

ID5059 L03 - more basis functions

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Today

- OOB
- Variants of basis functions: b-spline, bins
- Multidimensional bases: b-spline, others...
- Hyper-parameters and *tuning*

More generalisation error

- Previously saw k -fold cross validation
- A similar approach arises from bootstrapping: the *Out Of Bag* (OOB) error
- Bootstrapping...

My favourite equation

A model structure that will recur throughout this course (and almost every statistics course) is the apparently simple:

$$\mathbf{y} = f(\mathbf{X}, \boldsymbol{\theta}) + \mathbf{e}$$

If we are able to specify f as additive combination of the variables represented by \mathbf{X} then our problem appears very simple:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

Note ordinary multiple linear regression, analysis of variance, analysis of covariance, t -tests, polynomial regression and others fall under this model type - it is the specification of the bases in \mathbf{X} that is important.

Basis functions

- functions which are combined to produce more complex functions.
- usually simple themselves, but combine to create complex functions.
- several common methods may be viewed from the basis function perspective: polynomial regression, splines, (as we will see) regression trees, bin-smoothing, wavelet analysis, fourier analysis + many more.

Basis functions: piecewise constants

Divide the x -region(s) into K regions R_j , each having the same number of data points. Basis functions are:

$$b_j(x) = \begin{cases} 0 & x \notin R_j \\ 1 & x \in R_j \end{cases}$$

Now multiply each basis by the average of the outputs in that region.

This gives a discontinuous function, but is easy to derive and interpret.

Basis functions: piecewise constants

```
data(mcycle, package = "MASS")

# going to bin the data into 10 bins
binData <- cut(mcycle$times, breaks = seq(0, 60, length = 10)) %>%
  as.numeric() %>% as.data.frame() %>%
  rename(bin = ".")

# expand out to dummy variable to give a design matrix
binMatrix <- binData %>% fastDummies::dummy_cols(select_columns = "bin") %>%
  select(-bin) %>% mutate(y = mcycle$accel)
```

Basis functions: piecewise constants

binMatrix

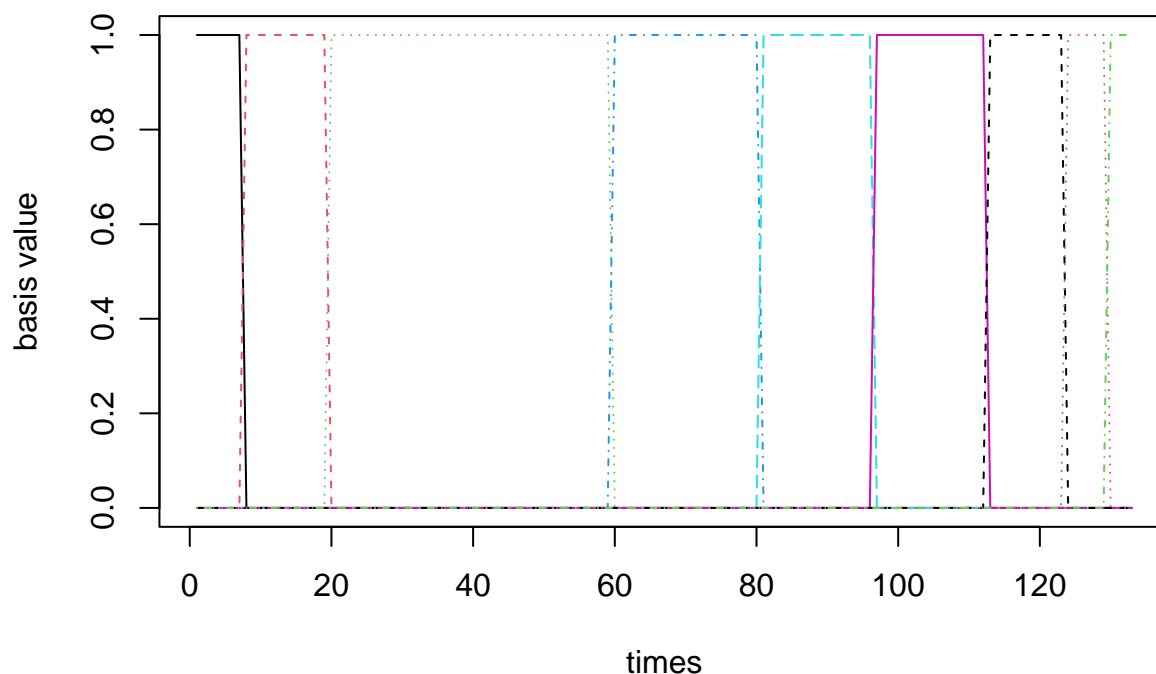
	bin_1	bin_2	bin_3	bin_4	bin_5	bin_6	bin_7	bin_8	bin_9	y
## 1	1	0	0	0	0	0	0	0	0	0.0
## 2	1	0	0	0	0	0	0	0	0	-1.3
## 3	1	0	0	0	0	0	0	0	0	-2.7
## 4	1	0	0	0	0	0	0	0	0	0.0
## 5	1	0	0	0	0	0	0	0	0	-2.7
## 6	1	0	0	0	0	0	0	0	0	-2.7
## 7	1	0	0	0	0	0	0	0	0	-2.7
## 8	0	1	0	0	0	0	0	0	0	-1.3
## 9	0	1	0	0	0	0	0	0	0	-2.7
## 10	0	1	0	0	0	0	0	0	0	-2.7
## 11	0	1	0	0	0	0	0	0	0	-1.3
## 12	0	1	0	0	0	0	0	0	0	-2.7
## 13	0	1	0	0	0	0	0	0	0	-2.7
## 14	0	1	0	0	0	0	0	0	0	-2.7
## 15	0	1	0	0	0	0	0	0	0	-5.4
## 16	0	1	0	0	0	0	0	0	0	-2.7
## 17	0	1	0	0	0	0	0	0	0	-5.4
## 18	0	1	0	0	0	0	0	0	0	0.0
## 19	0	1	0	0	0	0	0	0	0	-2.7
## 20	0	0	1	0	0	0	0	0	0	-2.7
## 21	0	0	1	0	0	0	0	0	0	0.0
## 22	0	0	1	0	0	0	0	0	0	-13.3
## 23	0	0	1	0	0	0	0	0	0	-5.4
## 24	0	0	1	0	0	0	0	0	0	-5.4
## 25	0	0	1	0	0	0	0	0	0	-9.3
## 26	0	0	1	0	0	0	0	0	0	-16.0
## 27	0	0	1	0	0	0	0	0	0	-22.8
## 28	0	0	1	0	0	0	0	0	0	-2.7

## 29	0	0	1	0	0	0	0	0	0	-22.8
## 30	0	0	1	0	0	0	0	0	0	-32.1
## 31	0	0	1	0	0	0	0	0	0	-53.5
## 32	0	0	1	0	0	0	0	0	0	-54.9
## 33	0	0	1	0	0	0	0	0	0	-40.2
## 34	0	0	1	0	0	0	0	0	0	-21.5
## 35	0	0	1	0	0	0	0	0	0	-21.5
## 36	0	0	1	0	0	0	0	0	0	-50.8
## 37	0	0	1	0	0	0	0	0	0	-42.9
## 38	0	0	1	0	0	0	0	0	0	-26.8
## 39	0	0	1	0	0	0	0	0	0	-21.5
## 40	0	0	1	0	0	0	0	0	0	-50.8
## 41	0	0	1	0	0	0	0	0	0	-61.7
## 42	0	0	1	0	0	0	0	0	0	-5.4
## 43	0	0	1	0	0	0	0	0	0	-80.4
## 44	0	0	1	0	0	0	0	0	0	-59.0
## 45	0	0	1	0	0	0	0	0	0	-71.0
## 46	0	0	1	0	0	0	0	0	0	-91.1
## 47	0	0	1	0	0	0	0	0	0	-77.7
## 48	0	0	1	0	0	0	0	0	0	-37.5
## 49	0	0	1	0	0	0	0	0	0	-85.6
## 50	0	0	1	0	0	0	0	0	0	-123.1
## 51	0	0	1	0	0	0	0	0	0	-101.9
## 52	0	0	1	0	0	0	0	0	0	-99.1
## 53	0	0	1	0	0	0	0	0	0	-104.4
## 54	0	0	1	0	0	0	0	0	0	-112.5
## 55	0	0	1	0	0	0	0	0	0	-50.8
## 56	0	0	1	0	0	0	0	0	0	-123.1
## 57	0	0	1	0	0	0	0	0	0	-85.6
## 58	0	0	1	0	0	0	0	0	0	-72.3
## 59	0	0	1	0	0	0	0	0	0	-127.2
## 60	0	0	0	1	0	0	0	0	0	-123.1
## 61	0	0	0	1	0	0	0	0	0	-117.9
## 62	0	0	0	1	0	0	0	0	0	-134.0
## 63	0	0	0	1	0	0	0	0	0	-101.9
## 64	0	0	0	1	0	0	0	0	0	-108.4
## 65	0	0	0	1	0	0	0	0	0	-123.1
## 66	0	0	0	1	0	0	0	0	0	-123.1
## 67	0	0	0	1	0	0	0	0	0	-128.5
## 68	0	0	0	1	0	0	0	0	0	-112.5
## 69	0	0	0	1	0	0	0	0	0	-95.1
## 70	0	0	0	1	0	0	0	0	0	-81.8
## 71	0	0	0	1	0	0	0	0	0	-53.5
## 72	0	0	0	1	0	0	0	0	0	-64.4
## 73	0	0	0	1	0	0	0	0	0	-57.6
## 74	0	0	0	1	0	0	0	0	0	-72.3
## 75	0	0	0	1	0	0	0	0	0	-44.3
## 76	0	0	0	1	0	0	0	0	0	-26.8
## 77	0	0	0	1	0	0	0	0	0	-5.4
## 78	0	0	0	1	0	0	0	0	0	-107.1
## 79	0	0	0	1	0	0	0	0	0	-21.5
## 80	0	0	0	1	0	0	0	0	0	-65.6
## 81	0	0	0	0	1	0	0	0	0	-16.0
## 82	0	0	0	0	1	0	0	0	0	-45.6

## 83	0	0	0	0	1	0	0	0	0	-24.2
## 84	0	0	0	0	1	0	0	0	0	9.5
## 85	0	0	0	0	1	0	0	0	0	4.0
## 86	0	0	0	0	1	0	0	0	0	12.0
## 87	0	0	0	0	1	0	0	0	0	-21.5
## 88	0	0	0	0	1	0	0	0	0	37.5
## 89	0	0	0	0	1	0	0	0	0	46.9
## 90	0	0	0	0	1	0	0	0	0	-17.4
## 91	0	0	0	0	1	0	0	0	0	36.2
## 92	0	0	0	0	1	0	0	0	0	75.0
## 93	0	0	0	0	1	0	0	0	0	8.1
## 94	0	0	0	0	1	0	0	0	0	54.9
## 95	0	0	0	0	1	0	0	0	0	48.2
## 96	0	0	0	0	1	0	0	0	0	46.9
## 97	0	0	0	0	0	1	0	0	0	16.0
## 98	0	0	0	0	0	1	0	0	0	45.6
## 99	0	0	0	0	0	1	0	0	0	1.3
## 100	0	0	0	0	0	1	0	0	0	75.0
## 101	0	0	0	0	0	1	0	0	0	-16.0
## 102	0	0	0	0	0	1	0	0	0	-54.9
## 103	0	0	0	0	0	1	0	0	0	69.6
## 104	0	0	0	0	0	1	0	0	0	34.8
## 105	0	0	0	0	0	1	0	0	0	32.1
## 106	0	0	0	0	0	1	0	0	0	-37.5
## 107	0	0	0	0	0	1	0	0	0	22.8
## 108	0	0	0	0	0	1	0	0	0	46.9
## 109	0	0	0	0	0	1	0	0	0	10.7
## 110	0	0	0	0	0	1	0	0	0	5.4
## 111	0	0	0	0	0	1	0	0	0	-1.3
## 112	0	0	0	0	0	1	0	0	0	-21.5
## 113	0	0	0	0	0	0	1	0	0	-13.3
## 114	0	0	0	0	0	0	1	0	0	30.8
## 115	0	0	0	0	0	0	1	0	0	-10.7
## 116	0	0	0	0	0	0	1	0	0	29.4
## 117	0	0	0	0	0	0	1	0	0	0.0
## 118	0	0	0	0	0	0	1	0	0	-10.7
## 119	0	0	0	0	0	0	1	0	0	14.7
## 120	0	0	0	0	0	0	1	0	0	-1.3
## 121	0	0	0	0	0	0	1	0	0	0.0
## 122	0	0	0	0	0	0	1	0	0	10.7
## 123	0	0	0	0	0	0	1	0	0	10.7
## 124	0	0	0	0	0	0	0	1	0	-26.8
## 125	0	0	0	0	0	0	0	1	0	-14.7
## 126	0	0	0	0	0	0	0	1	0	-13.3
## 127	0	0	0	0	0	0	0	1	0	0.0
## 128	0	0	0	0	0	0	0	1	0	10.7
## 129	0	0	0	0	0	0	0	1	0	-14.7
## 130	0	0	0	0	0	0	0	0	1	-2.7
## 131	0	0	0	0	0	0	0	0	1	10.7
## 132	0	0	0	0	0	0	0	0	1	-2.7
## 133	0	0	0	0	0	0	0	0	1	10.7

Basis functions: piecewise constants

```
matplot(as.matrix(binMatrix[,-10]), type = "n", ylab = "basis value", xlab = "times")
matlines(as.matrix(binMatrix[,-10]))
```



Basis functions: piecewise constants

```
# fit this to the data - using OLS aka squared error loss
binFit <- lm(y ~ . -1, data = binMatrix)

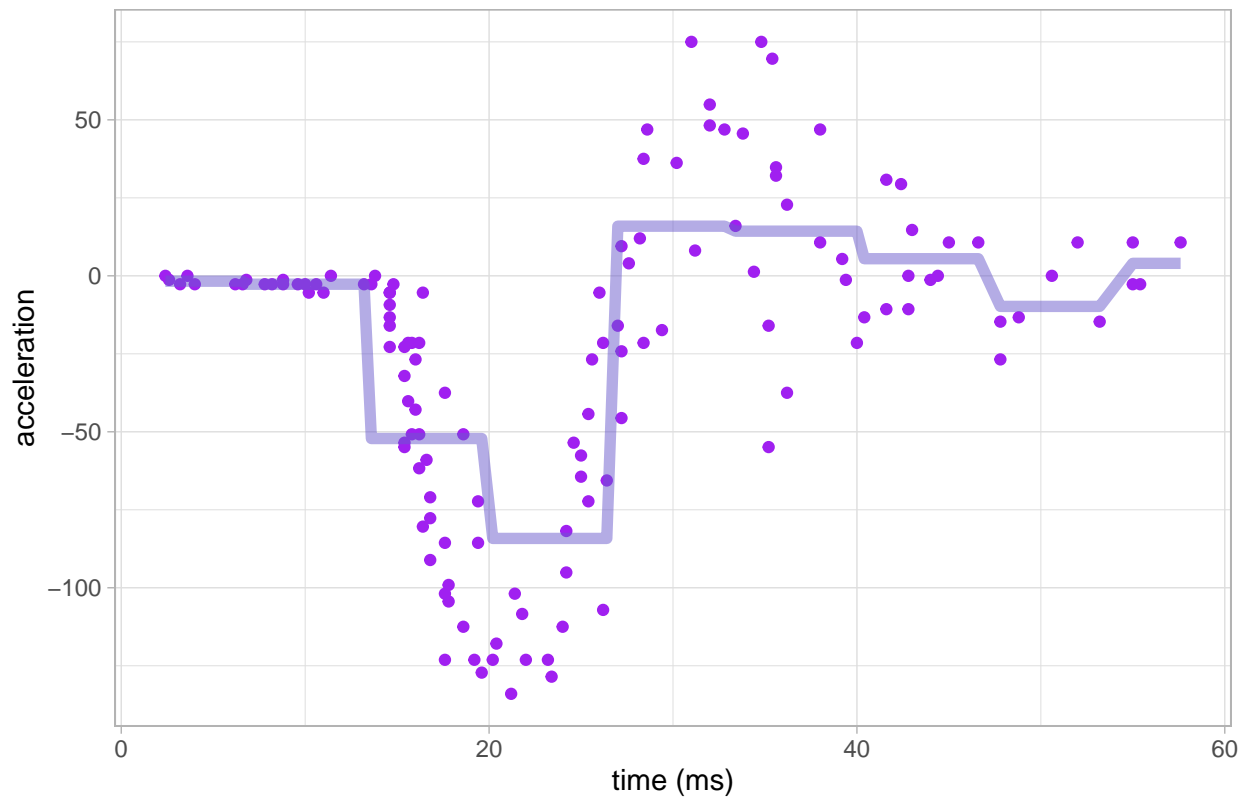
# add to the original data for plotting
plottingData <- mcycle %>% mutate(pred = fitted(binFit))

p <- ggplot(data=plottingData) +
  geom_point(aes(x=times, y=accel), col='purple', size=1.5) +
  xlab('time (ms)') + ylab('acceleration') + ggtitle('A wiggly relationship') +
  geom_line(aes(times, pred), col = "slateblue", alpha = 0.5, size = 2) +
  theme_light()
```

p

Basis functions: piecewise constants

A wiggly relationship



A general local univariate basis

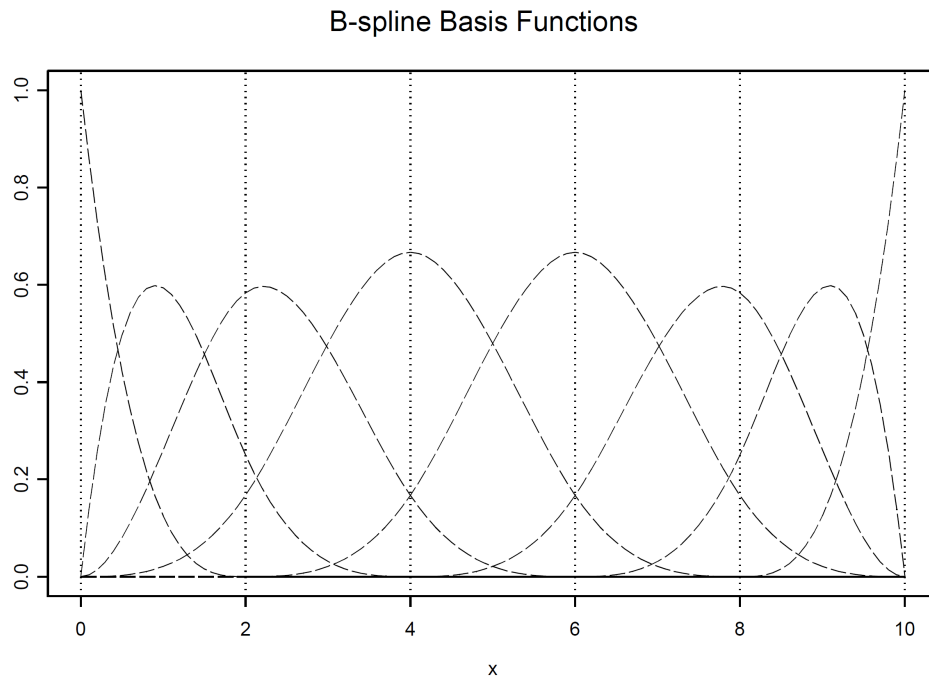
For calculation of a series of b-spline bases (B):

$$B_{i,j}(x) = \frac{x - \delta_i}{\delta_{i+j-1} - \delta_i} B_{i,j-1}(x) + \frac{\delta_{i+j} - x}{\delta_{i+j} - \delta_{i+1}} B_{i+1,j-1}(x)$$

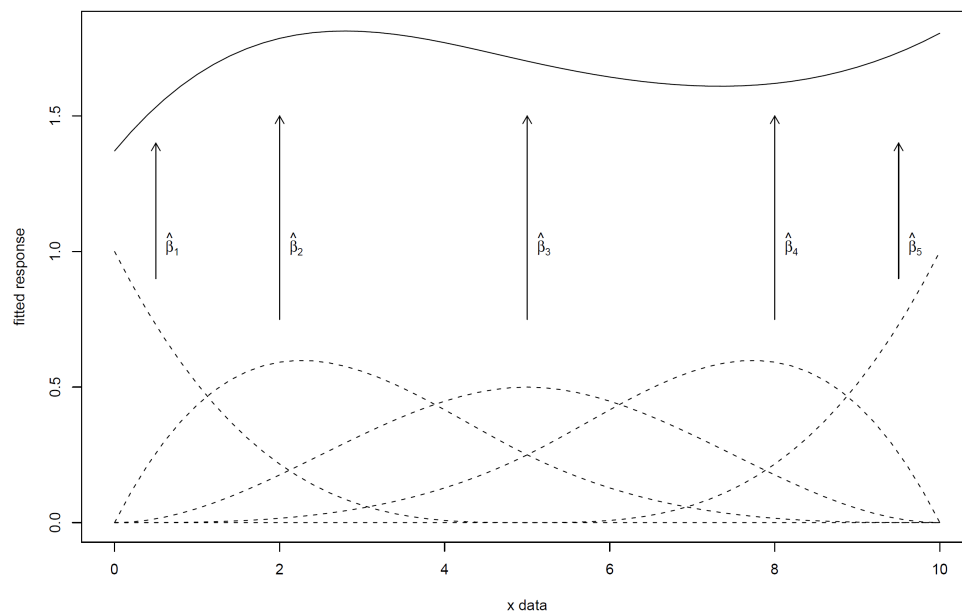
Where we start with:

$$B_{i,1}(x) = \begin{cases} 1 & \delta_i \leq x \leq \delta_{i+1}, \\ 0 & \text{otherwise.} \end{cases}$$

Example b-spline basis



Example b-spline basis



B-splines

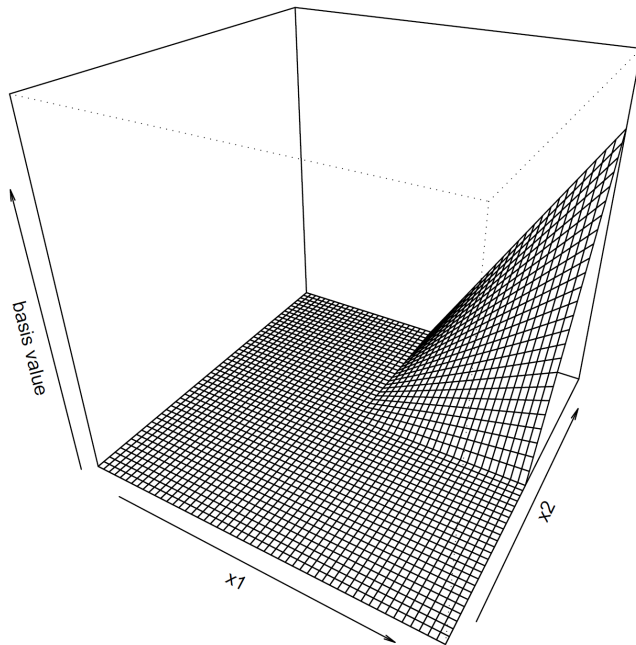
- B-splines are constructed to be zero outside some local region in x
- Calculations are relatively easy

- Curves can be as smooth as desired

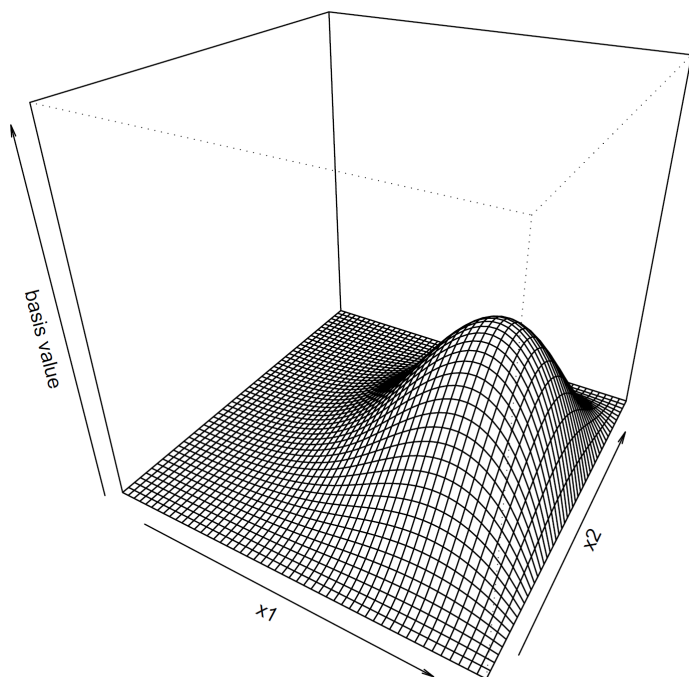
What about more dimensions?

- the result of multiplying a univariate basis function in one dimension against those of another
- results in a shape in higher dimensions
- two b-spline bases of degree 1 (linear) give tensor products that appear to be pyramids or ramps
- more curved bases such as 3rd degree (cubic) b-spline bases will give bump-like tensor products

Example b-spline basis



Example b-spline basis



Hyper-parameters

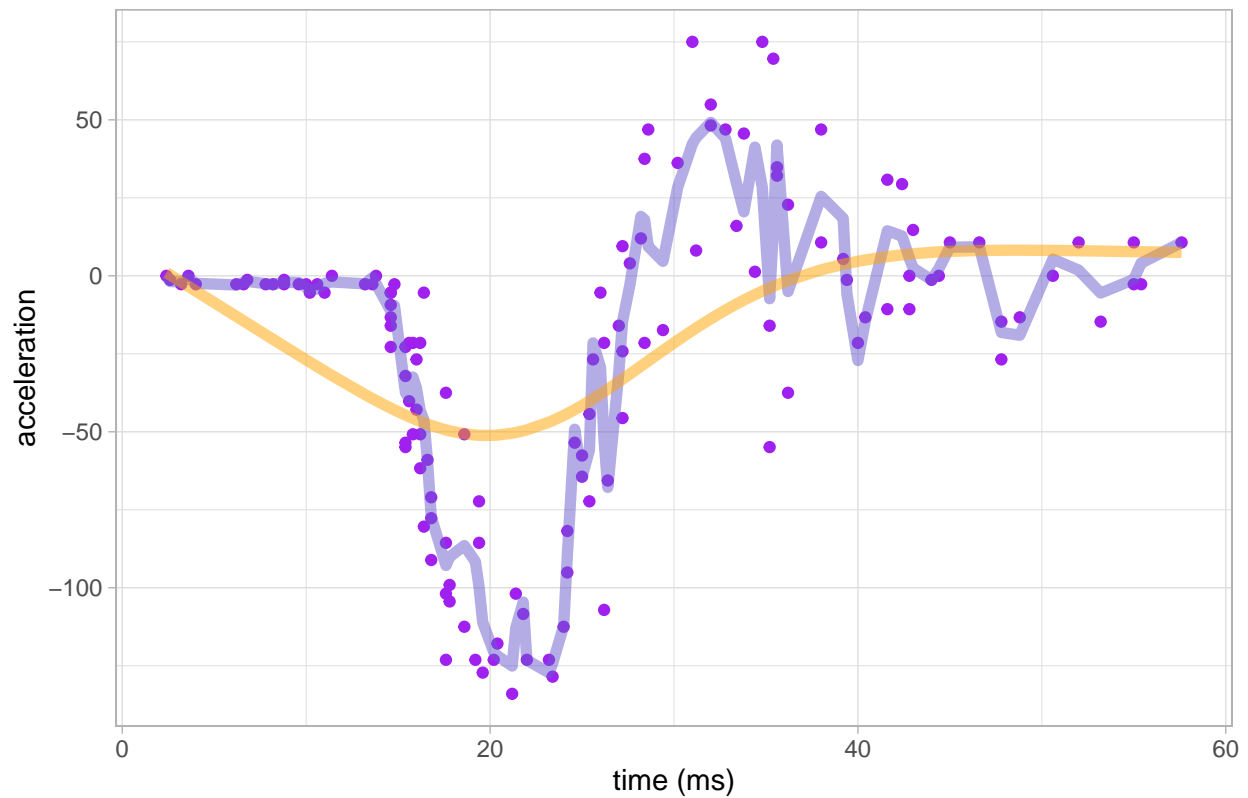
- For a particular f , we estimate its parameters against the loss function
- May be other parameters which govern the complexity/form of f : the *hyper-parameters* e.g. number of bases, band-width of a smoother, size of a neighborhood, learning rate of an NN, etc
- We minimise *generalisation error* to set these i.e. **model selection, rather than model fitting**
- This can be termed hyper-parameter *tuning*

Simple hyper-parameter example

- Splines can have a parameter that governs complexity
- *Smoothing splines* have a smoothing parameter that balances fidelity to data to complexity of curve - a hyper-parameter that needs setting (tuning)

Simpel hyper-parameter example

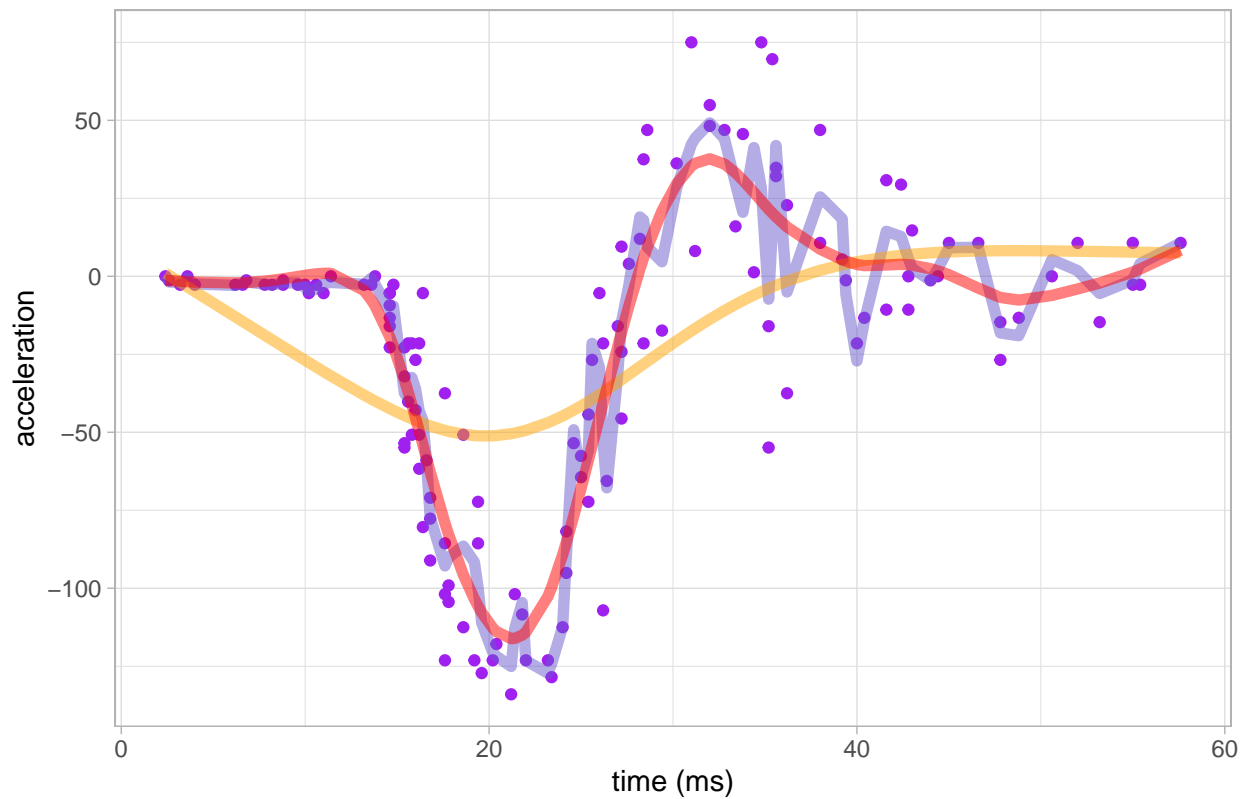
A wiggly relationship



Simple hyper-parameter example

```
## Warning in smooth.spline(x = mcycle$times, y = mcycle$accel, cv = T): cross-  
## validation with non-unique 'x' values seems doubtful
```

A wiggly relationship



Re-iterate

- *loss functions* for estimating model parameters given f
- *generalisation error* for model selection, hyper-parameter tuning

Keywords and Reading

- **bootstrapping and OOB, hyper-parameter, hyper-parameter tuning**
- James *et al*: Section 7.1 - 7.4
- HT&F: Section 5.1, 5.7
- Geron: page 29-31

Work through the associated L03 markdown document