CSC8639 Interim Report: Explaining Time Series Downsampling

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Introduction

Decision-makers must trust that the data being considered sufficiently represents the situation they are deciding on. Trusting the data means trusting which data points are selected, how this data collected and stored, and the capability of data practitioners to understand the quality, insights and limitations of it. This data pipeline can obscure or loose important information making it difficult to determine and explain that the data reliably and truthfully reflects the situation in question. Today's increasing volume of data makes this even more difficult (Yanzhe An and Wang (2022)).

This problem is particularly pertinent to collections of observations obtained through repeated measurements over time (Statistics (2023)), known as time series data. "[W]idely generated by industry and research at an increasing speed" (Yanzhe An and Wang (2022)), voluminous time series data is putting unprecedented demand on resources (Schlossnagle, Sheehy, and McCubbin (2021), Atlam, Walters, and Wills (2018)). This is forcing data practitioners to utilise methods, such as aggregation, windowing, and downsampling, that reduce data volumes to align with cost or time limitations, storage capabilities, and sustainability ambitions (Steinarsson (2013), Yanzhe An and Wang (2022), Tank (2020)). These reduction methods involve discarding data, which could result in the further loss of important information for decision-makers, and reduce the representativeness of the data.

However, discarding this data is a vital part of making voluminous time series understandable for human observation (Steinarsson (2013)). Downsampling reduces "...the number of data points while preserving the overall shape of the time series" (Donckt et al. (2023)), allowing the human eye to observe only the most valuable data points. Line graphs are an effective and popular method for visualising this data (Yunhai Wang and Yu (2023)). Despite effectively conveying the overall shape of the time series data (Aigner et al. (2008)), they offer little insight into which downsampling approach and parameters best represent the original data. Better visualising the impact of downsampling time series data, is likely help data practitioners confidently select their downsampling approach and better explain the insights and limitations of downsampled data. In doing so, data practitioners can better support decision-makers to trust the data they are considering.

Aim and Objectives

The research outlined by this interim report aims to improve how data practitioners better understand and explain the impact of downsampling time series data. It is hoped that this research will support data practitioners to determine and communicate whether data being considered by decision-makers reliably and truthfully reflects the situation in question, and help increase decision-makers trust in data-led decision-making.

To better understand and explain the impact of downsampling voluminous time series data, the research addresses the following five objectives:

- Develop a baseline understanding current downsampling algorithms' impact on original data sets by using the R package `ImputeTS` (Moritz and Bartiz-Beielstein (2017)) to compare visualisations of the original and compressed data.

- Conduct exploratory analysis to determine common properties of time series data, attempting to refine the 22 time series features identified by `catch22` (Lubba et al. (2022)) to identify the most useful features for comparing the impacts of downsampling algorithms on original time series data.
- Design comparative visualisations of the most useful features of time series data across different downsampling algorithms to help communicate their impacts on the original data.
- Survey existing metrics used to compare downsampled data representativeness to inform an evaluation method for this research.
- Conduct user research with data practitioners and decision-makers to understand how they engage with downsampled time series data and its trustworthiness.

The aim and objectives set out here are ambitious; it is likely that each objective could be an individual project and the author is a part-time student. Given this, this project will delivered iteratively; the research objectives will be continuously reviewed to successfully deliver the most impact in the available time.

Project Plan

This project is divided in to five activity themes (Milestones, Reading, Exploratory Data Analysis, Visualisation, User Research) and six phases (1-6) to deliver the research aim and objectives by 15 August 2023. This plan is visualised on the next page.

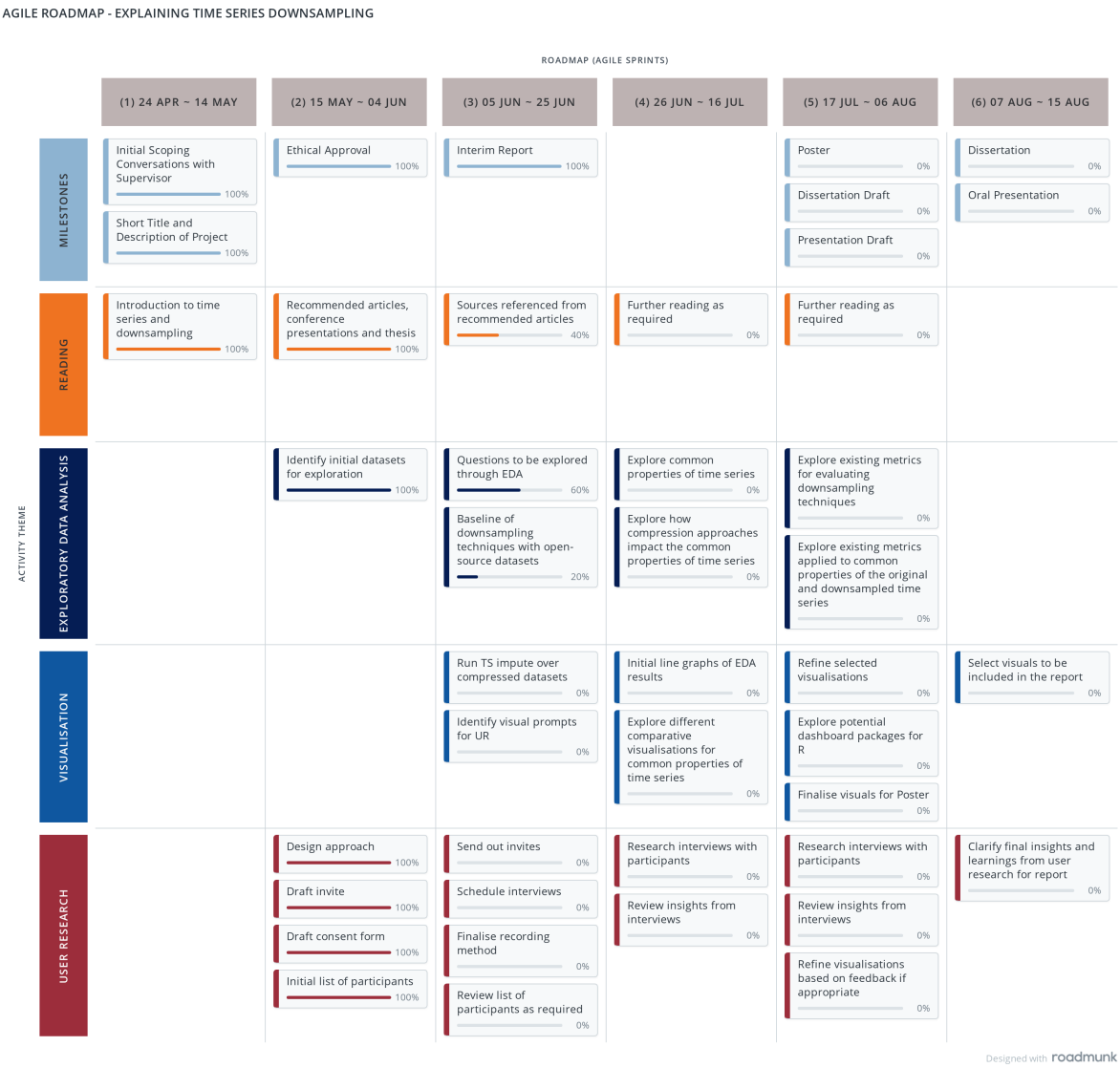
Overview of Progress

Progress on the project so far includes activity specified in phases (1) and (2) as well as some phase (3) activities, where progress to date is visualised as a percentage. Further details on this progress are set out below by activity theme:

- *Milestones:* Four meetings between the project supervisor and author have taken place, where the project scope, approach, aims and objectives have been clarified. A short title, description, and ethical approval have been submitted as required. The Data Management Plan is completed and shared in Annex A.
- *Reading:* Initial exploratory reading around time series data and downsampling was conducted before the supervisor recommended nine sources. These sources were read, and further reading of referenced sources is underway.
- *Exploratory Data Analysis:* The data sets for exploration were identified with support from the supervisor; the author has drafted questions to guide exploration and initial visual exploration is being conducted on selected data sets.
- *Visualisation:* Potential visuals for user research are being collated, but this activity theme is not a focus of phase (1) and (2).
- *User Research:* The approach to user research has been designed and discussed with the supervisor; invites, consent form,question list, and an initial list of participants are drafted. The invite, consent form, and question list are attached to this interim report (Annex B, C, and D).

Overview of Project

The visualisation of the project plan highlights the key activities within each theme across the project phases. Because of this iterative approach, it was agreed with the project supervisor that an agile approach was appropriate; the project plan is visualised as an agile roadmap. This visualisation, created on a platform provided by `roadmunk`, is interactive and will be updated to reflect the iterative nature of the project.



Project Risks and Mitigation

To be delivered successfully, there are several risks that this project may need to mitigate. These are set out in the table below with a risk rating of low, medium or high.

Impact	Likelihood	Risk	Mitigation
Low	High	Fewer people agreed to participate in User Research than expected.	Invites will be sent in a phased approach to enable further invites to be sent if response numbers are lower than expected.

Impact	Likelihood	Risk	Mitigation
Low	High	Number of decision-makers and data practitioners who agreed to participate in User Research is imbalanced.	The numbers for User Research are unlikely to be statistically significant for this project anyway, so any further limitations on the findings of User Research and their impact will be set out in the final report.
Low	Medium	Data availability and cleaning take a significant amount of time, and may detract from original research.	A subs-selection of open source data previous time series visualisation research has been chosen in mitigation.
Low	Medium	The outputs from User Research, such as interview content or personal details, are not stored and treated securely.	Consent forms will be collected prior to scheduling interviews and participants will be annonymised in a locked spreadsheet saved separated from the project. There will be no personal details associated with the interview content, which will also be saved in a locked folder separate from the project.
Medium	Medium	There are several elements of this project that are, to some extent, dependent on other project elements. For example, the exploratory data analysis and visualisation.	These dependencies are being mitigated by the agile approach to the project, allowing the author to adapt as needed, and clear communication with the supervisor.
High	Medium	The author is a part-time student working towards the same deadlines and criteria as full-time students.	The agile roadmap clearly sets out how the project is likely to progress, and the research objectives have been selected to help maximise impact if there are delays with some components. Progress will be clearly communicated to the supervisor, and an extension may be applied for if required.

This list of risks and mitigations will be reviewed and updated throughout the project as more may arise when the research is iterated.

Conclusion

The research of this project aims to improve how data practitioners better understand and explain the impact of downsampling time series data. This report has introduced the research topic by outlining why this matters, set out the research aim and objectives as well as progress so far, visualised the project plan and explained the risks that may need mitigated. The information provided in the report will be continuously reviewed in consultation with the project supervisor so that the research is delivers the most impact in the time available.

Annex A: Data Management Plan

0. Proposal name

Explaining Time Series Downsampling

1. Description of the data

1.1 Type of study

Improving how data practitioners better understand and explain the impact of downsampling time series data, this study includes time series data sets, exploratory analysis, of these datasets in R, user research and comparative surveys of compression algorithms, common evaluation metrics, and time series visualisations.

1.2 Types of data

Both quantitative data from open-source data sets and qualitative data from user research will be used in this study.

The quantitative data sets are being sourced from the Alan Turing Institute 'AnnotateChange' (https://github.com/alan-turing-institute/AnnotateChange) and 'Turing Change Point Dataset' (https://github.com/alan-turing-institute/TCPD/tree/master). The 'AnnotateChange' repository was created to collect annotations of time series data to construct the 'Turing Change Point Dataset' repository by Van den Burgh and Williams (2020). The publicly available data in these datasets will be used within the stipulated licensing agreement(s) stipulated by the data owner(s).

The qualitative data will be collected from interviews with decision-makers and practitioners..

1.3 Format and scale of the data

The qualitative data will be collected via recorded video calls with participants and notes taken in csv files.

The quantitative demo data from 'AnnotateChange' will be used initially as JSON scripts are provided. A subset of data is likely to be selected from the 'Turing Change Point Dataset', which includes 37 datasets of time series data from a variety of contexts as well as 5 quality control datasets. The data across these repositories are provided in different formats pending where the original data is hosted. The FAIR principles (Findability, Accessibility, Interoperability and Reusability) are satisfied by the Alan Turin Institute's use of these datasets as benchmark suites. The project will also utilise R, RStudio and a variety of R packages, like RMarkdown to ensure reproducibility.

2. Data collection / generation

2.1 Methodologies for data collection / generation

No new time series data will be collected for this study. The results created during this research will be clearly documented in the report, tables and reproducible code housed in GitHub (https://github.com/MoFrod/downsampling_timeseries/tree/main).

New data will be collected from interviews with data practitioners and decision-makers considering time series data. There is no data source that currently sets out the perspectives of these users, so new data is needed. This new qualitative data will be collected from a standardised list of interview questions that are asked to volunteer participants.

2.2 Data quality and standards

The quantitative data quality of the datasets is acceptable in line with the FAIR principles, and data cleaning will be conducted as required. The qualitative data quality cannot be determined until it is collected.

3. Data management, documentation and curation

3.1 Managing, storing and curating data.

The qualitative data generated by user research interviews will be stored in password protected

Annex B: Draft Invite for User Research

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User Research Invite

Dear _____,

You may remember that I am undertaking an MSc in Data Science with a specialisation in AI at Newcastle University.

Would you be willing to be interviewed for User Research that I'm conducting for my dissertation? The interview will be conducted by a video call in under an hour and focus on how decision-makers and data practitioners engage with and trust time series data. [*If not a data practitioner add*: , which are collections of observations obtained from repeated measurements over time.]

Please note that your contribution will be anonymised and that you will need to complete the attached consent form before we begin.

Any questions are always welcome.

Warm regards,

Morgan

Annex C: Draft Question List for User Research

Annex D: Draft Consent Form for User Research

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Consent Form – User Research

Dear _____,

Thank you for agreeing to participate in this research session. Your participation is helping build a better understanding how decision-makers and data practitioners engage with time series data.

The purpose of this research is to improve how data practitioners better understand and explain the impact of downsampling time series data. Today, industry and research are generating observations from repeated measurements over time (time series data) in unpresented volumes and increasing speeds. To collect, store and make this data understandable to humans, some data must be discarded; one process to do this is called downsampling. By improving how this process is understood and explained, it is hoped that this research will support data practitioners to communicate whether data being considered by decision-makers reliably and truthfully reflects the situation being decided on, and help increase decision-makers trust in data-led decision-making.

This research session will take the form of an interview, during which certain types of personal data may be collected. However, strict principles and processes for data collection and protection will be followed.

Information being collected:

- Personal data including name, job role and experience of data
- Personal views on the topic of this research
- You may be shown prototype data visualisations and asked for your feedback
- The research session will be recorded and notes taken to document your reflections

Privacy will be maintained by:

- Never sharing any recordings or information about you beyond the researcher and potentially the research supervisor
- All recordings and information collected will be treated as confidential, anonymised and stored in password protected folders
- Your comments may be published as part of this research, but your data will be anonymous – this means your name, identity and job role will not be linked in the research to anything you say or do

Please note:

- There are no right or wrong answers; the purpose of this session is to understand how people engage with a particular type of data
- You are not being evaluated in any way
- Your name will not be associated with any data collected during the session

How to contact the researcher or supervisor

If you have any questions, would like to withdraw from the research or have your data removed, please contact either:

- the researcher **Morgan Frodsham** at M.C.M.Frodsham2@newcastle.ac.uk
- the supervisor **Matthew Forshaw** at matthew.forshaw@newcastle.ac.uk

Annex E: References

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