Applied Spatial Data Analysis - Spatial Point and Lattice Data

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Contents

Chapter 1

Introduction

This book will guide you through the R codes for Spatial Point and Lattice Data Analysis.

The chapters will be made available on Tuesdays when we start a new week So please update your browser to access the codes for the relevant chapter.

Chapter 2

Spatial Point Pattern Analysis

2.1 Prerequisites

You need to have the following R packages installed and recalled into your library:

```r
library(sf)
library(spatstat)
library(spatstat.data)
library(ggplot2)
library(sp)
library(animation)
library(plotrix)
```

2.2 Datasets - Readily Available, Imported, Simulated Datasets

2.2.1 Swedishpines Dataset from spatstat.data library

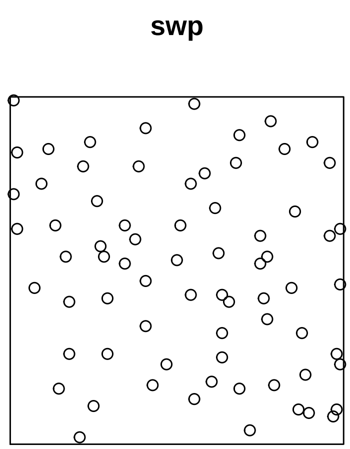
```r
data(swedishpines)
swp = spatstat::rescale(swedishpines)
class(swp)
```

```
## [1] "ppp"
```

```
summary(swp)
```

```
## Planar point pattern:  71 points
## Average intensity 0.7395833 points per square metre
##
## Coordinates are given to 1 decimal place
## i.e. rounded to the nearest multiple of 0.1 metres
##
## Window: rectangle = [0, 9.6] x [0, 10] metres
## Window area = 96 square metres
## Unit of length: 1 metre
```

```
plot(swp)
```



2.2.2 Clinics Dataset Using Simple Features (SF)

Download the data from the following:

https://web1.capetown.gov.za/web1/OpenDataPortal/DatasetDetail?DatasetName=Clinics

Extract the data frame into R:

```r
library(sf)
clinics_sf = st_read("C:/Users/01438475/Google Drive/UCTcourses/ASDA/DataSets/Clinics/SL_CLNC.shp
```

```
## Reading layer `SL_CLNC' from data source `C:\Users\01438475\Google Drive\UCTcourses\ASDA\DataS
## Simple feature collection with 149 features and 5 fields
## geometry type:  POINT
## dimension:      XY
## bbox:           xmin: 18.34268 ymin: -34.19491 xmax: 18.90847 ymax: -33.51262
## geographic CRS: WGS 84
```

```r
clinics_sf
```

```
## Simple feature collection with 149 features and 5 fields
## geometry type:  POINT
## dimension:      XY
## bbox:           xmin: 18.34268 ymin: -34.19491 xmax: 18.90847 ymax: -33.51262
## geographic CRS: WGS 84
## First 10 features:
##                                       LCTN              ATHY
## 1           C/O Adam/ Liedeman Street Mamre              PAWC
## 2                 Cnr Hermes & GrosvenorAve CITY OF CAPE TOWN
## 3              Hassen Kahn Ave Rusthof Strand              PAWC
## 4               61 Central Circle, Fish Hoek CITY OF CAPE TOWN
## 5                      Simon Street, Nomzamo CITY OF CAPE TOWN
## 6  C/O Musical and Hospital Street Macassar              PAWC
## 7              28 Church Street Somerset West CITY OF CAPE TOWN
## 8                        Fagan Street Strand CITY OF CAPE TOWN
## 9    Karbonkel Road, CMC Building, Hout Bay              PAWC
## 10                Midmar Street Groenvallei CITY OF CAPE TOWN
##                      NAME                CLASS       RGN
## 1               MAMRE CDC Community Day Centre   Western
## 2        SAXON SEA CLINIC               Clinic   Western
## 3            GUSTROUW CDC Community Day Centre   Eastern
## 4        FISH HOEK CLINIC               Clinic  Southern
## 5              IKWEZI CDC Community Day Centre   Eastern
## 6            MACASSAR CDC Community Day Centre   Eastern
## 7    SOMERSET WEST CLINIC               Clinic   Eastern
## 8  FAGAN STREET SATELLITE            Satellite   Eastern
## 9    HOUT BAY HARBOUR CDC Community Day Centre  Southern
## 10  GROENVALLEI SATELLITE            Satellite Tygerberg
##                      geometry
## 1  POINT (18.47692 -33.51262)
## 2  POINT (18.48881 -33.55012)
## 3  POINT (18.85211 -34.13472)
```

```
## 4  POINT (18.42632 -34.13669)
## 5  POINT (18.86622 -34.11375)
## 6  POINT (18.76369 -34.06105)
## 7  POINT (18.84814 -34.08579)
## 8   POINT (18.82979 -34.1162)
## 9   POINT (18.34268 -34.0549)
## 10 POINT (18.66701 -33.89165)
```

```
class(clinics_sf)
```

```
## [1] "sf"         "data.frame"
```

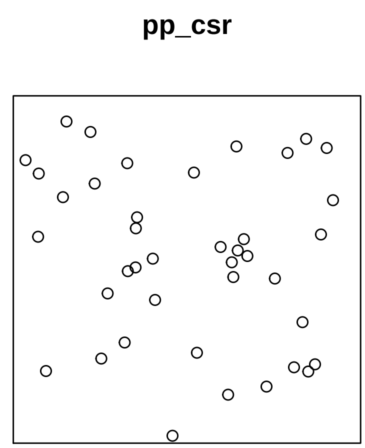
```
summary(clinics_sf)
```

```
##      LCTN                ATHY                NAME                CLASS          
##  Length:149         Length:149         Length:149         Length:149        
##  Class :character   Class :character   Class :character   Class :character  
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character  
##      RGN                     geometry  
##  Length:149         POINT        :149  
##  Class :character   epsg:4326    :  0  
##  Mode  :character   +proj=long...:  0  
```

2.2.3 Simulated Datasets

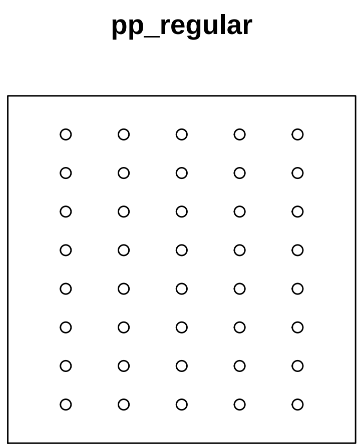
2.2.3.1 CSR Data Points

```
set.seed(135)
xy_csr <- matrix(runif(80), ncol=2)
pp_csr <- as.ppp(xy_csr, c(0,1,0,1))
plot(pp_csr)
```



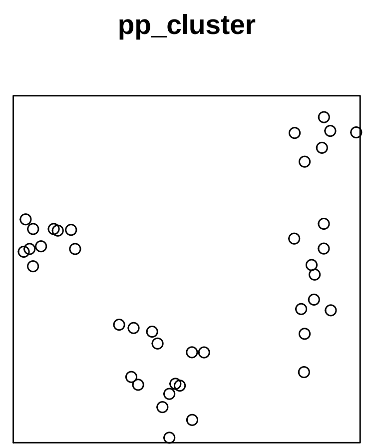
2.2.3.2 Regular Data Points

```
regular <- read.csv("C:/Users/01438475/Google Drive/UCTcourses/ASDA/regular.csv")
xy_regular <- matrix(cbind(regular$X,regular$Y), ncol=2)
pp_regular <- as.ppp(xy_regular, c(0,1,0,1))
plot(pp_regular)
```



2.2.3.3 Cluster Data Points

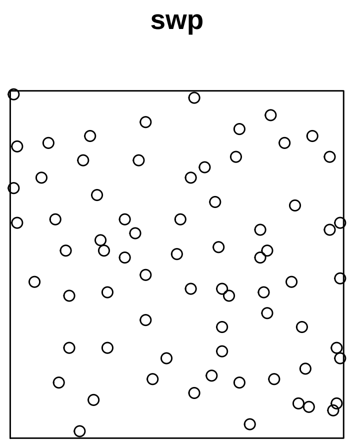
```
cluster <- read.csv("C:/Users/01438475/Google Drive/UCTcourses/ASDA/cluster.csv")
xy_cluster <- matrix(cbind(cluster$X,cluster$Y), ncol=2)
pp_cluster <- as.ppp(xy_cluster, c(0,1,0,1))
plot(pp_cluster)
```



2.3 Plotting Datasets

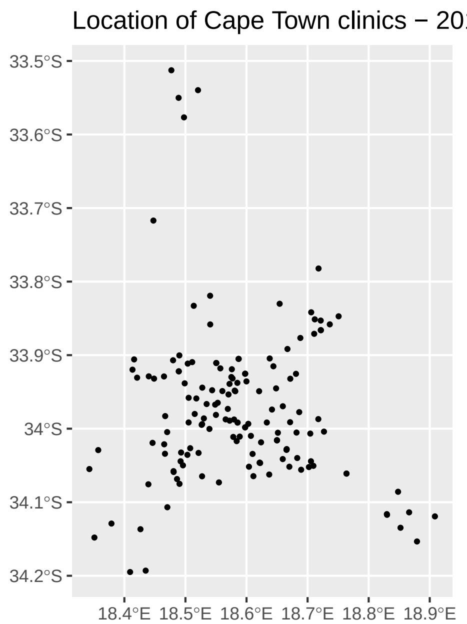
2.3.1 Basic plot() function

```r
plot(swp)
```



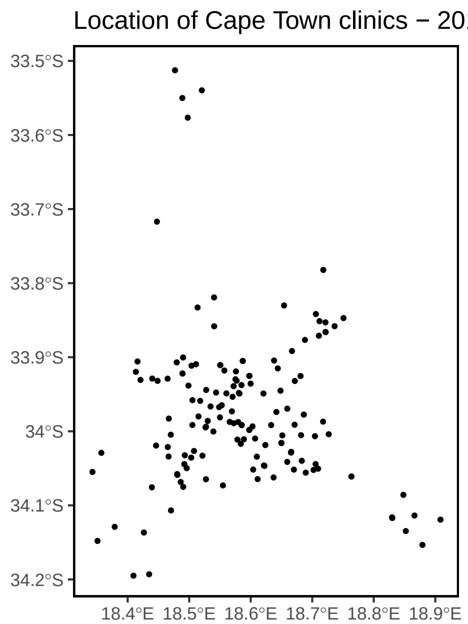
2.3.2 Basic ggplot() function - (sf) object

```
library(ggplot2)
plot1 = ggplot() +
  geom_sf(data = clinics_sf, size = .8, color = "black") +
  ggtitle("Location of Cape Town clinics - 2016") +
  # not specifying crs here, coord_sf will use the CRS defined in the first layer = "+p
  coord_sf()
plot1
```



2.3.3 ggplot() function with a bounding box - (sf) object

```
library(ggplot2)
plot2 = ggplot() +
  geom_sf(data = clinics_sf, size = .8, color = "black") +
  ggtitle("Location of Cape Town clinics - 2016") +
  coord_sf(xlim = c(18.34, 18.91), ylim = c(-34.19, -33.51262)) +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(colour = "black", size=1, fill=NA))
plot2
```



2.3.4 ggplot() with Electoral Wards Shape File

In order to plot using the electoral wards polygons, we need the sf data frame to be converted into Spatial Points Data Frame (sp).

```
clinics_sp <- as(clinics_sf, Class = "Spatial")
class(clinics_sp)
```

```
## [1] "SpatialPointsDataFrame"
## attr(,"package")
## [1] "sp"
```

Download the CPT electoral wards and import the shape file as follows:

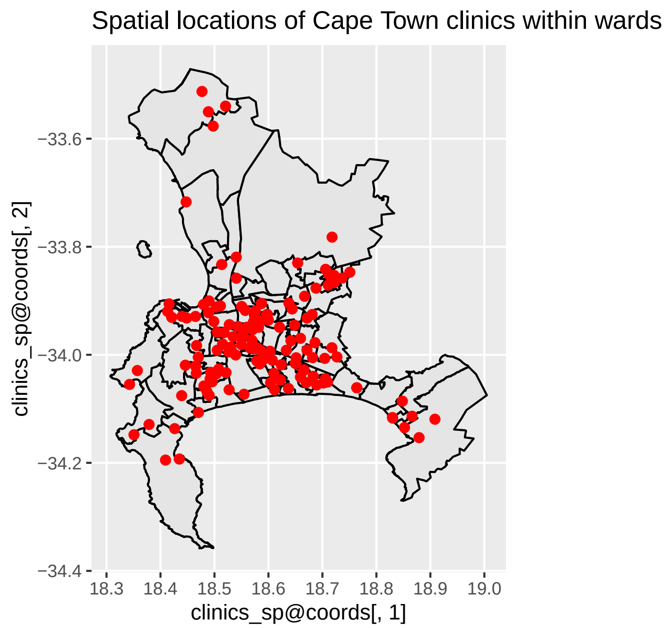
```
library(sf)
ct.wards_sf = st_read("C:/Users/01438475/Google Drive/UCTcourses/ASDA/DataSets/sa/CPT/e
```

```
## Reading layer `electoral wards for cpt' from data source `C:\Users\01438475\Google D
## Simple feature collection with 111 features and 9 fields
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: 18.30722 ymin: -34.35834 xmax: 19.00467 ymax: -33.47128
## CRS:            NA
```

```r
st_geometry_type(ct.wards_sf)
```

```
##   [1] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##   [6] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [11] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [16] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [21] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [26] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [31] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [36] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [41] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [46] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [51] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [56] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [61] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [66] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [71] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [76] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [81] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [86] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [91] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
##  [96] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
## [101] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
## [106] MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON MULTIPOLYGON
## [111] MULTIPOLYGON
## 18 Levels: GEOMETRY POINT LINESTRING POLYGON MULTIPOINT ... TRIANGLE
```

```r
library(ggplot2)
ggplot() +
  geom_sf(data = ct.wards_sf, size = .5, color = "black") +
  geom_point(aes(x = clinics_sp@coords[,1], y = clinics_sp@coords[,2]),
             data = clinics_sp@data, alpha = 1,size=2, color = "red")+
  ggtitle("Spatial locations of Cape Town clinics within wards") +
  coord_sf()
```



2.3.5 Plotting with google maps:

```
require("maps")
require("ggplot2")
```

First specify the outer boundaries of Google Map

```
require("ggmap")
caLongLat <-c(bbox(clinics_sp)[1,1], bbox(clinics_sp)[2,1], bbox(clinics_sp)[1,2],bbox
caLongLat
```

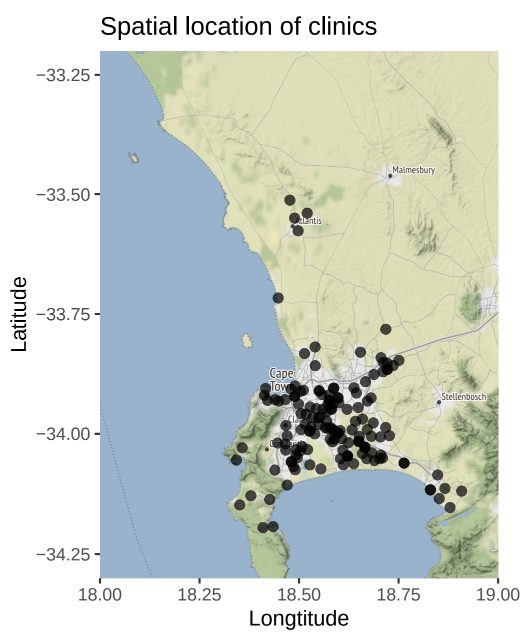
```
## [1]  18.34268 -34.19491  18.90847 -33.51262
```

```
caLongLat<-c(18, -34.3,  19, -33.2)
map <- get_map(location = caLongLat)
```

Google Map Plot

```
mapPoints <- ggmap(map) +
  geom_point(aes(x = clinics_sp@coords[,1], y = clinics_sp@coords[,2]),
             data = clinics_sp@data, alpha = 0.7,size=2)+
```

```
  labs(title="Spatial location of clinics",
       y="Latitude",x="Longtitude" )

mapPoints
```

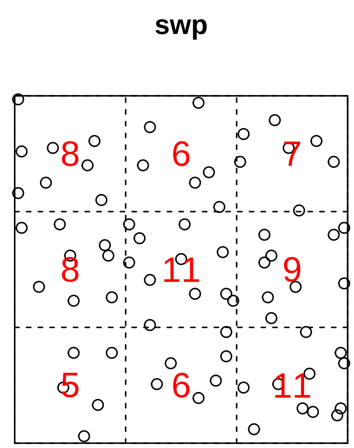


2.4 Quadrat Analysis - Quadrat Counts and Tests

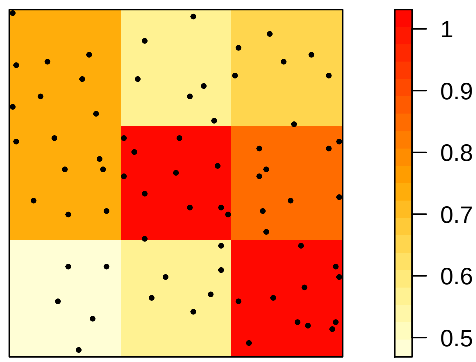
2.4.1 swp dataset

Quadrat counts:

```
Q3x3 = quadratcount(swp, nx=3, ny=3)
plot(swp)
plot(Q3x3, add=TRUE, col="red", cex=1.5, lty=2)
```




```
# Plot the density
cl <-  interp.colours(c("lightyellow", "orange" ,"red"), 20)

plot( intensity(Q3x3, image=TRUE), las=1, col=cl, main=NULL)
plot(swp, pch=20, cex=0.6, col="black", add=TRUE)  # Add points
```



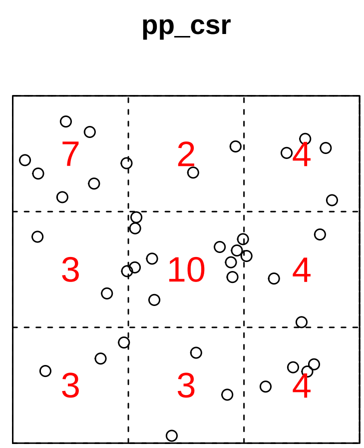
Quadrat test

```
Q3x3test = quadrat.test(swp, 3,3)
Q3x3test
```

```
##
##  Chi-squared test of CSR using quadrat counts
##
## data:  swp
## X2 = 4.6761, df = 8, p-value = 0.4169
## alternative hypothesis: two.sided
##
## Quadrats: 3 by 3 grid of tiles
```

2.4.2 Simulated CSR Pattern

```
Q3x3_csr = quadratcount(pp_csr, nx=3, ny=3)
plot(pp_csr)
plot(Q3x3_csr, add=TRUE, col="red", cex=1.5, lty=2)
```



Test:

```
Q3x3test_csr = quadrat.test(pp_csr, 3,3)
```

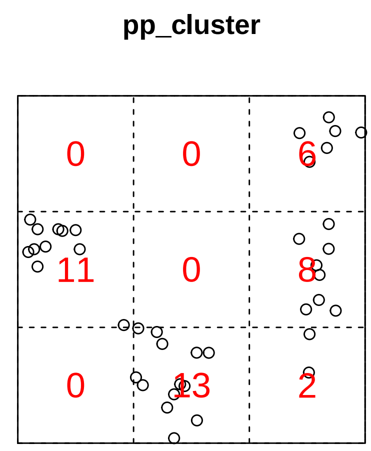
```
## Warning: Some expected counts are small; chi^2 approximation may be inaccurate
```

```
Q3x3test_csr
```

```
##
##  Chi-squared test of CSR using quadrat counts
##
## data:  pp_csr
## X2 = 11.3, df = 8, p-value = 0.3705
## alternative hypothesis: two.sided
##
## Quadrats: 3 by 3 grid of tiles
```

2.4.3 Simulated Cluster Pattern

```
Q3x3_cluster = quadratcount(pp_cluster, nx=3, ny=3)
plot(pp_cluster)
plot(Q3x3_cluster, add=TRUE, col="red", cex=1.5, lty=2)
```



Test:

```
Q3x3test_cluster = quadrat.test(pp_cluster, 3,3)
```

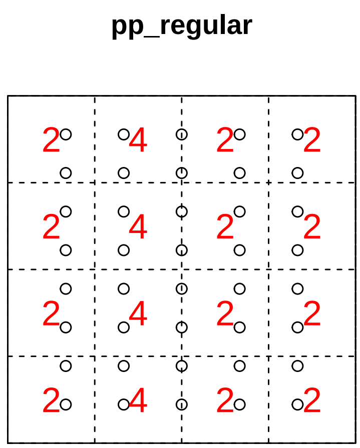
```
## Warning: Some expected counts are small; chi^2 approximation may be inaccurate
```

```
Q3x3test_cluster
```

```
##
##  Chi-squared test of CSR using quadrat counts
##
## data:  pp_cluster
## X2 = 48.65, df = 8, p-value = 1.484e-07
## alternative hypothesis: two.sided
##
## Quadrats: 3 by 3 grid of tiles
```

2.4.4 Simulated Regular Pattern

```
Q3x3_regular = quadratcount(pp_regular, nx=4, ny=4)
plot(pp_regular)
plot(Q3x3_regular, add=TRUE, col="red", cex=1.5, lty=2)
```



Test:

```
Q3x3test_regular = quadrat.test(pp_regular, 3,3)
```

```
## Warning: Some expected counts are small; chi^2 approximation may be inaccurate
```

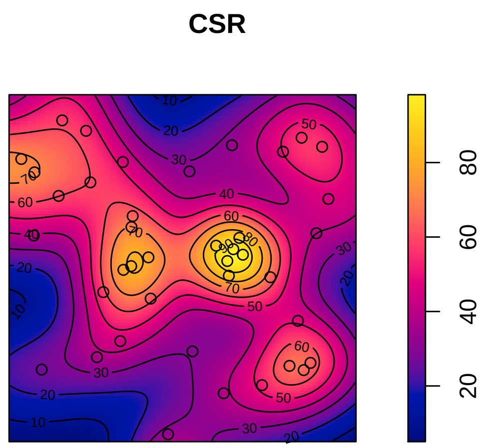
```
Q3x3test_regular
```

```
##
##  Chi-squared test of CSR using quadrat counts
##
## data:  pp_regular
## X2 = 4.55, df = 8, p-value = 0.3912
## alternative hypothesis: two.sided
##
## Quadrats: 3 by 3 grid of tiles
```

2.5 Kernel Density Smoothing

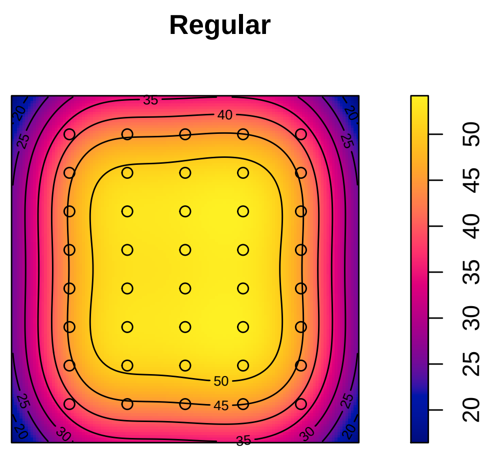
2.5.1 CSR Pattern

```r
den <- density(pp_csr, sigma = .1)
plot(den, main = "CSR")
plot(pp_csr, add=TRUE)
contour(den, add = TRUE)
```



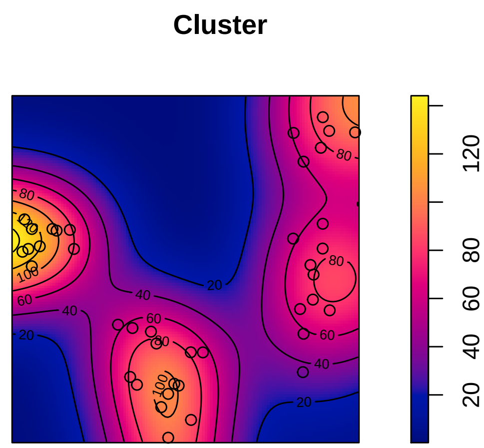
2.5.2 Regular Pattern

```r
den <- density(pp_regular)
plot(den, main = "Regular")
plot(pp_regular, add=TRUE)
contour(den, add=TRUE)
```



2.5.3 Cluster Pattern

```
den <- density(pp_cluster)
plot(den, main = "Cluster")
plot(pp_cluster, add=TRUE)
contour(den, add=TRUE)
```



2.6 Kernel Smoothing with a Covariate

2.6.1 Tropical rain forest trees dataset

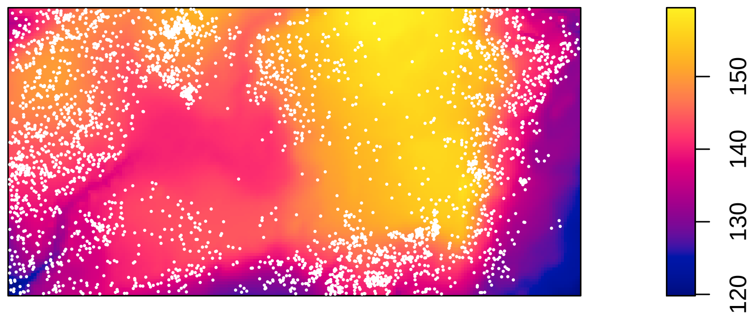
```
data("bei")
```

Assign the elevation covariate to a variable elev by typing

```
elev <- bei.extra$elev
```

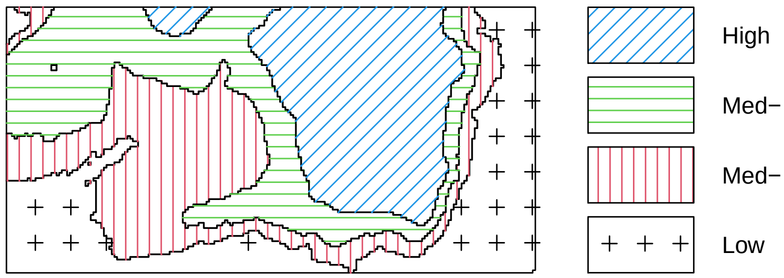
Plot the trees on top of an image of the elevation covariate.

```
plot(elev, main = "")
plot(bei, add = TRUE, cex = 0.3, pch = 16, cols = "white")
```



For the tropical rainforest data bei, it might be useful to split the study region into several sub-regions according to the terrain elevation:

```
b <- quantile(elev, probs=(0:4)/4, type=2)

Zcut <- cut(elev, breaks=b, labels=c("Low", "Med-Low", "Med-High", "High"))
textureplot(Zcut, main = "")
```



Convert the image from above to a tesselation, count the number of points in each region using quadratcount, and plot the quadrat counts.

```
V <- tess(image=Zcut)
qc <- quadratcount(bei, tess = V)
qc
```

```
## tile
##      Low  Med-Low Med-High     High
##      714      883     1344      663
```

The output shows the number of trees in each region. Since the four regions have equal area, the counts should be approximately equal if there is a uniform density of trees. Obviously they are not equal; there appears to be a strong preference for higher elevations (dropping off for the highest elevations).

Estimate the intensity in each of the four regions.

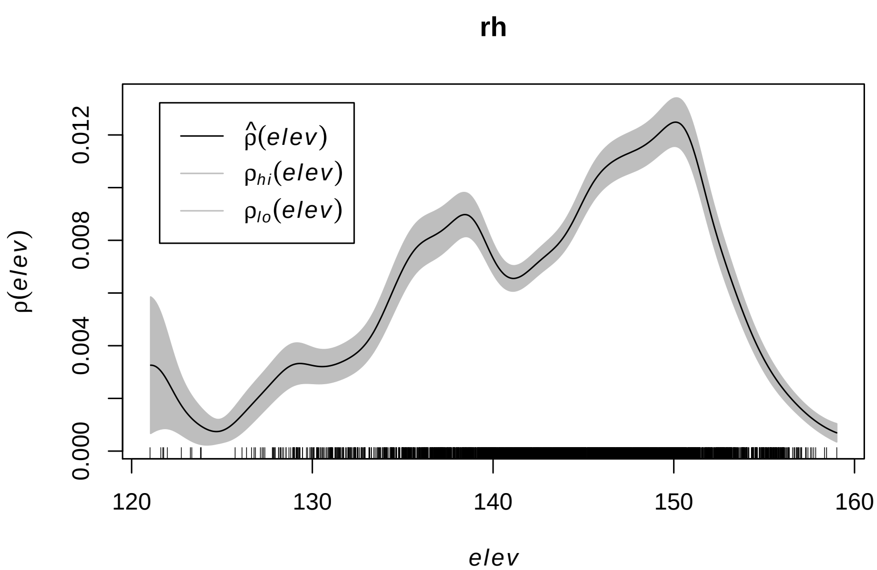
```
intensity(qc)
```

```
## tile
##         Low     Med-Low    Med-High        High
## 0.005623154 0.006960978 0.010593103 0.005228707
```

Assume that the intensity of trees is a function ((u) = (e(u))) where (e(u)) is the terrain elevation at location u.

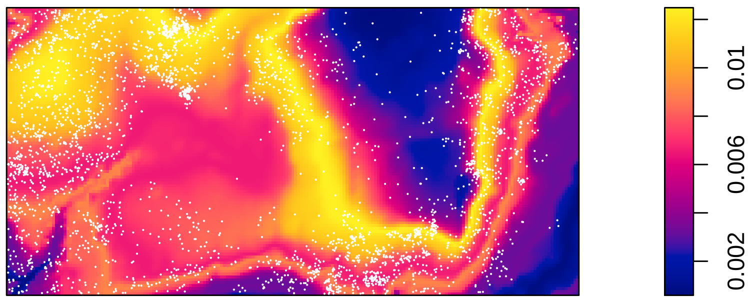
Compute a nonparametric estimate of the function ( ) and plot it by

```
rh <- rhohat(bei, elev)
plot(rh)
```



Compute the predicted intensity based on this estimate of ( ).

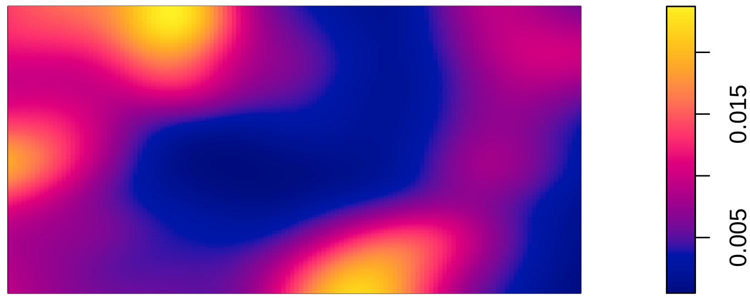
```
predictedrho <- predict(rh)
plot(predictedrho, main = "")
plot(bei, add = TRUE, cols = "white", cex = .2, pch = 16)
```



Compute a non-parametric estimate by kernel smoothing and compare with the predicted intensity above.

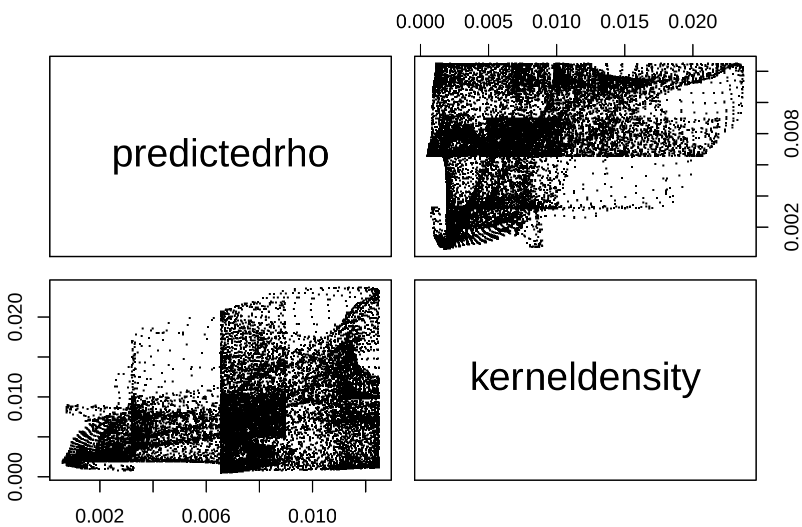
The kernel density estimate of the points is computed and plotted with the following code:

```
kerneldensity <- density(bei, sigma = bw.scott)
plot(kerneldensity, main = "")
plot(kerneldensity, add = TRUE, cols = "white", cex = .2, pch = 16)
```



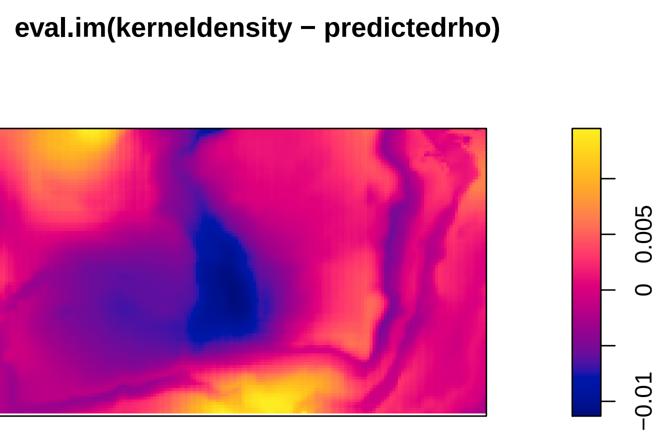
Compare the two

```r
pairs(predictedrho, kerneldensity)
```



```
plot(eval.im(kerneldensity-predictedrho))
```

```
## Warning: the images 'kerneldensity' and 'predictedrho' were not compatible
```



Which seems to be quite different form the predicted intensity.

2.7 Distance Measures and Tests

2.7.1 e2e Distances

2.7.1.1 swp dataset

```
PD = pairdist(swp)
class(PD)
```

```
## [1] "matrix" "array"
```

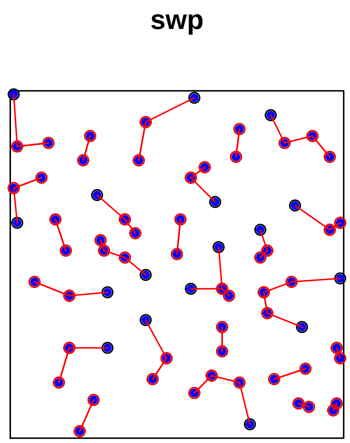
```
dm <- as.matrix(PD)
dm[1:5, 1:5]
```

```
##          [,1]     [,2]     [,3]     [,4]     [,5]
## [1,] 0.000000 2.700000 3.701351 1.503330 5.433231
## [2,] 2.700000 0.000000 1.004988 1.204159 2.765863
## [3,] 3.701351 1.004988 0.000000 2.200000 1.772005
## [4,] 1.503330 1.204159 2.200000 0.000000 3.931921
## [5,] 5.433231 2.765863 1.772005 3.931921 0.000000
```

```
diag(dm) <- NA
#dm[1:5, 1:5]
wdmin <- apply(dm, 1, which.min)

dmin <- apply(dm, 1, min, na.rm=TRUE)
head(dmin)
```

```
## [1] 1.5033296 0.8544004 1.0049876 0.9055385 1.0770330 0.8544004
```

```
# which is the same as nndist e2e=nndist(swp)

dmin = nndist(swp)

plot(swp)
xy = cbind(swp$x, swp$y)

ord <- rev(order(dmin))
far25 <- ord[1:71]
neighbors <- wdmin[far25]
points(xy[far25, ], col='blue', pch=20)
points(xy[neighbors, ], col='red')
# drawing the lines, easiest via a loop
for (i in far25) {
    lines(rbind(xy[i, ], xy[wdmin[i], ]), col='red')
}
```



2.7.1.2 Simulated CSR Pattern

```
e2e_csr = nndist(pp_csr)
e2e_csr
```

```
##  [1] 0.11056220 0.05419105 0.08163249 0.05574520 0.19907565 0.03191166
##  [7] 0.10456756 0.15049858 0.16325765 0.02841510 0.05044346 0.05419105
## [13] 0.10456756 0.07525211 0.02471890 0.08651227 0.03700818 0.06471165
## [19] 0.12663659 0.08163249 0.06471165 0.07525211 0.14362670 0.03195288
## [25] 0.09669706 0.03195288 0.09731910 0.04284774 0.11297958 0.03191166
## [31] 0.13454666 0.02841510 0.02471890 0.06711512 0.10924574 0.04269836
## [37] 0.09947882 0.03815278 0.14362670 0.10235020
```

```
PD = pairdist(pp_csr)
class(PD)
```

```
## [1] "matrix" "array"
```

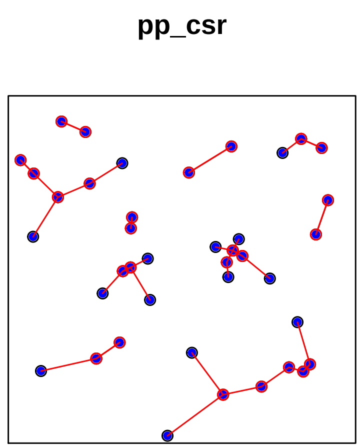
```
dm <- as.matrix(PD)
dm[1:5, 1:5]
```

```
##            [,1]      [,2]      [,3]      [,4]      [,5]
## [1,] 0.0000000 0.2930205 0.5163115 0.2844957 0.7955061
## [2,] 0.2930205 0.0000000 0.5975953 0.4633681 0.8993362
## [3,] 0.5163115 0.5975953 0.0000000 0.2546708 0.3017974
## [4,] 0.2844957 0.4633681 0.2546708 0.0000000 0.5130861
## [5,] 0.7955061 0.8993362 0.3017974 0.5130861 0.0000000
```

```
diag(dm) <- NA
#dm[1:5, 1:5]
wdmin <- apply(dm, 1, which.min)

dmin <- apply(dm, 1, min, na.rm=TRUE)
head(dmin)
```

```
## [1] 0.11056220 0.05419105 0.08163249 0.05574520 0.19907565 0.03191166
```

```
# which is the same as nndist e2e=nndist(swp)

dmin = nndist(pp_csr)

plot(pp_csr)
xy = cbind(pp_csr$x, pp_csr$y)

ord <- rev(order(dmin))
far25 <- ord[1:40]
neighbors <- wdmin[far25]
points(xy[far25, ], col='blue', pch=20)
points(xy[neighbors, ], col='red')
# drawing the lines, easiest via a loop
for (i in far25) {
    lines(rbind(xy[i, ], xy[wdmin[i], ]), col='red')
}
```



2.7.1.3 Simulated Cluster Pattern

```
e2e_cluster = nndist(pp_cluster)
e2e_cluster
```

```
##  [1] 0.01854666 0.03502091 0.01854666 0.04969353 0.03502091 0.03390187
##  [7] 0.01268286 0.05624330 0.01268286 0.03830134 0.04275255 0.02983313
## [13] 0.04275255 0.02983313 0.03774271 0.03774271 0.03391843 0.01376367
## [19] 0.01376367 0.03500058 0.08344093 0.06403124 0.05422191 0.08344093
## [25] 0.03500058 0.08988091 0.04304986 0.07202173 0.04586212 0.02906394
## [31] 0.08760076 0.11053898 0.04586212 0.02906394 0.05896243 0.07149045
## [37] 0.04361429 0.04361429 0.05745563 0.07483198
```

```
PD_cluster = pairdist(pp_cluster)
class(PD_cluster)
```

```
## [1] "matrix" "array"
```

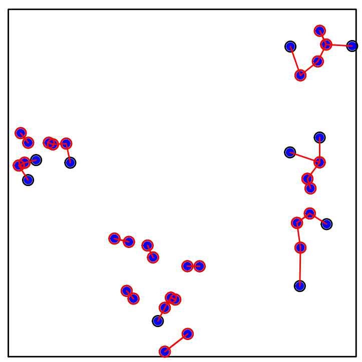
```
dm_cluster <- as.matrix(PD_cluster)
dm_cluster[1:5, 1:5]
```

```
##             [,1]       [,2]       [,3]       [,4]       [,5]
## [1,] 0.00000000 0.09345138 0.01854666 0.04969353 0.07093497
## [2,] 0.09345138 0.00000000 0.08597921 0.13688899 0.03502091
## [3,] 0.01854666 0.08597921 0.00000000 0.05097721 0.05847323
## [4,] 0.04969353 0.13688899 0.05097721 0.00000000 0.10757315
## [5,] 0.07093497 0.03502091 0.05847323 0.10757315 0.00000000
```

```r
diag(dm_cluster) <- NA
wdmin_cluster <- apply(dm_cluster, 1, which.min)

dmin_cluster <- apply(dm_cluster, 1, min, na.rm=TRUE)
head(dmin-cluster)
```

```
##              X          Y
## 1  0.080388175 -0.4397788
## 2  0.018557146 -0.5894417
## 3  0.034750612 -0.4767600
## 4 -0.001070259 -0.4526473
## 5  0.141971489 -0.4168896
## 6 -0.048015500 -0.5340536
```

```r
# which is the same as nndist e2e=nndist(swp)

dmin_cluster = nndist(pp_cluster)

plot(pp_cluster)
xy_cluster = cbind(pp_cluster$x, pp_cluster$y)

ord <- rev(order(dmin_cluster))
far25 <- ord[1:40]
neighbors <- wdmin_cluster[far25]
points(xy_cluster[far25, ], col='blue', pch=20)
points(xy_cluster[neighbors, ], col='red')
# drawing the lines, easiest via a loop
for (i in far25) {
    lines(rbind(xy_cluster[i, ], xy_cluster[wdmin_cluster[i], ]), col='red')
}
```



2.7.1.4 Simulated Regular Pattern

```
e2e_regular = nndist(pp_regular)
e2e_regular
```

```
##  [1] 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111
##  [8] 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111
## [15] 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111
## [22] 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111
## [29] 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111
## [36] 0.1111111 0.1111111 0.1111111 0.1111111 0.1111111
```

```
PD_regular = pairdist(pp_regular)
class(PD_regular)
```

```
## [1] "matrix" "array"
```

```
dm_regular <- as.matrix(PD_regular)
dm_regular[1:5, 1:5]
```

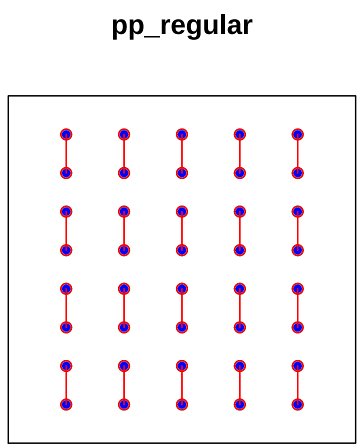
```
##           [,1]      [,2]      [,3]      [,4]      [,5]
```

```
## [1,] 0.0000000 0.1666667 0.3333333 0.5000000 0.6666667
## [2,] 0.1666667 0.0000000 0.1666667 0.3333333 0.5000000
## [3,] 0.3333333 0.1666667 0.0000000 0.1666667 0.3333333
## [4,] 0.5000000 0.3333333 0.1666667 0.0000000 0.1666667
## [5,] 0.6666667 0.5000000 0.3333333 0.1666667 0.0000000
```

```
diag(dm_regular) <- NA
wdmin_regular <- apply(dm_regular, 1, which.min)

dmin_regular <- apply(dm_regular, 1, min, na.rm=TRUE)
head(dmin-regular)
```

```
##             X             Y
## 1 -0.05610447 -0.0005489143
## 2 -0.27914228 -0.0569200607
## 3 -0.41836751 -0.0294786165
## 4 -0.61092147 -0.0553659112
## 5 -0.63425768  0.0879645408
## 6 -0.13475501 -0.1903105666
```

```
# which is the same as nndist e2e=nndist(swp)

dmin_regular = nndist(pp_regular)

plot(pp_regular)
xy_regular = cbind(pp_regular$x, pp_regular$y)

ord <- rev(order(dmin_regular))
far25 <- ord[1:40]
neighbors <- wdmin_regular[far25]
points(xy_regular[far25, ], col='blue', pch=20)
points(xy_regular[neighbors, ], col='red')
# drawing the lines, easiest via a loop
for (i in far25) {
    lines(rbind(xy_regular[i, ], xy_regular[wdmin_regular[i], ]), col='red')
}
```



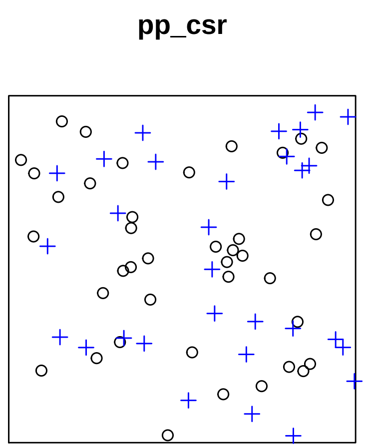
2.7.2 p2e Distances

Generate Random points

```
set.seed(23)
randompoints = matrix(runif(60),ncol=2)
#randompoints = matrix(runif(250),ncol=2)
```

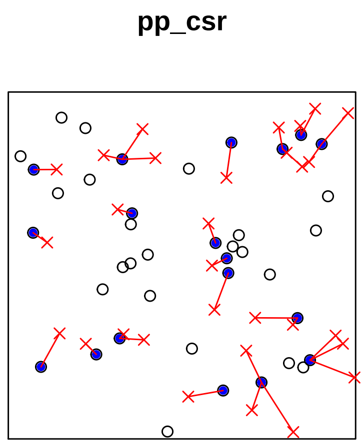
2.7.2.1 CSR Pattern

```
plot(pp_csr)
points(randompoints, col = "blue", pch=3)
```



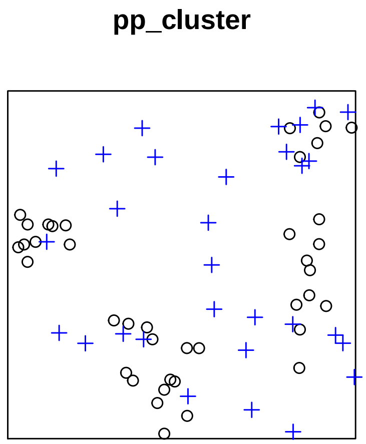

```
p2e_distances_csr = NULL
mins_csr = NULL
xy = cbind(pp_csr$x, pp_csr$y)


# sqrt((xy[2,1]-randompoints[1,1])^2+(xy[2,2]-randompoints[1,2])^2)
# sqrt((xy[1,1]-randompoints[2,1])^2+(xy[1,2]-randompoints[2,2])^2)


for(i in 1:dim(randompoints)[1]){
dist1 = matrix(pairdist(rbind(randompoints[i,],xy)),41)

p2e_distances_csr = c(p2e_distances_csr,min(dist1[2:41,1]))
mins_csr = c(mins_csr,which.min(dist1[2:41,1]))
}


plot(pp_csr)
ord <- rev(order(p2e_distances_csr))
far25 <- 1:dim(randompoints)[1]
neighbors <- mins_csr
points(randompoints, col='red', pch=4)
points(xy[mins_csr, ], col='blue', pch=20)
# drawing the lines, easiest via a loop
for (i in far25) {
```

```
  lines(rbind(xy[mins_csr[i], ], randompoints[i, ]), col='red')
}
```

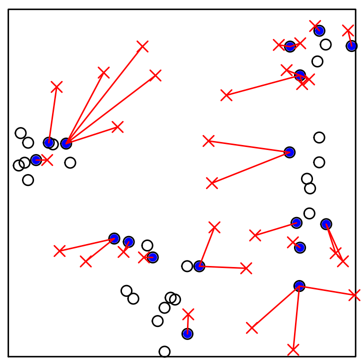


2.7.2.2 Cluster Pattern

```
plot(pp_cluster)
points(randompoints, col = "blue", pch=3)
```



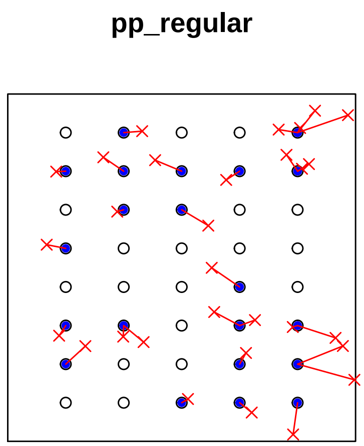

```
p2e_distances_cluster = NULL
mins_cluster = NULL
xy_cluster = cbind(pp_cluster$x, pp_cluster$y)

for(i in 1:dim(randompoints)[1]){
dist1 = matrix(pairdist(rbind(randompoints[i,],xy_cluster)),41)

p2e_distances_cluster = c(p2e_distances_cluster,min(dist1[2:41,1]))
mins_cluster = c(mins_cluster,which.min(dist1[2:41,1]))
}


plot(pp_cluster)
ord <- rev(order(p2e_distances_cluster))
far25 <- 1:dim(randompoints)[1]
neighbors <- mins_cluster
points(randompoints, col='red', pch=4)
points(xy_cluster[mins_cluster, ], col='blue', pch=20)
# drawing the lines, easiest via a loop
for (i in far25) {
  lines(rbind(xy_cluster[mins_cluster[i], ], randompoints[i, ]), col='red')
}
```



2.7.2.3 Regular Pattern

```
p2e_distances_regular = NULL
p2e_mins_regular = NULL
xy_regular = cbind(pp_regular$x, pp_regular$y)


for(i in 1:dim(randompoints)[1]){
dist1 = matrix(pairdist(rbind(randompoints[i,],xy_regular)),41)

p2e_distances_regular = c(p2e_distances_regular,min(dist1[2:41,1]))
p2e_mins_regular = c(p2e_mins_regular,which.min(dist1[2:41,1]))
}


plot(pp_regular)
ord <- rev(order(p2e_distances_regular))
far25 <- 1:dim(randompoints)[1]
neighbors <- p2e_mins_regular
points(randompoints, col='red', pch=4)
points(xy_regular[p2e_mins_regular, ], col='blue', pch=20)
# drawing the lines, easiest via a loop
for (i in far25) {
```

```
  lines(rbind(xy_regular[p2e_mins_regular[i], ], randompoints[i, ]), col='red')
}
```



2.7.3 Clark and Evans Index and Test

2.7.3.1 CSR Pattern

```
clarkevans(pp_csr)
```

```
##     naive  Donnelly       cdf
## 1.0135515 0.9443703 0.9719128
```

```
clarkevans.test(pp_csr)
```

```
##
##  Clark-Evans test
##  No edge correction
##  Z-test
##
## data:  pp_csr
## R = 1.0136, p-value = 0.8698
## alternative hypothesis: two-sided
```

2.7.3.2 Cluster Pattern

```r
clarkevans(pp_cluster)
```

```
##     naive  Donnelly       cdf
## 0.5852722 0.5453237 0.5621148
```

```r
clarkevans.test(pp_cluster)
```

```
##
##  Clark-Evans test
##  No edge correction
##  Z-test
##
## data:  pp_cluster
## R = 0.58527, p-value = 5.224e-07
## alternative hypothesis: two-sided
```

2.7.3.3 Regular Pattern

```r
clarkevans(pp_regular)
```

```
##    naive Donnelly      cdf
## 1.405457 1.309526 1.398362
```

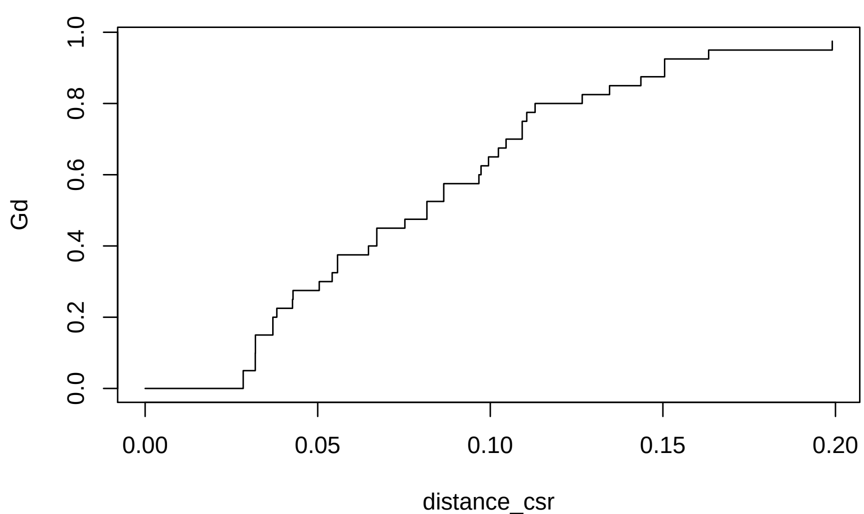
```r
clarkevans.test(pp_regular)
```

```
##
##  Clark-Evans test
##  No edge correction
##  Z-test
##
## data:  pp_regular
## R = 1.4055, p-value = 9.309e-07
## alternative hypothesis: two-sided
```

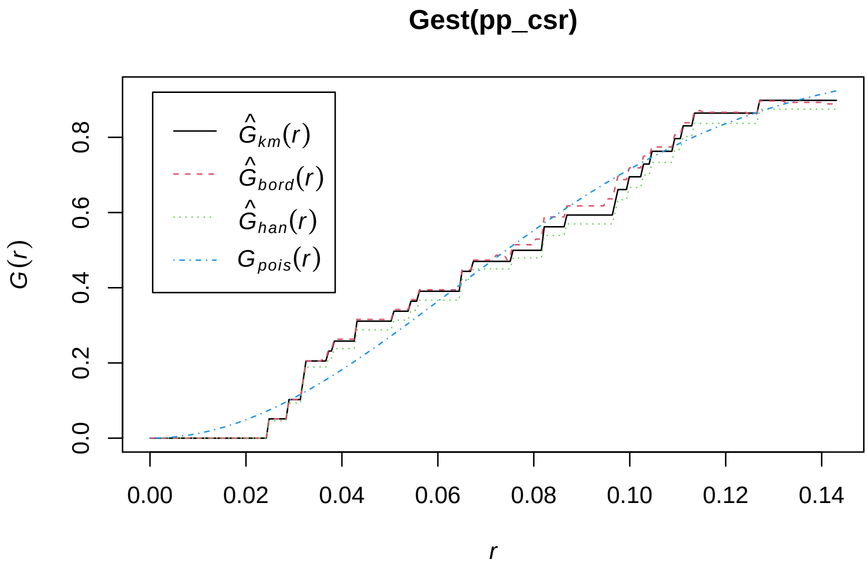
2.8 G Function

2.8.1 Simulated CSR Pattern

```
dmin_csr = nndist(pp_csr)
distance_csr <- c(0,sort(unique(dmin_csr)))
# compute how many cases there with distances smaller that each x
Gd <- sapply(distance_csr, function(x) sum(dmin_csr < x))
# normalize to get values between 0 and 1
Gd <- Gd / length(dmin_csr)
plot(distance_csr, Gd, type = "s")
```

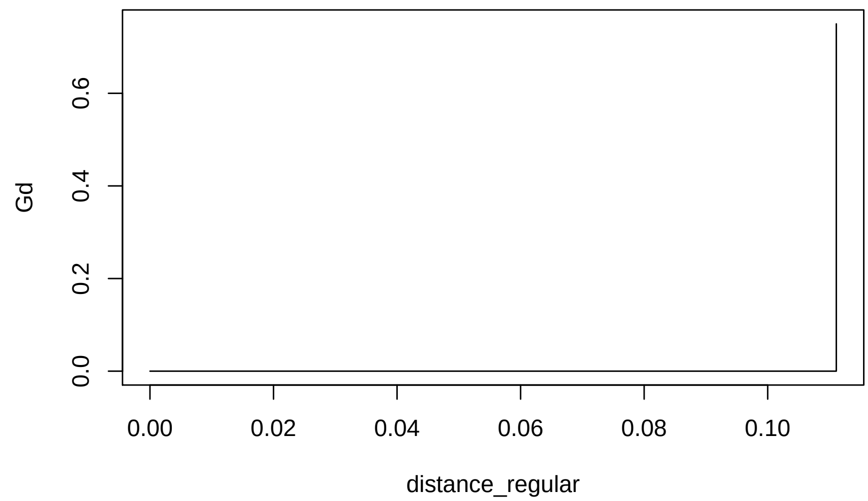



```
plot(Gest(pp_csr))
```

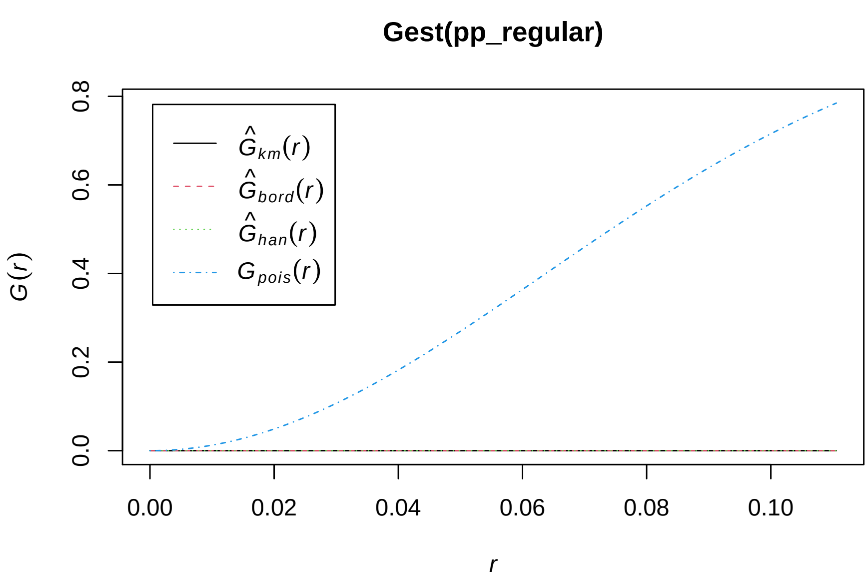


2.8.2 Simulated Regular Pattern

```
dmin_regular = nndist(pp_regular)
distance_regular <- c(0,sort(unique(dmin_regular)))
# compute how many cases there with distances smaller that each x
Gd <- sapply(distance_regular, function(x) sum(dmin_regular < x))
# normalize to get values between 0 and 1
Gd <- Gd / length(dmin_regular)
plot(distance_regular, Gd, type = "s")
```

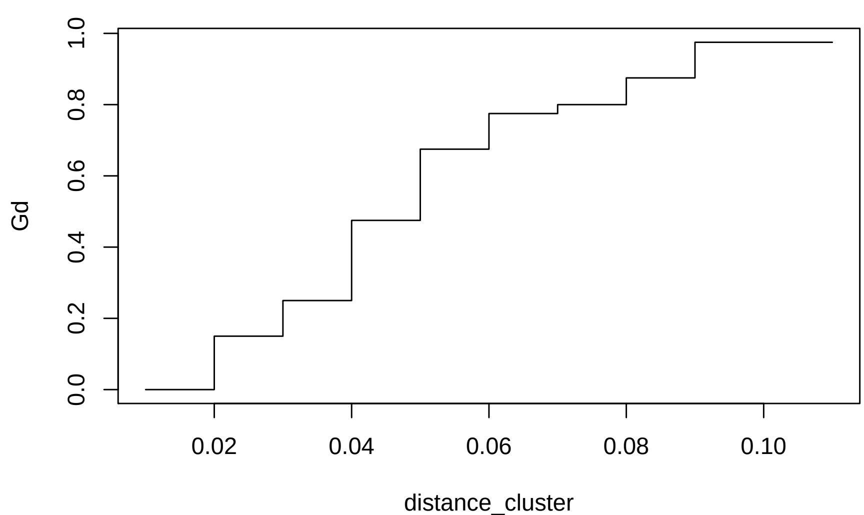



```r
plot(Gest(pp_regular))
```

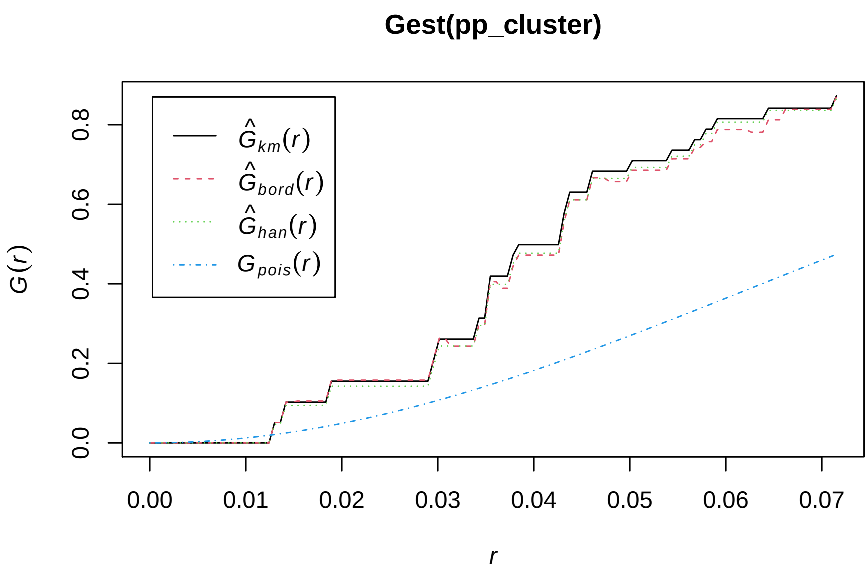


2.8.3 Simulated Cluster Pattern

```
dmin_cluster = nndist(pp_cluster)
# get the unique distances (for the x-axis)
distance_cluster <- sort(unique(round(dmin_cluster,2)))
# compute how many cases there with distances smaller that each x
Gd <- sapply(distance_cluster, function(x) sum(dmin_cluster < x))
# normalize to get values between 0 and 1
Gd <- Gd / length(dmin_cluster)
plot(distance_cluster, Gd, type = "s")
```




```
plot(Gest(pp_cluster))
```



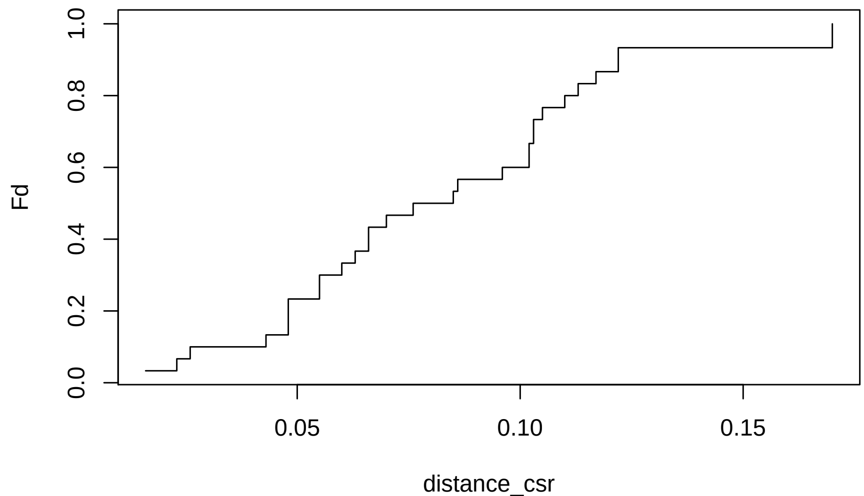
2.9 F Function

2.9.1 Simulated CSR Pattern

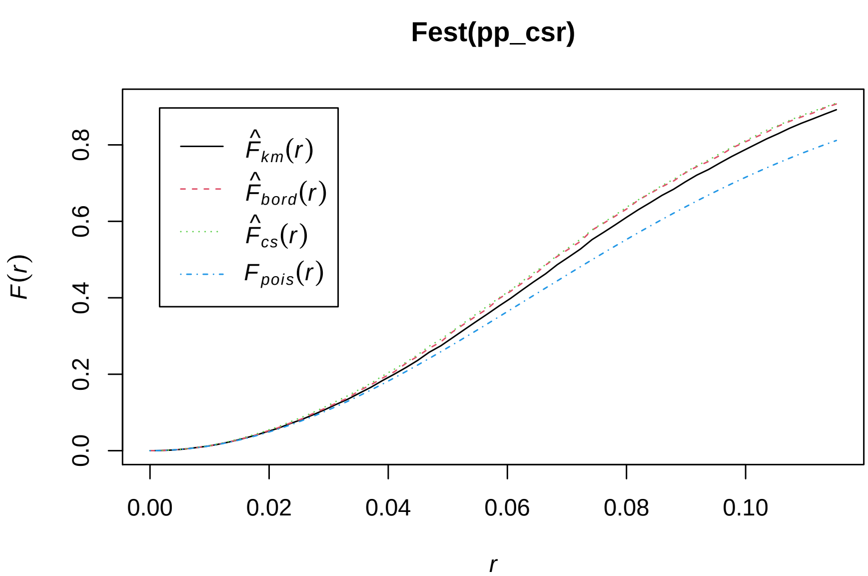
```
max(p2e_distances_csr)
```

```
## [1] 0.1698011
```

```
## [1] 1829.738
# get the unique distances (for the x-axis)
distance_csr <- sort(unique(round(p2e_distances_csr,3)))
# compute how many cases there with distances smaller that each x
Fd <- sapply(distance_csr, function(x) sum(p2e_distances_csr < x))
# normalize to get values between 0 and 1
Fd <- Fd / length(p2e_distances_csr)
plot(distance_csr, Fd, type = "s")
```




```r
plot(Fest(pp_csr))
```

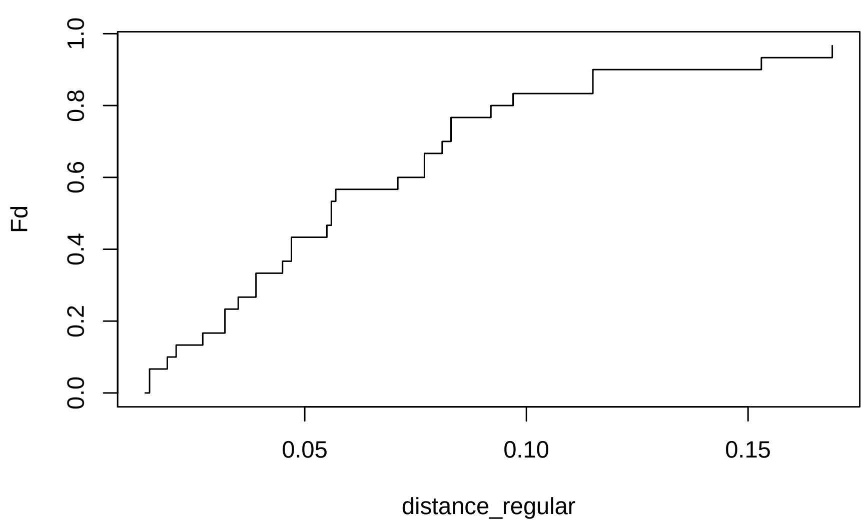


2.9.2 Simulated Regular Pattern

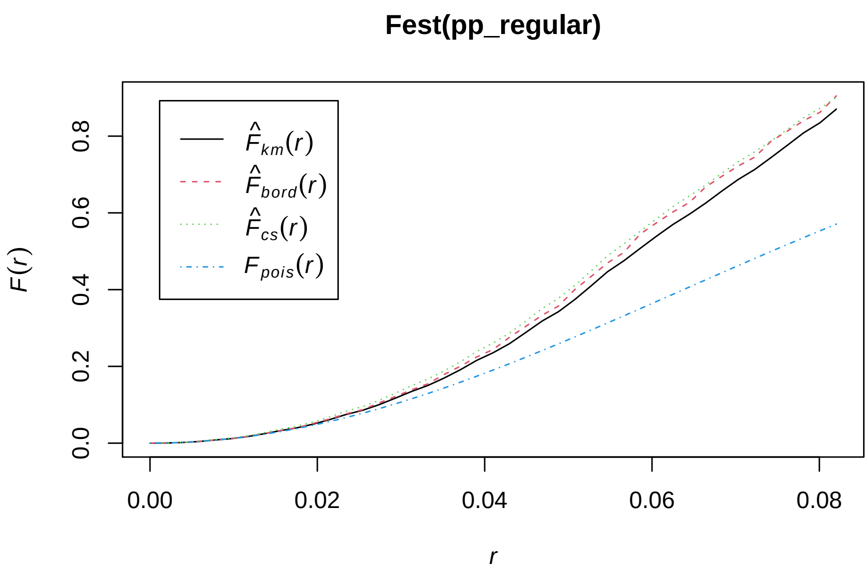
```
max(p2e_distances_regular)
```

```
## [1] 0.1694105
```

```
## [1] 1829.738
# get the unique distances (for the x-axis)
distance_regular <- sort(unique(round(p2e_distances_regular,3)))
# compute how many cases there with distances smaller that each x
Fd <- sapply(distance_regular, function(x) sum(p2e_distances_regular < x))
# normalize to get values between 0 and 1
Fd <- Fd / length(p2e_distances_regular)
plot(distance_regular, Fd, type = "s")
```




```
plot(Fest(pp_regular))
```

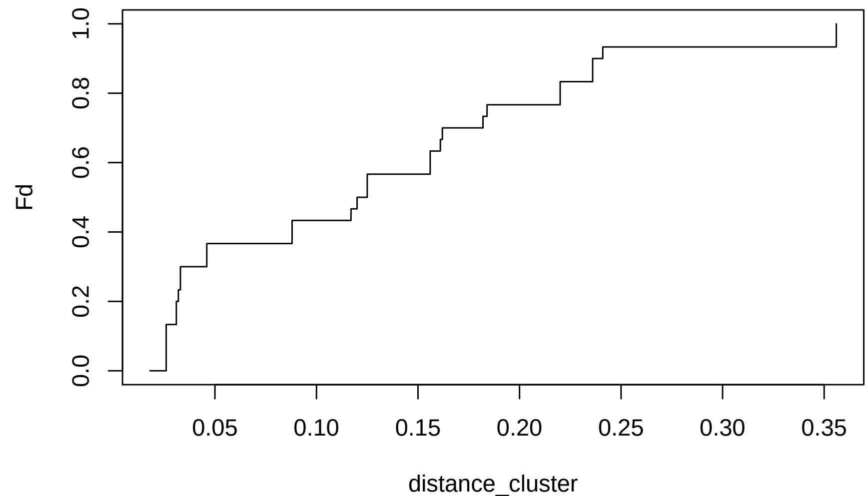


2.9.3 Simulated Cluster Pattern

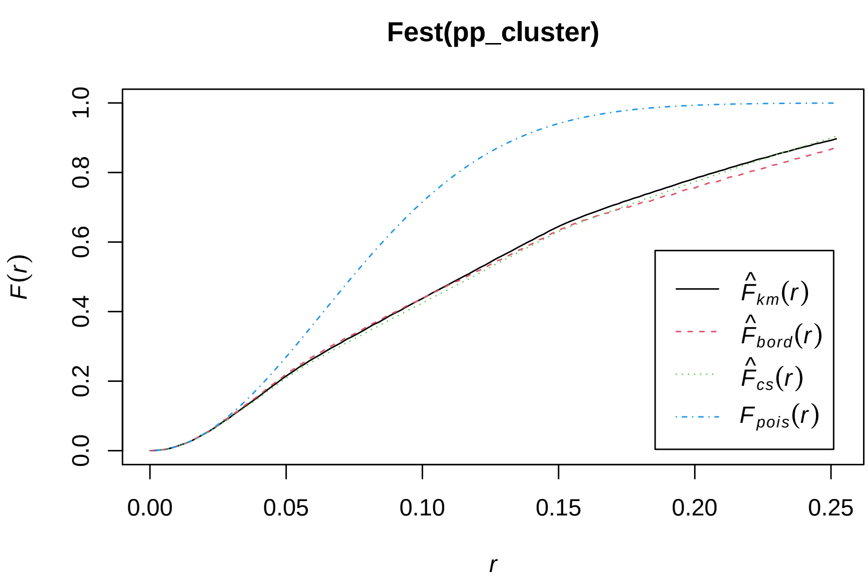
```
max(p2e_distances_cluster)
```

```
## [1] 0.3557434
```

```
## [1] 1829.738
# get the unique distances (for the x-axis)
distance_cluster <- sort(unique(round(p2e_distances_cluster,3)))
# compute how many cases there with distances smaller that each x
Fd <- sapply(distance_cluster, function(x) sum(p2e_distances_cluster < x))
# normalize to get values between 0 and 1
Fd <- Fd / length(p2e_distances_cluster)
plot(distance_cluster, Fd, type = "s")
```




```
plot(Fest(pp_cluster))
```

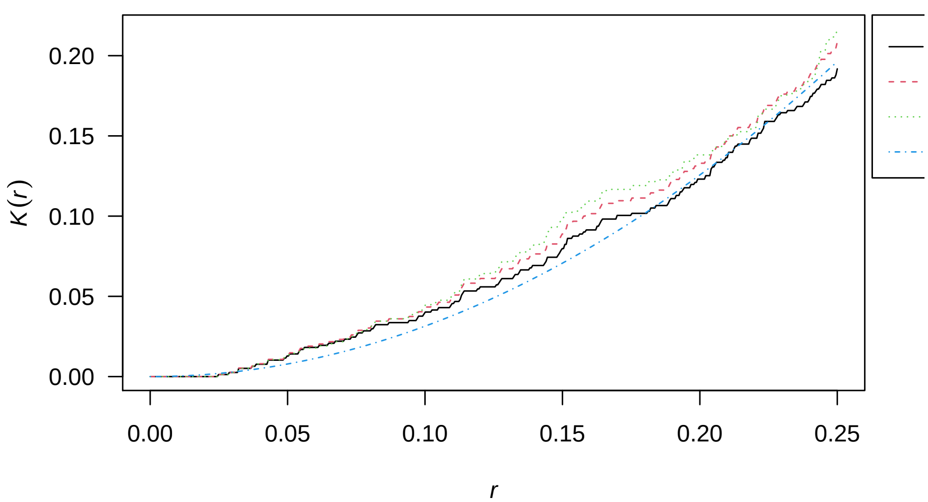


2.10 Ripley's K Function

2.10.1 Simulated CSR Pattern

```
K <- Kest(pp_csr)
plot(K, main=NULL, las=1, legendargs=list(cex=0.8, xpd=TRUE, inset=c(1.01, 0) ))
```

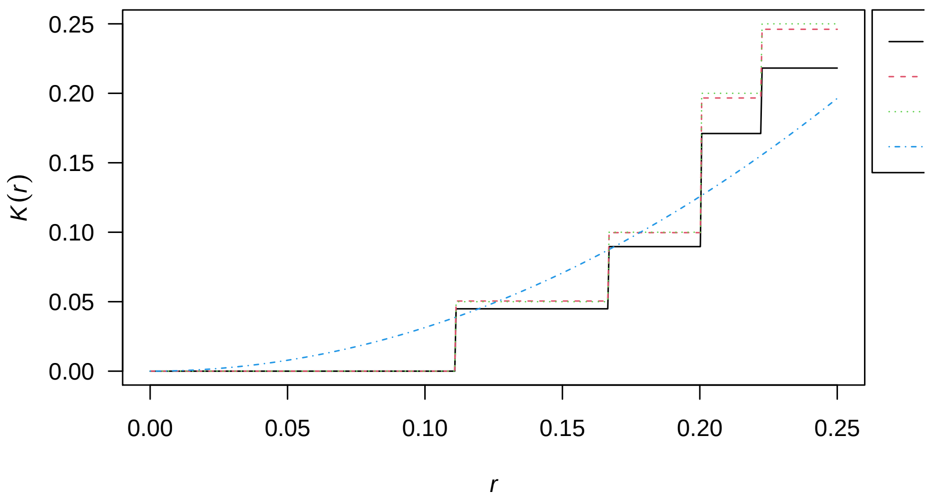
```
## Warning in min(D[scaledlegbox]): no non-missing arguments to min; returning Inf
```



2.10.2 Simulated Regular Pattern

```
K <- Kest(pp_regular)
plot(K, main=NULL, las=1, legendargs=list(cex=0.8, xpd=TRUE, inset=c(1.01, 0) ))
```

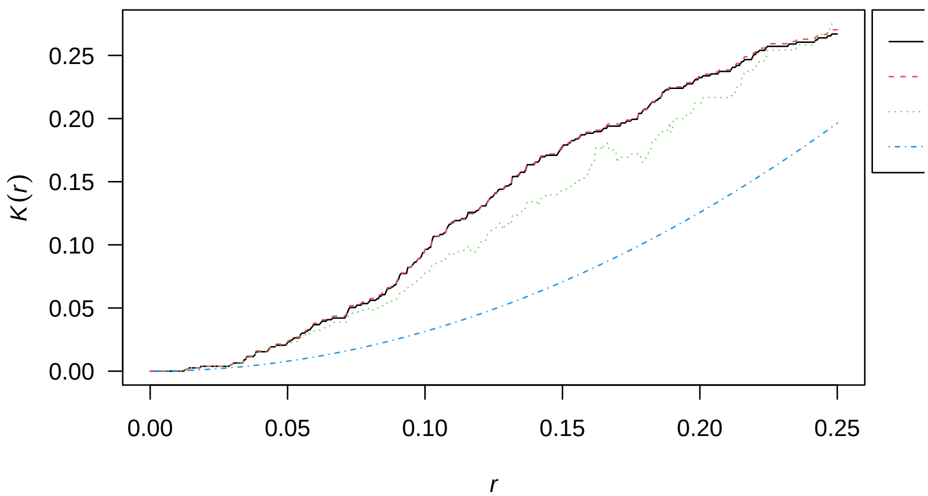
```
## Warning in min(D[scaledlegbox]): no non-missing arguments to min; returning Inf
```



2.10.3 Simulated Cluster Pattern

```
K <- Kest(pp_cluster)
plot(K, main=NULL, las=1, legendargs=list(cex=0.8, xpd=TRUE, inset=c(1.01, 0) ))
```

```
## Warning in min(D[scaledlegbox]): no non-missing arguments to min; returning Inf
```



2.11 References:

- R and Data Mining
- Susan Li - MBA
- Datacamp
- Dr Juwa Nyirenda's lecture notes

Chapter 3

Spatial Lattice Data Analysis

For this section, please update your browser on the 20th of October Tuesday.