Pitfalls in Applying **DATA SCIENCE & ANALYTICS TECHNIQUES TO SOFTWARE TESTING**

Learn how to safeguard against these Pitfalls

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In recent years, Data Science techniques is seen to be revolutionizing the Industry sectors ranging from Healthcare, Banking, and Communications to Narcotics. AI based techniques, over the years, have assured substantial outcome based promises where hitherto traditional analytical solutions fell short of delivering desired results.

Experts suggests that by 2020, 85% of CIOs will be piloting AI programs through a combination of buy, build and outsource efforts. There is need and drive to apply these techniques to software testing field. However, software testing poses its own unique challenges, which necessitates careful analysis before you can successfully apply them. This paper outlines some important pitfalls in applying AI/ML techniques and provides insights in avoiding those.
Introduction

Industry studies show that testing easily takes up about 25-30% of the total project cost on an average. With most organizations adopting the DevOps and CI/CD/CT methodologies, there is even more pressure on testing to be more efficient and align to the pace of these methodologies. This is one key driver for considering AI/ML based techniques to improve testing efficiency.

Steps involved in implementing Machine Learning

Before considering the Data Science techniques, it's important to understand the steps involved in their implementation. Following diagram is based on the CRISP-DM Data Mining standard.

*Figure 1: CRISP-DM Process*

- Define Problem / Opportunity
- Gather details (Assumptions, constraints, risks, resources etc)
- Formulate the goal / desired outcome
- Data Acquisition
- Preliminary/Exploratory Data Analysis
- Address quality issues – (Clean the data, identify features to use, standardize/normalize the data)
- Prepare data for modeling
- Determine type of problem and accordingly the suitable ML algorithm
- Build the model
- Assess the model performance
- Evaluate the model outcomes against the success criteria
- Select the model or Go back to previous steps
- Present the model and outcomes
- Deploy the model in live environment
- Monitor the performance
Business Understanding | Data Understanding

**Challenges**

1. **Are you solving the right problem?**
   Many testing problems are due to the incorrect testing tools, processes or techniques. A detailed test assessment can highlight these adversities, and suggest corrective ways to resolve them. It’s strongly recommended to first get the basics in place and then apply AI (Artificial Intelligence) techniques to further gain efficiencies if needed. Implementing AI based solutions is costly and should only be implemented to solve the right set of problems (those which cannot be solved using traditional techniques).

2. **Lack of sufficient data with sufficient quality?**
   Analytics and AI solutions are data-intensive. Normally, the more the data, better is the performance. One needs to carefully analyze if one has sufficient data with required quality. Key questions to ask:
   - Do we have required data available in our enterprise applications?
   - Is the data accessible for use? E.g. the testing release data is owned by the ALM team from a vendor. Are there processes in place to enable access to data owned by various teams?
   - Can the data access be automated through data pipelines or accessing it is a manual process? This is key to the successful deployment of the AI solution in production.
   - Is the data consistent across different teams? This is key to getting consistent results from AI based solutions. E.g. different teams follow different guidelines when it comes to writing test cases or defect reports. If this is the case, then it may reduce the overall effectiveness of AI based solutions.

*A lot of testing data is human generated E.g. test cases, defects, test specifications. The usefulness of such data can vary from project to project and may require extensive massaging before it can be rendered useful.*

*In contrast, machine generated data (examples - application logs, system metrics) is much more consistent and can provide consistent results. Data preprocessing can be automated to a larger extent compared to human-generated data.*
2 Data Preparation Modeling Model Evaluation

One critical challenge about the modeling is to develop a model that works for variety of data points and keeps working consistently. In general, it is observed that the models that work well under lab conditions fail dismally when deployed in production. Main challenges behind this cause are as follows:

1. Data characteristics undergo changes over time?

This is popularly known as the problem of Data Drift. In testing projects, this can happen for variety of reasons – some of them listed below

- Change in the test organization / leadership / team composition – These kind of organizational changes affect the testing process followed in subtle / explicit ways in turn affecting how testing data is generated. This directly impacts the model performance (mostly in adverse ways) which was trained on a snapshot of data taken in the past
- Change in the testing tools
- Major changes in the applications under test – These changes can be technical, architectural or compliance related. In general, the effect is similar to what is described in the previous point.

2. Models are trained on data that don’t represent all practical situations in live systems?

This may be caused due to lack of holistic problem understanding or due to lack of access to datasets from various applications, teams or departments. The end result is – the model performs well for some data points but not so well for the other. So it’s important that a comprehensive data selection and preparation activities are performed to make the model more general in nature.

An effective way to reduce the impact of these issues is to keep performing the data preparation / modeling activities at regular intervals to accommodate the changes to the data characteristics. Effective monitoring in live environment can also indicate the issues early after the deployment.

When we recently implemented Predictive Analytics solution for a Telecom Testing project, we noticed that the solutions performance (prediction accuracy) would vary based on certain practical release parameters. So we set up a weekly monitoring & review of predicted outcomes and improve the performance using various techniques. Retraining the algorithms with latest release data provided significant boost to the performance.
Deployment

Most machine learning articles, papers or tutorials focus on only the data analysis and modeling aspects of the overall process. While these are really important for the success of AI based solutions, they form only a part of the overall story. The less discussed aspect of the AI based solutions is the challenges and overheads encountered when the solution is deployed in production.

While the data preparation and modeling activity is done on a snapshot of data in non-production environment, you benefit from them only when the models are deployed in live. This involves additional engineering steps that may vary in terms of complexity based on what kind of problem you are solving.

*This can be as easy as presenting the results to senior management or can get as complex as building automated data pipelines to process and integrate data from various systems and making it ready for analytics in real time. These additional engineering efforts also need to be thoroughly tested before they can get deployed on production.*

Thus it’s important that, additional efforts need to be factored in when planning for the AI based solution implementation to avoid any delays at the end of the implementation process.

Another deployment related challenge is about the CI/CD and DevOps practices which are mature and efficient for traditional development. For machine learning development, they are still evolving and may take some time before they mature. E.g. For traditional software development, code version control is easily achieved using a range of version control systems. For Machine Learning applications, code and data also need to be versioned. Tools supporting these are still evolving.

Conclusion

AI based solutions can bring great benefits to any testing projects provided following aspects are thoroughly analyzed before the implementation.

- Are you solving the right problem?
- Do you have quality data in enough quantity? Does organization have measures in place to make data easily available?
- Do you have right skills available and planned the right budget for the implementation?
- Above all – do you have a data-centric culture that empowers the AI/Data Science teams to acquire and process the data for solving the business problems?
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