

Building better training data to predict children in hotel bookings

Suggested answers



Your Turn 1

Unscramble! You have all the steps from our knn_rec - your challenge is to *unscramble* them into the right order!

Save the result as knn_rec

```
step_normalize(all_numeric())
recipe(children ~ ., data = hotels)
step_rm(arrival_date)
step_date(arrival_date)
step_downsample(children)
step_holiday(arrival_date, holidays = holidays)
step_dummy(all_nominal_predictors())
step_zv(all_predictors())
```

Answer:

```
knn_rec <- recipe(children ~ ., data = hotels) |>
    step_date(arrival_date) |>
    step_holiday(arrival_date, holidays = holidays) |>
    step_rm(arrival_date) |>
    step_dummy(all_nominal_predictors()) |>
    step_zv(all_predictors()) |>
    step_normalize(all_numeric()) |>
    step_downsample(children)
knn_rec
```

```
— Recipe

— Inputs

Number of variables by role

outcome: 1
predictor: 21

— Operations

• Date features from: arrival_date

• Holiday features from: arrival_date

• Variables removed: arrival_date

• Dummy variables from: all_nominal_predictors()

• Zero variance filter on: all_predictors()

• Centering and scaling for: all_numeric()

• Down-sampling based on: children
```

Your Turn 2

Fill in the blanks to make a workflow that combines knn rec and with knn mod.

Answer:

https://info5001.infosci.cornell.edu/ae/ae-16-build-better-training-data-A.html

Model: nearest_neighbor()

— Preprocessor —

Your Turn 3

Edit the code chunk below to fit the entire knn_wflow instead of just knn_mod.

Answer:

```
√ Fold02: preprocessor 1/1
i Fold02: preprocessor 1/1, model 1/1

√ Fold02: preprocessor 1/1, model 1/1
i Fold02: preprocessor 1/1, model 1/1 (extracts)
i Fold02: preprocessor 1/1, model 1/1 (predictions)
i Fold03: preprocessor 1/1
√ Fold03: preprocessor 1/1
i Fold03: preprocessor 1/1, model 1/1

√ Fold03: preprocessor 1/1, model 1/1
i Fold03: preprocessor 1/1, model 1/1 (extracts)
i Fold03: preprocessor 1/1, model 1/1 (predictions)
i Fold04: preprocessor 1/1
√ Fold04: preprocessor 1/1
i Fold04: preprocessor 1/1, model 1/1

√ Fold04: preprocessor 1/1, model 1/1
i Fold04: preprocessor 1/1, model 1/1 (extracts)
i Fold04: preprocessor 1/1, model 1/1 (predictions)
i Fold05: preprocessor 1/1
✓ Fold05: preprocessor 1/1
i Fold05: preprocessor 1/1, model 1/1

√ Fold05: preprocessor 1/1, model 1/1
i Fold05: preprocessor 1/1, model 1/1 (extracts)
i Fold05: preprocessor 1/1, model 1/1 (predictions)
i Fold06: preprocessor 1/1
√ Fold06: preprocessor 1/1
i Fold06: preprocessor 1/1, model 1/1
```

```
√ Fold06: preprocessor 1/1, model 1/1
i Fold06: preprocessor 1/1, model 1/1 (extracts)
i Fold06: preprocessor 1/1, model 1/1 (predictions)
i Fold07: preprocessor 1/1
✓ Fold07: preprocessor 1/1
i Fold07: preprocessor 1/1, model 1/1

√ Fold07: preprocessor 1/1, model 1/1
i Fold07: preprocessor 1/1, model 1/1 (extracts)
i Fold07: preprocessor 1/1, model 1/1 (predictions)
i Fold08: preprocessor 1/1
✓ Fold08: preprocessor 1/1
i Fold08: preprocessor 1/1, model 1/1

√ Fold08: preprocessor 1/1, model 1/1
i Fold08: preprocessor 1/1, model 1/1 (extracts)
i Fold08: preprocessor 1/1, model 1/1 (predictions)
i Fold09: preprocessor 1/1
✓ Fold09: preprocessor 1/1
i Fold09: preprocessor 1/1, model 1/1

√ Fold09: preprocessor 1/1, model 1/1
i Fold09: preprocessor 1/1, model 1/1 (extracts)
i Fold09: preprocessor 1/1, model 1/1 (predictions)
i Fold10: preprocessor 1/1
√ Fold10: preprocessor 1/1
i Fold10: preprocessor 1/1, model 1/1

√ Fold10: preprocessor 1/1, model 1/1
i Fold10: preprocessor 1/1, model 1/1 (extracts)
```

```
i Fold10: preprocessor 1/1, model 1/1 (predictions)
# A tibble: 3 \times 6
  .metric
                                   n std_err .config
              .estimator mean
  <chr>>
              <chr>>
                         <dbl> <int>
                                        <dbl> <chr>>
1 accuracy
              binary
                         0.739
                                  10 0.00192 Preprocessor1_Model1
2 brier_class binary
                         0.175
                                  10 0.00143 Preprocessor1 Model1
                         0.830
                                  10 0.00352 Preprocessor1_Model1
3 roc_auc
              binary
```

Your Turn 4

Turns out, the same knn_rec recipe can also be used to fit a penalized logistic regression model using the lasso. Let's try it out!

```
plr_mod <- logistic_reg(penalty = .01, mixture = 1) |>
   set_engine("glmnet") |>
   set_mode("classification")

plr_mod |>
   translate()
```

Logistic Regression Model Specification (classification)

```
Main Arguments:
    penalty = 0.01
    mixture = 1

Computational engine: glmnet

Model fit template:
glmnet::glmnet(x = missing_arg(), y = missing_arg(), weights = missing_arg(),
        alpha = 1, family = "binomial")
```

Answer:

```
glmnet_wf <- knn_wf |>
    update_model(plr_mod)

glmnet_wf |>
    fit_resamples(resamples = hotels_folds) |>
    collect_metrics()
```

```
# A tibble: 3 \times 6
  .metric
              .estimator mean
                                    n std_err .config
  <chr>>
              <chr>
                         <dbl> <int>
                                         <dbl> <chr>>
1 accuracy
              binary
                         0.828
                                   10 0.00215 Preprocessor1_Model1
2 brier_class binary
                         0.139
                                   10 0.000876 Preprocessor1 Model1
3 roc_auc
              binary
                         0.873
                                   10 0.00209 Preprocessor1_Model1
```

Acknowledgments

- Materials derived from Tidymodels, Virtually: An Introduction to Machine Learning with Tidymodels by Allison Hill.
- Dataset and some modeling steps derived from A predictive modeling case study and licensed under a Creative Commons Attribution-ShareAlike 4.0 International (CC BY-SA) License.

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