**Assignment II: Failed Phases of Analytics Projects**  
Elizabeth Crawley  
Kent State University  
Spring 2025 Analytics in Practice

BA-54038-004  
Instructor Dr. Alan Brandyberry

April 17, 2025

**Analytics in Practice: Assignment II**

**Case 2: Fraud Detection in Banking**

The issue with the fraud detection may have been avoided had the system been tested in a real-time production environment. This would have been in the operationalization and model validation phases of the analytics lifecycle that were overlooked. While the model performed well during testing with historical data, it must not have been fully tested for performance in a real-time production environment, leading to significant operational disruption. ATM transactions were delayed or timed out, resulting in customer dissatisfaction and system failure.

Issues like this one could be avoided with rigorous performance testing under production-like conditions. The model existing but not being well developed could have been resolved during the validation phase. Additionally, the operationalization phase lacked foresight regarding the infrastructure requirements to support the model in real-time. To resolve this, developers should include stress-testing and simulate deployment environments during the evaluation phase. A phased or soft rollout could identify bottlenecks without disrupting the entire user base (Provost & Fawcett, 2013). Additionally, considering computational complexity and the Big-O notation of model operations, as described by freeCodeCamp (2019), could have helped anticipate and mitigate performance challenges.

**Case 3: Amazon Rekognition**

Amazon Rekognition’s issues are the result of the data understanding and model development phases. The model exhibited a clear bias against darker-skinned individuals, misidentifying them at a significantly higher rate than lighter-skinned individuals. This discrepancy stemmed from the lack of diversity in the training datasets, which were skewed heavily toward white males. As a result, the algorithm failed to generalize effectively across different demographics (Buolamwini & Gebru, 2018).

Addressing this issue requires diverse and representative data during the data preparation phase. Fairness and bias audits should be incorporated into model evaluation. Moreover, ethical considerations and responsible AI governance must be central throughout the lifecycle. Amazon could have implemented continuous monitoring, demographic performance evaluations, and transparency reporting to build a more inclusive and trustworthy system (Raji et al., 2020). Furthermore, interpretability in machine learning, as discussed by Molnar (2022), is crucial in uncovering biased behavior and improving stakeholder trust.

**Case 4: IBM Watson in Healthcare**

The IBM Watson case represents failures across multiple phases, including business understanding, data preparation, and deployment. IBM prematurely launched Watson into the healthcare domain without adequate preparation or customization for different clinical environments. The system was mostly trained on data from a single partner institution, Memorial Sloan Kettering Cancer Center, which caused biased treatment recommendations that did not generalize well across hospitals (Ross & Swetlitz, 2017).

This case emphasizes the importance of robust collaboration during the business understanding phase and the need for comprehensive, high-quality datasets in model development. Pilot programs and iterative testing could have revealed deficiencies before full-scale deployment. Additionally, engagement with clinical practitioners during the design and implementation phases would have ensured better alignment with real-world medical workflows. Understanding the "No Free Lunch" theorem (Brownlee, 2019a) is also essential here—it reminds us that a model optimized for one dataset or environment may not perform well across others.

**Case 5: AI for University Admission (Todai Robot)**

The Todai Robot project failed due to missteps in the problem definition and modeling phases. The task of passing the University of Tokyo entrance exam involves abstract reasoning, contextual understanding, and wide range knowledge integration—capabilities that remain challenging for AI. The researchers overestimated the current AI ability to perform such demanding tasks, leading to poor outcomes.

To avoid this problem, project scope should be aligned with technological ability. During the problem definition phase, realistic goals must be set. In model development, the use of advanced NLP models with context reasoning capabilities, could improve outcomes. An incremental approach to complexity and broader dataset integration would make such projects more viable (Marcus, 2018). Understanding the distinction between prediction and interpretation (Brownlee, 2019c) and setting appropriate expectations are critical when designing such complex systems.

**Case 6: Mars Orbiter**

The loss of the Mars orbiter due to a unit conversion error underscores failures in the data preparation, integration, and communication phases. NASA and Lockheed Martin used different measurement systems—metric and imperial, respectively—without proper synchronization. This systemic oversight in unit standardization led to a $125 million loss.

This case highlights the necessity for standardized data protocols and effective communication channels in collaborative projects. A robust governance framework should mandate consistency in data formats and measurement units. Automated checks and simulations could also prevent such errors. Ensuring shared understanding and accountability across teams is vital for success in high-stakes analytics projects (NASA, 1999). Effective communication practices, such as those outlined by UBC-MDS (2017), should be integral to any analytics initiative.

**References**

Brownlee, J. (2019a). No Free Lunch Theorem for Machine Learning. *Machine Learning Mastery*. https://machinelearningmastery.com/no-free-lunch-theorem-for-machine-learning/

Brownlee, J. (2019b). The Best Machine Learning Algorithm. *Machine Learning Mastery*. https://machinelearningmastery.com/the-best-machine-learning-algorithm/

Brownlee, J. (2019c). Model Prediction Versus Interpretation in Machine Learning. *Machine Learning Mastery*. https://machinelearningmastery.com/model-prediction-versus-interpretation-in-machine-learning/

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of the 1st Conference on Fairness, Accountability and Transparency*, 77–91.

Marcus, G. (2018). Deep learning: A critical appraisal. *arXiv preprint arXiv:1801.00631*.

Molnar, C. (2022). *Interpretable Machine Learning*. https://christophm.github.io/interpretable-ml-book/interpretability.html

NASA. (1999). *NASA releases report on Mars climate orbiter mishap*. Retrieved from https://mars.nasa.gov/msp98/news/mco991110.html

Provost, F., & Fawcett, T. (2013). *Data science for business: What you need to know about data mining and data-analytic thinking*. O’Reilly Media.

Raji, I. D., Gebru, T., Mitchell, M., Buolamwini, J., Lee, J., & Denton, E. (2020). Saving face: Investigating the ethical concerns of facial recognition auditing. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, 145–151.

Ross, C., & Swetlitz, I. (2017). IBM pitched its Watson supercomputer as a revolution in cancer care. It’s nowhere close. *STAT News*. Retrieved from https://www.statnews.com/2017/09/05/watson-ibm-cancer/

UBC-MDS. (2017). Communication in Data Science. *UBC Master of Data Science*. https://ubc-mds.github.io/2017-11-10-DSCI-542-communication/

freeCodeCamp. (2019). Big O Notation: Why It Matters and Why It Doesn’t. https://www.freecodecamp.org/news/big-o-notation-why-it-matters-and-why-it-doesnt-1674cfa8a23c/