DISCOVERING STATISTICS

Two-Way Independent ANOVA Using SPSS

Introduction

Up to now we have looked only at situations in which a single independent variable was manipulated. Now we move onto more complex designs in which more than one independent variable has been manipulated. These designs are called *Factorial Designs*. When you have two independent variables the corresponding ANOVA is known as a *two-way* ANOVA, and when both variables have been manipulated using different participants the test is called a two-way *independent* ANOVA (some books use the word *unrelated* rather than independent). So, a two-way independent ANOVA is used when two independent variables have been manipulated using different participants in all conditions.

The 'Beer-Goggles' Effect

A psychologist was interested in the effects of alcohol on mate selection at night-clubs. Her rationale was that after alcohol had been consumed, subjective perceptions of physical attractiveness would become more inaccurate (the well-known 'beer-goggles effect'). She was also interested in whether this effect was different for men and women. She picked 48 students: 24 male and 24 female. She then took groups of 8 participants to a night-club and gave them no alcohol (participants received placebo drinks of alcohol-free lager), 2 pints of strong lager, or 4 pints of strong lager. At the end of the evening she took a photograph of the person that the participant was chatting up. She then got a pool of independent raters to assess the attractiveness of the person in each photograph (out of 100). The data are presented in Table 1.

Table 1: Data for the beer-goggles effect

Alcohol	None		2 Pints		4 Pints	
Gender	Female	Male	Female	Male	Female	Male
	65	50	70	45	55	30
	70	55	65	60	65	30
	60	80	60	85	70	30
	60	65	70	65	55	55
	60	70	65	70	55	35
	55	75	60	70	60	20
	60	75	60	80	50	45
	55	65	50	60	50	40

We saw earlier in the module that one-way ANOVA could be conceptualized as a regression equation (a general linear model)—see Field (2013), Chapter 11 for more detail. We'll now consider how we extend this linear model to incorporate two independent variables. To keep things as simple as possible I want you to imagine that we have only two levels of the alcohol variable in our example (none and 4 pints). As such, we have two predictor variables, each with two levels. All of the general linear models we've considered take the general form of:

$$\text{outcome}_i = (\text{model}) + \text{error}_i$$

For example, when we encountered multiple regression in we saw that this model was written as:

$$Y_i = (b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n X_{ni}) + \varepsilon_i$$

Also, when we came across one-way ANOVA, we adapted this regression model to conceptualize our Viagra example, as:

$$\text{Libido}_i = (b_0 + b_2\text{high}_i + b_1\text{low}_i) + \varepsilon_i$$

In this model, the High and Low variables were dummy variables (i.e., variables that can take only values of 0 or 1). In our current example, we have two variables: **gender** (male or female) and **alcohol** (none and 4 pints). We can code each of these with zeros and ones, for example, we could code gender as male = 0, female = 1, and we could code the alcohol variable as 0 = none, 1 = 4 pints. We could then directly copy the model we had in one-way ANOVA:

$$\text{Attractiveness}_i = (b_0 + b_1\text{Gender}_i + b_2\text{Alcohol}_i) + \varepsilon_i$$

However, this model does not consider the interaction between gender and alcohol. If we want to include this term too, then the model simply extends to become (first expressed generally and then in terms of this specific example):

$$\text{Attractiveness}_i = (b_0 + b_1\text{A}_i + b_2\text{B}_i + b_3\text{AB}_i) + \varepsilon_i$$
$$\text{Attractiveness}_i = (b_0 + b_1\text{Gender}_i + b_2\text{Alcohol}_i + b_3\text{Interaction}_i) + \varepsilon_i$$

The question is: how do we code the interaction term? The interaction term represents the combined effect of **alcohol** and **gender**; to get any interaction term you simply multiply the variables involved. This is why you see interaction terms written as gender × alcohol, because in regression terms the interaction variable literally is the two variables multiplied by each other. For more detail about how all of the coding works read Field (2013), Chapters 10 and 12. For the purpose of this exercise all I really want you to understand is that (1) we're still fitting a linear model; (2) SPSS will code your predictors (independent variables) using the dummy coding that we have discussed before; and (3) we include an interaction term, which is coded by multiplying the dummy codes for any of the predictors involved in the interaction.

Two-Way Independent ANOVA Using SPSS

Inputting Data

TIP	
	→ Levels of between group variables go in a single column of the SPSS data editor.

Applying the rule above to the data we have here we are going to need to create 2 different coding variables (seeField, 2013, Chapter 3) in the data editor. These columns will represent gender and alcohol consumption. So, create a variable called **Gender** in the data editor and activate the *labels* dialog box. You should define value labels to represent the two genders. We have had a lot of experience with coding values, so you should be fairly happy about assigning numerical codes to different groups. I recommend using the code Male = 0, and Female = 1. Once you have done this, you can enter a code of zero or one in this column indicating to which group the participant belonged. Create a second variable called **Alcohol** and assign group codes by using the *labels* dialog box. I suggest that you code this variable with three values: Placebo (no Alcohol) = 1, 2 Pints = 2, and 4 pints = 3. You can now enter 1, 2 or 3 into this column to represent the amount of alcohol consumed by the participant. Remember that if you turn the value labels option on (🔢) you will see text in the data editor rather than the numerical codes. Now, the way this coding works is as follows:

Gender	Alcohol	Participant was ..
0	1	Male who consumed no alcohol
0	2	Male who consumed 2 pints
0	3	Male who consumed 4 pints
1	1	Female who consumed no alcohol
1	2	Female who consumed 2 pints
1	3	Female who consumed 4 pints

Once you have created the two coding variables, you can create a third variable in which to place the values of the dependent variable. Call this variable **attract** and use the *labels* option to give it the fuller name of 'Attractiveness of Date'. In this example, there are two independent variables and different participants were used in each condition:

hence, we can use the general factorial ANOVA procedure in SPSS. This procedure is designed for analysing between-group factorial designs.

→   Enter the data into SPSS.

→   Save the data onto a disk in a file called **BeerGoggles.sav**.

→   Plot an error bar graph of the mean attractiveness of mates across the different levels of alcohol.

→   Plot an error bar graph of the mean attractiveness of mates selected by males and females.

The Main Dialog Box

To access the main dialog box use the file path Analyze General Linear Model ▶ GLM Univariate... . The resulting dialog box is shown in Figure 1. First, select the dependent variable **Attractiveness** from the variables list on the left-hand side of the dialog box and drag it to the space labelled *Dependent Variable* or click on ⬆. In the space labelled *Fixed Factor(s)* we need to place any independent variables relevant to the analysis. Select **Alcohol** and **Gender** in the variables list (these variables can be selected simultaneously by holding down *Ctrl* while clicking on the variables) and drag them to the *Fixed Factor(s)* box (or click on ⬆). There are various options available to us, we only need worry about the ones covered in this handout (anyone interested in further options should read my 2013 textbook, chapter 13).
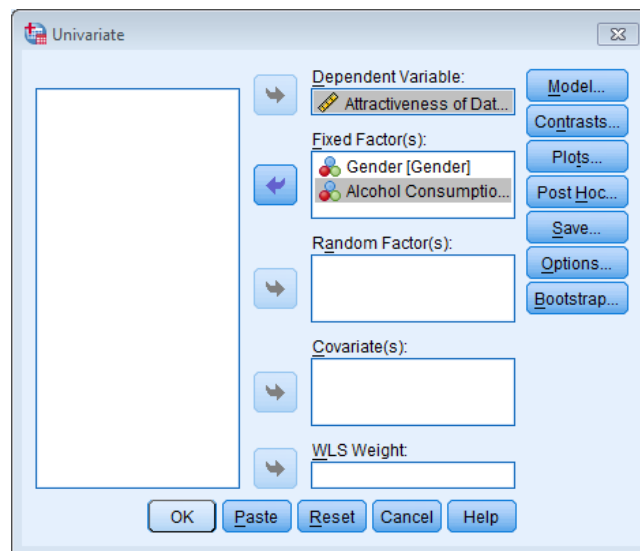

Figure 1: Main dialog box for univariate ANOVA

Simple and horrible looking graphs of Interactions

Click on Plots... to access the dialog box in Figure 2. The plots dialog box allows you to select line graphs of your data and these graphs are very useful for interpreting interaction effects (however, really we should plot graphs of the means before the data are analysed). We have only two independent variables, and the most useful plot is one that shows the interaction between these variables (the plot that displays levels of one independent variable against the other). In this case, the **interaction** graph will help us to interpret the combined effect of gender and alcohol consumption. Select **Alcohol** from the variables list on the left-hand side of the dialog box and drag it to the space labelled *Horizontal Axis* (or click on ⬆). In the space labelled *Separate Lines* place the remaining independent variable, **Gender**. It doesn't matter which way round the variables are plotted; you should use your discretion as to which way produces the most sensible graph. When you have moved the two independent variables to the appropriate box, click on Add and this plot will be added to the list at the bottom of the box. You can plot a whole variety of graphs, and if you had a third independent variable, you have the option of plotting different graphs for each level of that third variable by specifying a variable under the heading *Separate Plots*. When you have finished specifying graphs, click on Continue to return to the main dialog box.
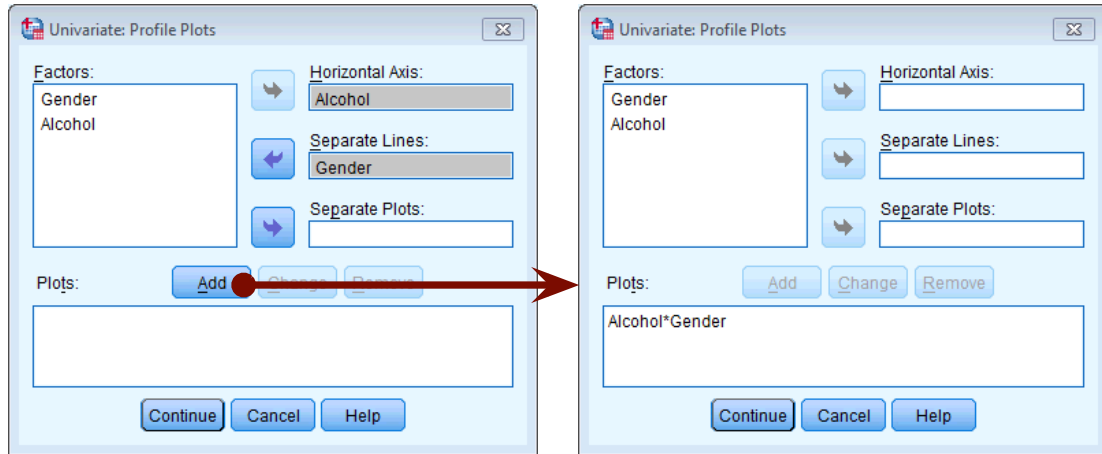
Figure 2: Specifying plots

Post Hoc Tests

The *post hoc* tests dialog box is obtained by clicking on [Post Hoc...] in the main dialog box (Figure 3). The variable **Gender** has only two levels and so we don't need to select *post hoc* tests for that variable (because any significant effects can reflect only the difference between males and females). However, there were three levels of the **Alcohol** variable (no alcohol, 2 pints and 4 pints); hence we can conduct *post hoc* tests (although remember that normally you would conduct contrasts *or post hoc* tests, not both). First, you should select the variable **Alcohol** from the box labelled *Factors* and transfer it to the box labelled *Post Hoc Tests for*. My recommendations for which *post hoc* procedures to use are in last weeks handout (and I don't want to repeat myself). Suffice to say you should select the ones in Figure 3! Click on [Continue] to return to the main dialog box.
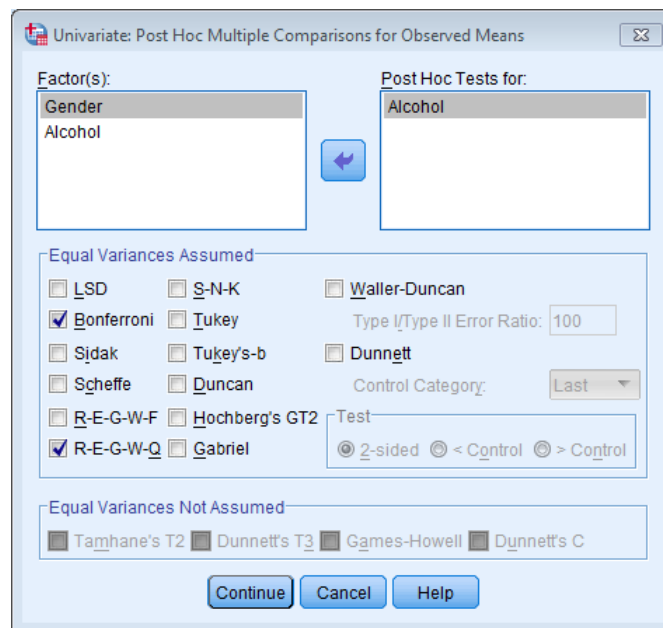

Figure 3: Dialog box for post hoc tests

Options

Click on [Options...] to activate the dialog box in Figure 4. The options for factorial ANOVA are fairly straightforward. First you can ask for some descriptive statistics, which will display a table of the means and standard deviations. This is a useful option to select because it assists in interpreting the final results. You can select the homogeneity of variance tests (see your handout on bias). Once these options have been selected click on [Continue] to return to the main dialog box.
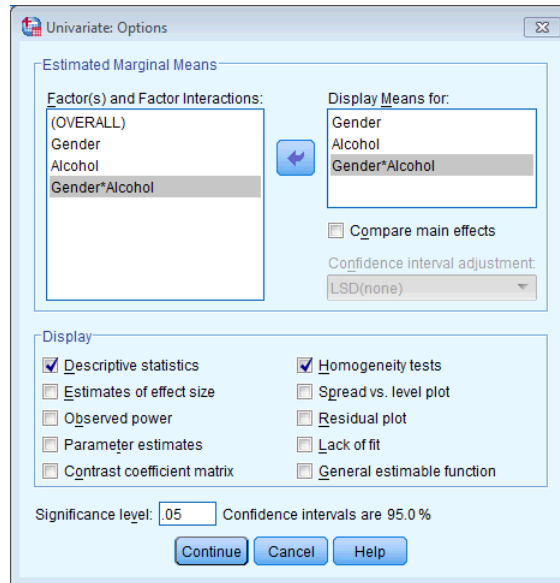
Figure 4: Dialog box for options

Bootstrapping

As with any ANOVA, the main dialog box contains the [Bootstrap...] button, which enables you to select bootstrapped confidence intervals for the estimated marginal means, descriptives and post hoc tests, but not the main *F* test. The main use of these is if you plan to look at the post hoc tests, which we are, so select the options in Figure 5. Once these options have been selected click on [Continue] to return to the main dialog box, then click on [OK] run the analysis.
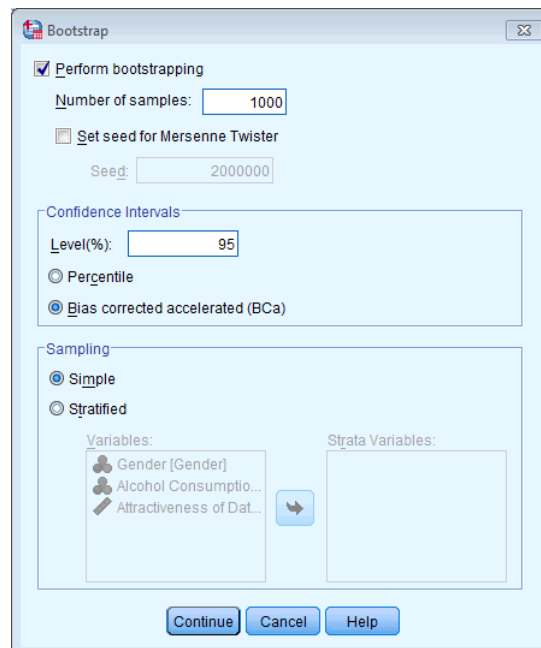

Figure 5: Bootstrap dialog box

Output from Factorial ANOVA

Output for the Preliminary Analysis

Output 1 shows a table of descriptive statistics produced because we asked for descriptives in the options dialog box (see Figure 4) (if you don't ask for bootstrapping this table will be a bit more straightforward); it displays the means, standard deviations, confidence intervals and number of participants in all conditions of the experiment. So, for

example, we can see that in the placebo condition, Males typically chatted up a female that was rated at about 67% on the attractiveness scale and the bootstrapped confidence interval for the mean ranges from 59.54 to 73.33. Females on the other hand selected a mate that was rated as 61% on that scale and the bootstrapped confidence interval for the mean ranges from 57.50 to 64.50. Note that the confidence intervals for the two groups overlap, implying that they might be from the same population. These means will be useful in interpreting the direction of any effects that emerge in the analysis.

Descriptive Statistics

Dependent Variable: Attractiveness of Date

Gender	Alcohol Consumption		Statistic	Bootstrap[a]				
				Bias	Std. Error	BCa 95% Confidence Interval	
						Lower	Upper
Male	None	Mean	66.88	−.14	3.73	59.54	73.33
		Std. Deviation	10.329	−.933[b]	2.392[b]	6.455[b]	11.852[b]
		N	8	0	3	4	13
	2 Pints	Mean	66.87	.07	4.50	57.58	75.70
		Std. Deviation	12.518	−1.200[c]	3.177[c]	7.303[c]	15.384[c]
		N	8	0	3	4	12
	4 Pints	Mean	35.63	.20	3.73	27.93	44.38
		Std. Deviation	10.836	−.891[b]	2.896[b]	6.071[b]	13.507[b]
		N	8	0	3	5	11
	Total	Mean	56.46	.19	3.65	48.57	64.49
		Std. Deviation	18.503	−.545	1.959	15.118	20.670
		N	24	0	3	18	30
Female	None	Mean	60.62	.08	1.75	57.50	64.50
		Std. Deviation	4.955	−.543[b]	1.450[b]	2.415[b]	6.292[b]
		N	8	0	3	4	12
	2 Pints	Mean	62.50	.08	2.30	57.50	67.00
		Std. Deviation	6.547	−.851[c]	1.755[c]	4.045[c]	7.500[c]
		N	8	0	3	4	12
	4 Pints	Mean	57.50	−.08	2.55	53.42	61.67
		Std. Deviation	7.071	−.689[c]	1.768[c]	3.932[c]	8.419[c]
		N	8	0	3	5	12
	Total	Mean	60.21	.01	1.29	57.62	62.88
		Std. Deviation	6.338	−.199	.709	5.111	7.143
		N	24	0	3	19	30
Total	None	Mean	63.75	−.06	2.16	59.48	68.06
		Std. Deviation	8.466	−.373	1.176	6.640	9.595
		N	16	0	3	11	22
	2 Pints	Mean	64.69	.09	2.56	59.72	70.00
		Std. Deviation	9.911	−.523	1.961	6.360	12.103
		N	16	0	3	11	22
	4 Pints	Mean	46.56	.12	3.54	39.40	53.77
		Std. Deviation	14.343	−.656	1.959	11.414	15.926
		N	16	0	3	11	21
	Total	Mean	58.33	.09	1.98	53.48	62.66
		Std. Deviation	13.812	−.295	1.577	10.987	16.114
		N	48	0	0	.	.

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

b. Based on 999 samples

c. Based on 998 samples

Output 1

Effect Sizes (Cohen's d)

We could use the means in Output 1 to compute effect sizes. For example, we might look at the effect of gender within each alcohol condition. Remember from earlier in the module that Cohen's *d* is the difference between two means divided by some estimate of the standard deviation of those means:

$$\hat{d} = \frac{\bar{X}_1 - \bar{X}_2}{s}$$

The *s* can be the standard deviation of the control group, or a pooled estimate (see the handout on One-way ANOVA, or Field, 2013, chapter 2). If we're looking at gender there isn't a logical control group so we should use a pooled estimate. Have a go at calculating these effect sizes. The results are in Table 2.

Table 2: Cohen's *d* for the effect of gender within each alcohol group

Comparison	S_p	d_{pooled}
No Pints (Male vs. Female)	8.10	0.77
2 Pints (Male vs. Female)	9.99	0.44
4 Pints (Male vs. Female)	9.15	−2.39

Levene's Test

Output 2 shows the results of Levene's test (see handouts on bias and one-way independent ANOVA). You should recall that a non-significant result (as found here) is indicative of the homogeneity of variance assumption being met. You should also bear in mind the various discussions we've had about being cautious in using tests such as Levene's.

Levene's Test of Equality of Error Variances[a]

Dependent Variable: Attractiveness of Date

F	df1	df2	Sig.
1.527	5	42	.202

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Gender + Alcohol + Gender * Alcohol

Output 2

The Main ANOVA Table

Output 3 is the most important part of the output because it tells us whether any of the independent variables have had an effect. The important things to look at in the table are the significance values of the independent variables. The first thing to notice is that there is a significant effect of alcohol (because the significance value is less than .05). The *F* ratio is highly significant indicating that the amount of alcohol consumed significantly effected who the participant would try to chat up. This effect means that overall, when we ignore whether the participant was male or female, the amount of alcohol influenced their mate selection. The best way to see what this means is to look at the bar chart that you (should) have plotted of the average mark for each level of alcohol (ignoring gender completely) — this shows the means in Output 1.

Tests of Between-Subjects Effects

Dependent Variable:Attractiveness of Date

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	5479.167[a]	5	1095.833	13.197	.000
Intercept	163333.333	1	163333.333	1967.025	.000
Gender	168.750	1	168.750	2.032	.161
Alcohol	3332.292	2	1666.146	20.065	.000
Gender * Alcohol	1978.125	2	989.062	11.911	.000
Error	3487.500	42	83.036		
Total	172300.000	48			
Corrected Total	8966.667	47			

a. R Squared = .611 (Adjusted R Squared = .565)

Output 3

TIP
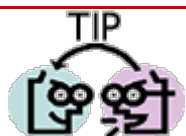
This effect should be reported as:

→ There was a significant main effect of the amount of alcohol consumed at the night-club, on the attractiveness of the mate that was selected, $F(2, 42) = 20.07$, $p < .001$.

Figure 6 shows that when you ignore gender the overall attractiveness of the selected mate is very similar when no alcohol has been drunk, and when 2 pints were drunk (the means of these groups are approximately equal). Hence, this significant main effect is *likely* to reflect the drop in the attractiveness of the selected mates when 4 pints has been drunk. This finding seems to indicate that a person is willing to accept a less attractive mate after 4 pints.
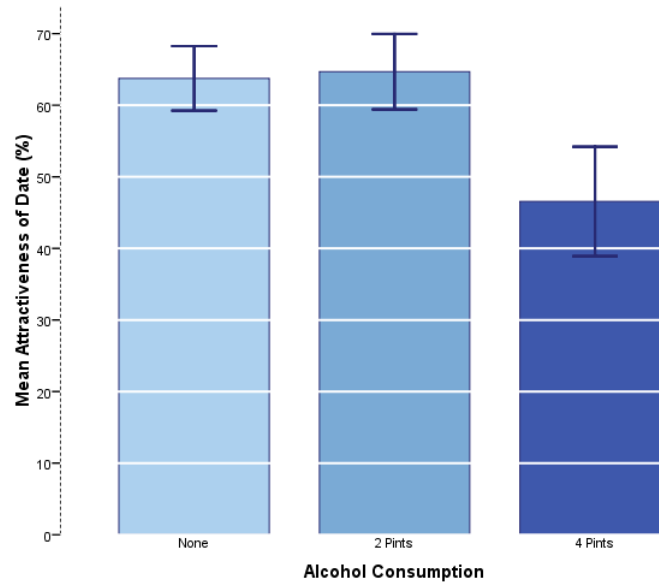

Figure 6: Graph showing the main effect of alcohol.

Output 3also reports the main effect of gender. This time the *F* ratio is not significant (*p* = .161, which is larger than .05). This effect means that overall, when we ignore how much alcohol had been drunk, the gender of the participant did not influence the attractiveness of the partner that the participant selected. In other words, other things being equal, males and females selected equally attractive mates. The meaning of this main effect can be seen in the error bar chart you were asked to plot at the beginning of this handout: it shows the average attractiveness of mates for men and women (ignoring how much alcohol had been consumed).

> **TIP**   This effect should be reported as:
>
> → There was a nonsignificant main effect of gender on the attractiveness of selected mates, $F(1, 42) = 2.03$, $p = .161$.
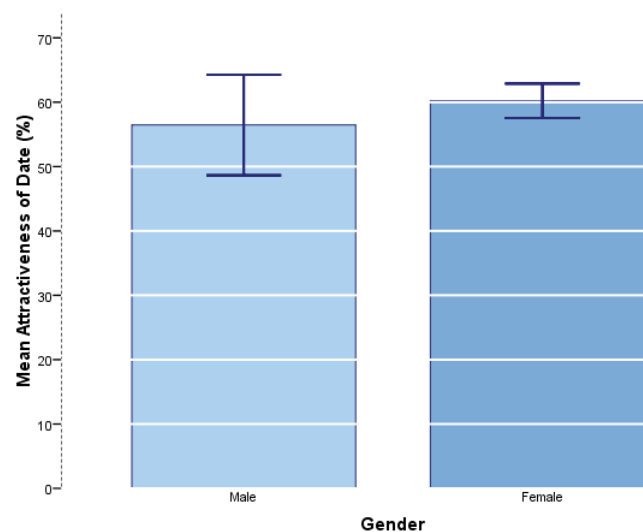
Figure 7: Graph to show the effect of gender on mate selection

Figure 7 shows that the average attractiveness of the partners of male and female participants was fairly similar (the means are different by only 4%). Therefore, this nonsignificant effect reflects the fact that the mean attractiveness was similar. We can conclude from this that, *ceteris paribus*, men and women chose equally attractive partners.

Finally, Output 3 tells us about the interaction between the effect of gender and the effect of alcohol. The *F* value is highly significant (because the *p*-value is less than .05).

> **TIP** This effect should be reported as:
>
> → There was a significant interaction between the amount of alcohol consumed and the gender of the person selecting a mate, on the attractiveness of the partner selected, *F*(2, 42) = 11.91, *p* < .001.
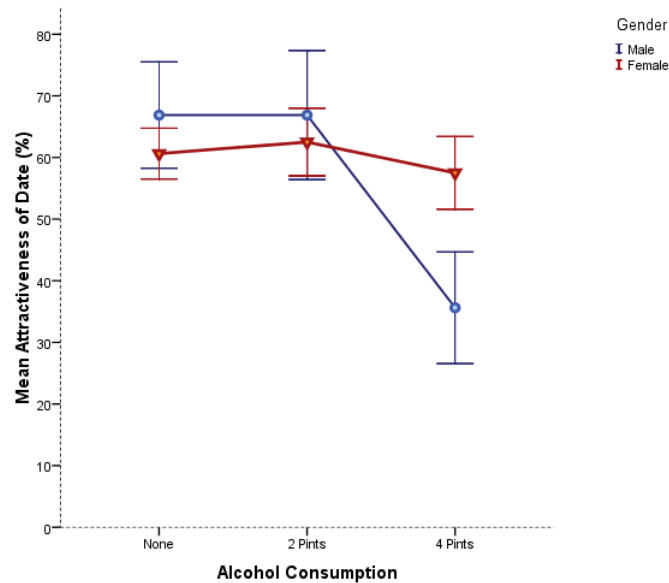

Figure 8: Graph of the interaction effect

What this actually means though, is that the effect of alcohol on mate selection was different for male participants than it was for females. The SPSS output includes a plot that we asked for (see Figure 2) which tells us something about the nature of this interaction effect. The graph that SPSS produces looks horrible and scales the y-axis such that the interaction effect is maximised. This, as we have seen in previous weeks is bad practice. Figure 8 shows a better graph that I edited to look nice☺.

Figure 8 shows that for women, alcohol has very little effect: the attractiveness of their selected partners is quite stable across the three conditions (as shown by the near-horizontal line). However, for the men, the attractiveness of their partners is stable when only a small amount has been drunk, but rapidly declines when more is drunk. A significant interaction effect is usually shown by non-parallel lines on a graph like this one. In this particular graph the lines actually cross, which indicates a fairly large interaction between independent variables. The interaction effect tells us that alcohol has little effect on mate selection until 4 pints have been drunk and that the effect of alcohol is prevalent only in male participants (so, basically, women maintain high standards in their mate selection regardless of alcohol, whereas men have a few beers and go for anything on legs!).

One interesting point that these data demonstrate is that we concluded earlier that alcohol significantly affected how attractive a mate was selected (the **alcohol** main effect); however, the interaction effect tells us that this is true only in males (females are unaffected). This shows how misleading main effects can be: it is usually the interactions between variables that are most interesting in a factorial design.

Post Hoc Analysis

The Bonferroni *post hoc* tests (Output 4) break down the main effect of alcohol and can be interpreted as if a one-way ANOVA had been conducted on the **Alcohol** variable (i.e., the reported effects for alcohol are collapsed with regard to gender). The tests show (both by the significance and whether the bootstrap confidence intervals cross zero) that when participants had drunk no alcohol or 2 pints of alcohol, they selected equally attractive mates, p = 1.00 (this is the maximum that p can be which reflects the fact that the means are almost identical). However, after 4 pints had been consumed, participants selected significantly less attractive mates than after both 2 pints ($p < .001$) and no alcohol ($p <$ .001). It is interesting to note that the mean attractiveness of partners after no alcohol and 2 pints were so similar that the probability of the obtained difference between those means is 1 (i.e. completely probable!). The R-E-G-W-Q test (Output 5) confirms that the means of the placebo and 2 pint conditions were equal whereas the mean of the 4-pint group was different. It should be noted that these post hoc tests ignore the interactive effect of gender and alcohol.

Multiple Comparisons

Dependent Variable: Attractiveness of Date

	(I) Alcohol Consumption	(J) Alcohol Consumption	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Bonferroni	None	2 Pints	−.94	3.222	1.000	−8.97	7.10
		4 Pints	17.19*	3.222	.000	9.15	25.22
	2 Pints	None	.94	3.222	1.000	−7.10	8.97
		4 Pints	18.13*	3.222	.000	10.09	26.16
	4 Pints	None	−17.19*	3.222	.000	−25.22	−9.15
		2 Pints	−18.13*	3.222	.000	−26.16	−10.09

Based on observed means.
 The error term is Mean Square(Error) = 84.527.
 *. The mean difference is significant at the

Bootstrap for Multiple Comparisons

Dependent Variable: Attractiveness of Date

	(I) Alcohol Consumption	(J) Alcohol Consumption	Mean Difference (I–J)	Bootstrap[a] Bias	Bootstrap[a] Std. Error	BCa 95% Confidence Interval Lower	BCa 95% Confidence Interval Upper
Bonferroni	None	2 Pints	−.94	.06	3.05	−6.72	5.23
		4 Pints	17.19	−.01	4.20	9.77	25.61
	2 Pints	None	.94	−.06	3.05	−5.07	6.56
		4 Pints	18.13	−.08	4.36	10.40	25.73
	4 Pints	None	−17.19	.01	4.20	−26.31	−8.52
		2 Pints	−18.13	.08	4.36	−27.33	−9.13

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples
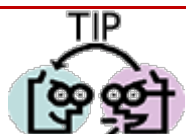
Output 4

Attractiveness of Date

	Alcohol Consumption	N	Subset 1	Subset 2
Ryan–Einot–Gabriel–Welsch Range[a]	4 Pints	16	46.56	
	None	16		63.75
	2 Pints	16		64.69
	Sig.		1.000	.772

Means for groups in homogeneous subsets are displayed.
 Based on observed means.
 The error term is Mean Square(Error) = 83.036.
 a. Alpha =

Output 5

> **TIP**
>
> These post hoc tests should be reported as:
>
> → Confidence intervals are based on 1000 bootstrap samples. Bonferroni post hoc tests showed that the attractiveness of partners was similar after no alcohol and 2 pints, M_{diff} = −0.94, 95% CI [−6.72, 5.23], p = 1; however, it was lower after 4 pints compared to none,

M_{diff} = 17.19, 95% CI [9.77, 25.61], p < .001 and significantly lower after 4 pints compared to 2, M_{diff} = 18.13, 95% CI [10.40, 25.73], p < .001.

Guided Example

Back in your week 1 handout on revising SPSS we came across an example based on Zhang, Schmader, and Hall (2013). The upshot of the study was that women who completed a maths test using a different name performed better than those who completed the test using their own name. (There were no such effects for men.) Zhang et al. concluded that performing under a different name freed women from fears of self-evaluation, allowing them to perform better. Table 3 contains a small subset of the data from Zhang et al.'s study.

Table 3: A subsample of Zhang et al.'s (2013) data

Male			Female		
Female Fake Name	Male Fake Name	Own Name	Female Fake Name	Male Fake Name	Own Name
33	69	75	53	31	70
22	60	33	47	63	57
46	82	83	87	34	33
53	78	42	41	40	83
14	38	10	62	22	86
27	63	44	67	17	65
64	46	27	57	60	64
62	27			47	37
75	61			57	80
50	29				

→ Enter the data into SPSS.

→ Save the data onto a disk in a file called **Zhang (2013).sav**.

→ Plot two error bar graphs of the mean test score (out of 100) across the different levels of participant sex, and the type name used on the test booklet.

→ Conduct a two-way independent ANOVA to see whether the test score was predicted by the participant's sex, the name used on the test booklet or their interaction.

What are the independent variables and how many levels do they have?

Your Answer:

What is the dependent variable?

Your Answer:

Describe the assumption of homogeneity of variance. Has this assumption been met? (Quote relevant statistics in APA format).

Your Answer:

Report the main effect of participant sex in APA format. Is this effect significant and how would you interpret it?

Your Answer:

Report the main effect of 'name used on the test booklet' in APA format. Is this effect significant and how would you interpret it?

Your Answer:

Report the interaction effect between participant sex and 'name used on the test booklet' in APA format. Is this effect significant and how would you interpret it?

Your Answer:

Do the results support Zhang et al.'s (2013) findings? Explain your answer.

Your Answer:

Task 1

People's musical tastes tend to change as they get older: my parents, for example, after years of listening to relatively cool music when I was a kid, subsequently hit their mid-forties and developed a worrying obsession with country and western music. This possibility worries me immensely because the future seems incredibly bleak if it is spent listening to Garth Brooks and thinking 'oh boy, did I underestimate Garth's immense talent when I was in my 20s'. So, I thought I'd do some research; I took two groups (**age**): young people (which I arbitrarily decided was under 40 years of age) and older people (above 40 years of age). I split each of these groups of 45 into three smaller groups of 15 and assigned them to listen to Fugazi, ABBA or Barf Grooks (**music**). I got each person to rate it (**liking**) on a scale ranging from −100 (I hate this foul music) through 0 (I am completely indifferent) to +100 (I love this music so much I'm going to explode).

Table 4: Fugazi data

Music	Fugazi		Abba		Barf Grooks	
Age	Young	Old	Young	Old	Young	Old
	96	-75	65	24	-54	69
	69	-98	86	30	-56	92
	61	-97	37	80	-97	76
	39	-75	59	75	-40	76
	94	-45	49	72	-65	81
	71	-73	59	60	-88	51
	62	-75	42	42	-77	27
	62	-75	88	90	-52	91
	38	-87	92	55	-54	97
	69	-49	41	60	-118	83
	40	-83	64	87	-41	56
	45	-77	73	56	-84	66
	86	-75	66	54	-66	122
	93	-98	73	74	-77	62
	68	-97	68	40	-103	65

→ Enter the data into SPSS.

→ Save the data onto a disk in a file called **Fugazi.sav**.

→ Plot two error bar graphs of the mean liking across the different levels of age and type of music respectively .

→ Conduct a two-way independent ANOVA to see whether liking ratings were affected by age, style of music or their interaction.

→ Answers can be found on the companion website of my book.

Task 2

There are reports of increases in injuries related to playing Nintendo Wii (http://ow.ly/ceWPj). These injuries were attributed mainly to muscle and tendon strains. A researcher hypothesized that a stretching warm-up before playing Wii would help lower injuries, and that athletes would be less susceptible to injuries because their regular activity makes them more flexible. She took 60 athletes and 60 non athletes (**athlete**), half of them played Wii and half watched others playing as a control (**wii**), and within these groups half did a 5-minute stretch routine before playing/watching whereas the other half did not (**stretch**). The outcome was a pain score out of 10 (where 0 is no pain, and 10 is severe pain) after playing for 4 hours (**injury**). The data are in the file **Wii.sav** conduct a three-way ANOVA to test whether athletes are less prone to injury, and whether the prevention program worked.

Answers are available on the companion website for my book (https://studysites.uk.sagepub.com/field4e/study/smartalex.htm).

Multiple Choice Tests

Complete the multiple choice questions for **Chapter 13** on the companion website to Field (2013): https://studysites.uk.sagepub.com/field4e/study/mcqs.htm. If you get any wrong, re-read this handout (or Field, 2013, Chapter 13) and do them again until you get them all correct.

References

Field, A. P. (2013). Discovering statistics using IBM SPSS Statistics: And sex and drugs and rock 'n' roll (4th ed.). London: Sage.

Terms of Use