

exams

February 17, 2020

```
[1]: import pandas as pd
import numpy as np
import statsmodels.api as sm
```

```
/nfs/kshedden/python3/lib/python3.7/site-
packages/statsmodels/compat/pandas.py:23: FutureWarning: The Panel class is
removed from pandas. Accessing it from the top-level namespace will also be
removed in the next version
data_klasses = (pandas.Series, pandas.DataFrame, pandas.Panel)
```

1 GEE analysis of test score data

Generalized estimating equations (GEE) can be used to analyze multilevel data that arises in educational research, for example when students taking a test are grouped into classrooms.

The examination data analyzed here are obtained from this page:
<http://www.bristol.ac.uk/cmm/learning/support/datasets/>

The data are in fixed-width format, we can load it as follows:

```
[2]: colspecs = [(0, 5), (6, 10), (11, 12), (13, 16), (17, 20)]
df = pd.read_fwf("../data/exam_scores/SCI.DAT", colspecs=colspecs, header=None)
df.columns = ["schoolid", "subjectid", "gender", "score1", "score2"]
df["female"] = 1*(df.gender == 1)
df = df.dropna()
```

Here is a basic model looking at the scores on exam 1 by gender, using the default independence working correlation structure.

```
[3]: # A school-clustered model for exam score 1 with no correlation.
model1 = sm.GEE.from_formula("score1 ~ female", groups="schoolid", data=df)
rslt1 = model1.fit()
print(rslt1.summary())
```

GEE Regression Results

```
=====
===
Dep. Variable:                score1    No. Observations:
1905
Model:                        GEE      No. clusters:
=====
```

```

73
Method:                      Generalized  Min. cluster size:
2
                        Estimating Equations  Max. cluster size:
104
Family:                      Gaussian    Mean cluster size:
26.1
Dependence structure:        Independence  Num. iterations:
2
Date:                        Mon, 17 Feb 2020  Scale:
451.997
Covariance type:              robust      Time:
19:21:02
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
Intercept      78.2136      1.864      41.960      0.000      74.560      81.867
female        -5.5292      1.183     -4.673      0.000     -7.848     -3.210
=====
Skew:                      -0.0935  Kurtosis:                      -0.0730
Centered skew:              0.1914  Centered kurtosis:              0.1835
=====

```

Here is the same mean structure model, now specifying that the students are exchangeably correlated within classrooms.

```

[4]: # A school-clustered model for exam score 1 with exchangeable correlations.
model2 = sm.GEE.from_formula("score1 ~ female", groups="schoolid",
                             cov_struct=sm.cov_struct.Exchangeable(), data=df)
rslt2 = model2.fit()
print(rslt2.summary())
print(model2.cov_struct.summary())

```

GEE Regression Results

```

=====
===
Dep. Variable:              score1  No. Observations:
1905
Model:                      GEE    No. clusters:
73
Method:                      Generalized  Min. cluster size:
2
                        Estimating Equations  Max. cluster size:
104
Family:                      Gaussian    Mean cluster size:
26.1
Dependence structure:        Exchangeable  Num. iterations:
7
Date:                        Mon, 17 Feb 2020  Scale:

```

456.642

Covariance type: robust Time:
19:21:03

	coef	std err	z	P> z	[0.025	0.975]
Intercept	79.2582	1.561	50.764	0.000	76.198	82.318
female	-3.9121	0.922	-4.243	0.000	-5.719	-2.105
Skew:		-0.0987	Kurtosis:			-0.0675
Centered skew:		0.1848	Centered kurtosis:			0.1751

The correlation between two observations in the same cluster is 0.422

Next we will pivot the exam scores so that each subject has two observations on a single “test” variable (one observation for the first test and one for the second test). This is a form of repeated measures, but since the tests are different, we also include a covariate indicating which test is being recorded. We now have two levels of repeated structure: two test scores per student, and multiple students per classroom. We can use a nested correlation structure to estimate the variance contributions from the two levels.

```
[5]: # Prepare to do a joint analysis of the two scores.
dx = pd.melt(df, id_vars=["subjectid", "schoolid", "female"],
             value_vars=["score1", "score2"], var_name="test",
             value_name="score")

[6]: # A nested model for subjects within schools, having two scores per subject.
model3 = sm.GEE.from_formula("score ~ female + test", groups="schoolid",
                             dep_data="0 + subjectid",
                             cov_struct=sm.cov_struct.Nested(), data=dx)

rslt3 = model3.fit()
print(rslt3.summary())
print(model3.cov_struct.summary())
```

GEE Regression Results

```
=====
===
Dep. Variable:                score    No. Observations:
3810
Model:                        GEE      No. clusters:
73
Method:                       Generalized  Min. cluster size:
4
                               Estimating Equations  Max. cluster size:
208
Family:                       Gaussian    Mean cluster size:
52.2
Dependence structure:         Nested     Num. iterations:
7
```

Date: Mon, 17 Feb 2020 Scale:
 388.593
 Covariance type: robust Time:
 19:21:03

```
=====
==
              coef      std err          z      P>|z|      [0.025
0.975]
-----
--
Intercept      75.0859      1.629      46.081      0.000      71.892
78.280
test[T.score2]  4.0950      1.564       2.618      0.009       1.030
7.160
female         1.7597      0.899       1.958      0.050      -0.002
3.521
=====
Skew:              -0.3370    Kurtosis:              0.2129
Centered skew:     -0.1909    Centered kurtosis:    0.4841
=====
              Variance
schoolid    119.911185
subjectid   57.843633
Residual    210.837685
```