TRANSFER LEARNING METHOD FOR ENERGY DISAGGREGATION

MSC DATA SCIENCE THESIS - INTERIM REPORT

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Transfer Learning For Energy Disaggregation

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1 Introduction

Non-intrusive load monitoring (NILM), also known as energy disaggregation, is a valuable technique for understanding and managing energy consumption at the individual appliance level. It enables the identification and analysis of energy usage patterns from aggregated data, providing insights that can aid energy providers, policymakers, and consumers in making informed decisions to optimize energy consumption and reduce waste [1].

The research on Non-Intrusive Load Monitoring (NILM) began with the influential work of George Hart in the mid-1980s [2] [3]. Hart introduced a broad range of attributes referred to as a "signature taxonomy". Hart [4] initially coined the concept of disaggregating the total energy and demonstrated that each appliance or device could be recognized using an appropriate LS feature, as shown in figure 1. He also defined the following three types of device models:

- Type 1: ON/OFF;
- Type 2: Finite state machine (FSM);
- Type 3: Continuously variable.

He concentrated on extracting more specific traits in his early tests in 1984. However, Hart later decided to focus exclusively on capturing transitions between steady-states, which caused many NILM algorithms created for low-frequency data (1 Hz or slower) to adopt a similar strategy by extracting only a small number of features. On the other hand, there have been a number of cases in the literature where researchers manually constructed feature extractors for high-frequency NILM (sampling at kHz or even MHz) to capture more information [5] [6].

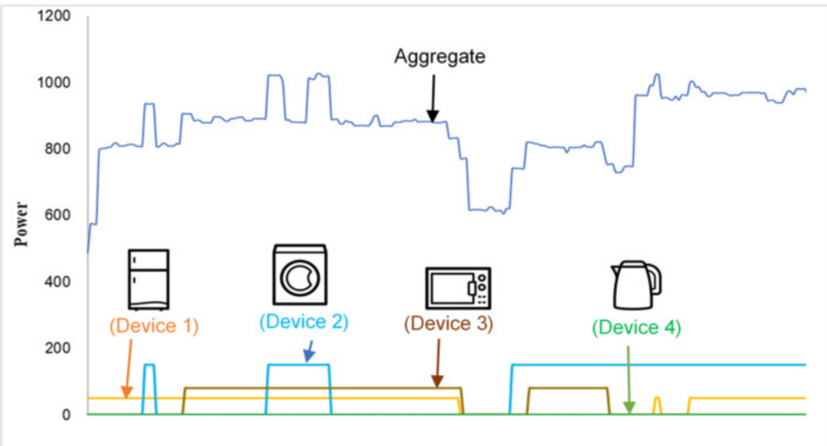

Figure 1: Concept of aggregate load profile and NILM. The task of NILM is to disaggregate the energy of each device and then identify it as shown in the colored plots.

Prior to 2012, manually designed feature detectors like SIFT [7] and DoG were the main methods for obtaining features in image categorization. However, Krizhevsky et al.'s algorithm [8] achieved considerable advancement in 2012, outperforming competing approaches in the ImageNet Large Scale Visual Recognition Challenge. Their method outperformed the second-best method, which had a 26% mistake rate, by achieving a remarkably low error rate of 15%. It's noteworthy that Krizhevsky et al. didn't use manually built feature detectors. Instead, they used a deep neural network that independently figured out how to separate a hierarchy of features from the unprocessed visual input. Since then, this ground-breaking method, known as deep learning, has taken over several fields, including automatic speech recognition and image categorization and even learning complex tasks like playing computer games from scratch [9]. However, energy disaggregation posed challenges, including limited labeled data and the complexity of distinguishing between different appliance signatures [1].

Following Krizhevsky's research and performance, his algorithm showcased deep learning techniques that have emerged as powerful tools for addressing complex pattern recognition problems. These techniques have shown great promise in the field of energy disaggregation, as deep learning models can learn intricate patterns and capture the unique characteristics of appliances from energy consumption data [10]. Transfer learning is a deep learning technique that has attracted a lot of attention since it uses pre-trained models on massive datasets to solve tasks that are similar but not the same [11]. By transferring knowledge from pre-trained models, transfer learning has the ability to solve the problem of little labeled data in NILM. These models can be fine-tuned on smaller NILM datasets after being trained on large datasets like ImageNet [11]. Using a deep learning model that has already been trained on a sizable dataset, such as ImageNet, and fine-tuning it on a smaller NILM dataset is known as transfer learning in NILM. The model can then specialize and adjust those generic features to the goal of energy disaggregation after learning them during the pre-training phase [12]. Transfer learning has been applied in NILM in a number of research, leading to considerable gains in energy disaggregation accuracy. For instance, [10] used deep neural networks with transfer learning for NILM and showed how well it could capture appliance-level energy use. They were able to increase the precision of energy disaggregation and enable more precise energy management by utilizing pre-trained models.

Other deep learning architectures, such as recurrent neural networks (RNNs), have also been used in NILM with transfer learning in addition to deep neural networks. RNNs that have already been trained and fine-tuned for energy disaggregation tasks were used by [12]. The models displayed improved generalization skills, enabling them to handle various appliance kinds and adapt to different household environments, and their findings demonstrated the advantages of transfer learning.

Transfer learning has benefits for NILM that go beyond increased generalization and accuracy. Because the beginning layers of the pre-trained models already have knowledge of generic features, transfer learning also cuts down on the amount of time needed to train NILM models. This significantly accelerates the training process and makes the models more practical for real-world energy disaggregation applications [13],[14]. Furthermore, transfer learning enables the development of NILM models that can effectively handle the challenges posed by limited labeled data. By leveraging the knowledge captured in pre-trained models, the adapted NILM models can extract relevant information from small datasets and generalize well to unseen instances, improving the overall performance of energy disaggregation [14]. In conclusion, the utilization of deep learning techniques, including transfer learning, in non-intrusive load monitoring holds great potential for addressing the challenges of accurate and efficient energy disaggregation [15]. The ability to leverage pre-trained models and adapt them to the specific task of NILM enables the development of models with improved accuracy, generalization capabilities, and reduced training time. This research direction facilitates more precise energy management and supports the transition towards sustainable and energy-efficient practices.

2 Aim and Objectives

2.1 Aim

This work seeks to understand the effective NILM system frameworks and review the performance of the benchmark algorithms. Following this, the paper proposes the approach of using transfer learning methods to achieve high-accuracy load disaggregation and tackles the problem of generalizability by investigating domain adaptation methods for energy disaggregation.

2.2 Objective

This work will have the following objectives:

- Using certain characteristics of the load signature (LS), such as statistical values like the data mean, peak, slope, median, mode, percentiles, range, variance, and standard deviation, it is vital to identify or categorize the event and the relevant device. It is possible to apply supervised (classification) or unsupervised (clustering) methods. We can comprehend load identification or disaggregation at the individual device level by repeating this method for a few data samples.
- Knowledge transfer from one building (the source domain) to another (the target domain) is a common step in the energy disaggregation process. The objective would be to investigate domain adaption methods designed expressly for energy disaggregation. With varying appliance kinds, usage patterns, and energy profiles, multiple buildings can be connected using this strategy.

Optional objectives time permitting:

- In addition to the data on energy use, including auxiliary data sources that might improve transfer learning. A few context-rich data sources are weather information, occupancy data, and appliance metadata. Accurate disaggregation could be enhanced by creating strategies to successfully integrate and utilize these supplementary data sources during the transfer learning process

3 Overview of Progress

In the initial phase of the project, an extensive review of the literature was conducted, specifically focusing on using neural networks for energy disaggregation. This literature review contributed to a deeper understanding of the subject matter and identified gaps in existing research. The UK-DALE dataset was downloaded from the UKERC EDC website. The dataset comprises recordings from five houses, capturing detailed information every six seconds. Specifically, recorded the active power consumption of individual appliances and the overall apparent power demand in all houses. Furthermore, in three houses, collected data at a sampling rate of 44.1 kHz for whole-house voltage and current, which was down-sampled to 16 kHz for storage. Additionally, calculated the active power, apparent power, and RMS voltage at a lower frequency of 1 Hz. In House 1, conducted recordings for a period of 655 days and meticulously captured data from nearly every appliance in the house. This resulted in a total of 54 separate channels of recorded information, although fewer channels were recorded during the initial stages of the dataset.

The project has initiated the data preprocessing stage with the help of NILMTK to help load the datasets. This stage involves cleaning and organizing the collected data to ensure its quality and suitability for analysis. Currently, the main focus is on conducting comprehensive preprocessing tasks, such as handling missing data, eliminating outliers, merging different channels, and extracting and loading appliance activations followed by standardization of the data. These steps are crucial to ensure that the data is ready for eda and implementing spectral clustering and GAN-NILM. As the project progresses, additional data analysis and model development will be carried out. Through evaluating and comparing different machine learning models using appropriate metrics, valuable insights will be gained to determine the best approach for energy disaggregation. Overall, significant progress has been made in terms of the literature review, data collection, and data preprocessing stages of the project.

4 Project Plan

The project is expected to be completed between April 24 and August 14, 2023. Figure 2 shows the project timeline in visual form. The project initially comprised studying Neural NILM, which is the application of neural networks to create a network architecture that can be used for energy disaggregation and compare its results on different datasets, to deduce the generalizability of the model. The whole literature review has been assembled and is prepared to be included in the final report. The project's execution phase is scheduled to last from June 9 to August 6. Work would be done initially on the exploratory data analysis followed by applying a clustering algorithm for different houses in the dataset to gather information regarding load disaggregation on the appliance level. During this timeframe, work would also be focussed on creating machine learning methods based on the transfer learning approach. This time would also be used to investigate the problem of generalizability by investigating domain adaptation methods GAN-NILM. Concurrently training and testing of the models will be performed in order to achieve an effective high accuracy.

If time permits, the study also seeks to investigate the dataset using the suggested architectures and evaluate the performance when auxiliary data such as appliance metadata is used. In conclusion, there are clearly defined deliverables for the project, and progress will be tracked continually throughout.

References

[1] A. Zoha, A. Gluhak, M. Imran, and S. Rajasegarar, "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey," *Sensors (Basel, Switzerland)*, vol. 12, pp. 16838–16866, 12 2012.

[2] G. W. Hart, "Prototype nonintrusive appliance load monitor. technical report, mit energy laboratory and electric power research institute," 1985.

[3] G. W. Hart, "Nonintrusive appliance load monitoring," *Proc. IEEE*, vol. 80, pp. 1870–1891, 1992.

[4] M. Ghaffar, S. Sheikh, N. Naseer, Z. Mohy-Ud-Din, H. Rehman, and M. Naved, "Non-intrusive load monitoring of buildings using spectral clustering," *Sensors*, vol. 22, p. 4036, 05 2022.

[5] S. Leeb, S. Shaw, and J. Kirtley, "Transient event detection in spectral envelope estimates for nonintrusive load monitoring," *IEEE Transactions on Power Delivery*, vol. 10, no. 3, pp. 1200–1210, 1995.

[6] N. Amirach, B. Xerri, B. Bruno, and C. Jauffret, "A new approach for event detection and feature extraction for nilm," *2014 21st IEEE International Conference on Electronics, Circuits and Systems, ICECS 2014*, pp. 287–290, 02 2015.

[7] D. Lowe, "Object recognition from local scale-invariant features," in *Proceedings of the Seventh IEEE International Conference on Computer Vision*, vol. 2, pp. 1150–1157 vol.2, 1999.

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, p. 84–90, may 2017.

[9] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. A. Riedmiller, A. K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, A. Sadik, I. Antonoglou, H. King, D. Kumaran, D. Wierstra, S. Legg, and D. Hassabis, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, pp. 529–533, 2015.

[10] J. Kelly and W. Knottenbelt, "Neural nilm: Deep neural networks applied to energy disaggregation," 11 2015.

[11] N. Batra, A. Singh, and K. Whitehouse, "Gemello: Creating a detailed energy breakdown from just the monthly electricity bill," *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016.

[12] M. DIncecco, S. Squartini, and M. Zhong, "Transfer learning for non-intrusive load monitoring," 2019.

[13] A. Verma, A. Anwar, M. A. P. Mahmud, M. Ahmed, and A. Kouzani, "A comprehensive review on the nilm algorithms for energy disaggregation," 2021.

[14] K. Li, J. Feng, J. Zhang, and Q. Xiao, "Adaptive fusion feature transfer learning method for nilm," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–12, 2023.

[15] A. M. A. Ahmed, Y. Zhang, and F. Eliassen, "Generative adversarial networks and transfer learning for non-intrusive load monitoring in smart grids," in *2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, pp. 1–7, 2020.

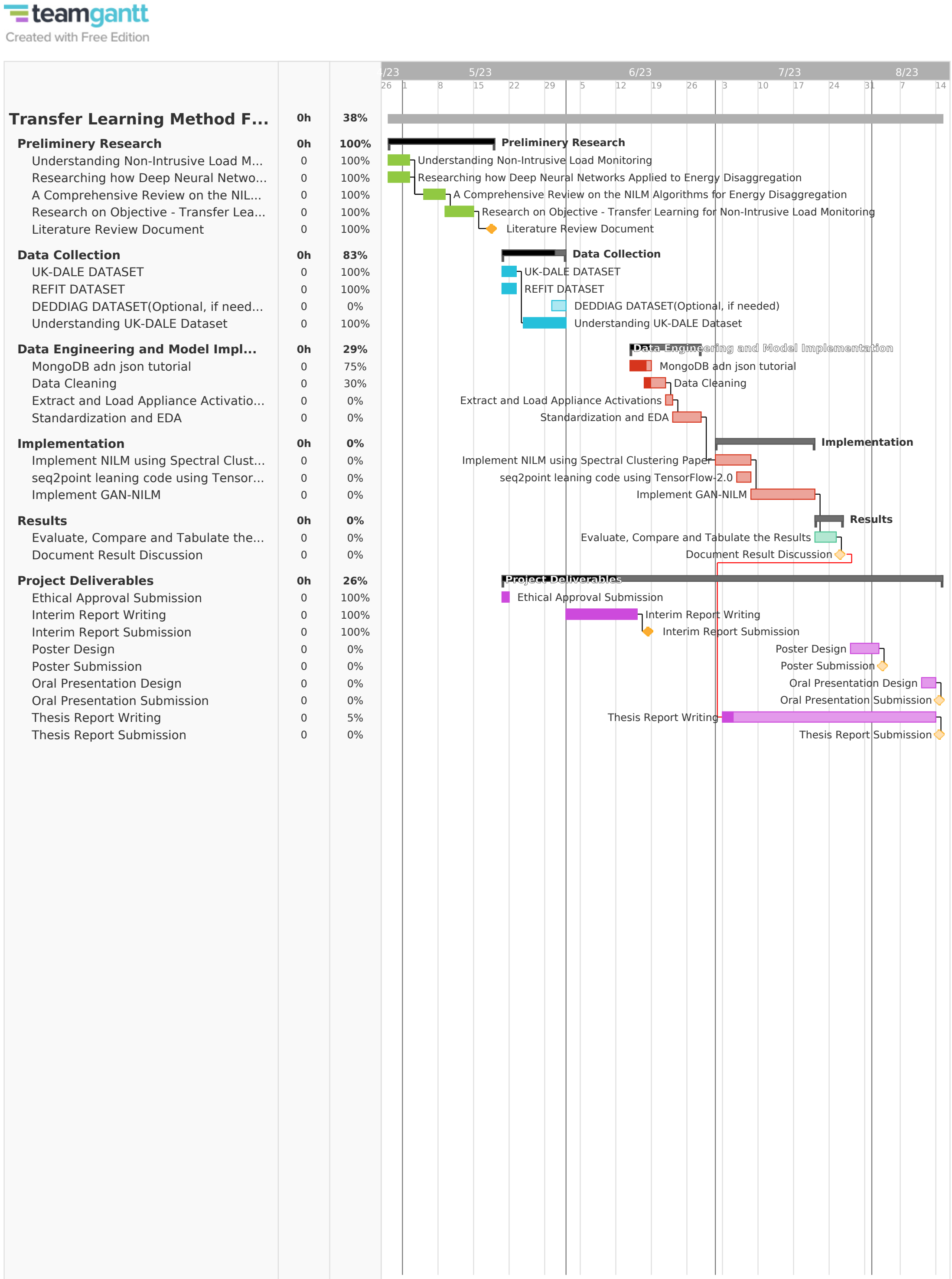

Figure 2: Gantt Chart of the proposed project. Tasks are to scale as per the date range, and dependencies are shown as lines.

DATA MANAGEMENT PLAN

DATA MANAGEMENT PLAN

0. Proposal name		
Project: Transfer Learning Method for Energy Disaggregation		
Author: Rohit Kumar	*Version: 1*	*Date: 12 June 2023*

1. Description of the data

1.1 Type of study

This work seeks to understand the effective NILM system frameworks and review the performance of the benchmark algorithms. Following this, the paper proposes the approach of using transfer learning methods to achieve high-accuracy load disaggregation and tackles the problem of generalizability by investigating domain adaptation methods for energy disaggregation.

1.2 Types of data

This dataset records the power demand from five houses. In each house, we record both the whole-house mains power demand every six seconds as well as the power demand from individual appliances every six seconds. In three of the five houses (houses 1, 2, and 5) we also record the whole-house voltage and current at 16 kHz.

1.3 Format and scale of the data

High speed (16 kHz) whole-house voltage and current data for 1 house. Data is stored in individual directories for each week. This dataset continues UK-DALE-2015: UK-DALE-16kHz.

Description: High speed (16 kHz) whole-house voltage and current data for 1 house. Data is stored in individual directories for each week. This dataset continues

Data Type: Time Series

Number of Records: 19500

Parameter Names: Timestamp (UNIX epoch = number of seconds since 1970/01/01 00:00 UTC) Appliance power consumption or Aggregate household power (N.B. some meters record active power (W) and some meters record apparent power (VA).

An HDF5 version of the 1-second and 6-second data (for use with NILMTK) is available on the UKERC EDC. The complete April 2017 version of the 16kHz dataset occupies 7.6 TBytes. The 16 kHz data are stored as a sequence of stereo FLAC files ("FLAC" stands for "Free Lossless Audio Codec"). Each FLAC file is about 200 MBytes. One channel is whole-house voltage, the other is whole-house current.

2. Data collection/generation

2.1 Methodologies for data collection/generation

The dataset was first collected by Jack Kelly and the team and is now present on the UKERC EDC website. The dataset comprises recordings from five houses, capturing detailed information every six seconds. Specifically, recorded the active power consumption of individual appliances and the overall apparent power demand in all houses. Furthermore, in three houses, collected data at a sampling rate of 44.1 kHz for whole-house voltage and current, which was down-sampled to 16 kHz for storage. Additionally, calculated the active power, apparent power, and RMS voltage at a lower frequency of 1 Hz. In House 1, conducted recordings for a period of 655 days and meticulously captured data from nearly every appliance in the house. This resulted in a total of 54 separate channels of recorded information, although fewer channels were recorded during the initial stages of the dataset. Notably, the recordings in House 1 will continue for the foreseeable future, enabling long-term observations. For the other four houses, recorded data for several months. Each of these houses recorded between 5 and 26 channels of individual appliance data, providing valuable insights into their energy consumption patterns.

2.2 Data Quality and Standards

When using the UK-DALE dataset for transfer learning in Non-Intrusive Load Monitoring (NILM), data quality and standards are crucial. Through data cleaning techniques like interpolation, smoothing, and outlier detection, it is crucial to resolve missing values, outliers, and inconsistencies in order to assure dependable and accurate findings. The dataset can be made consistent and comparable between various attributes and occurrences by normalizing it. The efficiency of transfer learning is increased by identifying the most instructive features for NILM using methods like correlation analysis or mutual information. The dataset's accurate annotation and labeling provide training and evaluation with ground truth data. Reproducibility is ensured by maintaining thorough metadata documentation, which includes information about data collection, preprocessing procedures, sensor specifications, and variable definitions.

3. Data management, documentation and curation

3.1 Managing storing, and curating data.

For use with the greater computing capacity provided by Google Colab Pro, the UK-DALE dataset has been downloaded and moved to a Google Drive account. There are no issues with its backup because the training data is openly accessible. However, training logs will contain information about the trained networks, including their designs and weights. These logs will be locally backed up and stored in the GitHub repository along with the project source.

3.2 Metadata Standards and data documentation

The network designs and hyperparameter information needed to train the models will be outlined in the main report's appendices. Specific hyperparameter values will be explicitly mentioned in a README file within the project's GitHub repository, together with training schemas and algorithms, to ensure reproducibility. Each training and validation cycle's duration, machine characteristics, and training environment will all be noted down. These specifics will be helpful for comparing the models' performance, particularly in situations where speedy execution is essential, like segmenting live images for autonomous vehicle applications.

4. Data security and confidentiality of potentially disclosive information

4.1 Formal information/data security standards

Since training data is entirely public data, security issues with third-party storage solutions (raised by ncl.ac.uk Working | University Library) are not a concern. Indeed, even any trained networks we create push towards a philanthropic cause meaning public distribution is encouraged.

5. Data sharing and access
5.1 Suitability for sharing *Yes, all of the information I'll be using is openly accessible, has received a lot of peer review, and has been extensively cited in numerous academic works. It will be encouraged to share code and experiments since this project intends to apply transfer learning methods to datasets that are currently available in the wild.* **5.2 Discovery by potential users of the research data** *All code libraries will exist within the public project GitHub repository (https://github.com/mustang-raven999). If the project successfully manages to fulfill its aim, the publication will be sought due to the universal application across domains for fair AI, whence a DOI will be generated to facilitate discovery.* **5.3 The study team's exclusive use of the data** *According to government guidelines, the research data will be stored and maintained indefinitely. The precise retention duration will be chosen and adhered to, ensuring the data's ongoing accessibility and availability. Adhering to specified preservation standards guarantees the study data's safekeeping and continuing upkeep, permitting its future reference, analysis, and prospective use in additional research projects.* **5.4 Restrictions or delays to sharing, with planned actions to limit such restrictions** *There are no substantial restrictions or delays in sharing the data as it is publicly available. Researchers can freely access and utilize these datasets without the need for additional licenses or approvals. The data from the sensors maintained by the UKERC EDC website can be easily accessed by anyone, enabling broad access and use for research purposes.*

6. Responsibilities
Are there any resources (e.g. storage/ training) that you will require to fulfil the plan? *Google Colab Pro+ ≈ £45 / month* *Google Drive Storage (100GB) ≈ £1.59 / month*

7. Relevant institutional, departmental or study policies on data sharing and data security

Policy	URL or Reference
Data Management Policy & Procedures	https://www.ncl.ac.uk/media/wwwnclacuk/research/files/ResearchDataManagementPolicy.pdf
Data Security Policy	https://services.ncl.ac.uk/itservice/help-services/security/
Institutional Information Security Policy	https://services.ncl.ac.uk/itservice/policies/InformationSecurityPolicy-v2_1%20SJ%20v0.1%20amended%202022-08-05.pdf