Apply machine learning to Performance trend analysis

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- Many test cases are executed for testing software packages
- Evaluate how each software package performs for an updated software package
- Tool or algorithm that can reduce workload of manual inspection

Objectives

- Detect the state of the CPU utilization (degrading, improving or steady state)
- Detect whether there is any change in the test environment that effects the CPU utilization

- Software release
- Software package - treated as a time point in the time series

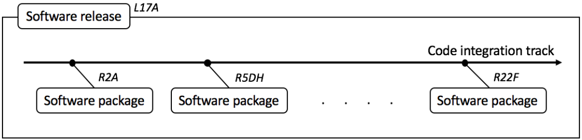


Figure: Several software packages that are launched in the timeline

- Test cases in QA capacity area on signaling capacity - treated as an observation in the dataset

Data is collected on January 20, 2017

Three datasets: Software release L16A, L16B, and L17B

- Sorted by software package version
- Filtered out test cases which are not executed properly
- Selected test case which has *lowest* value of the CPU utilization to represent a performance of a specific software package

In total, each dataset contains 64, 241, and 144 test cases, respectively

EventsPerSec: Event intensity

- Contains several *local events*
- Stores multiple values separated by a tab character
- Some local events are used as predictor variables
- Implement a function to split each element to columns

Response variable

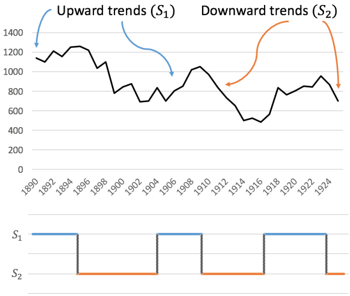
- TotCpu%: CPU utilization

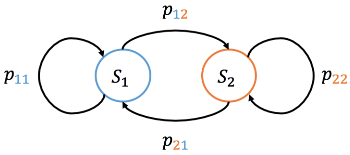
Predictor vairalbes

- EventsPerSec
  - RrcConnectionSetupComplete
  - Paging
  - X2HandoverRequest
- Test environments
  - DuProdName: Product hardware name
  - Fdd/Tdd: Different standard of LTE 4G Technology
  - NumCells: Number of cells in the base station

Markov switching model [Hamilton, 1989]

- Describe evolution of the process at different period of time
- Involve multiple structures that can characterize the time series behaviors in different states
- The switching mechanism between the states is assumed to be an unobserved Markov chain





Markov switching autoregressive model

$$y_t = X_t \beta_{S_t} + \phi_{1,S_t} y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2_{S_t})$$

Assuming that S_t denote an unobservable state variable
y_t is the observed value of time series at time t
X_t are the predictor variables of time series at time t
β_{S_t} are the coefficients in state S_t, where $S_t = 1, 2, ..., k$
ϕ_{1,S_t} is an autoregression coefficient at time $t-1$ in state S_t

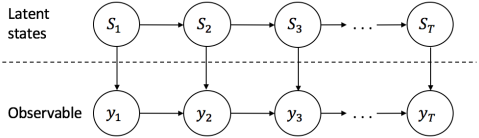


Figure: Model with additional dependencies at observation level

A coefficient of a predictor variable can have either different values in different state or a constant value in all state.

The variable that can take on different values is said to have a *switching effect*.

The variable which have the same coefficient in all states is the variable that does not have a switching effect, or said to have a *non-switching effect*.

When applying the Markov switching model, we need to decide on

- Number of states, k
- Number of switching coefficients in the model

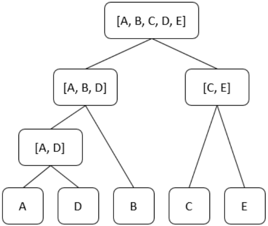
Based on the applied literature, the information criteria called the Bayesian Information Criterion is used to select these numbers

$$\mathrm{BIC} = -2\ln(L(\hat{\theta})) + m \cdot \ln(T)$$

Reduce overfitting problem by penalizing on the number of parameters in the model

E-divisive [James, 2016]

1. Non-parametric approach: more flexible as no assumption about the distribution is made
2. Detects multiple change point locations based on a divisive hierarchical estimation algorithm
3. Algorithm: Recursively partition a time series, and perform a permutation test to find the statistical significance of an estimated change point.
4. Remark: Obtain a rough idea of the change point location



- State of the CPU utilization is unknown

- State of the CPU utilization is unknown
- Simulated two datasets - Dataset 1 and Dataset 2 - with high and low persistent state, respectively.

$$y_t = \begin{cases} 10 + 0.6X_{1,t} - 0.9X_{2,t} + 0.5y_{t-1} + \varepsilon_t^{(1)} & \text{Normal} \\ 2 + 0.8X_{1,t} + 0.2y_{t-1} + \varepsilon_t^{(2)} & \text{Bad} \\ -12 + 0.7X_{1,t} + 0.2X_{2.t} - 0.2y_{t-1} + \varepsilon_t^{(3)} & \text{Good} \end{cases}$$

y_t is assumed to be value of a CPU usage
$x_{1,t} \sim U[50, 200]$
$x_{2,t} \sim U[0, 50]$
$\varepsilon_t^{(1)} \sim N(0,1), \quad \varepsilon_t^{(2)} \sim N(2,0.5), \quad \text{and} \quad \varepsilon_t^{(3)} \sim N(1,1)$

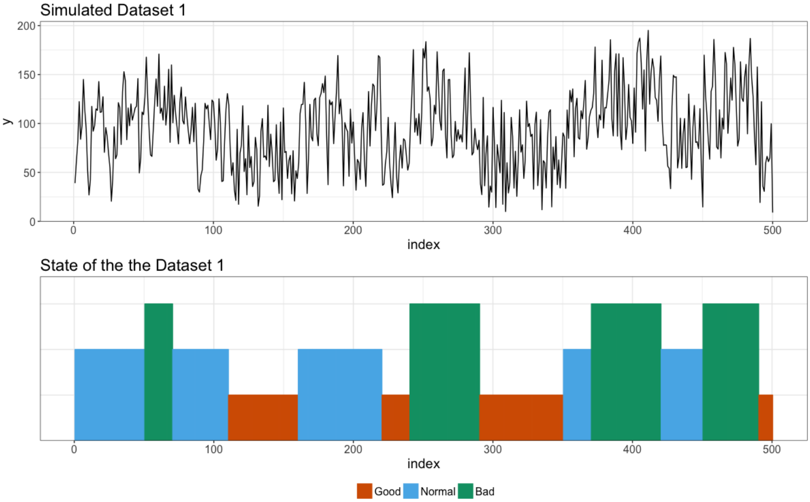


Figure: A simulated data of Dataset 1 and the period in the time series when observation is in each state.

Simulation study for model evaluation

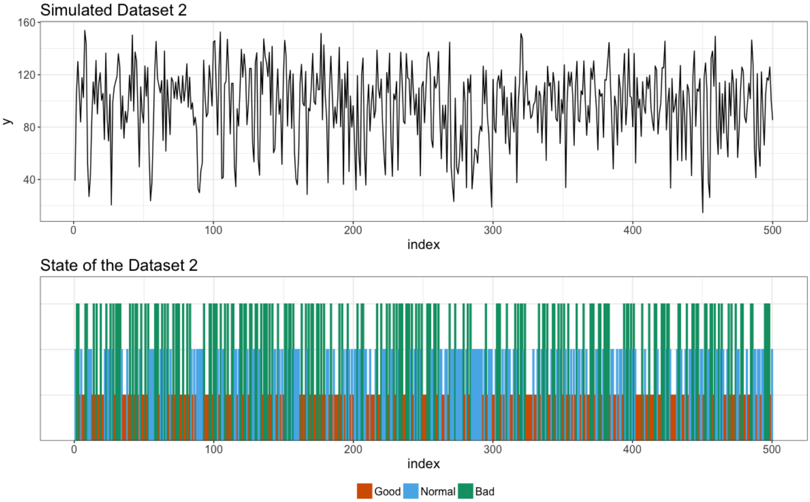


Figure: A simulated data of Dataset 2 and the period in the time series when observation is in each state.

Decide: Number of states

Hypothesis: Markov switching model with *two* or *three* states

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- BIC is one criteria to select the appropriate model but model output and plot should also be taken into account
- *Three-state* model are chosen for further analysis
- Remark: Higher number of states $k \geq 4$ are more likely to give worse results and were not considered

Decide: Number of switching coefficients in the model
Hypothesis: Test environments is possible to have non-switching effects

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- Software release L16A:

  Fdd/Tdd and *Numcells* are non-switching coefficients
- Software release L16B:

  DuProdName is non-switching coefficient
- Software release L17A:

  DuProdName, *Fdd/Tdd*, and *NumCells* are non-switching coefficients

Simulated Dataset 1 and Dataset 2

- E-divisive is less powerful in detecting changes
  $\rightarrow$ the method only look at the value of CPU utilization
- Both method detect changes at the same location
  $\rightarrow$ high probability to be an actual change
- Both method detect changes close to one another but not exact location
  $\rightarrow$ lower chance be a false alarm

Real data: Software release L16A

- E-divisive cannot detect any changes in the time series data
- No comparison is made

Real data: Software release L16B

- E-divisive method detects change-points at 130, 135, 153, and 170

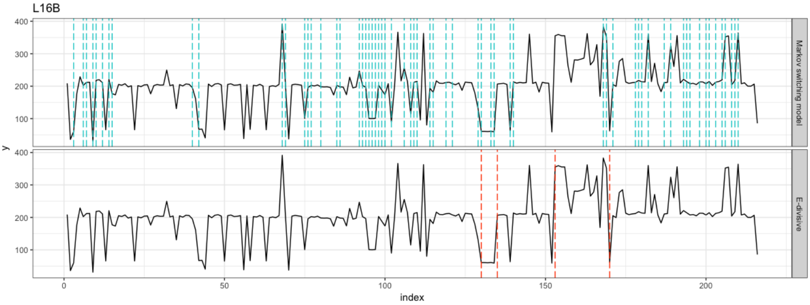

Figure: The estimated change point locations from both methods

Real data: Software release L17A

- E-divisive method detects change-point at 9, 77, 82, and 105

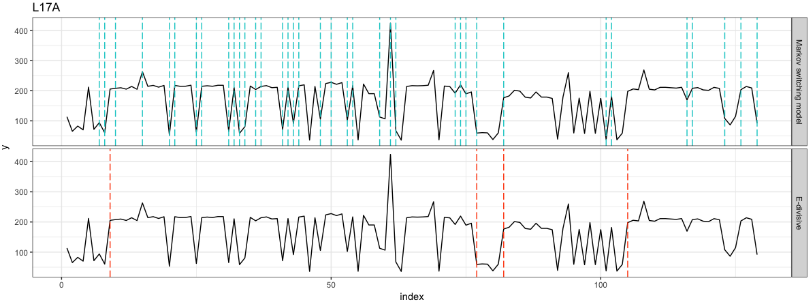

Figure: The estimated change point locations from both methods

Software release L16A

- State 1: Degradation
- State 2: Improvement
- State 3: Steady

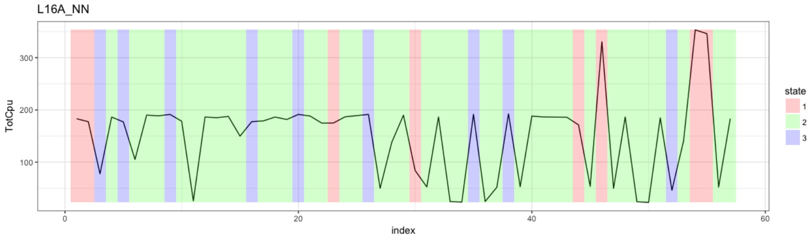

Figure: The CPU utilization showing the periods where the observation is in the specific state.

Software release L16B

- State 1: Degradation
- State 2: Improvement
- State 3: Steady

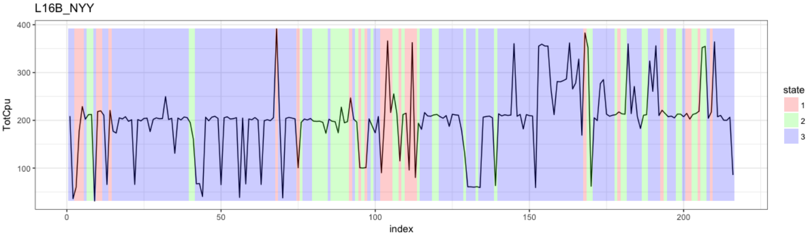

Figure: The CPU utilization showing the periods where the observation is in the specific state.

Software release L17A

- State 1: Degradation
- State 2: Improvement
- State 3: Steady

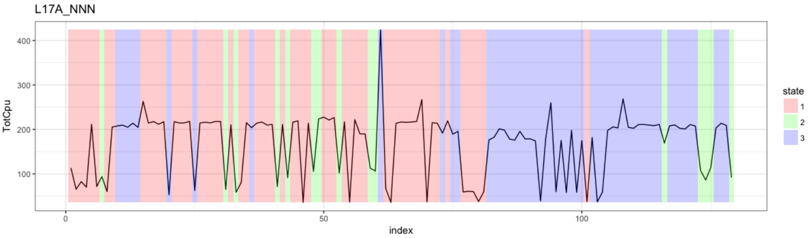

Figure: The CPU utilization showing the periods where the observation is in the specific state.

Effects of test environments -*DuProdName*, *Fdd/Tdd*, and *NumCells* - on the CPU utilization

- Software release L16A:
  Fdd/Tdd and *NumCells*
- Software release L16B:
  DuProdName and *NumCells*
- Software release L17A:
  DuProdName

- Software release L16A:
  Fdd/Tdd and *NumCells*
- Software release L16B:
  DuProdName and *NumCells*
- Software release L17A:
  DuProdName

Future work

- Larger dataset
- Consider on the other performance metrics (e.g.,memory usage and latency)
- Apply the Markov switching model to each QA Capacity test case type (one model for one type)
- Normalize feature set by introducing *weight* parameters
- Use semi-supervised learning algorithm (e.g., Self-Organizing Maps) if some test cases are labeled with state

James D Hamilton (1989)
A new approach to the economic analysis of nonstationary time series and the business cycle
Econometrica: Journal of the Econometric Society, pages 357-384.

Josep A. Sanchez-Espigares and Alberto Lopez-Moreno (2014)
MSwM: Fitting Markov Switching Models
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Nicholas A. James and David S. Matteson (2016)
ecp: Nonparametric Multiple Change Point Analysis of Multivariate Data
CRAN R.