

## **Python Inferential Statistics**

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DA 380 - Programming for Data Analytics

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## Python Inferential Statistics

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## Excel Inferential Statistics Practice Using BRFSS

First, an independent-samples  $t$ -test was conducted to compare average general health between people who exercise and people who don't. People who did not exercise ( $\bar{x} \approx 3.11$ ,  $s \approx 1.08$ ), on average, had a higher score than people who did exercise ( $\bar{x} \approx 2.46$ ,  $s \approx 0.96$ ). This difference was statistically significant,  $t(587) \approx 10.47$ ,  $p < 0.01$ . These results suggest that the general health differs between people who exercise and people who do not.

Next, a one-way analysis of variance (ANOVA) was conducted to examine differences in mean general health across 11 groups defined by annual household income. Mean and standard deviation of general health values for each group are approximately shown in Table 1. The overall effect was statistically significant,  $F(10, 1170) \approx 20.00$ ,  $p < 0.01$ . These results indicate that average general health differs among annual household income groups.

Then, a chi-squared test of independence was conducted to examine the association between exercise participation and median annual household income. The test indicated that the association was statistically significant,  $\chi^2(1, N = 1180) = 79.06$ ,  $p < 0.01$ . Examination of the contingency table, shown in Table 2, showed that people who did not exercise tend to be below (or equal to) the median annual household income; however, more people tend to participate in exercise in general. This pattern suggests that people who tend to not participate in exercise are more likely to have a lower annual household income than those who do, and vice versa.

Finally, a multiple linear regression analysis was conducted to examine whether exercise participation and disability status were associated with BMI. The overall regression model was statistically significant,  $F(2, 1344) \approx 17.97$ ,  $p < 0.01$ , and explained 2.60% of the variance in BMI ( $R^2 \approx 0.026$ ). Exercise participation was a significant predictor of BMI ( $\beta = 2.03$ ,  $p < 0.01$ ), and disability status was significant ( $\beta \approx 1.14$ ,

$p < 0.01$ ) as well. These results indicate that although there is not a strong linear relationship of exercise participation and disability status with BMI, the variables do have some relationship to BMI, and thus are associated with BMI.

Group	$\bar{x}$	$s$
1	3.58	1.24
2	3.24	1.10
3	3.12	1.18
4	3.31	1.14
5	3.01	1.03
6	2.69	1.01
7	2.61	1.00
8	2.44	0.91
9	2.18	0.86
10	2.17	0.84
11	2.00	0.75

**Table 1**

*Mean and Standard Deviation of General Health by Annual Household Income*

Median Annual Household Income	Participated in Exercise	Did not Participate in Exercise	Total
Less than or equal median household income	420	235	655
More than median household income	457	68	525
Total	877	303	1180

**Table 2**

*Contingency Table for Median Annual Household Income and Exercise Participation*

## Appendix A

### Python File

```
1 '''
2 Name: Lucas Hasting
3 Course: DA 380
4 Instructor: Dr. Michael Floren
5 Date: 2/24/2026
6 Description: Get inferential stats from brfss1_cleaned.csv
7 '''
8
9 #import needed libraries
10 import numpy as np
11 import pandas as pd
12 from scipy import stats
13 import statsmodels.api as sm
14 import statsmodels.formula.api as smf
15
16 #load the data
17 df = pd.read_csv("brfss1_cleaned.csv")
18
19 #is general health different between people who exercise vs. not? - T-TEST
20 print("GENHLTH vs. EXERANY2:",end="\n\n")
21 gen_hlth_exer = df.loc[df["EXERANY2"] == 1, "GENHLTH"].dropna()
22 gen_hlth_not_exer = df.loc[df["EXERANY2"] == 2, "GENHLTH"].dropna()
23
24 print(stats.ttest_ind(gen_hlth_not_exer, gen_hlth_exer, equal_var=False),
        end="\n\n")
25 print("Exercise:\n",gen_hlth_exer.agg(["mean", "std"]),end="\n\n",sep="")
26 print("No Exercise:\n",gen_hlth_not_exer.agg(["mean", "std"]),end="\n\n",
        sep="")
27
28 #general health across income groups - are they different? - ANOVA
```

```

29 print("INCOME3 vs. GENHLTH:",end="\n\n")
30 df["INCOME3_no_na"] = df["INCOME3"].dropna()
31 df["GENHLTH_no_na"] = df["GENHLTH"].dropna()
32 model_genhlth = smf.ols("GENHLTH_no_na ~ C(INCOME3_no_na)", data=df).fit()
33 print(sm.stats.anova_lm(model_genhlth))
34 print(df.groupby("INCOME3_no_na")["GENHLTH_no_na"].agg(["mean", "std"]),
        end="\n\n")
35
36 #association between exercise participation and median annual household
    income? - Ch^2
37
38 print("INCOME3 vs. GENHLTH:",end="\n\n")
39 df["EXERANY2_no_na"] = df["EXERANY2"].dropna()
40 df["income_bin_no_na"] = df["income_bin"].dropna()
41 print(df.groupby("EXERANY2_no_na")["income_bin_no_na"].value_counts())
42 print(stats.chi2_contingency(pd.crosstab(df["income_bin_no_na"], df["
    EXERANY2_no_na"]))),end="\n\n")
43
44 #BMI linearly correlated with disabled and exercise participation? - OLS
    Regression
45
46 print("BMI vs. EXERANY2 and disabled:",end="\n\n")
47 df["BMI_no_na"] = df["bmi"].dropna()
48 df["disabled_no_na"] = df["disabled"].dropna()
49 model_bmi = smf.ols("BMI_no_na ~ C(EXERANY2_no_na) + C(disabled_no_na)",
    data=df).fit()
50 print(sm.stats.anova_lm(model_bmi))
51 print(model_bmi.summary())

```

## Appendix B

### Python File Output

```

1 GENHLTH vs. EXERANY2:
2
3 TtestResult(statistic=np.float64(10.469372106336646), pvalue=np.float64
    (1.2428555292489605e-23), df=np.float64(586.6549314911825))
4
5 Exercise:
6 mean      2.458296
7 std       0.955383
8 Name: GENHLTH, dtype: float64
9
10 No Exercise:
11 mean      3.114058
12 std       1.081881
13 Name: GENHLTH, dtype: float64
14
15 INCOME3 vs. GENHLTH:
16
17              df      sum_sq  mean_sq      F      PR(>F)
18 C(INCOME3_no_na)    10.0    187.317149  18.731715  20.000458  1.892123e-34
19 Residual          1170.0  1095.780226   0.936564      NaN      NaN
20              mean      std
21 INCOME3_no_na
22 1.0          3.576923  1.238485
23 2.0          3.236842  1.101208
24 3.0          3.116279  1.179372
25 4.0          3.313725  1.140003
26 5.0          3.006579  1.026127
27 6.0          2.692308  1.010381
28 7.0          2.613953  1.002236
29 8.0          2.439024  0.914740

```

```

30 9.0          2.179348  0.859157
31 10.0         2.173469  0.837590
32 11.0         2.000000  0.746299
33
34 INCOME3 vs. GENHLTH:
35
36 EXERANY2_no_na  income_bin_no_na
37 1.0             1.0             457
38                0.0             420
39 2.0             0.0             235
40                1.0             68
41 Name: count, dtype: int64
42 Chi2ContingencyResult(statistic=np.float64(79.05919206447463), pvalue=np.
    float64(6.027662302195648e-19), dof=1, expected_freq=array
    ([[486.80932203, 168.19067797],
43      [390.19067797, 134.80932203]]))
44
45 BMI vs. EXERANY2 and disabled:
46
47                df          sum_sq      mean_sq          F          PR
    (>F)
48 C(EXERANY2_no_na)      1.0    1289.123160    1289.123160    28.073209    1.363661e
    -07
49 C(disabled_no_na)      1.0     361.244477     361.244477     7.866814    5.107537e
    -03
50 Residual              1344.0    61716.547295     45.920050          NaN
    NaN
51                OLS Regression Results
52 =====

53 Dep. Variable:          BMI_no_na    R-squared:
    0.026
54 Model:                  OLS    Adj. R-squared:

```

```

0.025
55 Method:                Least Squares    F-statistic:
    17.97
56 Date:                Sun, 22 Feb 2026    Prob (F-statistic):        1.99
    e-08
57 Time:                17:43:55    Log-Likelihood:
    -4487.2
58 No. Observations:        1347    AIC:
    8980.
59 Df Residuals:            1344    BIC:
    8996.
60 Df Model:                2
61 Covariance Type:        nonrobust
62 =====

63                coef      std err      t      P>|t|
    [0.025      0.975]
64 -----

65 Intercept                27.8740      0.238    117.343    0.000
    27.408      28.340
66 C(EXERANY2_no_na)[T.2.0]    2.0290      0.439     4.625    0.000
    1.168      2.890
67 C(disabled_no_na)[T.1]     1.1377      0.406     2.805    0.005
    0.342      1.933
68 =====

69 Omnibus:                740.497    Durbin-Watson:
    1.990
70 Prob(Omnibus):            0.000    Jarque-Bera (JB):
    14851.974
71 Skew:                    2.113    Prob(JB):
    0.00

```

72 Kurtosis: 18.709 Cond. No.

2.76

73 =====

74

75 Notes:

76 [1] Standard Errors assume that the covariance matrix of the errors is  
correctly specified.