be interesting to know, whether CA are continuous with respect to any of these pseudometrics, and whether some dynamical properties of CA can be derived from the properties of defining submeasures.

Acknowledgments

We thank Marcus Pivato and Francois Blanchard for careful reading of the paper and many valuable suggestions. The research was partially supported by the Research Program Project "Sycomore" (ANR-05-BLAN-0374).

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Dynamics and Evaluation: The Warm Glow of Processing Fluency

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Article Outline

Glossary

Evaluative responses Reactions reflecting an implicit or explicit assessment of stimulus' goodness or badness. Such reactions can be captured with judgments (liking, preference, choice), behavior (approach, avoidance, desire to continue or terminate), and physiology (peripheral and central). Strong evaluative reactions can develop into full-blown affective states, such as moods and emotion.

Fluency A general term used to describe efficiency of processing on perceptual and conceptual levels. Fluent processing is fast, error-free, and easy – a quality reflected in several dynamical properties (see next). The level of processing fluency can be monitored and influence evaluative as well as cognitive processes.

Processing dynamics Processing dynamic refers to content non-specific parameters characterizing a system's behavior at the level of individual units (e. g., neurons) or networks. Those dynamical parameters include (i) coherence of the signals within the system – the extent to which the signals arriving at a given unit from other units consistently dictate the same state, (ii) settling time – amount of time for the system to achieve a steady state, (iii) volatility – the number of units changing state, (iv) signal-to-noise ratio – overall strength of signals in the network, and (v) or differentiation – ratio of strongly activated to weakly activated units.

Mere-exposure effect Empirical observation that simple repetition (mere-exposure) of an initially neutral stimulus enhances people's liking for it. Because a typical result of simple repetition is enhancement of processing fluency (more efficient re-processing), this classic empirical phenomenon inspired research into evaluative consequences of changes in processing dynamics, and led to investigation of other variables that change processing dynamics, such as priming, duration, clarity, contrast, prototypicality or symmetry.

Definition of the Subject

A major goal of contemporary psychology, cognitive science and neuroscience is to understand the interactions of cognition and emotion – the mutual influences between thinking and feeling [11,41,101]. Sometimes such interactions are quite dramatic – as when emotions rob an individual of sound judgment (e. g., crimes of passions) or when emotions inspire an individual to transgress self-interest (e. g., acts of compassion). But most cognition-emotion interactions are more subtle. For example, seeing a well-balanced piece of art or a symmetric design may invoke a sense of aesthetic pleasure. Simply recognizing a familiar acquaintance on a street may evoke a sense of warm glow. A difficult to hear cell phone conversation may evoke a subtle sense of annoyance. And, in the first few days of being in a foreign country, people's faces just look "weird". This contribution deals with the nature of cognition-emotion interactions in these more subtle *everyday evaluative responses* – basic liking/disliking reactions that can be captured by people's preference judgments, behaviors, and physiological measures. Our special focus is on the role of non-specific, dynamical aspect of processing in the formation of evaluative responses. We show how the mechanisms underlying such responses can be understood using a combination of psychological experimentation and mathematical modeling grounded in physical models.

Introduction

Overview

The structure of our contribution is roughly as follows. First, we distinguish various sources of evaluative responses – non-specific processing dynamics and specific feature-based information. Next, we describe empirical work suggesting that evaluative reactions to processing dynamics can explain several common preference phenomena. Then, we describe some computational models of mechanisms underlying dynamics-affect connection. Finally, we discuss some neural underpinnings of the dynamic-affect connection and close with suggestions for future work.

Dynamical and Featural Information

You walk down a busy street and scan the passing faces. Some you like, some you do not. Why? Psychologists explore this question by focusing on the "how" and "what" of processing. The "how" refers to non-specific dynamical information about the quality of processing, and the "what" refers to specific feature-based information. Let us distinguish these two sources and briefly characterize their relationship.

During any kind of processing, sometimes even before any specific features are extracted from the stimulus, the mental system has access to a nonspecific source of information – the dynamics accompanying the processing of the stimulus. Historically, interest in the non-specific dynamics of processing originated in the field of metacognition [37,47,50]. This work highlighted that people monitor not only the content ("what") of mental representations, but also the "how" of processing, including such non-specific parameters as processing speed, ease, representation strength, volatility, and the degree of match between the incoming information and stored representations. Although there are substantial differences between these various parameters, it is common to refer to these non-specific aspects of processing with the general term of "*fluency*" (for reviews see [34,77]). As we describe shortly, the central idea guiding this review is that high fluency is typically associated with positive evaluations.

Evaluation is also obviously influenced by "what" is extracted – the stimulus' specific *features*. Thus, the overall positivity of a response to a face of a passing stranger will also depend on detection of such features (e. g., a smile or a symmetrical appearance), and on the perceivers idiosyncratic appraisals of these features (e. g., interest in meeting a stranger). There are many available reviews of the experimental and modeling work on featural processing in evaluation and emotion, so we will not repeat it here [1,3,76]. But we want to highlight a couple of things about the relation between dynamical and featural aspects of processing. First, both sources of information are available simultaneously, with each contributing to the net evaluative reaction. For example, positivity from detecting a smile can combine with positivity from high fluency of recognition. Second, the dynamical and featural sources can play off each other. For example, the same feature, such as symmetry, might create a positive reaction because of its implications (e. g., good health), but also make the face easier to recognize. In other words, a feature might not only create an evaluative reaction directly, but also indirectly, via its influence on the processing dynamics.

How is it Going? Linking Dynamics and Affect

The idea that dynamical aspects of information processing have affective implications has been discussed in several domains of research. The major proposals focus on the role of dynamics as cue to the quality of the internal state of the system, or as a cue to the quality of an external stimulus.

Feedback About Quality of Internal Processing

At least since Simon [81], psychologists assume that one function of affect to provide information about the internal state of the system. Thus, unless there is an obvious external cause for feeling good or bad, the presence of negative affect conveys that something is internally "wrong", whereas positive affect conveys that things are going "right" (e. g., [8]). More specifically, affect can provide information about the current state of cognitive operations. Thus, high fluency of a perceptual or a conceptual process indicates progress toward, for example, successful recognition of the stimulus or a successful solution of a task. Besides informing the organism that processing is going well, positive affect triggered by high fluency may play a motivational function and reinforce the successful strategy [62,91]. On the other hand, low fluency can be a signal of cognitive error or incompatibility, and play a motivational role in revision of a processing strategy [12,18]. These ideas converge with classic observations that mental states characterized by low coherence, such as cognitive dissonance, are unpleasant, as indicated by self-report as well as physiological measures of affect [24].

Feedback About Quality of External Stimuli

Processing dynamics can also have affective consequences because it informs (probabilistically) whether an external stimulus is good or bad. For example, it's known, at least since Titchener [90], that familiar stimuli elicit a "warm glow." Conversely, illusions of familiarity (oldness) can be produced through unobtrusive inductions of positive affect [20,60]. One reason for this warmth-familiarity link could be biological predispositions for caution in encounters with novel, and thus potentially harmful, stimuli Zajonc [101]. Other accounts suggest that familiarity is just a learned, "fast and frugal" heuristic for easily identifying choices that are in truth objectively better [21]. Similarly, as we discuss next, dynamics could offer a probabilistic cue regarding other valued properties of external stimuli, such as symmetry, prototypicality, etc.

Psychological Evidence for the Role of Fluency in Evaluation

So far, we have focused on theoretical reasons for the dynamics-affect connection. The specific empirical research on the role of dynamical information in affect has centered around five related variables: (i) repetition/mere exposure, (ii) priming, (iii) contrast, clarity, duration, (iv) symmetry and (v) prototypicality. As we show, all these preference phenomena are consistent with the notion that high processing fluency enhances evaluations (for more comprehensive review see [66,99]).

Mere-Exposure/Repetition

The "mere exposure effect" (MEE) is the observation that simple repetition enhances liking for an initially neutral stimulus [101]. Interestingly, all that is required for the MEE is that the stimulus is "merely" shown, however briefly or incidentally, to the individual – no reinforcement is required and the presentation can be even subliminal (for reviews see [5]). The reader has probably experienced this phenomenon many times. Thus, most melodies and paintings "grow on you" with repeated exposure, faces that are simply familiar tend to generate a "warm glow," and advertisers try to increase sales by simply repeating product's name or image. Anecdotes aside, empirical evidence for the mere exposure effects is quite robust. For example in a study by Monahan, Murphy, and Zajonc [51], participants were subliminally exposed to 25 pictures of novel ideographs, and were later asked to report their tonic mood. For some participants, each of the 25 ideographs was different, while for other participants, 5 different ideographs were repeated 5 times each. The results showed that participants who were subliminally exposed to repeated ideographs reported being in a better mood than participants exposed to 25 different ideographs. Additional evidence for the positivity of reactions from the mere exposure effect comes from studies that used facial electromyography (EMG). This technique relies on the observation that positive affective responses manifest themselves in incipient smiles, as reflected by higher activity over the cheek region – zygomaticus major – whereas negative affective responses manifest themselves in incipient frowns, as reflected by higher activity over the brow region – corrugator supercilii [7]. Harmon-Jones and Allen [25] observed that repeatedly presented stimuli elicited stronger EMG activity over the "smiling" region of the participants' face (cheek), indicative of positive affect, without changing the activity over the "frowning" region (brow).

There is now good evidence that the mere-exposure effect reflects changes in processing fluency – the ease of recognition (e. g., [6,34,36,45,79]) . Stimulus repetition speeds up stimulus recognition and enhances judgments of stimulus clarity and presentation duration, which are indicative of processing facilitation (e. g., [22,33]).

Priming

Based on the just mentioned research, we may expect that any variable that facilitates processing should result in increased liking, even under conditions of a single exposure. Several studies confirmed this possibility. In one of these studies (see Study 1 in [65]) participants were exposed to pictures of everyday objects (e. g., a desk, bird, or plane). The processing fluency of these target pictures was facilitated or inhibited by subliminal presentation of visual contours (e. g., [2]). Some target pictures were preceded by matched contours (e. g., contour of a desk followed by a picture of the desk), whereas others were preceded by mismatched contours (e. g., contour of a desk followed by a picture of a bird). Some participants were asked to indicate how much they liked the target pictures; other participants were asked to press a button as soon as they could recognize the object in the picture, thus providing an independent measure of processing ease. The data showed that pictures preceded by matched contours were recognized faster, indicating higher fluency, and were liked more than pictures preceded by mismatched contours.

Importantly, Winkielman and Cacioppo [95] provided evidence for the positivity of reactions caused by priming using the earlier-mentioned technique of facial electromyography (fEMG). High fluency was associated with stronger activity over the zygomaticus region (indicative of positive affect), but was not associated with stronger activity of the corrugator region (indicative of negative affect). This effect occurred in the first 3 seconds after the presentation of the stimulus, which was several seconds before participants made their overt judgments. This suggests a quick link between high fluency and positive affect.

Contrast, Clarity, and Duration

High contrast and clarity have repeatedly been identified as characteristics of aesthetically appealing objects (e. g., [86]). According to our proposal, these properties trigger liking because they facilitates processing. In one study (see Study 2 in [65]) we manipulated fluency through different degrees of figure-ground contrast, taking advantage of the observation that high contrast decreases identification speed [9]. Participants liked the same stimulus more when it was presented with higher contrast, and hence could be processed more fluently. In another study (see Study 3 in [65]) we manipulated fluency through subtle increases in presentation duration, taking advantage of the observation that longer presentation durations facilitate the extraction of information [44]. As expected, participants evaluated the same stimulus more positively when it was presented for a longer duration, even if they were were unaware that duration was manipulated. Winkielman and Cacioppo [95] replicated these results and also found corresponding changes in EMG activity, which suggests that high fluency elicits positive affect on the physiological level.

Symmetry

Humans and non-human animals show a widespread preference for symmetry [67]. This is often attributed to the biological value of symmetry as a signal of mate quality (e. g., [89]). However, we propose that symmetry is appealing at least partly because it facilitates information processing. After all, symmetrical stimuli are structurally simpler, and thus more fluent, than non-symmetrical stimuli. Support for this comes from studies on preference and fluency of abstract shapes [64]. These researchers asked participants to make preference judgments and also same-different judgments for symmetrical and asymmetrical shapes. The results showed that symmetrical shapes are not only more appealing, but also easier to identify than comparable asymmetrical shapes. This finding is compatible with earlier studies by Palmer and his colleagues showing that symmetry is preferred, as long as it facilitates information processing. Specifically, Palmer [58] presented the same symmetrical dot patterns (such that overall amount of information was held constant) in one of three orientations – vertically, diagonally, or horizontally – and asked participants to rate the figural goodness of each of the patterns. He found that dot patterns presented in the vertically symmetrical orientation received the highest figural goodness ratings, followed by those presented in the horizontally symmetrical orientation, with those presented in the diagonally symmetrical orientation receiving the lowest figural goodness ratings. Importantly, the figural goodness ratings paralleled earlier work by Palmer and Hemenway [59] on ease of symmetry detection: symmetry in the dot patterns presented in vertically symmetrical orientations was detected the fastest, followed by the symmetry in the horizontally symmetrical orientations, with the symmetry of the dot patterns presented in diagonally symmetrical orientations being the most difficult to detect. Since each of the patterns in the three orientations contained the same amount of information, this result suggests that symmetry makes any given stimulus more appealing because it facilitates the ability of the perceiver to detect redundant information and, as such, to more easily identify the stimulus.

Prototypicality

Another robust source of preference is prototypicality or "averageness" – in the sense of a stimulus providing the "best representation" of the category, or fitting its central tendency [67]. People show prototypicality preference for living objects, such as faces, fish, dogs and birds, and also for nonliving objects, such as color patches, furniture, wristwatches and automobiles [23,40]. This effect, known since Galton [19], has also been explained as reflecting evolved predisposition to interpret prototypicality as a cue to mate quality [88]. However, there is a more straightforward dynamical explanation. Given that prototypes are the most representative members of their categories, they are also fluent, as reflected in accuracy and speed of classification [66]. This raises the possibility that prototypes are liked *because* they are fluent. Winkielman, Halberstadt, Fazendeiro, and Catty [96] examined this idea in a series of three experiments. Participants first learned a category of random dot patterns (Experiment 1) or of common geometric patterns (Experiment 2) and then were presented with novel patterns varied across different levels of prototypicality. Participants classified these patterns into their respective categories as quickly as possible (measure of fluency), and also rated the attractiveness of each. A close relationship between fluency, attractiveness, and the level of prototypicality was observed. Both fluency and attractiveness increased with prototypicality. Importantly, when fluency was statistically controlled, the relation between prototypicality and attractiveness dropped by half (though it remained significant). This suggests that processing facilitation is important to, but not the sole cause of the "beauty-in-averageness" effect. Finally, Experiment 3 showed that viewing prototypical, rather than non-prototypical patterns elicited significantly greater EMG activity, suggesting that viewing prototypes involves genuine affective reactions.

In combination, the above studies, based on manipulations of repetition, figure-ground contrast, presentation duration, symmetry, and prototypicality consistently show that high perceptual fluency leads to more positive evaluations of the perceived stimuli. However, verbal descriptions of fluency are often vague and so fluency is often difficult to quantify – what exactly does it mean that one stimulus is more fluent than another? The answer to this question has been provided by computational models inspired by physical phenomena.

Computational Mechanisms

There is surprisingly little research on the role of dynamical parameters in cognition and emotion [55,61]. One notable exception is the Neural network approach, or connectionism, in which cognition is viewed in terms of the passage of activation among simple, neuron-like units organized in large, densely interconnected networks [73]. The individual units function as simple processors that can influence each other through connections, which vary in strength and sign (facilitatory or inhibitory). This massively interconnected and parallel architecture gives the neural network approach a certain neurophysiological realism and makes it suitable for a wide variety of applications. For more biological applications, one can conceptualize the network units as actual neurons, whereas for more psychological applications, one can treat the units as blocks of neurons or functional sub-systems [57]. Many different neural network architectures have been proposed that utilize dynamical parameters. Below we primarily focus on a proposal by Lewenstein and Nowak [42], which illustrates the role of dynamical parameters in learning and recognition using a simple attractor neural network [26]. Although this is in some regards an overly simplified model, the conceptual framework of the attractor network has been successfully expanded to more complicated applications, such as the plasticity-stability dilemma [52], and more realistic biological assumptions [54,84]. We address some of these more complex models later.

Fluency in a Hopfield Network

In a typical Hopfield network, representations are encoded as attractors of the network, i. e. states into which the network dynamics converge. The processing of information with the network can be seen as a gradual, evolving process, during which each neuron adjusts to the signal coming from other neurons. Because neurons are reciprocally connected, and because there are a large number of paths connecting one neuron to another, activation can reverberate dynamically through the network over simulated time steps until the network settles on the identified representation. For example, when presented with a to-be-recognized pattern, the network goes through a series of adjustments and after some time approaches a stable state, an attractor, corresponding to the "recognition" of a particular pattern.

Lewenstein and Nowak [42] proposed that a typical Hopfield model can be extended with a simple control mechanism, which allows the network to monitor the dynamics of its own processing. Such a control mechanism can measure a variety of dynamical parameters, such as settling time, volatility, signal strength, coherence, and so on. These formally related properties can then be used by the network to roughly monitor the quality of its own processing (e. g., is it going well?) as well as estimate the characteristics of the stimuli being processed (e. g., is it familiar).

Studies with this model focused on how monitoring the dynamical properties of cognition can allow the network to estimate proximity to its closest attractor during the recognition process. This, in turn, allows the network to estimate the likelihood that the presented pattern is "known", without requiring full specification for the manner in which the attractor is known. Specifically, two key dynamical properties were identified. The first property is the network's "volatility", or the proportion of neurons changing their state at a given point. When the incoming, "to-be-recognized" pattern matches or closely approximates a known pattern, corresponding to one of the attractors (memories), the network is characterized by a relatively small proportion of neurons changing their state. When the incoming pattern is novel, and thus does not approximate one of the attractors, the network is characterized by a large number of neurons changing their state. The second key dynamical property is the coherence of the signals received by the neurons. In the vicinity of an attractor (old pattern), the signals arriving from other neurons at a given neuron are consistent in that they belong to the same pattern. However, when the network is far from an attractor (new pattern), the signals arriving from other neurons at a given neuron dictate conflicting states and may provide partial matches to a variety of other patterns. A closely related criterion is the signal-to-noise ratio. In the vicinity of the attractor (old pattern), signals from other neurons typically add up, resulting in a relatively large summary signal dictating the state of a given neuron. However, far from an attractor (new pattern), signals from other neurons cancel each other, resulting in a relatively weak summary signal dictating the state of a given neuron. As a consequence, the processing of "old" patterns is characterized by a higher signal-to-noise ratio than the processing of "new" patterns.

Extension to Graded Representations and Incremental Change

Traditional Hopfield networks use simulated neurons that are either "on" or "off", with no graded signal between these states. More realistic simulated neurons use a continuous range of intermediary values, allowing a graded measure for the magnitude and speed of settling into attractor states (e. g., [57]). However, because many applications are focused on learning and representational change, large simulated time steps are used and settling occurs in less than 10 time steps, which makes it difficult to measure relatively subtle differences in settling time. For such applications, fluency is measured rather indirectly as differentiation – the magnitude of the most active units [42]. Providing a more direct measure of fluency based on speed of processing, we have used neural simulations with millisecond time steps, which allows measurement of the time needed to achieve peak activation [28,30]. Not only does this provide a measure of choice preference, but it can be used to indicate reaction times [29]. In these real-time simulations, habituation dynamics are implemented such that activation achieves a peak value, but then falls to a lower value with continued processing. Because well learned representations include stronger connections, and because activation is the driving force behind habituation, familiar representations reach a peak value more quickly as habituation occurs more quickly [31].

Fast Fluency

The modeling work on fluency also shed light on the puzzling phenomenon when the system responds affectively to a pattern before it is fully recognized ("preference without inference", Zajonc [101]). Processing speed, volatility, differentiation, and the onset of habituation are all measurements of fluency that allow the network to estimate whether a pattern is "new" or "old" (i. e., proximity to its closest attractor) prior to explicit identification of the pattern. For instance, it is possible to determine the familiarity of incoming stimuli by monitoring how frequently a mere 10% of the neurons change their state during the very first time step [42]. Similarly, a fast familiarity signal can be based on the early differentiation [53]. It is also worth noting that checking the coherence of incoming signals makes it possible to estimate not only the global novelty of the whole pattern, but also the novelty of fragments in the perceived pattern, such as elements of an object or objects in a scene [103]. As discussed earlier, because familiarity is affectively positive, all these mechanisms explain how one can "like" something before even knowing what it is.

Fluency and Self-Regulation

In addition to quick feedback about the valence of the incoming stimulus, the early pre-recognition of familiarity may be used to control the recognition process, so that known stimuli are processed differently than new ones.

This may be achieved by linking the outcome of pre-recognition based on monitoring the system dynamics to a control parameter (e. g., network's overall noise level) that influences the later stages of the recognition process. A number of specific models that involve a feedback loop between pre-recognition and the noise level have been proposed. For example, in the original model by Lewenstein and Nowak [42], unknown patterns raised the noise level, preventing false "recognition" of unfamiliar patterns – a common problem for neural networks. In another example, by monitoring its own early dynamics a network can switch between recognizing known patterns and learning novel patterns [104]. Yet another implementation of this control mechanism allows a network to recognize the emotional quality of the stimulus in the pre-recognition process and use this emotional pre-recognition to facilitate the recognition of stimuli that are relevant to this emotion [102]. For an extensive model of how such loops are used in self-regulation, see Nowak and Vallacher [55] and also Vallacher and Nowak [91].

Modeling Fluency-Affect Interactions: The Influence of Specific Variables

So far, we have discussed computational models of fluency in terms of more general principles. In this section, we show that such models can be used to precisely specify the processing dynamics that underlie affective responses in several concrete empirical phenomena discussed earlier. To recall, experimental psychological research found that positive affect can be enhanced by repetition, priming, figure-ground contrast, presentation duration, symmetry, and prototypicality. How does this work computationally?

Repetition

Drogosz and Nowak [14] used a dynamic attractor neural network to simulate the effect of repetition on liking and explicit recognition. Specifically, they modeled the results of a study by Seamon, Marsh, and Brody [78] who exposed participants to 50 repetitions of polygons, presented at very brief exposure times ranging from 2 to 48 milliseconds. As in other mere exposure experiments, participants showed an increased preference for repeated polygons, even those presented at 2 and 8 milliseconds. Moreover, their preference increased with increasing exposure times, but reached asymptote at 24 milliseconds. In contrast, explicit recognition was at chance at low durations (2 and 8 milliseconds), and then gradually increased up to 90% recognition at 48 milliseconds. The model by Drogosz and Nowak [14] showed that the relationship between preference and recognition as a function of exposure time can be simulated by assuming that the affective response represents a non-specific signal about the early dynamics of the network, as indexed by the estimated proportion of change in the first time step, whereas the recognition response represents a stabilization of the network on a specific pattern, which takes approximately 6 time steps. A psychological interpretation that can be attached to these simulation data is that at very short presentation durations, the participants only have access to the non-specific fluency signal, which elicits positive affect and influences their preference judgments. With progressively longer presentation duration, the fluency signal (affective response) increases only marginally, whereas the recognition response continues to grow until it reaches nearly perfect performance. The above simulations show that many prior exposures to a pattern establish a relatively strong memory for this pattern, whereas few prior exposures establish a relatively weak memory for the pattern. Test patterns with relatively stronger memories (i. e., stronger attractors) are processed with higher processing fluency (less volatility, more coherent signals) than test patterns with weaker or no memories. These differential fluency signals are picked up early on, as indicated by the simulation, and precede the extraction of stimulus information. Because the fluency signal is hedonically marked, it allows for evaluative responses prior to stimulus recognition, as initially reported by Kunst-Wilson and Zajonc [38].

Computational models of this type can also help us conceptualize the results of studies that used all novel patterns and manipulated the fluency of processing through procedures like figure-ground contrast, presentation duration, symmetry, prototypicality, and priming. To account for these effects, the model requires only minimal modifications. Specifically, the above simulations were carried out in attractor networks composed of neurons with binary states, where a state of the neuron corresponds either to the presence or the absence of the feature preferred by that neuron [26]. However, the same "fluency" criteria (volatility, coherence, differentiation) apply to networks with continuous neurons, where the state of a neuron encodes the degree to which a feature is present or activated [27,57].

Duration, Clarity and Contrast

The influence of these liking-enhancing variables can be conceptualized as reflecting a process in which patterns presented for longer time, greater clarity, and higher contrast are represented by more extreme values of activation. All this leads to stronger signals in the network, more differentiated states of the neurons, and faster settling.

Symmetry

This highly valued feature is easily incorporated because the representation of symmetrical patterns is stronger. This is due to simplicity and redundancy (e. g., in faces the left side of the symmetrical faces is identical to the right) and position-independence in recognition (e. g., symmetrical face looks the same from different angles). In contrast, the representation of asymmetrical features is weaker due to complexity and position-dependence [15,35].

Prototypicality

The effects of prototypicality (responsible for the 'beauty-in-averages' effect) can result from converging exemplars creating a strong attractor for a prototype. As a result, the recognition of a prototype pattern typically involves faster settling time, and less volatility [97]. Recent computational models of fluency using a support vector machine (a nonlinear classifier) have also shown that prototypical faces are located further from a face/non-face classification boundary, which allows for more efficient categorization [72].

Priming

In neural networks, priming corresponds either to the pre-activation of neurons that encode the pattern (activation-based priming) or to temporary changes in weights between the neurons (weight-based priming). The effects of the prime and the actual target sum up in determining the state of neurons. This results in more extreme values of activation (i. e., better differentiation) of the neurons for primed versus non-primed patterns.

As mentioned previously, fluency might be better captured by models that simulate the real-time, millisecond by millisecond processing of information. With such a model, we have explained a variety of empirical priming phenomena by including habituation dynamics (decrease in responding as a result of repetition or strong activation). In this model the presentation of a minimal prime (i. e., a brief duration or a single stimulus) immediately prior to a target induces a positive priming effect through pre-activation that boosts fluency. This is similar to the above mentioned pre-activation model. However, our model also predicted that presentation of an excessive prime (i. e., a long duration or repeated stimulus) immediately prior to a target would eliminate the positive priming effect, or perhaps even induce a negative priming effect. This occurs because habituation to the prime produces a disfluency in processing the target (i. e., the response to the target occurs slowly). This transition from positive to negative priming as a function of prime duration explained a variety of priming phenomena in the domain of word identification [28] and recognition memory [31].

We recently demonstrated in several experiments that this fluency-disfluency dynamic also applies to the domain of evaluation, more specifically, the appearance and disappearance of evaluative priming effects [32]. These experiments explored predictions for situations that should produce or eliminate priming as a function of prime duration, prime-target similarity and target salience. More specifically, when the prime-target similarity is low, such as with extremely valenced prime words and ideograph targets that have no meaning, habituation to the prime does not produce habituation to the target, and so empirically there is no correction effect even with long duration primes. Furthermore, when the target is itself minimal (e. g., a subliminally presented target word), then there is only an assimilative pre-activation effect because, again, habituation to the prime does not cause a change in target processing. In short, the fluency-based priming models can explain not only when the evaluative priming occurs, but also when it disappears.

In sum, the just discussed computational models show that manipulations such as repetition, priming, presentation duration, figure-ground contrast, clarity, prime-target similarity, and prototypicality change fluency in the network dynamics. These changes in fluency can trigger an affective response via the monitoring mechanisms discussed earlier.

Neural Basis of Fluency–Affect Connection

The assumptions guiding the just discussed psychological and computational models are consistent with neuroscience evidence. So far, this work has focused on low-level perceptual effects of stimulus repetition, response of higher-level value-coding system to previously exposed stimuli, and effects of processing coherence and conflict.

Perceptual Response

There is much evidence that novel stimuli elicit a non-specific, undifferentiated activity, which gradually decreases with repetition [82,85]. More specifically, single cell recording and neuroimaging studies suggest that stimulus repetition tends to decrease non-specific activation and leads to more selective firing [13,71]. One interpretation of these data is that stimulus familiarization leads to a gradual differentiation of the neurons that represent the incoming stimulus from neurons that do not represent the stimulus [48,54].

Response of Value-Coding Regions

A specific example of neuroscience research that examined connections between novelty and evaluation comes from Elliot and colleagues. Elliot, Dolan, and Frith [17] reported an fMRI study on the neural substrates of delayed matching to sample, as compared with delayed nonmatching to sample. In such a task, participants are initially shown an item and then are subsequently shown a pair of items whereby they have to identify either the item they saw or the one that they did not see. Significantly more activity occurred in the ventromedial OFC in the matching condition (while reprocessing an old item) as compared to the non-matching condition (while processing a novel item). This conclusion is consistent with results of an earlier PET study of the subliminal mere exposure effect by Elliot and Dolan [16]. In their study, when participants made preference judgments, repeated stimuli activated the medial PFC, an area closely connected to the medial OFC and that is also known for its role in reward processing. Notably, these neuroimaging studies showing activation of neural circuits involved in reward to repeated stimuli fit nicely with the earlier reviewed Harmon-Jones and Allen [25] EMG study showing greater zygomaticus activation to merely exposed items. Taken together, they highlight the multilevel hedonic consequences of mere exposure and, more generally, high processing fluency.

Processing Coherence and Conflict

There is also work on the neural basis of mechanisms involved in successful and unsuccessful integration of different cognitive representations [10]. Neuroimaging evidence highlights a particular role of the anterior cingulate cortex (ACC) [18,39]. Though originally thought of as primarily a "cognitive" structure, more recent studies suggest that enhanced ACC due to cognitive conflict is accompanied by negative affect and enhanced arousal [10]. If so, the ACC could provide a neural substrate by which processing coherence on the level of multiple representations translates into negative affect.

Future Directions

Several issues remain essential for further studies. First, we primarily focused on the role of perceptual sources of dynamical information. However, dynamical information is available across the entire processing spectrum, from simple pattern matching to semantic coherence of high-order conceptual content. Though there is some psychological work available on this issue, there is very little computational and neural work that deals with specific mechanisms [97]. Second, emerging evidence in psychology suggests that the impact of fluency is moderated by processing expectations – how much speed, effort, coherence is expected given the stimulus [93]. For example, the simulations by Drogosz and Nowak [14] discussed earlier were conducted using very similar patterns, as is typical in the mere-exposure studies. Accordingly, the absolute processing fluency of a given pattern was a reliable indicator of its "oldness." However, for the fluency signal to be informative in a more realistic situation, in which stimuli differ widely in overall signal strength, the network needs to scale the absolute value of the fluency signal for the particular pattern against the expected value [93] . A comparison between an observed value and an expected value can be derived with a computational likelihood ratio model, which is a class of model that has proven remarkably successful in explaining recognition memory based on familiarity [48,80]. Developing a similar Bayesian approach to fluency would likewise provide a precise account for the role of expectations in the study of affect. Finally, this contribution has emphasized the role of non-specific dynamical information in evaluation and has been silent on the role of specific stimulus features. However, we know very little about the interaction the proposed fluency based "how" and the content based "what" of processing, and exploring this interaction may prove a useful direction for future research.

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Dynamics on Fractals

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Article Outline

Glossary

Fractal Fractal structures are of two types: deterministic fractals and random fractals. The former involves repeated applications of replacing a given structural element by the structure itself. The process proceeds indefinitely, leading to *dilation symmetry*: if we magnify part of the structure, the enlarged portion looks the same as the original. Examples are the Mandelbrot–Given fractal and the Sierpinski gasket. A random fractal obeys the same properties (e. g. dilation symmetry), but only in terms of an ensemble average. The stereotypical example is the percolating network. Fractals can be constructed in any dimension, d, with for example, $d = 6$ being the mean-field dimension for percolating networks.

Fractal dimension The fractal dimension represents the "mass" dependence upon length scale (measuring length). It is symbolized by D_f, with the number of sites on a fractal as a function of the measurement length L being proportional to L^{D_f}, in analogy to a homogeneous structure embedded in a dimension d having mass proportional to the volume spanned by a length L proportional to L^d.

Spectral (or fracton) dimension The spectral (or fracton) dimension refers to the dynamical properties of fractal networks. It is symbolized by $\tilde{d}_\mathrm{s}$ and can be most easily thought of in terms of the density of states of a dynamical fractal structure (e. g. vibrations of a fractal network). Thus, if the excitation spectrum is measured as a function of energy ω, the density of states for excitations of a fractal network would be proportional to $\omega^{(\tilde{d}_\mathrm{s}-1)}$, in analogy to a homogeneous structure embedded in a dimension d having a density of states proportional to $\omega^{(d-1)}$.

Localization exponent Excitations on a fractal network are in general *strongly localized* in the sense that wave functions fall off more rapidly than a simple exponential, $\Psi(r) \sim \exp[-\{[r/\Lambda(\omega)]^{d_\phi}\}]$ where $\Lambda(\omega)$ is an energy dependent localization length, and the exponent d_ϕ is in general greater than unity.

Definition of the Subject

The dynamical properties of fractal networks are very different from homogeneous structures, dependent upon