Social bridges in urban purchase behavior

Xiaowen Dong

MIT Media Lab

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Bruno Lepri and Alex 'Sandy' Pentland

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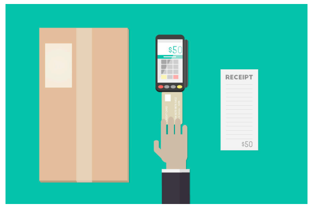
Introduction

New data sources about human behavior are emerging

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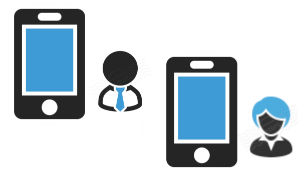
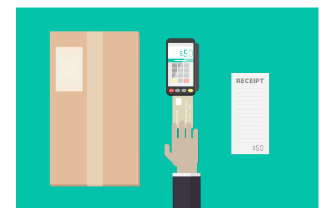
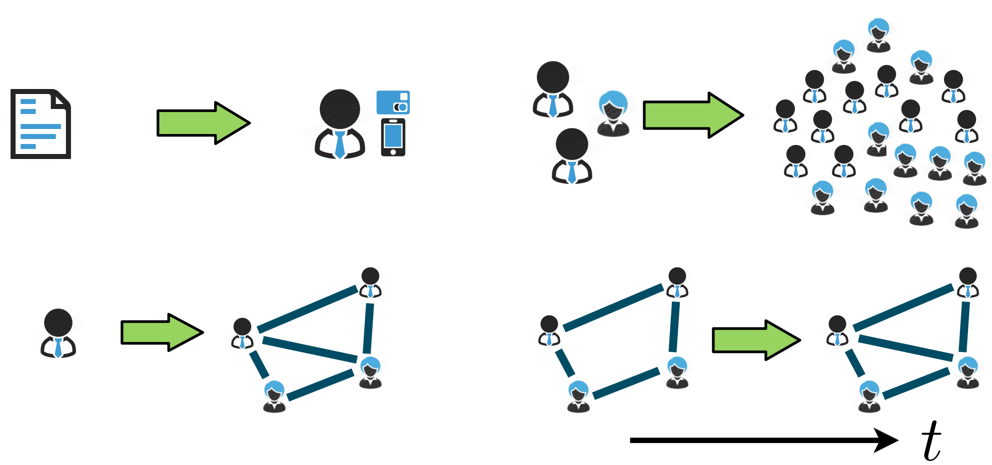



Computational social science (CSS):
A paradigm shift in social science



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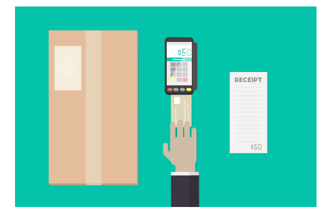

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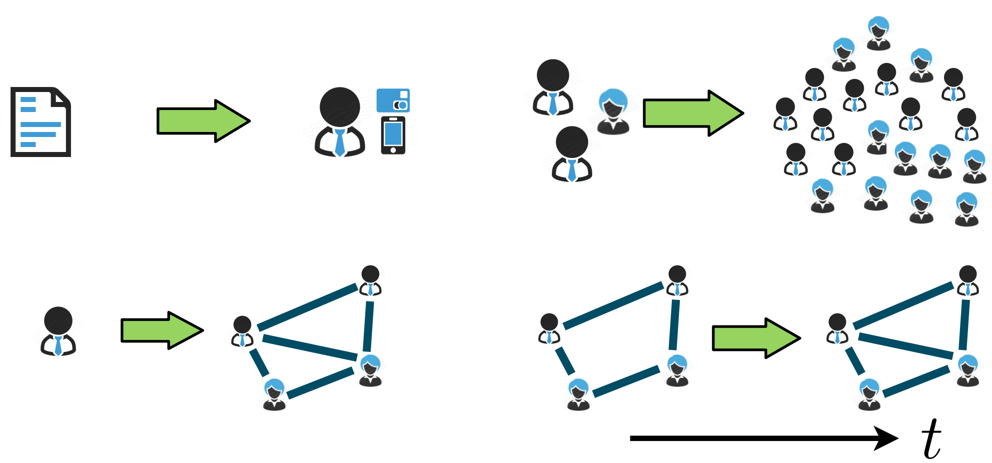

Practical impact

Current population management:

- demographics
- individual records
- static information

The new way:

- behavioral traits
- collective behavior
- dynamics

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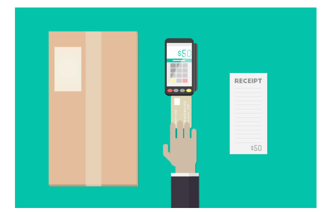

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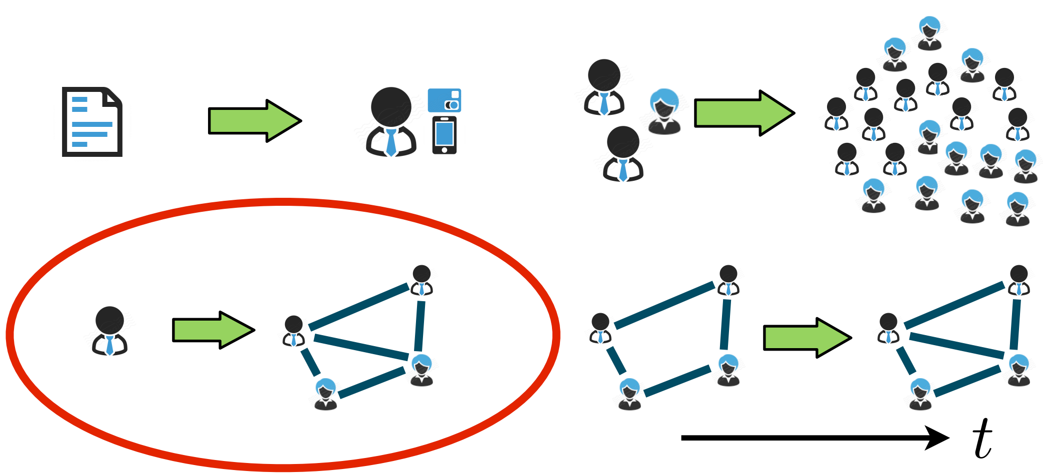

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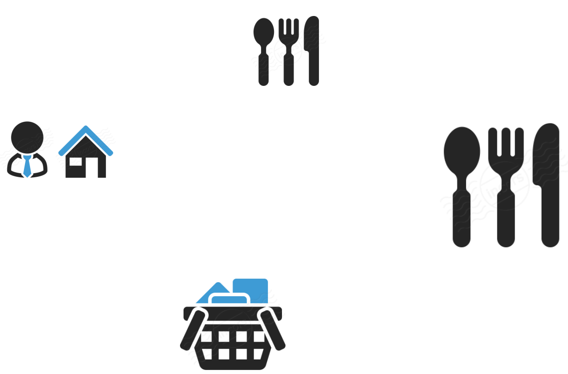
How communication affects human decision-making?

Introduction

Introduction

- Classical purchase behavior models treat individual purchases separately (Huff, 1964)



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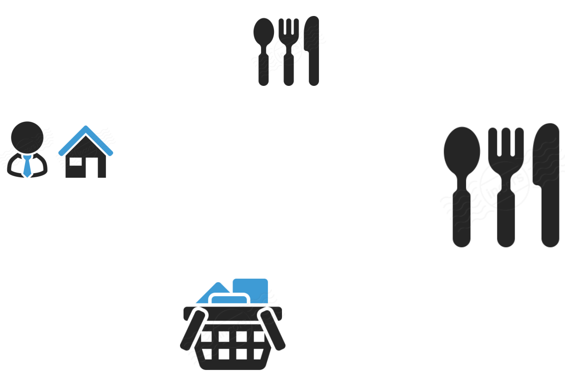

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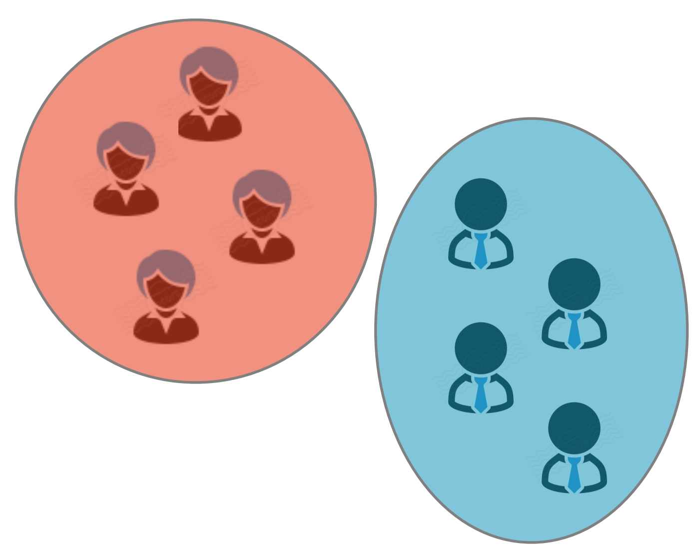
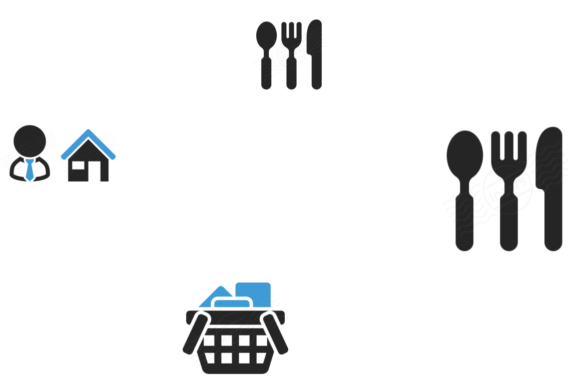


Introduction

- Classical purchase behavior models treat individual purchases separately (Huff, 1964)
- Study of purchase behavior influence is largely based on socio-demographics (Zeithaml, 1985)
- Word-of-mouth and physical exposure are powerful sources of behavioral propagation (Arndt, 1967; Bikhchandani, 1998; Algesheimer, 2005), but their effectiveness in modern city environment remains unknown



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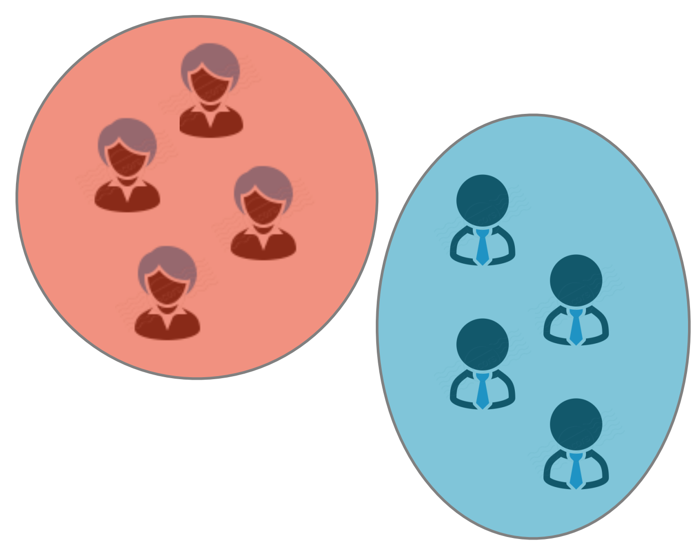
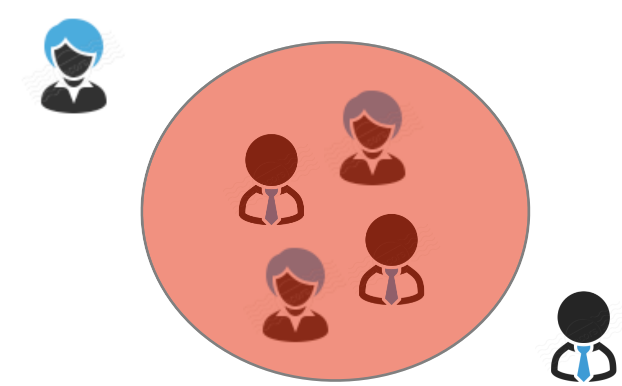
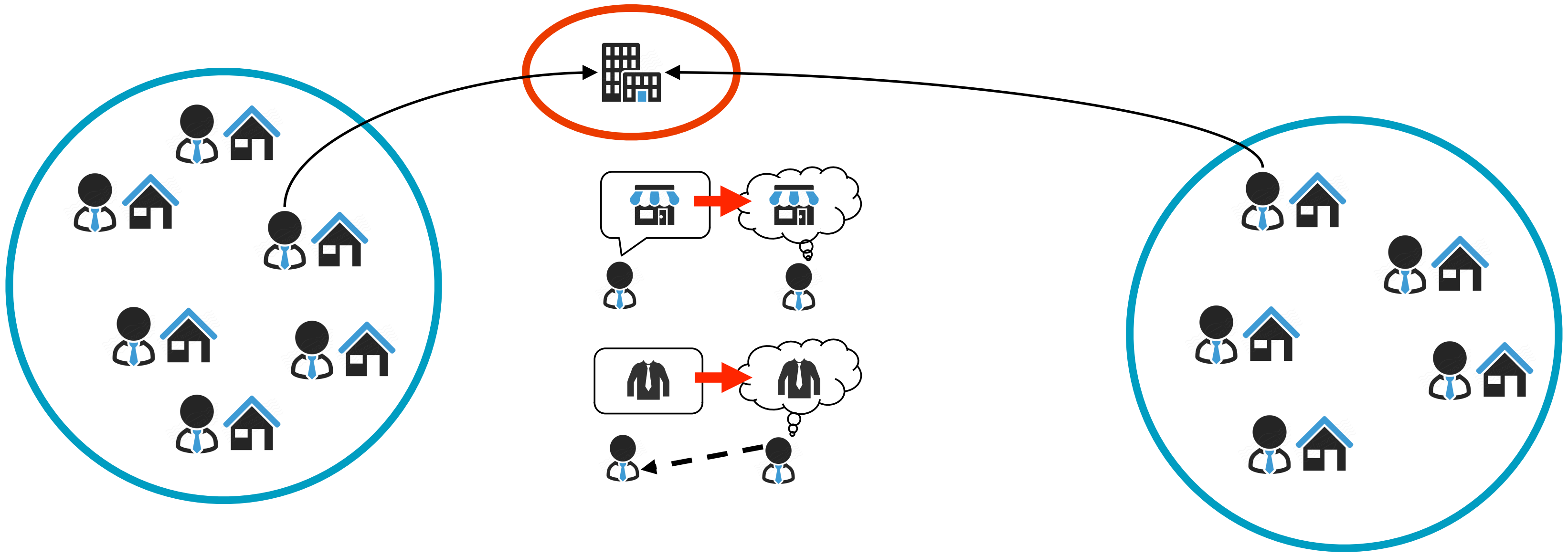




Introduction

- Hypothesis
  - Physical exposure at work environment promotes idea exchange



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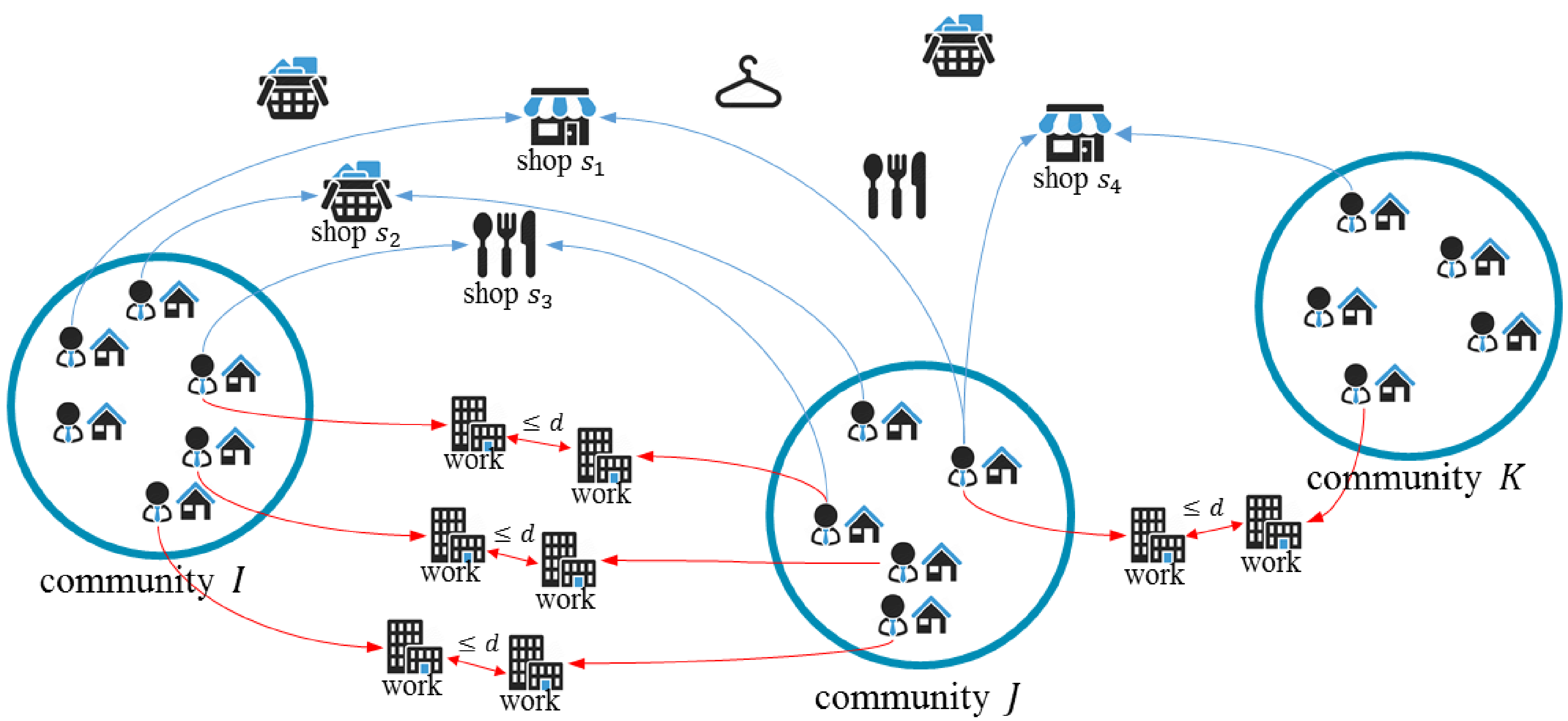
  - Physical exposure at work environment promotes idea exchange
  - Individuals living in different communities but sharing similar work locations act as social bridges between communities



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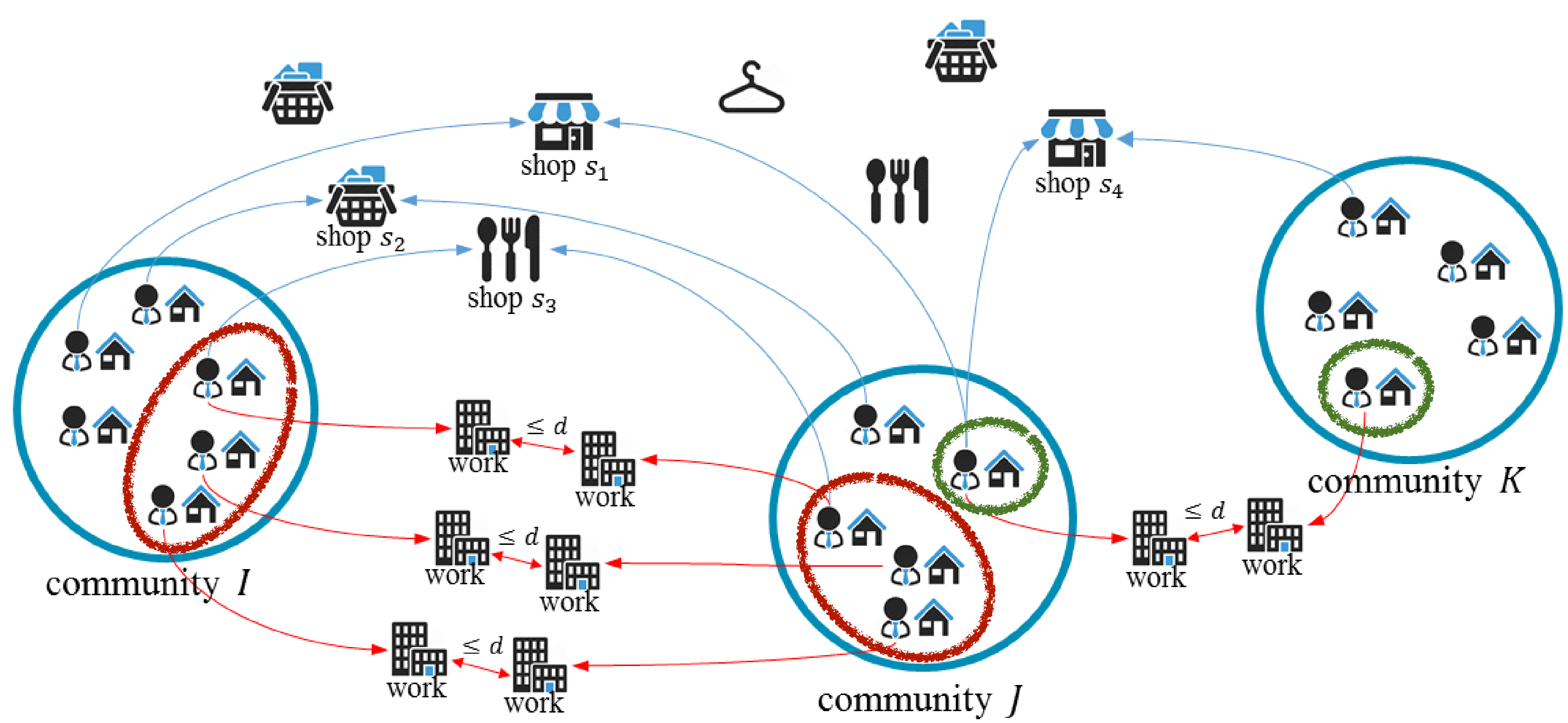

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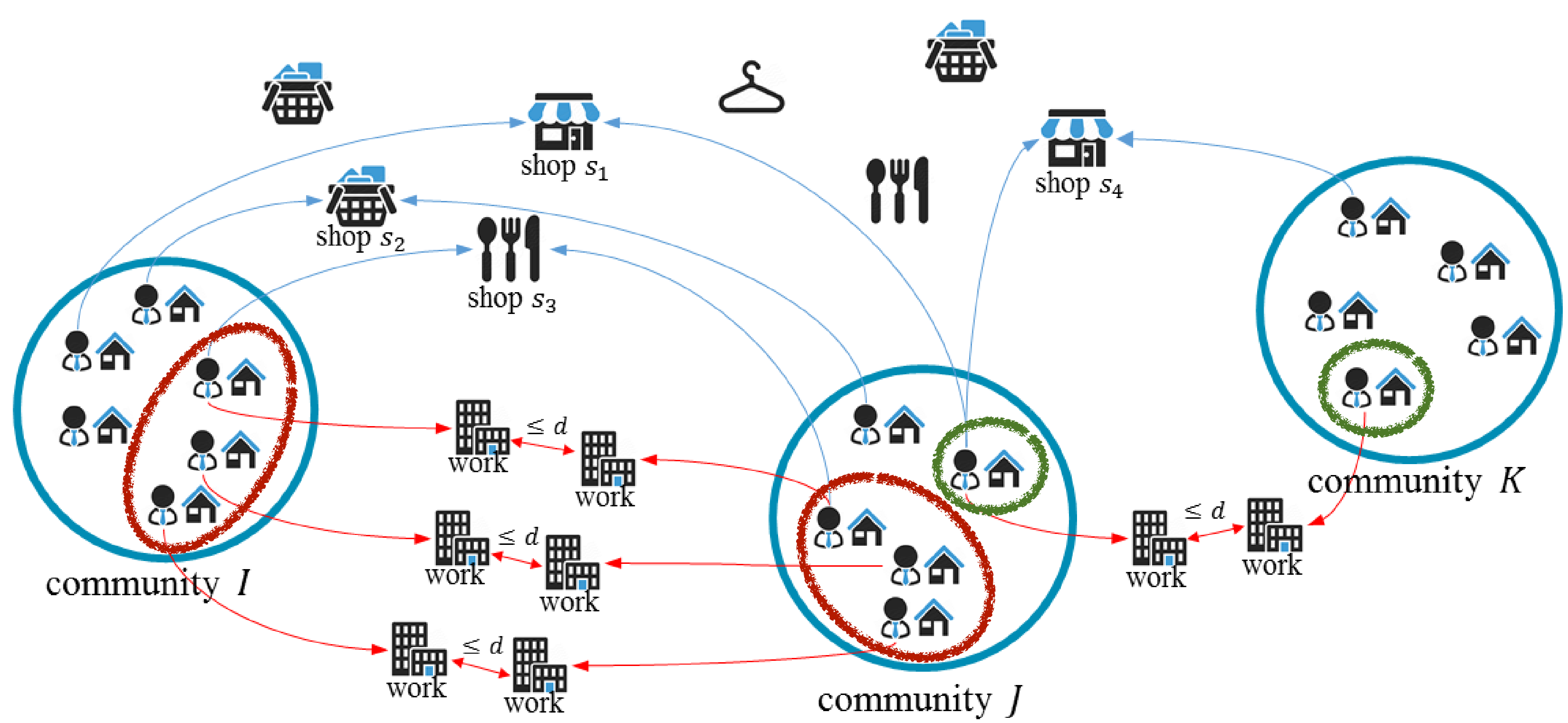
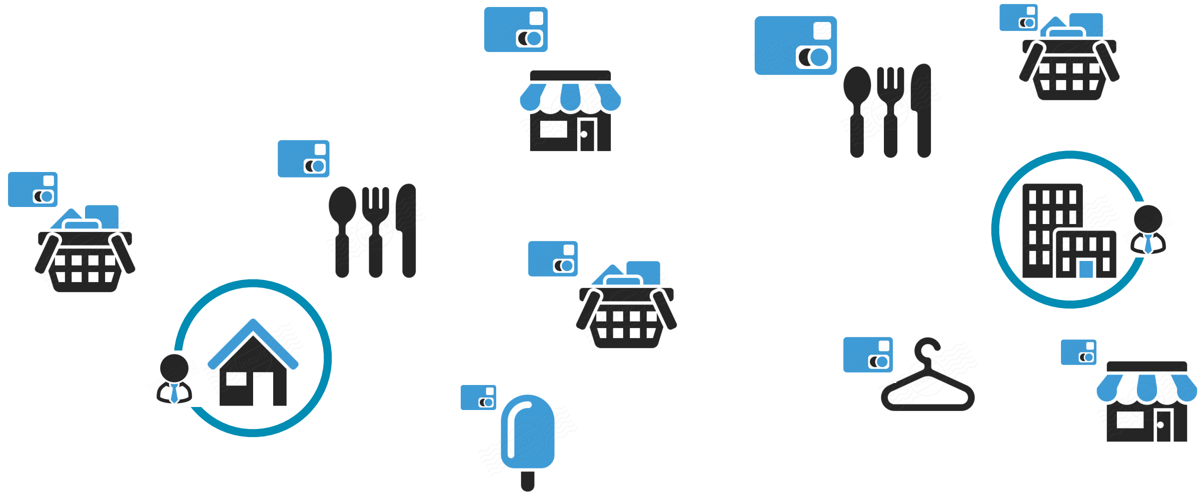
  - Physical exposure at work environment promotes idea exchange
  - Individuals living in different communities but sharing similar work locations act as social bridges between communities
- Test at city scale



Data set

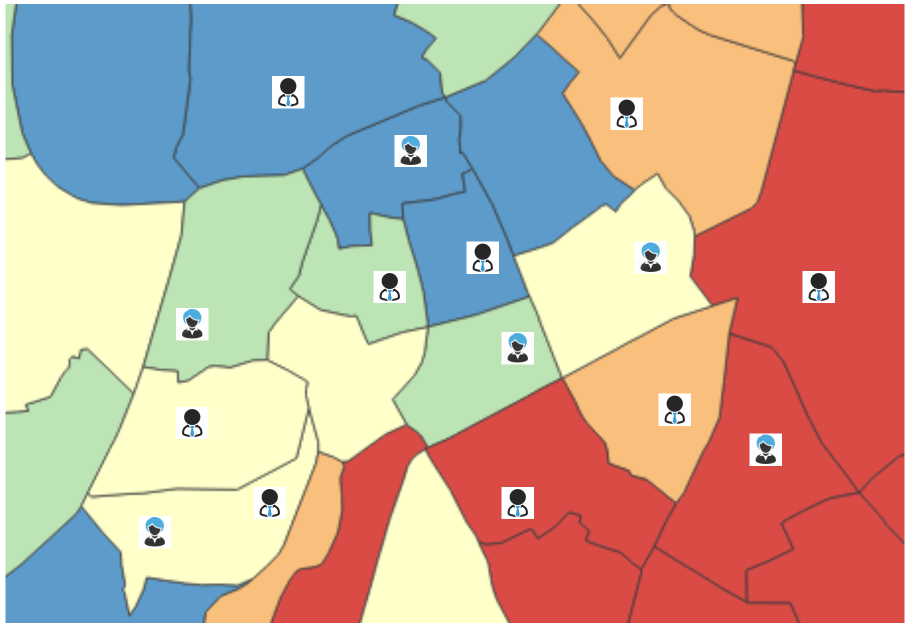
- A large-scale credit card transaction data set in two cities in an OECD country during 3 months



	City A	City B
# Customers	49K	9K
# Stores	110K	30K
# Transactions	2.3M	0.4M
% Female Customers	37.3%	31.9%
% Young (Below 30) Customers	20.5%	16.1%
% Single Customers	31.4%	22.7%
% College-Educated Customers	51.1%	47.5%
% Employed Customers	92.9%	92.1%
Median Income	2400	2100

Methods

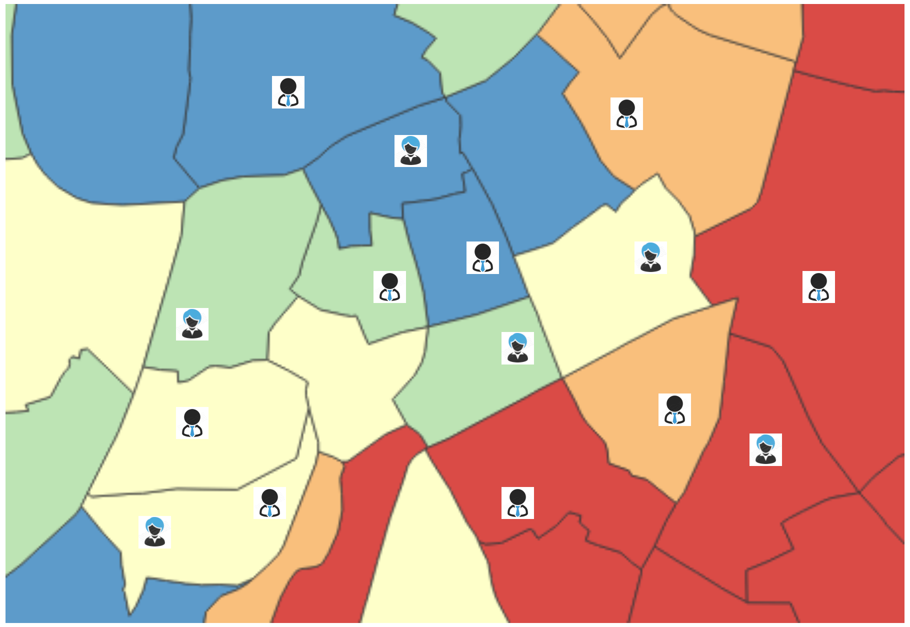
- Urban communities



Methods

- Urban communities
- Number of social bridges between communities

$$\mathrm{bdg}(I,J) = |\{i,j\}|$$
$$\text{s.t. } i \in I,\ j \in J,\ D(L_i, L_j) \leq d$$



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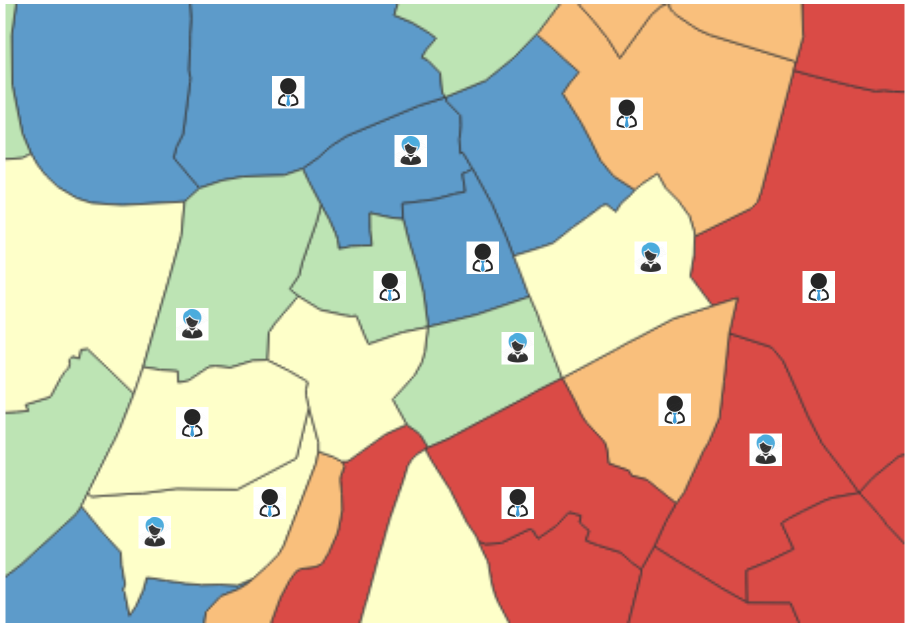

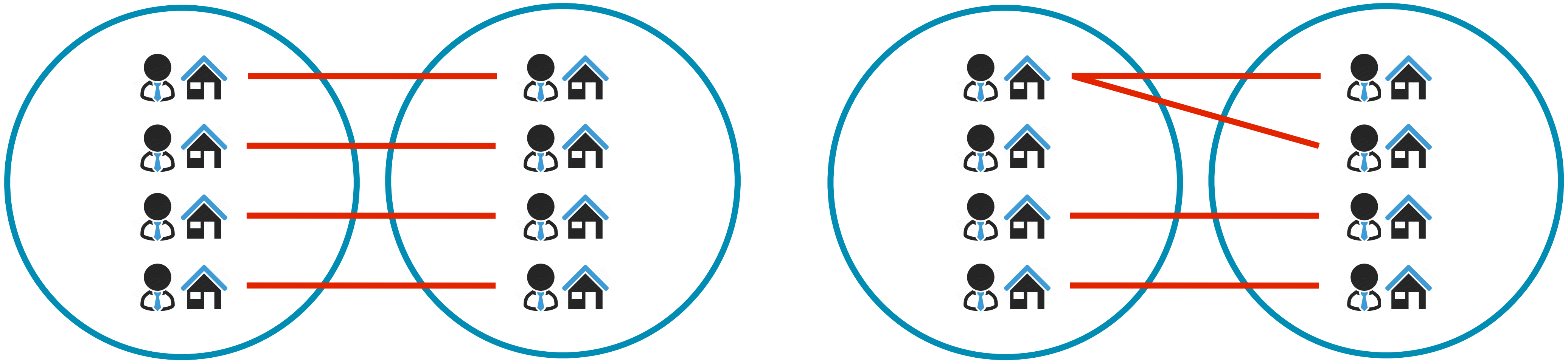

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Methods

- Three behavioral indexes
  - choice: number of co-visited stores
  - temporal: similarity between temporal distributions of purchases
  - spending: sum of differences in median spending amount of different categories

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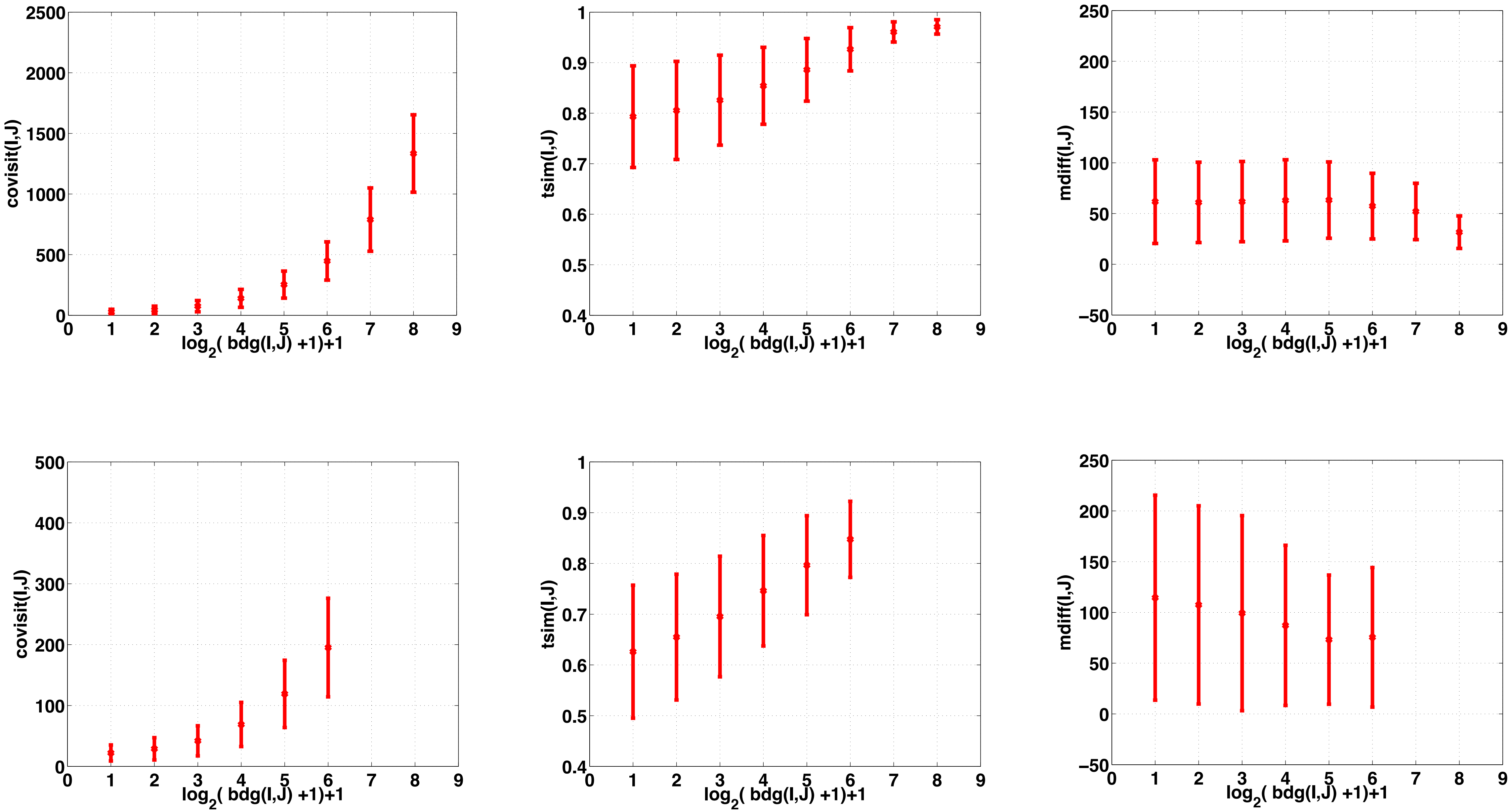
- Three behavioral indexes
  - choice: number of co-visited stores
  - temporal: similarity between temporal distributions of purchases
  - spending: sum of differences in median spending amount of different categories

- Remark
  - exclude transactions during working hours
  - exclude transactions at stores in home/work neighborhoods

Social bridge and behavioral indexes

City A

City B



Choice (co-visits)

Temporal

Spending

Social bridge and purchase similarity (co-visits)

- Multiple OLS regression analysis
  - dependent variable (DV): # co-visits (between community pair)
  - independent variables (IV): # social bridges
  - confounding variables: population, distance, demographics, income

Social bridge and purchase similarity (co-visits)

- Multiple OLS regression analysis
  - dependent variable (DV): # co-visits (between community pair)
  - independent variables (IV): # social bridges
  - confounding variables: population, distance, demographics, income
- Remark
  - entries are not independent in DV and IV
  - Quadratic Assignment Procedure (QAP) to test statistical significance
    - random shuffling of communities in DV
    - re-application of OLS

Social bridge and purchase similarity (co-visits)

- Regression coefficients

(a) City A

Indicator	β Coefficient	Confidence Interval
# Social Bridge	0.760 ***	[0.754, 0.766]
Population	0.102 ***	[0.095, 0.108]
Distance	0.094 ***	[0.090, 0.097]
Age	0.038 ***	[0.034, 0.042]
Gender	0.015 ***	[0.011, 0.019]
Marital Status	0.017 ***	[0.013, 0.021]
Education	0.046 ***	[0.042, 0.051]
Working Style	0.015 ***	[0.011, 0.019]
Income	0.034 ***	[0.030, 0.039]
Num. Obs.		61776
RMSE		0.465
Adj. R^2		0.784

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

(b) City B

Indicator	β Coefficient	Confidence Interval
# Social Bridge	0.410 ***	[0.393, 0.426]
Population	0.288 ***	[0.272, 0.305]
Distance	0.167 ***	[0.156, 0.179]
Age	0.060 ***	[0.048, 0.072]
Gender	0.155 ***	[0.143, 0.167]
Marital Status	0.023 ***	[0.011, 0.035]
Education	-0.008	[-0.021, 0.005]
Working Style	0.031 ***	[0.019, 0.043]
Income	0.085 ***	[0.072, 0.099]
Num. Obs.		12403
RMSE		0.643
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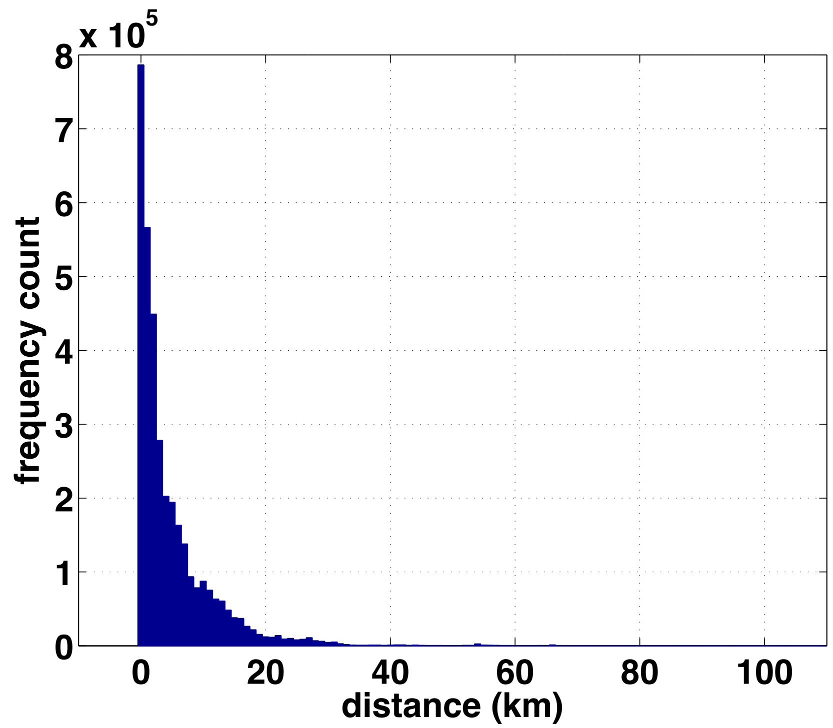
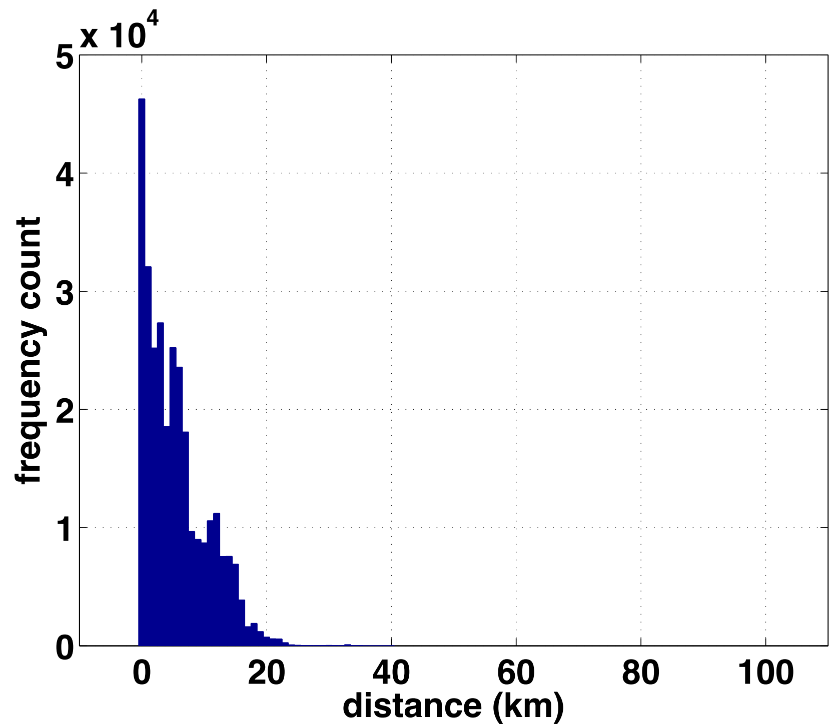
Social bridge is a stronger indicator of similar purchase behavior

Social bridge and purchase similarity (co-visits)

- Histogram of distance between co-visited store and co-working location



City A (62% > 2km)

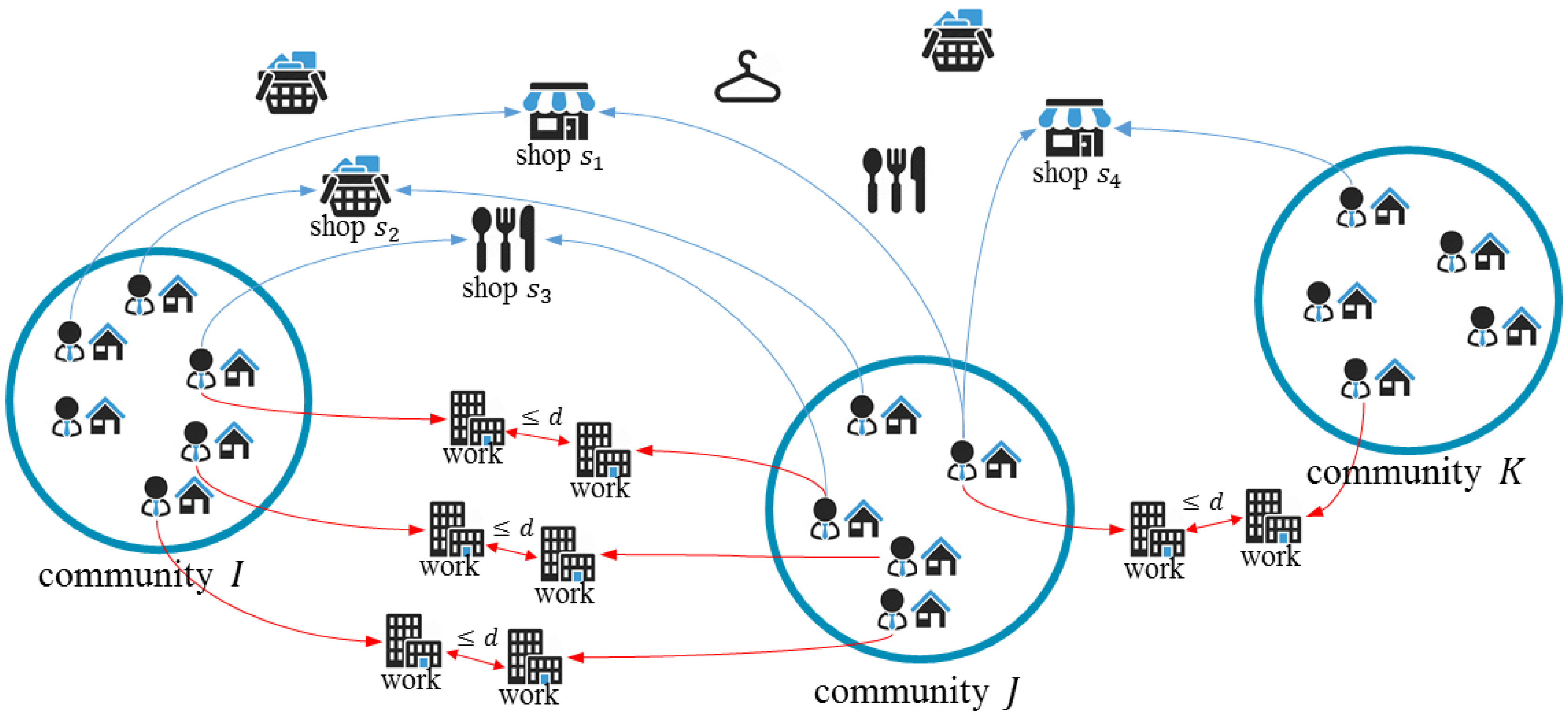


City B (74% > 2km)

Co-visitation is not simply due to proximity between co-visited store and co-working location

Co-visits by two types of customers

- Bridge customers vs. Non-bridge customers



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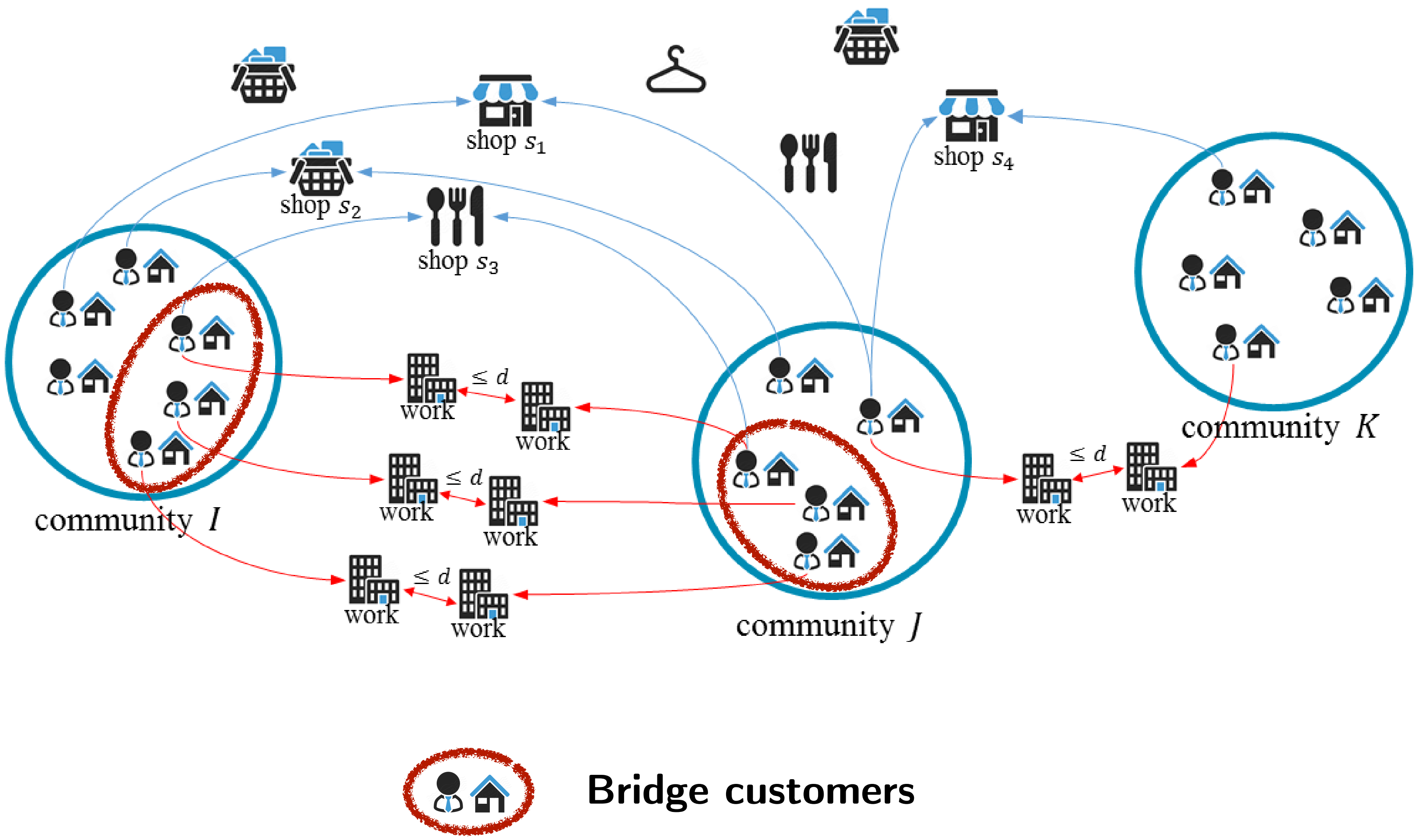

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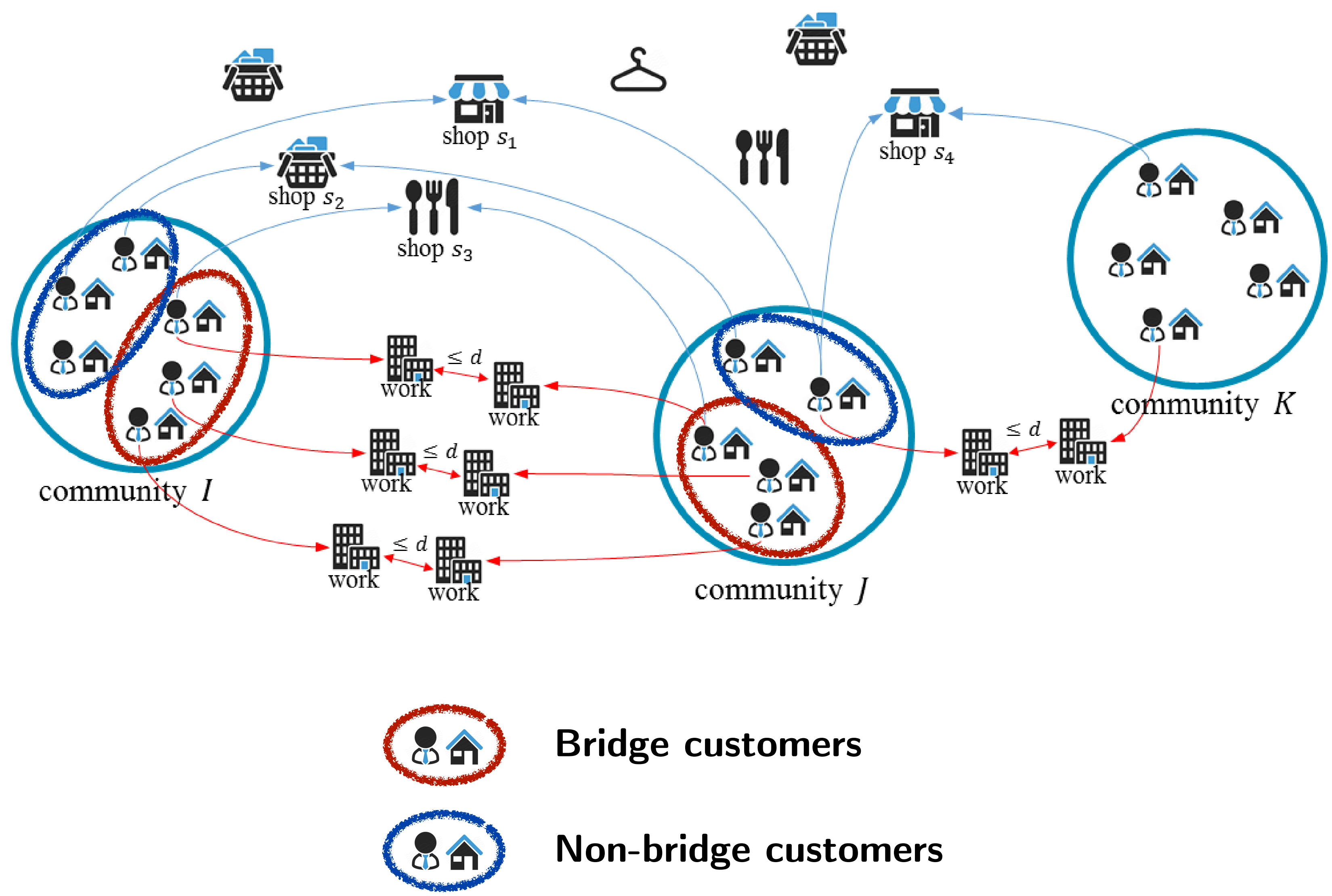
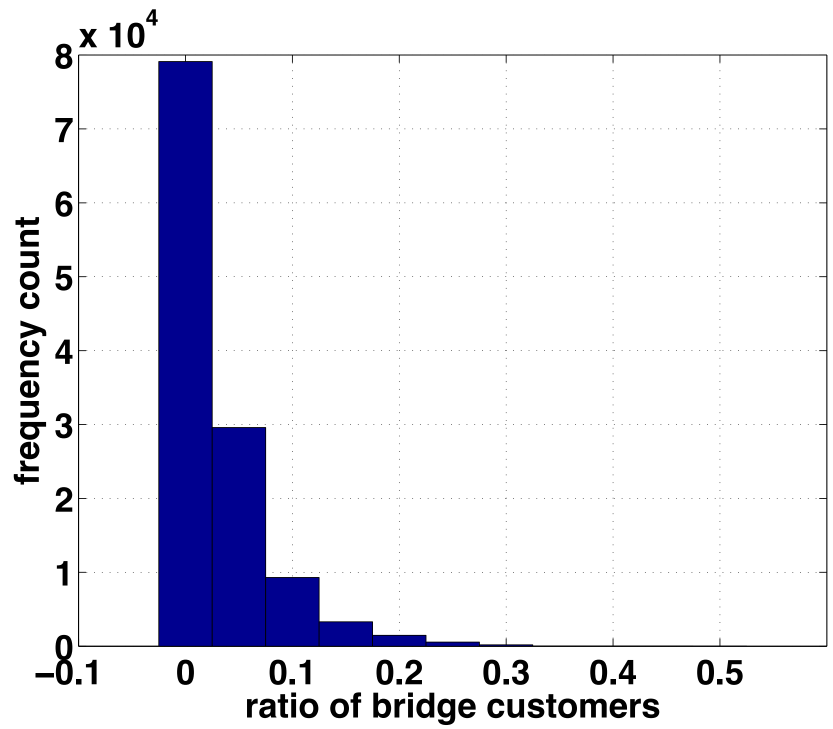
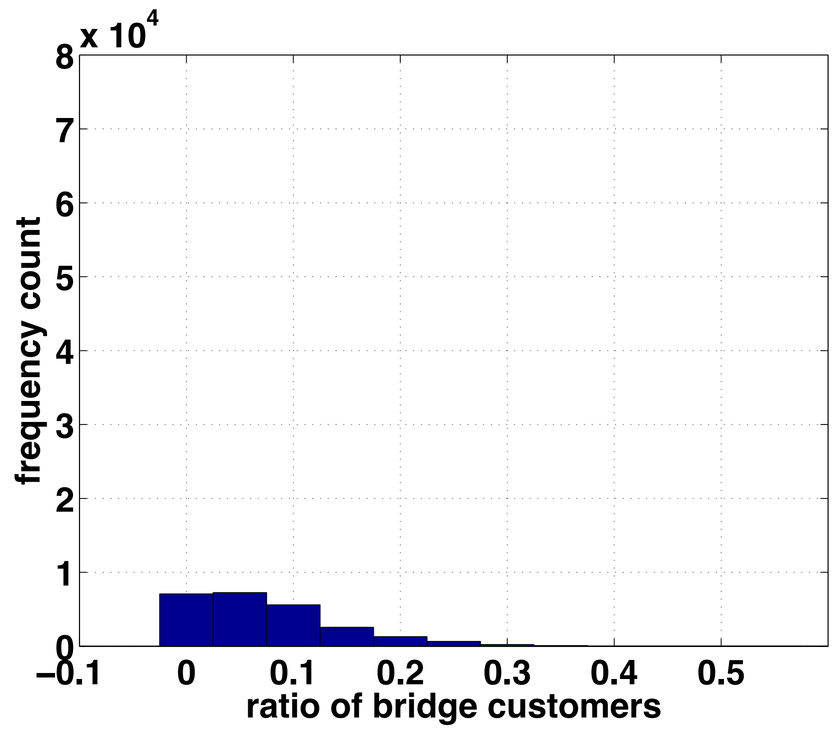


Co-visits by two types of customers

- Histogram of ratio of bridge customers



City A

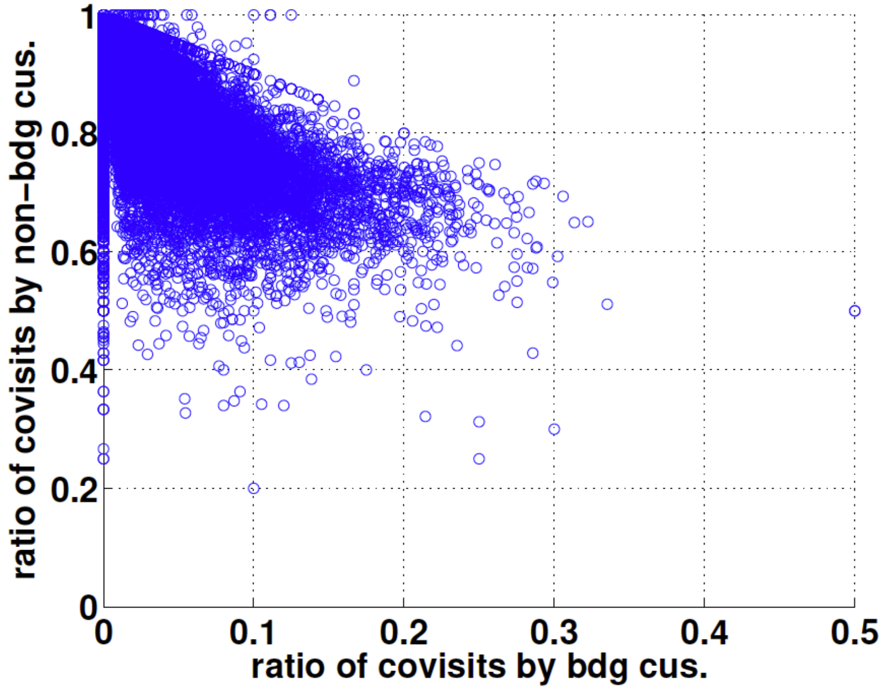


City B

Ratio of bridge customers are relatively small

Co-visits by two types of customers

- Percentage of co-visits by bridge customers



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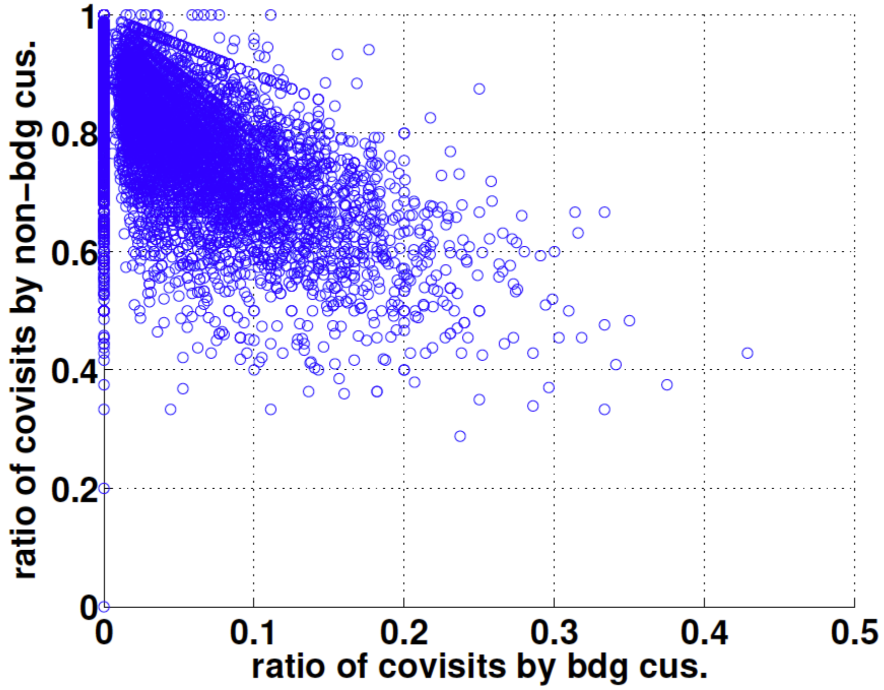

City B

A large portion of co-visits are by non-bridge customers

Co-visits by two types of customers

- Regression coefficients

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Co-Visits Types	β Coefficient	Confidence Interval	**Adj. R^2**
By All	0.760 ***	[0.754, 0.766]	0.784
By Bridge Cus.	1.005 ***	[0.999, 1.011]	0.766
By Non-Bridge Cus.	0.653 ***	[0.646, 0.660]	0.705

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

(b) City B

Co-Visits Types	β Coefficient	Confidence Interval	**Adj. R^2**
By All	0.410 ***	[0.393, 0.426]	0.586
By Bridge Cus.	0.717 ***	[0.700, 0.734]	0.558
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Social bridge is a indicator of similar purchase behavior even for non-bridge customers

Co-visits in three merchant categories

- Regression coefficients

(a) City A

Co-Visits Types	β Coefficient	Confidence Interval	**Adj. R^2**
Supermarkets	0.610 ***	[0.603, 0.618]	0.693
Restaurants	0.812 ***	[0.805, 0.818]	0.776
Clothing Stores	0.623 ***	[0.615, 0.631]	0.631

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

(b) City B

Co-Visits Types	β Coefficient	Confidence Interval	**Adj. R^2**
Supermarkets	0.291 ***	[0.274, 0.309]	0.537
Restaurants	0.445 ***	[0.426, 0.465]	0.399
Clothing Stores	0.330 ***	[0.312, 0.347]	0.539

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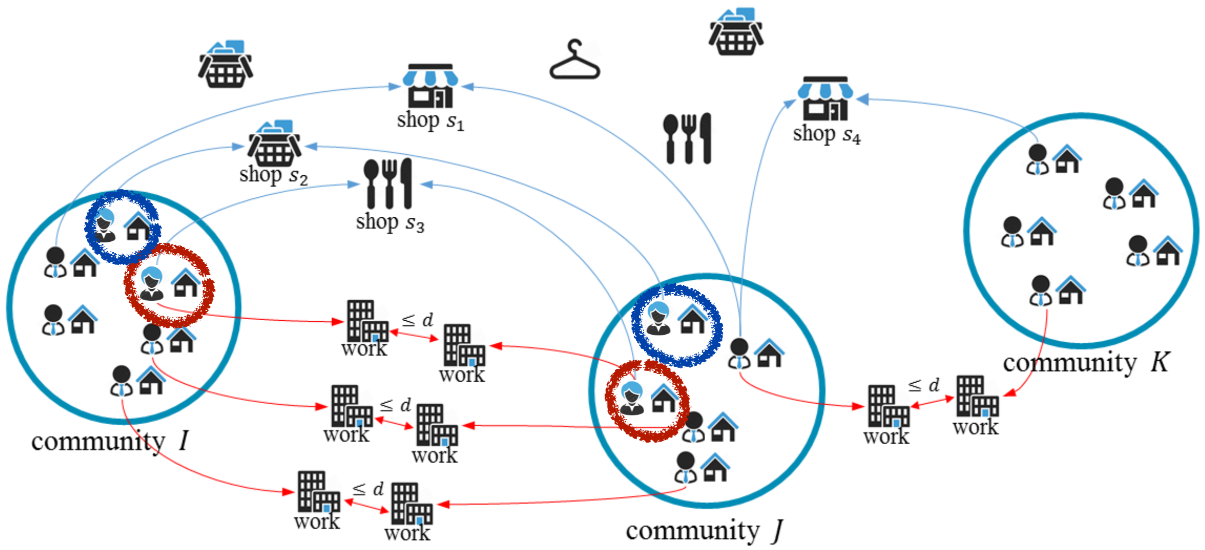
Effect of social bridge is stronger for restaurants but weaker for supermarkets

Gender difference in social bridge

- Regression coefficients



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Bridge Types	Co-Visits Types	β Coefficient	Confidence Interval	**Adj. R^2**
Female-Female	**By Non-Bridge Female**	0.527 ***	[0.520, 0.533]	0.625
Female-Female	**By Non-Bridge Male**	0.404 ***	[0.398, 0.411]	0.615
Male-Male	**By Non-Bridge Female**	0.360 ***	[0.352, 0.368]	0.543
Male-Male	**By Non-Bridge Male**	0.393 ***	[0.385, 0.400]	0.604

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(b) City B

Bridge Types	Co-Visits Types	β Coefficient	Confidence Interval	**Adj. R^2**
Female-Female	**By Non-Bridge Female**	0.327 ***	[0.311, 0.343]	0.340
Female-Female	**By Non-Bridge Male**	0.106 ***	[0.091, 0.120]	0.468
Male-Male	**By Non-Bridge Female**	-0.073 ***	[-0.092, -0.055]	0.261
Male-Male	**By Non-Bridge Male**	0.044 ***	[0.028, 0.060]	0.460

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Gender difference in social bridge

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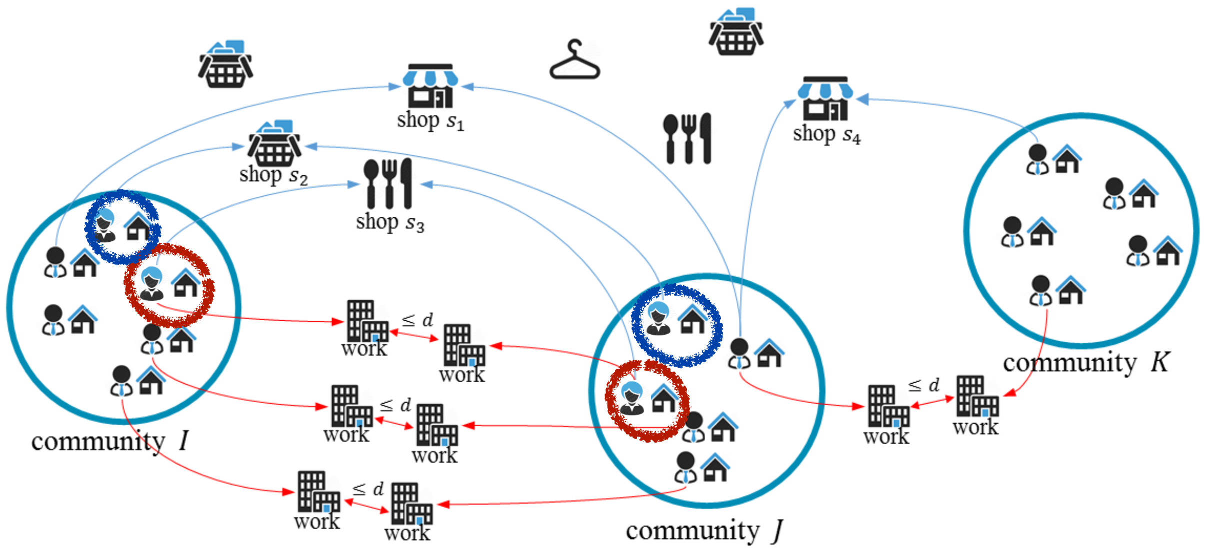

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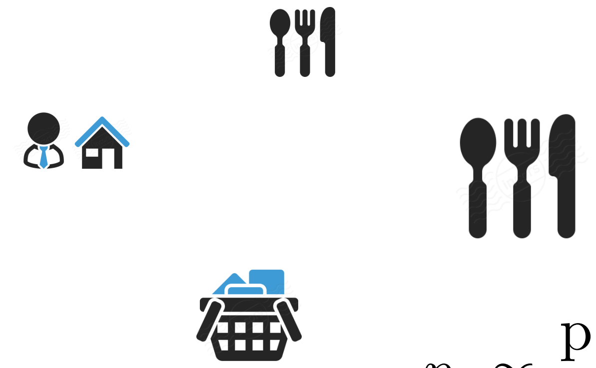
Male-Male	**By Non-Bridge Male**	0.044 ***	[0.028, 0.060]	0.460

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Female-female bridges show a stronger effect

Comparison with a null model

- Purchase choices are influenced by merchant popularity and location (Huff, 1964)



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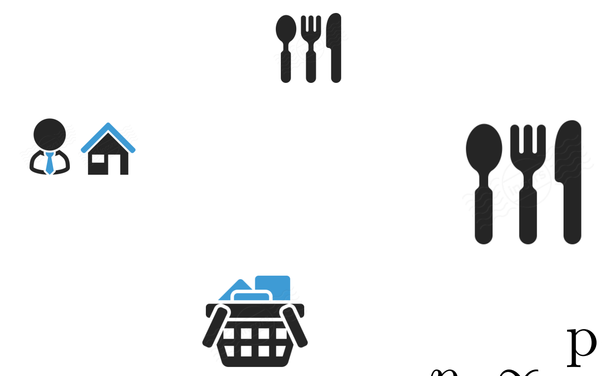

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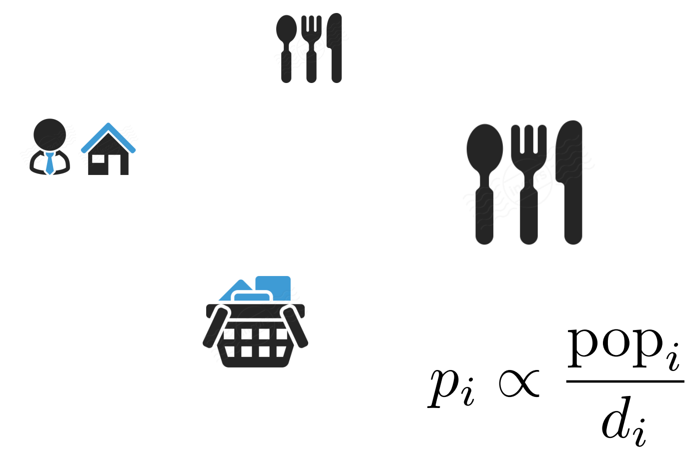

probability customer **i** visits store **s**

popularity of store **s**

distance between customer **i** and store **s**

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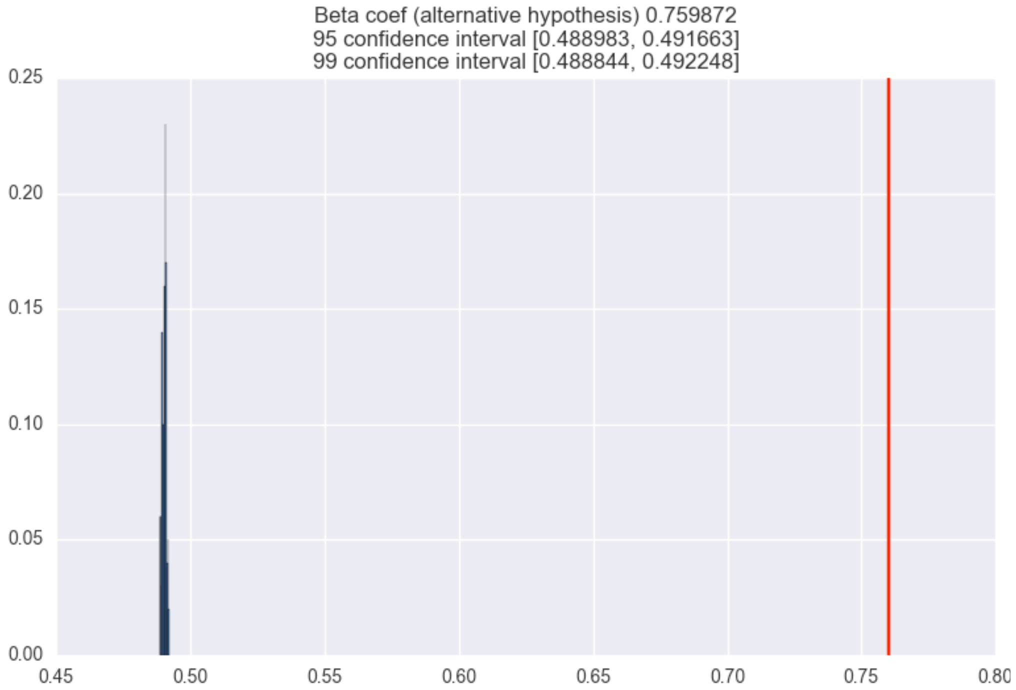
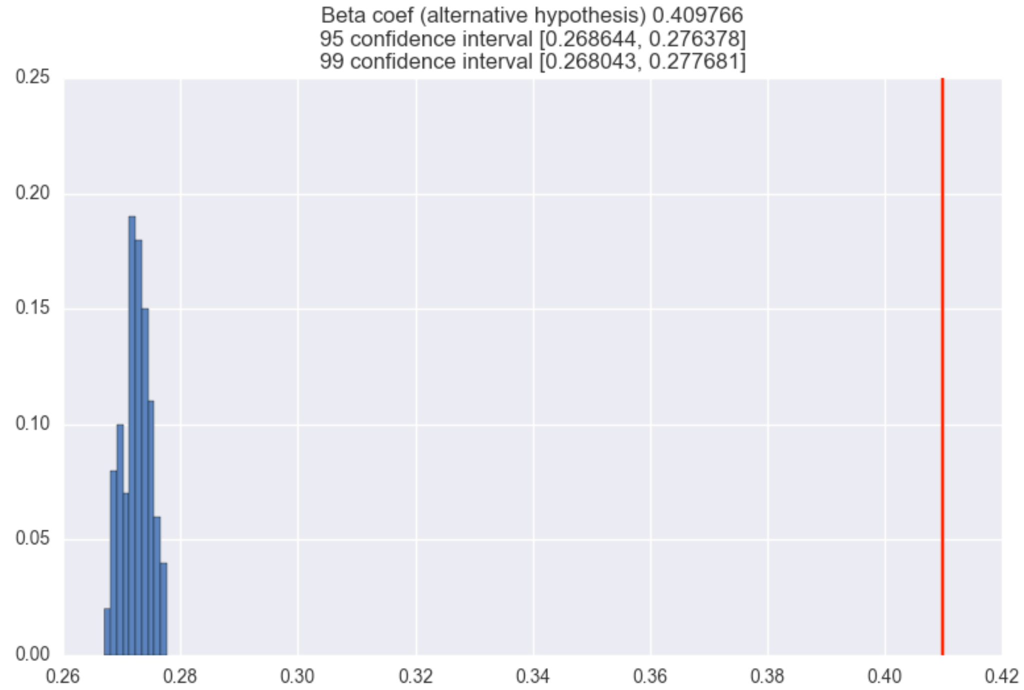


City A



City B

Effect of social bridge is not simply due to merchant popularity and location

Influence of distance threshold

- Regression coefficient as a function of distance **d**

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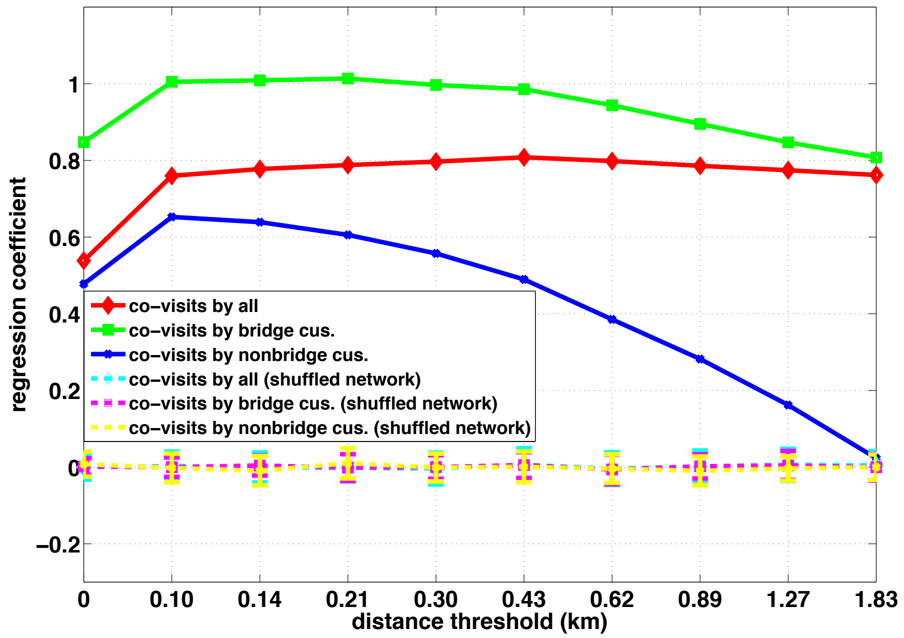

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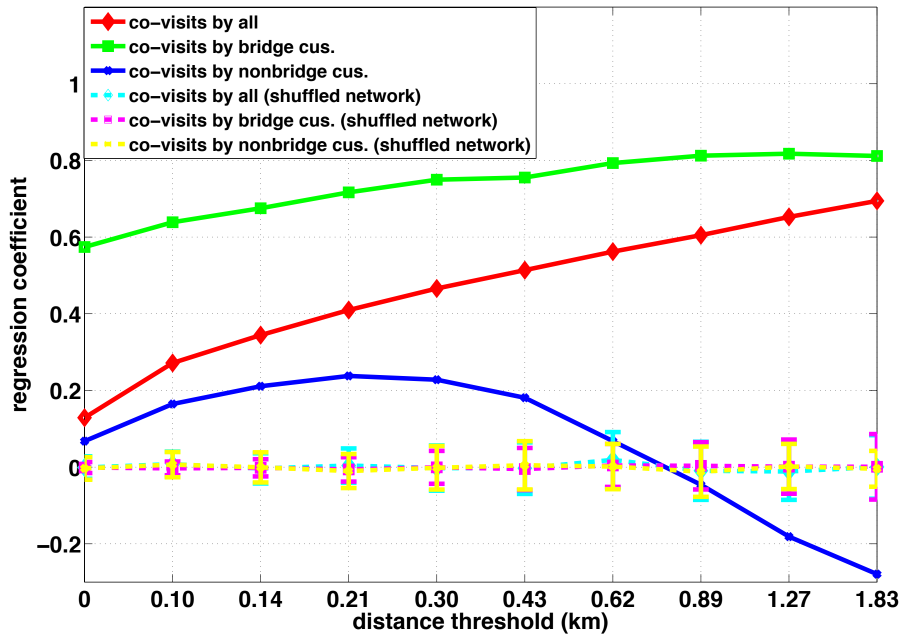

City B

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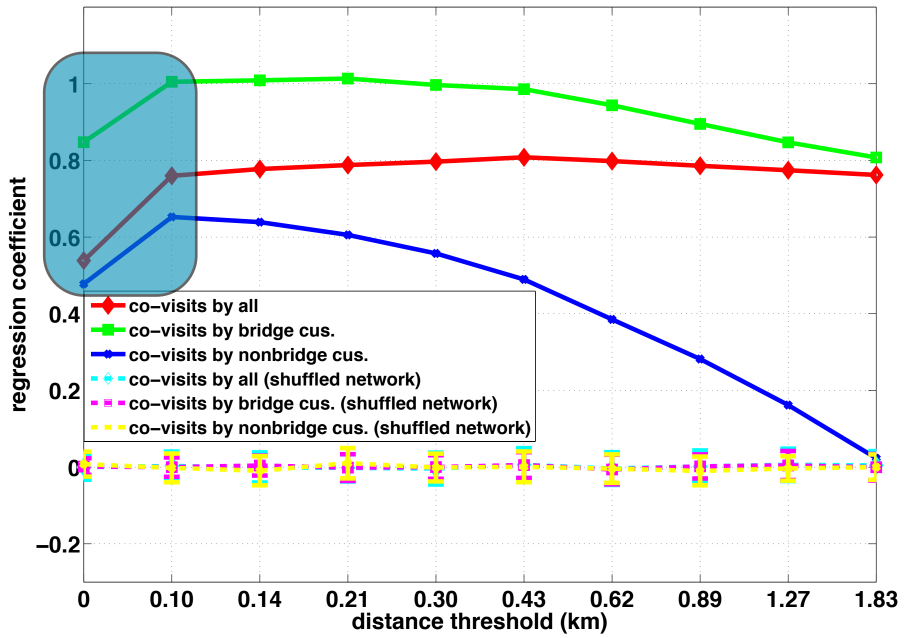

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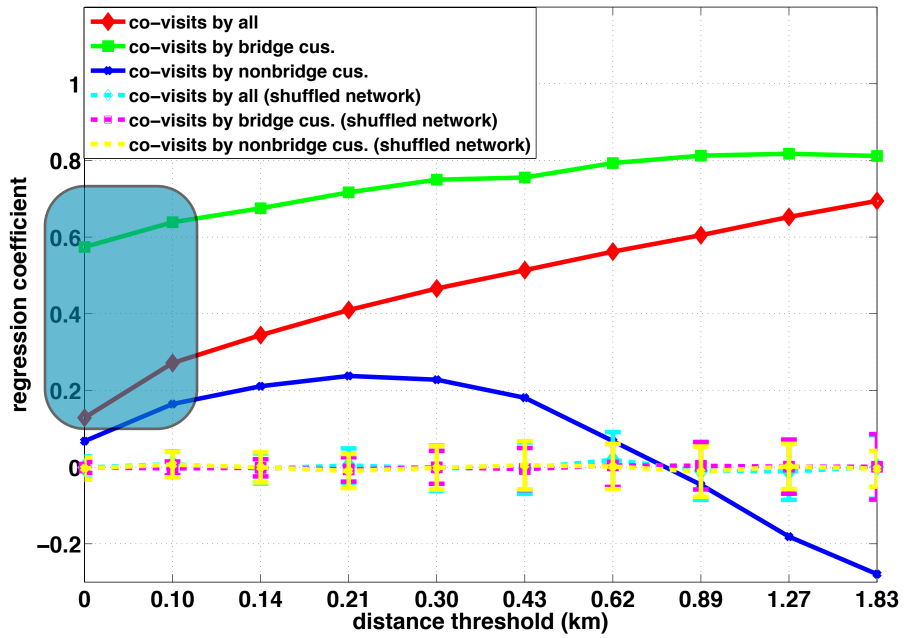

City B

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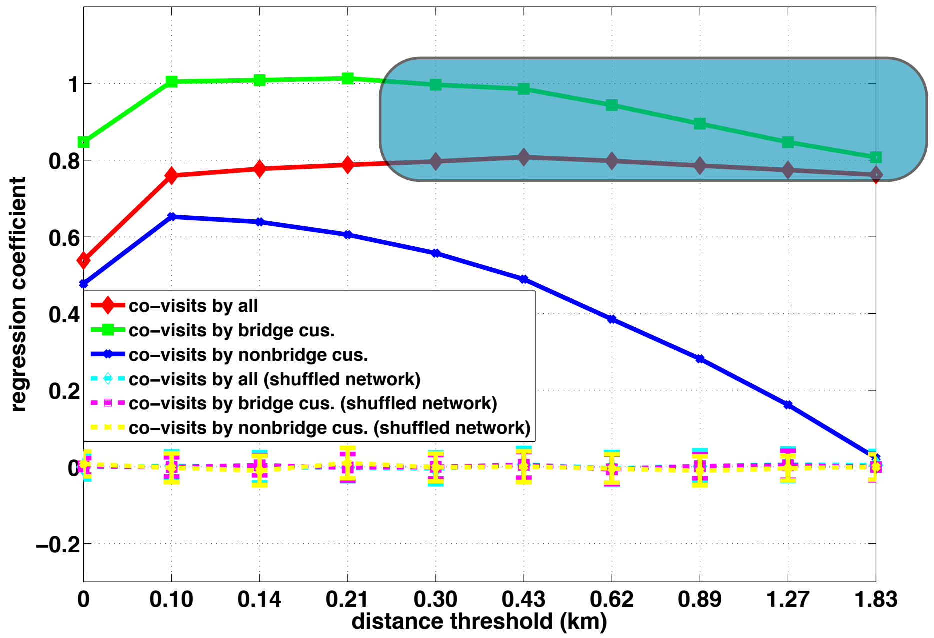

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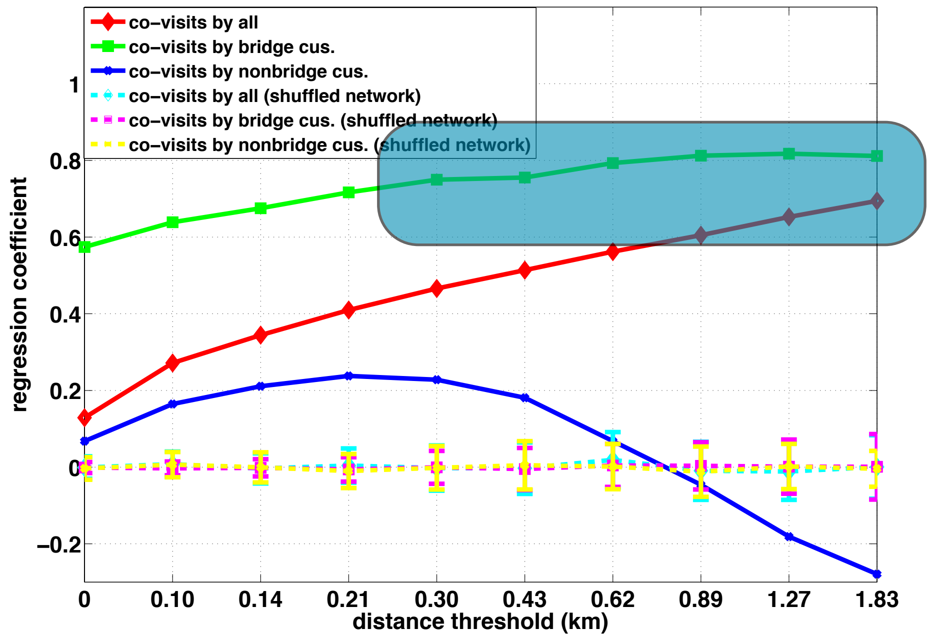

City B

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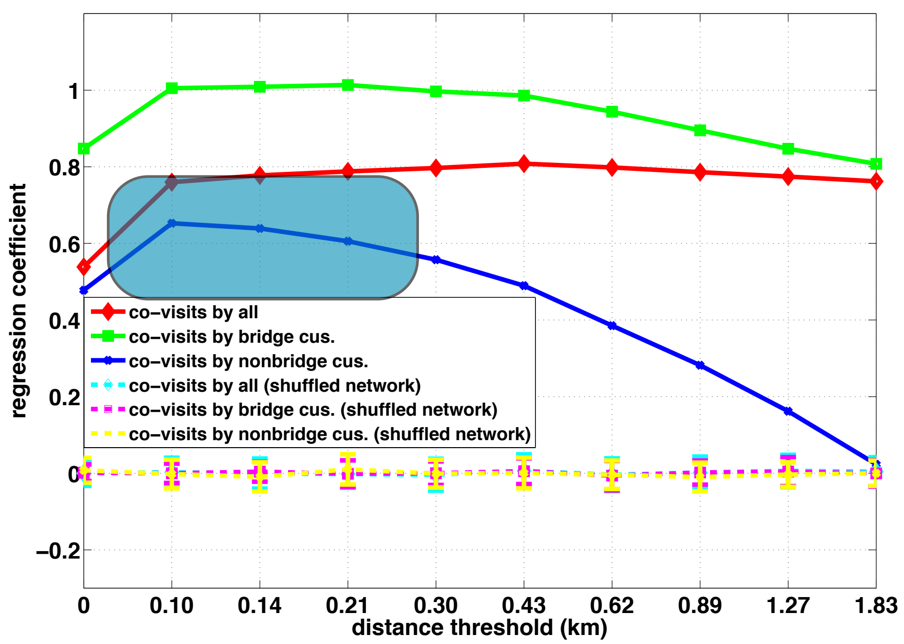

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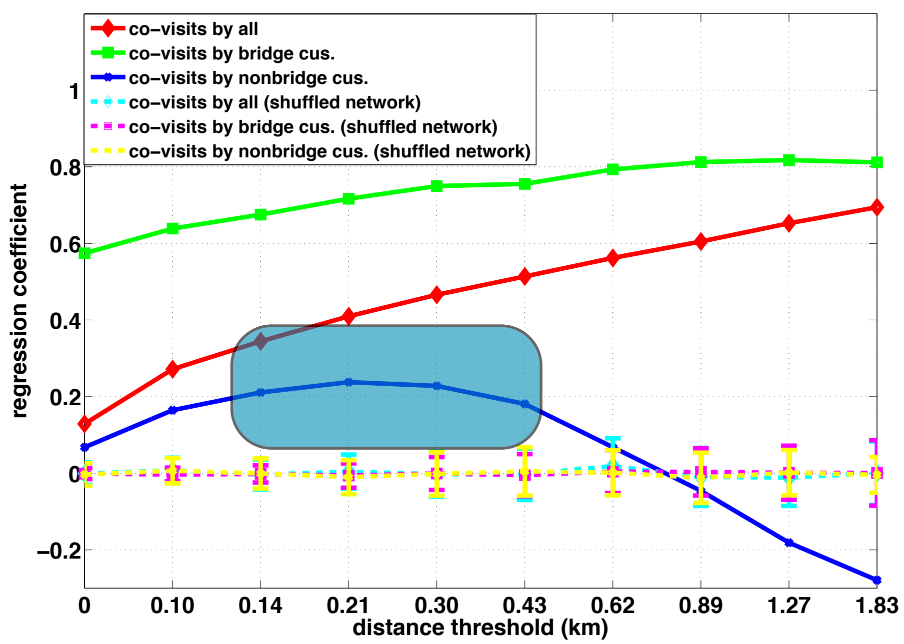

City B

Peak region of blue curve (co-visits by non-bridge customers) suggests geographical constraint for social bridge effect

Application: Prediction of co-visits

- Three-class classification: small, medium, large amount of co-visitation
- For each IV (feature), train on 20% of communities and test on the rest 80%, using LIBSVM (Chang, 2011)

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Indicator	City A	City B
# Social Bridge	72.5%	53.6%
Population	55.0%	50.4%
Distance	49.9%	45.4%
Age	40.0%	36.6%
Gender	35.1%	40.9%
Marital Status	35.3%	34.7%
Education	38.1%	39.0%
Working Style	38.3%	38.0%
Income	33.6%	36.1%

Social bridge is more efficient in predicting co-visitation than traditional factors

Discussion

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- Strong correlation can lead to applications such as behavior prediction and stratification, campaign targeting, and resource allocation