Deliverable D5.1 - Requirements of Affective Knowledge Extraction

LIMSI-CNRS

WP5 (T5.1)

Historique des modifications			
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Validation			
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1 Introduction

1.1 Aim

The aim of this document is identify the requirements for the task of affective knowledge extraction. It should describes the human computation process, in particular the input data, the games, and possible crowdsourcing experiences with their game associated design as well as the resources to be acquired.

1.2 Responsibility

The partner responsible the production of this document is LIMSI-CNRS.

2 Background and Related Work

2.1 Opinion and Sentiment Definition

2.1.1 Opinion

In the Merriam-Webster dictionary [1], opinion is defined as *"judgement about a person or thing"*. Opinions are usually defined as an opposite to facts ([Pak, 2012]). Many researches distinguish factual (objective) information from subjective one ([Pang and Lee, 2004]). If a fact is a piece of information which is commonly believed to be true, an opinion (subjective information) is the belief of an individual person. This implies that every opinion is assigned to its holder, since a different person may have a different belief or claim about the same topic, thus the need stressed in [Balahur et al., 2010] to clearly distinguish three perspectives when analyzing a documents: the one attached to the litteral meaning of the text, the author's point of view and the reader's point of view. The most common representation of a textual opinion expression, is a tuple containing its properties expressed along a few dimensions associated to the features relevant for the analysis at hand.

[Kim and Hovy, 2004] use a quadruple *[Topic, Holder, Claim, Sentiment]* which is defined as *"the Holder believes a Claim about the Topic, and in many cases associates a Sentiment, such as good or bad, with the belief"*.

[Liu, 2010] use a quintuple *[Entity, Aspect, Opinion Orientation, Holder, Time]* which is defined as *"an opinion is a positive or negative sentiment, attitude, emotion or appraisal about an entity or an aspect of the entity from an opinion holder. Positive, negative and neutral are called opinion orientations"*.

[Kobayashi et al., 2007] also use the quadruple notation *[Subject, Aspect, Holder, Evaluation]*, where *opinion holder* is the same element as in the two models of [Kim and Hovy, 2004] and [Liu, 2010], *subject* and *aspect* together correspond to *Topic* in the first and to both *Entity* and *Aspect* in the second. Table 1 gives an example for the three previous representation schemes.

[1] http://www.merriam-webster.com

[Kim and Hovy, 2004]	[Kobayashi et al., 2007]	[Liu, 2010]
Holder= Writer	Opinion holder= Writer	Holder= Writer
Topic= Powershot pictures	Subject= Powershot	Entity= Powershot
	Aspect= picture, colors	Aspect= picture, colors
Sentiment= positive		Opinion Orientation= positive
Claim= "colors are so beautiful"	Evaluation= beautiful	
		Time= "few days ago"

Table 1: Representations of the example *"I just bought a Powershot a few days ago. I took some pictures using the camera. Colors are so beautiful even when the flash is used."*, from [Kobayashi et al., 2007], according to [Kim and Hovy, 2004], [Kobayashi et al., 2007] and [Liu, 2010] opinion representation schemes.

2.1.2 Sentiment

Again according to the Merriam-Webster dictionary, a sentiment is *"an attitude, thought, or judgement prompted by feeling"*. The word *sentiment* is often used in a wide sense to refer to expressions of subjectivity, opinion, affect, attitude, orientation, feelings, emotions, and tone in the text. As we have seen in the previous example, sentiments are sometimes considered to be a part of an opinion such as in the model of [Kim and Hovy, 2004]. However, many researchers consider sentiments separately from opinions and define them as a personal judgement towards an entity prompted by feeling. The main characteristics of this judgement are *polarity* and *intensity* ([Martin and White, 2005]). A positive polarity may express a feeling of contentment, happyness, joy, or ecstasy, from the low intensity value of contentment to the maximally high intensity value of ecstaty. A negative polarity may express opposite sentiments: dicontentment, unhappyness, sadness, or grief from the low intensity value of discontentment to the high intensity of value of grief. Thus a sentiment is still described by a polarity which itself is described by an intensity, otherwise it cannot be considered as sentiment.

2.2 Opinion Mining and Sentiment Analysis Tasks

2.2.1 Subjectivity Analysis

Subjectivity analysis tasks consists in detecting the presence of subjecte information in a given text. Since different authors define sentiments and opinions in a different manner, subjectivity analysis can deal with sentiments (e.g. separating polar text from neutral text) as well as opinions (separating subjective statements from facts). [Wiebe, 2000] introduced lexical features in addition to the presence/abscence of syntactic categories to detect subjectivity in text. Later, [Wiebe et al., 2002] report on document-level subjectivity classification, using a k-nearest neighbor algorithm based on the total count of subjective words and phrases within each document. [Yu and Hatzivassiloglou, 2003] presented a fairly straightforward bayesian classifier using lexical information to distinguish between mostly factual and mostly opinion documents with very high precision and recall (F-measure of 97%). [Riloff and Wiebe, 2003] used first, two bootstrapping algorithms that exploit extraction patterns to learn sets of subjective nouns, then a naive bayes classifier using the subjective nouns, discourse features, and subjectivity clues identified in prior research to seperate subjective from factual documents. Recent researchs try to combine linguistic knowledge with information obtained with machine learning for subjectivity detection, for instance [Trivedi and Eisenstein, 2013] combined linguistic knowledge, in the form of discourse connectors, with latent variable subjectivity modeling (Support Vector Machine) to improve sentiment analysis at the document level.

2.2.2 Opinion and sentiment attributes identification

The bulk of the work in opinion mining and sentiment analysis concerns the task of identifying the following attributes (see [Pang and Lee, 2008] or [Pak, 2012]):

- *Opinion/sentiment holder:* extract from the text who holds the opinion or the sentiment.
- *target entity:* extract all entity expressions in the document, and group synonymous entity expressions into entity clusters.
- *opinion/sentiment aspect:* optional (depending on models), extract all aspect expressions of the entities, and group aspect expressions into clusters.
- *sentiment or claim:* determine the polarity (positive, negative, neutral) of each opinion or sentiment expressed on an entity or on an aspect of entity.

We use an example blog from [Liu, 2010] paper to illustrate these tasks:

(1) I bought an iPhone a few days ago. (2) It was such a nice phone.
(3) The touch screen was really cool. (4) The voice quality was clear too...

Task 1 : find the holder of the opinions in sentence (1), (2), (3) and (4) to be the author.
Task 2 : extract the opinion entity "iPhone"
Task 3 : extract the opinion aspects "screen" and "voice"
Task 4 : find that the four sentences express a positive opinion.

This identification can be performed at different levels of granularity, for instance in the opinion model used in the DOXA project [Paroubek et al., 2010], which is the most elaborate we have encountered so fare, three levels were defined:

- *macro*, which corresponds to the document level,
- *micro*, for the sentence level annotations, with a classical definition of sentence based on syntactic and typographic analysis.

The informations for the macro level are synthesized from the information of the micro level. Note that in addition to the three classical categories of opinion: positive, negative and neutral, the DOXA model defined the category “mixed” to be used when both positive and negative opinions are expresses about a target entity in roughly the same proportion, a different case from neutral, to be used when the statement about the target entity is objective. In this model there are 17 semantic categories of opinion, split into three broad classes regrouping respectively : the ones associated to affect, the ones associated to intellectual appreciation and the one pertaining to both previous classes.

2.2.3 Methods for Polarity Classification Task

Polarity classification is probably the most studied subproblem of sentiment analysis, for a survey see [Pak, 2012]. It is considered a binary classification problem. The goal of the task is to determine if a given text expresses a positive or negative attitude of its author regarding a specific topic.

Lexicon based approaches Much of the lexicon-based research has focused on using adjectives as indicators of the semantic orientation of text ([Hatzivassiloglou and McKeown, 1997], [Wiebe, 2000], [Hu and Liu, 2004], [Anthony M. C. Taboada and Voll, 2006]). In general, a list of adjectives and corresponding opinion values is compiled into a dictionary. For any given text, the adjectives are identified and annotated with their opinion value, using the dictionary scores. Finaly, the opinion scores are aggregated into a single score for the whole text. [Turney, 2002] has proposed an unsupervised method of classifying movie reviews into recommended and not recommended categories, based on the semantic orientation of adjectives and adverbs in the review. He showed that it is possible to use only a few semantically oriented words (namely, *excellent* and *poor*) to label other phrases co-occuring with them as positive or negative.

Dictionaries for lexicon-based approaches can be created manually, or automatically, using seed words to expand the list of words. [Pak and Paroubek, 2010] proposed an automatic approach to construct affective lexicons for different languages using emoticons as noisy sentiment label.

Statistical based approaches [Pang et al., 2002] have attempted to classify the movie reviews drawn from the Internet Movie Database (IMDB)[2] into positive and negative categories using machine-learning techniques with words and n-grams as feature to predict orientation at the document-level with up to 83% precision. More recently, [Pak and Paroubek, 2011] used sentence parsing dependency tree to represent a text as a collection of subgraphs, where nodes are words (or a wildcard) and edges represent relations between them. Such a representation allows to fill the information loss occurred when representing a text as a collection of n-grams without relation information. With such a model tested on movie-review dataset, an SVM classifier with features based on the extracted subgraphs yields a better performance (85% accuracy) than traditional system based on the unigram model.

[2]ttp://reviews.imdb.com/Revhiews/

2.3 Emotion

2.3.1 Definition

Following the definition proposed in the Merriam-Webster dictionary, an emotion is *a conscious mental reaction (as anger or fear) subjectively experienced as strong feeling usually directed toward a specific object and typically accompanied by physiological and behavioral changes in the body.* According to [Liu, 2010], *Emotions are our subjective feelings and thoughts.* The concept of emotions can be seen as a refinement of sentiments with a finer granularity of information. While sentiments are usually viewed as positive or negative, emotions define more particular types of human behavior or private state, first mentioned by [Quirk et al., 1985] then reused later by [Wiebe et al., 2005] and [Pang and Lee, 2008].

2.3.1.1 Discrete Theory

Most of the models surveyed in [Calvo and Sydney K. D'Mello, 2011] have adopted this approach. As per the *Discrete Emotion Theory*, all humans are thought to have an innate set of basic emotions that are cross-culturally recognizable. These basic emotions are described as "discrete" because they are believed to be distinguishable by an individual's facial expression and biological processes ([Panksepp, 1998], [Lövheim, 2012]). Various theorists have conducted studies in attempts to determine which are the basic emotions. Researchers have investigated several aspects of human emotion in order to arrive at a set of emotion categories that are universally acceptable ([Picard, 1995], [Picard, 1997]). [Ekman, 1970] has defined basic emotions as those that have universally accepted distinctive facial expressions, which was a source of inspiration for many other works in this direction [Ekman, 1972], [Izard, 1971], [Tomkins, 1984], [Plutchik, 1980], [Panksepp, 1998], [R. W. Levenson et al., 1990], [Ekman, 1999], [Jessica L. Tracy and Randles, 2011] or [Levenson, 2011]. The six basic emotions defined on this basis are *happiness, sadness, fear, anger, disgust, and surprise.* Table 6 lists a selection of list of basic emotion categories identified by different researchers, among them the model of [Panksepp, 1998] was defined from observation of animal brain responses and was hypothesized to be common to animals and humans.

The divergence of opinion about the number of basic emotions is matched by the divergence of opinion about their identity. Some lists of basic emotions include terms that are included in no other list, for instance [Jessica L. Tracy and Randles, 2011] made a comparative review of four models.

[Izard, 1971]	[Ekman et al., 1972]	[Plutchik, 1980]	[Panksepp, 1998]	[Ekman, 1999]	[Levenson, 2011]
Joy	Happyness	Joy			Enjoyment
			PLAY	Amusement	
				Excitement	
			MATING	Sensory pleasure	
			CARE		Love ?
Interest		Anticipation	SEEKING		Interest ?
				Satisfaction	
				Relief	Relief ? Contentment ?
				Contentment	
				Pride in achievement	
Surprise	Surprise	Surprise			Surprise
		Trust			
Fear	Fear	Fear	FEAR	Fear	Fear
Distress	Sadness	Sadness	PANIC LOSS	Sadness Distress	Sadness
Anger	Anger	Anger	RAGE	Anger	Anger
Disgust Contempt	Disgust Contempt	Disgust		Disgust	Disgust
				Contempt	
Shame Shyness				Shame	
				Embarassement	
				? Guilt ?	

Table 6: A Selection of List of "Basics" Emotions, note that question marks indicate emotions for which the author is not sure whether they fulfill all the criteria for being a basic emotion.

2.3.1.2 Dimensional Theories

Proposed as an alternative, because the discrete Theory does not match the "real“ structure of emotions. Dimensional approaches have long been studied by emotion theorists and evidence suggests the existence of at least two fundamental dimensions ([J. A. Russell et al., 2003]) : valence (i.e. pleasure/displeasure) and arousal (i.e. activation / desactivation), see Figure 2. In [J. A. Russell et al., 2003] they are believed to be universal primitives and called the feeling at any point on this two-dimensional space. A third dimension *dominance* was identified by [Bradley and Lang, 1999], particularily important to represent emotion in social context.

Circumplex model The circumplex model (see Figure 3) of emotion was first developed by [Russel, 1980]. Emotions are distributed in a two-dimensional circular space, containing arousal and valence dimensions. Arousal represents the vertical axis and valence represents the

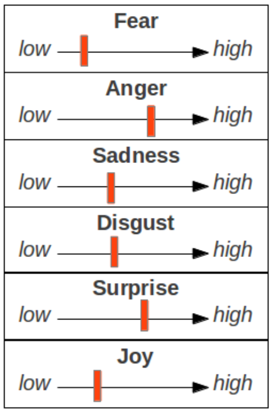

Figure 1: Discrete View of Emotion Labels

Figure 2: Dimensional View of Emotion Labels

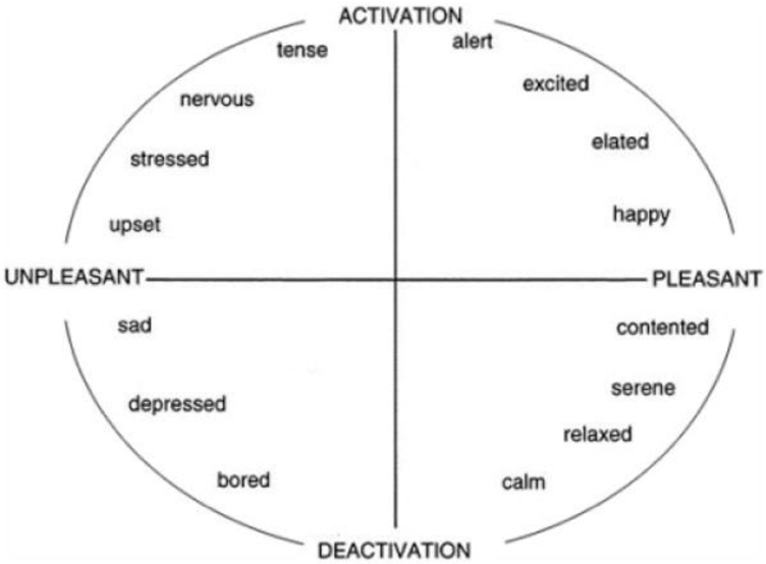

Figure 3: The Two-dimensional Circumplex Model

horizontal axis, while the center of the circle represents a neutral valence and a medium level of arousal. In this model, emotional states can be represented at any level of valence and arousal, or at a neutral level of one or both of these factors. Circumplex models have been used most commonly to test stimuli of emotion words, emotional facial expressions, and affective states.

Plutchik's model Robert Plutchik offers a three-dimensional model that is a hybrid of both basic-complex categories and dimensional theories. It arranges emotions in concentric circles where inner circles are more basic and outer circles more complex. Notably, outer circles are also formed by blending the inner circle emotions. Plutchik's model, as Russell's, emanates from a circumplex representation, where emotional words were plotted based on similarity ([Plutchik, 1980]). In computer science, Plutchik's model is often used, in different forms or versions, for tasks such as affective human-computer interaction or sentiment analysis.

2.4 Affective lexicons

2.4.1 ANEW

The Affective Norm for English Words (Bradley and Lang, 1999, Stevenson, Mikels and James, 2007) is one of several projects to develop sets of normative emotional ratings for collections of English words.

Affective Norms of English Words (ANEW) is a set of normative emotional ratings for 1034 English words developed by [Bradley and Lang, 1999] from the NIMH Center for Emotion and Attention (CSEA)[3] at the University of Florida . Language specific versions of ANEW exist for other languages : Spanish ([Redondo et al., 2007]) and German ([Võ et al., 2009]). Each word

[3] http://csea.phhp.ufl.edu/

of the ANEW database is associated to three scores of emotional assessment: valence (ranging from pleasant to unpleasant), arousal (ranging from calm to excited) and dominance (ranging from in-control to dominated), see Table 10.

Description	Word No.	Valence Mean(SD)	Arousal Mean(SD)	Dominance Mean (SD)	Word Frequency
anger	17	2.34 (1.32)	7.63 (1.91)	5.50 (2.82)	48
angry	18	2.85 (1.70)	7.17 (2.07)	5.55 (2.74)	45

Table 10: ANEW English database sample.

2.4.2 General Inquirer

The General Inquirer resource is a dictionary, initially part of text analysis system created at IBM ([Stone and Hunt, 1963]). It contains 11789 senses of 8641 English words, some words being polysemous. The words are mapped to one or more of 182 categories, the most interesting for us being the *positive* category, assigned to 1915 words and the *negative* one, assigned to 2291 words, while 7582 words are identified as devoid of polarity.

2.4.3 WordNet Affect

WordNet Affect ([Strapparava and Valitutti, 2004]) is a development based on WordNet ([Miller, 1995]), resulting from the selection and labeling of the synsets that reference affective meanings. It initially contained 2,874 synsets and 4,787 words. Table 12 gives a sample of the network.

Affective label	Example synsets
EMOTION	noun anger#1, verb fear#1
MOOD	noun animosity#1, adjective amiable#1
TRAIT	noun aggressiveness#1, adjective competitive#1
COGNITIVE STATE	noun confusion#2, adjective dazed#2

Table 12: WordNet Affect sample

2.4.4 SentiWordnet

SentiWordNet[4] ([Esuli and Sebastiani, 2006], [Baccianella et al., 2010]) is a lexical resource for sentiment analysis constructed by graph-based automatic annotation of WordNet synsets by means of numeric scores for: positiveness (*Pos*), negativeness (*Neg*), and objectivity (*Obj*).

[4] http://sentiwordnet.isti.cnr.it/

An excerpt of the SentiWordNet is provided in Table 13. SentiWordNet and WordNet Affect have been used in various works, see [Chaumartin, 2007].

Rank	Positive	Negative
1	good#n#2, goodness#n#2	abject#a#2
2	better_off#a#1	deplorable#a#1, distressing#a#2 lamentable#a#1, pitiful#a#2, sad#a#3 sorry#a#2

Table 13: SentiWordNet 3.0. sample

2.5 Opinion, sentiment, emotion: summing up

As we have seen in the previous sections, some opinion models consider sentiment as an opinion attribute ([Kim and Hovy, 2004]). Others, consider sentiments seperately from opinions and define them as a personal judgment towards an entity. In the same way, some sentiment language models consider that emotion and sentiment are equivalent and other models define emotions as a refinement of sentiments. So, there is no convention on the definition of these concepts (opinion, sentiment and emotion) and researchers use different terms to describe their work: *opinion mining, sentiment analysis, subjectivity analysis, emotion recognition, emotion mining, emotion detection.*

In our case, we propose to distinguish between the three dimensions: We define:

- **opinion** as the positive, negative or neutral **intellective** statement of an individual person *opinion holder* about a specific entity that we call the *opinion target.*
- **sentiment** as the positive or negative **affective-intellective** judgment of an individual person about a specific entity characterized by *polarity* and *intensity.*
- **emotion** as the positive or negative **affective** state of an individual person characterized by *polarity* and *intensity.* Unlike sentiment, emotion do not necessary have a target entity.

3 Dimensional aspects of Opinion, Sentiment and Emotion representations

3.1 Model Dimensions

Depending on the annotation task considered to be performed by crowdsourcing, the complexity of the model can vary from a single class model to a multidemnsional representation of opinions/sentiments/emotions (OSE). In the former case, the task in its simplest form resolves itself to providing a binary answer to the question whether a piece of text expresses an OSE or not. In the later case, the annotator has to identify in the OSE representation the location of the various instances of OSE expressed in a piece of text it is currently annotating, a difficult task since some of the OSE instances may overlap in the mind of the annotator. For instance, it may even be the case that the annotation task considered was precisely designed to collect information about deciding whether two OSE classes should be considered disjoint or not.

The previous survey of the literature and our own experience in the domain led us to propose the following 3 dimensions are sufficient to represent any OSE instance. Of course, other dimension could be considered depending on particular requirements of the annotation task considered, but we think that these 3 ought to have enough expressive power to cover the needs of most of the OSE annotation task we can envision at the time of writing.

3.1.1 Affectivity

The affectivity dimension relates to the degree of the affectivity over the opinion, sentiment or emotion. According to this dimension, we distinguish between intellective, affective-intellective and affective expressions e.g., *approval* (intellective) versus *joy* (affective) or *satisfaction* (affective-intellective) versus *hapiness* (affective). In our point of view, affectivity subsumes the arousal dimension of ANEW [Bradley and Lang, 1999] and appraisal expressions [Liu, 2010] belong to the intellective subdomain of affectivity.

3.1.2 Control

The control dimension relates to the degree of power over the affect, and helps to distinguish emotions initiated by the subject from those elicited by the environment e.g., contempt versus fear; this has also been called the strength, dominance, or confidence dimension in other models.

3.1.3 Valence

Valence dimension refers to how positive or negative the affect is; this is also referred to as subjective feeling of pleasantness or unpleasantness.

3.2 Fine-Grained Opinion/Sentiment/Emotion classes

Similarly, for the individual OSE the complexity and number of items to consider depends on the annotation task. In its simplest form, the annotator may be asked to provide a binary answer whether a piece of text can be said to express a given OSE or not, in that case the model has only one class. But the annotator may be asked to identify various OSE instances in the text and, depending on the context of the experiment, the number and structural arrangement in the model of the various OSE classes can be quite different from one task to another. For OSE representation in uComp, we propose to consider as baseline the DOXA representation.

3.2.1 DOXA opinion model

The DOXA model[Paroubek et al., 2010], developped for generic commercial opinion mining on Internet, is one of the richest model proposed so far in terms of the number of OSE defined, with 17 semantic categories[5]: 4 for opinion expressions, 2 for sentiment expressions and 12 for emotion expressions (given in Table Table 16).

#	Label	Dim.	DOXA Semantic Category
1	NEGATIVE SURPRISE	e-	negative surprise / negative amazement
2	DISCOMFORT	e-	discomfort / disturbance / embarassment
3	FEAR	e-	apprehension / fear / alarm
4	BOREDOM	e-	boredom
5	DISPLEASURE	e-	displeasure / deception
6	SADNESS	e-	sadness / resignation / despair
7	ANGER	e-	annoyance / irritation / nervousness / anger / exasperation
8	CONTEMPT	e-	contempts / disdain / reluctance / disgust / hate
9	DISATISFACTION	s-	disatisfaction / discontent
10	DEVALORIZATION	o-	disinterest / devalorization / depreciation
11	DISAGREEMENT	o-	disapproval / disagreement
12	VALORIZATION	o+	interest / valorization / appreciation
13	AGREEMENT	o+	understanding / approval / agreement
14	SATISFACTION	s+	satisfaction / contentment
15	POSITIVE SURPRISE	e+	positive surprise
16	APPEASEMENT	e+	relief / appeasement
17	PLEASURE	e+	pleasure / entertainment / joy / happiness /euphoria

Table 16: DOXA semantic categories of opinion/sentiment/emotion, e=emotion, s=sentiment, o=opinion, +=positive valence, -=negative valence.

3.2.2 I2B2 2011 T2 task emotion model

In the I2B2 2011 Task 2 challenge ([Pak et al., 2012]), participants were asked to find emotions in a collection of suicide notes written by people who have died by suicide. Table 21 proposes a mapping onto DOXA semantic categories for the thirteen emotion classes ([Pestian et al., 2010]) used in I2B2 to tag the sentences of the notes where emotions are expressed. Of course, in some cases the mapping may not reflect all of the semantic content of the I2B2 category, because the I2B2 taks is very specific. For instance, the mapping for the categories `guilt` and `blame` respectively to DISCOMFORT and CONTEMPT, may not take into account all of the social

[5]A Semantic Category refers to a " meaning category", i.e. a set of opinions, sentiments or emotions which are so semantically close as to be considered indiscernable.

aspects of the I2B2 emotion classes. Similarly the mapping of both `hopefulness` and `pride` to SATISFACTION entails a loss of information. Nevertheless, we see with this example that the DOXA semantic categories are rich and complete enough to make the mapping possible between the two representations.

I2B2 emotion class	corresponding DOXA semantic category
`hopelessness`	SADNESS
`guilt`	DISCOMFORT
`blame`	CONTEMPT
`anger`	ANGER
`sorrow`	SADNESS
`fear`	FEAR
`abuse`	DISPLEASURE
`love`	VALORIZATION
`thankfulness`	APPEASEMENT
`hopefulness`	SATISFACTION
`happiness_peacefulness`	PLEASURE
`pride`	SATISFACTION
`forgiveness`	APPEASEMENT

Table 19: I2B2 emotions classes proposed mapping to DOXA semantic categories

3.2.3 Complementary information classes

Often the OSE analysis taks will require identifying complementary information classes, which are not part of the OSE spectrum of concepts (often objective in nature) but are nevertheless required by the task at hand. For instance, in the DOXA project, the 2 semantics categories RECOMMANDATION_SUGGESTION and DEMAND_QUEY were added to complete the OSE representation in oder to be able to caracterize the information content of communication sent by customers to their service provider. Similarly, in I2B2, the two objective classes `instructions` and `information` were used to complete the emotion classes, since authors of the suicide notes were often giving instructions and/or providing information to their loved ones.

3.2.4 uComp semantic categories

Although the DOXA project and the I2B2 2011 Task 2 challenge took place at different times and had no connection, we see that the two extra sets of information classes added to the OSE representation were in each case quite similar. As a consequence, we think that uComp base representation should also have this 2 complementary semantic categories, namely:

Semantic category label	meaning
INFORMATION	when providing or querying for objective information,
INSTRUCTION	when a recommandation, suggestion, instruction, order or command is expressed.

Table 21: uComp basic complementary information semantic categories

Table 22 presents the 20 uComp semantic categories with their 3 dimensional location to which we have added a fourth one “i” for information, along with the different OSE associated to each category.

#	Label	Dim.	uComp Semantic Category
1	NEGATIVE SURPRISE	e-	negative surprise / negative amazement
2	DISCOMFORT	e-	discomfort / disturbance / embarassment / guilt
3	FEAR	e-	shyness / worry / apprehension / alarm fear / terror
4	BOREDOM	e-	boredom
5	DISPLEASURE	e-	displeasure / deception / abuse
6	SADNESS	e-	sadness / resignation / despair / sorrow / hopelessness
7	ANGER	e-	impatience / annoyance / irritation / nervousness / anger / exasperation
8	CONTEMPT	e-	reluctance / contempts / disdain / blame / disgust / hate
9	DISATISFACTION	s-	disappointment / disatisfaction / discontent / shame
10	DEVALORIZATION	o-	disinterest / devalorization / depreciation
11	DISAGREEMENT	o-	disapproval / disagreement
12	VALORIZATION	o+	interest / valorization / appreciation
13	AGREEMENT	o+	understanding / approval / agreement
14	SATISFACTION	s+	satisfaction / contentment / pride
15	POSITIVE SURPRISE	e+	positive surprise / positive amazement
16	APPEASEMENT	e+	relief / appeasement / peacefullness forgiveness / thankfullness
17	PLEASURE	e+	pleasure / entertainment / enjoyment / joy / happiness / euphoria / play
18	LOVE	e+	love / affection / care / tenderness / fondness / kindness / attachment / devotion / passion / envy / desire
19	INFORMATION	i	information / announcement / news / demand / query / question
20	INSTRUCTION	i	recommandation / suggestion / instruction / order /command

Table 22: uComp semantic categories of opinion/sentiment/emotion, e=emotion, s=sentiment, o=opinion, i=information, +=positive valence, -=negative valence.

4 Data Acquisition and Annotation

4.1 Annotation Scheme

4.1.1 Main Principles

The primary goal behind the annotation task is to identify the fine-grained opinion sentiment or emotion class expressed in a document or a part of it. To be as much generic as possible, we propose to re-use the DOXA approach which allows for annotating a document at:

- the macro level (whole document),
- and at the sentence level (micro annotation).

Not all annotation levels need not to be instanciated, in particular for very short documents like Tweets, it is very likely that either only the macro level (whole document) or the micro level (sentence), or both will be required, since a document is only often made of only one sentence.

4.1.2 Macro level Attributes

For each document, the annotators will be asked to complete the following information template with the attributes:

1. **SEMCAT1,SEMCAT2,SEMCAT3,SEMCAT4,SEMCAT5** up to 5 semantic categories taken from the Table 22 can be provided,
2. **HOLDER** will refer to the entity who made the OSE statement,
3. **TARGET** will point to the entity about which the OSE expression is made,
4. **POLARITY** whill hold valence information, taken from the following set: { `positive`, `negative`, `mixed`, `neutral` }. The `mixed` value will be used for documents or paragraph which express both positive and negative OSE expression about the TARGET in roughly equal proportions, while `neutral` will be reserved for tagging explicit statment of neutrality about the TARGET (e.g. "I don't care about the price"). Of course if `mixed` is used, the SEMCAT attribute must contain at least two values.
5. **INTENSITY** will qualify, the force of the OSE expressed about the TARGET, it will take its values from the two value set: { `low_medium`, `strong` }
6. **AFFECTIVITY** will qualify the OSE in the dimention intellectual/affective,
7. **CONTROL** will qualify the OSE in the dimention in-control/dominated,
8. **EXPOSE** (EXPression of OSE) the segment of the document or paragraph that the annotator judges to be the most representative of its OSE annotation. No restriction is put on the size, it can vary from a few words (e.g. one target word and one OSE word when the HOLDER is the author of the document itself and no SOURCE is identified.)

to a very large portion of the document. Depending on the specificity of the annotation task, one may consider a single continous chunk of text from the document or several discontinous segments to inform this attribute.

9. **SOURCE** will point to the entity who reported the OSE expression, e.g. in case of reported opinion, the SOURCE is different from the HOLDER of the OSE expression; in *"Paul said that John finds the new X is too expensive"*, we have SOURCE="Paul" and HOLDER="John".

Table 27 gives an example of uComp OSE annotation at the macro level. The attributes value must fulfill the following constraints:

1. the value of an attribute must be taken from the domain specified for this attribute.
2. if $POLARITY = mixed$ then more than one SEMCAT must be given,
3. $(POLARITY = neutral) => (SEMCAT1 = [INFORMATION])$

Document:	*In the movie X, the music was great but the story was boring*
SEMCAT1=	`VALORIZATION`
SEMCAT2=	`BOREDOM`
HOLDER=	a reference to the author of the document
TARGET=	a reference to the movie X
POLARITY=	`mixed`
INTENSITY=	`medium_low`
EXPOSE=	either the whole sentence or the 3 words: "X", "great" and "boring"
SOURCE=	a reference to the publisher of the document

Table 26: Sample uComp OSE annotation at the macro level.

4.1.3 Micro level Attributes

For each sentence (micro), the annotators will be required to complete a description to complete an information template comparable to the one used for the macro level but this time for each OSE expression present in the sentence. As a consequence, the micro level information template will have only one SEMCAT attribute and will not allow POLARITY to take the value `mixed` since descriptions are supposed to be atomic. In addition, the micro information template will have two extra attributes:

1. TARGET_ASPECT, to allow for one sublevel (ontologcal or whole/part relationship) of semantic specification in the target identification
2. NEGATION, which will hold a boolean value indicating the presence of a negation marker associated to the OSE.
3. MODIFIER, i.e. intensifiers like *very* or degree adverbs like *moderatly*

Document:	*In the movie X, the music was not good and the story very boring*
SEMCAT=	[`VALORIZATION`]
HOLDER=	a reference to the author of the document
TARGET=	a reference to X
TARGET_ASPECT=	a reference to movie music
POLARITY=	`negative`
INTENSITY=	`medium_low`
EXPOSE=	the words: “X, the music was not good”
SOURCE=	a reference to the publisher of the document
NEGATION=	True
MODIFIER=	NA
SEMCAT=	[`BOREDOM`]
HOLDER=	a reference to the author of the document
TARGET=	a reference to the movie X
TARGET_ASPECT=	a reference to movie story
POLARITY=	`negative`
INTENSITY=	`strong`
EXPOSE=	the words “and the story very boring”
SOURCE=	a reference to the publisher of the document
NEGATION=	False
MODIFIER=	"very”

Table 27: Sample uComp OSE annotation at the macro level.

5 XML DTD and example

5.1 XML DTD

Here is a DTD that implements the previous requirement defined in the previous section.

```
<?xml version="1.1" encoding="UTF-8"?>

<!-- XML Document Type Definition
     Authors:
       Amel Fraisse <fraisse@limsi.fr>
       Patrick Paroubek <pap@limsi.fr>

     Description:
       ucomp format for OSE model.

     Version: 2.0
-->
```

```
<!ELEMENT corpus (document)+ >

<!ATTLIST corpus id CDATA #IMPLIED >

<!ELEMENT document (content, OSE_AnnotationSet) >

<!ATTLIST document id CDATA #IMPLIED >

<!ELEMENT content (#PCDATA)>

<!ELEMENT OSE_AnnotationSet ((Macro_OSE_Annotation)?, (Micro_OSE_Annotation)+) >

<!ELEMENT Macro_OSE_Annotation EMPTY>

<!ATTLIST Macro_OSE_Annotation
                      ID     CDATA #REQUIRED
                      HOLDER CDATA #REQUIRED
                      HOLDER_offsetStart CDATA #IMPLIED
                      HOLDER_offsetEnd CDATA #IMPLIED
                      SEM_CAT_1  (negative_surprise|discomfort|fear|boredom|displeasure|
                                  sadness|anger|contempt|disatisfaction|devalorization|
                                  disagreement|valorization|agreement|satisfaction|
                                  positive_surprise|appeasement|love|information|
                                  instruction) #REQUIRED
                      SEM_CAT_2  (negative_surprise|discomfort|fear|boredom|displeasure|
                                  sadness|anger|contempt|disatisfaction|devalorization|
                                  disagreement|valorization|agreement|satisfaction|
                                  positive_surprise|appeasement|love|information|
                                  instruction) #REQUIRED
                      SEM_CAT_3  (negative_surprise|discomfort|fear|boredom|displeasure|
                                  sadness|anger|contempt|disatisfaction|devalorization|
                                  disagreement|valorization|agreement|satisfaction|
                                  positive_surprise|appeasement|love|information|
                                  instruction) #REQUIRED
                      SEM_CAT_4  (negative_surprise|discomfort|fear|boredom|displeasure|
                                  sadness|anger|contempt|disatisfaction|devalorization|
                                  disagreement|valorization|agreement|satisfaction|
                                  positive_surprise|appeasement|love|information|
                                  instruction) #REQUIRED
                      SEM_CAT_5  (negative_surprise|discomfort|fear|boredom|displeasure|
                                  sadness|anger|contempt|disatisfaction|devalorization|
                                  disagreement|valorization|agreement|satisfaction|
                                  positive_surprise|appeasement|love|information|
                                  instruction) #REQUIRED
                      POLARITY  (positive|negative|neutral|mixed) #REQUIRED
              INTENSITY (low_medium|strong) #IMPLIED
```

```
                TARGET CDATA #IMPLIED
                TARGET_ASPECT CDATA #IMPLIED
                TARGET_offsetStart CDATA #IMPLIED
                TARGET_offsetEnd   CDATA #IMPLIED
                AFFECTIVITY (intellectual|intellect_affect|affective) #IMPLIED
                CONTROL (dominated|partial_control|control) #IMPLIED
                offsetStart CDATA #IMPLIED
                offsetEnd CDATA #IMPLIED
                SOURCE CDATA #IMPLIED>

<!ELEMENT Micro_OSE_Annotation EMPTY>

<!ATTLIST Micro_OSE_Annotation
                ID CDATA #REQUIRED
                HOLDER CDATA #REQUIRED
                HOLDER_offsetStart CDATA #IMPLIED
                HOLDER_offsetEnd CDATA #IMPLIED
                SEM_CAT  (negative_surprise|discomfort|fear|boredom|displeasure|
                            sadness|anger|contempt|disatisfaction|devalorization|
                            disagreement|valorization|agreement|satisfaction|
                            positive_surprise|appeasement|love|information|
                            instruction) #REQUIRED
                POLARITY  (positive|negative|neutral) #REQUIRED
            INTENSITY (low_medium|strong) #IMPLIED
                TARGET CDATA #IMPLIED
                TARGET_ASPECT CDATA #IMPLIED
                TARGET_offsetStart CDATA #IMPLIED
                TARGET_offsetEnd   CDATA #IMPLIED
                AFFECTIVITY (intellectual|intellect_affect|affective) #IMPLIED
                CONTROL (dominated|partial_control|control) #IMPLIED
                EXPOSE_offsetStart CDATA #IMPLIED
                EXPOSE_offsetEnd   CDATA #IMPLIED
                SOURCE CDATA #IMPLIED
                NEGATION (true|false) #IMPLIED
            MODIFIER (true|false)  #IMPLIED
                MODIFIER_offsetStart CDATA #IMPLIED
                MODIFIER_offsetEnd   CDATA #IMPLIED >
```

5.2 An annotation example

Here is an example showing how to use the DTD given in the previous section.

```
<?xml version="1.0" encoding="UTF-8"?>
<!--DOCTYPE valid SYSTEM "./uComp_OSE_schema_xml_v2.dtd" -->
<corpus id="OSE_annotation_xml_example">
```

```
<document id="1">
<content>
In the movie X, the music was great but the story was boring
</content>
<OSE_AnnotationSet>
  <Macro_OSE_Annotation ID="1"
                        HOLDER="EXT_DB_REFERENCE_TO_AUTHOR"
      SEM_CAT_1="valorization"
      SEM_CAT_2="boredom"
      POLARITY="mixed"
      INTENSITY="low_medium"
      TARGET="EXT_DB_REFERENCE_TO_MOVIE_X"
      TARGET_offsetStart="8"
      TARGET_offsetEnd="12"
      AFFECTIVITY="affective"
      CONTROL="control"
      SOURCE="EXT_DB_REF_TO_PUBLISHER" />
  <Micro_OSE_Annotation ID="1"
      HOLDER="EXT_DB_REFERENCE_TO_AUTHOR"
      SEM_CAT="valorization"
      POLARITY="positive"
      INTENSITY="low_medium"
      TARGET="EXT_DB_REFERENCE_TO_MOVIE"
      TARGET_ASPECT="MOVIE_MUSIC"
      TARGET_offsetStart="16"
      TARGET_offsetEnd="25"
      AFFECTIVITY="intellect_affect"
      CONTROL="control"
      EXPOSE_offsetStart="27"
      EXPOSE_offsetEnd="35"
      SOURCE="EXT_DB_REF_TO_PUBLISHER" />
  <Micro_OSE_Annotation ID="2"
      HOLDER="EXT_DB_REFERENCE_TO_AUTHOR"
      SEM_CAT="boredom"
      POLARITY="negative"
      INTENSITY="low_medium"
      TARGET="EXT_DB_REFERENCE_TO_MOVIE"
      TARGET_ASPECT="MOVIE_STORY"
      TARGET_offsetStart="16"
      TARGET_offsetEnd="25"
      AFFECTIVITY="intellect_affect"
      CONTROL="control"
      EXPOSE_offsetStart="27"
      EXPOSE_offsetEnd="35"
      SOURCE="EXT_DB_REF_TO_PUBLISHER" />
</OSE_AnnotationSet>
```

```
</document>
</corpus>
```

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