Decision Trees as Sociotechnical Objects in Chatbot Design

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ABSTRACT

Designers of dialogue-driven systems and 'conversational' agents like chatbots face huge complexities, both in the rich meanings of language and its sophisticated sequential organisation. To this end designers are starting to work out what it means to treat 'conversation' as a design material. But the elephant in the room is that for the most part, *the* key way of managing the complexities of chatbot design is the decision tree, or some variant of this. Yet decision trees have received little scrutiny as sociotechnical objects which both provide purchase for—but also simultaneously significantly restrict—design practice. CUI research needs to ramp up its concern for various assumptions built into chatbot design processes, and the various stakeholders which may be at play.

CCS CONCEPTS

• **Human-centered computing → Interaction design process and methods**.

KEYWORDS

conversation design, decision trees, rule-based chatbots, corpus-based chatbots

ACM Reference Format:
Teresa Castle-Green, Stuart Reeves, Joel E. Fischer, Boriana Koleva. 2020. Decision Trees as Sociotechnical Objects in Chatbot Design. In *2nd Conference on Conversational User Interfaces (CUI '20), July 22–24, 2020, Bilbao, Spain.* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3405755.3406133

1 INTRODUCTION

We want to start with a simplistic classification of chatbots, making a distinction between rule-based and corpus-based. Corpus-based (or stochastic) chatbots [2, 4, 18] draw on training data from similar domains (e.g., GPT2 [21]) to learn and then generate probabilistic responses based on a model (or draw on search algorithms such as greedy or beam [13] to select responses from a dialogue graph). Rule-based chatbots, on the other hand, are hand-crafted through mapping out and designing possible interactional sequences anticipated to occur between system and user, the path through which is dictated specified rules: the **decision tree**. In spite of some impressive demonstrations of corpus-based chatbots, the latter, rule-based type probably form the most common approach given the purchase it provides for design. In contrast, corpus-based chatbots, while offering high flexibility in dealing with a broad range of interactions (training data dependent, of course), by definition they do not offer a designer much in the way of fine-grained control over user experience or shaping user journeys to arrival at particular endpoints. On the other hand, rule-based chatbots tend to be fragile, requiring extensive design input to shape a myriad of possible ways in which interaction might unfold, hence the adoption of decision tree based methods.

We believe there is little emphasis currently on understanding how decision trees are actually used. A persistent problem for chatbot design is the need to model or visualise synthesised 'conversation', thus enabling designers to do their work in the first place. This is at the heart of the decision tree concept as it is practiced in chatbot design methods. This is powerful as it enables collaborative design reasoning (for example, through sketching [6, 14, 19]), consultation with management or clients [7] and for mapping data flows and functionality. Diagramming is thus a crucial practical feature of chatbot design.

CUI '20, July 22–24, 2020, Bilbao, Spain

ACM ISBN 978-1-4503-7544-3/20/07…$15.00
https://doi.org/10.1145/3405755.3406133

2 DIAGRAMMING AND DECISION TREES

Diagrammatic representations for chatbot design are discussed both in academic research [9] and industry documentation [3, 8]. But we want to draw attention to the significance of examining techniques used to 'design' and/or visually represent chatbot structure and functionality (i.e., the foundation from which the rest of the conversational interface is based). Where these diagrams are mentioned in the literature it is mainly as passing comment about being simplistic, restrictive, unscaleable or as acknowledgement of the step in the process. An exception is [10] where crowdsourcing was used to build a dialogue graph.

What is the structure of the diagrams themselves? Methods used to diagrammatically represent the 'conversational' elements of chatbots tend to be branching structures representing either rule-based pre-mapped content or corpus-based dialogue graphs. Significant variation exists in the language used to point to the same basic technique and all the assumptions that are brought with this model of language interaction: industry and academic literature refer to diagrammatic representations of dialogue mapping in a number of ways, including conversation flow diagrams [8], decision trees [3], dialogue graphs [10], dialogue trees [9], stories [20] and paths [11]. This perhaps attests to a lack of attention that methods of chatbot design have received. Accordingly there is limited discussion about benefits and constraints generated as a result of using branched structures as the basis to model or generate conversation.

For example, diagramming techniques for rule-based chatbot design in particular involve some measure of 'shoehorning' conversational content into pre-defined structures based on the nature of the diagrams themselves. Decision trees in this context work on the premise of mapping out anticipated routes that a user may take when interacting with a chatbot. These work from intent through to end points at which a task or conversational interaction sequence is considered complete. Even corpus-based methods of chatbot design—while in some sense offering flexibility via probability mappings to dialogue graphs, meaning a greater capability in managing a much larger number of paths or branches—still ultimately might be relying upon a predefined branching structure.

Of course, decision trees are not specific to chatbot design. Their complex intellectual lineage [15] sees them feature in various statistics-related fields [17] often for modelling in decision making [16].

Crucially, decision trees were *not* designed specifically for the mapping of 'conversational' content, which is perhaps the source of dilemmas and issues of 'shoehorning' for chatbot designers. Firstly, the basis of a branching structure assumes that the system will be choosing one from a number of predefined options—we note that, where complex dialogue graphs are concerned this may be a vast number of options, and algorithms such as beam search try to mitigate this by using multiple hypotheses for selection [13]. Tree structures for hand-crafted decision trees or flow diagrams are, for practical organisational reasons, likely to be much smaller with even less flexibility due to predefined rules for outputting responses. We need to understand what else is at play in the sociotechnical circumstances of decision tree adoption and practice.

3 MOVING PARTS OF DECISION TREES

We think there are three key 'moving parts' which shape and are shaped by decision tree logic. In this way decision trees, as sociotechnical objects, can be seen to link these technological and human aspects of chatbot design.

3.1 Commoditised platforms

A core way decision tree structures are delivered to conversation designers is via commoditised platforms. Within industry these have become standards and are ubiquitous to chatbot development process, thus shaping the kind of chatbots found 'in the wild'. Instructions for developing chatbots using these platforms regularly mention using diagrams to map flows and functionality. For example, Shevat suggests creating workflows or stories to map interaction steps [20], Google include mapping of flows in their guidelines [8] and Amazon refer to decision trees for mapping shortest routes and system logic [3]. Although these examples provide limited detail on the mapping methods themselves it is seemingly central to the way they require data to be organised by designers and developers. A point made clearer by Google in relation to the change in name from API.AI to Dialogflow [1].

3.2 Design and Development Teams

Using a form of diagrammatic representation to work up the design of a chatbot allows designers to incorporate a form of sketching [6, 19] into their work. They can also use diagrams as an abstraction method to work through manipulation of data streams (e.g., to provide personalised insights from IoT data [5, 11]) and system functionality [12]. Using branching structures to represent these steps as sequential events early in the design process can be beneficial for these purposes. However, as design progresses it can become difficult to manage and map relationships between different branches. This raises the question; at what point does sketching and abstraction for design purposes become the underlying architecture of the chatbot itself? As mentioned earlier, there is a lack of focus on this element of chatbot design both in academic literature and industry documentation. While platform documentation suggests designers map functionality of chatbots, there is little or conflicting information as to how and when. For example, Shevat suggests functionality scripting first [20] whereas Google suggests creating flows after sample conversation [8]. It is worth reiterating commoditised platforms have a bearing here in the way they require content to be organised when incorporating into their system.

3.3 User Experience

The third key factor embroiled in putting decision trees into design practice is the relationship of these architectures to user experience. A branched structure can potentially restrict a user once they have begun to progress down a particular branch, thus almost leading or funnelling users after a certain point. This is particularly true in the case of task-based chatbots [20]. In some contexts, such as sales and marketing, where the funnel metaphor is already prevalent, this may be an intentional feature of the design. However, in other cases where designers are trying to provide flexibility to users the use of a branching structure may be counter intuitive. We suggest, particularly for 'designed' or rule-based chatbots, the type of diagram used and the consequences it has on the user experience produced be considered in the design process.

4 MOVING FORWARDS

This provocation paper highlights just some of the challenges surrounding the use of branching structures when designing rule-based chatbots: we feel that CUI research could do with more focus on decision trees as a design method. When used as the basis for chatbot development the benefits and constraints for various stakeholders are not yet fully understood. In particular, we posit these diagrams both offer flexibility to the designer and constrain the design itself. Generally within HCI the work of design and resources used are acknowledged as directly impacting the design produced. We therefore argue for a stronger focus on the diagrammatic resources available to designers to increase our understanding of how this can shape the user experience of designed chatbots.

We suggest three ways in which to move forward. 1) Attention should be given to this under-researched area. Alongside structured research, we urge more discussion around the role of diagrammatic methods including benefits or implications encountered. 2) Future research should seek to understand impacts these assumptions have on designed interfaces and explore other options. We are not suggesting that branched diagrams are not useful in their own right, just that any constraints they present to the design are acknowledged and where deemed not a good fit hybrid or alternative abstraction and visualisation methods be developed and shared with the wider community. 3) Design metaphors need to be reconsidered to suit both conversation-sensitive design in general and the user experience aims of the specific chatbot. For example, flows and topics rather than paths and branches.

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