Project Report, Stat 8801

Heidi Sutter, Yanjia Yu, Li Zhong, Megan Heyman, Yoo Jeong Jang, Abhishek Nandy

May 1, 2013

Executive Summary

The Problem Three teachers at a local high school conducted an experiment to study new styles of teaching delivery method: Tactile, Kinesthetic, Auditory, Visual. Two important questions were raised in this project

Is the new method helping students learn? To answer this we used linear regressions, checked necessary assumptions to make sure we get a valid conclusion. The main findings were

- On average, the new method improves students' performance of score change.
- For students with a high value on t, they benefit more than other students.

Does the new teaching method especially help any of the learning types? We did two sample t-test ascertaining that our data satisfies the necessary assumptions and found the following results The new teaching method is helpful for..

- Strong tactile learners, on all three units.
- Strong auditory learners for Unit 2.
- Strong kinesthetic and visual learners for Unit 3.

1 Description of the Problem

Objective of the experiment

- Compare new style to traditional style
- Does the new style help students learn better?
- Does learning preference affect learning?
- How much does each new delivery method help?
- Is it reasonable to use different style for different course material?

Design of the experiment

- Three chosen topics were taught
- For each topic, one class chosen as control group
- New style of teaching for two classes
- Traditional style for the control group
- Run order is randomized
- Record test scores before and after teaching each topic
- Record a higher learning score
- Record preference scores for new method

The data The data set has the following variables

- ID : Student identifier
- SEX : Gender of Student
- CLASS There are three classes 1,2,3
- P1, P2, P3: Pre-test score (out of 100) for UNIT = 1,2,3
- F1, F2, F3 Post-test score (out of 100) for UNIT = 1,2,3
- S1, S2, S3 Attitude score (out of 60) for UNIT = 1,2,3
- H1, H2, H3 Higher learning test score for UNIT = 1,2,3 (1,2,3 = partially correct, 4 = correct)

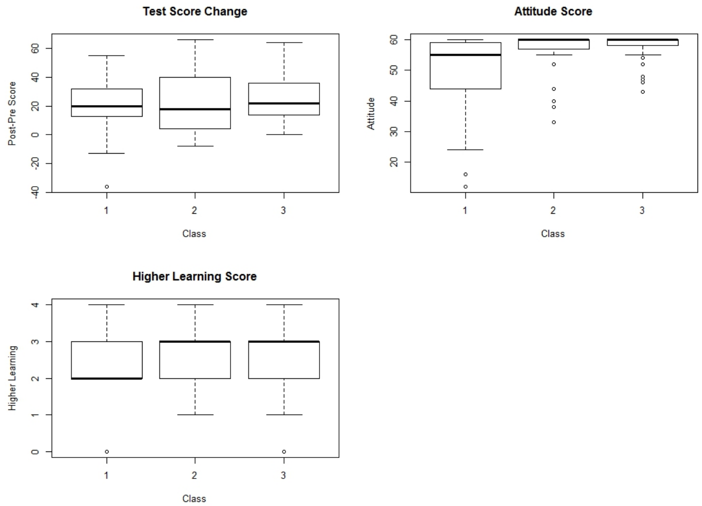
- T,K,A,V Learning Style Preference: T = Tactile, K = Kinesthetic A = Auditory, V = Visual (60+ ==¿ student has strong preference for that learning style)

3 science units (UNIT = 1,2,3) were taught to each class. For each UNIT, one class (the Control) was taught using traditional methods; the other two classes incorporated learning style preference activities. The Control group assignments for each UNIT were:
UNIT = 1 : Control = CLASS 3
UNIT = 2 : Control = CLASS 1
UNIT = 3 : Control = CLASS 2

2 Data Exploration

We begin our data exploration by defining a new variable: Test score change=Post test score- Pre test score=$Fi - Pi$, with $i = 1, 2, 3$. This helps us to determine whether and by how much the different teaching methods impact the change in scores. But at the same time it has a drawback that is we loose information about high and low scores, e.g. 100-70=60-30. However for our purposes the former is more important than the later. So defining and working with this variable is reasonable. We use box plots to determine the nature of distribution of the variables
Test Score Change, Higher Learning score and attitude scores with separate boxes for each class.

Findings from Box Plots recorded on each unit



- Boxplot of Test Score change: We see that the median of the three groups are pretty close to 20. The third class shows a slightly more positive change than the first class, the spread of both of the variables being roughly equal. The spread of this variable for the second class is largest among the three.

- Boxplot of Attitude score reveals that higher scores are predominant whereas presence of a few outlier is also noticeable.

- Boxplot of Higher Learning scores lead us to infer that the distribution of the data is roughly the same in each of the classes.

Correlation analysis We calculate the correlation between the potential Response variables viz, Test score difference, Attitude Score and Higher learning and see that correlation between the variables are relatively weak except for Test Score Difference and Higher learning Score.

	S	A	HL
S	1	0.05	0.42
A	-	1	0.10
HL	-	-	1

S=Score Change, A=Attitude, HL=Higher Learning

This preliminary analysis of data lead us to carry on our data analysis by considering change in score as our response. We also discover the following interesting fact.Of those having an attitude score of 40 or less

- 14 are in class 1 and the other 3 are in class 2
- 13 are female
- 2 in Unit 1, 9 in Unit 2, 6 in Unit 3
- 2 students gave low attitude scores on all three units
- One of these had failing scores on all 3 post tests The other failed only one post test but had A's on the others.

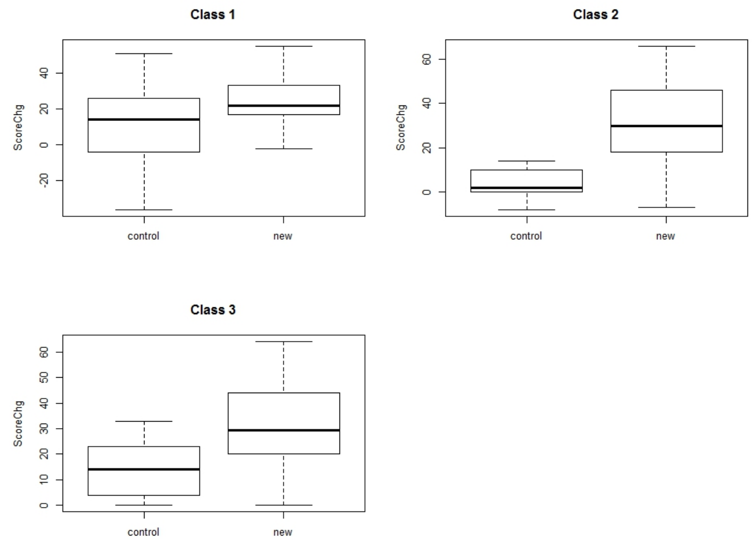
Some Interesting Statistics : *Learning Style Preference* (60+ on 1-100 scale) The following table gives the counts of the different combinations

of "strong preference learning styles" For example: the first entry in row 1 means "6 people only preferred tactile learning" the first entry in the second row (which contains a number) means "2 people strongly prefer tactile and kinesthetic learning" so we can read the entries of the table the rest of the way - "no one strongly prefers all 4 types of learning"

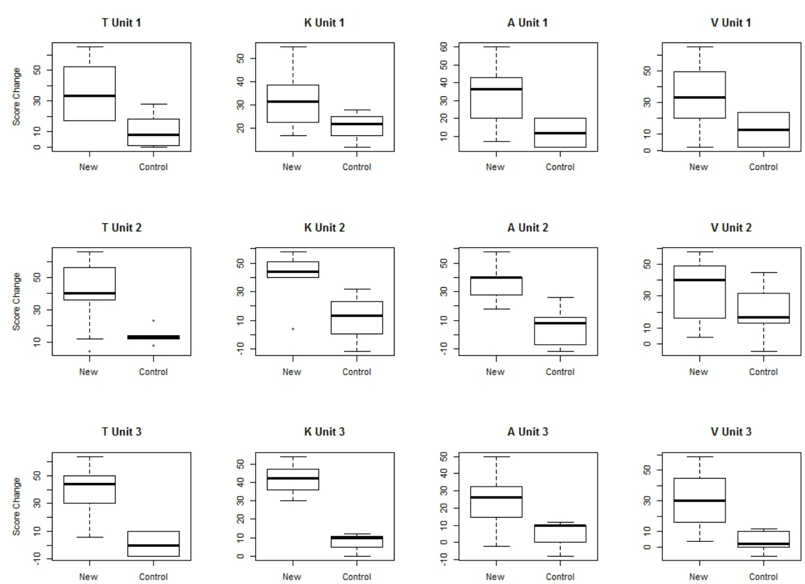
	T	K	A	V
	6	2	4	7
T	-	2	4	4
K	-	-	1	0
A	-	-	-	0
TK	-	-	1	4
AV	1	1	-	-
KAV	0	-	-	-

22 students did not have any strong preference.

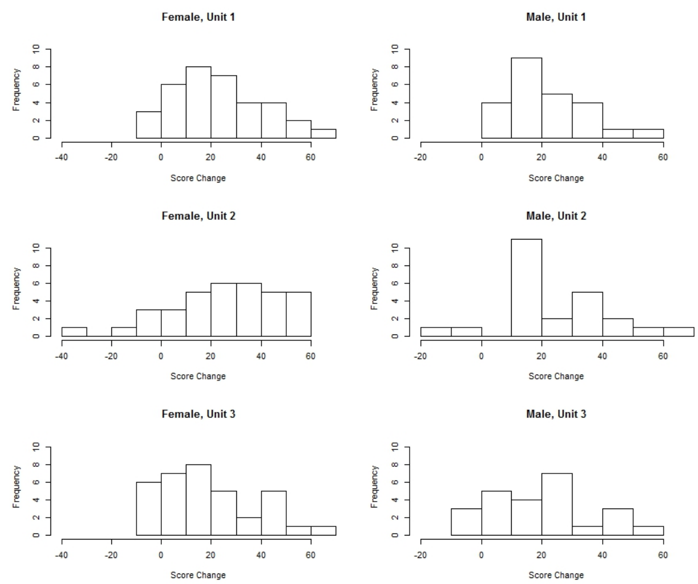
Method vs. Change in Test overall From the Box plot it appears that the median change in score is higher with the new method for all three classes.



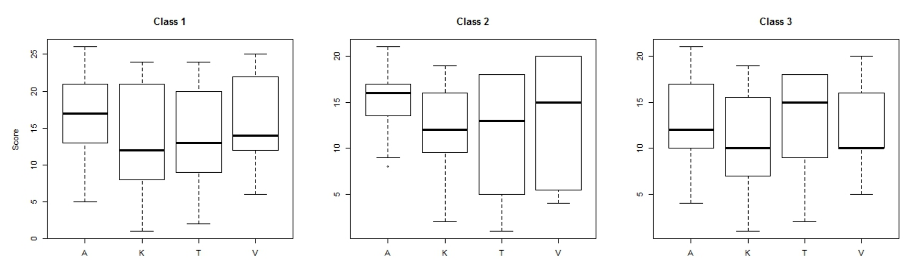
High T, K, A, V vs. Change in Test From the plot it appears for all units, those students with strong preference for the given learning style(TKAV) appeared to have a larger increase in test scores. the most drastic preferences seem to be in T, K students.



Unit and Gender with Score Change From the histograms, there does not seem to exist a clear pattern in change in score for the gender/unit interaction.



Summaries Covariate by Class The following box plots suggest that TKAV preferences seem to be fairly randomly spread between the three classes. The gender distribution are similar among classes.



	Male	**Female**
Class 1	9	12
Class 2	14	7
Class 3	11	10

The Data Analysis: Towards the answer to question 1- Is the new method helping students learn?

Linear Model Since each unit was taught to each of the classes, we considered both unit and class as blocks. There is no reason to assume interaction between these two variables. So we fit the model $m1 < -lm(y \sim sex * method * (t + k + a + v) + class + unit)$ where

- y: score change; sex: 1-Male, 0-Female; method: 1-New, 0-Traditional; t, k, a, v: 0-100; class, unit: block
- reasons:
- *unit* as a block (e.g.: gravitation, electrostatics, magnetism)
- *class* as a block (three teacher each teaches the same class through all three units)
- there is no significant interactions between *t, k, a, v*
- Since the design is unbalanced we do an anova type II test.

We present the results below

```
> car::Anova(m1)
Anova Table (Type II tests)
Response: y
             Sum Sq  Df F value    Pr(>F)
sex              69   1  0.3029  0.582877
method        14180   1 62.3825 5.124e-13 ***
t              1321   1  5.8108  0.017115 *
k                13   1  0.0580  0.809991
a                52   1  0.2270  0.634449
v               267   1  1.1757  0.279929
class           778   2  1.7120  0.183939
unit            490   2  1.0771  0.343145
sex:method      108   1  0.4753  0.491602
sex:t             5   1  0.0205  0.886250
sex:k            99   1  0.4352  0.510430
sex:a            31   1  0.1362  0.712620
sex:v           466   1  2.0501  0.154237
method:t       2430   1 10.6898  0.001331 **
method:k         12   1  0.0542  0.816200
```

```
method:a        502   1  2.2066  0.139479
method:v         33   1  0.1462  0.702749
sex:method:t     27   1  0.1172  0.732512
sex:method:k    106   1  0.4664  0.495681
sex:method:a      9   1  0.0392  0.843298
sex:method:v     18   1  0.0796  0.778173
Residuals     34779 153
```

Thus the variables method, t and the interactions between them are significant. However we want to do a variable selection using AIC, and we would always want to include the blocking variables. After choosing the optimal model, we see which variables are significant.

```
> library(MASS)
> stepAIC(lm(y~sex*method*(t+k+a+v)+class+unit),
+         scope = list(upper= y~sex*method*(t+k+a+v)+class+unit,
+                      lower= y~1+class+unit),direction="backward")
...
Call:
lm(formula = y ~ sex + method + t + a + v + class + unit + sex:v +
    method:t + method:a)
Coefficients:
(Intercept)         sex1      method1           t1            a
    11.3810      16.3395     -10.5335      -6.2979      -0.2237
          v       class2       class3        unit2        unit3
     0.2725      -2.3364       3.0217       1.9050      -2.2453
     sex1:v   method1:t1   method1:a
    -0.3464      20.7686       0.4128
```

So, we get the updated model m2: $y \sim sex + method + t + a + v + class + unit + sex : v + method : t + method : a$

```
> car::Anova(m2)
Anova Table (Type II tests)
Response: y
          Sum Sq  Df F value    Pr(>F)
sex           69   1  0.3215  0.571468
method     14180   1 66.0148 1.028e-13 ***
t           2105   1  9.8010  0.002065 **
a             30   1  0.1382  0.710560
v            280   1  1.3029  0.255349
```

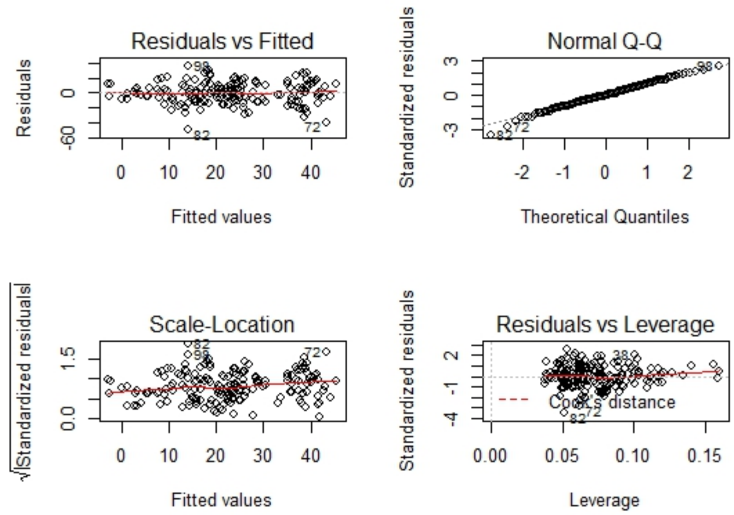
```
class        709   2  1.6513  0.194981
unit         495   2  1.1521  0.318525
sex:v        624   1  2.9036  0.090275 .
method:t    3843   1 17.8920 3.878e-05 ***
method:a     583   1  2.7118  0.101520
Residuals  35228 164

> summary(m2)
Call:
lm(formula = y ~ sex + method + t + a + v + class + unit + sex:v +
    method:t + method:a)
...
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  11.3810    15.2375   0.747   0.4562
sex1         16.3395    10.6097   1.540   0.1255
method1     -10.5335    13.6946  -0.769   0.4429
t1           -6.2979     4.0654  -1.549   0.1233
a            -0.2237     0.2170  -1.031   0.3041
v             0.2725     0.1414   1.927   0.0557 .
class2       -2.3364     2.7666  -0.845   0.3996
class3        3.0217     2.8180   1.072   0.2852
unit2         1.9050     2.7282   0.698   0.4860
unit3        -2.2453     2.7383  -0.820   0.4134
sex1:v       -0.3464     0.2033  -1.704   0.0903 .
method1:t1   20.7686     4.9100   4.230 3.88e-05 ***
method1:a     0.4128     0.2507   1.647   0.1015
```

Conclusion about the Influence of New Method

- On average, the new method improves students' performance of score change.
- For students with a high value on t or a, they benefit more than other students.

Model Diagnostic Finally we include the model diagnostics plot. They seem to look very good.



Some More analysis using SPSS

This problem is very similar to common problems dealt by psychologists, and it is a common and reasonable approach to fit hierarchical models. This is done using SPSS and the results are included in the following tables

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	14.526	3.518		4.129	.000	7.482	21.571
	taught by new teaching method for unit 1	13.074	4.272	.376	3.060	.003	4.518	21.629
2	(Constant)	16.472	4.742		3.473	.001	6.941	26.002
	taught by new teaching method for unit 1	3.751	5.891	.108	.637	.527	-8.087	15.589
	preference for learning style t	-11.220	8.048	-.334	-1.394	.170	-27.393	4.954
	preference for learning style k	11.675	10.171	.280	1.148	.257	-8.765	32.115
	preference for learning style a	1.138	11.539	.028	.099	.922	-22.050	24.326
	preference for learning style v	7.748	12.866	.207	.602	.550	-18.107	33.603
	interaction between t.type an intervention 1	21.868	9.604	.572	2.277	.027	2.568	41.168
	interaction between k.type an intervention 1	-13.376	12.072	-.282	-1.108	.273	-37.636	10.883
	interaction between a.type an intervention 1	5.726	12.870	.132	.445	.658	-20.138	31.590
	interaction between v.type an intervention 1	-.748	13.977	-.019	-.054	.958	-28.836	27.340

a. Dependent Variable: change score for unit 1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	13.667	4.018		3.401	.001	5.620	21.713
	taught by new teaching method for unit 2	18.412	5.007	.438	3.677	.001	8.386	28.439
2	(Constant)	16.834	5.576		3.019	.004	5.629	28.039
	taught by new teaching method for unit 2	7.823	7.049	.186	1.110	.273	-6.343	21.989
	preference for learning style t	4.503	10.201	.108	.441	.661	-15.998	25.003
	preference for learning style k	-2.679	10.880	-.052	-.246	.807	-24.543	19.186
	preference for learning style a	-12.699	10.227	-.254	-1.242	.220	-33.251	7.852
	preference for learning style v	-2.964	10.552	-.064	-.281	.780	-24.170	18.242
	interaction between t.type an intervention 2	10.883	11.931	.245	.912	.366	-13.093	34.859
	interaction between k.type an intervention 2	9.309	13.466	.150	.691	.493	-17.751	36.369
	interaction between a.type an intervention 2	14.268	12.772	.229	1.117	.269	-11.399	39.935
	interaction between v.type an intervention 2	-.727	12.574	-.014	-.058	.954	-25.995	24.540

a. Dependent Variable: change score for unit 2

Conclusion about the Influence of New Method

- On average, the new method improves students' performance of score change.
- For students with a high value on t, they benefit more than other students.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.737	3.085		.887	.379	-3.440	8.914
	taught by new teaching method for unit 3	25.538	3.746	.670	6.817	.000	18.036	33.040
2	(Constant)	3.356	4.210		.797	.429	-5.105	11.817
	taught by new teaching method for unit 3	20.132	4.835	.528	4.163	.000	10.415	29.849
	preference for learning style t	-6.967	5.261	-.189	-1.324	.192	-17.539	3.605
	preference for learning style k	8.052	7.114	.176	1.132	.263	-6.244	22.349
	preference for learning style a	1.956	5.994	.044	.326	.746	-10.090	14.001
	preference for learning style v	1.119	5.463	.027	.205	.839	-9.858	12.097
	interaction between t.type an intervention 3	24.644	6.579	.574	3.746	.000	11.422	37.866
	interaction between k.type an intervention 3	3.762	8.530	.068	.441	.661	-13.380	20.904
	interaction between a.type an intervention 3	-10.707	7.629	-.194	-1.403	.167	-26.038	4.624
	interaction between v.type an intervention 3	-9.655	7.301	-.175	-1.322	.192	-24.327	5.017

a. Dependent Variable: change score for unit 3

Towards answering second question: Does the new teaching method especially help any of the learning types?

The following are considered as the potential predictors

Tactile

Kinesthetic

Auditory

Visual

Teaching Method - Binary (1 if New, 0 if Control)

Now there are two approaches to answer the question in hand.

1. Linear Models

For each unit:
Score diff $\sim$ T + K + A + V + Method + two-way interactions

Here all the predictors are binary.

2. Two-Sample T-Tests

For each unit and teaching method, compare the average score difference for the new and control methods:
$H_0 : \mu_{new} = \mu_{control}$
$H_1 : \mu_{new} > \mu_{control}$
We however opt for the second method. Our next step would thus be to make and check assumptions.

Independent Samples We assume

- Students independently took tests
- However there is a possibility that there is a significant within class correlation.

Normality Assumptions(Shapiro - Wilks Test)

- There were 24 samples in total, two for each of the variables T, K, A , V and each of the 3 units.
- 20 of the samples met the normality assumption
- 2 samples failed to meet the assumption
- 2 samples had fewer than 3 data points

Variance Unequal variances of samples were accounted for while running the t-test.

Below we report the output and our conclusions based on our output
Bonferroni Adjusted P-Values

	T	K	A	V
Unit 1	0.0028	0.7444	0.9480	1.0000
Unit 2	0.0001	0.2326	0.0423	0.9994
Unit 3	0.0000	0.0002	0.1716	0.0259

Conclusions: The new teaching method is helpful for..

- Strong tactile learners, on all three units.
- Strong auditory learners for Unit 2.
- Strong kinesthetic and visual learners for Unit 3.