Assignment 02

MIS 64038 Analytics in Practice

Case 02 - Fraud Detection in Banking

In the case of the community bank's partnership with an analytics solution provider to develop a new fraud detection algorithm for ATM withdrawals, the failure can be attributed to several overlooked aspects and phases of the analytics project. Primarily, the problem seems to stem from inadequately planned operationalization and possibly inadequate data preparation.

Firstly, the operationalization phase (phase 6) appears to be deficient. While the model demonstrated acceptable performance during testing, it failed to perform adequately in the production environment. This suggests a lack of consideration for the scalability and efficiency of the model in real-world applications. Operationalization involves not only developing the model but also ensuring its seamless integration into existing systems and workflows. In this case, the model's slowness in the production environment led to significant disruptions in service, affecting customers' ability to withdraw funds from their accounts. To prevent such failures, it's critical to carefully assess the operational implications of deploying the model and to conduct sound performance testing in environments that reflect real-world conditions.

Secondly, the data acquisition and preparation phase (phase 3) might have been insufficiently addressed. While the bank provided historical data for model training, it's possible that the dataset did not adequately represent the diversity and complexity of real-world ATM transactions. Incomplete or biased data can lead to the development of models that perform well in controlled settings but fail when exposed to the variability and unpredictability of actual usage. Therefore, it's essential to ensure that the data used for model training is comprehensive, representative, and free from biases that could adversely impact model performance.

To resolve these issues, the bank and its analytics solution provider should revisit both the operationalization and data preparation phases of the project. In terms of operationalization, they should conduct detailed performance testing in simulated production environments to identify and address any scalability or efficiency issues before deployment. Additionally, they should collaborate closely with the bank's IT and operations teams to integrate the model seamlessly into existing systems and workflows.

In terms of data preparation, they should reassess the quality and representativeness of the training data, considering factors such as data volume, diversity, and potential biases. They may need to augment the existing dataset with additional sources of data or employ techniques such as data cleaning and preprocessing to improve its quality. By addressing these issues, they can enhance the robustness and effectiveness of the fraud detection algorithm and mitigate the risk of similar failures in the future.

Case 03 - Amazon Rekognition

The failure associated with Amazon Rekognition, particularly in its application by various government agencies and private entities, highlights critical oversights in both the data preparation and model planning/building phases of the analytics project. Further, it underscores the ethical considerations often overlooked in deploying AI systems, especially those with significant societal impact.

Firstly, the data preparation phase (phase 3) appears to have been inadequately addressed, leading to biases in the model's performance. The reliance on datasets greatly biased towards specific demographics, such as white males, resulted in significant disparities in the algorithm's accuracy across different groups. This bias can be attributed to the lack of diversity and representativeness in the training data, which failed to account for the variability present in real-world scenarios. To mitigate such biases, it's essential to use diverse and inclusive datasets that accurately reflect the population's demographics and characteristics.

Secondly, the model planning/building phase (phase 4) lacked adequate consideration for the ethical implications of deploying facial recognition technology, particularly in contexts involving law application and inspection. While the algorithm's technical performance may have met certain benchmarks during development, its real-world deployment raised significant concerns regarding privacy, civil liberties, and potential discriminatory outcomes. Ethical considerations should be connected to the model development process, guiding decisions about data collection, algorithm design, and application domains.

To address these issues, Amazon and other stakeholders must prioritize ethical and responsible AI practices by using facial recognition technology. This includes adopting transparent and inclusive processes for data collection and model development, conducting clear assessments and impact evaluations, and engaging with diverse stakeholders to request feedback and address concerns. Additionally, regulatory oversight and public inquiry can help ensure accountability and mitigate the risks associated with the misuse of AI technologies for surveillance and social control.

Case 04 - IBM Watson in Healthcare

The failure of IBM Watson in the healthcare industry can be attributed to several overlooked aspects and phases of the analytics project, including project discovery and definition, model planning/building, and operationalization. Additionally, the failure underscores the importance of collaboration between technology providers and domain experts to ensure the successful deployment of AI solutions in complex domains such as healthcare.

Firstly, the project discovery and definition phase (phase 1) seem to have been rushed, with insufficient consideration given to the unique challenges and requirements of applying AI to healthcare decision-making. The decision to introduce IBM Watson into the healthcare system may have been driven more by marketing pressures and technological push than a systematic understanding of the domain's complications. To avoid similar failures in the future, organizations must invest adequate time and resources in conducting comprehensive requirements assessments and feasibility studies before going on board AI projects.

Secondly, the model planning/building phase (phase 4) may have been compromised using biased or incomplete training data, resulting in suboptimal performance and limited generalizability. The reliance on data from a single development partner, MSKCC, may have introduced biases towards specific treatment procedures and patient populations, rendering the system less effective when applied to diverse healthcare settings. To address this issue, AI developers must prioritize the use of diverse and representative datasets, drawing from multiple sources to capture the full range of clinical variability and patient demographics.

Thirdly, the operationalization phase (phase 6) appears to have been inadequate, with inadequate attention given to the integration of IBM Watson into existing healthcare workflows and processes. The failure to engage with hospitals and clinicians to ensure the seamless adoption and utilization of the AI system likely contributed to its underperformance and ultimate rejection by end-users. Successful operationalization requires close collaboration between technology providers, healthcare professionals, and IT specialists to address workflow integration, usability, and change management challenges.

To rectify these shortcomings, IBM and other technology providers must adopt a more collaborative and iterative approach to AI development in healthcare. This includes engaging with healthcare stakeholders early and often throughout the project lifecycle, prioritizing transparency, accountability, and user-centered design principles, and conducting rigorous evaluations to assess both technical and clinical outcomes. By aligning technology development with the needs and realities of healthcare delivery, organizations can increase the likelihood of successful AI adoption and realization of its transformative potential.

Case 05 - AI for University Admission

The failure of the AI system, Todai, to perform adequately in cracking the entrance test for the University of Tokyo highlights critical oversights in both the data preparation and model planning/building phases of the analytics project. Furthermore, it underscores the limitations of AI in replicating human intellectual abilities, particularly in domains requiring nuanced understanding and interpretation.

Firstly, the data preparation phase (phase 3) appears to have been inadequately addressed, leading to the failure of the AI system in understanding and answering complex questions. The dataset used to train Todai may have lacked the scope and depth of information necessary to simulate the diversity and complexity of questions found in the university entrance exam. As a result, the AI system failed to generalize effectively to unseen scenarios, leading to poor performance during testing. To address this issue, developers must prioritize the collection of diverse and representative datasets, involving a wide range of question types and topics relevant to the target domain.

Secondly, the model planning/building phase (phase 4) may have overlooked the inherent limitations of AI in replicating human thinking processes, particularly in tasks requiring the ability to understand nuanced meanings and contexts. While AI systems excel in certain domains, such as pattern recognition and data analysis, they may struggle with tasks that involve complex reasoning, interpretation, and inference. To avoid overestimating the capabilities of AI systems, developers must adopt a more nuanced understanding of AI's strengths and limitations, focusing on tasks where AI can support rather than replace human expertise.

To address these challenges, developers must adopt a more holistic approach to AI development, incorporating insights from intellectual science, psychology, and education research to inform the design of AI systems for complex tasks. Additionally, developers must prioritize transparency in AI systems, enabling users to understand how decisions are made and providing opportunities for human intervention and oversight when needed. By aligning AI development with the realities of human cognition and expertise, developers can create more effective and trustworthy AI systems for a wide range of applications.

Case 06 - Mars Orbiter

The failure of the Mars Orbiter mission can be attributed to several ignored aspects and phases of the analytics project, including project discovery and definition, model planning/building, and operationalization. Additionally, the failure underscores the importance of robust quality assurance processes and effective communication between project stakeholders.

Firstly, the project discovery and definition phase (phase 1) appear to have failed to adequately address critical aspects of the mission, including the compatibility of measurement units between different teams and organizations. The failure to establish clear standards and protocols for data exchange and communication between Lockheed Martin's engineering team and NASA's internal team contributed to the misunderstanding and ultimately the loss of the satellite. To prevent similar failures in the future, organizations must prioritize thorough requirements analysis and stakeholder engagement during the project planning phase, ensuring that all relevant parties have a shared understanding of project objectives, constraints, and dependencies.

Secondly, the model planning/building phase (phase 4) may have overlooked the importance of implementing robust checks and balances to detect and correct errors before they propagate through the system. The failure to identify and rectify the discrepancy in measurement units between Lockheed Martin and NASA during the development and testing phases of the project underscores the need for sound quality assurance processes and independent verification and validation mechanisms. To mitigate the risk of similar errors in future missions, organizations must implement comprehensive testing protocols and risk management strategies, including scenario-based simulations and sensitivity analyses to identify and address potential failure modes.

Thirdly, the operationalization phase (phase 6) appears to have lacked effective management and governance mechanisms to ensure the integrity and reliability of mission-critical systems and processes. The failure to implement adequate safeguards and controls to prevent errors in data transmission and processing highlights the importance of robust change management and configuration control processes. To enhance operational readiness and resilience, organizations must invest in continuous monitoring and evaluation of mission-critical systems, incorporating feedback loops and corrective actions to address emerging issues and mitigate operational risks.

To address these shortcomings, NASA and its partners must adopt a more proactive and systematic approach to project management and risk mitigation, emphasizing collaboration, communication, and accountability across all phases of the project lifecycle. By incorporating lessons learned from past failures and investing in continuous improvement and innovation, organizations can enhance the success rate and reliability of future missions, advancing our understanding of the universe and expanding the limits of human knowledge and exploration.

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