UNIVERSITÀ DEGLI STUDI DI BARI
Facoltà di Scienze Matematiche, Fisiche e Naturali
Dipartimento di Informatica

Personalization: Learning User Profiles

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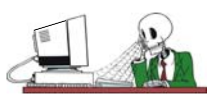
The general problem…

- Huge number of Web sites and volume of on-line data *(information overloading)*
  - Users overloaded with a large amount of information
  - Difficulty in finding relevant documents

- Consequence: searching may be time consuming!
  - Demand for automated user support
  - Need for intelligent solutions able to support users in finding documents according to their interests



...and problems in e-commerce

- Critical aspect in e-commerce
  - Millions of products for sale
  - Customers overloaded with a large amount of product information
  - Searching may be time consuming!

- Need for personalized solutions able to support customers in retrieving relevant products

User interests useful to achieve personalization

User Profiling

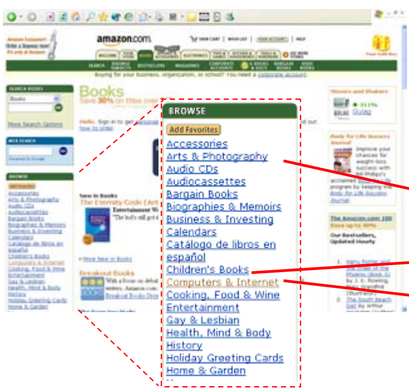
Personalization: User Profiles

USER PROFILE: RAPPRESENTAZIONE STRUTTURATA DEGLI INTERESSI E DELLE PREFERENZE DELL'UTENTE

- Questionnaire-based personalization
  - La definizione manuale di profili è un processo noioso per gli utenti
  - Gli utenti non aggiornano i loro profili
  - La personalizzazione potrebbe basarsi su dati non affidabili

Induzione di modelli di preferenze:
SUPERVISED MACHINE LEARNING

User Preferences: categories



Preferences

Arts & Photography
Children's books
Computers & Internet

User Preferences: items

Preferences

Arts & Photography
Children's books
Computers & Internet

content-based recommendations by learning from TEXT

Book description at Amazon.com

The system

ITem Recommender (ITR)

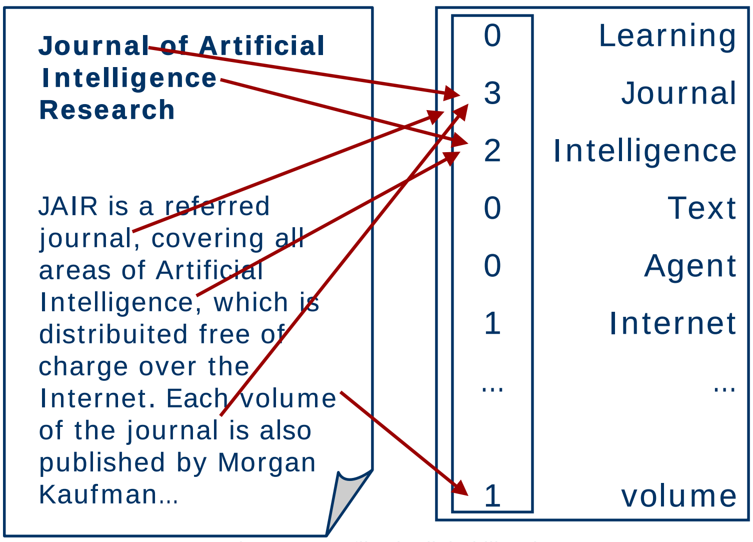
- Content-based item recommending on the basis of rates given by users
- Naïve Bayes text classification to assign a score (level of interest) to items according to the user preferences
  - ✓ Performance comparable to more complex algorithms
  - ✓ Increasing popularity in text classification
- Result: user profile containing the probabilistic model (words + frequencies) learned by the classifier

Document Representation

Molti metodi di text learning usano la reppresentazione *bag-of-words*

- Valore booleano che indica la presenza di una parola
- Frequenza della parola all'interno del documento
- Informazione aggiuntiva (word position, n-grams,...)

Document Representation: bag of words



Bag of words and slots

Journal of Artificial Intelligence Research

JAIR is a referred journal, covering all areas of Artificial Intelligence, which is distribuited free of charge over the Internet. Each volume of the journal is also published by Morgan Kaufman...

1	Journal
1	Intelligence
1	Artificial
1	Research

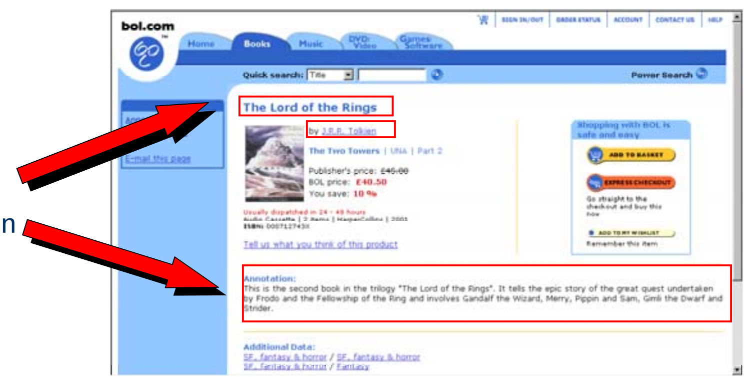
Slot "title"

2	Journal
1	Intelligence
1	Artificial
...	...

Slot "abstract"

Book Information at uk.bol.com

Book description



Utilizzo di tecniche basate sul contenuto: applicazione di metodi di text categorization alla descrizione testuale dei libri

Instance description

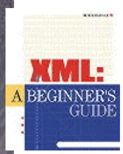
Book recommending on the Web

User Rates: 1-10

Instance (book)

- Title → {lord:1, ring:1}
- Authors → {j_tolkien:1}
- Annotation → {frodo:1, lord:1, ring:2,…}

BOW Extraction



{begin: 1, xml: 2, guid: 1, buzzword: 1, internet: 1, matur: 1, technolog: 1, power: 1, real: 1, world: 1, applic: 1, manag: 1, displa: 1, organ: 1 …}

BAG OF WORDS

TEXTUAL ANNOTATION

tokenization → Stopwords elimination → Stemming → Word Count

Bayes' Theorem

$$P(h \mid D) = \frac{P(D \mid h)P(h)}{P(D)}$$

$$h \in H$$

D: training data

h: hypothesis from the space H

Bayesian Learning

The *learner* considers a set H of candidate hypotheses and tries to find the most probable hypothesis by taking into account the observed data D

Maximum A Posteriori (MAP) hypothesis

$$\begin{aligned} h_{MAP} &\equiv \operatorname{argmax} P(h \mid D) \\ &= \operatorname{argmax} \frac{P(D \mid h)P(h)}{P(D)} \\ &= \operatorname{argmax} P(D \mid h)P(h) \end{aligned}$$

$$h \in H$$

Bayesian Learning

TEXT CLASSIFICATION

H={“user-likes”, “user-dislikes”}

Each instance (document) is represented by n attributes (keywords) $\{a_1, a_2, \ldots, a_n\}$

$$h_{MAP} = \operatorname{argmax} P(h_j \mid a_1, a_2, \ldots, a_n)$$

$$h_{MAP} = \operatorname{argmax} \frac{P(a_1, a_2, \ldots, a_n \mid h_j) P(h_j)}{P(a_1, a_2, \ldots, a_n)}$$

$$h_{MAP} = \operatorname{argmax} P(a_1, a_2, \ldots, a_n \mid h_j) P(h_j)$$

$$h_j \in H$$

Bayesian Learning

Indipendence assumption

Naive Bayes Classifier :

$$h_{MAP} = \operatorname{argmax} \boxed{P(h_j)} \prod_{i=1}^{n} \boxed{P(a_i \mid h_j)}$$

$$h_j \in H$$

The probabilities are estimated from data

Classification Phase

- Ogni libro è un vettore di bag of words (BOW), una BOW per ogni slot
- Ogni slot è indipendente dagli altri

Title: {lord :1, ring :1}

Authors: {j_tolkien :1}

Annotation: {epic :4, novel :2, lord :2, ring :3, elf :2,…}

Le probabilità a posteriori per un libro d_i sono così calcolate:

$$P(c_j \mid d_i) = \frac{\boxed{P(c_j)}}{P(d_i)} \prod_{m=1}^{|S|} \prod_{k=1}^{|b_{im}|} \boxed{P(t_k \mid c_j, s_m)^{n_{kim}}}$$

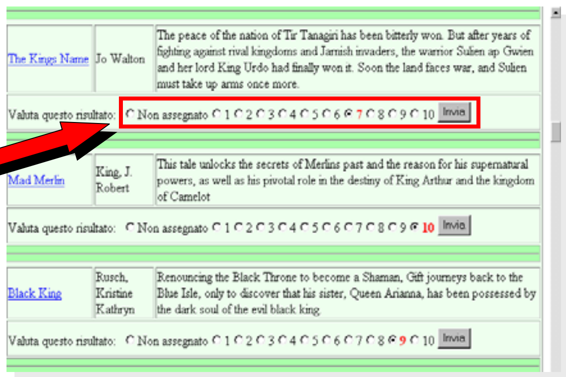
$S = \{s_1, s_2, \ldots, s_{|S|}\}$ è il set degli slots

b_{im} è la BOW nello slot s_m dell'istanza d_i

t_k è la k^{ma} word (che occorre n_{kim} volte nella BOW b_{im})

Acquisizione voti

Ogni utente giudica un set di libri di training in accordo con i suoi gusti, esprimendo un voto da 1 a 10



Sulla base dei giudizi dell'utente, il sistema apprende le sue preferenze su un particolare tipo di documenti in merito al topic di ricerca

Training

- $C = \{c_+, c_-\}$
  - c_+ likes rates 6-10
  - c_- dislikes rates 1-5

User rates r_i ➔ Weighted Instances

$$\boxed{\omega_+^i = \frac{r_i - 1}{9}} \quad \boxed{\omega_-^i = 1 - \omega_+^i}$$

$$\hat{P}(c_j) = \frac{\sum_{i=1}^{|TR|} \omega_j^i}{|TR|} \qquad \hat{P}(t_k \mid c_j, s_m) = \frac{O(t_k, c_j, s_m)}{L(c_j, s_m)}$$

training set cardinality

$$O(t_k, c_j, s_m) = \sum_{i=1}^{|TR|} \omega_j^i n_{kim} \qquad L(c_j, s_m) = \sum_{i=1}^{|TR|} \omega_j^i |b_{im}|$$

Example of ITR Profile

Profile for User: 117
Category: "Computer & Internet"

User ID: 117
Category: Computer & Internet
Class Priors: P(YES)= 0.6169947952025346 P(NO)= 0.3830052047974654

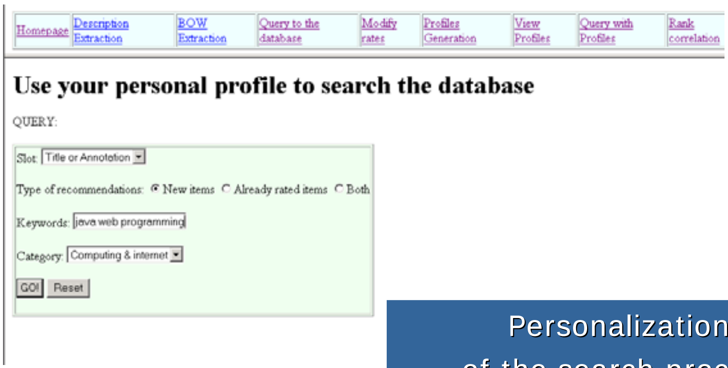
Slot: title

Feature	Strength
gam	2.4155710451915797
directx	2.2707400973131238
enterpris	1.6517008889069003
edit	1.5504909869753871
gem	1.4822827369488536
visu	1.4822827369488536
e-commerc	1.4822827369488534
...	
th	-2.303970881190259
sympos	-2.303970881190259
iee	-2.4741920310501264

The terms of the profile are ranked according to a *strength* measuring the discriminatory power of a word in classifying a book

$$strength(t_k, s_j) = \log\left(\frac{P(t_k \mid c_+, s_j)}{P(t_k \mid c_-, s_j)}\right)$$

Personalized Searching 1/2



Personalization
of the search process
using ITR PROFILES

Personalized Searching 2/2

Result set ranked by the classification value $P(c_+|d_i)$ computed by ITR

ITR & VIKEF

ITem Recommender (ITR) currently integrated in the *Personalization* component for *context-aware access*, *dissemination*, *visualization*, *knowledge sharing* and *collaboration* (WP6) within the 6FP Project IST-2003-507173 VIKEF

Virtual Information and Knowledge Environment Framework

Learning Preferences of Users Accessing Digital Libraries

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Overview

- ✓ Introduction
- ✓ User Profiling
- ✓ The COVAX project
- ✓ The Profile Extractor system in the COVAX architecture
  - ✓Extraction of User Profiles: the learning process
  - ✓Rules generation process
  - ✓Classification process
- ✓ Improve searching in COVAX

Introduction

- The World Wide Web has the potential to be the largest information source for Digital Libraries
- Limit of the Web: information overload problem
- Possible solution: personalization on the basis of the preferences of individual users

User Profiling

- *Personalization* within a Digital Library can occur along several directions:
  - *Explicit and implicit profiling*
  - *Static and dynamic profiling*
  - *Personal annotations*
  - *Person-dependent system behaviour*

The goal of the COVAX project

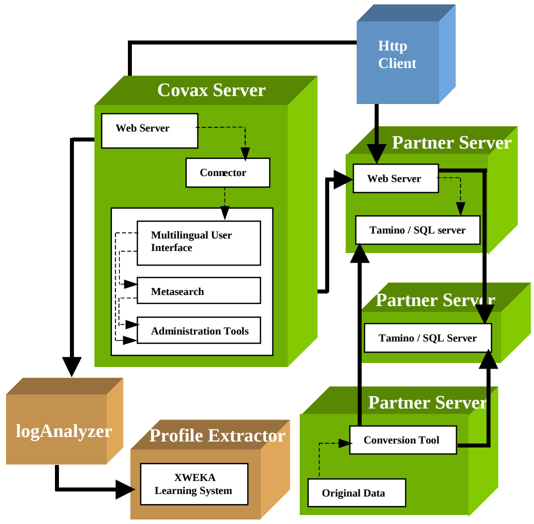
- **COVAX** (5FP IST-1999-11820) - **Contemporary Culture Virtual Archives in XML** - is a global system for search and retrieval, that increases accessibility via Internet to electronic resources regardless of their location.

HOW?

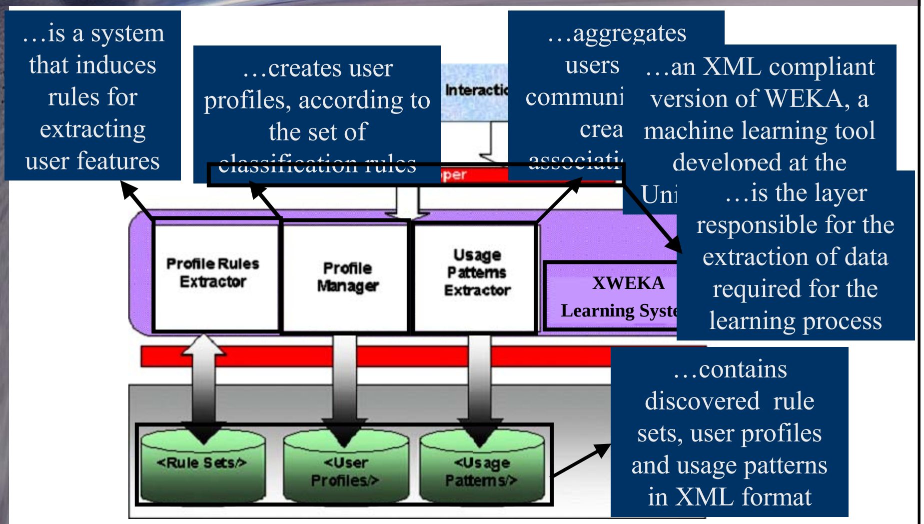
www.covax.org

- ✓ Using Web services for search and retrieval of documents
- ✓ Making accessible over the Internet existing documents in libraries, archives and museums
- ✓ Implementing standards to guarantee interoperability among systems

The Profile Extractor system in the COVAX architecture



The Profile Extractor architecture



Extraction of User Profiles: a ML process

Input: user instances classified in categories on the basis of preferences, abilities and goals.

Method: supervised learning techniques (decision trees, PART) provided by XWEKA.

Output: classification rules.

Profile Extractor: Input

Personal Data

- User_ID
- User_Type (citizen, researcher, scholar)

Interaction Data

- Number of Searches
  ∀ Collection and Database

Collection types:

Bibliographic (libraries)

Archive

Museum

Electronic_Text

Further personal data are not used for privacy problems

Databases:

Spanish libraries

ENEA scientific bibliographic

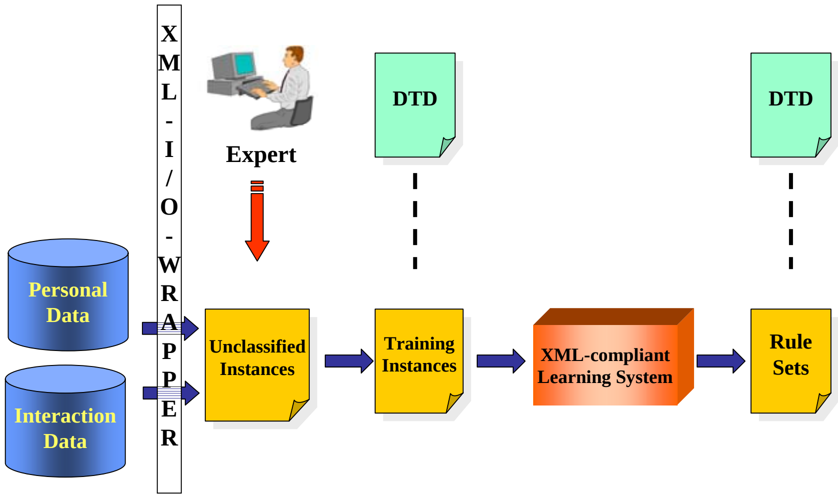
Naval Museum Computerized Library Museum Fronfeste Leather

Prix Multimedia Austria

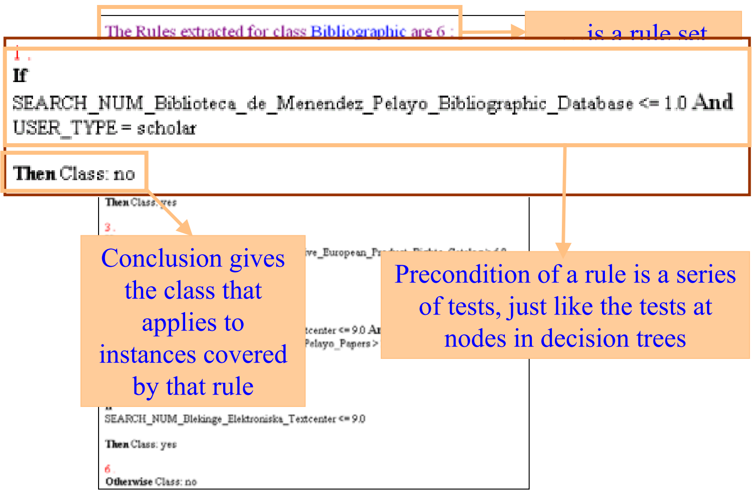
Blekinge Elektroniska Textcenter

etc…

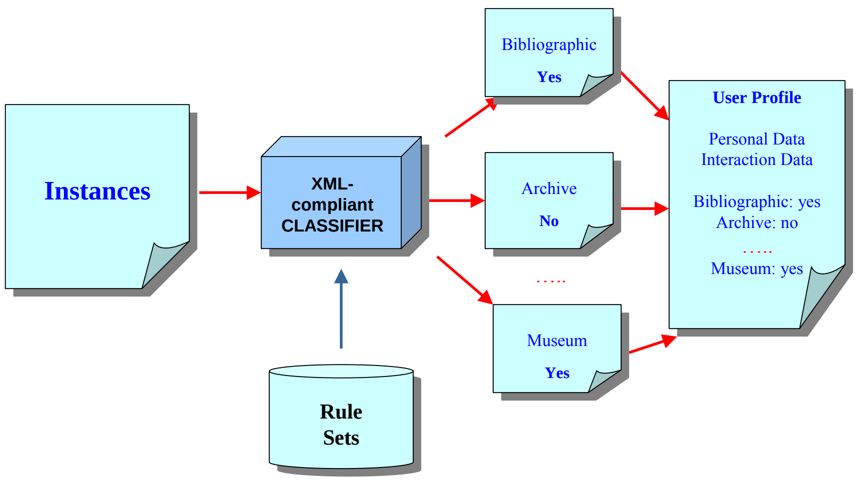
The classification rule generation process



Classification rules: an example

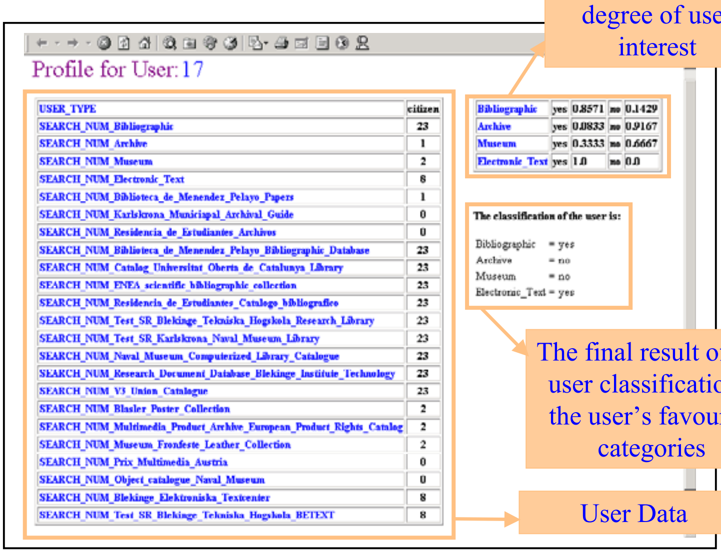


Classification process



User Profile: an example

The list of the 4 collections and the degree of user interest



Profile for User: 17

USER_TYPE	citizen
SEARCH_NUM_Bibliographic	23
SEARCH_NUM_Archive	1
SEARCH_NUM_Museum	2
SEARCH_NUM_Electronic_Text	8
SEARCH_NUM_Biblioteca_de_Menendez_Pelayo_Papers	1
SEARCH_NUM_Karlskrona_Municiapal_Archival_Guide	0
SEARCH_NUM_Residencia_de_Estudiantes_Archivos	0
SEARCH_NUM_Biblioteca_de_Menendez_Pelayo_Bibliographic_Database	23
SEARCH_NUM_Catalog_Universitat_Oberta_de_Catalunya_Library	23
SEARCH_NUM_ENEA_scientific_bibliographic_collection	23
SEARCH_NUM_Residencia_de_Estudiantes_Catalogo_bibliografico	23
SEARCH_NUM_Test_SR_Blekinge_Tekniska_Hogskola_Research_Library	23
SEARCH_NUM_Test_SR_Karlskrona_Naval_Museum_Library	23
SEARCH_NUM_Naval_Museum_Computerized_Library_Catalogue	23
SEARCH_NUM_Research_Document_Database_Blekinge_Institute_Technology	23
SEARCH_NUM_V3_Union_Catalogue	23
SEARCH_NUM_Blasler_Poster_Collection	2
SEARCH_NUM_Multimedia_Product_Archive_European_Product_Rights_Catalog	2
SEARCH_NUM_Museum_Fronfeste_Leather_Collection	2
SEARCH_NUM_Prix_Multimedia_Austria	0
SEARCH_NUM_Object_catalogue_Naval_Museum	0
SEARCH_NUM_Blekinge_Elektroniska_Textcenter	8
SEARCH_NUM_Test_SR_Blekinge_Tekniska_Hogskola_BETEXT	8

Bibliographic	yes	0.8571	no	0.1429
Archive	yes	0.0833	no	0.9167
Museum	yes	0.3333	no	0.6667
Electronic_Text	yes	1.0	no	0.0

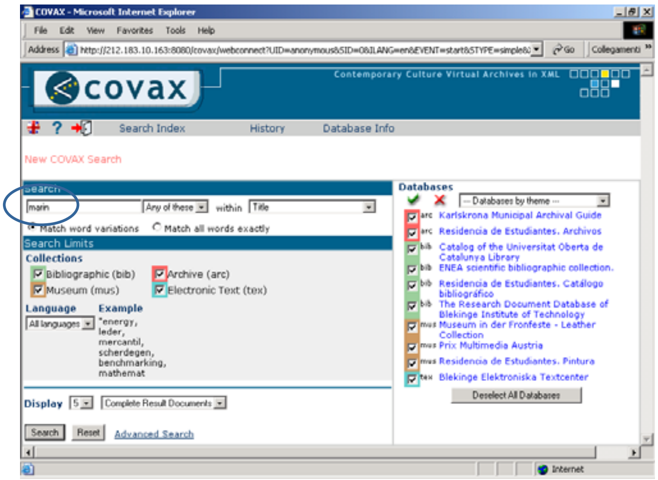
The classification of the user is:

Bibliographic = yes
Archive = no
Museum = no
Electronic_Text = yes

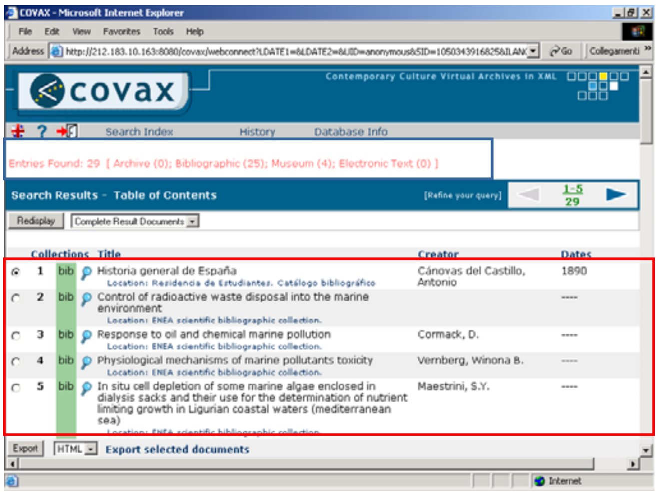
The final result of the user classification - the user's favourite categories

User Data

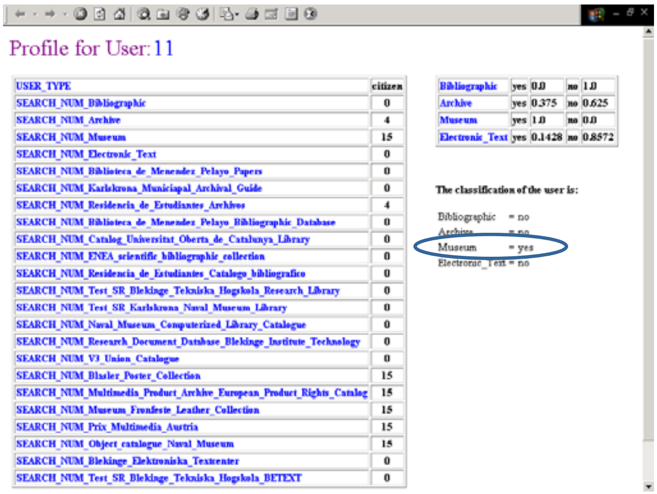
How to improve searching in COVAX



Scenario 1: user profile not available



Scenario 2 – user profile available



Profile for User: 11

USER_TYPE	citizen
SEARCH_NUM_Bibliographic	0
SEARCH_NUM_Archive	4
SEARCH_NUM_Museum	15
SEARCH_NUM_Electronic_Text	0
SEARCH_NUM_Biblioteca_de_Menendez_Pelayo_Papers	0
SEARCH_NUM_Karlskrona_Municiapal_Archival_Guide	0
SEARCH_NUM_Residencia_de_Estudiantes_Archivos	4
SEARCH_NUM_Biblioteca_de_Menendez_Pelayo_Bibliographic_Database	0
SEARCH_NUM_Catalog_Universitat_Oberta_de_Catalunya_Library	0
SEARCH_NUM_ENEA_scientific_bibliographic_collection	0
SEARCH_NUM_Residencia_de_Estudiantes_Catalogo_bibliografico	0
SEARCH_NUM_Test_SR_Blekinge_Tekniska_Hogskola_Research_Library	0
SEARCH_NUM_Test_SR_Karlskrona_Naval_Museum_Library	0
SEARCH_NUM_Naval_Museum_Computerized_Library_Catalogue	0
SEARCH_NUM_Research_Document_Database_Blekinge_Institute_Technology	0
SEARCH_NUM_V3_Union_Catalogue	0
SEARCH_NUM_Blasler_Poster_Collection	15
SEARCH_NUM_Multimedia_Product_Archive_European_Product_Rights_Catalog	15
SEARCH_NUM_Museum_Fronfeste_Leather_Collection	15
SEARCH_NUM_Prix_Multimedia_Austria	15
SEARCH_NUM_Object_catalogue_Naval_Museum	15
SEARCH_NUM_Blekinge_Elektroniska_Textcenter	0
SEARCH_NUM_Test_SR_Blekinge_Tekniska_Hogskola_BETEXT	0

Bibliographic	yes	0.0	no	1.0
Archive	yes	0.375	no	0.625
Museum	yes	1.0	no	0.0
Electronic_Text	yes	0.1428	no	0.8572

The classification of the user is:

Bibliographic = no
Archive = no
Museum = yes
Electronic_Text = no

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