Recommending Groups to Users based Both on Their Textual and Image Posts

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Abstract: This article focuses on the recommendation of Facebook groups to users, based on the post profile of each user on Facebook. In order to accomplish this task, texts and images provided by users are used as source of information, and the experiments showed that the combination of these two types of information gives results better than or equal to the results obtained when using separately these data. The proposed approach in this paper is simple and promising to recommend Facebook groups.

1 INTRODUCTION

The growth of online social networks, like Facebook, WhatsApp, Twitter and Instagram, has been tremendous in the last decade. Currently, there are over 2 billion users worldwide connected to at least one social network and the prospect is that this number will increase each year (Statista, 2016). These users post messages, images and videos and let them publicly accessible, so that any person can read the content and even interact with the user that shared it. As there are a huge amount of users on social networks, the number of messages shared is vast. Only for Facebook, it is estimated about 4 million of posts per minute (WERSM, 2015). This means that the amount of available data not only covers a significant portion of the world population, but it is also huge.

These data can be used to model user profiles and to identify their habits, interests, behavior patterns and other information about them. User profiles can be useful to provide a variety of applications, such as personalized search engines, recommender systems from friends and content, identification of users with malicious behavior and indication of products and services orientated to the interests and needs of users (Kosinski et al., 2013; Jin et al., 2013; Mislove et al., 2010). Regarding the marketing strategies, the availability of large volumes of data has been used in studies that seek to identify patterns and habits of consumers and whose analysis can serve as guidelines for large department stores and companies.

A common approach to identify relevant information from users is using the texts which are published on social networks, since they are very informative and they are the primary means of communication in most social networks. However, there are some facts and information which are difficult to extract solely from texts. In these texts there are misspellings, words with multiple semantic meanings and synonyms. Moreover, different languages in the world and the huge dictionary of words contained in each language are some of the difficulties. An option to get more information from users, and more precise profiles, is to use data from images and photographs. This option is feasible because it is very common users both disseminate text messages and the associated images on social networks.

In this context, this paper analyzes the use of texts and images on the task of recommending Facebook groups for users. To accomplish this task, a dataset of posts of Facebook groups was collected and, of this dataset, the users with the largest number of posts were selected. Based on the posts of these users and in the modelling of each group, the groups are recommended to each individual according to the affinity. The information was extracted from texts and images,

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and we carried out experiments with three types of approaches: one using only textual information, other using visual information and a final test combining both information. The results indicated that the use of two types of data sources can improve the results.

This work is organized as follows. In Section 2, we describe the procedures used for information extraction in texts and images. The dataset and its processing are presented in Section 3. The method to recommend groups is described in Section 4. In Section 5, we describe the experiments and analyze the results. Conclusions are presented in Section 6.

2 TECHNIQUES FOR INFORMATION EXTRACTION

2.1 Texts Representation

When working with texts, a series of procedures is necessary to facilitate the information retrieval. The pre-processing steps used in this work were performed as follows.

Initially, punctuation, non-alphanumeric characters and numbers were removed from the texts. After that, letters were passed to lower case and terms with low semantic value, known as stopwords (Baeza-Yates and Ribeiro-Neto, 1998), were removed, because they do not contribute with relevant information and they may damage the information retrieval task. Examples of stopwords are articles, prepositions and interjections.

After this procedure, the next step is to obtain the canonical form of words, that is, words without inflections, genre and plurals. This step is important because the computer is not able to understand that words like "teacher" and "teachers", which refer to the same categorical meaning. In this work we used the software CoGrOO (cogroo.sourceforge.net) which, among other things, obtain the canonical form of Portuguese words.

A fundamental step is to adopt an efficient way to represent texts such that they can be appropriately processed by a computer. One of the most popular forms of representation of texts is through the vector space model presented by Salton and Yang (1975). In this model, each document (or text) d_j is represented by a vector of n dimensions, each position i of this vector represents a term t_i that is associated with a weight $w_{i,j}$. In this work, $w_{i,j}$ is the number of times that term t_i occurred within the document d_j. Thus, the document d_j is represented as Equation 1:

$$d_j = \{w_{1,j}, w_{2,j}, \ldots, w_{n,j}\}. \tag{1}$$

For a set of D documents, a set of distinct terms is obtained and they constitute the dictionary of terms of D. When a term t_i does not occur within a document d_j, the weight $w_{i,j}$ of this term is equal to zero. With the vector space model is possible to use metrics such as Euclidean distance and cosine similarity to measure the degree of similarity between different documents. Each document is associated with a category represented by the set C.

Two additional steps are performed on the set of documents D. In the first step are removed terms with low discrimination power. In this work, we consider all the terms that appear only in one document, or appear in all documents in D. In the first case, the removal is motivated because it can be a misspelling or very rare word that does not influence the results, but increases the number of terms present in the documents, increasing the computational cost in the classification stage. In the second case, the presence of terms in all documents may be stopwords that were not removed from the set D.

The second additional step is the use of a technique called Inverse Document Frequency (IDF), which is utilized to increase the importance of the terms that appear in few documents and to reduce the weights of terms that appear in many documents (Salton and Yang, 1975). This weighting is combined with the term frequency of each term in each document, and obtain the new weight $\widehat{w_{i,j}}$ of the term t_i in document d_j. This new weight is calculated by Equation 2:

$$\widehat{w_{i,j}} = w_{i,j} \times idf_i, \quad idf_i = \log\left(\frac{|D|}{nd_i}\right), \tag{2}$$

where $w_{i,j}$ is the frequency of term t_i in document d_j, idf_i is the value of idf for the term t_i, $|D|$ is the number of documents in the set D, and nd_i is the number of documents that the term t_i appeared, that is, the number of documents that $w_{i,j} > 0$.

Finally, after all procedures, there are two data: one matrix M with $|D| \times n$ dimensions, representing the documents, and a vector N with $|D| \times 1$ dimensions, representing the vector of categories associated with the documents, where n is the number of distinct words in the set D.

2.2 Images Representation

Images also need a pre-processing step to extract relevant information and reduce the data dimensionality.

There are several methods to represent images in categorization tasks, but many of them are slow, complex, have many parameters to be adjusted or require a set of images with various elements labeled. In this work, we adopted the approach proposed in (de Souza Gazolli and Salles, 2012), because it is fast, simple and has no parameters for calibration, furthermore, its results are similar to other approaches.

The approach used in this work, called Contextual Mean Census Transform (CMCT), represents each image as a vector. This approach works on a grayscale image. On each pixel x of the image is centered a small mask 3×3 that performs an operation on the neighboring pixels to the pixel x. Firstly, the average intensity $\overline{I_x}$ of the image pixels under the mask is calculated. Next, the intensities of the neighboring pixels to the pixel x (N_x) are compared to $\overline{I_x}$.

If the intensity value of a pixel y (I_y) is greater than or equal to $\overline{I_x}$, a bit 1 is generated in the pixel of the mask 3×3 which is over the pixel y. Otherwise, a value 0 is generated in the same pixel of the mask. Equation 3 shows this calculation. After going through all the neighboring pixels of x, the mask 3×3 will have binary values in all positions, except in the central pixel. These values form a binary word of 8 bits, and it is converted into an integer between 0 and 255. This initial operation is called Modified Census Transform (MCT), or MCT8, because it forms words of 8 bits.

$$T_x = \otimes_{y \in N_x} \zeta(I_y, \overline{I_x}), \quad \zeta(m,n) = \begin{cases} 1, & m \geq n \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The number obtained in Equation 3 is stored in a pixel of a new image, whose position is related to the location of the pixel x. After passing the mask on all pixels of the original image, a new image is obtained. A histogram is computed from this new image, that is, the number of times which value has occurred in the new image. This histogram has 2^8 = 256 elements.

After this step, the MCT is passed over this new image and the histogram of the resulting image is obtained, again with 256 elements. The histograms of both images are concatenated to form a vector h of 512 elements. To avoid a very big difference between the values of the elements, and to achieve a better classification performance, logarithm operation is applied on the non-zero values of the vector h, as shown in Equation 4. Finally, the new vector $\tilde{h}$ is normalized by Equation 5.

$$\tilde{h}_i = 1 + \log(h_i) \quad \forall\, i \in \{1, \ldots, 512\} | h_i > 0. \tag{4}$$

$$\widehat{h_i} = \frac{\tilde{h}_i}{\sum_{i=1}^{512} \tilde{h}_i} \quad \forall\, i \in \{1, \ldots, 512\}. \tag{5}$$

The previous procedure is applied to each image of the dataset. As a result, a numerical matrix F with dimensions $W \times 512$ represents the images and a vector N with dimensions $W \times 1$ represents the vector of categories associated with the images, where W is the number of images in the dataset.

3 DATASETS

For the experiments were collected posts from six Brazilian groups of Facebook social network, in the period from 04/2011 to 07/2015, using Facebook4j API (facebook4j.org). The groups are on different subjects, such as nature, religion, politics, etc. Each post contains a set of fields, such as message, posting date, post ID, group name, link of image posted on Facebook, among others.

The second step was to collect the images. In this step, only the images found on Facebook were collected, because links of external pages could be broken. Moreover, we only collected images that had at least a minimum size of 15×15 pixels and a minimum size of 15 kB.

Then, we applied a filtering procedure on the collected data. This procedure has the function of removing all posts either with the empty message field or with empty link of image field. we also considered an empty image link if there is a link, but we did not collect the image. Finally, after these steps, the dataset is available to be used in our studies.

To accomplish the task of recommending groups to users based on their posts profiles, the following procedures were followed. Initially, the 20 users with the largest number of posts were identified. All posts from these 20 users were separated of the dataset, and these posts will be used to obtain information about user profiles and to recommend groups to the users. These data will be called user dataset.

After removing all posts from the 20 users of the dataset, the next step was to select randomly 1001 posts of each group. This number was selected so that the number of posts per group was equal.These posts will be used to get information about each group. These data will be called group dataset.

For each post of user and group datasets, a representation of the message in vector space model was obtained, as described in Section 2.1. Therefore, we obtained a matrix of messages of the user dataset with 4830×6183 dimensions, that is, 4830 posts and 6183 different terms, while the messages of the group dataset formed a matrix of 6006×6183.

For each dataset was obtained the vector representation of each image included in the posts. For this, the procedure described in Section 2.2 was used. For user dataset was obtained a matrix 4830×512, and for group dataset was obtained a matrix 6006×512.

Thus, each post in each dataset is represented by two vectors: a vector representing the message and the other one representing the image. With these matrices will be carried out the experiments.

4 METHOD TO RECOMMEND GROUPS TO USERS

The approach proposed to recommend groups is based on the post profile of each user. A classification algorithm will be initially trained with a matrix of the group dataset, which may be the matrix of text or image. After training, the equivalent matrix of user dataset will be presented to the classifier. That is, if the classifier is trained with a message matrix, the classifier will classify the message matrix of user dataset.

The classifier returns the group (class) most likely to be associated with the evaluated vector. At the end of this process, all vectors of the user matrix will be associated with a group by the classifier. After this step, for each user it is identified the number of posts associated with each one of the groups, so that a vector with g dimensions will be obtained, where g is the number of groups (in this work, g is equal to 6). The groups are recommended for the user from this vector. Table 1 shows a synthetic example of this result for two users and three groups. In this work, we recommend for each user the group associates with the predominant number of posts. In the case of Table 1, the user_1 is associated with G1 and user_2 with G3.

Table 1: Example of post categorization of 2 users.

User	G1	G2	G3
user_1	23	6	10
user_2	18	5	33

In this work, we used three classifiers: the classical kNN (k-nearest neighbors) algorithm with cosine similarity (Duda et al., 2001), kNN++ (Oliveira et al., 2015), which is a kNN in tree based on hierarchical class-conditional clustering proposed to reduce the computational cost of kNN, and SVM (Support Vector Machine) with histogram intersection kernel (Barla et al., 2003). Each technique has a set of parameters to be adjusted: k for kNN, k and l for kNN++ and c for SVM.

5 EXPERIMENTS AND RESULTS

Before using the proposed approach, the values of k and c of kNN and SVM, respectively, need to be defined. In the same way, the values of k and l of kNN++ need to be selected. A set of values were evaluated using the training data, and the parameter values that returned the highest values of performance metrics were used in the test data. We used in this work the accuracy as performance metric. For selecting the best parameters to each technique, accuracy was calculated as being equal to number of correctly classified posts by the total number of posts. For kNN, we evaluated the value of k in the range from 1 to 15, increasing it in steps of 1. For SVM, the value of c was evaluated from 1 to 15, increasing it in steps of 2. For kNN++, the evaluated values of k and l were both 5, 10 and 15. For evaluating the performance of recommendation of groups, accuracy is computed as being the number of users associated with the correct group by the total number of users.

Table 2: Results of experiments with separated data.

Information source	kNN	kNN++	SVM
Messages	**90.00%**	30.00%	**90.00%**
Images	90.00%	**95.00%**	85.00%

The second row of Table 2 shows the accuracy obtained on the 20 users when using only the information of the messages, while the third row shows the results when using only the images as information. The second, third and fourth columns show the results obtained by kNN, kNN++ and SVM, respectively.

As can be seen, kNN obtained results equal to or better than those one obtained by SVM to recommend groups from the messages or images used separately. kNN++ achieved the best result to recommend groups from images, but its result using only messages was significantly inferior to the results obtained by kNN and SVM. A possible reason for the weak performance of kNN++ on text data is the amount of zeros elements and each text vector. As this technique chooses a sample to represent a group of samples, if the chosen sample does not represent well the group of samples (common case when the number of elements equal to zero is high), the algorithm performance is harmed. Both information sources were useful to recommend groups, since the accuracy values were higher than 80% in all cases, with exception of the kNN++ result when using only messages.

A new set of experiments were performed combining text and image information, and this combination was performed in two ways. In the first one, two kNN are trained, one with text data and another one with image data, using the parameters found in the previous step. Thus, each post is classified twice: the text and the image, then the sum of the number of posts associated with each group is used to recommendation. The same procedure is performed by the kNN++ and SVM. In the second way, the text and image vectors are concatenated to form a single vector per post. The kNN, kNN++ and SVM parameters are selected as explained previously, and the results are obtained.

Table 3 indicates the results, where the second row presents the result when using two classifiers and the

Table 3: Results of experiments with both information sources.

Information source	kNN	kNN++	SVM
Two classifiers	**100.00%**	30.00%	90.00%
Concatenated vectors	**100.00%**	95.00%	**100.00%**

third row when the vectors are concatenated. The results of kNN, kNN++ and SVM are shown in the second, third and fourth columns, respectively. As can be seen for all classifiers, the results obtained with the concatenated vectors are better than using two classifiers. For kNN and SVM, these results are better than the results when using a single information source. In the case of kNN++, the concatenated vectors returned the same accuracy obtained when using only images data. These observations highlight the importance of using both types of information in recommendation tasks and classification. However, we believe that when using the approach with two classifiers a classifier may polarize the other one, because we used just a simple sum of groups per user. An evidence is the low accuracy of kNN++ with two classifiers, that is equal to result obtained when using only message information, even though the result using only images data is quite superior.

The results in Tables 2 and 3 were obtained using all collected posts from each user. However, it is convenient to have a good precision using a number of posts as small as possible. For this, the following analysis was performed: the number of posts per user was limited to the N most recent posts and calculated for each value of N the accuracy of group recommendation. The N values used were 1, 5, 10, 15, …, 100 posts. The graphics of Figures 1(a), 1(b) and 1(c) show the results obtained by the classifiers when using only text, only image and the concatenated vectors, respectively. Two of the 20 users had less than 100 posts, so for values greater than the number of posts were considered all user posts.

As can be seen in Figure 1(a), classical kNN achieved high levels of accuracy using only text to recommend groups to users. With only the latest post of each user has achieved an accuracy of 80% and with 10 posts was obtained a value of 95%. The kNN++ did not reach accuracy level as high as it was by kNN, and the accuracy remained stable at 30% with the number of posts above or equal to 10. The SVM results were slightly inferior to kNN results.

The graphics in Figure 1(b) indicate that kNN++ has a higher performance than the classical kNN and SVM to recommend groups when using image information. The accuracy of kNN++ is equal to or higher than the kNN and SVM accuracies for any number of posts. Furthermore, the kNN++ performance was more stable than that of kNN. The accuracy of SVM rose with the increasing of the number of posts, but it stabilized at 80%. The highest accuracy was obtained by kNN++ with 55 posts, and the accuracy value stabilized at 95%.

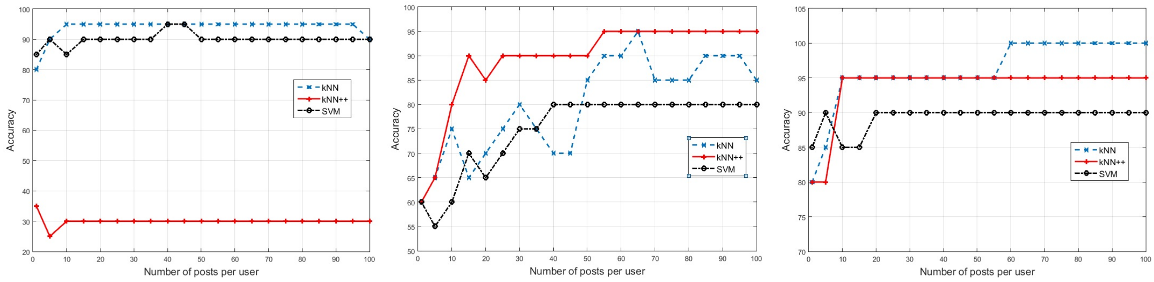
Finally, Figure 1(c) shows a combination of texts and images to recommend groups. When combining the results, classical kNN and kNN++ achieved accuracies of 80% with a single post, while SVM obtained 85%, with only one post. However, the accuracy of SVM stabilized at 90% with more posts, and achieved 100% with more than 100 posts per user. The accuracy of kNN and kNN++ increased to 95% when using 10 posts, and the kNN accuracy reached 100% with 60 or more posts.

Observing the experimental results, kNN achieved high accuracy (80% or above) with few posts when using text information (only text or text and image). When the kNN used only image information, a larger number of posts was necessary for it obtains high accuracy (above 80%), unfortunately, it is not always available in a real world a lot of posts per user. kNN++ achieved the worst accuracy when using only text information, on the other hand, it obtained the highest accuracy when using only image information. A possible reason for its weak performance on text data is the amount of zeros elements and each text vector, as explained previously. The accuracy of SVM was similar to kNN, when using only text. Nevertheless, its performance with few posts and using image data (only image or text and image) was inferior to those achieved by kNN++ and kNN. As SVM is a complex algorithm, kNN or kNN++ are supposed to be most appropriate choices.

In the context of computational cost, we observed that kNN++ was around 15 and 2 times faster than SVM and kNN to classify texts and the combination of images and texts, respectively. The computational cost of SVM and kNN to classify the same kind of data was similar each other. However, kNN++ took as much time as SVM to classify image data, and kNN was around of 4 times faster than SVM and kNN++.

6 CONCLUSIONS

In this paper was analyzed the use of texts and images shared by users on the task of recommending Facebook groups for them. Experimental results indicated that both information sources (text and images) are useful to perform appropriately this task, and high levels of accuracy were obtained using only one type of information, although the best results were obtained when texts and images data were used altogether. In the experimental results, it was also ob-



(a) (b) (c)

Figure 1: Accuracy per number of posts when using: (a) only text information, (b) only image information and (c) text and image information.

served that the use of a reasonable amount of posts per user to recommending groups increases the precision of the system, so that with 10 posts per user was possible to have an accuracy of 95%, when using texts and images, and with 60 posts was achieved up to 100% of accuracy.

Future research paths include to evaluate better methods for the unification of texts and images to recommend groups when the user shares only one another type of information, and to use larger datasets where the users can be recommended for a set of groups. In this latter case, the task is similar to multi-label classification and approaches of this field can be employed. An example of multi-label classification used for recommendation was presented in (de Oliveira et al., 2013).

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REFERENCES

Baeza-Yates, R. and Ribeiro-Neto, B. (1998). *Modern Information Retrieval*. Addison-Wesley, New York, first edition edition.

Barla, A., Odone, F., and Verri, A. (2003). Histogram intersection kernel for image classification. *Proceedings of 2003 International Conference on Image Processing*, 3:513–516.

de Oliveira, M. G., Ciarelli, P. M., and Oliveira, E. (2013). Recommendation of programming activities by multi-label classification for a formative assessment of students. *Expert Systems with Applications*, 40(16):6641–6651.

de Souza Gazolli, K. A. and Salles, E. O. T. (2012). A contextual image descriptor for scene classification. *Online Proceedings on Trends in Innovative Computing*, pages 66–71.

Duda, R. O., Hart, P. E., and Stork, D. G. (2001). *Pattern Classification*. Wiley-Interscience, New York, 2 edition.

Jin, L., Chen, Y., Wang, T., Hui, P., and Vasilakos, A. V. (2013). Understanding user behavior in online social networks: a survey. *IEEE Communications Magazine*, pages 144–150.

Kosinski, M., Stillwell, D., and Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences of the United States of America*, pages 1–4.

Mislove, A., Viswanath, B., Gummadi, K. P., and Druschel, P. (2010). You are who you know: inferring user profiles in online social networks. *Proceedings of the third ACM international conference on Web search and data mining*, pages 251–260.

Oliveira, E., Roatti, H., de Araujo Nogueira, M., Basoni, H. G., and Ciarelli, P. M. (2015). Using the cluster-based tree structure of k-nearest neighbor to reduce the effort required to classify unlabeled large datasets. *The 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management.*, pages 1–10.

Salton, G. and Yang, C. S. (1975). A vector space model for automatic indexing. *Communications of the ACM*, pages 613–620.

Statista (2016). Number of social network users worldwide from 2010 to 2019 (in billions). Technical report, http://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/.

WERSM (2015). How much data is generated every minute on social media? Technical report, http://wersm.com/how-much-data-is-generated-every-minute-on-social-media/.