Profile Diversity for Recommendation

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Outline

- 1. Recommendation for Scientific Data
 - Use case: botanic data (Pl@ntnet)
- 2. Profile Diversity
- 3. Distributed and Diversified Recommendation
- 4. Demo
- 5. Conclusion

On-Line Communities: Citizen Sciences Context*

- Accurate knowledge of plant identities, in different geographic localities is essential for:
 - agricultural development
 - plant diversity preservation
- Pl@ntnet project*:
 - Interactive plant indentification and
 - Collaborative Information Systems
- Big Data production



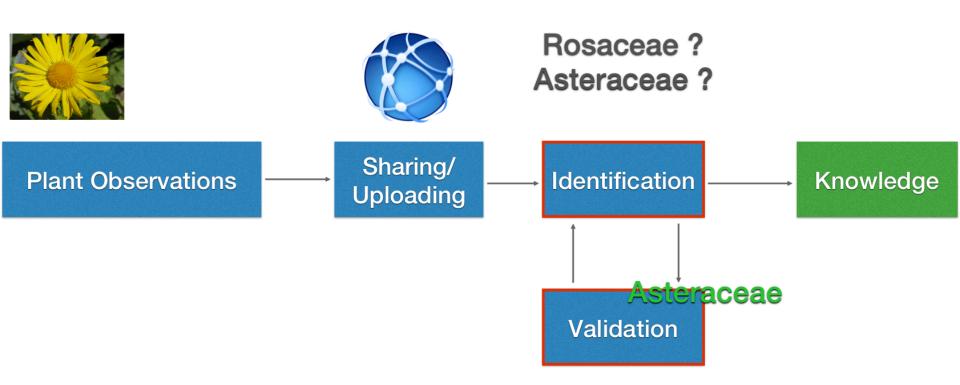
^{*}http://www.plantnet-project.org/page:projet?langue=en

Context

- Large scale of users with different goals, profiles and interests
- Quering such data requires careful method to be able to gain access to useful information.
- Ex: Grapevine plants identification and preservation, requires considerable knowledge of the potential of different grape varieties and their specific morphological characters



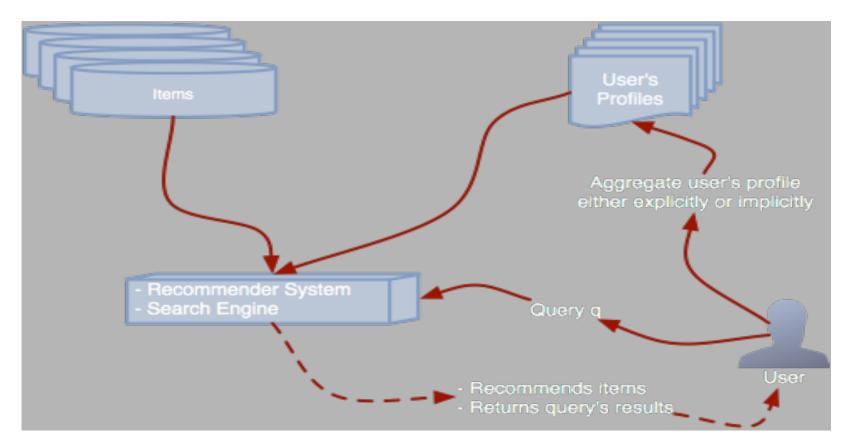
Plant Observation Process



General Problem:

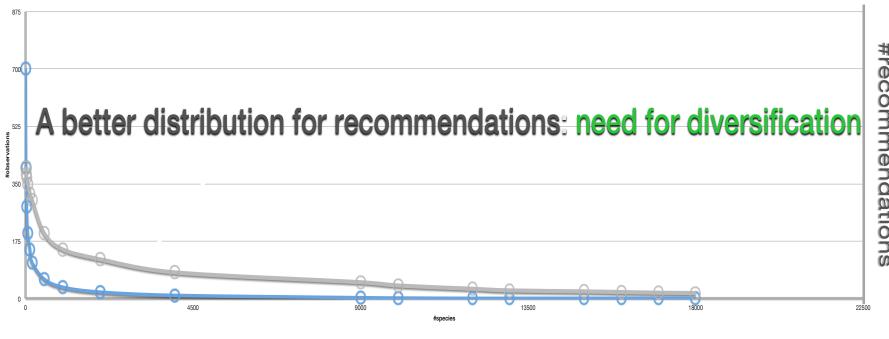
Retrieve/recommend the k most diverse plant observations given a query (e.g grapewine)?

Search and Recommendation



Seek to recommend items given a query

However typically recommendation methods tend to propose redondant or too popular items, because normally the **relevance** of an item wrt to query is based on **similarity or popularity**.



A few plants represents the majority of the observations

The majority of the plants are rarely observed

[1] JOLY, Alexis, GOËAU, Hervé, BONNET, Pierre, et al. Interactive plant identification based on social image data. Ecological Informatics, 2013. [2] http://www.bugwood.org, 2014

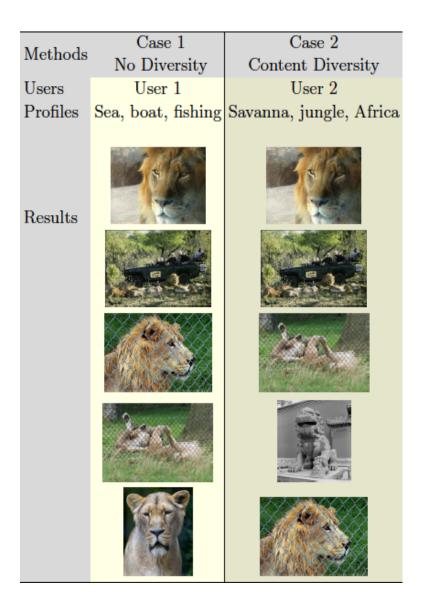
Diversification in Search in Search an Recommendation

- <u>Recall</u> in information retrieval is the fraction of the items that are relevant to the query that are successfully retrieved.
- Given query q and the candidates items for q, the diversity is mesured by mesuring the distance of among selected items in the response.





Use Case with Delicious



Content Diversity [Angel, Sigmod 2011] has been used with promising results However it presents low diversity gains due to:

- -poor content description
- semantic ambiguity

Ex: Java Language x Java Island

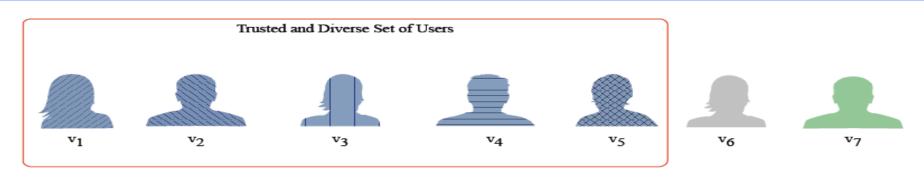
Profile Diversity*





- Users profiles are defined based on the items they share
- The relevancy takes into account similar and diversified users, wrt to the items they share.

With **profile diversity***, the recommended items, in addition to be relevant to the query, and to the user profile, also take into account the diverse relevant users profiles and their items.





Search and Recommendation

q = asteraceae		
Un-diversified	Profile Diversity	
Élodie Dujardin	Marie Dupont	Pierre Durand
**	7	

Table I: Search and recommendation example with profile diversity.

ASTERACEAE, Leucanthemum adustum - Montpellier (34)
ASTERACEAE, Leucanthemum atratum - Montpellier (34)
ASTERACEAE, Cichorium intybus - Montpellier (34)

(a) Élodie's Profile

ASTERACEAE, Cirsium vulgare - Palavas (34)
ASTERACEAE, Cichorium intybus - Paris (75)
ASTERACEAE, Crepis vesicaria - Montpellier (34)

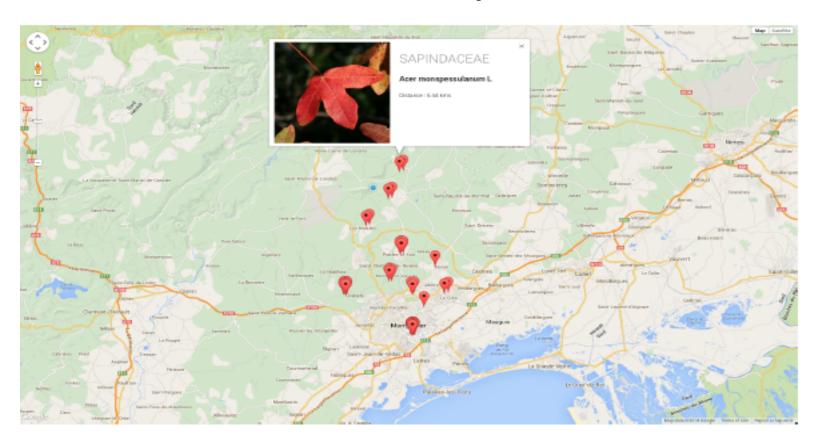
(b) Marie's profile.

RHAMNACEAE, Ramnus alaternus L. - Montpellier (34)
ASTERACEAE, Echinops ritro L. - Montpellier (34)
ASTERACEAE, Senecio doronicum - Montpellier (34)

(c) Pierre's profile.

Figure 2: User profiles.

Diversity of Plants in a Geographical Locality



Search and Recommendation Model

$$score(it_i, u, q) = rel(it, q) \times div_c(it_i | \{it_1, ..., it_{i-1}\}) \times div_p(u_{it_i} | u_{\{it_1, ..., it_{i-1}\}})$$
Relevance Content Diversity Profile Diversity

$$div_p(u_{it_i}|u_{\{it_1,...,it_{i-1}\}}) = \frac{1}{N} \times \sum_{v_n \in u_{it_i}} rel(u,v_n,q) \times \prod_{v_m \in u_{\{it_1,...,it_{i-1}\}}} 1 - red(v_n|v_m)$$

Profile Diversity

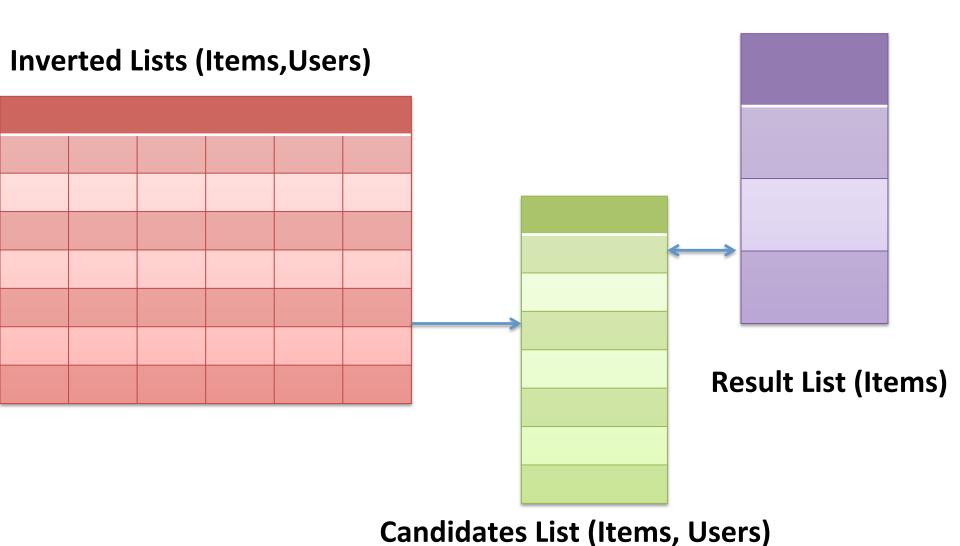
User Relevance

User Diversity

Good Compromise between Relevancy and Diversity

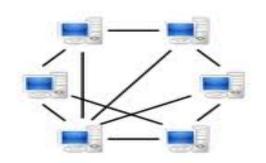
[Servajean et al. WWW 14]

Search and Diversified Recommendation



Distributed Recommendation for Citizen Sciences

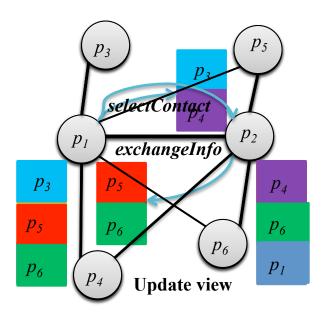
- Single users
 - Users keeps observations in their own workspace
 - Scales-up (more network traffic)
 - Better for privacy
- Multi-Sites center (local clouds)
 - Users keeps observations in the local site server
- Hybrid





Distributed Search and Recommendation Model

- Model: G =(U,I,E), U = users nodes, I = items, E = edges among users
- User profiles are defined based on the items they share
- **User network (U-net):** refers to the <u>cluster</u> of relevant users profiles a users *u* is aware of through epidemic protocols.
- An edge exists between a u and v, if v is in u's U-net.
- When a **keyword query** is submitted, it is recursively redirected to the **Top-n** similar users in the **U-net**, until TTL.
 - Each involved user computes recommend the most relevant items.



Diversity to increase Coverage

Coverage

- probability of finding relevant users to provide relevant items for a given query
- depends on the clustering metric
- Clustering metric
 - similarity (e.g. cosinus, jaccard, etc).[Draidi 10, Xiao 2011, Isaila 12,
 Kermarrec 12]
 - at each exchange p_I discovers new users and computes: similarity(profile(p_I), new profiles(p_i))
 - p_1 keeps only the most similar users p_i in its U-net
- Problem: Recall results are low, because a significant amount similar users are kept in similars users U-nets. How to increase the quality of the coverage?

Clustering Useful Users*

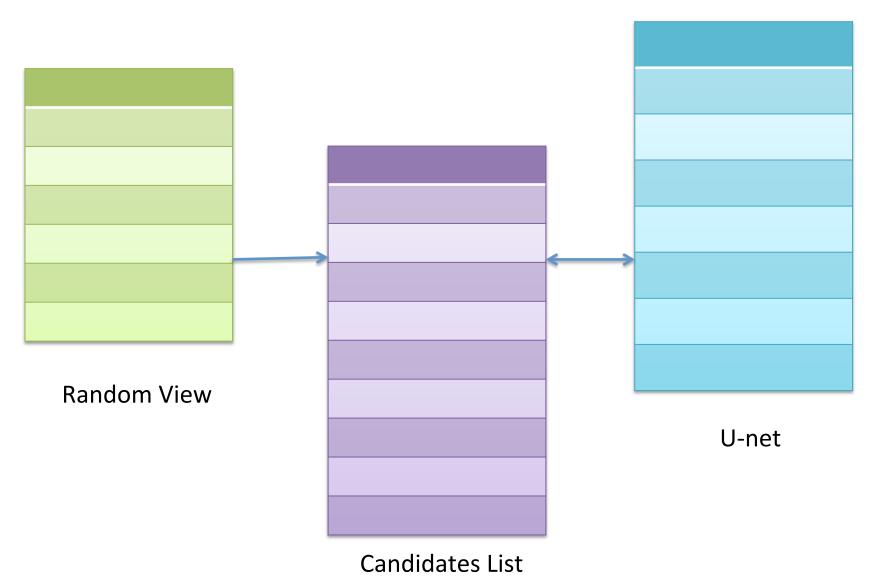
- What if we exploit usefulness instead of similarity?
 - The usefulness of new user profile is determined based on the set of users profiles previously clustered in U-Net.
 - At each epidemic, exchange, u_1 discovers new peers and computes usefulness(U-net, profile(u_1), new profiles(u_i)),

and keep only useful peers with best scores in u_i in U-net.

$$usefulness(v_j|v_{j+1},...,v_n) = rel(v_j) \times \prod_{i \in j+1,...,n} (1 - red(v_j,v_i))$$

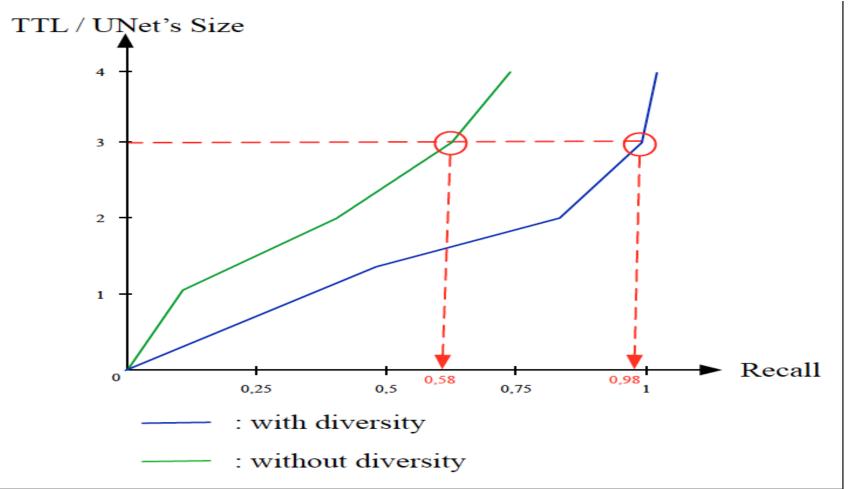
*[Servajean et al. Globe 14]

Dynamic Clustering Algorithm for Useful Users

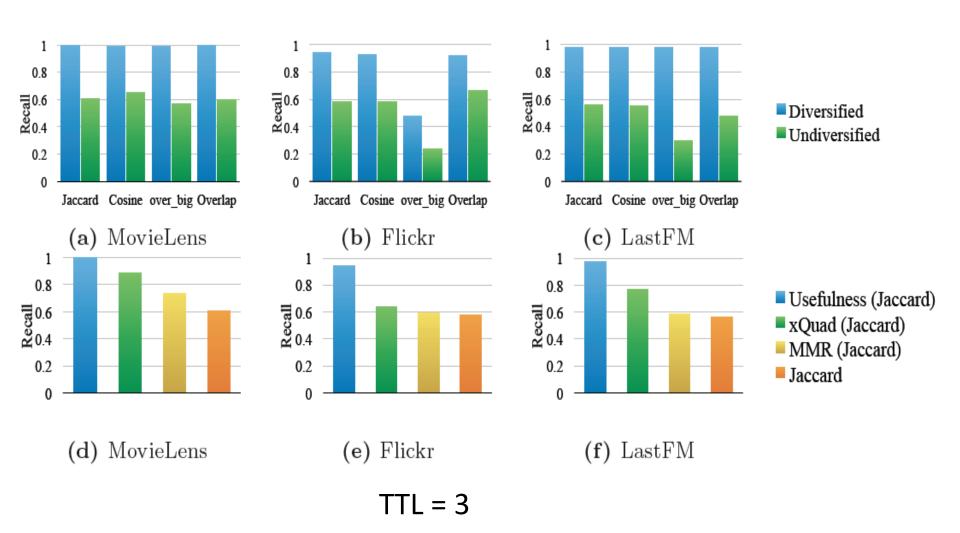


Experimental Results

Gains in Recall

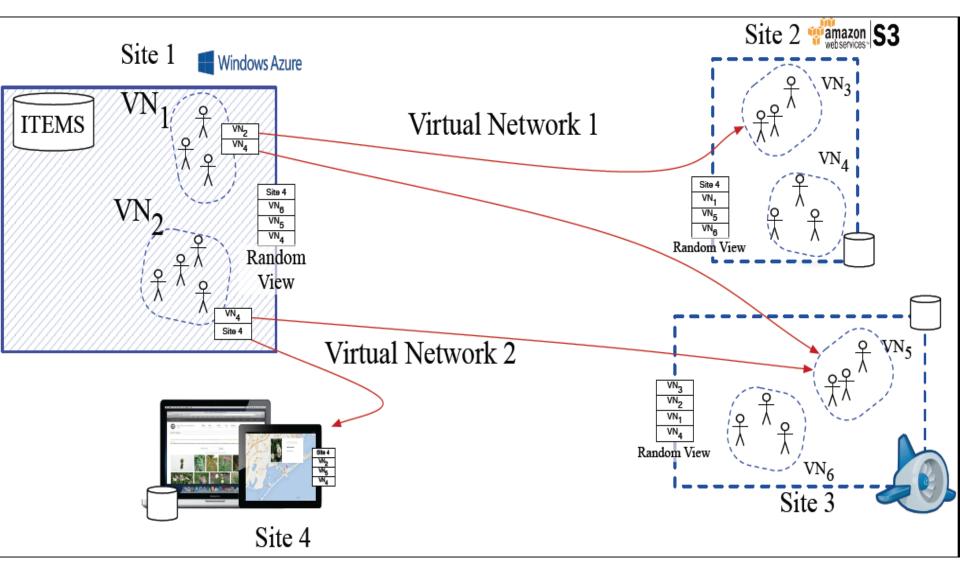


Experimental Results



For details: [Servajean et al. Globe 14]

Diversity in Multi-Site Recommendation*



[Servajean et al. BDA 14]



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