

Homework # 3 Solutions

Biostatistics 210

Question 1:

(a) Using the wide format data, `hwk3_wide.dta` explore the association between missing data at year 1 (`missing=1`) with the predictors collected at the baseline visit. Summarize what you find. Are baseline factors associated with a missing blood pressure at yr1?

I explore this through logistic regression with missingness at year 1 as the outcome (missing) and baseline diabetes, BMI, and SBP as the predictors.

```
. logistic missing bmi0 sbp0 baseline_dm, nolog
```

```
Logistic regression               Number of obs   =       2607
                                LR chi2(3)         =      1924.11
                                Prob > chi2         =       0.0000
Log likelihood = -840.00284       Pseudo R2      =       0.5339
```

missing	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
bmi0	1.001015	.0116856	0.09	0.931	.9783716	1.024182
sbp0	1.208036	.009221	24.76	0.000	1.190098	1.226245
baseline_dm	.8699221	.1267495	-0.96	0.339	.6538204	1.15745
_cons	7.80e-12	8.36e-12	-23.87	0.000	9.54e-13	6.37e-11

The baseline SBP appears to be the sole predictor of missing data at year 1 -- and it seems like it is a strong predictor.

(b) Does year 1 SBP (`sbp1`) appear to be associated with the indicator of missingness (`missing`)

It does.

```
. logistic missing sbp1
```

```
Logistic regression               Number of obs   =       2607
                                LR chi2(1)         =       517.63
                                Prob > chi2         =       0.0000
Log likelihood = -1543.2439       Pseudo R2      =       0.1436
```

missing	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
sbp1	1.055902	.0029136	19.71	0.000	1.050207	1.061628
_cons	.0005646	.0002117	-19.95	0.000	.0002707	.0011774

This mean. Year 1 SBP is different between those with missing and available value. But I would note that Year 1 SBP is not associated with missing data after adjustment for baseline factors -- this is the essence of the missing at random assumption.

```
. logistic missing sbp1 sbp0 bmi0 baseline_dm
```

```
Logistic regression      Number of obs   =      2607
                        LR chi2(4)         =      1924.14
                        Prob > chi2        =      0.0000
Log likelihood = -839.98794      Pseudo R2         =      0.5339
```

missing	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
sbp1	1.000695	.0040285	0.17	0.863	.9928306	1.008622
sbp0	1.207511	.0096962	23.48	0.000	1.188656	1.226666
bmi0	1.000975	.0116884	0.08	0.933	.9783266	1.024148
baseline_dm	.8684747	.1268182	-0.97	0.334	.6523209	1.156254
_cons	7.54e-12	8.22e-12	-23.49	0.000	8.90e-13	6.38e-11

Question 2: Classify the following scenarios as leading to missingness which is MCAR, MAR or NMAR (and explain your answer).

(a) missingness only depends on baseline SBP

This would be missing at random (MAR) -- missingness only depends on our data though a variable which is available on everyone.

(b) missingness only depends on baseline diabetes

This would be missing at random (MAR) -- missingness only depends on our data though a variable which is available on everyone.

(c) missingness only depends on BMI at year 1

This would be missing at random (MAR) -- missingness only depends on our data though a variable which is available on everyone.

(d) missingness only depends on SBP at year 1

This would be missing at not a random (MNAR) -- missingness depends on our data though the variable which is missing.

Question 3: Fill in the following table. Recall, you have the complete data and can take out the missing values by analyzing the subset with non-missing value (if missing==0)

	Mean SBP
Baseline	134.9
Year One (All Data)	135.2
Year One (Non-Missing Data)	127.5

```
. mean sbp0
Mean estimation      Number of obs   =    2607
```

```
-----+-----
            |      Mean   Std. Err.   [95% Conf. Interval]
-----+-----
      sbp0 |   134.8899   .3716866     134.1611     135.6187
-----+-----
```

```
mean sbp1
Mean estimation      Number of obs   =    2607
```

```
-----+-----
            |      Mean   Std. Err.   [95% Conf. Interval]
-----+-----
      sbp1 |   135.2056   .3761451     134.468     135.9432
-----+-----
```

```
. mean sbp1 if missing==0
Mean estimation      Number of obs   =    1384
```

```
-----+-----
            |      Mean   Std. Err.   [95% Conf. Interval]
-----+-----
      sbp1 |   127.5499   .4403621     126.686     128.4137
-----+-----
```

What is the mean change in SBP from baseline to year 1 with the complete data?

+0.3 mmHg

What is it using only the non-missing values at year 1?

-7.3mmHg

How do you explain the difference?

It appears that the available 1 year SBP is in people with lower baseline SBP (and the people with lower SBP at year 1 as a result of that). This means the apparent lower SBP at year 1 is not from within person changes but a shift in the population

4 . GEE

Question 4: *The model for the complete data is given as*

```
xtgee sbp i.visit , i(pptid) corr(indep) robust
```

(Std. Err. adjusted for clustering on pptid)

sbp	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
1.visit	.3156885	.3404026	0.93	0.354	-.3514883	.9828654
_cons	134.8899	.3716866	362.91	0.000	134.1614	135.6184

The model for the non-missing data is

GEE population-averaged model		Number of obs	=	3991
Group variable:	pptid	Number of groups	=	2607
Link:	identity	Obs per group: min	=	1
Family:	Gaussian	avg	=	1.5
Correlation:	independent	max	=	2
		Wald chi2(1)	=	202.53
Scale parameter:	328.1759	Prob > chi2	=	0.0000
Pearson chi2(3991):	1309750	Deviance	=	1309750
Dispersion (Pearson):	328.1759	Dispersion	=	328.1759

(Std. Err. adjusted for clustering on pptid)

sbp	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
1.visit	-7.340056	.5157637	-14.23	0.000	-8.350935	-6.329178
_cons	134.8899	.3716866	362.91	0.000	134.1614	135.6184

How does that compare with the average change (estimated by GEE) in SBP from baseline to year 1 using the data with non-missing values? Why are they different?

Note, that there is no effect of visit (change from baseline to year 1) in the complete data but a statistically significant one for the incomplete data. In the data with some values missing at year 1, the visit term is -7.3 points or exactly what was derived in question 3. The difference reflects the purely the dropouts with low baseline SBP.

Question 5: Fit first a model to the complete data

```
xtmixed sbp visit|| pptid:, ml
```

```
Log likelihood = -22227.365
```

Wald chi2(1)	=	0.86
Prob > chi2	=	0.3536

sbp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
visit	.3156885	.3403373	0.93	0.354	-.3513603	.9827373
_cons	134.8899	.3738508	360.81	0.000	134.1572	135.6226

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
pptid: Identity					
	sd(_cons)	14.6076	.2830671	14.06321	15.17308
	sd(Residual)	12.28754	.1701686	11.9585	12.62563

```
LR test vs. linear regression: chibar2(01) = 1094.96 Prob >= chibar2 = 0.0000
```

Then fit a model to the non-missing data

```
Log likelihood = -17052.336
```

Wald chi2(1)	=	2.17
Prob > chi2	=	0.1409

sbp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
visit	.6166597	.4188072	1.47	0.141	-.2041873	1.437507
_cons	134.8899	.3709222	363.66	0.000	134.1629	135.6169

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
pptid: Identity					
	sd(_cons)	15.02488	.3668638	14.32277	15.7614
	sd(Residual)	11.52964	.2497239	11.05043	12.02963

```
LR test vs. linear regression: chibar2(01) = 343.35 Prob >= chibar2 = 0.0000
```

Question 5: How do the mixed model results compare between missing and non-missing data?

For the non-missing dataset, We see that there is an estimated change of 0.32 mmHg in the complete data is identical to the one in the GEE model.

How does that compare with the average change (estimated by the mixed model) in SBP from baseline to year 1 using the data with non-missing values?

We see for the mixed model that there is an estimated change of 0.62 mmHg with missing data -- the effect is non-significant and we should not be surprised. The reason is related to the fact that the data missing at year 1 is MAR with respect to the baseline SBP. The mixed model is fit by maximum likelihood. Maximum likelihood seamlessly handles MAR missing data as long as the variables which define the MAR assumption are included in the model. They need not be included as predictors -- they can be included as an outcome. In this example, the variable which defines the MAR assumption is baseline SBP which ensures that maximum likelihood will handle the missing data. Note, that baseline SBP is an outcome in this model -- not a predictor.