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User Experiments of a Social, Faceted Multimedia Classification System

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Abstract. Internet document sharing systems such as Flickr store billions of user-contributed images. Many collections on the Web contain large numbers of multimedia objects such as images. While such systems are designed to encourage user contributions and sharing, they are not well-organized collections on any given subject and are not easy to browse for specific subject matters. We have built a system that systematically organizes a large multimedia collection into an evolving faceted classification. This paper discusses the evaluation of such a system through a number of usage studies in a university setting.

Keywords: Faceted classification, social classification, social computing

1 Introduction

Especially for large collections of multimedia documents (such as images and videos) the task of organizing them for searching and browsing can be significant. One approach to solving the problem is to distribute the cost to the users of the community that benefits form such an organization of the collection. We have built a system that supports the structuring of a large multimedia document collection into a multi-faceted classification. Besides automated programs, the approach utilizes collaborative human efforts to improve the quality of collection. Our fundamental belief is that a large, diverse group of people (students, teachers, etc.) can do better than a small team of librarians or editors in constructing a multimedia collection at a reduced cost.

We have built a system that improves browsing and searching access to a large, growing collection by supporting users to build a faceted (multi-perspective) classification schema collaboratively [F. Liuliu, 2010; K.Maly, 2010]. The system is targeted in particular to collections of photographs and images that, in general, have little textual metadata. A facet is an attribute (dimension) of an item in a collection that gives one perspective of that item. For example, in a collection of wine, "color" could be one facet. Other facets could be "origin", "price", etc. for the wine collection. This allows different users to navigate the collection using the facet of most interest to them. What is a good set of facets for a given collection is very much dependent on the given collection and the target users. Some commercial sites including Amazon and eBay use facet based classifications. The facets can evolve with time because of change in target users or change in interest of existing users in how they want to navigate the collection. For example, after a given facet schema has stabilized there may be a need to add another facet, for example, “healthy ingredients” for the wine collection. Some example categories in this facet are resveratrol, flavonoids, and non-flavonoids. For collections that grow in both volume and variety, a major challenge is to evolve the facet schema, and to reclassify existing objects into the modified facet schema. Centrally managed classification systems often find it difficult to adapt to evolving collections. It is hoped that through users’ collective efforts the faceted classification schema will evolve along with the user interests and thus help them navigate through the collection quickly and intuitively. Our system (a) allows users to build and maintain a faceted classification collaboratively, (b) enriches the user-created facet schema systematically, and (c) classifies documents into an evolving, user-managed facet schema automatically. Readers can explore the current system by browsing the African History Image Collection on our website (http://facet.cs.odu.edu/), shown in Figure 1.

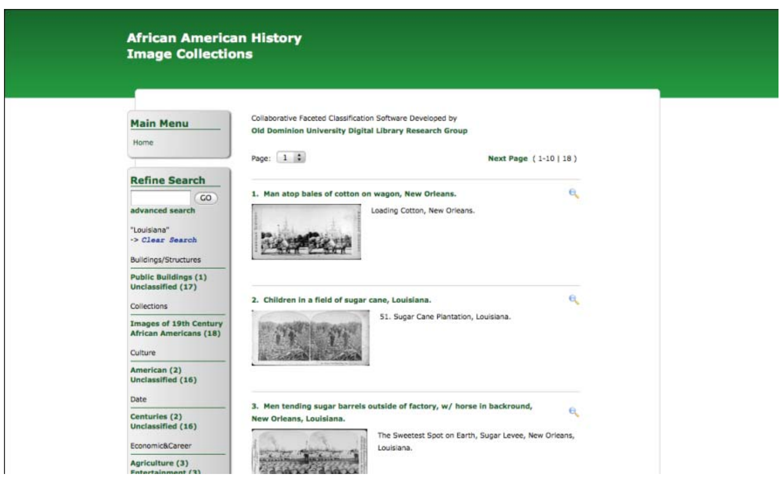

Figure 1.: Screenshot of the system front page

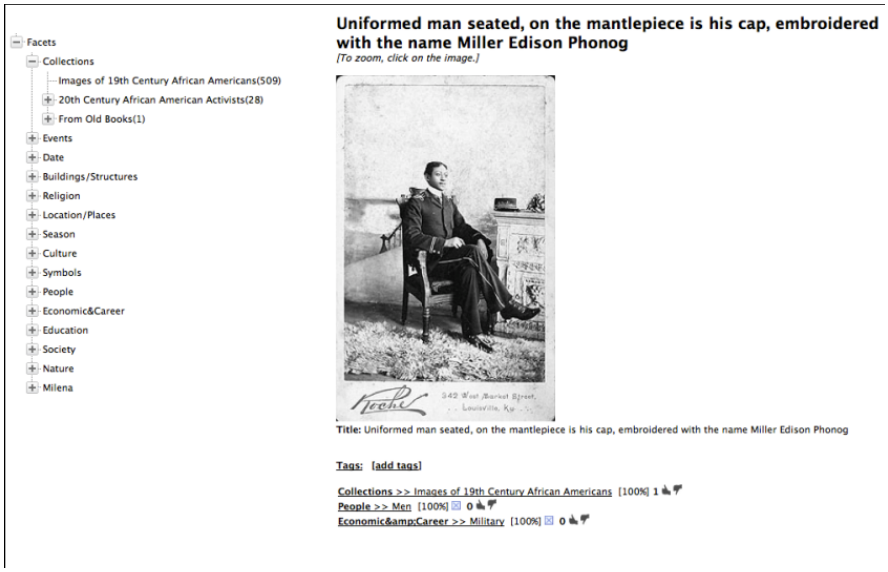

Figure 2. Screenshot of classification page

Figure 2 shows the page that allows the user to classify an image by dragging the image into any of the categories in the facet/category tree in the left panel. At the bottom are lists of current classifications of that image to various facets and the user has the ability to vote them up or down as to the user's thinking of its appropriateness.

In this paper, we focus on the evaluation of the system through usage studies. In section 2 we review the architecture and its implementation. In section 3 we describe the design for the experimental study followed by an analysis of the results in section 4. Sections 4 and 5 present discussions of the results and our conclusions.

2 Architecture and Implementation

The architecture of our system is shown in Figure 3. Users can not only tag (assign free-form keywords to) documents but also collaboratively build a faceted classification in a wiki fashion. Utilizing the metadata created by users' tagging efforts and harvested from other sources, the system helps improve the classification.

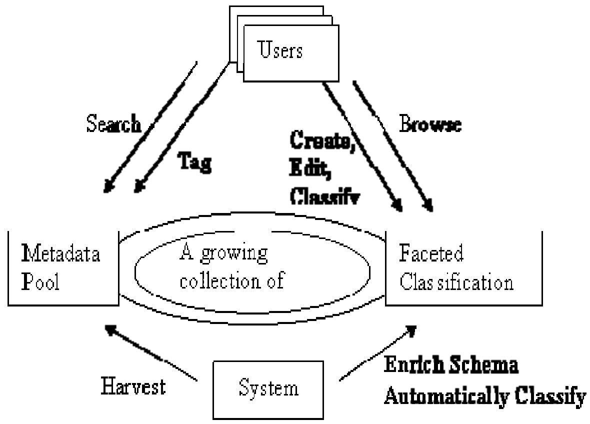

Figure 3. System architecture

We have developed a Web-based interface that allows users create and edit facets/categories similar to managing directories in the Microsoft File Explorer. Simply by clicking and dragging documents into faceted categories, users can classify (or re-classify) documents. All the files and documents are stored in a MySQL database. For automatic classification, we use a support vector machine method (Chang, C. and C. Lin, 2001) utilizing users' manual classification as training input. For systematic facet enrichment, we are use methods that create new faceted categories from free-form tags based on a statistical co-occurrence model and also WordNet (Pedersen, T., S. Patwardhan, 2004).

Note that the architecture has an open design so that it can be integrated with existing digital library and knowledge management systems. As such the system can be readily deployed to enrich existing digital library collections.

3 User Experiments

One of the primary goals of the project was to have users of large image collections be able to find images through directed browsing. The approach was to create effective facet classification schema of the collection and have the images themselves be properly classified all done collaboratively as an effort by the community. Hence one main thesis of our experiments was to see whether users will classify images as a social, community effort.

We developed a test protocol for a class of information technology students within the social networking module of that class. The test consisted of a description of the system, a demonstration of the system, short tutorials in how to use it, a pre-test survey, a set of tasks, and a post-test survey. The tasks, included such operations as 'find an image', and 'classify an image'. Students were placed into groups and members of a group rated the performance of the members in other groups. All operations by the students were monitored by the system and data collected into a data base. Together with the student surveys they formed the basis of our analysis. The design of our study and analysis was mostly influenced by work of ((Manski, 2000; Ross and Greene, 1977; Frey and Meier, 2004; Bourgeois and Horan, 2007) in the area of field studies in the context of members of the study interacting with each other.

4 Experimental Results and Analysis

We conducted a set of experiments in form of surveys and logging student's actions while they are working with our system in a class room environment. The objective of these experiments was to see how student's background influences the use of the system, and also to get usability feedback of our system. The survey had two components: pre-survey, and after-survey. The pre-survey was done before the student's were exposed to the facet system, and the after-survey was done when they had worked with the facet system. The pre-survey contains 35 questions to test the knowledge level of the students towards social networking. 121 students finished the questionnaire. In order to detect the possible correlation between the questions, factor analysis is done by the SPSS (Norusis, M, 1993) package with the questionnaire data. The objective of factor analysis is to group the questions based on the students responses resulting in smaller number of uncorrelated groups. The software created 12 groups, of which the first 8 groups have stronger factor loadings comparing with the latter groups. Each of these 8 groups, respectively, aims to measure students' knowledge level about: social net working, tagging activities, online game, blogs, blackboard, virtual reality sites, chat room and messaging. We show one of the first groups created in Table 1 along with the questions associated with that group

Rotated Component Matrix[a]

	Component						
	1	2	3	4	5	6	7
Answer 8	.814	-.015	-.103	.083	.075	-.029	.129
Answer 9	.788	-.065	-.032	-.052	.036	.039	.011
Answer 2	.749	.030	.211	.056	.008	-.068	.057
Answer 1	.738	.136	.209	.056	.002	.022	-.010
Answer 7	.722	.082	.064	-.105	.098	.136	-.098
Answer 11	.104	.845	-.064	.130	.096	.047	.012
Answer 12	.077	.841	-.075	.009	.064	.152	.032
Answer 10	-.086	.629	.248	-.066	-.007	-.107	-.132
Answer 31	.050	.045	.858	.131	.051	.137	.141
Answer 32	.165	.005	.819	.011	-.018	.098	.174
Answer 30	-.013	-.072	.487	.134	.130	.423	-.076
Answer 14	-.020	.055	.132	.867	-.080	.013	.061
Answer 15	.028	-.036	.007	.822	.118	-.006	-.064
Answer 13	.013	.202	.064	.579	.054	.246	-.207
Answer 34	.088	-.046	.111	.025	.843	.001	-.016
Answer 35	.045	.089	.059	.036	.833	-.134	.105

Table 1. Factor analysis of pre-experiment questionnaire

Within 121 students, 100 of them attended the after-survey. The after-survey focus on students' attitudes toward the system: how they feel about the system usage, whether they were satisfied about the system design. The factor analysis for the after-survey data aims to see what aspects of the system usage are likely to be correlated, and what are the strongest or weakest aspects of the system operation from the user perspective. There are 12 questions in the after-survey. The factor analysis indicated that the questionnaire was about students' attitudes towards the system in terms of: 1) general use, such as ease of use, dragging, and login issues; and 2) association and tagging operation, which are unique defined functions of the facet system.

Rotated Component Matrix[a]

	Component	
	1	2
Answer 12	.837	.170
Answer 8	.743	.052
Answer 11	.718	.150
Answer 10	.637	.284
Answer 9	.575	.460
Answer 7	.564	.113
Answer 2	.487	.334
Answer 1	.479	.424
Answer 3	.101	.755
Answer 4	.176	.716
Answer 5	.117	.704
Answer 6	.258	.602

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Table 2. Factor analysis of after-experiment survey

A comparison, shown in Figure 4, between pre-survey and after-survey shows whether the students' knowledge level of the social networking may have any influence to their satisfaction level to the system. The 100 data set by students who attended both the pre-survey and after-survey were chosen for the analysis. There is no significant pattern for the plots distribution, which means that although the students' pre-knowledge levels vary a lot, their evaluations to the system are relatively constant, and that the ease of the system usage is not related with the students' knowledge level.

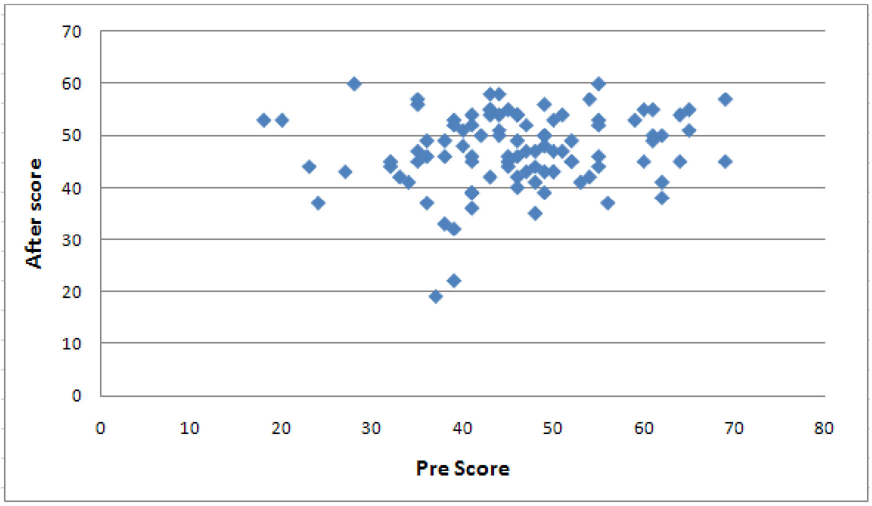

Figure 4. Pre-experiment survey vs. after-experiment survey

Students do categorizing, tagging, rating.etc, with the help of some other operations such as searching, expanding the categories, etc.

We also adopted factor analysis to explore which actions are closely related. The system recorded every action of each student. The factor analysis for actions considers each student as a data set, and each action as a variable (34 variables in total), to find out the possible correlation between the actions.

As shown in Table 3, it was found that: 1) the action to collapse category, expand category, associate item, add category, and rename category were close related, which are all categorizing-related actions; 2) the action to refine category/facet, clear refinement, view all categories of facet, view all facets and view tag cloud were included in the second group, which contained the ones about searching or viewing images; 3) the action to rename facet, upload image and click to upload image were in a same group, which showed that the students who's not satisfied about the existed facet contents are more likely to upload new images; 4) the action to view description, edit description and delete category were in grouped together, meaning that the ones who were not satisfied about the description are likely to delete category; 5) the action to rate item, rate association and view help file were in the same group by factor analysis, meaning that students need help when rating, which also helped to find out the perspective of our facet system for future improvement.

collapse category expand category associate item add category rename category	view description edit description delete category	select advanced search search terms clear refined category/facet
refine category/facet clear refinement view all categories of facet view all facets view tag cloud	view home page view welcome page view fewer facets	go to pref/next page
rename facet upload image click to upload image	rate item rate association view help file	tag item clear search
	go to page view item open classification page	delete facet add facet
		remove association

Table 3. Grouping actions for factor analysis

A linear regression model is used to find out how relevant the other actions are correlated with the actions associating items with faceted categories. Using the forward method, the entering order reflects the relative relevance of the correspondent independent variables. It was found that the order of the relevant independent variables entering the model is: collapse category, delete category, view all categories of facet, search terms, delete facet, view home page, view tag cloud, rate item, which shows that associating an item needs frequent browsing-related actions, and that associating an item may help students to find out the in-appropriate categorization and bring some modifications ("delete category", "delete facet", etc).

The longitude "African American History" experiment lasted from 09/24/09 to 12/15/09, 83 days in total. Data analysis by time indicated that: 1) Both "Search terms" and "open classification page" have two peaks, one for tagging and associating tasks, the other one for rating association; 2) With the facet enrichment, the classification became useful for the students; and 3) The action of rating association is concentrated to the later time period.

5 Discussion

All the experiments are objective-orientated. Students aim to finish the tasks of tagging, classifying and/or rating. It is observed that within three experiments following operational functions are used a lot: "expand category", "collapse category", "search terms" and "open classification page". These functions are specially owned by the system. The experiments show that these functions are very helpful for the students to finish their task. On the other hand, functions such as "add category", "remove category" and "rename facet/category" are used little.

ANOVA[i]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	48445.278	1	48445.278	88.844	.000 [a]
	Residual	64888.722	119	545.283		
	Total	113334.0	120			
2	Regression	53391.633	2	26695.816	52.552	.000 [b]
	Residual	59942.367	118	507.986		
	Total	113334.0	120			
3	Regression	57867.584	3	19289.195	40.688	.000 [c]
	Residual	55466.416	117	474.072		
	Total	113334.0	120			
4	Regression	61512.851	4	15378.213	34.424	.000 [d]
	Residual	51821.149	116	446.734		
	Total	113334.0	120			
5	Regression	63991.563	5	12798.313	29.828	.000 [e]
	Residual	49342.437	115	429.065		
	Total	113334.0	120			
6	Regression	66580.879	6	11096.813	27.058	.000 [f]
	Residual	46753.121	114	410.115		
	Total	113334.0	120			
7	Regression	68274.921	7	9753.560	24.460	.000 [g]
	Residual	45059.079	113	398.753		
	Total	113334.0	120			
8	Regression	70083.017	8	8760.377	22.685	.000 [h]
	Residual	43250.983	112	386.169		
	Total	113334.0	120			

a. Predictors: (Constant), collapse category

b. Predictors: (Constant), collapse category, delete category

c. Predictors: (Constant), collapse category, delete category, view all categories of facet

d. Predictors: (Constant), collapse category, delete category, view all categories of facet, search terms

e. Predictors: (Constant), collapse category, delete category, view all categories of facet, search terms, delete facet

f. Predictors: (Constant), collapse category, delete category, view all categories of facet, search terms, delete facet, view home page

g. Predictors: (Constant), collapse category, delete category, view all categories of facet, search terms, delete facet, view home page, view tag cloud

h. Predictors: (Constant), collapse category, delete category, view all categories of facet, search terms, delete facet, view home page, view tag cloud, rate item

i. Dependent Variable: associate item

Table 4. Model- “associating item” as Dependent Variable

The experiements show that modification-related functions are less likely to be used. Students are more likely to look through the existed tagging and classification records and do their own tagging and classification. The psychological issue behind is that for a social networking system, people prefer to refer to the existed records and establish their own new ones, but not to modify the existed old records.

In the factor analysis, all three experiments show the clustering for the actions which aim for different purposes: categorizing actions, searching and browsing and restarting. For the 1st experiment, which contains most data set and has strongest validity, there are some special findings: 1) The ones who's not quite satisfied about the existed facet contents are more likely to upload new images; 2) The ones who were not satisfied about the description are likely to delete category; 3) Students need help when rating.

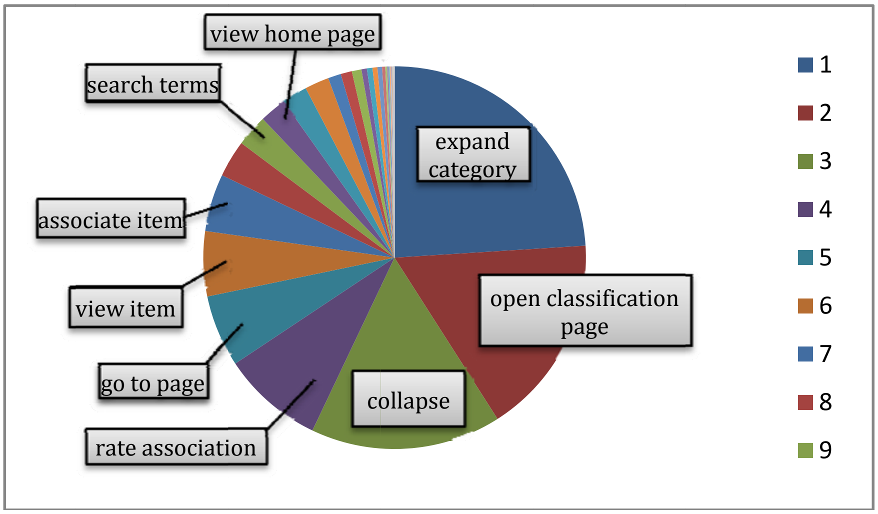

Figure 5. A breakdown of user actions

The psychological issue behind: for a social net-working system, people prefer to refer to the existed records and establish their own new ones, but not to modify the existed old records.

The facet system is a new system with a novel facet classification design idea. Our experiments provide empirical to explore the reaction of the future users to this system. We find that the user's knowledge level has no significant effects on the usage, which implies that our system does not require highly advanced Internet users. In order to finish the task, students have often chosen the facet-related features over traditional search, which indicates that for a large multimedia document collection, a multi-faceted classification schema is more efficient for information discovery.

6 Conclusion

In this paper, we present the results that how a social network system for communities classify the media objects in a collection using a facet classification schema. Defined by Boyd and Ellison (2007), a social network system is a web-based service allowing the users to construct their own profile and share a connection within the system. Our research indicates that when with arranged tasks, students still prefer to refer to the existed records and establish their own new ones, but not to modify the existed old records. Furthermore, it shows that the existed classification/facet structures are with most help for the students to do their own work. Now we are developing the system to include individual's personal classifications. Therefore, our future research will give more details such as how individual users influence each other through the information sharing process in a facet system, what information are most useful, and the identification of the most important users or information providers.

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