The Difficulties of Using Big Data for Cognitive Modeling and Predictive Analytics

Siddhidhatri Rohith Reddy Jaggari
LO55859

Introduction

- Integrating big data, predictive analytics, and cognitive modeling into preexisting systems is challenging due to different data formats, storage needs, processing demands, resistance to change, and lack of trained employees.

- Proper management and analysis of massive amounts of data is essential to avoid improper conclusions and decisions, which can be costly for smaller businesses.

- Ethical issues such as confidentiality, informed consent, and equity must be considered, and businesses must maintain their duty to safeguard the privacy of their customers. Implementing ethical principles and best practices, using cloud computing and modern storage solutions, and embracing standardized integration frameworks can help overcome these challenges.

Literature Review

- Data preparation can account for up to 80% of the time spent in big data analytics (Mughal & Raza, 2019). This highlights the importance of dedicating sufficient resources and attention to data preparation to ensure the accuracy and reliability of the results.

- Analyzing big data requires specialized skills and expertise in data science and statistics (Mughal & Raza, 2019). This underscores the importance of investing in developing these skills or seeking the support of experts to ensure effective analysis and interpretation of the data.

- Data interpretation requires a clear understanding of the business context and the problem being addressed (Mughal & Raza, 2019). This suggests the importance of ensuring that those involved in data interpretation are well-versed in the relevant business domain and understand the objectives and requirements of the analysis.

Predictive Analytics and Cognitive Modeling

Modeling the Mind

- Cognitive modeling is a computer method for studying human cognition and decision-making processes (Hao & Wang, 2016).
- Developing realistic models of human cognition is inherently complicated due to the influence of various factors such as individual variances, cultural and societal influences, and emotional states (Sun, 2008).
- Cognitive models may be hindered by assumptions and simplifications that may not map onto actual cognitive processes, reducing their generalizability and ability to make reliable predictions about human behavior (Jones & Thomas, 2019).

Predictive Analytics and Cognitive Modeling

Analytical Prediction

- The accuracy and reliability of input data are significant concerns in predictive analytics, as they can affect the reliability of forecasts and policy decisions (Shmueli & Koppius, 2011).
- The limitations of continuity between the past and the future can reduce the effectiveness of data-driven decision-making, particularly in situations where outside forces disrupt patterns or there is rapid environmental change (Lourenço & Jones, 2017).
- The lack of transparency and interpretability of machine learning models, particularly deep learning models, can raise ethical questions about accountability and justice in decision-making (Molnar, 2019).

Implementation Challenges

Compatibility with Preexisting Infrastructure

- Data incompatibility is a major challenge when incorporating cognitive modeling and predictive analytics with big data into preexisting systems (Pentland, 2015; Chen, Chiang, & Storey, 2012). Businesses must invest significant time and resources into preprocessing, cleaning, and standardizing data to ensure compatibility with these tools.
- Insufficient storage and computing power can also be a constraint when dealing with big data, which requires extensive memory and processing power (Pentland, 2015). Businesses may need to adopt cutting-edge storage technologies and parallel processing methods, which can be expensive and time-consuming.
- The shortage of qualified professionals in data science, machine learning, and domain knowledge can also be a challenge for businesses (Pentland, 2015). Demand for these professionals far exceeds supply, making it difficult for businesses to find and retain qualified employees.

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Implementation Challenges

Data Analysis and Management

- The storage and processing of massive datasets require advanced storage systems and scalable processing frameworks, which can be costly and time-consuming to implement and manage (Chakraborty & Sarkar, 2018; Zaharia et al., 2016).
- Analyzing massive datasets involves advanced analytical methods that require specialized knowledge to implement and interpret properly, and may lead to data quality concerns and misinformed decisions (Chakraborty & Sarkar, 2018).
- The management and analysis of massive datasets must also address privacy and security concerns, and businesses must keep up with the latest data management and analysis best practices and tools (Chakraborty & Sarkar, 2018).

Implementation Challenges

Ethical Considerations

- Protecting personal information is crucial when using cognitive modeling and predictive analytics. Companies must comply with data protection laws such as the GDPR to avoid fines and reputational damage. (Hao & Wang, 2016)
- Obtaining consent is an essential ethical factor, but it can be challenging to obtain in big data where data sources are numerous. Companies should seek express agreement whenever possible. (Hao & Wang, 2016)
- Unintentional biases in data can be reinforced by cognitive modeling and predictive analytics, leading to unfair or discriminatory decisions. To ensure fair and accurate results, businesses must thoroughly evaluate their algorithms and models for bias and correct them as needed. (Hao & Wang, 2016; Hossain & Hasan, 2019)

Possible Gains

Enhanced Capacity for Making Choices

- The success of data-driven decision-making depends on the quality of the underlying data. Yousuf & Iqbal (2017) emphasize that decisions based on data are only as good as the quality of the data used to make them. Therefore, businesses must ensure that their data is precise, complete, and timely in order to draw useful conclusions.
- The openness and clarity of cognitive models and predictive algorithms are important factors in the success of data-driven decision-making. Yousuf & Iqbal (2017) argue that businesses can better comprehend the reasoning behind data-driven recommendations and make educated decisions when models are both interpretable and transparent. Therefore, it is important for decision-makers to have access to models that are easy to understand and explain

Possible Gains

Enhanced Productivity

- Incorporating data-driven insights into organizational culture and processes is crucial for improving efficiency through cognitive modeling and predictive analytics (Pentland, 2015). To achieve this, businesses must ensure that the insights gained are disseminated to the appropriate parties and may need to introduce new procedures or shift company culture.
- Focusing on high-impact sectors is essential for maximizing the benefits of cognitive modeling and predictive analytics in improving efficiency (Pentland, 2015). Leaders must have a deep understanding of their organization's challenges, potential for growth, and inner workings to pinpoint areas where these technologies will have the biggest impact.
- The effectiveness of cognitive modeling and predictive analytics in improving efficiency depends on the quality of the models and algorithms used (Pentland, 2015). To ensure reliable insights, businesses must invest in the creation and improvement of these models, regularly check for errors, and update them as new information becomes available.

Problem-Solving: Surmounting Obstacles

- **Creating Commonly Used Integration Frameworks :** Standardized integration frameworks can improve interoperability and make implementations more efficient, but they may need to be regularly updated to keep up with the fast pace of technological advancements.

- **Using Cloud Services and State-of-the-Art Data Storage :** The use of cloud computing and modern storage technologies can greatly improve data management and analytics, making cognitive modeling and predictive analytics more accessible and cost-effective for organizations (Wu et al., 2014). However, businesses must also carefully consider and address potential risks associated with cloud computing, such as data security and privacy concerns, to ensure that they are adequately protected.

- **Setting Best Practices and Ethical Standards :** Explicit standards and procedures for handling data, including algorithm bias identification and mitigation, regular audits of data handling methods, and anonymization and encryption, are necessary for responsible and ethical cognitive modeling and predictive analytics (Hao & Wang, 2016). Involving diverse stakeholders in formulating ethical principles and best practices, such as data subjects, regulators, and industry experts, is also crucial for a balanced approach to ethical data usage.

Conclusion

- Overcoming obstacles in combining cognitive modeling and predictive analytics with large data can lead to improved decision-making and efficiency.

- Key steps towards unlocking the potential of these technologies include standardized integration frameworks, advanced storage solutions, and ethical guidelines and best practices.

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Thank you