

# Content-based recommendations via DBpedia and Freebase: a case study in the music domain

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# Introduction

- **Content-based Recommender Systems** base on the notion of similarity between items: obviously they need content
- **Web of Data** is an opportunity to foster knowledge-intensive applications
- Does the selection of the underlying knowledge graph affect the results of a recommendation engine?  
Experiments with **DBpedia** and **Freebase**
- Evaluation in terms of **accuracy, sales diversity** and **novelty**

# Recommender Systems

**Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be of use to a user.**

[F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, editors. **Recommender Systems Handbook**. Springer, 2011.]

lost.fm Music search Music Listen Events Charts Originals pablaturi

explore search movielens 6 ☆ ▲ p.tomeo87@gmail.com

top picks see more

MovieLens recommends these movies

The Shawshank Red	Schindler's List	Inception	About Time	Memento	Better Off Dead...	Drowning by Numbe	The Sixth Sense
1994 R 142 min	1993 R 195 min	2010 PG-13 148 min	2013 R 123 min	2000 R 113 min	1985 PG 97 min	1988 R 118 min	1999 PG-13 107 min

Recommended for you

- Il Teatro Degli Orrori**  
Similar to: [Ministri](#), [Le Luci Della...](#), [Caparezza](#)
- Perturbazione**  
Similar to: [Le Luci Della...](#)
- Marta Sui Tubi**  
Similar to: [Le Luci Della...](#), [Ministri](#)

Seeedit all

# Recommender Systems

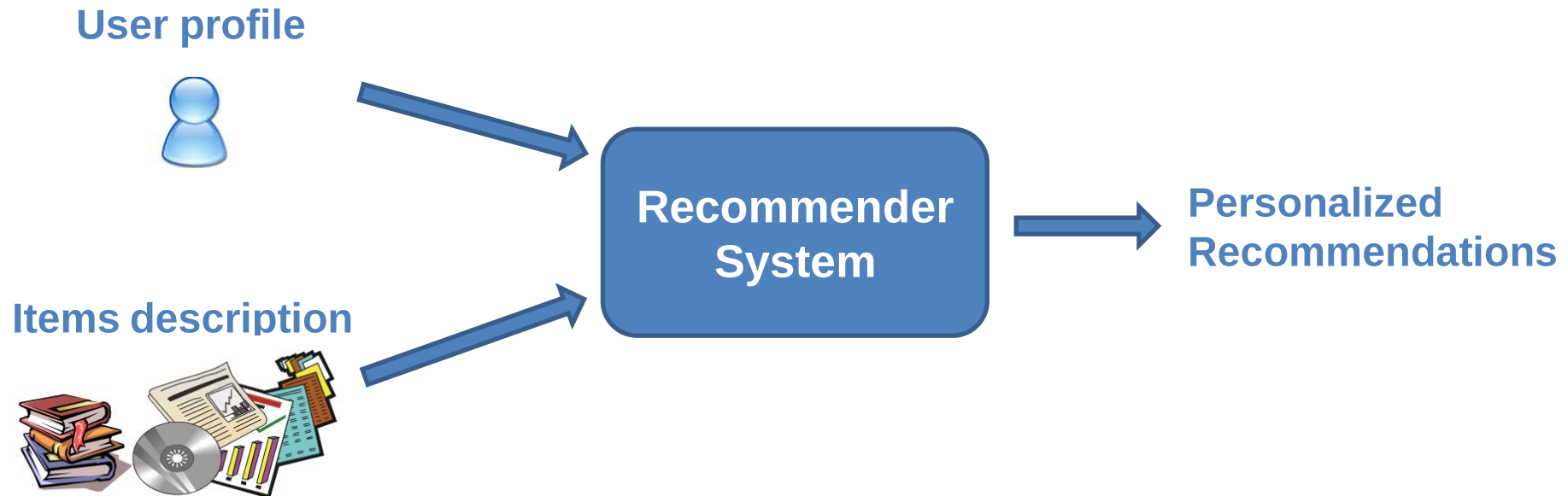
***Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be of use to a user.***

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- **Content-based filtering**
- Collaborative filtering

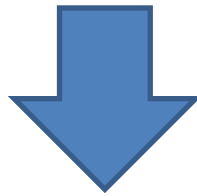
# Content-based RSs

*Content-based* RSs try to recommend items similar to those a given user has liked in the past. The recommendations are based upon a description of the items and a profile of the user's interests



# Main drawback: Limited Content Analysis

Quality of CB recommendations depends on quantity and quality of the features explicitly associated to the items

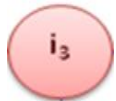


**We need domain knowledge  
and rich descriptions of the items**

P. Lops, M. de Gemmis, G. Semeraro. **Content-based Recommender Systems: State of the Art and Trends**. In Recommender Systems Handbook: A Complete Guide for Research Scientists & Practitioners, Chapter 3, Springer, 2010.

# Enrich Data model

*Catalog Items*



*Knowledge Graph*

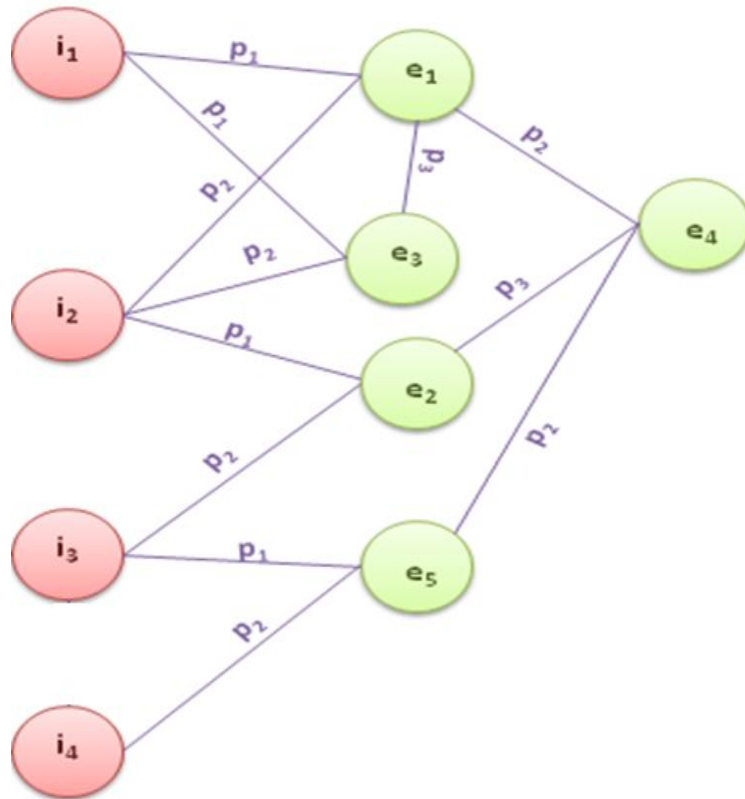


- 1 – Mapping (Entity linking)
- 2 – Subgraph extraction

# Enrich Data model

*Catalog Items*

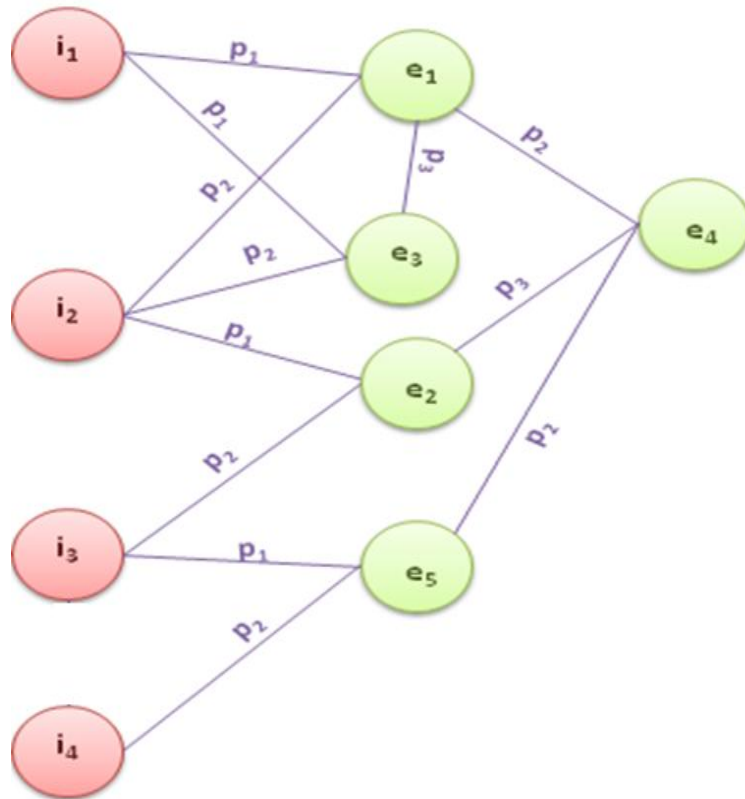
*Knowledge Graph*





# Feature-based Semantic Similarity

- 1 - describe resources as feature sets
- 2 - perform similarity calculation on them



one-hop features

i<sub>1</sub> -> {e<sub>1</sub>, e<sub>3</sub>}    i<sub>3</sub> -> {e<sub>2</sub>, e<sub>5</sub>}

i<sub>2</sub> -> {e<sub>1</sub>, e<sub>3</sub>}    i<sub>4</sub> -> {e<sub>5</sub>}

# Feature-based Semantic Similarity Metrics

## GbkSim

Graph-based Kernel

$$GbkSim(\alpha, \beta) = \frac{\sum_{i=1}^n a_i \times b_i}{\sqrt{\sum_{i=1}^n (a_i)^2} \times \sqrt{\sum_{i=1}^n (b_i)^2}}$$

## VsmSim

Vector Space Model

$$VsmSim_p(\alpha, \beta) = \frac{\sum_{i=1}^n a_{i,p} \times b_{i,p}}{\sqrt{\sum_{i=1}^n (a_{i,p})^2} \times \sqrt{\sum_{i=1}^n (b_{i,p})^2}}$$

## FuzzySim

Fuzzy Semantic

$$FuzzySim(\alpha, \beta) = aggr(S_1, S_2, \dots, S_n) = \sum_{j=1}^n b_j \cdot \varphi_j(m)$$

## Jaccard

Jaccard's index

$$Jaccard(\alpha, \beta) = \frac{|N_d(\alpha) \cap N_d(\beta)|}{|N_d(\alpha) \cup N_d(\beta)|}$$

# Content-based Recommender System

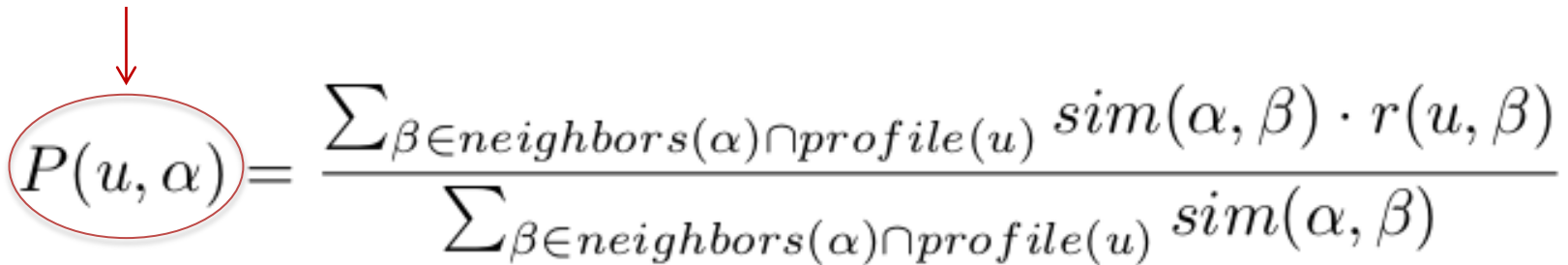
k-nearest neighbors algorithm

$$P(u, \alpha) = \frac{\sum_{\beta \in neighbors(\alpha) \cap profile(u)} sim(\alpha, \beta) \cdot r(u, \beta)}{\sum_{\beta \in neighbors(\alpha) \cap profile(u)} sim(\alpha, \beta)}$$

# Content-based Recommender System

## k-nearest neighbors algorithm

Probability that user  $u$  likes  $\alpha$


$$P(u, \alpha) = \frac{\sum_{\beta \in neighbors(\alpha) \cap profile(u)} sim(\alpha, \beta) \cdot r(u, \beta)}{\sum_{\beta \in neighbors(\alpha) \cap profile(u)} sim(\alpha, \beta)}$$

# Content-based Recommender System

## k-nearest neighbors algorithm

Computed with one of the similarity metrics introduced before

Probability that user  $u$  likes  $\alpha$

$$P(u, \alpha) = \frac{\sum_{\beta \in neighbors(\alpha) \cap profile(u)} sim(\alpha, \beta) \cdot r(u, \beta)}{\sum_{\beta \in neighbors(\alpha) \cap profile(u)} sim(\alpha, \beta)}$$

# Evaluation

# Dataset

Subset of Last.fm hetrec-2011



- 1000 most popular artists and bands
- cold users removal ( $\#ratings < avg$ )
- split 80-20% for each user

# Mapping

## With DBpedia

<http://sisinflab.poliba.it/semanticweb/lod/recsys/datasets/>

## With Freebase exploiting *owl:sameAs* in DBpedia

## Selection of 20% most popular properties from both

	DBpedia Ontology	Freebase
# incoming properties	24	220
# outgoing properties	18	280



# Evaluation Metrics

<b><u>Accuracy</u></b>	Precision Recall
<b><u>Sales Diversity</u></b>	Catalog coverage Entropy and Gini Index (Distribution)
<b><u>Novelty</u></b>	% Long-tail

# Evaluation Setting

## Four independent settings

one-hop	inbound and outbound features
	only outbound features

two-hop	inbound and outbound features
	only outbound features

## Top-N varying N from 1 to 50

# DBpedia vs Freebase

## ACCURACY

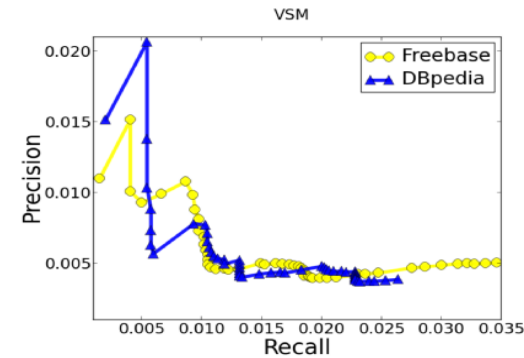
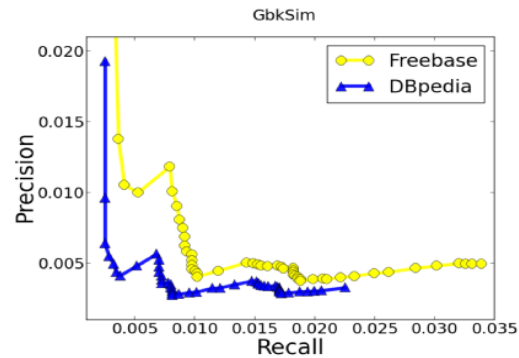
Freebase beats DBpedia  
except using VSM-Sim

## SALES DIVERSITY

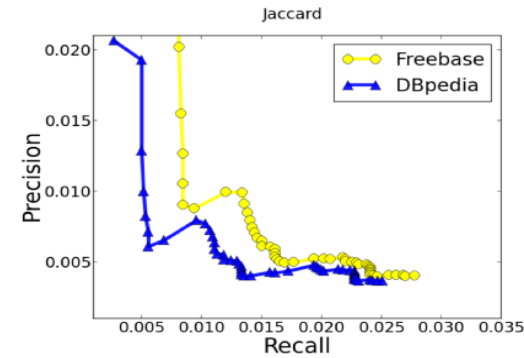
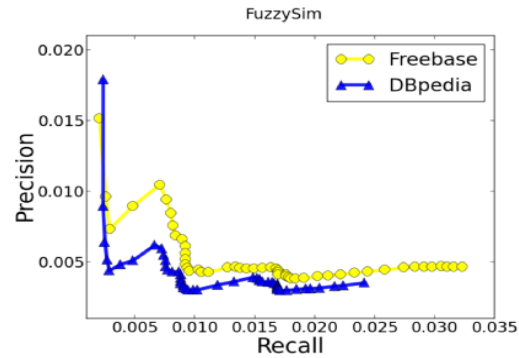
Freebase gives better coverage  
DBpedia better distribution

## NOVELTY

DBpedia beats Freebase



(a)



(b)

*One-hop and two-hop configurations obtain similar trends*

*Using both inbound and outbound properties gives better results*

# DBpedia vs Freebase

		Precision	Recall	Coverage	Entropy	Gini	%Long-tail
GbkSim	Top-10	Freebase	Freebase	Freebase	DBpedia	DBpedia	DBpedia
	Top-20	Freebase	Freebase	Freebase	DBpedia	DBpedia	DBpedia
	Top-30	Freebase	Freebase	Freebase	DBpedia	DBpedia	DBpedia
VsmSim	Top-10	Freebase	Freebase	Freebase	DBpedia	DBpedia	DBpedia
	Top-20	Freebase	DBpedia	DBpedia	DBpedia	DBpedia	DBpedia
	Top-30	Freebase	DBpedia	DBpedia	DBpedia	DBpedia	DBpedia
FuzzySim	Top-10	Freebase	Freebase	Freebase	DBpedia	DBpedia	DBpedia
	Top-20	Freebase	Freebase	Freebase	DBpedia	DBpedia	DBpedia
	Top-30	Freebase	Freebase	Freebase	DBpedia	DBpedia	DBpedia
Jaccard	Top-10	Freebase	Freebase	Freebase	Freebase	Freebase	DBpedia
	Top-20	Freebase	Freebase	Freebase	Freebase	DBpedia	DBpedia
	Top-30	Freebase	Freebase	Freebase	Freebase	Freebase	DBpedia

# One-hop vs two-hop

			Precision	Recall	Coverage	Entropy	Gini	%Long-tail
GbkSim	Top-10	Freebase	+	+	-	+	+	-
		DBpedia	-	-	+	-	-	-
	Top-20	Freebase	+	+	-	+	+	+
DBpedia		+	+	+	+	+	~	
Top-30	Freebase	+	+	-	+	+	~	
	DBpedia	+	+	+	~	+	-	
VsmSim	Top-10	Freebase	-	-	+	+	+	-
		DBpedia	-	-	+	+	+	-
	Top-20	Freebase	-	-	+	+	+	-
DBpedia		-	-	+	+	+	-	
Top-30	Freebase	-	-	+	+	+	-	
	DBpedia	-	-	+	+	-	-	
FuzzySim	Top-10	Freebase	-	-	-	+	+	-
		DBpedia	+	+	+	-	~	~
	Top-20	Freebase	+	+	~	+	+	-
DBpedia		+	+	+	~	+	+	
Top-30	Freebase	+	+	-	+	+	-	
	DBpedia	+	+	+	+	+	~	
Jaccard	Top-10	Freebase	-	-	+	+	~	+
		DBpedia	-	-	+	+	+	-
	Top-20	Freebase	-	-	+	-	-	-
DBpedia		-	-	+	+	+	-	
Top-30	Freebase	~	~	+	-	-	-	
	DBpedia	-	-	+	+	+	~	

# Discussion

Freebase brings higher accuracy and lower novelty  
it is richer and has a strong crowd-sourced nature

DBpedia gives better distribution (Gini and Entropy)  
but the coverage it provides is too low

Exploring up to two hops improves coverage and distribution  
but penalize novelty  
increase of connections among items but in particular  
among the most popular

# Conclusion

Comparison between DBpedia and Freebase for content-based recommendations in terms of Accuracy, Sales Diversity and Novelty

We showed that the choice of the right dataset might affect the performance of the system

# Future work

Same experiments using graph-based similarity metrics

Automated feature selection instead of most popular

## Q & A

Thanks for your  
attention!