Tidymodels

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Math 243: Stat Learning

November 22nd, 2021

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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`lda`	MASS	`predict(object)`
`glm`	stats	`predict(object, type = "response")`
`gbm`	gbm	`predict(object, type = "response", n.trees)`
`rpart`	rpart	`predict(object, type = "prob")`
`kknn`	kknn	`kknn(...)$prob`

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- Each method has significantly different methods for making class probability predictions
- Additionally, each model takes in different types of data arguments (vectors, model matrices, data frames, model formulas)

`tidymodels` goals

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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 (`mass`, `tree`, `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

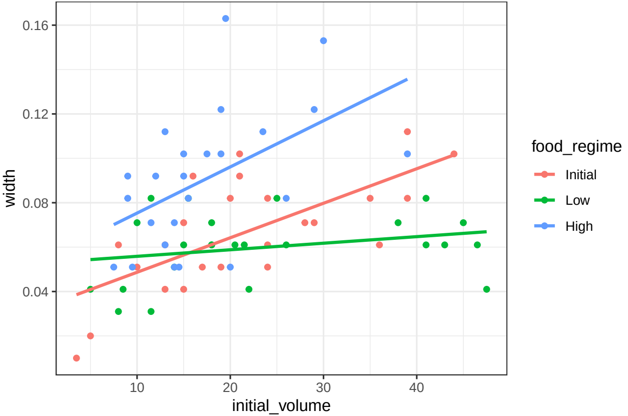
The Data

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



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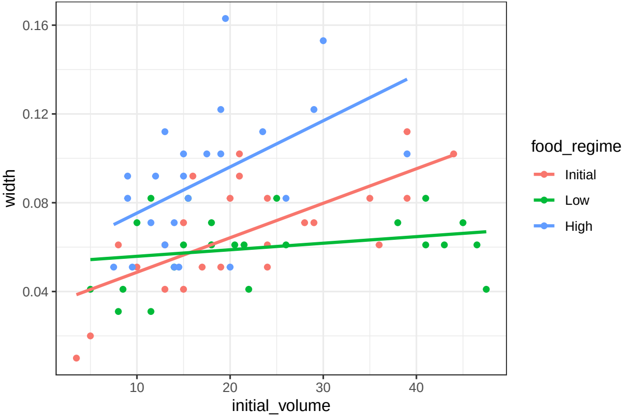

- Goal: Predict `width` as a function of `food_regime` and `initial_volume`.

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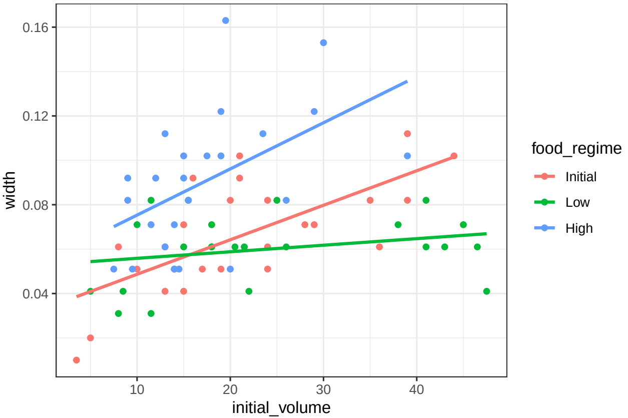

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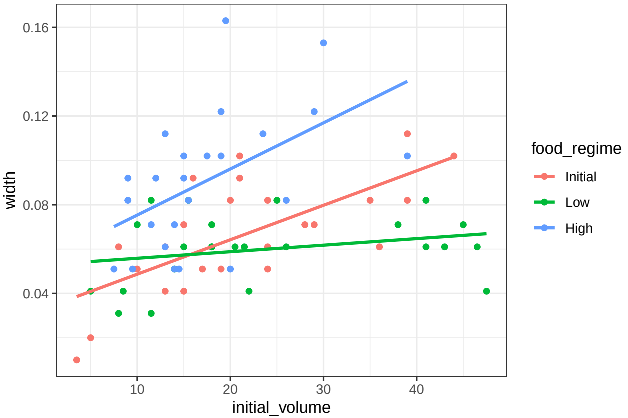

- Goal: Predict `width` as a function of `food_regime` and `initial_volume`.
  - Does an additive model seem appropriate?
  - One option might be a linear model with interaction terms.

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width ~ initial_volume + food_regime + initial_volume:food_regime
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```
library(parsnip)
linear_reg() %>%
  set_engine("lm")
```

```
## 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
##
## Fit time:  0ms
##
## 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()
```

term	estimate	std.error	statistic	p.value
(Intercept)	0.0331216	0.0096186	3.4434873	0.0010020
initial_volume	0.0015546	0.0003978	3.9077643	0.0002220
food_regimeLow	0.0197824	0.0129883	1.5230864	0.1325145
food_regimeHigh	0.0214111	0.0145318	1.4733993	0.1453970
initial_volume:food_regimeLow	-0.0012594	0.0005102	-2.4685525	0.0161638
initial_volume:food_regimeHigh	0.0005254	0.0007020	0.7484702	0.4568356

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

New Data

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- First, we generate data:

```
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)
conf_int_preds<-predict(lm_fit, new_data = new_urchins, type = "conf_int")
new_preds %>% kable()
```

.pred
0.0408948
0.0797608
0.0543803
0.0617621
0.0649329
0.1169338

```
conf_int_preds %>% kable()
```

.pred_lower	.pred_upper
0.0251382	0.0566514
0.0688612	0.0906605
0.0396403	0.0691204
0.0522641	0.0712601
0.0483265	0.0815393
0.0999144	0.1339532

Combining Data and Predictions

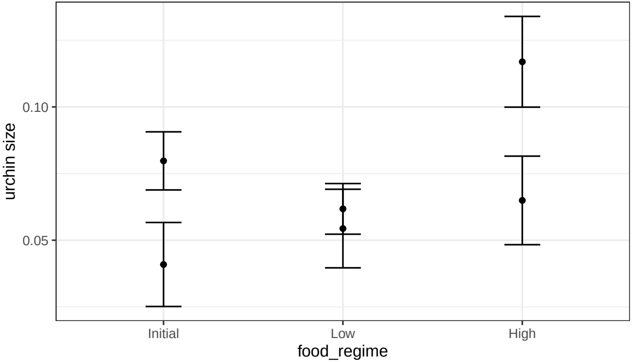
Because the result of `predict()` is tidy, we can easily combine it with the original data:

```
combined_data <- new_urchins %>% cbind(new_preds) %>% cbind(conf_int_preds)
combined_data %>% kable()
```

initial_volume	food_regime	.pred	.pred_lower	.pred_upper
5	Initial	0.0408948	0.0251382	0.0566514
30	Initial	0.0797608	0.0688612	0.0906605
5	Low	0.0543803	0.0396403	0.0691204
30	Low	0.0617621	0.0522641	0.0712601
5	High	0.0649329	0.0483265	0.0815393
30	High	0.1169338	0.0999144	0.1339532

Predictions Plot

```r
ggplot(combined_data, aes(x = food_regime)) +
  geom_point(aes(y = .pred)) +
  geom_errorbar(aes(ymin = .pred_lower, ymax = .pred_upper),width = .2) +
  labs(y = "urchin size")+theme_bw()
```



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` somewhat arbitrarily (we'll tune later); in any case, `glmnet` will still create models for all λ

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- `glmnet` requires us to indicate a value of `penalty` parameter λ to make predictions.
  - Here, we choose `penalty = 0.01` somewhat arbitrarily (we'll tune later); in any case, `glmnet` will still create models for all λ

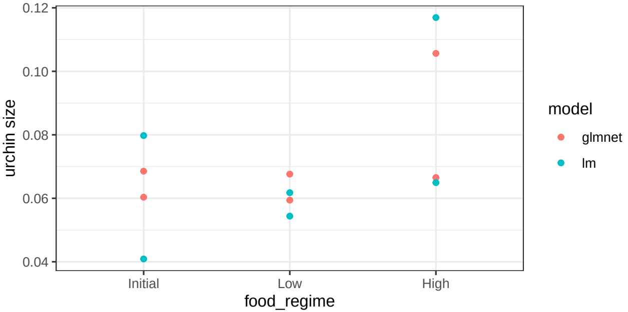
```
glmnet_fit <- glmnet_mod %>% fit(width ~ initial_volume*food_regime, data = sea_urchins)
tidy(glmnet_fit, penalty = .004) #penalty selects particular value of lambda
```

```
## # 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 %>% select(-.pred_lower, -.pred_upper )) %>%
  mutate(model = rep(c("glmnet","lm"), each = 6))
```

```
ggplot(two_models, aes(x = food_regime)) +
  geom_point(aes(y = .pred, color = model) ) +
  labs(y = "urchin size")+theme_bw()
```



Section 3

Preprocessing with recipes

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  - Transforms data to be on a different scale
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  - 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

```
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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## [29] "EnclosedPorch" "FullBath"      "HalfBath"
```

- Note that the variable `Id` is not useful as a predictor, but is useful for referring to houses in the data set.

Investigate Predictors

- Additionally, note that several of the variables are factors, so should be converted to a collection of dummy variables.

Investigate Predictors

- Additionally, note that several of the variables are factors, so should be converted to a collection of dummy variables.
- Moreover, for a few 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
```

Data Splitting

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```
library(rsample)
set.seed(1221)
data_split <- initial_split(house , prop = 3/4)
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

```
library(recipes)
house_rec <-
  recipe(SalePrice ~ ., data = train_data) %>%
  update_role(Id, new_role = "ID")
```

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```
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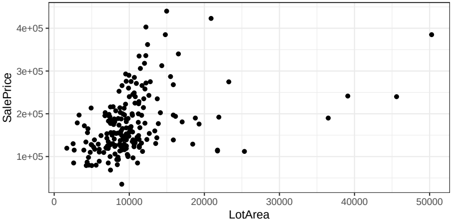
```

```
summary(house_rec)
```

```
## # A tibble: 31 x 4
##    variable      type    role      source
##    <chr>         <chr>   <chr>     <chr>
##  1 Id            numeric ID        original
##  2 Functional    nominal predictor original
##  3 BldgType      nominal predictor original
##  4 Foundation    nominal predictor original
##  5 LotShape      nominal predictor original
##  6 LandSlope     nominal predictor original
##  7 SaleCondition nominal predictor original
##  8 RoofMatl      nominal predictor original
##  9 ScreenPorch   numeric predictor original
## 10 MSSubClass    numeric predictor original
## # ... with 21 more rows
```

Add steps to recipes

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



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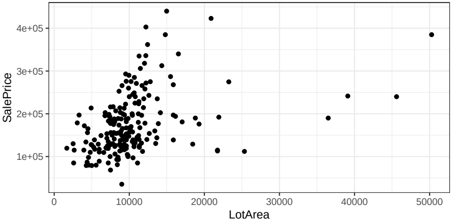
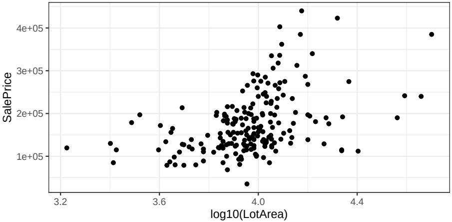


- Accuracy of a linear model may improve by performing log transformation on LotArea:



Adding steps to recipes

- Let's update our recipe:

```
house_rec <- house_rec %>%
  step_log(LotArea, base = 10)

house_rec
```

```
## Recipe
##
## Inputs:
##
##       role #variables
##         ID          1
##    outcome          1
##  predictor         29
##
## Operations:
##
## Log transformation on LotArea
```

Create New Variables from Old

- The original data set contains variables `FullBath` and `HalfBath`. But we want a measure of total number of baths:

$$\mathrm{TotalBath} = \mathrm{FullBath} + \frac{1}{2}\mathrm{HalfBath}$$

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- The original data set contains variables `FullBath` and `HalfBath`. But we want a measure of total number of baths:

$$\text{TotalBath} = \text{FullBath} + \frac{1}{2}\text{HalfBath}$$

- We can also add a mutate step in our recipe to do just this:

```
house_rec <- house_rec %>%
  step_mutate(TotalBath = FullBath+0.5*HalfBath) %>%
  step_rm(FullBath, HalfBath)

house_rec
```

```
## Recipe
##
## Inputs:
##
##       role #variables
##         ID          1
##    outcome          1
##  predictor         29
##
## Operations:
##
## Log transformation on LotArea
```

Create Dummy Variables

- Recall that 7 of our variables are factors (`Functional`, `BldgType`, `Foundation`, `LotShape`, `LandSlope`, `SaleCondition`, `RoofMatl`). To create appropriate dummy variables:

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

```
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##
## Inputs:
##
##       role #variables
##         ID          1
##    outcome          1
##  predictor         29
##
## Operations:
##
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## Variable mutation
## Delete terms FullBath, HalfBath
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- The first argument `all_nominal` selects all variables that are either factors or characters
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- The first argument `all_nominal` selects all variables that are either factors or characters
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Remove Problematic Predictors

- Finally, to avoid the situation where an infrequently occuring level doesn't exist in the training or test sets:

```
house_rec <- house_rec %>% step_zv(all_predictors())
house_rec
```

```
## Recipe
##
## Inputs:
##
##       role #variables
##         ID          1
##    outcome          1
##  predictor         29
##
## Operations:
##
## Log transformation on LotArea
## Variable mutation
## Delete terms FullBath, HalfBath
## Dummy variables from all_nominal(), -all_outcomes()
## Zero variance filter on all_predictors()
```

Remove Problematic Predictors

- Finally, to avoid the situation where an infrequently occuring level doesn't exist in the training or test sets:

```
house_rec <- house_rec %>% step_zv(all_predictors())
house_rec
```

```
## Recipe
##
## Inputs:
##
##       role #variables
##         ID          1
##    outcome          1
##  predictor         29
##
## Operations:
##
## Log transformation on LotArea
## Variable mutation
## Delete terms FullBath, HalfBath
## Dummy variables from all_nominal(), -all_outcomes()
## Zero variance filter on all_predictors()
```

- The `step_zv` verb removes columns from the training data which have a single value

Workflows

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

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**

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_dummy()
## * step_zv()
##
## -- Model ---------------------------------------------------------------------
## Linear Regression Model Specification (regression)
##
## Computational engine: lm
```

Fitting Models with Workflows

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

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

```
## # A tibble: 47 x 5
##    term          estimate  std.error statistic p.value
##    <chr>            <dbl>      <dbl>     <dbl>   <dbl>
##  1 (Intercept)  1920452.  3087160.       0.622 0.535
##  2 ScreenPorch       59.7      69.1      0.863 0.390
##  3 MSSubClass      -323.      129.      -2.50  0.0138
##  4 GarageCars      3602.     7179.       0.502 0.617
##  5 BedroomAbvGr    1509.     3933.       0.384 0.702
##  6 TotalBsmtSF       12.4       8.82     1.41  0.162
##  7 LotArea        20971.    20280.       1.03  0.304
##  8 OpenPorchSF      -17.0      37.0     -0.461 0.646
##  9 BsmtFullBath   16888.     5087.       3.32  0.00124
## 10 WoodDeckSF        18.5      17.9      1.03  0.305
## # ... with 37 more rows
```

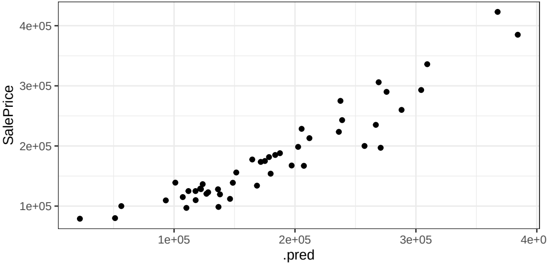
Making predictions with workflow

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

```
## # A tibble: 50 x 1
##      .pred
##      <dbl>
##  1 178531.
##  2 236275.
##  3 257502.
##  4 269208.
##  5  51212.
##  6 123668.
##  7 136742.
##  8 136343.
##  9 238991.
## 10     NA
## # ... with 40 more rows
```

Evaluate performance

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




```
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   27049.
## 2 rsq     standard       0.885
```

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   27049.
## 2 rsq     standard       0.885
```

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   27049.
## 2 rsq     standard       0.885
```

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

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

Delving Deeper

- Which observations are in each fold?

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

```
## <Analysis/Assess/Total>
## <135/15/150>
```

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

```
##     SalePrice   Id Functional BldgType Foundation
## 58      81000  387        Typ     1Fam      PConc
## 37     113000  240        Typ     1Fam     CBlock
## 85     124000  631        Typ     1Fam     BrkTil
## 108    183000  821        Typ     1Fam      PConc
## 192    340000 1418        Typ     1Fam      PConc
## 165     93000 1180       Min2     1Fam       Slab
```

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

```
##     SalePrice   Id Functional BldgType Foundation
## 193    271000 1427        Typ     1Fam      PConc
## 74     130000  499        Typ     1Fam      PConc
## 131    136500  997        Typ     1Fam     CBlock
## 123    169990  923        Typ     1Fam      PConc
## 82     240000  622        Typ     1Fam     CBlock
## 194    119000 1429        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 [135/15]> Fold01 <tibble [2 x 4]> <tibble [1 x 1]>
##  2 <split [135/15]> Fold02 <tibble [2 x 4]> <tibble [1 x 1]>
##  3 <split [135/15]> Fold03 <tibble [2 x 4]> <tibble [1 x 1]>
##  4 <split [135/15]> Fold04 <tibble [2 x 4]> <tibble [1 x 1]>
##  5 <split [135/15]> Fold05 <tibble [2 x 4]> <tibble [1 x 1]>
##  6 <split [135/15]> Fold06 <tibble [2 x 4]> <tibble [1 x 1]>
##  7 <split [135/15]> Fold07 <tibble [2 x 4]> <tibble [1 x 1]>
##  8 <split [135/15]> Fold08 <tibble [2 x 4]> <tibble [1 x 1]>
##  9 <split [135/15]> Fold09 <tibble [2 x 4]> <tibble [1 x 1]>
## 10 <split [135/15]> Fold10 <tibble [2 x 4]> <tibble [1 x 1]>
```

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   28540.    Preprocessor1_Model1
## 2 rsq     standard       0.874 Preprocessor1_Model1
```

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

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard   22605.    Preprocessor1_Model1
## 2 rsq     standard       0.884 Preprocessor1_Model1
```

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

```
## # A tibble: 2 x 4
##   .metric .estimator .estimate .config
##   <chr>   <chr>          <dbl> <chr>
## 1 rmse    standard   22019.    Preprocessor1_Model1
## 2 rsq     standard       0.876 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
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard   27049.
## 2 rsq     standard       0.885
```

CV Performance

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#Baseline
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  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   27049.
## 2 rsq     standard       0.885
```

- 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   24994.       10 1939.     Preprocessor1_Model1
## 2 rsq     standard       0.862    10    0.0237 Preprocessor1_Model1
```

Section 5

Tuning Hyperparameters

Building a LASSO model

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```
house_lasso_mod <- linear_reg(penalty =4 ) %>% set_engine("glmnet")
```

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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")
```

Building a LASSO model

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house_lasso_mod <- linear_reg(penalty =4 ) %>% set_engine("glmnet")
```

- 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(-5,5)), 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

```
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       0.00001 rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
##  2       0.00001 rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
##  3       0.000129 rmse   standard   24577.       10 1966.     Preprocessor1_Mod~
##  4       0.000129 rsq    standard       0.867    10    0.0209 Preprocessor1_Mod~
##  5       0.00167 rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
##  6       0.00167 rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
##  7       0.0215  rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
##  8       0.0215  rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
##  9       0.278   rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
## 10       0.278   rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
## 11       3.59    rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
## 12       3.59    rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
## 13      46.4     rmse    standard   24499.       10 1981.     Preprocessor1_Mod~
## 14      46.4     rsq     standard       0.868    10    0.0209 Preprocessor1_Mod~
## 15     599.      rmse    standard   23612.       10 2259.     Preprocessor1_Mod~
## 16     599.      rsq     standard       0.878    10    0.0111 Preprocessor1_Mod~
## 17    7743.      rmse    standard   28677.       10 3090.     Preprocessor1_Mod~
## 18    7743.      rsq     standard       0.844    10    0.0281 Preprocessor1_Mod~
## 19 100000        rmse    standard   67654.       10 5580.     Preprocessor1_Mod~
## 20 100000        rsq     standard     NaN         0   NA      Preprocessor1_Mod~
```

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      0.00001 rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
##  2      0.00001 rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
##  3      0.000129 rmse   standard   24577.       10 1966.     Preprocessor1_Mod~
##  4      0.000129 rsq    standard       0.867    10    0.0209 Preprocessor1_Mod~
##  5      0.00167 rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
##  6      0.00167 rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
##  7      0.0215  rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
##  8      0.0215  rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
##  9      0.278   rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
## 10      0.278   rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
## 11      3.59    rmse    standard   24577.       10 1966.     Preprocessor1_Mod~
## 12      3.59    rsq     standard       0.867    10    0.0209 Preprocessor1_Mod~
## 13     46.4     rmse    standard   24499.       10 1981.     Preprocessor1_Mod~
## 14     46.4     rsq     standard       0.868    10    0.0209 Preprocessor1_Mod~
## 15    599.      rmse    standard   23612.       10 2259.     Preprocessor1_Mod~
## 16    599.      rsq     standard       0.878    10    0.0111 Preprocessor1_Mod~
## 17   7743.      rmse    standard   28677.       10 3090.     Preprocessor1_Mod~
## 18   7743.      rsq     standard       0.844    10    0.0281 Preprocessor1_Mod~
## 19 100000       rmse    standard   67654.       10 5580.     Preprocessor1_Mod~
## 20 100000       rsq     standard     NaN         0   NA      Preprocessor1_Mod~
```

Which penalties?

- Focus just on optimal penalties for rmse:

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

```
## # A tibble: 5 x 7
##      penalty .metric .estimator   mean     n std_err .config
##        <dbl> <chr>   <chr>       <dbl> <int>   <dbl> <chr>
## 1 599.       rmse    standard   23612.    10   2259. Preprocessor1_Model08
## 2  46.4      rmse    standard   24499.    10   1981. Preprocessor1_Model07
## 3   0.00001  rmse    standard   24577.    10   1966. Preprocessor1_Model01
## 4   0.000129 rmse    standard   24577.    10   1966. Preprocessor1_Model02
## 5   0.00167  rmse    standard   24577.    10   1966. Preprocessor1_Model03
```

Which penalties?

- Focus just on optimal penalties for rmse:

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

```
## # A tibble: 5 x 7
##      penalty .metric .estimator   mean     n std_err .config
##        <dbl> <chr>   <chr>       <dbl> <int>   <dbl> <chr>
## 1 599.       rmse    standard   23612.    10   2259. Preprocessor1_Model08
## 2  46.4      rmse    standard   24499.    10   1981. Preprocessor1_Model07
## 3   0.00001  rmse    standard   24577.    10   1966. Preprocessor1_Model01
## 4   0.000129 rmse    standard   24577.    10   1966. Preprocessor1_Model02
## 5   0.00167  rmse    standard   24577.    10   1966. Preprocessor1_Model03
```

- Let's collect the best model:

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

```
## # A tibble: 1 x 2
##   penalty .config
##     <dbl> <chr>
## 1    599. 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_dummy()
## * step_zv()
##
## -- Model -------------------------------------------------------------------------
## Linear Regression Model Specification (regression)
##
## Main Arguments:
##   penalty = 599.484250318942
##
## 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. Let's do that:

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. Let's do that:

```
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   26889.    Preprocessor1_Model1
## 2 rsq     standard       0.883 Preprocessor1_Model1
```

```
final_lasso_fit$.predictions
```

```
## [[1]]
## # A tibble: 50 x 4
##      .pred  .row SalePrice .config
##      <dbl> <int>     <int> <chr>
##  1 178628.     1    181500 Preprocessor1_Model1
##  2 231755.     2    223500 Preprocessor1_Model1
##  3 247905.     3    200000 Preprocessor1_Model1
##  4 265349.     7    306000 Preprocessor1_Model1
##  5  58165.    12     80000 Preprocessor1_Model1
##  6 129233.    14    136500 Preprocessor1_Model1
##  7 135097.    16     98600 Preprocessor1_Model1
```