#### A survey of methods for time series change point detection Samaneh Aminikhanghahi, Diane J. Cook

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Sample time series and change points (*horizontal lines* indicate separate states)

### Motivation

- Medical condition monitoring
- Human activity analysis
- Climate change detection



## Changepoint detection variations

- Mean-changepoint
- Variance-changepoint
- Mean-variance changepoint



Days

#### Piece-wise linear CPD

ts\_ar['coerr\_1'] = piece\_wise\_ir\_cpa(ts\_ar, 'sea\_ratio', peice\_airr=23)



### ChangeFinder



### ChangeFinder

Change Finder [34,42,63] is another commonly used method which reduces the problem of change point detection into time series-based outlier detection. This method fits an auto regression (AR) model onto the data to represent the statistical behavior of the time series and updates its parameter estimates incrementally so that the effect of past examples is gradually discounted. Considering time series  $x_t$ , we can model the time series using an AR mode of the *k*th order by:

 $x_t = \omega x_{t-k}^{t-1} + \varepsilon$ 

where  $x_{t-k}^{t-1} = (x_{t-1}, x_{t-2}, ..., x_{t-k})$  are previous observations,  $\omega = (\omega_1, ..., \omega_k) \in \mathbb{R}^k$  are constants, and  $\varepsilon$  is a normal random variable generated according to a Gaussian distribution like white noise. By updating model parameters the probability density function at time *t* is calculated and we have a sequence of probability densities { $p_t : t = 1, 2, ...$ }. Next, an

#### Ruptures



Ruptures CPD model for Sed minutes of user 181042



#### **Ruptures**

The intuition behind PELT is that for a time step to be detected as a change point, it must reduce the segmentation cost by more than the penalty value that is added. If the cost reduction is less than the added penalty, the penalized cost will increase, and the time step will not be detected as a change point.

### Supervised methods

 Binary **Decision Tree** classification: **Nearest Neighbor** Support Vector Machine (SVM) changepoint / no Naïve Bayes **Multi Class** changepoint Classifiers **Baysian Net**  Virtual classifier Hidden Markov Model (HMM) **Conditional Random Field (CRF)** Gaussian Mixture Model (GMM) Supervised Method Support Vector Machine (SVM) **Binary Class Naïve Bayes** Classifiers **Logistic Regression** Virtual

Classifier

Fig. 3 Supervised methods for change point detection

### Metrics beyond accuracy, and f1scores

*G*-mean is commonly used as an indicator of CPD performance. This utilizes both sensitivity and specificity measures to assess the performance of the algorithm both in terms of the ratio of positive accuracy (sensitivity) and the ratio of negative accuracy (specificity).

$$G\text{-mean} = \sqrt{\text{Sensitivity} \times \text{Specificity}} = \sqrt{\frac{\text{TP}}{\text{TP} + \text{FN}}} \times \frac{\text{TN}}{\text{FP} + \text{TN}}$$

- Unsupervised methods
- Clustering,
- Outlier detection



Unsupervised methods – Model fitting

Yet another time series clustering approach is Model fitting, in which a change can be considered to occur when a new data item or block of data items do not fit into any of the existing clusters [60]. Assuming a data stream  $\{x_1, \ldots, x_i, \ldots\}$ , change point is occurred after data point  $x_i$ , if the following logical expression is true.

change = 
$$\bigwedge_{K}^{j=1} \left[ d\left( x_{i+1}, \text{center}\left( C_{j} \right) \right) > \text{radius}\left( C_{j} \right) \right]$$

where  $d(x_{i+1}, \text{center}(C_j))$  is the Euclidian distance between a newly incoming data point  $x_{i+1}$  and the center of cluster  $C_j$ , radius  $(C_j)$  is the radius of cluster j, K is the number of clusters, and  $\wedge$  is the logical and symbol. The radius of cluster C with n data point and mean value of  $\mu$  is:

radius (C) = 
$$\sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu)^2}{n}}$$

# Neural network –based detection Label with ruptures



# Labeling with ruptures

| [[148 | 186 | 153 | 108 | 146 | 155 | 125 | Θ   | Θ   | Θ   | 0   | 0]   |  |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|--|
| [146  | 155 | 125 | Θ   | 0   | Θ   | 0   | 0   | Θ   | 61  | 115 | 134] |  |
| [ 0   | 0   | 0   | 0   | 0   | 61  | 115 | 134 | 94  | 127 | 145 | 139] |  |
| [ 0   | 61  | 115 | 134 | 94  | 127 | 145 | 139 | 158 | 77  | 214 | 202] |  |
| [ 94  | 127 | 145 | 139 | 158 | 77  | 214 | 202 | 204 | 260 | 192 | 111] |  |
| [158  | 77  | 214 | 202 | 204 | 260 | 192 | 111 | 116 | 144 | 326 | 160] |  |
| [204  | 260 | 192 | 111 | 116 | 144 | 326 | 160 | 135 | 157 | 188 | 133] |  |
| [116  | 144 | 326 | 160 | 135 | 157 | 188 | 133 | 170 | 147 | 207 | 172] |  |
| [135  | 157 | 188 | 133 | 170 | 147 | 207 | 172 | 247 | 143 | 180 | 152] |  |
| [170  | 147 | 207 | 172 | 247 | 143 | 180 | 152 | 120 | 193 | 184 | 124] |  |
| [247  | 143 | 180 | 152 | 120 | 193 | 184 | 124 | 241 | 130 | 172 | 167] |  |
| [120  | 193 | 184 | 124 | 241 | 130 | 172 | 167 | 186 | 142 | 141 | 109] |  |
| [241  | 130 | 172 | 167 | 186 | 142 | 141 | 109 | 0   | 0   | 0   | 0]   |  |
| [186  | 142 | 141 | 109 | 0   | 0   | Θ   | 0   | 0   | 0   | 0   | 144] |  |
| [ 0   | 0   | 0   | 0   | 0   | 0   | 0   | 144 | 182 | 162 | 200 | 175] |  |
| [ 0   | 0   | 0   | 144 | 182 | 162 | 200 | 175 | 158 | 126 | 131 | 240] |  |
| [182  | 162 | 200 | 175 | 158 | 126 | 131 | 240 | 172 | 153 | 211 | 175] |  |

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# Changepoint detection with MLP



# Changepoint detection

Learning curves of changepoint detection with MLP v1 training 14 validation 12 10 8 6 4 2 -0 2.5 15.0 17.5 5.0 7.5 10.0 12.5 20.0 epochs

loss

Test accuracy: 0.8696682453155518



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