Service Intelligence Special Lecture:

An Example of Successful Service Intelligence R&D Projects

Presenter: Jongkyung Shin (UNIST AIGS, Ph.D. Candidate)

How to well conduct research or term project

1. Find the problem in the focal domain and define the most relevant research question

What is the target problem?
Why do we solve this problem?

2. Come up with many ideas to solve the problem with novel creative approaches

3. Develop your idea and create your own method

How to solve this problem in our own creative way?

- Identification or design of service content to be delivered to the customers or users
- Create a new method to solve the problem
- Create a framework for developing a novel intelligence

4. Prepare and conduct several experiments

Does the method work as we expected?

- Collect and analyze the data
- Performance verification, validation, comparison with existing methods

Does our method outperform existing methods?

What advantages does our method have over the existing ones?

5. Discuss and analyze the results of experiments and your contributions to the research literature and the focal domain

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- Contribution of your term project outcome to the improvement of focal service

Recommendation in Offline Stores: A Gamification Approach for Learning the Spatiotemporal Representation of Indoor Shopping

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Knowledge Discovery & Data Mining (KDD) Conference

Recommendation in Offline Stores: A Gamification Approach for Learning the Spatiotemporal Representation of Indoor Shopping

Jongkyung Shin*
Changhun Lee*†
Chiehyeon Lim†
shinjk1156@unist.ac.kr
messy92@unist.ac.kr
chlim@unist.ac.kr
Ulsan National Institute of Science and Technology
Ulsan, Republic of Korea

Yunmo Shin
Junseok Lim
ymshin@retailtech.co.kr
sharpjs@retailtech.co.kr
Retailtech Co., Ltd.
Seoul, Republic of Korea

ABSTRACT

With the current advancements in mobile and sensing technologies used to collect real-time data in offline stores, retailers and wholesalers have attempted to develop recommender systems to enhance sales and customer experience. However, existing studies on recommender systems have primarily focused on e-commerce platforms and other online services. They did not consider the unique features of indoor shopping in real stores such as the physical environments and objects, which significantly affect the movement and purchase behaviors of customers, thereby representing the "spatiotemporal contexts" that are critical to identifying recommendable items. In this study, we propose a gamification approach wherein a real store is emulated in a pixel world and a recurrent convolutional network is trained to learn the spatiotemporal representation of offline shopping. The superiority and advantages of our method over existing sequential recommender systems are demonstrated through a real-world application in a hypermarket. We believe that our work can significantly contribute to promoting the practice of providing recommendations in offline stores and services.

CCS CONCEPTS

• **Information systems → Recommender systems; Location based services.**

KEYWORDS

interactive recommender system, offline stores, indoor shopping, spatiotemporal representation, gamification, recurrent convolutional network, reinforcement learning

ACM Reference Format:
Jongkyung Shin, Changhun Lee, Chiehyeon Lim, Yunmo Shin, and Junseok Lim. 2022. Recommendation in Offline Stores: A Gamification Approach for Learning the Spatiotemporal Representation of Indoor Shopping. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD '22), August 14–18, 2022, Washington, DC, USA.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3534678.3539199

*Equal contribution
†Corresponding author

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1 INTRODUCTION

Recommender systems are one of the most popular and successful applications of data science. By learning the purchase records, a recommender system can support customers in searching for diverse items based on their various needs and implicit preferences [14, 41]. Numerous studies have applied traditional and modern data science techniques to develop real-world recommender systems that can learn customer needs and preferences for movies, books, and other items listed in e-commerce services [34, 39]. Owing to the flexibility of online environments that interact with customers in real-time, online services can immediately recognize the context of a customer's needs and promptly offer personalized recommendations [15]. It has been demonstrated that these advanced systems significantly improve customer experience and engagement in online services, thereby increasing profits [26, 41]. However, this is rare in "offline" actual stores (i.e., retail and wholesale stores). Although some related studies have investigated the simple application of traditional collaborative filtering techniques to identify recommendations for retail customers [27, 31], to the best of our knowledge, no study has demonstrated the successful use of advanced data science to interactively identify recommendable items for customers in real-world offline stores.

Unlike the simplified "online environment" of e-commerce websites and mobile applications, a recommender system for offline stores must consider the "offline environment," wherein customers are required to make physical movements that are constrained to the dynamics of offline shopping.[1] Thus, indoor shopping in real stores involves the following three unique features that pose challenges to the collection and learning of data. First, traces of a focal customer in an offline store form a unique item purchase sequence *and* route. Although two customers may purchase the same sequence of items, they typically use different routes. Second, customers interact with a store environment dynamically and in

[1]Customers in offline stores must make unavoidable movements and are constantly and sequentially exposed to the items that are not included in their original purchase plans during the movement. The physical constraints cause delays in accessing recommended items, and constantly expose customers to other items during their movements through the stores. These delays and exposure represent the "contexts" crucial for recommending specific items to customers when they are moving to access the target items. Therefore, in offline stores, the items near to the customer's current location can be considered for identifying potential recommendations.

Google Scholar

Top publications

Categories > Engineering & Computer Science > **Data Mining & Analysis**

	Publication	h5-index	h5-median
1.	ACM SIGKDD International Conference on Knowledge Discovery & Data Mining	114	196
2.	IEEE Transactions on Knowledge and Data Engineering	88	147
3.	International Conference on Artificial Intelligence and Statistics	85	119
4.	ACM International Conference on Web Search and Data Mining	69	133
5.	Journal of Big Data	55	104
6.	IEEE International Conference on Data Mining	53	81

KDD

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- Experiment: Comparison with different methods of the intelligence development
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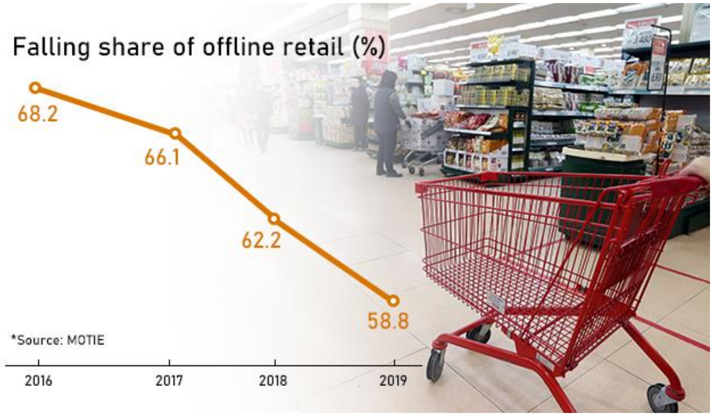
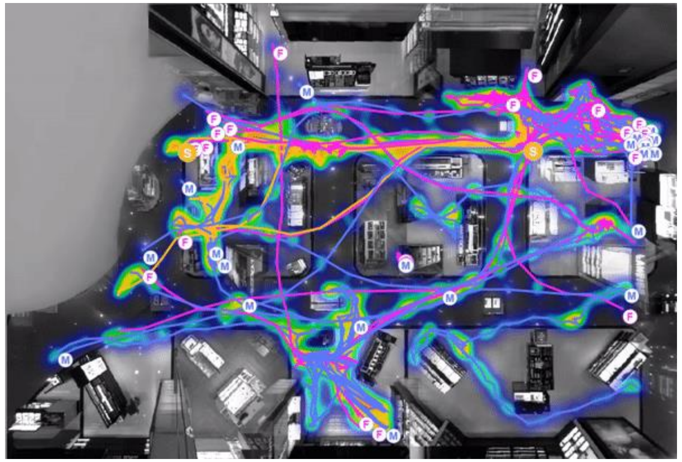
Background : Offline retail VS E-commerce

- Emerging the E-commerce, offline retail are losing market share every year
- Offline retailor have attempted to restore their market share and to increase customer's satisfaction
  - Reduction of congestion, Providing new experiences



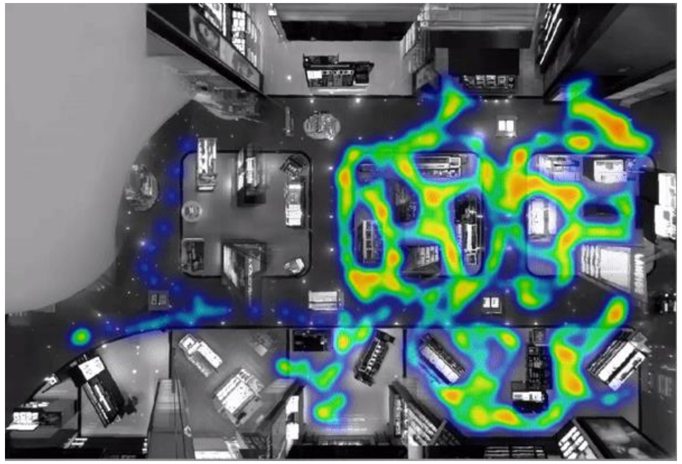
Background : Previous Attempts in Offline Retail



[1]

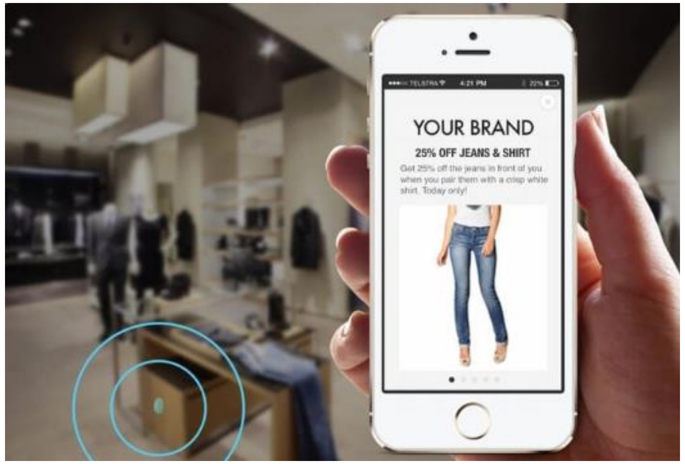
[2]

Smart shopping cart



[1]

Data analytics using cameras
(for reduction of congestion)



[3]

Location based recommender system
using beacon (Bluetooth)

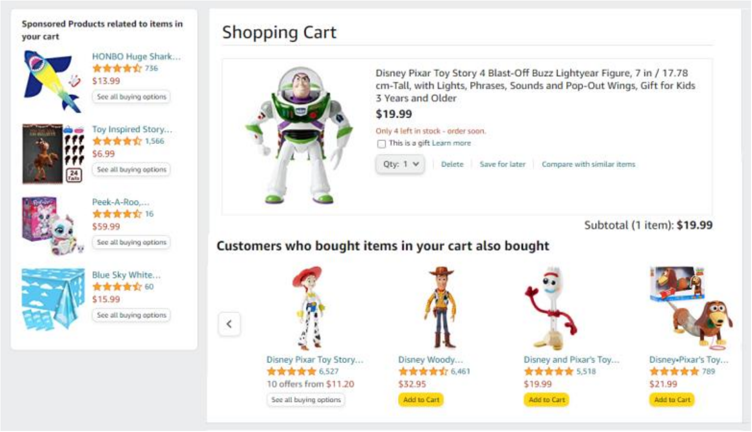
[1] https://www.prodcotech.com/shopper-paths-heatmaps/
[2] https://www.arabnews.com/node/1705276/business-economy
[3] https://www.plotprojects.com/blog/beacon-technology-in-retail-strategies-to-boost-sales/

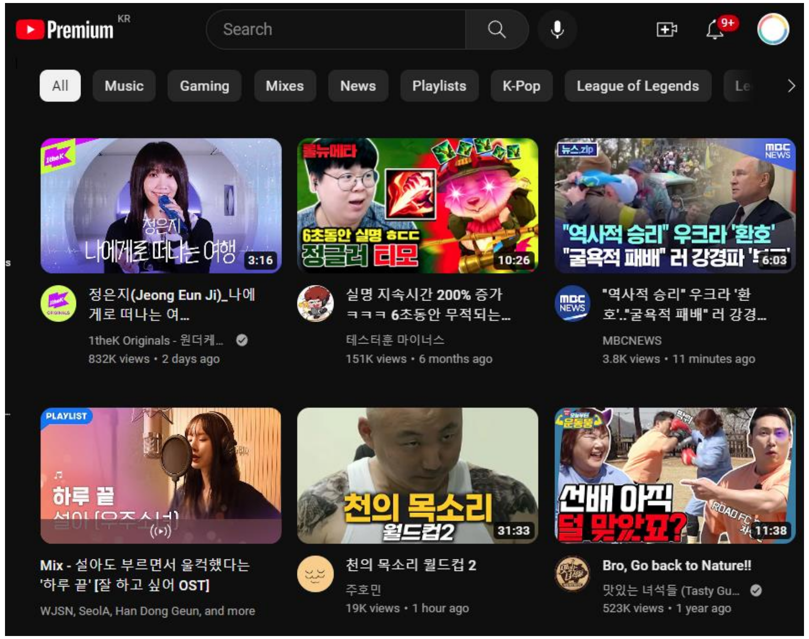
Background: Interactive recommendation in real-world

Product Recommendation

Media Contents Recommendation

SNS Contents Recommendation





Background: Recommendation domain

Research Category : Recommendation

Subcategories of recommendation

Sequential recommendation

Collaborate filtering

Interactive recommendation

Session based recommendation

…

Personalization

Real-time recommendation

Contents based recommendation

Background: Recommendation domain

Research Category : Recommendation

Subcategories of recommendation

Sequential recommendation

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Interactive recommendation

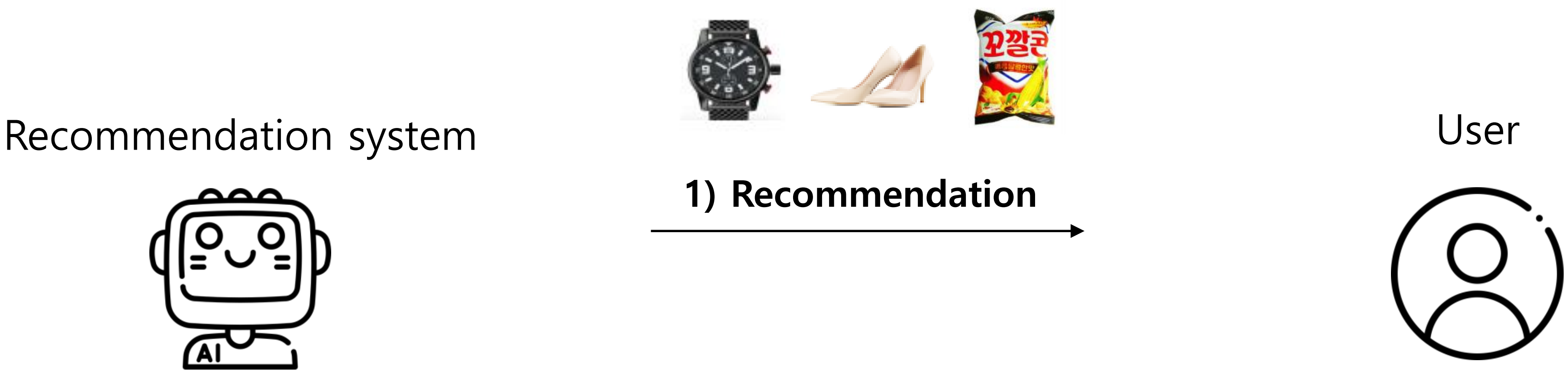
…

Personalization

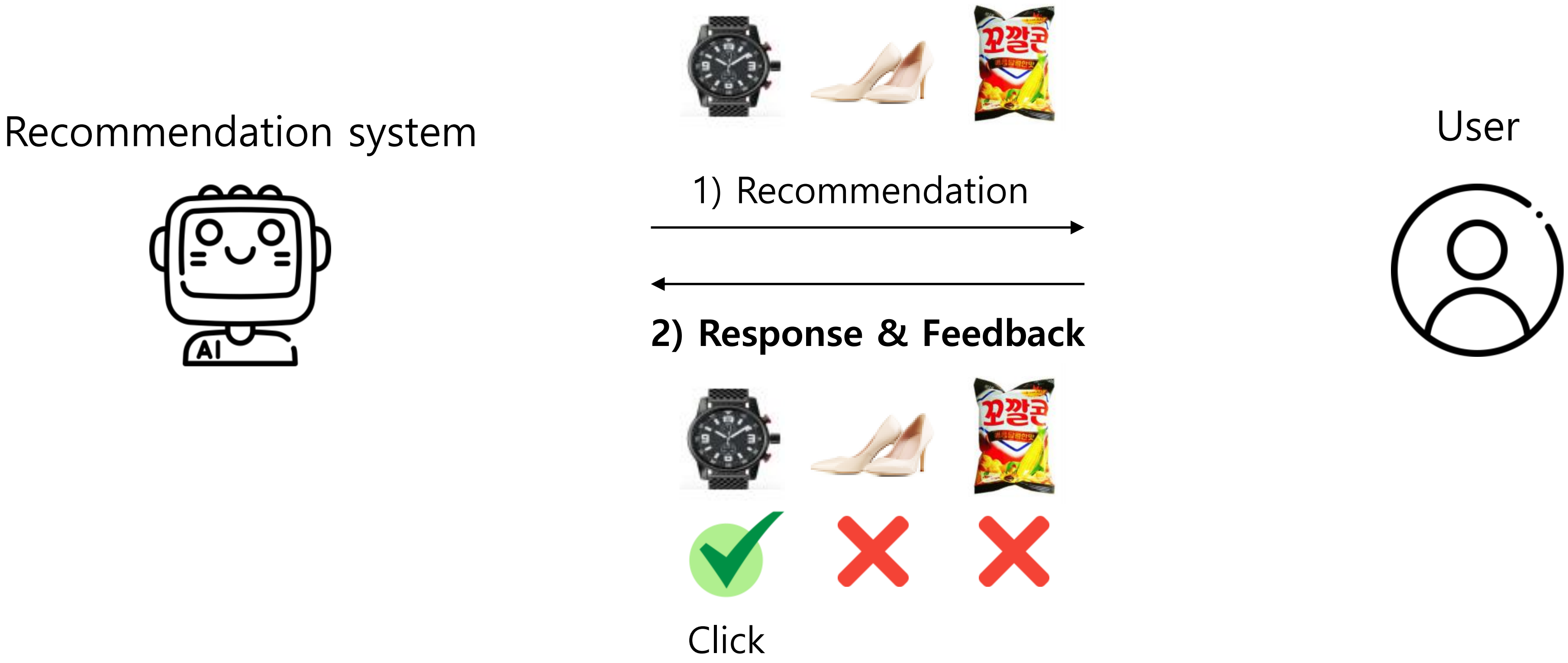
Real-time recommendation

Contents based recommendation

Background: What is the interactive recommendation?

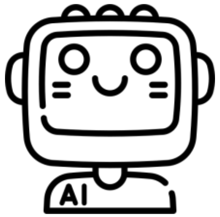


Background: What is the interactive recommendation?



Background: What is the interactive recommendation?

Recommendation system



3) **Update recommendation List**

1) Recommendation

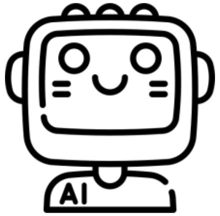
2) Response & Feedback

Click

User

Background: What is the interactive recommendation?

Recommendation system

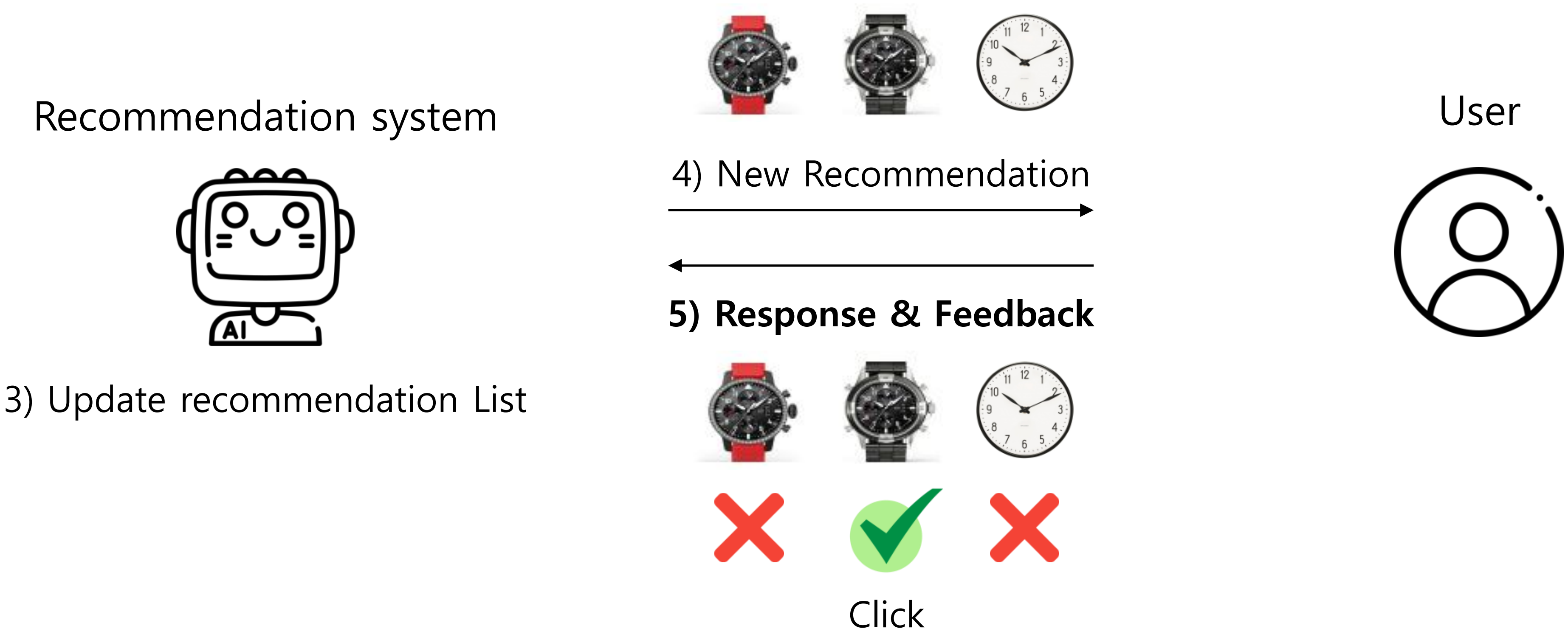


3) Update recommendation List

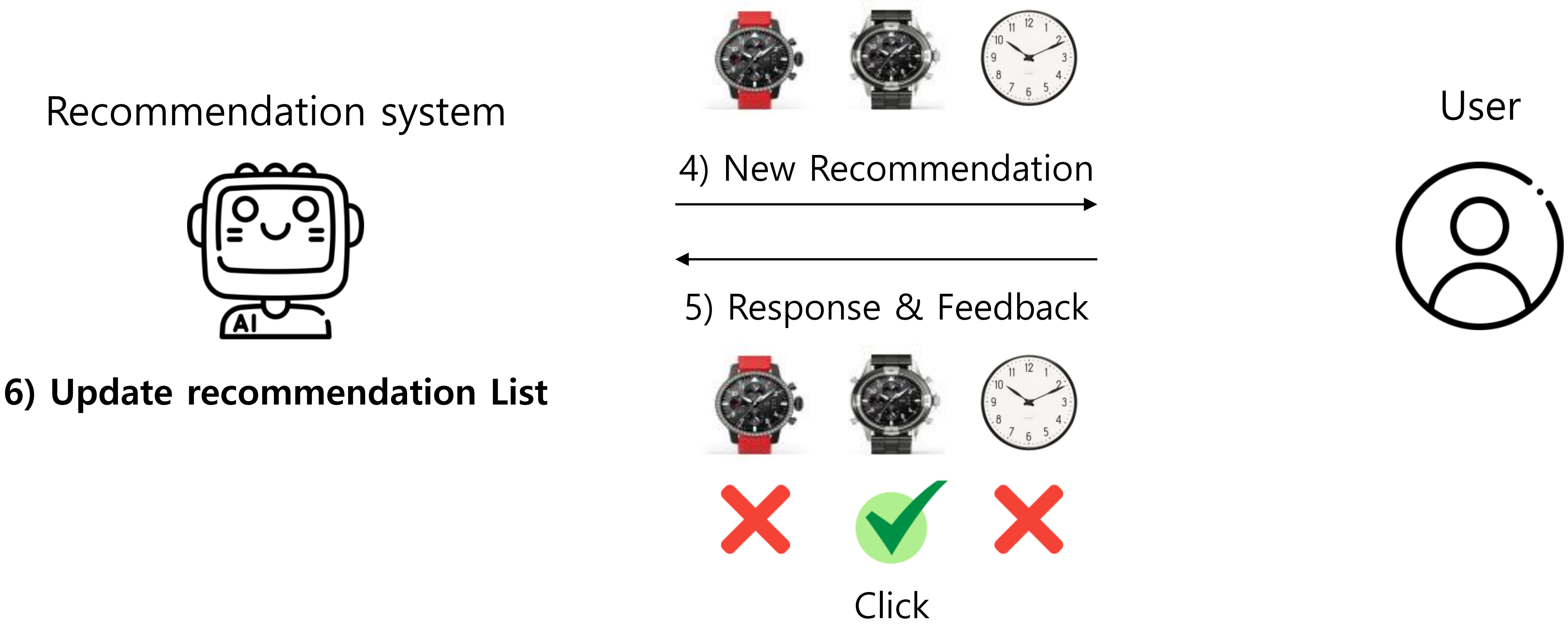
4) New Recommendation

User

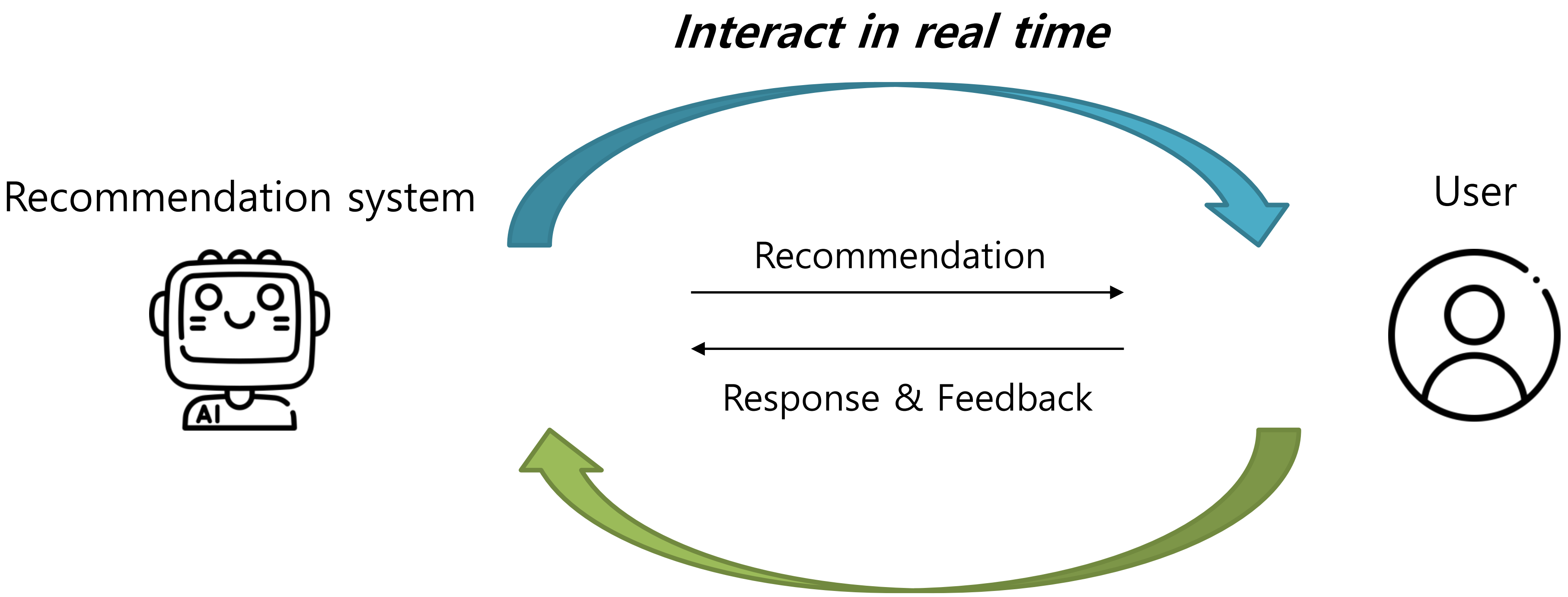
Background: What is the interactive recommendation?



Background: What is the interactive recommendation?



Background: What is the interactive recommendation?



Recommend in real-time by considering user preference and current interest

Background: Interactive recommendation in real-world

Product Recommendation

Media Contents Recommendation

SNS Contents Recommendation

Sales & **Customer Satisfaction**

Definition of a significant service problem and an idea to solve the problem

Offline retailors want

To increase sales

To increase # of loyal customers

From the perspective of service, they need…

To increase
Customers' satisfaction

To provide
New experience

Definition of a significant service problem and an idea to solve the problem

Main Goal: Interactive recommender system for offline store

Device

Recsys

Recommendation

[2]

Smart Shopping Cart

[3]

Smart Phone

Customer

Feedback

※ Note: **we assume this recommender system is for general customers (not for individual customer).**
Because many customers in offline stores may utilize smart devices (e.g., smart shopping carts) without logging-in owing to privacy concerns.

Identification or design of service contents to be delivered to the customers/users

If you are offline retailer…

And you want to increase the sales and customer's satisfaction

Is it possible to introduce interactive recommendation system in offline store?

Identification or design of service contents to be delivered to the customers/users

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And you want to increase the sales and customer's satisfaction

Is it possible to introduce interactive recommendation system in offline store?

If yes,

What do we need?
Which customer context in an offline store should we consider?
What is the specific characteristic of an offline store that an e-commerce does not have?
…

Identification or design of service contents to be delivered to the customers/users

If you are offline retailer…

And you want to increase the sales and customer's satisfaction

<u>Is it possible to introduce interactive recommendation system in offline store?</u>

If yes,

What do we need?
Which customer context in an offline store should we consider?
What is the specific characteristic of an offline store that an e-commerce does not have?
…

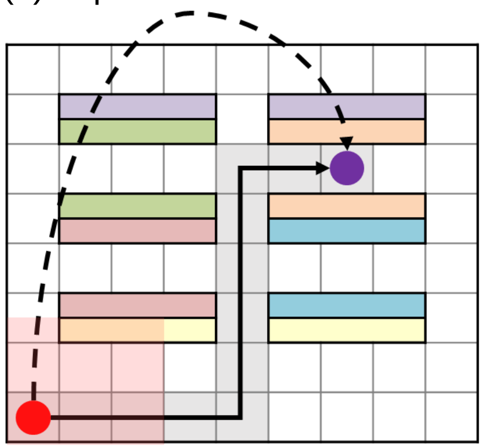
To answer this questions,

Let's do analysis and literature review!

Unique Features of Offline Retail Stores (1/2)

Main difference from e-commerce: Physical constraints (e.g., space, structure)

(1) Impossible movement



(2) Different items are exposed by location

<Comparison of customer behavior in the offline and online store>

Customer's behavior	Environment	
	Online store	Offline store
Entrance	Access Homepage/App	Visit a store
Search items	Use search engine	Walk around the store
Confirm recommended items	Watch through the device's screen	(Watch through the device's screen)
Adopt recommended items	Click the 'add on basket' button	Move toward item and load it
Purchase and pay	Click the 'payment' button	Move to counter and payment

(1) Current location determines where customers can go

(2) Current location determines what customers can see

→ Customer's spatial condition changes shopping behavior

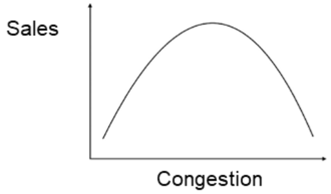
Context of customers can be continually changed by their location and structure of offline store

Unique Features of Offline Retail Stores (2/2)

Due to the limitation of space

Manage to maximize Sales ➚ ➡ **Congestion** ➚ ➡ **Sales** ➘

Congestion has **Inverted U-shaped relationship with sales** [4]

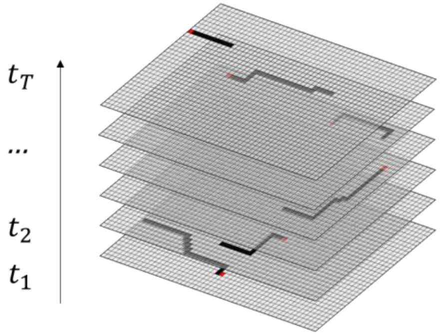


The retailers need to balance the trade-off between the congestion and sales of stores appropriately

[4] Yue Pan and Jennifer Christie Siemens. 2011. The differential effects of retail density: An investigation of goods versus service settings. Journal of Business Research 64, 2 (2011), 105–112

Identification or design of service contents to be delivered to the customers/users

Main Goal: Interactive recommender system for offline store



Sales & **Congestion**

(1) To capture <u>spatiotemporal context</u> of customers

(2) To control <u>sales operation</u> from the perspective of retailer

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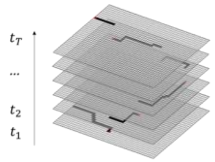
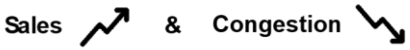
Own creative “Framework” of developing a novel service intelligence

Main Goal: Interactive recommender system for offline store



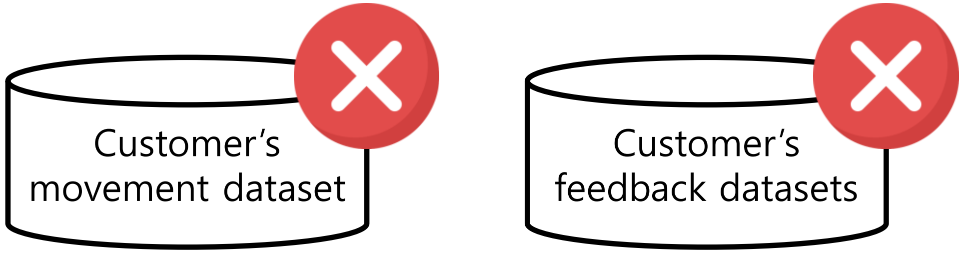


(1) To capture spatiotemporal context of customers

(2) To control sales operation from the perspective of retailer

Main Challenge: Hard to collect data that represent the spatiotemporal context and customer’s feedback

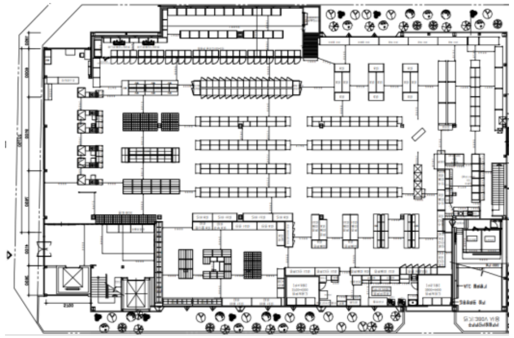
- Devices that can collect customers’ in-store behaviors are available only at a few store
- Installation of new sensors or devices costs a great deal of money



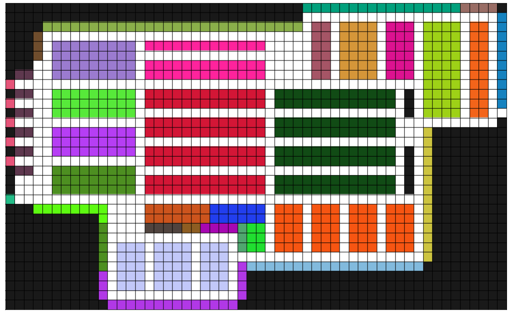
Own creative “Framework” of developing a novel service intelligence

Proposed Approach: Gamification approach for learning the spatiotemporal representation

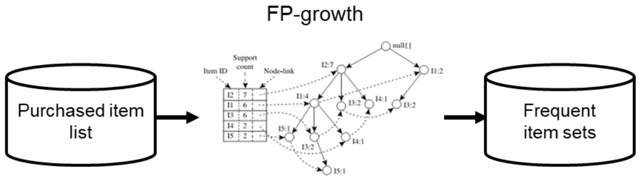
Floor plan and plan-o-gram



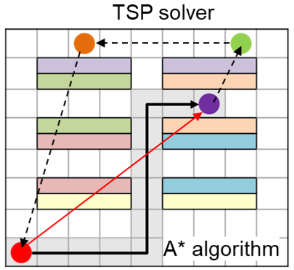
Emulate



Pixel world environment



< Initializing purchase plan >



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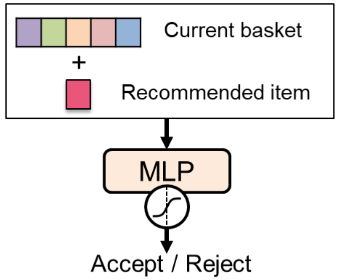
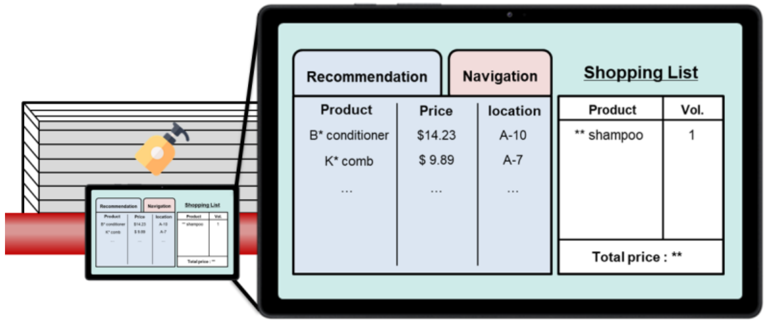
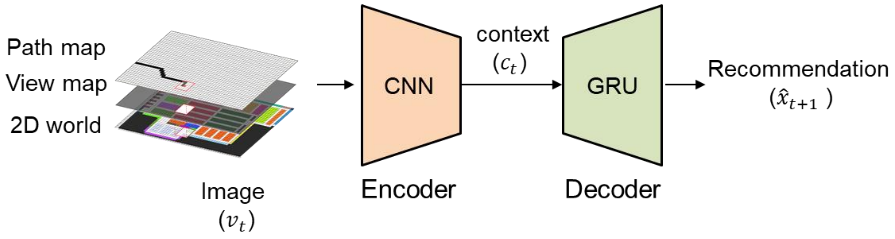


< Decision-making >

User model

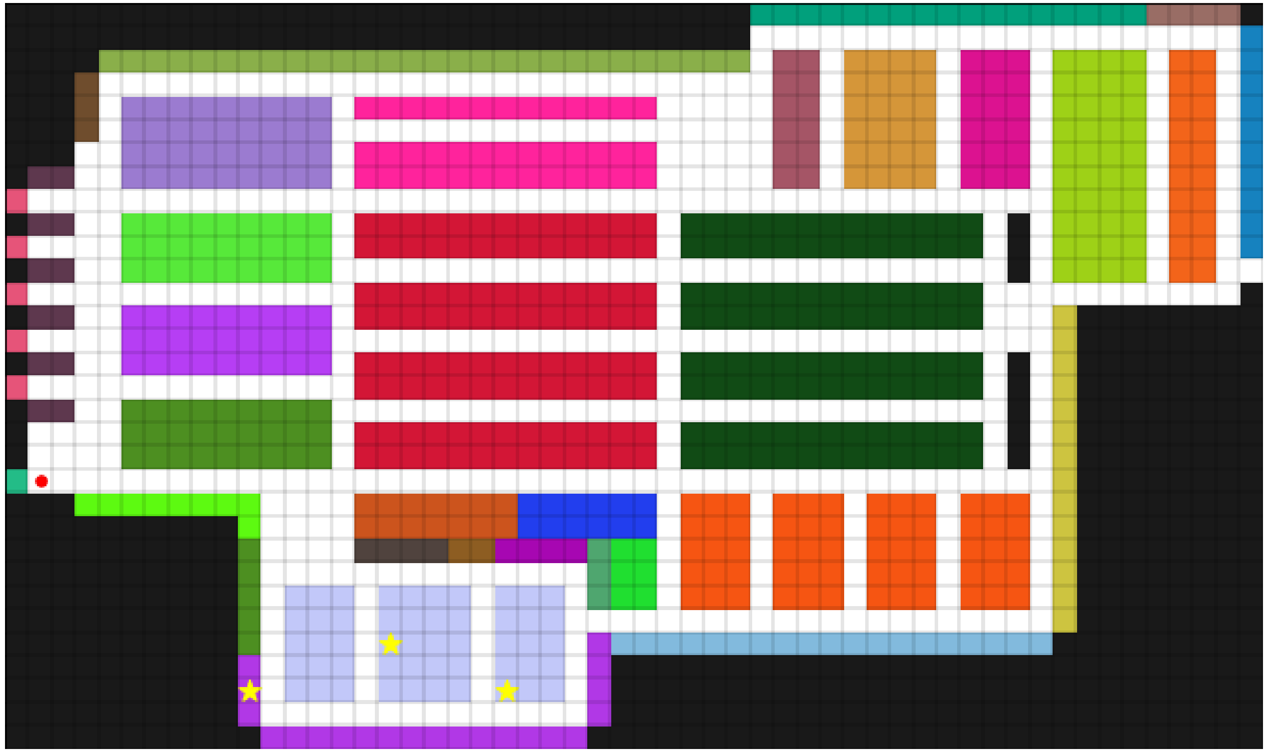


Recurrent convolutional network (RCN)



Recommender system

Example of Interactive Training Process

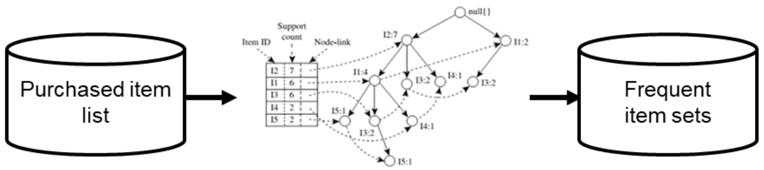


Red circle : current location of user model

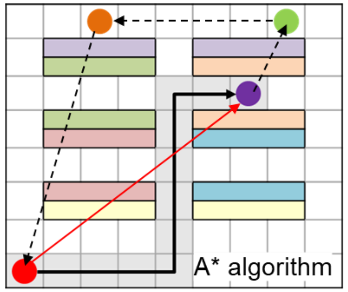
Black circle : user model's movement

Yellow star : location of an item in the initial purchase plan

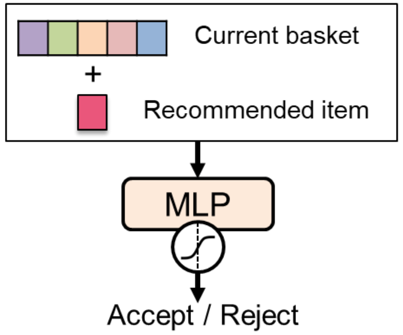
Blue star : location of the recommended item that user model accepts



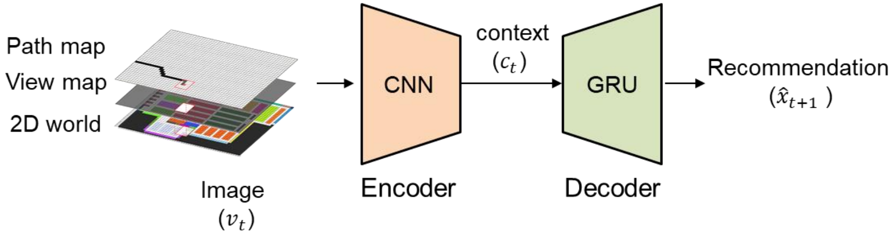
< Initializing purchase plan >



< Navigating >

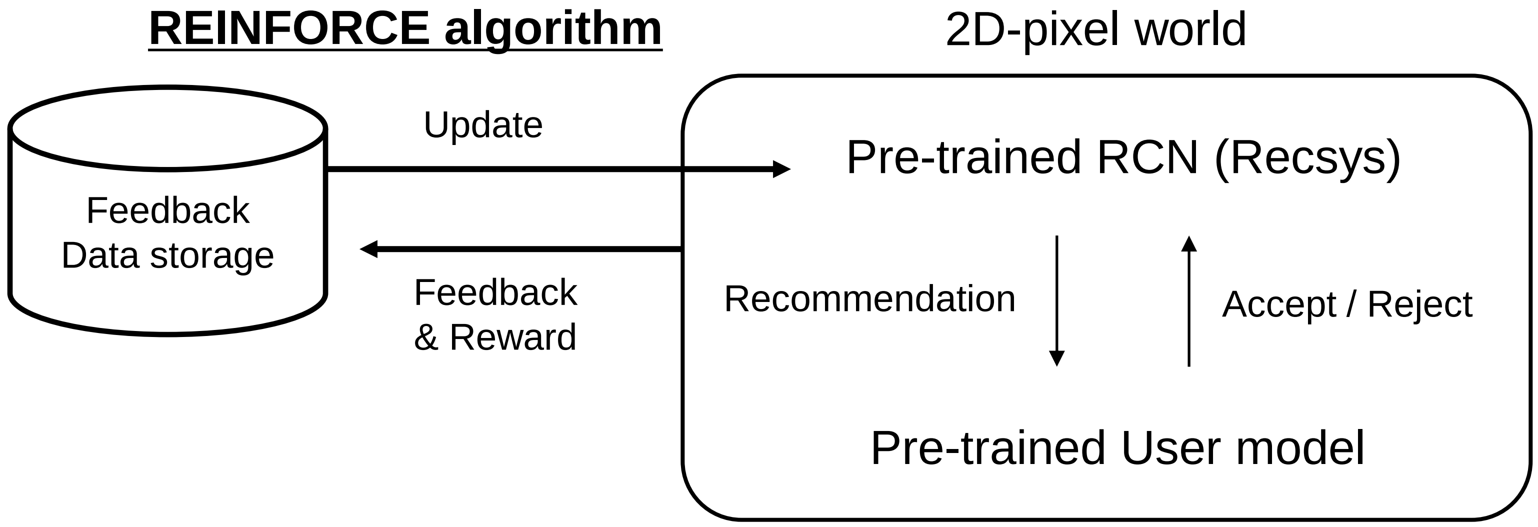


< Decision-making >



< Recurrent convolutional network (RCN) >

Reinforcement Learning for Recommendation and Operations Control



Operations Control

To maximize the sales→ Maximize total price of (accepted) recommended items (TPR)

To minimize the congestion in store → Minimize length of shopping (LOS)

Reward function : $R(\hat{x}_{1:T}) = (1-\lambda)\log\ \mathrm{TPR}_{\mathrm{scale}}(\hat{x}_{1:T})\ - \lambda\log\ \mathrm{LOS}_{scale}(\hat{x}_{1:T})$

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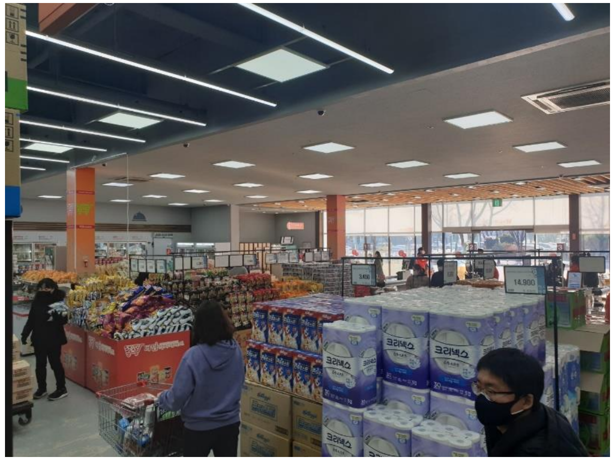
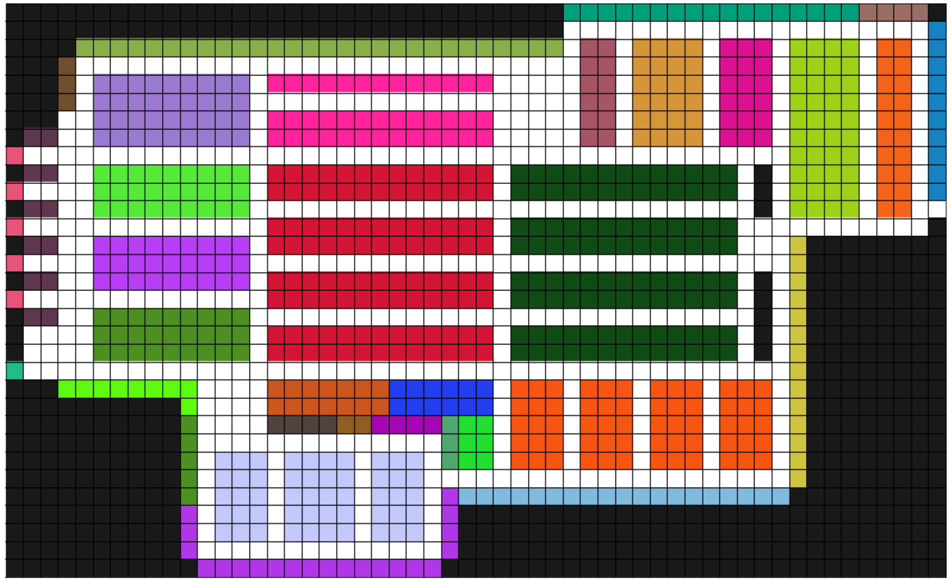
Real-world Datasets Used for Pre-and-Interactive Training

다담식자재마트 DADAM FOOD MART





Result of Pre-trained Recurrent Convolutional Network

- Performance comparison between RCN and sequential recommender systems
- The model considering spatiotemporal context works more effectively than the models that consider only a temporal context

Model	Item-brand-level relevance						
	HR@1	HR@5	Prec@5	NG@5	Prec@20	NG@20	MAP@20
PoP	0.0001	0.0175	0.0035	0.0073	0.0019	0.0137	0.0025
SeqPoP	0.0044	0.0312	0.0062	0.0172	0.0040	0.0308	0.0042
GRU4Rec	0.0073	0.0360	0.0072	0.0209	0.0044	0.0311	0.0056
Caser	0.0014	0.0051	0.0018	0.0035	0.0021	0.0090	0.0023
SASRec	0.0237	0.0374	0.0076	0.0303	0.0036	0.0389	0.0067
Ours	**0.0296**	**0.0918**	**0.0196**	**0.0611**	**0.0107**	**0.0873**	**0.0161**

Result of Interactive Training

- Test result of our model trained according to different λ values
- LOS control works as expected and TPR is maximized at λ = 0.5

	λ	Metric			
		Acceptance Rate (%)	LOS	TPR ($)	logP
Offline	-	**3.650**	153.13	19.50	-24.64
Online	1.0	2.288	**124.11**	6.14	**-0.003**
	0.75	2.288	**124.11**	6.14	-0.006
	0.5	3.215	157.78	**95.97**	-15.59
	0.25	2.033	137.96	29.16	-29.81
	0.0	2.083	126.38	31.46	-28.45

Table 2: The result of controlled recommendation

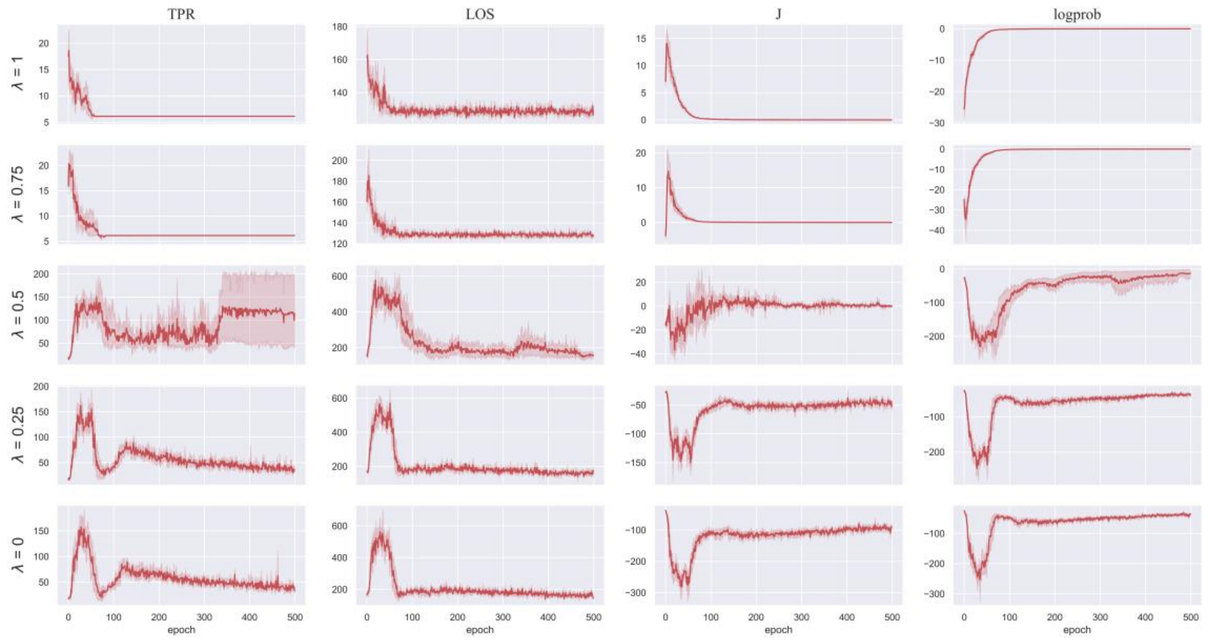
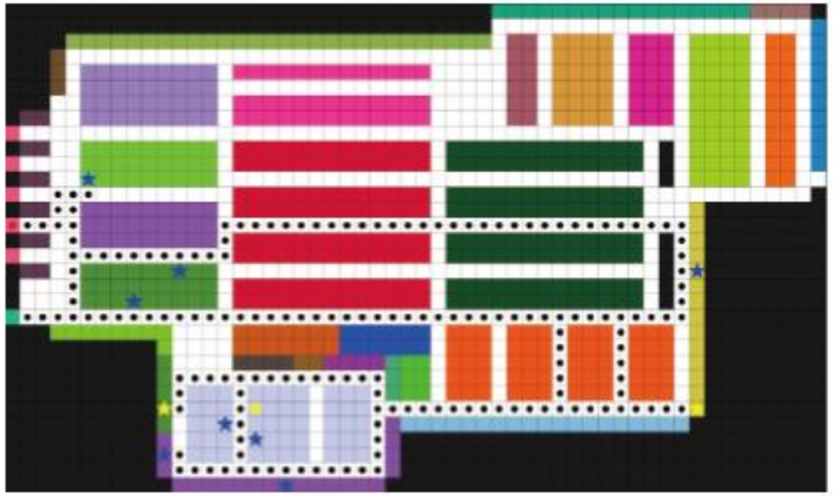


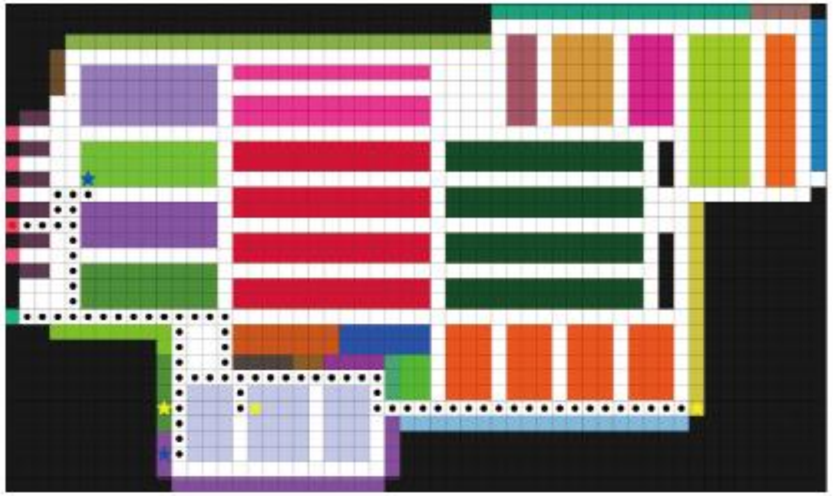
Figure 5: Recommendation control and policy convergence through online learning

Reward function : $R(\hat{x}_{1:T}) = (1-\lambda)\log\ \mathrm{TPR}_{\mathrm{scale}}(\hat{x}_{1:T})\ - \lambda \log\ \mathrm{LOS}_{scale}(\hat{x}_{1:T})$

Example of results visualized in the 2D-pixel world



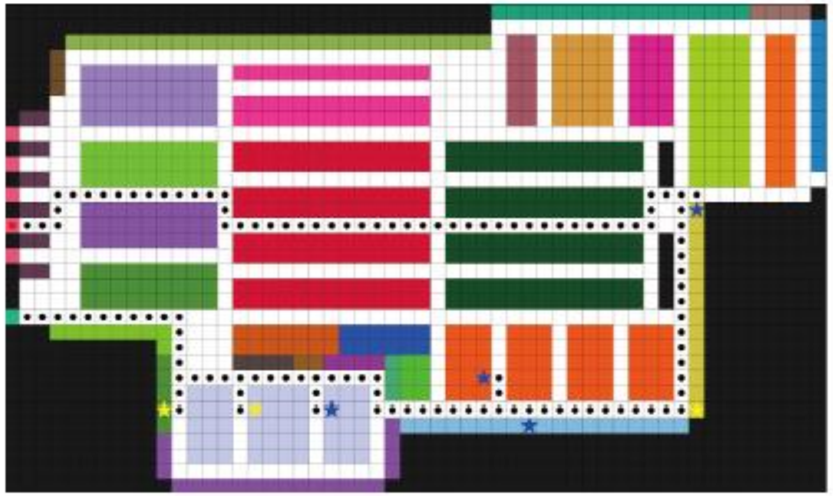
Offline learning



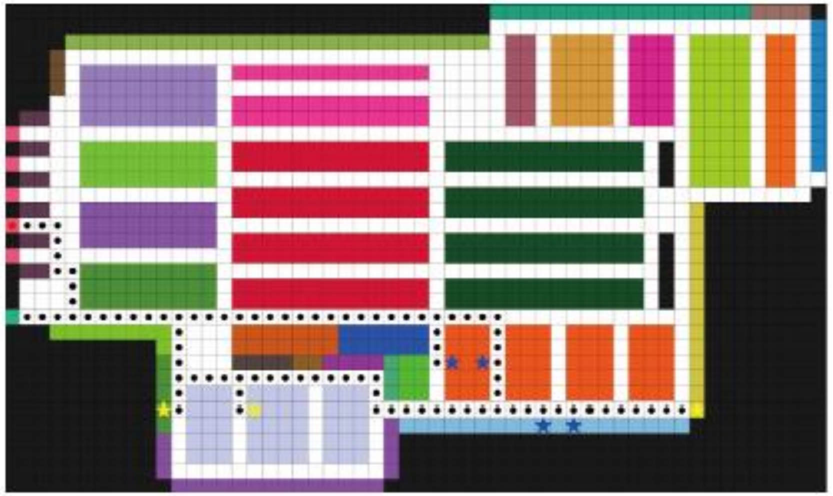
Online learning ($\lambda = 1$)

Only LOS control

LOS & TPR control



Online learning ($\lambda = 0.5$)



Online learning ($\lambda = 0$)

Only TPR control

Conclusion & Future Work

Conclusion

- We believe that our work will contribute to advancing many location-based services for offline stores, shopping malls, event venues, theme parks, production yards, and other physical environments that can be transformed into virtual environments
- The advantage of gamification approach
  - Do not need any devices that capture the spatiotemporal contexts in training
  - Can analyze the controllability of recommender system in terms of sales operation under the interactive scenario

Future Work

- Solving the existing problem of Recsys: Scalability issue, Personalization
- Reflecting the frequently changing sales management
- Development of an automatic generation engine that transform the floor plan into the pixel world.

Thank you

Presenter: Jongkyung Shin

E-mail : shinjk1156@unist.ac.kr

Paper

Github