

BA810: Team 2: Group Project

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10/01/2021

Setup and Load the Airbnb dataset and Train/Test split

```
library(data.table)
library(ggplot2)
library(ggthemes)
library(glmnet)

## Loading required package: Matrix

## Loaded glmnet 4.1-2

library(caTools)
# [, -1] means take all columns of the matrix except the first column, which is an index
dd <- fread("ab_updated.csv")[, -1]
# set seed for splitting training / test data
set.seed(810)
sample <- sample.split(dd$num, SplitRatio = .70)
train <- subset(dd, sample == TRUE)
test <- subset(dd, sample == FALSE)
# the [, -1] means take all columns of the matrix except the first column, which is an intercept
# splitting x and y train/test
x.train <- model.matrix( ~ . - host_since - zipcode, train)[, -2][, -1]
y.train <- train$log_price
x.test <- model.matrix( ~ . - host_since - zipcode, test)[, -2][, -1]
y.test <- test$log_price
```

Lasso Regression

Predict responses / Compute MSEs for Lasso

```
# use the cv.glmnet command to automatically select the best value for the lambda hyper-parameter.
fit.lasso <- cv.glmnet(x.train, y.train, alpha = 1, nfolds = 10)

# computing MSE on the training/test data
yhat.train.lasso <- predict(fit.lasso, x.train)
yhat.test.lasso <- predict(fit.lasso, x.test)

mse.train.lasso <- mean((y.train - yhat.train.lasso)^2)
mse.test.lasso <- mean((y.test - yhat.test.lasso)^2)

mse.train.lasso
```

```
## [1] 0.2077325
```

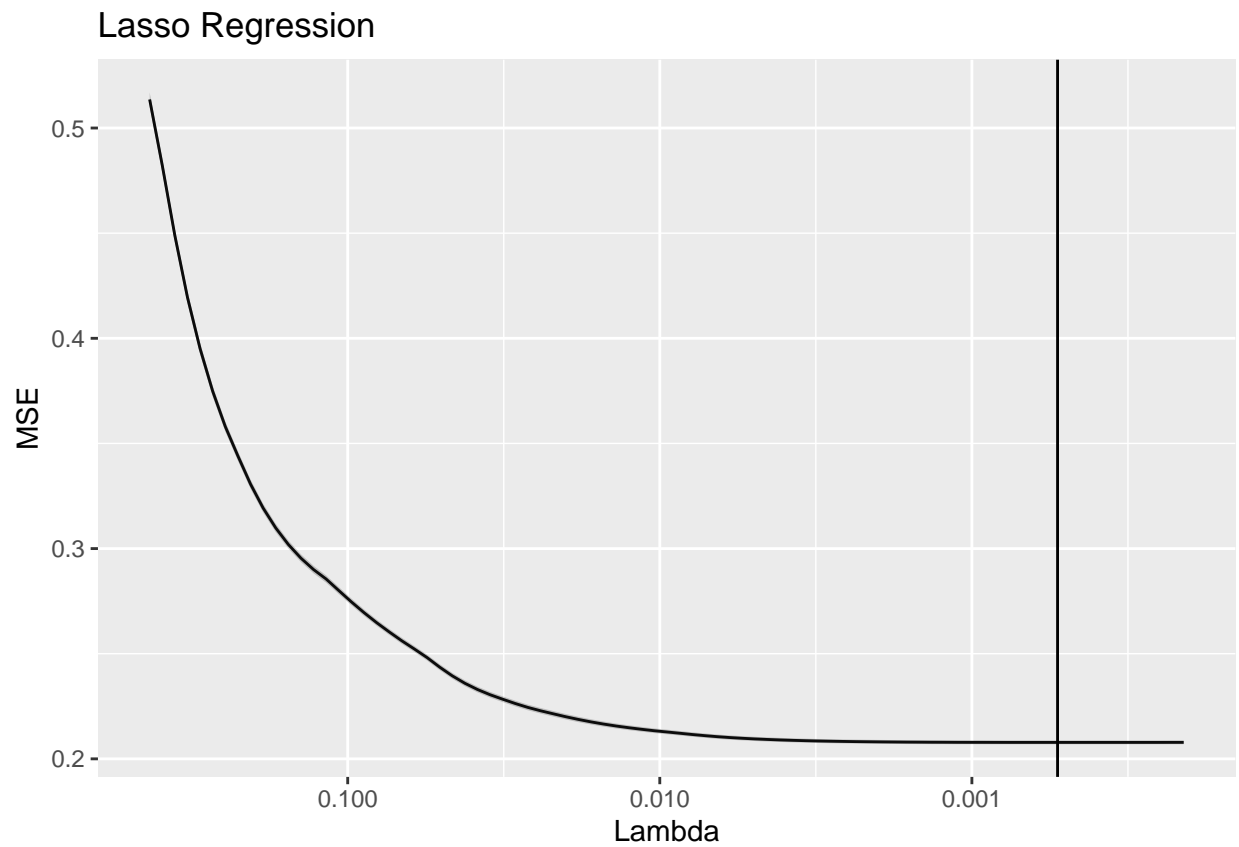
```
mse.test.lasso
```

```
## [1] 0.2106664
```

Lasso Lambda and MSE Graph

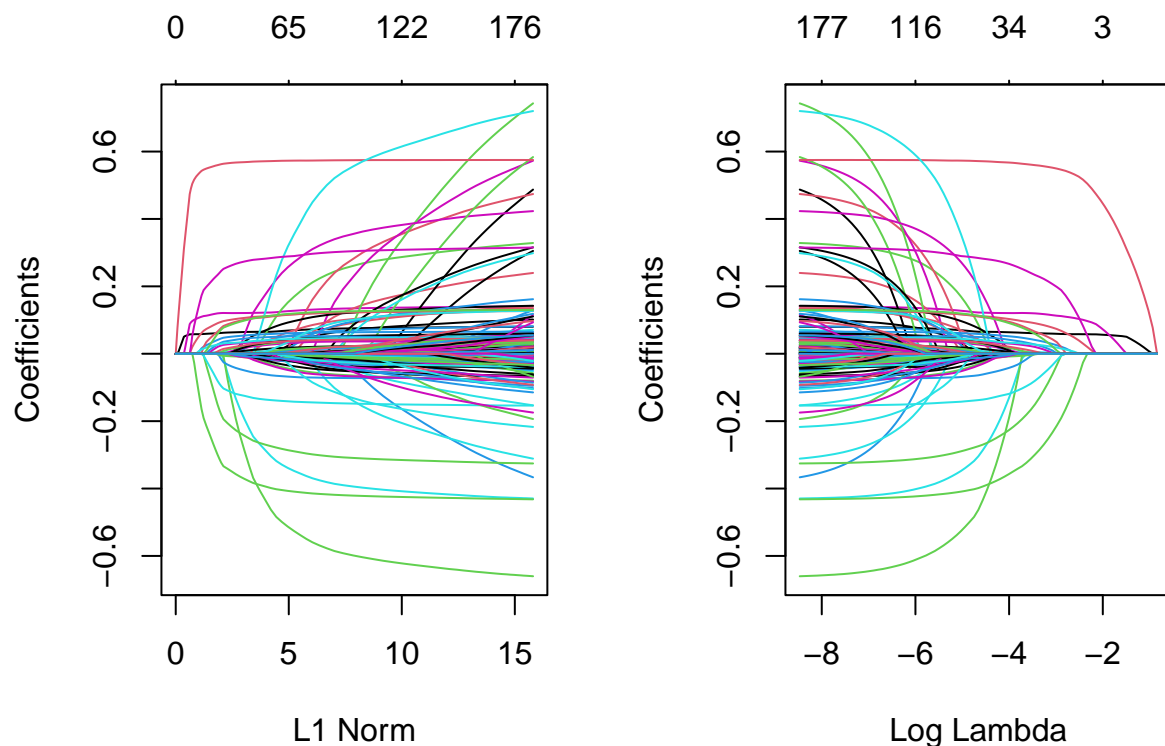
```
# manual function to reverse on x axis and scale at the same time on ggplot2
library("scales")
reverselog_trans <- function(base = exp(1)) {
  trans <- function(x) -log(x, base)
  inv <- function(x) base^(-x)
  trans_new(paste0("reverselog-", format(base)), trans, inv,
            log_breaks(base = base),
            domain = c(1e-100, Inf))
}
# The broom package takes the messy output of built-in functions in R, and turns them into tidy tibbles
library(broom)

tidied_cv <- tidy(fit.lasso)
glance_cv <- glance(fit.lasso)
g <- ggplot(tidied_cv, aes(lambda, estimate)) +
  geom_line() + scale_x_continuous(trans=reverselog_trans(10))
g <- g + geom_ribbon(aes(ymin = conf.low, ymax = conf.high), alpha = .25)
g <- g +
  geom_vline(xintercept = glance_cv$lambda.min) + ggtitle("Lasso Regression") +
  xlab("Lambda") + ylab("MSE")
g
```



Lasso Coefficients Graph

```
# each colored line represents the value taken by a different coefficient in your model, plot to show t  
op <- par(mfrow=c(1, 2))  
# L1 norm is the regularization term for Lasso  
plot(fit.lasso$glmnet.fit, "norm", label=TRUE)  
plot(fit.lasso$glmnet.fit, "lambda", label=TRUE)
```



```
par(op)
```

Lasso Coefficients

```
# examine the coefficients associated with min lambda.min, the value of lambda that gives minimum mean
# lambda.1se, the value of lambda that gives the most regularized model such that the cross-validated e
# One line of reasoning suggests using 1se because it hedges against overfitting by selecting a larger
lasso_coef <- coef(fit.lasso, s = fit.lasso$lambda.min)
lasso_coef_df <- data.frame(name = lasso_coef@Dimnames[[1]][lasso_coef@i + 1], coefficient = lasso_coef)
lasso_coef_df <- lasso_coef_df[order(lasso_coef_df[,2]),]
```

```
lasso_coef_df
```

```
##               name      coefficient
## 26      property_type_Hostel -6.537507e-01
## 44      'room_type_Shared room' -4.305645e-01
## 23      property_type_Dorm -4.263334e-01
## 27      property_type_Hut -3.298526e-01
## 55      city_Chicago -3.240001e-01
## 34      property_type_Tent -2.922666e-01
## 102     beachfront -2.081280e-01
## 94      air_purifier -1.703202e-01
## 136     lake_access -1.609626e-01
## 57      city_LA -1.535623e-01
## 28      'property_type_In-law' -1.388668e-01
```

```

## 123             free_parking_on_street -1.054627e-01
## 140             microwave -9.406879e-02
## 146             path_to_entrance_lit_at_night -9.308866e-02
## 73             self_check_in -8.885417e-02
## 121             fixed_grabBars_for_showers_and_toilet -8.180876e-02
## 80             wireless_internet -7.887103e-02
## 4             host_response_rate -7.793355e-02
## 118            ev_charger -7.430146e-02
## 115            doorman_entry -6.637377e-02
## 125            garden_or_backyard -6.636731e-02
## 86            kitchen -6.426921e-02
## 120            firm_mattress -5.612909e-02
## 111            disabled_parking_spot -4.376888e-02
## 45            bed_type_Airbed -4.346731e-02
## 18            property_type_Cabin -4.245442e-02
## 143            outlet_covers -4.065635e-02
## 8             beds -3.975853e-02
## 68            free_parking_on_premises -3.821602e-02
## 157            smoking_allowed -3.797718e-02
## 104            cats -3.750648e-02
## 155            'ski_in/ski_out' -3.635191e-02
## 48            cancellation_policy_moderate -3.114337e-02
## 159            table_corner_guards -3.111563e-02
## 167            window_guards -3.030258e-02
## 74            smoke_detector -2.895310e-02
## 105            children_books_and_toys -2.830168e-02
## 95            baby_bath -2.589733e-02
## 71            lock_on_bedroom_door -2.558131e-02
## 98            bathtub -2.488808e-02
## 166            wide_hallway_clearance -2.438925e-02
## 129            hangers -2.415256e-02
## 119            fireplace_guards -2.248289e-02
## 101            beach_essentials -2.129775e-02
## 72            pets_live_on_this_property -2.110975e-02
## 93            'accessible-height-bed' -1.674291e-02
## 69            host_greets_you -1.557147e-02
## 77            'translation_missing:_en.hosting_amenity_50' -1.546216e-02
## 25            'property_type_Guest suite' -1.513396e-02
## 149            private_entrance -1.504831e-02
## 89            stove -1.500148e-02
## 106            children_dinnerware -1.278246e-02
## 67            first_aid_kit -1.156566e-02
## 131            hot_water -1.105145e-02
## 70            laptop_friendly_workspace -1.064124e-02
## 83            essentials -1.009136e-02
## 138            long_term_stays_allowed -9.267491e-03
## 47            bed_type_Futon -9.229721e-03
## 163            wide_clearance_to_bed -9.084921e-03
## 78            wheelchair_accessible -8.639570e-03
## 76            'translation_missing:_en.hosting_amenity_49' -7.735661e-03
## 141            other -7.212209e-03
## 134            iron -6.146625e-03
## 92            'twentyfour-hour-check-in' -5.793289e-03
## 158            'step-free_access' -5.693596e-03

```

## 151	refrigerator	-4.354918e-03
## 135	keypad	-4.275497e-03
## 19	'property_type_Camper/RV'	-3.134233e-03
## 63	carbon_monoxide_detector	-2.259116e-03
## 164	'wide_clearance_to_shower_&_toilet'	-2.104000e-03
## 156	smart_lock	-1.939705e-03
## 154	safety_card	-1.753517e-03
## 91	washer	-1.525481e-03
## 96	baby_monitor	-8.994539e-04
## 13	property_type_Apartment	-7.965155e-04
## 103	bed_linens	-7.093798e-04
## 5	number_of_reviews	-4.727484e-04
## 53	cleaning_fee_True	-1.103995e-11
## 10	host_has_profile_pic_t	-5.764853e-12
## 12	host_identity_verified_t	-2.139934e-14
## 54	city_Boston	1.171682e-04
## 153	'room-darkening_shades'	2.054219e-04
## 150	private_living_room	8.921791e-04
## 49	cancellation_policy_strict	1.876498e-03
## 144	oven	2.240831e-03
## 139	luggage_dropoff_allowed	4.377478e-03
## 145	'pack_play/travel_crib'	5.224179e-03
## 99	bathtub_with_shower_chain	6.396286e-03
## 128	handheld_shower_head	6.558147e-03
## 85	heating	6.999668e-03
## 87	pool	7.278795e-03
## 6	review_scores_rating	7.870704e-03
## 162	'well-lit_path_to_entrance'	8.626830e-03
## 66	fire_extinguisher	8.932445e-03
## 65	'family/kid_friendly'	9.545790e-03
## 79	wide_entryway	1.012782e-02
## 132	hot_water_kettle	1.073695e-02
## 37	property_type_Townhouse	1.103180e-02
## 147	pocket_wifi	1.196511e-02
## 160	'washer/dryer'	1.204814e-02
## 137	lockbox	1.228082e-02
## 130	hot_tub	1.312763e-02
## 108	coffee_maker	1.344555e-02
## 124	game_console	1.352614e-02
## 107	cleaning_before_checkout	1.493024e-02
## 11	host_identity_verified_f	1.546096e-02
## 112	dishes_and_silverware	1.635588e-02
## 60	air_conditioning	1.760461e-02
## 81	breakfast	1.812348e-02
## 56	city_DC	2.072644e-02
## 122	flat_smooth_pathway_to_front_door	2.487535e-02
## 59	instant_bookable_f	2.550237e-02
## 88	shampoo	2.616256e-02
## 97	babysitter_recommendations	3.008649e-02
## 110	crib	3.054049e-02
## 109	cooking_basics	3.228367e-02
## 117	ethernet_connection	3.242087e-02
## 114	dogs	3.618092e-02
## 64	elevator_in_building	3.789952e-02

## 127	hair_dryer	3.805364e-02
## 142	other_pets	4.031454e-02
## 52	cleaning_fee_False	4.363631e-02
## 165	wide_doorway	4.582488e-02
## 116	dryer	4.637995e-02
## 29	property_type_Lighthouse	4.699311e-02
## 90	tv	4.778893e-02
## 100	bbq_grill	4.787636e-02
## 84	gym	4.792148e-02
## 152	'roll-in_shower_with_chair'	4.818915e-02
## 61	'buzzer/wireless_intercom'	4.831871e-02
## 161	waterfront	4.956793e-02
## 168	stair_gates	5.008072e-02
## 41	property_type_Villa	5.328951e-02
## 17	property_type_Bungalow	5.674829e-02
## 75	suitable_for_events	5.899697e-02
## 46	bed_type_Couch	6.494720e-02
## 62	cable_tv	6.537226e-02
## 2	accommodates	7.963604e-02
## 22	property_type_Condominium	8.027202e-02
## 148	private_bathroom	8.600407e-02
## 126	ground_floor_access	9.299023e-02
## 39	property_type_Treehouse	9.421557e-02
## 14	'property_type_Bed & Breakfast'	9.798327e-02
## 33	'property_type_Serviced apartment'	1.004836e-01
## 3	bathrooms	1.262735e-01
## 113	dishwasher	1.265201e-01
## 31	property_type_Other	1.279357e-01
## 133	indoor_fireplace	1.296031e-01
## 82	doorman	1.328125e-01
## 9	host_has_profile_pic_f	1.356890e-01
## 7	bedrooms	1.399332e-01
## 30	property_type_Loft	1.404397e-01
## 50	cancellation_policy_super_strict_30	1.538621e-01
## 15	property_type_Boat	2.281178e-01
## 36	property_type_Tipi	2.530297e-01
## 40	'property_type_Vacation home'	2.759620e-01
## 42	property_type_Yurt	2.896183e-01
## 58	city_SF	3.135850e-01
## 16	'property_type_Boutique hotel'	3.207937e-01
## 20	'property_type_Casa particular'	4.111677e-01
## 35	property_type_Timeshare	4.160817e-01
## 21	property_type_Castle	4.529490e-01
## 38	property_type_Train	5.103047e-01
## 24	'property_type_Earth House'	5.349895e-01
## 43	'room_type_Entire home/apt'	5.749637e-01
## 32	'property_type_Parking Space'	6.699858e-01
## 51	cancellation_policy_super_strict_60	7.013073e-01
## 1	(Intercept)	3.299046e+00

```
#print.data.frame(lasso_coef_df)
#write.csv(lasso_coef_df,file="lasso_coef_df.csv")
```

Ridge Regression

Predict responses / Compute MSEs for Ridge

```
# use the cv.glmnet command to automatically select the best value for the lambda hyper-parameter.  
# cv.glmnet returns a cv.glmnet object, a list with all the ingredients of the cross-validated fit  
fit.ridge <- cv.glmnet(x.train, y.train, alpha = 0, nfolds = 10)
```

```
# computing MSE on the training/test data  
yhat.train.ridge <- predict(fit.ridge, x.train)  
yhat.test.ridge <- predict(fit.ridge, x.test)  
  
mse.train.ridge <- mean((y.train - yhat.train.ridge)^2)  
mse.test.ridge <- mean((y.test - yhat.test.ridge)^2)  
  
mse.train.ridge
```

```
## [1] 0.2084374
```

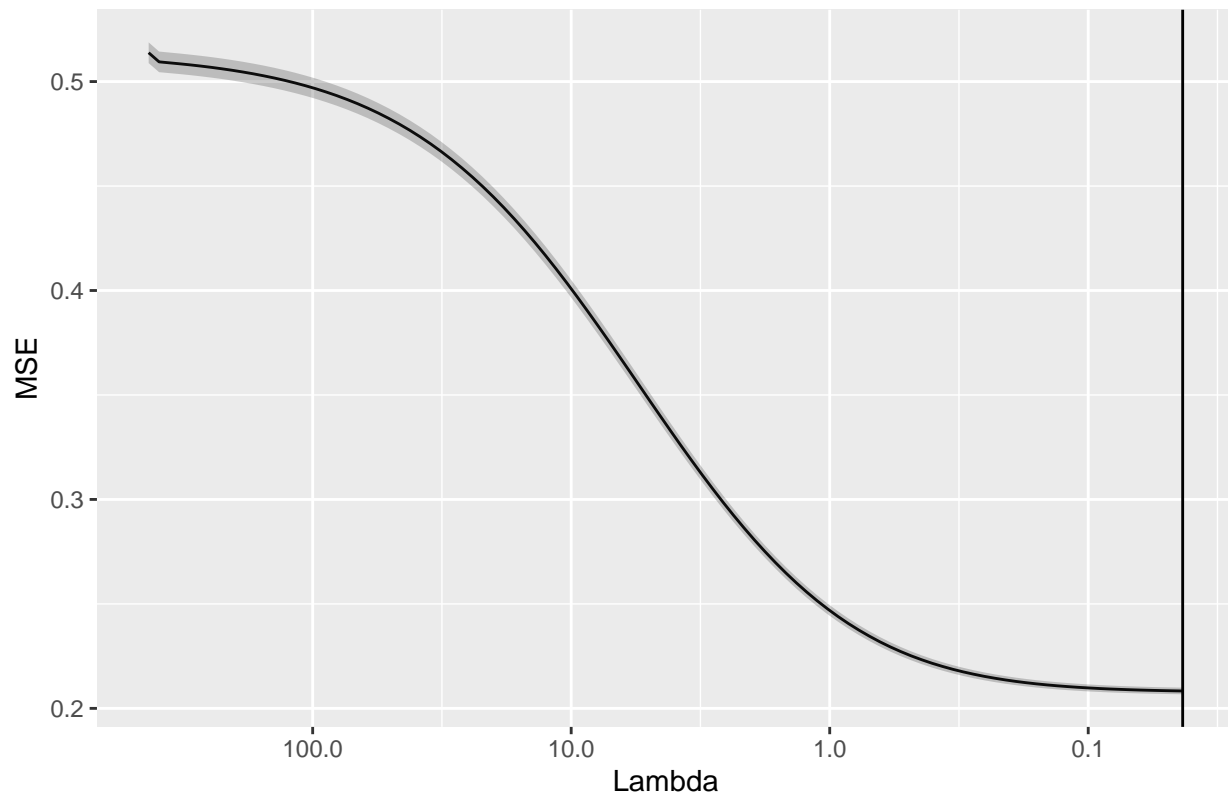
```
mse.test.ridge
```

```
## [1] 0.2116062
```

Ridge: Lambda and MSE Graph

```
tidied_cv <- tidy(fit.ridge)  
glance_cv <- glance(fit.ridge)  
g <- ggplot(tidied_cv, aes(lambda, estimate)) +  
  geom_line() + scale_x_continuous(trans=reverselog_trans(10))  
g <- g + geom_ribbon(aes(ymin = conf.low, ymax = conf.high), alpha = .25)  
g <- g +  
  geom_vline(xintercept = glance_cv$lambda.min) + ggtitle("Ridge Regression") +  
  xlab("Lambda") + ylab("MSE")  
g
```


Ridge Regression



Ridge Coefficients

```
ridge_coef <- coef(fit.ridge, s = fit.ridge$lambda.min)
ridge_coef_df <- data.frame(name = ridge_coef@Dimnames[[1]][ridge_coef@i + 1], coefficient = ridge_coef@
ridge_coef_df <- ridge_coef_df[order(ridge_coef_df[,2]),]
```

```
ridge_coef_df
```

```
##              name    coefficient
## 28      property_type_Hostel -0.7096236844
## 48    'room_type_Shared room' -0.6526095967
## 24      property_type_Dorm -0.4676235027
## 30      property_type_Hut -0.3813503720
## 37      property_type_Tent -0.3328564988
## 62              city_Chicago -0.2753736262
## 47    'room_type_Private room' -0.2426156612
## 107          air_purifier -0.2167968880
## 116          beachfront -0.2156975728
## 156          lake_access -0.1753778529
## 31    'property_type_In-law' -0.1614403643
## 140    free_parking_on_street -0.1240364905
## 64              city_LA -0.1180671693
## 167    path_to_entrance_lit_at_night -0.1164966084
## 134              ev_charger -0.1025825113
## 138    fixed_grabBars_for_showers_and_toilet -0.0982219989
## 177    'ski_in/ski_out' -0.0872895907
```

```

## 160                microwave -0.0809484327
## 131                doorman_entry -0.0754660264
## 4                 host_response_rate -0.0741274783
## 18                property_type_Cabin -0.0731167882
## 10                host_has_profile_pic_t -0.0705226012
## 91                wireless_internet -0.0697848062
## 127               disabled_parking_spot -0.0688564491
## 142               garden_or_backyard -0.0659238962
## 83                self_check_in -0.0641356230
## 22                property_type_Chalet -0.0634610101
## 137               firm_mattress -0.0593273053
## 98                kitchen -0.0580839511
## 49                bed_type_Airbed -0.0492408222
## 163               outlet_covers -0.0484540182
## 179               smoking_allowed -0.0422951642
## 77                free_parking_on_premises -0.0389192145
## 119               cats -0.0381386076
## 26                'property_type_Guest suite' -0.0371318715
## 190               window_guards -0.0357131659
## 189               wide_hallway_clearance -0.0353124261
## 19                'property_type_Camper/RV' -0.0346968462
## 181               table_corner_guards -0.0345880559
## 108               baby_bath -0.0338506029
## 115               beach_essentials -0.0322246468
## 121               children_books_and_toys -0.0320058240
## 80                lock_on_bedroom_door -0.0290716291
## 85                smoke_detector -0.0269528551
## 82                pets_live_on_this_property -0.0265307978
## 112               bathtub -0.0257471170
## 173               refrigerator -0.0253328241
## 148               hangers -0.0244771355
## 55                cancellation_policy_moderate -0.0233629291
## 136               fireplace_guards -0.0227111903
## 101               stove -0.0214694537
## 60                cleaning_fee_True -0.0194730972
## 8                 beds -0.0188890818
## 187               'wide_clearance_to_shower_&_toilet' -0.0186270252
## 155               keypad -0.0170895936
## 186               wide_clearance_to_bed -0.0168482723
## 105               'accessible-height-bed' -0.0164614076
## 78                host_greets_you -0.0164176424
## 88                'translation_missing:_en.hosting_amenity_50' -0.0163766858
## 122               children_dinnerware -0.0162256922
## 178               smart_lock -0.0158286585
## 109               baby_monitor -0.0157420108
## 68                instant_bookable_t -0.0148764432
## 51                bed_type_Futon -0.0146247805
## 29                property_type_House -0.0141593313
## 158               long_term_stays_allowed -0.0141439092
## 76                first_aid_kit -0.0141375557
## 171               private_entrance -0.0140539216
## 13                property_type_Apartment -0.0137669306
## 151               hot_water -0.0137208027
## 27                property_type_Guesthouse -0.0133716645

```

## 161	other	-0.0128826263
## 180	'step-free_access'	-0.0122410865
## 87	'translation_missing:_en.hosting_amenity_49'	-0.0113983467
## 94	essentials	-0.0100475887
## 79	laptop_friendly_workspace	-0.0092233651
## 12	host_identity_verified_t	-0.0080517379
## 89	wheelchair_accessible	-0.0074690029
## 97	internet	-0.0060549835
## 104	'twentyfour-hour-check-in'	-0.0059675716
## 154	iron	-0.0056968899
## 106	'accessible-height-toilet'	-0.0038717544
## 176	safety_card	-0.0037296998
## 117	bed_linens	-0.0036359846
## 72	carbon_monoxide_detector	-0.0031706317
## 168	patio_or_balcony	-0.0011792111
## 5	number_of_reviews	-0.0004750107
## 172	private_living_room	-0.0003054303
## 103	washer	-0.0002391618
## 40	property_type_Townhouse	0.0010342624
## 81	pets_allowed	0.0012538605
## 157	lockbox	0.0014624428
## 175	'room-darkening_shades'	0.0015903749
## 135	extra_blankets_and_pillows	0.0039059327
## 52	'bed_type_Pull-out Sofa'	0.0040216559
## 84	single_level_home	0.0040426504
## 159	luggage_dropoff_allowed	0.0053568134
## 54	cancellation_policy_flexible	0.0060868757
## 149	high_chair	0.0063175807
## 6	review_scores_rating	0.0075795570
## 165	'pack_play/travel_crib'	0.0077988615
## 11	host_identity_verified_f	0.0080997655
## 53	'bed_type_Real Bed'	0.0084961615
## 99	pool	0.0088803976
## 75	fire_extinguisher	0.0102209807
## 56	cancellation_policy_strict	0.0112591795
## 145	hand_or_paper_towel	0.0112609111
## 96	heating	0.0117090201
## 147	handheld_shower_head	0.0118484572
## 185	'well-lit_path_to_entrance'	0.0121461054
## 150	hot_tub	0.0133899639
## 152	hot_water_kettle	0.0139823874
## 69	air_conditioning	0.0143383327
## 67	instant_bookable_f	0.0144876008
## 146	hand_soap	0.0146459944
## 111	bath_towel	0.0150561373
## 74	'family/kid_friendly'	0.0154717200
## 141	game_console	0.0162550570
## 92	breakfast	0.0166609794
## 118	body_soap	0.0169822916
## 169	pocket_wifi	0.0189844413
## 90	wide_entryway	0.0189910986
## 182	toilet_paper	0.0192464059
## 59	cleaning_fee_False	0.0200607826
## 120	changing_table	0.0200868182

## 164	oven	0.0206006084
## 123	cleaning_before_checkout	0.0211783810
## 124	coffee_maker	0.0225288583
## 128	dishes_and_silverware	0.0245918696
## 100	shampoo	0.0259971400
## 113	bathtub_with_shower_chain	0.0261129101
## 65	city_NYC	0.0261282637
## 125	cooking_basics	0.0285091946
## 61	city_Boston	0.0297923933
## 139	flat_smooth_pathway_to_front_door	0.0335786718
## 110	babysitter_recommendations	0.0337605175
## 126	crib	0.0358479035
## 73	elevator_in_building	0.0359597524
## 133	ethernet_connection	0.0365389900
## 144	hair_dryer	0.0371825250
## 130	dogs	0.0378512084
## 17	property_type_Bungalow	0.0435908837
## 183	'washer/dryer'	0.0442660863
## 132	dryer	0.0446556641
## 102	tv	0.0467777665
## 44	property_type_Villa	0.0485231435
## 70	'buzzer/wireless_intercom'	0.0490873006
## 95	gym	0.0497156944
## 162	other_pets	0.0507902734
## 184	waterfront	0.0515576139
## 188	wide_doorway	0.0518036649
## 63	city_DC	0.0543507591
## 114	bbq_grill	0.0549308258
## 191	stair_gates	0.0559978163
## 50	bed_type_Couch	0.0629955720
## 86	suitable_for_events	0.0635980326
## 71	cable_tv	0.0646734821
## 2	accommodates	0.0687960136
## 23	property_type_Condominium	0.0689944074
## 9	host_has_profile_pic_f	0.0709624634
## 14	'property_type_Bed & Breakfast'	0.0755153666
## 170	private_bathroom	0.0916220029
## 166	paid_parking_off_premises	0.0996930929
## 143	ground_floor_access	0.1131279464
## 36	'property_type_Serviced apartment'	0.1147436127
## 129	dishwasher	0.1156905679
## 34	property_type_Other	0.1233835437
## 174	'roll-in_shower_with_chair'	0.1234691775
## 3	bathrooms	0.1236261499
## 93	doorman	0.1240677056
## 153	indoor_fireplace	0.1256646303
## 33	property_type_Loft	0.1281672495
## 42	property_type_Treehouse	0.1287814770
## 7	bedrooms	0.1306180894
## 32	property_type_Lighthouse	0.1690854914
## 57	cancellation_policy_super_strict_30	0.1773585430
## 15	property_type_Boat	0.2157646876
## 43	'property_type_Vacation home'	0.2918413724
## 45	property_type_Yurt	0.3016187347

```
## 39                property_type_Tipi 0.3054526586
## 46      'room_type_Entire home/apt' 0.3149083450
## 16      'property_type_Boutique hotel' 0.3153063349
## 66                city_SF 0.3257794557
## 38                property_type_Timeshare 0.4063196873
## 21                property_type_Castle 0.4475704926
## 20      'property_type_Casa particular' 0.4648299490
## 25      'property_type_Earth House' 0.6000140808
## 41                property_type_Train 0.6030287703
## 35      'property_type_Parking Space' 0.7007091713
## 58      cancellation_policy_super_strict_60 0.7388750167
## 1                (Intercept) 3.6584185155
```

Predict responses / Compute MSEs for Elastic Net

```
fit.elastic <- cv.glmnet(x.train, y.train, alpha = 0.5, nfolds = 10)

yhat.train.elastic <- predict(fit.elastic, x.train)
yhat.test.elastic <- predict(fit.elastic, x.test)

mse.train.elastic <- mean((y.train - yhat.train.elastic)^2)
mse.test.elastic <- mean((y.test - yhat.test.elastic)^2)

mse.train.elastic
```

```
## [1] 0.2074488
```

```
mse.test.elastic
```

```
## [1] 0.2104755
```

Elastic Net Coefficients

```
elastic_coef <- coef(fit.elastic, s = fit.elastic$lambda.min)
elastic_coef_df <- data.frame(name = elastic_coef@Dimnames[[1]][elastic_coef[i + 1], coefficient = elas
elastic_elastic_df <- elastic_coef_df[order(elastic_coef_df[,2]),]

elastic_coef_df
```

```
##                name    coefficient
## 1      (Intercept) 3.3786604758
## 2      accommodates 0.0798125953
## 3      bathrooms   0.1264918961
## 4      host_response_rate -0.0788099133
## 5      number_of_reviews -0.0004774579
## 6      review_scores_rating 0.0078809617
## 7      bedrooms     0.1402013262
## 8      beds        -0.0403519651
## 9      host_has_profile_pic_f 0.1064022114
## 10     host_has_profile_pic_t -0.0322465127
## 11     host_identity_verified_f 0.0117520499
## 12     host_identity_verified_t -0.0040579137
```

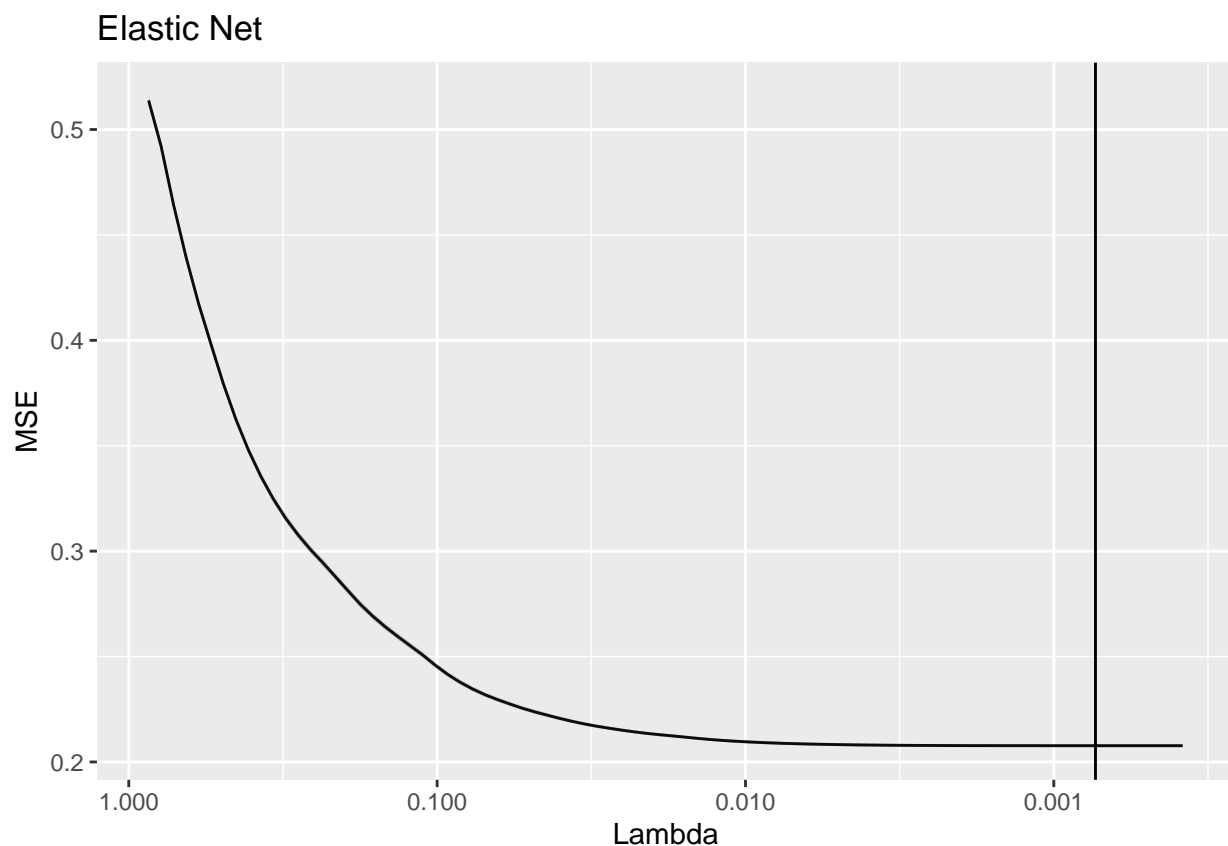
## 13	property_type_Apartment	-0.0009917444
## 14	'property_type_Bed & Breakfast'	0.0996773505
## 15	property_type_Boat	0.2338897131
## 16	'property_type_Boutique hotel'	0.3247024328
## 17	property_type_Bungalow	0.0596204792
## 18	property_type_Cabin	-0.0472243854
## 19	'property_type_Camper/RV'	-0.0068832926
## 20	'property_type_Casa particular'	0.4493635627
## 21	property_type_Castle	0.4635139860
## 22	property_type_Chalet	-0.0066265299
## 23	property_type_Condominium	0.0808613202
## 24	property_type_Dorm	-0.4281456743
## 25	'property_type_Earth House'	0.5546023274
## 26	'property_type_Guest suite'	-0.0178352723
## 27	property_type_Guesthouse	0.0010257657
## 28	property_type_Hostel	-0.6574458805
## 29	property_type_Hut	-0.3484526154
## 30	'property_type_In-law'	-0.1459431383
## 31	property_type_Lighthouse	0.0820264266
## 32	property_type_Loft	0.1414115046
## 33	property_type_Other	0.1296045565
## 34	'property_type_Parking Space'	0.7067046849
## 35	'property_type_Serviced apartment'	0.1097140217
## 36	property_type_Tent	-0.3019698738
## 37	property_type_Timeshare	0.4198562180
## 38	property_type_Tipi	0.2799570371
## 39	property_type_Townhouse	0.0120246569
## 40	property_type_Train	0.5482931656
## 41	property_type_Treehouse	0.1116472511
## 42	'property_type_Vacation home'	0.2872186794
## 43	property_type_Villa	0.0558476355
## 44	property_type_Yurt	0.3027421677
## 45	'room_type_Entire home/apt'	0.5576970769
## 46	'room_type_Private room'	-0.0168783613
## 47	'room_type_Shared room'	-0.4481439309
## 48	bed_type_Airbed	-0.0457286521
## 49	bed_type_Couch	0.0679286780
## 50	bed_type_Futon	-0.0106073109
## 51	cancellation_policy_moderate	-0.0310447882
## 52	cancellation_policy_strict	0.0025115395
## 53	cancellation_policy_super_strict_30	0.1581264012
## 54	cancellation_policy_super_strict_60	0.7112636276
## 55	cleaning_fee_False	0.0272960099
## 56	cleaning_fee_True	-0.0166989568
## 57	city_Boston	0.0014387416
## 58	city_Chicago	-0.3244783127
## 59	city_DC	0.0213691479
## 60	city_LA	-0.1535081545
## 61	city_SF	0.3143567584
## 62	instant_bookable_f	0.0156331950
## 63	instant_bookable_t	-0.0101246695
## 64	air_conditioning	0.0180378575
## 65	'buzzer/wireless_intercom'	0.0487444142
## 66	cable_tv	0.0654082043

## 67	carbon_monoxide_detector	-0.0023689783
## 68	elevator_in_building	0.0381476616
## 69	'family/kid_friendly'	0.0099056986
## 70	fire_extinguisher	0.0095819251
## 71	first_aid_kit	-0.0119362201
## 72	free_parking_on_premises	-0.0386007801
## 73	host_greets_you	-0.0162958314
## 74	laptop_friendly_workspace	-0.0109217997
## 75	lock_on_bedroom_door	-0.0259017127
## 76	pets_allowed	-0.0002639540
## 77	pets_live_on_this_property	-0.0227584040
## 78	self_check_in	-0.0919126673
## 79	single_level_home	0.0014103461
## 80	smoke_detector	-0.0289454971
## 81	suitable_for_events	0.0594434325
## 82	'translation_missing:_en.hosting_amenity_49'	-0.0077133668
## 83	'translation_missing:_en.hosting_amenity_50'	-0.0155831900
## 84	wheelchair_accessible	-0.0099998737
## 85	wide_entryway	0.0131940829
## 86	wireless_internet	-0.0799814534
## 87	breakfast	0.0186536705
## 88	doorman	0.1339940401
## 89	essentials	-0.0101697283
## 90	gym	0.0479057136
## 91	heating	0.0075852989
## 92	internet	0.0003869363
## 93	kitchen	-0.0650831837
## 94	pool	0.0077628348
## 95	shampoo	0.0265156672
## 96	stove	-0.0210951511
## 97	tv	0.0479856165
## 98	washer	-0.0063492301
## 99	'twentyfour-hour-check-in'	-0.0061527636
## 100	'accessible-height-bed'	-0.0172415472
## 101	air_purifier	-0.1820362321
## 102	baby_bath	-0.0286787526
## 103	baby_monitor	-0.0070772684
## 104	babysitter_recommendations	0.0324394763
## 105	bathtub	-0.0255692139
## 106	bathtub_with_shower_chain	0.0138349584
## 107	bbq_grill	0.0490200544
## 108	beach_essentials	-0.0264967169
## 109	beachfront	-0.2127509293
## 110	bed_linens	-0.0010399862
## 111	cats	-0.0374053897
## 112	changing_table	0.0039793609
## 113	children_books_and_toys	-0.0302835245
## 114	children_dinnerware	-0.0135922920
## 115	cleaning_before_checkout	0.0172488910
## 116	coffee_maker	0.0180275472
## 117	cooking_basics	0.0368201415
## 118	crib	0.0321413533
## 119	disabled_parking_spot	-0.0508907056
## 120	dishes_and_silverware	0.0257303961

## 121	dishwasher	0.1264376766
## 122	dogs	0.0381242151
## 123	doorman_entry	-0.0665574025
## 124	dryer	0.0506663986
## 125	ethernet_connection	0.0338473708
## 126	ev_charger	-0.0809063446
## 127	fireplace_guards	-0.0251613877
## 128	firm_mattress	-0.0586734959
## 129	fixed_grab_bars_for_showers_and_toilet	-0.0871870497
## 130	flat_smooth_pathway_to_front_door	0.0284764077
## 131	free_parking_on_street	-0.1101558834
## 132	game_console	0.0152833382
## 133	garden_or_backyard	-0.0686609486
## 134	ground_floor_access	0.1021159806
## 135	hair_dryer	0.0389876865
## 136	handheld_shower_head	0.0088200334
## 137	hangers	-0.0242133596
## 138	high_chair	0.0022063772
## 139	hot_tub	0.0134911061
## 140	hot_water	-0.0116587554
## 141	hot_water_kettle	0.0114434139
## 142	indoor_fireplace	0.1297745332
## 143	iron	-0.0065718017
## 144	keypad	-0.0031076492
## 145	lake_access	-0.1678597598
## 146	lockbox	0.0142943267
## 147	long_term_stays_allowed	-0.0108776918
## 148	luggage_dropoff_allowed	0.0050612226
## 149	microwave	-0.0982115428
## 150	other	-0.0099543106
## 151	other_pets	0.0461550878
## 152	outlet_covers	-0.0425176223
## 153	oven	0.0099274842
## 154	'pack_play/travel_crib'	0.0064931471
## 155	path_to_entrance_lit_at_night	-0.0992232767
## 156	patio_or_balcony	-0.0003786993
## 157	pocket_wifi	0.0151644888
## 158	private_bathroom	0.0917938557
## 159	private_entrance	-0.0151527485
## 160	private_living_room	0.0015031706
## 161	refrigerator	-0.0149670491
## 162	'roll-in_shower_with_chair'	0.0716481311
## 163	'room-darkening_shades'	0.0016018489
## 164	safety_card	-0.0021745921
## 165	'ski_in/ski_out'	-0.0524883030
## 166	smart_lock	-0.0010376609
## 167	smoking_allowed	-0.0385811200
## 168	'step-free_access'	-0.0084337487
## 169	table_corner_guards	-0.0359440915
## 170	'washer/dryer'	0.0159315831
## 171	waterfront	0.0521245648
## 172	'well-lit_path_to_entrance'	0.0097771827
## 173	wide_clearance_to_bed	-0.0131552080
## 174	'wide_clearance_to_shower_&_toilet'	-0.0089249993


```
## 175                wide_doorway  0.0504327265
## 176                wide_hallway_clearance -0.0293259271
## 177                window_guards -0.0318844415
## 178                stair_gates   0.0527039409
```

```
tidied_cv <- tidy(fit.elastic)
glance_cv <- glance(fit.elastic)
g <- ggplot(tidied_cv, aes(lambda, estimate)) +
  geom_line() + scale_x_continuous(trans=reverselog_trans(10))
g <- g + geom_ribbon(aes(ymin = conf.low, ymax = conf.high), alpha = .25)
g <- g +
  geom_vline(xintercept = glance_cv$lambda.min) + ggtitle("Elastic Net") +
  xlab("Lambda") + ylab("MSE")
g
```



```
# explicitly control the fold that each observation is assigned to via the foldid argument
foldid <- sample(1:10, size = length(y.train), replace = TRUE)
cv.1 <- cv.glmnet(x.train, y.train, foldid = foldid, alpha = 1)
cv.5 <- cv.glmnet(x.train, y.train, foldid = foldid, alpha = 0.5)
cv.0 <- cv.glmnet(x.train, y.train, foldid = foldid, alpha = 0)

par(mfrow = c(2,2))
plot(cv.1, col = "red", xlim=rev(c(-9,1)))
legend("topright", legend = c("Lasso/alpha=1"),
  pch = 19, col = c("red"))
```

```

plot(cv.5, col = "grey", xlim=rev(c(-9,1)))
legend("topright", legend = c("Elastic Net/alpha=.5"),
      pch = 19, col = c("red"));

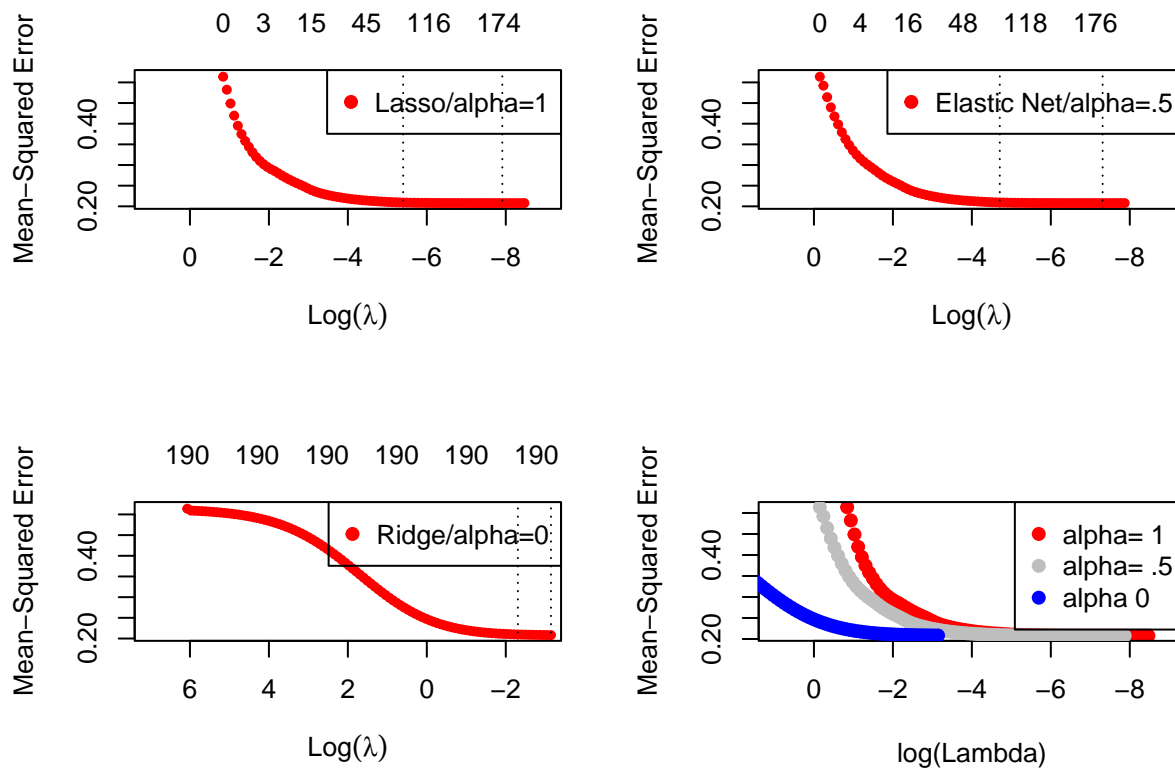
plot(cv.0, col = "blue", xlim=rev(c(-3,7)))
legend("topright", legend = c("Ridge/alpha=0"),
      pch = 19, col = c("red"))

plot(log(cv.1$lambda), cv.1$cvm, pch = 19, col = "red",
      xlab = "log(Lambda)", ylab = cv.1$name, xlim=rev(c(-9,1)))

points(log(cv.5$lambda), cv.5$cvm, pch = 19, col = "grey")

points(log(cv.0$lambda), cv.0$cvm, pch = 19, col = "blue")
legend("topright", legend = c("alpha= 1", "alpha= .5", "alpha 0"),
      pch = 19, col = c("red","grey","blue"))

```



The intervals estimate variance of the loss metric (red dots). They're computed using CV.
The vertical dotted lines show the locations of λ_{\min} and λ_{1se} .
The numbers across the top are the number of nonzero coefficient estimates.

Linear Regression

Forward / Backward Selection

```
library(data.table)
library(caret)
```

```
## Loading required package: lattice
```

```
library(olsrr)
```

```
##
```

```
## Attaching package: 'olsrr'
```

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

```
##
```

```
## rivers
```

```
dd<-fread('ab_updated.csv')
dd<-dd[,c(2:5,7:8,10:196)]
dd<-na.omit(dd)
dd.sample.size <- 72955
dd <- dd[sample(nrow(dd), dd.sample.size)]
# 70 - 30 split
smp_size <- floor(0.70 * nrow(dd))
train_ind <- sample(seq_len(nrow(dd)), size = smp_size)
train<-dd[train_ind, ]
test<-dd[-train_ind,]

trainControl<-trainControl(method='cv',number=2)
linearmodel2<-train(log_price~.,data=train,method='leapForward',
                    tuneGrid=data.frame(nvmax=1:170),
                    preProcess=NULL,trControl=trainControl)
```

```
## Warning in leaps.setup(x, y, wt = weights, nbest = nbest, nvmax = nvmax, : 21
## linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in leaps.setup(x, y, wt = weights, nbest = nbest, nvmax = nvmax, : 19
## linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in leaps.setup(x, y, wt = weights, nbest = nbest, nvmax = nvmax, : 17
## linear dependencies found
```

```
## Reordering variables and trying again:
```

```
Forward_result<-data.table(Variable=colnames(summary(linearmodel2$finalModel)[["which"]]),
                           Order_Add=(max(colSums(summary(linearmodel2$finalModel)[["which"]]))-colSums
linearmodel3<-train(log_price~.,data=train,method='leapBackward',
                    tuneGrid=data.frame(nvmax=1:170),
                    preProcess=NULL,trControl=trainControl)
```

```

## Warning in leaps.setup(x, y, wt = weights, nbest = nbest, nvmax = nvmax, : 20
## linear dependencies found

## Reordering variables and trying again:

## Warning in leaps.setup(x, y, wt = weights, nbest = nbest, nvmax = nvmax, : 19
## linear dependencies found

## Reordering variables and trying again:

## Warning in leaps.setup(x, y, wt = weights, nbest = nbest, nvmax = nvmax, : 17
## linear dependencies found

## Reordering variables and trying again:

Backward_result<-data.table(Variable=colnames(summary(linearmodel3$finalModel)[["which"]]),
                           Order_Remove=colSums(summary(linearmodel3$finalModel)[["which"]]))

Forward_result<-Forward_result[order(Forward_result[,2]),]
Backward_result<-Backward_result[order(-Backward_result[,2]),]
print(head(Forward_result,5))

##           Variable Order_Add
## 1:      (Intercept)         0
## 2: 'room_type_Entire home/apt' 0
## 3:      bedrooms          1
## 4:      city_SF           2
## 5:    accommodates          3

print(head(Backward_result,5))

##           Variable Order_Remove
## 1:      (Intercept)         170
## 2: 'room_type_Entire home/apt' 170
## 3:      bedrooms          169
## 4:    accommodates          168
## 5: 'room_type_Private room'    167

y_forward=predict(linearmodel2,test)
MSEtest_forward<-colMeans((test[,1]-y_forward)^2)
print(MSEtest_forward)

## log_price
## 0.2150757

y_bavkward=predict(linearmodel3,test)
MSEtest_backward<-colMeans((test[,1]-y_bavkward)^2)
print(MSEtest_backward)

## log_price
## 0.2134275

```

Predict responses / Compute MSEs for Linear Regression

```
y_forward=predict(linearmodel2,test)
MSEtest_forward<-colMeans((test[,1]-y_forward)^2)
print(MSEtest_forward)
```

```
## log_price
## 0.2150757
```

```
y_bavkward=predict(linearmodel3,test)
MSEtest_backward<-colMeans((test[,1]-y_bavkward)^2)
print(MSEtest_backward)
```

```
## log_price
## 0.2134275
```

Boosting

Predict responses / Compute MSEs for Boosting

```
### Generalized Boosted Regression Modeling (GBM)
# Setup
library(caTools)
library(data.table)
library(ggplot2)
library(ggthemes)
library(glmnet)
library(rpart)
library(rpart.plot)
theme_set(theme_bw())
library(scales)
library(gbm)
```

```
## Loaded gbm 2.1.8
```

```
# Splite Test and Train
```

```
ab <- fread("ab_updated.csv", stringsAsFactors = T)
ab <- ab[,-1] # remove the ID
ab <- ab[,-5] # remove host_since

set.seed(810)
sample = sample.split(ab$num, SplitRatio = .70)
ab.train = subset(ab , sample == TRUE)
ab.test = subset(ab, sample == FALSE)

ab.train.sample.size <- 5000
ab.train.sample <- ab.train[sample(nrow(ab.train), ab.train.sample.size)]

# Set sample dataset
f1 <- as.formula(log_price ~.)
x1.train.sample <- model.matrix(f1, ab.train.sample)[, -1]
```

```

y.train <- ab.train$log_price
y.train.sample <- ab.train.sample$log_price

x1.test <- model.matrix(f1, ab.test)[, -1]
y.test <- ab.test$log_price

# We will fit a boosted forest.
fit.btree <- gbm(f1,
                 data = ab.train.sample,
                 distribution = "gaussian",
                 n.trees = 1000,
                 interaction.depth = 2,
                 shrinkage = 0.01,
                 cv.folds = 5)

relative.influence(fit.btree)

```

```
## n.trees not given. Using 467 trees.
```

```

##               accommodates
##               3243.43869
##               bathrooms
##               2060.77185
##               host_response_rate
##               0.00000
##               number_of_reviews
##               675.92583
##               review_scores_rating
##               15.97592
##               zipcode
##               22975.42802
##               bedrooms
##               5362.12404
##               beds
##               0.00000
##               host_has_profile_pic_f
##               0.00000
##               host_has_profile_pic_t
##               0.00000
##               host_identity_verified_f
##               0.00000
##               host_identity_verified_t
##               0.00000
##               property_type_Apartment
##               0.00000
##               'property_type_Bed & Breakfast'
##               0.00000
##               property_type_Boat
##               0.00000
##               'property_type_Boutique hotel'
##               0.00000
##               property_type_Bungalow

```

```

##                                0.00000
##                property_type_Cabin
##                                0.00000
##                'property_type_Camper/RV'
##                                0.00000
##                'property_type_Casa particular'
##                                0.00000
##                property_type_Castle
##                                0.00000
##                property_type_Cave
##                                0.00000
##                property_type_Chalet
##                                0.00000
##                property_type_Condominium
##                                0.00000
##                property_type_Dorm
##                                0.00000
##                'property_type_Earth House'
##                                0.00000
##                'property_type_Guest suite'
##                                0.00000
##                property_type_Guesthouse
##                                0.00000
##                property_type_Hostel
##                                0.00000
##                property_type_House
##                                0.00000
##                property_type_Hut
##                                0.00000
##                'property_type_In-law'
##                                0.00000
##                property_type_Island
##                                0.00000
##                property_type_Lighthouse
##                                0.00000
##                property_type_Loft
##                                0.00000
##                property_type_Other
##                                0.00000
##                'property_type_Parking Space'
##                                0.00000
##                'property_type_Serviced apartment'
##                                0.00000
##                property_type_Tent
##                                0.00000
##                property_type_Timeshare
##                                0.00000
##                property_type_Tipi
##                                0.00000
##                property_type_Townhouse
##                                0.00000
##                property_type_Train
##                                0.00000
##                property_type_Treehouse

```

```

##                                0.00000
##      'property_type_Vacation home'
##                                0.00000
##      property_type_Villa
##                                0.00000
##      property_type_Yurt
##                                0.00000
##      'room_type_Entire home/apt'
##      16931.06678
##      'room_type_Private room'
##      0.00000
##      'room_type_Shared room'
##      337.60930
##      bed_type_Airbed
##      0.00000
##      bed_type_Couch
##      0.00000
##      bed_type_Futon
##      0.00000
##      'bed_type_Pull-out Sofa'
##      0.00000
##      'bed_type_Real Bed'
##      0.00000
##      cancellation_policy_flexible
##      0.00000
##      cancellation_policy_moderate
##      0.00000
##      cancellation_policy_strict
##      0.00000
##      cancellation_policy_super_strict_30
##      0.00000
##      cancellation_policy_super_strict_60
##      0.00000
##      cleaning_fee_False
##      0.00000
##      cleaning_fee_True
##      0.00000
##      city_Boston
##      0.00000
##      city_Chicago
##      0.00000
##      city_DC
##      0.00000
##      city_LA
##      0.00000
##      city_NYC
##      0.00000
##      city_SF
##      0.00000
##      instant_bookable_f
##      0.00000
##      instant_bookable_t
##      0.00000
##      air_conditioning

```



```

##                                0.00000
##      'buzzer/wireless_intercom'
##                                0.00000
##                                cable_tv
##                                0.00000
##      carbon_monoxide_detector
##                                0.00000
##      elevator_in_building
##                                0.00000
##      'family/kid_friendly'
##                                0.00000
##      fire_extinguisher
##                                0.00000
##      first_aid_kit
##                                0.00000
##      free_parking_on_premises
##                                0.00000
##      host_greets_you
##                                0.00000
##      laptop_friendly_workspace
##                                0.00000
##      lock_on_bedroom_door
##                                0.00000
##      pets_allowed
##                                0.00000
##      pets_live_on_this_property
##                                0.00000
##      self_check_in
##                                0.00000
##      single_level_home
##                                0.00000
##      smoke_detector
##                                0.00000
##      suitable_for_events
##                                0.00000
##      'translation_missing:_en.hosting_amenity_49'
##                                0.00000
##      'translation_missing:_en.hosting_amenity_50'
##                                0.00000
##      wheelchair_accessible
##                                0.00000
##      wide_entryway
##                                0.00000
##      wireless_internet
##                                0.00000
##      breakfast
##                                0.00000
##      doorman
##                                0.00000
##      essentials
##                                0.00000
##      gym
##                                0.00000
##      heating

```

```

##          0.00000
## internet
##          0.00000
## kitchen
##          0.00000
## pool
##          0.00000
## shampoo
##          0.00000
## stove
##          0.00000
## tv
##          0.00000
## washer
##          0.00000
## 'twentyfour-hour-check-in'
##          0.00000
## 'accessible-height-bed'
##          0.00000
## 'accessible-height-toilet'
##          0.00000
## air_purifier
##          0.00000
## baby_bath
##          0.00000
## baby_monitor
##          0.00000
## babysitter_recommendations
##          0.00000
## bath_towel
##          0.00000
## bathtub
##          0.00000
## bathtub_with_shower_chain
##          0.00000
## bbq_grill
##          0.00000
## beach_essentials
##          0.00000
## beachfront
##          0.00000
## bed_linens
##          0.00000
## body_soap
##          0.00000
## cats
##          0.00000
## changing_table
##          0.00000
## children_books_and_toys
##          0.00000
## children_dinnerware
##          0.00000
## cleaning_before_checkout

```

```

##             0.00000
##             coffee_maker
##             0.00000
##             cooking_basics
##             0.00000
##             crib
##             0.00000
##             disabled_parking_spot
##             0.00000
##             dishes_and_silverware
##             0.00000
##             dishwasher
##             0.00000
##             dogs
##             0.00000
##             doorman_entry
##             0.00000
##             dryer
##             0.00000
##             ethernet_connection
##             0.00000
##             ev_charger
##             0.00000
##             extra_blankets_and_pillows
##             0.00000
##             fireplace_guards
##             0.00000
##             firm_mattress
##             0.00000
##             fixed_grab_bars_for_showers_and_toilet
##             0.00000
##             flat_smooth_pathway_to_front_door
##             0.00000
##             free_parking_on_street
##             0.00000
##             game_console
##             0.00000
##             garden_or_backyard
##             0.00000
##             ground_floor_access
##             0.00000
##             hair_dryer
##             0.00000
##             hand_or_paper_towel
##             0.00000
##             hand_soap
##             0.00000
##             handheld_shower_head
##             0.00000
##             hangers
##             0.00000
##             high_chair
##             0.00000
##             hot_tub

```

```

##             0.00000
##             hot_water
##             0.00000
##             hot_water_kettle
##             0.00000
##             indoor_fireplace
##             10.66594
##             iron
##             0.00000
##             keypad
##             0.00000
##             lake_access
##             0.00000
##             lockbox
##             0.00000
##             long_term_stays_allowed
##             0.00000
##             luggage_dropoff_allowed
##             0.00000
##             microwave
##             0.00000
##             other
##             0.00000
##             other_pets
##             0.00000
##             outlet_covers
##             0.00000
##             oven
##             0.00000
##             'pack_play/travel_crib'
##             0.00000
##             paid_parking_off_premises
##             0.00000
##             path_to_entrance_lit_at_night
##             0.00000
##             patio_or_balcony
##             0.00000
##             pocket_wifi
##             0.00000
##             private_bathroom
##             0.00000
##             private_entrance
##             0.00000
##             private_living_room
##             0.00000
##             refrigerator
##             0.00000
##             'roll-in_shower_with_chair'
##             0.00000
##             'room-darkening_shades'
##             0.00000
##             safety_card
##             0.00000
##             'ski_in/ski_out'

```

```
##          0.00000
##          smart_lock
##          0.00000
##          smoking_allowed
##          0.00000
##          'step-free_access'
##          0.00000
##          table_corner_guards
##          0.00000
##          toilet_paper
##          0.00000
##          'washer/dryer'
##          0.00000
##          waterfront
##          0.00000
##          'well-lit_path_to_entrance'
##          0.00000
##          wide_clearance_to_bed
##          0.00000
##          'wide_clearance_to_shower_&_toilet'
##          0.00000
##          wide_doorway
##          0.00000
##          wide_hallway_clearance
##          0.00000
##          window_guards
##          0.00000
##          stair_gates
##          0.00000
```

```
# Train MSE
yhat.btree <- predict(fit.btree, ab.train.sample, n.trees = 467)
mse.btree <- mean((yhat.btree - y.train.sample) ^ 2)

print(mse.btree)
```

```
## [1] 0.164818
```

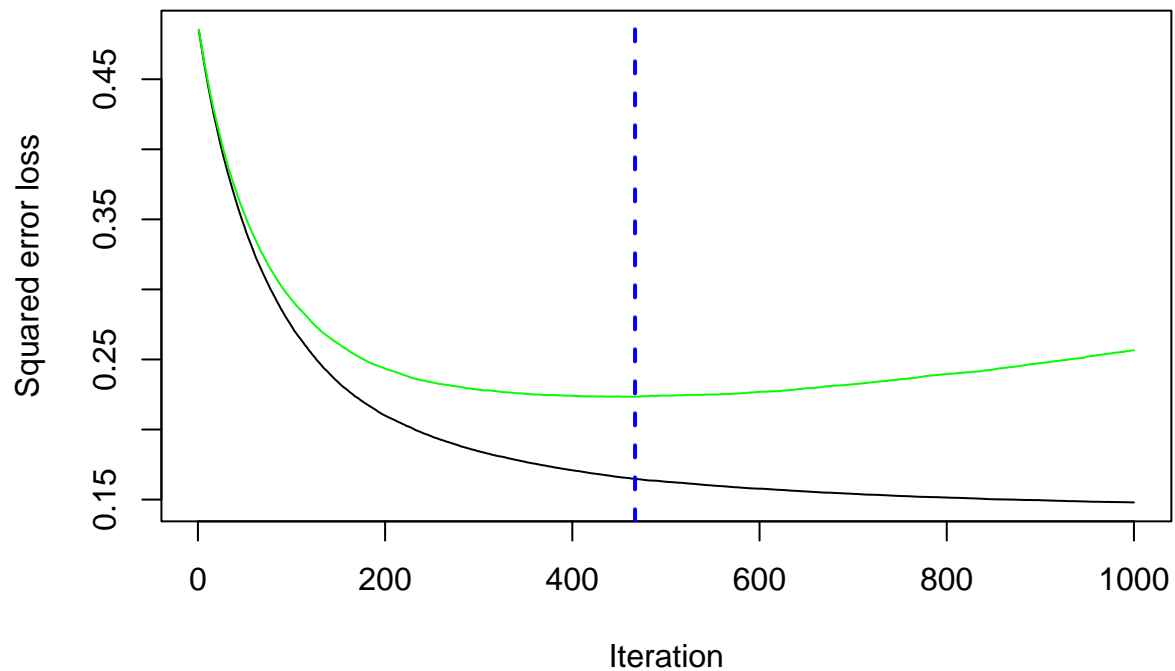
```
# Test MSE
yhat.test.btree <- predict(fit.btree, ab.test, n.trees = 467)
test.mse.btree <- mean((yhat.test.btree - y.test) ^ 2)
print(test.mse.btree)
```

```
## [1] 0.2110714
```

```
# get MSE and compute RMSE
min_MSE <- which.min(fit.btree$cv.error)
sqrt(fit.btree$cv.error[min_MSE])
```

```
## [1] 0.4726127
```

```
# plot loss function as a result of n trees added to the ensemble
gbm.perf(fit.btree, method = "cv")
```



```
## [1] 467
```

Random Forest

Predict responses / Compute MSEs for Random Forest

```
library(data.table)
library(ggplot2)
library(ggthemes)
library(glmnet)
library(caTools)
theme_set(theme_bw())

#read the file.
dd <- fread("/Users/jiazhijia/Desktop/810/ab.csv")
dd<-dd[,c(1:73,693:815)]#some columns are rather useless to our model and would also slow down the speed

#some column names are not readable for R.
names(dd)<-gsub(' ', '_ ', names(dd))
names(dd)<-gsub('/', '_ ', names(dd))
names(dd)<-gsub('-', '_ ', names(dd))
names(dd)<-gsub('&', '', names(dd))
```

```

names(dd)<-gsub('24_','',names(dd))
names(dd)<-gsub(',','',names(dd))
names(dd)<-gsub('"','',names(dd))
names(dd)<-gsub(':','',names(dd))

#test and train
set.seed(810)
sample = sample.split(dd$num, SplitRatio = .70)
train= subset(dd , sample == TRUE)
test= subset(dd, sample == FALSE)

#dataset too large! split into small data combine them in the end.
sample_train = sample.split(train$num, SplitRatio = .60)
train1= subset(train, sample_train == TRUE)
train2= subset(train, sample_train == FALSE)

#build model,setting ntree=500,try 14 variable in each split.
library(randomForest)

## randomForest 4.6-14

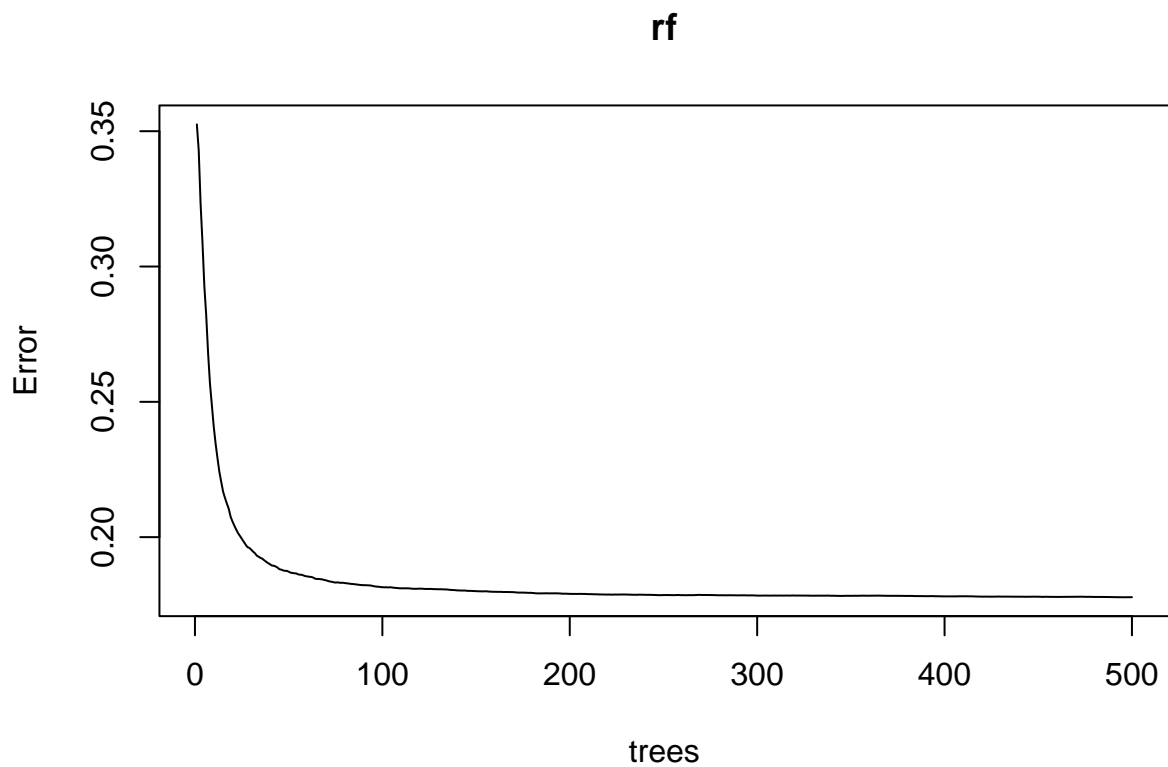
## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

rf <- randomForest(log_price~., data=train1, proximity=TRUE,ntree=500,mtry=sqrt(ncol(train1)),na.action=na.omit)
plot(rf)

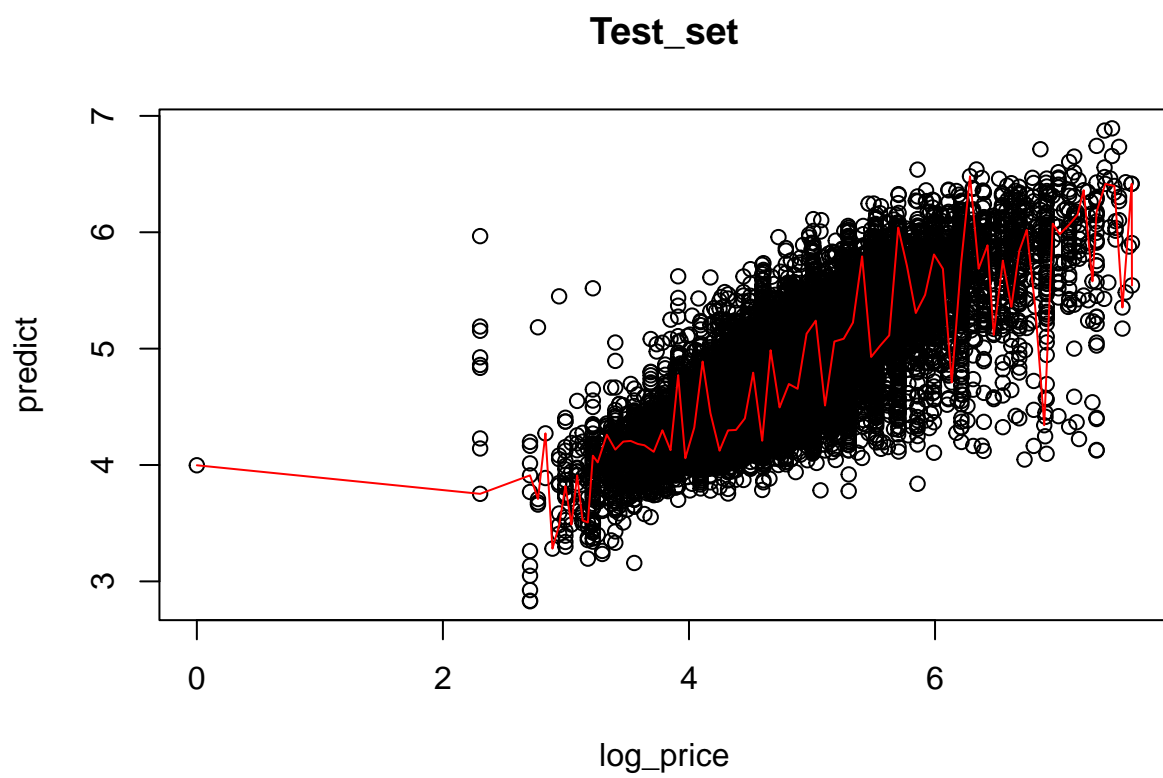
```



```
#see the performance on test data.
pred=predict(rf,test)
y_test<-test$log_price
mse_test=mean((y_test-pred)^ 2,na.rm=TRUE)
print(mse_test)
```

```
## [1] 0.1823137
```

```
#using plot to see the outcome.
plot(test$log_price,pred,main='Test_set',xlab='log_price',ylab='predict') +lines(lowess(test$log_price,
```

```
## integer(0)
```

```
varImpPlot(rf)
```

rf

room_type_Entire_home_apartment
accommodates
room_type_Private_room
bedrooms
zipcode
bathrooms
beds
host_since
number_of_reviews
room_type_Shared_room
review_scores_rating
tv
family_kid_friendly
cable_tv
city_SF
translation_missing_en: hosting_amenity_49
translation_missing_en: hosting_amenity_50
elevator_in_building
dryer
host_response_rate
indoor_fireplace
city_LA
property_type_House
property_type_Apartment
washer
laptop_friendly_workspace
city_DC
lock_on_bedroom_door
iron

