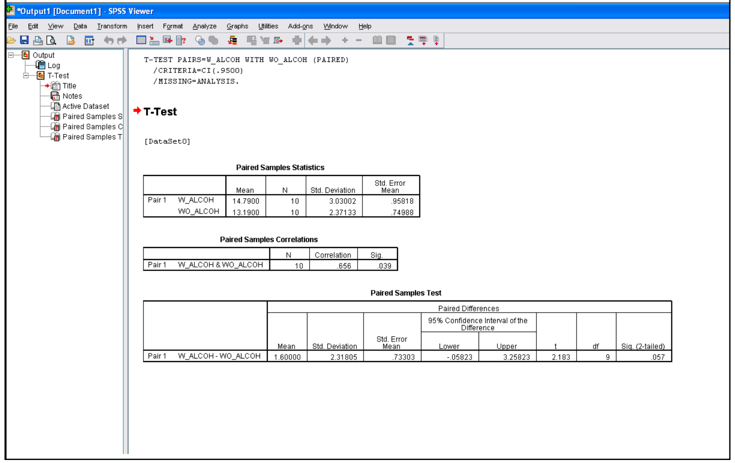
***One tailed t-test using SPSS:* Divide the probability that a two-tailed SPSS test produces. SPSS always produces two-tailed significance level.**



```
T-TEST PAIRS=W_ALCOH WITH WO_ALCOH (PAIRED)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.
```

T-Test

[DataSet0]

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	W_ALCOH	14.7900	10	3.03002	.95818
	WO_ALCOH	13.1900	10	2.37133	.74988

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	W_ALCOH & WO_ALCOH	10	.656	.039

Paired Samples Test

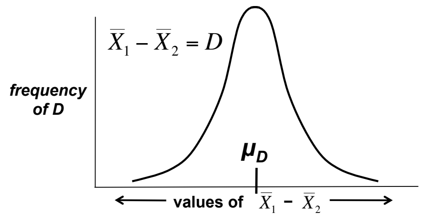
		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	W_ALCOH - WO_ALCOH	1.60000	2.31805	.73303	-.05823	3.25823	2.183	9	.057

One tailed vs two tailed tests: a normal distribution filled with a rainbow of colours

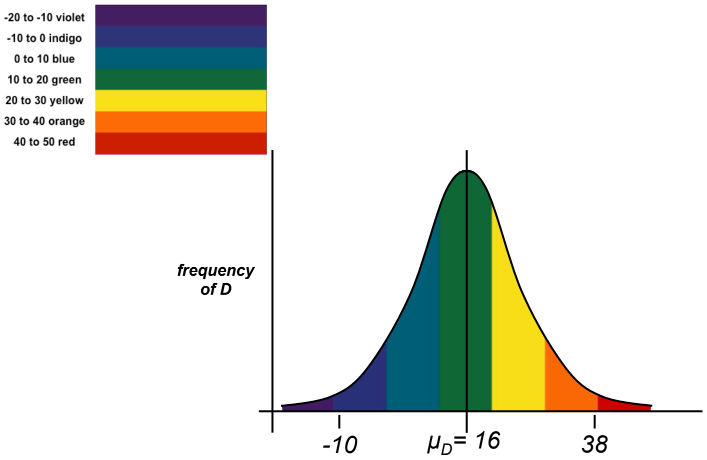
Trivial example: Height of 10 year old boys will be different from height of 14 year old boys. Samples N = 50

$\bar{X}_1$ **= height (14)**

$\bar{X}_2$ **= height (10)**



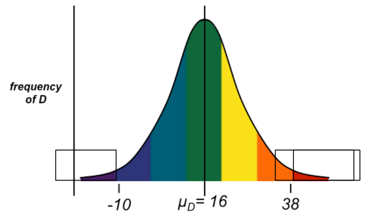
Frequency distribution of height differences (cm)



Non-directional hypothesis: Height of 14 year old boys will be different from height of 10 year old boys.

Directional hypothesis: Height of 14 year old boys will be greater than 10 year old boys.

We have agreed that we are willing to tolerate being wrong 5% of the time, which corresponds to 5% of the total area under the curve.



A word about Summation:

$$estimated\sigma_{\bar{X}_1-\bar{X}_2} = \sqrt{\frac{\sum(X_1-\bar{X}_1)^2 + \sum(X_2-\bar{X}_2)^2}{(n_1-1)+(n_2-1)} \times \left(\frac{1}{n_1}+\frac{1}{n_2}\right)}$$

	Subject group 1			Subject group 2	
	X_1			X_2	
Participant 1	13.0		Participant 1	11.1	
Participant 2	16.5		Participant 2	13.5	
Participant 3	16.9		Participant 3	11.0	
Participant 4	19.7		Participant 4	9.1	
Participant 5	17.6		Participant 5	13.3	
Participant 6	17.5		Participant 6	11.7	
Participant 7	18.1		Participant 7	14.3	
Participant 8	17.3		Participant 8	10.8	
Participant 9	14.5		Participant 9	12.6	
Participant 10	13.3		Participant 10	11.2	

Meaning of a summation sign → $\sum X_1 = 164.4$ $\quad \sum X_2 = 118.6$

$\bar{X}_1 = 16.44$ $\quad \bar{X}_2 = 11.86$

subject group 1

$$\sum X_1 = 164.4$$

$$\sum_{p=1}^{10} X_1 = 164.4$$

subject group 2

$$\sum X_2 = 118.6$$

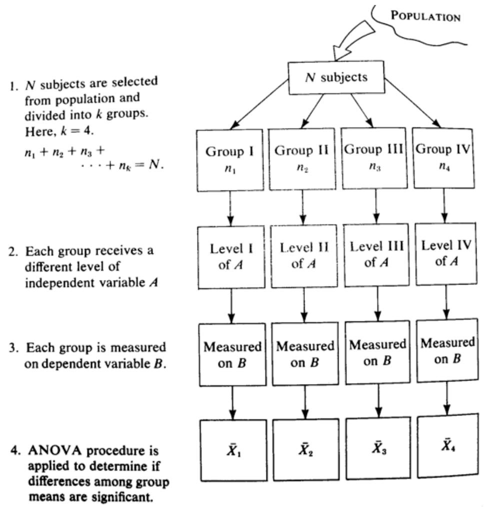
$$\bar{X}_2 = 11.86$$

$$\boxed{\sum_{p=1}^{10}(X_2-\bar{X})^2}$$

1 2 3 4

$$(X_2-\bar{X})^2 + (X_2-\bar{X})^2 + (X_2-\bar{X})^2 \quad \cdots$$

Analysis of Variance:



Tests for comparing three or more groups or conditions:

(a) Nonparametric tests:
Independent measures: Kruskal-Wallis.
Repeated measures: Friedman's.

(b) Parametric tests:
Analysis of Variance (ANOVA).
ANOVA is a whole family of tests: includes independent measures and repeated measures versions.

Why use ANOVA:

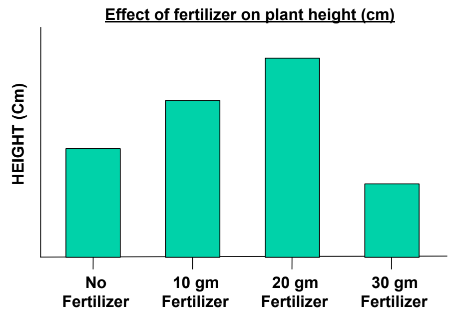
(a) ANOVA can test for *trends* in our data.

Population of seeds

↓

Randomly select 40 seeds

Trend analysis (too much of a good thing)



(b) ANOVA is preferable to performing many *t*-tests on the same data (avoids increasing the risk of Type 1 error).

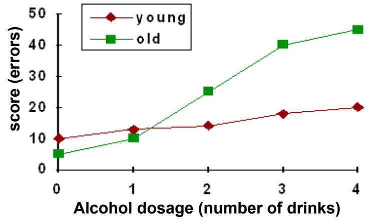
Suppose we have 3 groups. We will have to compare:

group 1 with group 2
group 1 with group 3
group 2 with group 3

Each time we perform a test there is (small) probability of rejecting the null hypothesis which is true. These probabilities add up. So we want a single test. Which is ANOVA.

(c) ANOVA can be used to compare groups that differ on two, three or more independent variables, and can detect *interactions* between them.

Age-differences in the effects of alcohol on motor coordination:



Logic behind ANOVA:

Variation in a set of scores comes from two sources:

Random variation from the subjects themselves (due to individual variations in motivation, aptitude, etc.)

Systematic variation produced by the experimental manipulation.

ANOVA compares the amount of systematic variation to the amount of random variation, to produce an *F*-ratio:

$$F = \frac{\text{systematic variation}}{\text{random variation ('error')}}$$

Another example*: *Effects of caffeine on memory

4 groups - each gets a different dosage of caffeine, followed by a memory test.

Systematic variation

Random variation

Group A (0 mg)	Group B (1 mg)	Group C (5 mg)	Group D (10 mg)
4	7	11	14
3	9	15	12
5	10	13	10
6	11	11	15
2	8	10	14
total = 20	total = 45	total = 60	total = 65
mean = 4	mean = 9	mean = 12	mean = 13
s.d. = 1.58	s.d. = 1.58	s.d. = 2.00	s.d. = 2.00

$$F = \frac{\text{systematic variation}}{\text{random variation ('error')}}$$

Large value of *F*: a lot of the overall variation in scores is due to the experimental manipulation, rather than to random variation between subjects.

Small value of *F*: the variation in scores produced by the experimental manipulation is small, compared to random variation between subjects.

One-way Independent-Measures ANOVA:

Use this where you have:
(a) *one* independent variable (which is why it's called "one-way");

(b) *one* dependent variable (you get only one score from each subject);

(c) each subject participates in only *one* condition in the experiment (which is why it is independent measures).

A one-way independent-measures ANOVA is equivalent to an independent-measures *t*-test, except that you have more than two groups of subjects.

CALCULATIONS

In practice, ANOVA is based on the *variance* of the scores. The variance is the standard deviation squared:

$$\text{variance} = \frac{\sum(X-\bar{X})^2}{N}$$

We want to take into account the number of subjects and number of groups. Therefore, we use only the top line of the variance formula (the *"Sum of Squares"*, or "*SS*"):

$$\text{sum of squares} = \sum(X-\bar{X})^2$$

We divide this by the appropriate "*degrees of freedom*" (usually the number of groups or subjects minus 1).

Effects of caffeine on memory:

4 groups - each gets a different dosage of caffeine, followed by a memory test.

Group A (0 mg)	Group B (1 mg)	Group C (5 mg)	Group D (10 mg)
4	7	11	14
3	9	15	12
5	10	13	10
6	11	11	15
2	8	10	14
total = 20	total = 45	total = 60	total = 65
mean = 4	mean = 9	mean = 12	mean = 13

$SS = \sum (X - \bar{X})^2$ **Three types of SS**

Total SS

Group A (0 mg)	Group B (1 mg)	Group C (5 mg)	Group D (10 mg)
4	7	11	14
3	9	15	12
5	10	13	10
6	11	11	15
2	8	10	14

Between groups SS

Group A (0 mg)	Group B (1 mg)	Group C (5 mg)	Group D (10 mg)
4	7	11	14
3	9	15	12
5	10	13	10
6	11	11	15
2	8	10	14

Within groups SS

Group A (0 mg)	Group B (1 mg)	Group C (5 mg)	Group D (10 mg)
4	7	11	14
3	9	15	12
5	10	13	10
6	11	11	15
2	8	10	14

The ANOVA summary table:

Source:	SS	df	MS	F
Between groups	245.00	3	81.67	25.13
Within groups	52.00	16	3.25	
Total	297.00	19		

***Total SS*: a measure of the total amount of variation amongst all the scores.**

***Between-groups SS*: a measure of the amount of variation between the groups. (This is due to our experimental manipulation).**

***Within-groups SS*: a measure of the amount of variation within the groups. (This *cannot* be due to our experimental manipulation, because we did the *same* thing to *everyone* within each group).**

(Total SS) = (Between-groups SS) + (Within-groups SS)

Source:	SS	df	MS	F
Between groups	245.00	3	81.67	25.13
Within groups	51.98	16	3.25	
Total	297.00	19		

Total degrees of freedom: **the number of subjects, minus 1.**

Between-groups degrees of freedom: **the number of groups, minus 1.**

Within-groups degrees of freedom:

Obtained by adding together

the number of subjects in group A, minus 1;

the number of subjects in group B, minus 1; etc.

(between-groups df) + (within-groups df) = (total df)

Assessing the significance of the F-ratio:

The bigger the F-ratio, the less likely it is to have arisen merely by chance.

Use the between-groups and within-groups d.f. to find the critical value of F.

Your F is significant if it is *equal to or larger* than the critical value in the table.

Here, look up the critical *F*-value for 3 and 16 d.f.

***Columns* correspond to between-groups d.f.; *rows* correspond to within-groups d.f.**

Here, go *along* 3 and *down* 16: critical *F* is at the intersection.

Our obtained *F*, 25.13, is *bigger* than 3.24; it is therefore significant at $p<.05$. (Actually it's bigger than 9.01, the critical value for a *p* of 0.001).

	1	2	3	4
1	161.4	199.5	215.7	224.6
2	18.51	19.00	19.16	19.25
3	10.13	9.55	9.28	9.12
4	7.71	6.94	6.59	6.39
5	6.61	5.79	5.41	5.19
6	5.99	5.14	4.76	4.53
7	5.59	4.74	4.35	4.12
8	5.32	4.46	4.07	3.84
9	5.12	4.26	3.86	3.63
10	4.96	4.10	3.71	3.48
11	4.84	3.98	3.59	3.36
12	4.75	3.89	3.49	3.26
13	4.67	3.81	3.41	3.18
14	4.60	3.74	3.34	3.11
15	4.54	3.68	3.29	3.06
16	4.49	3.63	**3.24**	3.01
17	4.45	3.20	3.20	2.96

Interpreting the Results:

A significant F-ratio merely tells us is that there is a statistically-significant difference between our experimental conditions; it does not say *where* the difference comes from.

In our example, it tells us that caffeine dosage does make a difference to memory performance.

BUT suppose the difference is ONLY between: Caffeine VERSUS No-Caffeine

AND There is NO difference between: Large dose of Caffeine VERSUS Small Dose of Caffeine

To pinpoint the source of the difference we can do:

(a) *planned comparisons* - comparisons between (two) groups which you decide to make *in advance* of collecting the data.

(b) *post hoc tests* - comparisons between (two) groups which you decide to make *after* collecting the data: Many different types - e.g. Newman-Keuls, Scheffé, Bonferroni.

Assumptions underlying ANOVA:

ANOVA is a parametric test (like the t-test)

It assumes:

(a) data are interval or ratio measurements;

(b) conditions show homogeneity of variance;

(c) scores in each condition are roughly normally distributed.

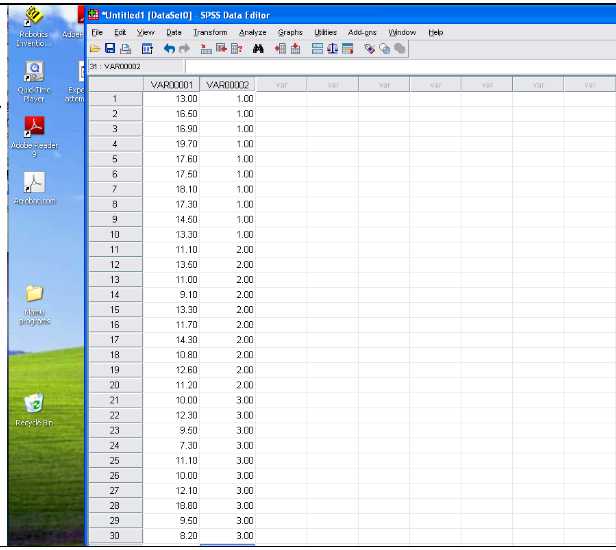
Using SPSS for a one-way independent-measures ANOVA on effects of alcohol on time taken on a motor task.

Three groups:

Group 1: two drinks
Group 2: one drink
Group 3: no alcohol

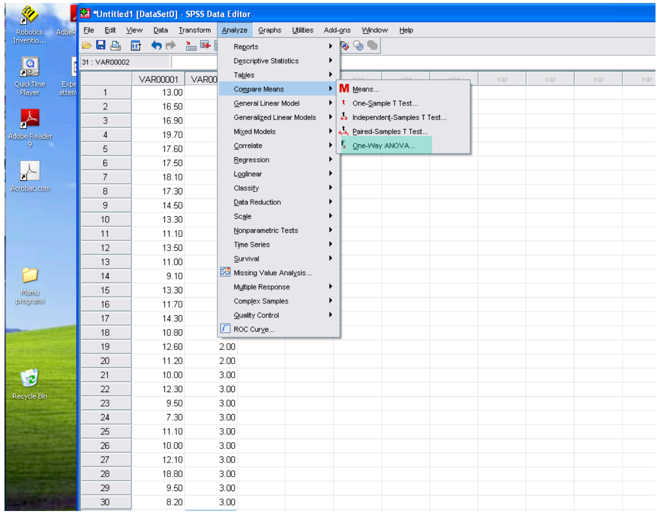
(Analyze > compare means > One Way ANOVA)

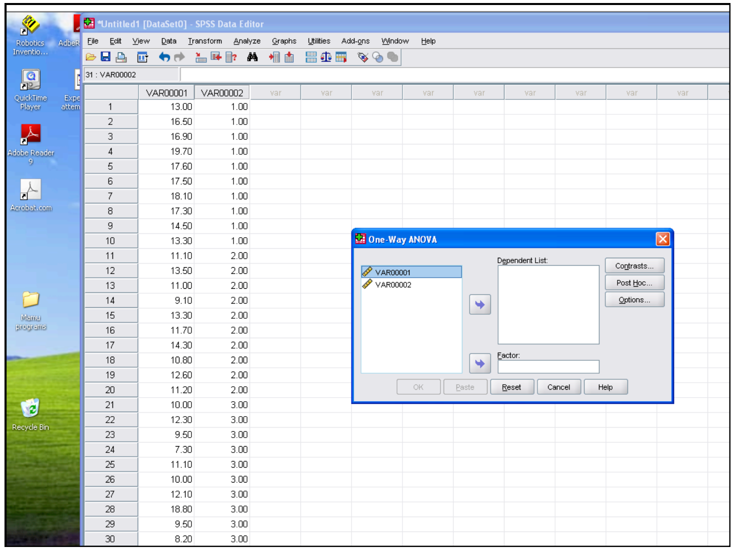
Data Entry

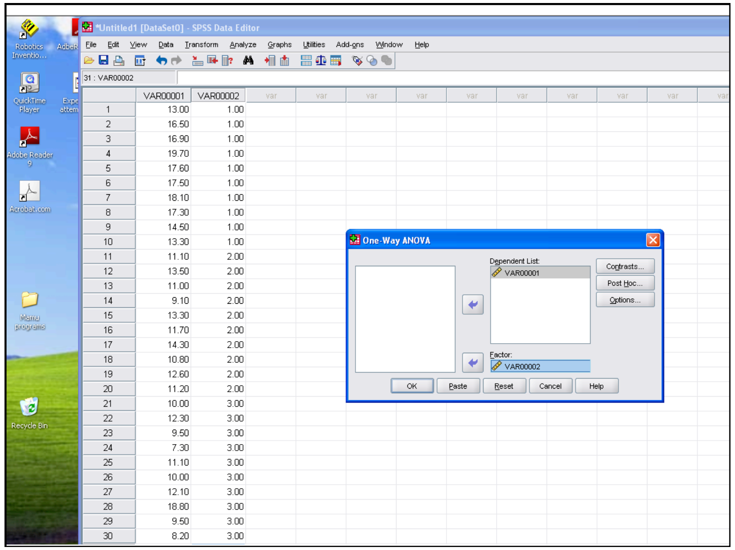


	VAR00001	VAR00002
1	13.00	1.00
2	16.50	1.00
3	16.90	1.00
4	19.70	1.00
5	17.60	1.00
6	17.50	1.00
7	18.10	1.00
8	17.30	1.00
9	14.50	1.00
10	13.30	1.00
11	11.10	2.00
12	13.50	2.00
13	11.00	2.00
14	9.10	2.00
15	13.30	2.00
16	11.70	2.00
17	14.30	2.00
18	10.80	2.00
19	12.60	2.00
20	11.20	2.00
21	10.00	3.00
22	12.30	3.00
23	9.50	3.00
24	7.30	3.00
25	11.10	3.00
26	10.00	3.00
27	12.10	3.00
28	18.80	3.00
29	9.50	3.00
30	8.20	3.00

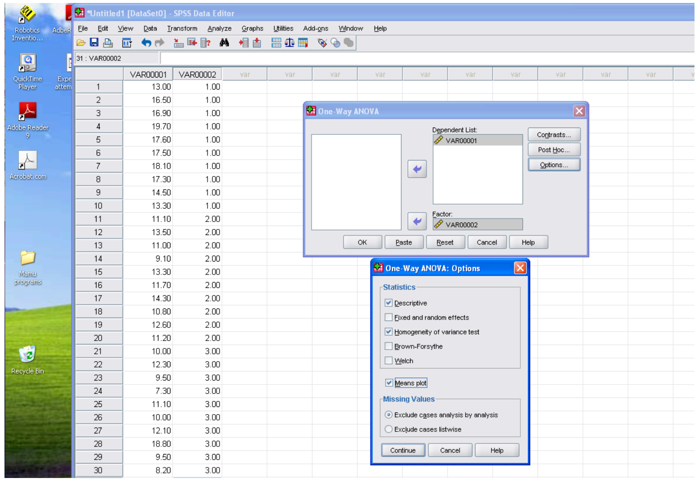
RUNNING SPSS



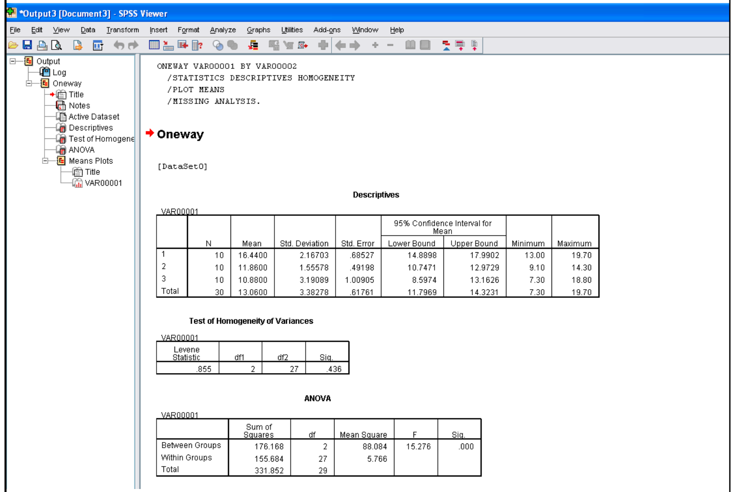




Click 'Options…'
Then Click Boxes: Descriptive; Homogeneity of variance test; Means plot



SPSS output



```
ONEWAY VAR00001 BY VAR00002
  /STATISTICS DESCRIPTIVES HOMOGENEITY
  /PLOT MEANS
  /MISSING ANALYSIS.
```

Oneway

[DataSet0]

Descriptives

VAR00001

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
1	10	16.4400	2.16703	.68527	14.8898	17.9902	13.00	19.70
2	10	11.8600	1.55578	.49198	10.7471	12.9729	9.10	14.30
3	10	10.8800	3.19089	1.00905	8.5974	13.1626	7.30	18.80
Total	30	13.0600	3.38278	.61761	11.7969	14.3231	7.30	19.70

Test of Homogeneity of Variances

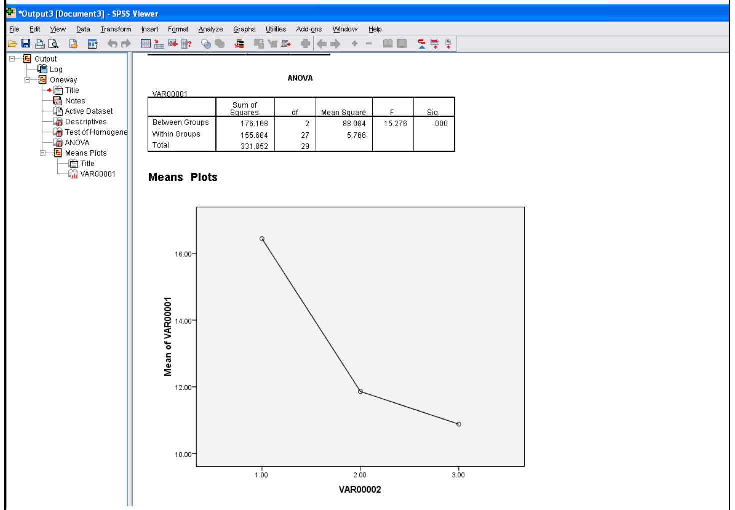
VAR00001

Levene Statistic	df1	df2	Sig.
.855	2	27	.436

ANOVA

VAR00001

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	176.168	2	88.084	15.276	.000
Within Groups	155.684	27	5.766		
Total	331.852	29			



ANOVA

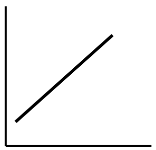
VAR00001

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	176.168	2	88.084	15.276	.000
Within Groups	155.684	27	5.766		
Total	331.852	29			

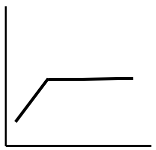
Means Plots

Trend tests:

(Makes sense only when levels of IV correspond to differing amounts of something - such as caffeine dosage - which can be meaningfully ordered).



Linear trend:



Quadratic trend:

(one change in direction)

Cubic trend: (two changes in direction)

With two groups, you can only test for a linear trend. With three groups, you can test for linear and quadratic trends. With four groups, you can test for linear, quadratic and cubic trends.

Conclusions:

One-way independent-measures ANOVA enables comparisons between 3 or more groups that represent different levels of one independent variable.

A parametric test, so the data must be interval or ratio scores; be normally distributed; and show homogeneity of variance.

ANOVA avoids increasing the risk of a Type 1 error.