MACS 30000 PS 2, Fall 2018

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Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

Imputing age and gender (3 points)

```
setwd("/Users/cosettelh/Documents/UChi_local/Grad_MPP/MACSS/persp-analysis_A18/Assignments/A2")

bestincome <- read.csv("BestIncome.txt", header = FALSE,
                        col.names = c("lab_inc", "cap_inc", "hgt", "wgt"))
incomeintel <- read.csv("IncomeIntel.txt", header = FALSE,
                         col.names = c("grad_year", "gre_qnt", "salary_p4"))
survincome <- read.csv("SurvIncome.txt", header = FALSE,
                        col.names = c("tot_inc", "wgt", "age", "female"))
```

```
print(bestincome)
as.data.frame(describe(bestincome, na.rm = TRUE))
stat.desc(bestincome)


print(survincome)
as.data.frame(describe(survincome, na.rm = TRUE))
stat.desc(survincome)

print(incomeintel)
as.data.frame(describe(incomeintel, na.rm = TRUE))
stat.desc(incomeintel)
```

(A)

OLS models help estimate an unknown outcome given several parameters. We can impute age and gender into BestIncome by using an OLS model based on an equation with SurveyIncome since both datasets have the variables weight and tot_inc can be computed with lab_inc and cap_inc.

```
#Adding tot_pop column
bestincome$tot_inc <- bestincome$lab_inc + bestincome$cap_inc
print(bestincome)
as.data.frame(describe(bestincome, na.rm = TRUE))
```

```
#Providing the OLS models
lm_age <- lm(age~tot_inc+wgt, data = survincome)
lm_female <- lm(female~tot_inc+wgt, data = survincome)

lm_age
```

```
##
## Call:
```

```
## lm(formula = age ~ tot_inc + wgt, data = survincome)
##
## Coefficients:
## (Intercept)      tot_inc          wgt
##  44.2096668    0.0000252   -0.0067221
```

```r
lm_female
```

```
##
## Call:
## lm(formula = female ~ tot_inc + wgt, data = survincome)
##
## Coefficients:
## (Intercept)      tot_inc          wgt
##   3.761e+00   -5.250e-06   -1.953e-02
```

So the equations are: age_form = 44.2096668+(tot_inc*0.0000252)+(wgt*-0.0067221) gen_form = 3.761+(tot_inc*-0.000005250)+(wgt*-0.01953)

(B)

```r
age_form <- 44.2096668+(bestincome$tot_inc*0.0000252)+(bestincome$wgt*-0.0067221)
gen_form <- 3.761+(bestincome$tot_inc*-0.000005250)+(bestincome$wgt*-0.01953)

bestincome$age <- age_form
bestincome$female <- gen_form

head(bestincome, 10)
```

```
##     lab_inc   cap_inc      hgt      wgt  tot_inc      age    female
## 1  52655.61  9279.510 64.56814 152.9206 61935.12 44.74248 0.4493007
## 2  70586.98  9451.017 65.72765 159.5344 80038.00 45.15422 0.2250934
## 3  53738.01  8078.132 66.26880 152.5024 61816.14 44.74230 0.4580933
## 4  55128.18 12692.670 62.91056 149.2182 67820.85 44.91569 0.4907093
## 5  44482.79  9812.976 68.67830 152.7264 54295.77 44.55128 0.4932014
## 6  55394.63 10769.461 67.37055 151.6027 66164.09 44.85791 0.4528382
## 7  62627.90  9730.261 64.54769 151.4220 72358.16 45.01522 0.4238484
## 8  54936.56  8712.628 63.08035 153.9178 63649.18 44.77898 0.4208276
## 9  52730.25  9260.990 63.41790 147.3275 61991.24 44.78150 0.5582392
## 10 60525.27 10310.989 65.31023 154.1793 70836.26 44.95833 0.3779877
```

```r
bestincome <- bestincome %>%
  mutate_at(vars(female), funs(round(.,0))) %>%
  select(-tot_inc)
```

```
## Warning: package 'bindrcpp' was built under R version 3.4.4
```

```r
head(bestincome, 10)
```

```
##     lab_inc   cap_inc      hgt      wgt      age female
## 1  52655.61  9279.510 64.56814 152.9206 44.74248      0
## 2  70586.98  9451.017 65.72765 159.5344 45.15422      0
## 3  53738.01  8078.132 66.26880 152.5024 44.74230      0
## 4  55128.18 12692.670 62.91056 149.2182 44.91569      0
## 5  44482.79  9812.976 68.67830 152.7264 44.55128      0
## 6  55394.63 10769.461 67.37055 151.6027 44.85791      0
```

```
## 7  62627.90  9730.261 64.54769 151.4220 45.01522      0
## 8  54936.56  8712.628 63.08035 153.9178 44.77898      0
## 9  52730.25  9260.990 63.41790 147.3275 44.78150      1
## 10 60525.27 10310.989 65.31023 154.1793 44.95833      0
```

(C)

See output table from imputed_vars

```r
imputed_vars <- bestincome %>% select(age, female)
imputed_vars <- as.data.frame(describe(imputed_vars, na.rm = TRUE))
imputed_vars <- imputed_vars %>% select(mean, sd, min, max, n)
imputed_vars
```

```
##            mean        sd      min      max     n
## age    44.89069 0.2191325 43.97643 45.70361 10000
## female  0.46140 0.4985327  0.00000  1.00000 10000
```

(D)

See table printed below:

```r
corr_matrix <- as_data_frame(cor(bestincome))
corr_matrix
```

```
## # A tibble: 6 x 6
##    lab_inc  cap_inc      hgt      wgt     age  female
##      <dbl>    <dbl>    <dbl>    <dbl>   <dbl>   <dbl>
## 1  1        0.00533  0.00279  0.00451  0.924  -0.167
## 2  0.00533  1        0.0216   0.00630  0.234  -0.0470
## 3  0.00279  0.0216   1        0.172   -0.0451 -0.135
## 4  0.00451  0.00630  0.172    1       -0.300  -0.777
## 5  0.924    0.234   -0.0451  -0.300    1       0.0724
## 6 -0.167   -0.0470  -0.135   -0.777    0.0724  1
```

Stationary and data drift (4 points)

```r
print(incomeintel)
```

The equation: salary_p4i = b0 + b1gre_qnti + ei

(A)

In plain words, the equation is for the salary is the predictor variable, and the GRE quantitative score is the predictor variable. b0 is the Y-intercept. ei is an error term. Using a linear regression model and inference from the graph, we compute the equation to be:

salary_p4i = 89541.29 - -25.76*gre_qnti + ei

The estimated Y-intercept coefficient is 89,541.29 and the estimated GRE score coefficient is -25.76. Their standard errors are 878.764 and 1.365 respectively. Both coefficients are significant at the 95% confidence level.

```r
Y_hat <- mean(incomeintel$salary_p4)
Y_hat
```

```
## [1] 74173.29
```

```r
incomeintel_lm <- lm(salary_p4 ~ gre_qnt, data = incomeintel)
incomeintel_lm
```

```
##
## Call:
## lm(formula = salary_p4 ~ gre_qnt, data = incomeintel)
##
## Coefficients:
## (Intercept)      gre_qnt
##    89541.29       -25.76
```

```r
summary(incomeintel_lm)
```

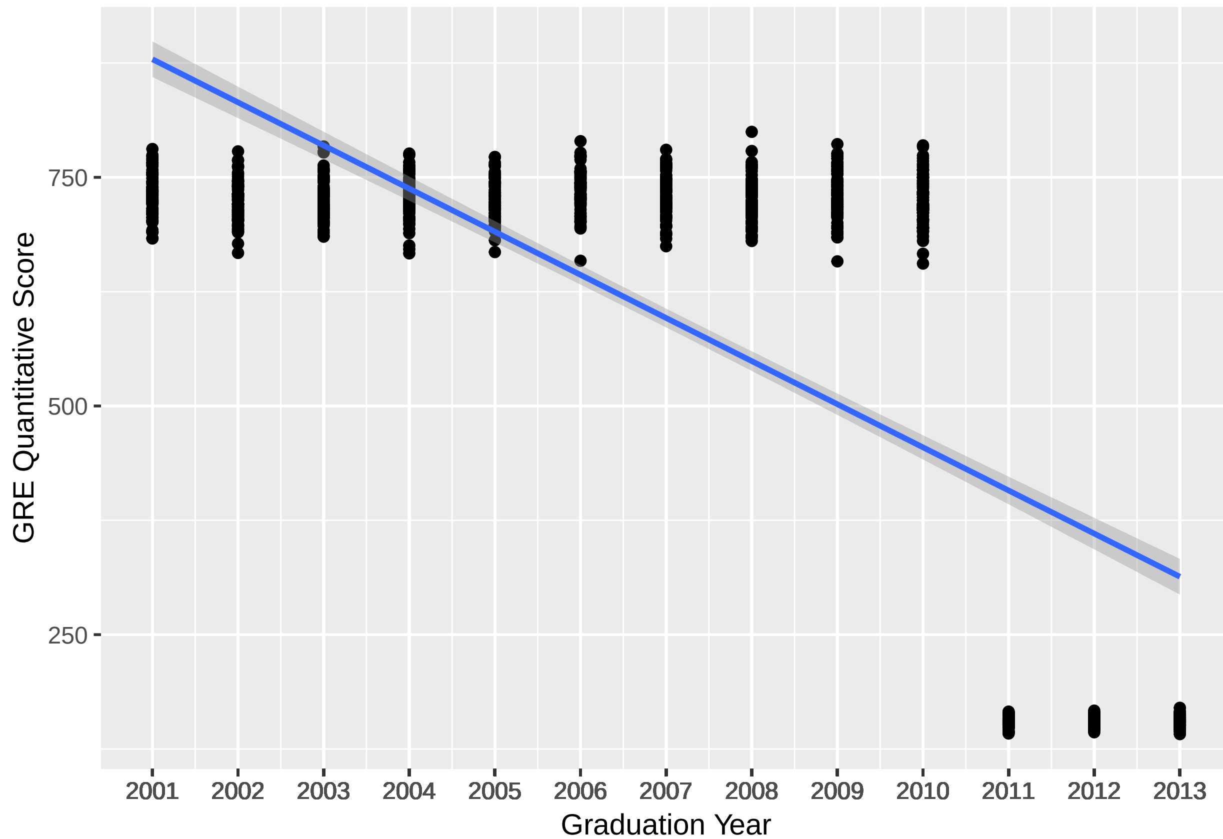
```
##
## Call:
## lm(formula = salary_p4 ~ gre_qnt, data = incomeintel)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -28761  -7049   -293   6549  37666
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 89541.293    878.764  101.89   <2e-16 ***
## gre_qnt       -25.763      1.365  -18.88   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10460 on 998 degrees of freedom
## Multiple R-squared:  0.2631, Adjusted R-squared:  0.2623
## F-statistic: 356.3 on 1 and 998 DF,  p-value: < 2.2e-16
```

(B)

The GRE quantitative scoring scale changed in 2011, from (200-800) at 10-point increments to now (130-170) at 1-point increments. This change is represented on the plot shown below with the huge gap in scores from 2010 to 2011, and a steeply decreasing line of best fit.

As such the data need to be adjusted to better compare recent score data to pre-2011 scores. A simple google search shows how the ETS compares old to new scores. For example, for Quant new 166-170 = 800 old and new 151 = 640-650 old.

```r
ggplot(data = incomeintel, aes(x = grad_year, y = gre_qnt)) +
  geom_point() +
  geom_smooth(method='lm') +
  scale_y_continuous(labels = scales::comma) +
  labs(x = "Graduation Year", y = "GRE Quantitative Score") +
  scale_x_continuous(labels = as.character(incomeintel$grad_year),
                     breaks = incomeintel$grad_year)
```




```
score_conv <- read_xlsx("new_scores.xlsx") #Reading in conversion table
```

```
## Warning in strptime(x, format, tz = tz): unknown timezone 'zone/tz/2018e.
## 1.0/zoneinfo/America/Chicago'
```

```
incomeintel <- incomeintel %>% #rounding scores from given data
  mutate("gre_qnt" <- ifelse(grad_year < 2011, round(gre_qnt, -1), round(gre_qnt,0))) %>%
  select(-(gre_qnt))

names(incomeintel)[3] <- "gre_qnt"
```

```
#joining on gre_qnt
income_est <- left_join(incomeintel, score_conv, by="gre_qnt")

income_est <- income_est %>%
  mutate("gre_qnt" <- ifelse(grad_year < 2011, current_scale, gre_qnt))

income_est <- income_est %>%
  select(-gre_qnt, -current_scale, -rank)
names(income_est)[3] <- "gre_qnt"
```

```
head(income_est)
```

```
##   grad_year salary_p4 gre_qnt
## 1      2001  67400.48     158
## 2      2001  67600.58     156
## 3      2001  58704.88     158
## 4      2001  64707.29     161
```

```
## 5      2001  51737.32     158
## 6      2001  64010.82     160
```

```r
head(incomeintel)
```

```
##   grad_year salary_p4 gre_qnt
## 1      2001  67400.48     740
## 2      2001  67600.58     720
## 3      2001  58704.88     740
## 4      2001  64707.29     770
## 5      2001  51737.32     740
## 6      2001  64010.82     760
```

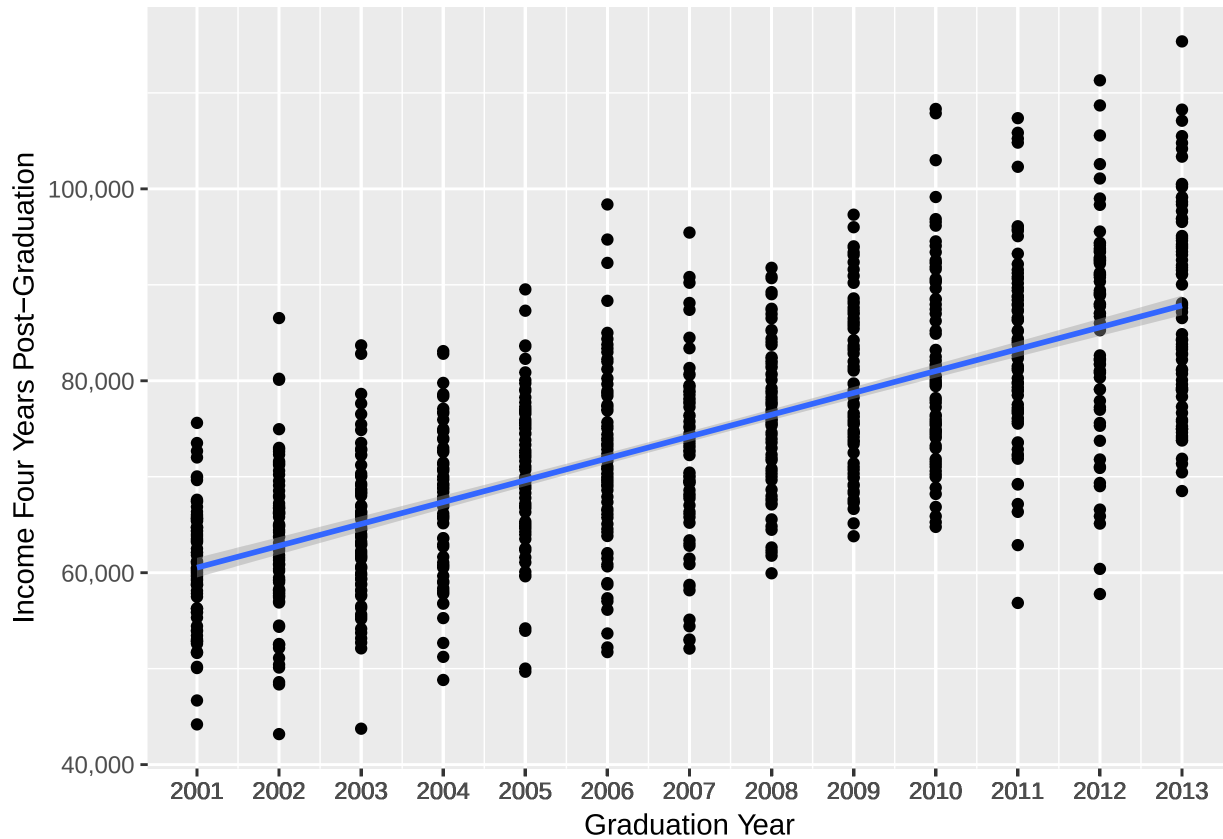
```r
head(score_conv)
```

```
## # A tibble: 6 x 3
##   gre_qnt current_scale  rank
##     <dbl>         <dbl> <dbl>
## 1     800           166    91
## 2     790           164    87
## 3     780           163    84
## 4     770           161    78
## 5     760           160    76
## 6     750           159    73
```

```r
#scores conversions are correct
```

(C)

```r
ggplot(data = income_est, aes(x = grad_year, y = salary_p4)) +
  geom_point() +
  geom_smooth(method='lm') +
  scale_y_continuous(labels = scales::comma) +
  labs(x = "Graduation Year", y = "Income Four Years Post-Graduation") +
  scale_x_continuous(labels = as.character(incomeintel$grad_year),
                     breaks = incomeintel$grad_year)
```




```
#Used: https://github.com/UC-MACSS/persp-analysis_A18/issues/13

base_year <- 2011

#mean salary by each year
avg_inc_by_year <- income_est %>%
  group_by(grad_year) %>%
  summarize(mean_salary = mean(salary_p4))

#growth rate in salaries across all 13 years
avg_growth_rate <- avg_inc_by_year %>%
  mutate((mean_salary - (lag(mean_salary, default = first(mean_salary))))/(lag(mean_salary, default = fi
names(avg_growth_rate)[3] <- "sal_growth_rate"

income_est <- left_join(income_est, avg_growth_rate, by = "grad_year")
head(income_est)
```

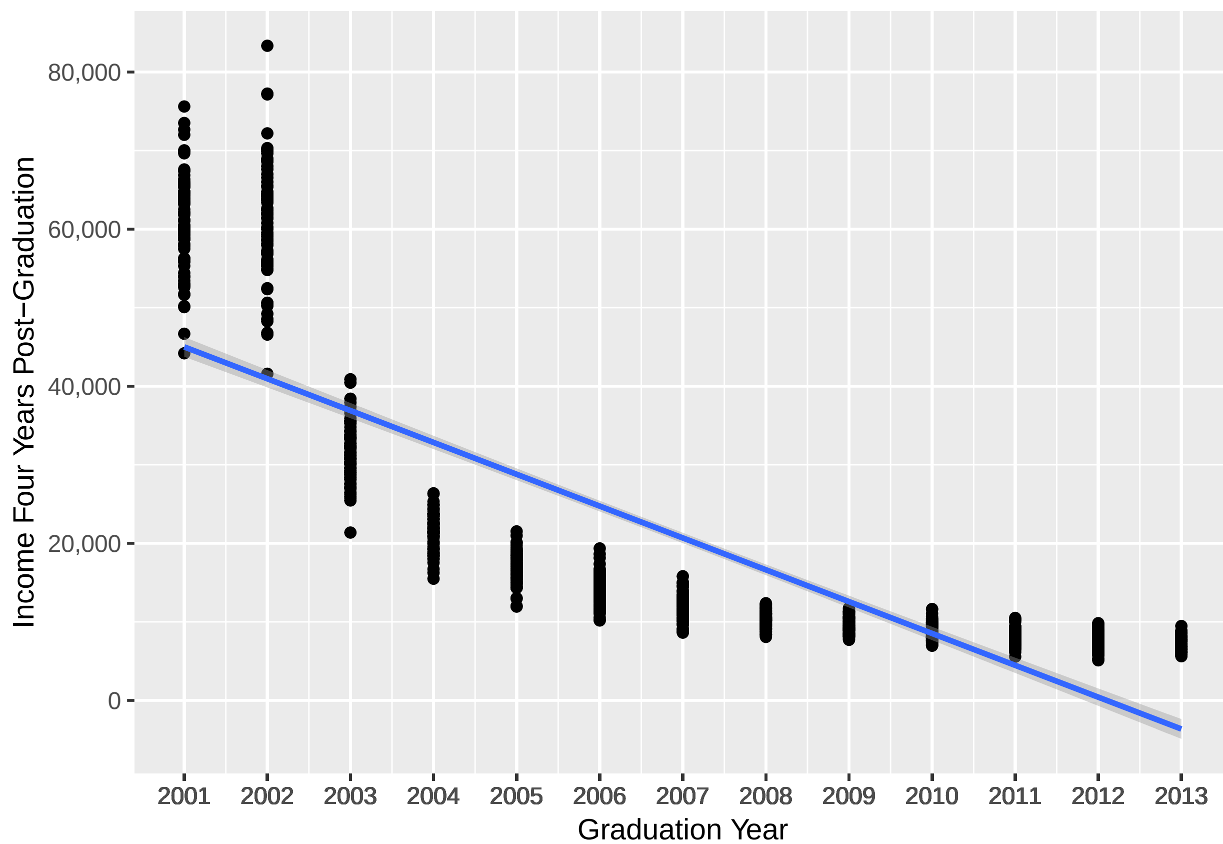
```
##   grad_year salary_p4 gre_qnt mean_salary sal_growth_rate
## 1      2001  67400.48     158    60710.71               0
## 2      2001  67600.58     156    60710.71               0
## 3      2001  58704.88     158    60710.71               0
## 4      2001  64707.29     161    60710.71               0
## 5      2001  51737.32     158    60710.71               0
## 6      2001  64010.82     160    60710.71               0
```

```
income_est <- income_est %>%
  mutate(new_salary = salary_p4 / ((1 + sal_growth_rate)*(grad_year - 2001)))
```

```r
income_estimate <- income_est %>%
  mutate("new_sal" = ifelse(new_salary == Inf, salary_p4, new_salary))
head(income_estimate)
```

```
##   grad_year salary_p4 gre_qnt mean_salary sal_growth_rate new_salary
## 1      2001  67400.48     158    60710.71               0        Inf
## 2      2001  67600.58     156    60710.71               0        Inf
## 3      2001  58704.88     158    60710.71               0        Inf
## 4      2001  64707.29     161    60710.71               0        Inf
## 5      2001  51737.32     158    60710.71               0        Inf
## 6      2001  64010.82     160    60710.71               0        Inf
##    new_sal
## 1 67400.48
## 2 67600.58
## 3 58704.88
## 4 64707.29
## 5 51737.32
## 6 64010.82
```

```r
ggplot(data = income_estimate, aes(x = grad_year, y = new_sal)) +
  geom_point() +
  geom_smooth(method='lm') +
  scale_y_continuous(labels = scales::comma) +
  labs(x = "Graduation Year", y = "Income Four Years Post-Graduation") +
  scale_x_continuous(labels = as.character(incomeintel$grad_year),
                     breaks = incomeintel$grad_year)
```



(D)

The new coefficients for the intercept and GRE quantitative score are -55284.7 and 485.5 respectively. standared errors are 28115.2 and 179.6. Essentially these salaries are adjusted according to the average growth rate for inflation on a year-to-year basis, so its showing that with each point-increase in the gre score, salary increases by only 485.50 whereas before, it decrased by 25.76. These are also significant at a 0.05 confidence level so we fail to reject the HO that higher intelligence (measured with GRE quant score) is associated with higher income.

```
income_lm <- lm(new_sal ~ gre_qnt, data = income_estimate)
income_lm
```

```
##
## Call:
## lm(formula = new_sal ~ gre_qnt, data = income_estimate)
##
## Coefficients:
## (Intercept)      gre_qnt
##    -55284.7        485.5
```

```
summary(income_lm)
```

```
##
## Call:
## lm(formula = new_sal ~ gre_qnt, data = income_estimate)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -20387 -11453  -8609   1925  63382
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -55284.7    28115.2  -1.966  0.04953 *
## gre_qnt        485.5      179.6   2.703  0.00698 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18500 on 998 degrees of freedom
## Multiple R-squared:  0.00727,    Adjusted R-squared:  0.006275
## F-statistic: 7.309 on 1 and 998 DF,  p-value: 0.006979
```

Assessment of Kossinets and Watts (2009) (3 points)