Safe models for risky decisions

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Chapter 1

Introduction

In everyday life, we often have to decide between options that differ in their immediate and long-term consequences. You may be tempted to eat a delicious piece of cake, but on the other hand, you might be afraid of gaining weight and getting diabetes, and consider eating an apple instead. Or imagine you are on a motor trip. You may choose to drive fast to experience excitement and adrenaline, but on the other hand, the danger of risking a heavy accident might convince you that it is more reasonable to drive slowly. Or yet another example, imagine you have to choose between one of the following two job opportunities: The first one comes with little challenges and opportunities for development, but is sufficiently paid and for an unlimited period; the alternative concerns a challenging job opportunity with new tasks and responsibilities, but that is limited to half a year. Which job opportunity would you prefer?

Risky decisions with unclear outcomes are the focus of much psychological research. To investigate how risky decisions are made in a controlled, experimental context, a large variety of tasks has been proposed. Popular examples are multi-armed bandit tasks or gambling tasks where participants are repeatedly asked to choose between at least two options (e.g., gambles) in such a way that they optimize their long-term outcomes. In this dissertation, I focus on a particular gambling task proposed in 1994 by Bechara, Damasio, Damasio, and Anderson, the Iowa gambling task (IGT; for alternative tasks, see the Balloon Analogue Risk Task, Lejuez et al., 2002; Wallsten, Pleskac, & Lejuez, 2005; the Columbia card task, Figner, Mackinlay, Wilkening, & Weber, 2009; and the Soochow gambling task, Lin, Chiu, & Huang, 2009).

In the IGT, participants are presented with four decks of cards; each card yields a reward and, occasionally, also a loss (see Figure 1.1 for an example screen shot of the IGT). Participants are told to repeatedly choose cards from the decks to optimize their long-term outcomes. Unbeknownst to the participants, two decks contain risky cards that have high immediate rewards on every trial but negative long-term outcomes because of occasionally very high losses, whereas the other two decks contain safe cards that have small immediate rewards on every trial and occasionally low losses, therefore resulting in positive long-term outcomes. For an overview of the payoff scheme, Table 1.1 presents the wins and losses associated with 10 example choices from each deck.

Participants can succeed on the IGT only when they learn to forego high immediate rewards and prefer the safe options (i.e., decks C and D) over the risky options. Bechara et al. (1994) claim that this choice behavior is characteristic for healthy participants and that they base their choices on the long-term outcomes of the decks. Such characteristic choice behavior of two typical healthy participants of Bechara et al. (1994) is presented in Figure 1.2. It is evident that the two participants “initially sampled all decks ( . . . ), but eventually switched to more and more selections
1. Introduction

Figure 1.1: Example screen shot of the IGT showing that a choice from the leftmost deck resulted in a reward of $100 and a loss of $0.

from the good decks C and D, with only occasional returns to decks A and B” (Bechara et al., 1994, p. 12).

In contrast to the successful IGT performance of healthy participants, Bechara et al. (1994) claim that patients with lesions to the ventromedial prefrontal cortex (vmPFC) — a part of the brain that is located at the frontal lobe at the bottom of the cerebral hemispheres — perform deficiently on the IGT. These vmPFC patients often make decisions that are irresponsible, risky, and go against their own interests. When confronted with a decision problem where the gains of immediate reward need to be weighted against the risks of long-term loss, vmPFC patients tend to focus on the immediate reward and disregard possible negative future outcomes of their choices, such as separation from family and friends, and loss of reputation and job (Bechara & Damasio, 2002; Dunn, Dalgleish, & Lawrence, 2006). The most famous vmPFC patient, Phineas Gage, survived an accident in which an iron rod lesioned his frontal cortex, causing a profound change in

Table 1.1: Wins and losses associated with 10 example choices from each deck of the IGT. Decks A and B are labeled as bad decks because they result in negative long-term outcomes, whereas the good decks (i.e., decks C and D) result in positive long-term outcomes. The last row shows, for each deck, the net outcome after 10 choices.

<table>
<thead>
<tr>
<th>Choice</th>
<th>Bad decks</th>
<th>Good decks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Deck A</td>
<td>Deck B</td>
</tr>
<tr>
<td>1</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>100, –150</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>100, –350</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>100, –300</td>
<td>100, –1250</td>
</tr>
<tr>
<td>6</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>7</td>
<td>100, –250</td>
<td>100</td>
</tr>
<tr>
<td>8</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>9</td>
<td>100, –200</td>
<td>100</td>
</tr>
<tr>
<td>10</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Net outcome</td>
<td>–250</td>
<td>–250</td>
</tr>
</tbody>
</table>
Figure 1.2: Deck selection profiles of two typical participants in Bechara et al. (1994)’s control group. These two participants first explore all decks, then gradually switch to the good decks, and only occasionally return to the bad decks.

Figure 1.3: Gage’s skull with an iron rod lesioning his ventromedial prefrontal cortex (downloaded October 2, 2016, from https://neurophilosophy.wordpress.com/2006/12/04/the-incredible-case-of-phineas-gage/).
1. Introduction

his decision-making abilities and social behavior (Figure 1.3). Prior to the accident, Gage was a hard-working, efficient, and responsible railroad construction foreman. However, after his accident he could not resume work because his behavior was impulsive, impatient, and antisocial. These symptoms are characteristic for vmPFC patients in general (Boes et al., 2011).

Due to the symptoms of patients with lesions to the vmPFC—in particular, their insensitivity to future consequences of their choices—these patients are assumed to prefer the risky options on the IGT (i.e., decks A and B). According to Bechara and his colleagues, the result of this “myopia for the future” is that the choice behavior of vmPFC patients is controlled primarily by immediate prospects, positive or negative (Bechara et al., 1994; Bechara, Tranel, & Damasio, 2000): “these subjects are unresponsive to future consequences, whatever they are, and are thus more controlled by immediate prospects” (Bechara et al., 1994, p. 14).

IGT performance is typically recorded for a clinical group and a control group. Subsequently, performance of the groups is compared using behavioral data analyses usually focusing on the overall proportion of choices from the good decks. Such analyses can tell us which choices participants made (e.g., that vmPFC patients made more risky choices than healthy participants), and how their preferences change as the task proceeds or as a reaction to experienced losses. However, behavioral data analyses cannot tell us whether, for example, the performance deficit of vmPFC patients was caused by a focus on immediate gains, poor memory, making it impossible for them to remember previously experienced payoffs associated with the different decks. In this dissertation, I argue that to overcome this shortcoming of behavioral data analyses, cognitive models should be used. These models make assumptions about the relevant psychological processes such as motivation (e.g., perceiving rewards as important as losses), memory (e.g., the ability to correctly remember past outcomes of the decks), and response consistency (e.g., the tendency to base decisions on one’s expectations about the decks), and how these processes interact to produce overt choice behavior.

Popular cognitive models for the IGT are so-called reinforcement learning (RL) models (Sutton & Barto, 1998). These models explain how autonomous agents learn to shape their decisions through trial and error, and all the experiences they had with each options up to the point of the decision. RL models are especially suitable for IGT data because of the repeated nature of the IGT that raises the question as to how much people explore the different options before they exploit the most profitable ones, and what drives this exploration-exploitation tradeoff. As will become apparent in this dissertation, there exist a large variety of RL models that have been applied to IGT data from various clinical groups. A prominent example is the study of Yechiam, Busemeyer, Stout, and Bechara (2005) using the Expectancy Valence model (EV; Busemeyer & Stout, 2002)—the first RL model that has been proposed for the IGT. This study presents the parameters of the EV model for 10 different clinical groups relative to the parameters of their respective control group of healthy participants (Figure 1.4). The purpose of this analysis was to understand differences between the 10 clinical groups in terms of the model parameters that reflect the psychological processes involved in risky decision making. According to Yechiam et al. (2005) Figure 1.4 suggests that there are two clusters of clinical populations with EV model parameters that clearly differ from the ones of their respective control group. The first cluster is located in the top right part of the figure. These groups are characterized by a high attention to gains and high attention to recent outcomes. The second cluster located in the left part of the figure contains clinical populations with a high attention to losses. The authors conclude that “these findings demonstrate the potential contribution of cognitive models in building bridges between neuroscience and behavior” (p. 973).

When relying on these models for clinical purposes, it is important that conclusions from the model parameters are meaningful. In this dissertation, I elaborate on aspects that have to be
taken into account to avoid premature conclusions. These aspects concern three areas: (1) model selection; (2) model fitting; and (3) model account for the data. I argue that all three areas, in particular the first two ones, can greatly profit from the use of Bayesian statistics instead of classical statistics (also known as frequentist statistics). Bayesian statistics is the practical and principled way to reason with uncertainty, and has become increasingly popular in mathematical psychology (Andrews & Baguley, 2013; Poirier, 2006).

In order to compare models (e.g., to find a suitable model for IGT data or to investigate whether two groups differ in specific model parameters), I advocate the gold standard of model selection in Bayesian statistics –the Bayes factor– and I illustrate several methods to obtain the Bayes factor for RL models. A crucial advantage of the Bayes factor is that it can be used not only to identify the model that is best supported by the data, but also to quantify the relative evidence that the data provide for two competing models.

In order to fit RL models to IGT data, I argue that the state-of-the-art method, that is, Bayesian hierarchical modeling, should be used. Bayesian hierarchical modeling incorporates both differences and commonalities between and within the participants of one group, and thereby yields more informative and accurate parameter inferences (Ahn, Lee, Kim, Busemeyer, & Brown, 2011; Horn, Pachur, & Mata, 2015; Lejarraga, Pachur, Frey, & Hertwig, 2016; Navarro, Griffiths, Steyvers, & Lee, 2006; Rouder & Lu, 2005; Rouder, Lu, Speckman, Sun, & Jiang, 2005; Rouder, Lu, Morey, Sun, & Speckman, 2008; Scheibehenne & Pachur, 2015; Shiffrin, Lee, Kim, & Wagenmakers, 2008; Wetzels, Vandekerckhove, Tuerlinckx, & Wagenmakers, 2010).

Finally, in order to assess the account of a model for the data, I argue that posterior predictives should be used. A major advantage of posterior predictives is that they also take the uncertainty of the parameter estimates into account (i.e., they make use of the entire posterior distribution) whereas frequentist methods commonly only use a point estimate (i.e., the maximum likelihood...
1. Introduction

In the remainder of the introduction, I will give an overview and a brief description of the problems to be addressed in the coming chapters.

1.1 Chapter Outline

Chapter 2 gives an overview of the performance of healthy participants on the IGT, and tests three key assumptions about the IGT performance of healthy participants: (1) healthy participants learn to prefer the good options over the bad options; (2) healthy participants show homogeneous choice behavior; and (3) healthy participants first explore the different options and then exploit the most profitable ones (see Figure 1.2). For this goal we use two extensive literature reviews and analysis of eight data sets. Our findings show that all three assumptions may be invalid and therefore question the prevailing interpretation of IGT data.

In Chapter 3 we use parameter space partitioning (PSP) to compare three popular RL models—the EV (Busemeyer & Stout, 2002) and Prospect Valence Learning (PVL; Ahn, Busemeyer, Wagenmakers, & Stout, 2008) model, and a combination of these models, the EV-PU model. The PSP method investigates which choice patterns the models generate across their entire parameter space to yield an indication of the data-fitting potential of the models. Ideally, choice patterns that are often observed in experiments should also occupy a large part of the parameter space of the model under consideration because in such a situation, the model is most likely to provide a good account for the data. PSP thus focuses on the flexibility of a model. In addition, PSP is a global model comparison technique because it is independent of a specific data set. Our results suggest that there is a large discrepancy between the choice patterns that are central to the models and the choice patterns that are often observed in experiments. Overall, our results suggest that the search of an appropriate IGT model has not yet come to an end.

Chapter 4 illustrates three important methods for model validation on the example of the PVL-Delta model—yet another combination of the EV and PVL models. The validation methods cover parameter recovery, parameter space partitioning, and test of specific influence. To assess parameter recovery we fit a model in an idealized scenario (i.e., the fitted model has also generated the data; data generation is based on representative parameter values and a representative number of trials and participants), and investigate whether the parameter estimates coincide with the data-generating parameter values. If the data-generating values cannot even be identified in an idealized scenario, this suggests that parameter estimates obtained from fitting real data may not be reliable indicators of the underlying psychological processes. The test of specific influence, on the other hand, assesses whether experimental manipulations that were intended to affect specific model parameters are also reflected by the parameter estimates. If participants are, for example, distracted during the IGT by means of a filler task, this manipulation should be reflected by the parameter capturing the memory process involved in IGT performance. Our results suggest that, despite a few shortcomings, the PVL-Delta model seems to be a better IGT model than the models discussed in Chapter 3.

In Chapter 5 we claim that parameters obtained from fitting an RL model to IGT data are often interpreted without sufficient assessment of the model’s account for the data in absolute terms. In order to avoid premature conclusions, we propose a minimum threshold of adequacy for two tests: the post hoc absolute fit test and the simulation method test. The post hoc absolute fit test assesses a model’s ability to fit an observed choice pattern when provided with information on the observed choices and payoffs. The simulation method test, on the other hand, assesses a model’s ability to generate the observed choice pattern with parameter values obtained from
model fitting. The crucial difference between the two tests is that the first test is guided by information on the observed choices and payoffs, whereas the second test makes predictions using new, unobserved payoff sequences. These tests are illustrated using two stylized data sets and five published data sets. Our results highlight that a model’s ability to fit a particular choice pattern does not guarantee that the model can also generate that same choice pattern. Future applications of RL models should carefully assess absolute model performance to avoid premature conclusions about the psychological processes that drive performance on the IGT.

The next chapter, Chapter 6, is a rejoinder to Konstantinidis, Speekenbrink, Stout, Ahn, and Shanks (2014)’s reply on Chapter 5. In this chapter, we clarify our initial goal, that is, to illustrate why assessment of absolute model performance is necessary to avoid premature conclusions about the psychological processes that drive performance on the IGT. In addition, we elaborate on the advantages and drawbacks of both the post hoc absolute fit method and the simulation method. Finally, we highlight the distinction between statistical aspects of model adequacy and psychological relevance of parameter estimates.

Chapter 7 argues that, by only considering the number of free parameters, the BIC post hoc fit criterion—the most popular method to compare RL models—does not correctly discount model complexity. A coherent and complete discounting of complexity is provided by the Bayes factor. We use Bayes factors that are obtained with a Monte Carlo method, known as importance sampling, in order to compare four RL models of the IGT. (i.e., the EV, PVL, PVL-Delta, and Value-Plus-Perseveration, VPP, models). The method is illustrated using a data pool of 771 healthy participants from 11 different studies. Our results provide strong evidence for the VPP model and moderate evidence for the PVL model, but little evidence for the EV and PVL-Delta models.

The next chapter, Chapter 8, focuses on bridge sampling, a Monte Carlo method for obtaining Bayes factors more general than importance sampling. We show that bridge sampling can be applied to a Bayesian hierarchical implementation of RL models in a straightforward manner. Such easy extension to hierarchical models presents a crucial advantage compared to importance sampling introduced in Chapter 7. For educational purposes, we first explain the bridge sampling method using a simple Beta-Binomial model. In the second part of Chapter 8, we apply bridge sampling to both an individual-level and hierarchical implementation of the EV model, and compare our results of the individual-level implementation to the ones reported in Chapter 7. Our results suggest that bridge sampling is an attractive method for mathematical psychologists who typically aim to approximate the marginal likelihood for a limited set of (complex, high-dimensional) models.

Chapter 9 proposes a suite of three complementary model-based methods for assessing the cognitive variables and processes underlying IGT performance: (1) Bayesian hierarchical parameter estimation; (2) Bayes factor model comparison; and (3) Bayesian latent-mixture modeling. To illustrate these Bayesian analysis techniques, we test the extent to which differences in decision style (i.e., intuitive, affective vs. deliberate, planned) explain differences in IGT performance. The Bayes factor model comparison is related to the one presented in Chapter 8, but here we do not compare different types of RL models; instead we focus on one specific RL model—the PVL-Delta model—and our model comparison concerns the question whether intuitive and deliberate decision makers differ on the parameters of this model. To quantify the evidence that the data provide for this hypothesis we use Bayes factors obtained by yet another method—the product space method. Our results challenge the notion that individual differences in intuitive and deliberative decision styles have a very broad impact on decision making, and that intuitive processes in healthy adults play a central role for IGT performance.

The final chapter of this thesis, Chapter 10, reuses the data from Chapter 9, and proposes a more elegant solution on how to compare model parameters across two groups avoiding a multi-step procedure. In particular, in Chapter 9 we first submitted participants’ responses to a decision style
questionnaire to a principal component analysis, and then classified participants as intuitive or deliberate depending on their factor scores; subsequently, we compared the model parameters of the two groups. In Chapter 10 we explain that this procedure can be erroneous. As a solution, we propose a Bayesian regression framework that can be used to extend existing RL models, but in general also other cognitive models. This framework allows researchers to quantify the evidential support for relationships between covariates (e.g., decision style) and model parameters using Bayes factors.