Tidymodels

Prof Wells

STA 295: Stat Learning

May 2nd, 2024

Outline

In today's class, we will...

- Discuss the `tidymodels` packages for model building in the `tidyverse` framework

Section 1

Intro to tidymodels

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Penalized Logistic	`glmnet`	`predict(object, s, type = "response")`
KNN	`kknn`	`kknn(...)$prob`
Naive Bayes	`naiveBayes`	`predict(object, type = "raw")`
Tree	`rpart`	`predict(object, type = "prob")`
Random Forest	`randomForest`	`predict(object, type = "prob")`
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- Each model has different methods for making class probability predictions
- Additionally, each model takes in different types of data arguments (vectors, model matrices, data frames, model formulas)

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- Packages and functions should be accessible and easily interpreted
- Outputs should be data frames (or tibbles) whenever possible
- Functions should be compatible with the %>% operator and functional programming
- Model objects should be compatible with `ggplot2`

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- Model objects should be compatible with `ggplot2`

`tidymodels` takes the mechanics from each individual model package (`glmnet`, `rpart`, `glm` etc.) and unifies the input and output

The `tidymodel` framework

1. Preprocess data using the `recipes` package
2. Create training-test data splits using the `rsample` package
3. Give a model a functional form and specify fitting method using the `parsnip` package
4. Fit the model, tidy the results, and make predictions using the `fit`, `tidy`, and `predict` functions
5. Estimate model performance using cross-validation from the `rsample` package
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We'll investigate each of these in-depth (although slightly out of order)

Section 2

Build a Model

The Data

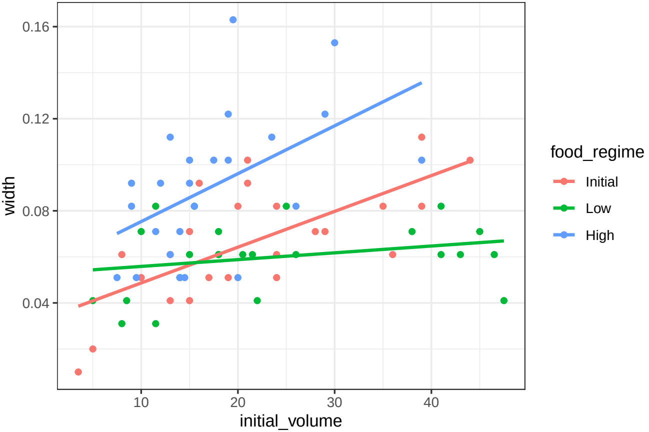
The sea_urchins data set explores the relationship between feeding regimes and size of sea urchins over time:

```
sea_urchins<-read_csv("https://tidymodels.org/start/models/urchins.csv") %>%
  setNames(c("food_regime", "initial_volume", "width")) %>%
  mutate(food_regime = factor(food_regime, levels = c("Initial", "Low", "High")))
head(sea_urchins)
```

```
## # A tibble: 6 x 3
##   food_regime initial_volume width
##   <fct>                <dbl> <dbl>
## 1 Initial                3.5 0.01
## 2 Initial                5   0.02
## 3 Initial                8   0.061
## 4 Initial               10   0.051
## 5 Initial               13   0.041
## 6 Initial               13   0.061
```

Scatterplot

```
sea_urchins %>%
  ggplot(aes(x = initial_volume, y = width, group = food_regime, color = food_regime)) +
  geom_point() + geom_smooth(method = lm, se = FALSE)
```



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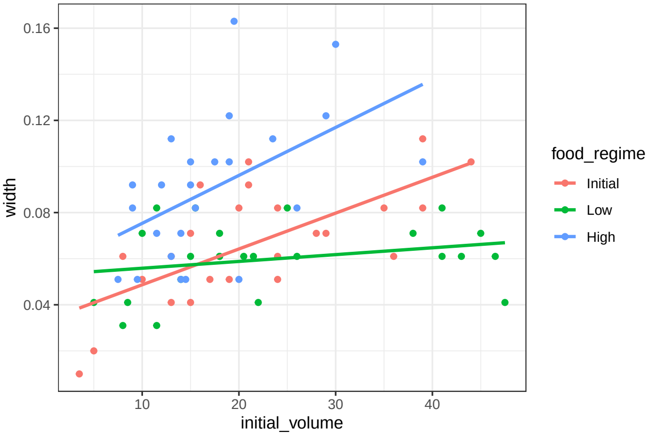

- Goal: Predict `width` as a function of `food_regime` and `initial_volume`.

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width ~ initial_volume + food_regime + initial_volume:food_regime
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linear_reg() %>%
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## Linear Regression Model Specification (regression)
##
## Computational engine: lm
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Now we create the model based on data using the `fit` function:

```
lm_mod<-linear_reg() %>%
  set_engine("lm")

lm_fit<- lm_mod %>%
  fit(width ~ initial_volume*food_regime, data = sea_urchins)
```

Results

The output of our `lm_fit` object:

```
lm_fit
```

```
## parsnip model object
##
##
## Call:
## stats::lm(formula = width ~ initial_volume * food_regime, data = data)
##
## Coefficients:
##                    (Intercept)                  initial_volume
##                      0.0331216                       0.0015546
##                 food_regimeLow                 food_regimeHigh
##                      0.0197824                       0.0214111
##  initial_volume:food_regimeLow  initial_volume:food_regimeHigh
##                     -0.0012594                       0.0005254
```

Summary Table

To get the traditional `summary` table:

```
tidy(lm_fit) %>% kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	0.033	0.010	3.443	0.001
initial_volume	0.002	0.000	3.908	0.000
food_regimeLow	0.020	0.013	1.523	0.133
food_regimeHigh	0.021	0.015	1.473	0.145
initial_volume:food_regimeLow	-0.001	0.001	-2.469	0.016
initial_volume:food_regimeHigh	0.001	0.001	0.748	0.457

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We can get goodness-of-fit measures using `glance`

```
glance(lm_fit) %>% kable(digits = 3)
```

r.squared	adj.r.squared	sigma	statistic	p.value	df	logLik	AIC	BIC	deviance	df.residual	nobs
0.462	0.421	0.021	11.345	0	5	178.594	-343.188	-327.251	0.03	66	72

Note that the output is a data frame with standard column names

New Data

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```
new_urchins <- expand.grid(initial_volume  = c(5,30),
                           food_regime = c("Initial", "Low", "High"))
new_urchins %>% kable()
```

initial_volume	food_regime
5	Initial
30	Initial
5	Low
30	Low
5	High
30	High

Make predictions

Then we make predictions

```
new_preds <- predict(lm_fit, new_data = new_urchins)
new_preds %>% kable(digits = 3)
```

.pred
0.041
0.080
0.054
0.062
0.065
0.117

Combining Data and Predictions

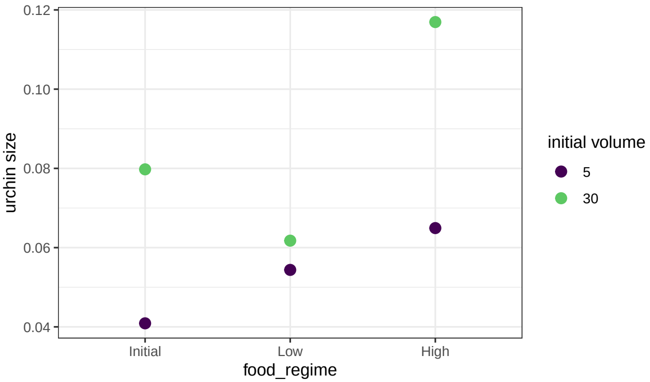
Because the result of `predict()` is tidy, we can easily combine it with the original data:

```
combined_data <- new_urchins %>% cbind(new_preds)
combined_data %>% kable(digits = 3)
```

initial_volume	food_regime	.pred
5	Initial	0.041
30	Initial	0.080
5	Low	0.054
30	Low	0.062
5	High	0.065
30	High	0.117

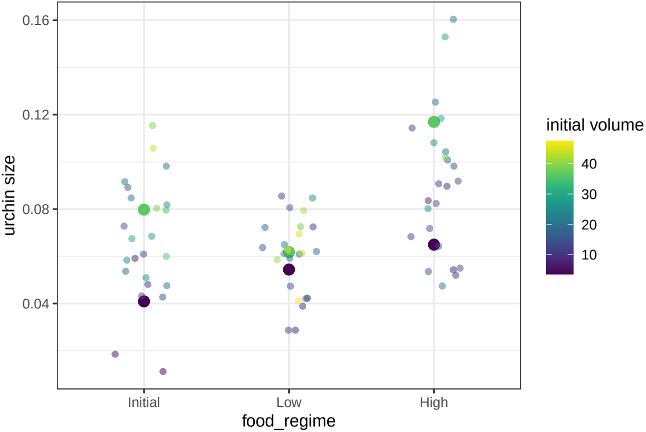
Predictions Plot

```r
ggplot(combined_data, aes(x = food_regime)) +
  geom_point(aes(y = .pred, color = initial_volume))
```



Predictions Plot

We can compare our predictions to the original data:



Using a different engine

LASSO?

- With only 3 predictors (`food_regime`, `initial_width` and the interaction term), its unlikely our model will be improved by Penalized Regression. But let's try anyway:

```
glmnet_mod<- linear_reg(penalty = 0.01, mixture = 1) %>% set_engine("glmnet")
```

- `mixture = 1` indicates LASSO (`mixture = 0` is used for Ridge Regression)
- `glmnet` requires us to indicate a value of `penalty` parameter λ to make predictions.
    - Here, we choose `penalty = 0.01` entirely arbitrarily; in any case, `glmnet` will still create models for all λ regardless of penalty selected

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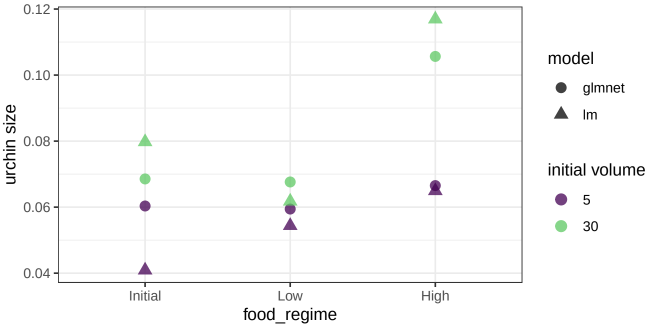
```
glmnet_fit <- glmnet_mod %>% fit(width ~ initial_volume*food_regime, data = sea_urchins)
tidy(glmnet_fit, penalty = .004) #penalty selects particular value of lambda; can be anything
```

```
## # A tibble: 6 x 3
##   term                           estimate penalty
##   <chr>                             <dbl>   <dbl>
## 1 (Intercept)                    0.0587     0.004
## 2 initial_volume                 0.000328   0.004
## 3 food_regimeLow                -0.000918   0.004
## 4 food_regimeHigh                0          0.004
## 5 initial_volume:food_regimeLow  0          0.004
## 6 initial_volume:food_regimeHigh 0.00124    0.004
```

Results from glmnet

```
new_glmnet_preds <- predict(glmnet_fit, new_data = new_urchins, penalty = 0.004)
combined_glmnet_data <- new_urchins %>% cbind(new_glmnet_preds)
two_models <- rbind(combined_glmnet_data,
                    combined_data) %>%
  mutate(model = rep(c("glmnet","lm"), each = 6))
```

```
ggplot(two_models, aes(x = food_regime)) +
  geom_point(aes(y = .pred, color = initial_volume, shape = model))
```



Section 3

Preprocessing with recipes

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- The `recipes` package assists with preprocessing before a model is trained
  - Converts qualitative predictors to dummy variables
  - Transforms data to be on a different scale
  - Transforms several predictors at the same time
  - Extracts features from variable
- The main advance of `recipes` is that it allows us combine several steps at once, in a reproducible fashion

House Prices

- The house data contains information on 30 predictors for 200 houses in Ames, Iowa

```
dim(house)
```

```
## [1] 200  31
```

```
names(house)
```

```
##  [1] "SalePrice"     "Id"            "Functional"    "BldgType"
##  [5] "Foundation"    "LotShape"      "LandSlope"     "SaleCondition"
##  [9] "RoofMatl"      "ScreenPorch"   "MSSubClass"    "GarageCars"
## [13] "BedroomAbvGr"  "TotalBsmtSF"   "LotArea"       "OpenPorchSF"
## [17] "BsmtFullBath"  "WoodDeckSF"    "OverallCond"   "YrSold"
## [21] "GrLivArea"     "MoSold"        "TotRmsAbvGrd"  "PoolArea"
## [25] "YearBuilt"     "GarageArea"    "OverallQual"   "Fireplaces"
## [29] "EnclosedPorch" "FullBath"      "HalfBath"
```

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  - The `rsample` package allows us to create stratified samples in addition to simple random samples
- By setting `strata = SalePrice`, we ensure that SalePrice values are balanced across the test and training sets.

```
library(rsample)
set.seed(1221)
data_split <- initial_split(house , prop = 3/4, strata = SalePrice)
train_data <- training(data_split)
test_data <- testing(data_split)
```

Create a recipe and update roles

- We now create a recipe for some data pre-processing

```
house_rec <- recipe(SalePrice ~ ., data = train_data) %>%
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- The variable `Id` is not useful as a predictor, but is useful for referring to houses in the data set. By setting it to the `ID` role, it will not be used for fitting models.

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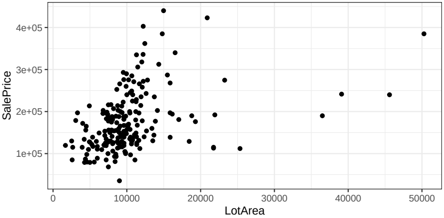
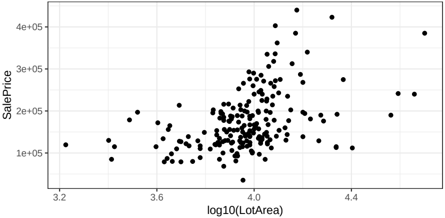
```
summary(house_rec)
```

```
## # A tibble: 31 x 4
##    variable      type      role      source
##    <chr>         <list>    <chr>     <chr>
##  1 SalePrice     <chr [2]> outcome   original
##  2 Id            <chr [2]> ID        original
##  3 Functional    <chr [3]> predictor original
##  4 BldgType      <chr [3]> predictor original
##  5 Foundation    <chr [3]> predictor original
##  6 LotShape      <chr [3]> predictor original
##  7 LandSlope     <chr [3]> predictor original
##  8 SaleCondition <chr [3]> predictor original
##  9 RoofMatl      <chr [3]> predictor original
## 10 ScreenPorch   <chr [2]> predictor original
## # i 21 more rows
```

Add steps to recipes

- Consider the relationship between of sale price and lot area:





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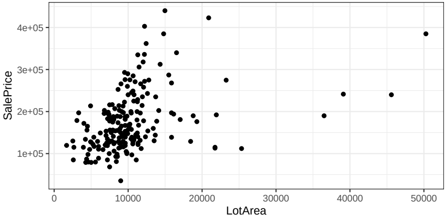

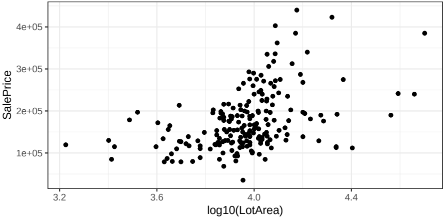

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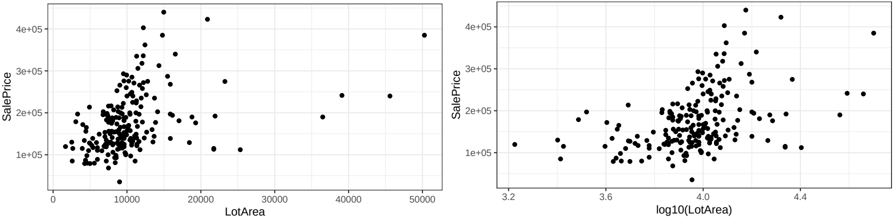

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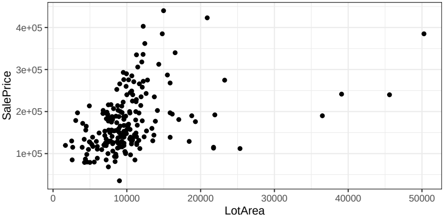

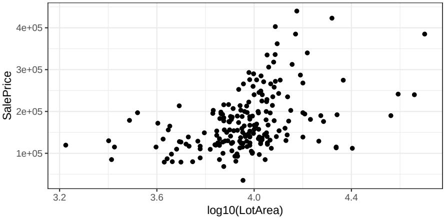

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- Note that for a few categorical variables, some levels are very underrepresented.

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```

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- To fix, we add `step_novel` to our recipe, which takes any new (previously unseen) factor level and groups them into a new factor called "new"

Imbalanced Predictors

- Note that for a few categorical variables, some levels are very underrepresented.

```
house %>% count(RoofMatl)
```

```
##   RoofMatl   n
## 1  CompShg 195
## 2  Membran   1
## 3  Tar&Grv   2
## 4  WdShake   1
## 5  WdShngl   1
```

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house_rec <- house_rec %>% step_novel(all_nominal())
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- To fix, we add `step_novel` to our recipe, which takes any new (previously unseen) factor level and groups them into a new factor called “new”

```
house_rec <- house_rec %>% step_novel(all_nominal())
```

- Here, we only apply this step to the nominal (i.e. categorical) variables

Creating Dummy Variables

Recall 7 of our variables are categorical, which will need to be converted to dummy variables for many models:

```
house %>% select_if(is.character) %>% names()
```

```
## [1] "Functional"    "BldgType"      "Foundation"    "LotShape"
## [5] "LandSlope"     "SaleCondition" "RoofMatl"
```

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```

To create appropriate dummy variables:

```
house_rec <- house_rec %>%  step_dummy(all_nominal(), - all_outcomes())
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```

To create appropriate dummy variables:

```
house_rec <- house_rec %>%  step_dummy(all_nominal(), - all_outcomes())
```

- Here, `all_nominal` selects all variables that are either factors or characters, while `-all_outcomes` removes any response variables from this step

Workflows

- Why create a recipe when we could just as easily perform the pre-processing steps using `dplyr`?

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1. The recipe allows us to apply the same procedures to both test and training data.
2. The recipe gives instructions for processing the data **without actually performing that action**

Workflows

- Why create a recipe when we could just as easily perform the pre-processing steps using `dplyr`?

1. The recipe allows us to apply the same procedures to both test and training data.
2. The recipe gives instructions for processing the data **without actually performing that action**

To use our recipe across several steps, we will use a *workflow*, which will

1. Process the recipe using the training set
2. Apply the recipe to the training set
3. Apply the recipe to the test set

Create the workflow

```
house_mod <- linear_reg() %>% set_engine("lm")

house_wflow <- workflow() %>%
  add_model(house_mod) %>%
  add_recipe(house_rec)

house_wflow
```

```
## == Workflow ==================================================================
## Preprocessor: Recipe
## Model: linear_reg()
##
## -- Preprocessor ----------------------------------------------------------------
## 5 Recipe Steps
##
## * step_log()
## * step_mutate()
## * step_rm()
## * step_novel()
## * step_dummy()
##
## -- Model ------------------------------------------------------------------------
## Linear Regression Model Specification (regression)
##
## Computational engine: lm
```

Fitting Models with Workflows

When we are ready to actually fit the model, we apply `fit` to the workflow:

```
house_fit <- house_wflow %>% fit(data = train_data)

house_fit %>% pull_workflow_fit() %>% tidy()
```

```
## # A tibble: 55 x 5
##    term          estimate  std.error statistic p.value
##    <chr>            <dbl>      <dbl>     <dbl>   <dbl>
##  1 (Intercept)  3341085.  3204406.       1.04  0.300
##  2 ScreenPorch       86.4       49.5      1.75  0.0834
##  3 MSSubClass      -209.       126.      -1.66  0.0997
##  4 GarageCars      4149.      6471.       0.641 0.523
##  5 BedroomAbvGr    -413.      3693.      -0.112 0.911
##  6 TotalBsmtSF       17.3        7.91     2.18  0.0312
##  7 LotArea        13247.     16943.       0.782 0.436
##  8 OpenPorchSF      -42.8       38.0     -1.13  0.263
##  9 BsmtFullBath   13913.      4542.       3.06  0.00279
## 10 WoodDeckSF        16.1       16.4      0.984 0.327
## # i 45 more rows
```

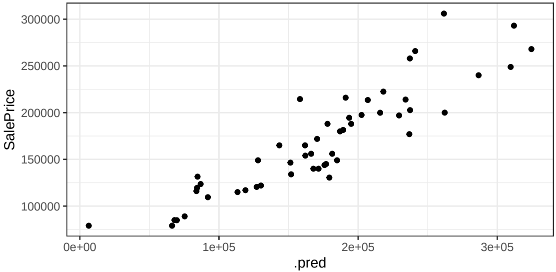
Making predictions with workflow

```
house_preds<- predict(house_fit, test_data)
house_preds
```

```
## # A tibble: 52 x 1
##      .pred
##      <dbl>
##  1 189262.
##  2 262209.
##  3 184852.
##  4 162068.
##  5 261673.
##  6 236809.
##  7  86811.
##  8 218140.
##  9 175821.
## 10  66268.
## # i 42 more rows
```

Evaluate performance

```r
house_results <- house_preds %>% cbind(test_data)
```




```r
rbind(
  rmse(house_results, truth = SalePrice, estimate = .pred),
  rsq(house_results, truth = SalePrice, estimate = .pred)
)
```

```
## # A tibble: 2 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard   30658.
## 2 rsq     standard       0.813
```

Section 4

Resampling

Resampling with `rsample`

- We previously built a linear model for `SalePrice` as a function of predictors in the `house` data and found the following accuracy measures on **test** data:

```
## # A tibble: 2 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard   30658.
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```

Resampling with rsample

- We previously built a linear model for SalePrice as a function of predictors in the house data and found the following accuracy measures on **test** data:

```
## # A tibble: 2 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard   30658.
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```

- But how typical are these estimates? Let's perform cross-validation.

```r
set.seed(271)
library(rsample)
folds <- vfold_cv(train_data, v = 10)
```

Delving Deeper

- Which observations are in each fold?

```
folds$splits[[1]]
```

```
## <Analysis/Assess/Total>
## <133/15/148>
```

```
folds$splits[[1]] %>% analysis() %>% head() %>% select(1:5)
```

```
##   SalePrice  Id Functional BldgType Foundation
## 1     80000  69        Typ     1Fam     CBlock
## 2     98600  92        Typ     1Fam     CBlock
## 3     87000 128        Typ     1Fam     BrkTil
## 4     97000 224        Typ     1Fam     CBlock
## 5    113000 240        Typ     1Fam     CBlock
## 6     85000 345        Typ   TwnhsE     CBlock
```

```
folds$splits[[1]] %>% assessment() %>% head() %>% select(1:5)
```

```
##   SalePrice   Id Functional BldgType Foundation
## 1    113000  423        Typ     1Fam     CBlock
## 2     92900 1091        Typ   Duplex       Slab
## 3    112000 1384        Typ     1Fam     BrkTil
## 4    144000   43        Typ     1Fam     CBlock
## 5    155000  118        Typ     1Fam      PConc
## 6    139000  575        Typ     1Fam     CBlock
```

Adding resampling to workflow

```
house_fit_resamples <- house_wflow %>% fit_resamples(folds)
house_fit_resamples
```

```
## # Resampling results
## # 10-fold cross-validation
## # A tibble: 10 x 4
##    splits           id     .metrics         .notes
##    <list>           <chr>  <list>           <list>
##  1 <split [133/15]> Fold01 <tibble [2 x 4]> <tibble [1 x 3]>
##  2 <split [133/15]> Fold02 <tibble [2 x 4]> <tibble [1 x 3]>
##  3 <split [133/15]> Fold03 <tibble [2 x 4]> <tibble [1 x 3]>
##  4 <split [133/15]> Fold04 <tibble [2 x 4]> <tibble [1 x 3]>
##  5 <split [133/15]> Fold05 <tibble [2 x 4]> <tibble [1 x 3]>
##  6 <split [133/15]> Fold06 <tibble [2 x 4]> <tibble [1 x 3]>
##  7 <split [133/15]> Fold07 <tibble [2 x 4]> <tibble [1 x 3]>
##  8 <split [133/15]> Fold08 <tibble [2 x 4]> <tibble [1 x 3]>
##  9 <split [134/14]> Fold09 <tibble [2 x 4]> <tibble [1 x 3]>
## 10 <split [134/14]> Fold10 <tibble [2 x 4]> <tibble [1 x 3]>
##
## There were issues with some computations:
##
##   - Warning(s) x10: prediction from a rank-deficient fit may be misleading
##
## Run `show_notes(.Last.tune.result)` for more information.
```

Metrics

- Let's look at the results:

```
house_fit_resamples$.metrics[[1]]
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard   27154.    Preprocessor1_Model1
## 2 rsq     standard       0.894 Preprocessor1_Model1
```

```
house_fit_resamples$.metrics[[2]]
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard   24092.    Preprocessor1_Model1
## 2 rsq     standard       0.932 Preprocessor1_Model1
```

```
house_fit_resamples$.metrics[[3]]
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard   31683.    Preprocessor1_Model1
## 2 rsq     standard       0.899 Preprocessor1_Model1
```

CV Performance

- How do the models do overall?

```
#Baseline
rbind(
  rmse(house_results, truth = SalePrice, estimate = .pred),
  rsq(house_results, truth = SalePrice, estimate = .pred)
)
```

```
## # A tibble: 2 x 3
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```
## # A tibble: 2 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard   30658.
## 2 rsq     standard       0.813
```

- Cross-validation:

```
collect_metrics(house_fit_resamples)
```

```
## # A tibble: 2 x 6
##   .metric .estimator      mean     n   std_err .config
##   <chr>   <chr>          <dbl> <int>     <dbl> <chr>
## 1 rmse    standard   27350.       10 1669.     Preprocessor1_Model1
## 2 rsq     standard       0.878    10    0.0187 Preprocessor1_Model1
```

Section 5

Tuning Hyperparameters

Building a LASSO model

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```
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- But we are really interested in finding the **BEST** value of λ. So instead

```
house_lasso_mod <- linear_reg(penalty = tune() ) %>% set_engine("glmnet")
```

- Let's fit the model and tune

```
lasso_grid <- grid_regular(penalty() %>% range_set(c(-4,4)), levels = 10)
lasso_wf <- workflow() %>% add_model(house_lasso_mod) %>% add_recipe(house_rec)
lasso_res <- lasso_wf %>% tune_grid(grid = lasso_grid, resamples = folds)
```

Results

```r
collect_metrics(lasso_res)
```

```
## # A tibble: 20 x 7
##          penalty .metric .estimator      mean     n   std_err .config
##            <dbl> <chr>   <chr>          <dbl> <int>     <dbl> <chr>
##  1      0.0001   rmse    standard   27066.       10 1622.     Preprocessor1_Mode~
##  2      0.0001   rsq     standard       0.881    10    0.0179 Preprocessor1_Mode~
##  3      0.000774 rmse    standard   27066.       10 1622.     Preprocessor1_Mode~
##  4      0.000774 rsq     standard       0.881    10    0.0179 Preprocessor1_Mode~
##  5      0.00599  rmse    standard   27066.       10 1622.     Preprocessor1_Mode~
##  6      0.00599  rsq     standard       0.881    10    0.0179 Preprocessor1_Mode~
##  7      0.0464   rmse    standard   27066.       10 1622.     Preprocessor1_Mode~
##  8      0.0464   rsq     standard       0.881    10    0.0179 Preprocessor1_Mode~
##  9      0.359    rmse    standard   27066.       10 1622.     Preprocessor1_Mode~
## 10      0.359    rsq     standard       0.881    10    0.0179 Preprocessor1_Mode~
## 11      2.78     rmse    standard   27066.       10 1622.     Preprocessor1_Mode~
## 12      2.78     rsq     standard       0.881    10    0.0179 Preprocessor1_Mode~
## 13     21.5      rmse    standard   27066.       10 1622.     Preprocessor1_Mode~
## 14     21.5      rsq     standard       0.881    10    0.0179 Preprocessor1_Mode~
## 15    167.       rmse    standard   26669.       10 1619.     Preprocessor1_Mode~
## 16    167.       rsq     standard       0.883    10    0.0165 Preprocessor1_Mode~
## 17   1292.       rmse    standard   26728.       10 2117.     Preprocessor1_Mode~
## 18   1292.       rsq     standard       0.880    10    0.0148 Preprocessor1_Mode~
## 19  10000        rmse    standard   32100.       10 2500.     Preprocessor1_Mode~
## 20  10000        rsq     standard       0.845    10    0.0209 Preprocessor1_Mode~
```

Results

```
collect_metrics(lasso_res)
```

```
## # A tibble: 20 x 7
##         penalty .metric .estimator     mean     n   std_err .config
##           <dbl> <chr>   <chr>         <dbl> <int>     <dbl> <chr>
##  1      0.0001  rmse    standard   27066.      10 1622.     Preprocessor1_Mode~
##  2      0.0001  rsq     standard       0.881   10    0.0179 Preprocessor1_Mode~
##  3      0.000774 rmse   standard   27066.      10 1622.     Preprocessor1_Mode~
##  4      0.000774 rsq    standard       0.881   10    0.0179 Preprocessor1_Mode~
##  5      0.00599 rmse    standard   27066.      10 1622.     Preprocessor1_Mode~
##  6      0.00599 rsq     standard       0.881   10    0.0179 Preprocessor1_Mode~
##  7      0.0464  rmse    standard   27066.      10 1622.     Preprocessor1_Mode~
##  8      0.0464  rsq     standard       0.881   10    0.0179 Preprocessor1_Mode~
##  9      0.359   rmse    standard   27066.      10 1622.     Preprocessor1_Mode~
## 10      0.359   rsq     standard       0.881   10    0.0179 Preprocessor1_Mode~
## 11      2.78    rmse    standard   27066.      10 1622.     Preprocessor1_Mode~
## 12      2.78    rsq     standard       0.881   10    0.0179 Preprocessor1_Mode~
## 13     21.5     rmse    standard   27066.      10 1622.     Preprocessor1_Mode~
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## 15    167.      rmse    standard   26669.      10 1619.     Preprocessor1_Mode~
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## 17   1292.      rmse    standard   26728.      10 2117.     Preprocessor1_Mode~
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## 19  10000       rmse    standard   32100.      10 2500.     Preprocessor1_Mode~
## 20  10000       rsq     standard       0.845   10    0.0209 Preprocessor1_Mode~
```

Which penalties?

- Focus just on optimal penalties for rmse:

```
lasso_res %>%
  show_best(metric = "rmse")
```

```
## # A tibble: 5 x 7
##       penalty .metric .estimator   mean     n std_err .config
##         <dbl> <chr>   <chr>       <dbl> <int>   <dbl> <chr>
## 1  167.       rmse    standard   26669.    10   1619. Preprocessor1_Model08
## 2 1292.       rmse    standard   26728.    10   2117. Preprocessor1_Model09
## 3    0.0001   rmse    standard   27066.    10   1622. Preprocessor1_Model01
## 4    0.000774 rmse    standard   27066.    10   1622. Preprocessor1_Model02
## 5    0.00599  rmse    standard   27066.    10   1622. Preprocessor1_Model03
```

Which penalties?

- Focus just on optimal penalties for rmse:

```
lasso_res %>%
  show_best(metric = "rmse")
```

```
## # A tibble: 5 x 7
##       penalty .metric .estimator   mean     n std_err .config
##         <dbl> <chr>   <chr>       <dbl> <int>   <dbl> <chr>
## 1  167.        rmse    standard   26669.    10   1619. Preprocessor1_Model08
## 2 1292.        rmse    standard   26728.    10   2117. Preprocessor1_Model09
## 3    0.0001    rmse    standard   27066.    10   1622. Preprocessor1_Model01
## 4    0.000774 rmse    standard   27066.    10   1622. Preprocessor1_Model02
## 5    0.00599  rmse    standard   27066.    10   1622. Preprocessor1_Model03
```

- Let's choose the best model:

```
best_lasso <- lasso_res %>% select_best(metric = "rmse")
best_lasso
```

```
## # A tibble: 1 x 2
##   penalty .config
##     <dbl> <chr>
## 1    167. Preprocessor1_Model08
```

Finalize the model

- We update or finalize our workflow with the values from `select_best`:

```
final_lasso_wf <- lasso_wf %>% finalize_workflow(best_lasso)
final_lasso_wf
```

```
## == Workflow ==================================================================
## Preprocessor: Recipe
## Model: linear_reg()
##
## -- Preprocessor --------------------------------------------------------------
## 5 Recipe Steps
##
## * step_log()
## * step_mutate()
## * step_rm()
## * step_novel()
## * step_dummy()
##
## -- Model ---------------------------------------------------------------------
## Linear Regression Model Specification (regression)
##
## Main Arguments:
##   penalty = 166.810053720006
##
## Computational engine: glmnet
```

Fit the Best Model

- Thus far, we've just focused on finding the best parameter. But we haven't actually built a LASSO model on training data, nor predicted on the test data. Let's do just that:

Fit the Best Model

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```
final_lasso_fit<-final_lasso_wf %>% last_fit(data_split )
final_lasso_fit$.metrics[[1]]
```

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard   28961.    Preprocessor1_Model1
## 2 rsq     standard       0.823 Preprocessor1_Model1
```

```
final_lasso_fit$.predictions[[1]] %>% head()
```

```
## # A tibble: 6 x 4
##     .pred  .row SalePrice .config
##     <dbl> <int>     <int> <chr>
## 1 187702.     1    181500 Preprocessor1_Model1
## 2 256420.     3    200000 Preprocessor1_Model1
## 3 182292.     4    149000 Preprocessor1_Model1
## 4 160247.     5    154000 Preprocessor1_Model1
## 5 262237.     7    306000 Preprocessor1_Model1
## 6 234814.     9    177000 Preprocessor1_Model1
```