Assignment II: MIS 64038 Analytics in Practice

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Case 1: Marketing Campaign

This case represents a classic scenario of missing one-minute detail in the whole data mining process which ultimately led to a disaster scenario for a major Canadian bank. The case involved a logistic response model being built by an external supplier (not us) for acquisition of new customers regarding a given bank product of a well-known Canadian bank. The model was built and worked very well when looking at validation results. This model was then implemented and actioned on within a future marketing campaign. During the development process, the tools that were used both generated the solution as well as the validation results. However, during the scoring process, the tool did not automatically generate the score. The user had to take the output equation results from the model development process and generate a scoring routine to score a given list of bank customers. In scoring, the user had to manually create the score by multiplying coefficients with variables. As part of this process, there was also a transformation of this equation to a logistic function. As part of this transformation, the user had to multiply the entire equation by -1. This fact of multiplying the equation by -1 was forgotten by the user when scoring the list of eligible customers. Guess what happened. Names with the highest scores represented the worst names with the opposite scenario happening for the lowest scores. The campaign went out by targeting names with the highest scores which ultimately resulted in horrific results.

When the supplier did the backend against a control random group of names promoted across all model deciles, they flipped the sign the right way to -1 and validated that the model worked quite well. Unfortunately, this did not appease the client's unhappiness as the bulk of their campaign names represented so-called targeted names within the top few deciles but who were in fact the worst names. From a net eligible universe of 500M names, the client ended up losing well in excess of $100M.

Example Answer:

There are at least two areas (phases) of the project that could be linked to the failure of the above project: the commination phase and the operationalization phase. As for the communication phase (phase 5), it seems that the third-party consulting firm failed to clearly communicate and/or emphasize enough on the importance of the steps needed to be taken to use the model's output. Generally, once an analytics model is handed to a team, the development team is responsible to commutate the details of how the model should be used and to train the end users who will be interacting with the model.

In addition, the model did not seem to have been properly operationalized (phase 6), as it required several manual operations which significantly increases the chance of errors. Automation should be used as much as possible to minimize the impact of human's errors. In addition, checks and balances and models' monitoring should be an integral part of the model's operationalization. This scenario might have been prevented if there were checks and balances as part of the implementation process. By checking score distributions as well as the model variable means within the targeted deciles during model development and the current list implementation, this error would have been caught. The user would have noted that significant changes in both score distribution as well as model variable means for the targeted deciles would have occurred between time of model development and the current list scoring run. They then would have investigated this further by checking their coding in further detail and would have caught the omission and corrected it by multiplying the equation by -1. They say that the devil is in the details, but in data mining the devil is in the data.

Case 2: Fraud Detection in Banking

A community bank partnered with an analytics solution provider to develop new fraud detection algorithm for ATM withdrawals. The bank provided historical data and the company trained a model that seemed to provide an acceptable performance when tested on the data. Once implemented, however, the bank faced a major tragedy: the algorithm was too slow in the production environment, and, as such, most ATM withdrawal requests were timed-out and customers were not able to withdraw from their accounts. Discuss which aspects of the project were ignored and which phase(s) of the analytics project, the problem can be associated to?

Answer:

The above project fails in following phases:

- **Operational Phase Failure.**

Operational Phase Failure:

The fundamental issue with the Banking fraud detection project appears to have been a failure during the operational phase of the project. When deployed in a true production environment after being constructed and tested in a sandbox environment, the model did not operate as expected. As a result, the algorithm processed ATM withdrawal requests at an abnormally sluggish rate, prohibiting many clients from accessing their accounts. There might be various reasons why the model failed in production. One reason is that variations between the operating and development environments were overlooked during the project. For instance, the solution provider may have created a model in a programming language other than the one utilized in the live environment. Other variables in hardware or software configurations might have impacted the algorithm's performance.

Another possibility is that the model development process was opaque. In other words, the IT team in charge of putting the model into operation may not have fully comprehended how it was created, notably the data conversions and techniques employed. This might have resulted in mistakes or omissions when reproducing the model in production, contributing to the algorithm's low performance.

Overall, this case emphasizes the importance of meticulous planning and execution during the operational phase of an analytics project. Before models can be used in the real world, they must be thoroughly tested and validated, and any potential discrepancies between operational and development environments must be recognized. Maintaining openness and communication throughout the project is also critical to ensuring that all stakeholders understand the project's goals and objectives.

Case 3: Amazon Rekognition

Amazon Rekognition is a cloud-based software as a service (SaaS) computer vision platform that was launched in 2016. It has been sold and used by a number of United States government agencies, including U.S. Immigration and Customs Enforcement (ICE) and Orlando, Florida police, as well as private entities. Rekognition provides a number of computer vision capabilities, which can be divided into two categories: Algorithms that are pre-trained on data collected by Amazon or its partners, and algorithms that a user can train on a custom dataset. In January 2019, MIT researchers published a peer-reviewed study asserting that Rekognition had more difficulty in identifying dark-skinned females than competitors such as IBM and Microsoft. In the study, Rekognition misidentified darker-skinned women as men 31% of the time, but made no mistakes for light-skinned men. The problem, AI researchers and engineers say, is that the vast sets of images the systems have been trained on skew heavily toward white men. In June 2020, Amazon announced it was implementing a one-year moratorium on police use of Rekognition, in response to the George Floyd protest. In May 2021, Amazon announced that they are extending its global ban on police use of its facial recognition software until further notice. Discuss which aspects of the project were ignored and which phase(s) of the analytics project, the problem can be associated to?

Answer:

The above project fails in following phases:

1. **Data preparation phase.**
2. **Operational failure.**

Data preparation phase:

- Amazon's misidentification of dark-skinned females Rekognition may be traced back to a number of overlooked areas of the analytics effort. A lack of diversity and prejudice in training data sets is one of the key causes. Because the data used to train the algorithm was significantly skewed toward white males, the system misread dark-skinned women.
- This issue is related to the analytics project's data collecting and preparation phase. The selection of training data sets is an important stage in the development of an effective machine learning model. In this situation, it appears that the dataset used to train the algorithm was not sufficiently diverse and may not have truly reflected the community for whom it was designed.
- When screening for face recognition, MIT researchers discovered that dark-skinned women are misidentified as men 31% of the time, but light-skinned men are not. This is because the model was mostly created using data from white men. This means that the data preparation

operation failed. Both people and robots require relevant facts to make an informed screening decision.

- The quality of decision-making will deteriorate. To construct accurate and efficient models that are both valid and trustworthy, good data preparation is essential. Any analytical model's accuracy is directly proportional to the quality of the data into which it is fed.

Operational failure:

- Even once the algorithm is implemented, the project will go through certain steps on its approach to deployment. During this step, the team should monitor and measure the model's performance on real-time data once it has been deployed. • If we apply new or unknown data to our algorithm, the model may fail because the distribution of the data we utilized may vary or the relationship between the model and data may change.
- It also appears that Amazon did not adequately test and confirm their algorithm before making it available to consumers. The problem with misidentification of dark-skinned women should have been found during the analytics project's testing phase. This emphasizes the need of testing and validation in verifying that the model performs as intended and has no unexpected consequences.
- Finally, the problems with Amazon Rekognition may be traced back to several stages of the analytics project, including data gathering and preparation, ethical concerns about implementing the technology, and testing and validation. It is critical to address these challenges in order to build machine learning models that are accurate, fair, and ethical.

Case 4: IBM Watson in Healthcare

Some time back, MD Anderson Cancer Center, the largest cancer center in the US, announced that it is going to introduce IBM Watson's computing system into the healthcare system. With the help of Artificial Intelligence, this system was supposed to accelerate the decision-making process of physicians while treating cancer tumors. But IBM Watson turned out to be a failure, as it did not deliver what it promised. It failed to analyze huge volumes of patients' health data and publish studies to offer cancer treatment options. Here, are a few possible reasons why IBM Watson flopped in the healthcare industry, according to the experts. The AI technology that Watson uses is not a problem. The problem is that it is not given enough time to gather quality data and use personalized medicine. IBM launched Watson in a hurry as something that can handle something as complex as healthcare. They were quite aggressive in the marketing of their product, without realizing the importance of making it competent first. Watson was supposed to be launched as a software product, in which oncologists can simply enter their patient data and receive commendable treatment recommendations. This was how IBM advertised its Watson Health, but it failed to deliver this effect. IBM failed to work with the hospitals to ensure the proper functioning of Watson. Another reason for Watson's failure is that IBM used data from its own development partner, MSKCC, to train it. Since the system is trained through the hospital's own data, the results it gave after queries were biased towards the hospital's own cancer treatments. It did not include data from other hospitals and other smaller clinical facilities. While such a trained system can be helpful in treating simple and generic cancer cases, complex ones need a different approach to the approach. Smaller hospitals cannot even access the same methods of

treatment as their bigger counterparts. Discuss which aspects of the project were ignored and which phase(s) of the analytics project, the problem can be associated to?

Answer:

The above project fails in following phases:

1. **Discovery Phase.**
2. **Data Preparation phase.**
3. **Model Building.**

Discovery Phase:

- IBM Watson's failure in healthcare was driven by a variety of issues, including a lack of time to collect enough data and administer personalised therapy. IBM rushed Watson to market without consulting with hospitals to ensure its proper operation. This shows that the period of data collection and preparation got insufficient attention and relevance.
- To create effective machine learning models for healthcare, the organization must first understand and identify the business issue, then define the project's aim, specify the sort of data required, and ensure that all resources are accessible to ensure the project's success. However, in the case of IBM Watson, the researchers focused entirely on their sample data set and used the model to review huge quantities of patient data and write articles to recommend cancer therapeutic options.
- Furthermore, the software was incapable of dealing with the complex healthcare systems. IBM failed to collect data from several sources and failed to focus on the project's scope, both of which would have helped with better modeling. In addition, the team failed to collect project pain points, which might have been used to enhance the model.
- Finally, the report underlines the need of proper planning and preparation for the analytics project. The company should emphasize data collection and preparation to ensure that machine learning models in the healthcare industry are accurate, fair, and ethical. In addition, the team should work with hospitals to ensure that the models are adapted to their specific requirements and pain points. By addressing these difficulties, machine learning models capable of providing tailored and effective cancer treatment options may be built.

Data Preparation phase:

Certainly. The importance of data preparation in analytics initiatives is emphasized in the essay, since it is the most crucial, iterative, and time-consuming process. During this stage, the firm establishes an analytic sandbox in which the team will work for the duration of the project, collecting data from multiple sources.

In the case of IBM Watson in the healthcare industry, the team was unable to obtain the necessary data, and the system was trained using data from MSKCC, the company's own development partner. Because the model was trained solely on hospital data, the results were biased toward the hospital's own cancer therapy.

To address this problem, the team may have collected data from multiple healthcare systems where the model was used (i.e., the client's healthcare systems) and considered tough scenarios. IBM may have gotten the required findings by combining a number of data sets, including their own, end-user system data sets, and tough instances. These data sets included their own data set, data sets from end-user systems, and difficult circumstances.

Furthermore, IBM Watson's failure in healthcare may be attributed to a lack of diverse data during the model training phase. The team only used data from its own development partner, MSKCC, and did not include information from other hospitals or smaller clinical centers. This means that the dataset used to train the algorithm does not accurately represent the population for whom it was intended.

Finally, the article emphasizes the need of excellent data preparation in analytics projects, as well as the need for diverse, representative data in the model training phase. By addressing these concerns, it is possible to create machine learning models that are accurate, fair, and ethical in the healthcare industry.

Model Building:

For starters, the firm relied on distorted data from its own healthcare system, which resulted in skewed cancer treatment outcomes. When the training data is inadequately diversified to represent the underlying population of interest, this is a common problem in machine learning. The training data used to create the model should be representative of the population being studied and bias-free.

Second, analysts did not prepare datasets correctly for testing, training, and production. This meant that the little data examined and reviewed could not provide solutions for complex cancer cases where other approaches could be necessary to anticipate the treatment. This topic emphasizes the need of proper data management, which includes cleaning, labeling, and partitioning the data into several groups in order to train, validate, and test the model.

Third, the model deployment process was not thoroughly verified and validated to ensure that the model works as intended with no unexpected consequences. This is a crucial stage in the machine learning process since models act differently in production than they do in controlled testing. Validation and testing ensure that the model's predictions are accurate, fair, and ethical.

These difficulties must be addressed in order to build successful machine learning models for healthcare. Machine learning models should be built using diverse, representative data and then tested and validated in production. Furthermore, proper cleaning, labeling, and partitioning into independent sets for training, validation, and testing should be included in data preparation. Finally, ensuring that machine learning models anticipate accurately, equitably, and ethically is crucial.

Case 5: AI for University Admission

The researchers tried to develop a robot Todai, to crack the entrance test for the University of Tokyo. Its one of the tasks that only humans can do with required efficiency but researchers thought they could train machines for this purpose. Unfortunately, the results were opposite to their expectations as AI was not smart enough in understanding the questions. It would be better to introduce a broad spectrum of related information in the robotic system; so, it can answer the questions rightly. Respective members from the National Institute of Information gave their statement about Todai: "It is not good at answering a type of question that requires

the ability to grasp the meaning in a broad spectrum". Discuss which aspects of the project were ignored and which phase(s) of the analytics project, the problem can be associated to?

Answer:

Below is the failure in this project:

- **Data preparation.**
- **Model planning.**

Scientists created a robot named Todai in order to pass the University of Tokyo entrance exam. While it is commonly considered that only humans can pass the examination with the needed efficiency, the researchers found that with sufficient training and the right methodology, machines might also pass the exam. However, according to the report, the researchers' algorithm for training the robot eventually failed catastrophically, resulting in the exact reverse of what was intended. Because the robot was unable to answer the majority of the exam questions, the researchers concluded that their approach was useless.

Data preparation:

Data preparation is an important step in the development of a successful machine learning model. It comprises acquiring, cleaning, and preparing data for the algorithm's training and testing. The model's accuracy and efficiency are greatly impacted by the quality and quantity of data used to train it.

The Todai robot's failure can be attributed to insufficient data preparation. The robot was designed to pass the University of Tokyo admission exam, which requires a deep understanding of a wide range of topics including language, mathematics, and science.

One of the Todai robot's major shortcomings was its inability to comprehend the meaning of a wide range of phrases. This suggests that the data used to train the model did not include a diverse enough set of words and phrases. As a result, the algorithm misinterpreted and misunderstood a significant percentage of the exam's words.

This issue may have been avoided if the scientists and researchers had used a broader range of data for model training. The more diverse the data, the better the model will learn to recognize and comprehend different words and phrases. Furthermore, incorporating more language and comprehension data would have improved the model's performance in comprehending and responding to test questions.

Model planning:

It is vital to realize that parallelization refers to the process of dividing huge workloads into smaller, more manageable subtasks that may be executed concurrently. Parallelization during the model planning phase can reduce the computational complexity of the model, resulting in more efficient data processing and improved performance.

Todai's inability to understand the meaning of a wide range of words might be attributed to a lack of parallelization throughout the model construction phase. By breaking down the labor of language comprehension into smaller, more manageable sub-tasks, the model may have been able to acquire and comprehend a broader range of words and phrases.

Furthermore, the model's scope and the particular challenges it may face must be examined. Todai's approach was developed in order to pass the University of Tokyo admission exam, which requires a thorough understanding of a wide range of courses as well as a high level of language comprehension. By failing to address these specific challenges throughout the model creation process, the researchers may have overlooked critical components that contributed to the model's poor performance.

Case 6: Mars Orbiter

In 1999, NASA took a $125 million dollar hit due to the loss of a Mars orbiter. The loss was later attributed to a mix-up in the units of measurement used by Lockheed Martin's engineering team and NASA's internal team-Lockheed was using English units of measurement and NASA was using more conventional metric system measurements. According to an internal review panel at NASA's Jet Propulsion Laboratory, "The loss of the orbiter] was an end-to-end process problem... something went wrong in our system processes in checks and balances that we have that should have caught this and fixed it." Fixing this "end-to-end" process problem likely would have prevented this loss. NASA also blamed Congressional budget constraints for a portion of the error. So, additional funding would have also helped. Discuss which aspects of the project were ignored and which phase(s) of the analytics project, the problem can be associated to?

Answer:

Below is the failure in this project:

- **Discovery phase**
- **Communication phase**
- **Operational phase**

Discovery phase:

The failure of the Mars orbiter project can be attributed to a lack of effective project planning, which is the first step in any analytical project. The team failed to adequately articulate the project's aim, specify the business problem, or identify the sort of data required. As a result of the debate over the units of measurement to be used, the orbiter was destroyed.

Data Preparation:

As previously noted, the discrepancy in the units of measurement used for the Mars orbiter project was not discovered until the data processing phase. Proper data preparation includes cleaning, transforming, and ensuring the consistency of the data to be used for the project.

Model Building:

Although it is not explicitly mentioned in the case, it is possible to assume that the project's failure can also be attributed to a lack of good model construction. The scientists neglected to account for variations in measuring units, which resulted in erroneous computations and the orbiter's loss. Proper model creation include selecting the appropriate algorithm, ensuring its accuracy, and evaluating its utility.

Communication phase:

In the mission of the Mars orbiter. This stresses the importance of clear communication throughout the analytics project, especially when dealing with data-related challenges like measurement units.

Proper communication between the two teams might have benefited in finding the measuring unit discrepancy early on, saving the orbiter's destruction. Furthermore, defined rules and standards for the usage of certain measurement units may have been set during the communication phase, which would have helped both teams stay on the same page.

As a result, having a good communication plan in place during the analytics project is crucial, where all stakeholders are brought up to date on progress and any discrepancies or challenges are addressed as soon as feasible. Effective communication may help to avoid potential disasters and ensure the success of the analytics project.

Conclusion:

The case studies demonstrate the significance of paying attention to all phases of the analytics project, ranging from data acquisition to model operationalization. Overlooking any of these stages may result in biased outcomes, model failure, or financial loss. It is crucial to test and validate analytics solutions on diverse datasets and ensure their seamless integration into existing workflows. Moreover, it is essential to establish realistic goals and manage expectations during the discovery and definition phase of the project, along with developing backup plans to handle potential issues that may arise. Overall, a successful analytics project necessitates a comprehensive approach that considers all aspects of the project from beginning to end.

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