# Lesson 20: Chapter 12

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**BSC Mathematics** 

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This model arises from the assumption that all the means are equal (our hull hypothesis). And thus, the sample means should follow

$$x_{ij} = \mu_i + \epsilon_{ij},$$

where  $i=1,\ldots,I$  and  $j=1,\ldots,n_i$  and  $\epsilon_{ij}$  all have  $N(0,\sigma)$  distribution.



The estimate for  $\sigma$  is  $s_p$  which is given by

$$\sqrt{\frac{(n_1-1)s_1^2+\cdots+(n_i-1)s_i^2}{(n_1-1)+\cdots+(n_i-1)}}.$$

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We always pool the standard deviation for a one-way ANOVA.

#### Definition (hypothesis for one-way ANOVA)

The null and alternative hypothesis for a one-way ANOVA are

$$H_0: \mu_1 = \cdots = \mu_i$$

 $H_a$ : not all of the  $\mu_i$  are equal.

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The conclusion of a one-way ANOVA can often be reached by finding the *P*-value from Minitab. We will also discuss how the computations might be done by hand.

#### Definition (sum of squares, degrees of freedom, and mean squares)

**Sum of squares** represent variation in the data. They are calculated by summing square deviations. There are three sources of variation in a one-way ANOVA.

$$SST = SSG + SSE$$

The **degrees of freedom** are associated with each sum of squares.

$$DFT = DFG + DFE$$

The **mean squares** are  $\frac{\text{sum of squares}}{\text{degrees of freedom}}$ .

Use the table below to calculate the values discussed in the previous slide.

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Source	DF	SS	MS	F
Groups	<i>I</i> – 1	$\sum_{\text{groups}} n_i (\bar{x}_i - \bar{x})^2$	SSG DFG	MSG/MSE
Error	N – I	$\sum_{\text{groups}} (n_i - 1) s_i^2$	SSE DFE	
Total	N - 1	$\sum_{\text{observations}} (x_{ij} - \bar{x})^2$		

#### Definition (one-way ANOVA *F* test)

To test the null hypothesis that three or more population means are the same versus the alternative that at least one of them if different from the others, use the F statistic

$$F = \frac{\mathsf{MSG}}{\mathsf{MSE}}.$$

The P-value is the probability that a random variable having the F(I-1,N-I) distribution is greater than or equal to the calculated value of the F statistic.

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This is a right-tailed F test.

In order to perform a one-way ANOVA test, the following requirements must be mets.

■ The smallest  $s_i$  must be larger than half of the largest  $s_i$  so that we can assume pooled standard deviations safely.

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- There must be only a single factor separating populations.

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- Each population should be roughly normal.
- The samples must be independent.
- There must be only a single factor separating populations.
- The samples must be SRSs.

#### Example (mean credit score)

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18-25	25-50	over 50
650	725	700
625	670	660
645	770	750
600	590	700
590	700	760
500		725
595		

#### Example (mean credit score)

	18-25	25-50	over 50
$\bar{x}$	600.71429	691	715.83333
S	50.450353	67.305275	36.934627
n	7	5	6

#### Example (mean credit score)

We want to see if the mean credit scores are the same across three age groups. We collect the following data from three SRSs.

	18-25	25-50	over 50
$\bar{x}$	600.71429	691	715.83333
S	50.450353	67.305275	36.934627
n	7	5	6

Thus,

$$s_p = \sqrt{\frac{6(50.450353)^2 + 4(67.305275)^2 + 5(36.934627)^2}{6+4+5}} = 51.777.$$

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n	7	5	6

Also, 
$$\bar{x}_{total} = 664.16667$$
, so we have

$$SSG = 7(600.71429 - 664.16667)^2 + 5(691 - 664.16667)^2 + 6(715.83333 - 664.1667)^2 = 47800.214.$$

#### Example (mean credit score)

We want to see if the mean credit scores are the same across three age groups. We collect the following data from three SRSs.

	18-25	25-50	over 50
Ī.	600.71429	691	715.83333
S	50.450353	67.305275	36.934627
n	7	5	6

Also, we have

$$\mathsf{SSE} = 6(50.450353)^2 + 4(67.305275)^2 + 5(36.934627)^2 = 40212.262.$$



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We want to see if the mean credit scores are the same across three age groups. We collect the following data from three SRSs.

	18-25	25-50	over 50
$\bar{x}$	600.71429	691	715.83333
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n	7	5	6

Thus, we must have SST = 40212.262 + 47800.214 = 88012.5.

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Source	DF	SS	MS	F
Groups	<i>l</i> – 1	$\sum_{ ext{groups}} n_i (ar{x}_i - ar{x})^2$	SSG DFG	MSG/MSE
Error	N-I	$\sum_{\text{groups}} (n_i - 1) s_i^2$	SSE DFE	
Total	N-1	$\sum_{ ext{observations}} (x_{ij} - \bar{x})^2$		

#### Example (mean credit score)

Source	DF	SS	MS	F
Groups	2	47800.214	SSG DFG	MSG/MSE
Error	N-I	$\sum_{\text{groups}} (n_i - 1) s_i^2$	SSE DFE	
Total	N - 1	$\sum_{\text{observations}} (x_{ij} - \bar{x})^2$		

#### Example (mean credit score)

Source	DF	SS	MS	F
Groups	2	47800.214	SSG DFG	MSG/MSE
Error	15	40212.262	SSE DFE	
Total	N-1	$\sum_{\text{observations}} (x_{ij} - \bar{x})^2$		

#### Example (mean credit score)

Source	DF	SS	MS	F
Groups	2	47800.214	SSG DFG	MSG/MSE
Error	15	40212.262	SSE DFE	
Total	17	88012.5		

#### Example (mean credit score)

Source	DF	SS	MS	F
Groups	2	47800.214	23900.107	8.915
Error	rror 15 40212.262		2680.817	
Total	17	88012.5		

#### Example (mean credit score)

Let's fill in our table:

Source	DF	SS	MS	F
Groups	2	47800.214	23900.107	8.915
Error	Error 15 40212.262		2680.817	
Total	17	88012.5		

Thus, the *P*-value for this test is P(F > 8.915) = 0.003.

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Total	17	88012.5		

Thus, the P-value for this test is P(F > 8.915) = 0.003. So if we conducted the one-way ANOVA at a 5% significance level, we would reject the null hypothesis. We would not support the claim that the mean credit scores are the same across all three of these age groups.

Note: The full one-way ANOVA test can be conducted in Minitab! You should make sure that you know how the one-way ANOVA table could be filled in given just a few SS and DF values, though!

Note: The full one-way ANOVA test can be conducted in Minitab! You should make sure that you know how the one-way ANOVA table could be filled in given just a few SS and DF values, though! Let's do one more test using Minitab.

#### Example (labor costs)

A company would like to see if its labor costs are the same over all four seasons. It takes a SRS of labor costs in each season over several years and gets the following data.

Spring	Summer	Fall	Winter
300000	295000	259000	260000
450000	430000	460000	475000
375000	380000	385000	380000
257000	277000	259000	300000
280000	285000	275000	290000
300000	299000	301000	298000
440000	445000	440500	444000
		1	

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ANOVA table						
Source	DF	SS	MS	F-Stat	P-value	
Columns	3	3.3774107e8	1.1258036e8	0.017332332	0.9968	
Error	24	1.558895e11	6.4953958e9			
Total	27	1.5622724e11				

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Error	24	1.558895e11	6.4953958e9			
Total	27	1.5622724e11				

Thus, we fail to reject the null hypothesis and support the claim that the labor costs are the same across all four seasons.