Retail 4.0: Market area analysis for in-store online order fulfillment services

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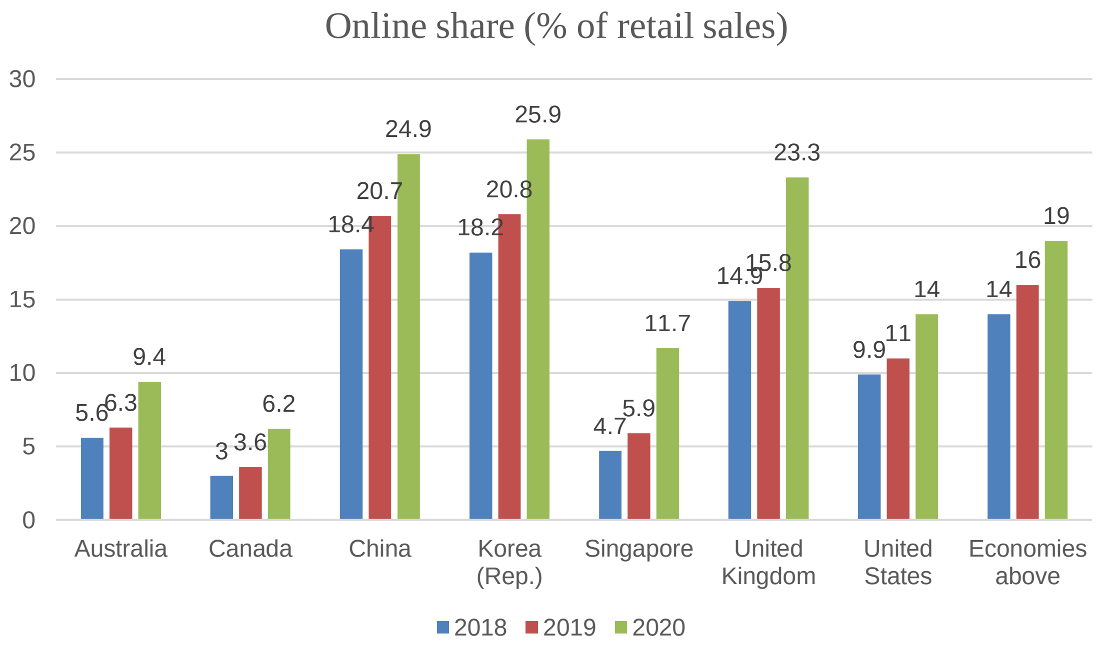
CONTENT

Background

- **Explosive growth of online shopping demand**
  In many countries, the turnover of B&M retailing shrink a lot.

- **Outbroke of COVID-19 accelerate the online purchasing behavior**
  The percentage of online shopping sales in the retail industries has increased to more than 20% as of 2020 in some countries including South Korea, China, and United Kingdom.

- **Therefore, conventional offline-based retailers added online sales channels**
  Such as, Walmart, Target, and Kroger try to leverage their existing offline distribution networks to help boost online sales.



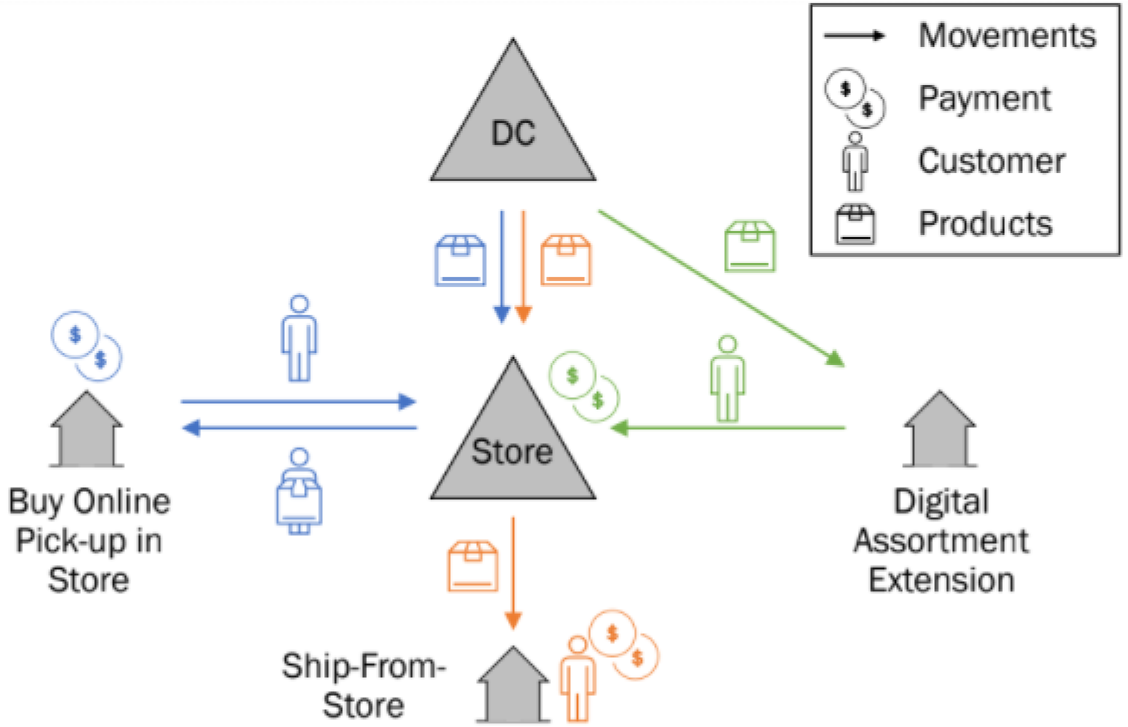
(Source: UNCTAD, based on national statistics offices.)

Research Objective

Advantages of in-store order fulfillment include **inventory pooling** effect of sharing on & offline inventory and **reduced delivery distance**.

However, it would be inefficient to allow all the stores to fulfill online orders for all the products.

Research objective:
To provide systematic store locations and product allocation strategies for in-store online order fulfillment in an omnichannel retail environment.

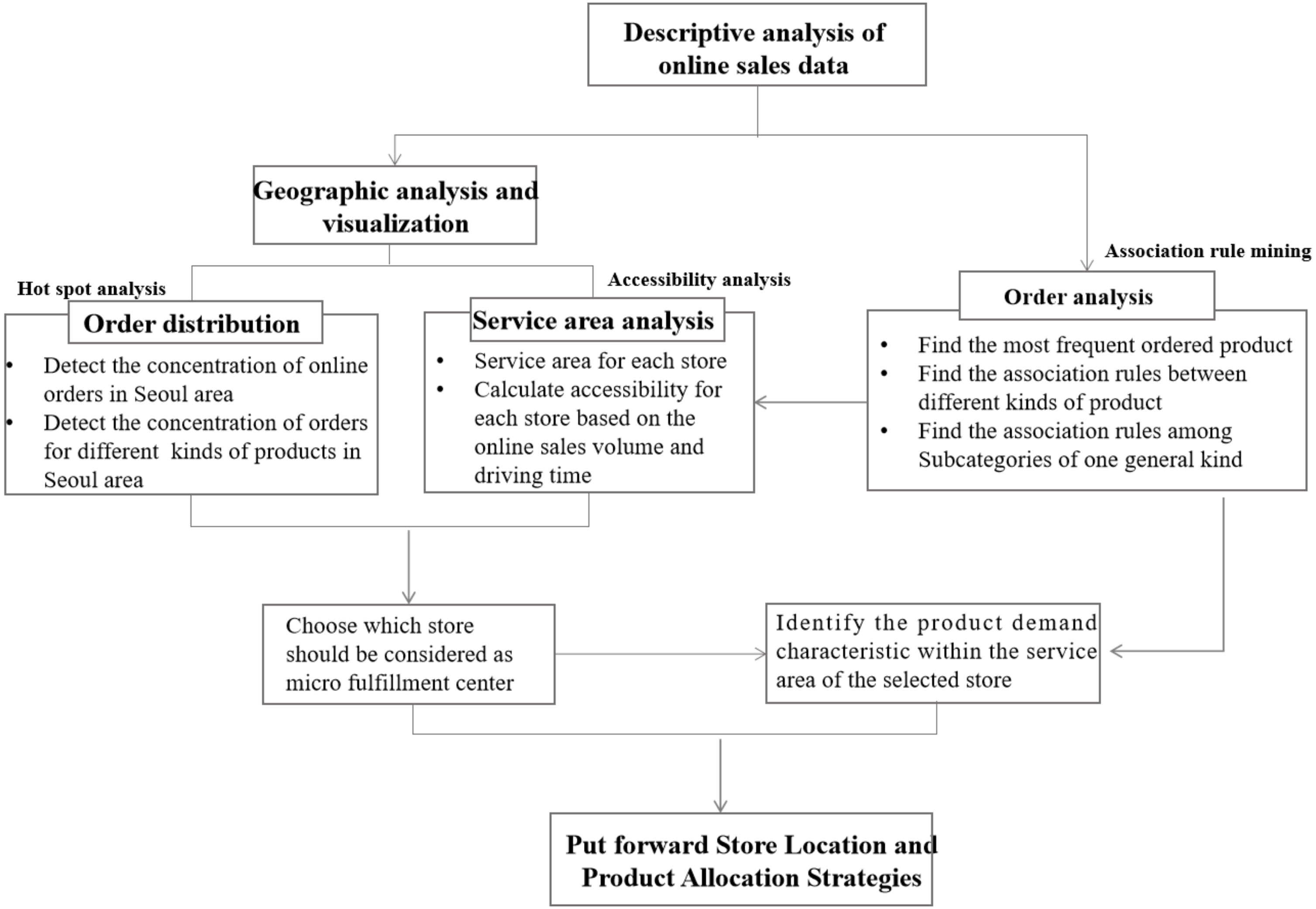


(source: Hübner et al., 2021)

Literature review

Topic	Contributions	Authors
Distribution network	In what circumstance are **integrated or decentralized networks** more beneficial to retailers.	Wollenburg et al., (2017) Hübner et al., (2016)
	Construct optimization model for **anticipatory shipping** of distribution networks with considering customers' purchase history.	Lee (2016) Viet et al. (2019)
	Last mile delivery for better service responsiveness and delivery efficiency on considering customer values, refund management.	Chhetri et al. (2017) Guerrero-Lorente et al. (2020)
Order fulfillment	Specific **inventory management for different order fulfillment strategies** to reduce stock out and reduce the operation costs.	Govindarajan et al. (2018) Bayram and Cesaret (2020) Saha and Bhattacharya (2020)
	Springing out of differnt kinds of order fulfillment services and their beneifit to boost retailers' revennue. For example, **showrooming, BOPS, STS, ROPS**.	Gao and Su (2016) Ishfaq and Raja (2018)
	Find out **factors that affect order fulfillment services choice**. Such as, retailing sales volume, pricing, product categories, and customers' features.	Serkan Akturk et al. (2018) He et al. (2021)

Research Framework



- **Research steps**

Firstly, we analyze the regional demand distribution of online sales data and the demand for different kinds of product categories.

Then, implement **hotspot analysis** for products with high demand to find out regional demand hotspots.

The **third** step is to identify the potential in-store order fulfillment stores based on the **accessibility** within their same-day delivery service area.

Finally, the **market basket analysis** is performed for mining the association rules of the target area to provide product allocation suggestions.

Hot spot analysis(G_i^*)

The G_i^* statistic computed for each feature location i in the dataset is a **Z-score**. Such locations are identified as **spatial clusters** if they are significantly different from complete spatial randomness (CSR) at a certain statistical significance level.

H_0: *the spatial location showing a completely random (uniform) distribution within a certain region.*

If the G_i^* statistic exceeds the critical value, the null hypothesis of CSR is rejected, and we can conclude that spatial cluster is detected at location i.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \quad (1)$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \quad (3)$$

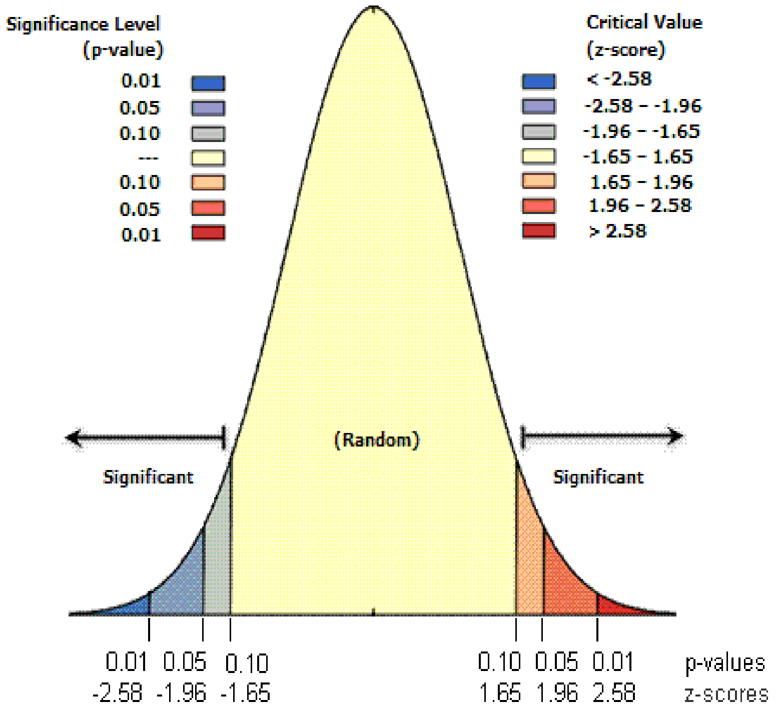
The G_i^* statistic is a z-score so no further calculations are required.

Source: ArcGIS Desktop

Hot spot analysis

Statistical significance test

Situation	Z-score of local G (Gi*)
High next to High (Hot-spot)	Strongly positive (> 2.58)
High next to Moderate	Moderately positive (1.96, 2.58)
Moderate next to Moderate	0
Random	0
High next to Low	Negative (-1.96, 0)
Moderate next to Low	Moderately negative (-2.58, -1.96)
Low next to Low (Cold-spot)	Strongly negative (< -2.58)



Source: Wikipedia

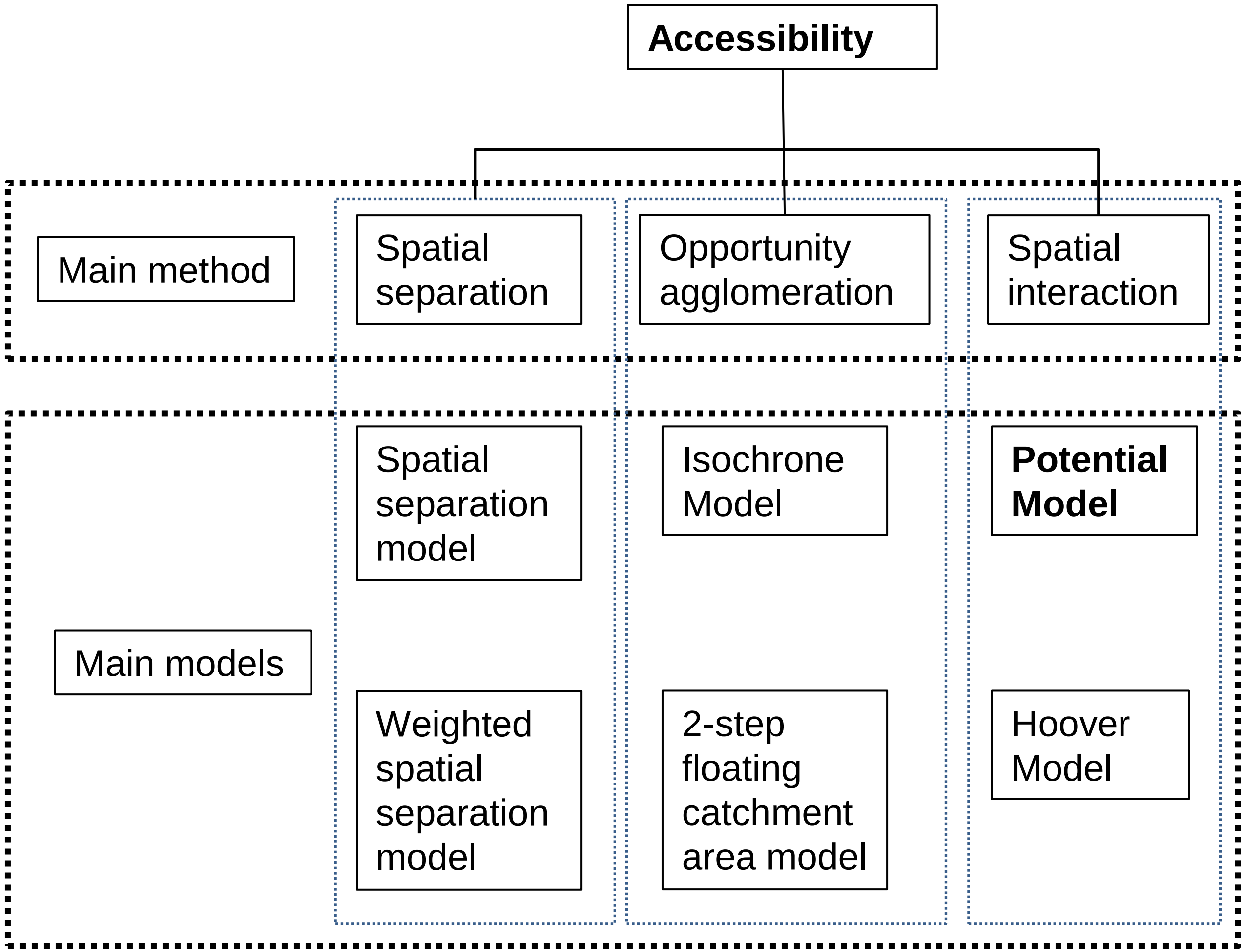
Accessibility analysis

Accessibility refers to a measure of the ease of reaching (and interacting with) destinations or activities distributed in space.

Potential model was proposed by Hansen in 1959. The model is derived from Newton's law of universal gravitation, and mainly uses potential indicators to evaluate spatial accessibility, the model is generally expressed as follows:

$$A_i = \sum_{j \in S} \frac{M_j}{t_{ij}} \qquad SA_i = \frac{A_i - \min\{A_i\}}{\max\{A_i\} - \min\{A_i\}}$$

where A_i means accessibility of each location i, S is the set of destinations within the boundary of service area; M_j refers to the demand at location j, t_{ij} is the travel time between location i and j.
SA is the standardized accessibility to be within the range of 0 and 1



Association rule mining

Concept

X,Y: itemset; X=>Y: an association rule; T: a set of transactions of a given database.

- **Support** is an indication of how frequently the itemset appears in the dataset.

$$\mathrm{supp}(X) = \frac{|\{X \subseteq T\}|}{|T|}$$

- **Confidence** is an indication of how often the rule has been found to be true.

$$\mathrm{conf}(X \Rightarrow Y) = \mathrm{supp}(X \cup Y)/\mathrm{supp}(X)$$

- **Lift** reflects the correlation of X and Y

$$\mathrm{lift}(X \Rightarrow Y) = \frac{\mathrm{supp}(X \cup Y)}{\mathrm{supp}(X) \times \mathrm{supp}(Y)}$$

Algorithm

Apriori algorithm(Agrawal and Srikant, 1994) is used for frequent item set mining and association rule learning over relational databases. The frequent item sets determined by Apriori can be used to determine association rules which highlight general trends in the database: this has applications in domains such as market basket analysis.

Example database with 5 transactions and 5 items

transaction ID	milk	bread	butter	beer	diapers
1	1	1	0	0	0
2	0	0	1	0	0
3	0	0	0	1	1
4	1	1	1	0	0
5	0	1	0	0	0

Source: Google search

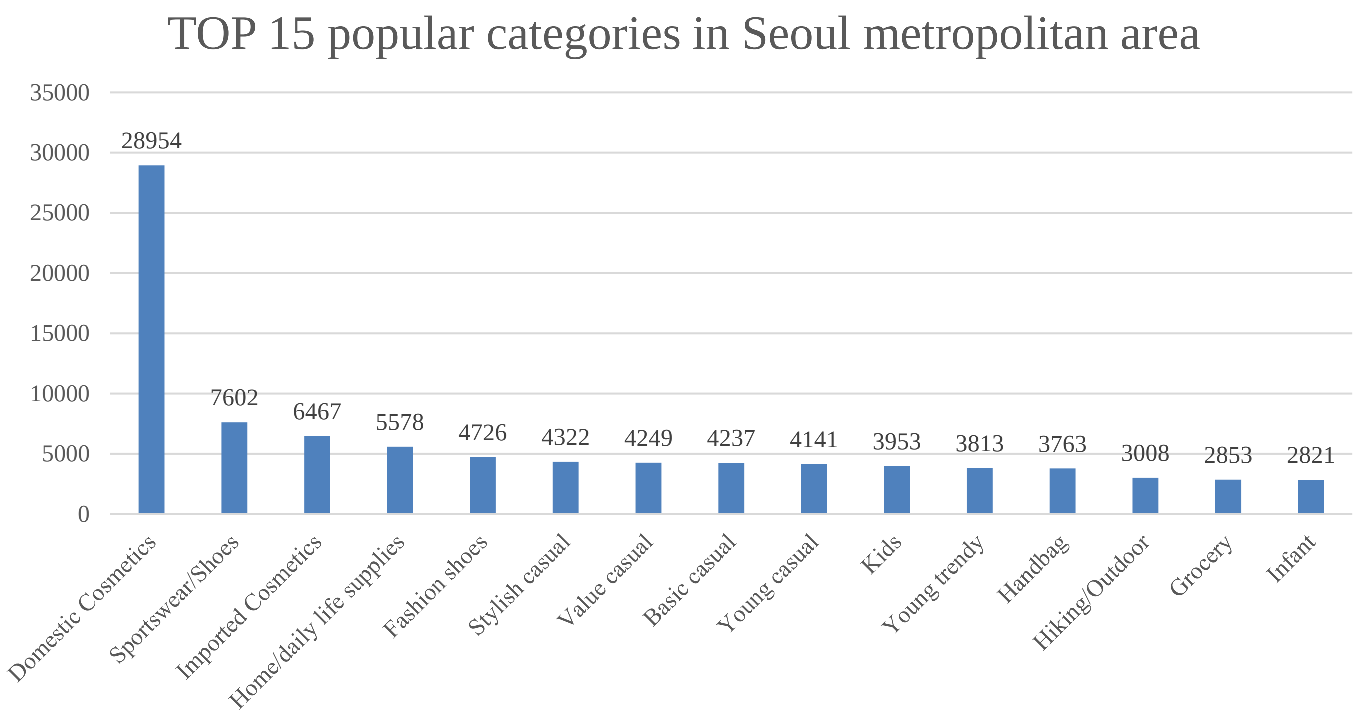
Data description

- Online sales records from the Korean offline-based online retailer (Company A)
- From March 2013 to May 2013.
- Company's self-operation part records (department sales data)
- The dataset contains 204,626 orders

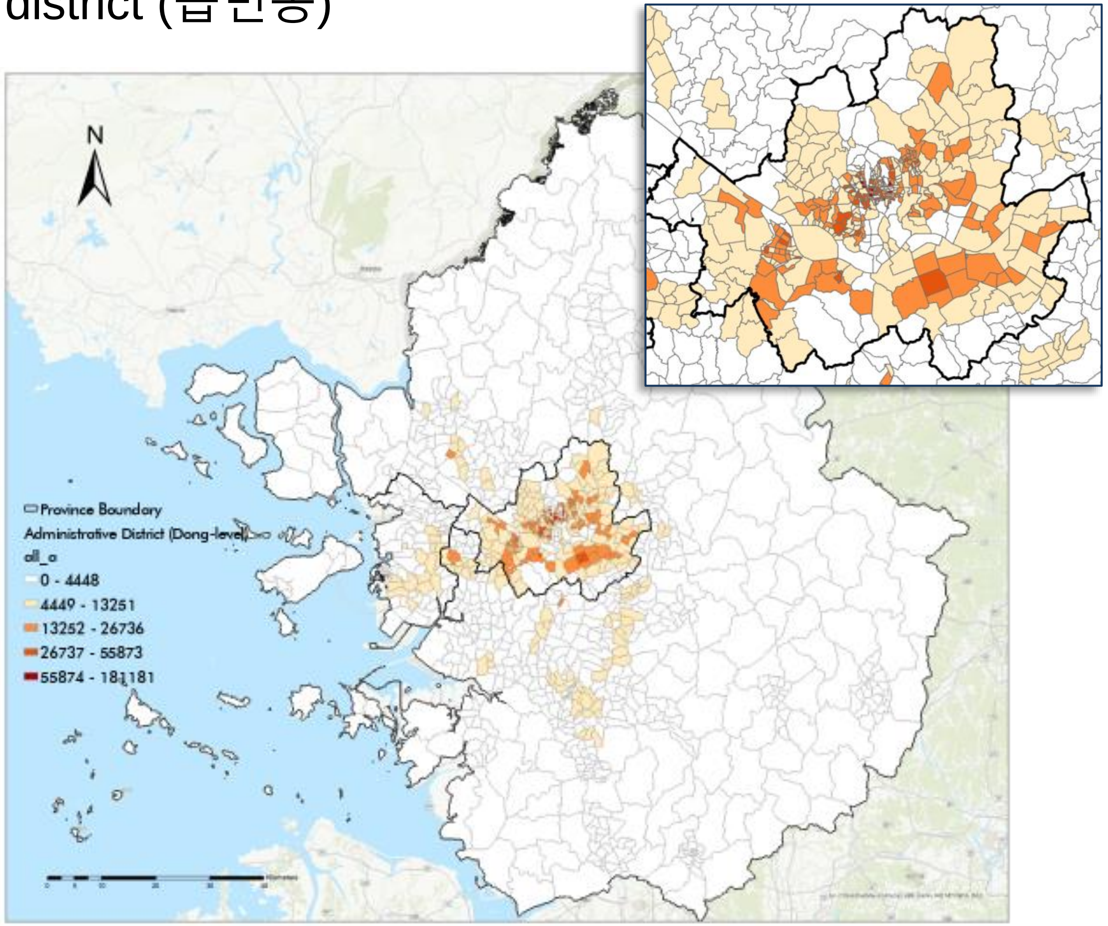
Main Category	Segment	Number of orders
Domestic cosmetics	Skin care set	28515
	Makeup	9802
	Misc set	8081
	Skin care	4313
	Makeup set	1850
	Men's care	1455
	Suncare	1182
	Perfume	270
	Body care	193
Sportswear/shoes	Shoes	8300
	New Sports Clothing/Shoes	3999
	Sweatsuit	1166
	T-shirt / Shirt	720
	Windbreaker/Jacket	578
	Pants/Skirt	338
	Jumper/Padded jacket	240
	Shirt	6
	…	

Descriptive analysis

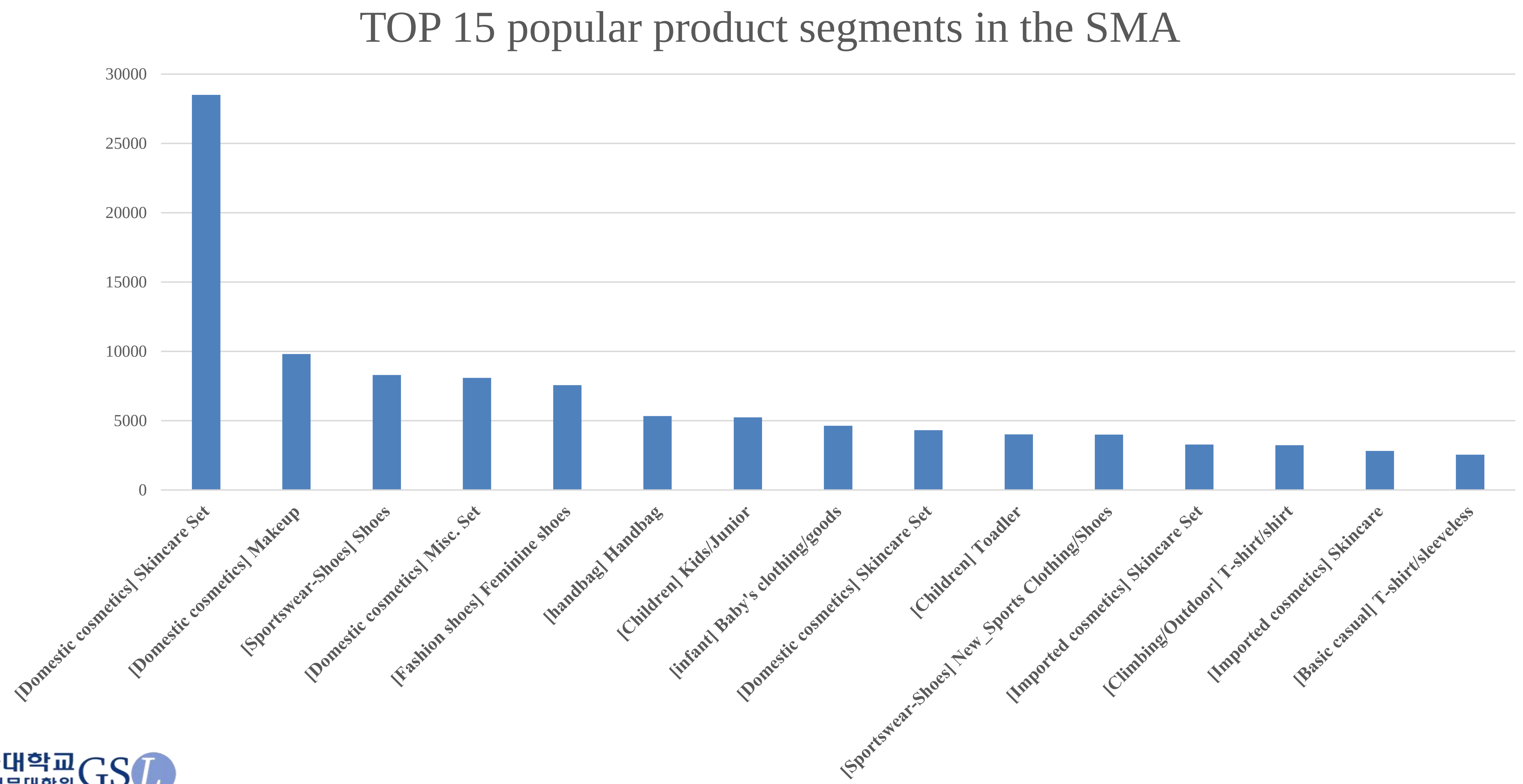
Product categories by number of orders in the Seoul Metro Area (SMA)



Spatial distribution of total number of orders by district (읍면동)



Descriptive analysis



Association rule mining: global-level

Association rule mining for the entire SMA

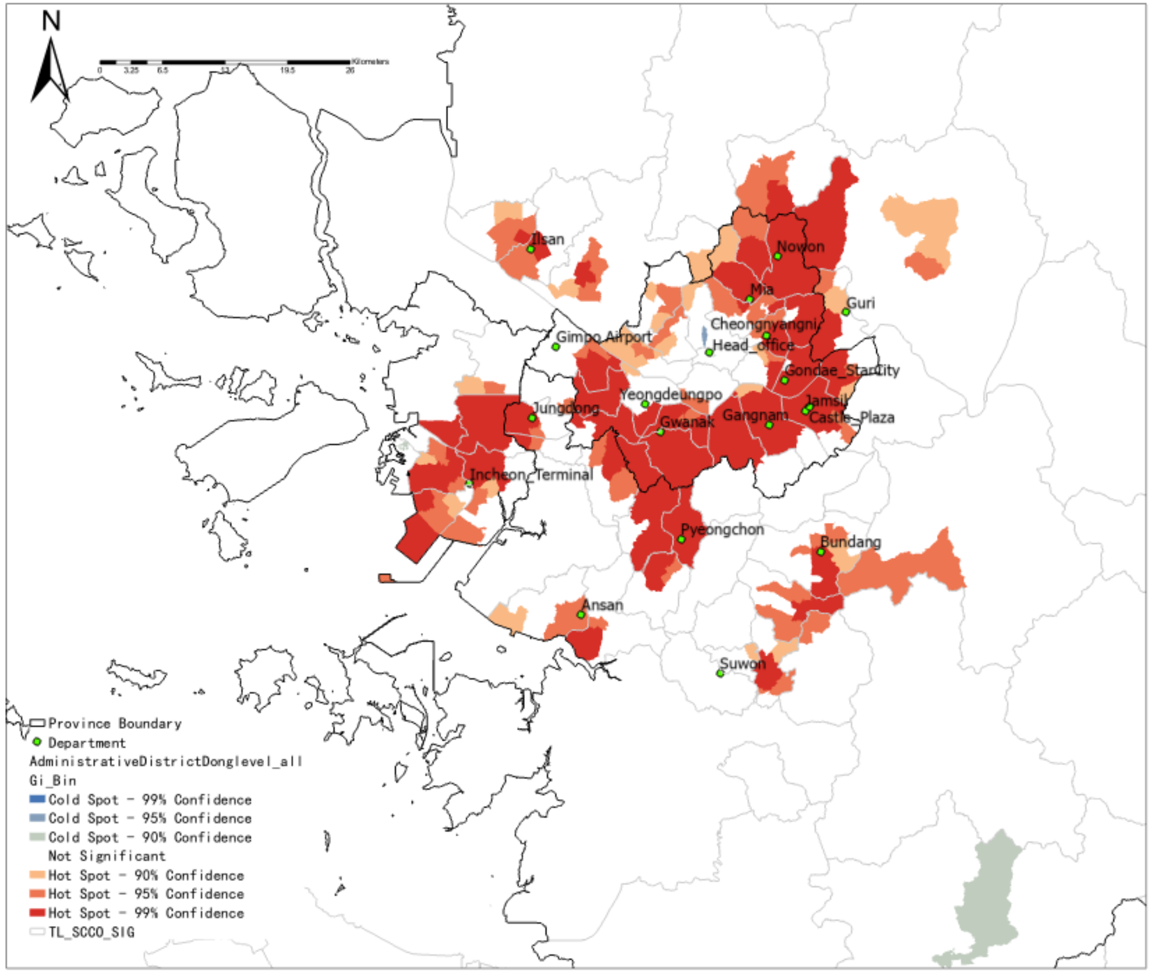
- Association rules for <u>products categories</u> in the SMA (**confidence** > **0.2;** **lift** > **2**)

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
Basic casual	Stylish casual	0.065763	0.077238	0.020735	0.315306	4.082269	0.015656	1.347700
Cool casual	Basic casual	0.022010	0.065763	0.005368	0.243902	3.708810	0.003921	1.235604
Cool casual	Stylish casual	0.022010	0.077238	0.005368	0.243902	3.157806	0.003668	1.220427
Young casual	Value casual	0.066233	0.071870	0.014025	0.211753	2.946349	0.009265	1.177461
Young casual	Young trendy	0.066233	0.070595	0.013488	0.203647	2.884747	0.008812	1.167078

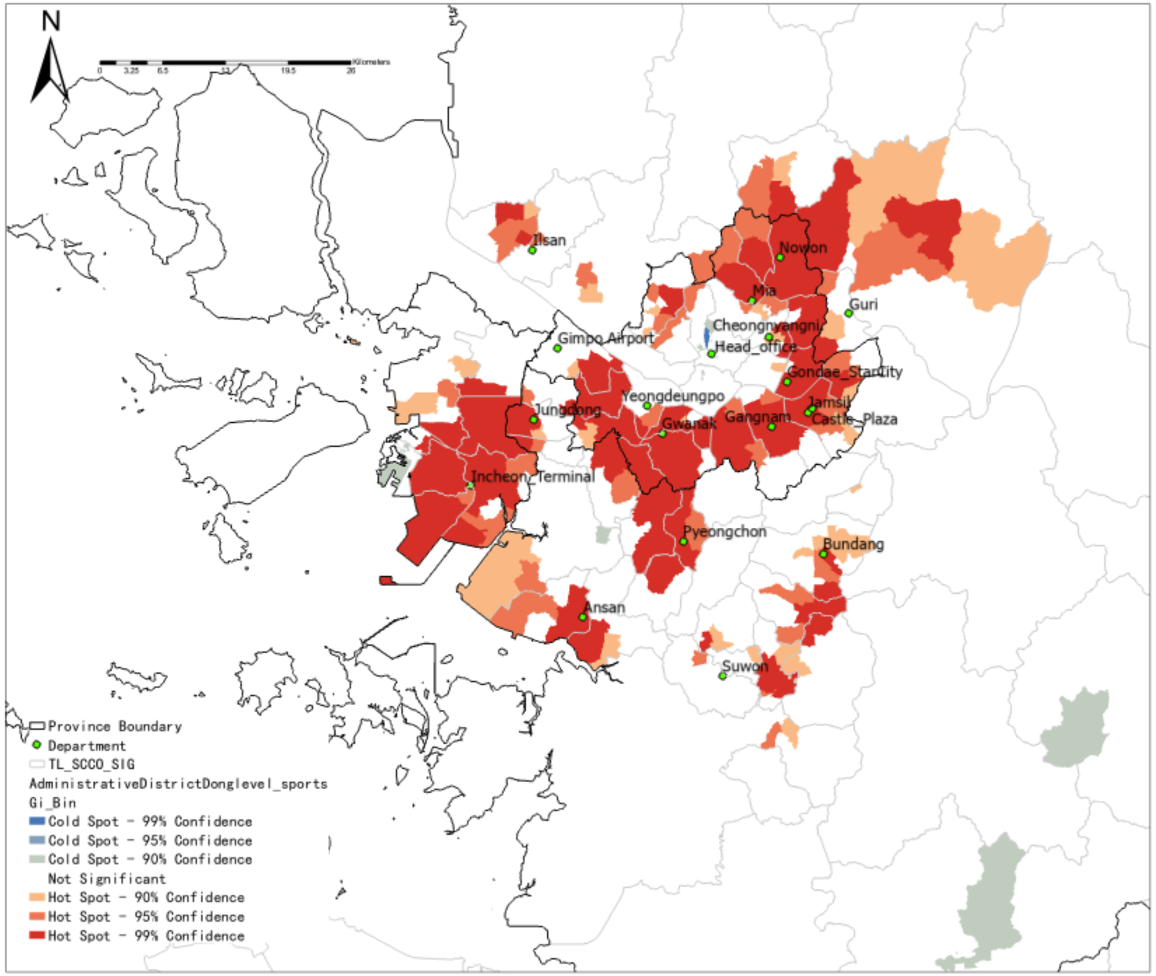
- Association rules for <u>products segments</u> in the SMA (**confidence** > **0.2;** **lift** > **2**)

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
[Imported cosmetics] Misc. Set	[Imported cosmetics] Body Care	0.019534	0.027555	0.005045	0.258278	9.373193	0.004507	1.311064
[Kids] Kids/Junior Clothes	[Sportswear-Shoes] Shoes	0.014748	0.075809	0.005433	0.368421	4.859889	0.004315	1.463303
[Imported cosmetics] Makeup Set	[Imported cosmetics] Skincare Set	0.022898	0.063777	0.005045	0.220339	3.454808	0.003585	1.200807
[Imported cosmetics] Skincare Set	[Imported cosmetics] Skincare	0.063777	0.075938	0.016688	0.261663	3.445753	0.011845	1.251546
[Imported cosmetics] Skincare	[Imported cosmetics] Skincare Set	0.075938	0.063777	0.016688	0.219761	3.445753	0.011845	1.199918
Imported cosmetics] Body Care	[Imported cosmetics] Skincare	0.027555	0.075938	0.006080	0.220657	2.905759	0.003988	1.185694

Results of Hot spots analysis

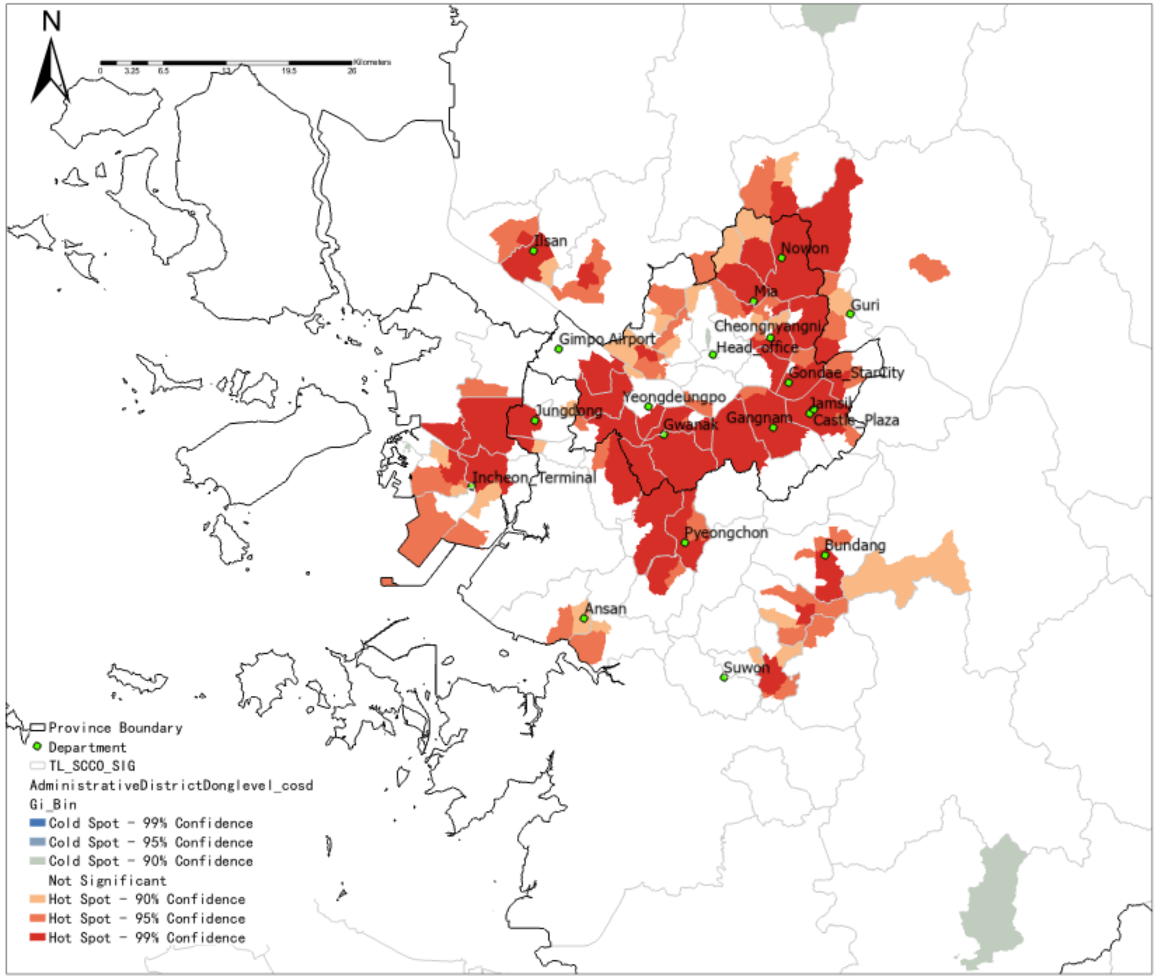


Hot spots for total orders

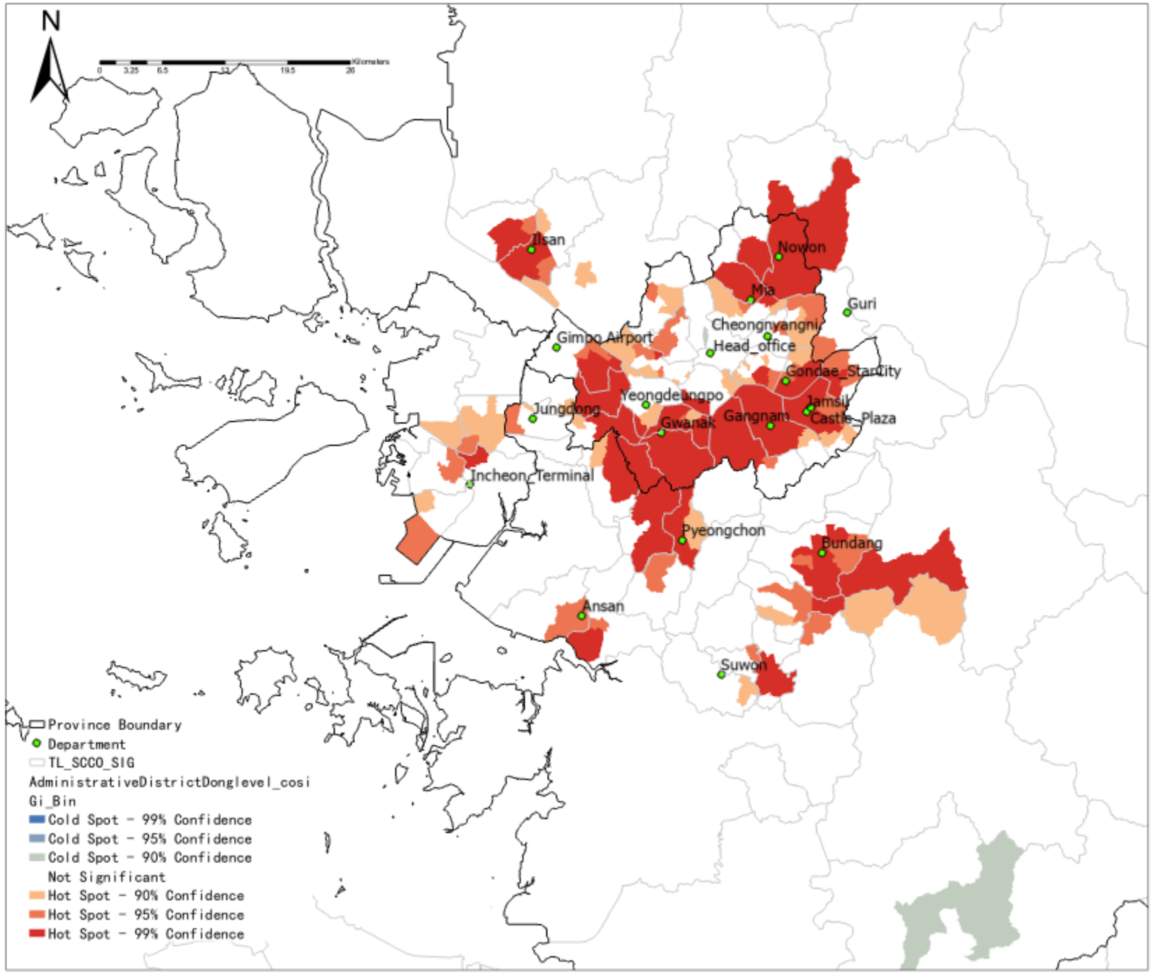


Hot spots for Sportswear/shoes

Results of Hot spots analysis



Hot spots for Domestic Cosmetics

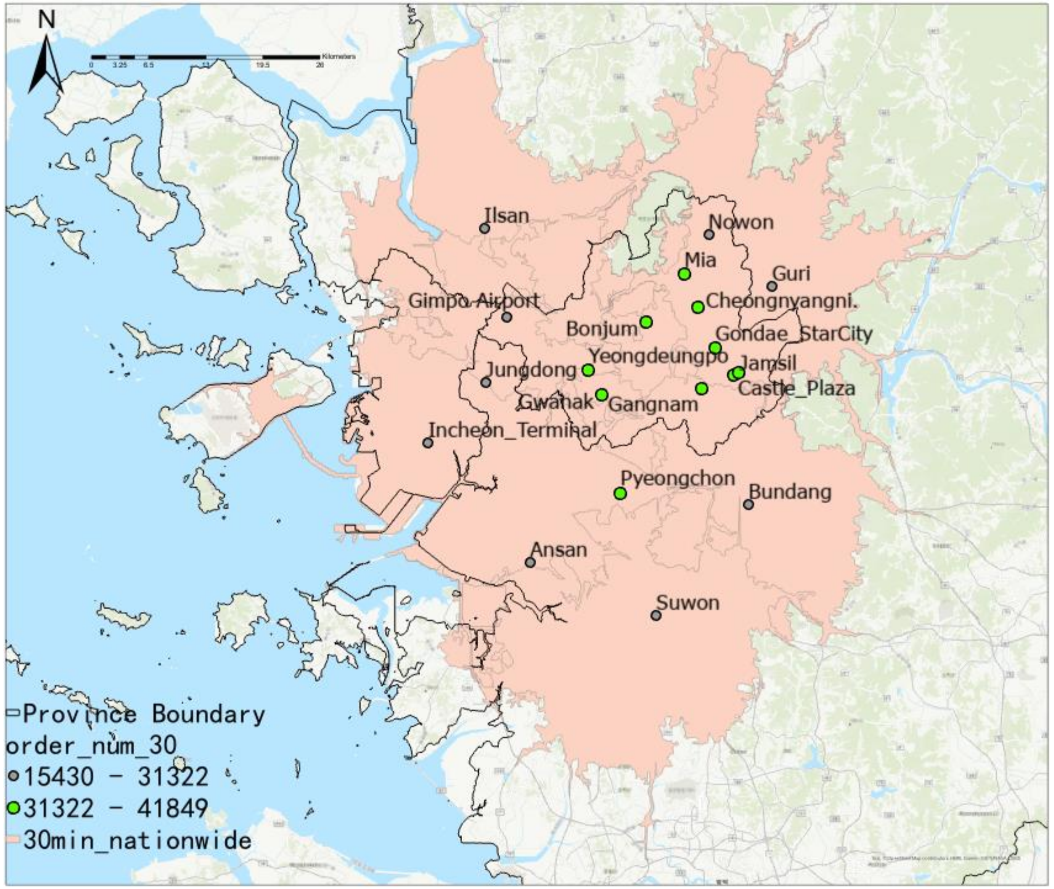


Hot spots for Imported Cosmetics

Service area for ship-from-store (SFS)

Range of the SFS service area: 30-minute driving time (same-day delivery)

Service of each store for ship-from-store (SFS) service



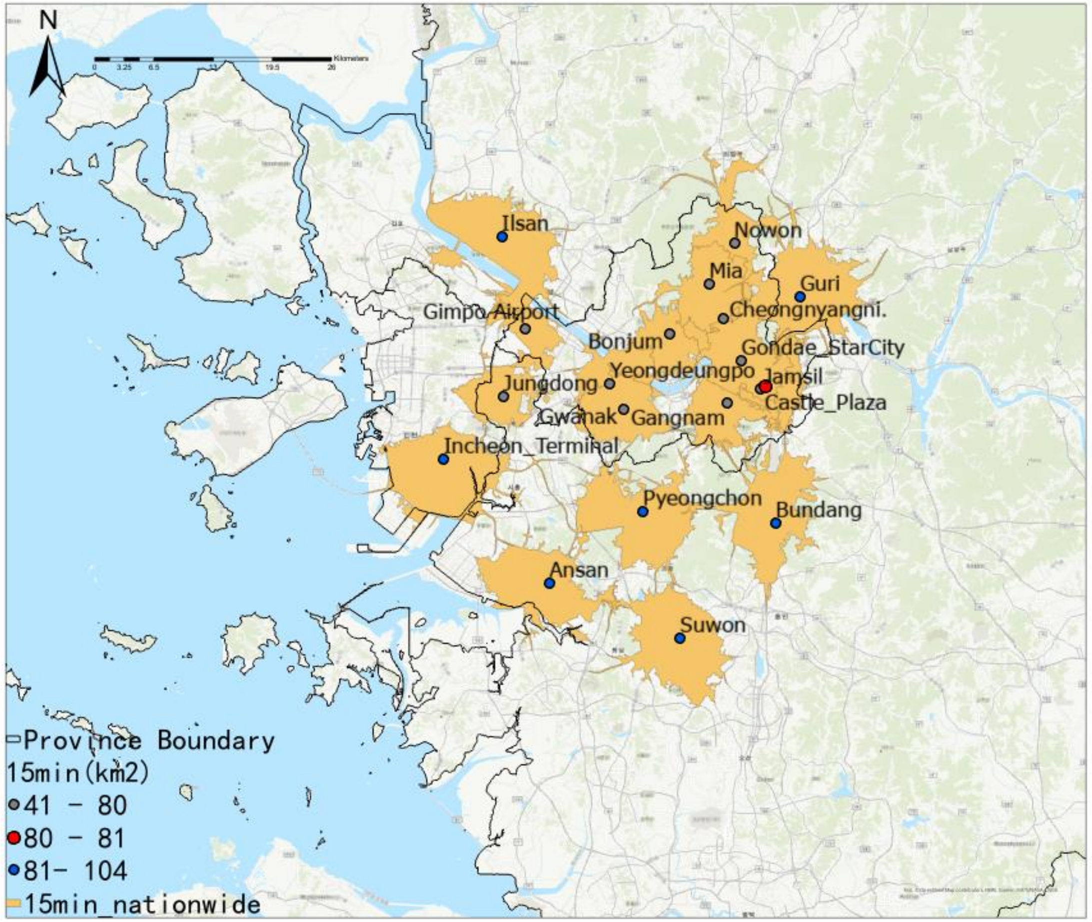
Accessibility of each store within the ship-from-store (SFS) service area

Store names	Accessibility			
	Total demands	Domestic Cosmetics	Imported Cosmetics	Sportswear /shoes
Castle plaza	1	0.956881877	0.793639109	0.917451972
Gangnam	0.975618291	1	1	0.704046263
Gondae star city	0.974998529	0.965803702	0.716754033	0.884772033
Bundang	0.910699497	0.886783365	0.809124515	1
Gimpo airport	0.747213843	0.731203662	0.484247272	0.8682224
Guri	0.681276288	0.605651831	0.413266538	0.740971088
Yongdeungpo	0.670917028	0.694898096	0.497909002	0.547129049
Jungdong	0.611266543	0.500296212	0.263646656	0.971245229
Jamsil	0.602224594	0.569077637	0.518440968	0.50638278
Pyongchon	0.52701068	0.525954437	0.308482056	0.737088476

Service area for buy-online & pick-up from store (BOPS)

Range of the BOPS service area: 15-minute driving time

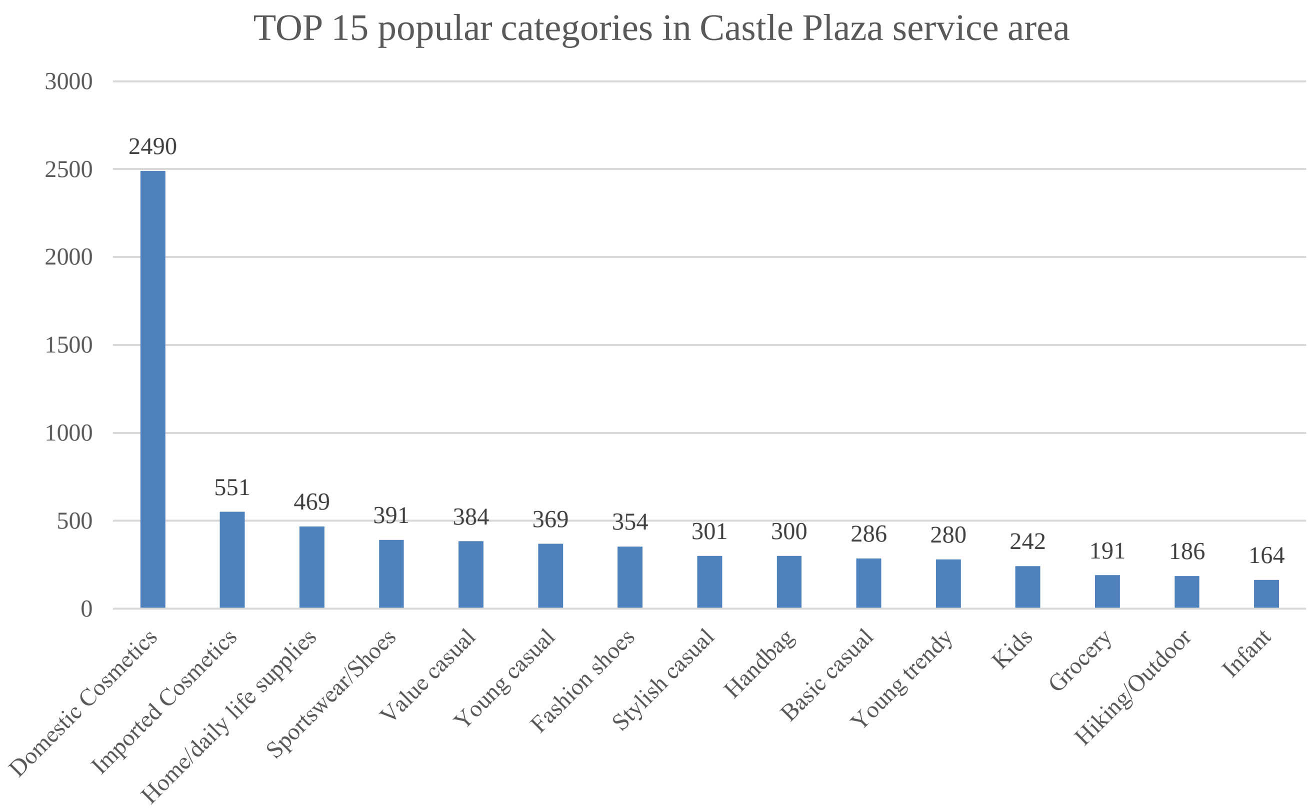
Service of each store for BOPS service



Standardized accessibility measure of each store within 15-minute service area

Stores	Accessibility			
	Total demands	Domestic Cosmetics	Imported Cosmetics	Sportswear /shoes
Gangnam	1	1	1	1
Castle plaza	0.746556932	0.634256506	0.552812309	0.968458795
Geondae star city	0.433973075	0.399866022	0.320727671	0.455377675
Jamsil	0.424030716	0.368143613	0.324773359	0.478428206
Jungdong	0.423179896	0.29683651	0.181042162	0.772910666
Bundang	0.327932831	0.282235534	0.3593111	0.468429259
Yongdeungpo	0.275136189	0.292054157	0.211426428	0.24969193
Chongnyangnij	0.245553634	0.318630782	0.051675453	0.195432788
Mia	0.236230923	0.179353742	0.235408081	0.277408878
Ilsan	0.211042019	0.219628698	0.22516704	0.259124268

- The top selling product category at both macro-level and local level (Castle Plaza store **domestic cosmetics**. However, it is 5 times higher than second place in the Castle Plaza 15-min service area, while 4 times higher in SMA.
- Although **sportswear/shoes** takes the second place in SMA, it reduce to the fourth in local area.
- **Stylish casual** is the most popular kind of clothing in SMA, while relatively less purchased in the local area.



Association rule mining: local level

Association rule mining within the BOPS service area of Castle Plaza store

- Association rules for products categories within the 15-minute service area of Castle Plaza store

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
Basic Casual	Stylish Casual	0.068398	0.071861	0.024242	0.354430	4.932134	0.019327	1.437705
Cool Casual	Stylish Casual	0.018182	0.071861	0.005195	0.285714	3.975904	0.003888	1.299394
Young Trendy	Young Casual	0.074459	0.082251	0.019913	0.267442	3.251530	0.013789	1.252800
Value Casual	Young Casual	0.068398	0.082251	0.018182	0.265823	3.231845	0.012556	1.250037
Value Casual	Young Trendy	0.068398	0.074459	0.013853	0.202532	2.720047	0.008760	1.160599

- Association rules for products segments within the 15-minute service area of Castle Plaza store

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
[Domestic Cosmetics] Body Care	[Domestic Cosmetics] Skincare	0.011058	0.131122	0.006319	0.571429	4.358003	0.004869	2.027383
[Imported Cosmetics] Makeup Set	[Imported Cosmetics] Skincare Set	0.023697	0.078989	0.006319	0.266667	3.376000	0.004447	1.255924
[Imported Cosmetics] Body Care	[Domestic Cosmetics] Skincare	0.030016	0.080569	0.007899	0.263158	3.266254	0.005481	1.247800
[Imported Cosmetics] Skincare Set	[Imported Cosmetics] Skincare	0.078989	0.080569	0.015798	0.200000	2.482353	0.009434	1.149289
[Domestic Cosmetics] Skincare Sun Care	[Domestic Cosmetics] Skincare	0.026856	0.131122	0.007899	0.294118	2.243090	0.004377	1.230911

Conclusions

Contributions:

- Identify clusters of high-demand density areas.
- Provide potential store locations for two kinds of in-store order fulfillment services: SFS and BOPS
- Provide correspoding allocation strategies based on regional and local demand features.

Limitations:

- The data used in this study is the online sales data of Company A’s online sales data in spring. In addition, the data itself lacks a lot of detailed information, such as information on the brands of specific products.
- Limited research region: only focus on Seoul metropolitan area
- Lack of considering the actual situation, such as the capacity of each store, overlapping service areas, and the presence of competitors in the vicinity.

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THANK YOU FOR YOUR ATTENTION.

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