

Homework#6

Neshma Simon

11/10/2020

Group Members: Fareha and Hertz

```
{r setup, include=FALSE}  
knitr::opts_chunk$set(echo = TRUE)
```

```
model_v1 <- lm(INCWAGE ~ AGE)
```

```
model_v2 <- lm(acs2017_ny$INCWAGE ~ acs2017_ny$AGE)
```

```
model_v3 <- lm(INCWAGE ~ AGE, data = acs2017_ny)  
model_logit1 <- glm(LABFORCE ~ AGE,family = binomial, data = acs2017_ny)
```

In this logit model, we check to see the status of women with ages between 25 and 55 who are in the lab

```
acs2017_ny$LABFORCE <- as.factor(acs2017_ny$LABFORCE)  
levels(acs2017_ny$LABFORCE) <- c("NA","Not in LF","in LF")
```

```
acs2017_ny$age_bands <- cut(acs2017_ny$AGE,breaks=c(0,25,35,45,55,65,100))  
table(acs2017_ny$age_bands,acs2017_ny$LABFORCE)
```

NA	Not in LF	in LF
(0,25]	31680	11717 13256
(25,35]	0	4271 20523
(35,45]	0	4064 18924
(45,55]	0	5406 21747
(55,65]	0	10563 18106
(65,100]	0	28701 5880

```
pick_use1 <- (acs2017_ny$AGE >25) & (acs2017_ny$AGE <= 55)  
dat_use1 <- subset(acs2017_ny, pick_use1)  
dat_use1$LABFORCE <- droplevels(dat_use1$LABFORCE)
```

```
model_logit1 <- glm(LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian + race_oth + Hispanic  
+ educ_hs + educ_somecoll + educ_college + educ_advdeg  
+ MARST,  
family = binomial, data = dat_use1)  
summary(model_logit1)
```

Call:

```
glm(formula = LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian +  
race_oth + Hispanic + educ_hs + educ_somecoll + educ_college +  
educ_advdeg + MARST, family = binomial, data = dat_use1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.5832	0.3544	0.4898	0.6531	1.4508

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.4685228	0.2448988	1.913	0.055732 .
AGE	0.0234645	0.0120812	1.942	0.052109 .
I(AGE^2)	-0.0003617	0.0001469	-2.463	0.013782 *
female	-0.6718196	0.0204038	-32.926	< 2e-16 ***
AfAm	-0.2242340	0.0279895	-8.011	1.13e-15 ***
Asian	-0.1303415	0.0373695	-3.488	0.000487 ***
race_oth	-0.0836070	0.0331696	-2.521	0.011716 *
Hispanic	0.1499195	0.0312545	4.797	1.61e-06 ***
educ_hs	0.9072897	0.0309561	29.309	< 2e-16 ***
educ_somecoll	1.4703761	0.0349971	42.014	< 2e-16 ***
educ_college	1.9526149	0.0370063	52.764	< 2e-16 ***
educ_advdeg	2.3771878	0.0436527	54.457	< 2e-16 ***
MARST	-0.0653027	0.0046961	-13.906	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 71408 on 74934 degrees of freedom

Residual deviance: 64991 on 74922 degrees of freedom

AIC: 65017

Number of Fisher Scoring iterations: 5

In this we're using education and marital status as variables to see how education and marital status e

```
model_logit2 <- glm(LABFORCE ~ AGE,
                    family = binomial, data = dat_use1)
```

```
summary(model_logit2)
```

Call:

```
glm(formula = LABFORCE ~ AGE, family = binomial, data = dat_use1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9021	0.6032	0.6259	0.6520	0.6735

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.864808	0.044962	41.475	<2e-16 ***
AGE	-0.009033	0.001064	-8.489	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 71408 on 74934 degrees of freedom

Residual deviance: 71336 on 74933 degrees of freedom

AIC: 71340

Number of Fisher Scoring iterations: 4

We wanted to use model_logit2 with just labor force and age as a way to compare the following data sets

```
model_logit3 <- glm(LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian + race_oth + Hispanic
+ educ_hs + educ_somecoll + educ_college + educ_advdeg
+ FAMSIZE,
family = binomial, data = dat_use1)
summary(model_logit3)
```

Call:

```
glm(formula = LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian +
race_oth + Hispanic + educ_hs + educ_somecoll + educ_college +
educ_advdeg + FAMSIZE, family = binomial, data = dat_use1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.6280	0.3457	0.4955	0.6553	1.4369

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.2451623	0.2377430	-1.031	0.302444
AGE	0.0325788	0.0120427	2.705	0.006825 **
I(AGE^2)	-0.0004113	0.0001470	-2.798	0.005146 **
female	-0.6745928	0.0204295	-33.021	< 2e-16 ***
AfAm	-0.2863821	0.0275035	-10.413	< 2e-16 ***
Asian	-0.1305968	0.0374776	-3.485	0.000493 ***
race_oth	-0.0957544	0.0332063	-2.884	0.003931 **
Hispanic	0.1218593	0.0312831	3.895	9.8e-05 ***
educ_hs	0.9266151	0.0309441	29.945	< 2e-16 ***
educ_somecoll	1.5032480	0.0349743	42.982	< 2e-16 ***
educ_college	2.0028058	0.0370521	54.054	< 2e-16 ***
educ_advdeg	2.4468515	0.0436390	56.070	< 2e-16 ***
FAMSIZE	0.0664596	0.0058801	11.302	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 71408 on 74934 degrees of freedom

Residual deviance: 65053 on 74922 degrees of freedom

AIC: 65079

Number of Fisher Scoring iterations: 5

```
model_logit4 <- glm(LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian + race_oth + Hispanic
+ educ_hs + educ_somecoll + educ_college + educ_advdeg
+ MARST + FAMSIZE,
family = binomial, data = dat_use1)
summary(model_logit4)
```

Call:

```
glm(formula = LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian +
race_oth + Hispanic + educ_hs + educ_somecoll + educ_college +
educ_advdeg + MARST + FAMSIZE, family = binomial, data = dat_use1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.6024	0.3462	0.4904	0.6533	1.4693

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.3905680	0.2451999	1.593	0.11119
AGE	0.0173019	0.0121191	1.428	0.15339
I(AGE^2)	-0.0002714	0.0001475	-1.840	0.06580 .
female	-0.6803756	0.0204615	-33.252	< 2e-16 ***
AfAm	-0.2308655	0.0280294	-8.237	< 2e-16 ***
Asian	-0.1493175	0.0374716	-3.985	6.75e-05 ***
race_oth	-0.0881713	0.0331875	-2.657	0.00789 **
Hispanic	0.1362644	0.0313217	4.350	1.36e-05 ***
educ_hs	0.9118417	0.0309869	29.427	< 2e-16 ***
educ_somecoll	1.4796793	0.0350513	42.215	< 2e-16 ***
educ_college	1.9729277	0.0371666	53.083	< 2e-16 ***
educ_advdeg	2.4022062	0.0438382	54.797	< 2e-16 ***
MARST	-0.0527822	0.0050385	-10.476	< 2e-16 ***
FAMSIZE	0.0425891	0.0062339	6.832	8.38e-12 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 71408 on 74934 degrees of freedom
Residual deviance: 64943 on 74921 degrees of freedom
AIC: 64971

Number of Fisher Scoring iterations: 5

```
model_logit5 <- glm(LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian + race_oth + Hispanic  
+ educ_hs + educ_somecoll + educ_college + educ_advdeg  
+ MARST + FAMSIZE + RELATE + RELATED,  
family = binomial, data = dat_use1)
```

summary(model_logit5)

Call:

```
glm(formula = LABFORCE ~ AGE + I(AGE^2) + female + AfAm + Asian +  
race_oth + Hispanic + educ_hs + educ_somecoll + educ_college +  
educ_advdeg + MARST + FAMSIZE + RELATE + RELATED, family = binomial,  
data = dat_use1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.6565	0.3228	0.4711	0.6318	1.7573

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.0322603	0.2498763	4.131	3.61e-05 ***
AGE	0.0130771	0.0123295	1.061	0.28886
I(AGE^2)	-0.0002720	0.0001500	-1.814	0.06974 .
female	-0.7592838	0.0210160	-36.129	< 2e-16 ***
AfAm	-0.1795140	0.0286135	-6.274	3.52e-10 ***

Asian	-0.1025814	0.0379683	-2.702	0.00690	**
race_oth	-0.0921546	0.0335918	-2.743	0.00608	**
Hispanic	0.1667801	0.0317853	5.247	1.55e-07	***
educ_hs	0.8232360	0.0317256	25.949	< 2e-16	***
educ_somecoll	1.3072221	0.0359129	36.400	< 2e-16	***
educ_college	1.7886759	0.0380032	47.066	< 2e-16	***
educ_advdeg	2.1959502	0.0446189	49.216	< 2e-16	***
MARST	0.0098808	0.0054456	1.814	0.06961	.
FAMSIZE	0.0067252	0.0064006	1.051	0.29339	
RELATE	-0.0846649	0.0882969	-0.959	0.33763	
RELATED	-0.0002771	0.0008608	-0.322	0.74754	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 71408 on 74934 degrees of freedom
 Residual deviance: 63347 on 74919 degrees of freedom
 AIC: 63379

Number of Fisher Scoring iterations: 5

We used model_logit2 to see the change in results without variables such as education, race, and marital