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A density explanation of valence asymmetries in recognition memory

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Abstract The density hypothesis states that positive information is more similar than negative information, resulting in higher density of positive information in mental representations. The present research applies the density hypothesis to recognition memory to explain apparent valence asymmetries in recognition memory, namely, a recognition advantage for negative information. Previous research explained this negativity advantage on the basis of valence-induced affect. We predicted that positive information's higher density impairs recognition performance. Two old–new word recognition experiments tested whether differential density between positive and negative stimuli creates a negativity advantage in recognition memory, over and above valence-induced affect. In Experiment 1, participants better discriminated negative word stimuli (i.e., less false alarms) and showed a response bias towards positive words. Regression analyses showed the asymmetry to be function of density and not of valence. Experiment 2 varied stimulus density orthogonal to valence. Again, discriminability and response bias were a function of density and not of valence. We conclude that the higher density of positive information causes an apparent valence asymmetry in recognition memory.

Keywords Valence asymmetries · Negativity bias · Recognition · Density · Affect

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Distinguishing between positive and negative information is essential for humans to navigate complex environments (Lewin, 1935); unsurprisingly, this distinction fundamentally influences human cognition as well. Previous research identified numerous asymmetries in the perception, processing, elaboration, storage, and retrieval of positive and negative information. These valence asymmetries are commonly explained by the affective potential of evaluative information (see Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001, for a review). Accordingly, the affective reaction of the organism alters cognitive information processing. A prominent example is the notion that negative information triggers deeper and more accommodative processing styles (Bless & Fiedler, 2006; Taylor, 1991).

A different perspective on valence asymmetries is provided by the density hypothesis (Unkelbach, Fiedler, Bayer, Stegmüller, & Danner, 2008), which claims that positive and negative information differ ecologically regarding their diversity. That is, besides the "hot" potential of evaluative information to influence emotions, motivations, and behavior (e.g., such as approach and avoidance), it is assumed that there are systematic "cold" differences between positive and negative information. These differences should not depend on the information's energetic potential, for example, due to its self- or survival relevance. Additionally, these differences exist independent of the emotional, motivational, or behavioral states of the organism (e.g., Lepper, 1994). Specifically, Unkelbach and colleagues suggested that there is a smaller diversity and therefore a higher similarity among positive information compared to negative information, leading to higher "density" of positive information in mental representations. They argued that this ecological difference might explain observed valence asymmetries in processing of evaluative information. For example, the authors showed that positive information is processed faster than negative information; not because of differential affective reactions, but because of the differential density of positive and negative information (Unkelbach et al., 2008a; Experiment 2). Here, we test whether the differential density of evaluative information influences recognition performance.

There is substantial evidence that stimulus similarity influences recognition memory. For example, perceptual recognition research shows that recognition is less accurate for prototypical stimuli (e.g., Busey & Tunnicliff, 1999); it is difficult to distinguish old from new stimuli when stimuli are highly similar. Specifically, similarity causes false recognition of stimuli that were not presented during a study phase, most prominently evident in the Deese–Roediger–McDermott (DRM) paradigm (Roediger & McDermott, 1995), for example when people falsely recall the word *sleep* after studying the words *bed*, *rest*, and *awake*. Given that positive information is overall more similar to other positive information, recognition of positive information should be less accurate than recognition of negative information. Positive information should provoke more false alarms and thus weaken recognition performance. In terms of signal detection analysis (Stanislaw & Todorov, 1999), this translates to better discriminability for negative stimuli and a stronger response bias for positive stimuli.

A considerable amount of empirical evidence for such differential valence effects in recognition is already available (Inaba, Nomura, & Ohira, 2005; Ohira, Winton & Oyama, 1998; Ortony, Turner & Antos, 1983; Robinson-Riegler & Winton, 1996). However, these effects have been traced back to the affective reaction of the organism in response to evaluatively and affectively connotated stimuli. Here, we will test whether positive and negative information's differential density accounts for the observed recognition asymmetry, over and above evaluative and affective influences. In the following, we provide an outline of the density hypothesis, explain how density and memory performance should be related, and compare predictions from density and affect-based explanations of recognition asymmetries.

The density hypothesis

The density hypothesis proposes that positivity comes with decreased diversity (Unkelbach, 2012; Unkelbach et al., 2008b). Differential diversity of positivity and negativity is evident in many different domains. Most generally, positive states typically constitute the norm while negative states constitute some kind of deviation from that norm (Clark & Clark, 1977). There is usually one normal and thus positive state which is characterized by the absence of many abnormal and thus negative states (e.g., being healthy means not having any of many health-related abnormalities). As a result, negative states display a larger diversity than positive states. This principle reaches into language as there is a larger vocabulary for negative states than for positive states. This was shown for English verbs (Semin & Fiedler, 1992), German personality traits (Leising, Ostrovski, & Borkenau, 2012), as well as for English and Spanish emotion words (Schrauf & Sanchez, 2004). Another example is facial attractiveness; attractive faces are alike, while there are many different ways to be unattractive (Potter, Corneille, Ruys, & Rhodes, 2007). The same principle extents to person perception in general as likable, or "positive" persons are perceived as more similar to one another compared to disliked persons (Leising, Ostrovski, & Zimmermann, 2013; Alves, Koch, & Unkelbach, under review). And finally, the effect is also present in emotional experiences as there is one basic positive emotion (joy), but multiple distinct negative emotions (anger, disgust, fear, sadness; Ekman & Friesen, 1971; see also Ortony & Turner, 1990).

Based on lower diversity, positive information displays higher density in spatial models of mental representations than negative information. The original measure of the density construct consisted of pairwise similarity ratings that were analyzed using a multidimensional scaling procedure (MDS; Krumhansl, 1978). Stimulus density was defined as the average Euclidean distance of a stimulus to all other stimuli of the same valence in a given stimulus set (Potter et al., 2007; Unkelbach et al., 2008b). As of now, we and others have found this density asymmetry for a variety of different stimulus classes including nouns, trait words, self-generated words, as well as IAPS pictures using different measures like multidimensional scaling the spatial arrangement method (SPAM; Goldstone, 1994) and Google co-frequency analysis (Bruckmüller & Abele, 2013; Koch, Alves, Krüger, & Unkelbach, 2015; Unkelbach, Guastella, & Forgas, 2008). In all these studies, participants judged positive stimuli as more similar to one another than negative stimuli. The density asymmetry seems to be a general and robust phenomenon of evaluative information ecologies (see Unkelbach, 2012, for a discussion).

Similarity as used in the current theoretical framework is defined by its experimental operationalization as spatial distance. When doing pairwise comparisons or spatial arrangements of stimuli, it is likely that participants rely on different components of similarity when making their judgments such as semantic similarity, feature overlap, associative strength, and frequency of co-occurrence (Maki & Buchanan 2008). For example, results from the Google co-frequency analysis show that positive words more frequently co-occur across web pages than negative words while this co-occurrence is substantially correlated to participant's similarity ratings (r = .60; Koch et al., 2015, see also Lund & Burgess, 1996). In a similar vein, people also group positive words into fewer categories than negative words (Koch et al., 2015). We suggest that higher perceived similarity, stronger associative relations, more frequent co-occurrences, and more inclusive categorizations of positive compared to negative information are all different observable phenomena of the same common principle. In the present work we refer to this principle as density in a spatial model of representation (e.g., Goldstone, 1994; Nosofsky, 1992; Shepard, 1987).

We believe the differential density of positive and negative information is ecological, not affective in nature. Affective reactions are located within the organism – that is, organisms react to stimuli depending on their individual state, their current motivational situation, or their learning history. Ecological effects are located in the environment and depend on its contextual structure. That is, an ecological property changes with regard to the environment, while an affective property changes with regard to the organism. Applied to evaluative information and the construct of density, the same stimulus might be similar to other stimuli in one environment, but dissimilar to other stimuli in another environment. Consequently, the differential effects of stimulus valence might shift depending on the structure of the information environment. However, as the data described above suggests, across most environments, positive stimuli seem to be more similar to one another than negative stimuli.

The proposition that information valence is ecologically confounded with information density has a number of implications for information processing. Stimulus density or similarity is a fundamental determent of cognitive processes ranging from attention (Nosofsky, 1986; Ward, Duncan, & Shapiro, 1997), visual search (Phillips, Takeda, & Kumada, 2006), storage (Mate & Baqués, 2009), retrieval (Glanzer, Knoppenaal, Nelson, 1972; Lewandowsky & Farrell, 2008; Nosofsky, 1988, 1991), and processing speed (Unkelbach et al., 2010) to evaluative judgments (Montoya, Horton, & Kirchner, 2008). The differential density might therefore account for a number of observed valence asymmetries in information processing (Unkelbach, 2012). The present work tests the explanatory power of the density hypothesis in the domain of recognition memory.

Density and memory performance

Increasing the similarity or relatedness among stimuli increases false alarm rates. This effect appears for stimuli such as alphanumeric characters (Flagg, 1976; Reitman & Bower, 1973), geometric shapes (Medin & Schaffer, 1978; Nosofsky, 1991; Nosofsky, Clark, & Shin, 1989), pictures (Koutstaal & Schacter, 1997; Strack & Bless 1994), faces (Busey & Tunnicliff, 1999; Vokey & Read, 1992), words (Brainerd, Reyna, Mojardin, 1999; Dyne, Humphreys, Bain, & Pike, 1990; Montefinese, Zannino, & Ambrosini, 2014; Postman, 1951; Roediger & McDermott, 1995), and sentences (Cantor & Engle, 1993; Holmes, Waters, & Rajaram, 1998).

One explanation for this similarity effect is provided by global activation theories of recognition memory. They assume that stimulus classifications as old or new depend on the signal strength or the echo that stimuli evoke from memory (Gillund & Shiffrin, 1984; Hintzman, 1988; Wixted, 2007). If the echo exceeds a recognition threshold, participants provide an “old” response. The echo strength of a given stimulus is a function of the summed similarity with presented (“old”) stimuli stored in memory (Fiedler, 1996; Nosofsky, 1988, 1991). The left part of Fig. 1 illustrates this principle in a simple subsymbolic memory network. The activation vectors represent information stored in memory and new information (e.g., new positive vs. new negative words); stimuli that are more similar to other stimuli produce stronger echos, and therefore, high similarity produces false alarms. Note again that similarity can have different components (semantic similarity, associative strength, co-occurrence) that might all increase echo strength.

As we assume that positive stimuli are more similar to one another than negative stimuli, the likelihood of falsely responding “old” to a new stimulus should be higher for positive stimuli. The right part of Fig. 1 illustrates the same principle for a symbolic network. However, this effect should arise independent of the specific memory architecture (e.g., symbolic vs. subsymbolic networks), as long as it allows to model similarity. The association between similarity and false alarms also follows from dual process models of recognition which assume false alarms to depend on the familiarity that a stimulus evokes (Mandler, 1980; Yonelinas, 1994). Similarly to the echo strength concept, familiarity is supposed to increases with increasing similarity among stimuli (Verde, 2004).

While similarity causes false recognition, it typically does not lead to an equal increase in hits which is why recognition performance is impaired for highly similar stimuli (Anderson & Reder, 1999; Cantor & Engle, 1993; Dyne et al. 1990; Shiffrin, Huber, & Marinelli, 1995; Verde, 2004). Using a global activation model, Zaki and Nosofsky (2001) predicted and found that a larger proportion of new stimuli are pushed past the response criterion than old stimuli because participants usually correctly classify the majority of stimuli.[1] Another explanation is provided by dual process models as they assume similarity affects familiarity and recollection in opposite ways (Mandler, 1980; Yonelinas, 1994). Similarity supposedly increases familiarity and thus false-alarm rates, but similarity makes the recollection of a specific stimulus more difficult (Gillund & Shiffrin, 1984; Wixted, Ghadisha, & Vera, 1997). As the correct recognition of old stimuli (“hit”) is a function of both, familiarity and recollection, similarity always produces a stronger increase in false alarms than in hits

[1] An additional assumption that has to be made for this asymmetry to occur is that participants do not respond “new” more often than “old” (response criterion<= 1).

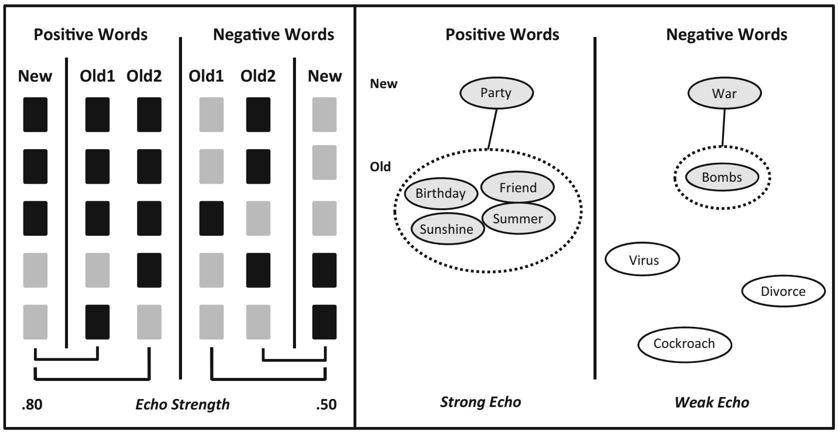

Fig. 1 The left part illustrates a subsymbolic memory model along with the memory echo strength (simple matching coefficient) for a new positive and a new negative word elicited by old positive and old negative words. Assuming positive words are more similar to one another than the negative words, the resulting echo is stronger for the new positive word than for the new negative word and so is the likelihood for a false alarm. The right part illustrates the same principle in a symbolic memory model

(Joordens & Hockley, 2000). Assuming that high similarity among stimuli increases false alarms without a corresponding increase in hits, we expected recognition advantages for negative stimuli over positive stimuli.

Affect or density?

Several studies already reported a similar recognition advantage for negative information over positive information. In a study by Ortony and colleagues (1983), false alarm rates for positive sentences were larger than for negative sentences, while hit rates were unaffected by valence. Using Jacoby's (1991) process dissociation paradigm, Robinson-Riegler and Winton (1996) reported that positive words were more likely to be falsely recognized under an exclusion instruction than negative words. Ohira and colleagues (1998) replicated this pattern using Japanese word stimuli. Inaba and colleagues (2005) also reported a recognition advantage for negative words as they found larger false alarm rates for positive words and equally large hit rates for positive and negative words.

All these studies provide an affective explanation for the recognition advantage of negative information. Accordingly, valenced stimuli elicit affective reactions within participants, which influence encoding. Specifically, "negative events appear to elicit more physiological, affective, cognitive, and behavioral activity and prompt more cognitive analysis than neutral or positive events" (Taylor, 1991, p. 67). As deeper encoding benefits memory performances (e.g., Craik & Tulving, 1975), negative information is expected to show the described recognition advantage.

A related idea suggests that negative mood/affect leads to accommodative, bottom-up processing that is sensitive to the details of the external world, while positive mood/affect leads to assimilative, top-down processing which relies on preformed internal schemas and heuristics (Bless & Fiedler, 2006). A number of findings suggest that an accommodative processing style benefits memory accuracy while an assimilative style produces false memories (Fiedler, Asbeck, & Nickel, 1991; Forgas, Goldenberg, & Unkelbach, 2009).

Besides processing depth and processing style, Monin (2003) postulated the "warm-glow" heuristic, claiming that people mistake positive affect for familiarity. The author showed that participants perceived attractive faces as more familiar (see also Garcia-Marques, Mackie, Claypool, & Garcia-Marques, 2004). Using an old–new recognition task, Monin (2003, Study 3) also found that participants erroneously recognized positive words more often than negative words. Such misperceptions of positive affect as familiarity could thus increase familiarity for positive stimuli and thereby cause false recognition.

The processing depth explanation, the processing style explanation, and the "warm-glow" heuristic all suggest the recognition asymmetry is caused by "hot" valence–based affect, that is, the energizing potential of evaluative information. In contrast, as delineated above, we predict the asymmetry to be based on "cold" stimulus density, a property that, albeit ecologically confounded with valence, does not require affect to exert an influence. Again, density is a property of a stimulus within its information ecology and is thus not fixed (Unkelbach, 2012). For example, the usually very distinct stimulus "bombs" has high density in the context of war and weapons, and accordingly will produce high rates of false alarms. But in the context of spiders and snakes, the stimulus "bombs" has low density and will produce few false alarms. While affect-based explanations predict general differences between positive and negative information, the present account allows for *a priori* predictable alternative outcomes depending on the respective information ecology.

Overview and predictions for the following experiments

We conducted two old-new recognition experiments to disentangle density effects in recognition from affective influences. Based on the density hypothesis, we predicted that false alarm rates are higher for positive words than for negative words, while the same should not be true for hit rates. Consequently, discriminability should be higher for negative words while positive words should elicit a stronger response bias. Crucially, we predicted this effect to depend on the similarity among the word stimuli (density) and not on the valence of the words as suggested by affect based-explanations. We tested these hypotheses using the same sample of word stimuli that were used by Unkelbach et al. (2008a) in their empirical test of the density hypothesis. It contains the 20 most positive and the 20 most negative words from a set of 92 words that are frequently used in experimental social psychology (Bargh, Chaiken, Govender, & Pratto, 1992; Fazio, Sanbonmatsu, Powell, & Kardes, 1986; Klauer & Musch, 1999; see Appendix). Using this stimulus sample ensures that stimuli have strong valence, and has the advantage that density parameters for the individual words, that is, their average similarity to the other stimuli in the set, are already available. In addition, it represents a standard and often used set of evaluative stimuli.

Experiment 1

Experiment 1 employed an old–new recognition task. First, we aimed at replicating a recognition advantage for negative words on the participant level. Next, regression analysis on the item level aimed to identify the underlying processes, by regressing stimuli's false alarm and hit rates on their valence and density. Additionally, the regression included word frequency, which has been shown to strongly influence recognition performance as well (Arndt & Reder, 2002; Glanzer & Adams, 1990).

Method

Participants and design One hundred eighty-three students (106 women and 77 men) of the University of Cologne participated for 3€ or course credit. All participants were native German speakers. Stimulus valence was the only experimental factor and was manipulated within participants.

Stimulus materials As described, the 20 most positive and the 20 most negative words based on German norm ratings by Klauer and Musch (1999), from a set of 92 frequently used attitude objects (Fazio et al., 1986), served as stimuli.

Procedure Participants arrived in the laboratory and were seated in front of a computer. After completing a consent form, the experimenter started a Visual Basic program that presented instructions, stimuli, and recorded the dependent variables. The program instructed participants to pay close attention while they would see several word series. The experiment had three phases, separated by two filler tasks. The first phase presented all 40 words in randomized order and was administered to familiarize participants with the stimuli and to make the subsequent recognition task more difficult.[2] Each stimulus appeared for 1,000 ms followed by a blank screen that appeared for 1,200 ms. Participants then worked on a filler task for about 8 minutes. The subsequent learning phase instructed participants to pay close attention while they would be presented with 20 out of the 40 word stimuli from the first phase. The program then presented 10 positive and 10 negative randomly selected words from the original 40 items. After a second filler task, which took about 5 minutes, the test phase presented all 40 stimuli and participants decided for each word, whether it was present during the learning phase or not. Participants indicated their decision by pressing either the "L" key ("The word was presented in the second phase") or the "A" key ("The word was NOT presented in the second phase"). Each phase of the experiment presented stimuli in a newly randomized order for each participant. Finally, participants were thanked, paid, and informed about the purpose of the experiment.

Results

Analysis across participants Prior to inferential analysis, we removed data from seven participants because their memory performance did not exceed chance. For the remaining participants, we calculated participants' false-alarm and hit rates separately for positive and negative stimuli. Figure 2 illustrates that the mean false alarm rates were significantly higher for positive stimuli than for negative stimuli, (M_{pos} = 0.29, $SD_{po\ s}$ = 0.19 vs. M_{neg} = 0.23, SD_{neg} = 0.17), $t(175) = 3.68$, $p < .001$, $d = 0.33$, while the hit rates for the positive words were only slightly higher than for the negative words (M_{pos} = 0.76, SD_{pos} = 0.16 vs. M_{neg} = 0.75, SD_{neg} = 0.16), $t(175) = 1.18$, $p = .241$.

Based on the hit- and false alarm rates, we calculated participants' signal detection parameters *d*' and *C* for the positive and negative words (Stanislaw & Todorov, 1999). Higher *d*' values indicate better discrimination ability, while *d*' = 0 indicates inability to distinguish between old and new stimuli. The response bias parameter *C* indicates the tendency to respond

[2] A pretest showed that old–new discriminations for the 40 word stimuli from Unkelbach et al. (2008a) produced ceiling effects (very few false alarms). We therefore familiarized participants with all 40 stimuli in the beginning to make the subsequent recognition task more difficult and to increase false-alarm rates.

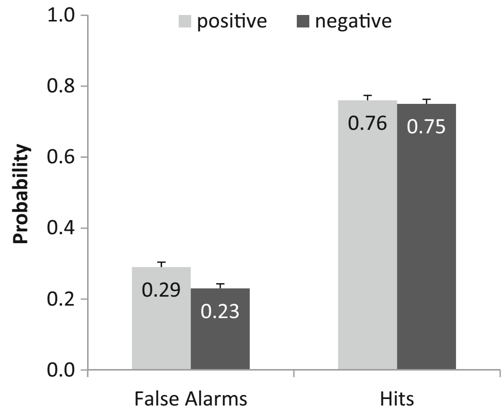

Fig. 2 False alarm and hit probabilities among the positive and negative word stimuli. The error bars represent standard errors of the means

"new" or "old." C values of 0 indicate no bias; C values higher than 0 indicate a tendency to respond "new," while C values lower than 0 indicate a tendency to respond "old." The data confirmed our hypothesis as d' was larger for the negative words (M = 1.59, SD = 0.81) than for the positive words (M = 1.46, SD = 0.80), $t(175) = 2.10$, $p = .038$, $d = 0.17$. In addition, C was larger for the negative words (M = 0.04, SD = 0.39) than for the positive words (M = -0.09, SD = 0.42), $t(175) = 3.32$, $p = .001$, $d = 0.33$. As predicted, participants' discrimination ability was higher for negative words, while participant's tendency to respond "old" was stronger for the positive than for the negative words.

Analyses across stimuli Having established the basic pattern, we tested our core hypothesis that stimulus density influences recognition performance independent of and beyond valence. We therefore calculated hit and false alarm rates separately for each stimulus.[3] In addition, we obtained density indices for each word from Unkelbach et al. (2008a). The density index designates the mean Euclidean distance of a word to all words of the same valence in a multidimensional space; thus, it is a metric of similarity. The multidimensional space is calculated based on pairwise similarity ratings using a multidimensional scaling procedure. To obtain a continuous measure for word valence, eight research assistants rated the words' valences on scales ranging from -5 (*negative*) to +5 (*positive*). In addition, we obtained word frequency estimates from Klauer and Musch (1999).

Two regression analyses tested the influences of density and valence on false alarms and hits. A first model predicted false alarms from word valence and frequency and found an influence of both predictors. More frequent words had a higher chance of being falsely recognized ($\beta = .36$, $p = .020$), a well-known phenomenon (e.g., Glanzer, Adams, Iverson, & Kim, 1993). In addition, positive words elicited more false alarms than negative words ($\beta = .29$, $p = .055$), even though this effect did not reach conventional levels of significance. We attribute this to a lack of power, as the item-level analysis had only 39 degrees of freedom. A second regression model added density as a predictor. Table 1 shows that when density was included, it was the strongest and only significant predictor of false alarms. Specifically, the partial correlation between valence and false alarms dropped from $r = .31$, $p = .055$ to $r = .05$, $p = .772$. Thus, density accounted for the effect of a word's valence on its probability to be falsely recognized.

Next, we conducted a similar regression procedure with hit rates as the criterion. Table 2 shows that neither valence nor density predicted hit rates. Frequency showed a marginally significant influence on hit rates, indicating that infrequent stimuli had a higher chance of being correctly recognized. This reflects typical word frequency effects in recognition (see Murdock, 2003, for a review).

Discussion

Experiment 1 replicated the standard valence asymmetry in recognition performance, that is, higher false alarm rates among positive stimuli and equal hit rates among positive and negative stimuli. As a result, discriminability was higher for negative stimuli and response bias was stronger for positive stimuli. Regression analyses on the item level explored the cause of this asymmetry. As expected, stimulus density was the best predictor of false alarms and fully accounted for the effect of valence on false alarms. Thus, Experiment 1 supported the idea that higher similarity among positive stimuli, as indexed by stimulus density, causes false recognition and thereby produces an apparent valence asymmetry.

Experiment 1 utilized the "natural" covariation of valence and density (i.e., positive information clusters more densely). Experiment 2 provides a stronger test and varied density and valence orthogonally between a "natural" and a "reversed" condition. If the density explanation holds true and the recognition asymmetry is not a function of valence per se, it should be possible to create ecologies in which negative stimuli produce more false alarms than positive stimuli.

Table 1 Results of a multiple regression analysis predicting a word's probability to be falsely classified as "old" (false alarm rate) from valence, density, and frequency across the 40 word stimuli

Predictor	β	t	p	Partial r^2	Simple correlation
Density	-.469	-2.82	.008	-.426	-.554
Valence	.046	0.29	.772	.048	.284
Frequency	.222	1.56	.128	.252	.351

[3] As the calculation of d' and C is valid only on the participant level, item level analysis was conducted on false-alarm and hit rated only.

Table 2 Results of a multiple regression analysis predicting a word's probability to be correctly classified as "old" (hit rate) from valence, density, and frequency across the 40 word stimuli

Predictor	β	t	p	Partial r^2	Simple correlation
Density	-.059	-0.30	.766	-.050	.470
Valence	.102	0.54	.592	.090	.137
Frequency	-.288	-1.71	.091	-.275	-.274

Experiment 2

Experiment 2's "natural" condition featured positive words that were similar and negative words that were dissimilar. The "reversed" condition featured positive words that were dissimilar and negative words that were similar, while mean stimulus valence was constant across conditions ($M_{\text{natural}} = 4.79$, $SD = 3.44$ vs. $M_{\text{reversed}} = 4.75$, $SD = 3.69$), $t(30) = 0.04$, $p = .97$. Figure 3 presents the stimuli plotted in a two-dimensional similarity space based on similarity ratings from Unkelbach et al. (2008a). This selection directly tested the affect and density explanations for recognition asymmetries. Affect-based explanations predict recognition to be a function of valence, which statistically translates into a main effect in the present design. The density-based explanation predicts recognition to be a function of stimulus similarity, which statistically translates into an interaction effect between valence and condition.

Method

Participants and design Seventy-four students (58 women, 16 men) of the University of Cologne participated for 3€ or course credit. All participants were native German speakers. Experiment 2 did not hinge on correlational variation of the variables but manipulated them via preselection. Therefore, the necessary participant sample was smaller than in Experiment 1. Participants were randomly assigned to the "natural" and "reversed" conditions; in the former condition, positive stimuli were more similar to one another than negative stimuli, while in the latter condition, negative stimuli were more similar to one another than positive stimuli.

Stimulus materials and procedure We created four stimulus subsets which realized the orthogonal combinations of valence and similarity (positive/similar; positive/dissimilar; negative/similar; negative/dissimilar). Each set contained eight stimuli from the 40 word stimuli used in Experiment 1. We selected stimuli based on density indices and additional visual inspection of the multidimensional scaling solution. Visual inspection was necessary as two stimuli might be very dissimilar to the whole set (resulting in low density) but very similar to each other. Visual inspection ensured that in such cases, only one of them was included in the subset. Using similarity ratings from Unkelbach et al. (2008a), we calculated new density indices (i.e., average Euclidean distances) for each word in each subset with lower values representing higher density. The respective means confirmed that words in the positive/similar ($M = 3.89$, $SD = 0.53$) and negative/similar ($M = 3.89$, $SD = 0.92$) subsets were more similar than those in the positive/dissimilar ($M = 7.34$, $SD = 0.81$) and negative/dissimilar ($M = 8.88$, $SD = 1.01$) subsets, $t(30) = 12.09$, $p < .001$. The dissimilar sets did not fully dissolve the confound between valence and density, as the positive/dissimilar words were still more similar compared to the negative/dissimilar words, $t(14) = 3.36$, $p = .005$. Yet, as Fig. 3 shows, the experimental density difference within a given condition was fully established. The four subsets did not differ in word frequency, $F(3,28) = 1.66$, $p = .198$.

We combined the positive/similar and negative/dissimilar subsets to serve as stimuli in the "natural" condition, while the positive/dissimilar and the negative/similar subsets served as stimuli in the "reversed" condition. Thus, each condition contained 16 word stimuli as illustrated in Fig. 3. For each participant, the computer randomly determined four of the eight positive and four of the eight negative stimuli as "old" stimuli and the

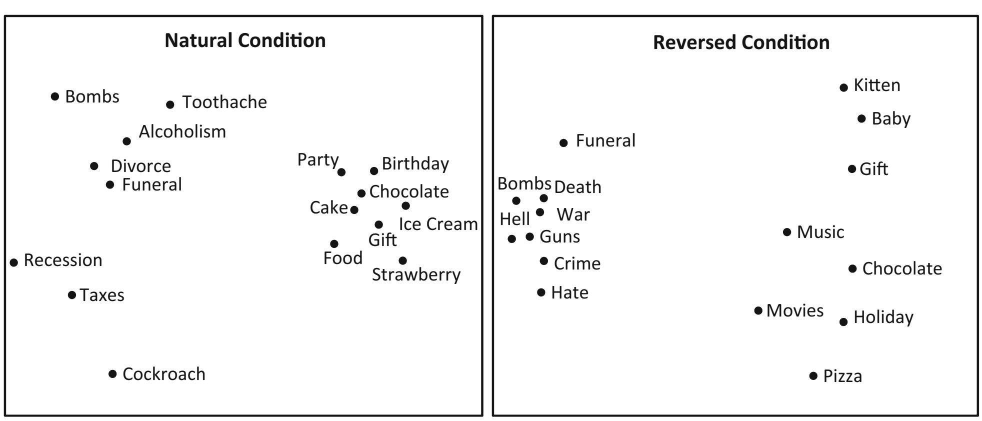

Fig. 3 Spatial density differences for the 16 stimuli in the natural condition and the 16 stimuli in the reversed condition in a two-dimensional similarity space

remaining as "new" stimuli. Except for the stimuli, the procedure of the recognition task was identical to that of Experiment 1. That is, the task consisted of three phases separated by to filler tasks. The first phase presented all 16 word stimuli in order to familiarize participants with the stimuli. After a first filler task, the subsequent learning phase presented eight randomly selected words (four positive and four negative) from the original 16 items. After a second filer task, the test phase presented all 16 stimuli, and participants decided for each word whether it was present during the learning phase or not.

Results

Analysis across participants Prior to inferential analyses, we removed data from three participants because their memory performance did not exceed chance. For the remaining participants, we calculated false alarm and hit rates separately for the positive and the negative stimuli. We conducted a 2(condition: natural vs. reversed) × 2(valence: positive vs. negative) ANOVA with repeated measures on the last factor and false alarm rates as the dependent variable. The analysis yielded a main effect of valence: false-alarm rates were higher for the positive words than for the negative words (M_{pos} = 0.28, SD_{pos} = 0.21 vs. M_{neg} = 0.21, SD_{neg} = 0.21), $F(1, 69) = 5.01$, $p = .028$, $\eta^2 = 0.07$. However, the predicted interaction explained a much larger part of variance. As the upper-left part of Fig. 4 shows, false-alarm rates were higher for positive words than for negative words in the natural condition, while the opposite was true in the reversed condition, $F(1, 69) = 25.14$, $p < .001$, $\eta^2 = 0.27$. Similar to Experiment 1, hit rates did not differ between experimental conditions (see the upper-right part of Fig. 4), all *F*s < 1, *ns*.

We then computed participants' SDT estimates separately for positive and negative words. First, we conducted a 2(condition: natural vs. reversed) x 2(valence: positive vs. negative) mixed ANOVA with repeated measures on the last factor and *d*' as the dependent variable. The only significant effect was the predicted interaction of condition and valence. As Fig. 4's lower-left part illustrates, *d*' was larger for negative words than for positive words in the natural condition, while in the "reversed" condition, *d*' was larger for positive words than for negative words, $F(1, 69) = 17.62$, $p < .001$, $\eta^2 = .20$.

We conducted the same analyses with *C* as dependent variable. This analysis yielded a main effect for valence: *C* was larger for negative words ($M = -0.06$, $SD = 0.48$) than for positive words ($M = -0.21$, $SD = 0.44$), $F(1, 69) = 4.68$, $p = .034$, $\eta^2 = .06$. However, a much larger part of variance was explained by the predicted interaction which is illustrated in Fig. 4's lower-right part: *C* was smaller for the positive words than for the negative words in the natural condition, while in the reversed condition, *C* was smaller for the negative words than for the positive words, $F(1, 69) = 11.27$, $p = .001$, $\eta^2 = .14$.

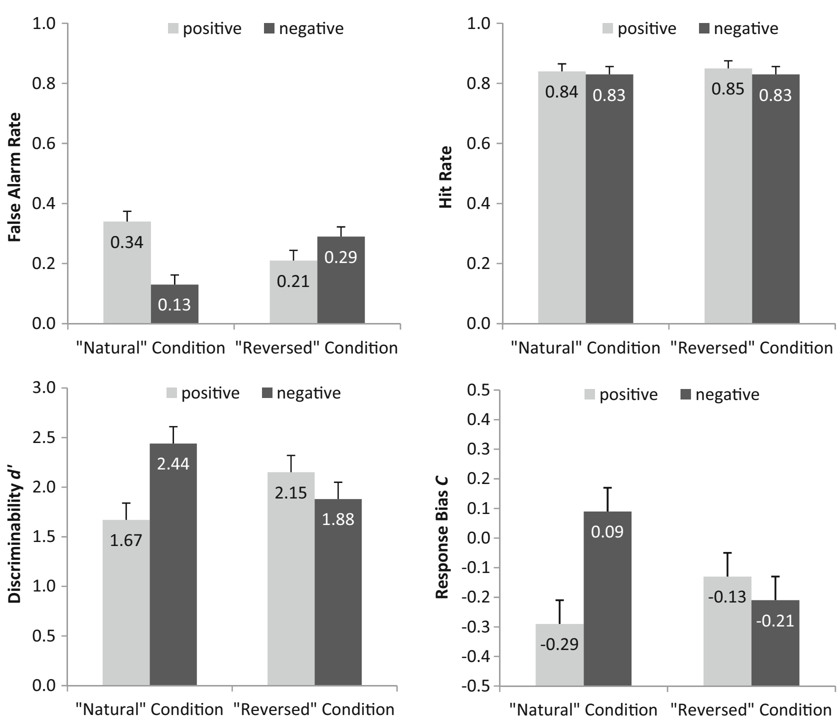

Fig. 4 False-alarm rates, hit rates, discriminability, and response bias for the positive and negative words when positive words are more similar than negative words ("natural" condition) and when negative words are more similar than positive words ("reversed" condition). Larger *d*' values indicate better discriminability. *C* values lower than 0 indicate a tendency to respond "old." The error bars represent standard errors of the mean

Analysis across stimuli Similar to Experiment 1, we tested the influence of density and valence on the stimulus level. Therefore, we again calculated hit and false alarm rates separately for each stimulus across both conditions. As there were 16 stimuli in each condition, we calculated a total of 32 hit- and false-alarm rates. Two of the same positive and two of the same negative stimuli were used in both conditions simultaneously (chocolate, gift, funeral, bombs). Thus, these stimuli appeared twice among the 32 stimuli. While they had the same valence values in both conditions, their density value varied due to the differential ecologies. Similar to Experiment 1, we conducted two regression analyses predicting false alarm rates and hit rates from valence, density, and frequency across all 32 words. As in Experiment 1, the density index was the only significant predictor for false alarm rates, while neither valence nor density had a significant influence on hit rates (see Tables 3 and 4).

Discussion

Experiment 2 supports the proposed influence of density on recognition memory: With increasing similarity among stimuli, false alarm rates increase while hit rates remain mostly unaffected. Consequently, discriminability decreases and response bias increases. Furthermore, by varying density and valence across two conditions, the influences of the two competing predictors were directly tested against each other. We created two stimulus ecologies: one included the natural confound between valence and density while the other represented a reversed ecology in which negative words were more similar to one another than positive words. The natural ecology produced higher false alarm rates for positive words, while the reversed ecology produced higher false alarm rates for negative words. Consequently, discriminability and response bias also changed as a function of the ecology as evident by the interaction effect of valence and condition. This pattern directly follows from the density explanation, but affect-based explanations would predict a main effect of stimulus valence on recognition performance. For example, if the "warm-glow" of positive words increased familiarity and thus false alarms, this should also be the case in a reversed ecology. Indeed, we found a main effect of valence on false alarm rates and response bias as well; however, this effect was much smaller than the interaction effect and might be due to the still-present confound between valence and density in our stimulus subsets. Item-level analyses confirmed this explanation; across both conditions, the density index predicted false-alarm rates, but a continuous measure of valence did not.

Table 3 Results of a multiple regression analysis predicting a word's probability to be falsely classified as "old" (false-alarm rate) from valence, density, and frequency across the 32 word stimuli

Predictor	β	t	p	Partial r^2	Simple correlation
Density	-.570	-3.56	.001	-.558	-.603
Valence	.162	1.07	.293	.199	.209
Frequency	.049	0.30	.765	.057	.227

Table 4 Results of a multiple-regression analysis predicting a word's probability to be correctly classified as "old" (hit rate) from valence, density, and frequency across the 32 word stimuli

Predictor	β	t	p	Partial r^2	Simple correlation
Density	.049	0.24	.812	.045	.008
Valence	.073	0.38	.708	.071	.054
Frequency	.096	0.47	.643	.088	.068

General discussion

The density hypothesis states that positive information is less diverse than negative information, resulting in differential density in mental representations (Unkelbach et al., 2008a). This differential density may account for apparent valence asymmetries in the processing of evaluative information (Unkelbach, 2012). While valence asymmetries are commonly explained as "hot," affect-induced processing asymmetries, the density hypothesis points to a "cold," ecology-related explanation of the same asymmetries.

The present work shows that higher density among positive stimuli impairs memory accuracy, and thereby creates a recognition advantage for negative stimuli. Our account thereby provides an alternative explanation for the recognition advantage of negative information that does not rely on the affective reaction of the organism (Inaba et al., 2005; Ohira, et al., 1998; Robinson-Riegler, & Winton, 1996). Two experiments showed that the density asymmetry creates a recognition advantage for negative stimuli over and above evaluative and affective influences.

Experiment 1 found the standard recognition valence asymmetry for 20 strongly positive and 20 strongly negative nouns frequently used in research on evaluative information processing. Similarly to past findings (Inaba et al., 2005; Ortony at al., 1983), false alarm rates for positive words were higher than for negative words while hit rates were mostly unaffected. Regression analyses supported the density explanation, as stimulus density was the best predictor for false alarm rates and fully accounted for any effects of valence. Hit rates were unaffected by both density and valence. Experiment 2 varied density and valence between conditions, and again, memory performance was a function of density and not of valence. Results showed that in a reversed ecology, in which negative stimuli were more similar than positive stimuli, false alarm rates were higher for negative words than for positive words, and, consequently, discriminability was higher for positive words and response bias was stronger for negative words. This pattern is incompatible with a processing depth, processing style, or a "warm-glow" explanation but directly follows from the density explanation. Although we do not claim that these explanations are generally wrong, the density effect dominated the valence influences, at least within the present paradigm and stimulus set.

Across both experiments, hit rates were unaffected by density and valence on the participant as well as on the stimulus level. While we predicted similarity to exert its influence predominantly on false alarms and not on hits, the absence of an association between valence and hits casts further doubt on a processing depth/style explanation. To our understanding, deeper and more accommodative encoding of stimuli should make it easier to correctly classify new and old stimuli likewise, and thereby produce an effect similar to the strength-based mirror effect (Glanzer & Adams, 1990). This effect describes the widely observed phenomenon that false alarm rates are smaller and hit rates are higher for strongly encoded stimuli compared to weakly encoded stimuli (e.g., Stretch & Wixted, 1998).

Limitations and open questions

The present work is limited by the fact that our observations are based on a sample of only 40 word stimuli. This poses the question of generalizability of our results in regard to the density asymmetry as well as to the recognition asymmetry. However, we did not generate the present set for our purposes but used an existing set introduced by Fazio et al. (1986), which is frequently used in cognitive research.

As of now, we are confident that the density asymmetry in this stimulus sample and the following processing differences are general phenomena observable across many different domains; the density asymmetry has been found for nouns, trait words, self-generated words, IAPS pictures, and mental representations of other people (Alves et al., 2015; Bruckmüller & Abele, 2013; Koch et al., 2015; Leising et al., 2012; Potter et al., 2007; Unkelbach et al., 2010; Unkelbach et al., 2008a, b). However, given the limitation of the stimulus sample used in the present work it remains unclear to what extent the present findings can be generalized to different stimulus sets and procedures other than the old-new recognition task. Future research should address possible density-driven recognition asymmetries in domains other than language such as person perception, faces, pictures, sounds, tastes, and life events, using more exhaustive stimulus sets, and alternative recognition paradigms, such as DRM lists or two alternative forced-choice tasks (e.g., Smith & Duncan, 2004).

Another open question relates to the different components of the density asymmetry and their contribution to the recognition effects reported here. As mentioned earlier, we argue positive information is less diverse than negative information, resulting in a higher density of positive information in mental representations. Higher density correlates with semantic similarity, associative strength, frequency of co-occurrence, and category inclusiveness (Koch et al., 2015), and may serve as the latent cause for observable valence asymmetries on these measures. The present experiments show that density strongly predicts recognition performance and accounts for valence effects; however, it is not clear which of the different components of density influences recognition. As argued earlier, there is good evidence that semantic similarity among stimuli increases false recognition (e.g., Montefinese et al., 2014). However, some researchers have challenged the idea that item noise itself influences recognition performance (e.g., Dennis & Humphreys, 2001; Maguire, Humphreys, Dennis, & Lee, 2010). Specifically, it was suggested that participants rely on category labels (i.e., animals vs. vegetables) that are associated with stimuli as part of the recognition process (Humphreys, Murray, & Koh, 2014). This would suggest that it is not the larger semantic similarity among positive stimuli that causes false recognition but the higher inclusiveness of positive categories. Likewise, it is possible that the greater tendency of positive stimuli to co-occur in the same context creates false recognition (e.g., Lund & Burgess, 1996). The ways in which word stimuli can be related to one another are multifaceted (e.g., Gagné, 2000; see also Estes & Jones, 2009), and future research should try to disentangle which kind of relatedness (e.g., semantic similarity, co-occurrence, category inclusiveness) influences recognition memory. It is possible that multiple processes simultaneously affect recognition in the same direction and thereby contribute the apparent valence asymmetry. Such a scenario would be in line with our conceptualization of the density asymmetry as it allows for multiple processes to be at work; interitem similarity and thus density may serve as the uniting latent cause for these multiple processes. As positive information is naturally less diverse than negative information, positive words are semantically more similar, co-occur more frequently within the same context, have stronger associative relations, and are divided into fewer categories than negative words (see Koch et al., 2015). All of these factors might increase false recognition, but would also relate to stimulus density.

Our results also imply that researchers who are interested in examining valence effects in cognition have to make an important decision regarding the stimulus sample. The sample can either incorporate the naturally occurring density asymmetry for the sake of external validity (e.g., Brunswik, 1955), or stimuli can be selected to wipe out this asymmetry in order to observe "pure" effects of valence. Examples for the latter strategy are studies that use the Deese–Roediger–McDermott recognition paradigm (e.g., Budson et al., 2006; Roediger & McDermott, 1995). These studies use lists that typically entail several associated words from specific positive or negative domains (e.g., sex, man, violate) that converge on a critical lure (e.g., rape; see Budson et al., 2006). The stimuli are often matched regarding their attributes, including strength of associative relation. In such a preselected stimulus sample we would not expect to find the typical density asymmetry. In fact, recent studies have shown that in recognition experiments using these DRM lists negative words elicit *more* false recognition than positive words which is contrary to the classical recognition asymmetry and to the results of the present experiments (Brainerd, Holliday, Reyna, Yang, & Toglia, 2010; Brainerd, Stein, Silveira, Rohenkohl, & Reyna, 2008). The authors argue that negative valence enhances the familiarity of the semantic content of critical distractors. Thus, it is possible that when the naturally occurring density asymmetry is controlled for, negative valence might *increase* perceived familiarity and thereby decrease memory accuracy. This is contrary to what affect-based accounts and the warm-glow heuristic would predict (e.g., Monin, 2003; Ohira et al., 1998).

The present findings might explain why in some experiments negative information has a recognition advantage and in other experiments, that pre-select stimuli to counterbalance associative relations (e.g., DRM experiments), and thereby erase the density asymmetry, the reversed is true. However, as another recent study that carefully controlled for associative relatedness of new and old stimuli did not find any difference in false recognition between positive and negative DRM lists, it is an open question whether affective valence per se influences recognition (Dehon, Larøi, & Van der Linden, 2010). Our research shows that controlling for stimulus density is crucial for any research aiming to examine “pure” valence effects.

Conclusions about valence, affect, and cognition

Valence asymmetries in cognitive processes are commonly explained to be a result of the affective response of the organism. Affect-based accounts require the assumption that the mere confrontation with a stimulus (e.g., the word *war*) elicits an affective reaction strong enough to influence its processing. However, we want to emphasize that humans can process affectively charged stimuli in a relatively “cold” and nonaffective way. Furthermore, valence asymmetries in cognitive performance might not always be due to the affective reaction of the organism but instead arise from the natural structure of the information ecology. One structural characteristic of evaluative information is that negative information is more diverse than positive information. Consequently, positive information has a higher density than negative information in people’s mental representation. We suggest density as an important variable that creates valence asymmetries independent of affect.

Finally, we want to point out that there is a large and convincing body of research on affect-induced processing asymmetries, and that we do not question their general existence. We do, however, want to call for caution, as positive and negative information does not only vary in affective potential but also in “cold” properties, like density. If these “cold” properties account for “hot” effects, it need not impact the functional outcomes—our memory is still more accurate for negative than for positive information—but it will substantially alter explanatory models, applications, and interventions.

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Appendix

Table 5

Table 5 List of 20 most positive and 20 most negative words that seved as stimuli (Bargh et al., 1992; Fazio et al., 1986; Klauer & Musch, 1999; Unkelbach et al., 2008a)

Negative		Positive	
Stimulus	German translation	Stimulus	German translation
War	Krieg	Cake	Kuchen
Hitler	Hitler	Kitten	Kätzchen
Bombs	Bomben	Chocolate	Schokolade
Alcoholism	Alkoholismus	Ice Cream	Eiscreme
Disease	Krankheit	Butterfly	Schmetterling
Toothache	Zahnschmerz	Baby	Baby
Hate	Hass	Pizza	Pizza
Funeral	Beerdigung	Food	Essen
Virus	Virus	Hawaii	Hawaii
Crime	Verbrechen	Birthday	Geburtstag
Death	Tod	Movies	Kino
Hell	Hölle	Strawberry	Erdbeere
Divorce	Scheidung	Gift	Geschenk
Cancer	Krebs	Flowers	Blumen
Guns	Gewehre	Party	Party
Recession	Rezession	Music	Musik
Garbage	Müll	Summer	Sommer
Litter	Abfall	Holiday	Urlaub
Cockroach	Kakerlake	Sunshine	Sonnenschein
Taxes	Steuern	Friend	Freund

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