EXPERIENTIAL LEARNING VIA DISTRIBUTED HARDWARE ACCESS IN COMPUTER ORGANIZATION

A case study

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(Summa Cum Laude)

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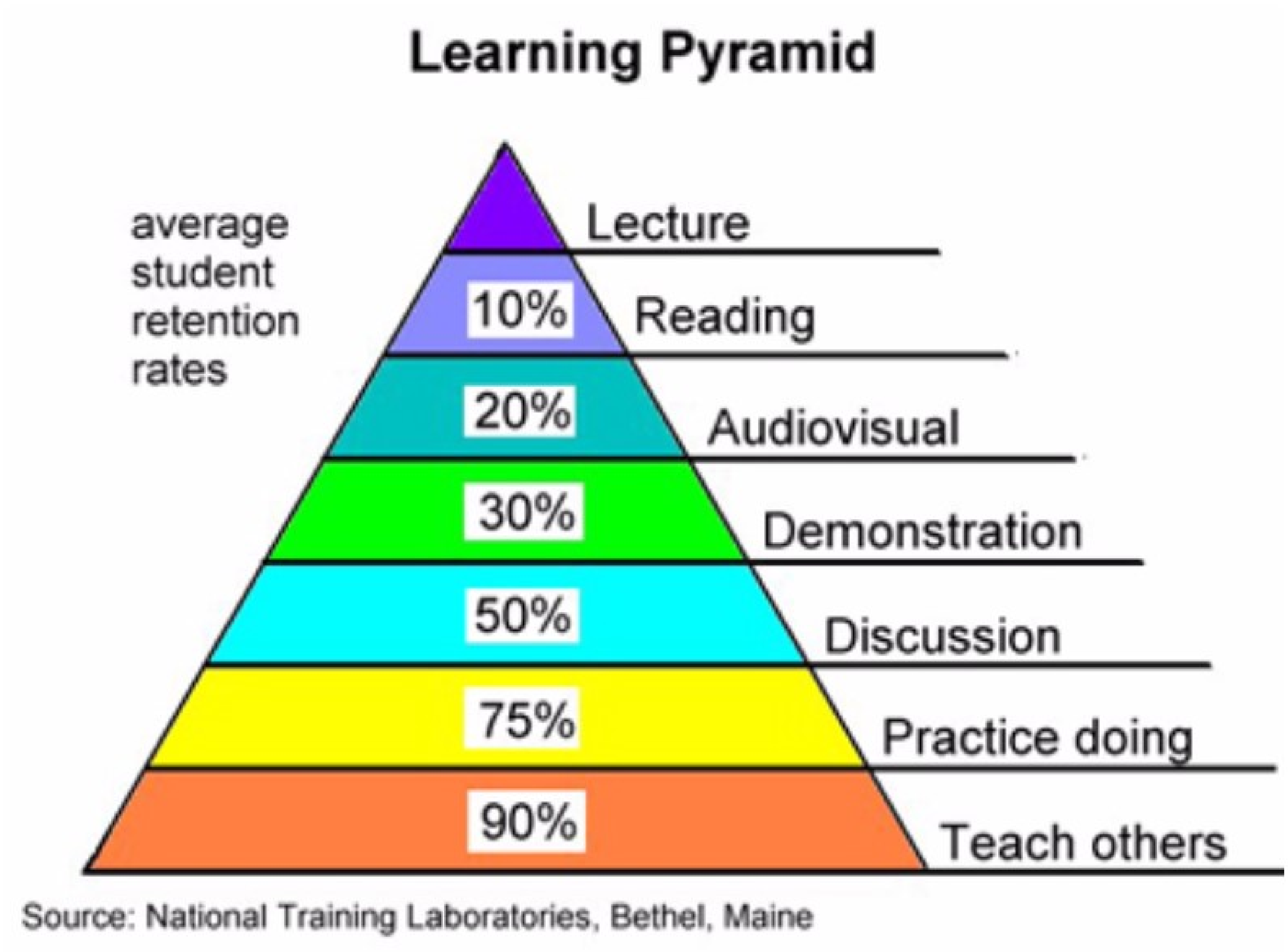
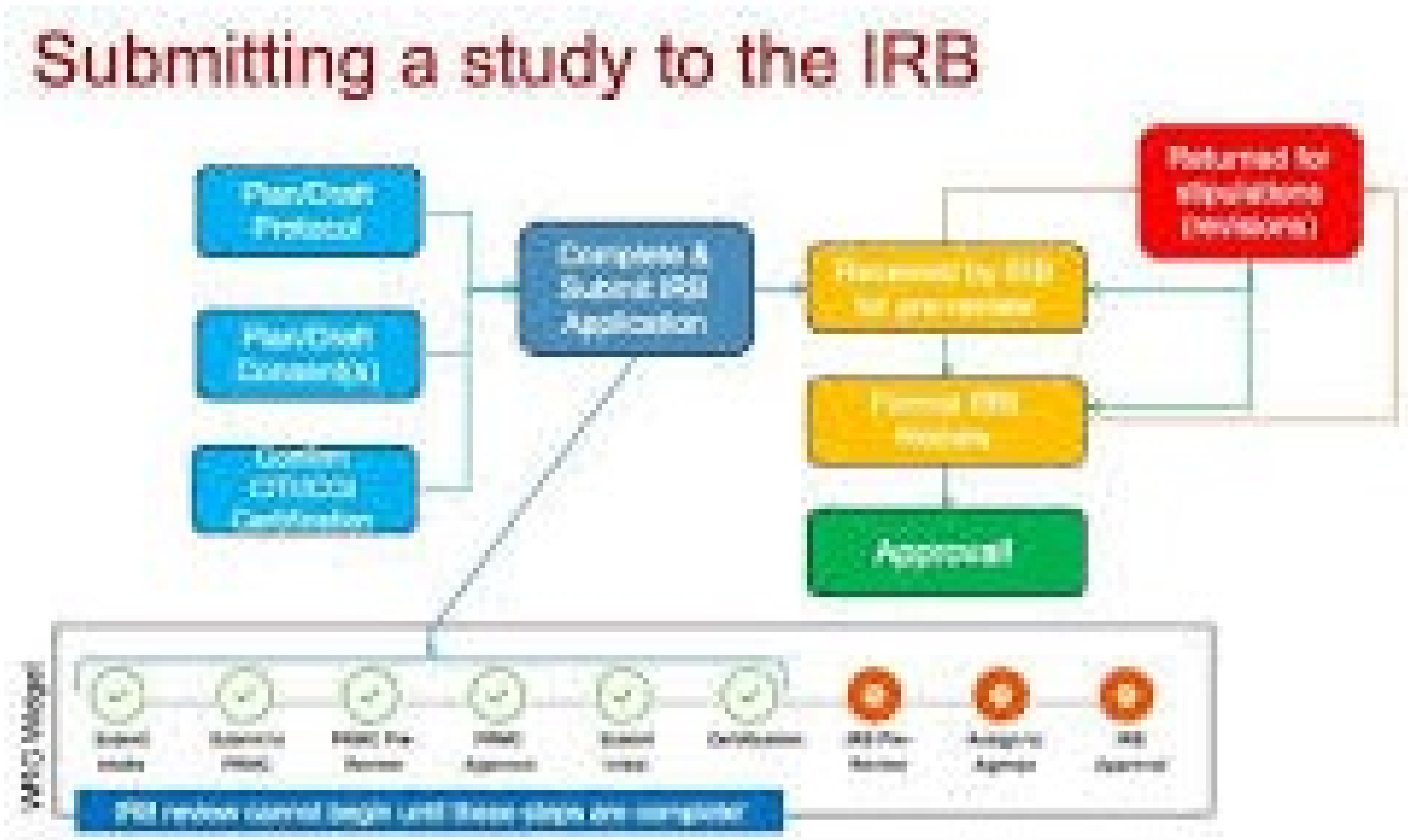
S.U.C.C.E.S.(s)

- Simple
- Unexpected
- Concrete
- Credible
- Emotional
- Story

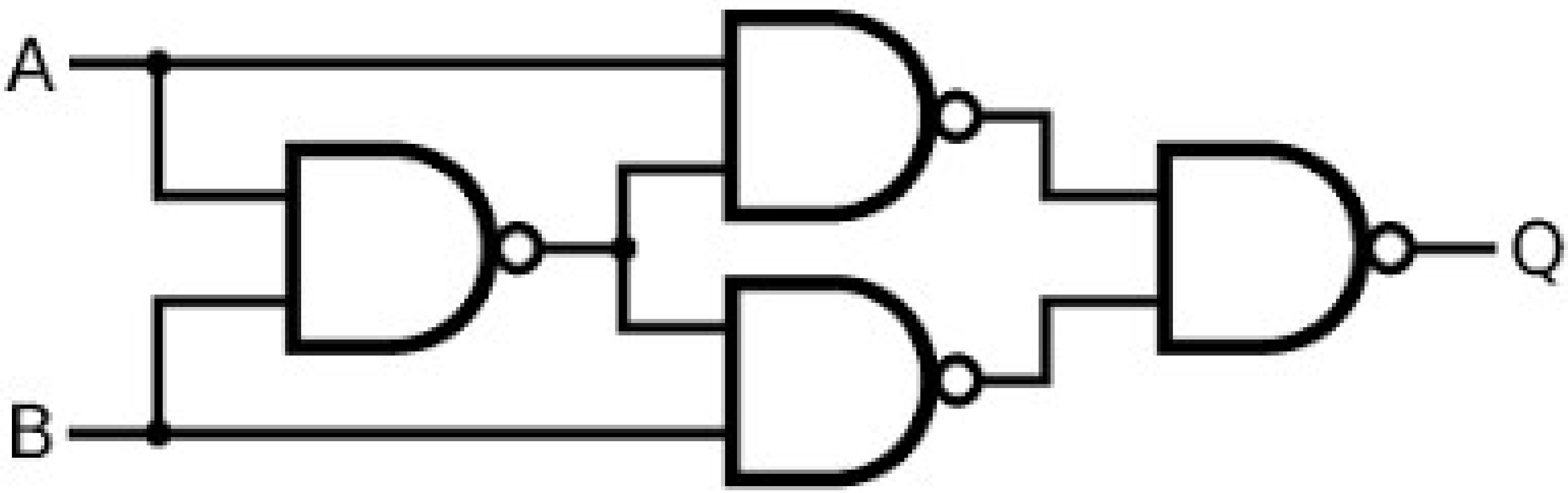
The lie that tells a truth



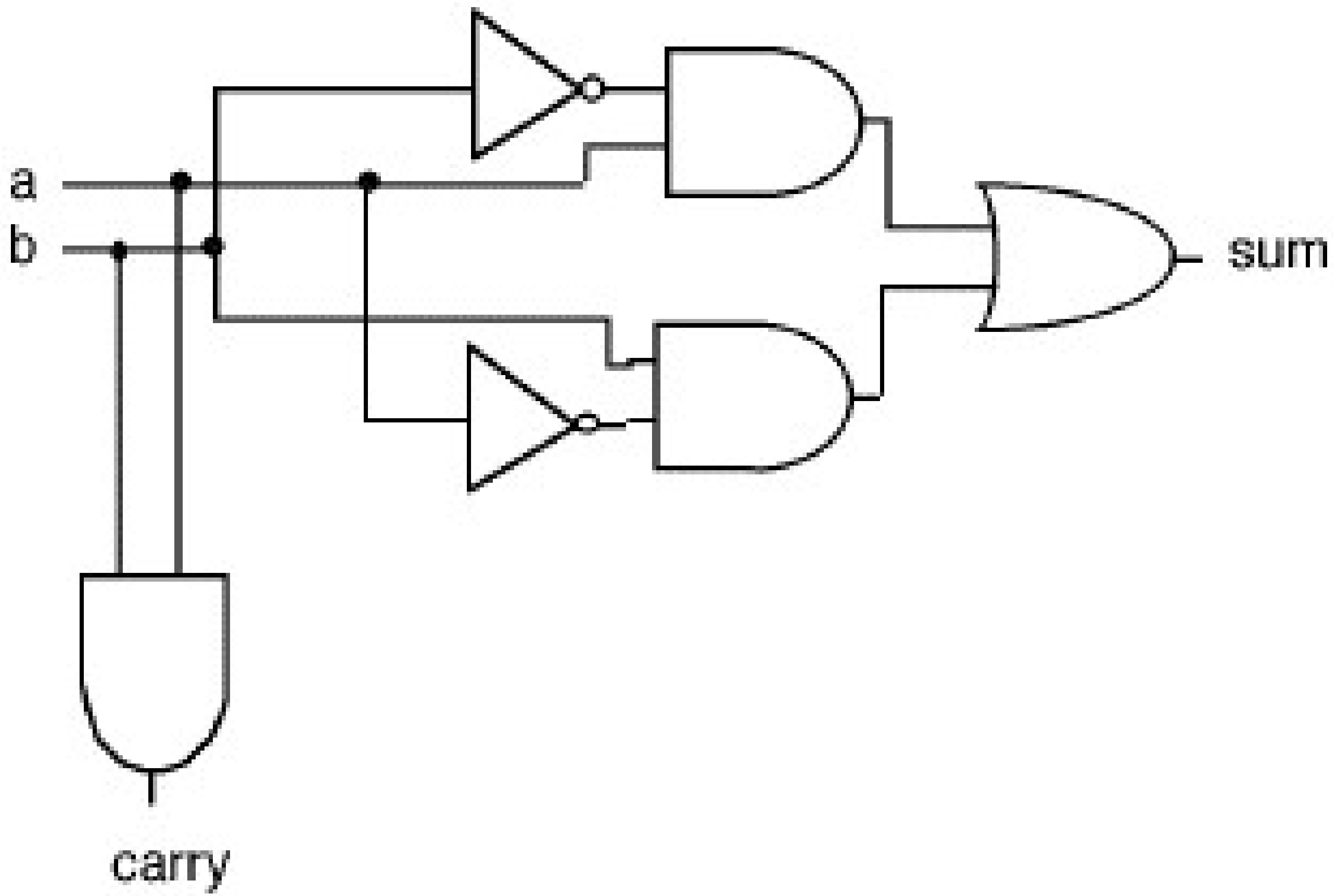
An experiment commenced



Mystery Circuit 1



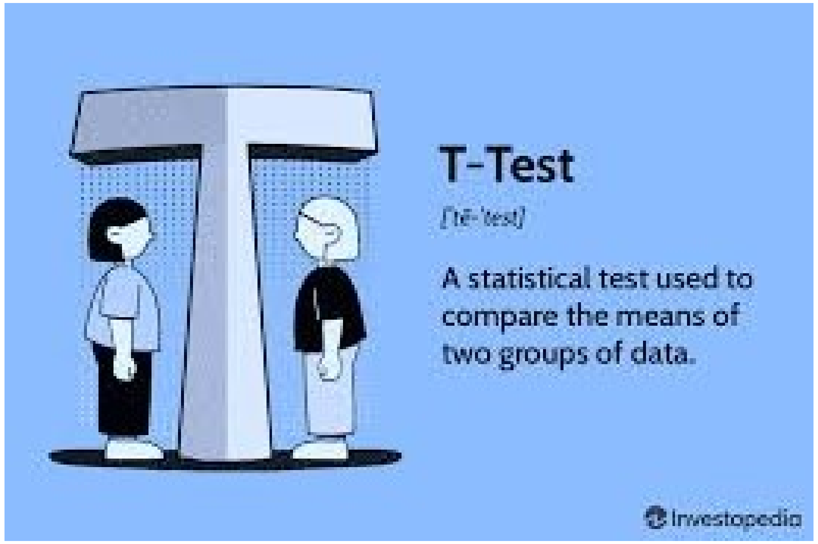
Mystery Circuit 2



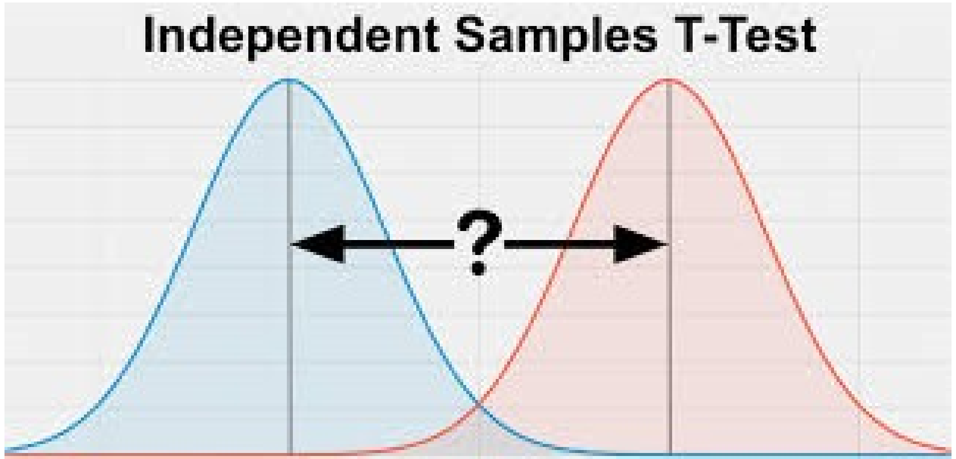
Our Null Hypotheses

- The intervention in teaching the course does NOT have an effect upon student learning
- The intervention in teaching the course does NOT have an effect upon student satisfaction as measured by anonymous teaching evaluations

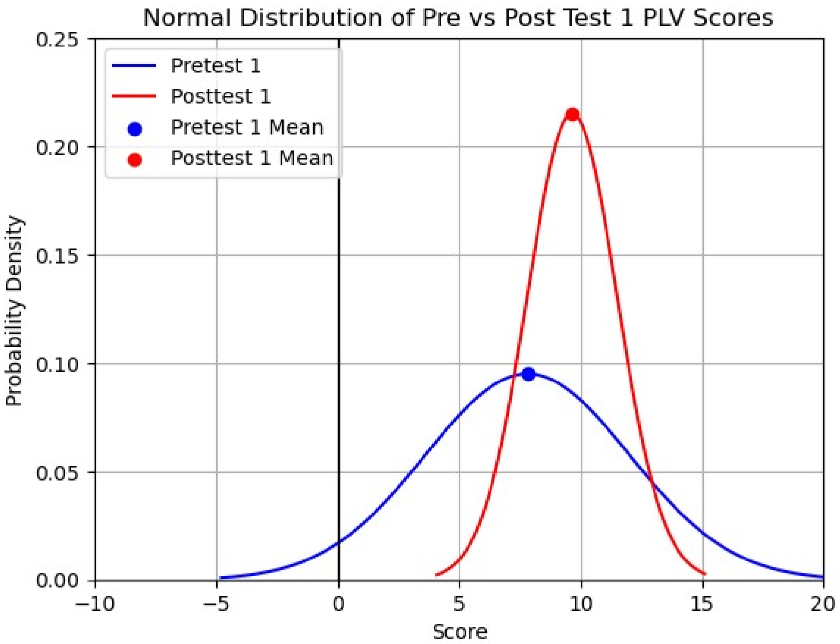
Evaluating whether the experiment succeeded



$$t = \frac{(\overline{x}_1 - \overline{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$



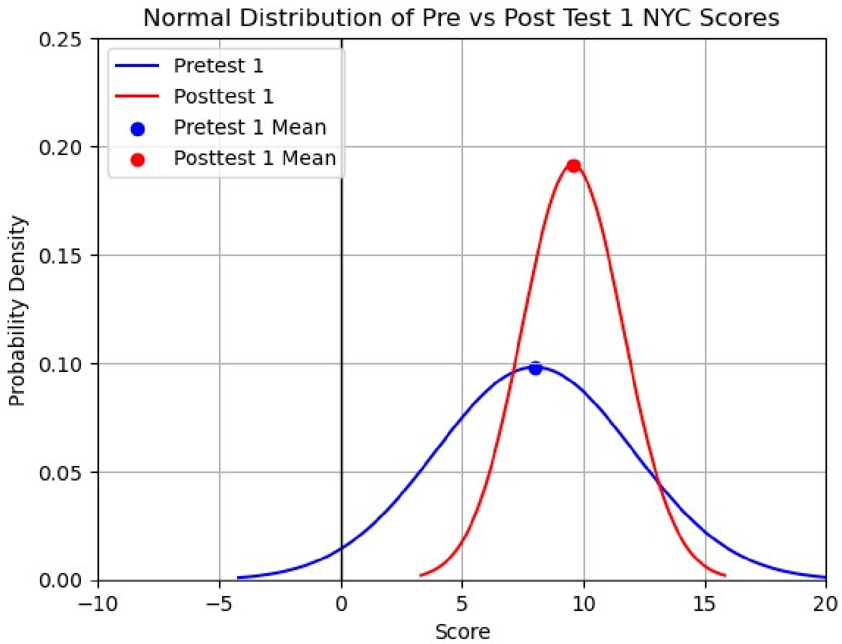
Measuring Results: Test 1 PLV



t-Test: Two-Sample Assuming Equal Variances		
PLV - Pre vs Post Test 1	*PreTest1*	*PostTest1*
Mean	7.8125	9.655172
Variance	17.64112903	3.448276
Observations	32	29
Pooled Variance	10.9055377	
Hypothesized Mean Difference	0	
df	59	
t Stat	-2.17637467	
P(T<=t) one-tail	**0.016771199**	
t Critical one-tail	1.671093032	
P(T<=t) two-tail	**0.033542398**	
t Critical two-tail	2.000995378	

Figure 1-0: Pre vs Post Test 1 PLV

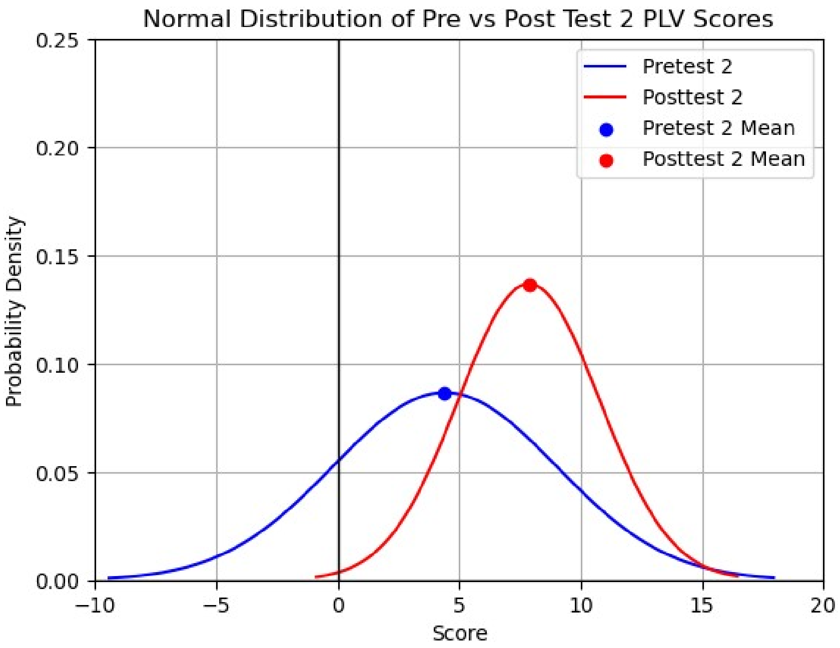
Measuring Results: Test 1 NYC



t-Test: Two-Sample Assuming Equal Variances		
NYC - Pre vs Post Test 1	*PreTest1*	*PostTest1*
Mean	8	9.565217
Variance	16.55172	4.347826
Observations	30	23
Pooled Variance	11.2873	
Hypothesized Mean Difference	0	
df	51	
t Stat	-1.68099	
P(T<=t) one-tail	**0.04944**	
t Critical one-tail	1.675285	
P(T<=t) two-tail	**0.098879**	
t Critical two-tail	2.007584	

Figure 2-0: Pre vs Post Test 1 NYC

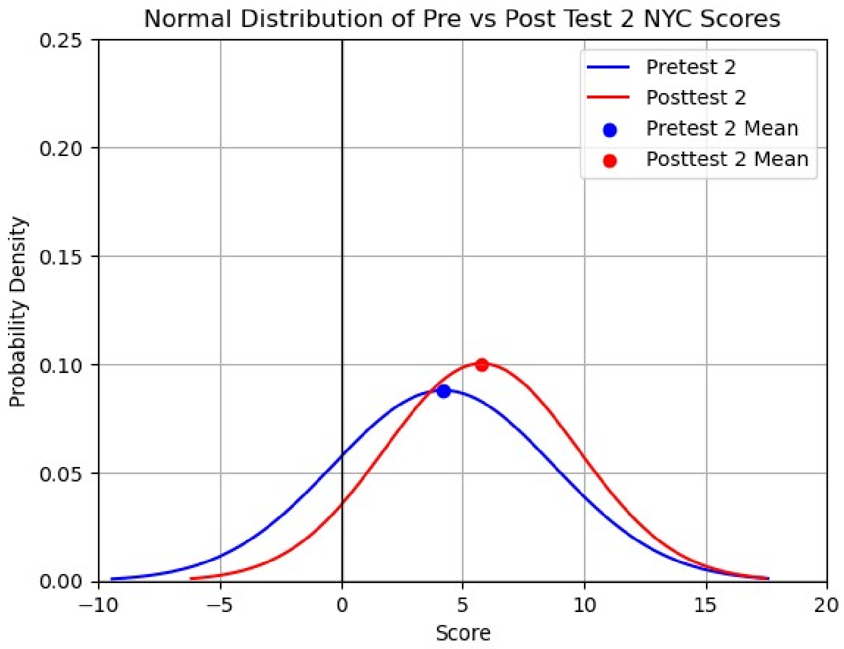
Measuring Results: Test 2 PLV



t-Test: Two-Sample Assuming Equal Variances		
PLV - Pre vs Post Test 2	*PreTest2*	*PostTest2*
Mean	4.408387097	7.874286
Variance	21.20870065	8.506514
Observations	31	28
Pooled Variance	15.19187553	
Hypothesized Mean Difference	0	
df	57	
t Stat	-3.41070388	
P(T<=t) one-tail	**0.000598467**	
t Critical one-tail	1.672028888	
P(T<=t) two-tail	**0.001196935**	
t Critical two-tail	2.002465459	

Figure 1-1: Pre vs Post Test 2 PLV

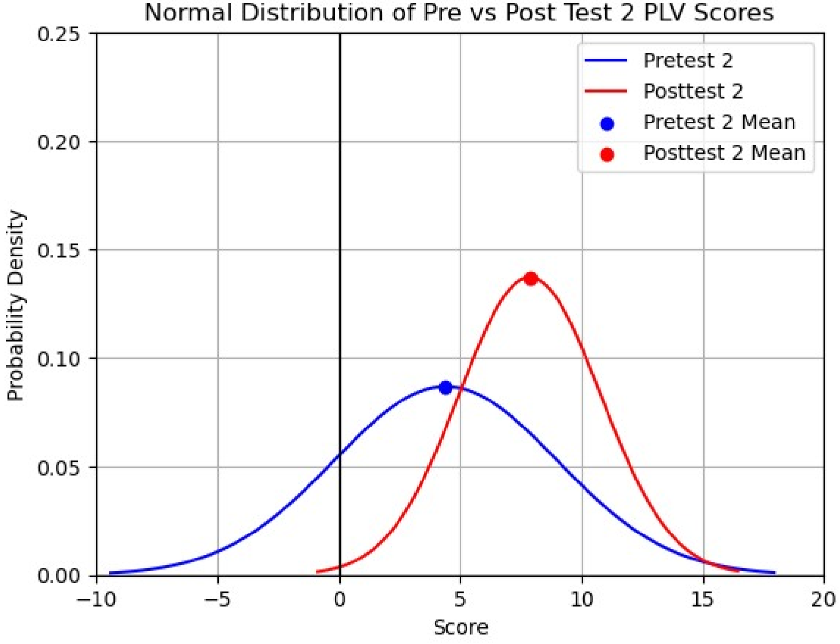
Measuring Results: Test 2 NYC

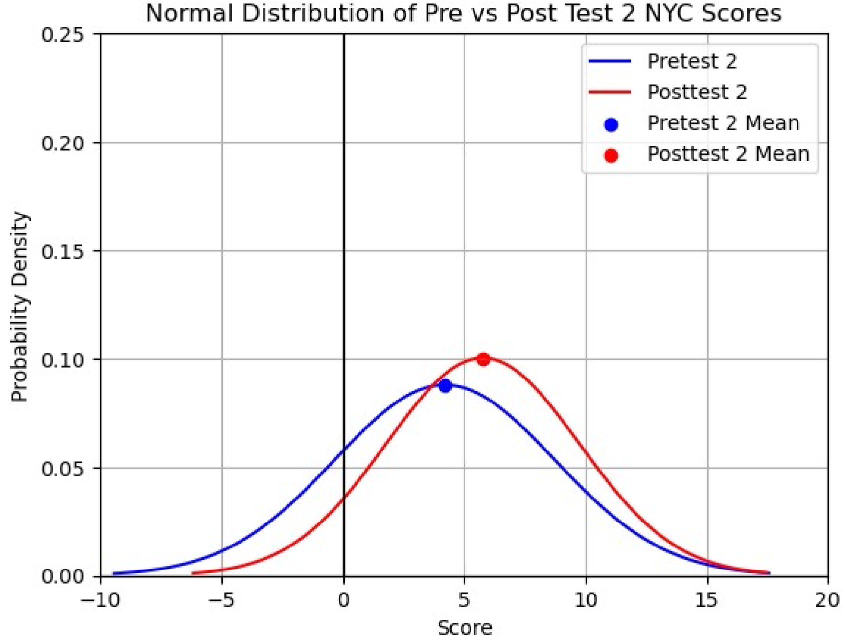


t-Test: Two-Sample Assuming Equal Variances		
NYC - Pre vs Post Test 2	*PreTest2*	*PostTest2*
Mean	4.2004	5.771429
Variance	20.6266	15.85234
Observations	25	21
Pooled Variance	18.45648	
Hypothesized Mean Difference	0	
df	44	
t Stat	-1.23541	
P(T<=t) one-tail	**0.111617**	
t Critical one-tail	1.68023	
P(T<=t) two-tail	**0.223235**	
t Critical two-tail	2.015368	

Figure 2-1: Pre vs Post Test 2 NYC

Test 2 Side by Side





t-Test: Two-Sample Assuming Equal Variances

PLV - Pre vs Post Test 2	*PreTest2*	*PostTest2*
Mean	4.408387097	7.874286
Variance	21.20870065	8.506514
Observations	31	28
Pooled Variance	15.19187553	
Hypothesized Mean Difference	0	
df	57	
t Stat	-3.41070388	
P(T<=t) one-tail	**0.000598467**	
t Critical one-tail	1.672028888	
P(T<=t) two-tail	**0.001196935**	
t Critical two-tail	2.002465459	

Figure 1-1: Pre vs Post Test 2 PLV

t-Test: Two-Sample Assuming Equal Variances

NYC - Pre vs Post Test 2	*PreTest2*	*PostTest2*
Mean	4.2004	5.771429
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Observations	25	21
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Hypothesized Mean Difference	0	
df	44	
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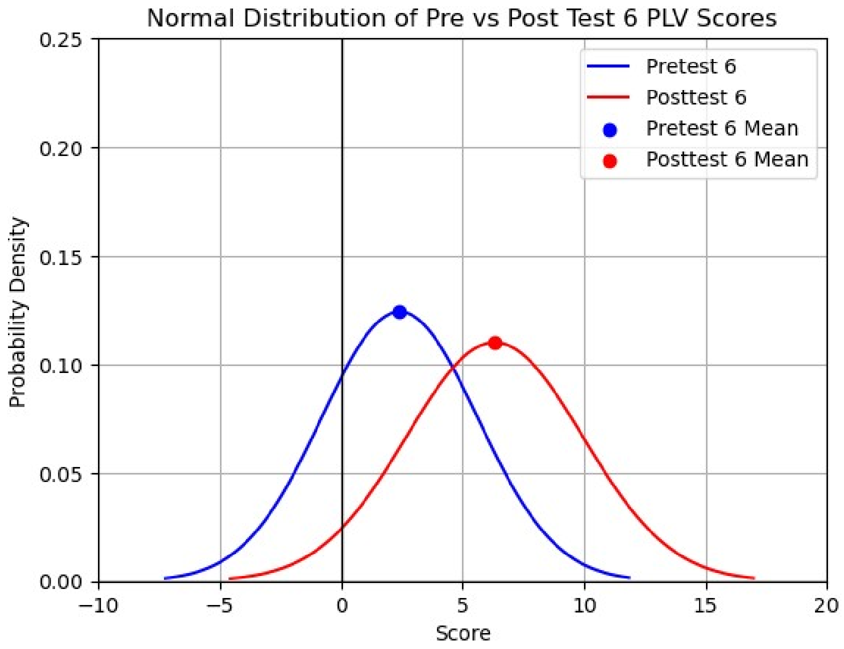
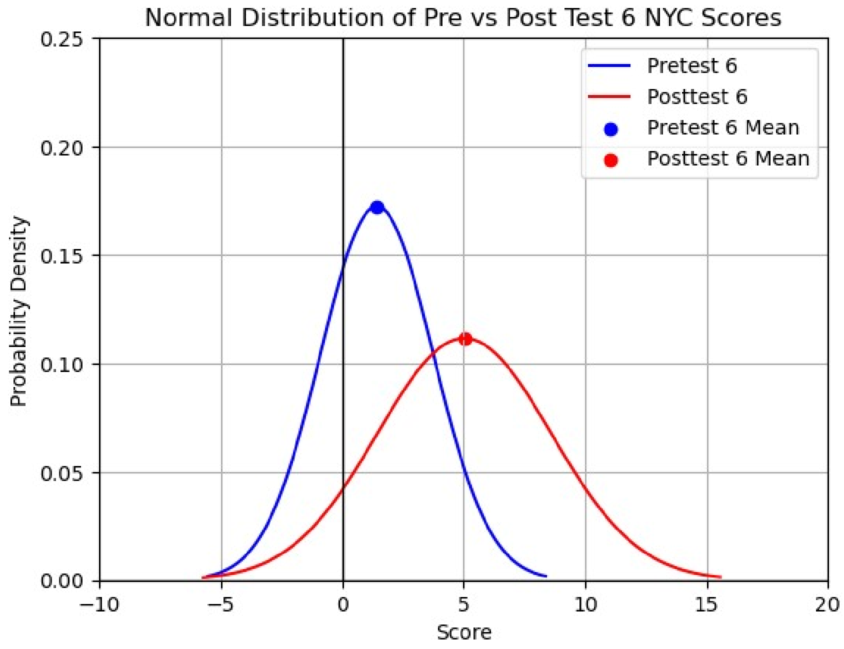
P(T<=t) one-tail	**0.111617**	
t Critical one-tail	1.68023	
P(T<=t) two-tail	**0.223235**	
t Critical two-tail	2.015368	

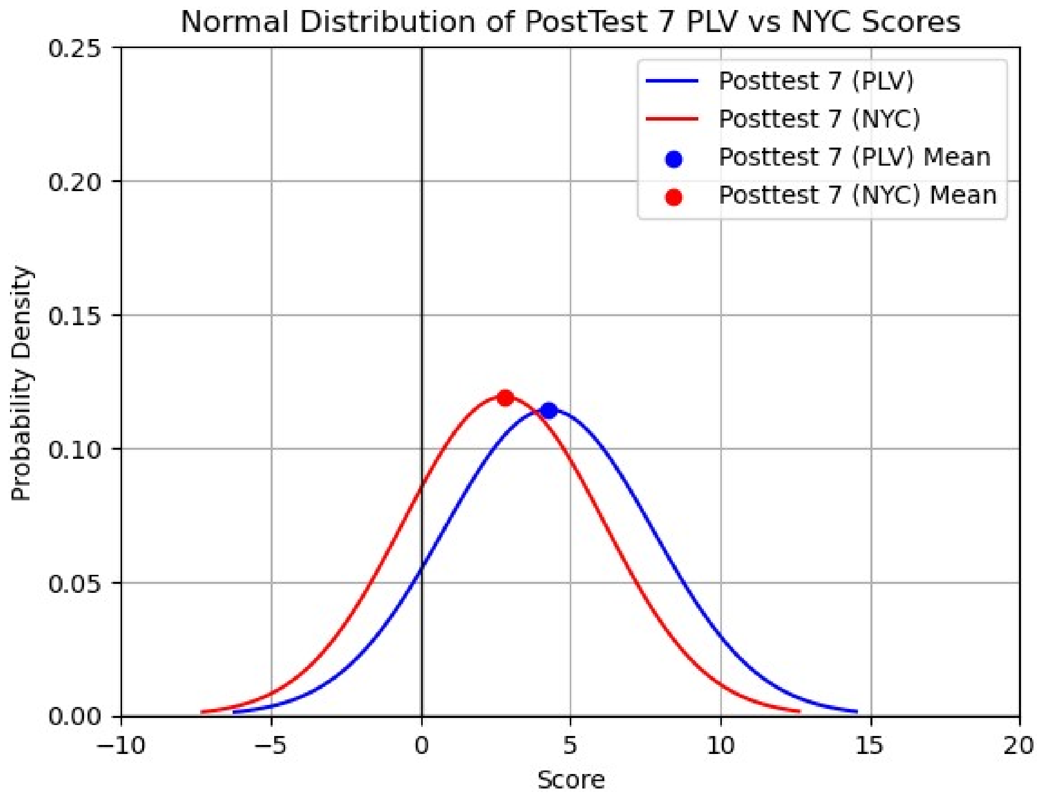
Figure 2-1: Pre vs Post Test 2 NYC

Test 6 Side by Side



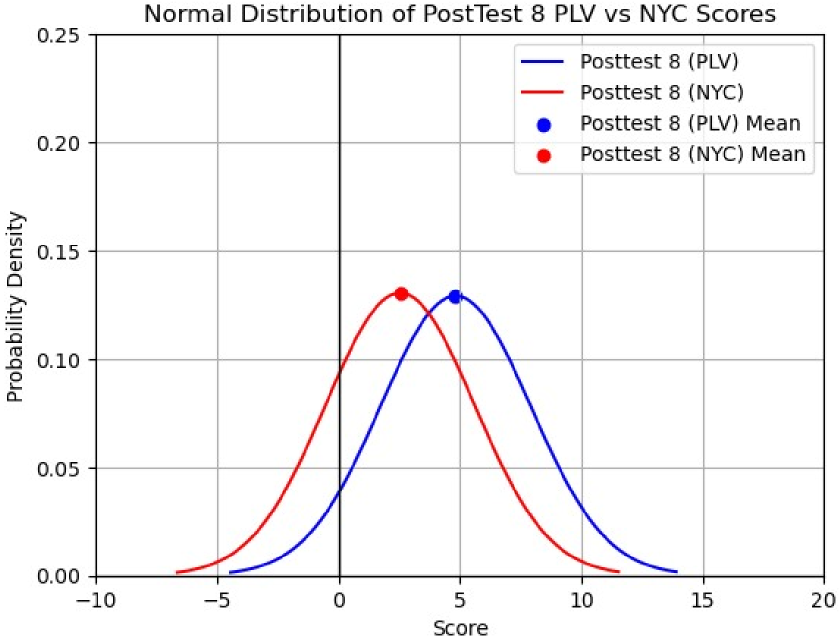


Test 7: Evaluating on Digital Logic



t-Test: Two-Sample Assuming Equal Variances		
	PostTest7 (PLV)	*PostTest7 (NYC)*
Mean	4.273076923	2.777777778
Variance	12.19682215	11.22571242
Observations	26	18
Pooled Variance	11.80375393	
Hypothesized Mean Difference	0	
df	42	
t Stat	1.419432026	
P(T<=t) one-tail	**0.081576428**	
t Critical one-tail	1.681952357	
P(T<=t) two-tail	**0.163152855**	
t Critical two-tail	2.018081703	

Test 8: Evaluating on Digital Logic



t-Test: Two-Sample Assuming Equal Variances		
	PostTest8 (PLV)	*PostTest8 (NYC)*
Mean	4.826	2.537647059
Variance	9.555316667	9.353381618
Observations	25	17
Pooled Variance	9.474542647	
Hypothesized Mean Difference	0	
df	40	
t Stat	2.364905005	
P(T<=t) one-tail	0.0114869	
t Critical one-tail	1.683851013	
P(T<=t) two-tail	0.022973799	
t Critical two-tail	2.02107539	

Teaching Evaluations, My most Important measure

Course questions - Spreadsheet analysis

	Invited	Resp	%	Agreement	Disagreement	Neutral	Your average	Subject avg.
The objectives of this course were clear.	16	10	63%	8	0	2	4.20	4.46
The course has satisfied the objectives.	16	10	63%	8	0	2	4.00	4.43
I would recommend this course to other students.	16	10	63%	7	2	1	3.80	4.34
The classes were interesting and informative.	16	10	63%	6	2	2	3.80	4.34

Course questions - Spreadsheet analysis

	Invited	Resp	%	Agreement	Disagreement	Neutral	Your average	Subject avg.
The objectives of this course were clear.	33	17	52%	15	1	1	4.24	4.48
The course has satisfied the objectives.	33	17	52%	15	0	2	4.41	4.43
I would recommend this course to other students.	33	18	55%	15	1	2	4.33	4.34
The classes were interesting and informative.	33	18	55%	16	1	1	4.44	4.33

Teaching Evaluations 2024, suggestions to improve

- *I think the course is fine as is/nothing/none*
- *The textbook was a solid and high–quality resource, but I still think that for students who learn more visually and struggle to maintain focus on lengthy and complicated chapters in a textbook, that more be done to accommodate that learning style, such as through more visuals/videos, slides, and examples.*

Teaching Evaluations 2024, Comments

What did you find most valuable about this course?

Comments
I found the FPGA labs to be very valuable because it gave us a chance to apply what we were learning.
I liked being able to set my own grade percentages because I know I am not a great test taker so having the option to set my assignments grade higher helped a lot.
The way Dr. Schmidt could explain low level stuff. Learning about how to code in C was also cool, but definitely a pain sometimes. Verilog was also very interesting.
MR SCHMIDT
leanred computer arch
Learning about computer programs and how they operate.
understanding memory management, the internals of a computer
I liked this class and the professor was very good
CS 232 with Dr. Schmidt took a profound dive into topics that I think many students aren't able to experience at this point in their academic careers. We delved deep into computer hardware, the Assembly language, FPGA, and many overlooked aspects of CS that, apparently, students in NYC don't experience. I think that even if students may not go into computer hardware and navigate more towards a software path, taking this course is still highly beneficial in programming the technology we work with frequently and understanding how it physically works.

Wrap-up and review

- Experiments: not just IN the class, but ON the class
- Experiential learning works to improve student satisfaction and student learning, though only the learning is statistically significant