How does rumination impact cognition? A first mechanistic model.

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Abstract

Rumination is a process of uncontrolled, narrowly-foused negative thinking that is often self-referential, and that is a hallmark of depression. Despite its importance, little is known about its cognitive mechanisms. Rumination can be thought of as a specific, constrained form of mind-wandering. Here, we introduce a cognitive model of rumination that we developed on the basis of our existing model of mind-wandering. The rumination model implements the hypothesis that rumination is caused by maladaptive habits of thought. These habits of thought are modelled by adjusting the number of memory chunks and their associative structure, which changes the sequence of memories that are retrieved during mind-wandering, such that during rumination the same set of negative memories is retrieved repeatedly. The implementation of habits of thought was guided by empirical data from an experience sampling study in healthy and depressed participants. On the basis of this empirically-derived memory structure, our model naturally predicts the declines in cognitive task performance that are typically observed in depressed patients. This study demonstrates how we can use cognitive models to better understand the cognitive mechanisms underlying rumination and depression.

Keywords: mind-wandering; rumination; associative memory; depression; sustained attention

Introduction

Rumination is the process of narrowly-focused uncontrolled repetitive negative thinking—mostly self-referential—that lies at the core of depression (Marchetti, Koster, Klinger, & Alloy, 2016; Nolen-Hoeksema & Morrow, 1991; Treynor, Gonzalez, & Nolen-Hoeksema, 2003). Despite the serious clinical consequences of this process, there is to date no coherent computational cognitive theory that describes it. While there are several verbal theories (Marchetti et al., 2016), those can only explain their own limited set of experiments and do not make quantitative predictions.

To develop a theory of rumination, we built on recent research and modeling of mind-wandering, because rumination can be thought of as a highly constrained form of mind-wandering (Christoff, Irving, Fox, Spreng, & Andrews-Hanna, 2016). Mind-wandering is a process of task-unrelated thinking that takes up approximately 50% of our time (Killingsworth & Gilbert, 2010; Smallwood & Schooler, 2015), and can sometimes help and sometimes hinder performance. For example, in very undemanding contexts, mind-wandering can serve useful functions for creativity (Baird et al., 2012) and planning (Baird, Smallwood, & Schooler, 2011). On the other hand, it disrupts performance when it takes away cognitive resources that are needed to perform the task, and this occurs in particular when mind-wandering is unintentional and uncontrolled (Seli, Risko, Smilek, & Schacter, 2016), as is the case with rumination. This could explain why people that suffer from rumination typically also report having difficulties concentrating.

So far, the theories of rumination can be broadly divided into three classes. One class of theories suggests that rumination arises from an increased bias towards negatively-valenced information (Dalgleish & Watts, 1990). When attention is focused more on negative information, this reduces ability to focus on other things (Whitmer & Gotlib, 2013). Another class of theories instead focuses on inhibition, and suggests that the primary deficit underlying rumination is an inability to disengage from information, in particular when this information is negative and self-focused (Whitmer & Banich, 2007). The third theory of rumination—which we refer to as "habits of thought"—focuses not on control processes such as attention and inhibition, but rather on the content of thoughts during mind-wandering. Patterns of memory associations that are frequently rehearsed can become something like an attractor (Cramer et al., 2016), and therefore will be replayed any moment there is time for mind-wandering. To start to distinguish between these different theories of rumination, it is helpful to specify them in more detail by implementing them in a cognitive architecture, and to simulate their predictions for performance on a simple sustained attention task. Here we will start by implementing the habits of thought theory, which is of interest because it exploits the fact that the ACT-R cognitive architecture is in essence a memory theory.

To implement our theory of rumination, we will make use of our own computational model of mind-wandering (Taatgen, van Vugt, Daamen, Katidioti, & Borst, submitted; van Vugt, Taatgen, Bastian, & Sackur, 2015). This model frames mind-wandering in terms of resource competition, in which task goals compete with mind-wandering goals, and mind-wandering occurs when that goal wins the competition. Mind-wandering is modelled as a process of memory retrieval. Consequently, the mind-wandering model is uniquely suited for implementing the third theory of rumination, which says that rumination is driven by the existence of thought habits that are maladaptive. We hypothesize that these thought patterns are what causes people to get caught

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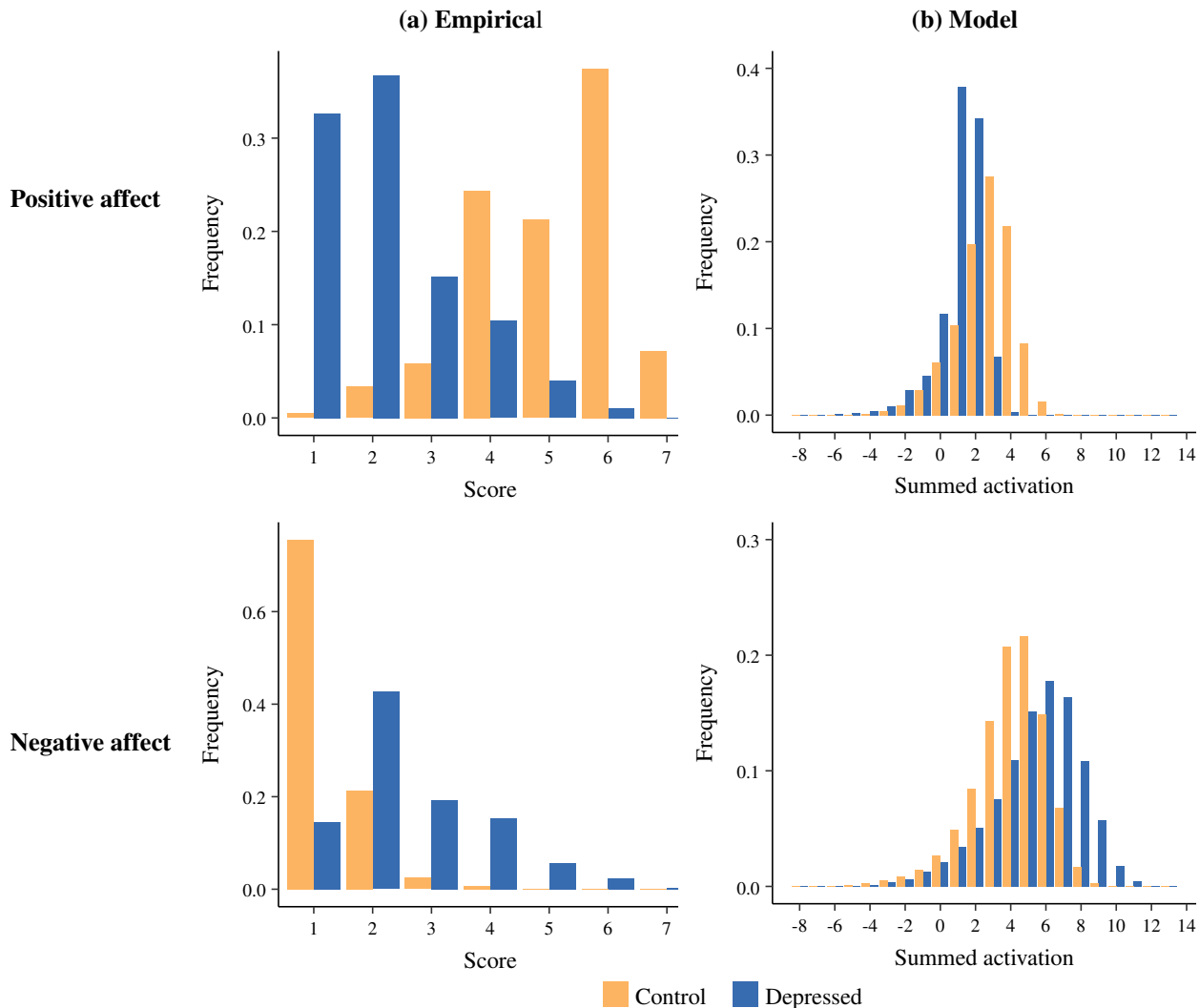
Figure 1: Reported positive and negative affect. (a) shows the frequency with which participants reported experiencing particular degrees of positive and negative affect in the experience sampling data, while (b) shows the summed activation of positive and negative chunks produced by the model (our closest proxy for the continuous affect ratings in the empirical data).

in a funnel of repetitive negative thinking, and disconnect from the current task, which leads to the perceived problems in concentration. This predicts that a model of rumination with exactly the same production rules but a different memory chunk structure should perform worse on a sustained attention task than a "healthy model." Later studies should implement the other two theories of rumination, and examine how their predictions may differ.

Methods

Mind-wandering model

We implemented our mind-wandering model (which forms the basis for the rumination model) in the adaptive control of thought-rational (ACT-R) architecture (Anderson, 2007; Anderson, Fincham, Qin, & Stocco, 2008). The model rests on two basic assumptions: firstly, there is a continuous competition between a mind-wandering and a task process, and con-

sequently, mind-wandering is likely to kick in when there is a spare moment in the task, and secondly, mind-wandering is primarily a process of memory retrieval (van Vugt et al., 2015; Taatgen et al., submitted); implemented as retrieving chunks from declarative memory. As is usual in ACT-R's memory retrieval, the most active chunk is the one that will be retrieved. Each chunk's activation is determined by three factors: the amount of recent use (more recent and more frequent use imply a larger chunk activation), the spreading activation from other chunks, and random activation noise. Since each chunk has a slot containing its emotional valence, the spreading activation ensures that chunks with the same emotional valence are more likely to follow each other than chunks with different emotional valence, in line with previous empirical results (van Vugt, Shahar, & Britton, 2012). The mind-wandering memory retrieval process continues until a memory chunk that is retrieved reminds the model of its main task.

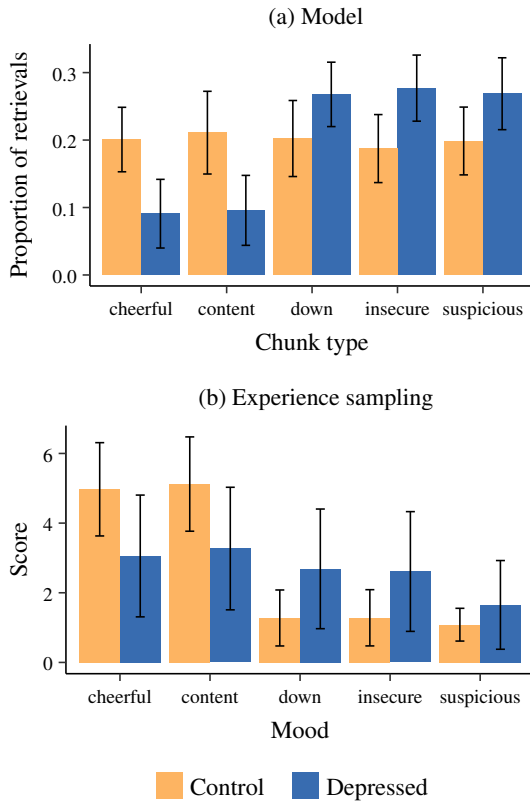(a) Model

(b) Experience sampling

Control   Depressed

Figure 2: The probability for memories being retrieved depends on their emotional valence. (a) The control model retrieves every mood more or less equally often, while the depressed model preferentially retrieves negatively-valenced items. (b) Empirical data shows that depressed participants experienced each mood with comparable intensity, while non-depressed controls displayed a bias towards positive moods. Error bars reflect standard error of the mean.

At that point, the main goal switches from mind-wandering to being on-task. During the period of mind-wandering, the retrieval module is busy retrieving memories, which means that responses to incoming stimuli will be done in automatic mode by giving the default response, and will not involve memory retrievals. In addition, since ongoing memory retrievals (which occur during mind-wandering) first have to be finished before a response is made, the mind-wandering process results in an increase in the variability of response times during mind-wandering, in line with behavioral findings (Bastian & Sackur, 2013; van Vugt & Broers, 2016).

The mind-wandering model was given a sustained attention to response task—SART (Cheyne, Carriere, & Smilek, 2009; Smallwood et al., 2004) to make testable predictions for behavioral. In this task, participants see a stream of digits, presented at a pace of one per three seconds, and they press a button whenever a digit is presented, except when it is the number three. The number three, the nogo stimulus, is presented on roughly 10% of the trials. This means that when participants do not pay attention, they will revert to an auto-

matic mode of responding, and fail to inhibit responses to the rare nogo stimuli.

Adaptations for modeling rumination

Our rumination model implemented the "habits of thought" theory of rumination. The main idea underlying this theory is that rumination consists of retrieval of a set of well-rehearsed thought patterns that are predominantly negative and self-referential. We tried out different methods for generating strong loops of self-referential negative thinking, and found that the most effective way was to increase the number of chunks with negative valence, such that these negative-valence chunks are more likely to be retrieved. This increase in the number of negative-valence chunks also increases the amount of spreading activation between them. Specifically, the non-depressed model has 55 chunks in total, 11 per mood (cheerful, content, down, insecure, suspicious—these moods were derived from the empirical data described below). The depressed model also has 55 chunks, but those consist of 5 chunks of each of the positive moods (cheerful and content), and 15 chunks of each of the negative moods (down, insecure and suspicious). For both models, the association strengths (S_{ji}'s) were 0.1 between moods of the same valence, and 0.01 between moods of different valence. These association strengths were chosen such that the spreading activations were roughly balanced with the base level activations, and slightly adjusted to better fit the empirical data. Our rumination models differ from our previous mind-wandering model in that there are two chunks that remind the user of the main task—one with positive and one with negative valence—instead of just one with a positive valence as was the case in the previous model.

To assess model performance, we simulated data for 100 participants suffering from rumination, and 100 participants with the usual model structure (i.e., without rumination). We chose for 100 participants because this is in the same ballpark as the empirical data. We then measured how many chunks of each mood the model recalled during mind-wandering episodes, together with their transition probabilities. These measures were compared to the experience sampling data described below to adjust the model. Once the models' memory structures were adjusted to exhibit thought contents similar to what was observed in the experience sampling data, we looked at the model's task performance, and examined whether rumination impaired performance on a simple go/nogo task (as would be expected).

Experience sampling data on depression

We configured the set of memory chunks and their associative structure on the basis of an experience sampling study (Wigman et al., 2015). In such a study, participants are prompted several times a day to respond to a brief questionnaire about their thoughts and experience. This study found that depressed patients had an increase in the number of negative-valence thoughts, more difficulty concentrating, and most importantly, a network of negative thoughts (specif-
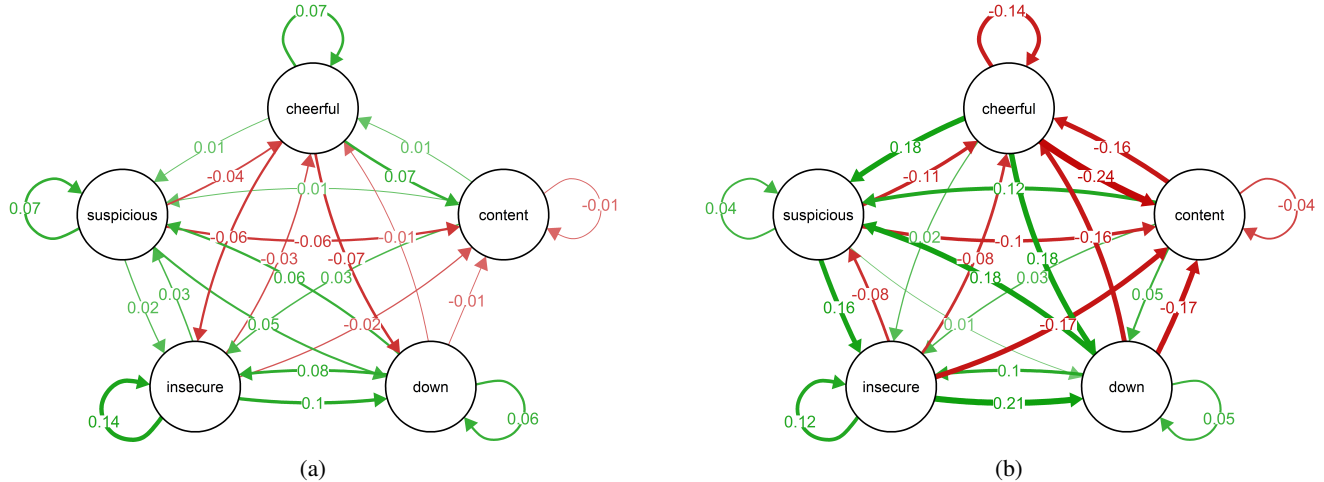
Figure 3: Transitions between different moods. (a) Difference between control and depressed networks in empirical data from Wigman et al. (2015) on the basis of regression coefficients. (b) Modeled network difference between depressed and control participants on the basis of transition probabilities. Green: control > depressed. Red: depressed > control.

ically, suspicious, down, and insecure) that was much more separate from the network of positive thoughts (content and cheerful) than in the control subjects. The experience sampling data we used in this study was collapsed across all participants in the depression and control groups. It contained data from 129 depressed patients and 212 non-depressed controls, who were sampled ten times per day for a period of 5-6 days.

Results

Average thought frequencies

Rumination is associated with increased negative memory and a prevalence of negatively valenced thought. To examine whether our model could reproduce those findings, we first compared the activation of positive-valence and negative-valence chunks, as well as the frequency of retrieval of the different subcategories. A challenge in this comparison is that the empirical data consists of the average rating of positive and negative emotions on a 7-point Likert scale, which has no direct correlate in the model. Since the judgment is supposed to reflect a participant's general mood, we used the summed activation of all positive/negative chunks as a proxy for positive and negative affect, respectively.

We were able to reproduce an increase in the summed memory activation of negative chunks, and a decrease in the summed memory activation of positive chunks (Figure 1(b)). We then examined how frequently positive and negative memory chunks were retrieved by healthy and depressed models. Figure 2(a) shows that while the healthy model retrieves positive and negative valence equally frequently, the depressed model tends to retrieve negative chunks more frequently (which then leads to a feedback loop, because these negative chunks then become more active, which makes it likely that they will be retrieved even more often). The empir-

ical data (Figure 2(b)) are somewhat similar, although here it appears as if healthy participants relatively suppress negative memory chunks. Note that this is at odds with a substantial body of literature that reports a negativity bias for depressed patients (Whitmer & Gotlib, 2013) instead of a positive facilitation in healthy controls (but see Levens and Gotlib (2010)).

Transitions between moods

A unique feature of the data presented in Wigman et al. (2015) was that not just frequencies of different types of thought were presented, but also the network of the transitions between different moods. In the empirical work by Wigman et al, these transitions were measured by fitting a multilevel linear mixed effect model to the data. Each score at time $t-1$ was used to predict the score at time point t, and this resulted in a fixed-effect coefficient for each connection between moods. The difference in magnitude of these coefficients between depressed and control participants is shown in Figure 3(a). The largest difference between healthy and depressed participants that our model needs to capture is an increase in the number of transitions between negative-valence chunks for the depressed patients, together with a decrease in the number of transitions between positive and negative valence chunks. As before, we cannot produce exactly the same measure in our model, which retrieves one memory chunk at a time. The closest approximation to the regression coefficients in the empirical data are transition probabilities between retrieved memory chunks with different moods. Figure 3(b) shows that when we measure the transitions for the depressed and control networks, we reproduce the somewhat stronger between-negative connectivity and the somewhat weaker positive-to-negative connectivity for the depressed model. Nevertheless, the modelled effects are not as strong as in the empirical data.
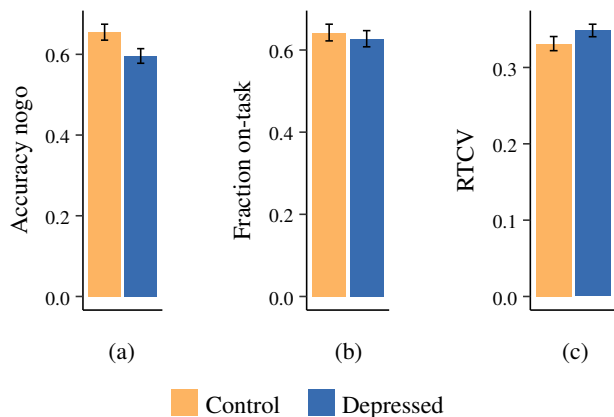
Figure 4: Comparison of performance of the control (orange) and rumination (blue) model on a sustained attention to response (go/nogo) task. The depressed model shows lower accuracy (a) but no difference in the fraction of mind-wandering (b),or coefficient of variation of response time to correct responses. Error bars reflect standard error of the mean.

Novel predictions: task performance

After having developed a rumination model by adapting the memory structure (i.e., thought patterns) on which it operates, we can examine how it performs on a cognitive task. In the data reported by Wigman et al. (2015), depressed participants reported having significantly more difficulty in concentrating than healthy controls ($t(4098.8)$=-44.1, $p < 2.2 * 10^{-16}$)[†]. Consequently, we predicted that the rumination model would exhibit an impairment on a sustained attention task that is typically used to measure mind-wandering, and that it would be distracted more frequently. Figure 4(a) shows that performance on a sustained attention to response task was worse for the depressed relative to the control model ($t(196.5)$=2.2, $p = 0.03$). A potential reason for this decline in performance is an increase in the amount of off-task thinking (Figure 4(b), although this change in off-task thinking was not statistically significant, $t(197.8)$=0.53, $p = 0.60$). There is also no significant difference in the coefficient of variation of response time (Figure 4(c); $t(195.1)$=1.39, $p = 0.17$), which is considered to be a sensitive index of off-task thinking.

Discussion

In summary, we have developed a novel approach to modeling psychopathology by means of cognitive architectures. We structured the model's memory on the basis of experience sampling data. We then used our existing mind-wandering model to make predictions for how performance on a sustained attention task would be impacted by rumination. We found that merely by modifying the structure and contents of the model's memory, we were able to produce retrieval frequencies and sequences similar to what was observed in the experience sampling study. In addition, our model predicted

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[†]T-tests used Welch's correction for degrees of freedom

impairments on a sustained attention task, in line with subjective reports of participants about difficulty with concentration.

While the model's performance was qualitatively in line with the observations from Wigman et al. (2015), we were not able to fit the exact patterns. This failure to fit may point at a structural limitation of our individual model, or of the general ACT-R cognitive architecture. It turned out to be very difficult to "create" cycles of rumination because ACT-R only adapts chunk activation, and not the associations between chunks, which may be the true habits of thought.

Another potential reason for this failure is our highly simplified representation of moods. Previous studies have represented mood in terms of physiology (Dancy, 2013) or in terms of expectations and desirability of the state of the world (Marsella & Gratch, 2009).

Our study makes an important contribution to the nascent field of computational psychiatry (Adams, Huys, & Roiser, 2016). So far, computational psychiatry involved mostly simple reinforcement learning models of psychiatric problems (but see Kottlors, Brand, and Ragni (2012)), while we demonstrated the utility of cognitive architectures. The advantage of using cognitive architectures compared to simpler theories, is that it is possible to simulate performance on many different tasks. Moreover, it becomes possible to examine changes in cognitive strategies (the "software of cognition") in the same context as changes in mental habits (the "hardware of cognition"), as we have demonstrated in this paper.

In summary, we have demonstrated how we can implement a cognitive theory of rumination, and make testable predictions about performance on a mind-wandering task. This leads to new avenues in better understanding what the exact mechanisms are that underlie rumination, and depression in general.

Acknowledgments

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