SPATIAL ECONOMETRICS

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Overview

- I. Introduction
- II. Data description
- III. Exploratory Analysis
- IV. Modeling
- V. Prediction
- VI. Conclusion

Objective

- ♦ Find the determinants of home to work commuting in Toulouse
- ♦ Spatial data analysis
- ♦ Fitting models
 - Simple OLS model without adjustment
 - OLS model with adjustment
 - Lag model with adjustment
 - Durbin model with adjustment
- **♦** Prediction

Data Description

Original Data Set

- **★ Xfile:** Explanatory Variables
- ♦ District: (.shp) Geographic variables
- **♦ Flux:** (.txt) Target Variable
 - 0's added to missing flows

Data we created:

- **★ Xo**: origin characteristics data (3600*3600)
- **★ Xd**: destination characteristics data (3600*3600)
- * Xo_intra, Xd_intra: internal flows for origin and destination
- * Xo_inter, Xd_inter: interregional flows for origin and destination

Data Analysis

♦ Xo: explanatory characteristics in origin

60 times

	name_district	ID_district	labour_force	activity_rate	employment	unemployment_rate	housing_units	origin	destination	flow
- 1	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	1	336
2	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	2	72
3	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	3	108
4	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	4	56
5	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	5	40
6	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	6	16
7	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	7	12
8	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	8	60
9	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	9	20
10	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	10	32
-11	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	11	52
12	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	12	8

Data Analysis

→ Xd: explanatory characteristics in destination

$$(1,2,\ldots,60),(1,2,\ldots,60)\ldots(1,2,\ldots60)$$

60 times

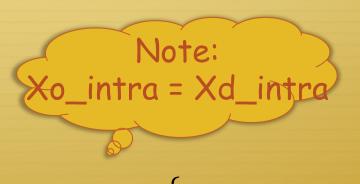
	name_district	ID_district	labour_force	activity_rate	employment	unemployment_rate	housing_units	origin	destination	flow
1	CAPITOLE	1	2364	43.10722101	1928	18.44331641	4588	1	1	336
2	ARNAUD-BERNARD	2	2936	37.97206415	2328	20.70844687	5664	1	2	72
3	SAINT-GEORGES	3	1464	41.30925508	1256	13.93442623	2964	1	3	108
4	SAINT-ETIENNE	4	2054	49.24478542	1713	16.21226874	2978	1	4	56
5	CARMES	5	2504	50.08	2126	14.89616613	3976	1	5	40
6	SAINT-CYPRIEN	6	1924	50.10416667	1536	19.75051975	2940	1	6	16
7	AMIDONNIERS	7	2288	41.66059723	1984	13.11188811	3612	1	7	12
8	COMPANS	8	2940	48.0706344	2452	16.05442177	4884	1	8	60
9	LES-CHALETS	9	3560	51.47484095	2896	18.08988764	5444	1	9	20
10	MATABIAU	10	3892	52.88043478	3152	18.80781089	6376	1	10	32
11	SAINT-AUBIN-DUPUY	11	4052	52.40558717	3236	19.84205331	6436	1	11	52
12	LE-BUSCA	12	4076	52.68872802	3472	14.62217861	5632	1	12	8

Data Analysis

- Characteristics of Internal Flows: Xo_intra, Xd_intra
- ♦ Characteristics of Interregional Flows: Xo_inter, Xd_inter

inter

	X _{o/d} _intra	Л	$X_{o/d}$
1→1	$\begin{bmatrix} x_{1,1} \end{bmatrix}$		
$1 \rightarrow 2$	0		λ
:	:		:
$2 \rightarrow 1$	0		λ
$2 \rightarrow 2$	$x_{2,2}$		C
$2 \rightarrow 3$	0		λ
:	:		:
:	:		
60 → 60	$\left[\begin{array}{c} x_{60,60} \end{array}\right]$		



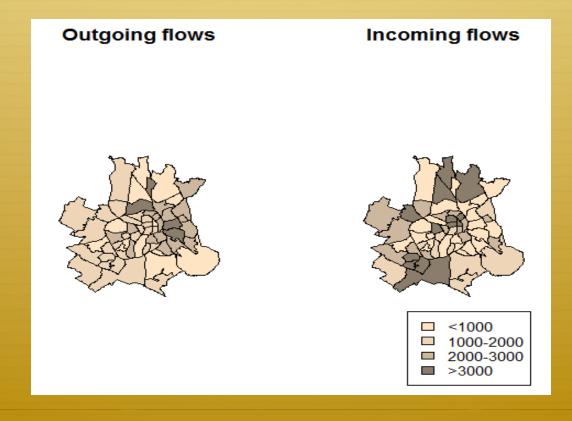
$$X_{i,j} = \begin{cases} X_{ij} & \text{If } i=j \\ 0 & \text{otherwise} \end{cases}$$

$$X_{i,j} = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{otherwise} \end{cases}$$

$$X_{i,j} = \begin{cases} 0 & \text{if } i=j \\ 0 & \text{otherwise} \end{cases}$$

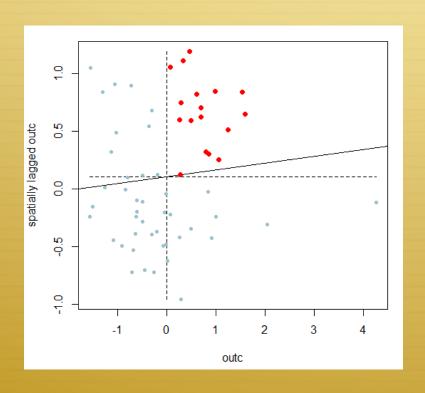
Outgoing Flow & Incoming Flow

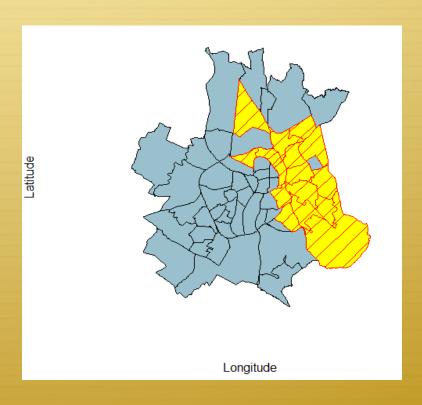
- Outgoing Flow: sum of the flows go to different destination for each origin
- ♦ Incoming Flow: sum of the flows from different origin for each destination



Exploratory Analysis - FLOWS

♦ Moran plot for outgoing flows

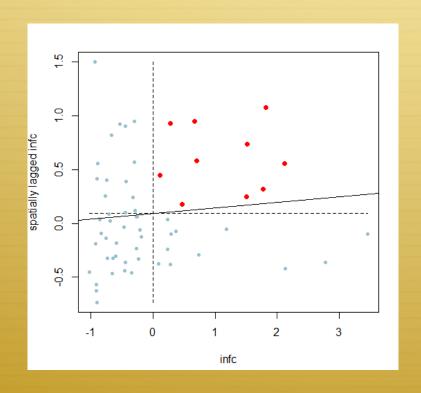


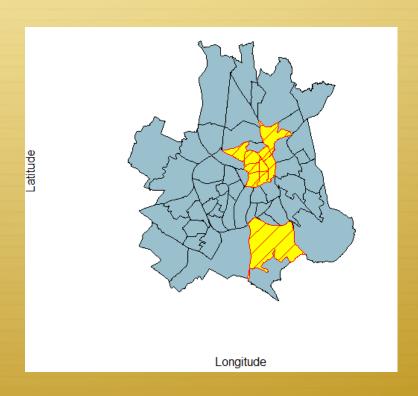


For regions with high outgoing flows, neighbours also have high outgoing flows!

Exploratory Analysis - FLOWS

♦ Moran plot for incoming flows

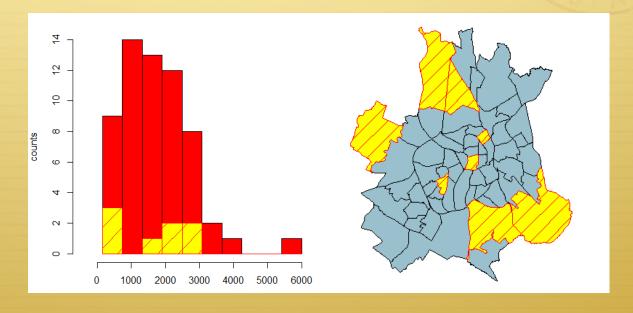




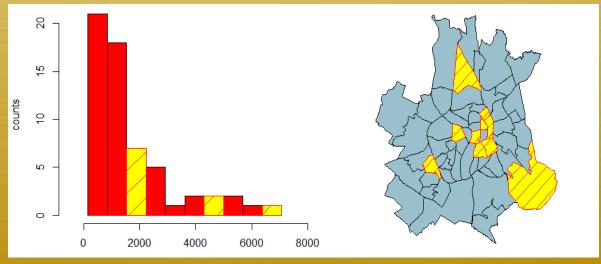
For regions with high incoming flows, neighbours also have high incoming flows!

Exploratory Analysis - FLOWS

Outgoing flows

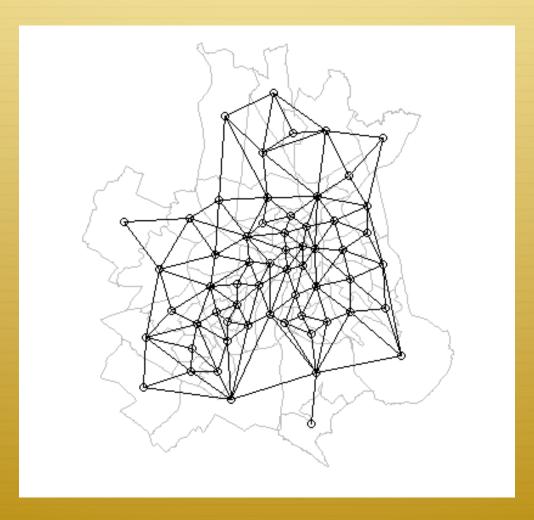


Incoming flows



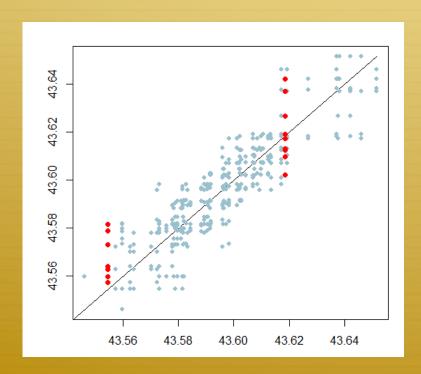
Exploratory Analysis – Weight Matrix

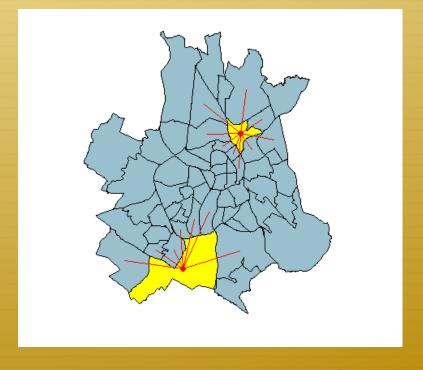
♦ Weight matrix constructed using common border method



Exploratory Analysis – Weight Matrix

- ♦ Point selected on map
- ♦ Number of neighbours marked on the graph by
- ♦ Variable : Latitude





Modeling

♦ Simple OLS model without adjustment (OLS)

$$Y = X_o \beta_o + X_d \beta_d + \varepsilon$$

♦ OLS model with adjustment (OLS_a)

$$Y = X_o \beta_o + X_d \beta_d + X_{\text{int}ra} \beta_{\text{int}ra} + \varepsilon$$

$$Y = \rho WY + X_o \beta_o + X_d \beta_d + X_{intra} \beta_{intra} + \varepsilon$$

Durbin model with adjustment (Durbin_a)

$$Y = \rho WY + (X_o + X_d + X_{\text{int}ra})\beta + \delta W(X_o + X_d + X_{\text{int}ra}) + \varepsilon$$

NOTE:
$$W = Wo + Wd = w \otimes I_{60} + I_{60} \otimes w$$

w = common boarder neighborhood matrix (60*60)

Results: OLS model V.S. OLS with adjustment

	Model: OLS		Model:OLS_a	
	estimate	p-value	estimate	p-value
intercept	1. 2700	0. 501555	1. 2093	0. 427134
dist	-608. 6000	< 2e-16 ***	-336. 4124	< 2e-16 ***
acro	0. 9775	< 2e-16 ***	0. 8142	< 2e-16 ***
lfd	0. 0302	0.000129 ***	0. 0279	1.37e-05 ***
acrd	0. 8526	6.37e-13 ***	0. 7141	1.15e-13 ***
unempd	-2. 4800	8. 48e-16 ***	-0.0520	3.41e-10 ***
hd	0.0118	< 2e-16 ***	-2. 2621	< 2e-16 ***
empd	-0.0533	1.63e-07 ***	0. 0120	< 2e-16 ***
l_o_intra	-	-	-0. 1388	0.001295 **
acr_o_intra	-	-	-1.6040	0.002999 **
em_o_intra	-	-	0. 2082	0.000243 ***
unem_o_intra	-	-	2. 0153	0. 212075
hou_o_intra	-	-	0. 0330	2.97e-07 ***
AIC	37584. 53		36029.68	

Effects of

- distance decrease
- employment rate of destination become positive
- house unit of destination become positive

AIC decrease:

model fit better

Procedure:

- ✓ OLS model with all the origin and destination explanatory variables
- ✓ Eliminate the non significant variables → OLS model above
 - Origin variables: activity rate
 - Destination variables: labor force, activity rate, employment, unemployment rate, house unit
- ✓ Add internal flows' characteristics for the significant variables (variables with intra) → OLS_a model above

Results: Lag Model and Durbin Model

♦ Why use lag model and durbin model?

Spatial autocorrelation check:

→ Moran Test on the residual of traditional gravity model (OLS_a)

P-value is very small:

- → Reject the H0: no spatial autocorrelation
- → The residuals has spatial autocorrelation
- → Use lag model or durbin model

Results: OLS model V.S. Lag Model

	Model:OLS_a		Model:LAG_a	
	estimate	p-value	estimate	p-value
intercept	1. 2093	0. 427134	-9. 5987	<2e-15 ***
dist	-336. 4124	< 2e-16 ***	45. 6277	0. 0700
acro	0.8142	< 2e-16 ***	0. 2384	0.0001 ***
1fd	0.0279	1.37e-05 ***	0. 0091	0. 0750
acrd	0.7141	1.15e-13 ***	0. 2251	0.0032 **
empd	0.0120	< 2e-16 ***	-0.0191	0.0036 **
unempd	-0.0520	3.41e-10 ***	-0. 7655	0.0001 ***
hd	-2. 2621	< 2e-16 ***	0. 0052	<1e-11 ***
l_o_intra	-0. 1388	0.001295 **	-0. 1424	<2e-5 ***
acr_o_intra	-1.6040	0.002999 **	-1. 4310	0.0008 ***
em_o_intra	0. 2082	0.000243 ***	0. 2112	<2e-6 ***
unem_o_intra	2. 0153	0. 212075	2. 5190	0.0484 *
hou_o_intra	0.0330	2.97e-07 ***	0. 0293	<8e-9 ***
rho			0. 38876	<2.22e-16 ***
AIC	36029.68		34590.06	

- Effects of distance and labor force of destination become not significant
- Rho is significant, which means there exits an autocorrelation of the flows
- AIC decreases a lot, model fits much better

Results: Durbin Model

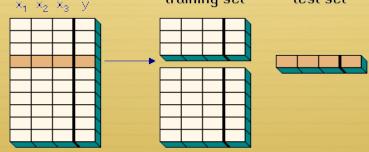
	Model:OLS_a			Model:OLS_a	
	estimate	p-value		estimate	p-value
intercept	-16. 5511	<2e-8 ***			
dist	-16. 2945	0. 5418			
acro	0. 1214	0. 1936	acro_lag	0. 0511	0. 4539
lfd	0. 0243	0.0066 **	lfd_lag	-0.0285	0.0002 ***
acrd	0. 4343	0.0007 ***	acrd_lag	-0. 2112	0. 0497 .
empd	-0.0429	0.0002 ***	empd_lag	0. 0399	<0.0000 ***
unempd	-1.3083	0.0001 ***	unempd_lag	1. 0380	0.0004 ***
hd	0.0104	<2e-13 ***	hd_lag	-0.0050	<0.0000 ***
l_o_intra	-0. 1351	<0.0000 ***	l_o_intra_lag	0. 2425	<0.0000 ***
acr_o_intra	-1.4861	<0.0003 ***	acr_o_intra_lag	2. 0040	0.0014 **
em_o_intra	0. 2010	<0.0000 ***	em_o_intra_lag	-0. 2994	<0.0000 ***
unem_o_intra	2. 3885	0.0471 .	unem_o_intra_lag	-7. 1636	0.0001 ***
hou_o_intra	0. 0290	<0.0000 ***	hou_o_intra_lag	-0.0103	0. 1104
rho	0. 38876	< 2.22e-16 ***			
AIC	34325.3				

- Rho is significant, the most of lag explanatory variables are significant
- AIC decreases a little bit

Prediction

Procedure:

♣ Eliminate randomly 10% of data, denote the remaining data by training set and the 10% of eliminated data by test set.
X1 X2 X3 Y
training set test set



♦ Construct model (eg, lag model) on training set

$$Y_{k}^{n.e} = \rho W^{n.e} Y_{k}^{n.e} + X_{k}^{n.e} \beta + \varepsilon$$

- \rightarrow obtain the estimated coefficients $(\hat{\beta}, \hat{\rho})$
- ♦ Predict on test set by using the coefficients we got

$$\hat{Y}_k^e = \hat{\rho} W^e Y_k^e + X_k^e \hat{\beta}$$

Evaluation of the Model

♦ Quadratic Mean Error (QME)

$$mean[(\hat{Y}_k - Y_k)^2]$$
 For k belongs to test set

♦ Relative Quadratic Error (RQE)

$$sum\left[\left(\frac{\hat{Y}_k - Y_k}{Y_k}\right)^2\right]$$
 For k belongs to test set

♦ Traditional Gravity Model V.S. Lag Model

	AIC	QME	RQE
Traditional Gravity Model	36029. 68	2266.525	3042.47
Lag Model	34590.06	2395.717	309.29

Conclusion

- ♦ Spatial Autocorrelation Present
- ♦ AIC gets lower when autocorrelation is taken into consideration
- ♣ Relative error lower in the lag model than the traditional gravity model