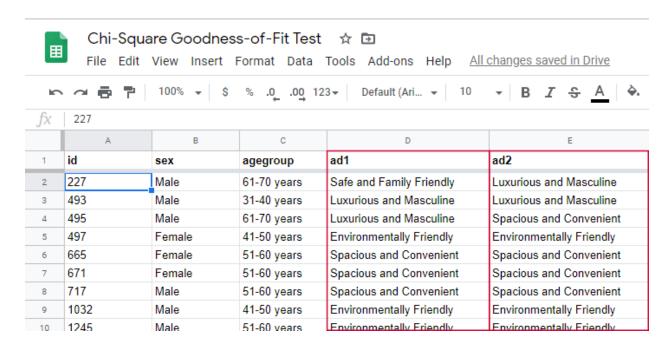
A chi-square goodness-of-fit test examines if a categorical variable has some hypothesized frequency distribution in some population.

Example - Testing Car Advertisements

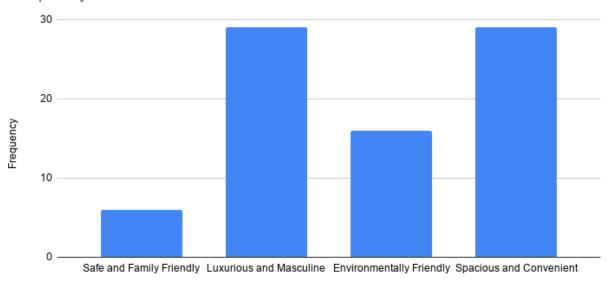
A car manufacturer wants to launch a campaign for a new car. They'll show advertisements -or "ads"- in 4 different sizes. For ad each size, they have 4 ads that try to convey some message such as "this car is environmentally friendly". They then asked N = 80 people which ad they liked most. The data thus obtained are in this Googlesheet, partly shown below.



So which ads performed best in our sample? Well, we can simply look up which ad was preferred by most respondents: the ad having the highest frequency is the mode for each ad size. So let's have a look at the frequency distribution for the first ad size -ad1- as visualized in the bar chart shown below.

Observed Frequencies and Bar Chart

Frequency Distribution for Ad1



The observed frequencies shown in this chart are

1. Safe and Family Friendly: 6

2. Luxurious and Masculine: 29

3. Environmentally Friendly: 16

4. Spacious and Convenient: 29

Note that ad1 has a bimodal distribution: ads 2 and 4 are both winners with 29 votes. However, our data only hold a sample of N = 80. Socan we conclude that ads 2 and 4 also perform best in the entire population? The chi-square goodness-of-fit answers just that. And for this example, it does so by trying to reject the null hypothesis that all ads perform equally well in the population.

Null Hypothesis

Generaly, the null hypothesis for a chi-square goodness-of-fit test is simply

H0:P01,P02,...,P0m,
$$\sum_{i=0m(P0i)=1}$$
H0:P01,P02,...,P0m, $\sum_{i=0m(P0i)=1}$

where P_{0i}P_{0i} denote population proportions for mm categories in some categorical variable. You can choose any set of proportions as long as they add up to one. In many cases, all proportions being equal is the most likely null hypothesis. For a dichotomous variable having only 2 categories, you're better off using

- a binomial test because it gives the exact instead of the approximate significance level or
- a z-test for 1 proportion because it gives a confidence interval for the population proportion.

Anyway, for our example, we'd like to show that some ads perform better than others. So we'll try to refute that our 4 population proportions are all equal and -hence- 0.25.

Expected Frequencies

Now, if the 4 population proportions really are 0.25 and we sample N = 80 respondents, then we expect each ad to be preferred by $0.25 \cdot 80 = 20$ respondents. That is,**all 4 expected frequencies are 20.**We need to know these expected frequencies for 2 reasons:

- computing our test statistic requires expected frequencies and
- the assumptions for the chi-square goodness-of-fit test involve expected frequencies as well.

Assumptions

The chi-square goodness-of-fit test requires 2 assumptions^{2,3}:

1. independent observations;

2. for 2 categories, each expected frequency EiEi must be at least 5.

For 3+ categories, each EiEi must be at least 1 and no more than 20% of all EiEi may be smaller than 5.

The observations in our data are independent because they are distinct persons who didn't interact while completing our survey. We also saw that all EiEi are $(0.25 \cdot 80 =) 20$ for our example. So this second assumption is met as well.

Formulas

We'll first compute the $\chi_2\chi_2$ test statistic as

$$\chi_2 = \sum (O_i - E_i)_2 E_i \chi_2 = \sum (O_i - E_i)_2 E_i$$

where

- OiOi denotes the observed frequencies and
- EiEi denotes the expected frequencies -usually all equal.

For ad1, this results in

$$\chi_2 = (16-20)220 + (29-20)220 + (9-20)220 + (29-20)220 = 18.7\chi_2 = (16-20)220 + (29-20)220 + (9-20)220 + (29-20)220 = 18.7\chi_2 = (16-20)220 + (29-20)220 + (29-20)220 + (29-20)220 = 18.7\chi_2 = (16-20)220 + (29-20)220 + (29-20)220 + (29-20)220 = 18.7\chi_2 = (16-20)220 + (29-20)220 + (29-20)220 + (29-20)220 = 18.7\chi_2 = (16-20)220 + (29-20)20 + (29-$$

If all assumptions have been met, $\chi_2\chi_2$ approximately follows a chi-square distribution with dfdf degrees of freedom where

$$df=m-1df=m-1$$

for mm frequencies. Since we have 4 frequencies for 4 different ads,

$$df=4-1=3df=4-1=3$$

for our example data. Finally, we can simply look up the significance level as

$$P(\chi_2(3)>18.7)\approx0.00032P(\chi_2(3)>18.7)\approx0.00032$$

We ran these calculations in this Googlesheet shown below.

	А	В	С	D	Е				
1	ad1	Observed Frequency	Expected Frequency	Residual	Chi-Square Points				
2	Environmentally Friendly	16	20	-4	8.0				
3	Luxurious and Masculine	29	20	9	4.05				
4	Safe and Family Friendly	6	20	-14	9.8				
5	Spacious and Convenient	29	20	9	4.05				
6	Grand Total	80	80	0	18.7				
7									
8	Chi-Square Value	18.7	"Ad pre	"Ad preferences were distributed unequally, $\chi^2(3) = 18.7$, p = 0.000."					
9	DF	3							
10	Р	0.00032	unequal						
11	Conclusion	Since p < 0.05, we reject the null hypothesis that all 4 ads have equal population pro							
12									

So what does this mean? Well, if all 4 ads are equally preferred in the population, there's a 0.00032 chance of finding our observed frequencies. Since p < 0.05, we reject the null hypothesis. **Conclusion**: some ads are preferred by more people than others in the entire population of readers.

Right, so it's safe to assume that the population proportions are not all equal. But precisely how different are they? We can express this in a single number: the effect size.

Effect Size - Cohen's W

The effect size for a chi-square goodness-of-fit test -as well as the chi-square independence test- is Cohen's W. Some rules of thumb¹ are that

- Cohen's W = **0.10** indicates a **small** effect size;
- Cohen's W = **0.30** indicates a **medium** effect size;
- Cohen's W = 0.50 indicates a large effect size.

Cohen's W is computed as
$$W=\sum_{i=1m}(P_{0i}-P_{ei})_2P_{ei}------\sqrt{W=\sum_{i=1m}(P_{0i}-P_{ei})}_2P_{ei}$$

where

- PoiPoi denote observed proportions and
- PeiPei denote expected proportions under the null hypothesis for
- · mm cells.

$$W=0.234---\sqrt{=0.483}W=0.234=0.483$$

We ran these computations in this Googlesheet shown below.

	A	В	С	D	E	F	
1	ad1	Observed Frequency	Observed Proportion	Expected Proportion	Residual Proportion	W Points	
2	Environmentally Friendly	16	0.2	0.25	-0.050	0.010	
3	Luxurious and Masculine	29	0.3625	0.25	0.113	0.051	
4	Safe and Family Friendly	6	0.075	0.25	-0.175	0.123	
5	Spacious and Convenient	29	0.3625	0.25	0.113	0.051	
6	Grand Total	80	1	1	0.000	0.234	
7							
8	Sum W points	0.234					
9	Cohen's W	0.483	← EFFECT SIZ				
10	Conclusion	This is roughly a large effect size: overall, the observed proportions differ quite a lot from the presumed					
11							

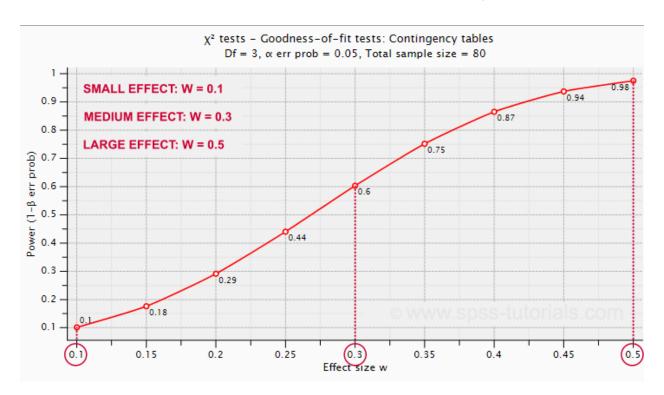
For ad1, the effect size WW = 0.483. This indicates a large overall difference between the observed and expected frequencies.

Power and Sample Size Calculation

Now that we computed our effect size, we're ready for our last 2 steps. First off, what about power? What's the probability demonstrating an effect if

- we test at $\alpha = 0.05$;
- we have a sample of N = 80;
- df = 3 (our outcome variable has 4 categories);
- we don't know the population effect size WW?

The chart below -created in G*Power- answers just that.



Some basic conclusions are that

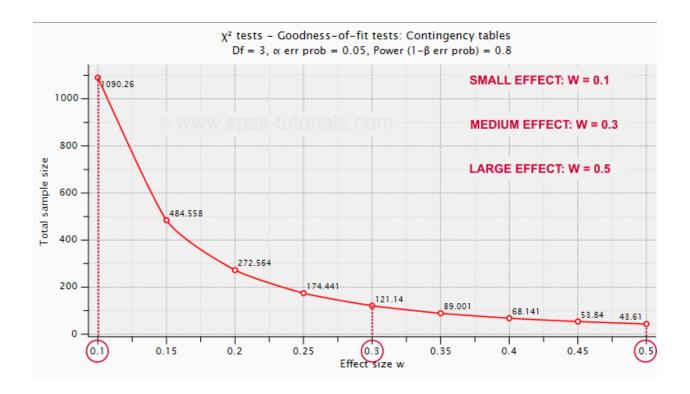
- power = 0.98 for a large effect size;
- power = 0.60 for a medium effect size;
- power = 0.10 for a small effect size.

These outcomes are not too great: we only have a 0.60 probability of rejecting the null hypothesis if the population effect

size is medium and N = 80. However, we can increase power by increasing the sample size. So **which sample sizes do we need** if

- we test at $\alpha = 0.05$;
- we want to have power = 0.80;
- df = 3 (our outcome variable has 4 categories);
- we don't know the population effect size WW?

The chart below shows how required sample sizes decrease with increasing effect sizes.



Under the aforementioned conditions, we have power ≥ 0.80

- for a large effect size if N = 44;
- for a medium effect size if N = 122;
- for a small effect size if N = 1091.