The News Recommendation Evaluation Lab (NewsREEL)

Recommender Algorithms for News Streams

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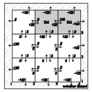
@Algorithms-Data-Challenges-Berlin (July 11th, 2016)

About Me

- Background: Computer Science
  - Focus: Artificial Intelligence / Business management applications
  - PhD: Algorithms for Distributed Information Retrieval Systems



- Research Project with Industry Partners at the
  - Information Retrieval / Information Management
  - Recommender Systems
  - Machine Learning
- The CrowdRec Project
  - Development of recommender algorithms focusing on heterogeneous data, real-time, context, streams

Objective

- Provide Recommendations for Online News Portals
- Live Evaluation based on #clicked recommendations (CTR)

Objective

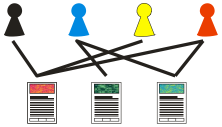
- Provide Recommendations for Online News Portals
- Challenges:
  - Continuous changes in the set of news items (new items, corrected items)
  - Continuous stream describing user-item interactions
  - Noisy user tracking (users do not login explicitly)
  - Several different news portals (local news, sports, tech news, …)
  - Time-dependent user preferences
  - Recommendation requests must be answered within 100ms
  - Scalability – concurrent requests
- Evaluation
  - Live user feedback

Outline

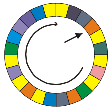
Introduction to Online Real-time Recommendations

- The News Recommendation Lab Challenge

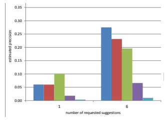
- Traditional recommender systems



- Stream-based recommender algorithms

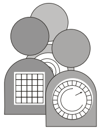


- Evaluation



- Technical Aspects

- Organizing a Challenge



- Conclusion & Future Plans

The News Recommendation Evaluation Lab Challenge in Detail

CLEF-NEWSREEL

NEWS RECOMMENDATION EVALUATION LAB

Overview

Many online news publishers display on the bottom of their articles a small widget box labelled "You might also be interested in", "Recommended articles", or similar where users can find a list of recommended news articles. Dependent on the actual content provider, these recommendations often consist of a small picture and accompanying text snippets.

While some publishers provide their own recommendations, more and more providers rely on the expertise of external companies such as **plista**, a data-driven media company which provides content and advertising recommendations for thousands of premium websites (e.g., news portals, entertainment portals). Whenever a user reads an article on one of their customers' web portals, the plista service provides a list of related articles. In order to outsource this recommendation task to plista, the publishers firstly have to inform them about newly created articles and updates on already existing articles on their news portal. In addition, whenever a user visits one of these online articles, the content provider forwards this request to plista. These clicks on articles are also referred to as impressions. Plista determines related articles which are then forwarded to the user and displayed in above mentioned widget box as recommendations.

H[illegible] large customer [illegible] plista processes millions of visi[illegible] in [illegible] a da[illegible] res[illegible] tea[illegible] th[illegible] o[illegible]unity to [illegible] recommendations. In the thirditeration of NEWSREEL which is organised as a campaign-style evaluation lab of **CLEF 2016**, we provide **two tasks** that address the challenge of real-time news re[illegible]mmendation. The first task allows [illegible]enchmarking news re[illegible] [illegible] algorith[illegible] [illegible] The se[illegible] ta[illegible] [illegible] using [illegible] novel recommender systems reference framework which has been developed within the FP7 project **CrowdRec**.

See also:

CLEF 2016
CLEF Initiative

Important Dates

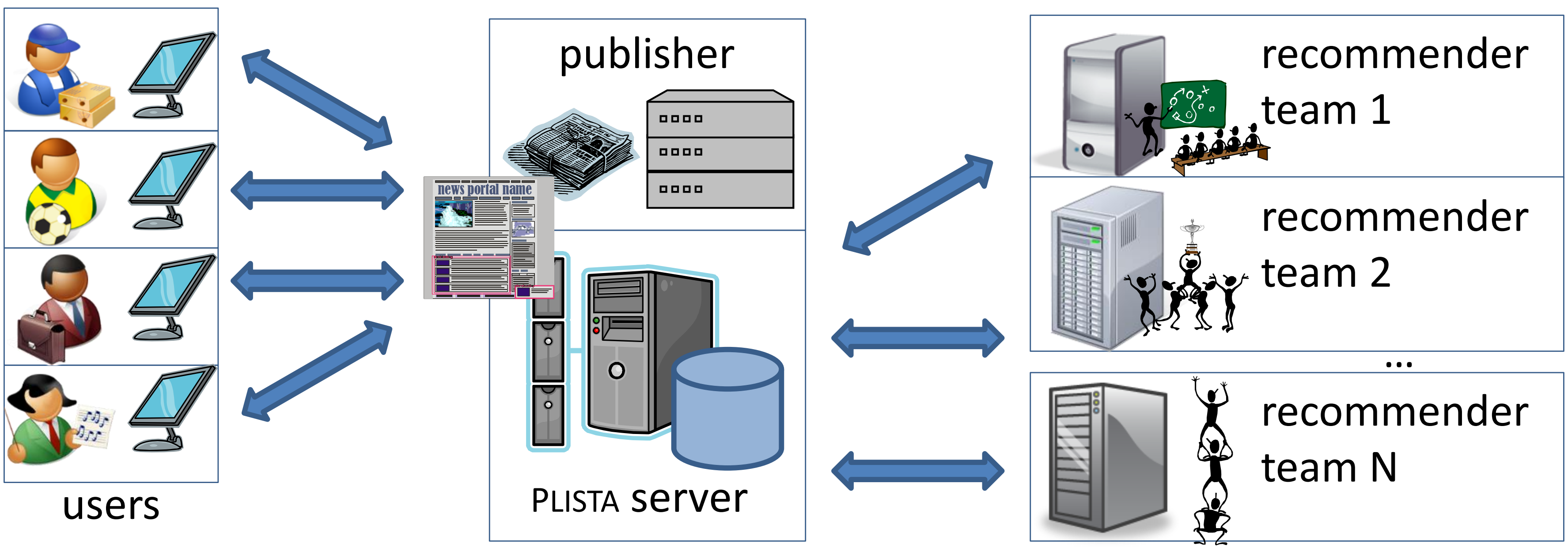
- Labs registration opens: 30 October 2015
- Registration Closes: 22 April 2016
- ~~End Evaluation Cycle: 4 May 2016~~
- End Evaluation Cycle: 20 May 2016
- Submission of Participant Papers [CEUR-WS]: 25 May 2016
- Submission of Lab Overviews [LNCS]: 3 June 2016
- Notification of Acceptance Lab Overviews [LNCS]: 10 June 2016
- Camera Ready Copy of Lab Overviews [LNCS] due: 17 June 2016
- Notification of Acceptance Participant Papers [CEUR-WS]: 17 June 2016
- Camera Ready Copy of Participant Papers and E[illegible]ended Lab Overviews [C[illegible]UR-WS] due: 1 July 2016
- CEUR-WS Working Notes Preview for checking: 22 July 201[illegible]
- CLE[illegible] 201[illegible] [illegible] 201[illegible]

@clefnewsreel

Task 1: decisive evaluation approaching. Have your recommenders up and running on 2 April 2016 to

The NewsREEL Challenge
Architecture (Online Evaluation)

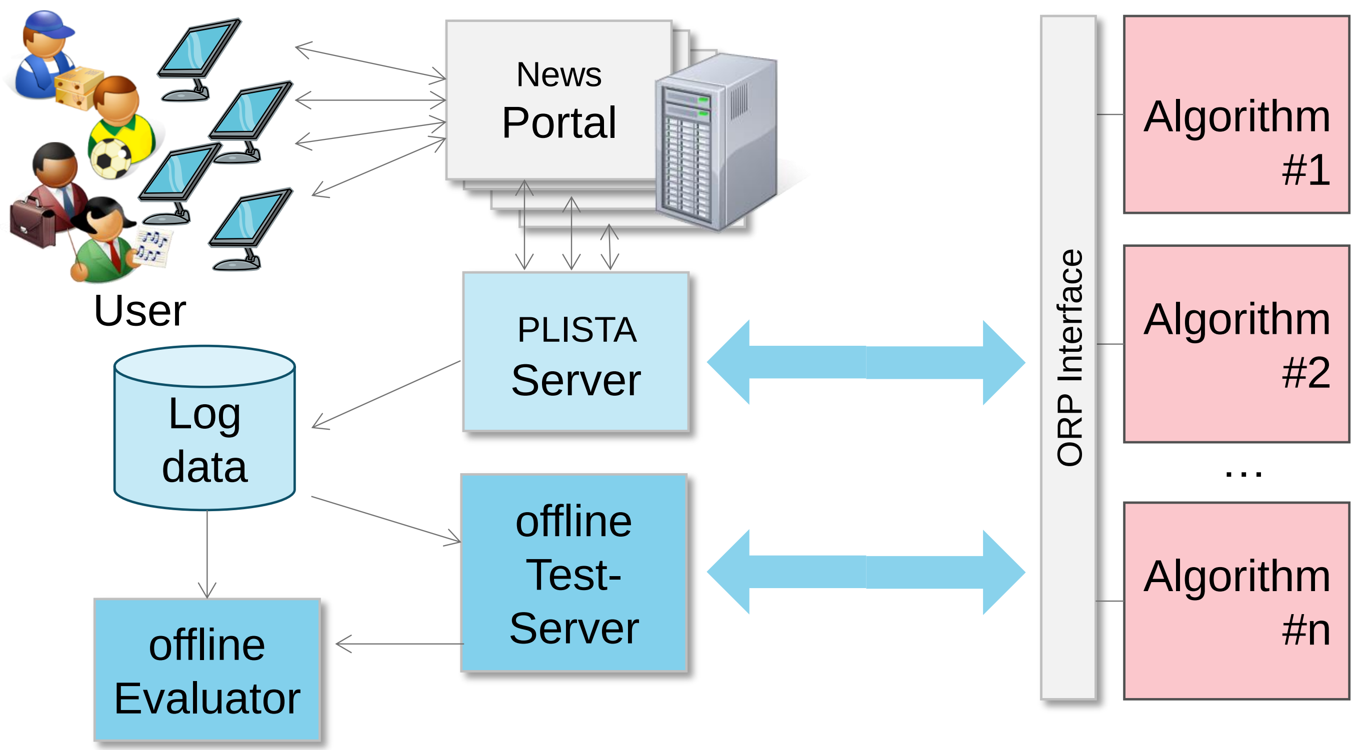
- NewsREEL Challenge Architecture
  - Different portals and recommender teams
  - Online evaluation based on user clicks



The NewsREEL Challenge

Architecture (Online and Offline Evaluation)

- NewsREEL Challenge Architecture
  - Different portals and recommender teams
  - Online evaluation based on user clicks



The NewsREEL Challenge
Provided Data

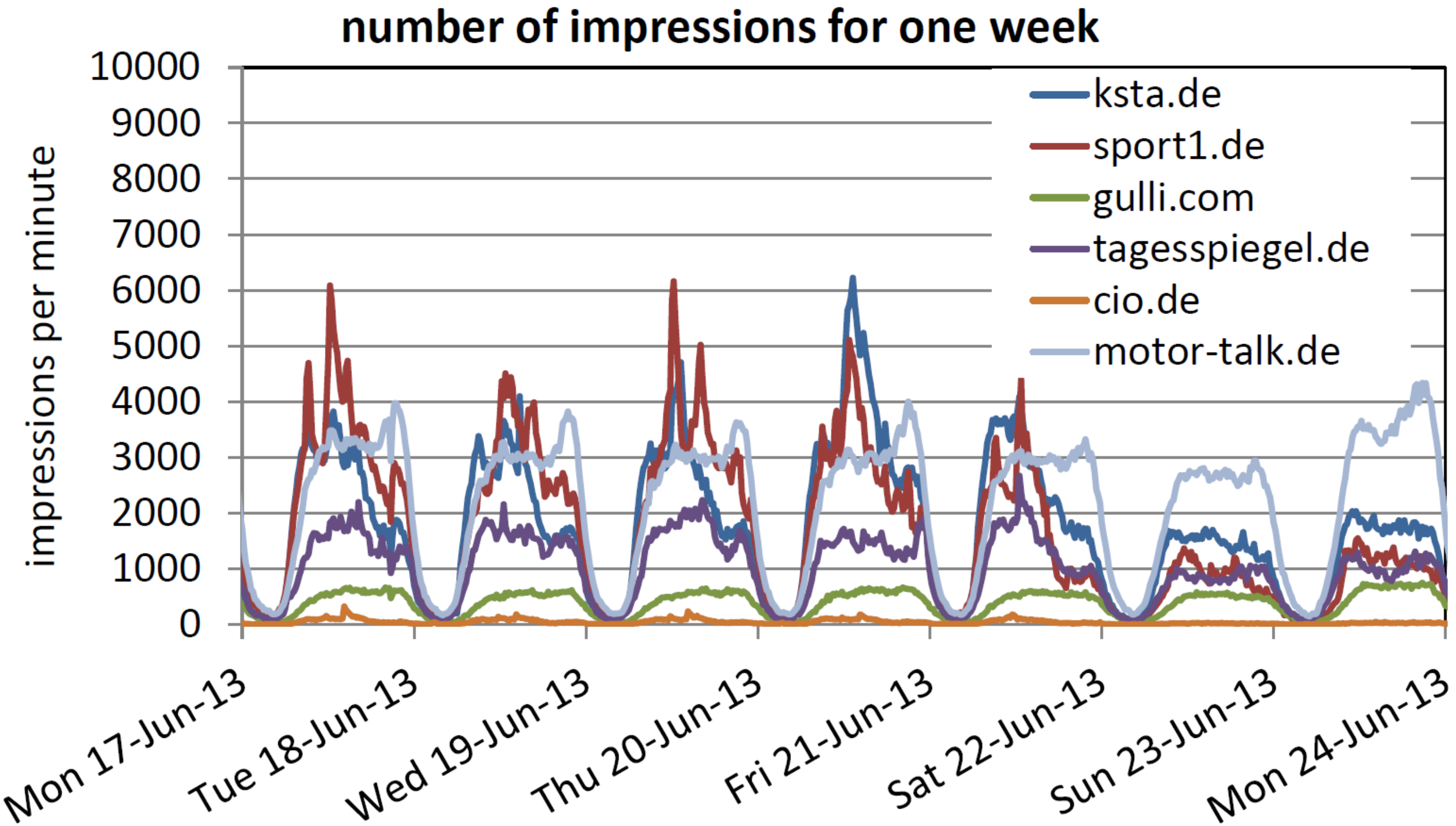
- 10GB log data / day
- JSON format
- Provided Information:
  - Item data
  - User-item interactions
  - Recommendation Requests
  - Error messages

{"recs": {"ints": {"3": [188752630, 186443351, 188900490, 188718683, 188619479, 188823393]}}, "event_type": "impression", "context": {"simple": {"82": 0, "62": 1979832, "63": 1840689, "49": 48, "67": 1928642, "68": 1851453, "69": 1851422, "80": 1982218, "81": 0, "24": 55, "25": 188932307, "27": 1677, "22": 1453961, "23": 23, "47": 504183, "44": 1851485, "42": 0, "29": 17332, "40": 1618697, "5": 0, "4": 68150, "7": 14684, "6": 573577, "9": 26888, "13": 2, "76": 1, "75": 1919991, "74": 1920088, "39": 748, "59": 1275566, "14": 33331, "17": 48985, "16": 48811, "19": 78119, "18": 5, "57": 354840161, "56": 1138207, "37": 1991332, "35": 315003, "52": 1, "31": 0}, "clusters": {"46": {"761805": 100, "472857": 100, "761809": 100}, "51": {"1": 255}, "1": {"7": 255}, "33": {"19840": 3, "513275": 10, "2180636": 5, "2934618": 4, "5518": 1, "2767420": 1, "26519": 2, "129348": 3, "234": 2, "9441716": 1, "9422": 5, "10666434": 2, "10388533": 7, "4050": 1}, "3": [55, 28, 34, 91, 23, 21], "2": [11, 11, 61, 60, 61, 26, 21], "64": {"3": 255}, "65": {"1": 255}, "66": {"12": 255}}, "lists": {"11": [13840], "8": [18841, 18842, 48511], "10": [10, 13, 1768, 1769, 1770]}}, "timestamp": 1405893599691}

{"recs": {"ints": {"3": [188675659, 177785300, 188684239, 188898567,

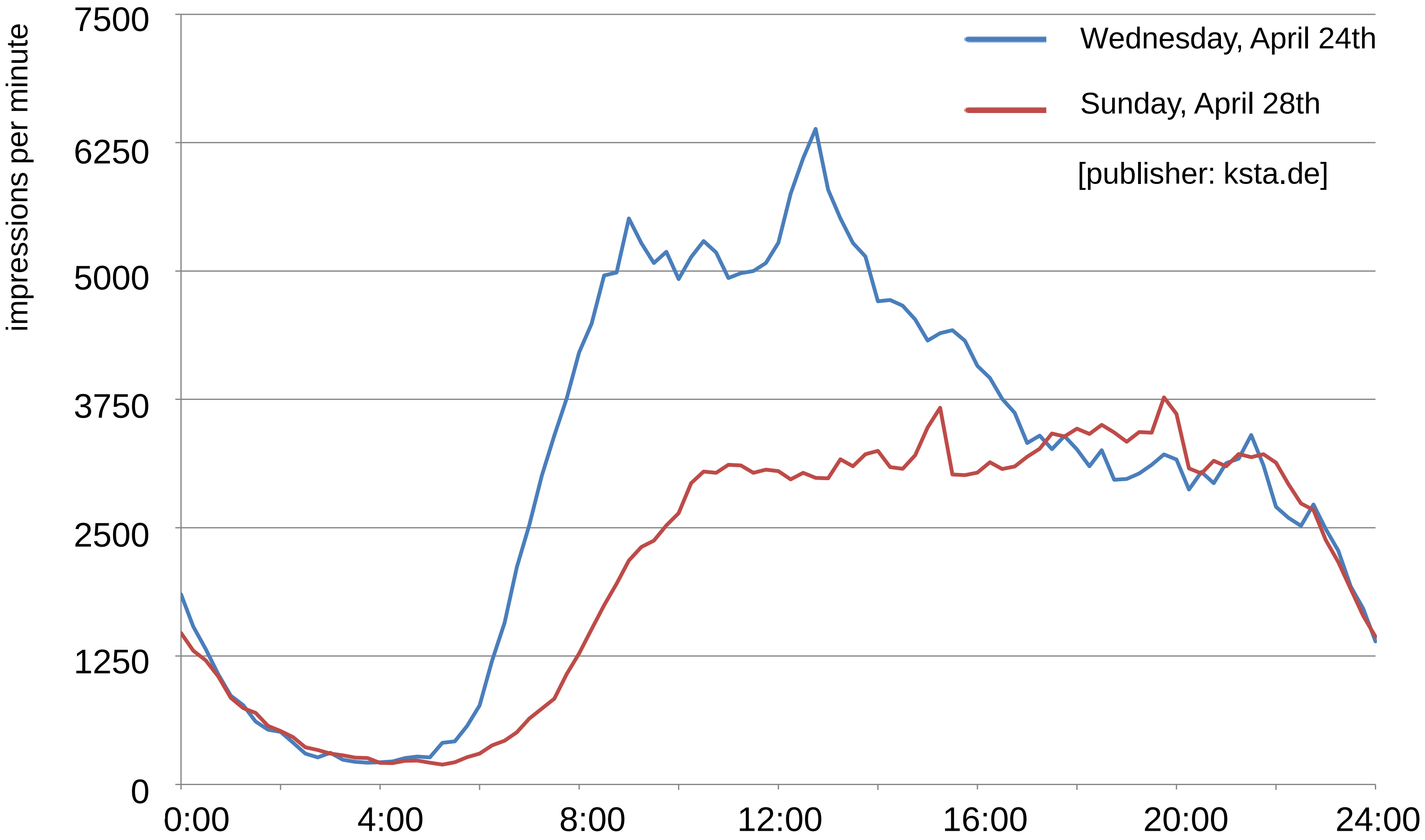
The NewsREEL Challenge

Impressions and Clicks for one Week (per domain)



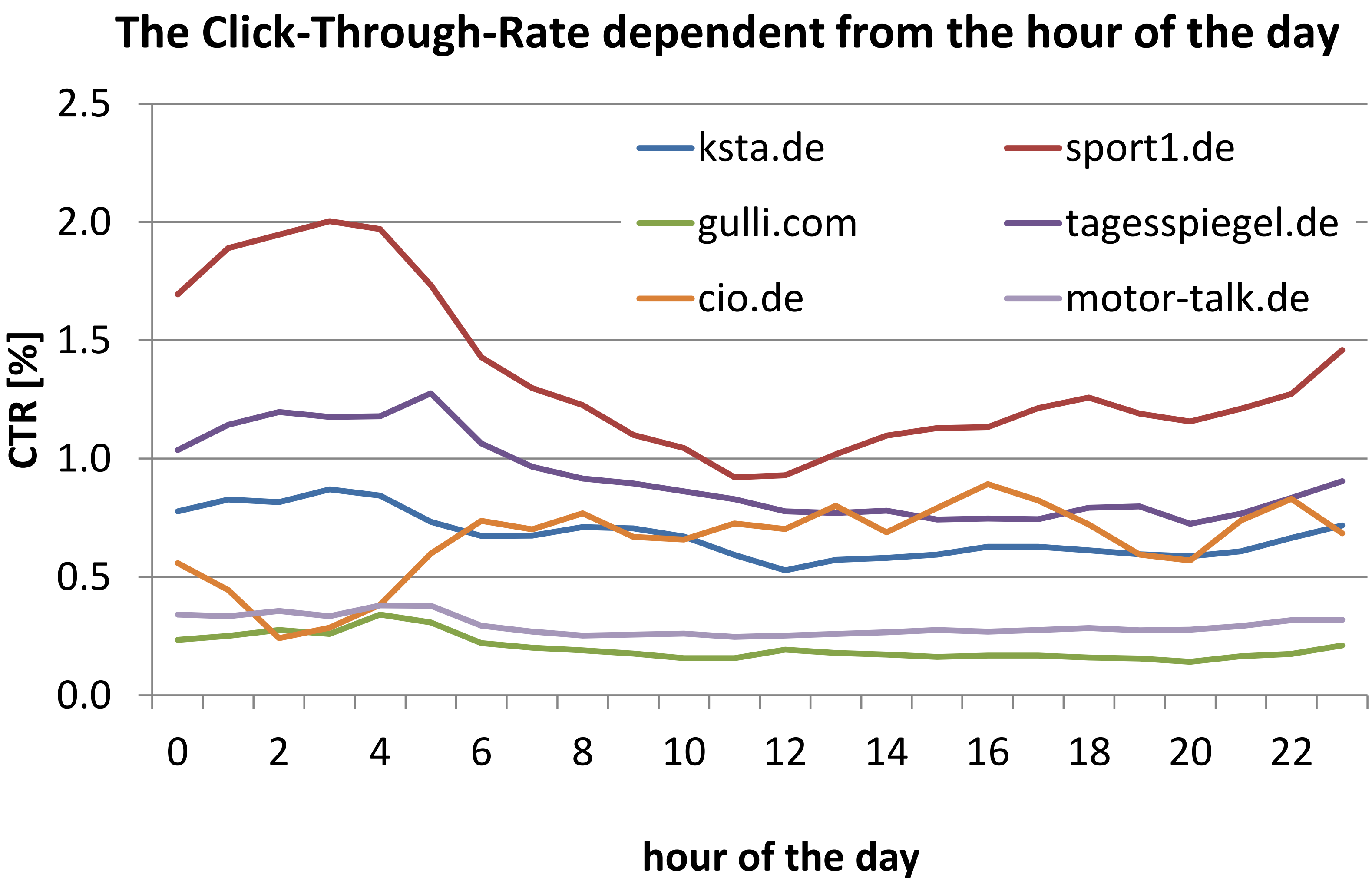
The NewsREEL Challenge

Impressions (Wednesday / Sunday)



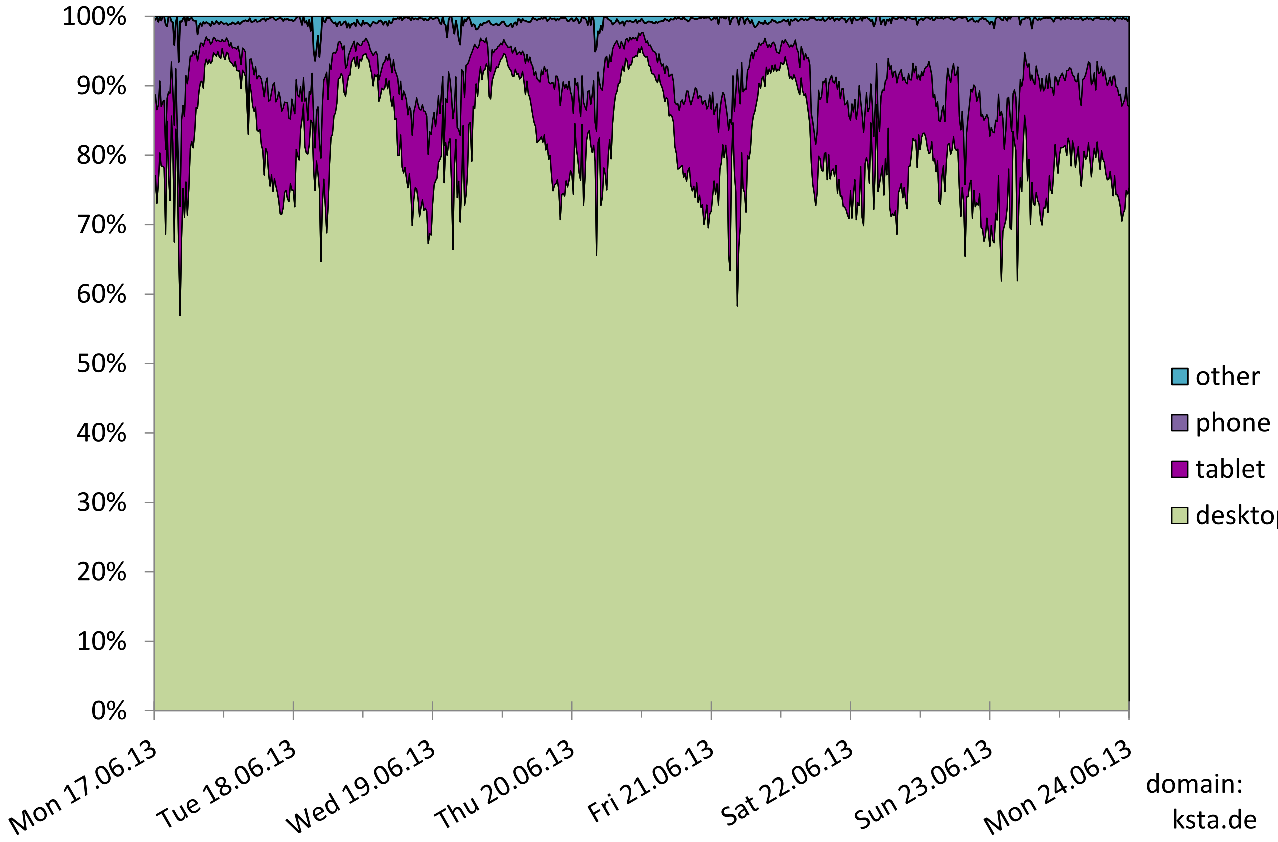
The NewsREEL Challenge

Time dependent Click-Through-Rate



The NewsREEL Challenge

Device usage



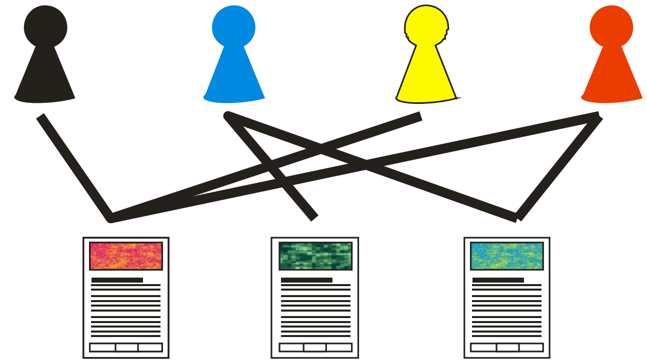
- Used interface devices and plugins give important information about the user's usage context

Traditional Recommender Systems

Motivation

State of the Art: Recommender Systems

- Collaborative Filtering Recommender based on a User-Item-Matrix
- Typical scenarios: Recommending
  - Books
  - Songs, movies
  - Products
  - Friends



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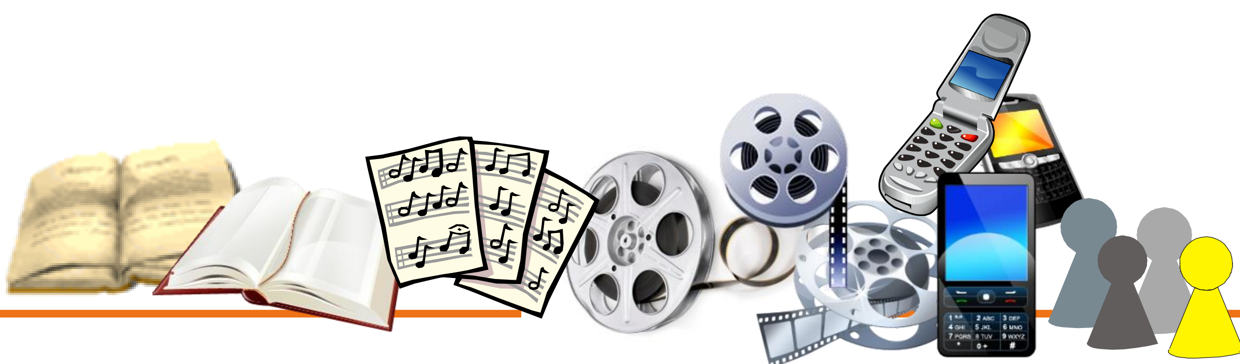
		1							1
	5							1	
5	2	5		2		3		5	1
	2								5
		3			3	3			
2				4					
			4		5		5		3
4	3								
5	5	5	5	5		4	5		4



Motivation

State of the Art: Recommender Systems

- Characteristic Properties
  - Huge user-item-matrix
  - Sparsity
  - Almost static matrix
- State-Of-The-Art Approach
  - Matrix-factorization methods
  - Heuristics and distributed processing
  - Neighborhood models

	1								1
		1							1
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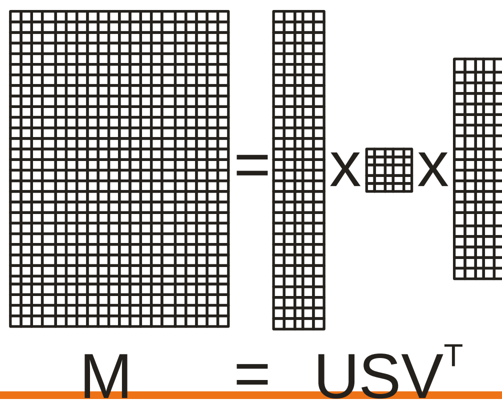
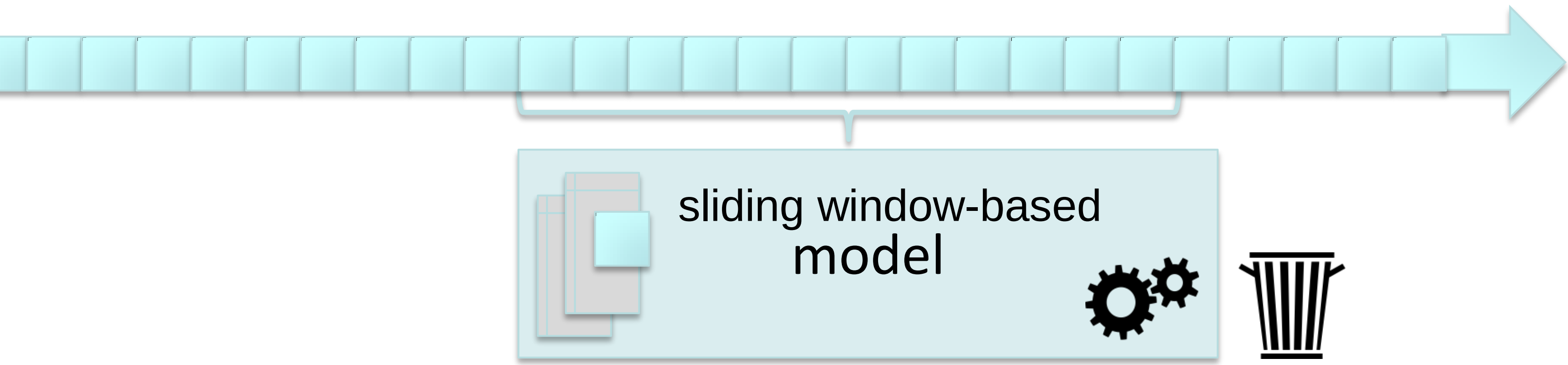


Recommendations based on Streams

Approach - Algorithms
Overview

- Optimize recommender algorithms for the streaming scenario
- Adapt Recommender Algorithms for Streams
- Continuously adapt the model used by the recommender; integrate new data, remove old data
- Start with simple algorithm!

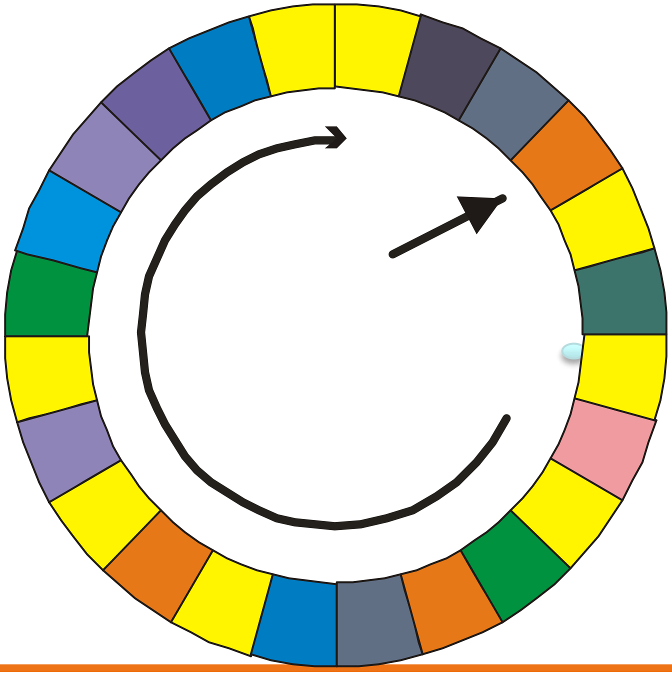


Approach - Algorithms

Most Recently Requested 1/2

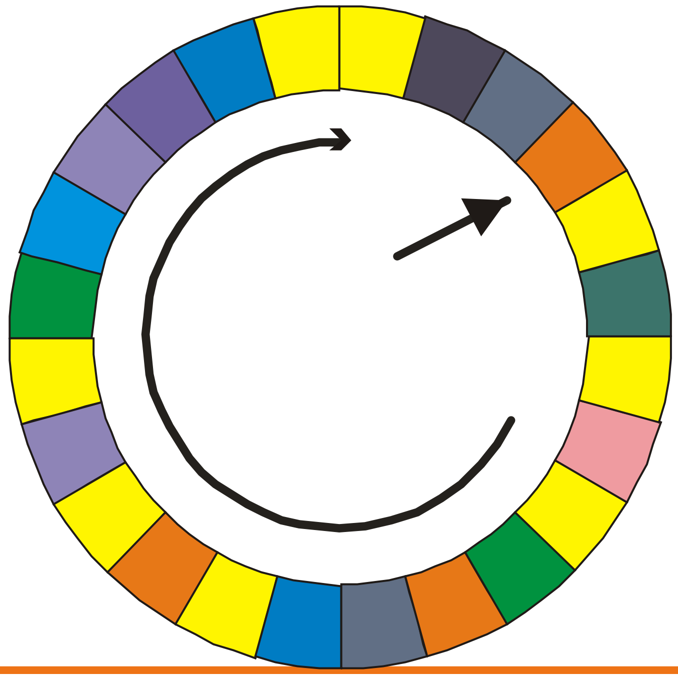
- <u>Idea</u>
  - Recommend the items most recently viewed by other users

- Implementation:
  - Store the last impression events in a ring buffer
  - Provide the most recent items as suggestions



Approach - Algorithms
Most Recently Requested 2/2

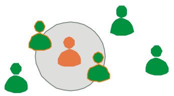
- Strengths
  - Fast, simplified synchronization
  - Biased towards popular items
  - Randomized recommendations
- Weaknesses
  - Not personalized
  - Does not consider the context



Approach - Algorithms

Adapt algorithms for stream-based scenarios

- Time-Frame-based Algorithms
  - Most-recently requested
  - Most-popular recommender
  - Most-popular sequence
  - User-based Collaborative Filtering
  - Item-based Collaborative Filtering
  - Content-based Filtering

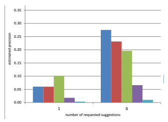


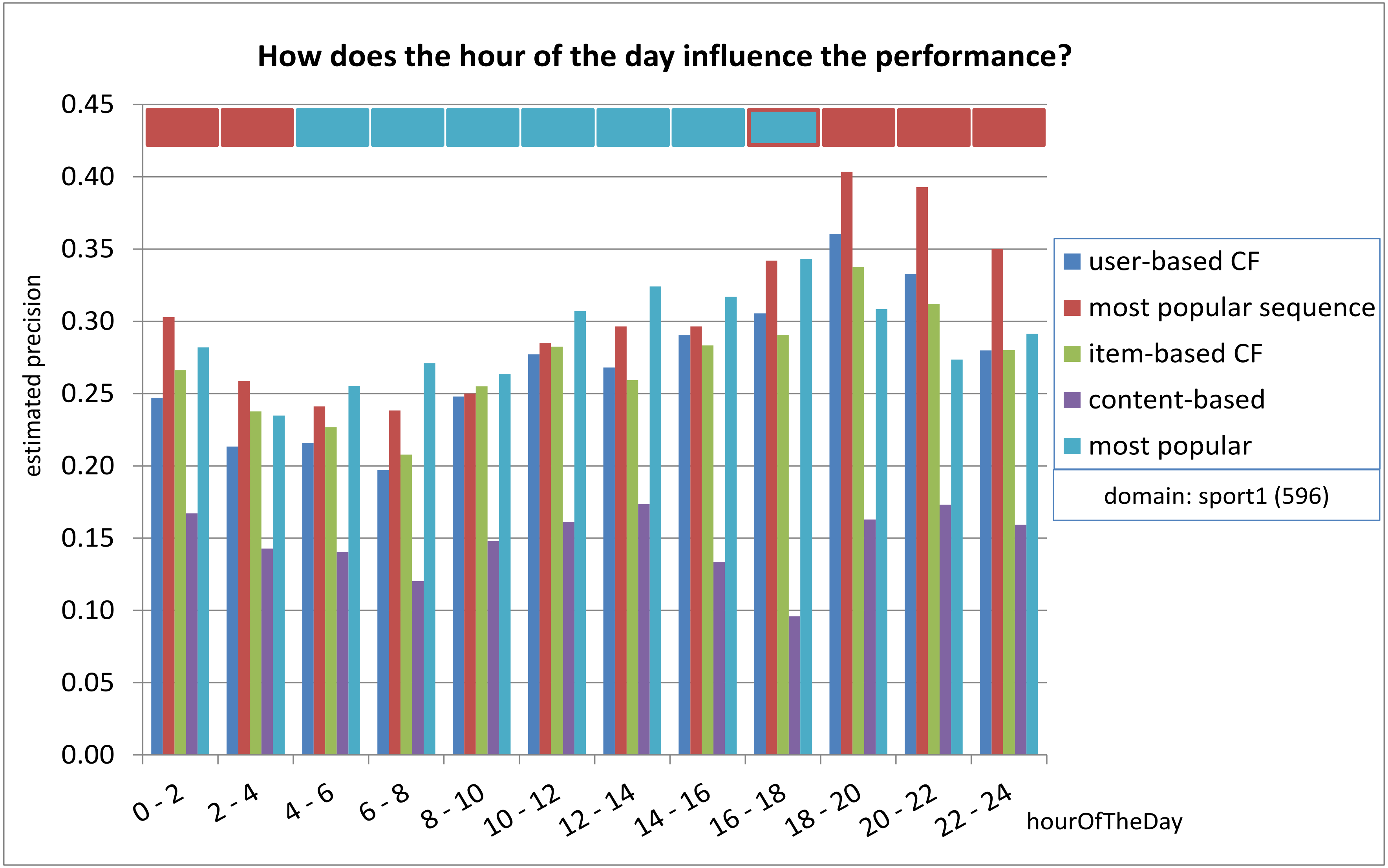
- Implement the Algorithms based on streams (fifo) or micro-batches

Evaluation

Evaluation Results

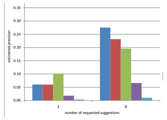
Recommendation precision dependent from the time of day

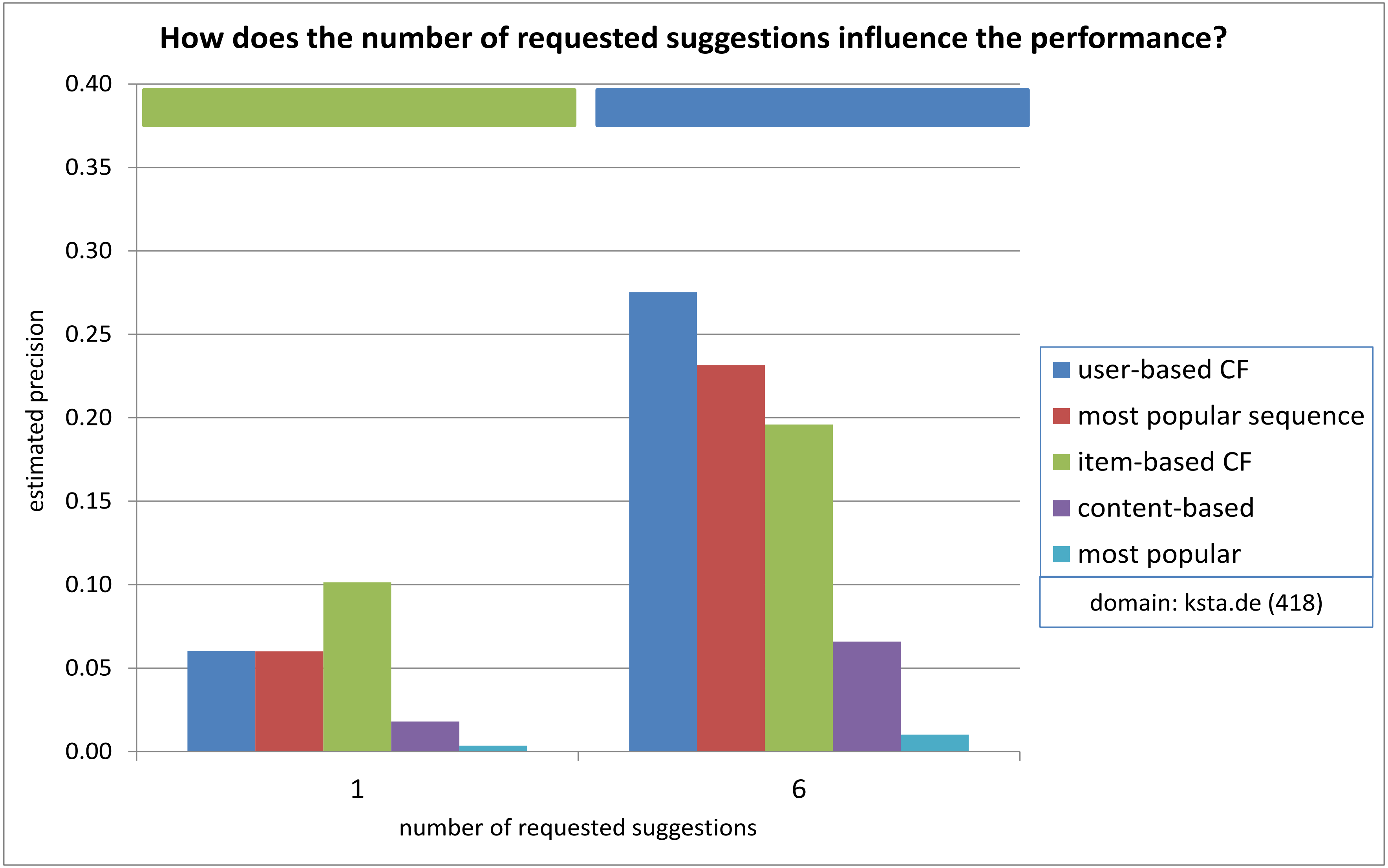




Evaluation Results

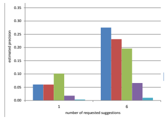
Recommendation precision dependent from # requested results

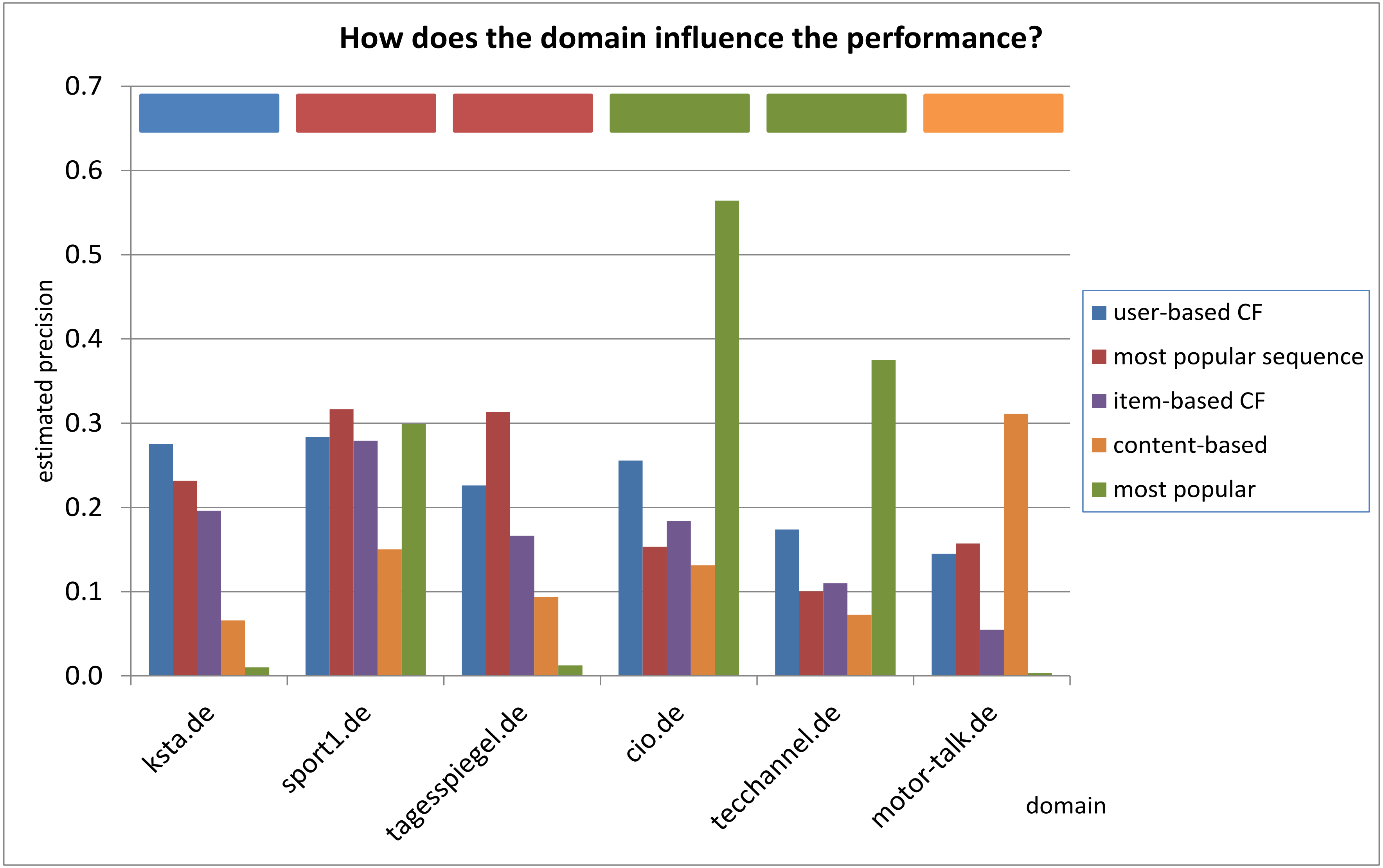




Evaluation Results

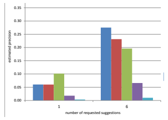
Recommendation precision dependent on the publisher





Evaluation Results

Discussion



- Timeframe-based Algorithms – Results
  - The portal and the time have a big influence on the results
  - Hidden parameters (e.g. the placement of recommendations) should be considered
  - Parameter optimization (e.g. size of the time window) is very important
  - Ensemble Algorithms combining several algorithms based on the context outperform single algorithms

Technical Requirements

How to ensure real-time recommendations?

Technical Requirements

Approach

- Ensure that messages are processed concurrently
  - Higher Priority for requests
  - Avoid global locks / synchronized blocks

- Choose a framework optimized for the expected number of messages
  - Java Concurrent Collections, Google Guava, Redis
  - Akka, Apache Flink, Apache Spark

Technical Requirements
Results

- In Memory-Approaches work well in NewsREEL as long as there are no extreme load peaks
  - Little overhead
  - Limited maintenance effort
- Apache Flink / Apache Spark are well-suited for building models, not for ensuring real-time responses
  - Delays in model updates are not critical in NewsREEL
  - Use distributed environments for learning the recommender models

Experiences from the NewsREEL challenge

Our Experience

- The scenario of online stream-based recommendations is new to most participants
- Live-Evaluation requires that the algorithm handles unexpected events
- Variance in the user behavior is a problem for many participants
- Tight time constraints make the challenge difficult to debug
- Provided example recommender component reduce the barrier for new participants, but participants tend to only slightly modify the templates instead of implementing new ideas
- A context-dependent bias in the average CTR makes it difficult to compare different strategies

Results

Conclusion

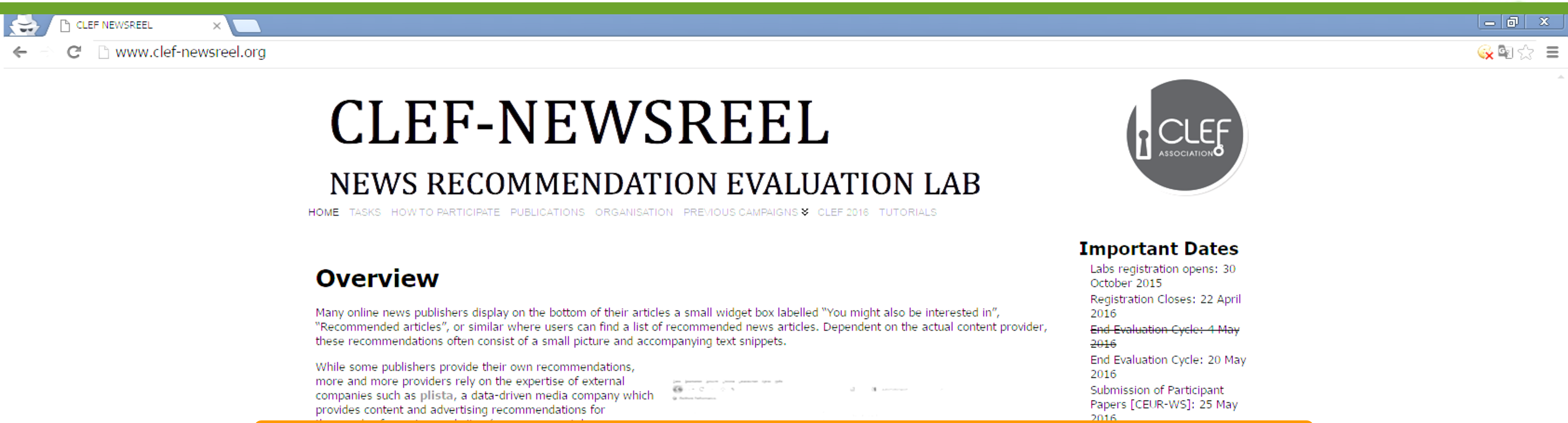
Providing News Recommendation is challenging

- Incorporate the time-dependent relevance in the recommender models
- The performance of the algorithms highly depends on the context. There is no overall best algorithm
- A parameter optimization is very important
- The continuous changes and the variance in the user behavior make the parameter optimization an complex task
- The optimal technical solution depends from the number of messages

The Future – NewsREEL in 2017

- The NewsREEL challenge will continue in 2017
- New Research Topics in 2017
  - Multi-Media Content
  - Multi-Lingual Content
  - Correlation between online and offline evaluation

Conclusion – Participate in NewsREEL 2017!



Heterogeneous data

+ Real-life Online Evaluation

+ Multiple Metrics

Challenging Research Topics

Thank you for your attention

- Questions?

- More Information:
  - Visit the NewsREEL challenge web site: *http://www.clef-newsreel.org/*
  - *Benchmarking News Recommendations: The CLEF NewsREEL Use Case* In SIGIR Forum December 2015, Volume 49 Number 2 *http://sigir.org/files/forum/2015D/p129.pdf*
  - The CrowdRec Project: *http://crowdrec.eu/*

Contact

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