FIU FLORIDA INTERNATIONAL UNIVERSITY

ELVES research laboratory

dpSmart: a Flexible Group based Recommendation Framework for Digital Repository Systems

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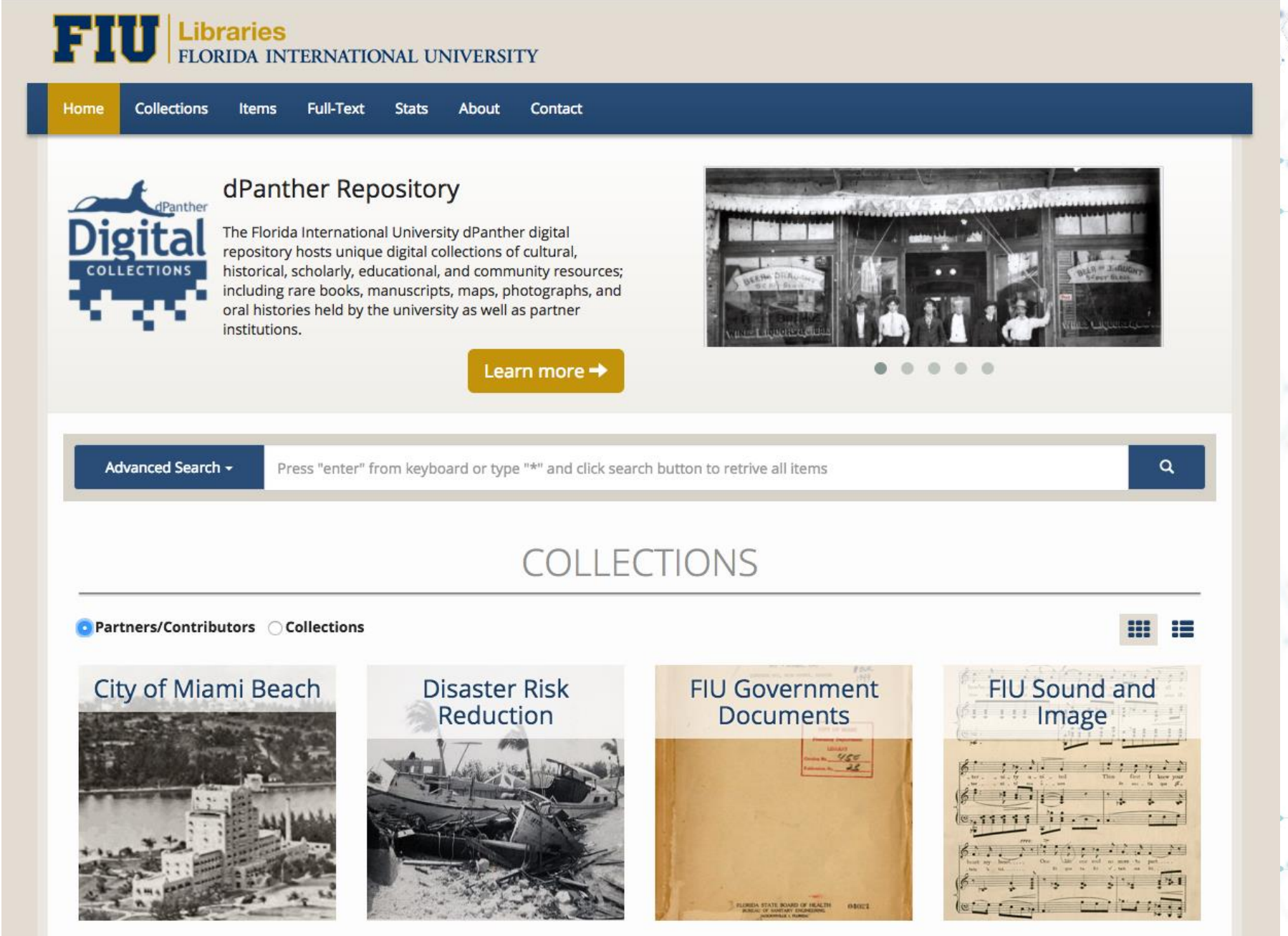
OUTLINE

1. Introduction
2. Related Work
3. System Design
4. Evaluation
5. Conclusion & Questions?

INTRODUCTION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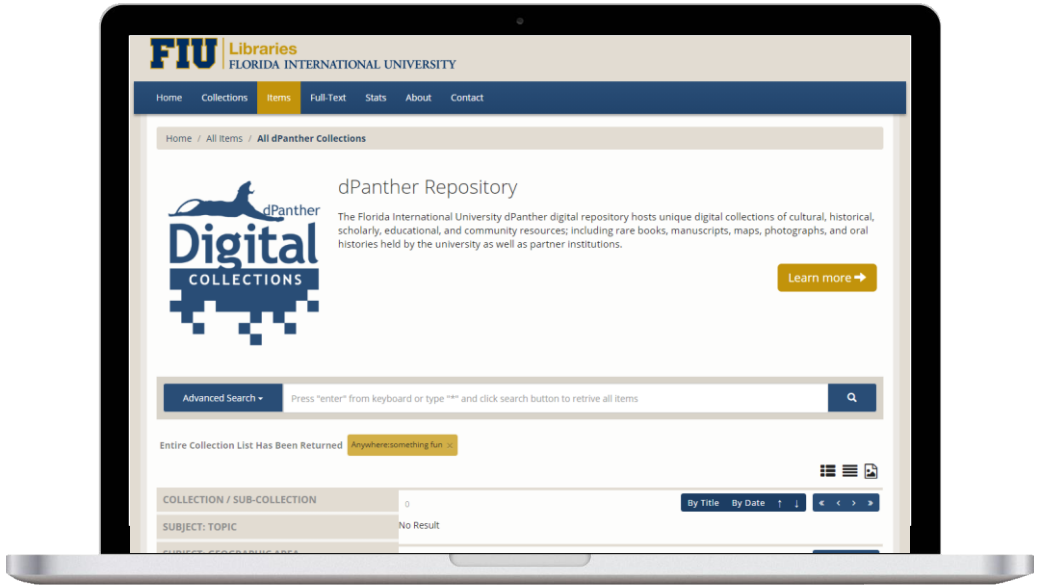
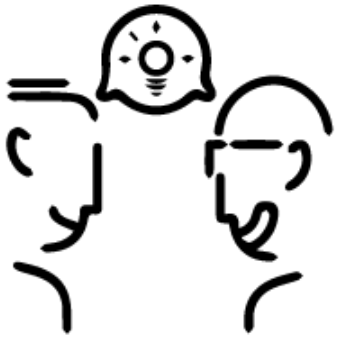


MAIN PROBLEMS

- **Limited Discoverability**
  - 12,376 (24.9%) out of the total 49,737
- **Lack of assistance to explore the system**
  - 700 clients out of 1,127 with a specific record when conducting search
- **Drop off visits**
  - 978,814 visits (58.8%) out of total **1,664,813** visits

General Problems for Digital Library Domain

What do the users WANT to know?
What do the users NEED to know?



Get to know the users & their region information

Awareness about the content

Awareness about the system condition (usages, statistic, user interactions)

Data Mining !! → **Recommendation System**

Challenges

Limited user information

Multiple Recommenders available

Side Effect (Noise)

Impact on the system performance

Intelligent Recommendation System (**dpsmart**)

Building User vectors from web log data only

Allowing multiple recommenders work collaboratively

Grouping Users from stereotyping model

Optimizing the algorithm with multi-process programming

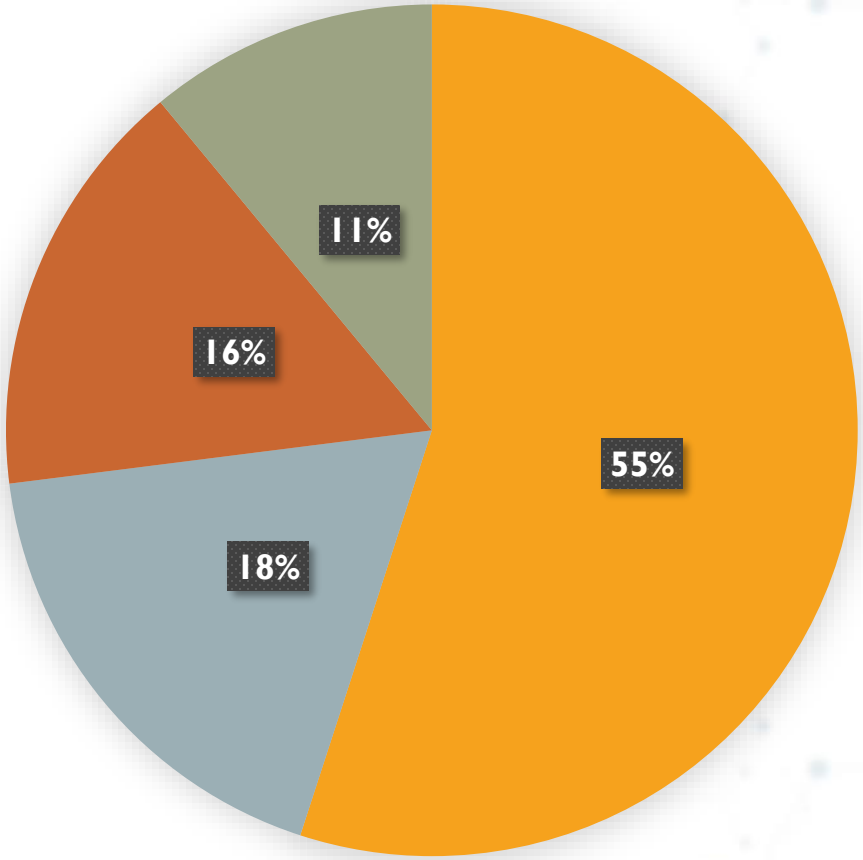
THE TECHNICAL CONTRIBUTIONS

- **Implementing a stereotype based recommendation system in real world system**
- **Avoiding the intensive labor works and automating the process from the log data extraction to model training.**
- **Avoiding the need of personal identifiable information and reducing the noise recommendation.**
- **Improving the system performing by using multi-process programming.**

RELATED WORKS

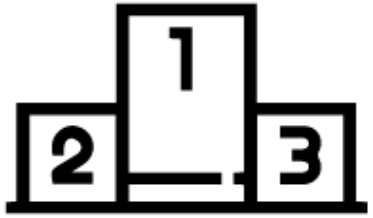
RECOMMENDERS

- **200** research articles were published
- **62** methods proposed



ADDITIONAL METHODS

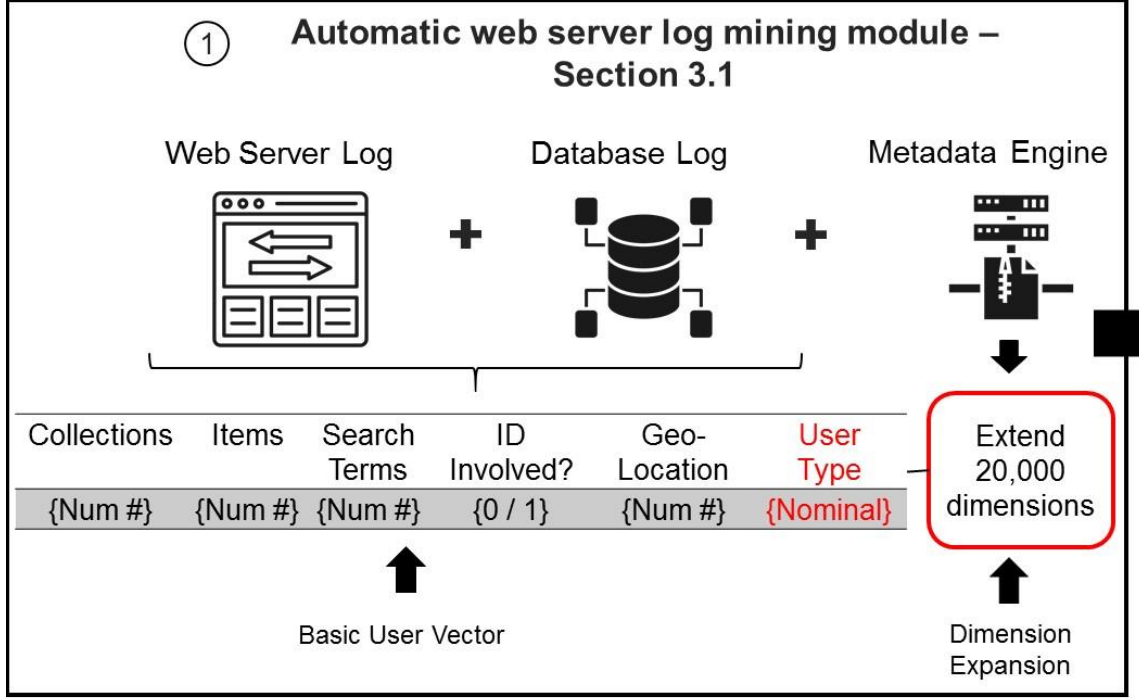
GLOBAL RELEVANCE

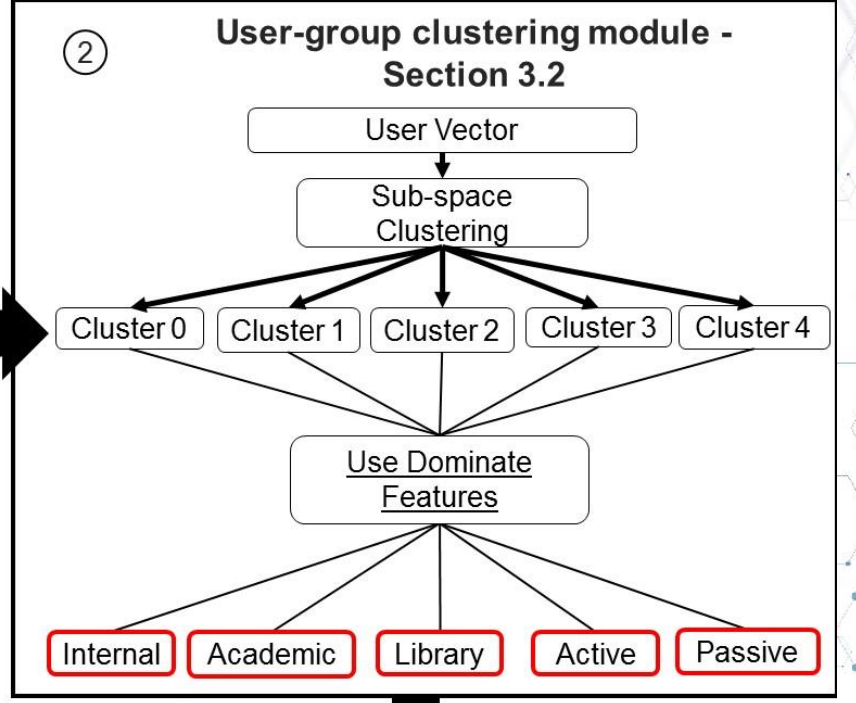


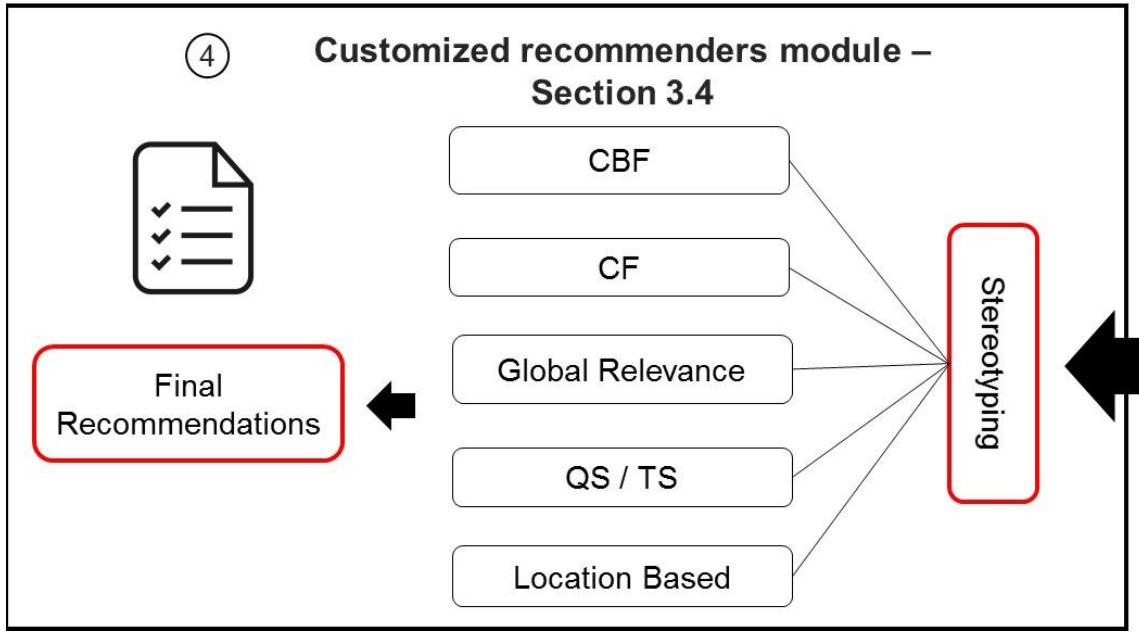
LOCATION BASED

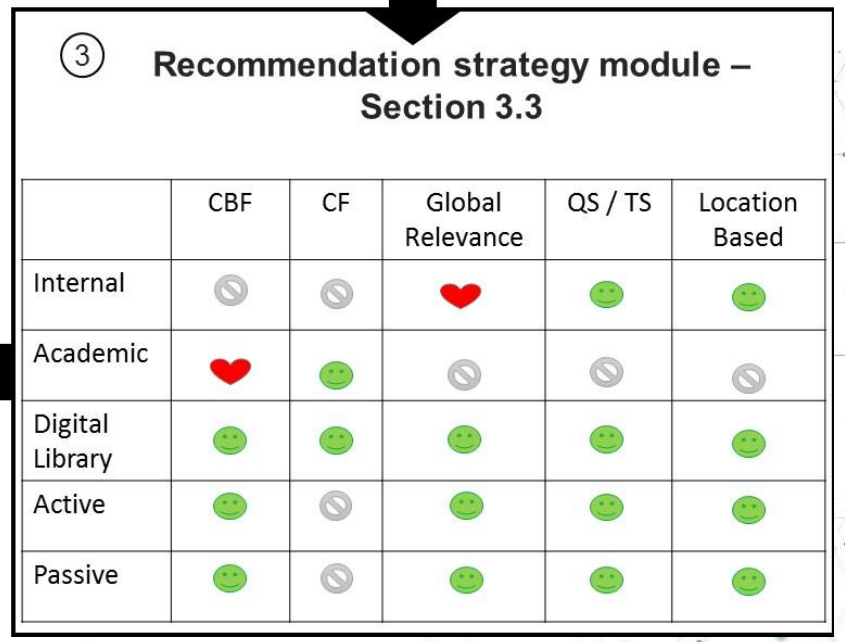
QUERY/TERM SUGGESTION (QS / TS)

SYSTEM DESIGN





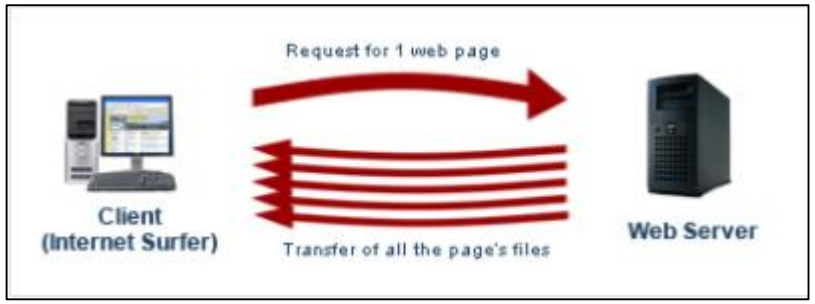




	CBF	CF	Global Relevance	QS / TS	Location Based
Internal	⊘	⊘	❤	☺	☺
Academic	❤	☺	⊘	⊘	⊘
Digital Library	☺	☺	☺	☺	☺
Active	☺	⊘	☺	☺	☺
Passive	☺	⊘	☺	☺	☺

AUTOMATIC WEB SERVER LOG MINING MODULE

Web Server Log



Database Log

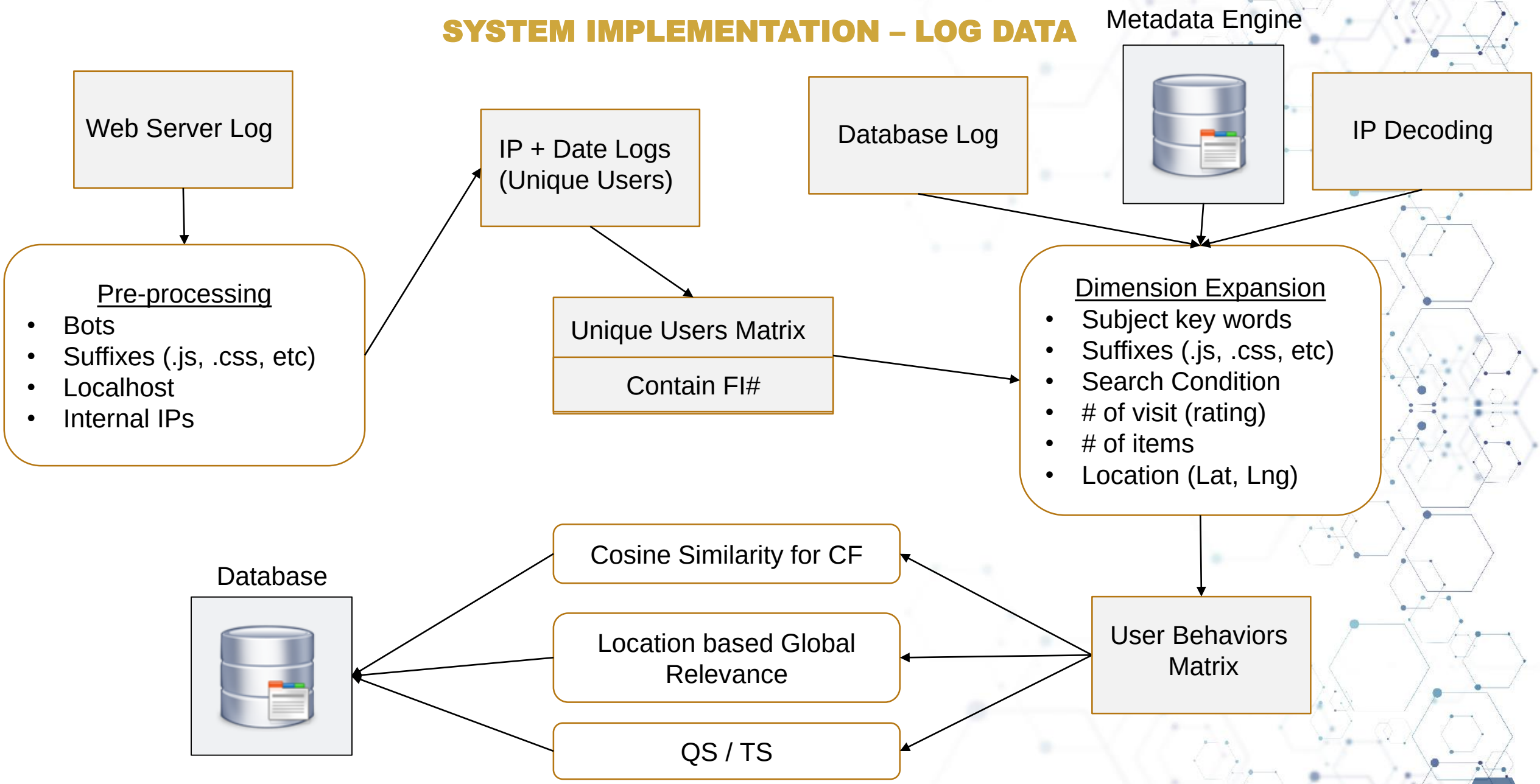
Metadata Engine

Users ➔

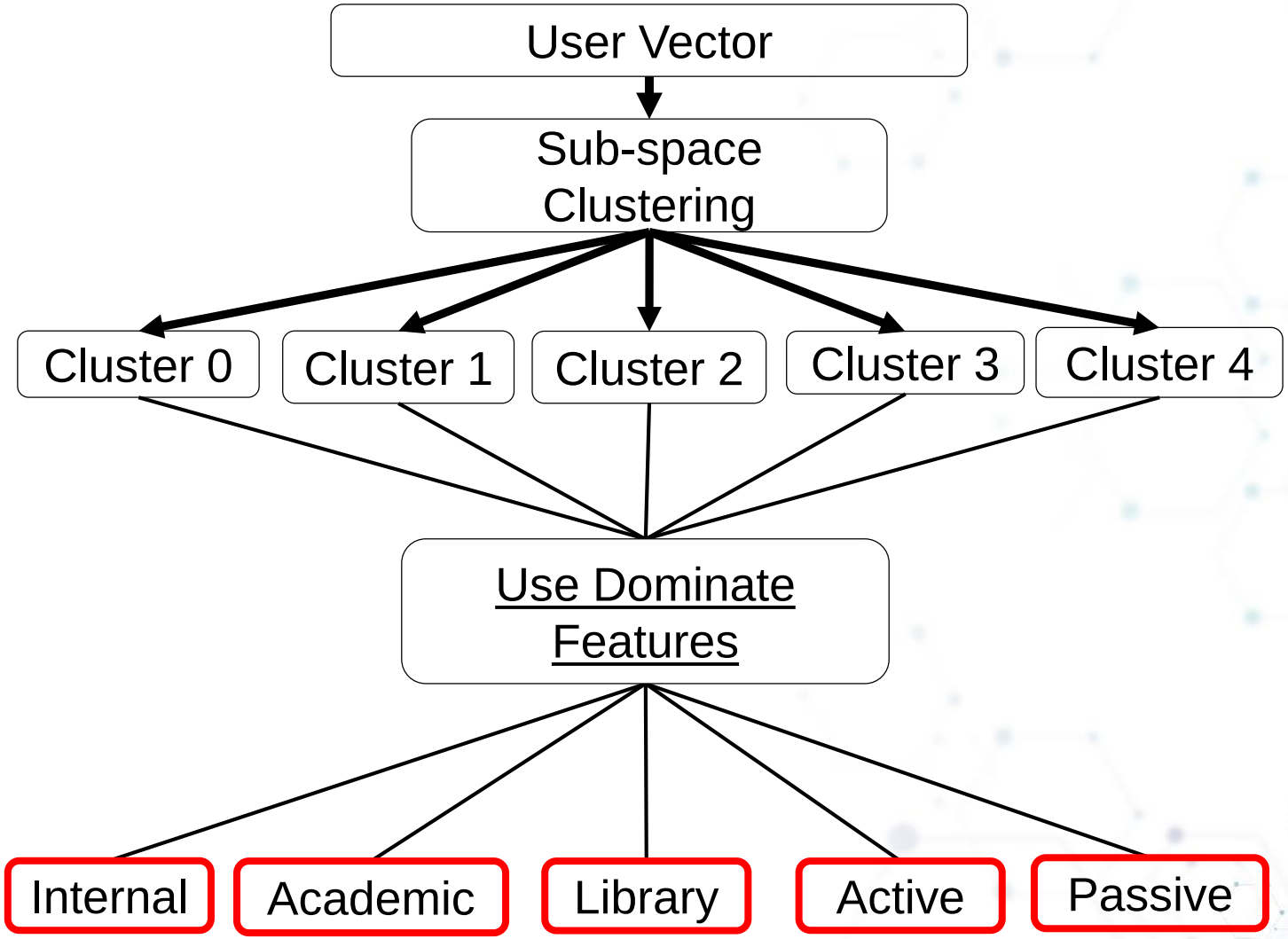
Collections	Items	Search Terms	ID Involved?	Geo-Location	User Type
{number}	{number}	{number}	{True / False}	{Number}	{Nominal}

By linking the records to the metadata content will extend 20,000 dimensions

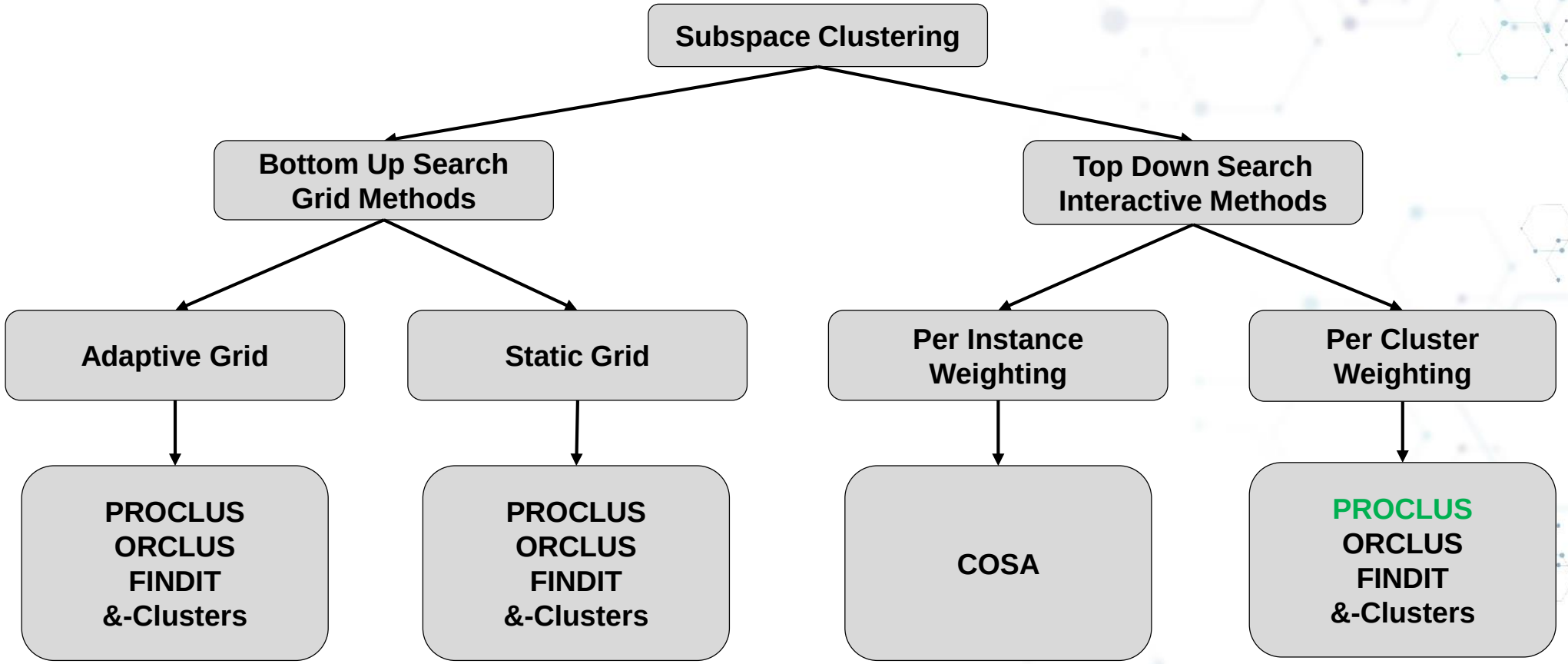
SYSTEM IMPLEMENTATION – LOG DATA



User-group clustering module - Section 3.2

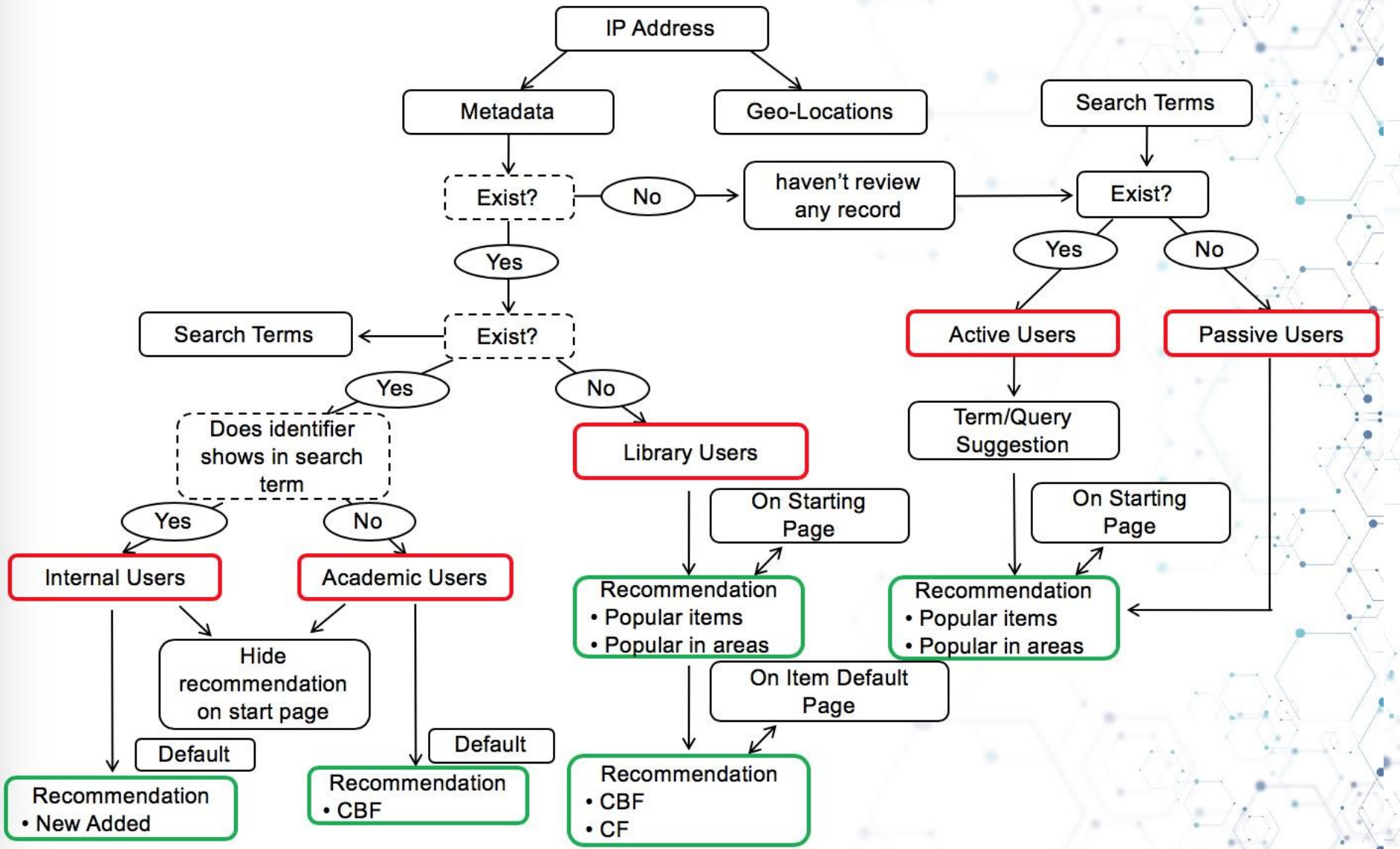


Subspace clustering



WEKA The University of Waikato + Opensubspace v3.31

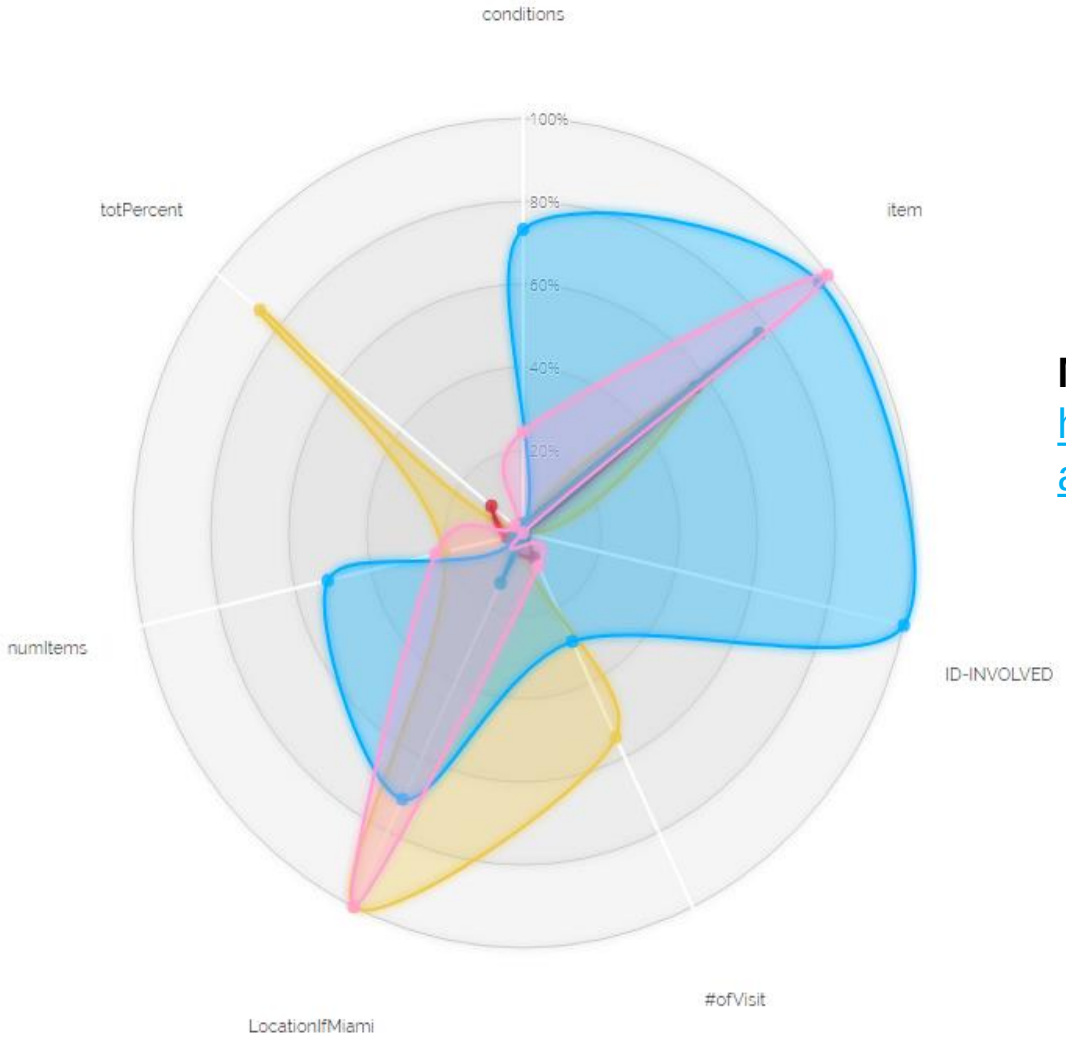
USE DOMINATE FEATUERES TO MARK USER GROUPS



SAMPLE USER RECOGNITION BY USING DOMINATE FEATURES

Basic User Vector: searches,item,idInvolved,numVisits,LocationIfMiami,numItems

- Cluster0:21238 (Active Web Users)
- Cluster1:2565 (Passive Web Users)
- Cluster2:97 (Digital Library Users)
- Cluster3:66 (Internal Users)
- Cluster4:667 (Acadamic Users)



More available here:
http://dpanther.fiu.edu/dpanther/dpsmart/usercluster/

RECOMMENDATION STRATEGY

	CBF	CF	Global Relevance	QS / TS	Location Based
Internal Users	⊘	⊘	❤	☺	☺
Academic Users	❤	☺	⊘	⊘	⊘
Digital Library Users	☺	☺	☺	☺	☺
Active Users	☺	⊘	☺	☺	☺
Passive Users	☺	⊘	☺	☺	☺

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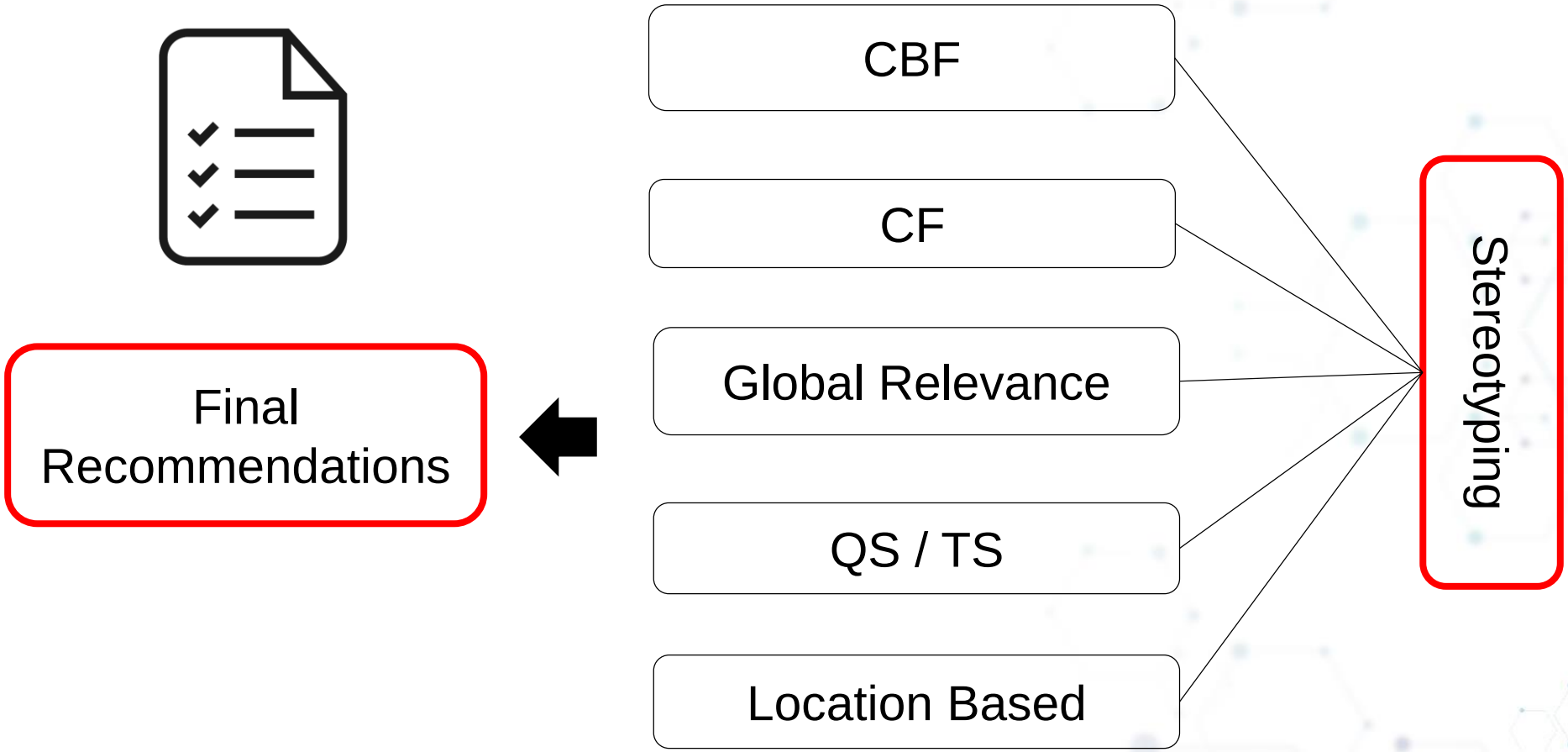
Customized recommenders module – Section 3.4



CUSTOMIZED RECOMMENDERS

1.Content based filter: calculate the item-similarity among one specific user to find a threshold to provide CB recommendation

$$SW_{(a,b)} = \frac{|\sum_{n=1}^{\infty}((A_n \cap B_n) * W_n)|}{|\sum_{n=1}^{\infty}((A_n \cup B_n) * W_n)|} \quad (2)$$

- Where SW is the weighted Jaccard Similarity
- a, b are any two items in dPanther system
- A,B are any pair metadata field from n selection metadata data fields between item a and b
- w is the weight assigned for a specific pair of one metadata field

2.Collaborative filtering: Calculate user similarity for current user to find if there is a similar user group. Calculation based on Cosine Similarity

$$S_{(i,j)} = \frac{\sum_{u \in U}(R_{(u,i)} - \overline{R}_u)(R_{(u,j)} - \overline{R}_u)}{\sqrt[2]{\sum_{u \in U}((R_{(u,i)} - \overline{R}_u)^2)}\sqrt[2]{\sum_{u \in U}((R_{(u,j)} - \overline{R}_u)^2)}} \quad (4)$$

- Where S is the cosine-based similarity
- U stands for the group of users who rate both item i and item j
- $R_{(u,i)} or R_{(u,j)}$ means the score for such the item by the user
- $\overline{R}_u$ is the average of the u-th userâĂŹs ratings

Very Slow!!!

CUSTOMIZED RECOMMENDERS

3. Global Relevance (GR): Frequency of subject key works appearance in high occurred words plus the location information

$$GR_u \propto N_i \quad where \quad L_i \in L_u \tag{6}$$

- Where GR is the Global Reference Score
- u is the current user
- i is the item in dPanther system
- N is the number of hits of item i
- L is the location information

4. Term Suggestion (TS) / Query Suggestion (QS): The similarity of the term to the metadata is generated by using the Jaccard index as suggestion by:

$$S_{(a,b)} = \frac{|DS_a \cap DS_b|}{|DS_a \cup DS_b|} \tag{7}$$

- Where S is the Similarity Score between the search term and the item subject keywords
- a is the input search term
- b is the item in the system
- DS is the data set consist of the key works

Very Slow!!!

EVALUATION

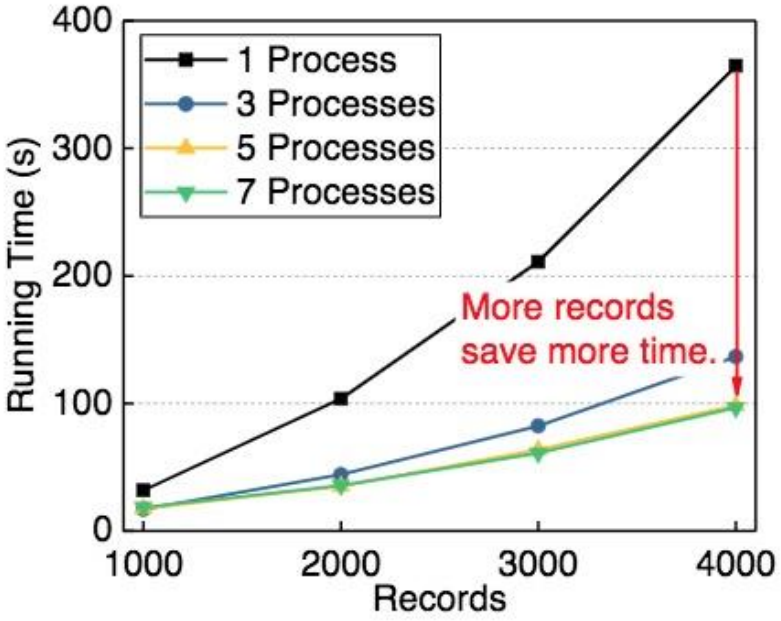
PURPOSE OF EVALUATION

- Whether the multiple-process programming algorithm improves the hosting Digital Repository Systems performance?
- When dpsmart integrated into the dPanther, what are the benefits of dpSmart regarding the **page views, bounce rate & drop-off rate**?
- How are the dPanther usability like **Avg. Time on Page, Avg. Page loading, Avg. Direction Time, Avg. Server Reponses Time, and Avg. Page Overload Time** improved by integrating dpSmart?

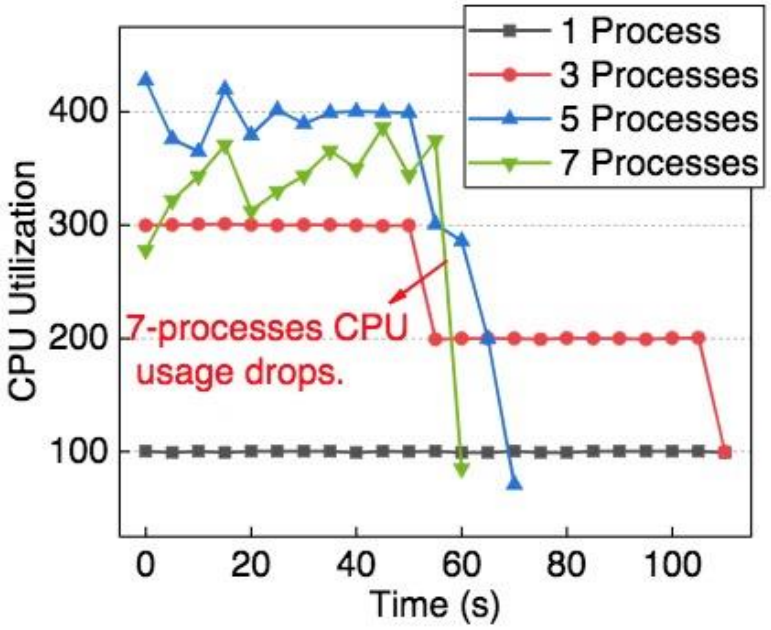
SYSTEM PERFORMANCE EVALUATION

Windows Machine
4 Cores of CPU
32 GB Memory

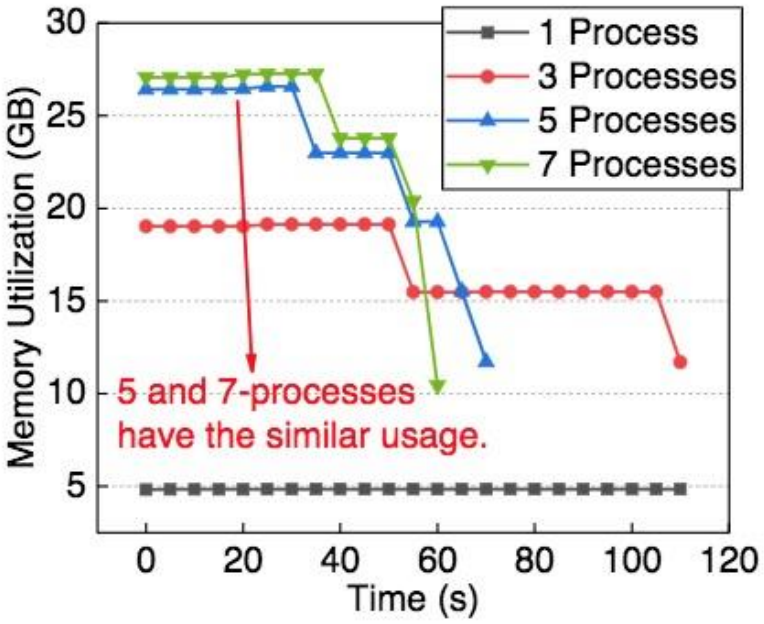
Randomly Selected 4,000 records to run the CBF with 1-process, 3-processes, 5-processes, and 7-processes respectively



(a) The Running Time Comparison.



(b) The CPU Usage.



(c) The Memory Usage.

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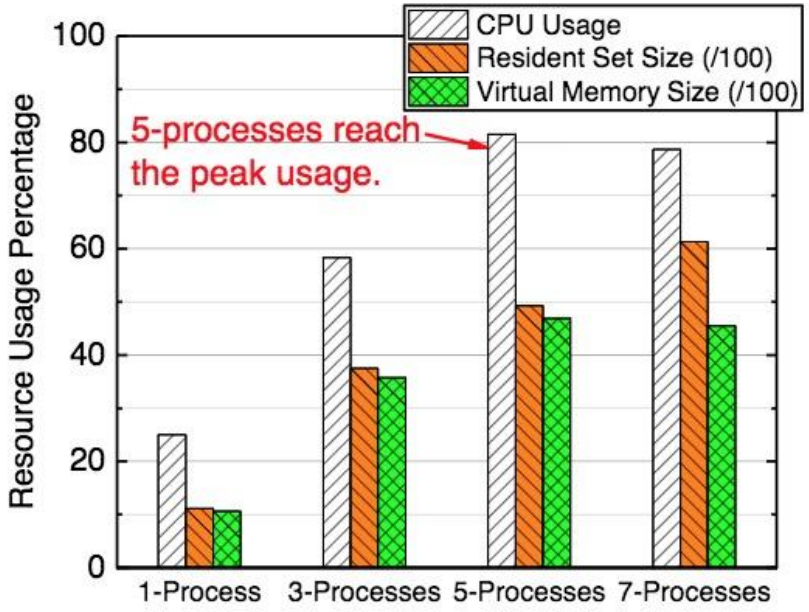


Fig. 4: The Average Usage of CPU, Memory and Virtual Memory by using 1-process, 3-processes, 5-processes, and 7-processes for the task of running 4000 records.

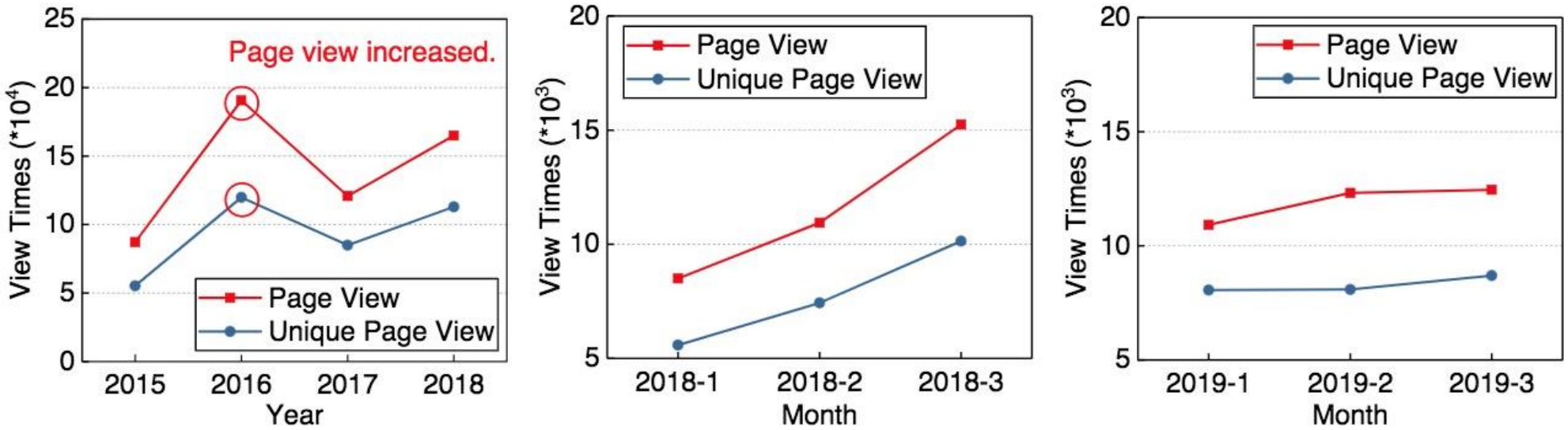
SYSTEM IMPACT EVALUATION

Experiment Time Line:

January, 2016
First module, customized recommender, implement

2018: Model rebuilding multiple times

January 2019: Entire framework implement



(a) The Page View Stats for the year 2015-2018. (b) The Page View Stats from Jan. to Mar., 2018. (c) The Page View Stats from Jan. to Mar., 2019

Fig. 5: The Page View Stats for the year from 2015 to 2018, from January to March in year 2018, and from January to March in year 2019.

SYSTEM IMPACT EVALUATION

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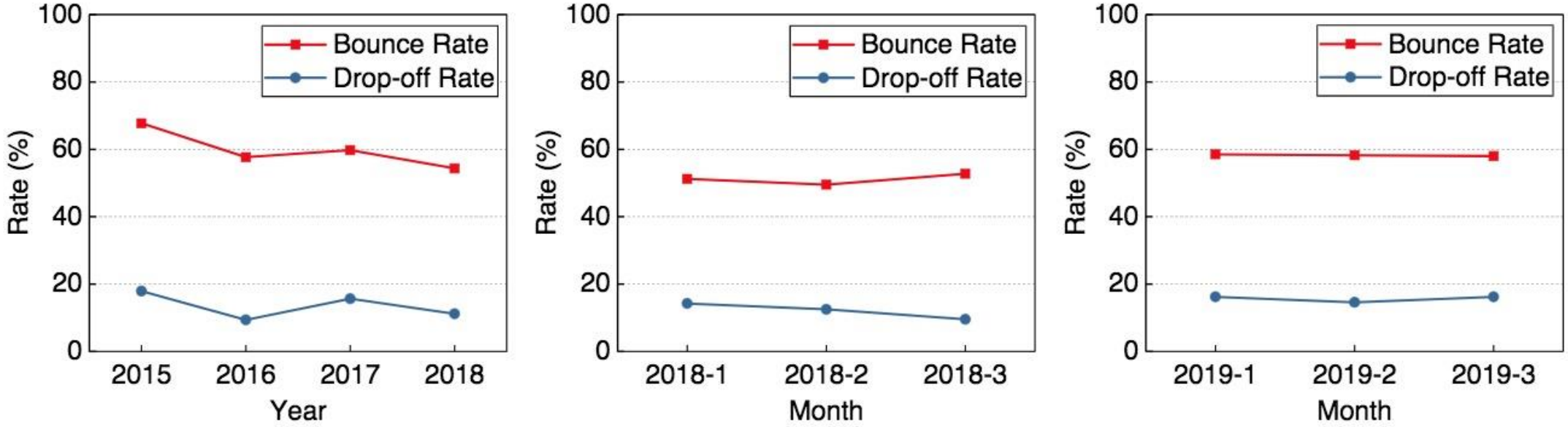

(a) The Bounce & Drop-off Rate from the Year 2015-2018.

(b) The Bounce & Drop-off Rate from Jan. to Mar., 2018.

(c) The Bounce & Drop-off Rate from Jan. to Mar., 2019

Fig. 6: The Bounce & Drop-off Rate for the year from 2015 to 2018, from January to March in year 2018, and from January to March in year 2019.

SYSTEM IMPACT EVALUATION

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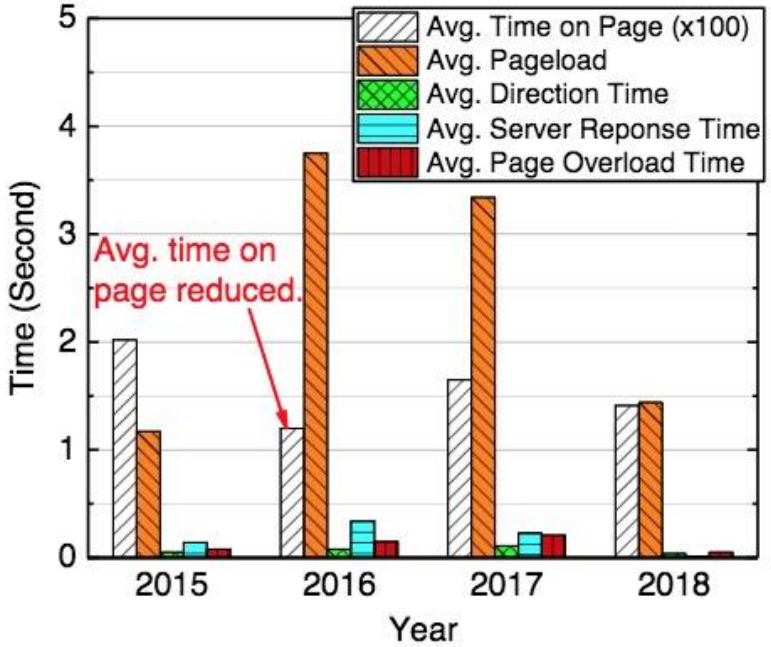

Fig. 7: The system usability statistics from 2015 to 2018.

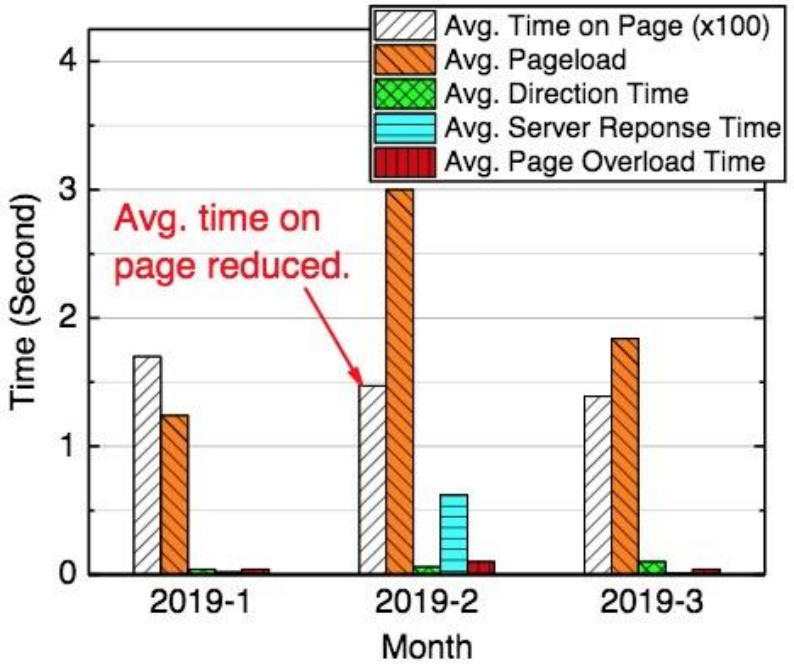

Fig. 8: The system usability statistics from Jan. to Mar., 2019.

CONCLUSION

1. Design **a flexible framework** that allow digital library can build their recommendation system purely from log data and metadata.
2. **Facilitate multiple popular recommenders** and implement it into a real-world Digital Repository System:dPanther (http://dpanther.fiu.edu).
3. Minimize the side effect (noisy recommendation) by **applying customizable group-based recommendation strategy**
4. The experimental evaluation shows that by applying the multi-process programming, the **model building time can be significantly reduced**.
5. The system usage statistics also indicate that during the evaluation time from January 2019 to February 2019, the Page Views have increased compared to 2018, **demonstrating the effectiveness of our proposed framework**.

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QUESTIONS