

Helping Course Developers Discover Learning Objects: An Empirical Comparison of Recommendation Strategies

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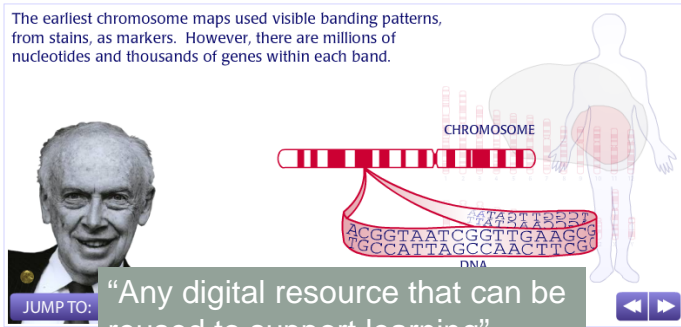
Learning Objects

Concept 39

A genome is an entire set of genes.

CONCEPT ANIMATION GALLERY VIDEO BIO PROBLEM LINKS

The earliest chromosome maps used visible banding patterns, from stains, as markers. However, there are millions of nucleotides and thousands of genes within each band.



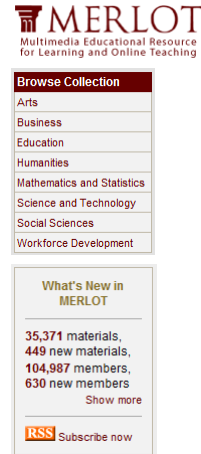
JUMP TO: "Any digital resource that can be reused to support learning" (Wiley, 2002)

Did you know? Craig Venter... for sequencing. Why is the genome divided into separate chromosomes?

From *DNA from the Beginning*, by J. D. Watson, D. A. Micklos, J. Witkowski, S. M. Lauter, S. Chan, C.-H. Yang, . . . L. C. Menges, 2002. Copyright 2002 by Cold Spring Harbor Laboratory. Reprinted with permission.

Problem: Learning Objects Are Underutilized

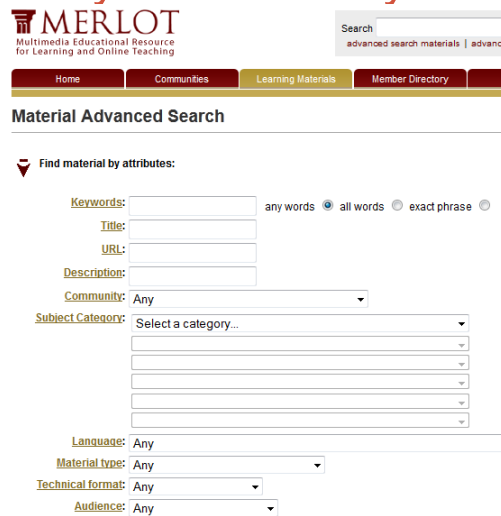
- Wide availability
 - 270,000 LOs in 8 large public repositories (Ochoa & Duval, 2009)
- Limited adoption
 - Only 20% reused, most only once (Ochoa, 2008)
 - “While large amounts of money have been invested in these resources [learning objects], educators have been slow to adopt them” (Cohen, 2010).



Screenshots from *Multimedia Educational Resource for Learning and Online Teaching*, by California State University Center for Distributed Learning, 2012. Copyright 1997-2012 by MERLOT. Reprinted with permission.

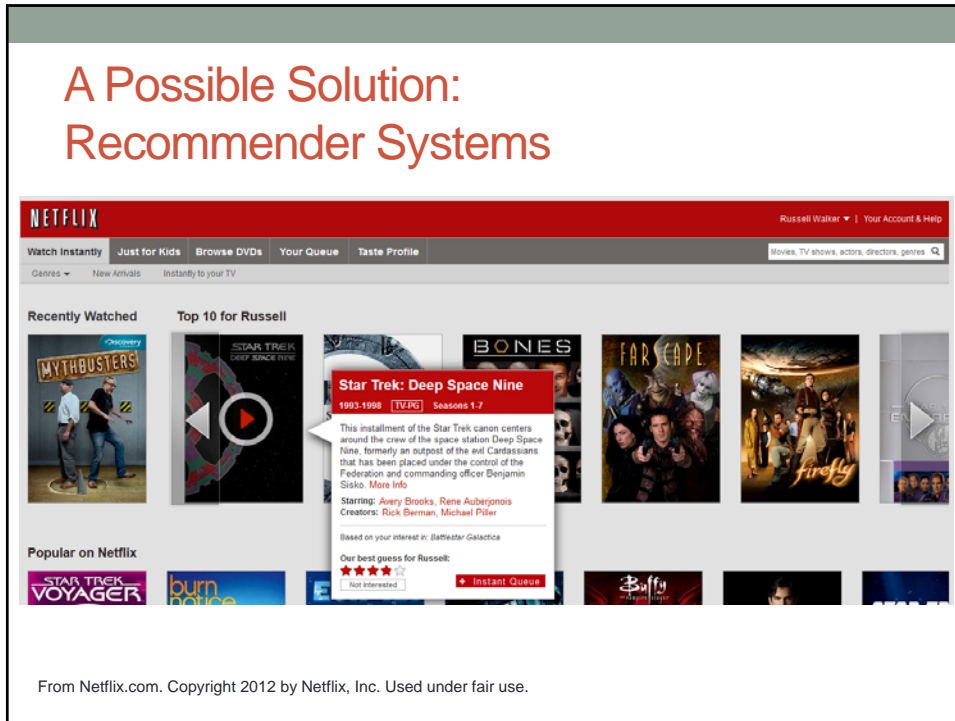
One Reason: Difficulty of Discovery

- Poor query formulation by users (Najjar, 2008)
- Search tools “not user friendly” (Najjar, 2008)
- “Immature” search tools (Ochoa, 2008)



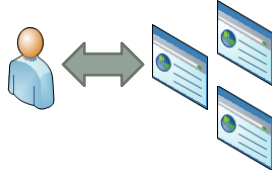
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A Possible Solution: Recommender Systems



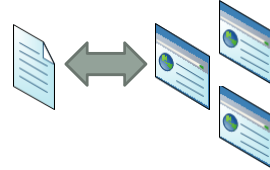
Recommendation Strategies

Content-Based/Profile Strategy



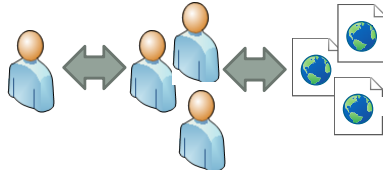
Active User Profile Learning Object Metadata

Content-Based/Syllabus Strategy



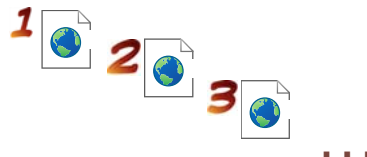
Course Syllabus Learning Object Metadata

Collaborative Filtering Strategy



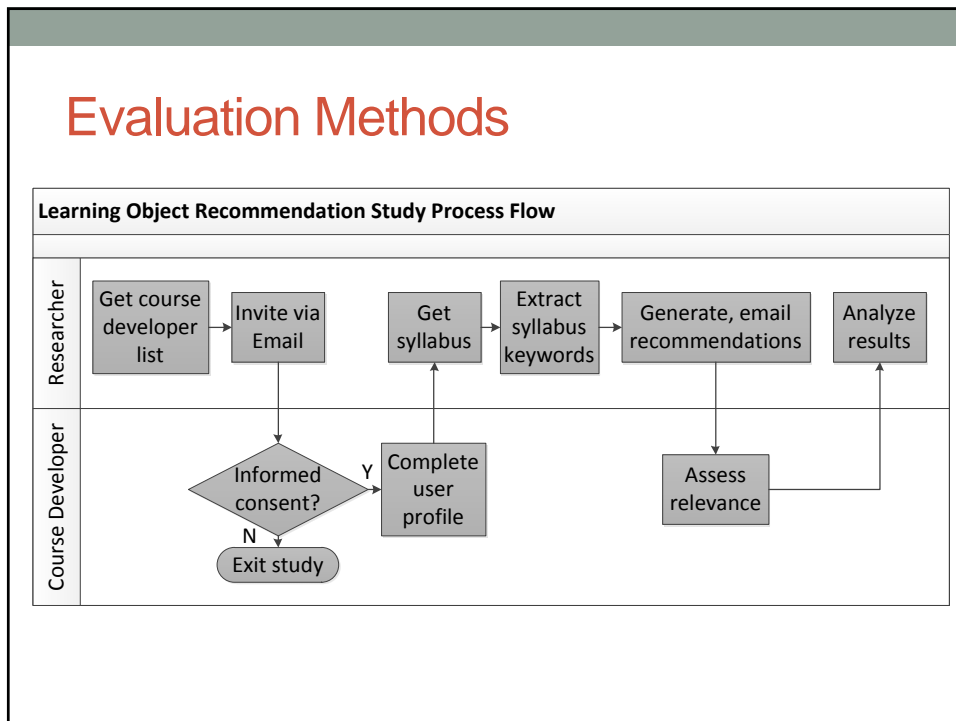
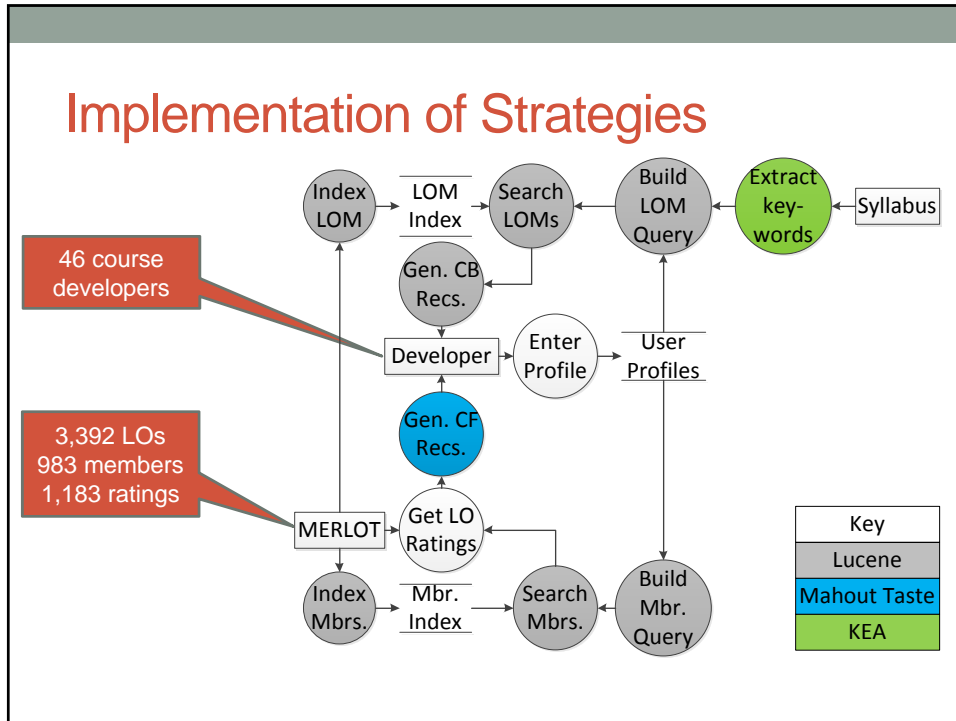
Active User Profile Similar User Profiles Preferred Learning Objects

Baseline Strategy



Highest-Rated Learning Objects Overall

(Koren, Bell, & Volansky, 2009; Symeonidis et al., 2006; Tang & McCalla, 2009; Tungare et al., 2006)

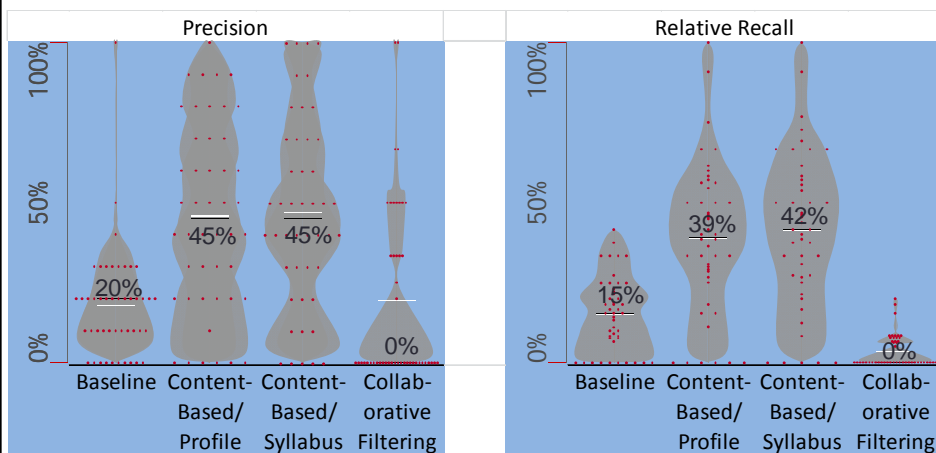


Evaluation Metrics

- Precision
 - $P = \frac{\text{relevant recommended objects}}{\text{all recommended objects}}$
 - Probability that a given recommended object will be relevant
- Recall (not used)
 - $R = \frac{\text{relevant recommended objects}}{\text{relevant objects in data set}}$
 - Probability that a given relevant object will be recommended
- Relative Recall
 - $RR = \frac{\text{relevant recommended objects (one system)}}{\text{relevant recommended objects (all systems)}}$
 - Comparative proxy for recall in large data sets

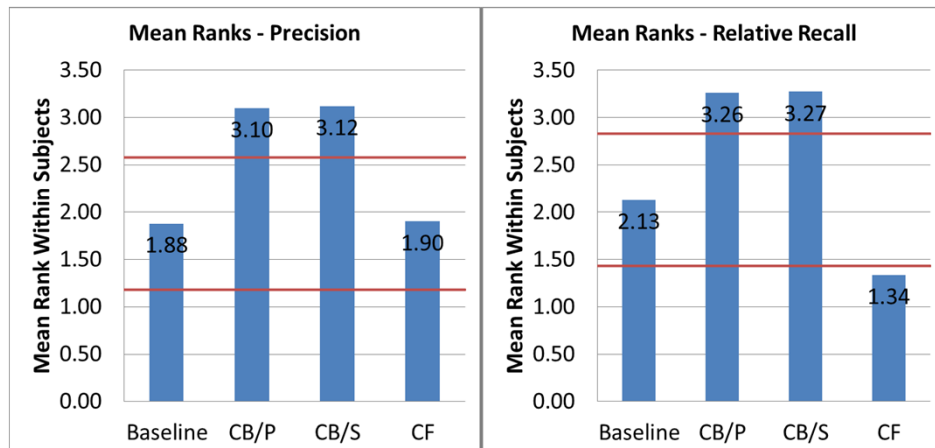
(Herlocker, Konstan, Terveen, & Riedl, 2004; Robinson & Wusteman, 2007)

Results: Beanplots of Precision and Relative Recall



Black horizontal line = median; white horizontal line = mean; gray outline = density trace.
(For a detailed description of beanplots, see Kampstra, 2008.)

Results: Within-Subjects Mean Ranks



CB/P = Content-Based/Profile; CB/S = Content-Based/Syllabus; CF = Collaborative Filtering. Rank 1 = lowest performance, 4 = highest performance. Red horizontal lines indicate baseline \pm Nemenyi critical distance for $p = .05$ significance level.

Discussion

- Conclusions
 - Content-based strategies appear promising
 - Recommendations with little or no additional user input may be feasible
 - Collaborative filtering performed surprisingly poorly
- Limitations
 - Single repository
 - Single subject category
 - Single institution
- Next Steps
 - Replicate in other data sets, subjects, and institutional settings
 - Further develop content-based strategies
 - Investigate reasons for poor collaborative filtering performance

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