# Diversity of User Viewpoints on Social Signals: a Study with YouTube Content

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**Abstract.** The user modelling community has started to exploit user contributed content on the Social Web for adaptation and personalisation. This abundant content depicts various viewpoints coming from a diverse user pool, which can be useful for broadening perspectives by pointing to aspects that users may be unaware of. The time is ripe to capture this diversity and exploit it for personalisation and adaptation in representative domains. The research presented in this paper considers a specific domain - social signals (body language and emotions) in interpersonal communication embedded in many everyday life activities (e.g. job interviews, meetings, sales). The digital traces on social signals users leave in the Social Web come from a variety of user backgrounds, and can provide a rich space to explore diversity of viewpoints. A study on the diversity of viewpoints on social signals related to job interviews is presented, using YouTube as a source for digital content. We present a methodology for collecting and aggregating user-generated content and apply a framework for semantic augmentation. The viewpoints are analysed based on YouTube user profiles. Strong dependency is found between user demographic characteristics (age, gender and location) and the concepts and context dimensions in user comments. This evidences that there is diversity in user viewpoints on social signals, which can be analysed further and exploited to augment user models.

**Keywords:** social web, viewpoint semantics, diversity, social signals

## 1 Introduction

The Social Web offers an abundance of user-generated content. Segments of this content embed valuable information about the users (contributors), becoming digital traces of the users. This can be used, if discovered, extracted and analysed, to augment existing user models and improve adaptation and personalisation. Recent trends in the Semantic Web community include exploitation of the digital traces to profile users for adaptive recommendations [1], aggregate and retrieve information [2] and align real-world events with virtual community discussions [3]. However, there are emerging expectations from the next generation of personalisation techniques, as the emphasis shifts from similarity to user-generated content, to approaches that exploit diversity of users' viewpoints [4]. If captured in a machine processable form, the diversity of viewpoints, emanating from different backgrounds and experiences, can bring valuable sources for user modelling. For example, a user focusing on one aspect can be pointed to an alternative perspective based on similarities and complementarities of user viewpoints.

The computer science community has recently started to elaborate on the notion of viewpoints. A user's perspective is informally introduced in [5] for bridging the semantic gap between different users' conceptualisations while aggregating events (broader happenings in real life, such as tourism travels) through media resources. However, the user profiles are not taken into account. In [6], a new dimension of functionality of recommender systems for products and news is proposed according to user beliefs, additionally to user characteristics. Polarity of opinions embedded in documents is discussed in [7-8] using probabilistic models. In information science, Munson and Resnick [9] elaborate on the diversity of political opinions and how individual viewpoints are affected and change. Although there is a notable effort to address the challenge of exploiting the diversity of viewpoints, the diversity regarding individual user factors (e.g. user demographics, occupation and experiences) has not been explored. Instead, the existing approaches focus mainly on polarity, missing thus the depth and the underlying semantics.

Our research considers an example application: technology-enhanced learning. Presenting diversity of viewpoints based on real-life experiences is one of the challenges of the next-generation learning systems [10-11]. The specific domain that our work focuses on is Interpersonal Communication (IC), which comprises a set of skills crucial for the knowledge society of the 21st century [12]. IC falls in the so called ill-defined domains where knowledge is difficult to model and is subject of different interpretations and viewpoints [13]. Capturing and exploiting diversity is a key challenge for such domains.

The key goal of our research is capturing viewpoints from social spaces and exploiting these viewpoint for adaptation and personalisation. In our previous work, we introduced `ViewS`, a framework for capturing viewpoints semantics [14]. An individual's viewpoint is defined as: *the focus and the collection of statements that a person develops when commenting on a human activity from a specific role*. `ViewS` was instantiated for capturing the semantics of viewpoints on social signals in IC activities. A case study on job interviews included YouTube videos and digital traces (comments in textual format) of users in a controlled environment. The study showed that semantic web technologies can be used for capturing social signal semantics and that there is diversity in users' viewpoints based on their background. Although the study found strong evidence of diversity on social signals, it considered only a closed, experimental social space where users, recruited by us, contributed comments on selected videos. Diversity of user viewpoints on social signals in open social spaces has still not been exploited.

This paper presents the next step in our work on capturing and exploiting viewpoint diversity considering open social spaces. We apply `ViewS` on YouTube content with users' digital traces (comments) related to social signals in job interviews. The research question addressed in this paper is:

> *Is there diversity of viewpoints on social signals in YouTube user comments, and what are the implications for augmenting user models?*

To address this research question, three main steps are followed (as shown in Figure 1): (i) content collection from YouTube (presented in Section 2), (ii) semantic augmentation of user digital traces with `ViewS` (presented in Section 3), and (iii) exploration of viewpoints (described in Section 4). Finally, in Section 5 we will summarise the findings and discuss the implications for augmenting user models.

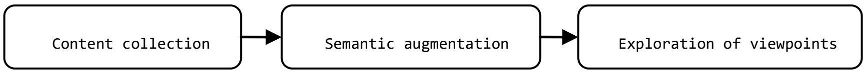


**Fig. 1.** The main steps to explore the diversity of viewpoints in YouTube use comments.

## 2 Content Collection

To collect user generated content on social signals in the job interview activity from the Social Web, we selected YouTube as the data source, based on the following assumptions:

- there is a plethora of digital activity objects including : (a) videos of job interviews (activity exemplars) and (b) videos about job interviews (guides and tips for successful job interviews and stories) which can stimulate discussions where some users contributed comments can include personal opinions and experiences;
- there is a plethora of users registered at YouTube;
- the web data space is up to date regarding new content being published and users registering; and
- ample user-generated content exists in the form of comments (and published media), because job interview is an activity that every person experiences several times in his/her life, either as applicant or interviewer.

Initially, simple queries were performed in the YouTube search engine and the collected sample was checked for relevance to job interviews, amount of results, amount of users contributing, as well as for identifying the content metadata structures that could improve the search if used as querying criteria. Regarding the YouTube metadata structures, five video categories were identified as candidate to contain job interview related content: `"How to & Style"`, `"Education"`, `"People and Blogs"`, `"Video blogging"` and `"Nonprofit and Activism"`. Hereafter, these categories will be referred for short as "Howto", "Education", "People", "Videoblog" and "Nonprofit" respectively. Other metadata found useful to utilise included: the search mode, for which “moderate safe mode” was selected[1], and the video tags which are presented as part of the filtering methodology in Section 3.2.

[1] Other modes include “none” and “strict”, however the differences in results’ content and number were not significant

### 2.1 YouTube Query Construction for Job Interview and Social Signals

The keywords used to construct queries for the YouTube search engine were collected from a study that aims at identifying competency questions related to job interviews to evaluate an ontology of activity models – AMOn [15] - including job interviews[2]. A script was provided to domain experts in the field of "job interviewing" in order to elicit competency questions. Five individuals considered experts including human resources managers with international experience and trainers at a staff development and recruitment centre, were consulted.

Each query is structured based on three components: <activity>, <activity aspect> and <context dimension>. Different combinations of these components were used to construct a set of 190 queries[3]. Table 1 shows the templates used for constructing the queries and examples.

**Table 1.** The query templates used to search YouTube for job interview related videos and corresponding examples.

| Query template | Query examples | |
|---|---|---|
| <activity> | <“interview”>< “job interview”> | 22 queries |
| <activity aspect> | <“applicant”>< “interviewer”> | |
| <activity>, <activity aspect> | <“interview"><"candidate”>,<“job interview"><" applicant”> | |
| <activity>, <context dimension> | <“job interview"><"social signals”>,<“job interview"><"non verbal cues”> | 168 queries |
| <activity>, <activity aspect>, <context dimension> | <“job interview"><"interviewer"><"body language”>,<“interview"><"candidate"><"emotional”> | |
| | **Total** | 190 |

### 2.2 Collected Corpus and Filtering Method

The queries were executed using the YouTube Data API[4]. The total number of videos collected from all the queries was 44,043 from which 15,064 were unique among the querying result sets. The total number of comments for the unique videos was 799,524. Most of the video results extracted using queries for the "Education" category, followed by "People". The "Videoblog" category did not provide any videos. The videos with the most comments were concentrated in the "People" video category.

For each set of video results (each query produces one set of videos), the videos that had no comments contributed from users were removed from the corpus. For each video the duplicate comments and the comments that included URIs were removed. This resulted to a total of 26,301 videos. The union of video result sets was produced by each query result video set and a set of 8,466 videos in the collected corpus.

2 ImREAL EU Project, deliverable D7.3: http://www.imreal-project.eu/
3 http://imash.leeds.ac.uk/ViewS/Resources/AUM2012/YouTubeQueries.xlsx
4 https://developers.google.com/youtube/2.0/developers_guide_dotnet

Identifying videos relevant to the job interview activity included a pre-study task where a sample of 4,282 videos were manually checked for relevancy based on the following criteria: (i) the video is related to job interview and does not contain advertising material, (ii) it is not a video of celebrity persons, political figures or other personalities, (iii) it is not a video of interviews relating to either than job recruitment, (iv) it is in English language or at least has English subtitles, and the comments are in English, (v) it solidly focused on the job interview process, excluding preparatory steps such as resume writing and post-interview actions (e.g. sending an appreciation e-mail to the company), and (vi) the video does not concern academic career interviews. The selected videos were examined, by checking the corresponding user-contributed tags. This allowed for automating the process of selecting relevant videos. The relevant videos, were those which were tagged with combinations of the terms "job" and "interview" (including plural variations).

Using the aforementioned tags as directives for selection resulted to a set of 716 videos[5] in the collected corpus. The "Howto" video category provided the most relevant videos (402) as well as the most comments (14,588).

The corpus was then semantically annotated with `ViewS` (see Section 3, identifying concepts and context dimensions of concepts in the textual comments). From this process the videos for which no comment was annotated were excluded (annotated: 513[6], not annotated: 203). Table 2 shows that the number of videos was reduced to approximately 71.6% (the video category “Howto” remained the most frequent), while the number of total comments has reduced to 98.2%. The annotation task removed all videos with a small number of comments (2.1 comments per video on average). In such cases, it is often that the comments concern appreciative to the video uploader content, instead of activity related content.

**Table 2.** Number of videos and comments f0r each video category after the annotation.

| **Corpus** | **Video category** | | | | **Total** |
|---|---|---|---|---|---|
| | Howto | Education | People | Nonprofit | |
| # videos | 288 | 107 | 108 | 10 | 513 |
| # comments | 14,348 | 1,567 | 7,433 | 367 | 23,715 |

## 2.3 YouTube Demographic User Profiles

The collected corpus was produced by 16,531 users (each user contributes 1.4 comments on average). For these users, 15,926 profiles were collected (other were private or the users had unsubscribed from the service). The collected profile variables included age, gender, location, hometown and language. Hometown and language were not available in the 79% of the cases and were disregarded. Age, gender and location were available (no missing data) for 84.3% (13,437) of the cases. From these, 1.44% users provided age more than 75 years and were disregarded. For the remainder of the paper, 13,243 user profiles (80.1% of the total) are used to illustrate the findings.

5 http://imash.leeds.ac.uk/ViewS/Resources/AUM2012/ YouTubeData__UnionAllRelevant_Combo_716.rar

6 http://imash.leeds.ac.uk/ViewS/Resources/AUM2012/ YouTubeDataAnalysis_UnionOfAll_Annotated_513.rar

Table 3 presents a summary of the user profiles. For the location attribute only the five most frequent are given.

**Table 3.** Summary of the collected YouTube demographic user profiles

| Profile variable | Summary |
|---|---|
| Age | min:13 max:75 median: 25 mean: 27.35 sd: 9.25311 |
| Gender | male:7498 female:5475 |
| Location | US:53.3% GB:10.1% CA:7.7% AU:3.6% IN:2.4% |

Age was discretised in four groups ( [13-20], [21-26], [27-37], and [38, 75] ) based on normal distribution of observations. A Chi-square test was performed to test for possible association between age and the number of users contributing to different video categories and the result showed significant dependency (p-value < 2.2e-16). As age increases, more users are contributing in “Education” and “Nonprofit” video categories (proportionally for each age group).

Regarding gender, male users focused proportionally more to "Education" and "Nonprofit" categories. Female users on the other hand, focused more to "Howto" "people" video categories than men. A strong association was shown between gender and number of users that contributed in different video categories with chi-square test (p-value < 2.2e-16).

Regarding users' location, an association was shown with the number of users contributing in different video categories (Chi-square p-value < 2.2e-16). Random sampling was then performed to balance observations of users located in US with number of observation of users in other locations. Examples cases in the summary results included that proportionally users from India were contributing to more "Education" related videos compared to users in other locations, and users from GB contributed to more videos in "Howto" and "People" categories than US users, and vice versa for "Education" and "Nonprofit".

## 3 Semantic Augmentation

The collected content has been semantically augmented using existing ontologies and exploiting information extraction tools, following the `ViewS` framework [14].

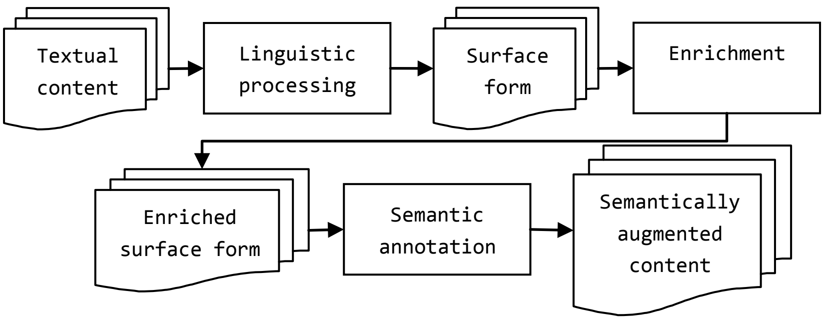


**Fig. 2.** Architecture of the semantic augmentation component in `ViewS`.

Figure 2 presents the architecture of the semantic augmentation of digital traces with ViewS. The digital traces comprise comments contributed from users. Each comment is first linguistically processed. This process includes traditional natural language processing modules such as sentence-splitting, tokenization, part-of-speech tagging and stemming using the Stanford parser[7]. This produces a surface form of the textual comment. The surface form is the passed to the enrichment module. The enrichment includes extraction of lexical derivations and synonyms using the WordNet lexical thesaurus[8], and extraction of similar words using the DISCO API[9]. Each enrichment method includes sense detection with WordNet and filtering of senses that are relevant to the domain of interpersonal communication and socials signals using the WordNet lexical categories and resource mappings to SUMO concepts[10]. The lexical categories and the set of concepts from SUMO have been selected by a domain expert. This process produces an enriched surface form of the comment which is then passed to the semantic annotation. Two ontological resources have been used to describe the social signals: the WordNet Affect[11] taxonomy of emotions and a body language ontology[12]. The annotation process produces textual content semantically augmented with links to concepts in the ontologies for social signals. More details regarding the semantic augmentation with ViewS can be found at [14], including the evaluation, and the qualitative and quantitative analysis of the semantic tagging.

Figure 3 (a) presents the summary of the annotated corpus for different video categories. The annotation was balanced –in terms of comments annotated with ViewS- between different categories. Figure 3 (b) presents the summary of concepts for each video category.

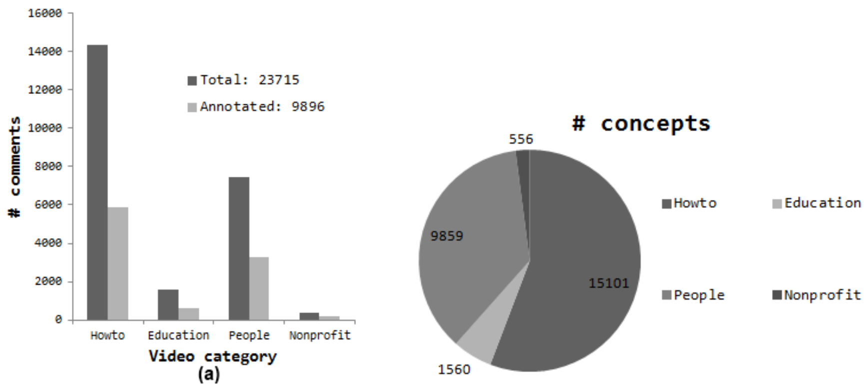


**Fig. 3.** Summaries of annotated comments (a) and concepts (b) for the video categories. The results are in line with the number of contributions for each video category by the users. Proportionally for each category the annotation is balanced to ~50%.

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7 http://nlp.stanford.edu/software/lex-parser.shtml
8 http://wordnet.princeton.edu/
9 http://www.linguatools.de/disco/disco_en.html
10 http://www.ontologyportal.org/
11 http://wndomains.fbk.eu/wnaffect.html
12 http://imash.leeds.ac.uk/ViewS/Resources/SWJSpecialIssue/BodyLanguage.owl

Table 4 presents the summary of the semantic augmentation process. In line with the number of contributions and users, the video categories “Howto” and “People” comprised the most distinct social signal related concepts.

**Table 4.** Summary of the semnatic augmentation with `ViewS`

| **Context dimension** | **# concepts** | **Ontology coverage** | **Video categories / ontology coverage** | | | |
|---|---|---|---|---|---|---|
| | | | **Howto** | **Education** | **People** | **Nonprofit** |
| **Emotion** | 7511 | 154 (50.6% of 304) | 129(42.4%) | 75(24.7%) | 134(44.1%) | 51(16.8%) |
| **Body language** | 13578 | 204 (58.3% of 350) | 174(49.7%) | 95(27.1%) | 168(48%) | 56(16%) |
| **Total** | 21089 | 358 | 303 | 170 | 302 | 107 |

## 4 Exploration of Viewpoints Diversity

The viewpoint semantics elicited with `ViewS` were explored in relation with the YouTube user profiles. Age, gender and location were tested separately with `<context dimension>` and <concept> in user’s viewpoint. For each pair `<profile variable, ViewS component>` chi-square tests of independency were performed, as well as qualitative operations regarding the commonalities and differences in terms of concepts identified in the diverse user profiles.

**Age**. Table 5 shows the number of concepts extracted by contributions from users of different age groups regarding the context dimensions (emotion and body language). It is shown that as age increases, more body language related concepts were elicited from the users' comments. Contrariwise, emotion related concepts are decreasing in number as age increases. Strong association was found as well regarding the age and number of concepts for each context dimension in different groups (p-value = 8.655e-10).

**Table 5.** Number of concepts regarding context dimensions in comments contributed by users in different age groups. Tha variables are signifficantly associated (p-value = 8.655e-10).

| | **Age group - number of concepts for context dimensions (%)** | | | |
|---|---|---|---|---|
| **Context Dimension** | **<20** | **21-26** | **27-37** | **>37** |
| Body language | 2130 (61.58%) | 4331 (64.76%) | 4210 (63.01%) | 2907 (68.22%) |
| Emotion | 1329 (38.42%) | 2357 (35.24%) | 2471 (36.99%) | 1354 (31.78%_ |
| **Total** | 3459 (100.00%) | 6688 (100.00%) | 6681 (100.00%) | 4261 (100.00%) |

Regarding the concepts that users in different age groups contributed in `ViewS`, chi-square tests showed again strong relation (p-value < 2.2e-16). To illustrate the diversity between users, the profiles are grouped at a cut point of age 26.5 years based on normal distribution of observations. Table 6 presents example concepts contributed by both groups, as well as concepts contributed exclusively from each group (for each group of concepts the number of total concepts is given in brackets). It is shown that older ages contributed more distinct social signal related concepts (65).

**Table 6.** Age groups – concepts: commonality and differnece examples.

| Example concepts contributed by age groups A: <26.5 and B: >26.5 | | |
|---|---|---|
| **Common (239)** | **Only in group A (39)** | **Only in group B (65)** |
| panic, shock, scare, handshake | bad-temper, insecurity, running hands through hair, sarcasm | distress, head nodding, cross-ing_legs, finger pointing a person |

**Gender**. Table 7 shows the number of concepts regarding context dimensions extracted by contributions from users of different gender. It is shown that male users provide proportionally more body language related concepts than female users. Contrariwise, female users focused more on emotion than male users. Gender and number of concepts regarding context dimensions were found significantly associated (p-value = 2.627e-10).

**Table 7.** Number of concepts regarding context dimensions in comments contributed by users of different gender. Tha variables are signifficantly associated (p-value = 2.627e-10).

| | Gender - number of concepts for context dimensions (%) | | | |
|---|---|---|---|---|
| **Context dimension** | **Female** | | **Male** | |
| Body language | 5407 | (61.90%) | 8171 | (66.14%) |
| Emotion | 3328 | (38.10%) | 4183 | (33.86%) |
| **Total** | 8735 | (100.00%) | 12354 | (100.00%) |

Table 8 presents example concepts that were commonly annotated with `ViewS` in comments from male and female users, as well as examples of exclusive concepts by each group. Strong association was also shown between gender and contributed concepts (p-value < 2.2e-16). It is observed that male users' contributions were annotated with more distinct concepts than female users' (72 for male and 24 for female).

**Table 8.** Gender – concepts: commonality and differnece examples.

| Example concepts contributed by gender | | |
|---|---|---|
| **Common (247)** | **Only by females (24)** | **Only by males (72)** |
| gum, interest, anxiousness, eye contact | crossed arm, antagonism, liking, looking left | threat, faked smile, eyebrow raising, impatience |

**Location**. The number of statements regarding context dimensions in users' contributions, was also found dependent to the users' location (`p-value < 2.2e-16`). Strong dependency was also found for the specific concepts that were extracted with `ViewS` (`p-value < 2.267e-10`). To illustrate the diversity according to users' location, two groups have been selected: individuals from US and from GB. To balance the output to the number of individuals, a random sample was selected form users located in US adjusted for the number of users located in GB. Table 9 shows the number of concepts regarding the context dimensions in users' contributions. Users located in GB provided proportionally more on emotion than those in US (this result stands for the whole data set, as well as for other samples generated randomly). Table 10 shows examples of concepts commonly extracted by contributions of US and GB located users, as well as exclusive concepts by each group (for the random sample).

**Table 9.** Number of concepts regarding context dimensions in comments contributed by users in US (adjusted sample) and GB.

| | Location - number of concepts for context dimensions (%) | | | |
|---|---|---|---|---|
| **Context dimension** | **US** | | **GB** | |
| Body language | 1246 | (65.30%) | 1195 | (62.63%) |
| Emotion | 662 | (34.70%) | 713 | (37.37%) |
| **Total** | 1908 | (100.00%) | 1908 | (100.00%) |

**Table 10.** Location – concepts: commonality and differnece examples (random sample).

| Example concepts contributed by location: US(adjusted random sample) and GB | | |
|---|---|---|
| **Common (149)** | **Only by US (59)** | **Only by GB (52)** |
| arm, mouth, shaking, anxiety | gum, confusion, optimism, criticism | refusal, chin-up, scare, surprise |

## 5 Implications for Augmenting User Models

We have presented a study that collects user comments from open social spaces (YouTube is used as an example), semantically augments these comments to capture social signal concepts (body language and emotion), and explores the diversity based on demographic user profiles. The study found strong dependency between user characteristics (age, gender and location) and the concepts and context dimensions in captured in the users comments.

Young users tend to notice more emotions, while older users' comments include more body language. There is a strong dependency between age and social signal concepts users mentioned, which shows that different age groups comment on different concepts. Examples have been shown of concepts mentioned by one age group but not mentioned by another. Splitting users into two groups (using the cut-off point 26.5 of the normal distribution), we have found that the group with the older users mentioned more distinct concepts.

Similarly, diversity was observed based on gender. Male users talk slightly more about body language than emotion, while female users talk slightly more about emotion than body language. The chi-square test has confirmed that the dependency between gender and context dimension (emotion/body language) is significant. Furthermore, male users provided more distinct concepts which were not mentioned by female users. A quick examination of the distinct concept sets for each group shows that they include both emotion and body language.

The findings show that location does not appear a very reliable parameter for examining diversity. Almost half of the users came from USA and the other most represented countries included Great Britain, Canada, Australia and India. These are mainly English speaking and there may not be much diversity regarding job interviews in these countries. Nevertheless, the chi-square analysis did show dependency between location and the social signals mentioned by users.

Overall, the study gives a strong support to the claim that social web provides a rich space to examine the diversity of viewpoints on social signals. As an example, it will be interesting to examine this diversity for selected videos and see if different groups that watch the same video make different points. Social web provides unprecedented reach to demographic data which can be used for deriving group profiles based on the concepts mentioned in the user generated content. This can provide stereotypical knowledge that can be used to derive/augment individual user models.

The study presented in the paper provides a starting point for further investigation to examine what the diversity is and how different viewpoints relate. Having semantic augmentation allows us to semantically compare viewpoints. Further analysis is planned to examine the differences in the concept space for the groups based on age, gender or location, and to identify possible group patterns. This can then be useful for deriving group profiles (stereotypes), which can help with handling cold start in adaptive systems (e.g. learning applications promoting user awareness of social signals).

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