Applications of Probabilistic Logics

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Probabilistic and logical reasoning are the cornerstones of many developments in artificial intelligence. Over the past 20 years, there has been a lot of attention to combining these two forms of reasoning. This has resulted in a rich variety of representations, languages and systems for dealing with probabilistic logical reasoning. These approaches have also been applied in machine learning context. In the first part of this talk, I shall provide a gentle introduction to such logics using ProbLog and ProPPR.

In the second part, I shall illustrate their use and promise on two challenging applications : in bioinformatics and in recommender systems. The first is based on ongoing work in Leuven with Dries Van Daele, the second on ongoing work with Sirawit Sopchoke and Prof. Masayuki Numao from ISIR, Osaka.

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Beyond Similarity: Serendipity Music Recommenders

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Recommender System – Introduction

- The more information available online, the harder for people to make choices
- Insufficient or limited experience leads to a poor decision

Recommender systems needed!

- Problem definition:
  - Given user *u* and target item *i*
  - Predict the unknown rating $r_{u,i}$
- Vs. information retrieval (IR)
  - IR – "I know what I'm looking for"
  - RecSys – "I'm not sure what I'm looking for"

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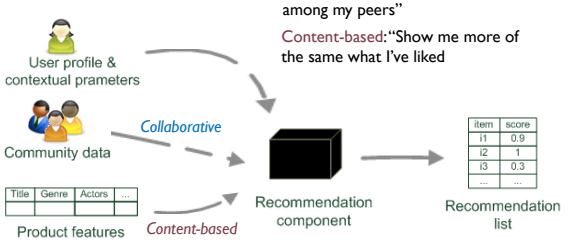
Recommender System – Traditional Approaches

- Collaborative Filtering vs. Content-based



[Radek Pelanek, 2011]

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Related Works – Music Recommendations

- Music Context-based
  - "X similar to (or influenced by) Y"
  - i.e. artist, tags, genre
- Music Content-based
  - "X and Y sound similar"
  - i.e. rhythm pattern, melodiousness
- Collaborative filtering
  - "People who listen to X also listen to..."
- Hybrid (combination)

All approaches based on similarity!

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Problems of Traditional Approaches:

1. Similarity bubble problem
   - Assume that the users want to see the content that's similar to what they already rate highly
   - (or, in case of collaborative filtering, the content their friends rate highly)

   No surprise!

2. Cold start problem
   - Lack of data for new users and new items

   Not effective recommendations!

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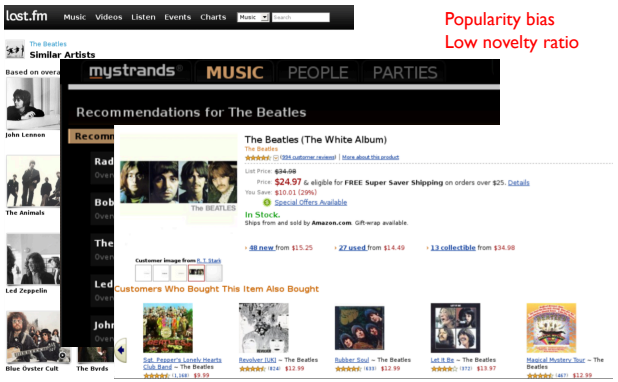
The Similarity Bubble



Popularity bias
Low novelty ratio

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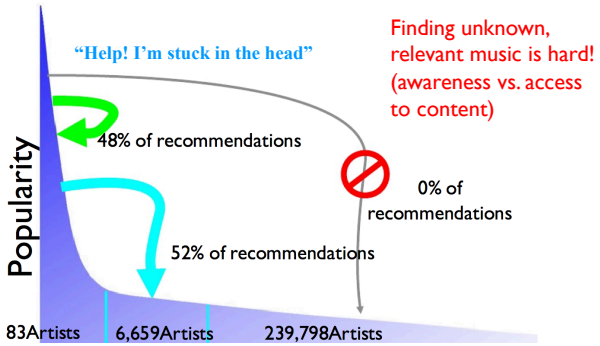
Similarity & The Limited Reach of Music Recommendation



Finding unknown, relevant music is hard! (awareness vs. access to content)

From [Oscar Celma 2011]

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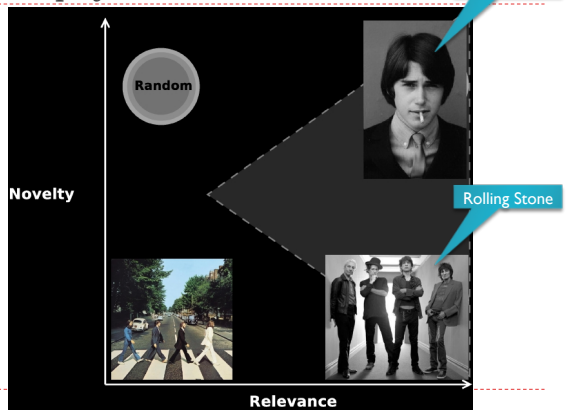
Serendipity in Music



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