DAI-Labor
Distributed Artificial Intelligence Laboratory

Incorporating Context and Trends In News Recommender Systems

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Motivation

- Recommender Systems have been developed as powerful tools
- Popular application domains: Entertainment (movies, books, music), and online shops
- Most recommender system use **Collaborative Filtering**
- Trained on **large static** datasets (describing user-item interactions)

Motivation

▶ News

- **Continuous changes** in set of news items, **frequent updates** in news items
- News must provide new/unknown information
- Users are interested in a wide spectrum of topics, e.g. unexpected **breaking news**
- The relevance of news depends on the **context**
- Most news are published online – users do not have to register explicitly

▶ Challenge

- Traditional CF-based approaches do not work well – due to the **cold-start problem** (item/user)
- The changes in the news sets require **continuous** model **updates**
- **Context** and user **habits** must be considered

Objectives

- Objectives
  - Analyze and optimize models for **recommending news**
  - Develop models for learning recommender models likely to **fit best the near future**
  - Models for incorporating **contexts** and **trends**

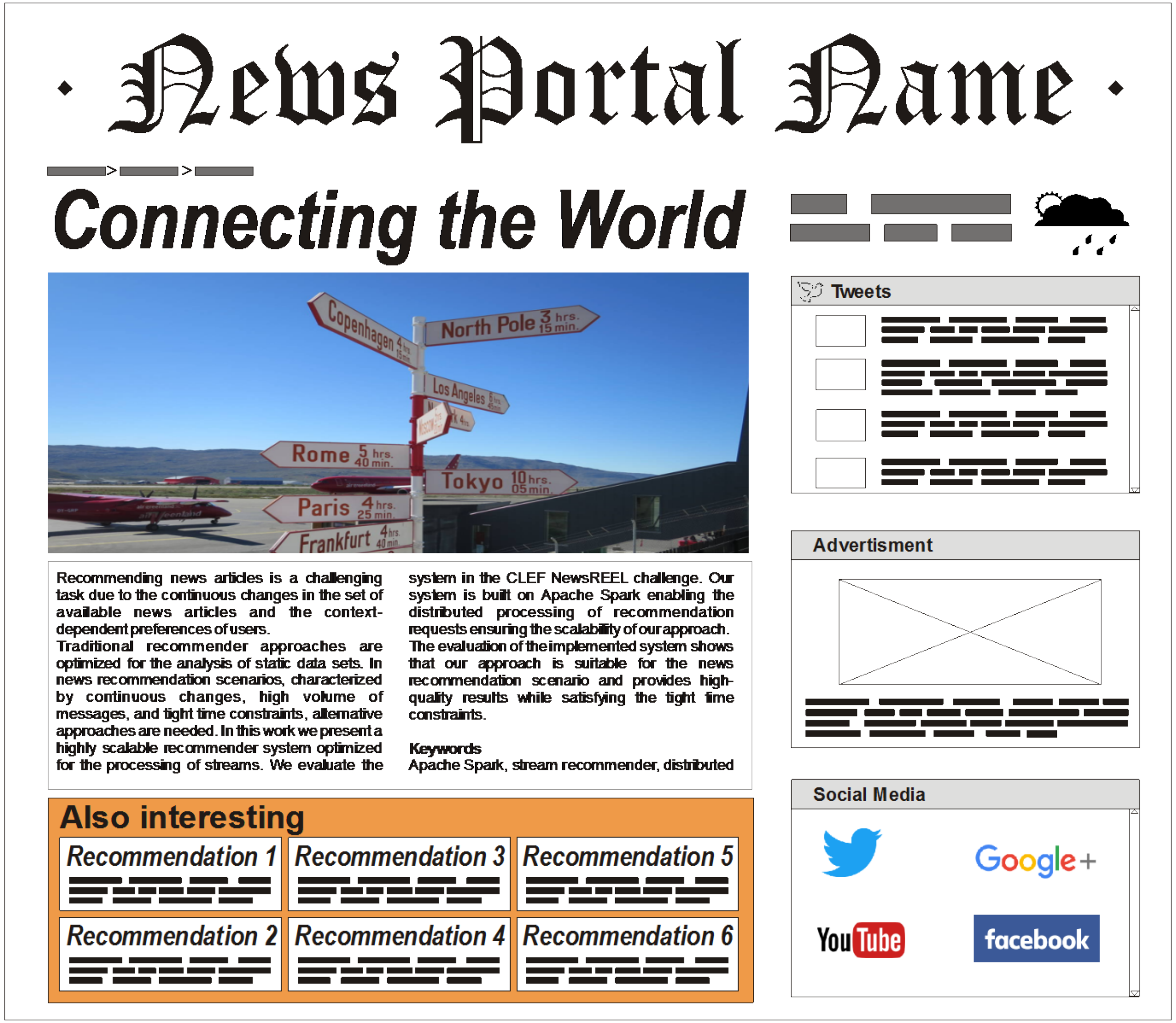
Outline

- Motivation
- **The analyzed News Recommendation Scenario**
- Approach
- Evaluation
- Conclusion

NewsREEL - Overview

▶ The NewsREEL Scenario

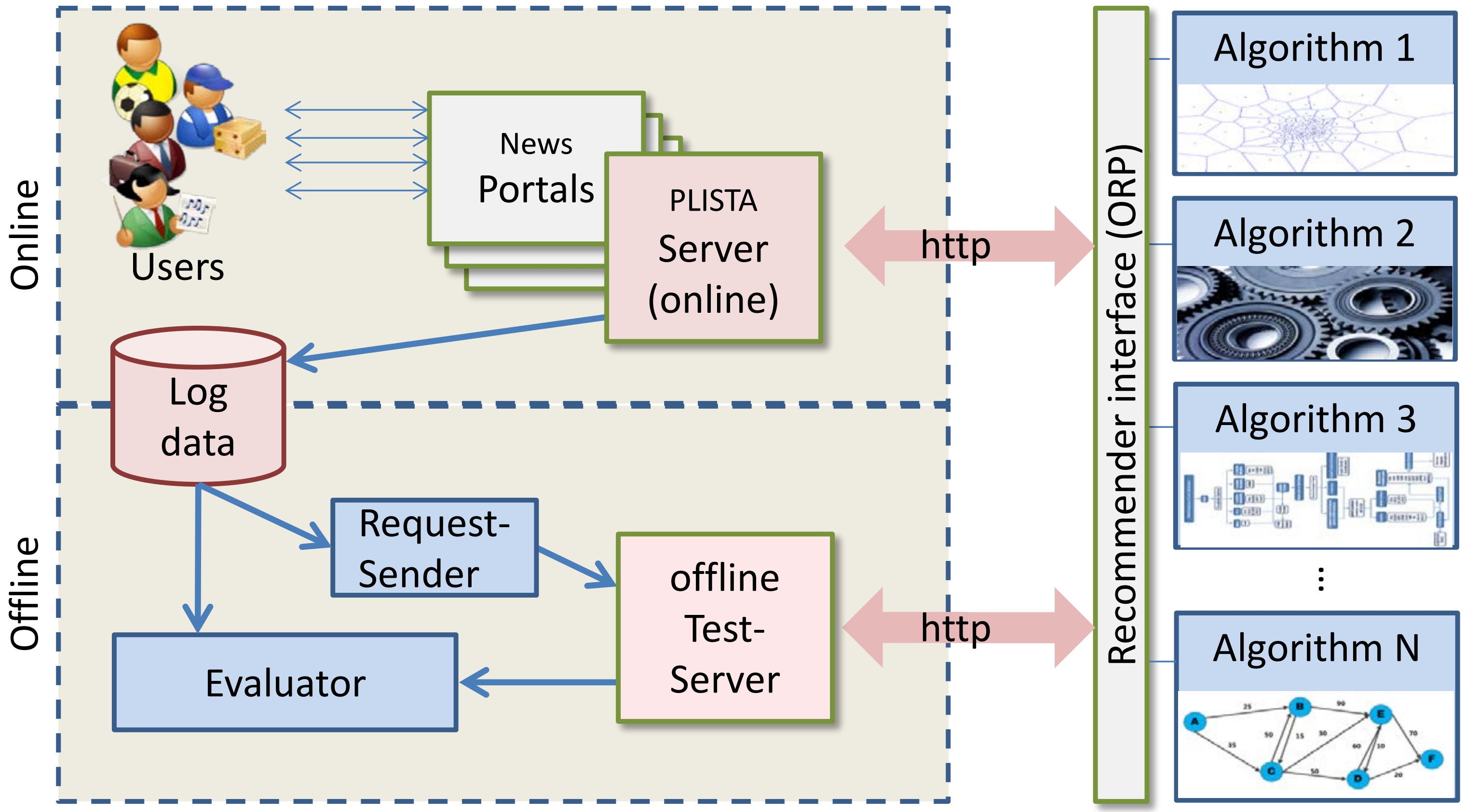
- Recommending News
- Online News Portals
- **Live user feedback**
- Evaluation with respect to CTR (Click-Through-Rate)
- Ensure **Technical constraints**



Problem Description

NewsREEL – Challenge Architecture

- The NewsREEL challenge architecture
  - **Online** – Live feedback | **Offline** – Replay log data
  - http-based communication, JSON-formatted data

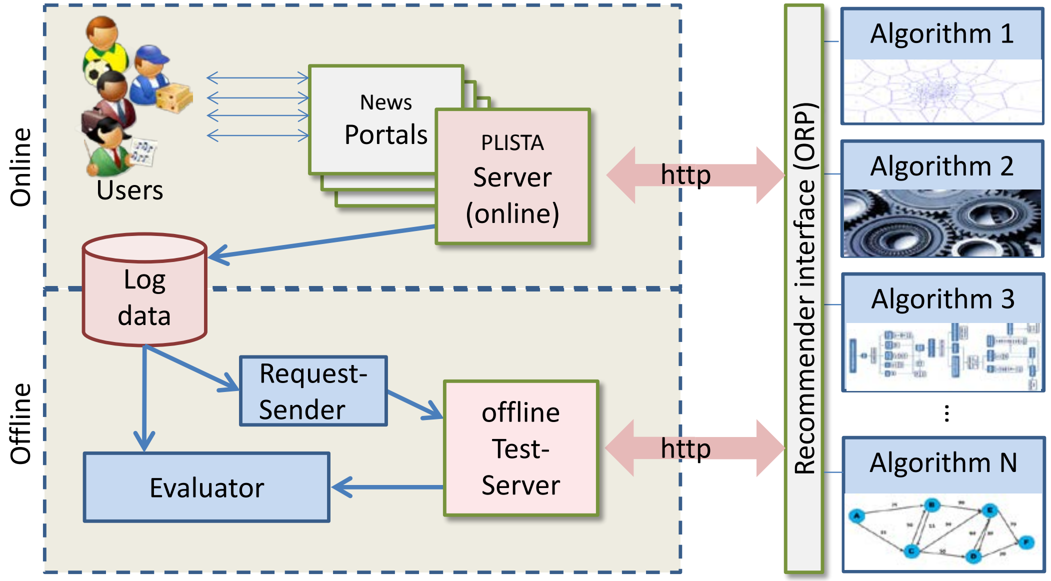


- Message types:
  - Item updates
  - Impressions
  - Recommendation requests
  - Clicks
  - Errors

NewsREEL – Challenge Architecture

The NewsREEL challenge key figures

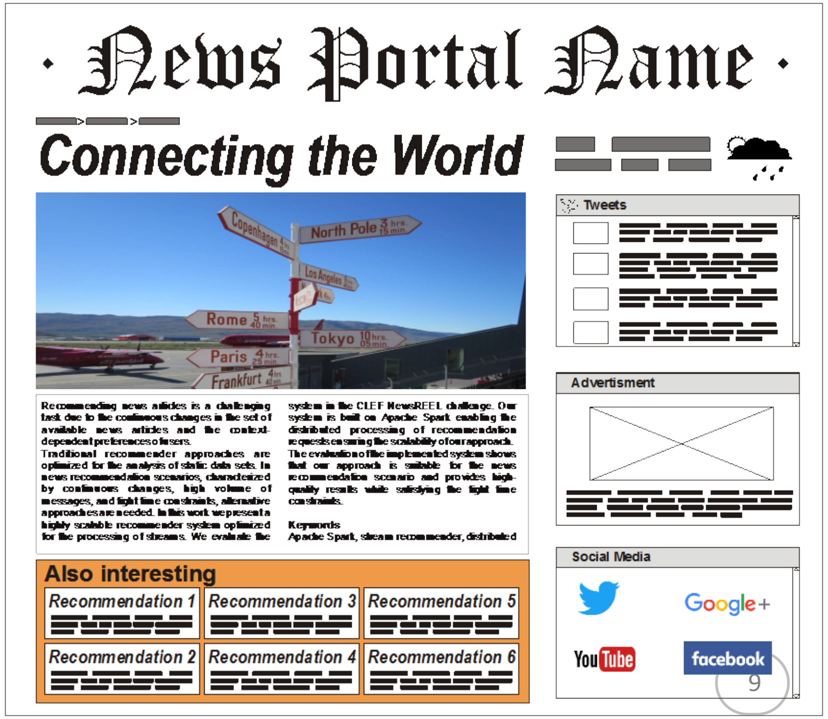
- Online
  - 3-5 new portals
  - 40 messages per second (typically)
    → up to 200 messages per second possible
- Offline
  - Data stream recorded over 2 month
  - 100 GB JSON data
  - Item creates, item updates, impressions, recommendation requests, clicks, errors



NewsREEL - Overview

- The NewsREEL Scenario
  - **Online / offline** (academic and industry-style evaluation)
  - **Live** evaluation / Large dataset – **real world data**
  - **Stream**-based recommendation (time and context as success-critical aspects)
  - **Dynamic** sets of users and items
  - **Multi-dimensional** benchmarking

- More Details available at:
  - **http://www.clef-newsreel.org/**



Outline

- Motivation
- The analyzed News Recommendation Scenario
- Data Analysis
- Approach and Evaluation
- Conclusion

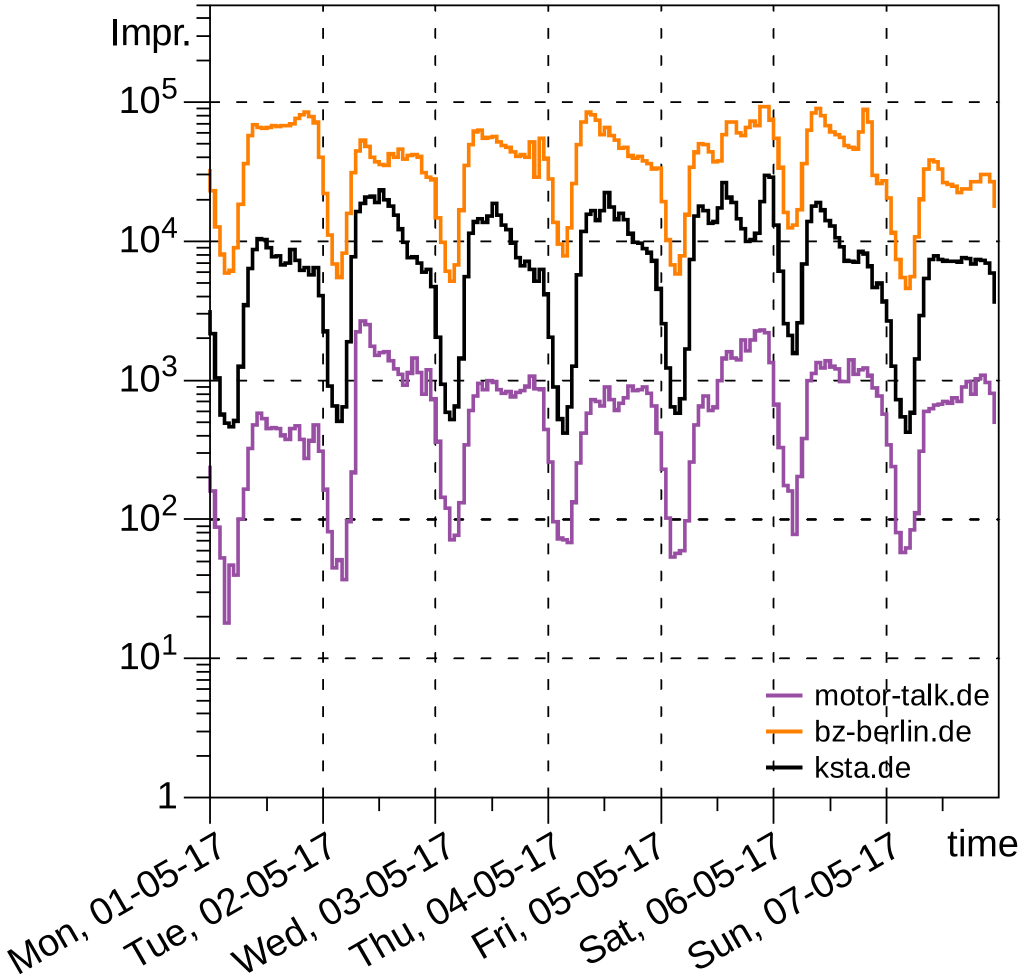
NewsREEL – Data Analysis

- **Data Analysis** with respect to **context** and temporal dynamics (**trends**)
  - Number of interactions in the system
  - Number of accepted recommendations
  - Device usage in the system
  - Item popularity
  - Item lifecycle
  - User reading preferences

NewsREEL – Data Analysis 1

- We analyze the number of **impressions over one week**

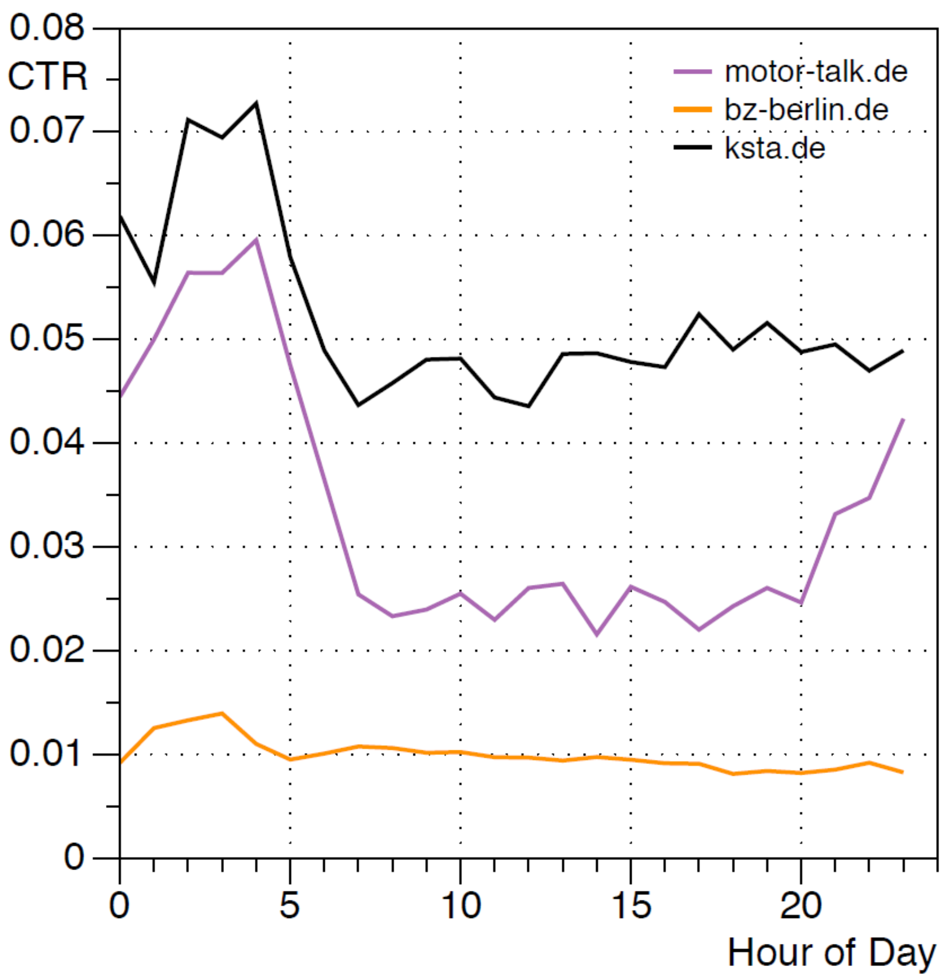
- Observations:
  - Huge changes in the number of impressions in the week
  - Day/night pattern
  - Working day / week end pattern
  - Highly domain dependent



NewsREEL – Data Analysis 2

- We analyze the fraction of **accepted recommendations over the day**

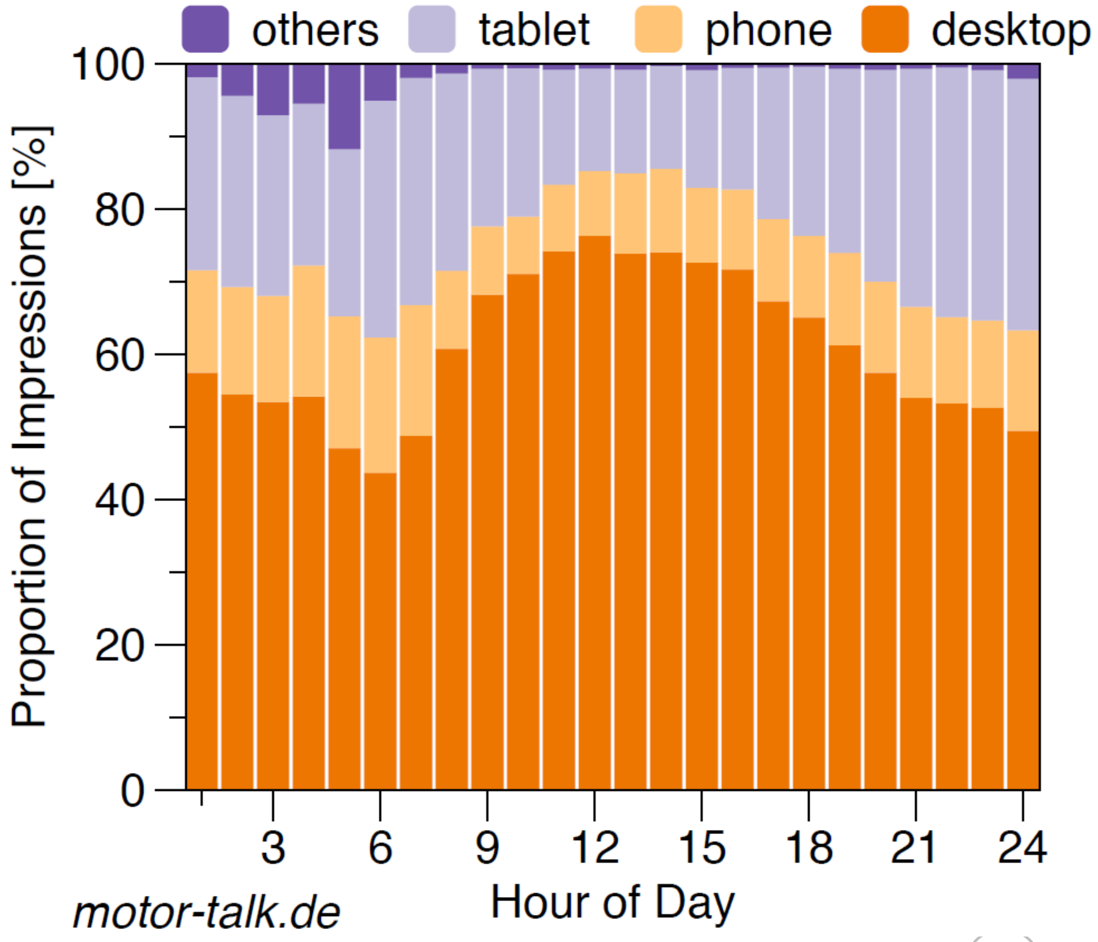
- Observations:
  - The CTR highly depends on the time and the domain
  - At night the CTR is higher than during the day (for most portals)



NewsREEL – Data Analysis 3

- How users consume news?
  What **devices** are mostly used?

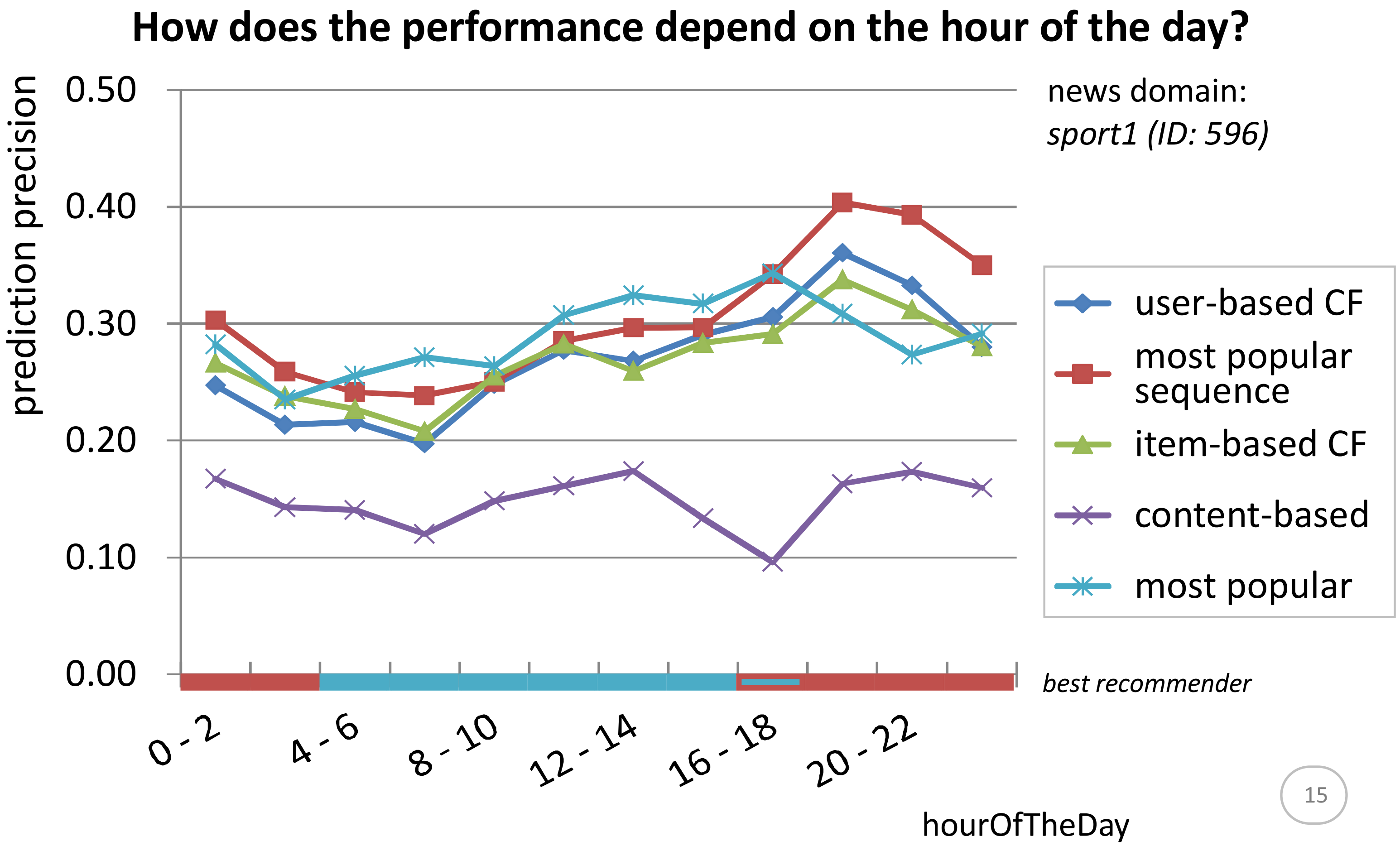
- Observations:
  - The proportion between the used devices changes significantly over the day.
  - The device used typically influences the user preferences and the presentation of recommendations.



NewsREEL – Data Analysis 4

- What recommender algorithm performs best?
  What type of recommendations do users expect.

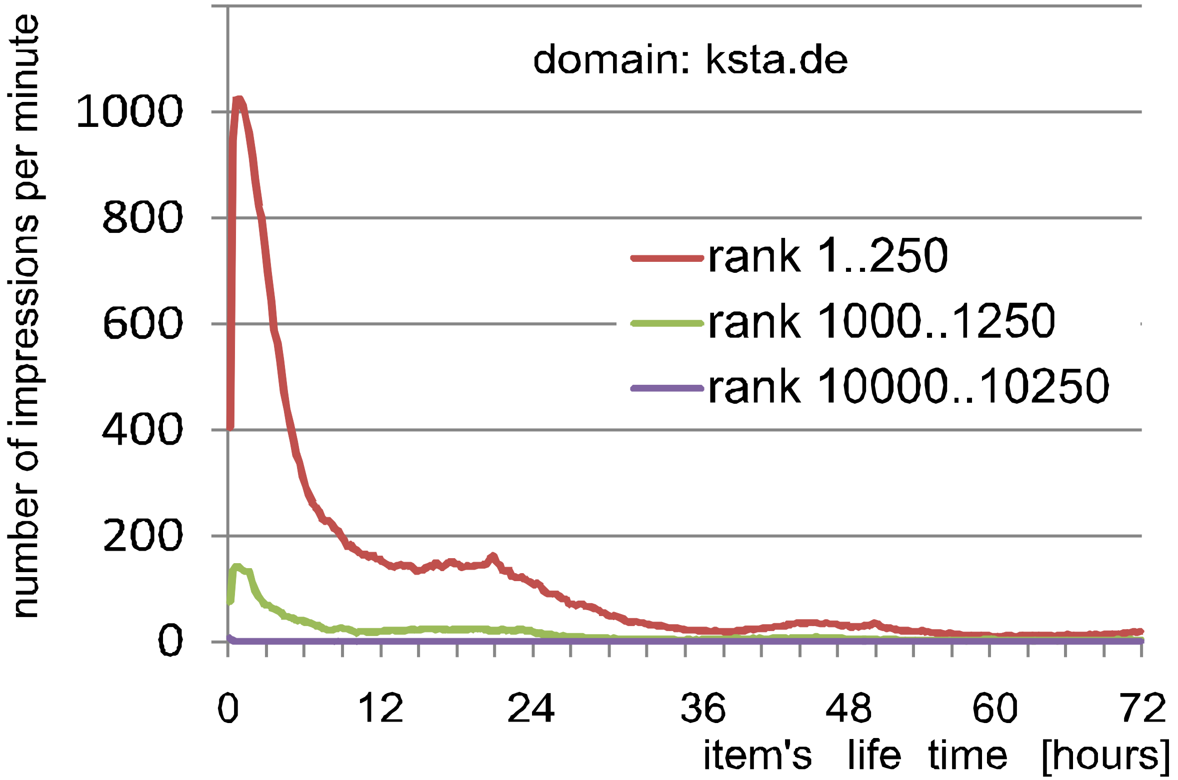
- Observations:
  - The recommender performance strongly depends on the time of day
  - Example: At night users tend to have a higher interests in longer news sequences



NewsREEL – Data Analysis 5

- How does the interest in specific items change over time?
  How does the **typical item lifecycle** look like?

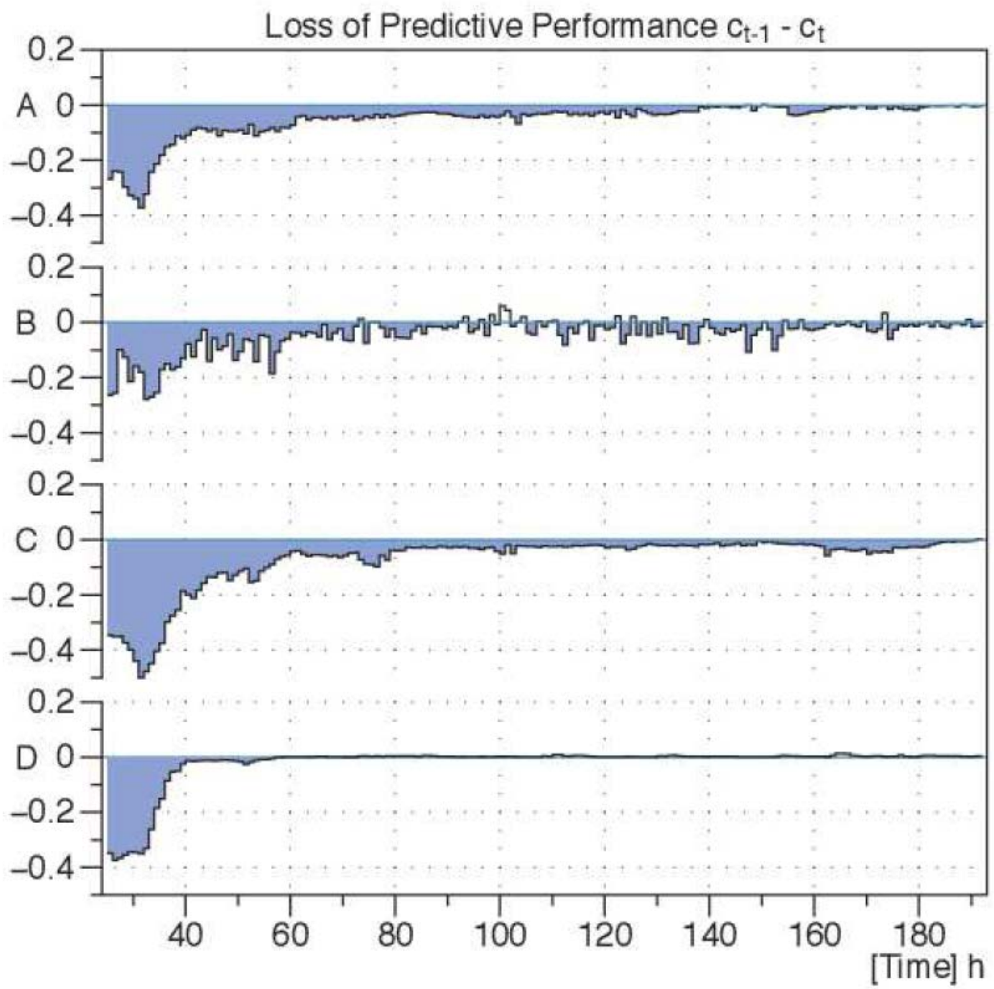
- Observations:
  - Items show a specific lifecycle
  - After the release the interest in the news items grows fast,
  - Having reached the maximum, the number of impressions decays exponentially



NewsREEL – Data Analysis 6

- How does the set of recommendable **items changes** over time?

- Observations:
  - We analyze the freshness of the recommender model
  - We analyze the loss of predictive performance



NewsREEL – Data Analysis – Summary – Research Question

- Conclusion
  - **Context** has an high influence of the user behavior / user preferences
  - **Dynamics** in the set of items
  - Static recommender models do not cover the requirements

- Research Questions:
  - How to optimize models for incorporating the context
  - How recommender models can considering
    the item lifecycle / trends in the item set

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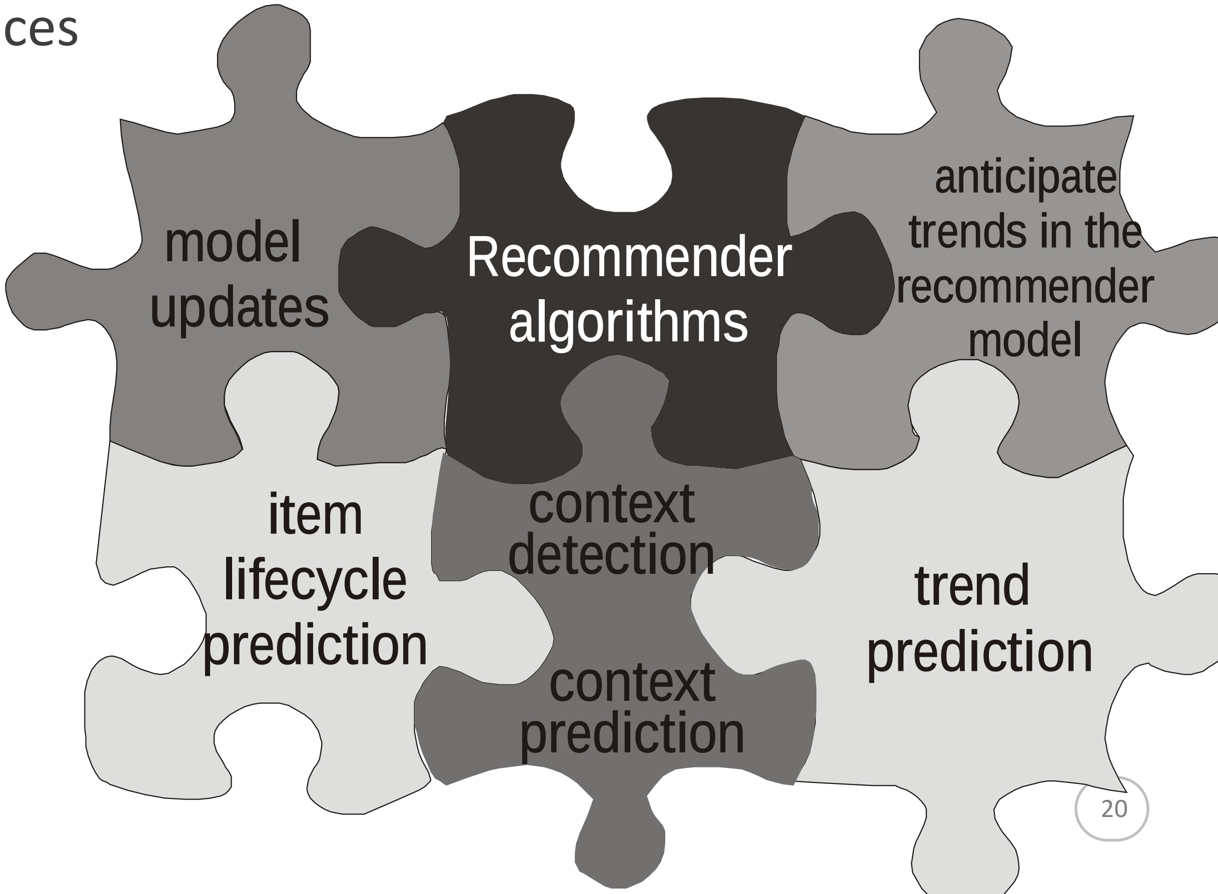
Models for Predicting the Context and Incorporating Trends

- Objective:
  - Study approaches for
    - Incorporating time-dependent preferences
    - The item life cycle
    - Adapting to current trends



Method 1: Idea

<u>Method 1:</u> Handle Data **streams** - Ensuring the model **freshness**

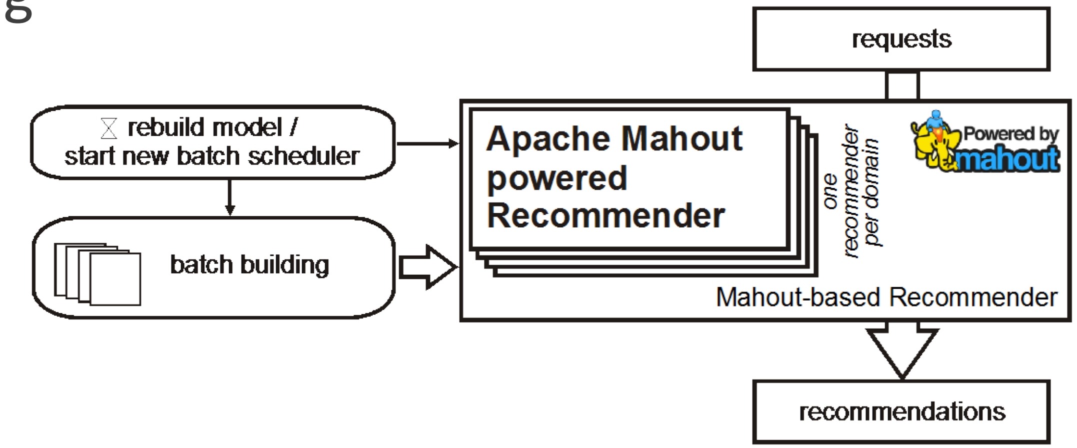
- Idea:
  - Aggregate stream data in batches
  - Use traditional recommender frameworks optimized for sets
  - Scheduler-based model updates

- Challenge
  - Components for parallelizing batch-building model-building, and computing recommendations
  - Definition of optimal batch sizes
  - Model building may slow down the recommender

Method 1: Evaluation – Discussion

Method 1: Ensuring the model freshness

- Evaluation - Discussion:
  - Works well in the typical news recommendation scenario
  - Use existing, mature recommender components
  - Delayed incorporation of trends
  - Cold-start problem cause by new batches
  - Load peaks when caused by model rebuilding

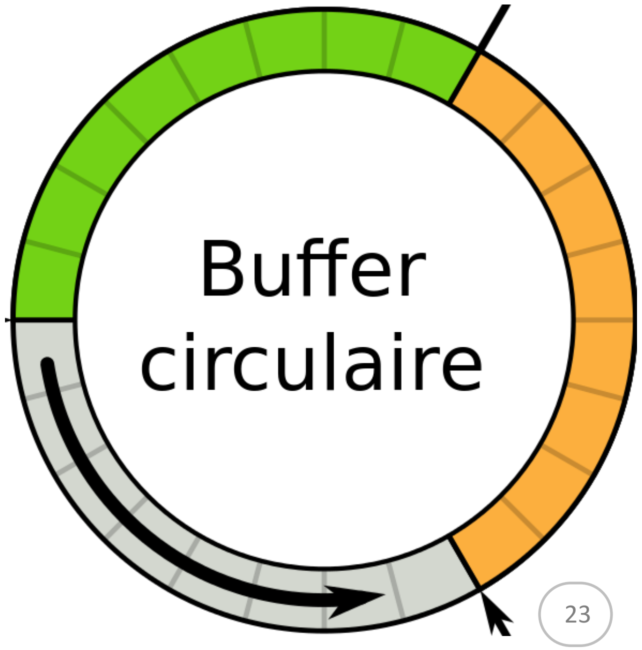


Method 2: Idea

<u>Method 2:</u> Handle Data **streams** - Ensuring the **continuous** model **freshness**

- Idea:
  - Continuous updates in order to ensure fast adaptation to new trends
  - Fixed model size (remove data when new data is added)

- Challenge
  - Adapt algorithms so that continuous updates are supported
  - Find optimal model size considering the context
  - Handle the concurrency of model updates and model deployment

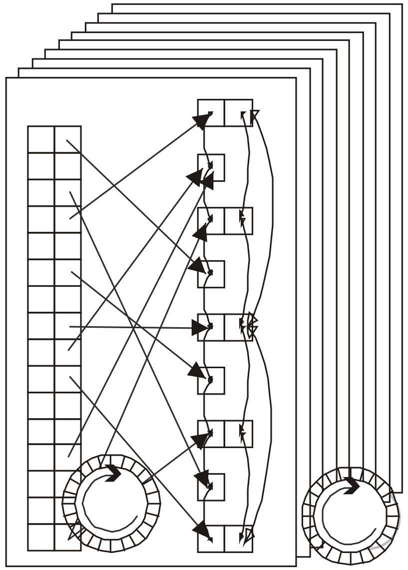


Approach

Method 2: Evaluation – Discussion

Method 2: Ensuring the continuous model freshness

- Evaluation - Discussion
  - Overcomes the most problems of batch-based model updates
  - Constant load in model adaptation
  - Limited complexity of the supported recommender models
  - Adapts faster than batch updates, but does not anticipate trends and changes in the context

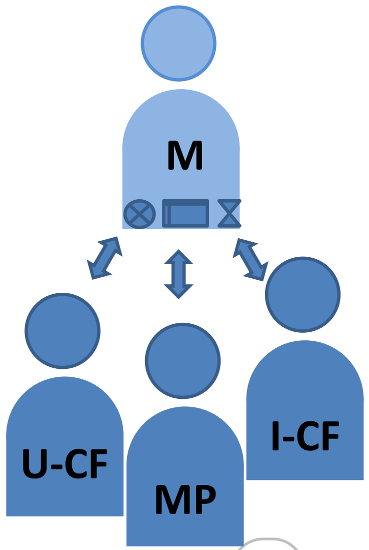


Method 3: Idea

Method 3: Recommender ensembles for specific contexts

- Idea:
  - Define an ensemble
  - Learn an algorithm for each relevant context
  - Learn what algorithm should be selected considering context and trends

- Challenge:
  - What are relevant contexts?
  - How to ensure that the context is relevant over time
  - Handle unexpected/unusual situations
  - How to ensure that enough training data exists (fine-grained contexts vs. significant amount of training data)



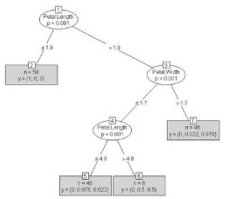
Method 3: Evaluation – Discussion

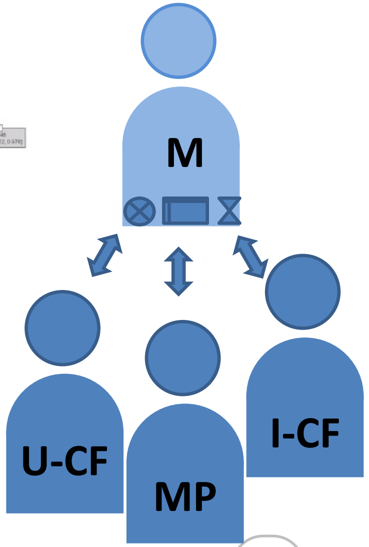
- Method 3: Recommender Ensembles for specific contexts

- Evaluation:
  - Works well for "normal" days
  - Cover well daily and weekly usage patterns
  - Anticipate periodical usage pattern

- Discussion:
  - Ensemble lead to a significantly higher complexity, several different algorithms must be trained
  - Rare events/contexts are often not well considered (due to limited training data)

```
getDomain = cio.de: most-popular (3985.0/325.0)
getDomain = ksta.de
|   workingDay = yes
|   |   getNumberOfRequestedResults = one
|   |   |   getHour <= 8: user-based-CF (1489.0/927.0)
|   |   |   getHour <= 10: mp-sequence (926.0/632.0)
|   |   |   getHour <= 14: item-based CF (1633.0/1061.0)
|   |   |   getHour <= 18: mp-sequence (1103.0/720.0)
|   |   |   getHour > 18: user-based-CF (710.0/435.0)
|   |   getNumberOfRequestedResults = more
|   |   |   getHour <= 8
...
```

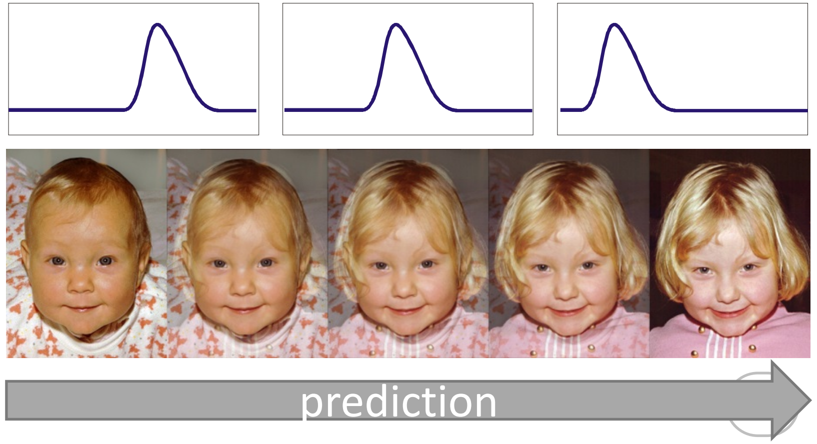




Method 4: Consider the item lifecycle

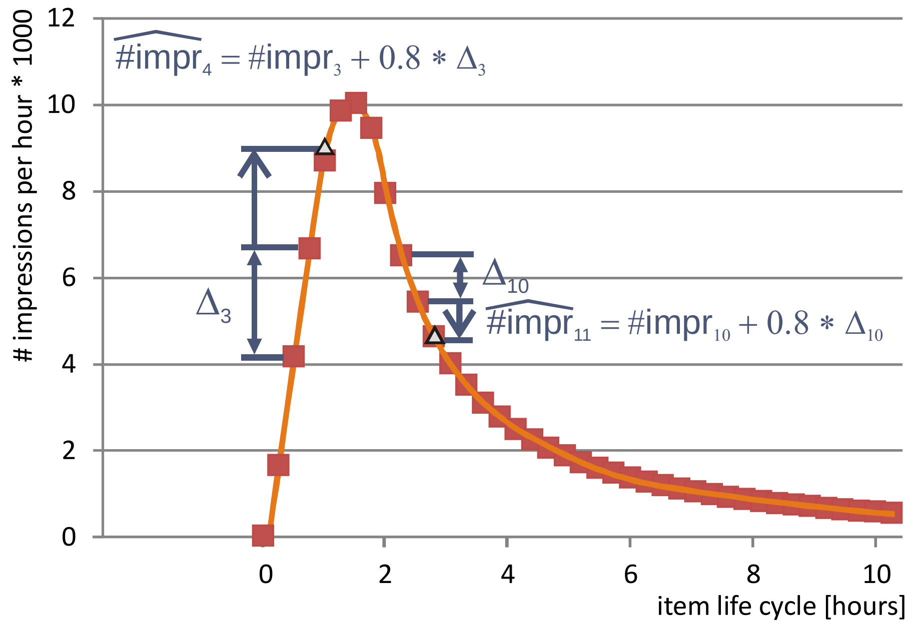
- Idea:
  - Traditionally, recommender are trained on past data
  - Knowing the item characteristic lifecycle for all items, we can predict the item characteristic in the near future
  - We can build a model fitting the near future best

- Challenges
  - Train a model allowing us to predict the lifecycle of all items
  - Fit the model parameters



Method 4: Consider the item lifecycle

- ▶ Evaluation – Discussion
  - Anticipate observed / periodically trends
  - Avoid the problem of late adaptation
  - The model cannot predict breaking events (untypical events)
  - Models computed based on predicted data are often noisy
  - An extended evaluation is needed



Discussion

- Discussion
  - Different approaches tailored for solving specific challenges
  - Each approach focus on one specific aspect – each approach has **specific strength and weaknesses**
  - The **combination is promising** but reduces the number of training data for each context/situation
  - Extended evaluation is needed, is planned for the next month

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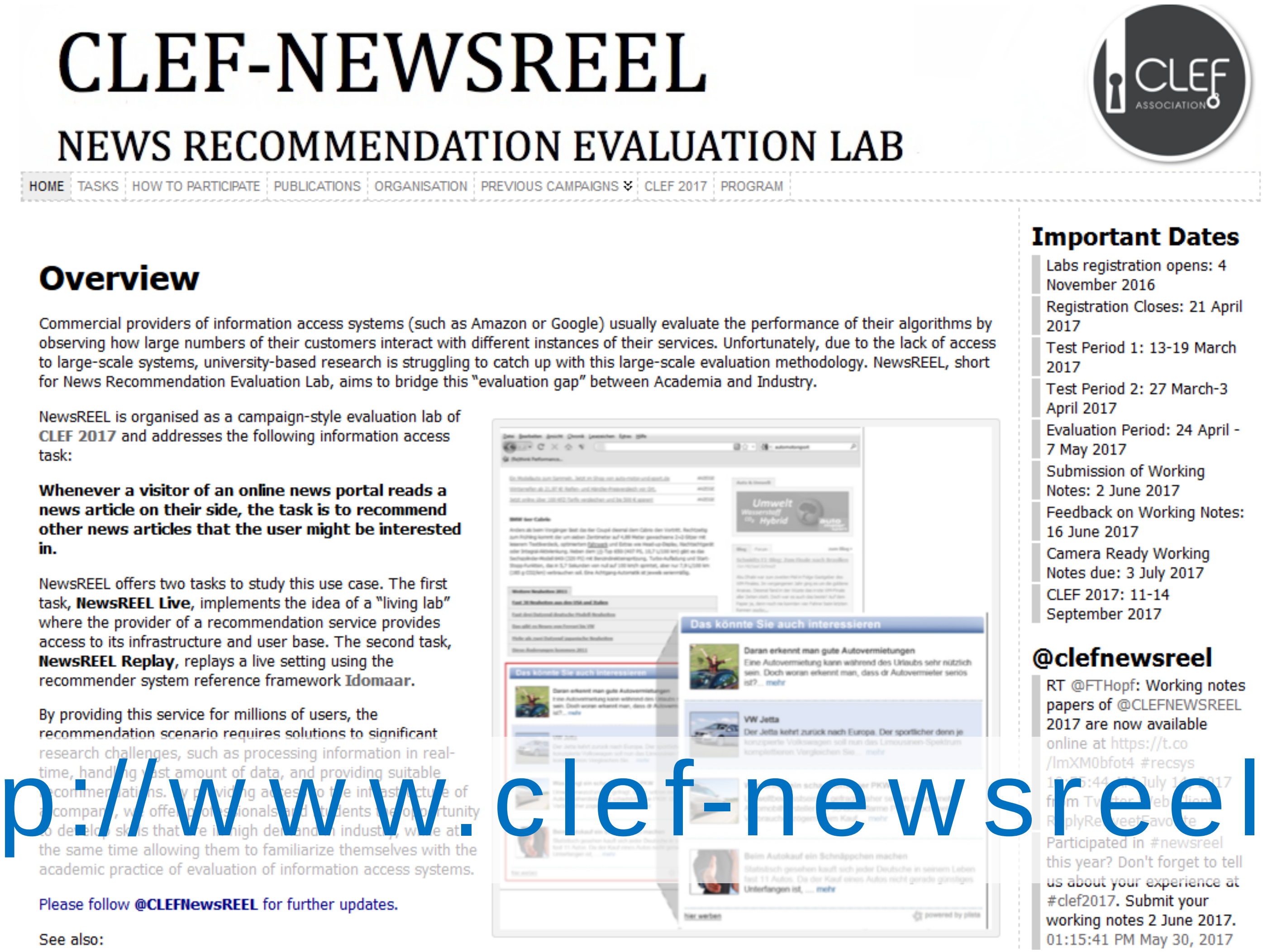
Conclusion

- Results
  - Recommender system require special methods for considering contexts and anticipating trends
  - We have presented four methods (each focusing on one aspect)
  - Improved performance compared with traditional static recommender models
  - Combination of different methods is promising
  - “news” are difficult to predict, user preferences are changing
    => news recommendation is challenging

- Future Work
  - Extended Evaluations
  - More combinations
  - Consider additional types of items, e.g., blogs

NewsREEL

Try our own ideas



http://www.clef-newsreel.org/

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