growth

February 17, 2020

1 GEE analysis of growth trajectories of children

GEE is commonly used in Longitudinal data analysis. Here we consider a dataset in which repeated measures of weight were made on young children. GEE allows us to use linear modeling techniques similar to OLS, and still rigorously account for the repeated measures aspect of the data.

The data we will use are obvtained from this page: http://www.bristol.ac.uk/cmm/learning/support/datase. These are the packages we will be using.

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

/nfs/kshedden/python3/lib/python3.7/sitepackages/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)

The data are in "fixed width" format, so we use some special techniques for reading them.

```
[2]: colspecs = [(0, 4), (4, 7), (7, 12), (12, 16), (16, 17)]
  df = pd.read_fwf("../data/growth/ASIAN.DAT", colspecs=colspecs, header=None)
  df.columns = ["Id", "Age", "Weight", "BWeight", "Gender"]
  df["Female"] = 1*(df.Gender == 2)
  df = df.dropna()
```

Some of the analyses below will use logged data.

```
[3]: df["LogWeight"] = np.log(df.Weight) / np.log(2)
df["LogBWeight"] = np.log(df.BWeight) / np.log(2)
```

The first model treats weight as a linear function of age, and ignores the repeated measures structure. The point estimates from this model are valid, but the standard errors are not.

```
[4]: model0 = sm.GLM.from_formula("Weight ~ Age + BWeight + Female", data=df)
    rslt0 = model0.fit()
    print(rslt0.summary())
```

Generalized Linear Model Regression Results

Dep. Variable:	Weight	No. Observations:	1572
Model:	GLM	Df Residuals:	1568
Model Family:	Gaussian	Df Model:	3
Link Function:	identity	Scale:	2.0045e+06
Method:	IRLS	Log-Likelihood:	-13634.
Date:	Mon, 17 Feb 2020	Deviance:	3.1431e+09

10:15:09 Pearson chi2:

3.14e+09

No. Iterations:

Covariance Type: nonrobust

========				========		========
	coef	std err	Z	P> z	[0.025	0.975]
Intercept	2601.2871	231.095	11.256	0.000	2148.350	3054.225
Age	10.1121	0.123	82.027	0.000	9.870	10.354
BWeight	0.8866	0.071	12.478	0.000	0.747	1.026
Female	-520.3096	71.478	-7.279	0.000	-660.404	-380.215

Here is a GEE model with the same mean structure as in the cell above, but using GEE gives us meaningful standard errors.

GEE Regression Results

===

Time:

Dep. Variable: Weight No. Observations:

1572

Model: GEE No. clusters:

568

Method: Generalized Min. cluster size:

1

Estimating Equations Max. cluster size:

5

Family: Gaussian Mean cluster size:

2.8

Dependence structure: Independence Num. iterations:

3

Date: Mon, 17 Feb 2020 Scale:

2004506.825

Covariance type: robust Time:

10:15:10

	coef	std err	z	P> z	[0.025	0.975]
Intercept Age	2601.2871 10.1121	268.766 0.111	9.679 90.912	0.000	2074.515	3128.059 10.330
BWeight Female	0.8866 -520.3096	0.086 79.384	10.367 -6.554	0.000	0.719 -675.900	1.054
======================================	-520.3096 ======	79.384 =======	-6.554 	0.000 ======	-675.900	-364.719
Skew: Centered sl	kew:		3683 Kurto 2702 Cente	sis: red kurtosi	s:	0.1819 0.0109
========	========	========		========	========	========

Now we fit the same model as a log/log regression. Specifically, the relationship between weight in childhood at a given age and birth weight has a log/log relationship. This means that when comparing two children of the same sex whose birthweights differed by a given percentage, say x, then their childhood weights at a given age differ on average by a corresponding percentage $b \cdot x$, where b is the coefficient of LogBWeight. Typically we anticipate that $0 \le b \le 1$ in this type of regression. If $b \approx 1$ then, say, two kids whose weights at birth differend by 20%% will continue to have weights differing by 20%% as they age. If b < 1, then the 20%% difference at birth will attenuate as the kids age.

GEE Regression Results

===

Dep. Variable: LogWeight No. Observations:

1572

Model: GEE No. clusters:

568

Method: Generalized Min. cluster size:

1

Estimating Equations Max. cluster size:

5

Family: Gaussian Mean cluster size:

Dependence structure: Independence Num. iterations:

2

Date: Mon, 17 Feb 2020 Scale:

0.094

Covariance type: robust Time:

10:15:10

========	=======					=======
	coef	std err	Z	P> z	[0.025	0.975]
Intercept	9.0936	0.501	18.151	0.000	8.112	10.076

=========	========		=========	========	========	========
Centered ske	w:	-0.2	631 Center	red kurtosis	:	-0.8613
Skew:		-0.0	690 Kurtos	::::::::::::::::::::::::::::::::::::::		-0.9649
Female	-0.0910	0.014	-6.439 	0.000	-0.119 	-0.063
Famala.	0 0010	0 014	C 420	0 000	0 110	0.062
LogBWeight	0.2839	0.043	6.599	0.000	0.200	0.368
Age	0.0018	1.86e-05	95.480	0.000	0.002	0.002

It isn't very likely that weight varies either linearly or exponentially with age. We can use splines to capture a much broader range of relationships.

```
[7]: model3 = sm.GEE.from_formula("LogWeight ~ bs(Age, 4) + LogBWeight + Female", __
   rslt3 = model3.fit()
   print(rslt3.summary())
```

	GEE Regression Results							
===		=======		=========		======		
Dep. Variable:		LogWe	eight N	o. Observation	ns:			
1572								
Model:			GEE N	o. clusters:				
568								
Method:		General	ized M	in. cluster si	ize:			
1								
5	Esti	mating Equat	cions M	ax. cluster si	ıze:			
Family:		Cauc	ssian M	ean cluster si	izo.			
2.8		Gaus	sstan r	ean Cluster Si	ıze.			
Dependence struc	cture:	Independ	lence N	um. iterations	S:			
2								
Date:		Mon, 17 Feb	2020 S	cale:				
0.024								
Covariance type:	:	ro	bust T	ime:				
10:15:10								
=	=======	========	:======	========		======		
	coef	std err	Z	P> z	Γ0.025			
0.975]					-			
Intercept	7.9489	0.384	20.675	0.000	7.195			
8.702								
bs(Age, 4)[0] 1.074	0.9993	0.038	26.229	0.000	0.925			
bs(Age, 4)[1] 1.677	1.6037	0.037	42.999	0.000	1.531			
bs(Age, 4)[2]	1.8115	0.064	28.180	0.000	1.685			

Skew: Centered skew:		0.1011 0.2006	Kurtosis Centered	: kurtosis:		0.9305 4.5751
LogBWeight 0.402 Female -0.064	0.3375	0.033	10.193 -7.719	0.000	0.273	
1.937 bs(Age, 4)[3] 1.932	1.8769	0.028	67.049	0.000	1.822	

It is quite possible that the relationships between birth weight and childhood weight differ between girls and boys. An interaction captures this possibility.

```
[8]: model4 = sm.GEE.from_formula("LogWeight ~ bs(Age, 4) + LogBWeight*Female", _
    rslt4 = model4.fit()
   print(rslt4.summary())
```

GEE Regression Results								
===	=======	========	=======	=======	:========			
Dep. Variable:		LogWeight	No. Obse	rvations:				
1572								
Model:		GEE	No. clus	ters:				
568								
Method:	G	eneralized	Min. clu	ster size:				
1								
	Estimating	Equations	Max. clu	ster size:				
5								
Family:		Gaussian	Mean clu	ster size:				
2.8								
Dependence structure:	In	dependence	Num. ite	rations:				
2								
Date:	Mon, 1	7 Feb 2020	Scale:					
0.024								
Covariance type:		robust	Time:					
10:15:10								
	=======		=======		:========			
====	•			5 2. I. I.	[0, 00 <u>[</u>			
0.075]	coei	std err	Z	P> z	[0.025			
0.975]								
Intercept	8.0705	0.621	12.991	0.000	6.853			
9.288								
bs(Age, 4)[0]	0.9988	0.038	26.309	0.000	0.924			

0.143 ====================================	=======	0.1026 0.2000	 Kurtosis: Centered kur	:======== :+	0.9416 4.576	
1.049 LogBWeight:Female	0.0228	0.062	0.371	0.711	-0.098	
0.432 Female	-0.3500	0.714	-0.490	0.624	-1.749	
1.933 LogBWeight	0.3270	0.054	6.103	0.000	0.222	
1.935 bs(Age, 4)[3]	1.8779	0.028	67.290	0.000	1.823	
1.677 bs(Age, 4)[2]	1.8095	0.064	28.255	0.000	1.684	
1.073 bs(Age, 4)[1]	1.6042	0.037	43.008	0.000	1.531	

Although GEE does not require us to specify an accurate covariance structure, we will have more power if we do so. We will also learn something about the strength of the within-subject dependence that we would not learn when using the independence model.

```
[9]: model5 = sm.GEE.from_formula("LogWeight ~ bs(Age, 4) + LogBWeight + Female", □
→groups="Id",

cov_struct=sm.cov_struct.Exchangeable(), data=df)

rslt5 = model5.fit()

print(rslt5.summary())

print(rslt5.cov_struct.summary())
```

GEE Regression Results

______ Dep. Variable: LogWeight No. Observations: 1572 GEE Model: No. clusters: 568 Method: Generalized Min. cluster size: Estimating Equations Max. cluster size: 5 Family: Gaussian Mean cluster size: 2.8 Dependence structure: Num. iterations: Exchangeable 6 Date: Mon, 17 Feb 2020 Scale: 0.024 Covariance type: robust Time: 10:15:11

==========						
0.975]	coef	std err	z	P> z	[0.025	
_						
Intercept 8.472	7.7638	0.361	21.482	0.000	7.055	
	0.9613	0.032	29.705	0.000	0.898	
	1.6186	0.031	52.824	0.000	1.559	
	1.7834	0.054	32.797	0.000	1.677	
	1.8689	0.024	77.722	0.000	1.822	
LogBWeight	0.3543	0.031	11.410	0.000	0.293	
Female -0.058	-0.0796	0.011	-7.363	0.000	-0.101	
Skew: Centered skew:				kurtosis:		0.9295 4.6793

The correlation between two observations in the same cluster is 0.466

In genral, it is better to use the default "robust" approach for covariance estimation. This allows the covariance model to be mis-specified, while still yielding valid parameter estimates and standard errors. If you are very confident that your working covariance model is correct, you can specify the "naive" approach to covariance estimation. In this case, the standard errors will be meaningful only if the working correlation model is correct.

```
[10]: model6 = sm.GEE.from_formula("LogWeight ~ bs(Age, 4) + LogBWeight + Female", □

→groups="Id",

cov_struct=sm.cov_struct.Exchangeable(), data=df)

rslt6 = model6.fit(cov_type="naive")

print(rslt6.summary())
```

GEE Regression Results

===

Dep. Variable: LogWeight No. Observations:

1572

Model: GEE No. clusters:

568

Method: Generalized Min. cluster size:

1

Estimating Equations Max. cluster size:

5

Family: Gaussian Mean cluster size:

2.8

Dependence structure: Exchangeable Num. iterations:

6

Date: Mon, 17 Feb 2020 Scale:

0.024

Covariance type: naive Time:

10:15:12

============				========	========	
=	coef	std err	Z	P> z	[0.025	
0.975]						
-						
Intercept 8.253	7.7638	0.249	31.119	0.000	7.275	
bs(Age, 4)[0] 1.030	0.9613	0.035	27.482	0.000	0.893	
bs(Age, 4)[1] 1.683	1.6186	0.033	49.210	0.000	1.554	
bs(Age, 4)[2] 1.898	1.7834	0.058	30.567	0.000	1.669	
bs(Age, 4)[3] 1.921	1.8689	0.027	69.786	0.000	1.816	
LogBWeight	0.3543	0.021	16.490	0.000	0.312	
Female -0.058	-0.0796	0.011	-7.356	0.000	-0.101	
Skew:		0.1188	Kurtosis			0.9295
Centered skew:		0.1842	Centered	kurtosis:		4.6793
