Chapter 14

Machine Information Behaviour

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Introduction

Most services and resources in academic libraries are grounded in an understanding of human information behaviour. Collections, systems, programs, and processes acknowledge and influence the ways in which people "need, seek, manage, give, and use information in different contexts."[1] Effectively, the library and the academy are in service to human information behaviour (HIB).

While the importance of HIB will remain, the proliferation of machine learning (ML) systems presents a new challenge to academic library services and resources. Increasingly, academic libraries need to consider the implications of machine information behaviour (MIB) and how those behaviours influence the services, resources, and programs they offer. Understanding MIB is a response to Bourg's challenge that algorithms be viewed as "a new kind of patron" necessitating a transformation in the manner in which the library responds.[2]

Algorithmic decision-making systems are ubiquitous, powerful, sometimes opaque, often invisible, and, most importantly, consequential in our everyday lives.[3] As these systems become more autonomous, even if in restricted domains, they will be utilized for recommendations and predictions regarding increasingly complex problems. However, "the danger is not so much in delegating cognitive tasks, but in distancing ourselves from—or in not knowing about—the nature and precise mechanisms of that delegation."[4] Understanding MIB will be essential to assuring veracity and engendering the trust necessary for delegation and use.

This chapter presents a preliminary conceptual model of machine information behaviour as a starting point upon which to build further elaborations and contextualizations. Using

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Wilson's general theory of information behaviour as a scaffold, the model will incorporate the main functional components of these systems (i.e., computation, data, and algorithms) while also positioning them in the social, political, and economic environments.[5] Prominent in the model will be the three core elements present and active in any ML system: representation, evaluation, and optimization.[6]

Academic Libraries and Artificial Intelligence

The pioneering work in the 1980s and 1990s from LIS scholars and practitioners such as Linda C. Smith, Charles W. Bailey, Karen Spärck Jones, and F. W. Lancaster explored practical applications for AI in academic libraries, including the use of expert systems for reference service and information retrieval.[7] Following the hiatus of the "AI winter," brought about by the limitations of expert systems, renewed LIS interest in AI began in the 2010s and has grown substantially in recent years.[8] That said, the majority of this work has again focused more on practical applications of AI and less on its foundational implications.

Examples of work investigating the larger implications for LIS include search, discovery, reference and collections, and information literacy.[9] These and other critiques of AI in LIS have identified various failures and shortcomings related to bias, unfairness, discrimination, and accuracy. Often, these are linked to training data (or its preparation) and generically to the algorithms in question. However, as cognitive delegation to machine learning increases in many aspects of academic libraries and librarianship, an analysis and understanding of the complete contextual implementation of machine learning is required. The specific techniques and strategies of machine learning utilized at various stages of model training have a material downstream effect on information behaviour.

Applying an information behaviour (IB) lens to machine learning allows for a deeper understanding of the nature and consequences of this technology. Just as human information behaviour has shaped academic libraries, so too will machine information behaviour be a critical factor and have a profound impact.

Machine Behaviour and Machine Information Behaviour

Foundational to MIB is the concept of machine behaviour, "the scientific study of behaviour exhibited by intelligent machines [involving] a class of actors with particular behavioural patterns and ecology [requiring] the integrated study of algorithms and the social environments in which algorithms operate."[10] The authors advocate for the use of human behaviour research methods for research into machine behaviour. They caution, however, that "even if borrowing existing behavioural scientific methods can prove useful for the study of machines, machines may exhibit forms of intelligence and behaviour that are qualitatively different—even alien—from those seen in biological agents."[11]

A critique of Rahwan et al. suggests that the fields of cybernetics, science and technology studies (STS), sociology, and anthropology have for years undertaken similar approaches.[12] In the specific area of IB, however, this is not the case. The description of machine behaviour by Rahwan et al. provides a framework for the study of MIB in the context of HIB, allowing for behaviours that are both similar and different. Arising from this, machine information behaviour can be defined in the same terms as human information behaviour: systems or agents that "need, seek, manage, give, and use information in different contexts."

Conceptual Models

A conceptual model "provides a working strategy, a scheme" comprised of concepts, components, relationships, events, and changes.[13] Stafford notes, "The usefulness of a model lies in how it informs us about the potential relationships between features of the world."[14] Box famously observed that "all models are wrong but some are useful" emphasizing their role as always incomplete and emergent maps that attempt to define causality and provide a context for further research.[15] As a result, "models must be built by an interactive feedback process in which an initial parsimonious model may be modified."[16]

Any MIB model must consider knowledge representations (symbolic, statistical, and subsymbolic), learning methods (supervised, unsupervised, self-supervised, and reinforcement learning), specific algorithms, computational environments, and data sources for training and use.[17] It must also include the sociotechnical aspects of algorithmic systems that include the political, economic, and social implications of this technology.[18] The proposed MIB model is a starting point for an ongoing assessment through the application of further empirical studies.

Artificial Intelligence, Explainable AI, and MIB

Artificial intelligence (AI) is a broad term encompassing a variety of theories, strategies, and techniques to accomplish intelligent systems. Different approaches are used to represent knowledge, assess accuracy, and optimize results. The information behaviours of these approaches exhibit both similarities and differences. Selecting a particular AI method to accomplish a task dictates the resulting MIB.

Expert systems leverage human expertise codified into rules and logic statements.[19] These systems are "brittle" because of their limited domain knowledge and difficulties in knowledge base updating. However, their processes and outcomes are highly transparent and open to inspection. Neural networks and deep learning systems utilize big data, complex algorithms, and extensive computation to make predictions and recommendations based on probabilistic models.[20] These systems are opaque; they lack transparency and resist explanation. Recently, ML models have been critiqued for their lack of contextual awareness.[21] All AI systems either balance computational power and human intervention or preference one of them.

In a provocative blog post, Rich Sutton, the leading proponent of reinforcement learning, claimed that "the biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin …the only thing that matters in the long run is the leveraging of computation."[22] Sutton's argument refutes the role of human knowledge engineering in AI. Preferencing computation accepts that in MIB, "intelligence is not an information problem, it's a computational problem."[23] Allowing computers to maximize their specific strengths will generate processes and discoveries unmatched by humans and resulting in what Beatrice Fazi calls beneficial "alien thought."[24]

A bias in favour of computation, however, has contributed to the opacity of neural networks (*black boxes*).[25] If the information behaviours of these systems are largely opaque, what accountability measures are required to ensure veracity and to engender trust? The field of *explainable AI* (XAI) attempts to answer these questions through a variety of strategies, techniques, and process.[26] While XAI is largely the domain of computer science and engineering, there is a strong case for leadership from academic libraries and librarianship.[27] A model of machine information behavior is an XAI strategy because it provides an abstraction of a complex system with the goal of explaining concepts, relationships, and actions.

HIB and MIB

A number of general human information behaviour models have been proposed.[28] The model developed by Wilson over a number of years culminated in his 2016 "general theory" of human information behaviour and is used to illustrate the intersection of HIB and MIB.[29]

Wilson's HIB model can be redrawn to preserve the core concepts, recognize his separation of information processing and information use, reinforce the iterative nature of many of the components, and to put it in a format more emendable to overlaying the core functions of an AI system.[30]

Wilson's model has seven foundational concepts: person-in-context, information need, activating mechanisms, intervening variables, information seeking behaviours, information processing, and information use. Unique contributions of Wilson's model are the concepts of activating mechanisms and intervening variables. Activating mechanisms are enablers and contributing theories (e.g., stress/coping theory, risk/reward theory, social learning theory) that bridge the gap between context and information seeking and use. Intervening variables, initially called "barriers" and later expanded to include more general contextual variables (e.g., environment, role, demographic, psychological, and information source characteristics), identify influences that have a material impact on information behaviour, especially during the seeking and processing stages.[31]

These broad concepts and their interactions are sufficiently inclusive to account for the IB theories that focus on specific contexts and roles. The interactions among these concepts are non-linear. Activating mechanisms, intervening variables, and information seeking behaviours interact throughout an IB process or event. Similarly, information need, while an initiating event, is also a context that is refined throughout the seeking and use process.[32]

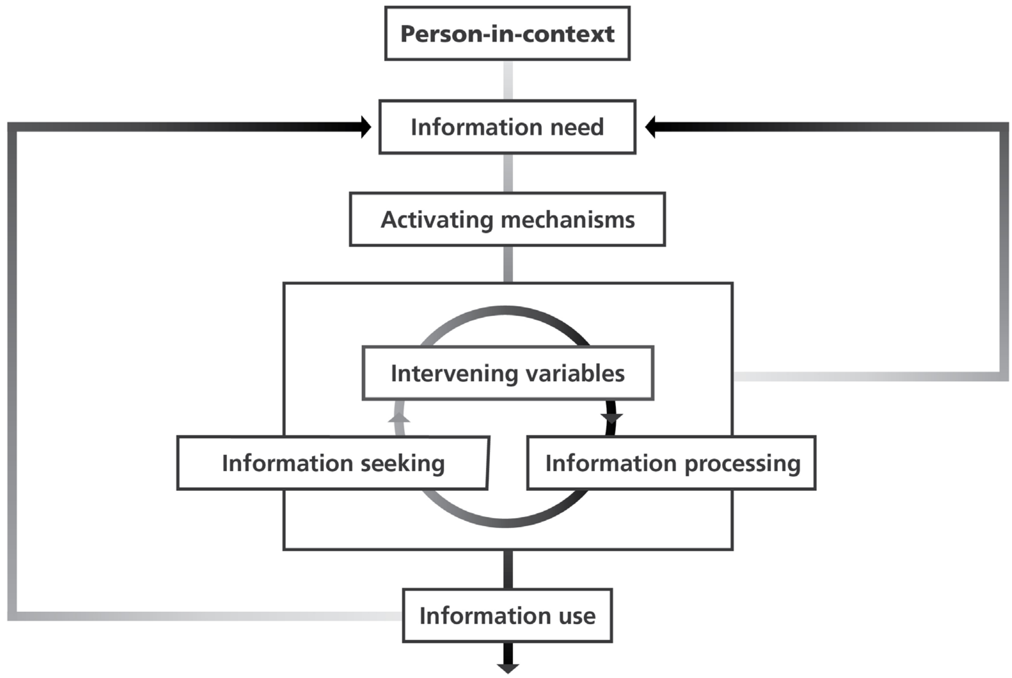

Figure 14.1
Wilson's General Theory of Information Behaviour (redrawn by the author).

There are three core functions common to all AI models: representation, evaluation, and optimization.[33]

Figure 14.2
Machine learning model.

Representation is how knowledge is expressed (e.g., rules, logic, vectors) as well as how the data is structured and understood. Evaluation is the scoring function of the model and how well the model fits the data. Optimization is the process that searches for the best model using specific testing and refinement techniques. The optimization and evaluation components iterate as model parameters and hyperparameters are adjusted and the result tested against the objective function (e.g., accuracy, similarity). While these processes are implemented differently according to the ontology that frames the intelligent machine (e.g., symbolic, statistical, subsymbolic), all are present and all influence MIB.[34]

By superimposing the core elements of machine learning on Wilson's general theory of information behaviour, the result is an illustrative and contextual interpretation of machine information behaviour.

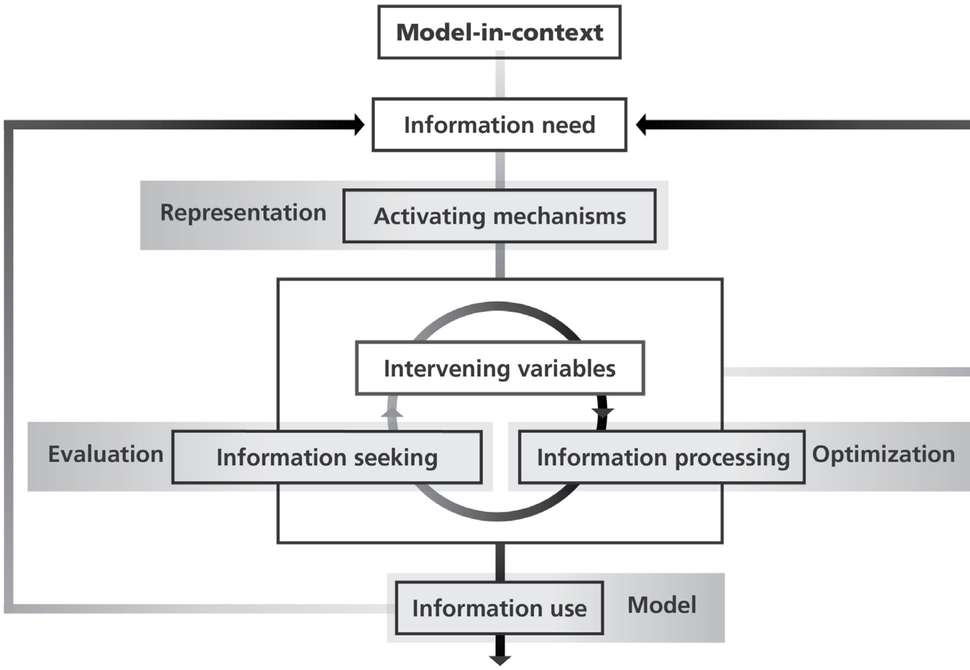

Figure 14.3
A preliminary machine information behaviour model.

All the components of this preliminary model can be elaborated to further define MIB. A brief examination of activating mechanisms, intervening variables, and information seeking and processing in the context of machine behaviour illustrates some of those characteristics.

Activating Mechanisms

An example of an activating mechanism in MIB is the ontology or paradigm at the core of the AI model. These consist of symbolists, connectionists, evolutionaries, Bayesians, and analogizers.[35] Each of these has a different concept of knowledge representation, learning methods, evaluation metrics, and optimization techniques. While not mutually exclusive, these ontologies prescribe or preference specific processes and representations that dictate subsequent actions and affect possible outcomes.

Another example is the process of data preparation, widely viewed as 80 percent of the effort in building a model, which cleanses and formats data in a manner consistent with the selected ontology (e.g., rules, vectors). This data preparation directly influences the subsequent evaluation metrics and methods as well as the optimization benchmarks and techniques.

Intervening Variables

As with the HIB model, intervening variables in MIB can come from a wide variety of sources, with each having different but material effects on information behaviour. For example, regulation and legislation may require systems to conform in specific ways. The global influence of the EU's General Data Protection Regulation (GDPR), with its notional "right to explanation," has driven widespread requirements for XAI.[36] Models (including assemblages into systems and agents) must be able to respond to demands for interpretability, transparency, and explainability.

Computation capacity is another important variable. The "combinatorial explosion" resulting from large information spaces can result in excessive computational demands.[37] Hence, computational availability and efficiency are significant variables that impact how long and to what depth the model can be trained.[38]

Information Seeking and Information Processing

These are iterative steps in both HIB and MIB. In HIB, these are approaches to resolving the information gap or need (e.g., active or passive search, passive attention, ongoing search) and to evaluate and synthesize that information for subsequent use. In MIB, these are the approaches to evaluation and optimization. Information seeking, intervening variables, and information processing come together to interrogate data, create hypotheses, and form (and test) interim models. Effective information processing is key to MIB, and a wide variety of strategies and techniques are employed. This aspect of MIB is an optimization process and is analogous to the stages in Dervin's sense-making model.[39]

AI-Authorship: An Example

In 2019, Springer Nature published *Lithium-Ion Batteries: A Machine-Generated Summary of Current Research*.[40] The author is identified as "Beta Writer," an AI. The book production process, a collaboration between various machine learning processes and human editors, is fully documented in the introduction.[41] The book is an annotated bibliography of 151 key research publications in the field algorithmically selected, categorized, and summarized by "off-the-shelf" ML techniques and natural language processing (NLP) tools. It consists of four thematic chapters, each with an introduction, topic subsections with document summaries, conclusion, related works, and references. As an experiment in scholarly publishing, Springer Nature is fully transparent about the processes and decisions, successful and otherwise. The book is a useful example of MIB. Since it is not a fully autonomous machine learning process, the book is better viewed as a collaboration where the information behaviours reflect those of both humans and the machine learning algorithms.

The book production process can be seen as an iteration through the proposed MIB model (figure 14.3) while addressing specific tasks: preprocessing data, structure generation, text generation, and post-processing. Depending on the task and the iteration, core information behaviours can be identified and their implications recognized. Information need remains a human-directed behavior. However, aspects such as *activating mechanisms*, *information seeking*, *information processing*, and *intervening variables* illustrate MIB.

For example, various *activating mechanisms* include data preprocessing and setting similarity metrics for eventual topic clustering. Algorithmic processing of the approximately one thousand core documents for linguistic and semantic normalizations, the use of word embedding (a domain-specific issue in specialized areas, such as chemistry), and the production of the term-document matrix used to determine document similarity, all shaped the determination of chapters and their sections during the selection and clustering processes.

The iterations through *information seeking* and *information processing* illustrate the behaviour of the clustering and summarization algorithms. For example, the clustering algorithm and tuning for similarity sensitivity both impact document relatedness and confidence levels regarding inclusion in chapter sections. In generating chapter topics and then subsection topics within these, different clustering algorithms were tested (hierarchical clustering through tree structures and recursive non-hierarchical clustering). The latter was eventually used as the former resulted in lengthy processing times and uneven homogeneity among chapters. The structure of the book was algorithmically generated but, as with most ML systems, certain parameters were set and tuned by the editors (e.g., the target number of chapters and sections, the maximum number of documents per section, term frequency metrics, and the type of stemming and other normalizations used). The choice of another clustering algorithm, such as HDBSCAN, would have resulted in the autonomous determination of many of these parameters.

Document summarizations were drawn from the abstracts. A variety of techniques were used and critiqued by content experts: unsupervised extractive, supervised extractive summarization, extended abstracts (reformulated, compressed, and enriched), and a weighted combined ranking that utilized all three approaches. Ultimately, extended abstracts were used because of errors attributable to the other techniques and to the nature of the subject domain. While abstractive summarization is a preferred algorithmic approach, extractive summarization proved more reliable and readable.

Intervening variables can be identified by their presence and, in some cases, by their absence. Called a “minimalist implementation” by the book editors, this conservative approach resulted in the use of less complex algorithms and more moderate parameter settings to favour recall over precision and to enhance trustworthiness among the science community readership. A robust chemistry-specific ontology was not used, although examples such as the Springer Nature SciGraph would have been helpful. The availability and use of knowledge graphs (domain-specific as well as broader contextual mappings) are significant intervening variables in MIB. Human intervention in the algorithmic decisions was limited. Content experts moved only nine documents to different chapters and removed only eight from the final key research documents algorithmically selected.

The ML model used to generate the book has many hyperparameters set by humans and parameters learned by the algorithms. For example, these parameters directly affect the nature of the document selection and categorization as well as the manner in which the text summarization is constructed and presented. A future priority for the book is "to provide a user interface that allows a user to switch parameters on the fly and see and evaluate the modification obtained by this and thus optimize the machine-generated text according to personal preferences."[42] Such a dynamic reconstruction of the book would allow readers to impose their own tolerances for scope, precision and recall, and trustworthiness. This, in effect, would allow the user to modify the MIB of the machine learning model (i.e., the book).

Conclusion

Academic libraries, and the academy more generally, have both shaped and been shaped by human information behaviours. Artificial intelligence, through the significant advances of machine learning with neural networks and deep learning, has resulted in increasingly autonomous systems being used for complex predictions and recommendations. Bourg's "new patron" obligates academic libraries to understand machine information behaviour with the same attention previously applied to human information behaviour.

The challenges of ML are significant and well-documented. This is a technology with great promise and menacing peril. However, as de Mul and van den Berg observed, if cognitive delegation occurs, it must happen with a clear understanding of the nature, characteristics, and implications of the systems or agents we wish to use and trust.[43] The preliminary model of machine information behaviour presented here is merely a starting point. It is a means to focus attention on MIB and to position academic libraries and librarianship as a critical community for the exploration of this emerging field.

Endnotes

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