Aalto University
School of Science
Bachelor's Programme in Science and Technology

Video change point detection based on viewing statistics

Bachelor's Thesis

April 17, 2022

Saskia Kivistö

Aalto University
School of Science
Bachelor's Programme in Science and Technology

ABSTRACT OF
BACHELOR'S THESIS

Author:	Saskia Kivistö
Title of thesis:	Utilisation of viewing statistics in detecting NPVR closing credits
Date:	April 17, 2022
Pages:	
Major:	Computer Science
Code:	SCI3027
Supervisor:	Assistant Professor Parinya Chalermsook
Instructor:	Wanchote Jiamjitrak, M.Sc. (Tech) (Department of Computer Science)
Abstract	
Keywords:	change point detection,
Language:	English

Aalto-yliopisto
Perustieteiden korkeakoulu
Teknistieteellinen kandidaattiohjelma

KANDIDAATINTYÖN TIIVISTELMÄ

Tekijä:	Saskia Kivistö
Työn nimi:	Lopputekstien paikannus NPVR tallenteesta katsomistilastoja hyödyntäen
Päiväys:	17. huhtikuuta 2022
Sivumäärä:	
Pääaine:	Tietotekniikka
Koodi:	SCI3027
Vastuuopettaja:	Apulaisprofessori Parinya Chalermsook
Työn ohjaaja(t):	DI Wanchote Jiamjitrak (Tietotekniikan laitos)
Tiivistelmä	
Avainsanat:	muutospisteiden havaitseminen,
Kieli:	englanti

Contents

1 Introduction

Watching television used to be a very time-sensitive activity. If one wanted to see a TV program they had to watch it when it was broadcasted. Videocassette recorders brought the freedom to store programs and to choose freely when to watch them. However, recording programs for later viewing has one major inconvenience. Programs are not broadcasted strictly according to the schedule of the Electronic program guide (EPG). Sometimes programs start earlier or end later than what is stated in the EPG. To ensure that the entire program is recorded, recording must start before the EPG start time and end after the EPG end time. This usually results in some non-program content being included in the recording. Skipping over the non-program content can be frustrating for the person watching the recording.

Knowing when the program truly starts and ends would solve the issue, but this information is not generally available. This leaves the option to detect the start and end of the program from the recording. Various artificial intelligence solutions have been devised [2] [3] [5] [9], but as program content can be quite varied it is difficult to find an universal solution.

Network personal video recorder (NPVR) is a type of service for recording broadcast TV programs for later viewing. Instead of storing recordings on the users local device, NPVR stores recordings on the content providers server. For every program listed in the EPG, a single recording is created and stored on the server. The users who record the same program will receive the same video from the server.

The start and end times of NPVR recordings are determined by the scheduling information given in the EPG, but some margin is added on both ends to ensure that the entire program is recorded. Similar to storing the recordings locally, this typically leads to non-program content being included in recordings. However, NPVR has a certain advantage over local storage. Users who have recorded the same program will watch the exact same recording, and statistics of which parts of the recording users watch and which parts they skip can be collected and analysed.

The goal of this thesis is to study whether user viewing behaviour can be used to determine when the start and end credits and advertisement breaks occur in an NPVR recording. I am writing this thesis for an NPVR service provider company. From the perspective of an NPVR service provider, detecting the location of core program content is useful for the following reasons. Firstly, less storage space is needed if the surplus contet is discarded. Secondly, it is convenient for the customers if the relevant content of a recording is pre-identified and they do not have to search for it.

The thesis is structured as follows. Section 2 gives an overview on the characteristics of the viewing behavioiur data. Section 3.1 discusses the theoretical background of signal change point detection from the perspective of this specific use case. Result evaluation and validation is discussed in section 3.2. In section 4.1 the Python scientific library `ruptures` is used to detect change points. The results are evaluated in section 4.2. Section 5 discussion considers the viability of using user viewing behaviour for change point detection, based on the previous sections. Lastly, the main points of this thesis are summarised in section 6 conclusions.

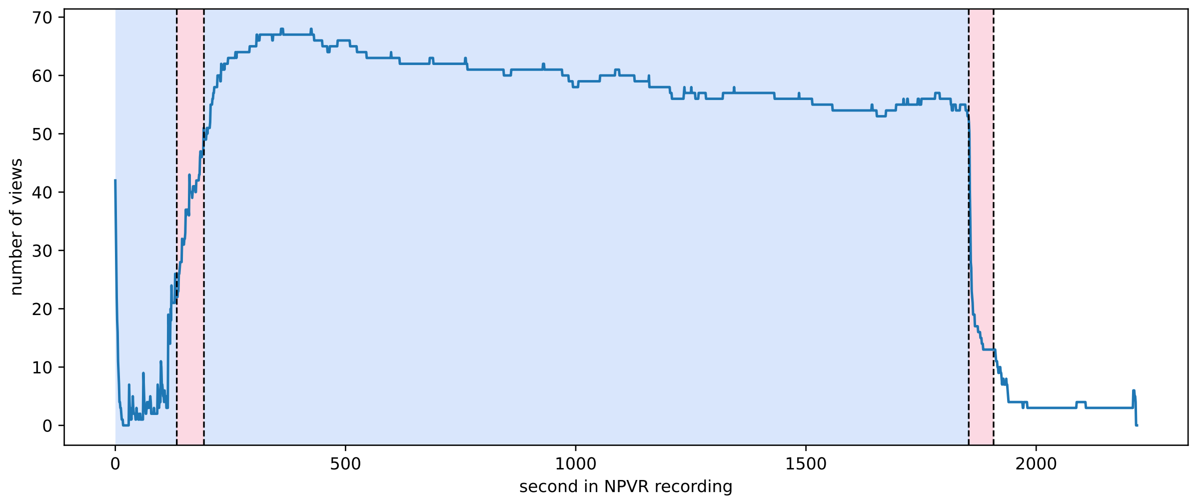
2 User viewing behaviour data

Whenever an NVPR video is watched by a user, certain metrics about the viewing event are saved. The main reason for collecting viewing metrics is the monitoring of the amount of views and the user experience quality. From the metrics of one view, it can be calculated which parts of the video the user watched and which parts they skipped. When this data is aggregated from multiple views of the same recording, an overview of what parts of the recording users typically watch is acquired. This type of recording specific aggregated view count is referred to as user behaviour data in this thesis.

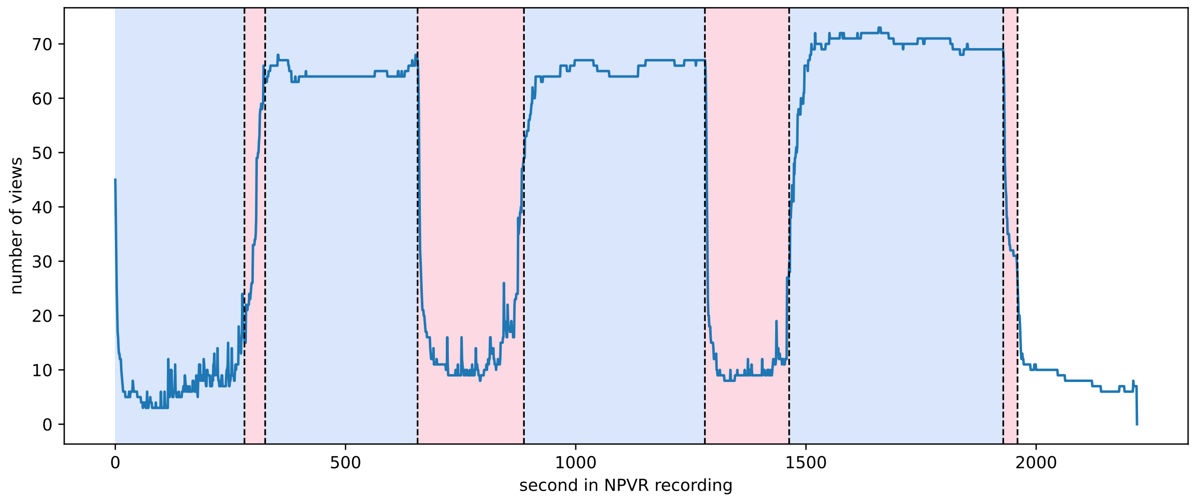
The content of an NPVR recoring can be categorised into start credits, core program content, advertisement breaks, end credits and non-program content at the very beginning and end of a recording. Every recording has core program content and end credits, but not all recordings have start credits or advertisement breaks. Core program content is considered relevant for the users, while non-program content and advertisement breaks are considered irrelevant. The relevancy of start and end credits is something in between, since many users prefer to skip them, but they still belong to the program and are not extra content as such.

In this thesis, starting credits, advertisement breaks and end credits will be referred to as change segments. The start and end points of the aforementioned will be referred to as change points. The goal of this thesis is to find a suitable method to determine at least the approximate location of change points.

Two examples of user viewing behaviour data are illustrated in Figure 1. The data in both figures consists of a sample of 100 user views, but the views are from two different TV programs. Figure 1a views are from a sitcom episode and Figure 1b views are from an episode of a soap opera. The episodes are divided into one second-long segments, and calculated for each segment is the number of user views in which the segment was watched. The segments are plotted on the horizontal axis, and the number of user views per segment is plotted on the vertical axis. For example, 63 users from the sample of 100 users watched the part of the sitcom episode between 0:10:00 - 0:10:01 (600 on the



(a) 30 min sitcom episode without advertisements, 100 views



(b) 30 min soap opera episode with two advertisement breaks, 100 views

Figure 1: Visualisation of user viewing behaviour for two example recordings

horisontal axis in Figure 1a).

The change segments are indicated with a red background and the change points are marked with a vertical dashed line. In Figure 1b there are a total of four change segments, which correspond to start credits, two advertisement breaks and end credits, respectively. Figure 1a episode has no advertisement breaks. The change points were checked by hand from both of the videos. It can be seen from the figures that a steep increase in views occurs when the actual program content begins, and correspondingly there is a steep decrease in views when the program content shifts to advertisements or closing credits.

3 Theoretical background

3.1 Signal change detection

Locating video content changes from user viewing behaviour time series data can be formulated as a signal processing problem, more precisely as a change point detection problem. Signal change point detection is quite widely researched topic, since it has applications in multiple fileds such as network traffic data analysis [6] [8], bio-informatics [7] [13] and climatology [10] [12].

Change point detection problems can be divided into two main categories, depending on whether the change detection must be done for incoming data in near real-time, or not. Methods solving the former case are referred to as online algorithms. Offline algorithms solve the latter case, and they differ from the online algorithms by getting the entire dataset as input and typically being more computationally complex, but also by detecting the changes more accurately.

Offline methods can be divided into two categories, based on whether the number of changes in the dataset is known beforehand, or not. If the number of change points is not known, an extra step is needed to determine it. There are multiple methods for doing this.

$$c_{L_2}(y_{a.b}) = \sum_{t=a+1}^{b} \|y_t - \overline{y}_{a.b}\|_2^2 \tag{1}$$

3.2 Result evaluation and validation

In order to asses the accuracy of the output of the chosen algorithms, there are some metrics as presented in Truong et al. [11] literature review.

4 Empirical research

4.1 Ground truth

In order to evaluate how well a method detects change points, a ground truth is needed for comparison. Ground truth can be obtained by having a person look at a video recording and having them write down the timestamps of the change points.

I have collected the start and end times of the change points from 174 NPVR recordings by hand with a margin of error of ± 1 seconds. The sample consists of episodes from

9 different TV series. The recordings are listed in Table 1 categorised by series. The episodes from series 1.-5. were recorded from non-commercial channels, that have no advertisement breaks. Every recording in the sample has at least one hundred user views.

# series	# episodes	# ad breaks	episode length	genre
1.	32	0	30 min	sitcom
2.	8	0	45 min	drama
3.	30	0	45 min	drama
4.	4	0	50 min	drama
5.	10	0	50 min	drama
6.	35	1	30 min	soap opera
7.	31	2	30 min	soap opera
8.	15	3 (most)	60 min (most)	reality show
9.	9	4	90 min	reality show

Table 1: Sample recordings categorized by series

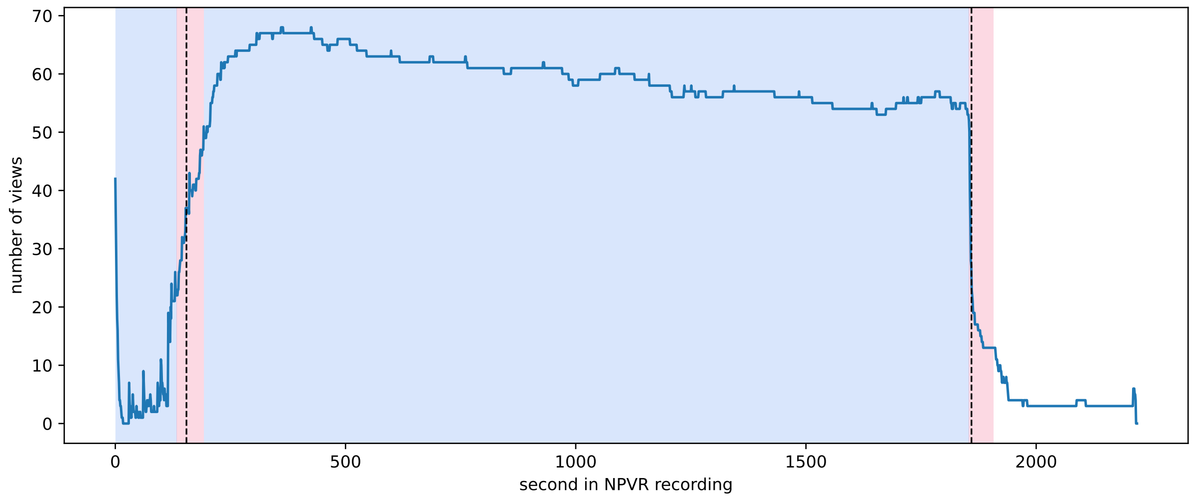
4.2 Change point detection with `ruptures` library

A Python library called `ruptures` was used for the change point detection. `ruptures` is based on the findings of a literature reviw conducted by Truong et al. [11] which examined various methods for offline change point detection. Selected algorithms examined in the literature review are implemented in `ruptures`.

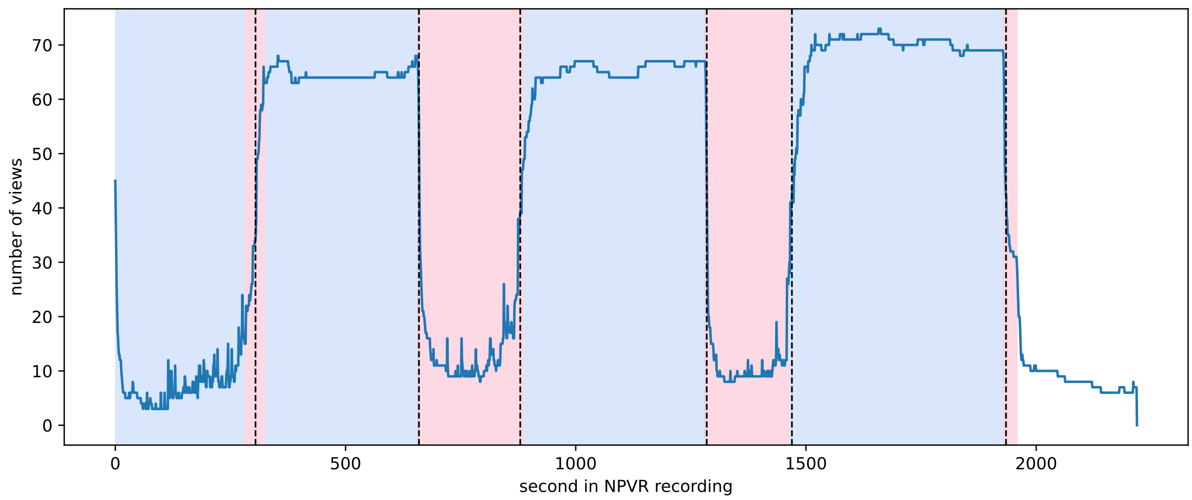
Choosing the most suitable algorithm for this use-case can be done by considering the three aspects of change detection methods discussed in the literature review: cost-function, search method and constraint. Accuracy is more important than low computational complexity, so optimal method is preferable to an approximate one. `ruptures` has two optimal search methods `Opt` and `Pelt`. The difference between them is that `Opt` works only when the number of change points is know beforehand, and `Pelt` is used for unknown number of change points. `Opt` was first introduced by Bellman [1] for an unrelated problem and `Pelt` was first indroduced by Killick et al. [4].

`Opt` and `Pelt` can be used with three different cost functions c_{L1}, c_{L2} and c_{rbf}.

An example of `Pelt` output with cost function c_{L2} is visualised in Figure 2. The viewing behaviour data is the same as in Figure 1. The difference between the figures is that in Figure 2 the vertical dashed lines mark the change points determined by `ruptures` instead of the real changepoints checked by hand. The start and end times of advertisement breaks were found fairly accurately, but for the start and end credits only one change point was found. The change point for the closing credits seems to align with the beginning of the credits. The change point for the start credits falls in the middle of the start credits.



(a) `Pelt` c_{L2} output for Figure 1a data



(b) `Pelt` c_{L2} output for Figure 1b data

Figure 2: `Pelt` c_{L2} output for Figure 1 data

4.3 Results

5 Discussion

It is non-trivial to find an universal solution that works regardless of the number of advertisemet breaks and the length of the recording. When linear constraint is used, like in `Pelt`, a different penalty value would be optimal for non-commercial and commercial channels.

6 Conclusions

References

[1] Bellman, R. *On a routing problem.* Quarterly of Applied Mathematics. 1958, vol. 16 :1. P. 87–90. Available at: doi:10.1090/qam/102435.

[2] Berrani, S.-A. & Manson, G. & Lechat, P. *A non-supervised approach for repeated sequence detection in TV broadcast streams.* Signal Processing: Image Communication. 2008, vol. 23:7. P. 525–537. Available at: doi:10.1016/j.image.2008.04.018.

[3] Ibrahim, Z. A. A. & Gros, P. *TV Stream Structuring.* ISRN Signal Processing. 2011, vol. 2011. P. 1–17. Available at: doi:10.5402/2011/975145.

[4] Killick, R. & Fearnhead, P. & Eckley, I. A. *Optimal Detection of Changepoints With a Linear Computational Cost.* Journal of the American Statistical Association. 2012, vol. 107:500. P. 1590–1598. Available at: doi:10.1080/01621459.2012.737745.

[5] Kompatsiaris, Y. & Merialdo, B. & Lian, S. *TV Content Analysis: Techniques and Applications.* CRC Press, 2012. ISBN 978-1-4398-5562-1.

[6] Lévy-Leduc, C. & Roueff, F. *Detection and localization of change-points in high-dimensional network traffic data.* The Annals of Applied Statistics. 2009, vol. 3:2. P. 637–662. Available at: doi:10.1214/08-AOAS232.

[7] Liu, S. & Wright, A. & Hauskrecht, M. *Change-point detection method for clinical decision support system rule monitoring.* Artificial Intelligence in Medicine. 2018, vol. 91. P. 49–56. Available at: doi:10.1016/j.artmed.2018.06.003.

[8] Lung-Yut-Fong, A. & Lévy-Leduc, C. & Cappé, O. *Distributed detection/localization of change-points in high-dimensional network traffic data.* Statistics and Computing. 2012, vol. 22:2. P. 485–496. Available at: doi:10.1007/s11222-011-9240-5.

[9] Manson, G. & Berrani, S.-A. *Automatic TV Broadcast Structuring.* International Journal of Digital Multimedia Broadcasting. 2010, vol. 2010. P. e153160. Available at: doi:10.1155/2010/153160.

[10] Reeves, J. & Chen, J. & Wang, X. L. & Lund, R. & Lu, Q. *A Review and Comparison of Changepoint Detection Techniques for Climate Data.* Journal of Applied Meteorology and Climatology. 2007, vol. 46:6. P. 900–915.

[11] Truong, C. & Oudre, L. & Vayatis, N. *Selective review of offline change point detection methods.* Signal Processing. 2020, vol. 167. P. 107299. Available at: doi:10.1016/j.sigpro.2019.107299.

[12] Verbesselt, J. & Hyndman, R. & Newnham, G. & Culvenor, D. *Detecting trend and seasonal changes in satellite image time series.* Remote Sensing of Environment. 2010, vol. 114:1. P. 106–115. Available at: doi:10.1016/j.rse.2009.08.014.

[13] Vert, J.-p. & Bleakley, K. Fast detection of multiple change-points shared by many signals using group LARS. *Advances in Neural Information Processing Systems*, volume 23. Curran Associates, Inc., 2010.