

Theses of Doctoral (PhD) Dissertation

**THE ROT MODEL: MODELING THE ROLE OF HIDDEN
CAUSAL FACTORS IN COVARIANCE-BASED CAUSAL
LEARNING**

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The aim of the dissertation, definition of the topic

In the dissertation, we describe the ROT model, a Bayesian cognitive model intended to explain causal learning. Based on others' study results and our experiments, we judge its fit to human data. Our purpose is to determine if the model provides similar estimates to humans if similar information is available to both. An appropriate fit of the model may support its suitability for explaining human causal learning and may form the basis for further refining the model.

Among early pioneers in research on thinking about causal relationships in psychology is Jean Piaget, who primarily examined children's interpretation of causal phenomena that can be grasped on a physical level (such as the movement of clouds and celestial bodies, wind formation, bicycle, and steam engine operation, etc.), to explore the nature and process of cognitive development more thoroughly (Piaget, 1930). Social psychology has dealt primarily with causal attribution within the area of social relationships – the problem of how to identify agents who can be held responsible for certain consequences (Kelley, 1973). We can also mention Albert Michotte, an early researcher of causal thinking. He initiated an in-depth study of a perceptual phenomenon, the launching effect, the „spreading” of the movement of a moving object to another stationary object.

By the end of the twentieth century, the interest in cognitive psychology and psychology in causal thinking revived. This interest was much more general than previous approaches, not limited to perceptual phenomena or social or physical domains. Its focus was causal learning, the acquisition of knowledge of causal relationships. A novelty in the study of causal learning was the use of various modern tools and procedures in mathematics and computer science, which also provided an exact and shared language for the discussions about causal relationships. Another characteristic was the relegation of Hume's previously dominant philosophy of causation, and prioritization of Kant's ideas (for example, reflected in a greater emphasis on top-down processes), and modern tools in statistics, including the application of Bayesian statistics. The integration of three fields (computer science, philosophy, and statistics) has made it possible to analyze causal learning – and, more generally, causal thinking – in a much broader and more effective way than before (Glymour, 2003; Holyoak és Cheng, 2011).

According to a recent review (Danks, 2009), we can distinguish two major areas of research in causal thinking, among which integration is incomplete. A typical thread of research focuses on the use of causal knowledge, such as the study of causal (predictive and diagnostic) reasoning (Cummins, 1995; Kurucz, 2010; Sloman&Hagmayer, 2006), or decisions based on causal knowledge (Joyce, 1999). Another group of research deals with the acquisition of causal knowledge and includes research of perceptual learning of causal relationships (e.g., White, 1995) and causal induction, an inference-based form of learning, during which we infer the existence or absence of causal relationships based on available data. In causal induction, we consider the learning of causal relationships an inductive problem to be solved by our cognitive system. Here we may have various information at our disposal, which are essentially non-causal. Based on this information, we try to infer the existence or absence of a causal relationship. The role of the information on the co-occurrence of the events in question is central, and other types of data are also important, such as temporal distribution of events (order and temporal distance of events, predictability; e.g. Lagnado et al. 2007), information on the consequences of interventions (e.g. Steyvers et al., 2003), or certain prior expectations or abstract knowledge of causal relationships (e.g. Dennis&Ahn, 2001; Luhmann&Ahn, 2011; Griffiths&Tenenbaum, 2009).

The ROT model described in the dissertation is a Bayesian cognitive model of causal learning and especially causal induction. In the learning process, the model attributes a central role to those hidden causal factors that cannot be observed in the learning situation. This property of the model is also reflected in its name (ROT is an acronym that stands for the Hungarian equivalent of the term hidden causal factors). In the following, we briefly outline the characteristics of the ROT model as a Bayesian model, describe the central assumptions that formed the basis for several decisions during the construction of the model, and present the most important aspects of the operation of the model.

Some of the distinguishing features of the Bayesian approach to cognitive modeling compared to other approaches (e.g., symbolic or connectionist) are that probabilities represent knowledge and beliefs to talk about different levels of them. A further property is that it models cognitive performance as probabilistic inference. The general form of this inference is the Bayesian

inference, which describes a rational way to review beliefs in the face of new data. Another unique feature of the approach is that it uses content-specific mathematical tools, so-called structured representations, adapted to the characteristics of the field of knowledge to be modeled. These structured representations are suitable for deriving probabilistic inferences. The representation of knowledge and beliefs as probabilities, and the central role of probabilistic inferences, make Bayesian models particularly useful in examining our cognitive performances for which available information is noisy, incomplete, or uncertain, such as text comprehension, category learning, causal learning, or sensorimotor coordination. The value of the approach is shown by the fact that Bayesian models have proven to be especially successful in these areas (for an overview, see Chater&Oaksford, 2008).

The estimation of the ROT model is based on covariation information, that is the co-occurrence of two events (the antecedent – i. e. the potential cause, and the consequence). Assuming that both the antecedent and the consequent in each case can be either present or absent, the covariation information consists of the following possible cases:

1. The antecedent and the consequence both were present
2. The antecedent was present; the consequence was absent
3. The antecedent was absent; the consequence was present
4. Both the antecedent and the consequence were absent

The ROT model considers hidden causal factors that cannot be observed in the learning situation as the primary source of uncertainty. The most critical steps of the model's estimation process are the revision uncertainty about the presence of hidden causal factors based on the covariation information, and then the revision of the hypotheses about the causal relationship in question, during which the co-occurrence of the antecedent and consequence, as well as the uncertainty about the hidden causal factors, are also taken into account.

The ROT model provides its estimate in the form of exact computation. We had to accept several assumptions to perform these calculations during this computation. We sought to ensure that the central assumptions of our model, which inspired several decisions during model building, were empirically grounded and reflected specific characteristics of the human cognitive system. Certain other assumptions were simple ad hoc assumptions whose sole purpose

was to ensure that the model's calculations can be carried out. Our central assumptions are that people think of causal relationships as deterministic relationships (e.g., Frosch&Johnson-Laird, 2011; Schulz&Sommerville, 2006), they try to find explanations for the observed events, which are typically causal explanations (Keil, 2006; Lombrozo, 2006). Moreover, these explanations include references to causal factors that can either bring about the consequence (generative causal factors) or prevent the consequence from occurring (preventive causal factors, e.g., Cummins et al., 1991; Cummins, 1995). Providing ROT model estimates in the form of an exact calculation also allows for a rigorous assessment of the fit to human data.

Applied methods

During the empirical testing of the ROT model, we followed two strategies. On the one hand, we looked in the literature for studies where researchers also asked participants to assess the causal relationship between simple events (more precisely, to judge their certainty of the existence of a causal relationship) based on the aggregated covariation information provided to them. On the other hand, we designed and conducted three experiments to test the model's fit based on our data. We also designed a further experiment to examine the generalizability of the ROT model in a learning situation for which the model was not prepared. In this situation, the covariation information was not available in the summarized form. The participants got the information one case at a time. After each case, they had to judge how certain they are in the existence of the causal relationship. The literature refers to this type of causal learning as online learning.

In the literature, we searched for research reports where participants had to form judgments about simple causal relationships between events. They had merely covariation information about the co-occurrence of events in a summary form. Because the study of the strength of causal relationships in this field is much more common, we found only some studies that met our expectations. These were two experiments by Griffiths & Tenenbaum (2005), an experiment by Lu et al. (2008), and an experiment by Saito Shimazaki (2013).

Griffiths & Tenenbaum (2005) reported three experiments, of which experiments 2 and 3 were appropriate for us. In these experiments, participants were given cards that contained covariation information depicting the associations between certain chemicals and gene expression. Participants had to

line up these cards so that the first was the one that implied the absence of the causal relationship between the chemical and gene expression. The last implied the existence of the causal relationship between the chemical and gene expression. Based on the results of the two experiments, we examined whether the ROT model ranks each covariation information similarly to the participants so that the fit could be judged on an ordinal scale based on the results.

In their 3rd experiment, Lu et al. (2008) outlined the study of a pharmaceutical company as a context in which participants were tasked with judging the headache-inducing effect of different minerals. Accordingly, they had several covariation information (15 in total) depicting the co-occurrence of a mineral and headache. They varied the number of cases available and the probability of the consequence (headache) given the presence and absence of the antecedent (mineral). Participants had to rate on a quasi-analog scale from 0 to 100 how confident they were that a particular mineral would cause a headache. 0 meant that they were confident that the mineral would not cause a headache, and 100 indicated that they were sure the mineral was causing a headache. Given causal judgments on such a fine scale allowed us to judge the fit of the ROT model on a near-interval scale. Here we examined fit by establishing the extent to which the model's estimates can explain the variability in the participants' mean judgments to the conditions.

In the experiment of Saito and Shimazaki (2013), participants had to determine whether one of two bacteria propagates the other? Participants were given information about the co-occurrence of pairs of bacteria. In each case, they were to judge each bacteria whether it propagates the other. Essentially this resulted in four possible response combinations in each case (neither one of the bacteria propagates the other, both bacteria propagate the other, one propagates the other, and vice versa).

To verify the fit of the ROT model based on our data, we conducted four experiments. The first three experiments were about how the ROT model can predict changes in participants' responses to manipulating the covariation information. In the fourth experiment, we tested the fit of the ROT model in an online learning situation, which we didn't consider during model building.

We conducted each of our experiments online. The sample was recruited using a crowdsourcing service. Given the online nature of the experiments, participants were given short, simple tasks. During the experiments, participants

were to imagine themselves in the place of a missionary, who notices in an indigenous village, that strange skin rashes appeared in several natives and discovered that one of the wells in the village is contaminated. Based on this, he/she tries to determine if the contaminated water caused the rash by examining several natives for a skin rash and asking if he/she drank from the water. In experiments 1-3, the results were available to participants in the form of summarized covariation information. In the fourth experiment, we presented the cases one by one. We asked participants to judge on a scale how confident they are that there is a causal relationship between the contaminated water and the rashes. The lowest value of the scale meant that they are confident that there was no causal relationship, and the highest value implied confidence that there was a causal relationship.

In our experiments, we manipulated the characteristics of the covariation information available to the participants. In experiments 1 and 3, we manipulated the probability of the consequence (skin rashes) given the presence or absence of the antecedent (drinking from the contaminated water) – in experiment 1, the number of available cases was low, whereas the covariation information in experiment 3 contained significantly more cases. In experiment 2, the probability of the consequence given the absence of the antecedent and the number of available cases were manipulated. In experiment 4, we manipulated the difference in the probability of the consequence given the presence and absence of the antecedent so that from a normative point of view, the covariation information indicated a generative causal relationship, a preventive causal relationship, or no relationship at all.

Results listed as theses

Thesis 1:

The ROT model can be considered a possible valid explanation for covariance-based causal learning (causal induction) and may be suitable for examining the characteristics of human causal learning.

In re-analyzing the reports found in the literature, we found that the estimates of the ROT model showed an adequate fit to the judgments made by the study participants. In both experiments of Griffiths and Tenenbaum (2005), we found that the ROT model ranked each covariation information in the same way as the vast majority of participants. Thus the fit judged on an ordinal scale

was perfect. In Lu et al.'s (2008) experiment, the estimates given by the ROT model represented a particularly good explanatory power in predicting the participants' judgments ($R^2=0,95-0,99$). It is important to note that this was achieved by considering the number of cases available in the covariation information so that we examined the conditions where the covariation information contained a small number of cases and those that contained a large number separately. In the experiment of Saito and Shimazaki (2013), the ROT model was able to predict the most common responses of the participants in most of the 15 covariation information used in the experiment. Thirteen responses were accurately predicted by the estimates of the ROT model, which indicates a high level of agreement (*Cohen-féle* $\kappa=0,8$).

In two of our experiments, the estimates of the ROT model proved to be suitable for predicting participants' responses to different covariation information and showed a very good fit to the participants' mean responses ($R^2=0,89-0,95$). In our second experiment, where we also manipulated the number of cases in the covariation information, we found a worse fit. Based on a closer examination of the results, participants may have made less use of the information provided by the number of cases than the ROT model. When we considered the number of cases, the estimates of the model ranked in the same way as the participants' responses.

The findings with Lu et al.'s (2008) experiment and our second experiment also suggested that the ROT model attributes much more importance to the amount of data available than the participants. The model's estimates were much more polarized, more extreme when there were more data in the covariation information.

Thesis 2:

In causal learning, we underestimate the role of the amount of data available; we do not make full use of the information it contains.

In both our second experiment and a re-analysis of Lu et al.'s (2008) experiment, we found that the estimates of the ROT model showed poor or moderate fit to the study participants' responses. The fit proved to be moderate ($R^2=0,62$) in the experiment of Lu et al. (2008), whereas in our second experiment, it was especially bad ($R^2=0,02$). In both cases, however, we observed that participants' responses did not show the polarization of judgments

that we would have expected from the estimations of the ROT model, according to which causal judgments become more extreme as the number of cases increases. Considering the number of cases in the covariation information, i.e., checking the fit separately for covariation information containing different case numbers, it proved to be excellent for both studies. Given that the ROT model embodies a normatively optimal solution for causal induction, such a change in the fit may suggest that the participants did not fully utilize the information in the number of cases available in the covariation information.

Thesis 3:

The generalizability of the ROT model is limited to the online learning situation, where the cases that make up the covariation information arrive one at a time and are not available in a summarized form.

In the fourth experiment, the ROT model estimates were derived as proposed by Danks et al. (2003), during which an estimate was given in each step based on complete covariation information containing the frequencies of all the different types of cases, and these frequencies were updated in each step with the new case.

In this experiment, we found that the learning curves calculated from the participants' judgments showed similarities to the learning curves estimated by the ROT model in the different conditions. However, we also observed the fundamentally conservative nature of participants' responses compared to the ROT model. The estimates of the ROT model showed moderate correlations with the learning curve of individual participants.

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A PhD értekezés alapjául szolgáló közlemények

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In: The 1st Conference on Information Technology and Data Science. Ed.: Fazekas István, Hajdú András, Debreceni Egyetem, Debrecen, 40-42, 2020.

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A közlő folyóiratok összesített impakt faktora (az értekezés alapjául szolgáló közleményekre): 0

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