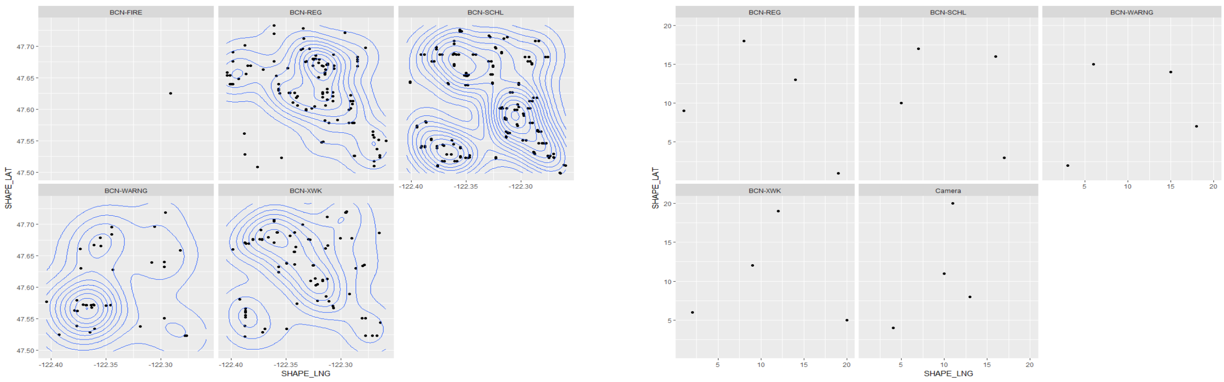
Analysis of Geospatial Data of Seattle

Zhen Qin, 12/12/2017

1 Point Patterns of Beacons and Cameras

This report concerns beacons, cameras and flow counts in Seattle from 2008-2011 using R. First, the point patterns of beacons and cameras are analysed and visualized, then this part focuses on the relationship between cameras and beacons for each type. Traffic Cameras data and the Traffic Beacons data are from here, which include longitude, latitude and beacon categories.

Above all the report utilizes dplyr to filter the data by shape and select necessary variables. It is worthwhile to note that in beacons one point that is far away from other points is regarded as an outlier and removed.



(a) Contour Plot for Each Type

(b) K-means Cluster Centers

Figure 1.1: The figure with two images

A contour plot is generated for learning about density and distribution of beacons for types. As can be seen in the Figure 1.1(a), from the contour plot it is clear that there is only one BCN-FIRE beacon in the region, so when analyse points pattern of beacons, BCN-FIRE beacons will not be considered. Then after extracting data of other four categories, K-means cluster is used to compute centers of the groups. Note that here I set K to be 4 for reasons that are discussed below.

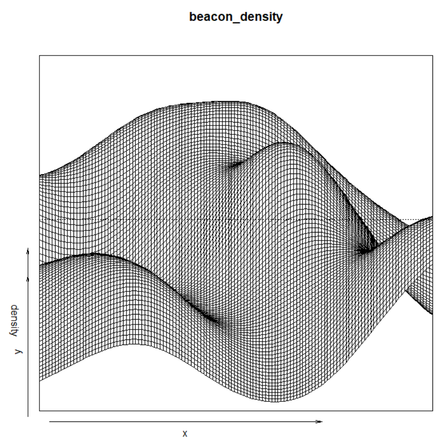


Figure 1.2: Beacon Density

Suppose that most beacon points are gathered in some patterns for each beacon type. This report uses spatstat to create a point pattern process variable that contains the shapes of beacons. In order to show the density of points, a 3-D density plot is generated as Figure 1.2. The x-axis and y-axis stand for longitude and latitude, and the z-axis stands for density of points. Four hills are shown in Figure 1.2, so there are four areas that have big density, which means the choice of K is reasonable.

Back to the result of clustering, the Figure 1.1(b) shows that BCN-REG and BCN-XWK share the similar pattern with cameras points. According to the codebook, BCN-FIRE is Fire Beacon, BCN-REG is Regulatory Beacon, BCN-SCHL is School Beacon, BCN-WARNG is Warning Beacon, and BCN-XWK is Crosswalk Beacon. So the conclusion is very natural and intuitive because most cameras should be set near regulatory beacons and crosswalk beacons in order to monitor road conditions.

2 Average Yearly Increasing Flow Counts

For more analysis, 2008-2011 Traffic Flow Counts datasets including longitude, latitude and flow counts are provided here. In this part, the result in the first part is repeated in an analytical method, and then the centers of camera groups are used to compute average yearly increasing rate of flow counts for each group.

In the package spatstat Ripley's K-function is used to characterize point patterns. Basically the bivariate version of the function tells you whether you observe more or less points within a given radius that it would be expected under complete spatial randomness. Suppose $E(i, j, r)$ reports the number of type j events within a given radius of type i events. It is calculated as follows:

$$K_{i,j}(r) = \lambda_j^{-1} E(i, j, r) \tag{2.1}$$

The Figure 2.1 provides information of K functions, in which i and j are shown in titles. In the top-left and bottom-right subfigures, the red dash line, i.e. the standard K line is above the black line, i.e. the theoretical line. This suggests beacons and cameras are significantly distributed without randomness, and the summary is supported by the result in part 1. So the conclusion is convincing and valid: BCN-REG and BCN-XWK share the similar pattern with cameras points.

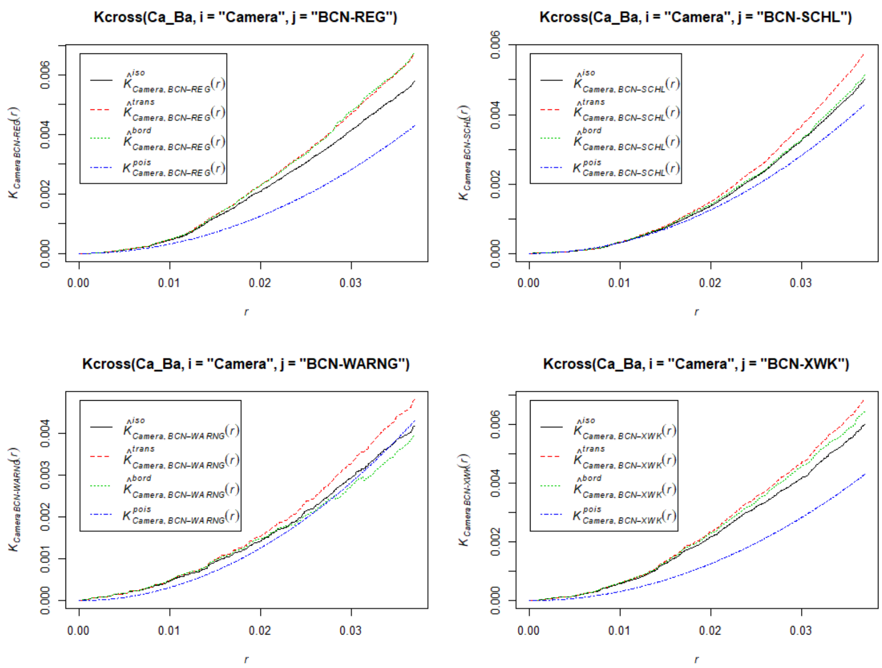


Figure 2.1: Kcross Functions

Finally, we consider the yearly increasing rate of flow counts in different areas marked by cameras groups. The R package dplyr is used to compute the values. For the purpose of classification, k-nearest neighbors algorithm is performed on the combined dataset with k = 1. The table 2.1 shows the fourth group has the biggest average yearly increasing rate of flow counts.

Group	Center Longitude	Center Latitude	Increasing Rate
1	-122.2940	47.54581	1.013864
2	-122.3367	47.69160	1.016910
3	-122.3262	47.61495	1.018208
4	-122.3475	47.56336	1.027711

Table 2.1: Average Yearly Increasing Rate for Each Group