# Cornerstone hypothesis tests: T and $\chi^2$ !

#### Review

- 1. Functions
- 2. Z-Tests
- 3. Integrating Power, Z-Tests, and Functions

## Today

- 1. One Sample T-Tests
- 2. The  $\chi^2$  test
- 3. Discussion: Are you a Neo-Fischerian?

#### Enter the Z-Test

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We call it a Z-Score because we correct by the standard error based on a known POPULATION standard deviation.

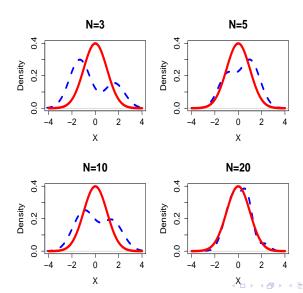


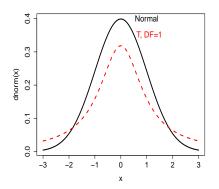
#### William "Student" Gosset

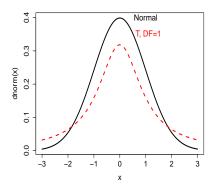
- Quality control often works with small samples
- Small samples are seldom normal
- ► AND we rarely know the TRUE population SD



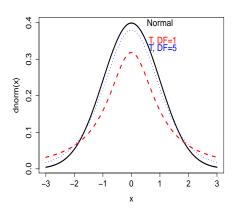
R. A. Fisher







DF = Degrees of Freedom = Sample Size - # of Estiamted Parameters For t, this is n-1



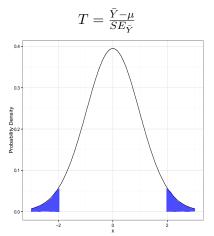
#### T Versus Z

$$Z = \frac{\bar{Y} - \mu}{\sigma / \sqrt{n}}$$

$$T = \frac{\bar{Y} - \mu}{s / \sqrt{n}}$$

- ► For T, we calculate the sample standard error
- ▶ T is more useful if < 30 samples

#### Exercise: Gimme a T (function)



Write a oneSampleT function using pt(). Write a SE function, too. Challenge: make it return additional information of your choice.

#### Exercise: Gimme a T (function)

```
#SE first
se <- function(sample) sd(sample) / (sqrt(length(sample)))
#now T
oneSampleT <- function(sample, mu=0){
   t <- (mean(sample) - mu) / se(sample)

2 * pt(abs(t), df=length(sample)-1, lower.tail=F)
}</pre>
```

#### Exercise: Gimme a T (function)

```
samp<-rnorm(50, 1)</pre>
t.test(samp)
  One Sample t-test
# data: samp
# t = 5.25, df = 49, p-value = 3.264e-06
# alternative hypothesis: true mean is not equal to 0
# 95 percent confidence interval:
# 0.4985 1.1167
# sample estimates:
# mean of x
    0.8076
oneSampleT(samp)
# [1] 3.264e-06
```

#### Extensions of the One-Sample T-test

$$T = \frac{\bar{Y} - \mu}{s / \sqrt{n}}$$

- When values represent differences between paired treatments, this is a paired T-test
- Often used to assess whether a parameter is different from 0
- $\blacktriangleright$  If  $\bar{Y}$  is the difference between two means, s and n become pooled
- Pooling involves a variety of formulae accommodating differences in SE and N



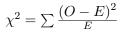
► Test Goodness of fit between observed and expected values

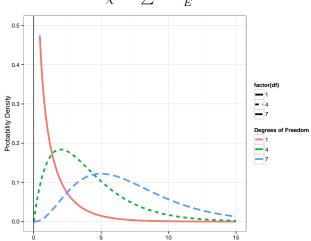
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- ► Test **Goodness of fit** between observed and expected values
- If there is no difference, deviations should be normally distributed noise
- ▶ Summing up + and differences is problematic so we square!
- ▶ The square of a normal distribution is the  $\chi^2$  distribution!
- ▶ The  $\chi^2$  is defined by degrees of freedom = n-1!





When would you use a  $\chi^2$  test?



## Assumptions of the $\chi^2$

- 1. No expected values less that 1
- 2. 80% of the expected values must be >5

What happens if I violate the assumptions? Combine categories or use a different test.

The number of tomato plants that failed due to disease in a farm should follow a negative binomial distribution in any given year with 2 plants dying and an overdispersion parameter of 5. Famer Dale seeded tomato plants in 100 different plots. Looking across his field, he finds the following pattern of mortality.

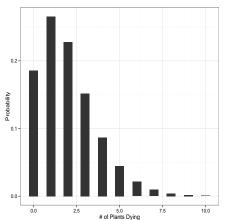
0 plants died: 9 plots 1 plants died: 23 plots 2 plants died: 22 plots 3 plants died: 18 plots 4 plants died: 19 plots >4 plants died: 9 plots

Was this an anomolously bad year?



#### What are our Expectations?

Negative Binomial with a  $\mu$  of 2 and dispersion parameter of 5.



```
100*dnbinom(0:4, mu=2, size=5)

# [1] 18.593 26.562 22.767 15.178 8.673

100*(pnbinom(4, mu=2, size=5, lower.tail=FALSE))

# [1] 8.225
```

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100*(pnbinom(4, mu=2, size=5, lower.tail=FALSE))

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```

0 plants died: 9 plots, 18.59 expected 1 plants died: 23 plots, 26,56 expected 2 plants died: 22 plots, 22.77 expected 3 plants died: 18 plots, 15.17 expected 4 plants died: 19 plots, 8.67 expected >4 plants died: 9 plots, 8.23 expected

```
observed \leftarrow c(9,23,22,18,19,9)
expected < c(100*dnbinom(0:4, mu=2, size=5),
              100*(pnbinom(4, mu=2, size=5, lower.tail=FALSE)))
chisq<-sum((observed-expected)^2/expected)</pre>
chisq
# [1] 18.35
pchisq(chisq, df=6-1, lower.tail=FALSE)
# [1] 0.002543
```

#### Extensions of the $\chi^2$ test

$$\chi^2 = \sum \frac{(O-E)^2}{E}$$

- Modification for small sample size
- Exact tests (e.g., Fisher's Exact) to look at exact predictions of probabilities
- ► Goodness of fit to evaluate whether we have a good model