Image-based Dietary Information Mining for Community Creation in a Social Network

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ABSTRACT

We present the initial results of an investigation on automated community formation in a social networking site, named *FoodLog*, that manages dietary information of its users. The site analyzes photos submitted by users, to estimate the dietary composition of their daily meals. In order to automatically identify natural groupings among meals consumed by different users, we apply simple expectation maximization algorithm on a selected data set from this site. Visual observation of images from the resulting clusters proves that the groupings actually correspond to different categories of meals. We demonstrate how communities of users can be formed by assigning them to clusters. We also discuss the steps that should follow this initial study, and possible future directions.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; H.3.5 [**Information Storage and Retrieval**]: Online Information Services

General Terms

Algorithms, Experimentation

Keywords

FoodLog, dietary data mining, clustering, multimedia

1. INTRODUCTION

Increased attention to dietary control in the field of healthcare, and the development of infrastructure for web 2.0 based services, has resulted in a number of *Social Networking Sites* (SNS) that support dietary control and dietary information management. Some of these networks provide resources for planning healthier meals and exercising schedules, and tools for calculating indices such as Body Mass Index (BMI) and daily calorie consumption [8][9]. Some others allow users to regularly record their meals and other related information. *Diet Nikki* [12] is an SNS that allows users to record their meals and weight daily. *FoodLog* [10], developed in our earlier research, allows its users to record and share dietary information by submitting photos of their daily meals.

Some people prefer to work on dietary management as a group. Working in a group enables them to get advice and encouragement, share resources, compete with others to reach milestones, and also enjoy related activities. Several dietary management systems support group based interactions such as writing comments on users' posts, adding friends, and forming communities [12] [9] [11]. JogNote [11] provides a facility for a user to link to another user with similar goals and regularly compare his/her own performance.

For community-based dietary management to be effective, it is essential for a user to find a community that has similar dietary preferences and goals. This is usually done by manually searching through the posts from different users. If communities can be automatically formed and/or recommended to users, they will find it much easier to start interactions with others.

At the current state, social networking sites "suggest" potential friends and communities to their users by analyzing their profiles. There also exists some research in motivating contributors on social networks [5] and recommending friends based on social multimedia [6]. Newman and Girvan [4] propose a set of algorithms for community discovery in generic networks. A more recent study by Leskovec et al. [3] investigates the discovery of meaningful communities in large social networks. However, to our knowledge, automatic SNS community creation for dietary management is not available at the moment.

In this paper, we present the initial results of our investigations on automatically forming communities in FoodLog. We cluster a selected set of dietary data extracted from food images submitted by users, to find natural groupings among them. Thereafter, we analyze the results and attempt to interpret them. We also demonstrate that the results can be used to automatically form communities with similar meal preferences. After a brief discussion on FoodLog-specific issues in automated community formation, we conclude the paper outlining the future directions.

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2. SOCIAL NETWORK AND DATA

This research is based on a web-based dietary management system called FoodLog. The following sub-sections outline the functionality of FoodLog and describe the data collection used for clustering.

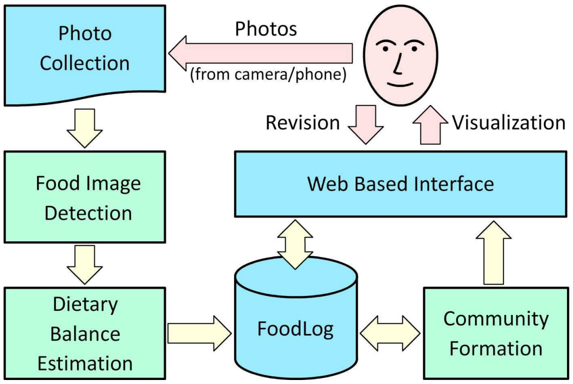

Figure 1: Functional Overview of FoodLog.

2.1 Overview of FoodLog

Most dietary control programs require participants to regularly record detailed information regarding their meals. FoodLog was designed with the intention of making this task easier. A FoodLog user records his dietary information by submitting photos of his/her daily meals, taken with a digital camera and/or a camera phone. The images are first analyzed to verify that they are photos of food. An algorithm based on Support Vector Machine Learning of both local and global image features [1] is used for this purpose. The dietary balance of the meals is calculated according to the "Food Balance Guide" by the Ministry of Agriculture, Forestry and Fisheries of Japan [7]. It categorizes food into five dietary components: grains, vegetables, meat/beans, fruit, and dairy products. The quantity of food from each component is measured using the unit "serving (SV)." While not as precise as the number of calories, this provides a reasonable description of dietary balance of a meal. An algorithm based on color histograms, DCT coefficients and SIFT features [2] is used to estimate the dietary composition of each food image. The results are stored together with other image metadata such as the date, time and location (if available). The collection of thus recorded data forms a log of the user's meals.

The user can log on to FoodLog using a web browser and view the photos and dietary information in different formats. He/she can "review" the balance information for a given meal, by correcting any error in estimation of dietary balance and marking a checkbox to verify the balance information. The user can also specify three additional attributes for a given image. If the meal included drinks and/or sweets, their quantities can be specified. A *rating* between 0 and 5, with 5 being the best rating, can be assigned to a meal.

At the current state of the system, there is little interaction among different users. A user can browse images submitted by other users, in descending order of rating. This makes using the system more interesting, as it allows a user to look for "good food" as recommended by other users. However, there is no facility to form communities of multiple users. Figure 1 outlines the functionality of FoodLog, together with the proposed addition of community formation.

2.2 Data Collection

FoodLog has been open to the public since March 2009. The site underwent a major upgrade in April 2010, and

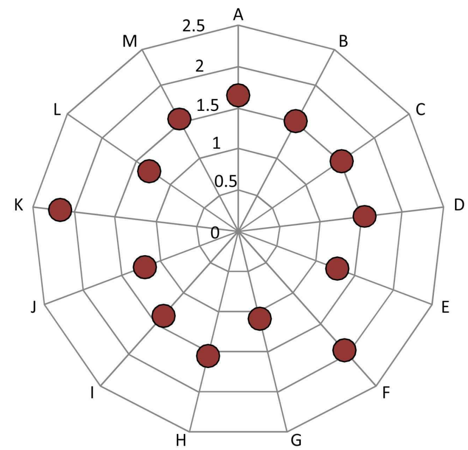

Figure 2: Deviation of balances for different users.

its current functionality slightly differs from that described above. However, the description is correct for data considered in this work, which were extracted at the end of March 2010. At the time, FoodLog had 343 registered users. These users had uploaded 8214 images that show the meals, snacks and drinks that they consumed. The dietary balance information for 1323 of these images had been reviewed by 24 users. Each of these users had reviewed approximately 10% to 50% of the dietary balance information for his/her meals. We created a "snapshot" of this data collection for our research on automatic community creation.

We start our analysis with dietary data that has been reviewed by users, to minimize the effect of errors in image analysis on the results. After filtering these data to remove users who had reviewed only a small number of images, we selected a data set corresponding to 1293 images from 13 users for our initial study.

3. DATA MINING

3.1 Distance Measures for Dietary Balance

In order to estimate how healthy a given meal is, it is necessary to define a quantitative measure on how much a given meal deviates from a well-balanced meal. The ideal dietary balance for a given person depends on a number of parameters such as age, health condition and lifestyle. However, for simplicity, we define the ideal balance of a meal as one that contains one third of the daily food intake recommended by *Food Balance Guide* specification, with the same relative proportions of the components. We define the deviation d of the dietary balance of a given meal from the ideal balance specified above as

$$d = \sqrt{\frac{(G-G_I)^2}{G_I^2} + \frac{(M-M_I)^2}{M_I^2} + \frac{(V-V_I)^2}{V_I^2} + \frac{(F-F_I)^2}{F_I^2} + \frac{(D-D_I)^2}{D_I^2}}$$

G, M, V, F, D denote the number of servings of grains, meat/beans, vegetables, fruit and dairy products respectively in a given meal. $G_I = 2.0$, $M_I = 1.33$, $V_I = 1.83$, $F_I = 0.67$, and $D_I = 0.67$ are the corresponding quantities of dietary components in a balanced meal as defined above.

Table 1: Statistics for the Collection of Clusters

Cluster	No. of Images	Dietary Components					Other Attributes			d
		Grains	Meat	Vegetables	Fruit	Dairy	Drinks	Sweets	Rating	
Cluster 0	284	2.1119	1.7121	1.1539	0.0688	0.0000	0.0007	0.1030	1.9861	1.43
Cluster 1	39	0.9435	0.4066	0.0000	0.0228	0.3128	0.0209	0.3118	0.0359	1.75
Cluster 2	101	1.3867	1.8526	0.9994	0.0005	0.0000	0.0000	1.1973	0.0039	1.97
Cluster 3	682	1.4762	1.6845	0.8941	0.1058	0.0040	0.0000	0.0000	0.0000	1.45
Cluster 4	63	1.2384	1.2796	0.6402	0.3991	0.2998	0.0100	0.6254	2.8117	1.19
Cluster 5	89	1.5611	2.007	1.5767	0.0554	0.0047	0.3852	0.0269	2.7392	1.47
Cluster 6	35	1.3208	1.4695	0.9305	0.2136	0.4019	0.0000	0.0000	0.0000	0.99

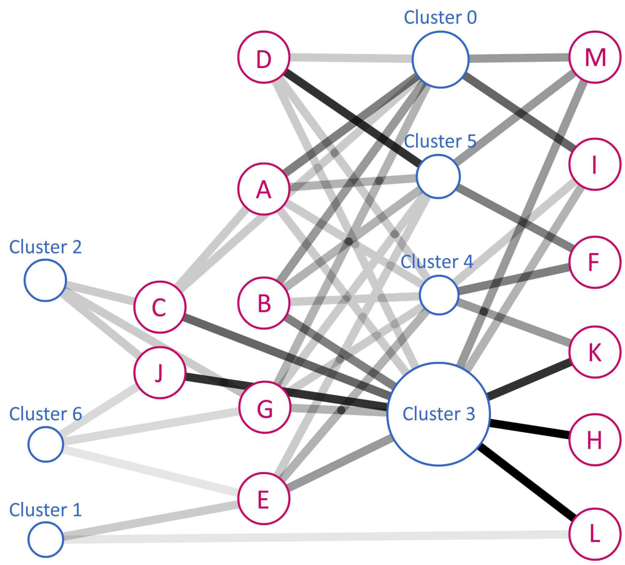

Figure 3: Result of clustering food images.

The above equation is a Euclidean distance calculation where the deviation of each component is normalized by its ideal proportion. This results in a higher value of d for a meal that deviates more from the relative balance of the components. Figure 2 plots the values of d for the users in the selected data set. The users are labeled with alphabetic characters A to K. It is evident that all of the users deviate from the ideal dietary balance by more than one unit (normalized serving). Detailed inspection of the images showed that this was mainly due to the lack of consumption of dairy products and vegetables.

3.2 Clustering Reviewed Images

Our objective here is to find natural groupings in food images, according to the dietary composition of the meals they depict. The dietary information corresponding to a given image is a function of eight variables; the quantities of the five dietary components, and the three user-specified attributes (described in Section 2.1). In addition to these variables, it also depends on latent variables such as the meal preferences and dietary constraints of the users. We used Expectation Maximization (EM) algorithm for clustering the data set, due to its effectiveness in working with incomplete data and latent variables. Simple EM algorithm with a minimum standard deviation of 1×10^{-6} was used. The clustering process converged within 100 iterations.

Table 2: Membership of users in different clusters

User	Images in cluster(%)						
	0	1	2	3	4	5	6
A	58.3	0.0	0.0	8.3	8.3	25.0	0.0
B	25.3	0.0	1.4	42.3	7.0	23.9	0.0
C	9.2	4.8	10.4	70.4	1.7	3.0	0.4
D	11.1	0.0	0.0	5.6	5.6	77.8	0.0
E	0.0	16.7	0.0	33.3	16.7	16.7	16.7
F	0.0	0.0	0.0	0.0	50.0	50.0	0.0
G	19.3	0.4	13.4	31.9	11.8	12.2	10.9
H	0.0	0.0	0.0	100.0	0.0	0.0	0.0
I	73.4	0.0	0.0	20.1	5.6	0.9	0.0
J	0.0	4.4	13.3	75.6	0.0	0.0	6.7
K	0.0	0.0	0.0	66.7	33.3	0.0	0.0
L	1.0	8.2	3.1	81.6	1.0	2.0	3.1
M	33.3	0.0	0.0	33.3	0.0	33.3	0.0

4. RESULTS

The clustering process resulted in seven clusters. Table 1 summarizes the attributes of these clusters. The largest cluster consisted of 682 images, which was approximately 53% of all images. The smallest cluster contained 35 images, approximately 3% of all images.

Figure 3 provides an overview of the results of clustering. The clusters are labeled as *Cluster N* where N ranges from 0 to 6. The area of each circle corresponding to a cluster is proportional to the number of images contained in that cluster. A line connecting a user node to a cluster node implies that images submitted by the user are present in that cluster. The opacity of the line corresponds to the number of images. It is evident that most of the users share images with multiple clusters. Only one user (user H) has all his/her images contained in a single cluster. The number of lines connected to a user node represents the variety of the food he/she consumes (assuming regular uploading of food images). Table 2 summarizes how the images uploaded by each user are distributed among clusters. It is evident that some patterns of membership exist. For example, a large proportion of images from users A, E and I are contained in *Cluster 0*. Such patterns can be useful in identifying similarities between the dietary habits of different users.

Figure 4 shows what types of food the clusters correspond to, and their relative dietary balance. The radar chart shows the normalized Euclidean distance from the center of each cluster to the ideal dietary composition of a meal. The images in the rectangle at the bottom center of the image show a few example meals that are close to this composition. The other rectangles contain example food images from corre-

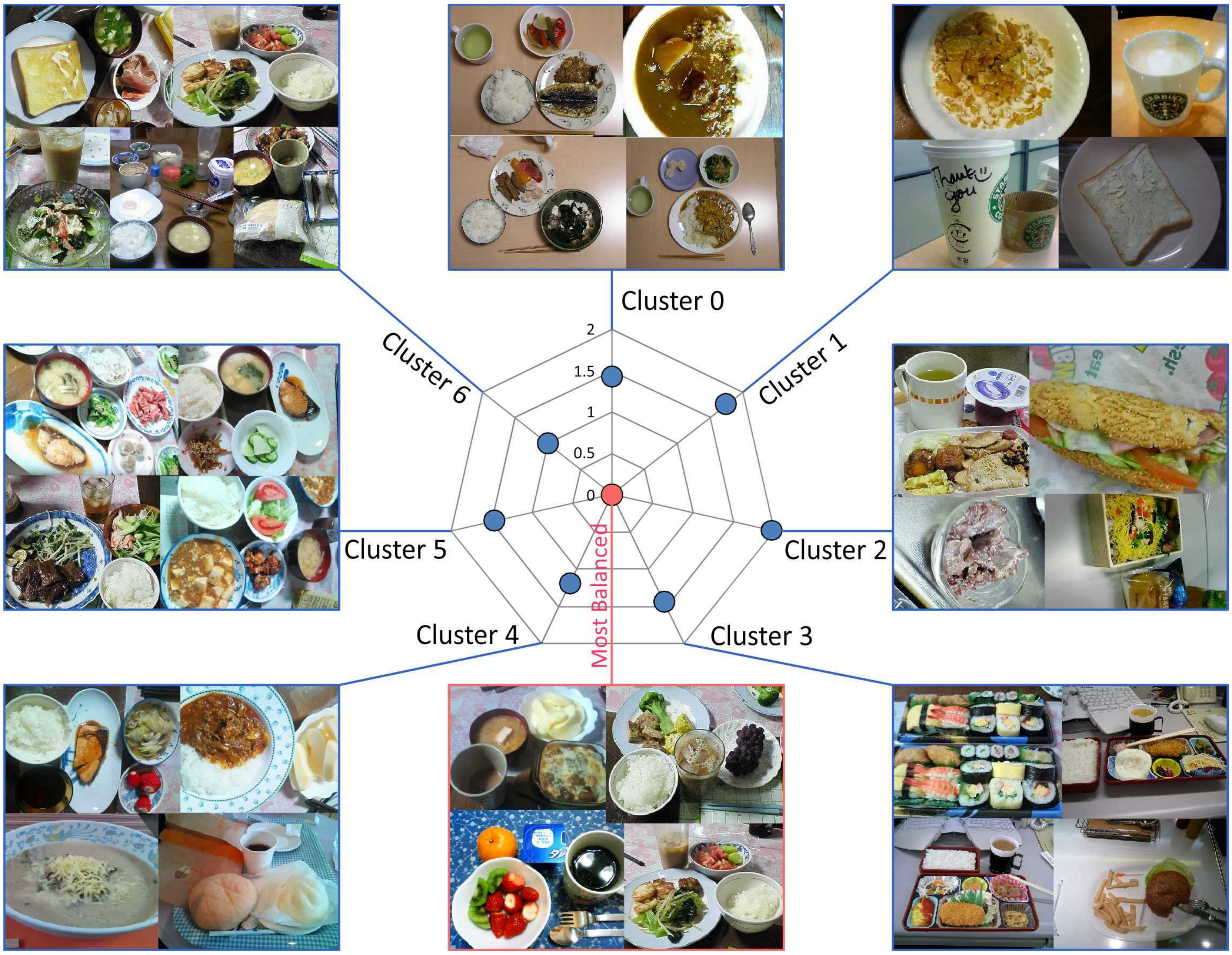

Figure 4: Relative positioning of clusters with respect to the ideal balance of a meal, and example images from each cluster.

sponding clusters. It is evident that some clusters are very distinct. For example, *Cluster 1* consists of very light meals and drinks such as cereal and coffee. *Cluster 3* consists of various types of packed food. *Cluster 6*, which has the best dietary balance, corresponds to meals with a wide variety of dishes.

As a first attempt to form groups of users, we calculated the distance matrix between different users and clusters. Each user was assigned to cluster that is closest to him/her. Figure 5 illustrates the result of cluster assignment. An example image from each cluster is included in the graph for easy identification of the clusters. It is evident that *Cluster 1* and *Cluster 2* do not have any users assigned to them. The reason for this is that they contain images of food that are not regularly eaten by the selected set of users. On the other hand, *Cluster 4* mostly consists of set meals that are more common.

These results come from a data set that is reviewed by users. If the error in non-reviewed dietary information has zero mean and low standard deviation, the results should be applicable to all images, and therefore all users. We carried out another experiment using both reviewed and non-reviewed data for the same 13 users who had contributed to the previous data set. This data set consisted of 4357 images. We applied nearest neighbor rule (based on Euclidean distance) to assign each image to the cluster with the closest dietary composition. Observation of the results showed that five of the seven clusters still preserved the original grouping. *Cluster 3* and *Cluster 4*, however, had grown much larger and included a considerable number of images with incorrectly estimated dietary composition. Detailed investigation of dietary balance information showed that the problem is caused by the large, non-zero mean error of the "meat or beans" component.

5. DISCUSSION

The results of clustering food images using reviewed dietary information can be summarized as follows:

- There is a natural grouping among dietary information corresponding to different users
- Observation of sample images show that the clusters

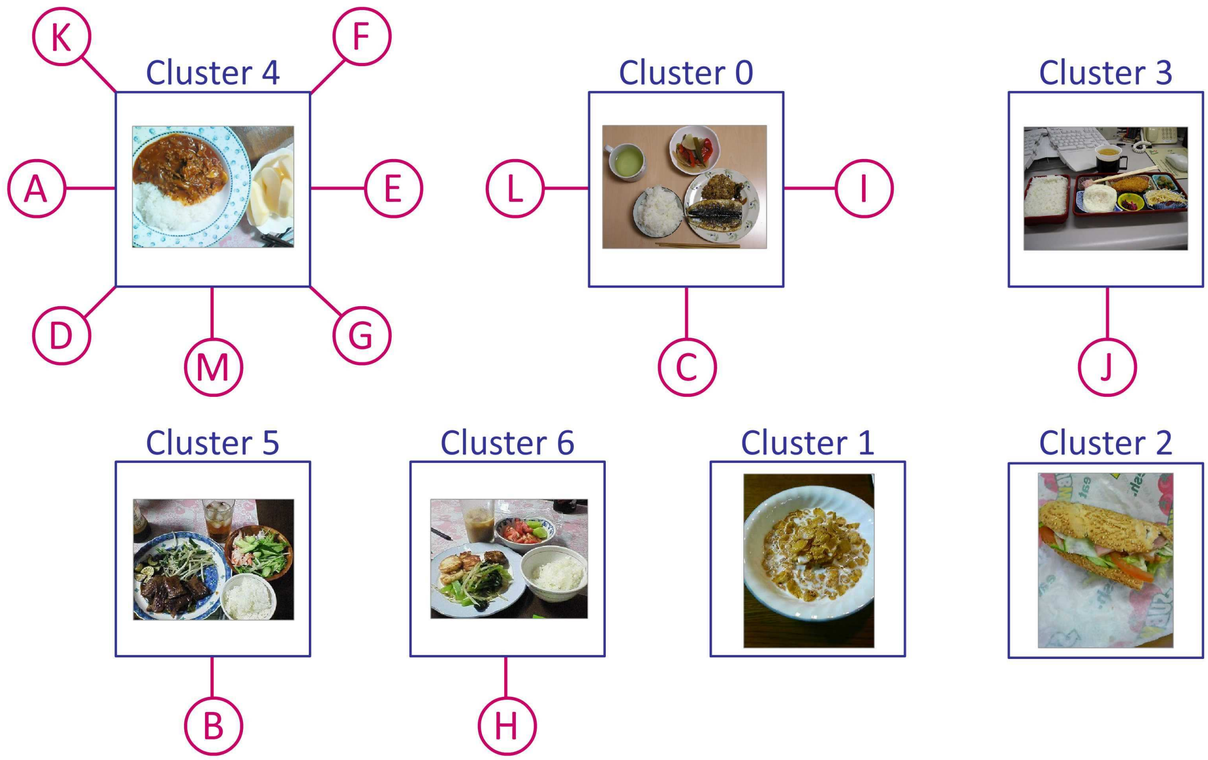

Figure 5: Example communities formed by assigning users to clusters.

are meaningful; that is, similar types of food have been clustered together

- The dietary behavior of a user can be identified by observing the clusters that he/she has images in
- Assigning users in to the closest clusters results is a convenient method to initially group users according to their dietary behavior

The main problem with the existing system is the error in dietary balance estimation that makes clustering less accurate. One possibility is to use only the reviewed images for clustering so that the results are more accurate. However, only 8% of the users review the dietary balance information. Further, it was evident that even those who reviewed the information did not correct all of the errors in their data. Therefore, community formation based only on reviewed information will seriously limit its effectiveness. Instead, improved dietary balance estimation and use of other attributes (such as image features and meal times) can be used for further analysis and clustering of non-reviewed data.

The distance measure d as defined in Section 3.1 is somewhat simple, and does not reflect the relative intake of specific dietary components. Distances between individual components can be used to identify bad dietary habits of users and provide feedback to them.

Another important task is to identify the exact methods for forming communities with the results of clustering. The demonstrated method of grouping people by the nearest cluster can form communities of people who have similar dietary preferences. This can allow people to easily find photos of meals that suit their preferences, and find more information about them by interacting with other users. Another possibility is to assign a user to a cluster with a better dietary balance than he/she currently maintains. This might start interactions that lead to the improvement of the user's dietary habits. Therefore, it is necessary to identify the objectives and interests of both the users and the social network, before designing such methods. Another important issue is to keep communities sufficiently small, when dealing with a large number of users. It will also be necessary to come up with methods for evaluating the effectiveness of automatic community formation.

The number of FoodLog users was fairly low during the first year, mainly because the system was not advertised. Most users found out about the system by word of mouth, or by seeing demonstrations in exhibitions. FoodLog was upgraded and re-launched with press releases, on the 30^{th} of April 2010. By the 31^{th} of May 2010, FoodLog had 1446 registered users and 25057 images of meals. These numbers are much larger compared to the data collection described in Section 2.2. With the rapid growth of the site and its data collection, we will be able to build up on the proposed algorithms, and evaluate them in more detail.

6. CONCLUSION

We presented the initial results of mining a collection of data from a social network related to dietary management. It was possible to obtain a natural grouping of food images submitted by different users, according to the dietary information that were detected by a computer vision based system and then reviewed by users. The results show that it is possible to form communities of users by employing such natural groupings.

It is possible to make clustering and community formation more accurate and applicable to all users, by improving the accuracy of dietary balance estimation. On the other hand, features derived from images can also be used for more accurate clustering. Currently, we are investigating the objectives and strategies for automatic community formation. Work is also in progress to modify FoodLog infrastructure to facilitate community-based interaction. With its recent upgrade and launch as a public service, we expect Foodlog to grow in terms of both the number of users and the amount of content.

Acknowledgments

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