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Assignment II: MIS 64038 Analytics in Practice

Case 2: Fraud Detection in Banking

The fraud detection analytics project encountered difficulties during phase six of the ***operationalization*** and phase three of ***model development***. While the model performed well with historical data, it faltered when deployed in the live production environment, unable to handle the workload effectively. The oversight during development neglected scalability and real-time feasibility considerations, leading to operational failures such as timeouts and customer inconvenience during ATM withdrawals (Chaudhary).

The critical aspect that seems to have been overlooked or underestimated is the computational performance and efficiency needs of the model in the production setting. The model's inference process was excessively slow, resulting in timeouts and hindering customers from completing their ATM withdrawals.

The following challenge can be *addressed* by implementing the following measures:

- Firstly, both the bank and the analytics provider must focus on refining the operationalization process to ensure the model's effectiveness in live production. This entails rigorous testing in a simulated environment before actual deployment, verifying its capability to handle real-time ATM transactions and accommodate high volumes of requests. If necessary, adjustments to the model may be needed, potentially requiring a return to the development phase (Chaudhary). Additionally, establishing a dedicated support team for prompt issue resolution is crucial for maintaining system functionality and customer satisfaction.

- Secondly, by conducting an extensive performance evaluation of the model in a simulated production environment during the planning and construction phases (phases 3 and 4). This analysis will help pinpoint potential performance bottlenecks early on, allowing for optimizations or adjustments to the model's architecture or computational resources (Chaudhary).
- Thirdly, engaging the stakeholders and IT teams responsible for the production environment during the planning phase (phase 3) to grasp the computational limitations, hardware specifications, and infrastructure constraints. This collaboration will aid in crafting a model that meets the performance criteria of the production environment (Paliwal).
- Lastly, by ensuring adequate allocation of computational resources (e.g., GPU, TPU, or distributed computing) to the production environment to manage the model's computational demands effectively (Chaudhary).

By addressing these aspects during the appropriate phases of the analytics project, the bank could have mitigated the risk of failure and achieved a successful deployment of the fraud detection model in the production environment.

Case 3: Amazon Rekognition

A significant concern with Amazon Rekognition is its struggle to accurately identifying dark-skinned females, as highlighted in a peer-reviewed study by MIT researchers. This bias is attributed to the algorithms being trained on imbalanced datasets primarily focused on white men (Iranmanesh). The project team may not have adequately considered potential biases in the training data and algorithms, leading to insufficient testing and evaluation before public release, which could have uncovered biases earlier. Even the subsequent model, developed after the George Floyd incident, was halted before fulfilling its intended duration (Paliwal). The challenges with Amazon Rekognition span across the analytics project's data preparation, model building, and model testing phases.

In short, the Rekognition model displayed bias in recognizing dark-skinned females, stemming from the unbalanced training dataset. The project team neglected to adequately acknowledge and rectify potential biases within the training data and algorithms. Additionally, they did not conduct comprehensive testing and evaluation of the model before its public release.

To address these problems, the following steps can be taken:

1. During the ***data preparation*** phase, the team should:
    - Expand the collection of training data to encompass greater diversity, reflecting a more balanced portrayal of various skin tones and genders within the target population. This can be achieved through utilizing more diverse training data, enhancing fairness metrics, and employing techniques like oversampling minority groups and data augmentation to boost data diversity (Iranmanesh).
    - Utilize data augmentation methods, such as image manipulation, to enhance the diversity of the training dataset (Paliwal).
    - Integrate techniques for detecting and addressing algorithm bias, such as adversarial training, to reduce the model's sensitivity to skin color and facial characteristics, and to enhance model robustness in recognizing skin color and facial features changes. Given

the model's relevance to human-centric tasks, thorough testing involving a diverse group of individuals during development and testing phases is crucial to ensure comprehensive and fair performance (Paliwal).

- Adjust the weighting of training data to achieve a balance in representing diverse demographic groups (Iranmanesh).
- Seek guidance from external specialists to conduct audits on the model for algorithmic bias.

2. During the ***model testing phase***, the team should:

- Engage a diverse panel, including individuals from underrepresented demographics, to meticulously assess the model's performance and pinpoint any lingering biases.
- Establish rigorous fairness metrics and criteria for acceptance to ensure the model aligns with desired standards of fairness and inclusivity (Chaudhary).

Case 4: IBM Watson in Healthcare

The IBM Watson project encountered neglect across multiple phases of the analytics project, ultimately leading to its failure. In the ***data collection phase***, IBM hurriedly implemented the program without allocating sufficient time to gather high-quality data for personalized medicine (Herper).

Additionally, IBM heavily relied on training data from its development partner, MSKCC, resulting in biased outcomes and limited treatment suggestions. This lack of data diversity caused the program to fall short in delivering the promised medication recommendations to oncologists. The absence of varied data from numerous healthcare providers and institutions contributed to Watson's incapacity to address intricate cancer scenarios and deliver personalized treatment guidance (Hernandez).

Moreover, during the ***model development and testing phase***, IBM made another misstep. Initially envisioned as a software product, where oncologists input patient data to receive reliable treatment suggestions, IBM failed to collaborate with other hospitals and smaller clinics adequately. IBM overlooked the necessity of integrating domain-specific medical expertise and expert insights into Watson's decision-making process. This lack of collaboration, coupled with inadequate testing, prevented IBM from meeting expectations (Hernandez).

Furthermore, IBM's aggressive marketing of Watson without ensuring its competence first led to unrealistic expectations and frustration among healthcare professionals expecting revolutionary changes in cancer treatments. This failure can be attributed to shortcomings in the ***communication phase*** (Herper).

To *rectify* these issues and achieve success, IBM must take essential actions.

First, IBM needs to prioritize gathering high-quality, diverse, and inclusive datasets from various healthcare providers, hospitals, and clinical establishments during phase two of the ***data collection phase***. This approach will help in reducing biases and ensure that the model receives training on a comprehensive array of medical data (Hernandez).

Engage domain experts, such as oncologists, medical researchers, and healthcare practitioners, throughout the ***model planning*** and construction phases. Their insights and guidance will prove invaluable in integrating medical expertise, best practices, and treatment protocols into the model. Thorough testing post-implementing necessary changes will help identify any remaining issues before the system's real-world launch (Herper).

Conducting thorough ***testing of the model*** and assessment of the model's performance and recommendations alongside healthcare professionals and subject matter experts before rolling it out (phase 4) (Herper).

Establishing a feedback loop and continuous learning mechanism to integrate new medical knowledge, research findings, and data into the model regularly, thereby maintaining its relevance and precision over time (Hernandez).

By addressing these issues across multiple phases of the analytics project and fostering collaboration between technical specialists and domain experts, IBM could have better aligned Watson's capabilities with the practical demands of the healthcare sector.

Case 5: AI for University Admission

A project aimed at creating an AI robot named Todai to take entrance exams at the University of Tokyo ended in failure unexpectedly. The failure resulted from various shortcomings throughout the project phases, leading to unexpected outcomes. Developers assumed that AI, after training, could perform tasks typically done only by humans during exams. However, researchers may not have fully grasped the limitations of AI in comprehending exam questions, necessitating more advanced techniques (Mirza).

A significant issue in the project was identified in the ***data preparation phase***, where researchers failed to gather and synthesize a wide range of information related to the robot's system, impacting its understanding of exam questions. Insufficient efforts in feature engineering, model selection, and model training to address the complexity of the university entrance exam (McGoogan).

Furthermore, problems were encountered in the ***feature engineering, model selection, and model training phases*** to address the complexity of the university entrance exam. Linguistic features crucial for question comprehension might have been overlooked during feature engineering (McGoogan). The model selected may have been too simplistic to handle the exam's complexity, leading to poor performance. And, the absence of thorough testing of the Todai robot across various scenarios and conditions (Mirza).

To *rectify* the project's course, essential changes are needed, i.e.,

1. ***During data preparation:***

- Gathering and organizing an inclusive dataset containing various exam questions and pertinent contextual details (e.g., linguistic attributes, intricacy levels).
- Refining and converting the data into a suitable format for efficient utilization by the AI model (McGoogan).

2. In the ***model development*** stage:

- Implementing advanced natural language processing techniques to enhance the AI model's understanding of the exam's complexities and subtleties.
- Exploring sophisticated machine learning models like transformer-based architectures, tailored for handling university entrance exam challenges (Mirza).
- Iteratively training and optimizing the model, integrating inputs from education and AI domain specialists (McGoogan).

3. Throughout ***model testing***:

- Constructing a comprehensive testing framework mirroring diverse exam scenarios, encompassing question variations, linguistic intricacies, and time constraints (Mirza).
- Engaging a diverse cohort of participants, including university stakeholders, for feedback and validation of the Todai robot's performance (McGoogan).
- Continuously enhancing the model and testing protocols based on insights derived from these assessments (Mirza).

Additionally, a thorough data cleaning, integration, selection, and transformation in the data preparation phase ensures high-quality data for model development. Incorporating example questions from the entrance exam into the model and employing natural language processing and sentiment analysis techniques can enhance question understanding (Mirza). Adjusting the weightage of feature engineering methods based on properly organized data and rigorous testing under various conditions are also crucial steps (McGoogan).

Case 6: Mars Obiter

The case study delves into the Mars Orbiter project's failure, attributed to communication gaps and data standardization issues between NASA and Lockheed Martin, alongside inadequate planning and testing of the model. This analytics project encountered failures in multiple phases. In the ***data preparation phase***, there was a misalignment in units of measurement between NASA and Lockheed Martin's engineering team, leading to data mix-ups and the orbiter's loss (Eucler and Jolly). Additionally, insufficient resource planning in the ***model planning phase***, influenced by budget constraints, hindered project success. Inadequate testing during the ***model testing phase*** resulted in unexpected outcomes (Holtz).

In this case, the *key issues* highlighted include:

1. Communication and standardization challenges regarding data format (metric vs. English units) between NASA and Lockheed Martin (Iranmanesh).

2. Deficiencies in planning and budget allocation, leading to resource inadequacies for achieving project goals (Eucler and Jolly).

3. Insufficient testing of the model pre-launch, resulting in unforeseen outcomes.

To *address* these challenges effectively, the following steps are recommended:

1. Data Preparation:

- Fostering clear communication and consensus between NASA and Lockheed Martin on a standardized unit of measurement and ensuring data accuracy (Holtz).
- Implementing robust data validation and quality control mechanisms to ensure consistent and accurate data formats (Eucler and Jolly).

2. Model Planning:

- Conducting a comprehensive assessment of resource needs, including budget, personnel, and infrastructure requirements (Holtz).
- Communicating resource requirements to relevant stakeholders and securing necessary funding and support (Holtz).
- Implementing checks and balances at each project stage, conducting regular audits, and enforcing quality control measures will reveal potential drawbacks (Eucler and Jolly).

3. Model Testing:

- Developing a thorough testing plan covering diverse scenarios, edge cases, and potential failure modes.
- Conducting rigorous testing involving cross-functional teams and subject matter experts pre-launch (Holtz).
- Defining clear evaluation criteria and metrics for assessing model and system performance and reliability (Eucler and Jolly).

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