

Smoothing

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Key ideas

- · Sometimes there are non-linear trends in data
- We can use "smoothing" to try to capture these
- · Still a risk of overfitting
- Often hard to interpret

CD4 Data

```
time cd4 age packs drugs sex cesd id

1279 -2.990 814 6.17 3 1 5 -3 30183

2190 -2.990 400 -6.02 0 0 3 -4 41406

1167 -2.984 467 13.94 0 1 1 0 30046

1427 -2.957 749 -4.54 0 1 -1 -7 30498

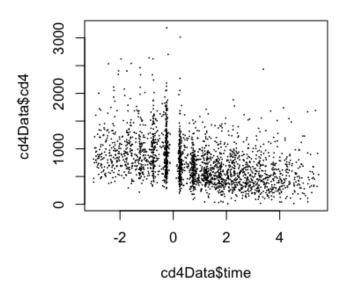
2032 -2.951 1218 5.57 3 1 5 3 41032

1813 -2.949 1015 -9.15 2 1 0 -7 40375
```

http://www.cbcb.umd.edu/~hcorrada/PracticalML/

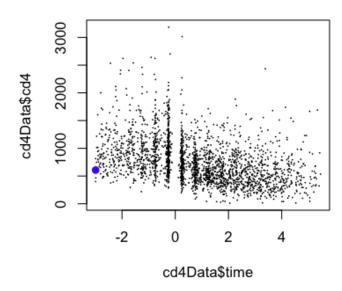
CD4 over time

plot(cd4Data\$time,cd4Data\$cd4,pch=19,cex=0.1)



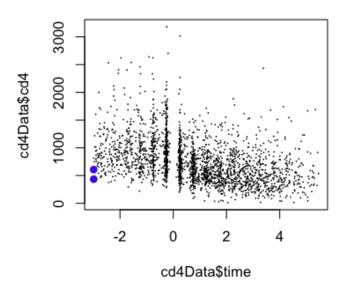
Average first 2 points

```
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)
points(mean(cd4Data$time[1:2]),mean(cd4Data$cd4[1:2]),col="blue",pch=19)
```



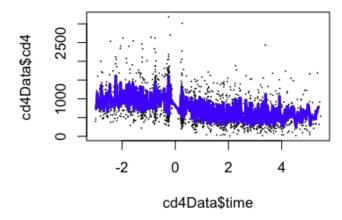
Average second and third points

```
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)
points(mean(cd4Data$time[1:2]),mean(cd4Data$cd4[1:2]),col="blue",pch=19)
points(mean(cd4Data$time[2:3]),mean(cd4Data$cd4[2:3]),col="blue",pch=19)
```



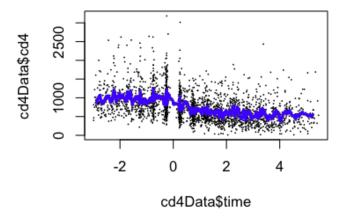
A moving average

```
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)
aveTime <- aveCd4 <- rep(NA,length(3:(dim(cd4Data)[1]-2)))
for(i in 3:(dim(cd4Data)[1]-2)){
    aveTime[i] <- mean(cd4Data$time[(i-2):(i+2)])
    aveCd4[i] <- mean(cd4Data$cd4[(i-2):(i+2)])
}
lines(aveTime,aveCd4,col="blue",lwd=3)</pre>
```



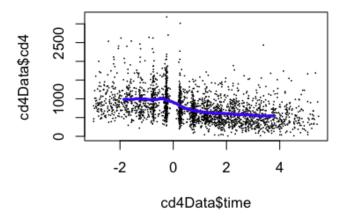
Average more points

```
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)
aveTime <- aveCd4 <- rep(NA,length(11:(dim(cd4Data)[1]-10)))
for(i in 11:(dim(cd4Data)[1]-2)){
   aveTime[i] <- mean(cd4Data$time[(i-10):(i+10)])
   aveCd4[i] <- mean(cd4Data$cd4[(i-10):(i+10)])
}
lines(aveTime,aveCd4,col="blue",lwd=3)</pre>
```



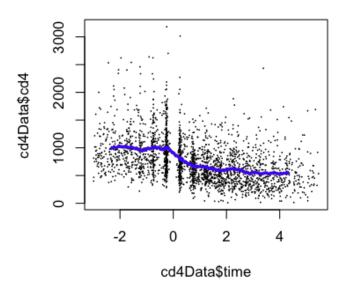
Average many more

```
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)
aveTime <- aveCd4 <- rep(NA,length(201:(dim(cd4Data)[1]-200)))
for(i in 201:(dim(cd4Data)[1]-2)){
    aveTime[i] <- mean(cd4Data$time[(i-200):(i+200)])
    aveCd4[i] <- mean(cd4Data$cd4[(i-200):(i+200)])
}
lines(aveTime,aveCd4,col="blue",lwd=3)</pre>
```



A faster way

```
filtTime <- as.vector(filter(cd4Data$time,filter=rep(1,200))/200)
filtCd4 <- as.vector(filter(cd4Data$cd4,filter=rep(1,200))/200)
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1); lines(filtTime,filtCd4,col="blue",lwd=3)</pre>
```



Averaging = weighted sums

```
filtCd4 <- as.vector(filter(cd4Data$cd4,filter=rep(1,4))/4)
filtCd4[2]</pre>
```

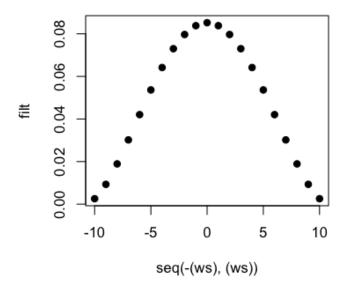
```
[1] 607.5
```

```
sum(cd4Data$cd4[1:4] * rep(1/4,4))
```

```
[1] 607.5
```

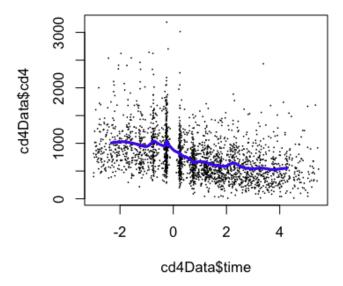
Other weights -> should sum to one

```
ws = 10; tukey = function(x) pmax(1 - x^2, 0)^2
filt= tukey(seq(-ws,ws)/(ws+1)); filt=filt/sum(filt)
plot(seq(-(ws),(ws)), filt, pch=19)
```



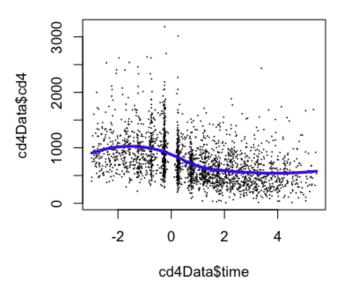
Other weights -> should sum to one

```
ws = 100; tukey = function(x) pmax(1 - x^2,0)^2
filt= tukey(seq(-ws,ws)/(ws+1)); filt=filt/sum(filt)
filtTime <- as.vector(filter(cd4Data$time,filter=filt))
filtCd4 <- as.vector(filter(cd4Data$cd4,filter=filt))
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1); lines(filtTime,filtCd4,col="blue",lwd=3)</pre>
```



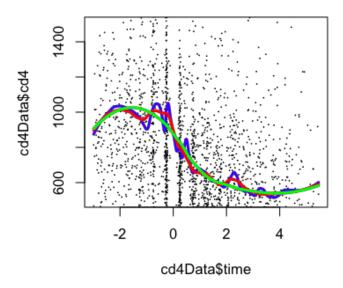
Lowess (loess)

```
lw1 <- loess(cd4 ~ time,data=cd4Data)
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)
lines(cd4Data$time,lw1$fitted,col="blue",lwd=3)</pre>
```



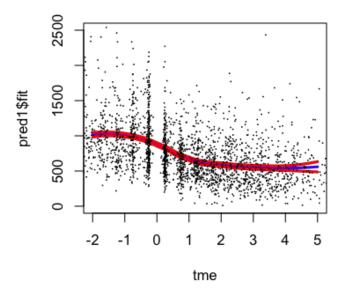
Span

```
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1,ylim=c(500,1500))
lines(cd4Data$time,loess(cd4 ~ time,data=cd4Data,span=0.1)$fitted,col="blue",lwd=3)
lines(cd4Data$time,loess(cd4 ~ time,data=cd4Data,span=0.25)$fitted,col="red",lwd=3)
lines(cd4Data$time,loess(cd4 ~ time,data=cd4Data,span=0.76)$fitted,col="green",lwd=3)
```



Predicting with loess

```
tme <- seq(-2,5,length=100); pred1 = predict(lw1,newdata=data.frame(time=tme),se=TRUE)
plot(tme,pred1$fit,col="blue",lwd=3,type="l",ylim=c(0,2500))
lines(tme,pred1$fit + 1.96*pred1$se.fit,col="red",lwd=3)
lines(tme,pred1$fit - 1.96*pred1$se.fit,col="red",lwd=3)
points(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)</pre>
```



Splines

$$Y_i = b_0 + \sum_{k=1}^{K} b_k s_k(x_i) + e_i$$

 Y_i - outcome for *i*th observation

 b_0 - Intercept term

 b_k - Coefficient for kth spline function

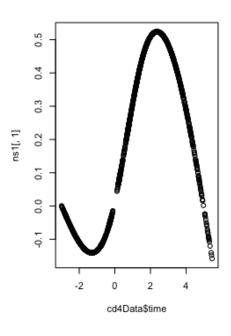
 s_k - kth spline function

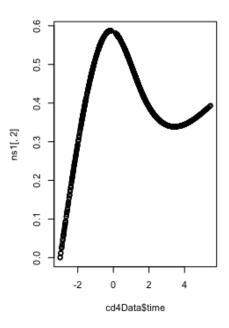
 x_i - covariate for *i*th observation

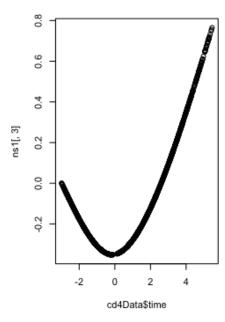
 e_i - everything we didn't measure/model

Splines in R

```
library(splines)
ns1 <- ns(cd4Data$time,df=3)
par(mfrow=c(1,3))
plot(cd4Data$time,ns1[,1]); plot(cd4Data$time,ns1[,2]); plot(cd4Data$time,ns1[,3])</pre>
```







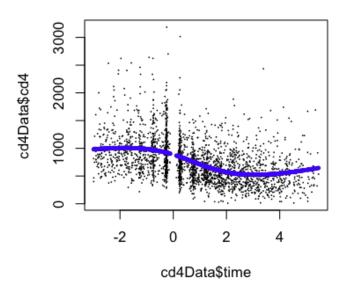
Regression with splines

```
lm1 <- lm(cd4Data$cd4 ~ ns1)
summary(lm1)</pre>
```

```
Call:
lm(formula = cd4Data$cd4 ~ ns1)
Residuals:
  Min
         10 Median 30
                            Max
-780.0 -242.4 -61.3 169.5 2263.7
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
                        33.9 29.01 < 2e-16 ***
(Intercept)
             982.0
     -611.3 32.6 -18.78 < 2e-16 ***
ns11
         -373.7 79.4 -4.71 2.6e-06 ***
ns12
          -374.8 41.2 -9.09 < 2e-16 ***
ns13
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 357 on 2372 degrees of freedom
Multiple R-squared: 0.203, Adjusted R-squared: 0.202
                                                                                     19/21
F-statistic: 202 on 3 and 2372 DF, p-value: <2e-16
```

Fitted values

```
plot(cd4Data$time,cd4Data$cd4,pch=19,cex=0.1)
points(cd4Data$time,lm1$fitted,col="blue",pch=19,cex=0.5)
```



Notes and further resources

Notes:

- · Cross-validation with splines/smoothing is a good idea
- Do not predict outside the range of observed data

Further resources:

- Hector Corrada Bravo's Lecture Notes
- Rafa Irizarry's Lecture Notes on smoothing, On splines
- · Elements of Statistical Learning
- Advanced Data Analysis from An Elementary Point of View