Exploiting the Diversity of User Preferences for Recommendation

Saúl Vargas and Pablo Castells
{saul.vargas, pablo.castells}@uam.es

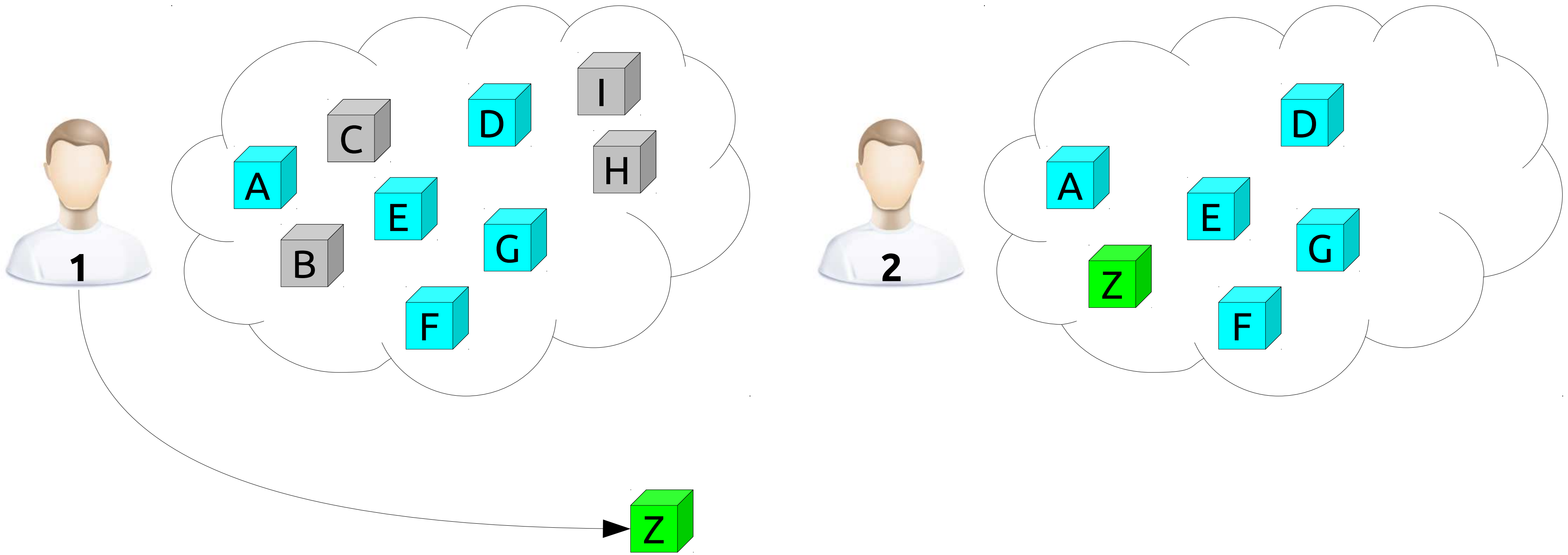
IRG

UAM

Item Recommendation

Collaborative Filtering

- Collaborative filtering techniques match users with similar preferences, or items with similar choice patterns from users, in order to make recommendations.



Diversity in Recommendation (I)

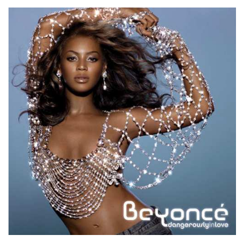
- Somebody could receive the following recommendations from a music on-line retailer:

Born This Way

Lady Gaga

Pink Friday

Nicki Minaj



Dangerously in Love

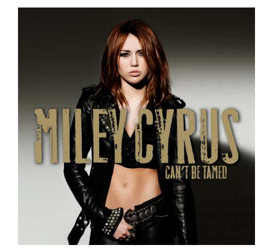
Beyoncé

Born This Way – The Remix

Lady Gaga

Femme Fatale

Britney Spears



Can't be Tamed

Miley Cyrus

Teenage Dream

Katy Perry

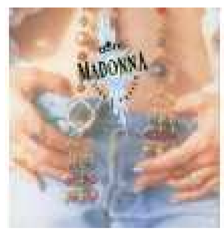
- Some observations:
  - *Lack of diversity:* pop albums from female singers.
  - Some of them are *redundant*.
- **This is not a good recommendation.**

Diversity in Recommendation (II)

- Some time ago, I received the following set of music recommendations:

Wrecking Ball
B. Springsteen

Not your Kind of People
Garbage



Like a Prayer
Madonna

Choice of Weapon
The Cult

Sweet Heart Sweet Light
Spiritualized

The Light the Dead See
Soulsavers

Little Broken Hearts
Norah Jones

- Some observations:
  - Different authors and genres.
  - Not similar between them.
- **These are much better recommendations!**

Relation to Search Result Diversification (I)

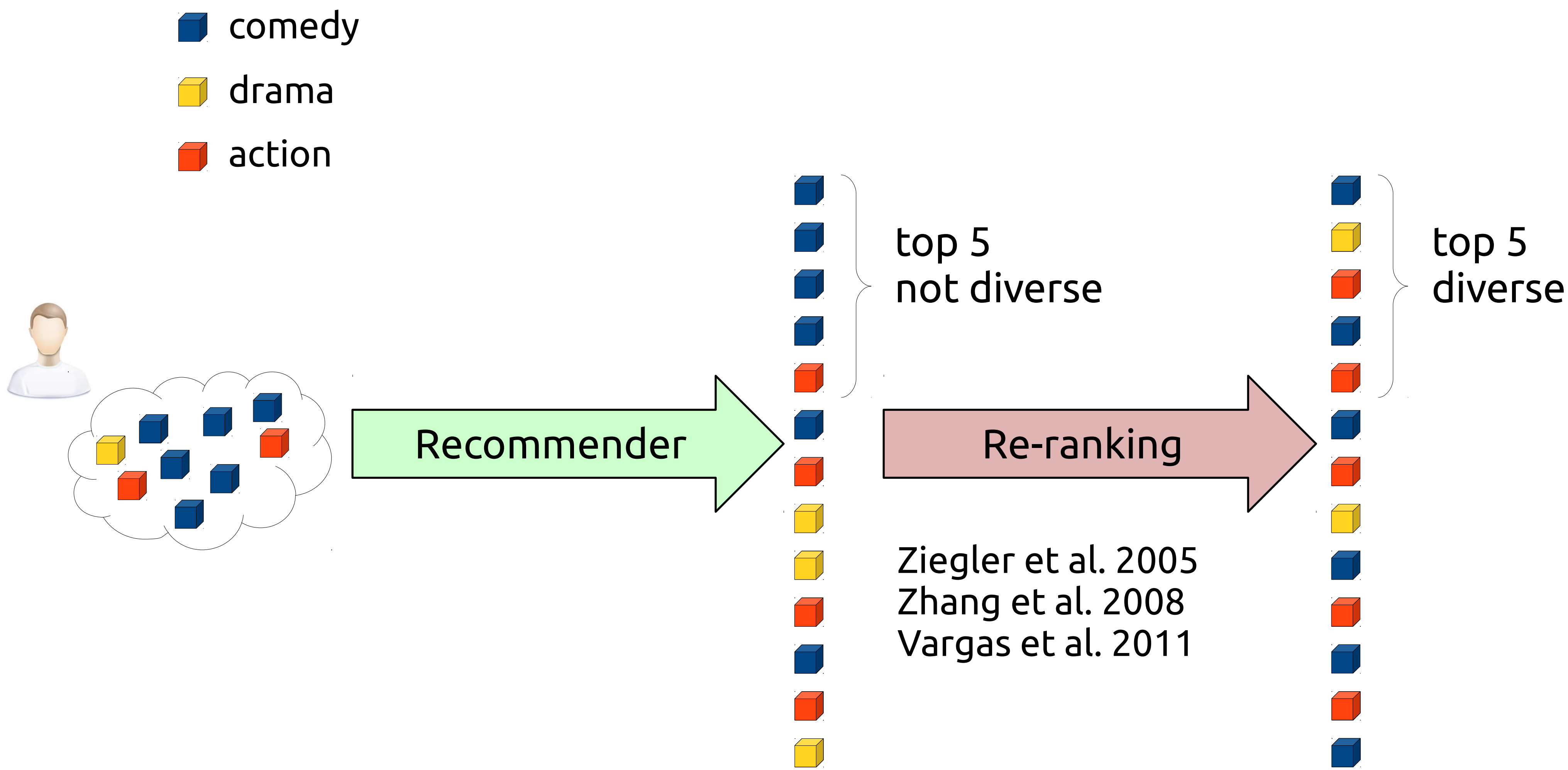
q = "java"

?

Relation to Search Result Diversification (II)

- Some concepts need to be translated:
  - Query → User and Profile
  - Document → Item
  - Subtopic → Category of items
- We considered two recommendation domains with different categorizations (units of diversity):
  - Movie recommendations: genres
  - Music artists recommendation: user-generated tags

Re-Ranking for Diversification



Explicit Diversification (I)

- Previous work has adapted search result diversification techniques by considering **explicitly** the diversity of the items in an initial top-N recommendation.
- Using the same principle, we can adapt the xQuAD re-ranking algorithm (Santos et al.).

Explicit Diversification (II)

$$S \leftarrow S \cup \{\underset{i \in R \setminus S}{\operatorname{argmax}} \, \lambda \, p(i|u) + (1-\lambda) \; p(i, \bar{S}|u)\}$$

$$p(i, \bar{S}|u) = \sum_{c} p(c|u) \, p(i|c,u) \prod_{j \in S} (1 - p(j|c,u))$$

$$p(c|u) = \frac{\sum_{j \in \mathbf{u}} r(u,j) \, [c \in \mathbf{j}]}{\sum_{c'} \sum_{j \in \mathbf{u}} r(u,j) \, [c' \in \mathbf{j}]}$$

$$p(i|c,u) = \frac{s(u,i) \, [c \in \mathbf{i}]}{\sum_{j \in R} s(u,j) \, [c \in \mathbf{j}]}$$

Explicit Diversification (III)

- The aspect-specific item probability p(i|c,u) could be further refined and integrated in the recommendation process.
- **The diversity is not a property of the initial recommendation list, but of the user profile.**
- We adapt the idea of query reformulation of the xQuAD framework.

Query reformulations

- We adapt the idea of query reformulation of the xQuAD framework:

q = “java”

q_1 = “java island”

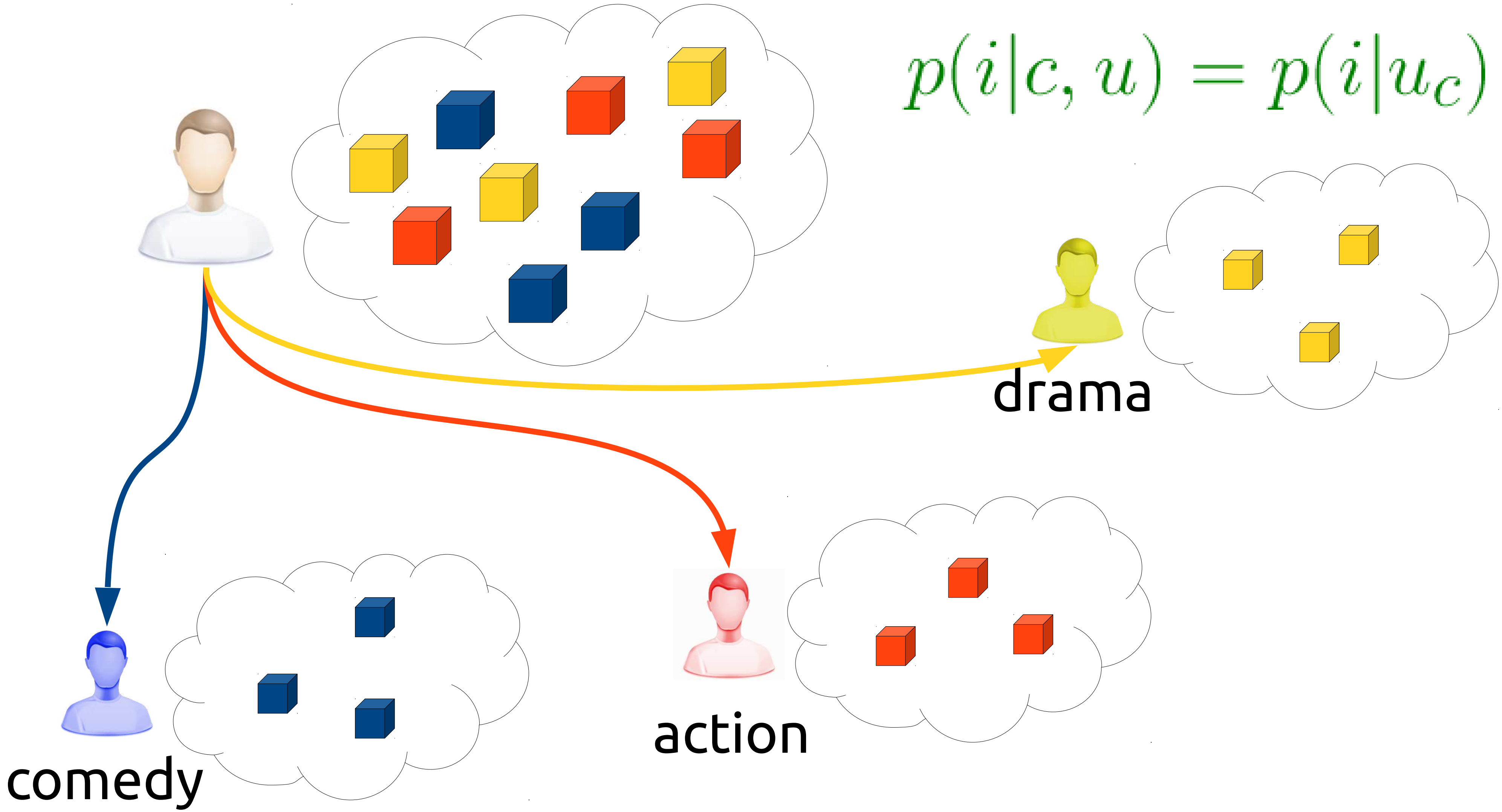
q_2 = “java programming”

q_3 = “java coffee”

$$p(d|c,q) = p(d|q_c)$$

Sub-Profiles (I)

$$p(i|c,u) = p(i|u_c)$$



User Pools for CF (I)

- As mentioned, collaborative filtering approaches use other users' profiles to generate recommendations.
- Now we have the original complete profiles and different sub-profiles, what can we do with them?
- We consider different *user pools* for recommendation.

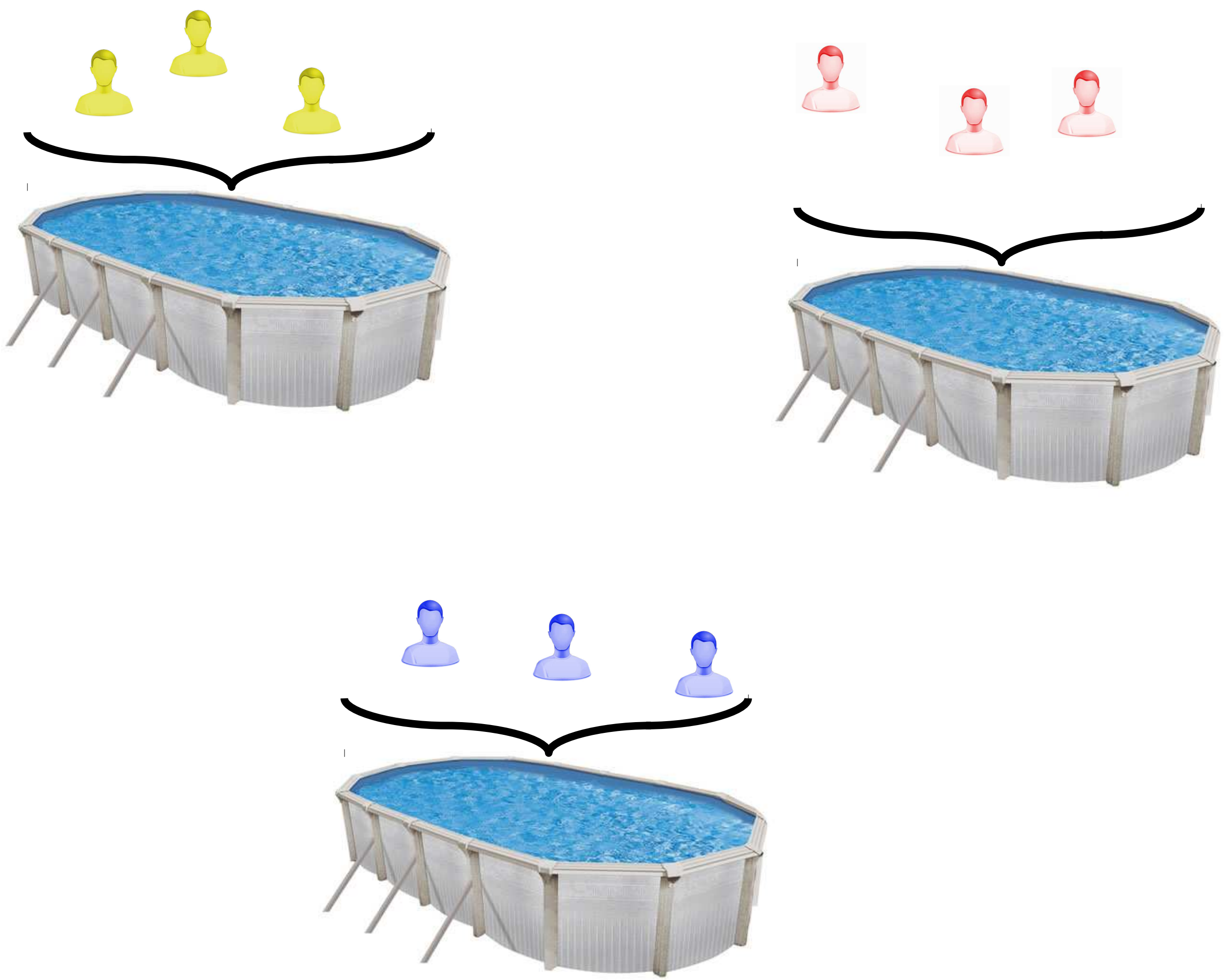
User Pools for CF (II)

Sub-users
and
Users

User Pools for CF (III)

Sub-users only

User Pools for CF (IV)



Category
Sub-users

Experiments (I)

- Datasets:
  - MovieLens1M: 6040 users, 3706 movies with genres.
  - Last.fm 1K (by Ò. Celma): ~1000 users, ~150.000 artists with user-provided tags.
- Recommendation algorithms:
  - Baselines: pLSA, and MF.
  - Re-ranking strategies: xQuAD-adapted explicit and sub-profile diversifications (with all three considered user pool selections).

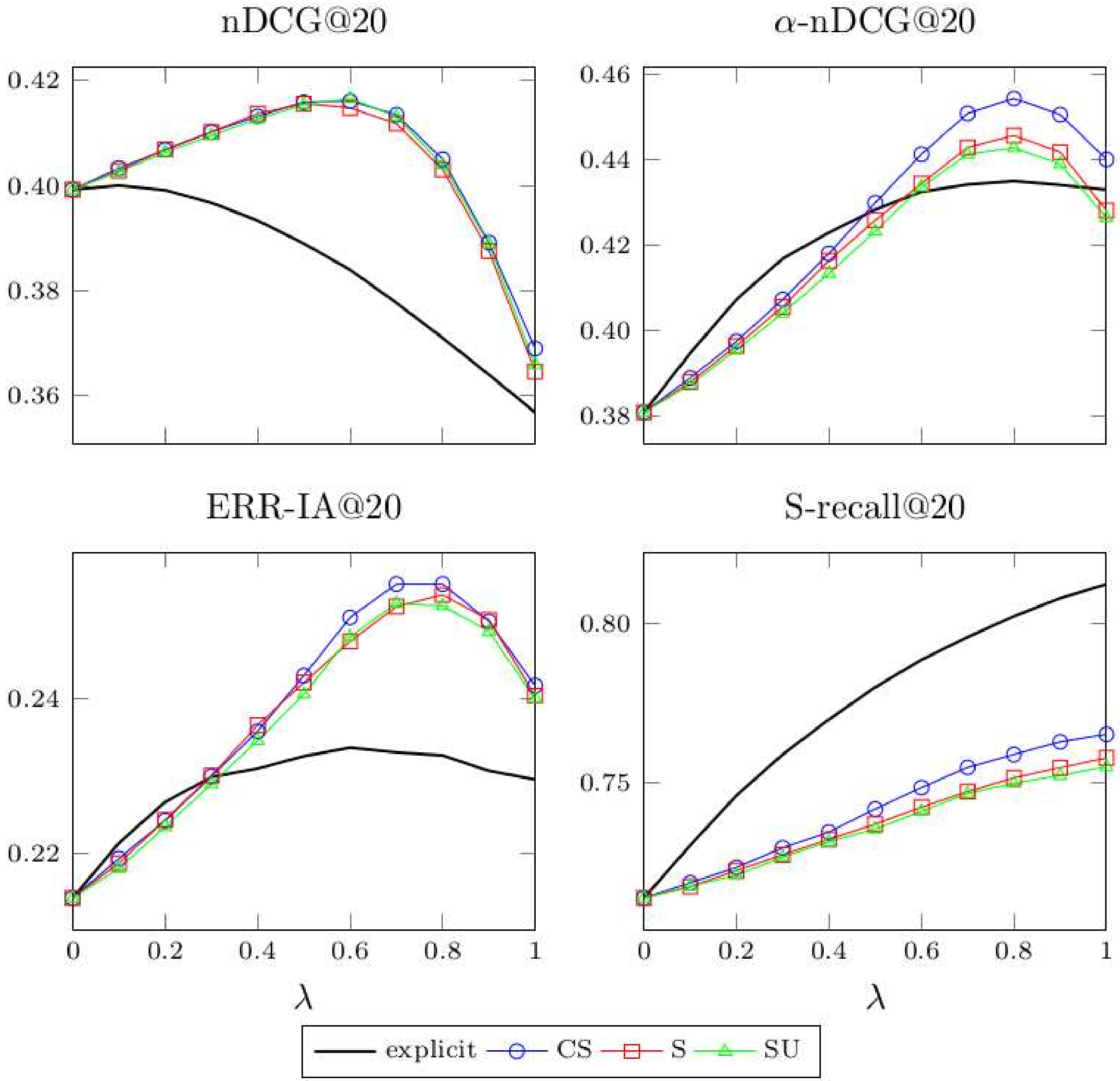
Experiments (II)

- Evaluation methodology:
  - MovieLens1M: 5-fold cross-validation.
  - Last.fm: 60-40% temporal split.
  - *TestItems*: the recommender is asked to rank the items in the user's test set and the rest of the items in the other users' test (assumed to be not relevant).
- Metrics:
  - Accuracy: nDCG@20
  - Accuracy & Diversity: α-nDCG@20, ERR-IA@20
  - Pure diversity: S-recall@20

Scalability of Diversification Algorithms

- The proposed approach has a high computational cost for Last.fm experiments with user tags:
  - MovieLens1M: 17.58 sub-profiles per user.
  - Last.fm: ~12,007 sub-profiles per user
- We propose to consider only the top-20 sub-profiles of each user.

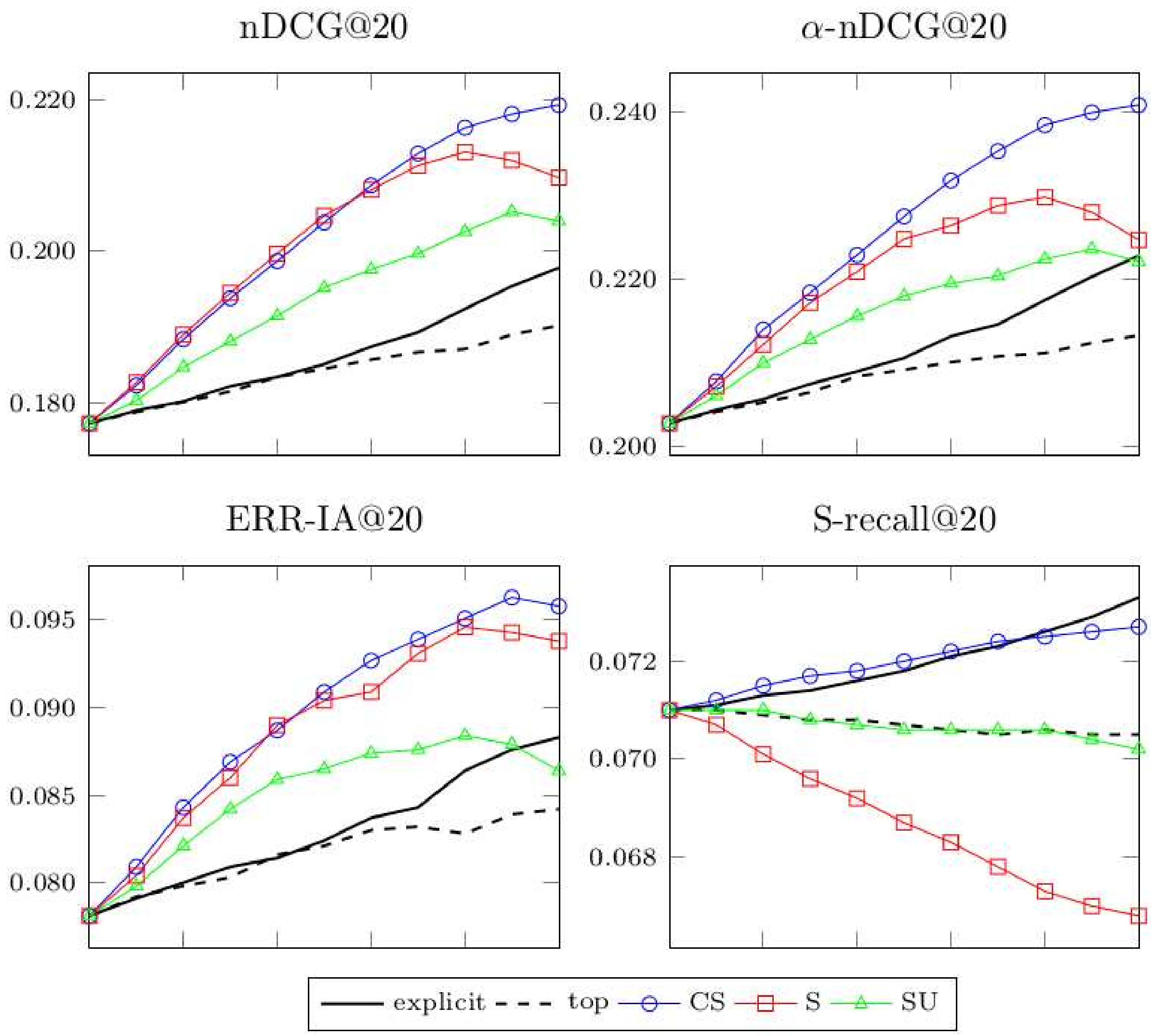
Results (I)



pLSA in MovieLens1M

- Explicit diversification degrades accuracy.
- Sub-profile diversifications show improvements in all metrics.
- CategorySubusers is slightly better than the others.

Results (II)



pLSA in Last.fm

- Sub-profile diversifications differ.
- SubusersOnly degrades S-recall, SubusersAndUsers does not improve it.
- CategorySubusers is clearly better than the others.

Conclusions

- We exploited the diversity within user-profiles to enhance the diversity of search results.
- The proposed approach is very competitive compared to explicit diversification approaches.
- We proposed a simple yet effective solution for when the number of sub-profiles is large.

Thanks for your attention!
Questions?