IGNITE Defect Predict provides early insights to prevent application failure

Real-world experience in Defect Predict

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Abstract:

- Clients today want more for less and the IBM test mantra of "Test Less, Test Right" helps address this by placing the IGNITE Defect Predict solution at the heart of the solution.
- This document outlines an original approach to defect prediction initiated within IGNITE Defect Predict application and how it instantly derives predictions based on historic records of past defect behaviors. It describes the machine learning approach, text preprocessing and modeling used to transform and benefit typical engagements, moving them from a defect detection experience to defect prevention.

Introduction

"Test Less, Test Right" has been a mantra within the IBM test practice for a few years now. The key objective is to improve client experience through solutions that will provide insights into the key decision-making capabilities.

This paper outlines one solution that uses this as part of its ethos.

What is IGNITE Defect Predict?

Currently, project managers have limited insight to the future flow of defects during various phases of testing.

In addition, the resource planning to fix the defects is reactive based on volumes of the defects raised.

IGNITE Defect Predict provides the capability to anticipate the patterns in which the defects will be raised, and provides the insight to test managers to plan early and manage the defects. This capability also enables the test managers to anticipate when the testing lifecycle should end.

What problem does this solve?

Up to this point, project managers have used a mix of algorithmic or best-guess approach to defect predictions. The impact of getting this wrong is increased defect releases into production and risk to the business brand.

Any predictive approaches around defects or tests leverage traditional S-Curve algorithms, Rayleigh distribution theory, or Poisson distribution. These approaches are based on either calculative approaches or discrete probability distributions, which are used to express the probability of a given number of events occurring in a fixed interval of time. These approaches do not consider the positive or negative behaviors inherent in a varying social group like a development or test team.

As a result, project managers struggle to get any insight into the peak flow for defects and apply a best-guess approach to defect prediction when the defects inflow beats the traditional perceived defect volumes.

This results in reactive decision-making for the ramp up or ramp down of resources in the lifecycle, overrun of budgets, and schedule delay.

How is IGNITE Defect Predict different?

IGNITE Defect Predict uses an enterprise's own historical defect patterns as a basis to predict future defect patterns. Based on cognitive modeling techniques, it is singularly different to traditional approaches as the historic defect patterns highly influence the outcomes.

IGNITE Defect Predict helps prevent schedule delays and cost overruns

Consider a project manager of a global bank client who has already planned for certain resource capacity to be available for the current release of the solution. During initial stages of the system integration testing phase, he has noticed a huge inflow of environmental defects. Therefore, he needs to immediately plan for additional resources to ensure the schedule is not impacted—increasing resource cost of the original budget.

If we provide the project manager with the insight on the anticipated defect pattern (as in Figure 1) and the impact of the same to the release, the project manager will be able to plan early and take corrective actions to prevent the risk of schedule delay and cost overrun.

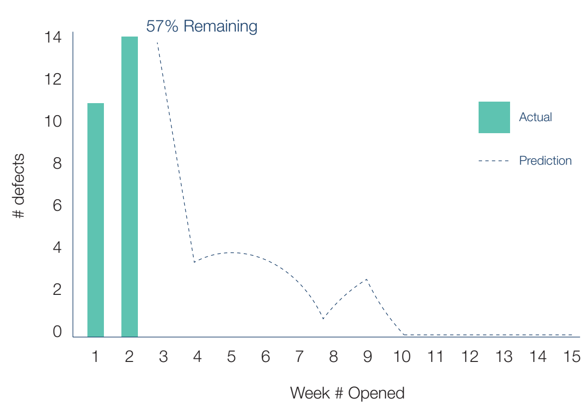

Figure 1. IGNITE Defect Predict prediction example

IGNITE Defect Predict provides the following insight to the project manager to make decisions at the right time:

- Predicted defect volumes for each of the subsequent weeks
- Categorization based on history of past observations
- Impact assessment of the defects on the release
- Insight into defects yet to be uncovered during the remainder of the testing phase

IGNITE Defect Predict uses cognitive technology to learn and predict

IGNITE Defect Predict uses a Machine Learning Statistical analysis approach for pattern recognition to make data-driven predictions. In addition, it includes a self-calibrating model to readjust the defect prediction pattern based on the current defect pattern—this is a core element of cognition. Other cognitive elements include cognitive computing and artificial intelligence.

A dynamic model is used to continuously adjust based on new data

Dynamic linear regression is the most commonly used predictive analysis. Regression estimates are used to describe data and to explain the relationship between one dependent variable and one or more independent variables.

Within IGNITE Defect Predict, we use a dynamic regression model to make itself adjust with the change in the actual in-progress data.

Two steps to defect prediction

Defect prediction is a two-step process. In the first step, we get a weekly defect estimate for each category. In the second step, we need to calculate the percentage of the remaining defect for a new application or current release.

Step1:

Weekly defect estimation is generated by the dynamic linear regression method. Different factors such as phase indicator, number of test cases to be executed, development team size, testing phase duration, and cumulative number of defects already encountered intuitively impacts the number of defects logged per week.

A combination of manual and automated processes for data collection and preparation, model building, validation and visualization are used to apply the intuitive factors and come up with the best possible set of predictors.

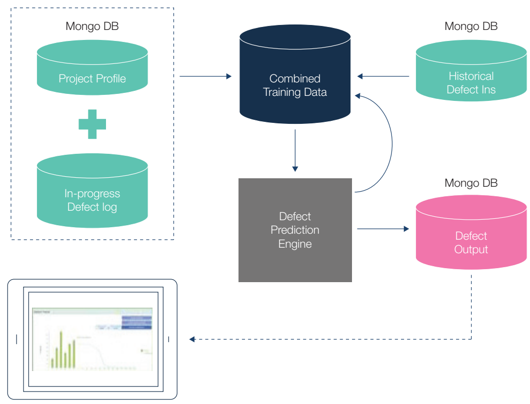

Figure 2. Approach to defect prediction

Data collection and preparation

In this step, the testing environment, lifecycle and various factors are captured.

Polling is then completed with various stakeholders. Test leads will gather uncaptured factors and merge with defect log. Next, all the data is put into a uniform format and standardized for input to the tool.

Data preparation is an automated process where the input data (historical defect data and in-progress defect data) are merged and pre-processed to create a training data set.

If the historical data of the projects is similar based on the project features, which influence defect distribution at various testing phases, then these projects are grouped into specific segments and the model needs to be trained using those segments. Cluster analysis and tree-based machine learning methods are used to obtain such segments.

Model setup and tuning

A dynamic regression-based model is used to predict the leftover defects. A one-time process involving the following steps is required to identify the best set of factors and setup the model.

1. Identify the predictors highly correlated with the response variable and predictors that are collinear (for selective exclusion).
2. Use stepwise regression (backward) to select a set of variables to be included in the model.
3. Calculate the Variance Inflation Factor (VIF). Exclude predictors with high multicollinearity.
4. Check P-Value for significance (where P-value is the statistical representation of the Probability Value).

The model tunes itself with the addition of the latest defects to the in-progress defect dataset.

Example: One of the regression equations came as below:
Weekly no. defects ~
(beta0 +
beta1 * week number +
beta2 * cumulative defects till last week +
beta3 * test-phase +
beta4 * number of test cases)
Where,
Beta0 – Intercept
Betas – Coefficients of the independent factors

Model validation

The k-fold validation (a model evaluation method) is performed on defects that are excluded from the historical defect data and on new defects included from live input to create an incremental weekly defects trend.

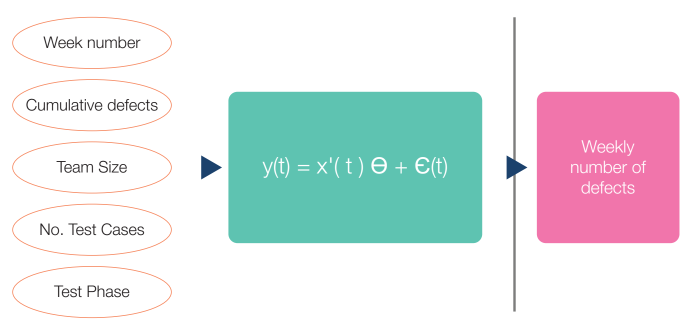

Figure 3. Example regression equation within Defect Predict

Step2:

The trained prediction model and the project complexity profile parameters play a significant role in influencing the defect prediction trends.

- The model is integrated with the defect management tool to provide the current defect trends.
- The model is self-calibrated at regular intervals based on the current defect trends and project complexity profile parameters.

- The model retains the learning through calibration process, as modified historical defect pattern for future recalibration.
- The output of the prediction engine is presented on the user interface.

Conclusion

Implementing IGNITE Defect Predict enables early insight into the defect patterns to answer:

- When do I stop testing?
- How many resources do I need to close the defects?
- How many more defects are yet to be uncovered?

This also helps the project managers to:

- Proactively plan resource allocation
- Avoid schedule delay
- Control budget overrun

References

[1] IEEE Software, Volume 22, Issue 6. "Building effective defect-prediction models in practice". November - December 2005.
[2] George A.F. Seber, Alan J. Lee. "Linear regression analysis". John Wiley & Sons. January 20, 2012.

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