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# Extending Contexts to Multi-Entity Recommender Systems

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# Extending Contexts to Multi-Entity RecSys

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- Questions
  - Can we build or utilize CARS in a system which does not have explicit contexts info?
  - Or, are there any connections between CARS and other types of the recommender systems?

# Extending Contexts to Multi-Entity RecSys

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- Related Issues or Topics
  - Revisit contexts & Context-Aware RecSys (CARS)
  - Utilize CARS without “contexts”?
    - Contextual vs Conditional
    - Case study in Multi-Entity RecSys

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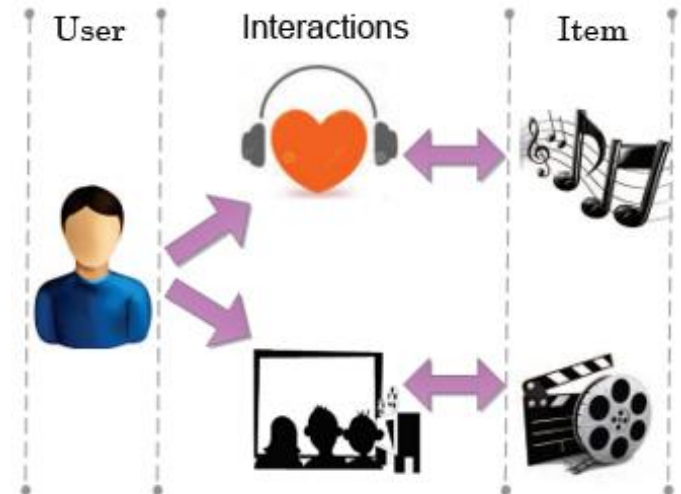
# Contexts & CARS: A Revisit

# Notion of Contexts

- "Context is any information that can be used to characterize the situation of an entity" by Anind K. Dey, 2001
- In recommender systems
  - Entity: the end user
  - Situation: the interactions between users and the system
    - Listen to a song
    - Watch a movie
    - Shop items on Amazon.com
    - ....

# Notion of Contexts

- What are the context variables
  - Attributes of the situation or the interactions
    - Time, location
    - Weather, budget
    - Companion, etc
  - Dynamic attributes of the user
    - Emotion states
    - Objectives or intentions



Everytime when you repeat these interactions or behaviors,  
the values in these variables may change!

# Interactive & Dynamic

- Context and its importance may change

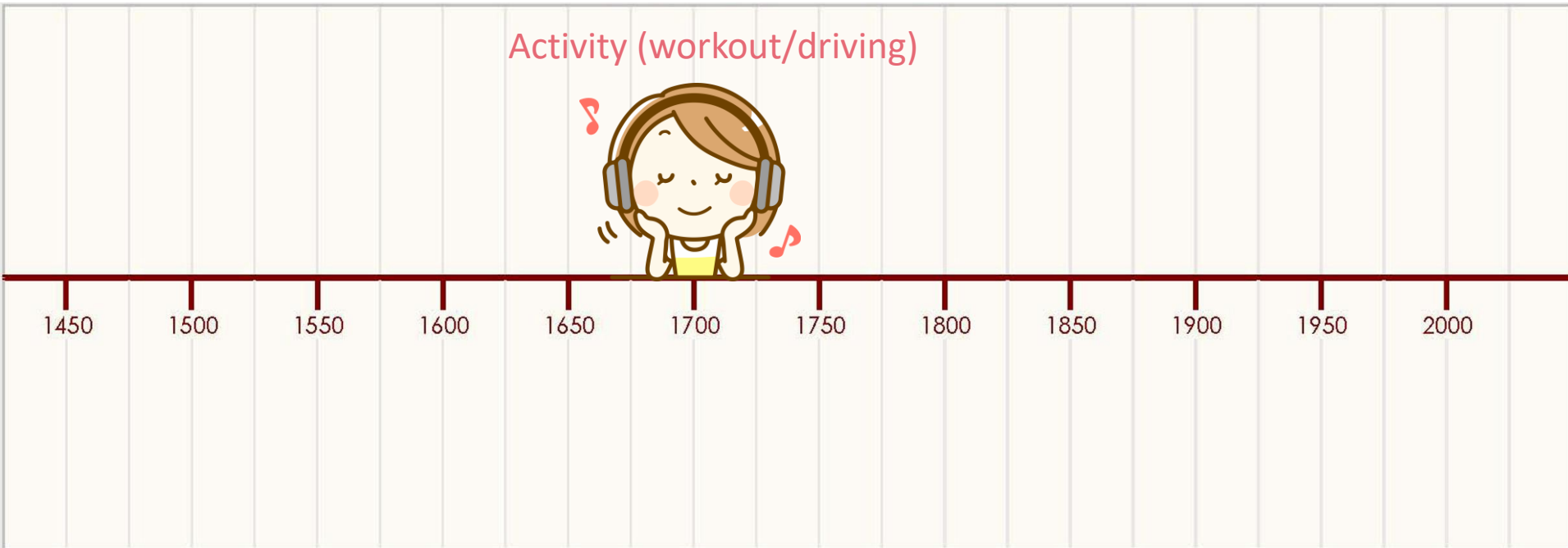
Time and Location



1450 1500 1550 1600 1650 1700 1750 1800 1850 1900 1950 2000

# Interactive & Dynamic

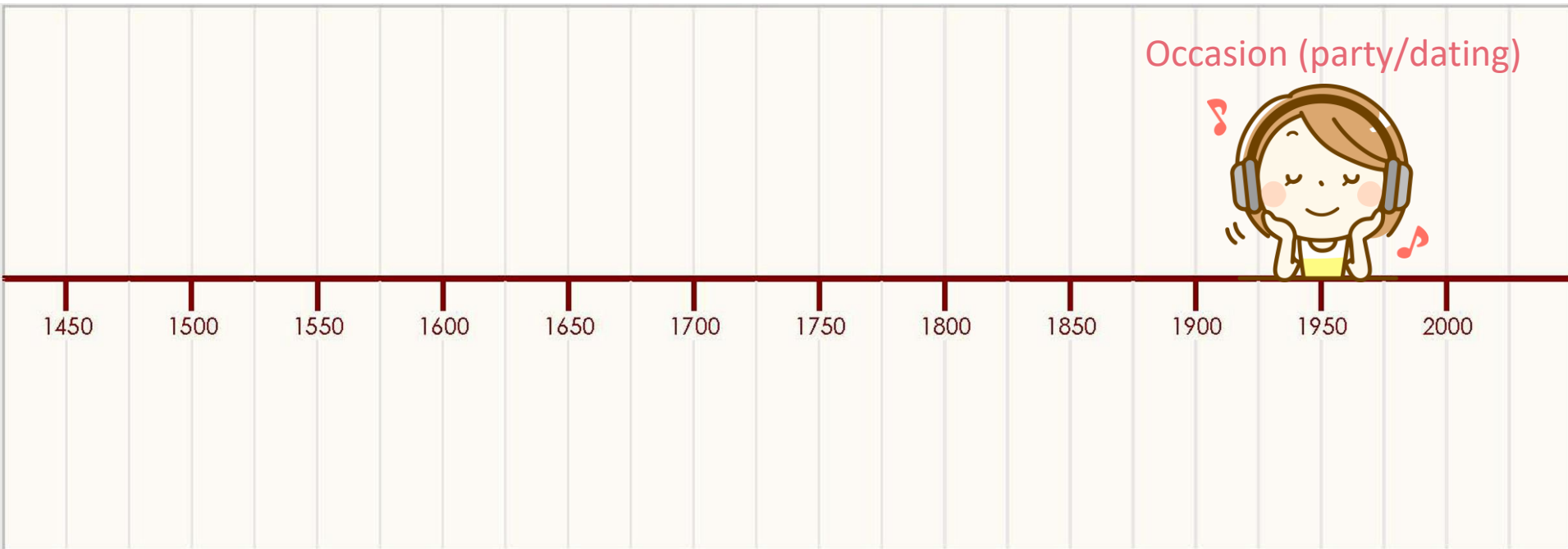
- Context and its importance may change





# Interactive & Dynamic

- Context and its importance may change



# Notion of Contexts

- Gediminas Adomavicius, Bamshad Mobasher, Francesco Ricci, Alexander Tuzhilin. "Context-Aware Recommender Systems", AI Magazine, 2011

| How Contextual Factors Change | Knowledge of the RS about the Contextual Factors |                                       |                                |
|-------------------------------|--|---------------------------------------|--------------------------------|
|                               | Fully Observable                                 | Partially Observable                  | Unobservable                   |
| Static                        | Everything Known about Context                   | Partial and Static Context Knowledge  | Latent Knowledge of Context    |
| Dynamic                       | Context Relevance Is Dynamic                     | Partial and Dynamic Context Knowledge | Nothing Is Known about Context |

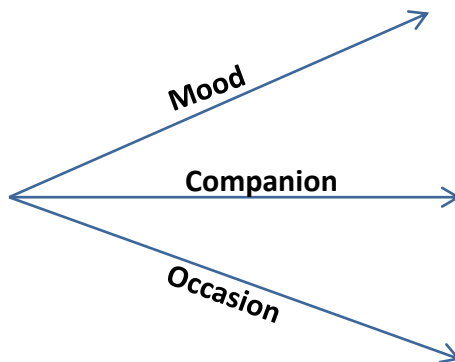
# What is Context-Awareness

- “Context-Awareness” is popular in Ubiquitous computing, such as smart home devices
- Components
  - Sensors
  - Detections
  - Adaptive Actions



# Context-Aware Systems

- Context-Aware Systems are adaptive systems
- In context-aware recommender systems
  - Assumption: user preferences or decisions may vary from contexts to contexts



# Development of CARS

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- Static CARS (patterns may not change frequently)
  - CARSKit library is used in this category  
<https://github.com/irecsys/CARSKit>
    - Contexts are fully observed
    - Patterns are fixed
- Interactive CARS
  - Conversational RecSys
  - Session-based RecSys

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# Contexts: “New” Notion

# Build CARS without Explicit Contexts

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- I want to build CARS...
  - Do we need to collect contexts?
  - It may be time-consuming & cost-expensive
- Can we extend the notion of contexts?

# Contextual vs Conditional

- Contextual Predictions
  - Predictions by given a set of contexts
- Conditional Predictions
  - Predictions by assuming some conditions are true

Contextual Recommendations  $\approx$   
Conditional Recommendations





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# Multi-Entity RecSys

# Multi-Entity Recommender Systems

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- Multi-Entity or Multi-Dimension RecSys are the recommender systems which are built on multi-dimensional data
- More dimensions rather than users & items
- Examples
  - Context-Aware RecSys
  - Multi-Criteria RecSys
  - Tag-based RecSys

# Context-Aware Recommender Systems

- Example of the context-aware data set

| User | Item | Rating | Time    | Location | Companion |
|------|------|--------|---------|----------|-----------|
| U1   | T1   | 3      | Weekend | Home     | Kids      |
| U1   | T2   | 5      | Weekday | Home     | Partner   |
| U2   | T2   | 2      | Weekend | Cinema   | Partner   |
| U2   | T3   | 3      | Weekday | Cinema   | Family    |
| U1   | T3   | ?      | Weekend | Cinema   | Kids      |

# Multi-Criteria Recommender Systems

- Additional preferences on aspects of the items

**My ratings for this hotel**

|                   |  |
|-------------------|--|
| ●●●●○ Value       | ●●●●○ Check in / front desk                    |
| ●●●●○ Rooms       | ●●●●○ Service                                  |
| ●●●●○ Location    | ●●●●○ Business service (e.g., internet access) |
| ●●●●○ Cleanliness |  |

**Date of stay** September 2008  
**Visit was for** Other  
**Traveled with** Solo traveler  
**Age group** 35-49  
**Member since** March 05, 2005  
**Would you recommend this hotel to a friend?** Yes

| User | Item | Rating | Location | Room Size | Cleanliness |
|------|------|--------|----------|-----------|-------------|
| U1   | T1   | 3      | 3        | 3         | 3           |
| U2   | T2   | 5      | 5        | 5         | 5           |
| U3   | T2   | 2      | 2        | 3         | 3           |
| U4   | T3   | 3      | 3        | 2         | 3           |

# Tag-Based Recommender Systems

- Users assign tags on the items
- Explicit ratings are optional

## ACMRecSys

@ACMRecSys

The official twitter feed for the [#RecSys](#) community. Next conference: Online, Worldwide, 22nd-26th September 2020. [#RecSys2020](#)

| User | Item | Rating | Tag1 | Tag2 | Tag3 |
|------|------|--------|------|------|------|
| U1   | T1   | 3      | 1    | 0    | 0    |
| U2   | T2   | 5      | 1    | 1    | 0    |
| U3   | T2   | 2      | 0    | 0    | 1    |
| U4   | T3   | 3      | 0    | 1    | 1    |

# Multi-Entity Recommender Systems

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- They have the same characteristics
  - More than two dimensions
  - They are not demographic info or item features
  - Either user interactions or attributes of the interactions
    - CARS: contexts are the attributes of the interactions
    - Multi-Criteria: user ratings on different criteria
    - Tag-based: tag usage

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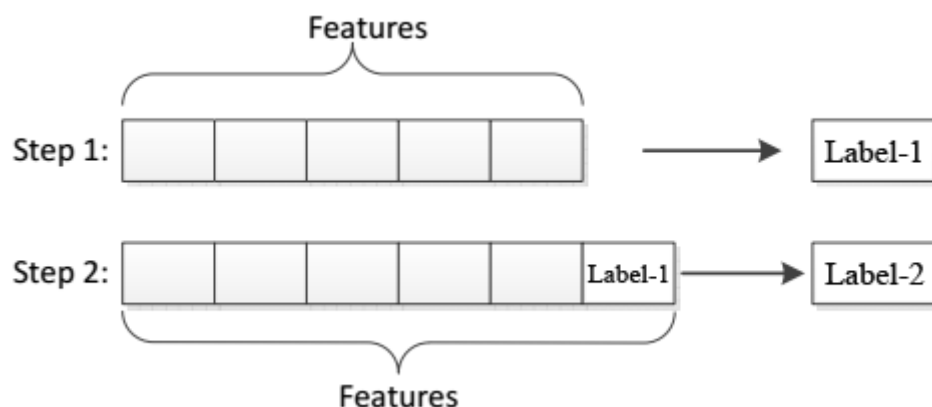
# Multi-Entity RecSys with Conditions/Contexts

# Multi-Entity Recommender Systems

- Extending Contexts/Conditions to them

- Chains-Based Methods

- Read, J., Pfahringer, B., Holmes, G., & Frank, E. (2011). **Classifier chains** for multi-label classification. Machine learning, 85(3), 333.



- ☐ Define a label sequence
- ☐ Predict labels in queue
- ☐ Previous predictions added as new features for next prediction



# Multi-Entity Recommender Systems

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- We extend chains to RecSys
  - Multi-Criteria  $\Rightarrow$  Criteria Chains
  - Context-Aware  $\Rightarrow$  Context Chains
  - Tag-Based RecSys  $\Rightarrow$  Tag Chains

# Multi-Criteria Recommender Systems

- Criteria Chains

- Zheng, Yong. "Criteria chains: a novel multi-criteria recommendation approach." In Proceedings of the 22nd International Conference on Intelligent User Interfaces, pp. 29-33. 2017.



- Given your tastes on different criteria in mind (i.e., conditional process), would you like to finally book this hotel (i.e., final overall rating)?

# Multi-Criteria Recommender Systems

- Criteria Chains

**Table 1. Example of Rating Data from TripAdvisor**

| User  | Item  | Rating | Room | Check-in | Service |
|-------|-------|--------|------|----------|---------|
| $U_1$ | $T_1$ | 3      | 3    | 4        | 3       |
| $U_2$ | $T_2$ | 4      | 4    | 4        | 5       |
| $U_3$ | $T_1$ | ?      | ?    | ?        | ?       |

Step 1. define the sequence, Room  $\rightarrow$  Checkin  $\rightarrow$  Service

Step 2. predict  $U_3$ 's rating on  $T_1$  in criterion "Room"

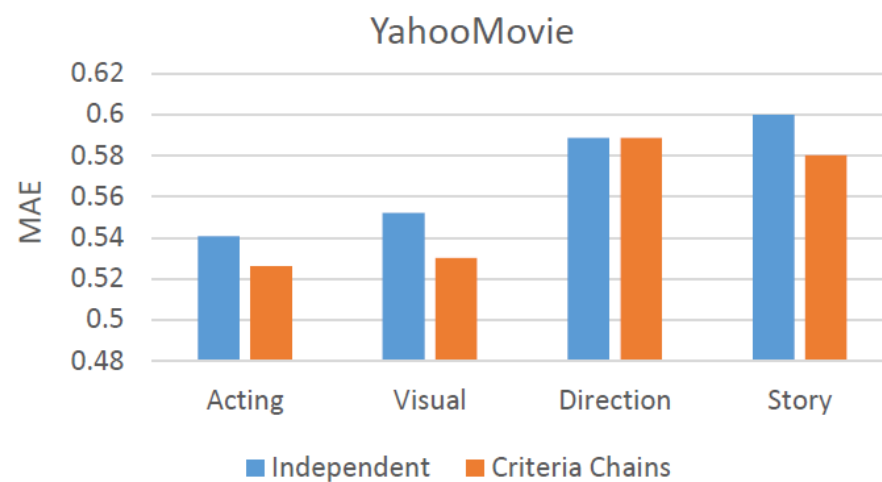
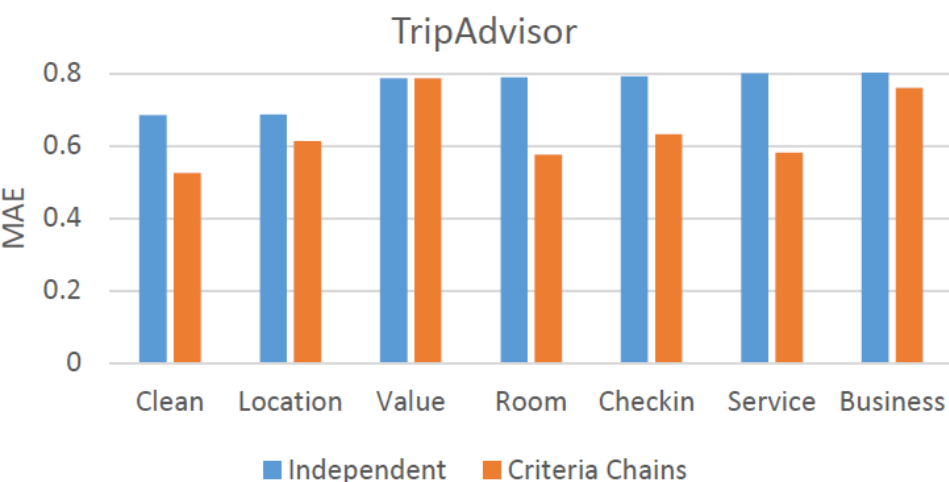
[Step 3].  $U_3 + T_1 + \text{Rating}_{\text{room}} = \text{Rating}_{\text{checkin}}$

[Step 4].  $U_3 + T_1 + \text{Rating}_{\text{room}} + \text{Rating}_{\text{checkin}} = \text{Rating}_{\text{service}}$

[Step 5].  $U_3 + T_1 + \text{Rating}_{\text{room}} + \text{Rating}_{\text{checkin}} + \text{Rating}_{\text{service}}$   
 $= U_3$ 's predicted overall rating on  $T_1$

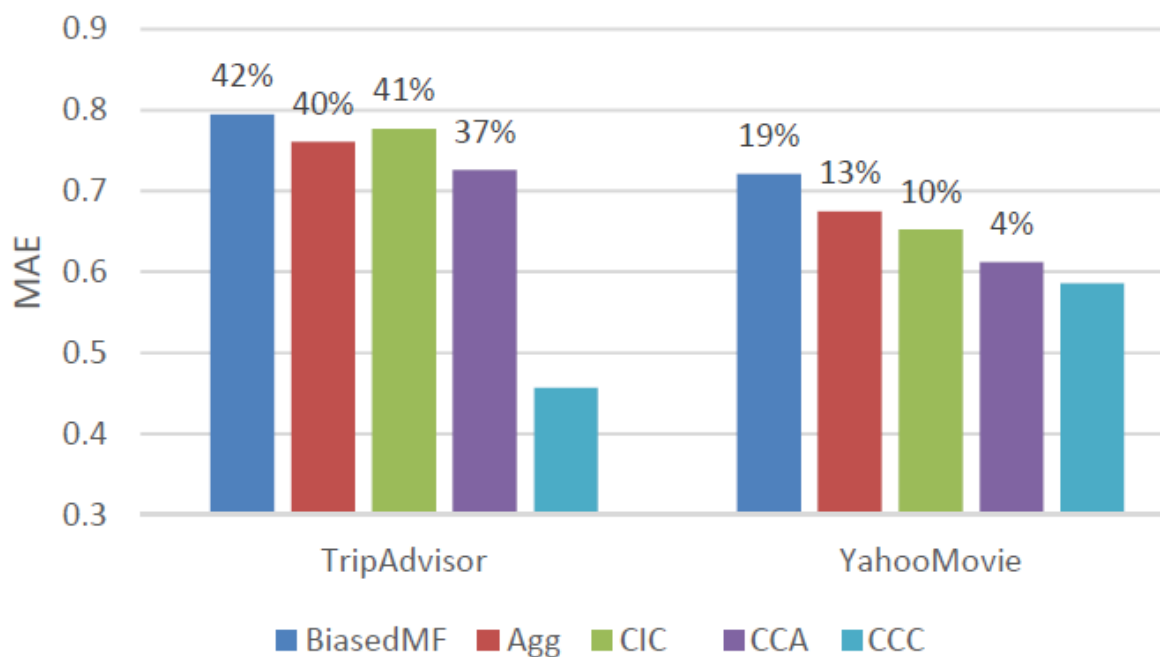
# Multi-Criteria Recommender Systems

- **Criteria Chains** can better predict multi-criteria ratings



# Multi-Criteria Recommender Systems

- **Criteria Chains** can better predict overall ratings  
CIC, CCA & CCC are different aggregation methods



# Multi-Entity Recommender Systems

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- Advantages

- No more new algorithms
- Chain method delivers a new pipeline
- Existing algorithms can be applied

- Challenges & Risks

- Define the sequence in the chain, i.e., information gain
- Personalized the sequence for users or user groups
- Wrong predictions may affect next predictions

# Context-Aware Recommender Systems

- Context Chains

- Zheng, Yong, and Alisha Anna Jose. "Context-aware recommendations via sequential predictions." In Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing, pp. 2525-2528. 2019.

| User  | Item  | Rating | Time    | Location | Companion |
|-------|-------|--------|---------|----------|-----------|
| $U_1$ | $T_1$ | 3      | weekend | home     | alone     |
| $U_1$ | $T_1$ | 5      | weekend | cinema   | partner   |
| $U_1$ | $T_1$ | ?      | weekday | home     | family    |

Table 1: Contextual Rating Data

| User  | Item  | Rating | Time      | Location | Companion |
|-------|-------|--------|-----------|----------|-----------|
| $U_1$ | $T_1$ | 3      | weekend:4 | home     | alone     |
| $U_1$ | $T_1$ | 5      | weekend:4 | cinema   | partner   |
| $U_1$ | $T_1$ | ?      | weekday:3 | home     | family    |

Table 2: Example: First-Step Prediction

| User  | Item  | Rating | Time      | Location | Companion |
|-------|-------|--------|-----------|----------|-----------|
| $U_1$ | $T_1$ | 3      | weekend:4 | home     | alone:3   |
| $U_1$ | $T_1$ | 5      | weekend:4 | cinema   | partner:5 |
| $U_1$ | $T_1$ | ?      | weekday:3 | home     | family:2  |

Table 3: Example: Second-Step Prediction

| User  | Item  | Rating | Time      | Location | Companion |
|-------|-------|--------|-----------|----------|-----------|
| $U_1$ | $T_1$ | 3      | weekend:4 | home:3   | alone:3   |
| $U_1$ | $T_1$ | 5      | weekend:4 | cinema:5 | partner:5 |
| $U_1$ | $T_1$ | ?      | weekday:3 | home:3   | family:2  |

Table 4: Example: Third-Step Prediction

- By this way, we create finer-grained context conditions
- Convert predicted ratings to binary rates, to reduce sparsity

# Context-Aware Recommender Systems

- Context Chains

- Zheng, Yong, and Alisha Anna Jose. "Context-aware recommendations via sequential predictions." In Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing, pp. 2525-2528. 2019.

MAE Results

|                |             | Food                 | Restaurant           | DePaulMovie          | CoMoDa             | Frappe               |
|----------------|-------------|----------------------|----------------------|----------------------|--------------------|----------------------|
| Baselines      | MF          | 0.9234               | 0.9782               | 0.7040               | 0.8215             | 0.3809               |
|                | UISplitting | 0.8048               | 0.8233               | 0.7130               | 0.7750             | 0.3781               |
|                | SPF         | 0.8996               | 0.8082               | 0.7220               | 0.8188             | 0.3818               |
|                | CAMF        | 0.8461               | 0.8706               | 0.6800               | <b>0.6867</b>      | 0.3789               |
|                | TF          | 0.9659               | 0.9537               | 0.6920               | 0.8506             | 0.3921               |
| Context Chains | SeqN        | <b>0.6804</b><br>○○● | <b>0.7199</b><br>○○● | <b>0.6236</b><br>○○● | <b>0.6845</b><br>○ | <b>0.3532</b><br>○○● |
|                | SeqB        | 0.6811               | 0.7225               | 0.6271               | 0.6757             | 0.3525               |
| Improvement    |             | 15.45%               | 10.93%               | 8.29%                | 0.3%               | 6.77%                |



# Tag-Based Recommender Systems

- Tag Chains (in progress..)
  - Recommend items to a user by given a set of tags

| User | Item | Rating | Tag1 | Tag2 | Tag3 |
|------|------|--------|------|------|------|
| U1   | T1   | 3      | 1    | 0    | 0    |
| U2   | T2   | 5      | 1    | 1    | 0    |
| U3   | T2   | 2      | 0    | 0    | 1    |

- Challenge: too many tag dimensions
- Solution: using tag clusters as dimensions

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# Summary & Discussions

# Contextual vs Conditional

- Contextual Systems
  - Predictions by given a set of contexts
- Conditional Systems
  - Predictions by assuming some conditions are true

Contextual Recommendations  $\approx$   
Conditional Recommendations



# Summary

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- We consider the process of decision making as multiple steps in a chain
- Conditional Predictions
  - Predict outcomes conditional on previous predictions
  - The chain method defines a pipeline
  - No new algorithms were developed
  - Add user preferences to these additional dimensions
  - CARS rating prediction models can be utilized
- Utilize context-aware predictions without explicit contexts information, but in a conditional process

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