

User Interest Modeling Based on Image Semantics (Postprint)

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Abstract

Objective: User interest modeling in social network environments is crucial for friend recommendation and precision marketing. This paper proposes a user interest modeling method based on image semantics that utilizes images shared by Sina Weibo users, aiming to more accurately predict users' true interests. **Method:** Based on acquiring image data from Sina Weibo users, high-level semantics of images are employed to represent user interest features. An image semantics classifier is trained using SVM based on these features for prediction. **Results:** Experimental results demonstrate that the model established in this paper can predict users' true interests with considerable accuracy. The classification accuracy for 169 users reaches 97.38%, with a recall rate of 98.92% and an F-value of 98.14%. **Limitations:** Due to the limited experimental image dataset, it fails to completely cover all user interest categories. **Conclusion:** The model can predict user interests with considerable accuracy based on images shared by users, demonstrating the effectiveness of high-level image semantics, while also providing a theoretical and technical foundation for research on applications of high-level image semantics.

Full Text

Preamble

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With the rapid development of machine learning and deep learning technologies, research on user interest modeling based on image semantics has gained

significant attention. Deep neural networks (DNN, CNN, RNN) have demonstrated powerful capabilities in image semantic classification tasks [20-21]. In 2014, Google proposed GoogLeNet, which achieved breakthrough results in image classification by employing deep convolutional neural networks to automatically learn image features, providing new approaches for user interest modeling based on image semantics.

2.3 Application of Image Semantics in User Interest Modeling

Image semantics plays a crucial role in user interest modeling [23-24]. You et al. crawled image data from social platforms and used deep neural networks to extract high-level semantic features for gender prediction and user interest profiling. Segalin et al. analyzed images shared by users on Flickr, Facebook, and Instagram, extracting visual features (such as color, texture, and composition) as inputs to predict user personality traits. Yang et al. utilized deep convolutional neural networks (such as AlexNet) to extract semantic features from images posted by users, achieving user interest classification. Yang also employed deep learning methods to analyze images from Flickr, extracting semantic information to infer user interests, including scene categories (e.g., travel, food) and object categories (e.g., cars, pets). Sasaki et al. used convolutional neural networks to extract features from user-posted images, analyzing emotional contagion effects through smile detection. These studies demonstrate that image semantics provides rich information for user interest modeling, though most rely on low-level visual features. With the development of deep learning, high-level semantic features offer new possibilities for user interest modeling.

Current research primarily extracts image features through deep learning and uses classifiers for user interest prediction. The process involves: first, obtaining user-shared image data; second, extracting semantic features from these images using deep neural networks; and finally, training classifiers (such as SVM or AdaBoost) to predict user interests. The core challenge lies in “how to effectively utilize high-level semantic information from images for accurate user interest modeling.” Therefore, this study employs deep learning-based image semantic analysis methods to construct user interest models.

3.1 Problem Definition

User interest classification based on images can be formulated as follows: Given a user U with an image set $Uv = \{x_1, x_2, x_3, \dots, x_n\}$ and a classification function f , the user’s interest label set is $Y = \{y_1, y_2, y_3, \dots, y_i\}$. The goal is to learn a mapping $f(Uv) \rightarrow Y$, where y_i represents the user’s interest category.

The learning process for this mapping function involves two key steps: (1) extracting semantic features from user images; (2) training the classification function f using machine learning algorithms (such as SVM [29], AdaBoost [30]) to map image features to interest categories. This study focuses on “how to leverage high-level semantic features automatically extracted by deep neural networks for user interest modeling,” aiming to build user interest models through deep learning-based image semantic analysis.

3.2 User Interest Classification and Semantic Interest Feature Representation

User interest classification requires effective feature representation of images. This study employs Python-based deep learning frameworks to extract semantic features from images. Five interest categories are defined: travel, fashion, comics, model, and food. For each category, semantic features are extracted as follows: (1) using pre-trained convolutional neural networks (e.g., VGG, ResNet) for feature extraction; (2) representing each image as a high-dimensional feature vector; (3) aggregating features from all images of a user to form a user-level interest representation.

Formally, for user U with image set $I = \{i_1, i_2, i_3, \dots, i_n\}$ (where n is the number of images), each image i is processed by a deep network to obtain its feature representation. The feature set for all images is $F = \{f_1, f_2, f_3, \dots, f_j, \dots, f_m\}$, where m is the number of features and f_j represents the j -th feature dimension. User interest classification is then performed based on this feature representation, where the core idea is “using high-level semantic features extracted by deep networks from user-shared images to represent and classify user interests.”

3.3 User Interest Recognition Based on Images

User interest recognition consists of two stages: feature extraction and classification. This study uses deep convolutional neural networks to extract features from images in five categories: travel, fashion, comics, model, and food. The dataset includes 169 users, with each user having approximately 300 images, totaling 50,700 images. After data cleaning, 785 valid images remain. Features extracted by the deep network serve as input to the classifier.

For user U with image set $I = \{i_1, i_2, i_3, \dots, i_n\}$, the deep network extracts semantic features for each image. A Support Vector Machine (SVM) is then trained for classification. For n images, the prediction results form a set $P = \{p_1, p_2, p_3, \dots, p_i\}$, where $p_i \in L$ (the label set). The frequency of each category is calculated using $\text{count}(x, P)$, which counts occurrences of label x in P . The category with the highest frequency is selected as the user’s primary interest.

4.1 Data Collection and Processing

Data was collected from 48 initial users, expanded to 169 Sina Weibo users. For each user, 300 images were crawled using their IDs and URLs via Python scripts, totaling 50,700 images across five categories. After validation, 785 images were retained for training.

For each user U with image set $I = \{i_1, i_2, i_3, \dots, i_n\}$, deep network features are extracted as described in Equation (1), where n is the number of images for user U .

The user interest classification process involves: (1) extracting 1,008-dimensional feature vectors for each of the 169 users' images (deep features); (2) normalizing features to $[0,1]$ range; (3) converting to LIBSVM format: `label 1:value1 2:value2 3:value3...`, where label $\{0,1,2,3,4\}$ corresponds to travel, fashion, comics, model, and food categories; (4) training SVM using LIBSVM with 1,008 features per sample.

LIBSVM parameters are set as: kernel type $t = 0$ (linear kernel), SVM type $s = 1$ (v-SVC). The `svm-train.exe` utility trains the model, and `svm-predict.exe` performs classification.

Ten-fold cross-validation is employed: 169 users are divided into 10 folds (17 users per fold). Nine folds are used for training and one for testing in each iteration. The average accuracy across 10 iterations yields the final performance metric.

4.3 Results Evaluation

Evaluation metrics include Precision (P), Recall (R), and F-value (F).

The experimental results on 169 users are summarized in Table 1:

Table 1: User Interest Classification Results

Interest Category	Precision	Recall	F-value
Travel	95.56%	94.59%	96.77%
Fashion	97.17%	97.38%	94.59%
Comics	98.81%	98.92%	97.73%
Model	94.59%	98.36%	97.98%
Food	98.14%	—	—

Overall performance: Precision = 97.38%, Recall = 98.92%, F-value = 98.14%. The model achieves high accuracy across all categories, with particularly strong

performance for comics and food categories. Fashion and travel categories also show robust results, while the model category exhibits slightly lower precision but high recall.

The results demonstrate that deep learning-based image semantic features effectively capture user interests. High-level semantics (e.g., scene objects, visual themes) provide discriminative information for classification. The SVM classifier successfully leverages these features to achieve accurate user interest prediction.

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Author Contribution Statement

Zeng Jin: Conceptualization, methodology, software, writing-original draft; Lu Wei: Methodology, validation, formal analysis; Ding Heng: Data curation, investigation; Chen Haihua: Supervision, project administration.

Conflict of Interest Statement

The authors declare no competing financial interests.

Support Data

Data Availability: The image dataset used in this study is available at: <http://www.infotech.ac.cn>

Dataset: data.rar (Image Semantic Features for User Interest Modeling)

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Abstract: [Objective] This paper aims to predict the user's interests accurately with a new modeling method based on the semantics of images shared on the microblogs. [Methods] First, we crawled the image data of Sina microblogging users. Then, we used high-level semantic information from these images. Finally, we predicted user's interests based on the image semantic classifier by the SVM training. [Results] The proposed method could predict user's interests effectively. Among the 169 Sina microblogging users, the precision, recall and F-values were 97.38%, 98.92% and 98.14%, respectively. [Limitations] The size of the test corpus needs to be expanded to have more comprehensive results. [Conclusions] The proposed model could predict user's interests effectively, which lays some theoretical and technical foundations for the application of high-level image semantics.

Keywords: Image Semantic; User Interest Modeling; Social Network; Support Vector Machine

Note: Figure translations are in progress. See original paper for figures.

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