

Optimizing Changepoint Detection through Deep Learning-based Penalty Tuning

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1. Problem

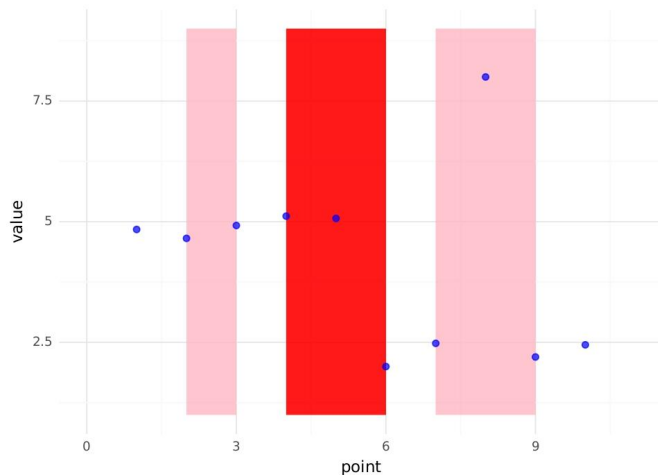
2. Review

3. Method

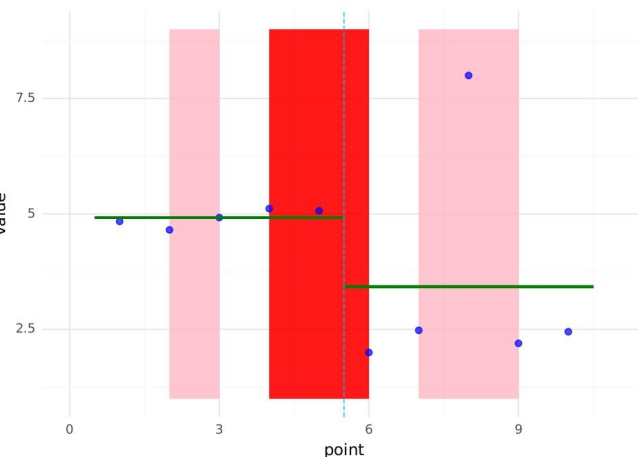
4. Results

We have a sequence with labels (negative or positive regions)

We apply the algorithm (OPART, LOPART) and return a set of changepoints (or breakpoints)



Algorithm



1. Problem

2. Review

3. Method

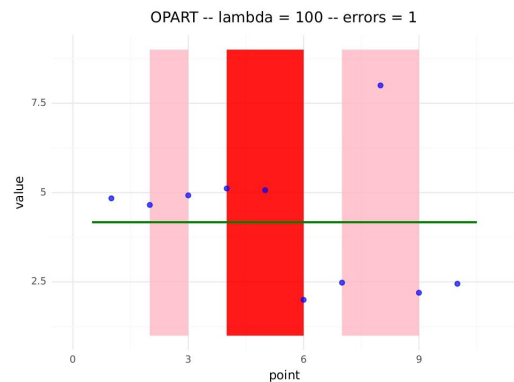
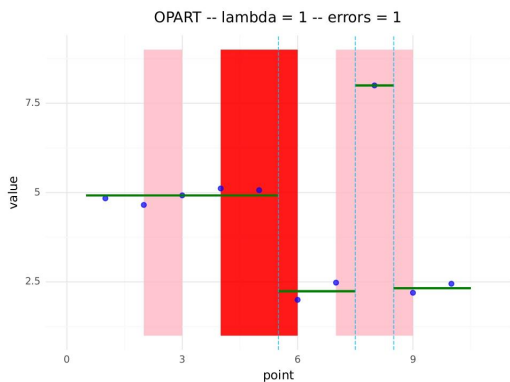
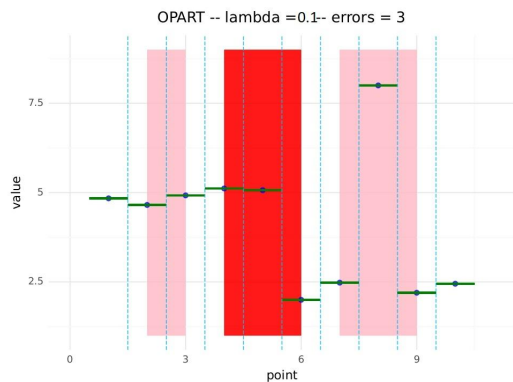
4. Results

There is a fixed penalty parameter of the algorithms (OPART, LOPART), which is λ

`OPART(sequence, λ)` = `set_of_changepoints`

`LOPART(sequence, labels, λ)` = `set_of_changepoints`

With varying values of λ , different results are produced. See examples below:

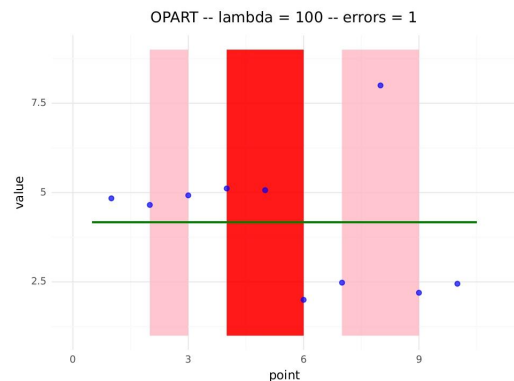
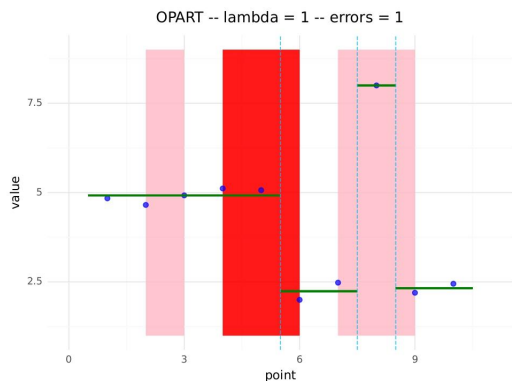
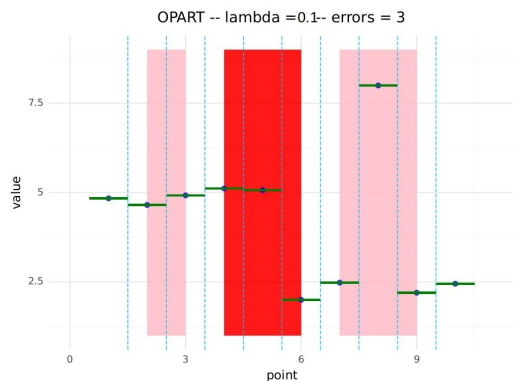


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So from the example, we see that $\lambda=0.1$ is not good, $\lambda=1$ is maybe better.

My research goal is to identify the optimal λ that minimize the number of predicted label errors

1. Problem

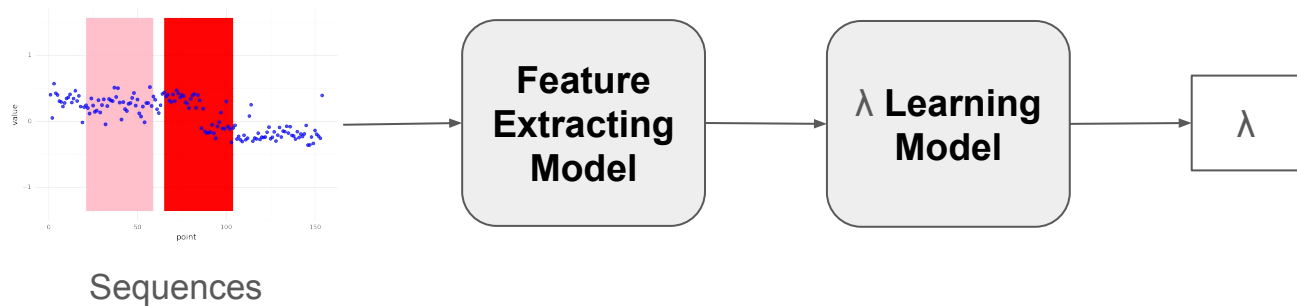
2. Review

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From the sequences, how can we learn λ

Below is the general model

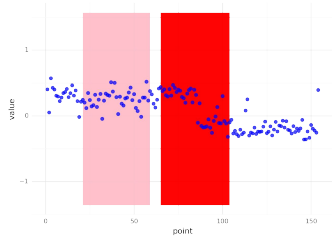


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**Feature
Extracting
Model
(M1)**

**λ Learning
Model
(M2)**

λ

1. Bayesian Information Criterion (BIC)

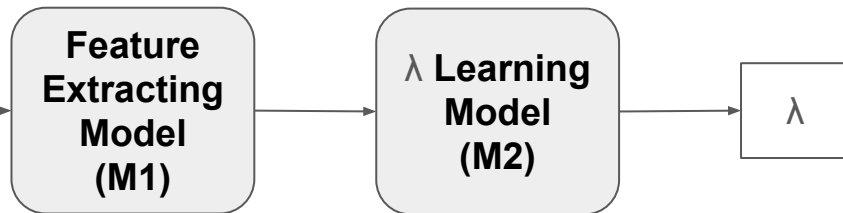
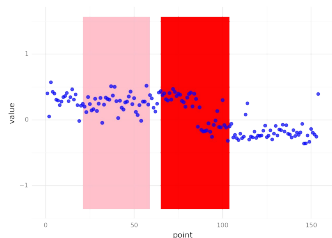
- M1: $x = \log(N)$ where N is the sequence length.
- M2: $\lambda = x$

1. Problem

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2. Linear

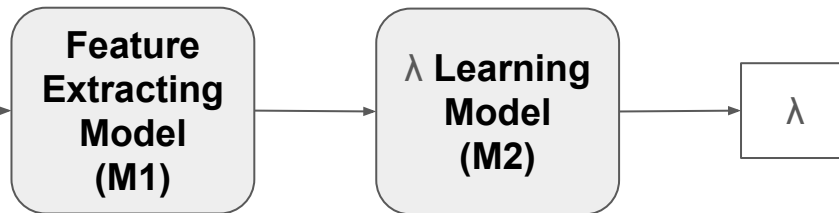
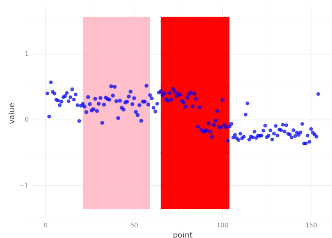
- M1: $x = \log(\log(N))$ where N is the sequence length.
- M2: $\lambda = \exp(xw + \beta)$ where w and β are the model's parameters.

1. Problem

2. Review

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Summary

	BIC	Linear
M1	$x = \log(N)$	$x = \log(\log(N))$
M2	$\lambda = x$	$\lambda = \exp(xw + \beta)$

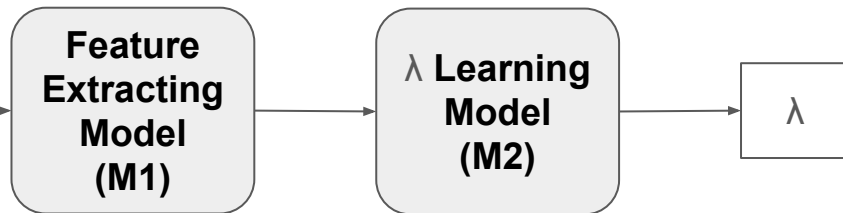
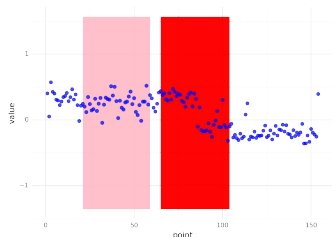
Innovation: Using different type of models for M1 and M2

1. Problem

2. Review

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I have two approaches for selecting models M1 and M2

- Approach 1:

- M1: consider a set of features that I can manually extract from a sequence (length, mean, variance, ...), then using visualization to select the useful ones.
- M2: multilayer perceptron (MLP)

- Approach 2:

- M1: Recurrent Neural Network (RNN)
- M2: linear model

To learn a model M2, we need data X and target y:

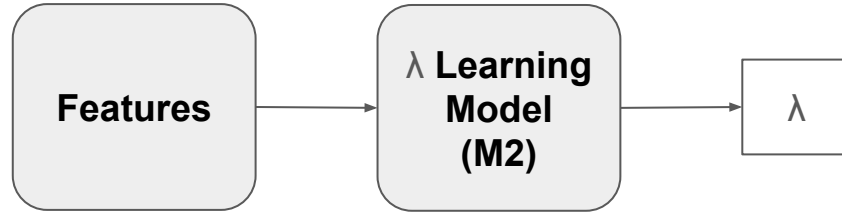
- X is the set of features (output of M1)
- y is the $(m1, m2)$: for each sequence, I run OPART with $\lambda = 10^m$ where $m \in \{-5, -4.5, \dots, 5\}$. Then choose the interval $(m1, m2)$ that minimizes the number of train label errors. (For example, for sequence 1, $(m1, m2) = (-3, 3)$)

1. Problem

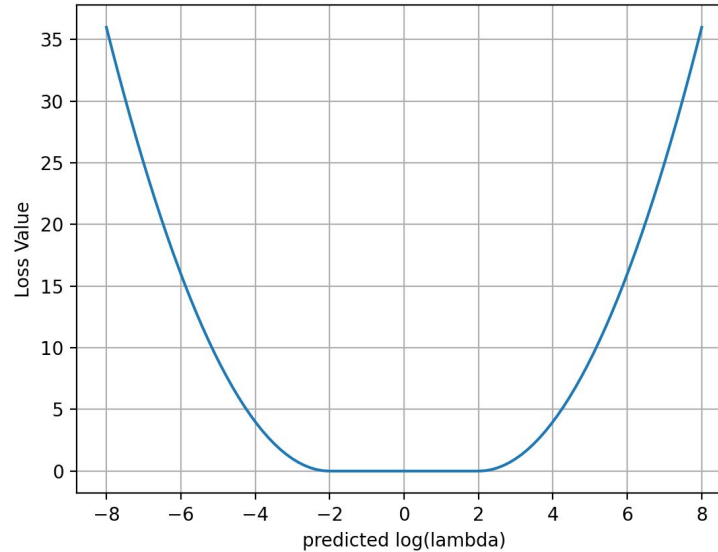
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Loss Function: Mean Square Hinge Error (for example, $(m_1, m_2) = (-3, 3)$) with margin = 1



1. Problem

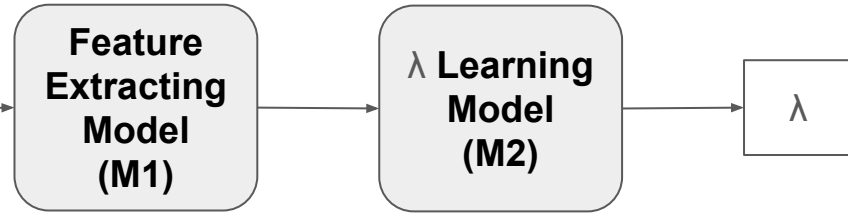
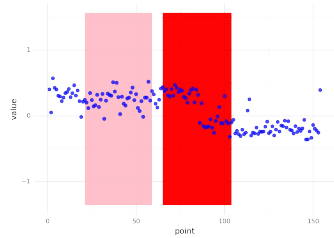
2. Review

3. Method

a. Approach 1

b. Approach 2

4. Results



Approach 1:

- M1: I consider 7 features
 - Standard deviation
 - Mean
 - Range Value
 - Absolute skewness
 - Kurtosis
 - Length
 - Sum of difference between two consecutive points

Then I visualize each of them with respect to the target interval $(m1, m2)$ to pick the useful ones.

- M2: multilayer perceptron (MLP)

1. Problem

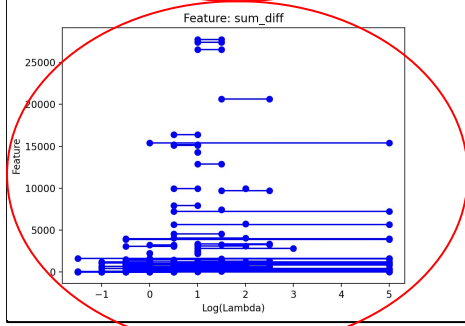
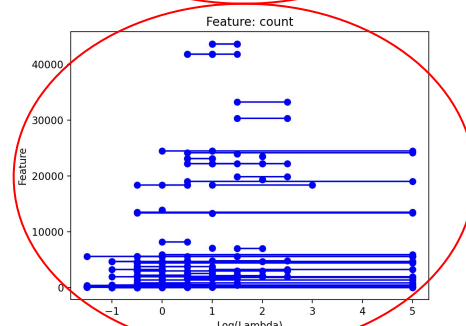
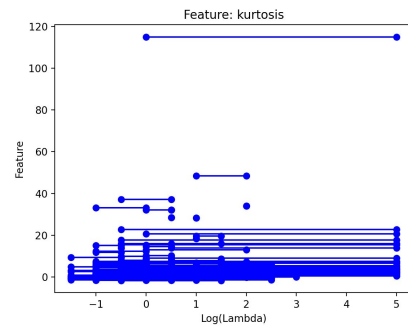
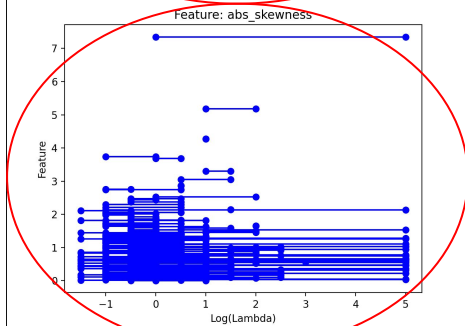
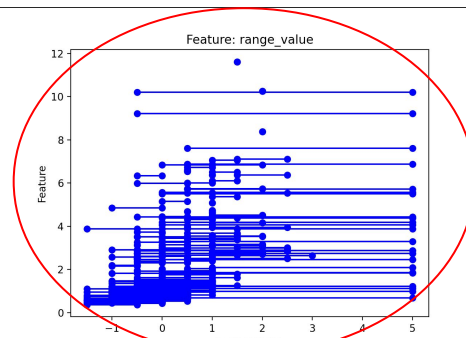
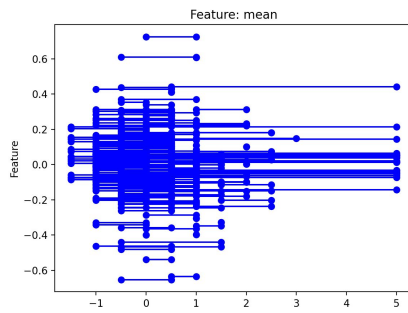
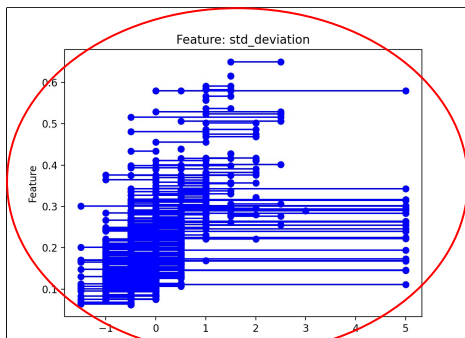
2. Review

3. Method

a. Approach 1

b. Approach 2

4. Results



1. Problem

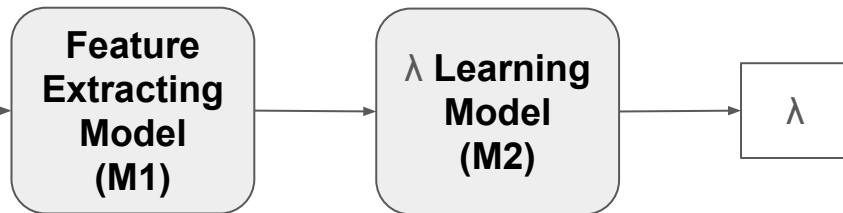
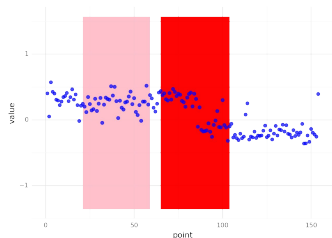
2. Review

3. Method

a. Approach 1

b. Approach 2

4. Results



Approach 1 comparison with the previous works

	BIC	Linear	Approach 1
M1	$x = \log(N)$	$x = \log(\log(N))$	<pre>x1 = std(seq) x2 = range(seq) x3 = skew(seq) x4 = len(seq) = N x5 = sum_diff(seq)</pre>
M2	$\lambda = x$	$\lambda = \exp(xw + \beta)$	<pre>log(λ) = MLP(x1, x2, x3, x4, x5)</pre>

1. Problem

2. Review

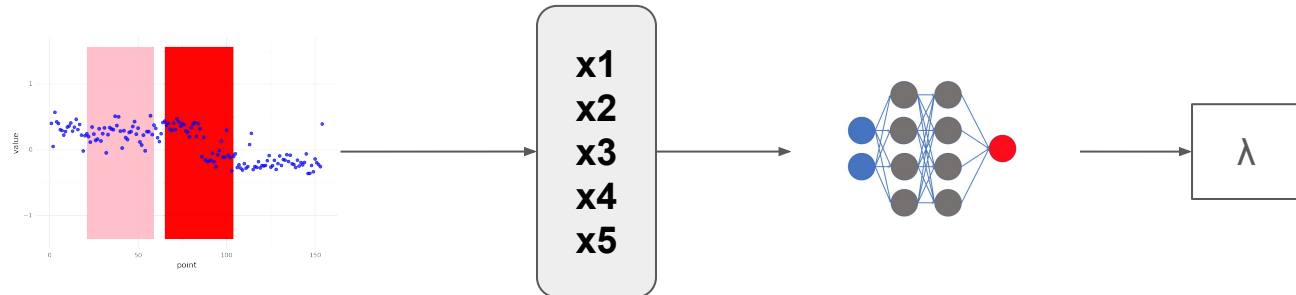
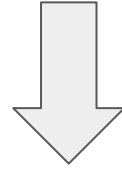
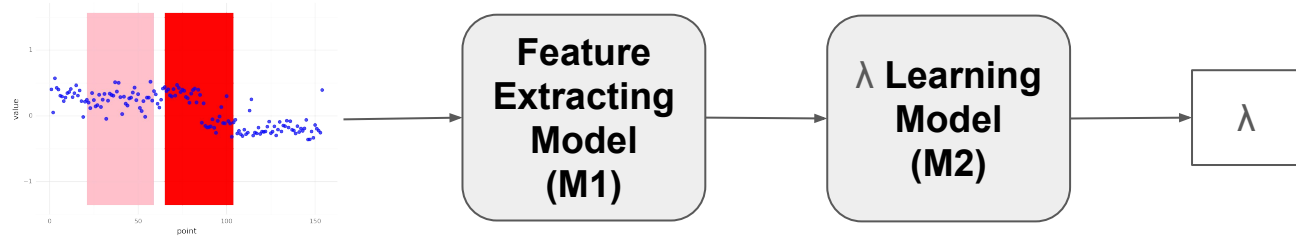
3. Method

a. Approach 1

b. Approach 2

4. Results

Approach 1



1. Problem

2. Review

3. Method

a. Approach 1

b. Approach 2

4. Results

Approach 2

- M1: Recurrent Neural Network (RNN)
- M2: Linear model

The reason I chose RNN to be the M1 (extracting features from sequences) because this type of model can:

- Take into inputs with different length
- Produce the fixed length output
- Can learn features from sequences (like mean, standard variation, length, ...) so I hope this model can produce some useful features that I did not consider on the approach 1.

1. Problem

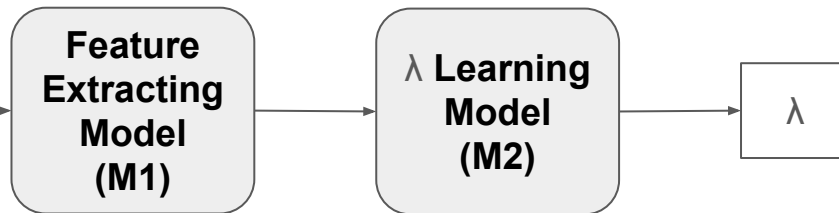
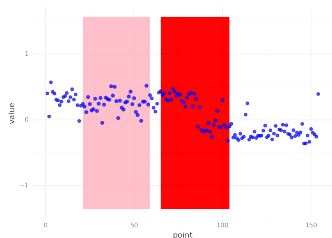
2. Review

3. Method

a. Approach 1

b. Approach 2

4. Results



Approach 2 comparison with the previous works

	BIC	Linear	Approach 2
M1	$x = \log(N)$	$x = \log(\log(N))$	$\mathbf{x} = \text{RNN}(\text{seq})$
M2	$\lambda = x$	$\lambda = \exp(xw + \beta)$	$\lambda = \exp(\mathbf{xw} + \beta)$

1. Problem

2. Review

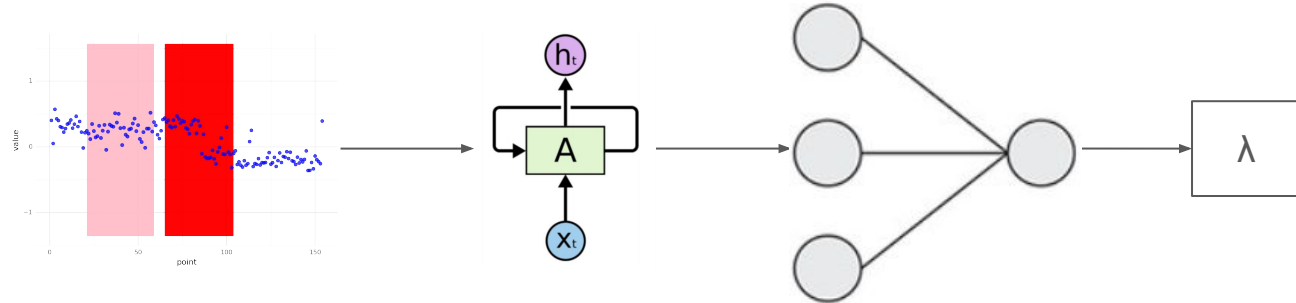
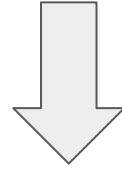
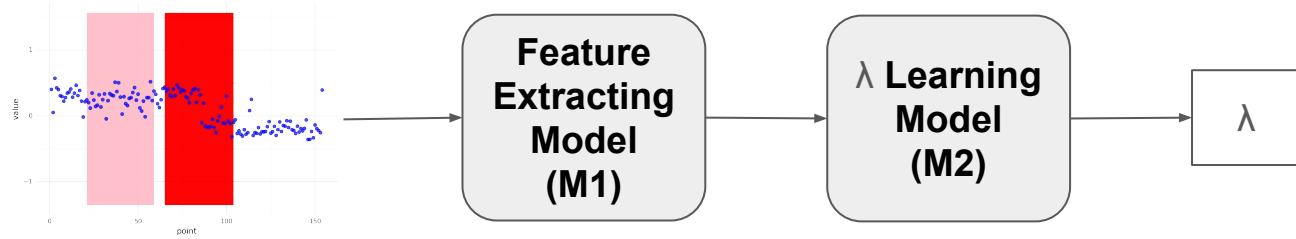
3. Method

a. Approach 1

b. Approach 2

4. Results

Approach 2



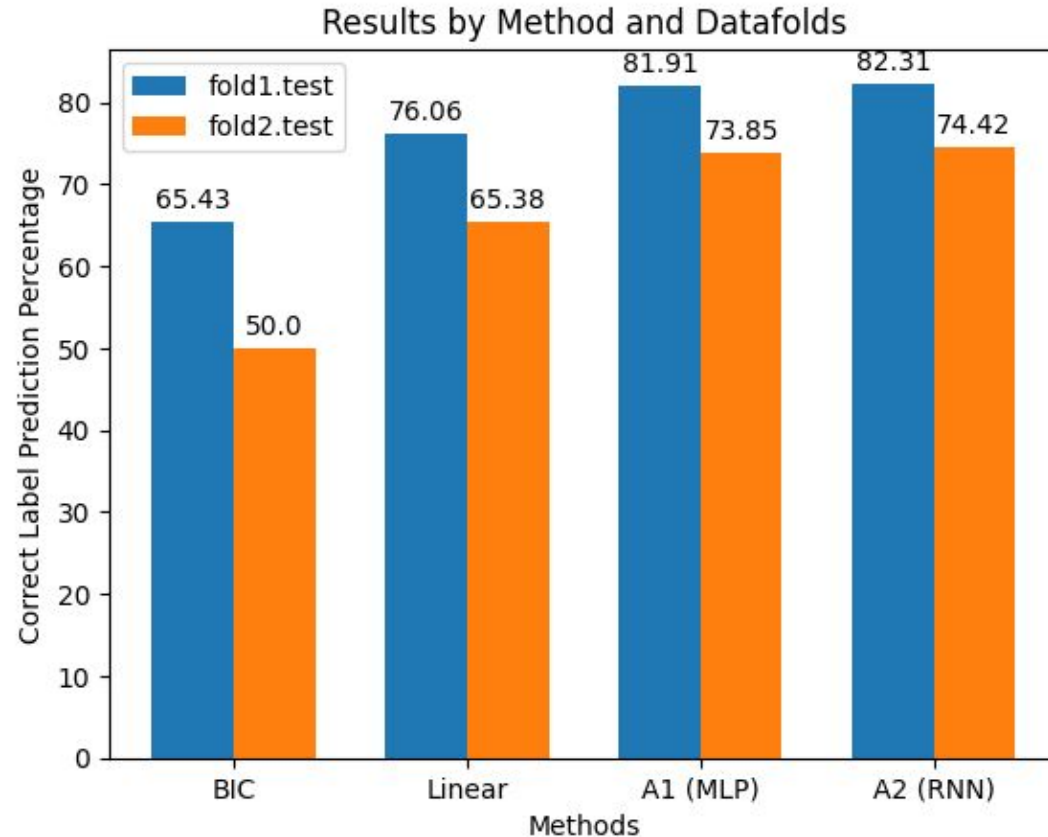
1. Problem

2. Review

3. Method

4. Results

Using each method (4 of them) to predict λ , and I apply `OPART(seq_i, λ_i)` for each sequence, get the set of changepoints. Then I can calculate the correct predicted label percentage.



THANK YOU FOR LISTENING