

# Rcpp Portfolio

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For this portfolio, we use Rcpp to fit an adaptive kernel smoothing regression model.

We first generate data according to the model

$$y_i = \sin(\alpha \pi x^3) + z_i \quad \text{with} \quad z_i \sim \mathcal{N}(0, \sigma^2)$$

In this case we take  $\alpha = 4$  and  $\sigma = 0.2$ .

```
library(dplyr)
```

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
##   filter, lag
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##   intersect, setdiff, setequal, union
```

```
library(ggplot2)
```

```
n <- 400
```

```
alpha <- 4
```

```
sigma <- 0.2
```

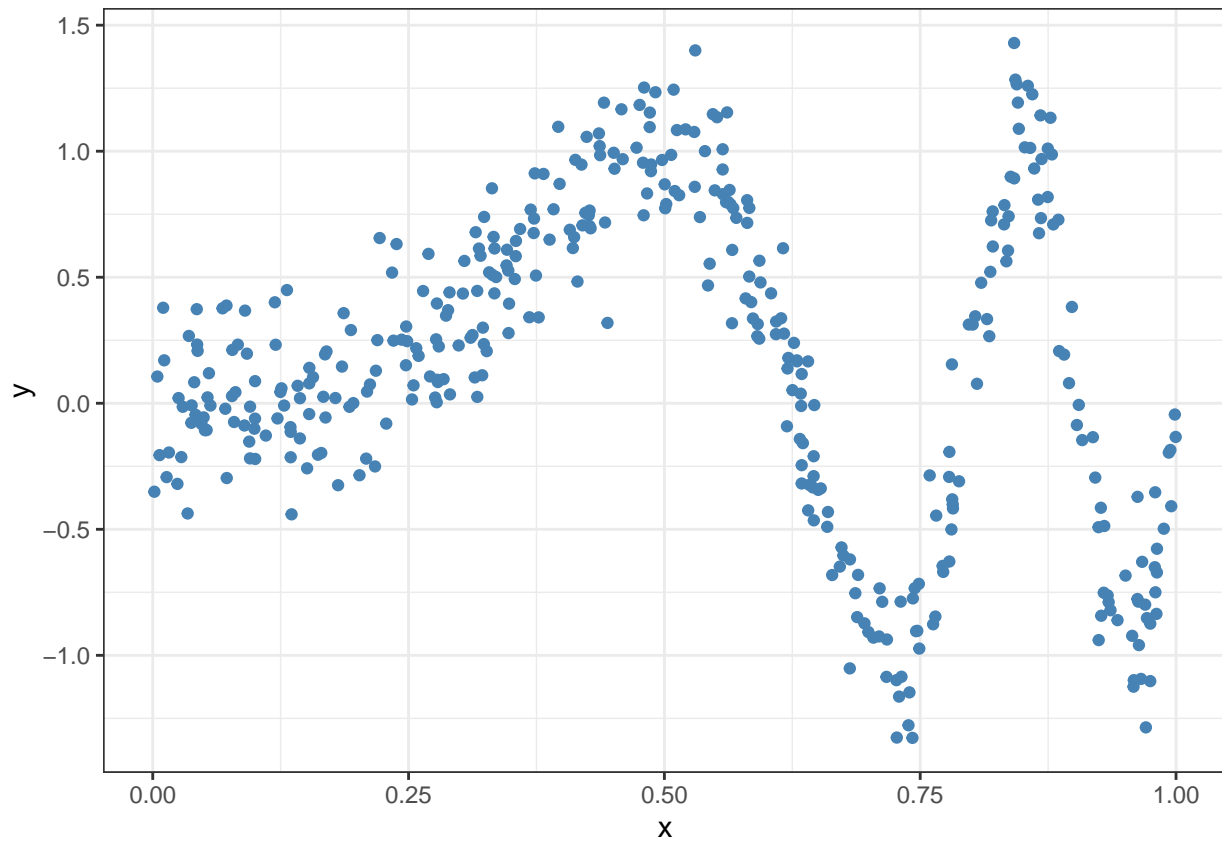
```
x <- runif(n)
```

```
y <- sin(alpha * pi * x^3) + rnorm(n, sd = sigma)
```

```
data <- tibble(x = x, y = y)
```

```
ggplot(data = data, aes(x, y))+
```

```
  geom_point(color = "steelblue")
```



## The Kernel Smoother

We model  $\mu(x) = \mathbb{E}(y|x)$  by

$$\hat{\mu}(x) = \frac{\sum_{i=1}^n \kappa_{\lambda}(x, x_i) y_i}{\sum_{i=1}^n \kappa_{\lambda}(x, x_i)}$$

where we take  $\kappa_{\lambda}$  to be a Gaussian kernel with variance  $\lambda^2$ .

We implement this with the following function:

```
meanKRS <- function(y, x, xnew, lambda){
  n <- length(x)
  nnew <- length(xnew)

  mu <- numeric(nnew)

  for (i in 1:nnew){

  }
}
```