Change Point Detection for Time Series: Application on Human Gait Anomaly Detection

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Abstract

In time series analysis, Change Point Detection (CPD) which is the task to find the points (change points) where the statistical properties of a process changes is an important task especially in applications where timely detection would help decision-making such as in health monitoring, finance and cybersecurity applications. The current project explores CPD methods on a real-world univariate dataset, gaitHunt1, which can be found in the UCR Time Series Anomaly Archive. The goal is to detect changes in human gait signals indicating potential injury, fatigue, or neurologic anomalies. Two major methods will be used: 1) Bayesian Online Change Point Detection (BOCPD) and 2) offline algorithms based on Ruptures library. The study would assess these approaches based on accuracy, interpretability, computational performance, and robustness. Outcomes will be compared to the labeled anomalous area of the dataset which gives a realistic baseline to measure the performance of CPD on these datasets. These findings are hoped to assist in the development of interpretable CPD strategies directed at areas such as behavioral and health monitoring.

Declaration

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- [x] I have used GenAI tools to:

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    - [x] help me understand key theories and concepts.

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Contents

Introduction & Background

Change point detection (CPD) has become an essential analytical technique in time series in recent years, with applications in a wide range of domains, including finance, energy management, cybersecurity, and health monitoring. Detection of change points in time series where the statistical characteristics dramatically change is important in applications such as early warning systems, such as in risk assessment, surveillance, quality control of industrial processes and system diagnostics [3]. With modern systems generating more and more high-frequency, real-time data, the need for computationally efficient, accurate, and interpretable CPD methods is growing [16].

Change point detection methods will be investigated and applied to univariate time series data in this project, using the gaitHunt1 dataset from the UCR Time Series Anomaly Archive [14]. The dataset has a time series of gait measures originating from a human with a clearly demarcated anomaly region. This dataset is especially applicable to health and activity monitoring, as it can be used to identify deviations from the normal movements of subjects, which may guide toward injuries, fatigue or neurological disorders [25]. This dataset was chosen as it represents a realistic and meaningful scenario to validate CPD methods.

We place this study in a general framework of anomaly detection in the real world using machine learning. Statistical and algorithmic approaches, like Bayesian Online Change Point Detection [1] and the Ruptures library [21], will be implemented and tested regarding performance to identify the anomaly segment in the gaitHunt1 dataset. Also, if and how these methods are interpretable, and how they might fail in the presence of noise or natural human behaviour signals will be discussed.

Outside of these common methods, significant recent work has emphasized the value of scalable and flexible CPD efforts. The PELT algorithm, for instance, provides linear computational time complexity (and thus is suitable for large-scale applications) and is accessible through the Ruptures library [12]. Tutorials from Analytics Vidhya on change point detection describe end to end workflows and reproducible code, community-driven resources to implement CPD in Python [2]. These resources will guide the project's development practices and support methodological rigor.

Literature Review

Change point detection (CPD) has become a key research topic in time series analysis for its fundamental impact on early anomaly detection and system monitoring. Change point is the time at which the statistical properties of a time series, such as mean, variance, or distribution change significantly. This type of concept is widely used in practical domains such as healthcare, energy use, financial market monitoring, and cyber-attack detection [3].

We explore several classical and modern approaches to tackle CPD. Of the statistical methods BOCPD (Bayesian Online Change Point Detection) is a commonly used baseline because it has the ability to continually update beliefs with every new observation, meaning it can run in real time [1]. The Pruned Exact Linear Time (PELT) algorithm offers a more scalable offline solution, guaranteeing linear computational cost while estimating same detection accuracy [15]. Several more recent frameworks including Ruptures [21] offer flexible implementations of multiple CPD algorithms (including dynamic programming and kernel-based methods), PELT, and window-based segmentation for python-based workflows. Analytics Vidhya has interactive tutorials and all the code snippets to implement the end-to-end methods in real settings [2].

Also, deep learning methods have been considered. While models like LSTMs and Transformers can be utilized for time series anomaly detection [18], the poor interpretability combined with a high computational cost of training often renders these models unusable in practical CPD scenarios [8]. Theses approaches, known as hybrid approaches, have been promising in maintaining a balance between performance and explainability, where statistical baselines were maintained while neural feature extractors were added [20]. Given the focus of this project on explainability and robustness of CPD methods on real data, interpretable algorithms will be prioritized and benchmarked on the gaitHunt1 dataset, a labeled human gait sequence with a known anomaly window [9]. The Advantage This dataset allows for the objective evaluation of algorithm performance.

Multiple review studies show that benchmarking CPD methods is still challenging due to inconsistent datasets, lack of clarity of evaluation metrics, and biased baselines [16], [5]. Community critiques have identified that most published evaluations of CPDs fail to calibrate their estimates at baseline, leading to overoptimistic claims of performance [12]. Thus, this project will consist of a critical evaluation of the outputs of each method used, the application of standardised metrics (precision, recall, F1-score, detection delay), and transparency in the reporting of methods for a fair and reproducible assessment.

Aims and Objectives

This work will investigate, develop and evaluate various methods including some of machine learning and statistical methods to detect change points in a univariate time-series data, and particularly including the gaitHunt1 dataset. This human activity pattern with a well-defined anomalous region along with normal events, is realistic dataset which can be used for evaluation of CPD based anomaly detection. The intention is to develop a technically sound and comprehensible method that is computationally manageable, but also allows a critical reflection on the suitability in the commonly used detection algorithms of the suspect values present in the data.

The project will start with a thorough theoretical overview of classical and contemporary CPD methods, as we list in the following: statistical models such as Bayesian Online Change Point Detection (BOCPD), Pruned Exact Linear Time (PELT) algorithm and kernel-based methods and hybrid ones wherein a statistical baseline, for instance BOCPD, is combined with a neural feature extractor. A more extensive exploratory analysis will ensue, allowing the use of Python libraries to plot the time series, observe trends and the anomaly region, and to use smoothing, Z-score normalization, or to remove outliers, if need be, to enhance the quality of the model input.

Two main CPD algorithms will be employed: online detection of distributional changes via BOCPD along with an offline method from Ruptures library (e.g., PELT or window-based segmentation) such that we can evaluate how online detection compares to offline detection. This work is unique against existing literature in that a direct and reproducible comparison of these approaches is conducted using the same conditions and frameworks – responding to known artefacts that exist in the field of CPD where standard benchmarks and evaluation matrix do not exist. Performance of the model will be evaluated quantitatively and qualitatively using precision, recall, F1-score, detection delay, and computational efficiency metrics.

Moreover, the stability of the computational techniques will be evaluated in synthetical time series experiments with noise levels and anomaly types controlled generated with tools such as TimeSynth or TS-GAN, for which we find that such an aspect is overlooked in many of real world datasets only experiments. Reproducibility and transparency will, of course, be a cornerstone of the entire development process: both version controlled Jupyter Notebooks and Docker containers will be employed to maintain environment consistency. Finally, the work seeks to make a more practical rather than just technical contribution, by providing advice on how developers and practitioners can choose between different CPD methods in the field of behavioural monitoring and other time sensitive anomaly detection settings.

Data and Tools

This could be realized by evaluating the methods of online and offline change point detection (CPD) using the gaitHunt1 dataset. We will compare the efficacy of these techniques in a controlled environment. Recent reviews reinforce the need for comparability in benchmarks used for CPD evaluation [16], which justifies the rationale of the side-by-side analysis. Moreover, advances in unsupervised CPD emphasize the trade-off between detection accuracy against computational complexity [8], [21]. Another method which will be also considered is the Pruned Exact Linear Time (PELT) algorithm, as it has a linear computational cost and is fitted in most of the offline detection scenarios [15]. These circumstances will guide both the choosing and the use of models.

Python libraries NumPy, Pandas and Matplotlib will be used for loading and visualization of data. Anomaly regions will be highlighted and time series will be analyzed for trends, seasonality and noise [2]. Preprocessing techniques such as smoothing, normalization, outlier removal can also be applied to improve input quality. Synthetic time series can be generated using approaches designed to test model robustness under different conditions, such as TimeSynth [19] or TS-GAN [6], allowing controlled experiments with varying amounts of noise and types of anomalies.

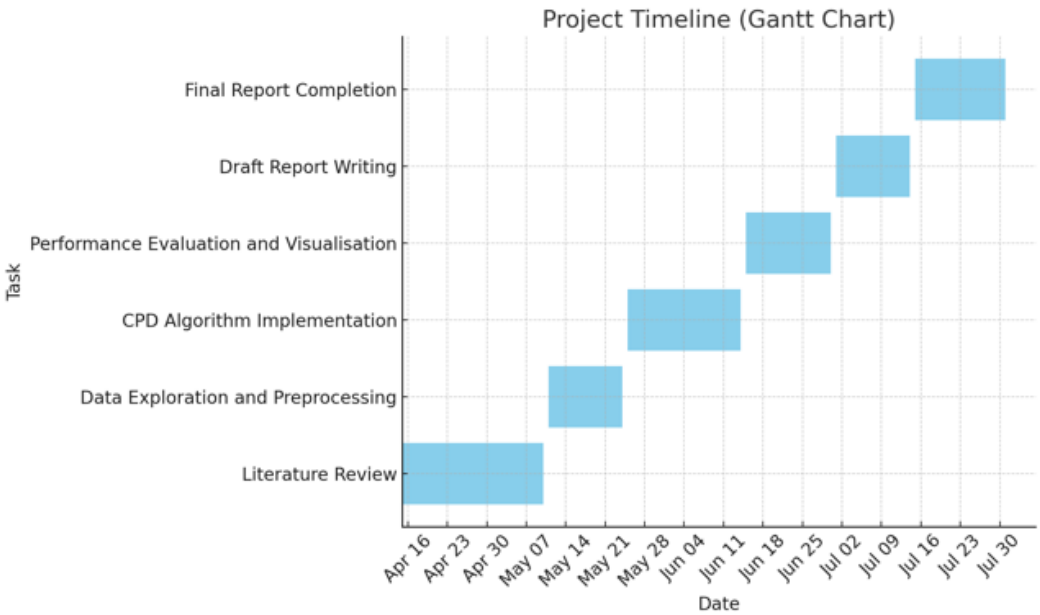
We will take two primary approaches. We will first apply Bayesian Online Change Point Detection (BOCPD) for on-line detection of distributional changes [1]. Second, this library will offer access to multiple offline algorithms such as kernel-based detection, window-based segmentation and dynamic programming methods like PELT [21]; [15]. From each of the categories, at least one separate method will be chosen for the comparative analysis keeping the online v/s offline approach in mind. For quantitative evaluation, predicted change points will be compared with the labelled anomaly window in gaitHunt1. Metrics will include precision, recall, F1-score, detection delay and computational efficiency [12]. By visualising the data and algorithm we will qualitative help interpreting the behaviour. We will ensure reproducibility using Docker containers to isolate the Python environment and dependencies [4], and version-controlled Jupyter notebooks.

The code will be implemented using solely Python, using NumPy and Pandas for data management, Matplotlib and Seaborn for visuals, and Ruptures [3], BOCPD-related libraries

[1], and TimeSynth [19] for algorithms. In the event sufficient time has been allocated, synthetic data experiments will be performed to additionally verify method robustness across differently simulated environments. It will utilize the gaitHunt1 dataset from the UCR Time Series Anomaly Archive, containing univariate human gait readings with a clearly labelled anomaly interval [9]. The entire data analysis and algorithm development will take place in Python (version 3., leveraging libraries like NumPy and Pandas for data processing, Matplotlib and Seaborn for plots, Ruptures for running offline change point detection algorithms: PELT, kernel-based, etc. It will leverage open-source code related to Bayesian Online Change Point Detection, to enable real-time analysis. If time allows or other synthetic time series generation methods such as TimeSynth or TS-GAN may be employed to test for robustness [19]. All work will be developed and documented in Jupyter Notebooks with environment reproducibility via Docker containers [4]. We will manage version control with Git, and a private GitHub repository will be used. No proprietary software or bespoke hardware will be needed, and the project should be feasible on normal academic computing resources.

Project Management

The project is planned over a 12-week period during Term 3. The timeline is organized into phases to facilitate systematic development, experimentation, and reporting. Progress will be monitored regularly using a logbook, with schedule adjustments made as needed.



This plan is structured to ensure consistent progress, incorporating evaluation and refinement phases to address potential implementation challenges or scope adjustments.

The gaitHunt1 dataset is publicly available, fully anonymised, and is intended for benchmarking in academic settings, so we were not using personal or sensitive data which would require formal ethical approval [9]. But we do need to acknowledge some project risks and ways to manage them: The performance of the algorithm is uncertain, challenging us with either undetected change point expectations or inconsistent (e.g., temporal) detections, to mitigate we will be implementing multiple methods and a benchmark will help establish the best solution; the use of a single dataset restricts generalisation potential which may warrant examining other archives or creating synthetic data if time allows; and narrow time-frames create a chance of delays during development or evaluation, which will be mitigated through weekly check-in meetings to capture progress, agile reporting to strike a balance between fidelity and "last user" timelines and detection of blockers with a constant tracking of identified issues within established risk management practices [22]. Further, a documented risk register ought to maintain continuous monitoring of such risks, together with the support of a supervisor, ensuring that whenever there are any probable challenges, these will be addressed in a timely manner to ensure the project runs on track [23], [24].

Conclusion

Core of the project consists of applying and evaluating change point detection algorithms on real 11-dimensional time series uncovered via an unmonitored gait analysis to identify whether or not significant changes in human movement patterns occurred elsewhere within the study have subsequent applicability to modelling physiological autoregressive time series data. Methods include Bayesian Online Change Point Detection [1] and algorithms from the Ruptures library [21] that identify changes in statistical trends, which is the primary indicator of gait anomalies in human movement. The labelled anomaly region in the dataset is a suitable testbed to examine the performance of the various techniques under controlled conditions.

The project aims to generate a series of reproducible benchmarks, as well as a modular Python toolkit for CPD research [12] by focusing on quantitative accuracy metric (precision, recall, F1-score, detection delay) and qualitative interpretability analyses. Through a structured methodology and careful evaluation of performance with a critical discussion of limitations and trade-offs [8], [15], the study is anticipated to shape the current best practices in CPD while guiding practitioners with selecting suitable methods for behavioural monitoring applications.

Expected deliverables from the project include a comparative report explaining strengths and weaknesses of algorithms tested, an open-source implementation with documented examples, and recommendations for future work, including extending the analysis to multivariate gait datasets or embedding deep-learning feature extractors in hybrid CPDs [20]. These results collectively deliver theoretical knowledge and practice-oriented best practices to help in the continuous adoption of explainable CPD solutions in practice, in areas where timely anomaly detection is crucial.

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