Class Notes

Statistical Computing & Machine Learning

Class 19

Aside: Is continuity always good?

Regression discontinuity video

Quantiles

Show the ecdf() of some data. Invert this to get the quantiles. Show mosaic::qdata() and mosaic::pdata() as inverses. quantile() is the original version of this.

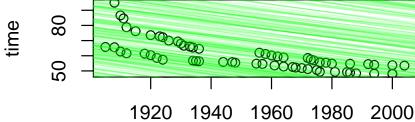
Standard errors and error bands

```
mod <- lm(time ~ year, data=SwimRecords)</pre>
summary(mod)
##
## Call:
## lm(formula = time ~ year, data = SwimRecords)
##
## Residuals:
##
      Min
                1Q Median
                                30
                                       Max
## -9.8385 -4.2293 0.5861 3.2304 23.6035
##
## Coefficients:
                Estimate Std. Error t value
##
## (Intercept) 567.24200
                         53.86572 10.531
## year
               -0.25988
                            0.02759 -9.419
##
               Pr(>|t|)
## (Intercept) 2.91e-15 ***
## year
              1.96e-13 ***
## ---
## Signif. codes:
    0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.351 on 60 degrees of freedom
## Multiple R-squared: 0.5966, Adjusted R-squared: 0.5898
## F-statistic: 88.72 on 1 and 60 DF, p-value: 1.958e-13
```

Do bootstrap replications

Generate random values of slope and intercept and add those to the plot.

```
slopes <- rnorm(500, mean = -0.26, sd = 0.028)
intercepts <- rnorm(length(slopes), mean=567.2, sd=53.9)
if(!is.null(knitr::current_input() ))
   plot(time ~ year, data=SwimRecords)
for(k in 1:length(slopes))
   abline(intercepts[k], slopes[k], col=rgb(0,1,0, .2))</pre>
```



year

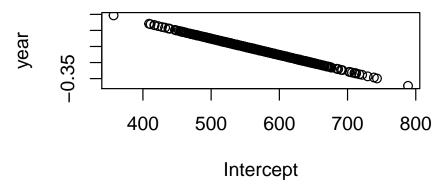
Why the disagreement between the bootstrapped coefficients and the random generation of slopes and intercepts?

```
rands <- matrix(rnorm(500, sd=2), ncol=2)
# 2 so that we cover 95% interval</pre>
```

```
better <- rands %*% chol(vcov(mod))
means <- matrix(c(567.2, -0.26), byrow = TRUE,ncol=2, nrow=nrow(better))
better <- better + means
if(!is.null(knitr::current_input() ))
    plot(time ~ year, data=SwimRecords)
for(k in 1:nrow(better))
    abline(better[k,1], better[k,2], col=rgb(0,0,1, .2))</pre>
### 1920 1940 1960 1980 2000
```

year

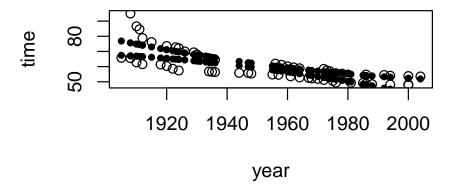
with(reps, plot(Intercept, year))



To generate standard error at a set of points:

```
rowSums(MM %*% vcov(mod) * MM)
# note standard multiplication *

MM <- model.matrix(time ~ year, data=SwimRecords)
SE <- rowSums(MM %*% vcov(mod) * MM)
top <- fitted(mod) + 2*SE
bottom <- fitted(mod) - 2*SE
if(!is.null(knitr::current_input() ))
    plot(time ~ year, data=SwimRecords)
points(MM[,2], top, pch=20)
points(MM[,2], bottom, pch=20)</pre>
```



Polynomial bases

```
X <- data.frame(year = 1890:2020)
X$sex <- rep(c("F","M"), length=nrow(X))

The raw polynomials

x <- 0:100
funs <- outer(x, 0:5, FUN = '^')
svd(funs)$d

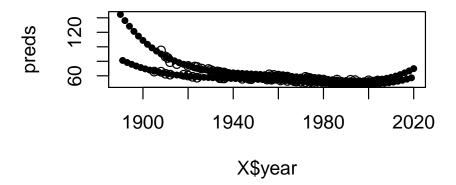
## [1] 3.098450e+10 3.407944e+07 1.068421e+05
## [4] 8.098882e+02 1.681222e+01 1.794720e+00

mod <- lm(time ~ sex*outer(year, 0:5, FUN = '^'), data=SwimRecords)
plot(time ~ year, data=SwimRecords)
with(SwimRecords, points(year, fitted(mod), pch=20))</pre>
```

1920 1940 1960 1980 2000

year

```
preds <- predict(mod, newdata = X)
## Warning in predict.lm(mod, newdata = X):
## prediction from a rank-deficient fit may be
## misleading
plot(X$year, preds, pch=20)
with(SwimRecords, points(year, time))</pre>
```



Orthogonal polynomials

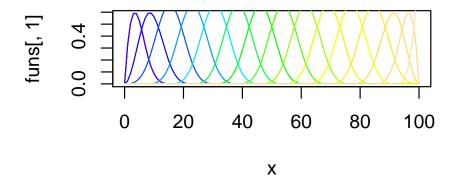
```
svd(funs)$d
```

```
## [1] 1 1 1 1 1 1 1 1 1 1
```

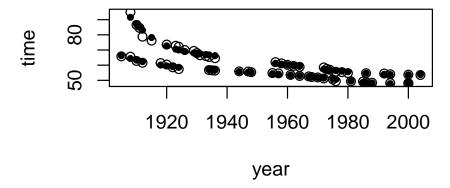
Splines

B-splines

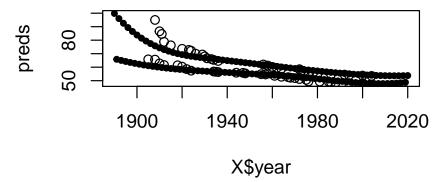
```
x <- 0:100
funs <- splines::bs(x, df = 15)
plot(x, funs[,1], type="l")
for (k in 1:ncol(funs))
  lines(x, funs[,k], col=topo.colors(ncol(funs))[k])</pre>
```



```
mod <- lm(time ~ sex * splines::bs(year, df=5), data=SwimRecords)
plot(time ~ year, data=SwimRecords)
with(SwimRecords, points(year, fitted(mod), pch=20))</pre>
```

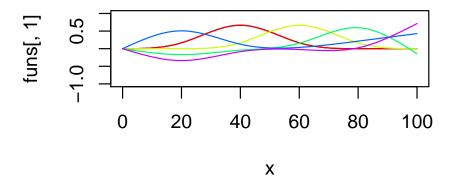


```
preds <- predict(mod, newdata = X)
plot(X$year, preds, pch=20)
with(SwimRecords, points(year, time))</pre>
```

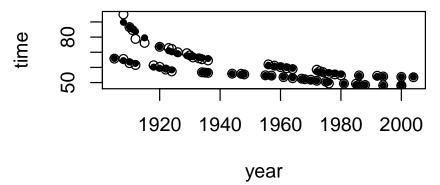


Natural splines

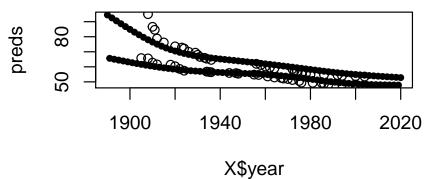
```
x <- 0:100
funs <- splines::ns(x, df = 5)
plot(x, funs[,1], type="l", ylim=c(-1,1))
for (k in 1:ncol(funs))
  lines(x, funs[,k], col=rainbow(ncol(funs))[k])</pre>
```



```
mod <- lm(time ~ sex * splines::ns(year, df=5), data=SwimRecords)
plot(time ~ year, data=SwimRecords)
with(SwimRecords, points(year, fitted(mod), pch=20))</pre>
```



```
preds <- predict(mod, newdata = X)
plot(X$year, preds, pch=20)
with(SwimRecords, points(year, time))</pre>
```



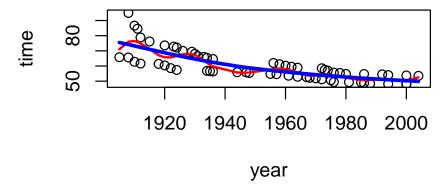
Smoothing splines

```
mod <- with(SwimRecords, smooth.spline(year, time, df = 15))
mod2 <- with(SwimRecords, smooth.spline(year, time, cv = TRUE))
## Warning in smooth.spline(year, time, cv =
## TRUE): cross-validation with non-unique 'x'
## values seems doubtful</pre>
```

mod2\$df

[1] 3.47454

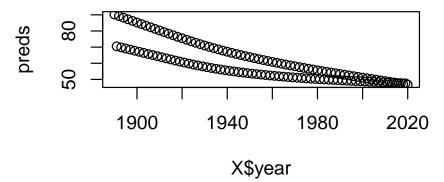
plot(time ~ year, data=SwimRecords)
lines(mod, col="red", lwd=2)
lines(mod2, col="blue", lwd=3)



Smoothers in k dimensions

GAMS

library(gam) mod <- gam(time ~ sex * s(year, 2), data=SwimRecords) preds <- predict(mod, newdata=X) plot(X\$year, preds)</pre>



Programming Activity

Finish up Day 16 Programming Activity.

Look at the smoothness.

Calculate the second derivative and integrate its absolute value over the interval.