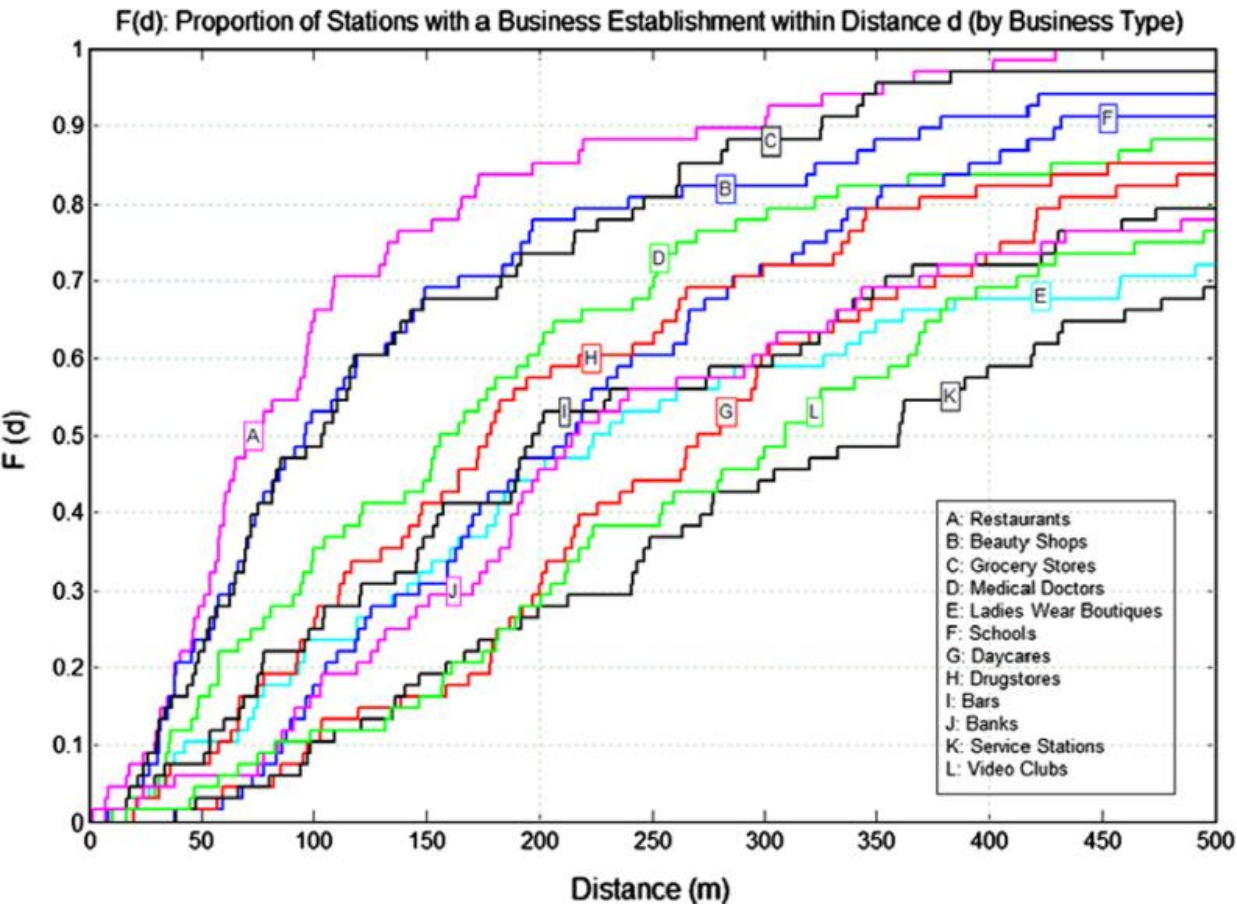
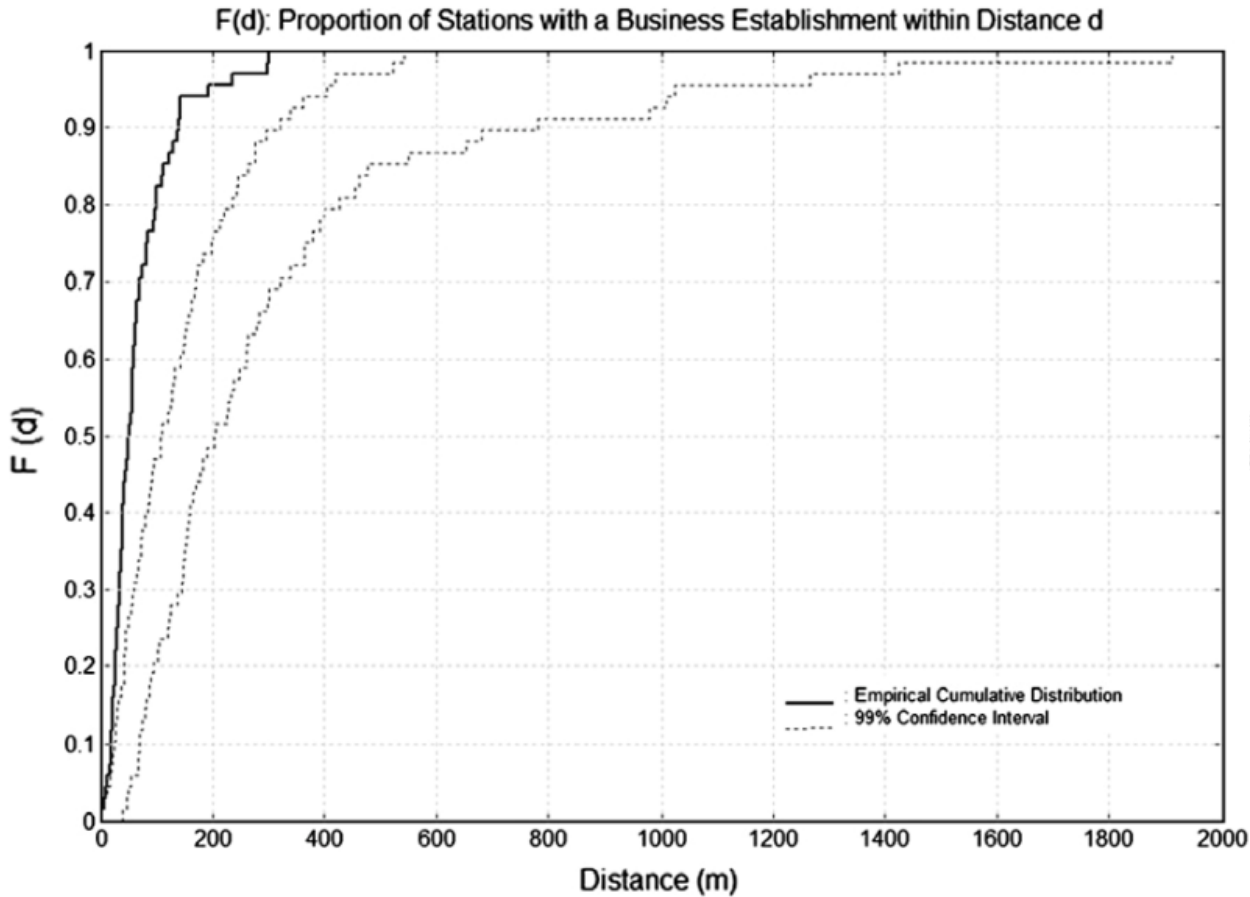




點空間型態 綜合演練

空間分析 2019.05.06
TA 杜承軒



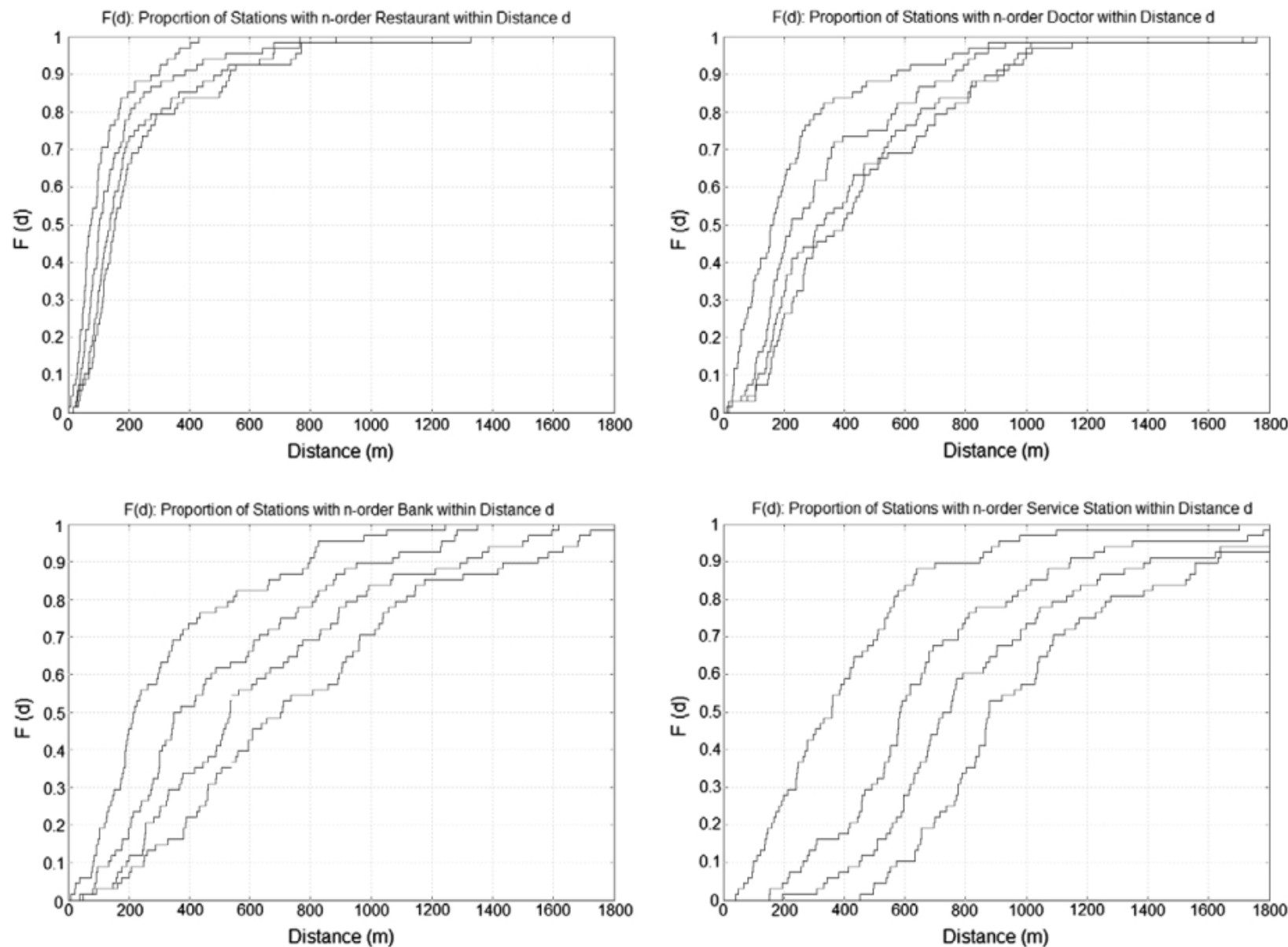


Fig. 4. Spatial clustering of selected establishment types (higher order neighbors).

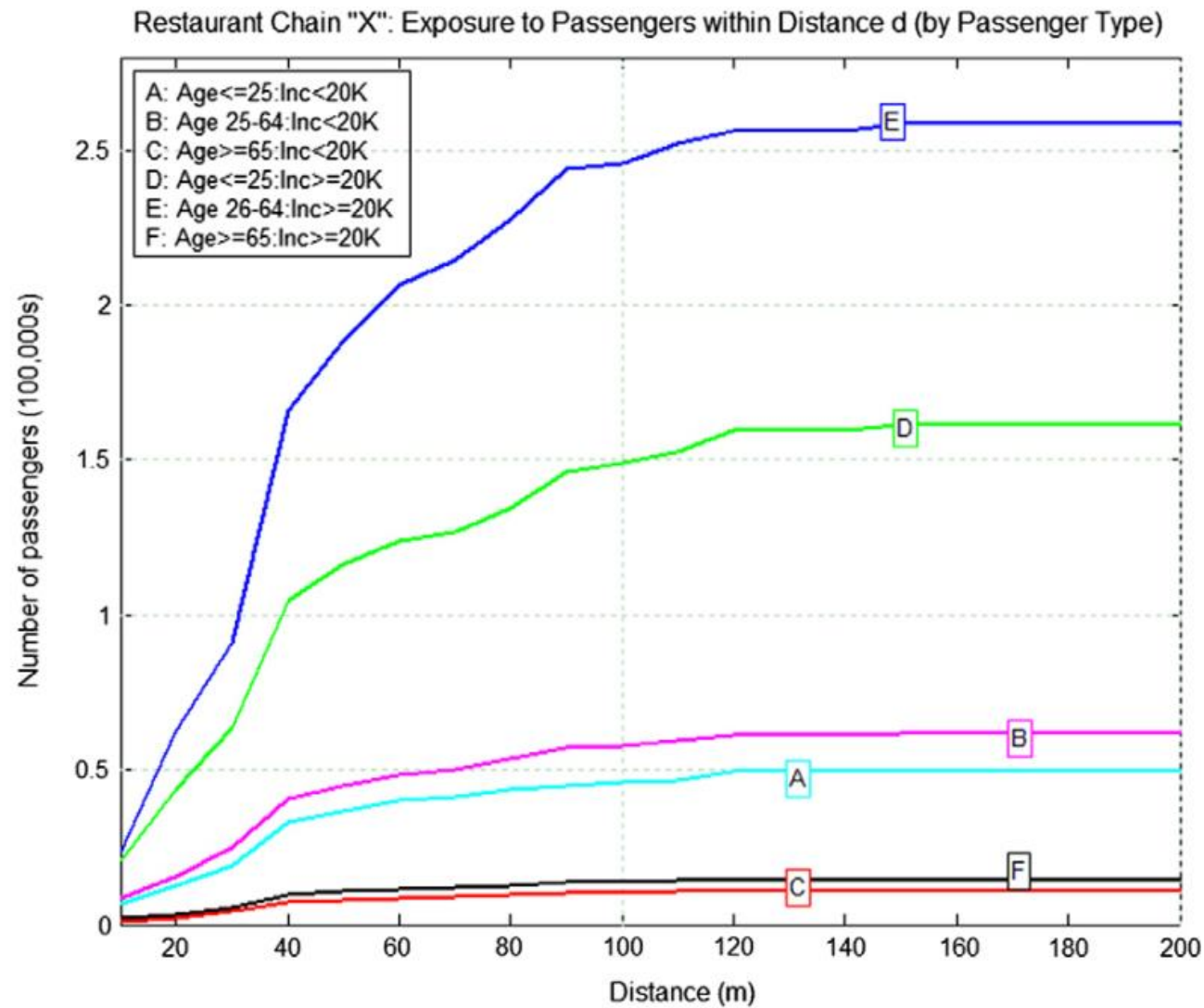
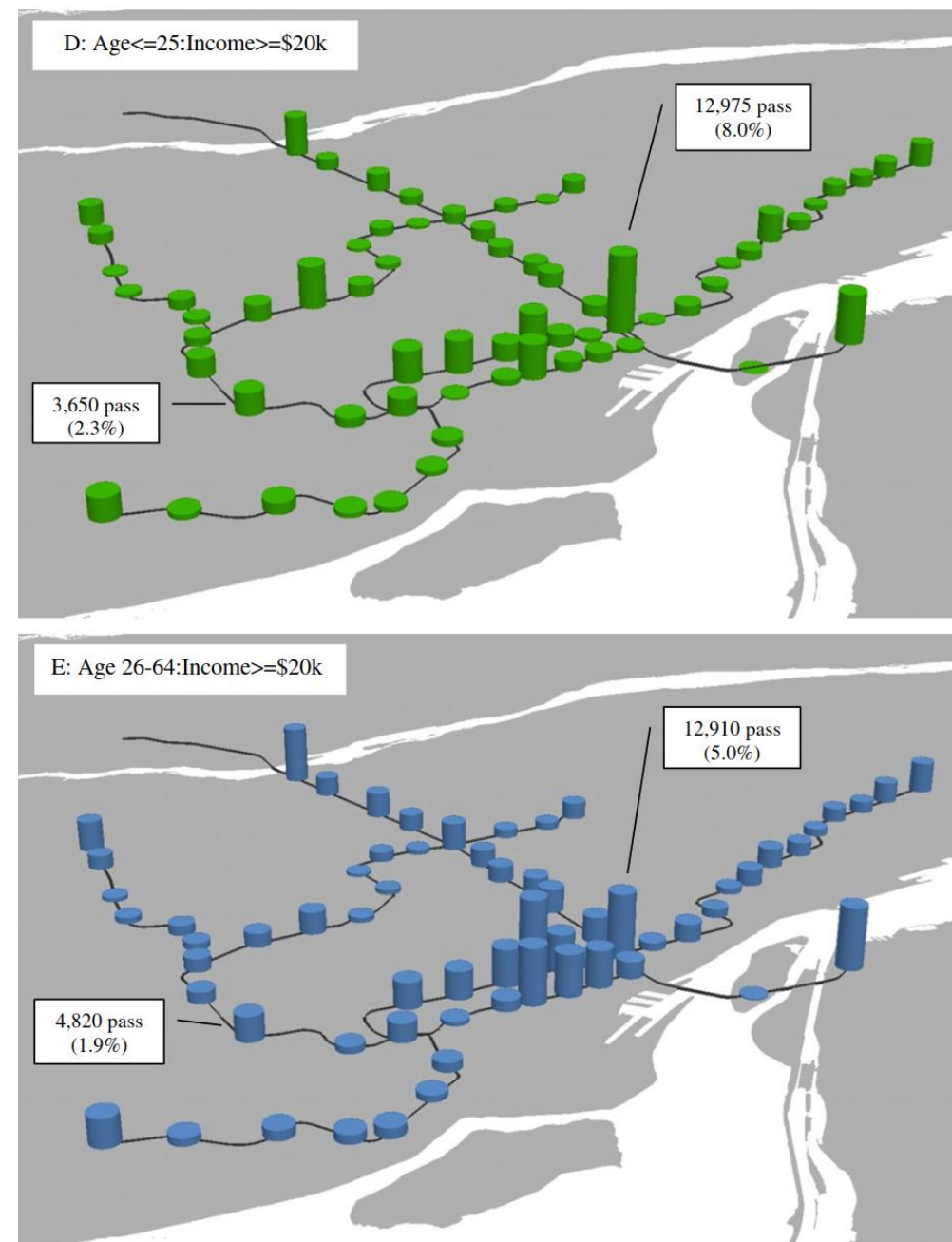


Fig. 5. Exposure of establishment of restaurant chain "X" to different passenger types by distance.



空間中的人口分析看出商業活動與交通站的聚集與吸引效應：

一、商業活動在地鐵站附近的群聚現象

二、怎樣的商業比較容易聚集在車站？

三、從人的指標評估環境，以年齡、收入做分界，看出不同的分布情形，
如收入較高的壯年可能多在市中心等等

KERNEL DENSITY ESTIMATION

Kernel density estimation is an interpolation technique that generalizes individual point locations or events, s_i , to an entire area and provides density estimates, $\lambda(s)$, at any location within the study region R . From a visual point of view it can be thought of a three-dimensional sliding kernel function $K(\bullet)$ that 'visits' every location s (see figure 1).

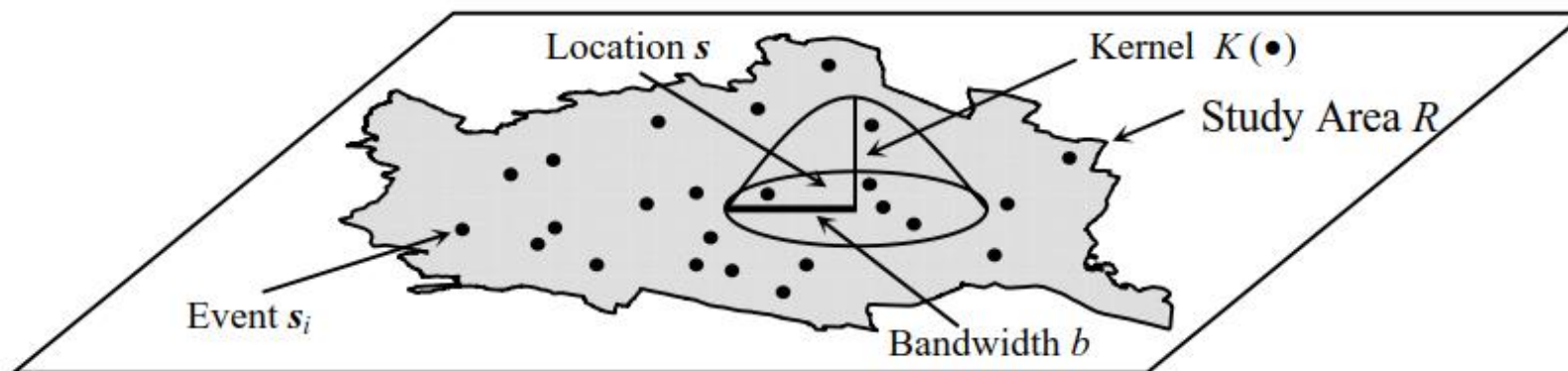


Figure 1: Kernel estimation of a point pattern (Fischer, 2001)

Before the two groups of retailers could be compared to each other, a weighting parameter was developed to assign different weights to different outlet types. The weights are based on the average gross sales per outlet based on the average sales area. It became evident, that the ratio of hypermarket : supermarket : large and small outlets equalled about 5 : 3 : 1. Thus, the outlets were weighted with this ratio for further analysis (table 1).

<i>Outlet type</i>	<i>Average gross sales per outlet [Mio €]</i>		<i>Weighting ratio (w)</i>
	<i>1998</i>	<i>2001</i>	
Hypermarkets (>1,000m ²)	11.42	11.68	5
Supermarkets (400-1,000m ²)	2.14	2.23	3
Large and small grocery outlets	0.67	0.71	1

Table 1: Average gross sales based on outlet types in the Upper Austrian market and weighting ratios (ACNielsen, 2002 and 1999, own calculations)

In addition to the average sales per outlet type, population density is also allowed for in the analysis. Therefore, the final weight parameter (W_i) has the following functional form:

$$W_i = (w) (p) \tag{7}$$

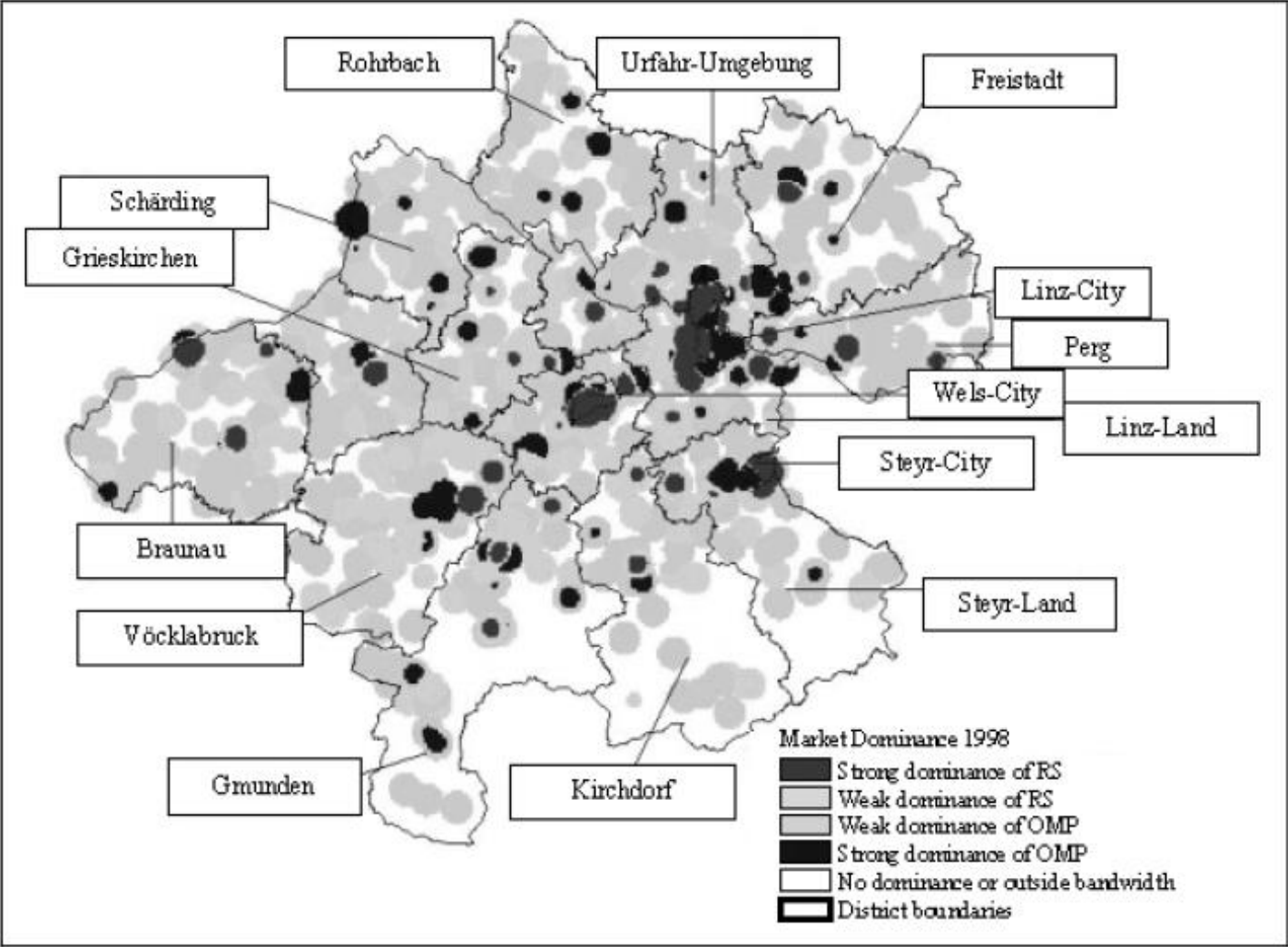


Figure 4: Market dominance in Upper Austria in 1998
(ArcAustria Data Program, WIGeoGIS Vienna, 1998)

KDE

ggtern

```
kde2d(x, y, h, n = 25, lims = c(range(x), range(y)))
```

讀檔

計算KDE

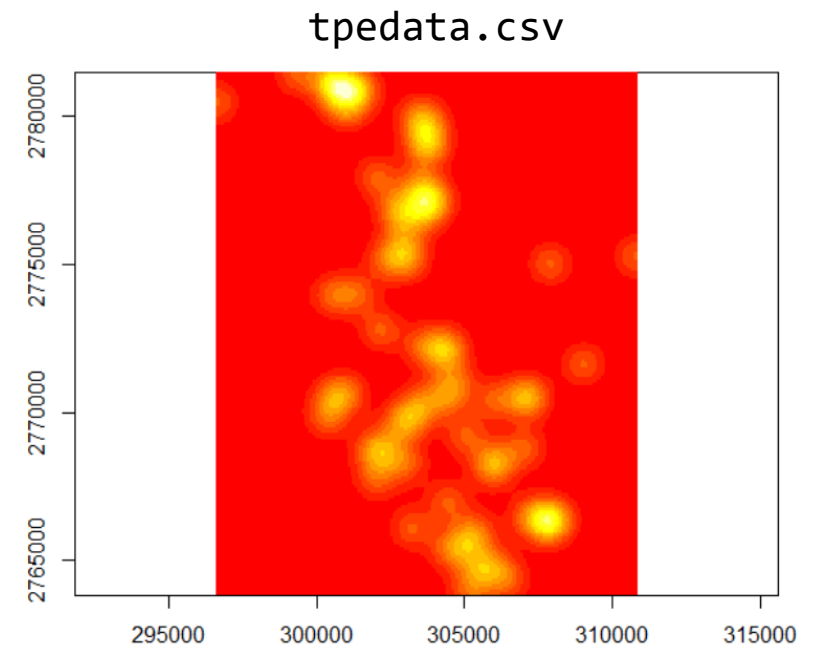
```
kde.pts = kde2d(xcoord, ycoord, 1500, 50)
```

搜尋半徑 網格數量
(單方向)

繪圖

```
image(kde.pts, asp=1) #KDE圖
```

xy比例一樣



Dual KDE

ggtern

```
kde2d(x, y, h, n = 25, lims = c(range(x), range(y)))
```

讀檔

```
TPE=readOGR(.....)
```

```
TPE_lim=c(TPE@bbox[1,], TPE@bbox[2,]) #劃定邊界
```

計算KDE

```
kde1 = kde2d(x1,y1,1000,50,TPE_lim) #確認範圍一致
```

```
kde2 = kde2d(x2,y2,1000,50,TPE_lim)
```

KDE相減

同splancs的方法

```
kde.diff = kde1  
kde.diff$z = kde1$z-kde2$z
```

繪圖

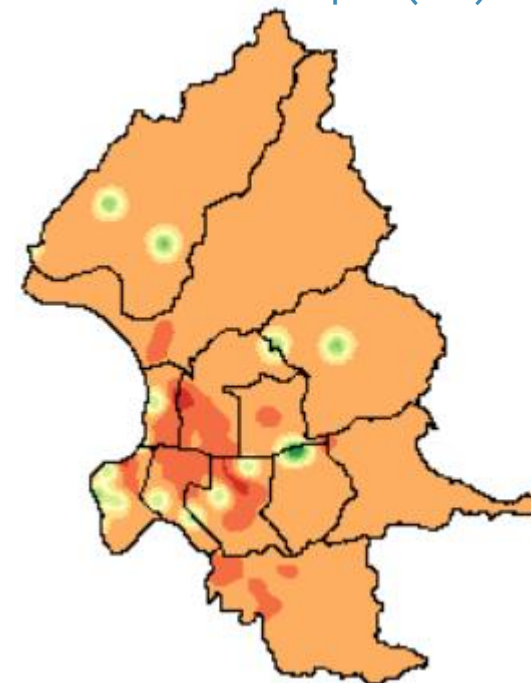
```
image(kde.pts, asp=1) #KDE圖
```

```
masker=poly.outer(as.points(TPE@bbox[1,],  
TPE@bbox[2,]),TPE) #建立遮罩
```

```
add.masking(masker, col="white") #覆蓋遮罩
```

```
plot(TPE,add=T) #加邊框
```

PT1-PT2
col=brewer.pal(.....)



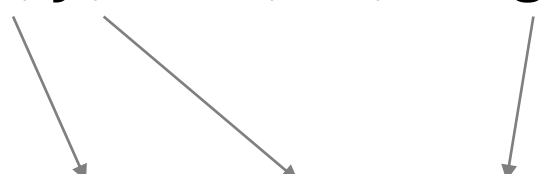
Weighted
KDE

ggtern

```
kde2d.weighted(x, y, h, n = 25, lims = c(range(x), range(y)), w)
```

計算KDE

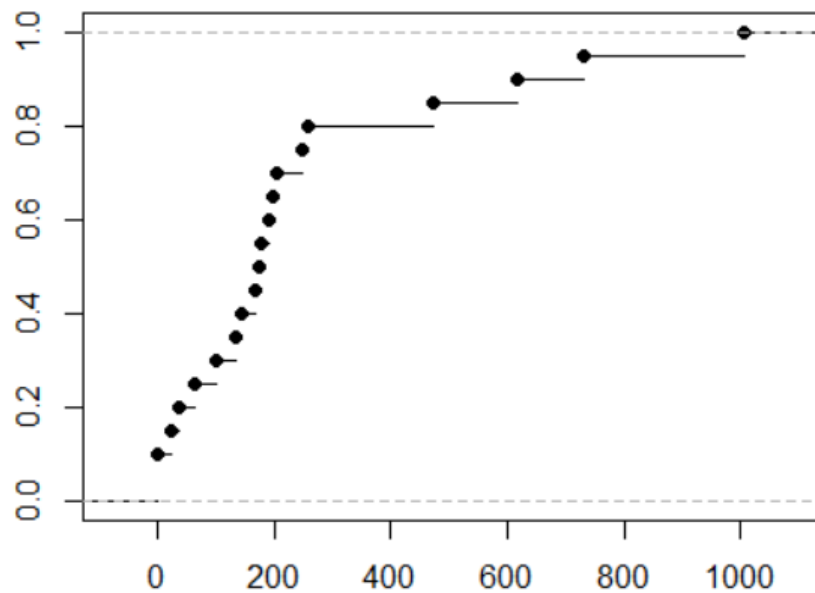
```
Kde.w = kde2d.weighted(x, y, 1000, 50, weights)
```



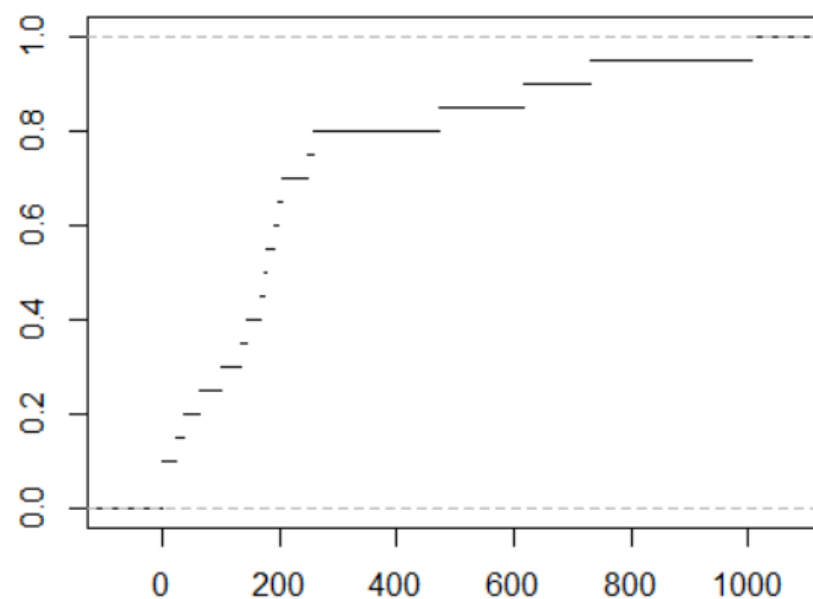
X	Y	W
301905	2779551	1.26
301692	2769025	3.25
304126	2769248	3.95
300076	2769041	5.45
306460	2775395	1.63
303025	2768395	3.86
299044	2768237	2.96
308974	2775350	4.23

F(d)繪圖

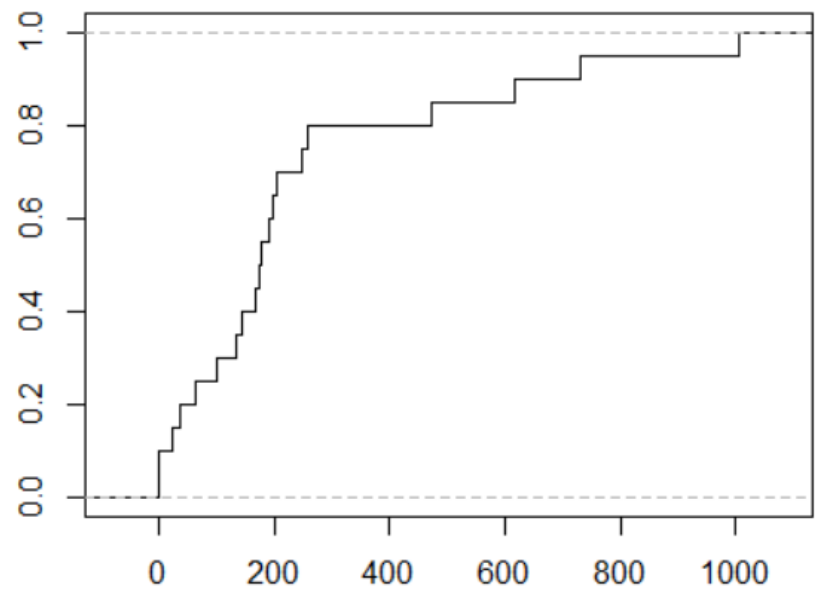
`plot(ecdf(x))`



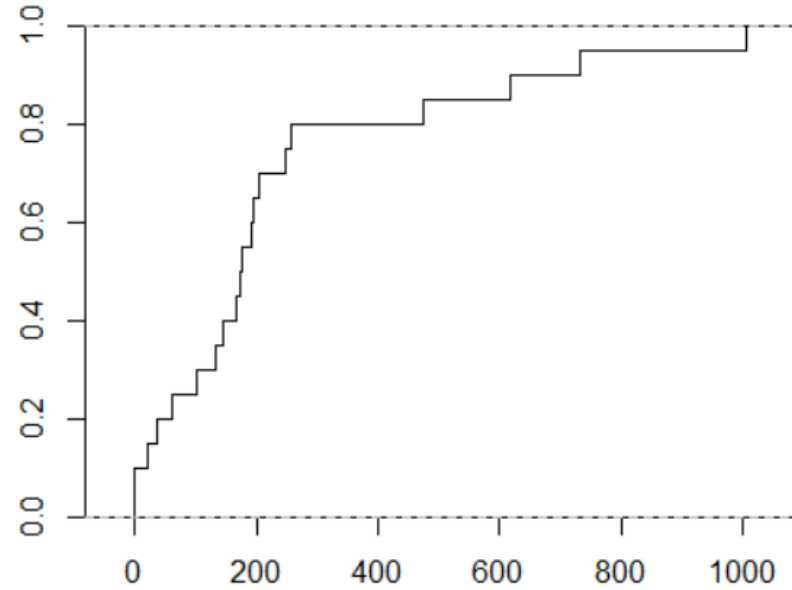
`plot(ecdf(x), cex=0)`



`plot(ecdf(x), cex=0, verticals=T)`



`plot(ecdf(x), cex=0, verticals=T, xaxs="i", yaxs="i")`



實作練習

1. (5%) 參考論文 [Reading_Dual.KDE.pdf](#), 考慮銷售等級與人口密度加權, 繪製出麥當勞(MIC)與肯德基(KFC)之間的 **Dual KDE** 地圖。
 - 參數設定：
 - 銷售等級：使用速食店資料中 **TYPE99** 欄位
 - 人口密度：利用所在**行政區的人口密度**來計算
 - 搜尋半徑：設定為 **2 公里**
2. (5%) 參考論文 [Reading_Geodemographics.pdf](#), **Figure 4** 中, 繪製出高階鄰居(higher order neighbors)的 **F** 函數。請依照此方法, 繪製出**肯德基前四鄰近的麥當勞的 F 函數**(參考以上論文, 畫在同一張圖上)。