

final-project-machine-learning

Merly Klaas

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```
#Import data
dat <- import(here("data","dat-category.csv"))

str(dat)
```

```
## 'data.frame':    583 obs. of  80 variables:
## $ facilityid      : int  1001 1101 2002 2101 3001 3101 4002 4101 5001 5002 ...
## $ id_overall      : num  1.55 1.68 1.67 1.25 2.54 ...
## $ sd              : num  0 0 0 0 0 0 0 0 0 0 ...
## $ smp             : num  0 0 0 0 0 0 0 0 0 0 ...
## $ hs              : num  1 0.33 1 0.5 1 0.67 0.5 0.75 1 1 ...
## $ s1              : num  0 0.67 0 0.5 0 0.33 0.5 0.25 0 0 ...
## $ group           : chr   "treatment" "control" "treatment" "control" ...
## $ type            : chr   "KB" "TK" "KB" "TK" ...
## $ teach_num       : int   1 3 2 2 2 3 2 4 1 2 ...
## $ sup_pnpm        : chr   "No" "No" "No" "No" ...
## $ sup_gov         : chr   "Yes" "Yes" "Yes" "Yes" ...
## $ sup_uni         : chr   "No" "No" "No" "No" ...
## $ sup_private     : chr   "No" "No" "No" "No" ...
## $ sup_ngo         : chr   "No" "No" "No" "No" ...
## $ sup_himpaudi    : chr   "No" "No" "No" "No" ...
## $ sup_socind      : chr   "No" "Yes" "No" "Yes" ...
## $ freq_wk         : num   3 6 3 6 3 6 0.3 6 2 2 ...
## $ duration        : int  120 180 120 120 120 150 120 120 120 120 ...
## $ tot_student     : int  23 40 29 23 33 15 43 43 30 37 ...
## $ ratio           : int  23 13 15 12 17 5 22 11 30 19 ...
## $ room_age_separate : int  0 0 1 0 0 0 0 0 0 0 ...
## $ parents_inv     : chr   "Yes" "Yes" "No" "Yes" ...
## $ refresher_training : chr   "Yes" "Yes" "Yes" "No" ...
## $ visit_gov       : int   4 2 0 0 1 0 0 0 5 1 ...
## $ room_avail      : int   1 1 2 1 1 1 1 1 1 1 ...
## $ book            : int   1 1 1 1 1 3 1 1 1 1 ...
## $ book_no         : int  25 60 11 23 20 NA 20 5 35 10 ...
## $ clean_water     : int   0 0 0 0 1 0 0 0 0 0 ...
## $ toilet          : int   0 0 0 0 1 2 0 0 0 0 ...
## $ bin             : int   1 1 0 1 1 1 1 1 0 1 ...
## $ sink            : int   0 2 0 0 1 0 0 0 0 0 ...
## $ weight_scale    : int   1 0 1 0 1 0 1 2 0 0 ...
## $ heigth          : int   0 0 1 0 1 0 1 2 1 1 ...
## $ head_measure    : int   0 0 0 0 0 0 0 0 0 0 ...
## $ firstaid        : int   1 2 1 0 0 0 1 0 0 0 ...
## $ facilities      : int   17 23 16 8 21 14 11 12 14 9 ...
```

```
## $ population      : int  970 970 1115 1115 1134 1134 1209 1209 1218 1218 ...
## $ household       : int  287 287 397 397 384 384 279 279 299 299 ...
## $ poor_hh         : int   90 90 112 112 254 254 100 100 119 119 ...
## $ poor_pct        : num  31.4 31.4 28.2 28.2 66.1 ...
## $ poor_level      : chr   "Moderate-High" "Moderate-High" "Moderate-High" "Moderate-High" ...
## $ bpd             : chr   "Yes" "Yes" "Yes" "Yes" ...
## $ bpd_meet        : int   0 0 0 0 1 1 6 6 1 1 ...
## $ cp_koperasi     : int   4 4 1 1 1 1 4 4 1 1 ...
## $ cp_gotong_royong : int   4 4 4 4 4 4 4 4 4 4 ...
## $ cp_karangta3a   : int   3 3 4 4 4 4 4 4 3 3 ...
## $ cp_health       : int   1 1 1 1 1 1 1 1 1 1 ...
## $ cp_women        : int   4 4 4 4 4 4 4 4 4 4 ...
## $ cp_labor        : int   4 4 4 4 4 4 4 4 4 4 ...
## $ mean_cp         : num   3.33 3.33 3 3 3 ...
## $ safe_play       : int   3 3 3 3 3 3 3 3 2 2 ...
## $ safe_clean      : int   2 2 2 2 3 3 3 3 2 2 ...
## $ safe_availplayground: int  1 1 3 3 3 3 3 3 3 3 ...
## $ safe_noharm     : int   3 3 3 3 3 3 4 4 3 3 ...
## $ safe_noconflict : int   3 3 3 3 3 3 3 3 3 3 ...
## $ safe_ownership  : int   3 3 3 3 3 3 3 3 3 3 ...
## $ mean_safe       : num   2.5 2.5 2.83 2.83 3 ...
## $ pp_raskin       : int   1 1 1 1 1 1 1 1 1 1 ...
## $ pp_blt          : int   2 2 2 2 1 1 1 1 2 2 ...
## $ pp_pkh          : int   1 1 1 1 1 1 1 1 1 1 ...
## $ pp_jamkesmas    : int   4 4 4 4 4 4 4 4 4 4 ...
## $ pp_kur          : int   1 1 1 1 1 1 1 1 1 1 ...
## $ pp_wash         : int   2 2 2 2 2 2 2 2 2 2 ...
## $ pp_pnpminf      : int   2 2 2 2 2 2 4 4 2 2 ...
## $ pp_pnpmeco      : int   4 4 4 4 1 1 3 3 1 1 ...
## $ pp_pnpmsoc      : int   1 1 1 1 1 1 1 1 1 1 ...
## $ pp_pnpmgen      : int   1 1 1 1 1 1 1 1 1 1 ...
## $ mean_pp         : num   1.9 1.9 1.9 1.9 1.5 1.5 1.9 1.9 1.6 1.6 ...
## $ market         : num   0.5 0.5 6 6 1 1 15 15 80 80 ...
## $ capital_district : num   0.7 0.7 6 6 9 ...
## $ capital_regency : num  100 100 98 98 113 113 95 95 80 80 ...
## $ capital_prov    : num  320 320 288 288 309 309 360 360 275 275 ...
## $ bank           : num  100 100 98 98 113 113 95 95 80 80 ...
## $ terminal        : num  100 100 98 98 113 113 15 15 80 80 ...
## $ health_service  : num   0.3 0.3 6 6 9 ...
## $ hospital        : num  100 100 98 98 113 113 95 95 70 70 ...
## $ primary_sc      : num   1 1 0.5 0.5 0.5 0.5 1 1 1 1 ...
## $ junior_sc       : num   0.7 0.7 1.5 1.5 1 ...
## $ high_school     : num   2 2 1.5 1.5 1 1 3.5 3.5 2 2 ...
## $ university      : num  100 100 98 98 113 113 95 95 80 80 ...
```

```
ff_glmpse(dat)
```

```
## $Continuous
##               label var_type   n missing_n
## facilityid    facilityid   <int> 583         0
## id_overall    id_overall   <dbl> 583         0
## sd            sd          <dbl> 583         0
## smp           smp         <dbl> 583         0
## hs            hs          <dbl> 583         0
```

## s1	s1	<dbl>	583	0
## teach_num	teach_num	<int>	583	0
## freq_wk	freq_wk	<dbl>	582	1
## duration	duration	<int>	582	1
## tot_student	tot_student	<int>	583	0
## ratio	ratio	<int>	583	0
## room_age_separate	room_age_separate	<int>	582	1
## visit_gov	visit_gov	<int>	583	0
## room_avail	room_avail	<int>	583	0
## book	book	<int>	583	0
## book_no	book_no	<int>	541	42
## clean_water	clean_water	<int>	583	0
## toilet	toilet	<int>	583	0
## bin	bin	<int>	583	0
## sink	sink	<int>	583	0
## weight_scale	weight_scale	<int>	583	0
## heigth	heigth	<int>	583	0
## head_measure	head_measure	<int>	583	0
## firstaid	firstaid	<int>	583	0
## facilities	facilities	<int>	583	0
## population	population	<int>	583	0
## household	household	<int>	579	4
## poor_hh	poor_hh	<int>	566	17
## poor_pct	poor_pct	<dbl>	564	19
## bpd_meet	bpd_meet	<int>	571	12
## cp_koperasi	cp_koperasi	<int>	583	0
## cp_gotong_royong	cp_gotong_royong	<int>	583	0
## cp_karangta3a	cp_karangta3a	<int>	583	0
## cp_health	cp_health	<int>	583	0
## cp_women	cp_women	<int>	583	0
## cp_labor	cp_labor	<int>	583	0
## mean_cp	mean_cp	<dbl>	583	0
## safe_play	safe_play	<int>	583	0
## safe_clean	safe_clean	<int>	583	0
## safe_availplayground	safe_availplayground	<int>	583	0
## safe_noharm	safe_noharm	<int>	583	0
## safe_noconflict	safe_noconflict	<int>	583	0
## safe_ownership	safe_ownership	<int>	583	0
## mean_safe	mean_safe	<dbl>	583	0
## pp_raskin	pp_raskin	<int>	583	0
## pp_blt	pp_blt	<int>	583	0
## pp_pkh	pp_pkh	<int>	583	0
## pp_jamkesmas	pp_jamkesmas	<int>	583	0
## pp_kur	pp_kur	<int>	583	0
## pp_wash	pp_wash	<int>	583	0
## pp_pnpminf	pp_pnpminf	<int>	583	0
## pp_pnpmeeco	pp_pnpmeeco	<int>	583	0
## pp_pnpmsoc	pp_pnpmsoc	<int>	583	0
## pp_pnpngen	pp_pnpngen	<int>	583	0
## mean_pp	mean_pp	<dbl>	583	0
## market	market	<dbl>	583	0
## capital_district	capital_district	<dbl>	583	0
## capital_regency	capital_regency	<dbl>	583	0
## capital_prov	capital_prov	<dbl>	583	0

## bank	bank	<dbl>	583	0
## terminal	terminal	<dbl>	583	0
## health_service	health_service	<dbl>	583	0
## hospital	hospital	<dbl>	583	0
## primary_sc	primary_sc	<dbl>	583	0
## junior_sc	junior_sc	<dbl>	583	0
## high_school	high_school	<dbl>	583	0
## university	university	<dbl>	583	0
##	missing_percent	mean	sd	min quartile_25
## facilityid	0.0	155464.0	87835.4	1001.0 81551.5
## id_overall	0.0	2.9	1.0	1.0 2.2
## sd	0.0	0.0	0.0	0.0 0.0
## smp	0.0	0.0	0.1	0.0 0.0
## hs	0.0	0.6	0.4	0.0 0.2
## s1	0.0	0.4	0.4	0.0 0.0
## teach_num	0.0	3.2	1.8	1.0 2.0
## freq_wk	0.2	5.3	1.2	0.3 4.2
## duration	0.2	136.0	80.7	15.0 120.0
## tot_student	0.0	35.8	21.0	0.0 21.5
## ratio	0.0	13.2	7.5	0.0 8.0
## room_age_separate	0.2	0.6	0.5	0.0 0.0
## visit_gov	0.0	2.2	3.0	0.0 0.0
## room_avail	0.0	1.7	0.9	1.0 1.0
## book	0.0	1.1	0.5	0.0 1.0
## book_no	7.2	72.7	123.3	2.0 15.0
## clean_water	0.0	0.9	0.6	0.0 1.0
## toilet	0.0	0.9	0.6	0.0 1.0
## bin	0.0	1.0	0.5	0.0 1.0
## sink	0.0	0.7	0.7	0.0 0.0
## weight_scale	0.0	0.8	0.5	0.0 0.0
## heigth	0.0	0.7	0.5	0.0 0.0
## head_measure	0.0	0.5	0.5	0.0 0.0
## firstaid	0.0	1.0	0.6	0.0 1.0
## facilities	0.0	20.6	6.4	1.0 16.5
## population	0.0	4346.8	3090.9	316.0 1908.0
## household	0.7	1312.8	1067.9	92.0 520.5
## poor_hh	2.9	465.5	460.9	23.0 168.0
## poor_pct	3.3	36.8	16.0	5.6 24.7
## bpd_meet	2.1	2.8	2.0	0.0 1.0
## cp_koperasi	0.0	3.8	0.7	1.0 4.0
## cp_gotong_royong	0.0	3.7	0.5	1.0 4.0
## cp_karangta3a	0.0	3.5	0.7	1.0 3.0
## cp_health	0.0	2.9	1.4	1.0 1.0
## cp_women	0.0	3.9	0.4	1.0 4.0
## cp_labor	0.0	4.0	0.2	1.0 4.0
## mean_cp	0.0	3.6	0.3	2.7 3.5
## safe_play	0.0	3.0	0.4	1.0 3.0
## safe_clean	0.0	2.9	0.4	1.0 3.0
## safe_availplayground	0.0	1.9	1.0	1.0 1.0
## safe_noharm	0.0	3.1	0.5	1.0 3.0
## safe_noconflict	0.0	3.1	0.5	1.0 3.0
## safe_ownership	0.0	3.0	0.4	1.0 3.0
## mean_safe	0.0	2.8	0.3	1.7 2.7
## pp_raskin	0.0	1.0	0.2	1.0 1.0

## pp_blt	0.0	2.0	0.4	1.0	2.0
## pp_pkh	0.0	2.7	1.5	1.0	1.0
## pp_jamkesmas	0.0	3.9	0.3	1.0	4.0
## pp_kur	0.0	2.7	1.4	1.0	1.0
## pp_wash	0.0	2.3	1.3	1.0	1.0
## pp_pnpminf	0.0	3.6	0.8	1.0	4.0
## pp_pnpmeco	0.0	3.6	1.0	1.0	4.0
## pp_pnpmsoc	0.0	1.9	1.3	1.0	1.0
## pp_pnpmgen	0.0	1.8	1.3	1.0	1.0
## mean_pp	0.0	2.6	0.5	1.4	2.2
## market	0.0	6.4	19.9	0.0	0.7
## capital_district	0.0	6.9	9.7	0.0	3.0
## capital_regency	0.0	33.3	47.5	1.0	12.0
## capital_prov	0.0	379.5	1571.3	2.0	40.0
## bank	0.0	10.1	18.4	0.0	2.0
## terminal	0.0	18.2	41.6	0.0	3.0
## health_service	0.0	1.9	4.5	0.0	0.2
## hospital	0.0	26.4	41.4	0.5	8.0
## primary_sc	0.0	4.3	58.6	0.0	0.1
## junior_sc	0.0	1.8	2.5	0.0	0.3
## high_school	0.0	4.4	5.0	0.0	1.0
## university	0.0	30.3	41.4	0.1	9.0
##	median	quartile_75	max		
## facilityid	155102.0	229102.5	310101.0		
## id_overall	2.8	3.6	5.7		
## sd	0.0	0.0	0.7		
## smp	0.0	0.0	1.0		
## hs	0.5	1.0	1.0		
## sl	0.4	0.8	1.0		
## teach_num	3.0	4.0	18.0		
## freq_wk	6.0	6.0	14.0		
## duration	120.0	150.0	1920.0		
## tot_student	31.0	44.0	190.0		
## ratio	12.0	16.0	59.0		
## room_age_separate	1.0	1.0	1.0		
## visit_gov	1.0	3.0	24.0		
## room_avail	1.0	2.0	7.0		
## book	1.0	1.0	3.0		
## book_no	30.0	77.0	999.0		
## clean_water	1.0	1.0	2.0		
## toilet	1.0	1.0	2.0		
## bin	1.0	1.0	2.0		
## sink	1.0	1.0	2.0		
## weight_scale	1.0	1.0	2.0		
## heigth	1.0	1.0	2.0		
## head_measure	0.0	1.0	2.0		
## firstaid	1.0	1.0	2.0		
## facilities	22.0	25.0	34.0		
## population	3427.0	6041.0	16605.0		
## household	925.0	1886.0	7776.0		
## poor_hh	308.0	612.0	3790.0		
## poor_pct	34.5	45.4	100.0		
## bpd_meet	3.0	3.5	11.0		
## cp_koperasi	4.0	4.0	4.0		

```

## cp_gotong_royong      4.0      4.0      4.0
## cp_karangta3a         4.0      4.0      4.0
## cp_health             4.0      4.0      4.0
## cp_women              4.0      4.0      4.0
## cp_labor              4.0      4.0      4.0
## mean_cp               3.7      4.0      4.0
## safe_play             3.0      3.0      4.0
## safe_clean            3.0      3.0      4.0
## safe_availplayground  1.0      3.0      3.0
## safe_noharm           3.0      3.0      8.0
## safe_noconflict       3.0      3.0      8.0
## safe_ownership        3.0      3.0      4.0
## mean_safe             2.8      3.0      4.3
## pp_raskin             1.0      1.0      2.0
## pp_blt                2.0      2.0      4.0
## pp_pkh                4.0      4.0      4.0
## pp_jamkesmas          4.0      4.0      4.0
## pp_kur                3.0      4.0      4.0
## pp_wash               2.0      4.0      4.0
## pp_pnpminf            4.0      4.0      4.0
## pp_pnpmeco            4.0      4.0      4.0
## pp_pnpmsoc            1.0      3.0      4.0
## pp_pnpmgen            1.0      3.0      4.0
## mean_pp               2.6      2.9      3.6
## market                2.5      5.0     250.0
## capital_district      5.0      7.0     118.0
## capital_regency       20.0     35.0     415.0
## capital_prov          90.0    180.0    10000.0
## bank                  5.0     10.0     160.0
## terminal              7.0     15.0     390.0
## health_service        0.8      2.0      50.0
## hospital              15.0     27.0     390.0
## primary_sc            0.3      0.5     999.0
## junior_sc             1.0      2.5      30.0
## high_school           3.0      6.0      32.0
## university            18.0     35.0     350.0
##
## $Categorical
##
##      label var_type    n missing_n missing_percent
## group      group    <chr> 583         0          0.0
## type        type    <chr> 583         0          0.0
## sup_pnpm    sup_pnpm <chr> 583         0          0.0
## sup_gov     sup_gov  <chr> 583         0          0.0
## sup_uni     sup_uni  <chr> 583         0          0.0
## sup_private sup_private <chr> 583         0          0.0
## sup_ngo     sup_ngo  <chr> 583         0          0.0
## sup_himpaudi sup_himpaudi <chr> 583         0          0.0
## sup_socind  sup_socind <chr> 583         0          0.0
## parents_inv parents_inv <chr> 583         0          0.0
## refresher_training refresher_training <chr> 583         0          0.0
## poor_level  poor_level <chr> 583         0          0.0
## bpd         bpd      <chr> 583         0          0.0
##
##      levels_n levels levels_count levels_percent
## group        2      -      -      -

```

```
## type          4      -      -      -
## sup_pnpm      3      -      -      -
## sup_gov       3      -      -      -
## sup_uni       3      -      -      -
## sup_private   3      -      -      -
## sup_ngo       3      -      -      -
## sup_himpaudi  3      -      -      -
## sup_socind    3      -      -      -
## parents_inv   2      -      -      -
## refresher_training 2      -      -      -
## poor_level    5      -      -      -
## bpd           2      -      -      -
```

```
dat %>%
select_if((is.character()))%>%
Hmisc::describe()
```

```
## .
##
## 13 Variables      583 Observations
## -----
## group
##      n missing distinct
##    583      0         2
##
## Value      control treatment
## Frequency    346      237
## Proportion   0.593    0.407
## -----
## type
##      n missing distinct
##    583      0         4
##
## Value      KB      RA      TK      TPQ
## Frequency   304     52    222     5
## Proportion 0.521 0.089 0.381 0.009
## -----
## sup_pnpm
##      n missing distinct
##    534     49         2
##
## Value      No Yes
## Frequency  427 107
## Proportion 0.8 0.2
## -----
## sup_gov
##      n missing distinct
##    534     49         2
##
## Value      No Yes
## Frequency   103 431
## Proportion 0.193 0.807
## -----
## sup_uni
```

```

##      n missing distinct
##    534      49        2
##
## Value      No   Yes
## Frequency   501   33
## Proportion 0.938 0.062
## -----
## sup_private
##      n missing distinct
##    534      49        2
##
## Value      No   Yes
## Frequency   506   28
## Proportion 0.948 0.052
## -----
## sup_ngo
##      n missing distinct
##    534      49        2
##
## Value      No   Yes
## Frequency   505   29
## Proportion 0.946 0.054
## -----
## sup_himpaudi
##      n missing distinct
##    534      49        2
##
## Value      No   Yes
## Frequency   510   24
## Proportion 0.955 0.045
## -----
## sup_socind
##      n missing distinct
##    534      49        2
##
## Value      No   Yes
## Frequency   261  273
## Proportion 0.489 0.511
## -----
## parents_inv
##      n missing distinct
##    583       0        2
##
## Value      No   Yes
## Frequency    57  526
## Proportion 0.098 0.902
## -----
## refresher_training
##      n missing distinct
##    583       0        2
##
## Value      No   Yes
## Frequency   112  471
## Proportion 0.192 0.808

```



```
## -----
## poor_level
##      n missing distinct
##    564      19        4
##
## Value          High          Low Moderate-High  Moderate-Low
## Frequency          201           26          299           38
## Proportion        0.356        0.046        0.530        0.067
## -----
## bpd
##      n missing distinct
##    583      0         2
##
## Value          3  Yes
## Frequency          6  577
## Proportion 0.01 0.99
## -----
```

```
blueprint <- recipe(x = dat,
  vars = colnames(dat),
  roles = c('ID', 'outcome', rep('predictor', 78))) %>%
  step_indicate_na(all_predictors()) %>%
  step_zv(all_numeric()) %>%
  step_impute_mean(all_numeric_predictors()) %>%
  step_impute_mode(all_nominal()) %>%
  step_poly("poor_pct", degree=3) %>%
  step_normalize(all_numeric_predictors()) %>%
  step_dummy(all_nominal(), one_hot=TRUE)

blueprint
```

```
## Recipe
##
## Inputs:
##
##      role #variables
##      ID      1
##      outcome  1
##      predictor 78
##
## Operations:
##
## Creating missing data variable indicators for all_predictors()
## Zero variance filter on all_numeric()
## Mean imputation for all_numeric_predictors()
## Mode imputation for all_nominal()
## Orthogonal polynomials on "poor_pct"
## Centering and scaling for all_numeric_predictors()
## Dummy variables from all_nominal()
```

```
view(blueprint %>% prep() %>% summary)
```

Split the data for: training and test subsets. . Let the training data have the 80% of cases and the test data have the 20% of the cases. Set the seed to 1031000 for any random sampling process before splitting data.

```

set.seed(1031000)
loc      <- sample(1:nrow(dat), round(nrow(dat) * 0.8))
ind_tr   <- dat[loc, ]
ind_te   <- dat[-loc, ]

dim(ind_tr)

```

```
## [1] 466 80
```

```
dim(ind_te)
```

```
## [1] 117 80
```

```

# Randomly shuffle the training dataset

set.seed(1031000) # for reproducibility

ind_tr = ind_tr[sample(nrow(ind_tr)),]

# Create 5 folds with equal size

folds = cut(seq(1,nrow(ind_tr)),breaks=10,labels=FALSE)

# Create the list for each fold

my.indices <- vector('list',10)

for(i in 1:10){
  my.indices[[i]] <- which(folds!=i)
}

cv <- trainControl(method = "cv",
                   index  = my.indices)

```

Model 1 Ridge Regression**

```

gridrd <- data.frame(alpha = 0, lambda = seq(0.01,3,.01))
gridrd

```

```

##      alpha lambda
## 1      0  0.01
## 2      0  0.02
## 3      0  0.03
## 4      0  0.04
## 5      0  0.05
## 6      0  0.06
## 7      0  0.07
## 8      0  0.08
## 9      0  0.09

```

## 10	0	0.10
## 11	0	0.11
## 12	0	0.12
## 13	0	0.13
## 14	0	0.14
## 15	0	0.15
## 16	0	0.16
## 17	0	0.17
## 18	0	0.18
## 19	0	0.19
## 20	0	0.20
## 21	0	0.21
## 22	0	0.22
## 23	0	0.23
## 24	0	0.24
## 25	0	0.25
## 26	0	0.26
## 27	0	0.27
## 28	0	0.28
## 29	0	0.29
## 30	0	0.30
## 31	0	0.31
## 32	0	0.32
## 33	0	0.33
## 34	0	0.34
## 35	0	0.35
## 36	0	0.36
## 37	0	0.37
## 38	0	0.38
## 39	0	0.39
## 40	0	0.40
## 41	0	0.41
## 42	0	0.42
## 43	0	0.43
## 44	0	0.44
## 45	0	0.45
## 46	0	0.46
## 47	0	0.47
## 48	0	0.48
## 49	0	0.49
## 50	0	0.50
## 51	0	0.51
## 52	0	0.52
## 53	0	0.53
## 54	0	0.54
## 55	0	0.55
## 56	0	0.56
## 57	0	0.57
## 58	0	0.58
## 59	0	0.59
## 60	0	0.60
## 61	0	0.61
## 62	0	0.62
## 63	0	0.63

## 64	0	0.64
## 65	0	0.65
## 66	0	0.66
## 67	0	0.67
## 68	0	0.68
## 69	0	0.69
## 70	0	0.70
## 71	0	0.71
## 72	0	0.72
## 73	0	0.73
## 74	0	0.74
## 75	0	0.75
## 76	0	0.76
## 77	0	0.77
## 78	0	0.78
## 79	0	0.79
## 80	0	0.80
## 81	0	0.81
## 82	0	0.82
## 83	0	0.83
## 84	0	0.84
## 85	0	0.85
## 86	0	0.86
## 87	0	0.87
## 88	0	0.88
## 89	0	0.89
## 90	0	0.90
## 91	0	0.91
## 92	0	0.92
## 93	0	0.93
## 94	0	0.94
## 95	0	0.95
## 96	0	0.96
## 97	0	0.97
## 98	0	0.98
## 99	0	0.99
## 100	0	1.00
## 101	0	1.01
## 102	0	1.02
## 103	0	1.03
## 104	0	1.04
## 105	0	1.05
## 106	0	1.06
## 107	0	1.07
## 108	0	1.08
## 109	0	1.09
## 110	0	1.10
## 111	0	1.11
## 112	0	1.12
## 113	0	1.13
## 114	0	1.14
## 115	0	1.15
## 116	0	1.16
## 117	0	1.17

## 118	0	1.18
## 119	0	1.19
## 120	0	1.20
## 121	0	1.21
## 122	0	1.22
## 123	0	1.23
## 124	0	1.24
## 125	0	1.25
## 126	0	1.26
## 127	0	1.27
## 128	0	1.28
## 129	0	1.29
## 130	0	1.30
## 131	0	1.31
## 132	0	1.32
## 133	0	1.33
## 134	0	1.34
## 135	0	1.35
## 136	0	1.36
## 137	0	1.37
## 138	0	1.38
## 139	0	1.39
## 140	0	1.40
## 141	0	1.41
## 142	0	1.42
## 143	0	1.43
## 144	0	1.44
## 145	0	1.45
## 146	0	1.46
## 147	0	1.47
## 148	0	1.48
## 149	0	1.49
## 150	0	1.50
## 151	0	1.51
## 152	0	1.52
## 153	0	1.53
## 154	0	1.54
## 155	0	1.55
## 156	0	1.56
## 157	0	1.57
## 158	0	1.58
## 159	0	1.59
## 160	0	1.60
## 161	0	1.61
## 162	0	1.62
## 163	0	1.63
## 164	0	1.64
## 165	0	1.65
## 166	0	1.66
## 167	0	1.67
## 168	0	1.68
## 169	0	1.69
## 170	0	1.70
## 171	0	1.71

## 172	0	1.72
## 173	0	1.73
## 174	0	1.74
## 175	0	1.75
## 176	0	1.76
## 177	0	1.77
## 178	0	1.78
## 179	0	1.79
## 180	0	1.80
## 181	0	1.81
## 182	0	1.82
## 183	0	1.83
## 184	0	1.84
## 185	0	1.85
## 186	0	1.86
## 187	0	1.87
## 188	0	1.88
## 189	0	1.89
## 190	0	1.90
## 191	0	1.91
## 192	0	1.92
## 193	0	1.93
## 194	0	1.94
## 195	0	1.95
## 196	0	1.96
## 197	0	1.97
## 198	0	1.98
## 199	0	1.99
## 200	0	2.00
## 201	0	2.01
## 202	0	2.02
## 203	0	2.03
## 204	0	2.04
## 205	0	2.05
## 206	0	2.06
## 207	0	2.07
## 208	0	2.08
## 209	0	2.09
## 210	0	2.10
## 211	0	2.11
## 212	0	2.12
## 213	0	2.13
## 214	0	2.14
## 215	0	2.15
## 216	0	2.16
## 217	0	2.17
## 218	0	2.18
## 219	0	2.19
## 220	0	2.20
## 221	0	2.21
## 222	0	2.22
## 223	0	2.23
## 224	0	2.24
## 225	0	2.25

##	226	0	2.26
##	227	0	2.27
##	228	0	2.28
##	229	0	2.29
##	230	0	2.30
##	231	0	2.31
##	232	0	2.32
##	233	0	2.33
##	234	0	2.34
##	235	0	2.35
##	236	0	2.36
##	237	0	2.37
##	238	0	2.38
##	239	0	2.39
##	240	0	2.40
##	241	0	2.41
##	242	0	2.42
##	243	0	2.43
##	244	0	2.44
##	245	0	2.45
##	246	0	2.46
##	247	0	2.47
##	248	0	2.48
##	249	0	2.49
##	250	0	2.50
##	251	0	2.51
##	252	0	2.52
##	253	0	2.53
##	254	0	2.54
##	255	0	2.55
##	256	0	2.56
##	257	0	2.57
##	258	0	2.58
##	259	0	2.59
##	260	0	2.60
##	261	0	2.61
##	262	0	2.62
##	263	0	2.63
##	264	0	2.64
##	265	0	2.65
##	266	0	2.66
##	267	0	2.67
##	268	0	2.68
##	269	0	2.69
##	270	0	2.70
##	271	0	2.71
##	272	0	2.72
##	273	0	2.73
##	274	0	2.74
##	275	0	2.75
##	276	0	2.76
##	277	0	2.77
##	278	0	2.78
##	279	0	2.79

```
## 280      0    2.80
## 281      0    2.81
## 282      0    2.82
## 283      0    2.83
## 284      0    2.84
## 285      0    2.85
## 286      0    2.86
## 287      0    2.87
## 288      0    2.88
## 289      0    2.89
## 290      0    2.90
## 291      0    2.91
## 292      0    2.92
## 293      0    2.93
## 294      0    2.94
## 295      0    2.95
## 296      0    2.96
## 297      0    2.97
## 298      0    2.98
## 299      0    2.99
## 300      0    3.00
```

```
ridge_mod <- caret::train(blueprint,
                           data      = ind_tr,
                           method    = "glmnet",
                           tuneGrid  = gridrd,
                           trControl = cv)

ridge_mod
```

```
## glmnet
##
## 466 samples
## 79 predictor
##
## Recipe steps: indicate_na, zv, impute_mean, impute_mode, poly, normalize, dummy
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 419, 419, 420, 419, ...
## Resampling results across tuning parameters:
##
##   lambda  RMSE      Rsquared  MAE
##   0.01    0.8954980  0.3184985  0.7140117
##   0.02    0.8954980  0.3184985  0.7140117
##   0.03    0.8954980  0.3184985  0.7140117
##   0.04    0.8954980  0.3184985  0.7140117
##   0.05    0.8942442  0.3193028  0.7128977
##   0.06    0.8901482  0.3217710  0.7096716
##   0.07    0.8865964  0.3239794  0.7067947
##   0.08    0.8834648  0.3259961  0.7041966
##   0.09    0.8806941  0.3278432  0.7018362
##   0.10    0.8782569  0.3295182  0.6997187
##   0.11    0.8760759  0.3310662  0.6977422
##   0.12    0.8741258  0.3324945  0.6958802
##   0.13    0.8723843  0.3338071  0.6941502
```


##	0.14	0.8708273	0.3350097	0.6926061
##	0.15	0.8694315	0.3361122	0.6911916
##	0.16	0.8681671	0.3371394	0.6898891
##	0.17	0.8670290	0.3380845	0.6887582
##	0.18	0.8659929	0.3389630	0.6877140
##	0.19	0.8650719	0.3397539	0.6867412
##	0.20	0.8642259	0.3404989	0.6858105
##	0.21	0.8634672	0.3411764	0.6849267
##	0.22	0.8627784	0.3418013	0.6841446
##	0.23	0.8621650	0.3423602	0.6836088
##	0.24	0.8616039	0.3428806	0.6831073
##	0.25	0.8611073	0.3433403	0.6826736
##	0.26	0.8606467	0.3437756	0.6822475
##	0.27	0.8602406	0.3441585	0.6818356
##	0.28	0.8598688	0.3445128	0.6814335
##	0.29	0.8595356	0.3448331	0.6810412
##	0.30	0.8592440	0.3451096	0.6807004
##	0.31	0.8589737	0.3453694	0.6804063
##	0.32	0.8587381	0.3455952	0.6801293
##	0.33	0.8585317	0.3457890	0.6798783
##	0.34	0.8583409	0.3459705	0.6796429
##	0.35	0.8581772	0.3461281	0.6794144
##	0.36	0.8580382	0.3462565	0.6791951
##	0.37	0.8579142	0.3463707	0.6789774
##	0.38	0.8578083	0.3464700	0.6787668
##	0.39	0.8577194	0.3465500	0.6786029
##	0.40	0.8576452	0.3466141	0.6784741
##	0.41	0.8575818	0.3466691	0.6783575
##	0.42	0.8575334	0.3467117	0.6782542
##	0.43	0.8574995	0.3467344	0.6781539
##	0.44	0.8574769	0.3467442	0.6780528
##	0.45	0.8574632	0.3467463	0.6779548
##	0.46	0.8574581	0.3467436	0.6778586
##	0.47	0.8574613	0.3467294	0.6777685
##	0.48	0.8574746	0.3467028	0.6776858
##	0.49	0.8574934	0.3466716	0.6776031
##	0.50	0.8575226	0.3466341	0.6775275
##	0.51	0.8575577	0.3465904	0.6774636
##	0.52	0.8576020	0.3465324	0.6774160
##	0.53	0.8576528	0.3464672	0.6773665
##	0.54	0.8577084	0.3463977	0.6773311
##	0.55	0.8577700	0.3463277	0.6773042
##	0.56	0.8578319	0.3462574	0.6772856
##	0.57	0.8579013	0.3461747	0.6772921
##	0.58	0.8579764	0.3460855	0.6773196
##	0.59	0.8580558	0.3459922	0.6773472
##	0.60	0.8581403	0.3458985	0.6773768
##	0.61	0.8582256	0.3458078	0.6774044
##	0.62	0.8583152	0.3457085	0.6774334
##	0.63	0.8584092	0.3456035	0.6774680
##	0.64	0.8585066	0.3454949	0.6775016
##	0.65	0.8586070	0.3453840	0.6775364
##	0.66	0.8587121	0.3452732	0.6775840
##	0.67	0.8588145	0.3451682	0.6776322

##	0.68	0.8589204	0.3450547	0.6776796
##	0.69	0.8590300	0.3449359	0.6777233
##	0.70	0.8591430	0.3448137	0.6777668
##	0.71	0.8592590	0.3446886	0.6778195
##	0.72	0.8593787	0.3445629	0.6778788
##	0.73	0.8594957	0.3444454	0.6779458
##	0.74	0.8596138	0.3443255	0.6780161
##	0.75	0.8597343	0.3441995	0.6780951
##	0.76	0.8598581	0.3440694	0.6781781
##	0.77	0.8599840	0.3439372	0.6782599
##	0.78	0.8601124	0.3438030	0.6783419
##	0.79	0.8602434	0.3436693	0.6784252
##	0.80	0.8603706	0.3435453	0.6785064
##	0.81	0.8604975	0.3434215	0.6785859
##	0.82	0.8606253	0.3432924	0.6786702
##	0.83	0.8607555	0.3431602	0.6787566
##	0.84	0.8608881	0.3430253	0.6788428
##	0.85	0.8610222	0.3428895	0.6789286
##	0.86	0.8611565	0.3427542	0.6790139
##	0.87	0.8612941	0.3426207	0.6791144
##	0.88	0.8614275	0.3424949	0.6792200
##	0.89	0.8615620	0.3423665	0.6793244
##	0.90	0.8616979	0.3422328	0.6794273
##	0.91	0.8618359	0.3420961	0.6795280
##	0.92	0.8619764	0.3419568	0.6796286
##	0.93	0.8621179	0.3418166	0.6797288
##	0.94	0.8622608	0.3416754	0.6798317
##	0.95	0.8624051	0.3415356	0.6799357
##	0.96	0.8625473	0.3414029	0.6800388
##	0.97	0.8626878	0.3412737	0.6801417
##	0.98	0.8628279	0.3411414	0.6802446
##	0.99	0.8629684	0.3410075	0.6803577
##	1.00	0.8631103	0.3408720	0.6804786
##	1.01	0.8632541	0.3407344	0.6806040
##	1.02	0.8633990	0.3405961	0.6807290
##	1.03	0.8635450	0.3404568	0.6808575
##	1.04	0.8636906	0.3403203	0.6809856
##	1.05	0.8638371	0.3401871	0.6811125
##	1.06	0.8639798	0.3400605	0.6812384
##	1.07	0.8641225	0.3399331	0.6813631
##	1.08	0.8642650	0.3398023	0.6814933
##	1.09	0.8644077	0.3396706	0.6816223
##	1.10	0.8645522	0.3395371	0.6817569
##	1.11	0.8646982	0.3394020	0.6819037
##	1.12	0.8648451	0.3392662	0.6820508
##	1.13	0.8649929	0.3391297	0.6822066
##	1.14	0.8651395	0.3389964	0.6823611
##	1.15	0.8652881	0.3388647	0.6825162
##	1.16	0.8654325	0.3387404	0.6826650
##	1.17	0.8655770	0.3386166	0.6828123
##	1.18	0.8657201	0.3384903	0.6829584
##	1.19	0.8658634	0.3383627	0.6831060
##	1.20	0.8660074	0.3382342	0.6832587
##	1.21	0.8661530	0.3381040	0.6834115

##	1.22	0.8662996	0.3379728	0.6835638
##	1.23	0.8664471	0.3378409	0.6837156
##	1.24	0.8665951	0.3377086	0.6838671
##	1.25	0.8667415	0.3375798	0.6840167
##	1.26	0.8668907	0.3374510	0.6841701
##	1.27	0.8670357	0.3373299	0.6843192
##	1.28	0.8671802	0.3372101	0.6844666
##	1.29	0.8673236	0.3370895	0.6846124
##	1.30	0.8674668	0.3369664	0.6847576
##	1.31	0.8676095	0.3368436	0.6849001
##	1.32	0.8677535	0.3367194	0.6850425
##	1.33	0.8678986	0.3365938	0.6851850
##	1.34	0.8680447	0.3364675	0.6853269
##	1.35	0.8681914	0.3363405	0.6854686
##	1.36	0.8683387	0.3362133	0.6856101
##	1.37	0.8684837	0.3360897	0.6857492
##	1.38	0.8686323	0.3359647	0.6858922
##	1.39	0.8687773	0.3358467	0.6860346
##	1.40	0.8689204	0.3357321	0.6861744
##	1.41	0.8690639	0.3356170	0.6863155
##	1.42	0.8692054	0.3355001	0.6864582
##	1.43	0.8693471	0.3353823	0.6866008
##	1.44	0.8694887	0.3352645	0.6867418
##	1.45	0.8696313	0.3351456	0.6868828
##	1.46	0.8697749	0.3350255	0.6870237
##	1.47	0.8699193	0.3349048	0.6871643
##	1.48	0.8700644	0.3347834	0.6873047
##	1.49	0.8702095	0.3346622	0.6874448
##	1.50	0.8703534	0.3345434	0.6875830
##	1.51	0.8704986	0.3344248	0.6877224
##	1.52	0.8706434	0.3343089	0.6878647
##	1.53	0.8707856	0.3341980	0.6880102
##	1.54	0.8709272	0.3340882	0.6881545
##	1.55	0.8710684	0.3339783	0.6882980
##	1.56	0.8712078	0.3338665	0.6884404
##	1.57	0.8713473	0.3337545	0.6885879
##	1.58	0.8714867	0.3336425	0.6887357
##	1.59	0.8716269	0.3335296	0.6888862
##	1.60	0.8717680	0.3334158	0.6890381
##	1.61	0.8719098	0.3333012	0.6891913
##	1.62	0.8720523	0.3331860	0.6893491
##	1.63	0.8721948	0.3330710	0.6895068
##	1.64	0.8723374	0.3329562	0.6896641
##	1.65	0.8724781	0.3328445	0.6898191
##	1.66	0.8726215	0.3327317	0.6899757
##	1.67	0.8727628	0.3326233	0.6901287
##	1.68	0.8729023	0.3325183	0.6902792
##	1.69	0.8730415	0.3324139	0.6904315
##	1.70	0.8731803	0.3323097	0.6905828
##	1.71	0.8733170	0.3322040	0.6907322
##	1.72	0.8734540	0.3320977	0.6908812
##	1.73	0.8735902	0.3319921	0.6910285
##	1.74	0.8737272	0.3318857	0.6911800
##	1.75	0.8738650	0.3317785	0.6913378

##	1.76	0.8740034	0.3316705	0.6914955
##	1.77	0.8741424	0.3315621	0.6916530
##	1.78	0.8742821	0.3314529	0.6918105
##	1.79	0.8744213	0.3313444	0.6919675
##	1.80	0.8745607	0.3312360	0.6921240
##	1.81	0.8746982	0.3311307	0.6922786
##	1.82	0.8748380	0.3310244	0.6924344
##	1.83	0.8749768	0.3309207	0.6925882
##	1.84	0.8751137	0.3308206	0.6927392
##	1.85	0.8752496	0.3307222	0.6928889
##	1.86	0.8753860	0.3306232	0.6930386
##	1.87	0.8755203	0.3305247	0.6931861
##	1.88	0.8756538	0.3304247	0.6933328
##	1.89	0.8757873	0.3303248	0.6934788
##	1.90	0.8759204	0.3302252	0.6936236
##	1.91	0.8760541	0.3301250	0.6937683
##	1.92	0.8761883	0.3300242	0.6939131
##	1.93	0.8763232	0.3299227	0.6940579
##	1.94	0.8764586	0.3298206	0.6942026
##	1.95	0.8765945	0.3297181	0.6943471
##	1.96	0.8767304	0.3296157	0.6944913
##	1.97	0.8768662	0.3295134	0.6946353
##	1.98	0.8770009	0.3294134	0.6947779
##	1.99	0.8771354	0.3293145	0.6949199
##	2.00	0.8772718	0.3292149	0.6950631
##	2.01	0.8774064	0.3291186	0.6952038
##	2.02	0.8775399	0.3290245	0.6953428
##	2.03	0.8776725	0.3289318	0.6954830
##	2.04	0.8778057	0.3288386	0.6956233
##	2.05	0.8779372	0.3287461	0.6957619
##	2.06	0.8780671	0.3286523	0.6958992
##	2.07	0.8781976	0.3285580	0.6960365
##	2.08	0.8783270	0.3284648	0.6961721
##	2.09	0.8784568	0.3283712	0.6963077
##	2.10	0.8785872	0.3282769	0.6964433
##	2.11	0.8787180	0.3281822	0.6965789
##	2.12	0.8788494	0.3280868	0.6967145
##	2.13	0.8789811	0.3279913	0.6968498
##	2.14	0.8791132	0.3278953	0.6969849
##	2.15	0.8792451	0.3277996	0.6971197
##	2.16	0.8793769	0.3277043	0.6972543
##	2.17	0.8795083	0.3276097	0.6973880
##	2.18	0.8796386	0.3275166	0.6975229
##	2.19	0.8797703	0.3274230	0.6976641
##	2.20	0.8799023	0.3273298	0.6978049
##	2.21	0.8800317	0.3272412	0.6979425
##	2.22	0.8801605	0.3271540	0.6980792
##	2.23	0.8802890	0.3270673	0.6982154
##	2.24	0.8804180	0.3269800	0.6983537
##	2.25	0.8805450	0.3268938	0.6984908
##	2.26	0.8806709	0.3268062	0.6986267
##	2.27	0.8807972	0.3267180	0.6987629
##	2.28	0.8809228	0.3266308	0.6988995
##	2.29	0.8810485	0.3265434	0.6990373

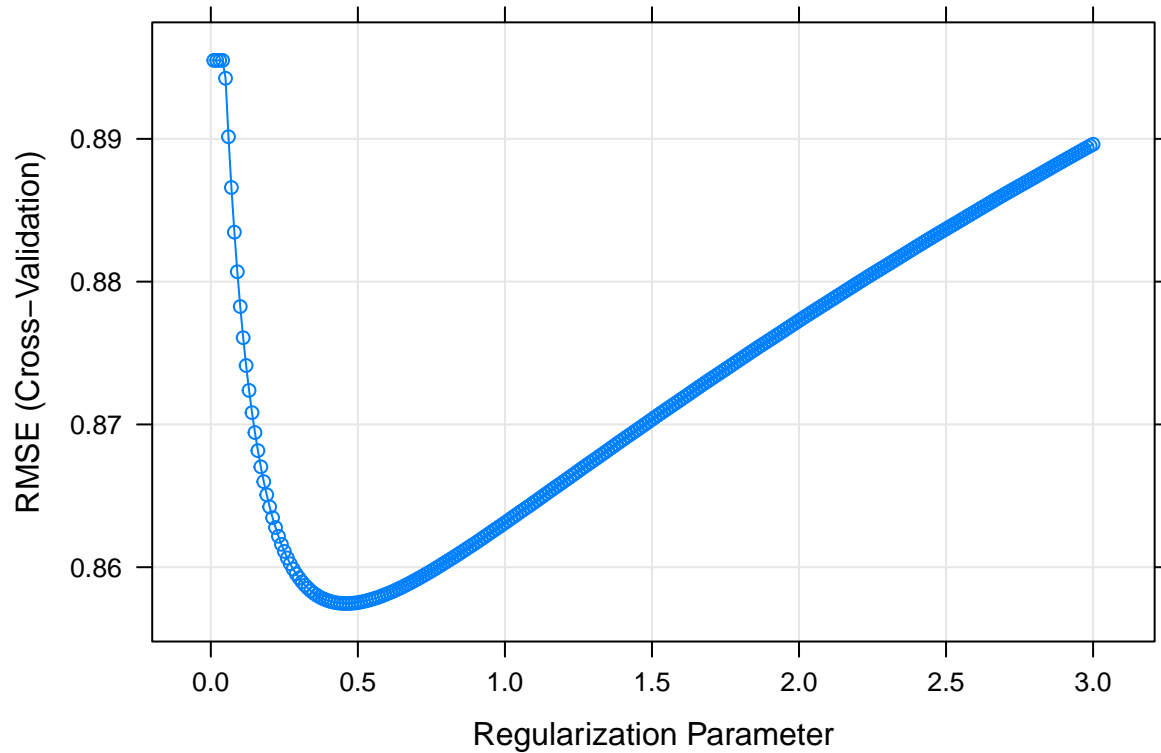
##	2.30	0.8811746	0.3264555	0.6991758
##	2.31	0.8813011	0.3263671	0.6993161
##	2.32	0.8814281	0.3262783	0.6994565
##	2.33	0.8815555	0.3261890	0.6995968
##	2.34	0.8816834	0.3260989	0.6997371
##	2.35	0.8818118	0.3260084	0.6998775
##	2.36	0.8819398	0.3259184	0.7000175
##	2.37	0.8820677	0.3258285	0.7001573
##	2.38	0.8821953	0.3257392	0.7002965
##	2.39	0.8823217	0.3256522	0.7004341
##	2.40	0.8824489	0.3255648	0.7005722
##	2.41	0.8825771	0.3254770	0.7007112
##	2.42	0.8827035	0.3253924	0.7008545
##	2.43	0.8828294	0.3253089	0.7009995
##	2.44	0.8829540	0.3252274	0.7011431
##	2.45	0.8830791	0.3251454	0.7012892
##	2.46	0.8832042	0.3250633	0.7014383
##	2.47	0.8833272	0.3249819	0.7015853
##	2.48	0.8834488	0.3248999	0.7017313
##	2.49	0.8835707	0.3248176	0.7018777
##	2.50	0.8836918	0.3247361	0.7020226
##	2.51	0.8838128	0.3246549	0.7021669
##	2.52	0.8839342	0.3245734	0.7023112
##	2.53	0.8840558	0.3244914	0.7024556
##	2.54	0.8841779	0.3244090	0.7025999
##	2.55	0.8843002	0.3243263	0.7027442
##	2.56	0.8844230	0.3242431	0.7028884
##	2.57	0.8845460	0.3241596	0.7030325
##	2.58	0.8846693	0.3240757	0.7031766
##	2.59	0.8847923	0.3239924	0.7033204
##	2.60	0.8849150	0.3239093	0.7034638
##	2.61	0.8850380	0.3238262	0.7036071
##	2.62	0.8851592	0.3237458	0.7037487
##	2.63	0.8852809	0.3236651	0.7038927
##	2.64	0.8854037	0.3235841	0.7040369
##	2.65	0.8855263	0.3235036	0.7041806
##	2.66	0.8856470	0.3234265	0.7043221
##	2.67	0.8857675	0.3233499	0.7044631
##	2.68	0.8858873	0.3232744	0.7046032
##	2.69	0.8860074	0.3231985	0.7047434
##	2.70	0.8861275	0.3231227	0.7048830
##	2.71	0.8862457	0.3230475	0.7050202
##	2.72	0.8863624	0.3229718	0.7051559
##	2.73	0.8864795	0.3228956	0.7052916
##	2.74	0.8865963	0.3228198	0.7054266
##	2.75	0.8867126	0.3227447	0.7055605
##	2.76	0.8868291	0.3226693	0.7056944
##	2.77	0.8869459	0.3225935	0.7058283
##	2.78	0.8870630	0.3225174	0.7059622
##	2.79	0.8871803	0.3224409	0.7060962
##	2.80	0.8872980	0.3223642	0.7062301
##	2.81	0.8874159	0.3222871	0.7063639
##	2.82	0.8875341	0.3222096	0.7064976
##	2.83	0.8876526	0.3221319	0.7066313

```
## 2.84 0.8877708 0.3220545 0.7067648
## 2.85 0.8878886 0.3219777 0.7068978
## 2.86 0.8880067 0.3219005 0.7070308
## 2.87 0.8881237 0.3218251 0.7071624
## 2.88 0.8882402 0.3217505 0.7072932
## 2.89 0.8883575 0.3216758 0.7074242
## 2.90 0.8884753 0.3216008 0.7075554
## 2.91 0.8885925 0.3215270 0.7076857
## 2.92 0.8887085 0.3214554 0.7078144
## 2.93 0.8888242 0.3213844 0.7079427
## 2.94 0.8889392 0.3213144 0.7080702
## 2.95 0.8890545 0.3212441 0.7081977
## 2.96 0.8891700 0.3211736 0.7083253
## 2.97 0.8892843 0.3211041 0.7084508
## 2.98 0.8893964 0.3210342 0.7085744
## 2.99 0.8895085 0.3209640 0.7086993
## 3.00 0.8896208 0.3208935 0.7088244
##
## Tuning parameter 'alpha' was held constant at a value of 0
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were alpha = 0 and lambda = 0.46.
```

```
ridge_mod$bestTune
```

```
##      alpha lambda
## 46      0    0.46
```

```
plot(ridge_mod)
```



```
predict_te_ridge <- predict(ridge_mod, ind_te)
rsq_te <- cor(ind_te$id_overall, predict_te_ridge)^2
rsq_te
```

```
## [1] 0.3010392
```

```
mae_te <- mean(abs(ind_te$id_overall - predict_te_ridge))
mae_te
```

```
## [1] 0.6469945
```

```
rmse_te <- sqrt(mean((ind_te$id_overall - predict_te_ridge)^2))
rmse_te
```

```
## [1] 0.8004419
```

Model 2 Random forest

```
gridrf <- expand.grid(mtry = 30, splitrule='variance', min.node.size=2)
gridrf
```

randomly sample 30 predictors

```
## mtry splitrule min.node.size
## 1 30 variance 2

# Run the Random Forest by iterating over num.trees using the
# values 5, 20, 40, 60, ..., 200
```

```
nbags <- c(5,seq(from = 20,to = 200, by = 20))

bags <- vector('list',length(nbags))

for(i in 1:length(nbags)){

  bags[[i]] <- caret::train(blueprint,
                             data      = ind_tr,
                             method    = 'ranger',
                             trControl = cv,
                             tuneGrid  = gridrf,
                             num.trees = nbags[i],
                             importance = "impurity",
                             max.depth = 60)

  print(i)
}
```

```
## Loading required namespace: e1071
```

```
##
```

```
## Attaching package: 'e1071'
```

```
## The following object is masked from 'package:Hmisc':
```

```
##
```

```
## impute
```

```
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10
## [1] 11
```

```
rmsees <- c()

for(i in 1:length(nbags)){

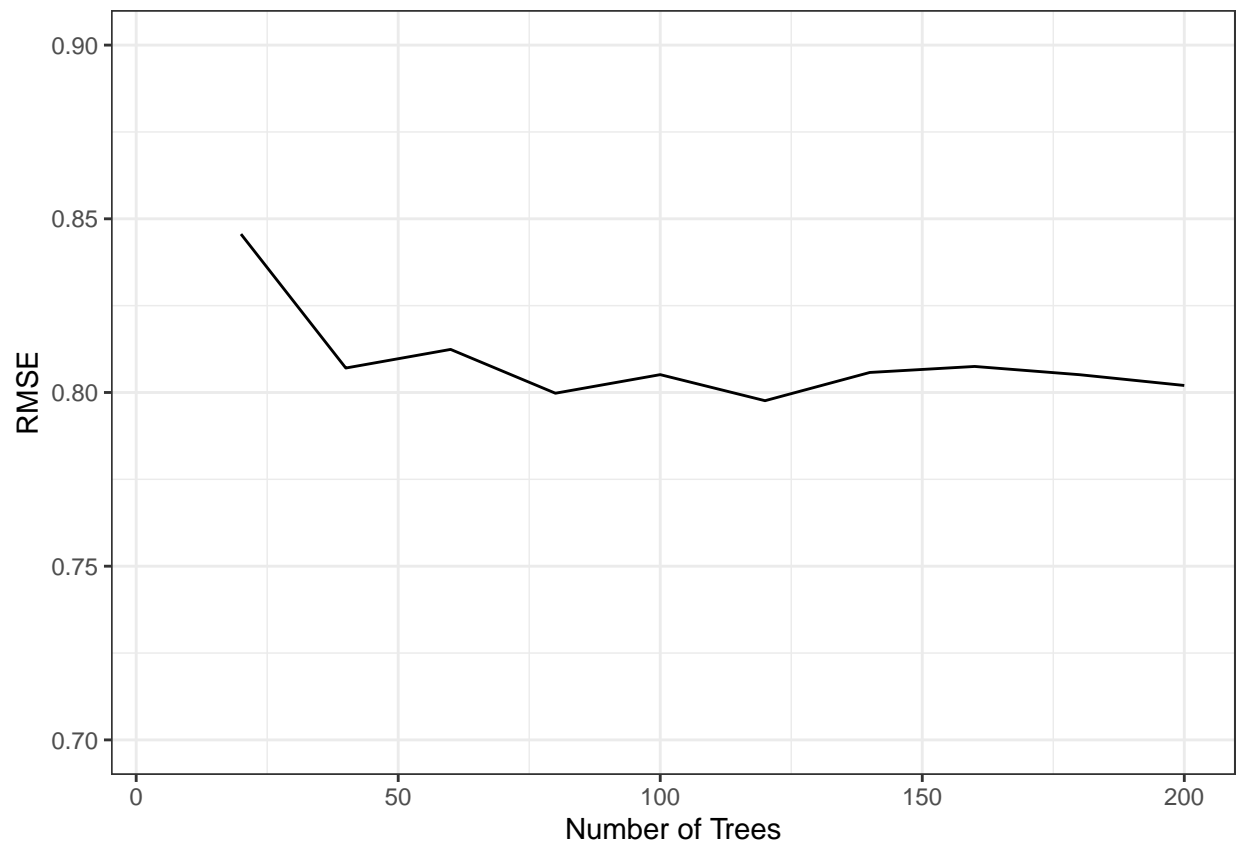
  rmsees[i] = bags[[i]]$results$RMSE

}
```



```
ggplot()+
  geom_line(aes(x=nbags,y=rmses))+
  xlab('Number of Trees')+
  ylab('RMSE')+
  ylim(c(0.7,0.90))+
  theme_bw()
```

```
## Warning: Removed 1 row containing missing values ('geom_line()').
```



```
nbags[which.min(rmses)]
```

```
## [1] 120
```

```
nbags
```

```
## [1] 5 20 40 60 80 100 120 140 160 180 200
```

Although the model with 80 trees has the lowest RMSE for training test I test the rest of number of trees and found that the 200 trees (bag 11th) yielded largest predictive power for the test data.

```
predicted_te <- predict(bags[[11]],ind_te)
```

```
# MAE
```

```
mean(abs(ind_te$id_overall - predicted_te))
```

```
## [1] 0.6116961
```

```
# RMSE
```

```
sqrt(mean((ind_te$id_overall - predicted_te)^2))
```

```
## [1] 0.74823
```

```
# R-square
```

```
cor(ind_te$id_overall,predicted_te)^2
```

```
## [1] 0.4018192
```

Model 3 Gradient Boosting Trees

```
require(doParallel)
```

```
## Loading required package: doParallel
```

```
## Loading required package: foreach
```

```
##
```

```
## Attaching package: 'foreach'
```

```
## The following objects are masked from 'package:purrr':
```

```
##
```

```
## accumulate, when
```

```
## Loading required package: iterators
```

```
## Loading required package: parallel
```

```
ncores <- 10
```

```
cl <- makePSOCKcluster(ncores)
```

```
registerDoParallel(cl)
```

```
# Grid Settings
```

```
grid <- expand.grid(shrinkage = 0.1,  
                   n.trees = 1:500,  
                   interaction.depth = 5,
```

```

n.minobsinnode = 10)

gbm1 <- caret::train(blueprint,
  data      = ind_tr,
  method    = 'gbm',
  trControl = cv,
  tuneGrid  = grid,
  bag.fraction = 1,
  verbose   = FALSE)

gbm1$times

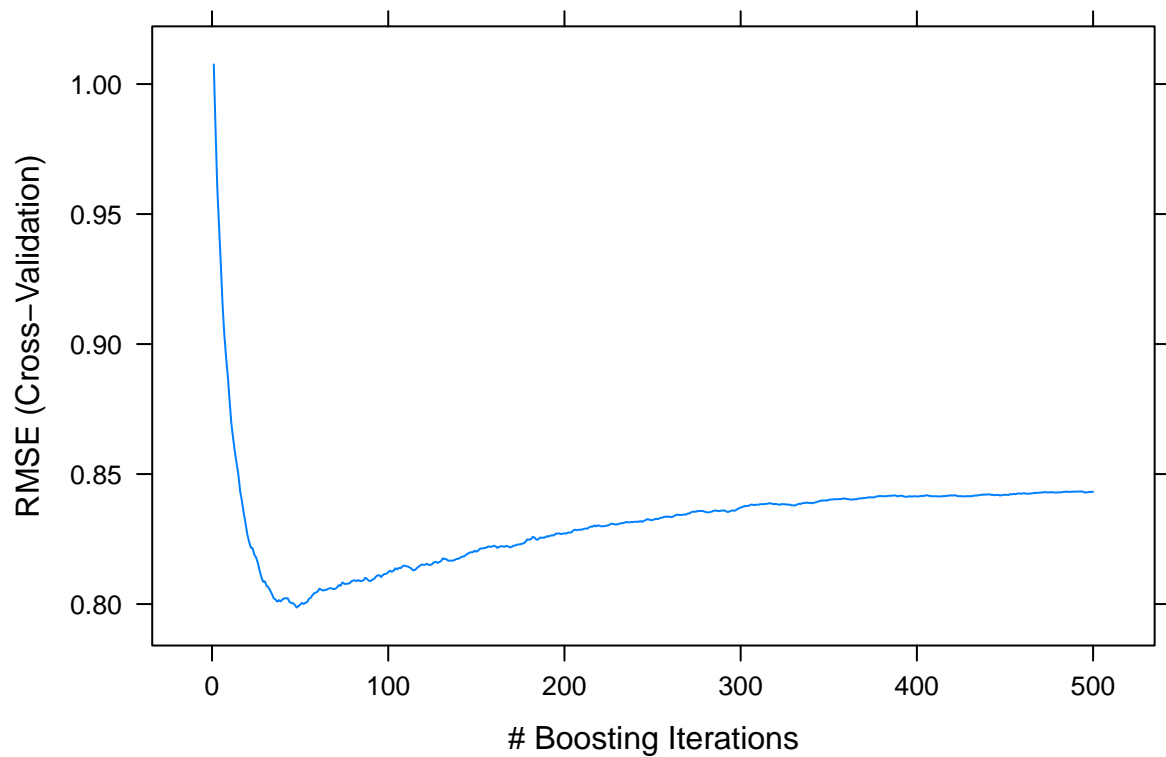
```

```

## $everything
##   user system elapsed
##  1.076   0.235   20.162
##
## $final
##   user system elapsed
##  0.333   0.004    0.338
##
## $prediction
## [1] NA NA NA

```

```
plot(gbm1,type='l')
```



Tune the interaction depth and n.minobsinnode

```
gbm1$results[which.min(gbm1$results$RMSE),]
```

```
##      shrinkage interaction.depth n.minobsinnode n.trees      RMSE Rsquared
## 48         0.1              5             10      48 0.7986829 0.4283728
##           MAE      RMSESD RsquaredSD      MAESD
## 48 0.6228667 0.0633913  0.1093515 0.06315197
```

#We will fix the n.of trees to 52 onwards

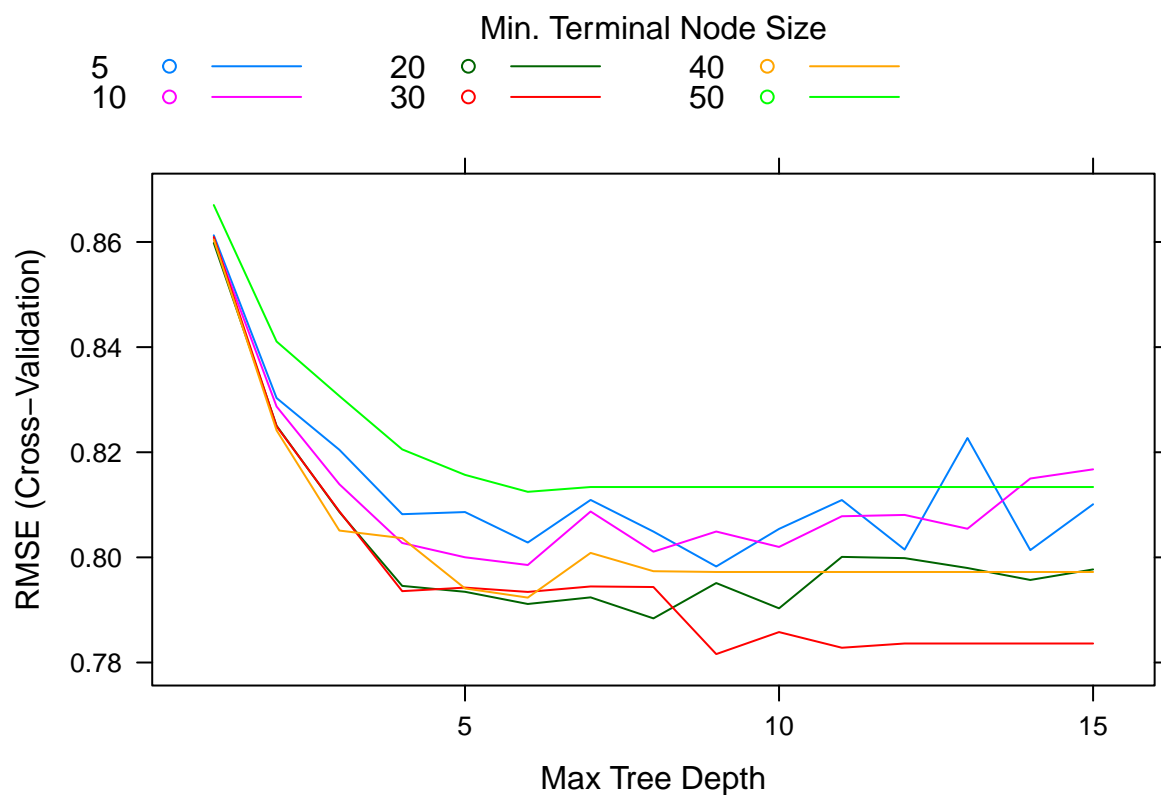
```
grid <- expand.grid(shrinkage      = 0.1,
                   n.trees        = 52,
                   interaction.depth = 1:15,
                   n.minobsinnode  = c(5,10,20,30,40,50))
```

```
gbm2 <- caret::train(blueprint,
                     data      = ind_tr,
                     method    = 'gbm',
                     trControl = cv,
                     tuneGrid  = grid,
                     bag.fraction = 1,
                     verbose   = FALSE)
```

```
gbm2$times
```

```
## $everything
##   user  system elapsed
## 1.487   1.036 202.338
##
## $final
##   user  system elapsed
## 0.445   0.007   0.452
##
## $prediction
## [1] NA NA NA
```

```
plot(gbm2,type='l')
```



```
gbm2$bestTune
```

```
##      n.trees interaction.depth shrinkage n.minobsinnode
## 52      52              9      0.1          30
```

```
gbm2$results[which.min(gbm2$results$RMSE),]
```

```
##      shrinkage interaction.depth n.minobsinnode n.trees      RMSE  Rsquared
## 52      0.1          9          30      52 0.7816028 0.4549474
##      MAE      RMSESD RsquaredSD      MAESD
## 52 0.6009909 0.07665079 0.1269779 0.07179077
```

```
predicted_te <- predict(gbm2, ind_te)
```

```
# MAE
```

```
mean(abs(ind_te$id_overall - predicted_te))
```

```
## [1] 0.5840144
```

```
# RMSE
```

```
sqrt(mean((ind_te$id_overall - predicted_te)^2))
```

```
## [1] 0.7309066
```

```
# R-square
cor(ind_te$id_overall,predicted_te)^2
```

```
## [1] 0.4207848
```

Tune in the n.trees to be 1 to 8000

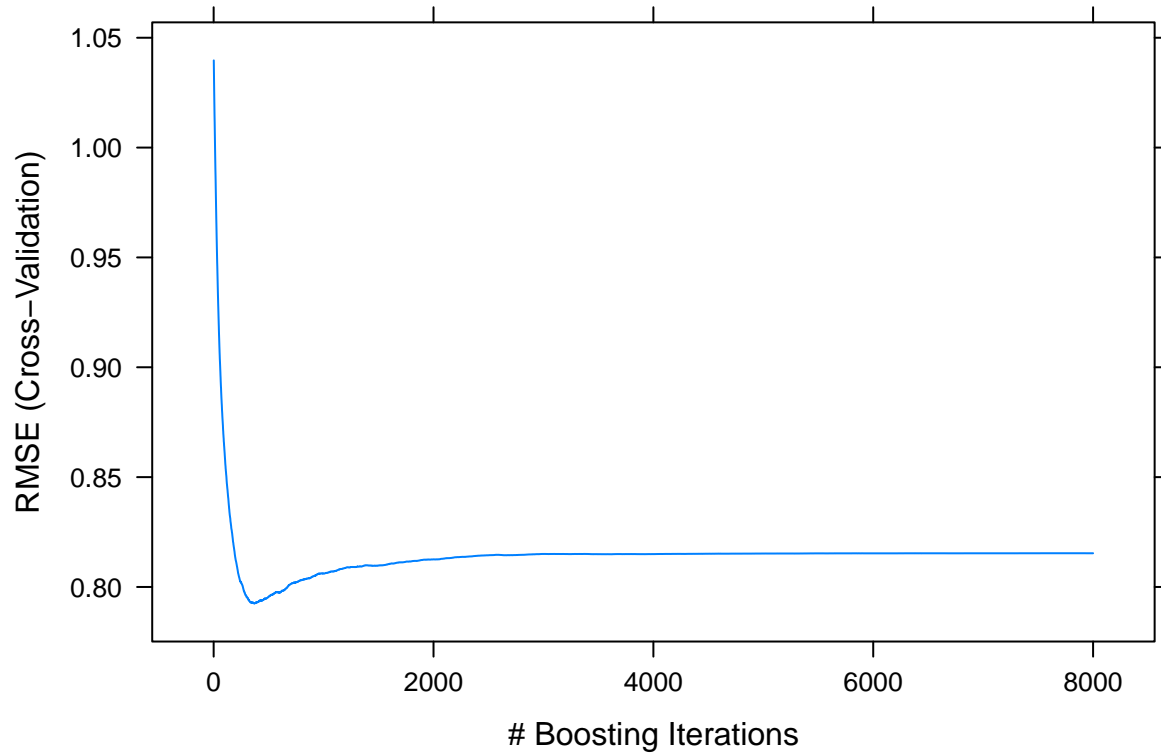
```
grid <- expand.grid(shrinkage      = 0.01,
                   n.trees        = 1:8000,
                   interaction.depth = 13,
                   n.minobsinnode  = 20)
```

```
gbm3 <- caret::train(blueprint,
                     data      = ind_tr,
                     method    = 'gbm',
                     trControl = cv,
                     tuneGrid  = grid,
                     bag.fraction = 1,
                     verbose= FALSE)
```

```
gbm3$times
```

```
## $everything
##   user  system elapsed
## 4.445   0.246 149.137
##
## $final
##   user  system elapsed
## 2.642   0.017   2.667
##
## $prediction
## [1] NA NA NA
```

```
plot(gbm3,type='l')
```



```
gbm3$results[which.min(gbm3$results$RMSE),]
```

```
##      shrinkage interaction.depth n.minobsinnode n.trees      RMSE  Rsquared
## 372      0.01          13          20      372 0.7924743 0.4385012
##      MAE      RMSESD RsquaredSD      MAESD
## 372 0.6164906 0.07177164 0.1237469 0.06140102
```

```
predicted_te <- predict(gbm3,ind_te)
```

```
# MAE
```

```
mean(abs(ind_te$id_overall - predicted_te))
```

```
## [1] 0.5944563
```

```
# RMSE
```

```
sqrt(mean((ind_te$id_overall - predicted_te)^2))
```

```
## [1] 0.7432849
```

```
# R-square
```

```
cor(ind_te$id_overall,predicted_te)^2
```

```
## [1] 0.4006313
```

```
perf <- matrix(c(0.434, 0.598,0.731,0.419,0.584,0.731,0.301,0.646,0.80),ncol=3,byrow=TRUE)
colnames(perf) <- c("R-Squared","MAE","RMSE")
rownames(perf) <- c("Random Forest","Gradient Boosting Tree", "Ridge Regularized Regression")
perf <- as.table(perf)
perf
```

```
##
## R-Squared MAE RMSE
## Random Forest 0.434 0.598 0.731
## Gradient Boosting Tree 0.419 0.584 0.731
## Ridge Regularized Regression 0.301 0.646 0.800
```

```
vip(bags[[11]],num_features = 10, geom = "point") + theme_bw()
```

