

Causes and effects in Dichotomous Comparative Judgments: an information-theoretical system of plausible mechanism

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Abstract

Dichotomous Comparative Judgment (DCJ) requires judges to compare pairs of stimuli to determine which one exhibits a higher degree of a specific trait. DCJ has proven effective and reliable across various fields (Pollitt, 2012b; Jones, 2015; van Daal et al., 2019; Bartholomew et al., 2018; Lesterhuis, 2018; Bartholomew and Williams, 2020; Marshall et al., 2020; Boonen et al., 2020). However, despite the method's widespread use, existing literature lacks a clear explanation of the complexities and assumptions underpinning the DCJ system, as well as the plausible mechanisms through which DCJ data could be generated. This study addresses these issues by representing DCJ within the framework of causal inference. Specifically, utilizing the structural approach, the study develops a scientific model to clarify plausible causal assumptions and mechanisms inherent in the DCJ system. The study then translates this model into a probabilistic statistical model to estimate statistical relationships and infer causal effects within the system. This research provides a robust probabilistic foundation for the statistical analysis of DCJ data, building upon Thurstone's law of comparative judgment (1927). Its findings offer valuable insights for researchers and analysts designing and implementing DCJ experiments.

Keywords: causal inference, probability, Thurstone, comparative judgement, directed acyclic graph, structural causal models, statistical modeling

1. Introduction

In contemporary contexts, Thurstone's law of comparative judgment (1927) primarily refers to the method of *dichotomous* comparative judgment (DCJ, Pollitt, 2012a,b). In DCJ, a judge assesses the relative manifestation of a *trait* within a pair of stimuli. This assessment results in a dichotomous value indicating which stimulus possesses a

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higher degree of the trait. After different judges perform multiple rounds of pairwise comparisons, an outcome vector is produced. This vector is modeled using the Bradley-Terry-Luce model (BTL, [Bradley and Terry, 1952](#); [Luce, 1959](#)), which creates a score that corresponds with the trait of interest. This score is then used to rank the stimuli from lowest to highest or to evaluate the influence of certain variables on the stimuli's positions in the ranking.

DCJ has proven effective in assessing competencies and traits predominantly within the educational realm, as demonstrated by [Pollitt \(2012b\)](#), [Jones \(2015\)](#), [van Daal et al. \(2019\)](#), [Bartholomew et al. \(2018\)](#), [Lesterhuis \(2018\)](#), [Bartholomew and Williams \(2020\)](#), and [Marshall et al. \(2020\)](#). However, its application transcends education, as exemplified by [Boonen et al. \(2020\)](#). The methodology has also evolved to include multiple, as opposed to pairwise comparisons ([Luce, 1959](#); [Plackett, 1975](#)), and to accommodate comparisons with ordinal outcomes ([Tutz, 1986](#); [Agresti, 1992](#)). Overall, research suggests that DCJ offers an alternative and efficient approach to measurement and evaluation, characterized by its reliability and validity ([Lesterhuis, 2018](#); [van Daal, 2020](#); [Marshall et al., 2020](#); [Bouwer et al., 2023](#)). Nevertheless, despite the method's widespread use, existing literature lacks a clear representation of the plausible mechanisms through which DCJ data could be generated. Particularly, there is no depiction of the complexity and the assumptions underpinning the DCJ system, nor how different assessment factors can potentially influence the observed DCJ outcome.

According to [Verhavert et al. \(2019\)](#) and [van Daal \(2020\)](#), several assessment factors interact and influence the method's outcome. These factors include the number and characteristics of the stimuli, their *proximity* in terms of the assessed trait, the number of comparison per stimulus, and the pairing algorithm used. Furthermore, since the method relies on judges' assessments, the number and characteristics of judges, their *discrimination* abilities, and the number of comparisons per judge also play pivotal roles. Moreover, when the stimuli represent sub-units of higher-levels units, factors such as the number and characteristics of these units, along with their *proximity* in terms of the assessed trait, can significantly influence the outcome. For instance, [van Daal et al. \(2019\)](#) assessed academic writing skills of university students (units) using multiple argumentative essays (sub-units).

Although several studies have examined the individual impact of these factors on the method's reliability ([Bramley, 2015](#); [Pollitt, 2012b](#); [Bramley and Vitello, 2019](#); [Verhavert et al., 2019](#); [Crompvoets et al., 2022](#); [van Daal et al., 2017](#); [Gijzen et al., 2021](#); [Bouwer et al., 2023](#)), none, to the best of the authors' knowledge, have provided a transparent depiction of the DCJ system and the mechanisms generating the DCJ outcome. This study aims to fill this gap by representing DCJ within the framework of causal inference. Specifically, utilizing the structural approach, the study develops a scientific model to clarify plausible causal assumptions and mechanisms inherent in the DCJ system. The study then translates the scientific model into a probabilistic statistical model. This model aims to produce statistical estimates to draw inferences about plausible causal relationships within the DCJ system.

Ultimately, this study provides a robust causal and probabilistic foundation for the statistical analysis of DCJ data, building upon Thurstone's law of comparative judgment ([1927](#)). Consequently, its findings offer valuable insights for researchers and analysts

designing and implementing DCJ experiments.

2. Theoretical framework

This section introduces fundamental concepts in causal inference, such as directed acyclic graphs (DAGs), structural causal models (SCMs), and the flow of association and causation in graphs. The section is not a comprehensive description of causal inference methods. Readers interested in deeper exploration should consult introductory papers like [Pearl \(2010\)](#), [Rohrer \(2018\)](#), [Pearl \(2019\)](#), and [Cinelli et al. \(2020\)](#). They may also find introductory books such as [Pearl and Mackenzie \(2018\)](#), [Neal \(2020\)](#) and [McElreath \(2020\)](#) useful. For more advanced study, seminal intermediate papers like [Neyman \(1923\)](#), [Rubin \(1974\)](#), [Spirtes et al. \(1991\)](#), and [Sekhon \(2009\)](#), as well as books such as [Pearl \(2009\)](#), [Morgan and Winship \(2014\)](#) and [Hernán and Robins \(2020\)](#) are recommended.

2.1. The structural approach to causal inference

In statistics, *causal inference* refers to the process of identifying the causes of a phenomenon and estimating their effects using data ([Shaughnessy et al., 2010](#); [Neal, 2020](#)). Unlike classical statistical modeling, which focuses solely on summarizing data and inferring associations, causal inference provides a coherent mathematical notation for analyzing causes and counterfactuals ([Pearl, 2009](#)).

Counterfactuals represent scenarios *contrary to fact*, where alternative *potential* outcomes resulting from a cause are neither observed nor observable ([Neal, 2020](#); [Counterfactual, 2024](#)). According to [Pearl and Mackenzie \(2018\)](#), counterfactuals are the foundation of causal inference and occupy the highest level of cognitive abstraction in the ladder of causation, followed by intervention and association. Nevertheless, despite their abstract nature, counterfactuals enable the development of a *theory of the world* that explains why specific causes have specific effects and what occurs in their absence ([Pearl and Mackenzie, 2018](#)). They achieve this by translating causal statements into counterfactual statements, that is, statements about “what would have happened in the world under different circumstances.”

Several approaches to causal inference and counterfactuals exist, but two are particularly prominent: the potential outcomes approach, also known as the Neyman-Rubin causal model ([Neyman, 1923](#); [Rubin, 1974](#)), and the structural approach ([Pearl, 2009](#); [Pearl et al., 2016](#)). Both approaches employ rigorous mathematical notation to characterize causal inference, but they do so in different ways ([Neal, 2020](#)). The potential outcomes approach relies on counterfactual notation, whereas the structural approach employs the do-operator and structural causal models (SCM, [Pearl, 2009](#); [Pearl et al., 2016](#)). Despite these differences, both notations can be expressed in terms of the other, and both approaches provide methods for using experimental and observational data to estimate causal effects ([Pearl, 2010](#)).

Nevertheless, the structural approach offers an additional key advantage over the potential outcomes approach: it enables the graphical representation of any system through directed acyclic graphs (DAG, [Gross et al., 2018](#); [Neal, 2020](#)). DAGs are heuristics that can effectively convey the assumed causal structure of a system. They do not represent

detailed statistical models but allow researchers to deduce which statistical models can provide valid causal inferences, assuming the causal structure depicted in the DAG is accurate (McElreath, 2020).

2.2. Directed acyclic graphs (DAG)

Graph theory is a branch of mathematics focused on the study of graphs. Graphs are mathematical structures modeling pairwise relations between objects. They can represent physical relations, such as electrical circuits and roadways, and less tangible structures, such as ecosystems and sociological relations. Graphs have proven useful in various fields, including computer science, operations research, and the natural and social sciences (Gross et al., 2018).

In statistics, one application incorporating concepts from graph theory is causal inference. Specifically, the structural approach to causal inference uses directed acyclic graphs (DAG) to provide a formal and graphical representation of the causal structure of a system (Neal, 2020). In this context, a *graph* is a collection of nodes connected by edges, where nodes represent random variables. The term *directed* indicates that the edges of the graph extend from one node to another, with arrows showing the direction of causal influence. Moreover, the term *acyclic* indicates the causal influences do not form a loop, meaning the influences do not cycle back on themselves (McElreath, 2020).

One key advantage of DAGs is that, regardless of complexity, they can represent various causal structures using only five fundamental building blocks (Neal, 2020; McElreath, 2020; Morgan and Winship, 2014). Figure 1 illustrates these blocks. Figure 1a depicts two unconnected nodes, representing an scenario where variables X_1 and X_2 are not causally related. Figure 1b shows two connected nodes, illustrating a scenario where a parent node X_1 exerts a causal influence on a child node X_2 . Consequently, X_2 is considered a *descendant* of X_1 . Figure 1c depicts a *chain* (or *pipe*), where X_1 influences X_2 , and X_2 influences X_3 . In this configuration, X_1 is a parent node of X_2 , and X_2 a parent node of X_3 . Furthermore, the DAG shows that X_1 is an *ancestor* of X_3 and that the relationship between these variables is entirely *mediated* by X_2 . Figure 1d illustrates a *fork*, where variables X_1 and X_3 are both influenced by X_2 . In this scenario X_2 is a parent node of both X_1 and X_3 . Finally, Figure 1e depicts a *collider*, also known as *immorality*, where variables X_1 and X_3 are concurrent causes of X_2 . In this configuration, X_1 and X_3 are not causally related to each other but both influence X_2 .

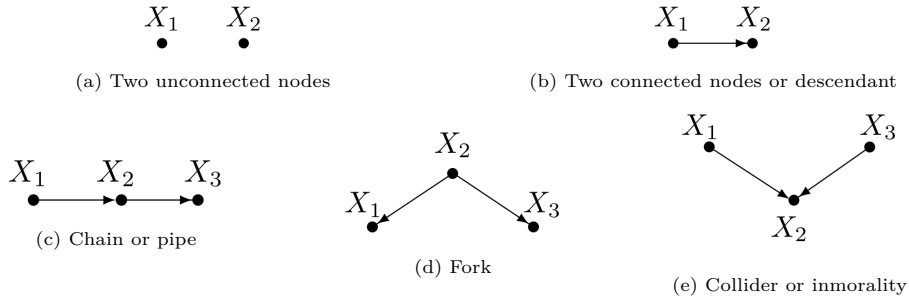


Figure 1: DAG's fundamental building blocks.

Given the heuristic nature of DAGs, a motivating example can help illustrate the use of the five fundamental building blocks to construct a system’s causal structure. This example can also help to clarify some additional conventions for drawing DAGs.

Consider a research problem where the causal effect of a variable T on an outcome Y needs to be investigated. Additionally, the problem suggests that a variable X potentially influences both T and Y . Such scenarios are not hard to imagine. For instance, T might represent different treatments that could affect the recovery from cancer Y , while X could denote the patient’s age. Similarly, in the context of a DCJ study like the one described by Boonen et al. (2020), T could represent the duration of a child’s cochlear implant use, which might influence the child’s overall speech quality Y , with X indicating the child’s hearing status. Note that these descriptions do not specify the type of data or the functional forms of the variables, highlighting the heuristic nature of DAGs. (not a bad example, but I prefer one using writing skills)

Figure 2 presents two graphs illustrating the plausible causal structure of the motivating example. Figure 2a shows the *simplified* DAG. In this graph, the variables of interest or *endogenous* variables $V = \{T, X, Y\}$ are depicted as solid black circles, indicating that they are observed variables. The arrows in the graph reflect the expected direction of causal influences among the variables. In contrast, Figure 2b depicts the *magnified* version of the DAG. This graph includes, in addition to the endogenous variables, the *exogenous* variables $E = \{e_T, e_X, e_Y\}$. These exogenous variables are commonly referred to as *disturbances* or *errors*, because they represent factors not explicitly modeled. They are depicted as open circles, indicating their unobserved nature. These exogenous variables are often omitted for simplicity, resulting in the simplified DAG in Figure 2a. However, including them in the graph can be advantageous in certain scenarios, as they can help to highlight potential issues related to conditioning and confounding (Cinelli et al., 2020). These concepts are introduced in the next section.

Furthermore, a detailed examination of both figures reveals the presence of at least four of the five fundamental building blocks. Figure 2a displays multiple descendants, evident in pairwise relations such as $X \rightarrow T$, $X \rightarrow Y$, and $T \rightarrow Y$. It also illustrates a fork with $X \rightarrow \{T, Y\}$. Similarly, Figure 2b features multiple two-unconnected nodes, evident in the pairwise relations $\{e_T \perp\!\!\!\perp e_X\}$, $\{e_T \perp\!\!\!\perp e_Y\}$, and $\{e_X \perp\!\!\!\perp e_Y\}$, as well as colliders such as $\{X, e_T\} \rightarrow T$ and $\{X, T, e_Y\} \rightarrow Y$. The symbol $\perp\!\!\!\perp$ denotes a concept known as *d-separation*, which roughly implies the independence of the variables. This concept is introduced in the next section.

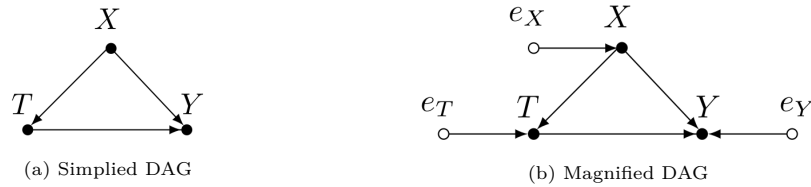


Figure 2: DAGs for a plausible causal structure in a system.

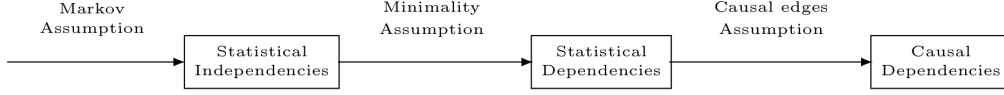


Figure 3: The flow of association and causation in graphs. Extracted from Neal (2020, 31)

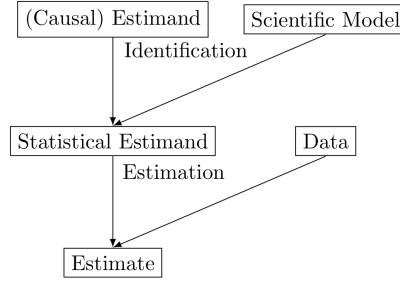


Figure 4: Identification-Estimation flowchart. Extracted from Neal (2020, 32)

2.3. The flow of association and causation in graphs

2.4. But where does it all fit?

3. Theory

3.1. A scientific model for the DCJ

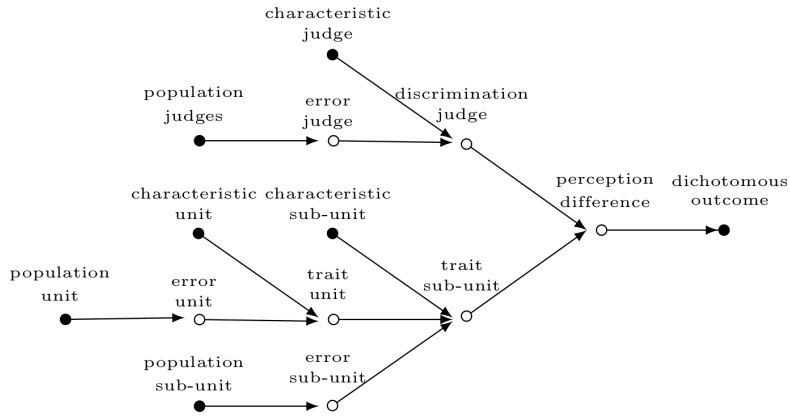


Figure 5: DCJ causal diagram, simplified description

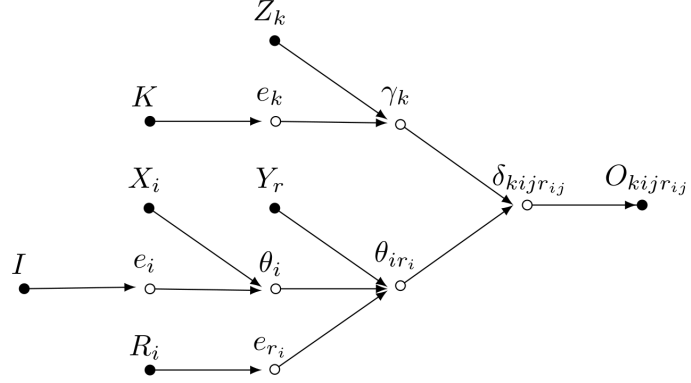


Figure 6: DCJ causal diagram, simplified mathematical description

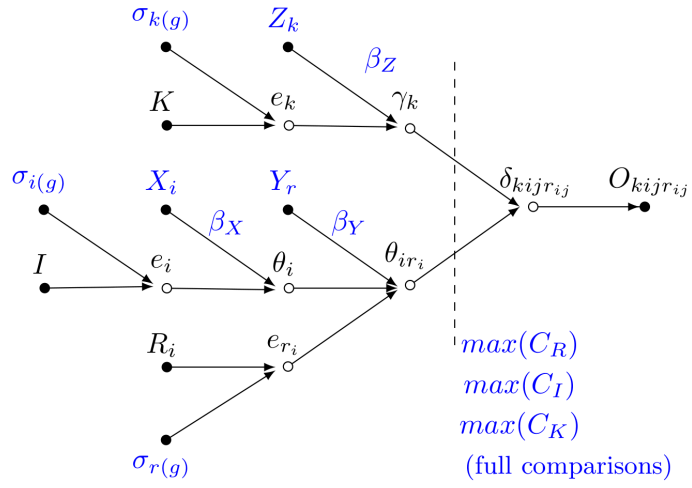


Figure 7: DCJ causal diagram, population mathematical description

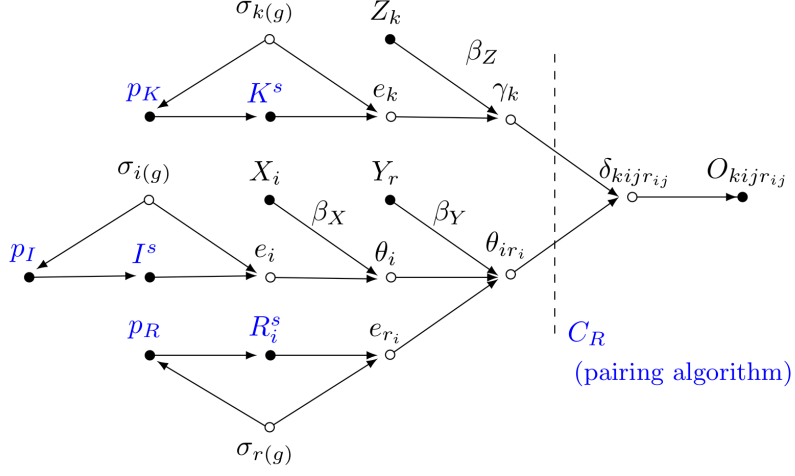


Figure 8: DCJ causal diagram, sample with comparisons mathematical description

3.2. Probabilities assumptions of the scientific model

3.3. From the scientific to statistical model

3.4. Let's talk about Thurstone

4. Discussion

4.1. Findings

4.2. Limitations and further research

5. Conclusion

Declarations

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6. Appendix

- 6.1. Why do we need to estimate judges' abilities?*
- 6.2. Latent variables as a mean of imputation*
- 6.3. Other comparative scenarios*

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