

# Baseline and Regression Models

12/07/2019

```
# load necessary packages
```

```
library(readr)
library(dplyr)
library(GGally)
library(ggplot2)
library(car)
```

```
us <- read_csv("https://raw.githubusercontent.com/kanam12/ieor142finalproject/master/us_suicides_merged.csv")
#names(suicides)[9] <- "suicides_rate"
```

```
suicides <- us %>% select(-age, - `country-year`, -country)
```

```
set.seed(377)
```

```
train.ids = sample(nrow(suicides), 0.70*nrow(suicides))
train = suicides[train.ids,]
test = suicides[-train.ids,]
```

## Baseline Model

```
base_mod <- mean(suicides$`suicides/100k pop`)
```

## Linear Regression

```
set.seed(377)
```

```
exp_mod <- lm(`suicides/100k pop` ~ ., data = train)
```

```
summary(exp_mod)
```

```
##
## Call:
## lm(formula = `suicides/100k pop` ~ ., data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -15.9676  -3.2243   0.1071   2.9260  21.1764
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -6.561e+02  1.330e+03  -0.493   0.62221
## year           2.763e-01  7.131e-01   0.387   0.69873
## sexmale        8.961e+00  9.126e+00   0.982   0.32713
## suicides_no    2.155e-03  3.863e-04   5.579 6.39e-08 ***
```

```
## population          -6.970e-07  8.892e-08  -7.839  1.39e-13 ***
## `HDI for year`      1.605e+02  1.736e+02   0.925  0.35600
## `gdp_for_year ($)`  2.110e-12  2.369e-12   0.891  0.37394
## `gdp_per_capita ($)` -1.112e-03  8.393e-04  -1.325  0.18633
## generationBoomers   5.670e+00  1.378e+00   4.113  5.33e-05 ***
## generationSilent     3.280e+00  1.241e+00   2.643  0.00875 **
## generationG.I. Generation 1.108e+01  1.713e+00   6.469  5.33e-10 ***
## generationMillenials -2.833e+00  1.360e+00  -2.083  0.03825 *
## generationGeneration Z -6.841e+00  2.624e+00  -2.607  0.00969 **
## depression_percentage -3.811e-01  3.736e+00  -0.102  0.91884
## drug_death_rate      1.284e-01  7.705e-02   1.666  0.09699 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.205 on 245 degrees of freedom
## Multiple R-squared:  0.8063, Adjusted R-squared:  0.7952
## F-statistic: 72.84 on 14 and 245 DF,  p-value: < 2.2e-16
```

```
vif(exp_mod) #- perfect multicollinearity
```

```
##              GVIF Df GVIF^(1/(2*Df))
## year          283.510832  1    16.837780
## sex           140.526937  1    11.854406
## suicides_no    7.524014  1     2.742994
## population     5.056416  1     2.248648
## `HDI for year` 108.411003  1    10.412060
## `gdp_for_year ($)` 688.789938  1    26.244808
## `gdp_per_capita ($)` 747.303383  1    27.336850
## generation      6.593310  5     1.207565
## depression_percentage 140.933912  1    11.871559
## drug_death_rate  7.158119  1     2.675466
```

```
#alias(exp_mod)
```

```
set.seed(377)
```

```
lin_mod <- lm(`suicides/100k pop` ~ . - `gdp_per_capita ($)`, data = train)
```

```
summary(lin_mod)
```

```
##
## Call:
## lm(formula = `suicides/100k pop` ~ . - `gdp_per_capita ($)`,
##     data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.4011  -2.8929  -0.0201   3.1459  21.7702
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -8.033e+02  1.327e+03  -0.605  0.54555
## year           4.072e-01  7.073e-01   0.576  0.56535
## sexmale        9.896e+00  9.113e+00   1.086  0.27856
## suicides_no    2.207e-03  3.849e-04   5.735  2.85e-08 ***
## population    -7.068e-07  8.875e-08  -7.964  6.18e-14 ***
## `HDI for year`  1.158e+01  1.325e+02   0.087  0.93041
```

```
## `gdp_for_year` ($) -6.552e-13 1.123e-12 -0.583 0.56026
## generationBoomers 5.617e+00 1.380e+00 4.070 6.33e-05 ***
## generationSilent 3.237e+00 1.242e+00 2.606 0.00973 **
## generationG.I. Generation 1.098e+01 1.714e+00 6.404 7.62e-10 ***
## generationMillenials -2.814e+00 1.362e+00 -2.067 0.03983 *
## generationGeneration Z -6.503e+00 2.615e+00 -2.486 0.01357 *
## depression_percentage 9.775e-02 3.724e+00 0.026 0.97908
## drug_death_rate 1.313e-01 7.713e-02 1.703 0.08988 .
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.215 on 246 degrees of freedom
## Multiple R-squared: 0.8049, Adjusted R-squared: 0.7946
## F-statistic: 78.06 on 13 and 246 DF, p-value: < 2.2e-16
```

```
vif(lin_mod)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## year          278.073514 1      16.675536
## sex           139.686347 1      11.818898
## suicides_no    7.446130 1       2.728760
## population     5.021576 1       2.240887
## `HDI for year` 62.964063 1       7.934990
## `gdp_for_year` 154.381650 1      12.425041
## generation     6.499695 5       1.205839
## depression_percentage 139.615852 1      11.815915
## drug_death_rate 7.152034 1       2.674329
```

```
set.seed(377)
```

```
lin_mod2 <- lm(`suicides/100k pop` ~ . - `gdp_per_capita` ($) - year, data = train)
```

```
summary(lin_mod2)
```

```
##
## Call:
## lm(formula = `suicides/100k pop` ~ . - `gdp_per_capita` ($) -
##   year, data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.1604  -3.1161   0.0812   2.8675  21.6604
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -4.094e+01  8.748e+01  -0.468  0.6402
## sexmale        8.762e+00  8.885e+00   0.986  0.3250
## suicides_no    2.218e-03  3.840e-04   5.776 2.29e-08 ***
## population    -7.041e-07  8.850e-08  -7.955 6.44e-14 ***
## `HDI for year`  6.657e+01  9.169e+01   0.726  0.4685
## `gdp_for_year` -7.668e-14  5.014e-13  -0.153  0.8786
## generationBoomers  5.583e+00  1.377e+00   4.055 6.72e-05 ***
## generationSilent  3.218e+00  1.240e+00   2.595  0.0100 *
## generationG.I. Generation 1.102e+01  1.710e+00   6.443 6.07e-10 ***
## generationMillenials -2.785e+00  1.359e+00  -2.049  0.0415 *
## generationGeneration Z -6.641e+00  2.601e+00  -2.553  0.0113 *
```

```
## depression_percentage      -3.698e-01  3.630e+00 -0.102  0.9189
## drug_death_rate            1.282e-01  7.683e-02  1.668  0.0966 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.206 on 247 degrees of freedom
## Multiple R-squared:  0.8046, Adjusted R-squared:  0.7951
## F-statistic: 84.77 on 12 and 247 DF,  p-value: < 2.2e-16
```

```
vif(lin_mod2)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## sex              133.155360  1      11.539296
## suicides_no       7.429999  1       2.725803
## population        5.007900  1       2.237834
## `HDI for year`    30.238331  1       5.498939
## `gdp_for_year ($)` 30.843074  1       5.553654
## generation        6.356335  5       1.203153
## depression_percentage 132.977265  1      11.531577
## drug_death_rate    7.115567  1       2.667502
```

```
set.seed(377)
```

```
lin_mod3 <- lm(`suicides/100k pop` ~ . - `gdp_per_capita ($)` - year - sex, data = train)
```

```
summary(lin_mod3)
```

```
##
## Call:
## lm(formula = `suicides/100k pop` ~ . - `gdp_per_capita ($)` -
##     year - sex, data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.1977  -3.1137   0.0782   3.0937  21.5800
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.068e+01  7.009e+01  0.152  0.87905
## suicides_no     2.241e-03  3.832e-04  5.846 1.58e-08 ***
## population     -7.064e-07  8.847e-08 -7.985 5.25e-14 ***
## `HDI for year`  2.963e+01  8.368e+01  0.354  0.72355
## `gdp_for_year ($)` 1.219e-13  4.592e-13  0.265  0.79090
## generationBoomers  5.563e+00  1.377e+00  4.041 7.09e-05 ***
## generationSilent  3.331e+00  1.235e+00  2.697  0.00747 **
## generationG.I. Generation 1.105e+01  1.710e+00  6.462 5.43e-10 ***
## generationMillenials -2.703e+00  1.356e+00 -1.993  0.04739 *
## generationGeneration Z -6.535e+00  2.599e+00 -2.515  0.01254 *
## depression_percentage -3.906e+00  5.635e-01 -6.931 3.60e-11 ***
## drug_death_rate    1.296e-01  7.681e-02  1.687  0.09293 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.206 on 248 degrees of freedom
## Multiple R-squared:  0.8039, Adjusted R-squared:  0.7952
## F-statistic: 92.4 on 11 and 248 DF,  p-value: < 2.2e-16
```

```
vif(lin_mod3)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## suicides_no      7.402857  1      2.720819
## population        5.004313  1      2.237032
## `HDI for year`    25.192748  1      5.019238
## `gdp_for_year ($)` 25.868829  1      5.086141
## generation        6.284809  5      1.201792
## depression_percentage 3.205765  1      1.790465
## drug_death_rate    7.113163  1      2.667051
```

```
# remove variables that are not significant
```

```
set.seed(377)
```

```
lin_mod4 <- lm(`suicides/100k pop` ~ . - `gdp_for_year ($)` - `gdp_per_capita ($)` - year - sex, data = t
```

```
summary(lin_mod4)
```

```
##
## Call:
## lm(formula = `suicides/100k pop` ~ . - `gdp_for_year ($)` - `gdp_per_capita ($)` -
##   year - sex, data = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.4038  -3.0834   0.1028   3.0491  21.6051
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -6.596e+00  2.597e+01  -0.254  0.79974
## suicides_no      2.251e-03  3.805e-04   5.915 1.09e-08 ***
## population     -7.099e-07  8.730e-08  -8.132 2.00e-14 ***
## `HDI for year`   5.045e+01  2.911e+01   1.733  0.08430 .
## generationBoomers  5.542e+00  1.372e+00   4.040 7.12e-05 ***
## generationSilent  3.358e+00  1.228e+00   2.733  0.00672 **
## generationG.I. Generation 1.106e+01  1.706e+00   6.484 4.76e-10 ***
## generationMillenials -2.651e+00  1.340e+00  -1.979  0.04895 *
## generationGeneration Z -6.356e+00  2.505e+00  -2.538  0.01177 *
## depression_percentage -3.878e+00  5.527e-01  -7.016 2.15e-11 ***
## drug_death_rate    1.327e-01  7.576e-02   1.751  0.08110 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.194 on 249 degrees of freedom
## Multiple R-squared:  0.8038, Adjusted R-squared:  0.7959
## F-statistic: 102 on 10 and 249 DF, p-value: < 2.2e-16
```

```
lin_mod5 <- lm(`suicides/100k pop` ~ . - `gdp_for_year ($)` - `HDI for year` - `gdp_per_capita ($)` - year - sex,
               data = train)
```

```
summary(lin_mod5)
```

```
##
## Call:
## lm(formula = `suicides/100k pop` ~ . - `gdp_for_year ($)` - `HDI for year` -
##   `gdp_per_capita ($)` - year - sex - `HDI for year`, data = train)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.289   -3.002   -0.117    3.230   20.683
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      3.815e+01  2.857e+00  13.354 < 2e-16 ***
## suicides_no      2.110e-03  3.733e-04   5.653 4.29e-08 ***
## population      -7.623e-07  8.225e-08  -9.268 < 2e-16 ***
## generationBoomers    5.602e+00  1.377e+00   4.069 6.33e-05 ***
## generationSilent     3.905e+00  1.192e+00   3.276  0.0012 **
## generationG.I. Generation 9.855e+00  1.564e+00   6.302 1.32e-09 ***
## generationMillenials -1.682e+00  1.222e+00  -1.376  0.1701
## generationGeneration Z -4.237e+00  2.195e+00  -1.931  0.0547 .
## depression_percentage -3.834e+00  5.543e-01  -6.917 3.85e-11 ***
## drug_death_rate      2.253e-01  5.393e-02   4.178 4.07e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.219 on 250 degrees of freedom
## Multiple R-squared:  0.8014, Adjusted R-squared:  0.7943
## F-statistic: 112.1 on 9 and 250 DF, p-value: < 2.2e-16
```

---

```
# OSR-squared of newest seasonal model
base_predictions <- rep(base_mod, nrow(test))

***confirm if this is correct
base_SSE = sum((train$`suicides/100k pop` - rep(base_mod, nrow(train)))^2)
base_SST = sum((train$`suicides/100k pop` - mean(train$`suicides/100k pop`))^2)
base_R2 = 1 - base_SSE/base_SST

base_SSE = sum((test$`suicides/100k pop` - base_predictions)^2)
base_SST = sum((test$`suicides/100k pop` - mean(train$`suicides/100k pop`))^2)
base_OSR2 = 1 - base_SSE/base_SST

# this builds a vector of predicted values on the test set
lin_predictions <- predict(lin_mod5, newdata = test)

lin_SSE = sum((test$`suicides/100k pop` - lin_predictions)^2)
lin_SST = sum((test$`suicides/100k pop` - mean(train$`suicides/100k pop`))^2)
lin_OSR2 = 1 - lin_SSE/lin_SST

####----- need to compare change in OSR2

exp_predictions <- predict(exp_mod, newdata = test)

exp_SSE = sum((test$`suicides/100k pop` - exp_predictions)^2)
exp_SST = sum((test$`suicides/100k pop` - mean(train$`suicides/100k pop`))^2)
exp_OSR2 = 1 - exp_SSE/exp_SST
# # OSR-squared of the initial exploratory model
# exp_predictions <- predict(mod_exp, newdata = wrangler_test)
#
```

```

# exp_SSE = sum((wrangler_test$WranglerSales - exp_predictions)^2)
# exp_SST = sum((wrangler_test$WranglerSales - mean(wrangler_train$WranglerSales))^2)
# exp_OSR2 = 1 - exp_SSE/exp_SST

# compare change in R-squared and OSR-squared between the two models

***confirm if R^2 for baseline is correct
R2 <- c("base_R2" = base_R2, "exp_OR2" = summary(exp_mod)$r.squared, "lin_R2" = summary(lin_mod5)$r.squared)
R2

##      base_R2      exp_OR2      lin_R2
## -0.00054829  0.80628055  0.80143721

OSR2 <- c("base_OSR2" = base_OSR2, "exp_OSR2" = exp_OSR2, "lin_OSR2" = lin_OSR2)
OSR2

##      base_OSR2      exp_OSR2      lin_OSR2
## 0.003987337 0.741355507 0.735686902

```

# CART, RF, Boosting

12/13/2019

```
library(dplyr) # data manipulation

##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##   filter, lag
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

library(caTools) # splits
library(ggplot2) # plot graph
library(randomForest) # Random Forest

## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##   margin
## The following object is masked from 'package:dplyr':
##
##   combine

library(rpart)
library(rpart.plot)
library(caret)

## Loading required package: lattice

library(lubridate)

##
## Attaching package: 'lubridate'
## The following object is masked from 'package:base':
##
##   date

library(gbm)

## Loaded gbm 2.1.5

library(boot)

##
## Attaching package: 'boot'
```



```
## The following object is masked from 'package:lattice':
##
##      melanoma
```

```
OSR2 <- function(predictions, test, train) {
  SSE <- sum((test - predictions)^2)
  SST <- sum((test - mean(train))^2)
  r2 <- 1 - SSE/SST
  return(r2)
}
```

```
us <- read.csv("us_suicides_merged_no_na.csv")
```

```
suicide_us <- us %>% select(year, sex, suicides_no, population, suicides.100k.pop, HDI.for.year, gdp_f
```

```
suicide_us$year <- as.factor(suicide_us$year)
```

```
# split data for us
set.seed(377)
train.ids_us = sample(nrow(suicide_us), 0.70*nrow(suicide_us))
train_us <- suicide_us[train.ids_us,]
test_us <- suicide_us[-train.ids_us,]
```

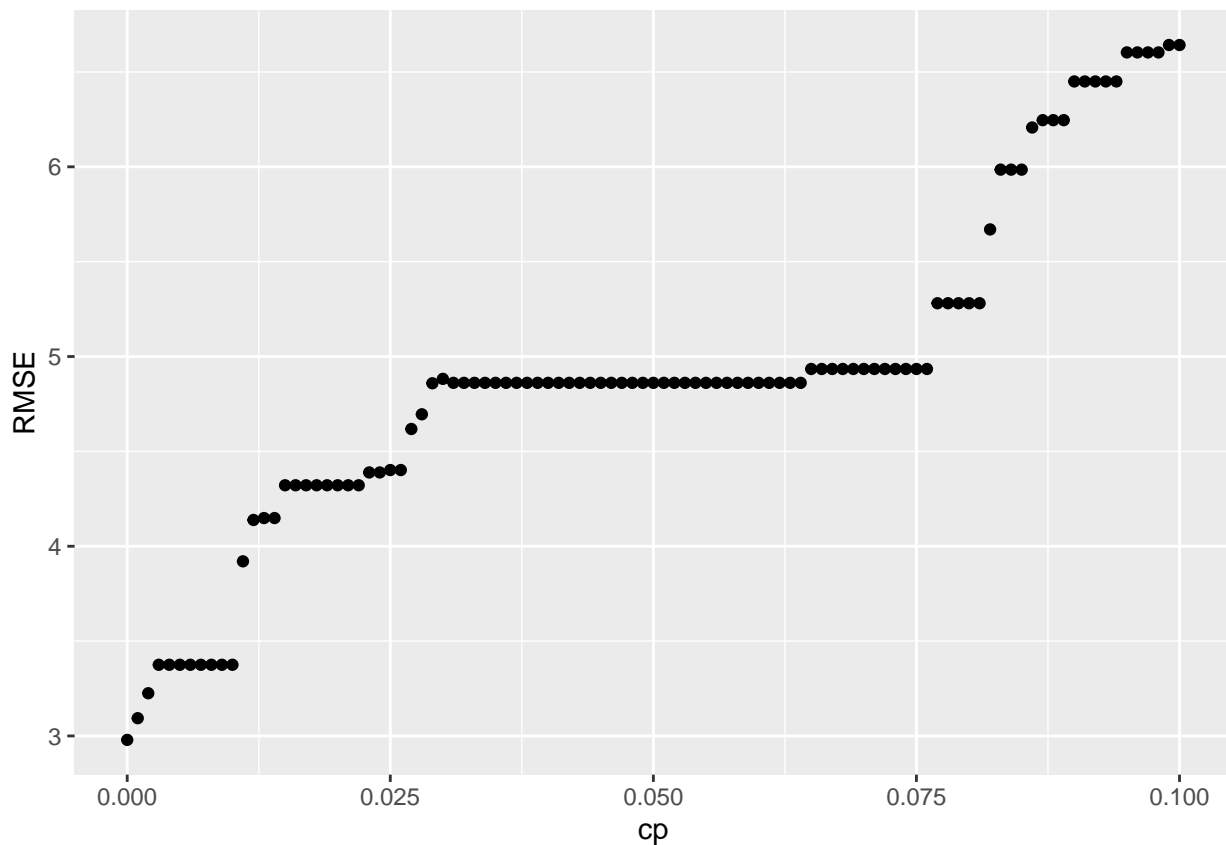
## CART

```
set.seed(377)
```

```
us_train.cart = train(suicides.100k.pop ~ .,
  data = train_us,
  method = "rpart",
  tuneGrid = data.frame(cp=seq(0, 0.1, 0.001)),
  trControl = trainControl(method="cv", number=10),
  metric = "RMSE")
us_train.cart$bestTune
```

```
##      cp
## 1  0
```

```
ggplot(us_train.cart$results, aes(x=cp, y=RMSE)) + geom_point()
```



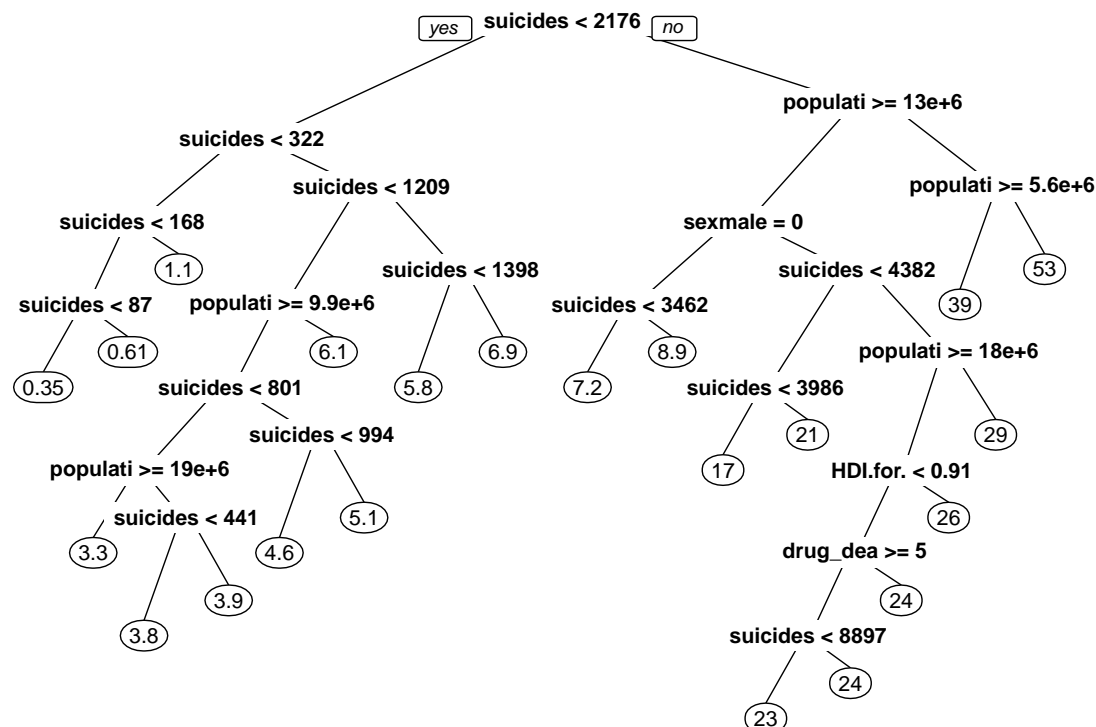
```
us_train.cart$results
```

##	cp	RMSE	Rsquared	MAE	RMSESD	RsquaredSD	MAESD
## 1	0.000	2.979329	0.9299221	1.199689	3.225845	0.1279826	0.7136592
## 2	0.001	3.093575	0.9277967	1.404896	3.194623	0.1285093	0.6913812
## 3	0.002	3.225177	0.9234075	1.554537	3.217963	0.1315820	0.7476110
## 4	0.003	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 5	0.004	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 6	0.005	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 7	0.006	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 8	0.007	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 9	0.008	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 10	0.009	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 11	0.010	3.375140	0.9194188	1.738446	3.157827	0.1314394	0.7601279
## 12	0.011	3.920498	0.9041719	2.305750	2.903154	0.1267028	0.6481499
## 13	0.012	4.138473	0.8952126	2.487929	2.919139	0.1304562	0.7615112
## 14	0.013	4.148571	0.8954976	2.485649	2.928927	0.1289138	0.7723281
## 15	0.014	4.148571	0.8954976	2.485649	2.928927	0.1289138	0.7723281
## 16	0.015	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 17	0.016	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 18	0.017	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 19	0.018	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 20	0.019	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 21	0.020	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 22	0.021	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 23	0.022	4.321436	0.8799357	2.518585	3.284802	0.1667361	0.8338564
## 24	0.023	4.388922	0.8755937	2.607405	3.422550	0.1734971	1.0382248

## 25	0.024	4.388922	0.8755937	2.607405	3.422550	0.1734971	1.0382248
## 26	0.025	4.401650	0.8750325	2.635935	3.449401	0.1748987	1.0841685
## 27	0.026	4.401650	0.8750325	2.635935	3.449401	0.1748987	1.0841685
## 28	0.027	4.618113	0.8704746	2.761382	3.361284	0.1724605	1.0469658
## 29	0.028	4.695637	0.8680869	2.780571	3.338454	0.1714471	1.0421989
## 30	0.029	4.859037	0.8660092	2.899967	3.245508	0.1704052	0.9986216
## 31	0.030	4.882301	0.8666749	2.910465	3.225638	0.1708483	0.9861274
## 32	0.031	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 33	0.032	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 34	0.033	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 35	0.034	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 36	0.035	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 37	0.036	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 38	0.037	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 39	0.038	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 40	0.039	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 41	0.040	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 42	0.041	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 43	0.042	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 44	0.043	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 45	0.044	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 46	0.045	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 47	0.046	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 48	0.047	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 49	0.048	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 50	0.049	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 51	0.050	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 52	0.051	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 53	0.052	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 54	0.053	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 55	0.054	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 56	0.055	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 57	0.056	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 58	0.057	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 59	0.058	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 60	0.059	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 61	0.060	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 62	0.061	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 63	0.062	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 64	0.063	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 65	0.064	4.861378	0.8679781	2.899746	3.240825	0.1715778	0.9970946
## 66	0.065	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 67	0.066	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 68	0.067	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 69	0.068	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 70	0.069	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 71	0.070	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 72	0.071	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 73	0.072	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 74	0.073	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 75	0.074	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 76	0.075	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 77	0.076	4.934361	0.8606146	3.059289	3.398389	0.1905633	1.3213671
## 78	0.077	5.280960	0.8462010	3.362222	3.443466	0.1883127	1.5240413

```
## 79 0.078 5.280960 0.8462010 3.362222 3.443466 0.1883127 1.5240413
## 80 0.079 5.280960 0.8462010 3.362222 3.443466 0.1883127 1.5240413
## 81 0.080 5.280960 0.8462010 3.362222 3.443466 0.1883127 1.5240413
## 82 0.081 5.280960 0.8462010 3.362222 3.443466 0.1883127 1.5240413
## 83 0.082 5.670020 0.8203833 3.656730 3.311591 0.1868571 1.4931868
## 84 0.083 5.985219 0.8024132 3.897906 3.138200 0.1804592 1.3748995
## 85 0.084 5.985219 0.8024132 3.897906 3.138200 0.1804592 1.3748995
## 86 0.085 5.985219 0.8024132 3.897906 3.138200 0.1804592 1.3748995
## 87 0.086 6.207410 0.7891493 4.068535 2.992776 0.1745661 1.2807708
## 88 0.087 6.245957 0.7861506 4.156334 3.060970 0.1780620 1.3742501
## 89 0.088 6.245957 0.7861506 4.156334 3.060970 0.1780620 1.3742501
## 90 0.089 6.245957 0.7861506 4.156334 3.060970 0.1780620 1.3742501
## 91 0.090 6.450051 0.7771554 4.303759 2.948063 0.1716057 1.2971819
## 92 0.091 6.450051 0.7771554 4.303759 2.948063 0.1716057 1.2971819
## 93 0.092 6.450051 0.7771554 4.303759 2.948063 0.1716057 1.2971819
## 94 0.093 6.450051 0.7771554 4.303759 2.948063 0.1716057 1.2971819
## 95 0.094 6.450051 0.7771554 4.303759 2.948063 0.1716057 1.2971819
## 96 0.095 6.603046 0.7687192 4.419024 2.789900 0.1629593 1.1658689
## 97 0.096 6.603046 0.7687192 4.419024 2.789900 0.1629593 1.1658689
## 98 0.097 6.603046 0.7687192 4.419024 2.789900 0.1629593 1.1658689
## 99 0.098 6.603046 0.7687192 4.419024 2.789900 0.1629593 1.1658689
## 100 0.099 6.642118 0.7712096 4.477140 2.754341 0.1657459 1.0781541
## 101 0.100 6.642118 0.7712096 4.477140 2.754341 0.1657459 1.0781541
```

```
mod.us_cart <- us_train.cart$finalModel
prp(mod.us_cart)
```



```
us_test.cart = as.data.frame(model.matrix(suicides.100k.pop ~ . + 0, data=test_us))

predcart_us = predict(mod.us_cart, newdata=us_test.cart)
#predcart_us$results
```

```
cart.tab.us <- table(test_us$suicides.100k.pop, predcart_us)
cart.tab.us
```

```
##      predcart_us
##      0.35125 0.608571428571429 1.09722222222222 3.26 3.75555555555556
## 0.28      1      0      0      0
## 0.31      1      0      0      0
## 0.37      1      0      0      0
## 0.39      1      0      0      0
## 0.41      1      0      0      0
## 0.42      1      0      0      0
## 0.43      0      1      0      0
## 0.44      1      0      0      0
## 0.45      0      1      0      0
## 0.74      0      1      0      0
## 0.78      0      1      0      0
## 0.83      0      0      1      0
## 0.88      0      0      1      0
## 0.92      0      0      1      0
## 1.02      0      0      2      0
## 1.14      0      0      2      0
## 1.24      0      0      1      0
## 1.3       0      0      1      0
## 1.33      0      0      1      0
## 3.03      0      0      0      1
## 3.12      0      0      0      0
## 3.32      0      0      0      0
## 3.61      0      0      0      0
## 3.72      0      0      0      0
## 3.77      0      0      0      0
## 3.85      0      0      0      0
## 3.88      0      0      0      0
## 4         0      0      0      0
## 4.08      0      0      0      0
## 4.23      0      0      0      0
## 4.32      0      0      0      0
## 4.36      0      0      0      0
## 4.59      0      0      0      0
## 4.73      0      0      0      0
## 4.77      0      0      0      0
## 4.81      0      0      0      0
## 4.95      0      0      0      0
## 5.06      0      0      0      0
## 5.07      0      0      0      0
## 5.17      0      0      0      0
## 5.38      0      0      0      0
## 5.47      0      0      0      0
## 5.61      0      0      0      0
## 5.77      0      0      0      0
## 6.02      0      0      0      0
## 6.17      0      0      0      0
## 6.21      0      0      0      0
## 6.29      0      0      0      0
## 6.4       0      0      0      0
```

##	6.76	0	0	0	0	0
##	6.8	0	0	0	0	0
##	6.91	0	0	0	0	0
##	7.06	0	0	0	0	0
##	7.11	0	0	0	0	0
##	7.3	0	0	0	0	0
##	7.38	0	0	0	0	0
##	7.48	0	0	0	0	0
##	7.83	0	0	0	0	0
##	7.9	0	0	0	0	0
##	8.99	0	0	0	0	0
##	16.09	0	0	0	0	0
##	16.15	0	0	0	0	0
##	16.16	0	0	0	0	0
##	16.64	0	0	0	0	0
##	17.2	0	0	0	0	0
##	17.5	0	0	0	0	0
##	18.01	0	0	0	0	0
##	19.57	0	0	0	0	0
##	20	0	0	0	0	0
##	20.98	0	0	0	0	0
##	21.26	0	0	0	0	0
##	21.89	0	0	0	0	0
##	21.92	0	0	0	0	0
##	22.24	0	0	0	0	0
##	22.25	0	0	0	0	0
##	22.41	0	0	0	0	0
##	22.61	0	0	0	0	0
##	22.62	0	0	0	0	0
##	23.3	0	0	0	0	0
##	23.45	0	0	0	0	0
##	23.57	0	0	0	0	0
##	23.88	0	0	0	0	0
##	24	0	0	0	0	0
##	24.01	0	0	0	0	0
##	24.03	0	0	0	0	0
##	24.12	0	0	0	0	0
##	24.62	0	0	0	0	0
##	24.76	0	0	0	0	0
##	24.78	0	0	0	0	0
##	24.86	0	0	0	0	0
##	25.02	0	0	0	0	0
##	25.06	0	0	0	0	0
##	25.48	0	0	0	0	0
##	25.52	0	0	0	0	0
##	25.61	0	0	0	0	0
##	25.62	0	0	0	0	0
##	26.34	0	0	0	0	0
##	26.41	0	0	0	0	0
##	26.52	0	0	0	0	0
##	26.71	0	0	0	0	0
##	27.05	0	0	0	0	0
##	27.93	0	0	0	0	0
##	28.11	0	0	0	0	0

##	36.53	0	0	0	0	0
##	37.11	0	0	0	0	0
##	45.15	0	0	0	0	0
##	52.33	0	0	0	0	0
##	57.85	0	0	0	0	0
##	predcart_us					
##	3.93727272727273	4.59416666666667	5.132	5.78153846153846	6.07375	
##	0.28	0	0	0	0	0
##	0.31	0	0	0	0	0
##	0.37	0	0	0	0	0
##	0.39	0	0	0	0	0
##	0.41	0	0	0	0	0
##	0.42	0	0	0	0	0
##	0.43	0	0	0	0	0
##	0.44	0	0	0	0	0
##	0.45	0	0	0	0	0
##	0.74	0	0	0	0	0
##	0.78	0	0	0	0	0
##	0.83	0	0	0	0	0
##	0.88	0	0	0	0	0
##	0.92	0	0	0	0	0
##	1.02	0	0	0	0	0
##	1.14	0	0	0	0	0
##	1.24	0	0	0	0	0
##	1.3	0	0	0	0	0
##	1.33	0	0	0	0	0
##	3.03	0	0	0	0	0
##	3.12	1	0	0	0	0
##	3.32	1	0	0	0	0
##	3.61	0	0	0	0	0
##	3.72	1	0	0	0	0
##	3.77	0	0	0	0	0
##	3.85	0	0	0	0	0
##	3.88	0	1	0	0	0
##	4	0	1	0	0	0
##	4.08	1	0	0	0	0
##	4.23	1	0	0	0	0
##	4.32	0	1	0	0	0
##	4.36	0	1	0	0	0
##	4.59	1	0	0	0	0
##	4.73	0	1	0	0	0
##	4.77	0	1	1	0	0
##	4.81	0	0	0	0	1
##	4.95	0	0	1	0	0
##	5.06	0	0	1	0	0
##	5.07	0	0	0	0	1
##	5.17	1	0	0	0	0
##	5.38	0	0	2	0	0
##	5.47	0	0	0	0	1
##	5.61	0	0	0	1	0
##	5.77	0	0	0	0	0
##	6.02	0	0	0	0	0
##	6.17	0	0	0	0	1
##	6.21	0	0	0	1	0

##	6.29	0	0	0	1	0
##	6.4	0	0	0	0	1
##	6.76	0	0	0	0	0
##	6.8	0	0	0	0	0
##	6.91	0	0	0	0	0
##	7.06	0	0	0	0	0
##	7.11	0	0	0	0	0
##	7.3	0	0	0	0	0
##	7.38	0	0	0	0	0
##	7.48	0	0	0	0	0
##	7.83	0	0	0	0	0
##	7.9	0	0	0	0	0
##	8.99	0	0	0	0	0
##	16.09	0	0	0	0	0
##	16.15	0	0	0	0	0
##	16.16	0	0	0	0	0
##	16.64	0	0	0	0	0
##	17.2	0	0	0	0	0
##	17.5	0	0	0	0	0
##	18.01	0	0	0	0	0
##	19.57	0	0	0	0	0
##	20	0	0	0	0	0
##	20.98	0	0	0	0	0
##	21.26	0	0	0	0	0
##	21.89	0	0	0	0	0
##	21.92	0	0	0	0	0
##	22.24	0	0	0	0	0
##	22.25	0	0	0	0	0
##	22.41	0	0	0	0	0
##	22.61	0	0	0	0	0
##	22.62	0	0	0	0	0
##	23.3	0	0	0	0	0
##	23.45	0	0	0	0	0
##	23.57	0	0	0	0	0
##	23.88	0	0	0	0	0
##	24	0	0	0	0	0
##	24.01	0	0	0	0	0
##	24.03	0	0	0	0	0
##	24.12	0	0	0	0	0
##	24.62	0	0	0	0	0
##	24.76	0	0	0	0	0
##	24.78	0	0	0	0	0
##	24.86	0	0	0	0	0
##	25.02	0	0	0	0	0
##	25.06	0	0	0	0	0
##	25.48	0	0	0	0	0
##	25.52	0	0	0	0	0
##	25.61	0	0	0	0	0
##	25.62	0	0	0	0	0
##	26.34	0	0	0	0	0
##	26.41	0	0	0	0	0
##	26.52	0	0	0	0	0
##	26.71	0	0	0	0	0
##	27.05	0	0	0	0	0



##	27.93	0		0	0		0	0
##	28.11	0		0	0		0	0
##	36.53	0		0	0		0	0
##	37.11	0		0	0		0	0
##	45.15	0		0	0		0	0
##	52.33	0		0	0		0	0
##	57.85	0		0	0		0	0
##	predcart_us							
##	6.88636363636364	7.1625	8.865	16.9827272727273	21.1638888888889			
##	0.28	0	0	0	0			0
##	0.31	0	0	0	0			0
##	0.37	0	0	0	0			0
##	0.39	0	0	0	0			0
##	0.41	0	0	0	0			0
##	0.42	0	0	0	0			0
##	0.43	0	0	0	0			0
##	0.44	0	0	0	0			0
##	0.45	0	0	0	0			0
##	0.74	0	0	0	0			0
##	0.78	0	0	0	0			0
##	0.83	0	0	0	0			0
##	0.88	0	0	0	0			0
##	0.92	0	0	0	0			0
##	1.02	0	0	0	0			0
##	1.14	0	0	0	0			0
##	1.24	0	0	0	0			0
##	1.3	0	0	0	0			0
##	1.33	0	0	0	0			0
##	3.03	0	0	0	0			0
##	3.12	0	0	0	0			0
##	3.32	0	0	0	0			0
##	3.61	0	0	0	0			0
##	3.72	0	0	0	0			0
##	3.77	0	0	0	0			0
##	3.85	0	0	0	0			0
##	3.88	0	0	0	0			0
##	4	0	0	0	0			0
##	4.08	0	0	0	0			0
##	4.23	0	0	0	0			0
##	4.32	0	0	0	0			0
##	4.36	0	0	0	0			0
##	4.59	0	0	0	0			0
##	4.73	0	0	0	0			0
##	4.77	0	0	0	0			0
##	4.81	0	0	0	0			0
##	4.95	0	0	0	0			0
##	5.06	0	0	0	0			0
##	5.07	0	0	0	0			0
##	5.17	0	0	0	0			0
##	5.38	0	0	0	0			0
##	5.47	0	0	0	0			0
##	5.61	0	0	0	0			0
##	5.77	1	0	0	0			0
##	6.02	1	0	0	0			0

##	6.17	0	0	0	0	0
##	6.21	0	0	0	0	0
##	6.29	0	0	0	0	0
##	6.4	0	0	0	0	0
##	6.76	0	1	0	0	0
##	6.8	0	1	0	0	0
##	6.91	1	0	0	0	0
##	7.06	1	0	0	0	0
##	7.11	0	1	0	0	0
##	7.3	0	1	0	0	0
##	7.38	0	1	0	0	0
##	7.48	0	1	0	0	0
##	7.83	0	1	0	0	0
##	7.9	1	0	0	0	0
##	8.99	0	0	1	0	0
##	16.09	0	0	0	1	0
##	16.15	0	0	0	1	0
##	16.16	0	0	0	1	0
##	16.64	0	0	0	1	0
##	17.2	0	0	0	1	0
##	17.5	0	0	0	1	0
##	18.01	0	0	0	0	1
##	19.57	0	0	0	1	0
##	20	0	0	0	1	0
##	20.98	0	0	0	0	1
##	21.26	0	0	0	0	1
##	21.89	0	0	0	0	1
##	21.92	0	0	0	0	1
##	22.24	0	0	0	0	1
##	22.25	0	0	0	0	0
##	22.41	0	0	0	0	0
##	22.61	0	0	0	0	0
##	22.62	0	0	0	0	0
##	23.3	0	0	0	0	0
##	23.45	0	0	0	0	1
##	23.57	0	0	0	0	0
##	23.88	0	0	0	0	0
##	24	0	0	0	0	0
##	24.01	0	0	0	0	0
##	24.03	0	0	0	0	0
##	24.12	0	0	0	0	0
##	24.62	0	0	0	0	0
##	24.76	0	0	0	0	0
##	24.78	0	0	0	0	0
##	24.86	0	0	0	0	0
##	25.02	0	0	0	0	0
##	25.06	0	0	0	0	0
##	25.48	0	0	0	0	0
##	25.52	0	0	0	0	0
##	25.61	0	0	0	0	0
##	25.62	0	0	0	0	0
##	26.34	0	0	0	0	0
##	26.41	0	0	0	0	0
##	26.52	0	0	0	0	0

##	26.71	0	0	0	0	0
##	27.05	0	0	0	0	0
##	27.93	0	0	0	0	0
##	28.11	0	0	0	0	0
##	36.53	0	0	0	0	0
##	37.11	0	0	0	0	0
##	45.15	0	0	0	0	0
##	52.33	0	0	0	0	0
##	57.85	0	0	0	0	0
##	predcart_us					
##	23.0911764705882 24.0785714285714 24.47 26.1814285714286					
##	0.28	0		0	0	0
##	0.31	0		0	0	0
##	0.37	0		0	0	0
##	0.39	0		0	0	0
##	0.41	0		0	0	0
##	0.42	0		0	0	0
##	0.43	0		0	0	0
##	0.44	0		0	0	0
##	0.45	0		0	0	0
##	0.74	0		0	0	0
##	0.78	0		0	0	0
##	0.83	0		0	0	0
##	0.88	0		0	0	0
##	0.92	0		0	0	0
##	1.02	0		0	0	0
##	1.14	0		0	0	0
##	1.24	0		0	0	0
##	1.3	0		0	0	0
##	1.33	0		0	0	0
##	3.03	0		0	0	0
##	3.12	0		0	0	0
##	3.32	0		0	0	0
##	3.61	0		0	0	0
##	3.72	0		0	0	0
##	3.77	0		0	0	0
##	3.85	0		0	0	0
##	3.88	0		0	0	0
##	4	0		0	0	0
##	4.08	0		0	0	0
##	4.23	0		0	0	0
##	4.32	0		0	0	0
##	4.36	0		0	0	0
##	4.59	0		0	0	0
##	4.73	0		0	0	0
##	4.77	0		0	0	0
##	4.81	0		0	0	0
##	4.95	0		0	0	0
##	5.06	0		0	0	0
##	5.07	0		0	0	0
##	5.17	0		0	0	0
##	5.38	0		0	0	0
##	5.47	0		0	0	0
##	5.61	0		0	0	0

##	5.77	0	0	0	0
##	6.02	0	0	0	0
##	6.17	0	0	0	0
##	6.21	0	0	0	0
##	6.29	0	0	0	0
##	6.4	0	0	0	0
##	6.76	0	0	0	0
##	6.8	0	0	0	0
##	6.91	0	0	0	0
##	7.06	0	0	0	0
##	7.11	0	0	0	0
##	7.3	0	0	0	0
##	7.38	0	0	0	0
##	7.48	0	0	0	0
##	7.83	0	0	0	0
##	7.9	0	0	0	0
##	8.99	0	0	0	0
##	16.09	0	0	0	0
##	16.15	0	0	0	0
##	16.16	0	0	0	0
##	16.64	0	0	0	0
##	17.2	0	0	0	0
##	17.5	0	0	0	0
##	18.01	0	0	0	0
##	19.57	0	0	0	0
##	20	0	0	0	0
##	20.98	0	0	0	0
##	21.26	0	0	0	0
##	21.89	0	0	0	0
##	21.92	0	0	0	0
##	22.24	0	0	0	0
##	22.25	1	0	0	0
##	22.41	1	0	0	0
##	22.61	1	0	0	0
##	22.62	0	1	0	0
##	23.3	1	0	0	0
##	23.45	0	0	0	0
##	23.57	0	1	0	0
##	23.88	0	1	0	0
##	24	0	0	0	1
##	24.01	1	0	0	0
##	24.03	0	0	1	0
##	24.12	0	1	0	0
##	24.62	0	0	0	0
##	24.76	0	0	1	0
##	24.78	0	0	1	0
##	24.86	0	0	0	1
##	25.02	0	0	1	0
##	25.06	0	0	0	0
##	25.48	0	0	1	0
##	25.52	0	0	0	1
##	25.61	0	0	1	0
##	25.62	0	0	1	0
##	26.34	0	0	0	1

##	26.41	0	0	0	0
##	26.52	0	0	0	1
##	26.71	0	0	0	0
##	27.05	0	0	0	1
##	27.93	0	0	0	1
##	28.11	0	0	0	1
##	36.53	0	0	0	0
##	37.11	0	0	0	0
##	45.15	0	0	0	0
##	52.33	0	0	0	0
##	57.85	0	0	0	0
##	predcart_us				
##	29.0328571428571 38.67125 53.46				
##	0.28	0	0	0	
##	0.31	0	0	0	
##	0.37	0	0	0	
##	0.39	0	0	0	
##	0.41	0	0	0	
##	0.42	0	0	0	
##	0.43	0	0	0	
##	0.44	0	0	0	
##	0.45	0	0	0	
##	0.74	0	0	0	
##	0.78	0	0	0	
##	0.83	0	0	0	
##	0.88	0	0	0	
##	0.92	0	0	0	
##	1.02	0	0	0	
##	1.14	0	0	0	
##	1.24	0	0	0	
##	1.3	0	0	0	
##	1.33	0	0	0	
##	3.03	0	0	0	
##	3.12	0	0	0	
##	3.32	0	0	0	
##	3.61	0	0	0	
##	3.72	0	0	0	
##	3.77	0	0	0	
##	3.85	0	0	0	
##	3.88	0	0	0	
##	4	0	0	0	
##	4.08	0	0	0	
##	4.23	0	0	0	
##	4.32	0	0	0	
##	4.36	0	0	0	
##	4.59	0	0	0	
##	4.73	0	0	0	
##	4.77	0	0	0	
##	4.81	0	0	0	
##	4.95	0	0	0	
##	5.06	0	0	0	
##	5.07	0	0	0	
##	5.17	0	0	0	
##	5.38	0	0	0	

##	5.47	0	0	0
##	5.61	0	0	0
##	5.77	0	0	0
##	6.02	0	0	0
##	6.17	0	0	0
##	6.21	0	0	0
##	6.29	0	0	0
##	6.4	0	0	0
##	6.76	0	0	0
##	6.8	0	0	0
##	6.91	0	0	0
##	7.06	0	0	0
##	7.11	0	0	0
##	7.3	0	0	0
##	7.38	0	0	0
##	7.48	0	0	0
##	7.83	0	0	0
##	7.9	0	0	0
##	8.99	0	0	0
##	16.09	0	0	0
##	16.15	0	0	0
##	16.16	0	0	0
##	16.64	0	0	0
##	17.2	0	0	0
##	17.5	0	0	0
##	18.01	0	0	0
##	19.57	0	0	0
##	20	0	0	0
##	20.98	0	0	0
##	21.26	0	0	0
##	21.89	0	0	0
##	21.92	0	0	0
##	22.24	0	0	0
##	22.25	0	0	0
##	22.41	0	0	0
##	22.61	0	0	0
##	22.62	0	0	0
##	23.3	0	0	0
##	23.45	0	0	0
##	23.57	0	0	0
##	23.88	0	0	0
##	24	0	0	0
##	24.01	0	0	0
##	24.03	0	0	0
##	24.12	0	0	0
##	24.62	1	0	0
##	24.76	0	0	0
##	24.78	0	0	0
##	24.86	0	0	0
##	25.02	0	0	0
##	25.06	1	0	0
##	25.48	0	0	0
##	25.52	0	0	0
##	25.61	0	0	0

```
##    25.62          0          0          0
##    26.34          0          0          0
##    26.41          1          0          0
##    26.52          0          0          0
##    26.71          1          0          0
##    27.05          0          0          0
##    27.93          0          0          0
##    28.11          0          0          0
##    36.53          0          1          0
##    37.11          0          1          0
##    45.15          0          1          0
##    52.33          0          0          1
##    57.85          0          0          1
```

```
print("CART OSR2:")
```

```
## [1] "CART OSR2:"
```

```
OSR2(predcart_us, test_us$suicides.100k.pop, train_us$suicides.100k.pop)
```

```
## [1] 0.9883818
```

## Random Forest

```
set.seed(377)
```

```
mod.rf.us <- randomForest(suicides.100k.pop ~ ., data = train_us, mtry = 5, nodesize = 5, ntree = 500)
```

```
pred.rf.us <- predict(mod.rf.us, newdata = test_us) # just to illustrate
pred.rf.us[1:5]
```

```
##          1          7          16          21          26
## 4.859536 1.050132 24.295192  7.247386 20.566757
```

```
importance(mod.rf.us)
```

```
##              IncNodePurity
## year              721.5390
## sex              6873.8985
## suicides_no      20017.7699
## population       12227.8713
## HDI.for.year      248.8317
## gdp_for_year....   268.8887
## gdp_per_capita.... 222.9683
## generation        2319.3296
## depression_percentage 4389.2658
## drug_death_rate    1101.7067
```

```
set.seed(377)
```

```
train.rf.us <- train(suicides.100k.pop ~ .,
                     data = train_us,
                     method = "rf",
                     tuneGrid = data.frame(mtry=1:5),
                     trControl = trainControl(method="cv", number=5, verboseIter = TRUE),
                     metric = "RMSE")
```

```

## + Fold1: mtry=1
## - Fold1: mtry=1
## + Fold1: mtry=2
## - Fold1: mtry=2
## + Fold1: mtry=3
## - Fold1: mtry=3
## + Fold1: mtry=4
## - Fold1: mtry=4
## + Fold1: mtry=5
## - Fold1: mtry=5
## + Fold2: mtry=1
## - Fold2: mtry=1
## + Fold2: mtry=2
## - Fold2: mtry=2
## + Fold2: mtry=3
## - Fold2: mtry=3
## + Fold2: mtry=4
## - Fold2: mtry=4
## + Fold2: mtry=5
## - Fold2: mtry=5
## + Fold3: mtry=1
## - Fold3: mtry=1
## + Fold3: mtry=2
## - Fold3: mtry=2
## + Fold3: mtry=3
## - Fold3: mtry=3
## + Fold3: mtry=4
## - Fold3: mtry=4
## + Fold3: mtry=5
## - Fold3: mtry=5
## + Fold4: mtry=1
## - Fold4: mtry=1
## + Fold4: mtry=2
## - Fold4: mtry=2
## + Fold4: mtry=3
## - Fold4: mtry=3
## + Fold4: mtry=4
## - Fold4: mtry=4
## + Fold4: mtry=5
## - Fold4: mtry=5
## + Fold5: mtry=1
## - Fold5: mtry=1
## + Fold5: mtry=2
## - Fold5: mtry=2
## + Fold5: mtry=3
## - Fold5: mtry=3
## + Fold5: mtry=4
## - Fold5: mtry=4
## + Fold5: mtry=5
## - Fold5: mtry=5
## Aggregating results
## Selecting tuning parameters
## Fitting mtry = 5 on full training set

```



```
train.rf.us$results
```

```
##      mtry      RMSE Rsquared      MAE      RMSESD RsquaredSD      MAESD
## 1      1 9.824508 0.8696212 7.994422 0.9381334 0.040652349 0.5209140
## 2      2 6.502285 0.9248426 4.913252 0.8379313 0.007879139 0.4761299
## 3      3 4.769440 0.9495409 3.396341 0.7533864 0.010192692 0.4333536
## 4      4 3.711369 0.9646292 2.495179 0.6784323 0.007789490 0.3832441
## 5      5 3.069317 0.9735388 2.018823 0.5291298 0.005027661 0.3227183
```

```
best.rf.us <- train.rf.us$finalModel
```

```
us.test_rf = as.data.frame(model.matrix(suicides.100k.pop ~ . + 0, data = test_us))
```

```
pred.best.rf_us <- predict(best.rf.us, newdata = us.test_rf)
pred.best.rf_us[1:5]
```

```
##           1           7           16           21           26
## 6.398268  3.707426 23.008092  7.826827 21.054450
```

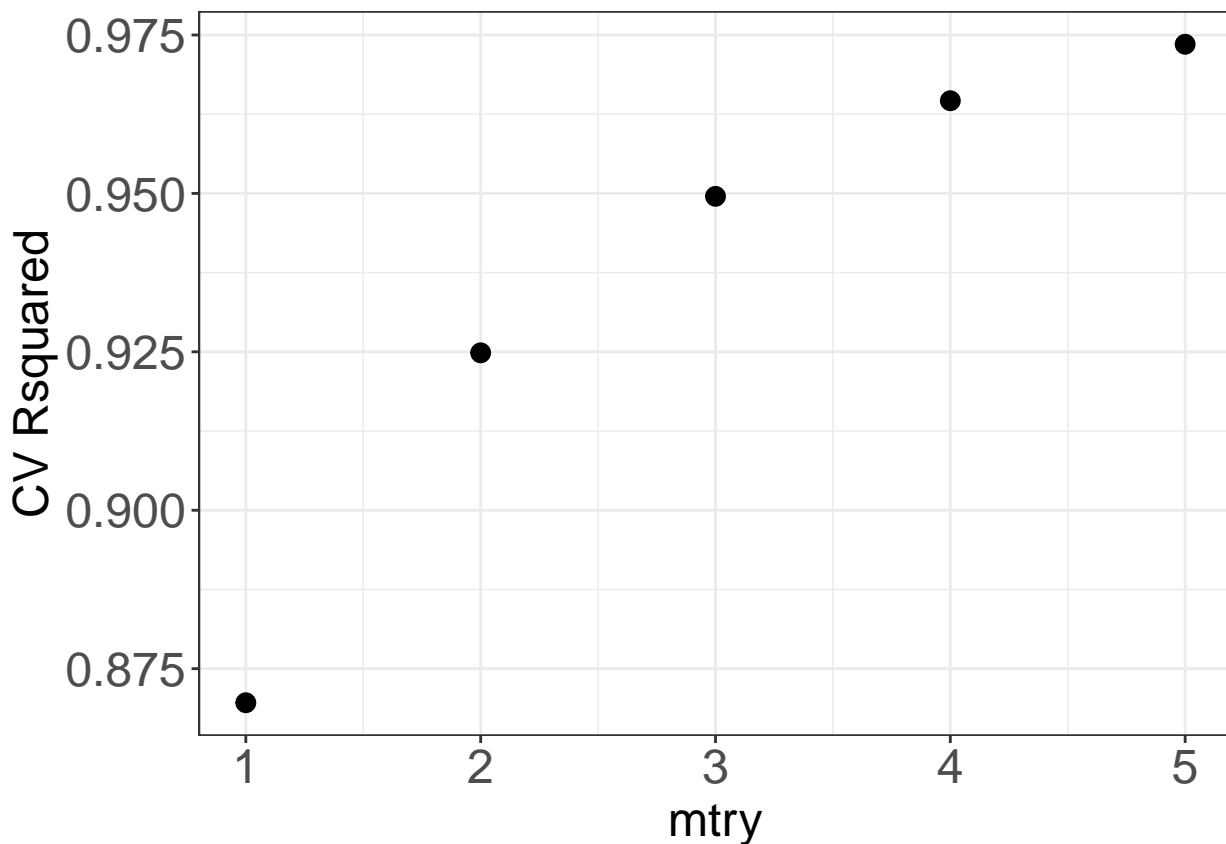
```
print("Random Forests OSR2:")
```

```
## [1] "Random Forests OSR2:"
```

```
OSR2(pred.best.rf_us, test_us$suicides.100k.pop, train_us$suicides.100k.pop)
```

```
## [1] 0.9645385
```

```
ggplot(train.rf.us$results, aes(x = mtry, y = Rsquared)) + geom_point(size = 3) +
  ylab("CV Rsquared") + theme_bw() + theme(axis.title=element_text(size=18), axis.text=element_text(size=12))
```



mtry = 10

```
set.seed(377)
train.rf.us_mtryTen <- train(suicides.100k.pop ~ .,
                             data = train_us,
                             method = "rf",
                             tuneGrid = data.frame(mtry=1:10),
                             trControl = trainControl(method="cv", number=5, verboseIter = TRUE),
                             metric = "RMSE")
```

```
## + Fold1: mtry= 1
## - Fold1: mtry= 1
## + Fold1: mtry= 2
## - Fold1: mtry= 2
## + Fold1: mtry= 3
## - Fold1: mtry= 3
## + Fold1: mtry= 4
## - Fold1: mtry= 4
## + Fold1: mtry= 5
## - Fold1: mtry= 5
## + Fold1: mtry= 6
## - Fold1: mtry= 6
## + Fold1: mtry= 7
## - Fold1: mtry= 7
## + Fold1: mtry= 8
## - Fold1: mtry= 8
## + Fold1: mtry= 9
## - Fold1: mtry= 9
## + Fold1: mtry=10
## - Fold1: mtry=10
## + Fold2: mtry= 1
## - Fold2: mtry= 1
## + Fold2: mtry= 2
## - Fold2: mtry= 2
## + Fold2: mtry= 3
## - Fold2: mtry= 3
## + Fold2: mtry= 4
## - Fold2: mtry= 4
## + Fold2: mtry= 5
## - Fold2: mtry= 5
## + Fold2: mtry= 6
## - Fold2: mtry= 6
## + Fold2: mtry= 7
## - Fold2: mtry= 7
## + Fold2: mtry= 8
## - Fold2: mtry= 8
## + Fold2: mtry= 9
## - Fold2: mtry= 9
## + Fold2: mtry=10
## - Fold2: mtry=10
## + Fold3: mtry= 1
## - Fold3: mtry= 1
## + Fold3: mtry= 2
## - Fold3: mtry= 2
```

```
## + Fold3: mtry= 3
## - Fold3: mtry= 3
## + Fold3: mtry= 4
## - Fold3: mtry= 4
## + Fold3: mtry= 5
## - Fold3: mtry= 5
## + Fold3: mtry= 6
## - Fold3: mtry= 6
## + Fold3: mtry= 7
## - Fold3: mtry= 7
## + Fold3: mtry= 8
## - Fold3: mtry= 8
## + Fold3: mtry= 9
## - Fold3: mtry= 9
## + Fold3: mtry=10
## - Fold3: mtry=10
## + Fold4: mtry= 1
## - Fold4: mtry= 1
## + Fold4: mtry= 2
## - Fold4: mtry= 2
## + Fold4: mtry= 3
## - Fold4: mtry= 3
## + Fold4: mtry= 4
## - Fold4: mtry= 4
## + Fold4: mtry= 5
## - Fold4: mtry= 5
## + Fold4: mtry= 6
## - Fold4: mtry= 6
## + Fold4: mtry= 7
## - Fold4: mtry= 7
## + Fold4: mtry= 8
## - Fold4: mtry= 8
## + Fold4: mtry= 9
## - Fold4: mtry= 9
## + Fold4: mtry=10
## - Fold4: mtry=10
## + Fold5: mtry= 1
## - Fold5: mtry= 1
## + Fold5: mtry= 2
## - Fold5: mtry= 2
## + Fold5: mtry= 3
## - Fold5: mtry= 3
## + Fold5: mtry= 4
## - Fold5: mtry= 4
## + Fold5: mtry= 5
## - Fold5: mtry= 5
## + Fold5: mtry= 6
## - Fold5: mtry= 6
## + Fold5: mtry= 7
## - Fold5: mtry= 7
## + Fold5: mtry= 8
## - Fold5: mtry= 8
## + Fold5: mtry= 9
## - Fold5: mtry= 9
```

```
## + Fold5: mtry=10
## - Fold5: mtry=10
## Aggregating results
## Selecting tuning parameters
## Fitting mtry = 10 on full training set

train.rf.us_mtryTen$results

##      mtry      RMSE Rsquared      MAE      RMSESD RsquaredSD      MAESD
## 1      1 9.882207 0.8543650 8.035307 1.0023155 0.036784552 0.6113408
## 2      2 6.620567 0.9187419 4.985777 0.9989036 0.023054109 0.5563487
## 3      3 4.875914 0.9456037 3.456866 0.7017972 0.007218984 0.4125931
## 4      4 3.752569 0.9659937 2.568780 0.6596917 0.006132700 0.3727510
## 5      5 3.000041 0.9743157 1.975137 0.5458457 0.005464792 0.3490734
## 6      6 2.617097 0.9784615 1.669313 0.5002927 0.004488329 0.3125495
## 7      7 2.349818 0.9807843 1.408615 0.4467046 0.006388239 0.2691800
## 8      8 2.211275 0.9820666 1.316461 0.3986787 0.005339521 0.2288858
## 9      9 1.990433 0.9844981 1.167108 0.4789708 0.007932799 0.2326738
## 10     10 1.889257 0.9860799 1.087407 0.3959739 0.005604698 0.2008353

best.rf.us_mtryTen <- train.rf.us_mtryTen$finalModel

pred.best.rf.us_mtryTen <- predict(best.rf.us_mtryTen, newdata = us.test_rf)
pred.best.rf.us_mtryTen[1:5]

##           1           7           16           21           26
## 5.047776 1.655800 24.156776 7.160834 20.078536

print("Random Forests OSR2:")

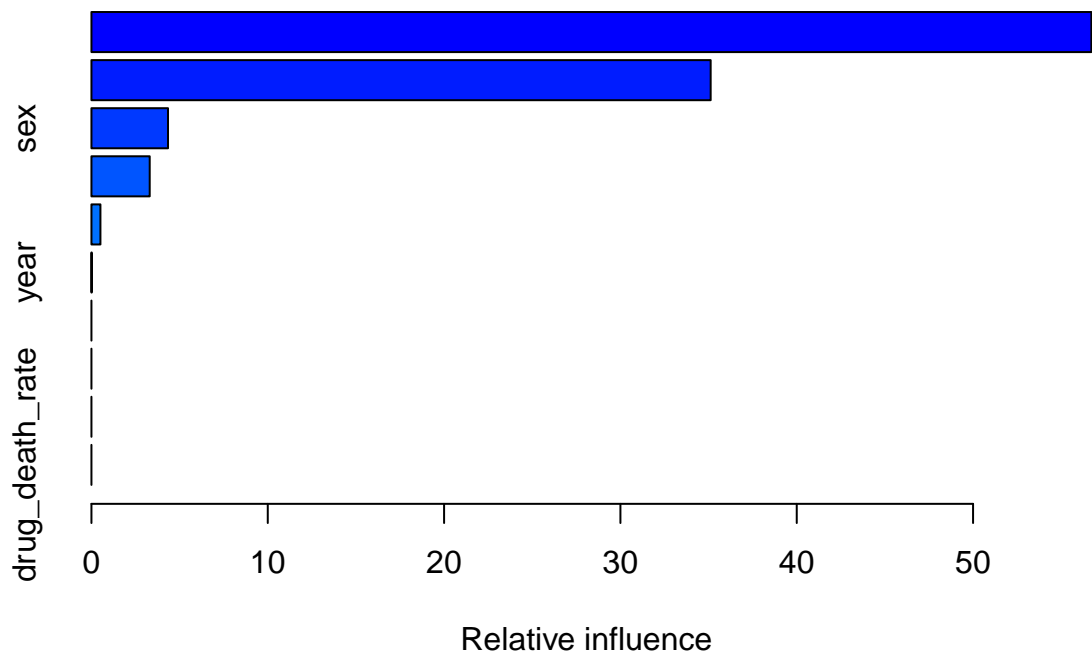
## [1] "Random Forests OSR2:"

OSR2(pred.best.rf.us_mtryTen, test_us$suicides.100k.pop, train_us$suicides.100k.pop)

## [1] 0.9928406
```

## Boosting

```
mod.boost <- gbm(suicides.100k.pop ~ .,
  data = train_us,
  distribution = "gaussian",
  n.trees = 1000,
  shrinkage = 0.001,
  interaction.depth = 2)
summary(mod.boost)
```



```
##               var      rel.inf
## suicides_no    suicides_no 56.71060064
## population     population 35.11841374
## sex            sex        4.34138880
## depression_percentage depression_percentage 3.30468990
## generation     generation 0.51025724
## year           year       0.01464967
## HDI.for.year   HDI.for.year 0.00000000
## gdp_for_year.... gdp_for_year.... 0.00000000
## gdp_per_capita.... gdp_per_capita.... 0.00000000
## drug_death_rate drug_death_rate 0.00000000
```

```
pred.boost <- predict(mod.boost, newdata = test_us, n.trees=1000)
OSR2(pred.boost, test_us$suicides.100k.pop, train_us$suicides.100k.pop)
```

```
## [1] 0.7628486
```

```
## took a while to run -- not super amazing OSR~2
# test_us_mm = as.data.frame(model.matrix(suicides.100k.pop ~ . + 0, data = test_us))
#
# gbmGrid <- expand.grid(interaction.depth = c(1,2,4,6,8,10),
#                         n.trees = (1:75)*500,
#                         shrinkage = 0.001,
#                         n.minobsinnode = 10)
# fitControl <- trainControl(## 10-fold CV
#                             method = "repeatedcv",
#                             number = 5,
#                             ## repeated ten times
#                             repeats = 5)
# set.seed(377)
# gbmFit2 <- train(suicides.100k.pop ~ ., data = train_us,
#                  method = "gbm",
#                  trControl = fitControl,
#                  verbose = FALSE,
```

```

#           tuneGrid = gbmGrid)
#
# gbm.best <- gbmFit2$finalModel
# gbm.pred.best.boost <- predict(gbm.best, newdata = test_us_mm, n.trees = 11500)
# OSR2(gbm.pred.best.boost, test_us$suicides.100k.pop, train_us$suicides.100k.pop)

## same results as above
# tGrid = expand.grid(n.trees = 1000, interaction.depth = 2, shrinkage = 0.001, n.minobsinnode = 10)tGr
#
# set.seed(377)
# train.boost <- train(suicides.100k.pop ~ .,
#                       data = train_us,
#                       method = "gbm",
#                       tuneGrid = tGrid,
#                       trControl = trainControl(method="cv", number=5,
#                                                verboseIter = FALSE),
#                       metric = "RMSE",
#                       distribution = "gaussian",
#                       verbose = FALSE)
# train.boost
# best.boost <- train.boost$finalModel
# pred.best.boost <- predict(best.boost, newdata = test_us_mm, n.trees = 11500) # can use same model ma
#
# ggplot(train.boost$results, aes(x = n.trees, y = Rsquared, colour = as.factor(interaction.depth))) +
#   ylab("CV Rsquared") + theme_bw() + theme(axis.title=element_text(size=18), axis.text=element_text(s
#   scale_color_discrete(name = "interaction.depth")

# OSR2(pred.best.boost, test_us$suicides.100k.pop, train_us$suicides.100k.pop)
# #Out-of-sample MAE:
# sum(abs(test_us$suicides.100k.pop - pred.best.boost))/nrow(test_us_mm)

```

# timeseries

12/18/2019

```
library(dplyr)

##
## Attaching package: 'dplyr'
##
## The following objects are masked from 'package:stats':
##
##   filter, lag
##
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
library(ggplot2)
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
##
## The following object is masked from 'package:base':
##
##   date
```

## Time series

```
OSR2 <- function(predictions, test, train) {
  SSE <- sum((test - predictions)^2)
  SST <- sum((test - mean(train))^2)
  r2 <- 1 - SSE/SST
  return(r2)
}
```

```
# R2 with a particular baseline
BaselineR2 <- function(predictions, truth, baseline) {
  SSE <- sum((truth - predictions)^2)
  SST <- sum((truth - baseline)^2)
  r2 <- 1 - SSE/SST
  return(r2)
}
```

```
# Load data and check it out
us_ts = read.csv("us_suicides_merged_no_na.csv")
str(us_ts)
```

```
## 'data.frame':   372 obs. of  14 variables:
## $ country      : Factor w/ 1 level "United States": 1 1 1 1 1 1 1 1 1 1 ...
## $ year         : int  1985 1985 1985 1985 1985 1985 1985 1985 1985 1985 ...
## $ sex          : Factor w/ 2 levels "female","male": 1 2 1 2 1 2 1 2 1 2 ...
## $ age          : Factor w/ 6 levels "15-24 years",...: 1 1 2 2 3 3 4 4 5 5 ...
## $ suicides_no  : int   854 4267 1242 5134 2105 6053 73 205 1568 5302 ...
```

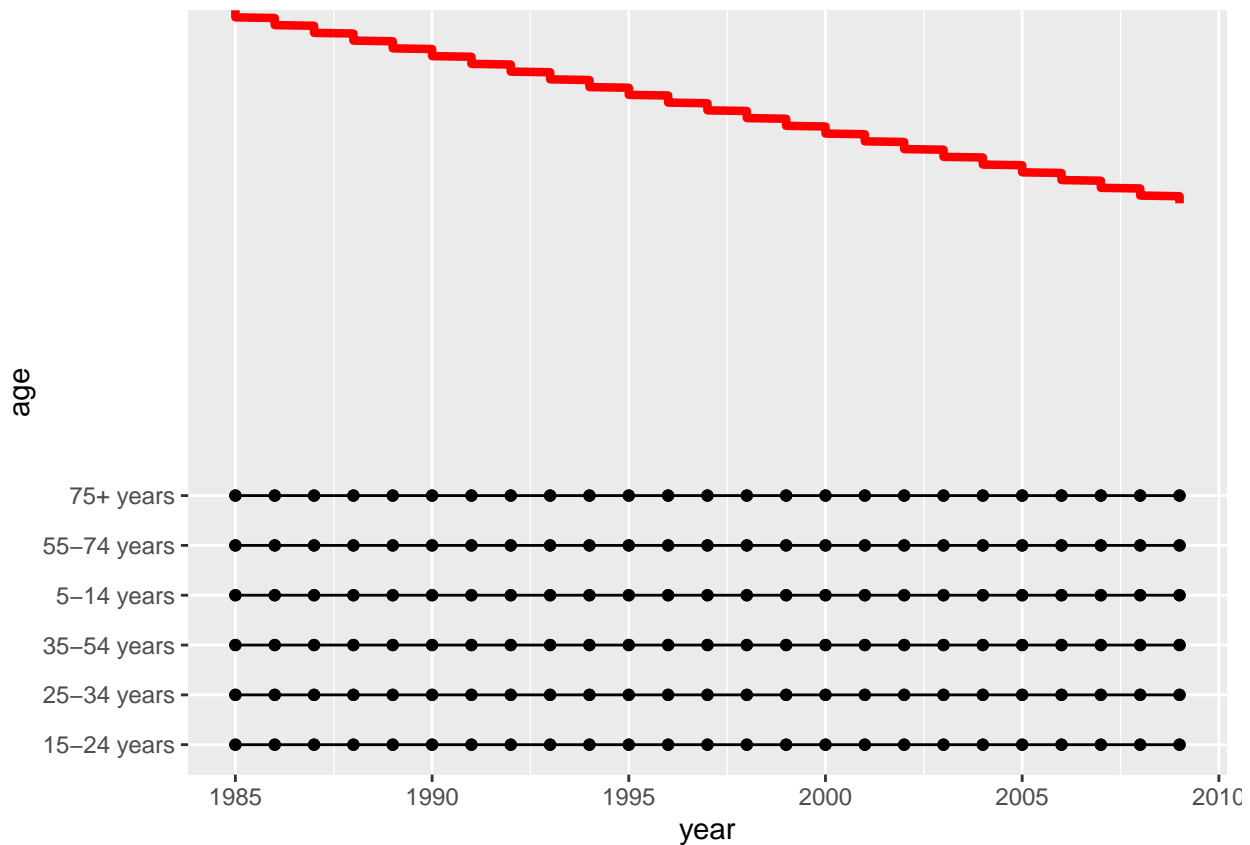
```
## $ population      : int  19589000 19962000 21041000 20986000 27763000 26589000 16553000 1737000
## $ suicides.100k.pop : num  4.36 21.38 5.9 24.46 7.58 ...
## $ country.year     : Factor w/ 31 levels "United States1985",...: 1 1 1 1 1 1 1 1 1 ...
## $ HDI.for.year     : num  0.841 0.841 0.841 0.841 0.841 0.841 0.841 0.841 0.841 0.841 ...
## $ gdp_for_year.... : num  4.35e+12 4.35e+12 4.35e+12 4.35e+12 4.35e+12 ...
## $ gdp_per_capita... : int   19693 19693 19693 19693 19693 19693 19693 19693 19693 19693 ...
## $ generation       : Factor w/ 6 levels "Boomers","G.I. Generation",...: 3 3 1 1 6 6 3 3 2 2 ...
## $ depression_percentage: num  6.52 3.52 6.52 3.52 6.52 ...
## $ drug_death_rate   : num  0 0 0 0 0 ...

# Use 2013 as testing data
train_ts <- us_ts %>% filter(year < 2010)
test_ts <- us_ts %>% filter(year >= 2010)
```

## BUILDING MODELS:

```
# Linear trend model training data -- Make a new column for the time period
# number (1, 2, ...). The dplyr syntax is a little tricky here -- n() is the
# number of rows in salesTrain, and seq_len(n()) returns the vector 1, 2, ...,
# n(). The end result is that we added a new variable called TimePeriod that
# takes values 1, 2, ..., n().
trainLM_ts<- train_ts %>% mutate(TimePeriod = seq_len(n()))
# Build and plot linear trend model
modLM <- lm(suicides.100k.pop~TimePeriod, data=trainLM_ts)
ggplot(trainLM_ts, aes(x=year, y=age)) +
  geom_line() +
  geom_point() +
  geom_line(aes(y=predict(modLM)), col="red", lwd=1.5)
```





### Random Walk model training data

```
trainRW_ts <- train_ts %>% mutate(LastYear = c(rep(NA, 12), head(suicides.100k.pop, -12)))
head(trainRW_ts, 15)
```

##	country	year	sex	age	suicides_no	population
## 1	United States	1985	female	15-24 years	854	19589000
## 2	United States	1985	male	15-24 years	4267	19962000
## 3	United States	1985	female	25-34 years	1242	21041000
## 4	United States	1985	male	25-34 years	5134	20986000
## 5	United States	1985	female	35-54 years	2105	27763000
## 6	United States	1985	male	35-54 years	6053	26589000
## 7	United States	1985	female	5-14 years	73	16553000
## 8	United States	1985	male	5-14 years	205	17370000
## 9	United States	1985	female	55-74 years	1568	21366000
## 10	United States	1985	male	55-74 years	5302	17971000
## 11	United States	1985	female	75+ years	466	7469000
## 12	United States	1985	male	75+ years	2177	4064000
## 13	United States	1986	female	15-24 years	844	19313000
## 14	United States	1986	male	15-24 years	4276	19715000
## 15	United States	1986	female	25-34 years	1261	21391000

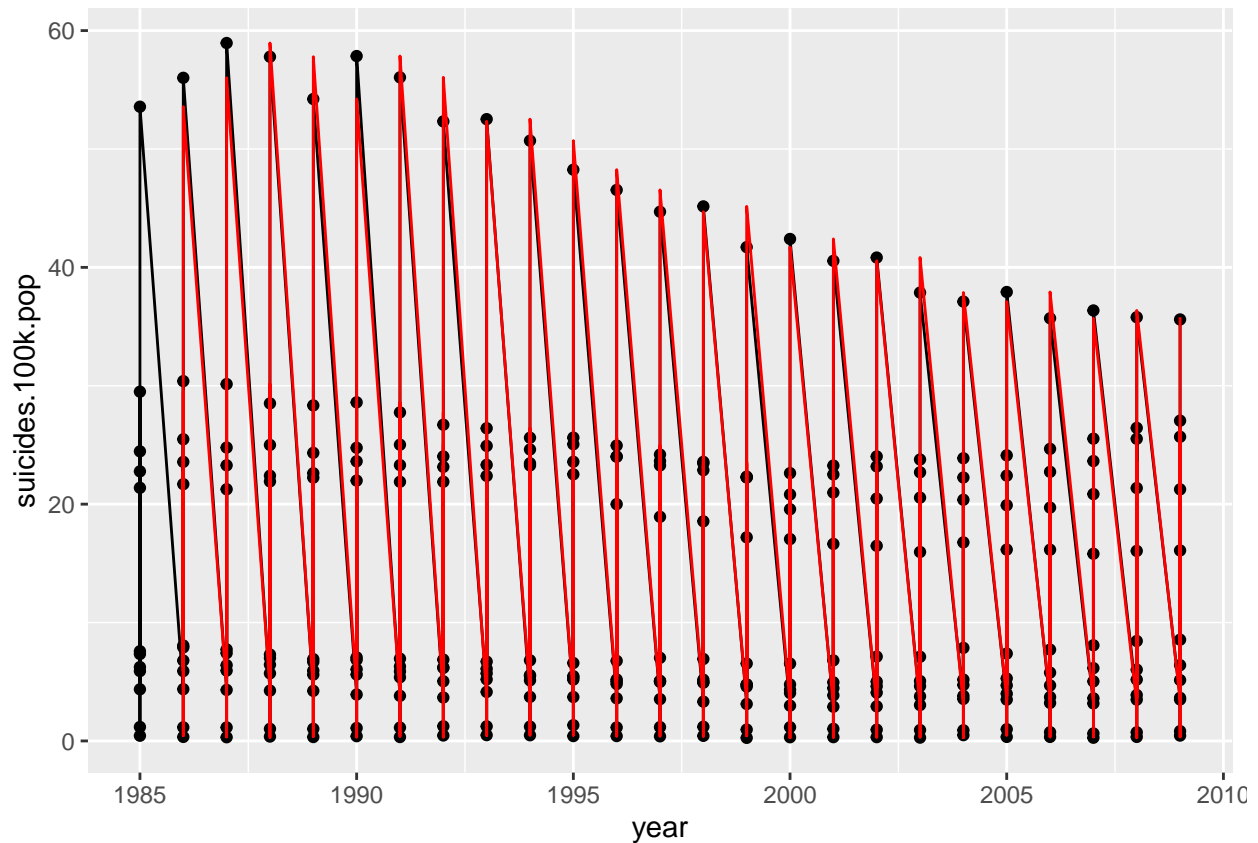
##	suicides.100k.pop	country.year	HDI.for.year	gdp_for_year....
## 1	4.36	United States1985	0.841	4.346734e+12
## 2	21.38	United States1985	0.841	4.346734e+12
## 3	5.90	United States1985	0.841	4.346734e+12
## 4	24.46	United States1985	0.841	4.346734e+12
## 5	7.58	United States1985	0.841	4.346734e+12

```
## 6      22.77 United States1985      0.841      4.346734e+12
## 7      0.44 United States1985      0.841      4.346734e+12
## 8      1.18 United States1985      0.841      4.346734e+12
## 9      7.34 United States1985      0.841      4.346734e+12
## 10     29.50 United States1985      0.841      4.346734e+12
## 11      6.24 United States1985      0.841      4.346734e+12
## 12     53.57 United States1985      0.841      4.346734e+12
## 13      4.37 United States1986      0.850      4.590155e+12
## 14     21.69 United States1986      0.850      4.590155e+12
## 15      5.90 United States1986      0.850      4.590155e+12
##      gdp_per_capita....      generation depression_percentage
## 1      19693      Generation X      6.519361
## 2      19693      Generation X      3.520442
## 3      19693      Boomers      6.519361
## 4      19693      Boomers      3.520442
## 5      19693      Silent      6.519361
## 6      19693      Silent      3.520442
## 7      19693      Generation X      6.519361
## 8      19693      Generation X      3.520442
## 9      19693 G.I. Generation      6.519361
## 10     19693 G.I. Generation      3.520442
## 11     19693 G.I. Generation      6.519361
## 12     19693 G.I. Generation      3.520442
## 13     20588      Generation X      6.274631
## 14     20588      Generation X      3.520368
## 15     20588      Boomers      6.274631
##      drug_death_rate LastYear
## 1      0.00000000      NA
## 2      0.00000000      NA
## 3      0.00000000      NA
## 4      0.00000000      NA
## 5      0.00000000      NA
## 6      10.69852941      NA
## 7      0.20000000      NA
## 8      0.20000000      NA
## 9      0.00000000      NA
## 10     0.00000000      NA
## 11     7.46761333      NA
## 12     7.46761333      NA
## 13     0.00000000      4.36
## 14     0.03970588      21.38
## 15     0.00000000      5.90
```

```
#random walk aka moving average
```

```
# Plot with an additional red line for our predictions as before
ggplot(trainRW_ts, aes(x=year, y=suicides.100k.pop)) +
  geom_line() +
  geom_point() +
  geom_line(aes(y=LastYear), col="red")
```

```
## Warning: Removed 12 rows containing missing values (geom_path).
```



```
# Proportion of percentages for which difference is more than 1.
table(abs(trainRW_ts$suicides.100k.pop-trainRW_ts$LastYear) >= 1)
```

```
##
## FALSE TRUE
## 255 33
```

```
# Compute training set R2
# Note that we need to remove the first observation since there is no
# prediction. This is achieved using tail(..., -1) which says to take all but
# the first observation.
BaselineR2(tail(trainRW_ts$LastYear, -12),
            tail(trainRW_ts$suicides.100k.pop, -12),
            mean(trainRW_ts$suicides.100k.pop))
```

```
## [1] 0.9965203
```

AR model

```
# We need to add sales yesterday and sales two days ago for the two term AR model
# head(.., -2) says take all but the last two
trainAR_ts <- train_ts %>%
  mutate(LastYear=c(rep(NA, 12), head(suicides.100k.pop, -12))) %>%
  mutate(TwoYearsAgo = c(rep(NA, 24), head(suicides.100k.pop, -24)))
# Do the regression with one lag term
mod2a <- lm(suicides.100k.pop~LastYear, data=trainAR_ts)
summary(mod2a)
```

```
##
```

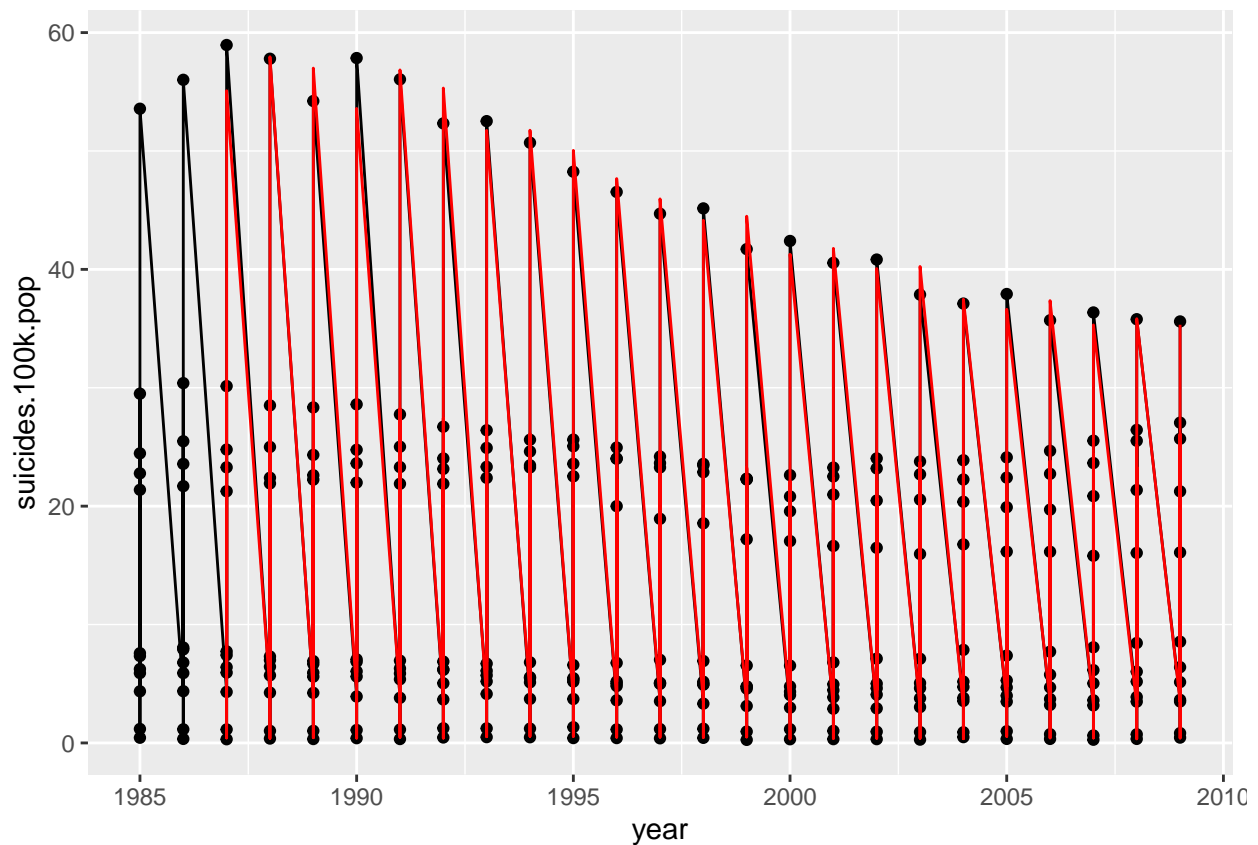
```
## Call:
## lm(formula = suicides.100k.pop ~ LastYear, data = trainAR_ts)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.0903 -0.2250 -0.0333  0.2597  4.2370
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.06576    0.06478   1.015   0.311
## LastYear     0.98759    0.00334 295.699 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7699 on 286 degrees of freedom
## (12 observations deleted due to missingness)
## Multiple R-squared:  0.9967, Adjusted R-squared:  0.9967
## F-statistic: 8.744e+04 on 1 and 286 DF, p-value: < 2.2e-16
```

```
# 2-term autoregressive model
mod2b <- lm(suicides.100k.pop~LastYear+TwoYearsAgo, data=trainAR_ts)
summary(mod2b)
```

```
##
## Call:
## lm(formula = suicides.100k.pop ~ LastYear + TwoYearsAgo, data = trainAR_ts)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.9838 -0.2199 -0.0377  0.2289  4.2588
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.07916    0.06455   1.226   0.221
## LastYear     0.93990    0.05792  16.229 <2e-16 ***
## TwoYearsAgo  0.04414    0.05727   0.771   0.442
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.751 on 273 degrees of freedom
## (24 observations deleted due to missingness)
## Multiple R-squared:  0.9969, Adjusted R-squared:  0.9968
## F-statistic: 4.333e+04 on 2 and 273 DF, p-value: < 2.2e-16
```

```
# Plot with an additional red line for our predictions as before
ggplot(trainAR_ts, aes(x=year, y=suicides.100k.pop)) +
  geom_line() +
  geom_point() +
  geom_line(aes(y=predict(mod2b, newdata=trainAR_ts)), col="red")
```

```
## Warning: Removed 24 rows containing missing values (geom_path).
```



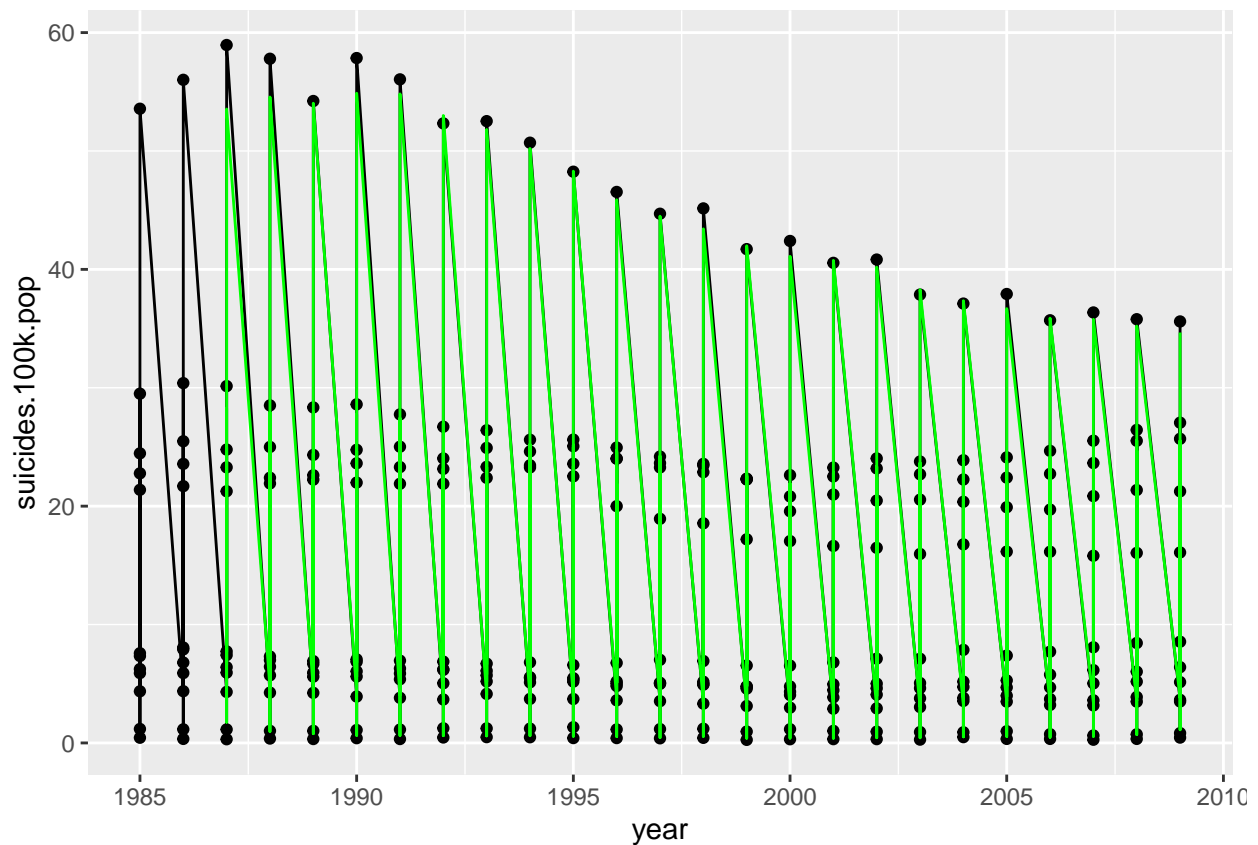
```
## Trying Random Forest
library(randomForest)
```

```
## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##   margin
## The following object is masked from 'package:dplyr':
##
##   combine
```

```
set.seed(349)
```

```
# Plug in all of the variables that we've created
mod.rf <- randomForest(suicides.100k.pop ~ LastYear + TwoYearsAgo + year, data = tail(trainAR_ts, -24))
ggplot(trainAR_ts, aes(x=year, y=suicides.100k.pop)) +
  geom_line() +
  geom_point() +
  geom_line(aes(y=predict(mod.rf, newdata=trainAR_ts)), col="green")
```

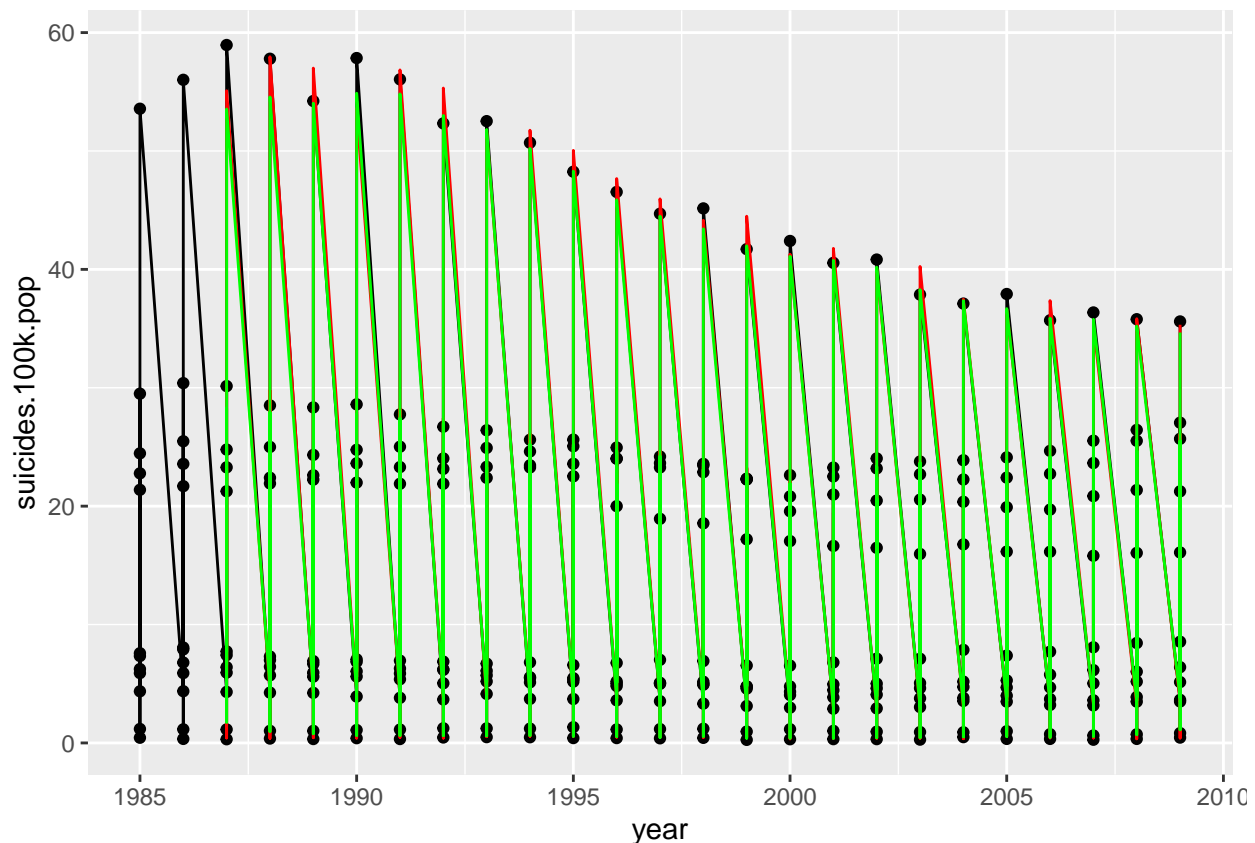
```
## Warning: Removed 24 rows containing missing values (geom_path).
```



```
# Both on the same plot:
ggplot(trainAR_ts, aes(x=year, y=suicides.100k.pop)) +
  geom_line() +
  geom_point() +
  geom_line(aes(y=predict(mod2b, newdata=trainAR_ts)), col="red") +
  geom_line(aes(y=predict(mod.rf, newdata=trainAR_ts)), col="green")
```

```
## Warning: Removed 24 rows containing missing values (geom_path).
```

```
## Warning: Removed 24 rows containing missing values (geom_path).
```



```
# Create Test Set
test_ts_final <- test_ts %>%
  mutate(LastYear=c(rep(NA, 12), head(suicides.100k.pop, -12))) %>%
  mutate(TwoYearsAgo = c(rep(NA, 24), head(suicides.100k.pop, -24)))

# Test set prediction and OSR~2
pred.test <- predict(mod2b, newdata = test_ts_final)
OSR2(tail(pred.test, -24), trainAR_ts$suicides.100k.pop, tail(test_ts_final$suicides.100k.pop, -24))

## Warning in test - predictions: longer object length is not a multiple of
## shorter object length
## [1] 0.9090414

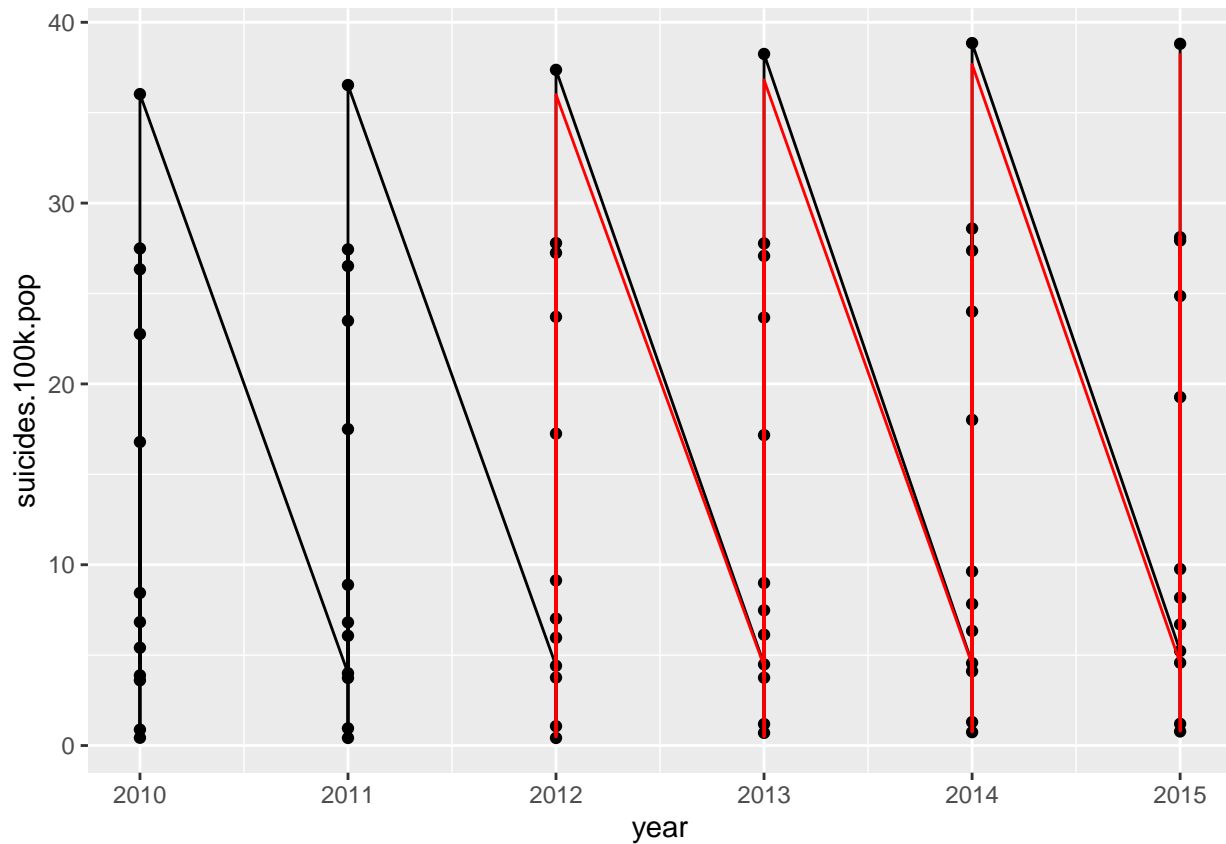
pred.test.rf <- predict(mod.rf, newdata = test_ts_final)
OSR2(tail(pred.test.rf, -24), trainAR_ts$suicides.100k.pop, tail(test_ts_final$suicides.100k.pop, -24))

## Warning in test - predictions: longer object length is not a multiple of
## shorter object length
## [1] 0.8945664

# we should test with a greater fraction in test set or go with random forest maybe?

# Test set plots
ggplot(test_ts_final, aes(x=year, y=suicides.100k.pop)) +
  geom_line() +
  geom_point() +
  geom_line(aes(y=pred.test), col="red")
```

```
## Warning: Removed 24 rows containing missing values (geom_path).
```



```
ggplot(test_ts_final, aes(x=year, y=suicides.100k.pop)) +  
  geom_line() +  
  geom_point() +  
  geom_line(aes(y=pred.test), col="red") +  
  geom_line(aes(y=pred.test.rf), col="green")
```

```
## Warning: Removed 24 rows containing missing values (geom_path).
```

```
## Warning: Removed 24 rows containing missing values (geom_path).
```



