

Linear Regression II



EDS 232
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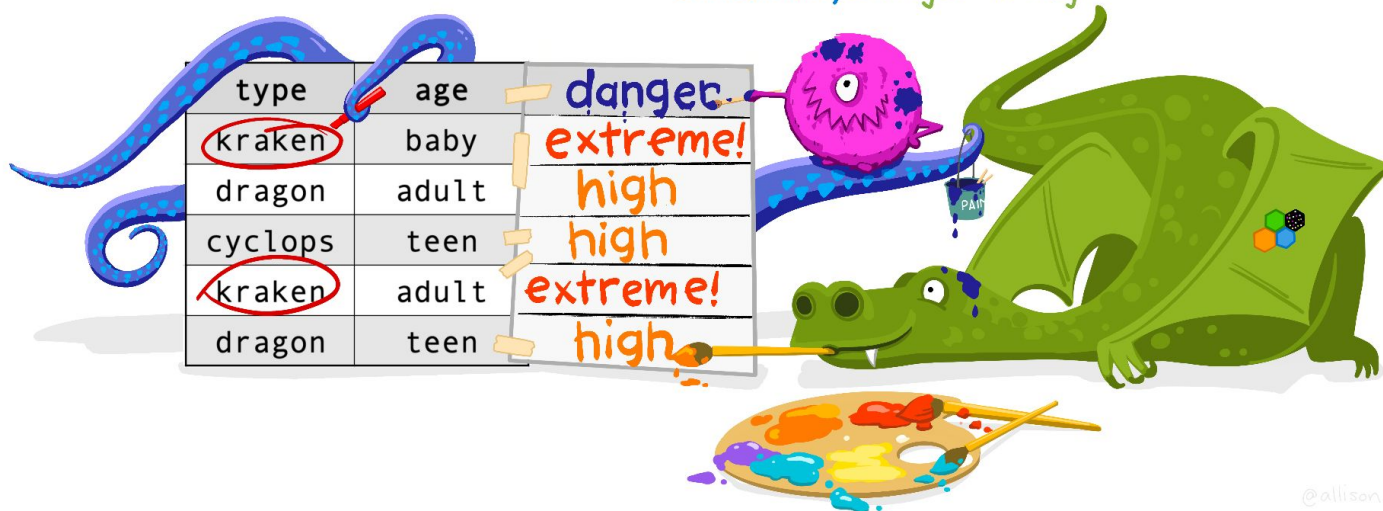
Following up from last time...

`dplyr::case_when()` IF ELSE...
(but you love it?)

df %>% ^{ADD COLUMN 'danger'}

```
mutate(danger = case_when(type == "kraken" ~ "extreme!",  
                           TRUE ~ "high"))
```

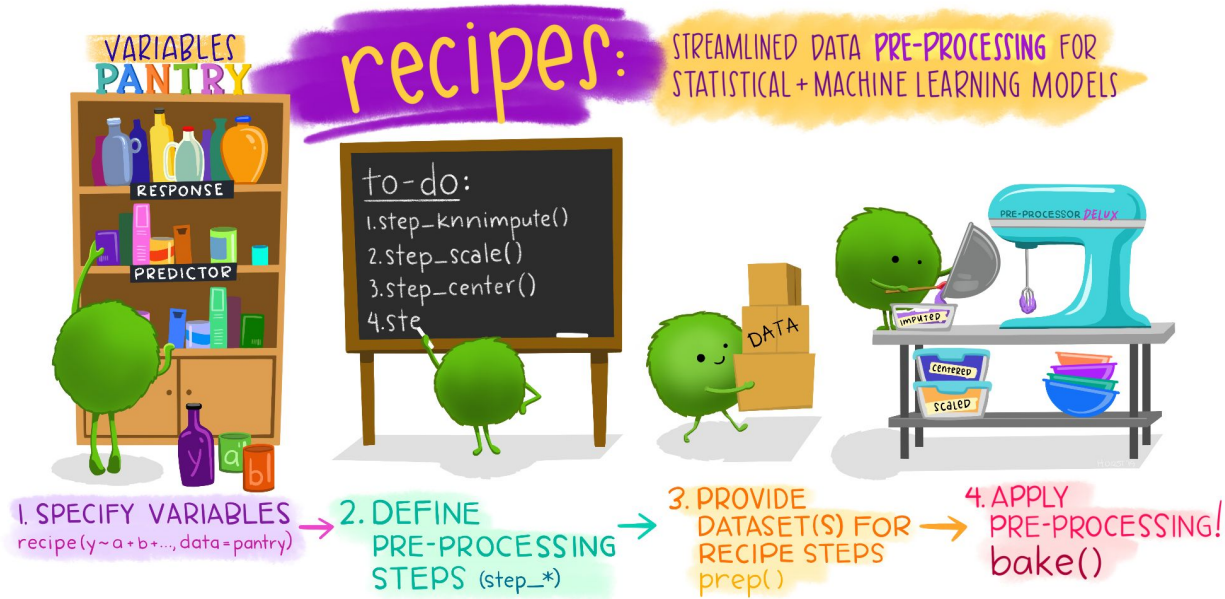
IF type is kraken THEN danger is extreme!
TRUE ~ "high"
OTHERWISE, danger is high.



More context for tidymodels

Model preprocessing

A recipe prepares your data for modeling



A recipe is a specification of intent

- Recipes allow us to specify the preprocessing steps to carry out on the data to prepare it for modeling

A recipe is a specification of intent

- Recipes allow us to specify the preprocessing steps to carry out on the data to prepare it for modeling
 - Encoding predictors
 - Computing polynomials of degree n ...

Recipe code

```
example_recipe <- recipe(outcome ~ predictor, data = your_data) %>%  
  step_integer(all_predictors(), zero_based = TRUE)
```


Prepping and baking your recipe

`prep()`: executes the transformations specified in your recipe onto some data (usually training data)

`bake()`: takes a prepped recipe and applies it to a data set (usually the test)

ML Modeling Process

- **Define**
 - Specify what type of model will it be. Define some parameters.
- **Fit**
 - Capture patterns from provided data. The heart of the modeling process.
- **Predict**
 - Use the model.
- **Evaluate**
 - How accurate are the model's predictions?

Specifying a model in tidymodels

- **Specify the model based on mathematical structure**
 - Linear regression, random forest, KNN, etc.
- **Specify an engine for fitting the model**
 - Usually which software package to use
- **Declare mode of the model (when required)**
 - Numeric outcome = regression, qualitative outcome = classification

Specifying a model in tidymodels

```
example_spec <- linear_reg() %>%  
  set_engine("lm") %>%  
  set_mode("regression")
```

Workflow Bundles Model Components

```
example_wf <- workflow() %>%  
  add_recipe("some_recipe") %>%  
  add_model("some_spec")
```

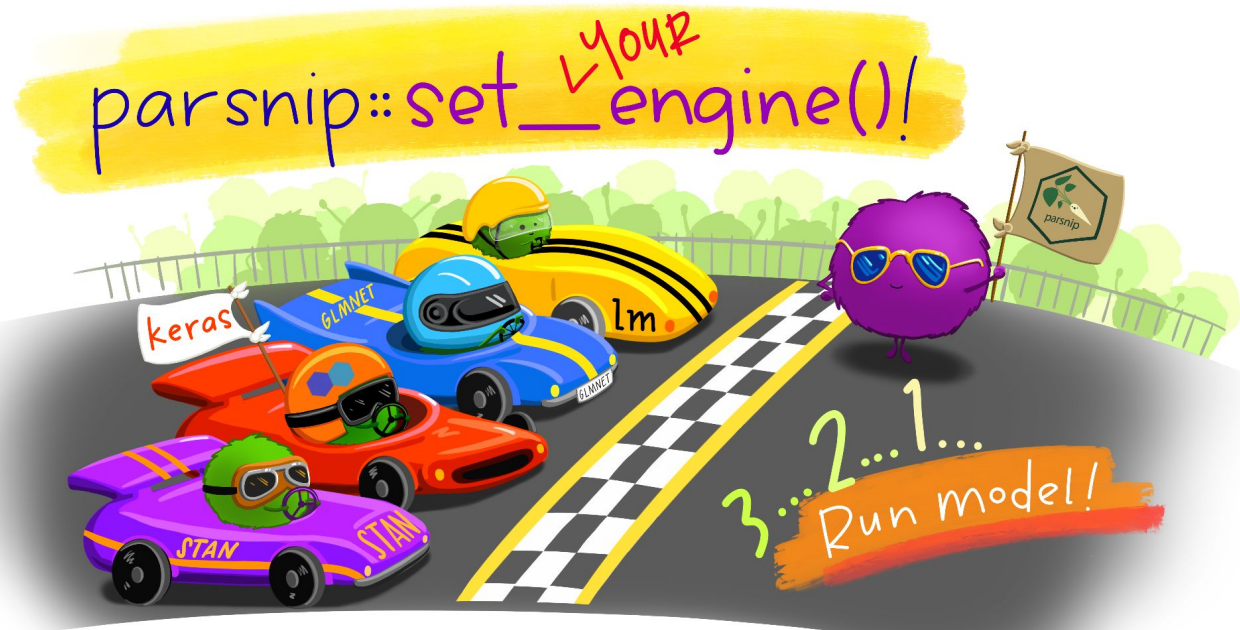
Why use a workflow()?

- Simplify workspace
- Prepping and fitting with a single call
- Simplified custom tuning
- Postprocessing

Why use a workflow()?

- Simplify workspace
- Prepping and fitting with a single call
- *Simplified custom tuning*
- *Postprocessing*

parsnip()



a standardized interface for fitting models
and making predictions.

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Fitting a model

- Parsnip allows us to be indifferent to the interface of the underlying model
 - Simply use `fit()` to estimate the model

Parsnip is tidy

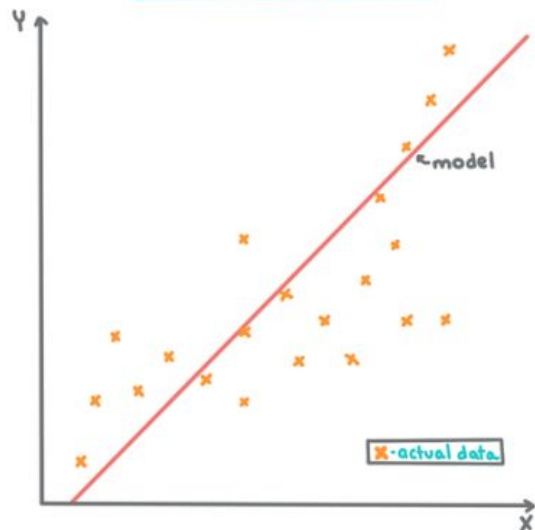
Table 3.1: Heterogeneous argument names for different modeling functions.

Function	Package	Code
<code>lda()</code>	MASS	<code>predict(object)</code>
<code>glm()</code>	stats	<code>predict(object, type = "response")</code>
<code>gbm()</code>	gbm	<code>predict(object, type = "response", n.trees)</code>
<code>mda()</code>	mda	<code>predict(object, type = "posterior")</code>
<code>rpart()</code>	rpart	<code>predict(object, type = "prob")</code>
various	RWeka	<code>predict(object, type = "probability")</code>
<code>logitboost()</code>	LogitBoost	<code>predict(object, type = "raw", nIter)</code>
<code>pamr.train()</code>	pamr	<code>pamr.predict(object, type = "posterior")</code>

Using Model Results

Today's Lab...more pumpkins

LINEAR REGRESSION



HOW IT WORKS

establishes a relationship between X and Y .

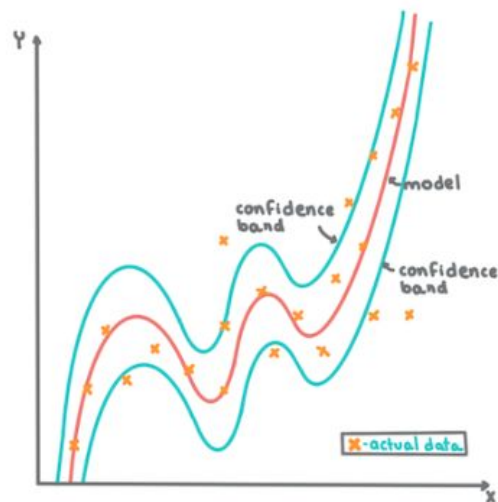
EXAMPLE

$$Y = b + mX$$

GOAL

optimize the slope (m) to reduce loss

POLYNOMIAL REGRESSION



HOW IT WORKS

type of linear regression where Y is modeled as an n^{th} degree polynomial of X .

EXAMPLE

$$Y = b + m_1X + m_2X^2 + \dots + m_nX^n$$

GOAL

optimize the coefficients $[m_1, m_2, \dots, m_n]$ to reduce loss.

@DASANI_DECODED

