空間分析 (Geog 2017) | 台大地理系 Spatial Analysis

點型態分析:最鄰近分析法

Point Pattern Analysis: Nearest Neighbor Analysis

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Outline

- Analyzing global point patterns: Overview
- Nearest Neighbor Analysis (NNA)
 - Test statistic: R scale
 - Statistical Significance Test
 - Comparing with theoretical random pattern
 - Monte Carlo significance test
 - K-order NNA
- G(d) Function

Point Pattern Analysis

- Analyzing Global Patterns
 - Nearest Neighbor Analysis
 - Distance-based Functions
 - Density-based Methods





(b) Dispersion/Uniform

Properties of Spatial Point Patterns

- First-order Property (measuring the intensity)
 - First order property indicates the intensity of a process, mean number of events per unit area at point p.
 - The concept is similar to the mean as the first order statistics in statistical theory.
- Second-order Property (measuring the dependency)
 - Second order property of a spatial point pattern indicates
 spatial dependency of a process, mean number of paired
 events per unit area, like between point p and q.

Nearest Neighbor Analysis (NNA)

measures the average distance from each point in the study area to **its nearest point**.

10 - 12	20	•		• ¹⁷	From	To	Distance	From	То	Distance
	Ť.				1	9	2.32	11	20	2.55
8 -	•	11	•5	• ⁶ 7	2	10	2.43	12	20	2.39
e – 15				•	3	8	0.81	13	4	1.85
•					4	19	1.56	14	13	2.67
4 -				• ²	5	6	1.05	15	12	3.58
	13	3 1	8		6	7	0.3	16	18	0.29
2 - 14	4	•8		• ¹⁰	7	6	0.3	17	9	0.37
	•				8	3	0.81	18	16	0.29
o -	•19				9	17	0.37	19	4	1.56
0 2	4	6	8		10	2	2.43	20	12	2.39

Nearest Neighbor Analysis (NNA)

 The NNA compares the average distance between nearest neighbors to that of a random pattern
 大於 隨機分布的平均距離: Dispersed
 小於 隨機分布的平均距離: Clustered

R Scale (r_{obs} / r_{exp})

• For theoretical random pattern: r_{exp} =



Theoretical Random Pattern

- Spatial analysis techniques compare observed point patterns to ones generated by an independent random process (IRP) also called complete spatial randomness (CSR). CSR/IRP satisfy two conditions:
- Any event has equal probability of being in any location, a 1st order effect.
- The location of one event is independent of the location of another event, a 2nd order effect.

Theoretical Random Pattern



Average nearest distance of theoretical random pattern

Dispersed/ uniform

The expected mean distance for a completely dispersed distribution

$$\overline{d}_{e} = \frac{1}{\sqrt{n}}$$

Divide the number of features by the area of the study area, and take the square root...then divide the result into I



IA

Random



	Nearest			Noarost			
Point	Neighbor	Distance	Point	Neighbor	Distance		F
1	2	1	1	3	2.2		
2	3	0.1	2	4	2.2		
3	2	0.1	3	4	2.2		
4	5	1	4	5	2.2		
5	4	1	5	7	2.2		
6	5	2	6	7	2.2		
7	6	2.7	7	8	2.2		
8	10	1	8	9	2.2		
9	10	1	9	10	2.2		
10	9	1	10	9	2.2		
		10.9			22		
r	1.09		r	2.2			_
Area of			Area of				Are
Region	50		Region	50			Re
Density	0.2		Density	0.2			Dei
Expected			Expected				EX
Mean	1.118034		Mean	1.118034			ivie
R	0.974926		R	1.96774			ĸ
				$\sum r$			
			\overline{r} =				
				n		_	

Nearest										
Point	Neighbor	Distance								
1	2	0.1								
2	3	0.1								
3	2	0.1								
4	5	0.1								
5	4	0.1								
6	5	0.1								
7	6	0.1								
8	9	0.1								
9	10	0.1								
10	9	0.1								
		1								
r	0.1									
Area of										
Region	50									
Density	0.2									
Expected										
Mean	1.118034									
R	0.089443									

 $R = \frac{r}{\bar{r}(e)}$

 $d = \frac{n}{area}$ $\bar{r}(e) = \frac{.5}{\sqrt{d}}$

R Scale

- R = 0 (completely clustered)
- R = 1 (random)
- R = 2.149 (completely dispersed)



Average Nearest Neighbor Distance

	D.obs	D.exp	R	Result
情境1	3.157	7.958	0.397	Cluster
情境2	40	13.5	2.424	Disperse
情境3	14.486	11.207	1.293	Random



Significance Test of NNA: 1. Comparing with Theoretical Random Pattern



Average Nearest Neighbor Distance

Significance Test of NNA



Standard Error of R-scale

- To describe the likelihood that any differences occur purely by chance
 - The calculated difference is relatively small compared to the std. error then the difference is statistically insignificant

- The Std. Error for the obs. distance
 - $SE_r = 0.26136 / \sqrt{(n^2/A)}$

$$Z_{R} = (r_{obs} - r_{exp}) / SE_{r}$$

The difference will be statistically significant if
 -1.96 < Z_R < 1.96 (for α=0.05) two tailed
 (For single tailed 1.96 will changed as 1.645)



Significance Test of NNA: 2. Monte Carlo Significance Test



- The significance of any departures from CSR can be evaluated using simulated "confidence envelopes"
- Simulate many (eg. 100) spatial point processes
- Rank all the simulations
- Pull out the 5th and 95th values
- Plot these as the 95% confidence intervals

Monte Carlo Significance Test



Average Nearest Neighbor Distance

Monte Carlo Significance Test



Why needs Higher Order NNA?





K-order Nearest Neighbor Distance



K-order Nearest Neighbor Indices: Example



K-Order Nearest Neighbor Indices

Order of Nearest Neighbor Index

研讀教科書教材 TEXT_NNA.pdf

CALCULATING THE AVERAGE DISTANCE BETWEEN FEATURES

The nearest neighbor index is based on the research of ecologists Philip Clark and Frances Evans, who developed the method in the 1950s to quantify patterns in distributions of various plant species. In this method, the GIS finds the distance between each feature and its closest neighbor, then calculates the average (or mean) of these distances.

What the nearest neighbor index measures

The nearest neighbor index measures how similar the mean distance is to the expected mean distance for a hypothetical random distribution. The index is either the difference between the two or the ratio of the observed distance divided by the expected distance.

Calculating the observed mean distance

To get the distance from each feature to its nearest neighbor, the GIS essentially calculates the distance from each feature to all other features in the set, then finds the shortest distance, the nearest neighbor to the feature.



R Lab: Introducing spatstat package

http://spatstat.org/



Spatstat: Introducing PPP format

schools_sf <- st_read("Schools.shp")</pre>

```
bnd <- st_bbox(schools_sf)
```

> DHuk-St		15_517	
> bnd			
xmin	ymin	xmax	ymax
155883.0	2535016.0	207754.2	2588604.0

x.coor <- schools_sf\$X_coor y.coor <- schools_sf\$Y_coor x.range <- c(bnd[1],bnd[3]) y.range <- c(bnd[2],bnd[4]) schools_pp1 <- ppp(x.coor, y.coor, x.range, y.range)</pre>

schools_pp1



Spatstat: Introducing PPP format (2)

schools_sf <- st_read("Schools.shp")
TN_BND <- st_read("TainanCounty.shp")</pre>

coord <- st_coordinates(schools_sf)
Windows <- as.owin(TN_BND)
schools_pp2 <- as.ppp(coord, Windows)</pre>

PPP format: setting the boundary coordinates of a polygon

schools_pp2



Average nearest neighbor distance --using nndist()

spatstat (version 1.64-1)

nndist: Nearest neighbour distances



Description

Computes the distance from each point to its nearest neighbour in a point pattern. Alternatively computes the distance to the second nearest neighbour, or third nearest, etc.

calculating the area
x<-x.range[2]-x.range[1]
y<-y.range[2]-y.range[1]
sqr.area<- x*y</pre>

nnd<-nndist(schools_pp1, k=1) d1<-mean(nnd) # Tainan School rd<- 0.5/sqrt(424/sqr.area) # theoretical random pattern r.scale <- d1/rd

R code: K-order Nearest Neighbor Distance

nndist(schools_pp1, k=1:20)

		> nndis	t(schools_pp	1, k=1:20)			
			dist.1	dist.2	dist.3	dist.4	dist.5
	(- [1,]	3293.07708	3906.5673	4060.5085	4248.9399	5542.0873
		[2,]	668.73292	2118.0747	2905.5489	3127.5107	3195.0453
		[3,]	327.91614	362.3026	914.1177	1146.8717	1333.7450
		[4,]	139.67384	306.3700	982.9686	984.7296	1329.9439
		[5,]	139.67384	176.0771	865.0065	961.6888	1466.0069
		[6,]	176.07710	306.3700	690.3840	1042.5882	1317.7148
		[7,]	666.12329	690.3840	865.0065	982.9686	1518.2910
		[8,]	1562.80945	1762.7531	1795.1202	2195.3224	2959.6642
Schoolid	J	[9,]	756.48794	1028.4560	1287.6734	1462.6867	1504.4356
Schoolid	J	[10,]	673.42023	849.8465	997.4824	1028.4560	1322.5454
		[11,]	211.31029	1504.4356	1544.2539	1953.0921	2064.9741
		[12,]	240.39489	1795.1202	1922.6266	2634.6808	2710.5818
		[13,]	240.39489	1562.8095	2095.2726	2657.0145	2735.3344
		[14,]	246.63068	464.6477	978.4555	1100.1906	1333.7450
		[15,]	246.63068	678.1678	1220.2986	1324.5051	1572.0850
		[16,]	54.12947	1925.9305	2217.4034	2273.8727	2284.3634
		[17,]	54.12947	1978.5555	2166.0443	2225.3922	2327.4399
		- [18,]	1146.87169	1183.3835	1400.9277	1660.7438	1854.3505
							ノ
					\neg		
					k-orde	ſ	

The Second-order Property: Distance-based Methods

- Nearest Neighbor Analysis (NNA)
- G Function: G(d)
- F Function: F(d)
- Ripley's K Functions: K (d) and L(d)



G Function: **G**(d)

The G function is defined as the cumulative frequency distribution of the nearest-neighbor distances

$$G(d) = \frac{\#(d_{\min}(\mathbf{x}_i) < d)}{n}$$

G(d) gives the proportion (since the count is divided by n) of nearest-neighbor distances that are less than distance d.





		Nearest					
Event	Х	У	neighbor	r _{min}			
1	66.22	32.54	10	25.59			
2	22.52	22.39	4	15.64			
3	31.01	81.21	5	21.14			
4	9.47	31.02	8	24.81			
5	30.78	60.10	3	9.00			
6	75.21	58.93	10	21.14			
7	79.26	7.68	12	21.94			
8	8.23	39.93	4	9.00			
9	98.73	42.53	6	21.94			
10	89.78	42.53	6	21.94			
11	65.19	92.08	6	34.63			
12	54.46	8.48	7	24.81			

計算範例:產生 G Function, G(r)

			Nearest									
Event	х	у	neighbor	r _{min}								
1	66.22	32.54	10	25.59	1							
2	22.52	22.39	4	15.64								
3	31.01	81.21	5	21.14	0.75							
4	9.47	31.02	8	24.81								
5	30.78	60.10	3	9.00	•							
6	75.21	58.93	10	21.14	U.5							
7	79.26	7.68	12	21.94								
8	8.23	39.93	4	9.00	0.25							
9	98.73	42.53	6	21.94								
10	89.78	42.53	6	21.94	0							
11	65.19	92.08	6	34.63	0							
12	54.46	8.48	7	24.81		0	9	15	22	25	26	35
								Dis	tance	e (r)		

- The shape of G-function tells us the way the events are spaced in a point pattern
- Clustered : G increases rapidly at short distance
- Uniform : G increases slowly up to distance where most events spaced, then increases rapidly







R code: G(d) Function

```
nnd<-nndist(School.ppp, k=1)
G = ecdf(nnd)
plot(G, main="G function", xlim=c(0,5000))</pre>
```

TN.Windows<-owin(xrange=x.range, yrange=y.range)
nn1<-rpoint(424, win=TN.Windows)
plot(nn1)</pre>

```
nnd1<-nndist(nn1, k=1)
G1 = ecdf(nnd1)
lines(G1,col='blue')</pre>
```



How do we examine significance ? Significant departure from Complete Spatial Randomness (CSR)

- The significance of any departures from CSR (either
 - clustering or uniform) can be evaluated using simulated "confidence envelopes"
- Simulate many (eg. 1000) spatial point processes and estimate the G function for each of these
- Rank all the simulations
- Pull out the 5th and 95th G(r) values
- Plot these as the 90% confidence intervals



R Lab: Generating Random Points: rpoint()

TN.Windows<-owin(xrange=x.range, yrange=y.range)
nn1<-rpoint(424, win=TN.Windows)</pre>

nn2<- rpoint(415, win = PTS_bnd)
plot(nn2, pch=16)</pre>

nn2



nn1



顯著性檢定的圖示

單尾檢定 (one-tailed test)

H0: G(r) <= Gr(r) of random 95th percentile

H1: G(r) > Gr(r) of random 95th percentile

If reject H0, it can conclude that

It shows a **statistically significant clustering** pattern (p-value < 0.05)





r

本週實習: Analysis of Nearest-Neighbor Distances

- 圖資:
 - □ 台南市學校 schools.shp
 - □ 台南市邊界 TainanCounty.shp
- 分析方法:
 - (以行政區範圍為研究區邊界)
 - 1. Nearest Neighbor Analysis
 - 2. K-order Nearest Neighbor Indices
 - G 3. G Function
 - 用Monte Carlo Simulation檢定統計顯著性



School.ppp2





K-order Nearest Neighbor Distances

Nearest Neighbor Analysis

Monte Carlo Significance Test





G Function



實習教學影片、簡報檔與程式碼

https://wenlab501.github.io/GEOG2017/



本週作業

利用課堂提供的資料,利用Nearest-Neighbor Distances,
 比較任兩個縣市信仰「觀音菩薩」的村落型祭祀圈的寺廟
 空間群聚特性,並討論之。(包括: Nearest Neighbor Analysis,
 K-order Nearest Neighbor Distances(or Indices), and G(d) Function)

參考答案:台北市 vs.台南市

Nearest Neighbor Analysis



K-order Nearest Neighbor Distances





參考答案:台北市 vs.台南市

G(d) Function



Comparison: Monte Carlo Simulation of G function Taipei and Tainan

