Hyperparameters and Validation

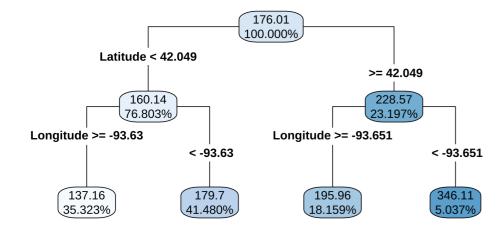
K Arnold

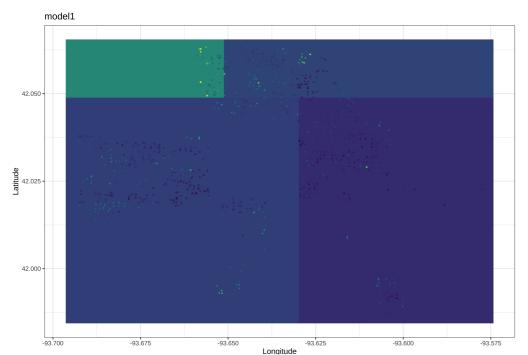
```
data(ames, package = "modeldata")
ames all <- ames %>%
 filter(Gr Liv Area < 4000, Sale Condition == "Normal") %>%
 mutate(across(where(is.integer), as.double)) %>%
 mutate(Sale Price = Sale Price / 1000)
rm(ames)
set.seed(10) # Seed the random number generator
ames split <- initial split(ames all, prop = 2 / 3)
ames train <- training(ames split)</pre>
ames test <- testing(ames split)</pre>
model1 <-
  decision_tree(mode = "regression", tree_depth = 2) %>%
  fit(Sale_Price ~ Latitude + Longitude, data = ames_train)
model2 <-
  decision_tree(mode = "regression", tree_depth = 30) %>%
  fit(Sale_Price ~ Latitude + Longitude, data = ames_train)
model3 <-
  decision_tree(mode = "regression", cost_complexity = 1e-6, min_n = 2) %>%
  fit(Sale_Price ~ Latitude + Longitude, data = ames_train)
```

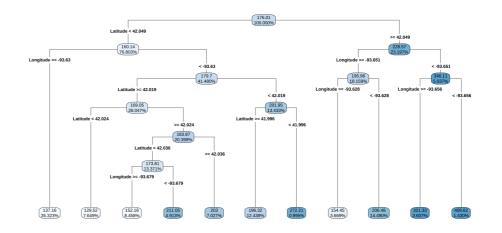
This week

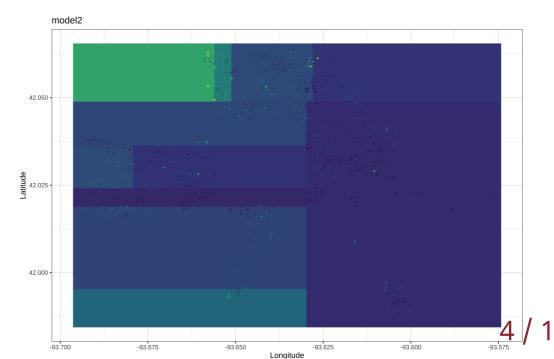
- *Today*: how modeling decisions affect performance; why validate?
- Wednesday: how to validate?
- Friday: cross-validation lab

Decision Trees









Q&A

- How do we *train* a decision tree?
- The model: "choose your own adventure": at each step, check one simple condition about one variable (e.g., Latitude < 42.05)
- Goal: find the best tree (for regression: minimize MSE)
- Approach: greedy algorithm: try all possible splits, keep the best one, repeat.
 - I missed one of the check-in quizzes (or even weekly quizzes)!

Email me.

Is midterm project individual?

At this point, yes.

Objectives

- Identify modeling decisions that affect the performance of decision tree and linear regression models, including:
 - Choice of model type
 - Pre-processing steps
 - Hyperparameter settings
- Explain the importance of *validation* for assessing and comparing models.

Which model to use

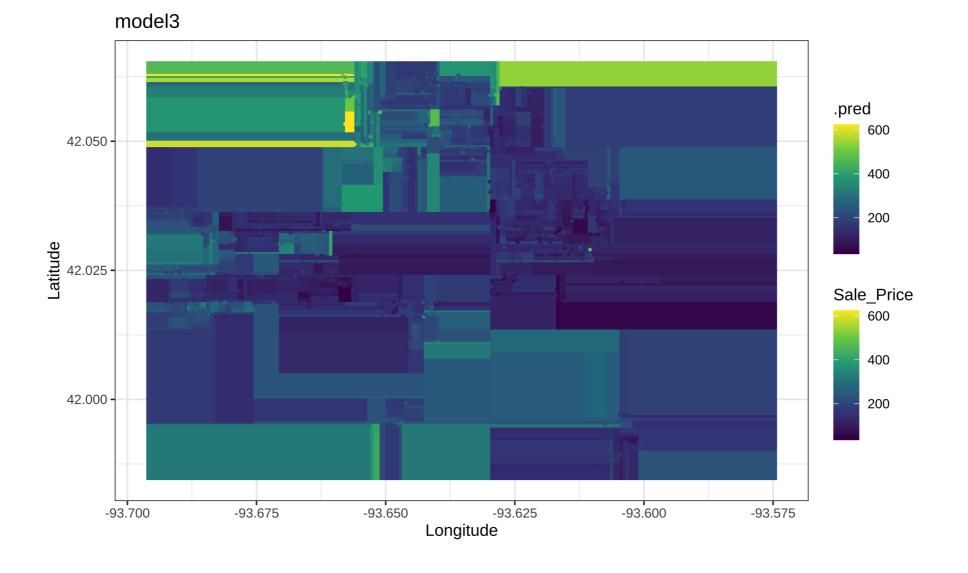
- Which model to use
- Shifting and scaling features

- Which model to use
- Shifting and scaling features
- Hyperparameters: Tree depth, number of observations per leaf, ...

Hyperparameters for Decision Trees

```
model1 <-
  decision_tree(mode = "regression", tree_depth = 2) %>%
  fit(Sale_Price ~ Latitude + Longitude, data = ames_train)
model2 <-
  decision_tree(mode = "regression", tree_depth = 30) %>%
  fit(Sale_Price ~ Latitude + Longitude, data = ames_train)
model3 <-
  decision_tree(mode = "regression", cost_complexity = 1e-6, min_n = 2) %>%
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```

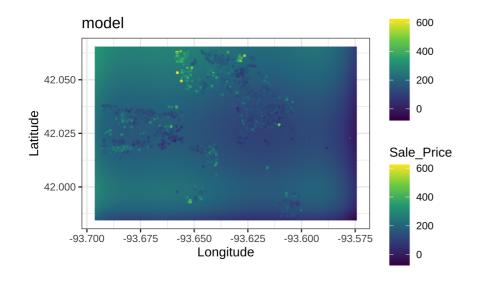
- Tree depth: how many levels of decisions
- Leaf size: how many observations need to be in each leaf node
- Complexity penalty: how much improvement for a split to be "worth it"



Hyperparameters for Linear Regression

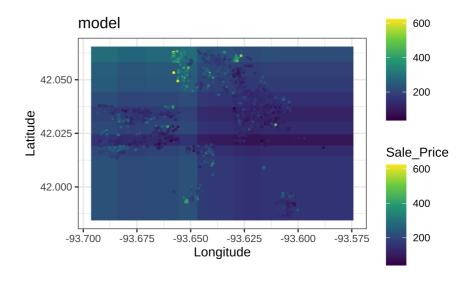
```
recipe <-
  recipe(Sale_Price ~ Latitude + Longitude, dans
step_poly(Latitude, Longitude, degree = 5)</pre>
```

```
model <- workflow() %>% add_recipe(recipe) %>% add_model(linear_reg()) %>%
  fit(ames_train)
show_latlong_model(ames_train, model)
```



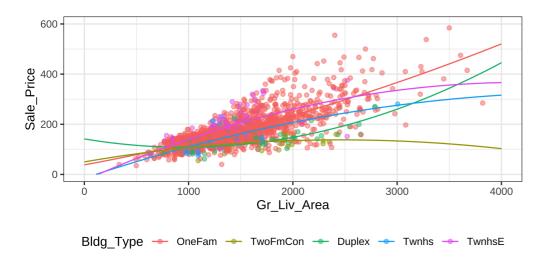
recipe < recipe(Sale_Price ~ Latitude + Longitude, da step_discretize(Latitude, Longitude, num_brea</pre>

```
model <- workflow() %>% add_recipe(recipe) %>% add_model(linear_reg()) %>%
  fit(ames_train)
show_latlong_model(ames_train, model)
```



Polynomial and interaction features

```
recipe <-
  recipe(Sale_Price ~ Gr_Liv_Area + Bldg_Type,
  step_dummy(Bldg_Type) %>%
  step_interact(
    ~ Gr_Liv_Area:starts_with("Bldg_Type")) %>%
  step_poly(
    starts_with("Gr_Liv_Area"), degree = 2)
```



```
recipe <-
  recipe(Sale_Price ~ Gr_Liv_Area + Bldg_Type,
  step_dummy(Bldg_Type) %>%
  step_interact(
    ~ Gr_Liv_Area:starts_with("Bldg_Type")) %>%
  step_poly(
    starts_with("Gr_Liv_Area"), degree = 5)
```

