Using Time Series Models for Defect Prediction in Software Release Planning

James Tunnell
Central Washington University
Computational Science Program

March 30, 2015

Outline

Introduction

Release Planning Objectives

- Two primary objectives of software release planning are:
  - Improving functionality
  - Maintaining quality
- Both of these objectives are constrained by limits on development time and cost.

Quality Control

- Software defects (bugs) are inevitable
- Sufficient time should be available to ensure good quality (by testing and bug-fixing)
- Otherwise, there is a risk of
  - Low quality (failure to meet objective)
  - Schedule slip (failure to respect constraint)
- This quality control (QC) time can be allowed for by limiting the scope of work in the planned release

Quality Control (cont'd)

- To support release planning, QC time can be estimated
- Assumption: QC time depends (at least partly) on the number of software defects introduced
- Then, a basis for estimating QC time would be the predicted number of defects

Defect Prediction

- Approaches to defect prediction tend to focus on either
  - Code analysis
    - Lines of code
    - Number of decisions
    - Code churn
  - Historical information
    - Regression analysis
    - Time series modeling
- A multivariate time series model with exogenous inputs was chosen

Defect Prediction using Code Analysis

- Approaches using code analysis:
  - Akiyama used lines of code (LOC), number of decisions, and the number of subroutine calls [1]
  - Gafney also used LOC [5]
  - Henry and Kafura use information taken from design documents [6]
  - Nagappan and Ball use relative code churn (lines modified) [8]
- These approaches all depend on specific design or implementation information
- This information is not available at the release planning stage

Defect Prediction using Historical Information

- Approaches using historical information:
  - Li et al. extrapolate parameters of a regression model [7]
  - Singh et al. use an ARIMA time series model [9]
- Both approaches are non-specific to design or implementation
- However, neither approach is explanatory

Motivation

Release Plan Optimization

- A release plan is formed by selecting features and improvements to work on
- Release plans can be compared by the expected revenue they will generate
- This optimization problem is posed as The Next Release Problem (NRP)

Release Plan Optimization (cont'd)

- The NRP is an abstract optimization problem
- In practice, QC time should be considered to ensure constraints are respected
- With the help of a defect prediction model, QC time can be estimated
- In this context, release plans are being compared
- For a defect prediction model to be useful, it should depend in some way on the basic elements of the release plan (planned new features and improvements)

Explanatory Model

- Assumption: the number of defects in the future depends on more than just the number of defects in the past
- A defect prediction model that depends only on previous numbers of defects is not explanatory
- Such a non-explanatory model would always predict the same number of defects

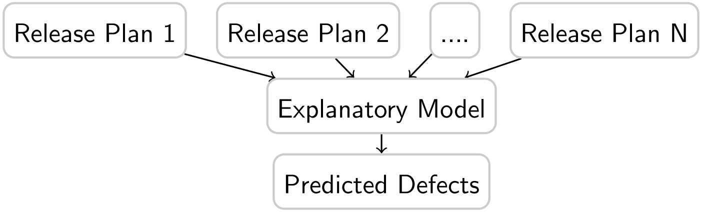

Figure : *A non-explanatory model.*

Explanatory Model (cont'd)

- A model could also depend on the key factors of a release plan
- This would be an explanatory model structure
- Such a model can potentially predict a different number of defects for every release plan

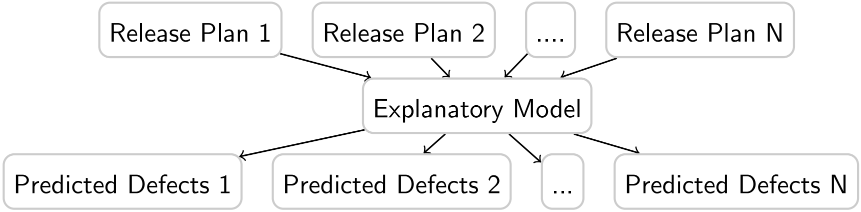

Figure : *An explanatory model.*

Time Series Modeling

Time Series

- A time series is a collection of observations that occur in order
- The process underlying a time series is assumed to be stochastic (non-deterministic)
- Each observation might depend on one or more previous observations
- This dependence is termed autocorrelation

Autoregressive Models

- A basic autoregressive (AR) model is a linear combination of previous values
- A white noise term accounts for stochastic fluctuation
- An $AR(p)$ model for predicting a value X at time t is

$$X_t = c + \sum_{i=1}^{p} \phi_t X_{t-1} + \epsilon_t \tag{1}$$

where $\phi_1, \phi_2, ..., \phi_p$ are the p parameters, c is a constant, and ϵ_t is the white noise term

Autoregressive Models (cont'd)

- Extending the AR model to be multivariate results in a Vector AR (VAR) model
- This model can support time series for defect count, improvements, and new features

Endogeneity and Exogeneity

- Under a VAR model, the behavior of each time series is explained by both its own past values and the past values of the other time series
- This makes the variables endogenous
- An alternative is that a time series is only used to explain other time series
- This type of explanatory variable is called exogenous, and could be considered an input
- Exogenouse variables are not explained by the model

Endogeneity and Exogeneity (cont'd)

- The desired model does not need to explain features and improvements
- Instead, these are used to explain defects
- Planned features and improvements can be made exogenous
- By also considering exogenous variables, a VAR model would become a VARX model

Stationarity

- A stationary time series has time-invariant statistics
- The time series models so far require time series to be stationary
- Differencing a non-stationary series may produce a stationary series
- Stationary can be determined by testing for trends

Deterministic Trends

- A time series with a deterministic trend has a non-constant mean
- The time series movements will generally follow the deterministic function
- Fluctuations above or below this function are non-permanent
- Such a time series is said to be stationary around a deterministic trend

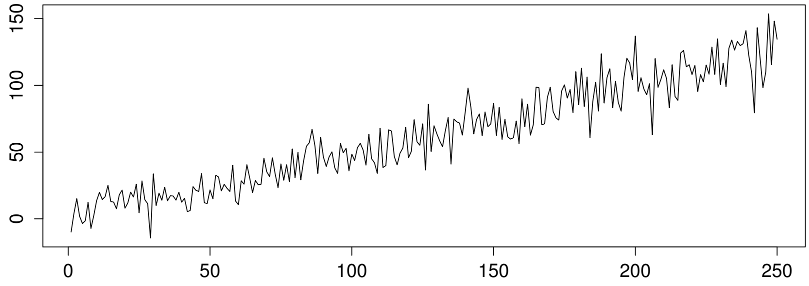

Figure : *Time series with a deterministic trend.*

Stochastic Trends

- A stochastic trend shows permanent effects due to random variations
- A series with stochastic trend will not necessarily fluctuate only close to the area of a deterministic function
- A time series with stochastic trend is non-stationary
- Differencing can be used to remove a stochastic trend

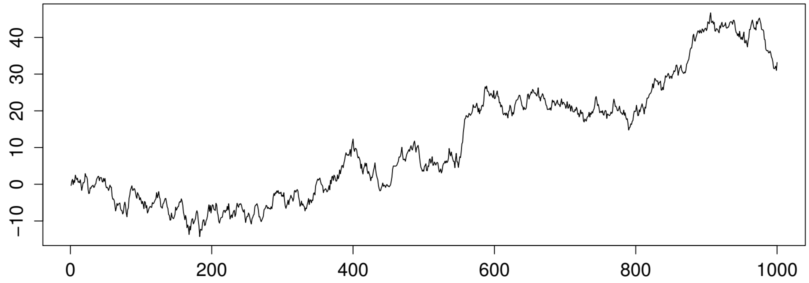

Figure : *Time series with a stochastic trend.*

Stationarity Testing

- A pure AR model of a time series with stochastic trend contains a unit root [4]
- Testing for the presence of a unit root can therefore be used to test for non-stationarity
- A unit-root test starts with the null hypothesis that an AR model has a unit root
- The alternative hypothesis is that an AR model of the time series does not have a unit root
- Next, a test statistic is measured
- If the test statistic is below the chosen significance level, the null hypothesis is rejected
- Rejecting the null hypothesis provides reason to accept the alternative hypothesis
- The Augmented Dickey Fuller (ADF) test is commonly used for unit root testing

Stationarity Testing (cont'd)

- On the other hand is a stationarity test
- This test starts with the null hypothesis that a time series is stationary around a deterministic trend
- If the test statistic is above some significance level, this shows that the null hypothesis can be accepted
- Then the time series should be considered stationary
- The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test can be applied for testing stationarity.

Modeling Methodology

Time Series Modeling Methodology

- Time series modeling methodology typically involves
  1. Specification
  2. Estimation
  3. Diagnostic Checking
  4. Selection

Specification & Estimation

- A $VARX(p)$ model is specified by choosing an order p
- Model order is the number of autoregressive terms
- This affects the number of parameters included in the model
- To avoid having too many parameters relative to the number of observations, we use

$$p_{max} = \left\lfloor \frac{n}{mK_{min}} \right\rfloor \tag{2}$$

  - n is the number of time samples
  - m is the number of time series
  - K_{min} is the minimum acceptable ratio of observations to parameters

- Models parameters are estimated for orders $1, 2, ..., p_{max}$

Diagnostic Checking

- Diagnostics can tell if a model should be rejected
- First diagnostic is for stability
  - AR model can have infinite impulse response
  - To be stable, the roots of the characteristic equation must lie outside the unit circle [3, p. 56]
  - Equivalently, the inverse of the roots must lie inside the unit circle
- Next diagnostic is residual autocorrelation
  - Model residuals should be indistinguishable from white noise
  - White noise is uncorrelated (no autocorrelation)
  - Ljung-Box test forms a statistic from the autocorrelation of the residuals

Model Selection

- Model selection criteria are used to compare models according to their fit
- penalties for residual error and the number of parameters
- Some common selection criteria
    - Akaike Information Criterion (AIC)
    - AIC with correction (AICc)
    - Bayesian Information Criterion (BIC)
- Parameter penalty is more severe for BIC and AICC than for AIC [2]
- AIC will be used, since the number of parameters is already limited in the specification step

Data Methodology

Data source

- Data for time series modeling will be derived from project historical data
- This historical data can be found in the project issue tracking system (ITS)
- The issues in an ITS can be bugs, features, improvements, etc.
- The *MongoDB* software project was selected to try out the modeling methodology
    - The project has been actively developed since 2009
    - Data from versions 0.9.3 through 3.0.0-rc6 are used
    - This dataset contained 7042 issues

Data Collection

- *MongoDB* uses *JIRA* for issue tracking and project management
- Issue data was exported from the project's JIRA web interface as XML data
- Issue data was extracted from the XML, and the following fields were kept:
  - Creation date
  - Resolution date
  - Type
  - Priority

Data Cleansing

- Not all of the data was preserved for modeling
- No-change issues
  - Only issues with resolution *fixed*, *complete*, or *done* were kept
  - Other issues did not result in any change, and were not included
- Orphan sub-tasks
  - Issues that are sub-tasks are first converted to be the same type as the parent issue
  - Sub-tasks whose parent issue is not in the dataset are considered orphans, and discarded
  - Orphan sub-tasks can not be identified as improvement or new feature
  - 20 (0.28%) orphaned sub-tasks were in the dataset

Data Sampling

- The dataset was operated on to prepare it for time series modeling
- First, data was sampled at regular intervals, measuring
  - Number of bugs created
  - Number of improvements resolved
  - Number of new features resolved
- A 7-day sampling period was used

Data Sampling (cont'd)

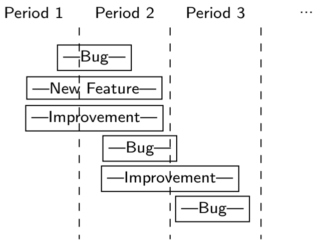

Figure : *Sampling example issue data.*

Period	Improvements Resolved	New Features Resolved	Bugs Created
1	0	0	1
2	1	1	1
3	1	0	1

Table : *Results of sampling example issues.*

Establishing Stationarity

- Establish stationarity by testing
    - ADF unit root test
    - KPSS stationariy test
- If test results agree, then no differencing is necessary
- Otherwise, difference data and retest

Time Windowing

- Assumption: the software development process underlying a given project might change over time
- The VARX model does not accommodate a changing process
- To account for a changing process, data will be time windowed
- Data will be used for modeling only if it occurs within the time window
- This should limit the amount of process change the model is exposed to

Results

MongoDB Time Series Data

Time series data was obtained by sampling the *MongoDB* dataset with a 7-day sample period

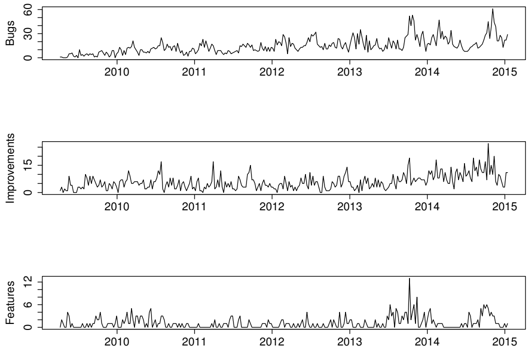

Figure : *MongoDB time series data*

Stationarity & Differencing

- At first, ADF and KPSS test results disagreed
- After differencing, test results agreed

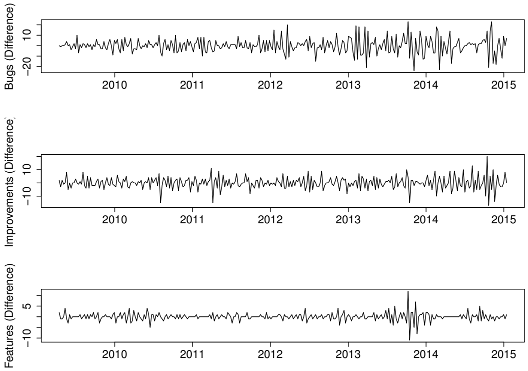

Figure : *MongoDB time series data after differencing*

Time Windowing

- A 78-week time window (approximately 18 months) was chosen
- Three of these windowed periods, non-overlapping, were used for modeling
- Since the data is being differenced, the first sample (week) is skipped
- These windowed periods are denoted W_{2-79}, W_{80-157}, and $W_{158-235}$
- Modeling methodology is applied to each

Model Specification, Estimation, and Diagnostic Checking

- Using $K_{min} = 4$, maximum model order is obtained by

$$p_{max} = \left\lfloor \frac{78}{(3)(4)} \right\rfloor = \lfloor 6.5 \rfloor = 6 \qquad (3)$$

- Models of order 1 through $p_{max} = 6$ were estimated for diagnostic checking
- All models were found to be stable
- Several model orders were found to be inadequate by the Ljung-Box test:
  - Orders 1-2 for period W_{2-79}
  - Order 5 for period $W_{158-235}$

Model Selection

- Models found to be stable and not inadequate were considered for selection
- A different model was selected for each windowed period
- Lower AIC score is better

	AIC score		
Model order	W_{2-79}	W_{80-157}	$W_{158-235}$
1	N/A	**429.8**	**477.9**
2	N/A	439.3	482.4
3	400.8	440.9	489.7
4	**400.3**	450.2	499.9
5	404.0	456.7	N/A
6	414.9	461.7	508.8

Table : *Results of model selection, using AIC score to compare models of different order.*

One-step Predictions

The fit for each selected model is demonstrated by plotting one-step predictions along with actual values.

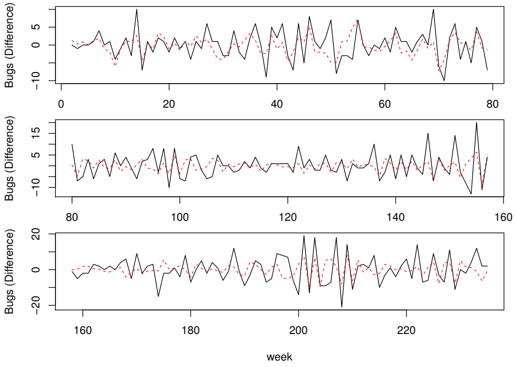

Figure : *Actual values (solid) vs. one-step predictions (dotted), for each model selected by AIC score.*

Forecasting Results

- A range of hypothetical future values for improvements and new features were used to make defect predictions
- This simulates the use of defect prediction for release planning
- Single-step, out-of-sample forecast
- Inputs were differenced, and difference was removed from output
- Results include 75% and 90% confidence intervals
- Forecast results are shown only for the first time window, W_{2-79}

Forecasting Results (cont'd)

- The actual number of improvements and features was 4 and 0
- Actual number of bugs was 18
- For the actual input values, the 90% confidence interval does not include 18

Table : *Forecasting at the end of the first time window, W_{2-79}.*

Improvements	Features	90% low	75% low	Mean	75% high	90% high
2	0	5.61	6.72	9.31	11.89	13.00
2	1	5.54	6.66	9.24	11.82	12.93
2	2	5.48	6.59	9.17	11.75	12.86
2	3	5.41	6.52	9.1	11.69	12.8
4	0	6.4	7.51	10.09	12.68	13.79
4	1	6.33	7.44	10.03	12.61	13.72
4	2	6.27	7.38	9.96	12.54	13.65
4	3	6.2	7.31	9.89	12.48	13.59

Forecasting Results (cont'd)

- Low accuracy for the predictions is concerning
- For the next window, W_{80157}, the actual number of future bugs was 17
- This was inside the 90% confidence interval, which spanned from 13.38 to 18.00
- How useful is the VARX model in general, considering these conflicting results?
- To find out, a sliding 78-week window was used
- The sliding window started at the first sample period, and was shifted by one sample period after modeling
- Only the actual number of improvements and features were used in this forecasting

Sliding Window Results

- Errors between the mean forecasted and actual number of bugs is shown as a histogram
- The histogram appears to be normally distributed (good)
- The variability is quite large (bad)
- The actual number of bugs was inside the 90% confidence interval for 23.87% of the sliding window ranges

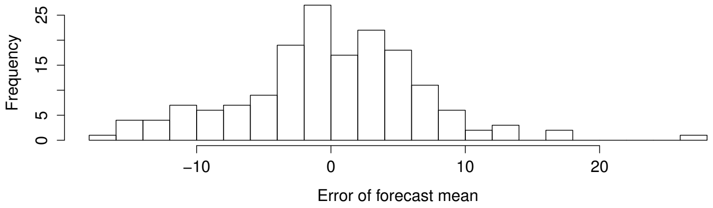

Figure : *Histogram of errors in forecast mean obtained using a 78-week sliding window.*

Conclusion & Future Work

Conclusions

- The VARX modeling methodology was successfully applied to the time series data collected from the *MongoDB* project
- Models were created for each of three time windows
- A model was selected for each window
- Forecast results using the models were inconclusive
- A better picture of the prediction performance was obtained using a sliding window
- This resulted in a normally distributed error in the mean forecasted values
- A low proportion (23.87%) of the sliding window ranges included the actual number of bugs in the 90% confidence interval
- These results may indicate that a VARX model will not be useful to make predictions for the the MongoDB dataset

Future Work

Having applied the VARX time series model to one project dataset, a next step is to apply the methodology to other software project data sets, such as *Eclipse* or *Mozilla*, to more conclusively determine the model's usefulness.

References I

F. Akiyama.
An example of software system debugging.
In *IFIP Congress (1)*, volume 71, pages 353–359, 1971.

S. Bisgaard and M. Kulahci.
Time series analysis and forecasting by example.
John Wiley & Sons, 2011.

G. E. P. Box, G. M. Jenkins, and G. C. Reinsel.
Time Series Analysis.
John Wiley, 2008.

P. H. Franses.
Time series models for business and economic forecasting.
Cambridge university press, 1998.

References II

J. E. Gaffney.
Estimating the number of faults in code.
Software Engineering, IEEE Transactions on, SE-10(4):459–464, July 1984.

S. Henry and D. Kafura.
The evaluation of software systems' structure using quantitative software metrics.
Software: Practice and Experience, 14(6):561–573, 1984.

P. L. Li, M. Shaw, J. Herbsleb, B. Ray, and P. Santhanam.
Empirical evaluation of defect projection models for widely-deployed production software systems.
SIGSOFT Softw. Eng. Notes, 29(6):263–272, Oct. 2004.

References III

N. Nagappan and T. Ball.
Use of relative code churn measures to predict system defect density.
In *Software Engineering, 2005. ICSE 2005. Proceedings. 27th International Conference on*, pages 284–292. IEEE, 2005.

L. L. Singh, A. M. Abbas, F. Ahmad, and S. Ramaswamy.
Predicting software bugs using arima model.
In *Proceedings of the 48th Annual Southeast Regional Conference*, page 27. ACM, 2010.