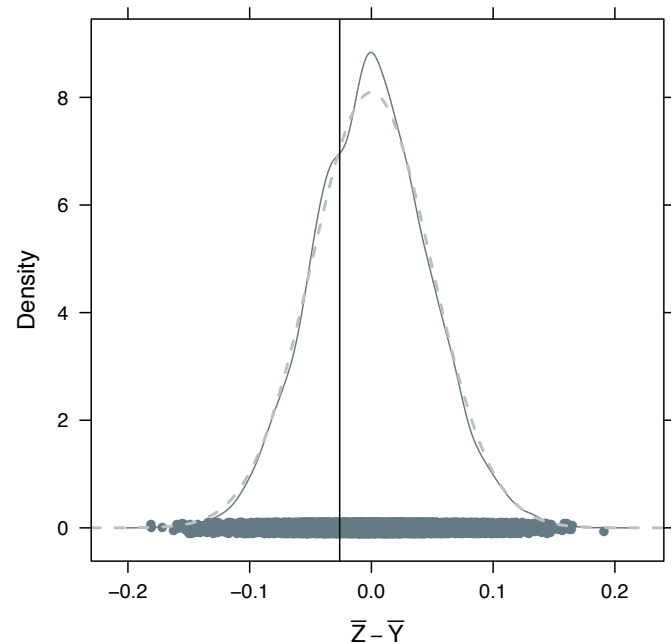
Underlying true dist'ns,
upholding the null
hypothesis of equal means



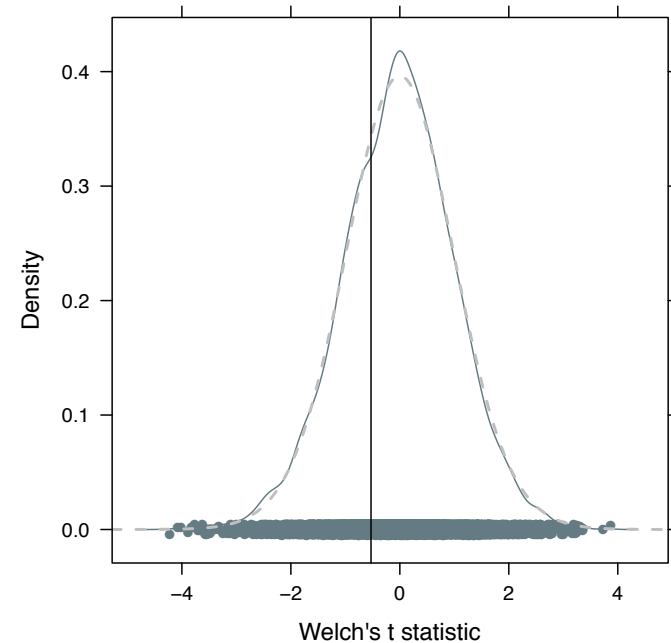
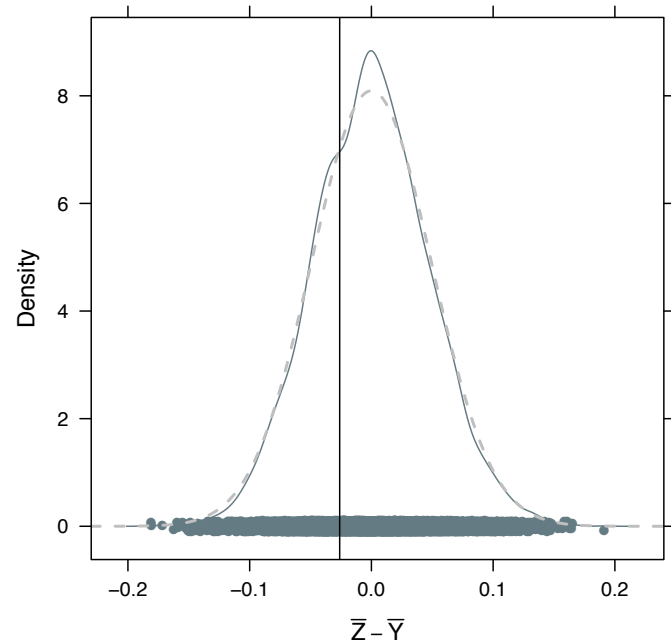
... and many many
more *in silico*
repeats of this
experiment ...

Here's the observed difference in
sample means, the Welch's t
statistic, and the associated p-value
from the first 6 *in silico* datasets:

	smDiff	tStat	pVal
1	-0.049219079	-1.1866161	0.2449818
2	-0.012561184	-0.2422272	0.8099760
3	-0.063784868	-1.2212680	0.2298243
4	0.028180921	0.7100104	0.4827649
5	0.008151974	0.1881476	0.8525778
6	0.018928289	0.4349598	0.6661791



Empirical distribution of 10,000 observations, under the null of equal means, of the difference in sample means (left) and Welch's two sample t statistic (right). Overlaid w/ normal / t theoretical distributions (dashed line). Sample mean difference and t statistic from the real Irs4 data showed w/ vertical line.



Let's sanity check the canned p-values. What proportion of these sample mean differences or Welch statistics are as or more extreme than what we observed?

```
miniDat$gene: Irs4
```

```
Welch Two Sample t-test
```

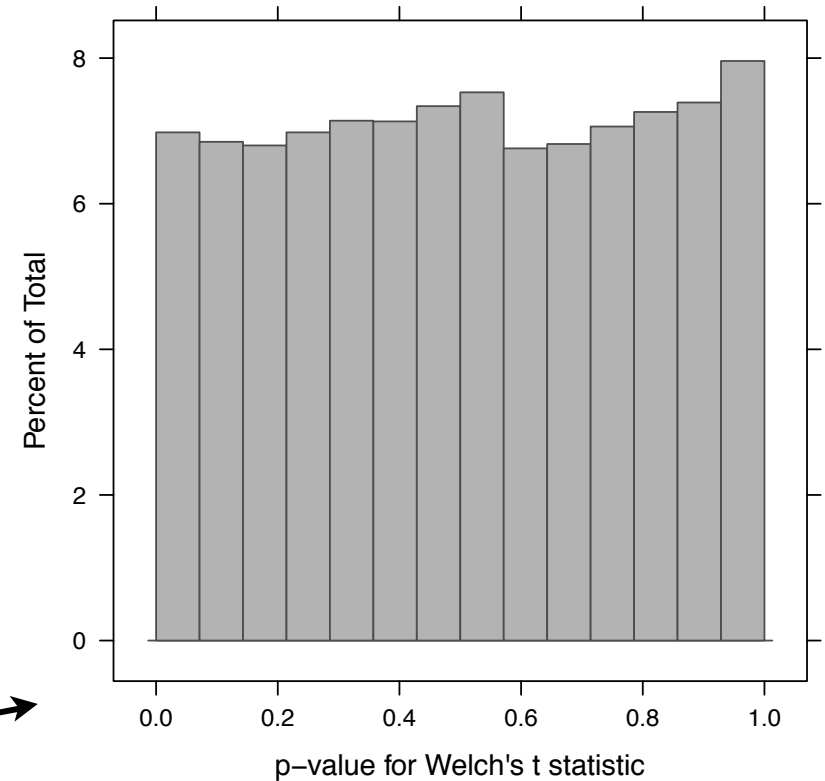
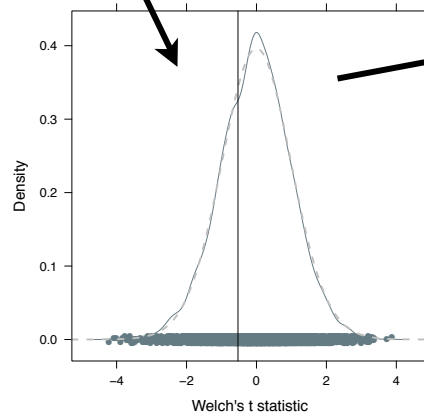
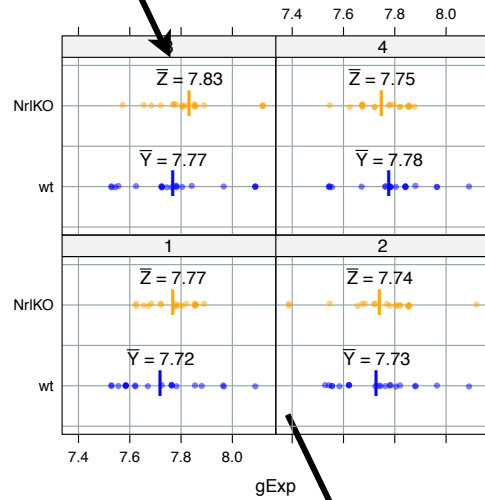
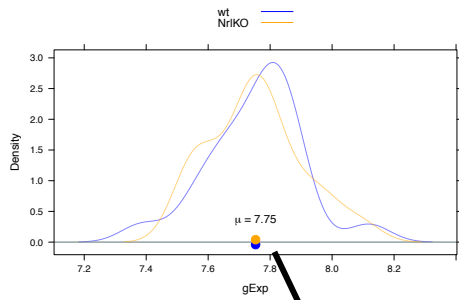
```
data: gExp by gType
```

```
t = 0.5289, df = 36.948, p-value = 0.6001
```

```
> mean(abs(bootTestStats$tStat) >= abs(welchStat))
[1] 0.5942
```

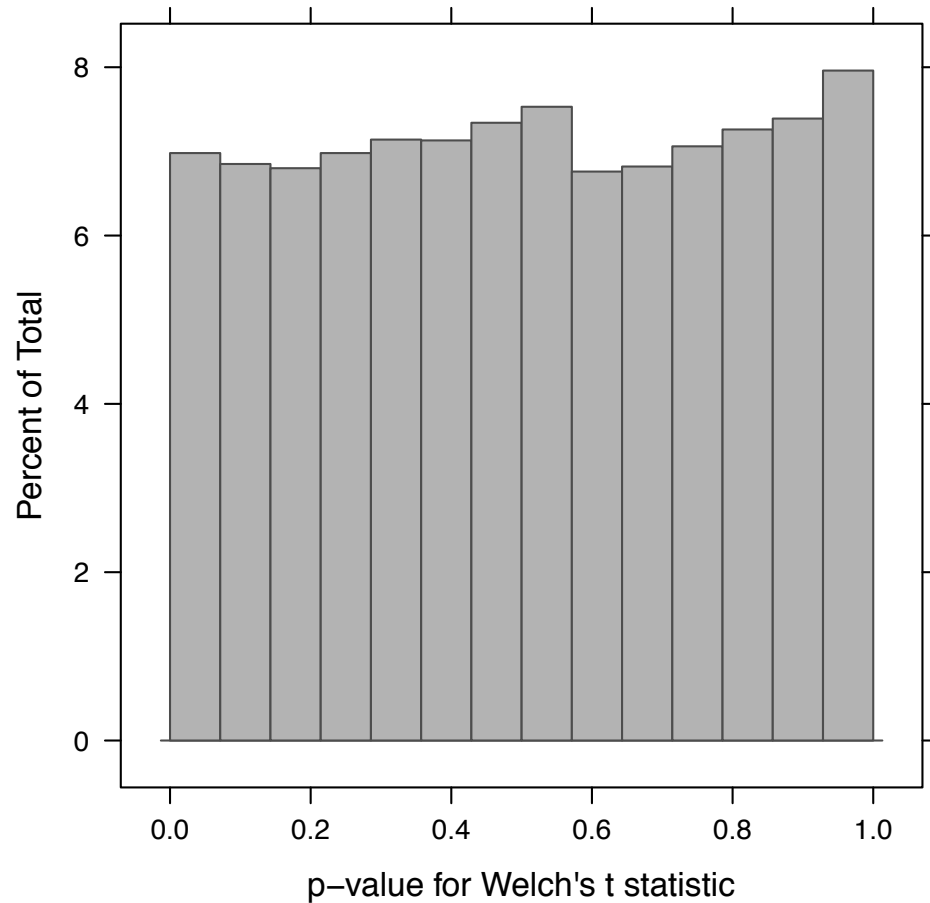
```
> mean(abs(bootTestStats$smDiff) >= abs(theDiff))
[1] 0.5818
```

Pretty bang on!



What does the distribution of the p-values look like when the null hypothesis holds?

What does the distribution of the p-values look like when the null hypothesis holds?



$$V(\bar{X}_n - \bar{Y}_n) = \frac{\sigma_X^2}{n_X} + \frac{\sigma_Y^2}{n_Y}$$

True variance of difference of sample means depends on the underlying variance of the data and the sample sizes.

$$\hat{V}(\bar{X}_n - \bar{Y}_n) = \text{"pooled"} \hat{\sigma}^2 \left[\frac{1}{n_X} + \frac{1}{n_Y} \right] \text{ assuming } \sigma_X^2 = \sigma_Y^2$$

$$\hat{V}(\bar{X}_n - \bar{Y}_n) = \hat{\sigma}_{\bar{X}_n - \bar{Y}_n}^2 = \frac{s_X^2}{n_X} + \frac{s_Y^2}{n_Y} \text{ assuming } \sigma_X^2 \neq \sigma_Y^2$$

Sample variance is used to estimate it.

$$T = \frac{\bar{X}_n - \bar{Y}_n}{\hat{\sigma}_{\bar{X}_n - \bar{Y}_n}} \quad \text{Under } H_0, T \sim t_{n_X + n_Y - 2} \text{ or } t_{\text{<sthg ugly>}}$$

What if the underlying variance could be reduced dramatically?

Less variance means same apparent effect is much more statistically significant.

```
> with(lDat,  
+       by(lDat, sigStat, function(yo) {  
+         t.test(obs ~ rv, yo)  
+       })))
```

sigStat: big

Welch Two Sample t-test

data: obs by rv

t = 0.7314, df = 58, p-value = 0.4675

<snip, snip>

sample estimates:

mean in group x	mean in group y
0.1269433	-0.0618942

sigStat: small

Welch Two Sample t-test

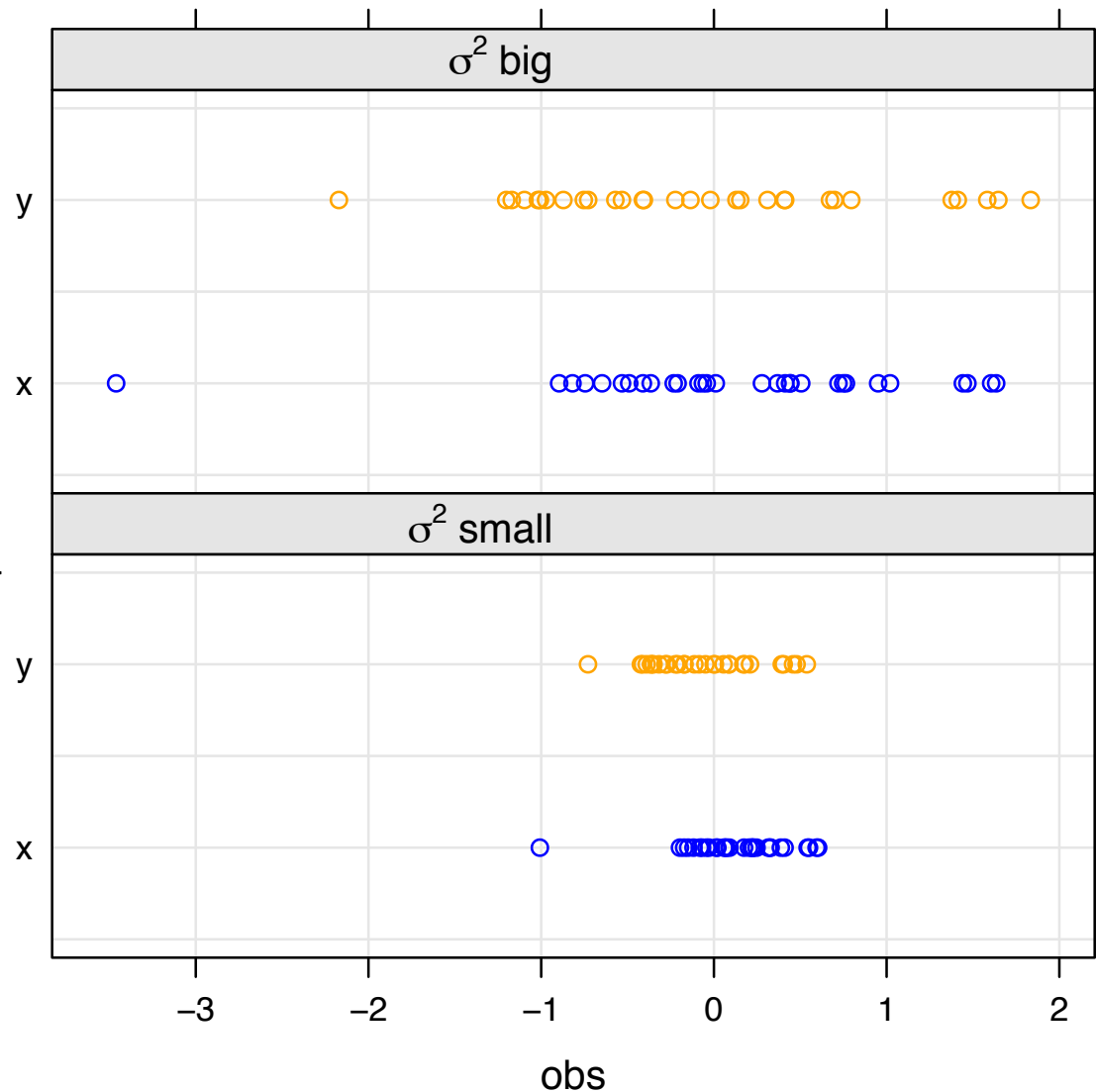
data: obs by rv

t = 2.3128, df = 58, p-value = 0.02430

<snip, snip>

sample estimates:

mean in group x	mean in group y
0.1269433	-0.0618942



note: using simulated data not seen yet today

$$V(\bar{X}_n - \bar{Y}_n) = \frac{\sigma_X^2}{n_X} + \frac{\sigma_Y^2}{n_Y}$$

True variance of difference of sample means depends on the underlying variance of the data and the sample sizes.

$$\hat{V}(\bar{X}_n - \bar{Y}_n) = \text{"pooled"} \hat{\sigma}^2 \left[\frac{1}{n_X} + \frac{1}{n_Y} \right] \text{ assuming } \sigma_X^2 = \sigma_Y^2$$

$$\hat{V}(\bar{X}_n - \bar{Y}_n) = \hat{\sigma}_{\bar{X}_n - \bar{Y}_n}^2 = \frac{s_X^2}{n_X} + \frac{s_Y^2}{n_Y} \text{ assuming } \sigma_X^2 \neq \sigma_Y^2$$

Note that sample sizes appear in denominators throughout.

$$T = \frac{\bar{X}_n - \bar{Y}_n}{\hat{\sigma}_{\bar{X}_n - \bar{Y}_n}} \quad \text{Under } H_0, T \sim t_{n_X + n_Y - 2} \text{ or } t_{\text{<sthg ugly>}}$$

What if the sample size gets cut way down?

Smaller sample means same apparent effect is much less statistically significant.*

```
> with(mDat,  
+       by(mDat, n, function(yo) {  
+         t.test(obs ~ rv, yo)  
+       })))  
n: big
```

Welch Two Sample t-test

data: obs by rv

t = 0.7314, df = 58, p-value = 0.4675

<snip, snip>

sample estimates:

mean in group x	mean in group y
0.1269433	-0.0618942

n: small

Welch Two Sample t-test

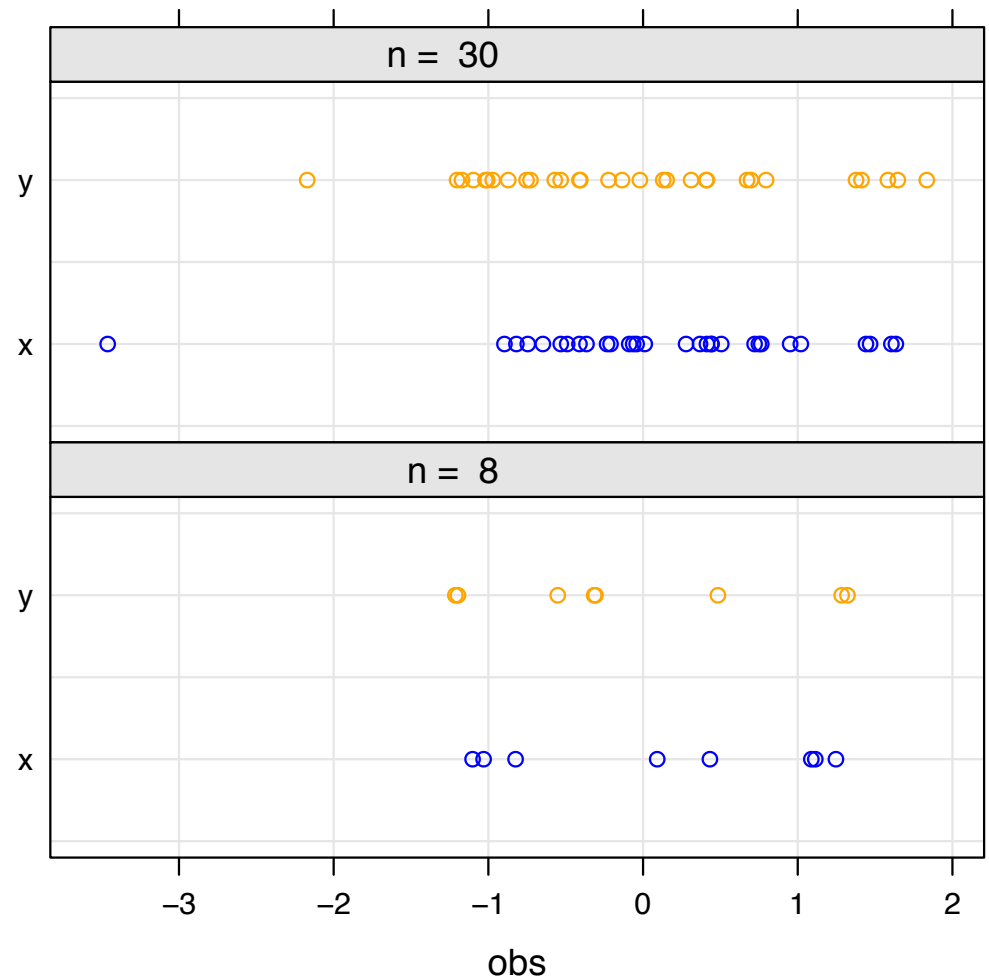
data: obs by rv

t = 0.3777, df = 14, p-value = 0.7113

<snip, snip>

sample estimates:

mean in group x	mean in group y
0.1269433	-0.0618942



* I also held the sample variance constant here.

What if you don't wish to assume the underlying data is normally distributed AND you aren't sure your samples are large enough to invoke CLT?

What are alternatives to the t test?

First, one could use the t test statistic but use a bootstrap approach to obtain statistical significance. Later lecture on this. Plus, we basically demonstrated that today.

Alternatively, there are nonparametric tests that are available here:

Wilcoxon rank sum test, aka Mann Whitney, uses ranks

Kolmogorov-Smirnov uses the empirical CDF

Wilcoxon test

Rank all the data, ignoring the grouping variable

Test stat = sum of the ranks for one group
(optionally, subtract the minimum possible which
is $n_Y (n_Y + 1)/2$)

(Alternative but equivalent formulation based on
the number of y_i, z_i pairs for which $y_i \geq z_i$)

Null distribution of such statistics can be
worked out or approximated

```
miniDat$gene: Irs4
```

Wilcoxon rank sum test with continuity correction

```
data: gExp by gType
W = 220.5, p-value = 0.3992
alternative hypothesis: true location shift is not equal to 0
```

```
miniDat$gene: Nrl
```

Wilcoxon rank sum test with continuity correction

```
data: gExp by gType
W = 379, p-value = 1.178e-07
alternative hypothesis: true location shift is not equal to 0
```

```
miniDat$gene: Irs4
```

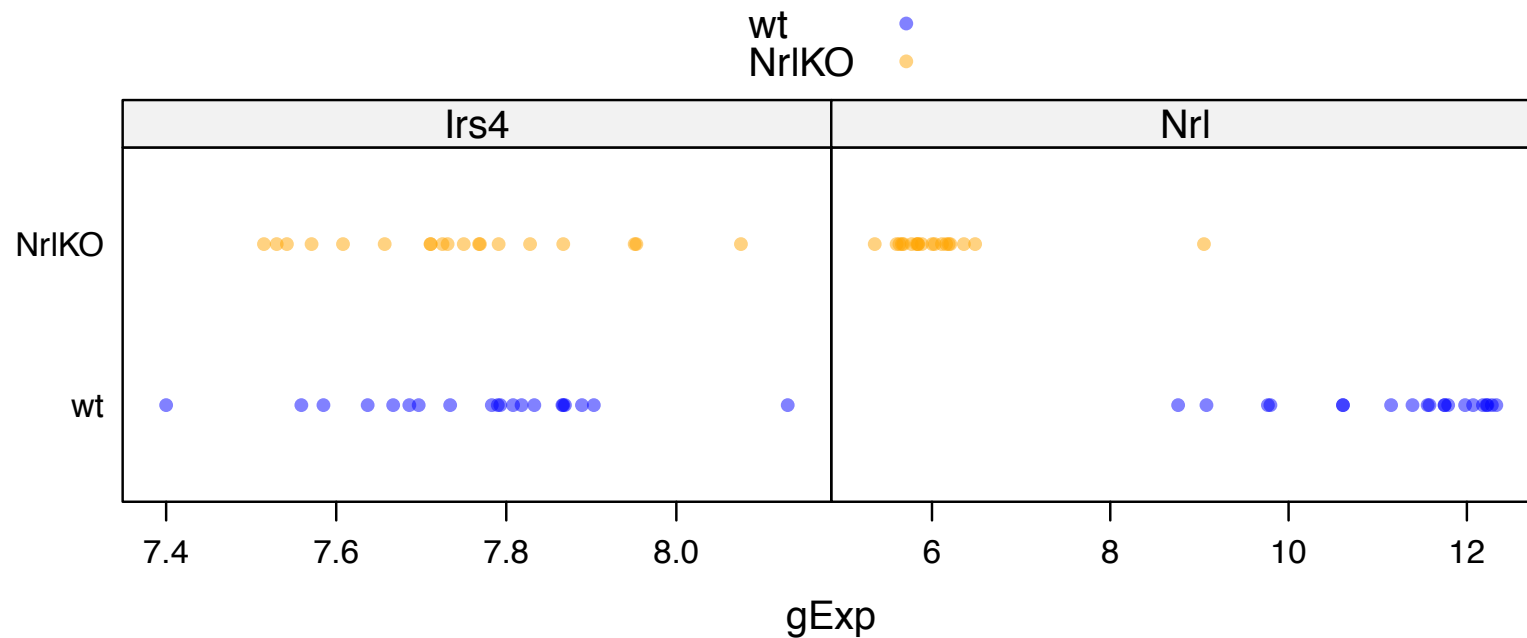
Welch Two Sample t-test

```
data: gExp by gType
t = 0.5289, df = 36.948, p-value = 0.6001
<snip, snip>
```

```
miniDat$gene: Nrl
```

Welch Two Sample t-test

```
data: gExp by gType
t = 16.9486, df = 34.005, p-value < 2.2e-16
<snip, snip>
```



Kolmogorov-Smirnov test (two sample)

Null hypothesis: $F = G$, i.e. distributions are same

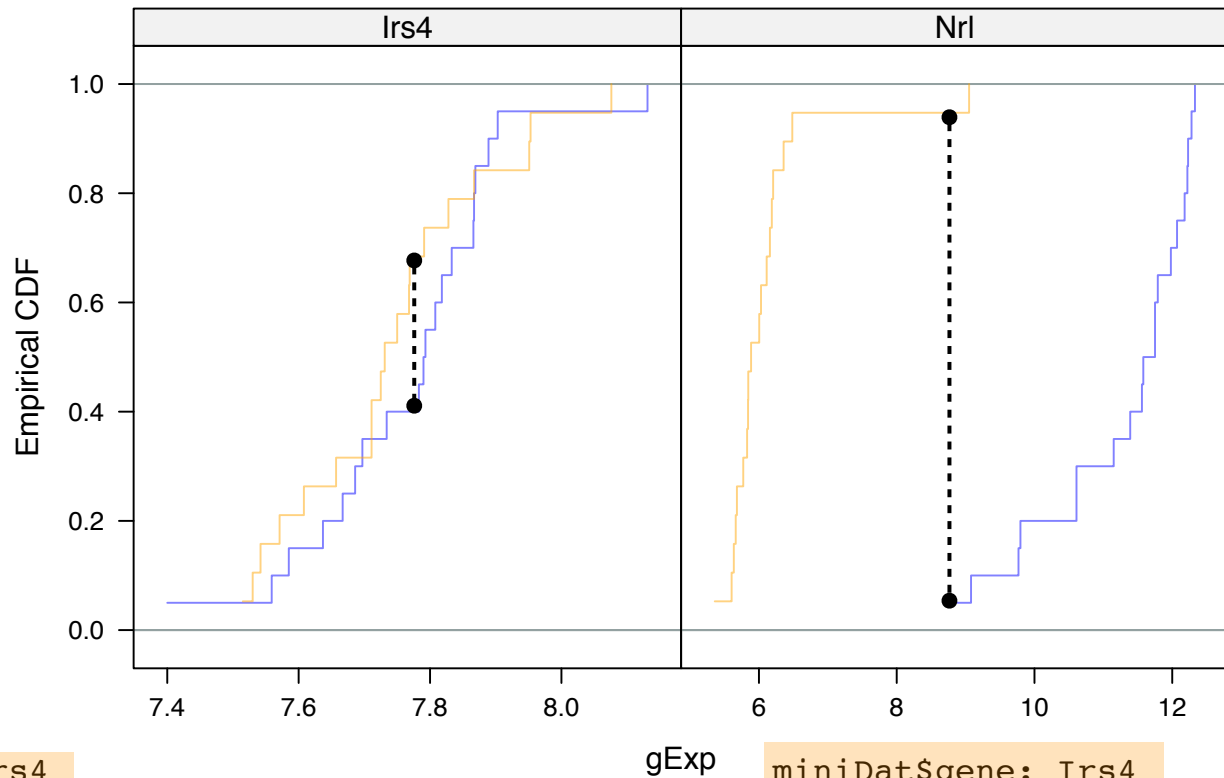
Estimate each CDF with the empirical CDF (ECDF)

$$\hat{F}(x) = \frac{1}{n} \sum_i I[x_i \leq x]$$

Test statistic is the maximum of the absolute difference between the ECDFs

$$\max |\hat{F}(x) - \hat{G}(x)|$$

Null distribution does not depend on F, G (!)
(I'm suppressing detail here.)



miniDat\$gene: Irs4

gExp

miniDat\$gene: Irs4

Two-sample Kolmogorov-Smirnov test

data: theDat\$gExp[theDat\$gType == "wt"] and theDat\$gExp[theDat\$gType == "NrlKO"]

D = 0.2842, p-value = 0.4107

alternative hypothesis: two-sided

Welch Two Sample t-test

data: gExp by gType

t = 0.5289, df = 36.948, p-value = 0.6001

<snip, snip>

miniDat\$gene: Nrl

Two-sample Kolmogorov-Smirnov test

data: theDat\$gExp[theDat\$gType == "wt"] and theDat\$gExp[theDat\$gType == "NrlKO"]

D = 0.95, p-value = 4.603e-08

alternative hypothesis: two-sided

miniDat\$gene: Nrl

Welch Two Sample t-test

data: gExp by gType

t = 16.9486, df = 34.005, p-value < 2.2e-16

<snip, snip>

Errors in hypothesis testing

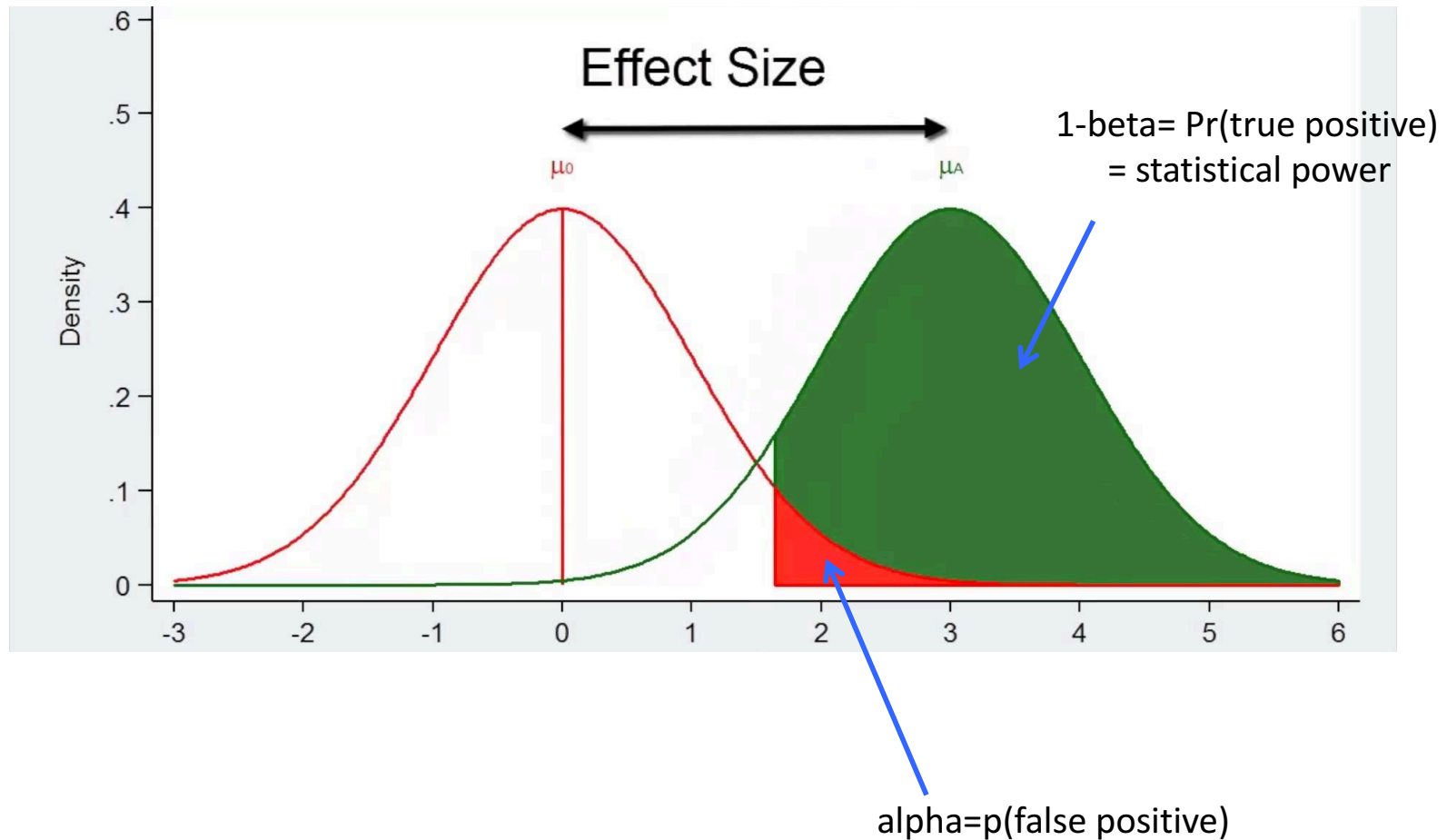
		Actual Situation "Truth"	
Decision		H_0 True	H_0 False
Don Not Reject H_0		Correct Decision $1-\alpha$	Incorrect Decision Type II Error β
	Reject H_0	Incorrect Decision Type I Error α	Correct Decision $1-\beta$

$\alpha = P(\text{Type I Error})$ $\beta = P(\text{Type II Error})$

Power = $1 - \beta$

Statistical power

The probability that your experiment will generate data (a result) that is convincing enough to lead you to reject the null hypothesis



Statistical Power

- Power must be low when H_0 is true
 - Think about it...
- Power will be higher when
 - The true difference is larger
 - The sample size is larger
 - The within-group variability is smaller