

# Browser-Oriented Universal Cross-Site Recommendation and Explanation based on User Browsing Logs

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# Outline

- Research Background
- Research Topic
- Current Achievements
- Research Plans

# Personalized Recommender Systems

- Personalized Recommender Systems
  - Attempts to recommend the items of potential interests
- Widely integrated into many commercial systems
  - Especially the many online shopping websites



- Help to increase the online traffic and profits
  - Amazon online book shop: 30% profits comes from RS
  - Forrester: 1/3 of the customers takes the recommendation when they noticed them

# Related Work

- Content-based Recommendation
  - Content-based Recommender Systems [Pazzani2005]
  - Auto Profile Construction for Recommendation [Sugiyama2004]
- Collaborative Filtering based Recommendation
  - User-based Collaborative Filtering [Resnick1994]
  - Item-based Collaborative Filtering [Sarwar2001]
  - Matrix Factorization based Collaborative Filtering [Koren2009]
- Hybrid Recommendation models
  - Hybrid Recommender Systems [Burke2002]
  - Content-based, Collaborative Recommendation [Marko1999]

# Problems

- They still focus on the vertical recommender systems
  - Although RS is getting more and more noticed
  - Still mostly restricted in inner-site/domain recommendation
    - Product recs in online shopping
    - Related article recs in online medias
    - Video, movie or music recs
  - The recommendation engine of the Web mainly consists of many independent vertical recommenders.

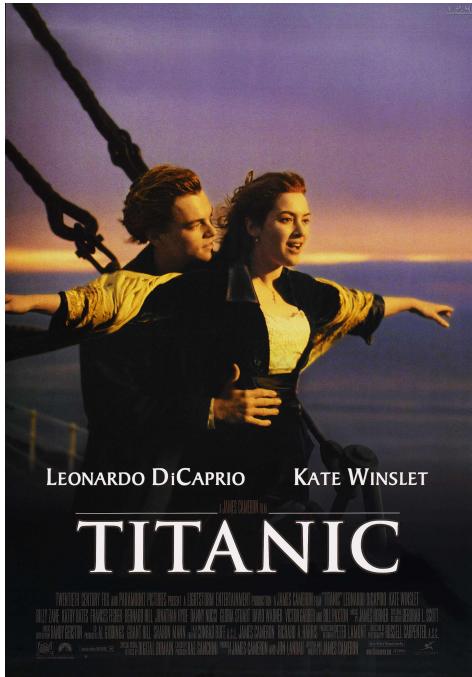


# Research Topic

Browser-Oriented Universal Cross-Site Recommendation  
and Explanation based on User Browsing Logs

# Understanding Universal Recommendation

- Universal recommendation: A CASE STUDY.



Homogeneous items from the same sites



Heterogeneous items from other websites.

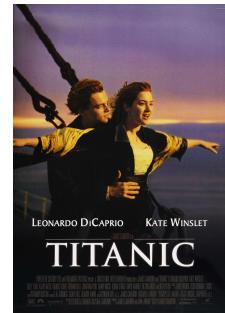
# Understanding Universal Recommendation

- Major characteristics of vertical recommendation
  - Single domain: Recs are usually from the same product domain
  - Inner-site: Recs are usually the products/items from the inner-site
  - Additional: Usually comes in the form of an additional application
- Major characteristics of universal recommendation
  - Cross-domain: The ability to recommend items from other domains
  - Inter-site: Recommended items are not necessarily from the same site
  - Fundamental: Comes in the form of a fundamental application when the user is surfing online

# Why to Construct Universal Recommenders

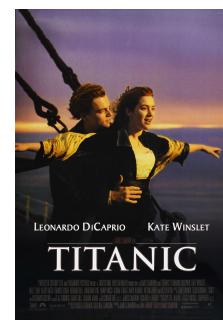
- Why inter-domain/site

- Vertical recs are homogeneous
    - Single domain / Inner-site
    - This applies to most current RS
      - E.g. Related video / article recommendation



- Underlying problem

- Difficult to discover user needs from other potential aspects
  - Further restricts the application and business model of RS



Music?



Purchasing?



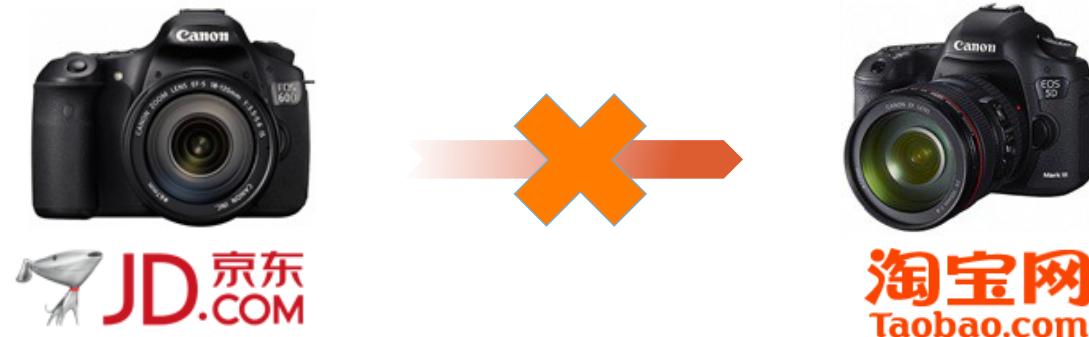
Games?

# Difficulties of Universal Recommender

- Difficulties of constructing a universal recommender system
  - Lack of inter-site user behavior data



- Restrictions from the business aspects



# The Solutions

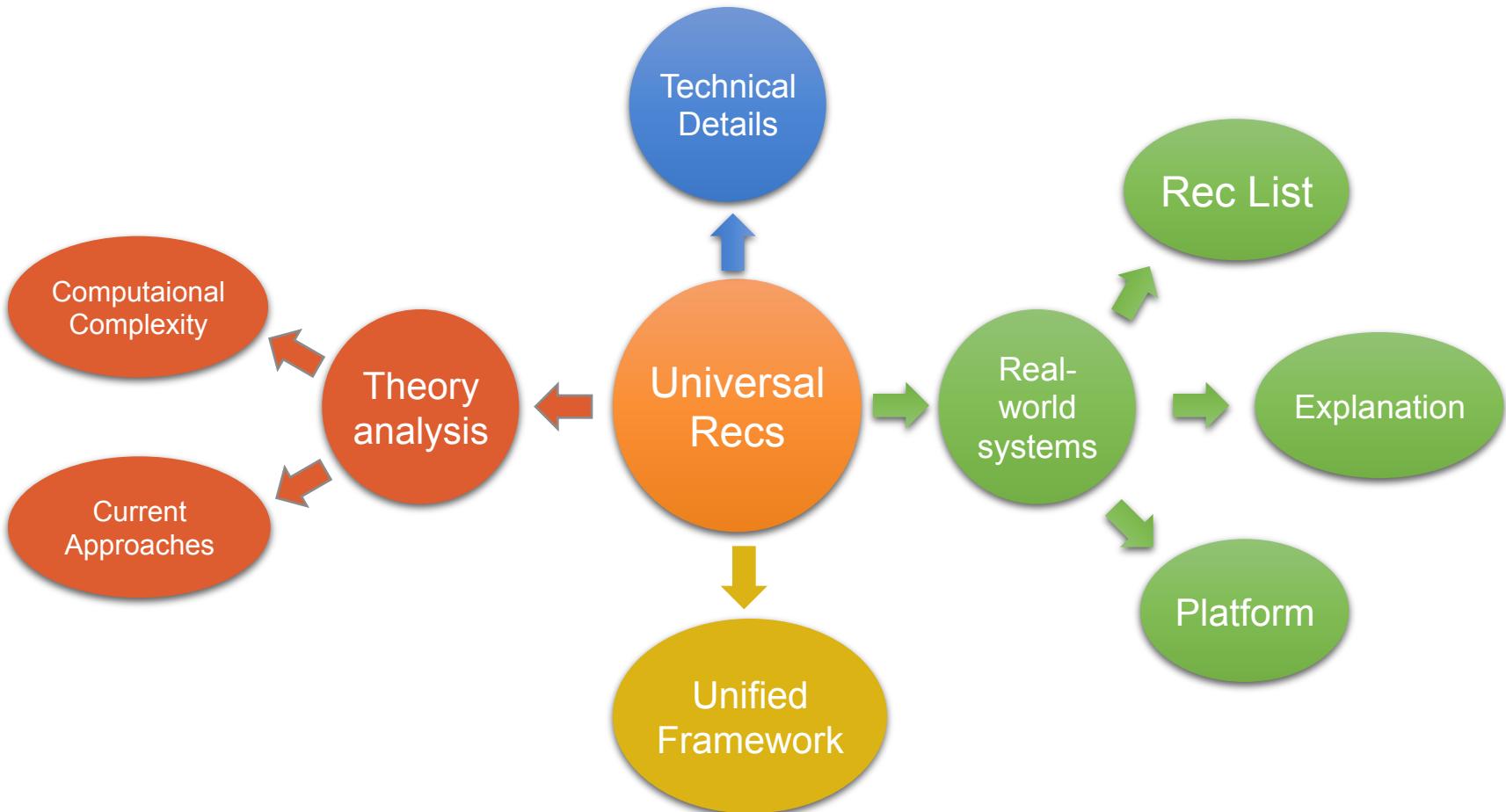
- Corresponding solutions to the problems
  - Incorporating search engine / browser log data



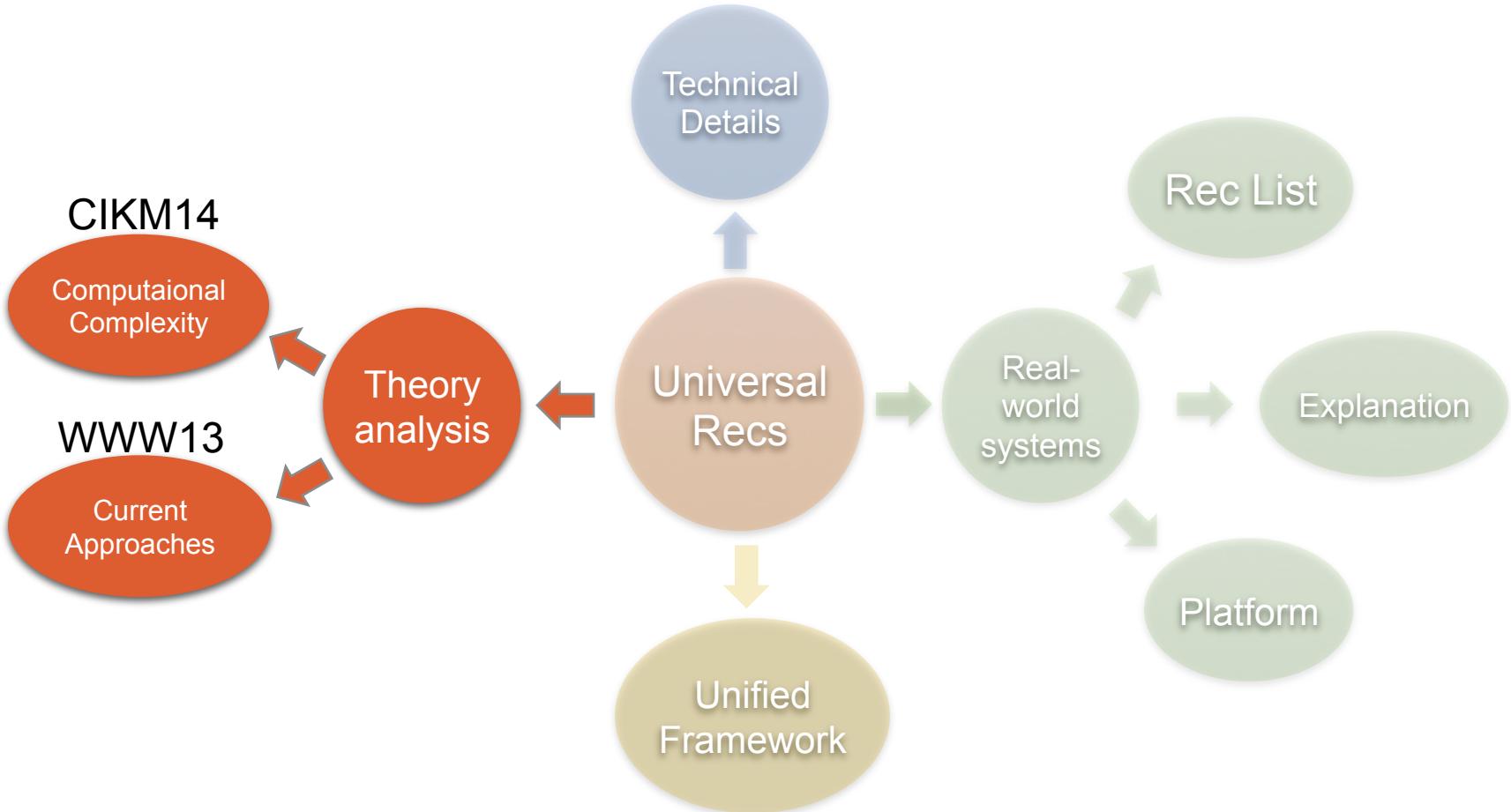
- Browser-oriented recommendation: which offers a recommendation platform independent of a specific web



# The Approach



# Theoretical Analysis (CIKM14 & WWW13)



# Theoretical Analysis (CIKM14 & WWW13)

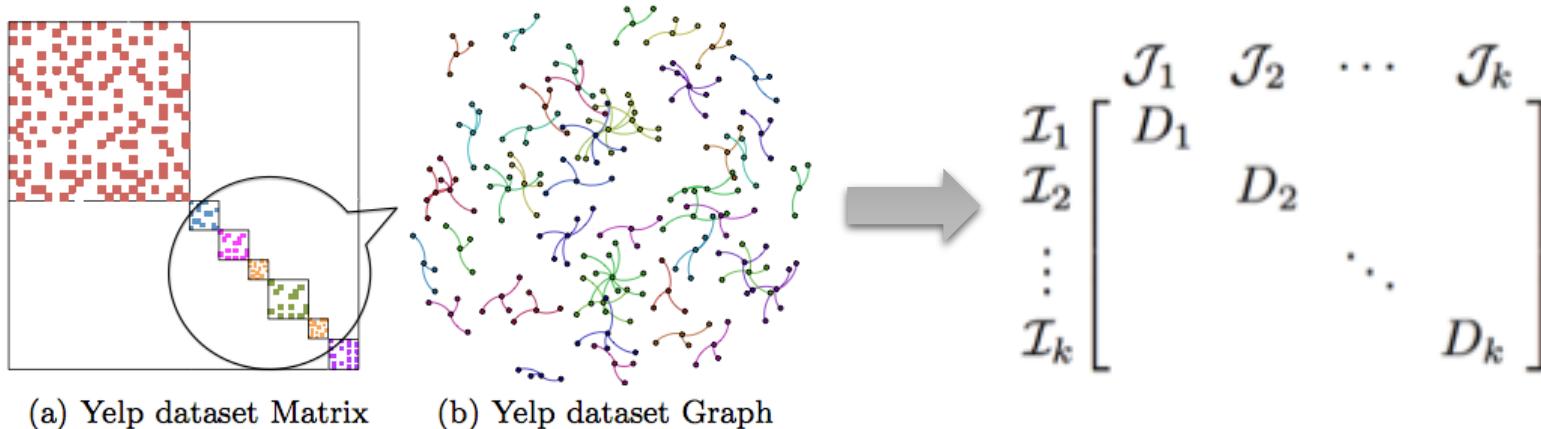
- Universal recommendation from a technical point of view
  - The classical rating prediction problem for universal rec
    - Rating prediction on a Block Diagonal Form (BDF) matrix

$$\begin{matrix} & \mathcal{J}_1 & \mathcal{J}_2 & \cdots & \mathcal{J}_k \\ \mathcal{I}_1 & D_1 & & & \\ \mathcal{I}_2 & & D_2 & & \\ \vdots & & & \ddots & \\ \mathcal{I}_k & & & & D_k \end{matrix}$$

- Lack of inter-site user behavior data
  - Which means that there is no data in off-diagonal areas

# Theoretical Analysis – Computational Complexity (CIKM14)

- Lack of inter-site data brings severe problems [CIKM14]
  - Nearest-neighbors methods are invalid: no way to compute similarity
  - CF based on Matrix Factorization are also invalid
    - We prove these are at least  $O(r!)$  equal valued minima ,  $r=50\sim100$
    - Predictions for off-diagonal areas given by MF are meaningless



<sup>1</sup>CIKM'14, Understanding the Sparsity: Augmented Matrix Factorization with Sampled Constraints on Unobservables.

# Theoretical Analysis – Parallelization (WWW13)

- Localized Matrix Factorization (LMF) based on BDF matrices [WWW13]:
  - Many commonly used MF algorithms (SVD/NMF) can be parallelized in LMF
  - Equal to its single routine algorithm, rather than its approximation
    - Which offers a unified framework for large-scale parallel MF and CF

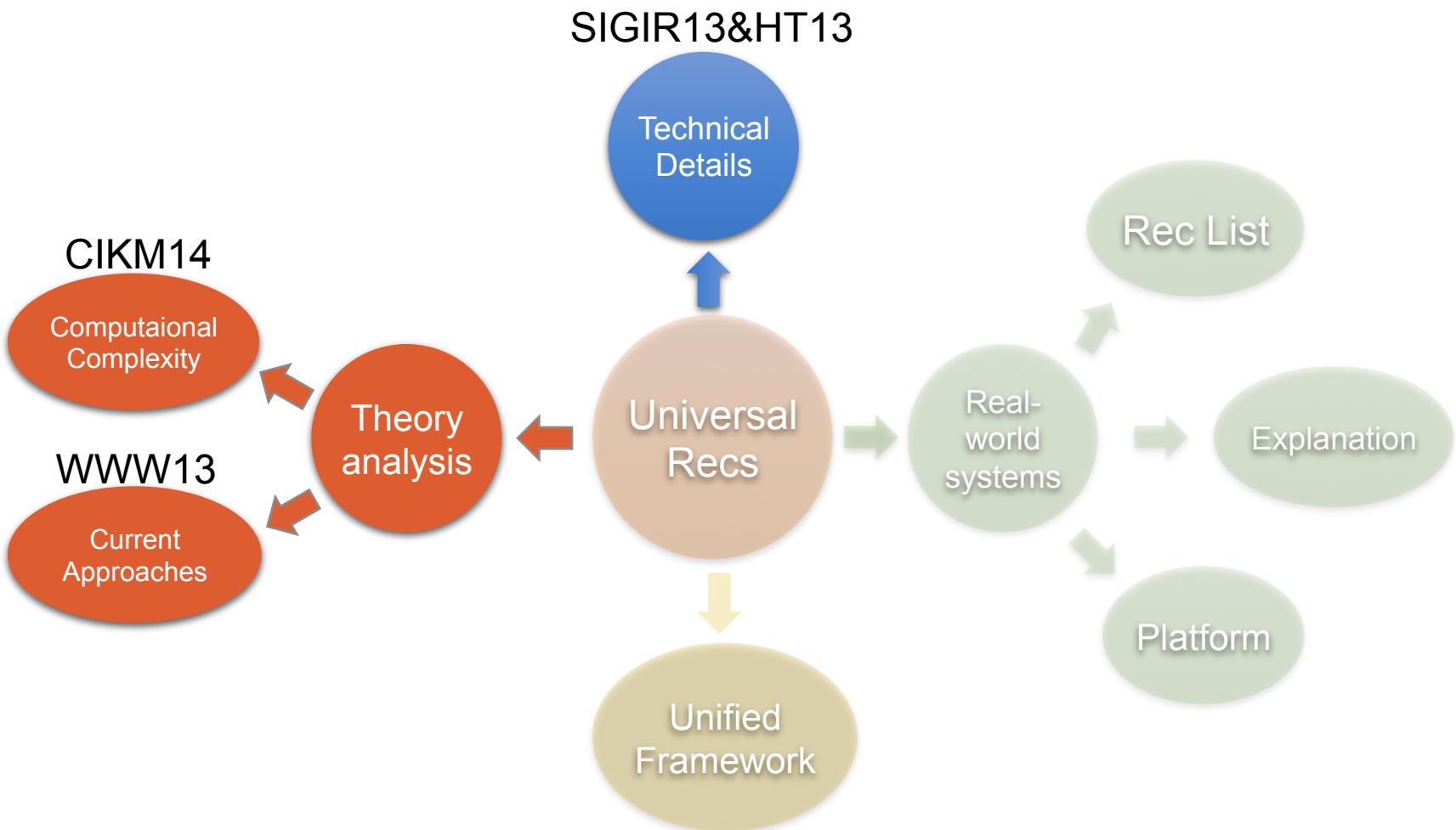
$$\begin{array}{c}
 \left[ \begin{array}{cc|c} D_{11} & C_{11} & \\ \hline D_{12} & C_{12} & \\ R_{11} & R_{12} & B_1 \end{array} \right] \quad \left[ \begin{array}{c} C_1^1 \\ C_1^2 \\ C_1^3 \end{array} \right] \quad \left[ \begin{array}{c} D_2 \\ C_2 \end{array} \right] \\
 \left[ \begin{array}{ccc|c} & & C_1^1 & \\ \hline R_1^1 & R_1^2 & R_1^3 & R_2 \\ & & & B \end{array} \right]
 \end{array} \rightarrow \begin{array}{ccc}
 \left[ \begin{array}{ccc} D_{11} & C_{11} & C_1^1 \\ R_{11} & B_1 & C_1^3 \\ R_1^1 & R_1^3 & B \end{array} \right] & \tilde{X}_{12} & \tilde{X}_{13} \\
 \tilde{X}_{21} & \left[ \begin{array}{ccc} D_{12} & C_{12} & C_1^2 \\ R_{12} & B_1 & C_1^3 \\ R_1^2 & R_1^3 & B \end{array} \right] & \tilde{X}_{23} \\
 \tilde{X}_{31} & \tilde{X}_{32} & \left[ \begin{array}{cc} D_2 & C_2 \\ R_2 & B \end{array} \right]
 \end{array}$$

$$X = \begin{bmatrix} X_1 & & \\ & X_2 & \\ & & \ddots \\ & & & X_k \end{bmatrix} \approx f(UV^T) = f\left(\begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_k \end{bmatrix} \begin{bmatrix} V_1^T & V_2^T & \cdots & V_k^T \end{bmatrix}\right) = f\left(\begin{bmatrix} U_1 V_1^T & U_1 V_2^T & \cdots & U_1 V_k^T \\ U_2 V_1^T & U_2 V_2^T & \cdots & U_2 V_k^T \\ \vdots & \vdots & \ddots & \vdots \\ U_k V_1^T & U_k V_2^T & \cdots & U_k V_k^T \end{bmatrix}\right)$$

<sup>1</sup>CIKM'14, Understanding the Sparsity: Augmented Matrix Factorization with Sampled Constraints on Unobservables.

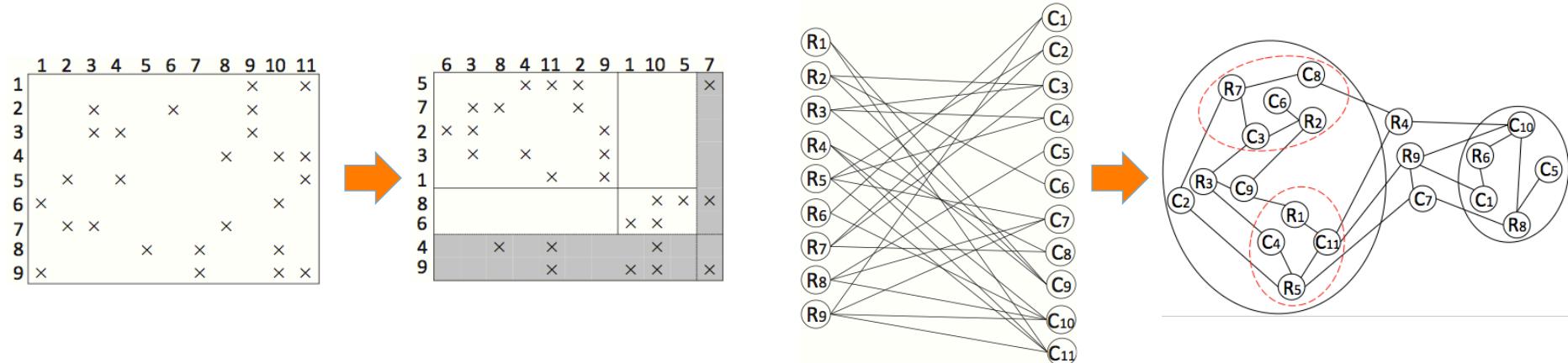
<sup>2</sup>WWW'13, Localized Matrix Factorization for Recommendation based on Matrix Block Diagonal Forms.

# Technical Details (SIGIR13 & HT13)



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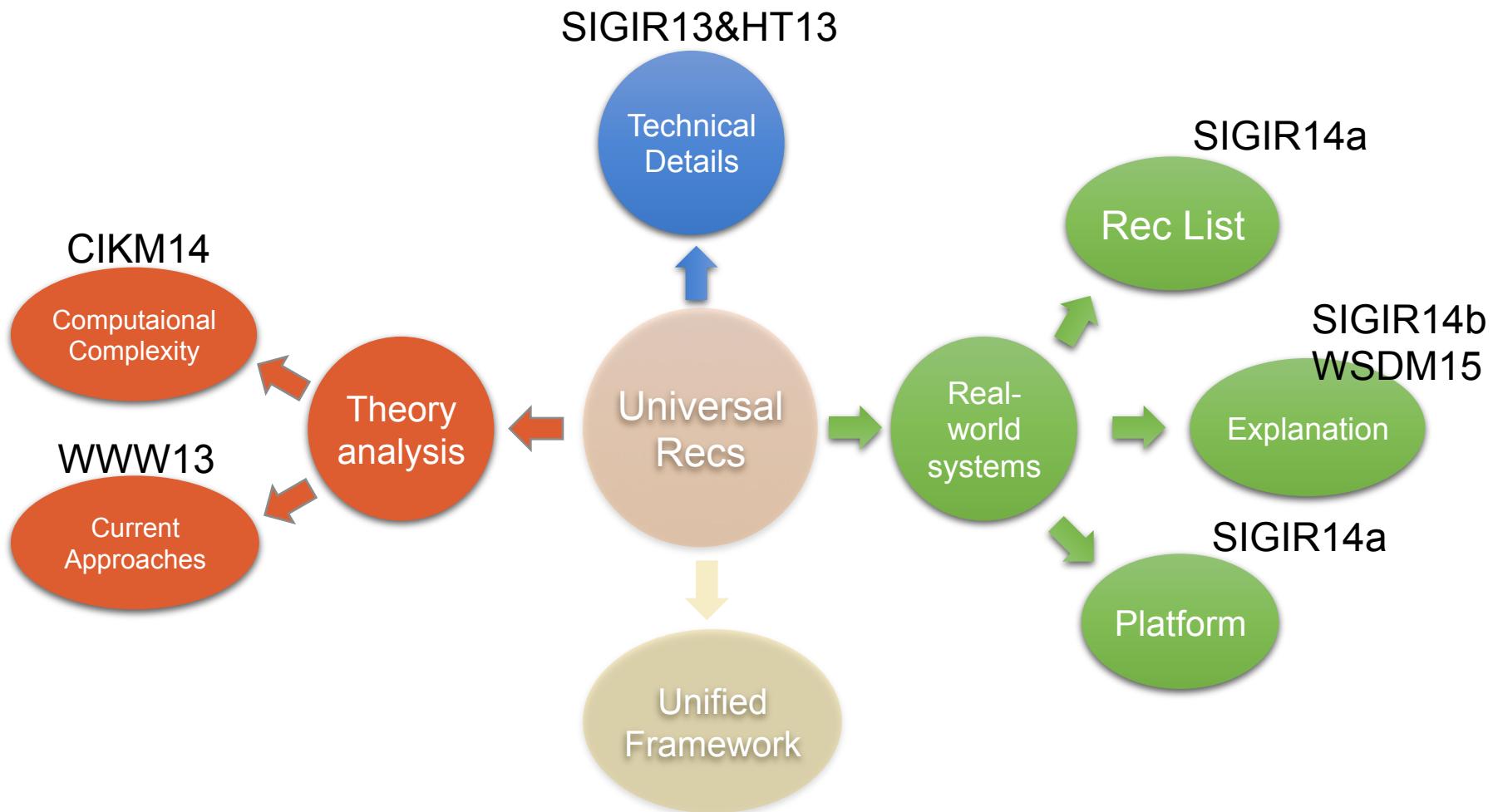
- Use LMF in real-world systems [SIGIR13,HT13]
  - We prove that the bordered BDF structure on matrices is equal to conducting community detection on its bipartite graph
  - Which offers an intuition of the application of LMF in real-world systems
  - And provides a unified mathematical framework for the application of community detection in recommender systems



<sup>1</sup>SIGIR'13, Improve Collaborative Filtering through Bordered Block Diagonal Form Matrices.

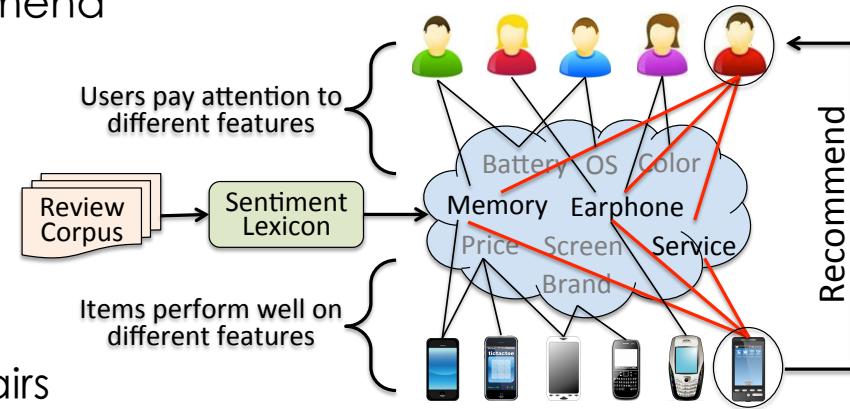
<sup>2</sup>Hypertext'13, A General Collaborative Filtering Framework based on Matrix Bordered Block Diagonal Forms.

# Real-world System (SIGIR14a & SIGIR14b)



# Realization in Real-world Systems – the Recommendation Explanation (SIGIR14a/b)

- Recommendation Explanations [SIGIR14a]
  - Seems more important in universal recommend
  - To persuade a user to examine a rec in an unfamiliar website
- Phrase-level sentiment analysis [SIGIR14b]
  - Mine the product features automatically
  - Extract Product Feature – User Opinion pairs
    - e.g. Camera Lens – Long
  - Construct the feature-level recommendation explanations automatically
- Examples
  - This camera performs well on Lens, which feature you may concern
  - We know the concerned features of a user from his/her historical reviews



<sup>1</sup>SIGIR 2014a, Explicit Factor Models for Explainable Recommendation based on Phrase-level Sentiment Analysis.

<sup>2</sup>SIGIR 2014b, Boost Phrase-level Polarity Labeling with Review-level Sentiment Classification.

# Realization in Real-world Systems - Browser-Oriented Recommendation (SIGIR14a)

- How to provide cross-site recommendation?
  - Provide recommendations by web browsers directly! [SIGIR14a]
  - An independent recommendation platform from specific websites.
    - To solve the problem that the websites have no intention to provide recommendations from other sites.
    - Also offer us brand new business models
  - Browsers further enrich cross-site user behavior data with browsing logs
    - Help to better understand the user needs, even real-time needs



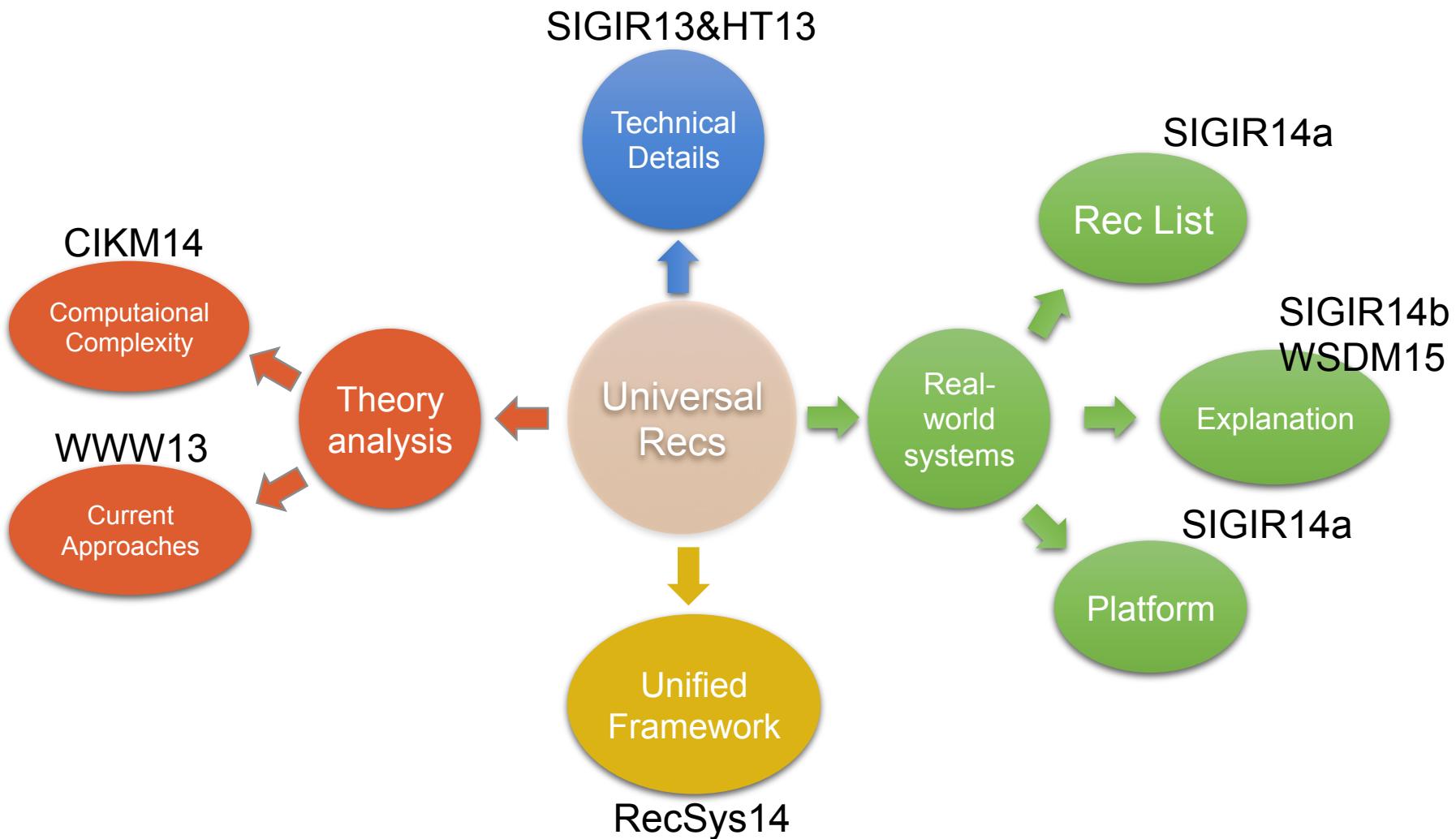
# Realization in Real-world Systems -

## Content-based Recommendation

- Search engines and browsers provides rich content information
    - User queries
    - Textual content
    - User profiles
    - Item/product profiles
  - Content-based rec further improves performance
    - By enriching the results of CF algorithms
    - To provide more informed recommendations

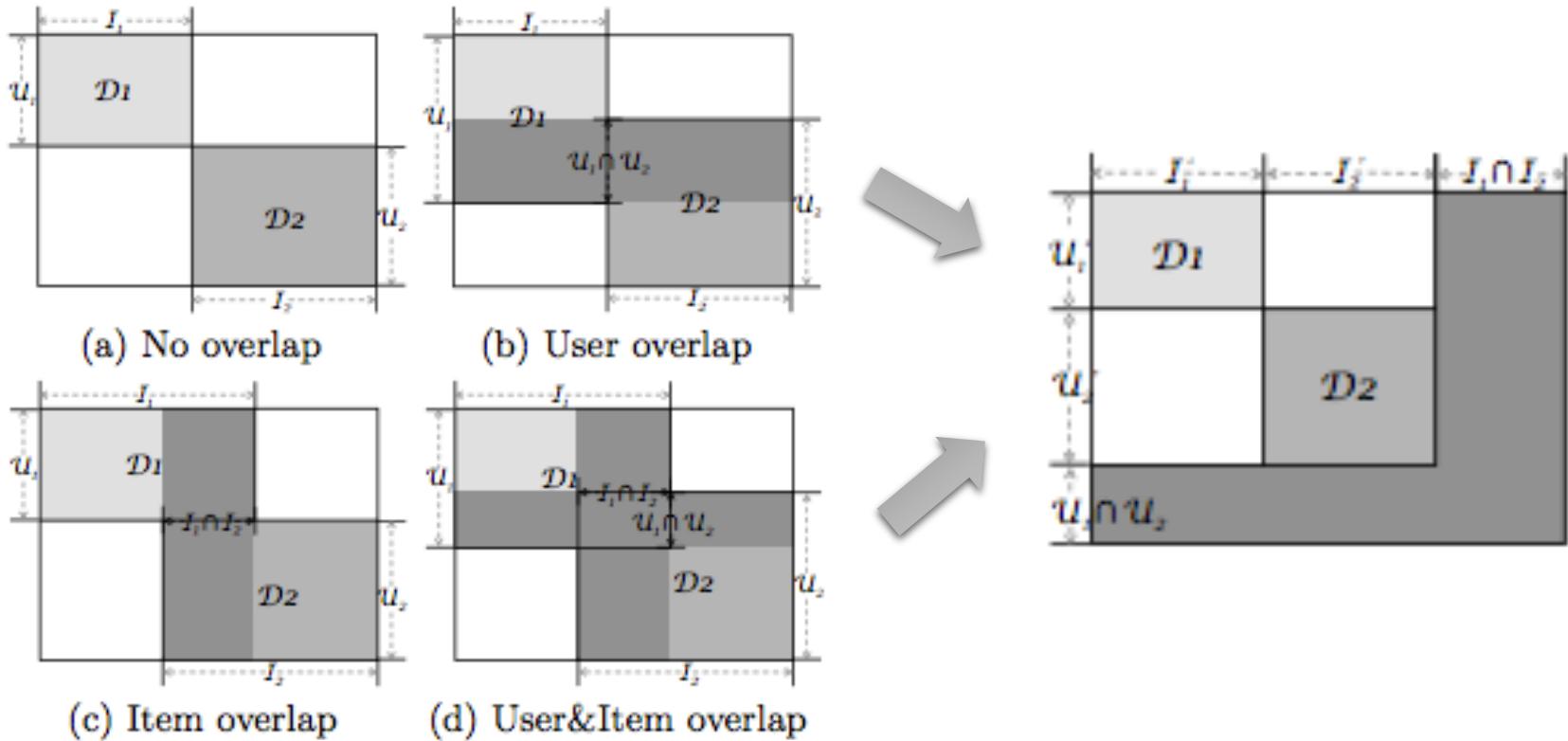


# Unified Framework (RecSys14)



# Unified Framework for Universal Recommendation (RecSys14)

- We propose a unified framework to incorporate inter-site information for universal recommendation [RecSys14]:



- This can be generalized to multiple site relations

<sup>1</sup>RecSys'14, Browser-Oriented Universal Cross-Site Recommendation and Explanation based on User Browsing Log

# Incorporating Inter-site User Behavior Data by Search Engines / Browsers

- Search engine / browser logs as inter-site data
  - Provides row and column borders for BDF structures

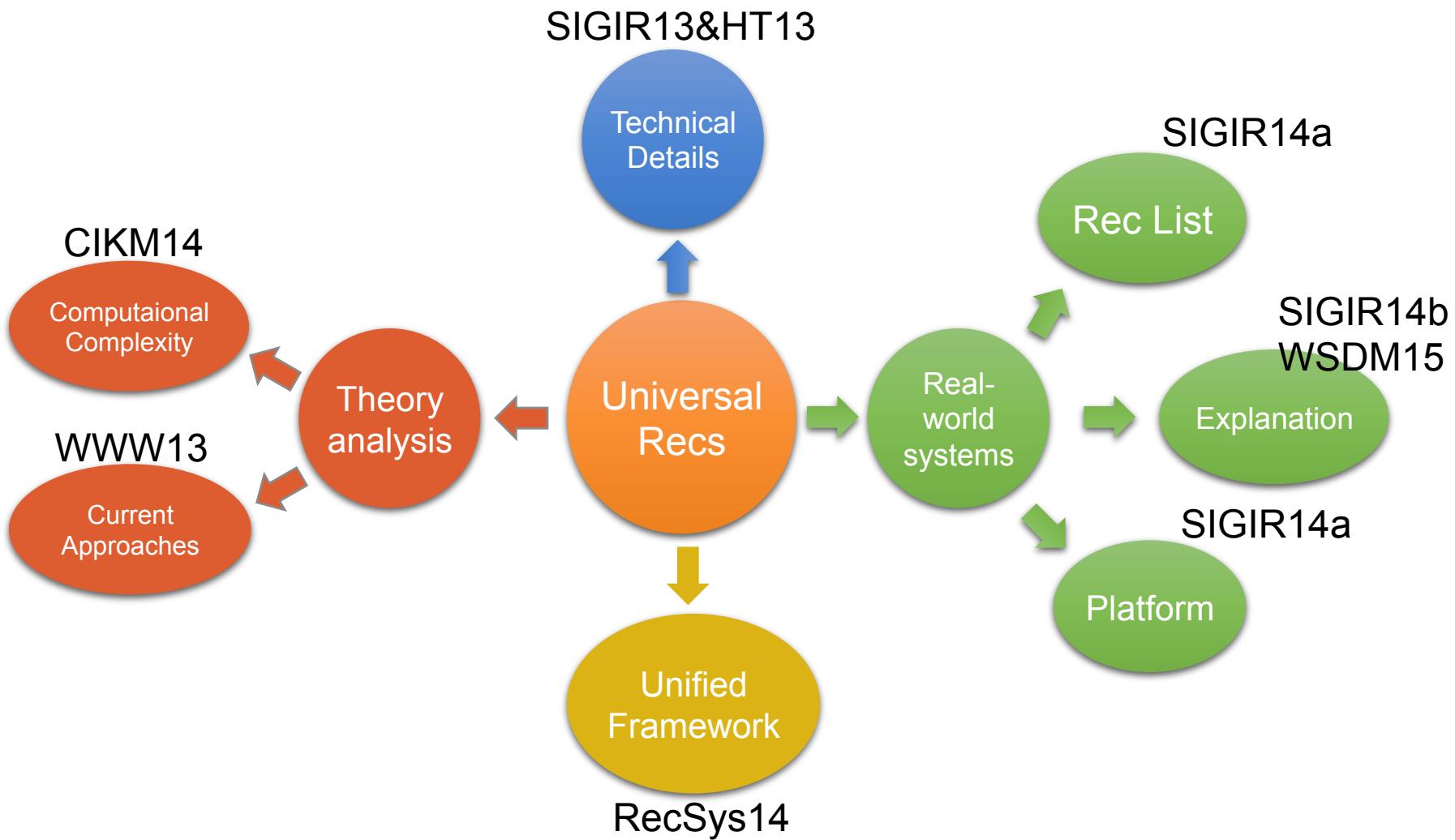
$$\begin{array}{c} \mathcal{J}_1 \quad \mathcal{J}_2 \quad \cdots \quad \mathcal{J}_k \\ \mathcal{I}_1 \left[ \begin{array}{cccc} D_1 & & & \\ & D_2 & & \\ & & \ddots & \\ & & & D_k \end{array} \right] \end{array} \xrightarrow{\hspace{1cm}} \begin{array}{c} \mathcal{J}_1 \quad \mathcal{J}_2 \quad \cdots \quad \mathcal{J}_k \quad \mathcal{J}_B \\ \mathcal{I}_1 \quad \mathcal{I}_2 \quad \vdots \quad \mathcal{I}_k \quad \mathcal{I}_B \left[ \begin{array}{ccccc} D_1 & D_2 & & & C_1 \\ & & \ddots & & C_2 \\ & & & D_k & C_k \\ R_1 & R_2 & \cdots & R_k & B \end{array} \right] \end{array}$$

- e.g. The product co-occurrence information in sessions
  - Users search for the Ocean Heart necklace after searching for Titanic
  - Provides row borders to the BDF structured matrix
- e.g. Item dis-ambiguity results of the user queries
  - Provides column borders to the BDF structured matrix
- They make it possible to conduct collaborative filtering<sup>1,2</sup>

<sup>1</sup>WWW 2013, Localized Matrix Factorization for Recommendation based on Matrix Block Diagonal Forms.

<sup>2</sup>SIGIR 2013, Improve Collaborative Filtering through Bordered Block Diagonal Form Matrices.

# Universal Recommendation



# Other Research Bases

- Data acquiresments and Research Platform
  - Our lab cooperates with a major commercial search engine company in China (SoGou.com)
  - We have large-scale search engine and browser logs
  - The company has a famous web-browser product and large-scale real-world users
    - helps to conduct real scenario experiments
  - Pre-research results provide firm research foundations for this research topic

# Universal Recommendation

