

ANOVA - Lab

Introduction

In this lab, you'll get some brief practice generating an ANOVA table (AOV) and interpreting its output. You'll also perform some investigations to compare the method to the t-tests you previously employed to conduct hypothesis testing.

Objectives

In this lab you will:

- Use ANOVA for testing multiple pairwise comparisons
- Interpret results of an ANOVA and compare them to a t-test

Load the data

Start by loading in the data stored in the file 'ToothGrowth.csv':

```
# Your code here
import pandas as pd
df = pd.read_csv('ToothGrowth.csv')
df.head()

<style scoped> .dataframe tbody tr th:only-of-type { vertical-align: middle; }
   .dataframe tbody tr th {
       vertical-align: top;
   }
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       text-align: right;
   }
```

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	len	supp	dose
0	4.2	VC	0.5
1	11.5	VC	0.5
2	7.3	VC	0.5
3	5.8	VC	0.5
4	6.4	VC	0.5

Generate the ANOVA table

Now generate an ANOVA table in order to analyze the influence of the medication and dosage:

```
#Your code here
import statsmodels.api as sm
from statsmodels.formula.api import ols

formula = 'len ~ C(supp) + C(dose)'
lm = ols(formula, df).fit()
```

```
table = sm.stats.anova_lm(lm, typ=2)
print(table)

sum_sq df F PR(>F)
C(supp) 205.350000 1.0 14.016638 4.292793e-04
C(dose) 2426.434333 2.0 82.810935 1.871163e-17
Residual 820.425000 56.0 NaN NaN
```

Interpret the output

Make a brief comment regarding the statistics and the effect of supplement and dosage on tooth length:

```
# Both dose and supplement type are impactful. At first glance, dosage seems to be t
```

Compare to t-tests

Now that you've had a chance to generate an ANOVA table, its interesting to compare the results to those from the t-tests you were working with earlier. With that, start by breaking the data into two samples: those given the OJ supplement, and those given the VC supplement. Afterward, you'll conduct a t-test to compare the tooth length of these two different samples:

```
# Your code here
oj_lengths = df[df.supp=='0J']['len']
vc_lengths = df[df.supp=='VC']['len']
```

Now run a t-test between these two groups and print the associated two-sided p-value:

```
# Calculate the 2-sided p-value for a t-test comparing the two supplement groups
from scipy import stats
stats.ttest_ind(oj_lengths, vc_lengths, equal_var=False)[1]
0.06063450788093387
```

A 2-Category ANOVA F-test is equivalent to a 2-tailed t-test!

Now, recalculate an ANOVA F-test with only the supplement variable. An ANOVA F-test between two categories is the same as performing a 2-tailed t-test! So, the p-value in the table should be identical to your calculation above.

Note: there may be a small fractional difference (>0.001) between the two values due to a rounding error between implementations.

```
# Your code here; conduct an ANOVA F-test of the oj and vc supplement groups.
# Compare the p-value to that of the t-test above.
# They should match (there may be a tiny fractional difference due to rounding error formula = 'len ~ C(supp)'
lm = ols(formula, df).fit()
table = sm.stats.anova_lm(lm, typ=2)
print(table)
```

```
sum_sq df F PR(>F)
C(supp) 205.350000 1.0 3.668253 0.060393
Residual 3246.859333 58.0 NaN NaN
```

Run multiple t-tests

While the 2-category ANOVA test is identical to a 2-tailed t-test, performing multiple t-tests leads to the multiple comparisons problem. To investigate this, look at the various sample groups you could create from the 2 features:

```
for group in df.groupby(['supp', 'dose'])['len']:
    group_name = group[0]
    data = group[1]
    print(group_name)

('OJ', 0.5)
('OJ', 1.0)
('OJ', 2.0)
('VC', 0.5)
```

```
('VC', 1.0)
('VC', 2.0)
```

While bad practice, examine the effects of calculating multiple t-tests with the various combinations of these. To do this, generate all combinations of the above groups. For each pairwise combination, calculate the p-value of a 2-sided t-test. Print the group combinations and their associated p-value for the two-sided t-test.

```
# Your code here; reuse your t-test code above to calculate the p-value for a 2-side
# for all combinations of the supplement-dose groups listed above.
# (Since there isn't a control group, compare each group to every other group.)
from itertools import combinations
groups = [group[0] for group in df.groupby(['supp', 'dose'])['len']]
combos = combinations(groups, 2)
for combo in combos:
    supp1 = combo[0][0]
    dose1 = combo[0][1]
    supp2 = combo[1][0]
    dose2 = combo[1][1]
    sample1 = df[(df.supp == supp1) & (df.dose == dose1)]['len']
    sample2 = df[(df.supp == supp2) & (df.dose == dose2)]['len']
    p = stats.ttest ind(sample1, sample2, equal var=False)[1]
    print(combo, p)
    # Note that while ANOVA also concluded that all factors were significant,
    # these p-values are substantially lower.
```

```
(('OJ', 0.5), ('OJ', 1.0)) 8.784919055161479e-05
(('OJ', 0.5), ('OJ', 2.0)) 1.3237838776972294e-06
(('OJ', 0.5), ('VC', 0.5)) 0.006358606764096813
(('OJ', 0.5), ('VC', 1.0)) 0.04601033257637553
(('OJ', 0.5), ('VC', 2.0)) 7.196253524006043e-06
(('OJ', 1.0), ('OJ', 2.0)) 0.039195142046244004
(('OJ', 1.0), ('VC', 0.5)) 3.6552067303259103e-08
(('OJ', 1.0), ('VC', 1.0)) 0.001038375872299884
(('OJ', 1.0), ('VC', 2.0)) 0.09652612338267014
(('OJ', 2.0), ('VC', 0.5)) 1.3621396478988818e-11
(('OJ', 2.0), ('VC', 1.0)) 2.3610742020468435e-07
(('OJ', 2.0), ('VC', 1.0)) 6.811017702865016e-07
(('VC', 0.5), ('VC', 1.0)) 6.811017702865016e-08
(('VC', 0.5), ('VC', 2.0)) 9.155603056638692e-05
```

Summary

In this lesson, you implemented the ANOVA technique to generalize testing methods to multiple groups and factors.

Releases

No releases published

Packages

No packages published

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Languages

Jupyter Notebook 80.1%

• **Python** 19.9%