Developing changepoint methodology motivated by climate applications

Rebecca Killick, Clemenson University

Global warming is always a hot topic and whatever side of the fence you sit on, you cannot deny the data that the climate is changing - regardless of attributing a cause to that. These changes have huge impacts on individual lives all over the world. In the UK we have had warmer summers and milder winters (at least in southern parts of the UK!) and more extreme weather events than earlier in the twentieth century. Most people have a storm, flooding or drought story, or know someone who has.

In this talk, I will share some of my own stories about working with the data behind the headlines, mostly in temperature time series from across the globe. I will provide an introduction to the changepoint models I use to describe these temperature data and provide commentaries on working with environmental scientists and media engagement. From the statistical side, I am hoping that you will take away some insights into why changepoint models are useful, an intuition of (and some R packages for) how to apply these models to any data, and the key challenges you may come across in doing so. In littering my talk with anecdotes about interdisciplinary work, I am hoping to convey both the joys and realities of taking this approach to motivate those who haven't taken this path yet, whilst simultaneously building a shared connection with those who have.

Efficient Data Integration Techniques in Some Modern Applications

Kun Liu, JPMorgan Chase & Company

Modern data science often requires integrating information from heterogeneous sources to support timely and reliable decision-making. This talk discusses efficient data integration techniques motivated by several modern applications, including online monitoring of large-scale data streams, consensus sequential detection over distributed networks, clinical trial analysis, and robust statistical inference with contaminated data. I will highlight how scalable statistical procedures can combine local information into useful global decisions, with emphasis on methods that remain computationally feasible, statistically efficient, and robust in complex real-world settings. The talk will also connect these methodological ideas to broader applications in finance, healthcare, manufacturing, and security, where data-driven decisions must often be made under uncertainty and at scale.

Slope-Aware RDP for Slope Changepoint Detection

Meenu Rani, Indian Institute of Technology Ropar

This talk addresses the problem of detecting changes in the slope of a regularly observed time series. The Ramer-Douglas-Peucker method is commonly used to simplify curves by keeping the most important points that describe their overall shape. In this work, we introduce a slope-aware version of this method for identifying points where the trend of a time series changes. Instead of choosing a technical threshold, the proposed method uses only the desired number of changepoints and then selects the most relevant points of slope change. The method is simple to use, computationally efficient, and can be applied directly to the original time series. In simulation studies, its ability to locate changepoints improves as the signal becomes clearer. One possible application is in financial data, where the method can help identify changes in the trend of stock prices, market indices, or other financial time series.

Online Change Point Detection Based on Machine Learning Approach

Ayten Yiğiter, Hacettepe University

The change point problem arises in many fields, including financial time series analysis, signal processing, and statistical process control. It concerns the identification of structural changes in the statistical properties of sequentially observed data. Such changes typically arise from shifts in the parameters of the underlying data-generating process and may be reflected in changes in statistical moments or other characteristics of the observed series. Accurate detection of change points is of considerable importance, as it directly influences data modeling, forecasting accuracy, and subsequent decision-making processes.

In the literature, change point detection methods are generally categorized into two main settings: offline and online detection. In addition, different methodologies have been proposed depending on whether the underlying change occurs abruptly or evolves gradually over time. In this study, the online change point detection problem is investigated using an approach that incorporates machine learning components. The proposed approach is evaluated using real-world datasets, and its performance is compared with existing methods to demonstrate its effectiveness and practical applicability.