

STAT 500: HW7

Jasmine Mou

11/14/2017

1. Using the `teengamb` dataset with `gamble` as the response and the other variables as predictors. Implement the following variable selection methods to determine the “best” model:

```
data(teengamb, package="faraway")
lm_gamble <- lm(gamble~., data=teengamb)
summary(lm_gamble)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	22.55565063	17.1968034	1.3116188	1.967736e-01
## sex	-22.11833009	8.2111145	-2.6937062	1.011184e-02
## status	0.05223384	0.2811115	0.1858118	8.534869e-01
## income	4.96197922	1.0253923	4.8391032	1.791882e-05
## verbal	-2.95949350	2.1721503	-1.3624718	1.803109e-01

- (a) Backward elimination

Set the α_{crit} to be 0.05. With the full model, we can see the variable `status` has the largest p -value over 0.05, and is not that significant in influencing `gamble`. Refit the model without `status`.

```
lm_gamble <- update(lm_gamble, . ~ . - status)
summary(lm_gamble)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	24.138972	14.7685884	1.634481	1.094591e-01
## sex	-22.960220	6.7705747	-3.391177	1.502436e-03
## income	4.898090	0.9551179	5.128256	6.643750e-06
## verbal	-2.746817	1.8252807	-1.504874	1.396672e-01

Now `verbal` becomes the predictor with the largest p -value over 0.05. Refit the model with the removal of `verbal`.

```
lm_gamble <- update(lm_gamble, . ~ . - verbal)
summary(lm_gamble)$coefficients
```

	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	4.040829	6.3943499	0.6319374	5.306977e-01
## sex	-21.634391	6.8087973	-3.1774174	2.717320e-03
## income	5.171584	0.9510477	5.4377755	2.244878e-06

Up to this stage, all variable's p -value are less than α_{crit} except for the intercept. Thus the best model selected with backward elimination is:

$$\text{gamble} = 4.041 - 21.634 * \text{sex} + 5.172 * \text{income}$$

- (b) AIC

For each size of model p , do exhaustive search to find the variables that produce the minimum RSS.

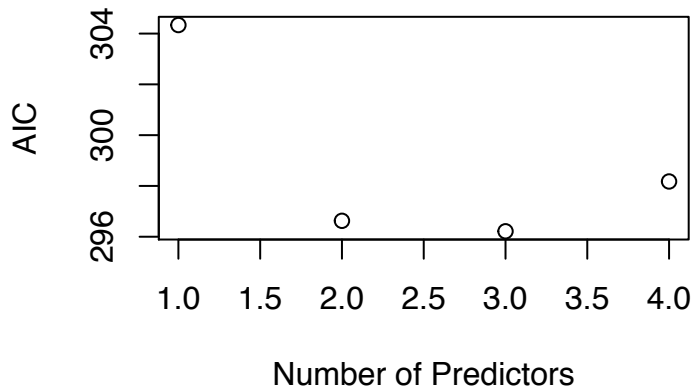
```
require(leaps)
b <- regsubsets(gamble~., data=teengamb)
rs <- summary(b)
rs$which
```

```
##      (Intercept)    sex status income verbal
## 1          TRUE FALSE   FALSE   TRUE  FALSE
## 2          TRUE  TRUE   FALSE   TRUE  FALSE
## 3          TRUE  TRUE   FALSE   TRUE   TRUE
## 4          TRUE  TRUE   TRUE    TRUE   TRUE
```

Compute and plot AIC. We can see that AIC is minimized by choosing 3 predictors, which are *income*, *sex*, and *verbal* from the logical matrix above. Fit the linear model with these predictors. According to the fitted summary coefficients, the best model determined by AIC will be

$$\text{gamble} = 24.139 + 4.898 * \text{income} - 22.960 * \text{sex} - 2.747 * \text{verbal}$$

```
n = dim(teengamb)[1]
p = dim(teengamb)[2]-1
AIC <- n * log(rs$rss/n) + (2:(p+1))*2
plot(AIC ~ I(1:p), ylab="AIC", xlab="Number of Predictors")
```



```
lm_gamble <- lm(gamble~income+sex+verbal, data=teengamb)
summary(lm_gamble)$coefficients
```

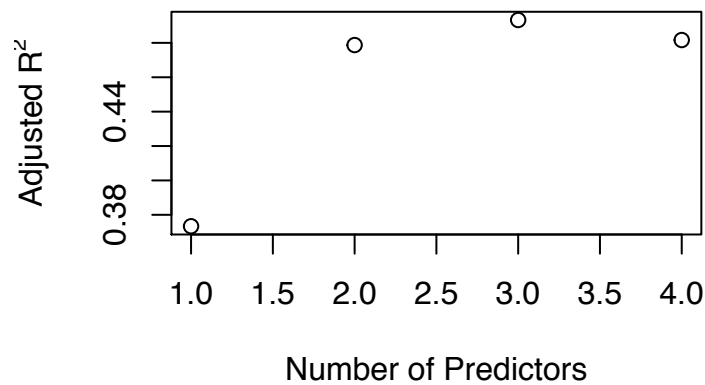
```
##      Estimate Std. Error  t value    Pr(>|t|)
## (Intercept)  24.138972 14.7685884  1.634481 1.094591e-01
## income       4.898090  0.9551179  5.128256 6.643750e-06
## sex         -22.960220  6.7705747 -3.391177 1.502436e-03
## verbal      -2.746817  1.8252807 -1.504874 1.396672e-01
```

(c) Adjusted R^2

Plot R^2 with the number of predictors used. We can see that R^2 achieves the maximum when 3 predictors are used. Thus the best model selected with Adjusted R^2 is the same model selected with AIC:

$$\text{gamble} = 24.139 + 4.898 * \text{income} - 22.960 * \text{sex} - 2.747 * \text{verbal}$$

```
plot(rs$adjr2 ~ I(1:p), xlab="Number of Predictors", ylab=expression(paste("Adjusted ", R^2)))
```



```
which.max(rs$adjr2)
```

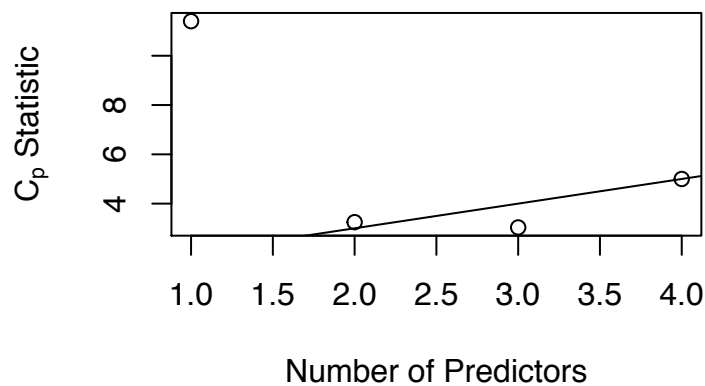
```
## [1] 3
```

(d) Mallows C_p

Plot C_p against the number of predictors used. We can see only the models with 3 and 4 predictors are on or below the $C_p = p+1$ line, C_p Statistic is minimized when the number of predictors is 3. Thus the best model selected with Mallows C_p is the same model selected with AIC:

$$\text{gamble} = 24.139 + 4.898 * \text{income} - 22.960 * \text{sex} - 2.747 * \text{verbal}$$

```
plot(rs$cp ~ I(1:p), xlab="Number of Predictors", ylab=expression(paste(C[p], " Statistic")))
abline(1,1)
```



```
which.min(rs$cp)
```

```
## [1] 3
```

```

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title: 'STAT 500: HW7'
author: "Jasmine Mou"
date: "11/14/2017"
output: pdf_document
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```

1. Using the `teengamb` dataset with `gamble` as the response and the other variables as predictors. Implement the following variable selection methods to determine the "best" model:

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```

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```{r}
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Now `verbal` becomes the predictor with the largest p-value over 0.05. Refit the model with the removal of `verbal`.

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*Up to this stage, all variable's p-value are less than α_{crit} except for the intercept. Thus the best model selected with backward elimination is: $\text{\$\$ gamble} = 4.041 - 21.634 * \text{sex} + 5.172 * \text{income} \text{\$\$}$ *

(b) AIC

For each size of model p, do exhaustive search to find the variables that produce the minimum RSS.

```

```{r, warning=FALSE, message=FALSE}
require(leaps)
b <- regsubsets(gamble~., data=teengamb)
rs <- summary(b)
rs$which
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```

*Compute and plot AIC. We can see that AIC is minimized by choosing 3 predictors, which are `income`, `sex`, and `verbal` from the logical matrix above. Fit the linear model with these predictors. According to the fitted summary coefficients, the best model determined by AIC will be $\text{\$\$ gamble} = 24.139 + 4.898 * \text{income} - 22.960 * \text{sex} - 2.747 * \text{verbal} \text{\$\$}$ *

```

```{r, fig.width=4, fig.height=3}
n = dim(teengamb)[1]
p = dim(teengamb)[2]-1
AIC <- n * log(rs$rss/n) + (2:(p+1))*2
plot(AIC ~ I(1:p), ylab="AIC", xlab="Number of Predictors")

lm_gamble <- lm(gamble~income+sex+verbal, data=teengamb)
summary(lm_gamble)$coefficients
```

```

(c) Adjusted R^2

*Plot R^2 with the number of predictors used. We can see that R^2 achieves the maximum when 3 predictors are used. Thus the best model selected with Adjusted R^2 is the same model selected with AIC: $Y = 24.139 + 4.898 * \text{income} - 22.960 * \text{sex} - 2.747 * \text{verbal}$

```

```{r, fig.width=4, fig.height=3}
plot(rs$adjr2 ~ I(1:p), xlab="Number of Predictors",
ylab=expression(paste("Adjusted ", R^2)))
which.max(rs$adjr2)
```

```

(d) Mallows SC_p

*Plot SC_p against the number of predictors used. We can see only the models with 3 and 4 predictors are on or below the $SC_p = p+1$ line, SC_p Statistic is minimized when the number of predictors is 3. Thus the best model selected with Mallows SC_p is the same model selected with AIC: $Y = 24.139 + 4.898 * \text{income} - 22.960 * \text{sex} - 2.747 * \text{verbal}$

```

```{r, fig.width=4, fig.height=3}
plot(rs$cp ~ I(1:p), xlab="Number of Predictors",
ylab=expression(paste(C[p], " Statistic")))
abline(1,1)
which.min(rs$cp)
```

```