

Complement, Composite and Context: The 3C-Law to Build Multidomain Recommender Systems

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- Shoujin Wang has been working as a research fellow at RMIT University, Australia.
- He obtained his PhD in Data Analytics from University of Technology Sydney in 2018.
- His main research interests include data mining, machine learning and recommender systems.

Dr. Qi Zhang
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- Qi Zhang received his first Ph.D. from the Department of Computer Science and Engineering, Beijing Institute of Technology, China in 2020.
- Currently, he is an AI scientist in DeepBlue Academy of Sciences, and a Ph.D. candidate in Analytics at University of Technology Sydney, Australia.
- His research interests include recommender systems, learning to hash, machine learning and general artificial intelligence.

Dr. Zhong Yuan Lai

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- Dr. Zhong Yuan Lai obtained his PhD from the University of Bonn, Germany in 2017.
- He was subsequently postdoc researcher at Fudan University before assuming his current position as researcher at the DeepBlue Academy of Sciences.

Dr. Liang Hu



- Liang Hu received dual Ph.D. degrees from Shanghai Jiao Tong University, China and University of Technology Sydney, Australia.
- His research interests include recommender systems, machine learning, data science and general intelligence.
- He has published more than 40 papers in top-rank international conferences and journals, including WWW, IJCAI, AAI, ICDM, ICWS, TOIS, IEEE-IS, and etc.

Goal

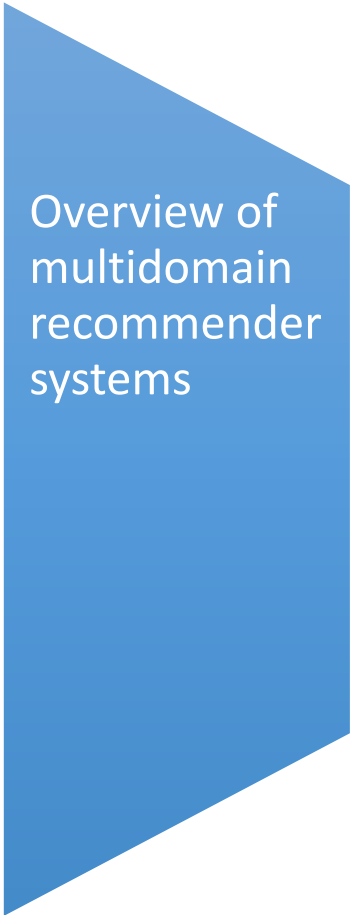
Providing a comprehensive understanding of how to build state-of-the-art **multidomain recommender systems** with **complex data and relations across various domains**



Agenda

- Overview of multidomain recommender systems (Liang Hu, 25 mins)
- Multi-item domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-user domain recommender systems (Qi Zhang, 20 mins)
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-spatial domain recommender systems (Qi Zhang 20 mins)
- Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-goal domain recommender systems (Liang Hu, 20 mins)
- Summary (Liang Hu, 5 mins)

Outline

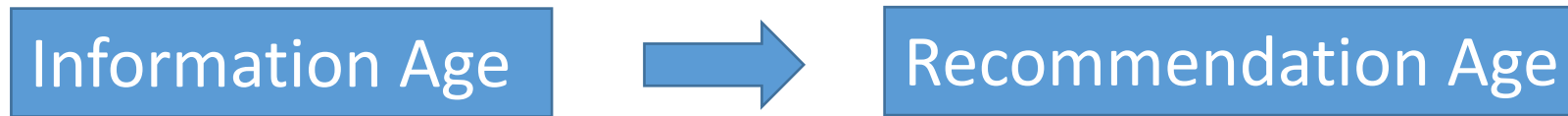


Overview of
multidomain
recommender
systems

- Overview of recommender systems
- Challenges of recommender systems
- A case study of multidomain recommender systems
- The 3C-law to build multidomain recommender systems

What are recommender systems

- Recommender systems (push information) are the evolution of information retrieval systems (pull information).



Pull mode (IRS):

Query → Matched Results → Manual Filtering

Push mode (RS):

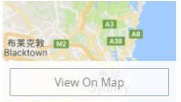
Potential Requirement → Machine Filtering → Recommendation

Anderson, C. (2006). *The long tail: Why the future of business is selling less of more*


Recommender systems have occupied our life

What to eat

Food & Drink



View On Map



Map data ©2018 Google

sort by Relevance

Up to 67% off Room Hire with Drinks for Four
Dynasty Karaoke
Up to ten party-goers can add more zing to their night out with a private room hire featuring a glass of house wine, beer or soft drink each
Haymarket • 2.2 km
★★★★☆ (52)
\$72 From \$24
[View Deal](#)


Up to 60% off Japanese BBQ Special for Two
Taisho Wagyu Japanese BBQ
Zetland • 5 km
90+ bought
\$98 From \$58

Up to 43% off French Fine Dining with Cocktails
The Little Snail
The Little Snail • 1.7 km
★★★★★ (2,181)
\$154 From \$88


Up to 57% off Darts + Beer or Mix Drinks for 2
The Century Bar
Sydney • 1.9 km
★★★★★ (7)
\$44 From \$19

Up to 57% off Festive Buffet + Delivery
CNI Catering
★★★★★ (29)
\$299.50 From \$149


Which to dress




Men's Compression Shorts
20+ bought
From \$15




Skechers Shoes for Women and Men
70+ bought
From \$59




Customised Build-A-Brick Cap
30+ bought
From \$19



Women's Knitted Ugg Boots
90+ bought
\$219 From \$65



Ralph Lauren Polo Shirt
250+ bought
\$129 From \$59



Two-Piece Men's Thermal Wear Set
20+ bought
From \$25

Where to go

UTS Building 25 AAI, 12/2 Blackfriars St
Burwood, New South Wales 2134

Add destination

Route options CLOSE

Avoid: ☐ Highways ☐ Tolls ☐ Ferries

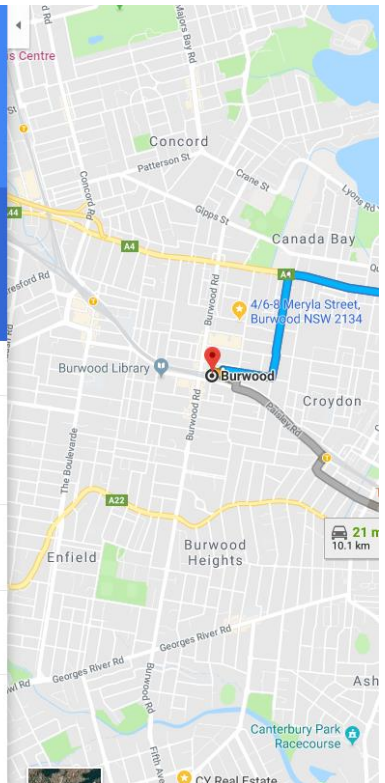
Distance units: ☒ Automatic ☐ miles ☐ km

[Send directions to your phone](#)

via Great Western Hwy/Parramatta Rd **18 min**
Fastest route, the usual traffic
10.5 km
[DETAILS](#)

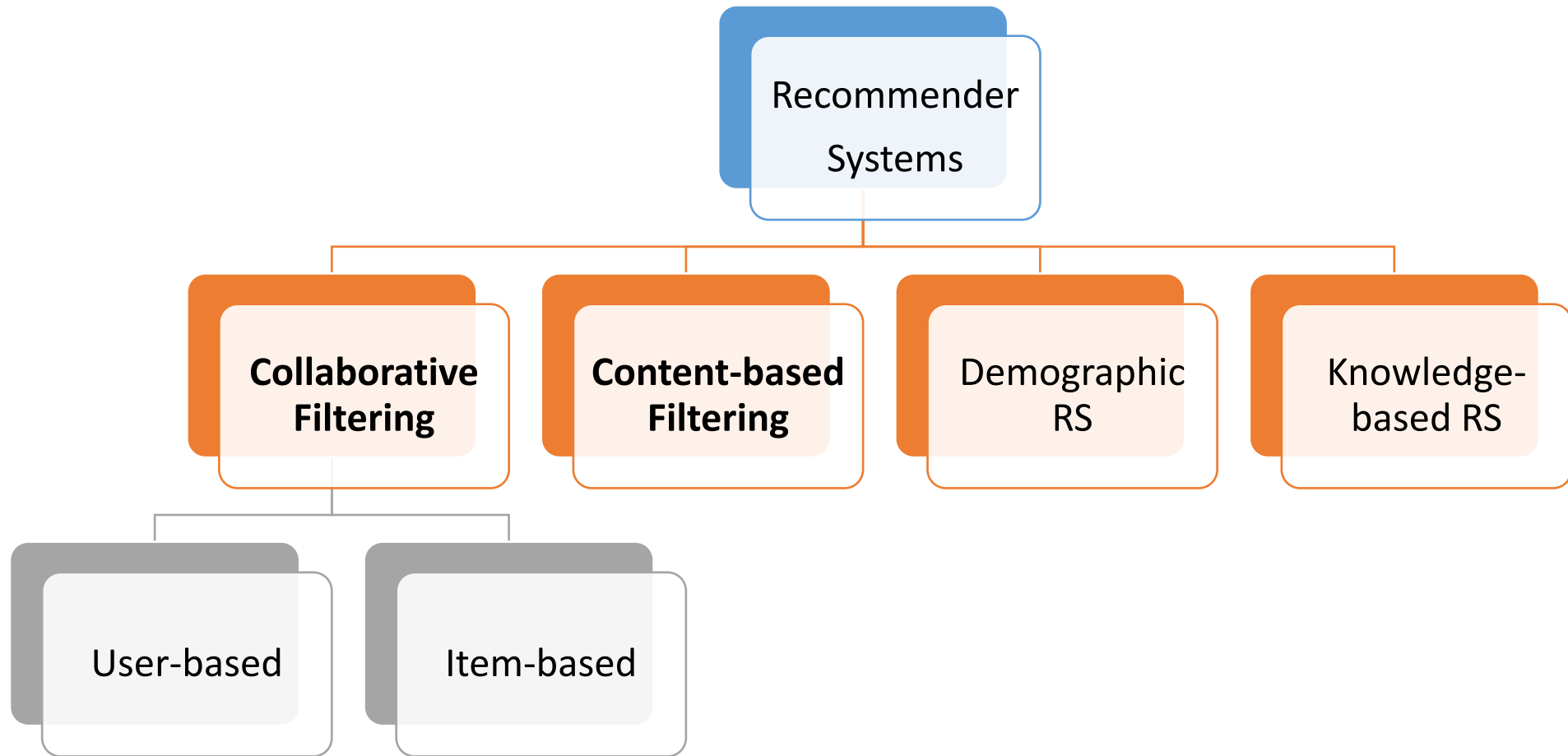
via Great Western Hwy/Parramatta Rd/A22 **21 min**
10.1 km

via A4 **21 min**
11.4 km



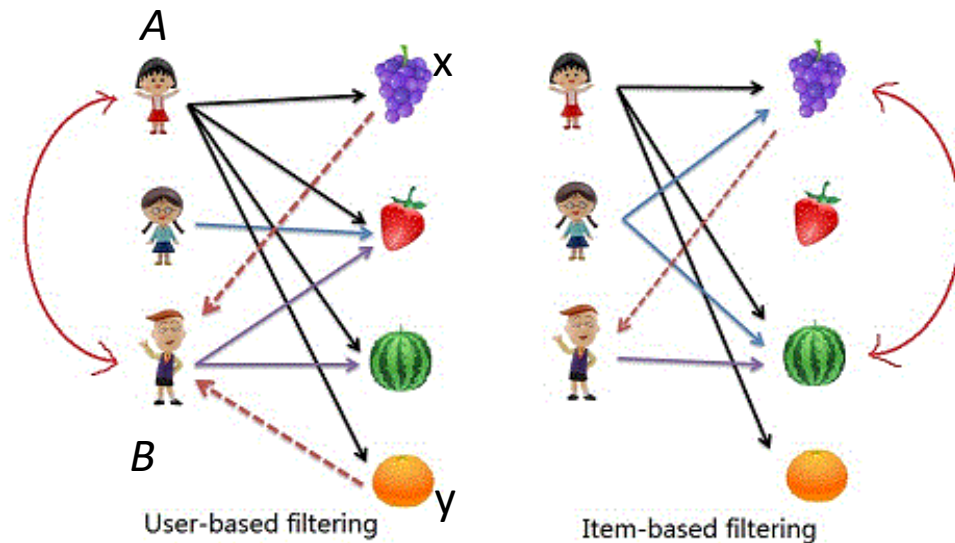
Map showing route from UTS Building to Burwood, New South Wales 2134. The route is highlighted in blue on a map of the area, passing through Concord, Canada Bay, and Burwood. Key locations marked include Burwood Library, Burwood Heights, and Canterbury Park Racecourse.

Classic recommender systems



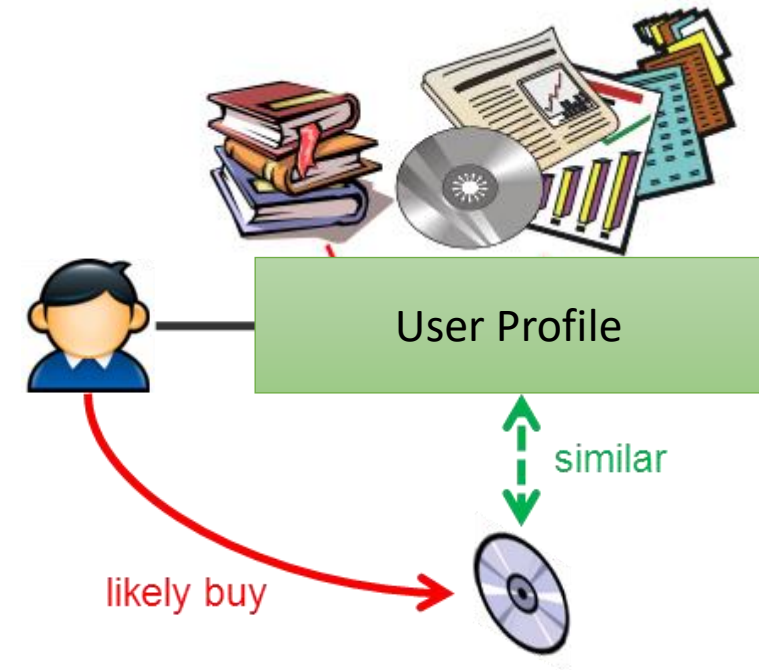
Collaborative Filtering (CF)

- Intuition (user-based filtering): If user **A** related to user **B** and **A** bought x and y , then **B** bought x tend to buy y .
- Famous examples(item-based filtering): Amazon.com's recommender system
- Facebook, MySpace, LinkedIn use collaborative filtering to recommend new friends, groups, and other social connections.



Content-based Filtering (CBF)

- CBF is based on the features of items
 - Attributes of items
 - Description of items
 - Text of an article
- User profile is built with the features of historical items
- Recommend items according to user profile



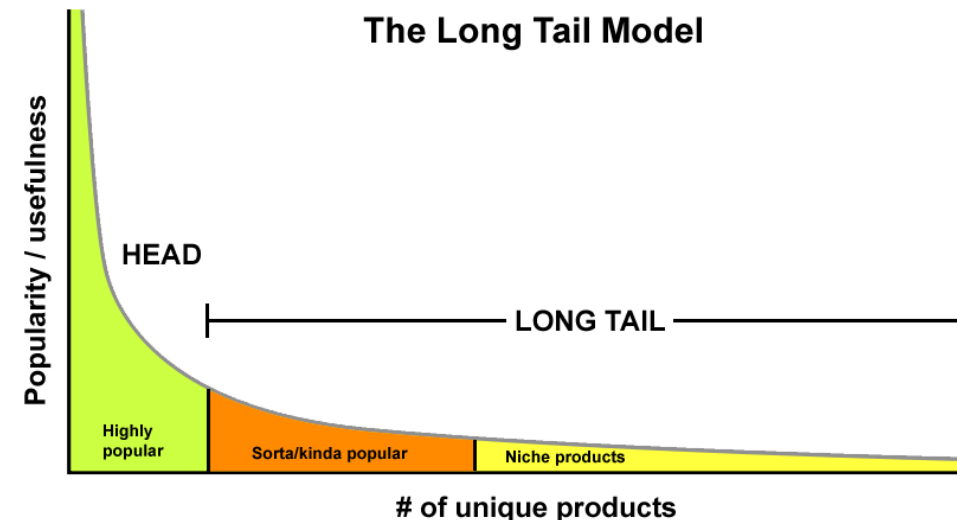
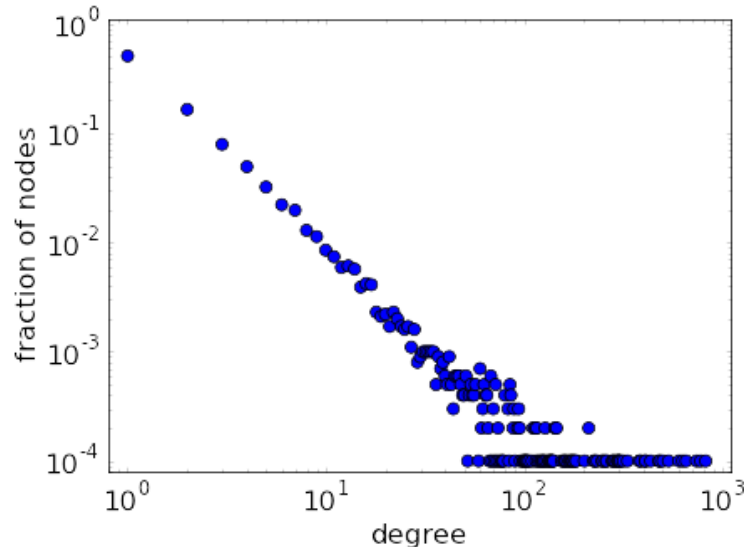
Outline

Overview of
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systems

- Overview of recommender systems
- **Challenges of recommender systems**
- A case study of multidomain recommender systems
- The 3C-law to build multidomain recommender systems

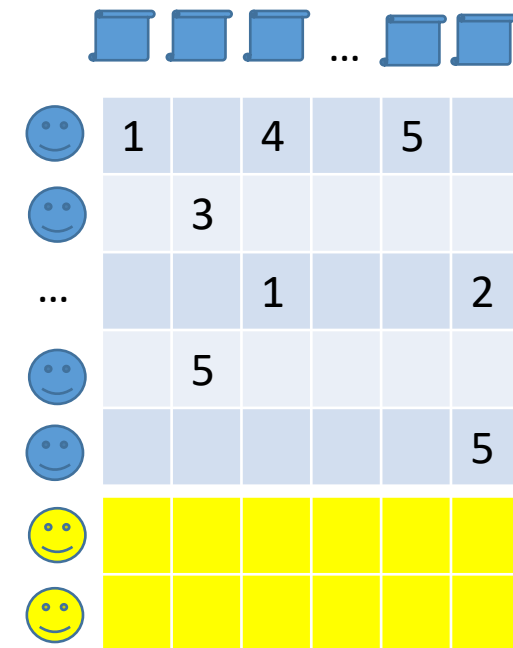
Data characteristics in recommender systems

- Power law or Long tail distribution
 - Data associated with the **majority** of users are **insufficient** and even **absent** in real world.
 - In most recommender systems, the **majority** of users/items only associated with very **few data** while only **minority** of users/items have **sufficient data**



Challenges in collaborative filtering

- Data Sparsity
 - In real-world recommender systems, the user-item matrix is very sparse.
- Cold Start
 - When **new users or new items** are added, the system cannot recommend to these users and these items.
- Scalability
 - There are **millions of users and products** in real systems.
 - Large amount of computation
 - Large storage

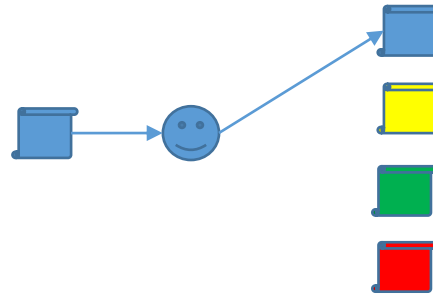


The diagram illustrates a user-item matrix. The columns represent items, indicated by blue trash can icons at the top, and the rows represent users, indicated by smiley face icons on the left. The matrix is sparse, with most cells being empty (light blue). Some cells contain numerical ratings. The first five rows are associated with blue smiley faces, while the last two rows are associated with yellow smiley faces. The first five items are associated with blue trash can icons, and the last two items are associated with yellow trash can icons. The matrix shows that new users (yellow smiley faces) have no ratings, and new items (yellow trash can icons) have no ratings, illustrating the cold start problem. The sparsity of the matrix also illustrates the data sparsity challenge.

				...		
	1		4		5	
		3				
...			1			2
		5				
						5

Challenges in content-based filtering

- Limited Content Analysis
 - System has a limited amount of information on its users or the content of its items.
- Over-specialization
 - The system can only recommend items that highly similar with user's profile, the user is limited to be recommended items similar to those already rated.



Question: what's the main cause of these challenges?

- Data Sparsity
- Cold Start
- Limited Content Analysis
- Over-specialization

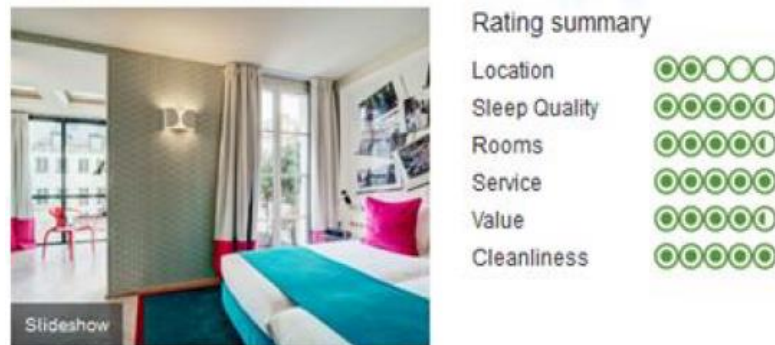
Data insufficiency
in a single domain

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Case study: recommendations for a travel



Expedia

Stays Flights Cars Packages Things to do More travel

Leaving from Shanghai, China (PVG-Pudong Intl.)

Going to Sydney (and vicinity), New South Wales, Aust...

Travelers 1 room, 3 travelers

Preferred class Economy

Departing Dec 13

Returning Dec 21

☐ Direct flights only

☐ I only need accommodations for part of my trip

Search

Choose your stay > Choose departing flight > Choose returning flight > Review your trip

Trip prices include roundtrip flight + stay, taxes, and fees.

What we are paid impacts our sort order

Sort by Recommended

Stay flexible with free cancellation for the property

We recommend booking a stay with free cancellation for the property in case your plans change.

Filter properties by free cancellation

Ad

Ovolo 1888 Darling Harbour

Pyrmont

Book now to receive Ovolo Extras

Free mini bar replenished daily + Wi-Fi included, plus Self Service Laundry inclusive and also Gym Access at no extra cost

4.7/5 Exceptional (997 reviews)

\$11,081 per person includes flight + stay

Unreal Deal

Swissotel Sydney

Sydney Central Business District

Free Cancellation Property

4.5/5 Wonderful (1,278 reviews)

\$11,118 per person includes flight + stay

Search by property name

e.g. Best Western

Filter by

Neighborhood

☒ Sydney (and vicinity)

☐ Homebush

☐ Bankstown NSW / RWA R

Multi-item domain recommendation

- Item types
 - E.g., flights, stays, cars
- Item relations:
 - E.g., destination (flight), location (hotel)

Expedia

English List your property Support Trips Sign in

Stays Flights Cars Packages Things to do More travel

Leaving from Shanghai, China (PVG-Pudong Intl.)

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View in a map

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e.g. Best Western

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Multi-user domain recommendation

- User groups
 - E.g., family vs. colleagues for stays
- Social relations:
 - E.g., local food recommendations according to your local friends



Xindalu-China Kitchen
4.6/5 436 Reviews
\$\$\$\$ Shanghai Cuisine

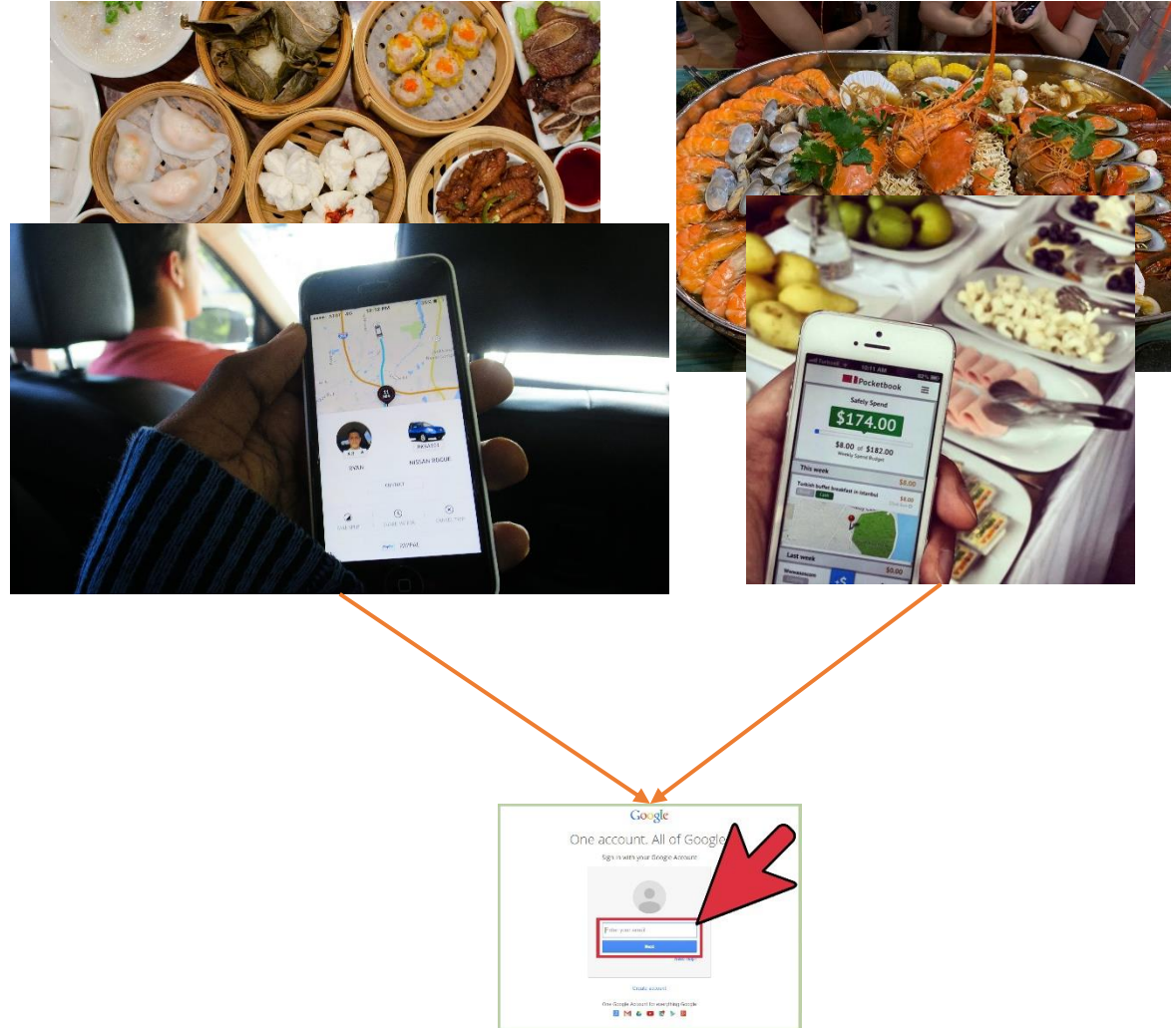
PHÉNIX
4.8/5 59 Reviews
\$\$\$\$ Western-style

4.7/5 534 Reviews
\$\$\$\$ Shanghai Cuisine

Fu He Hui
4.7 15 586 Reviews
\$\$\$\$ Vegetarian

Multi-spatial domain recommendation

- Geographic points
 - E.g., Chinese food restaurants (Hongkong), Seafood restaurants (Sydney)
- Systems/Sites:
 - E.g., Uber (google account), Eats Apps (google account)



Multi-temporal domain recommendation

- Sessions:
 - E.g. a shopping transaction may help travel package recommendation
- Time period:
 - E.g., preferences of breakfast (morning) help to recommend dinner (evening)

Recent transaction



Travel package



Breakfast

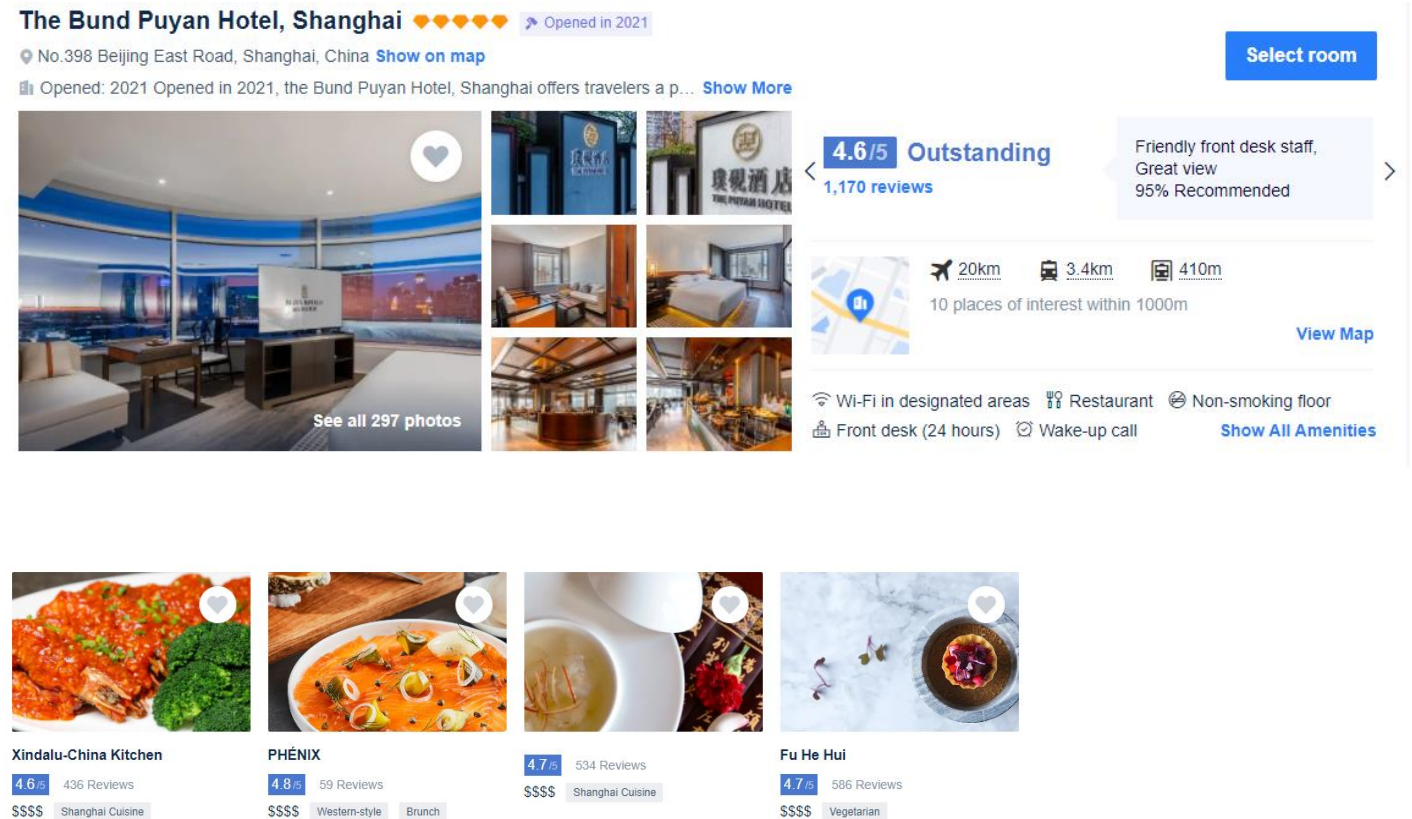


Dinner



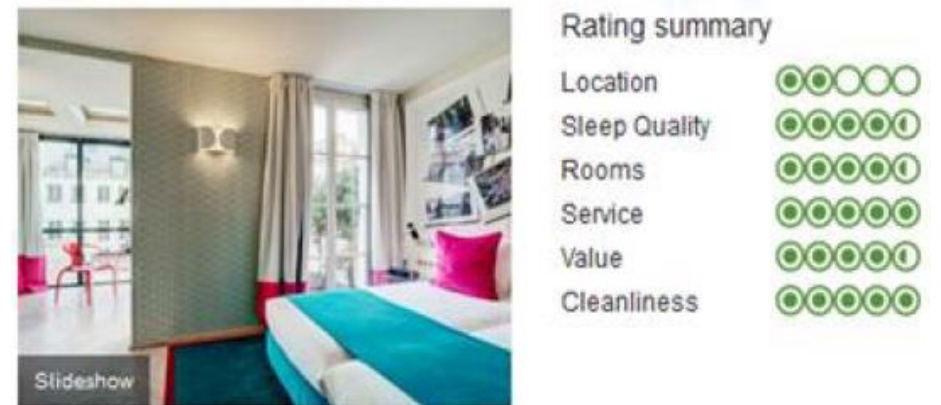
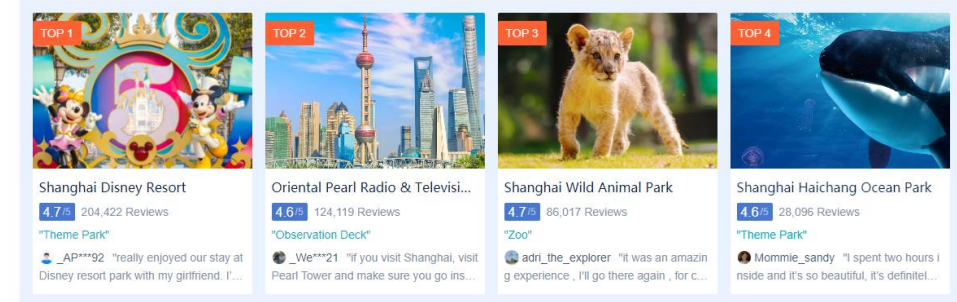
Multi-data domain recommendation

- Modalities:
 - E.g. rating, description, photos, geo information
- Distributions:
 - Ratings have different distributions for different domains, e.g., food vs stays
 - The content of image distribution is also different, e.g., color distributions between food and stays.

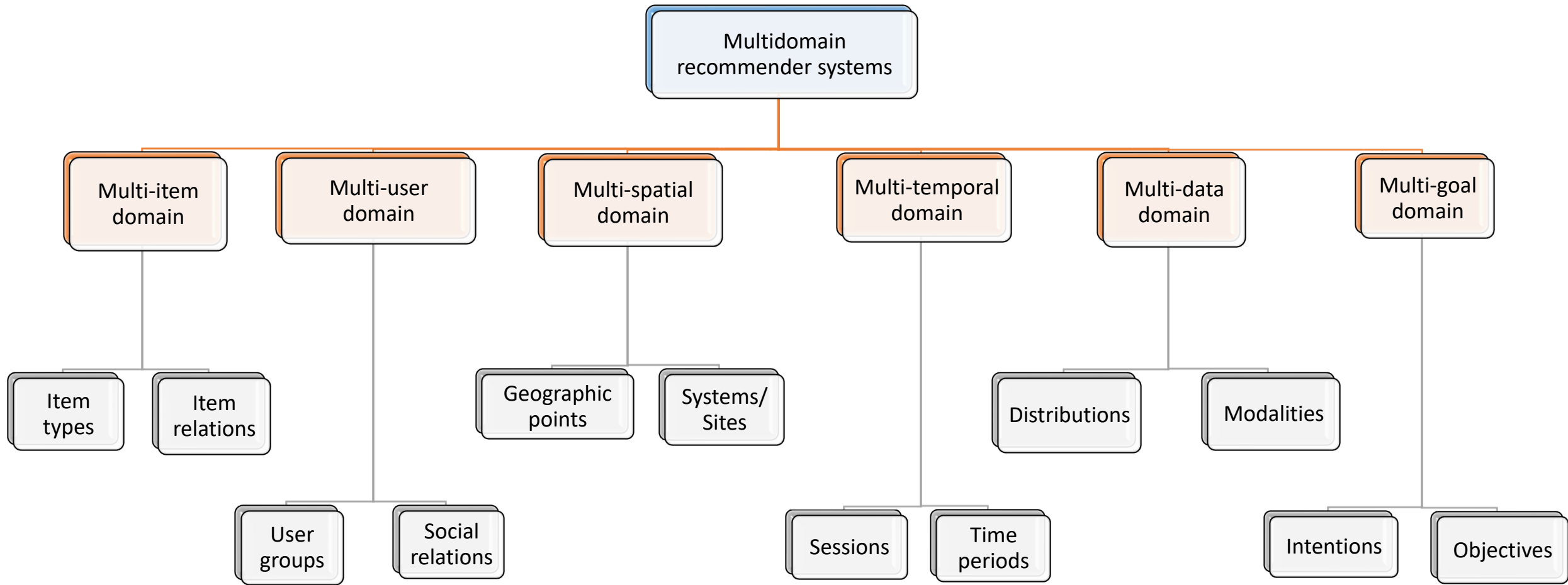


Multi-goal domain recommendation

- Intentions:
 - A travel often consists of multiple intentions:
 - E.g. visiting attractions, enjoy local food.
- Objectives:
 - Multiple criteria:
 - E.g. location, cleanliness, services
 - Multiple tasks:
 - E.g. booking the cheapest flight and a sea view hotel



Multidomain RSs covered in this tutorial

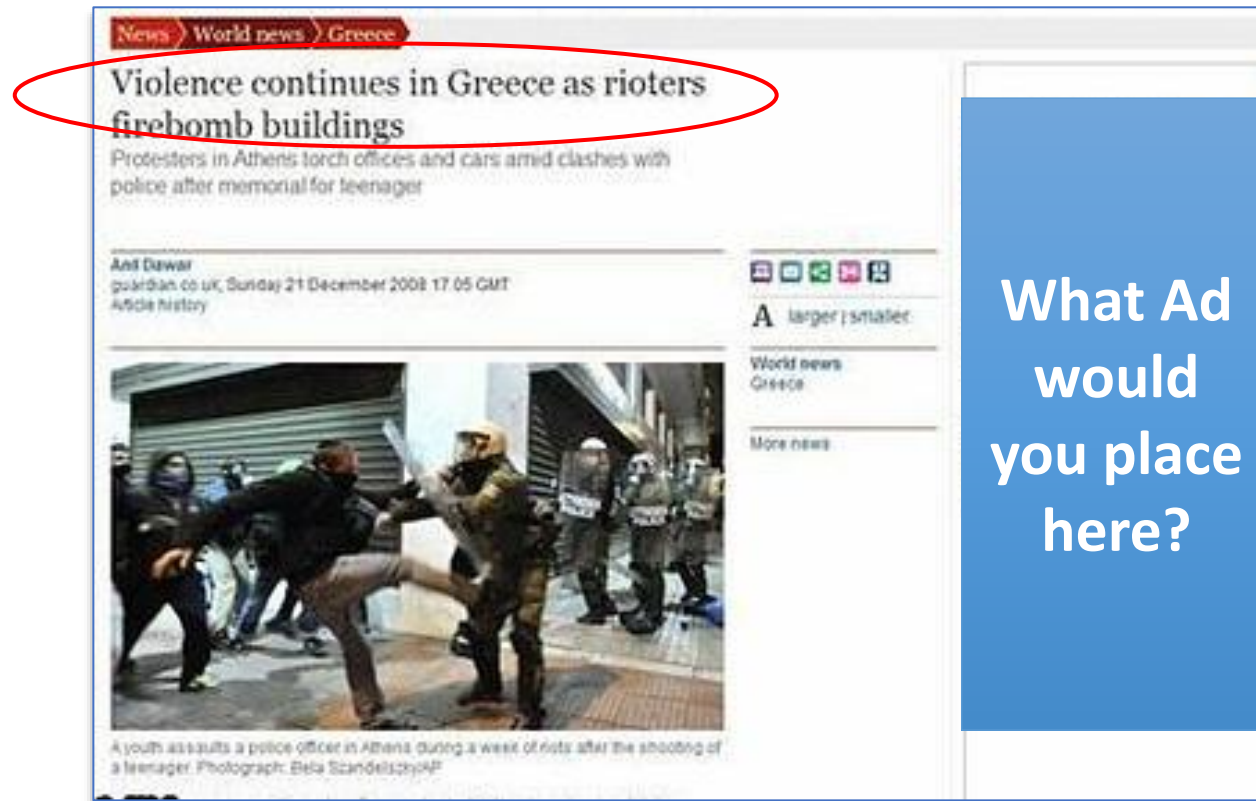


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Data complexity challenges to build multidomain recommender systems



**Irrelevant and
Damaging to Brand**

Non-IIDness in multidomain RS modeling

- Heterogeneities:

- Data types, attributes, sources, aspects, ...
- Formats, structures, distributions, relations, ...
- Learning outcomes

Not identically distributed.

- Coupling relationships:

- Within and between values, attributes, objects, sources, aspects, ...
- Structures, distributions, relations, ...
- Methods, models, objectives...
- Outcomes, impact, ...

Not independent distributed.

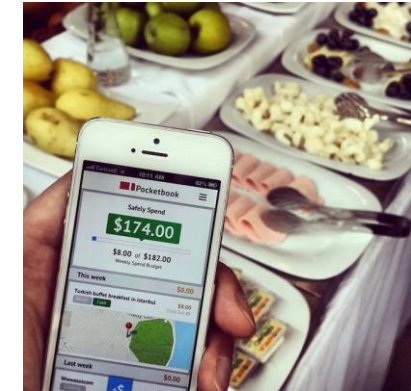
Non-IIDness

3C law: complement, composite, context

- Complement
 - To provide a complete view for recommendation by leveraging complement information over multiple domains.
- Composite
 - To provide comprehensive views for recommendation by integrating composite information over multiple domains.
- Context
 - To provide a conscious view for recommendation by considering context information over multiple domains.

Examples: complement information

- Transfer Uber histories for local restaurant recommendation



- Multimodal modeling for describing a hotel

The Bund Puyan Hotel, Shanghai ★★★★★ Opened in 2021
No.398 Beijing East Road, Shanghai, China [Show on map](#)
Opened: 2021 Opened in 2021, the Bund Puyan Hotel, Shanghai offers travelers a p... [Show More](#)

[Select room](#)

4.6/5 Outstanding
1,170 reviews

Friendly front desk staff,
Great view
95% Recommended

[View Map](#)

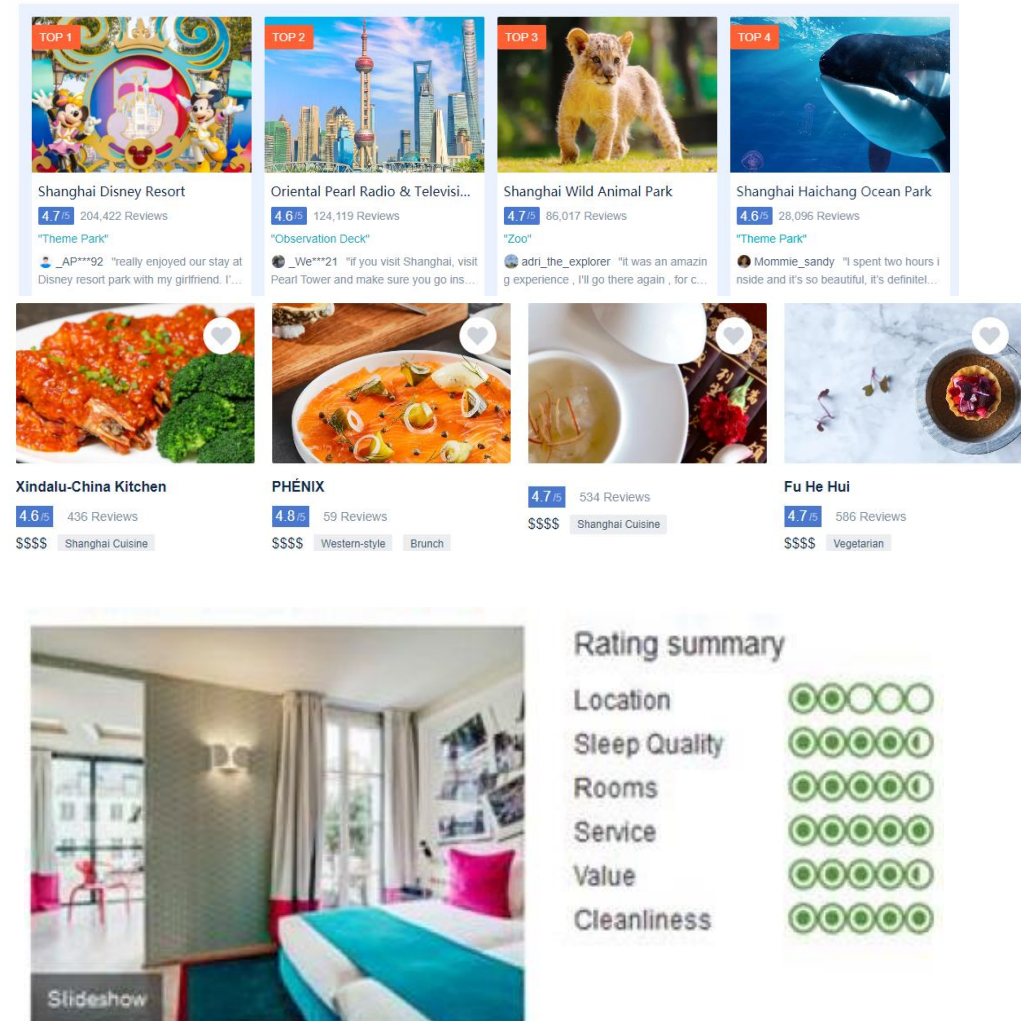
20km 3.4km 410m
10 places of interest within 1000m

Wi-Fi in designated areas Restaurant Non-smoking floor
Front desk (24 hours) Wake-up call [Show All Amenities](#)

[See all 297 photos](#)

Examples: composite information

- A travel consists of multiple requirements, including attraction, food, and living
- A recommendation for a hotel needs to comprehensively consider multiple aspects



Examples: context information

- A recommendation needs to consider the time and location

Breakfast



Dinner



- A recommendation needs to consider the preferences of all members in a user group



Multidomain recommender systems: The way to the metaverse of recommendations



Xindalu-China Kitchen
4.6 436 Reviews
SSSS Shanghai Cuisine



PHENIX
4.8 59 Reviews
SSSS Western-style Brunch



Fu He Hui
4.7 534 Reviews
SSSS Shanghai Cuisine



Fu He Hui
4.7 586 Reviews
SSSS Vegetarian



Shanghai Disney Resort
4.7 204,422 Reviews
"Theme Park"
_AP***92 "really enjoyed our stay at Disney resort park with my girlfriend. I..."



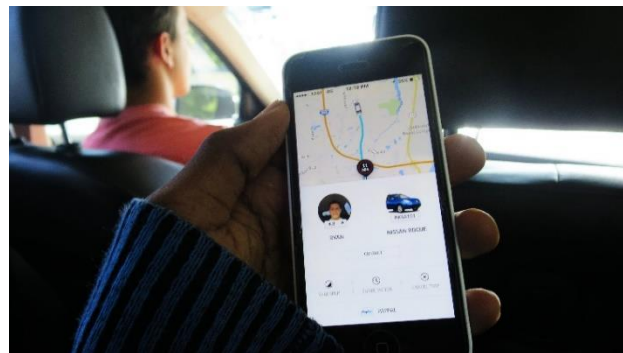
Oriental Pearl Radio & Television
4.6 124,119 Reviews
"Observation Deck"
_We***21 "if you visit Shanghai, visit Pearl Tower and make sure you go ins..."



Shanghai Wild Animal Park
4.7 86,017 Reviews
"Zoo"
adri_the_explorer "It was an amazing experience, I'll go there again, for c..."



Shanghai Haichang Ocean Park
4.6 28,096 Reviews
"Theme Park"
Mommie_sandy "I spent two hours inside and it's so beautiful, it's definitely..."



Rating summary

Location	○○○○○
Sleep Quality	○○○○○
Rooms	○○○○○
Service	○○○○○
Value	○○○○○
Cleanliness	○○○○○

Next chapter

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- Multi-user domain recommender systems (Qi Zhang, 20 mins)
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-spatial domain recommender systems (Qi Zhang 20 mins)
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