



PGE 338 Data Analytics and Geostatistics

Lecture 7b: Confidence Intervals and Hypothesis Testing

Lecture outline . . .

- Concepts
- Analytical Hypothesis Testing
- Bootstrap Hypothesis Testing
- Examples

Introduction

General Concepts

Univariate

PDF / CDF

Statistics

Distributions

Heterogeneity

Hypothesis

Bivariate

Time Series Analysis

Spatial Analysis

Machine Learning

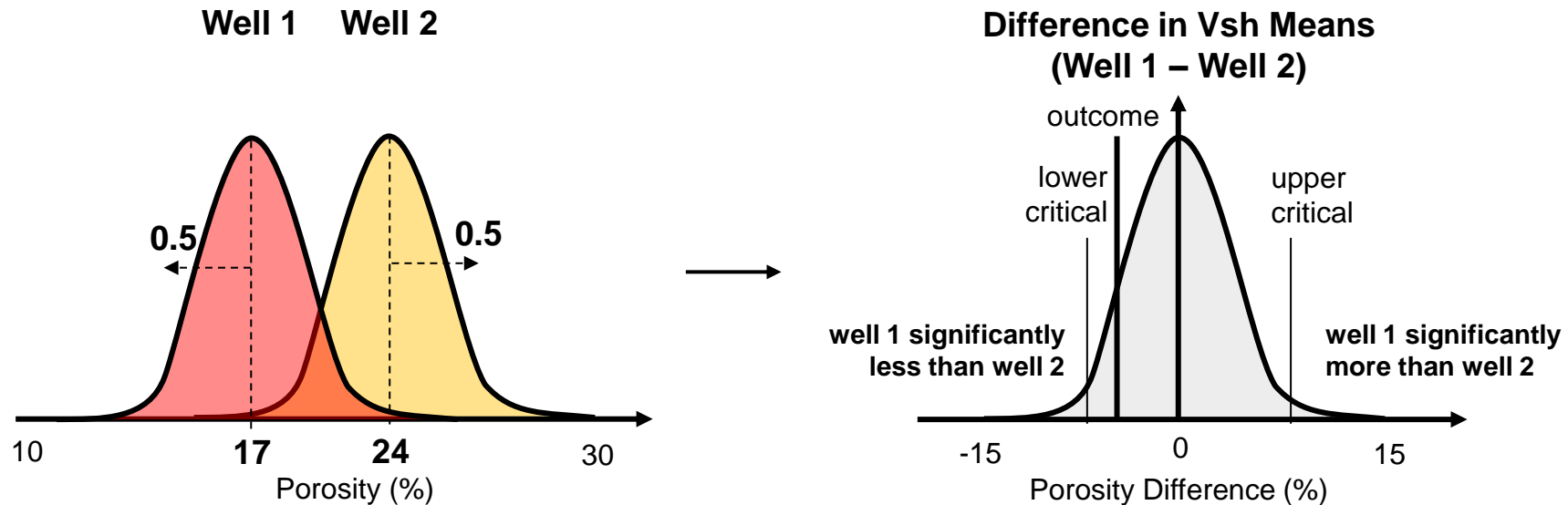
Uncertainty Analysis



Motivation

We need to report uncertainty and significance!

- Otherwise, we do not know if any of our results are meaningful.



Average fraction of shale uncertainty models that appear to be different (left), but is that different significant (right).

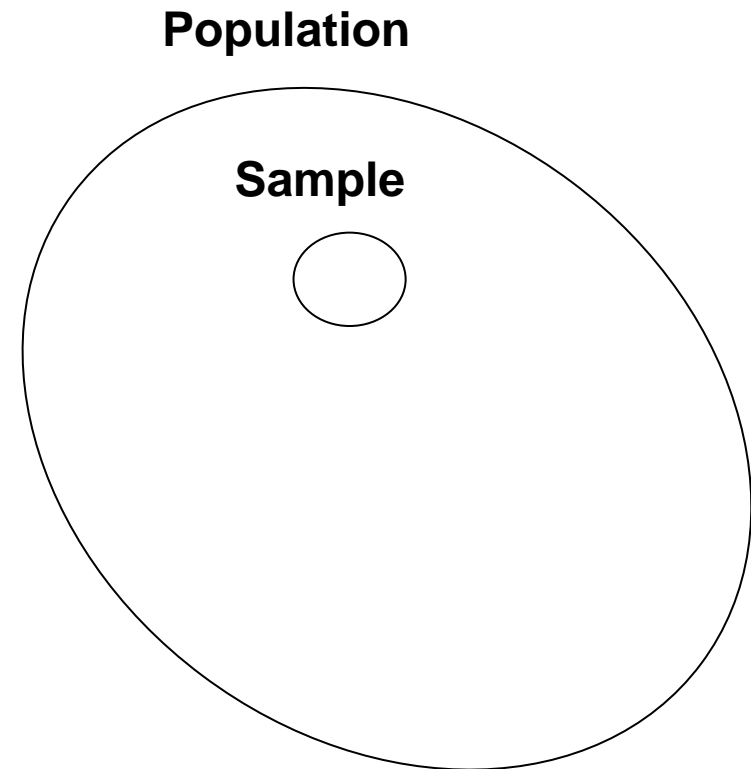
- For example, are these wells from the same reservoir?



Review of Nomenclature

Recall our Nomenclature for sample statistics and population parameters.

	Sample	Population
proportion	\hat{p}	p
mean	\bar{x}	μ
standard deviation	s	σ
variance	s^2	σ^2





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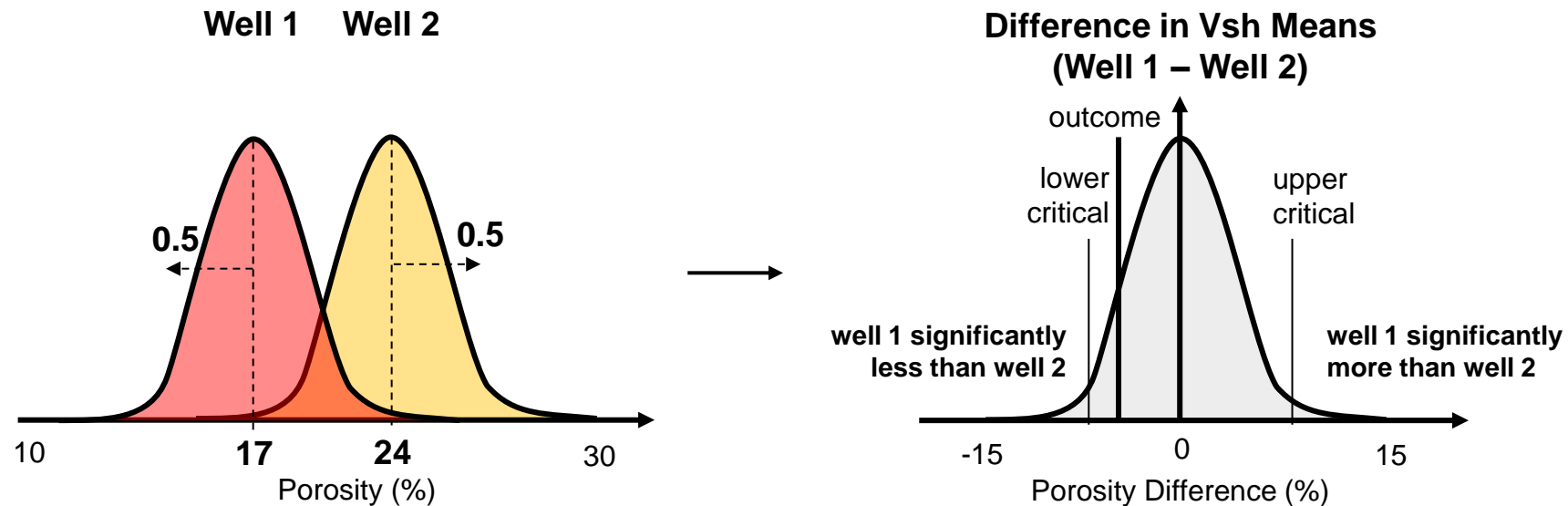
Uncertainty Analysis



From Confidence Intervals to Hypothesis Testing

Confidence Intervals are Useful – Error in your Measure!

- What about this situation? Two measures with error, did they come from the same population?



Average porosity uncertainty models that appear to be different (left), but is that difference significant (right).

- Impact:** Is the new offset well drilling through the same type of rock as the previous wells? If so, let's use our previously optimized completion method. If not, we have to determine new completion parameters. This may delay and increase cost of additional drilling.
- This is hypothesis testing.** e.g. Our metric and the theoretical distribution is the difference in means of samples.



Hypothesis Testing

Definitions and Design

- **Hypothesis:** A statement about a population parameter
- **Method:** start by accepting the null hypothesis, H_0 , and then test it.
- **Null Hypothesis (H_0) and Alternative Hypothesis (H_1)** are two complementary hypotheses in a hypothesis testing problem
 - H_0 – no effect, e.g. means are the same, one is not larger, difference due to limited samples and random effect
 - H_1 – a significant difference, the effect we are checking for
- **Sampling Distributions** are the theoretical distributions given the null hypothesis is true.
 - **Student's t-test, Independent 2-sample:** Compares the means of two sample sets
 - **F-test of equality of 2 variances:** Compares the variances of two sample sets
 - **Chi-Square test:** Compares entire histograms of two sample sets
- **Result:**
 - **Reject the null hypothesis**, evidence to support the alternative hypothesis H_1
 - **Fail to reject the null hypothesis**, retain the null hypothesis, H_0
- **Error Types:**
 - **Type 1 error:** incorrectly rejecting the null hypothesis (false positive)
 - **Type 2 error:** incorrectly retaining the null hypothesis (false negative)

↳ hypothesis lives to fight another day



Hypothesis Testing Example Designs

Example Hypotheses

Collected data from a new well. Does this new data come from the same population as the previous wells or is there a geological discontinuity?

- Test if the means are the same between the new data and the old data.

$H_0: \mu_n = \mu_p$, the well data is from the same population as the previous wells.

$H_1: \mu_n \neq \mu_p$, the well is from a different population than the previous wells.

Applied a new lab measurement for permeability from core data. Does the new method result in consistent amount of permeability variance?

- Test if the variance is the same between the two methods.

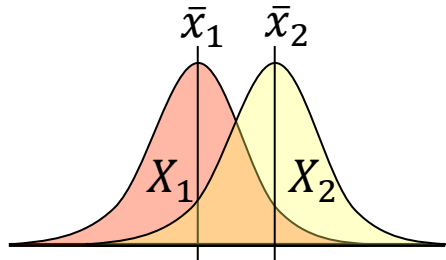
$H_0: \sigma_{m1}^2 = \sigma_{m2}^2$, the permeability variance of the two methods is the same.

$H_1: \sigma_{m1}^2 \neq \sigma_{m2}^2$, the permeability variance of the two methods is different.



Hypothesis Testing Difference in Means

$$H_0: \mu_1 = \mu_2$$
$$H_1: \mu_1 \neq \mu_2$$



Given 2 samples are the means significantly different?

Method:

1. Calculate test statistic, e.g., t-statistic, \hat{t} , (measure, $\bar{x}_1 - \bar{x}_2$, divided by the standard error), in *standard deviation, from the null hypothesis*.
2. Look up the critical value, e.g., $t_{critical}$, from a table or a function, *confidence level interval in standard deviations based on alpha and degrees of freedom*. t-dist mean is 0.0.
3. Compare the test statistic to the critical value, e.g.:

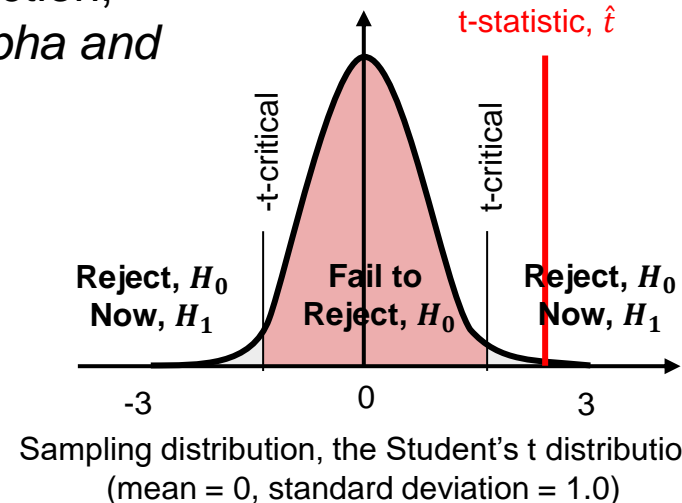
Fail to reject H_0 if $-t_{critical} < \hat{t} < t_{critical}$
Reject H_0 if $\hat{t} < -t_{critical}$ or $\hat{t} > t_{critical}$

Confidence Level
↓

Degrees of freedom

	90%	95%	99%
	Tail area probability, α		
df	0.05	0.025	0.005
1	6.314	12.706	63.657
2	2.920	4.303	9.925
3	2.353	3.182	5.841
4	2.132	2.776	4.604
5	2.015	2.571	4.032
6	1.943	2.447	3.707
7	1.895	2.365	3.499
8	1.860	2.306	3.355
9	1.833	2.262	3.250
10	1.812	2.228	3.169
11	1.796	2.201	3.106
12	1.782	2.179	3.055
13	1.771	2.160	3.012
14	1.761	2.145	2.977
15	1.753	2.131	2.947
16	1.746	2.120	2.921
18	1.734	2.101	2.878
20	1.725	2.086	2.845
22	1.717	2.074	2.819
24	1.711	2.064	2.797
26	1.706	2.056	2.779
28	1.701	2.048	2.763
30	1.697	2.042	2.750
40	1.684	2.021	2.704
60	1.671	2.000	2.660
∞	1.645	1.960	2.576

$t_{critical}$ table from
Jensen et al., (2000).





Hypothesis Testing Difference in Means

Test: is well 1 in better rock than well 2 (by average porosity)?

One Tail Test:

$H_0: \mu_1 \leq \mu_2$, the well 1 average porosity is less than or equal to the well 2 average porosity.

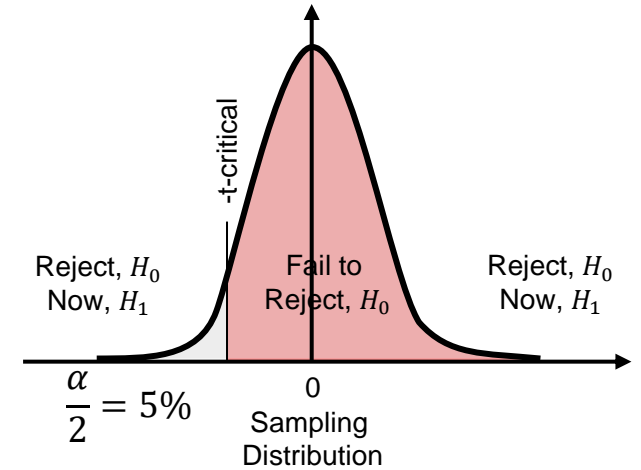
$H_1: \mu_1 > \mu_2$, the well 1 average porosity is greater than well 2 average porosity.

Test: are wells 1 and 2 in different rock (according to average porosity)?

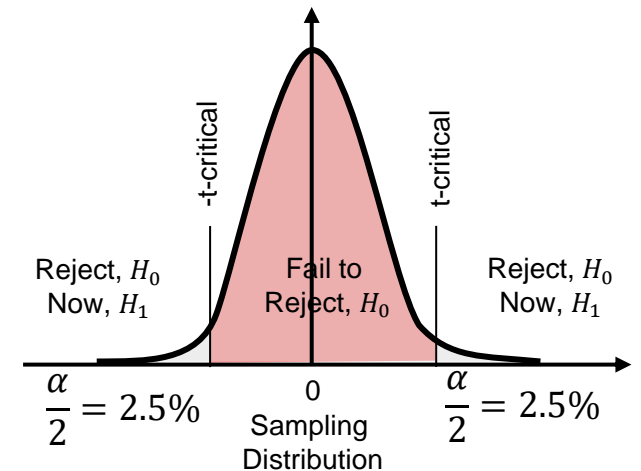
Two Tail Test:

$H_0: \mu_1 = \mu_2$, the well 1 & 2 average porosity are the same.

$H_1: \mu_1 \neq \mu_2$, the well 1 & 2 average porosity are the different.



One tail test at alpha = 0.05.

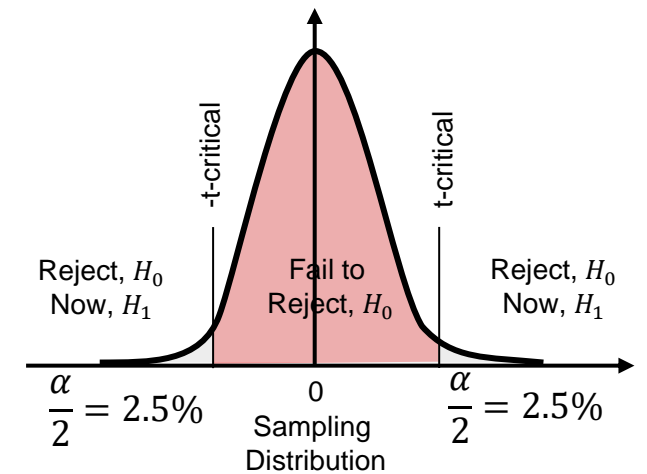
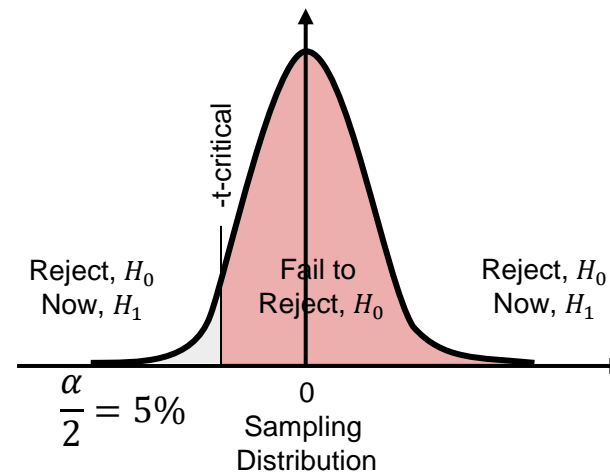


Two tail test at alpha = 0.05.



Hypothesis Testing Difference in Means

One tail test at $\alpha = 0.05$.



Two tail test at $\alpha = 0.05$.



Limitations of Hypothesis Testing

Limitations of Hypothesis Testing:

- Publication Bias – only publish results that reject the null
 - Recall, α probability of false positive
 - Data mining for any effect will find insignificant differences that look significantly different (by random)
 - Many studies have selectively reported significant results
- Very small sample sizes, poorly understood phenomenon
 - Can't demonstrate conformity with the test assumptions
- Other Data Issues, Poor Sampling Practice
 - Contamination of sample 'clever Hans effect'
 - Placebo effect, impact of subject motivation

Due to these there is some mistakes and skepticism concerning the use of hypothesis testing in publications.



Clever Hans, the horse that could do math in the early 1900s.



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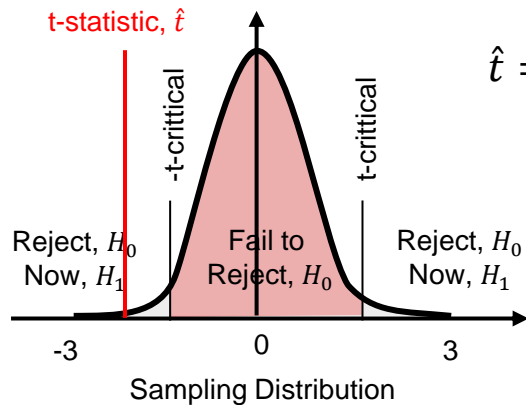


Hypothesis Testing Difference in Means

The Student's t-test, equal variances, pooled variance method (William Gosset, 1876-1937)

The t-statistic is:

The Pooled Variance Test in Python: `SciPy.stats.ttest_ind(X1,X2)`



$$\hat{t} = \frac{|\bar{x}_1 - \bar{x}_2|}{\sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right) \left(\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}\right)}} = \frac{\text{measure}}{\text{standard error}} = t \text{ statistic}, \hat{t}$$

$$t_{critical} = \left| t\left(\frac{\alpha}{2}, n_1 + n_2 - 2\right) \right|$$

Cumulative probability

Degrees of freedom

$\alpha = 1.0 - \text{confidence level}$

Alpha level

Excel `t.inv($\frac{\alpha}{2}, n_1 + n_2 - 2$)`

Python `SciPy.stats.t.ppf($\frac{\alpha}{2}, n_1 + n_2 - 2$)`

If $-t_{critical} < \hat{t} < t_{critical}$ then we fail to reject the null hypothesis. Our current hypothesis remains that there is no difference between the means.

We can get the $t_{critical}$ value from our \hat{t} and d.f. using a table or a calculator (<http://www.statisticshowto.com/t-score-formula/>), see Excel `t.inv` or Python `SciPy.stats.t.ppf` functions.

This method assumes that the **variables are Gaussian distributed**, and the **standard deviations are not significantly different**.



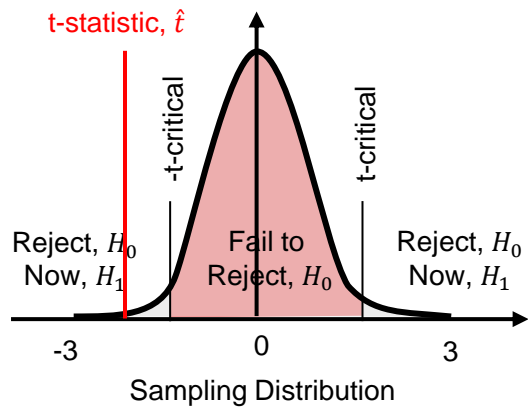
Hypothesis Testing Difference in Means

The Student's t-test for unequal variances, Welch's t-test (Bernard Welch, 1911-1989)

The Welch's t-test in Python: `SciPy.stats.ttest_ind(X1,X2,equal_var=False)`

The t statistic is:

$\alpha = 1.0 - \text{confidence level}$



$$\hat{t} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)}} = \frac{\text{measure}}{\text{standard error}} = t \text{ statistic}, \hat{t}$$
$$t_{critical} = \left| t\left(\frac{\alpha}{2}, \nu\right) \right|$$

Alpha level Degrees of freedom

$$\nu = \frac{\left(\frac{1}{n_1} + \frac{1}{n_2}\right)^2}{\frac{1}{n_1^2(n_1 - 1)} + \frac{1}{n_2^2(n_2 - 1)}}$$
$$u = \frac{s_2^2}{s_1^2}$$

If $-t_{critical} < \hat{t} < t_{critical}$ then we fail to reject the null hypothesis. Our current hypothesis remains that there is no difference between the means.

We can get the $t_{critical}$ value from our \hat{t} and d.f. using a table or a calculator (<http://www.statisticshowto.com/t-score-formula/>), see Excel `t.inv` or Python `SciPy.stats.t.ppf` functions.

This method assumes that the variables are Gaussian distributed, and variances are unequal. Welch's t-test.



Hypothesis Testing Difference in Means

Example #1 Hypothesis Test for Difference in Means, Equal Variance Method

The Problem:

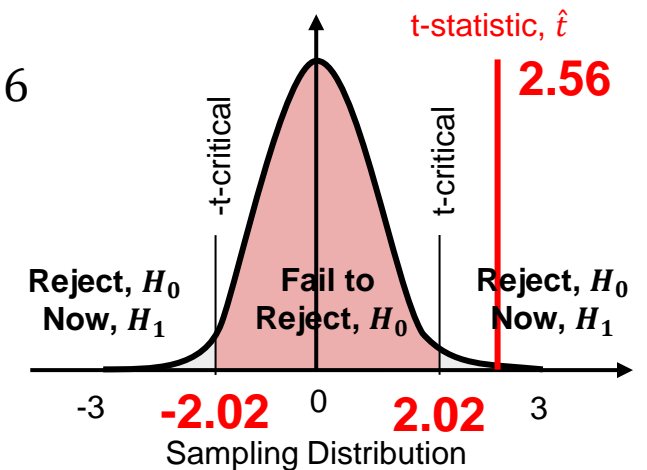
- Well 1 (20 samples, mean porosity = 13%, st. dev. = 2%)
- Well 2 (25 samples, mean porosity = 15%, st. dev. = 3%)
- At a 95% confidence level ($\alpha = 0.05$) test $H_0: \mu_1 = \mu_2$

Recall:

$\text{Alpha} = 1 - \text{Confidence Level}$

$$\text{t-statistic } \hat{t} = \frac{\text{Measure } |13\% - 15\%|}{\text{SE } \sqrt{\left(\frac{1}{20} + \frac{1}{25}\right) \left(\frac{(20-1)4 + (25-1)9}{20 + 25 - 2}\right)}} = \frac{2}{0.78} = 2.56$$

$$\text{t-critical } t_{critical} = \left| t\left(\frac{0.05}{2}, 20 + 25 - 2\right) \right| = \pm 2.02$$



If $\hat{t} = 2.56$ is outside interval $-2.02 < \hat{t} < 2.02$; therefore, we **reject the null hypothesis**. We adopt the alternative hypothesis that $H_1: \mu_1 \neq \mu_2$

If the means are significantly different, then the distributions are significantly different, and we are drilling potentially new rock.



Hypothesis Testing Difference in Means

Example #2 Hypothesis Test for Difference in Means, Equal Variance Method

The Problem:

- Determine if the two data sets came from the same reservoir unit. Compare the two sets of sample for porosity uploaded on Canvas website (data set PorositySample2Units.xlsx).
- At a 95% confidence level ($\alpha = 0.05$) test $H_0: \mu_1 = \mu_2$
- Use pooled variance method.

$$\hat{t} = \frac{|\bar{x}_1 - \bar{x}_2|}{\sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right) \left(\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}\right)}}$$

$$t_{critical} = \left| t\left(\frac{\alpha}{2}, n_1 + n_2 - 2\right) \right|$$

$t_{critical} \rightarrow \text{T.INV.2T}(\alpha, n_1 + n_2 - 2)$ or $\text{T.INV}(\alpha/2, n_1 + n_2 - 2)$ in Excel.



Hypothesis Testing Difference in Means

Example #2 Hypothesis Test for Difference in Means, Equal Variance Method

The Problem:

- Determine if the two data sets came from the same reservoir unit. Compare the two sets of sample for porosity uploaded on Canvas website (data set PorositySample2Units.xlsx).
- At a 95% confidence level ($\alpha = 0.05$) test $H_0: \mu_1 = \mu_2$
- Use pooled variance method.

$$\hat{t} = \frac{|0.16 - 0.20|}{\sqrt{\left(\frac{1}{20} + \frac{1}{20}\right) \left(\frac{(20-1)0.0008 + (20-1)0.0021}{20+20-2}\right)}} = 2.981$$

$$t_{critical} = \left| t\left(\frac{0.05}{2}, 20+20-2\right) \right| = \pm 2.02$$

Result:

Reject $H_0: \mu_1 = \mu_2$

Adopt $H_1: \mu_1 \neq \mu_2$

\therefore 2 different reservoir units.



Hypothesis Testing

Difference in Means in Excel

Example #3 Hypothesis Test for Difference in Means, Equal Variance & Welch's Methods

The Problem:

- set up in an Excel sheet for any dataset. It calculates the sample statistics and completes the test.

A. Pooled t procedure

1. Sample Statistics		3. Calculate t_{stat} and $t_{critical}$		4. Check criteria	
X1	mean: 0.08 st. dev: 1.22 count: 105	Measure: 0.20 Standard Error: 0.19	t_{stat} : 1.09 $t_{critical}$: 1.97	$-t_{critical}$: -1.971 t_{stat} : 1.092 $t_{critical}$: 1.971	
X2	mean: -0.12 st. dev: 1.47 count: 105				
2. Specify Alpha Level				5. Evaluate p-value.	
Level: 0.05				p-value: 27.59%	

B. Unequal variances

1. Sample Statistics		3. Calculate t_{stat} and $t_{critical}$		4. Check criteria	
X1	mean: 0.08 st. dev: 1.22 count: 105	Measure: 0.20 Standard Error: 0.19	t_{stat} : 1.09 $t_{critical}$: 1.97	$-t_{critical}$: -1.972 t_{stat} : 1.092 $t_{critical}$: 1.972	
X2	mean: -0.12 st. dev: 1.47 count: 105	F : 1.43 dof : 5.43E-04 n : 201.3			
2. Specify Alpha Level				5. Evaluate p-value.	
Level: 0.05				p-value: 27.59%	

Difference in means hypothesis test demonstration in Excel, file is Difference_in_means.xlsx.



Hypothesis Testing Difference in Means in Python

Hypothesis Test for Difference in Means, Equal Variance & Welch's Methods

The Problem:

- Difference in means hypothesis tests in Python



Data Analytics

Confidence Intervals and Hypothesis Testing in Python in Python

Michael Pyrcz, Associate Professor, The University of Texas at Austin

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This is a tutorial / demonstration of **Confidence Intervals and Hypothesis Testing in Python**. In Python, the SciPy package, specifically the Stats functions (<https://docs.scipy.org/doc/scipy/reference/stats.html>) provide excellent tools for efficient use of statistics.

I have previously provided these examples worked out by-hand in Excel (https://github.com/GeostatsGuy/LectureExercises/blob/master/Lecture7_CI_Hypoth_eg_R.xlsx) and also in R (https://github.com/GeostatsGuy/LectureExercises/blob/master/Lecture7_CI_Hypoth_eg_R). In all cases, I use the same dataset available as a comma delimited file (<https://git.io/fxLA4>).

This tutorial includes basic, typical confidence interval and hypothesis testing methods that would commonly be required for Engineers and Geoscientists including:

1. Student-t confidence interval for the mean and proportion
2. Student-t hypothesis test for difference in means (pooled variance)
3. Student-t hypothesis test for difference in means (difference variances), Welch's t Test
4. F-distribution hypothesis test for difference in variances

Caveats

I have not included all the details, specifically the test assumptions in this document. These are included in the accompanying course notes, [Lec08_hypothesis.pdf](#).

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import scipy.stats as stats
```

```
1 df = pd.read_csv('https://raw.githubusercontent.com/GeostatsGuy/GeoDataSets/master/PorositySample2Units.csv')
2 X1 = df['X1'].values; X2 = df['X2'].values
```

```
1 alpha = 0.05
2 t_critical = stats.t.ppf(alpha/2, len(X1)+len(X2)-2)
3
4 t_pooled, p_pooled = stats.ttest_ind(X1, X2) # assuminng equal variance
5 if(t_pooled < t_critical or t_pooled > -1*t_critical):
6     print('t-critical and t-statistic are ' + str(np.round(t_critical,2)) + ' ≤ ' + str(np.round(t_pooled,2)) +
7         ' ≤ ' + str(np.round(-1*t_critical,2)) + '; therefore, reject the null hypothesis')
8 else:
9     print('t-critical and t-statistic are ' + str(np.round(t_critical,2)) + ' ≤ ' + str(np.round(t_pooled,2)) +
10         ' ≤ ' + str(np.round(-1*t_critical,2)) + '; therefore, fail to reject the null hypothesis')
```

t-critical and t-statistic are -2.02 ≤ -2.98 ≤ 2.02; therefore, reject the null hypothesis

```
1 alpha = 0.05
2 t_critical = stats.t.ppf(alpha/2, len(X1)+len(X2)-2)
3
4 t_welch, p_welch = stats.ttest_ind(X1, X2, equal_var = False) # assuminng unequal variance, Welch's t-test
5 if(t_welch < t_critical or t_welch > -1*t_critical):
6     print('t-critical and t-statistic are ' + str(np.round(t_critical,2)) + ' ≤ ' + str(np.round(t_welch,2)) +
7         ' ≤ ' + str(np.round(-1*t_critical,2)) + '; therefore, reject the null hypothesis')
8 else:
9     print('t-critical and t-statistic are ' + str(np.round(t_critical,2)) + ' ≤ ' + str(np.round(t_welch,2)) +
10         ' ≤ ' + str(np.round(-1*t_critical,2)) + '; therefore, fail to reject the null hypothesis')
```

t-critical and t-statistic are -2.02 ≤ -2.98 ≤ 2.02; therefore, reject the null hypothesis

Short Python demonstration with PorositySample2Units dataset.

Difference in means hypothesis test demonstration in Python, file is PythonDataBasics_ConfidenceInterval_HypothesisTesting.xlsx.



Hypothesis Testing Difference in Variances

The F-test for Difference in Variance (Snedecor and Cochran, 1989)

- Compares variances of two distributions
 - Example: comparison of the heterogeneity of two samples sets (e.g., from 2 wells) to determine if the wells have different heterogeneity

Requirements:

- The sample and population distributions are of both samples are Gaussian, but at 5% alpha with similar number of samples it is robust if non-normal (not Gaussian distributed).

The test:

- **Null hypothesis**, $H_0: \sigma_2^2 / \sigma_1^2 = 1.0$, where $\sigma_2^2 > \sigma_1^2$. The data comes from independent random samples from normal distributions with equal variances
- **Alternative hypothesis**, $H_1: \sigma_2^2 / \sigma_1^2 > 1.0$: The data comes from populations with unequal variances



Hypothesis Testing Difference in Variances

The F-test (Snedecor and Cochran, 1989)

- The F-test statistic

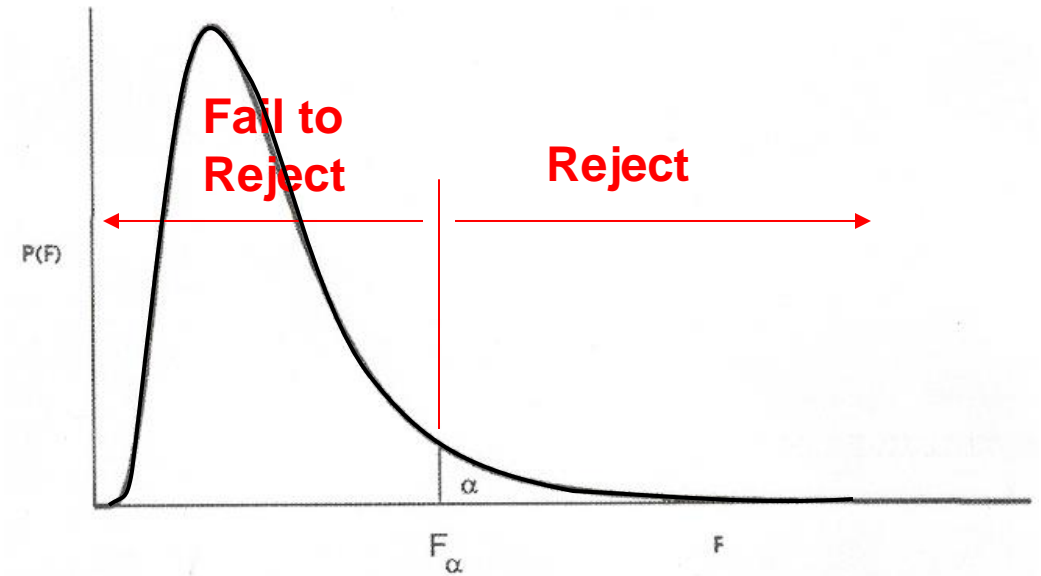
$$\hat{F} = \frac{s_a^2}{s_b^2} \quad \text{where } s_a^2 > s_b^2$$

if $\hat{F} < F_{critical}$ then we fail to reject H_0 and state that the two variances are not significantly different.

$$F_{critical} = f(n_a - 1, n_b - 1, \alpha)$$

Degrees of Freedom

Alpha Level



F-distribution with reject and fail to reject regions.



Hypothesis Testing Difference in Variances

How to calculate the $F_{critical}$ values?

- A table of $F_{critical}$ at a specific α level.
- Excel - `F.INV(1- α , $n_a - 1$, $n_b - 1$)`
- Python - `scipy.stats.f.ppf(1- α , $n_a - 1$, $n_b - 1$)`,

F		Degrees of Freedom in the Numerator																			
$\alpha = 0.05$		1	2	3	4	5	6	7	8	9	10	12	15	20	25	30	40	50	100	200	1000
Degrees of Freedom in the Denominator	1	161.4	199.5	215.7	224.6	230.2	234.0	236.8	238.9	240.5	241.9	243.9	245.9	248.0	249.3	250.1	251.1	251.8	253.0	253.7	254.2
	2	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38	19.40	19.41	19.43	19.45	19.46	19.46	19.47	19.48	19.49	19.49	19.49
	3	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81	8.79	8.74	8.70	8.66	8.63	8.62	8.59	8.58	8.55	8.54	8.53
	4	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00	5.96	5.91	5.86	5.80	5.77	5.75	5.72	5.70	5.66	5.65	5.63
	5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77	4.74	4.68	4.62	4.56	4.52	4.50	4.46	4.44	4.41	4.39	4.37
	6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10	4.06	4.00	3.94	3.87	3.83	3.81	3.77	3.75	3.71	3.69	3.67
	7	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68	3.64	3.57	3.51	3.44	3.40	3.38	3.34	3.32	3.27	3.25	3.23
	8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39	3.35	3.28	3.22	3.15	3.11	3.08	3.04	3.02	2.97	2.95	2.93
	9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18	3.14	3.07	3.01	2.94	2.89	2.86	2.83	2.80	2.76	2.73	2.71
	10	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02	2.98	2.91	2.85	2.77	2.73	2.70	2.66	2.64	2.59	2.56	2.54
	12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80	2.75	2.69	2.62	2.54	2.50	2.47	2.43	2.40	2.35	2.32	2.30
	15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59	2.54	2.48	2.40	2.33	2.28	2.25	2.20	2.18	2.12	2.10	2.07
	20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39	2.35	2.28	2.20	2.12	2.07	2.04	1.99	1.97	1.91	1.88	1.85
	25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28	2.24	2.16	2.09	2.01	1.96	1.92	1.87	1.84	1.78	1.75	1.72
	30	4.17	3.32	2.92	2.69	2.53	2.42	2.33	2.27	2.21	2.16	2.09	2.01	1.93	1.88	1.84	1.79	1.76	1.70	1.66	1.63
	40	4.08	3.23	2.84	2.61	2.45	2.34	2.25	2.18	2.12	2.08	2.00	1.92	1.84	1.78	1.74	1.69	1.66	1.59	1.55	1.52
	50	4.03	3.18	2.79	2.56	2.40	2.29	2.20	2.13	2.07	2.03	1.95	1.87	1.78	1.73	1.69	1.63	1.60	1.52	1.48	1.45
	100	3.94	3.09	2.70	2.46	2.31	2.19	2.10	2.03	1.97	1.93	1.85	1.77	1.68	1.62	1.57	1.52	1.48	1.39	1.34	1.30
	200	3.89	3.04	2.65	2.42	2.26	2.14	2.06	1.98	1.93	1.88	1.80	1.72	1.62	1.56	1.52	1.46	1.41	1.32	1.26	1.21
	1000	3.85	3.00	2.61	2.38	2.22	2.11	2.02	1.95	1.89	1.84	1.76	1.68	1.58	1.52	1.47	1.41	1.36	1.26	1.19	1.11

Table to look up $F_{critical}$ values at $\alpha = 0.05$.



Hypothesis Testing Difference in Variances

Example #1 Hypothesis Test for Difference in Variance

The Problem:

- Are the variances different for well 1 and well 2 at $\alpha = 0.05$?
- Variance: well 1 variance = $4\%^2$ with 20 samples, well 2 variance = $9\%^2$ with 25 samples

$$\hat{F} = \frac{9}{4} = 2.25$$

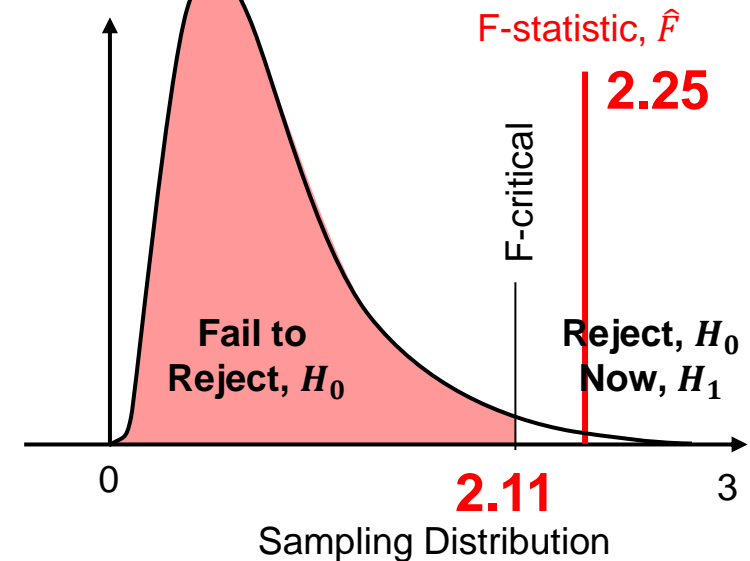
if $\hat{F} \leq F_{critical}$ then we fail to reject H_0 and state that the two variances are not significantly different.

$$F_{critical} = f(25 - 1, 20 - 1, 0.05) = 2.11$$

Degrees of Freedom

Significant Level

$\hat{F} > F_{critical}$, Reject H_0 , variances are significantly different.





Hypothesis Testing Difference in Variances

Example #2 Hypothesis Test for Difference in Variance

The Problem:

- Determine if the two data sets came from the same reservoir unit. Compare the two sets of sample for porosity uploaded on Canvas website (dataset PorositySample2Units.xlsx).
- Are the variances significantly different at a 95% confidence level?

$$\hat{F} = \frac{s_a^2}{s_b^2} \quad \text{where} \quad s_a^2 > s_b^2$$

$$F_{critical} = f(n_a - 1, n_b - 1, \alpha)$$

if $\hat{F} < F_{critical}$ then we fail to reject H_0 and state that the two variances are not significantly different.



Hypothesis Testing Difference in Variances in Python

Hypothesis Test for Difference in Variance

The Problem:

- Determine if the two data sets came from the same reservoir unit. Compare the two sets of sample for porosity uploaded on Canvas website (dataset PorositySample2Units.xlsx).
- Are the variances significantly different at a 95% confidence level?



Data Analytics

Confidence Intervals and Hypothesis Testing in Python in Python

Michael Pircz, Associate Professor, The University of Texas at Austin

[Twitter](#) | [GitHub](#) | [Website](#) | [Google Scholar](#) | [Book](#) | [YouTube](#) | [LinkedIn](#)

This is a tutorial / demonstration of **Confidence Intervals and Hypothesis Testing in Python**. In Python, the SciPy package, specifically the Stats functions (<https://docs.scipy.org/doc/scipy/reference/stats.html>) provide excellent tools for efficient use of statistics.

I have previously provided these examples worked out by-hand in Excel (https://github.com/GeostatsGuy/LectureExercises/blob/master/Lecture7_CI_Hypoth_eg_R.xlsx) and also in R (https://github.com/GeostatsGuy/LectureExercises/blob/master/Lecture7_CI_Hypoth_eg_R). In all cases, I use the same dataset available as a comma delimited file (<https://git.io/fxLA4>).

This tutorial includes basic, typical confidence interval and hypothesis testing methods that would commonly be required for Engineers and Geoscientists including:

1. Student-t confidence interval for the mean and proportion
2. Student-t hypothesis test for difference in means (pooled variance)
3. Student-t hypothesis test for difference in means (difference variances), Welch's t Test
4. F-distribution hypothesis test for difference in variances

Caveats

I have not included all the details, specifically the test assumptions in this document. These are included in the accompanying course notes, Lec08_hypothesis.pdf.

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import scipy.stats as stats
```

```
1 df = pd.read_csv('https://raw.githubusercontent.com/GeostatsGuy/GeoDataSets/master/PorositySample2Units.csv')
2 X1 = df['X1'].values; X2 = df['X2'].values
```

```
1 var_X1 = np.var(X1); var_X2 = np.var(X2)
2 f_stat = np.max([var_X1, var_X2]) / np.min([var_X1, var_X2])
3 if var_X1 > var_X2:
4     f_critical = stats.f.ppf(1-alpha, len(X1)-1, len(X2)-1)
5 else:
6     f_critical = stats.f.ppf(1-alpha, len(X2)-1, len(X2)-1)
7 if f_stat > f_critical:
8     print('f-statistic and f-critical are ' + str(np.round(f_stat,2)) + ' > ' + str(np.round(f_critical,2))
9         + '; therefore, reject the null hypothesis')
10 else:
11     print('f-statistic and f-critical are ' + str(np.round(f_stat,2)) + ' ≤ ' + str(np.round(f_critical,2))
12         + '; therefore, fail to reject the null hypothesis')
```

f-statistic and f-critical are 2.67 > 2.17; therefore, reject the null hypothesis

Short Python demonstration with PorositySample2Units dataset.

Difference in means hypothesis test demonstration in Python, file is PythonDataBasics_ConfidenceInterval_HypothesisTesting.xlsx.



Hypothesis Testing Difference in Variances in Excel

Hypothesis Test for Difference in Variance

The Problem:

- Determine if the two data sets came from the same reservoir unit. Compare the two sets of samples for porosity variance in dataset Porosity2Units.xlsx.
- Spreadsheet is 'Difference_in_variances_demo.xls'

f-test for difference in variances

1. Sample Statistics

X1

mean	0.16
var	0.00077
count	20

X2

mean	0.20
var	0.0021
count	20

2. Specify Alpha Level

Level 0.05

3. Calculate f_{stat} and $f_{critical}$

fstat	2.67	$F_{0.05, N_1-1, N_2-1}$
fcritical	2.17	
P(F<=f) one tail	1.92%	

4. Check criteria

f_{stat}		$f_{critical}$	Test
2.668	<	2.168	$F > F_{0.05, N_1-1, N_2-1}$

H1: Reject the null hypothesis.

5. Evaluate p-value.

p-value 1.92% < 5.0%

Reject if probability is less than confidence level.

6. Check with EXCEL built-in F-test

p-value 1.92%

Difference in variance hypothesis test demonstration in Excel, file is Difference_in_variance.xlsx.



Hypothesis Testing

Comparing Two Distributions

The Chi-Square Test (Karl Pearson, 1900)

- Compares two distributions
- Test the entire distribution, not just the mean or variance!
- Apply to any distribution
- **Null hypothesis:** The two distributions are the same
- **Alternative hypothesis:** The two distributions are different
- Commonly applied to see if a sample distribution matches an 'expected' theoretical distribution, e.g., is the data histogram Gaussian?



Hypothesis Testing

Comparing Two Distributions

The Chi-Square Test for Difference in Histograms (Karl Pearson, 1900)

- n data are grouped in K classes (n should be above 30)
- The appropriate test statistic is:

$$\hat{\chi}^2 = \sum_{i=1}^K \frac{(O_i - E_i)^2}{E_i}$$

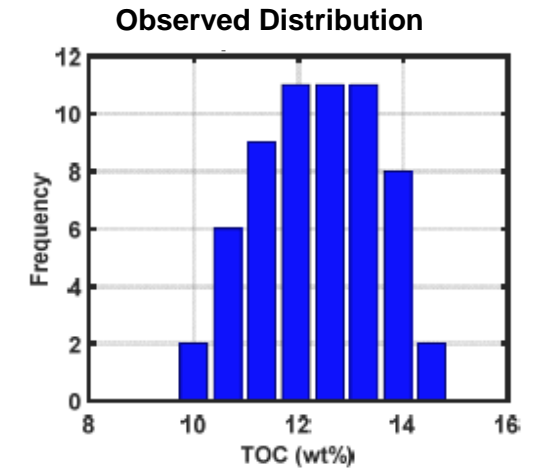
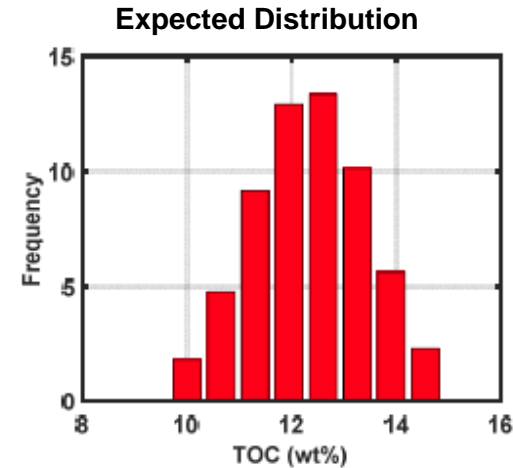
Observed Frequency

Expected Frequency

$$\hat{\chi}^2_{critical} \rightarrow \hat{\chi}^{2-1}(1 - \alpha, K - 3)$$

if $\hat{\chi}^2 < \hat{\chi}^2_{critical}$, fail to reject the null hypothesis.
The two distributions are not significantly different.

if $\hat{\chi}^2 > \hat{\chi}^2_{critical}$, reject the null hypothesis two histograms are significantly different.



Expected and observed histograms, with the same bins for comparison of frequencies.

Degrees of Freedom

$$\phi = K - Z$$

of parameters + 1, e.g., for Gaussian $Z = 3$.

number of classes (number of histogram bins)



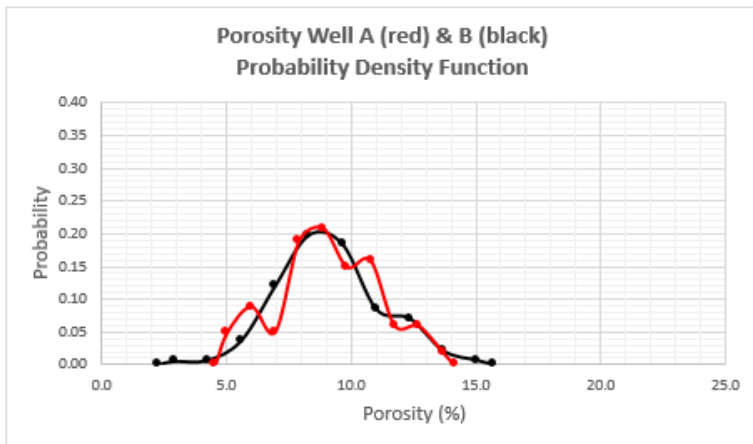
Hypothesis Testing

Comparing Two Distributions

Example #1 Chi-Square Test for Difference in Histograms

The Problem:

- compare 2 histograms in the Excel spreadsheet, Q-Qplot_Chi_Sq_Demo.xlsx, that calculates:
 1. *stochastic realizations of two porosity distributions*
 2. *Q-Q plot*
 3. *Chi Square test*



Two normalized histograms. Note, should be a bar chart.

Chi-Square Test for Difference In Distributions

min	2.2
max	15.7

Bins	2.24	3.59	4.94	6.29	7.63	8.98	10.33	11.68	13.03	14.38
	3.59	4.94	6.29	7.63	8.98	10.33	11.68	13.03	14.38	15.72
Freq A	0	1	6	16	28	24	18	9	3	0
Freq B	1	0	6	17	28	26	12	10	3	2
(A-B)^2/B	1.0		0.0	0.1	0.0	0.2	3.0	0.1	0.0	2.0

Degrees of Freedom	nbins	9	Φ	6
--------------------	-------	---	--------	---

Chi-Square Test Result	H_0 :	χ^2	6.3	<	$\chi^2_{critical}$	12.6	Fail to Reject
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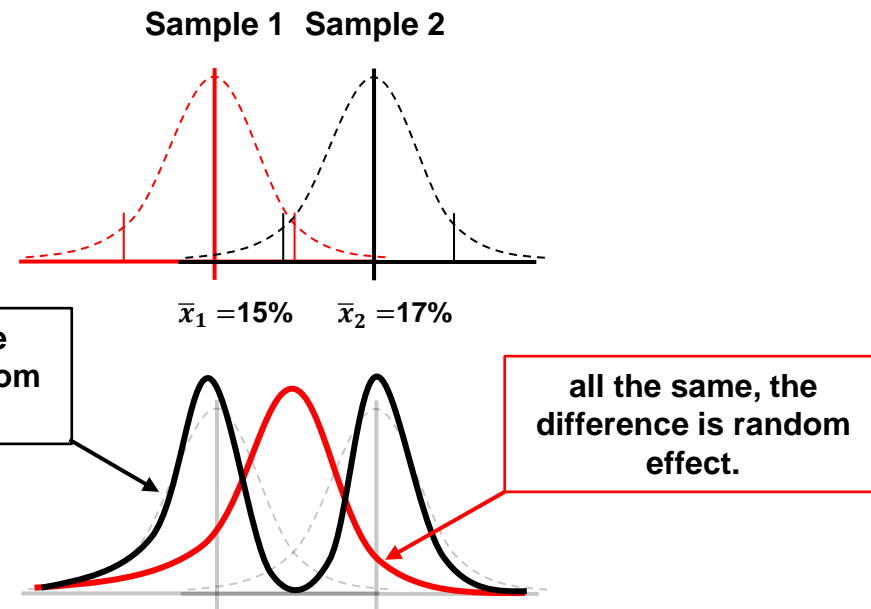
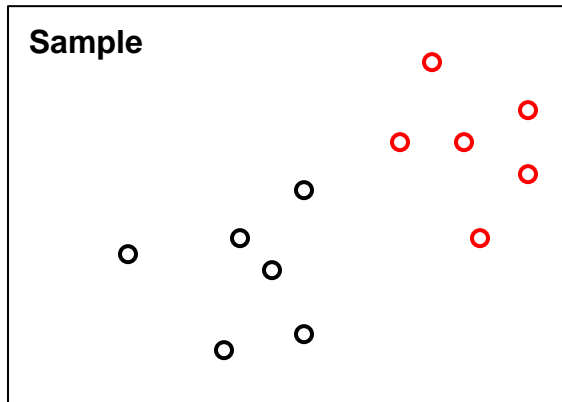
Calculation steps for Chi-Square test for difference in histograms.



Hypothesis Testing Take 2

The Problem:

- You have 2 datasets (1 and 2), did they come from the same population?
- If you had 2 datasets from the same population. They could look different!



- There is structure in random!



Hypothesis Testing Take 2

The Problem:

- Belief in the law of small numbers

Psychological Bulletin
1971, Vol. 76, No. 2, 105-110

BELIEF IN THE LAW OF SMALL NUMBERS

AMOS TVERSKY AND DANIEL KAHNEMAN¹

Hebrew University of Jerusalem

People have erroneous intuitions about the laws of chance. In particular, they regard a sample randomly drawn from a population as highly representative, that is, similar to the population in all essential characteristics. The prevalence of the belief and its unfortunate consequences for psychological research are illustrated by the responses of professional psychologists to a questionnaire concerning research decisions.

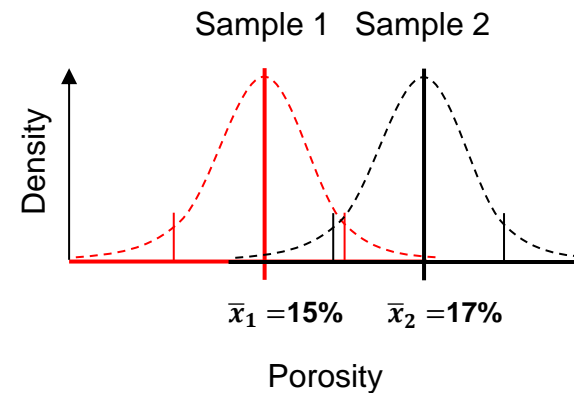
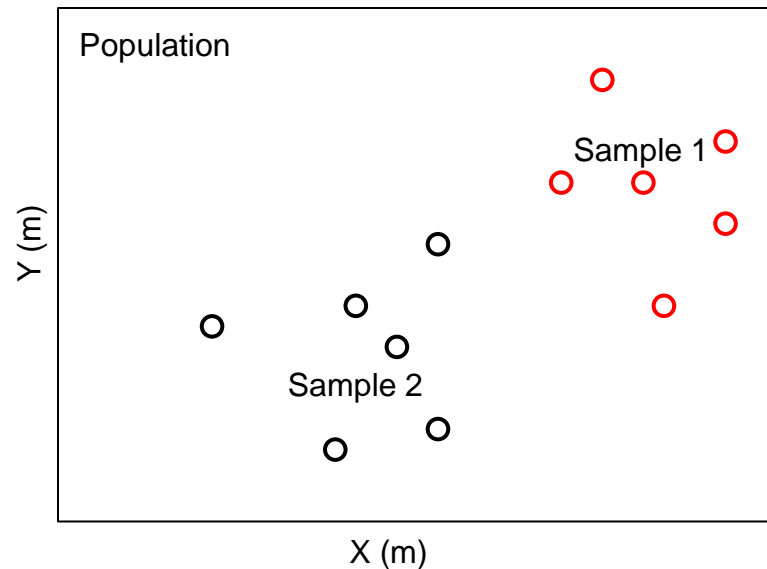
- That samples randomly drawn from a population as highly representative.
- Any statistic, e.g., mean, variance, P13 etc. will be the same!



Hypothesis Testing Take 2

The Solution:

- What are you going to compare?
 - Mean, variance, binned frequencies?
- To start, set up the hypothesis test: $\mu_1 = \mu_2$ they come from populations with the same mean; therefore, they could be the same population. **If the means are different, can't be the same population.**



Sample (red and black) locations (left) and schematic of sample distributions (rights).



Hypothesis Testing Take 2

The Solution:

- Hypothesis test:

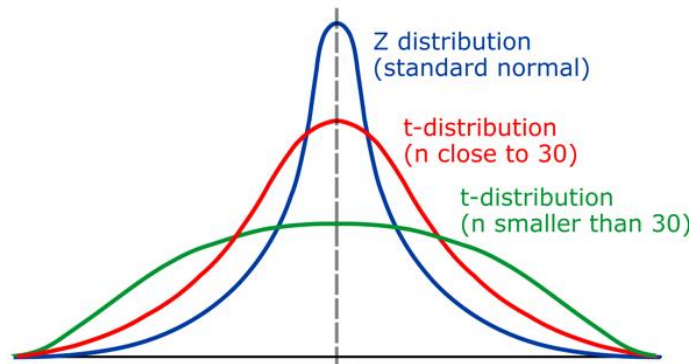
$$H_0: \mu_1 = \mu_2$$
$$H_1: \mu_1 \neq \mu_2,$$

Recall hypothesis is with regard to population parameters not sample statistics.

- Decide on the metric?

$$\bar{x}_1 - \bar{x}_2$$

- What is the sampling distribution we would expect
 - Difference of 2 Gaussian random variables with small sample size and unknown σ



Schematic of possible sampling distributions.

student's t distribution



Hypothesis Testing Take 2

The Solution:

- Hypothesis test:

$$H_0: \mu_1 = \mu_2$$

$$H_1: \mu_1 \neq \mu_2,$$

Recall hypothesis is with regard to population parameters not sample statistics.

- Decide on the metric?

$$\bar{x}_1 - \bar{x}_2$$

- What is the sampling distribution we would expect – Student's t distribution.
- But how much difference is significant?
 - Standard error tells us how much spread due to random effect, small sample and variability in samples.

$$\sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right) \left(\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}\right)}$$

standard error for Student's t difference in means with equal variance



The Solution:

- Hypothesis test:

$$H_0: \mu_1 = \mu_2$$
$$H_1: \mu_1 \neq \mu_2,$$

Recall hypothesis is with regard to population parameters not sample statistics.

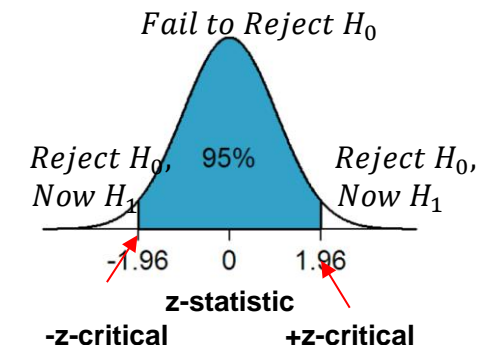
- Decide on the metric?

$$\bar{x}_1 - \bar{x}_2$$

- What is the sampling distribution we would expect – Student's t distribution.

- But how much difference is significant?
$$\sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right) \left(\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}\right)}$$

- What is the threshold for random effect at an alpha level?
 - this is how our metric should be distributed if both samples were sampled from distributions with the same mean.





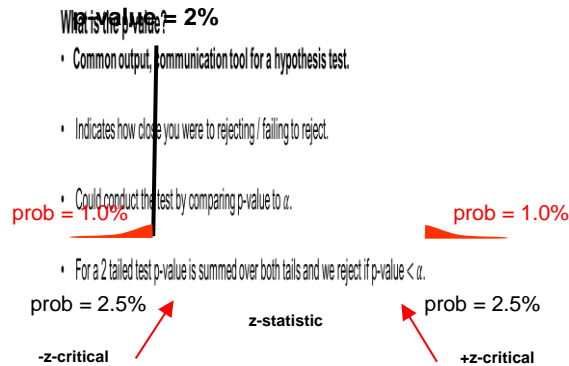
Hypothesis Testing Take 2

What is the p-value?

- **Common output, communication tool for a hypothesis test.**
- Indicates how close you were to rejecting / failing to reject.
- Could conduct the test by comparing p-value to α .
- For a 2 tailed test p-value is summed over both tails and we reject if p-value $< \alpha$.

P02 Outcome

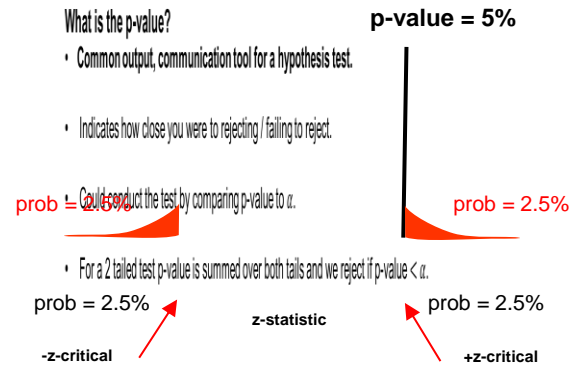
Reject H_0



Alpha Level = 5%

P97.5 Outcome

Reject H_0



P30 Outcome

Fail to Reject H_0

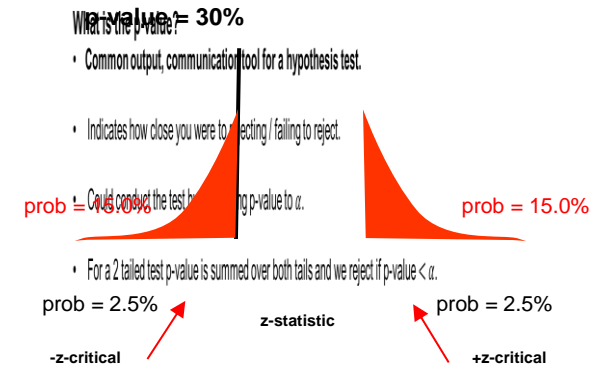


Illustration of t statistics that result in p-values of 2%, 5% and 30% respectively.



PGE 338 Data Analytics and Geostatistics

Lecture 7b: Confidence Intervals and Hypothesis Testing

Lecture outline . . .

- Bootstrap Hypothesis Testing

Introduction

General Concepts

Univariate

PDF / CDF

Statistics

Distributions

Heterogeneity

Hypothesis

Bivariate

Time Series Analysis

Spatial Analysis

Machine Learning

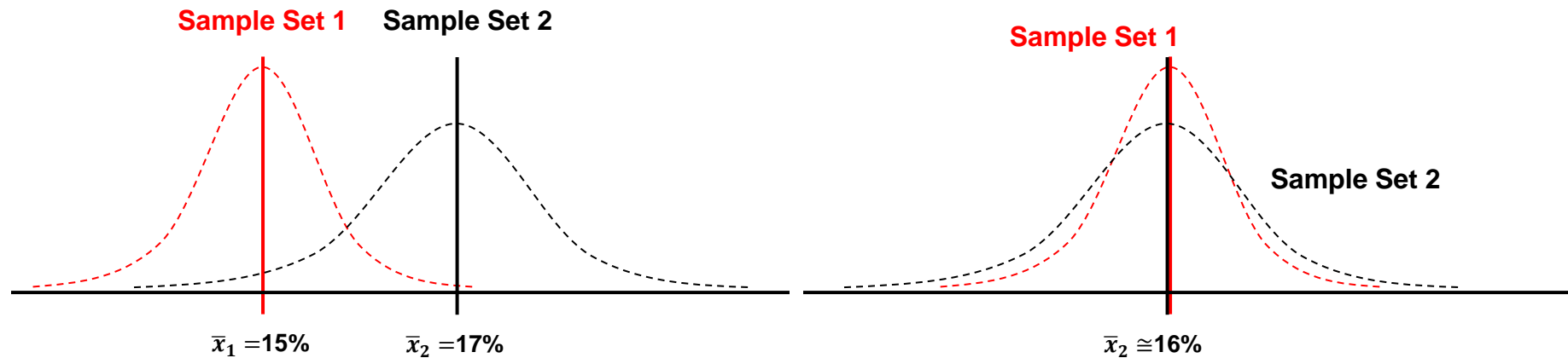
Uncertainty Analysis



Hypothesis Testing Take 3!

We can apply bootstrap to calculate the sampling distribution for hypothesis testing. E.g., difference in means hypothesis test:

1. Shift the 2 sample sets to have the mean of the combined sample set (1 and 2 together), ensure $H_0: \mu_1 = \mu_2$ state is true.



2. Bootstrap, n_1 and n_2 samples with replacement from each distribution.
3. Calculate a realization of the t statistic.

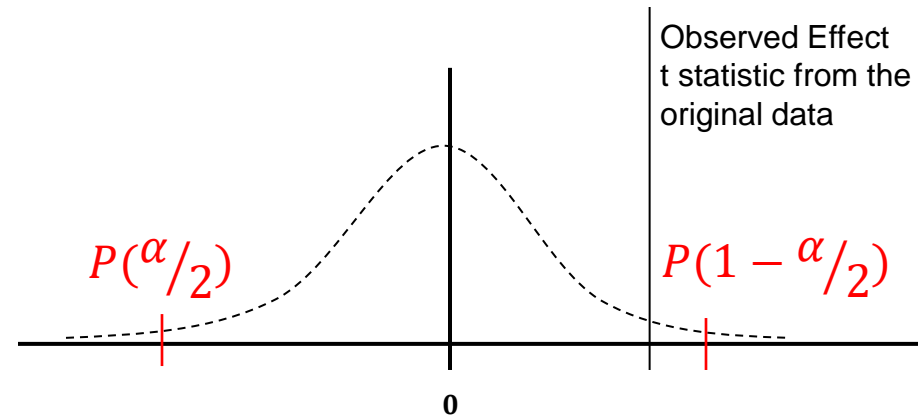
$$\hat{t}^\ell = \frac{\bar{x}_1^\ell - \bar{x}_2^\ell}{\sqrt{\left(\frac{s_1^{2\ell}}{n_1} + \frac{s_2^{2\ell}}{n_2}\right)}}$$



Hypothesis Testing Take 3!

We can apply bootstrap to calculate the sampling distribution for hypothesis testing. E.g., difference in means hypothesis test:

4. Repeat 'L' (number of realizations) times to calculate the t statistic sampling distribution (empirically), given the $H_0: \mu_1 = \mu_2$ size of the sample sets, n_1 and n_2 , and associated dispersion, s_1^2 and s_2^2



t statistic sampling distribution given $H_0: \mu_1 = \mu_2$ is true.

4. Calculate empirical bounds, percentiles, $P(\alpha/2)$ and $P(1 - \alpha/2)$
5. Calculate the observed effect, t statistic from the original data with original means and compare with the empirical bounds.



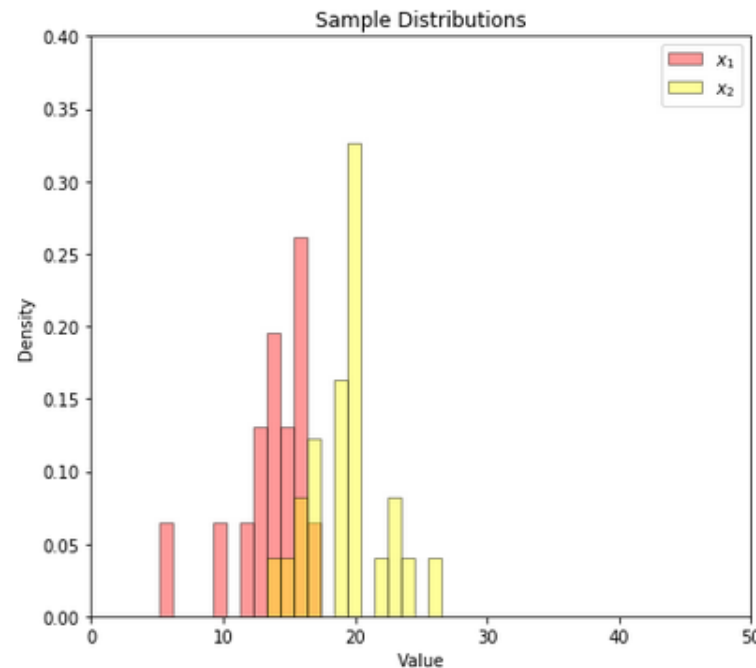
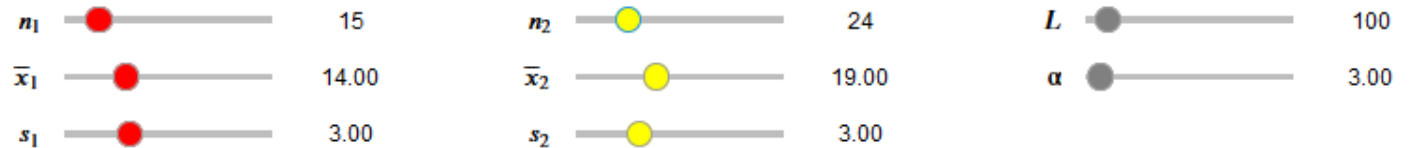
Hypothesis Testing Take 3!

Example #1 Bootstrap Hypothesis Test for Difference in Means

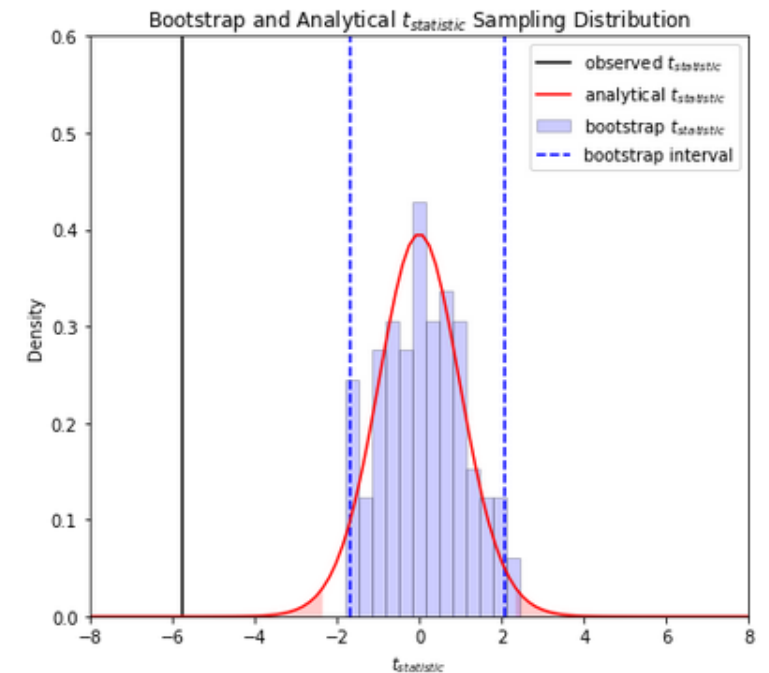
The Problem:

- Interactive demonstration
- Specify the sample distributions
- Monte Carlo simulate the samples
- Perform analytical and bootstrap hypothesis tests

Interactive Hypothesis Testing, Difference in Means, Analytical & Bootstrap Methods, Michael Pycz, Associate Professor, The University of Texas at Austin



2 sample sets.



Bootstrap and analytics sampling distributions and observed effect.

Jupyter notebook Python interactive demonstration 'Interactive_Hypothesis_Testing.ipynb'.



PGE 338 Data Analytics and Geostatistics

Lecture 7b: Confidence Intervals and Hypothesis Testing

Lecture outline . . .

- Examples

Introduction

General Concepts

Univariate

PDF / CDF

Statistics

Distributions

Heterogeneity

Hypothesis

Bivariate

Time Series Analysis

Spatial Analysis

Machine Learning

Uncertainty Analysis



Confidence Intervals / Hypothesis Testing in Python

Walk Through:

Confidence Intervals and Hypothesis Testing in Python demo.



Data Analytics

Confidence Intervals and Hypothesis Testing in Python in Python

Michael Pyrcz, Associate Professor, The University of Texas at Austin

[Twitter](#) | [GitHub](#) | [Website](#) | [GoogleScholar](#) | [Book](#) | [YouTube](#) | [LinkedIn](#)

This is a tutorial / demonstration of **Confidence Intervals and Hypothesis Testing in Python**. In Python, the SciPy package, specifically the Stats functions (<https://docs.scipy.org/doc/scipy/reference/stats.html>) provide excellent tools for efficient use of statistics.

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This tutorial includes basic, typical confidence interval and hypothesis testing methods that would commonly be required for Engineers and Geoscientists including:

1. Student-t confidence interval for the mean
2. Student-t hypothesis test for difference in means (pooled variance)
3. Student-t hypothesis test for difference in means (difference variances), Welch's t Test
4. F-distribution hypothesis test for difference in variances

Confidence intervals and hypothesis testing in Python with file
PythonDataBasics_ConfidenceInterval_HypothesisTesting.ipynb.



Confidence Intervals / Hypothesis Testing in Python

Walk Through:

Confidence Intervals and Hypothesis Testing in Python demo in file:



Subsurface Data Analytics

Confidence Intervals and Hypothesis Testing for Subsurface Data Analytics in Python

Michael Pyrcz, Associate Professor, University of Texas at Austin

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Reporting Uncertainty and Significance

With confidence intervals and hypothesis testing we have the opportunity to report uncertainty and to report significance in our statistics.

and significance with our results

Illustration of Confidence Intervals and Hypothesis Testing in Python for Subsurface Modeling. In Python, the SciPy package, functions (<https://docs.scipy.org/doc/scipy/reference/stats.html>) provide excellent tools for efficient use of statistics.

Basic, typical confidence interval and hypothesis testing methods that would commonly be required for Engineers and Geoscientists

Confidence interval for the mean
t-test for difference in means (pooled variance)
F-test for difference in means (difference variances), Welch's t Test
Chi-square test for difference in variances

Based on standard methods with their associated limitations and assumptions. For more information see:

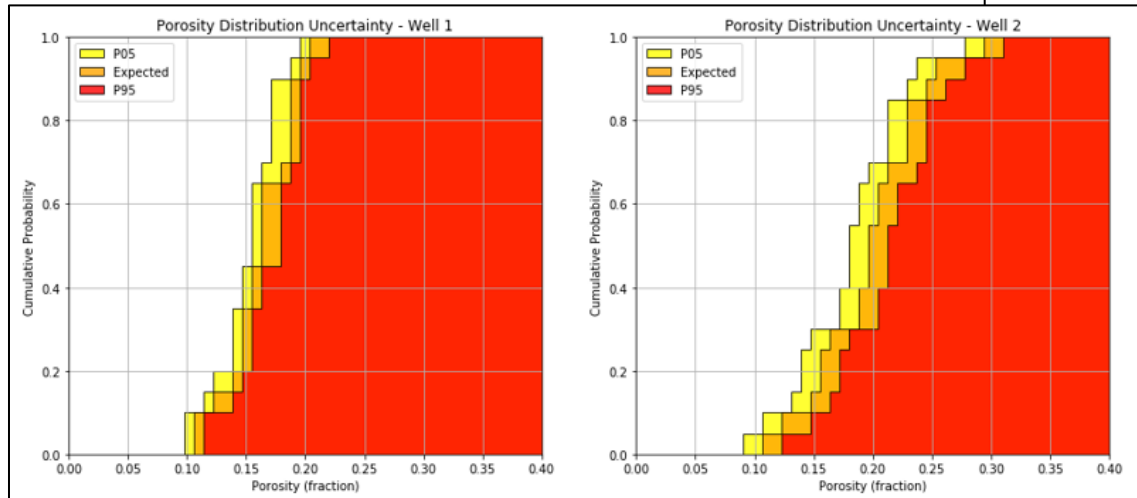
[this Lecture](#)

[this Lecture](#)

Code and workflow on Bootstrap <https://git.io/fhgUW> for a general, empirical approach to assess uncertainty in statistics.

Workflows for subsurface data analytics, geostatistics and machine learning:

• [R](#)

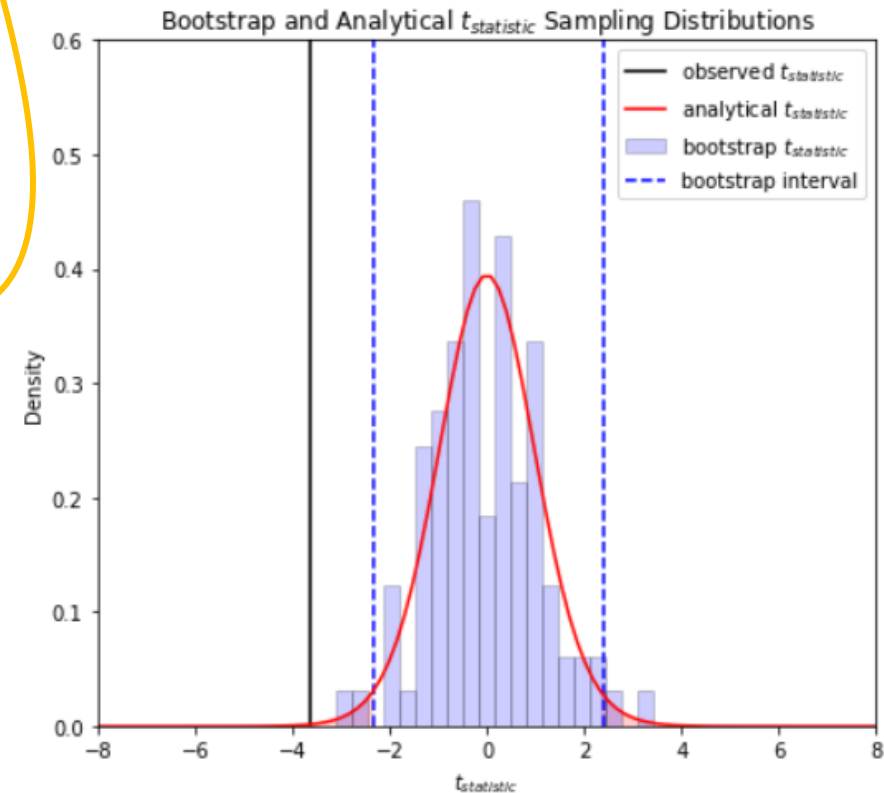
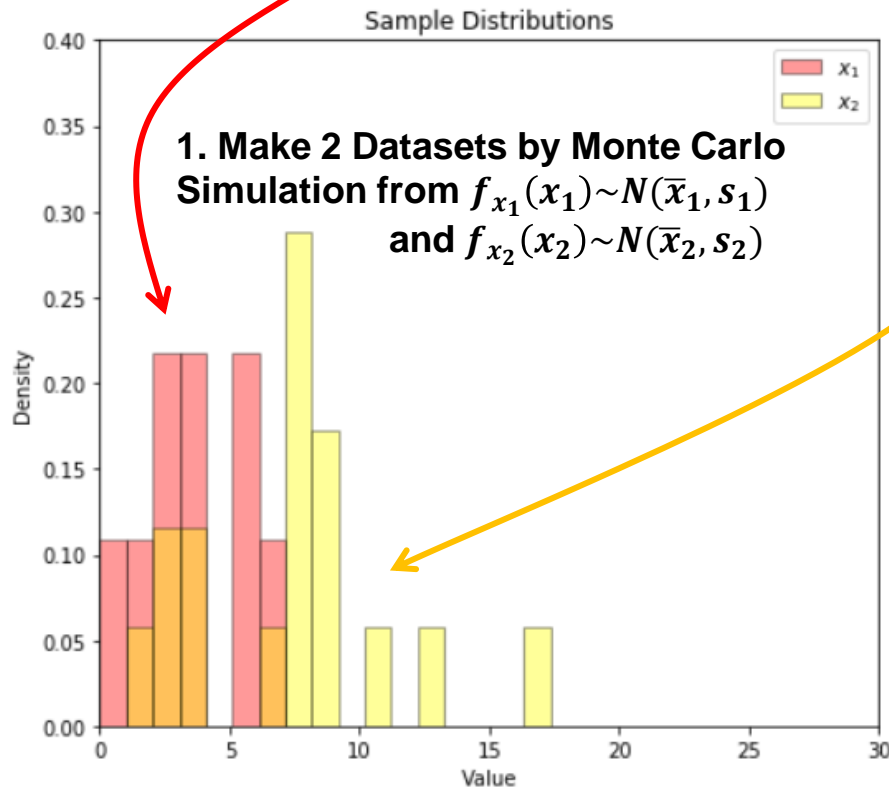
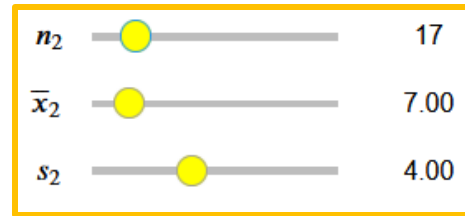
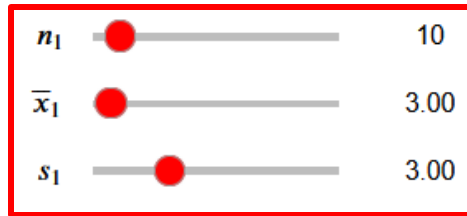


Confidence intervals and hypothesis testing in Python with file Subsurface_MachineLearning_Confidence_Hypothesis.ipynb



Confidence Intervals / Hypothesis Testing in Python

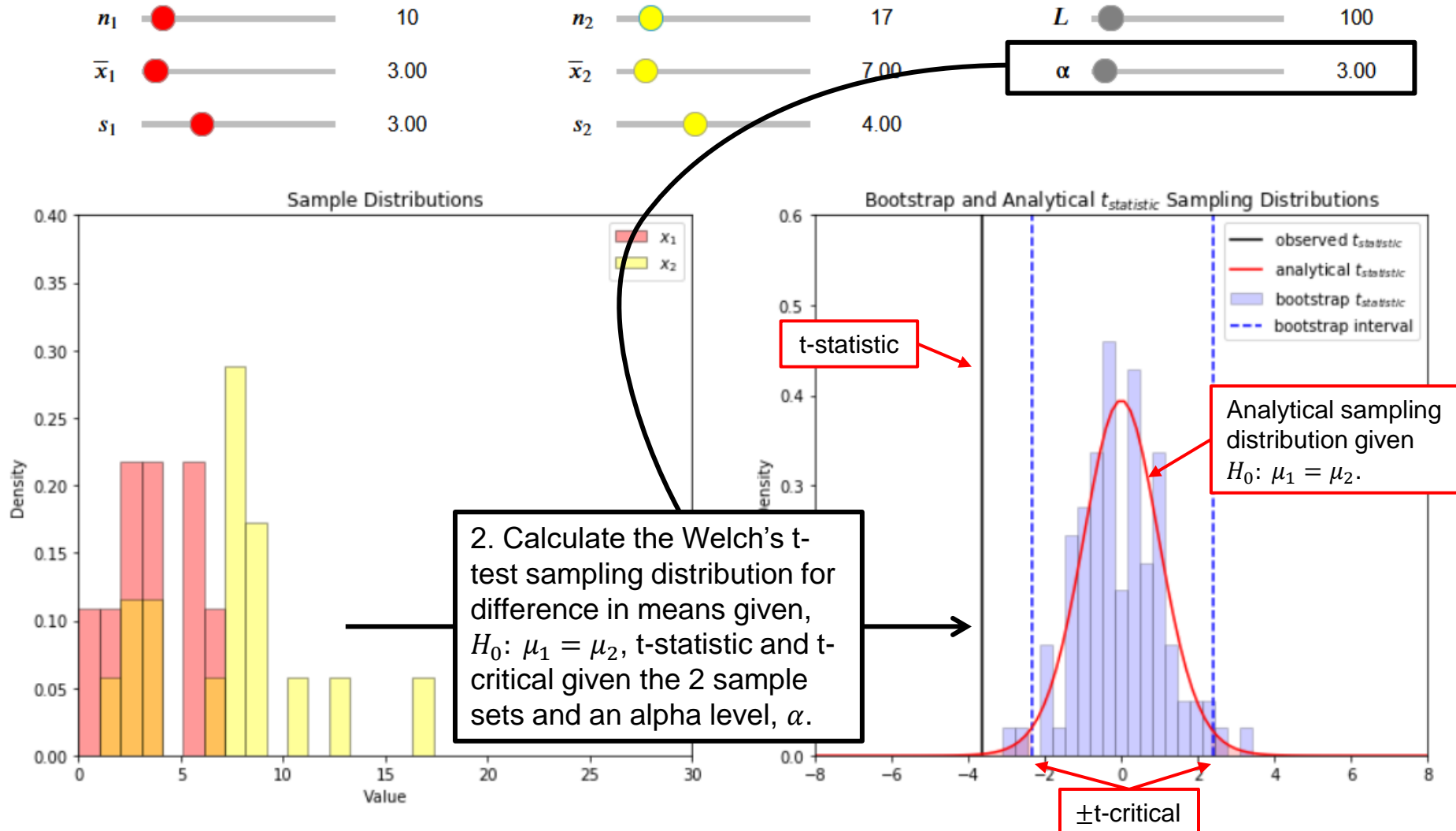
Interactive Hypothesis Testing, Difference in Means, Analytical & Bootstrap Methods, Michael Pyrcz, Associate Professor, The University of Texas at Austin





Confidence Intervals / Hypothesis Testing in Python

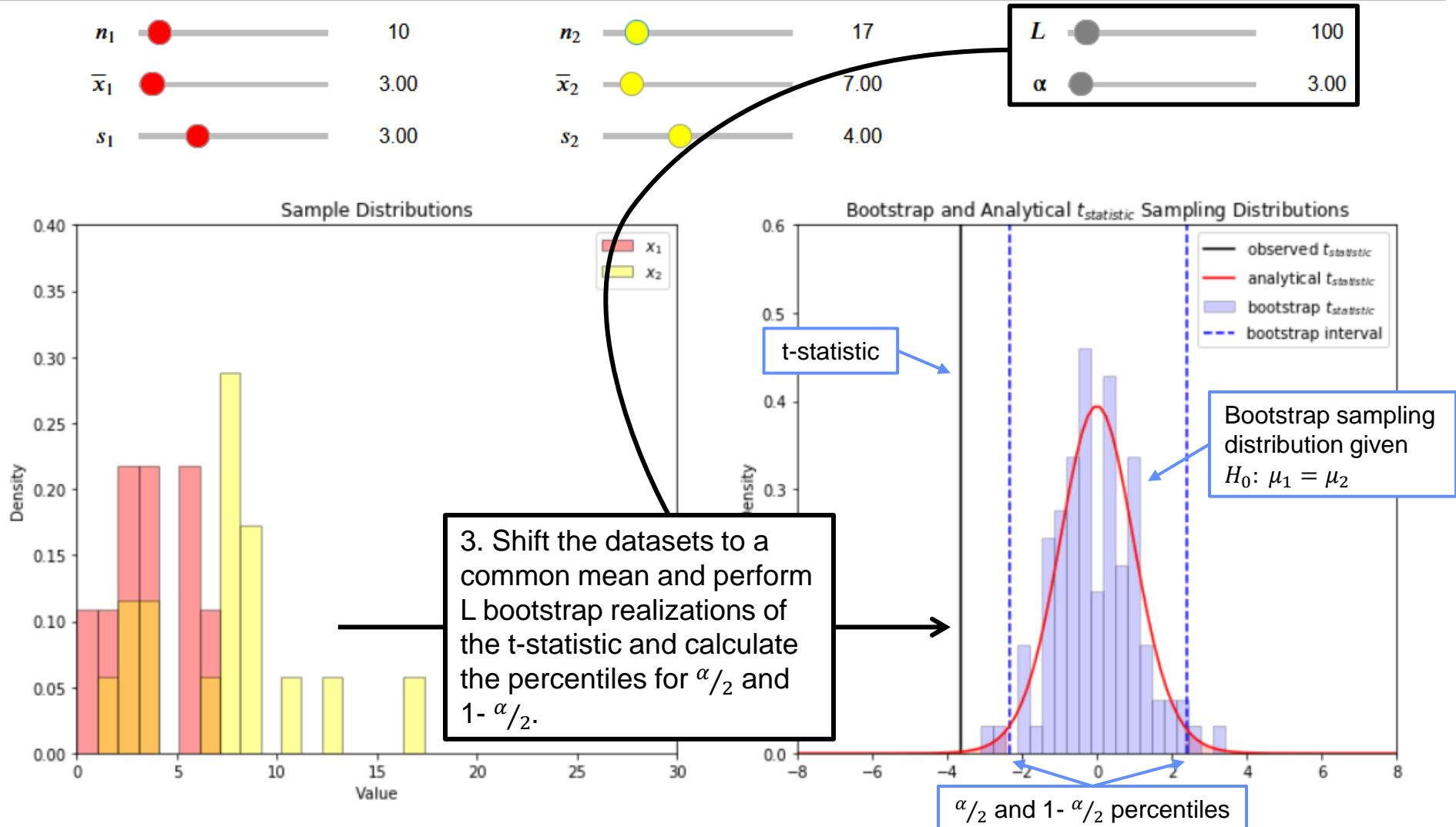
Interactive Hypothesis Testing, Difference in Means, Analytical & Bootstrap Methods, Michael Pyrcz, Associate Professor, The University of Texas at Austin





Confidence Intervals / Hypothesis Testing in Python

Interactive Hypothesis Testing, Difference in Means, Analytical & Bootstrap Methods, Michael Pyrcz, Associate Professor, The University of Texas at Austin





Confidence Intervals / Hypothesis Testing in Python

Experiential Learning, Evaluate the Impact of Each of These:

- Sample Sizes for dataset 1 n_1 , and 2, n_2 .
- Sample Means for dataset 1, \bar{x}_1 , and 2, \bar{x}_2 .
- Sample Standard Deviations for dataset 1 s_1 , and 2, s_2 .
- Alpha level, α
- Number of bootstrap realizations, L



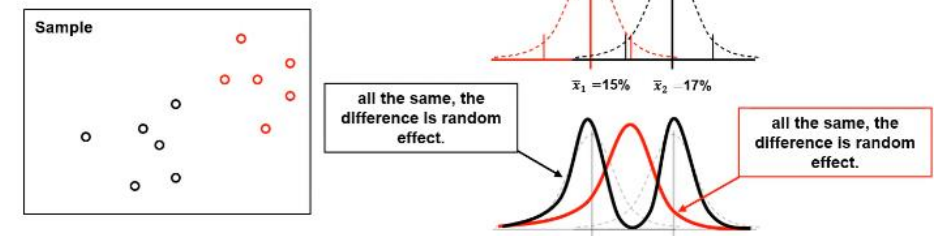
Search



Hypothesis Testing Take 2



- Problem:
 - You have 2 datasets (1 and 2), did they come from the same population?
 - If you had 2 datasets from the same population. They could look different!



- The difference may be just a random outcome from the same distribution or indicate there are two distinct populations.

07e Python Data Analytics: Hypothesis Testing Interactive

I recorded a walkthrough of this interactive demonstration, <https://youtu.be/bcb3m3LBtRk>.



PGE 338 Data Analytics and Geostatistics

Lecture 7b: Confidence Intervals and Hypothesis Testing

Lecture outline . . .

- Concepts
- Analytical Hypothesis Testing
- Bootstrap Hypothesis Testing
- Examples

Introduction

General Concepts

Univariate

PDF / CDF

Statistics

Distributions

Heterogeneity

Hypothesis

Bivariate

Time Series Analysis

Spatial Analysis

Machine Learning

Uncertainty Analysis