Sequence-Aware Recommender Systems

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Acknowledgements

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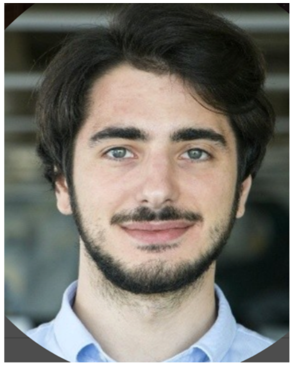


Basic reading

- M. Quadrana, P. Cremonesi, D. Jannach, Sequence-Aware Recommender Systems, ACM Computing Surveys, 2018

Slides and hands-on

git.io/fxTtV

About you?

Agenda

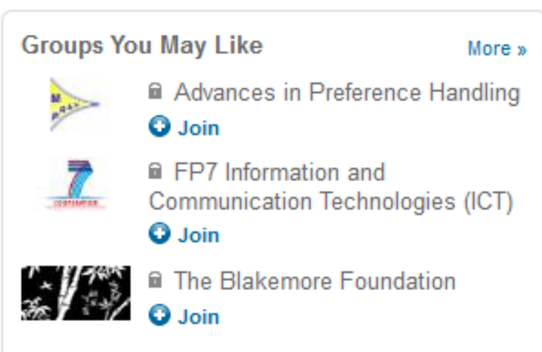
- 09:00 – 09:45 Introduction & Problem Definition
- 09:45 – 10:30 Algorithms I
- 10:30 – 11:00 Coffee break
- 11:00 – 11:30 Algorithms II
- 11:30 – 12:00 Evaluation
- 12:00 – 12:20 Hands-on
- 12:20 – 12:30 Conclusion / Questions

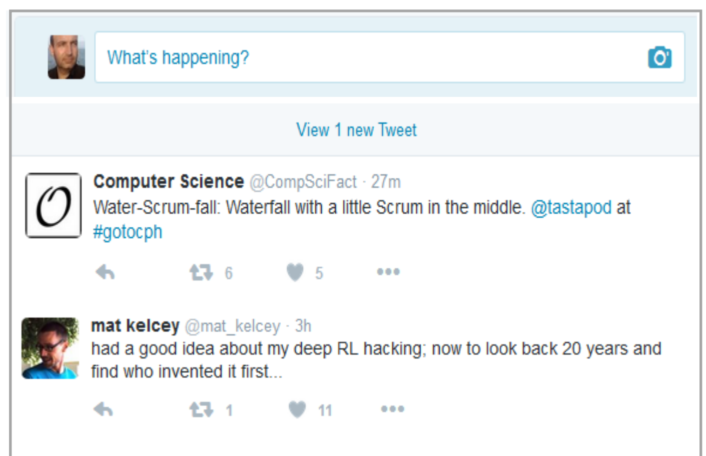
Introduction & Problem Definition

Recommender Systems

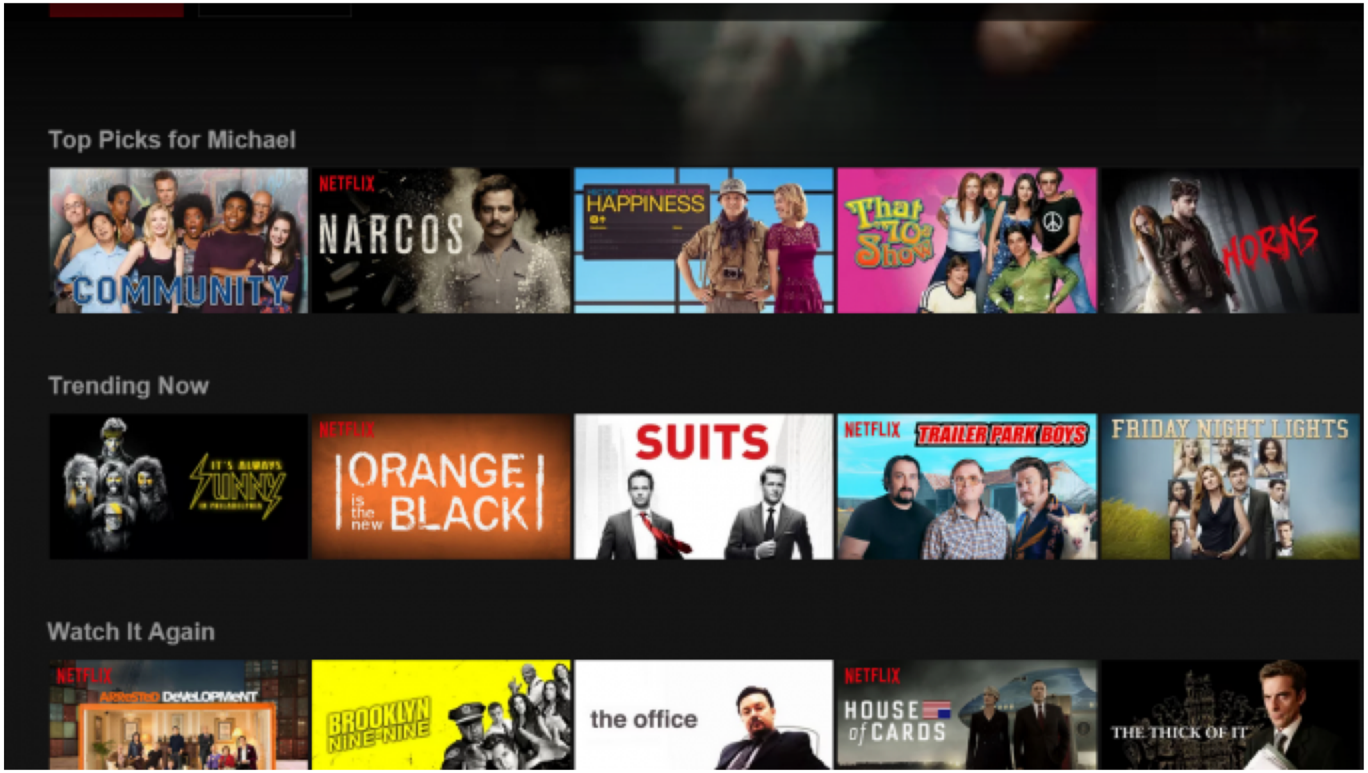
- A central part of our daily user experience
  - They help us locate potentially interesting things
  - They serve as filters in times of information overload
  - They have an impact on user behavior and business

Recommendations everywhere





Recommendations everywhere



A field with a history

- 1970s: Early roots in IR and what was called "Selective Dissemination of Information"
- 1990s: A field develops, "content-based" approaches, Collaborative Filtering
- 2000s and beyond: The Netflix Prize and its implications
- Today and the future:
  - Deep learning everywhere
  - But are we focusing on the most important problems?

The recommendation problem

- A very general definition:
  - "Find a good/optimal selection of items to place in the recommendation lists of users"
- The corresponding questions:
  - What determines a good/optimal selection?
    - Help users find something new?
    - Show the user alternatives to a certain item?
    - The diversity of the recommendations?
  - Good or optimal for whom?
    - The consumer, the platform or retailer, the manufacturer, all of them?

Jannach, D. and Adomavicius, G.: "***Recommendations with a Purpose***". In: Proceedings of the 10th ACM Conference on Recommender Systems (RecSys 2016). Boston, Massachusetts, USA, 2016, pp. 7-10

A common problem abstraction

- Recommendation as a matrix completion task

	Item1	Item2	Item3	Item4	Item5
Alice	5	?	4	4	?
User1	3	1	?	3	3
User2	?	3	?	?	5
User3	3	?	1	5	4
User4	?	5	5	?	1

- Goal:
  - Learn/optimize a prediction function from the data
- Quality assessment:
  - Prediction error on the test data

But, think again of about this one

- Past ratings do not play an obvious role
- There's seemingly not even personalization
- Nonetheless, it is a key application example in the literature

More real-world problems

- User intent
- Short-term intent/context vs. long term taste
- Order can matter
- Order matters (constraints)
- Interest drift
- Reminders
- Repeated purchases

User intent

- Our user searched and listened to “Last Christmas” by Wham!
- Should we, …
  - Play more songs by Wham!?
  - More pop Christmas songs?
  - More popular songs from the 1980s?
  - Play more songs with controversial user feedback?
  - Play the song again?

User intent

- Customers who bought ....

Roll over image to zoom in

Minnow Sports

Minnow Sports Aluminum Baseball Bat For Baseball & Teeball

8 customer reviews

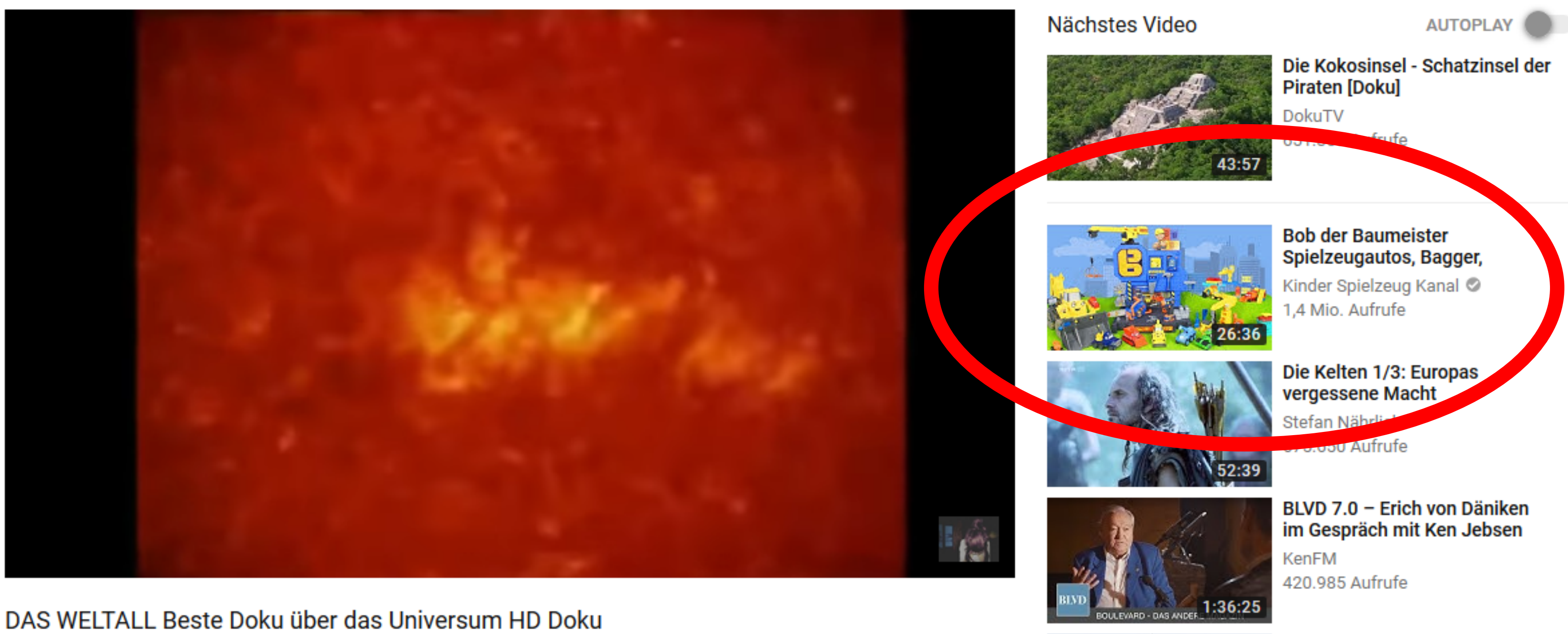
Price: ~~$29.99~~
Sale: $19.99
You Save: $10.00 (33%)

In Stock.
This item does not ship to **Germany**. Please check other sellers who may ship internationally. Learn more
Sold by BBro Store and Fulfilled by Amazon. Gift-wrap available.

Item Display Length:
32.0 inches

- Made from lightweight high grade Aluminum alloy for faster swing speed
- Ultra-thin 32" handle with All Sports grip for increased stability and accuracy
- Stylish design featuring full rolled-over end for ultimate performance
- Ideal for all levels of baseball players from practice to matches
- 32 inches in length & 24 ounces

YouTube



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Bob der Baumeister Spielzeugautos, Bagger,
Kinder Spielzeug Kanal
1,4 Mio. Aufrufe
26:36
Die Kelten 1/3: Europas vergessene Macht
52:39
BLVD 7.0 – Erich von Däniken im Gespräch mit Ken Jebsen
KenFM
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BLVD
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Short-term and long-term

- Here's what the customer purchased in the past

- Now, the user returns and looks at these items

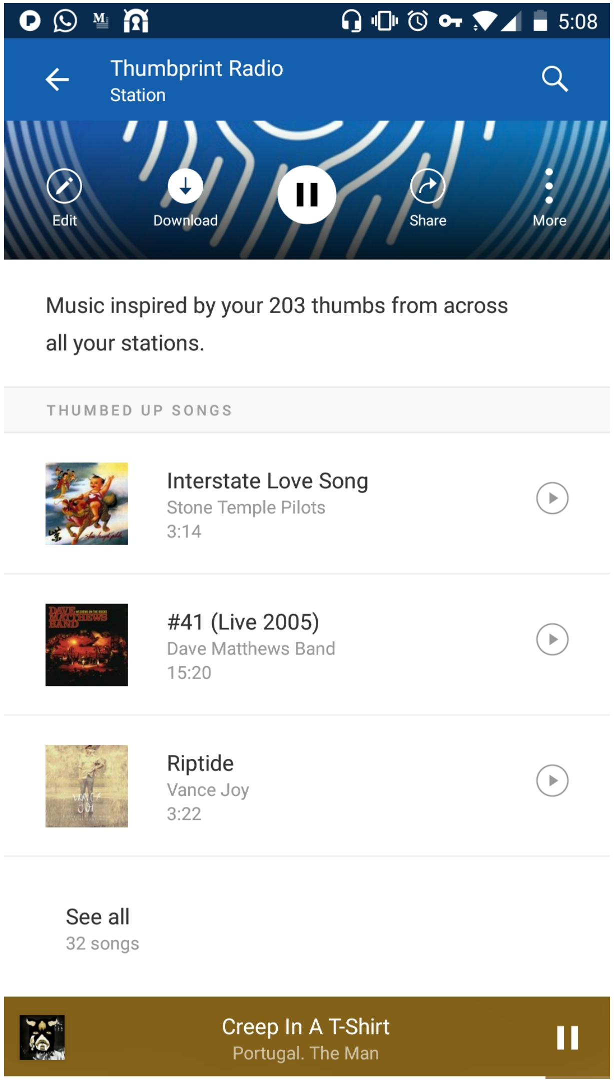
Short-term and long-term

- What to recommend?
- Some plausible options
  - Only shoes
  - Mostly Nike shoes
  - Maybe also some T-shirts

- With the basic matrix completion abstraction
  - Mostly Nike T-shirts and trousers might be recommended
  - Is this what we expect?

Order can matter

- Next-track music recommendation
- What we recommend next should suit the previous tracks and playlist purpose, e.g.,
  - consistent mood or
  - increasing or decreasing the tempo



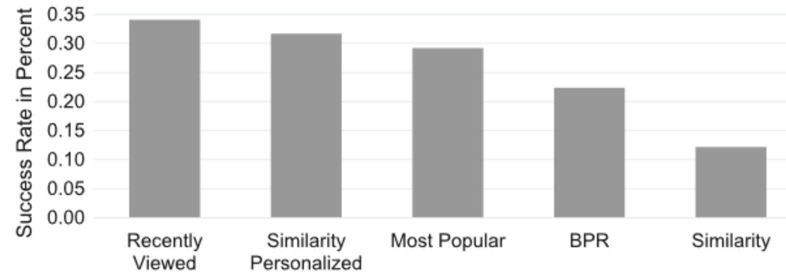
Order matters (order constraints)

- Is it meaningful to recommend Star Wars III, if the user has not seen the previous episodes?

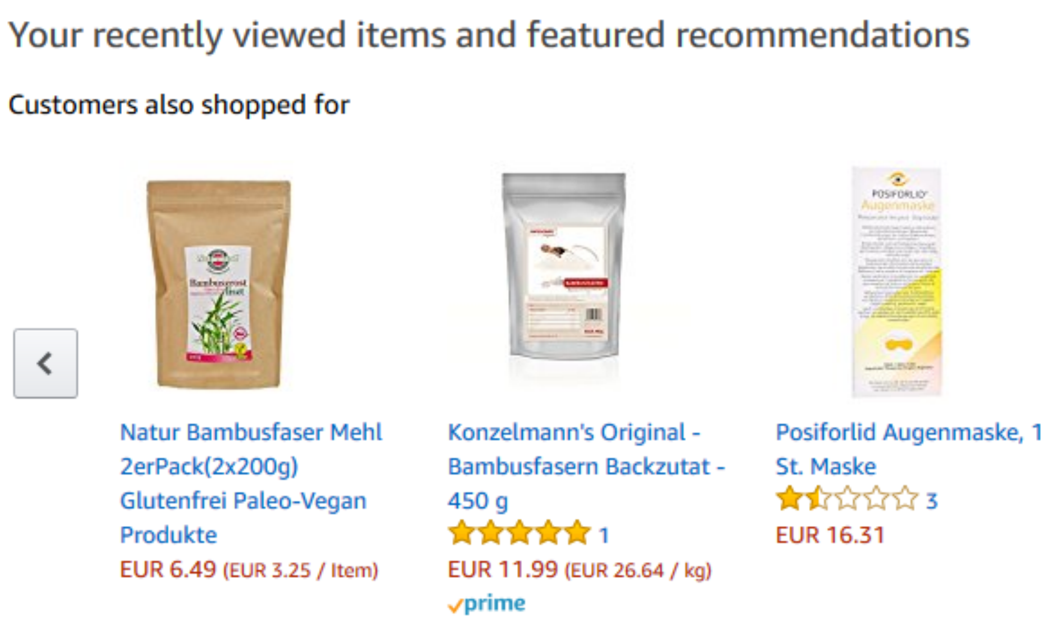
Interest drift

- Before and after having a family

Reminders



- Should we recommend items that the user already knows?
- Amazon and many others do



Repeated purchases

- When should we remind users through recommendations?

https://www.shopify.com/blog/customer-retention-strategies

Remember matrix completion

- Data aspects
  - Some aspects, e.g. short-term/long-term interests, can be partially covered with rating time stamps

	Item1	Item2	Item3	Item4	Item5
Alice	5	?	4	4	?
User1	3	1	?	3	3
User2	?	3	?	?	5
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    - But only if the rating time point relates to the consumption
  - Several aspects can not, like repeated purchases or reminders
- Algorithmic aspects
  - Special-purpose algorithms are required beyond rating prediction and item ranking
  - E.g., when or how often to remind a user
  - E.g., to detect individual interest drifts or global trends

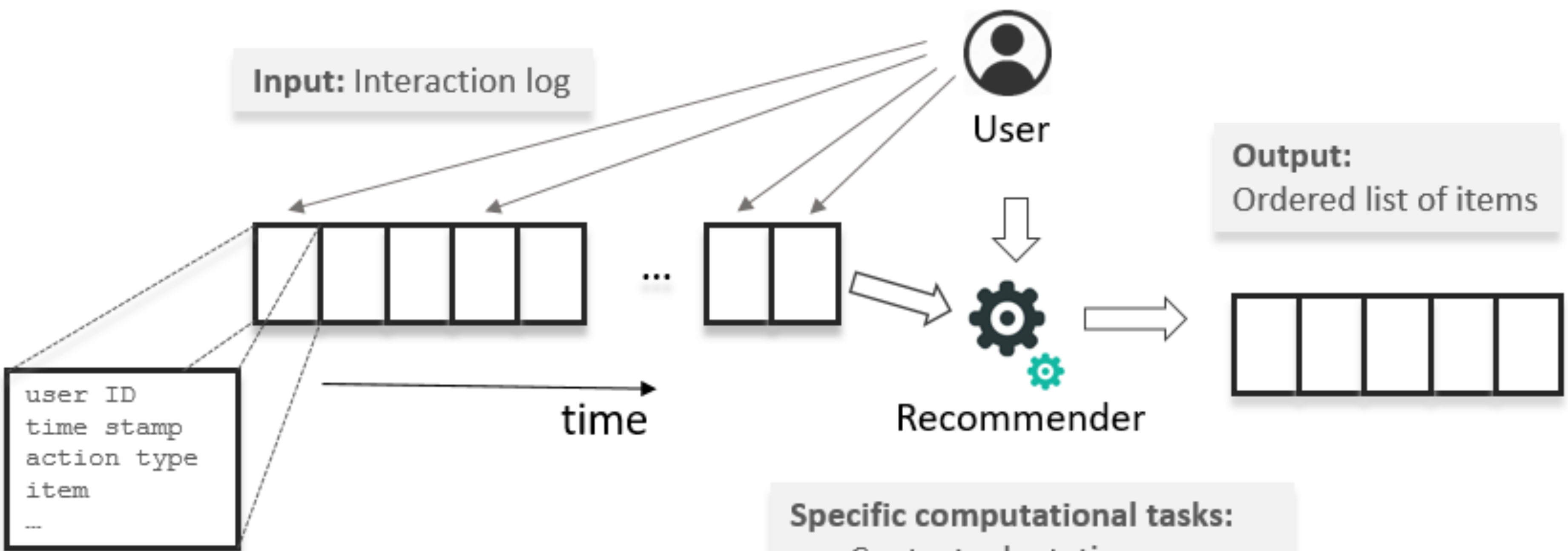
Real-world data

- In real-world applications, we usually do not have lots of explicit ratings
- However, there often are detailed application logs:
  - Sequential logs of user interactions
  - Interactions have different types (item view, purchase, …)
  - There can be multiple interactions of one user with the same item

Sequence-Aware Recommenders

- A family of recommender systems that
  - uses different types of input data, i.e., sequential interaction logs (enriched clickstream data)
  - implements alternative or complementary algorithmic tasks
  - addresses a number of the described practical problem settings

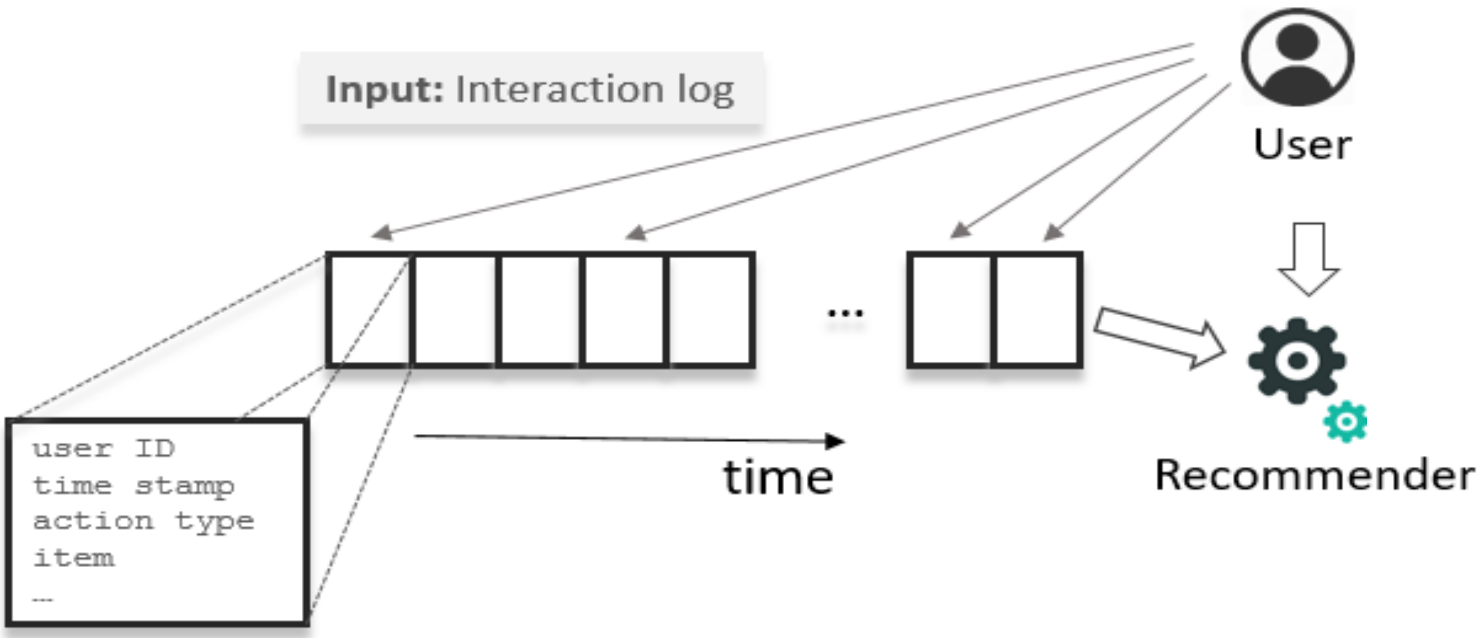
Problem characterization



Specific computational tasks:
- Context adaptation
- Trend detection
- Repeated recommendation
- Consideration of constraints

Inputs

- Ordered or time-stamped set of user actions
  - of known or anonymous users
  - actions are often connected with items
    - except, e.g., search or category navigation

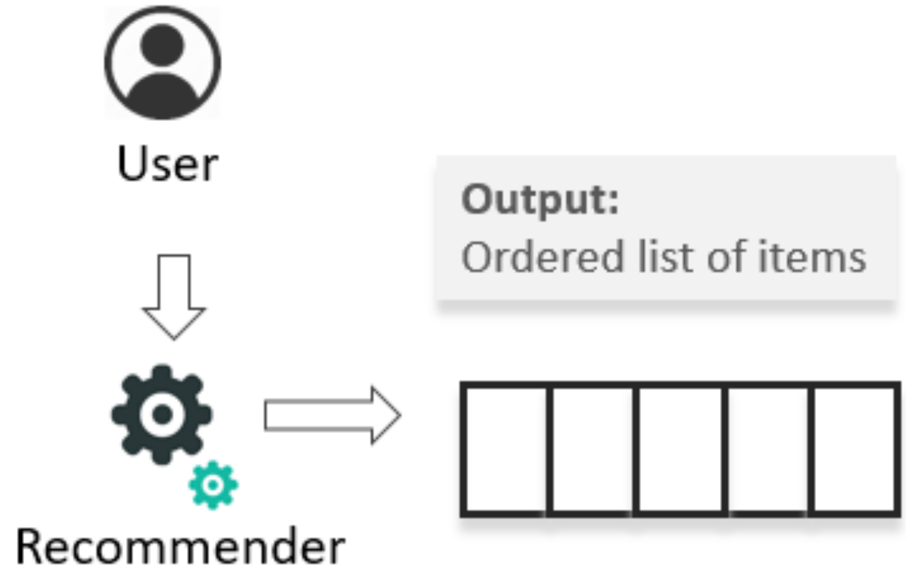


Inputs

- Different types of actions
  - Item purchase/consumption, item view, add-to-catalog, add-to-wish-list, …
- Attributes of actions: user/item details, context
  - Dwelling times, item discounts, etc.

Output

- One or more ordered list of items (as usual)
- The list can have different interpretations, based on goal, domain, application scenario
  - Show a list of alternatives to the last viewed item
  - Show a set of accessories for the last viewed item
  - Show a sequence of objects to be consumed sequentially or a list of recommended actions
  - Order can be strict or weak



Computational tasks

- Traditional:
  - Predict a relevance score for unseen items or create a ranking of unseen items
- Sequence-aware recommenders, e.g.:
  - Find sequence-related patterns in the data e.g., co-occurrence patterns, sequential patterns, distance patterns
  - Reason about order constraints, weak and strong
  - Relate patterns with user profile and current point in time e.g., items that match the current session

Formal characterization

- For item ranking or list generation
- Some definitions
  - U: users
  - I: items
  - L: ordered list of items
  - $L_u^{(s)}$: past sequence s of actions for user $u \in U$
  - A: set of all user sequences $L_u^{(s)}$ for all users $u \in U$

Formal characterization

- Data, definitions
  - U: users, I: items, L: ordered list of items
  - $L_u^{(s)}$: past sequence s of actions for user $u \in U$
  - A: set of all user sequences $L_u^{(s)}$ for all users $u \in U$

  - L^* : set of all possible lists L of length up to k
  - $f(u, L)$: utility function, with $u \in U$ and $L \in L^*$
  - $L_u = \underset{L \in L^*}{\operatorname{argmax}} f(u, L) \quad u \in U$
- Task:
  - Learn $f(u, L)$ from sequences A of past user actions

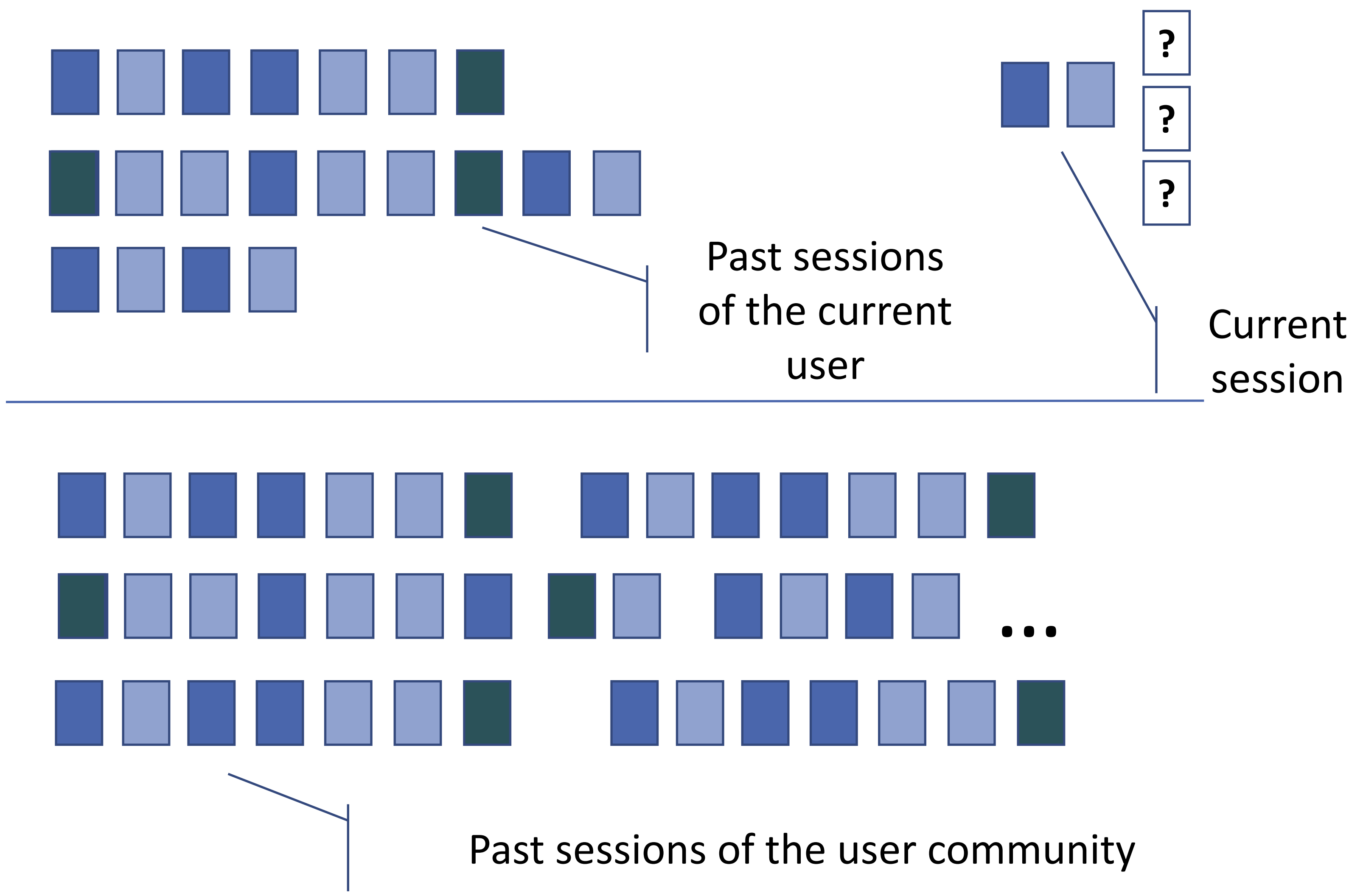
Utility function

- Not limited to scoring individual items
- The utility of entire lists can be assessed
  - including, e.g., transition between objects, fulfillment of order constraints, diversity aspects
- The design of the utility function depends on the purpose of the system
  - provide logical continuation
  - show alternatives
  - show accessories
  - …

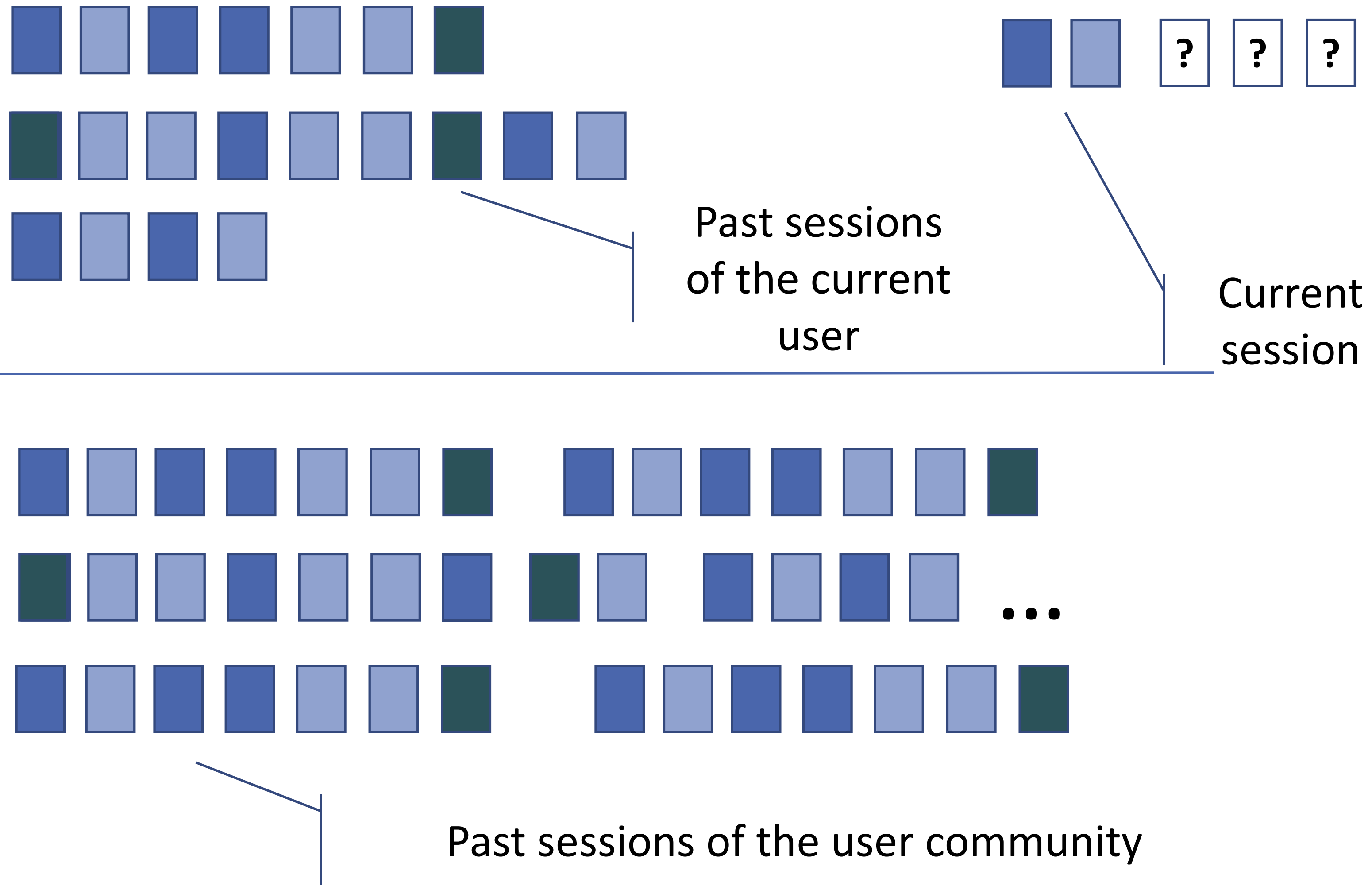
Operationalizing the Research Problem

- Background
  - Intention of user is not known, not clear if we should recommend more similar items or, e.g., accessories
- Computational task, simplified to:
  - Predict subsequent user action(s), given
    - the last N actions by the user (e.g., in the current session)
    - other types of information (community behavior, metadata, …)
- Evaluation
  - Use standard IR measures (precision, recall, MRR , …)
  - Some interaction log datasets are publicly available
    - But can be biased

A Problem Abstraction



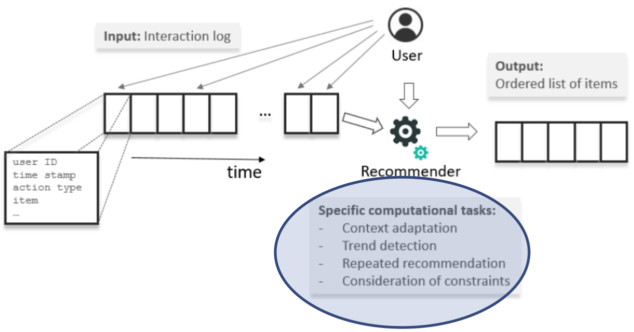
A Problem Abstraction



Relation to other areas

- Implicit feedback recommender systems
  - Sequence-aware recommenders are often built on implicit feedback signals (action logs)
  - Problem formulation is however not based on matrix completion
- Context-aware recommender systems
  - Sequence-aware recommenders often are special forms of context-aware systems
  - Here: Interactional context is relevant, which is only implicitly defined through the user's actions
- Time-aware recommender systems
  - Sequence-aware recommenders do not necessarily need explicit timestamps

Categorization of tasks



- Four main categories
  - Context Adaptation
  - Trend detection
  - Repeated recommendation
  - Consideration of order constraints and sequential patterns
- Note:
  - Categories are not mutually exclusive
  - All types of problems based on the same problem characterization, but with different utility functions, and using the data in different ways

Context adaptation

- Traditional context-aware recommenders are often based on the representational context
  - defined set of variables and observations, e.g., weather, time of the day etc.
- Here, the interactional context is relevant
  - no explicit representation of the variables
  - contextual situation has to be inferred from user actions

Context adaptation

- How much past information do we consider?
- Last-N interactions based recommendation:
  - Often used in Next-Point-Of-Interest recommendation scenarios
  - In many cases only the very last visited location is considered
  - Also: “Customers who bought … also bought …”
- Reasons to limit oneself:
  - Not more information available
  - Previous information not relevant

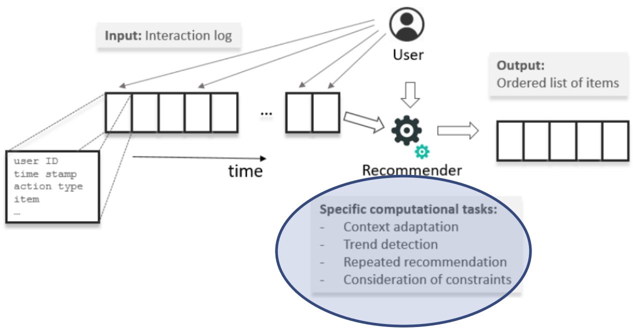
Context adaptation

- How much past information do we consider?
- Session-based recommendation:
  - Short-term only
  - Only last sequence of actions of the current user is known
  - User might be anonymous
- Session-aware recommendation:
  - Short-term + Long-term
  - In addition, past session of the current user are known
  - Allows for personalized session-based recommendation

Context adaptation

- Application-specific considerations
- What to find?
  - Next
  - Alternatives
  - Complements
  - Continuations
- What to pick?
  - One
  - All
  - Some

Trend detection



- Less explored than context adaptation
- Community trends:
  - Consider the recent or seasonal popularity of items, e.g., in the fashion domain and, in particular, in the news domain
- Individual trends:
  - E.g., natural interest drift over time, because of influence of other people, because of a recent purchase, because something new was discovered (e.g., a new artist)

D. Jannach, M. Ludewig, and L. Lerche: **Session-based Item Recommendation in E-Commerce: On Short-Term Intents, Reminders, Trends, and Discounts.** User-Modeling and User-Adapted Interaction, 2017

Repeated Recommendation

- Identifying repeated user behavior patterns
  - Recommendation of repeat purchases or actions
    - E.g., ink for a printer, next app to open after call on mobile
  - Patterns can be mined from the individual or the community as a whole
- Repeated recommendations as reminders
  - Remind users of things they found interesting in the past
    - To remind the of things they might have forgotten
    - As navigational shortcuts, e.g., in a decision situation
- Timing as an interesting question in both situations

Order considerations

- Constraints
  - External domain knowledge: strict or weak ordering constraints
  - Strict, e.g., sequence of learning courses
  - Weak, e.g., when recommending sequels to movies
- Observed sequential patterns
  - Information that is mined from the user behavior
    - Learn that one movie is always consumed after another
    - Predict next web page, e.g., using sequential pattern mining techniques

Summary of first part

- Matrix completion abstraction not well suited for many practical problems
  - In reality, rich user interaction logs are available
- Different types of information can be derived from the sequential information in the logs
  - And be used for special recommendation tasks, in particular for the prediction of the next action
- Coming next:
  - Algorithms and evaluation