A Semantic Approach to Extract Individual Viewpoints from User Comments on an Activity

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Abstract. A vast amount of user contributed content about real world human activity exists in social web spaces (e.g. videos and user stories or comments in YouTube) rich of personal experiences and opinions which intuitively reflects reality settings. This content can be a useful source for enriching the learning experience in simulated environments, if exploited in an appropriate context for the learner. An interesting observed characteristic of the user contributed content is the diversity of viewpoints. A novel approach for multi-viewpoint knowledge elicitation and representation to enable intelligent content retrieval is being investigated, and conducted within one of the use cases of the ImReal EU project. The job interview process has been selected for studying the intricacy in interpersonal communications, focusing on the emotion and body language signals dimensions, and the different individual viewpoints of the activity. Work in progress presented in this paper includes an analysis of the problem domain, the information extraction process and preliminary results.

Keywords: Activity, Individual viewpoint, Emotion, Body Language

1 Introduction

Simulated environments, where learners are involved in simulated situations and perform activities that resemble actual job activities provide powerful learning tools for developing soft skills in ill-defined domains[1]. Such environments will have a strong presence in the future intelligent learning technologies, especially in the area of workplace training, where adaptation and personalization will play a key role[2]. Conventional adaptation approaches model users based on their interaction within the simulated environment and adapt accordingly. However, to be effective, training environments for adults should offer learning experiences *directly relevant to the real world job context* and *aligned with the learner's needs in practice* [3]. The challenge is that real world activities are affected by dynamic conditions and complex situations which are hard to capture into the simulated world, whereas a simulated environment embeds predefined scenarios with fixed parameters.

On the other hand, there is a vast amount of user contributed social content about real world activity (e.g. user comments or stories) providing rich content of information about people's personal experiences and opinions. This abundance of user generated digital content provides potentially useful traces that can reflect what happens in the real world. Although this content can be a useful source for enriching the learning experience and bridge the simulated settings with reality, it has not been exploited to date, designating a key research challenge:

Can digital traces from the social spaces be used to construct a model of the real-world activity and context, and how can this model improve adaptation in simulated learning environments and enable intelligent content retrieval?

As part of the above research challenge, in this paper we present work in progress on the implementation of a novel approach to collect and analyze user comments on social media, particularly comments on videos populated in a YouTube-like environment, in order to:

Identify key concepts related to specific activity and determine individual viewpoints on the activity

An ontology-based information extraction process is proposed to support the above key objectives. The Job Interview activity has been selected as a case study for this work. Section 2 presents the case study (focusing on emotions and body language in interviews), and provides an initial analysis of the potential use of the comments collected by a YouTube-like environment. Section 3 reports on the technicalities and the implemented information extraction algorithm, while Section 4 presents the results to date. Finally, Section 5 concludes with a discussion on the current approach with regard to related work, and future plans.

2 Case Study – The Job Interview Activity

This research is being conducted within one of the use cases of the ImReal[1] EU project, which aims at developing simulated environments for Immersive Reflective Experience-based Adaptive Learning. The job interview process is selected for further investigation as it exemplifies a key challenge that ImReal addresses: developing soft skills within simulated environments for training in work-place interpersonal communication. Additionally, a wealth of related media content is available on the web, which can be used to illustrate our approach.

The focus of this study is on capturing users' experience on the effect of emotions and body language which may affect the interpersonal communications. The videos act as a catalyst to simulate discussions and recall of personal experiences.

2.1 Content Collection

In order to enable users to make comments on specified snippets within an online video, a system has been developed to: (i) provide links to a sample of YouTube videos on job interview (Fig 1) and (ii) enable the participants in the research study to

[1] http://www.imreal-project.eu

interact with a video by selecting snippets (Fig 1, a) and commenting on each snippet (Fig 1, b)(please refer to Section 4 for descriptive details). A snippet has a start and stop time relative to the beginning of the video.

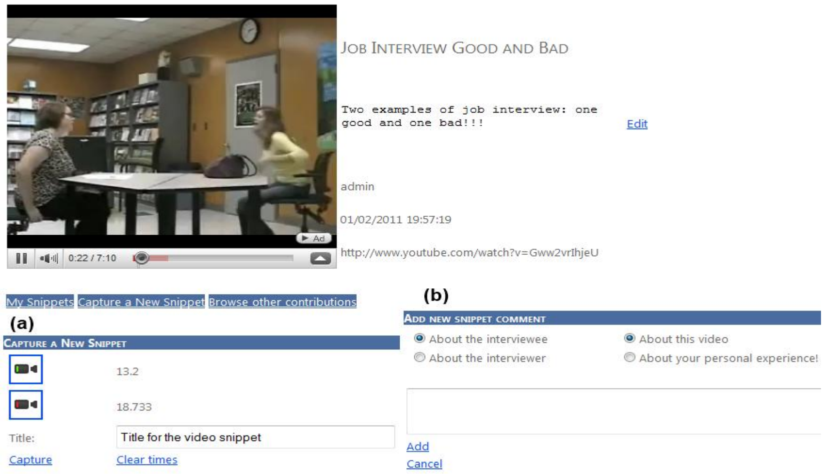


Fig. 1. A screenshot from the implemented snippet to collect content. Participants (a) partition the video into snippets and (b) add comments indicating the actor and if it relates directly to the video or it refers to the participant's personal experience

The comments are in free text. Users can indicate (i) whether a comment corresponds to the interviewer or the interviewee, and (ii) whether it relates directly to the video (Table1, C1) or it refers to the user's personal life (e.g. an experience or opinion) which was triggered by observing this particular video snippet (Table 1, C2). Indicating the actor of the activity (i.e. the interviewee or the interviewer) that the comment refers to resulted after evaluating the elicitation process with Social Scientists, who showed that the actor of the activity is a core component for analyzing the comments. Furthermore, providing personal experience related comments allows the potential to capture not only important concepts as presented in a video but also key aspects that are possibly missing in the video and reveal relevance to real life.

The output of this YouTube-like environment is a collection of snippets with comments from users who have been watching the videos.

Table 1. Comments of the same participant on a video snippet. C1 relates directly to the video, while C2 refers to the participant's personal experience. Both correspond to the interviewee.

Comment Text
C1 : *"The interviewee rushes into the room."*
C2 : *"I had a similar situation when a candidate rushed to the interview showing little interest. This made me think immediately that I would not wish to work with them. However, I had to force myself to keep calm and positive, to ensure the candidate is given sufficient attention."*

2.2 Understanding User Comments and Viewpoints

The collection of user comments is the starting point for the analysis. As mentioned before, the focus of this study is on emotions and body language. We refer to body language as the set of non-verbal behavioural cues. It instantiates instruments of communication, which a person adopts to express the emotions that affect him/her during the activity. These cues are transformed through the process of communication into social signals for other persons and conclude to the development (atomic or collective) of emotional intelligence[4].

Recognizing both emotion and body language cues comprise a set of two very important soft skills to be developed in interpersonal communication, particularly in a dyadic interaction such as in a job interview. Non-verbal communication carries most of the social meaning (about two thirds comparing with verbal communication). It illustrates emotional states, regulates the flow of interaction and provides valuable feedback to both actors in the activity. Awareness and recognition of behavioural cues accounts great value in social interactions[5].

Table 2 presents a set of comments provided by four different users watching the videos in our pilot system. The comments correspond to the beginning of the same job interview video, which includes actions such as entrance of the interviewee to the meeting room and handshaking. With regard to the focus of analysis we aim to capture key concepts on the **emotion** of the actors and the **non-verbal behavioural cues**. For example, in C3, some key concepts include: "*handshaking*", "*without manners*", "*disrespectful*", in C4: "*handshake*", "*ignore*", "*shake my hand*", in C5: "*feel*", "*discomfort*", "*confusion*", "*behaviour*", and in C6: "*understanding*", "*comfortable*".

Table 2. Example comments on the same part of the job interview video, showing different individual viewpoints. The underlined words/phrases indicate key concepts of the activity that we aim to capture regarding the emotions and body language.

Comment text	Refers to	User
C3 : *"Avoids the <u>handshaking</u>. Shows a person <u>without manners</u>, completely <u>rude</u> and <u>disrespectful</u> and maybe inappropriate for the job."*	Interviewee	u_2
C4 : *"I remember a situation when I offered a <u>handshake</u> and was <u>ignored</u>...I could not understand why. Later on, I realised what might be the reason. The person is a strict Muslim and me being a woman, it might not be permitted for him to <u>shake my hand</u>!"*	Interviewee	u_3
C5 : *"The interviewer may <u>feel</u> <u>discomfort</u> and <u>confusion</u> due to the unexpected <u>behaviour</u> of the interviewee. The interviewer may be thinking that she would not wish to work with people who do not take her (or the job) seriously."*	Interviewer	u_4
C6 : *"She appears very <u>understanding</u> of the situation and tries to make the interviewee feel <u>comfortable</u> even though she is late."*	Interviewer	u_5

Three types of diverse observations between the users are detected. The first type concerns the focus of observation with respect to the actors in the activity, i.e. the interviewee or the interviewer. For example, u_2 and u_3 focus on the interviewee, while u_4 and u_5 focus on the interviewer. The second type concerns the diverse approaches to characterize the same actor in the same part of the video. For example, although both u_4 and u_5 focus on the interviewer, u_4 points to a feeling of discomfort, while u_5 considers a sense of understanding of the situation. The third type concerns the context of comment, hence the interpretation of an event is affected by prior personal experience, e.g. the comment from u_3 corresponds to a personal real life experience.

Hereupon, we define an **individual viewpoint** as: *the focus and the collection of statements that a person develops when observing an activity*. In order to extrapolate the different viewpoints in the experimental study, each participant was given a questionnaire to complete prior to the interaction with the system. The questionnaire included quantitative as well as qualitative variables, which aim to extract measurements of their experience with job interviews and perceptions about the application of emotion and body language as communicative tools in the activity.

3 Semantic Approach for Comment Analysis

This section describes a semantic approach for analysing the user comments and extracting concepts, related to emotions and body language, with the correct meaning. The approach consists of three main steps, as shown in Figure 2.

Text pre-processing takes as input the comment in free text format and outputs linguistically tagged text. **Semantic pre-processing** inputs the linguistically tagged text and outputs a semantically tagged text with identified concepts. **Knowledge-statements extraction** uses the semantically tagged concepts and outputs knowledge statements extracted by queries over the ontologies.

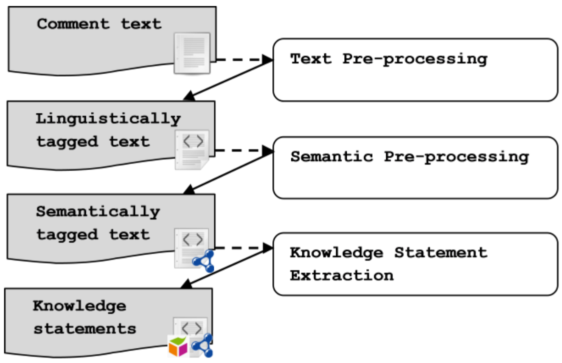


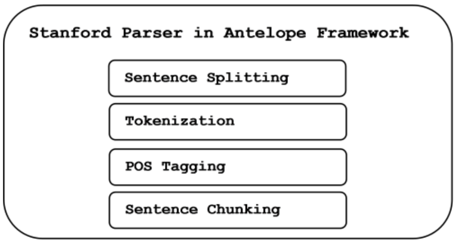
Fig. 2. The information extraction process: the comment passes through three processing steps: text pre-processing, semantic pre-processing and knowledge statement extraction

The steps are explained below using C5 (from Table 2) as an illustrative example.

3.1 Text Pre-processing

The text pre-processing step comprises NLP techniques for text analysis using the Antelope NLP framework[2]. Sentence splitting, sentence tokenization, Part of Speech (POS) tagging for each word and sentence chunking to extract meaning pieces of text inside the sentence that can stand alone, are performed using the Stanford parser for linguistic text analysis. This enables the linguistic tagging. Each word is assigned a POS tag and particular words are filtered out (e.g. articles and punctuation). Table 3 presents the processing components in text pre-processing step (left) and a short explanation of the resulted text structure that consists the output (right) and passes to the semantic pre-processing.

Table 3. The text pre-processing components and an illustrartion of the output

Text pre-processing components	Example output [for C5 from Table 2]
	Only the underlined words are passed to the next layer from the first sentence: “The[article] interviewer[noun] may[verb] feel[verb] discomfort[noun] and[conjunction] confusion[noun] due[adverb] to[preposition] the[article] unexpected[adjective] behaviour[noun] of[preposition] the[article] interviewee[noun]. ...”

3.2 Semantic Pre-processing

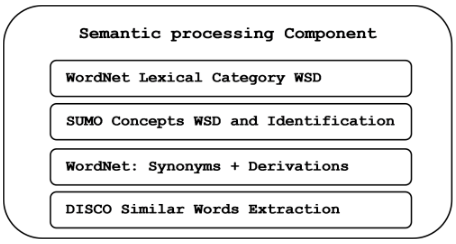
The semantic pre-processing includes the ontology-based word sense disambiguation (WSD) and linguistic semantic text expansion components. Two filters are applied for WSD, since each word along with the corresponding POS tag can have more than 1 senses in English language:

1. Selection of words and word senses according to specific lexical categories defined within WordNet to directly exclude those which are not significant for the application domain, i.e. job interview activity. Example lexical categories that are used for sense disambiguation as relevant to the domain are presented in Appendix.
2. Exploitation of the Suggested Upper Merged Ontology (SUMO), which provides direct mappings of English word units to concepts. From SUMO, 231 concepts out of 4,558 were selected as significant to the application domain, and the inclusion set has been validated with domain experts. The resulted concepts were used as word sense disambiguation indicators (second filter). Example SUMO concepts that are used as filters for sense disambiguation are presented in Appendix.

[2] Proxem. *Antelope NLP Framework*. Available from: www.proxem.com/Default.aspx?tabid=119.

The linguistic and semantic expansion followed comprises of WordNet Lexicon queries, where synonyms and word lexical derivations were extracted to expand the word set, now in the context of the application domain. Furthermore, DISCO[3] has been exploited to retrieve distributionally similar words from the Wikipedia corpus, and the semantic filters discussed above have been applied respectively. Table 4 presents the main processing components for semantic analysis and example output.

Table 4**.** The semantic pre-processing components and an illustration of the output.

Semantic pre-processing components	Example output [for C5 from Table 2]
	The word due is removed from the text, as its sense has subsuming mapping to the SUMO concept `Path`: "a route along which motion occurs". Contrarily, the word discomfort has two senses "the state of being tense…" and "an uncomfortable feeling…" which have subsuming mappings to the SUMO concepts: `StateOfMind` and `EmotionalState` respectively. From DISCO, the word appears to be strongly related with the word frustration that again has significant to the domain conceptual mappings as well as its derivation discomfiture. Similar results are returned from other words that correspond to valid domain concepts, e.g. behaviour is recognized as a `TraitAttribute`

3.3 Knowledge Statements Extraction

The final step consists of the knowledge statement extraction methods applied for the semantically filtered and linguistically enriched text structure. Regarding the focus of analysis of the activity (see Section 2.2), emotion and body language cues are in the focus of the methodology. Two ontologies have been developed. The WordNet Affect taxonomy of emotions has been translated to RDF/XML format consisting of 304 concepts related with `subClassOf` axioms. An ontology to conceptualize body language has been developed following a rich taxonomy of non-verbal behavioural cues[4] and [4].The ontology includes 15 concepts and 319 instances. Two properties are used to assert axioms: `isExpressesBy` relates `<body language signal> [domain]` (e.g. eye shrug, teeth grinding) with `<body part>` (e.g. eyes, arms etc.), `<physical object>` (e.g. pen, gum, tie etc.), `<non-physical object> [range]` (e.g. handshake); `hasPossibleMeaning`

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[3] Peter Kolb. *DISCO: A Multilingual Database of Distributionally Similar Words*. In *Proceedings of KONVENS-2008*, Berlin, 2008.

[4] Body Language: How to read body language signs and gestures, available from: http://www.businessballs.com/body-language.htm

relates <body language signal> [domain] with <body language signal meaning> [range] (e.g. frustration, defensiveness, interest etc.). Inverse properties have also been implemented. Figure 3 (a) and 3(b) show a small portion of the emotion and body language taxonomies respectively.

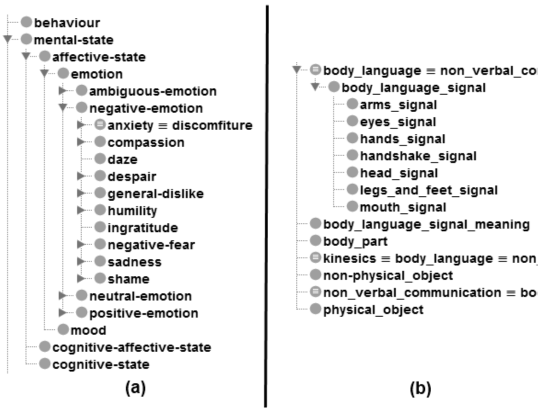
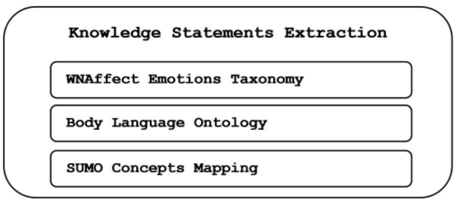


Fig. 3. Portions of the hierarchies of (a) WNAffect emotion and (b) body language ontologies

Each of the ontologies was pre-processed and index tables with concepts (and instances for the body language ontology) were constructed to increase querying efficiency. Reasoning was then performed for each identified concept in the text on the two ontologies to elicit potential knowledge statements. Table 5 presents the main processing components for knowledge statements extraction (left) and a short explanation of the output focused on the word *"discomfort"*.

Table 5. The knolwedge statement extraction components and illustration of the output.

Knowledge statements extraction	**Example output [for C5 from Table 2]**
	The word discomfort is used as example here to demonstrate the knowledge elicitation that its similar words mentioned above enable. Example ontology statements resulted from reasoning for the words discomfiture and frustration on the WNAffect and body language ontologies respectively include: **WNAffect** – discomfiture reasoning: "discomfiture**" has equivalent** "anxiety"; "anxiety**" is a kind of** "negative-motion"; "anxiety**" is a kind of** "Emotion". **Body Language** – frustration reasoning: "frustration" **appears possibly when** "nail_biting"; "frustration**" appears possibly when** "eye_shrug".

For each comment, the output of the analysis is a tree structure enriched with knowledge statements, as well as meta-data linking to modelling elements including: the video resource, the video snippet that the comment was added for, the user that added the comment, and indicators for the actor that the comment refers to and whether it corresponds directly to the video or to personal experience (Section 2.1).

4 Summary of the Output

To date, a total of 5 example job interview videos have been annotated by 10 users, providing in total 139 video snippets (for 8 job interview examples, as each video can have more than one interview example) and 193 textual comments. The set of textual comments was treated as a unified corpus for further analysis, as described in Section 3.

From the total of 193 comments, 127 were referring to the interviewee and 66 to the interviewer. 143 comments were related to the activity presented in the video (97 to the interviewee and 46 to the interviewer) and 50 to users' personal experiences (30 as interviewee and 20 as interviewer). 152 comments were linked to emotion concepts, 168 to body language concepts, 144 to both and 17 to none.

From the analysis of comments, 174 unique words were extracted and linked to 274 unique concepts related to emotion (distinct 92) and body language (distinct 91). Each word was linked to concepts following the approach from Section 3

- as direct word (7.2% linked to emotions and 12.2% linked to body language);
- as a result of DISCO similarity (56% - emotions and 42.6% - body language);
- as a synonym (14.4% - emotions and 12.1% - body language);
- as a linguistic derivation (21.6% - emotions and 26.4% - body language).

As discussed in Section 3, each concept is linked with one or more SUMO domains according to its sense. Table 6 presents the five most frequent SUMO domains identified with example concepts from the corpus for both emotion and body language (refer to the Appendix for examples of the SUMO domain).

Table 6. SUMO domains identified in the corpus with example concepts.

	SUMO domain (frequency (%))	Example concepts from corpus
Emotion	SubjectiveAssessmentAttribute (25%)	*despair, shame, encouragement*
	EmotionalState (23%)	*anxiousness, confidence, euphoria*
	PsychologicalAttribute (15%)	*wonder, humility, calmness*
	TraitAttribute (5%)	*contempt, optimism, hostility*
	NormativeAttribute (3%)	*oppression, approval, forgiveness*
Body Language	SubjectiveAssessmentAttribute (24%)	*pressure, negativity, upset*
	EmotionalState (7%)	*nervousness, excitement, dissatisfaction*
	PsychologicalAttribute (7%)	*combative, readiness, doubt*
	Artifact (6%)	*body, pen, tie,*
	SocialInteraction (3%)	*confidence, greeting, lying*

Based on the questionnaire, the experience of each participant with the interview process was indicated (participants were asked of the number of interviews undertaken both as an interviewee and as an interviewer using a categorical scale with values). Users were also asked to indicate the importance of emotion and body language in the job interview activity. Out of 10 users in the study, 1 had much experience as interviewee (over 15 interviews) and 3 had much experience as interviewers (over 15 interviews), 9 were not much experienced as interviewees and 7 not experienced as interviewers. 7 of them replied that emotion is important, while the users that gave negative answer or they did not know, were 1 much experienced as interviewee and nowise as interviewer, and 2 with little experience as interviewees but much experienced as interviewers. 9 of them replied that body language is important, while the one that did not know was much experienced as interviewer.

90% of the comments related to personal experience and 65% were referring to the interviewee were contributed mostly by users with either little experience as interviewees or interviewers, and similarly, the same class of users provided the highest proportion of video related comments (70%) and comments referring to the interviewer (78/%). These users also contributed the highest rate of comments linked to emotion (73%) and body language (72%).

Comments from users with little experience as interviewees were mainly linked to the *SubjectiveAssessmentAttribute* (24%), *EmotionalState* (14%), and *PsychologicalAttribute* (10%) domains from SUMO. Comments from those with much experience as interviewees were linked with the same domains but in highest rates (approximately 2-3% additional rate). Users with much experience as interviewers, contributed also comments mostly to linked to these domains in highest rates (over 3% additional rate). Other domains were also included in the resulted sets for experienced interviewers, e.g. *SocialRole* (2.5%), *BodyMotion* (1.5%) and *SocialInteraction* (3%), whilst not so important –in terms of frequency rates - for the classes of users mentioned above. Overall, users with experience as interviewers commented about the interviewers, while the other users tend to focus on interviewees. This indicates that people recognise body language and emotions related to the role they have experienced most and miss these aspects in the role they have not had experience in. We are currently further processing the data, together with collecting more comments and user profiles. If this hypothesis is confirmed, this will give an indication that users' experience with body language and emotions may be related to the comments they make.

5 Discussion and Future Work

Much work has been done in technology-enhanced learning, focusing on intelligent environments for experiential workplace learning. Job-related experiences are captured through these environments for organizational knowledge [7] or every-day computer based tasks in work promoting self regulated learning [8], and in academia writing skills are being developed by sharing students' experiences [9]. Records of job-related activities (e.g. videos) have been used in [10] to create pedagogical scenarios for experiential learning. We aim to distinguish from these projects in four points: include multi-viewpoints in the activity model; advance the knowledge elicitation process by implementing methods to provide user-awareness of related activities; provide more expressive models to augment digital content; and test augmented video resources in simulated settings for learning. Furthermore, this work contributes to a new stream in user modelling utilizing ‘real-world’ work context models to improve adaptation[11], and using digital traces from social content to derive user profiles [12]. Instead of explicit user profiling, we will provide a mechanism for deriving an extended context model which preserves different viewpoints on an activity, and can be used to improve adaptation, as well as a source for clustering and profiling users. Similarly to [13], we focus on awareness and recognition of social signals to empower adaptation, but we are applying it to job interviews where diverse interpretations should be catered for.

Emotions and body language have a strong presence in the corpus collected, following the indications given to users prior to system interaction. The results gathered so far empower the feasibility for context capturing. The expressivity of body language ontology will be increased by redesigning concepts, instances and relations and the information extraction algorithm will be refined accordingly, regarding also the linguistic ontology pre-processing as needed. So far the SUMO concepts have been validated only for precision, while recall has to be addressed. The plan is to explore further the relations in SUMO with rule based reasoning techniques, identify recalled concepts and validate the consistency of the sub-ontology. Similarly, the next step is to formally evaluate the NLP tools used and the corresponding implemented algorithms.

A more uniformed corpus has to be collected in terms of user profiles to normalize the distribution of experiences and conclude more explanatory results. The extraction of individual viewpoints appears feasible, however, more thorough analysis has to be undertaken in order to identify possible relations, e.g. between the experience of participants and the concepts identified in the corpus, derive patterns between the concepts extracted from comments and shape the activity model according to time and context. Evaluation steps will include validation with domain experts and exemplification of simulated context queries for content retrieval, involving users from the research study.

Acknowledgement

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Appendix

Examples of WordNet lexical categories and SUMO concepts used for word sense disambiguation and filtering.

WordNet lexical categories	SUMO concepts
[noun.act] : acts or actions	[SubjectiveAssessmentAttribute]: a kind of normative attribute for a subject
[noun.artifact] :man-made objects	[SocialInteraction]: interactions between cognitive agents such as humans
[noun.attribute]: attributes of people and objects	[SocialRole]: specifies the position or status of a cognitive agent (as human) within an organization or other group
[noun.body]: body parts	[Agent]: something or someone that can act on its own and produce changes in the world
[noun.cognition]: cognitive processes and contents	[NormativeAttribute]: attributes that are specific to morality, legality, aesthetics, etiquette, etc. Many of these attributes express a judgment that something ought or ought not to be the case
[noun.communication]: communicative processes and contents	[Artifact]: an object that is the product of a making
[noun.feeling]: feelings and emotions	[BodyMotion]: any motion where the agent is an organism and the patient is a body part
[noun.motive]: goals	[EmotionalState]: the class of attributes that denote emotional states of organisms
[noun.person]: people	[StateOfMind]: transient features of a creature's behavioral/ psychological make-up
[verb.motion]: walking, flying, swimming	[Perception]: sensing some aspect of the material world
[verb.perception]: seeing, hearing, feeling	[FormalMeeting]: any meeting which is the result of planning and whose purpose is not socializing
[verb.cognition]: thinking, judging, analyzing, doubting	[BodyPart]: …small components of complex organs
[verb.communication]: telling, asking, ordering, singing	[PsychologicalAttribute]: attributes that characterize the mental or behavioral life of an organism
[verb.contact]: touching, hitting, tying, digging	[TraitAttribute]: attributes that indicate the behavior/ personality traits of an organism
[verb.emotion]: feeling	[RegulatoryProcess]: an guiding whose aim is the enforcement of rules or regulations