

# Advanced Statistical Modelling: Ridge Regression

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## Choosing the penalization parameter $\lambda$

The objective of this exercise is to implement Ridge Regression with two different approaches:  $MSPE_{val}(\lambda)$  and  $MSPE_{k-CV}(\lambda)$ . In both cases we are going to take as input data the following:

- Matrix  $x$  and vector  $y$  corresponding to the training sample.
- Matrix  $x_{val}$  and vector  $y_{val}$  corresponding to the validation set.
- Vector  $lambda.v$  of candidate values for  $\lambda$ .

We are going to output for each element  $\lambda$  in  $lambda.v$  and the value of the  $MSPE_{val}(\lambda) / MSPE_{k-CV}(\lambda)$ . Furthermore, we are going to plot these values against  $\log(1 + \lambda) - 1$ .

Once we have build these two functions, we are going to use the prostate data used in class. We are going to choose a  $\lambda$  according to:

- Behaviour in the validation set (30 validations not included in the training sample)
- 5-fold, 10-fold cross-validation.
- Compare our results with those obtained with leave-one-out and generalized cross-validation.

## Ridge regression based on $MSPE_{val}(\lambda)$

In order to choose the penalization parameter  $\lambda$ , we are going to write a function implementing the ridge regression penalization parameter  $\lambda$  choice based on the minimization of the  $MSPE_{val}(\lambda)$ .

```
ridge <- function(x, y, x.val, y.val, lambda.v) {  
  result <- data.frame(lambda=lambda.v, mspe=rep(0,length(lambda.v)),  
                        df=rep(0,length(lambda.v)))  
  
  x.svd <- svd(x)  
  for(i in 1:length(lambda.v)) {  
    lambda <- lambda.v[i]  
    d_inv <- diag(1/(x.svd$d*x.svd$d - lambda))  
    xx_inv <- t( solve( t(x) %*% x + lambda*diag(1,ncol(x)) ))  
    beta <- xx_inv %*% t(x) %*% y  
    y.hat <- x.val %*% beta  
    mspe <- sum((y.val - y.hat)^2) / length(y.val)  
    df <- sum(x.svd$d^2 / (x.svd$d^2 + lambda))  
    result$mspe[i] <- mspe  
    result$df[i] <- df  
  }  
  plot(mspe~log(1+lambda), result, col=2)  
  lambda.min <- result$lambda[which.min(result$mspe)]  
  abline(v=log(1+lambda.min),col=2,lty=2)  
  plot(mspe~df, result, col=3)  
  df.min <- result$df[which.min(result$mspe)]  
  abline(v=df.min,col=3,lty=2)  
  return(result)  
}
```

## Ridge regression based on $MSP E_{k-CV}(\lambda)$

Now, we will write an R function implementing the ridge regression penalization parameter  $\lambda$  choice based on k-fold cross-validation  $MSP E_{kCV}(\lambda)$

```
ridge_cv <- function(x, y, lambda.v, cv=10) {
  result <- data.frame(lambda=lambda.v, mspe=rep(0,length(lambda.v)),
    df=rep(0,length(lambda.v)))
  for(i in 1:length(lambda.v)) {
    lambda.v[i] <- lambda.v[i]
    folds <- createFolds(1:nrow(x), k = cv)
    result.cv <- data.frame(mspe=rep(0,cv), df=rep(0,cv))
    for(j in 1:cv) {
      fold <- folds[[j]]
      x.train <- x[-fold,]
      y.train <- y[-fold]
      x.val <- x[fold,]
      y.val <- y[fold]
      x.svd <- svd(x.train)
      d <- x.svd$d
      v <- x.svd$v
      d_inv <- diag(1/(d*d - lambda.v[i]))
      xx_inv <- t( solve( t(x.train) %*% x.train + lambda.v[i]*diag(1,ncol(x)) ))
      beta <- xx_inv %*% t(x.train) %*% y.train
      y.hat <- x.val %*% beta
      mspe <- sum((y.val - y.hat)^2) / length(y.val)
      df <- sum(d^2 / (d^2 + lambda.v[i]))
      result.cv$mspe[j] <- mspe
      result.cv$df[j] <- df
    }
    result$mspe[i] <- mean(result.cv$mspe)
    result$df[i] <- mean(result.cv$df)
  }
  plot(mspe~log(1+lambda), result, col=2)
  lambda.min <- result$lambda[which.min(result$mspe)]
  abline(v=log(1+lambda.min),col=2,lty=2)
  plot(mspe~df, result, col=3)
  df.min <- result$df[which.min(result$mspe)]
  abline(v=df.min,col=3,lty=2)

  return(result)
}
```

## Comparison between penalization parameters of $MSP E_{val}(\lambda)$ and $MSP E_{k-CV}(\lambda)$

```
ridge_loocv_gcv <- function(x, y, lambda.v) {
  l <- length(lambda.v)
  result <- data.frame(lambda=lambda.v, loocv=rep(0,l), gcv=rep(0,l),df=rep(0,l))
  n <- nrow(x)
  x.svd <- svd(x)
  d <- x.svd$d
  v <- x.svd$v
```

```

u <- x.svd$u
for(i in 1:l) {
  lambda <- lambda.v[i]
  d_inv <- diag(1/(d^2 - lambda))
  xx_inv <- t( solve( t(x) %*% x + lambda*diag(1,ncol(x)) ))
  beta <- (xx_inv %*% t(x)) %*% y
  y.hat <- x %*% beta
  df <- sum(d^2 / (d^2 +lambda))
  h <- x %*% xx_inv %*% t(x)
  result$loocv[i] <- sum( ( y - y.hat)/(1 - diag(h)) )^2 ) / n
  result$gcv[i] <- sum( ( y - y.hat)/(1 - df/n) )^2 ) / n
  result$df[i] <- df
}
plot(loocv~log(1+lambda), result, col=2)
lambda.min <- result$lambda[which.min(result$loocv)]
abline(v=log(1+lambda.min),col=2,lty=2)
plot(loocv~df, result, col=3)
df.min <- result$df[which.min(result$loocv)]
abline(v=df.min,col=3,lty=2)
plot(gcv~log(1+lambda), result, col=2)
lambda.min <- result$lambda[which.min(result$gcv)]
abline(v=log(1+lambda.min),col=2,lty=2)
plot(gcv~df, result, col=3)
df.min <- result$df[which.min(result$gcv)]
abline(v=df.min,col=3,lty=2)
return(result)
}

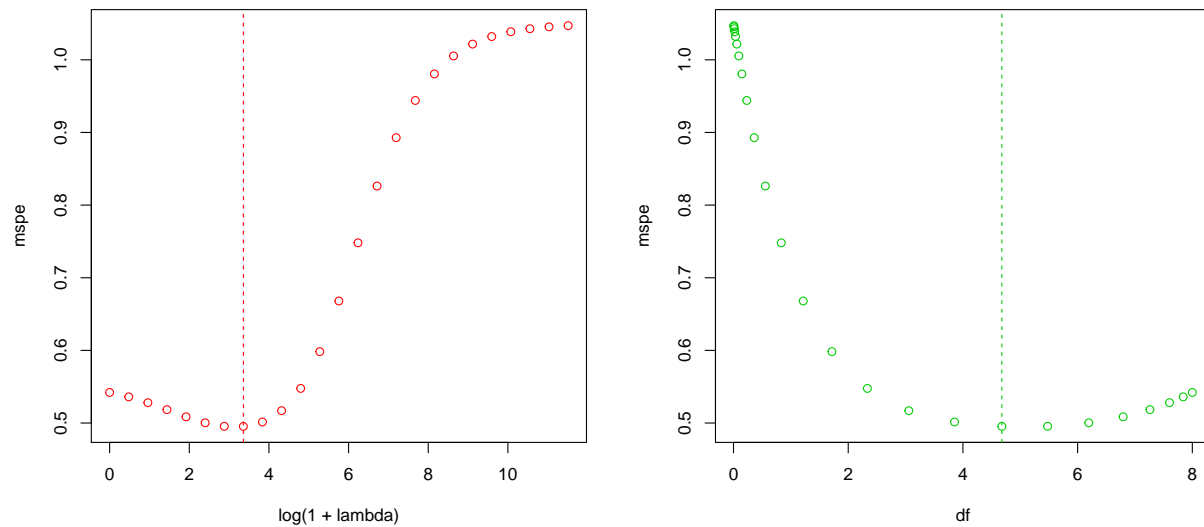
```

## Validation

```

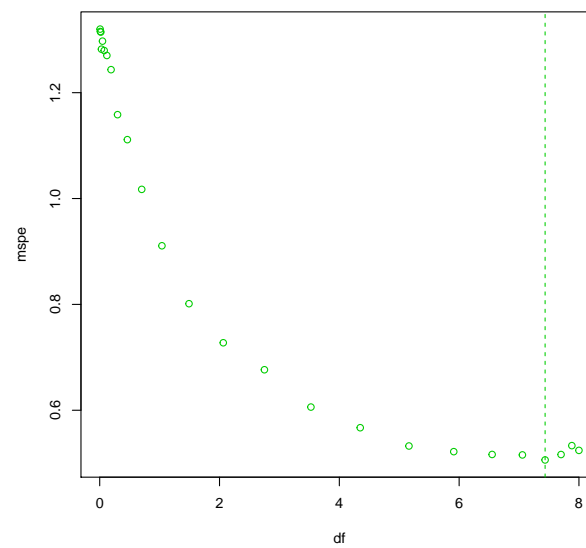
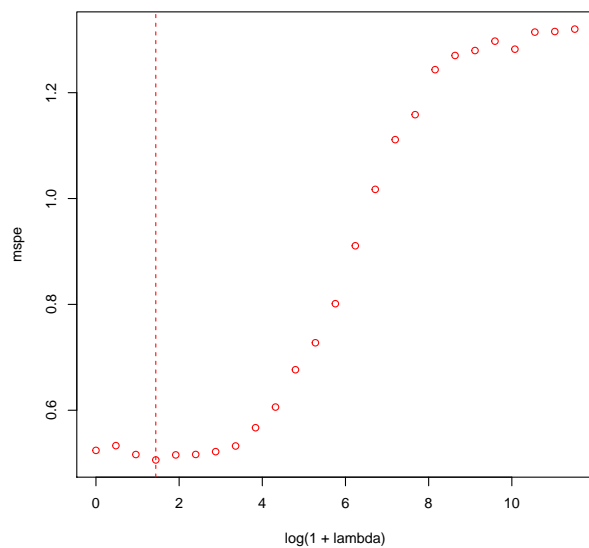
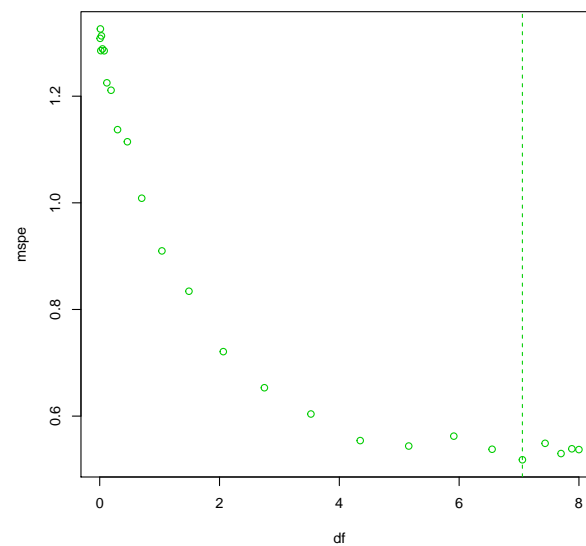
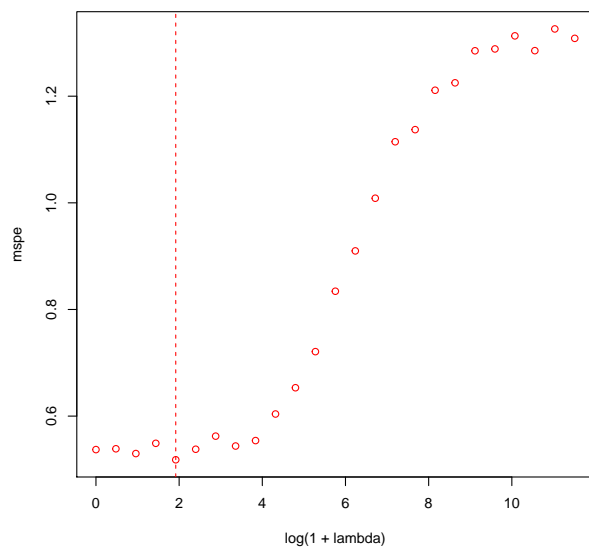
op<-par(mfrow=c(1,2))
result.valid <- ridge(x, y, x.val, y.val, lambda.v)

```



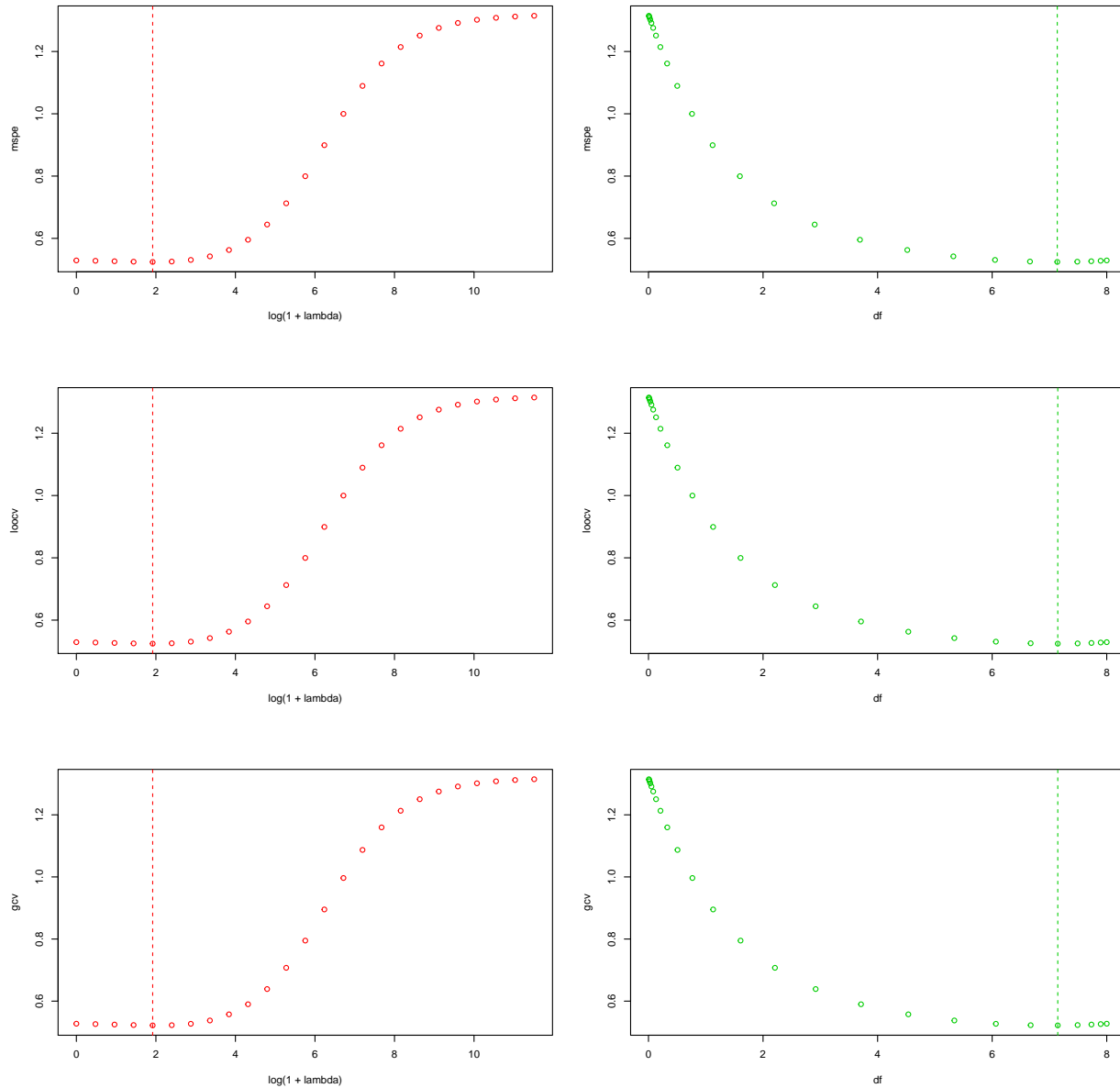
## 5-fold and 10-fold CV

```
x <- scale(data[,1:8], center = T, scale = T)
y <- scale(data[,9], center = T, scale = F)
op<-par(mfrow=c(2,2))
result.5.cv <- ridge_cv(x, y, cv = 10, lambda.v)
result.10.cv <- ridge_cv(x, y, cv = 10, lambda.v)
```



## LOOCV and GCV

```
op<-par(mfrow=c(3,2))
result.loocv <- ridge_cv(x, y, cv = nrow(x), lambda.v) #n-fold CV
result.loocv.gcv <- ridge_loocv_gcv(x, y, lambda.v)
```



We observe that the results of MSPE seem more stable in the LOOCV and GCV compared to 5-fold and 10-fold CV, as one would expect given the small size of the dataset. Furthermore, the validation set results are also relatively stable, although with a different curve than for the LOOCV/GCV.

## Ridge regression for the Boston Housing data

The Boston Housing dataset is a classical dataset which contains the values of 506 suburbs of Boston corresponding to 1978. This dataset can be found in many places but we are going to use a version with some corrections that was provided to us, which additionally includes the UTM coordinates of the geographical centers of each neighborhood. Therefore, the variables are the following:

Variable	Description	Type
CRIM	per capita crime rate by town	Numeric
ZN	proportion of residential land zoned for lots over 25,000 sq.ft.	Numeric
INDUS	proportion of non-retail business acres per town	Numeric
CHAS	Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)	Factor
NOX	nitric oxides concentration (parts per 10 million)	Numeric
RM	average number of rooms per dwelling	Numeric
AGE	proportion of owner-occupied units built prior to 1940	Numeric
DIS	weighted distances to five Boston employment centres	Numeric
RAD	index of accessibility to radial highways	Numeric
TAX	full-value property-tax rate per \$10,000	Numeric
PTRATIO	pupil-teacher ratio by town	Numeric
B	$1000(\text{Bk} - 0.63)^2$ where Bk is the proportion of blacks by town	Numeric
LSTAT	% lower status of the population	Numeric
MEDV	Median value of owner-occupied homes in \$1000's	Numeric

In this exercise we are going to use ridge regression on the Boston Housing dataset to fit the regression model where the response variable is *MEDV* and the explanatory variables are the remaining 13 variables shown in the list. As we can see when loading the data, there are more variables than the ones listed (*TOWN*, *TOWNNO*, *LONG*, *LAT*, *CMEDV*). We decided not to use them since the statement explicitly defines which to use.

```
load("boston.Rdata")
names(boston.c)

## [1] "TOWN"    "TOWNNO"  "TRACT"   "LONG"    "LAT"     "MEDV"    "CMEDV"
## [8] "CRIM"    "ZN"      "INDUS"   "CHAS"    "NOX"     "RM"      "AGE"
## [15] "DIS"     "RAD"     "TAX"     "PTRATIO" "B"        "LSTAT"

dataset <- boston.c[, -c(1:5)] ##"TOWN"    "TOWNNO"  "TRACT"   "LONG"    "LAT"
dataset$CMEDV <- NULL
```

Beside from eliminating variables, we divided the dataset between train and test. To do so, we have decided to do 3/4 training, 1/4 test.

```
set.seed(42)
trainIndex <- createDataPartition(dataset$MEDV, p = 0.75, list = F)
train <- dataset[trainIndex,]
test <- dataset[-trainIndex,]
```

```
train

##      MEDV      CRIM      ZN INDUS CHAS      NOX      RM      AGE      DIS RAD TAX
## 1  24.0  0.00632  18.0  2.31    0  0.5380  6.575  65.2  4.0900  1 296
## 2  21.6  0.02731   0.0  7.07    0  0.4690  6.421  78.9  4.9671  2 242
## 3  34.7  0.02729   0.0  7.07    0  0.4690  7.185  61.1  4.9671  2 242
## 4  33.4  0.03237   0.0  2.18    0  0.4580  6.998  45.8  6.0622  3 222
## 5  36.2  0.06905   0.0  2.18    0  0.4580  7.147  54.2  6.0622  3 222
## 6  28.7  0.02985   0.0  2.18    0  0.4580  6.430  58.7  6.0622  3 222
```

## 8	27.1	0.14455	12.5	7.87	0	0.5240	6.172	96.1	5.9505	5	311
## 9	16.5	0.21124	12.5	7.87	0	0.5240	5.631	100.0	6.0821	5	311
## 10	18.9	0.17004	12.5	7.87	0	0.5240	6.004	85.9	6.5921	5	311
## 12	18.9	0.11747	12.5	7.87	0	0.5240	6.009	82.9	6.2267	5	311
## 16	19.9	0.62739	0.0	8.14	0	0.5380	5.834	56.5	4.4986	4	307
## 17	23.1	1.05393	0.0	8.14	0	0.5380	5.935	29.3	4.4986	4	307
## 19	20.2	0.80271	0.0	8.14	0	0.5380	5.456	36.6	3.7965	4	307
## 21	13.6	1.25179	0.0	8.14	0	0.5380	5.570	98.1	3.7979	4	307
## 23	15.2	1.23247	0.0	8.14	0	0.5380	6.142	91.7	3.9769	4	307
## 27	16.6	0.67191	0.0	8.14	0	0.5380	5.813	90.3	4.6820	4	307
## 28	14.8	0.95577	0.0	8.14	0	0.5380	6.047	88.8	4.4534	4	307
## 29	18.4	0.77299	0.0	8.14	0	0.5380	6.495	94.4	4.4547	4	307
## 30	21.0	1.00245	0.0	8.14	0	0.5380	6.674	87.3	4.2390	4	307
## 31	12.7	1.13081	0.0	8.14	0	0.5380	5.713	94.1	4.2330	4	307
## 32	14.5	1.35472	0.0	8.14	0	0.5380	6.072	100.0	4.1750	4	307
## 33	13.2	1.38799	0.0	8.14	0	0.5380	5.950	82.0	3.9900	4	307
## 34	13.1	1.15172	0.0	8.14	0	0.5380	5.701	95.0	3.7872	4	307
## 35	13.5	1.61282	0.0	8.14	0	0.5380	6.096	96.9	3.7598	4	307
## 36	18.9	0.06417	0.0	5.96	0	0.4990	5.933	68.2	3.3603	5	279
## 37	20.0	0.09744	0.0	5.96	0	0.4990	5.841	61.4	3.3779	5	279
## 38	21.0	0.08014	0.0	5.96	0	0.4990	5.850	41.5	3.9342	5	279
## 39	24.7	0.17505	0.0	5.96	0	0.4990	5.966	30.2	3.8473	5	279
## 41	34.9	0.03359	75.0	2.95	0	0.4280	7.024	15.8	5.4011	3	252
## 42	26.6	0.12744	0.0	6.91	0	0.4480	6.770	2.9	5.7209	3	233
## 44	24.7	0.15936	0.0	6.91	0	0.4480	6.211	6.5	5.7209	3	233
## 48	16.6	0.22927	0.0	6.91	0	0.4480	6.030	85.5	5.6894	3	233
## 51	19.7	0.08873	21.0	5.64	0	0.4390	5.963	45.7	6.8147	4	243
## 53	25.0	0.05360	21.0	5.64	0	0.4390	6.511	21.1	6.8147	4	243
## 56	35.4	0.01311	90.0	1.22	0	0.4030	7.249	21.9	8.6966	5	226
## 57	24.7	0.02055	85.0	0.74	0	0.4100	6.383	35.7	9.1876	2	313
## 58	31.6	0.01432	100.0	1.32	0	0.4110	6.816	40.5	8.3248	5	256
## 59	23.3	0.15445	25.0	5.13	0	0.4530	6.145	29.2	7.8148	8	284
## 60	19.6	0.10328	25.0	5.13	0	0.4530	5.927	47.2	6.9320	8	284
## 61	18.7	0.14932	25.0	5.13	0	0.4530	5.741	66.2	7.2254	8	284
## 62	16.0	0.17171	25.0	5.13	0	0.4530	5.966	93.4	6.8185	8	284
## 63	22.2	0.11027	25.0	5.13	0	0.4530	6.456	67.8	7.2255	8	284
## 64	25.0	0.12650	25.0	5.13	0	0.4530	6.762	43.4	7.9809	8	284
## 66	23.5	0.03584	80.0	3.37	0	0.3980	6.290	17.8	6.6115	4	337
## 67	19.4	0.04379	80.0	3.37	0	0.3980	5.787	31.1	6.6115	4	337
## 68	22.0	0.05789	12.5	6.07	0	0.4090	5.878	21.4	6.4980	4	345
## 69	17.4	0.13554	12.5	6.07	0	0.4090	5.594	36.8	6.4980	4	345
## 72	21.7	0.15876	0.0	10.81	0	0.4130	5.961	17.5	5.2873	4	305
## 73	22.8	0.09164	0.0	10.81	0	0.4130	6.065	7.8	5.2873	4	305
## 74	23.4	0.19539	0.0	10.81	0	0.4130	6.245	6.2	5.2873	4	305
## 75	24.1	0.07896	0.0	12.83	0	0.4370	6.273	6.0	4.2515	5	398
## 77	20.0	0.10153	0.0	12.83	0	0.4370	6.279	74.5	4.0522	5	398
## 79	21.2	0.05646	0.0	12.83	0	0.4370	6.232	53.7	5.0141	5	398
## 80	20.3	0.08387	0.0	12.83	0	0.4370	5.874	36.6	4.5026	5	398
## 81	28.0	0.04113	25.0	4.86	0	0.4260	6.727	33.5	5.4007	4	281
## 82	23.9	0.04462	25.0	4.86	0	0.4260	6.619	70.4	5.4007	4	281
## 83	24.8	0.03659	25.0	4.86	0	0.4260	6.302	32.2	5.4007	4	281
## 84	22.9	0.03551	25.0	4.86	0	0.4260	6.167	46.7	5.4007	4	281
## 86	26.6	0.05735	0.0	4.49	0	0.4490	6.630	56.1	4.4377	3	247
## 88	22.2	0.07151	0.0	4.49	0	0.4490	6.121	56.8	3.7476	3	247

## 89	23.6	0.05660	0.0	3.41	0	0.4890	7.007	86.3	3.4217	2	270
## 91	22.6	0.04684	0.0	3.41	0	0.4890	6.417	66.1	3.0923	2	270
## 92	22.0	0.03932	0.0	3.41	0	0.4890	6.405	73.9	3.0921	2	270
## 94	25.0	0.02875	28.0	15.04	0	0.4640	6.211	28.9	3.6659	4	270
## 95	20.6	0.04294	28.0	15.04	0	0.4640	6.249	77.3	3.6150	4	270
## 98	38.7	0.12083	0.0	2.89	0	0.4450	8.069	76.0	3.4952	2	276
## 99	43.8	0.08187	0.0	2.89	0	0.4450	7.820	36.9	3.4952	2	276
## 100	33.2	0.06860	0.0	2.89	0	0.4450	7.416	62.5	3.4952	2	276
## 102	26.5	0.11432	0.0	8.56	0	0.5200	6.781	71.3	2.8561	5	384
## 104	19.3	0.21161	0.0	8.56	0	0.5200	6.137	87.4	2.7147	5	384
## 107	19.5	0.17120	0.0	8.56	0	0.5200	5.836	91.9	2.2110	5	384
## 108	20.4	0.13117	0.0	8.56	0	0.5200	6.127	85.2	2.1224	5	384
## 109	19.8	0.12802	0.0	8.56	0	0.5200	6.474	97.1	2.4329	5	384
## 110	19.4	0.26363	0.0	8.56	0	0.5200	6.229	91.2	2.5451	5	384
## 111	21.7	0.10793	0.0	8.56	0	0.5200	6.195	54.4	2.7778	5	384
## 112	22.8	0.10084	0.0	10.01	0	0.5470	6.715	81.6	2.6775	6	432
## 113	18.8	0.12329	0.0	10.01	0	0.5470	5.913	92.9	2.3534	6	432
## 114	18.7	0.22212	0.0	10.01	0	0.5470	6.092	95.4	2.5480	6	432
## 115	18.5	0.14231	0.0	10.01	0	0.5470	6.254	84.2	2.2565	6	432
## 116	18.3	0.17134	0.0	10.01	0	0.5470	5.928	88.2	2.4631	6	432
## 118	19.2	0.15098	0.0	10.01	0	0.5470	6.021	82.6	2.7474	6	432
## 119	20.4	0.13058	0.0	10.01	0	0.5470	5.872	73.1	2.4775	6	432
## 120	19.3	0.14476	0.0	10.01	0	0.5470	5.731	65.2	2.7592	6	432
## 121	22.0	0.06899	0.0	25.65	0	0.5810	5.870	69.7	2.2577	2	188
## 122	20.3	0.07165	0.0	25.65	0	0.5810	6.004	84.1	2.1974	2	188
## 123	20.5	0.09299	0.0	25.65	0	0.5810	5.961	92.9	2.0869	2	188
## 124	17.3	0.15038	0.0	25.65	0	0.5810	5.856	97.0	1.9444	2	188
## 125	18.8	0.09849	0.0	25.65	0	0.5810	5.879	95.8	2.0063	2	188
## 126	21.4	0.16902	0.0	25.65	0	0.5810	5.986	88.4	1.9929	2	188
## 128	16.2	0.25915	0.0	21.89	0	0.6240	5.693	96.0	1.7883	4	437
## 131	19.2	0.34006	0.0	21.89	0	0.6240	6.458	98.9	2.1185	4	437
## 132	19.6	1.19294	0.0	21.89	0	0.6240	6.326	97.7	2.2710	4	437
## 133	23.0	0.59005	0.0	21.89	0	0.6240	6.372	97.9	2.3274	4	437
## 134	18.4	0.32982	0.0	21.89	0	0.6240	5.822	95.4	2.4699	4	437
## 136	18.1	0.55778	0.0	21.89	0	0.6240	6.335	98.2	2.1107	4	437
## 137	17.4	0.32264	0.0	21.89	0	0.6240	5.942	93.5	1.9669	4	437
## 140	17.8	0.54452	0.0	21.89	0	0.6240	6.151	97.9	1.6687	4	437
## 142	14.4	1.62864	0.0	21.89	0	0.6240	5.019	100.0	1.4394	4	437
## 143	13.4	3.32105	0.0	19.58	1	0.8710	5.403	100.0	1.3216	5	403
## 144	15.6	4.09740	0.0	19.58	0	0.8710	5.468	100.0	1.4118	5	403
## 145	11.8	2.77974	0.0	19.58	0	0.8710	4.903	97.8	1.3459	5	403
## 146	13.8	2.37934	0.0	19.58	0	0.8710	6.130	100.0	1.4191	5	403
## 147	15.6	2.15505	0.0	19.58	0	0.8710	5.628	100.0	1.5166	5	403
## 148	14.6	2.36862	0.0	19.58	0	0.8710	4.926	95.7	1.4608	5	403
## 149	17.8	2.33099	0.0	19.58	0	0.8710	5.186	93.8	1.5296	5	403
## 150	15.4	2.73397	0.0	19.58	0	0.8710	5.597	94.9	1.5257	5	403
## 152	19.6	1.49632	0.0	19.58	0	0.8710	5.404	100.0	1.5916	5	403
## 153	15.3	1.12658	0.0	19.58	1	0.8710	5.012	88.0	1.6102	5	403
## 156	15.6	3.53501	0.0	19.58	1	0.8710	6.152	82.6	1.7455	5	403
## 157	13.1	2.44668	0.0	19.58	0	0.8710	5.272	94.0	1.7364	5	403
## 158	41.3	1.22358	0.0	19.58	0	0.6050	6.943	97.4	1.8773	5	403
## 159	24.3	1.34284	0.0	19.58	0	0.6050	6.066	100.0	1.7573	5	403
## 162	50.0	1.46336	0.0	19.58	0	0.6050	7.489	90.8	1.9709	5	403
## 163	50.0	1.83377	0.0	19.58	1	0.6050	7.802	98.2	2.0407	5	403



##	165	22.7	2.24236	0.0	19.58	0	0.6050	5.854	91.8	2.4220	5	403
##	166	25.0	2.92400	0.0	19.58	0	0.6050	6.101	93.0	2.2834	5	403
##	167	50.0	2.01019	0.0	19.58	0	0.6050	7.929	96.2	2.0459	5	403
##	168	23.8	1.80028	0.0	19.58	0	0.6050	5.877	79.2	2.4259	5	403
##	169	23.8	2.30040	0.0	19.58	0	0.6050	6.319	96.1	2.1000	5	403
##	170	22.3	2.44953	0.0	19.58	0	0.6050	6.402	95.2	2.2625	5	403
##	171	17.4	1.20742	0.0	19.58	0	0.6050	5.875	94.6	2.4259	5	403
##	172	19.1	2.31390	0.0	19.58	0	0.6050	5.880	97.3	2.3887	5	403
##	173	23.1	0.13914	0.0	4.05	0	0.5100	5.572	88.5	2.5961	5	296
##	174	23.6	0.09178	0.0	4.05	0	0.5100	6.416	84.1	2.6463	5	296
##	175	22.6	0.08447	0.0	4.05	0	0.5100	5.859	68.7	2.7019	5	296
##	176	29.4	0.06664	0.0	4.05	0	0.5100	6.546	33.1	3.1323	5	296
##	178	24.6	0.05425	0.0	4.05	0	0.5100	6.315	73.4	3.3175	5	296
##	179	29.9	0.06642	0.0	4.05	0	0.5100	6.860	74.4	2.9153	5	296
##	180	37.2	0.05780	0.0	2.46	0	0.4880	6.980	58.4	2.8290	3	193
##	181	39.8	0.06588	0.0	2.46	0	0.4880	7.765	83.3	2.7410	3	193
##	182	36.2	0.06888	0.0	2.46	0	0.4880	6.144	62.2	2.5979	3	193
##	184	32.5	0.10008	0.0	2.46	0	0.4880	6.563	95.6	2.8470	3	193
##	186	29.6	0.06047	0.0	2.46	0	0.4880	6.153	68.8	3.2797	3	193
##	187	50.0	0.05602	0.0	2.46	0	0.4880	7.831	53.6	3.1992	3	193
##	188	32.0	0.07875	45.0	3.44	0	0.4370	6.782	41.1	3.7886	5	398
##	189	29.8	0.12579	45.0	3.44	0	0.4370	6.556	29.1	4.5667	5	398
##	190	34.9	0.08370	45.0	3.44	0	0.4370	7.185	38.9	4.5667	5	398
##	191	37.0	0.09068	45.0	3.44	0	0.4370	6.951	21.5	6.4798	5	398
##	192	30.5	0.06911	45.0	3.44	0	0.4370	6.739	30.8	6.4798	5	398
##	193	36.4	0.08664	45.0	3.44	0	0.4370	7.178	26.3	6.4798	5	398
##	195	29.1	0.01439	60.0	2.93	0	0.4010	6.604	18.8	6.2196	1	265
##	196	50.0	0.01381	80.0	0.46	0	0.4220	7.875	32.0	5.6484	4	255
##	197	33.3	0.04011	80.0	1.52	0	0.4040	7.287	34.1	7.3090	2	329
##	198	30.3	0.04666	80.0	1.52	0	0.4040	7.107	36.6	7.3090	2	329
##	199	34.6	0.03768	80.0	1.52	0	0.4040	7.274	38.3	7.3090	2	329
##	200	34.9	0.03150	95.0	1.47	0	0.4030	6.975	15.3	7.6534	3	402
##	202	24.1	0.03445	82.5	2.03	0	0.4150	6.162	38.4	6.2700	2	348
##	203	42.3	0.02177	82.5	2.03	0	0.4150	7.610	15.7	6.2700	2	348
##	204	48.5	0.03510	95.0	2.68	0	0.4161	7.853	33.2	5.1180	4	224
##	205	50.0	0.02009	95.0	2.68	0	0.4161	8.034	31.9	5.1180	4	224
##	206	22.6	0.13642	0.0	10.59	0	0.4890	5.891	22.3	3.9454	4	277
##	208	22.5	0.25199	0.0	10.59	0	0.4890	5.783	72.7	4.3549	4	277
##	209	24.4	0.13587	0.0	10.59	1	0.4890	6.064	59.1	4.2392	4	277
##	212	19.3	0.37578	0.0	10.59	1	0.4890	5.404	88.6	3.6650	4	277
##	213	22.4	0.21719	0.0	10.59	1	0.4890	5.807	53.8	3.6526	4	277
##	214	28.1	0.14052	0.0	10.59	0	0.4890	6.375	32.3	3.9454	4	277
##	216	25.0	0.19802	0.0	10.59	0	0.4890	6.182	42.4	3.9454	4	277
##	218	28.7	0.07013	0.0	13.89	0	0.5500	6.642	85.1	3.4211	5	276
##	219	21.5	0.11069	0.0	13.89	1	0.5500	5.951	93.8	2.8893	5	276
##	220	23.0	0.11425	0.0	13.89	1	0.5500	6.373	92.4	3.3633	5	276
##	221	26.7	0.35809	0.0	6.20	1	0.5070	6.951	88.5	2.8617	8	307
##	223	27.5	0.62356	0.0	6.20	1	0.5070	6.879	77.7	3.2721	8	307
##	225	44.8	0.31533	0.0	6.20	0	0.5040	8.266	78.3	2.8944	8	307
##	226	50.0	0.52693	0.0	6.20	0	0.5040	8.725	83.0	2.8944	8	307
##	227	37.6	0.38214	0.0	6.20	0	0.5040	8.040	86.5	3.2157	8	307
##	228	31.6	0.41238	0.0	6.20	0	0.5040	7.163	79.9	3.2157	8	307
##	230	31.5	0.44178	0.0	6.20	0	0.5040	6.552	21.4	3.3751	8	307
##	231	24.3	0.53700	0.0	6.20	0	0.5040	5.981	68.1	3.6715	8	307

##	234	48.3	0.33147	0.0	6.20	0	0.5070	8.247	70.4	3.6519	8	307
##	235	29.0	0.44791	0.0	6.20	1	0.5070	6.726	66.5	3.6519	8	307
##	236	24.0	0.33045	0.0	6.20	0	0.5070	6.086	61.5	3.6519	8	307
##	237	25.1	0.52058	0.0	6.20	1	0.5070	6.631	76.5	4.1480	8	307
##	239	23.7	0.08244	30.0	4.93	0	0.4280	6.481	18.5	6.1899	6	300
##	240	23.3	0.09252	30.0	4.93	0	0.4280	6.606	42.2	6.1899	6	300
##	242	20.1	0.10612	30.0	4.93	0	0.4280	6.095	65.1	6.3361	6	300
##	243	22.2	0.10290	30.0	4.93	0	0.4280	6.358	52.9	7.0355	6	300
##	244	23.7	0.12757	30.0	4.93	0	0.4280	6.393	7.8	7.0355	6	300
##	246	18.5	0.19133	22.0	5.86	0	0.4310	5.605	70.2	7.9549	7	330
##	247	24.3	0.33983	22.0	5.86	0	0.4310	6.108	34.9	8.0555	7	330
##	248	20.5	0.19657	22.0	5.86	0	0.4310	6.226	79.2	8.0555	7	330
##	249	24.5	0.16439	22.0	5.86	0	0.4310	6.433	49.1	7.8265	7	330
##	250	26.2	0.19073	22.0	5.86	0	0.4310	6.718	17.5	7.8265	7	330
##	251	24.4	0.14030	22.0	5.86	0	0.4310	6.487	13.0	7.3967	7	330
##	252	24.8	0.21409	22.0	5.86	0	0.4310	6.438	8.9	7.3967	7	330
##	254	42.8	0.36894	22.0	5.86	0	0.4310	8.259	8.4	8.9067	7	330
##	255	21.9	0.04819	80.0	3.64	0	0.3920	6.108	32.0	9.2203	1	315
##	256	20.9	0.03548	80.0	3.64	0	0.3920	5.876	19.1	9.2203	1	315
##	258	50.0	0.61154	20.0	3.97	0	0.6470	8.704	86.9	1.8010	5	264
##	260	30.1	0.65665	20.0	3.97	0	0.6470	6.842	100.0	2.0107	5	264
##	262	43.1	0.53412	20.0	3.97	0	0.6470	7.520	89.4	2.1398	5	264
##	264	31.0	0.82526	20.0	3.97	0	0.6470	7.327	94.5	2.0788	5	264
##	265	36.5	0.55007	20.0	3.97	0	0.6470	7.206	91.6	1.9301	5	264
##	266	22.8	0.76162	20.0	3.97	0	0.6470	5.560	62.8	1.9865	5	264
##	267	30.7	0.78570	20.0	3.97	0	0.6470	7.014	84.6	2.1329	5	264
##	268	50.0	0.57834	20.0	3.97	0	0.5750	8.297	67.0	2.4216	5	264
##	269	43.5	0.54050	20.0	3.97	0	0.5750	7.470	52.6	2.8720	5	264
##	270	20.7	0.09065	20.0	6.96	1	0.4640	5.920	61.5	3.9175	3	223
##	271	21.1	0.29916	20.0	6.96	0	0.4640	5.856	42.1	4.4290	3	223
##	273	24.4	0.11460	20.0	6.96	0	0.4640	6.538	58.7	3.9175	3	223
##	274	35.2	0.22188	20.0	6.96	1	0.4640	7.691	51.8	4.3665	3	223
##	275	32.4	0.05644	40.0	6.41	1	0.4470	6.758	32.9	4.0776	4	254
##	276	32.0	0.09604	40.0	6.41	0	0.4470	6.854	42.8	4.2673	4	254
##	277	33.2	0.10469	40.0	6.41	1	0.4470	7.267	49.0	4.7872	4	254
##	279	29.1	0.07978	40.0	6.41	0	0.4470	6.482	32.1	4.1403	4	254
##	280	35.1	0.21038	20.0	3.33	0	0.4429	6.812	32.2	4.1007	5	216
##	281	45.4	0.03578	20.0	3.33	0	0.4429	7.820	64.5	4.6947	5	216
##	282	35.4	0.03705	20.0	3.33	0	0.4429	6.968	37.2	5.2447	5	216
##	283	46.0	0.06129	20.0	3.33	1	0.4429	7.645	49.7	5.2119	5	216
##	285	32.2	0.00906	90.0	2.97	0	0.4000	7.088	20.8	7.3073	1	285
##	286	22.0	0.01096	55.0	2.25	0	0.3890	6.453	31.9	7.3073	1	300
##	287	20.1	0.01965	80.0	1.76	0	0.3850	6.230	31.5	9.0892	1	241
##	288	23.2	0.03871	52.5	5.32	0	0.4050	6.209	31.3	7.3172	6	293
##	289	22.3	0.04590	52.5	5.32	0	0.4050	6.315	45.6	7.3172	6	293
##	290	24.8	0.04297	52.5	5.32	0	0.4050	6.565	22.9	7.3172	6	293
##	291	28.5	0.03502	80.0	4.95	0	0.4110	6.861	27.9	5.1167	4	245
##	292	37.3	0.07886	80.0	4.95	0	0.4110	7.148	27.7	5.1167	4	245
##	294	23.9	0.08265	0.0	13.92	0	0.4370	6.127	18.4	5.5027	4	289
##	296	28.6	0.12932	0.0	13.92	0	0.4370	6.678	31.1	5.9604	4	289
##	297	27.1	0.05372	0.0	13.92	0	0.4370	6.549	51.0	5.9604	4	289
##	299	22.5	0.06466	70.0	2.24	0	0.4000	6.345	20.1	7.8278	5	358
##	301	24.8	0.04417	70.0	2.24	0	0.4000	6.871	47.4	7.8278	5	358
##	303	26.4	0.09266	34.0	6.09	0	0.4330	6.495	18.4	5.4917	7	329

##	304	33.1	0.10000	34.0	6.09	0	0.4330	6.982	17.7	5.4917	7	329
##	305	36.1	0.05515	33.0	2.18	0	0.4720	7.236	41.1	4.0220	7	222
##	306	28.4	0.05479	33.0	2.18	0	0.4720	6.616	58.1	3.3700	7	222
##	307	33.4	0.07503	33.0	2.18	0	0.4720	7.420	71.9	3.0992	7	222
##	308	28.2	0.04932	33.0	2.18	0	0.4720	6.849	70.3	3.1827	7	222
##	309	22.8	0.49298	0.0	9.90	0	0.5440	6.635	82.5	3.3175	4	304
##	311	16.1	2.63548	0.0	9.90	0	0.5440	4.973	37.8	2.5194	4	304
##	313	19.4	0.26169	0.0	9.90	0	0.5440	6.023	90.4	2.8340	4	304
##	314	21.6	0.26938	0.0	9.90	0	0.5440	6.266	82.8	3.2628	4	304
##	316	16.2	0.25356	0.0	9.90	0	0.5440	5.705	77.7	3.9450	4	304
##	317	17.8	0.31827	0.0	9.90	0	0.5440	5.914	83.2	3.9986	4	304
##	318	19.8	0.24522	0.0	9.90	0	0.5440	5.782	71.7	4.0317	4	304
##	319	23.1	0.40202	0.0	9.90	0	0.5440	6.382	67.2	3.5325	4	304
##	320	21.0	0.47547	0.0	9.90	0	0.5440	6.113	58.8	4.0019	4	304
##	321	23.8	0.16760	0.0	7.38	0	0.4930	6.426	52.3	4.5404	5	287
##	322	23.1	0.18159	0.0	7.38	0	0.4930	6.376	54.3	4.5404	5	287
##	323	20.4	0.35114	0.0	7.38	0	0.4930	6.041	49.9	4.7211	5	287
##	324	18.5	0.28392	0.0	7.38	0	0.4930	5.708	74.3	4.7211	5	287
##	327	23.0	0.30347	0.0	7.38	0	0.4930	6.312	28.9	5.4159	5	287
##	328	22.2	0.24103	0.0	7.38	0	0.4930	6.083	43.7	5.4159	5	287
##	330	22.6	0.06724	0.0	3.24	0	0.4600	6.333	17.2	5.2146	4	430
##	331	19.8	0.04544	0.0	3.24	0	0.4600	6.144	32.2	5.8736	4	430
##	332	17.1	0.05023	35.0	6.06	0	0.4379	5.706	28.4	6.6407	1	304
##	333	19.4	0.03466	35.0	6.06	0	0.4379	6.031	23.3	6.6407	1	304
##	334	22.2	0.05083	0.0	5.19	0	0.5150	6.316	38.1	6.4584	5	224
##	335	20.7	0.03738	0.0	5.19	0	0.5150	6.310	38.5	6.4584	5	224
##	336	21.1	0.03961	0.0	5.19	0	0.5150	6.037	34.5	5.9853	5	224
##	337	19.5	0.03427	0.0	5.19	0	0.5150	5.869	46.3	5.2311	5	224
##	338	18.5	0.03041	0.0	5.19	0	0.5150	5.895	59.6	5.6150	5	224
##	340	19.0	0.05497	0.0	5.19	0	0.5150	5.985	45.4	4.8122	5	224
##	341	18.7	0.06151	0.0	5.19	0	0.5150	5.968	58.5	4.8122	5	224
##	343	16.5	0.02498	0.0	1.89	0	0.5180	6.540	59.7	6.2669	1	422
##	345	31.2	0.03049	55.0	3.78	0	0.4840	6.874	28.1	6.4654	5	370
##	346	17.5	0.03113	0.0	4.39	0	0.4420	6.014	48.5	8.0136	3	352
##	347	17.2	0.06162	0.0	4.39	0	0.4420	5.898	52.3	8.0136	3	352
##	349	24.5	0.01501	80.0	2.01	0	0.4350	6.635	29.7	8.3440	4	280
##	350	26.6	0.02899	40.0	1.25	0	0.4290	6.939	34.5	8.7921	1	335
##	351	22.9	0.06211	40.0	1.25	0	0.4290	6.490	44.4	8.7921	1	335
##	352	24.1	0.07950	60.0	1.69	0	0.4110	6.579	35.9	10.7103	4	411
##	353	18.6	0.07244	60.0	1.69	0	0.4110	5.884	18.5	10.7103	4	411
##	355	18.2	0.04301	80.0	1.91	0	0.4130	5.663	21.9	10.5857	4	334
##	356	20.6	0.10659	80.0	1.91	0	0.4130	5.936	19.5	10.5857	4	334
##	358	21.7	3.84970	0.0	18.10	1	0.7700	6.395	91.0	2.5052	24	666
##	359	22.7	5.20177	0.0	18.10	1	0.7700	6.127	83.4	2.7227	24	666
##	360	22.6	4.26131	0.0	18.10	0	0.7700	6.112	81.3	2.5091	24	666
##	361	25.0	4.54192	0.0	18.10	0	0.7700	6.398	88.0	2.5182	24	666
##	363	20.8	3.67822	0.0	18.10	0	0.7700	5.362	96.2	2.1036	24	666
##	365	21.9	3.47428	0.0	18.10	1	0.7180	8.780	82.9	1.9047	24	666
##	366	27.5	4.55587	0.0	18.10	0	0.7180	3.561	87.9	1.6132	24	666
##	367	21.9	3.69695	0.0	18.10	0	0.7180	4.963	91.4	1.7523	24	666
##	369	50.0	4.89822	0.0	18.10	0	0.6310	4.970	100.0	1.3325	24	666
##	370	50.0	5.66998	0.0	18.10	1	0.6310	6.683	96.8	1.3567	24	666
##	373	50.0	8.26725	0.0	18.10	1	0.6680	5.875	89.6	1.1296	24	666
##	374	13.8	11.10810	0.0	18.10	0	0.6680	4.906	100.0	1.1742	24	666

##	375	13.8	18.49820	0.0	18.10	0	0.6680	4.138	100.0	1.1370	24	666
##	376	15.0	19.60910	0.0	18.10	0	0.6710	7.313	97.9	1.3163	24	666
##	379	13.1	23.64820	0.0	18.10	0	0.6710	6.380	96.2	1.3861	24	666
##	380	10.2	17.86670	0.0	18.10	0	0.6710	6.223	100.0	1.3861	24	666
##	382	10.9	15.87440	0.0	18.10	0	0.6710	6.545	99.1	1.5192	24	666
##	383	11.3	9.18702	0.0	18.10	0	0.7000	5.536	100.0	1.5804	24	666
##	384	12.3	7.99248	0.0	18.10	0	0.7000	5.520	100.0	1.5331	24	666
##	385	8.8	20.08490	0.0	18.10	0	0.7000	4.368	91.2	1.4395	24	666
##	386	7.2	16.81180	0.0	18.10	0	0.7000	5.277	98.1	1.4261	24	666
##	387	10.5	24.39380	0.0	18.10	0	0.7000	4.652	100.0	1.4672	24	666
##	388	7.4	22.59710	0.0	18.10	0	0.7000	5.000	89.5	1.5184	24	666
##	389	10.2	14.33370	0.0	18.10	0	0.7000	4.880	100.0	1.5895	24	666
##	390	11.5	8.15174	0.0	18.10	0	0.7000	5.390	98.9	1.7281	24	666
##	392	23.2	5.29305	0.0	18.10	0	0.7000	6.051	82.5	2.1678	24	666
##	394	13.8	8.64476	0.0	18.10	0	0.6930	6.193	92.6	1.7912	24	666
##	396	13.1	8.71675	0.0	18.10	0	0.6930	6.471	98.8	1.7257	24	666
##	397	12.5	5.87205	0.0	18.10	0	0.6930	6.405	96.0	1.6768	24	666
##	398	8.5	7.67202	0.0	18.10	0	0.6930	5.747	98.9	1.6334	24	666
##	399	5.0	38.35180	0.0	18.10	0	0.6930	5.453	100.0	1.4896	24	666
##	400	6.3	9.91655	0.0	18.10	0	0.6930	5.852	77.8	1.5004	24	666
##	401	5.6	25.04610	0.0	18.10	0	0.6930	5.987	100.0	1.5888	24	666
##	402	7.2	14.23620	0.0	18.10	0	0.6930	6.343	100.0	1.5741	24	666
##	404	8.3	24.80170	0.0	18.10	0	0.6930	5.349	96.0	1.7028	24	666
##	405	8.5	41.52920	0.0	18.10	0	0.6930	5.531	85.4	1.6074	24	666
##	407	11.9	20.71620	0.0	18.10	0	0.6590	4.138	100.0	1.1781	24	666
##	408	27.9	11.95110	0.0	18.10	0	0.6590	5.608	100.0	1.2852	24	666
##	409	17.2	7.40389	0.0	18.10	0	0.5970	5.617	97.9	1.4547	24	666
##	410	27.5	14.43830	0.0	18.10	0	0.5970	6.852	100.0	1.4655	24	666
##	411	15.0	51.13580	0.0	18.10	0	0.5970	5.757	100.0	1.4130	24	666
##	412	17.2	14.05070	0.0	18.10	0	0.5970	6.657	100.0	1.5275	24	666
##	417	7.5	10.83420	0.0	18.10	0	0.6790	6.782	90.8	1.8195	24	666
##	418	10.4	25.94060	0.0	18.10	0	0.6790	5.304	89.1	1.6475	24	666
##	419	8.8	73.53410	0.0	18.10	0	0.6790	5.957	100.0	1.8026	24	666
##	421	16.7	11.08740	0.0	18.10	0	0.7180	6.411	100.0	1.8589	24	666
##	422	14.2	7.02259	0.0	18.10	0	0.7180	6.006	95.3	1.8746	24	666
##	423	20.8	12.04820	0.0	18.10	0	0.6140	5.648	87.6	1.9512	24	666
##	425	11.7	8.79212	0.0	18.10	0	0.5840	5.565	70.6	2.0635	24	666
##	426	8.3	15.86030	0.0	18.10	0	0.6790	5.896	95.4	1.9096	24	666
##	427	10.2	12.24720	0.0	18.10	0	0.5840	5.837	59.7	1.9976	24	666
##	428	10.9	37.66190	0.0	18.10	0	0.6790	6.202	78.7	1.8629	24	666
##	429	11.0	7.36711	0.0	18.10	0	0.6790	6.193	78.1	1.9356	24	666
##	430	9.5	9.33889	0.0	18.10	0	0.6790	6.380	95.6	1.9682	24	666
##	431	14.5	8.49213	0.0	18.10	0	0.5840	6.348	86.1	2.0527	24	666
##	432	14.1	10.06230	0.0	18.10	0	0.5840	6.833	94.3	2.0882	24	666
##	433	16.1	6.44405	0.0	18.10	0	0.5840	6.425	74.8	2.2004	24	666
##	434	14.3	5.58107	0.0	18.10	0	0.7130	6.436	87.9	2.3158	24	666
##	435	11.7	13.91340	0.0	18.10	0	0.7130	6.208	95.0	2.2222	24	666
##	436	13.4	11.16040	0.0	18.10	0	0.7400	6.629	94.6	2.1247	24	666
##	437	9.6	14.42080	0.0	18.10	0	0.7400	6.461	93.3	2.0026	24	666
##	438	8.7	15.17720	0.0	18.10	0	0.7400	6.152	100.0	1.9142	24	666
##	439	8.4	13.67810	0.0	18.10	0	0.7400	5.935	87.9	1.8206	24	666
##	440	12.8	9.39063	0.0	18.10	0	0.7400	5.627	93.9	1.8172	24	666
##	441	10.5	22.05110	0.0	18.10	0	0.7400	5.818	92.4	1.8662	24	666
##	442	17.1	9.72418	0.0	18.10	0	0.7400	6.406	97.2	2.0651	24	666

##	443	18.4	5.66637	0.0	18.10	0	0.7400	6.219	100.0	2.0048	24	666
##	444	15.4	9.96654	0.0	18.10	0	0.7400	6.485	100.0	1.9784	24	666
##	446	11.8	10.67180	0.0	18.10	0	0.7400	6.459	94.8	1.9879	24	666
##	447	14.9	6.28807	0.0	18.10	0	0.7400	6.341	96.4	2.0720	24	666
##	449	14.1	9.32909	0.0	18.10	0	0.7130	6.185	98.7	2.2616	24	666
##	450	13.0	7.52601	0.0	18.10	0	0.7130	6.417	98.3	2.1850	24	666
##	451	13.4	6.71772	0.0	18.10	0	0.7130	6.749	92.6	2.3236	24	666
##	452	15.2	5.44114	0.0	18.10	0	0.7130	6.655	98.2	2.3552	24	666
##	454	17.8	8.24809	0.0	18.10	0	0.7130	7.393	99.3	2.4527	24	666
##	455	14.9	9.51363	0.0	18.10	0	0.7130	6.728	94.1	2.4961	24	666
##	457	12.7	4.66883	0.0	18.10	0	0.7130	5.976	87.9	2.5806	24	666
##	458	13.5	8.20058	0.0	18.10	0	0.7130	5.936	80.3	2.7792	24	666
##	459	14.9	7.75223	0.0	18.10	0	0.7130	6.301	83.7	2.7831	24	666
##	461	16.4	4.81213	0.0	18.10	0	0.7130	6.701	90.0	2.5975	24	666
##	462	17.7	3.69311	0.0	18.10	0	0.7130	6.376	88.4	2.5671	24	666
##	463	19.5	6.65492	0.0	18.10	0	0.7130	6.317	83.0	2.7344	24	666
##	466	19.9	3.16360	0.0	18.10	0	0.6550	5.759	48.2	3.0665	24	666
##	467	19.0	3.77498	0.0	18.10	0	0.6550	5.952	84.7	2.8715	24	666
##	468	19.1	4.42228	0.0	18.10	0	0.5840	6.003	94.5	2.5403	24	666
##	469	19.1	15.57570	0.0	18.10	0	0.5800	5.926	71.0	2.9084	24	666
##	470	20.1	13.07510	0.0	18.10	0	0.5800	5.713	56.7	2.8237	24	666
##	471	19.9	4.34879	0.0	18.10	0	0.5800	6.167	84.0	3.0334	24	666
##	472	19.6	4.03841	0.0	18.10	0	0.5320	6.229	90.7	3.0993	24	666
##	473	23.2	3.56868	0.0	18.10	0	0.5800	6.437	75.0	2.8965	24	666
##	474	29.8	4.64689	0.0	18.10	0	0.6140	6.980	67.6	2.5329	24	666
##	475	13.8	8.05579	0.0	18.10	0	0.5840	5.427	95.4	2.4298	24	666
##	476	13.3	6.39312	0.0	18.10	0	0.5840	6.162	97.4	2.2060	24	666
##	477	16.7	4.87141	0.0	18.10	0	0.6140	6.484	93.6	2.3053	24	666
##	478	12.0	15.02340	0.0	18.10	0	0.6140	5.304	97.3	2.1007	24	666
##	479	14.6	10.23300	0.0	18.10	0	0.6140	6.185	96.7	2.1705	24	666
##	480	21.4	14.33370	0.0	18.10	0	0.6140	6.229	88.0	1.9512	24	666
##	483	25.0	5.73116	0.0	18.10	0	0.5320	7.061	77.0	3.4106	24	666
##	484	21.8	2.81838	0.0	18.10	0	0.5320	5.762	40.3	4.0983	24	666
##	485	20.6	2.37857	0.0	18.10	0	0.5830	5.871	41.9	3.7240	24	666
##	486	21.2	3.67367	0.0	18.10	0	0.5830	6.312	51.9	3.9917	24	666
##	488	20.6	4.83567	0.0	18.10	0	0.5830	5.905	53.2	3.1523	24	666
##	490	7.0	0.18337	0.0	27.74	0	0.6090	5.414	98.3	1.7554	4	711
##	492	13.6	0.10574	0.0	27.74	0	0.6090	5.983	98.8	1.8681	4	711
##	493	20.1	0.11132	0.0	27.74	0	0.6090	5.983	83.5	2.1099	4	711
##	494	21.8	0.17331	0.0	9.69	0	0.5850	5.707	54.0	2.3817	6	391
##	495	24.5	0.27957	0.0	9.69	0	0.5850	5.926	42.6	2.3817	6	391
##	496	23.1	0.17899	0.0	9.69	0	0.5850	5.670	28.8	2.7986	6	391
##	497	19.7	0.28960	0.0	9.69	0	0.5850	5.390	72.9	2.7986	6	391
##	498	18.3	0.26838	0.0	9.69	0	0.5850	5.794	70.6	2.8927	6	391
##	499	21.2	0.23912	0.0	9.69	0	0.5850	6.019	65.3	2.4091	6	391
##	500	17.5	0.17783	0.0	9.69	0	0.5850	5.569	73.5	2.3999	6	391
##	501	16.8	0.22438	0.0	9.69	0	0.5850	6.027	79.7	2.4982	6	391
##	502	22.4	0.06263	0.0	11.93	0	0.5730	6.593	69.1	2.4786	1	273
##	503	20.6	0.04527	0.0	11.93	0	0.5730	6.120	76.7	2.2875	1	273
##	505	22.0	0.10959	0.0	11.93	0	0.5730	6.794	89.3	2.3889	1	273
##	506	11.9	0.04741	0.0	11.93	0	0.5730	6.030	80.8	2.5050	1	273
##		PTRATIO		B	LSTAT							
##	1	15.3	396.90		4.98							
##	2	17.8	396.90		9.14							

## 3	17.8	392.83	4.03
## 4	18.7	394.63	2.94
## 5	18.7	396.90	5.33
## 6	18.7	394.12	5.21
## 8	15.2	396.90	19.15
## 9	15.2	386.63	29.93
## 10	15.2	386.71	17.10
## 12	15.2	396.90	13.27
## 16	21.0	395.62	8.47
## 17	21.0	386.85	6.58
## 19	21.0	288.99	11.69
## 21	21.0	376.57	21.02
## 23	21.0	396.90	18.72
## 27	21.0	376.88	14.81
## 28	21.0	306.38	17.28
## 29	21.0	387.94	12.80
## 30	21.0	380.23	11.98
## 31	21.0	360.17	22.60
## 32	21.0	376.73	13.04
## 33	21.0	232.60	27.71
## 34	21.0	358.77	18.35
## 35	21.0	248.31	20.34
## 36	19.2	396.90	9.68
## 37	19.2	377.56	11.41
## 38	19.2	396.90	8.77
## 39	19.2	393.43	10.13
## 41	18.3	395.62	1.98
## 42	17.9	385.41	4.84
## 44	17.9	394.46	7.44
## 48	17.9	392.74	18.80
## 51	16.8	395.56	13.45
## 53	16.8	396.90	5.28
## 56	17.9	395.93	4.81
## 57	17.3	396.90	5.77
## 58	15.1	392.90	3.95
## 59	19.7	390.68	6.86
## 60	19.7	396.90	9.22
## 61	19.7	395.11	13.15
## 62	19.7	378.08	14.44
## 63	19.7	396.90	6.73
## 64	19.7	395.58	9.50
## 66	16.1	396.90	4.67
## 67	16.1	396.90	10.24
## 68	18.9	396.21	8.10
## 69	18.9	396.90	13.09
## 72	19.2	376.94	9.88
## 73	19.2	390.91	5.52
## 74	19.2	377.17	7.54
## 75	18.7	394.92	6.78
## 77	18.7	373.66	11.97
## 79	18.7	386.40	12.34
## 80	18.7	396.06	9.10
## 81	19.0	396.90	5.29
## 82	19.0	395.63	7.22

## 83	19.0	396.90	6.72
## 84	19.0	390.64	7.51
## 86	18.5	392.30	6.53
## 88	18.5	395.15	8.44
## 89	17.8	396.90	5.50
## 91	17.8	392.18	8.81
## 92	17.8	393.55	8.20
## 94	18.2	396.33	6.21
## 95	18.2	396.90	10.59
## 98	18.0	396.90	4.21
## 99	18.0	393.53	3.57
## 100	18.0	396.90	6.19
## 102	20.9	395.58	7.67
## 104	20.9	394.47	13.44
## 107	20.9	395.67	18.66
## 108	20.9	387.69	14.09
## 109	20.9	395.24	12.27
## 110	20.9	391.23	15.55
## 111	20.9	393.49	13.00
## 112	17.8	395.59	10.16
## 113	17.8	394.95	16.21
## 114	17.8	396.90	17.09
## 115	17.8	388.74	10.45
## 116	17.8	344.91	15.76
## 118	17.8	394.51	10.30
## 119	17.8	338.63	15.37
## 120	17.8	391.50	13.61
## 121	19.1	389.15	14.37
## 122	19.1	377.67	14.27
## 123	19.1	378.09	17.93
## 124	19.1	370.31	25.41
## 125	19.1	379.38	17.58
## 126	19.1	385.02	14.81
## 128	21.2	392.11	17.19
## 131	21.2	395.04	12.60
## 132	21.2	396.90	12.26
## 133	21.2	385.76	11.12
## 134	21.2	388.69	15.03
## 136	21.2	394.67	16.96
## 137	21.2	378.25	16.90
## 140	21.2	396.90	18.46
## 142	21.2	396.90	34.41
## 143	14.7	396.90	26.82
## 144	14.7	396.90	26.42
## 145	14.7	396.90	29.29
## 146	14.7	172.91	27.80
## 147	14.7	169.27	16.65
## 148	14.7	391.71	29.53
## 149	14.7	356.99	28.32
## 150	14.7	351.85	21.45
## 152	14.7	341.60	13.28
## 153	14.7	343.28	12.12
## 156	14.7	88.01	15.02
## 157	14.7	88.63	16.14

## 158	14.7	363.43	4.59
## 159	14.7	353.89	6.43
## 162	14.7	374.43	1.73
## 163	14.7	389.61	1.92
## 165	14.7	395.11	11.64
## 166	14.7	240.16	9.81
## 167	14.7	369.30	3.70
## 168	14.7	227.61	12.14
## 169	14.7	297.09	11.10
## 170	14.7	330.04	11.32
## 171	14.7	292.29	14.43
## 172	14.7	348.13	12.03
## 173	16.6	396.90	14.69
## 174	16.6	395.50	9.04
## 175	16.6	393.23	9.64
## 176	16.6	390.96	5.33
## 178	16.6	395.60	6.29
## 179	16.6	391.27	6.92
## 180	17.8	396.90	5.04
## 181	17.8	395.56	7.56
## 182	17.8	396.90	9.45
## 184	17.8	396.90	5.68
## 186	17.8	387.11	13.15
## 187	17.8	392.63	4.45
## 188	15.2	393.87	6.68
## 189	15.2	382.84	4.56
## 190	15.2	396.90	5.39
## 191	15.2	377.68	5.10
## 192	15.2	389.71	4.69
## 193	15.2	390.49	2.87
## 195	15.6	376.70	4.38
## 196	14.4	394.23	2.97
## 197	12.6	396.90	4.08
## 198	12.6	354.31	8.61
## 199	12.6	392.20	6.62
## 200	17.0	396.90	4.56
## 202	14.7	393.77	7.43
## 203	14.7	395.38	3.11
## 204	14.7	392.78	3.81
## 205	14.7	390.55	2.88
## 206	18.6	396.90	10.87
## 208	18.6	389.43	18.06
## 209	18.6	381.32	14.66
## 212	18.6	395.24	23.98
## 213	18.6	390.94	16.03
## 214	18.6	385.81	9.38
## 216	18.6	393.63	9.47
## 218	16.4	392.78	9.69
## 219	16.4	396.90	17.92
## 220	16.4	393.74	10.50
## 221	17.4	391.70	9.71
## 223	17.4	390.39	9.93
## 225	17.4	385.05	4.14
## 226	17.4	382.00	4.63



## 227	17.4	387.38	3.13
## 228	17.4	372.08	6.36
## 230	17.4	380.34	3.76
## 231	17.4	378.35	11.65
## 234	17.4	378.95	3.95
## 235	17.4	360.20	8.05
## 236	17.4	376.75	10.88
## 237	17.4	388.45	9.54
## 239	16.6	379.41	6.36
## 240	16.6	383.78	7.37
## 242	16.6	394.62	12.40
## 243	16.6	372.75	11.22
## 244	16.6	374.71	5.19
## 246	19.1	389.13	18.46
## 247	19.1	390.18	9.16
## 248	19.1	376.14	10.15
## 249	19.1	374.71	9.52
## 250	19.1	393.74	6.56
## 251	19.1	396.28	5.90
## 252	19.1	377.07	3.59
## 254	19.1	396.90	3.54
## 255	16.4	392.89	6.57
## 256	16.4	395.18	9.25
## 258	13.0	389.70	5.12
## 260	13.0	391.93	6.90
## 262	13.0	388.37	7.26
## 264	13.0	393.42	11.25
## 265	13.0	387.89	8.10
## 266	13.0	392.40	10.45
## 267	13.0	384.07	14.79
## 268	13.0	384.54	7.44
## 269	13.0	390.30	3.16
## 270	18.6	391.34	13.65
## 271	18.6	388.65	13.00
## 273	18.6	394.96	7.73
## 274	18.6	390.77	6.58
## 275	17.6	396.90	3.53
## 276	17.6	396.90	2.98
## 277	17.6	389.25	6.05
## 279	17.6	396.90	7.19
## 280	14.9	396.90	4.85
## 281	14.9	387.31	3.76
## 282	14.9	392.23	4.59
## 283	14.9	377.07	3.01
## 285	15.3	394.72	7.85
## 286	15.3	394.72	8.23
## 287	18.2	341.60	12.93
## 288	16.6	396.90	7.14
## 289	16.6	396.90	7.60
## 290	16.6	371.72	9.51
## 291	19.2	396.90	3.33
## 292	19.2	396.90	3.56
## 294	16.0	396.90	8.58
## 296	16.0	396.90	6.27

## 297	16.0	392.85	7.39
## 299	14.8	368.24	4.97
## 301	14.8	390.86	6.07
## 303	16.1	383.61	8.67
## 304	16.1	390.43	4.86
## 305	18.4	393.68	6.93
## 306	18.4	393.36	8.93
## 307	18.4	396.90	6.47
## 308	18.4	396.90	7.53
## 309	18.4	396.90	4.54
## 311	18.4	350.45	12.64
## 313	18.4	396.30	11.72
## 314	18.4	393.39	7.90
## 316	18.4	396.42	11.50
## 317	18.4	390.70	18.33
## 318	18.4	396.90	15.94
## 319	18.4	395.21	10.36
## 320	18.4	396.23	12.73
## 321	19.6	396.90	7.20
## 322	19.6	396.90	6.87
## 323	19.6	396.90	7.70
## 324	19.6	391.13	11.74
## 327	19.6	396.90	6.15
## 328	19.6	396.90	12.79
## 330	16.9	375.21	7.34
## 331	16.9	368.57	9.09
## 332	16.9	394.02	12.43
## 333	16.9	362.25	7.83
## 334	20.2	389.71	5.68
## 335	20.2	389.40	6.75
## 336	20.2	396.90	8.01
## 337	20.2	396.90	9.80
## 338	20.2	394.81	10.56
## 340	20.2	396.90	9.74
## 341	20.2	396.90	9.29
## 343	15.9	389.96	8.65
## 345	17.6	387.97	4.61
## 346	18.8	385.64	10.53
## 347	18.8	364.61	12.67
## 349	17.0	390.94	5.99
## 350	19.7	389.85	5.89
## 351	19.7	396.90	5.98
## 352	18.3	370.78	5.49
## 353	18.3	392.33	7.79
## 355	22.0	382.80	8.05
## 356	22.0	376.04	5.57
## 358	20.2	391.34	13.27
## 359	20.2	395.43	11.48
## 360	20.2	390.74	12.67
## 361	20.2	374.56	7.79
## 363	20.2	380.79	10.19
## 365	20.2	354.55	5.29
## 366	20.2	354.70	7.12
## 367	20.2	316.03	14.00

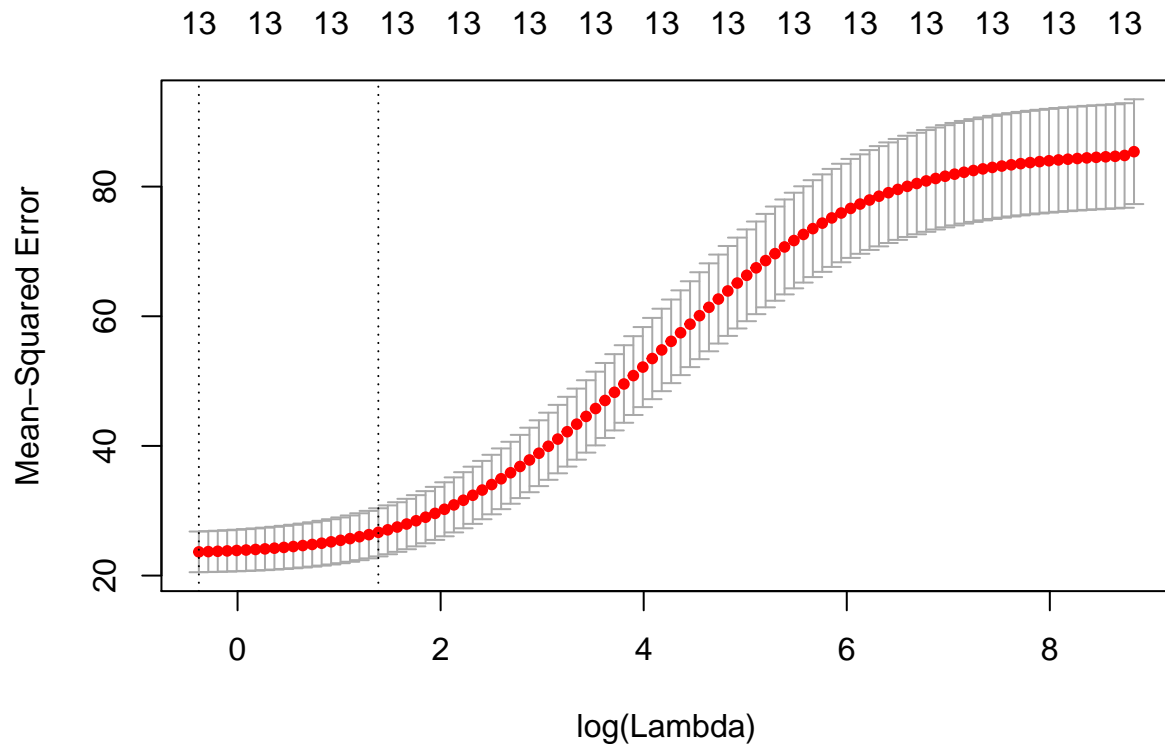
## 369	20.2	375.52	3.26
## 370	20.2	375.33	3.73
## 373	20.2	347.88	8.88
## 374	20.2	396.90	34.77
## 375	20.2	396.90	37.97
## 376	20.2	396.90	13.44
## 379	20.2	396.90	23.69
## 380	20.2	393.74	21.78
## 382	20.2	396.90	21.08
## 383	20.2	396.90	23.60
## 384	20.2	396.90	24.56
## 385	20.2	285.83	30.63
## 386	20.2	396.90	30.81
## 387	20.2	396.90	28.28
## 388	20.2	396.90	31.99
## 389	20.2	372.92	30.62
## 390	20.2	396.90	20.85
## 392	20.2	378.38	18.76
## 394	20.2	396.90	15.17
## 396	20.2	391.98	17.12
## 397	20.2	396.90	19.37
## 398	20.2	393.10	19.92
## 399	20.2	396.90	30.59
## 400	20.2	338.16	29.97
## 401	20.2	396.90	26.77
## 402	20.2	396.90	20.32
## 404	20.2	396.90	19.77
## 405	20.2	329.46	27.38
## 407	20.2	370.22	23.34
## 408	20.2	332.09	12.13
## 409	20.2	314.64	26.40
## 410	20.2	179.36	19.78
## 411	20.2	2.60	10.11
## 412	20.2	35.05	21.22
## 417	20.2	21.57	25.79
## 418	20.2	127.36	26.64
## 419	20.2	16.45	20.62
## 421	20.2	318.75	15.02
## 422	20.2	319.98	15.70
## 423	20.2	291.55	14.10
## 425	20.2	3.65	17.16
## 426	20.2	7.68	24.39
## 427	20.2	24.65	15.69
## 428	20.2	18.82	14.52
## 429	20.2	96.73	21.52
## 430	20.2	60.72	24.08
## 431	20.2	83.45	17.64
## 432	20.2	81.33	19.69
## 433	20.2	97.95	12.03
## 434	20.2	100.19	16.22
## 435	20.2	100.63	15.17
## 436	20.2	109.85	23.27
## 437	20.2	27.49	18.05
## 438	20.2	9.32	26.45

## 439	20.2	68.95	34.02
## 440	20.2	396.90	22.88
## 441	20.2	391.45	22.11
## 442	20.2	385.96	19.52
## 443	20.2	395.69	16.59
## 444	20.2	386.73	18.85
## 446	20.2	43.06	23.98
## 447	20.2	318.01	17.79
## 449	20.2	396.90	18.13
## 450	20.2	304.21	19.31
## 451	20.2	0.32	17.44
## 452	20.2	355.29	17.73
## 454	20.2	375.87	16.74
## 455	20.2	6.68	18.71
## 457	20.2	10.48	19.01
## 458	20.2	3.50	16.94
## 459	20.2	272.21	16.23
## 461	20.2	255.23	16.42
## 462	20.2	391.43	14.65
## 463	20.2	396.90	13.99
## 466	20.2	334.40	14.13
## 467	20.2	22.01	17.15
## 468	20.2	331.29	21.32
## 469	20.2	368.74	18.13
## 470	20.2	396.90	14.76
## 471	20.2	396.90	16.29
## 472	20.2	395.33	12.87
## 473	20.2	393.37	14.36
## 474	20.2	374.68	11.66
## 475	20.2	352.58	18.14
## 476	20.2	302.76	24.10
## 477	20.2	396.21	18.68
## 478	20.2	349.48	24.91
## 479	20.2	379.70	18.03
## 480	20.2	383.32	13.11
## 483	20.2	395.28	7.01
## 484	20.2	392.92	10.42
## 485	20.2	370.73	13.34
## 486	20.2	388.62	10.58
## 488	20.2	388.22	11.45
## 490	20.1	344.05	23.97
## 492	20.1	390.11	18.07
## 493	20.1	396.90	13.35
## 494	19.2	396.90	12.01
## 495	19.2	396.90	13.59
## 496	19.2	393.29	17.60
## 497	19.2	396.90	21.14
## 498	19.2	396.90	14.10
## 499	19.2	396.90	12.92
## 500	19.2	395.77	15.10
## 501	19.2	396.90	14.33
## 502	21.0	391.99	9.67
## 503	21.0	396.90	9.08
## 505	21.0	393.45	6.48

```
## 506      21.0 396.90  7.88
```

```
x <- model.matrix(MEDV~., train)[,-1]
y = train$MEDV
y.test = y[-trainIndex]
```

```
#perform cross-validation to choose tuning parameter lambda
cv.out <- cv.glmnet(x, y, alpha = 0)
plot(cv.out)
```



```
bestlambda <- cv.out$lambda.min #lambda that results in lowest cross validation error
grid <- 10^seq(10,-2,length = 100) #from 10^10 to 10^-2
ridge.mod <- glmnet(x,y,alpha= 0, lambda = grid, thresh = 1e-12)
#make predictions for lambda = bestlambda
ridge.pred <- predict(ridge.mod, s=bestlambda, newx = x[-trainIndex,])
```

```
library(plotmo)
```

```
glmcoef<-coef(ridge.mod,bestlambda )
coef.increase<-dimnames(glmcoef[glmcoef[,1]>0,0])[[1]]
coef.decrease<-dimnames(glmcoef[glmcoef[,1]<0,0])[[1]]

#get ordered list of variables as they appear at smallest lambda
allnames<-names(coef(ridge.mod)[,
  ncol(coef(ridge.mod))][order(coef(ridge.mod)[,
  ncol(coef(ridge.mod))],decreasing=TRUE)])
```

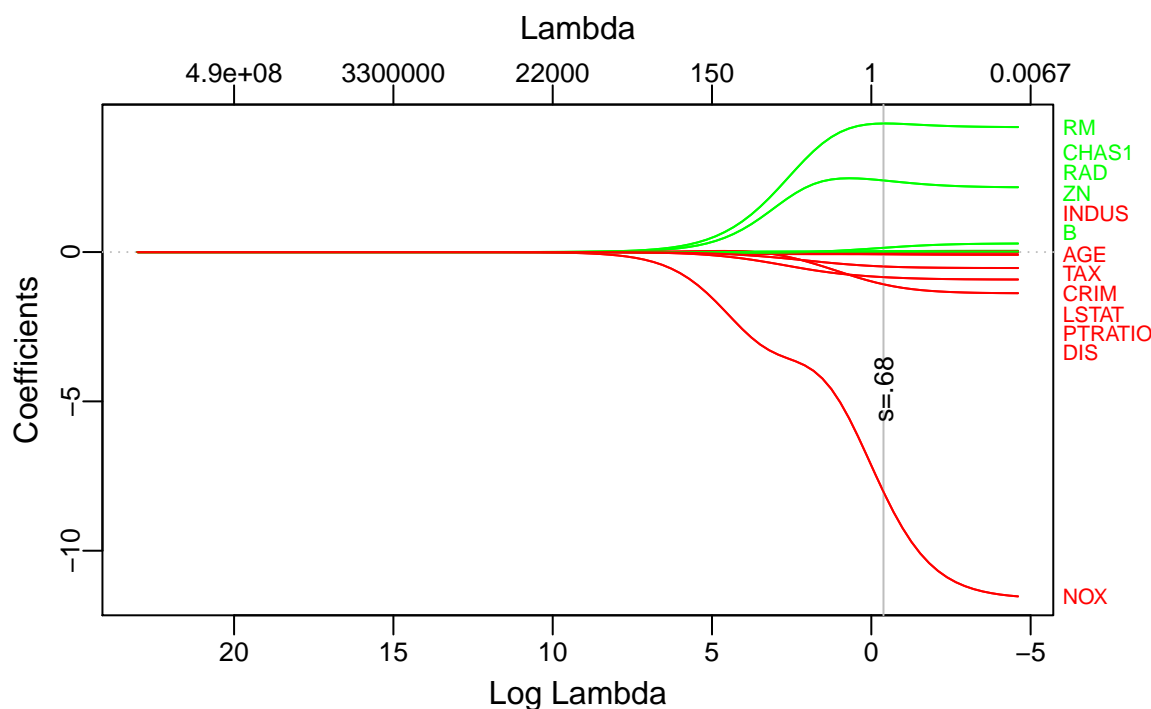
```

#remove intercept
allnames<-setdiff(allnames,allnames[grep("Intercept",allnames)])

#assign colors
cols<-rep("gray",length(allnames))
cols[allnames %in% coef.increase]<-"green"      # higher medv is good
cols[allnames %in% coef.decrease]<-"red"        # lower medv is not

plot_glmnet(ridge.mod,label=TRUE,s=bestlambda,col=cols)

```



To select the best model, we now use 10x10-CV using the lambda that best minimised the error in cross-validation, which is lambda.ridge.

```

trainContrl <- trainControl (method="repeatedcv", number=10, repeats=10)
model <- train(MEDV ~ ., data = train, trControl=trainContrl, method='glmnet', tuneGrid=expand.grid(alpha=0, lambda=bestlambda))
model.ridge.FINAL <- glmnet(x, y, alpha = 0, lambda = bestlambda)

normalized <- (length(train$MEDV)-1)*var(train$MEDV)
NMSE.ridge.train.error <- crossprod(predict (model) - train$MEDV) / normalized
normTest <- (length(test$MEDV)-1)*var(test$MEDV)
sse_raw <- test$MEDV - model.ridge.FINAL$a0- data.matrix(test[, -dim(train)[2]]) %*% model.ridge.FINAL$b
sse <- crossprod (as.matrix(sse_raw))

NMSE.ridge.test.error <- sse/normTest

```

Table 2: Model Errors Summary

regression_method	train_MSE	test_MSE
ridge regression	0.255	4101.969