Explore the data

Our modeling goal is to estimate the relationship of
expected tournament wins by seed from this week’s #TidyTuesday dataset. This is similar to the
“average” column in the FiveThirtyEight table in this article. This was what I was most interested in when I saw this data, but I was pretty confused about what was going on this table at first! Many thanks to
Tom Mock for helping out my understanding.

Let’s start by reading in the data.

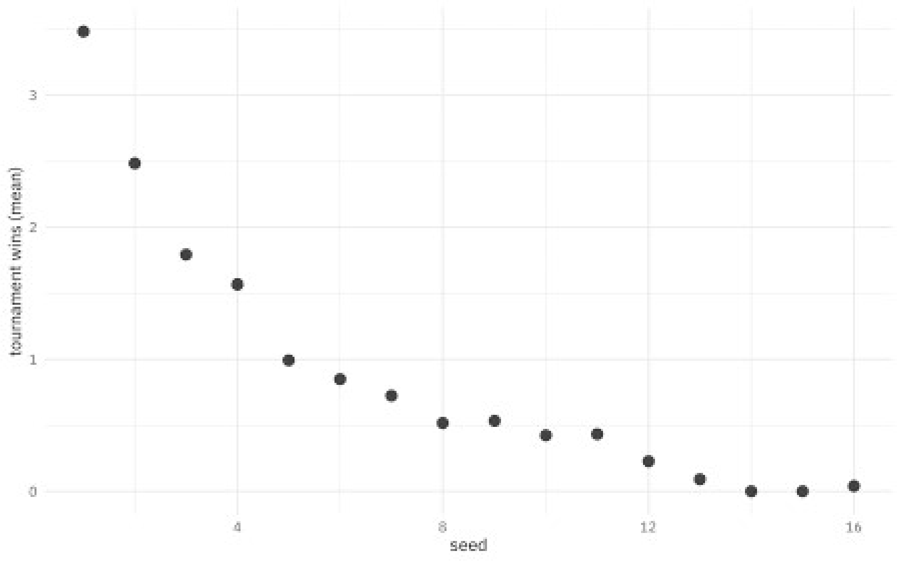
```
library(tidyverse)
tournament <- read_csv("https://raw.githubusercontent.com/rfordatascience/tidytuesday/
master/data/2020/2020-10-06/tournament.csv")

tournament
```

```
## # A tibble: 2,092 x 19
##      year school  seed conference conf_w conf_l conf_percent conf_place
reg_w
##
##  1  1982 Arizo…     4 Western C…     NA     NA           NA  -
23
##  2  1982 Auburn     7 Southeast…     NA     NA           NA  -
24
##  3  1982 Cheyn…     2 Independe…     NA     NA           NA  -
24
##  4  1982 Clems…     5 Atlantic …      6      3         66.7 4th
20
##  5  1982 Drake      4 Missouri …     NA     NA           NA  -
26
##  6  1982 East …     6 Independe…     NA     NA           NA  -
19
##  7  1982 Georg…     5 Southeast…     NA     NA           NA  -
21
##  8  1982 Howard     8 Mid-Easte…     NA     NA           NA  -
14
##  9  1982 Illin…     7 Big Ten        NA     NA           NA  -
21
## 10  1982 Jacks…     7 Southwest…     NA     NA           NA  -
28
## # … with 2,082 more rows, and 10 more variables: reg_l ,
## #   reg_percent , how_qual , x1st_game_at_home ,
## #   tourney_w , tourney_l , tourney_finish , full_w ,
## #   full_l , full_percent
```

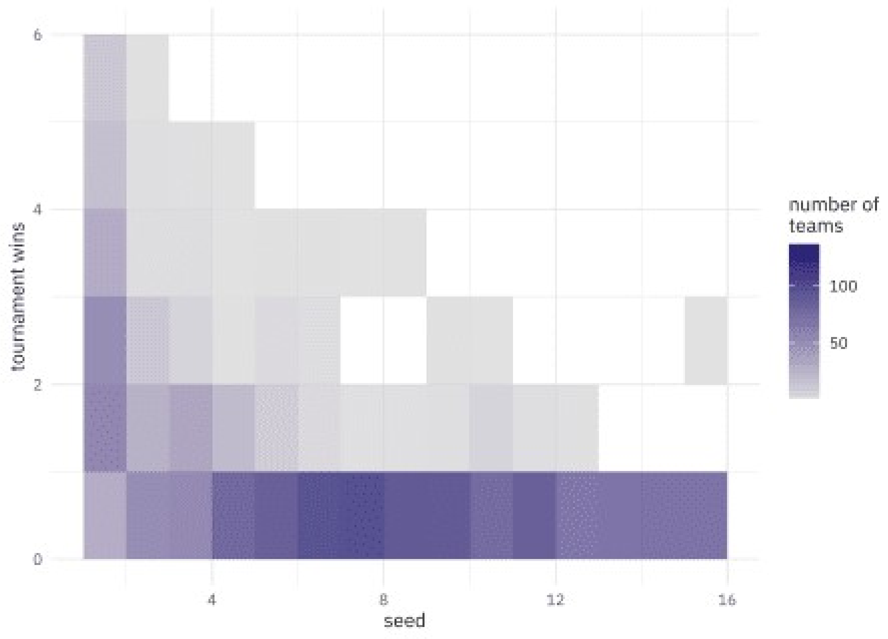
We can look at the mean wins by seed.

```
tournament %>%
  group_by(seed) %>%
  summarise(exp_wins = mean(tourney_w, na.rm = TRUE)) %>%
  ggplot(aes(seed, exp_wins)) +
  geom_point(alpha = 0.8, size = 3) +
  labs(y = "tournament wins (mean)")
```



Let’s visualize all the tournament results, not just the averages.

```
tournament %>%
  ggplot(aes(seed, tourney_w)) +
  geom_bin2d(binwidth = c(1, 1), alpha = 0.8) +
  scale_fill_gradient(low = "gray85", high = "midnightblue") +
  labs(fill = "number of\nteams", y = "tournament wins")
```



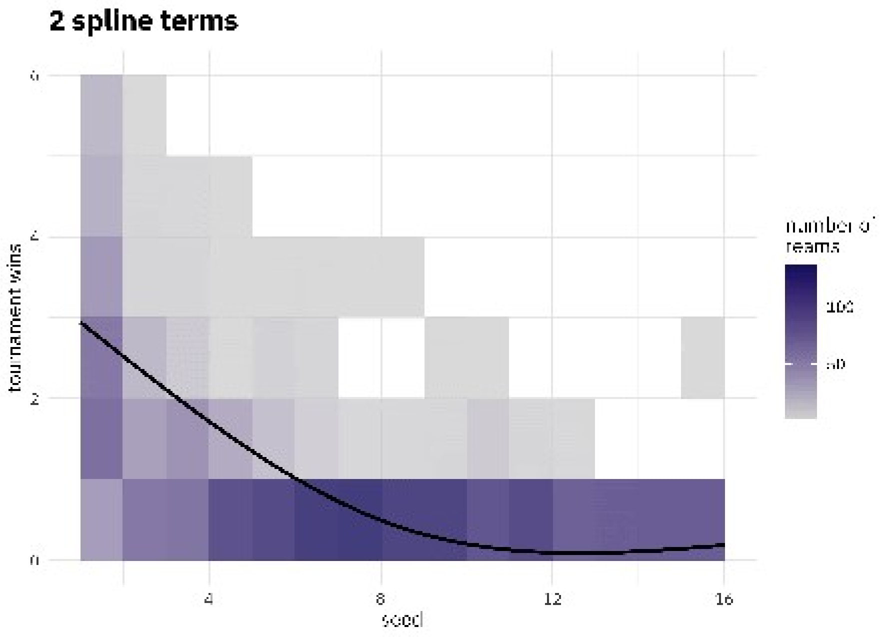
We have a lot of options to deal with data like this (curvy, integers, all greater than zero) but one straightforward option are
splines. Splines aren’t perfect for this because they aren’t constrained to stay greater than zero or to always decrease, but they work pretty well and can be used in lots of situations. We have to choose the **degrees of freedom** for the splines.

```
library(splines)

plot_smoother <- function(deg_free) {
  p <- ggplot(tournament, aes(seed, tourney_w)) +
    geom_bin2d(binwidth = c(1, 1), alpha = 0.8) +
    scale_fill_gradient(low = "gray85", high = "midnightblue") +
    geom_smooth(
      method = lm, se = FALSE, color = "black",
      formula = y ~ ns(x, df = deg_free)
    ) +
    labs(
      fill = "number of\nteams", y = "tournament wins",
      title = paste(deg_free, "spline terms")
    )

  print(p)
}

walk(c(2, 4, 6, 8, 10, 15), plot_smoother)
```



As the number of degrees of freedom goes up, the curves get more wiggly. This would allow the model to fit a more complex relationship, perhaps too much so give our data. We can *tune* this hyperparameter to find the best value.

Build a model

We can start by loading the tidymodels metapackage, and splitting our data into training and testing sets.

```
library(tidymodels)

set.seed(123)
tourney_split <- tournament %>%
  filter(!is.na(seed)) %>%
  initial_split(strata = seed)

tourney_train <- training(tourney_split)
tourney_test <- testing(tourney_split)
```

We are going to use
resampling to evaluate model performance, so let’s get those resampled sets ready.

```
set.seed(234)
tourney_folds <- bootstraps(tourney_train)
tourney_folds
```

```
## # Bootstrap sampling
## # A tibble: 25 x 2
##    splits              id
##
##  1  Bootstrap01
##  2  Bootstrap02
##  3  Bootstrap03
##  4  Bootstrap04
##  5  Bootstrap05
##  6  Bootstrap06
##  7  Bootstrap07
##  8  Bootstrap08
##  9  Bootstrap09
## 10  Bootstrap10
## # … with 15 more rows
```

Next we build a recipe for data preprocessing. It only has one step!

- First, we must tell the `recipe()` what our model is going to be (using a formula here) and what our training data is.
- For our first and only step, we create new spline terms from the original `seed` variable. We don’t know what the best value for the degrees of freedom is, so we will `tune()` it. We can set an `id` value for the tuneable parameter to more easily keep track of it, if we want.

The object `tourney_rec` is a recipe that has **not** been trained on data yet, and in fact, we can’t do this because we haven’t decided on a value for `deg_free`.

```
tourney_rec <- recipe(tourney_w ~ seed, data = tourney_train) %>%
  step_ns(seed, deg_free = tune("seed_splines"))

tourney_rec
```

```
## Data Recipe
##
## Inputs:
##
##       role #variables
##    outcome          1
##  predictor          1
##
## Operations:
##
## Natural Splines on seed
```

Next, let’s create a model specification for a linear regression model, and the combine the recipe and model together in a workflow.

```
lm_spec <- linear_reg() %>% set_engine("lm")

tourney_wf <- workflow() %>%
  add_recipe(tourney_rec) %>%
  add_model(lm_spec)

tourney_wf
```

```
## ══ Workflow ════════════════════════════════════════════════════════════
════════════════════════════════
## Preprocessor: Recipe
## Model: linear_reg()
##
## ── Preprocessor ──────────────────────────────
──────────────────────────────────────────────────────────
## 1 Recipe Step
##
## ● step_ns()
##
## ── Model ────────────────────────────────────────────────────────────
───────────────────────────────────
## Linear Regression Model Specification (regression)
##
## Computational engine: lm
```

This workflow is almost ready to go, but we need to decide what values to try for the splines. There are several different ways to
create tuning grids, but if the grid you need is very simple, you might prefer to create it by hand.

```
spline_grid <- tibble(seed_splines = c(1:3, 5, 7, 10))
spline_grid
```

```
## # A tibble: 6 x 1
##   seed_splines
##
## 1            1
## 2            2
## 3            3
## 4            5
## 5            7
## 6           10
```

Now we can put this all together! When we use `tune_grid()`, we will fit each of the options in the grid to each of the resamples.

```
doParallel::registerDoParallel()
save_preds <- control_grid(save_pred = TRUE)

spline_rs <-
  tune_grid(
    tourney_wf,
    resamples = tourney_folds,
    grid = spline_grid,
    control = save_preds
  )

spline_rs

## # Tuning results
## # Bootstrap sampling
## # A tibble: 25 x 5
##    splits           id         .metrics        .notes          .predictions
##
##  1
```

We have now fit each of our candidate set of spline features to our resampled training set!

Evaluate model

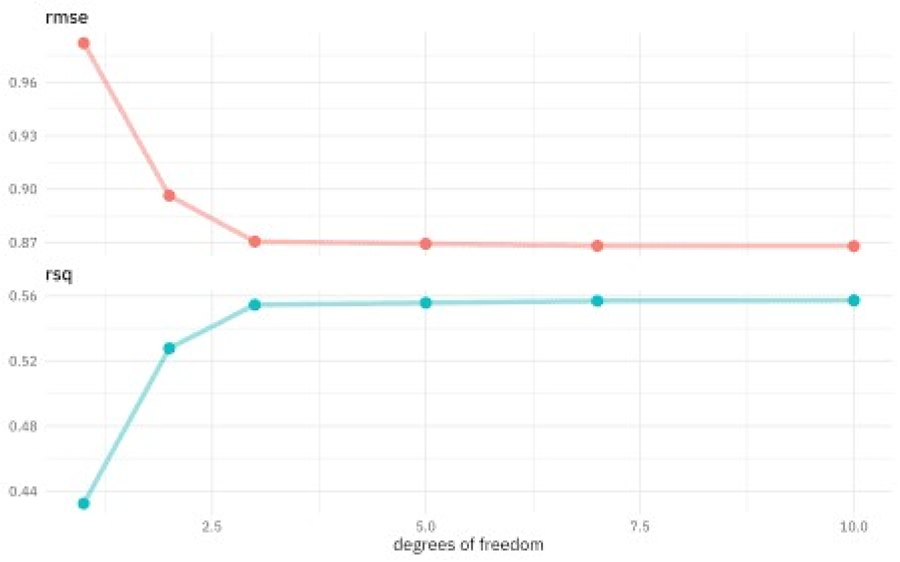
Now let’s check out how we did.

```
collect_metrics(spline_rs)

## # A tibble: 12 x 7
##    seed_splines .metric .estimator  mean     n std_err .config
##
##  1            1 rmse    standard   0.982    25 0.00741 Recipe1
##  2            1 rsq     standard   0.432    25 0.00372 Recipe1
##  3            2 rmse    standard   0.896    25 0.00749 Recipe2
##  4            2 rsq     standard   0.528    25 0.00486 Recipe2
##  5            3 rmse    standard   0.871    25 0.00727 Recipe3
##  6            3 rsq     standard   0.554    25 0.00518 Recipe3
##  7            5 rmse    standard   0.869    25 0.00730 Recipe4
##  8            5 rsq     standard   0.556    25 0.00541 Recipe4
##  9            7 rmse    standard   0.868    25 0.00718 Recipe5
## 10            7 rsq     standard   0.557    25 0.00537 Recipe5
## 11           10 rmse    standard   0.868    25 0.00693 Recipe6
## 12           10 rsq     standard   0.557    25 0.00538 Recipe6
```

Looks like the model got better and better as we added more degrees of freedom, which isn’t too shocking. In what way did it change?

```
collect_metrics(spline_rs) %>%
  ggplot(aes(seed_splines, mean, color = .metric)) +
  geom_line(size = 1.5, alpha = 0.5) +
  geom_point(size = 3) +
  facet_wrap(~.metric, ncol = 1, scales = "free_y") +
  labs(x = "degrees of freedom", y = NULL) +
  theme(legend.position = "none")
```



The model improved a lot as we increased the degrees of freedom at the beginning, but then continuing to add more didn't make much difference. We could choose the numerically optimal hyperparameter with `select_best()` but that would choose a more wiggly, complex model than we probably want. We can choose a *simpler* model that performs well, within some limits around the numerically optimal result. We could choose either by percent loss in performance or within one standard error in performance.

```
select_by_pct_loss(spline_rs, metric = "rmse", limit = 5, seed_splines)

## # A tibble: 1 x 9
##   seed_splines .metric .estimator  mean     n std_err .config .best .loss
##
## 1            2 rmse    standard   0.896    25 0.00749 Recipe2 0.868  3.27

select_by_one_std_err(spline_rs, metric = "rmse", seed_splines)

## # A tibble: 1 x 9
##   seed_splines .metric .estimator  mean     n std_err .config .best .bound
##
## 1            3 rmse    standard   0.871    25 0.00727 Recipe3 0.868  0.875
```

Looks like 2 or 3 degrees of freedom is a good option. Let's go with 3, and update our tuneable workflow with this information and then fit it to our training data.

```
final_wf <- finalize_workflow(tourney_wf, tibble(seed_splines = 3))
```

```
tourney_fit <- fit(final_wf, tourney_train)
tourney_fit

## ══ Workflow [trained] ══════════════════════════════
═══════════════════════════════════════════════════════
## Preprocessor: Recipe
## Model: linear_reg()
##
## ── Preprocessor ──────────────────────────────
────────────────────────────────────────────────────────
## 1 Recipe Step
##
## ● step_ns()
##
## ── Model ─────────────────────────────────────────────
──────────────────────────────────
##
## Call:
## stats::lm(formula = ..y ~ ., data = data)
##
## Coefficients:
## (Intercept)    seed_ns_1    seed_ns_2    seed_ns_3
##       3.272       -1.855       -5.590       -1.822
```

We can predict from this fitted workflow. For example, we can predict on the testing data and compute model performance.

```
tourney_test %>%
  bind_cols(predict(tourney_fit, tourney_test)) %>%
  metrics(tourney_w, .pred)

## # A tibble: 3 x 3
##   .metric .estimator .estimate
##
## 1 rmse    standard       0.877
## 2 rsq     standard       0.545
## 3 mae     standard       0.609
```

Pretty good! We can also predict on other kinds of new data. For example, let’s recreate the

“average” column in the FiveThirtyEight table on expected wins.

```
predict(tourney_fit, new_data = tibble(seed = 1:16))

## # A tibble: 16 x 1
##       .pred
```

```
##
##   1  3.27
##   2  2.61
##   3  1.99
##   4  1.45
##   5  1.02
##   6  0.738
##   7  0.574
##   8  0.492
##   9  0.456
##  10  0.429
##  11  0.380
##  12  0.307
##  13  0.216
##  14  0.110
##  15 -0.00482
##  16 -0.125
```

It's close! This isn't a huge surprise, since we're fitting curves to data in a straightforward way here, but it's still good to see. You can also see why splines aren't perfect for this task, because the prediction isn't constrained to positive values.