Cut-n-Reveal: Time-Series Segmentations with Explanations

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ACM Reference Format:
NIKHIL MURALIDHAR, LIANGZHE CHEN, ANIKA TABASSUM, SUPRIYA CHINTHAVALI, NAREN RAMAKRISHNAN, and B. ADITYA PRAKASH. 2019. Cut-n-Reveal: Time-Series Segmentations with Explanations. *ACM Trans. Web* 9, 4, Article 39 (January 2019), 3 pages. https://doi.org/0000001.0000001

1 APPENDIX

1.1 Additional Discussion About CnR-UV Explanation Formulation

Our goal with learning each e_i vector is to learn a *local* explanation of 'culprit' time series at a particular cut-point i in the segmentation. Hence, our design is a deliberate attempt to uncover local explanations per cut-point, free of untoward global temporal influence from other cut-points. In addition, optimizing each e_i separately also enables parallelization aiding in scalability of the explanation formulation.

1.2 CnR-UV Explanation Formulation Compared with Attention Mechanisms

We may assume that the explanation step (that identifies the 'culprit' time series) in our case, represents a kind of attention mechanism (popular in encoder-decoder architectures) over each time series for each cut point. This is because the explanation model essentially can be considered as a learned scoring function that given a cut point c and a set of time series (similar to a set of encoder hidden states $\mathbf{H}$), learns a scoring function $\mathbf{S}$ that assigns scores to each of the time series in $\mathbf{H}$ considering their behavior around the cutpoint c_i. However, our mechanism is slightly more sophisticated than traditional attention mechanisms as we are also able to jointly model spatial constraints between counties, while learning the explanation weights as opposed to traditional attention mechanisms which use straight forward similarity functions like cosine similarity to calculate attention energies.

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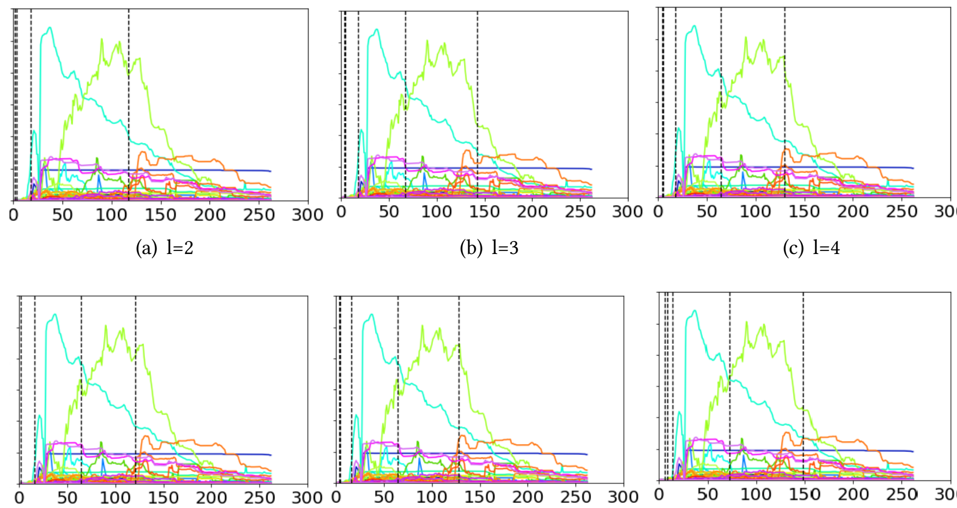
1559-1131/2019/1-ART39 $15.00
https://doi.org/0000001.0000001

1.3 Effect of Changing Latent Dimension on CnR-UV Segmentation

In Fig. 1 we show CnR-UV segmentation on Hurricane Harvey with varying values of latent dimension l. The segmentation results don't vary much with varying l, keeping other hyperparameters constant. This indicates that the CnR-UV segmentation model is not overly sensitive to variation in the latent dimension.



(a) l=2 (b) l=3 (c) l=4

(d) l=5 (e) l=6 (f) l=8

Fig. 1. CnR-UV segmentation results (vertical dashed lines) for the Hurricane *Harvey* varying l values to check robustness. The segmentation performance indicates that the CnR-UV model is not overly sensitive to changes in l. For the actual experimental results on all hurricanes we used $l = 5$.

1.4 Additional Scalability Comparison of CnR-UV with Baseline Models

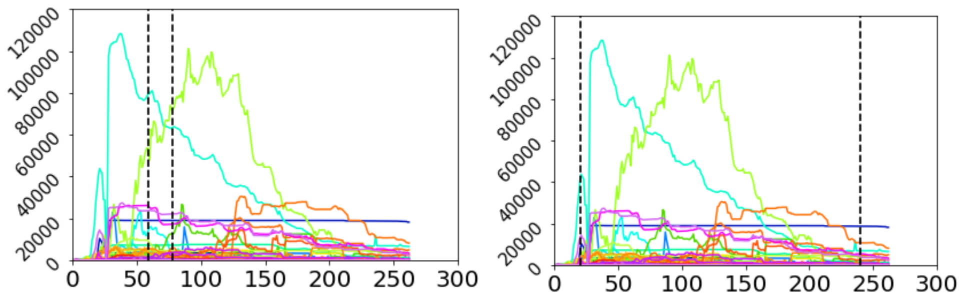
We recorded the running time of the baselines TICC, Dynammo, and Floss in Table 1 varying number of timeseries. Dynammo did not converge when number of timeseries ≥ 30.

Table 1. Scalibility Experiment on Baselines Varying Number of Timeseries

Number of timeseries	CnR-UV	TICC	Floss	Dynammo
15	179.07	6.69	5.63	44.28
30	180.35	25.97	10.66	–
60	173.44	99.88	21.07	–
120	184.50	342.81	41.97	–
240	190.47	771.20	84.12	–
480	210.45	3855.13	167.03	–

1.5 Baseline Results on Hurricane Dataset

We show the results of two best performing baseline models TICC and Floss on segmentating the hurricane Harvey power failure data in Fig. 2. TICC did not converge for hurricane Irma, and Matthew while Floss gives similar segments as in Harvey for both the hurricanes, i.e., one at the very beginning, other at the very end.



(a) TICC segments (b) Floss segments

Fig. 2. TICC and FLOSS segmentation results (vertical dashed lines) for the Hurricane *Harvey*. We noticed that both these models do not capture many important phases of the hurricane failure process like the CnR-UV model does (see Fig. 1).

1.6 Hyperparameter Values of Baselines

We note all the baseline hyperparameter values in Table 2. For TICC, we used window-size= 5,$\lambda = 11e - 2$, $\beta = 5$, threshold= $2e^{-5}$

Table 2. Baseline Hyperparameter Values

Dataset	**TICC** Number of Clusters	**Floss** Sub-Sequence Length	**Dynammo** Error Threshold
Synthetic	5	4	50
NILM	8	4	45
ChickenDance 1	8	5	73
ChickenDance 2	8	4	35
WalkJog 1	3	4	95
WalkJog 2	3	4	65
GrandMal	2	10	85