Stuart E. Middleton

IT Innovation Dept of Electronics and Computer Science University of Southampton United Kingdom

Email: sem@it-innovation.soton.ac.uk Web: http://www.ecs.soton.ac.uk/~sem99r



Recommender systems

- User profiling in recommender systems
- Ontological user profiling
- Experimentation
- Future work



Recommender systems

WWW information overload **Recommender** systems Collaborative filters (several commercial examples) **Content-based filters** Hybrid filters Knowledge acquisition Monitoring should be unobtrusive Explicit feedback should be optional Positive examples easier to acquire than negative examples Problem domains Books, Music, News, Web pages, E-commerce... On-line academic research paper recommendation

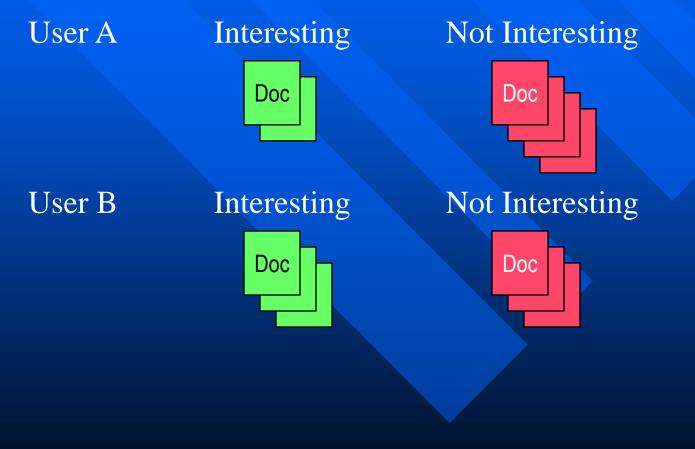


User profiling in recommender systems

Binary class representation 'Interesting' and 'not interesting' examples Machine learning classifies new information



User profiling in recommender systems
 Binary class profile representation





User profiling in recommender systems

Binary class profile representation

'Interesting' and 'not interesting' examples
Machine learning classifies new information

Multi-class profile representation

Classes represent domain categories
Examples can be shared between users



User profiling in recommender systems

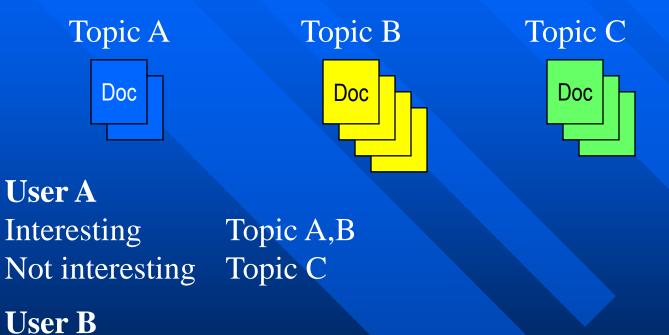
Topic B,C

Topic A

Interesting

Not interesting

Multi-class profile representation





User profiling in recommender systems

Binary class profile representation

'Interesting' and 'not interesting' examples
Machine learning classifies new information

Multi-class profile representation

Classes represent domain categories
Examples of classes can be shared

Knowledge-based profile representation

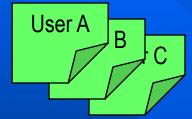
Interviews and questionnaires
Asserted facts in a knowledge base



User profiling in recommender systems

Knowledge-based profile representation

Questionnaires



User A

- User A -> (interested, topic A) (interested, topic B)
- User A -> (not interested, topic C)

User B

User B -> (interested,topic B) (interested, topic C) User B -> (not interested, topic A)



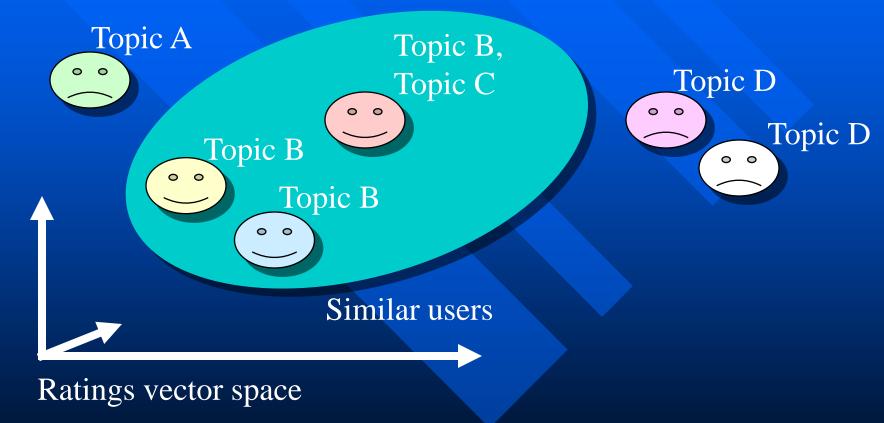
User profiling in recommender systems

Binary class profile representation 'Interesting' and 'not interesting' examples Machine learning classifies new information Multi-class profile representation Classes represent domain categories Examples of classes can be shared Knowledge-based profile representation Interviews and questionnaires Asserted facts in a knowledge based Ratings-based profile representation **Relevance** ratings Statistical techniques find useful correlations



• User profiling in recommender systems

Ratings-based profile representation





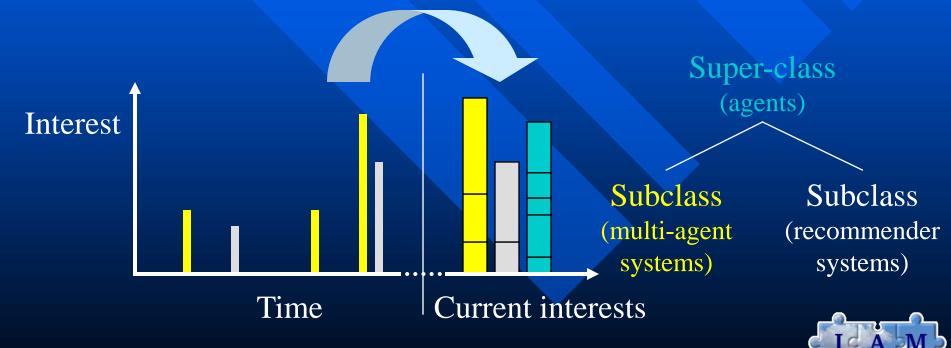
Ontological user profiling

Ontological profiling Multi-class profile representation Profile topics match ontology classes Ontology contains relationships between classes Inference to assist profiling Infer related topics of probable interest Profile bootstrapping External ontological knowledge can bootstrap profiles Overcome the cold-start problem Profile visualization Ontological terms understood by users Visualize profiles and acquire direct feedback on them



Experimentation

Profile inference [Quickstep] Time/Interest profile Is-a hierarchy infers topic interest in super-classes Time decay function biases towards recent interests



Ontological user profiling seminar 1.10.2002

Experimentation

Profile inference [Quickstep] Time/Interest profile Is-a hierarchy infers topic interest in super-classes Time decay function biases towards recent interests

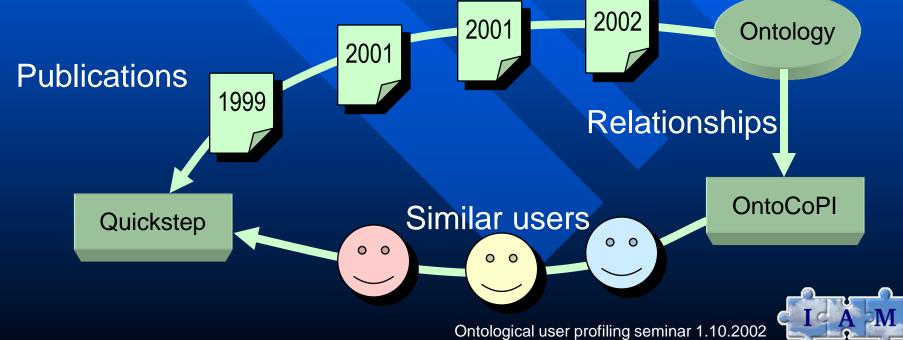
	Recommendation accuracy	Good topics
Ontological	11%	97%
Unstructured	9%	90%
	2% better	7% better





Experimentation

Bootstrapping [Quickstep, OntoCoPI] External ontology Publications and personnel data (AKT ontology) New-system cold-start New-user cold-start



Experimentation

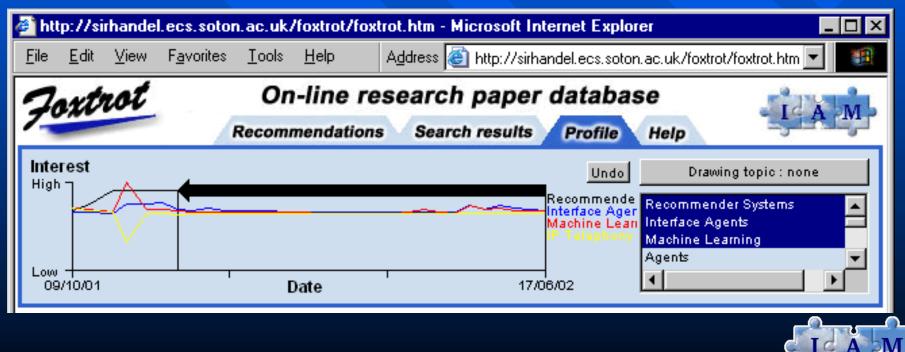
Bootstrapping [Quickstep, OntoCoPI] External ontology Publications and personnel data (AKT ontology) New-system cold-start New-user cold-start

	Profile precision	Profile error rate
New-system	35%	6%
New-user	84%	55%



Experimentation

Profile visualization [Foxtrot] Time/Interest visualized Users could draw their own profiles on the graph Profile feedback thus acquired



Experimentation

Profile visualization [Foxtrot] Time/Interest visualized Users could draw their own profiles on the graph Profile feedback thus acquired Recommendation Profile accuracy accuracy 20-35% **Profile feedback** 2-5% **Relevance feedback** 1% 18-25% 10% better 2-5% better



10% = 1 per set

Future work

More ontological relationships Project membership, Related research areas, Common technology, etc. Task profiling Users often multi-task Task modelling will allow more than just general profiles Agent metaphor Multi-agent system with other users agents Trade personal information Buy in external ontological information



Conclusions

Ontological user profiling works Couples inference and machine learning techniques Allows use of external ontologies Profiles are understood by users Applicable to more than just recommender systems Other domains Other technologies

