Setup

```r
library(tidyverse)
library(tidymodels)
```

Orig data from Antonio, Almeida, and Nunes (2019) - https://doi.org/10.1016/j.dib.2018.11.126 (https://doi.org/10.1016/j.dib.2018.11.126) - Data dictionary - https://github.com/rfordatascience/tidytuesday/tree/master/data/2020/2020-02-11#data-dictionary (https://github.com/rfordatascience/tidytuesday/tree/master/data/2020/2020-02-11#data-dictionary)

Data basics

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

```
## Rows: 50000 Columns: 23
```

```
## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr  (11): hotel, children, meal, country, market_segment, distribution_chan...
## dbl  (11): lead_time, stays_in_weekend_nights, stays_in_week_nights, adults,...
## date  (1): arrival_date
```

```
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
glimpse(hotels)
```

```
## Rows: 50,000
## Columns: 23
## $ hotel                          <fct> City_Hotel, City_Hotel, Resort_Hotel, R…
## $ lead_time                      <dbl> 217, 2, 95, 143, 136, 67, 47, 56, 80, 6…
## $ stays_in_weekend_nights        <dbl> 1, 0, 2, 2, 1, 2, 0, 0, 0, 2, 1, 0, 1, …
## $ stays_in_week_nights           <dbl> 3, 1, 5, 6, 4, 2, 2, 3, 4, 2, 2, 1, 2, …
## $ adults                         <dbl> 2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 1, 2, …
## $ children                       <fct> none, none, none, none, none, none, chi…
## $ meal                           <fct> BB, BB, BB, HB, HB, SC, BB, BB, BB, BB,…
## $ country                        <fct> DEU, PRT, GBR, ROU, PRT, GBR, ESP, ESP,…
## $ market_segment                 <fct> Offline_TA/TO, Direct, Online_TA, Onlin…
## $ distribution_channel           <fct> TA/TO, Direct, TA/TO, TA/TO, Direct, TA…
## $ is_repeated_guest              <dbl> 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, …
## $ previous_bookings_not_canceled <dbl> 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, …
## $ assigned_room_type             <fct> A, K, A, A, F, A, C, A, D, A, D, D, A, …
## $ booking_changes                <dbl> 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
## $ deposit_type                   <fct> No_Deposit, No_Deposit, No_Deposit, No_…
## $ days_in_waiting_list           <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
## $ customer_type                  <fct> Transient-Party, Transient, Transient, …
## $ average_daily_rate             <dbl> 80.75, 170.00, 8.00, 81.00, 157.60, 49.…
## $ required_car_parking_spaces    <fct> none, none, none, none, none, none, non…
## $ total_of_special_requests      <dbl> 1, 3, 2, 1, 4, 1, 1, 1, 1, 1, 0, 1, 0, …
## $ arrival_date                   <date> 2016-09-01, 2017-08-25, 2016-11-19, 20…
```

```
hotels %>%
  count(children) %>%
  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
```

Test train split

```
set.seed(123)

splits = initial_split(hotels, strata = children)

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

Checking on strata split

```
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
```

Creating the validation set

```
set.seed(1234)
val_set = validation_split(hotel_train, strata = children, prop = 0.8)
val_set
```

```
## # Validation Set Split (0.8/0.2)  using stratification
## # A tibble: 1 × 2
##   splits               id
##   <list>               <chr>
## 1 <split [30000/7500]> validation
```

Logistic Regression model

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

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

```
lr_model = logistic_reg() %>%
  set_engine("glm")

lr_model %>%
  translate()
```

```
## 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

```
holidays = c("AllSouls", "AshWednesday", "ChristmasEve", "Easter",
              "ChristmasDay", "GoodFriday", "NewYearsDay", "PalmSunday")

lr_recipe = recipe(children ~ ., data = hotel_train) %>%
  step_date(arrival_date) %>%
  step_holiday(arrival_date, holidays = holidays) %>%
  step_rm(arrival_date) %>%
  step_rm(country) %>%
  step_dummy(all_nominal_predictors()) %>%
  step_zv(all_predictors())

lr_recipe
```

```
## Recipe
##
## Inputs:
##
##       role #variables
##    outcome          1
##  predictor         22
##
## Operations:
##
## Date features from arrival_date
## Holiday features from arrival_date
## Delete terms arrival_date
## Delete terms country
## Dummy variables from all_nominal_predictors()
## Zero variance filter on all_predictors()
```

```
lr_recipe %>%
  prep() %>%
  bake(new_data = hotel_train)
```

```
## # A tibble: 37,500 × 76
##    lead_time stays_in_weekend_nights stays_in_week_nigh… adults is_repeated_gue…
##        <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
## # … with 37,490 more rows, and 71 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>, arrival_date_year <dbl>,
## #   arrival_date_AllSouls <dbl>, arrival_date_AshWednesday <dbl>,
## #   arrival_date_ChristmasEve <dbl>, arrival_date_Easter <dbl>,
## #   arrival_date_ChristmasDay <dbl>, arrival_date_GoodFriday <dbl>, …
```

Workflow

```
lr_workflow = workflow() %>%
  add_model(lr_model) %>%
  add_recipe(lr_recipe)
```

Fit

```
lr_fit = lr_workflow %>%
  fit(data = hotel_train)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
lr_fit
```

```
## ══ Workflow [trained] ══════════════════════════════════════════════════════════
## Preprocessor: Recipe
## Model: logistic_reg()
##
## ── Preprocessor ────────────────────────────────────────────────────────────────
## 6 Recipe Steps
##
## • step_date()
## • step_holiday()
## • step_rm()
## • step_rm()
## • step_dummy()
## • step_zv()
##
## ── Model ───────────────────────────────────────────────────────────────────────
##
## Call:  stats::glm(formula = ..y ~ ., family = stats::binomial, data = data)
##
## Coefficients:
##                         (Intercept)                            lead_time
##                          -2.543e+02                           -1.287e-03
```

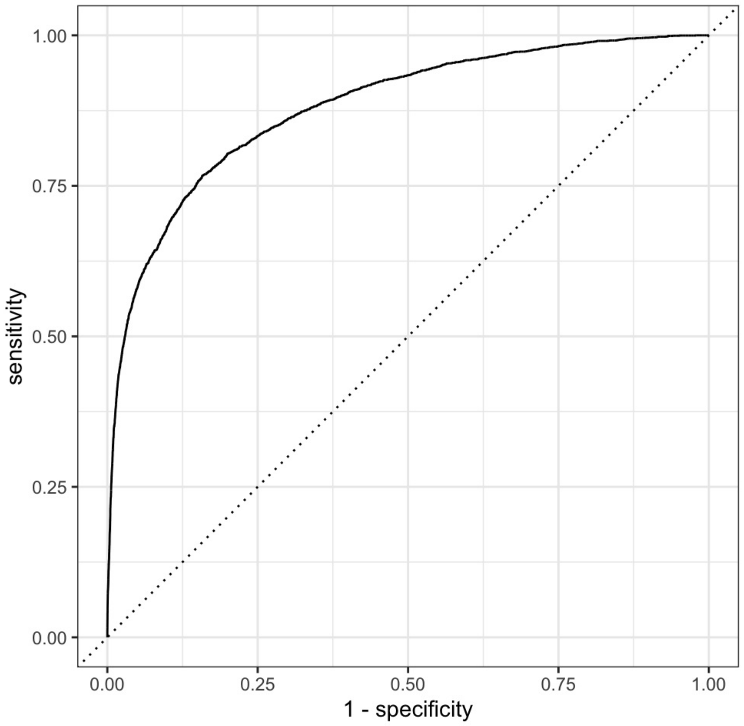
```
##              stays_in_weekend_nights                 stays_in_week_nights
##                            5.231e-02                           -3.433e-02
##                               adults                    is_repeated_guest
##                            7.328e-01                            3.962e-01
##               previous_cancellations       previous_bookings_not_canceled
##                            2.147e-01                            3.728e-01
##                      booking_changes                 days_in_waiting_list
##                           -2.396e-01                            6.415e-03
##                   average_daily_rate            total_of_special_requests
##                           -1.049e-02                           -4.936e-01
##                    arrival_date_year                arrival_date_AllSouls
##                            1.344e-01                            1.006e+00
##             arrival_date_AshWednesday            arrival_date_ChristmasEve
##                            2.019e-01                            5.328e-01
##                  arrival_date_Easter            arrival_date_ChristmasDay
##                           -9.749e-01                           -6.875e-01
##              arrival_date_GoodFriday             arrival_date_NewYearsDay
##                           -1.593e-01                           -1.185e+00
##              arrival_date_PalmSunday                  hotel_Resort_Hotel
##                           -6.243e-01                            9.581e-01
##                              meal_FB                              meal_HB
##                           -6.348e-01                           -3.799e-02
##                              meal_SC                       meal_Undefined
##                            1.285e+00                           -1.938e-01
##         market_segment_Complementary             market_segment_Corporate
##                           -1.345e+01                           -1.213e+01
##                market_segment_Direct                market_segment_Groups
##                           -1.314e+01                           -1.217e+01
##         market_segment_Offline_TA.TO             market_segment_Online_TA
##                           -1.353e+01                           -1.362e+01
##          distribution_channel_Direct             distribution_channel_GDS
##                           -4.351e-01                            1.384e+01
```

```
##          distribution_channel_TA.TO       distribution_channel_Undefined
##                           3.958e-02                           -1.933e+01
##                 reserved_room_type_B                 reserved_room_type_C
##                          -1.247e+00                           -2.512e+00
##                 reserved_room_type_D                 reserved_room_type_E
##                           1.170e+00                            4.205e-01
##                 reserved_room_type_F                 reserved_room_type_G
##                          -1.483e+00                           -2.270e+00
##                 reserved_room_type_H                 reserved_room_type_L
##                          -3.492e+00                            1.327e+01
##                 assigned_room_type_B                 assigned_room_type_C
##                          -5.158e-01                           -1.922e+00
##
## ...
## and 34 more lines.
```

```
# collect_metrics(lr_fit)

lr_perf = lr_fit %>%
  augment(new_data = hotel_train) %>%
  select(children, starts_with(".pred"))


lr_perf %>%
  yardstick::roc_curve(
    children,
    .pred_children
  ) %>%
  autoplot()
```




```
lr_perf %>%
  roc_auc(children, .pred_children)
```

```
## # A tibble: 1 × 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 roc_auc binary         0.881
```

```
lr_perf %>%
  precision(children, .pred_class)
```

```
## # A tibble: 1 × 3
##   .metric   .estimator .estimate
##   <chr>     <chr>          <dbl>
## 1 precision binary         0.719
```

```
lr_perf %>%
  conf_mat(children, .pred_class)
```

```
##             Truth
## Prediction children  none
##   children     1075   420
##   none         1952 34053
```

Using validation split

```
lr_val_fit = lr_workflow %>%
  fit_resamples(val_set)

lr_val_fit
```

```
## # Resampling results
## # Validation Set Split (0.8/0.2)  using stratification 
## # A tibble: 1 × 4
##   splits               id         .metrics         .notes          
##   <list>               <chr>      <list>           <list>          
## 1 <split [30000/7500]> validation <tibble [2 × 4]> <tibble [0 × 1]>
```

```
collect_metrics(lr_val_fit)
```

```
## # A tibble: 2 × 6
##   .metric  .estimator  mean     n std_err .config             
##   <chr>    <chr>      <dbl> <int>   <dbl> <chr>               
## 1 accuracy binary     0.936     1      NA Preprocessor1_Model1
## 2 roc_auc  binary     0.865     1      NA Preprocessor1_Model1
```

Fitting a lasso model

For the mixture argument `1` -> Lasso, `0` -> Ridge, other -> elastic net.

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

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_model %>%
  parameters()
```

```
## Collection of 1 parameters for tuning
##
##  identifier    type    object
##     penalty penalty nparam[+]
```

```r
lasso_recipe = recipe(children ~ ., data = hotel_train) %>%
  step_date(arrival_date) %>%
  step_holiday(arrival_date, holidays = holidays) %>%
  step_rm(arrival_date) %>%
  step_rm(country) %>%
  step_dummy(all_nominal_predictors()) %>%
  step_zv(all_predictors()) %>%
  step_normalize(all_predictors())

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

```
## # A tibble: 37,500 × 76
##    lead_time stays_in_weekend_nights stays_in_week_nigh… adults is_repeated_gue…
##        <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
## # … with 37,490 more rows, and 71 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>, arrival_date_year <dbl>,
## #   arrival_date_AllSouls <dbl>, arrival_date_AshWednesday <dbl>,
## #   arrival_date_ChristmasEve <dbl>, arrival_date_Easter <dbl>,
## #   arrival_date_ChristmasDay <dbl>, arrival_date_GoodFriday <dbl>, …
```

```
lasso_workflow = workflow() %>%
  add_model(lasso_model) %>%
  add_recipe(lasso_recipe)
```

Tuning the model

```
lasso_res = lasso_workflow %>%
  tune_grid(
    val_set,
    grid = tibble(
      penalty = 10^seq(-4, -1, length.out = 30)
    ),
    control = control_grid(save_pred = TRUE),
    metrics = metric_set(roc_auc)
  )
```

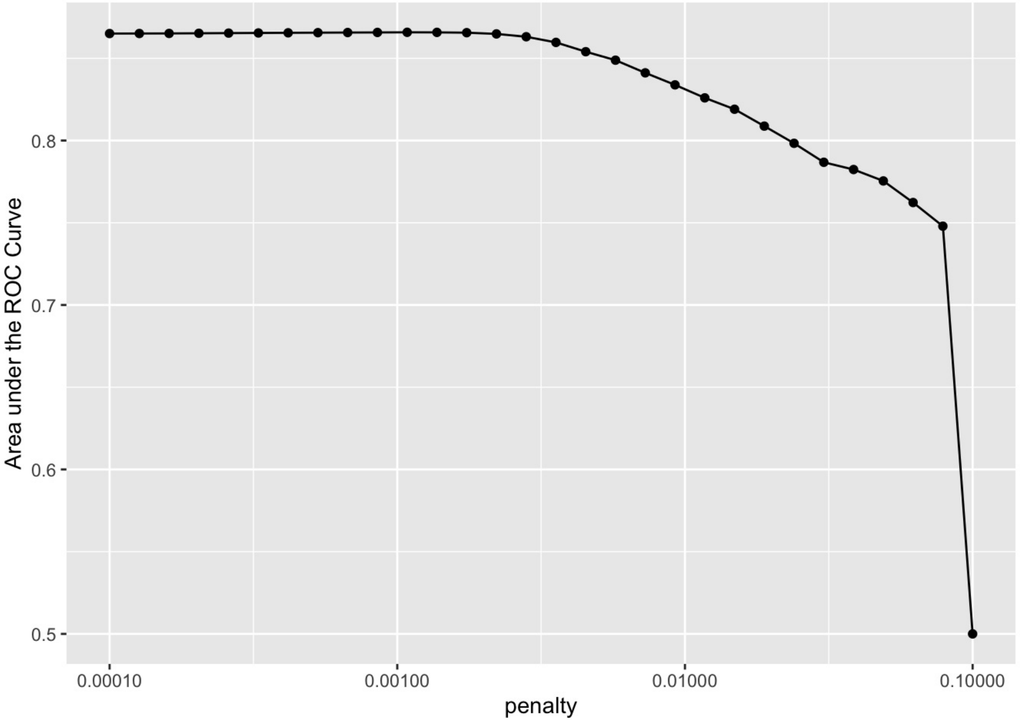
```
lasso_res
```

```
## # Tuning results
## # Validation Set Split (0.8/0.2)  using stratification
## # A tibble: 1 × 5
##   splits               id         .metrics          .notes      .predictions
##   <list>               <chr>      <list>            <list>      <list>
## 1 <split [30000/7500]> validation <tibble [30 × 5]> <tibble [0… <tibble [225,00…
```

```
lasso_res %>%
  collect_metrics()
```

```
## # A tibble: 30 × 7
##     penalty .metric .estimator  mean     n std_err .config
##       <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
##  1 0.0001   roc_auc binary     0.865     1      NA Preprocessor1_Model01
##  2 0.000127 roc_auc binary     0.865     1      NA Preprocessor1_Model02
##  3 0.000161 roc_auc binary     0.865     1      NA Preprocessor1_Model03
##  4 0.000204 roc_auc binary     0.865     1      NA Preprocessor1_Model04
##  5 0.000259 roc_auc binary     0.865     1      NA Preprocessor1_Model05
##  6 0.000329 roc_auc binary     0.865     1      NA Preprocessor1_Model06
##  7 0.000418 roc_auc binary     0.866     1      NA Preprocessor1_Model07
##  8 0.000530 roc_auc binary     0.866     1      NA Preprocessor1_Model08
##  9 0.000672 roc_auc binary     0.866     1      NA Preprocessor1_Model09
## 10 0.000853 roc_auc binary     0.866     1      NA Preprocessor1_Model10
## # … with 20 more rows
```

```
lasso_res %>%
  collect_metrics() %>%
  ggplot(aes(x = penalty, y = mean)) +
    geom_point() +
    geom_line() +
    ylab("Area under the ROC Curve") +
    scale_x_log10(labels = scales::label_number())
```




```
lasso_res %>%
  show_best("roc_auc", n=10)
```

```
## # A tibble: 10 × 7
##     penalty .metric .estimator  mean     n std_err .config
##       <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
##  1 0.00108  roc_auc binary     0.866     1      NA Preprocessor1_Model11
##  2 0.00137  roc_auc binary     0.866     1      NA Preprocessor1_Model12
##  3 0.000853 roc_auc binary     0.866     1      NA Preprocessor1_Model10
##  4 0.000672 roc_auc binary     0.866     1      NA Preprocessor1_Model09
##  5 0.000530 roc_auc binary     0.866     1      NA Preprocessor1_Model08
##  6 0.00174  roc_auc binary     0.866     1      NA Preprocessor1_Model13
##  7 0.000418 roc_auc binary     0.866     1      NA Preprocessor1_Model07
##  8 0.000329 roc_auc binary     0.865     1      NA Preprocessor1_Model06
##  9 0.000259 roc_auc binary     0.865     1      NA Preprocessor1_Model05
## 10 0.000204 roc_auc binary     0.865     1      NA Preprocessor1_Model04
```

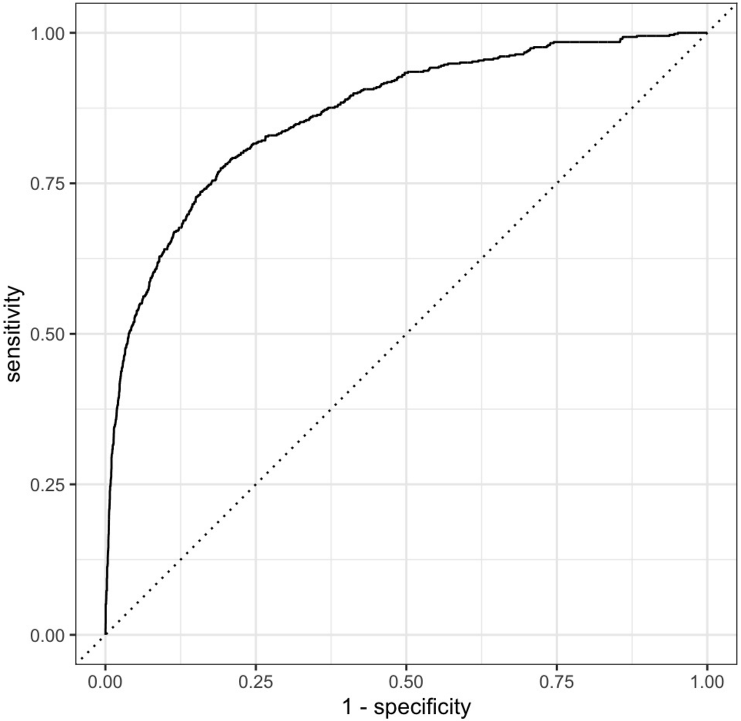
```
lasso_best = lasso_res %>%
  collect_metrics() %>%
  mutate(mean = round(mean, 2)) %>%
  arrange(desc(mean), desc(penalty)) %>%
  slice(1)

lasso_best
```

```
## # A tibble: 1 × 7
##   penalty .metric .estimator  mean     n std_err .config
##     <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1 0.00174 roc_auc binary      0.87     1      NA Preprocessor1_Model13
```

```
lasso_best_pred = lasso_res %>%
  collect_predictions(parameters = lasso_best)

lasso_best_pred %>%
  roc_curve(children, .pred_children) %>%
  autoplot()
```

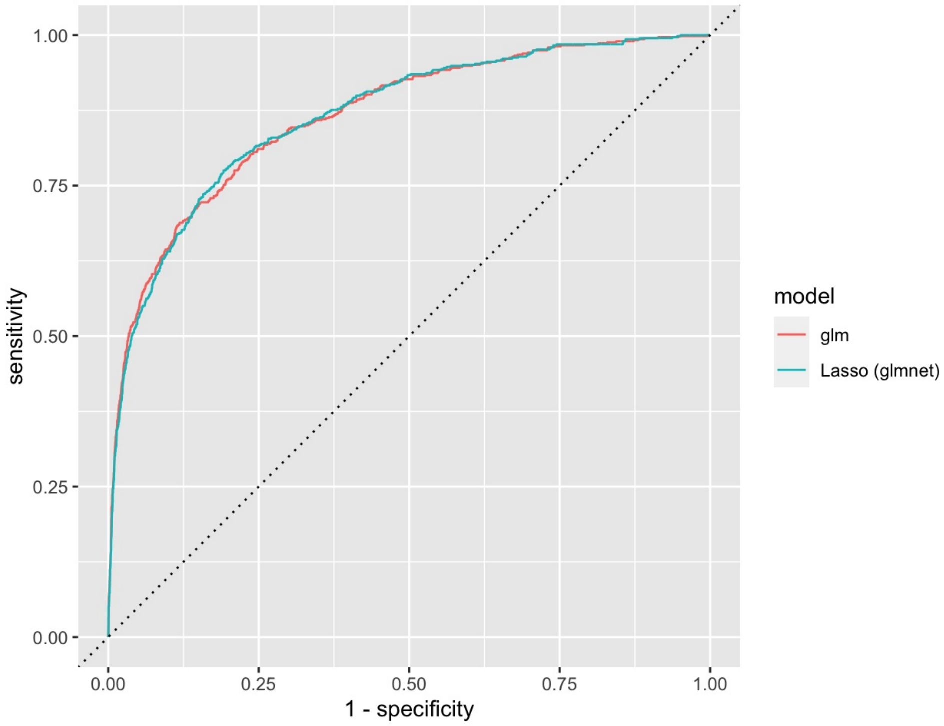


Comparing models

```r
lr_val_fit = lr_workflow %>%
  fit_resamples(
    val_set,
    control = control_resamples(save_pred=TRUE)
  )



bind_rows(
  lr_val_fit %>%
    collect_predictions() %>%
    roc_curve(children, .pred_children) %>%
    mutate(model = "glm"),
  lasso_best_pred %>%
    roc_curve(children, .pred_children) %>%
    mutate(model = "Lasso (glmnet)")
) %>%
  ggplot(aes(x=1-specificity, y=sensitivity, col=model)) +
    geom_path() +
    geom_abline(lty = 3) +
    coord_equal()
```



Random Forest

```r
rf_model = rand_forest(mtry = tune(), min_n = tune(), trees = 100) %>%
  set_engine("ranger", num.threads = 4) %>%
  set_mode("classification")

rf_recipe = recipe(children ~ ., data = hotel_train) %>%
  step_date(arrival_date) %>%
  step_holiday(arrival_date) %>%
  step_rm(arrival_date)

rf_workflow = workflow() %>%
  add_model(rf_model) %>%
  add_recipe(rf_recipe)

rf_model %>%
  parameters()
```

```
## Collection of 2 parameters for tuning
##
##  identifier  type    object
##        mtry  mtry nparam[?]
##       min_n min_n nparam[+]
##
## Model parameters needing finalization:
##    # Randomly Selected Predictors ('mtry')
##
## See `?dials::finalize` or `?dials::update.parameters` for more information.
```

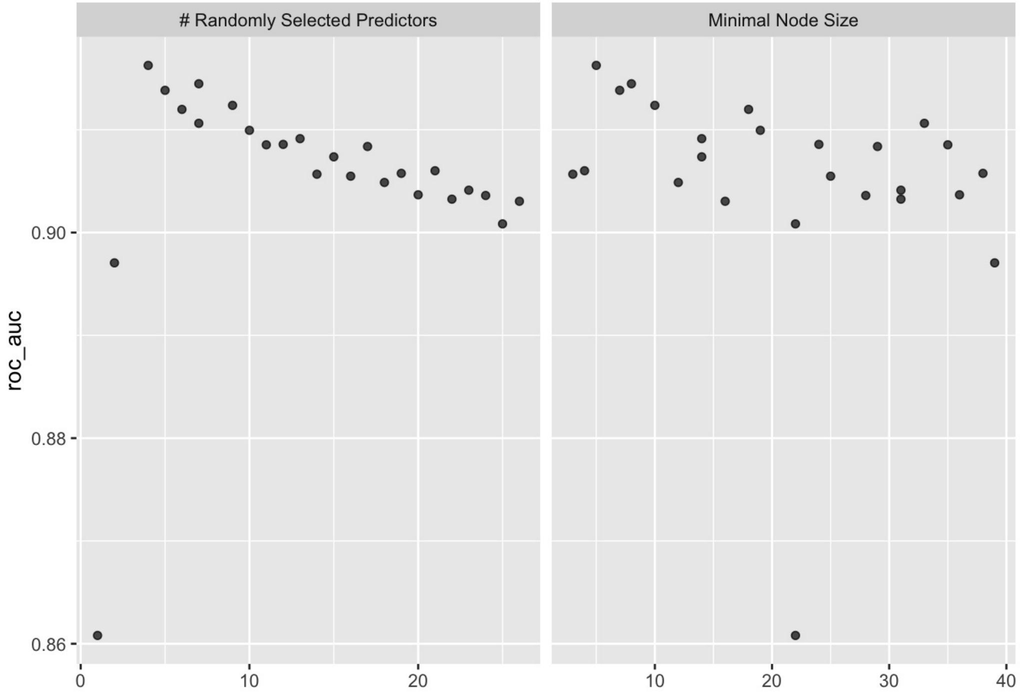
```
rf_res = rf_workflow %>%
  tune_grid(
    val_set,
    grid = 25,
    control = control_grid(save_pred = TRUE),
    metrics = metric_set(roc_auc)
  )
```

```
## i Creating pre-processing data to finalize unknown parameter: mtry
```

```
rf_res %>%
  show_best(metric = "roc_auc")
```

```
## # A tibble: 5 × 8
##    mtry min_n .metric .estimator  mean     n std_err .config
##   <int> <int> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1     4     5 roc_auc binary     0.916     1      NA Preprocessor1_Model08
## 2     7     8 roc_auc binary     0.914     1      NA Preprocessor1_Model23
## 3     5     7 roc_auc binary     0.914     1      NA Preprocessor1_Model13
## 4     9    10 roc_auc binary     0.912     1      NA Preprocessor1_Model11
## 5     6    18 roc_auc binary     0.912     1      NA Preprocessor1_Model20
```

```
autoplot(rf_res)
```



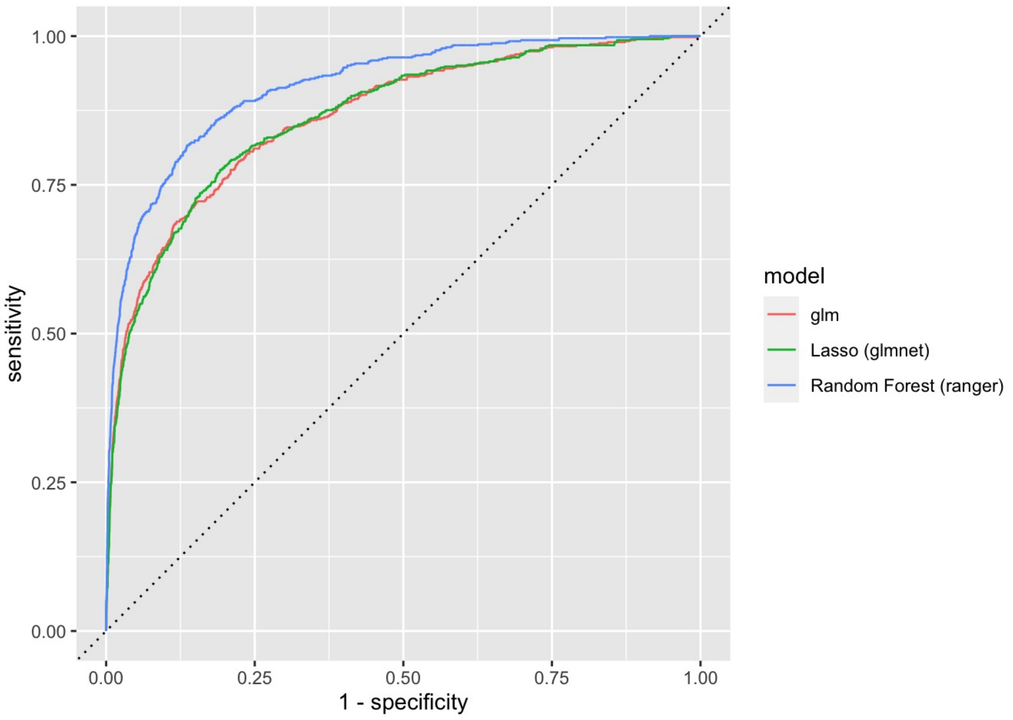
Randomly Selected Predictors
Minimal Node Size
roc_auc
0.90
0.88
0.86
0
10
20
10
20
30
40

```
rf_best = rf_res %>%
  select_best(metric = "roc_auc")

rf_best_pred = rf_res %>%
  collect_predictions(parameters = rf_best)
```

Compare

```
bind_rows(
  lr_val_fit %>%
    collect_predictions() %>%
    roc_curve(children, .pred_children) %>%
    mutate(model = "glm"),
  lasso_best_pred %>%
    roc_curve(children, .pred_children) %>%
    mutate(model = "Lasso (glmnet)"),
  rf_best_pred %>%
    roc_curve(children, .pred_children) %>%
    mutate(model = "Random Forest (ranger)")
) %>%
  ggplot(aes(x=1-specificity, y=sensitivity, col=model)) +
    geom_path() +
    geom_abline(lty = 3) +
    coord_equal()
```



1.00
0.75
0.50
0.25
0.00
sensitivity
0.00
0.25
0.50
0.75
1.00
1 - specificity
model
glm
Lasso (glmnet)
Random Forest (ranger)