# Applying Machine Learning to LTE/5G Performance Trend Analysis

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- Many test cases are executed for testing software packages
- Evaluate the performance of an updated software package by visualizing the graph
- 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 data
- 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 L17A

- Sorted by software package version
- Filtered out test cases which are not executed properly
- Selected test case which has the *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

Response variable

- TotCpu%: CPU utilization

Predictor variables

- local events in 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

Method

- Markov switching model
- E-divisive method
- Tools

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 $t$
$X_t$ is a design matrix containing the predictor variables of time series at time $t$
$\beta_{S_t}$ are a column vector of the coefficients in state $S_t$, where $S_t = 1, 2, ..., k$
$\phi_{1,S_t}$ is an autoregression coefficient at time $t-1$ in state $S_t$

## Markov switching autoregressive model

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Assuming that $S_t$ denote an unobservable state variable

A coefficient of a predictor variable can have either different values in different state, $\beta_{S_t}$, or a constant value in all state, $\beta$.

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

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

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

R programming

- Markov switching model is performed using *MSwM* package [Sanchez-Espigares, 2014]
  Various extensions and modifications were made in the package
  For example,
  → Make it more stable to use with categorical variables
  → State prediction function
  → Plot for visualizing the results
- E-divisive method is performed using *ecp* package [James, 2016]

Results and Discussion

- Markov switching model
  - Analysis I: Number of state
  - Analysis II: Number of switching coefficients
- E-divisive method
- Comparison between both methods
  - Simulated data
  - Real data
- State inference on the results from the Markov switching model

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 (BIC) is used for model selection

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

where, $m$ is the number of parameters and $T$ is the number of observations

BIC attempts to reduce an overfitting problem by penalizing on the number of parameters in the model

Analysis I: Number of states
Hypothesis: Markov switching model with *two* or *three* states

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- Model with lower BIC value is preferable
- However, model output along with plot should also be taken into account as well

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- Model with lower BIC value is preferable
- However, model output along with plot should also be taken into account as well
- Two-state model offered less details, and plots were unrealistic and difficult to make an interpretation
- **Three-state** model was chosen for further analysis as it provided more intepretable plots and better fit
- Remark: Higher number of states $k \geq 4$ are more likely to give worse results and were not considered

Analysis II: Number of switching coefficients in the model
Hypothesis: Test environments (*DuProdName*, *Fdd/Tdd*, and *Numcells*) is possible to have non-switching effects

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- *Recall: The variable whose coefficient is constant in all states are said to have a non-switching effect*
- Attempt to reduce the number of parameters to be estimated in the model
- Algorithm used numerical optimization
  $\rightarrow$ more estimated parameters will make the obtained result unstable
- Each dataset of the software release was tested with different models
- Three final models for each dataset were obtained

- Apply the E-divisive method to all three datasets of the software release L16A, L16B, and L17A
- Input: the value of the CPU utilization

- In the real data, the state of the CPU utilization is unknown $\rightarrow$ Evaluation of the model can't be made

- In the real data, the state of the CPU utilization is unknown $\rightarrow$ Evaluation of the model can't be made
- Simulated two datasets (Dataset 1 and Dataset 2) with the ground truth about the state.
  The real models for each state are

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

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

## Simulation study for model evaluation

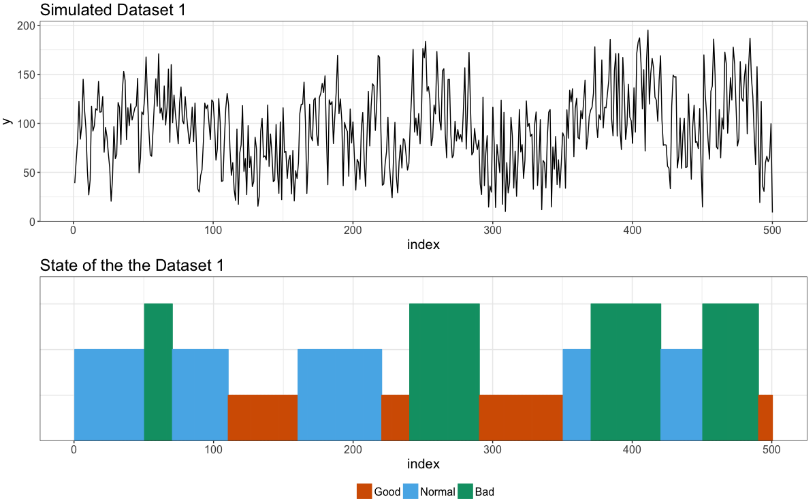


Figure: A simulated data of Dataset 1 and the period in the time series when observation is in each state.

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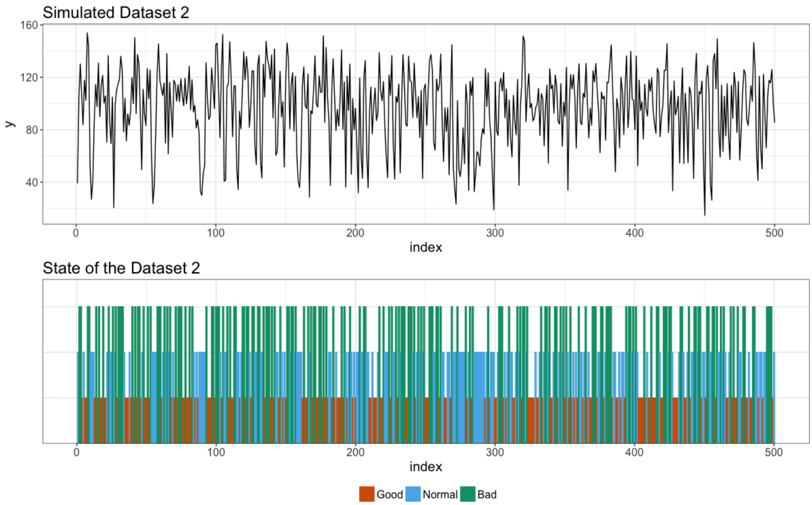


Figure: A simulated data of Dataset 2 and the period in the time series when observation is in each state.

Apply the Markov switching model and the E-divisive method to the simulated Dataset 1 and Dataset 2, it is found that

Apply the Markov switching model and the E-divisive method to the simulated Dataset 1 and Dataset 2, it is found that

- Both methods detect changes at the same location
  $\rightarrow$ high probability to be an actual change
- Both methods detect changes close to one another but not at the exact location
  $\rightarrow$ lower chance to be a false alarm

Real data: Software release L16A

- E-divisive cannot detect any changes in the time series data

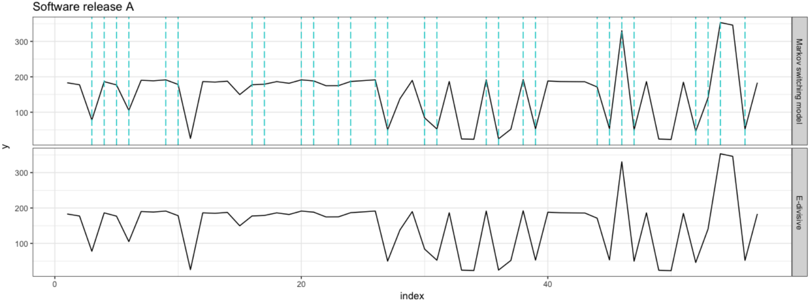


Figure: Top: Results from the Markov switching model, Bottom: The change point locations from the E-divisive

# Real data: Software release L16B

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

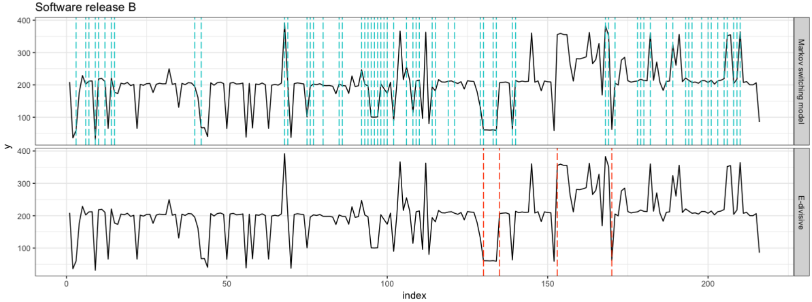


Figure: Top: Results from the Markov switching model, Bottom: The change point locations from the E-divisive

Real data: Software release L17A

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

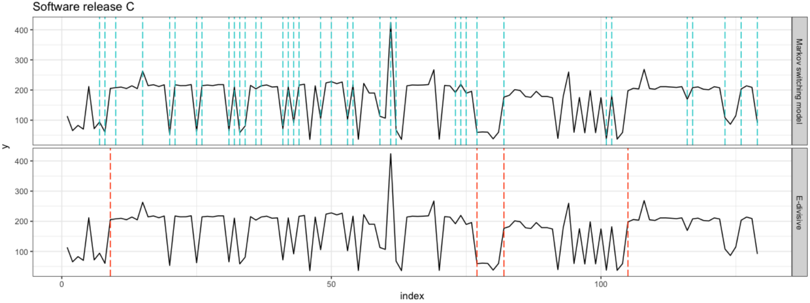


Figure: Top: Results from the Markov switching model, Bottom: The change point locations from the E-divisive

# Software release L16A

Software release L16A

- State 1: Degradation

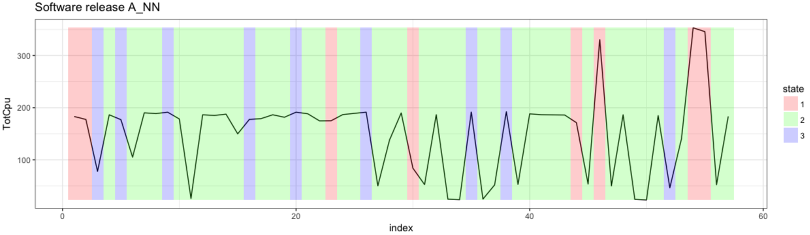


Figure: The CPU utilization showing the periods where the observation is in the specific state.

## Software release L16B

- State 1: Degradation

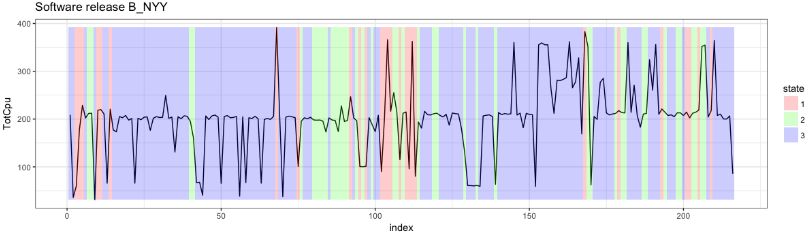


Figure: The CPU utilization showing the periods where the observation is in the specific state.

## Software release L17A

- State 1: Degradation

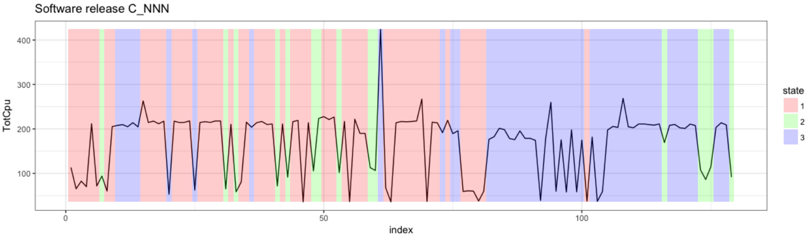


Figure: The CPU utilization showing the periods where the observation is in the specific state.

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*

- Markov switching model is able to identify any changes between states rather well, despite some false alarms and missed detections
- E-divisive method is less powerful as it can detect fewer changes and failed to detect many changes
  $\rightarrow$ the method only take into account the value of the CPU utilization
- Both methods could be used together to confirm the state change

- Require more extensive data
- Consider on the other performance metrics (e.g.,memory usage and latency)
- Apply the Markov switching model to each QA Capacity test case type (i.e., one model for one type of test case)
- Normalize feature set by introducing *weight* parameters
- Use semi-supervised learning algorithm if some test cases are labeled with state
  $\rightarrow$ combining clustering-based and classification-based methods

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
*CRAN R.*

Nicholas A. James and David S. Matteson (2016)
ecp: Nonparametric Multiple Change Point Analysis of Multivariate Data
*CRAN R.*