



HAL
open science

Towards a non-oriented approach for the evaluation of odor quality

Massissilia Medjkoune, Sébastien Harispe, Jacky Montmain, Stéphane Cariou, Jean-Louis Fanlo, Nicolas Fiorini

► **To cite this version:**

Massissilia Medjkoune, Sébastien Harispe, Jacky Montmain, Stéphane Cariou, Jean-Louis Fanlo, et al.. Towards a non-oriented approach for the evaluation of odor quality. International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems IPMU 2016, Jun 2016, Eindhoven, Netherlands. 10.1007/978-3-319-40596-4_21 . hal-01485002

HAL Id: hal-01485002

<https://hal.science/hal-01485002>

Submitted on 7 Jun 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Towards a non-Oriented Approach for the Evaluation of Odor Quality

Massissilia Medjkoune^{1,2}, Sébastien Harispe¹, Jacky Montmain¹, Stéphane Cariou²,
Jean-Louis Fanlo² and Nicolas Fiorini¹

1- Laboratory of Computer Science and Production Engineering (LGI2P), Ecole des Mines
d'Alès, Parc Scientifique Georges Besse, F30035 Nîmes cedex 5, France

2- Laboratory of Engineering for Industrial Environment (LGEI), Ecole des mines d'Alès, 6
avenue de Clavières, 30319 Alès cedex, France
firstname.name@mines-ales.fr

Abstract. When evaluating an odor, non-specialists generally provide descriptions as bags of terms. Nevertheless, these evaluations cannot be processed by classical odor analysis methods that have been designed for trained evaluators having an excellent mastery of professional controlled vocabulary. Indeed, currently, mainly oriented approaches based on learning vocabularies are used. These approaches too restrictively limit the possible descriptors available for an uninitiated public and therefore require a costly learning phase of the vocabulary. The objective of this work is to merge the information expressed by these free descriptions (terms) into a set of non-ambiguous descriptors best characterizing the odor; this will make it possible to evaluate the odors based on non-specialist descriptions. This paper discusses a non-oriented approach based on Natural Language Processing and Knowledge Representation techniques - it does not require learning a lexical field and can therefore be used to evaluate odors with non-specialist evaluators.

Keywords: Sensorial Analysis, Distributional Semantics, Information Fusion, Taxonomy, Odor Quality, Non-oriented Approach

1 Introduction, problem and objective

According to several surveys, people have become increasingly sensitive to issues related to pollution and environment - see for example ISAAC study [1] and Aphekom study [2]. In particular, in large cities and large industrial areas, people have become increasingly attentive to air pollution. Indeed, odors are considered to be the second reason for complaint after noise. They are often considered to be aggressions and are generally perceived as threats for individual health. In this context, numerous companies focus on finding solutions to improve their image and their relationship with neighboring populations of industrial sites. It is therefore essential for these companies to control and to measure the acceptability related to their air emissions – and therefore to have tools at their disposal to perform these analyses. Assessing the acceptability of an odor is to check that the odor is not associated to an

unpleasant character. Studying the acceptability of an odor therefore relies on the ability to analyze the natural language descriptions qualifying the odor.

The evaluation of odor quality is also considered vital for companies that want to remain competitive. Indeed, the quality of an odor highly impacts product design since smell plays a central role in defining the identity of a product - the odor of a product may have both positive and negative effects on product perception – almost everybody will remind the often artificial and carefully designed sweet smell of his favorite candy. Odor quality has therefore a direct impact on sells, which explains that controlling this product characteristic is of major importance for brands.

The smell is the image that the brain has made in the presence of odor molecules. An odor is commonly characterized using three notions: (i) its intensity, which depends on the concentration of the odorous substance of the inspired air; (ii) its hedonic tone, which assigns a pleasant or an unpleasant character to the smell, and (iii) its quality, i.e. to what the odor refers to, that can be translated by linguistic descriptors. The quality refers to the perceived odor and remains the most subjective propriety of olfactory perception - as it relies on the personal memories of individuals [3].

In this setting, the complexity of evaluating odor quality returns to the difficulty to analyze odor descriptions. Currently, industrials have long relied on well-defined evaluation procedures in the framework of costly sensorial analyses sessions that have been designed for carefully analyzing, controlling and selecting odors [13]. Such evaluations of odors quality are commonly made through controlled linguistic descriptors provided by trained specialists capable of distinguishing precise panels of odors. Among the approaches proposed in the literature, the wheel of odors and odor fields are often used to qualify odors [4][5]. These methods use an oriented approach based on a common referential to qualify the odors, which facilitates their characterization. Indeed, forcing evaluators to use specific descriptors facilitates understanding, interpreting and processing the results. Nevertheless, a learning phase in which valid descriptors have to be learned is required to use such methods. This (i) prevents their use by non-specialists, (ii) implies additional training costs, and (iii) limits the number of evaluators and experiments that can be used to evaluate an odor. In this article, we propose an alternative to this costly and restrictive approach by defining an automatic approach enabling to evaluate odors based on non-specialist descriptions. The aim of this work is therefore to propose an approach for evaluating an odor by analyzing natural language descriptions provided by non-specialists. The proposed approach is non-oriented and requires neither prior training nor learning of a specific lexical field by the evaluators.

We consider that the terms used by non-specialists to describe the quality of an odor are free, *i.e.* it is here assumed that people provide their assessments using their own words and vocabulary. Therefore, contrary to descriptions provided by experts in oriented approaches, the terms we have to deal with are not part of an implicit controlled and standardized vocabulary defining the terms commonly used for character-

izing (specific) odors. The purpose of our work is therefore to identify the descriptors that best describe the smell by analyzing natural language descriptions provided by non-specialists. In this paper, we focus on the special case where we want an odor to be described by a set of non-ambiguous descriptors. These descriptors—denoted concepts in the rest of the paper—are assumed to be partially ordered into taxonomy $\mathcal{O} = (\preceq, C)$, with C the set of concepts. The aim of this work is therefore to summarize the quality of an odor into a conceptual annotation, *i.e.* set of concepts.

For a given odor evaluation, a description provided by non-expert is assumed to be a set of terms in which each term may be associated to an intensity (the intensity degree is defined to be between 1 and 5, the higher its value, the more important the related term is in the smell description). As an example, the description d provided by an evaluator testing the smell of yoghurt could be the following:

$d = [(orange, 4); (lemon, 4); (butter, 3); (brownsugar, 1); (lemoncake, 2)]$

The problem we face can therefore simply be formulated by the following question: how to fusion the information expressed by description d in order to formally characterize the odor of the evaluated yoghurt into a conceptual annotation (set of partially-ordered concepts)? Defining a model for answering this question requires characterizing the semantics, *i.e.* meaning, of the terms used in the description, *e.g.* intuitively, looking at description d , people understand that the terms "orange" and "lemon" refer to "citrus fruits" (putting aside the problem of ambiguity). This is because our knowledge about the world provides us a taxonomical organization we can use to derive conclusions on the basis of deductive reasoning. Indeed, we know that the concepts Orange and Lemon both refer to specific types of concept Citrus-fruit, *i.e.* formally $Orange \preceq Citrus\text{-}fruit$ and $Lemon \preceq Citrus\text{-}fruit$ which implies that the description d implicitly refers to the concept Citrus-fruit, a concept that could therefore be a good candidate to characterize the odor. Such a reasoning approach relies on a taxonomic knowledge organization partially ordering concepts. However, in other cases, such reasoning is also based on the consideration of the semantic proximity between concepts, *e.g.* Lemon cake contains Lemon which reinforces the fact that Citrus-fruit seems to be relevant to describe the odor of yoghurt, despite the fact that, strictly speaking, Lemon cake is not ordered to Lemon and Citrus-fruit.

For defining our approach, we intuitively propose to consider that a term evokes concepts (*e.g.* the term *lemon cake* evokes with some degrees the concepts Lemon and Cake). Automatically assessing the degree with which a term evokes a concept is a difficult task. First we have to consider the fact that no consensus could be obtained in numerous cases – the appraisal may vary a lot between two persons since it depends on subjective notions. Second, even if our will is to mimic only one person estimation, it would require formalizing too much complex and extensive knowledge to represent all the interactions between the concepts. To tackle this complex problem, we propose to take advantage of distributional semantics models for evaluating term proximity with regard to their usage (*i.e.* meaning). These models are based on the distributional hypothesis which, in linguistics, states that words that are used and

occur in the same contexts tend to purport similar meanings [10]. The first step to obtain such a model is to analyze word co-occurrences in a large corpus of texts (*e.g.* Wikipedia). These co-occurrences are used to derive a model, usually a matrix, providing a vector representation of terms. Finally, two terms can be compared by analyzing their vector representations; a variety of measures have been proposed for that purpose [6], *e.g.* cosine measure. Since distributional semantics models enable us to compare terms with regards to their semantics, we next consider that measuring the similarity between a term and a concept returns to calculate the similarity between the term and the labels (terms) associated to this concept – the labels are provided in the input taxonomy. As an example, the degree to which the term *lemon cake* evokes the concept `Lemon` will be estimated using the semantic proximity between the term *lemon cake* and the label of the concept `Lemon` (*e.g.* *lemon, citrus medica*).

The following section presents the model we propose for deriving term vector representations. They will next be used by fusion information techniques to derive the description of the odor.

2 Modeling

The model is composed of two principal parts; the first consists in defining a correspondence between the terms and the concepts of the taxonomy, *i.e.* to represent the terms and the labels related to concepts as vectors on a given vocabulary T . By comparing the vector representations, we will then compute the degree to which a term evokes a concept. The second part consists to aggregate the terms of a description in order to obtain a synthetic set of concepts (conceptual annotation) which formally best characterizes the odors.

In order to ease the readability of this section, the various notations which will be used to introduce the model are listed below:

- C : the set of concepts, $C = \{c_1, c_2, \dots, c_n\}, |C| = n$
- $\mathcal{O} = (\preceq, C)$: the taxonomy partially ordering the set of concepts
- T : the set of terms that constitute the vocabulary
- T_e : the set of terms of the description provided by the evaluator e to qualify the odor, $T_e = \{t_1^e, t_2^e, \dots, t_{k_e}^e\}, T_e \subset T$;
- L_c : the set of labels associated to concept c , with $L_c \subset T$.

2.1 Computing conceptual annotations from terms

The vector representations of the terms (including concepts' labels) are used to estimate to which degree a term of the description evokes a concept. Informally, the strength of evocation a term has with regard to a concept can be regarded as the semantic proximity between the term and the concept. The correspondence or measure the semantic proximity between terms and concepts cannot be established in a straightforward manner without considering the labels (*i.e.*, terms) associated to the

concepts. For this, we first define a correspondence between the terms and labels that refer to concepts. This correspondence between terms and concepts is defined as the measure of proximity between terms and labels associated to concepts.

The proximity between terms and concepts will be defined by $\sigma_{TC}: T \times C \rightarrow [0,1]$, according to the measure σ_{TT} which assesses the proximity of two terms $\sigma_{TT}: T \times T \rightarrow [0,1]$. Numerous measures for comparing terms have already been proposed in the literature [6] - co-occurrences or pointwise mutual information are classical ones in texts analysis. Then, the semantic proximity between a term t and a concept c can be estimated, for example, as the maximum of the similarity values between the term and the labels associated with the concept c : $\sigma_{TC}(t, c) = \max_{l \in L_c} \sigma_{TT}(t, l)$ with L_c the set of labels associated to the concept c .

The objective of this step is to synthesize the information expressed by the terms of a description T_e to characterize the odor through a conceptual annotation. To this aim, it is required to aggregate the information conveyed by the vector representations of the terms composing T_e . This conceptual annotation, $annot(T_e)$, with $annot: 2^T \rightarrow 2^C$, can be computed as follows:

$$annot(T_e) = \bigcup_{t \in T_e} \{c \in C \mid \max_{c \in C} \sigma_{TC}(t, c)\} \quad (1)$$

This model considers a simple one-to-one correspondance between terms and concepts. When two terms in T_e evoke the same concept no redundancy will be considered. The main drawback of this strategy is that long descriptions may lead to large conceptual annotations. In those cases, a conceptual summary of $annot(T_e)$ is desired. The situation is similar when there are several evaluators who individually provide descriptions that are to be conceptually synthesized. This summary is not so obvious because it requires having in mind the way concepts are organized in the taxonomy to make simplistic but relevant factorizations, *i.e.*, eliminate redundancies of too similar concepts but retain concepts that evoke obviously different ideas related to the perception of the odor.

2.2 Summarizing conceptual annotations

Let $E = \{e_1, e_2, \dots, e_s\}$ be the set of evaluators. We consider that each evaluator e_i provides a set of terms characterizing the quality of the same odor. Using the model introduced in section 2.1, a set of concepts $annot(T_{e_i})$ can be associated to each individual bag of terms T_{e_i} .

In the following, we propose an algorithm to semantically summarize a set of semantic annotations. When the number of evaluators s is not too large (*e.g.*, sensorial analysis sessions are composed of 6 or 8 evaluators), we search for a conceptual summary $annot^*$ that synthesizes the individual conceptual annotations. We suppose the search space to be 2^{f_0} where $f_0 = \bigcup_{c \in \bigcup_{i=1}^s annot(T_{e_i})} Anc(c)$, and $Anc(c)$ is the set of inclusive ancestors of concept c in the sense of the taxonomic order of $\mathcal{O} = (\preceq, C)$ (*i.e.*, the set of concepts composed of c and the concepts that subsume c). The search

for $annot^*$ can be expressed as an optimization problem as proposed in [8]. The objective function is associated to a consistency criterion: $annot^*$ must be as similar as possible to all the annotations it summarizes. The second criterion is a concision constraint: a summary is by definition synthetic.

The similarity between a summarizing annotation $annot \in 2^{f_0}$ and the annotations $annot(T_{e_i})$ can be modelled using a taxonomic semantic similarity measure used to compare groups of concepts (groupwise measure). The objective function is then:

$$g_1(annot) = \frac{1}{s} \sum_{i=1}^s sim_g(annot, annot(T_{e_i})) \quad (2)$$

with $sim_g: 2^C \times 2^C \rightarrow [0,1]$ the groupwise semantic similarity measure.

The optimal solution $annot^*$ must be as consistent as possible under the concision constraint. The more concepts in (*e.g.*, $annot = f_0 = \cup_{i=1}^s annot(T_{e_i})$), the more precise the summary and the more likely $g_1(annot)$ value is high but in return not synthetic at all. The concision is defined as a penalty function with regard to the number of concepts in the annotation:

$$g_2(annot) = \mu |annot| \quad (3)$$

where $\mu \in [0,1]$ is a parameter controlling the importance of the constraint.

Finally, the function to be maximized is:

$$g(annot) = g_1(annot) - g_2(annot) \quad (4)$$

$$\text{and } annot^* = \operatorname{argmax}_{annot \in 2^{f_0}} g(annot)$$

Finding an exact optimal solution according to the objective function is not feasible when $|f_0|$ becomes large. Fiorini *et al.* have proposed a local heuristic using a greedy algorithm to remove one after the other elements from f_0 until $annot^*$ is found - details on the parameterization and performances of this algorithm are provided in [8][9] and are not discussed in the following practical case.

3 Practical case

The distributional models used for computing the proximity of terms are of critical importance for summarizing the term descriptions. Various approaches for computing and comparing word-vector representations have been proposed in the literature. Even if some strategies have been proved to be better suited for some specific use cases, the selection of the best-suited strategy for practical cases is still an open question and therefore requires domain-specific analyses and parameter settings [6]. In this study, several models using different parameter settings have been tested to compute word-vector representations. Considering the different parameter settings, obtained models differ (i) on the way the set of terms T is computed, (ii) on the size of vector representations, and (iii) on the semantics of each dimension of the vectors that are finally considered. A brief discussion on the different models that have been tested in this

study is proposed in this section. All tested models have been obtained from the analysis of a lemmatized version of Wikipedia – English version 2015 – and have been computed using open source code (that will be made available if the paper is accepted).

The set of terms T is of major importance and must be carefully built since it defines the terms provided by the evaluators that can be mapped into concepts – ideally we want $\bigcup_{i=1}^s T_{e_i} \subset T$, *i.e.* we don't want to lose any information provided by a term description. The set of terms T also defines the taxonomy concepts that can be associated to evaluator term descriptions. Indeed, it's important to stress that it will not be possible to process the terms provided by the evaluators that are not in T since it will not be possible to compare them to the (labels of the) concepts defined in the taxonomy. Similarly, it will be impossible to take advantage of the concept for which the labels are not in T - those labels could not be used to link a term description into the conceptual space, which will also hamper the performance of the treatment. In this study, two approaches have been evaluated to distinguish the set of terms T :

1. Considering a custom English dictionary built from the free dictionary Wiktionary ($m = 200k$);
2. Applying some restrictions on the grams and bi-grams that can be found into Wikipedia, *e.g.* by only considering the words that have at least been seen 10 or 50 times in the whole corpora ($m_{10} = 1.2M, m_{50} = 209k$).

In all cases, the vector representations of the terms composing T have first been computed into $\mathbb{R}^{|T|}$ only considering syntagmatic relationships between words, *i.e.* by analyzing co-occurrences of words in a specific window size (30 and 100 words have been used for the experiments). Using such a model a term $t \in T$ is represented as a vector $\vec{t} = [coocc(t, t_i)]_{i=0,|T|}$, with $coocc: T \times T \rightarrow \mathbb{N}$ the function used to compute the number of times two words co-occurred into the same term window. A model in which $\vec{t} = [pmi(t, t_i)]_{i=0,|T|}$ has also been tested where $pmi(x, y) = \frac{p(x/y)}{p(x)}$ is the pointwise mutual information of (x, y) ; and p holds for probability. Since the set T is large, specific reduction techniques have next been applied on the models in order to reduce the size of term vectors, *e.g.* by only considering dimensions that are associated to the most frequent words – reductions based on matrix factorization techniques, such as Single Value Decomposition, could have been used but have not been tested in this study. Reducing vector sizes is not only useful to reduce computational time but also has the benefit to remove some noises that will hamper vector comparison. Based on the tested models, the proximity between two terms, *i.e.* $\sigma_{TT}: T \times T \rightarrow [0,1]$, is computed using cosine similarity between vector representations. Therefore the set of terms $T_e \subset T$ provided by an evaluator e is summarized by a conceptual annotation according to equation (1).

In the illustrative following example, a naïve evaluator has been invited to assess the quality of a set of honey items. It is assumed that we have a non-specialist evaluator, who is prompted to smell and then verbalize the odor by a set of terms in natural language. Let us suppose $T_e = \{cappuccino; grape\}$. The proximity between cappucci-

no (resp. grape) and its 40 closest terms in the sense of the proximity measure are provided in the Table 1. This result has been obtained with a model built from a collection of 10^6 texts of Wikipedia, the proximity measure is based on co-occurrences of terms in the corpus and the terms' co-occurrences have been computed with a symmetric 100 wide sliding window. A restriction $|T| = 3000$ has been applied in this practical case.

Table 1: *grape* and *cappuccino* closest terms (scores are rounded up to 10^{-2})

cappuccino			grape		
0	1.0	cappuccino	0	0.99	grape
1	0.95	latte	1	0.94	vineyard
2	0.92	espresso	2	0.93	winemaking
3	0.91	macchiato	3	0.92	winery
4	0.89	cortado	4	0.92	varietal
5	0.88	fluid ounce	5	0.92	viticulture
6	0.88	latte macchiato	6	0.92	winemaker
7	0.87	portafilter	7	0.92	Chardonnay
8	0.87	coffee bean	8	0.91	vine
9	0.87	coffee cup	9	0.91	grape wine
10	0.86	ristretto	10	0.90	wine grape
11	0.85	lait	11	0.90	doc
12	0.85	coffee maker	12	0.90	blanc
13	0.85	americano	13	0.90	Sauvignon blanc
14	0.82	quarter glass	14	0.90	phylloxera
15	0.81	coffee liqueur	15	0.89	planting
16	0.81	half-caf	16	0.89	terroir
17	0.81	doppio	17	0.89	appellation
18	0.81	crema	18	0.89	Syrah
19	0.81	nong	19	0.89	dessert wine
20	0.80	barista	20	0.87	tasting
21	0.79	frappe	21	0.87	AOC
22	0.79	coffee pot	22	0.86	mildew
23	0.78	mocha	23	0.85	Cabernet Sauvignon
24	0.77	tastebud	24	0.85	Chianti
25	0.77	teaspoon	25	0.85	vintage
26	0.77	milk tea	26	0.85	Merlot
27	0.76	hyperforeignism	27	0.84	spoilage
28	0.76	sade	28	0.84	Riesling
29	0.76	sugar spoon	29	0.83	grapevine
30	0.74	froth	30	0.83	winepress
31	0.72	demerara	31	0.83	vintner
32	0.70	chaus	32	0.83	ice wine
33	0.70	piloncillo	33	0.82	Pinot Noir
34	0.69	Pharisee	34	0.82	wine bottle
35	0.69	chicory	35	0.82	wine
36	0.67	ice cube	36	0.82	wine cellar
37	0.65	chocolate milk	37	0.82	Montrachet
38	0.64	milk chocolate	38	0.82	riesling
39	0.63	Red Eye	39	0.82	vigneron

The results in Table 1 merely illustrate the *intuitive* notion of proximity: they are clearly debatable even if they suitably match with the intuitive terms we might commonly relate to cappuccino (resp. grape). The evaluation of the model would obvi-

ously require a test campaign which is out of the scope of this paper. Our aim here is rather to propose a general processing pipe from sets of terms in natural language to the synthetic conceptual annotation that summarizes the collective evaluation quality into notions that make sense for professional of specific domains. Each part of this pipe will be deeper analyzed in future works.

The set of terms $T_e = \{cappuccino; grape\}$ provided by an evaluator e is conceptualized according to equation (1). The taxonomy that is used to compute this conceptual annotation has been built from the sensory analysis applied to honey proposed in [11] where an odor and aroma wheel for honey sensory analysis is provided (Figure 1). An "odor or aroma wheel" is a popular visual scheme for diagramming the range of smells that characterize a particular food or beverage. A well-known example is the wine aroma wheel, developed in 1984 by University of California-Davis chemist Ann Noble. It is laid out like a dartboard, with broad flavor categories (e.g., "fruity") near the center and specific examples of that category (e.g., "strawberry") on the outer ring. As a consequence, this abstraction hierarchy is interpreted in our framework as the partial order that organizes the concepts of our field of application. The taxonomy has been built with the free open-source taxonomy editor PROTEGE (see extract at the right side of Figure 1) [12].

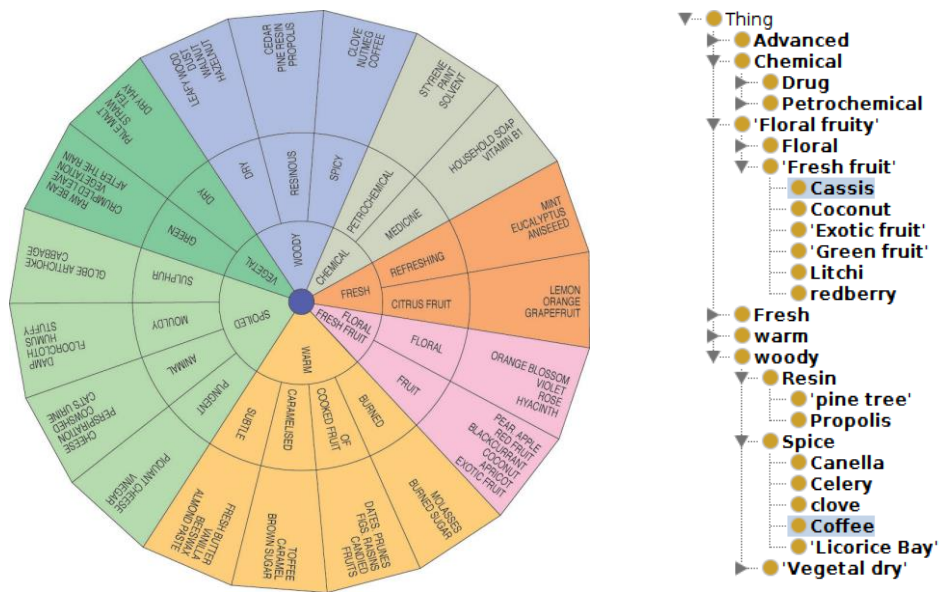


Figure 1: (left) odor and aroma wheel for honey sensory analysis; (right) interpretation of the wheel as the partial order of a taxonomic relation

The Figure 1 both provides the odor wheel of [11] and our free interpretation into a taxonomic order whose part is illustrated at the right part of the figure. The wheel provides both the concepts of the domain and their specificity levels that are interpreted in the ontological model. This interpretation should be deeper discussed: the trans-

lation of the abstraction hierarchy of odors the wheel captures and the taxonomic order based on the relationships `rdfs:subClassOf` do not match so easily and should be more precisely analyzed in future works – since it may impact both the conceptual annotation calculus and in the summary of conceptual annotations. In our example, the conceptual annotation related to $T_e = \{cappuccino; grape\}$ is $annot(T_e) = \{coffee; blackcurrant\}$ where `Coffee` and `Blackcurrant`, two concepts of the aroma wheel, they then make sense for professionals in the honey sector (note that `Blackcurrant` and `Cassis` are equivalent).

Our approach tries to mimic the analysis of naïve descriptions in natural language a professional sensorial analysis operator could perform. The vocabulary used to describe the smell is not limited and it does not require learning any specific vocabulary. The way the verbal descriptions are gathered and interpreted as well as the formal descriptors chosen is more or less arbitrary and often depends on the operator. For that purpose, our approach is supposed to automate the identification of the sets of concepts (descriptors) in order to increase both the reliability and the performance of the process. This automation should also allow expanding the assessment of the quality of odors to large groups of evaluators as it is the case in the analysis of olfactory nuisances around industrial sites.

To validate our model in future works, the sensory profiles evaluators provide will be compared to the ones our approach generates; we will use a groupwise similarity measure to compare the two groups conceptual annotations as basic metrics. Let us note T_{e_i} the set of terms the evaluator e_i provides and CI_{e_i} , the conceptual interpretation the operator in charge of the sensorial analysis proposes, and finally $annot(T_{e_i})$ the semantic annotation our approach relates to T_{e_i} as proposed in this paper. Basically, the relevancy of our algorithm is function of $sim_g(CI_{e_i}, annot(T_{e_i}))$. We will analyze the statistical distribution of the errors $\varepsilon_i = (1 - sim_g(CI_{e_i}, annot(T_{e_i})))$. This distribution will have to be read in conjunction with the deviations $\delta_{ij} = (1 - sim_g(CI_{e_i}, CI_{e_j}))$. Indeed, the more homogeneous the interpreted evaluations CI_{e_i} , the more obvious the olfactory test seems to be and the smaller the standard deviation of ε_i should be. δ_{ij} should also be used to calibrate or normalize ε_i . The relevancy of conceptual annotations cannot be envisaged in the same way whereas even experts disagree in their assessments.

4 Conclusion and perspectives

Evaluating the quality of odors is important for industrials to control the acceptability of odors related to its air emissions. The evaluation of odor quality also plays a very vital role in sensory analysis: pleasant smell of product increases the likelihood a product appeal to customers. Nowadays, industrial oriented approaches for assessing the quality of odors mostly require structured and controlled vocabularies that implies expensive and long training phases for experienced assessors. To address this issue,

we propose an approach that automates the process of assessing the quality of an odor. Non-oriented, this approach is based on semantic analysis and does not require learning a lexical field - it that can therefore be used to evaluate odors with non-specialist natural language descriptions. Distributional models commonly used in natural language processing are introduced to capture the relationships between naïve terms and professional standardized descriptors. Finally, optimization and clustering techniques allow identifying the conceptual annotation that best summarizes the natural language descriptions and therefore the initially informal evaluations of odor quality.

In future works, the evaluation of the approach will require several test campaigns. A database on smells of candies is under construction. Expert and novice assessments are gathered for 6 candy types. Another database concerns flavor descriptions in red and white wines. The parameterization of the distributional model will be one of the major issues during this validation phase. We will also have to pay a particular attention on the effect the interpretation of the odor/aroma wheels into our taxonomic partial orders could have. In our current framework, the terms are represented as vectors on a given vocabulary T ; it is also envisaged to project these representations onto the conceptual space C in order to take into account the similarity between concepts in the vector representation.

Interestingly, this non-oriented approach for identifying the quality of odors appears to be an actual cognitive automation of the task entrusted to expert operators in sensorial analysis. It opens interesting perspectives for developing scalable sensorial analyses to large sets of evaluators when assessing olfactory nuisances around industrial site.

5 References

1. M. I. Asher, S. Montefort, B. Björkstén, C. K. Lai, D. P. Strachan, S. K. Weiland, and H. Williams, “Worldwide time trends in the prevalence of symptoms of asthma, allergic rhinoconjunctivitis, and eczema in childhood: ISAAC Phases One and Three repeat multicountry cross-sectional surveys”, *Lancet*, vol. 368, no. 9537, pp. 733–743, 2006.
2. C. Declercq, M. Pascal, O. Chanel, M. Corso, A. Lefranc, and S. Medina, “Impact sanitaire de la pollution atmosphérique dans neuf villes françaises. Résultats du projet Aphekom”, *Rev. Epidemiol. Sante Publique*, vol. 60, pp. S60–S61, 2012.
3. S. David, D. Dubois, C. Rouby, and B. Schaal, “L’expression des odeurs en français : Analyse lexicale et représentation cognitive”, *Intellectica*, vol. 24, no. 1, pp. 51–83, 1997.
4. C. Léger, “Smells supervision setting by AIR NORMAND, air pollution monitoring network Smells, straight perceptible nuisances”, *Pollut. Atmos.*, vol. 47, no. 187, pp. 373–384, 2005.
5. I. H. Suffet and P. Rosenfeld, “The anatomy of odour wheels for odours of drinking water , wastewater , compost and the urban environment”, *Water Sci. Technol.*, vol. 55, no. 5, pp. 335–344, 2007.

6. S. Harispe, S. Ranwez, S. Janaqi, and J. Montmain, "Semantic Similarity from Natural Language and Ontology Analysis", *Synth. Lect. Hum. Lang. Technol.*, vol. 8, no. 1, pp. 1–254, 2015.
7. S. Harispe, D. Sánchez, S. Ranwez, S. Janaqi, and J. Montmain, "A framework for unifying ontology-based semantic similarity measures: A study in the biomedical domain", *J. Biomed. Inform.*, vol.48, pp. 38–53, 2014.
8. N. Fiorini, "Semantic similarities at the core of generic indexing and clustering approaches", PhD thesis of the Université de Montpellier, 2015.
9. N. Fiorini, S. Ranwez, S. Harispe, V. Ranwez, and J. Montmain, "USI at BioASQ 2015 : a semantic similarity-based approach for semantic indexing", *Work. Notes Conf. Labs Eval. Forum (CLEF), Toulouse, Fr.*, 2015.
10. Z. Harris, "Distributional structure", *Word*, vol.10 (23): 146–162, 1954.
11. M. Piana, L. Oddo, A. Bentabol, E. Bruneau, S. Bogdanov *et al.*, "Sensory analysis applied to honey: state of the art", *Apidologie, Springer Verlag*, 35 (Suppl. 1), pp.S26-S37. <10.1051/apido:2004048>. <hal-00891892>, 2004.
12. M. Horridge, H. Knublauch, A. Rector, R. Stevens, and C. Wroe, C., "A Practical Guide To Building OWL Ontologies Using The Protégé-OWL Plugin and CO-ODE Tools Edition 1.0", *University of Manchester*, 2004.
13. B. Standard, "Air quality–Determination of odour concentration by dynamic olfactometry", *BS EN*, 13725, 2003.