The Language of Smell: Connecting Linguistic and Psychophysical Properties of Odor Descriptors

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Abstract

The olfactory sense is a particularly challenging domain for cognitive science investigations of perception, memory, and language. Although many studies show that odors often are difficult to describe verbally, little is known about the associations between olfactory percepts and the words that describe them. Quantitative models of how odor experiences are described in natural language are therefore needed to understand how odors are perceived and communicated. In this study, we develop a computational method to characterize the olfaction-related semantic content of words in a large text corpus of internet sites in English. We introduce two new metrics: olfactory association index (OAI, how strongly a word is associated with olfaction) and olfactory specificity index (OSI, how specific a word is in its description of odors). We validate the OAI and OSI metrics using psychophysical datasets by showing that terms with high OAI have high ratings of perceived olfactory association and are used to describe highly familiar odors. In contrast, terms with high OSI have high inter-individual consistency in how they are applied to odors. Finally, we analyze Dravnieks's (1985) dataset of odor ratings in terms of OAI and OSI. This analysis reveals that terms that are used broadly (applied often but with moderate ratings) tend to be olfaction-unrelated and abstract (e.g., "heavy" or "light"; low OAI and low OSI) while descriptors that are used selectively (applied seldom but with high ratings) tend to be olfaction-related (e.g., "vanilla" or "licorice"; high OAI). Thus, OAI and OSI provide behaviorally meaningful information about olfactory language. These statistical tools are useful for future studies of olfactory perception and cognition, and might help integrate research on odor perception, neuroimaging, and corpus-based linguistic models of semantic organization.

Keywords: odour naming, odour identification, sensory lexicon, sensory-semantic integration, distributional semantics, computational linguistics

1. Introduction

Among the domains of human experience, olfaction is regarded as evocative but elusive. Olfactory perception and cognition were long considered intangible for scientific analysis, and already Plato stated that "the varieties of smell have no name" and are therefore unfit for abstract reasoning (Plato, transl. 1925, section 67a). The weak association between olfactory perception and language has in the past decades been observed in both linguistic and psychophysical settings. Language scholars have noted that odors often lack consistent and specific terminologies in Indo-European languages (Buck, 1949) and modern cross-cultural research suggests that olfaction plays a subordinate role in most languages (San Roque et al., 2015). Meanwhile, experimental psychological studies have shown that it is surprisingly difficult to name common household odors without visual or verbal cues (e.g., Cain, 1979; de Wijk & Cain, 1994; Desor & Beauchamp, 1974; Engen & Pfaffman, 1960). Whether this limited integration of odor and language is a consequence of human cortical organization (Olofsson & Gottfried, 2015b, 2015a; Olofsson et al., 2014; Olofsson, Rogalski, Harrison, Mesulam, & Gottfried, 2013) or due to a lack of an adequate olfactory vocabulary in western languages (Majid, 2015; Majid & Burenhult, 2014) is debated. Little is still known about how language terms are used to evaluate odors.

The observed limitations in olfactory language have prompted numerous attempts to structure standardized odor vocabularies and develop "primary odor descriptors" for the purpose of classifying odors more consistently (for review, see Kaeppler & Mueller, 2013). However, such attempts have generally been unsuccessful in describing large and diverse sets of odors, and no consensus has therefore been reached regarding which classification system that is most efficient (Kaeppler & Mueller, 2013). Recent work on sensory lexicons for olfaction has aimed at organizing descriptors into perceptual classes with hierarchies of specificity (for review, see Lawless & Civille, 2013). This work, however, has lacked a general linguistic foundation in natural language usage, as it has only been applied to specific food products, and has typically required groups of expert panelists to assess the applicability and meaning of each descriptor. More work is needed to develop a general understanding of how everyday odor experiences are described in natural language.

In a related line of research, considerable effort has been put into computational analyses of descriptor-to-odor ratings (e.g., Dravnieks, 1985), primarily with the aim to probe the distribution of odors and descriptors in perceptual space, to detect clusters, and to estimate the minimal number of dimensions necessary to fully characterize an olfactory percept or descriptor (Castro, Ramanathan, & Chennubhotla, 2013; Khan et al., 2007; Koulakov, Kolterman, Enikolopov, & Rinberg, 2011; Kumar, Kaur, Auffarth, & Bhondekar, 2015; Madany Mamlouk, Chee-Ruiter, Hofmann, & Bower, 2003; Wnuk & Majid, 2014; Zarzo & Stanton, 2006; for review, see Berglund & Höglund, 2012). Physicochemical odorant properties have also been included in such analyses in efforts to predict perceptual qualities from molecular structure (Keller et al., 2017; Khan et al., 2007; Kumar et al., 2015; Snitz et al., 2013). However, the role of the odor vocabulary and its semantic organization has been neglected.

In order to ultimately understand how associations between odor percepts and semantic concepts are learned, it is necessary to develop robust quantitative approaches that capture how olfactory perceptual qualities are described in natural language, without the artificial constraints imposed by experimental rating paradigms. In fact, the impact of language usage on the efficacy of learning to name sensory percepts has been demonstrated for colors (Ramscar, Yarlett, Dye, Denny, & Thorpe, 2010), but has been poorly studied in the case of odors.

The current literature on computational linguistics, which provides numerous techniques for using text corpora to quantify the affective valence, sentiments, personality traits, and other information embedded in written text (see, e.g., Kern et al., 2016; Ravi & Ravi, 2015), can be used to quantify sensory information in natural language. For example, Mitchell et al. (2008), used a text corpus to estimate how strongly related a set of sample words were to sensory modalities by analyzing their co-occurrence with keywords such as “smell”, “hear”, and “see”. These data were used to predict the fMRI patterns of neural activity elicited by the words. Similarly, Louwerse and Connell (2011) combined co-occurrence statistics of adjectives with dimensionality reduction techniques to predict how strongly words are perceived to be associated with visual, haptic, auditory, gustatory, and olfactory perception. These results were compared to experimental ratings of the perceived strength of association between the same adjectives and the five sensory modalities (Lynott & Connell, 2009). The modality ratings by Lynott and Connell (2009) were also employed recently by Winter (2016), who combined them with corpus data to show that words related to chemosensation generally are more emotionally loaded than words linked to other sensory modalities.

In the present study, we use computational linguistic techniques to quantify the olfactory semantic content of words. We combine statistical tools from the linguistic fields of domain ontology learning, distributional semantic models and word sense disambiguation—traditionally used to determine the topical relatedness and hierarchical relationships of words—to outline, in part, the domain ontology of odor descriptors. We then combine this analysis with olfactory psychophysical data to demonstrate how perceptual and linguistic properties of odor-describing language can be interconnected. We first use a large text corpus to characterize odor descriptors in terms of their association to olfaction and specificity of use in olfactory contexts. To quantify these properties, we introduce a metric for olfactory association, meaning how strongly a descriptor is related to olfactory experiences relative other linguistic contexts, and a metric for olfactory specificity, meaning how many odor contexts a descriptor is applied to and, as such, how specific it is in describing odors. We then relate these metrics to psychophysical quantities. Our method provides a novel integration of linguistic theory with psychophysics and gives new insights into how language maps onto the elusive experiential domain of olfaction.

2. Methods and materials

2.1 Corpus

We employed the University of Maryland Baltimore County WebBase corpus of English texts (Han, Kashyap, Finin, & Weese, 2013), which contains approximately three billion words acquired from 100 million web pages from more than 50,000 websites. This corpus was selected on account of its relatively large size and its cleaned data in which duplications, non-English texts, unwanted characters and HTML-text have been removed. We switched all uppercase letters into lowercase letters, removed all punctuation marks except for full stops, and turned all hyphenated compound words into open compound words by replacing all hyphens occurring within words with a single space.

2.2 Odor descriptors

Descriptors were adapted from four studies: Dravnieks (1985); Lynott and Connell (2009); Moss, Miles, Elsley, and Johnson (2016); and Snitz et al. (2016). The descriptors used by Snitz et al. (2016) were the same as those used by Dravnieks (1985). We used alternative spellings (e.g., “licorice” and “liquorice”) as well as alterative names (e.g., “cotton candy” and “candy floss”) for each descriptor.

Descriptors that contained multiple words separated by a comma (e.g., “fruity, citrus”), a slash mark, or by parentheses, thereby implying multiple alternatives, were split into separate descriptors (“fruity” and “citrus”). After splitting these alternatives, the same psychophysical odor ratings were attributed to each separate descriptor.

Non-descriptive words, such as conjunctions, were removed together with modifying words that were deemed redundant (e.g., “juice” in “grape juice”, “Cuban” in “Cuban cigar smoke” and “modern day” in “hospital modern day”). The descriptors “fruity, other than citrus”, “practical man”, “hot stuff male”, and “crushed grass” were excluded, the first three deemed too abstract and the last redundant, as the descriptor “grass” was already included. In the descriptor set taken from Moss et al. (2016), descriptors composed of mixtures of multiple words (the label containing an ampersand symbol) were excluded, as we did not take odor mixtures into consideration.

We excluded descriptors that were identical to the olfactory keywords used to distinguish between olfaction-related and olfaction-unrelated contexts (see section 2.4 for details). Thus, we removed the descriptors “aromatic” and “fragrant” from Dravnieks’s (1985) list of descriptors, and “aromatic”, “fragrant”, and “scented” from Lynott and Connell’s (2009) descriptor list. The final set of descriptors (available in Supplementary Material) contained a total of 174 descriptors from Dravnieks (1985), 420 descriptors from Lynott and Connell (2009) and 193 descriptors from Moss et al. (2016).

2.3 Preprocessing of search words

Most human languages inflect words to fit their role in an utterance. The different inflectional forms can indicate number (singular or plural), gradation (comparative, superlative), tense (past, present, and others), and other dimensions and categories. English is unusual in that the number of forms is relatively small compared to other languages. The different forms of a word are collectively called a lexeme, represented by a lemma, the base form of the word. Since much of the inflectional variation had no relevance for our purposes here, we counted all occurrences of a lexeme together (commonly referred to as lemma frequency), and did not distinguish between the different inflectional forms. In other words, we took all inflectional forms of odor descriptors into account when searching through the corpus. The adjectives used in the study by Lynott and Connell (2009) were exempted from preprocessing and were searched for only in the inflectional form provided in the original study, in order to be able to compare the results to other computational studies of associations between these words and sensory modalities (Louwerse & Connell, 2011).

2.4 Disambiguating olfaction-related from olfaction-unrelated descriptor usage

Each odor descriptor was extracted from the corpus together with the four preceding and four succeeding words within the same sentence. The snippet of words surrounding a descriptor was defined as the *context*. A context was determined to be olfaction-related if it contained an olfaction-associated keyword, for example “smell”, “scent”, “odor”, or “aroma” (see Supplementary Material for complete word list). All inflectional forms of such a keyword were considered when searching through a context. We defined the olfactory keywords a priori as a set of words that exclusively relate to odor or flavor perceptions in general, but not to any specific odor or flavor, and thereby can serve as indicators that allow for the separation of olfaction-related and olfaction-unrelated contexts. Our method can thus be viewed as a simple implementation of the decision list technique for word sense disambiguation introduced by Yarowsky (1995). A similar method was used by Mitchell et al. (2008) to estimate the relevance of words to different sensory modalities.

The choice of a context window size of $4+4$ words was motivated by previous studies on semantic relations in distributional language statistics (Karlgren & Sahlgren, 2001; Sahlgren, 2006), which demonstrate that word-space models employing relatively narrow windows ($2+2$ or $3+3$ words) around a focus word provide optimal results on tests of semantic similarity, synonymy measures, and syntactic role identification. Similarly, narrow windows (containing <16 words in total) also perform optimally in tests on word frequency-based estimates of semantic similarity (Terra & Clarke, 2003). A wider context window (tens or hundreds of words) would have provided a greater recall of olfaction-related contexts, but at the cost of increasing noise and reducing precision, as immediate or close adjacency in the linguistic string is the strongest indicator of relative relevance for terms in language (Karlgren & Sahlgren, 2001).

2.5 Descriptor usage across odors

In section 3.5 of the Results, we investigated how OAI and OSI reflect odor descriptor usage across a large set of odors, by placing the descriptors in OAI-OSI space and combining this mapping with statistics on odor ratings for each descriptor. The results in section 3.5 were produced using the catalog of odor-to-descriptor ratings published by Dravnieks (1985), a commonly used psychophysical dataset on odor descriptor scaling that includes a large and diverse set of English language descriptors rated for a large set of odors. The ratings in the original dataset are termed percentages of applicability (PA) and range from 0 to 100, where 0 indicates that the descriptor is completely inapplicable to an odor, while a rating of 100 indicates that the descriptor perfectly matches an odor.

In this study, only the 144 monomolecular odors in Dravnieks’s dataset were considered, and ratings of value zero were excluded from calculations. Thus, after the preprocessing of the list of descriptors (see section 2.2), the dataset comprised a total of 144 odors rated according to 174 descriptors. We calculated the *mean rating, median rating, maximum rating,* and *standard deviation of ratings* for each descriptor using its ratings across odors. In addition, we calculated the *kurtosis of the ratings* and the *geometric mean of the kurtosis and the maximum rating* for each descriptor. The kurtosis was calculated according to Pearson's definition, that is,

$$\mathrm{Kurt}\left[X\right] = \mathrm{E}\left[\left(\frac{X-\mu}{\sigma}\right)^4\right] = \frac{\mu_4}{\sigma^4} \tag{1}$$

where E is the expectation operator, X is a random variable (the rating in this case), μ is the mean, μ_4 is the fourth central moment, and σ is the standard deviation.

2.6 Data analysis

Correlation coefficients were calculated with Pearson's *r*, with the exception of section 3.2, where the distribution of data was heavily skewed and Spearman's rank correlation coefficient *ρ* was used instead. Whenever the correlation between OAI or OSI and a psychophysical rating variable was tested, we also tested the correlation between the same psychophysical rating and the total log frequency of the descriptors. Since the log frequency of words is a common and simple linguistic statistic, this test was conducted in order to ensure that an observed association between a variable of interest and OAI or OSI would be specific, because correlations that give similar results for word frequency and OAI or OSI, would likely be trivial. Since our variables of interest (OAI, OSI and frequency) are not analytically independent, we used separate, simple correlations instead of a multiple regression model.

In section 3.3, where the correlation between linguistic metrics and several psychophysical quantities is tested (i.e., multiple comparisons are performed), the risk of false positives (type I errors) is controlled using false discovery rate correction (Benjamini & Hochberg, 1995).

It should be noted that OAI and OSI cannot be quantified for descriptors that never occur in olfaction-related contexts. Such descriptors were therefore excluded from all analyses involving OAI or OSI, but were included in our analyses involving total corpus frequencies. Thus, correlation sample sizes vary.

2.7 Supplementary material

Data files containing the odor descriptors, olfactory keywords, OAIs, OSIs, and log normalized frequencies are publicly available, along with Python code for reproducing the figures in this report, at the Open Science Framework (osf.io/sn4tp).

3. Results

3.1 Definition of olfactory association and specificity

Two essential tasks in the process of delineating a linguistic domain ontology are to determine which terms belong to the domain of interest and to order these terms in a taxonomy ranging from highest generality at the top (terms with broad definitions) to highest specificity at the bottom (terms with narrow definitions). Following this approach, we first set out to quantify how strongly related a given word is to the domain of olfaction, and thereafter to quantify how specific the word is within this domain. To this end, we used the University of Maryland Baltimore County WebBase corpus (Han, Kashyap, Finin, & Weese, 2013), comprising circa three billion words, to analyze the frequency of odor descriptors in olfaction-related and olfaction-unrelated written contexts. A context, which was defined as the window of ± 4 words immediately surrounding a given descriptor, was classified as olfaction-related if it contained an olfaction-associated keyword (e.g., “smell”, “odor”, “aroma”, or “scent”). If the context did not contain any of the olfactory keywords, it was deemed unrelated to olfaction (for details, see Methods and Materials). Similar techniques have previously been applied for word sense disambiguation (Yarowsky, 1995) and to estimate the strength of association between words and different sensory modalities (Mitchell et al., 2008). Based on the frequency of descriptors in olfaction-related and olfaction-unrelated contexts, we introduced two metrics to characterize the association to and specificity within the domain of odor descriptors.

First, we defined the *olfactory association index* (OAI), a measure of the degree to which the semantic content of a descriptor is considered to relate to olfactory perception. We defined OAI as the $\log_2$ probability that the context in which a descriptor *d* occurs is olfaction-related as opposed to olfaction-unrelated, as follows:

$$\mathrm{OAI}(d) = \log_2 \frac{f_{olf}(d)}{f_{tot}(d)} \qquad (2)$$

where $f_{tot}(d)$ is the total frequency of *d* and $f_{olf}(d)$ is the frequency of *d* in olfaction-related contexts. Similar metrics have been proposed to estimate how relevant words are in different text contexts (Magnini, Strapparava, Pezzulo, & Gliozzo, 2001; Park, Patwardhan, Visweswariah, & Gates, 2008). The definition of OAI is, with the exception of an added constant which is identical for all descriptors, mathematically equivalent to the pointwise mutual information between *d* and the olfaction-associated keywords (see Appendix for derivation). The pointwise mutual information of words was first introduced as a metric of semantic similarity by Church and Hanks (1990), and has been shown to perform well on frequency-based synonymy tests (Terra & Clarke, 2003). According to equation (2), a low OAI value indicates that a descriptor seldom is used in olfaction-related contexts relative to other contexts and, according to our hypothesis, that it is semantically less associated to odor perception and, hence, less meaningful in the description of odors. Inversely, a higher OAI value indicates that a descriptor is perceived to be semantically more related to olfactory experience. The maximum possible OAI-value (zero) indicates that a descriptor is exclusively used in contexts pertaining to olfaction.

Second, we defined the *olfactory specificity index* (OSI) as the negative log probability of an olfaction-related context containing descriptor *d*, that is,

$$\mathrm{OSI}(d) = -\log_2 P_{olf}(d) \tag{3}$$

The probability $P_{olf}(d)$ is estimated as

$$P_{olf}(d) = \frac{f_{olf}(d)}{\sum_{\forall d \in D} f_{olf}(d)} \tag{4}$$

where *D* is the set of all descriptors of interest. The OSI is an information-theoretic estimate of the amount of information contained in a descriptor about contexts pertaining to olfaction. In line with previous uses of such metrics to quantify concreteness versus abstractness (Ryu & Choi, 2004), we hypothesized that a high OSI (i.e., high information content and sparse usage in olfaction-related contexts) implies that a descriptor is more specific and used to describe a small number of concrete odor percepts (e.g., a specific odor source). Conversely, a low OSI would indicate that a descriptor is more common in olfaction contexts and, therefore, used to describe many different odors. Hence, it would be less specific.

3.2 OAI strongly correlates with the rated olfactory association of descriptors

We first tested the prediction that the OAI reflects the degree to which a descriptor is perceived to be olfaction-related. To this end, we used the data reported by Lynott and Connell (2009), where a large number of adjectives were rated on their level of association to visual, auditory, haptic, olfactory, and gustatory sensation. We calculated the OAI of each word (see Methods and Materials for details) and tested its correlation with the mean rated strength of association between the word and each of the sensory modalities. As a follow-up analysis, we also tested the correlation of the log frequency of the words (in all contexts) with their modality ratings. This test indicates how well the commonness of a word alone (quantified by the log frequency) can predict associations to sensory modalities. It thereby serves as a reference to which the performance of OAI can be compared. The results are presented in Table 1. In order to avoid the risk of inflated correlations due to the heavily skewed distribution of ratings (approximately 62% of all data points in Figure 1 have an olfactory association rating of <1), we calculated correlations with Spearman's rank correlation ρ, which is non-parametric and therefore does not require normally distributed data.

We found the OAI to be strongly correlated with ratings of olfactory association ($\rho = .693$, $p = 4.2 \times 10^{-57}$, $n = 390$, Fig. 1). By comparison, Louwerse and Connell (2011) used a single algorithm to model the association of Lynott and Connell's words to all five sensory modalities. This method achieved a correlation of .458 between predicted and rated olfactory association.

The OAI also correlated strongly with ratings of gustatory association ($\rho = .676$, $p = 2.0 \times 10^{-53}$, $n = 390$). This result was expected given that the olfactory and gustatory ratings are strongly correlated in the original data (Lynott & Connell, 2009), presumably because these two sensory modalities often are conflated, especially for food products (see, e.g., Auvray & Spence, 2008). The correlations between OAI and ratings of visual, haptic, and auditory association were negative and of weak to moderate strength. Again, this was expected given the negative correlations between olfactory/gustatory ratings and visual/haptic/auditory ratings (Lynott & Connell, 2009).

The total log frequency, on the other hand, exhibited weak, negative correlations with olfactory and gustatory ratings ($\rho = -.182$, $p = 1.8 \times 10^{-4}$, $n = 420$ and $\rho = -.120$, $p = .013$, $n = 420$, respectively). Instead, total frequency appeared to be more strongly linked to the visual-haptic association of words, as these correlations were positive and of moderate strength. Visual and haptic ratings, just like olfactory and gustatory ratings, have been shown to be strongly linked to each other (Lynott & Connell, 2009).

Based on these results, we concluded that the OAI is a valid predictor of how strongly a word is perceived to be associated to the sense of olfaction.

Table 1

The relation between OAI of adjectives and their rated association to sensory modalities according to Lynott and Connell (2009).

Sensory modality	**OAI**	**$\log_2$ frequency**
Olfactory	.693***	−.182***
Gustatory	.676***	−.120*
Visual	−.403***	.456***
Haptic	−.210***	.215***
Auditory	−.346***	.063

Note. Ratings for the all sensory modalities features were taken from Lynott and Connell (2009). Each value represents the Spearman correlation coefficient between the mean ratings of association to each sensory modality and the calculated value of linguistic metric: OAI ($n = 390$) or log frequency in all contexts ($n = 420$) (* $p < .05$, *** $p < .001$, no star indicates $p > .05$).

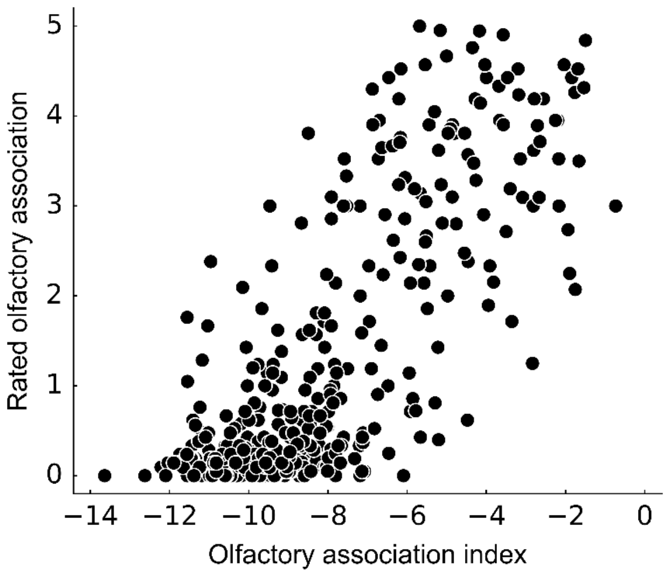

Fig. 1. The OAI of an odor descriptor strongly predicts its mean rated olfactory association in the sensory modality rating data published by Lynott and Connell (2009).

(*Single column*)

3.3 OAI correlates with perceived odor familiarity

As additional validation of our framework, we asked whether the OAI of odor labels can be used to predict evaluations of the perceptual properties of the odors themselves. We hypothesized that an odor whose name carries a stronger olfactory connotation most likely is more prevalent in the surrounding environment, in order for a strong association between the name and the percept to develop. Hence, we hypothesized that the label corresponding to a familiar odor (e.g., "lemon" or "vanilla") should have a high OAI, whereas an unfamiliar odor should be linked to a label with weaker olfactory connotations and, thus, a lower OAI.

To test this prediction, we used data published in a recent study by Moss et al. (2016), in which 200 odorants were evaluated according to 11 rating scales: familiarity, intensity, pleasantness, irritability, content availability, complexity, age of acquisition, frequency (i.e., odor commonness, not to be confused with linguistic frequency), describability, verbalizability, and hedonic strength (i.e., absolute deviation of valence from neutral). For each odorant listed by the authors, we used its provided labels as descriptors (e.g. "banana" for banana odor) and calculated their OAI and OSI (see Methods and Materials for more details). The OAI and OSI values were uncorrelated for these descriptors (Pearson's $r = -.131$, $p = .094$, $n = 165$). We calculated the Pearson correlations between the 11 perceptual features and the OAIs of the descriptors. In follow-up analyses, we also performed the same correlations with OSI, and total log frequency of the descriptors in all corpus contexts, hypothesizing that these correlations would be weaker and nonsignificant.

Since many of the 11 perceptual features correlate with each other (Moss et al., 2016) and, thus, contain some degree of overlapping information, testing their correlation with a single linguistic metric can be considered multiple tests of a single hypothesis. In such a setting, it is necessary to ensure a low risk of false positives (type I errors) (Rice, 1989). To this end, we applied false discovery rate correction (Benjamini & Hochberg, 1995). The results are provided in full detail in Table 2, with the plot in Figure 2 highlighting the relation between OAI and rated familiarity. Correlations in Table 2 that were deemed significant remained so even after applying Bonferroni correction, according to which a test was considered significant only if it satisfied $p \leq .05/11 = 4.5 \times 10^{-3}$, which is a more conservative condition.

We found that descriptor OAI had a moderate but highly significant positive correlation with six of the 11 odor quality evaluations: familiarity, pleasantness, content availability, frequency, describability, and verbalizability. The correlations with familiarity (

$r = .313$, $p = 4.4 \times 10^{-5}$, $n = 165$, Fig. 2) and frequency ($r = .311$, $p = 4.7 \times 10^{-5}$, $n = 165$) directly support our hypothesized link between descriptor OAI and odor commonness. As expected, descriptors of high familiarity tended to be words with stronger olfaction-association (high OAI), such as “liquorice” and “peppermint”, while those of low familiarity were relatively unassociated to olfaction (low OAI), such as “old house”, “mahogany”, and “shore” (Fig. 2). Given the correlation between the OAI, familiarity and frequency, it is no surprise that the OAI also correlated with pleasantness, content availability, describability, and verbalizability, since all these six perceptual features correlate positively with each other (Moss et al., 2016). In particular, the correlation between odor familiarity and odor naming success (here assumed to be represented by describability and verbalizability) has been reported previously in the psychological literature (Distel & Hudson, 2001).

Moreover, the OAI of a descriptor was found to have a significant negative correlation with the rated irritability and complexity of the corresponding odor, as well as with the estimated age of odor acquisition (see Table 2). Again, this is to be expected considering that these three odor characteristics are negatively correlated with odor familiarity (Moss et al., 2016); odors introduced early in life can be expected to be perceived as less irritable, less complex and more familiar compared to odors introduced later in life.

Furthermore, we found the OAI to be uncorrelated with intensity and hedonic strength. Both intensity and hedonic strength are measures of the absolute strength of the elicited olfactory percepts, without information regarding the valence (positive or negative) of the experience. These properties appear to have no significant links to OAI.

Importantly, neither the OSI nor the total log frequency was found to correlate significantly with any of the perceptual odor features.

These results strongly suggest that the OAI provides a meaningful characterization of the perceived olfactory connotation of words, and that this connotation is linked to perceptual qualities of the corresponding odors.

Table 2

Relating the OAI and OSI of descriptors with the perceptual features of their corresponding odors.

Perceptual feature	**OAI**	**OSI**	**$\log_2$ frequency**
Familiarity	.313***	−.113	−.068
Intensity	−.107	.049	−.008
Pleasantness	.304***	−.040	−.100
Irritability	−.293***	.048	.098
Content availability	.286***	−.123	−.040
Hedonic strength	−.084	.072	−.020
Complexity	−.268**	.144	.001
Age of acquisition	−.267**	.137	.036
Frequency	.311***	−.137	−.032
Describability	.309***	−.127	−.042
Verbalizability	.246**	−.127	−.026

Note. Ratings for the all perceptual features were taken from Moss et al. (2016). Each value represents the Pearson correlation coefficient between a perceptual odor feature and a linguistic metric for the corresponding odor name: OAI ($n = 165$), OSI ($n = 165$), or total log frequency ($n = 188$). Two and three stars indicate significance under the conditions of false discovery rates of at most .01 and .001, respectively. No star indicates $p > .05$.

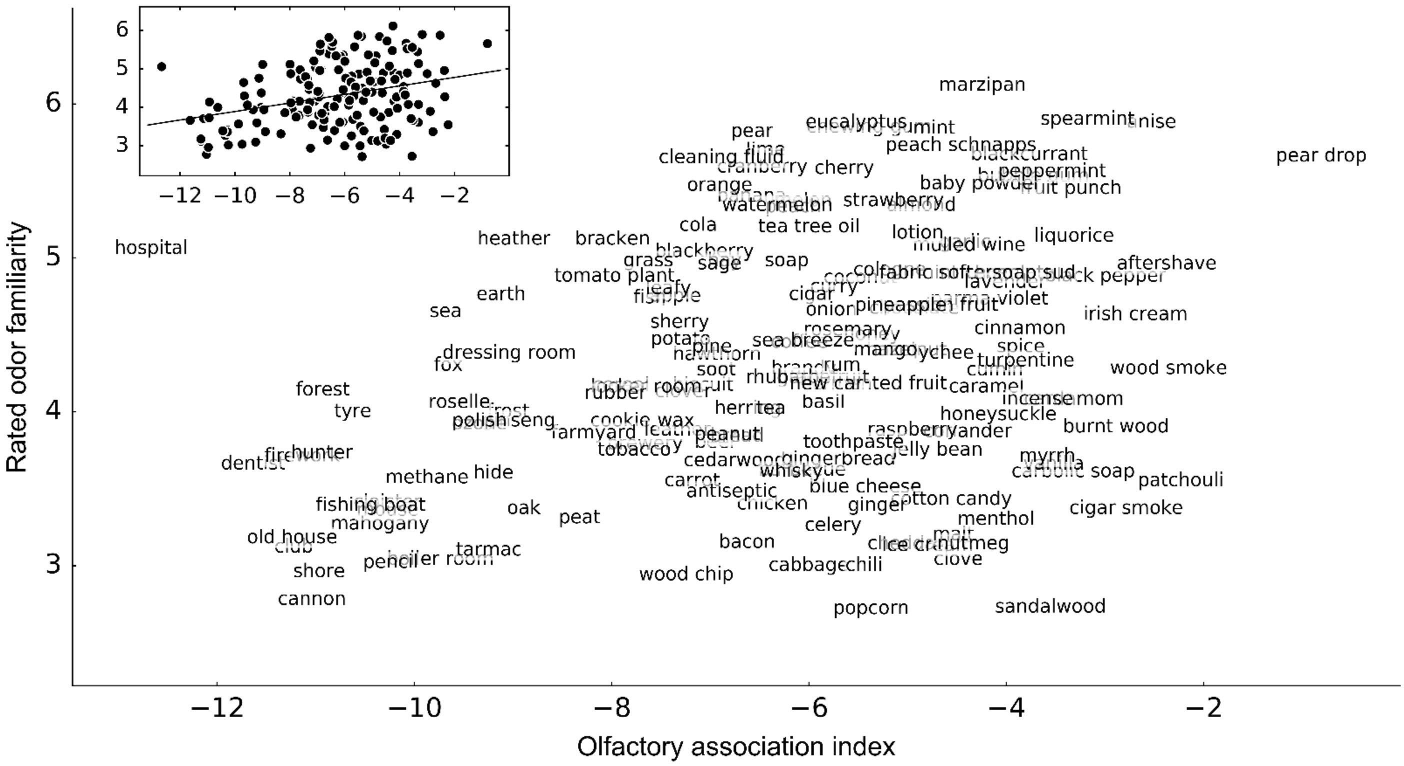

Fig. 2. The relation between the perceived familiarity of odors and the OAI of the corresponding odor descriptor. Descriptors with a strong association to olfaction (i.e., high OAI, e.g., “strawberry”, “spearmint”, “liquorice”, “aftershave”) tend to be linked to familiar odors, while descriptors weakly linked to olfaction and which may be difficult to interpret as descriptions of odors (i.e., low OAI, e.g., “old house”, “shore”, “mahogany”, “tarmac”) belong to odors not perceived as familiar. Familiarity ratings were taken from Moss et al. (2016). Inset: The same plot as in the larger figure, where each dot represents a descriptor. There is a significant positive correlation between the rated odor familiarity and OAI (see Table 2).

(*Double column*)

3.4 Descriptors with low OSI are applied inconsistently across individuals

Most odor names refer to specific sources, but attempts to identify "primary odors", that is, broad odor categories, have not been successful (Kaeppler & Mueller, 2013). We reasoned that general descriptors (e.g., "fruity" or "pungent") are associated with a wider range of possible olfactory percepts and, consequently, allow for a more varied usage across different individuals, compared to descriptors applied exclusively to a few smells (e.g., "banana"). We therefore hypothesized that high OSI would be associated with high inter-individual consistency with which a descriptor is matched to a given odor.

To test this prediction, we used the descriptor-to-odor rating data published by Snitz et al. (2016), where 23 subjects rated 10 odorants according to the descriptors used by Dravnieks (1985). We first calculated the coefficient of variance (standard deviation divided by the mean) of the ratings across subjects for each descriptor and each odor. This served as a quantification of the spread of ratings across subjects normalized by the average rating in the group. The rating inconsistency for each descriptor was then estimated by calculating the mean coefficient of variance of each descriptor across all odors. Correlations between linguistic metrics and rating inconsistency were calculated with Pearson's *r*.

In line with our predictions, we found that the OSI for the descriptors had a moderate but highly significant negative correlation with the inconsistency in descriptor ratings ($r = -.250$, $p = 9.9 \times 10^{-4}$, $n = 170$, Fig. 3). As shown in Figure 3, many descriptors located at the higher end of the OSI scale (high consistency) are compound words, meaning general descriptors preceded by modifiers that specify the descriptor, for example "stale tobacco smoke", "smoked fish", "burnt milk", and "cooked vegetable". This is in agreement with the notion of descriptor specificity, since a modifier serves to narrow the scope of the succeeding noun and thereby makes the compound word more specific (compare previous examples with "smoke", "fish", "milk", and "vegetable").

In follow-up analyses, we replaced the OSI with total log frequency (across all corpus contexts), as well as OAI, hypothesizing that there would be weak and nonsignificant correlations in these cases. Indeed, rating inconsistency had no significant correlation with neither the total log frequency ($r = .138$, $p = .069$, $n = 174$) nor with the OAI ($r = .129$, $p = .093$, $n = 170$) of the descriptors. Moreover, the OAI and OSI values for the descriptors were uncorrelated ($r = .100$, $p = .194$, $n = 170$). Accordingly, we concluded that the OSI is a useful predictor of how consistently individuals judge a label to apply to a specific odor.

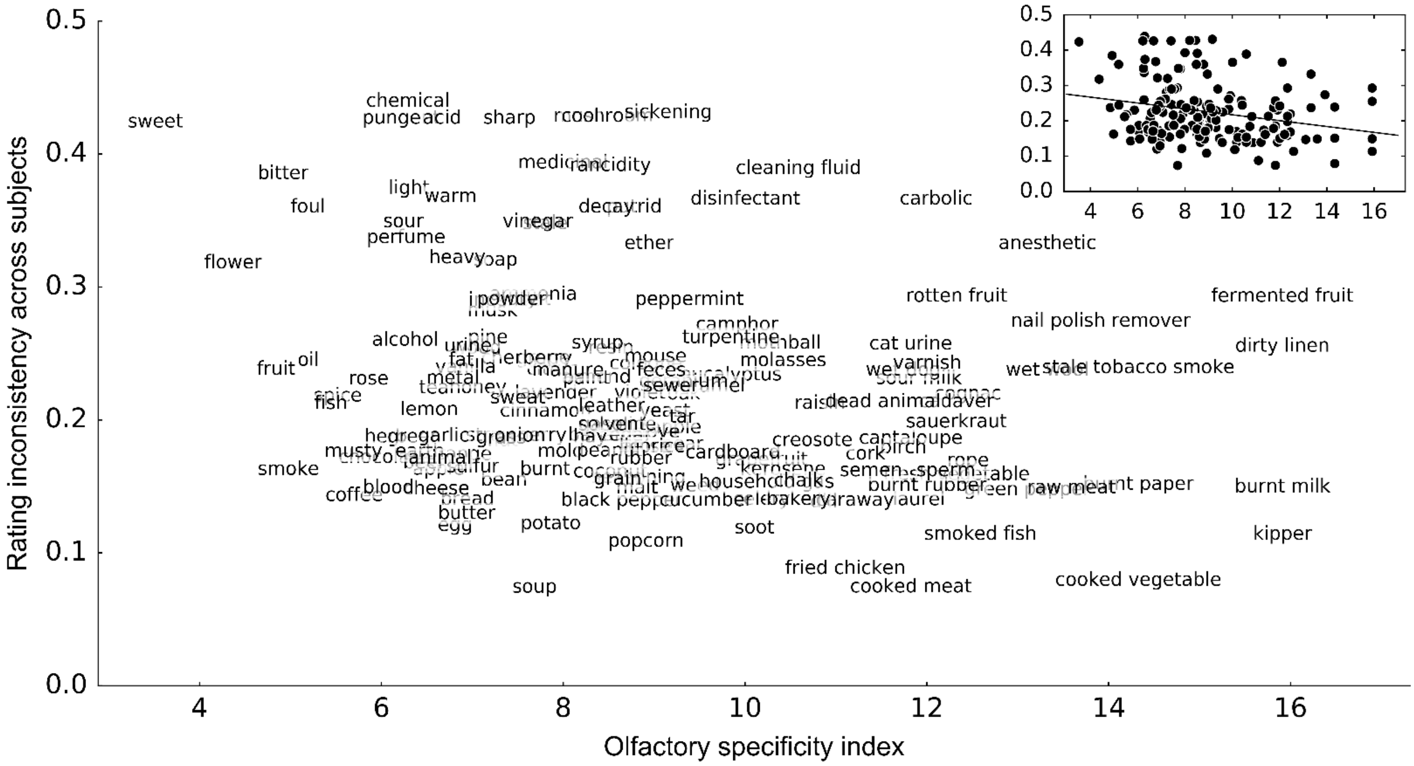

Fig. 3. The OSI of odor descriptors in relation to the inter-individual inconsistency with which they are rated to match odors. The inconsistency was estimated using rating data published by Snitz et al. (2016). Inset: There is a moderate but significant negative correlation between the variables. Thus, there is less agreement across individuals as to how well an abstract descriptor (low OSI, e.g. “foul”, “pungent”, “flower”, “warm”) matches a certain odor, compared to how well a concrete descriptor (high OSI, e.g. “kipper”, “smoked fish”, “laurel”) matches it.

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3.5 Exploratory analyses: Integrating odor ratings with OAI and OSI

Having validated the OAI and OSI dimensions, we conducted a set of exploratory analyses based on these metrics in combination with additional data on descriptor ratings across a large set of odors. By mapping a large psychophysical dataset onto our OAI-OSI space, we wanted to understand which types of odor descriptors that can be found in different regions of this space, and how they are employed across a large selection of odors. This might be useful for future olfactory research, as it may help researchers select informative perceptual attributes more efficiently when preparing psychophysical rating experiments.

We utilized the rating data for descriptor-to-odor applicability published by Dravnieks (1985). We first calculated the OAI and OSI of each descriptor adapted from this dataset and placed it in a 2D Cartesian space with OAI and OSI as axes (Fig. 4). Based on the coordinates in OAI-OSI space, we find it helpful to conceptualize descriptors as falling into one of four quadrants: *high OAI-high OSI*, highly odor-associated and perceptually concrete descriptors (often source-based) such as “wet wool”, “burnt rubber”, and “stale tobacco smoke”; *high OAI-low OSI*, highly odor-associated but perceptually broad words such as “foul”, “pungent”, and “sweet”; *low OAI-high OSI*, concrete words that are relatively unassociated to olfactory descriptions, such as “rope”, “raw meat”, and “birch”; *low OAI-low OSI*, perceptually broad words with little association to olfaction, such as “light”, “heavy”, and “warm”.

For each individual descriptor, we used all its non-zero ratings across all 144 monomolecular odors in the dataset and calculated the mean, median, and maximum rating, as well as the standard deviation across ratings. We then superimposed these rating statistics onto the location of the corresponding descriptors in OAI-OSI space (Fig. 5a, b, c, and d, respectively). These projections enable the linking of descriptors with similar psychophysical statistics to descriptors with similar linguistic statistics and semantic compositions. We found that descriptors with the highest mean and median ratings formed a cluster primarily of words that were abstract (low OSI) and had weak olfactory connotations (low OAI). Many of these words were instead often associated with vision or somatosensation (e.g., “light”, “heavy”, “warm”, “sharp”, and “green”, the exception being “woody”; see Fig. 5a, b).

On the other hand, descriptors with high standard deviations and high maximum ratings were descriptors that often had a relatively strong olfactory connotation (high OAI) and average to low specificity (e.g., “licorice”, “mint”, “sweet”, see Fig. 5c, d). In comparison, the low OAI-low OSI descriptors mentioned in the previous paragraph had comparatively lower maximum ratings as well as slightly lower standard deviations.

Given these initial results, we hypothesized that the cluster of abstract, non-olfactory words (low OAI-low OSI) salient in Figures 5a and 5b comprised descriptors used in the broadest sense to describe odors, meaning that they are consistently applied with moderate ratings to many odors but not strongly to any particular odor, thereby exhibiting a rating distribution that is centered at a high mean and high median, but has a low spread and reaches a relatively low maximum value. In contrast, the strongly olfaction-related descriptors highlighted in Figure 5c and 5d are applied in a selective way to describe odors. This means that they are perceived to be inapplicable for the majority of odors and are therefore given mostly low ratings, with the exception of a small number of odors, in which case the descriptors are perceived to be a strong match and are rated very high. These descriptors should therefore exhibit a sharp rating distribution with many low values and a small number of ratings scattered at higher values, thereby yielding low means and medians but high standard deviations and maximum values. In other words, selective descriptors should exhibit more long-tailed rating distributions (more ratings at values far from the mean) than broad descriptors. To test this hypothesis, we calculated the Pearson kurtosis of the rating distribution (see Methods and Materials) for each descriptor (Fig. 5e). Kurtosis is a metric used to characterize the shape of distributions and is higher for a distribution with infrequent but extreme values (long tails), and lower for a distribution with frequent values of moderate deviation from the mean (short tails). As predicted, the kurtosis was higher for descriptors with high OAI and average to low OSI (selective descriptors). To further visualize the concentration of selective descriptors, we plotted the geometric mean of the kurtosis and the maximum rating (Fig. 5f). Descriptors scoring high on this metric were those used both very selectively (high kurtosis) and with a high maximum rating (e.g., “vanilla”, “licorice”, “coconut”, “lemon”, “mint”, “cinnamon”, “clove”).

To further demonstrate the differences between broad and selective descriptors, we plotted the rating distributions of the descriptors with highest means and medians (i.e., the broadest descriptors: “light”, “heavy”, “woody”; see Fig. 6a) and descriptors with highest geometric mean of kurtosis and maximum rating (i.e., the most selective descriptors: “vanilla”, “coconut”, “licorice”; see Fig. 6b). These results, representing the extremes regarding broad and selective descriptors, illustrate the ways in which these two types of descriptors are used. Broad descriptors exhibited a concentrated rating distribution centered at moderate levels, while selective descriptors primarily receive near-zero ratings except for a few cases where they match the odor strongly.

Finally, Figures 5a, b, c, and d show that descriptors of high OSI (the lower half of OAI-OSI space) are characterized by low mean, median, and maximum ratings, as well as low standard deviations across ratings. These statistics indicate rating distributions that are essentially tightly concentrated at very low values. This suggests, in turn, that odor descriptors with high specificity (i.e., sparse usage in everyday olfactory language) are not useful to describe odors, even if they have a high association to olfaction (e.g., “wet wool”, “burnt rubber”, “sour milk”). In other words, such descriptors could be removed from odor rating experiments with minor loss of psychophysical information, and be replaced with more practical descriptors.

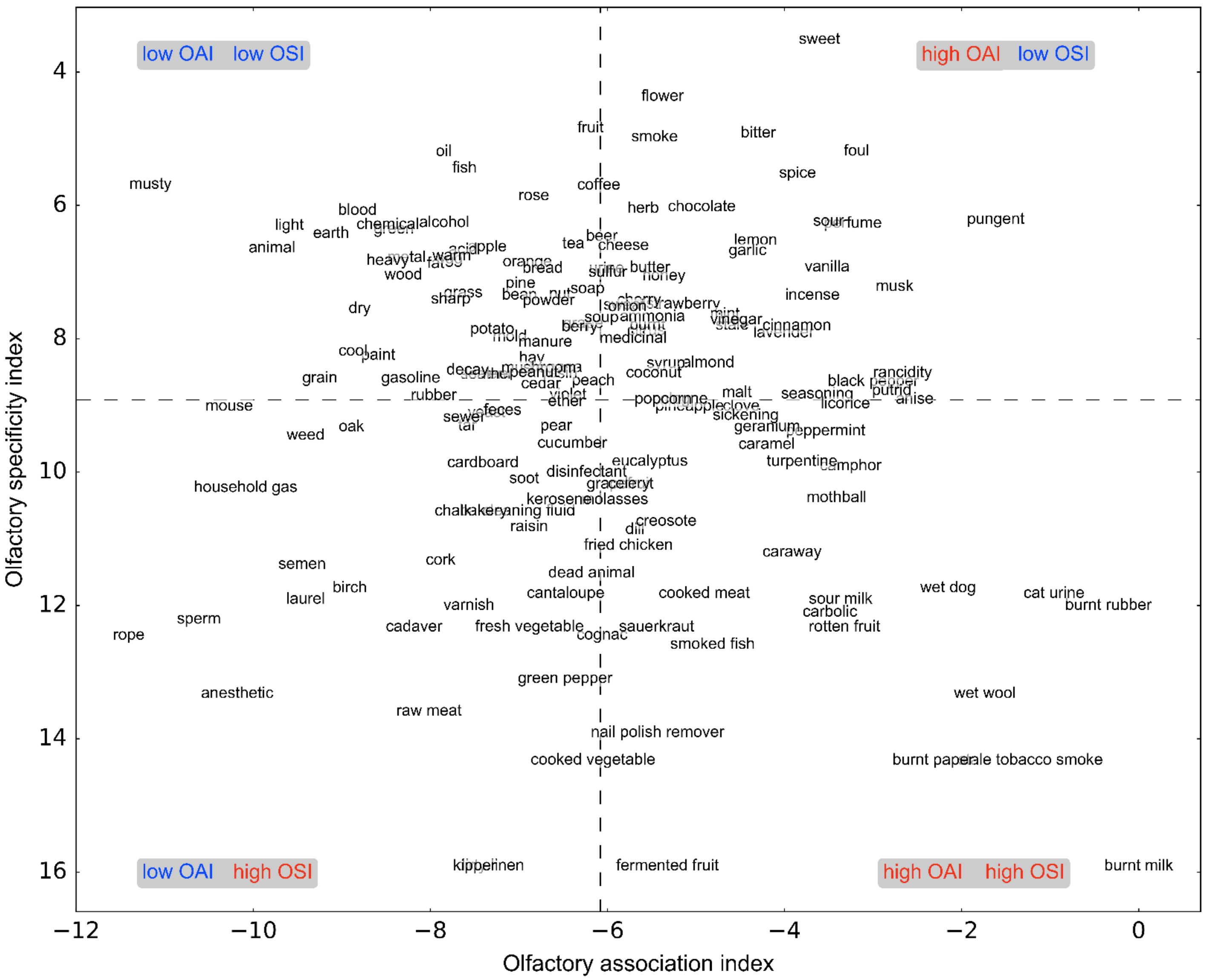

Fig. 4. Projection of Dravnieks's (1985) odor descriptors onto OAI-OSI space. Note that the OSI axis is inverted, so that descriptors with high OSI are located in the lower part of the plot. The dashed lines represent the mean values in each dimension, and we divide the descriptors based on the four quadrants of this space. These results from our exploratory analysis indicate that olfactory evaluation research should consider a combination of descriptors high in OAI and low to average OSI, while avoiding descriptors with very high OSI, as their applicability may be negligible. Note that descriptors were extracted from the corpus in all possible inflections, and thus words such as "musty" also include noun forms ("must"), which in this case likely affected its position in the OAI-OSI space.

(*Double column*)

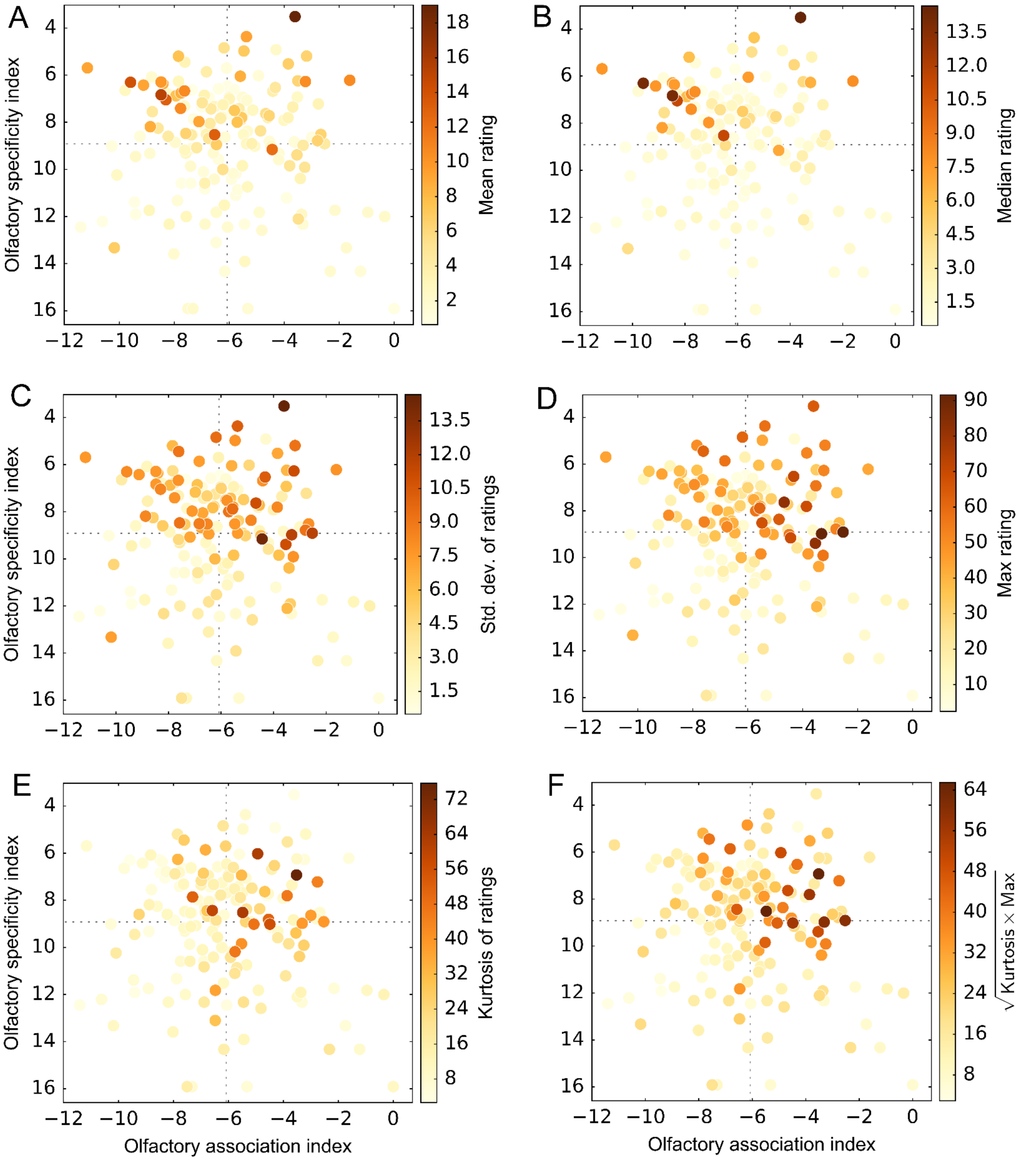

Fig. 5. Integration of psychophysical and linguistic statistics. Each dot corresponds to a descriptor and the color represents the value of the (A) mean rating, (B) median rating, (C) standard deviation of ratings, (D) maximum rating, (E) kurtosis of ratings, and (F) geometric mean of kurtosis and maximum rating. Vertical and horizontal

dashed lines represent the mean of all OAI and OSI values, respectively. Descriptors and ratings were adapted from the dataset published by Dravnieks (1985).

(*Double column*)

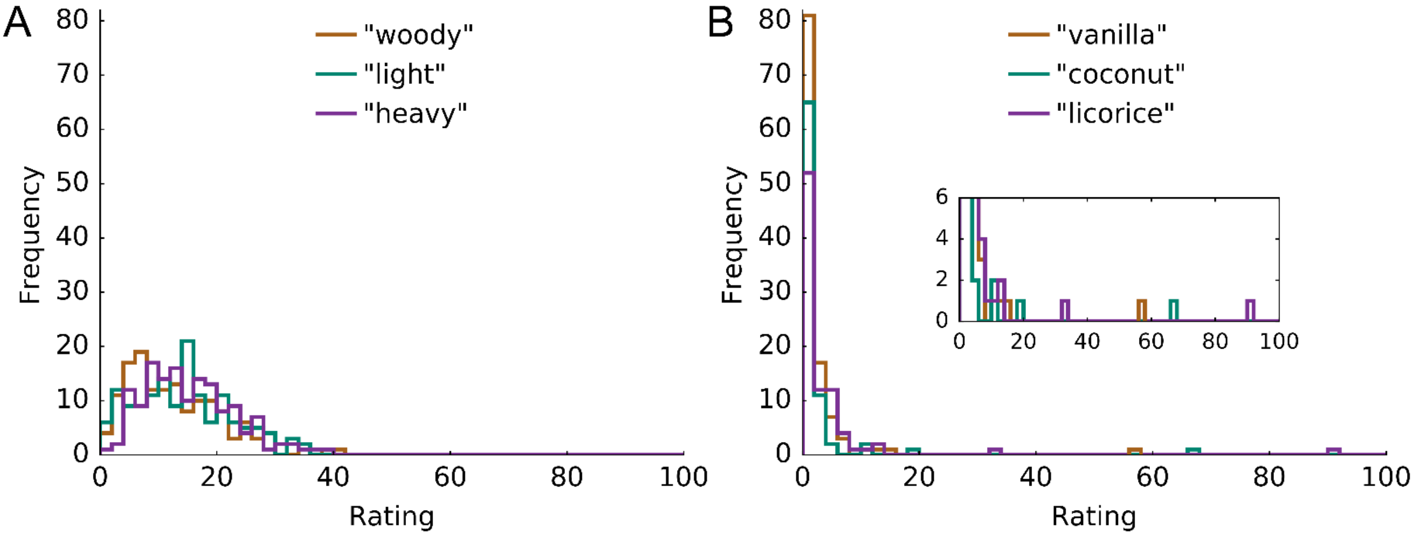

Fig. 6. Odor descriptors applied broadly and selectively to odors exhibit different types of rating distributions. (A) Rating distributions for the broadest descriptors, i.e., those with highest mean and median ratings, but relatively small standard deviation and maximum ratings. (B) Rating distributions for the most selective descriptors, i.e., those with highest geometric mean of rating kurtosis and maximum rating. Insert shows a magnified lower end of the frequency range, to highlight that the selective descriptors only occasionally generate high ratings.

(Double column)

4. Discussion

4.1 Summary

How people describe olfactory experiences in words has received little attention in cognitive research. Such research is needed because the properties of odor-describing language influences odor identification (Cain, 1979; de Wijk & Cain, 1994; Rouby et al., 2005), segmentation (Russell & Boakes, 2011), quality and hedonics (Djordjevic et al., 2008; Herz & von Clef, 2001; for review, see Stevenson, 2011), as well as odor-evoked brain activity (Bensafi et al., 2014). Moreover, the establishment of associations between odors and words affects olfactory recognition (Frank, Rybalsky, Brearton, & Mannea, 2011; see review by Larsson, 1997) and discrimination (Rabin, 1988). In sum, language fundamentally shapes olfactory processes. We used a large, web-based, English text corpus to analyze the frequency of descriptors in olfaction-related versus olfaction-unrelated contexts, and we constructed a two-dimensional odor-language space based on two statistical quantities: *olfactory association index* (*OAI*; a metric of how strongly associated a word is to olfactory contexts) and *olfactory specificity index* (*OSI*; capturing the number of odor contexts a descriptor may be used in). Using large psychophysical datasets, we found support for several predictions, indicating that the OAI-OSI space captures behaviorally relevant information about how odors are described. Descriptors with high OAI (e.g., “strawberry”, “spearmint”, “licorice”) are considered to be highly olfaction-associated words, and are used to describe odors of high familiarity and pleasantness. Descriptors with low OSI (e.g., “flower”, “pungent”, “warm”), on the other hand, were inconsistently applied to describe odors, suggesting that there is a lack of agreement on how more general odor descriptors apply to particular odors and that the OSI partly captures this variability.

We finally demonstrated how an analysis of olfactory association and specificity may provide further insights into how olfactory descriptors are used in odor evaluations. Here, we projected descriptors from Dravnieks (1985) onto OAI-OSI space together with psychophysical statistics based on Dravnieks’s odor rating data. This revealed that descriptors that are used most broadly across odors and thus receive highest mean ratings are not those that are highly olfaction-associated, but instead are olfaction-unrelated and abstract. In fact, they appear to often be words appropriated from other sensory modalities (e.g., “light”, “heavy”, “warm”). In contrast, descriptors that are applied selectively in odor ratings tend to be olfaction-associated and used at average rates in written odor contexts (e.g., “vanilla”, “coconut”, “licorice”). Interestingly, odor descriptors with high specificity (applicable only to a small set of specific odors, e.g. “wet wool”, “burnt rubber”, “sour milk”) tend to receive overall low ratings, and might in fact be useless for odor evaluation research, despite being highly associated with odor experiences.

Given that odor naming is more accurate for familiar odors (Distel & Hudson, 2001), it is not surprising to find that olfaction-associated descriptors, whose corresponding odors are more familiar, tend to be used more selectively than other descriptors. However, it is remarkable that the most broadly used descriptors in the odor rating data are abstract words that are not specific to olfaction. This behavior could possibly reflect an inability to mentally retrieve accurate odor descriptors, therefore replacing them with descriptors that are very abstract and olfaction-unrelated, in an attempt to vaguely describe the percept. However, it could also be the case that these descriptors are perceived as hypernyms (super-sets or umbrella terms) in the olfactory language. Hypernyms are, per definition, abstract or general in meaning, and can be expected to be applied often since they match a large number of odors (see, e.g., Kumar et al., 2015). In this sense, their weak links to olfaction could then simply be a reflection of the English language lacking labels dedicated to large classes of odor percepts, thereby impelling people to appropriate descriptors from other sensory modalities (Majid & Burenhult, 2014). Our novel finding that these most broadly used odor descriptors lack olfactory association and are inconsistently applied to odors is quantitative evidence of how everyday olfactory language is limited.

4.2 Theoretical foundation of OAI and OSI

The mathematical formulation of our metrics OAI and OSI is based on a linguistic theoretical framework called distributional semantics. Distributional semantic models fundamentally rely on a set of assumptions about the nature of language and meaning known as the "distributional hypothesis" (Sahlgren, 2008), which states that words occurring in the same contexts tend to have similar meaning (Harris, 1968). These models can be used to yield representations of semantic relations between words on varying levels of abstraction, ranging from simple co-occurrence counts via probabilistic language models and semantic spaces to inferred rule systems. As such, distributional semantic models are, from a psychological perspective, of great interest due to their potential to elucidate the perceptual content of sensory vocabularies, and can be employed to compute measures of term specificity, substitutability, combinability, and topical relatedness, depending on the processing of corpus statistics (for reviews, see e.g. Cohen & Widdows, 2009; Lenci, 2008). In the present study, co-occurrence data is used to measure topical association between target terms (the descriptors) and the notion of olfactory perception in general linguistic usage, the latter represented by terms such as "smell" and "odor". These models could be further refined, but as our study has demonstrated, even first order collocation statistics yielded noticeably meaningful results.

4.3 Future directions and applications

This study is an initial step in a wider effort to develop a large-scale ontology of odor descriptors based on their perceptual connotations and hierarchies, to tie these properties to psychophysical quantities and, by extension, to reveal the associative links between olfactory perception and lexical semantics. Naturally, such information would also be valuable for understanding the nature of olfactory perception, language, and memory.

There are primarily two avenues where a perceptual mapping of olfactory language would be directly valuable for cognitive research. First, metrics such as OAI and OSI could be used to understand how olfactory processing might depend on the semantic properties of odor labels and their accessibility. Our metrics offer a way to classify olfactory words in terms of their "olfactory-perceptual content", which is different from their purely semantic meaning. The OAI-OSI space can be flexibly used to characterize how the natural olfactory vocabulary differs according to developmental stage, neurological condition, sensory expertise, and cultural background. For example, previous studies report odor identification differences in young versus old people (Cain et al., 1995; de Wijk & Cain, 1994; Larsson & Bäckman, 1997; Lehrner, Glück, & Laska, 1999), patients with pre-diagnostic dementia versus healthy individuals (Stanciu et al., 2014), synesthetes versus non-synesthetes (Speed & Majid, 2017), professional tasters versus novices (Croijmans & Majid, 2016; Zucco, Carassai, Baroni, & Stevenson, 2011), and English-speakers versus speakers of languages with more odor-dedicated vocabularies (Majid & Burenhult, 2014). Such differences could be reflected in the ontologies of the respective odor languages. For example, odor descriptors in languages with highly odor-dedicated vocabularies can be expected to exhibit a narrow distribution of OAI-values with a high mean, indicating that descriptors are almost exclusively used for olfactory descriptions. Western languages, by comparison, should exhibit a broader OAI distribution shifted toward lower OAI values, indicating a wider range of olfactory association strengths in descriptors. It should be noted, however, that calculations of OAI and OSI in different languages may require that context windows are modified to be compatible with the grammatical and syntactic rules of each language. Regarding professional tasters and laymen, the former have been reported to use a more source-based flavor language, whereas laymen rely more on evaluative terms (Croijmans & Majid, 2016). Source-based terms (e.g., "lemon" or “strawberry”) would, most likely, be characterized by a high OAI, while evaluative terms, in many cases being general words without any particular relation to olfactory experiences (e.g., “pleasant” or “disgusting”), would have a lower OAI. One can also expect evaluative words to tend to have lower OSI, in line with their wider applicability and more frequent usage among laymen.

In a second avenue of cognitive research, our work is part of an effort to apply sophisticated methods for quantifying word relevance and specificity (see, e.g., Caraballo & Charniak, 1999; Lenci & Benotto, 2012) within the domain ontology of olfactory language and use these tools in combination with neuroimaging techniques to link cognitive odor-language processes to neural activity patterns. Previous studies have examined neural correlates of processing odor-related versus odor-unrelated words (González et al., 2006), abstract versus concrete words (Wang, Conder, Blitzer, & Shinkareva, 2010), and different types of odor labels (Bensafi et al., 2014). Since these studies used binary word categories, it would be relevant to examine how neural activity is altered as a function of a gradual shift along the OAI and OSI axes. It should further be noted that there is a difference between conventional word concreteness and concreteness in terms of olfactory perception. As an example, one would expect “sweet” and “fragrant” to be rated as less concrete than “lemony” and “peachy” in the odor vocabulary, as “sweet” and “fragrant” can be expected to be hypernyms that cover many different odor percepts and are located higher in the taxonomy of odor descriptors than “lemony” and “peachy”. However, in conventional concreteness rating data, ”sweet” and “fragrant” are instead rated as more concrete than “lemony” and “peachy” (Brysbaert, Warriner, & Kuperman, 2014). It would therefore be of great interest to investigate the distributed cortical networks linked to the processing of words with different olfactory concreteness.

It should be noted that linguistic investigations of olfaction could be compromised by the fact that taste/gustation and olfaction are sometimes conflated in everyday language, as both these sensory impressions are integrated in flavor perception during eating and drinking (Auvray & Spence, 2008). This is also underscored by the strong correlation between rated olfactory and gustatory association of words (Lynott & Connell, 2009). This confusion, however, is asymmetrical, as most food odors are described as tastes (as in “this candy tastes like cherry”) while taste words are only occasionally used to describe odors (as in “this perfume smells sweet”). Indeed, all flavor qualities beyond the five gustatory dimensions (sweet, salty, bitter, sour, and umami) require retronasal activation of the olfactory neural system in order to be successfully identified (Mozell, Smith, Smith, Sullivan, & Swender,

1969) and can therefore be regarded as olfactory components of the flavor stimulus. Written flavor descriptions are therefore pertinent to an analysis of the language of odor perceptions. While noise in the form of genuine taste descriptions could mistakenly be included in such an analysis, the four descriptors related exclusively to taste in this study (“sweet”, “salty”, “bitter”, “sour”) constitute 2-3% of a set of roughly 150-200 descriptors, and can therefore be expected to have a negligible influence on the results and conclusions regarding odor-describing language as a whole.

In conclusion, we introduced a two-dimensional space that characterizes perceptual olfactory connotations of English-language odor descriptors using text corpus statistics, and we validated these dimensions with data from psychophysical evaluations. This framework can be useful in both basic and applied olfactory science, by stimulating further research on quantitative associations between olfactory perception and language domains.

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Appendix

A1. Derivation of OAI from pointwise mutual information

The pointwise mutual information (denoted *I*) of two outcomes *x* and *y* is generally defined as

$$I\left(x, y\right) = \log_2 \frac{P(x, y)}{P(x)P(y)} \qquad \text{(A1)}$$

where $P(x)$ and $P(y)$ denote the individual probabilities of *x* and *y*, respectively, while $P(x, y)$ is the joint probability of *x* and *y* (Fano, 1961). In other words, the pointwise mutual information is the ratio of the observed probability of *x* and *y* occurring together (numerator) to the probability of *x* and *y* occurring together assuming the two outcomes are independent of each other (denominator). In the linguistic setting of this study, we are interested in the pointwise mutual information of a descriptor *d* and an olfaction-related keyword *w*, given their co-occurrence in word windows. We can therefore write this quantity as

$$I\left(d, w\right) = \log_2 \frac{P_{obs}(d, w)}{P_{indep}(d, w)} \qquad \text{(A2)}$$

where $P_{obs}(d, w)$ is the observed probability of *d* and *w* occurring together in a given word window while $P_{indep}(d, w)$ is the probability of the two co-occurring under the assumption of independence. We can write $P_{indep}(d, w)$ as

$$P_{indep}(d, w) = P(d)P(w)P\left(d^{\mathsf{C}} \cap w^{\mathsf{C}}\right)^{t-2} t(t-1) + \text{higher order terms} \qquad \text{(A3)}$$

where $P(d)$ and $P(w)$ denote the individual probabilities of finding *d* and *w*, respectively, at a given position in the corpus, $P(d^{\mathsf{C}} \cap w^{\mathsf{C}})$ is the probability of neither *d* nor *w* occurring at a position in the corpus ($^{\mathsf{C}}$ denotes complement), and $t \geq 2$ is the is the number of words included in the word window (window size). The first term in equation (A3) accounts for the probability of *d* and *w* occurring precisely once within the window. In this case, other words occur $t-2$ times and the factor $t(t-1)$ accounts for the permutations of *d* and *w* that are possible within the word window. The higher order terms, accounting for two or more occurrences of *d* and *w*, include the factors $P(d)$ and $P(w)$ more than once. However, note that

$$P(d) = \frac{f(d)}{N} \text{ and } P(w) = \frac{f(w)}{N} \qquad \text{(A4, A5)}$$

where $f(d)$ and $f(w)$ are the frequencies of *d* and *w*, respectively, throughout the corpus, and *N* is the total number of words in the corpus. Since the frequency of a given descriptor is in the order of magnitude of 10^3–10^4 while N is in the order of magnitude of 10^9, the individual probabilities are several orders of magnitude smaller than one ($P(d), P(w) \ll 1$). Higher order terms in equation (A3), which include $P(d)^n$ and $P(w)^n$ where $n \geq 2$, are therefore negligible. Furthermore, we apply the same reasoning to note that

$$P\left(d^{\mathsf{C}} \cap w^{\mathsf{C}}\right) = \frac{N - f(d) - f(w)}{N} \approx \frac{N}{N} = 1 \tag{A6}$$

Inserting equations (A4), (A5), and (A6) into (A3) yields

$$P_{indep}(d,w) \approx \frac{f(d)}{N} \cdot \frac{f(w)}{N} \cdot 1^{t-2} \cdot t(t-1) = \frac{f(d)\, f(w) t(t-1)}{N^2} \tag{A7}$$

Regarding the observed probability of d and w co-occurring, we note that

$$P_{obs}(d,w) = P_{obs}(w \mid d)\left(P(d) P(d^{\mathsf{C}})^{t-1} t + \text{higher order terms}\right) \tag{A8}$$

where $P_{obs}(w \mid d)$ is the conditional probability of finding w in the word window given that d is already present in it. The sum of terms within the parentheses is the total probability of finding d at least once in a word window of size t, and the first term represents the probability of finding d precisely once within the word window. Again, the factor t accounts for the fact that the probability of finding d precisely once at any of the t slots in the word window equals the probability of finding d at one slot (i.e. $P(d)$) multiplied by the t number of possible permutations. Higher order terms representing the probability of multiple occurrences of d within a word window are disregarded for the same reasons as stated in the paragraph before equation (A6). The conditional probability in (A8) is given by

$$P_{obs}(w \mid d) = \frac{f(d,w)}{f(d)} \tag{A9}$$

where $f(d,w)$ denotes the frequency of d and w co-occurring within a word window. We also note, in analogy to equation (A6), that

$$P(d^{\mathsf{C}}) = \frac{N - f(d)}{N} \approx \frac{N}{N} = 1 \tag{A10}$$

Inserting equations (A4), (A9), and (A10) in (A8) yields

$$P_{obs}(d,w) \approx \frac{f(d,w)}{f(d)} \cdot \frac{f(d)}{N} \cdot 1^{t-1} \cdot t = \frac{f(d,w) t}{N} \tag{A11}$$

We now insert equations (A7) and (A11) into equation (A2). This yields

$$I(d,w) \approx \log_2\left(\frac{f(d,w)t}{N} \middle/ \frac{f(d)f(w)t(t-1)}{N^2}\right) = \\ = \log_2\left(\frac{f(d,w)}{f(d)} \frac{N}{f(w)(t-1)}\right) = \log_2 \frac{f(d,w)}{f(d)} + K \tag{A12}$$

where

$$K = \log_2 \frac{N}{f(w)(t-1)} \tag{A13}$$

For the sake of clarity, we make a small change of notation in the final expression of equation (A12) using $f(d,w) = f_{olf}(d)$ and $f(d) = f_{tot}(d)$. This leads to

$$I(d,w) \approx \log_2 \frac{f_{olf}(d)}{f_{tot}(d)} + K \tag{A14}$$

This shows that the pointwise mutual information of *d* and *w* is equal to OAI(*d*) plus a constant *K*. The constant, however, depends only on the corpus size *N*, the window size *t*, and the frequency $f(w)$. One can therefore omit *K* when comparing the ranking of the pointwise mutual information of different descriptors and the same *w*, provided that the corpus is the same and the same window size is used for all descriptors.

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