# Kernel Density Estimation Assignment 1

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### Kernel Density Estimation

Kernels

Let  $K: \mathbb{R} \longrightarrow [0, \infty)$  with properties

$$K(x) = K(-x), \quad \forall x \in \mathbb{R}$$
 (1)

$$1 = \int_{\mathbb{R}} K(x) dx \tag{2}$$

and  $X_1, X_2, \dots X_n$  be random variables with density f. Then

$$\hat{f}(x) = \frac{1}{n\lambda} \sum_{i=1}^{n} K\left(\frac{x - x_i}{\lambda}\right)$$
 (3)

is the kernel density estimate of f with bandwidth  $\lambda > 0$  and kernel K.

### Implementation of Kernel Density Estimate

```
R_dens_for <- function(x, p, kernel, bandwidth) {
    m <- length(p)
    n <- length(x)
    result <- numeric(m)
    for(i in 1:m) {
        result[i] <- result[i] + kernel((p[i] - x[j]) / bandwidth)
    }
}
result / (n * bandwidth)
}</pre>
```

#### Testing the Implementation

Epanechnikov Kernel

Use the kernel density estimate on the epanechnikov kernel given by

$$K(x) = \frac{3}{4}(1 - x^2)1_{[0,1]}(x). \tag{4}$$

Implemented in R as

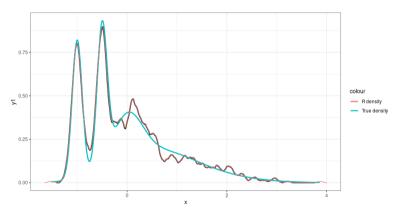
```
e_kernel <- function(x) {
  0.75 * (1 - x^2) * (abs(x) <= 1)
}</pre>
```

#### The Test Case

#### Gaussian Mixture

### Plotting the Densities

With  $\lambda=0.1$  we plot the estimated density together with R's default density implementation and the true density.



#### Bandwidth Selection

#### Leave-One-Out Cross Validation

We persue bandwidth selection through leave-one-out cross validation. Let

$$\hat{f}_{\lambda}^{-i} = \frac{1}{(n-1)\lambda} \sum_{j \neq i}^{n} K\left(\frac{x_i - x_j}{\lambda}\right). \tag{5}$$

We then select the bandwidth

$$\hat{\lambda}_{\text{CV}} = \arg\max_{\lambda > 0} \sum_{i=1}^{n} \log \hat{f}_{\lambda}^{-i}. \tag{6}$$

#### Implementation of LOOCV Bandwidth Selection

Bandwidth Selection and Oracle Bandwidth as Comparison

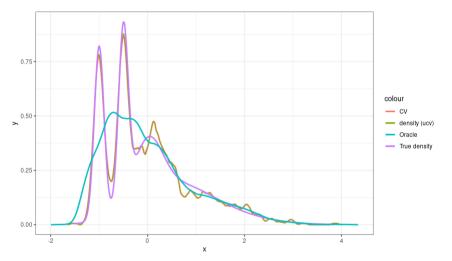
```
bw cv R2 <- function(x, kernel, max bw = 2) {</pre>
  cv func <- function(1) {</pre>
    if(1 < .Machine$double.eps) Inf</pre>
    n <- length(x)
    K <- numeric(n)</pre>
    for(i in 1:n) {
      K[i] \leftarrow sum(kernel((x[i] - x[-i]) / 1))
    cv <- sum(log(K[K > .Machine$double.eps]))
    n * log((n - 1) * 1) - cv
  suppressWarnings(optimize(cv_func, c(0, max_bw)))$minimum
bw_oracle <- function(x, kernel) {</pre>
  n <- length(x)</pre>
  K <- integrate(function(x) kernel(x)^2, -Inf, Inf)$value</pre>
  sigma2 <- integrate(function(x) kernel(x) * x^2, -Inf, Inf)$value
  sigma \leftarrow min(sd(x), IQR(x) / 1.34)
  (8 * sqrt(pi) * K / (3 * sigma2^2))^(1/5) * sigma * n^(-1/5)
```

### Implementation of Kernel Density Estimate with Bandwidth Selection

```
dens_R1 <- function(x,
                    kernel.
                    bandwidth.
                    points = 512L) {
  if(is.function(bandwidth)) {
    bw <- bandwidth(x, kernel, ...)</pre>
  } else {
    bw <- bandwidth
  p \leftarrow seq(min(x) - bw, max(x) + bw, length.out = points)
  v <- R_dens_for(x, p, kernel, bw)
  structure(
    list(
      x = p,
      bw = bw
    class = "dens"
```

### Plotting the Density Estimate with Bandwidth Selection

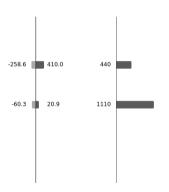
The LOOCV bandwidth is 0.1155167 and the oracle bandwidth is 0.4746436.



### Profiling the Implementation

#### Profiling the Kernel Density Estimation

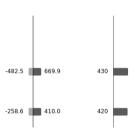
```
dens R1 <- function(x,
                   kernel.
                   bandwidth.
                   points = 512L) {
  if(is.function(bandwidth))
    bw <- bandwidth(x, kernel)
  } else {
    bw <- bandwidth
  p \leftarrow seg(min(x) - bw, max(x) + bw, length.out = points)
  y <- R dens for(x, p, kernel, bw)
  structure(
    list(
      x = p
      y = y
      bw = bw
    class = "dens"
```



### Profiling the Implementation

#### Profiling the Bandwidth Selection

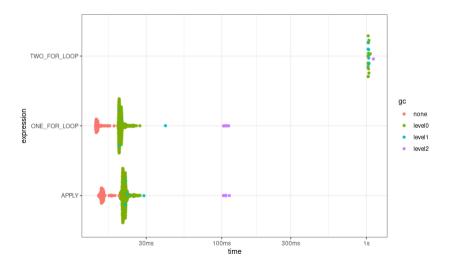
```
bw_cv_R2 <- function(x, kernel) {
    cv_func <- function(t) {
        if(l < ,Machinesdouble.eps) Inf
        n <- length(x)
        K <- numeric(n)
        for(i in 1:n) {
             K(i) <- sum(kernel((x[i] - x[-i]) / l))
        }
        c v <- sum(log(K[K > .Machine$double.eps]))
        n * log((n - 1) * l) - cv
    }
    suppressWarnings(optimize(cv_func, c(0, 2)))$minimum
}
```



### Alternative Implementations of Calculating the Density Estimate

```
R dens <- function(x, p, kernel, bandwidth) {
 m <- length(p)
 n \leftarrow length(x)
 result <- numeric(m)
 for(i in 1:m) {
    result[i] <- sum(kernel((p[i] - x) / bandwidth))
 result / (n * bandwidth)
R_dens_for <- function(x, p, kernel, bandwidth) {</pre>
 m <- length(p)
 n \leftarrow length(x)
 result <- numeric(m)
 for(i in 1:m) {
   for(j in 1:n) {
      result[i] <- result[i] + kernel((p[i] - x[i]) / bandwidth)
 result / (n * bandwidth)
R_dens_apply <- function(x, p, kernel, bandwidth) {
  app_func <- function(t) sum(kernel((t - x) / bandwidth))</pre>
 result <- sapply(p, app_func)
 result / (length(x) * bandwidth)
```

## Benchmarking Alternative Implementations using bench Package

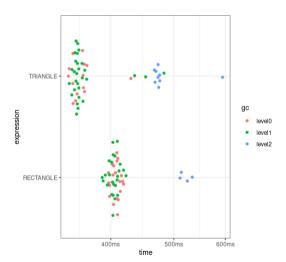


### Benchmarking Alternative Implementations using bench Package Table

#### Alternative LOOCV Implementations

```
Let K_{i,j} = K((x_i - x_i)/\lambda) and notice K_{i,j} = K_{i,j}.
bw_cv_R <- function(x, kernel, max_bw = 2) {</pre>
  cv_func <- function(1) {</pre>
    if(1 < .Machine$double.eps) Inf</pre>
    n <- length(x)</pre>
    K <- numeric(n)</pre>
    for(i in 2:n) {
      index <- 1:(i - 1)
      tmp <- kernel((x[i] - x[index]) / 1)</pre>
       K[i] \leftarrow K[i] + sum(tmp)
      K[index] <- K[index] + tmp[index]</pre>
    cv <- sum(log(K[K > .Machine$double.eps]))
    n * log((n - 1) * 1) - cv
  suppressWarnings(optimize(cv_func, c(0, max_bw)))$minimum
```

## Alternative LOOCV Implementation Benchmarks



### Alternative LOOCV Implementation Benchmarks

```
expression median mem_alloc

<bch:expr> <bch:tm> <bch:byt>
1 TRIANGLE 357ms 433MB
2 RECTANGLE 407ms 738MB
```

Implementing the kernel in RCPP

Implementing the kernel in RCPP could improve performance per the profiling.

```
// [[Rcpp::export]]
NumericVector e_kernel_cpp(NumericVector x) {
  int n = x.size();
  NumericVector result(n);
  for(int i = 0; i < n; ++i)
    result[i] = std::abs(x[i]) <= 1 ? 0.75 * (1 - x[i] * x[i]) : 0;
  return result;
}</pre>
```

Calling Kernel from R in RCPP

Calling Kernel from R in RCPP

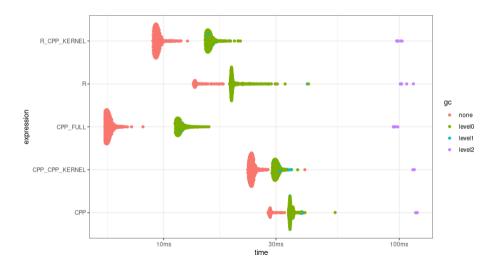
```
// [[Rcpp::export]]
double bw_cv_rcpp_partial(NumericVector x,
                          Function kernel.
                          double bandwidth) {
  int n = x.size();
  NumericVector K(n):
  double result:
  for(int i = 1; i < n; ++i) {
    Range r = Range(0, i - 1);
    NumericVector tmp = kernel((x[r] - x[i]) / bandwidth);
    for(int j = 0; j < i; ++j)
      K[i] += tmp[i], K[i] += tmp[i];
  for(int s = 0: s < n: ++s)
    if(K[s] > std::numeric_limits<double>::min()) result += std::log(K[s]);
 return n * log((n - 1) * bandwidth) - result;
```

Full RCPP Implementation

Full RCPP Implementation

```
// [[Rcpp::export]]
double bw_cv_rcpp(NumericVector x,
                  double bandwidth) {
  int n = x.size():
  NumericVector K(n):
  double result:
  for(int i = 1: i < n: ++i) {
    Range r = Range(0, i - 1);
    Numeric Vector tmp = e_kernel_cpp((x[i] - x[r]) / bandwidth);
    for(int j = 0; j < i; ++j)
      K[i] += tmp[i], K[i] += tmp[i];
  for(int s = 0: s < n: ++s)
    if(K[s] > std::numeric_limits<double>::min()) result += std::log(K[s]);
  return n * std::log((n - 1) * bandwidth) - result:
```

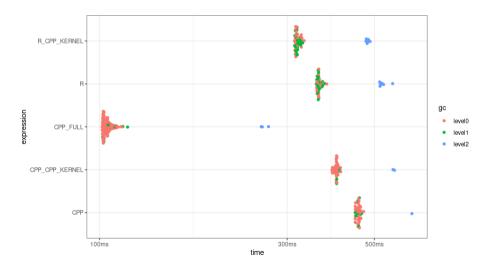
## Benchmarking RCPP Density Calculation



## Benchmarking RCPP Density Calculation Table

	expression	median	mem_alloc
	<bch:expr></bch:expr>	<bch:tm></bch:tm>	<bch:byt></bch:byt>
1	CPP_FULL	5.73ms	15.7MB
2	R_CPP_KERNEL	9.28ms	18.2MB
3	R	13.62ms	35.5MB
4	CPP_CPP_KERNEL	23.66ms	18.2MB
5	CPP	28.32ms	35.4MB

## Benchmarking RCPP Bandwidth Selection Plot



## Benchmarking RCPP Bandwidth Selection Table

	expression	median	mem_alloc
	<bch:expr></bch:expr>	<bch:tm></bch:tm>	<bch:byt></bch:byt>
1	CPP_FULL	5.73ms	15.7MB
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5	CPP	28.32ms	35.4MB

### Improving Further Using R's C API

#### Implementation of Density Calculation

```
#include <Rinternals.h>
#include <R h>
SEXP C_dens(SEXP x, SEXP p, SEXP kernel, SEXP bw, SEXP rho) {
  int n = length(x), m = length(p);
  SEXP dens = PROTECT(allocVector(REALSXP, m));
  SEXP tmp = PROTECT(allocVector(REALSXP, n));
  SEXP K_Call = PROTECT(lang2(kernel, R_NilValue));
  double *x_ = REAL(x), *p_ = REAL(p), *tmp_ = REAL(tmp), *dens_ = REAL(dens);
  double bw = REAL(bw)[0]:
  memset(dens_, 0, sizeof(double) * m);
  for(int i = 0; i < m; ++i) {
    for(int j = 0; j < n; ++j)
      tmp_{[j]} = (p_{[i]} - x_{[j]}) / bw_{:j}
    SETCADR(K_Call, tmp);
    SEXP result = eval(K_Call, rho):
    double *result_ = REAL(result):
    for(int j = 0; j < n; ++j)
      dens_[i] += result_[j];
    dens \lceil i \rceil /= n * bw :
  UNPROTECT(3):
  return dens:
```

#### Improving Further Using R's C API

#### Implementation of LOOCV

```
#include <Rinternals.h>
#include <R.h>
#include <float.h>
SEXP C_cv(SEXP x, SEXP fn, SEXP lambda, SEXP rho) {
 if(REAL(lambda)[0] < DBL EPSILON) return ScalarReal(INFINITY):
 int n = length(x):
 SEXP K = PROTECT(allocVector(REALSXP, n));
 SEXP fn_call = PROTECT(lang2(fn, R_NilValue));
 SEXP out = PROTECT(ScalarReal(0.0));
 double *x_ = REAL(x), *K_ = REAL(K), *out_ = REAL(out);
 double h = REAL(lambda)[0]:
 memset(K_, 0, sizeof(double) * n);
 for(int i = 1: i < n: ++i) {
    SEXP tmp = PROTECT(allocVector(REALSXP, i));
    double *tmp_ = REAL(tmp);
    for(int k = 0; k < i; ++k)
      tmp [k] = (x [i] - x [k]) / h :
    SETCADR(fn_call, tmp);
    SEXP s = eval(fn call, rho):
    double *s = REAL(s):
   UNPROTECT(1):
   for(int j = 0; j < i; ++j) {
    K [i] += s [i]:
     K_{[j]} += s_{[i]}:
 for(int i = 0: i < n: ++i)
   if(K_[i] > DBL_EPSILON) *out_ += log(K_[i]);
  *out_ = n * log((n - 1) * h_) - (*out_);
 UNPROTECT(3):
 return out:
```

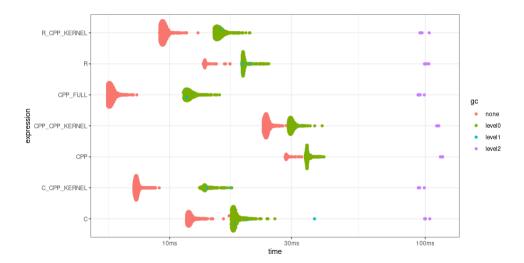
### Improving Further Using R's C API

Calling the C Code

Compile to shared library using R CMD SHLIB command. If used in a package a little more work is required. For now just used dyn.load function in R to link the shared library.

```
bw_cv <- function(x, kernel, max_bw = 2) {
  cv_func <- function(1) .Call("C_cv", x, kernel, 1, environment())
  suppressWarnings(optimize(cv_func, c(0, max_bw)))$minimum
}</pre>
```

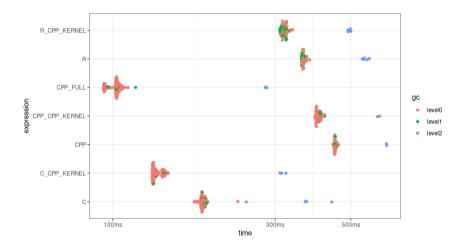
## Benchmarking All Density Calculation Implementations



## Benchmarking All Density Calculation Implementations Table

	expression	median	$mem_alloc$
	<bch:expr></bch:expr>	<bch:tm></bch:tm>	<bch:byt></bch:byt>
1	CPP_FULL	5.81ms	15.7MB
2	C_CPP_KERNEL	7.42ms	10.4MB
3	R_CPP_KERNEL	9.39ms	18.2MB
4	C	11.89ms	27.6MB
5	R	13.74ms	35.5MB
б	CPP_CPP_KERNEL	23.9ms	18.2MB
7	CPP	28.7ms	35.4MB

## Benchmarking All LOOCV Implementations



### Benchmarking All LOOCV Implementations

Table

	expression	median	mem_alloc
	<bch:expr></bch:expr>	<bch:tm></bch:tm>	<bch:byt></bch:byt>
1	CPP_FULL	103ms	124MB
2	C_CPP_KERNEL	133ms	163MB
3	C	183ms	279MB
4	R_CPP_KERNEL	320ms	317MB
5	R	363ms	433MB
б	CPP_CPP_KERNEL	401ms	162MB
7	CPP	450ms	278MB

#### Final implementation

```
dens <- function(x,
                  kernel.
                  bandwidth = bw cv.
                  points = 512L) {
  if(is.function(bandwidth)) {
    bw <- bandwidth(x, kernel, ...)</pre>
  } else {
    bw <- bandwidth
  p \leftarrow seq(min(x) - bw, max(x) + bw, length.out = points)
  y <- .Call("C_dens", x, p, kernel, bw, environment())
  structure(
    list(
      x = p,
      y = y,
      bw = bw
    class = "dens"
```