

# Regression

Haoyu Yue

2021/2/28

## Continuous Regression

Import all packages and clean the environment

```
library(haven)
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.0 --

## v ggplot2 3.3.2      v purrr   0.3.4
## v tibble  3.0.3      v dplyr  1.0.2
## v tidyr   1.1.2      v stringr 1.4.0
## v readr   1.4.0      v forcats 0.5.0

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
```

```
library(pander)
library(dplyr)
rm(list=ls())
```

Import the data

```
#
data <- read.csv("https://raw.githubusercontent.com/Group8-GovAnalyticsProject/Merging/main/final_merged.csv")
```

State the hypotheses

```
# Hypothesis 1: Positive rate increases as median age larger.
hypo1=formula(precount_positive~median_age)
# Hypothesis 2: Positive rate increases as median age larger, income decreases.
hypo2=formula(precount_positive~median_age*median_hhold_inc)
```

## Build and compute the regression models

```
model_1=glm(hypo1,  
            data=data,  
            family="gaussian")  
model_2=glm(hypo2,  
            data=data,  
            family="gaussian")
```

## Read the result

*Result for model/hypotheses 1*

```
pander(summary(model_1))
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	34.46	4.58	7.524	3.713e-13
median_age	-0.4703	0.118	-3.985	8.064e-05

(Dispersion parameter for gaussian family taken to be 159.4836 )

Null deviance:	64731 on 391 degrees of freedom
Residual deviance:	62199 on 390 degrees of freedom

*Result for model/hypotheses 2*

```
pander(summary(model_2))
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	42.1	11.13	3.782	0.00018
median_age	-0.3418	0.2863	-1.194	0.2332
median_hhold_inc	-0.0002015	0.0001148	-1.755	0.08011
median_age:median_hhold_inc	1.954e-06	2.833e-06	0.6898	0.4907

(Dispersion parameter for gaussian family taken to be 141.6419 )

Null deviance:	64731 on 391 degrees of freedom
Residual deviance:	54957 on 388 degrees of freedom

*Compare the two models and find the better one*

```
anova(model_1,model_2,test="Chisq")
```

```
## Analysis of Deviance Table
```

```
##
## Model 1: precount_positive ~ median_age
## Model 2: precount_positive ~ median_age * median_hhold_inc
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      390      62199
## 2      388      54957  2   7241.5 7.911e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Due to the p-value = 7.911e-12, these two models has statistical differences. And model 2 is better than model 1 because DF and residential are smaller.

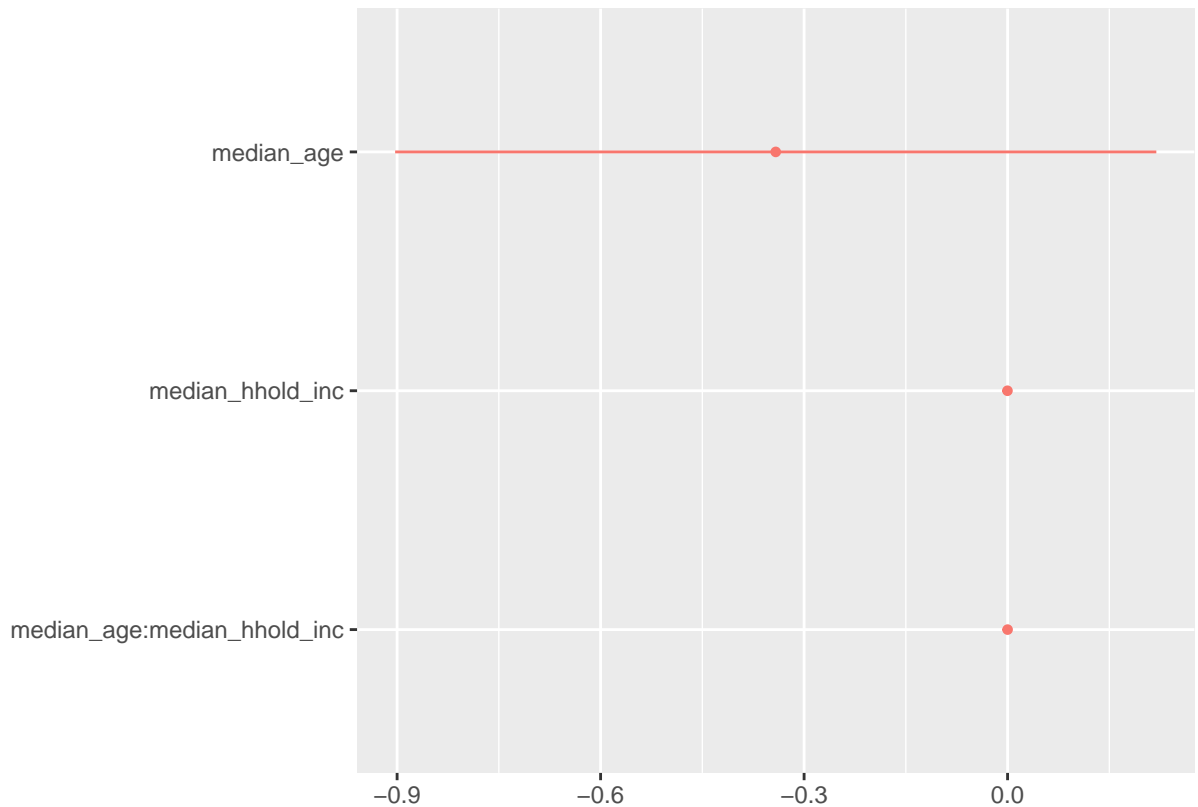
```
RSquare_1 <- rsq::rsq(model_1,adj=T)
RSquare_2 <- rsq::rsq(model_2,adj=T)
```

## Summart plots

```
library(dotwhisker)
```

```
## Registered S3 method overwritten by 'broom.mixed':
##   method      from
##   tidy.gamlss broom
```

```
library(ggplot2)
dwplot(model_2,by_2sd = F)
```



## Binary Regression

There is no binary data in our data, so we would like to add a column called `high_risk`, which means the percent of positive is more than the median of it.

```
data$high_risk <- ifelse(data$precount_positive > median(data$precount_positive), 1, 0)
data$high_risk <- factor(data$high_risk)
```

State the hypotheses

```
# Hypothesis 3: High risk or not has relationship with median age.
hypo3=formula(high_risk~median_age)
# Hypothesis 4: High risk or not has relationship with median age and median income.
hypo4=formula(high_risk~median_age*median_hhold_inc)
```

Build and compute the regression models

```
model_3=glm(hypo3,
            data=data,
            family="binomial")
```

```
model_4=glm(hypo4,
             data=data,
             family="binomial")
```

## Read the result

*Result for model/hypotheses 3*

```
pander(summary(model_3))
```

	Estimate	Std. Error	z value	Pr(> z )
<b>(Intercept)</b>	3.691	0.8312	4.441	8.96e-06
<b>median_age</b>	-0.1016	0.02165	-4.692	2.708e-06

(Dispersion parameter for binomial family taken to be 1 )

Null deviance:	539.7 on 391 degrees of freedom
Residual deviance:	514.7 on 390 degrees of freedom

*Result for model/hypotheses 4*

```
pander(summary(model_4))
```

	Estimate	Std. Error	z value	Pr(> z )
<b>(Intercept)</b>	1.772	2.669	0.6639	0.5067
<b>median_age</b>	0.01805	0.07044	0.2563	0.7978
<b>median_hhold_inc</b>	1.961e-06	2.884e-05	0.06798	0.9458
<b>median_age:median_hhold_inc</b>	-7.555e-07	7.468e-07	-1.012	0.3117

(Dispersion parameter for binomial family taken to be 1 )

Null deviance:	539.7 on 391 degrees of freedom
Residual deviance:	455.8 on 388 degrees of freedom

*Compare the two models and find the better one*

```
lmtest::lrtest(model_3,model_4)
```

```
## Likelihood ratio test
##
## Model 1: high_risk ~ median_age
## Model 2: high_risk ~ median_age * median_hhold_inc
##   #Df LogLik Df Chisq Pr(>Chisq)
## 1    2 -257.34
## 2    4 -227.92  2 58.837  1.674e-13 ***
```

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

Model\_4 is chosen for this hypotheses.

### Get marginal effects

```
library(margins)
(marginINFO = margins(model_4))
```

```
## Average marginal effects
```

```
## glm(formula = hypo4, family = "binomial", data = data)
```

```
##   median_age median_hhold_inc
##      -0.01067      -5.332e-06
```

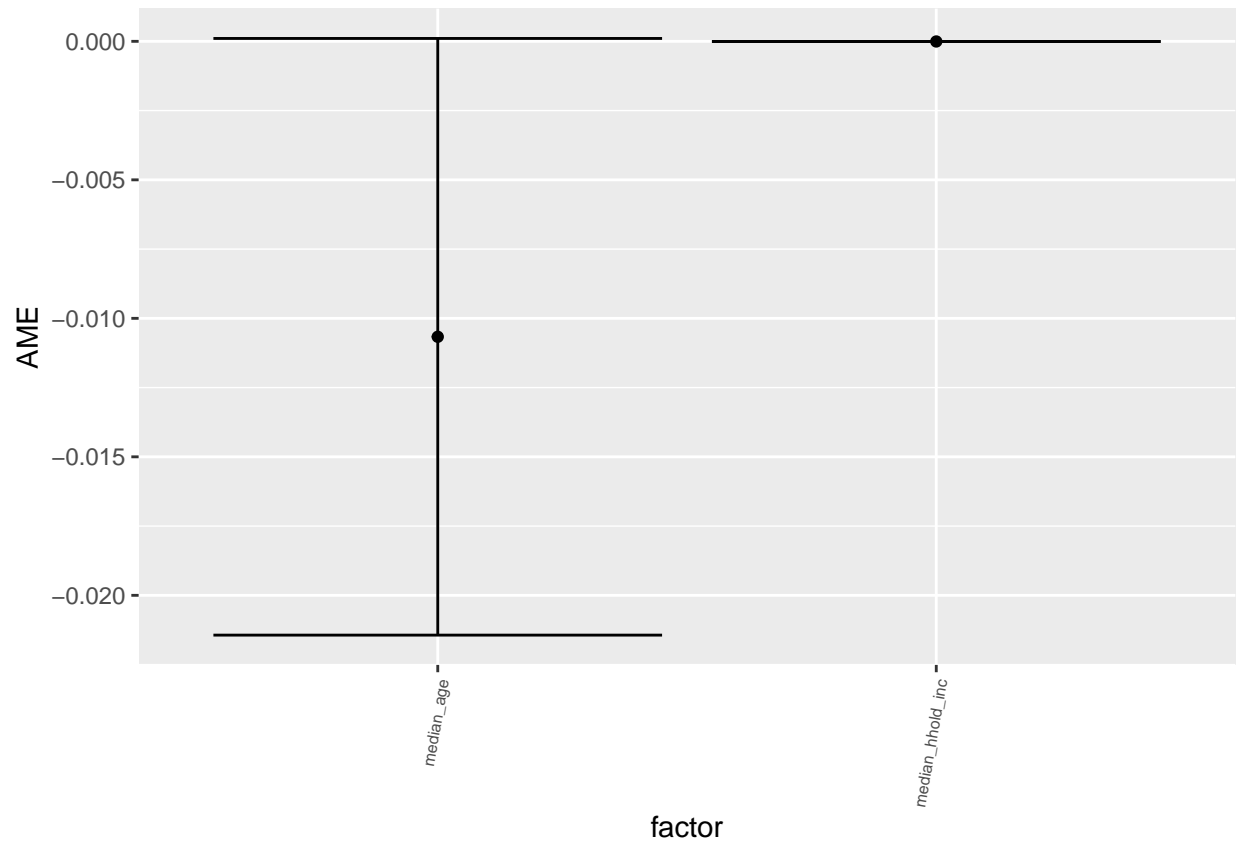
```
(marginSUMM=summary(marginINFO))
```

```
##           factor      AME      SE      z      p    lower    upper
##      median_age -0.0107 0.0055 -1.9410 0.0523 -0.0214  0.0001
## median_hhold_inc -0.0000 0.0000 -5.0004 0.0000 -0.0000 -0.0000
```

### Get some plots

```
base= ggplot(marginSUMM,
             aes(x=factor, y=AME))
base= base + geom_point()

plotMargins = base + theme(axis.text.x = element_text(angle = 80,size = 6,hjust = 1))
plotMargins +geom_errorbar(aes(ymin=lower, ymax=upper))
```



```
persp(model_4)
```

