Week 11: Splines

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04/04/23

Overview

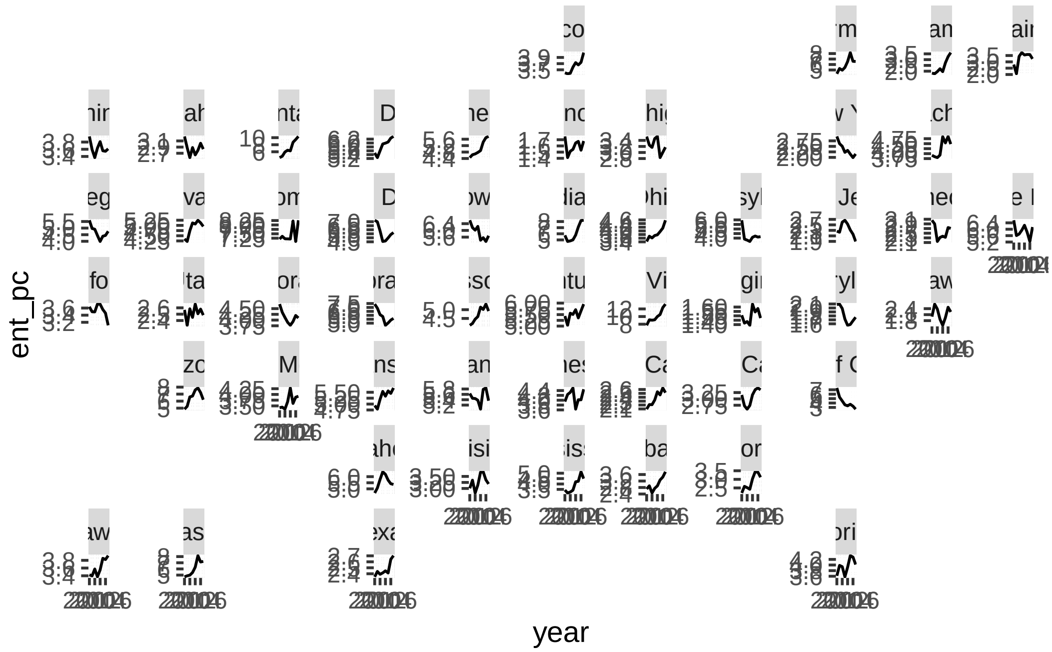
In this lab you'll be fitting a second-order P-Splines regression model to foster care entries by state in the US, projecting out to 2030.

```
library(tidyverse)
library(here)
library(rstan)
library(tidybayes)
source(here("code/getsplines.R"))
```

Here's the data

Question 1

Make a plot highlighting trends over time by state. Might be a good opportunity to use `geofacet`. Describe what you see in a couple of sentences.



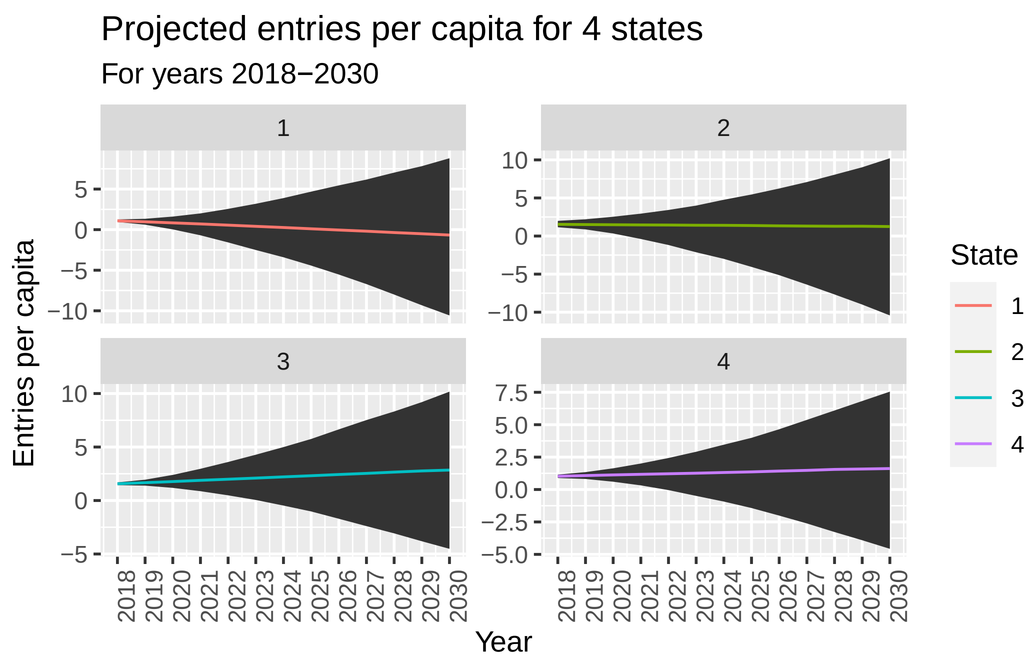
Question 2

Fit a hierarchical second-order P-Splines regression model to estimate the (logged) entries per capita over the period 2010-2017. The model you want to fit is

$$
\begin{aligned}
y_{st} &\sim N(\log \lambda_{st}, \sigma^2_{y,s}) \\
\log \lambda_{st} &= \alpha_k B_k(t) \\
\Delta^2 \alpha_k &\sim N(0, \sigma^2_{\alpha,s}) \\
\log \sigma_{\alpha,s} &\sim N(\mu_\sigma, \tau^2)
\end{aligned}
$$

Where $y_{s,t}$ is the logged entries per capita for state s in year t. Use cubic splines that have knots 2.5 years apart and are a constant shape at the boundaries. Put standard normal priors on standard deviations and hyperparameters. Project forward entries per capita to 2030. Pick 4 states and plot the results (with 95% CIs). Note the code to do this in R is in the lecture slides.

Question 3




```
<ggproto object: Class ScaleDiscrete, Scale, gg>
    aesthetics: colour
    axis_order: function
    break_info: function
    break_positions: function
    breaks: waiver
    call: call
    clone: function
    dimension: function
    drop: TRUE
    expand: waiver
    get_breaks: function
    get_breaks_minor: function
    get_labels: function
    get_limits: function
    guide: legend
    is_discrete: function
    is_empty: function
    labels: California Mississippi Ohio Texas
    limits: NULL
    make_sec_title: function
```

```
make_title: function
map: function
map_df: function
n.breaks.cache: NULL
na.translate: TRUE
na.value: grey50
name: waiver
palette: function
palette.cache: NULL
position: left
range: <ggproto object: Class RangeDiscrete, Range, gg>
    range: NULL
    reset: function
    train: function
    super:  <ggproto object: Class RangeDiscrete, Range, gg>
rescale: function
reset: function
scale_name: manual
train: function
train_df: function
transform: function
transform_df: function
super:  <ggproto object: Class ScaleDiscrete, Scale, gg>
```

Question 4 (bonus)

P-Splines are quite useful in structural time series models, when you are using a model of the form

$$f(y_t) = \text{systematic part} + \text{time-specific deviations}$$

where the systematic part is model with a set of covariates for example, and P-splines are used to smooth data-driven deviations over time. Consider adding covariates to the model you ran above. What are some potential issues that may happen in estimation? Can you think of an additional constraint to add to the model that would overcome these issues?

Answer When we add covariates to the model- it would be difficult to interpret if the trends in time series happen due to covariates or due to splines. So some constraints are required to be added. We can perhaps transform the spline function to detrend it, such as by differencing. I also came across the function to constrained B-splines using the R library cobs:

```
#co <- cobs(x, y, lambda=-1)
```