More Tidymodels

Lecture 23

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Hotels Data

Original data from Antonio, Almeida, and Nunes (2019), see data dictionary here

```
hotels = read_csv(
  'https://tidymodels.org/start/case-study/hotels.csv'
) |>
  mutate(
    across(where(is.character), as.factor)
  )
```

The data

```
1 glimpse(hotels)
```

```
Rows: 50,000
Columns: 23
$ hotel                         <fct> City_Hotel, City_Hotel, Resort_Hotel, Resort_Hotel, Re…
$ lead_time                     <dbl> 217, 2, 95, 143, 136, 67, 47, 56, 80, 6, 130, 27, 16, …
$ stays_in_weekend_nights       <dbl> 1, 0, 2, 2, 1, 2, 0, 0, 0, 2, 1, 0, 1, 0, 1, 1, 1, 4, …
$ stays_in_week_nights          <dbl> 3, 1, 5, 6, 4, 2, 2, 3, 4, 2, 2, 1, 2, 2, 1, 1, 2, 7, …
$ adults                        <dbl> 2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, …
$ children                      <fct> none, none, none, none, none, none, children, children…
$ meal                          <fct> BB, BB, BB, HB, HB, SC, BB, BB, BB, BB, BB, BB, BB, BB…
$ country                       <fct> DEU, PRT, GBR, ROU, PRT, GBR, ESP, ESP, FRA, FRA, FRA,…
$ market_segment                <fct> Offline_TA/TO, Direct, Online_TA, Online_TA, Direct, O…
$ distribution_channel          <fct> TA/TO, Direct, TA/TO, TA/TO, Direct, TA/TO, Direct, TA…
$ is_repeated_guest             <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ previous_cancellations        <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ previous_bookings_not_canceled <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ reserved_room_type            <fct> A, D, A, A, F, A, C, B, D, A, A, D, A, D, A, A, D, A, …
$ assigned_room_type            <fct> A, K, A, A, F, A, C, A, D, A, D, D, A, D, A, A, D, A, …
$ booking_changes               <dbl> 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4, …
$ deposit_type                  <fct> No_Deposit, No_Deposit, No_Deposit, No_Deposit, No_Dep…
$ days_in_waiting_list          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 236, 0, 0, 0…
$ customer_type                 <fct> Transient-Party, Transient, Transient, Transient, Tran…
$ average_daily_rate            <dbl> 80.75, 170.00, 8.00, 81.00, 157.60, 49.09, 289.00, 82.…
$ required_car_parking_spaces   <fct> none, none, none, none, none, none, none, none, none,
```

Factors

```
1 map_int(hotels, ~ length(levels(.x))) |> keep(~ .x > 0) |> sort()
```

```
                  hotel                  children required_car_parking_spaces 
                      2                         2                         2 
          deposit_type             customer_type                      meal 
                      3                         4                         5 
distribution_channel            market_segment        reserved_room_type 
                      5                         7                         9 
  assigned_room_type                   country 
                     10                       155 
```

The model

Our goal is to develop a model that is able to predict whether a booking will include children or not based on the other characteristics of the booking.

```
1 hotels |>
2   count(children) |>
3   mutate(prop = n/sum(n))
```

```
# A tibble: 2 × 3
  children     n   prop
  <fct>    <int>  <dbl>
1 children  4038 0.0808
2 none     45962 0.919
```

Stratifying the test/train split

```
set.seed(123)

hotel_split = initial_split(
  hotels, strata = children
)

hotel_train = training(hotel_split)
hotel_test = testing(hotel_split)
```

```
dim(hotel_train)
```

```
[1] 37500    23
```

```
dim(hotel_test)
```

```
[1] 12500    23
```

```
hotel_train |>
  count(children) |>
  mutate(prop = n/sum(n))
```

```
# A tibble: 2 × 3
  children     n   prop
  <fct>    <int>  <dbl>
1 children  3027 0.0807
2 none     34473 0.919
```

```
hotel_test |>
  count(children) |>
  mutate(prop = n/sum(n))
```

```
# A tibble: 2 × 3
  children     n   prop
  <fct>    <int>  <dbl>
1 children  1011 0.0809
2 none     11489 0.919
```

Logistic Regression model

```
1 show_engines("logistic_reg")
```

```
# A tibble: 7 × 2
  engine    mode
  <chr>     <chr>
1 glm       classification
2 glmnet    classification
3 LiblineaR classification
4 spark     classification
5 keras     classification
6 stan      classification
7 brulee    classification
```

```
1 lr_model = logistic_reg() |>
2   set_engine("glm")
```

```
1 translate(lr_model)
```

```
Logistic Regression Model Specification (classification)

Computational engine: glm

Model fit template:
stats::glm(formula = missing_arg(), data = missing_arg(), weights = missing_arg(),
    family = stats::binomial)
```

Recipe

```
lr_recipe = recipe(children ~ ., data = hotel_train) |>
  step_date(arrival_date, features = c("dow", "month"), label=TRUE) |>
  step_mutate(
    season = case_when(
      arrival_date_month %in% c(12, 1, 2) ~ "Winter",
      arrival_date_month %in% c(3, 4, 5) ~ "Spring",
      arrival_date_month %in% c(6, 7, 8) ~ "Summer",
      arrival_date_month %in% c(9, 10, 11) ~ "Fall"
    ) |>
      factor(levels = c("Winter", "Spring", "Summer", "Fall"))
  ) |>
  step_rm(arrival_date, arrival_date_month) |>
  step_rm(country) |>
  step_unknown(season) |>
  step_dummy(all_nominal_predictors()) |>
  step_zv(all_predictors())
```

```r
lr_recipe |>
  prep() |>
  bake(new_data = hotel_train)
```

```
# A tibble: 37,500 × 56
   lead_time stays_in_weekend_nights stays_in_week_nights adults is_repeated_guest
       <dbl>                   <dbl>                <dbl>  <dbl>              <dbl>
 1         2                       0                    1      2                  0
 2        95                       2                    5      2                  0
 3        67                       2                    2      2                  0
 4        47                       0                    2      2                  0
 5        56                       0                    3      0                  0
 6         6                       2                    2      2                  0
 7       130                       1                    2      2                  0
 8        27                       0                    1      1                  0
 9        46                       0                    2      2                  0
10       423                       1                    1      2                  0
# ℹ 37,490 more rows
# ℹ 51 more variables: previous_cancellations <dbl>, previous_bookings_not_canceled <dbl>,
#   booking_changes <dbl>, days_in_waiting_list <dbl>, average_daily_rate <dbl>,
#   total_of_special_requests <dbl>, children <fct>, hotel_Resort_Hotel <dbl>, meal_FB <dbl>,
#   meal_HB <dbl>, meal_SC <dbl>, meal_Undefined <dbl>, market_segment_Complementary <dbl>,
#   market_segment_Corporate <dbl>, market_segment_Direct <dbl>, market_segment_Groups <dbl>,
#   market_segment_Offline_TA.TO <dbl>, market_segment_Online_TA <dbl>, …
```

Workflow

```
( lr_work = workflow() |>
    add_model(lr_model) |>
    add_recipe(lr_recipe)
)
```

```
══ Workflow ════════════════════════════════════════════════════════
Preprocessor: Recipe
Model: logistic_reg()

── Preprocessor ────────────────────────────────────────────────────
7 Recipe Steps

• step_date()
• step_mutate()
• step_rm()
• step_rm()
• step_unknown()
• step_dummy()
• step_zv()

── Model ───────────────────────────────────────────────────────────
Logistic Regression Model Specification (classification)

Computational engine: glm
```

Fit

```
( lr_fit = lr_work |>
    fit(data = hotel_train) )
```

```
══ Workflow [trained] ══════════════════════════════════════
Preprocessor: Recipe
Model: logistic_reg()

── Preprocessor ────────────────────────────────────────────
7 Recipe Steps

• step_date()
• step_mutate()
• step_rm()
• step_rm()
• step_unknown()
• step_dummy()
• step_zv()

── Model ───────────────────────────────────────────────────

Call:  stats::glm(formula = ..y ~ ., family = stats::binomial, data = data)

Coefficients:
                       (Intercept)
                         17.121622
                         lead_time
                         -0.001154
           stays_in_weekend_nights
                          0.054898
```

Tidy

```
lr_fit |>
  broom::tidy() |>
  arrange(p.value) |>
  print(n=100)
```

```
# A tibble: 56 × 5
   term                 estimate std.error statistic  p.value
   <chr>                   <dbl>     <dbl>     <dbl>    <dbl>
 1 average_daily_rate  -1.04e-2   5.14e-4 -20.3     1.40e-91
 2 total_of_special_r… -4.73e-1   2.64e-2 -17.9     9.93e-72
 3 assigned_room_type… -1.19e+0   7.79e-2 -15.3     9.80e-53
 4 reserved_room_type…  1.22e+0   8.91e-2  13.7     1.34e-42
 5 reserved_room_type… -2.57e+0   1.92e-1 -13.4     1.05e-40
 6 hotel_Resort_Hotel   8.28e-1   6.21e-2  13.3     1.65e-40
 7 adults               6.46e-1   4.97e-2  13.0     1.35e-38
 8 assigned_room_type… -1.77e+0   1.45e-1 -12.2     2.63e-34
 9 meal_SC              1.28e+0   1.26e-1  10.2     2.78e-24
10 reserved_room_type… -2.25e+0   2.27e-1  -9.92    3.45e-23
11 booking_changes     -2.29e-1   2.54e-2  -9.03    1.66e-19
12 reserved_room_type… -1.53e+0   1.79e-1  -8.53    1.42e-17
13 reserved_room_type… -1.55e+0   1.95e-1  -7.96    1.70e-15
14 reserved_room_type… -3.38e+0   4.44e-1  -7.62    2.63e-14
15 assigned_room_type… -2.13e+0   3.01e-1  -7.09    1.30e-12
16 assigned_room_type… -1.01e+0   1.43e-1  -7.09    1.30e-12
17 assigned_room_type… -1.06e+0   1.75e-1  -6.08    1.24e- 9
18 assigned_room_type… -1.20e+0   2.16e-1  -5.54    3.06e- 8
19 lead_time           -1.15e-3   3.07e-4  -3.76    1.73e- 4
20 previous_bookings    3.50e-1   1.07e-1   3.26    1.13e- 3
```

Logistic regression predictions

```
( lr_train_perf = lr_fit |>
    augment(new_data = hotel_train) |>
    select(children, starts_with(".pred")) )
```

```
# A tibble: 37,500 × 4
   children .pred_class .pred_children .pred_none
   <fct>    <fct>                <dbl>      <dbl>
 1 none     none               0.0709      0.929
 2 none     none               0.0332      0.967
 3 none     none               0.00982     0.990
 4 children children           0.920       0.0798
 5 children none               0.441       0.559
 6 children none               0.115       0.885
 7 none     none               0.0656      0.934
 8 none     none               0.0931      0.907
 9 none     none               0.0220      0.978
10 none     none               0.0539      0.946
# ℹ 37,490 more rows
```

```
( lr_test_perf = lr_fit |>
    augment(new_data = hotel_test) |>
    select(children, starts_with(".pred")) )
```

```
# A tibble: 12,500 × 4
   children .pred_class .pred_children .pred_none
   <fct>    <fct>                <dbl>      <dbl>
 1 none     none               0.0194      0.981
 2 none     none               0.0221      0.978
 3 none     children           0.723       0.277
 4 none     none               0.0721      0.928
 5 none     none               0.000687    0.999
 6 none     none               0.000665    0.999
 7 none     none               0.111       0.889
 8 none     none               0.0464      0.954
 9 none     none               0.0652      0.935
10 none     none               0.103       0.897
# ℹ 12,490 more rows
```

Performance metrics (within-sample)

```
conf_mat(lr_train_perf, children, .pred_class)
```

```
          Truth
Prediction children  none
  children     1059   418
  none         1968 34055
```

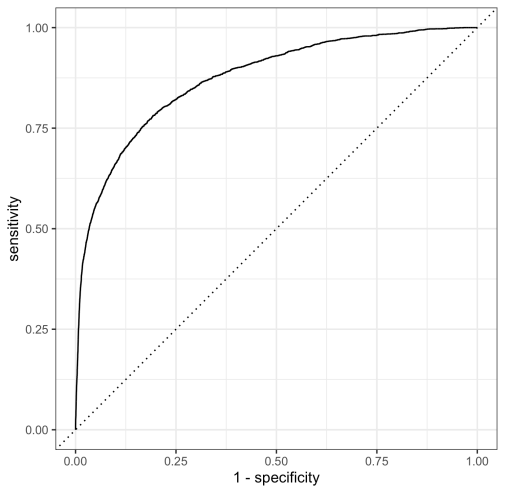
```
accuracy(lr_train_perf, children, .pred_class)
```

```
# A tibble: 1 × 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 accuracy binary         0.936
```

```
precision(lr_train_perf, children, .pred_class)
```

```
# A tibble: 1 × 3
  .metric   .estimator .estimate
  <chr>     <chr>          <dbl>
1 precision binary         0.717
```

```
yardstick::roc_curve(lr_train_perf, children, .pred
  autoplot()
```




```
roc_auc(lr_train_perf, children, .pred_children)
```

```
# A tibble: 1 × 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 roc_auc binary         0.874
```

Performance metrics (out-of-sample)

```
conf_mat(lr_test_perf, children, .pred_class)
```

```
          Truth
Prediction children  none
  children      341   134
  none          670 11355
```

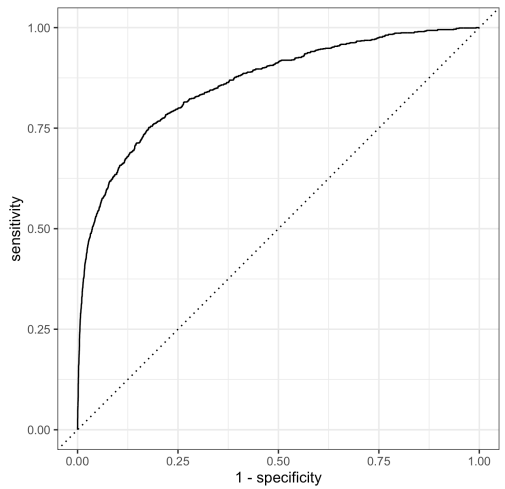
```
accuracy(lr_test_perf, children, .pred_class)
```

```
# A tibble: 1 × 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 accuracy binary         0.936
```

```
precision(lr_test_perf, children, .pred_class)
```

```
# A tibble: 1 × 3
  .metric   .estimator .estimate
  <chr>     <chr>          <dbl>
1 precision binary         0.718
```

```
yardstick::roc_curve(lr_test_perf, children, .pred_
  autoplot()
```

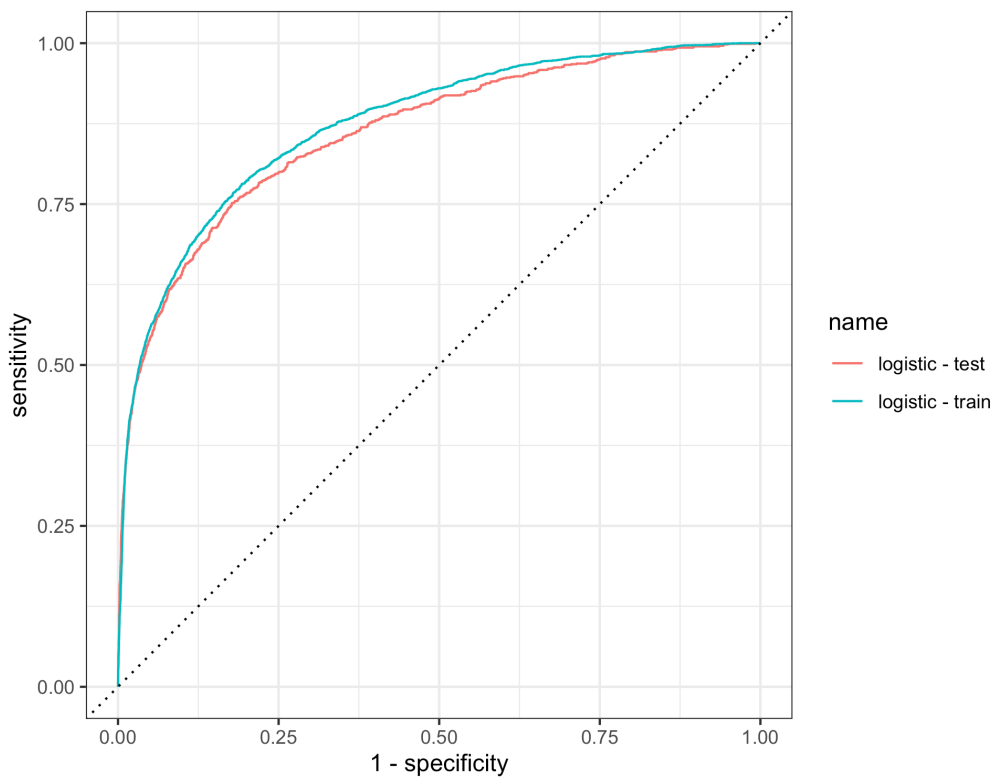



```
roc_auc(lr_test_perf, children, .pred_children)
```

```
# A tibble: 1 × 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 roc_auc binary         0.861
```

Combining ROC curves

```
bind_rows(
  lr_train_perf |> mutate(name = "logistic - train"),
  lr_test_perf |> mutate(name = "logistic - test")
) |>
  group_by(name) |>
  yardstick::roc_curve(children, .pred_children) |>
  autoplot()
```



Metric sets

```
1 (hotel_metrics = metric_set(accuracy, roc_auc, sensitivity, specificity, brier_class))
```

```
A metric set, consisting of:
- `accuracy()`, a class metric          | direction: maximize
- `roc_auc()`, a probability metric     | direction: maximize
- `sensitivity()`, a class metric       | direction: maximize
- `specificity()`, a class metric       | direction: maximize
- `brier_class()`, a probability metric | direction: minimize
```

```
1 hotel_metrics(lr_train_perf, truth = children, estimate = .pred_class, .pred_children)
```

```
# A tibble: 5 × 3
  .metric     .estimator .estimate
  <chr>       <chr>          <dbl>
1 accuracy    binary        0.936
2 sensitivity binary        0.350
3 specificity binary        0.988
4 roc_auc     binary        0.874
5 brier_class binary        0.0519
```

Lasso

Lasso Model

For this we will be using the `glmnet` package which supports fitting lasso, ridge and elastic net models.

$$\min_{\beta_0,\beta} \frac{1}{N} \sum_{i=1}^{N} w_i l\left(y_i, \beta_0 + \beta^T x_i\right) + \lambda \left[(1-\alpha)\|\beta\|_2^2/2 + \alpha\|\beta\|_1\right],$$

```
lasso_model = logistic_reg(penalty = tune(), mixture = 1) |>
  set_engine("glmnet")
```

- `mixture` (α) determines the type of model fit
  - `1` for Lasso,
  - `0` for Ridge,
  - other for elastic net.
- `penalty` (λ) is the penalty term for coefficient size.

```r
lasso_model |>
  hardhat::extract_parameter_set_dials()
```

```
Collection of 1 parameters for tuning

 identifier    type    object
    penalty penalty nparam[+]
```

```r
lasso_model |>
  translate()
```

```
Logistic Regression Model Specification (classification)

Main Arguments:
  penalty = tune()
  mixture = 1

Computational engine: glmnet

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

Lasso Recipe

Lasso (and Ridge) models are sensitive to the scale of the model features. As such it is necessary to normalize all features before fitting the model.

```
lasso_recipe = lr_recipe |>
  step_normalize(all_predictors())
```

```
lasso_recipe |>
  prep() |>
  bake(new_data = hotel_train)
```

```
# A tibble: 37,500 × 56
   lead_time stays_in_weekend_nights stays_in_week_nights adults is_repeated_guest
       <dbl>                   <dbl>                <dbl>  <dbl>             <dbl>
 1    -0.858                -0.938                -0.767  0.337            -0.213
 2     0.160                 1.09                  1.32   0.337            -0.213
 3    -0.146                 1.09                 -0.245  0.337            -0.213
 4    -0.365                -0.938                -0.245  0.337            -0.213
 5    -0.267                -0.938                 0.278 -3.59             -0.213
 6    -0.814                 1.09                 -0.245  0.337            -0.213
 7     0.544                 0.0735               -0.245  0.337            -0.213
 8    -0.584                -0.938                -0.767 -1.63             -0.213
 9    -0.376                -0.938                -0.245  0.337            -0.213
10     3.75                  0.0735               -0.767  0.337            -0.213
# ℹ 37,490 more rows
# ℹ 51 more variables: previous_cancellations <dbl>, previous_bookings_not_canceled <dbl>,
#   booking_changes <dbl>, days_in_waiting_list <dbl>, average_daily_rate <dbl>,
#   total_of_special_requests <dbl>, children <fct>, hotel_Resort_Hotel <dbl>, meal_FB <dbl>,
#   meal_HB <dbl>, meal_SC <dbl>, meal_Undefined <dbl>, market_segment_Complementary <dbl>,
#   market_segment_Corporate <dbl>, market_segment_Direct <dbl>, market_segment_Groups <dbl>,
#   market_segment_Offline_TA.TO <dbl>, market_segment_Online_TA <dbl>, …
```

Lasso workflow

```
( lasso_work = workflow() |>
    add_model(lasso_model) |>
    add_recipe(lasso_recipe)
)
```

```
══ Workflow ════════════════════════════════════════════════════════════════════
Preprocessor: Recipe
Model: logistic_reg()

── Preprocessor ────────────────────────────────────────────────────────────────
8 Recipe Steps

• step_date()
• step_mutate()
• step_rm()
• step_rm()
• step_unknown()
• step_dummy()
• step_zv()
• step_normalize()

── Model ───────────────────────────────────────────────────────────────────────
Logistic Regression Model Specification (classification)

Main Arguments:
  penalty = tune()
  mixture = 1

Computational engine: glmnet
```

v-folds for hyperparameter tuning

```
1 ( hotel_vf = rsample::vfold_cv(hotel_train, v=5, strata = children) )
```

```
#  5-fold cross-validation using stratification
# A tibble: 5 × 2
  splits               id
  <list>               <chr>
1 <split [30000/7500]> Fold1
2 <split [30000/7500]> Fold2
3 <split [30000/7500]> Fold3
4 <split [30000/7500]> Fold4
5 <split [30000/7500]> Fold5
```

grid search

```
( lasso_grid = lasso_work |>
    tune_grid(
      hotel_vf,
      grid = tibble(
        penalty = 10^seq(-4, -1, length.out = 10)
      ),
      control = control_grid(save_pred = TRUE),
      metrics = metric_set(roc_auc)
    )
)
```

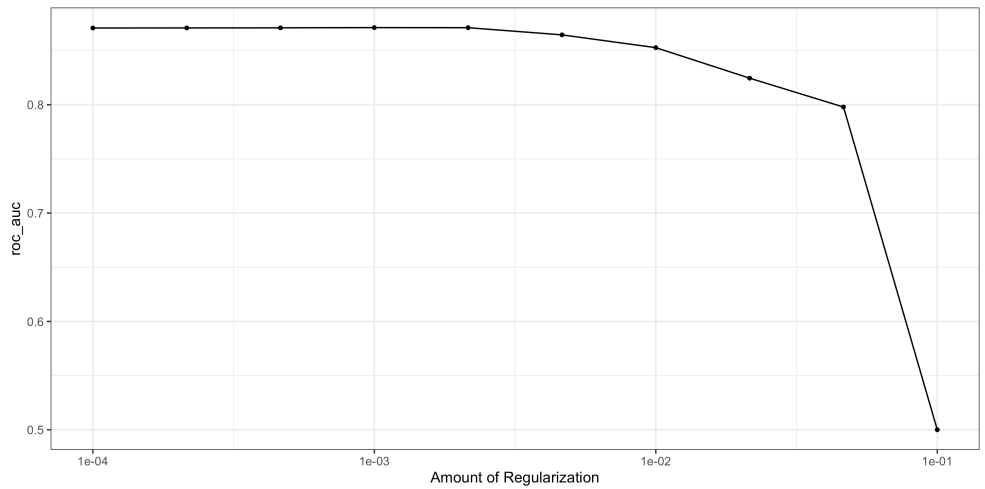
```
# Tuning results
# 5-fold cross-validation using stratification
# A tibble: 5 × 5
  splits               id    .metrics .notes   .predictions
  <list>               <chr> <list>   <list>   <list>
1 <split [30000/7500]> Fold1 <tibble> <tibble> <tibble>
2 <split [30000/7500]> Fold2 <tibble> <tibble> <tibble>
3 <split [30000/7500]> Fold3 <tibble> <tibble> <tibble>
4 <split [30000/7500]> Fold4 <tibble> <tibble> <tibble>
5 <split [30000/7500]> Fold5 <tibble> <tibble> <tibble>
```

Results

```
1 lasso_grid |>
2   collect_metrics()
```

```
# A tibble: 10 × 7
    penalty .metric .estimator  mean     n std_err
      <dbl> <chr>   <chr>      <dbl> <int>   <dbl>
 1 0.0001   roc_auc binary     0.871     5 0.00412
 2 0.000215 roc_auc binary     0.871     5 0.00419
 3 0.000464 roc_auc binary     0.871     5 0.00419
 4 0.001    roc_auc binary     0.871     5 0.00414
 5 0.00215  roc_auc binary     0.871     5 0.00399
 6 0.00464  roc_auc binary     0.865     5 0.00361
 7 0.01     roc_auc binary     0.853     5 0.00459
 8 0.0215   roc_auc binary     0.825     5 0.00684
 9 0.0464   roc_auc binary     0.798     5 0.00670
10 0.1      roc_auc binary     0.5       5 0
# ℹ 1 more variable: .config <chr>
```

```
1 lasso_grid |>
2   autoplot()
```



The “Best” models

```
lasso_grid |>
  show_best(metric = "roc_auc", n=5)
```

```
# A tibble: 5 × 7
   penalty .metric .estimator  mean     n std_err .config
     <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
1 0.001    roc_auc binary     0.871     5 0.00414 pre0_mod0…
2 0.00215  roc_auc binary     0.871     5 0.00399 pre0_mod0…
3 0.000464 roc_auc binary     0.871     5 0.00419 pre0_mod0…
4 0.000215 roc_auc binary     0.871     5 0.00419 pre0_mod0…
5 0.0001   roc_auc binary     0.871     5 0.00412 pre0_mod0…
```

```
( lasso_best = lasso_grid |>
    select_best() )
```

```
# A tibble: 1 × 2
  penalty .config
    <dbl> <chr>
1   0.001 pre0_mod04_post0
```

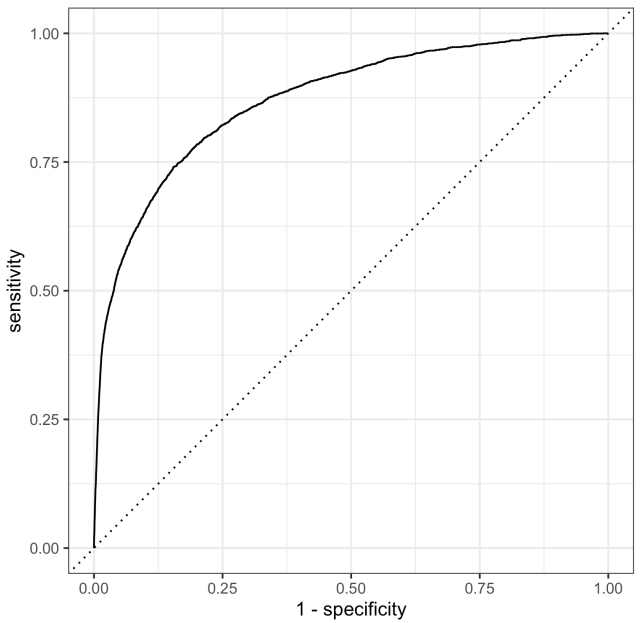
Extracting predictions

Since we used `control_grid(save_pred = TRUE)` in `tune_grid()` we can recover the predictions for the out-of-sample values for each fold

```
( lasso_train_perf = lasso_grid |>
    collect_predictions(parameters = lasso_best) )
```

```
# A tibble: 37,500 × 7
   .pred_children .pred_none id    children  .row penalty
            <dbl>      <dbl> <chr> <fct>    <int>   <dbl>
 1         0.0338      0.966 Fold1 none         2   0.001
 2         0.0116      0.988 Fold1 none         3   0.001
 3         0.0103      0.990 Fold1 none        17   0.001
 4         0.0827      0.917 Fold1 children    22   0.001
 5         0.839       0.161 Fold1 children    27   0.001
 6         0.0357      0.964 Fold1 none        28   0.001
 7         0.0103      0.990 Fold1 none        30   0.001
 8         0.0432      0.957 Fold1 none        38   0.001
 9         0.0204      0.980 Fold1 none        44   0.001
10         0.00831     0.992 Fold1 none        49   0.001
# ℹ 37,490 more rows
# ℹ 1 more variable: .config <chr>
```

```r
lasso_train_perf |>
  roc_curve(children, .pred_children) |>
  autoplot()
```




```r
lasso_train_perf |>
  roc_auc(children, .pred_children)
```

```
# A tibble: 1 × 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 roc_auc binary         0.871
```

Re-fitting

Typically with a tuned model we update the workflow (or model) with the optimal parameter values and then refit using the *complete* training data,

```
lasso_work_tuned = finalize_workflow(
  lasso_work,
  lasso_best
)

( lasso_fit = lasso_work_tuned |>
    fit(data=hotel_train) )
```

```
══ Workflow [trained] ══════════════════════════════════════════
Preprocessor: Recipe
Model: logistic_reg()

── Preprocessor ────────────────────────────────────────────────
8 Recipe Steps

• step_date()
• step_mutate()
• step_rm()
• step_rm()
• step_unknown()
• step_dummy()
• step_zv()
• step_normalize()

── Model ───────────────────────────────────────────────────────

Call:  glmnet::glmnet(x = maybe_matrix(x), y = y, family = "binomial",      alpha = ~1)
```

```
   Df  %Dev   Lambda
1   0  0.00 0.080750
2   1  2.56 0.073580
3   2  5.06 0.067040
4   3  7.45 0.061090
5   3  9.79 0.055660
```

Test Performance (out-of-sample)

```
lasso_test_perf = lasso_fit |>
  augment(new_data = hotel_test) |>
  select(children, starts_with(".pred"))
```

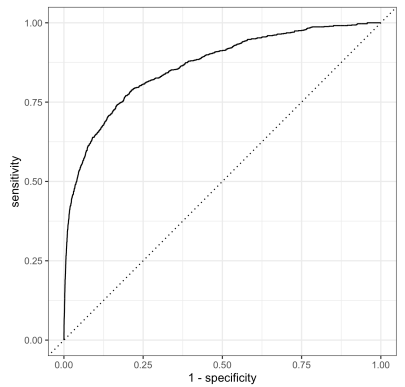
```
conf_mat(lasso_test_perf, children, .pred_class)
```

```
          Truth
Prediction children  none
  children      331   120
  none          680 11369
```

```
hotel_metrics(lasso_test_perf, truth = children, e
```

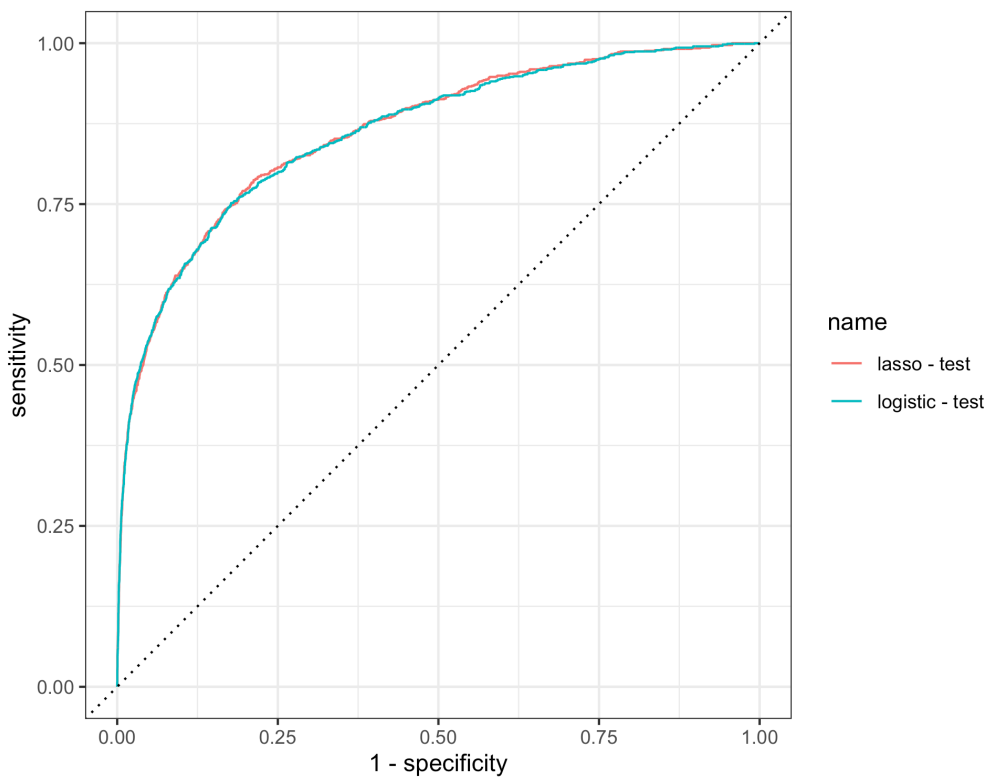
```
# A tibble: 5 × 3
  .metric     .estimator .estimate
  <chr>       <chr>          <dbl>
1 accuracy    binary         0.936
2 sensitivity binary         0.327
3 specificity binary         0.990
4 roc_auc     binary         0.863
5 brier_class binary         0.0523
```

```
yardstick::roc_curve(lasso_test_perf, children, .p
  autoplot()
```



Comparing models

```
bind_rows(
  lr_test_perf |> mutate(name = "logistic - test"),
  lasso_test_perf |> mutate(name = "lasso - test")
) |>
  group_by(name) |>
  yardstick::roc_curve(children, .pred_children) |>
  autoplot()
```



Decision tree

Decision tree models

```
1 show_engines("decision_tree")
```

```
# A tibble: 5 × 2
  engine mode
  <chr>  <chr>
1 rpart  classification
2 rpart  regression
3 C5.0   classification
4 spark  classification
5 spark  regression
```

```
1 dt_model = decision_tree(
2   tree_depth = tune(),
3   min_n = tune(),
4   cost_complexity = tune()
5 ) |>
6   set_engine("rpart") |>
7   set_mode("classification")
```

Recipe & workflow

Same recipe as before but we skip dummy coding as it is not needed by rpart.

```
dt_recipe = recipe(children ~ ., data = hotel_train) |>
  step_date(arrival_date, features = c("dow", "month"), label=TRUE) |>
  step_mutate(
    season = case_when(
      arrival_date_month %in% c(12, 1, 2) ~ "Winter",
      arrival_date_month %in% c(3, 4, 5) ~ "Spring",
      arrival_date_month %in% c(6, 7, 8) ~ "Summer",
      arrival_date_month %in% c(9, 10, 11) ~ "Fall"
    ) |>
      factor(levels = c("Winter", "Spring", "Summer", "Fall"))
  ) |>
  step_rm(arrival_date, arrival_date_month) |>
  step_rm(country)
```

```
dt_work = workflow() |>
  add_model(dt_model) |>
  add_recipe(dt_recipe)
```

Tuning

```
( dt_grid = grid_regular(
    cost_complexity(),
    tree_depth(),
    min_n(),
    levels = 3
) )
```

```
# A tibble: 27 × 3
   cost_complexity tree_depth min_n
             <dbl>      <int> <int>
 1    0.0000000001          1     2
 2    0.00000316            1     2
 3    0.1                   1     2
 4    0.0000000001          8     2
 5    0.00000316            8     2
 6    0.1                   8     2
 7    0.0000000001         15     2
 8    0.00000316           15     2
 9    0.1                  15     2
10    0.0000000001          1    21
# ℹ 17 more rows
```

```
dt_tune = dt_work |>
  tune_grid(
    hotel_vf,
    grid = dt_grid,
    control = control_grid(save_pred = TRUE)
    metrics = hotel_metrics
  )
```

How many decision tree models were fit by `tune_grid()`?

Tuning results

```
dt_tune |>
  collect_metrics() |>
  arrange(desc(mean))
```

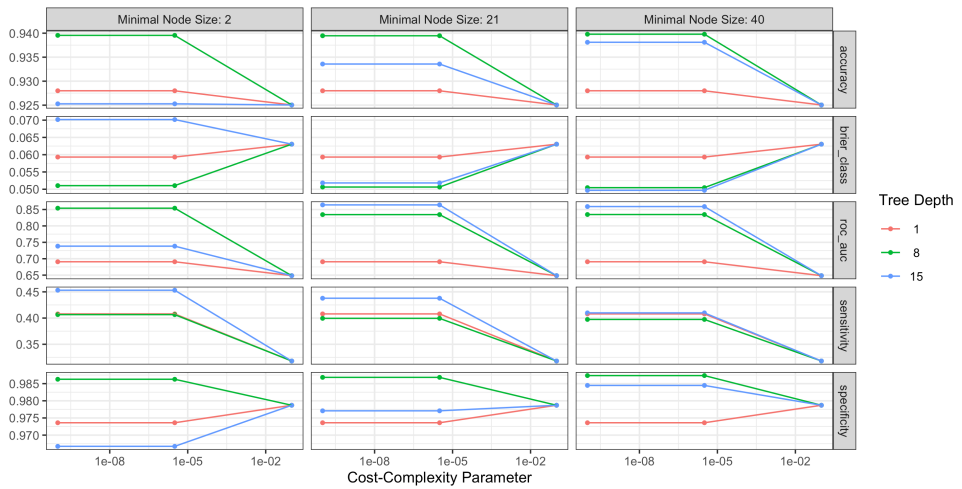
```
# A tibble: 135 × 9
   cost_complexity tree_depth min_n .metric .estimator  mean
             <dbl>      <int> <int> <chr>   <chr>      <dbl>
 1    0.0000000001          8    40 specif… binary     0.987
 2    0.00000316            8    40 specif… binary     0.987
 3    0.0000000001          8    21 specif… binary     0.987
 4    0.00000316            8    21 specif… binary     0.987
 5    0.0000000001          8     2 specif… binary     0.986
 6    0.00000316            8     2 specif… binary     0.986
 7    0.0000000001         15    40 specif… binary     0.984
 8    0.00000316           15    40 specif… binary     0.984
 9    0.1                   1     2 specif… binary     0.979
10    0.1                   1    21 specif… binary     0.979
# ℹ 125 more rows
# ℹ 3 more variables: n <int>, std_err <dbl>, .config <chr>
```

“Best” parameters

```
1 dt_tune |>
2   show_best(metric = "roc_auc")
```

```
# A tibble: 5 × 9
  cost_complexity tree_depth min_n .metric
            <dbl>      <int> <int> <chr>
1    0.0000000001         15    21 roc_auc
2    0.00000316           15    21 roc_auc
3    0.0000000001         15    40 roc_auc
4    0.00000316           15    40 roc_auc
5    0.0000000001          8     2 roc_auc
# ℹ 5 more variables: .estimator <chr>,
#   mean <dbl>, n <int>, std_err <dbl>,
#   .config <chr>
```

```
1 autoplot(dt_tune)
```



Re-fitting

```
(dt_best = dt_tune |>
  select_best(metric = "roc_auc"))
```

```
# A tibble: 1 × 4
  cost_complexity tree_depth min_n .config
            <dbl>      <int> <int> <chr>
1    0.0000000001         15    21 pre0_mod08_post0
```

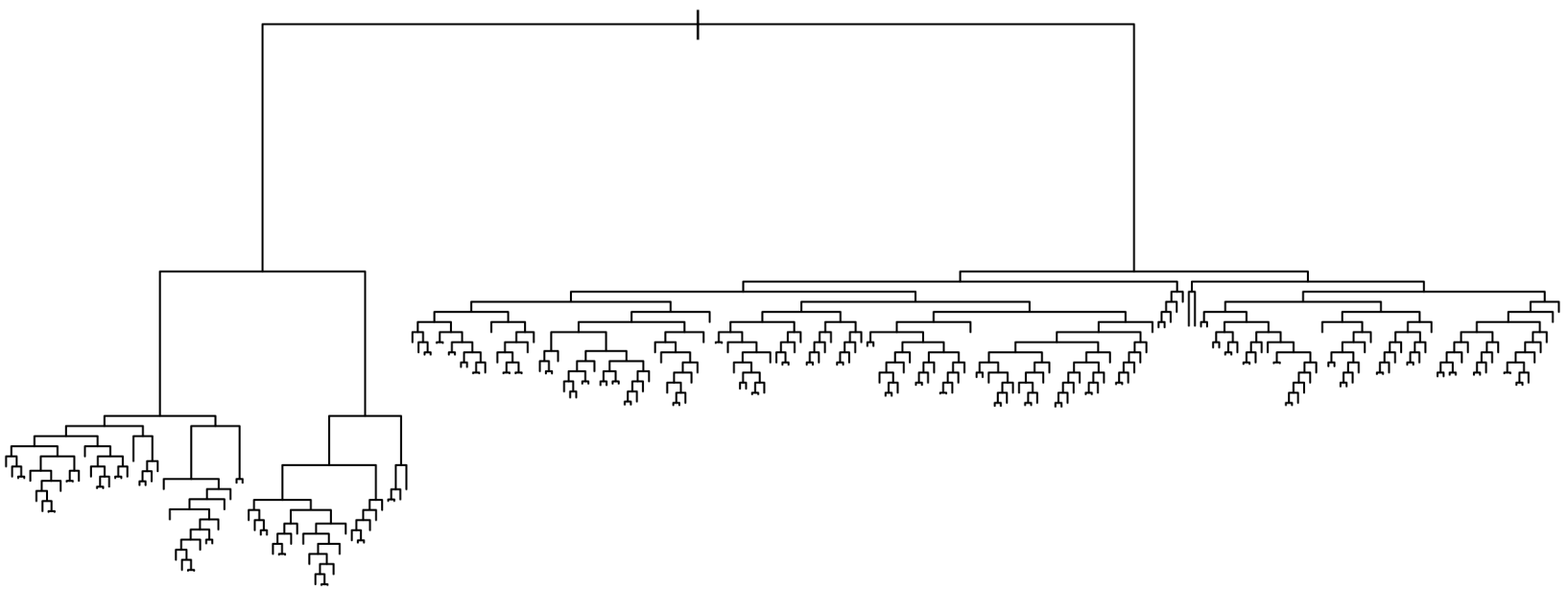
```
dt_work_tuned = finalize_workflow(
  dt_work,
  dt_best
)

( dt_fit = dt_work_tuned |>
    fit(data=hotel_train))
```

```
══ Workflow [trained] ══════════════════════════════════════
Preprocessor: Recipe
Model: decision_tree()

── Preprocessor ────────────────────────────────────────────
4 Recipe Steps

• step_date()
• step_mutate()
• step_rm()
• step_rm()

── Model ───────────────────────────────────────────────────
n= 37500

node), split, n, loss, yval, (yprob)
```

```
  * denotes terminal node

1) root 37500 3027 none (0.080720000 0.919280000)
  2) reserved_room_type=C,F,G,H 2147  910 children (0.576152771 0.423847229)
    4) market_segment=Online_TA 1218  350 children (0.712643678 0.287356322)
      8) average_daily_rate>=140.715 890  196 children (0.779775281 0.220224719)
       16) adults< 2.5 769  139 children (0.819245774 0.180754226)
         32) booking_changes< 0.5 581   77 children (0.867469880 0.132530120)
           64) hotel=City_Hotel 363   26 children (0.928374656 0.071625344)
            128) reserved_room_type=E 311   15 children (0.951768489 0.048231511) *
```

Model extraction

```
dt_fit |>
  hardhat::extract_fit_engine() |>
  plot()
```



Test Performance (out-of-sample)

```
1 dt_test_perf = dt_fit |>
2   augment(new_data = hotel_test) |>
3   select(children, starts_with(".pred"))
```

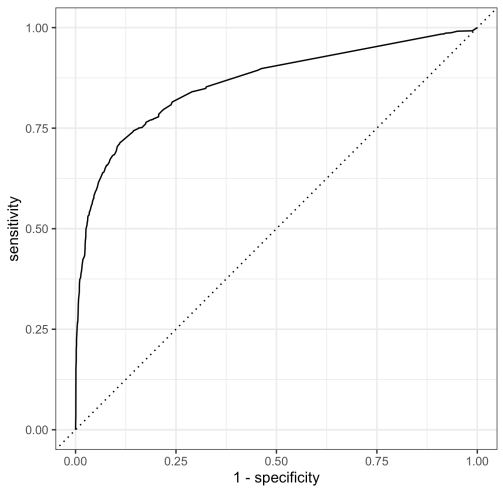
```
1 conf_mat(dt_test_perf, children, .pred_class)
```

```
          Truth
Prediction children  none
  children      450   268
  none          561 11221
```

```
1 hotel_metrics(dt_test_perf, truth = children, esti
```

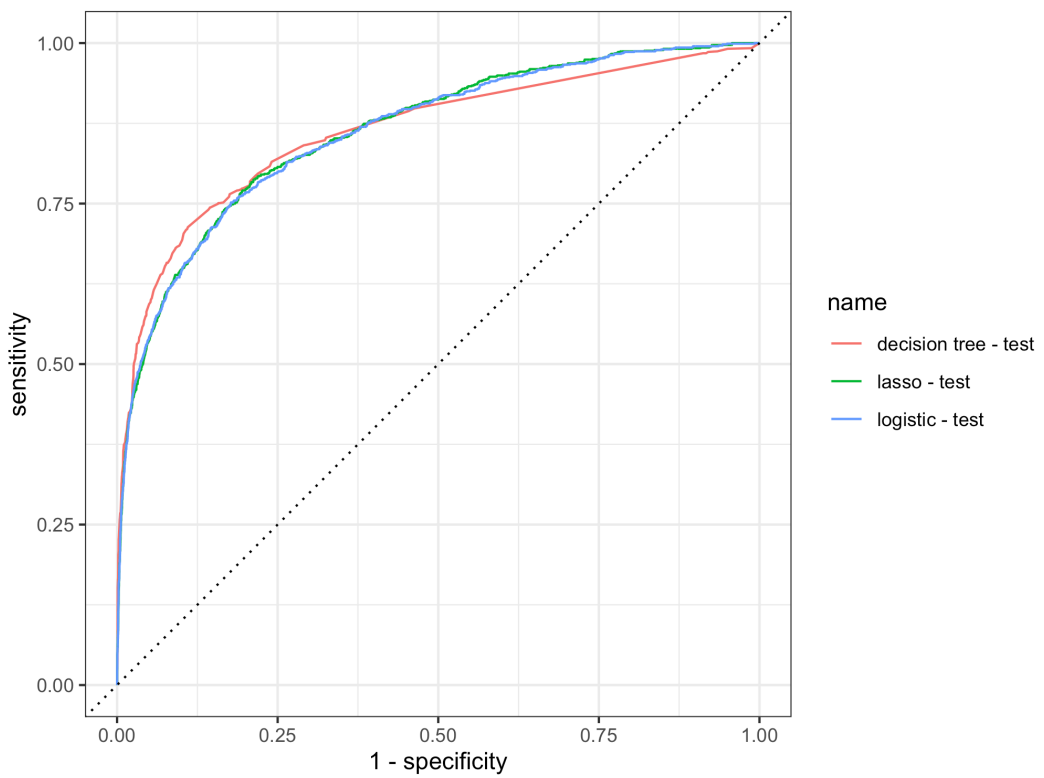
```
# A tibble: 5 × 3
  .metric     .estimator .estimate
  <chr>       <chr>          <dbl>
1 accuracy    binary         0.934
2 sensitivity binary         0.445
3 specificity binary         0.977
4 roc_auc     binary         0.862
5 brier_class binary         0.0512
```

```
1 yardstick::roc_curve(dt_test_perf, children, .pred_
2   autoplot()
```



Comparing models

```
bind_rows(
  lr_test_perf |> mutate(name = "logistic - test"),
  lasso_test_perf |> mutate(name = "lasso - test"),
  dt_test_perf |> mutate(name = "decision tree - test")
) |>
  group_by(name) |>
  yardstick::roc_curve(children, .pred_children) |>
  autoplot()
```



Random Forest

Random forest models

```
1 show_engines("rand_forest")
```

```
# A tibble: 9 × 2
  engine       mode
  <chr>        <chr>
1 ranger       classification
2 ranger       regression
3 randomForest classification
4 randomForest regression
5 spark        classification
6 spark        regression
7 grf          classification
8 grf          regression
9 grf          quantile regression
```

```
1 rf_model = rand_forest(mtry = tune(), min_n = tune(), trees = 100) |>
2   set_engine("ranger", num.threads = 1) |>
3   set_mode("classification")
```

Recipe & workflow

We again skip dummy coding in the recipe as it is not needed by ranger.

```
rf_recipe = dt_recipe
```

```
rf_work = workflow() |>
  add_model(rf_model) |>
  add_recipe(rf_recipe)
```

Tuning - automatic grid search

```
rf_tune = rf_work |>
  tune_grid(
    hotel_vf,
    grid = 10,
    control = control_grid(save_pred =
    metrics = metric_set(roc_auc)
  )
```

```
rf_tune |>
  collect_metrics() |>
  arrange(desc(mean))
```

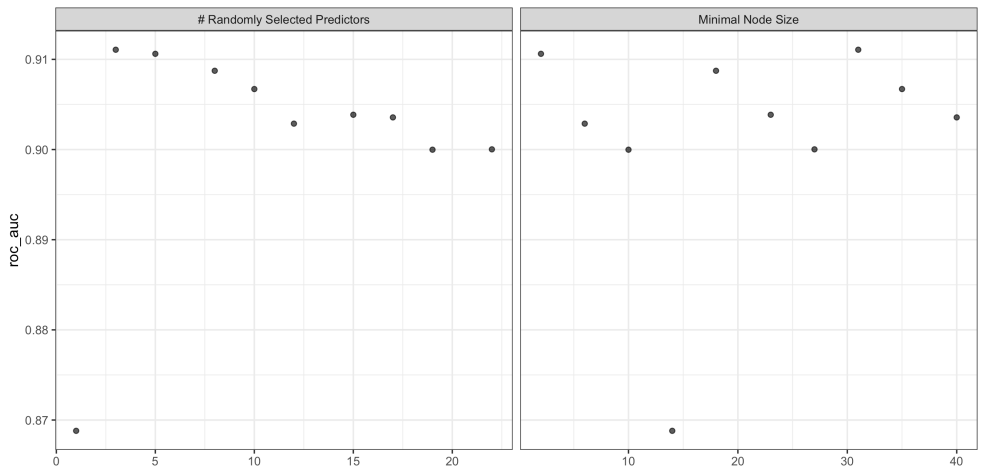
```
# A tibble: 10 × 8
    mtry min_n .metric .estimator  mean     n std_err
   <int> <int> <chr>   <chr>      <dbl> <int>   <dbl>
 1     3    31 roc_auc binary     0.911     5 0.00406
 2     5     2 roc_auc binary     0.911     5 0.00445
 3     8    18 roc_auc binary     0.909     5 0.00417
 4    10    35 roc_auc binary     0.907     5 0.00414
 5    15    23 roc_auc binary     0.904     5 0.00404
 6    17    40 roc_auc binary     0.904     5 0.00424
 7    12     6 roc_auc binary     0.903     5 0.00401
 8    22    27 roc_auc binary     0.900     5 0.00428
 9    19    10 roc_auc binary     0.900     5 0.00339
10     1    14 roc_auc binary     0.869     5 0.00412
# ℹ 1 more variable: .config <chr>
```

“Best” parameters

```
1  rf_tune |>
2    show_best(metric = "roc_auc")
```

```
# A tibble: 5 × 8
   mtry min_n .metric .estimator  mean     n
  <int> <int> <chr>   <chr>      <dbl> <int>
1     3    31 roc_auc binary     0.911     5
2     5     2 roc_auc binary     0.911     5
3     8    18 roc_auc binary     0.909     5
4    10    35 roc_auc binary     0.907     5
5    15    23 roc_auc binary     0.904     5
# ℹ 2 more variables: std_err <dbl>,
#   .config <chr>
```

```
1  autoplot(rf_tune)
```



Re-fitting

```
rf_best = rf_tune |>
  select_best(metric = "roc_auc")
```

```
rf_work_tuned = finalize_workflow(
  rf_work,
  rf_best
)

( rf_fit = rf_work_tuned |>
    fit(data=hotel_train) )
```

```
══ Workflow [trained] ══════════════════════════════════════
Preprocessor: Recipe
Model: rand_forest()

── Preprocessor ────────────────────────────────────────────
4 Recipe Steps

• step_date()
• step_mutate()
• step_rm()
• step_rm()

── Model ───────────────────────────────────────────────────
Ranger result

Call:
 ranger::ranger(x = maybe_data_frame(x), y = y, mtry = min_cols(~3L,      x), num.trees = ~100, min.node.size =

Type:                             Probability estimation
Number of trees:                  100
Sample size:                      37500
```

```
Number of independent variables:  22
Mtry:                             3
Target node size:                 31
Variable importance mode:         none
Splitrule:                        gini
```

Test Performance (out-of-sample)

```
1 rf_test_perf = rf_fit |>
2   augment(new_data = hotel_test) |>
3   select(children, starts_with(".pred"))
```

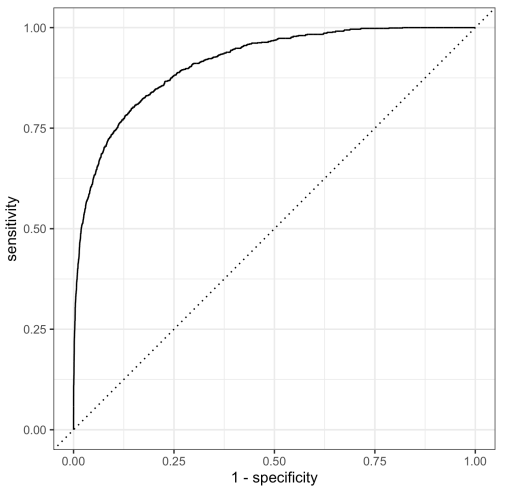
```
1 conf_mat(rf_test_perf, children, .pred_class)
```

```
          Truth
Prediction children  none
  children      324    59
  none          687 11430
```

```
1 hotel_metrics(rf_test_perf, truth = children, esti
```

```
# A tibble: 5 × 3
  .metric     .estimator .estimate
  <chr>       <chr>          <dbl>
1 accuracy    binary         0.940
2 sensitivity binary         0.320
3 specificity binary         0.995
4 roc_auc     binary         0.912
5 brier_class binary         0.0469
```

```
1 yardstick::roc_curve(rf_test_perf, children, .pred_
2   autoplot()
```



Comparing models

```
bind_rows(
  lr_test_perf |> mutate(name = "logistic - test"),
  lasso_test_perf |> mutate(name = "lasso - test"),
  dt_test_perf |> mutate(name = "decision tree - test"),
  rf_test_perf |> mutate(name = "random forest - test")
) |>
  group_by(name) |>
  yardstick::roc_curve(children, .pred_children) |>
  autoplot()
```